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SOLUTION FOR WORD REORDERING ENGLISH-TURKISH SMT

by

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ABSTRACT

SOLUTION FOR WORD REORDERING ENGLISH-TURKISH SMT

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Keywords: Statistical Machine Translation, Word Alignment, Word Reordering, Turkish Language, Linguistic Knowledge.

Statistical Machine Translation (SMT) is the process of automatically translating sentences by examining many samples of human-produced translation. To help with word alignment of statistically translated sentences between languages having significantly different word orders, word reordering is required. In this thesis, the characteristics of the Turkish language and its challenges for SMT are outlined. Then, by the use of morphological analysis and syntactic rules based on linguistic knowledge, we propose reordering the sentences that are already translated into Turkish.

ÖZET

İNGİLİZCE TÜRKÇE İSTATİKSEL MAKİNE ÇEVİRİSİNDE KELİME SIRASINI YENİDEN DÜZENLEME ÇÖZÜMÜ

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İstatistiksel Makine Çevirisi, insanlar tarafından yapılmış bir çok çeviri örneklerini inceleyerek otomatik olarak bir dilden başka bir dile çeviri yapma işlemidir. Birbirinden oldukça farklı kelime dizilişlerine sahip diller arasında yapılmış istatistiksel çevirilerde kelimelerin karşılıklı olarak hizalanabilmesine yardımcı olmak için, kelime sırasının yeniden düzenlenmesine ihtiyaç duyulur. Bu tezde, Türk diline ait karakteristik özellikler ve İstatistiksel Makina Çevirisi için olan zorluklar ortaya konulmuştur. Daha sonra da, kök analizi ve dilsel bilgiye dayanan cümle yapısına ait kurallar yardımıyla , Türkçe'ye çevirilmiş cümlelerin kelime sıralarını yeniden düzenleme önerilmektedir.

Dedicated to my Family

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LIST OF SYMBOLS/ABBREVIATIONS

Symbol	Explanation
BLEU	Bilingual Evaluation Understudy
IWSLT	International Workshop on Spoken Language Translation
MT	Machine Translation
NLP	Natural Language Processing
POS	Part-of-speech
SMT	Statistical Machine Translation
SOV	Subject-Object-Verb
SVO	Subject-Verb-Object
TDK	Türk Dil Kurumu (Turkish Language Association)

CHAPTER 1

INTRODUCTION

Translation is the process of converting one sentence in a language into another language, without changing the meaning. As the computers emerged, people thought of benefiting from them. Machine Translation (MT) is automatically translating from a source language into a target language by using computers [1].

An approach to MT, which is characterized by the use of machine learning methods, is called Statistical Machine Translation (SMT). SMT treats the translation as a machine learning problem. First, many samples of human translation input-output pairs are examined, then SMT algorithms automatically learn how to translate. The corresponding translation for each word or phrase is determined according to the usage frequency in the training collection.

SMT systems have some limitations. One of these limitations is that SMT may not provide good results between languages having significantly different word orders. Correctly placing the words in a sentence is crucial to properly convey the meaning of a sentence after translations. It has been observed that one gets better alignments and hence better translation results when the word orders of the source and target languages are more or less the same. When word orders are different as in the English-Turkish pair, a solution is needed to align the words properly, to convey the same meaning in the two sentences.

The main problem for English-Turkish SMT is the word order difference. To solve this problem, the researchers have proposed reordering. Reordering is mostly affected by syntactic structure of the target language. For instance, the typical sentence order in English sentences is subject-verb-object (SVO), whereas in Turkish it is very flexible. After translations, words may not be in correct places, reducing the translation performance;

therefore, a reordering solution is needed.

To correctly reorder the words, our proposed approach is based on syntactic rules. First a morphological analyzer is used. Then a tagger is used to obtain Turkish part-of-speech (POS) tags. And finally, using POS tags words are reordered based on Turkish grammar rules. This thesis is organized as follows: in Chapter 2, a short review of Turkish language characteristics is presented. In Chapter 3, the challenges of Turkish SMT are described. Related work and discussion are presented in Chapter 4, and proposed approach for word reordering English-Turkish SMT results are presented in Chapter 5. In Chapter 6 the experiments set up, training collections, test collections and SMT system is explained. Finally, in Chapter 7 the study is concluded with an outlook to future work.

CHAPTER 2

TURKISH LANGUAGE CHARACTERISTICS

Turkish language is one of the ancient languages over the world , which dates back more than 5000 years. It is in the same family of Altaic languages as well as Mongolic, Tungusic, Korean and Japonic in the Altaic branch. Today, Turkish is spoken mainly by more than 200 million people over the world, including the different accents [2]. In the field of Natural Language Processing (NLP), languages like Turkish have some unique features which create a number of challenges. Its agglutinative morphological structure, grammatical operators, such as vowel harmony and voicing and its free constituent order are some of the issues to be handled during Turkish language processing. In this chapter, a brief history about Turkish language is given first. Its origin and the phases it has passed through are provided. After presenting the place of Turkish language in the world, a bird's eye view of Turkish language structure and linguistic characteristics of Turkish are presented.

2.1. Turkish Language

2.1.1. History of Turkish Language

Turkish is a very ancient language dates back to 3000 B.C. The oldest written records are found on stone monuments, which are called Orhon inscriptions [3]. The inscriptions were written in the Old Turkic language, called Orhon script. These monuments document the social and political life of the Gökturk Dynasty.

In Early Middle Ages (6th-11th centuries), with the Turkic expansion, Turkic language speaking people spread across Central Asia. During the 11th century, a group of the Oğuz Turks, called the Selçuks, brought their language, Oğuz Turkic, into Anatolia. It can be considered as the direct ancestor of today's Turkish language. The language during the Ottoman Empire period (1299-1922) is termed as Ottoman Turkish, which was a mixture of Turkish, Persian, and Arabic. Everyday Turkish was known as “rough Turkish”, spoken by the less-educated lower and also rural members of society. However, because of containing a high percentage of native vocabulary, rough Turkish served as a basis for the modern Turkish language.

Turkish language that is spoken in Turkey can be classified into three periods: Old Anatolian Turkish (from 13th to 15th centuries); Ottoman Turkish (between the 16th and the 19th century) and 20th century Turkish.

During the time of the Anatolian Selçuks and their descendants Karamanogulları, some efforts were made to reward Turkish language. One of them is the acceptance of Turkish as the official language and another is the publication of a Turkish dictionary. Ancient Anatolian Turkish was in use till 1299. Although there is a heavy influence of Islam, the number of foreign origin words was very low in written Anatolian Turkish literature.

After the 16th century foreign terms dominated in written texts. A great passion for using Arabic and Persian vocabulary in science and literature influenced the spoken language in the Ottoman palace and its surroundings profoundly. As a result, two different types of language appeared. One with foreign elements dominated, mostly used in the palace versus another used by the public, called spoken Turkish.

In the mid-19th century, reformation and nationalism influenced profoundly the Turkish community. With the declaration of the Republic in 1923, adopting a new alphabet which is adequate for Turkish people gained much importance. Ottoman Turkish alphabet was a mixture of Persian and Arabic alphabet and used only three vowels. In Turkish eight vowels are required to correctly sound Turkish words. Omitting some of the vowels in the Arabic script made it difficult to read and write for Turkish words. Besides Ottoman alphabet has redundant consonants. For example, there are variations of **z**, which are totally different consonants in Arabic but have an indistinguishable sound in Turkish. Therefore, Atatürk, the founder of Turkish Republic, had the Latin alphabet adapted to the Turkish vowel system. He also founded Turkish Linguistic Association(TDK), which succeeded to replace many loanwords of Arabic and Persian origin with their Turkish replacements.

2.1.2. Turkish Language in the World

Turkish belongs to the Altay branch of the Ural-Altaic linguistic family. Turkic languages, along with other languages, such as Mongolian, Tungusic, Korean and Japonic languages, is a group of closely related languages that form a subfamily of the Altaic languages. It can be claimed that the "Turkish" languages spoken in the region between Mongolia and Turkey can be named as Turkic languages, and the term "Turkish" refers to the language spoken mainly in Turkey, Northern Cyprus, and partially in Macedonia, Kosovo and Romania, officially.

The fundamental characteristic features, which distinguish the Ural-Altaic languages from the Indo-European languages and universal within the Turkic family, are as follows:

- Agglutination,
- The absence of gender,
- Vowel harmony,
- Adjectives precede nouns,
- Verbs come at the end of the sentence.

The Turkic languages may be classified into four major branches and two separate branches. Four major branches consist of a southwestern (SW), a northwestern (NW), a southeastern (SE), and a northeastern (NE) branch. Çuvash and Khalaj form separate branches. Turkish is classified as a member of the South-West group, which is also known as the Oğuz group.

The Oğuz branch comprises three groups. The West Oğuz group (SWw) consists of Turkish, Azerbaijani, and Gagauz. The East Oğuz group (SWe) consists of Turkmen and Horasan Turkic. A southern group (SWs) is formed by Afşar.

Modern Turkish is spoken mainly by more than 200 million people in Turkey, Cyprus, Balkans, Middle East, Western East and in Southeastern European countries; Azerbaijani is spoken in Azerbaijan, and in some parts of Iran; Gagauz is spoken mainly in Moldova, Bulgaria [2]. Turkmen and Khorasan Turkic are spoken in Turkmenistan and northeastern Iran respectively. Afşar and related dialects are spoken in Iran and Afghanistan [4]. Turkic languages, which are closely related, include Turkish, Azerbaijani (Azeri), Kazak, Kırgız, Tatar, Türkmen, Uygur, Özbek, and many others spoken from the Balkans across Central Asia into northwestern China and southern Siberia.

Throughout the history, a wide geographical area has been stepped by Turks. Turkic-speaking groups penetrated other regions of the world from the Eurasian steppes. They took their language with them. A wide area spanning from today's Mongolia to the East Europe in the west, and to the northern Africa in the south met with Turkic languages.

The four main branches of Turkic family (Uygur, Oğuz, Kıpçak, and Bulgar) were distinguished in the earliest known period. Because of further expansion, Turkic branch underwent further divergence. For example, Oğuz progressed mainly southeastward, toward Iran, Anatolia. Close interactions with Persian resulted in impacts on culture and language. Later, the land ruled by Ottoman Empire, supported the usage of Turkish in these areas. For instance, in Bulgaria, Macedonia, and Greece, where once used to be under the sovereignty of Ottomans, there are over a million Turkish speakers.

Later because of economical factors, a lot of Turkish-speaking people migrated to Europe, as guest workers. For Instance, over 3.5 million Turkish speakers live in Germany and other European countries. Also 40000 Turkish speakers live today in the United States.

Because of the distances traveled, dialects and accents have emerged. In today's world there are 23 written Turkic languages: Turkish, Azerbaijani, Gagauz, Turkmen, Karaçay-Balkar, Crimean Tatar, Kumyk, Karaim, Tatar, Chuvaş, Bashkir, Nogay, Kazakh, Karakalpak, Kırgız, Özbek, Uygur, Altay, Khakas, Shor, Tyvan, Tofa, and Sakha.

Turkish has several dialects such as, Danubian, Eskisehir, Razgrad, Dinler, Rumelian, Karamanlı, Edirne, Gaziantep, and Urfa. There are some other classifications like Southwestern, Central Anatolia, Eastern, Rumelian, and Kastamonu dialects. Modern standard Turkish is based on the İstanbul dialect of Anatolian.

2.2. Turkish as Agglutinative Language

Turkish language has a very rich vocabulary and has the potential to increase the number of words almost infinitely. In Turkish, words are constructed using inflectional and derivation suffixes linked to a root. It is possible to add more than one suffix. This way of affixation is very productive. Phonetic, morphological and syntactic structure of Turkish language is matured.

Turkish is an agglutinative language and almost always uses affixes. Affixes are important because, they indicate the grammatical function of the word, called part-of-speech (POS). Generally they are suffixes and rarely, for specific purposes, prefixes are used. The only prefix usage is for intensifying adjectives or adverbs. For instance, if the adjective <green> "yeşil" is to be intensified it takes a prefix and becomes <all-green > "yemyeşil";

Table 2.1. Cases of a word according to the suffix it takes

Case	Suffix	English Meaning	Turkish
Nominative	(none)	<(the) school>	okul
Genitive	-in	<the school's> <of the school>	okul**un**
Dative	-e	<to the school>	okul**a**
Accusative	-i	<the school>	okul**u**
Ablative	-den	<from the school >	okul**dan**
Locative	-de	<in the school>	okul**da**

A single word can have multiple affixes and these can also be used to create new words. It is possible to create a verb from a noun root, or a noun from a verbal root. The successively using suffixes can produce long words, e.g.:
<You are said to be one of those that we have not been able to convert to be a Czechoslovak>
"Çekoslovakyalılaştıramadıklarımızdanmışsınız".

To show how suffixation affects a word, examples in the following subsections will be given. First of all, it is possible to change the case of a word as shown in Table 2.1.

Table 2.2. Inflections of a word according to the suffix it takes

English	Turkish
<(the) school>	okul
<(the) schools>	okul**lar**
<your (singular) school>	okul**un**
<your (plural/formal) school>	okul**unuz**
<my school>	okul**um**
<at my school>	okul**umda**
<of your schools>	okul**larınızın**
<from your schools>	okul**larınızdan**

Secondly, it is possible to change the inflection of a word by suffixes as shown in Table 2.2.

Thirdly, tenses are formed by adding suffixes, properly. There are 9 simple and 20 compound tenses in Turkish, some of which are given in Table 2.3.

Table 2.3. Derivations of “to come” according to the suffix it takes

English	Turkish
<come> (imperative)	gel
<you came>	gel**din**
<you have come>	gel**mişsin**
<you are coming>	gel**iyorsun**
<you come>	gel**irsin**
<you will come>	gel**eceksin**
<(If only) you come>	gel**sen**
<Come (cursing)>	gel**esin**
<you must come>	gel**melisin**
<...>	...

As it can be seen, by adding various suffixes to stems, grammatical function of words are determined. A Turkish word can change its meaning and its grammatical tag by taking inflectional and derivation suffixes. Table 2.4 presents words created by adding suffixes to the root word, <break> “kır”.

Table 2.4. Meaning change of root **“break”** according to the suffix it takes

English	Turkish	Grammatical Function
<break> (imperative)	kır	verb
<be broken>	kır**ıl**	passive verb
<fragile>	kır**ılgan**	adjective
<fragility>	kır**ılganlık**	noun
<fragilities>	kır**ılganlıklar**	plural noun

Along with its agglutinative structure, more than one word can be combined to form a single noun, with a totally different meaning. For example, <lady> hanım + <hand> el + <accusative> -i →< a kind of flower> hanımeli

Also, more than one word can form a noun phrase. For example: Ayşe’nin kitabı: <Ayşe> (Special name), -nin genitive form; <kitap> (book), -ı:possesive →Ayşe’s book (not an ordinary book).

Although there is no gender for words like in German, separate suffixes on nouns indicate both gender and number. This is observed generally with loanwords from Arabic. Number is marked by a corresponding plural suffix.

Table 2.5. Examples of gender and number indication with suffixes

English	Turkish	Gender	Number
<teacher>	muallim	male	single
<teacher>	muallim**e**	female	single
<teachers>	muallim**ler**	male	plural
<teachers>	muallim**eler**	female	plural

An example is presented in Table 2.5. As a general rule, a verb consists of a verb stem + inflection marker + subject suffix.

2.3. Linguistic Characteristics of Turkish

In Turkish eight vowels are necessary to sound all Turkish words. That is one of the main reasons that triggered the script revolution, because Ottoman Turkish alphabet contained only three vowels. The vowels of the Turkish language are, in their alphabetical order, <a>, <e>, <ı>, <i>, <o>, <ö>, <u>, <ü>. Vowels can be classified according to three features: Their being “front-back”, “rounded-unrounded” and “narrow-wide”, as shown in Table 2.6.

Table 2.6. The vowels of the Turkish language

Vowel	front - back	rounded - unrounded	narrow-wide
a	back	unrounded	wide
e	front	unrounded	wide
ı	back	unrounded	narrow
i	front	unrounded	narrow
o	back	round	wide
ö	front	round	wide
u	back	round	narrow
ü	front	round	narrow

In an agglutinative language like Turkish, affixes are important. Indeed, they indicate the grammatical function of the word. The role of the word in a sentence is called part-of-speech (POS) tag of a word. The order of the words is also important. Because it creates the syntax information. Word order in simple Turkish sentences is generally subject-object-verb (SOV) unlike English. By changing the position of a word in a sentence, it is possible to emphasize the importance of a certain word or phrase. As a general rule, it can be said that the word before the verb has the stress without exception. For instance, if we want to stress the word <school> (the indirect object) for the sentence “Ahmet went to school”, we place the word <to school> “okula” just before the verb <went> “gitti” and on Turkish side it would be “Ahmet **okula** gitti”. If the stress is to be placed on <Ahmet> (the subject), it would be “Okula **Ahmet** gitti” which means “it’s Ahmet who went to school”. Six different emphasis can be provided by different constituent orders as given in Table 2.7.

Table 2.7. Six possible constituent orders with their corresponding emphasis

Order	English	Turkish
SOV	<Ahmet saw Ayşe.>	Ahmet Ayşe'yi gördü
OSV	<It was Ahmet who saw Ayşe.>	Ayşe'yi Ahmet gördü
VSO	<Ahmet saw Ayşe (but was not really supposed to see her.)>	Gördü Ahmet Ayşe'yi
VOS	<Ahmet saw Ayşe (and I was expecting that.)>	Gördü Ayşe'yi Ahmet
SVO	<It was Ahmet who saw Ayşe (it could be someone else, also.)>	Ahmet gördü Ayşe'yi
OVS	<Ahmet saw Ayşe (but he could have seen someone else.)>	Ayşe'yi gördü Ahmet

2.4. Conclusion

Turkish is an agglutinative language with morphemes attached to a root word. Words are formed by productive affixations of multiple suffixes to root words. The root words are influenced by Arabic, Persian, Greek, Armenian, French, Italian, German and English. Almost all morphemes have systematic variations depending on respective vowels and sometimes in boundary consonants. It is quite common to construct words which correspond to a sentence in English. The number of possible words that can be generated from a single noun or a verb root can be millions [5]. Nouns do not have any classes nor are there any markings of grammatical gender. The grammatical function of the word is determined according to the affixes it takes. The dominant constituent order in Turkish is SOV. However all six constituent orders are possible. The word before the verb has the stress. It is possible to emphasize the importance of a certain word or phrase by placing it in front of the predicate. For all these reasons, Turkish morphology creates challenges for the components of a statistical machine translation (SMT) systems. In the following chapter, the challenges of Turkish SMT are presented.

CHAPTER 3

CHALLENGES OF TURKISH SMT

In the previous chapter, a brief history about Turkish language and Turkish language structure are presented. Turkish language has some characteristic properties that create a number of challenges for SMT. Its morphological structure, influence of grammatical operators, alignment problems in translating sentences from one language into another, homonyms, compound nouns and its free constituent order are some of the topics covered in this section.

Firstly, the challenges encountered in morphological analysis are presented. Grammatical operators such as vowel harmony and consonant assimilation or voicing are also evaluated. Then difficulties in correctly finding a proper meaning and influence of homonyms and compound nouns are shown. Finally, alignment problems that are observed due to constituent order differences between Turkish and other languages like English are presented.

3.1. Morphological Analysis

Turkish is an agglutinative language. It means, words are formed by adding morphemes to roots, like putting beads on a string. Almost all morphemes have systematic variations depending on vowels and boundary consonants. One of the fundamental characteristic features is vowel harmony, which is the principle that a Turkish word conforms. It has two major branches and the second one has two sub-branches:

- Back vowels are used with back vowels, and front vowels are used with front vowels. (For example: <mirrorless> “aynasız”, <kitty> “kedicik”).

- Unrounded vowels are proceeded by unrounded vowels (For example: <strawberry> “çilek”). Rounded vowels are preceded by either narrow-rounded vowels or wide-unrounded vowels (For example: <tiredness> “yorgunluk”, <drive> “sürmek”).

There are some exceptions to the vowel harmony rules. Although it is possible, there does not need to be a harmony between vowels in compound words and loanwords. For example, <lady> “hanım” + <hand> “eli” = <a flower kind> “hanımeli”.

There are also some native Turkish exception words that do not obey vowel harmony, such as <mother, apple, which, brother> ”anne, elma, hangi, kardeş”. In these cases, suffixes harmonize with the final vowel. Additionally, Turkish words obey consonant harmony. Basically, words ending with any of the following consonants, “f, s, t, k, ç, ş, h, p”, can take morphemes which starts with a consonant among them.

According to the information provided above, the English morpheme <from> corresponds to the following four Turkish morphemes: -den, -dan, -ten and -tan as shown below:

- <from the picture> Resimden $\rightarrow$vowel harmony
- <from the package> Paketten $\rightarrow$ consonant harmony
- <from the car> Arabadan $\rightarrow$ vowel harmony
- <from the street> Sokaktan $\rightarrow$ consonant and vowel harmony

The suffixes of a word play an important role in the grammatical function of words. However, it is a complicated task to isolate the suffixes from the root of a word. Indeed, all the cases above including the exceptions should be considered.

3.2. Finding the Correct Translation

In order to correctly translate a Turkish word into another language, first, the proper meaning of the Turkish word must be detected. Since the words can change their meanings by taking suffixes and the grammatical function is determined by the suffixes it takes, an exact analysis is required. The root along with each and every suffix of the word must be determined [6]. However, in some cases, suffixes makes it difficult to find the root. For example:

- <Book>Kitap-Kitabı: the last consonant is softening(called voicing)
- <Picture>Resim-Resimi: the last consonant is not softening
- <Table>Masa-Masayı: before the accusative, “y” is inserted.

Another challenge in translating a sentence from one language into another is finding the correct translation in the presence of homonyms. Homonyms are the words that has the exact writings but with different meanings. The correct meaning can only be understood with context information. For instance, the following Turkish word has three meanings and therefore, corresponds to three different words in English. Kara: <Black>; <Land>; <(Towards) Snow>.

When compound nouns are used with suffixes, another challenge exists. In these cases, suffixes makes it difficult to find the correct meaning, as in the following example:

- balayı<honeymoon>
- bal<honey>, ayı<bear>, ay<moon>, ay<month>.
- bal ayı: <honey and bear>, <honey month>
- bal ayısı<honey bear>,
- ayı balı<bear honey>; ayın balı<honey of the month>

As seen above, there can be an ambiguity because of the confusion between some root words and some shorter root words with suffixes.

3.3. Alignment Problem

Correctly placing the words in a sentence is crucial to properly convey the meaning of a sentence. The same case holds for NLP field. It has been observed that one gets better alignments and hence better translation results when the word orders of the source and target languages are more or less the same, as shown in Figure 3.1. When word orders are different, a solution is needed to align the words properly, to convey the same meaning in the two sentences.

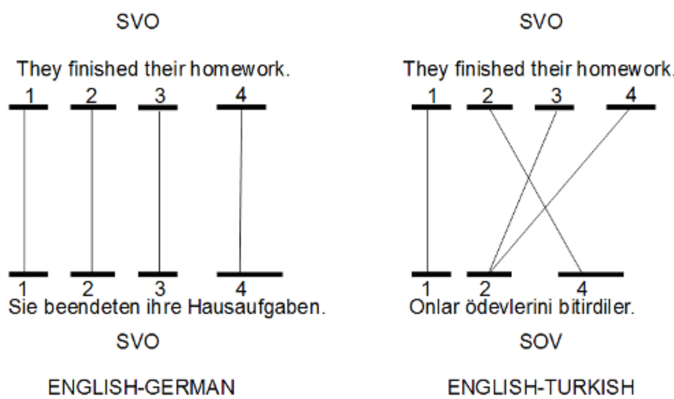

Figure 3.1. Word orders for ENGLISH-GERMAN and ENLISH-TURKISH.

In Turkish, six different meanings can be conveyed with the same words, just by reordering them in six different ways as mentioned in Table 2.7. Therefore, in order to properly convey the same meaning when translating an English sentence into Turkish, requires correctly aligning the words.

What's more, words are formed by productive affixations of multiple suffixes to root words. It is possible to create a single word which correspond to a sentence or a complete phrase in English as shown in Figure 3.2. A single word in Turkish is translated into 13 words in English. Both number of words and positions of the words are not the same. In some cases, a word does not exist either on English side or on Turkish side. It can be seen that, the alignments are not straightforward.

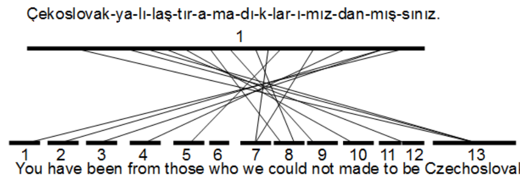

Figure 3.2. Word alignments for a long Turkish word.

3.4. Conclusion

As mentioned previously, the alignment between typologically different languages may become very complicated due to different constituent orders and morphological structures [7]. For example, English and Turkish can be considered rather distant languages because, English has very limited morphology and fundamentally obeys to fixed SVO constituent order, whereas Turkish has a very flexible (but SOV dominant) constituent order. Constituent order differences between source and target languages makes it harder to align.

On the English side, a Turkish word may align with a complete phrase, and sometimes these phrases on the English side could be discontinuous [7, 8]. It can be said that, the alignments are not straightforward. Additionally, number of tokens on both sides does not have to be the same.

Furthermore, Turkish is an agglutinative language with not only a very rich but also a productive derivation and inflectional morphology. Since a Turkish word can change its meaning, a morphological analysis is necessary. Allomorphs, voicing and other grammatical operators can cause false results.

Finding the correct translation depends on syntax information; so, translating with correct meaning is a challenge.

CHAPTER 4

RELATED WORKS AND DISCUSSION

Translation is the process of converting one sentence in a language into another language, without changing the meaning. Translation is not word-by-word substitution. A translator must interpret how each element in the sentence may influence another. To fully understand characteristics of translation, it would be wise to know something about human translation. Experts seem to agree that, three things should exist in a proficient translator [9]:

- proficiency in the source language,
- understanding of the subject matter,
- good knowledge of the target language.

That's how the quality of translation can fulfill the information needs of the requester. Another aspect of a good translation is being done in reasonable speed. In the past, 100 pages in 30 days or in other words, approximately 3 pages per day was the average translation time [9].

As the computers emerged, people thought of benefiting from them. Machine Translation (MT) is automatically translating from a source language into a target language by utilizing computers [1]. It is desirable to have a machine translated output from a source text. However, most of the time, it is not translated exactly the same as the human translator, because machines cannot have proficiency or understanding. In this case, it can be considered as a machine learning problem. An approach to MT, which is characterized by the use of machine learning methods, is called Statistical Machine Translation (SMT)

[10]. It is not a rule based translation; rather; it is statistical. The corresponding translation for each word or phrase is determined according to the usage frequency in the training collection.

In this chapter, firstly, a brief introduction and history of SMT is given. Additionally, recent research in SMT and some applications are presented. Then, SMT studies on Turkish are evaluated. Finally, a discussion of the related works is given.

4.1. SMT In General and Recent Researches

The idea of automatic translation dates back to the invention of the modern digital computer. It was Warren Weaver, who in 1949 suggested that the problem can be addressed by using statistical methods and ideas of information theory [10]. Statistical Machine Translation (SMT) is an approach to MT, which is characterized by the use of machine learning methods [10]. In other words, by examining many samples of human translation input-output pairs, SMT algorithms automatically learn how to translate. For this purpose, a text is presented to a human translator and get translated output, which is called a parallel corpora, bi-text, multi-text or parallel text. Then, a learning algorithm is applied to the previously translated text. After learning and being able to create the same translation output as human, it is expected to be able to translate previously unseen sentences. If enough parallel corpora and a toolkit is obtained, it is possible to construct a MT system for any language pair in very short time.

There are two motives behind the need for MT. First of all, there is a constant growth of information needs. One of these needs is dissemination of information in multiple languages. For example multilingual governments, such as European Union, are interested in such kind of dissemination.

Other consumers of translation are the users who are interested in the assimilation of information not in their native language. It could be a wide range of users spanning from intelligence agencies and researchers to casual Internet users. Internet has made such information easily accessible, as a result there is a rising demand from these users.

After 1980's MT services became available on the Internet. In 1988, the first online MT service was provided to 4.5 million users of the French postal service's Minitel network by the Systran Centre in Paris. It could make translations between the following language pairs: French-English, German-English, and English-French [11].

The first global accessibility of MT on the Internet was by the system called Babel Fish. Surprisingly, the users referred to the system for language learning purposes [12, 13]. Then another reason for usage emerged. People were using it as an entertainment tool for translations or to translate idioms [14].

Immediately following the Babel Fish, other MT providers started to offer free online services. By 2000 there were at least ten companies other than Babel Fish, such as AltaVista and CompuServe. Today, several projects, of which are mostly open-source SMT toolkits, are freely available [15, 16, 35, 18].

Since, it has become a useful service for all of us, it is good to mention Google Translate (GT) [17]. It is a translation service provided by Google to translate a word, a phrase, a section of text or an entire web page into more than 50 languages and serves more than 200 million people daily. GT, not only translates words or sentences, but also translates pages. As declared by Google, GT's goal is to make information universally accessible and useful, regardless of the language in which it's written. To decide the best translation words that conveys the same meaning as the source language, GT looks for patterns in many documents. GT machine dates back to 2001. It started with six languages. At that time it was a rule based MT. In 2006, Google started using Statistic MT. This method doesn't use language translation rules; rather, it uses statistical methods. However, to make statistical model, bilingual corpora, which is a database of source and target sentences, is required. The more number of sentences, the better statistical model works. So, it is time consuming to make bilingual corpora. But, because it doesn't depend on any linguistic rule, SMT can be easily used to make fast translations between any languages.

In MT, there are some existing challenges in four key MT tasks, which are alignment, decoding, evaluation, and re-ranking. But MT is not a theoretical subject; rather, it's a real application. Today people probably use services like Google Translate during their daily activities. The best way to learn the above mentioned challenges in the four aspects, is to work on them and build a MT system. This can be done with a number of open-source toolkits such as Moses [18]. However, these systems are not designed for teaching or learning. Usually, they are treated as black boxes.

Recently, a group of academic personnel from Johns Hopkins University. have come up with a new idea [19]. Their goal for students is to learn the key techniques in MT by implementing them. They have presented students brief but complete components of a statistical MT system (word alignment, decoding, evaluation, and re-ranking).

On the days GT emerged, benefiting from SMT in Turkish language started to gain popularity. In 2006, El-Kahlout et al. [8] presented the first observations and problems for a SMT system from English to Turkish. Using a 20K aligned parallel copora, a baseline word model was trained and then to obtain an improvement upon the baseline system, morphological structure was exploited. They tried to discover the relations between morphemes and function words in both languages correspondingly. Later, in 2007 Oflazer and El-Kahlout [6] studied different sub-lexical representational units in SMT work from English to Turkish. They compared the results with word-based baseline.

In 2014, The effects of parallel corpus quality and size are evaluated in English-to-Turkish SMT by Yıldız et al. [38]. Because parallel corpora plays a crucial role in SMT systems, they classified parallel sentence pairs as either high-quality or poor-quality and as a result obtained 600K high-quality parallel sentence pairs out of 1 million parallel English-Turkish sentence pairs. They showed that although the size of parallel corpus is a major factor in translation performance; with a smaller high-quality corpora it is possible to obtain good results.

4.2. BLEU measure

Before discussing Turkish SMT, we introduce the BLEU measure. BLEU stands for Bilingual Evaluation Understudy. BLEU, which is one of the most popular metrics, has become the standard evaluation metric in MT since it was introduced in 2002 because of some properties like being fully automated and inexpensive. The quality of machine-translated text output against multiple references can be evaluated using BLEU.

The evaluation is necessary, because most of the time, texts are not translated with good quality like the human translator's. With quality, the similarity between a machine's output and that of a human is aimed. The closer a machine translation is to an expert human translation, the better its quality. This is the logic behind BLEU. It is observed that, BLEU is one of the metrics that can achieve a high correlation with human judgments [20, 21]. There is a need for evaluating the quality of a MT output from adequacy, fidelity and fluency perspectives. Previously it was done by human evaluators. However, most of the time human evaluations of machine translation are expensive because skilled human judges are required. Besides, it takes too much time to accomplish the evaluation. MT progress strongly depends on evaluation. Developers of MT systems need to monitor the effect of daily changes to their systems to improve their systems.

Papineni et al. proposed a method of automatic MT evaluation, which is called BLEU [20]. It can be considered as an automated understudy to skilled human judges. It is quick, inexpensive, language-independent, and highly correlates with human evaluation. BLEU can be used to accelerate the MT research and development cycle because developers can benefit from an inexpensive automatic evaluation.

Translation performance is measured according to a numerical metric. Closeness to a professional human translation is the central idea to judge the quality of a machine translation. It requires two components: a numerical closeness metric and a corpus of gold standard human reference translations.

BLEU always creates an output value between 0 and 1, which indicates how similar the candidate and reference texts are. The values closer to 1 representing more similar texts. Sometimes they are shown in percentage. Note that, even few human translations will reach a score of 1. The candidate texts must be identical to a reference translation. Therefore, it is not necessary to attain a score of 1.

BLEU uses a modified form of precision to compare a candidate translation against multiple reference translations. Precision is relevant fraction of the candidate sentence and recall is the appearing fraction of the reference sentences in the candidate sentence. Modification of simple precision is necessary because MT systems are known to generate more words than that are in a reference text. This is shown as in Table 4.1 given in [20].

Table 4.1. BLEU Example

Candidate	the the the the the the the
Reference Sentence 1	the cat is on the mat
Reference Sentence 2	there is a cat on the mat

Of the seven words in the candidate translation, all of them appear in the reference translations. Therefore the unigram precision of the candidate is

$$P_1 = \frac{m_r}{m_t} = \frac{7}{7} = 1$$

where m_r is number of words from the candidate that are found in the reference, and m_t is the total number of words in the candidate. The modification in BLEU calculation is done by taking its maximum total count, m_{max}, in any of the reference translations. For the candidate translation, the count m_r of each word is clipped to a maximum of m_{max} for that word.

$$P_1^* = \begin{cases} \frac{m_{max}}{m_t} & \text{if } m_r > m_{max} \\ \frac{m_r}{m_t} & \text{if } m_r \leq m_{max} \end{cases} \tag{4.1}$$

In the table above, the word *the* appears twice in reference 1, and once in reference 2. Thus m_r is clipped to 2. m_r is then summed over all words in the candidate. This sum is then divided by the total number of words in the candidate translation. In the above example, the modified unigram precision score would be:

$$P_1^* = \frac{2}{7}$$

Using individual words as the unit of comparison is not enough to indicate a strong correlation. Instead, BLEU computes the same modified precision metric using n-grams. The highest length which has the "highest correlation with monolingual human judgments" was found to be four [22]. So, 1-gram, 2-gram, 3-gram and 4-gram metrics are evaluated.

In addition, to prevent short translations, which can produce very high precision scores, a brevity penalty is used. Then, to produce BLEU score for the whole corpus, the modified precision scores for the segments are combined using the geometric mean multiplied by a brevity penalty to prevent very short candidates from receiving too high a score. Let r be the total length of the reference corpus, and c the total length of the candidate translation corpus. If c ≤ r, the brevity penalty applies. It is defined as $e^{(1-r/c)}$ in [20].

$$BP = \begin{cases} 1 & \text{if c} > r \\ e^(1 - r/c) & \text{if c} \leq r \end{cases} \tag{4.2}$$

As a result, BLEU score is calculated as in Equation 4.3. Geometric average of the modified n-gram precisions, p_n, are calculated using n-grams up to length N. The positive weights, w_n, in the equation are chosen to be summing to one. If uniform weights are preferred, w_n = $1/N$, where N is taken as 4.

$$BLEU = BP \cdot exp\left(\sum_{n=1}^{N} w_n \cdot logP_n^*\right) \tag{4.3}$$

Now that, BLEU metric is introduced, it is time to present the milestones in Turkish SMT.

4.3. Turkish SMT

One of the first studies on Turkish SMT was about to find a solution for alignment problem. For this purpose, El-Kahlout et al. [8] proposed using sub-lexical structures.

Because, Turkish word may align with a complete English sentence and sometimes these English sentences can be discontinuous. First, they presented challenges and preliminary results for developing a SMT system from English to Turkish. Using approximately 22,500 aligned sentences they started with a baseline model. Also, a representation of the parallel texts in morpheme level is provided, and the sentences are aligned at that level. They used parallel corpus of about 22,500 sentences, which can be considered as relatively small. They compared the results with a baseline word-to-word translation model. At the end they improved the BLEU score from the baseline of 0.0752 to 0.0913.

Later, Oflazer et al. [6] followed their approach of exploiting morphology, and developed a process consisting of segmenting Turkish words into lexical morphemes and tagging the English side using TreeTagger [23]. They were inspired from research works in [24, 25] that previously addressed the usage of morphology in SMT from or into morphologically richer languages. For example, Niessen et al. [24] used morphological decomposition to improve alignment quality. They claimed that by benefiting from interdependencies of related inflected forms, bilingual training data can be better exploited. By the combination of their suggested methods, an improvement of the translation results was presented on two German-English collections. Minkov et al. [25] used morphological post-processing on the output side using structural information and information from the source side, to improve SMT quality. They utilized a set of morphological and syntactic knowledge sources from both Russian and Arabic sentences in a probabilistic model, and evaluated their contribution in generating both source and target sentences. They concluded that 24% relative boost in BLEU scores (from 20.22 to 25.08 BLEU points) can be achieved by utilizing a representation between unsegmented word forms and morphologically fully segmented forms [6].

Mermer et al. [26] studied supervised segmentation comprising morphological analysis, disambiguation and manually-crafted rules. Later they presented unsupervised Turkish morphological segmentation (TMS) for statistical machine translation (SMT) [27], which had not been addressed in previous works. They compared unsupervised segmentation against two baselines: no segmentation and their previous study in [26] with supervised segmentation results. They concluded that while unsupervised segmentation improves translation BLEU scores (0.5140 for word-based baseline, 0.5455 for unsupervised segmentation and 0.5946 for supervised segmentation) over the word-based baseline; it did not reach the performance of task-optimized supervised segmentation.

El-Kahlout et al. studied reordering in English side to make it appear more Turkish like [6]. They used morphological segmentation and disassembled the Turkish words into their lexical morphemes. They tagged the English side using TreeTagger [23], which provides a part-of-speech (POS) tag for each word. Their study was based on the idea that in Turkish, most surface distinctions are the results of word-internal phenomena like vowel harmony. By using lexical morphemes instead of surface morphemes, different phonological forms corresponded to the same set of words/tags in English, after translations. For example, the two Turkish surface morphemes "+ler" and "+lar" have different pronunciations. They both indicate plurality and both are translated to "+s" on English side. In their research they considered four cases, each of which has different morphological representations on the Turkish side. In all cases, BLEU was measured for word-based representation. The four cases in [23] are as the following:

- Baseline: Full word representation of both Turkish and English sentences. For instance, the form <of his table> "masasının" would be used on the Turkish side and "tables" on the English side.
- Full Morphological Segmentation: For the previous example, three tokens (masa+sı+nın") on Turkish side and two tokens (table+s") on English side.
- Root+Morphemes Segmentation: For English words, it is the same as it is in case two. For Turkish sentences, a single morpheme group is used, yielding two tokens (masa + sının").
- Selective Morphological Segmentation: Certain Turkish morphemes cannot be aligned with anything on the English side. For example, Turkish "sı" does not have a corresponding unit on the English side. Therefore, morphemes with unalignment percentage over 80% are considered as part of the root. So, the same word is represented as two tokens (masası+ nın"). English words are represented as in the second case above.

The best BLEU results are obtained with selective morphological segmentation (22.81) resulting 46.8% improvement compared to the baseline (15.53).

Cakmak et al. focused on English-Turkish language pairs [7]. They stripped the words down to their stems and suffixes. The usage of morphological units in the training stage reduced the alignment error rate by 40%. A new test corpus of 300 manually aligned sentences is released together with their study.

Although Turkish SMT has attracted much attention in Turkish natural language processing community, there is still a need for more work on this field. First of all, there is still need for more parallel data. The availability of parallel corpora is much more limited, even for English-Turkish pair. Also, complex agglutinative structure of Turkish, makes it harder to detect the proper translation. In the following section, discussion of related work is presented.

4.4. Discussion of related work

The previous researchers have not studied reordering on Turkish side because of the complexity and agglutinative nature of Turkish characteristics. Some of them evaluated reordering on English side, as mentioned above However, this approach contains some drawbacks. First of all, some tokens are missing on English or Turkish side. For instance, <Ayşe's book> "Ayşe'nin kitabı" can be aligned as follows:

1: 1 ; → "Ayşe" : "Ayşe"

2: 2 ; → " 's" : "+nin"

3: 3; → "book" : "kitap"

4: - ; → ø : "+ı"

The last token on Turkish side does not have a corresponding token on English side. Or <The most beautiful house> "En güzel ev" can be aligned as follows:

1: - ; → "The" : ø

2: 1 ; → "most" : "en"

3: 2 ; → "beautiful" : "güzel"

4 : 3 ; → "house" : "ev"

The first token on English side does not have a corresponding token on Turkish side.

As a second drawback, one can argue that making English sentences Turkish-like is also a complicated process, which contains challenges, as mentioned in [28]. One of those challenges is the usage of the preposition "of", which brings up special difficulties. For example, in noun phrases like "United States of America", the "of" does not correspond to a genitive morpheme on the Turkish equivalent for "America". It's translation is not "Amerika'nın Birleşik Devletleri"; its correct translation should be "Amerika Birleşik Devletleri". What is more, noun phrases located on both sides of "of" have to be extracted and interchanged. Bracketing errors for more than one noun phrases makes the situation more difficult. For example, the complex noun phrase "The election of the president of United States of America", has a nested structure like "The election of [the president of [United States of America]]". Furthermore, for all prepositions, preceding tags should also be checked and the first step of extraction procedure should be finding the patterns. In addition to all the above, reordering on English side to make sentences appear like Turkish is English-Turkish pair dependent. To make sentences appear like another language, requires a different reordering algorithm. So for every language pair, a different algorithm is needed. On the other hand, if reordering on Turkish side is preferred, it will be language pair independent. Because, after translating sentences into Turkish, the same reordering algorithm will be used.

4.5. Conclusion

The process of obtaining a machine translated output from sentences by examining a number of human-produced translation samples and using machine learning methods is called Statistical Machine Translation. Modern needs, such as dissemination of information in multiple languages have accelerated the studies on this field. Since MT services became available on the Internet in 1980's, a lot of research has been carried out. Today, it is possible to get MT output from a word, a phrase, a section of text or even an entire web page into more than 50 languages. Although Turkish SMT have gained popularity since 2006, there is still a need for more work on this field. Limited amount of parallel data and complex agglutinative structure of Turkish are two major disadvantages. The main problem for English-Turkish SMT is the word order. Studies on Turkish SMT has focused on segmentation comprising morphological analysis, disambiguation and reordering in English side to make it appear more Turkish like. However, reordering in English side contains some drawbacks, such as missing tokens, computational burden, special difficulties that stem from usage of the preposition "of" and language pair dependencies. Therefore, as a new approach, reordering in Turkish side is proposed, which will be covered in the following chapter.

CHAPTER 5

PROPOSED APPROACH FOR REORDERING

As explained in the previous chapter, the main problem for English-Turkish SMT is the word order. To solve this problem, the researchers have proposed reordering on English side to make English sentences appear more Turkish like [28]. For this purpose, they first disassembled the Turkish words into their lexical morphemes and tagged each word with their part-of-speech (POS) tags on the English side using TreeTagger [23]. In addition to the advantages of reordering on English side, there are also some disadvantages, as mentioned in the previous chapter. Nevertheless, their reordering idea is a fruitful avenue to pursue. Therefore, as a further improvement, reordering on Turkish side is proposed in this chapter.

To reorder the Turkish sentences, first a morphological analyzer is used. Then a tagger is used to obtain Turkish POS tags. And finally, words are reordered based on Turkish grammar rules. In this chapter, first our proposed approach is explained by giving some examples. Then, the rules used for reordering are presented and our proposed system is described.

5.1. Proposed Approach

To correctly reorder the words, our proposed approach is based on syntactic rules. In order to reorder the words on Turkish side and apply the rules, we need to obtain their POS tags and classify the words according to their POS tags. Affixes are important in Turkish because, they indicate the grammatical function of the word. A Turkish word can change its meaning and its grammatical tag by taking inflectional and derivation suffixes.

After obtaining a POS tag for each word, words are reordered. Figure 5.1 explains how reordering is carried out. To reorder the unordered words in Turkish, syntactic rules are used.

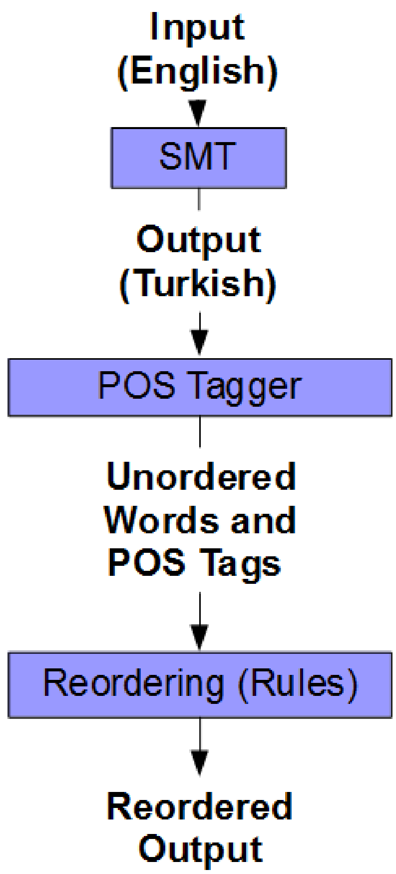

Figure 5.1. Reordering Process.

5.2. Syntactic Rules

In our approach, the four rules that we adopt are given as the following:

1. **Rule 1**: Sentences are split into segments according to commas, full-stops, exclamations, question marks.
2. **Rule 2**: Within each segment all the words are tagged along with their POSs.
3. **Rule 3**: Predicates are placed at the end of each segment, to provide SOV constituent order.
4. **Rule 4**: If there are no predicates or cannot be obtained by POS tagger, couldBePredicate flag will be false; therefore, the order of the sentence is not changed

and left as it is.

Before applying any rules a pre-process is mandatory. Because there some items, such as $20,000 or 10.000m, which will be confused with punctuation marks that are put at the end of segments. These items are replaced as $20<COMA>000 or 10<POINT>000m, so they are processed as single items. At the end of reordering process, the items are reverted to their original forms.

Punctuation marks, such as comma and semi-colon, are important signs to indicate a completeness in terms of meaning. Therefore, using these punctuation marks, sentences are divided into segments and reordering is done within each segment. So, the first thing is splitting sentences into segments. To explain the first rule, the sentence below can be given:

<The man came, sat at the table. They cheered suddenly.>

"geldi adam, oturdu masaya. onlar sevindi birden."

This sentence contains two full-stops and one comma. As a result three segments are created and reordering is performed on each segment. Segments are "geldi adam," , "oturdu masaya." , "onlar sevindi birden." . Once the segments are determined, second rule is applied to each segment and all the words are tagged along with their POSs. Words can have more than one POS tag and all of them are taken into consideration. The objective is to determine the predicate in each segment. There can be a confusion between bare verbs and nouns, therefore a further analysis is required to confirm that they are predicates. For example, Turkish word "at" has two meanings: <throw> and <horse>. Only the first one is a verb, while the second one is a noun. Therefore, predicates are specially handled. For this purpose two lists (*Predicates* and *CouldBePredicates* list) and two boolean flags (*couldBePredicate* and *definitelyPredicate*) are used.

Predicates list is the list of known POS tags, which are regarded as predicates. *CouldBePredicates* list is used for exceptions. Their POS tags are not considered as predicates. However, they have a predicate usage in some cases. That's why, an exception list is needed. For each word, if among its all POSs, at least one POS is among the Predicates list, then it's *couldBePredicate* flag is true. If the word is an exception and it is among the *CouldBePredicates* list, then it's *couldBePredicate* flag is again true. If all of the possible POSs for a word are among the Predicates list, then it's *definitelyPredicate* flag is true. If none of the POSs is among the *Predicates* list and it is not listed in the *CouldBePredicates* list, then it's *couldBePredicate* flag is false.

For example, "geldi" has "FIIL KOK FIIL GECMISZAMAN DI" tag and it is on the *Predicates* list. It's *couldBePredicate* flag is set as true. Also, since all the possible (which is the only one) POS tag is among the *Predicates* list, it's *definitelyPredicate* flag is set as true. As another example, "adam" has "ISIM" and "ISIM KOK ISIM SAHIPLIK BEN IM" tags. The first tag is on neither *Predicates* list nor *CouldBePredicates* list. However, the second tag is on the *CouldBePredicates* list. Because, it is possible to have a such sentence "O ada benim adam". In that case, the word "adam" is used as predicate. Therefore, *definitelyPredicate* flag is false, but *couldBePredicate* flag is true. As third example, "masaya" has 'ISIM KOK ISIM YONELME E" tag. It is on neither Predicates list nor *CouldBePredicates* list. As a result, both *definitelyPredicate* flag and *couldBePredicate* flag are false.

For the first segment, one *definitelyPredicate* and one *couldBePredicate* is obtained. Because of the superiority of *definitelyPredicate*, "geldi" is placed at the end of the first segment. For the second segment, the predicate is "oturdu". for the third one, "sevindi" is the predicate. At the end, all the predicates are placed at the end of each segment to provide SOV constituent order. The final output after the reordering will be the following:

<The man came, sat at the table. They cheered suddenly.>

"adam geldi, masaya oturdu. onlar birden sevindi."

5.3. Syntactic Rules Implementation

To implement our reordering system, a Java code is developed and its corresponding algorithm is given in Appendix A. The rest of the work is evaluating the morphemes of the words. As stated previously, grammatical function of a word is determined by the suffixes it takes. Therefore, syntactic rules are required to decide a word is a predicate or not by examining the suffixes. For this purpose 398 cases are created manually according to the Turkish language charcterictics and given in Appendix B. If one of the POS tags of a word matches one of these cases, it can be considered as a predicate.

The implementation consist of preprocessing, reordering and post-processing. Preprocessing and post-processing are used to prevent confusion of digits or similar characters from punctuation marks. Preprocessing replaces these characters with their replacements and post-processing reverts them back to their original forms.

5.4. Illustrative Example

Table 5.1 demonstrates how reordering is done according to Figure 5.1. The sentence contains two commas and one full-stop. The first two segments are composed of single words. The third segment needs reordering. The word “harcamaktadırlar” is recognized as predicate and placed at the end based on *Rule 2*.

Table 5.1. Reordering By Placing The Predicate At The End

State	Sentence
English	Currently, taxpayers, spend about 60000 dollars per year.
SMT Output	Şimdi, vergi ödeyenler, harcamaktadırlar yaklaşık 60000 dolar yılda.
Reordered Output	Şimdi, vergi ödeyenler , yaklaşık 60000 dolar yılda harcamaktadırlar.

According to the rules above, there is a possibility of multiple predicates can exist in the same segment. During the reordering process, omitting one of the predicates or swapping the predicates can produce wrong results. In order to avoid such side effects, the existence of a conjunction word is inspected. A conjunction word is assumed to split the segment into subsegments. therefore a *ConjunctionsList* file is used to keep the list of known conjunctions. If the algorithm detects multiple predicates in the same segment, it checks every word inside the segment for existence on the *ConjunctionsList*. If a word is listed, the segment is subdivided up to the conjunction, reordered immediately and then reordering continues as usual.

5.5. Conclusion

In this chapter, an approach to solve the word order problem for English-Turkish SMT is presented. Words are reordered on Turkish side. SOV dominant structure is used to reorder, by placing the predicates at the end. Since affixes play an important rule to decide the grammatical function of a word, a morphological analysis is utilized to detect the predicates. To correctly reorder the words, four syntactic rules are used. For this purpose, an algorithm is created and implemented in Java language. In the following chapter, the performance of the algorithm is evaluated using test collections based on the BLEU measure.

CHAPTER 6

RESULTS AND DISCUSSION

In the previous chapter, to solve the word order problem for English-Turkish SMT an approach is presented. To evaluate the performance of the algorithm a test collection is required. Also, a measurement system is needed to universally determine whether it is successful or not and to observe the effect of reordering. We use Zemberek [32] as a POS tagger and MOSES [30] as a SMT system.

6.1. Zemberek POS Tagger

Most of the Turkish IR research studies developed their own stemmer. However, the most used stemmers are Snowball [31] and Zemberek [32]. Snowball is a stemmer developed using Snowball6 string processing language where Turkish words are analyzed with an affix stripping approach without any dictionary lookups. Zemberek is a stemmer designed for Turkish language and based on a root dictionary. It provides root forms of given words using a root dictionary-based parser combined with Natural Language Processing algorithms. It handles special cases for suffixes and can be used as a lemmatizer based stemmer. For these reasons, Zemberek has better performances than other stemmers [33].

Using Zemberek, each word's affixes and roots are determined. So, by inspecting the affixes, grammatical tag of each word is determined. The code is tuned to use columns as punctuation marks to separate the tags. For the sentence *"geldi adam, oturdu masaya.*

onlar sevindi birden", zemberek generates the following tagged words:

<came>geldi: FIIL KOK FIIL GECMISZAMAN DI:

<The man>adam: ISIM: ISIM KOK ISIM SAHIPLIK BEN IM:

<sat>oturdu: FIIL KOK FIIL GECMISZAMAN DI:

<at the table>masaya: ISIM KOK ISIM YONELME E:

<they>onlar: ZAMIR: ZAMIR KOK ISIM COGUL LER:

<cheered> sevindi: FIIL KOK FIIL GECMISZAMAN DI: ISIM KOK ISIM SAHIPLIK SEN IN IMEK HIKAYE DI:

<suddenly>birden: SAYI KOK ISIM CIKMA DEN: SAYI KOK SAYI KESIR DE ISIM SAHIPLIK SEN IN:

6.2. Moses SMT System

Moses, is an open source phrase-based decoder for SMT, which has an acceptable run time performance [18]. It is not commercial; so, it can be used by researchers who wish to do SMT research and look for a phrase-based SMT decoder, easily.

Koehn et al. [18] created this phrase-based decoder. Phrase-based translation means contiguous segments of words in the source sentence are mapped to contiguous segments of words in the target sentence. Phrase-based translation is one of the major advances in SMT. Previously, SMT is done word by word. Moses is not the first phrase-based decoder. There have been a number of implementations of phrase-based decoders for SMT before Moses, such as, Pharaoh [34] and Alignment Template System (ATS) [35]. However, most of these systems are not publicly available.

Moses decoder consists of 2 libraries (with totally 20,000 lines of code) corresponding to the language model construction and the learning process. In our experiments, we collected 20 GB Turkish collection from different Web sources (public websites, news websites, universities web, etc.). For the learning process, we use the two IWSLT collections described in sub-section 6.3.2.

6.3. Experiments Set up

As stated previously, SMT treats the translation as a machine learning problem. First, many samples of human translation input-output pairs are examined, then SMT algorithms automatically learn how to translate. In order to do that, training translations are performed by humans (native speakers). A text is presented to a human translator and get translated output, which is called a parallel corpus. Then, a learning algorithm is applied to the previously translated text. If enough parallel corpora is provided and learning process is completed, the SMT system becomes able to create the same translation output as human. At that point, it can be expected to be able to translate previously unseen sentences for any language pairs.

Also, in order to evaluate the performance of the Turkish SMT system we need a test collection. It must be complete collection, that is, translations are either assessed or accomplished by humans. Due to lack of standard test collections in Turkish, Turkish SMT is a field that has not achieved much interest compared to other languages. That's why some of the researchers in Turkish SMT built their own test collections. For our evaluation, we use 2 different collections: the collection used in [7] and two collections from IWSLT2010 [36] and IWSLT2011 [37].

6.3.1. 300 Aligned Sentences [7]

Test data is collected from language proficiency exams organized by ÖSYM (Student Selection and Placement Center of Turkey) which are high quality exact translations for English-Turkish. The data are manually aligned by using a manual annotation software that has been specially developed, so that the user annotates the parallel sentences by aligning the morphological units.

The collection characteristics are presented in Table 6.1. The total number of English sentences is 4711 and the total number of Turkish sentences is 3528. In average, each English sentence contains 15.71 words and each Turkish sentence contains 11.76 words. This information is also a good indicator of the word alignment problem. Because when

Table 6.1. Collection Description

Description	EN	TUR
Total number of Sentences	300	300
Total number of Terms	4711	3528
Average Number of Terms by Sentences	15.71	11.76

translated, an average Turkish sentence corresponds to a longer English sentence and alignments are not straightforward.

Table 6.2. BLEU Scores Baseline

	BLEU Scores			
System	1-gram	2-gram	3-gram	4-gram
EN $\rightarrow$ TR	39.83	20.27	11.26	7.49
TR $\rightarrow$ EN	52.06	31.62	20.15	13.37

Table 6.2 shows our preliminary results without applying our proposed alignment approach. These results are used as a baseline to evaluate our approach. The first observation is that Turkish-English translation is performing better than English-Turkish translation. The reason is that English language characteristics are less complex than Turkish language. Comparing 1-gram (each word is considered individually) and 2-gram results (evaluation based on two consecutive words), we can observe that BLEU score decreases significantly. The BLEU scores of 3-gram and 4-gram are very weak, due to words misalignment, compared to the Turkish-English results.

Table 6.3. BLEU Scores After Reordering

	BLEU Scores			
System	1-gram	2-gram	3-gram	4-gram
EN $\rightarrow$ TR	39.83	20.29	12.54	9.19

Table 6.3 shows our results after applying our proposed alignment approach. Since our approach is not modifying the translation results, 1-gram results are the same as in Table 6.2. 2-gram BLEU score result is quite the same as the baseline results. For the 3-gram and 4-gram BLEU score results, our approach increases the performances due to

words reordering. Indeed, 3-gram BLEU score is 12.54 (11.36% better than the baseline) and 4-gram BLEU score is 9.19 (22.69% better than the baseline).

Despite the performances improvement, the results are still less than our expectations for three main reasons. The first reason is related to the translation quality. Since our approach is applied after the translation process, it is affected directly by the translation results. If translation has weak performances, which is the case here, our approach performances are also weak. Translation quality is also related to the collection used to create the language model and the collection used during the learning process. Since the 300 sentences used to evaluate our approach are collected from language proficiency exams, they have specific vocabulary and specific linguistic characteristics. On the other hand, the language model is constructed based on a general text collection collected from different websites. Then the language model constructed is completely different from the 300 sentences language. When it comes to the learning process, the SMT system is trained on human-human dialogs collection in the travel domain (IWSLT 2010) and on public talks collection on a variety of topics (IWSLT 2011). The two collections topics are different from the language proficiency exams collection test. That leads to a poor translation quality.

The second reason, more directed to our approach, is the collection small size can not let the approach to apply the rules. Indeed, the number of applied rules is 521 for the 300 sentences. As mentioned in [38], the more parallel sentences (for training and for testing) the higher BLEU score performances. For this reason, a second set of experiments is done on bigger size collections in subsection 6.3.2.

The third reason is about the BLEU measure used to evaluate the performances. Authors in [39] proposed BLEU+ measure as an alternative to evaluate agglutinative languages translation performances. The main aim of BLEU+ is to benefit from the information coded in surface form in the target language having very productive inflectional and derivational morphology. Evaluating 2-gram, 3-gram and 4-gram in the case of Turkish language is not an easy task given that it can be a single word. For example, BLEU measure is looking for a 2-gram in the target language corresponding to the 2-gram of the source language, but the 2-gram in the Turkish language can be 1-gram; some for the case of 3-gram and 4-gram.

6.3.2. IWSLT2010 and IWSLT2011 Collections

International Workshop on Spoken Language Translation (IWSLT) is an evaluation campaign for evaluation translation systems. During IWSLT2010 and IWSLT2011, a Turkish-English evaluation track is proposed; but English-Turkish evaluation is not proposed. Indeed, the two collections are not parallel aligned collection but comparable collections. We use the two collections to evaluate our proposed approach for reordering without evaluating the translation performances. English sentences used for IWSLT 2010 Evaluation Campaign are composed of 21230 words and 1568 lines as shown in Table 6.4. The collection is a composition of human-human dialogs in the travel domain.

Table 6.4. Statistics for IWSLT 2010 test collection

Information	Statistics
# of words	21230
# of lines	1568
# of rules applied	2658

Table 6.5 presents IWSLT2011 collection statistics. It is composed by 16720 words and 1284 lines. It is a collection of public talks on a variety of topics. Each line may contain multiple sentences, each of which can be a single word or multiple words.

Table 6.5. Statistics for IWSLT 2011 test collection

Information	Statistics
# of words	16720
# of lines	1284
# of rules applied	2014

The manual translations are obtained from TED open translation project, which are created by multiple contributers [40]. Also as a second source, human subjective evaluation is used. In other words, hired experts are not used, rather crowd-sourced data through Amazons Mechanical Turk are used. By this approach costs are reduced without sacrificing quality significantly [29].

Table 6.6. Top 5 most used predicate cases for IWSLT 2010 test collection

Predicate Case	Frequency
FIIL KOK FIIL EMIR SIZ IN	540
FIIL KOK FIIL GENISZAMAN IR	263
FIIL KOK FIIL GECMISZAMAN DI	220
FIIL KOK FIIL SIMDIKIZAMAN IYOR	162
FIIL KOK FIIL GECMISZAMAN DI FIIL KISI BEN	125

Table 6.6 and Table 6.7 present the results of using the algorithm and applying it to IWSLT 2010 and IWSLT 2011 collections.

Table 6.7. Top 5 most used predicate cases for IWSLT 2011 test collection

Predicate Case	Frequency
FIIL KOK FIIL EMIR SIZ IN	399
FIIL KOK FIIL GECMISZAMAN DI	206
FIIL KOK FIIL GENISZAMAN IR	190
ISIM KOK IMEK HIKAYE DI	109
FIIL KOK FIIL GECMISZAMAN DI FIIL KISI BEN	103

The processing time is 44 seconds for IWSLT 2010 test collection and 30 second for IWSLT 2011 test collection .

Despite the different collections topics, we can observe that the most used predicate cases are the same except one rule. Indeed, the rule *FIIL KOK FIIL EMIR SIZ IN* is the most used for both collections.

6.4. Conclusion

In this chapter the experimentation framework, performance of the approach and discussion of the results are presented. Because translated sentences are tagged, Zemberek

POS tagger functionalities are detailed. To perform the English-Turkish translation, open source MOSES SMT system is used. As a first experiment, 300 English-Turkish parallel collection is used. Results show an improvement of the 2-gram, 3-gram and 4-gram performances. The second experiment is performed on two larger size collections from IWSLT evaluation campaign. Results also show that the approach has a reasonably processing time.

CHAPTER 7

CONCLUSION

Translation is the process of converting one sentence in a language into another language, without changing the meaning. An approach to MT, which is characterized by the use of machine learning methods, is called SMT. In this thesis, Turkish language characteristics are presented and Turkish SMT challenges are addressed. The research concentrates on English-Turkish reordering approach. Related works limitations are discussed. One of these limitations is that SMT may not provide good results between languages having significantly different word orders, like the English-Turkish pair. To correctly reorder the words, an approach that is based on syntactic rules is proposed. First a morphological analyzer is used and a tagger is used to obtain Turkish part-of-speech (POS) tags. And finally, using POS tags words are reordered based on Turkish grammar rules.

Evaluation is performed on two different collection test types. The first collection is a parallel collection. Compared to the baseline, the approach results show an improvement of the 2-gram, 3-gram and 4-gram performances. Due to the small size of the test collection, an evaluation on two larger size collections is performed to test the algorithm performance. The results show that reordering has a positive effect on SMT performances. Even if this improvement is less than the expectations, the proposed approach can be used as a first step to establish a language independent methodology for reordering Turkish translated sentences.

Since the approach is linguistic based, a limitation is the manually defined syntactical rules. To add or to modify the syntactic rules list a manual process is used. The whole process is done by examining the output of the reordering algorithm and comparing it with the reference. Whenever it is detected that a predicate is not placed at the end of the segment, its corresponding POS tag is added at the end of the Predicates lists. Thus, it is not possible to claim that all the cases are included. Because, from the collections, it easy to detect high frequency cases; whereas it is hard to extract the rare cases. Focusing on a semi-supervised syntactical rules learning approach to enrich the rules list is planned.

The approach presented in this thesis has both advantages and disadvantages. A major disadvantage is working with Turkish agglutinative structure. It is a hard task to accomplish reordering on Turkish side. Only four rules are implemented in the code. It would be better to increase the number of rules by taking pronouns and adjectives into consideration. Also, phrases can be used to improve the alignment. The major advantage of the approach is its being independent from the source language. Any SMT system that takes Turkish as a target language, can benefit from our approach, by using it as a post-processing tool.

As a future work, it is planned to go in a deeper investigation of the BLEU+ measure to avoid the BLEU measure limitations when it comes to an agglutinative language like Turkish language. More experimentation is also planned on a different languages than English language. A planned study is to use an agglutinative language as a source language.

APPENDIX A: REORDERING ALGORITHM

main

```
Sequence = new Sentence();
File1 = WordAndPOSs;
forall entries NewWord ϵ File1 do begin //add the NewWord to the Sequence
   Sequence.add(NewWord);
   if(NewWord=”.” OR NewWord=”,” OR NewWord=”;”) then begin //stop adding and reorder the sequence
      reorderedSequence =reorder(Sequence);
   end
end
```

reorder(Sequence)

```
Sequence.NumberOfPredicates=0;
forall Lemma ϵ Sequence do begin
   for (i=0;i<Sequence.size();i++) begin
      searchVerb(Lemma(i)); //Search whether it is among the definitelyPredicates and couldBePredicates list
   end
   if(Lemma(i).definitelyPredicate=true) then begin //if its definitelyPredicate is true
      Sequence.PredicateFound=true;
      Sequence.PredicatePosition=i;
      Sequence.NumberOfPredicates++;
   end
end
if (Sequence.PredicateFound=true) then begin // If Predicate is found, place it at the end
   Position=Sequence.PredicatePosition;
   Predicate=Lemma(Position);
   Sequence.remove( Lemma(Position) );
   Sequence.add( Sequence.size()-1, Predicate);
   Sequence.PredicatePosition=Sequence.size()-2;
end
else begin //If definitelyPredicate is NOT found, check for the couldBePredicate candidates.
   for (int i=0;(i<Sequence.Lemmas.size()) ;i++) begin

         if(Lemma(i).couldBePredicate=true) then begin //If it has the possibility to be a Predicate.
            Sequence.PredicateFound=true;
            Sequence.PredicatePosition=i;
            Position=Sequence.PredicatePosition;
            Predicate=Lemma(location);
            Sequence.add( Sequence.size()-1, Predicate);
            Sequence.PredicatePosition=Sequence.size()-2;
         end
      end
   end
   //If there are multiple PREDICATEs, the sequence is divided into subsegments
   if (Sequence.NumberOfPredicates> then begin
      Sequence=split(Sequence);
   end
```

split(Sequence)

```
Result = new Sentence ();
beginning=0;
for (i=0;i<Sequence.size() ;i++) begin
   oneWord=””;
   enough=false;
   File2 = ConjunctionsList;
   forall entries oneWord ϵ File2 do begin
      //if it is a conjunction OR it is the last lemma of the sequence
      if( Lemma(i)=oneWord OR i=Sequence.size()-1 ) then begin
         SubSequence = new Sentence ();
         for(j=begining;j<=i;j++) do begin )//add all the lemmas up to the next conjunction
            SubSequence.add(Lemma(j));
         end
         beginning=i+1;
         ReorderedSubSequence = new Sentence ();
         ReorderedSubSequence=reorder(SubSequence);
         Result.add(ReorderedSubSequence);
         enough=true; //Lemma(i) is a conjunction, so stop searching
      end
      while (enough!=true) do begin
         return Result;
      end
   end
end
```

APPENDIX B: MANUALLY DEFINED PREDICATE CASES

Predicate Cases

1. FIIL
2. FIIL KOK FIIL GENISZAMAN IR IMEK HIKAYE DI
3. FIIL KOK FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI BEN IM
4. FIIL KOK FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI SEN SIN
5. FIIL KOK FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI BIZ IZ
6. FIIL KOK FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI SIZ SINIZ
7. FIIL KOK FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI ONLAR LER
8. FIIL KOK FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR IMEK HIKAYE DI
9. FIIL KOK FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI BEN IM
10. FIIL KOK FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI SEN SIN
11. FIIL KOK FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI BIZ IZ
12. FIIL KOK FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI SIZ SINIZ
13. FIIL KOK FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI ONLAR LER
14. FIIL KOK FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI
15. FIIL KOK FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BEN IM
16. FIIL KOK FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI SEN SIN
17. FIIL KOK FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BIZ IZ
18. FIIL KOK FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI SIZ SINIZ
19. FIIL KOK FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI ONLAR LER
20. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI
21. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BEN IM
22. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI SEN SIN
23. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BIZ IZ
24. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI SIZ SINIZ
25. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI ONLAR LER
26. FIIL KOK FIIL GECMISZAMAN MIS ISIM TANIMLAMA DIR
27. FIIL KOK FIIL GECMISZAMAN MIS IMEK HIKAYE DI
28. FIIL KOK FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI BEN IM
29. FIIL KOK FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI SEN SIN
30. FIIL KOK FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI BIZ IZ
31. FIIL KOK FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI SIZ SINIZ
32. FIIL KOK FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI ONLAR LER
33. FIIL KOK FIIL OLUMSUZLUK ME FIIL GECMISZAMAN MIS IMEK HIKAYE DI
34. FIIL KOK FIIL OLUMSUZLUK ME FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI BEN IM
35. FIIL KOK FIIL OLUMSUZLUK ME FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI SEN SIN
36. FIIL KOK FIIL OLUMSUZLUK ME FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI BIZ IZ
37. FIIL KOK FIIL OLUMSUZLUK ME FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI SIZ SINIZ
38. FIIL KOK FIIL OLUMSUZLUK ME FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI ONLAR LER
39. FIIL KOK FIIL BELIRTME DIK
40. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL GECMISZAMAN DI
41. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL GECMISZAMAN DI FIIL KISI BEN
42. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL GECMISZAMAN DI FIIL KISI SEN
43. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL GECMISZAMAN DI FIIL KISI BIZ
44. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL GECMISZAMAN DI FIIL KISI SIZ
45. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL GECMISZAMAN DI FIIL KISI ONLAR
46. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL GECMISZAMAN DI
47. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL GECMISZAMAN DI FIIL KISI BEN
48. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL GECMISZAMAN DI FIIL KISI SEN
49. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL GECMISZAMAN DI FIIL KISI BIZ
50. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL GECMISZAMAN DI FIIL KISI SIZ
51. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL GECMISZAMAN DI FIIL KISI ONLAR
52. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL GECMISZAMAN MIS
53. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL GECMISZAMAN MIS FIIL KISI BEN
54. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL GECMISZAMAN MIS FIIL KISI SEN
55. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL GECMISZAMAN MIS FIIL KISI BIZ
56. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL GECMISZAMAN MIS FIIL KISI SIZ
57. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL GECMISZAMAN MIS FIIL KISI ONLAR
58. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL GECMISZAMAN MIS

59. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL GECMISZAMAN MIS FIIL KISI BEN
60. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL GECMISZAMAN MIS FIIL KISI SEN
61. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL GECMISZAMAN MIS FIIL KISI BIZ
62. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL GECMISZAMAN MIS FIIL KISI SIZ
63. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL GECMISZAMAN MIS FIIL KISI ONLAR
64. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR
65. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR FIIL KISI BEN
66. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR FIIL KISI SEN
67. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR FIIL KISI BIZ
68. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR FIIL KISI SIZ
69. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR FIIL KISI ONLAR
70. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR
71. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR FIIL KISI BEN
72. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR FIIL KISI SEN
73. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR FIIL KISI BIZ
74. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR FIIL KISI SIZ
75. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR FIIL KISI ONLAR
76. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI
77. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BEN IM
78. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI SEN SIN
79. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BIZ IZ
80. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI SIZ SINIZ
81. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI ONLAR LER
82. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI
83. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BEN IM
84. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI SEN SIN
85. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BIZ IZ
86. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI SIZ SINIZ
87. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI ONLAR LER
88. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR FIIL KISI ONLAR IMEK HIKAYE DI
89. FIIL KOK FIIL BERABERLIK IS FIIL ETTIRGEN TIR FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR FIIL KISI ONLAR IMEK HIKAYE DI
90. FIIL KOK FIIL BERABERLIK IS FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI
91. FIIL KOK FIIL BERABERLIK IS FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI ISIM KISI BEN IM
92. FIIL KOK FIIL BERABERLIK IS FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI ISIM KISI SEN IN
93. FIIL KOK FIIL BERABERLIK IS FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI ISIM KISI BIZ IZ
94. FIIL KOK FIIL BERABERLIK IS FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI ISIM KISI SIZ SINIZ
95. FIIL KOK FIIL BERABERLIK IS FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI ISIM KISI ONLAR LER

96. FIIL KOK FIIL BERABERLIK IS FIIL OLUMSUZLUK ME FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI
97. FIIL KOK FIIL BERABERLIK IS FIIL OLUMSUZLUK ME FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI ISIM KISI BEN IM
98. FIIL KOK FIIL BERABERLIK IS FIIL OLUMSUZLUK ME FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI ISIM KISI SEN IN
99. FIIL KOK FIIL BERABERLIK IS FIIL OLUMSUZLUK ME FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI ISIM KISI BIZ IZ
100. FIIL KOK FIIL BERABERLIK IS FIIL OLUMSUZLUK ME FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI ISIM KISI SIZ SINIZ
101. FIIL KOK FIIL BERABERLIK IS FIIL OLUMSUZLUK ME FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI ISIM KISI ONLAR LER
102. FIIL KOK FIIL BERABERLIK IS FIIL OLUMSUZLUK ME FIIL GELECEKZAMAN ECEK ISIM KISI ONLAR LER IMEK HIKAYE DI
103. FIIL KOK FIIL BERABERLIK IS FIIL OLUMSUZLUK ME FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI
104. FIIL KOK FIIL DONUSUM ECEK
105. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN DI
106. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN DI FIIL KISI BEN
107. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN DI FIIL KISI SEN
108. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN DI FIIL KISI BIZ
109. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN DI FIIL KISI SIZ
110. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN DI FIIL KISI ONLAR
111. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN MIS
112. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN MIS FIIL KISI BEN
113. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN MIS FIIL KISI SEN
114. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN MIS FIIL KISI BIZ
115. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN MIS FIIL KISI SIZ
116. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN MIS FIIL KISI ONLAR
117. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN MIS IMEK HIKAYE DI
118. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI BEN IM
119. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI SEN SIN
120. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI BIZ IZ
121. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI SIZ SINIZ
122. ISIM KOK ISIM DONUSUM LE FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI ONLAR LER
123. FIIL KOK FIIL DONUSUM MEZ
124. FIIL KOK FIIL DONUSUM MIS ISIM TANIMLAMA DIR
125. FIIL KOK FIIL EDILGEN IL FIIL ETTIRGEN TIR
126. FIIL KOK FIIL EDILGEN IL FIIL YETENEK EBIL FIIL GENISZAMAN IR
127. FIIL KOK FIIL EMIR SIZ IN
128. FIIL KOK FIIL EMIR O SIN
129. FIIL KOK FIIL EMIR ONLAR SINLER
130. FIIL KOK FIIL ETTIRGEN TIR FIIL EMIR SIZ IN
131. FIIL KOK FIIL ETTIRGEN TIR FIIL EMIR O SIN
132. FIIL KOK FIIL ETTIRGEN TIR FIIL EMIR ONLAR SINLER
133. FIIL KOK FIIL ETTIRGEN TIR
134. FIIL KOK FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR
135. FIIL KOK FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR FIIL KISI BEN
136. FIIL KOK FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR FIIL KISI SEN
137. FIIL KOK FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR FIIL KISI BIZ
138. FIIL KOK FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR FIIL KISI SIZ
139. FIIL KOK FIIL ETTIRGEN TIR FIIL SIMDIKIZAMAN IYOR FIIL KISI ONLAR
140. FIIL KOK FIIL ETTIRGEN TIR FIIL GECMISZAMAN DI
141. FIIL KOK FIIL ETTIRGEN TIR FIIL GECMISZAMAN DI FIIL KISI BEN
142. FIIL KOK FIIL ETTIRGEN TIR FIIL GECMISZAMAN DI FIIL KISI SEN
143. FIIL KOK FIIL ETTIRGEN TIR FIIL GECMISZAMAN DI FIIL KISI BIZ
144. FIIL KOK FIIL ETTIRGEN TIR FIIL GECMISZAMAN DI FIIL KISI SIZ
145. FIIL KOK FIIL ETTIRGEN TIR FIIL GECMISZAMAN DI FIIL KISI ONLAR
146. FIIL KOK FIIL ETTIRGEN TIR FIIL GECMISZAMAN MIS
147. FIIL KOK FIIL ETTIRGEN TIR FIIL GECMISZAMAN MIS FIIL KISI BEN
148. FIIL KOK FIIL ETTIRGEN TIR FIIL GECMISZAMAN MIS FIIL KISI SEN
149. FIIL KOK FIIL ETTIRGEN TIR FIIL GECMISZAMAN MIS FIIL KISI BIZ
150. FIIL KOK FIIL ETTIRGEN TIR FIIL GECMISZAMAN MIS FIIL KISI SIZ
151. FIIL KOK FIIL ETTIRGEN TIR FIIL GECMISZAMAN MIS FIIL KISI ONLAR
152. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GENISZAMAN IR
153. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GENISZAMAN IR FIIL KISI BEN
154. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GENISZAMAN IR FIIL KISI SEN
155. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GENISZAMAN IR FIIL KISI BIZ
156. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GENISZAMAN IR FIIL KISI SIZ
157. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GENISZAMAN IR FIIL KISI LER

158. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR
159. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR FIIL KISI BEN
160. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR FIIL KISI SEN
161. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR FIIL KISI BIZ
162. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR FIIL KISI SIZ
163. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR FIIL KISI LER
164. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR IMEK RIVAYET MIS
165. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR IMEK RIVAYET MIS ISIM KISI BEN IM
166. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR IMEK RIVAYET MIS ISIM KISI SEN SIN
167. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR IMEK RIVAYET MIS ISIM KISI SIZ SINIZ
168. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR IMEK RIVAYET MIS ISIM KISI BIZ IZ
169. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR IMEK RIVAYET MIS ISIM KISI ONLAR LER
170. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI
171. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BEN IM
172. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI SEN SIN
173. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI SIZ SINIZ
174. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BIZ IZ
175. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI ONLAR LER
176. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GECMISZAMAN DI
177. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GECMISZAMAN DI FIIL KISI BEN
178. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GECMISZAMAN DI FIIL KISI SEN
179. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GECMISZAMAN DI FIIL KISI BIZ
180. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GECMISZAMAN DI FIIL KISI SIZ
181. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GECMISZAMAN DI FIIL KISI LER
182. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GECMISZAMAN MIS
183. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GECMISZAMAN MIS FIIL KISI BEN
184. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GECMISZAMAN MIS FIIL KISI SEN
185. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GECMISZAMAN MIS FIIL KISI BIZ
186. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GECMISZAMAN MIS FIIL KISI SIZ
187. FIIL KOK FIIL ETTIRGEN TIR FIIL YETENEK EBIL FIIL GECMISZAMAN MIS FIIL KISI LER
188. FIIL KOK FIIL GECMISZAMAN DI
189. FIIL KOK FIIL GECMISZAMAN DI FIIL KISI BEN
190. FIIL KOK FIIL GECMISZAMAN DI FIIL KISI SEN
191. FIIL KOK FIIL GECMISZAMAN DI FIIL KISI BIZ
192. FIIL KOK FIIL GECMISZAMAN DI FIIL KISI SIZ
193. FIIL KOK FIIL GECMISZAMAN DI FIIL KISI ONLAR
194. FIIL KOK FIIL GECMISZAMAN MIS
195. FIIL KOK FIIL GECMISZAMAN MIS FIIL KISI BEN
196. FIIL KOK FIIL GECMISZAMAN MIS FIIL KISI SEN
197. FIIL KOK FIIL GECMISZAMAN MIS FIIL KISI BIZ
198. FIIL KOK FIIL GECMISZAMAN MIS FIIL KISI SIZ
199. FIIL KOK FIIL GECMISZAMAN MIS FIIL KISI ONLAR
200. FIIL KOK FIIL GECMISZAMAN MIS IMEK HIKAYE DI
201. FIIL KOK FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI BEN IM
202. FIIL KOK FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI SEN SIN
203. FIIL KOK FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI BIZ IZ
204. FIIL KOK FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI SIZ SINIZ
205. FIIL KOK FIIL GECMISZAMAN MIS IMEK HIKAYE DI ISIM KISI ONLAR LER
206. FIIL KOK FIIL GELECEKZAMAN ECEK
207. FIIL KOK FIIL GELECEKZAMAN ECEK FIIL KISI BEN
208. FIIL KOK FIIL GELECEKZAMAN ECEK FIIL KISI SEN
209. FIIL KOK FIIL GELECEKZAMAN ECEK FIIL KISI BIZ
210. FIIL KOK FIIL GELECEKZAMAN ECEK FIIL KISI SIZ
211. FIIL KOK FIIL GELECEKZAMAN ECEK FIIL KISI ONLAR
212. FIIL KOK FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI
213. FIIL KOK FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI ISIM KISI BEN IM
214. FIIL KOK FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI ISIM KISI SEN SIN

215. FIIL KOK FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI ISIM KISI BIZ IZ
216. FIIL KOK FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI ISIM KISI SIZ SINIZ
217. FIIL KOK FIIL GELECEKZAMAN ECEK IMEK HIKAYE DI ISIM KISI ONLAR LER
218. FIIL KOK FIIL GENISZAMAN IR
219. FIIL KOK FIIL GENISZAMAN IR FIIL KISI BEN
220. FIIL KOK FIIL GENISZAMAN IR FIIL KISI SEN
221. FIIL KOK FIIL GENISZAMAN IR FIIL KISI BIZ
222. FIIL KOK FIIL GENISZAMAN IR FIIL KISI SIZ
223. FIIL KOK FIIL GENISZAMAN IR FIIL KISI ONLAR
224. FIIL KOK FIIL GENISZAMAN IR IMEK HIKAYE DI
225. FIIL KOK FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI BEN IM
226. FIIL KOK FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI SEN SIN
227. FIIL KOK FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI BIZ IZ
228. FIIL KOK FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI SIZ SINIZ
229. FIIL KOK FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI ONLAR LER
230. FIIL KOK FIIL GENISZAMAN IR IMEK HIKAYE DI FIIL KOK FIIL ETTIRGEN TIR
231. FIIL KOK FIIL ISTEK E FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI
232. FIIL KOK FIIL ISTEK E FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BEN IM
233. FIIL KOK FIIL ISTEK E FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI SEN SIN
234. FIIL KOK FIIL ISTEK E FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BIZ IZ
235. FIIL KOK FIIL ISTEK E FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI SIZ SINIZ
236. FIIL KOK FIIL ISTEK E FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI ONLAR LER
237. FIIL KOK FIIL MASTAR MEK IMEK HIKAYE DI
238. FIIL KOK FIIL OLDURGAN T FIIL SIMDIKIZAMAN IYOR
239. FIIL KOK FIIL OLDURGAN T FIIL SIMDIKIZAMAN IYOR FIIL KISI ONLAR IMEK HIKAYE DI
240. FIIL KOK FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR
241. FIIL KOK FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR FIIL KISI SEN
242. FIIL KOK FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR FIIL KISI ONLAR
243. FIIL KOK FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR IMEK HIKAYE DI
244. FIIL KOK FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI BEN IM
245. FIIL KOK FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI SEN SIN
246. FIIL KOK FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI BIZ IZ
247. FIIL KOK FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI SIZ SINIZ
248. FIIL KOK FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR IMEK HIKAYE DI ISIM KISI ONLAR LER
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250. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BEN IM
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252. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BIZ IZ
253. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI SIZ SINIZ
254. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI ONLAR LER
255. FIIL KOK FIIL SIMDIKIZAMAN IYOR
256. FIIL KOK FIIL SIMDIKIZAMAN IYOR FIIL KISI BEN
257. FIIL KOK FIIL SIMDIKIZAMAN IYOR FIIL KISI SEN
258. FIIL KOK FIIL SIMDIKIZAMAN IYOR FIIL KISI BIZ
259. FIIL KOK FIIL SIMDIKIZAMAN IYOR FIIL KISI SIZ
260. FIIL KOK FIIL SIMDIKIZAMAN IYOR FIIL KISI ONLAR
261. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR
262. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR FIIL KISI BEN
263. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR FIIL KISI SEN
264. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR FIIL KISI BIZ
265. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR FIIL KISI SIZ
266. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR FIIL KISI ONLAR
267. FIIL KOK FIIL SIMDIKIZAMAN IYOR FIIL KISI ONLAR IMEK HIKAYE DI
268. FIIL KOK FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI
269. FIIL KOK FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BEN IM
270. FIIL KOK FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI SEN SIN
271. FIIL KOK FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BIZ IZ
272. FIIL KOK FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI SIZ SINIZ
273. FIIL KOK FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI ONLAR LER
274. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI
275. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BEN IM
276. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI SEN SIN
277. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI BIZ IZ
278. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI SIZ SINIZ
279. FIIL KOK FIIL OLUMSUZLUK ME FIIL SIMDIKIZAMAN IYOR IMEK HIKAYE DI ISIM KISI ONLAR LER

280. FIIL KOK FIIL YETENEK EBIL FIIL GENISZAMAN IR
281. FIIL KOK FIIL YETENEK EBIL FIIL GENISZAMAN IR FIIL KISI BEN
282. FIIL KOK FIIL YETENEK EBIL FIIL GENISZAMAN IR FIIL KISI SEN
283. FIIL KOK FIIL YETENEK EBIL FIIL GENISZAMAN IR FIIL KISI BIZ
284. FIIL KOK FIIL YETENEK EBIL FIIL GENISZAMAN IR FIIL KISI SIZ
285. FIIL KOK FIIL YETENEK EBIL FIIL GENISZAMAN IR FIIL KISI ONLAR
286. FIIL KOK FIIL YETERSIZLIK E FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR
287. FIIL KOK FIIL YETERSIZLIK E FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR FIIL KISI BEN
288. FIIL KO FIIL YETERSIZLIK E FIIL OLUMSUZLUK ME GENISZAMAN IR FIIL KISI SEN
289. FIIL KOK FIIL YETERSIZLIK E FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR FIIL KISI BIZ
290. FIIL KOK FIIL YETERSIZLIK E FIIL OLUMSUZLUK ME FIIL GENISZAMAN IR FIIL KISI SIZ
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