Predicting Financial Sentiment Through Pretrained Language Models

1 Introduction and Related Work

Language models have become a key step to achieve state-of-the art results in many different Natural Language Processing (NLP) tasks. Leveraging the huge amount of unlabeled texts nowadays available, they provide an efficient way to pre-train continuous word representations that can be fine-tuned for a downstream task, along with their contextualization at the sentence level. This has been widely demonstrated for English using contextualized representations [2, 6, 4, 7, 3, 11].

Natural language processing tasks, such as question answering, machine translation, reading comprehension, and summarization, are typically approached with supervised learning on task specific datasets. We demonstrate that language models begin to learn these tasks without any explicit supervision when trained on a new dataset of millions of webpages called WebText. When conditioned on a document plus questions, the answers generated by the language model reach 55 F1 on the CoQA dataset - matching or exceeding the performance of 3 out of 4 baseline systems without using the 127,000+ training examples. The capacity of the language model is essential to the success of zero-shot task transfer and increasing it improves performance in a log-linear fashion across tasks. Our largest model, GPT-2, is a 1.5B parameter Transformer that achieves state of the art results on 7 out of 8 tested language modeling datasets in a zero-shot setting but still underfits WebText. Samples from the model reflect these improvements and contain coherent paragraphs of text. These findings suggest a promising path towards building language processing systems which learn to perform tasks from their naturally occurring demonstrations [8]

The use of robo-readers to analyze news texts is an emerging technology trend in computational finance. In recent research, a substantial effort has been invested to develop sophisticated financial polarity-lexicons that can be used to investigate how financial sentiments relate to future company performance. However, based on experience from other fields, where sentiment analysis is commonly applied, it is well-known that the overall semantic orientation of a sentence may differ from the prior polarity of individual words.

2 Experiments

Using BERT models in finance have also been used in the literature [1, 10]. Other pretrained models have also been used [9].

Sentence	easyJet expects resilient demand to withstand security fears.
Aspect Level 1	Corporate
Aspect Level 2	Risks
Sentiment Score	0.165
Target	easyJet

Table 1: An example entry from FiQA

We do not have many financial datasets for financial tasks.

2.1 FiQA

The provided training dataset for WWW '18 [5] contains a total of 1174 examples from news headlines and tweets. Each example contains the sentence and the sentence snippet associated with the target entity, aspect, and sentiment score. A sample FiQA entry is shown in 1. A Level 1 Aspect label takes on one of 4 possible labels (Corporate, Economy, Market or Stock), and our Level 2 Aspect label takes on one of 27 possible labels (Appointment, Risks, Dividend Policy, Financial, Legal, Volatility, Coverage, Price Action, etc.). The original dataset contained a small number of multilabel examples, however, we considered this number too few to train a meaningful multilabel classifier. Thus, we slightly stray from the original WWW '18 task for the purpose of this research. Finally, sentiment score takes on a continuous value between -1 and 1 – most negative to most positive.

We can use FiQA dataset for both classification purpose in terms of aspect levels, and regression purpose in terms of sentiment score.

A large collection of financial reports published annually by publicly-traded companies is employed to conduct our experiments; moreover, two analytical techniques – regression and ranking methods – are applied to conduct these analyses [**?**].

Reuter's and Bloomberg dataset: Datasets are in Emre's email. `https://github.com/philipperemy/financial-news-dataset`

Reuter's news dataset: `https://github.com/duynht/financial-news-dataset`

NLTK's corpus `https://www.kaggle.com/boldy717/reutersnltk#__sid=js0`

Fed Meeting Notes `https://fraser.stlouisfed.org/title/federal-open-market-commit browse=2020s`

FOMC Statements Scraper https://github.com/souljourner/FOMC-Statements-Minutes-Scraper Some cleaned transcripts https://github.com/ali-wetrill/FOMCTranscriptAnalysis

Another source for datasets: https://rstudio-pubs-static.s3.amazonaws.com/495650_c9c874694f164fb5948031801079157f.html#3_data

https://sraf.nd.edu/textual-analysis/resources/#LM%20Sentiment%20Word%20Lists

Finally, the texts are stemmed using the Porter stemmer when needed.

10K dataset together with volatilities http://ifs.tuwien.ac.at/ admire/financialvolatility/

Recently, unsupervised pre-training of language models on large corpora has significantly improved the performance of many NLP tasks. The language models are pretained on generic corpora such as Wikipedia. However, sentiment analysis is a strongly domain dependent task. Financial sector has accumulated large scale of text of financial and business communications. Therefore, leveraging the success of unsupervised pretraining and large amount of financial text could potentially benefit wide range of financial applications.

Recent progress in pre-trained neural language models has significantly improved the performance of many natural language processing (NLP) tasks. In this paper we propose a new model architecture DeBERTa (Decoding-enhanced BERT with disentangled attention) that improves the BERT and RoBERTa models using two novel techniques. The first is the disentangled attention mechanism, where each word is represented using two vectors that encode its content and position, respectively, and the attention weights among words are computed using disentangled matrices on their contents and relative positions. Second, an enhanced mask decoder is used to replace the output softmax layer to predict the masked tokens for model pretraining. We show that these two techniques significantly improve the efficiency of model pre-training and performance of downstream tasks. Compared to RoBERTaLarge, a DeBERTa model trained on half of the training data performs consistently better on a wide range of NLP tasks, achieving improvements on MNLI.

Recent progress in pre-trained neural language models has significantly improved the performance of many natural language processing (NLP) tasks.

We show that these two techniques significantly improve the efficiency of model pre-training and performance of downstream tasks. In financial domain, the same is observed.

BERT and its variants have significantly enhanced word vector representation. Here, we will focus on specific BERT application on financial datasets.

Financial Phrasebank

http://www.cs.cmu.edu/ ark/10K/data/ Metadata var

10K downloads: https://pypi.org/project/sec-edgar-downloader/. Filing date is in each text file.

extract MDA and tokenize new files in Noah's website can be used to clean the dataset. CIK Ticker Mapping: https://www.sec.gov/include/ticker.txt

Corporate Reports 10-K & 10-Q The most important text data in finance and business communication is corporate report. In the United States, the Securities Exchange Commission (SEC) mandates all publicly traded companies to file annual reports, known as Form 10-K, and quarterly reports, known as Form 10-Q. This document provides a comprehensive overview of the company's business and financial condition. Laws and regulations prohibit companies from making materially false or misleading statements in the 10-Ks. The Form 10-Ks and 10-Qs are publicly available and can be accesses from SEC website. We obtain 60,490 Form 10-Ks and 142,622 Form 10-Qs of Russell 3000 firms during 1994 and 2019 from SEC website. We only include sections that are textual components, such as Item 1 (Business) in 10-Ks, Item 1A (Risk Factors) in both 10- Ks and 10-Qs and Item 7 (Managements Discussion and Analysis) in 10-Ks.

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