Machine Learning Final Project Presentation

Introduction & Peer Reviews Reply

Group 45

National Tsing Hua University

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1. Introduction
2. Peer Reviews Reply

motivation

In our project, our aim is to fine-tune the BERT model to match the performance of the task-specific model (such as FinBERT) on a dataset collected from recent news titles and articles.

our results

We fine tuned some models to meet the f1 score from our baseline model - FinBERT, compared the performances of the trained models, and simply built a website to show the ideas.

1. Introduction
2. Peer Reviews Reply

problem 1

It's a very interesting topic and we really liked the presentation. However, we have a few questions:

- How do you ensure the data collected from financial news and social media is relevant and unbiased?
- Have you tested the model' s predictions against actual market movements? It would be interesting to see if positive or negative sentiment in social media has an impact to stock or cryptocurrency price.
- What kind of preprocessing steps are applied to handle noisy data from social media?

reply for problem 1

- We use some technique such as replacing some words with other words in similar meaning to augment our data in order to make the number of each classes the same.
- Thanks to giving us this suggestion, we only focused on comparing result with other models, so we have not yet tested it against trends in the real life and we may try your suggestion.
- The preprocessing step we take is to filter some unused symbols, such as https:// when there are some links in the sentences. However, we do not first detect whether the sentences and their labels are noisy manually since this is also a situation that we hope our model is able to classify.

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problem 2

In the methodology, you mentioned that you remove all non-alphanumeric characters. We would like to ask: what would happen if special characters, such as currency symbols and percentages, were removed? Would this affect the meaning of the text (e.g., 12% $\rightarrow$ 12)?

reply for problem 2

This is a good question and suggestion. However, in the objective of our project, we mainly focus on the sentimental terms such as "Exceeded expectations" or "Losses" in the financial sentences. The symbols behind the numbers, or even the numbers would not be the main point when classifying the sentences.

problem 3

In your research, you chose to analyze only the headlines of news articles without delving into the full content. However, in actual news reporting, headlines are often exaggerated or emotionally charged to attract readers' attention, which might not align with the article's full content. How do you balance this potential discrepancy in your sentiment analysis results? Have you considered incorporating the full article content for further analysis?

reply for problem 3

First to clarify the potential misunderstanding, in our data set, we also labeled the sentences in the financial article to be our training data. For this question, we do not think that the exaggeration will have significant influence on the predicted result because we mainly focus on the sentiment and no matter how strong the sentiment is, the result will not alter.

problem 4

Awesome work! I know that removing special letters makes our job easier, since news often contains symbol like % $ &, will it affect the result if you remove them?

reply for problem 4

Same reason as for the previous question.

problem 5

I noticed that your team combined multiple models during your experiment and clearly showed the result of each one. However, I was wondering if your team knew what each part/combination does that can impact the result the way it does as seen in the result, so that users with specific needs might be able to try out different combinations according to your observations to try to satisfy their specific needs.

reply for problem 5

There may be some misunderstadings. The models we present in the video is not what users can select but the improvement when we were experimenting.

problem 6

Can this result be expand to more specefic reaction such as shocking or confident etc.

reply for problem 6

This is a good recommendation. And the model can also expand to more labels. However, the initial object of our project is to give the probabilities of the financial news' sentiments (positive, negative, and neutral) and our dataset are labeled to be the three classes.

problem 7

The results are impressive in terms of both training time and accuracy, and the technique you used is straightforward and efficient. However, I wonder if simply identifying the sentiment of news is always sufficient. Do you think your training approach could also be applied to models that generate short summaries or capture more nuanced sentiments, such as 'shocking,' 'concerning,' or 'stable'?

reply for problem 7

- Our training approach can also applied to other tasks, but in our project, we need to change the model to meet other tasks.
- We can change the sentiment labels to more classes by using another Dense layer at the final output layer.