FED Sentiment Analysis

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***Abstract*—In this document, we will consider the problem of using NLP to model FOMC meeting sentiment. Through this experiment, we gained a greater understanding of groundwork for setting up sentiment models and derive some small discoveries through the exploration.**

I. Introduction

In the context of current financial events where real estate prices are near an all time high and inflation skyrocketing through the roof, many investors are looking to the central bank to help provide shelter. Hence, it has been becoming ever more important to be able to understand the FED's thoughts and decisions. In support of this effort, we can build models that will attempt to capture the FED's sentiment on the market or discover patterns that were previously untouched. In this document, we will go over the data pre-processing, exploratory analysis conducted on the available data, and review the final model results.

II. Analysis Process

Here I will detail the setup of the analysis.

A. Data Sources

As part of the FED's process of building standardized expectations for monetary policy decisions, they created the Federal Open Market Committee that meet eight times a year to discuss and provide guidance on future monetary policy. The contents as well as the results of the meeting are provided officially through three components; statements, press conferences, and meeting minutes. There are other sources as well but these would be the data that we will use to analyze the Fed's sentiment.

B. Data Pre-Processing

The data is sourced directly from FOMC's website via web scraping, and then segmented and reformatted. Rates data is pulled from FRED St. Louis' website manually, although they can be retrieved via API with an account.

C. Lexical Sentiment Analysis

One approach that I used to analyze the sentiment was through lexical classification. In particular, I used Loughran and McDonald's word sentiment list used to define sentiment in a finance context. The lexicon contains over ten thousand words of which 3000 are labelled negative and 300 are labelled positive. It might be worth investigating why such an imbalance exists at a future date. Utilizing this lexicon and word negation (negation based on close proximity context), we can model positivity/negativity over time projected on top of rate changes. Note that for this analysis, we do not do lemmatization and stemming since the dictionary analyzes words by variation (one form may imply a meaning that is different from another).

D. LSTM Classifier

Finally, I attempted an approach using a LSTM neural network to model a relationship between a piece of text and the rate change direction (increase, no change, decrease). We use GloVe to provide the embedding vectors and employ dropout and to try to mitigate overfitting. We use cross-entropy loss over softmax to classify into one of $\{1, 0, -1\}$, representing the policy direction post meeting.

III. Results

A. Document Sentiment Over Time

As part of the lexical sentiment analysis we can observe the change in tone of the various documents over time. Consider the visualizations below:

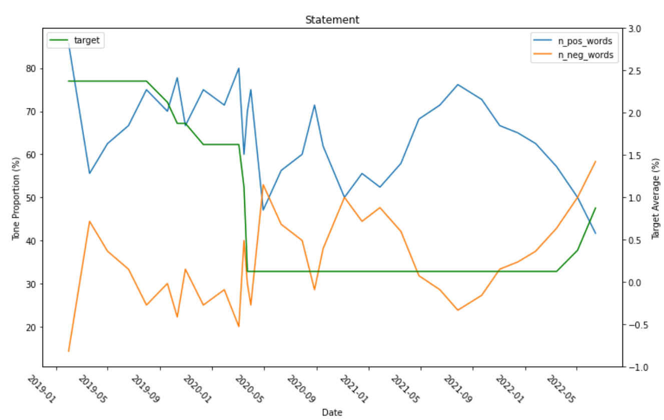

Fig. 1. 2019-2022

As we can see through through figures 1-3, the relationship between the average target rate and lexcial sentiment of the documents do not demonstrate a clear relationship. The noise in the text data is too high to make any meaningful assumptions. As the time horizon is short, it is also difficult to see if it is at least capturing a greater macro trend. The document with the least amount of noise is the statement, and within the past 6 months, there appears to be a gradual change in sentiment, with the tone turning negative for the first time since COVID-19 outbreak. We should note that the

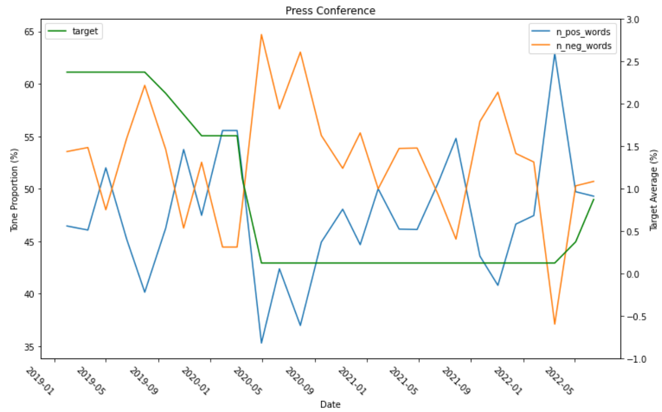

Fig. 2. 2019-2022

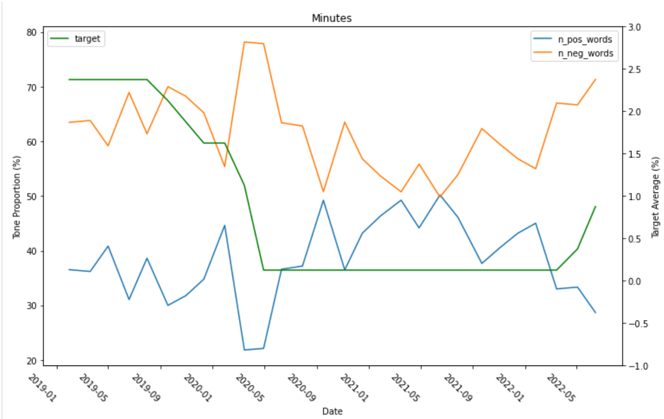

Fig. 3. 2019-2022

overall tone from the statement has historically always been positive, and thus the recent shift to negative tone could be of significance.

I also conducted an analysis of the most popularly used words by sentiment as well as overall. An example segment of the tables is shown below:

2021-11-03	2021-12-15	2022-01-26	2022-03-16	2022-05-04	2022-06-15
bottlenecks	force	problems	force	unemployment	unemployment
force	unemployment	force	unemployment	difficult	difficult
difficult	persistent	persistent	slow	slow	slowing
unemployment	concerns	questions	hardship	unemployed	declining
imbalances	bottlenecks	unemployment	slowing	recession	seriously

Fig. 4. Top 5 Negative Words

The rest of the data is omitted but for recent history, it is clear that inflation continues to be top of mind for the FED, with an increased (compared to two years ago) concern for the labor market. The positive words have generally shown to have stability as becoming more popular.

2021-11-03	2021-12-15	2022-01-26	2022-03-16	2022-05-04	2022-06-15
inflation	inflation	inflation	inflation	inflation	inflation
employment	labor	policy	market	policy	policy
market	policy	market	policy	market	rate
labor	rate	rate	labor	labor	market
policy	market	labor	rate	financial	supply
economy	employment	financial	strong	rate	labor
supply	economic	federal	monetary	supply	rates
economic	economy	economic	economic	economic	economic
financial	conditions	monetary	supply	monetary	prices
pace	federal	time	price	price	federal

Fig. 5. Top 10 Words (cleaned)

B. *LSTM Classifier Performance*

Upon finishing training the LSTM model against the FOMC text data, the evaluated validation and test performance demonstrated poor accuracy, with test performance standing at 77% (red line). See the chart below for a visualization of model accuracy.

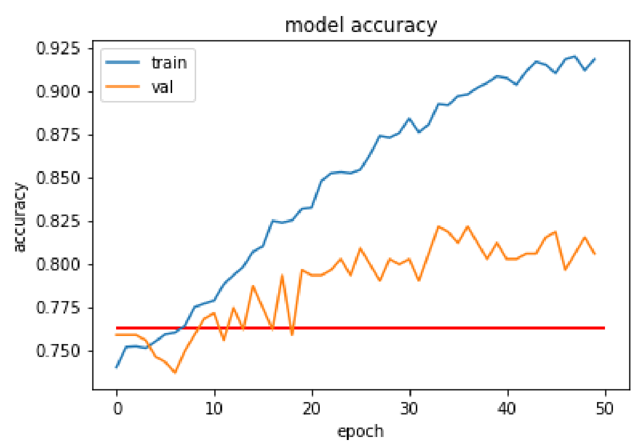

Fig. 6. LSTM over 50 epochs

Overall, the model began over-fitting as we iterated over epochs demonstrated by the mismatch in performance between training/validation and test. If we take a look at the confusion matrix (figure 7), we in fact see that performance has benefited from the concentration of results in the "hold" zone. At least it seems like the data rarely classifies in the opposite direction when the policy does change.

IV. Thoughts and Improvements

With the analysis conducted, we can see that modelling the FED's performance requires more in-depth research to effectively model. Alternative data sources could be pivotal to taking it to the next level. With the preliminary ground work

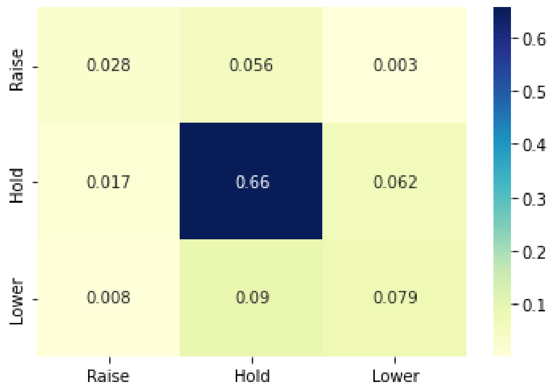

Fig. 7. Confusion Matrix

conducted in this analysis, it would be insufficient to gather deeply insightful information, although we have potentially been able to grasp a glimpse of some indicators such as the recent tone inversion and labor market focus.