Who's to say what's funny? A computer using Language Models and Deep Learning, that's who!

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Abstract

Humor is a defining characteristic of human beings. Our goal is to develop methods that automatically detect humorous statements and rank them on a continuous scale. In this paper we report on results using a Language Model approach, and outline our plans for using methods from Deep Learning.

1 Introduction

Computational humor is an emerging area of research that ties together ideas from psychology, linguistics, and cognitive science. *Humor generation* is the problem of automatically creating humorous statements (e.g., (Stock and Strapparava, 2003), (Özbal and Strapparava, 2012)). *Humor detection* seeks to identify humor in text, and is sometimes cast as a binary classification problem that decides if some input is humorous or not (e.g., (Mihalcea and Strapparava, 2006), (Zhang and Liu, 2014), (Shahaf et al., 2015), (Miller and Gurevych, 2015)). However, our focus is on the continuous and subjective aspects of humor.

We learn a particular sense of humor from a data set of tweets which are geared towards a certain style of humor (Potash et al., 2016). This data consists of humorous tweets which have been submitted in response to hashtag prompts provided during the Comedy Central TV show @*midnight with Chris Hardwick*. Since not all jokes are equally funny, we use Language Models and methods from Deep Learning to allow potentially humorous statements to be ranked relative to each other.

2 Language Models

We used traditional Ngram language models as our first approach for two reasons :

1. Ngram language models can learn a certain style of humor by using examples of that as the training data for the model, and

2. they assign a probability to each input they are given, making it possible to rank statements relative to each other.

Thus, Ngram language models make relative rankings of humorous statements based on a particular style of humor, thereby accounting for the continuous and subjective nature of humor.

We began this research by participating in SemEval-2017 Task 6 #HashtagWars: Learning a Sense of Humor (Potash et al., 2017). This included two subtasks : Pairwise Comparison (Subtask A) and Semi-ranking (Subtask B). Pairwise comparison asks a system to choose the funnier of two tweets. Semi-ranking requires that each of the tweets associated with a particular hashtag be assigned to one of the following categories : top most funny tweet, next nine most funny tweets, and all remaining tweets.

Our system estimated tweet probabilities using Ngram language models. We created models from two different corpora - a collection of funny tweets from the @midnight program, and a corpus of news data that is freely available for research[1]. We scored tweets by assigning them a probability based on each model. Tweets that have a higher probability according to the funny tweet model are considered funnier since they are more like the humorous training data. However, tweets that have a lower probability according to the news language

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[1]http://www.statmt.org/wmt11/featured-translation-task.html

model are viewed as funnier since they are least like the (unfunny) news corpus. We took a standard approach to language modeling and used bigrams and trigrams as features in our models. We used KenLM (Heafield et al., 2013) with modified Kneser-Ney smoothing and a back-off technique as our language modeling tool.

Table 1 shows our results for both data sets when trained on bigrams and trigrams. The accuracy and distance measures are defined by the task organizers (Potash et al., 2017). We seek high accuracy in picking the funnier tweet (Subtask A) and low distance (from the gold standard) in organizing the tweets into categories (Subtask B).

Data	Ngram	Accuracy (A)	Distance (B)
tweets	trigram	0.397	0.967
tweets	bigram	0.406	0.944
news	trigram	0.627	0.872
news	bigram	0.624	0.853

Table 1: Experimental results

These results show that models trained on the news data have a significant advantage over the tweets model, and that bigram models performed slightly better than trigrams. We submitted trigram models trained on news and tweets to the official evaluation of SemEval-2017 Task 6. The trigram language models trained on the news data placed fourth in Subtask A and first in Subtask B.

We believe that the significant advantage of the news data over the tweet data is caused by the much larger quantity of news data available. The tweet data only consists of approximately 21,000 tweets, whereas the news data totals approximately 6.2 GB of text. In the future we intend to collect more tweet data, especially those participating in the ongoing #HashtagWars staged nightly by @midnight. We also plan to experiment with equal amounts of tweet data and news data, to see if one has an inherent advantage over the other.

Finally, our language models performed better on subtask A, the pairwise comparison, suggesting that the ranking problem is more demanding and will require further development. To that end we are considering the use of neural network and Deep Learning approaches, which we will discuss in the following section.

3 Deep Learning

Our system performed well in the SemEval task, confirming the ability of language models to detect humor with focusing on its continuous and subjective nature. Going forward, language models certainly can characterize humor in a more comprehensive way with more complex implementations.

Recently, studies have shown that Recurrent Neural Networks (RNN) such as LSTM neural networks are exceptionally powerful in language modeling based on its ability to take into account of all preceding words over a word sequence (Sundermeyer et al., 2012) (Sundermeyer et al., 2015). Also, in their work of learning a sense of humor, (Potash et al., 2016) points out that due to the high portion of out of vocabulary (OOV) words generated by puns in the humorous tweet data, character-level Constitutional Neural Networks (CNN) model would be more suitable for capturing the single-token puns comparing to token level models. In addition, (Kim et al., 2015)'s study proves that character-level neural language models outperform state-of-art word-level neural language models. Moving forward, considering the promising future of neural networks, we would like to build a character-level neural language model (NLM) which relies on both LSTM RNN and character-level CNN to improve our current system performance.

Last but not the least, (Potash et al., 2016) states that external knowledge is crucial in order to detecting humor from the tweet dataset based on its nature. In the future we intend to make use of external knowledge in the NLM in possibly two ways: With a deeper understanding of what kinds of external knowledge are the most useful such as movie and book titles, celebrity and song names, one is to incorporate them as features in the NLM; The other is to combine the NLM with a Neural Turing Machine (NTM) (Graves et al., 2014), which is particularly designed for interacting with external interfaces, with a profound and solid study of NTM.

4 Conclusion

Humor has not been addressed broadly in current computational research area. Our research focuses on humor detection, developing systems that can capture its continuous and subjective nature.

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