Annotating the Tweebank Corpus on Named Entity Recognition and Building NLP Models for Social Media Analysis

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Abstract
Social media data such as Twitter messages ("tweets") pose a particular challenge to NLP systems because of their short, noisy, and colloquial nature. Tasks such as Named Entity Recognition (NER) and syntactic parsing require highly domain-matched training data for good performance. To date, there is no complete training corpus for both NER and syntactic analysis (e.g., part of speech tagging, dependency parsing) of tweets. While there are some publicly available annotated NLP datasets of tweets, they are only designed for individual tasks. In this study, we aim to create Tweebank-NER, an English NER corpus based on TweeboParser on Tweebank V1, train state-of-the-art (SOTA) Tweet NLP models on TB2, and release an NLP pipeline called Twitter-Stanza. We annotate named entities in TB2 using Amazon Mechanical Turk and measure the quality of our annotations. We train the Stanza pipeline on TB2 and compare with alternative NLP frameworks (e.g., FLAIR, spaCy) and transformer-based models. The Stanza tokenizer and lemmatizer achieve SOTA performance on TB2, while the Stanza NER tagger, part-of-speech (POS) tagger, and dependency parser achieve competitive performance against non-transformer models. The transformer-based models establish a strong baseline in Tweebank-NER and achieve the new SOTA performance in POS tagging and dependency parsing on TB2. We release the dataset and make both the Stanza pipeline and BERTweet-based models available "off-the-shelf" for use in future Tweet NLP research. Our source code, data, and pre-trained models are available at: https://github.com/social-machines/TweeboNLP

Keywords: text annotation, noisy text, NLP toolkit, Twitter, named entity recognition, tokenization, lemmatization, part-of-speech tagging, dependency parsing

1. Introduction
Researchers use text data from social media platforms such as Twitter and Reddit for a wide range of studies including opinion mining, socio-cultural analysis, and language variation. Messages posted to such platforms are typically written in a less formal style than what are found in conventional data sources for NLP models, namely news articles, papers, websites, and books. Processing the noisy and informal language of social media is challenging for traditional NLP tools because such messages are usually short in length and irregular in spelling and structure. In response, the NLP community has been constructing language resources and building NLP pipelines for social media data, especially for Twitter.
Annotating social media language resources is important to the development of NLP tools. Foster et al. (2011) is the one of the earliest attempts to annotate tweets in the Penn Treebank (PTB) format. Following a similar PTB-style convention suggested by Schneider et al. (2013), Kong et al. (2014) created TweeboParser on Tweebank V1. However, the PTB annotation guidelines leave many annotation decisions unspecified and are therefore unsuitable for informal and user-generated text. After Universal Dependencies (UD) (Nivre et al., 2016) was introduced to enable consistent annotation across different languages and genera...
in POS tagging and NER is based on BERT pre-trained on a large number of tweets [Nguyen et al. (2020). However, these efforts (1) are often no longer main-
tained (Ritter et al., 2011; Kong et al., 2014), (2) do not contain publicly available NLP models (e.g., NER, POS tagger) (Nguyen et al., 2020), (3) are written in C/C++ or R with complicated dependencies and instal-
lation process (e.g., Twpipe (Liu et al., 2018) and UD-
Pipe (Straka et al., 2016)), making them difficult to be
integrated into Python frameworks and to be used in an “off-the-shelf” fashion. Many modern NLP tools
in Python such as spaCy 1, Stanza (Qi et al., 2020),
and FLAIR (Akbik et al., 2019) have been developed
for standard NLP benchmarks but have never been
adapted to Tweet NLP tasks. In this study, we choose
Stanza over other NLP frameworks because (1) the
Stanza framework achieves SOTA or competitive per-
formance on many NLP tasks across 66 languages (Qi
et al., 2020), (2) Stanza supports both CPU and GPU
training and inference while transformer-based models
(e.g., BERTweet) need GPU, (3) Stanza shows superior
performance against spaCy in our experiments despite
slower speeds, (4) Stanza is competitive in speed com-
pared with FLAIR of similar accuracy (Qi et al., 2020),
but the FLAIR dependency parser is still under develop-
ment.

In this paper, we annotate Tweebank V2 on NER to cre-
ate Tweebank-NER and also build Tweet NLP mod-
els based on Stanza and transformer models. We run
additional experiments to answer the following ques-
tions: (1) How is the quality of the NER annota-
tions? (2) Do NER models trained on existing Twitter
NER data perform well on Tweebank-NER? (3) How
do Stanza models perform compared with other NLP
frameworks on the core Tweet NLP tasks? (4) How do
transformer-based models perform compared with tra-
ditional models on these tasks? Our contributions are
as follows:

• We annotate Tweebank V2, the main treebank
for English Twitter NLP tasks, on NER. This
annotation not only provides a new benchmark
(Tweebank-NER) for Twitter NER but also
makes Tweebank a complete dataset for both syn-
tactic tasks and NER, making it suitable for train-
ning multi-task learning models in POS tagging,
dependency parsing, and NER.

• We leverage the Stanza framework to present an
accurate and fast Tweet NLP pipeline called
Twitter-Stanza. It includes NER, tokeniza-
tion, lemmatization, POS tagging, and depen-
dency parsing modules, and it supports both CPU
and GPU computation.

• We compare Twitter-Stanza against existing
models for each presented NLP task, con-
firming that Stanza’s simple neural architecture
is effective and suitable for tweets. Among non-
transformer models, the Twitter-Stanza token-
er and lemmatizer achieve SOTA performance
on TB2, and its POS tagger, dependency parser,
and NER model obtain competitive performance.

• We also train transformer-based models to estab-
lish a strong baseline on the Tweebank-NER
benchmark and SOTA performance in POS tag-
ging and dependency parsing on TB2. We up-
load the BERTweet-based NER and POS tag-
gers to the Hugging Face Hub: https://
huggingface.co/TweebankNLP

• We release our data, models, and code. Our
Twitter-Stanza pipeline is highly compat-
ible with Stanza’s Python interface and is simple
to use in an “off-the-shelf” fashion. We hope
that our Twitter-Stanza and Hugging Face
BERTweet models can serve as a convenient NLP
tool and a strong baseline for future research and
applications of Tweet analytic tasks.

2. Dataset and Annotation Scheme
In this study, we primarily work on the Tweebank V2
dataset and develop its NER annotations through rigor-
ous annotation guidelines. We also evaluate the quality
of our annotations, showing that it has a good F1 inter-
annotator agreement score.

2.1. Datasets and Annotation Statistics

| Dataset     | Train | Dev  | Test |
|-------------|-------|------|------|
| Tweets      | 1,639 | 710  | 1,201|
| Tokens      | 24,753| 11,742|19,112|
| Avg. token per tweet | 15.1  | 16.6 | 15.9 |
| Annotated spans | 979   | 425  | 750  |
| Annotated tokens | 1,484 | 675  | 1183 |
| Avg. token per span | 1.5   | 1.6  | 1.6  |

Table 1: Annotated corpus statistics.

2.2. Annotation Guidelines
We follow the CoNLL 2003 guidelines 2 to annotate
targeted entities. We are aware that some NER anno-
tations (e.g., English OntoNotes) have more than four
classes. We adopt the standard four-class CoNLL 2003
NER guidelines for two reasons. One on hand, adopt-
ing a more fine-grained annotation scheme is more
challenging for human annotators. The 4-class scheme

https://spacy.io/
is already quite challenging for humans since the inter-annotator agreement is low for the MISC class. On the other hand, Tweebank is relatively small, with only 3,550 tweets. An annotation scheme with more classes than that will mean fewer instances per class, and greater difficulty for NER models to learn efficiently. To help annotators understand the guidelines, we provide multiple examples for each rule and ask annotators to read them before the task. Our task focuses on the following four named entities:

- **PER:** persons (e.g., Joe Biden, joe biden, Ben, 50 Cent, Jesus)
- **ORG:** organizations (e.g., Stanford University, stanford, IBM, Black Lives Matter, WHO, Boston Red Sox, Science Magazine, NYT)
- **LOC:** locations (e.g., United States, usa, China, Boston, Bay Area, CA, MT Washington)
- **MISC:** named entities which do not belong to the previous three. (e.g., Chinese, chinese, World Cup 2002, Democrat, Just Do It, Top 10, Titanic, The Shining, All You Need Is Love)

To handle challenges in tweets, we also add requirements consistent with (Ritter et al., 2011): (1) ignore numerical entities (MONEY, NUMBER, ORDINAL, PERCENT), (2) ignore temporal entities (DATE, TIME, DURATION, SET), (3) "At mentions" are not named entities (e.g., allow “Donald Trump” but not @DonaldTrump), (4) #hashtags are not named entities (e.g., allow “BLM” but not “#BLM”), (5) URLs are not named entities (e.g., disallow https://www.google.com/).

### 2.3. Annotation Logistics

We use the Qualtrics platform to design the sequence labeling task and Amazon Mechanical Turk to recruit annotators. We first launch a pilot study, annotate each of the 100 tweets, and discuss tweets with divergent annotations. Based on the pilot study, we develop a series of annotation rules and precautions. During the recruiting process, each annotator is given an overview of annotation conventions and our guidelines, after which they are asked to complete the qualification test. We consider a significant error to be one in which any URL, @USER, or hashtag is labeled as a named entity; or one in which the PERSON, LOCATION, and ORG categories are confused with each other.

After all tweets have been annotated by at least 3 annotators, we merge the annotation results and create the Tweebank-NER dataset in the BIO format (Ratinov and Roth, 2009). In the merging process, if at least two annotators give the annotation result for a tweet, we use that result as the final annotation. Otherwise, we discuss and re-annotate the tweet to reach a consensus.

We identify 178 span annotations whose three annotations are different from each other and decide their gold annotations collectively by two authors. We find that one of the three annotators’ answers is the same as the final annotation for 155 out of the 178 annotations.

### 2.4. Annotation Quality

We first evaluate the quality of the annotations using a measure of inter-annotator agreement (IAA). For NER, Cohen’s Kappa is not the best measure because it needs the number of negative cases, but NER is a sequence tagging task. Therefore, we follow previous work (Hripcsak and Rothschild, 2005; Grouin et al., 2011; Brandsen et al., 2020) to use the token-level pairwise F1 score calculated without the O label as a better measure for IAA in NER (Deleger et al., 2012). In Table 2 we observe that PER, LOC, and ORG have higher F1 agreement than MISC, showing that MISC is more difficult to annotate than the other classes. We also provide the additional Kappa measure ($\kappa = 0.347$) on annotated tokens to provide some insights, although it significantly underestimates IAA for NER. Finally, we calculate the scores by comparing the crowdsourced annotators against our own internal annotations on 100 sampled examples, obtaining a similar F1 score (0.71).

| Label | Quantity | F1 |
|-------|----------|----|
| PER   | 777      | 84.6 |
| LOC   | 317      | 74.4 |
| ORG   | 541      | 71.9 |
| MISC  | 519      | 50.9 |
| Overall | 2,154   | 70.7 |

Table 2: Number of span annotations per entity type and Inter-annotator agreement scores in pairwise F1.

We analyzed the 178 annotations passed to the merge step, finding that the proportion of each label is 8.4% (LOC), 15.2% (PER), 29.2% (ORG), and 47.2% (MISC). These numbers show that MISC is the most challenging class for human annotators and ORG is also relatively difficult compared to LOC and PER. This confirms the IAA measured in pairwise F1 in Table 2 because the MISC has the lowest F1 (50.9%) and ORG has the second lowest F1 (71.9%).

In the future, we suggest a few ways to improve the annotation quality. The first way is to increase the number annotators per tweet in both the initial and merge stages. Second, hiring a small number of experienced annotators instead of using crowdsourcing platforms will make the annotations more consistent. Third, adopting a human-in-the-loop approach allows annotators to focus on difficult instances from MISC and ORG, which can reduce the cost and improve the performance of the models at the same time.
3. Methods for NLP Modeling

Stanza is a state-of-the-art and efficient framework for many NLP tasks (Qi et al., 2020; Zhang et al., 2021) and it supports both NER and syntactic tasks. We use Stanza to train NER models as well as syntactic models (tokenization, lemmatization, POS tagging, dependency parsing) on TB2. For more detailed information on Stanza, we refer the readers to the Stanza paper (Qi et al., 2020) and its current website [1]. We use Twitter GloVe embeddings (Pennington et al., 2014) with 100 dimensions in our experiments and the default parameters in Stanza for training.

Alternative NLP frameworks such as spaCy, FLAIR, transformers, and spaCy-transformers are compared with Stanza. Both spaCy and FLAIR are open-source NLP frameworks for NER and syntactic tasks. Transformers is a library of pre-trained transformer models for NLP and it provides a TokenClassification module [2] which is adopted for NER and POS tagging. We denote these models as HuggingFace-BERTweet in our experiments. The spaCy-transformers framework provides the spaCy interface to combine pre-trained representations from transformer-based language models and its own NLP models via Hugging Face’s transformers. To train spaCy, we adopt the default NER setting [3] and the default syntactic NLP pipeline [4]. For FLAIR, we train its NER and syntactic modules with the default settings as well. For spaCy-transformers models, we fine-tune BERTweet-base and XLM-RoBERTa-base language models via spaCy-transformers for NER, POS Tagging, and dependency parsing [5]. We denote them as spaCy-BERTweet and spaCy-XLM-RoBERTa in the paper. BERTweet (Nguyen et al., 2020) is the first public large-scale language model for English tweets based on RoBERTa and XLM-RoBERTa-base is a multilingual version of RoBERTa-base. All transformer-based models show strong performance in Tweet NER and POS tagging (Nguyen et al., 2020). The architecture and training details of the models above can be found at our public repository.

3.1. Named Entity Recognition

In this paper, we adopt the four-class convention to define NER as a task to locate and classify named entities mentioned in unstructured text into four predefined categories: PER, ORG, LOC, and MISC (Sang and De Meulder, 2003). We use the Stanza NER architecture for training and evaluation, which is a contextualized string representation-based sequence tagger (Akbik et al., 2018). This model contains a forward and a backward character-level LSTM language model to extract token-level representations and a BiLSTM-CRF sequence labeler to predict the named entities. We also train the default NER models for SpaCy, FLAIR, HuggingFace-BERTweet, and spaCy-BERTweet for comparison.

3.2. Syntactic NLP Tasks

3.2.1. Tokenization

Tokenizers predict whether a given character in a sentence is the end of a token. The Stanza tokenizer jointly works on tokenization and sentence segmentation, by modeling them as a tagging problem over character sequences. In accordance with previous work (Gimpel et al., 2010; Liu et al., 2018), we focus on the performance in tokenization, as tweets are usually short with a single sentence.

To compare with spaCy, we train a spaCy tokenizer named char_pretokenizer.v1. FLAIR uses spaCy’s tokenizer, so we exclude it from comparison. We also include baselines mentioned in previous work (Kong et al., 2014; Liu et al., 2018). Twokenizer (O’Connor et al., 2010) is a regex-based tokenizer and does not adapt to the UD tokenization scheme. Stanford CoreNLP (Manning et al., 2014), spaCy, and UDPipe v1.2 (Straka and Straková, 2017) are three popular NLP frameworks re-trained on TB2. Twpipe tokenizer (Liu et al., 2018) is similar to UDPipe, but replaces GRU in UDPipe with an LSTM and uses a larger hidden unit number. We do not compare with transformer-based models because they use subword-level tokenization schemes like WordPiece (Wu et al., 2016) and BPE (Sennrich et al., 2015).

3.2.2. Lemmatization

Lemmatization is the process of recovering each word in a sentence to its canonical form. We train the Stanza lemmatizer on TB2, which is implemented as an ensemble model of a dictionary-based lemmatizer and a neural seq2seq lemmatizer. We compare the Stanza lemmatizer against three lemmatizers from spaCy, NLTK, and FLAIR (Table 7). Both NLTK and spaCy lemmatizer are rule-based and use a dictionary to look up the canonical form given a word and it POS tag. The FLAIR lemmatizer is a char-level seq2seq model. We provide gold POS tags for lemmatization.

3.2.3. POS Tagging

POS tagging assigns each token in a sentence a POS tag. We train the Stanza POS tagger, a bidirectional long short-term memory network as the basic architecture to predict the universal POS (UPOS) tags. We ignore the language-specific POS (XPOS) tags because TB2 only contains UPOS tags.
We also train the default POS taggers for SpaCy, FLAIR, HuggingFace-BERTweet, spaCy-XLM-RoBERTa. We include performance from existing work in Tweet POS tagging: (1) Stanford CoreNLP tagger, (2) Owoputi et al. (2013)’s word cluster–enhanced greedy tagger, (3) Owoputi et al. (2013)’s word cluster–enhanced tagger with CRF, (4) Ma and Hovy (2016)’s neural tagger, (5) BERTweet-based POS tagger (Nguyen et al., 2020). The first four models were re-trained on the combination of TB2 and UD_English-EWT (Ann Bies, Justin Mott, Colin Warner, Seth Kulick, 2012) training sets, whereas the BERTweet-based tagger was fine-tuned solely on TB2. HuggingFace-BERTweet has the same architecture implementation as Nguyen et al. (2020).

3.2.4. Dependency Parsing
Dependency parsing predicts a syntactic structure for a sentence, where every word in the sentence is assigned a syntactic head that points to either another word in the sentence or an artificial root symbol. Stanza’s dependency parser combines a Bi-LSTM-based deep biaffine neural parser (Dozat and Manning, 2017) and two linguistic features, which can significantly improve parsing accuracy (Qi et al., 2018). Gold-standard tokenization and automatic POS tags are used. We also re-train spaCy, spaCy-BERTweet, and spaCy-XLM-RoBERTa dependency parsers with their default parser architecture. We compare our Stanza models with previous work: (1) Kong et al. (2014)’s graph-based parser with lexical features and word cluster and it uses dual decomposition for decoding, (2) Dozat and Manning (2017)’s neural graph parser with biaffine attention, (3) Ballesteros et al. (2013)’s neural greedy stack LSTM parser, (4) an ensemble model of 20 transition-based parsers (Liu et al., 2018), (5) A distilled graph-based parser of the previous ensemble model (Liu et al., 2018). These models are all trained on TB2+UD_English-EWT. We are aware that Stymne (2020) trained a transition-based upparser (de Lhoneux et al., 2017) on a combination of TB2, UD_English-EWT, and more out-of-domain data (English GUM Zeldes, 2017, LinES Ahrenberg, 2007, ParTUT Sanguinetti and Bosco, 2015) to further boost model performance, but we do not experiment with this data combination to be consistent with Liu et al. (2018).

4. Evaluation
We train the NER and syntactic NLP models described above with 1) TB2 training data (the default data setting), 2) TB2 training data + extra Twitter data (the combined data setting). For the combined data setting, we add the training and dev sets from other data sources to TB2’s training and dev sets respectively. Specifically, we add WNUT17 (Derczynski et al., 2017) for NER. For syntactic NLP tasks, we add UD_English-EWT (Ann Bies, Justin Mott, Colin Warner, Seth Kulick, 2012). We pick the best models based on the corresponding dev sets and report their performance on their TB2 test sets. For each task, we compare Stanza models with existing studies and alternative NLP frameworks.

4.1. Performance in NER

| Systems                     | F1    |
|-----------------------------|-------|
| spaCy (TB2)                 | 52.20 |
| spaCy (TB2+W17)             | 53.89 |
| FLAIR (TB2)                 | 62.12 |
| FLAIR (TB2+W17)             | 59.08 |
| HuggingFace-BERTweet (TB2)  | 73.71 |
| HuggingFace-BERTweet (TB2+W17) | 74.35 |
| spaCy-BERTweet (TB2)        | 73.79 |
| spaCy-BERTweet (TB2+W17)    | 74.15 |
| Stanza (TB2)                | 60.14 |
| Stanza (TB2+W17)            | 62.53 |

Table 3: NER comparison on the TB2 test set in entity-level F1. “TB2” indicates to use the TB2 train set for training. “TB2+W17” indicates to combine TB2 and WNUT17 train sets for training.

4.1.1. Main Findings
The NER experiments presented in Table 3 show that the Stanza NER model (TB2+W17) achieves the best performance among all non-transformer models. At the same time, the Stanza model is up to 75% smaller than the second-best FLAIR model (Qi et al., 2020). For transformer-based approaches, spaCy-BERTweet and HuggingFace-BERTweet have close performance to each other. The HuggingFace-BERTweet approach trained on TB2+W17 achieves the highest performance (74.35%) on Tweebank-NER, establishing a strong benchmark for future research. We also find that combining the training data from both WNUT17 and TB2 improves the performance of spaCy, FLAIR, Stanza, and BERTweet-based models.

4.1.2. Confusion Matrix Analysis
In Figure 1 we plot a confusion matrix for all four entity types and “O”, the label for tokens that do not belong to any of these types. The diagonal and the vertical blue lines are expected because the cells on the diagonal are when the algorithm predicts the correct entity and the vertical line is when the algorithm mistakes an entity for the “O” entity, which is the most common error for NER. We notice that MISC entities are easily mistaken as “O”, which corresponds to the annotation statistics in Table 2 where MISC has the lowest IIA score in pairwise F1. Thus, MISC is the most challenging of the four types for both humans and machines.
### Error Analysis

We identify the most common error types that Stanza (TB2+W17) makes on the TB2 test in Figure 1 predicting PER, LOC, ORG, MISC to be O. We pick some representative examples for each error type, shown in Table 4. For the **PER → O** error type, every first letter in a word is capitalized and the model fails to recognize the famous investor “Warren Buffett” in such a context. We find that person entities with abbreviations (e.g., “GD” for “G-dragon”), lower case (e.g., “kush” for “Kush”), or irregular contextual capitalization are challenging to the NER system. For the **LOC → O** error type, the structure to encode location is complicated and sometimes interrupted by the parentheses and dashes (e.g., “-day Adventist Church”). In this case, it is caused by the fact that “Seventh-day” is tokenized into three words in TB2. For the **ORG/MISC → O** examples, “Guess Who” is a rock band and “Sounds Live Feels Live” is a concert tour by Australian pop-rock band 5 Seconds of Summer. These named entities tend to contain common English verbs with their first letters capitalized. It is difficult to annotate them correctly if the model does not have access to world and domain knowledge. Our analysis points to the future Twitter NER research to introduce text perturbations into training and to encode commonsense knowledge into NER modeling.

### NER Models Trained on WNUT17

We train spaCy, FLAIR, Stanza, HuggingFace-BERTweet, and spaCy-BERTweet NER models on the four-class version of WNUT17 and evaluate their performance on the TB2 test. In Table 5, we compare the performance of these models trained on WNUT17 against the ones trained on TB2. We show that the performance of all the models drops significantly if we use the pre-trained model from WNUT17, meaning the Tweebank–NER dataset is still challenging for current NER models and can be used as an additional benchmark to evaluate NER models.

### Performance in Syntactic NLP Tasks

Apart from NER, we train and evaluate Stanza models for tokenization, lemmatization, POS tagging, and dependency parsing by leveraging TB2 and UD English-EWT. For each task, we compare our models against previous work on the TB2 test set.

#### 4.2.1. Tokenization Performance

In Table 6 we observe that the Stanza model trained on TB2 outperforms Twpipe tokenizer, the previous SOTA model, and it achieves slightly higher performance than the spaCy tokenizer. We also find that blending TB2 and UD English-EWT for training brings down the tokenization performance slightly. This is probably because the data source of UD English-EWT, which is collected from weblogs, newsgroups, emails, reviews, and Yahoo! Answers, represents a different dialect from Twitter English.

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*We pick Stanza over BERTweet for error analysis because we only aimed to publish the Stanza pipeline at the beginning. We eventually publish the BERTweet models too.*
Table 6: Tokenizer comparison on the TB2 test set. “TB2” indicates to use TB2 for training. “TB2+EWT” indicates to combine TB2 and UD English-EWT for training. Note that the first four results are rounded to one decimal place by Liu et al., (2018).

| System            | F1  |
|-------------------|-----|
| Twokenizer        | 94.6|
| Stanford CoreNLP  | 97.3|
| UDpipe v1.2       | 97.4|
| Twpipe            | 98.3|
| spaCy (TB2)       | 98.57|
| spaCy (TB2+EWT)   | 95.57|
| Stanza (TB2)      | 98.64|
| Stanza (TB2+EWT)  | 98.59|

Table 7: Lemmatization results on the TB2 test set. “TB2” is to use TB2 for training. “TB2+EWT” is to combine TB2 and UD English-EWT for training.

| System            | F1  |
|-------------------|-----|
| NLTK              | 88.23|
| spaCy             | 85.28|
| Flair (TB2)       | 96.18|
| Flair (TB2+EWT)   | 84.54|
| Stanza (TB2)      | 98.25|
| Stanza (TB2+EWT)  | 85.45|

Table 8: POS Tagging comparison in accuracy on the TB2 test set. “TB2” is to use TB2 for training. “TB2+EWT” is to combine TB2 and UD English-EWT for training. Please note that the first five results are rounded to one decimal place by Liu et al., (2018).

| System            | UPOS |
|-------------------|------|
| Stanford CoreNLP  | 90.6 |
| Owoputi et al. (2013) (greedy) | 93.7 |
| Owoputi et al. (2013) (CRF)     | 94.6 |
| Ma and Hovy (2016)   | 92.5 |
| BERTweet (Nguyen et al., 2020) | 95.2 |
| spaCy (TB2)         | 86.72|
| spaCy (TB2+EWT)     | 88.84|
| FLAIR (TB2)         | 87.85|
| FLAIR (TB2+EWT)     | 88.19|
| spaCy-BERTweet (TB2) | 87.61|
| spaCy-BERTweet (TB2+EWT) | 86.31|
| spaCy-XLM-RoBERTa (TB2) | 93.90|
| spaCy-XLM-RoBERTa (TB2+EWT) | 93.75|
| Stanza (TB2)        | 93.20|
| Stanza (TB2+EWT)    | 93.53|

4.2.3. POS Tagging Performance

As shown in Table 7, the Stanza model outperforms the other two rule-based (NLTK and spaCy) and one neural (FLAIR) baseline approaches on TB2. This is not surprising because the Stanza ensemble lemmatizer makes good use of both ruled-based dictionary lookup and seq2seq learning. Similar to what we observe in the tokenization experiments, the combined data setting brings down the performance of FLAIR and Stanza models.

Table 8: POS Tagging comparison in accuracy on the TB2 test set. “TB2” is to use TB2 for training. “TB2+EWT” is to combine TB2 and UD English-EWT for training. Please note that the first five results are rounded to one decimal place by Liu et al., (2018).

4.2.4. Dependency Parsing Performance

For dependency parsing experiments, spaCy-XLM-RoBERTa (TB2) achieves the SOTA performance (Table 9), surpassing Liu et al. (2018) (Ensemble) by 0.42% in UAS. Besides that, the Stanza parser achieves the same UAS score and has a close LAS score (−0.3%) compared to this best non-transformer performance (UAS 82.1% + LAS 77.9%) reported by the distilled parser. As mentioned, the ensemble model is 20 times larger in size compared to the Stanza parser, although the former performs better. Finally, we confirm that the combination of TB2 and UD English-EWT training sets boost the performance for non-transformer models. The data combination brings down the performance of transformer-based models, which is consistent with our observations in tokenization, POS tagging, and dependency parsing.

5. Conclusion

In this paper, we introduce four-class named entities to Tweebank V2, a popular Twitter dataset within the Universal Dependencies framework, creating a new..
Finally, we publish our dataset and release the performance in POS tagging and dependency parsing.

We also train BERT-based methods to establish a strong baseline against existing work and NLP frameworks. Our Stanza models show SOTA performance on tokenization, lemmatization, POS tagging, and dependency parsing on the TB2 test set. “TB2” indicates to use TB2 for training. “TB2+EWT” indicates to combine TB2 and UD English-EWT for training. Note that the first six results are rounded to one decimal place by Liu et al., (2018).

| System | UAS | LAS |
|--------|-----|-----|
| Kong et al. (2014) | 81.4 | 76.9 |
| Dozat et al. (2017) | 81.8 | 77.7 |
| Ballesteros et al. (2015) | 80.2 | 75.7 |
| Liu et al. (2018) (Ensemble) | 83.4 | 79.4 |
| Liu et al. (2018) (Distillation) | 82.1 | 77.9 |
| spaCy (TB2) | 66.93 | 58.79 |
| spaCy (TB2 + EWT) | 72.06 | 63.84 |
| spaCy-BERTweet (TB2) | 76.32 | 71.72 |
| spaCy-BERTweet (TB2+EWT) | 76.18 | 69.28 |
| SpaCy-XLM-RoBERTa (TB2) | 83.82 | 79.39 |
| SpaCy-XLM-RoBERTa (TB2+EWT) | 81.02 | 75.43 |
| Stanza (TB2) | 79.28 | 74.34 |
| Stanza (TB2 + EWT) | 82.10 | 77.60 |

Table 9: Dependency parsing comparison on the TB2 test set. “TB2” indicates to use TB2 for training. “TB2+EWT” indicates to combine TB2 and UD English-EWT for training.

NER benchmark called Tweebank-NER. We evaluate our annotations and observe good inter-annotator agreement score in pairwise F1 for NER annotation. We train Twitter-specific NLP models (NER, tokenization, lemmatization, POS tagging, dependency parsing) on the dataset with Stanza and compare our models against existing work and NLP frameworks. Our Stanza models show SOTA performance on tokenization and lemmatization and competitive performance in NER, POS tagging, and dependency parsing on TB2. We also train BERT-based methods to establish a strong benchmark on Tweebank-NER and achieve SOTA performance in POS tagging and dependency parsing on TB2. Finally, we publish our dataset and release the Stanza pipeline Twitter-Stanza, which is easy to download and use with Stanza’s Python interface. We also release the BERTweet-based NER and POS tagger on Hugging Face Hub. We hope that our research not only contributes annotations to an important dataset but also enables other researchers to use off-the-shelf NLP models for social media analysis.

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