NATURAL LANGUAGE PROCESSING

Modeling Topic Trends in FOMC Meetings

By Giri • Updated on February 4, 2022

Topic modeling can help to analyze trends in FOMC meeting transcripts—this article shows you how.

Contents

The Federal Open Market Committee (FOMC) sets monetary policy in the US. It has 12 members who meet 8 times per year to discuss interest rates and other economic matters. Investors pay close attention to the outcomes from these meetings—they can have significant consequences for US and global financial markets.

The minutes of FOMC meetings are released three weeks after each meeting. Through the minutes, investors can get a better understanding of the content of FOMC meetings. This helps with interpreting FOMC decisions and understanding the possible consequences for financial markets.

In this article I show how topic modeling, an area of natural language processing (NLP), can help to analyze the content of FOMC meetings. I use Latent Dirichlet Allocation (LDA), a popular topic modeling approach, to identify the key themes, or topics, discussed in the meeting minutes.

Topic modeling and LDA

Topic modeling is a form of unsupervised learning that can be applied to unstructured text data. It identifies groups of words or phrases that have similar meaning—topics—using statistical techniques.

LDA works by assuming that each document has a mix of underlying (latent) topics, and that each topic is made up of words from a specified dictionary. By observing the words within a set of documents, LDA infers the topics that fit with those words based on a probabilistic framework.

The mix of topics in a chronological series of text documents, such as FOMC minutes, changes over time. With LDA, you can observe this changing mix. The changing mix of FOMC topics is of interest to investors and market observers as it indicates areas of relative focus in FOMC discussions.

For a hands-on example of topic modeling using LDA, see this article.

Analysis approach

I analyze trends in the FOMC minutes using the following approach:

- Collect the FOMC minutes to be analyzed
- Prepare the minutes for analysis
- Run an LDA model on the minutes
- Extract the changing mix of topics over time

The LDA model requires:

- The set of minutes transcripts being analyzed—the corpus—which we'll use for training the model and for topic analysis
- The dictionary of words to form the model vocabulary—this can be derived from the corpus

I implement LDA using the gensim package in **Python**. Gensim is a powerful yet accessible package for topic modeling in Python.

My analysis draws upon the work of academic and industry research into FOMC topic modeling (Jegadeesh and Wu and Saret and Mitra). Researchers and practitioners are increasingly using NLP approaches to gain better insights into financial market dynamics. This article presents one such approach.

Implementation in Python

In the following, I first set out the full code, then I step through and explain the key sections of code to implement the analysis in Python (v3.7.7).

The full code:

Full Code - Topic Trends in FOMC Meetings

```
#######################################
### TOPIC MODELING OF FOMC MINUTES ###
#######################################

### IMPORT LIBRARIES ###

import requests
import re
from bs4 import BeautifulSoup
import pandas as pd
import numpy as np
import gensim
import gensim.corpora as corpora
from gensim import models
import matplotlib.pyplot as plt
import spacy
from pprint import pprint
from wordcloud import WordCloud
from mpl_toolkits import mplot3d
import matplotlib.pyplot as plt

nlp = spacy.load("en_core_web_lg")
nlp.max_length = 1500000 # In case max_length is set to lower than this (ensure sufficient memory)

### GRAB THE DOCUMENTS BY PARSING URLs ###

# Define URLs for the specific FOMC minutes
URLPath = r'https://www.federalreserve.gov/monetarypolicy/fomcminutes'
URLExt = r'.htm'

# List for FOMC minutes from 2007 onward
MinutesList = ['20071031', '20071211', # 2007 FOMC minutes (part-year on new URL format)
           '20080130', '20080318', '20080430', '20080625', '20080805', '20080916', '20081029', '20081216', # 2
           '20090128', '20090318', '20090429', '20090624', '20090812', '20090923', '20091104', '20091216', # 2
           '20100127', '20100316', '20100428', '20100623', '20100810', '20100921', '20101103', '20101214', # 2
           '20110126', '20110315', '20110427', '20110622', '20110809', '20110921', '20111102', '20111213', # 2
           '20120125', '20120313', '20120425', '20120620', '20120801', '20120913', '20121024', '20121212', # 2
           '20130130', '20133020', '20130501', '20130619', '20130731', '20130918', '20131030', '20131218', # 2
           '20140129', '20140319', '20140430', '20140618', '20140730', '20140917', '20141029', '20141217', # 2
           '20150128', '20150318', '20150429', '20150617', '20150729', '20150917', '20151028', '20151216', # 2
           '20160127', '20160316', '20160427', '20160615', '20160727', '20160921', '20161102', '20161214', # 2
           '20172001', '20170315', '20170503', '20170614', '20170726', '20170920', '20171101', '20171213', # 2
           '20180131', '20180321', '20180502', '20180613', '20180801', '20180926', '20181108', '20181219', # 2
           '20190130', '20190320', '20190501', '20190619', '20190731', '20190918', '20191030', '20191211', # 2
           '20200129', '20200315', '20200429', '20200610', '20200729'] # 2020 FOMC minutes

### SETTING UP THE CORPUS ###

FOMCMinutes = [] # A list of lists to form the corpus
FOMCWordCloud = [] # Single list version of the corpus for WordCloud
FOMCTopix = [] # List to store minutes ID (date) and weight of each para

# Define function to prepare corpus
def PrepareCorpus(urlpath, urlext, minslist, minparalength):

    fomcmins = []
    fomcwordcloud = []
    fomctopix = []

    for minutes in minslist:

        response = requests.get(urlpath + minutes + urlext) # Get the URL response
        soup = BeautifulSoup(response.content, 'lxml') # Parse the response

        # Extract minutes content and convert to string
        minsTxt = str(soup.find("div", {"id": "content"})) # Contained within the 'div' tag

        # Clean text - stage 1
        minsTxt = minsTxt.strip()  # Remove white space at the beginning and end
```

```
        minsTxt = minsTxt.replace('\r', '') # Replace the \r with null
        minsTxt = minsTxt.replace(' ', ' ') # Replace " " with space.
        minsTxt = minsTxt.replace(' ', ' ') # Replace " " with space.
        while '  ' in minsTxt:
            minsTxt = minsTxt.replace('  ', ' ') # Remove extra spaces

        # Clean text - stage 2, using regex (as SpaCy incorrectly parses certain HTML tags)
        minsTxt = re.sub(r'(<[^>]*>)|' # Remove content within HTML tags
                         '([_]+)|' # Remove series of underscores
                         '(http[^\s]+)|' # Remove website addresses
                         '((a|p)\.m\.)', # Remove "a.m" and "p.m."
                         '', minsTxt) # Replace with null

        # Find length of minutes document for calculating paragraph weights
        minsTxtParas = minsTxt.split('\n') # List of paras in minsTxt, where minsTxt is split based on new lin
        cum_paras = 0 # Set up variable for cumulative word-count in all paras for a given minutes transcript
        for para in minsTxtParas:
            if len(para)>minparalength: # Only including paragraphs larger than 'minparalength'
                cum_paras += len(para)

        # Extract paragraphs
        for para in minsTxtParas:
            if len(para)>minparalength: # Only extract paragraphs larger than 'minparalength'

                topixTmp = [] # Temporary list to store minutes date & para weight tuple
                topixTmp.append(minutes) # First element of tuple (minutes date)
                topixTmp.append(len(para)/cum_paras) # Second element of tuple (para weight), NB. Calculating

                # Parse cleaned para with SpaCy
                minsPara = nlp(para)

                minsTmp = [] # Temporary list to store individual tokens

                # Further cleaning and selection of text characteristics
                for token in minsPara:
                    if token.is_stop == False and token.is_punct == False and (token.pos_ == "NOUN" or token.p
                        minsTmp.append(token.lemma_.lower()) # Convert to lower case and retain the lemmatized
                        fomcwordcloud.append(token.lemma_.lower()) # Add word to WordCloud list
                fomcmins.append(minsTmp) # Add para to corpus 'list of lists'
                fomctopix.append(topixTmp) # Add minutes date & para weight tuple to list for storing

    return fomcmins, fomcwordcloud, fomctopix

# Prepare corpus
FOMCMinutes, FOMCWordCloud, FOMCTopix = PrepareCorpus(urlpath=URLPath, urlext=URLExt, minslist=MinutesList, mi

# Generate and plot WordCloud for full corpus
wordcloud = WordCloud(background_color="white").generate(','.join(FOMCWordCloud)) # NB. 'join' method used to
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.show()

### NUMERIC REPRESENTATION OF CORPUS USING TF-IDF ###

# Form dictionary by mapping word IDs to words
ID2word = corpora.Dictionary(FOMCMinutes)

# Set up Bag of Words and TFIDF
corpus = [ID2word.doc2bow(doc) for doc in FOMCMinutes] # Apply Bag of Words to all documents in corpus
TFIDF = models.TfidfModel(corpus) # Fit TF-IDF model
trans_TFIDF = TFIDF[corpus] # Apply TF-IDF model

### SET UP LDA MODEL ###

SEED = 130 # Set random seed
NUM_topics = 8 # Set number of topics
ALPHA = 0.15 # Set alpha
ETA = 1.25 # Set eta

# Train LDA model using the corpus
lda_model = gensim.models.LdaMulticore(corpus=trans_TFIDF, num_topics=NUM_topics, id2word=ID2word, random_stat

# Print topics generated from the training corpus
pprint(lda_model.print_topics(num_words=10))

### CALCULATE COHERENCE SCORE ###

# Set up coherence model
coherence_model_lda = gensim.models.CoherenceModel(model=lda_model, texts=FOMCMinutes, dictionary=ID2word, coh
```

```python
# Calculate and print coherence
coherence_lda = coherence_model_lda.get_coherence()
print('-'*50)
print('\nCoherence Score:', coherence_lda)
print('-'*50)

### GENERATE WEIGHTED TOPIC PROPORTIONS FOR CORPUS ###

para_no = 0 # Set document counter
for para in FOMCTopix:
    TFIDF_para = TFIDF[corpus[para_no]] # Apply TFIDF model to individual minutes documents
    # Generate and store weighted topic proportions for each para
    for topic_weight in lda_model.get_document_topics(TFIDF_para): # List of tuples ("topic number", "topic pr
        FOMCTopix[para_no].append(FOMCTopix[para_no][1]*topic_weight[1]) # Weights are the second element of t
    para_no += 1

### GENERATE AGGREGATE TOPIC MIX OVER EACH MINUTES TRANSCRIPT ###

# Form dataframe of weighted topic proportions (paragraphs) - include any chosen topic names
FOMCTopixDF = pd.DataFrame(FOMCTopix, columns=['Date', 'Weight', 'Inflation', 'Topic 2', 'Consumption', 'Topic

# Aggregate topic mix by minutes documents (weighted sum of paragraphs)
TopixAggDF = pd.pivot_table(FOMCTopixDF, values=['Inflation', 'Topic 2', 'Consumption', 'Topic 4', 'Market', '

# Plot results - select which topics to print
TopixAggDF.plot(y=['Inflation', 'Consumption', 'Market', 'Policy'], kind='line', use_index=True)

### PRINT TOPIC WORD CLOUDS ###

topic = 0 # Initialize counter
while topic < NUM_topics:
    # Get topics and frequencies and store in a dictionary structure
    topic_words_freq = dict(lda_model.show_topic(topic, topn=50)) # NB. the 'dict()' constructor builds dictio
    topic += 1

    # Generate Word Cloud for topic using frequencies
    wordcloud = WordCloud(background_color="white").generate_from_frequencies(topic_words_freq)
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis("off")
    plt.show()

### TEST COHERENCE BY VARYING KEY PARAMETERS ###

# Coherence values for varying eta
def compute_coherence_values_ETA(corpus, dictionary, num_topics, seed, alpha, texts, start, limit, step):
    coherence_values = []
    model_list = []
    for eta in range(start, limit, step):
        model = gensim.models.LdaMulticore(corpus=corpus, id2word=dictionary, num_topics=num_topics, random_st
        model_list.append(model)
        coherencemodel = gensim.models.CoherenceModel(model=model, texts=texts, dictionary=dictionary, coheren
        coherence_values.append(coherencemodel.get_coherence())
    return model_list, coherence_values

model_list, coherence_values = compute_coherence_values_ETA(corpus=trans_TFIDF, dictionary=ID2word, num_topics

# Plot graph of coherence values by varying eta
limit=175; start=115; step=5;
#x = range(start, limit, step)
x_axis = []
for x in range(start, limit, step):
    x_axis.append(x/100)
plt.plot(x_axis, coherence_values)
plt.xlabel("Eta")
plt.ylabel("Coherence score")
plt.legend(("coherence"), loc='best')
plt.show()

# Coherence values for varying seed
def compute_coherence_values_SEED(corpus, dictionary, alpha, num_topics, eta, texts, start, limit, step):
    coherence_values = []
    model_list = []
    for seed in range(start, limit, step):
        model = gensim.models.LdaMulticore(corpus=corpus, id2word=dictionary, alpha=alpha, num_topics=num_topi
        model_list.append(model)
        coherencemodel = gensim.models.CoherenceModel(model=model, texts=texts, dictionary=dictionary, coheren
        coherence_values.append(coherencemodel.get_coherence())
    return model_list, coherence_values
```

```
model_list, coherence_values = compute_coherence_values_SEED(corpus=trans_TFIDF, dictionary=ID2word, alpha=ALP

# Plot graph of coherence values by varying seed
limit=165; start=60; step=5;
x = range(start, limit, step)
plt.plot(x, coherence_values)
plt.xlabel("Random Seed")
plt.ylabel("Coherence score")
plt.legend(("coherence"), loc='best')
plt.show()

# Coherence values for varying alpha
def compute_coherence_values_ALPHA(corpus, dictionary, num_topics, seed, eta, texts, start, limit, step):
    coherence_values = []
    model_list = []
    for alpha in range(start, limit, step):
        model = gensim.models.LdaMulticore(corpus=corpus, id2word=dictionary, num_topics=num_topics, random_st
        model_list.append(model)
        coherencemodel = gensim.models.CoherenceModel(model=model, texts=texts, dictionary=dictionary, coheren
        coherence_values.append(coherencemodel.get_coherence())
    return model_list, coherence_values

model_list, coherence_values = compute_coherence_values_ALPHA(dictionary=ID2word, corpus=trans_TFIDF, num_topi

# Plot graph of coherence values by varying alpha
limit=20; start=1; step=1;
x_axis = []
for x in range(start, limit, step):
    x_axis.append(x/20)
plt.plot(x_axis, coherence_values)
plt.xlabel("Alpha")
plt.ylabel("Coherence score")
plt.legend(("coherence"), loc='best')
plt.show()

# Coherence values for varying number of topics
def compute_coherence_values_TOPICS(corpus, dictionary, alpha, seed, eta, texts, start, limit, step):
    coherence_values = []
    model_list = []
    for num_topics in range(start, limit, step):
        model = gensim.models.LdaMulticore(corpus=corpus, id2word=dictionary, alpha=alpha, num_topics=num_topi
        model_list.append(model)
        coherencemodel = gensim.models.CoherenceModel(model=model, texts=texts, dictionary=dictionary, coheren
        coherence_values.append(coherencemodel.get_coherence())
    return model_list, coherence_values

model_list, coherence_values = compute_coherence_values_TOPICS(corpus=trans_TFIDF, dictionary=ID2word, alpha=A

# Plot graph of coherence values by varying number of topics
limit=11; start=2; step=1;
x = range(start, limit, step)
plt.plot(x, coherence_values)
plt.xlabel("Number of Topics")
plt.ylabel("Coherence score")
plt.legend(("coherence"), loc='best')
plt.show()
```

Stepping through the code:

Import libraries

We'll need libraries for requesting and parsing minutes transcripts from the FOMC website (requests and BeautifulSoup), text pre-processing (regular expressions and SpaCy), analyzing and displaying results (pandas, numpy, wordcloud and matplotlib) and LDA modeling (gensim).

Import libraries

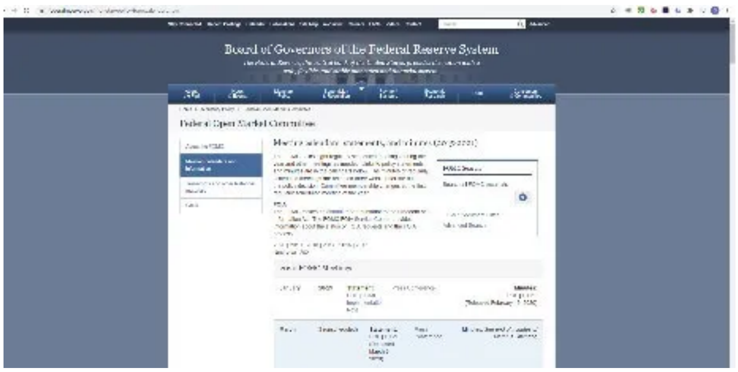
```
import requests
import re
```

```
from bs4 import BeautifulSoup
import pandas as pd
import numpy as np
import gensim
import gensim.corpora as corpora
from gensim import models
import matplotlib.pyplot as plt
import spacy
from pprint import pprint
from wordcloud import WordCloud
from mpl_toolkits import mplot3d
import matplotlib.pyplot as plt

nlp = spacy.load("en_core_web_lg")
nlp.max_length = 1500000 # In case max_length is set to lower than this (ensure sufficient memory)
```

Sourcing FOMC minutes

You can source FOMC minutes transcripts directly from the FOMC website.



Minutes transcripts on the FOMC website

For this analysis, I sourced minutes of FOMC meetings from October 2007 to July 2020 (the period for which current HTML formatting applies). This provides a good sample—from the aftermath of the 2007 financial crisis to the period following the 2020 COVID-19 pandemic.

I set up variables for the first part of the URL path (`URLPath`) and the URL extension (`URLExt`), as these are common elements of the URL path for all the minutes transcripts. I then create a list of dates for the minutes being analyzed (`MinutesList`).

Setting up URL paths for sourcing FOMC minutes transcripts

```
# Define URLs for the specific FOMC minutes
URLPath = r'https://www.federalreserve.gov/monetarypolicy/fomcminutes'
URLExt = r'.htm'

# List for FOMC minutes from 2007 onward
MinutesList = ['20071031', '20071211', # 2007 FOMC minutes (part-year on new URL format)
            '20080130', '20080318', '20080430', '20080625', '20080805', '20080916', '20081029', '20081216', # 2
            '20090128', '20090318', '20090429', '20090624', '20090812', '20090923', '20091104', '20091216', # 2
            '20100127', '20100316', '20100428', '20100623', '20100810', '20100921', '20101103', '20101214', # 2
            '20110126', '20110315', '20110427', '20110622', '20110809', '20110921', '20111102', '20111213', # 2
            '20120125', '20120313', '20120425', '20120620', '20120801', '20120913', '20121024', '20121212', # 2
            '20130130', '20133020', '20130501', '20130619', '20130731', '20130918', '20131030', '20131218', # 2
            '20140129', '20140319', '20140430', '20140618', '20140730', '20140917', '20141029', '20141217', # 2
            '20150128', '20150318', '20150429', '20150617', '20150729', '20150917', '20151028', '20151216', # 2
            '20160127', '20160316', '20160427', '20160615', '20160727', '20160921', '20161102', '20161214', # 2
            '20172001', '20170315', '20170503', '20170614', '20170726', '20170920', '20171101', '20171213', # 2
```

```
          '20180131', '20180321', '20180502', '20180613', '20180801', '20180926', '20181108', '20181219', # 2
          '20190130', '20190320', '20190501', '20190619', '20190731', '20190918', '20191030', '20191211', # 2
          '20200129', '20200315', '20200429', '20200610', '20200729'] # 2020 FOMC minutes
```

Setting up the corpus

The corpus is the collection of FOMC meeting transcripts that we're analyzing. It's also used for training our LDA model.

There are a number of steps in setting up the corpus:

- Text pre-processing—we clean the transcripts by removing special characters, extra spaces, stop words and punctuation, then lemmatizing and selecting the parts-of-speech that we wish to retain (nouns, adjectives and verbs) (*see this description to learn more about text pre-processing in natural language workflows*)
- Extract paragraphs from each of the transcripts—analysis by paragraph lends to better LDA analysis, but we ignore small paragraphs as they don't add much value (I use a variable called `minparalength` to set the minimum length of paragraph extracted)
- Set up lists—containing (i) the paragraphs from all the FOMC minutes (`FOMCMinutes`) as a 'list of lists', where each sub-list is a paragraph—this is a format suitable for input into the LDA model, (ii) a single list of all the paragraphs (`FOMCWordCloud`), ie. not a 'list of lists', which is used for generating a word cloud of the corpus, and (iii) a list containing the date and 'weight' of each paragraph in the corpus (`FOMCTopix`)—this is needed to aggregate the topic mixes of each paragraph into a combined topic mix for each meeting (see later).

To calculate the weight of each paragraph, I first calculate the total number of characters in each minutes transcript and store this in a variable called `cum_paras`. Then, for each paragraph I calculate the paragraph's length (number of characters `len(para)`) and divide it by `cum_paras` to arrive at the weight for that paragraph in the minutes transcript. I store the result in `FOMCTopix`.

Note that the total weights of all paragraphs in a given minutes transcript will sum to 1.

To set up the corpus, I define a function called `PrepareCorpus` which steps through each of the minutes transcripts, sources it and applies the above steps.

Function to prepare the FOMC minutes corpus

```
FOMCMinutes = [] # A list of lists to form the corpus
FOMCWordCloud = [] # Single list version of the corpus for WordCloud
FOMCTopix = [] # List to store minutes ID (date) and weight of each para

# Define function to prepare corpus
def PrepareCorpus(urlpath, urlext, minslist, minparalength):

    fomcmins = []
    fomcwordcloud = []
    fomctopix = []
```

```
    for minutes in minslist:

        response = requests.get(urlpath + minutes + urlext) # Get the URL response
        soup = BeautifulSoup(response.content, 'lxml') # Parse the response

        # Extract minutes content and convert to string
        minsTxt = str(soup.find("div", {"id": "content"})) # Contained within the 'div' tag

        # Clean text - stage 1
        minsTxt = minsTxt.strip()  # Remove white space at the beginning and end
        minsTxt = minsTxt.replace('\r', '') # Replace the \r with null
        minsTxt = minsTxt.replace(' ', ' ') # Replace " " with space.
        minsTxt = minsTxt.replace(' ', ' ') # Replace " " with space.
        while '  ' in minsTxt:
            minsTxt = minsTxt.replace('  ', ' ') # Remove extra spaces

        # Clean text - stage 2, using regex (as SpaCy incorrectly parses certain HTML tags)
        minsTxt = re.sub(r'(<[^>]*>)|' # Remove content within HTML tags
                         '([_]+)|' # Remove series of underscores
                         '(http[^\s]+)|' # Remove website addresses
                         '((a|p)\.m\.)', # Remove "a.m" and "p.m."
                         '', minsTxt) # Replace with null

        # Find length of minutes document for calculating paragraph weights
        minsTxtParas = minsTxt.split('\n') # List of paras in minsTxt, where minsTxt is split based on new lin
        cum_paras = 0 # Set up variable for cumulative word-count in all paras for a given minutes transcript
        for para in minsTxtParas:
            if len(para)>minparalength: # Only including paragraphs larger than 'minparalength'
                cum_paras += len(para)

        # Extract paragraphs
        for para in minsTxtParas:
            if len(para)>minparalength: # Only extract paragraphs larger than 'minparalength'

                topixTmp = [] # Temporary list to store minutes date & para weight tuple
                topixTmp.append(minutes) # First element of tuple (minutes date)
                topixTmp.append(len(para)/cum_paras) # Second element of tuple (para weight), NB. Calculating

                # Parse cleaned para with SpaCy
                minsPara = nlp(para)

                minsTmp = [] # Temporary list to store individual tokens

                # Further cleaning and selection of text characteristics
                for token in minsPara:
                    if token.is_stop == False and token.is_punct == False and (token.pos_ == "NOUN" or token.p
                        minsTmp.append(token.lemma_.lower()) # Convert to lower case and retain the lemmatized
                        fomcwordcloud.append(token.lemma_.lower()) # Add word to WordCloud list
                fomcmins.append(minsTmp) # Add para to corpus 'list of lists'
                fomctopix.append(topixTmp) # Add minutes date & para weight tuple to list for storing

    return fomcmins, fomcwordcloud, fomctopix
```

We can now call the above function to prepare our corpus.

Prepare corpus

```
# Prepare corpus
FOMCMinutes, FOMCWordCloud, FOMCTopix = PrepareCorpus(urlpath=URLPath, urlext=URLExt, minslist=MinutesList, mi
```

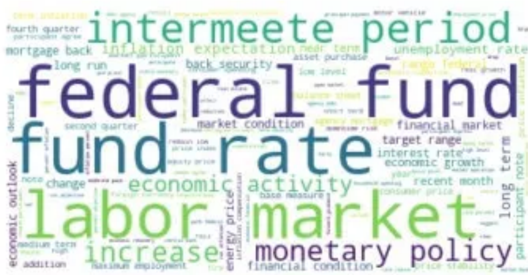
I set `minparalength` to 200—this seems to be a good length for capturing paragraphs which have meaningful content. Shorter paragraphs tend to contain greetings or administrative comments.

Inspecting the corpus

We can see what the prepared corpus looks like by generating a word cloud.

Generate word cloud

```
# Generate and plot WordCloud for full corpus
wordcloud = WordCloud(background_color="white").generate(','.join(FOMCWordCloud)) # NB. 'join' method used to
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.show()
```



Word cloud of FOMC minutes corpus

We see a number of words in the corpus that are typical of FOMC meetings, including “federal”, “fund rate”, “market” and “monetary policy”.

Training the LDA model

To train our LDA model, we first need to form a dictionary from our corpus. We map the corpus to word IDs, then convert the words using a bag-of-words approach and finally apply TF-IDF to the result. This process is called text representation.

Text representation

```
# Form dictionary by mapping word IDs to words
ID2word = corpora.Dictionary(FOMCMinutes)

# Set up Bag of Words and TFIDF
corpus = [ID2word.doc2bow(doc) for doc in FOMCMinutes] # Apply Bag of Words to all documents in corpus
TFIDF = models.TfidfModel(corpus) # Fit TF-IDF model
trans_TFIDF = TFIDF[corpus] # Apply TF-IDF model
```

We use TF-IDF as it produces better results than using bag-of-words alone. TF-IDF adjusts for words that appear frequently but have low semantic value, relative to words that appear infrequently but with higher semantic value. This favors words which have more meaning in the context of the corpus.

For more information about bag-of-words, TF-IDF and other text representations, see this description.

We next select the model parameters that we wish to use and run the model.

Run LDA model

```
SEED = 130 # Set random seed
```

```
NUM_topics = 8 # Set number of topics
ALPHA = 0.15 # Set alpha
ETA = 1.25 # Set eta

# Train LDA model using the corpus
lda_model = gensim.models.LdaMulticore(corpus=trans_TFIDF, num_topics=NUM_topics, id2word=ID2word, random_stat
```

The parameters shown above are key inputs for an LDA model. `NUM_topics`, in particular, needs to be set by the user. The other parameters (`SEED`, `ALPHA` and `ETA`) help to produce better results with fine-tuning.

To learn more about LDA parameters and the process for fine-tuning them, please see this [description of LDA model evaluation](#).

How do we evaluate the results of our LDA model?

There are quantitative approaches for doing this, but when applied to a text corpus it's helpful to produce results that have a sensible human interpretation. This requires judgement.

In terms of quantitative measures, a common measure for evaluating LDA models is the *coherence score*. This measures the semantic similarity (likeness of meaning) between the words in each topic of an LDA model. All else equal, a higher coherence score is better.

We can measure the coherence of our model using the `CoherenceModel` in gensim.

Calculate the model coherence

```
# Set up coherence model
coherence_model_lda = gensim.models.CoherenceModel(model=lda_model, texts=FOMCMinutes, dictionary=ID2word, coh

# Calculate coherence
coherence_lda = coherence_model_lda.get_coherence()
```

The coherence score for our model is:

> Coherence Score: 0.63779581

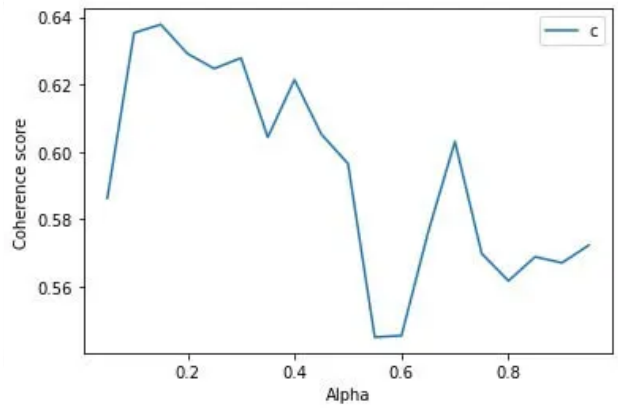
This is a fairly good result, based on careful selection of the above parameters.

How did we arrive at our parameters?

In choosing the number of topics (`NUM_topics`), I was guided by Jegadeesh and Wu, who choose 8 topics for their LDA model—I chose the same, as it tended to produce sensible topic interpretations.

To select the other parameters, you can explore the effect of changing parameter values on model coherence—refer the section *TEST COHERENCE BY VARYING KEY PARAMETERS* in the full code listing.

A test of coherence by varying alpha, for instance, results in the following plot (refer full code listing):



LDA model coherence by varying alpha

The above plot suggests that an alpha of 0.15 produces a high coherence—this is the value of alpha adopted.

Note that by setting the `SEED` parameter, we ensure that the model will produce the same results with repeated runs.

Analyzing the topic mix

Since we're using the same corpus for training and analysis, we don't need to run the trained LDA model on a new set of documents. Instead, we can go straight to analyzing the corpus.

Our goal is to calculate the topic mix for each of the minutes transcripts in the corpus. By plotting the topic mix over the chronological sequence of the meetings (since each meeting occurred on a given date), we can observe any trends or changes in the topic mix over time.

Recall that we divided our corpus into individual paragraphs, hence our model will produce a topic mix for each paragraph of each transcript in the corpus. The topic mix is a proportionate allocation to each of the (`NUM_topics`) topics in the model for each paragraph. The proportions across all topics in the paragraph will sum to 1.

We now need to convert these paragraph-level topic mixes to document-level topic mixes (ie. to create an aggregate topic mix for each meeting).

Once again I was guided by Jegadeesh and Wu. They calculate document-level topic mixes (each document being a minutes transcript in our case) using a weighted sum of paragraph-level topic mixes—I adopt the same approach.

We've already calculated each paragraph's weight when we set up our corpus and stored it in `FOMCTopix`. Let's call these weights the 'document-weight' of each paragraph. Using this, we generate aggregate topic mixes as follows:

- Extract the topic mix for each paragraph and store the result in `FOMCTopix` alongside the paragraph's meeting date and its document-weight
- Multiply each topic proportion in the paragraph's topic mix by the paragraph's document-weight
- For each document (ie. individual meeting transcript), sum the topic proportions, topic by topic, across all topics for all paragraphs in the transcript

We will end up with the weighted topic mixes for each minutes transcript, where the weights are based on the relative lengths of the paragraphs within each transcript.

I extract each paragraph's topic mix using the `get_document_topics` method of gensim and append the results to `FOMCTopix`, which is in a list format. I then convert this list to a data frame object and call the `pivot_table` method to sum the topic proportions across all paragraphs within each minutes transcript.

Generate weighted topic proportions for all paragraphs

```
para_no = 0 # Set document counter
for para in FOMCTopix:
    TFIDF_para = TFIDF[corpus[para_no]] # Apply TFIDF model to individual minutes documents
    # Generate and store weighted topic proportions for each para
    for topic_weight in lda_model.get_document_topics(TFIDF_para): # List of tuples ("topic number", "topic pr
        FOMCTopix[para_no].append(FOMCTopix[para_no][1]*topic_weight[1]) # Weights are the second element of t
    para_no += 1

# Form dataframe of weighted topic proportions (paragraphs) - include any chosen topic names
FOMCTopixDF = pd.DataFrame(FOMCTopix, columns=['Date', 'Weight', 'Inflation', 'Topic 2', 'Consumption', 'Topic

# Aggregate topic mix by minutes documents (weighted sum of paragraphs)
TopixAggDF = pd.pivot_table(FOMCTopixDF, values=['Inflation', 'Topic 2', 'Consumption', 'Topic 4', 'Market', '
```

Note that I have assigned names to some of the topics in the above code—I'll discuss this in the next section.

Interpreting topics

Although LDA topic modeling is a quantitative process, the identified topics may not always lend themselves to easy interpretation. You can apply judgment in how you label and select topics depending on your analysis.

You can explore topic contents by generating word clouds.

Generate topic word clouds

```
topic = 0 # Initialize counter
while topic < NUM_topics:
    # Get topics and frequencies and store in a dictionary structure
```

```
    topic_words_freq = dict(lda_model.show_topic(topic, topn=50)) # NB. the 'dict()' constructor builds dictio
    topic += 1

    # Generate Word Cloud for topic using frequencies
    wordcloud = WordCloud(background_color="white").generate_from_frequencies(topic_words_freq)
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis("off")
    plt.show()
```

In our case, I had set 8 topics in the modeling (`NUM_topics` = 8) based on guidance from Jegadeesh and Wu [1]. This resulted in topics that had a high coherence and good interpretability. Not all of the 8 topics were entirely useful however—some of them were a bit 'noisy' and didn't add much to the analysis. I therefore chose 4 topics on which to focus.

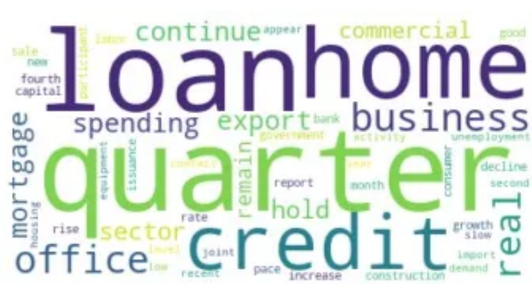
Saret and Mitra also used 8 topics in their modeling but reconfigured this into a smaller number of topics (6 in their analysis), based on what they considered to be sensible interpretations.

For the 4 topics which I chose, I assigned labels based on the words in the topics and also in comparison with labels used by Jegadeesh and Wu. The topics and labels that I chose are:

- Inflation
- Consumption
- Market
- Policy

The word clouds for these topics are shown below.

Word cloud of INFLATION topic



Word cloud of CONSUMPTION topic

Word cloud of MARKET topic

Word cloud of POLICY topic

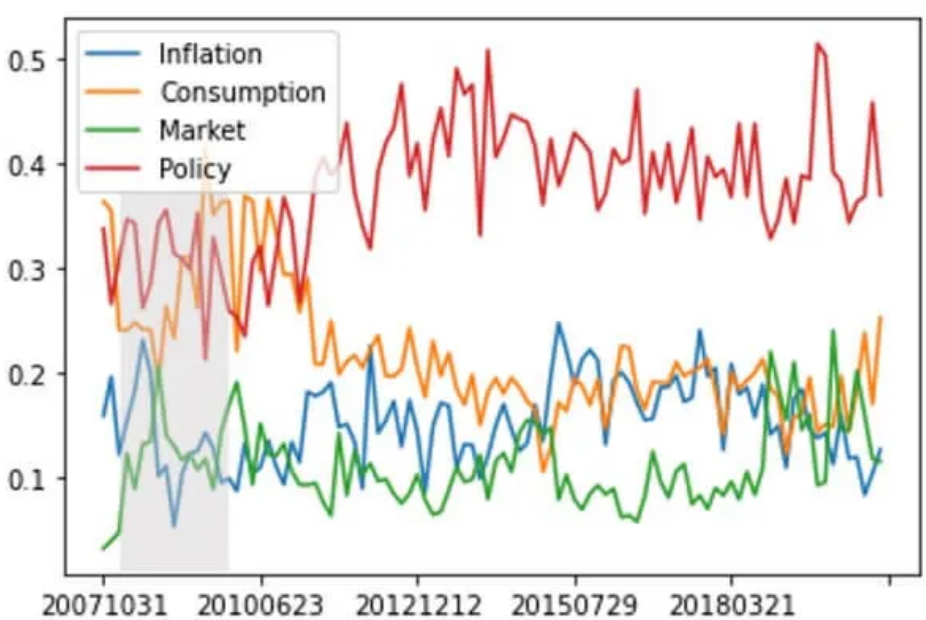
Topic mix results

We're now ready to plot the topic mix of our chosen topics over time.

Plot topic mix over time

```
# Plot results - select which topics to print
TopixAggDF.plot(y=['Inflation', 'Consumption', 'Market', 'Policy'], kind='line', use_index=True)
```

Let's see what this looks like:



Date

Topic mix over time of FOMC minutes

The shaded region (2008–09) represents a US recession period (NBER-designated). The x-axis shows the date of FOMC meetings and the y-axis shows the proportion of each meeting that each topic makes up, based on our analysis.

Interpreting the results

We observe the following from our plot of the FOMC topic mix over time:

- There is a noticeable variation in the topic mix over time, particularly for the *policy* and *consumption* topics
- There was a significant increase in the time allocated to discussing *policy* in the period following the 2008–09 recession, and this coincided with a significant reduction in the time spent discussing *consumption*
- Time spent discussing *inflation* and the *market* has been more stable, albeit with a higher proportion during the recession and some divergence during 2014–2018 (ie. more time on *inflation* and less time on the *market*)

These observations appear to make sense in light of historical circumstances.

Policy discussions in particular have been an important area for the FOMC since the 2008–09 recession. This reflects the role that monetary policy has had on US financial markets since then, and the significant policy decisions that the FOMC has made (eg. changing the federal funds target rate from over 5% in 2007 to below 0.25% by 2009).

The increase in time spent discussing inflation since 2014 (until recently) reflects the degree of concern the FOMC has had around the management of inflation (which has been persistently low).

Similarly, it's not surprising that more time than usual has been spent discussing financial markets during the recession and also more recently (starting from a low level prior to 2007). There were important market operations that were initiated or amended during these times.

While subject to some judgment and interpretation, the LDA model has provided a useful quantitative synopsis of the FOMC topic mix over time. This illustrates the potential for NLP techniques to assist the money management process.

In the words of Saret and Mitra:

> "Market observers trying to glean insights from [FOMC] meeting minutes once needed to rely on the

> "Market observers trying to glean insights from [FOMC] meeting minutes once needed to rely on the subjective interpretation of so-called expert "Fed watchers" or their own interpretation. Now, asset allocators can apply natural language processing techniques to extract insights from the FOMC's published meeting minutes, turning qualitative inputs into more easily analyzed, quantitative data."
>
> J. N. Saret and S. Mitra, *An AI Approach to Fed Watching* (2016), Two Sigma Street View, pp. 3-4

Conclusion

Topic modeling is a versatile and evolving area of natural language processing. In this article, we've seen how topic modeling can be used to observe the changing mix of topics in a text corpus over time.

Such use cases have the potential for a range of real-world applications. In relation to money management, topic modeling is already being added to the toolkit for making sense of financial markets (as evidenced by Saret and Mitra).

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