Information Extraction from

Federal Open Market Committee Statements

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Abstract

We present a novel approach to unsupervised information extraction by identifying and extracting relevant concept-value pairs from textual data. The system's building blocks are domain agnostic, making it universally applicable. In this paper, we describe each component of the system and how it extracts relevant economic information from U.S. Federal Open Market Committee[1] (FOMC) statements. Our methodology achieves an impressive 96% accuracy for identifying relevant information for a set of seven economic indicators: household spending, inflation, unemployment, economic activity, fixed investment, federal funds rate, and labor market.

1 Introduction

While there are many information extraction approaches described in the literature (Niklaus et al. 2018; Jeanhee and Shawn, 2005), there are few that can extract targeted concept-value pairs with sentiment scores and are universally applicable to various data types. In addition, many systems require training data or additional corpora to draw meaningful statistics from. We built a framework that does not make use of predefined language patterns or any additional training data to extract targeted concept-value pairs with sentiment scores, across various data types. In addition, the framework provides a means to derive a semantic representation of unstructured data along with supporting sentiment analysis. We applied it to extract a set of economic concepts and their associated values in FOMC statements.

Financial events and information relevant to stakeholders are disseminated at constantly, yielding massive amounts of textual data. In recent years, unstructured textual data has become an important source of information for various financial systems, (Xing et al. 2018). While some textual data is created at high frequencies, *e.g.*, news headlines, others as-necessary, *e.g.* SEC[2] filings, others are generated at pre-defined time intervals, *e.g.* FOMC statements.

The statements appear roughly every 6 weeks but if special circumstances arise, like the Covid-19 pandemic at the beginning of 2020, additional statements are released accordingly. Each FOMC statement lays out the direction of U.S. monetary policy. These statements include the federal funds rate, one of the most important economic indicators. In addition, they contain information about inflation, unemployment, economic growth, and monetary supply. The language used in these statements is carefully selected; every word included is intentional due to the market moving effects of these statements.

[1] https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm
[2] https://www.sec.gov/

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Barcelona, Spain (Online), December 12, 2020.

Changes in wordings have shown to bring major effects on markets (Gurkaynak et al., 2005) and directions of market movements have shown to be correlated with statement sentiment scores (Rosa, 2011).

In essence, the most important economic aspects in the statement are federal funds rate, household spending, inflation, unemployment, economic activity, fixed investment, and labor market conditions. Identifying and extracting these concepts along with what is said about them would not only provide a semantic representation of the statement but give rise to a fast integration, as soon as release time, of crucial economic data. Results can be easily and timely integrated into decision making processes, without any human effort. They can be used to derive short- and long-term interest rates, foreign exchange rates, employment rates, economic output, and the supply of credit and demand for investment.

Furthermore, providing sentiment analysis for each economic concept will make the extracted information more valuable to both humans and financial systems.

In the next sections we are going to present our information extraction system, each of its components, and how we applied it to extract economic concept-value pairs from FOMC statements.

2 Problem Statement

In this study we propose an unsupervised information extraction framework that is able to extract concept-value pairs from textual data. In addition, our approach differentiates itself from other methods in that it also assigns a sentiment score to each extracted pair. Unsupervised extraction refers to the fact that no training set was provided to the system at the time it was built.

We built this system to extract seven economic concepts and their values from FOMC statements. While the framework is universal and can be applied to any other unstructured textual data without further tuning, we anchor the system's description around FOMC statements. To show that we can apply the framework to other types of data, in the Results section we present system outputs on a sample of short news articles. Table 1 provides an example of an expected output for the information extracted.

FOMC statement	Expected output
January 29, 2020 Federal Reserve issues FOMC statement For release at 2:00 p.m. EST Share Information received since the Federal Open Market Committee met in December indicates that the labor market remains strong and that economic activity has been rising at a moderate rate. Job gains have been solid, on average, in recent months, and the unemployment rate has remained low. Although household spending has been rising at a moderate pace, business fixed investment and exports remain weak. On a 12-month basis, overall inflation and inflation for items other than food and energy are running below 2 percent. Market-based measures of inflation compensation remain low; survey-based measures of longer-term inflation expectations are little changed. Consistent with its statutory mandate, the Committee seeks to foster maximum employment and price stability. The Committee decided to maintain the target range for the federal funds rate at 1-1/2 to 1-3/4 percent. The Committee judges that the current stance of monetary policy is appropriate to support sustained expansion of economic activity, strong labor market conditions, and inflation returning to the Committee's symmetric 2 percent objective. The Committee will continue to monitor the implications of incoming information for the economic outlook, including global developments and muted inflation pressures, as it assesses the appropriate path of the target range for the federal funds rate. In determining the timing and size of future adjustments to the target range for the federal funds rate, the Committee will assess realized and expected economic conditions relative to its maximum employment objective and its symmetric 2 percent inflation objective. This assessment will take into account a wide range of information, including measures of labor market conditions, indicators of inflation pressures and inflation expectations, and readings on financial and international developments. Voting for the monetary policy action were Jerome H. Powell, Chair; John C. Williams, Vice Chair; Michelle W. Bowman; Lael Brainard; Richard H. Clarida; Patrick Harker; Robert S. Kaplan; Neel Kashkari; Loretta J. Mester; and Randal K. Quarles. Implementation Note issued January 29, 2020	**household spending**: have moderated **inflation**: 2 percent **unemployment**: has stayed low **economic activity**: has been rising at a moderate rate **fixed investment**: have moderated from their strong fourth-quarter readings **federal funds rate**: 1-1/2 to 1-3/4 percent **labor market**: has continued to strengthen

Table 1. Example of an FOMC statement with expected output.

Investigating the expected output in Table 1, the problem we address is a concept-value or key-value pair extraction task. One important aspect to mention is that while we know that we aim to extract values for a targeted set of economic factors it is not necessarily true that the exact factor *e.g.* "economic activity" is present in the statement. More so, when the concept is present it can appear in many places and the system must choose which occurrence to output. As an example, there are many places where "inflation" is mentioned in the above statement, "*survey-based measures of longer-term inflation expectations are little changed, on balance*", "*but the Committee is monitoring inflation developments closely*", "*Inflation on a 12-month basis is expected to move up…*" etc., but the only mention that is of interest is the one that contains the rate, "*have continued to run below 2 percent*".

As mentioned earlier, our approach does not stop at just identifying and selecting key-value pairs. It also assigns a sentiment score to the pair. The sentiment score reflects the tone of the language used to describe the factor, either positive or negative with values between -1 and 1. The sentiment does not take into account the financial aspect but is lexically driven. For example, "unemployment: has stayed low", has a negative score since the language used to describe the factor uses words associate with a negative sentiment, even though economically speaking, a low unemployment rate is a positive economic outcome. However, this can be easily remedied by flagging the factors for which the sentiment scores need to be inversed. As a result, the score of the above example will change polarity to become positive.

In summary, we tackle a concept-value pair information extraction task with sentiment analysis. We focus the task on FOMC statements but build a universal solution for any unstructured textual data.

The following sections describe the building blocks that constitute our methodology.

3 Related Work

While there is a rich body of literature on information extraction, (Saidul and Vincent Ng, 2014; Chung and Murphy, 2005) there are not many studies that address a concept-value pair extraction task with sentiment analysis for financial text. Sentiment analysis for financial data has been a hot research interest for both natural language processing and finance fields. There is a large body of literature on how to perform this task with solutions falling in two main categories: lexical resource-based, (Loughran and McDonald, 2011; Ke et al., 2019) and machine-learning based, (Zhang et al., 2018). The financial domain tends to prefer the former mainly due to ease of use and efficiency, (Kearney and Liu, 2014).

Our methodology, unlike related research, makes use of the extraction layer to derive better sentiment scores. We have tried off-the shelf solutions for adding sentiment scores but none of the options were acceptable, (Tang et al., 2009). A large majority of off-the-shelf solutions are built on product reviews, making them unsuitable for financial data, mostly due to poor coverage and resulting neutral sentiment scores. The literature, mostly on identification of features of product reviews (Zhang and Liu, 2014) makes use of similar building blocks, but our methodology does not heavily rely on problem constraints *e.g.,* use of opinion or sentiment words for aspect identification or it does not yield as comprehensive output as ours. Also, systems that return sentiment scores for very short texts, even for financial data are not widely supported. While we make use of a pre-existing lexical resource, we enhance it with a graph-based methodology to weigh in the importance of each word a technique we have not seen previously. Therefore, the end-to-end architecture that we propose becomes a complete coherent solution.

In terms of FOMC sentiment analysis our method stands out in comparison to other research for the fact that we assign a sentiment score to individual economic concepts rather than to the statement as a whole (Cannon. 2015). We provide individual sentiment scores for the most salient economic aspects mentioned in the statement, giving users more powerful decision tools.

While there is a considerable body of literature around FOMC analysis, a substantial amount is focused on mining meeting notes rather than the statement itself, e.g., identify covered topics in minutes (Hansen et al., 2015) and predict economic indicators like equity and interest rate volatilities (Boukus and Rosenberg, 2006). Compared to other studies on FOMC statement analysis, our solution brings improvements in terms of both methodology and granularity of the information it extracts.

4 Methodology

To this point, we have laid the groundwork of the solution proposed and the problem tackled. In this section, we are going to detail our proposed methodology and each building block it contains. Our concept-value pair information extraction system is rooted in dependency parsing outcome, with each subsequent step making use of the previous one, all leading up to a sentiment analysis and a concept-value pair filtering step. In a nutshell, the main components our framework makes use of are as follows:

1. Dependency parsing
2. Concept-value pair extraction

3. Sentiment analysis
4. Concept-value pair filtering

While the end results are relevant concept-value pairs, the input data for our system is the .html file of the statement. The textual body is extracted using the BeautifulSoup[3] package.
Figure 1 depicts an overview of our proposed methodology.

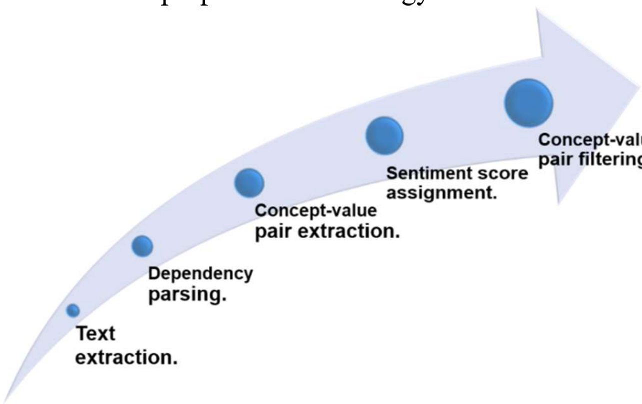

Figure 1. Methodology overview.

In the following subsections we describe each individual component of the system.

4.1 Dependency parsing information and concept-value pair extraction

While we build our framework on top of a few textual analysis components, syntactic dependency information represents the central part of the methodology we propose. We decided to do this because in the absence of any labeled data, syntactic information is a rich source of knowledge. Also, the language used is grammatically correct resulting in highly accurate parsed data. Finally, sentences tend to be short and factual, allowing for important information to be captured by primary dependency relations.

We obtain dependency parsing information by using the Stanford CoreNLP[4] engine on the entire body of a statement. After we retrieve parsed data, the system begins to build concept-value pairs by identifying each "**nsubj**" relation. With all relations identified, the next steps focus on adding targeted dependents, in a recursive manner, to each component of the relation. The below steps highlight the way our methodology makes uses of dependency information:

1. Run each sentence of the statement through the parser.
2. Identify subject-verb relation, "**nsubj**", where **POS=NN***.
3. For both **Subject** and **Governor** entities in the "**nsubj**" relation:
    a. Attach right dependents, if their syntactic relation is part of a *pre-defined set*.
    b. Attach left dependents, if their syntactic relation is part of a *pre-defined set*.
    c. If the **POS** of any added dependents is part of a *pre-defined set*, re-run the steps in 3.

There are few pre-defined sets of syntactic information we mention in the above algorithm, syntactic relations for left and right dependents, these are two different sets, and POS information for when to recursively call the algorithm. While our method is unsupervised, the sets of syntactic relations mentioned above were fine-tuned from a process that manually analyzed system results on 3 years of FOMC statements, 2013 through 2015, a total of around 15 statements. We started with lists derived by using the meaning of the syntactic relations then adjusted them by analyzing the results.

Figure 2 shows the parse result of a sentence, the starting point of the process.

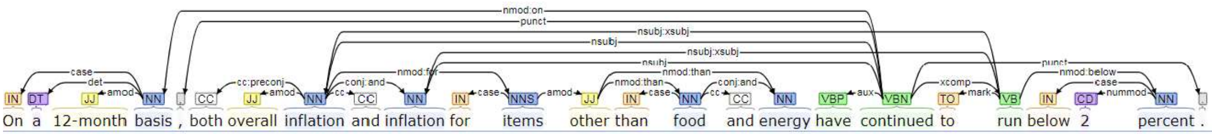

Figure 2. Dependency parsing output.

[3] https://www.crummy.com/software/BeautifulSoup/bs4/doc/
[4] https://stanfordnlp.github.io/CoreNLP/

The outcome of running the algorithm consists of a list of concept-value pairs, rooted in **nsubj** relations. The **key** is the **Subject** with its chosen dependents and the **value** is the **Governor** with its dependents. For a better understanding of the pair extraction step, we added an example bellow.
The concept-pair extraction steps are as follows:

1. **Subject relations:**
    1. "inflation" – "continued"
    2. "inflation" – "continued"
2. **Subject relations dependents:**
    1. "inflation" – "continued"
        1. "**inflation**" -> [both overall **inflation** and inflation [for]$_2$ items]$_1$
        2. "**continued**" -> [have **continued** [to]$_2$ run [below 2]$_3$ [percent]$_2$]$_1$
    2. "inflation" – "continued"
        1. "**inflation**" -> [**inflation**]$_1$
        2. "**continued**" -> [have **continued** [to]$_2$ run [below 2]$_3$ [percent]$_2$]$_1$
3. **Extracted key-value pairs:**
    1. **both overall inflation and inflation for items - have continued to run below 2 percent**
    2. **inflation - have continued to run below 2 percent**

4.2 Sentiment analysis

Subsequent to the dependency parsing module is the sentiment analysis step. Each concept-pair extracted in the previous step will receive a sentiment score.

Since we tried off-the-shelf tools, without being able to successfully capture the sentiment of the language used in the statements, the vast majority of scores turn neutral, we decided to perform this step with a custom-based solution. In fact, it is well known that sentiment analysis tools that are trained on customer product reviews, like the vast majority of available tools, are not suitable for financial texts. Loughran and McDonald (2011) found out that a large majority of negative words aren't negative if used in financial contexts. As an example, the word "bond" in non-financial data carries a positive connotation, but in finance is just a financial instrument that carries an objective charge.

Our proposed solution is rooted in SentiWordNet, (Esuli Andrea and Sebastiani, 2010) a lexical resource based on WordNet[5]. In SentiWordNet, each word is associated with three scores: objective, positive, and negative. These scores are obtained using a statistical model. We decided to use this resource to leverage the lexical and semantic nature of WordNet and the part-of-speech information. It provided superior results even though it is not specifically tuned for financial data. It also allowed us to derive custom sentiment scores and to easily and efficiently perform a sentiment analysis step.

To make our sentiment score more meaningful we accounted for, only the words that belong to the top key phrases extracted by the TextRank algorithm, (Mihalcea and Tarau, 2004). The algorithm identifies the most central key phrases in the text by using a rank-based graph method.

Given the above observations around our sentiment analysis component, the approach we implement to derive a sentiment score for the value of each concept-pair is as follows:

1. Run the TextRank algorithm on the statement to identify top keyphrases
2. For each value word that belongs to the selected keyphrases, calculate the (positive – negative) SentiWordNet score, taking into account POS information.
    a. If negation present, negate value.
3. Compute concept-value pair sentiment score as the average of the scores from step 2.

Using the approach described above, below are some examples of assigned scores:

- *advanced: 0.1406*
- *remains elevated: 0.0729*
- *continued to advance: 0.0417*
- *declined: -0.0893*

[5] https://wordnet.princeton.edu/

- *has stayed low: -0.2051*

From these examples we can observe how our method is able to capture various nuances of the language: "*declined*" has a lower score than "*has stayed low*". At the end of this step, our framework assigns a sentiment score for each extracted pair with values ranging from -1 to 1.

4.3 Concept-value pair filtering

The last component we implement is a selection step where we only select one concept-value pair for each of the economic factors of interest from all extracted concept-value pairs. The ultimate goal is to expose the one concept-value pair that captures the right information, as presented in Table 1.

The way we conduct this phase is by implementing a set of functions that act as adjustable knobs. One function is aimed to filter and identify relevant pairs by searching the economic factor in either the key, the value, or both parts of a pair. Another function supports a search step that allows for both string and embedding-based matching. Here, an embedding space of the implementer's choice can be used.

Besides the availability of robust search strategies, we also defined and implemented a set of targeted constraints a pair needs to follow *e.g.,* should contain numbers, returns only the shortest pair, etc. While the method has some default behavior and returns the best shortest match it also supports the return of the entire set of best matches.

One of the most robust features of the system is the fact that it is very easy to enhance it to target additional economic factors *e.g.,* job status. In order to achieve this, simply name a new factor of interest and if necessary, define which constraints the pairs need to follow.

Below are some examples of extracted pairs that show the language variations the method is able to capture. The text in bold represents the concept part of the pair while the underlined text is the value.

- *On a 12-month basis, overall* ***inflation*** *and the measure excluding food and energy prices have declined and <u>are running below 2 percent</u>.*
- ***Labor market conditions*** *<u>improved</u>, with the* ***unemployment rate*** *<u>declining further</u>.*
- *Recent data suggest that* ***growth of household spending*** *<u>moderated from its strong fourth-quarter pace</u>, while* ***business fixed investment*** *<u>continued to grow strongly</u>.*
- ***Household spending*** *<u>has continued to rise moderately</u> while* ***business fixed investment*** *<u>has remained soft</u>.*

The filtering module is the last step, at the end of which the best concept-value pairs are identified.

5 Results

For each given statement and for each economic factor, the system will return a single best concept-value pair with a sentiment score. When measuring the system's performance on how well it is able to identify and extract the correct pairs, both precision and recall stand at **96%**. These results are manually obtained on a dataset of 30 statements of 5 years, 2016 to 2020, inclusive.

The cases where the method is not identifying or extracting the correct information are mostly due to one of the following reasons: the quality of the parsing output, search match, *e.g.* while the method extracts the pair "*investment - advanced more quickly in recent months"* the filtering step fails to select it due to missing string match with "fixed investment", and occasionally large variations in the language of the statement that do not allow the method to extract the complete relevant value.

The default system output is an .xlsx file that contains the extracted concept-value pairs and their sentiment scores. This format can be easily integrated with automatic systems. In addition, to show how the extracted information can be used for human consumption, Figure 3 presents results obtained over a period of 8 years, 2013 to 2020, for two of the economic factors. We used bars to represent federal-funds rates, one of the most important economic information, and labels to depict economic factors values. We color coded the bars to reflect the sentiment scores, red color encodes a positive sentiment while blue a negative one. Sentiment intensity is reflected in the darkness of the color. In addition, the lower part of the plot captures the sentiment score throughout the years providing users with a historic view of how the sentiment of an economic factor changes and how it is correlated with the federal funds rate.

As we can observe, our method is not only able to identify and surface the right information but also provides a sentiment analysis history for the economic factors. This aspect in itself represents a

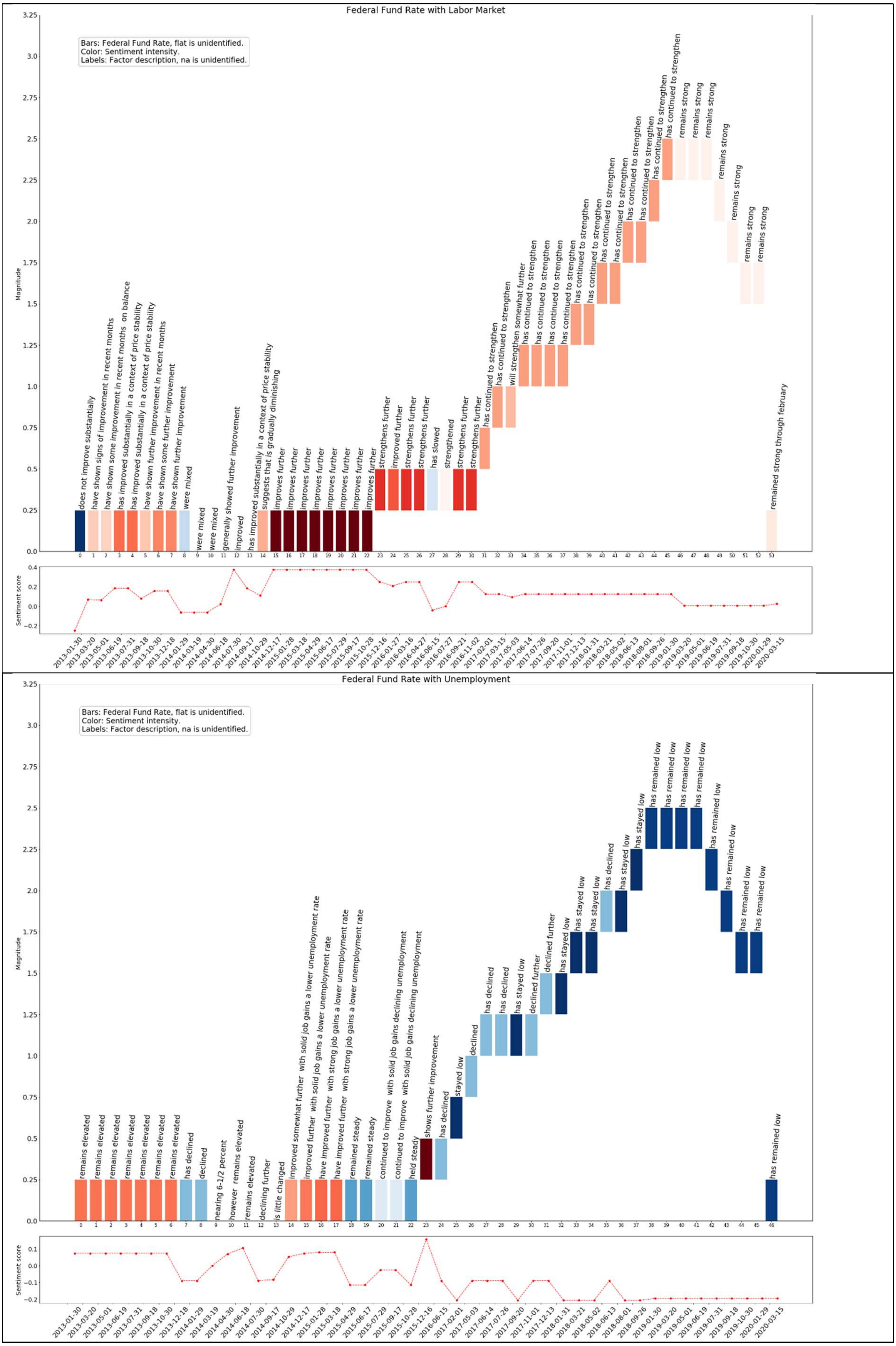

Figure 3. System results on FOMC statements.

valuable source of information for financial systems that try to predict the type of economy we could expect. More so, the extracted concept-value pairs can provide a semantic representation of an FOMC statement given that it captures the most salient information. Revealing such a semantically charged representation allows both humans and financial systems to easily compare and contrast how various economic aspects change throughout the years.

For a more complete analysis we run our methodology on news articles. Figure 4 presents results on the following news body "*The U.S. dollar declined against most major foreign currencies yesterday, although the drop was softened when bond prices failed to advance Tuesday's rally. The dollar began weakening in Europe as interest rates fell there for dollar deposits. The decline continued in New York trading, which was thin, although the dollar recovered slightly when bond prices began falling. Lower bond prices translate into higher long-term interest yields, which make dollar denominated investments more attractive. The bond market later closed little-changed from Tuesday. 'This is the first time in a while that we've gone back to trading off interest rates, and my feeling is it will continue between now and the (U.S.) election,' said Daniel Holland, an assistant vice president at Discount Corp., New York. In late New York trading, the dollar fell to 3.0210 West German marks from 3.0318 marks on Tuesday. The British pound rose to $1.2223 from $1.2155. In early Tokyo trading Thursday, the dollar strengthened against the Japanese currency, to 245.45 yen from 245.13 yen late yesterday in New York.*"[6]

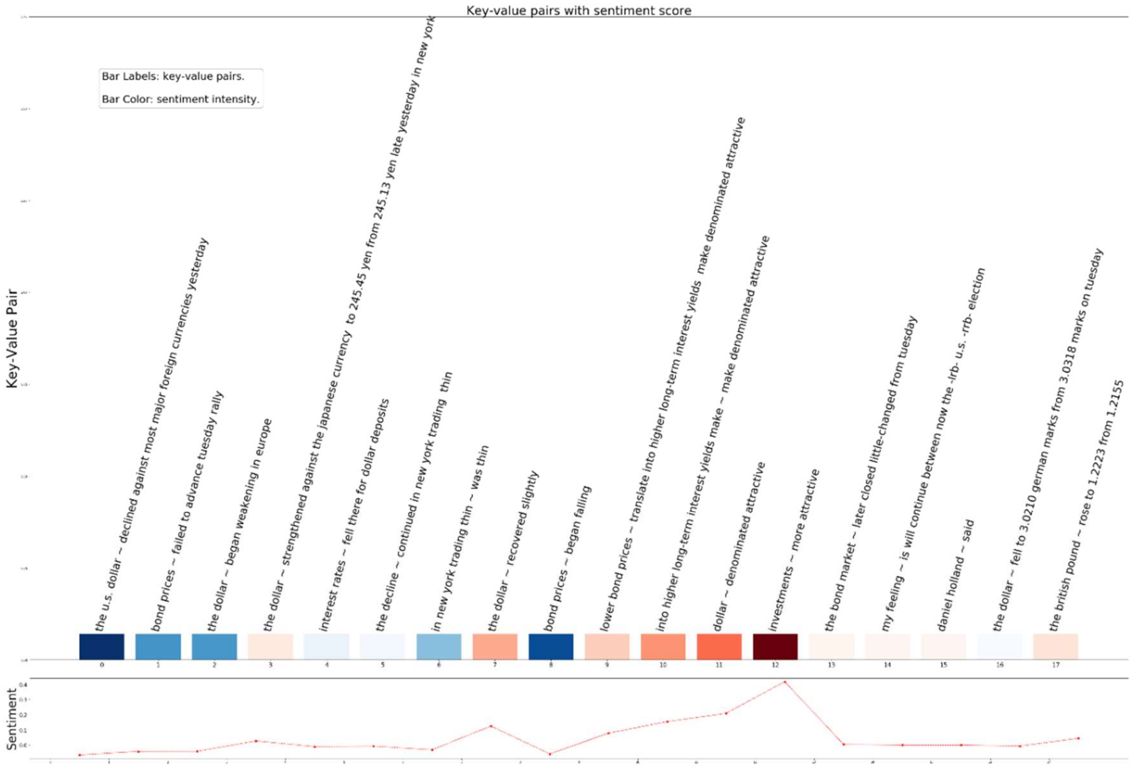

Figure 4. System results on news.

The extracted key-value pairs show that we can easily obtain a semantic summary of what has been mentioned in the body along with the sentiment it conveys. Results support the fact that our methodology extracts important information from a variety of textual data.

6 Conclusions

In this study we presented a novel unsupervised information extraction system with sentiment analysis. Our proposed architecture is robust, as it can be extended to support new targeted concepts, it can easily adapt to user-defined constraints, and it can be tuned to vary the amount of information it returns. We achieve 96% accuracy at extracting relevant concept pairs from FOMC statements and we show that we can use the same methodology on completely different data than the one used for tuning.

[6] https://www.figure-eight.com/data-for-everyone/

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