Affects of Named Entities on Amazon Sentiment Analysis

Abstract

1 Introduction

Sentiment Analysis looks into extracting subjective information from a source. Some words has more weight in sentiment analysis compared to other words. With reviews from Amazon, name entities are mentioned in the review text.

There has been plenty of models on predicting sentiment analysis of Amazon reviews. The top 3 models; accurancies unsupervised data augmentation for consistency training [6], deep pyramid convolutional neural networks for text categorization [1], and disconnected recurrent neural networks for text categorization [5]; all has been tested with Amazon product reviews from users. Although those models accurancies are between 60%-70% percent, does simplifing the name enitities into one word affect Amazon sentiment analysis in positive or negative accurancies. The possiblility of removing the context of named entity affects the training and tests of sentiment analysis.

2 Related Work

Specific words has neutral, positive, or negative polarity when it comes to sentiment analysis. Recognizing Contextual Polarity in Phrase-Level Sentiment Analysis research determined a new stragety of figuring out polarity of words in senitment analysis. The research did not look into the part of speech of these words, but showed how some words can have no impact to sentiment analysis.

Research into subjectivity compared with objectivity of a word looked into parts of speech affects of sentiment analysis from Bing Liu [3]. It has been noted from Bing Liu sentiment analysis on subjectivity that adjectives, adverbs, nouns, and verbs can obtain sentiment detail. Furthermore, an object in object extraction from sentiment is a noun, proper noun, and sometimes a verb. The paper didn't look into named entities give the impacts of training with the context of the named entities.

3 Task

The task is to see if named entities contains necessary information is needed for sentiment analysis in Amazon product reviews models. The difference between each similar model is one data is trained on Amazon product review while the other model is trained on same Amazon product review that replaced named entities with a mask. The goal is to compare the two models to see if removing named entities has any impacts on sentiment analysis.

4 Method

Amazon product review data comes with a rating and review that can be used for training. The product must parse out named entities with a replacement mask to represent there is a named entity, however, removes the context of the named entity. An example of removing named entities context can be shown.

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"It's just like having $100. Except I
couldn't get Walmart to accept it.
Apparently you can only use it on the
interweb at Amazon."

Detect Amazon and Walmart as named entity,
so replaced with <NNP>

"It's just like having $100. Except I
couldn't get <NNP> to accept it.
Apparently you can only use it on
the interweb at <NNP>."
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4.1 LUKE

LUKE is an entity extraction model that can be used for extracting entities in an Amazon product review. LUKE-500K pre-trained data had an F1 score of 94.3 on named entity recognition from

CoNLL-2003 dataset [7]. This gives the capability for machine to detect the named entity in a passage. Knowing where the entity names are in the passage, those words can be replaced with one mask, so the context of the named entity is not known. To conclude, LUKE will parse out the named entity before sending the review text to the model.

4.2 albert-base-v2

Albert is pretrained BERT model on BookCorpus [2]. The pretrained model is used to understand the english language. The purpose of Albert is to have a pretrained model ready to for fine tuning. Reason for albert is the fine-tuned task of making decision based on whole sentences. The fine-tuning process will learn from Amazon product review text to classify the rating of the review. The rating of the review will show the sentiment analysis of the fine-tuned model.

5 Experiments

The Amazon product review data came from University of California, San Diego Amazon product review dataset [4]. The data consists of the rating and the review text that came with the rating for training and testing. The rating from 1-5 will be used for the sentiment feeling of the Amazon review.

5.1 Parsing Named Entities

From each category of Amazon product review, there is two copies of the same product review. One copy has the original Amazon product review text. The second copy has the review text parsed out named entities with a mask (NNP). There is at least 10,000 Amazon product reviews for each category that was used for the models. This leaves over 1,000 review text being tested for evaluation of the model.

5.2 Training the Models

The albert-base-v2 will be used for fine-tuning on detecting sentiment analysis. Each model requiring training will be done with 60% training, 20% validation, and 20% testing. The models will be tested on accurancy between the Amazon product reviews untouched and the review that has named entity replaced with a mask. The only change with the models is the text has named entity parsed out. This will show how the model compares with or without the context of the proper noun.

When training with albert pretrained model, the PyTorch seed is set to 1324224321 to reduce random when training the model. Moreover, the learning rate, batch size, and number of epochs stays the same. Keeping these values the same will ensure the only change between the two models is the review text being masked or not.

5.3 Results

Shown in figure 1.1, the left column is the category the Amazon product review data was in. The middle column is the original unaltered product review text accurancy for testing evaluation after training. The right column is the alterate prduct review with named entity detected by LUKE to be replaced with a mask testing accurancy after training on masked review text.

albert-base-v2 fine-tuned accurancy

Category	Ori. Accur.	LUKE Accur.
Video Games (1 e.)	0.789	0.779
Video Games (5 e.)	0.784	0.775
Appliances (1 e.)	0.740	0.712
Appliances (5 e.)	0.712	0.714
Toys and Games (1 e.)	0.853	0.850
Toys and Games (5 e.)	0.841	0.846
All Beauty (1 e.)	0.809	0.801
All Beauty (5 e.)	0.781	0.801

6 Conclusion

Conclusion.

References

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