OPEN DOMAIN FACTOID QUESTION ANSWERING SYSTEM

TEK YANITLI SORULAR İÇİN AÇIK ALANLI SORU YANITLAMA SİSTEMİ

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ETHICS

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- all cited studies have been fully referenced
- I did not do any distortion in the data set
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10 September 2015

FARHAD SOLEIMANIAN GHAREHCHOPOGH

ABSTRACT

OPEN DOMAIN FACTOID QUESTION ANSWERING SYSTEM

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Question Answering (QA) is a field of Artificial Intelligence (AI) and Information Retrieval (IR) and Natural Language Processing (NLP), and leads to generating systems that answer to questions natural language in open and closed domains, automatically. Question Answering Systems (QASs) have to deal different types of user questions. While answers for some simple questions can be short phrases, answers for some more complex questions can be short texts. A question with a single is known as a factoid question, and a question answering system that deals with factoid questions is called a factoid QAS.

In this thesis, we present a factoid QAS that consists of three phases: question processing, document/passage retrieval, and answer processing. In the question processing phase, we consider a new two-level category structure using machine learning techniques to generate search engine from user questions queries. Our factoid QAS uses the

World Wide Web (WWW) as its corpus of texts and knowledge base in document/passage retrieval phase. Also, it is a pattern-based QAS using answer pattern matching technique in answer processing phase.

We also present a classification of existing QASs. The classification contains early QASs, rule based QASs, pattern based QASs, NLP based QASs and machine learning based QASs. Also, our factoid QAS uses two-level category structure which included 17 coarse-grained and 57 fine-grained Categories. The system utilizes from category structure in order to extract answers of questions consists of 570 questions originated from TREC-8, TREC-9 questions as training dataset and 570 other questions and TREC-8, TREC-9, and TREC-10 questions as testing datasets.

In our QAS, the query expansion step is very important and it affects the overall performance of our QAS. When an original user question is given as a query, the amount of retrieved relevant documents may not be enough. We present an automatic query expansion approach based on query templates and question types. New queries are generated from query templates of question categories and the category of a user question is found by a Naïve Bayes classification algorithm. New expanded queries are generated by filling gaps in query templates with two appropriate phrases. The first phrase is the question type phrase and it is found directly by the classification algorithm. The second phrase is the question phrase and it is detected from possible question templates by a Levenshtein distance algorithm.

Query templates for question types are created by analyzing possible questions in those question types. We evaluated our query expansion approach with two-level category structure with factoid question type's include in TREC-8, TREC-9 and TREC-10 conference datasets. The results of our automatic query expansion approach outperform the results of manual query expansion approach.

After automatically learning answer patterns by querying the web, we use answer pattern sets for each question types. Answer patterns extracts answers from retrieved related text segments, and answer pattern can be generalization with Named Entity Recognition (NER). The NER is a sub-task of Information Extraction (IE) in answer processing phase and classifies terms in the textual documents into redefined categories of interest such as location name, person name, date of event and etc. The ranking of answers is based on frequency counting and Confidence Factor (CF) values of answer patterns.
The results of the system show that our approach is effective for question answering and it accomplishes 0.58 values Mean Reciprocal Rank (MRR) for our corpus fine-grained category class, 0.62 MRR values for coarse-grained category structure and 0.55 MRR values for evaluation by testing datasets on TREC-10. The results of the system have been compared with other QASs using standard measurement on TREC datasets.

Keywords: Question Answering Systems, Natural Language Processing, Machine Learning, Pattern Matching, Factoid Question.

ÖZET

TEK YANITLI SORULAR İÇİN AÇIK ALANLI SORU YANITLAMA SİSTEMİ

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Soru Yanıtlama (SY), Yapay Zeka (YZ), Bilgi Tarama (IR) ve Doğal Dil İşleme (DDİ) bilim dalıdır ve doğal dil içerisindeki açık ve kapalı çalışma alanlarında soruları yanıtlayan sistemleri oluşturmayı otomatik olarak beraberinde getirir. Soru Yanıtlama Sistemleri (SYS) çeşitli kullanıcı sorularına değinmek durumundadır. Bazı basit sorulara verilen cevaplar kısa cümlecikler olurken, daha karmaşık sorular için verilen cevaplar kısa metinler olabilir. Basit cevaplı bir soru tek yanıtlı soru olarak tanımlanır ve tek yanıtlı sorularla ilgilenen soru cevaplama sistemine de tek yanıtlı SYS denir.

Bu Tezde, üç aşamadan oluşan tek yanıtlı SYS sunmaktayız: soru işleme, metin tarama ve cevap işleme. Soru işleme aşamasında, otomatik öğrenme teknikleri kullanarak kullanıcıların sorguladıkları sorulardan arama motoru elde etmek için yeni bir iki-aşamalı kategori yapısı ele almaktayız. Tezimizde yer alan tek yanıtlı SYS, metinler

üzerinde temel yapı olarak internet kullanmakta ve metin tarama aşamasında bilgi odaklı tarama yapmaktadır. Bu aynı zamanda, cevap işleme aşamasında cevap kalıbını eşleştirme tekniği kullanarak şablona dayalı bir SYS’dır.

Buna ek olarak, mevcut SYS’lerin sınıflandırmasını da sunmaktayız. Bu sınıflandırma, erken SYS’ler, kurala dayalı SYS’ler, şablona dayalı SYS’ler, NLP odaklı SYS’ler ve otomatik öğrenmeye dayalı SYS’ler gibi olguları kapsar. Kullandığımız tek yanıtlı SYS, aynı zamanda, 17 kaba-taneli ve 57 ince-taneli kategoriyi içeren iki aşamalı kategori yapısı kullanır. Bu sistem, TREC-8 ve TREC-9’dan ilham alınan 570 soru ile eğitilip ve 570 diğer sorular, TREC-8, TREC-9 , ve TREK-10 verilerile test edilmiştir.

SYS’mizde, sorguyu genişletme aşaması oldukça önemlidir ve genel olarak tüm performansı etkiler. Orijinal bir kullanıcı sorusu sorgulanmak üzere verildiğinde, elde edilen uygun dökümanlar yeterli olmayabilir. Bu durumda, sorgu şablonları ve soru tiplerine dayanan otomatik sorgu genişletme yaklaşımı sunmaktayız. Yeni sorgular, soru kategorilerinin sorgu şablonlarından elde edilir ve kullanıcı sorusunun kategorisi Naïve Bayes sınıflandırma algoritması tarafından bulunur. Genişletilmiş yeni sorgular, sorgu örüntüdaki boşlukları iki uygun sözcük öbeği ile doldurarak elde edilir. İlk öbek soru tipi öbeğidir ve doğrudan sınıflandırma algoritması tarafından bulunur. İkinci öbek soru öbeğidir ve olası soru şablonlarından Levenshtein uzaklık algoritması ile saptanır.

Soru tipleri için sorgu şablonları, o soru tipleri içindeki olası soruları analiz ederek oluşturulur. Bu tezde, sorgu genişletme yaklaşımımızı TREC-8, TREC-9 ve TREC-10 konferans verilerinde yer alan tek yanıtlı soru tipleriyle iki aşamalı değerlendirmekteyiz. Otomatik sorgu genişletme yaklaşımımızın sonuçları elle yapılan sorgu genişletme yaklaşımı sonuçlarından daha iyi çıkmaktadır.

Ağı sorgulayarak cevap kalıplarını otomatik olarak öğrendikten sonra, her soru tipi için cevap kalıbı gruplarını kullanmaktayız. Cevap kalıpları, ilgili metin bölümlerinden bulunan cevapları çekip alır ve bu cevap kalıbı Adlandırılmış Varlık Onayı (AVO) ile genellenebilir. AVO, cevap işleme aşamasındaki Bilgi Taramanın (BT) ikincil işidir ve metinsel dökümanlardaki terimleri yer ismi, kişi ismi, olay tarihi, vb gibi yeniden tanımlanmış kategoriler içerisinde sınıflandırır. Cevapların sıralanması, cevap kalıplarındaki frekans hesabı ve Güvenirlik Faktörü (GF) değerlerine bağlıdır.

Sistemin sonuçları, yaklaşımımızın soru cevaplama için etkili olduğunu ve temel ince-taneli kategori sınıfımız için 0.58 Ortalama Karşılıklı Sıra (OKS) değeri, kaba-taneli kategori yapısı için 0.62 OKS değeri ve TREC-10 üzerinde veri kümelerini test ederek yapılan değerlendirme için 0.55 OKS değeri elde ettiğini gösteriyor. Sistemin sonucu, TREC veri kümeleri üzerinde standart ölçme kullanarak diğer SYS'ler ile kıyaslanmıştır.

Anahtar Kelimeler: Soru Yanıtlama Sistemleri, Doğal Dil İşleme, Makine Öğrenmesi, Örüntü Eşleştirme, Tek Yanıtlı Soru.

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SYMBOLS AND ABBREVIATIONS

Symbols

Abbreviations

QAS	Question Answering System
NLP	Natural Language Processing
WWW	World Wide Web
IR	Information Retrieval
IE	Information Extraction
FAQ	Frequently Asked Question
MRR	Mean Reciprocal Rank
TREC	Text Retrieval Conference
CLEF	Cross Language Evaluation Forum
NTCIR	NII Test Collection for IR systems
POS	Part of Speech
SMT	Statistical Machine Translation
ASQA	Academia Sinica QAS
SVM	Support Vector Machine
CF	Confidence Factor
CRF	Conditional Random Field

1. Introduction

Question Answering (QA) is a field of Artificial Intelligence (AI) and Natural Language Processing (NLP) and Information Retrieval (IR), and it is concerned with generating systems that answer to natural language questions in open and closed domains, automatically. QA researchers deal with a massive set of different question types. Most new Question Answering Systems (QASs) use natural language documents as their knowledge source. NLP techniques process questions and extract answers from retrieved texts. Also, an increasing number of QASs use the World Wide Web (WWW) as their source of text and knowledge. In this chapter, we consider the general concepts of the thesis, QASs and their types. A factoid question is a question with a single phrase with answer. In this thesis, our emphasis is on factoid questions and what we want to find answers for these factoid questions.

QASs generally consist of several phases: question processing, document/passage retrieval, and answer processing. During question processing phase, question classification is performed first, in order to determine the type of a given natural language question. Then a query or a number of queries are created from question words by selecting important words and removing others. In some cases, queries can be expanded by adding more related query words along with using morphological variations of query words. With the help of created queries, the related documents which include possibly the answer of the given question are retrieved during related document retrieval phase. During answer processing phase, an answer is attempted to be composed from these retrieved documents.

1.1 Question Answering Systems

QA is a fast growing research area the focus on different types of questions to response natural language questions. The basic aim of a

QAS is to find exact and short correct answers for user's questions. For example, a user expects an exact answer ("Ankara") for the question "What is the capital of Turkey?", and he does not want to read the passages or documents which match with the words like "capital" and "Turkey". Although a search engine can return a set of documents for a given query to locate the desired information for that query, it does not return an answer for the question indicated by that query. QASs accept questions given in a natural language and extract short correct answers for those questions.

QASs have to deal with different types of questions. While answers for some simple questions can be short phrases, answers for some more complex questions can be short texts. The question types considered by QASs can be categorized as factoid questions, definition questions, list questions, complex questions, and speculative questions. A factoid question is considered as the simplest of question types since a factoid question can have only a single correct answer which is a phrase. A list question can have many possible answers and these possible answers are collected as a list of phrases. A complex question can have sub-questions and the answers of these sub-questions are combined to answer that complex question. A definition question normally does not have a short phrase answer and its answer is normally a short text containing several sentences. A speculative question is difficult to answer since its answer cannot be directly extracted from related documents and reasoning techniques have to be employed in order to get an answer for that speculative question.

QASs have attracted attention of studies for several years. Developed QASs are presented and evaluated in Text Retrieval Conferences (TREC) [1, 2, and 3], NII Test Collection for IR systems (NTCIR) conferences [4, 5] and Cross Language Evaluation Forum (CLEF) [6]. TREC conferences prepared evaluation sets containing factoid and non-factoid questions in order to evaluate competing QASs.

QASs use structured databases or natural language text documents in order to extract answers of questions. Information resources of some hybrid QASs are constructed by a combination of natural language text documents and structured databases. A lot of QASs use the WWW as their corpus of text and knowledge sauce. The QASs that use only databases for their information resources directly get results of questions from these databases. On the other hand, QASs that use natural language text resources have to employ some kind of Information Extraction (IE) techniques in order to find answers. For that reason, those systems use answer extraction patterns to obtain results from natural language texts.

Currently, natural language text documents obtained from the WWW are used as underlying knowledge sources in most of QASs. These systems have to employ IR techniques in order to get documents containing answers of questions. They combine various NLP techniques to detect and explore exact and proper answers from these documents. QASs that use IR techniques retrieve passages or whole documents using IR queries created from user questions. For this purpose, these QASs require NLP and IR methods to obtain the parts of documents that contain answers. Some of these systems only return passages containing answers without extracting answers from these passages.

Most of QASs are composed of a question classifier component which investigates question types and answer types. After that, proper queries are generated in order to get documents from the web and several components with NLP techniques are used to recognize parts of documents that are very likely to contain answers with filtering with respect to types of possible candidate answers. For example, if the question is “Who invented phone?” the filtering component returns text parts which contain passages including person names and question related words. The final component is answer processing which determines that the answer candidate is indeed an answer or not using pattern matching techniques. Almost, all QASs in the literature apply some supervised learning methods in order to learn their proposed models. The amount of learned data has an impressive impact on system’s efficiencies.

1.2 Categories of QASs

QASs can answer various kinds of questions. These questions can be specific domain questions or can be domain independent questions. QASs that deal only with questions in a specific domain are referred to close domain (domain oriented or restricted domain) QASs. On the other hand, QASs that deal with domain independent questions are referred to open domain QASs. An efficient approach to improve the accuracy of a QAS is to restrict the domain of questions by reducing the size of knowledge base and this is the main motivation for close domain QASs. The set of analysis patterns using a domain specific vocabulary can be made automatically or manually by restricting them into subject domain. Thus, the analysis patterns in a specific domain can be created more accurately with respect to the analysis patterns in open domains. For example, some close domain QASs are designed for medicine domain [7], geography domain [5], baseball domain [4] and geography START [8]. Open domains QASs do not put any restriction on question domains and they have to use much bigger knowledge resources [9]. They attempt to extract relevant answers from large text collections. The main goal of open domain QASs is to answer all possible input questions regardless of time and topic. For this reason, the most of the open domain QASs use the WWW as their knowledge resources. Some open domain QASs are like the ones presented in [10, 11, 12 and 13]. In open domain QA, there are no restrictions on the scope of the questions which a user can ask, on the other hands questions in closed domain QASs are specific questions in a special domain such as meteorology [14], medicine [15], agriculture [16] and etc. Closed QASs deal with only specific types of questions [9, 17], and they generate answers for these specific questions in that domain.

Another way to categorize QASs is with respect to their information resources. QASs obtain their information from databases or the WWW and they can be called as database QASs and web based QASs, respectively. The older database QASs have used databases to hold answers of possible questions and they converted user questions to database queries in order to get answers from these databases. Web based QASs use search engines e.g. Yahoo, Google, Yandex and Bing to retrieve web pages that potentially include answers to asked questions. Although most of the web based QASs are open domain QASs domain oriented web based QASs. Some of the web based QASs examples are MULDER [18], NSIR [19] and etc.

The systems that use web pages as information resource can be also called as IR based QASs. The IR based QASs use a search engine to retrieve documents. Most of IR based QASs retrieve a set of documents or passages as responses to the respective query, and extracts answers from these documents. IE methods are applied in order to parse questions and to extract answers from the retrieved documents. IR based systems may need some methods such as named entity tagging, pattern elements and relations, correlated elements and general elements for extraction of required information in order to answer questions. Although some IR based QASs [20] try to extract answers from the related retrieved documents, some other IR based systems [21] only return the related retrieved passages as answers.

Since some QASs use rules to parse questions and extract answers from related documents, they are also named as rule based QASs. A broad coverage of NLP techniques are used in order to achieve high accuracy QASs. Some popular rule based QASs are QUARC [22] and Noisy channel [23] that use heuristic rules with the help of lexical and semantic characteristics in asked questions. For each type of questions, rule based QASs may use rules simply to determine question types or to generate relevant queries for questions. Rules are also used to extract answers from documents and these rules can be manually created or learned. Additionally, "Why", questions are concerned with causal information, systems should discover several useful keywords for investigating intentions. The causal relationships and discourse structure undoubtedly can be very beneficial for answering why-type questions. In fact, in order to extract answers for why-type questions, it is necessary to extract causal relations and some other relations from target documents. If one element of these relations matches to question sentence, other element matches with answer for the question.

1.3 Question Types in QASs

The QA is retrieving a specific part of related documents responding to a user asked questions. First stage for developing a QAS is the identification of the type of the asked question correctly. Questions can be divided into five categories [24]: factoid questions, list questions, definition questions, speculative questions, and complex questions. Although the main concentration of this thesis is factoid questions we will go through all question types in this section.

1.3.1. Factoid Questions

The QASs that are designed for factoid questions are called as factoid QASs. A factoid question has a unified single correct answer. A factoid question's answer can be extracted from retrieved text passages [25] as a single phrase. Factoid questions are the most convenient level in comparison of other types. The instances of factoid questions are presented with their answers as shown below. The following factoid questions have only one correct answer.

Q1: What is the capital of Turkey? Answer: Ankara

Q2: When was the department of computer engineering established in Hacettepe University? Answer: 1976

Q3: Who is the preeminent leader and freedom fighter of Indian nationalism? Answer: Gandhi

1.3.2. List Questions

A list question expects a list of phrase as its answers. A list question can be considered a's a factoid question and the answer is attempted to find a list of best answers for this factoid question. List QASs gather a set of exact and complete answers to responding asked question. For example Q4, Q5 and Q6 are examples for the list question type.

Q4: Which are the top universities in Ankara? Answer: Hacettepe, METU, Bilkent, Gazi, Ankara.

Q5: How many professors are in the computer engineering department of Hacettepe University? Answer: 25 Professors

Q6. Which programs are active in the computer engineering department of Hacettepe University? Answer: B.S, M.S, Integrated Ph.D, and Ph.D.

Where, Q4, Q5 and Q6 are list questions, because each question has a list of factoid answers.

1.3.3. Definition Questions

A definition QAS assembles a list of sentences or complementary short phrases from retrieved related documents. More sophisticated techniques are required to gather information and extract relevant passages for definition questions. This QA is a task of answering definitional questions, such as Q7 and Q8 as follows:

Q7: Who is Farhad Soleimanian Gharehchopogh?

Q8: What is the QAS?

It should be noted that "what" type of questions are the most difficult type of questions because they seek a staggering diversity of answers.

1.3.4. Complex Questions

A complex question includes some sub-questions for the primary question, and it is decomposed into sub-questions. The decomposition of a complex question by using syntactic and semantic decomposition strategies is a common method to extract answers of the complex question types. These decomposition strategies use NLP and reasoning approaches [25]. For example, "Where is the office of Microsoft Company leader?" top question can be divided into two sub-questions and then the answer of the first sub-question is found. In the next step, we use the answer of the first sub-question is used for finding the answer of the second sub-question. As shown in the following example, Q10 and Q11 are sub-questions of Q9.

- Q9: Where is the office of Microsoft Company leader?
- Q10: Who is the Microsoft Company leader? Answer: Bill Gates
- Q11: Where is Bill gates office? Answer: Washington

Of course, complex questions can be divided in to more than two sub questions. For example, the complex question is "What is the room telephone number of Microsoft Company leader?" Q12, Q13 and Q14are sub-questions of this complex question:

- Q12: Who is Microsoft leader? Answer: Bill Gates
- Q13: What is the number of Bill Gates's Room? Answer: Room X
- Q14: What is the room X's telephone number? Answer : Y

1.3.5. Speculative Questions

In the speculative question, reasoning and knowledge based techniques are used to categorize question topic. The reasoning techniques are temporal reasoning, evidential reasoning and etc. These questions answered to gather retrieved related passages. Examples of that question types are:

- Q15: Will we commence to study NLP lecture in the next term?
- Q16: Are we unanimous in this enthusiastic reception?

1.4 Factoid QASs

QASs that deal with factoid questions are called factoid QASs. Factoid questions have single correct answers such as country, place, person name, author name and etc. As a subset of QA, factoid QA focuses on questions which have syntactic and/or semantic entities as their answers. The factoid QASs has many important real world applications and the Factoid QASs and factoid questions are the main topic of this thesis. Table 1.1 shows some factoid questions in English, and their answers together with answer types.

Table 1.1. Factoid Questions, Their Answers and Answer Types.

Question	Answer	Answer Type
What is the biggest city of Turkey?	Istanbul	City
What is the color of sky?	Blue	Color
Who is the Author of Joomla! Book?	Khalifehlou	PersonName
Where is Gandhi birth place??	India	Country

The retrieved passages with one short text segments contain possible answers of these questions. A similarity measure can be used between questions and candidate answers passages in order to resolve the mismatch between possible question answers and answer forms [25]. In order to assign, the similarity measure of both questions and candidate answer patterns has to be processed. The factoid QASs seek factual tidbits of information for factoid question types under a unified view.

A typical factoid QAS retrieves related documents from an integrated knowledge source in order to answer given user questions. Although the possible knowledge source can be a database holding related information, most of QASs use WWW as their knowledge sources. And also, the knowledge source of the QAS described in this thesis is the WWW environment.

New related queries should be generated from user questions in order to retrieve related documents which contain answers of user questions. The step of generating and expanding related queries is an important phase of this thesis since the documents containing corrects answers of users questions should be retrieved in order to extract answers from these documents query expansion phase including category recognition with a classification method.

Answer patterns have been used to extract correct answers from retrieved texts by answer pattern matching methods. The answer patterns describe the relations between Question Phrases and their own Answer Phrases. The usage of the question phrases and their own answer phrases leads to the requirement of answer patterns, and they are extracted patterns from different sentences. Therefore, factoid QASs is asked in order for a factoid question to be seen as a relation between a question phrase and an answer phrase. For example, the answer patterns of “Author_of_Book” question type define the relationship between books and Author of those books, and or the answer patterns of “Color” question type which defines the relationship between things and their colors.

1.5 Outline of the Thesis

The QA classification which is presented in five categories: Early QASs, pattern matching based QASs, rule based QASs, NLP based QASs will be explained in the next chapter. The next chapter also illustrates typical architecture and future of factoid QASs. The architecture of our factoid QAS is described in Chapter 3. In Chapter 4, the machine learning based question processing and query expansion phases are explained. Answer processing is the next phase after question document/passage retrieval which is detailed in Chapter 5. Evaluation metrics are explained in Chapter 6 and the proposed factoid question system is compared with other QASs using standard datasets such as TREC datasets. Finally, this thesis is concluded in Chapter 7.

2. Related Works

2.1 Overview

In this chapter, we present a classification of QASs based on how they can answer questions and their techniques with focus on styles, metrics, sample systems, and structures of them, respectively are discussed. They are categorized as early QASs, pattern matching based QASs, rule based QASs, NLP based QASs and machine learning based QASs. Then, the proposed factoid QAS architecture is given. After that, performances of factoid QASs are discussed.

2.2 Question Answering Classification

Although the early QASs were basically natural language interfaces to database systems, QASs today can answer different types of questions by getting answers from relevant web pages. QASs can be classified as non-factoid and factoid according to the types of questions they deal with. Factoid QASs deal with mainly factoid questions and a factoid question has a single phrase as an answer. We can categorize QASs that deal with question types other than factoid questions as non-factoid QASs. An example of subset of question answering is factoid QASs that focus on questions whose answers are syntactic and/or semantic entities such as organization or person names. Factoid questions have single exact answers which can be extracted from short text segments [25]. Factoid QASs try to accurately extract exact answers in retrieved documents for factoid questions such as “When was X born?”. Although, the main concentration of this thesis is our factoid QAS and its evaluations, some factoid and non-factoid QASs are reviewed and that is before more comprehensive stature of our factoid QAS are discussed. We categorize QASs as early QASs, pattern based

QASs, rule based QASs, NLP based QASs and machine learning based QASs.

2.2.1 Early QASs

Two of the well-known early QASs are BASEBALL [4] and LUNAR [26] systems. The questions related with the US baseball league were answered by BASEBALL over a period of one year. On the other hand, the questions about geological analysis of rocks that are returned by the Apollo moon missions were answered by LUNAR. Actually, LUNAR is presented at a lunar science convention and it answered 90% of the questions in its own domain. These systems work by analyzing the given question to create a database query and by submitting this database query to the background database holding answers in order to find out the answer of the given question. They can be thought as simple natural language interfaces for database systems.

QASs focus to provide inquirers with direct, precise answers to their questions, by employing IE and NLP methods instead of presenting huge amounts of documents which are potentially relevant for the questions posed by inquirers. During the past decades, there were many cases of early QASs which have been created by researchers in this domain like START [8] system. The main characteristic of START is its ability to find answers about cities, countries, lakes, maps, and known people as well as its ability to find just direct information to user's question rather than indication of a list of relative documents. Another example of early QASs is "ask.com" which is very similar to a search engine approaches and also can answer questions that are asked in natural language. Regarding this, it is uses documents, images, news and videos and others form internet information to answer questions.

Some other early systems are SHRDLU [27], Eliza [28], QUALM [15] and MYCIN [29]. All of them use databases as background knowledge base and they use natural language interfaces to databases. SHRDLU is a QAS which is as able to answer the questions in the physics domain Eliza answers questions in medical domain and use simple pattern matching methods. MYCIN is an expert system in medical domain for infectious disease diagnosis with natural language interface, and it can be seen as a QAS because it tries to answer questions in that medical domain. QUALM is also a QAS in medical domain which handle questions related to human memory organization.

2.2.2 Pattern Matching based QASs

Although early systems used databases as knowledge resources, newer systems use text documents as knowledge resources. These text documents mostly are obtained from the web. Since answers are not directly available and they are parts of these text documents, QASs should be able to extract these answers from these documents. One way to extract answers from text documents is to use pattern matching approaches. Some of the open domain systems that use pattern matching approaches are shown in Table 2.1.

Table 2.1 Pattern Matching based QASs.

Name	Date	Language	Parser	Resource of Answers
Er and Cicekli [25]	2013	Turkish	Pattern Matching based Methods	Webs
Whittaker et al [11]	2006	Chinese, Swedish, English and Japanese	Statistical Pattern Classification	Database
Aranea [12]	2002	English	Pattern Matching	Database
AskDragon [13]	2009	English	Pattern Matching	Web
Nakakura and Fukumoto [10]	2008	English	Pattern Matching	Database

The QA problem can be reviewed from several points such as simple surface pattern matching, automated reasoning. On the other hand, Wang in [30] believes that syntactic and semantic variations are real issues in answering extraction when a question word exists in answer passage. For example, QALC [31] which is an open domain QAS for English factoid questions uses syntactic and semantic variations for each query. Another related open domain approach which is presented in [32] retrieves answers from a large collection of frequently asked question (FAQ) pages by creation semantic structures of FAQ pages.

Nakakura and Fukumoto [10] developed a non-factoid QAS with "why", "definition" and "how" question types and extracted patterns for these question types are used. In their system, the question data set of NTCIR is used for the performance evaluation, and their performance is low because of short question patterns and short answer extraction patterns. Also, Collins-Thompson et.al. [33] presented an approach which uses different retrieval methods and compare their effects in terms of QA performance. The model proposed in [14] focuses on aerologic district by predicting the weather information based on answer patterns in close domain of QASs. Some of the present open domain QASs such as Mulder [18], Webclopedia [34], AnswerBus [35] and Lamp [36] also use answer and question patterns. Greenwood and Saggion [37] proposed two open domain systems for factoid, list and definition questions. They use regular expression patterns in order to locate candidate answers. Their first system which deals with list and factoid questions extracts regular expansion patterns using the web in off-line mode, and their second system deals with definition questions. In on-line mode, according to extracted knowledge for each new question, the second system used processing of a corpus of regular expansion patterns. Their results are reported over question sets from the QA track of TREC-11 and TREC-12 [37].

In the candidate answer scoring, there are three factors for candidate answers which are the similarity of the sentence containing a candidate answer to the query, the distance of a candidate answer to non-functional query words and the semantic compatibility of candidate answer. One of the important aspects of the QA task is the ability to pinpoint the answer using certain restrictions on structures of candidate answers. Using named entities for candidate answers puts restrictions on candidate answers and candidate answers should satisfy certain structures. For example, Lee et.al. [38] proposed the hybrid architecture for the cross language factoid QA, called ASQA (Academia Sinica QAS). The system includes six types of factoid questions: organization names, person names, times, artifacts, numbers and location names.

2.2.3. Rule based QASs

The rule based QASs are based on a huge number of rules to capture every case that can been a countered in a national language domain. A prominent instance of a rule based QAS is a domain specific expert system that uses rules to make deductions or choices.

QArabPro [39] is a rule based QAS which takes different types of questions in Arabic language including "how" and "why" types of questions. It has three main phases which are question analysis, document/passage retrieval and answer extraction. They use if-then rules in order to extract answers from texts. Their rules are hand-coded rules for each type of questions.

PiQASso [40] is a QAS which consists of two major components: a paragraph indexing and retrieval subsystem as well as a question answering subsystem. This system is a vertical system which employs textual analysis, keyword search and semantic filtering. PiQASso uses the rule the case of an answer type.

QUARC [22] is a rule based QAS in which wh_questions (what, who, why, where, when, which) have been answered by the proposed system. The parser of the system determines two proper nouns. A PROPER_NOUN is defined as a noun phrase in which all words are capitalized and PROPER_NOUN contains at least one “human” word. The QUARC system uses if-then rules which assign four possible point values. The fundamental aim of these values is to evaluate the relative importance of each clue.

AskMSR [41] exploits redundancy in result summaries returned by web search engines. This rule based system generates a decision tree to predict whether correct answers appear based on features derived from questions. For example, the weight of the best rewrite rule depends on the total number of matching passages retrieved and the numbers of no-matching passages retrieved for retrieved matching passages, matching patterns are also identified.

Zhenqiu [42] presents a rule based QAS to classify and extract answers from a library. This system parses questions and extracts their keywords by thesaurus based segmentation approach. Then, the system searches the four databases (common, professional, synonyms, and historical question databases) by attention to keywords to discover candidate questions. In the answering processing phase, the system processes similarity between the new questions and candidate history questions achieved the required threshold after completed word segmentation.

Cui et. al. [43] constructed a rule based FQAS which uses NUS [44] document/passage retrieval component created by fuzzy relation matching and query expansion. Dependency relations of fuzzy matching are gathered by matching degree between relation paths in the related passages and the questions. In order to find relation paths, the system utilizes iterative expansion maximization and mutual information.

2.2.4. NLP based QASs

The mostly factoid questions are questions whose answers are syntactic/semantic entities such as a person's name, numbers, dates, locations and organizations names. In the past years and lately, there have been many researches to generate factoid QASs with named entities. For example, Aranea [12] is a factoid QAS which is organized around a modular framework that extracts answers from WWW by means knowledge mining and knowledge annotation methods. Knowledge annotation method uses semi-structured database techniques categories of common questions. Knowledge mining approach uses statistical methods in order to leverage a wide range of data on web to overcome many NLP challenges. The knowledge annotation method is a sub-task of the system used by Omnibase [45, 46] and START [8] systems.

In an earlier work by Surdeanu et. al. [7], a QAS is proposed to handle speech transcriptions which can be adapted to automatic transcriptions and the strength system comes from IR oriented methodologies with a number of NLP tools such as a part of speech (POS) tagging and Named Entity Recognition (NER). They analyze the system on transcriptions of spontaneous speech from several 1-hour-long seminars. Their results show that the system achieves excellent performance. Also, they illustrate that the combination of NLP and IR technologies increases overall robustness of the system.

To be precise in the answers for factoids, Hammo et. al. [47] perform factual processing of the question from a linguistic view in order to match user needs. Their proposed system which is called QARAB is the result of a combination of traditional IR technologies with sophisticated NLP methods. They adopt a keyword matching method which matches simple structures extracted from both question and candidate passages retrieved by IR phase. They also used an existing tagger to tag words and determine names. The IR system in QARAB uses Salton's vector space model [48]. It assembles text corpus from Al-Raya newspaper and constructs an inverted file system. It also uses relational database management system in the construction of IR module which is initially presented by Lundquist et. al. [49]. The target of IR module is to look for the corpus to extract relevant passages which are related to the user's queries.

The NLP part of QARAB system [47] is a collection of linguistic tools to tokenize and tag Arabic texts, by identifying several features of the tokens. The tokenizes which extracts tokens the type finder which assigns a POS to each token, the feature identifier which identifies features of each word. The proper noun phrase parser which marks proper nouns are the components in QARAB system. The success of this system comes from the amount of available tools used for Arabic language [47] to generate a concise and correct answer in a timely manner.

To investigate the impact of document/passage retrieval quality, re-ranking baseline search results using a trained model are presented by Bilotti et.al. in [50]. The architecture of the proposed system is composed of four components: question analysis, baseline search, trained ranking model and answer generation. The question analysis component analyzes input questions, the baseline search component retrieves the passage with IR techniques into the desired passage set, the trained ranking model re-ranks passages in the set and the answer generation component generates target answers. They prove that their system is able to process complex linguistic and semantic constraints including keywords and named entity features on query time. By the type system decomposition, they propose an algorithm based on element and relation types in the type system to selecting atomic constraints. The trained ranking model achieves 20% improvement in precision over baseline keyword [51] retrieval models.

Birini et. al. [52] propose an Arabic factoid QAS called QAS for Arabic Language (QASAL). QASAL inputs are natural language questions written in Arabic and its outputs are the most proper and exact answers. Their proposed system is composed of three components: question analysis, document/passage retrieval and answer extraction components. Input questions are processed in the question analysis module by queries and generating keywords, and then IR methodologies retrieve passages. Answers are generated from extracted relevant passages candidate answer. In the answer extraction, answer extortion techniques are employed on candidate answers and finally appropriate answers are detected.

Bonet and Comas [53] use a new Statistical Machine Translation (SMT) based approach to extract exact answers to response to natural language questions. In their approach, the translation of the question is an answer. They used n-best translations of a question to identify similar sentences in the retrieved related documents which contain the real answer. Answer extraction is done by a full machine translation system. The proposed method is validated with TREC-9 to TREC-16 datasets for question answer evaluation. In SMT, the probability of each translation is given by the Bayes theorem [54] and the best answer for a question is the most probable one.

Bian and Liu [55] present a new factoid QAS to find right answers as a general ranking framework for real IR from social media. It is necessary to address both relevance and quality of factual IR problems. As a result, they display their method as highly impressive at retrieving well-formed, factual answers to questions.

2.2.5. Machine Learning based QASs

However, ASQA [38] is a factoid QAS that uses InfoMap [56] for sentence pattern matching and machine learning based Support Vector Machines (SVM)technique [57] to identify question types of the Chinese questions. In the earlier work [58] on ASQA, the architecture of system includes four main phases: question processing, document/passage retrieval, answer extraction, and answer ranking.

Sibyl [21] is a factoid QAS that uses supervised machine learning methods. The system presents several levels of linguistic information for QA. The IR techniques are applied on spoken word documents presented by Coma et. al. [21]. The architecture of the Sibyl system is composed of three main phases which are question processing, document/passage retrieval, and answer extraction. Question processing phase generates a set of query terms called keywords, and then identifying what is the expected type of answer for this question. Document/passage retrieval phase is called an IR engine and this phase retrieves documents and related passages using keywords and expected type of the answer. The answer extraction phase extracts proper answers from retrieved related passages using NER, to select candidate answers. Sibyl employs machine learning approach at the word level to pinpoint candidates by means of NER. In the answer extraction module, answer candidates are recognized as a set of named entities. Then they are ranked by means of a scoring function returned as possible answers [21] which contains pattern matching between information extracted from question phrase and information extracted from the retrieved document. The results of Sibyl indicate that syntactic information is very beneficial to rank candidates.

Dominguez-Sal and Surdeanu [59] present a factoid QAS that was completely based on machine learning techniques. It is composed of three components: question processing with one-to-one mapping from question type to the category of expected answer, passage processing and finally answer extraction. The answer extraction section identifies relevant answers from achieved passage set with NER that trained on CONLL corpus [60]. The answer extraction classifier use three different machine learning methods: maximum entropy [61], AdaBoost [62], and SVM.

2.3 Factoid QASs Architecture

A typical factoid QAS is composed of three parts: question processing, document/passage retrieval, and answer processing. The first part analyzes the user question and then prepares queries. After that, the second phase tries to retrieve relevant documents containing answers from knowledge resources. The last step extracts answers from retrieved documents. The structure of a typical factoid QAS is given in Figure 2.1.

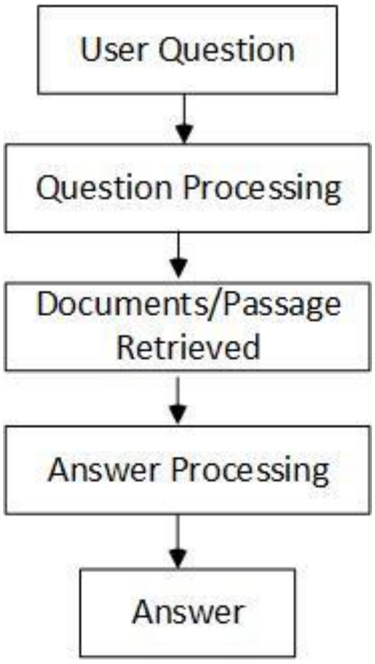

Figure 2.1. General Architecture of a Typical Factoid QAS.

2.3.1. Question Processing

In the question processing phase, questions are analyzed in order to determine question type and generate queries. The first task in question processing phase is to identify user question type from its structure. The second task in question processing phase is to generate queries for given user questions.

In this phase, a question type detector can be implemented by supervised machine learning techniques. Question type detector firstly detects the type to the asked question and then it gathers the question phrase with regard to its related answer phrase. According to this, question patterns can be used to identify question types in the question type detector module. For instance, Webclopedia question typology [10, 63] includes 276 handcrafted question patterns to detect 180 question types. The question type identifier uses question-question type pairs to identify question type phrase. This level has special importance due to the fact that correct answer detection depends on correct question type detection. Some of question types in factoid question domain refer to person name, name of palace, date of birth, date of death, number, and locations such as cities and etc.

Query expansion can be separated into two categories, manual and automatic query expansion. This module generates a knowledge based query or a search engine query. Indeed, queried queries contain of question phrase and answer phrase pairs.

- Manual Query Expansion: Queries are expanded manually by a human expert. Clearly, formulating queries manually from documents are hard. Manually query expansion is simple and there are no need to complex operations and implementations.
- Automatic Query Expansion: Query expansion by main query, query expansion by change of words and query expansion by member selected phrases is some examples of automatic query

expansion methods. Automatic query expansion is faster than manual query expansion.

2.3.2. Document Passage/Retrieval

In this phase, the first task is the document retrieval that uses IR methods to extract the small portion of documents from wide range of text documents. The extracted documents are processed to extract related passages in the document/passage retrieval phase. The related passages have potential to include expected answer. A sample method is to use keywords in the query in order to find related passage in retrieved document.

In order to have more effective document/passage retrieval phase, the query expansion phase has to expand the scope of user questions to retrieve more related documents which contain correct answers of user questions. Therefore, multiple search engine queries are generated from the original user question. This approach leads to an increase in the amount of retrieved documents with correct answers, and correct answers for user questions can be extracted more easily from these documents. Thus, the success of the query expansion in the retrieval of documents with correct answers directly affects the performance of the QAS.

2.3.3. Answer Processing

After related passages are retrieved, the answer is extracted from the returned passages. QA researchers use different techniques to extract expected correct answers, successfully. For example answer pattern matching [25] is a technique to extract answers using learned patterns.

A question processing component determines expected answer types and uses typically an IR engine to generate appropriate queries. If the expected answer types are incorrect in these components, it is likely to detect incorrect candidate answers in the following components. Question classification has an important role in question type detection. Answer processing module can use NER to classify and extract mentions of rigid designators from texts such as suitable names, biological species, and temporal expressions.

2.4 Performance of Factoid QASs

Today's, most QA studies focus on the heavy syntactic/semantic analysis of text like complete parsing of text, advanced query expansion and semantic role labeling of, grammatical correct text. In the literature, researchers unanimously claim that the combination of IR methodologies and NLP techniques increase overall robustness. But low resource requirements as well as fewer processing cycles are the main advantage in order to generate real-time QASs [59].

Fully machine learning based factoid QASs and some other types of QASs have extremely heavy cost of development or customization. In the document ranking techniques are learned depending on features such as baseline retrieval model scores [50] and term count statistics [51]. Some of machine learning based classifiers in document ranking are maximum entropy, AdaBoost, and SVM. The accuracy and latency of current factoid QASs can be improved by increasing quality of designed real-time document/passage retrieval components.

In order to build real-time and high performance factoid QASs, it is necessary to expand extraction rules and to improve scoring methods for answer candidates. The major challenge in answer extraction phases of factoid QASs is the requirements of syntactic and semantic analysis for questions [13]. Generally, the combination of NLP and IR technologies increases overall robustness in designed factoid QASs.

QASs user receives more unified answers that are extracted from retrieved relevant documents. The use of machine learning based approaches to knowledge based determinations is promoted by TREC evaluation increasingly on the open domain systems.

One other important aspect of a QA task is the ability to specify the expected type of answer in order to match it with named entities which are recognized in documents [50]. The in-depth studies conducted in this area shows that the NER quality can be improved by modern machine learning techniques.

Question analysis consists of two major outcomes sought under semantic and syntactic analysis of question type and query formulation. Developers seek to create a balance between two criteria: precision and recall. QASs put extra restrictions on matching conditions of candidate answers to increase precision of extracted answers.

Recent developments in NLP makes it possible to have better question analysis, proper syntactic and semantic sentence interpreter and high speed query expansion. A more sophisticated alignment may allow matching answer sentences with questions more accurately [33]. Also the categorization of expected question types under factoid, list, definition, complex and speculative has more potential in the creation answers more precisely. On the other hand, the question analysis may put the question in to a broader category. This can increase the possibility of matching and therefore it increases the retrieval recall. The promising developments of QASs are examined and their influence is anticipated. Query expansion systems of the surveyed systems lead to transformation questions into structured queries. A query expansion system aim to facilitate answer extraction processes.

The most of surveyed factoid QASs in this research are QAs based on IR systems. In these systems, asked questions are given in natural language. The discussed systems use different levels of processing such as classification of question types and expected answer types, transformation of questions into the structured query languages queries and semantic analysis of questions by recent interests in query expansion models. In addition textual databases next generation of factoid QASs might work with of image, audio and video database. In addition, this study highlighted many research questions to be surveyed in the recent years such as the development of more sophisticated NLP methods in question classification and formulation, the development of effective methods for answer generation from conflicting evidences, and more integrated utilization of logical and case based reasoning mechanisms available in answer extraction.

Despite all efforts to constructing effective factoid QASs, they are still in infancy. Future systems in this domain have vast capability with high tolerance to overcome shortages of current factoid QASs like confusion generation in answering factoid questions when their expression has been changed. We think that not in too distant future, factoid QASs with outstanding developments will have more improved and sufficient abilities.

3. Architecture of Factoid QAS

3.1 Overview

In this chapter, the general architecture of our factoid QAS is described. Our QAS which is designed for factoid questions is given in English. The general phases of our factoid QAS that include question processing, document/passage retrieval, and answer processing phases are explained. TREC conferences prepared evaluation sets containing factoid and non-factoid questions in order to evaluate competing QASs. In our system, the evaluation of our presented approach which is a pattern based approach has been done using human-made factoid questions corpus and factoid question datasets in TREC-8 [64], TREC-9 [65] and TREC-10 [66].

The overview of our factoid QAS involved three phases:

- Question Processing
- Document/Passage Retrieval
- Answer Processing

In this thesis, we present developed a pattern based on query expansion approach machine learning techniques for question classification and a pattern matching approach based on named entity tagging in answer processing phase for our factoid QAS. We also use answer patterns for related passage extraction. Figure 3.1 illustrates three general phases of our system.

3.2 Factoid QAS Architecture

To answer a factoid question, it is necessary to use machine learning techniques and/or NLP tools. Questions in Table 3.1 are some examples of factoid questions in our system. The answer of a factoid question is stated in retrieved documents explicitly. So, queries are generated from a factoid question to investigate relented passage containing correct unified answers. Each of the answers in Table 3.1 can be found in a text passage that contains an expected answer. A similarity measure can be used between the questions and candidate answer passages in order to resolve the mismatch between the questions and answer types [25].

Question processing component determine expected answers type and uses a typical search engine to generate appropriate queries. If the expected answers are incorrect in this section, it is likely to detect incorrect candidate answers in the next phase. Question classification has a significant role in question type phrase and question phrase detection. Table 3.1 shows some factoid questions and their answer types and answers.

Table 3.1. Sample Factoid Questions in English.

No.	Question	Answer	Answer Type
1	What is the Biggest City of Turkey?	Istanbul	City
2	What is the Color of sky?	Blue	Color
3	Where is Albert Einstein's Birth place?	Germany	Country
4	Who is the President of Italy?	Sergio Mattarella	President
5	Who is the Author of Steve Jobs?	Walter	Author
6	What is the Longest Ruling Dynasty in Georgia?	Isaacson Bagrationi	Dynasty
7	What is the Tallest Building in Turkey?	Istanbul Sapphire	Tallest Building
8	What is the Calendar Type in Denmark?	Gregorian	Calendar Type

The architecture of our factoid QAS is shown in Figure 3.1

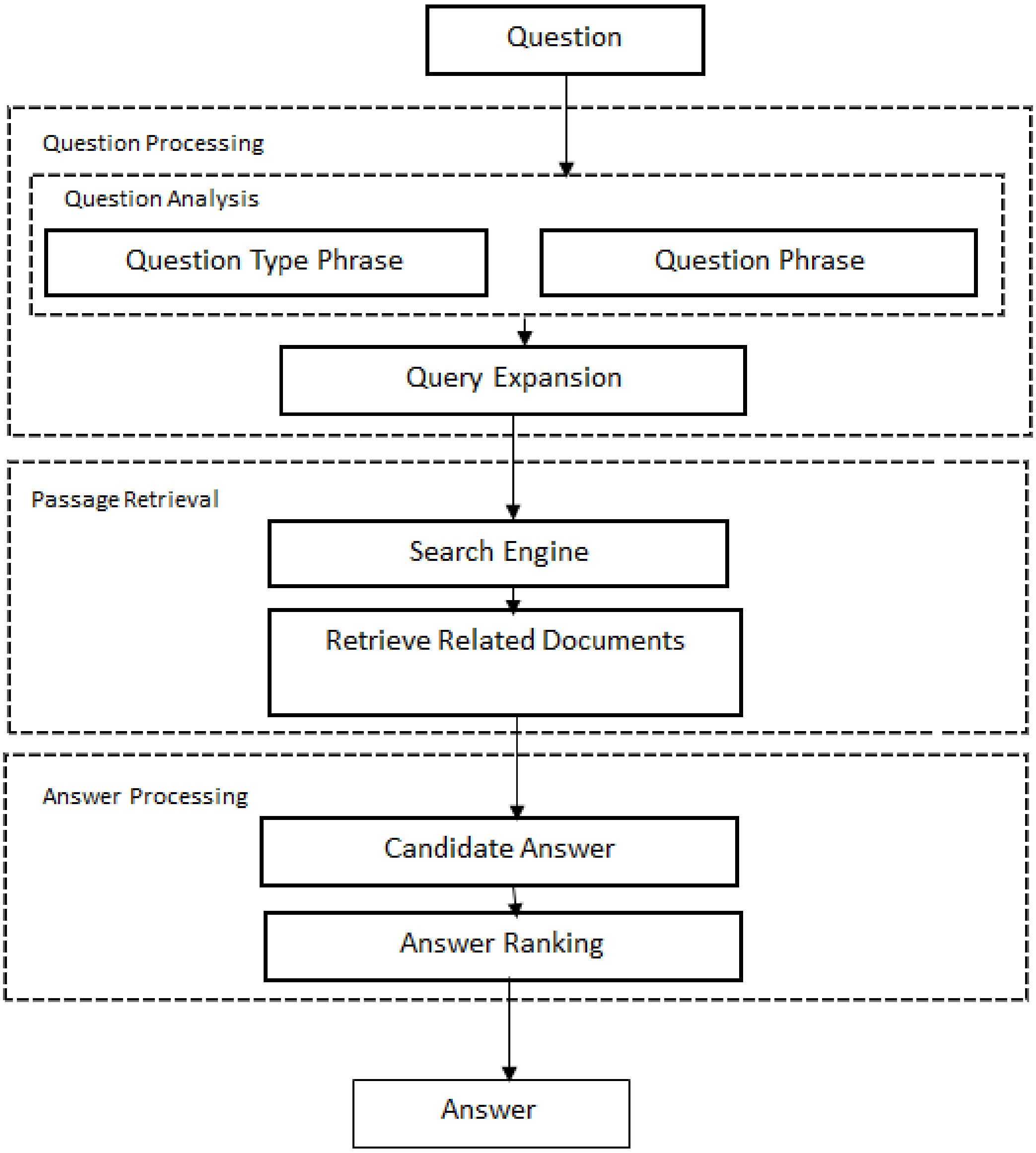

Figure 3.1. Architecture of Factoid QAS

The question is considered as the input of the system. The architecture of factoid QAS as shown Figure 3.1, is composed of three components: question processing, document/passage retrieval, and answer processing. First phase is question processing. In this phase question type phrase is used for identifying question type.

When users submit questions as queries to a search engine, they want to reach related documents with answers to their questions. Although some related documents can be retrieved when a user question is submitted directly as a query, the amount of related documents may not be satisfactory. Queries can be expanded by generating new queries from user questions in order to retrieve more related documents. The query for a user question which brings the most related documents can be seen as the best query for that question. The main aim of a query expansion system is to generate new queries for a given question so that they can bring more related documents.

In the document/passage retrieval phase, search engine has a significant role to gather relevant documents using generated queries. Relevant documents have high potential to contain relevant passages. Relevant passages have candidate answers of user asked questions from system.

Answer processing phase starts after document/passage retrieval phase. Candidate answer generates the first answer processing component. Answer patterns are regular expressions and have important roles in the candidate answer extraction from retrieved documents. Candidate answers are processed by answer pattern and the ranking of candidate answers is done using answer evaluation. Finally, the answer of a question is returned back by the factoid QAS.

Chapter 4 explains details of question processing component. Question phrased question type phrase and detection queries are explained in that chapter in detailed way generation by machine learning techniques.

In each question type, a same question can be represented with different question strings. For example, the question "When was Bill Gates born?" can be considered with different question string such as "When was Bill Gates birthday?" question or "What date was Bill Gates born?" question.

3.3 Question Processing

In a QAS, the query expansion step is very important and it affects the overall performance of that QAS. When an original user question is used as a query, the amount of retrieved relevant documents may not be enough. Users expect more related documents for their questions, but more related documents can only be retrieved with expanded queries. In our system, question processing phase involved seven sub tasks are listed below:

- Two-Level Category Structure
- Identifying Question Type phrase
- Identifying Question Phrase
- Generating Queries
- Building a set of Question-Answer Pairs
- Pinpointing Related Documents
- Selecting Best Query templates

In question processing phase, we present an automatic query expansion approach based on query templates and question types. New queries are generated from query templates of question categories and the category of a user question is found by a Naïve Bayes classification algorithm. New expanded queries are generated by filling gaps in patterns with two appropriate phrases. The first phrase is the question type phrase and it is found directly by the classification algorithm. The second phrase is the question phrase and it is detected from possible question patterns by a Levenshtein distance algorithm. Query templates for question types are created by analyzing possible questions in those question types.

We evaluated our query expansion approach in the system with 570 different factoid questions, also identified factoid questions in TREC-8, TREC-9 in training section and also in the testing section with 570 different factoid questions and identified factoid TREC-10 conference datasets.

3.3.1. Two-Level Category Structure

Question types have important roles in identifying expected answer types. For example, the question "When was Bill Gates born?" the question type is birthday and the expected answer type to be date of birth for person. Therefore, we present the two-level category structure for all of question types in our QAS. Most of the QASs use one-level structure for identifying question types such as in [25] and some other presented two-level structure for question type class such as in [20] has six coarse-grained and 50 fine-grained question classes. The two-level category structure in our system consists of 17 coarse-grained categories and 57 fine-grained categories. We pinpoint the question types which have the same question patterns in one coarse-grained category. Clearly, the question is "What is the capital of Poland?" and the other question is "What is the biggest city of Egypt?" and "What is the official language of Iran?", as shown in Table 3.2, all of three sentences have similar question templates.

Table 3.2. Sample of Two-Level Category Structure.

No	Question	Question Template	Question Type	Similarity of Question Template
1	What is the capital of Poland?	What is the X of Y?	Capital	Yes
2	What is the biggest city of Egypt?	What is the X of Y?	Biggest City	Yes
3	What is the official language of Iran?	What is the X of Y?	Official Language	Yes
4	Who is the Author of HTML?	Who is the X of Y?	Author	No

Where X stands for question type phrase and Y stands for question phrase in the question of Table 3.2. For instance, X stands for capital and Y stands for Poland in the question (1): "What is the capital of Poland?", therefore the questions (1), (2) and (3) have the similar question patterns and we can classify them into one category say

Category 1 and the question (4) is classified in coarse-grained category 3, because it has no similar question template with other question (1), (2) and (3). The question type classification of our presented two-level category structure is given in Table 3.3 and Table 3.4.. Also, other question types such as mayor, abbreviation, birthday, and others are classified based on this approach as shown in Table 3.3 and Table 3.4.

3.3.2. Identifying Question Type Phrase

In our system, 17 categories and 57 question types are used for evaluation factoid QAS. Each question type represents a factoid question, and we prepared 10 different factoid questions for each question type. Thus, we have 570 factoid questions in order to evaluate our system. Since our questions are factoid questions, they have answer phrases as results of those questions. This means that the answer of each factoid question is recorded for evaluation purposes. For each factoid question in our evaluation set, we found its question type using our Naive Bayes classification algorithm. Thus, the Question_Type_Phrase string is found for that factoid question. Also, 17 categories and 57 Question type phrase are classified in Table 3.3 and Table 3.4.

Table 3.3. Factoid QAS: Categories and Question Type (A)

No.	Question Type and Descriptions
1	**Question Type:** Capital, Biggest City, Official Language, Official Religion, Largest River, Highest Mountain, Biggest Lake, Calendar Type, Currency, Government Type, Tallest Building, Longest Ruling Dynasty of Country **Descriptions:** These question types define the relation between a country and its specifications such as capital of country, tallest building of country and etc.
2	**Question Type:** Minister **Descriptions:** This question type define the relation between a country and its ministers such as prime minister, culture minister, agriculture minister and etc.
3	**Question Type**: Author, President, Film Director, Boss, Inventor, King, Discoverer, Founder, Parliament Speaker, Mayor, Governor, Football Head Coach, Leader of Revolution, Killer, Producer, Creator, Prophet **Descriptions:** These question types define relation between country, city, thing, revolution, company and their specifications such as author of Book, Founder of Company, Parliament speaker of country, Mayor of City and etc.
4	**Question Type:** Date of Birth, Date of Death **Descriptions:** This question type defines relation between a person and the date that the person born or died.
5	**Question Type:** Earthquake in city, Explosion in City, Festival in City, Flood in City, Political Event in Country, Revolution in Country, Storm in City, Volcanic in City, Wildfire in City **Descriptions:** These question types define relations between events in city/country such as earthquake and the date that the events happened.
6	**Question Type:** Population **Descriptions:** This question type define relation between a country and the population of country
7	**Question Type:** Holy Book, Color Code **Descriptions:** These questions types define relations between a country, city, thing and holy book of country, code of country/city and color of Things.
8	**Question Type:** Headquarters of International Organization Place, Airport Places, Birth Place, Holy Place, Company Place **Descriptions:** These question types define relations between headquarters, airports, birth, holy, company and the place where they are located or born.
9	**Question Type:** Biggest Producer **Descriptions:** This question type defines relation between a Biggest Producer of thing and its Country/Company.
10	**Question Type:** Nationality **Descriptions**: This question type defines relation between a person and the nationality of that person.
11	**Question Type:** Attachment to Continents **Descriptions:** This question type defines relation between a country and the attachment to continent of that country.

Table 3.4. Factoid QAS: Categories and Question Type (B)

No.	Question Type and Descriptions
12	**Question Type:** Construct/Establish **Descriptions:** This question type defines relation between an event and the date that this event is constructed or established.
13	**Question Type:** Another Name for Person, Zip Code for City, Gestation Period for Organisms **Descriptions:** This question types define relations between a person/ city/ organism and their name /zip code/ gestation period.
14	**Question Type:** Signing a Contract **Descriptions:** This question type defines relation a contract and the person who signed that contract.
15	**Question Type:** First Coach, Founding Member, Science Father **Descriptions:** This question types define relations between a first coach/founding member/science father and their related person.
16	**Question Type:** Begin **Descriptions:** This question type defines relation between the events and the date that the events begin.
17	**Question Type:** Abbreviation **Descriptions:** This question type defines relation between an abbreviation and the meaning that the abbreviation stands for that.

The correct identification of question types has a key role in the correct identification of answer types. There are mainly two approaches to identify the question types: Question pattern matching methods and Machine learning methods. Our system uses a machine learning method, and Naive Bayes classification technique to identify question types.

Question types are identified by question patterns which are regular expressions. Webclopedia question typology [67] analyzed multilingual question, automated semantics-based term expansion, and answer specification as well as in the question answering direction, it involved 276 handcrafted question patterns to detect 180 question types. The question type identifier uses question-question type pairs to identify question type phrase. The collection of question patterns is gathered to its relation for each question type in the first approach. If the questions match with the question patterns, the relevant question types have been allocated to those questions. For example, a question pattern is given:

“What is the nationality of Question_Phrase?”

Where question pattern is associated with “nationality” question type (described in Table 3.2). If a question sentence matches with this question pattern, its Question_Type_Phrase (question type) is identified as “nationality”.

Also, supervised machine learning methods can identify question type phrases for each question sentence. These methods use training and testing datasets, and they include the questions and their hand-written question types. The correct answers depend on the correct identification of answer types. To support statistical learning for question type identification, we have developed a new method. The category of a user question is found by a Naïve Bayes classification algorithm. We benefit from classification algorithm to correctly classify of question types. The approach, described in this thesis, is based on machine learning methods in question type identification phase. The details of how the presented approach with Naïve Bayes classifier identifies question types are presented in Chapter 4.

3.3.3. Identifying Question Phrase

Question phrase identification with question patterns is simple. But, with machine learning approach, it is remained as a challenge, how can correctly identify question phrase. For example, suppose a user asks this question:

“What is the capital of Germany?”

In our system, capital is as “Question Type Phrase” and Germany is as “Question Phrase”. In order to pinpoint question phrase in the machine learning based approach, new expanded queries are generated by filling gaps in patterns with two appropriate phrases. The first phrase is the question type phrase and it is found directly by the classification algorithm. The second phrase is the question phrase and it is detected from possible question patterns by a Levenshtein distance algorithm which is explained in Chapter 4.

3.3.4. Generating Queries

After question type phrase and question phrase identification, using the query templates of the category in which that question type belongs to, automatic queries are generated for the proposed factoid question. A set of query templates is used in the query expansion phase. The handcrafted query templates building is a very time consuming task for machine learning based methods. On the other hand, it has potential to incomplete generation of handcrafted query templates. Therefore, we query the web a search engine and automatically learning patterns. The library of automatic and manual queries for each question type also exists.

In our proposed approach, each category has between 3 and 9 automatic query templates. This means that the number of generated automatic queries for a given question is between 3 and 9 for each category. In addition, 3 or 4 manual queries are generated for each factoid question depending on their categories. The library of queries patterns of our system is not hand-build but the library of our queries patterns are learned by using question-answer pairs, automatically. The details of automatic and manual query expansion are given in Chapter 4.

3.3.5. Building a set of Question-Answer Pairs

In our system, a collection of question-answer pairs is built for each question type. The collection of question-answer pairs is hand-written. The question-answer pairs are to be corrected. The set of question-answer pairs for the "Biggest_City_of_Country" question type (from Category 1) is given in Table 3.5. These question-answer pairs are used in query template and answer pattern extraction and our training and testing corpus.

Table 3.5. Sample Question-Answer Pairs for Query template and Answer Pattern Extraction.

No.	Question Phrase	Answer Phrase
1	Turkey	Istanbul
2	Iran	Tehran
3	India	Mumbai
4	France	Paris
5	Germany	Berlin
6	Saudi Arabia	Riyadh
7	Japan	Tokyo
8	Canada	Toronto
9	United States	New York
10	United Kingdom	London

Also, the same set of these question-answer pairs is used in learning of query template and answer extraction phases by machine learning methods.

3.3.6. Pinpointing Related Passages

Related Passages have potential to contain candidate answers. The related documents are retrieved by generated queries via Google API search engine and relevant passages are extracted from these retrieved related documents. For example, a related document for the question "What is the capital of Canada?" which is retrieved by a search engine is given as follows:

Ottawa is the capital of Canada. It stands on the south bank of the **Ottawa** River in the eastern portion of Southern Ontario. **Ottawa** borders Gatineau, Quebec; the two form the cores of the **Ottawa**–Gatineau census metropolitan area (CMA) and the **National Capital Region** (NCR).

The underlined phrase is the answer for "What is the capital of Canada?" question. For input questions in the system, new queries can be generated directly using original question words by simple transformation rules, or new queries can be generated by using different patterns which semantically captures the meaning of the original question. The first approach is called manual query expansion [68] since generated queries can only contain question words and they are obtained by simple transformations such as deleting some words or replacing some words with their synonyms. The second approach is called automatic query expansion because the structure of generated queries can be significantly different than the structure of the original question.

In automatic query expansion approach [68, 69, 70, 71, 72, and 73] new queries can be generated even though they are completely different than the original question and they may contain different words because those queries semantically capture the intention of the original question. In this thesis, we present an automatic query expansion approach in which new queries are generated depending on categories of questions and patterns which try to capture semantic intentions of questions in those categories. Some systems use both approaches together and they are called as hybrid query expansion systems. In our system, we use manual queries in addition to automatic queries in order to compare their performances.

3.3.7. Selecting Best Query Templates

In order to select best query templates for each question type, we evaluated the generated query templates with two factors. The factors are the number of correctly answered questions (count) and MRR values. After generating query template (automatic and manual) and collecting relevant passages, we compute these factors. Count is related to the number of correct answers which are found for each query in each category. We assign these factors to each query template that is extracted in the second phase. At the end of this phase, the query templates whose impacting factors that are under a certain threshold are eliminated and other query templates which have the highest performance are selected as the best query templates for each question type.

The automatic query is called AQ_i and manual query is called MA_i. Each query template has two impacting factors. The reliability of a query template is determined by means of the values of its impacting factors. The impacting factor of a query template is similar to the precision of that query template. To assign these impacting factors, we use four attributes:

- $Count_{True}$: Number of times that the query template matches a sentence and the extracted answer is correct.
- $Count_{False}$: Number of times that the query template matches a sentence and the extracted answer is incorrect.
- $Count_{Total}$: total number of times that the query template matches a sentence.
- MRR: is the mean multiplicative inverse of the rank of the first correct answer.

Each query template has its own Count and MRR attributes. The steps of the impacting factors assignment in detail are explained in detail in Chapter 4 and Chapter 6.

3.4 Document/Passage Retrieval

The document/passage retrieval phase is related with search engines and generated query templates. Queries are produced by pattern, the question phrase and the question type of a question which are categorized into the best query templates of each category in queries are submitted to the search engines (e.g. Google API, Yahoo, Yandex and Bing) to retrieve documents from the web. For each question type, we retrieve the top 20 related documents by means of question processing and document/passage retrieval phases. Documents evaluations are performed by considered evaluation measures.

3.5 Answer Processing

Answer patterns can be learned automatically or manually. In our system, answer patterns are learned automatically by querying the Web. Answer patterns are used in answer processing phase of our factoid QAS. For example, it the user asks "What is the capital of France?", the below passage is retrieved from the web for the question and the underlined word in the below retrieved passage is the expected answer.

<u>**Paris**</u> (1944-present) With the liberation of Paris in 1944, Charles de Gaulle established the Provisional Government of the French Republic, restoring Paris as the **French capital**. **Paris** is the **capital** and most populous city of **France**. Situated on the Seine River, in the north of the country, it is in the center of the Île-de-France region, also known as the region parisienne, "Paris Region".

3.5.1. Answer Pattern Extraction

Answer pattern matching or answer template matching is sub-task in answer pattern extraction phase of factoid QAS. Question phrase and question type phrase are given as inputs to factoid QAS. A set of answer patterns is used in the answer pattern extraction phase. There are different answer pattern techniques:

- Raw String: After determination of answer pattern's boundary, only the question and answer phrases are replaced by Question_Phrase and Answer_Phrase, respectively.
- Raw String with Question Type: After raw string technique is applied, the answer type replaced with Question_Type_Phrase is added to the answer patterns extracted by raw string technique.

- Stemmed String: After determination of answer pattern's boundary, all of the words in the boundary are stemmed and all affixes of the words are removed.
- Stemmed String with Answer Type: After stemmed string technique is applied, the answer type replaced with Question_Type_Phrase is added to the answer patterns extracted by stemmed string technique.
- Named Entity Tagged String: After determination of answer pattern's boundary, the NER tags of all words are extracted from the passages. Therefore, all words have to be replaced with their named entity tags.

In our approach, we use Stanford NER [74] in answer pattern extraction to replace all of words with their own named entity tags. Also, the words whose NER cannot be identified are not replaced and remain as they are. All sentences are tagged before answer pattern matching phase.

3.5.2. Answer Pattern Matching

After tagging answer pattern, learning phase of pattern is started. If an answer pattern matches a sentence, an answer is extracted from that sentence. The question phrase and question type phrase are inputs of the system and the answer is the output of the system. The extracted answer can be generated regarding to its NE tagging.

The retrieved related documents come from the document/passage retrieval phase. From related documents, the sentences which contain Question_Phrase and Question_Type_Phrase are selected. These selected sentences are stored as extracted answer patterns. Then all of the words in these patterns or tagged with the NER. After tagging, if the answer pattern matches with extracted question-answer pairs for each question type, then the retrieved pattern is considered member of our pattern set for that question type. Otherwise, it is not a member of that pattern set.

For each question type, other all answer patterns are learned. The reliable answer patterns are selected wit result to their CFs. In Chapter 5, the answer processing is given in detail.

3.5.3 Answer Ranking

After pattern matching task, the answer patterns whose impacting factors are under a given threshold are eliminated and remained patterns are ranked. The eliminated patterns are unreliable and they have to be potential to extract incorrect answers. This task leads to learning of reliable patterns for each question type in this stage and they are ready to be used in answer processing phase of factoid QAS. For answer ranking, there are different approaches.

- The first approach is based on impacting factors involved Count and MRR.
- The second approach is based on Precision, Recall, CF, F-measure and MRR.

The first approach is explained in Chapter 4 and the second approach is considered in Chapter 5 and Chapter 6. In this chapter, we introduce our factoid QAS and its own phases included question processing, document/passage retrieval, and answer processing, generally. In Chapter 4, our question processing and query expansion approaches are explained in detail.

4 Question Processing

4.1 Overview

QASs generally consist of three phases and one of the critical phases is the query expansion phase. The task of the query expansion phase is to expand the scope of user questions in order to retrieve more related documents which contain correct answers of user questions. Therefore, multiple search engine queries are generated from the original user question. These generated queries retrieve documents and related passages with correct answers, in addition to the user question. This approach leads to an increase in the amount of retrieved documents with correct answers, and correct answers for user questions can be extracted more easily from these documents. Thus, the success of the query expansion in the retrieval of documents with correct answers directly affects the performance of the QAS.

There are several related researches on query expansion in information retrieval domain for instance [75, 76]. Hah et. al. [77] presented a new query expansion approach with adaptation on engineers personalized information needs. They extend the domain ontology and indexing engineering documents, learning user profiles and are able to generate personalized queries and retrieval information. In our system, during the query expansion, automatically learned patterns from sample questions are used to expand user questions.

Colace et. al. [78] presented a method in which query expansion uses a relevance feedback method to generate queries with structured representation. Each structured representation includes weighted pairs of words. The pairs of words were selected based on probabilistic topic model. They compared the weighted pairs of words with the method for term extraction based on Kullback Leibler Divergency [79]. Generated queries extract relevance documents in relevance feedback method and peruse whether or not these documents are useful to generate new queries [69]. These relevance feedbacks are obtained from documents to response the generated queries.

Liu and Huang [80] presented a technique for medical query expansion using category-related terms in generated queries. They generate queries from natural language descriptions of their intended questions by finding medically related terms for words appearing in descriptions and using them in generated queries. In the selection of medically related terms, they use correlation between these terms and description words. In our system, we use query templates for categories in order to generate queries, and these patterns are created from a collected set of questions in those categories, furthermore those patterns may contain semantically related words with original questions.

Skowron and Araki [81] also use an automatic query expansion approach for QASs. They expand user questions using learned patterns depending on part of speech tags of question words. They learn patterns from questions and answer sets. We also use patterns to expand user questions and our patterns depend on user question types and sets of possible question structures for those question types. The query templates in our system are extracted from possible question structures.

Malo et. al. [82] presented Wikipedia based query expansion approach. Queries are expanded using Wikipedia semantics and a set of relevance statements which are provided by users. Query learning process is accomplished by a genetic programming approach. They claim that the usage of Wikipedia semantics in the creation of queries improves the success of queries. Query words are selected with respect to their semantic relatedness with user provided relevance statements.

Billerbeck et. al. [83] presented a new method to expand automatic queries by term selection from past user query which they are related with relevance documents. In [84], it has been described that past queries are useful in effective document retrieval. In query association, generated queries are related with documents which have high similarity in their contents. They show that these generated associations can present adoption with documents in which describe their contents fairly [85]. Successful evaluation of expanded queries is assessed by the relevance of retrieved documents from WWW. In our system, the evaluation of our presented query expansion approach which is a pattern based approach has been done using our corpus and datasets in TREC-8 [64], TREC-9 [65] and TREC-10 [66].

Abouenour et. al. [86] presented a method for query expansion in Arabic WordNet with structural passage retrieval based on distance density n-gram model, and they used the distance density n-gram method to improve the passage ranking process. This method extracts similarities between retrieved passages and related user questions [87, 88, and 89] and they claim that density based method is an effective model for QASs. In our presented question expansion method, when the user's question type is found, the category and the question type phrase are used in the expansion of that user question.

Knowledge based query expansion approaches use different knowledge resources such as Wikipedia, Concept-Net and WordNet to generate expanded queries using relevant documents in these databases in order to improve query expansion process [90, 91, and 92].

4.2 Query Expansion

A QAS is a system which retrieves related documents from an integrated knowledge source in order to answer given user questions. Although knowledge sources can be databases holding information, most of QASs use WWW as a knowledge source. New related queries should be generated from user questions in order to retrieve related documents which contain answers of user questions. The step of generating and expanding related queries is an important phase of a QAS since the documents containing corrects answers of user questions should be retrieved in order to extract answers from these documents. With the help of generated queries, most related documents can be retrieved.

Queries are generated directly or indirectly from user questions. If a query is generated just using words appearing in a question, we can say that the query is generated manually. On the other hand, if a query is generated using patterns which do not appear in the original question, it can be categorized as automatic query. In this thesis, we describe our approach in automatic query expansion in addition to a manual query expansion approach. Although manually generated queries can retrieve related documents, most related documents can be retrieved automatically expanded queries. Thus, an effective design of the query expansion part of a QAS plays the significant role in the success of QAS.

4.2.1. Manual Query Expansion

In order to generate manual queries, queries are created using original question words and templates available in original question. Manual query expansion is performed by means of exchanging words of a question or cleaning some of its words. Since manual query expansion is directly depends on the structure of a user question, simple operations will be enough. In our proposed query expansion approach, we also generate manual queries. We use these manually generated queries to retrieve documents from the internet using a search engines. Later, the success of these manually created queries is compared with our automatically created queries in Section 4.2.2.

In our manual query expansion, we directly use templates in user questions. In addition to using original question words, we also use some synonym words for words appearing in questions in order to expand a manually created query. A synonym word table is compiled in order to generate manual queries in our system. We generate the following four types of manual queries for a given question.

- Manual Query Type 1: Original question has been selected as a query by adding double quotes before and after the question words. This means that the original question is given as a query to our underlying search engine.
- Manual Query Type 2: Only Wh-question word appearing in the user question is cleaned and double quotes are added to create the query. For "What is the capital of France", we delete "what" question word and remaining words together with double quotes will be our manual query ("is the capital of France").
- Manual Query Type 3: Preposition words are cleaned and double quotes are added. For example, the manual query "What is capital France" is generated for the question "What is the capital of France".
- Manual Query Type 4: A synonym dictionary has been added to the system and we use synonym words instead of main words in the question. This synonym dictionary holds synonym words for most common words. Thus, the manual query is generated by replacing a word with its synonym. In this method, the manual query is "What is highest peak of Turkey" for the question "What is the highest mountain of Turkey?".

4.2.2. Automatic Query Expansion

Automatic query expansion leads to faster answer retrievals for questions. In automatic query expansion, it is expected to have an ability to expand given questions for all forms of questions. For example, categories of questions and generating new templates of questions can be learned from question examples. An ability to generate new query templates indicates that the QAS has the capability to reach the related documents that contain most likely answers for questions. By this approach, the system can also gain information about how to retrieve documents that most likely contain candidate answers. Furthermore, it can learn which words are important in the retrieval of answers for a question, even if those words are not available in that question.

Although generating a manual query is simple, complex query expansion operations in manual query expansions do not exist. Queries that are produced to determine data correlation by applying automatic query expansion methods deliver more advantages. In general, the error amount in automatic methods is less than manual methods. Although hybrid query expansion approaches get advantages of both manual and automatic query expansion approaches, they have challenges to select expanded queries.

4.3 Generation of Query

Depending on question types, different types of queries can be successful to retrieve correct answers. This means that different query templates should be used to retrieve the documents containing correct answers depending on question types. For example, certain query templates can be successful to retrieve related documents to find the answer of a capital question but same query templates may not be so successful to retrieve related documents for an author question. Here, we present an automatic query expansion method to produce queries depending on question categories.

4.3.1. Find Question Type Phrase

We presented two-level category structure with collection of 570 different factoid questions, identified factoid questions of TREC-8 [64] and TREC-9 [65] for training model. And also, in the testing section the collection of 570 factoid questions and identified factoid TREC-10 [66] questions is our corpus.

In each question type, a same question can be represented with different question strings. For example, a capital question type may contain question strings such as “What is the capital of Italy?”, and “What is the name of the capital of France?”. For each question type, a list of possible questions is populated manually and with the help of questions in TREC data set. Later, we use these lists of possible questions in order to determine the question type of a given user query using a Naive Bayes classification algorithm. For each question type, there is a Question_Type_Phrase which is used in the generation of automatic queries for a given question. For example, the Question_Type_Phrase for the capital question type is the phrase “capital”. When the question type of a given user question is determined by the Naive Bayes classification algorithm, the Question_Type_Phrase is also determined for that question.

4.3.2. Find Question Phrase

Each question type is also associated with a list of unique question templates. These question templates are the question strings which are selected from the list of possible questions of that question type and their question phrases are replaced with a string Question_Phrase. The question phrase of a factoid question is the entity string appearing in the question and the information about that entity is sought by that question. For example, if “What is the capital of Italy?” is a possible question, Italy is the Question_Phrase in that question because the information about Italy is asked for. Italy is replaced by the string Question_Phrase in order to create the question template “What is the capital of Question_Phrase?” After the question type of a given user query is determined, question templates are used to determine the string corresponding to Question_Phrase in a given user question.

4.3.3. Production Query

Depending on structural similarities of questions, 57 questions types are divided into 17 question categories. In other words, question types in a same category have structural similarities. For example, since question strings in the capital question type ("What is the capital city of Italy?"), and the biggest city question type ("What is the biggest city of France?") have similar structures, they reside in the same category. These 17 question categories are manually constructed by analyzing possible question lists of 57 question types.

Each question category is associated with a list of automatic query templates. An automatic query template is a string with four variables in the following forms:

- α1 Question_Type_Phrase α2 Question_Phrase α3
- α1 Question_Phrase α2 Question_Type_Phrase α3
- α1 Question_Phrase α2
- α1 Question_Type_Phrase α2

Where Question_Type_Phrase and Question_Phrase are variables which are replaced with appropriate strings depending on the given user question. Strings α1, α2 and α3 are ground strings of templates and they can be empty. For example, "Question_Type_Phrase of Question_Phrase" is a query template where α2 is the word "of". In this template, α1 and α3 are empty strings. Question_Type_Phrase and Question_Phrase are replaced with appropriate strings which are determined with the help of the user question. From the user question "What is the capital of Germany?", Question_Type_Phrase can be determined as "capital" and Question_Phrase can be determined as

"Germany". Thus, the query "capital of Germany" can be generated automatically by our system.

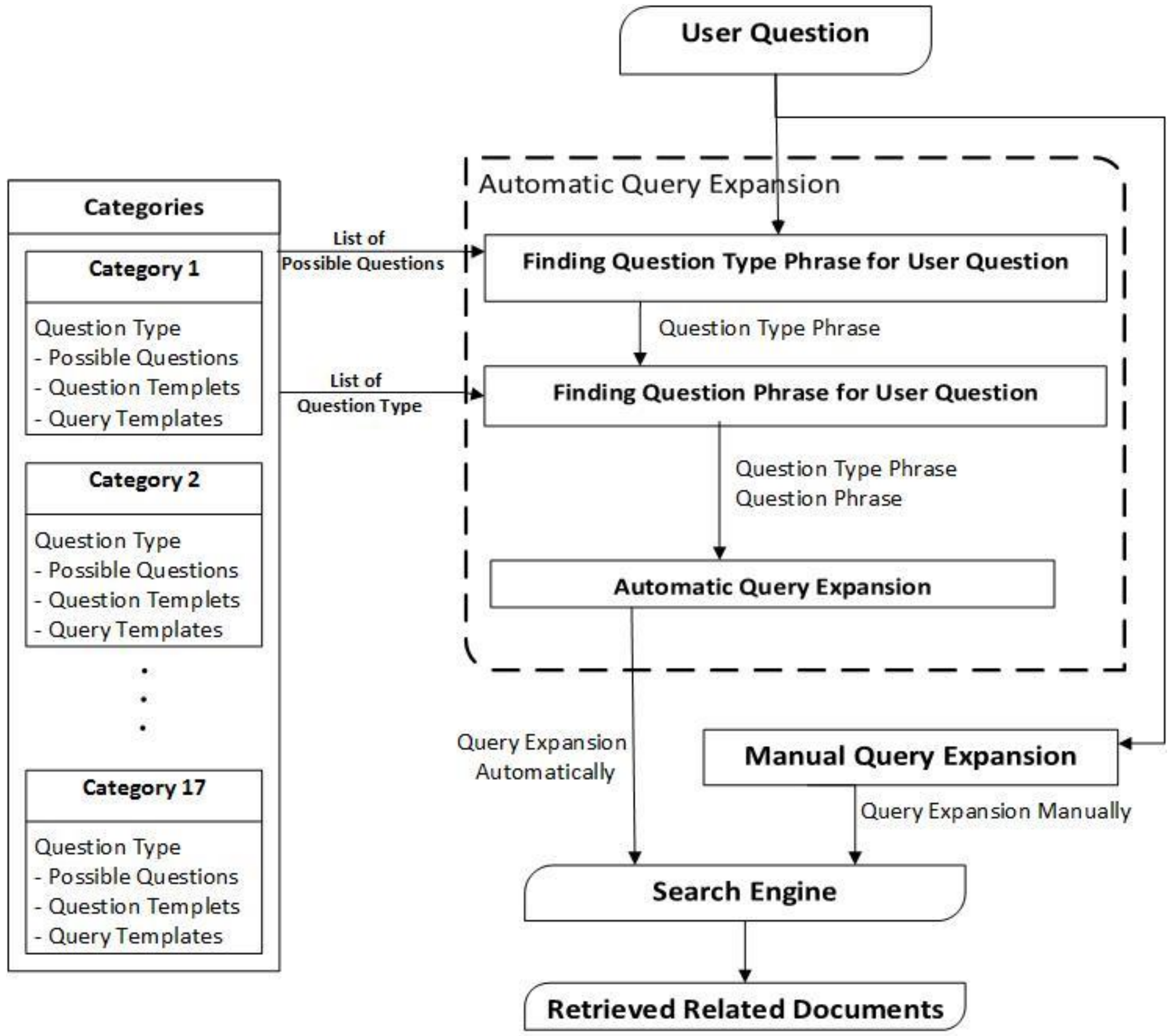

Figure 4.1. Architecture of Our Query Expansion System.

The general architecture of our query expansion system is given in Figure 4.1. According to Figure 4.1, our system uses a list of categories as a knowledge resource. Each category contains a list of question types, and query templates for that category. Each question type is associated with a list of possible questions and a list of question templates for that question type. Each question type also has a string which is used to fill Question_Type_Phrase in query expansion.

From a given user question, two sets of queries are generated. The first set is automatically generated queries using query templates and the second set is the set of manual queries which are directly generated from the user question. In order to generate automatic queries, the question type is found first and then the question phrase is found. When the question type is found, the category and the Question_Type_Phrase for that user question are determined. Automatic queries are generated from query templates by filling the gaps in those templates with found Question_Type_Phrase and question phrase. Manual queries are just created from the user query by dropping certain words from the user question.

The question type of the user question is found using a version of a Naive Bayes classification algorithm. Since we have 57 question types, our classification algorithm determines which one of these question types is most probable for the given user question. The list of possible questions of a question type is treated as training documents of that question types. Words of the user question are compared with words appearing in the lists of possible questions in order to determine the most probable question type. The category of the user question is the category of most found probable question type. Thus, the Question_Type_Phrase and the category of the user question are determined by this Naive Bayes classification algorithm.

After the question type is determined, the question templates of that question type are used to find the question phrase for the user question. The given user question is compared with these question templates by a version of Levenshtein distance algorithm [93]. With this algorithm, the question template with the minimum distance with the user question is selected as the most similar template. The differing part corresponding to the question phrase between this most similar question template and the user question are extracted as the question phrase string for that user question. For example, if the question template “What is the capital of Question_Phrase?” is the most similar template for the user question “What is the capital of Germany?”, the differing part in the user question is the string “Germany” and it is selected as Question_Phrase for that user question.

4.4 Evaluation of Queries

57 question types are used for the evaluation of our system. Each question type represents a factoid question in our system, and we prepared 10 different factoid questions for each question type. Thus, we have 570 factoid questions in order to evaluate our system. Since our questions are factoid questions, they have answer phrases as results of those questions. This means that the answer of each factoid question is recorded for evaluation purposes.

For each factoid question in our evaluation set, we found its question type using our Naive Bayes algorithm. Thus, the Question_Type_Phrase string is found for that factoid question. Then, the usage of the query templates of the category which that question type belongs to, are generated as automatic queries for that factoid question. Since each category has between 3 and 9 automatic query templates, the number of generated automatic queries for the given question is between 3 and 9. In addition, 3 or 4 manual queries are generated for each factoid question depending on their categories.

Each generated query is executed using the search engines (Google API, Yahoo, Yandex, and Bing), and the first 10 documents are retrieved. Then the number of how many times the answer phrase of that factoid question appears in each retrieved document is found. Then the average number of answer phrases in the first 10 documents is calculated and the MRR value is calculated for that factoid question. Since we submitted 10 factoid questions for each question type, the average number of answers phrases and average MRR values for a question type are average values of the results of those 10 factoid questions. After finding the average number of answer phrases and the MRR value of each question type, the average values of categories are computed from the results of question types.

The first category has 7 automatic query templates and 4 manual queries which are described in Section 4.2.1. The automatic query templates for Category 1 are as follows:

AQ1: “Question_Type_Phrase in Question_Phrase”

AQ2: “name of the Question_Type_Phrase in Question_Phrase“

AQ3: “considered as the Question_Type_Phrase of Question_Phrase“

AQ4: “current Question_Type_Phrase of Question_Phrase”

AQ5: “of Question_Phrase is considered as the Question_Type_Phrase”

AQ6: “of Question_Phrase is Question_Type_Phrase of it”

AQ7: “in Question_Phrase is the Question_Type_Phrase“

For each factoid question, Question_Type_Phrase and Question_Phrase are determined, and actual search engine query is generated using them. For example, for the factoid question “What is the capital of Spain?”, “capital” is determined as Question_Type_Phrase and “Spain” is determined as Question_Phrase. Thus, “current capital of Spain” is used by AQ4 for this factoid question. Then, the first 10 documents are retrieved as a result of this query and the total number of answer phrase (“Madrid”) appearing in these 10 documents is found as Answer_Phrase_Count for that query. Also the reciprocal rank for this query is computed using the reciprocal rank formulae 1/rank where rank is the position of the first document contains at least one answer phrase. If the first document contains at least one answer phrase, rank will be 1. If the third document contains answer phrase and the first two documents do not contain answer phrase, rank will be 3.

The first category has 12 question types, and the results of these question types are given in Table 4.1, Table 4.2, and Table 4.3. Answer_Phrase_Count in Table 4.1, Table 4.2, and Table 4.3 is the average number of Answer_Phrase_Count of 10 factoid questions in that question type for that query. The MRR value in Table 4.1, Table 4.2, and Table 4.3 is the average of MRR values of those 10 factoid questions. The MRR value for each query is calculated using the formula (4.1) [94].

$$\mathrm{MRR} = \frac{1}{|Q|}\sum_{i=1}^{|Q|}\frac{1}{\mathrm{rank}_i}. \tag{4.1}$$

Where |Q| is 10 since there are 10 factoid questions for each question type.

According to Table 4.1, Table 4.2, and Table 4.3, Answer_Phrase_Count for "Official_Language_of_Country" question type is 385.9 and MRR value is 0.95 for automatic query 7 (AQ7). This means that the results of this query contain 385.9 answer phrases on the average. The MRR value 0.95 means that 9 of 10 factoid questions have reciprocal rank 1 and the other one has 0.5. The best result for Answer_Phrase_Count (408.6) is accomplished by automatic query 5 (AQ5) for this question type. The best MRR value is 1.0 for this question type and it is accomplished by different query templates indicating that the correct answer is found in the first document for all questions of those query templates. According to Table 4.1, Table 4.2, and Table 4.3, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

Table 4.1. Answer_Phrase_Count and MRR Results for Question Types in Category 1 (A).

Question Types	longest River of Country		Question Types	Highest Mountain of Country	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	129.8	0.95	**AQ1**	149.3	1.00
AQ2	143.5	0.90	**AQ2**	111.2	1.00
AQ3	149.7	0.95	**AQ3**	107.7	1.00
AQ4	135.8	0.88	**AQ4**	124.1	1.00
AQ5	133.6	0.95	**AQ5**	121.8	1.00
AQ6	118.5	0.95	**AQ6**	125.0	1.00
AQ7	119.0	0.90	**AQ7**	131.8	0.95
MQ1	37.8	0.83	**MQ1**	13.2	0.69
MQ2	45.6	0.60	**MQ2**	110.2	0.73
MQ3	124.3	0.95	**MQ3**	141.6	1.00
MQ4	50.2	0.87	**MQ4**	79.9	0.93

Question Types	Tallest Building in Country		Question Types	Longest Ruling Dynasty in Country	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	62.9	0.85	**AQ1**	119.4	0.85
AQ2	81.4	0.85	**AQ2**	153.9	0.90
AQ3	86.3	0.85	**AQ3**	122.5	0.82
AQ4	74.6	0.71	**AQ4**	114.3	0.72
AQ5	93.3	0.85	**AQ5**	165.3	0.95
AQ6	88.9	0.85	**AQ6**	151.8	0.88
AQ7	76.2	0.90	**AQ7**	150.0	0.83
MQ1	44.7	0.59	**MQ1**	140.4	0.85
MQ2	49.3	0.53	**MQ2**	109.2	0.71
MQ3	84.4	0.85	**MQ3**	148.9	0.87
MQ4	0.0	0.00	**MQ4**	0.0	0.00

Table 4.2. Answer_Phrase_Count and MRR Results for Question Types in Category 1(B).

Question Types	Capital of Country		Question Types	Official Language of Country	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	456.5	0.95	**AQ1**	398.5	1.00
AQ2	452.3	0.95	**AQ2**	368.4	1.00
AQ3	266.8	0.78	**AQ3**	359.9	1.00
AQ4	316.1	0.90	**AQ4**	353.9	1.00
AQ5	437.7	0.83	**AQ5**	408.6	1.00
AQ6	445.1	0.85	**AQ6**	339.9	0.95
AQ7	472.6	0.95	**AQ7**	385.9	0.95
MQ1	84.2	0.68	**MQ1**	60.4	0.85
MQ2	500.7	1.00	**MQ2**	263.5	1.00
MQ3	242.6	0.75	**MQ3**	254.3	0.90
MQ4	108.3	0.88	**MQ4**	104.7	0.90
Question Types	**Biggest Lake in Country**		**Question Types**	**Calendar Type in Country**	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	74.2	0.93	**AQ1**	118.5	0.88
AQ2	75.5	0.93	**AQ2**	137.9	1.00
AQ3	74.3	0.93	**AQ3**	140.6	0.86
AQ4	76.9	0.95	**AQ4**	150.3	1.00
AQ5	82.4	0.93	**AQ5**	137.1	0.90
AQ6	71.4	1.00	**AQ6**	110.8	0.92
AQ7	66.7	0.93	**AQ7**	136.8	0.95
MQ1	26.6	0.40	**MQ1**	105.0	0.95
MQ2	12.9	0.28	**MQ2**	83.1	0.71
MQ3	77.0	0.88	**MQ3**	113.6	0.92
MQ4	0.0	0.00	**MQ4**	76.1	0.86

Table 4.3. Answer_Phrase_Count and MRR Results for Question Types in Category 1 (C).

Question Types	**Official Religion of Country**		**Question Types**	**Biggest City of Country**	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	100.8	1.00	**AQ1**	112.4	1.00
AQ2	110.9	1.00	**AQ2**	83.1	1.00
AQ3	113.8	1.00	**AQ3**	153.9	1.00
AQ4	99.5	1.00	**AQ4**	159.4	1.00
AQ5	114.5	1.00	**AQ5**	210.8	1.00
AQ6	104.3	1.00	**AQ6**	75.6	1.00
AQ7	99.0	1.00	**AQ7**	84.2	1.00
MQ1	66.3	0.82	**MQ1**	18.4	0.80
MQ2	16.1	0.48	**MQ2**	100.9	0.69
MQ3	92.2	1.00	**MQ3**	82.2	1.00
MQ4	41.6	0.90	**MQ4**	151.5	0.93
Question Types	**Types of Government**		**Question Types**	**Currency in Country**	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	36.8	0.91	**AQ1**	320.1	1.00
AQ2	37.3	0.87	**AQ2**	253.5	0.90
AQ3	46.0	0.95	**AQ3**	153.8	0.87
AQ4	37.2	1.00	**AQ4**	335.7	0.95
AQ5	55.8	0.95	**AQ5**	149.7	0.95
AQ6	36.3	0.86	**AQ6**	261.9	0.96
AQ7	33.5	0.93	**AQ7**	266.9	0.88
MQ1	26.6	0.68	**MQ1**	125.9	0.90
MQ2	47.5	0.92	**MQ2**	121.1	0.73
MQ3	30.4	0.85	**MQ3**	111.1	0.70
MQ4	18.4	0.65	**MQ4**	121.8	0.93

As shown in Table 4.4, the average of Answer_Phrase_Count and MRR are given for category 1. It means that, we calculate sum of 12 question types' values and divide them per number of question types. Based on the results of Table 4.4, the best average Answer_Phrase_Count is accomplished by automatic query 5 (AQ5) and the best average MRR is achieved by automatic query 1 (AQ1). Also, between queries, the worst average Answer_Phrase_Count and MRR is accomplished by manual query 1 (MQ1). According to Table 4.4, the best

Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

Table 4.4. Answer_Phrase_Count and MRR Results for 12 Question Types in Category 1**.**

Query Name	Average Answer_Phrase_Count	Average MRR
AQ1	171.49	0.95
AQ2	164.90	0.95
AQ3	147.14	0.92
AQ4	161.56	0.93
AQ5	173.27	0.95
AQ6	159.39	0.94
AQ7	167.24	0.94
MQ1	60.58	0.76
MQ2	117.10	0.71
MQ3	126.61	0.90
MQ4	64.20	0.68

The Category 2 has 7 automatic query templates and 4 manual queries. The automatic query templates for Category 2 with minister question types are as follows:

AQ1: "Question_Type_Phrase minister in Question_Phrase"

AQ2: "Question_Type_Phrase minister of Question_Phrase‟

AQ3: "current Question_Type_Phrase minister of Question_Phrase"

AQ4: "Question_Phrase's Question_Type_Phrase minister"

AQ5: "elected as Question_Type_Phrase minister in Question_Phrase"

AQ6: "elected as Question_Phrase Question_Type_Phrase minister"

AQ7: "considered as current Question_Type_Phrase minister in Question_Phrase"

For each factoid question, Question_Type_Phrase and Question_Phrase are determined, and actual search engine query is generated using them. For example, for the factoid question "Who is the prime minister in Turkey?", "prime minister" is determined as Question_Type_Phrase and

“Turkey” is determined as Question_Phrase. Thus, “Turkey’s prime minister” is used by AQ4 for this factoid question. Then, the first 10 documents are retrieved as a result of this query and the total number of answer phrase (“AhmetDavutoglu”) appearing in these 10 documents is found as Answer_Phrase_Count for that query. Also, we can utilize other types of minister instead of prime minister such as country minister, culture minister, and agriculture minister and so on in this question type.

The Category 2 has 12 question types, and the results of these question types are given in Table 4.5. Answer_Phrase_Count in Table 4.5 is the average number of Answer_Phrase_Count of 10 factoid questions (for prime minister) in that question type for that query. MRR value in Table 4.5 is the average of MRR values of those 10 factoid questions. The MRR value for each query is calculated using the MRR formulae.

Table 4.5. Answer_Phrase_Count and MRR Average Results for Question Types in Category 2.

Query Name	Average Answer_Phrase_Count	Average MRR
AQ1	41.5	0.93
AQ2	42.4	0.90
AQ3	45.4	0.93
AQ4	33.5	0.95
AQ5	28.6	0.93
AQ6	26.9	0.93
AQ7	43.9	0.96
MQ1	2.5	0.22
MQ2	2.9	0.23
MQ3	16.4	0.70

According to Table 4.5, average Answer_Phrase_Count for prime minister question type is 43.9 and MRR value is 0.95 for automatic query 7 (AQ7). This means that the results of this query contain 43.9 answer phrases on the average. The MRR value 0.95 means that 9 of 10 factoid questions have reciprocal rank 1 and the other one has 0.5. The best result for average Answer_Phrase_Count (45.4) is accomplished by automatic query 3 (AQ3) for this question type. The best average MRR value is 0.96 for automatic query 7 (AQ7) question type and it is accomplished by different query templates indicating that the correct answer is found in the first document for all questions of those query templates. According to Table 4.5, the best average Answer_Phrase_Count values and the best average MRR values are obtained by mostly automatic query templates.

The Category 3 has 9 automatic query templates and 4 manual queries. The automatic query templates for category 3 with 12 question types are as follows:

AQ1: "Question_Type_Phrase of Question_Phrase"

AQ2: "Question_Type_Phrase's name of Question_Phrase"

AQ3: "Question_Phrase's Question_Type_Phrase"

AQ4: "person is the Question_Type_Phrase of Question_Phrase"

AQ5: "considered as the Question_Type_Phrase of Question_Phrase"

AQ6: "one is the Question_Type_Phrase of Question_Phrase"

AQ7: "name of the Question_Type_Phrase of Question_Phrase"

AQ8: "done the Question_Phrase"

AQ9: "name of the Question_Phrase's Question_Type_Phrase"

For each factoid question, Question_Type_Phrase and Question_Phrase are determined, and actual search engine query is generated using them. For example, for the factoid question "Who is the president of Turkey?", "president" is determined as Question_Type_Phrase and "Turkey" is determined as Question_Phrase. Thus, "Turkey's president" is used AQ3 for this factoid question. Then, the first 10 documents are retrieved as a result of this query and the total number of Answer_Phrase ("RecepTayyipErdogan") appearing in these 10 documents is found as Answer_Phrase_Count for that query.

The Category 3 has 14 question types, and the results of these question types are given in Table 4.6, Table 4.7, Table 4.8, and Table 4.9. Answer_Phrase_Count in Table 4.6, Table 4.7, Table 4.8, and Table 4.9 is the number of Answer_Phrase_Count of 10 factoid questions in that question type for that query. MRR value in Table 4.6, Table 4.7, Table 4.8, and Table 4.9 is the MRR values of those 10 factoid questions. The MRR value for each query is calculated using the MRR formulae.

Table 4.6. Answer_Phrase_Count and MRR Results for 14 Question Types in Category 3 (A).

Question Types	**Author of Book**		**Question Types**	**Country President**	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	76.4	0.88	**AQ1**	57.5	0.82
AQ2	53.5	0.80	**AQ2**	16.8	0.76
AQ3	67.0	0.95	**AQ3**	59.5	0.87
AQ4	81.2	0.82	**AQ4**	37.3	0.78
AQ5	64.2	0.86	**AQ5**	20.6	0.42
AQ6	79.2	0.93	**AQ6**	27.0	0.84
AQ7	63.9	0.92	**AQ7**	41.4	0.81
AQ8	78.0	0.86	**AQ8**	19.5	0.80
AQ9	60.7	0.87	**AQ9**	48.7	0.65
MQ1	52.2	0.93	**MQ1**	17.0	0.92
MQ2	43.1	0.77	**MQ2**	39.2	0.82
MQ3	63.8	0.87	**MQ3**	16.0	0.33
MQ4	60.0	0.80	**MQ4**	7.3	0.49
Question Types	**Discoverer**		**Question Types**	**Founder**	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	26.4	0.83	**AQ1**	85.3	0.95
AQ2	23.7	0.88	**AQ2**	90.0	0.88
AQ3	19.5	0.75	**AQ3**	72.9	0.86
AQ4	44.3	0.83	**AQ4**	90.4	1.00
AQ5	53.3	0.86	**AQ5**	80.3	0.88
AQ6	22.7	0.88	**AQ6**	88.8	1.00
AQ7	32.4	0.79	**AQ7**	88.7	0.95
AQ8	33.4	0.75	**AQ8**	57.8	0.66
AQ9	19.8	0.83	**AQ9**	78.4	0.95
MQ1	21.7	0.59	**MQ1**	19.6	0.42
MQ2	19.4	0.53	**MQ2**	33.6	0.46
MQ3	12.8	0.59	**MQ3**	73.0	0.85
MQ4	3.4	0.05	**MQ4**	2.7	0.05

Table 4.7. Answer_Phrase_Count and MRR Results for 14 Question Types in Category 3 (B).

Question Types	Mayor		Question Types	Government	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	30.2	0.71	**AQ1**	51.7	1.00
AQ2	18.5	0.81	**AQ2**	32.4	0.95
AQ3	38.2	0.71	**AQ3**	58.5	1.00
AQ4	19.1	0.63	**AQ4**	18.3	0.82
AQ5	17.8	0.78	**AQ5**	36.8	1.00
AQ6	26.0	0.66	**AQ6**	40.6	1.00
AQ7	40.6	0.78	**AQ7**	50.4	1.00
AQ8	30.2	0.71	**AQ8**	34.9	1.00
AQ9	40.8	0.77	**AQ9**	54.7	1.00
MQ1	10.1	0.43	**MQ1**	15.2	0.56
MQ2	26.8	0.80	**MQ2**	38.1	0.93
MQ3	18.6	0.57	**MQ3**	13.0	0.45
MQ4	0.0	0.00	**MQ4**	47.6	0.70
Question Types	**Killer**		**Question Types**	**creator**	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	69.5	0.87	**AQ1**	41.9	1.0
AQ2	74.3	0.87	**AQ2**	40.0	0.88
AQ3	79.5	0.87	**AQ3**	34.1	1.00
AQ4	84.5	1.00	**AQ4**	37.9	1.00
AQ5	88.0	0.83	**AQ5**	33.3	1.00
AQ6	81.0	0.83	**AQ6**	37.4	1.00
AQ7	91.2	0.83	**AQ7**	43.7	0.93
AQ8	61.8	0.87	**AQ8**	35.8	0.88
AQ9	63.0	0.87	**AQ9**	35.1	0.82
MQ1	31.3	0.37	**MQ1**	25.7	0.71
MQ2	6.5	0.46	**MQ2**	22.8	0.60
MQ3	52.5	0.50	**MQ3**	11.4	0.45
MQ4	57.7	0.50	**MQ4**	13.7	0.45

Table 4.8. Answer_Phrase_Count and MRR Results for 14 Question Types in Category 3 (C).

Question Types	Film Director		Question Types	Inventor	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	44.9	1.00	**AQ1**	75.4	0.90
AQ2	39.5	0.85	**AQ2**	89.5	0.95
AQ3	51.7	0.95	**AQ3**	72.6	0.90
AQ4	36.6	0.87	**AQ4**	85.0	0.82
AQ5	46.1	1.00	**AQ5**	79.8	0.95
AQ6	47.7	1.00	**AQ6**	75.1	0.95
AQ7	38.1	0.95	**AQ7**	85.0	0.87
AQ8	36.0	0.92	**AQ8**	81.6	0.90
AQ9	37.4	1.00	**AQ9**	78.7	0.85
MQ1	11.4	0.58	**MQ1**	7.6	0.45
MQ2	30.2	0.82	**MQ2**	24.4	0.64
MQ3	42.6	1.00	**MQ3**	44.4	0.83
MQ4	46.0	0.87	**MQ4**	1.2	0.05
Question Types	**King**		**Question Types**	**Parliament Speaker**	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	43.8	1.00	**AQ1**	147.8	0.69
AQ2	21.9	1.00	**AQ2**	16.6	0.72
AQ3	52.4	1.00	**AQ3**	23.4	0.75
AQ4	39.5	0.67	**AQ4**	16.8	0.61
AQ5	19.0	0.92	**AQ5**	16.6	0.62
AQ6	44.9	1.00	**AQ6**	20.4	0.61
AQ7	44.1	1.00	**AQ7**	148.4	0.61
AQ8	43.8	1.00	**AQ8**	6.8	0.81
AQ9	55.3	1.00	**AQ9**	21.6	0.72
MQ1	13.4	0.66	**MQ1**	21.4	0.61
MQ2	20.4	0.84	**MQ2**	16.0	0.56
MQ3	46	0.80	**MQ3**	21.4	0.81
MQ4	0.0	0.00	**MQ4**	1.2	0.09

Table 4.9. Answer_Phrase_Count and MRR Results for 14 Question Types in Category 3 (D).

Question Types	Football head of coach		Question Types	Leader of Revolution	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	35.2	0.90	**AQ1**	20.2	0.89
AQ2	23.4	0.80	**AQ2**	26.3	0.83
AQ3	30.8	0.80	**AQ3**	23.3	0.92
AQ4	24.9	0.83	**AQ4**	29.8	0.83
AQ5	27.7	0.90	**AQ5**	28.3	0.92
AQ6	30.4	0.90	**AQ6**	17.3	0.92
AQ7	34.4	0.90	**AQ7**	22.2	0.81
AQ8	11.4	0.74	**AQ8**	20.2	0.75
AQ9	30.9	0.90	**AQ9**	20.2	0.92
MQ1	30.3	0.90	**MQ1**	19.0	0.58
MQ2	32.2	0.85	**MQ2**	1.8	0.33
MQ3	33.6	0.90	**MQ3**	20.8	0.89
MQ4	16.1	0.74	**MQ4**	15.3	0.58

According to Table 4.6, Table 4.7, Table 4.8, and Table 4.9, Answer_Phrase_Count for "Author_of_Book" question type is 51.7 and MRR value is 1 for automatic query 2 (AQ2). This means that the results of this query contain 51.7 answer phrases on the average. The MRR value 1 means that 10 of 10 factoid questions have reciprocal rank 1. The best result for Answer_Phrase_Count (46.1) is accomplished by automatic query 5 (AQ5) for question type (Film_Director). The best MRR value is 1.0 for this question type and it is accomplished by different query templates indicating that the correct answer is found in the first document for all questions of those query templates. According to Table 4.6, Table 4.7, Table 4.8, and Table 4.9, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

Table 4.10. Answer_Phrase_Count and MRR Average Results for 14 Question Types in Category 3.

Query Name	Average Answer_Phrase_Count	Average MRR
AQ1	57.6	0.89
AQ2	40.4	0.86
AQ3	48.8	0.88
AQ4	46.1	0.82
AQ5	43.7	0.85
AQ6	45.6	0.89
AQ7	58.9	0.87
AQ8	39.4	0.83
AQ9	46.1	0.87
MQ1	21.1	0.62
MQ2	25.3	0.67
MQ3	33.6	0.70
MQ4	19.4	0.38

As shown in Table 4.10, the average of Answer_Phrase_Count and MRR are given. It means that, we calculate sum of 14 question types' values and divide them per number of question types. Based on the results of Table 4.10, the best average Answer_Phrase_Count is accomplished by automatic query 7 (AQ7), and the best average MRR is achieved by automatic query 6 (AQ6). Also, between queries, the worst average Answer_Phrase_Count and MRR is accomplished by manual query 4 (MQ4). According to Table 4.10, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

The Category 4 has 6 automatic query templates and 4 manual queries. The automatic query templates for this category with 6 question types are as follows:

AQ1: “Question_Type_Phrase’s birthday”

AQ2: “time is the Question_Type_Phrase’s birthday”

AQ3: “Question_Type_Phrase born”

AQ4: “year was Question_Type_Phrase born”

AQ5: “year is registered as the year of Question_Type_Phrase’s birth”

AQ6: "Question_Type_Phrase's date of birth"

For each factoid question, Question_Type_Phrase is determined, and actual search engine query is generated using it. For example, for the factoid question "When is Mahatma Gandhi's birthday?", "Mahatma Gandhi" is determined as Question_Type_Phrase. Thus, "Mahatma Gandhi's birthday" is used AQ1 for this factoid question. Then, the first 10 documents are retrieved as a result of this query and the total number of answer phrase ("October 2, 1869") appearing in these 10 documents is found as Answer_Phrase_Count for that query.

The Category 4 has 1 question types, and the results of these question types are given in Table 4.11. Answer_Phrase_Count in Table 4.11 is the number of Answer_Phrase_Count of 10 factoid questions in that question type for that query. MRR value in Table 4.11 is the MRR values of those 10 factoid questions. The MRR value for each query is calculated using the MRR formulae.

Table 4.11. Answer_Phrase_Count and MRR Average Results for 1 Question Types in Category 4.

Query Name	Answer_Phrase_Count	MRR
AQ1	13.9	0.71
AQ2	14.4	0.77
AQ3	17.0	0.95
AQ4	16.4	0.95
AQ5	11.3	0.64
AQ6	17.5	0.85
MQ1	5.5	0.47
MQ2	6.1	0.45
MQ3	6.0	0.48
MQ4	3.8	0.53

According to Table 4.11, average Answer_Phrase_Count for "Born" question type is 17.5 and MRR value is 0.85 for automatic query 6 (AQ6). This means that the results of this query contain 17.5 answer phrases on the average. The MRR value 0.85 means that 10 of 10 factoid questions have reciprocal rank 0.85. The best result for Answer_Phrase_Count

(17.5) is accomplished by automatic query 6 (AQ6) for question type (Born). The best MRR value is 0.95 for this question type and it is accomplished by different query templates indicating that the correct answer is found in the first document for all questions of those query templates. According to Table 4.11, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

The Category 5 has 9 automatic query templates and 4 manual queries. The automatic query templates for category 5 with 7 question types are as follows:

AQ1: "year did the Question_Type_Phrase happen in Question_Phrase"

AQ2: "Question_Type_Phrase in Question_Phrase"

AQ3: "date was Question_Type_Phrase in Question_Phrase"

AQ4: "Question_Type_Phrase occurred in Question_Phrase"

AQ5: "year is registered as Question_Type_Phrase in Question_Phrase"

AQ6: "date was Question_Type_Phrase occurred in Question_Phrase"

AQ7: "Question_Type_Phrase happen in Question_Phrase"

AQ8: "year was Question_Type_Phrase happen in Question_Phrase"

AQ9: "date was Question_Type_Phrase happen in Question_Phrase"

For each factoid question, Question_Type_Phrase and Question_Phrase are determined, and actual search engine query is generated using them. For example, for the factoid question "In which year did the explosion happen in Texas?", "explosion" is determined as Question_Type_Phrase and "Texas" is determined as Question_Phrase. Thus, "explosion in Texas" is used AQ2 for this factoid question. Then, the first 10 documents are retrieved as a result of this query and the total number of answer phrase ("April 17, 2013") appearing in these 10 documents is found as Answer_Phrase_Count for that query.

The Category 5 has 7 question types, and the results of these question types are given in Table 4.12 and Table 13. Answer_Phrase_Count in Table 4.12 and Table 13 is the number of Answer_Phrase_Count of 10 factoid questions in that question type for that query. MRR value in Table 4.12 and Table 13 is the MRR values of those 10 factoid questions. The MRR value for each query is calculated using the MRR formulae.

Table 4.12. Answer_Phrase_Count and MRR Results for 7 Question Types in Category 5 (A).

Question Types	**Earthquake**		**Question Types**	**Explosion**	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	133.0	0.87	**AQ1**	47.5	0.75
AQ2	135.5	0.87	**AQ2**	23.7	0.75
AQ3	170.2	0.87	**AQ3**	21.2	0.75
AQ4	153.5	1.00	**AQ4**	37.4	0.66
AQ5	147.5	0.75	**AQ5**	18.9	0.58
AQ6	161.0	1.00	**AQ6**	38.4	0.77
AQ7	132.5	0.83	**AQ7**	70.9	0.52
AQ8	148.8	0.87	**AQ8**	63.4	0.66
AQ9	151.0	1.00	**AQ9**	41.0	0.80
MQ1	5.5	0.62	**MQ1**	85.8	0.66
MQ2	142.5	0.50	**MQ2**	64.5	0.73
MQ3	5.5	0.62	**MQ3**	76.6	0.76
MQ4	3.2	0.25	**MQ4**	36.0	0.50
Question Types	**Revolutions**		**Question Types**	**Storm**	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	147.1	0.95	**AQ1**	51.2	0.95
AQ2	135.8	0.87	**AQ2**	94.1	0.82
AQ3	146.2	0.85	**AQ3**	117.5	0.70
AQ4	210.8	0.95	**AQ4**	66.4	0.72
AQ5	106.1	0.85	**AQ5**	62.8	0.44
AQ6	217.9	1.00	**AQ6**	73.6	0.88
AQ7	142.9	0.90	**AQ7**	50.2	0.85
AQ8	152.1	0.95	**AQ8**	64.3	0.95
AQ9	217.4	0.95	**AQ9**	127.0	0.92
MQ1	75.7	0.95	**MQ1**	94.8	0.82
MQ2	68.5	0.78	**MQ2**	43.9	0.78
MQ3	91.3	0.95	**MQ3**	84.4	0.79
MQ4	9.2	0.35	**MQ4**	43.4	0.95

Table 4.13. Answer_Phrase_Count and MRR Results for 7 Question Types in Category 5 (B).

Question Types	Flood		Question Types	Political Events	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	42.5	0.90	**AQ1**	101.2	0.74
AQ2	30.4	0.93	**AQ2**	23.9	0.45
AQ3	42.9	0.93	**AQ3**	31.3	0.59
AQ4	37.5	0.82	**AQ4**	19.9	0.53
AQ5	34.0	0.71	**AQ5**	47.0	0.93
AQ6	34.8	0.93	**AQ6**	80.8	0.60
AQ7	39.5	0.83	**AQ7**	94.7	0.54
AQ8	36.6	0.95	**AQ8**	92.2	0.64
AQ9	44.7	0.90	**AQ9**	109.3	0.77
MQ1	43.0	0.95	**MQ1**	19.2	0.46
MQ2	40.4	0.95	**MQ2**	11.8	0.30
MQ3	36.5	0.90	**MQ3**	19.5	0.48
MQ4	0.0	0.00	**MQ4**	0.0	0.00

Question Types	Wildfire	
Query Name	**Answer_Phrase_Count**	**MRR**
AQ1	48.3	0.95
AQ2	53.4	0.90
AQ3	54.1	0.95
AQ4	55.6	1.00
AQ5	59.7	1.00
AQ6	53.6	1.00
AQ7	52.7	0.95
AQ8	52.2	0.95
AQ9	55.4	1.00
MQ1	52.0	0.95
MQ2	53.4	0.90
MQ3	58.8	0.88
MQ4	51.7	0.92

According to Table 4.12 and Table 13, Answer_Phrase_Count for "Earthquake" question type is 151 and MRR value is 1 for automatic query 9 (AQ9). This means that the results of this query contain 151 answer phrases on the average. The MRR value 1 means that 10 of 10 factoid questions have reciprocal rank 1. The best result for Answer_Phrase_Count (170.25) is accomplished by automatic query 3

(AQ3) for question type (Earthquake). The best MRR value is 0.875 for this question type and it is accomplished by automatic query 3 (AQ3) template indicating that the correct answer is found in the first document for all questions of those query templates. According to Table 4.14, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

Table 4.14. Answer_Phrase_Count and MRR Average Results for 7 Question Types in Category 5.

Query Name	Answer_Phrase_Count	MRR
AQ1	81.5	0.87
AQ2	71.0	0.80
AQ3	83.4	0.81
AQ4	83.1	0.81
AQ5	68.0	0.75
AQ6	94.3	0.88
AQ7	83.3	0.77
AQ8	87.1	0.85
AQ9	106.5	0.91
MQ1	53.7	0.77
MQ2	60.7	0.71
MQ3	53.2	0.77
MQ4	20.5	0.42

In Table 4.14, the averages of Answer_Phrase_Count and MRR for Category 5 are given. It means that we calculate sum of 7 question type's values and divide them per number of question types. Based on the results of Table 4.14, the best average Answer_Phrase_Count is accomplished by automatic query 9 (AQ9) and the best average MRR is achieved by automatic query 9 (AQ9) too. Also, between queries, the worst average Answer_Phrase_Count and MRR is accomplished by manual query 4 (MQ4). According to Table 4.14, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

The Category 6 has 4 automatic query templates and 4 manual queries. The automatic query templates for category 6 with 1 question types are as follows:

AQ1: "live in Question_Type_Phrase"

AQ2: "people are there in Question_Type_Phrase"

AQ3: "Question_Type_Phrase' are there in Question_Phrase"

AQ4: "is the Question_Type_Phrase of Question_Phrase"

For each factoid question, Question_Type_Phrase and Question_Phrase are determined, and actual search engine query is generated using them. For example, for the factoid question "How many people live in Iran?", "Population" is determined as Question_Type_Phrase and "Iran" is determined as Question_Phrase. Thus, "Population are there in Iran" is used AQ3 for this factoid question. Then, the first 10 documents are retrieved as a result of this query and the total number of answer phrase ("77.45 million") appearing in these 10 documents is found as Answer_Phrase_Count for that query.

The Category 6 has 1 question type, and the results of this question type are given in Table 4.15. Answer_Phrase_Count in Table 4.15 is the number of Answer_Phrase_Count of 10 factoid questions in that question type for that query. MRR value in Table 4.15 is the MRR values of those 10 factoid questions. The MRR value for each query is calculated using the MRR formulae.

Table 4.15. Answer_Phrase_Count and MRR Results for 1 Question Type in Category 6.

Query Name	Average Answer_Phrase_Count	Average MRR
AQ1	39.7	0.49
AQ2	39.2	1.00
AQ3	137	1.00
AQ4	84.7	0.92
MQ1	63.5	0.79
MQ2	36.2	0.89
MQ3	36.8	0.47
MQ4	8.3	0.39

According to Table 4.15, Answer_Phrase_Count for "Population" question type is 137 and MRR value is 1 for automatic query 3 (AQ3). This means that the results of this query contain 137 answer phrases on the average. The MRR value 1 means that 10 of 10 factoid questions have reciprocal rank 1. The best result for Answer_Phrase_Count (84.66) is accomplished by automatic query 4 (AQ4) for question type (population). The best MRR value is 1.0 for the automatic question type 2 and 3 (AQ2 and AQ3) and it is accomplished by different query templates indicating that the correct answer is found in the first document for all questions of those query templates. According to Table 4.15, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

The Category 7 has 9 automatic query templates and 4 manual queries. The automatic query templates for Category 7 with 3 question types are as follows:

AQ1: "Question_Type_Phrase of Question_Phrase"

AQ2: "Question_Phrase Question_Type_Phrase"

AQ3: "name of the Question_Type_Phrase of Question_Phrase‟

AQ4: "Question_Type_Phrase Used in Question_Phrase"

AQ5: "Question_Phrase of Question_Type_Phrase"

AQ6: "Question_Type_Phrase does the Question_Phrase use"

AQ7: “Question_Phrase does Question_Type_Phrase use”

AQ8: “Question_Type_Phrase’s Question_Phrase”

AQ9: “name of the Question_Type_Phrase Question_Phrase”

For each factoid question, Question_Type_Phrase and Question_Phrase are determined, and actual search engine query is generated using them. For example, for the factoid question “What is the Muslim of bible?”, “Muslim” is determined as Question_Type_Phrase and “bible is determined as Question_Phrase. Thus, “Bible of Muslim” is used AQ5 for this factoid question. Then, the first 10 documents are retrieved as a result of this query and the total number of answer phrase (“Koran”) appearing in these 10 documents is found as Answer_Phrase_Count for that query.

The Category 7 has 3 question types, and the results of these question types are given in Table 4.16. Answer_Phrase_Count in Table 4.16 is the number of Answer_Phrase_Count of 10 factoid questions in that question type for that query. MRR value in Table 4.16 is the MRR values of those 10 factoid questions. The MRR value for each query is calculated using the MRR formulae.

Table 4.16. Answer_Phrase_Count and MRR Results for 3 Question Types in Category 7.

Question Types	Holy Book		Question Types	Color	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	73.3	0.83	**AQ1**	143.8	0.93
AQ2	75.0	0.88	**AQ2**	144.2	0.85
AQ3	71.0	0.77	**AQ3**	228.0	1.00
AQ4	76.8	0.75	**AQ4**	171.0	0.85
AQ5	553.8	0.83	**AQ5**	1072.1	0.77
AQ6	84.8	0.80	**AQ6**	115.0	0.95
AQ7	75.7	0.78	**AQ7**	127.2	0.90
AQ8	76.2	0.83	**AQ8**	86.4	0.78
AQ9	75.3	0.83	**AQ9**	242.2	0.95
MQ1	39.4	0.52	**MQ1**	41.1	0.77
MQ2	52.3	0.40	**MQ2**	160.9	0.74
MQ3	5.8	0.48	**MQ3**	111.6	0.90
MQ4	52.2	0.50	**MQ4**	24.4	0.41

Question Types	Code	
Query Name	**Answer_Phrase_Count**	**MRR**
AQ1	114.7	0.83
AQ2	114.1	0.83
AQ3	110.8	0.95
AQ4	89.5	0.95
AQ5	750.1	0.78
AQ6	76.5	0.95
AQ7	74.1	0.88
AQ8	103.5	0.75
AQ9	111.5	0.95
MQ1	73.1	0.80
MQ2	59.0	0.77
MQ3	118.7	0.95
MQ4	0.2	0.10

According to Table 4.16, Answer_Phrase_Count for "Holy_Book" question type is 553.8 and MRR value is 0.8 for automatic query 5 (AQ5). This means that the results of this query contain 84.8 answer phrases on the average. The MRR value 0.8 means that 8 of 10 factoid questions have reciprocal rank 1. The best result for Answer_Phrase_Count is accomplished by query 5 (AQ5) for question type (Holy_Book). The best

MRR value is 0.83 for this question type and it is accomplished by different query templates indicating that the correct answer is found in the first document for all questions of those query templates. According to Table 4.17, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

Table 4.17. Average of Answer_Phrase_Count and MRR Results for 3 Question Types in Category 7.

Query Name	Average Answer_Phrase_Count	Average MRR
AQ1	110.6	0.87
AQ2	111.1	0.86
AQ3	136.6	0.91
AQ4	112.4	0.85
AQ5	792.0	0.79
AQ6	92.1	0.90
AQ7	92.3	0.86
AQ8	88.7	0.79
AQ9	143.0	0.91
MQ1	51.2	0.70
MQ2	90.7	0.64
MQ3	78.7	0.78
MQ4	25.6	0.34

According to Table 4.17, the averages of Answer_Phrase_Count and MRR for Category 7 are given. It means that, we calculate sum of 7 question type's values and divide them per number of question types. Based on the results of Table 4.17, the best average Answer_Phrase_Count is accomplished by automatic query 5 (AQ5) is 792.0 and the best average MRR is 0.91 achieved by automatic query 9 (AQ9) too. Also, between queries, the worst average Answer_Phrase_Count and MRR is accomplished by manual query 4 (MQ4) is 25.6 and 0.34, respectively. According to Table 4.17, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

The Category 8 has 8 automatic query templates and 4 manual queries. The automatic query templates for Category 8 with 4 question types are as follows:

AQ1: "Question_Type_Phrase's Question_Phrase"

AQ2: "Question_Phrase Question_Type_Phrase been located "

AQ3: "Question_Type_Phrase of Question_Phrase"

AQ4: "Question_Phrase Question_Type_Phrase"

AQ5: "Question_Type_Phrase of Question_Phrase"

AQ6: "Cities is the Question_Type_Phrase of Question_Phrase"

AQ7: "Considered as the Question_Type_Phrase of Question_Phrase"

AQ8: "Considered as the Question_Phrase of Question_Type_Phrase"

For each factoid question, Question_Type_Phrase and Question_Phrase are determined, and actual search engine query is generated using them. For example, for the factoid question "In which city has the NATO headquarters been located?", "Headquarters" is determined as Question_Type_Phrase and "NATO" is determined as Question_Phrase. Thus, "Headquarters of NATO" is used AQ3 for this factoid question. Then, the first 10 documents are retrieved as a result of this query and the total number of answer phrase ("Brussels") appearing in these 10 documents is found as Answer_Phrase_Count for that query.

The Category 8 has 4 question types, and the results of these question types are given in Table 4.18 and Table 4.19. Answer_Phrase_Count in Table 4.18 and Table 4.19 is the number of Answer_Phrase_Count of 10 factoid questions in that question type for that query. MRR value in Table 4.18 and Table 4.19 is the MRR values of those 10 factoid questions. The MRR value for each query is calculated using the MRR formula.

Table 4.18. Answer_Phrase_Count and MRR Results for 4 Question Types in Category 8 (A).

Question Types	Headquarters		Question Types	Airport Places	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	13.7	0.74	**AQ1**	243.8	0.80
AQ2	11.6	0.56	**AQ2**	162.0	0.73
AQ3	9.2	0.59	**AQ3**	139.8	0.73
AQ4	20.6	0.56	**AQ4**	164.6	0.78
AQ5	18.2	0.59	**AQ5**	174.5	0.79
AQ6	17.4	0.64	**AQ6**	250.5	0.77
AQ7	20.2	0.52	**AQ7**	176.1	0.65
AQ8	19.1	0.67	**AQ8**	259.2	0.74
MQ1	18.8	0.65	**MQ1**	226.2	0.90
MQ2	18.2	0.68	**MQ2**	197.5	0.75
MQ3	10.8	0.65	**MQ3**	252.3	0.87
MQ4	31.0	0.23	**MQ4**	0.0	0.00

Table 4.19. Answer_Phrase_Count and MRR Results for 4 Question Types in Category 8 (B).

Question Types	Birth Place		Question Types	Company	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	109.1	0.83	**AQ1**	23.7	0.95
AQ2	78.7	0.90	**AQ2**	15.1	0.72
AQ3	94.7	0.80	**AQ3**	15.3	0.66
AQ4	90.9	0.80	**AQ4**	14.6	0.87
AQ5	127.2	0.90	**AQ5**	20.0	0.75
AQ6	87.3	0.83	**AQ6**	11.1	0.37
AQ7	91.5	0.95	**AQ7**	12.8	0.51
AQ8	78.0	0.85	**AQ8**	5.2	0.15
MQ1	59.1	0.65	**MQ1**	16.9	0.62
MQ2	54.9	0.58	**MQ2**	13.9	0.62
MQ3	59.1	0.65	**MQ3**	13.4	0.68
MQ4	32.1	0.20	**MQ4**	13.2	0.66

According to Table 4.18 and Table 4.19, Answer_Phrase_Count for "Birth_Place" question type is 91.5 and MRR value is 0.95 for automatic query 7 (AQ7). This means that the results of this query contain 91.5 answer phrases on the average. The MRR value 0.95 means that 10 of 10 factoid questions have reciprocal rank 0.95. The best result for Answer_Phrase_Count (94.7) is accomplished by automatic query 3 (AQ3) for question type (birth_place). The best MRR value is 0.95 for this question type and it is accomplished by automatic query 7 (AQ7) template indicating that the correct answer is found in the first document for all questions of those query templates. According to Table 4.20, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

Table 4.20. Average of Answer_Phrase_Count and MRR Results for 4 Question Types in Category 8.

Query Name	Average Answer_Phrase_Count	Average MRR
AQ1	78.1	0.67
AQ2	53.5	0.58
AQ3	51.8	0.56
AQ4	58.1	0.60
AQ5	68.0	0.61
AQ6	73.3	0.52
AQ7	60.1	0.53
AQ8	72.1	0.48
MQ1	64.2	0.56
MQ2	71.1	0.53
MQ3	67.1	0.57
MQ4	15.3	0.22

According to Table 4.20, the averages of Answer_Phrase_Count and MRR for category 8 are given. It means that we calculate sum of 4 question type's values and divide them per number of question types. Based on the results of Table 4.20, the best average Answer_Phrase_Count is accomplished by automatic query 1 (AQ1) is 78.06 and the best average MRR is 0.67 achieved this query, too. Also, between queries, the worst average Answer_Phrase_Count and MRR is accomplished by manual query 4 (MQ4) is 15.26 and 0.22, respectively. According to Table 4.20, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

The Category 9 has 7 automatic query templates and 4 manual queries. The automatic query templates for Category 9 with 1 question types are as follows:

AQ1: "Question_Type_Phrase Question_Phrase been located"

AQ2: "Question_Phrase of Question_Type_Phrase"

AQ3: "Question_Phrase Question_Type_Phrase"

AQ4: "countries are the Question_Type_Phrase of Question_Phrase"

AQ5: "considered as the Question_Type_Phrase of Question_Phrase"

AQ6: "considered as the Question_Phrase of Question_Type_Phrase"

AQ7: "countries are the Question_Phrase of Question_Type_Phrase"

For each factoid question, Question_Type_Phrase and Question_Phrase are determined, and actual search engine query is generated using them. For example, for the factoid question "In which country has the oil-producing biggest producer been located?", "Biggest Producer" is determined as Question_Type_Phrase and "Oil-producing" is determined as Question_Phrase. Thus, "biggest producer Oil-producing been located" is used AQ1 for this factoid question. Then, the first 10 documents are retrieved as a result of this query and the total number of answer phrase ("Russia") appearing in these 10 documents is found as Answer_Phrase_Count for that query.

The Category 9 has 1 question types, and the results of these question types are given in Table 4.21. Answer_Phrase_Count in Table 4.21 is the number of Answer_Phrase_Count of 10 factoid questions in that question type for that query. MRR value in Table 4.21 is the MRR values of those 10 factoid questions. The MRR value for each query is calculated using the MRR formulae.

Table 4.21. Answer_Phrase_Count and MRR Average Results for 1 Question Types in Category 9.

Query Name	Average Answer_Phrase_Count	Average MRR
AQ1	75.9	1.00
AQ2	50.5	1.00
AQ3	49.5	1.00
AQ4	44.7	1.00
AQ5	52.1	0.90
AQ6	68.2	1.00
AQ7	70.8	1.00
MQ1	79.7	1.00
MQ2	72.7	0.95
MQ3	62.6	1.00
MQ4	43.8	0.63

According to Table 4.21, Answer_Phrase_Count for "Biggest_Producer" question type is 75.9 and MRR value is 1 for automatic query 1 (AQ1). This means that the results of this query contain 75.9 answer phrases on the average. The MRR value 1 means that 10 of 10 factoid questions have reciprocal rank 1. The best result for Answer_Phrase_Count (79.7) is accomplished by query 1 (AQ1) for "Biggest_Producer" question type. The best MRR value is 1.0 for this question type and it is accomplished by different query templates indicating that the correct answer is found in the first document for all questions of those query templates.

The Category 10 has 9 automatic query templates and 3 manual queries. The automatic query templates for Category 10 with 1 question types are as follows:

AQ1: "Question_Type_Phrase of Question_Phrase‟

AQ2: "Question_Phrase Question_Type_Phrase"

AQ3: "Name of the Question_Type_Phrase Question_Phrase‟

AQ4: "Question_Type_Phrase Question_Phrase is used"

AQ5: "Question_Type_Phrase does Question_Phrase use"

AQ6: "Question Phrase's Question_Type_Phrase"

AQ7: “name of the Question_Type_Phrase of Question_Phrase”

AQ8: “Question_Phrase belong Question_Type_Phrase”

AQ9: “Question_Type_Phrase is Question_Phrase belonging”

For each factoid question, Question_Type_Phrase and Question_Phrase are determined, and actual search engine query is generated using them. For example, for the factoid question “What is the nationality of Napoleon Bonaparte?”, “nationality” is determined as Question_Type_Phrase and “Napoleon Bonaparte” is determined as Question_Phrase. Thus, “Napoleon Bonaparte’s nationality” is used AQ6 for this factoid question. Then, the first 10 documents are retrieved as a result of this query and the total number of answer phrase (“French”) appearing in these 10 documents is found as Answer_Phrase_Count for that query.

The Category 10 has 1 question types, and the results of these question types are given in Table 4.22. Answer_Phrase_Count in Table 4.22 is the number of Answer_Phrase_Count of 10 factoid questions in that question type for that query. MRR value in Table 4.22 is the MRR values of those 10 factoid questions.

Table 4.22. Average of Answer_Phrase_Count and MRR Average Results for 1 Question Types in Category 10.

Query Name	Average Answer_Phrase_Count	Average MRR
AQ1	129.9	0.90
AQ2	130.2	0.85
AQ3	131.2	1.00
AQ4	155.5	0.95
AQ5	123.2	0.90
AQ6	125.0	0.90
AQ7	135.7	1.00
AQ8	111.6	0.95
AQ9	117.3	0.87
MQ1	6.7	0.80
MQ2	16.9	0.83
MQ3	127.9	0.80

According to Table 4.22, Answer_Phrase_Count for "Nationality" question type is 155.5 and MRR value is 0.95 for automatic query 4 (AQ4). This means that the results of this query contain 155.5 answer phrases on the average. The MRR value 0.95 means that 9 of 10 factoid questions have reciprocal rank 1 and 1 factoid question have reciprocal rank is 0.5. The best result for Answer_Phrase_Count (155.5) is accomplished by query 4 (AQ4) for nationality question type. The best MRR value is 1.0 for automatic query 3 (AQ3) and automatic query 7 (AQ7) in this question type and it is accomplished by different query templates indicating that the correct answer is found in the first document for all questions of those query templates. According to Table 4.22, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

The Category 11 has 5 automatic query templates and 4 manual queries. The automatic query templates for Category 11 with 1 question types are as follows:

AQ1: "Question_Phrase Question_Type_Phrase been located"

AQ2: "Question_Type_Phrase of Question_Phrase"

AQ3: "considered as the Question_Type_Phrase of Question_Phrase"

AQ4: "parties is the Question_Phrase Question_Type_Phrase"

AQ5: "Question_Phrase Question_Type_Phrase"

For each factoid question, Question_Type_Phrase and Question_Phrase are determined, and actual search engine query is generated using them. For example, for the factoid question "In which part has the Iran continent been located?", "continent" is determined as Question_Type_Phrase and "Iran" is determined as Question_Phrase. Thus, "continent of Iran" is used AQ2 for this factoid question. Then, the first 10 documents are retrieved as a result of this query and the total number of answer phrase ("Asia") appearing in these 10 documents is found as Answer_Phrase_Count for that query.

The Category 11 has 1 question types, and the results of this question type are given in Table 4.23. Answer_Phrase_Count in Table 4.23 is the number of Answer_Phrase_Count of 10 factoid questions in that question type for that query. MRR value in Table 4.23 is the MRR values of those 10 factoid questions.

Table 4.23. Answer_Phrase_Count and MRR Average Results for 1 Question Type in Category 11.

Query Name	Answer_Phrase_Count	MRR
AQ1	203.3	1.00
AQ2	128.2	1.00
AQ3	218.2	0.95
AQ4	112.7	0.59
AQ5	178.9	0.95
MQ1	298.9	1.00
MQ2	298.8	1.00
MQ3	313.9	1.00
MQ4	11.0	0.37

According to Table 4.23, Answer_Phrase_Count for "Continent" question type is 203.3 and MRR value is 1 for automatic query 1 (AQ1). This means that the results of this query contain 203.3 answer phrases on the average. The MRR value 1 means that 10 of 10 factoid questions have reciprocal rank 1. The best result for Answer_Phrase_Count (313.9) is accomplished by manual query 3 (MQ3) for question type (continent). The best MRR value is 1.0 for this question type and it is accomplished by different query templates indicating that the correct answer is found in the first document for all questions of those query templates. According to Table 4.23, the best Answer_Phrase_Count values are obtained by manual query template and the best MRR values is obtained by automatic query template in this category.

The Category 12 has 6 automatic query templates and 3 manual queries. The automatic query templates for Category 12 with 1 question type are as follows:

AQ1: "Question_Phrase Question_Type_Phrase constructed"

AQ2: "Question_Phrase's Question_Type_Phrase constructed"

AQ3: "Question_Phrase's Question_Type_Phrase established"

AQ4: "Constructed Question_Phrase's Question_Type_Phrase"

AQ5: "Established Question_Phrase's Question_Type_Phrase"

AQ6: "Question_Type_Phrase of Question_Phrase"

For each factoid question, Question_Type_Phrase and Question_Phrase are determined, and actual search engine query is generated using them. For example, for the factoid question "When was London's Docklands Light Railway constructed?", "Docklands Light Railway" is determined as Question_Type_Phrase "London" is determined as Question_Phrase. Thus, "constructed London's Docklands Light Railway" is used AQ5 for this factoid question. Then, the first 10 documents are retrieved as a result of this query and the total number of answer phrase ("1987") appearing in these 10 documents is found as Answer_Phrase_Count for that query.

The Category 12 has 1 question types, and the results of these question types are given in Table 4.24. Answer_Phrase_Count in Table 4.24 is the number of Answer_Phrase_Count of 10 factoid questions in that question type for that query. MRR value in Table 4.24 is the MRR values of those 10 factoid questions.

Table 4.24. Answer_Phrase_Count and MRR Average Results for 1 Question Type in Category 12.

Query Name	Average Answer_Phrase_Count	Average MRR
AQ1	23.8	1.00
AQ2	21.9	0.92
AQ3	23.7	1.00
AQ4	26.1	0.90
AQ5	8.9	0.17
AQ6	10.3	0.16
MQ1	4.0	0.42
MQ2	14.7	0.36
MQ3	2.8	0.45

According to Table 4.24, Answer_Phrase_Count for "Construct" question type is 23.8 and MRR value is 1 for automatic query 1 (AQ1). This means that the results of this query contain 23.8 answer phrases on the average. The MRR value 1 means that 10 of 10 factoid questions have reciprocal rank 1. The best result for Answer_Phrase_Count (26.1) is accomplished by automatic query 4 (AQ4) for this question type. The best MRR value is 1.0 for this question type and it is accomplished by automatic query 1 and automatic query 3 (AQ1 and AQ3) templates indicating that the correct answer is found in the first document for all questions of those query templates. According to Table 4.24, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

The Category 13 has 5 automatic query templates and 4 manual queries. The automatic query templates for Category 13 with 3 question types are as follows:

AQ1: "Question_Type_Phrase for Question_Phrase"

AQ2: "of Question_Type_Phrase for Question_Phrase"

AQ3: "Question_Type_Phrase of Question_Phrase"

AQ4: "current Question_Type_Phrase of Question_Phrase"

AQ5: "Question_Phrase is the Question_Type_Phrase"

For each factoid question, Question_Type_Phrase and Question_Phrase are determined, and actual search engine query is generated using them. For example, for the factoid question "What is another name of Maize?", "Another_Name" is determined as Question_Type_Phrase and "Maize" is determined as Question_Phrase. Thus, "another name of Maize" is used AQ3 for this factoid question. Then, the first 10 documents are retrieved as a result of this query and the total number of answer phrase ("Corn") appearing in these 10 documents is found as Answer_Phrase_Count for that query.

The Category 13 has 3 question types, and the results of these question types are given in Table 4.25. Answer_Phrase_Count in Table 4.25 is the number of Answer_Phrase_Count of 10 factoid questions in that question type for that query. MRR value in Table 4.25 is the MRR values of those 10 factoid questions.

Table 4.25. Answer_Phrase_Count and MRR Results for 3 Question Types in Category 13.

Question Types	**Another Name**		**Question Types**	**Country Code**	
Query Name	**Answer_Phrase_Count**	**MRR**	**Query Name**	**Answer_Phrase_Count**	**MRR**
AQ1	119.8	0.87	**AQ1**	38.3	0.80
AQ2	109.6	0.87	**AQ2**	14.5	0.75
AQ3	116.1	0.87	**AQ3**	33.7	0.80
AQ4	188.5	0.77	**AQ4**	5.5	0.69
AQ5	111.5	0.87	**AQ5**	22.7	0.75
MQ1	85.7	0.77	**MQ1**	17.7	0.64
MQ2	52.0	0.77	**MQ2**	30.7	0.62
MQ3	109.8	0.82	**MQ3**	17.3	0.85
MQ4	149.6	0.90	**MQ4**	45.0	0.68

Question Types	**Gestation Period**	
Query Name	**Answer_Phrase_Count**	**MRR**
AQ1	27.3	0.73
AQ2	27.5	0.73
AQ3	28.3	0.68
AQ4	26.5	0.86
AQ5	25.9	0.78
MQ1	14.0	0.80
MQ2	13.4	0.76
MQ3	27.3	0.78
MQ4	27.9	0.67

According to Table 4.25, Answer_Phrase_Count for "Another_Name" question type is 188.5 and MRR value is 0.77 for automatic query 4 (AQ4). This means that the results of this query contain 188.5 answer phrases on the average. The MRR value 0.77 means that 10 of 10 factoid questions have reciprocal rank 0.77. The best result for Answer_Phrase_Count (188.5) is accomplished by automatic query 1

(AQ1) for "Another_Name" question type. The best MRR value is 0.9 for this question type and it is accomplished by manual query 4 (MQ4) template indicating that the correct answer is found in the first document for all questions of those query templates. According to Table 4.26, the best Answer_Phrase_Count values are obtained by mostly automatic query templates.

Table 4.26. Answer_Phrase_Count and MRR Average Results for 3 Question Type in Category 13.

Query Name	Average Answer_Phrase_Count	Average MRR
AQ1	61.8	0.80
AQ2	50.5	0.79
AQ3	59.4	0.79
AQ4	73.5	0.78
AQ5	53.4	0.78
MQ1	39.1	0.74
MQ2	32.1	0.72
MQ3	51.5	0.82
MQ4	74.2	0.75

According to Table 4.26, the averages of Answer_Phrase_Count and MRR for category 13 are given. It means that we calculate sum of 3 question type's values and divide them per number of question types. Based on the results of Table 4.26, the best average Answer_Phrase_Count is accomplished by manual query 4 (MQ4) is 74.2 and the best average MRR is 0.80 achieved by automatic query 1 (AQ1). Also, between queries, the worst average Answer_Phrase_Count and MRR is accomplished by manual query 2 (MQ2) is 32.1 and 0.72, respectively. According to Table 4.26, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

The Category 14 has 3 automatic query templates and 3 manual queries. The automatic query templates for Category 14 with 1 question type are as follows:

AQ1: "Question_Type_Phrase Question_Phrase"

AQ2: "Question_Type_Phrase's Question_Phrase constructed"

AQ3: “Question_Type_Phrase’s Question_Phrase established”

AQ4: “constructed Question_Type_Phrase’s Question_Phrase”

AQ5: “established Question_Type_Phrase’s Question_Phrase“

AQ6: “Question_Phrase of Question_Type_Phrase”

For each factoid question, Question_Type_Phrase and Question_Phrase are determined, and actual search engine query is generated using them. For example, for the factoid question “When was the Panama Canal constructed?”, “Panama Canal” is determined as Question_Type_Phrase and “Constructed” is determined as Question_Phrase. Thus, “Panama Canal constructed” is used AQ1 for this factoid question. Then, the first 10 documents are retrieved as a result of this query and the total number of answer phrase (“1914”) appearing in these 10 documents is found as Answer_Phrase_Count for that query.

The Category 14 has 1 question types, and the results of these question types are given in Table 4.27. Answer_Phrase_Count in Table 4.27 is the number of Answer_Phrase_Count of 10 factoid questions in that question type for that query. MRR value in Table 4.27 is the MRR values of those 10 factoid questions. The MRR value for each query is calculated using the MRR formulae.

Table 4.27. Answer_Phrase_Count and MRR Average Results for 1 Question Type in Category 14.

Query Name	Average Answer_Phrase_Count	Average MRR
AQ1	23.8	1.00
AQ2	21.9	0.91
AQ3	23.7	1.00
MQ1	4.0	0.42
MQ2	14.7	0.36
MQ3	2.8	0.45

According to Table 4.27, Answer_Phrase_Count for “Construction” question type is 23.8 and MRR value is 1 for automatic query 1 (AQ1). This means that the results of this query contain 23.8 answer phrases on the average. The MRR value 1 means that 10 of 10 factoid questions have reciprocal rank 1. The best result for Answer_Phrase_Count (23.8) is accomplished by query 1 (AQ1) for Construction question type. The best MRR value is 1.0 for this question type and it is accomplished by different query templates indicating that the correct answer is found in the first document for all questions of those query templates. According to Table 4.27, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

The Category 15 has 9 automatic query templates and 4 manual queries. The automatic query templates for Category 15 with 3 question types are as follows:

AQ1: "considered to be the Question_Type_Phrase of Question_Phrase"

AQ2: "Question_Type_Phrase of Question_Phrase"

AQ3: "past Question_Type_Phrase of Question_Phrase"

AQ4: "name of the Question_Type_Phrase of Question_Phrase"

AQ5: "Question_Phrase's Question_Type_Phrase"

AQ6: "elected as Question_Type_Phrase of Question_Phrase"

AQ7: "elected as Question_Phrase's Question_Type_Phrase"

AQ8: "considered as Question_Type_Phrase of Question_Phrase"

AQ9: "name of the Question_Phrase's Question_Type_Phrase"

For each factoid question, Question_Type_Phrase and Question_Phrase are determined, and actual search engine query is generated using them. For example, for the factoid question "Who was the first coach of the Cleveland Browns?", "first coach" is determined as Question_Type_Phrase and "Cleveland Browns" is determined as Question_Phrase. Thus, "First coach of Cleveland browns" is used AQ2 for this factoid question. Then, the first 10 documents are retrieved as a result of this query and the total number of answer phrase ("Mike

Pettine") appearing in these 10 documents is found as Answer_Phrase_Count for that query.

The Category 15 has 3 question types, and the results of these question types are given in Table 4.28. Answer_Phrase_Count in Table 4.28 is the number of Answer_Phrase_Count of 10 factoid questions in that question type for that query. MRR value in Table 4.28 is the MRR values of those 10 factoid questions.

Table 4.28. Answer_Phrase_Count and MRR Results for 3 Question Types in Category 15.

Question Types	**First Coach**		**Question Types**	**Funding Member**	
Query Name	**Answer_Phrase _Count**	**MRR**	**Query Name**	**Answer_Phrase _Count**	**MRR**
AQ1	18.9	1.00	**AQ1**	46.6	0.95
AQ2	23.7	0.95	**AQ2**	41.5	1.00
AQ3	823.7	0.95	**AQ3**	41.5	1.00
AQ4	15.6	1.00	**AQ4**	59.2	1.00
AQ5	26.2	1.00	**AQ5**	52.8	1.00
AQ6	24.9	0.95	**AQ6**	42.1	1.00
AQ7	10.5	0.90	**AQ7**	26.7	0.95
AQ8	12.2	0.95	**AQ8**	33	0.90
AQ9	21.5	0.95	**AQ9**	52.6	1.00
MQ1	5.6	0.47	**MQ1**	22.1	0.90
MQ2	9.8	0.45	**MQ2**	19.8	0.58
MQ3	22.4	1.00	**MQ3**	48.9	1.00
MQ4	11.7	0.54	**MQ4**	50.2	1.00

Question Types	**Science Father**	
Query Name	**Answer_Phrase _Count**	**MRR**
AQ1	112.6	0.93
AQ2	112.1	0.90
AQ3	112.1	0.90
AQ4	89.0	0.83
AQ5	102.1	0.83
AQ6	102.5	0.90
AQ7	49.2	0.60
AQ8	70.8	0.80
AQ9	88.8	0.95
MQ1	111.4	0.90
MQ2	69.9	0.78
MQ3	77.6	0.77

MQ4	79.4	0.55

According to Table 4.28, Answer_Phrase_Count for "First_Coach" question type is 26.2 and MRR value is 1.0 for automatic query 5 (AQ5). This means that the results of this query contain 26.2 answer phrases on the average. The MRR value 1.0 means that 10 of 10 factoid questions have reciprocal rank 1. The best result for Answer_Phrase_Count (26.2) is accomplished by query 5 (AQ5) for "First_Coach" question type. The best MRR value is 1.0 for this question type and it is accomplished by query templates indicating that the correct answer is found in the first document for all questions of those query templates. According to Table 4.29, the best Answer_Phrase_Count values are obtained by mostly automatic query templates.

Table 4.29. Answer_Phrase_Count and MRR Average Results for 3 Question Type in Category 15.

Query Name	Average Answer_Phrase_Count	Average MRR
AQ1	59.4	0.96
AQ2	59.1	0.95
AQ3	59.1	0.95
AQ4	54.6	0.94
AQ5	60.4	0.94
AQ6	56.5	0.95
AQ7	28.8	0.82
AQ8	38.7	0.88
AQ9	54.3	0.97
MQ1	46.4	0.76
MQ2	33.2	0.61
MQ3	49.6	0.92
MQ4	47.1	0.70

According to Table 4.29, the averages of Answer_Phrase_Count and MRR for Category 15 are given. It means that we calculate sum of 7 question type's values and divide them per number of question types. Based on the results of Table 4.29, the best average Answer_Phrase_Count is accomplished by automatic query 5 (AQ5) is 60.4 and the best average MRR is 0.97 achieved by automatic query 9 (AQ9). Also, between queries, the worst average Answer_Phrase_Count is accomplished by automatic query 7 (AQ7) is 28.8 and the worst average MRR is accomplished by manual query 2 (MQ2) is 0.61. According to Table 4.29, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

The Category 16 has 4 automatic query templates and 3 manual queries. The automatic query templates for Category 16 with 1 question type are as follows:

AQ1: “did Question_Phrase Question_Type_Phrase‟

AQ2: “date did Question_Phrase Question_Type_Phrase”

AQ3: “year did Question_Type_Phrase Question_Phrase”

AQ4: “did Question_Type_Phrase Question_Phrase”

For each factoid question, Question_Type_Phrase and Question_Phrase are determined, and actual search engine query is generated using them. For example, for the factoid question “when did the industrial revolution begin?”, “Begin” is determined as Question_Type_Phrase and “Industrial Revolution” is determined as Question_Phrase. Thus, “did Industrial revolution begin” is used AQ1 for this factoid question. Then, the first 10 documents are retrieved as a result of this query and the total number of answer phrase (“1850s”) appearing in these 10 documents is found as Answer_Phrase_Count for that query.

The Category 16 has 1 question type, and the results of these question types are given in Table 4.30. Answer_Phrase_Count in Table 4.30 is the number of Answer_Phrase_Count of 10 factoid questions in that question type for that query. MRR value in Table 4.30 is the MRR values of those 10 factoid questions.

Table 4.30 Answer_Phrase_Count and MRR Average Results for 1 Question Type in Category 16.

Query Name	Average Answer_Phrase_Count	Average MRR
AQ1	53.9	0.93
AQ2	60.5	1.00
AQ3	59.8	0.93
AQ4	59.5	1.00
MQ1	41.2	0.71
MQ2	17.9	0.69
MQ3	13.3	0.61

According to Table 4.30, Answer_Phrase_Count for "Begin" question type is 60.5 and MRR value is 1 for automatic query 2 (AQ2). This means that the results of this query contain 60.5 answer phrases on the average. The MRR value 1.0 means that 10 of 10 factoid questions have reciprocal rank 1. The best result for Answer_Phrase_Count (60.5) is accomplished by automatic query 2 (AQ2) for this question type. The best MRR value is 1.00 for this question type and it is accomplished by query templates indicating that the correct answer is found in the first document for all questions of those query templates. According to Table 4.30, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

The Category 17 has 5 automatic query templates and 3 manual queries. The automatic query templates for Category 17 with 1 question type are a**s follows:

AQ1: "Question_Type_Phrase Question_Phrase mean"

AQ2: "Question_Type_Phrase Question_Phrase stands for"

AQ3: "Question_Phrase is the Question_Type_Phrase for"

AQ4: "Question_Type_Phrase of Question_Phrase"

AQ5: "Question_Phrase's Question_Type_Phrase mean"

For each factoid question, Question_Type_Phrase and Question_Phrase are determined, and actual search engine query is generated using them.

For example, for the factoid question "What does the abbreviation NASA mean?", "Abbreviation" is determined as Question_Type_Phrase and "NASA" is determined as Question_Phrase. Thus, "Abbreviation NASA mean" is used AQ1 for this factoid question. Then, the first 10 documents are retrieved as a result of this query and the total number of answer phrase ("National Aeronautics and Space Administration") appearing in these 10 documents is found as Answer_Phrase_Count for that query.

The Category 17 has 1 question types, and the results of these question types are given in Table 4.31. Answer_Phrase_Count in Table 4.31 is the number of Answer_Phrase_Count of 10 factoid questions in that question type for that query. MRR value in Table 4.31 is the MRR values of those 10 factoid questions.

Table 4.31. Answer_Phrase_Count and MRR Average Results for 1 Question Type in Category 17.

Query Name	Answer_Phrase_Count	MRR
AQ1	23.1	0.90
AQ2	24.1	0.90
AQ3	19.7	0.88
AQ4	21.0	0.95
AQ5	28.1	0.95
MQ1	4.2	0.34
MQ2	10.5	0.40
MQ3	12.3	0.41

According to Table 4.31, Answer_Phrase_Count for "Abbreviation" question type is 28.1 and MRR value is 0.95 for automatic query 5 (AQ5). This means that the results of this query contain 28.1 answer phrases on the average. The MRR value 0.95 means that 9 of 10 factoid questions have reciprocal rank 1 and 1 factoid questions have reciprocal rank 0.5. The best result for Answer_Phrase_Count (28.1) is accomplished by query 5 (AQ5) for question type (Abbreviation). The best MRR value is 0.95 for this question type and it is accomplished by automatic query 4 and query 5 (AQ4 and AQ5) template indicating that the correct answer is found in the first document for all questions of those query templates.

According to Table 4.31, the best Answer_Phrase_Count values and the best MRR values are obtained by mostly automatic query templates.

Table 4.32 gives average values for automatic query templates and manual query templates in order to compare their results. Automatic queries are much better than manual queries for almost all categories. Although Answer_Phrase_Count results for manual queries are slightly better than automatic query results for some categories, automatic queries have better MRR values for all categories.

Table 4.32. Average Results of all Categories.

Category Name	Average of Answer_Phrase_Count		Average of MRR	
	Automatic Query expansion	Manual Query expansion	Automatic Query expansion	Manual Query expansion
Category 1	163.5703	92.1211	0.9389	0.6715
Category 2	37.4571	10.9000	0.9333	0.4758
Category 3	47.4038	24.8680	0.8631	0.5949
Category 4	15.0833	5.3500	0.8108	0.4822
Category 5	84.238	47.0411	0.8294	0.6689
Category 6	75.1252	36.2082	0.8507	0.6361
Category 7	186.5407	65.5182	0.8589	0.6109
Category 8	64.3924	58.3350	0.5679	0.4703
Category 9	58.8143	64.7000	0.9857	0.8960
Category 10	130.2875	67.2000	0.9313	0.8250
Category 11	190.0333	207.900	0.9158	0.7889
Category 12	19.1167	7.1667	0.6896	0.4089
Category 13	59.7166	49.2042	0.7867	0.7554
Category 14	23.7333	25.8500	0.8367	0.7385
Category 15	51.4625	44.0669	0.9500	0.7460
Category 16	58.4250	21.1333	0.9666	0.6714
Category 17	21.9750	13.775	0.9083	0.5269

4.5 Selecting Best Query Templates

The proposed template based query expansion system generated between 3 to 9 automatic queries and between 3 to 4 manual queries. Our query templates are created by analyzing possible question templates for question types. The generated queries are evaluated in the terms of Count and MRR values. The results show that automatic query templates have better results than manual query templates. The queries with higher values of Count and MRR values have better performance. The effective performances of these queries lead to increase affectivity and speed of system. Regarding this, we selected 5 best queries based on highest values of Count and other 5 best queries based on highest values of MRR. Therefore, our system uses between 5 to 10 best queries to retrieve related passages. In the Chapter 5, the answer processing phase by using related retrieved passages is explained.

5 Answer Processing

5.1. Overview

The final phase of our factoid QA system is answer processing. Answers are extracted from the passages returned by the document/passage retrieval phase using answer patterns. In this chapter, using answer pattern, how to build answer patterns and how to extract candidate answers and the ranking method for the extracted candidate answers are discussed.

We develop an approach for answer processing with a question type classifier based on answer patterns. Answer patterns are created from the retrieved documents for the questions in the training set. Figure 5.1 gives the answer processing phase in our system. Answer ranking is based on frequency counting. The Pattern sets are used to extract candidate answers and then the candidate answers are stored based on their own frequencies.

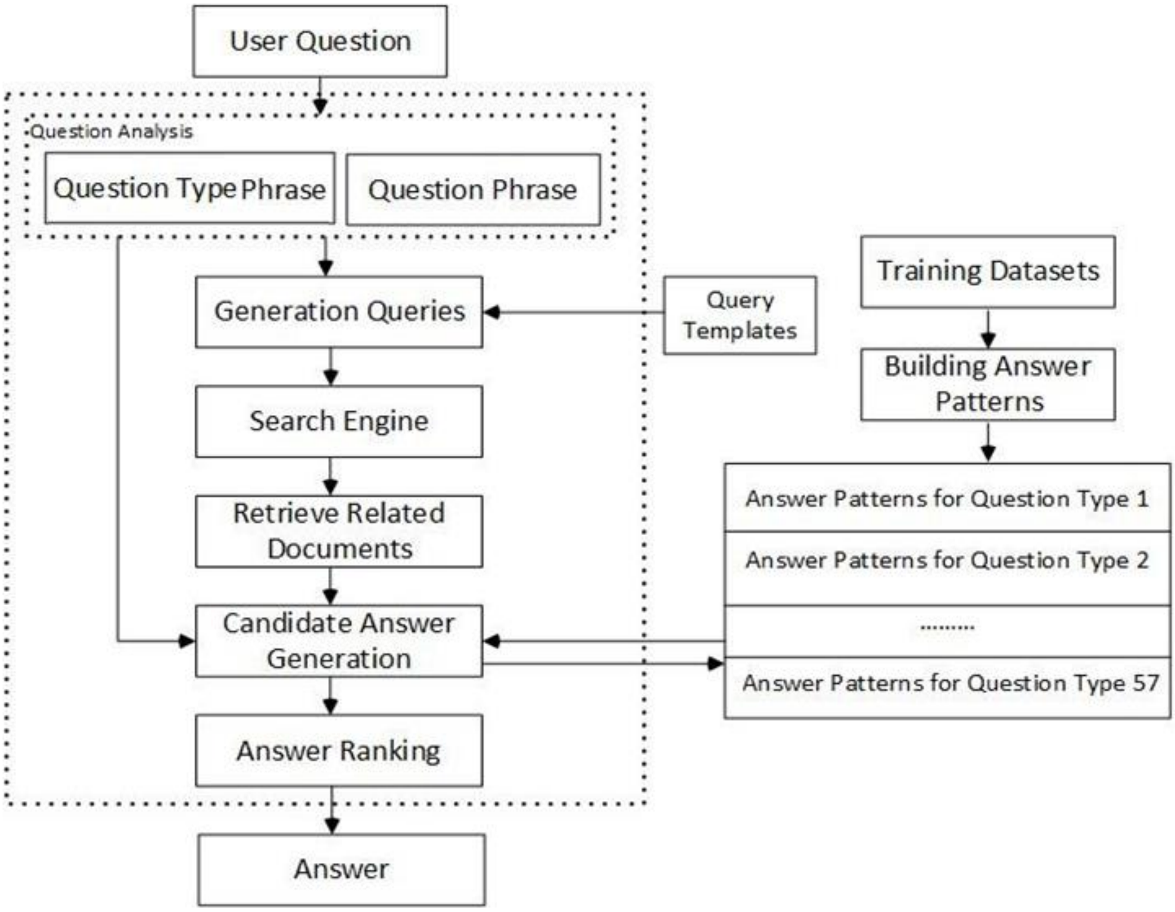

Figure 5.1. Answer Processing Phase

The question type and question phrase are extracted from user question, and they are used as inputs in the system. Our system uses answer patterns for each question type to extract the answer. Answers patterns have been built automatically. The system uses 570 questions as training dataset to built answer patterns with question generalization. Question generalization are applied by exchanging question words with question phrase, question type words with question type phrase and answer words with answer phrase. The system uses the NER system of Stanford University to tag named entities leading to generate answer patterns. Section 5.3 explains automatic learning of answer patterns.

5.2 Answer Extraction Methods

There are different techniques to extract answers from retrieved passages: answer type matching and answer pattern matching. The answer type matching method is not a subject of this thesis, and we use answer pattern matching method to extract answers in our question answering system.

5.2.1. Answer Type Matching

In answer type matching technique, a NER system is used to tag the words in the passages. The passages with no expected answer types are filtered out. The tagged words with correct NE tags are extracted as answers. For the question "What is the official language of Turkey?" the answer type is "Official Language". The following passage contains named entity tags of words with the expected answer type, "Official Language".

The official language of Turkey (COUNTRY) is Turkish (OFFICIAL LANGUAGE). According to Article 42 of the Constitution of Turkey (COUNTRY): No language other than Turkish (LANGUAGE) shall be taught as a mother tongue to Turkish (OFFICIAL LANGUAGE) citizens at any institutions of training or education.

The underlined word "Turkish" can be extracted as an answer by answer type matching technique. If there are multiple answers (Official Language), each of them are considered as separate answers extracted from the passage by this technique as shown below:

The official language of Turkey (COUNTRY), Turkish (OFFICIAL LANGUAGE), is the first language spoken by 90% of the 63m population. Arabic (OFFICIAL LANGUAGE) is spoken by 1.2% of the Turkey's (COUNTRY) population.

The underlined words "Turkish" and "Arabic" are extracted as answer by answer type matching technique. The first answer "Turkish" is correct answer for this question "What is the official language of Turkey?" and the second answer "Arabic" is incorrect.

5.2.2. Answer Pattern Matching

Answer pattern matching is another technique for answer extraction. After passages are retrieved, answer pattern matching uses textual patterns to extract answers from retrieved passages. Patterns that are used in the extraction of answers in the answer processing phase are called answer patterns. Answer patterns are regular expressions containing two variables that represent answer phrase and question phrase, respectively. If an answer pattern matches with the sentence extracted from the passage, then this sentence contains answer phrase, and it is extracted by this answer pattern. This answer can be either correct or incorrect. Possible answers which match sentences with answer patterns are inserted into the candidate answer list. Each answer pattern has a Confidence Factor (CF), and the CF of an answer indicates how reliable this answer pattern is.

Answer patterns can be learned automatically or created manually. Manual creation of answer patterns is a time consuming task and they may be incomplete. In this thesis, answer patterns are learned automatically by querying the web. The search engines (Google API, Yahoo, Yandex and Bing) are used to retrieve related documents and passages. Let us assume that the question is “What is official language of Turkey?” and there is an answer pattern “the *Answer_Phrase* language serves as the official language of *Question_Phrase*” for “Official Language” question type. In this answer pattern Answer_Phrase variable stands for answer phrase and Question_Phrase variable stands for question phrase. The Question_Phrase variable in this of pattern is replaced by the question phrase “Turkey” obtained from the user query, and this instantiated pattern can match with a part of the following sentence. The underlined word matches with Answer_Phrase variable in the pattern and it is identified as an answer.

The question type and the question phrase are identified in the question processing phase.

The <u>Turkish</u> language serves as the official language of Turkey, where it is spoken by approximately 60 million people.

Some of previous QA systems also used answer pattern matching techniques to find answers [10, 13, 25, and 95]. TREC-10 QA track presents a set of predefined textual patterns in the candidate answers to extract answers [96]. Ephyra [97] is another pattern matching based QAS in which pattern matching techniques are used in question processing and answer processing phases. Our system uses automatically learned answer patterns to extract answers.

5.3. Building Answer Patterns

In this thesis, we use answer patterns to extract answers from the retrieved passages. In order to build answer patterns, we give 10 question-answer pairs for each of the question types to our QAS and answer patterns are created with the help to this question-answer pair training corpus. For instance, in the question type "capital", question-answer pair is "Iran-Tehran". After giving this pair to our system, the documents containing this pair are retrieved and the sentences which have both of "Iran-Tehran" are extracted from the retrieved documents. Then, Question_Phrase stands for "Iran" and Answer_Phrase stands for "Tehran". Thus, an answer pattern can be created from the sentence that can generalize both of them. Another question-answer pair example is "Turkey-Ankara". After giving this question-answer pair to our system, the sentences which have both of "Turkey-Ankara" are extracted. Similarly, Question_Phrase stands for "Turkey" and Answer_Phrase stands for "Ankara". All of the extracted sentences contain question phrases and answer phrases for 10 question-answer phrases in the training dataset are gathered so that answer patterns can be created from them.

In the first step, we prepare the sets of question-answer pairs for each question type. These sets are built manually. For example, the question-answer pair set for the question type "Biggest_City_of_Country" is given in Table 5.1. Each line includes a pair of question phrase and answer phrase.

Table 5.1. Question-Answer Pair for "Biggest_City_of_Country".

Question-Answer Pair	
Question Phrase	**Answer Phrase**
Turkey	Istanbul
Iran	Tehran
Syria	Aleppo
India	Mumbai
China	Shanghai
Germany	Berlin
France	Paris
Afghanistan	Kabul
Saudi Arabia	Riyadh
Japan	Tokyo

After question-answer pairs are prepared, query expansion uses these question-answer pairs for querying the web by the search engines and in order to find 20 related documents. We preprocess documents by breaking them into sentences and select the sentences that contain both of the question phrase and the answer phrase. The following passage is retrieved by querying the web. We aim to show how a pattern is extracted from the document. The question is "What is the biggest city in Iran?" and the question type is "Biggest_City_of_Country".

> Iran has one of the highest urban population growth rates in the world. From 1950 to 2002, the urban proportion of the population increased from 27% to 60%. <u>Tehran, with a population of 8.2 million (2012 census), is the largest city in Iran and is the nation's capital.</u> Tehran is home to around 11% of Iran's population. It is the hub of the country's communication and transport networks.

In the passage, the underlined sentence is remained as an answer pattern. Because, both of question phrase "Iran" and answer phrase "Tehran" exist in the sentence. The question phrase stands for question word and answer phrase stands for answer word. Other sentences are eliminated and the remained sentence returned back as answer pattern which is given in the follows:

Answer_Phrase, with a population of 8.2 million (2012 census), is the largest city in Question_Phrase and is the nation's capital.

All of retrieved documents are preprocessed similarly and extracted sentences for each question type are our answer patterns, and these are referred to Top Patterns. After completing this phase for training dataset, we can generalize these gathered sentences. We use NER system of Stanford University [74] for generalization of the sentences in the corpus which contains both of question phrases and answer phrases.

5.3.1. Passage Generalization with NER

Named entities are widely used in QASs. NER is a sub-task of IE in answer processing phase. NER classifies terms in the textual documents into re-defined categories of interest such as location name, person name, date of event and etc. There are different classifiers which are used to perform NER, and NER is used in many of QASs [98, 99, 100, 101, and 102]. NER matches text strings with pre-defined lists of entities and recognizes text segments which are being used as entities in a given text. Our approach uses a named entity recognizer in the answer processing phase for the generalization of answer patterns. It is important because the performance of the system can be increase by patterns generalization. Generalized patterns have potential to match with more text strings and find more correct answers in different contexts which have both question phrase and answer phrase.

Stanford University NER system [74] tags word segments in a sentence as entities such as person name, company name, organization name and etc. For example, if a sentence has date and location text segments, the date text segments is tagged as “net_date” and the location segment is tagged as “net_location”. A location can be city name, country name, river name, and so on. Stanford University NER system is also known as a linear chain Conditional Random Field (CRF) classifier. Table 5.2 describes named entities in Stanford University NER system.

Table 5.2. Named Entity Types in Stanford University NER System.

Named Entities	**Tags of Named Entities**
Location	net_location
Time and Date	net_date
Organization	net_organization
Person	net_person
Miscellaneous	net_ miscellaneous
Number	net_number

Stanford University NER system is used to generalize sentences in the retrieved related passages. Because after generalization, these sentences/patterns have potential to extract more correct answers while they have different location names or different organization names.

For example, the passage is as follows which querying from the web for question “Who invented Laptop?”(Answer: Adam Osborne).

The laptop was invented by Adam Osborne in 1981

In the latter sentence, question phrase stands for “Laptop” and answer phrase stands for “Adam Osborne”.

The Question_Phrase was invented by Answer_Phrase in 1981

By using NER, net_date stands for 1981 and the sentence is as follows:

The Question_Phrase was invented by Answer_Phrase in net_date

This pattern is a more generalized pattern. Instead of net_date word, we can use other dates. Also, instead of Question_Phrase and Answer_Phrase, we can use other question and answer words. For instance, we can use this pattern for other questions such as "Who is the inventor of Telephone?" or "Who invented gravity?" to extract answer. In this pattern, our aim is to extract person name. Since, using net_date instead of any type of date isn't issue. Generalization by using NER leads to use the pattern "The Question_Phrase was invented by Answer_Phrase in net_date" to extract answer for questions with the question type "inventor".

For each question type, this workflow continued to constructing all of answer patterns, generally. After collecting all answer patterns that are the sentences that have both the Answer_Phrase and Question_Phrase in the passage, they are stored together with their frequencies.

5.3.2. Building Top Patterns

Possible answer patterns are extracted using a training dataset containing 570 question-answer pairs. This training datasets contains 10 question-answer pairs for each of 57 questions types. The confidence factors (CFs) of extracted patterns are calculated using this training dataset. Some answer patterns can be extracted from more than one sentence. The sentences that are used in the answer pattern extraction can have similar structure or they can have similar structures after some of their text segments are replaced with named entities. The frequency count of an answer pattern indicates the number of the sentences that are used in the extraction of that pattern. The CF of an answer pattern determines the reliability of that pattern. In order to build Top Patterns, we use a train dataset which contains 570 question-answer pairs, and the web is queried by using these training question-answer pairs.

For each extracted answer pattern, we assign a CF. At the end of this task, the answer patterns whose is CFs are under a certain threshold are eliminated. The reliability of an answer pattern is specified by its CF value. Three attributes are used in the calculation of a CF value:

- **TrueA**: Number of times that the answer pattern matches with a sentence and the extracted answer is correct.
- **FalseA**: Number of times that the answer pattern matches with a sentence and the extracted answer is incorrect.
- **Total**: Number of times that the answer pattern matches with a sentence and the extracted answer is correct or incorrect.

Each answer pattern has its own TrueA, FalseA and Total attributes. In the calculation of a CF, we use formula (5.1) as follows:

$$CF = (TrueA+1)/ (Total+2) \qquad (5.1)$$

Question-answer pairs that are used in the extraction of answer patterns are also used in the assignment of CFs. The average results of CFs of answer patterns for question type "capital" are given in Table 5.3.

For the question "capital" in Table 5.3, there are 20 learned answer patterns with CF values. The number of reliable answer patterns can be different depending on the question type. For example, there are only 19 reliable answer patterns with CFs greater than 0.5 in Table 5.4.

Table 5.3. Top Patterns and Avg. CF for Question Type "Capital".

Pattern #	Pattern	Average CF
1	capital of Question_Phrase is Answer_Phrase	0.95
2	the capital city of Question_Phrase is Answer_Phrase	0.91
3	the capital of Question_Phrase is called Answer_Phrase and it has a population of net_number	0.86
4	the capital of Question_Phrase is Answer_Phrase and net_miscellaneous	0.83
5	Answer_Phrase is the capital city of Question_Phrase	0.79
6	Answer_Phrase capital city of Question_Phrase	0.75
7	Answer_Phrase is the capital (and largest city) of Question_Phrase	0.71
8	Answer_Phrase the capital of Question_Phrase is net_miscellaneous	0.70
9	the capital and largest city of Question_Phrase is Answer_Phrase	0.67
10	the current capital of Question_Phrase is Answer_Phrase	0.65
11	Answer_Phrase - the capital of Question_Phrase	0.61
12	Answer_Phrase is the capital of Question_Phrase net_miscellaneous	0.60
13	ancient city and capital of Question_Phrase near Answer_Phrase	0.59
14	the net_attribute made Answer_Phrase capital of their league of nations mandate for Question_Phrase	0.58
15	the capital of modern Question_Phrase is Answer_Phrase	0.58
16	Answer_Phrase is the capital and the largest city of Question_Phrase	0.58
17	the capital of Question_Phrase is the city state of Answer_Phrase	0.57
18	Answer_Phrase became the capital of Question_Phrase in net_number	0.57
19	Answer_Phrase the capital of Question_Phrase	0.55
20	Answer_Phrase (the capital of Question_Phrase)	0.53

Table 5.4. Top Patterns and Avg. CF for question Type "King".

Pattern #	Pattern	Average CF
1	net_miscellaneous of king Answer_Phrase of Question_Phrase	0.69
2	king Answer_Phrase of Question_Phrase net_miscellaneous	0.68
3	Answer_Phrase becomes king of Question_Phrase	0.65
4	list of state visits made by Answer_Phrase of Question_Phrase	0.63
5	king Answer_Phrase of Question_Phrase celebrated his net_miscellaneous	0.62
6	Answer_Phrase is the king of Question_Phrase	0.62
7	Answer_Phrase (net_attribute) is the king of Question_Phrase	0.62
8	Answer_Phrase (net_attribute) is the reigning king of Question_Phrase	0.61
9	king Answer_Phrase of Question_Phrase was net_miscellaneous	0.60
10	king Answer_Phrase is now ruler of Question_Phrase after net_miscellaneous	0.60
11	Answer_Phrase (net_miscellaneous) is the reigning king of Question_Phrase	0.60
12	Answer_Phrase (net_miscellaneous) is the current king of Question_Phrase	0.60
13	Question_Phrase is a constitutional monarchy headed by prince Answer_Phrase	0.59
14	king Answer_Phrase of Question_Phrase celebrated net_attribute	0.59
15	king Answer_Phrase of Question_Phrase visited net_miscellaneous	0.58
16	Answer_Phrase (net_miscellaneous) is the king of Question_Phrase	0.58
17	king Answer_Phrase of Question_Phrase net_miscellaneous	0.56
18	how old is Answer_Phrase of Question_Phrase	0.56
19	the current monarch of Question_Phrase is Answer_Phrase	0.54
20	king Answer_Phrase, the grand old king of Question_Phrase	0.49

5.3.3 Building Best Patterns

After constructing pattern sets for each question type, five patterns with higher average CF values are remained and other patterns with lower average CF values are eliminated. As shown in Table 5.5, patterns are eliminated and the rest of them remained as five Best Patterns for question type "capital". Eliminated patterns are filtered out as unreliable patterns and the possibility of extracting correct answer of these patterns is low. Therefore, these patterns are not used in the question answering phase for test sets.

Table 5.5. Best Patterns for Question Type "Capital".

Pattern #	Patterns	Average CF
1	capital of Question_Phrase is Answer_Phrase	0.95
2	the capital city of Question_Phrase is Answer_Phrase	0.91
3	the capital of Question_Phrase is called Answer_Phrase and it has a population of net_number	0.86
4	the capital of Question_Phrase is Answer_Phrase and net_miscellaneous	0.83
5	Answer_Phrase is the capital city of Question_Phrase	0.79

In the other words, after eliminating unreliable Top answer patterns with lower average CF, the first five patterns (with highest average CF) are selected best patterns for each question type. They have higher potential to produce correct answers. Table 5.6 gives the average CFs of Best Patterns for the question type "King".

Table 5.6. Best Patterns for Question Type "King".

Pattern #	Patterns	Average CF
1	net_miscellaneous of king Answer_Phrase of Question_Phrase	0.69
2	king Answer_Phrase of Question_Phrase net_miscellaneous	0.68
3	Answer_Phrase becomes king of Question_Phrase	0.65
4	list of state visits made by Answer_Phrase of Question_Phrase	0.63
5	Answer_Phrase is the king of Question_Phrase	0.62

5.4 Answer Extraction

Our answer extraction approach is based on answer pattern matching method in order to extract answers. After identifying question type and question phrase for each user question, the answer extraction task is performed by Best Patterns. In our approach, for each question type, we have a specialized pattern set and each specialized pattern set contains five Best Patterns for that question type. The answer extraction phase uses its own pattern set to extract candidate answers. The pattern sets for question types are given in Appendix B.

5.4.1 Candidate Answer

After creating Best Patterns for question types, we use the pattern set of a question type which is the identified question type of a user question in order to produce a candidate answer for that questions. We do not consider CFs of answer patterns in the determination of the candidate answer. This means that all of patterns are used to extract possible candidate answers. We list the candidate answers based on higher frequency and the candidate answer with highest frequency is our candidate answer.

In this chapter, we explain the answer processing phase of our factoid QAS. The system overall evaluation and comparison with other QASs are explained in the Chapter 6.

6 Comparison and Evaluation

6.1 Overview

Several experiments have been performed for the evaluation of the system. First, performance evaluation metrics are explained, and then the performance results of the system for question answering are provided. The system is evaluated with TREC-8, TREC-9, TREC-10 datasets (Appendix C) and 10 question-answer pairs for each question type that are given in Appendix A. Also, the results compared with other QASs using TREC-8, TREC-9 and TREC-10 datasets. In addition, the learned patterns namely Best Patterns for question types are given in Appendix B, and they are the patterns that are used in the evaluations.

6.2 Evaluation Methods

The evaluation metrics are based on answers returned back by the system for test datasets for question types that are included in fine-grained and coarse-grained categories. The evaluation metrics and the attributes that are used in their calculations are follows:

- **Number of Test Questions:** This is the number of question-answer pairs for each question type in test sets.
- **Number of Returned Answers:** This is the number of answers which are returned by the system for test questions. The answers may be correct or incorrect.
- **Number of Correct Answers (Count):** This is the number of correct answers returned by the system for test questions.
- **Number of Incorrect Answers:** This is presents the number of correct answers returned by the system for test questions.
- **Precision:** Number of Correct Answers / Number of Returned Answers

- **Recall:** Number of Correct Answers / Number of Test Questions
- **F-Measure:** 2*(Recall * Precision) / (Recall+ Precision)
- **CF:** This is the confidence of the answer of a question and it is a equal to (Number of True Answers + 1) / (Number of True Answers + Number of False Answers + 2). In this calculation, Number of True Answers is the number of correct answers in the list of extracted answers for that question and Number of False Answers is the number of incorrect answers in that list.
- **Answer in Row:** This returns the correct answer which row/place. This metric is important to calculate MRR.
- **MRR:** Rank of the First Correct Answer in the List of Possible answers. If the correct answer is in the first row, then MRR is 1. If the answer is incorrect then the MRR value is 0. Also, if the correct answer is in the second row, then the MRR value is 0.5 and so on.

6.3 Training and Testing

For training the system, we use 570 question-answer pairs originated from TREC-8 and TREC-9 datasets. To test the system, we use another 570 question-answer pairs, factoid questions from TREC-8, TREC-9 and TREC-10 datasets. The test set with 570 questions contains 10 questions for each of 57 question types. Table 6.1 describes TREC datasets which are used for performance evaluation and comparison of the systems with other QASs. The 200 questions are in the TREC-8 with 135 identified factoid questions, TREC-9 (693 questions) with 322 identified factoid question and TREC-10 (500 questions) with 171 identified factoid questions are included for evaluation. The non-factoid questions of TREC-8, TREC-9 and TREC-10 are excluded from evaluation. These datasets are used to present the effectiveness of the system in question-answer processing phases. During evaluations test questions are categorized into 17 coarse-grained categories and into 57 fine-grained categories.

Table 6.1. Description of TREC Datasets.

Datasets	Number of Questions	Number of Identified Factoid Questions
TREC-8	200	135
TREC-9	693	322
TREC-10	500	171

Table 6.2 shows MRR, precision, Recall, CF, F-measure results of the question classifier in coarse-grained categorization for the test set with 570 questions. Avg. MRR of a category is the average value of MRR values of questions in that category, and Avg. CF of a category is the average value of CF values of questions of that category. The results of the system show that the Category 8 (Avg. MRR= 0.867) has the highest average MRR value among 17 question categories. Based on metric F-measure, the Category 4 (F-measure=0.842) has greater value than other categories in this categorization. Also, the Category 8 with 0.948 has greater value than other question categories. The Category 11 is better value (Avg. CF= 0.712) than other 16 question categories based on average of CF metric.

Table 6.2. Results in Coarse-Grained Categorization.

Category	Avg. MRR	F-measure	Recall	Precision	Avg. CF
1	0.599	0.606	0.575	0.649	0.434
2	0.483	0.300	0.300	0.300	0.097
3	0.543	0.473	0.436	0.534	0.295
4	0.800	0.842	0.800	0.889	0.645
5	0.696	0.647	0.614	0.694	0.299
6	0.850	0.700	0.700	0.700	0.446
7	0.678	0.575	0.567	0.585	0.422
8	0.867	0.807	0.733	0.948	0.523
9	0.633	0.600	0.600	0.600	0.246
10	0.600	0.600	0.600	0.600	0.398
11	0.700	0.700	0.700	0.700	0.712
12	0.400	0.471	0.400	0.571	0.281
13	0.317	0.332	0.300	0.383	0.278
14	0.600	0.600	0.600	0.600	0.374
15	0.494	0.433	0.433	0.433	0.318
16	0.533	0.588	0.500	0.714	0.539
17	0.800	0.800	0.800	0.800	0.453

Table 6.3 and Table 6.4 show average MRR, precision, Recall, CF, F-measure results of the question classifier in fine-grained categorization for the test set of 570 questions. The question Category 47 (Avg. CF= 0.712) has greater value than other 56 question categories based on average CF metric. The QASs presented in TREC [1, 66] uses MRR for performance evaluation of the systems. The average MRR (Avg. MRR= 1.0) of our system for fine-grained classification is higher than the others for Category 3. The MRR value 1.0 means that 10 of 10 question-answer pairs have reciprocal rank 1.

Table 6.3 Results in Fine-Grained Categorization (A).

Category	Avg. MRR	F-measure	Recall	Precision	Avg. CF
1	0.350	0.778	0.700	0.875	0.451
2	0.800	0.737	0.700	0.778	0.664
3	1.000	1.000	1.000	1.000	0.553
4	0.750	0.737	0.700	0.778	0.617
5	0.717	0.600	0.600	0.600	0.324
6	0.858	0.800	0.800	0.800	0.554
7	0.500	0.526	0.500	0.556	0.395
8	0.650	0.600	0.600	0.600	0.164
9	0.450	0.500	0.400	0.667	0.531
10	0.400	0.316	0.300	0.333	0.159
11	0.383	0.300	0.300	0.300	0.257
12	0.333	0.375	0.300	0.500	0.538
13	0.483	0.300	0.300	0.300	0.097
14	0.800	0.600	0.600	0.600	0.221
15	0.525	0.400	0.400	0.400	0.208
16	0.450	0.421	0.400	0.444	0.239
17	0.550	0.444	0.400	0.500	0.274
18	0.333	0.235	0.200	0.286	0.346
19	0.750	0.600	0.600	0.600	0.328
20	0.583	0.500	0.500	0.500	0.199
21	0.383	0.316	0.300	0.333	0.155
22	0.633	0.556	0.500	0.625	0.170
23	0.550	0.588	0.500	0.714	0.325
24	0.700	0.632	0.600	0.667	0.561
25	0.300	0.429	0.300	0.750	0.435
26	0.350	0.375	0.300	0.500	0.315
27	0.700	0.526	0.500	0.556	0.354
28	0.800	0.842	0.800	0.889	0.645
29	0.900	0.800	0.800	0.800	0.368
30	0.617	0.421	0.400	0.444	0.182
31	0.833	0.700	0.700	0.700	0.174
32	0.450	0.444	0.400	0.500	0.181
33	0.850	0.800	0.800	0.800	0.310
34	0.500	0.625	0.500	0.833	0.543
35	0.725	0.737	0.700	0.778	0.335
36	0.850	0.700	0.700	0.700	0.446
37	0.533	0.600	0.600	0.600	0.282
38	0.700	0.526	0.500	0.556	0.405
39	0.800	0.600	0.600	0.600	0.578
40	0.200	0.267	0.200	0.400	0.432

Table 6.4 Results in Fine-Grained Categorization (B).

Category	Avg. MRR	F-measure	Recall	Precision	Avg. CF
41	0.900	0.800	0.800	0.800	0.343
42	0.550	0.400	0.400	0.400	0.260
43	0.400	0.533	0.400	0.800	0.348
44	0.550	0.421	0.400	0.444	0.184
45	0.633	0.600	0.600	0.600	0.246
46	0.600	0.600	0.600	0.600	0.398
47	0.700	0.700	0.700	0.700	0.712
48	0.400	0.471	0.400	0.571	0.281
49	0.400	0.400	0.400	0.400	0.285
50	0.250	0.222	0.200	0.250	0.150
51	0.300	0.375	0.300	0.500	0.397
52	0.600	0.600	0.600	0.600	0.374
53	0.400	0.400	0.400	0.400	0.333
54	0.400	0.400	0.400	0.400	0.319
55	0.683	0.500	0.500	0.500	0.300
56	0.533	0.588	0.500	0.714	0.539
57	0.800	0.800	0.800	0.800	0.453

Our approach presents the two-level category structure for question classification. Since, we evaluate the proposed factoid QAS within presented two-level category structure in question classification model. Identifying factoid question in TREC-8, TREC-9 and TREC-10 datasets is automatically performed by our factoid QAS.

6.4 Evaluation of Overall Results

For performance evaluation, we use 570 question-answer pairs in two-level category structure model. The first level contains 17 coarse-grained categories and the second level contains 57 fine-grained categories as question classification model. The effect of presented question classification model in two levels is evaluated by Precision, Recall, F-measure and average CF and average MRR rate. In Table 6.5, we evaluated the results of each classification presented in our approach. The coarse-grained classification has 17 categories and also the fine-grained approach has 57 categories. The results show the effectiveness of coarse-grained approach. Our coarse-grained categorization approach gives the best results based on all of performance metrics.

Table 6.5. Comparison Fine-Grained and Coarse-Grained Results.

Approach	**Question Types**	**Avg. CF**	**Precision**	**Recall**	**F-measure**	**Avg. MRR**
Coarse-grained	with 17 Categories	0.398	0.629	0.568	0.593	0.623
Fine-grained	with 57 Categories	0.355	0.590	0.516	0.545	0.581

The input question types are correctness reflection of correct answer. Since, overall performance of the system strongly depends on the rate of correctly identifying question type. In our question classification model, the system cannot return any of the category structure for each asked question and even it is difficult to be categorized. Because, the system uses pre-defined question types which cover all valid questions. Combining the coarse-grained categories leads to higher average MRR than using the fine-grained categories (from 0.581 to 0.623). Using 570 training questions, the question classifier achieves more than 0.629 precision in coarse-grained categories.

Table 6.6 Our System Results on TREC Datasets.

Datasets	**Number of Questions**	**Number of Factoid Questions**	**Number of Answers**	**Number of Correct Answers**	**Precision**	**Recall**	**F-measure**	**Avg. MRR**
TREC-8	200	135	115	85	0.739	0.630	0.680	0.739
TREC-9	693	322	288	164	0.569	0.509	0.538	0.612
TREC-10	500	171	134	83	0.619	0.485	0.544	0.560

Table 6.6 gives the results of our systems on TREC-8, TREC-9 and TREC-10 datasets. Our measures are based on the number of factoid questions in the datasets. The questions that are identified as non-factoid questions are eliminated. The "number of answers" measure is the number of total retrieved answers (correct and incorrect answers). The "number of correct answers" is the number of correct answers, and the "number of incorrect answer" is the number of incorrect answers. The average MRR values for TREC-8 is 0.739, for TREC-9 is 0.612 and for TREC-10 is 0.560. We comprise our system and other QASs that have been tests on the same TREC datasets. The results that are given in Table 6.7 are related to MRR values for well-known QASs which are used for TREC-10 for testing the system performance and comparison. As shown in Table 6.7, the system [96] has the highest MRR value 0.676. The second best system is [20] with MRR value 0.563 based on the TREC-provided relevant set. Also, this system along with document/passage retrievers has MRR value 0.342. Moreover, the third best system based on MRR value 0.560 is our factoid QAS that used TREC-10 dataset.

Table 6.7. A Selection Results for the QASs in TREC-10 Dataset.

No.	System	MRR-value
1	Yen et. al. [20] (with TREC-provided relevant set)	0.563
2	Yen et. al. [20] (document/passage retrievers)	0.342
3	U. Southern California, ISI [103]	0.450
4	IBM [89]	0.390
5	Soubbotin, M.M., [96]	0.676
6	Brill et. al. [41]	0.238
7	MultiText, University of Waterloo [104]	0.460
8	Ravichandran and Hovy [105]	0.381
9	Hovy et. al. [106]	0.515
10	NTCIR3 QAC1 [107]	0.300
11	NTCIR4 QAC2 [107]	0.500
12	Kazawa et. al. [108]	0.228
13	Hong and Davison[109]	0.468
14	Monz [110] (with 500 bytes)	0.370
15	Monz [110] (with 250 bytes)	0.340
16	Our Method	**0.560**

Table 6.8 describes the performance of well-known QASs on different datasets based on MRR values. Most of the QASs used MRR measure to evaluate overall performance of the system. Since, the MRR value is not a good measure to evaluate these systems, since they use different datasets for evaluation such as TREC-6, CLEF 2009, Pascal™ Encyclopedia, TREC-8, TREC-9, TREC-10, TREC-11, TREC-12, and TREC-13.

Table 6.8. A Synoptic of Selection Results for the QASs in Different Datasets.

No.	System	Approach	Datasets	MRR-value
1	Heie et. al. [111]	Statically Data-driven Model	TREC-6	0.214
2	Comas et. al. [21]	with Heuristic Re-rank	CLEF 2009	0.404
3	Comas et. al. [21]	with Syntactic Re-rank	CLEF 2009	0.425
4	Oh et. al. [112]	with Baseline	Pascal™ Encyclopedia	0.621
5	Oh et. al. [112]	with Strategy-driven	Pascal™ Encyclopedia	0.661
6	Oh et. al. [112]	with Compositional	Pascal™ Encyclopedia	0.715
7	Li [113]	with Syntactic and Heuristic Ranking	TREC-9	0.743
8	Shen et. al. [114]	Pattern matching and Maximum Entropy Model Ranking	TREC-8 to TREC-12	0.310
9	Cui et. al. [43]	Fuzzy Relation Matching and Term Density Ranking	TREC-8 to TREC-10	0.493
10	Shen et. al. [97]	Dependency Relation Path Correlation and Maximum Entropy Model Ranking	TREC-8 to TREC-13	0.670
11	Shen et. al. [97]	Density and Maximum Entropy Model Ranking	TREC-8 to TREC-13	0.450
12	Shen et. al. [97]	Syntactic Pattern Matching	TREC-8 to TREC-13	0.560
13	Shen et. al. [97]	Strict Matching	TREC-8 to TREC-13	0.570
14	Shen et. al. [97]	Answer pattern matching	TREC-8 to TREC-13	0.600
15	Our Method	Machining Learning Model, automatic query expansion and Pattern Matching	TREC-8 to TREC-10	**0.625**

The QASs in Table 6.8 use different methods to answer extraction and approaches. Our system results that are based on MRR measure is the average of MRR values 0.625 in TREC-8, TREC-9 and TREC-10 datasets. Our approach uses machine learning based method and automatic query expansion in question processing phase and answer pattern matching technique in answer processing phase, and other systems use different approaches as shown in Table 6.8. The systems in Table 6.8 consist of factoid and non-factoid QASs, but the systems that are shown in Table 6.9 are factoid QASs.

In our approach, the two-level category structure of question classification model has an important role to identify answer type. On the other hand, the correctness of the question type identification in question processing phase affects direct reflection on results of answers type identification in answer processing phase. According that, question type identification is important in the factoid QASs.

We aim to compare well-known different factoid QASs in the terms of MRR, additional features and their structures. Table 6.9 is evaluated the synoptic features of factoid QASs base on presented metrics.

Table 6.9. Comparison between Factoid QASs Performance Evaluation

#	Name	Question Processing	Features	Document /Passage Retrieval	Answer Extraction	NER	Data sets	MRR-value
1	DFKI [101]	handcrafted syntactic/semantic rules	gazetteers, not tuned statistical models	Lucene IR engine	candidate ranking based on frequency	words and NEs	CLEF 2007	0.170
2	INAOE [102]	handcrafted rules	regular expressions	Indri IR engine	candidates sorted by passage retrieval confidence score	words, NEs and phonetics	CLEF 2007	0.360
3	CUT [100]	handcrafted rules	Stanford NER, rules with classification	passage ranking based on retrieval score	candidate ranking based on keyword distance and retrieval score	words, NEs, and POS	TREC-8	0.220
4	LIMSI [99]	handcrafted rules	words, lemmas, named entities, morphological derivations, and synonymic relations	passage ranking based on search descriptors	ranking based on either keyword distance and redundancy, Bayesian modeling, or tree distance	handcrafted rules with statistical POS	TREC-8-9	0.710
5	Sibyl [21]	multiclass perceptron classifier relevance-feedback	Lexical, Syntactic And Semantic and NER	text-based passage retriever with IR engine	syntactic parsing and heuristic baseline	NER handcrafted knowledge	CLEF 2009	0.300
6	Ephyra [115]	question patterns	-	-	Learning by question-answer pairs	-	TREC-8-9	0.360
7	Our Method	Automatic query expansion with machine learning based Question Classification Model	Stanford NER	text-based passage retriever with IR engine	Automatic Learning by question-answer pairs and re-ranking by frequency	NEs, Automatic answer patterns	TREC-8-9-10	**0.625**

As shown in Table 6.9, some of factoid QAS are compared and evaluated based on MRR values, participated methods in question processing, document/passage retrieval, and answer processing phases. The system in [100] and our approach used Stanford named entity recognizer for tagging named entities. However, the system in [100] also used the CRF Part-of-Speech (POS) tagger for English. They also provided handcrafted rules in question processing phase. DFKI [101] utilized from Lucene IR Engine for retrieving expected candidate answers. Ranking candidate answer also was based on frequency counting. While [99] presented three methods such as answer scoring that consists of distance based answering scoring, answer scoring through Bayesian modeling, transformation-based answer re-ranking.

INAOE is presented by Barragan et. al. [102] which provided handcrafted rules as question analysis and Indri IR engine for extracting the passage which contain candidate answers. The passage processing has to be done by NER, passage segmentation, phonetic codification, and passage representation. The ranking method was based on CF with using regular expression.

Ephyra [115] uses two types of pattern learning approach in query formulation and answer selection. In query formulation component, the question pattern matching interpret question and generate related queries. Answer pattern matching method was also used to extract answers.

Sibyl [21] is another factoid QAS which uses answer types that are predicted using a multiclass perceptron classifier. Question processing phase uses keywords in query generation task. The generated queries are used to retrieve related passages and expected answer types. Using NER in Sibyl leads to tagging of words and to selecting candidate answers.

Our system uses question classification model based on machine learning technique in question processing phase. The passages retriever is in the document/passage retrieval phase by search engines and in the answer processing phase, NER tags all of the words. Also, the average result of MRR in TREC-8 to TREC-10 datasets is 0.625.

7 Conclusion and Future Works

Factoid QASs focus to provide inquirers with direct, precise answers to their questions, by employing IE and NLP methods instead of presenting huge amounts of documents, which are relevant for the questions posed by inquirers potentially. Factoid QASs try to accurately extract exact answers in retrieved documents for factoid questions.

We proposed a factoid QAS, which includes three phases: question processing, document/passage retrieval, and answer processing. Question processing phase uses a classification algorithm to investigate question-type phrases. It presents a new automatical template based approach by querying the web. The document/passage retrieval phase utilizes manual and automatical queries using the search engines to retrieve related documents and passages. The system uses machine learning techniques and linguistic tools of NLP field to question analysis and generalization of Pattern sets. The answer processing phase is based on pattern matching technique. Learning phase of answer patterns is done automatically.

In this thesis, we identified the potential of machine learning techniques in question processing phase and pattern matching technique in answer phase for English factoid QAS. The presented methods are compared based on the number of answers (count) and MRR based on question processing and evaluation of query expansion approach.

The proposed system for factoid questions utilizes a Naive Bayes classification algorithm to determine question types and new queries are generated from query templates, which belong to categories of those question types. New queries are generated by filling gaps in templates with two appropriate phrases. The first phrase is found indirectly by classification algorithm and the second phrase is extracted from possible question templates by a Levenshtein distance algorithm. Our query templates are created by analyzing possible question templates for question types and the performance of each of them has been evaluated by the average of Answer_Phrase_Count and average of MRR values in all categories.

Our approach in answer processing is based on answer pattern matching. The system uses NER in answer processing phase for generalization of the given contexts. It is important due to the fact that the performance of the system is increased by patterns generalization. Generalized patterns have potential to adopt with more text strings and find more correct answers in different contexts which have both question phrase and answer phrase. After that with counting the sentences, which have both answer phrase and question phrase in the retrieved passages, have to be stored based on frequencies. The ranking of answers relies on the frequency counting and CF values.

Our system uses the training datasets originated from TREC-8 and TREC-9 question-answer pairs contained in the 570 questions in our corpus. The corpus has a two-level category structure in which the first level contains 17 coarse-grained question classes and the second level comprises 57 fine-grained question classes.

Furthermore, the system is tested with the other 570 questions in our test corpus and TREC-8, TREC-9, and TREC-10 datasets for each question type. The training phase does not contain question-answer pairs from the TREC-10 dataset. The TREC-8, TREC-9 and TREC-10 datasets are used to present the effectiveness of the system compared with other QASs.

One of the advantages of our implemented answer processing approach by using answer pattern matching technique is that each of the answer patterns can contain more than one answer phrase. Another advantage is that in the answer patterns can handle long-distance relationships between question phrases and the answer phrases for each question types in our categorization. Another strength of the system is automatically investigating factoid questions and non-factoid questions. The system eliminates non-factoid questions and remained questions are processed to extract correct answers.

We conclude automatic query expansion by using machine learning techniques which are powerful new expansion methods for QAS. Our question classification algorithm has potential to investigate question types and the presented two-level category structure which affects the overall performance of the system. The performance evaluation of the system by using MRR for our two-level category structure is 0.62 in coarse-grained category and 0.58 in fine-grained category in the test section. The MRR for testing on TREC-10 data set is 0.560 and overall average results of MRR is 0.625 for TREC-8 to TREC-10 datasets. The performance of coarse-grained category structure and TREC-10 dataset are close.

Although we do not use the answer documents for creations of query templates, they can be used for query expansion. Query templates can be created automatically from possible answer patterns and this is can be future work topic. Using other machine learning and answer pattern matching techniques individually is arguable as future works.

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APPENDIX A: TRAINING AND TESTING CORPUS

In this section, Question-Answer pairs used for 57 question types are given. These question types are: Answer patterns are learned for each question type by using the 10 question-answer pairs in Train Set. The system is evaluated by using the remaining 10 question-answer pairs in Test Set.

Table A.1. Question Type “Biggest City”

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Turkey	Istanbul	Canada	Toronto
Iran	Tehran	United States	New York
Syria	Aleppo	Ukraine	Kiev
India	Mumbai	United Kingdom	London
China	Shanghai	Uzbekistan	Tashkent
Germany	Berlin	South Korea	Seoul
France	Paris	North Korea	Pyongyang
Afghanistan	Kabul	Denmark	Copenhagen
Saudi Arabia	Riyadh	Spain	Madrid
Japan	Tokyo	Italy	Rome

Table A.2. Question Type “Official Language”

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Iran	Persian	France	French
Turkey	Turkish	Uzbekistan	Uzbek
United Kingdom	English	Canada	English
Azerbaijan	Azerbaijani	Ukraine	Ukrainian
Egypt	Arabic	Japan	Japanese
Italy	Italian	Afghanistan	Pashto and Dari
Syria	Arabic	Bahrain	Bahrain
Germany	German	Spain	Spanish
Greece	Greek	India	Hindi
Saudi Arabia	Arabic	Denmark	Danish

Table A.3. Question Type "Capital"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Turkey	Ankara	Egypt	Cairo
Azerbaijan	Baku	Japan	Tokyo
France	Paris	Egypt	Cairo
Iran	Tehran	United Kingdom	London
India	New Delhi	Uzbekistan	Tashkent
Iraq	Baghdad	Afghanistan	Kabul
China	Beijing	South Korea	Seoul
Germany	Berlin	Ukraine	Kiev
Russia	Moscow	North Korea	Pyongyang
Syria	Damascus	Italy	Rome

Table A.4. Question Type "Official Religion"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Turkey	Islam	Russia	orthodoxy
Iran	Islam	Ukraine	Orthodox
Germany	Christianity	Gabon	Christianity
China	Buddhist	Nepal	Hindu
Syria	Sunni Muslims	Nigeria	Christian
Greece	Orthodoxy	USA	Christian
Iraq	Islam	United Kingdom	Christianity
Ireland	Christianity	Sweden	Christian
Qatar	Islam	Denmark	Christianity
Uzbekistan	Islam	South Korea	Buddhism

Table A.5. Question Type "Largest River"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Iran	Karun	Ukraine	Dnieper
Azerbaijan	Kura	Nepal	Ghaghra
Turkey	Kizilirmak	Egypt	Nile
Germany	Danube	Nigeria	Niger River
United Kingdom	Severn	Sweden	Gota alv-Klaralven
Brazil	Amazon	Belarus	Dnieper

Spain	Ebro	Scandinavia	Gota alv-Klaralven
India	Indus	Tajikistan	Syr Darya
China	Yangtze	Denmark	Gudena
Portugal	Tagus	Italy	Po

Table A.6. Question Type "Highest Mountain"

Train Set		**Test Set**	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Portugal	Pico	Australia	Kosciuszko
Turkey	Ararat	Pakistan	K2
Iran	Damavand	Libya	Bikku Bitti
Azerbaijan	Bazard	France	Mont Blanc
Germany	Zugspitze	India	Kanchenjunga
Syria	Hermon	Russia	Elbrus
Greece	Olympus	England	Scafell
Afghanistan	Noshaq	Gabon	Mont Iboundji
Canada	Logan	Nigeria	Chappal Waddi
Spain	Teide	Denmark	Ejer

Table A.7. Question Type "Biggest Lake"

Train Set		**Test Set**	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Iran	Urmia	France	Bourget
Syria	Assad	Africa	Victoria
Greece	Kastoria	Japan	Biwa
Egypt	Nasser	USA	Superior
Brazil	Agua	Sweden	Vanern
Spain	Mar Menor	Tajikistan	Karakul
India	Wular	Nepal	Rara
Uzbekistan	Aral	Iraq	Tharthar
Kazakhstan	Balkhash	Turkey	Van
China	Dongting	Northern Ireland	Lough Neagh

Table A.8. Question Type "Calendar Type"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Spanish	Gregorian	Italy	Gregorian
Iran	Solar Hijri	Turkey	Rumi
India	Gregorian	Germany	Gregorian
China	Gregorian	Spain	Gregorian
Greece	Gregorian	Denmark	Gregorian
Afghanistan	Solar	Poland	Gregorian
Germany	Gregorian	Nepal	Bikram Sambat
USA	Gregorian	Norway	Gregorian
Russia	Gregorian	Brazil	Gregorian
Saudi Arabia	Islamic	Pakistan	Gregorian

Table A.9. Question Type "Currency"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Iran	Rial	Italy	Euro
Turkey	Lira	Nepal	Nepalese rupee
Azerbaijan	Manat	Brazil	Brazilian real
Iraq	Iraqi dinar	Sweden	Swedish krona
Greece	Euro	Denmark	Danish krone
Kazakhstan	Tenge	Norway	Norwegian krone
Malaysia	Ringgit	Poland	Polish zloty
Qatar	Rial	United Kingdom	Pound sterling
Germany	Euro	Egypt	Egyptian pound
United State America	Dollar	Australia	Dollar

Table A.10. Question Type "Type of Government"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Turkey	Republic	Spain	Monarchy
Iran	Republic	France	republic
Germany	Federal republic	Italy	republic
Qatar	Monarchy	Gabon	republic
Uzbekistan	Presidential	USA	Federal
Greece	Republic	England	Monarchy
China	Communist	Pakistan	republic
India	Federal	Ukraine	republic
Libya	Republic	Peru	republic
Bahrain	Monarchy	Kenya	republic

Table A.11. Question Type "Tallest Building"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Turkey	Istanbul Sapphire	Spain	Torre de Cristal
Iran	Milad	United Kingdom	Shard
United Arab Emirates	burj khalifa	Ukraine	Klovski Descent
Greece	Athens Towers	Italy	Citylife
Germany	Commerzbank	Norway	Radisson Blu Plaza Hotel
Kazakhstan	Northern Lights Astana	Uzbekistan	National Bank of Uzbekistan
Japan	Skytree	Tajikistan	Hyatt Regency Dushanbe
Egypt	Cairo Tower	Jordan	Le Royal Hotel
Qatar	Dubai	South Korea	Northeast Asia Trade Tower
USA	trade center	India	Imperial Tower 1

Table A.12. Question Type "Longest Ruling Dynasty"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Turkey	Ottoman	Korea	Choson Dynasty
Iran	Parthian Empire	Vietnam	Le
united kingdom	Charles	Belgium	Belle
China	Zhou	Denmark	Danish colonial Empire
India	Pandyan	Georgia	Bagrationi
Greece	Seleucid	Tonga	Tui
Mongolia	Mongolian	Korean Peninsula	Silla
Japan	Yamato	Nigeria	Bornu Empire
North Africa	Almoravid	Britain	Queen
Iraq	Akkadian	Borneo	Bruneian Empire

Table A.13. Question Type "Minister"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Turkey	Ahmet Davutoglu	Uganda	Ruhakana Rugunda
Iraq	Haider al-Abadi	Ukraine	Arseniy Yatsenyuk
Azerbaijan	Artur Rasizade	Belarus	Andrei Kobyakov
United Kingdom	Ahmed Maiteeq	Italy	Matteo Renzi
Uzbekistan	Shavkat Mirziyoyev	Jordan	Abdullah Ensour
Kazakhstan	Karim Masimov	Egypt	Ibrahim Mahlab
Russia	Medvedev	Tajikistan	RASULZODA
Germany	Angela Merkel	Uzbekistan	Mirziyoyev
India	Narendra Modi	France	Manuel Valls
Japan	Shinzo Abe	Spain	Mariano Rajoy

Table A.14. Question Type "Author"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Star Wars	George Lucas	Thinking, Fast and Slow	Daniel Kahneman
The Story of my Life	Mary Karr	Wright Brothers	David McCullough
Hatchet	Gary Paulsen	Heritage	Sean Brock
Namesake	Jhumpa Lahiri	Science of Interstellar	Kip Thorne
Wonder	Palacio	Steve Jobs	Walter Isaacson
Crank	Ellen Hopkins	Rust: The Longest War	Jonathan Waldman
Book Thief	Markus Zusak	LEGO Ideas Book	Daniel Lipkowitz
Gone Girl	Gillian Flynn	Wedding Planner & Organizer	Mindy Weiss
Karma Cola	Gita Mehta	Thunderstruck	Erik Larson
Giver	Lois Lowry	Artists and Their Cats	Alison Nastasi

Table A.15. Question Type "President"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Turkey	Recep Tayyip Erdogan	Ukraine	Petro Poroshenko
Iran	Hassan Rouhani	Uganda	Yoweri Museveni
USA	Barack Obama	Kenya	Uhuru Kenyatta
Russia	Vladimir Putin	Tanzania	Jakaya Kikwete
Germany	Joachim Gauck	Italy	Sergio Mattarella
Spain	Mariano Rajoy Brey	Belarus	Alexander Lukashenko
Pakistan	Mamnoon Hussain	Poland	Bronisław Komorowski
Greece	Karolos Papoulias	Tajikistan	Emomali Rahmon
China	Jinpingl	Taiwan	Ma Ying-jeou

Peru	Ollanta Humala	Uzbekistan	Islam Karimov

Table A.16. Question Type "Director"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Kingdom of Solomon	Shahriar Bahrani	Atlee Kumar	Raja Rani
Maze Runner	Wes Ball	Boyhood	Richard Linklater
Armageddon	Michael Bay	Interstellar	Christopher Nolan
Lucy	Luc Besson	Whiplash	Damien Chazelle
Forrest Gump	Robert Zemeckis	Godzilla	Gareth Edwards
Piyanist	Roman Polanski	Selma	Ava DuVernay
Casablanca	Michael Curtiz	Fury	David Ayer
Gandhi	Richard Attenborough	Berandal	Gareth Evans
Jaws	Steven Spielberg	Divergent	Neil Burger
Lagaan	Ashutosh Gowariker	Noah	Darren Aronofsky

Table A.17. Question Type "Inventor"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Laptop	Bill Moggridge	Apgar score	Virginia Apgar
Telephone	Alexander Graham Bell	Argand lamp	Ami Argand
airplane	Wright brothers	Edwin Howard Armstrong	FM radio
Dynamite	Alfred Nobel	String trimmer	George Ballas
Electric Light	Thomas Edison	gas turbine	John Barber
Phonograph	Thomas Edison	stereo	Alan Blumlein
Steam Engine	Thomas Savery	Ethernet	David Boggs
automobile	Karl Benz	crescograph	Jagdish Chandra Bose

railway engine	George Stephenson	Wetsuit	Hugh Bradner
Algebra	Al-Khwarizmi	Chamberland filter	Charles Chamberland

Table A.18. Question Type “Discoverer”

Train Set		**Test Set**	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Gravity	Isaac Newton	Alzheimer's disease	Alois Alzheimer
golden ratio	Phidias	Mitochondrion	Richard Altmann
USA	Christopher Columbus	polonium	Marie Skłodowska-Curie
Electron	J.J. Thomson	radium	Marie Skłodowska-Curie
atomic nucleus	Ernest Rutherford	penicillin	Alexander Fleming
Redshift	Edwin Hubble	static electricity	Ancient Greeks
Quantum	Max Planck	bioelectricity	Luigi Galvani
Vaccine	Edward Jenner	electricity	Benjamin Franklin
DNA Structure	Francis Crick	Francium	Marguerite Catherine Perey
Polymerase	Arthur Kornberg	X-rays	Wilhelm Conrad Roentgen

Table A.19. Question Type “Founder”

Train Set		**Test Set**	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Apple Company	Steve Jobs	Ford Motor Company	Henry Ford
Google	Larry Page and Sergey Brin	Toshiba Company	Tanaka Hisashige
Java	James Gosling	Huawei company	Ren Zhengfei

Microsoft	Bill Gates	Honda company	Takeo Fujisawa, Soichiro Honda
jet airways	Naresh Goyal	Nokia company	Fredrik Idestam, Leo Mechelin
popeyes	Al Copeland	Lenovo company	Liu Chuanzhi
youtube	had Hurley	BlackBerry company	Mike Lazaridis
Fascism	Benito Mussolini	HTC company	Peter Chou, Cher Wang
Sociology	Auguste Comte	ASUS company	Wayne Hsieh, Ted Hsu, MT Liao, TH Tung
zionism	Theodor Herzl	General Electric company	Thomas Edison

Table A.20. Question Type "King".

Train Set		**Test Set**	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
England	Queen Elizabeth	Saudi Arabia	Salman
Bahrain	Hamad Al Khalifa	Swaziland	Mswati III
Spain	Felipe VI	Lesotho	Letsie III
Germany	Wilhelm II	Morocco	Mohammed VI
Sweden	Carl XVI Gustaf	Jordan	Abdullah II
Netherlands	Willem-Alexander	Norway	Harald V
Belgium	Philippe of Belgium	Oman	Sultan Qaboos
Liechtenstein	Alois	Thailand	Bhumibol Adulyadej
Monaco	Albert II	Japan	Akihito
Denmark	Margrethe II	Kuwait	Sabah Al-Ahmad

Table A.21. Question Type "Parliament Speaker"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Iranian	Ali Larijani	United Kingdom	John Bercow
India	Sumitra Mahajan	Swedish	Urban Ahlin
Germany	Norbert Lammert	Turkey	Cemil Çiçek
Pakistan	Sardar Ayaz Sadiq	Canada	Andrew Scheer
Azerbaijan	Ogtay Asadov	Chechen	Dukuvakha Abdurakhman ov
Armenia	Eduard Sharmazanov	Kenya	Justin Bedan Njoka Muturi
Iraqi	Salim al-Jabouri	Ghana	Edward Doe Adjaho
South Africa	Baleka Mbete	Bangladesh	Shirin Sharmin Chowdhury
Uzbekistan	Nurdinjon Ismailov	Lebonan	Nabih Berri
Russia	Valentina Matviyenko	India	Lok Sabha

Table A.22. Question Type "Mayor"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Izmir	Aziz Kocaoglu	Rome	Ignazio Roberto Maria Marino
Ankara	Melih Gokcek	Kabul	Mohammad Yunus Nawandish
Tehran	Mohammad Bagher Ghalibaf	Toronto	John Tory
Moscow	Sergey Sobyanin	Washington, D.C.	Muriel Bowser
London	Boris Johnson	Boston	Marty Walsh
phoenix	Greg Stanton	Berlin	Michael Muller
zephyrhills	Daniel W. Burgess	Beijing	Wang Anshun

new york	Bill de Blasio	Detroit	Mike Duggan
atlanta	Kasim Reed	Baku	Hajibala Ibrahim oglu Abutalybov
Kiev	Vitali Klitschko	Adana	Aytac Durak

Table A.23. Question Type "Governor"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
California	Jerry Brown	Michigan	Rick Snyder
moscow	Andrei Vorobyov	Maryland	Larry Hogan
Ebonyi state	Martin Elechi	Tehran	Seyyed Hossein Hashemi
Washington	Jay Inslee	Georgia	Nathan Deal
South Dakota	Dennis Daugaard	Florida	Rick Scott
New York	Andrew Cuomo	Massachusetts	Charlie Baker
North Dakota	Jack Dalrymple	Illinois	Bruce Rauner
Texas	Greg Abbott	Ohio	John Kasich
Virginia	Terry McAuliffe	Adana	Mustafa Biyik
Tokyo	Shintaro Ishihara	Madrid	Manuela Carmena

Table A.24. Question Type "Football Head Coach"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Iran	Carlos Queiroz	texas a&m Aggies	Kevin Sumlin
Russia	Fabio Capello	Alabama Crimson Tide	Nick Saban
Georgia	Mark Richt	Greece	Derek Mason
Fiu	Ron Turner	Notre Dame Fighting Irish	Brian Kelly
Japan	Alberto Zaccheroni	Auburn Tigers	Gus Malzahn
Argentina	Diego Maradona	Dallas Cowboys	Jason Garrett

Esteghlal	Amir Ghalenoei	University of Arizona	Rich Rodriguez
Galatasaray	Cesare Prandelli	Michigan Wolverines	Jim Harbaugh
Kansas jayhawks	Charlie Weis	Kansas Jayhawks	Clint Bowen
Vanderbilt	Derek Mason	USC	Steve Sarkisian

Table A.25. Question Type "Leaders of Revolution"

Train Set		**Test Set**	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Iran Islamic	Ayatollah Khomeini	Indian	Gandhi
French	Napoleon Bonaparte	Russianof 1917	Vladimir Lenin
Bolshevik	Joseph Stalin	Abbasid	Abdallah ibn Ali
October	Vladimir Lenin	Siamese	Mandarin Phetracha
Egyptian	Muslim Brother	La Paz	Pedro Murillo
Haitian	Napoleon Bonaparte	Serbian	Napoleon Bonaparte
American	George Washington	fascist national	Benito Mussolini
	Ataturk	Brazilian	Getulio Vargas
Civilization	Sid Meier	Febrerista	Rafael Franco
animal	Napoleon	democratic	Romulo Betancourt

Table A.26. Question Type "Killer"

Train Set		**Test Set**	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
John Fitzgerald Kennedy	Lee Harvey Oswald	Lincoln	John Wilkes Booth
Abraham Lincoln	John Wilkes Booth	James A. Garfield	Charles J. Guiteau
Mahatma Gandhi	Nathuram Godse	William McKinley	Leon Czolgosz
Wendy Lee Coffield	Green River	McKinley	Leon Czolgosz

Michael	Murray	Chris Kyle	Eddie Ray Routh
Mary White	Linda Clark	Nicole Laube	Jaime Tinoco
The Watcher	Hank McCoy	lee harvey oswald	Jack Ruby
Eric Garne	RAGE	King Philip II	Pausanias
Bhutto Family	Musharraf	king Duncan	Macbeth
Demons	Prana	Yolanda Saldivar	San Antonio

Table A.27. Question Type “Creator”

Train Set		**Test Set**	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
character James Bond	Ian Fleming	Visa	Dee Hock
Transformers	Hasbro	Marvel Comics	Martin Goodman
Moonwalk	Michael Jackson	telephone	Alexander Graham Bell
First Car	Karl Benz	Dynamite	Alfred Nobel
Periodic Table	Dmitri Mendeleev	Basketball	James Naismith
Google	Larry Page	Gucci	Guccio Gucci
Quiet Riot	Randy Rhoads	Huawei	Ren Zhengfei
Computer mouse	Douglas Engelbart	Instagram	Kevin Systrom, Mike Krieger
Penicillin	Alexander Fleming	Shotokan karate	Gichin Funakoshi
Bitcoin	Satoshi Nakamoto	Volleyball	William G. Morgan

Table A.28. Question Type “Birthday”

Train Set		**Test Set**	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Mahatma Gandhi	October 2, 1869	Lincoln	February 12, 1809
Elizabeth II	April 21, 1926	John F. Kennedy	May 29, 1917
Ataturk	May 19, 1881	James A. Garfield	November 19, 1831
Fatih Terim	September 4, 1953	William McKinley	January 29, 1843

Barack Obama	August 4, 1961	Karl Benz	November 25, 1844
Sibel Can	August 1, 1970	Larry Page	March 26, 1973
Shakira	February 2, 1977	Alexander Fleming	August 6, 1881
Ali Daei	March 21, 1969	Dr. Seuss	March 2, 1904
Hillary Rodham	October 26, 1947	Alfred Nobel	October 21, 1833
Drake	October 24, 1986	Guccio Gucci	March 26, 1881

Table A.29. Question Type "Earthquake"

Train Set		**Test Set**	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Japan	March 11, 2011	Virginia	August 23, 2011
Haiti	January 12 2010	Pakistan	September 24, 2013
Bam Iran	December 26, 2003	San Francisco	April 18, 1906
New Zealand	22 February 2011	Kobe	January 17th 1995
San Francisco	April 18, 1906	Kanto	September 1, 1923
Sichuan	May 12, 2008	Hawke's Bay	February 3, 1931
Chile	May 22, 1960	Nisqually	February 28, 2001
Christchurch	22 February 2011	georgia	February 15, 2014
Murchison	17 June 1929	Kefalonia	28 January 2014
Adana	June 27, 1998	*Mexico*	18 April 2014

Table A.30. Question Type "Explosion"

Train Set		**Test Set**	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Texas	2013	Harlem	2014
Boston	2013	U.S.S. Maine	1898
Chernobyl	1986	Hiroshima	1945

Ukraine	1986	Nagasaki	1945
Halifax	2012	Minor Scale	1985
Ferguson	2014	Tunguska	1908
coronation street	2010	Mount Tambora Eruption	1815
Japan	1945	Chernobyl nuclear	April 26, 1986
Waco	2013	Suruc	July 20 2015
Halifax	1917	Hastings	8 May 2015

Table A.31. Question Type “Flood”

Train Set		**Test Set**	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Calgary	2013	Lynmouth	1952
Boscastle	2004	Valencia	1957
Colorado	2013	Arno River	1966
Johnstown	1889	Vargas	1999
Mozambique	2000	Southern Leyte mudslide	2006
Hurricane Hazel	1954	China	1964
South Fork Dam	1889	Germany and Denmark	1634
Indian Ocean Tsunami	2004	portugal	1967
China Floods	1931	Black Hills	1972
Yangtze river	1931	Nigeria	July 2012

Table A.32. Question Type “Final Coup”

Train Set		**Test Set**	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Iran	1953	Czechoslovakia	1948
Turkey	1980	Kyrgyzstan	2010
Greece	1967	Kenya	1982
Spanish	1982	Madagascar	2009
Azerbaijani	1995	Mauritania	2008
Iraq	1958	Venda	1990
Kenya	1982	Zanzibar	1964
honduras	2009	South Vietnam	1963
afghanistan	1973	Nigeria	2015
Cypriot	1974	Egypt	2013

Table A.33. Question Type “Revolution”

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Iran	1979	Peloponnese	1770
French	1789	Vendee	1793
Greece	1821	La Paz	1809
Russian	1917	Mexican War	1810
Egyptian	2011	Guatemala	1871
Syrian	2011	Deccan Riots	1875
Saur	1978	Therisso	1905
Bolshevik	1917	Wilhelmshaven mutiny	1918
Mexican	1910	Young Turk	1908
Chinese	1949	Ukraine	2014

Table A.34. Question Type “Storm”

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Germany	2014	Gloria	1985
Afghanistan	2013	Gilbert	1988
Iran	2014	Hugo	1989
Novosibirsk	2014	Opal	1995
bulgaria	2014	Isabel	2003
london	2013	Ivan	2004
sderot	2011	Katrina	2005
Nemo	2013	Rita	2005
hercules	2014	Wilma	2005
Darwin	2013	Andrew	1992

Table A.35. Question Type “wildfire”

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
BlackDragon	1987	Tasmanian	1967
BlackThursday	1851	Eastern seaboard	1994
BlackFriday	1939	Canberra	2003
BlackSunday	1955	BlackSaturday	2009
Western	1961	Texas	2011

Australian			
Weekend	2014	Chicago Fire	October 10, 1871
Cerro Grande Fire	May 11, 2000	Peshtigo Fire	October 8, 1871
Jasper Fire	August 24, 2000	Lynchburg	Mar 6, 2015
Texas	September 15,1987	Edmonton	July 16, 2014
Michigan	1981	Colorado	Jun 13, 2013

Table A.36. Question Type “Population”

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Iran	77.45	Brazil	200.4
Turkey	74.93	Afghanistan	30.55
Russia	143.5	Canada	35.16
Germany	80.62	United States	318.9
Spain	47.27	Azerbaijan	9.417
Jordan	6.459	Armenia	2.977
France	66.03	China	1.357 billion
Greece	11.03	India	1.252 billion
Bulgaria	7.265	Netherlands	16.8
Kazakhstan	17.04	Kuwait	3.2

Table A.37. Question Type “Holy Book”

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Muslim	Quran	Sikh	Guru Granth Sahib
Buddhist	Tripitaka	Christianity	Old Testament
Jewish	Torah	Shinto	Kojiki
Hindu	Vedas	Islamic	Quran
Shaiva Siddhanta	Tirumurai	Zoroastrian	sacred texts
Hermeticism	Hermetica	Tibetan Buddhism	Tibetan Kang yur and Teng yur
Śruti	Vedas	Catholicism	Canon of Trent

Saktism	Sakta Tantras	Protestantism	Jewish Tanak h
Vaishnavism	Vaikhanasa Samhitas	Gnosticism	Nag Hammadi library
Druidism	Mabinogion	Discordianism	Principia Discordia

Table A.38. Question Type "Color"

Train Set		**Test Set**	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Sky	Blue	Banana	yellow
tomato	Red	Gold	Golden
blood	Red	Coriander	Green
loyalty	Blue	Basil	Green
Carbon	Black	Mentha	Green
Uranus	blue-green	Turmeric	yellow
sea	Blue	Saffron	Red
Turkey Flag	Red	Cinnamon	Brown
mucus plug	Red	Lemon	yellow
Forest	Green	Cucumber	Green

Table A.39. Question Type "Code Number"

Train Set		**Test Set**	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Iran	+98	UK	+44
Turkey	+90	France	+33
USA	+1	China	+86
Japan	+81	India	+91
Azerbaijan	+994	Belarus	+375
Russia	+7	Belgium	+32
Germany	+49	Sweden	+46
Spain	+34	Kenya	+254
Portugal	+351	Nepal	+977
Australia	+61	Greece	+30

Table A.40. Question Type "Headquarters"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
NATO	Brussels	LG	Seoul
UNOG	New York	ASUS	Beitou District, Taipei
CERN	Geneva	Google	Mountain View
ICDO	Geneva	Nokia	Espoo, Uusimaa
ILO	Paris	Sony	Tokyo
ITU	Vatican	Intel	Santa Clara, California
IBO	Geneva	IBM	Armonk, New York
IPU	New York	Microsoft	Redmond, Washington
OCHA	Panama	Samsung	Suwon
ISO	Jersey	HTC	New Taipei City

Table A.41. Question Type "Airport Place"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Logan	Boston	Portland	Portland
McCarran	Las Vegas Valley	Charlotte Douglas	Charlotte
Tempelhofer Field	Berlin	O'Hare	Chicago
Birmingham	Birmingham	Orly	Paris
London Heathrow	London	Tabriz	Tabriz
London Stansted	London	Heydar Aliyev	Baku
John F. Kennedy	New York	Gander	Gander
Bristol	London	Windsor	Windsor
Istanbul Ataturk	Istanbul	Imam Khomeini	Tehran
Edinburgh	Scotland	Mehrabad	Tehran

Table A.42. Question Type "Birthplace"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Edgar Allan Poe's	Boston	Kevin Systrom	Holliston
Shakespeare's	Stratford-upon-Avon	John Adams	Massachusetts
Jesus	Judea	Steve Chen	Taiwan
Hayedeh	Kermanshah	Alexander Fleming	Scotland
Lord Krishna	Mathura	Larry Page	Michigan
Muhammad	Mecca	Gandhi	Porbandar
Obama	Honolulu	Guccio Gucci	Florence
pope francis	Buenos Aires	Alfred Nobel	Stockholm
Mitt Romney Detroit	United States	Ataturk	Thessaloniki
Zeno of Elea	Italy	george washington	Virginia

Table A.43. Question Type "Holy Place"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Imam Kazim	Musa al-Kadhim	Paromeos Monastery	Nitrian Desert
King David's Tomb	Bethlehem	Saint Marina	Qalamoun
Mary	Jerusalem	Amarnath Temple	Jammu and Kashmir
Marian	Annai Velangkanni	Kamakhya Temple	Assam
Imam Reza	Mashhad	Mookambika	Kollur
Mevlana Rumi	Konya	Somnath temple	Gujarat
Ayatollah Khomeini	Behesht-e Zahra	National Marian	Mariamabad
Imam Ali	Najaf	Matsuo Taisha	Kyoto
Imam Hussain	Karbala	Kamo	Kyoto
Prophet Muhammad's tomb	Medina	Shah Ismael Safavi	Ardabil

Table A.44. Question Type “Company Located”

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Microsoft	Washington	Nokia	Finland
Intel	Texas	IBM	Armonk, New York
LG	Seoul	HTC	New Taipei City, Taiwan
samsung	South Korean	Sony	Minato, Tokyo
Apple	California	Dell	Round Rock, Texas
Google	California	Toshiba	Minato, Tokyo
Yahoo	California	Adidas	Herzogenaurach, Bavaria
Asus	Taiwan	Nike	Beaverton
PepsiCo	China	Huawei	Shenzhen, Guangdong
Nintendo	Kyoto	Traxtor	Tabriz

Table A.45. Question Type “Largest Producer”

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
oil-producing	Russia	Cheese	United States
Coffee	Brazil	steel	Luxembourg
Opium	Afghanistan	Corn	United States
Cotton	China	Watermelon	China
Wine	Spain	Coal	China
Rice	China	Carrots	China
Eggplant	China	kiwifruit	New Zealand
Sugar	United States	Ginger	India
Blueberries	China	Saffron	Iran
Crop	China	Tea	China

Table A.46. Question Type “Nationality”

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Mahatma Gandhi	Indian	Abraham Lincoln	American
Farhad Mehrad	Iranian	Steve Jobs	American
Mustafa Kemal Ataturk	Turkish	Bill Gates	American
Napoleon Bonaparte	French	Warren Buffett	American
Alexander the Great	Macedonian	Niki Karimi	Iranian
Radamel Falcao	Colombian	Ebru Gundes	Turkish
Ali Daei	Iranian	Elnaz Shakerdoust	Iranian
Pascale Machaalani	Lebanese	Alfred Nobel	Swedish
Susan Ward	American	Mahmoud Hessaby	Iranian
Alexander Fleming	British	Kemal Sunal	Turkish

Table A.47. Question Type “Attachment to Continent”

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Iran	Asia	United Kingdom	Europe
India	Asia	Sudan	Africa
China	Asia	Belarus	Europe
Germany	Europe	Belgium	Europe
Pakistan	Asia	Sweden	Europe
Japan	Asia	South Korea	Asia
Greece	Europe	Turkey	Asia
Nigeria	Africa	Kenya	Africa
Egypt	Africa	Finland	Europe
Bulgaria	Europe	Nepal	Asia

Table A.48. Question Type "Establish"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Panama Canal	1914	Bay Bridge	1933
berlin wall	1961	Coit tower	1933
Eiffel tower	1887	Suez Canal	1869
Washington Monument	1792	Leaning Tower of Pisa	1360
sydney opera house	1958	Telstra Tower	1980
empire state building	1929	Erie Canal	1825
Milad Tower	1999	League of Nations	1919
CN Tower	1973	United States Coast Guard	1790
Sydney Harbour Bridge	1924	Zion National Park	1919
Brooklyn Bridge	1870	Grand Canyon National Park	1919

Table A.49. Question Type "Another Name"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
CPU	central processing unit	IBM	International Business Machines Corporation
Maize	Corn	Lactic acid	2-hydroxypropanoic acid
Netherland	Holand	Acetic acid	ethanoic acid
Pareto Distribution Diagram	Pareto chart	cancer	Carcinoma
heart attack	myocardial infarction	White blood cells	leukocytes or leucocytes
homogeneous mixture	Solution	water cycle	hydrologic cycle
resume	CV	quadrilateral	Quadrangle
Alprazolam	Xanax	yangtze river	Long River

thrombocytes	Platelet	mitral valve	bicuspid valve
sugar alcohol	Xylitol	tricuspid valve	right atrioventricular valve

Table A.50. Question Type "Zip Code"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Chambiges	75008	BULGER	15019
Aquaforte	A0A	ALBION	16475
Avondale	85323	ALBA	16910
Angat	3012	HARWICK	15049
Balagtas	3016	CUDDY	15031
Baliuag	3006	ELRAMA	15038
Bustos	3007	MIDLAND	15059
Alumpit	3003	MONESSEN	15062
Bocaue	3018	ROCHESTER	90074
Bulacan	3017	Ajalvir	28864

Table A.51. Question Type "Gestation Period"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
humans	280	Cow	63
Dog	63	Coyote	150
cat	66	Donkey	370
Horses	340	Lion	110
mouse	20	Red Fox	49
Sheep	147	Tiger	105
Goats	150	Skunk	66
grey squirrels	44	Panther	91
Roborovski hamster	22	Cattle	270
Turkeys	28	Mice	20

Table A.52. Question Type "Signing a Contract"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Magna Carta	King John	Mayflower Compact	Pilgrims
Iraq	George W.	Atlantic	winston

Withdrawal	Bush	Charter	churchill
Usa Patriot Act	George W. Bush	Munich pact	Adolf Hitler
civil rights act	Lyndon Johnson	Missouri Compromise	James Monroe
Declaration Of Independence First	John Hancock	Monroe Doctrine	James Monroe
giving pledge	Bill and Melinda Gates and Warren Buffett	Morrill Act	Abraham Lincoln
Surrender of Japan	Mamoru Shigemitsu	emancipation proclamation	Abraham Lincoln
lausanne covenant	Billy Graham	Nafta agreement	Bill Clinton
yale covenant	Rick Warren	treaty of paris	John Adams
young plan	Dawes Plan	social security act	Franklin D. Roosevelt

Table A.53. Question Type "First Coach"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Cleveland Browns	Mike Pettine	Patriots	Lou Saban
washington redskins	Jay Gruden	Miami Heat	Ron Rothstein
sydney swans	John Longmire	Ravens	Ted Marchibroda
dallas cowboys	Jerry Jones	Cowboys	Tom Landry
fremantle dockers	Ross Lyon	Stanford Cardinal	Walter Camp
denver broncos	Dan Reeves	Indiana Hoosiers	Arthur B. Woodford
lakers	Byron Scott	Red Raiders	Ewing Y. Freeland
jacksonville jaguars	Gus Bradley	Michigan Wolverines	Frank Crawford, Mike Murphy
seahawks	Jack Patera	Auburn Tigers	George Petrie
San Diego Chargers	Mike McCoy	UAB Blazers	Jim Hilyer

Table A.54. Question Type "Founding Member"

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
Pink Floyd	Syd Barrett	Nokia	Fredrik Idestam, Leo Mechelin
beatles	John Lennon	IBM	Thomas J. Watson
Metallica	James Hetfield	Dell	Michael S. Dell
led zeppelin	Jimmy Page	Nike	Phil Knight and Bill Bowerman
Opec	Iran, Iraq, Kuwait, Saudi Arabia and Venezuela	Apple	Steve Jobs
Naacp	Du Bois, Ida B. Wells, Archibald Grimke, Henry Moskowitz, Mary White Ovington, Oswald Garrison Villard, William English Walling, Florence Kelley	Sony	Masaru Ibuka, Akio Morita
Microsoft	Bill Gates and Paul Allen	LinkedIn	Reid Hoffman, Konstantin Guericke, Jean-Luc Vaillant, Allen Blue, Eric Ly
Google	Larry Page and Sergey Brin	Gucci	Guccio Gucci
Harlem globetrotters	Abe Saperstein	justice league	Kal-El Clark, Batman,

			Bruce Wayne, PrincessDiana, Barry Allen, Hal Jordan, Orin Arthur Curry
Trans-Siberian Orchestra	Jon Oliva, Al Pitrelli and Robert Kinkel	european union	Konrad Adenauer, Joseph Bech, Johan Beyen, Winston Churchill, Alcide De Gasperi, Walter Hallstein, Sicco Mansholt, Jean Monnet, Robert Schuman, Paul-Henri Spaak, Altiero Spinelli

Table A.55. Question Type "Science Father"

Train Set		**Test Set**	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
psychology	Wilhelm Wundt	genetics	Gregor Mendel
History	Herodotus	Ichthyology	Peter Artedi or Petrus Arctaedius
Computer	Charles Babbage	lichenology	Erik Acharius
Taxonomy	Carl Linnaeus	paleontology	Georges Cuvier
nuclear bomb	Robert Oppenheimer	English geology	William Smith
Hebrews	Abraham	toxicology	Mathieu Orfila
Trigonometry	Hipparchus	Green Chemistry	Anastas
periodic table	Dmitri Mendeleev	Audiology	Raymond T Carhart

Social Darwinism	Herbert Spencer	cryonics	Robert Chester Wilson Ettinger
Greek Tragedy	Aeschylus	Plastic Surgery	Sushruta

Table A.56. Question Type “Begin”

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
industrial revolution	1850	Vietnam war	1955
civil war	1861	twitter	2006
American Revolution	1775	Instagram	2010
Aztec Empire	1521	LinkedIn	2003
Gold Rush	1848	Intel	1968
holocaust	1933	Toshiba	1939
Yemassee War	1715	French Revolution	1789
World War 1	1914	Cold war	1947
facebook	2004	National Lottery	1986
Hip Hop	1970	Holocaust	1933

Table A.57. Question Type “Mean”

Train Set		Test Set	
Question Phrase	**Answer Phrase**	**Question Phrase**	**Answer Phrase**
NASA	National Aeronautics and Space Administration	IBM	International Business Machines
ATM	Automated Teller Machine	USA	United States of America
ISO	International Standards Organization	AAA	apply to affected area
Wi-Fi	wireless fidelity	BNF	British National Formulary
IEEE	Institute of Electrical and Electronics	ASP	Active Server Pages

	Engineers		
YOLO	you only live once	FIFA	Federation International de Football Association
LOL	Laughing out loud	IP	Internet Protocol
HTML	HyperText Markup Language	mg	milligram
E.g	for example	ADS	Asymmetric digital subscriber line
IT	Information Technology	RUP	Rational Unified Process

APPENDIX B: ANSWER BEST PATTERNS

Answer patterns have to be learning. Then, the answer patterns which are unreliable or too specific are eliminated. The reliable answer patterns called as *Best Patterns* are given in this section.

Table B.1. Best Patterns for Question Type “Biggest City”

No	Patterns	Average CF
1	being the biggest city in Question_Phrase, Answer_Phrase offers a unique cosmopolitan experience	0.88
2	Answer_Phrase, net_miscellaneous, largest city and seaport of Question_Phrase	0.82
3	the capital and the largest city of Question_Phrase net_miscellaneous, Answer_Phrase is located on net_miscellaneous	0.79
4	net_number places in Question_Phrase that aren't Answer_Phrase	0.72
5	Answer_Phrase, largest city in Question_Phrase	0.70

Table B.2. Best Patterns for Question Type “Official Language”

No	Patterns	Average CF
1	Answer_Phrase is the official language of Question_Phrase and net_miscellaneous	0.99
2	the official language of Question_Phrase is Answer_Phrase	0.98
3	official language of Question_Phrase is Answer_Phrase	0.98
4	net_attribute official language of Question_Phrase is Answer_Phrase and net_attribute	0.92
5	Answer_Phrase is the official language of Question_Phrase	0.85

Table B.3. Best Patterns for Question Type "Capital"

No	Patterns	Average CF
1	capital of Question_Phrase is Answer_Phrase	0.95
2	the capital city of Question_Phrase is Answer_Phrase	0.91
3	the capital of Question_Phrase is called Answer_Phrase and it has a population of net_number	0.86
4	the capital of Question_Phrase is Answer_Phrase and net_miscellaneous	0.83
5	Answer_Phrase is the capital city of Question_Phrase	0.79

Table B.4. Best Patterns for Question Type "Official Religion"

No	Patterns	Average CF
1	the main religion in Question_Phrase is Answer_Phrase	0.63
2	Answer_Phrase is the dominant religion in Question_Phrase	0.62
3	the official religion of Question_Phrase is Answer_Phrase and net_miscellaneous	0.59
4	Answer_Phrase is the official religion in Question_Phrase and Answer_Phrase law net_miscellaneous	0.59
5	net_miscellaneous that the official religion of Question_Phrase is Answer_Phrase and the net_miscellaneous	0.58

Table B.5. Best Patterns for Question Type "Largest River"

No	Patterns	Average CF
1	Answer_Phrase is the longest river in Question_Phrase	0.70
2	the Answer_Phrase is the largest river in Question_Phrase	0.62
3	the Answer_Phrase is the longest river in Question_Phrase net_miscellaneous	0.61
4	the Answer_Phrase is the largest river in Question_Phrase net_miscellaneous	0.58
5	Answer_Phrase is the largest river in Question_Phrase net_miscellaneous	0.57

Table B.6. Best Patterns for Question Type "Highest Mountain"

No	Patterns	Average CF
1	Answer_Phrase is the highest mountain in Question_Phrase net_miscellaneous	0.80
2	Answer_Phrase is the highest mountain in Question_Phrase	0.79
3	mount Answer_Phrase is the highest mountain in Question_Phrase	0.78
4	mount Answer_Phrase is the highest mountain in Question_Phrase net_miscellaneous	0.76
5	the highest mountain in Question_Phrase is mount Answer_Phrase	0.62

Table B.7. Best Patterns for Question Type "Laugh Biggest Lake"

No	Patterns	Average CF
1	lake Answer_Phrase is the largest lake in Question_Phrase and net_miscellaneous	0.59
2	rally protesting Question_Phrase over Answer_Phrase turns violent	0.58
3	it is the largest natural lake in Question_Phrase and the net_number largest lake after the artificial Answer_Phrase	0.58
4	the largest lake in Question_Phrase (net_miscellaneous) is Answer_Phrase in net_miscellaneous	0.57
5	Answer_Phrase (net_miscellaneous) is the largest lake in Question_Phrase net_miscellaneous	0.54

Table B.8. Best Patterns for Question Type "Calendar Type"

No	Patterns	Average CF
1	the Answer_Phrase calendar was taken to Question_Phrase net_miscellaneous	0.58
2	the currency in Question_Phrase is the Answer_Phrase (net_attribute)	0.52
3	net_miscellaneous Question_Phrase - Answer_Phrase – calendar	0.51
4	Answer_Phrase (net_attribute) net_attribute is the official calendar of Question_Phrase	0.51
5	net_miscellaneous Question_Phrase - Answer_Phrase	0.50

Table B.9. Best Patterns for Question Type "Currency"

No	Patterns	Average CF
1	the Answer_Phrase is the currency in Question_Phrase (net_attribute)	0.65
2	the Answer_Phrase is the currency of Question_Phrase	0.63
3	Answer_Phrase is the currency of Question_Phrase	0.59
4	Question_Phrase Answer_Phrase the currency of Question_Phrase	0.56
5	net_number the Answer_Phrase is the currency used in Question_Phrase	0.55

Table B.10. Best Patterns for Question Type "Type of Government"

No	Patterns	Average CF
1	Question_Phrase is a Answer_Phrase whose net_miscellaneous	0.60
2	Question_Phrase is a Answer_Phrase	0.59
3	Question_Phrase is a constitutional Answer_Phrase	0.57
4	the Answer_Phrase of Question_Phrase is a net_miscellaneous	0.54
5	Answer_Phrase of Question_Phrase is net_miscellaneous	0.52

Table B.11. Best Patterns for Question Type "Tallest Building"

No	Patterns	Average CF
1	Answer_Phrase is the tallest building in Question_Phrase net_miscellaneous	0.55
2	the Answer_Phrase is the tallest building in Question_Phrase	0.54
3	the tallest building in Question_Phrase is the Answer_Phrase (net_miscellaneous) in net_miscellaneous	0.53
4	Answer_Phrase was also briefly the tallest building in Question_Phrase when net_miscellaneous	0.53
5	the Answer_Phrase building is the tallest building in Question_Phrase	0.51

Table B.12. Best Patterns for Question Type "Longest Ruling Dynasty"

No	Patterns	Average CF
1	the Answer_Phrase dynasty was the longest dynasty to rule in Question_Phrase	0.54
2	Answer_Phrase (net_miscellaneous) Question_Phrase's longest - ruling dynasty, net_miscellaneous	0.54
3	the Answer_Phrase dynasty that reigned in the present - day Question_Phrase started its rule net_miscellaneous	0.53
4	the Answer_Phrase dynasty in Question_Phrase is the longest ruling dynasty in history	0.53
5	net_miscellaneous the Answer_Phrase were the longest ruling dynasty in Question_Phrase	0.53

Table B.13. Best Patterns for Question Type "Minister"

No	Patterns	Average CF
1	prime minister of the Question_Phrase Answer_Phrase	0.57
2	the incumbent prime minister of Question_Phrase is Answer_Phrase of the net_miscellaneous	0.54
3	Question_Phrase names Answer_Phrase new prime minister	0.54
4	Question_Phrase parliament re-elect Answer_Phrase as prime minister	0.53
5	Question_Phrase names Answer_Phrase new prime minister net_miscellaneous	0.53

Table B.14. Best Patterns for Question Type "Author"

No	Patterns	Average CF
1	Question_Phrase by Answer_Phrase	0.85
2	Question_Phrase is a novel by Answer_Phrase published net_attribute	0.68
3	a talk with Question_Phrase author Answer_Phrase	0.67
4	Question_Phrase (Answer_Phrase) on net_location	0.66
5	Question_Phrase by Answer_Phrase (net_attribute author)	0.64

Table B.15. Best Patterns for Question Type "President"

No	Patterns	Average CF
1	the current president of Question_Phrase is Answer_Phrase	0.69
2	net_miscellaneous and president of Question_Phrase Answer_Phrase in net_location	0.65
3	Answer_Phrase elected net_number president of Question_Phrase	0.65
4	Answer_Phrase elected net_number president of Question_Phrase - net_attribute	0.63
5	Answer_Phrase takes over as Question_Phrase president	0.62

Table B.16. Best Patterns for Question Type "Director"

No	Patterns	Average CF
1	Question_Phrase director Answer_Phrase	0.80
2	net_attribute Question_Phrase director Answer_Phrase	0.75
3	the director of Question_Phrase, Answer_Phrase	0.73
4	Answer_Phrase is the director of Question_Phrase	0.62
5	Question_Phrase director Answer_Phrase dies net_attribute	0.61

Table B.17. Best Patterns for Question Type "Inventor"

No	Patterns	Average CF
1	Answer_Phrase is commonly credited as the inventor of the net_number practical Question_Phrase	0.71
2	the Answer_Phrase status as inventors of the Question_Phrase has net_miscellaneous	0.69
3	the Answer_Phrase status as inventors of the Question_Phrase has net_attribute	0.64
4	Answer_Phrase inventor of Question_Phrase	0.60
5	Answer_Phrase invented Question_Phrase and net_attribute	0.60

Table B.18. Best Patterns for Question Type "Discoverer"

No	Patterns	Average CF
1	Question_Phrase was discovered by Answer_Phrase	0.66
2	Answer_Phrase discovered Question_Phrase net_miscellaneous	0.62
3	Answer_Phrase is responsible for discovering an incomplete formula for Question_Phrase	0.61
4	net_miscellaneous did Answer_Phrase discover besides Question_Phrase	0.60
5	what did Answer_Phrase discover besides Question_Phrase	0.59

Table B.19. Best Patterns for Question Type "Founder"

No	Patterns	Average CF
1	Answer_Phrase the founder of Question_Phrase net_number	0.73
2	Answer_Phrase was the founder of the Question_Phrase	0.71
3	is Answer_Phrase the founder of Question_Phrase	0.66
4	Question_Phrase founder Answer_Phrase joins net_attribute	0.63
5	Question_Phrase was founded by Answer_Phrase while net_miscellaneous	0.61

Table B.20. Best Patterns for Question Type "King"

No	Patterns	Average CF
1	net_miscellaneous of king Answer_Phrase of Question_Phrase	0.69
2	king Answer_Phrase of Question_Phrase is net_miscellaneous	0.68
3	Answer_Phrase becomes king of Question_Phrase	0.65
4	list of state visits made by Answer_Phrase of Question_Phrase	0.63
5	Answer_Phrase is the king of Question_Phrase	0.62

Table B.21. Best Patterns for Question Type "Parliament Speaker"

No	Patterns	Average CF
1	Answer_Phrase elected as a speaker of net_miscellaneous	0.65
2	Question_Phrase parliament speaker Answer_Phrase and net_miscellaneous	0.64
3	Question_Phrase parliament speaker Answer_Phrase is net_miscellaneous	0.61
4	net_miscellaneous Question_Phrase parliament speaker Answer_Phrase has net_miscellaneous	0.58
5	net_miscellaneous speaker of the Question_Phrase parliament Answer_Phrase will net_miscellaneous	0.56

Table B.22. Best Patterns for Question Type "Mayor"

No	Patterns	Average CF
1	mayor of Question_Phrase Answer_Phrase	0.59
2	Answer_Phrase (mayor of Question_Phrase)	0.59
3	Question_Phrase mayor Answer_Phrase saves net_miscellaneous	0.57
4	Answer_Phrase was elected mayor of Question_Phrase net_miscellaneous	0.51
5	mayor Answer_Phrase is the net_date mayor of Question_Phrase	0.49

Table B.23. Best Patterns for Question Type "Governor"

No	Patterns	Average CF
1	the all progressives congress has called for the impeachment of governor Answer_Phrase of Question_Phrase	0.64
2	net_miscellaneous and current governor of Question_Phrase is Answer_Phrase	0.64
3	the current governor of Question_Phrase is Answer_Phrase	0.62
4	governor Answer_Phrase of Question_Phrase net_miscellaneous	0.62
5	the current governor of Question_Phrase state is Answer_Phrase	0.60

Table B.24. Best Patterns for Question Type "Football Head Coach"

No	Patterns	Average CF
1	new Question_Phrase football head coach Answer_Phrase addresses net_miscellaneous	0.63
2	Question_Phrase football head coach Answer_Phrase had net_miscellaneous	0.60
3	Answer_Phrase was named the net_miscellaneous head coach in Question_Phrase history on net_miscellaneous	0.56
4	Question_Phrase coach Answer_Phrase on net_miscellaneous	0.54
5	Question_Phrase head coach Answer_Phrase has net_miscellaneous	0.53

Table B.25. Best Patterns for Question Type "Leaders of Revolution"

No	Patterns	Average CF
1	a democratic revolution in Question_Phrase, led by Answer_Phrase	0.63
2	although Answer_Phrase is still referred to in Question_Phrase as the "leader of the net_attribute revolution, " net_miscellaneous	0.60
3	Answer_Phrase - leader of Question_Phrase independence movement	0.58
4	Answer_Phrase (net_attribute) the foremost political leader of the Question_Phrase independence movement	0.52
5	Answer_Phrase (net_miscellaneous) commanded the continental army in Question_Phrase revolutionary net_miscellaneous	0.50

Table B.26. Best Patterns for Question Type "Killer"

No	Patterns	Average CF
1	why did Answer_Phrase kill Question_Phrase	0.61
2	Answer_Phrase at his trial for the murder of Question_Phrase	0.61
3	Answer_Phrase kill Question_Phrase	0.59
4	net_miscellaneous of Answer_Phrase in the killing of Question_Phrase	0.58
5	Answer_Phrase shot Question_Phrase at net_miscellaneous	0.57

Table B.27. Best Patterns for Question Type "Creator"

No	Patterns	Average CF
1	Question_Phrase was founded by Answer_Phrase while net_attribute	0.63
2	net_miscellaneous attempts to identify Question_Phrase creator Answer_Phrase	0.61
3	Answer_Phrase (the creator of Question_Phrase)	0.61
4	Question_Phrase was invented by Answer_Phrase and was net_miscellaneous	0.59
5	Answer_Phrase invented the Question_Phrase	0.58

Table B.28. Best Patterns for Question Type "Birthday"

No	Patterns	Average CF
1	Question_Phrase was born on Answer_Phrase	0.74
2	Question_Phrase was born on Answer_Phrase in net_location (net_miscellaneous)	0.69
3	Question_Phrase was born Answer_Phrase in net_location	0.57
4	Question_Phrase (born Answer_Phrase)	0.57
5	Question_Phrase was born in net_location on Answer_Phrase	0.55

Table B.29. Best Patterns for Question Type "Earthquake"

No	Patterns	Average CF
1	Question_Phrase earthquake of Answer_Phrase	0.90
2	the Question_Phrase earthquake of Answer_Phrase	0.77
3	net_miscellaneous the Question_Phrase earthquake of Answer_Phrase	0.76
4	Question_Phrase Answer_Phrase earthquake	0.65
5	the Answer_Phrase Question_Phrase earthquake was net_miscellaneous	0.64

Table B.30. Best Patterns for Question Type "Explosion"

No	Patterns	Average CF
1	explosion in Question_Phrase Answer_Phrase	0.68
2	net_miscellaneous an explosion in Question_Phrase on Answer_Phrase	0.63
3	atomic bomb dropped on Question_Phrase - Answer_Phrase	0.56
4	the Answer_Phrase explosion of net_miscellaneous	0.53
5	Answer_Phrase | explosion at Question_Phrase	0.51

Table B.31. Best Patterns for Question Type "Flood"

No	Patterns	Average CF
1	net_miscellaneous related to Question_Phrase flood of Answer_Phrase	0.64
2	Answer_Phrase Question_Phrase - net_miscellaneous	0.62
3	the devastating impact of Question_Phrase in Answer_Phrase was net_miscellaneous	0.60
4	Question_Phrase in Answer_Phrase led to a net_miscellaneous	0.58
5	the Answer_Phrase Question_Phrase flood was a net_attribute	0.57

Table B.32. Best Patterns for Question Type "Final Coup"

No	Patterns	Average CF
1	net_attribute the Answer_Phrase coup in Question_Phrase net_miscellaneous	0.63
2	net_miscellaneous role in the Answer_Phrase coup in Question_Phrase from the net_miscellaneous	0.62
3	net_miscellaneous in Question_Phrase during the Answer_Phrase coup	0.60
4	the net_attribute coup in Question_Phrase Answer_Phrase	0.59
5	the Answer_Phrase Question_Phrase coup net_attribute	0.59

Table B.33. Best Patterns for Question Type "Revolution"

No	Patterns	Average CF
1	the Question_Phrase revolution Answer_Phrase: net_miscellaneous	0.72
2	net_attribute since the Answer_Phrase Question_Phrase revolution	0.58
3	net_attribute the Answer_Phrase Question_Phrase revolution has net_attribute	0.52
4	the Question_Phrase revolution: from net_date to Answer_Phrase	0.49
5	the Question_Phrase revolution, Answer_Phrase to net_date	0.49

Table B.34. Best Patterns for Question Type "Storm"

No	Patterns	Average CF
1	Question_Phrase was a hurricane that net_attribute in Answer_Phrase	0.62
2	Question_Phrase slammed into the net_attribute on Answer_Phrase	0.59
3	hurricane Question_Phrase (Answer_Phrase) is a net_attribute	0.55
4	Question_Phrase was the net_attribute named storm net_attribute began Answer_Phrase	0.49
5	Question_Phrase was net_attribute during the Answer_Phrase season net_attribute	0.49

Table B.35. Best Patterns for Question Type "Wildfire"

No	Patterns	Average CF
1	in the Answer_Phrase Question_Phrase net_miscellaneous	0.66
2	Question_Phrase fires of Answer_Phrase	0.63
3	net_miscellaneous Question_Phrase bushfires of Answer_Phrase	0.63
4	the great Question_Phrase fire of Answer_Phrase in the net_miscellaneous	0.59
5	the Question_Phrase bushfires of Answer_Phrase were net_location	0.58

Table B.36. Best Patterns for Question Type "Population"

No	Patterns	Average CF
1	according to the two links below the last Question_Phrase demographic statistics bring the population to just over Answer_Phrase people	0.63
2	the total population in Question_Phrase was last recorded at Answer_Phrase million people net_attribute	0.61
3	net_miscellaneous population of Question_Phrase was estimated at Answer_Phrase	0.58
4	in net_date, the estimated total population in Question_Phrase amounted to approximately Answer_Phrase people	0.58
5	net_attribute the population of Question_Phrase was Answer_Phrase	0.57

Table B.37. Best Patterns for Question Type "Holy Book"

No	Patterns	Average CF
1	the Answer_Phrase also known as Answer_Phrase more than a holy book for the Question_Phrase	0.61
2	the Question_Phrase bible is called Answer_Phrase	0.60
3	the Answer_Phrase - the Question_Phrase holy book	0.60
4	the term Answer_Phrase can refer loosely to the entire Question_Phrase bible	0.57
5	Answer_Phrase can also be used to refer to the whole Question_Phrase bible	0.53

Table B.38. Best Patterns for Question Type "Color"

No	Patterns	Average CF
1	displayed at right is the web colour light Question_Phrase Answer_Phrase	0.64
2	Question_Phrase is Answer_Phrase	0.63
3	your Question_Phrase gets its Answer_Phrase color net_attribute	0.62
4	the Answer_Phrase color of the Question_Phrase is net_miscellaneous	0.62
5	how can she paint the Question_Phrase without Answer_Phrase paint	0.62

Table B.39. Best Patterns for Question Type "Code Number"

No	Patterns	Average CF
1	Answer_Phrase - dialing code for Question_Phrase	0.81
2	Answer_Phrase - country code for Question_Phrase	0.81
3	Question_Phrase country code Answer_Phrase country code net_number	0.74
4	the Question_Phrase country code Answer_Phrase will allow you to call Answer_Phrase from another country	0.73
5	Question_Phrase telephone code Answer_Phrase is net_miscellaneous	0.73

Table B.40. Best Patterns for Question Type "Headquarters"

No	Patterns	Average CF
1	net_miscellaneous Question_Phrase headquarters in Answer_Phrase	0.64
2	Question_Phrase has its headquarters in Answer_Phrase	0.59
3	Question_Phrase headquarters - city of Answer_Phrase	0.56
4	Question_Phrase office at Answer_Phrase	0.54
5	net_miscellaneous to Question_Phrase headquarters in Answer_Phrase	0.50

Table B.41. Best Patterns for Question Type "Airport Place"

No	Patterns	Average CF
1	Answer_Phrase airport hotel | net_number points by Answer_Phrase Question_Phrase airport	0.89
2	Answer_Phrase (Question_Phrase net_attribute)	0.67
3	Question_Phrase international airport - net_miscellaneous - Answer_Phrase	0.65
4	Answer_Phrase Question_Phrase airport | Answer_Phrase, ma united states	0.64
5	Answer_Phrase Question_Phrase international airport net_miscellaneous	0.63

Table B.42. Best Patterns for Question Type "Birthplace"

No	Patterns	Average CF
1	Question_Phrase was born in Answer_Phrase	0.71
2	Question_Phrase, was born in Answer_Phrase , net_miscellaneous	0.68
3	net_attribute Question_Phrase was born in Answer_Phrase	0.68
4	birthplace Answer_Phrase | Question_Phrase	0.68
5	Question_Phrase was born in Answer_Phrase approximately	0.59

Table B.43. Best Patterns for Question Type "Holy Place"

No	Patterns	Average CF
1	Question_Phrase shrine, Answer_Phrase	0.60
2	the Question_Phrase shrine in Answer_Phrase is net_attribute	0.56
3	Question_Phrase temple in Answer_Phrase is the net_attribute	0.54
4	the Question_Phrase temple at Answer_Phrase district in net_attribute	0.52
5	net_miscellaneous of the holy shrine of Question_Phrase on Answer_Phrase	0.52

Table B.44. Best Patterns for Question Type "Company Located"

No	Patterns	Average CF
1	Question_Phrase net_miscellaneous in Answer_Phrase	0.63
2	Question_Phrase is boosting sales in Answer_Phrase at net_miscellaneous	0.61
3	Question_Phrase has found success in Answer_Phrase by net_miscellaneous	0.58
4	Question_Phrase (net_miscellaneous) is a Answer_Phrase	0.57
5	Question_Phrase is on the lookout for a flashier location to do business in Answer_Phrase	0.56

Table B.45. Best Patterns for Question Type "Biggest Producer"

No	Patterns	Average CF
1	Question_Phrase production in Answer_Phrase	0.79
2	Answer_Phrase Question_Phrase production	0.70
3	Answer_Phrase is the net_number largest producer of Question_Phrase net_miscellaneous	0.61
4	Answer_Phrase has historically been one of the biggest producers of Question_Phrase	0.61
5	Question_Phrase production in Answer_Phrase and net_miscellaneous	0.58

Table B.46. Best Patterns for Question Type "Nationality"

No	Patterns	Average CF
1	net_attribute Question_Phrase was an Answer_Phrase by nationality	0.62
2	Question_Phrase was born on net_date, in Answer_Phrase	0.58
3	Question_Phrase net_attribute is an Answer_Phrase retired net_miscellaneous	0.57
4	Question_Phrase was born on net_date in Answer_Phrase	0.56
5	Question_Phrase net_attribute is a Answer_Phrase pop - folk singer, net_attribute	0.56

Table B.47. Best Patterns for Question Type "Attachment to Continent"

No	Patterns	Average CF
1	the country of Question_Phrase is in the Answer_Phrase continent net_miscellaneous	0.61
2	the country of Question_Phrase is in the Answer_Phrase continent and net_attribute	0.59
3	Question_Phrase is in the continent of Answer_Phrase	0.59
4	Question_Phrase is located on the continent of Answer_Phrase	0.57
5	Question_Phrase is part of the continent of Answer_Phrase	0.56

Table B.48. Best Patterns for Question Type "Establish"

No	Patterns	Average CF
1	the first complete Question_Phrase net_miscellaneous on Answer_Phrase	0.58
2	net_miscellaneous in Answer_Phrase, the Question_Phrase has net_miscellaneous	0.57
3	net_miscellaneous of Question_Phrase was net_miscellaneous in Answer_Phrase	0.56
4	Question_Phrase was constructed in Answer_Phrase	0.55
5	construction of the Question_Phrase started on Answer_Phrase	0.55

Table B.49. Best Patterns for Question Type "Another Name"

No	Patterns	Average CF
1	a Answer_Phrase is another name for a Question_Phrase	0.59
2	the Answer_Phrase or Question_Phrase is net_miscellaneous	0.57
3	Question_Phrase is another name for Answer_Phrase but net_attribute	0.57
4	Answer_Phrase another name for Question_Phrase	0.57
5	Question_Phrase is another word for Answer_Phrase	0.55

Table B.50. Best Patterns for Question Type "Zip Code"

No	Patterns	Average CF
1	net_miscellaneous in Answer_Phrase Question_Phrase net_miscellaneous	0.70
2	net_miscellaneous in zip code Answer_Phrase Question_Phrase	0.61
3	net_miscellaneous in the Question_Phrase area Answer_Phrase zip code net_miscellaneous	0.54
4	the zip codes for Question_Phrase, Answer_Phrase, net_miscellaneous	0.49
5	the zip code for Question_Phrase is Answer_Phrase	0.49

Table B.51. Best Patterns for Question Type "Gestation Period"

No	Patterns	Average CF
1	the gestation period for Question_Phrase is generally from Answer_Phrase with net_miscellaneous	0.62
2	the gestation period for Question_Phrase is Answer_Phrase	0.60
3	gestation in a Question_Phrase is Answer_Phrase in net_miscellaneous	0.57
4	the gestation period for Question_Phrase is generally from net_number to net_number days with an average of Answer_Phrase	0.56
5	the gestation period for Question_Phrase is around Answer_Phrase	0.55

Table B.52. Best Patterns for Question Type "Signing a Contract"

No	Patterns	Average CF
1	Answer_Phrase and the Question_Phrase	0.63
2	the Question_Phrase was signed by Answer_Phrase in net_miscellaneous	0.56
3	net_miscellaneous day Answer_Phrase signed the Question_Phrase	0.55
4	the Question_Phrase was an agreement between Answer_Phrase and net_miscellaneous	0.55
5	Question_Phrase forbids Answer_Phrase to interfere net_miscellaneous	0.55

Table B.53. Best Patterns for Question Type "First Coach"

No	Patterns	Average CF
1	Question_Phrase coach Answer_Phrase knows net_miscellaneous	0.60
2	Question_Phrase head coach Answer_Phrase has net_miscellaneous	0.56
3	when Question_Phrase' head coach Answer_Phrase spoke net_miscellaneous	0.54
4	Question_Phrase have leader in Answer_Phrase	0.49
5	Question_Phrase coach Answer_Phrase is net_miscellaneous	0.49

Table B.54. Best Patterns for Question Type "Founding Member"

No	Patterns	Average CF
1	net_miscellaneous founding members (Answer_Phrase) net_miscellaneous	0.62
2	Question_Phrase was founded by Answer_Phrase while net_miscellaneous	0.58
3	Answer_Phrase was a founding member of Question_Phrase and net_miscellaneous	0.58
4	Question_Phrase founding member Answer_Phrase (net_miscellaneous)	0.57
5	Answer_Phrase founded Question_Phrase in net_attribute	0.55

Table B.55. Best Patterns for Question Type "Science Father"

No	Patterns	Average CF
1	Answer_Phrase the father of Question_Phrase	0.64
2	Answer_Phrase father of Question_Phrase	0.64
3	Answer_Phrase is the man most commonly identified as the father of Question_Phrase	0.59
4	Answer_Phrase considered to be the father of Question_Phrase	0.59
5	why was Answer_Phrase considered the father of the Question_Phrase	0.57

Table B. 56. Best Patterns for Question Type "Begin"

No	Patterns	Average CF
1	the Question_Phrase began Answer_Phrase	0.63
2	the Answer_Phrase an underground urban movement known as Question_Phrase began to net_miscellaneous	0.62
3	Question_Phrase has made a considerable social impact since its inception in the Answer_Phrase	0.59
4	the Question_Phrase net_attribute from Answer_Phrase to net_miscellaneous	0.57
5	the Question_Phrase revolution began in Answer_Phrase	0.49

Table B.57. Best Patterns for Question Type "Mean"

No	Patterns	Average CF
1	the definition of Question_Phrase is Answer_Phrase	0.81
2	Answer_Phrase abbreviation Question_Phrase	0.72
3	Question_Phrase stands for Answer_Phrase	0.65
4	Question_Phrase means Answer_Phrase	0.64
5	Question_Phrase (Answer_Phrase) is net_miscellaneous	0.64

APPENDIX C: FACTOID TREC DATASETS

To the system evaluation, we evaluated the overall performance of the system with TREC datasets. Our factoid QAS uses identified factoid questions of TREC-8 and TREC-9 datasets in training model and in the testing model, identified factoid questions of TREC-10 to be evaluated. In this Appendix, the identified factoid questions of TREC-8, TREC-9 and TREC-10 datasets by the system are considered, respectively.

Table C.1. Factoid Questions in TREC-8

No	Question	Answer
1	What is the name of the managing director of Apricot Computer	Peter Horne
2	When did Nixon die	April 22, 1994
3	When was London's Docklands Light Railway constructed	1987
4	When did Nixon visit China	1972
5	What is the length of border between the Ukraine and Russia	1,971
6	What date did Emperor Hirohito die	1926
7	When did Jaco Pastorius die	1987
8	When did Beethoven die	March 26, 1827
9	Who is the author of the book, "The Iron Lady: A Biography of Margaret Thatcher"	Hugo Young
10	Name the designer of the shoe that spawned millions of plastic imitations, known as "jellies"	Andrea Pfister
11	What country is the biggest producer of tungsten	China
12	Who was the leader of the Branch Davidian Cult confronted by the FBI in Waco, Texas in 1993	David Koresh
13	Where was Ulysses S. Grant born	Point Pleasant, Ohio
14	Where is Inoco based	Norwich
15	What is the largest city in Germany	Berlin
16	Who was the first Taiwanese President	Ying
17	Which company created the Internet browser Mosaic	Netscape Communications
18	What is the name of the highest mountain in Africa	Kilimanjar

		o
19	Where was George Washington born	Westmoreland County
20	Who is the director of the international group called the Human Genome Organization (HUGO) that is trying to coordinate gene - mapping research worldwide	Victor McKusick
21	Who is the mayor of Marbella	Jesus Gil y Gil
22	Where is the massive North Korean nuclear complex located	Yongbyun
23	Who is the president of Stanford University	Donald Kennedy
24	When was the women's suffrage amendment ratified	February, 1972
25	What is the acronym for the rating system for air conditioner efficiency	SEER
26	Who invented the road traffic cone	David Morgan
27	Where is Microsoft's corporate headquarters located	Redmond, Wash
28	Who was President of Costa Rica in 1994	Rafael Angel Calderon
29	What is the longest river in the United States	Mississippi
30	Where is the Taj Mahal	Agra
31	How many inhabitants live in the town of Ushuaia	30,000
32	What is the tallest building in Japan	Tokyo Skytree
33	Who is the founder of Scientology	Ron Hubbard
34	Who wrote the song, “Stardust”	Hoagy Carmichael
35	Name a film that has won the Golden Bear in the Berlin Film Festival	Kilimanjaro
36	Who came up with the name, El Nino	Peruvian fishermen
37	What does El Nino mean in Spanish	boy child
38	What language is most commonly used in Bombay	Marathi
39	What country is the worlds leading supplier of cannabis	Ghana
40	How many people live in the Falklands	2,000
41	Who killed Lee Harvey Oswald	Jack Ruby
42	Who is the President of Ghana	Jerry John

		Rawlings
43	What two researchers discovered the double- helix structure of DNA in 1953	James Watson and Francis Crick
44	Who won the first general election for President held in Malawi in May 1994	Bakili Muluzi
45	What is the capital of Uruguay	Montevide o
46	What famous communist leader died in Mexico city	Leon Trotsky
47	Who is the president of the Spanish government	Felipe Gonzalez
48	What is the population of Ulan Bator, capital of Mongolia	Some 600,000
49	Who is the prime minister of Japan	Tomiichi Murayama
50	How many people live in Tokyo	12 million
51	What is the capital of California	Sacrament o
52	Who wrote "The Pines of Rome"	Respighi
53	Who wrote "Dubliners"	JAMES JOYCE
54	Who wrote "Hamlet"	Shakespea re
55	What is the capital of Kosovo	Pristina
56	Where was Harry Truman born	Lamar
57	What nationality is Pope John Paul II	Polish
58	Who was President of Afghanistan in 1994	Mohamme d Najibullah
59	Who is the director of intergovernmental affairs for the San Diego county	John Sweeten
60	How many people in Tucson	over 500,000
61	What is the capital of Congo	Brazzaville
62	What is the capital of Italy	Rome
63	What is the capital of Sri Lanka	Colombo
64	What was the name of the computer in "2001: A Space Odyssey"	HAL
65	When was Queen Victoria born	1837
66	Where was Lincoln assassinated	Ford Theater
67	Where is Qatar	Asia
68	Where is the highest point in Japan	Fuji
69	How tall is the Matterhorn	14,776

		feet
70	How tall is the replica of the Matterhorn at Disneyland	147-foot
71	How tall is Mt. Everest	29,028
72	How far is Yaroslavl from Moscow	155 miles
73	How long does it take to travel from Tokyo to Niigata	2 hours
74	How much did Mercury spend on advertising in 1993	Pounds 12m
75	How rich is Bill Gates	$81.6 billion
76	Which city has the oldest relationship as a sister city with Los Angeles	Nagoya
77	How long did the Charles Manson murder trial last	9.5-month
78	What are the Valdez Principles	10 point environmental agenda
79	Which country is Australia's largest export market	China
80	What is the brightest star visible from Earth	Sirius
81	What is the legal blood alcohol limit for the state of California	0.08%
82	What brand of white rum is still made in Cuba	Havana Club
83	What nuclear powered Russian submarine sank in the Norwegian Sea on April 7, 1989	Komsomolets
84	What is the name of the promising anticancer compound derived from the pacific yew tree	taxol
85	What novel inspired the movie Blade Runner	Do Androids Dream Of Electric Sheep
86	What is the second highest mountain peak in the world	K2
87	What is Grenada's main commodity export	nutmeg
88	What state does Charles Robb represent	Virginia
89	Which team won the Super Bowl in 1968	Green Bay Packers
90	How many people died when the Estonia sank in 1994	more than 900
91	How many people on the ground were killed from the bombing of Pan Am Flight 103 over Lockerbie, Scotland, December 21, 1988	259
92	What is considered the costliest disaster the insurance industry has ever faced	Hurricane Andrew

93	What cancer is commonly associated with AIDS	Kaposi sarcoma
94	How many moons does Jupiter have	four moons
95	Who won the Nobel Peace Prize in 1991	Aung San Suu Kyi
96	Who received the Will Rogers Award in 1989	Frank Sinatra
97	Who won two gold medals in skiing in the Olympic Games in Calgary	Tomba
98	Who is the Queen of Holland	Queen Beatrix
99	Who was President Cleveland's wife	Frances Folsom
100	who was the first American in space	Alan Shepard
101	Name the first private citizen to fly in space	Christa McAuliffe
102	Who was the lead actress in the movie "Sleepless in Seattle"	Meg Ryan
103	Who was the second man to walk on the moon	Buzz Aldrin
104	Who is the voice of Miss Piggy	Frank Oz
105	Who was the first doctor to successfully transplant a liver	Thomas Starzl
106	Who released the Internet w'2orm in the late 1980s	Robert Morris
107	In 1990, what day of the week did Christmas fall on	Tuesday
108	At what age did Rossini stop writing opera	37
109	Who is section manager for guidance and control systems at JPL	Laura Faye Tenenbaum
110	Who is the Voyager project manager	Norm Haynes
111	Who first circum navigated the globe	Ferdinand Magellan
112	Who is the leading competitor of TransUnion Company	Experian and Equifax
113	Who was Secretary of State during the Nixon administration	Henry Alfred Kissinger
114	Which city in China has the largest number of foreign financial companies	Shanghai
115	Where does most of the marijuana entering the	Mexico

	United States come from	
116	Where did Dylan Thomas die	New York
117	Where is the Bulls basketball team based	Chicago
118	Where is Dartmouth College	Hanover
119	Where is the Keck telescope	Hawaii
120	How many people does Honda employ in the U.S.	25,000
121	Where is South Bend	United States
122	Where did the Battle of the Bulge take place	Belgium
123	Where is the actress, Marion Davies, buried	Hollywood Memorial Park
124	When did the Jurassic Period end	130 million years ago
125	When did communist control end in Hungary	1989
126	When was China's first nuclear test	1964
127	In which year was New Zealand excluded from the ANZUS alliance	1986
128	What did John Hinckley do to impress Jodie Foster	Tried to kill President Reagan
129	In what year did Ireland elect its first woman president	1990
130	In what year did Joe DiMaggio compile his 56-game hitting streak	1941
131	When did the original Howdy Doody show go off the air	1960
132	When was the battle of the Somme fought	1916
133	When did French revolutionaries storm the Bastille	1789
134	When was Yemen reunified	1990
135	How many consecutive baseball games did Lou Gehrig play	2130

Table C.2. Factoid Questions in TREC-9

No	Question	Answer
1	What was the name of the first Russian astronaut to do a spacewalk	Alexei Leonov
2	Name the first Russian astronaut to do a spacewalk	Alexei Leonov
3	Who was the first Russian astronaut to walk in space	Alexei Leonov
4	Who was the first Russian astronaut to do a spacewalk	Alexei Leonov
5	What was the death toll at the eruption of Mount Pinatubo	847
6	What is the wingspan of a condor	3.2
7	How tall is the giraffe	14 to 19
8	How tall is Kilimanjaro	19,340
9	What is one of the cities that the University of Minnesota is located in	Duluth
10	What city is Massachusetts General Hospital located in	Boston
11	What city is 94.5 KDGE Radio located in	Dallas
12	What city is the Orange Bowl in	Miami
13	The Orange Bowl is in what city	Miami
14	The Orange Bowl is located in what city	Miami
15	Where is the Orange Bowl	Miami
16	Where is the location of the Orange Bowl	Miami
17	Where can one find Rider College	New Jersey
18	Where is Rider College located	New Jersey
19	What is the location of Rider College	New Jersey
20	Rider College is located in what city	New Jersey
21	Where is Rider College	New Jersey
22	Where can you find the Venus flytrap	North Carolina
23	Where is Tornado Alley	Texas
24	Where is Webster University	St. Louis
25	The Kentucky Horse Park is close to which American city	Lexington
26	Where is the Kentucky Horse Park located	Lexington
27	Where is the Kentucky Horse Park	Lexington
28	What city is the Kentucky Horse Park near	Lexington
29	The Kentucky Horse Park is located near what city	Lexington
30	Where is the Smithsonian Institute located	Washington D.C
31	Where is Kings Canyon	Sierra Nevada
32	Where is the Mayo Clinic	Minnesota
33	Where did Woodstock take place	Bethel,

		New York
34	Where is Tufts University	Medford/Somerville
35	Where is the Thomas Edison Museum	NJ
36	What city the Kentucky Horse Park is near	Lexington
37	What city in Florida is Sea World in	Orlando
38	Where is Glasgow	Scotland
39	Where is Melbourne	Australia
40	Where is the Kalahari desert	Namibia
41	Where is Basque country located	Spain
42	What province is Edmonton located in	Alberta
43	What is the most common kind of skin cancer in the U.S.	squamous cell carcinoma
44	When did the American Civil War end	1865
45	What year was Janet Jackson's first album released	1982
46	What year did the Vietnam War end	1975
47	When did the royal wedding of Prince Andrew and Fergie take place	July 1986
48	When is Bastille Day	14 July 1789
49	Where is Belize located	Central America
50	Where is the Danube	Europe
51	Where is Romania located	Europe
52	Where is Venezuela	South America
53	What continent is Bolivia on	South America
54	Where is the Orinoco	South America
55	What is the population of Japan	112.90 million
56	How many people live in Chile	17216945
57	How large is Missouri's population	5,079,385
58	What's the population of Mississippi	21,203 million
59	What's the population of Biloxi, Mississippi	46,000
60	What is the population of the Bahamas	250,000
61	What is the population of Kansas	2.49 million
62	What is the population of Mozambique	14.5 million
63	How many people lived in Nebraska in the mid-1980s	1,605,000

64	What is the population of Ohio	11 million
65	What is the population of the United States	249,632,692
66	What is the population of Mexico	8.84 million
67	What is Black Hills, South Dakota most famous for	Mount Rushmore
68	What is Francis Scott Key best known for	The Star-Spangled Banner
69	What are Cushman and Wakefield known for	Fiat Chrysler
70	Aspartame is also known as what	NutraSweet
71	Aspartame is known by what other name	NutraSweet
72	What is D.B. Cooper known for	skyjacker
73	What is Betsy Ross famous for	first American flag
74	What other name were the "Little Rascals" known as	Our Gang
75	What makes Black Hills, South Dakota a tourist attraction	Mount Rushmore
76	What are the Black Hills known for	Mount Rushmore
77	What tourist attractions are there in Reims	Cathedral
78	What are the names of the tourist attractions in Reims	Cathedral
79	What do most tourists visit in Reims	Cathedral
80	What attracts tourists to Reims	Cathedral
81	What are tourist attractions in Reims	Cathedral
82	What could I see in Reims	Cathedral
83	What is worth seeing in Reims	Cathedral
84	What can one see in Reims	Cathedral
85	What is Jane Goodall famous for	primatologist
86	What is Jane Goodall known for	primatologist
87	Why is Jane Goodall famous	primatologist
88	What made Jane Goodall famous	primatologist
89	Ray Charles is best known for playing what instrument	piano
90	What instrument does Ray Charles play	piano
91	Musician Ray Charles plays what instrument	piano

92	Ray Charles plays which instrument	piano
93	What's the most famous tourist attraction in Rome	Coliseum
94	What is Giorgio Vasari famous for	biographer
95	Who invented the paper clip	Johan Vaaler
96	Who invented the electric guitar	Les Paul
97	Who invented baseball	Abner Doubleday
98	Who made the first airplane that could fly	Orville and Wilbur Wright
99	Who invented television	Paul Nipkow
100	Who made the first airplane	Orville and Wilbur Wright
101	Who invented the game Scrabble	Alfred Butts
102	Name an American made motorcycle	Harley Davidson
103	Who invented paper	Tsai
104	Who invented the radio	Guglielmo Marconi
105	Who invented basketball	James Naismith
106	Who invented the game bowling	ancient Egyptians
107	Who invented silly putty	General Electric
108	What is the name of the inventor of silly putty	General Electric
109	Silly putty was invented by whom	General Electric
110	Who was the inventor of silly putty	General Electric
111	Who started the Dominos Pizza chain	Tom Monaghan
112	Name a flying mammal	Bats
113	What is the nickname of Pennsylvania	Keystone State
114	What is Alice Cooper's real name	Vincent Fernier
115	Mississippi is nicknamed what	Magnolia State
116	What is the nickname for the state of Mississippi	Magnolia State
117	What is the state nickname of Mississippi	Magnolia

		State
118	Mississippi has what name for a state nickname	Magnolia State
119	What is a nickname for Mississippi	Magnolia State
120	What is the nickname of the state of Mississippi	Magnolia State
121	What is the name of the second space shuttle	Columbia
122	What's another name for aspartame	Amino Sweet
123	What is the name of the Jewish alphabet	alef-bet
124	What is the Jewish alphabet called	alef-bet
125	The Jewish alphabet is called what	alef-bet
126	The Jewish alphabet is known as what	alef-bet
127	What's the formal name for Lou Gehrig's disease	amyotrophic lateral sclerosis
128	What is the real name of the singer, Madonna	Madonna Louise Veronica Ciccone
129	What is another name for nearsightedness	myopia
130	What is a synonym for aspartame	NutraSweet
131	Aspartame is also called what	NutraSweet
132	What is the name of a Greek god	Poseidon
133	What is leukemia	blood cancer
134	What do you call a group of geese	gaggle
135	What is the primary language of the Philippines	Filipino
136	What language is mostly spoken in Brazil	Portuguese
137	Who killed Martin Luther King	James Earl Ray
138	Who assassinated President McKinley	Leon Czolgosz
139	Who shot Billy the Kid	Sheriff Pat Garrett
140	What killed Bob Marley	cancer
141	What was the cause of Bob Marley's death	cancer
142	What caused the death of Bob Marley	cancer
143	Who was the first U.S. president ever to resign	Nixon
144	Who is the president of Bolivia	Evo Morales
145	Who was the 21st U.S. President	Chester A. Arthur

146	Who was the 33rd president of the United States	Harry Truman
147	Who was the oldest U.S. president	Ronald Reagan
148	What does the abbreviation OAS stand for	Organization of American States
149	What does NAFTA stand for	North American Free Trade Agreement
150	What does NASA stand for	National Aeronautics and Space Administration
151	What does EKG stand for	electrocardiogram
152	What is TCI	Therapeutic Crisis Intervention
153	What does CNN stand for	Cable News Network
154	What is the abbreviation for Original Equipment Manufacturer	OEM
155	What does CPR stand for	cardio pulmonary resuscitation
156	What does SIDS stand for	Sudden Infant Death Syndrome
157	CNN is the abbreviation for what	Cable News Network
158	CNN is an acronym for what	Cable News Network
159	How do you abbreviate "Original Equipment Manufacturer"	OEM
160	What is the abbreviation for Original Equipment Manufacturer	OEM
161	What does caliente translate to in English	hot
162	What is the English meaning of caliente	hot
163	What is the meaning of caliente	hot

164	What is the English translation for the word "caliente"	hot
165	What is the meaning of "CPR"	Cardiopulmonary Resuscitation
166	What does the acronym CPR mean	Cardiopulmonary Resuscitation
167	What do the initials CPR stand for	Cardiopulmonary Resuscitation
168	CPR is the abbreviation for what	Cardiopulmonary Resuscitation
169	What does caliente mean	hot
170	What's the abbreviation for limited partnership	LP
171	What does hazmat stand for	hazardous materials
172	Hazmat stands for what	hazardous materials
173	What is the definition of hazmat	hazardous materials
174	What state does MO stand for	Missouri
175	What is the name of the longest ruling dynasty of Japan	Yi
176	When was Babe Ruth born	1895
177	When was Dick Clark born	November 30, 1929
178	When is Dick Clark's birthday	November 30, 1929
179	What is Dick Clark's date of birth	November 30, 1929
180	What is Martin Luther King Jr.'s real birthday	January 15, 1929
181	Where was Tesla born	1856
182	When was John D. Rockefeller born	10 July 1839
183	When was Beethoven born	1770
184	When was Nostradamus born	1503
185	Who wrote the book, "Song of Solomon"	Toni Morrison
186	Who wrote the book, "Huckleberry Finn"	Mark Twain
187	Who wrote "The Scarlet Letter"	Nathaniel

		Hawthorne
188	Who wrote “An Ideal Husband”	Oscar Wilde
189	Who wrote the book, “The Grinch Who Stole Christmas”	Dr. Seuss
190	Who wrote “The Pit and the Pendulum”	Edgar Allan Poe
191	Who was the author of the book about computer hackers called “The Cuckoo's Egg: Tracking a Spy Through the Maze of Computer Espionage”	Clifford Stoll
192	Who wrote the song, “Silent Night”	Franz Xaver Gruber
193	Who wrote the song, “Boys of Summer”	Don Henley
194	Where was Pythagoras born	Greek
195	Where was John Adams born	Braintree, Mass
196	Where was Poe born	Boston
197	What was Poe's birthplace	Boston
198	What was the birthplace of Edgar Allen Poe	Boston
199	Where is Poe's birthplace	Boston
200	What's the tallest building in New York City	World Trade Center
201	When was the first railroad from the east coast to the west coast completed	1869
202	When was Microsoft established	1975
203	When was the Brandenburg Gate in Berlin built	1791
204	When was the NFL established	1920
205	When was the Hoover Dam constructed	1936
206	When was Hurricane Hugo	1989
207	When did the California lottery begin	1985
208	When was “the Great Depression”	1929
209	Who found Hawaii	Captain Cook
210	Who built the first pyramid	King Zoser
211	Who is the founder of the Wal-Mart stores	Sam Walton
212	What is California's capital	Sacrament o
213	What is the capital of Burkina Faso	Ouagadoug ou
214	What is the capital of Haiti	Port-Au-Prince
215	Who is the prophet of the religion of Islam	Muhamma d

216	Who was the first coach of the Cleveland Browns	Paul Brown
217	Who was the first king of England	King William
218	Who is the emperor of Japan	Akihito
219	Who is the monarch of the United Kingdom	Elizabeth II
220	When was the San Francisco fire	April 18, 1906
221	When was the Triangle Shirtwaist fire	1911
222	What's the longest river in the world	Amazon
223	Who was considered to be the father of psychology	Sigmund Freud
224	What nationality was Jackson Pollock	American artist
225	Jackson Pollock was a native of what country	American artist
226	Jackson Pollock is of what nationality	American artist
227	What was the nationality of Jackson Pollock	American artist
228	What is the world's highest peak	Mt. Everest
229	What is the highest mountain in the world	Mt. Everest
230	Name the highest mountain	Mt. Everest
231	What is the name of the tallest mountain in the world	Mt. Everest
232	What is the tallest mountain	Mt. Everest
233	Where is Logan International located	Boston
234	What is the zip code for Fremont, CA	94537
235	What is the zip code for Parsippany, NJ	07054
236	What year did Hitler die	1945
237	Where are the headquarters of Eli Lilly	Indianapolis
238	What king was forced to agree to the Magna Carta	King John
239	What monarch signed the Magna Carta	King John
240	Which king signed the Magna Carta	King John
241	Who was the king who was forced to agree to the Magna Carta	King John
242	What king signed the Magna Carta	King John
243	Who was the king who signed the Magna Carta	King John
244	Where is Logan Airport	Boston
245	What city is Logan Airport in	Boston
246	Logan International serves what city	Boston
247	Logan International is located in what city	Boston
248	What city's airport is named Logan International	Boston
249	What city is served by Logan International Airport	Boston
250	What is measured in curies	radioactivity
251	When did the Chernobyl nuclear accident occur	April 26,

		1986
252	Who was the founding member of the Pink Floyd band	Roger Waters
253	What city does McCarren Airport serve	Las Vegas
254	What city is served by McCarren Airport	Las Vegas
255	McCarren Airport is located in what city	Las Vegas
256	What is the location of McCarren Airport	Las Vegas
257	Where is McCarren Airport located	Las Vegas
258	Where is McCarren Airport	Las Vegas
259	What's the name of the Tokyo Stock Exchange	TSE
260	Where is Burma	Asia
261	Where is the Isle of Man	Europe
262	What is the date of Boxing Day	the day after Christmas
263	When is Boxing Day	the day after Christmas
264	Boxing Day is celebrated on what date	the day after Christmas
265	What date is Boxing Day	the day after Christmas
266	What is the date of Bastille Day	July 14 1789
267	Bastille Day occurs on which date	July 14 1789
268	Who was Charles Lindbergh's wife	Anne Morrow Lindbergh
269	What's the name of Pittsburgh's baseball team	Pittsburgh Pirates
270	What is Pittsburg's baseball team called	Pittsburgh Pirates
271	The major league baseball team in Pittsburgh is called what	Pittsburgh Pirates
272	Name Pittsburgh's baseball team	Pittsburgh Pirates
273	What was the name of the Titanic's captain	Edward John Smith
274	What is the name of Joan Jett's band	Blackhearts
275	What was the name of the “Little Rascals” dog	Pete
276	What breed of dog was the “Little Rascals” dog	Pete
277	What is the name of the art of growing miniature trees	bonsai
278	Italy is the largest producer of what	wine

279	What U.S. Government agency registers trademarks	Patent and Trademark Office
280	How many hexagons are on a soccer ball	20
281	How long do hermit crabs live	30 years
282	How much in miles is a ten K run	6.2 miles
283	Where do hyenas live	Africa
284	Where did the Maya people live	Mexico
285	What city did the Flintstones live in	Bedrock
286	Who coined the term " cyberspace" in his novel "Necromancer"	William Gibson
287	Where did the ukulele originate	Portugal
288	Where does chocolate come from	Cocoa
289	What is the largest variety of cactus	saguaro
290	What is sake	Japanese rice wine
291	What is a Stratocaster	guitar
292	What is a meerkat	mongoose
293	What is a nanometer	one billionth of a meter
294	What is anorexia nervosa	an eating disorder
295	What is saltpeter	potassium nitrate
296	What is Tyvek	synthetic material
297	What is titanium	metal
298	What is pandoro	sweet Italian bread
299	What is "Nine Inch Nails"	rock band
300	What is cribbage	card game
301	What university was Woodrow Wilson President of	Princeton
302	Woodrow Wilson was president of which university	Princeton
303	Name the university of which Woodrow Wilson was president	Princeton
304	Woodrow Wilson served as president of what university	Princeton
305	What is the name of the vaccine for chicken pox	Varivax
306	What is Tyvek	synthetic material
307	Winnie the Pooh is what kind of animal	bear
308	What species was Winnie the Pooh	bear
309	Winnie the Pooh is an imitation of which animal	bear
310	What was the species of Winnie the Pooh	bear

311	At what speed does the Earth revolve around the sun	30 km/s
312	What is the chemical formula/name for napalm	naphthenic and palmitic acids
313	What is the occupation of Nicholas Cage	actor
314	What is Nicholas Cage's profession	actor
315	What is Nicholas Cage's occupation	actor
316	Who is Zebulon Pike	brigadier general
317	What is the equivalent of the Red Cross in the Middle East	Red Crescent
318	What is the name of the Islamic counterpart to the Red Cross	Red Crescent
319	Name the Islamic counterpart to the Red Cross	Red Crescent
320	What is the Islamic equivalent of the Red Cross	Red Crescent
321	What is the name given to the Islamic counterpart of the Red Cross	Red Crescent
322	What is the Islamic counterpart to the Red Cross	Red Crescent

Table C.3. Factoid Questions in TREC-10

No	Question	Answer
1	Who developed the vaccination against polio	Jonas Salk
2	Who developed the Macintosh computer	Steve Jobs
3	Who founded American Red Cross	Clara Barton
4	What river in the US is known as the Big Muddy	Mississippi
5	What is the name given to the Tiger at Louisiana State University	LSU
6	What is a group of frogs called	Colony
7	What is a group of turkeys called	flock
8	What was W.C. Fields ' real name	William Claude Duke field
9	What is Shakespeare's nickname	Bard of Avon
10	Who discovered radium	Marie and Pierre Curie
11	Who discovered x-rays	Wilhelm Conrad Roentgen
12	Who discovered America	Christopher Columbus
13	Who discovered oxygen	Joseph Priestley
14	Who was the first person to reach the North Pole	Robert Edwin Peary
15	Who wrote the hymn "Amazing Grace"	Amazing Grace
16	Who wrote "The Divine Comedy"	Dante Alighieri
17	Who invented the hula hoop	Arthur K
18	Who invented the slinky	Richard James
19	Who invented the telephone	Alexander Graham Bell
20	Who invented the calculator	Blaise Pascal
21	Who invented the instant Polaroid camera	Edwin H. Land
22	Who invented Trivial Pursuit	Chris Haney and Scott

		Abbott
23	Who killed John F. Kennedy	Lee Harvey Oswald
24	Who is the Prime Minister of Canada	Stephen Harper
25	Who was the first U.S. president to appear on TV	Franklin D. Roosevelt
26	Who was elected president of South Africa in 1994	Nelson Mandela
27	Who was the 23rd president of the United States	Benjamin Harrison
28	Who is the governor of Alaska	Bill Walker
29	Who was the first vice president of the U.S.	John Adams
30	What is the fourth highest mountain in the world	Lhotse
31	What is Susan B. Anthony's birthday	15 Feb. 1820
32	When was Thomas Jefferson born	April 13, 1743
33	What year was Mozart born	January 27, 1756
34	When was Abraham Lincoln born	Feb. 12, 1809
35	When was Rosa Parks born	February 4, 1913
36	When was President Kennedy shot	Nov. 22, 1963
37	What day and month did John Lennon die	Dec. 8, 1980
38	What currency does Argentina use	peso
39	What currency does Luxembourg use	Euro
40	What currency do they use in Brazil	BRL
41	What type of currency is used in Australia	Dollar
42	What currency is used in Algeria	Algerian Dinar
43	What year did the Andy Griffith show begin	1960
44	What year did WWII begin	Sept. 1, 1939
45	When was the telephone invented	1876
46	What is the population of Venezuela	467557
47	What is the population of Australia	23,13 million
48	What is the population of China	1.355 billion
49	What is the population of Seattle	3,610,105

50	What is the population of Nigeria	96.40 Million
51	What does the abbreviation SOS mean	Sosyoloji
52	What does cc in engines mean	cubic centimeters
53	What does the technical term ISDN mean	Integrated Services Digital Network
54	What does I.V. stand for	Intravenous
55	What does USPS stand for	United States Postal Service
56	What does CPR stand for	cardiopulmonary resuscitation
57	What does the acronym NASA stand for	National Aeronautics and Space Administration
58	What does NASA stand for	National Aeronautics and Space Administration
59	What continent is Argentina on	South America
60	What is the capital of Ethiopia	Addis Ababa
61	What is the capital of Persia	Tehran
62	What is the capital of Zimbabwe	Harare
63	What is the capital of Yugoslavia	Belgrade
64	What is the capital of Mongolia	Ulan Bator
65	What is the largest city in the world	Tokyo
66	What Canadian city has the largest population	Montreal
67	What country did Ponce de Leon come from	Spain
68	When did Elvis Presley die	1977
69	What is the gestation period for a cat	66
70	When were William Shakespeare’s twins born	1585
71	What is another name for vitamin B1	tiyamin

72	What is another astronomic term for the Northern Lights	Aurora Borealis
73	What continent is Egypt on	Africa
74	When was Lyndon B. Johnson born	1908
75	What New York City structure is also known as the Twin Towers	World Trade Center
76	What is the most frequently spoken language in the Netherlands	Dutch
77	What is sodium chloride	salt
78	What planet is known as the "red" planet	Mars
79	What does "Sitting Shiva" mean	seven
80	Who was the first African American to play for the Brooklyn Dodgers	Jackie Robinson
81	What is Australia's national flower	Acacia pycnantha
82	What is Hawaii's state flower	Yellow hibiscus
83	What is the Illinois state flower	Violet
84	What is the state flower of Michigan	apple blossom
85	What is bipolar disorder	Manic-depressive illness
86	What is Teflon	brand name
87	What is amitriptyline	Tricyclic antidepres sant
88	What is phosphorus	chemical element
89	What is osteoporosis	disease of the bones
90	What is strep throat	contagious disease
91	What is Ursa Major	constellati on
92	What is myopia	refractive error
93	Who painted the ceiling of the Sistine Chapel	Michel Angelo
94	What is the life expectancy of a dollar bill	18-22 months
95	What is the colorful Korean traditional dress called	Honbok
96	What is the primary language in Iceland	Icelandic
97	What is the abbreviation for Texas	TX
98	What is the heaviest naturally occurring element	Uranium

99	What is the largest city in the U.S.	New York
100	What color is indigo	rainbow
101	When was Ulysses S. Grant born	1822
102	What is the most common eye color	Brown
103	What is the world's population	7 Billion
104	What is a baby lion called	Cub
105	What does ciao mean	hello or goodbye
106	How do you measure earthquakes	Richter Scale
107	What does a barometer measure	atmospheric pressure
108	What color are crickets	light
109	When did Idaho become a state	July 3, 1890
110	When did Hawaii become a state	1959
111	What year did Oklahoma become a state	1907
112	What was J.F.K.'s wife's name	Jacqueline Kennedy Onassis
113	In which state would you find the Catskill Mountains	New York
114	Where is the Savannah River	Augusta
115	Where is the Little League Museum	South Williamsport
116	Where is the Eiffel Tower	Paris
117	Where is John Wayne airport	California
118	What county is Phoenix, AZ in	Maricopa County
119	What county is Modesto, California in	Stanislaus County
120	Where is the Grand Canyon	Arizona
121	Where is the tallest roller coaster located	Orlando
122	Where is the Mason/Dixon line	between Pennsylvania and Maryland
123	What city's newspaper is called "The Star"	Kansas
124	Where is the Holland Tunnel	New York
125	What French ruler was defeated at the battle of Waterloo	Napoleon
126	What is the birthstone for June	pearl, moonstone, and Alexandrit

		e
127	What is the birthstone of October	opal and tourmaline
128	When is the summer solstice	June 21
129	When was the first stamp issued	1840
130	When was Algeria colonized	1830
131	Which president was unmarried	James Buchanan
132	When did the Hindenberg crash	May 6, 1937
133	What is New York's state bird	Eastern bluebird
134	What is Maryland's state bird	Baltimore oriole
135	What is the Ohio state bird	Cardinal
136	When was the first liver transplant	March 1, 1963
137	How many Great Lakes are there	five
138	When did John F. Kennedy get elected as President	1960
139	What is the diameter of a golf ball	1.68
140	What is the earth's diameter	7,926
141	What year did the Titanic sink	April 14th, 1912
142	What was the name of the plane Lindbergh flew solo across the Atlantic	the Spirit of St. Louis
143	What monastery was raided by Vikings in the late eighth century	Lindisfarn e
144	What is the smallest bird in Britain	gold crest
145	What breed of hunting dog did the Beverly Hillbillies own	Dukes
146	What is the rainiest place on Earth	Mawsynra m
147	What is the most popular sport in Japan	baseball
148	What is the active ingredient in baking soda	Sodium Bicarbonat e
149	What type of polymer is used for bulletproof vests	Kevlar
150	What was the name of the first U.S. satellite sent into space	Explorer I
151	What precious stone is a form of pure carbon	diamond
152	What river runs through Rowe, Italy	Tiber
153	What year did Canada join the United Nations	1945
154	What strait separates North America from Asia	Bering Strait

155	What is the oldest university in the US	Harvard
156	What is done with worn or outdated flags	burning
157	What hemisphere is the Philippines in	Eastern Hemisphere
158	Who lived in the Neuschwanste in castle	King Ludwig II
159	Who is the tallest man in the world	Sultan Kosen
160	Who was the first man to fly across the Pacific Ocean	Pangborn
161	What is the electrical output in Madrid, Spain	220 volts
162	Material called linen is made from what plant	Flax
163	What is pastrami made of	beef
164	What is plastic made of	oil
165	What is the statue of liberty made of	copper
166	What year did the U.S. buy Alaska	1867
167	What are the two houses of the Legislative branch	federal governme nt
168	How many hearts does an octopus have	three
169	What did Edward Binney and Howard Smith invent in 1903	Crayola Crayons
170	What instrument did Glenn Miller play	trombone
171	What is the deepest lake in the US	Crater Lake

CURRICULUM VITAE

Credentials

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Persian (Native), Azeri (Native), Arabic (Intermediate), Turkish (Excellent), English (Advanced)

Work Experience

Senior Lecturer in Department of Computer Engineering, Islamic Azad University, Science and Research Branch and Urmia Branch, West Azerbaijan, Iran.

Area of Experience

Natural Language Processing, Machine learning, Software Cost Estimation, Operating and Distributed Systems

Project and Budgets

Publications

Oral and Poster Presentations