“Let’s Eat Grandma”: When Punctuation Matters in Sentence Representation for Sentiment Analysis

Mansooreh Karami*, Ahmadreza Mosallanezhad*, Michelle V Mancenido, Huan Liu

Arizona State University, Tempe AZ, USA
{mkarami, amosalla, mmanceni, huanliu}@asu.edu

Abstract

Neural network-based embeddings have been the mainstream approach for creating a vector representation of the text to capture lexical and semantic similarities and dissimilarities. In general, existing encoding methods dismiss the punctuation as insignificant information; consequently, they are routinely eliminated in the pre-processing phase as they are shown to improve task performance. In this paper, we hypothesize that punctuation could play a significant role in sentiment analysis and propose a novel representation model to improve syntactic and contextual performance. We corroborate our findings by conducting experiments on publicly available datasets and verify that our model can identify the sentiments more accurately over other state-of-the-art baseline methods.

Introduction

According to a famous legend, Julius Caesar had decided to grant amnesty to one of his unscrupulous generals, who had been fated to be executed. “Execute not, liberate,” Caesar had ordered his guards. However, the message had been delivered with a small but calamitous error: “Execute, not liberate.”

In an age where people’s opinions are often crowd-sourced as text data over the internet, sentiment analysis has become a prevalent Natural Language Processing technique (NLP). The goal of sentiment analysis is to identify people’s attitudes or opinions on products, services, and documents, among others (Liu 2015). Traditional sentiment classification methods run on complex feature engineering and use embeddings independent of context. Current word and sentence embedding tools, such as word2vec (Mikolov et al. 2013), GloVe (Pennington, Socher, and Manning 2014), and BERT (Devlin et al. 2019) create low-dimensional latent representations that use distances between vectors to calculate semantic proximity and infer context. Further, pre-trained embeddings on public corpora such as Wikipedia are widely used as they reduce the non-trivial computational time of training NLP-related tasks. BERT, an example of a pre-trained language model, addresses limitations of the other methods by incorporating context from both directions. BERT serves as the current gold standard for NLP tasks, including sentence-level sentiment analysis.

Often in these pre-trained language models, punctuation is filtered out in the pre-processing stage or treated as an ordinary word in the data (Li, Wang, and Eisner 2019). Intuitively, the misplacement or elimination of these symbols changes the original meaning or obscures a text’s implicit sentiment (Altrabsheh, Cooe, and Fallahkhair 2014; Wang et al. 2014; Pang, Lee, and Vaithyanathan 2002). For example, “No investments will be made over three years” and “No, investments will be made over three years” have drastically different meanings and implications, but BERT, as a representation tool, will ignore the use of the comma; under BERT, the vector representations of these two sentences are nearly the same.

Due to the evident limitations of methods such as BERT, the value of including punctuation to improve sentiment analysis task performance is the primary focus of this paper. But first, we address the more fundamental objective of developing a methodology for representing and recording the syntactic and contextual information that could be derived from punctuation. We approach this by using parsing trees, due to evidence showing the correlation between a text’s punctuation and syntactic structure (Li, Wang, and Eisner 2019). More specifically, we propose an encoder that integrates structural and textual embeddings for the purpose of identifying sentence-level sentiments more accurately.

We summarize our main contributions as follows:

• We investigate whether the inclusion of punctuation in text representations will bend the syntactic tree differently (Related Work and Proposed Model section);
• We develop and evaluate a methodology that augments the structure of the sentences to the original word embedding (Proposed Model section);
• We provide case studies to demonstrate that our model yields better task performance over current state-of-the-art methods trained on the IMDB, Rotten Tomatoes, and Stanford Sentiment Treebank datasets (Experiments section);
• We confirm that the state-of-the-art word and sentence embedding techniques do not differentiate between sentences with and without punctuation (Experiments section).

*Authors contributed equally to this work.
Related Work

Sentiment Analysis

Sentiment analysis, also known as opinion mining, is the task of analyzing subjects’ emotions, opinions, sentiments, attitudes, and evaluations to detect polarity toward entities such as products, services, organizations, individuals, issues, events, and topics (Liu 2015). Sentiment analysis is widely used by businesses and organizations to analyze consumer inputs not only to improve and provide insights on products and services (Serrano-Guerrero et al. 2015; Mosallanezhad, Beigi, and Liu 2019) but also to affect decision-making in recommender systems (Zhang et al. 2014; Beigi et al. 2020). Sentiments also can be used as features in other real-life applications. For instance, the polarity of the sentiments expressed by users (i.e. their feelings, panics, and concerns) during disaster events can improve the decision making for the first-responders (Nazer et al. 2017; Beigi et al. 2016), and the sentiments would be a valuable characteristic beside text content and network patterns for bot detection on social media data (Varol et al. 2017; H. Nazer et al. 2019).

Sentiment analysis typically happens along three major levels of textual data (Liu 2013): (1) the document level which seeks to assign a sentiment label to an entire document; (2) the sentence level which identifies a sentence’s polarity as either positive or negative (and in some cases, neutral); and (3) aspect-based which aims to specify a fine-grained analysis towards a specific aspect or feature. In this paper, we investigate sentiment at the sentence level to determine if a group of words expresses a positive or negative sentiment.

Embeddings

Word and sentence embeddings are used to map the text to vector representation such that the distance between the vectors corresponds to their semantic proximity. word2vec (Mikolov et al. 2013) had been the gold standard in word embeddings since it was introduced in 2013. Although this neural network-based model could effectively encode the semantic and syntactic meaning of the text into vectors, word2vec is sub-optimal for syntax-based problems such as Part-of-Speech (POS) tagging or dependency parsing (Ling et al. 2015). In recent years, embeddings such as BERT (Devlin et al. 2019) improved on term-based embeddings by not only encoding the semantic of words but also their contextualized meanings (i.e. terms and their context). Despite proving its usefulness across a wide range of tasks in NLP, BERT has been shown lacking in some aspects, such as common sense, pragmatic inferences, and the meaning of negations (Ettinger 2020).

One prevailing issue in sentiment analysis is that these representations typically failed to distinguish between words with similar contexts but opposite sentiment polarities (e.g., wonderful vs. terrible) because they were mapped to vectors that were closely contiguous in the latent space (Zhang, Wang, and Liu 2018). Thus, researchers proposed various word embedding methods to also encode sentiments (Maa et al. 2011; Labutov and Lipson 2013; Bespalov et al. 2011). In this work, we designed a novel sentence embedding for sentiment analysis task.

Punctuation in NLP

Punctuation has long been considered the visual equivalent of spoken-language prosody, thus only providing cues that aid a text’s readability. However, Nunberg (Nunberg 1990) argued that punctuation is more than that. He defined it as a linguistic subsystem related to [lexical] grammar that conveys rich information about the structural relations among the elements of a text (Nunberg 1990).

In NLP, the inclusion of punctuation marks has been shown to be useful in syntactic processing (Jones 1995; Jamshid Lou, Wang, and Johnson 2019) and could be used to enhance grammar induction in unsupervised dependency parsing. As an example, Spitkovsky et al. (Spitkovsky, Alfeshaw, and Jurafsky 2011) showed improved performance by splitting sentences at their punctuation to impose parsing restrictions over their fragments. Additionally, punctuation marks have been shown to add extra value to the sentiment (Altrabsheh, Cooce, and Fallahkhaiai 2014; Wang et al. 2014; Pang, Lee, and Vaithyanathan 2002) and could be used to create more meaningful syntax trees (Li, Wang, and Eisner 2019; Agarwal et al. 2011).

Despite evidence that incorporating punctuation improves aspects of an NLP’s performance, very few NLP models make significant use of these symbols.

Tree-Structured Encoders

Tree-structured encoders, which have been shown to perform as well as their sequential counterparts, are representations constructed from the syntactic structure of groups of words or sentences. An example of a tree-structured encoder is the Tree-LSTM, a generalization of the long short term memory (LSTM) architecture that accounts for the topological structure of sentences (Tai, Socher, and Manning 2015). Each unit in the Tree-LSTM is comprised of values provided by the input vector and the hidden states of its children (as derived from the syntactic tree); in contrast, the standard LSTM only considers the hidden states from the previous time step. Tree-LSTM was inspired by an RNN-based compositional model that captured the parent representation in syntactic trees (Socher et al. 2011; 2013).

In addition to changing the LSTM architecture, another method to capture the syntactic structure of sentences is by directly using the LSTM architecture to code the syntactic structures. Liu et. al. (Liu et al. 2017) encoded the variable-length syntactic information, i.e. the path from leaf node to the root node in the constituency or dependency tree, into a fixed-length vector representation to embed the structural characteristics of the sentences on neural attention models for machine comprehension tasks. To jointly learn syntax and lexicon, Shen et al. (Shen et al. 2017) proposed a Parsing-Reading-Predict neural language model (PRPN) that learns the syntactic structure from an unannotated corpus and uses the learned structure to form a premier language model. There has also been some work that extended the Transformer (Vaswani et al. 2017) architecture for syntactic coding. Ahmed et al. (Ahmed, Samee, and Mercer...
Sentence Embedding for Sentiment Analysis

In the following, we describe the sentence and structural encoder, (2) the structural encoder, and (3) the text classifier. The general framework of our proposed model is illustrated in Figure 1. The proposed model has three major components: (1) the sentence encoder that captures the input context, (2) the syntactic tree encoder, and (3) the sentiment analysis classifier.

Proposed Model

We hypothesized that due to the effect of punctuation on the constituency structures of the sentences, adding the structural embedding of the sentences can improve the vector representation of the models. The general framework of our proposed model is illustrated in Figure 1. The proposed model has three major components: (1) the sentence encoder, (2) the structural encoder, and (3) the text classifier. In the following, we describe the sentence and structural encoders and discuss how these two methods are integrated into a robust framework that improves embedding and classification performance.

Sentence Embedding for Sentiment Analysis

In sentiment analysis, textual data is first converted into vectors or matrices. The ability of recurrent neural networks (RNNs) to model order-sensitive data makes it an effective choice for modeling textual data, where the order of words alter the contextual meaning. Our framework uses a bi-directional gated recurrent unit (BiGRU), an RNN that models contextual meanings more effectively than unidirectional networks (Kiperwasser and Goldberg 2016).

To create the text embeddings, a sample, \( x_i = [w_1 \ w_2 \ ... \ w_M] \), is passed through an embedding layer which converts each word \( w_j \) to its representation. This layer has a tensor of dimension \( |V| \times d_W \), where \( V \) is the vocabulary and \( d_W \) is the dimension of the word embeddings. The representations will be fed to a BiGRU that yields the following \( M \) outputs:

\[
(\widehat{h}_m, \widehat{h}_m) = \text{BiGRU}(w_m, (\widehat{h}_{m-1}, \widehat{h}_{m-1}))
\]  

where \( \widehat{h}_m \) and \( \widehat{h}_m \) are, respectively, the forward and backward outputs of the BiGRU at time step \( m \in M \).

Next, the forward and backward outputs from BiGRU are concatenated to form a fixed-length context vector, \( H_m = \text{Concat}(\widehat{h}_m, \widehat{h}_m) \). Fixing the length of the vectors is necessary because neural networks are notorious for having difficulty handling long sequences (Chung et al. 2014).

Further, to establish a comprehensive context vector, an attention mechanism was included by augmenting a location-based attention layer (Luong, Pham, and Manning 2015). The weighted average of the importance values \( a_m \in H_m \) provided by the attention layer creates the final context vector:

\[
H' = \sum_{i} a_i H_i
\]  

where \( a_m \) and \( H_m \) are, respectively, the forward and backward outputs of the BiGRU at time step \( m \in M \).

Using the context vector \( H' \) with a Multi-Layer Perceptron (MLP) classifier yields good performance on sentiment analysis tasks (Yang et al. 2016; Sachin et al. 2020). Information learned from BiGRU, as described in this subsection, will be combined with the encoded syntactic structure of the sentence. This will enhance the context vector to include salient information provided by punctuation.
The Enhanced Embedding

We use a constituency tree to analyze sentence structure and organize words into nested constituents. In the constituency tree, words are represented by the leaves while the internal nodes show the phrasal (e.g. S, NP and VP) or pre-terminal Part-Of-Speech (POS) categories (Table 1). Edges in the tree indicate the set of grammar rules. Figure 2 shows an example of a constituency tree that demonstrates the parsing of a sample sentence.

![Constituency Tree Example]

Table 1: The most common Part-Of-the-Speech tags.

| Tag | Meaning |
|-----|---------|
| S   | Sentence |
| N   | Noun     |
| ADJ | Adjective|
| ADV | Adverb   |
| P   | Preposition |
| CON | Conjunction|
| PRO | Pronoun  |
| INT | Interjection|
| V   | Verb     |

Subsequent to the generation of the syntactic tree, we adopt the approach in Liu et al. (Liu et al. 2017) to capture syntactic information. We use the traversal of the syntactic tree $T$ to pass it through a bi-directional GRU and create a representation of $T$. Because the order of the nodes in a tree impact the traversal result, we use BiGRU to create a correct representation:

$$ (\mathbf{\tilde{h}}_t, \mathbf{\tilde{h}}_t) = \text{BiGRU}(l_t, (\mathbf{\tilde{h}}_{t-1}, \mathbf{\tilde{h}}_{t-1})) $$  

where $l$ is the value of the tree node and $\mathbf{\tilde{h}}_t$ shows the BiGRU output given the $l_t$ as input. We consider the last output of the BiGRU, $H_T = \text{Concat}(\mathbf{\tilde{h}}_t, \mathbf{\tilde{h}}_t)$, as the context of the syntactic tree.

Finally, to balance the effect of the extracted contexts, the context of the text $H'$ and the context of its syntactic tree $H_T$ are passed through a feed-forward neural network to create the enhanced text representation:

$$ H_F = \text{MLP}(H', H_T) $$

where $H_F$ is the enhanced text representation containing the text’s semantic information and information about its syntactic tree. This enhanced representation could now be used for sentiment analysis tasks.

Experiments

In this section, we conduct experiments to evaluate the effectiveness of our method in sentiment analysis tasks. We pose three major research questions:

- Q1) How do other methods behave and perform when punctuation is included in the input text?
- Q2) How well does the proposed method incorporate the effect of the punctuation in the sentence embeddings?
- Q3) How well does the proposed model perform in sentiment analysis tasks?

Sentence embeddings with and without punctuation are generated to answer questions Q1 and Q2. To answer Q3, we use three popular datasets for sentiment analysis tasks and compare the performance of the proposed model with other baselines.

Data

Three publicly available datasets – IMDB, Rotten Tomatoes, and Stanford Sentiment Treebank (SST) – were used to evaluate and compare the proposed method with other baselines. The IMDB movie reviews data set contains 50,000 movie reviews, with each review labeled as ‘positive’ or ‘negative’. In a similar fashion, the Rotten Tomatoes dataset contains 480,000 movie reviews from the Rotten Tomatoes website, labeled as ‘fresh’ (positive) or ‘rotten’ (negative). Finally, as a more challenging task, we consider the SST-5 dataset, which consists of 10,855 samples labeled 1 to 5. Table 2 summarizes some key statistics of each dataset. We used 10-fold cross-validation to compare the proposed model with other baselines.
Implementation Details

In this subsection, we discuss the parameters and implementation details of the proposed model for conducting the experiments. We first select each textual data’s first 128 words before feeding the data to the model (we observed that majority of textual data has less than 128 words; further, this cutoff point was observed to contain the majority of salient information for classification). Next, we extract the syntactic tree for each sentence, in the spirit of (Liu et al. 2017). Finally, to combine both context vectors, we use a simple location-based attention layer (Luong, Pham, and Manning 2015) for creating the context vector. The integrated context vector is used for text classification. The neural network classifier consists of three layers with 512, 128, and $C$ number of neurons, respectively, where $C$ is the number of the classes. Model parameters $\theta$ and the data labels $y$ are updated using a cross-entropy loss function in the training phase:

$$L(\theta) = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{C} y_{ij} \log(p_{ij}),$$

where $N$ is the number of samples. We use the Adam optimizer (Kingma and Ba 2014) to update the parameters of the network.

Experimental Design

Several embedding methods are implemented to generate sentence representations for comparison with the proposed model. The vectors created by these sentence encoders are used as inputs to the three-layered neural network classifier. Each sentence representation method is described below:

- **BERT** (Devlin et al. 2018): Bidirectional Encoder Representations from Transformers is a model used for various NLP tasks, including sentiment analysis. In this paper, a pre-trained BERT is used to extract the sentence embeddings.
- **BiGRU** similar to the approach in Melamud et al. (Melamud, Goldberger, and Dagan 2016), we design a baseline that uses a bidirectional GRU to create a context vector based on the input text. Each word is replaced by its corresponding GloVe vector and passed through a bidirectional Gated Recurrent Unit. The final output of the BiGRU is then considered as the context vector.
- **SEDT-LSTM** similar to the BiGRU method, but uses a location-based attention layer (Luong, Pham, and Manning 2015) for creating the context vector.

| Dataset | # Samples | # Class |
|---------|-----------|---------|
| IMDB    | 50,000    | 2       |
| RT      | 480,000   | 2       |
| SST-5   | 10,855    | 5       |

Table 2: The statistics of the datasets

| Dataset | Model | IMDB  | Rotten Tomatoes | SST-5 |
|---------|-------|-------|-----------------|-------|
| BiGRU   | 77.8  | 70.3  | 25.8            |
| BiGRU+Attn | 79.8  | 70.5  | 31.2            |
| BERT    | 81.4  | 71.7  | 44.8            |
| SEDT-LSTM | 80.6  | 72.0  | 38.2            |
| Proposed | 83.2  | 74.3  | 45.2            |

Table 3: Performance (accuracy) comparison with different baselines without the punctuation

| Dataset | Model | IMDB  | Rotten Tomatoes | SST-5 |
|---------|-------|-------|-----------------|-------|
| BiGRU   | 77.3  | 69.1  | 23.5            |
| BiGRU+Attn | 79.2  | 70.0  | 24.8            |
| BERT    | 81.4  | 71.6  | 44.8            |
| SEDT-LSTM | 80.6  | 72.0  | 38.2            |
| Proposed | 83.2  | 74.3  | 45.2            |

Table 4: Performance (accuracy) comparison with different baselines with the punctuation

Discussion and Experimental Results

Q1. Figure 3 shows the similarity between sentence embeddings with and without punctuation in the text. To calculate the similarity between embeddings, we use the cosine similarity measure:

$$\text{CosineSim}(E_w, E_{wo}) = \frac{E_w \cdot E_{wo}}{|E_w|||E_{wo}|},$$

where $E_w$ and $E_{wo}$ are the sentence embeddings with and without punctuation, respectively.
where $E_w$ and $E_{wo}$ are the sentence embeddings with and without punctuation, respectively. The cosine similarity measure is close to 1.0 if the context vectors are close to each other.

In Figure 3 (a-b), it is observable that BERT and Recurrent Neural Networks (BiGRU+Attn) have higher similarity measures, implying that they do not produce different embeddings for sentences with and without punctuation. The minimum similarity between embeddings for these models is about 0.9. This finding corroborates our hypothesis that these models consider punctuation as just another word in the data, strongly justifying the development of an enhanced representation method.

Additionally, the inferiority of the baselines in accounting for punctuation is pronounced when these methods are compared with the proposed method on the IMDB, Rotten Tomatoes, and SST-5 datasets. Table 3 shows the accuracy of the baseline models on the datasets, when punctuation is excluded, while Table 4 shows similar information, when punctuation is included. It is evident that the performance of the baselines are agnostic to the use of punctuation. For the baselines, inclusion of the punctuation is almost irrelevant and generally lowered the performance of these models for NLP tasks.

\textbf{Q2.} Figure 3 (c-d) shows the trend of cosine similarity when the syntactic information is augmented with the word embedding. The lower similarity values, ranging from as low as 0.10 to only as high as 0.90, indicate that the representation vectors of sentences with and without punctuation are distinct. While the SEDT-LSTM model show promising results, the proposed model still outperforms SEDT-LSTM in the sentiment analysis task. This difference can be explained by the fact that in our model, we used BiGRU to create latent information from multiple constituency trees related to a specific text, which in turn is fed with the GloVe embeddings to a new MLP neural network to learn an enhanced sentence representation. On the other hand, SEDT-LSTM uses a dependency tree to extract words in the path leading from word $w$ to the root of the tree; this is then used as an input to LSTM and the output is concatenated with the GloVe vector of $w$. SEDT-LSTM does not account for the syntactic tree, as we did in our model.

The cosine similarity of several sentences were also calculated to investigate how the methods compare when the punctuation is removed. We combined the IMDB and Rotten Tomatoes datasets to create a larger dataset, which is accept-
| Index | With punctuation | Without punctuation | Proposed | SEDT-LSTM | BERT | BiGRU+Attn |
|-------|-----------------|-------------------|----------|-----------|------|-----------|
| 1     | Now, my friends, listen to me. | Now my friends listen to me | 0.56     | 0.67      | 0.97 | 0.95      |
| 2     | Help. wanted. | Help wanted | 0.51     | 0.45      | 0.99 | 0.99      |
| 3     | What? Is this thing called ‘love’? | What is this thing called love | 0.75     | 0.78      | 0.98 | 0.99      |
| 4     | a gorgeously strange movie, heaven is deeply concerned with morality, but it refuses to spell things out for viewers. | a gorgeously strange movie, heaven is deeply concerned with morality but it refuses to spell things out for viewers | 0.89     | 0.91      | 0.98 | 0.99      |
| 5     | Her favorite pies were lemon meringue, apple, and pecan. | Her favorite pies were lemon meringue apple and pecan. | 0.83     | 0.93      | 0.98 | 0.97      |
| 6     | No, investments will be made in United States | No investments will be made in United States | 0.57     | 0.55      | 0.96 | 0.96      |
| 7     | if you go, pack your knitting needles. | if you go pack your knitting needles. | 0.43     | 0.67      | 0.97 | 0.98      |
| 8     | it’s a fine, old-fashioned movie, which is to say it’s unburdened by pretensions to great artistic significance. | it's a fine old fashioned movie which is to say it s unburdened by pretensions to great artistic significance. | 0.95     | 0.94      | 0.98 | 0.99      |
| 9     | The talents of the actors helps “Moonlight Mile” rise above its heart-on-its-sleeve writing. | the talents of the actors helps moonlight mile rise above its heart on its sleeve writing. | 0.97     | 0.95      | 0.97 | 0.98      |
| 10    | when the plot kicks in, the film loses credibility. | when the plot kicks in the film loses credibility. | 0.48     | 0.78      | 0.96 | 0.94      |

Table 5: Examples of sentences with and without punctuation alongside their cosine similarity using different embedding methods. The proposed method can incorporate the syntactic tree’s information better than the baselines.

Table 4 shows a comparison of the performance our proposed model and the baseline methods, with respect to sentiment analysis tasks on the three datasets. Results show that our model outperforms the state-of-the-art models across all datasets (including the more challenging SST-5), whether or not the method implicitly considered sentence structure. Among competing baselines that do not consider the sentence structure, BERT is the best performing. However, our proposed model still outperforms this gold standard despite the large amount of pre-training conducted. SEDT-LSTM, a structural embedding model, is shown to be a runner-up in terms of accuracy, but the richer sentence embedding designed into our model points to the direction that the syntactic structure of the sentences could play a significant role in sentiment analysis tasks.

**Conclusion and Future Work**

In this paper, we proposed a methodology for sentence embeddings that consider punctuation as a salient feature of textual data. By leveraging on the association between punctuation and syntactic trees, our model yielded embeddings that were consistently able to convey the contextual meaning of sentences in sentiment analysis tasks. We compared our proposed model to state-of-the-art baselines, including BERT, the gold standard for NLP tasks. The proposed model in this paper outperformed these baselines in distinguishing between sentences with and without punctuation (via a cosine similarity measure), distinguishing between sentences that require punctuation to be sensible, and performing accurately on classifying opinions for the IMDB, Rotten Tomatoes, and SST-5 datasets. A possible direction for future research is to use syntactic trees for other NLP-related tasks, such as automated chat bots and machine comprehension tasks.

**References**

Agarwal, A.; Xie, B.; Vovsha, I.; Rambow, O.; and Passonneau, R. 2011. Sentiment Analysis of Twitter Data. In Proceedings of the Workshop on Language in Social Media (LSM 2011), 30–38. Portland, Oregon: Association for
Ahmed, M.; Samee, M. R.; and Mercer, R. E. 2019. You Only Need Attention to Traverse Trees. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, 316–322.

Altrabsheh, N.; Cocea, M.; and Fallahkhair, S. 2014. Sentiment analysis: towards a tool for analysing real-time students feedback. In 2014 IEEE 26th international conference on tools with artificial intelligence, 419–423. IEEE.

Beigi, G.; Hu, X.; Maciejewski, R.; and Liu, H. 2016. An Overview of Sentiment Analysis in Social Media and Its Applications in Disaster Relief, 313–340. Cham: Springer International Publishing. ISBN 978-3-319-30319-2. doi: 10.1007/978-3-319-30319-2_13. URL https://doi.org/10.1007/978-3-319-30319-2_13

Beigi, G.; Mosallanezhad, A.; Guo, R.; Alvari, H.; Nou, A.; and Liu, H. 2020. Privacy-aware recommendation with private-attribute protection using adversarial learning. In Proceedings of the 13th International Conference on Web Search and Data Mining, 34–42.

Bespalov, D.; Bai, B.; Qi, Y.; and Shokoufandeh, A. 2011. Sentiment classification based on supervised latent n-gram analysis. In Proceedings of the 20th ACM international conference on Information and knowledge management, 375–382.

Chung, J.; Gulcehre, C.; Cho, K.; and Bengio, Y. 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555.

Devlin, J.; Chang, M.-W.; Lee, K.; and Toutanova, K. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Devlin, J.; Chang, M.-W.; Lee, K.; and Toutanova, K. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), 4171–4186. Minneapolis, Minnesota: Association for Computational Linguistics. doi:10.18653/v1/N19-1423. URL https://www.aclweb.org/anthology/N19-1423

Ettinger, A. 2020. What BERT is not: Lessons from a new suite of psycholinguistic diagnostics for language models. Transactions of the Association for Computational Linguistics 8: 34–48.

H. Nazer, T.; Davis, M.; Karami, M.; Akoglu, L.; Koelle, D.; and Liu, H. 2019. Bot Detection: Will Focusing on Recall Cause Overall Performance Deterioration? In Thomson, R.; Bisgin, H.; Dancy, C.; and Hyder, A., eds., Social, Cultural, and Behavioral Modeling, 39–49. Cham: Springer International Publishing. ISBN 978-3-030-21741-9.

Jamshid Lou, P.; Wang, Y.; and Johnson, M. 2019. Neural Constituency Parsing of Speech Transcripts. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), 2756–2765. Minneapolis, Minnesota: Association for Computational Linguistics. doi:10.18653/v1/N19-1282. URL https://www.aclweb.org/anthology/N19-1282

Jones, B. 1995. Exploring the role of punctuation in parsing natural text. arXiv preprint cmp-lg/9505024.

Joshi, V.; Peters, M.; and Hopkins, M. 2018. Extending a parser to distant domains using a few dozen partially annotated examples. arXiv preprint arXiv:1805.06556.

Kingma, D. P.; and Ba, J. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

Kiperwasser, E.; and Goldberg, Y. 2016. Simple and accurate dependency parsing using bidirectional LSTM feature representations. Transactions of the Association for Computational Linguistics 4: 313–327.

Labutov, I.; and Lipson, H. 2013. Re-embedding words. In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), 489–493.

Li, X. L.; Wang, D.; and Eisner, J. 2019. A generative model for punctuation in dependency trees. Transactions of the Association for Computational Linguistics 7: 357–373.

Lin, Z.; Feng, M.; Santos, C. N. d.; Yu, M.; Xiang, B.; Zhou, B.; and Bengio, Y. 2017. A structured self-attentive sentence embedding. arXiv preprint arXiv:1703.03130.

Ling, W.; Dyer, C.; Black, A. W.; and Trancoso, I. 2015. Two/too simple adaptations of word2vec for syntax problems. In Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, 1299–1304.

Liu, B. 2012. Sentiment analysis and opinion mining. Synthesis lectures on human language technologies 5(1): 1–167.

Liu, B. 2015. Sentiment analysis: Mining opinions, sentiments, and emotions. Cambridge University Press.

Liu, R.; Hu, J.; Wei, W.; Yang, Z.; and Nyberg, E. 2017. Structural embedding of syntactic trees for machine comprehension. arXiv preprint arXiv:1703.00572.

Luong, M.-T.; Pham, H.; and Manning, C. D. 2015. Effective approaches to attention-based neural machine translation. arXiv preprint arXiv:1508.04025.

Maas, A.; Daly, R. E.; Pham, P. T.; Huang, D.; Ng, A. Y.; and Potts, C. 2011. Learning word vectors for sentiment analysis. In Proceedings of the 49th annual meeting of the association for computational linguistics: Human language technologies, 142–150.

Melamud, O.; Goldberger, J.; and Dagan, I. 2016. context2vec: Learning generic context embedding with bidirectional lstm. In Proceedings of the 20th SIGNLL conference on computational natural language learning, 51–61.

Mikolov, T.; Chen, K.; Corrado, G.; and Dean, J. 2013. Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781.
Mosallanezhad, A.; Beigi, G.; and Liu, H. 2019. Deep Reinforcement Learning-based Text Anonymization against Private-Attribute Inference. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), 2360–2369.

Nazer, T. H.; Xue, G.; Ji, Y.; and Liu, H. 2017. Intelligent disaster response via social media analysis a survey. ACM SIGKDD Explorations Newsletter 19(1): 46–59.

Nunberg, G. 1990. The linguistics of punctuation. 18. Center for the Study of Language (CSLI).

Pang, B.; Lee, L.; and Vaithyanathan, S. 2002. Thumbs up? Sentiment classification using machine learning techniques. arXiv preprint cs/0205070.

Pennington, J.; Socher, R.; and Manning, C. D. 2014. Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), 1532–1543.

Sachin, S.; Tripathi, A.; Mahajan, N.; Aggarwal, S.; and Nagrath, P. 2020. Sentiment Analysis Using Gated Recurrent Neural Networks. SN Computer Science 1(2): 1–13.

Serrano-Guerrero, J.; Olivas, J. A.; Romero, F. P.; and Herrera-Viedma, E. 2015. Sentiment analysis: A review and comparative analysis of web services. Information Sciences 311: 18–38.

Shen, Y.; Lin, Z.; Huang, C.-W.; and Courville, A. 2017. Neural language modeling by jointly learning syntax and lexicon. arXiv preprint arXiv:1711.02013.

Socher, R.; Lin, C. C.; Manning, C.; and Ng, A. Y. 2011. Parsing natural scenes and natural language with recursive neural networks. In Proceedings of the 28th international conference on machine learning (ICML-11), 129–136.

Socher, R.; Perelygin, A.; Wu, J.; Chuang, J.; Manning, C. D.; Ng, A. Y.; and Potts, C. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In Proceedings of the 2013 conference on empirical methods in natural language processing, 1631–1642.

Spitkovsky, V. I.; Alshawi, H.; and Jurafsky, D. 2011. Punctuation: Making a point in unsupervised dependency parsing. In Proceedings of the Fifteenth Conference on Computational Natural Language Learning, 19–28.

Tai, K. S.; Socher, R.; and Manning, C. D. 2015. Improved semantic representations from tree-structured long short-term memory networks. arXiv preprint arXiv:1503.00075.

Varol, O.; Ferrara, E.; Davis, C. A.; Menczer, F.; and Flammini, A. 2017. Online human-bot interactions: Detection, estimation, and characterization. arXiv preprint arXiv:1703.03107.

Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, L.; and Polosukhin, I. 2017. Attention is all you need. In Advances in neural information processing systems, 5998–6008.