Use of Machine Translation to Obtain Labeled Datasets for Resource-Constrained Languages

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Abstract
The large annotated datasets in NLP are overwhelmingly in English. This is an obstacle to progress for other languages. Unfortunately, obtaining new annotated resources for each task in each language would be prohibitively expensive. At the same time, commercial machine translation systems are now robust. Can we leverage these systems to translate English-language datasets automatically? In this paper, we offer a positive response to this for natural language inference (NLI) in Turkish. We translated two large English NLI datasets into Turkish and had a team of experts validate their quality. As examples of the new issues that these datasets help us address, we assess the value of Turkish-specific embeddings and the importance of morphological parsing for developing robust Turkish NLI models.

1 Introduction
Many tasks in natural language processing have been transformed in recent years by the introduction of very large annotated datasets. Prominent examples include paraphrase (Ganitkevitch et al., 2013), parsing (Nivre et al., 2016), question answering (Rajpurkar et al., 2016), machine translation (MT; Bojar et al., 2014), and natural language inference (NLI; Bowman et al., 2015; Williams et al., 2018a).

Unfortunately, outside of parsing and MT, these datasets tend to be in English. This is not only an obstacle to progress on other languages, but it also limits the field of NLP itself: English is generally not a representative example of the world’s languages when it comes to morphology, syntax, or spelling conventions and other kinds of standardization (Munro, 2012), so it’s risky to assume that models and results for English will generalize to other languages.

A natural response to these gaps in our dataset coverage might be to launch new annotation efforts for multiple languages. However, this would likely be prohibitively expensive. For example, based on the costs of SNLI (Bowman et al., 2015) and MultiNLI (Williams et al., 2018a), we estimate that each large dataset for NLI would cost upwards of US $50,000 if created completely from scratch.

At the same time, commercial MT systems have improved dramatically in recent years. They now offer high-quality translations between hundreds of language pairs. This raises the question: can we use these MT systems to translate English-language datasets and use the translated versions to drive more genuinely multilingual development in NLP?

In this paper, we offer evidence that the answer to this question is “yes”. Using Amazon Translate, we translated SNLI and MultiNLI from English into Turkish, at a tiny fraction of the cost of creating new Turkish NLI datasets from scratch. Turkish is an interesting challenge case in this context, since it is very different from English, most notably in its complex morphology and very free word order. This is likely to stress-test English-to-Turkish MT systems and also present new challenges for NLI. We refer to these datasets collectively as NLI-TR.

In our validation phase (Section 3), a team of Turkish–English bilingual speakers assessed the quality of a large sample of the translations in NLI-TR. They found the quality to be very high, which suggests that these translated datasets can provide a foundation for NLI work in Turkish.

As an example of the new issues in NLI that these translations help us to address, we consider the role of pretraining and morphological parsing in successful NLI systems for Turkish (Section 4). For these experiments, we fit classifiers on top of pretrained BERT parameters (Devlin et al., 2019). This allows us to compare the original BERT-base release, the multilingual BERT embeddings released by the BERT team, and the Turkish BERT (BERTurk) embeddings of Schweter (2020). We
find that the BERTurk embeddings are superior to the others for NLI-TR.

We then assess the use of two morphological parsers for Turkish as preprocessing steps: Zem-berek (Akın and Akın, 2007) and Turkish Morphology (Ozturk et al., 2019). We find that the parsers help where training data is sparse, but the need for a parser disappears as the training data increases. This is a striking finding: one might have thought that Turkish would require morphological parsing given its complex word-formation processes. It might be regarded as welcome news, though, since the parsers are expensive to run. In Section 4.2, we report on some new optimizations of existing tools to make the relevant parsing jobs feasible, but we would still like to avoid these steps if possible, and it seems that we can for NLI.

2 Related Work

Early in the development of textual entailment tasks, Mehdad et al. (2010) argued for multilingual versions of them. This led to subsequent explo-
Rations of a variety of techniques, including crowdsourcing translations (Negri and Mehdad, 2010; Negri et al., 2011), relying on parallel corpora to support reasoning across languages (Mehdad et al., 2011), and automatically translating datasets using MT systems (Mehdad et al., 2010). This research informed SemEval tasks in 2012 (Negri et al., 2012) and 2013 (Negri et al., 2013) exploring the viability of multilingual NLI. From the perspective of present-day NLI models, these datasets are very small, but they could be used productively as challenge problems.

More recently, Conneau et al. (2018) reinvig-
Orated work on multilingual NLI with their XNLI dataset. XNLI provides expert-translated evaluation sets from English into 14 other languages, including Turkish. These are valuable resources for pushing NLI research beyond English. How-
Ever, having test sets doesn’t support direct training on target language data, which is likely to lead to lower overall performance for the resulting systems than we would expect from in-language training.

Although it was not the main focus of the XNLI effort, Conneau et al. distributed translations of MultiNLI into other languages, including Turk-
Ish. This helped them form a strong baseline for their cross-lingual models, which proved superior in their assessments. However, the quality of the translation system plays a crucial here, as the au-
Thors note. Our hope for NLI-TR is that it supports effective in-language training.

XNLI’s primary focus on test sets rather than training is justified by a wide body of recent results on cross-lingual transfer learning. Multilingual embeddings (embeddings trained on multilingual corpora) have played an important role in these develop-
ments. The BERT team (Devlin et al., 2018) released multilingual embeddings and demonstrated their value using XNLI. At the same time, BERT models have been released for a variety of individual languages (see Wolf et al., 2019) and specialized domains (Alsentzer et al., 2019; Lee et al., 2020). While we might expect the language- and domain-specific embeddings to be superior for the kind of data they were trained on, the multilin-
Gual versions might be more efficient in large-scale deployments in diverse environments. Balancing these trade-offs is challenging. Here, we offer some insight into these trade-offs for Turkish.

Turkish is a morphologically-rich language in which new word forms are freely created using suffixation. A word in Turkish bears morpho-syntactic properties in the sense that phrases formed of several words in languages like English can be expressed with a single word form. Several mor-
Phological parsers (Akın and Akın, 2007; Ozturk et al., 2019; Sak et al., 2009) and morphological dis-
Ambiguation systems (Sak et al., 2011) have been developed for Turkish. The state-of-the-art morph-
ological analyzers can parse with success rates around 95%. We use two of these parsers in this work to evaluate the role of morphology on NLI systems (Section 4.2).

3 Creating and Validating NLI-TR

3.1 English NLI Datasets

We translated the Stanford Natural Language Inference Corpus (SNLI; Bowman et al., 2015) and the Multi-Genre Natural Language Inference Corpus (MultiNLI; Williams et al., 2018b) to create labeled NLI datasets for Turkish, NLI-TR.

SNLI contains ≈570K semantically related En-
Glish sentence pairs. The semantic relations are entailment, contradiction, and neutral. The premise sentences for SNLI are image captions from the Flickr30K corpus (Young et al., 2014), and the hypothesis sentences were written by crowdworkers. SNLI texts are mostly short and structurally simple. We translated SNLI while respecting the train, development (dev), and test splits.
Table 1: Comparative statistics for the English and Turkish NLI datasets. The Turkish translations have larger vocabularies and lower token counts due to the highly agglutinating morphology of Turkish as compared to English.

| Dataset   | Fold       | Token Count | Vocab Size (Cased) | Vocab Size (Uncased) | Token Count | Vocab Size (Cased) | Vocab Size (Uncased) |
|-----------|------------|-------------|--------------------|----------------------|-------------|--------------------|----------------------|
| SNLI      | Train      | 5900366     | 38565              | 32696                | 4298138     | 78786              | 66599                |
|           | Dev        | 120900      | 6664               | 6224                 | 88668       | 11455              | 10176                |
|           | Test       | 120776      | 6811               | 6340                 | 88533       | 11547              | 10259                |
| MultiNLI  | Train      | 6356136     | 81937              | 66082                | 4397213     | 216590             | 187053               |
|           | Matched Dev| 161152      | 14493              | 12659                | 112192      | 27554              | 24872                |
|           | Mismatched Dev| 170692    | 12847              | 11264                | 119691      | 26326              | 23941                |

MultiNLI comprises \( \approx 433K \) sentence pairs in English, and the pairs have the same semantic relations as SNLI. However, MultiNLI spans a wider range of genres, including travel guides, fiction and non-fiction texts, dialogue, and journalism. As a result, the texts are generally more complex than SNLI. In addition, MultiNLI contains matched and mismatched dev and test sets, where the sentences in the former set are from the same sources as the training set, whereas the latter consists of texts from different genres than those found in the training set. We translated the training set and both dev sets for NLI-TR.

### 3.2 Automatic Translation Effort

As we noted in Section 1, Turkish is a resource-constrained language with few labeled datasets compared to English. Furthermore, Turkish has a fundamentally different grammar from English that could hinder transfer-learning approaches. These facts motivate our effort to translate SNLI and MultiNLI from English to Turkish. We employ an automatic MT system for this in the hope that it will deliver sufficiently high-quality translations that we can use the resulting dataset for NLI research and system development in Turkish.

We used Amazon Translate, a commercial neural machine translation service. Translation of all folds of SNLI and MultiNLI cost just US $2K (vs. the \( \approx \text{US} \) $100K we would expect for replicating these two datasets from scratch). We refer to the translated datasets as SNLI-TR and MultiNLI-TR, and collectively as NLI-TR. Table 2 shows translation examples from both datasets.

SNLI-TR and MultiNLI-TR are different from SNLI and MultiNLI in terms of token counts and vocabulary sizes. Table 1 illustrates these features before and after translation. For each fold in each dataset, translation decreased the number of tokens in the corpus, but it increased the vocabulary sizes drastically, in both the cased and uncased versions. Both these differences are expected: the agglutinating nature of Turkish means that many multi-word expressions in English naturally translate into individual words. For instance, the four-word English expression “when in your apartment” can be translated to the single word “evinizdeyken”.

Table 1 also reflects the complexity difference between SNLI and MultiNLI that we noted in Section 3.1. Though SNLI contains more sentence pairs than MultiNLI, it has fewer tokens and a smaller vocabulary.

### 3.3 Translation Quality Assurance

Two major risks arise when using MT systems to translate NLI datasets. First, the translation quality might simply be poor. Second, even if the individual sentences are translated correctly, the nature of the mapping from the source to the target language might affect the semantic relations between sentences. For example, English has the words “boy” and “girl” to refer male and female children, and both those words can be translated to a gender-neutral Turkish word “cocuk”. Now, consider a premise sentence “A boy is running” and its contradiction pair “A girl is running”. Both sentences can be translated fluently into the same Turkish sentence, “Cocuk kouyor”, which changes the semantic relation from contradiction to entailment.

Thus, to determine the viability of NLI-TR as a tool for NLI research, we must assess both translation quality and the consistency of the NLI labels. To do this, we assembled a team of ten Turkish–English bilingual speakers who were familiar with the NLI task and were either MSc. candidates or graduates in a relevant field.

For our expert evaluation, we focused initially on SNLI-TR. We grouped the translations into ex-
| SNLI | English | Turkish |
|------|---------|---------|
| Premise | Three men are sitting near an orange building with blue trim. | Üç adam mavi süslemeli turuncu bir binanın yanında oturuyor. |
| Entailment | Three males are seated near an orange building with blue trim. | Üç erkek mavi süsülü turuncu bir binanın yakınında oturuyor. |
| Contradiction | Three women are standing near a yellow building with red trim. | Üç kadın kırmızı süslemeli sarı bir binanın yanında duruyor. |
| Neutral | Three males are seated near an orange house with blue trim and a blue roof. | Üç erkek mavi süsülü ve mavi çatılı turuncu bir evin yakınında oturuyor. |

| MultiNLI | English | Turkish |
|----------|---------|---------|
| Premise | All rooms have color TV, alarm clock/radio, en-suite bathrooms, real hangers, and shower massage. | Tüm odalarda renkli TV, çalar saat/radyo, en-suite banyo, gerçek askılar ve duş masajı vardır. |
| Entailment | All rooms also contain a ceiling fan and outlets for electronics. | Tüm odalarda ayrıca tavan vanti-latörü ve elektronik prizler bulunmaktadır. |
| Contradiction | You will not find a TV or alarm clock in any of the rooms. | Odaların hiçbirinde TV veya çalar saat bulunmamaktadır. |
| Neutral | Color TVs, alarms, and hangers can be found in all rooms. | Tüm odalarda renkli TV’ler, alarmlar ve askılar bulunur. |

Table 2: Sample translations from SNLI and MultiNLI into NLI-TR. Each premise is associated with a hypothesis from each of the three NLI categories.

ample sets of 4 sentences as in Table 2, where the first sentence (premise) is semantically related to the rest (hypotheses). We distributed the sets to the experts so that each set was examined by 5 randomly chosen experts and each expert co-examined approximately the same number of sets with each other expert. Each expert evaluated the translation by (i) grading the translation quality between 1 and 5 (inclusive; 5 the best) and (ii) checking if the semantic relation was altered by the translation. In total, 250 example sets (1000 translated sentences) were examined.

Table 3 reports the average quality grade and percentage of preserved semantic relations for each SNLI dataset split. These results are extremely reassuring: average translation quality is near 5 (ceiling) for all the splits, and label consistency is similarly very high. Our comparable effort for MultiNLI-TR is ongoing, but so far the results look equally strong for those translations.

To assess the reliability of the translation quality scores, we calculated the Intra-Class Correlation (ICC; McGraw and Wong 1996). ICC is frequently adopted in medical studies to assess ordinal annotations provided by randomly chosen experts drawn from a team. Its assumptions align well with our evaluation scheme. We obtained an ICC of 0.9083, which suggests excellent agreement (Cicchetti, 1994; Hallgren, 2012).

We also computed Krippendorff’s alpha (Krippendorff, 1970), which is an inter-annotator agreement metric used more commonly in NLP. This metric is suitable for both nominal and ordinal annotations involving multiple annotators. We calculate intercoder reliability of the ordinally-scaled translation quality score as 0.61, and our label consistency annotations yielded a score of 0.75. These values suggest less overall agreement than our ICC values do, but they are still acceptable, and ICC is arguably the more appropriate metric for our study. Krippendorff’s alpha is generally used for large, diverse annotation teams, and its penalties for disagreements are known to be harsh.

Overall, then, it seems that we can trust our estimates of translation quality and label consistency, both of which are very high, thereby justifying further research using NLI-TR.

4 Experiments

To the best of our knowledge, NLI-TR is the first large NLI dataset in Turkish. Here, we report on case studies analyzing the effect of pretraining and
of morphological parsing on Turkish NLI systems. We offer these initial experiments largely to show that NLI-TR is a valuable resource.

4.1 Case Study I: Comparing BERT models on Turkish NLI Datasets

The arrival of pretrained model-sharing hubs (e.g., Tensorflow Hub,\textsuperscript{1} PyTorch Hub,\textsuperscript{2} and Hugging Face Hub\textsuperscript{3}) has democratized access to Transformer-based models (Vaswani et al., 2017), which are mostly in English. Combined with the abundance of labeled English datasets for fine-tuning, this has increased the performance gap between English and resource-constrained languages.

Here, we use NLI-TR to analyze the effects of pretraining Transformer-based models. We compare three BERT models trained on different corpora and fine-tune them using NLI-TR. The results help quantify the importance of having high-quality, language-specific resources.

4.1.1 Experimental Settings

We compared BERT-English (BERT-EN), BERT-Multilingual, and BERTurk (Schweter, 2020). BERT-EN is the original BERT-base model released by Devlin et al. (2018), which used an English-only corpus for training. BERT-Multilingual was released by the BERT team as well, and was trained on a corpus containing texts from 104 languages, including Turkish. Schweter’s BERTurk also uses the same model architecture and is trained on a Turkish corpus (\approx 30GB). We assess cased and uncased versions of each model.

We fine-tuned each model on train folds of NLI-TR separately and fixed the maximum sequence length to 128 for all experiments. Similarly, we used a common learning rate of $2 \times 10^{-5}$ and batch size of 8 with no gradient accumulation. We fine-tuned each model for 3 epochs using Hugging Face’s Transformers Library (Wolf et al., 2019). We evaluated the models on the test set of SNLI-TR and the \textit{matched} and \textit{mismatched} dev splits of MultiNLI-TR. Table 4 reports the accuracy of each model on the evaluation sets.

4.1.2 Results

Table 4 demonstrates that NLI-TR can be used to train very high quality Turkish NLI models. We observe that every model performed better on the test fold of SNLI-TR than the dev folds of MultiNLI-TR, which is an expected outcome given the greater complexity of MultiNLI compared to SNLI. The translation effort seems to have preserved this fundamental difference between the two datasets.

In addition, BERTurk (Cased), which was trained on a Turkish corpus, achieved the highest accuracy, and BERT-Multilingual (Cased), which utilized a smaller Turkish corpus, was ranked the second, consistently on every evaluation fold. The ranking emphasizes the importance of having a Turkish corpus for pretraining. Finally, every cased model outperformed its uncased counterpart, suggesting that casing provides valuable information to models for NLI in general.

4.2 Case Study II: Comparing Morphological Parsers on Turkish NLI Datasets

Turkish is an agglutinating language in which suffixes are commonly cascaded to create new words. This makes morphological parsing crucial for many applications. In this case study, we evaluate the effect of such morphological analysis by comparing three models with different morphological approaches on NLI-TR. We train a BERT model from scratch utilizing each approach for pretraining from Section 4.1 and used NLI-TR for fine-tuning. This leads to the striking result that morphology adds additional information where data is sparse, but its importance shrinks as the dataset grows larger.

| Split   | Translation Quality | Label Consistency |
|---------|---------------------|-------------------|
| Train   | 4.56 (0.78)         | 89.40%            |
| Dev     | 4.46 (0.90)         | 90.00%            |
| Test    | 4.45 (0.86)         | 81.90%            |
| All     | 4.46 (0.88)         | 85.95%            |

Table 3: Translation quality and label consistency of the translations in SNLI-TR based on expert judgements. For the quality ratings (1–5), we report mean and standard deviation (in parentheses). For label consistency, we report the percentage of SNLI-TR labels judged consistent with the original label.

\textsuperscript{1}https://github.com/tensorflow/hub
\textsuperscript{2}https://pytorch.org/hub
\textsuperscript{3}https://huggingface.co/models
Table 4: Accuracy results for the publicly available BERT models on NLI-TR. The cased BERTurk model performed the best in all three evaluations, highlighting the value of language-specific resources for NLI.

4.2.1 Experimental Settings

Morphological Parsers We used Zemberek (Akın and Akın, 2007) and Turkish Morphology (Oztürel et al., 2019) as parsers and compared them with an approach that does not apply morphological parsing.

Zemberek is a mainstream Turkish NLP library used in research (Büyük, 2020; Kuyumcu et al., 2019; Özter et al., 2018; Can, 2017; Dehkharghani et al., 2016; Gulcehre et al., 2015) and applications such as iOS 12.2 and Open Office. It has 67,755 entries in its lexicon and uses a rule-based parser.

Turkish Morphology is an OpenFST-based (Allauzen et al., 2007) morphological parser that was recently released by Google Research. Its lexicon contains 47,202 entries.

Out of the box, Zemberek can parse 23K tokens per minute, whereas Turkish Morphology can process only 53. We sped up Turkish Morphology to parse 11 times more tokens per minute by implementing a dynamic programming wrapper (Bellman, 1953) that increased the cache hit ratio to 89.9%. This technique is used by Zemberek already.

Pretraining We wanted to conduct a wide range of experiments on a limited budget. Thus, we opted to use one-tenth (≈3GB) of the Turkish corpus used by BERTurk (Schweter, 2020) to pretrain all the BERT models. We split the dataset into 30 equal shards for parallel processing, where each shard comprises 1M sentences. We analyzed each token morphologically using Zemberek and Turkish Morphology and trained a BERT model using the stems of the tokens only. For the model that does not utilize morphological information, we used tokens as they are. We used the BertWordPieceTokenizer class of HuggingFace Tokenizers4 with the same set of parameters for each model.

We trained each model on a single Tesla V100 GPU of NVIDIA DGX-1 system, allocating 128GB memory for 1 day. We used an effective batch size of 128 with gradient accumulation to address memory limitations. We shuffled all shards prior to training to reduce the adverse effects of variance across the sentence styles in the different shards (Goodfellow et al., 2016).

Finetuning We fine-tuned each model on NLI-TR with the same setting as in Section 4.1, with the exception that we trained for only 1 epoch. We measured the accuracy on the evaluation sets with an interval of 1000 training steps to observe the effect of morphological parsing as the dataset grew. Figure 1 reports the accuracy of all models with respect to fine-tuning steps on NLI-TR evaluation sets, and Table 5 shows final accuracy numbers.

4.2.2 Results

Figure 1 suggests that morphological parsing is beneficial where the training set is small, but that its importance largely disappears for large training sets. This is reflected also in the final results in Table 5. We conjecture that this unexpected result traces to the fact that the models under consideration create contextual embeddings of both word and subword tokens (Kudo, 2018; Kudo and Richardson, 2018; Sennrich et al., 2016). Given a sufficiently large dataset, it might be that this can approximate the effects of morphological parsing.

The trends are not uniform for SNLI-TR and MultiNLI-TR. For SNLI-TR, all three models display a similar learning curve, with only a slight

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4https://github.com/huggingface/tokenizers
Table 5: Accuracy results for different morphology approaches on NLI-TR. To facilitate running many experiments, these results are for pretraining on just one-tenth of the Turkish corpus used by BERTurk and fine-tuning on NLI-TR for just one epoch.

|                | Test  | Matched Dev | Mismatched Dev |
|----------------|-------|-------------|----------------|
| No Parser      | 76.59%| 58.24%      | 60.01%         |
| Zemberek       | 76.71%| 59.01%      | 60.44%         |
| Turkish Morphology | 76.36% | 60.13%      | 62.00%         |

Figure 1: Dev-set accuracy for the two morphological parsers and a model without morphological parsing. The x-axis tracks the size of the training set. We find that morphological parsing is generally helpful in early rounds, when the training set is very small, but that its importance diminishes as the training set increases. These effects are especially clear for the two MultiNLI-TR dev sets.
edge for Zemberek early on. For MultiNLI-TR, models with morphological parsers are more differentiated. However, all three models converge to similar performance at the end of training on both datasets (Table 5).

In light of these findings, we suggest avoiding the use of morphological parsers for Turkish NLI where the training set is large, since the benefits of such parsers are generally not enough to offset the cost of running them.

5 Conclusion

In this study, we propose a cost- and time-efficient approach to obtaining labeled datasets in resource-constrained languages: machine translation. We machine-translated SNLI and MultiNLI to create the first full NLI dataset of Turkish, NLI-TR. Though English to Turkish translation is a stress-test for MT systems due to the different linguistic structures of the two languages, a team of experts validated the quality and consistency of the translations, suggesting that NLI-TR can in fact help address the paucity of datasets for Turkish NLI.

As two illustrative case studies, we used NLI-TR to analyze the effects of in-language pretraining and morphological analysis on NLI performance. We observed that a Turkish-only pretraining regime can enhance Turkish models significantly, and that morphology is arguably worthwhile only when the training dataset is small. We propose that MT be more widely adopted for advancing NLP studies on resource-constrained languages. MT can efficiently transfer large and expensive-to-create labeled datasets from English to other languages in many NLP tasks. And, last but not least, MT will only get cheaper, faster, and better over time, thereby further strengthening our core claims.

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