A Twitter Corpus for Named Entity Recognition in Turkish

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Abstract

This paper introduces a new Turkish Twitter Named Entity Recognition dataset. The dataset, which consists of 5000 tweets from a year-long period, was labeled by multiple annotators with a high agreement score. The dataset is also diverse in terms of the named entity types as it contains not only person, organization, and location but also time, money, product, and tv-show categories. Our initial experiments with pretrained language models (like BertTurk) over this dataset returned F1 scores of around 80%. We share this dataset publicly.

Keywords: Twitter, Named Entity Recognition, Turkish

1. Introduction

Named Entity Recognition (NER), a subtask of information extraction is used to identify predefined named entities (NEs) such as temporal and numerical expressions alongside person, location, or organization names. Researchers have achieved outstanding results in well-studied languages such as English for the NER task, which has been used as part of several other NLP tasks such as summarization, question answering, and entity linking. However, it remains a subject of study for languages that lack sufficient research and resources, such as Turkish.

There are several reasons for this. First of all, the majority of previous studies in Turkish NER focused on formal writings that comply with grammatical and spelling rules (Tür et al., 2003; Tatar and Cicekli, 2011). In limited studies to date (Çelikkaya et al., 2013; Okur et al., 2018), the application of the developed NER models to informal texts such as mini-blogs has yielded poor results. Nevertheless, with the growth in the amount of social media content, the need to recognize NEs in these noisy texts has increased.

In addition, apart from the NE types defined by the Message Understanding Conference (MUC) series (Grishman and Sundheim, 1996), new NE types have not been adequately studied for Turkish except for a few studies (Kıçık et al., 2014). However, investigating different types of NEs helps improving the results when these NE types are tailored to other NLP tasks.

Another significant issue in Turkish NER studies is that most of the datasets, especially the informal ones, are not publicly available. Only Kıçık et al. (2014) and Kıçık and Can (2019) released their datasets of tweets publicly by providing the tweet IDs. However, these two datasets are limited both in terms of diversity and size.

In this work, we introduce a new dataset for Turkish NER gathered from Twitter distributed uniformly across months over a long time. We included under-studied NE types in our label set and obtained a high agreement score among multiple annotators. We also present some initial results on this dataset. Since transformer-based models outperform in many NLP tasks, we experimented with different variations of these models on our dataset as well. The dataset is publicly available at https://github.com/SU-NLP/SUNLP-Twitter-NER-Dataset.

The rest of this paper is organized as follows: Section 2 discusses the overview of NER in Turkish; Section 3 describes the details of the data collection and annotation processes; Section 4 presents our initial experiments on the developed NER model and discusses our results; and finally, Section 5 concludes the paper.

2. Related Work

There are several attempts to create formal or informal datasets in the Turkish NER. The first Turkish NER dataset, which is also the largest one with 500K tokens, is a dataset of news articles annotated with NE categories of person, organization, and location (Tür et al., 2003). Later, Tatar and Cicekli (2011) built a relatively small formal news dataset on terrorism with 55K tokens. In this study, both the money and percent NE types were included in the annotation process. With a rule-based system, they achieved an F1 score of 91.08% in this dataset. In a later study (Kıçık et al., 2016), 89.85% was obtained with a rule-based method on a substantially small dataset of 20K words constructed using news.

Although the number of informal datasets is greater than the formal ones, none of them is close to the size of the Tür et al. (2003) dataset. The first study introduced three informal datasets from different sources (Çelikkaya et al., 2013). Their Twitter dataset contains 5K tweets with 54K tokens. A forum with hardware product evaluations provided the broadest dataset, which contained 54K words. Another dataset was created with text-to-speech data converted by a mobile assistant application, and all of them were annotated with the seven basic NE types (person, location, organization, time, date, money, percentage). The largest dataset on informal texts was created by Tantug (2015).
from Twitter, labeling 9,358 tweets with seven basic categories. Unfortunately, these datasets are not publicly available.

Within an hour, Kucuk et al. (2014) collected 2300 tweets from Twitter and labeled them with person, location, organization, money, date, time, and percentage tags. They also put all TV shows, songs, and products under the MISC category. This dataset is limited due to covering a short period of time.

Another dataset was introduced on user-generated content from different domains, such as customer reviews, social media posts, blogs, and forums (Seker and Eryigit, 2017).

A recent study annotated 1,065 tweets about Turkish sports teams with person, location, and organization labels. In this dataset, the labeling was performed by a single annotator (Kucuk and Can, 2019). Another limitation of this dataset is that tweets are about a very specific domain. The statistics about all these Turkish datasets are presented in Table 1.

The majority of studies on Turkish NER have been conducted with (Tur et al., 2003) dataset since it is the largest dataset available. Earlier studies concentrated on statistical and rule-based systems, whereas recent research has focused on deep learning approaches. As a statistical method, Tur et al. (2003) applied an approach based on the Hidden Markov Models. CRF-based methods were later proposed by Yeniterzi (2011) Seker and Eryigit (2012), Kucuk and Yazici (2012) Tatar and Cicikli (2011) experimented with rule-based approaches in their small datasets. The first study to utilize a neural network was Demir and Ozgur (2013) which developed a regularized averaged perceptron on the Tur et al. (2003) news dataset. Later studies have explored the BiLSTM model on top of CRF through different embedding settings, such as utilizing characters or morphological features (Kuru et al., 2016) Gunes and Tantug (2018) Gungor et al. (2019).

With the popularity of pretrained language models, recent Turkish NER studies have begun to use these models as well. The current state-of-the-art model was achieved by Aras et al. (2021) with a 95.95% F1 score by implementing a CRF layer on top of the BERTurk2 model. Although the scores achieved in the formal datasets are considerably high, the results are significantly low when these methods are applied to the informal ones. When Celikkaya et al. (2013) applied the same system presented in the Seker and Eryigit, 2012 to their datasets, F1 scores of 19% on Twitter, 50.84% on speech, and 5.6% on the forum were obtained. One of the important factors causing this decrease from 91.94% to 19% in the transition from the news to Twitter data is that they carried out the training process over the news dataset since there was not sufficient Twitter data for training. A multilingual rule-based approach developed by Kucuk and Steinberger (2014) obtained 38.01% on Celikkaya et al. (2013) and 48.13% on Kucuk et al. (2014). The first study that used an informal dataset for training is Tantug (2015) and achieved a 64.03% F1 score with a CRF-based method. Okur et al. (2018) obtained 48.96% F1 score on Celikkaya et al. (2013) by utilizing a Word2Vec trained on a large informal dataset in a regularized averaged multi-class perceptron model.

### 3. NER Dataset

In this section, we describe the dataset collection and annotation steps in detail. We also provide an analysis of the collected annotations.

#### 3.1. Data Collection

The data was collected through the Twitter streaming API from June 2020 to June 2021. We obtained approximately 65 million tweets in this period using the top trending topics in Turkey. Although the tweets covered a wide range of topics due to the broad time interval, hotly-debated events may dominate other subjects in several time intervals. Since it is beneficial to include varied topics to improve the generalizability of the current systems, we tried to generate a diverse dataset. Furthermore, since not all tweets contain a named entity, in order to get the most out of the annotation process, we used several heuristics while creating the dataset.

The following steps were performed for selecting tweets to be annotated. Firstly, tweets that have the same content without considering mentions, hashtags, and URLs were eliminated. After this near duplicate removal, in order to increase the chance of including a NE, we only kept the tweets with a character length

| Dataset       | Source      | Number of Tokens | Number of NEs | Availability |
|---------------|-------------|------------------|---------------|--------------|
| Formal        | News        | 500K             | 40K           | Available    |
| (Tur et al., 2003) | News        | 20K              | 1,425         | Not Available|
| (Kucuk et al., 2016) | News        | 55K              | 5,672         | Not Available|
| Tatar and Cicikli, 2011 | News        | 108K             | 7,747         | Not Available|
| Informal      | Twitter     | 54K              | 1,437         | Not Available|
| (Celikkaya et al., 2013) | Twitter     | 108K             | 7,747         | Not Available|
| Tantug, 2015  | UGC         | 43K              | 1,162         | Not Available|
| Seker and Eryigit, 2017 | Twitter     | 21K              | 1,322         | Only Tweet IDs |
| Kucuk et al., 2014 | Twitter     | -                | 1,879         | Only Tweet IDs |
| Kucuk and Can, 2019 | Twitter     | -                | 1,879         | Only Tweet IDs |

Table 1: Formal and informal NER datasets in Turkish.
greater than 50 and removed the rest. Moreover, to ensure having at least one NE in the tweet, we fed our remaining tweets to an effective NER model and selected those that had at least one previously unseen NE in its predictions. For this model, we used a BERT [Devlin et al., 2018] model pretrained on large Turkish corpora and fine-tuned it on a well-studied and largest Turkish NER corpus (Tür et al., 2003). This corpus contains only person, organization, and location entities, therefore it is limited but still better than no filtering at all. After this filtering, in order to guarantee a diversity of topics, we decided that any one hashtag can be in a maximum of 3 tweets. After this final filtering, we randomly selected 5,000 tweets from the remaining ones and manually annotated them. The dataset contains a total of 126,228 words, with an average of 25.24 words per tweet.

3.2. Named Entity Types
In addition to the most common three NE types, person, location, and organization, four other NE types have been annotated in this data set. We followed the definitions in the MUC [Grishman and Sundheim, 1996] for NE types PERSON, ORGANIZATION, LOCATION, and MONEY. The remaining two types are PRODUCT and TV-SHOW. We defined PRODUCT as an item produced or manufactured by people or corporations. Songs, books, movies, Instagram, and an iPhone can be given as examples for this class. We noticed that Turkish TV shows are often among the trending hashtag topics on Twitter. Therefore, we used a more specific type as the TV Show category for soap operas, reality programs, and other TV shows broadcast on TV. Besides, we have considered time and date expressions as part of the TIME class. We did not include percentages in numerical expressions as we could not see any significant number of samples in the annotation process.

3.3. Annotation Process
Our annotation team consists of four undergraduate students whose native language is Turkish. We distributed the selected 5000 tweets to these annotators and made sure that each tweet was annotated by two annotators. Label Studio, an open-source labeling tool, was used during the annotation process due to its user-friendly and easy-to-learn interface.

In addition to the context in tweets, annotators also labeled the hashtags if it is a NE as a whole (except for the # character). Hashtags in which the NE is only a part of, were not annotated as Named Entity. For example, if the hashtag is #Fenerbahçe, it was labeled as ORGANIZATION. However, if the hashtag is #SampiyonFenerbahçe, this token was labeled as OTHER.

The inter-annotator agreement was measured for all tweets in our dataset. The Cohen kappa score is 0.94 when all tokens are included (including the OTHER label). It is 0.87 when only the seven NEs are considered (without the OTHER label). There were 845 disagreements among the 5,000 tweets. After a detailed examination of these conflicts, we observed that the annotators mostly disagreed in the following two situations: ORGANIZATION vs. LOCATION and ORGANIZATION vs. PRODUCT.

For the conflicts between ORGANIZATION and LOCATION annotators usually could not agree on whether countries were mentioned as a place or a state. For example, consider the following tweets:

• LOCATION: We are going to the beautiful beaches of Turkey on vacation in summer.

• ORGANIZATION: Negotiations between Turkey and the USA continue.

The first tweet refers to Turkey as a location since it is about its coasts, whereas in the second tweet, it is an organization since the tweet is about the negotiations between governments. Some annotators had a hard time differentiating these concepts in some tweets.

Another popular conflicting case is deciding whether a named entity is a PRODUCT or ORGANIZATION. Although our annotators accurately categorized the corporations as organizations, in some cases, their goods were annotated as organizations instead of a product. For instance, while the company Apple is an organization, iPhone is a product of this company. Unfortunately, this becomes more challenging when both the company and product share the same name. For instance, in the following tweets, Google is used as a search engine product in the first one and a company in the second one:

• PRODUCT: If you are not sure, just ask it to Google.

• ORGANIZATION: I will start working at Google starting next month :)

Our expert author on the NER task resolved these conflicts one-by-one manually. In the finalized dataset, we have a total of 11,081 NEs, with the largest classes being PERSON, ORGANIZATION, and LOCATION. The number of distinct NEs is 7,231. Table 2 illustrates the distribution of the NEs in our dataset.

According to Table 2 common NE types are also the most common ones here. PERSON is the most frequent type. It is followed by ORGANIZATION and LOCATION. Time expressions are very common on Twitter, hence the high frequency of TIME is also expected. PRODUCT and TVSHOW are low in frequency, but one should not forget that TVSHOW can be considered as a type of PRODUCT, therefore when considered together, it is quite high in frequency.

2https://huggingface.co/dbmdz/bert-base-turkish-128k-uncased
3https://labelstud.io/
| NE Type   | Count |
|-----------|-------|
| PERSON    | 5,526 |
| ORGANIZATION | 2,956 |
| LOCATION  | 1,243 |
| TIME      | 608   |
| PRODUCT   | 334   |
| TV-SHOW   | 255   |
| MONEY     | 159   |
| **Total** | **11,081** |

Table 2: The distribution of NEs in our dataset.

### 3.4. Annotation Format

The adapted annotation format for our dataset is the **IOB2** tagging scheme, also known as **BIO** (Sang and Veenstra, 1999). In this format, **B-** stands for the NE beginning with that token. And if the entity is followed by more tokens, they take **I-** tags, which stand for **INSIDE**. An example of a **IOB2** format is illustrated in Table 3.

| Tokens                        | IOB2 tags |
|-------------------------------|-----------|
| Sergen                        | B-PERSON |
| Yalcın                        | I-PERSON |
| Beşiktaş                      | B-ORGANIZATION |
| ta                            | O         |
| kaldı                         | O         |
| Bölent                       | B-PERSON |
| Uslu                         | I-PERSON |
| çarpci                       | O         |
| değerlendirmelerde           | O         |
| bulundu                      | O         |

Table 3: Example of the IOB2 format

### 4. Named Entity Recognition Model

In this section, we present our baseline NER models built with our Twitter dataset described in Section 3.

#### 4.1. Experimental Setup

Firstly, we replaced the URL links with **$URL** special token, as they do not add any knowledge to the context of tweets. In addition, **@USER** token was used instead of mentions in the tweets in order to ensure privacy. Using these specific tokens is also useful for modeling since the tokenizers of the pretrained models we use, probably do not know the representation of these words anyway. We conducted our experiments on validation and test sets, each consisting of 750 randomly selected tweets. The remaining 3,500 tweets were used for training. The results were reported with Precision, Recall, and F1 metrics computed for the entire NE spans.

#### 4.2. Models

Since transformer-based pre-trained models outperform in a variety of NLP tasks and datasets, we investigated variations of these models as a baseline in this paper.

BERTurk, BERT_loodos⁴ and ALBERT_loodos⁵ transformer models which were pretrained on Turkish corpora were used. Similarly, various multilingual models mBERT⁶ and XLM-RoBERTa⁷ were applied to our task.

For the Turkish models, the type of text utilized during pretraining is different. While the BERTurk model was pre-trained on the Turkish Wikipedia dump, the OSCAR⁷ and the OPUS⁸ datasets, which contain fewer spelling and grammatical errors, the data used in Loodos’ training includes informal text such as Twitter and online blogs. The same corpora were utilized in the training of both BERT_loodos and ALBERT_loodos as well.

All the BERT models listed above are base models, and each feed-forward layer has 12 encoder layers and 768 hidden units. The XLM-RoBERTa model consists of 24 layers and 1024 hidden units.

#### 4.3. Experiments and Results

The results obtained on the test and validation sets are summarized in Table 4. As shown in the table, all models pretrained on Turkish except for ALBERT gave better results than the multilingual models, as expected. Among the Turkish BERT models, BERT_loodos consistently outperforms other models in both validation and test sets. This shows the positive impact of texts’ domain in the pretraining phase of these large LM models.

In order to observe the effect of the training set on performance clearly, we trained the BERT models on (Tür et al., 2003) since it is the only available dataset and has enough instances to perform training. Scores are presented in Table 5. In the test data set, our results were calculated over the PERSON, LOCATION, and ORGANIZATION tags because only these three NE types were labeled in the (Tür et al., 2003). As expected, the models that were trained using our training set outperformed the models trained on (Tür et al., 2003). Even though (Tür et al., 2003) dataset is a larger one, it is comprised of properly written media articles, and the sources utilized were from the years 1997-1998, which are somewhat ancient. Among the BERT models trained with our data, BERT_loodos again achieved better scores than the other model across all metrics. We also explored the performance of models for each named entity category. The scores are listed in Table 6. Not surprisingly, BERT_loodos outperformed in all classes except for PRODUCT. In this category, multilingual models achieved a better result. Since non-Turkish songs and foreign products are popular in dif-

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⁴https://github.com/Loodos/turkish-language-models
⁵https://huggingface.co/bert-base-multilingual-cased
⁶https://huggingface.co/xlm-roberta-base
⁷https://oscar-corpus.com/
⁸https://opus.nlpl.eu/
Table 4: Results of Transformer-based Models on Validation and Test Sets.

| Model                  | Val Set Recall | Test Set Recall | Val Set Precision | Test Set Precision | Val Set F1 Score | Test Set F1 Score |
|------------------------|----------------|-----------------|-------------------|--------------------|------------------|-------------------|
| BERTurk                | 84.31          | 85.02           | 80.24             | 78.63              | 83.12            | 81.37             |
| BERT_loodos            | 84.99          | 80.00           | 83.56             | 84.49              | 84.27            | 82.18             |
| ALBERT_loodos          | 71.81          | 74.05           | 74.73             | 69.80              | 73.24            | 71.86             |
| mBERT                  | 78.95          | 76.61           | 74.15             | 73.41              | 76.48            | 74.98             |
| XLM-RoBERTa           | 81.39          | 82.76           | 77.42             | 73.89              | 82.76            | 79.36             |

Table 5: Comparison of Formal and Informal Dataset on Person, Location, and Organization.

| NE Class       | BERTurk | BERT_loodos | ALBERT_loodos | mBERT | XLM-RoBERTa |
|----------------|---------|-------------|--------------|-------|-------------|
| PERSON         | 0.87    | 0.88        | 0.78         | 0.80  | 0.83        |
| LOCATION       | 0.77    | 0.81        | 0.64         | 0.64  | 0.67        |
| ORGANIZATION   | 0.77    | 0.80        | 0.72         | 0.72  | 0.75        |
| TIME           | 0.89    | 0.90        | 0.83         | 0.86  | 0.88        |
| PRODUCT        | 0.32    | 0.37        | 0.43         | 0.52  | 0.46        |
| TV-SHOW        | 0.49    | 0.57        | 0.35         | 0.52  | 0.49        |
| MONEY          | 0.88    | 0.93        | 0.88         | 0.75  | 0.85        |

Table 6: F1 Score on Test Set for Each NE

5. Conclusion

In this paper, we introduced and made publicly available a new Twitter dataset for NER with high agreement scores in Turkish. Besides the common NE types, we also included new categories, PRODUCT, and TV-SHOW. We obtained initial scores with various transformer-based models on our validation and test sets. A BERT model pre-trained on a blend of formal and informal texts yielded the highest score. Besides, on the validation and test sets, we compared our training set with (Tür et al., 2003), which is the most studied data set in the literature. Models that used our training set during the fine-tuning phase achieved significantly higher scores than other models.

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