

Quantitative Research

Welcome to the Machine (Learning): An NLP framework for analyzing the Fed's monetary policy statements

- The following research note describes a natural language processing (NLP) technique that classifies and interprets the central bank's statements
- The model classified the semantics of each of the Fed monetary policy statements in 23 preponderant topics
- The most important finding was the degree of strength, given that the model can explain 9 out of 10 rate movements. The model also defines the range of variation of the terminal reference rate
- Analyzing today's statement, the model suggests a terminal rate between 3.5 and 4.25% (upper range)

Fed's topics classification. The Federal Open Market Committee (FOMC) statement is the primary tool that the monetary authority uses to communicate its monetary policy. It contains the target range for the federal funds rate, transmits its medium-term perspective on the US economy, and offers insights on the outcome of future votes. However, the interpretation of the Fed's monetary policy statement could be subject to a certain subjectivity due to the existence of behavioral biases that limit an objective interpretation.

The following research note describes a natural language processing (NLP) technique that classifies and interprets the central bank's statements. In addition, it also provides a methodology to confirm whether the communication made by the Central Bank is consistent with the monetary policy implemented.

NLP and Machine Learning. In recent years, machine learning (ML) has evolved to discover common features in verbal and written communication. Quantitative research techniques have gained ground in the application of solutions for the financial industry. Following this trend, the present study uses new methodologies for the analysis and processing of unstructured data.

Text mining is a tool used for extracting a summary from a set of documents. This is commonly referred to as a corpus. Central bank communication usually includes terms or phrases that convey significant messages related to the economy's evolution and can be extracted with the appropriate text mining tools. In the sentiment analysis literature, Natural Language Processing (NLP) methods are used to build dictionaries that can be associated with sentiments.

Unstructured data, such as Fed statements, provide a large amount of information. Unlike traditional methods of macroeconomic analysis, it is necessary to use NLP techniques to extract value from the statements. As a result, the main source of information for this study are the Fed's monetary policy statements from 1978 to 2022.

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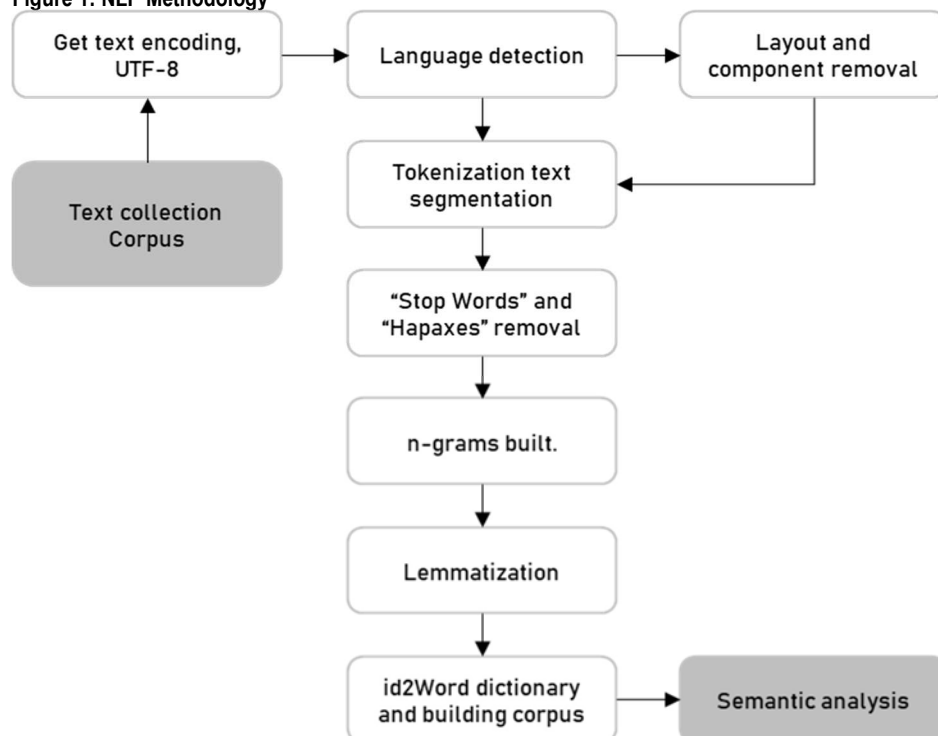
Winners of the award for best economic forecasters for Mexico in 2021, granted by Refinitiv



Document for distribution among the general public

The NLP model was carried out using Python, since the monetary policy statements are available in PDF and HTML formats. In total, 326 Fed statements were considered for our model (August 1978 to July 2022). The following figure shows the treatment applied to the press releases:

Figure 1: NLP Methodology



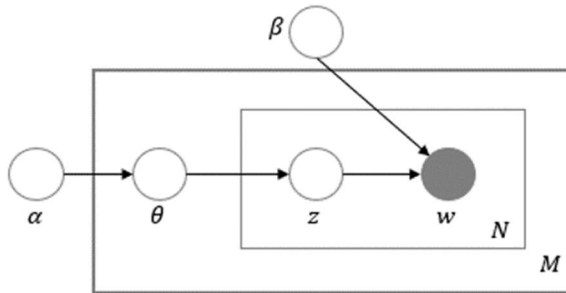
Source: Giuseppe Bruno, Text mining and sentiment extraction in Central Bank documents, IEEE International Conference on Big Data, 2016

The data engineering implemented starts-off by downloading and cleaning the text of the statements. Then, NLP techniques were applied to extract the most valuable information contained in the documents. Next, words that didn't added value (*stop words*), that appeared only once within the corpus (*hapaxes*), and that were present in 100% of the documents were eliminated. In addition, n-grams composed of 2 or more tokens (minimum processed text unit) were constructed, given that they could have high relevance in the interpretation of the document, for example: low inflation, high inflation; low unemployment, high unemployment; economic growth, etc. Finally, lemmatization techniques were used to reduce the words to their common root, to condense the size of the text and eliminate the unnecessary noise. As a result, a clean corpus was obtained.

It is important to highlight that the above-mentioned cleaning process is extremely important to build the ML classification model. Prior to the model, a bag of words (BoW) was built as the main input for defining a dictionary used during the modeling process.

The model was estimated using Latent Dirichlet Allocation (LDA). These assume that each statement can be represented by a mixture of topics, and each topic is described by a bag of words (BoW), the following figure is a general representation of the LDA model.

Figure 2: Graphic Representation of a LDA Model



For each document w in a corpus D :

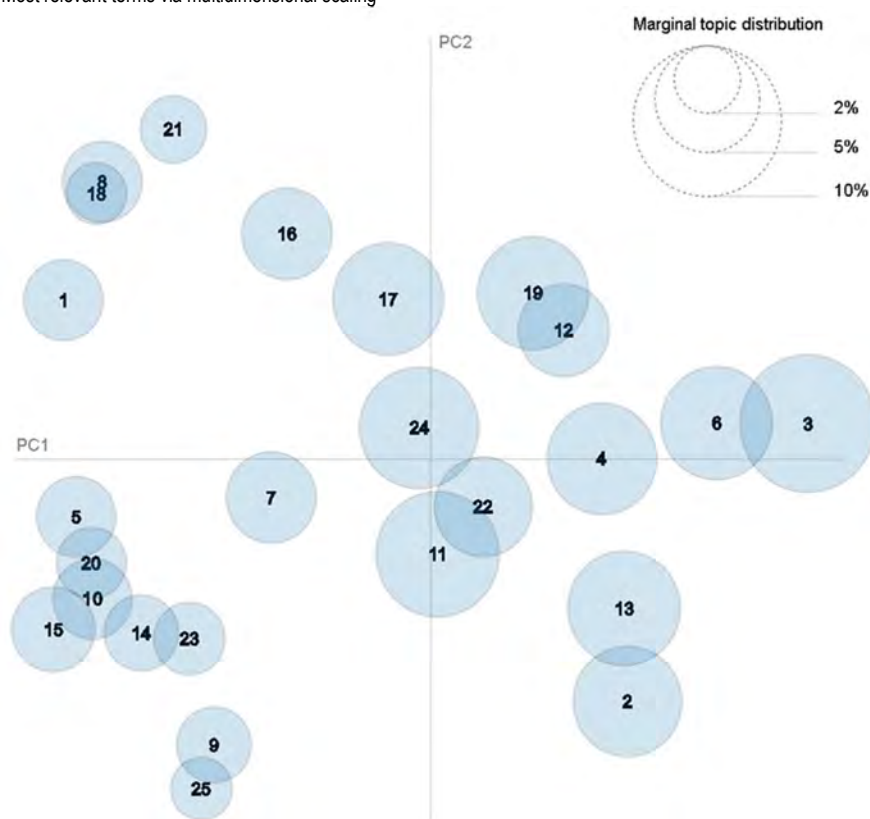
1. Choose $N \sim \text{Poisson}(\xi)$.
2. Choose $\theta \sim \text{Dir}(\alpha)$.
3. For each of the N words w_n :
 - (a) Choose a topic $z_n \sim \text{Multinomial}(\theta)$.
 - (b) Choose a word w_n from $p(w_n|z_n, \beta)$, a multinomial probability conditioned on the topic z_n

Source: D.M Blei, A.Y. Ng, and M.I. Jordan. Latent dirichlet allocation. The Journal of Machine Learning Research, 3:993-1022, 2003.

LDA is a generative model that describes how the documents within a dataset were created. In this context, a dataset is a collection of documents, and a document is a collection of words. Hence, the generative model describes how each document is represented by these words. Initially, it is assumed that there are K topic distributions within the set of documents, meaning that each K of the K multinomial distributions contains V elements, where V is the number of terms in our corpus.

The classification model identified the most relevant topics in the corpus built from the Federal Reserve Bank statements (refer to Chart 1). The bubble chart shows each of the topics defined in all the monetary policy statements. The size of the bubble explains the preponderance of the topic, while the dissimilarity that exists between the topics is represented by the distance between each of the bubbles; that is, the greater the distance, the greater the dissimilarity between the topics.

Chart 1: Intertopic Distance Map
Most relevant terms via multidimensional scaling



Source: Banorte

The bubble chart is a visual tool that helped find the optimal number of topics to classify all monetary policy statements. It is important to highlight that the ML model was trained through iterative processes that allowed to identify the optimal hyperparameters of the model to categorize the latent topics within the corpus.

To evaluate the efficiency of the model, two intrinsic metrics were used:

- 1) **Perplexity** allows us to measure how well the model predicts a sample. In the NLP context, it tells us the level of uncertainty that the model has by assigning probabilities to the text; that is, how much entropy the text has (the higher the entropy, the higher the level of uncertainty of the model). The closer this measure is to zero (including negative values), the more relevant the words are. However, the optimization of this measure does not necessarily reflect a better interpretation of the topics, since it is possible to have high perplexity and a null business sense relation.
- 2) **Coherence**. This metric helps us measure the degree of similarity in the semantics of the most relevant words within the topics. There are different coherence measures. In this case we use the “ C_v ” measure, based on subarrays, segmentation of top words, cosine distances and the use of NMPI (Normalized Mutual Point Information). The higher coherence, the more similar the semantics.

The optimal scenario is low perplexity combined with high coherence. However, a higher level of coherence is more relevant than low perplexity. In the search for the highest coherence, we use a variant of the LDA application, the “LDAMallet” model. The latter uses Gibbs sampling, unlike the standard LDA model which uses variational Bayesian methods. It is important to emphasize that both models require a priori the number of topics in which they will classify our corpus.

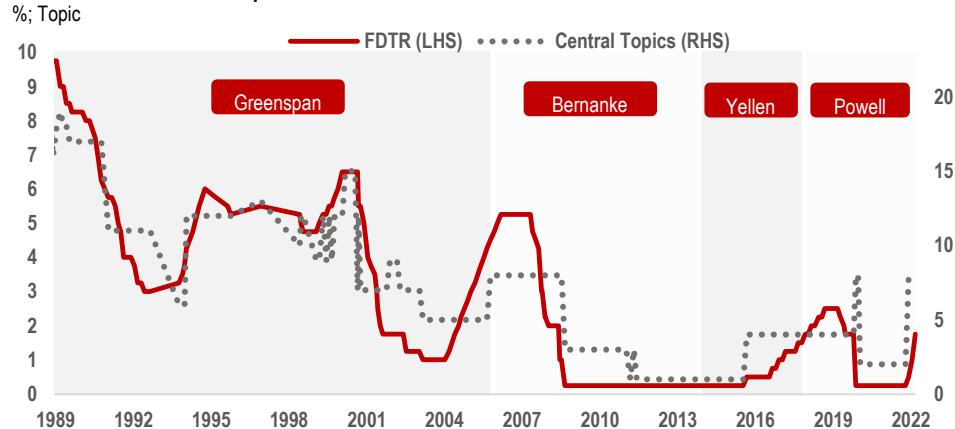
The elbow method was used to establish the optimal number of topics. An interval between 10 and 30 topics was established to measure the performance of the LDAMallet model to analyze their respective coherence. The method showed that the optimal scenario were 25 topics, with an approximate coherence of 0.43. The standard LDA model with the same scenario obtained a 0.39 coherence. Consequently, the LDAMallet model was chosen for the classification.

The LDAMallet model classified each monetary policy statement within the 25 topics. For this classification, the model establishes the weight that each topic has and assigns the one with the greatest magnitude. Even though 25 topics were identified in the corpus, the allocation resulted in 23 relevant topics.

Subsequently, the relationship between the Fed funds rate and the semantic classification obtained was analyzed (refer to Chart 2). **The most important finding was the degree of strength, given that the model can explain 9 out of 10 rate movements. The model also defines the range of variation of the terminal reference rate (refer to Chart 3).**

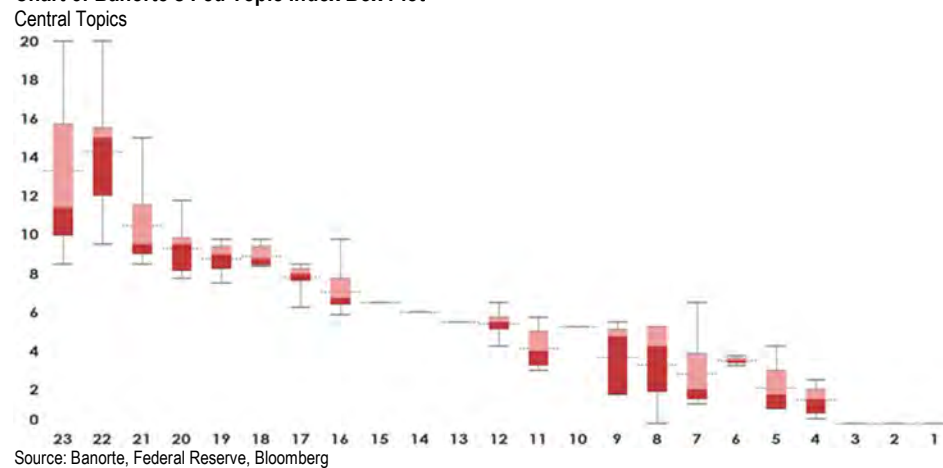
The model suggests a terminal rate between 3.5 and 4.25% (upper range). After today’s monetary policy announcement, the model classified this statement with a topic that anticipates the terminal rate between 3.5% and 4.25% The model also confirms the Fed’s congruence in its communication.

Chart 2: Banorte’s Fed Topic Index vs Fed Funds Rate



Source: Banorte, Federal Reserve, Bloomberg

Chart 3: Banorte's Fed Topic Index Box Plot



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