FOMC Minutes Analysis

Can minutes forecast interest rate changes?

Group 4D-Intelli
Members: Yuhang Xia, Chonwai Ho, Hyun Jin Cho, Xueyang Wei, Jiahao Sun, Cheng Peng
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Progress Check

Research

Web Scrapping

Tokenization & Bag of Words

TF-IDF

4D-Intelli

Progress Check

FOMC Minutes Analysis

Web Scrapping	100%: Complete Scraping of FOMC data
Data Merging	100%: Scrapped text data evaluated and merged using pandas dataframe
Tokenization	100%: Completed using package sklearn
Bag of Words	100%: Bag of Word analysis using package sklearn and NLTK Counter packager
Tf-idf	100%: Tf-idf have been applied to minutes
Machine Learning	10%: Research findings and machine learning tools under discussion

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Research Papers

- The Information Content of FOMC Minutes (Boukus and Rosenberg 2006)
- Latent semantic analysis of the FOMC statements (Panagiotis Mazis, Andrianos Tsekrekos, 2017)

Purpose

- The two papers identifies the textual patterns and themes to examine the impact on the US Treasury market
- The later paper was built on top of Boukus and Rosenberg, 2006 and extends their findings

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Latent semantic analysis of the FOMC statements

Keep Mitigating Risk & Improving Return

Data Set

- Uses FOMC statements from 2003 to 2014
- A total of 99 minutes

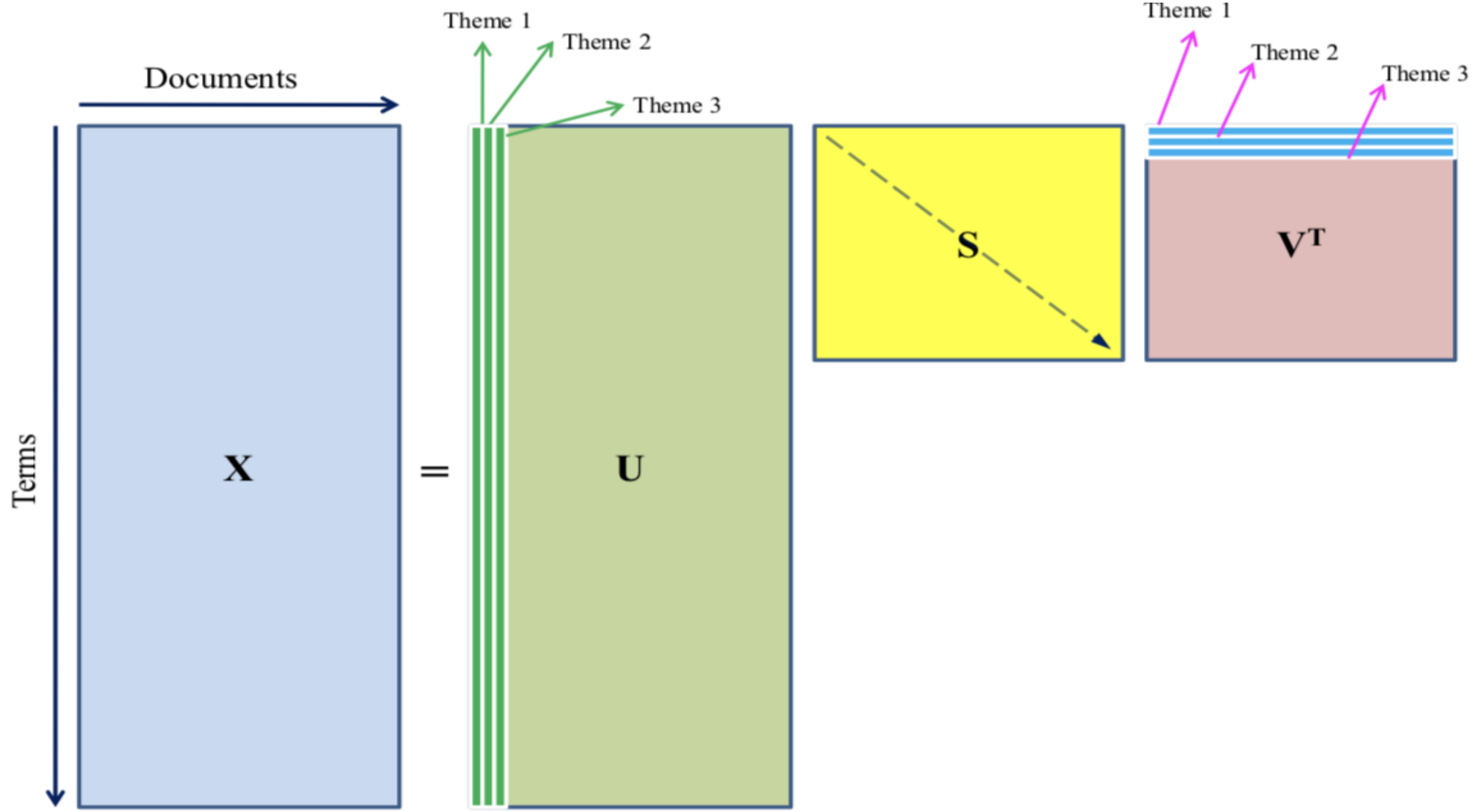
Text Processing

- Eliminate text formatting
- Remove stop words
- Lemmatization
- Porter Stemming
- Filter using LM list

Analysis

- Latent Semantic Analysis(LSA)
- Extract themes using singular value decomposition (SVD)

Latent semantic analysis of the FOMC statements



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Latent semantic analysis of the FOMC statements

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Conclusion

- Mazis and Tsekrekos were able to use LSA to explain total policy variation
- Establishes the use of LSA to produce a set of themes to characterize the FOMC statements
- Increased communication and transparency of the FOMC has enhanced the understanding of future Fed actions
- It is a challenging task due to the nuanced and multifaced tone of the minutes!

Other Papers

- Have minutes helped to predict fed funds rate changes? (Jung 2016)
- Evaluating qualitative forecasts: The FOMC minutes, 2006–2010 (Stekler and Symington, 2015)

Web Scrapping

What does this code do? – Beautiful Soup and Requests

```
from bs4 import BeautifulSoup
import requests
import re
import urllib.request
import os

base_url = "https://www.federalreserve.gov/monetarypolicy/fomchistorical"

transcript_links = {}
for year in range(1968, 1993):
  html_doc = requests.get(base_url + str(year) +'.htm')
  soup = BeautifulSoup(html_doc.content, 'html.parser')
  links = soup.find_all("a", string=re.compile('Minutes*'))
  link_base_url = "https://www.federalreserve.gov"
  transcript_links[str(year)] = [link_base_url + link["href"] for link in links]
  print("Year Complete: ", year)
```

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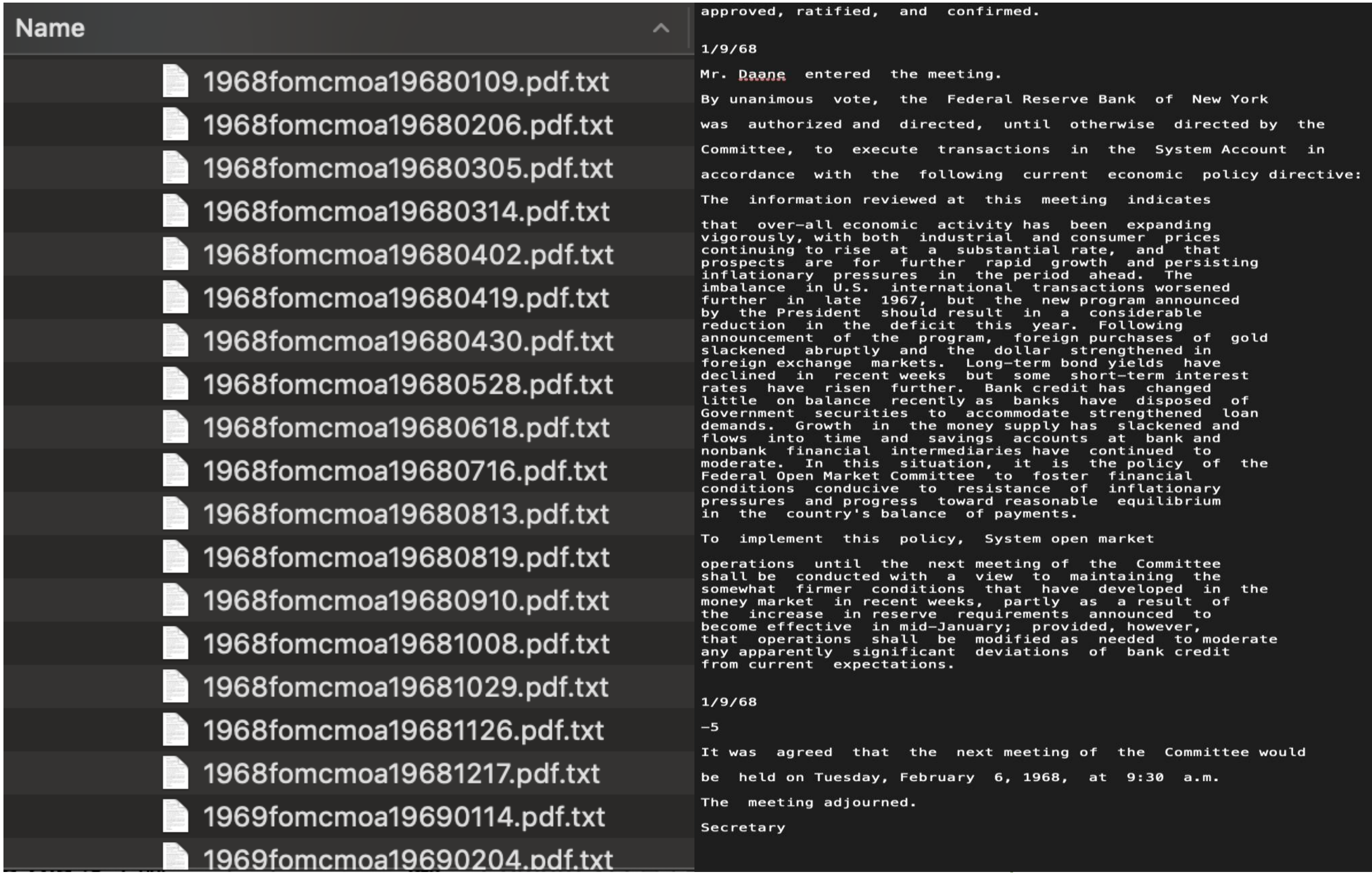
Web Scrapping

What does this code do? – Beautiful Soup and Requests

```
for year in transcript_links.keys():
    if not os.path.exists("./feddata/" + year):
        os.makedirs("./feddata/" + year)
    for link in transcript_links[year]:
        response = urllib.request.urlopen(str(link))
        name = re.search("[^/]*$", str(link))
        print(link)
        with open("./feddata/" + year + "/" + name.group(), 'wb') as f:
            f.write(response.read())
        print("file uploaded")
```

Loading Data



Tokenization & Bag of Words(BoW)

Data Processing

```
def lem_term(document):
    document = re.sub('\d+|\_', '', document)
    wnl = WordNetLemmatizer()
    tokens = word_tokenize(document)
    lem_token = [wnl.lemmatize(word) for word in tokens]
    for char in (['.', ',']):
        while char in lem_token:
            lem_token.remove(char)
    document = ' '.join(lem_token)
    re.sub('\+d','',document)
    return document
```

Tokenization & Bag of Words(BoW)

Bag of words

```
#%% bag of words with sklearn
vectorizer = CountVectorizer(stop_words = 'english',lowercase = True)
AnnualBow = vectorizer.fit_transform(corpus)
df_AnnualBow = pd.DataFrame(AnnualBow.A,columns = vectorizer.get_feature_names())

##remove thoes meaningness words
for col in ['year','month','day','mr','meeting','committee']:
    try:
        df_AnnualBow.pop(col)
    except:
        continue
minutes_BoW_sk2 = pd.concat([minutes,df_AnnualBow],axis = 1)
```

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Tf-Idf

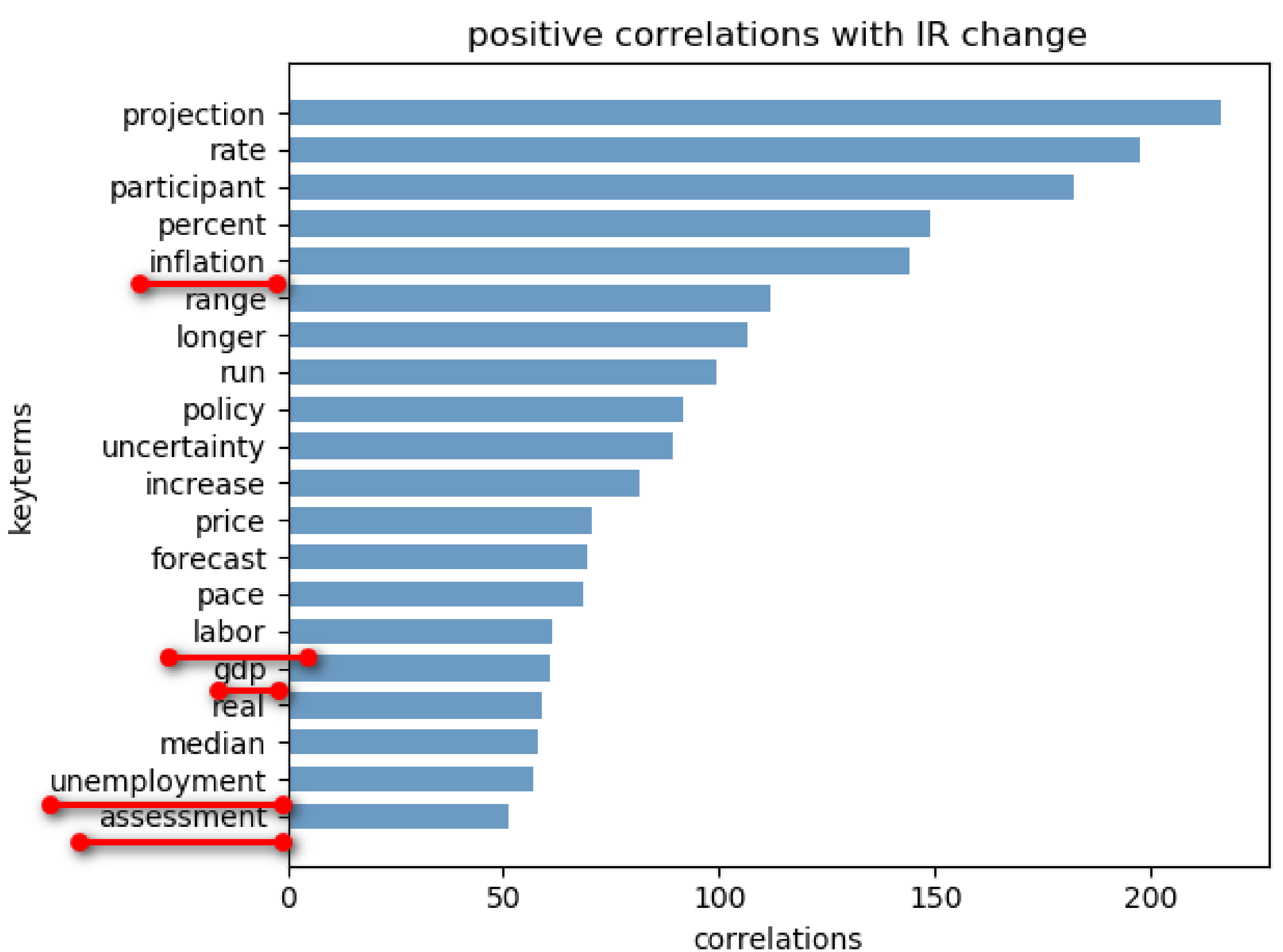
Assign weights by tf-idf model

```
v = TfidfVectorizer(stop_words='english', max_df=0.9)
tfidf = v.fit_transform(corpus)
df_Annualtfidf = pd.DataFrame(tfidf.A,columns = v.get_feature_names())

for col in ['year','month','day','mr','meeting']:
    try:
        df_Annualtfidf.pop(col)
    except:
        continue

minutes_tfidf_sk = pd.concat([minutes,df_Annualtfidf],axis = 1)
```

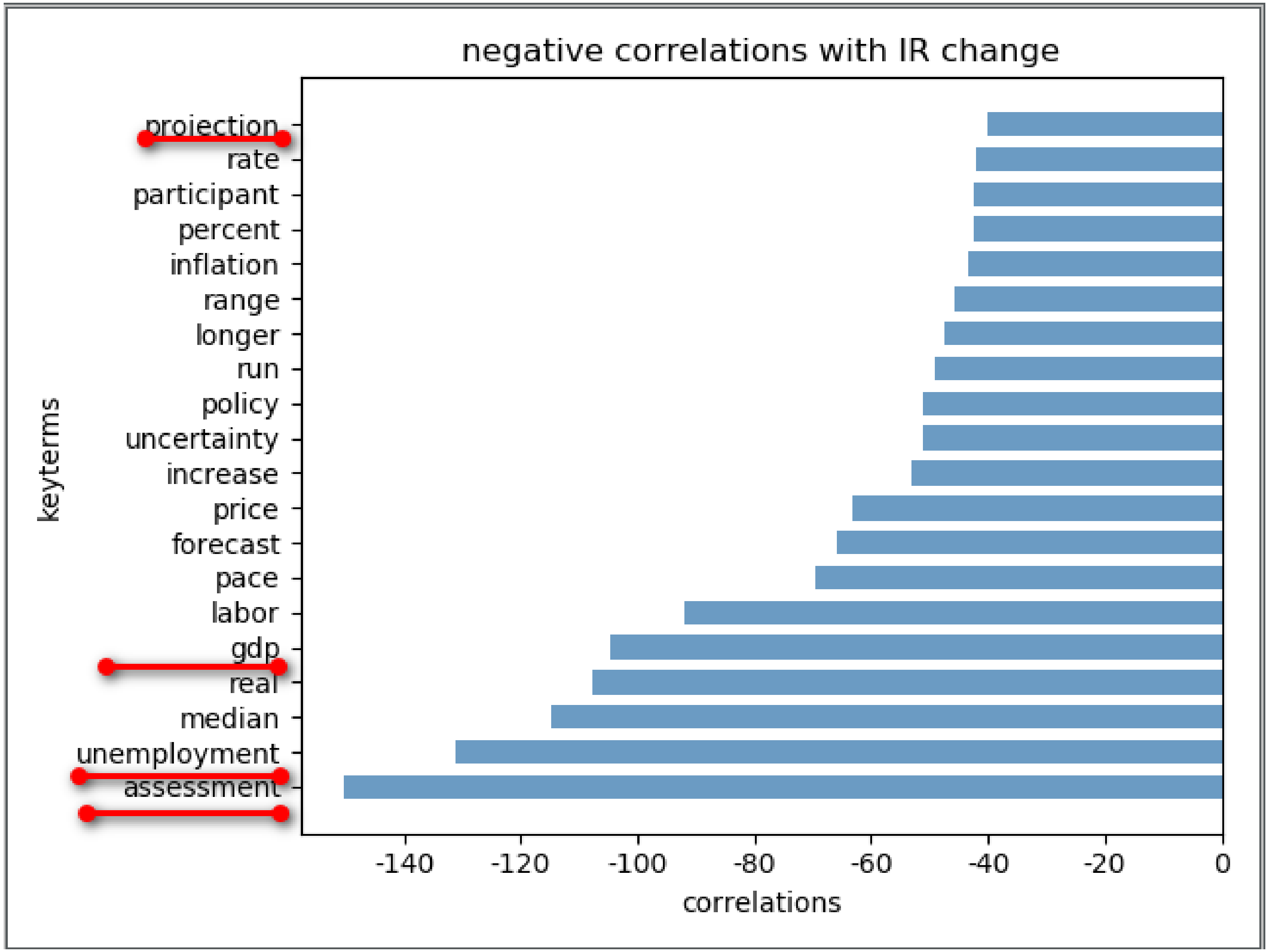
Preliminary analysis and what to do next?

```
correlations = [np.correlate(bow_IR_cor2['IR_Change'],bow_IR_cor2[term])[0]
                for term in list(bow_IR.columns[8:])]

IR_corKeyterm = pd.DataFrame({'keyterms':keyterms,'correlations':correlations})
bottom10 = IR_corKeyterm.sort_values(by = 'correlations') >> head(20)
top10 = IR_corKeyterm.sort_values(by = 'correlations') >> tail(20)
#%% plot graph
## first with positive correlations
import matplotlib.pyplot as plt
import matplotlib
matplotlib.rcParams['axes.unicode_minus'] = False

correlation = top10['correlations']
keyterms = top10['keyterms']
plt.barh(range(len(keyterms)), correlation, height=0.7, color='steelblue', alpha=0.8)
plt.yticks(range(len(keyterms)), keyterms)
plt.xlabel("correlations")
plt.ylabel('keyterms')
plt.title("positive correlations with IR change")
plt.show()
```

Preliminary analysis and what to do next?



Negative results with IR change



OLS Regression Results

Dep. Variable:	IR_Change	R-squared:	0.022
Model:	OLS	Adj. R-squared:	0.012
Method:	Least Squares	F-statistic:	2.121
Date:	Fri, 08 Mar 2019	Prob (F-statistic):	0.0618
Time:	19:26:05	Log-Likelihood:	172.94
No. Observations:	469	AIC:	-333.9
Df Residuals:	463	BIC:	-309.0
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0212	0.010	-2.178	0.030	-0.040	-0.002
projection	0.0005	0.001	0.350	0.726	-0.002	0.003
inflation	8.921e-05	0.001	0.132	0.895	-0.001	0.001
unemployment	0.0008	0.002	0.341	0.733	-0.004	0.005
gdp	-0.0023	0.004	-0.599	0.550	-0.010	0.005
assessment	0.0045	0.005	0.877	0.381	-0.006	0.015

Omnibus:	311.938	Durbin-Watson:	1.243
Prob(Omnibus):	0.000	Jarque-Bera (JB):	6534.033
Skew:	-2.518	Prob(JB):	0.00
Kurtosis:	20.579	Cond. No.	50.5

OLS Regression Results

Dep. Variable:	IR_Change	R-squared:	1.000
Model:	OLS	Adj. R-squared:	1.000
Method:	Least Squares	F-statistic:	2.141e+28
Date:	Fri, 08 Mar 2019	Prob (F-statistic):	0.00
Time:	19:22:52	Log-Likelihood:	14909.
No. Observations:	469	AIC:	-2.974e+04
Df Residuals:	428	BIC:	-2.957e+04
Df Model:	40		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-7.477e-16	7.23e-16	-1.034	0.302	-2.17e-15	6.73e-16
unemployment	-3.721e-16	1.04e-16	-3.575	0.000	-5.77e-16	-1.68e-16
median	4.476e-16	1.35e-16	3.310	0.001	1.82e-16	7.13e-16
real	4.168e-16	1.03e-16	4.044	0.000	2.14e-16	6.19e-16
gdp	-4.077e-16	1.56e-16	-2.609	0.009	-7.15e-16	-1.01e-16
labor	-2.277e-17	6.51e-17	-0.350	0.727	-1.51e-16	1.05e-16
pace	3.014e-16	5.59e-17	5.389	0.000	1.91e-16	4.11e-16
forecast	-9.541e-17	1.14e-16	-0.835	0.404	-3.2e-16	1.29e-16
price	-3.652e-16	3.51e-17	-10.397	0.000	-4.34e-16	-2.96e-16
increase	7.86e-17	5.65e-17	1.391	0.165	-3.25e-17	1.9e-16
uncertainty	5.727e-16	1.13e-16	5.046	0.000	3.5e-16	7.96e-16
policy	3.253e-17	3.65e-17	0.890	0.374	-3.93e-17	1.04e-16
run	2.043e-16	8.24e-17	2.480	0.014	4.24e-17	3.66e-16
longer	-1.947e-16	7.8e-17	-2.497	0.013	-3.48e-16	-4.15e-17
range	1.897e-17	3.83e-17	0.495	0.621	-5.63e-17	9.43e-17
inflation	2.822e-16	3.22e-17	8.756	0.000	2.19e-16	3.46e-16

Latent Dirichlet allocation (LDA)

Data processing:

- Customize stop words
- Build the bigram and trigram models

```
stop_words = stopwords.words('english')
stop_words.extend(['meeting', 'january', 'mr', 'committee','federal'])

nlp = spacy.load('en_core_web_sm',disable=['parser', 'ner'])
```

...

```
def sent_to_words(sentences):
    for sentence in sentences:
        yield(gensim.utils.simple_preprocess(str(sentence), deacc=True))  # deacc=True removes punctuations
```

```
bigram = gensim.models.Phrases(corpus, min_count=5, threshold=100) # higher threshold fewer phrases.
trigram = gensim.models.Phrases(bigram[corpus], threshold=100)

# Faster way to get a sentence clubbed as a trigram/bigram
bigram_mod = gensim.models.phrases.Phraser(bigram)
trigram_mod = gensim.models.phrases.Phraser(trigram)
```

Latent Dirichlet allocation (LDA)

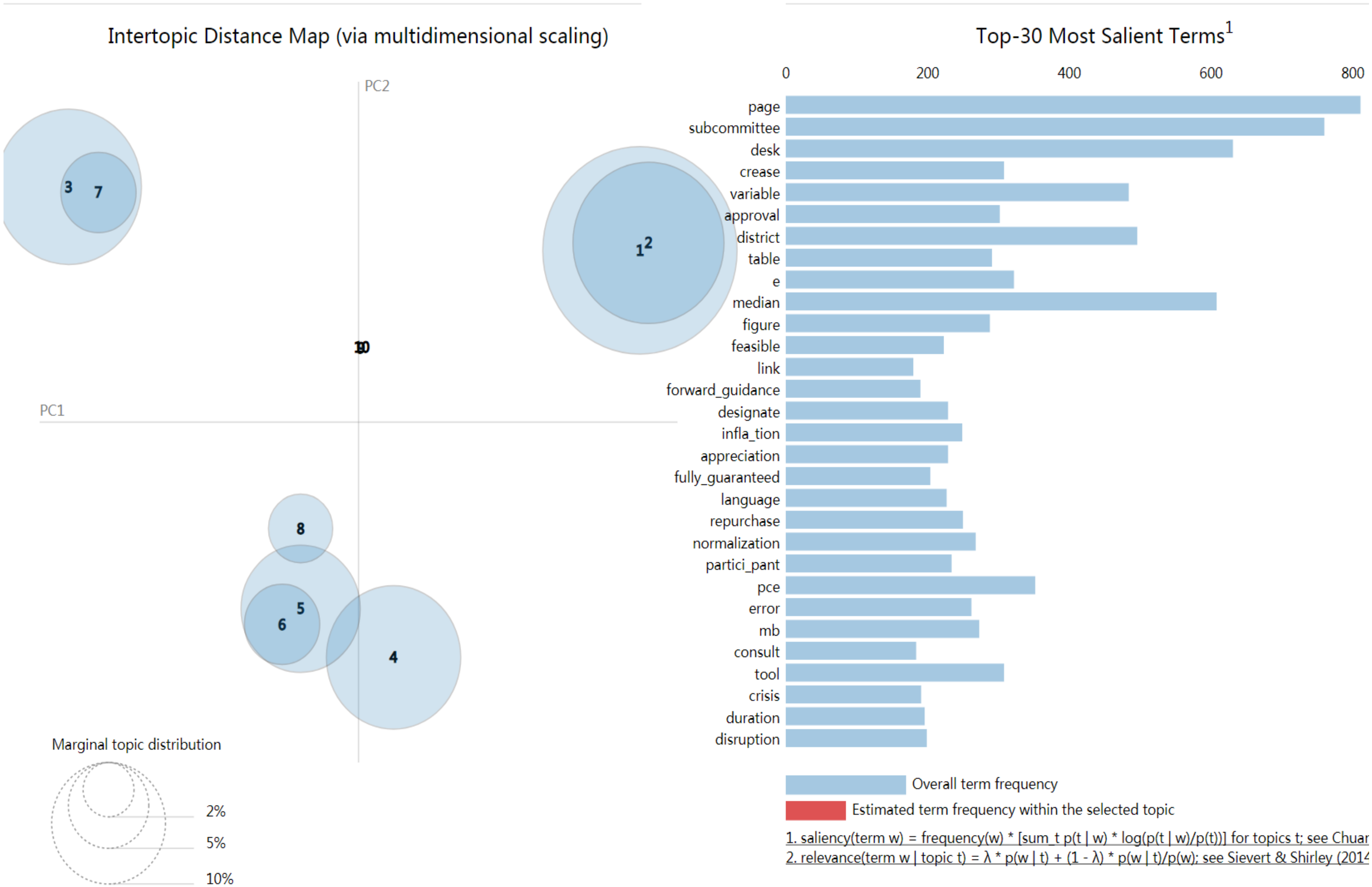
Establish models

C:\Users\Jesse\
:\Downloads\LDA

```
corpus_no_stops = remove_stopwords(corpus)
corpus_bigrams = make_bigrams(corpus_no_stops)
data_lemmatized = lemmatization(corpus_bigrams, allowed_postags=['NOUN', 'ADJ', 'VERB', 'ADV'])
# Create Dictionary
id2word = corpora.Dictionary(data_lemmatized)
id2word.filter_extremes(no_below=3, no_above=0.2)
# Create Corpus
texts = data_lemmatized
# Term Document Frequency
corpus = [id2word.doc2bow(text) for text in texts]
```

...

```
lda_model = gensim.models.ldamodel.LdaModel(corpus=corpus,
                                            id2word=id2word,
                                            num_topics=10,
                                            random_state=100,
                                            update_every=1,
                                            chunksize=100,
                                            passes=10,
                                            alpha='auto',
                                            per_word_topics=True)
```


Intertopic Distance Map (via multidimensional scaling)
PC2
PC1
3
7
1
2
10
8
5
6
4
Marginal topic distribution
2%
5%
10%
Top-30 Most Salient Terms1
0
200
400
600
800
page
subcommittee
desk
crease
variable
approval
district
table
e
median
figure
feasible
link
forward_guidance
designate
infla_tion
appreciation
fully_guaranteed
language
repurchase
normalization
partici_pant
pce
error
mb
consult
tool
crisis
duration
disruption
Overall term frequency
Estimated term frequency within the selected topic
1. saliency(term w) = frequency(w) * [sum_t p(t | w) * log(p(t | w)/p(t))] for topics t; see Chuar
2. relevance(term w | topic t) = λ * p(w | t) + (1 - λ) * p(w | t)/p(w); see Sievert & Shirley (2014

References

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Evaluating qualitative forecasts: The FOMC minutes, 2006–2010 (Stekler and Symington, 2015)

Whats Next???

Thank You!!!