Automatic Lexical Text Simplification for Turkish
Ahmet Yavuz Uluslu
University of Zurich
Department of Computational Linguistics
Andreasstrasse 15, Zürich, Switzerland
ahmetyavuz.uluslu@uzh.ch

Abstract
In this paper, we present the first automatic lexical simplification system for the Turkish language. Recent text simplification efforts rely on manually crafted simplified corpora and comprehensive NLP tools that can analyse the target text both in word and sentence levels. Turkish is a morphologically rich agglutinative language that requires unique considerations such as the proper handling of inflectional cases. Being a low-resource language in terms of available resources and industrial-strength tools, it makes the text simplification task harder to approach. We present a new text simplification pipeline based on pretrained representation model BERT together with morphological features to generate grammatically correct and semantically appropriate word-level simplifications.

Keywords: Turkish, automatic text simplification, lexical simplification

1. Introduction
The goal of the lexical simplification task is to replace complex words with simpler alternatives. There are many groups of people that can benefit from this including children, people with cognitive disabilities and non-native speakers (Paetzold and Specia, 2016; Rello et al., 2013a). The common assumption among linguists is that those who are familiar with the vocabulary of a text can often understand the meaning even if they have problems with grammatical structures. Automatic lexical simplification thus can become an effective method to make text accessible for different audiences.

Turkish, the most widely spoken language in the Turkic language family, is the official language of Turkey with 80 million speakers. It is a morphologically rich agglutinative language. Text simplification for Turkish exhibits a number of challenge due to lack of linguistic resources and dissimilarity to other covered languages. Turkish is considered to be a low resource language in terms of standard linguistic resources (Cieri et al., 2016). Recently there has been an initiative by different research groups to release datasets and tools publicly. To name a few, some of the necessary lexical resources for modern text simplification such as WordNet has become available (Bakay et al., 2021) and multiple Turkish Treebanks were successfully integrated into Universal Dependencies (Türk et al., 2021). However, the lack of parallel corpora for different tasks and domains renders data-driven approaches such as Neural Text Simplification ineffective.

There has not been a comprehensive conceptual study on text simplification in Turkish. Different simplification methods should be proposed for the target audience and they should be subjected to experimentation to show their effectiveness. Simplification methods can be found insignificant on their (Rello et al., 2013b) and can be used mixed with other techniques to improve the text accessibility. We admit that currently unavailable clinical insight is required for our work to have any practical importance for people with special needs. More psycholinguistic research is needed to establish what constitutes a simple language for different groups. Therefore, we simply focus on building a general-purpose lexical simplification pipeline for Turkish to lay the foundations of further research.

Figure 1: An example lexical simplification by LS-BERT pipeline

LS-BERT is a lexical simplification method that generates substitute words with pretrained encoders (Qiang et al., 2021). Our paper builds a similar pipeline and adapts BERTurk (Schweter, 2020) to handle challenges of Turkish text simplification by using additional features. We present a new manually constructed dataset for complex word identification. We evaluated our proposed system automatically, and released our code and lexical resources open-source.

2. Related Work
Text simplification is the process of simplifying the content of the original text while retaining the mean-
ing and preserving the grammaticality. It focuses on the simplification of vocabulary and the syntactic structures in the text. Early text simplification systems were rule-based, relying on lexical resources such as WordNet and other linguistic databases for a predefined set of complex words to substitute words with simpler alternatives (Carroll et al., 1998). The major limitation of such an approach was the identification of complex words (Shardlow, 2014). Rule-based systems relied heavily on word frequencies and ignored the context. The synonym replacement also required simplification rules for every word or general rules that failed to account for different linguistic relationships. Even with integration of N-gram language models to understand the word context, simplification algorithms had limited understanding of the whole sentence.

With the availability of complex and simple parallel corpora (Coster and Kauchak, 2011), data-driven methods started to produce adequate results. Recent research treated text simplification task as a monolingual machine translation problem (Tang et al., 2019). Statistical machine translation (SMT) algorithms were the first techniques to be used for text simplification (Wubben et al., 2012). It was followed by the recent developments in neural machine translation (NMT). Researchers started to apply the new trend of deep learning based machine translation models on the text simplification problem. (Wang et al., 2016) The study built a model based on long short-term memory (LSTM) encoder-decoder and successfully shown that it was able to learn simplification rules such as sorting, reversing, replacing and substitution of words. The study proved an increased capacity of simplification and LSTM-based encoder-decoders outperformed their statistical counterparts.

There has been relatively little research on text simplification in Turkish (Torunoglu-Selamet et al., 2016; Özkan and Ercan, 2018). The first study proposed various syntax-level simplification rules but did not cover lexical simplification. Some of the proposed rules such as paratactic sentence simplification appear to exist only at a conceptual level and practical implementations were uncovered. The system should be evaluated on actual complex sentences to assess the robustness of defined rules against text cohesion (Sidharthan, 2006). The target group of the study seem to be not defined clearly and the group names preteens (8-12) and children (0-18) are used interchangeably. The latter study approaches the text simplification problem from the modernisation perspective and trains a statistical machine translation model on a parallel corpus constructed with the original and modernised version of Turkish classics.

3. **Turkish Text Simplification**

The lack of parallel data in Turkish limits the applicability of data-driven approaches. However, unsupervised language models may still be employed for low-resource languages as it only requires a large corpus of raw text. BERT-based pretrained language models has shown to be effective for masked language modeling (Devlin et al., 2018). LSBERT exploits this to generate suitable simplifications for complex words (Qiang et al., 2021). This method considers the whole sentence context, and it is shown to generate coherent and cohesive sentences. BERTurk, a community driven BERT model for Turkish is available to implement this approach (Schweter, 2020). We create a similar pipeline which consists of the following three steps: complex word identification, substitute generation, substitute selection.

### 3.1. Complex Word Identification

The most common first step in lexical simplification is to identify which words are considered complex by the target audience (Shardlow, 2013). Complex words may be identified by different features such as word length, syllable count, and word frequency. General purpose text simplification systems focus on replacing infrequent words with frequent alternatives. The number of syllables and vowels may become important in special situations such as vowel dyslexia (Güven and Friedmann, 2021).

We trained a POS (Part-of-speech) tagger on BOUN Treebank to establish what sentence parts are targeted by the simplification pipeline (Türk et al., 2021). The PoS tagger (Lample et al., 2016) achieved F1 score of 0.89 on the test set. The complex sentence is first PoS tagged and only words with predefined set of tags Nouns (NN), adjectives (ADJ), verbs (VB), adverbs (ADV) are checked for their frequency inside the Turkish section of the wordfreq corpus (Speer et al., 2018). The corpus includes crawled Wikipedia entries, movie subtitles, tweets and web pages.

We observed two different conditions where predefined word lists and naive frequency based algorithms failed to capture fundamental aspects of language. We provided sentence examples to address context-awareness and morphological complexity.

Turkish is a morphologically rich agglutinative language. It can produce very complex sentences with only a few words. These words may appear frequently in everyday speech and written language. It can then go unnoticed by the frequency algorithm. Non-native speakers tend to have a hard time grasping unfamiliar concepts. Infrequent and long words are already known to affect dyslexia (Rello et al., 2013a). Recently, morphological complexity in Turkish words are also shown to affect sentence comprehension in students with dyslexia (Dodur and Miray, 2021).

1. **Morphological Complexity:**

   In: Çevrendekilerle iyi geçinmelisin.

   In EN: You should get along well with those
around you.

Complex words identified: None

The frequency algorithm does not identify the pronoun ‘çevrendekilerle’ (A3pl+Pnon+Ins) as a complex word. It is possible to disambiguate the pronoun depending on the sentence context and break it down into two words to reduce morphological complexity. The lexical simplification affects the overall sentence complexity and results in a clear and concise outcome. The syntax of the sentence was also affected by this change, therefore it may be an overstep depending on the definition of the lexical simplification task.

Figure 2: Dependency Visualisation Before Simplification

In: Çevrendekilerle iyi geçinmelisin.
Out: Çevrendeki insanlarla iyi geçinmelisin.
Simplification: Çevrendeki (-lerle) insanlarla

Figure 3: Dependency Visualisation After Simplification

2. Contextual Information:

In: Hak söz söyleyenin dostu az olur.
In EN: S/he who speaks truth has few friends.

Complex words identified: None

The frequency algorithm does not identify the word hak (justice, truth, right) as a complex word. Since the word has several meanings and repeatedly used in compound verbs (hak etmek, hakkı olmak, hak görmek) and nouns (hak sahibi, miras hakkı), it frequently appears inside the corpus. This usage is now considered an old practice, and it can be simplified for a certain age group and education background. It is impossible to identify such words without contextual information.

In: Hak söz söyleyenin dostu az olur.
Out: Doğru söz söyleyenin dostu az olur.
Simplification: Doğru (-Hak)

Complex word identification problem has recently been treated as a sequence labelling task (Gooding and Kochmar, 2019). Data-driven models take word context into account and they avoid the necessity of extensive feature engineering to address linguistic complexity. We manually crafted an annotated complex word identification dataset to experiment with sequence models. We followed the annotation guideline of CWI Shared Task 2018 (Yimam et al., 2018). The author whose native tongue is Turkish assumed the target group of preteens proceeding into high school level study with limited exposure to Arabic and Persian rooted words in the Turkish language. 1000 complex sentences from the Bilkent Creative Writing dataset and 2000 complex sentences from Wikipedia were annotated. This is not a complete study or dataset, as CWI Shared Task included multiple annotators with different assumed roles to construct a corpus of 90.000 sentences (Yimam et al., 2018). We regardless make our data and code open-source for further study.

| Total Dataset | Training Data | Test Data |
|---------------|---------------|-----------|
| 3k Sentences  | 2650 Sentences| 350 Sentences|

Table 1: Turkish CWI Dataset

A sequence labelling based word-level BiLSTM model was trained to predict the binary complexity of words annotated in the dataset. The model F1 score was 0.64 for complex word class and the overlap between frequency-based algorithm was 67.3%. We have previously explored the differences behind the two approaches, however, without comprehensive benchmark data statistical results are not robust enough for further analysis.

3.2. Substitute Generation

The aim of substitution generation is to produce substitute candidates for a complex word. We produce substitute candidates using the pre-trained language model BERT (Devlin et al., 2018). BERT is a self-supervised method based on the encoder part of the transformer architecture. The model is trained on two language tasks: masked language modeling and next sentence prediction. Masked language model is the objective of predicting the next word in a sequence given its left and right context. Next sentence prediction is the task of
given a pair of sentences predicting if the second sentence in the pair is the subsequent sentence in the original document. BERT accomplishes the masked language modelling task by replacing random words with special token [MASK] during training. In our simplification pipeline, we follow the LS-BERT study (Qiang et al., 2021) and replace the identified complex word with a [MASK] symbol to produce the substitute candidates based on BERT. Bi-directional nature of the model allows candidate generation depending on the whole sentence context.

3.3. Substitute Selection
The substitution selection is the decision step to filter and select which one of the candidate substitutions is the simplest choice and fits the context of the complex word best. The candidates are ranked based on BERT prediction probability, word frequency and semantic similarity.

BERT probability distribution:
BERT returns the probability distribution of vocabulary corresponding to the masked word given a complex word identified sentence. The results are calculated based on the attention mechanism and depend on the sentence context. Therefore, the higher the probability, the more relevant the candidate for the original sentence. It is possible to rank the candidates accordingly.

Language model feature:
A substitution candidate should fit in the context of the words that come before and after the original term. In non-context lexical simplification systems, n-gram language models are implemented to verify grammaticality (Qasmi et al., 2020). Bi-directional nature of BERT already accounts for grammaticality depending on the sentence context. We simply add another ranking measure to evaluate compatibility between the whole sentence and the limited word frame context. It is possible to mask nearby words back to front for each candidate to calculate the overall loss and rank accordingly.

Semantic similarity:
The semantic similarity is calculated based on the cosine similarity between the GloVe vector of the original word and the candidate substitution.

Frequency comparison:
Frequency-based approaches were covered during the complex word identification. We make use of a similar algorithm as a supportive measure in substitute selection. We rank the substitution candidates according to their appearance in the wordfreq corpus (Speer et al., 2018).

LS-BERT algorithm makes use of an additional measure called PPDB feature. It analyses a paraphrase corpus to see if the complex word and the substitution occurred inside a paraphrase pair. They conclude that this feature had the least impact in overall performance. We were not able to find a comprehensive paraphrase corpus with over hundred million examples, therefore we exclude it from our study. The performance of substitution candidates are averaged to calculate the final ranking score. The foremost candidate replaces the complex word if and only if it has a higher frequency and it has a better loss outcome in the language modelling.

4. Evaluation
We could not find any simplified parallel corpus sentence pairs for Turkish. To evaluate our simplification system, we manually simplified a reserved subset of our CWI dataset that was not included in the training process. The final parallel corpus contained 500 complex sentences and their corresponding lexical simplifications. We adhered to the CWI dataset guidelines and assumed the role of a student with pre-high school education background. The complex sentences were taken from the same resources: Wikipedia and a university-level Turkish writing corpus. The simplifications were created by the author whose native language is Turkish and has a background in linguistics. The simplification pipeline first identified the complex word, and BERT generated the substitute candidates. The ranking algorithm included different features to pick the best candidate. We decided to take core parts of the algorithm, the probability distribution and frequency analysis as our baseline of evaluation and show the improvement in performance after the addition of each feature.

We evaluate our system outputs using standard evaluation metrics for text simplification: BLEU and SARI (Xu et al., 2016). BLEU score for the evaluation of text simplification was recently disputed (Sulem et al., 2018). However, our method is out of scope for the major shortcomings mentioned such as sentence splitting. We regardless provide the score for comparison with other studies.

| Model                | BLEU | SARI |
|----------------------|------|------|
| BERT (Prob + Freq)   | 70.30| 35.52|
| + Similarity         | 76.84| 37.36|
| + LM                 | 78.25| 37.40|

Table 2: Results of Automatic Evaluation

5. Conclusion & Future Work
This paper presents the first automatic lexical text simplification system for Turkish. We also present a complex word identification dataset for Turkish, and create a small simplified parallel corpus for benchmarking text simplification tasks. Our model achieves a BLEU score of 78.25 and a SARI score of 37.40 on automatic evaluation. In our future work, we would like to expand our previously created datasets with multiple annotators and address the simplification shortcomings in multi-word expressions and morphologically complex words in Turkish.
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Appendix A: Example Simplification Outputs

|   | 1 | Bu kitapları zamanında babam nesretti.  
Bu kitapları zamanında babam yazdı.  
My father wrote these books at the time. |
|---|---|---|
| 2 | 2 | Devlet meseleleri derin bir ekonomi bilgisi gerektirir.  
Devlet sorunları ayrıntılı bir ekonomi bilgisi gerektirir.  
State problems require a detailed knowledge of economics. |
| 3 | 3 | Sayın katılımcı, hitap tonunuz ortama münasip değil.  
Sayın katılımcı, ses tonunuz ortama uygun değil.  
Dear participant, your tone of voice is not suitable for the occasion. |
| 4 | 4 | Modern tıbbın çözemediği dermansız hastalıklar vardır.  
Modern tıbbın çözemediği çaresiz hastalıklar vardır.  
There are incurable diseases that modern medicine cannot solve. |
| 5 | 5 | Ona bir sonraki hatasında musamaha gösteremeyeceğimizi söyledim.  
Ona bir sonraki hatasında hoşgörü gösteremeyeceğimizi söyledim.  
I told her I wouldn’t tolerate her next mistake. |

Table 3: Examples of sentence simplification by the following order: complex sentence, simplification output, English translation.