Sentiment Extraction Project On

BANK OF ENGLAND

Minutes | Speeches | ECB/FED*

Richard Xia **20/07/2020**

Data Mining and Pre-Processing

Dictionary Based Baseline Model

Topic Modelling and Language Filtering

Model Extensions:
ECB & FED documents | Key Speaker | Advanced model

293 words

Dictionary size is smaller than other existing method
124 positive word | 169 negative word

6 Topics

Split language into 6 different topics and construct topical sentiments

Effective out-of-sample

Dictionary was trained based on BOE documents before 2010, and still captures interest rate sentiment until 2020.

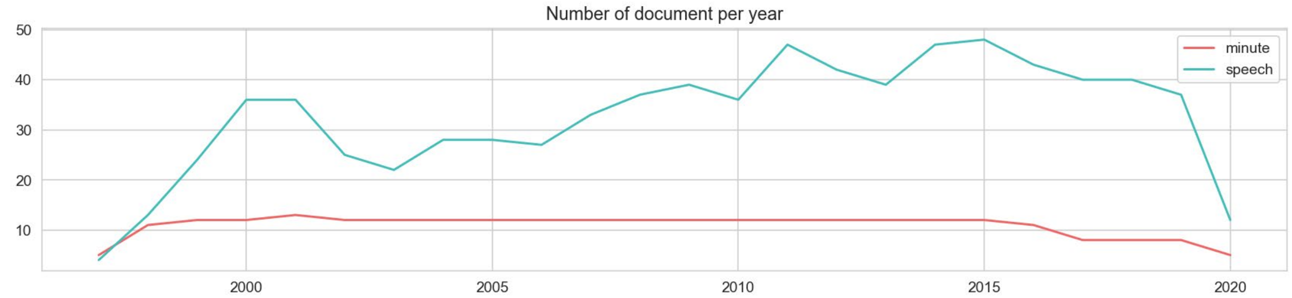
STEP 1: Data mining and Pre-processing

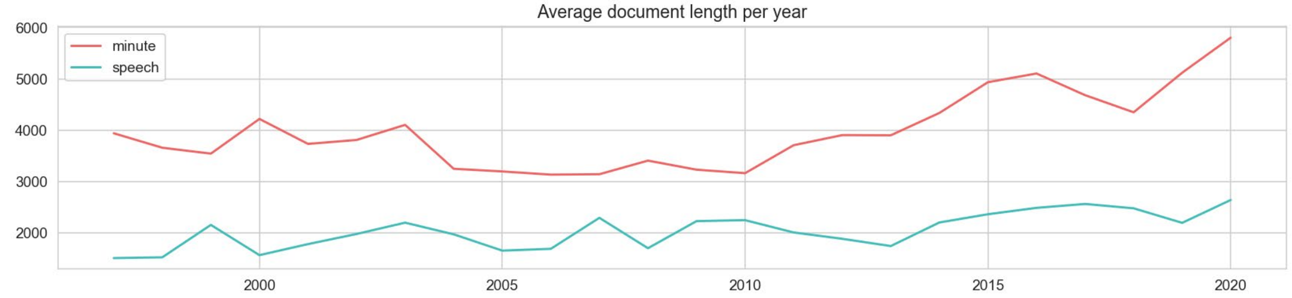
SUMMARY ON PRE-PROCESSING

Text Data: BOE speech, minutes and statement
Numerical Data: Monthly LIBOR 1Y/6M/3M/1M rate, UK base rate
Work with existing dictionary: L&M Dictionary and Financial Stability Dictionary
Preprocessing: Stop-word removal, lemmatization, Stemming etc.
Total 1044 document: From 1997 to 2020
Monthly updated sentiment: Training dictionary until **2009-12-31**, Out-of-sample (OFS) text from 2010-01-01

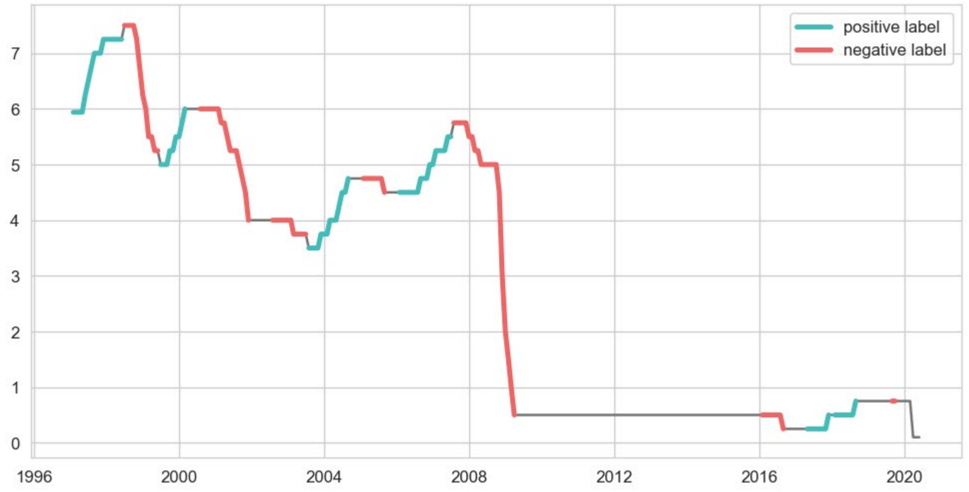
Minutes/Statement
- **Less Frequently updated**: 261 available text from 1997-2020
- **The text is more structured**: It has headers for each section

Speech
- **More Frequently updated**: 783 available text from 1997-2020
- **The text is less structured**: It has different format: Report / opening speech...

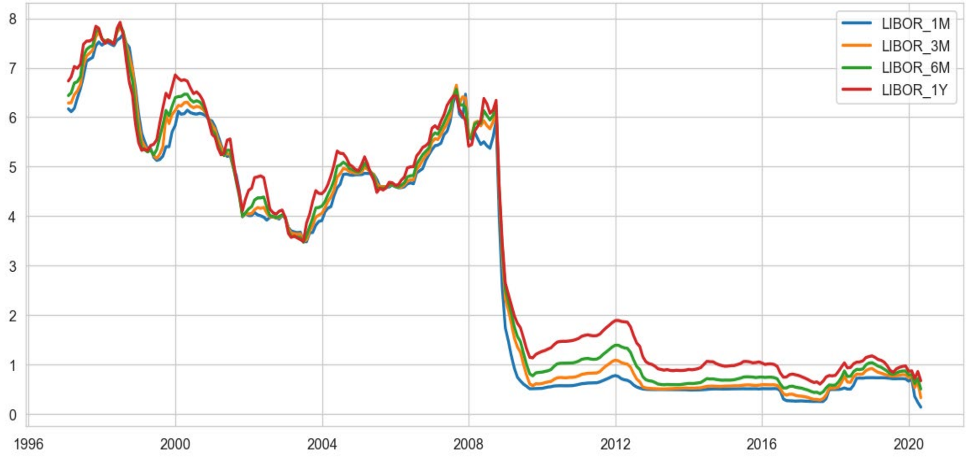




LABEL 1, 0, -1 SENTIMENT BASED ON BASE RATE



QUANTIFY MODEL PERFORMANCE BASED ON LIBOR RATE



Minutes/Statement

Structured with section header

Financial markets

2 Following the turbulence in asset prices over the summer and into the early autumn, financial market sentiment had improved somewhat over the month, with volatility falling across a range of asset classes and a recovery in the prices of some risky assets. Despite this, however, short-term and longer-term interest rates in the United Kingdom remained lower than at the time of the August *Inflation Report*. The key question for discussion, therefore, was what accounted for this lower yield curve.

3 Since the Committee's October policy meeting, equity prices had risen by 1% in the United Kingdom, by 6% in the United States, by 7% in the euro area and by 9% in China. Both high-yield and investment-grade corporate bond spreads had narrowed internationally, and there had been some tentative signs of renewed flows into some emerging market mutual funds. Oil prices were little changed, although they remained 13% lower than at the time of the August *Inflation Report*. Measures of implied volatility for US equity prices and oil prices had fallen back to their lowest levels since mid-August, and there had been falls on the month, too, in interest-rate implied volatility. Taken together, these were indicative of some modest improvement in investor sentiment.

The international economy

9 Recent data news in the international economy had on balance continued to be disappointing. Some of the recent data for the United States had been weaker than expected, and indicators of activity in emerging market economies outside China had generally continued to weaken. Although there had been little news overall on the near-term outlook for China itself, or for the euro area, the relevant central banks had either loosened monetary policy or had signalled that they would consider doing so. Among emerging economies there was considerable variation in prospects and uncertainty about the extent to which advanced economies, including the United Kingdom, were vulnerable to a sharper slowdown.

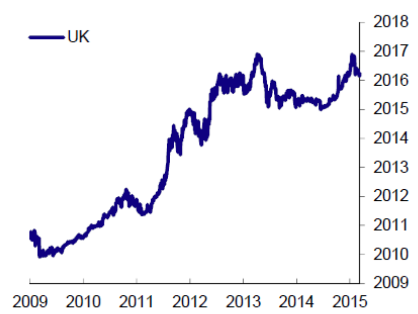
Speech

1. Unrelated sentences

Let me begin by thanking the Lord Mayor and his team for their gracious hospitality once again. The Guildhall really is a fantastic venue, and I want to take this opportunity, as we approach the end of your term as Lord Mayor, to salute you for the emphasis that you have put on the broader role of finance in society, the broader role of the City of London in the UK economy and in the global economy, and your broader contributions to society. City Giving Day is but one example of that, and we are all very much in your debt for your enormous contribution.

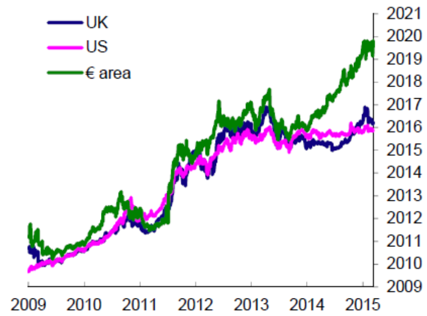
2. Graph Explanation

Chart 1: Date of first rate rises implied by forward market interest rates



Sources: Bloomberg and Bank calculations. Notes: The y axis shows the date at which the instantaneous forward OIS curve reaches 25bps above Bank Rate.

Chart 2: Date of first rate rises implied by forward market interest rates



Sources: Bloomberg and Bank calculations. Notes: The y axis shows the date at which the instantaneous forward OIS curve reaches 25bps above Bank Rate for the UK; the ECB main refinancing rate for the euro area; the top of the FOMC target range for the US.

3. References

Bell, D and Blanchflower, D (2013), 'Underemployment in the UK Revisited', *National Institute Economic Review No. 224*

Bernanke, B (2006), 'Global economic integration: what's new and what's not?', *remarks at the Federal Reserve Bank of Kansas City's Thirtieth Annual Economic Symposium, Jackson Hole*, available at: www.federalreserve.gov/boarddocs/speeches/2006/20060825/default.htm.

STEP 2: Construction of Baseline model

Constructing straightforward bag-of-word dictionary-based models BOE raw documents

LM and FS Dictionary Sentiment

LM dictionary: Loughran and McDonald, 2011   229 words
Trained on 50115 pieces of SEC-10K reports from 1994 to 2008

FS dictionary: Constructing a Dictionary for Financial Stability   original 391 words, 250 unique words
Trained on 982 financial stability reports of 62 countries, ECB, and IMF published between 2000 and 2015. The word is classified by human identification.

Step 1: Load the positive and negative words

LM Dict	Entry	sentiment
0	account	Neutral
1	accru	Positive
2	agenc	Neutral

FS Dict	Entry	sentiment
0	abl	Positive
1	abnorm	Negative
2	abrupt	Negative

Step 2: Calculate co-occurrence with the text

For each document, calculate the number of positive sentiment word occurred and negative words.

Step 3: Calculate sentiment of one text

Positive_score: sum of the **number** of positive sentiment word occurred
Negative_score: sum of the **number** of negative sentiment word occurred

Text sentiment = (Positive_score − Negative_score) / (Positive_score + Negative_score)

Step 4: Monthly average and exponential weighted average (halflife = 3)

For all texts published in the same month (eg: May), their sentiments are averaged to calculated a monthly value. And then it is exponentially moving averaged with half-life equalling 3 month.

The final sentiment are classified as the sentiment for next month (eg: June)

Current Method Problem

Speech is noisy with lots of unrelated text.
Sentiment will fluctuate as major of the text are speech.

Self-created Dictionary Sentiment

Step 1: Create Co-occurrence matrix

First, label document based on whether base rate move up/down/unchanged within next 6 months.
Then, calculate number of times a word occur in a positive/negative/neutral sentiment document

	negative count	positive count	neutral count	p percentage no neutral	n percentage no neutral	sentiment
examin	14	44	9	0.759	0.241	Positive
smooth	15	38	19	0.717	0.283	Positive
exceed	25	52	17	0.675	0.325	Positive
downgrad	11	1	4	0.083	0.917	Negative
turmoil	36	3	2	0.077	0.923	Negative
downsw	4	0	9	0.000	1.000	Negative

Step 2: Filtered Positive/negative sentiment words

Positive word: Occur > 50 times and 'p percentage no neutral' >0.55 and maximum 100 words
Negative word: Occur > 50 times and 'n percentage no neutral' >0.55 and maximum 100 words

Step 3: Including additional word from FS dictionary

Additional Positive word: Positive in FS dictionary and 'p percentage no neutral' >0.5
Additional Negative word: Negative in FS dictionary and 'n percentage no neutral' >0.5

Step 4: Calculate sentiment of one document

Positive_score: sum of **'p percentage no neutral'** for each positive word occurred
Negative_score: sum of **'n percentage no neutral'** for each negative word occurred
Text sentiment = (Positive_score − Negative_score) / (Positive_score + Negative_score)

Step 5: Monthly average and exponential weighted average (halflife = 3)

For all texts published in the same month (eg: May), their sentiments are averaged and exponentially moving averaged with half-life equalling 3 month.

The final sentiment are classified as the sentiment for next month (eg: June)

BOE interest rate sentiment construction

Data mining and Pre-processing | **Baseline model** | Language Filtration | Model Extensions | Appendix

	LM Dictionary	FS Dictionary	Self-created
Positive			
Negative			

Summary on the sentiment

FS dictionary better than LM:
LM dictionary barely capture any useful sentiments in the central bank statements
FS dictionary in contrast can explain approximately 30% of the fluctuation in Libor rate

Performance decay significantly for speech:
All three dictionaries perform significantly worse after 2009/12/31, and our own model performance completely vanished after the training period.

This could due to the change in language in the speech, **whereas the performance of minutes was fairly consistent**. This also prove that the language of speech does not change significantly overtime

Performance slightly varies across different Horizons:
Generically speaking, the model perform the best on 6M horizon, which is understandable that the document is labelled based on whether is rate change in next 6 months.

LM Dictionary — Correlation between sentiments calculated and various monthly timeseries

Size: 229 words	All	All OFS	Speech	Speech OFS	Minute	Minute OFS
LIBOR_1Y 1M Horizon	**0.028**	**-0.069**	-0.001	-0.152	**0.084**	**0.174**
LIBOR_1Y 3M Horizon	**0.060**	**-0.008**	0.011	-0.148	**0.124**	**0.267**
LIBOR_1Y 6M Horizon	**0.054**	**-0.028**	0.027	-0.120	**0.109**	**0.227**
LIBOR_1Y 1Y Horizon	**0.128**	**0.166**	0.166	-0.139	**0.022**	**-0.030**

FS Dictionary

Size: 250 words	All	All OFS	Speech	Speech OFS	Minute	Minute OFS
LIBOR_1Y 1M Horizon	**0.279**	**-0.014**	0.221	-0.118	**0.327**	**0.275**
LIBOR_1Y 3M Horizon	**0.331**	**-0.022**	0.246	-0.170	**0.379**	**0.323**
LIBOR_1Y 6M Horizon	**0.319**	**-0.084**	0.239	-0.192	**0.371**	**0.224**
LIBOR_1Y 1Y Horizon	**0.255**	**-0.069**	0.268	-0.025	**0.170**	**-0.165**

Self-created

Size: 319 words	All	All OFS	Speech	Speech OFS	Minute	Minute OFS
LIBOR_1Y 1M Horizon	**0.351**	**0.051**	0.345	-0.058	**0.387**	**0.344**
LIBOR_1Y 3M Horizon	**0.452**	**0.041**	0.415	-0.137	**0.512**	**0.457**
LIBOR_1Y 6M Horizon	**0.524**	**0.065**	0.455	-0.145	**0.617**	**0.508**
LIBOR_1Y 1Y Horizon	**0.527**	**0.158**	0.491	0.090	**0.548**	**0.248**

LM Dictionary | FS Dictionary | Self-created

Positive

Negative

Summary on the sentiment

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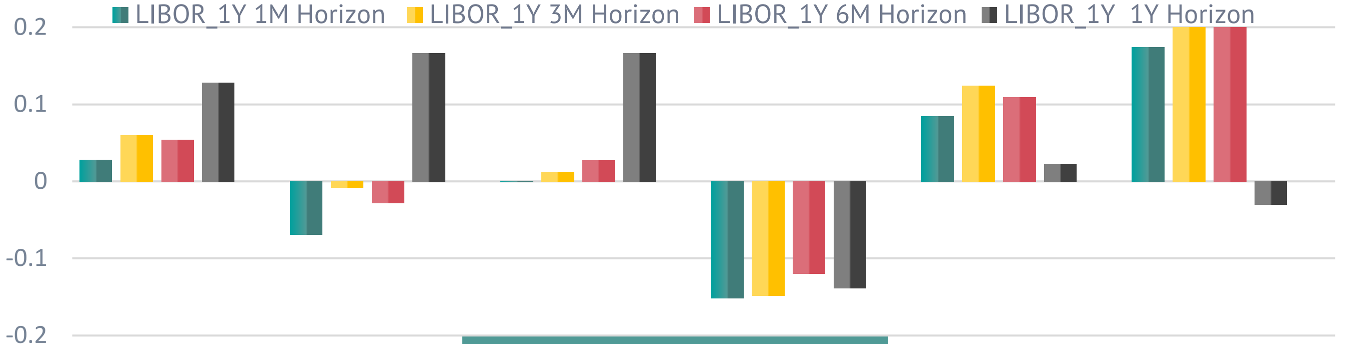
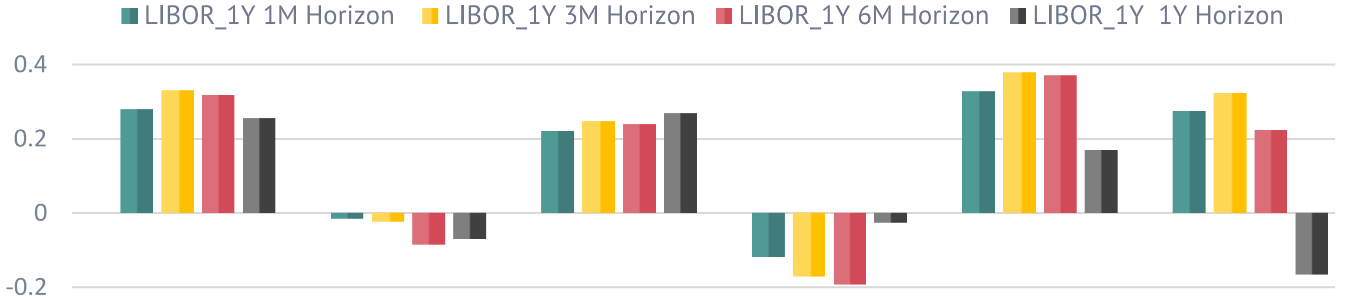
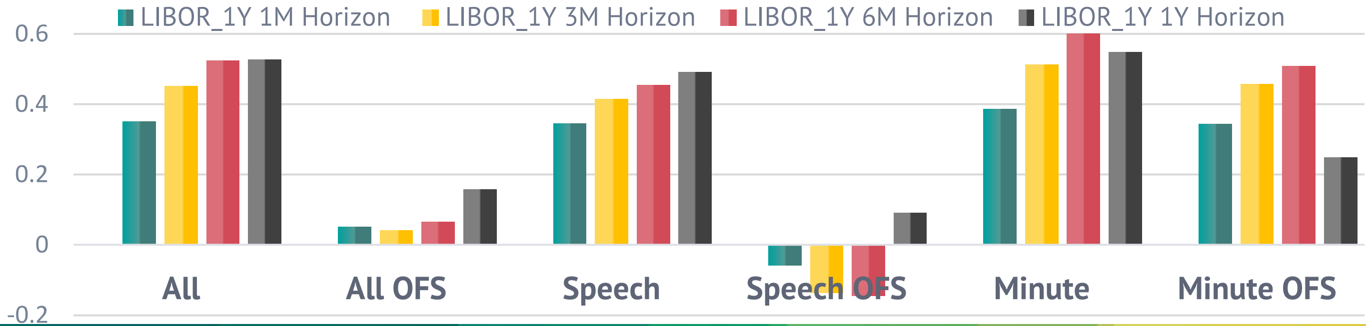
LM Dictionary



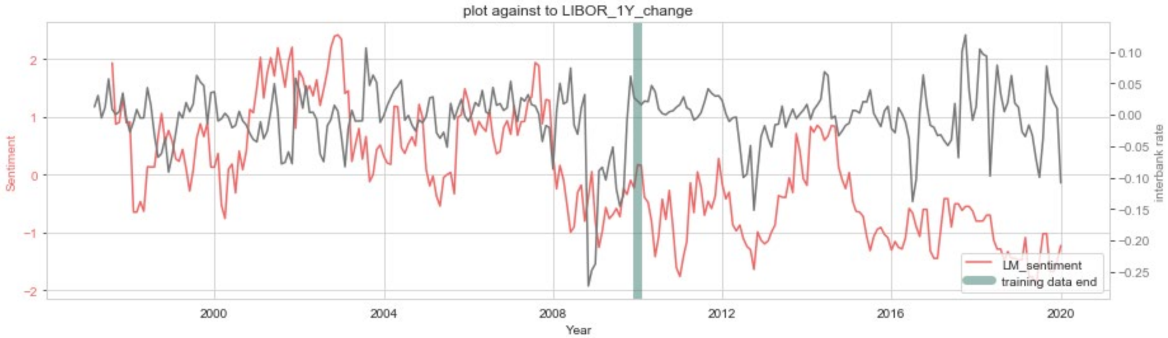
FS Dictionary

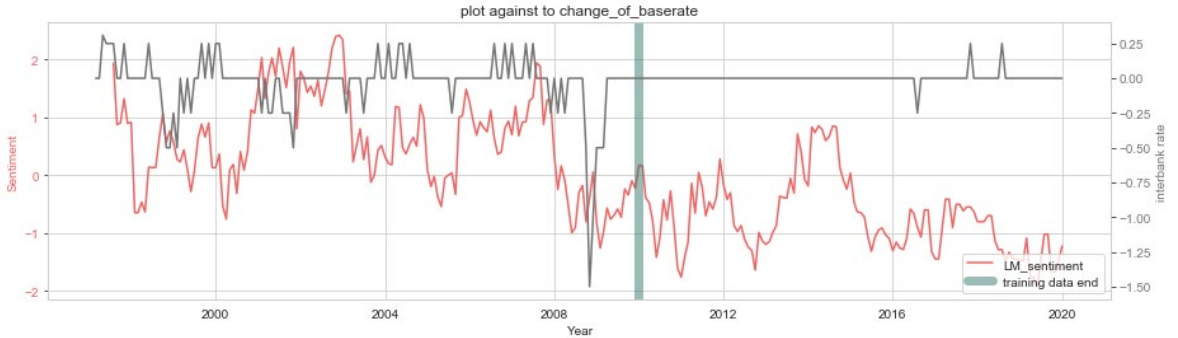


Self-created

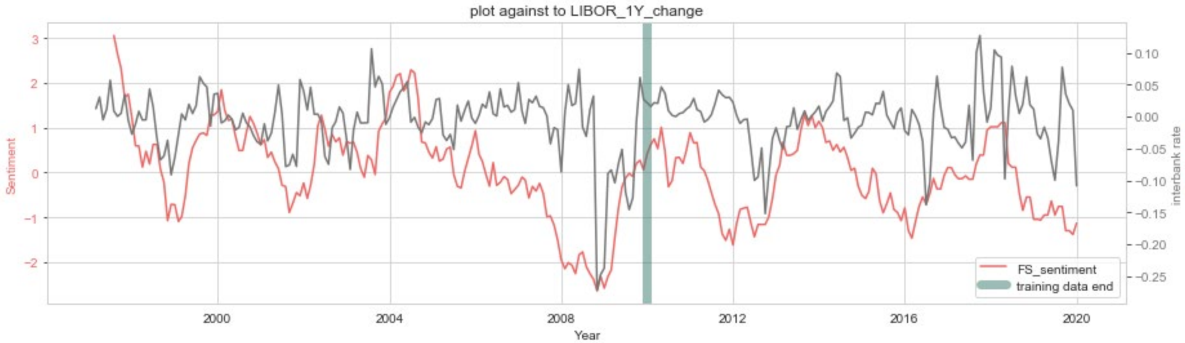


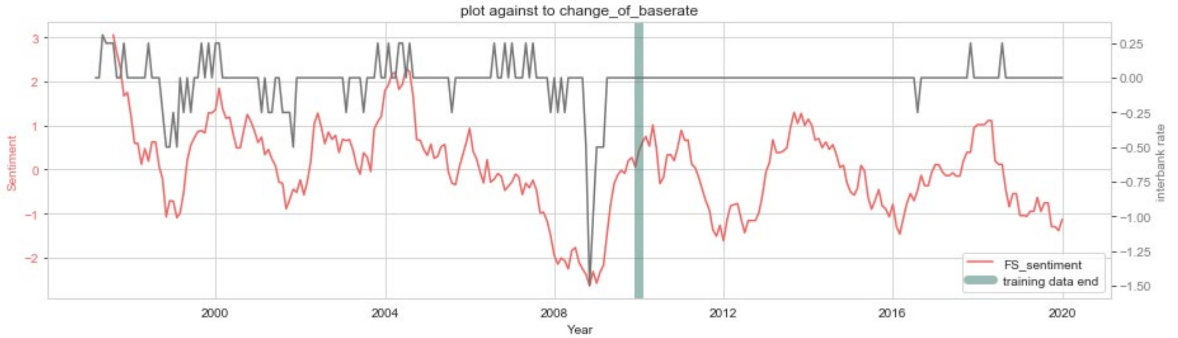
LM dictionary sentiment



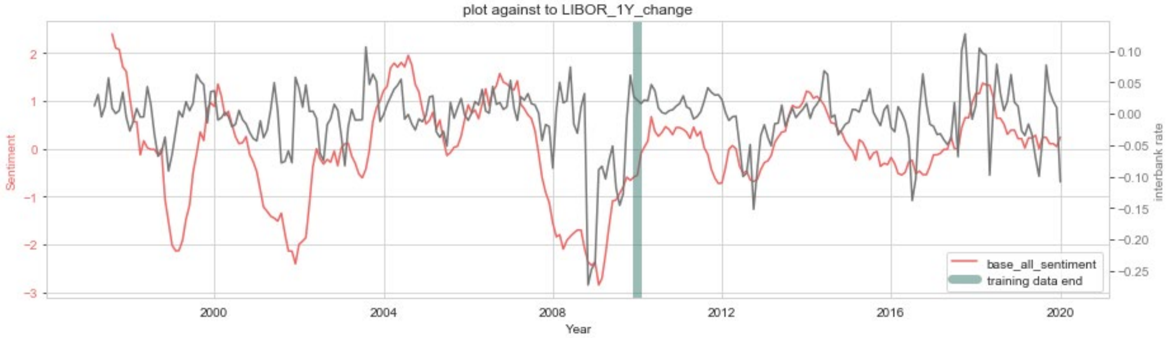


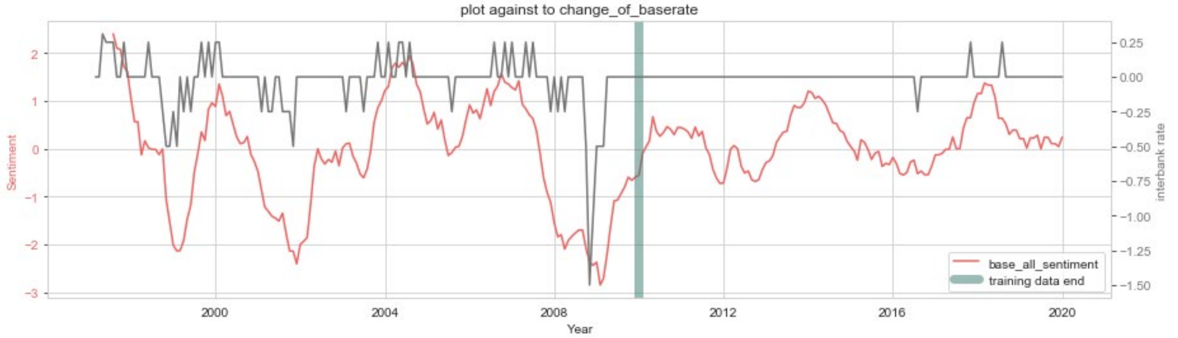
FS dictionary sentiment





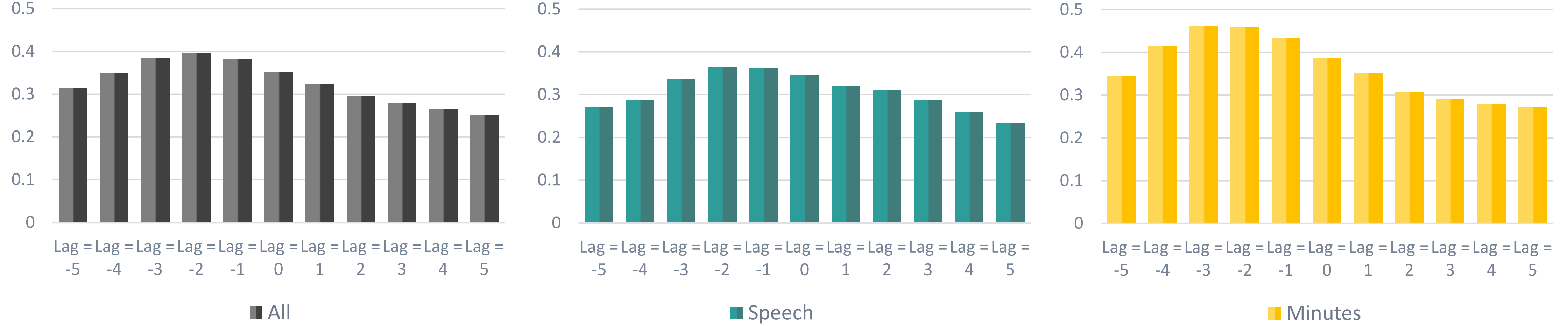
Self-created sentiment





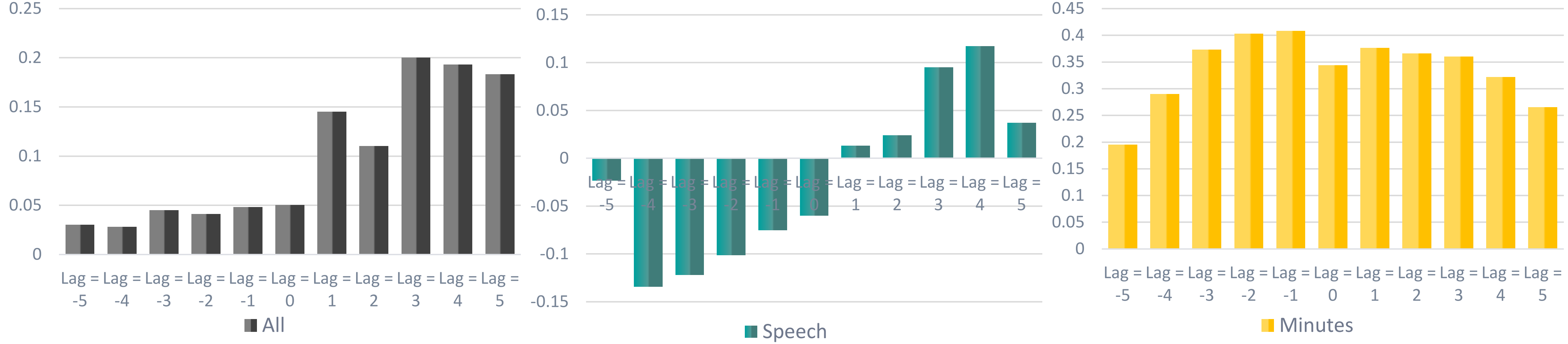
All period lagged correlation with LIBOR 1Y 1M Horizon

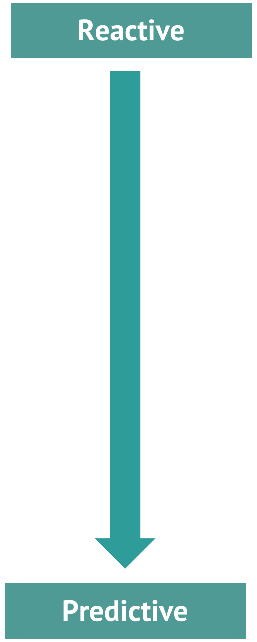
Unit: Months



OFS period lagged correlation with LIBOR 1Y 1M Horizon

Unit: Months





Summary on Baseline Model

STEP 1: Working with public & existing dictionary

LM dictionary: 229 words on SEC-10K reports
FS dictionary: 250 words on 62 countries' financial stability reports
Sentiment: **(N_Positive – N_negative) / (N_Positive + N_negative)**

STEP2: Creating my own dictionary on BOE

Criteria: Frequency > 50 times. & Probability of P/N given this word occurred > 55% .
P/N Score : Probability of document is P/N given this word show
Sentiment: **(Positive_score – Negative_score) / (Positive_score + Negative_score)**

STEP 3: Comparing sentiments

Language Matters: FS dictionary, trained on central banks, performs better than LM dictionary
Self-created model: Standard bag-of-word dictionary-based method has better performance than two other existing models across all documents.

STEP 4: Discovering difference between minutes and speech

Minutes language consistent: Sentiment constructed on minutes has similar correlation in both training and out-of-sample periods, proving standard dictionary based method works.
Speech language changes: Sentiment constructed on speech decays significantly with nearly no correlation during the out-of-sample period, suggesting speech language changes across time and additional language filtering is needed.
Lead-lag: We observe change in style where minutes start to explain more about future policy and has increased lagged performance.

STEP 3: Topic Modeling and Language Filtration

Use topic modelling to cluster the topics in minutes and remove noise in speech

Latent Dirichlet Allocation (LDA) for minutes paragraph clustering

Even though minutes text are structure into different sections, and though for the most time the headers of each section are similar, but it is tedious to clusters all similar headers into one header. So I used LDA to merge uncommon headers into the **6 most popular headers.**

Header name in 2019	Header name in 2002
'Monetary Policy Summary, December 2019',	'The world economy',
'Monetary and financial conditions',	'Money, credit and asset prices',
'The international economy',	'Demand and output',
'Demand, output, money and credit',	'The labour market',
'Supply, costs and prices',	'Prices and costs',
'The immediate policy decision'	'Other considerations',
	'The immediate policy decision'

Step 1: Load raw minutes text

Load minutes files from word. And because the minutes are very structured, we could identify the titles of each section based on the formatting.

Step 2: Merge the scattered topics and identify most frequent titles

As we could see above, the header names is not consistent, we first manually merge some obviously same header together. Then, we could have frequency for different headers.

And I found 6 most frequent header: Financial markets, The immediate policy decision, Growth and inflation projection, Money, credit, demand and output, Supply, costs and prices, The international economy

Step 3: Apply LDA and clustering result overlaps with 6 most popular title

Train LDA on set of paragraphs that **do not belong to those 6 headers.** But I found LDA topic clustering result is highly similar to the 6 header I have, which proves the LDA model has been trained successfully. So I apply this LDA model on these paragraphs and rename its title to the clustering result from LDA model..

Then all paragraphs in minutes has been assign one of the 6 topics and we can then develop topical sentiment accordingly.

Financial markets

1. growth
2. price
3. inflat
4. remain
5. labour
6. expect
7. data
8. survey
9. q
10. fall
11. market
12. indic

The immediate policy decision

1. bank
2. vote
3. unanim
4. maintain
5. purchas
6. billion
7. issuanc
8. reserv
9. financ
10. bond
11. stock
12. monetari

Growth and inflation projection

1. inflat
2. project
3. forecast
4. rate
5. would
6. interest
7. target
8. chang
9. expect
10. market
11. period
12. mpc

Money, credit, demand and output

1. output
2. credit
3. discus
4. money
5. euro
6. turn
7. decis
8. committe
9. polici
10. immedi
11. market
12. would

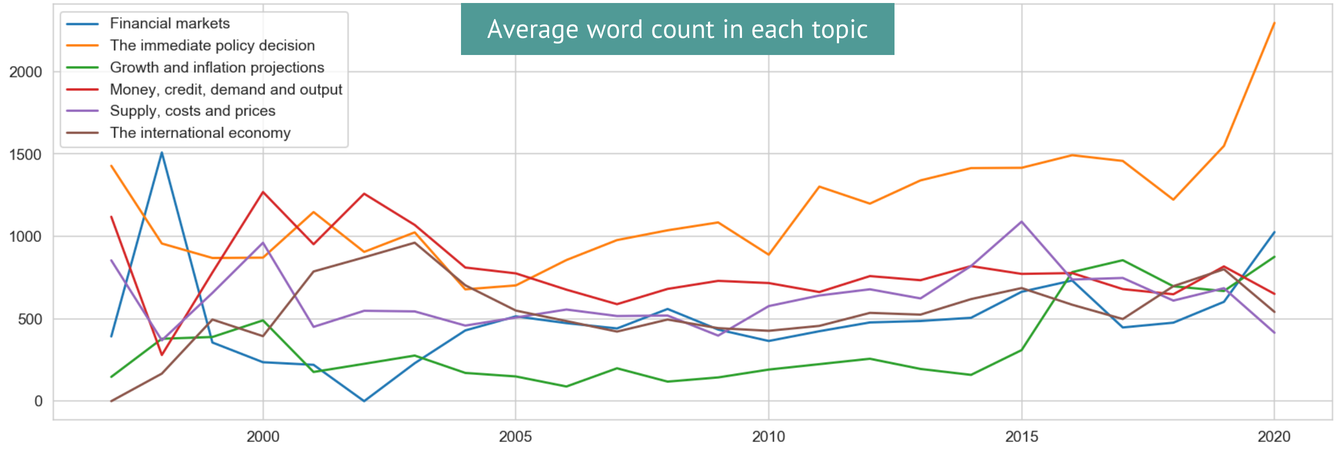
Supply, costs and prices

1. monetari
2. appropri
3. polici
4. exist
5. trade
6. weaker
7. stanc
8. incom
9. job
10. mpc
11. circumst
12. except

The international economy

1. concern
2. dollar
3. scenario
4. oper
5. reason
6. market
7. immedi
8. director
9. decis
10. chief
11. rapid
12. yield

Average word count in each topic



LDA for speech language selection

As we could see from previous chart, the speech language has lot of noises in term of non-relevant language. To improve the accuracy of the sentiment:

Step 1: Load raw speech text

Speech text are more chaotic with many different type of text inside. The following are removed:
Numbers / mathematics equation / footnotes / references

After the raw noise removal, I split the speech text into sentences

Step 2: Apply LDA classification on each sentence

I could use the LDA model that is trained on minutes in previous step and then applying on each sentence of speech. If one sentence has some economical meaning, it will fall into one of the 6 topics we have learnt. If the sentence is non relevant, we could see that we will have an ambiguous classification result.

After all sentences in every speech being filtered, we pass the this new set of document into the previous 3 dictionary and compare the sentiment performance.

Here I keep the sentence if the biggest group probability is greater than 0.65.

Only 36.3% of all words in speech are kept, the rest of the words contain information less useful for interest rate sentiments.

Example of language selection

Some firms may temporarily switch to very simple and resilient supply chains, even if more costly, and gradually revert to more complex but cheaper supply chains over time if that proves possible

Exclude [(0, 0.226), (1, 0.126), **(2, 0.543),** (3, 0.034), (4, 0.034), (5, 0.034)]

However, I think it is likely that, provided inflation expectations remain contained, the background of ample labour market slack and subdued activity levels will keep a lid on labour costs and margins, so that inflation will remain fairly limited as long as activity is well below its pre-Covid trend.

Include [(0, 0.028), (1, 0.061), **(2, 0.747),** (3, 0.029), (4, 0.0288), (5, 0.105)]

The resources that allowed the UK and other major economies to operate at their pre-Covid levels are, to a large extent, still intact

Exclude [(0, 0.256), (1, 0.042), **(2, 0.589),** (3, 0.037), (4, 0.038), (5, 0.038)]

Or, to put it a different way, when considering risks of persistent above-target inflation before we have recovered most of the lost ground, my attitude is I will believe it if and when I see it

Include [(0, 0.037), (1, 0.037), (2, 0.093), (3, 0.037), **(4, 0.759),** (5, 0.036)]

That is not where you would find the smoking gun

Exclude [(0, 0.058), (1, 0.324), (2, 0.058), **(3, 0.446),** (4, 0.057), (5, 0.058)]

Self-created dictionary sentiment

Summary on the sentiment

Performance decay less significantly:
The new modelled dictionaries perform worse after 2009/12/31, but it still shows relatively high correlation with the dictionary.

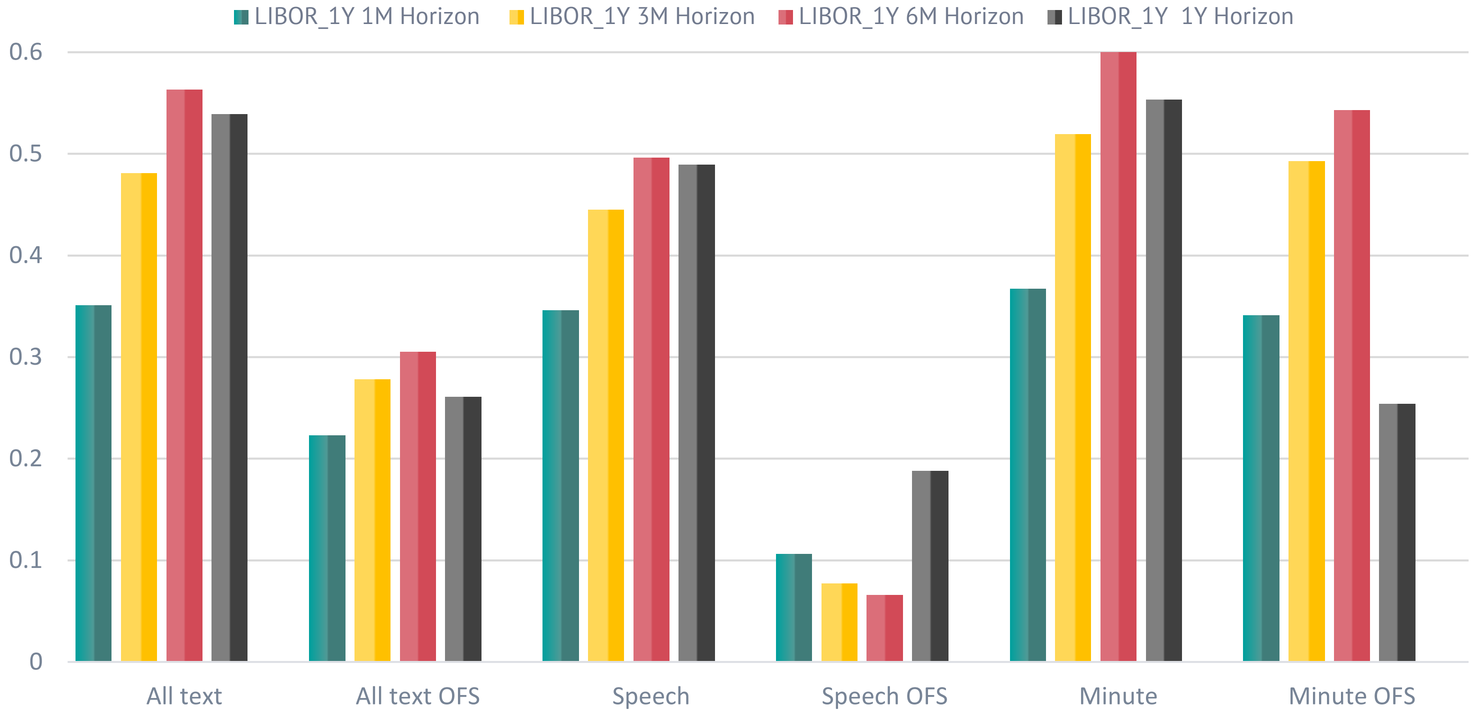
This is because the noises in the speech has been filtered and the model could avoid the irrelevant words. The LDA model make sure the language in speech kept is similar to minutes.

Performance slightly varies across different Horizons :
Generically speaking, the model perform the best on 6M horizon, which is understandable that the document is labelled based on whether is rate change in next 6 months.

The noise in the speech has been removed

Correlation between all period and OFS period is less fluctuated

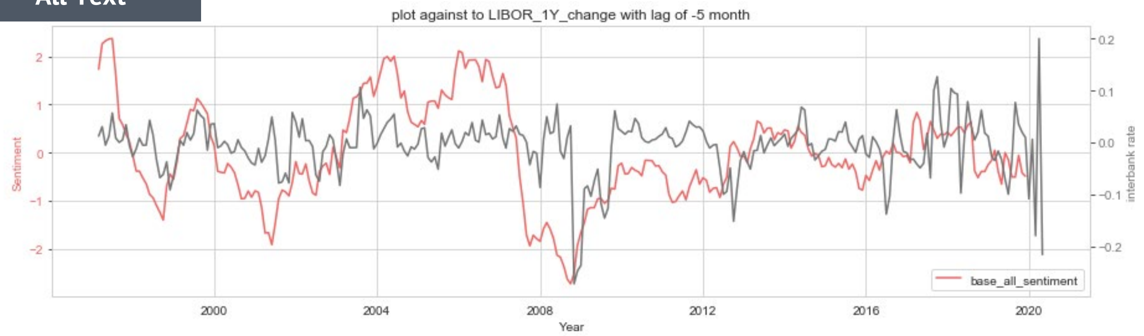
Size: 293 words	All text	All text OFS	Speech	Speech OFS	Minute	Minute OFS
LIBOR_1Y 1M Horizon	**0.351**	**0.223**	0.346	0.106	**0.367**	**0.341**
LIBOR_1Y 3M Horizon	**0.481**	**0.278**	0.445	0.077	**0.519**	**0.493**
LIBOR_1Y 6M Horizon	**0.563**	**0.305**	0.496	0.066	**0.614**	**0.543**
LIBOR_1Y 1Y Horizon	**0.539**	**0.261**	0.489	0.188	**0.553**	**0.254**



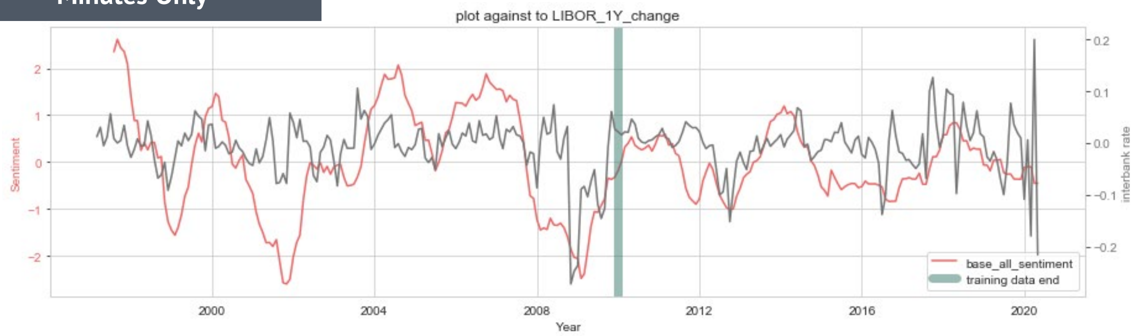
BOE interest rate sentiment construction

Data mining and Pre-processing | Baseline model | **Language Filtration** | Model Extensions | Appendix

All Text

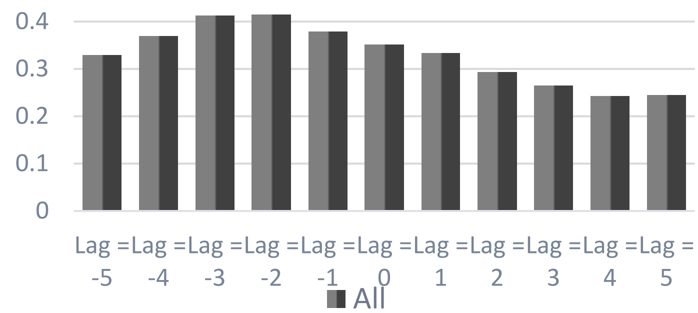


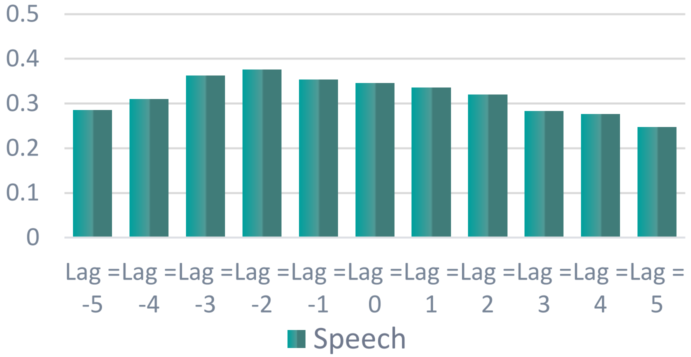
Minutes Only

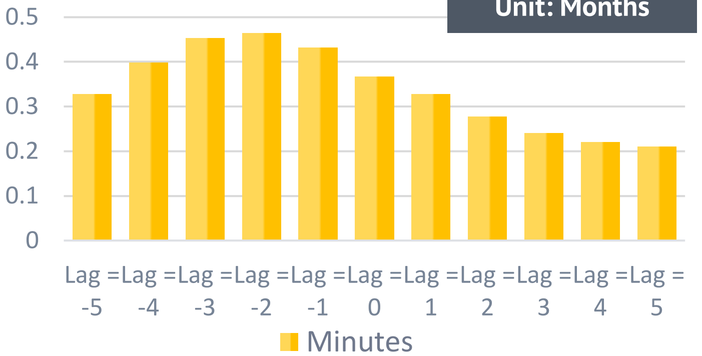


All period lagged correlation with LIBOR 1Y

Unit: Months

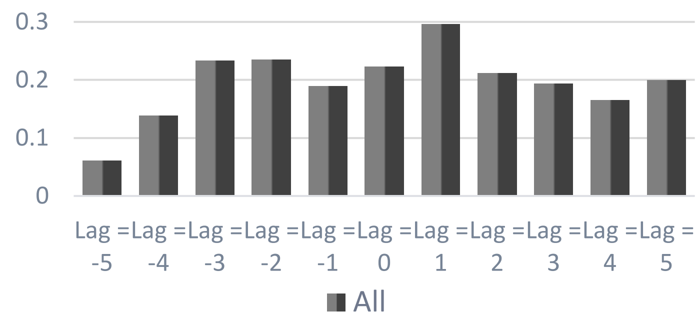


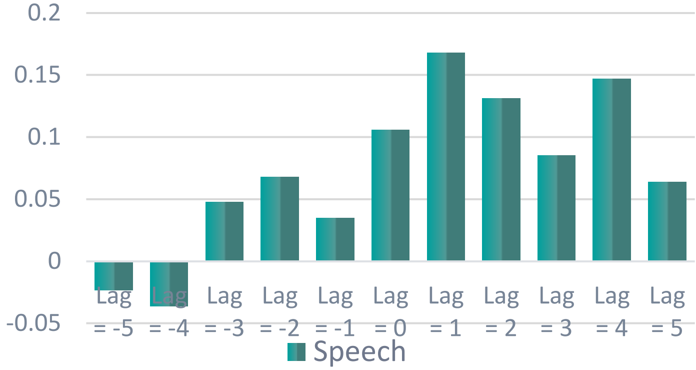


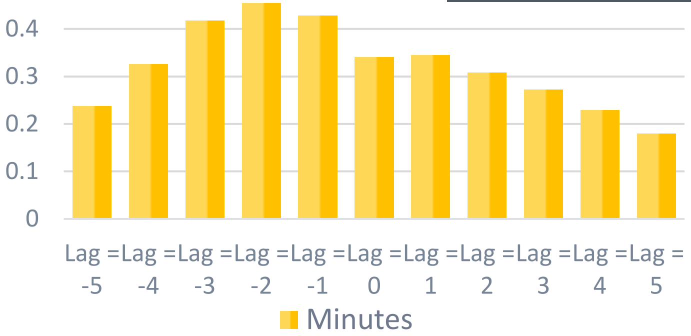


OFS period lagged correlation with LIBOR 1Y

Unit: Months







Reactive

Predictive

LDA topical dictionary

Because LDA model is able to segmentize the dataset into **6 most popular topics:**

'Financial markets', 'The international economy', 'growth and inflation projections', 'Money, credit, demand and output', 'Supply, costs and prices', 'The immediate policy decision'

We are able to construct wordlists that are most important in each of the 6 topics and construct an independent topical sentiments based on those words.

word cloud for topic: Financial markets

word cloud for topic: Money, credit, demand and output

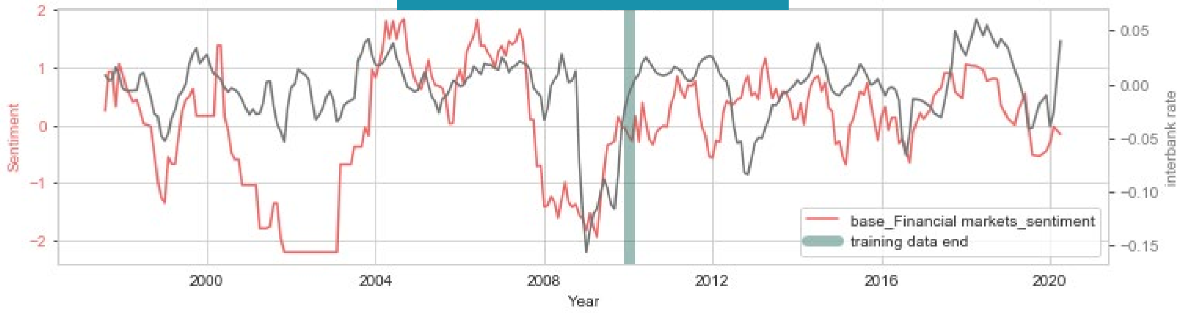
word cloud for topic: The immediate policy decision

word cloud for topic: Supply, costs and prices

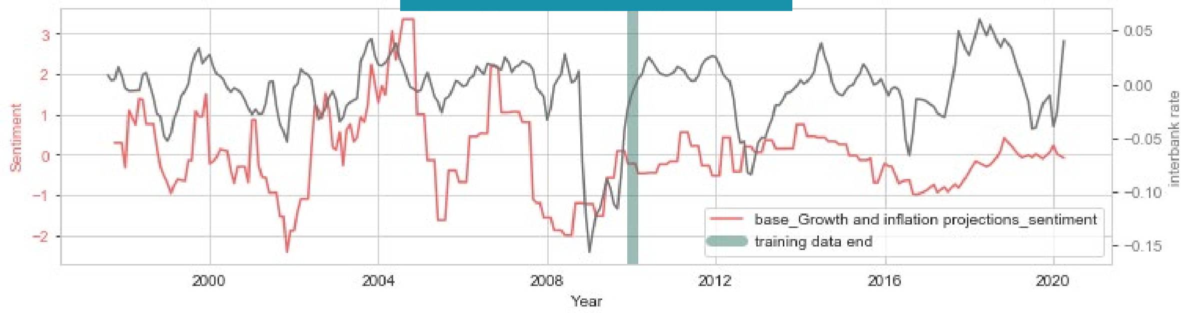
word cloud for topic: Growth and inflation projections

word cloud for topic: The international economy

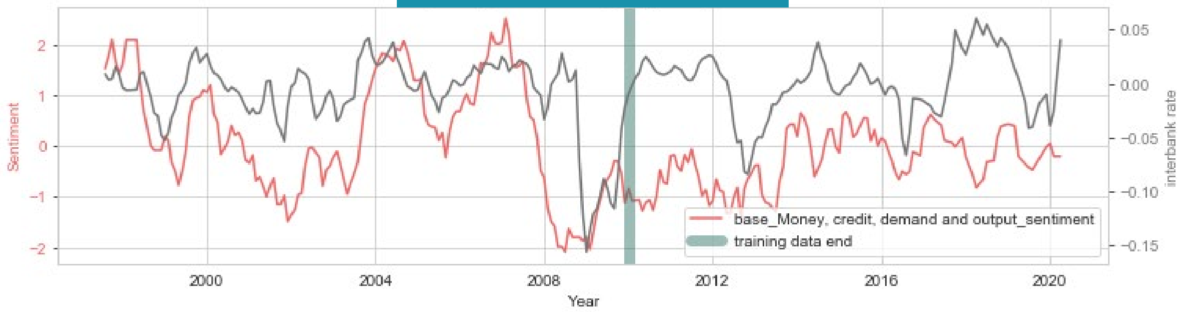
Financial markets



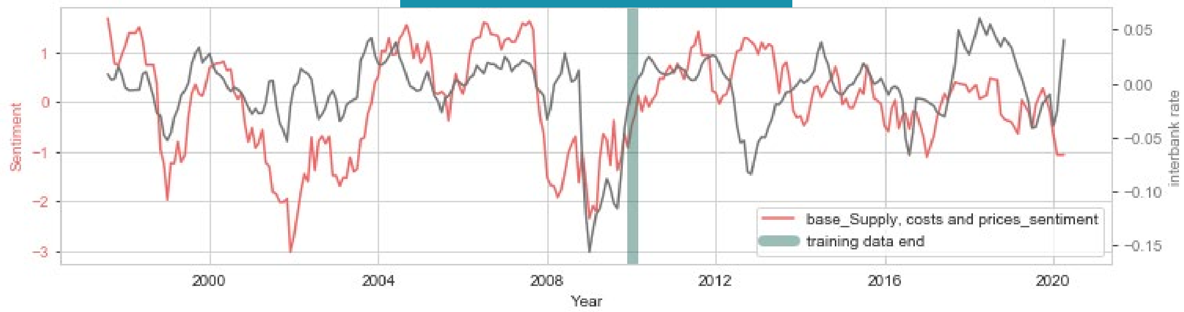
Growth and inflation projection



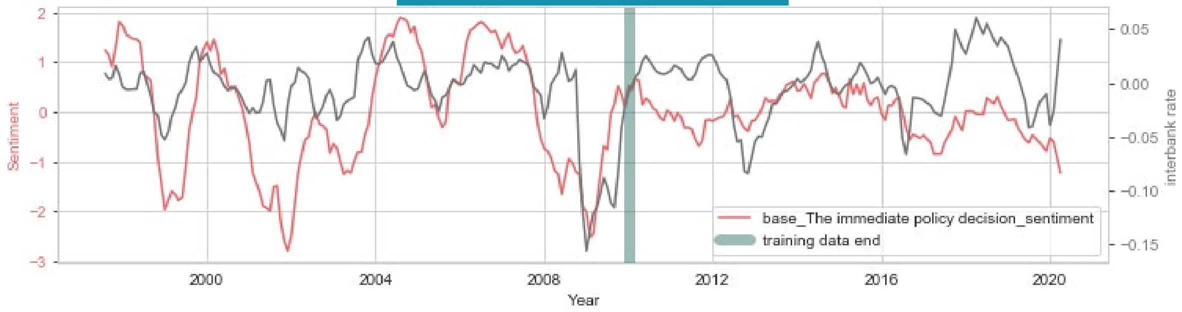
Money, credit, demand and output



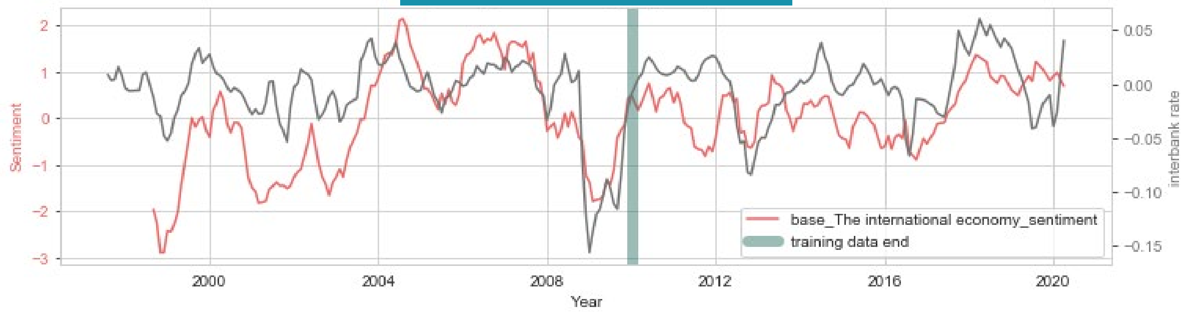
Supply, costs and prices



The immediate policy decision



The international economy



Summary on Language filtered model

LDA on Minutes

1. Train LDA on Minutes

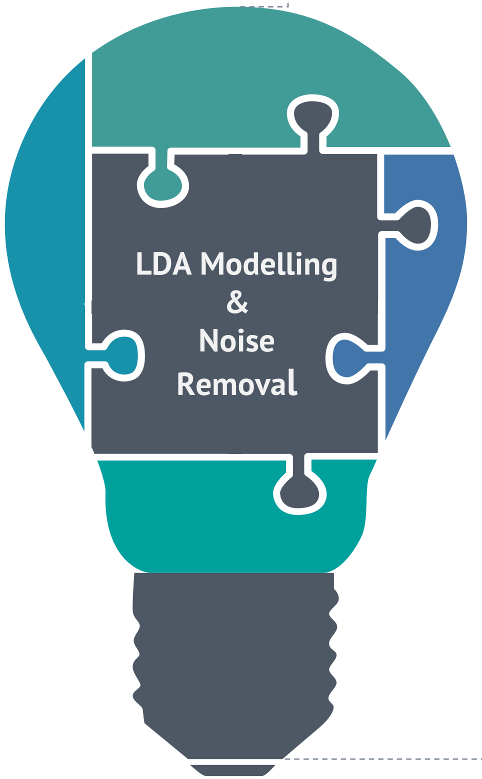
- Rank popularity of headers based on frequency
  - Then train LDA on paragraphs that have headers which are different from top 6 headers

2. Classify Less Popular Headers

Use the LDA clustering result to classify the less popular headers into one of the 6 most popular headers (topics)

3. Topical Sentiment Constructed

Construct sentiment based on paragraphs that belongs to each of the topics



LDA on Speech

1. Raw Noise Removal

Split speech into sentences.
Remove reference / equations / footnotes

2. Apply LDA on Sentences

Use LDA model trained on minutes and Remove the sentences that has ambiguous classification result.

3. Performance Improved

Only 36.3% of original words in speech are kept.
OFS performance improve significantly

Baseline Model

Size: 319 words	All text	All text OFS	Speech	Speech OFS	Minute	Minute OFS
LIBOR_1Y_change	**0.351**	**0.050**	0.345	-0.060	**0.387**	**0.344**

Language Filtered

Size: 293 words	All text	All text OFS	Speech	Speech OFS	Minute	Minute OFS
LIBOR_1Y_change	**0.351**	**0.223**	0.346	0.106	**0.367**	**0.341**

STEP 4: Model Extensions

Extensions to different countries, to a higher frequency sentiment, and to a Machine-Learnt Model

Performance difference between key speaker and Non key speaker

Key speaker including:

Mervyn King | Spencer Dale | Ben Broadbent | Charles Bean | Edward George
Mark Carney | Andy Haldane

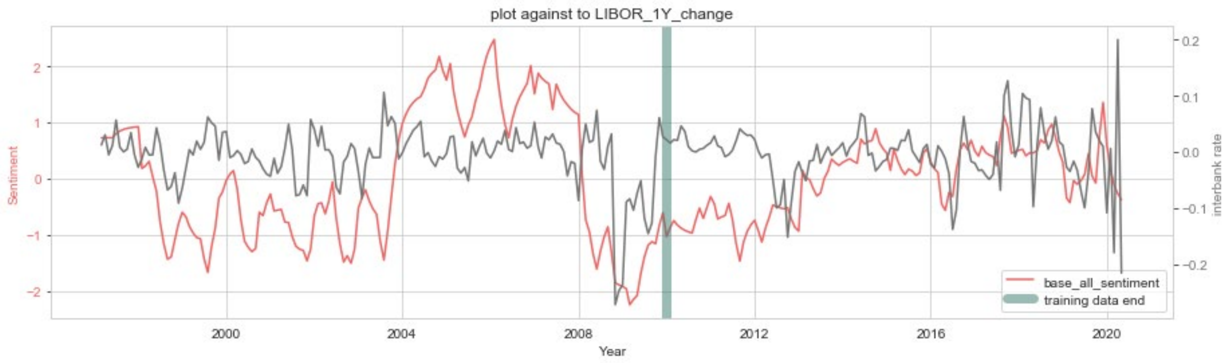
Correlation difference

	Key speaker sentiment	Non key speaker sentiment	difference
LIBOR_1Y_change	0.258	0.218	-15.5%
LIBOR_6M_change	0.298	0.229	-23.2%
LIBOR_3M_change	0.282	0.206	-27.0%
LIBOR_1M_change	0.279	0.201	-28.0%

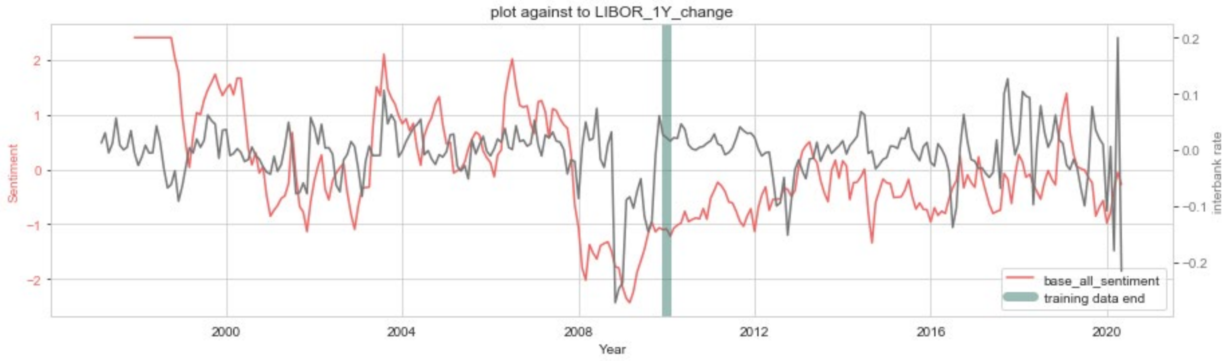
Summary:

- We could spot the difference between the two group of speakers. Key Speaker sentiment is more important than non key speaker
- If we reverse the process, then speeches' correlation to LIBOR rate can act as an indicator for quantifying the importance of a speaker

Key Speaker



Non-Key Speaker



Dictionary performance on ECB and FED document

Validate the economical sense of BOE dictionary :

If apply the dictionary, **that is trained based on Bank of England**, to European Central Bank (ECB) and the Federal Reserve (FED) documents, we can validate the economical meaning of the dictionary we created.

ECB data	BOE dictionary	BOE OFS	FS dictionary	FS OFS	LM Dictionary	LM OFS
EUR_LIBOR_1Y	**0.332**	**0.265**	0.311	0.252	0.176	0.235

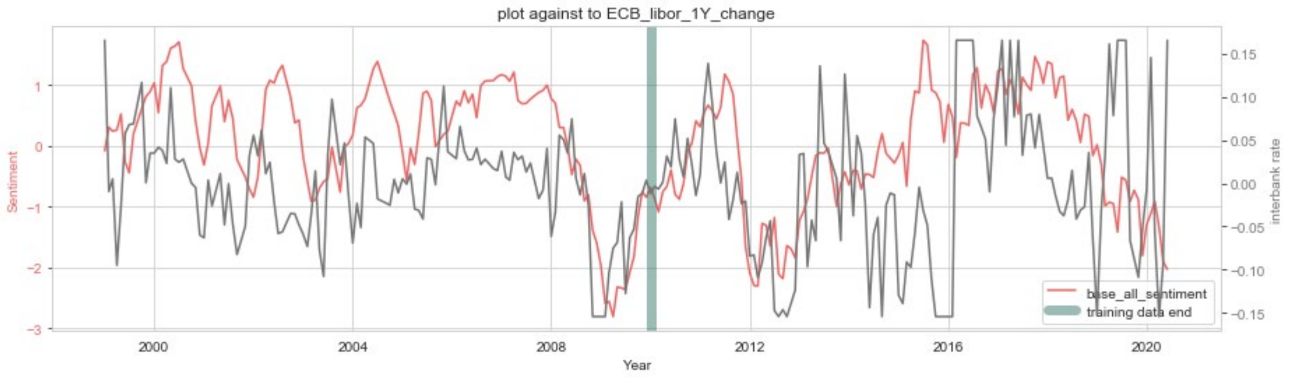
FED data	BOE dictionary	BOE OFS	FS dictionary	FS OFS	LM Dictionary	LM OFS
US_LIBOR_1Y	**0.368**	**0.174**	0.273	0.074	0.092	0.242

Based on the result shown above, we could see the dictionary we have trained can be applied on both the federal reserve and European central bank minutes. And it outperform the general Financial stability dictionary and show the consistence of performance in full period and out-of-sample periods.

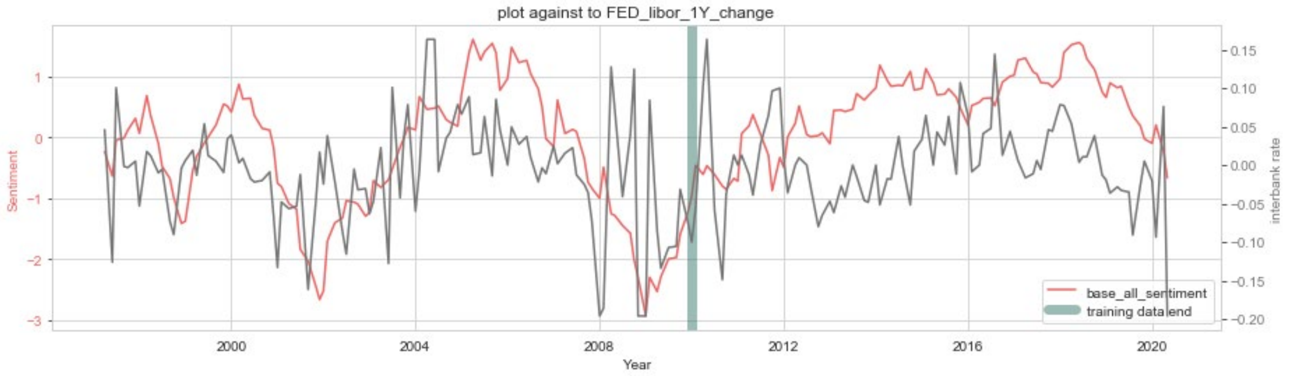
Language cross bank are similar

From the data above, we could also conclude that the language between bank are similar and a common dictionary can conclude sentiment on different banks.

Sentiment applied on ECB documents and EUR LIBOR 1Y rate



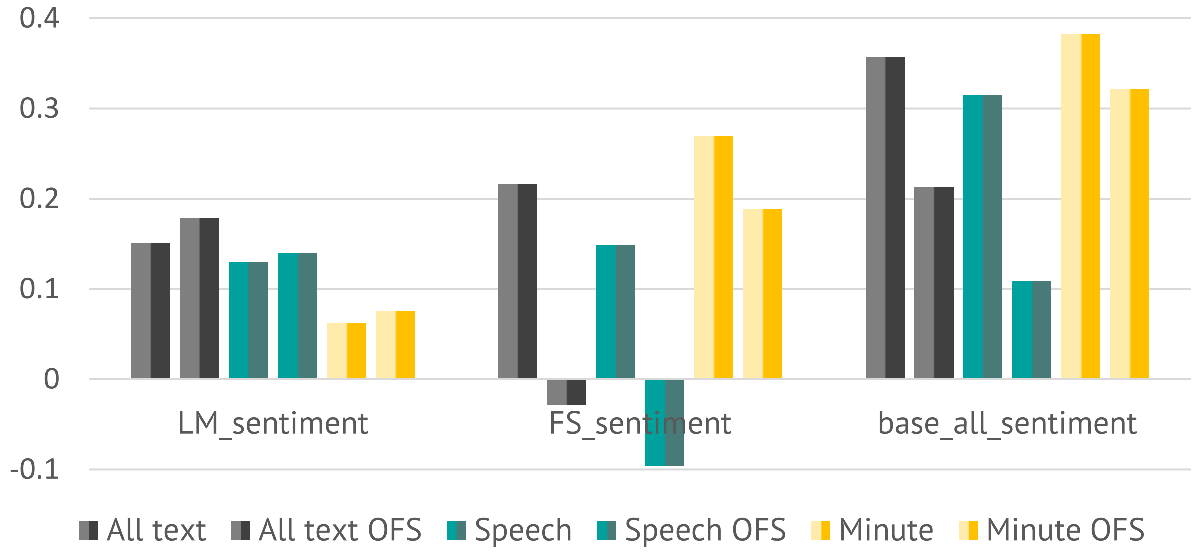
Sentiment applied on FED documents and US LIBOR 1Y rate



Construct daily central bank sentiment

Step 4: Monthly average and exponential weighted average (halflife = 3)

LIBOR_1Y_daily 1M Horizon	All text	All text OFS	Speech	Speech OFS	Minute	Minute OFS
LM_sentiment	0.151	0.178	0.13	0.14	0.062	0.075
FS_sentiment	0.216	-0.028	0.149	-0.096	0.269	0.188
base_all_sentiment	**0.357**	**0.213**	**0.315**	**0.109**	**0.382**	**0.321**



Step 4: 60 days exponentially weighted moving average on sentiments

Summary on the sentiment

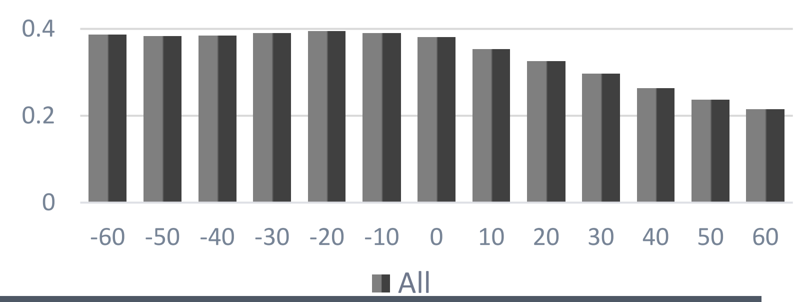
On daily sentiment, our model significantly out-perform FS dictionary
The FS dictionary sentiment is even negative in OFS period, but our model still have a significant high correlation with the documents. And the performance is very consistent on minutes in both full sample and out-of-sample period

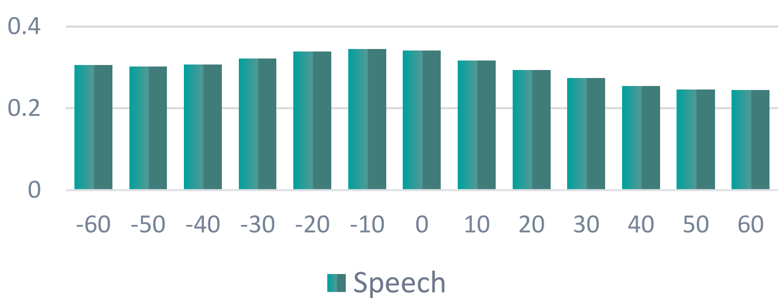
The correlation decay slowly (graph in next page):
The lead-lag plot is actually of daily updated sentiment is actually similar to monthly updated sentiment. The correlation still exist even after 30 days, and in all three periods:

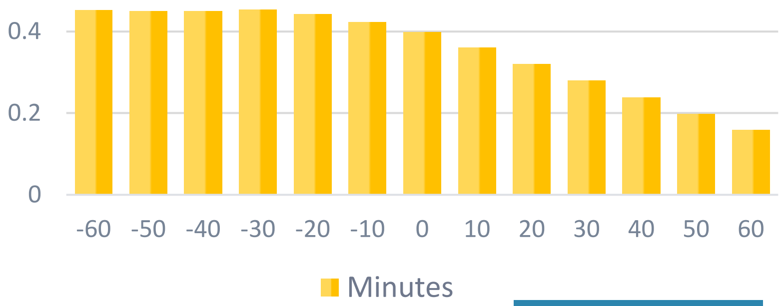
1997-2008: pre financial crisis
2008-2016: post financial crisis
2016-2020: post Brexit

1997-2008 lagged correlation with LIBOR 1Y Daily sentiment

Unit: Days

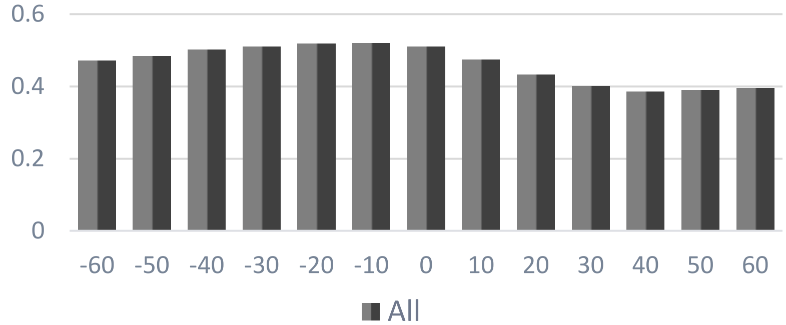


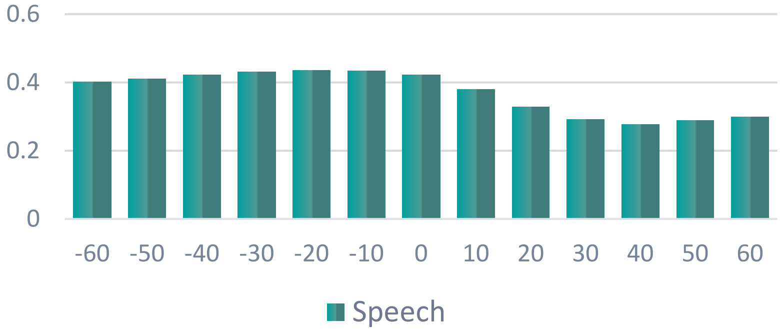


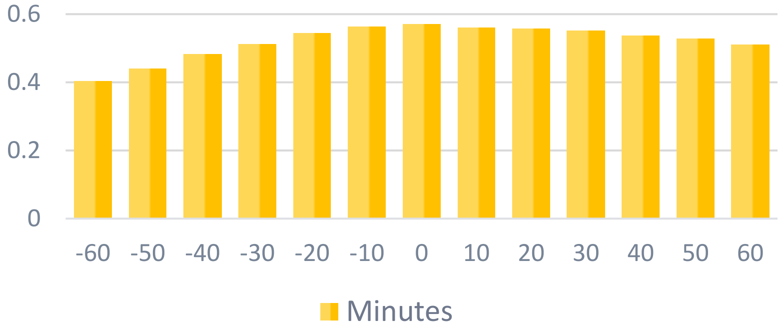


2009-2016 lagged correlation with LIBOR 1Y Daily sentiment

Unit: Days

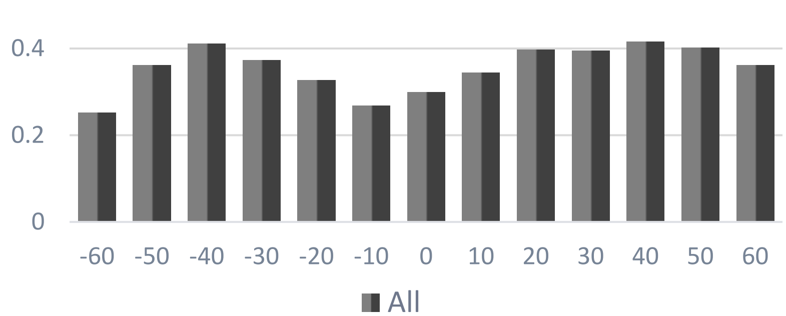


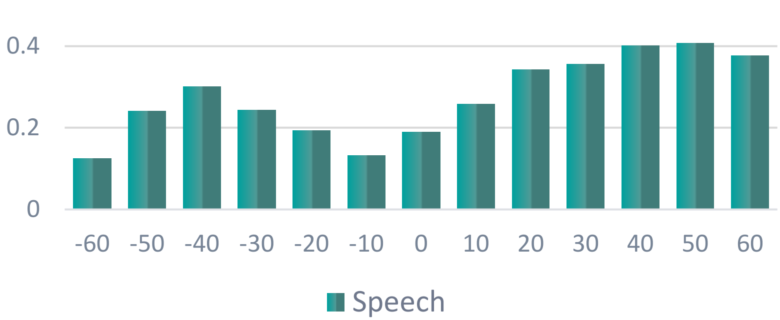


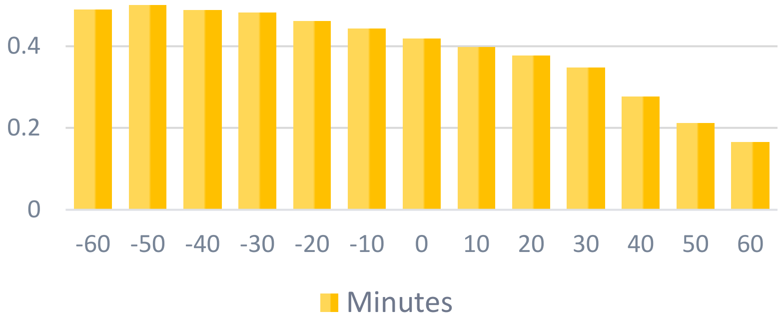


2016-2020 lagged correlation with LIBOR 1Y Daily sentiment

Unit: Days







One step forward: Multinomial Naïve Bayesian Sentiment based on dictionary

Step 1: Use the dictionary learnt in Section 3 as a feature reduction method

The 1044 documents contain more than 4000 different words

Use the dictionary learnt in the precious section, which only contains **293 words**.
Only consider those words and ignore all other vocabularies in the dataset.
We could finalise the dataset size of 1044*293 (Term-Doc matrix)

Step 2: Convert Term-doc matrix with tf-idf weighting

Term frequency–inverse document frequency, is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus. Convert the number of word occurrence to the importance.

	computer	data	pinch	result	sugar
apricot	0	0	1	0	1
pineapple	0	0	1	0	1
digital	2	1	0	1	0
information	1	6	0	4	0

	computer	data	pinch	result	sugar
apricot	0.00	0.00	0.05	0.00	0.05
pineapple	0.00	0.00	0.05	0.00	0.05
digital	0.11	0.05	0.00	0.05	0.00
information	0.05	0.32	0.00	0.21	0.00

Step 3: Pass the dataset to Multinomial Naïve Bayesian model

- We already have the document label for each of the document: **1 -1 & 0**
- Each word will learn its importance towards each of the classifications, which is the probability of the document is 1, 0 or -1 given this word occurs.
- The final prediction is just the label that has the highest probability given the words that occurred in the document.
- We could have two final result:
  1. the classification of the document 1, -1 or 0
  2. the probability of the document fall into label 1 (positive sentiment)

Step 4: Exponential moving average to finalise sentiment

We apply rolling window to both classification and probabilities to get two set of sentiments.

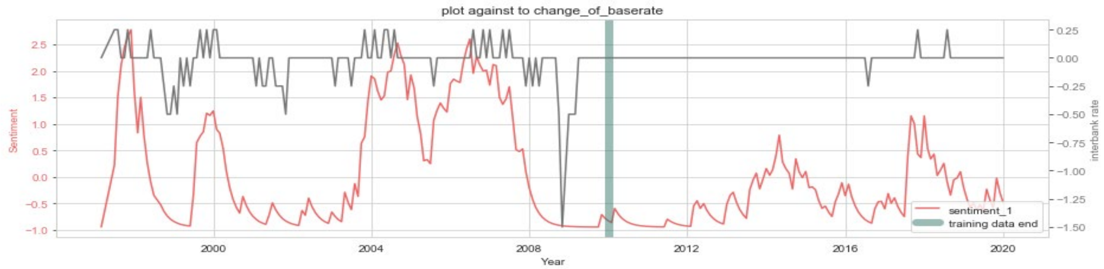
Classification sentiment

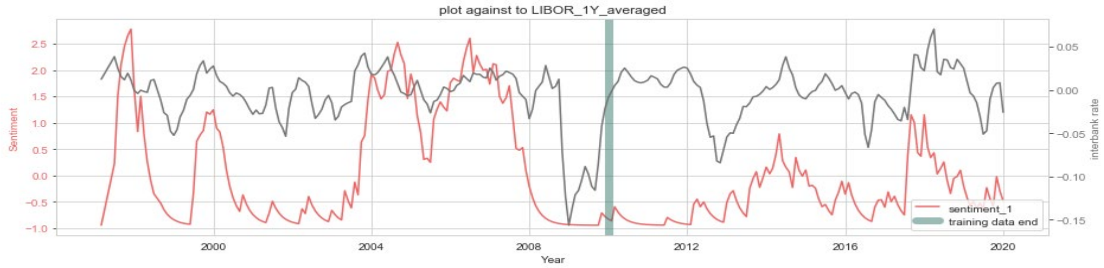
Size: 293 words	All text	All text OFS	Speech	Speech OFS	Minute	Minute OFS
LIBOR_1Y_change	**0.285**	**0.340**	0.271	0.228	**0.297**	**0.324**
LIBOR_6M_change	**0.310**	**0.376**	0.286	0.285	**0.330**	**0.339**
LIBOR_3M_change	**0.303**	**0.379**	0.288	0.367	**0.324**	**0.303**
LIBOR_1M_change	**0.265**	**0.281**	0.261	0.315	**0.301**	**0.179**

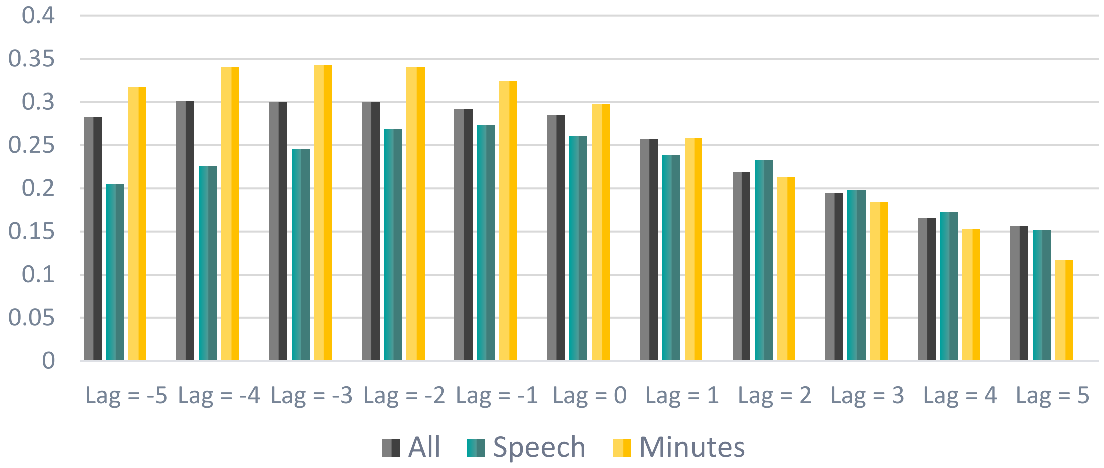
Probability sentiment

Size: 293 words	All text	All text OFS	Speech	Speech OFS	Minute	Minute O0FS
LIBOR_1Y_change	**0.344**	**0.260**	0.360	0.039	**0.349**	**0.310**
LIBOR_6M_change	**0.387**	**0.311**	0.388	0.097	**0.403**	**0.347**
LIBOR_3M_change	**0.380**	**0.291**	0.375	0.113	**0.417**	**0.340**
LIBOR_1M_change	**0.362**	**0.186**	0.369	0.080	**0.440**	**0.238**

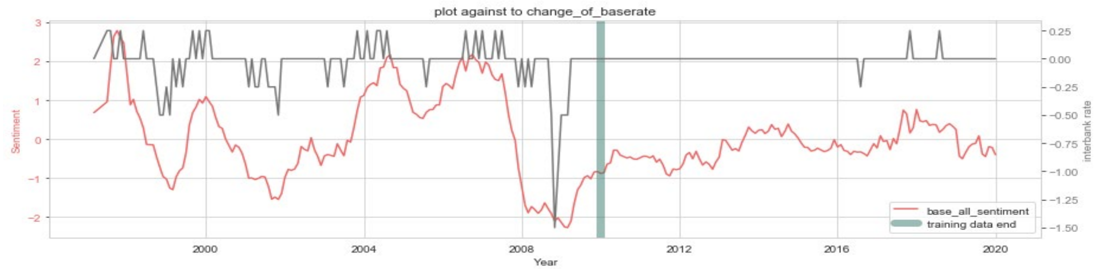
Classification sentiment

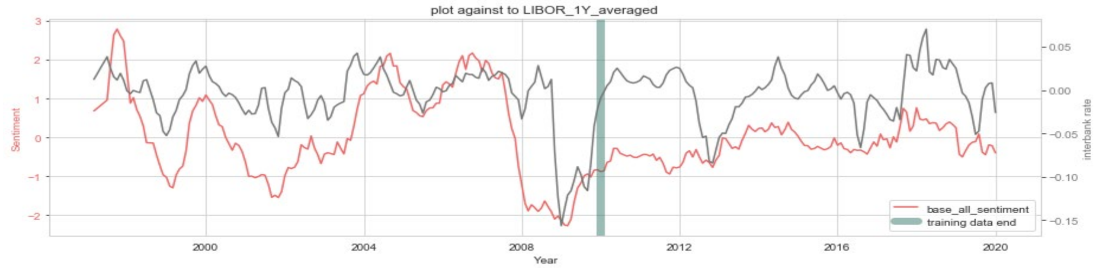


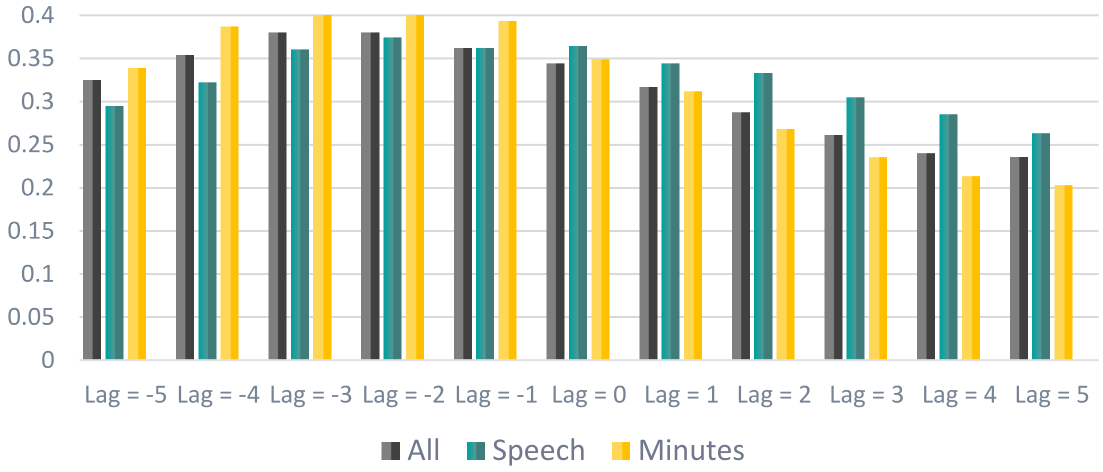




Probability sentiment







Richard Xia 20/07/2020

THANK YOU FOR WATCHING

Data Mining → Baseline Model → Language Filtered → Model Extensions → Possible Future work

1. Pre-Processing

- Stop-word removal, lemmatization, stemming
- 261 minutes and 783 speech
- Monthly LIBOR rate and UK base rate

2. Pure-dictionary based method

- FS perform better than LM dictionary
- Minutes perform consistent
- Speech performance decays after training period
- Most predictive 6 month horizon

3. Latent Dirichlet Allocation

- Split paragraphs in minutes into 6 different topics
- Remove Noise in Speech
- Performance More consistent
- 293 words

4. Apply different text and models

- Split speech by speaker
- Sentiment dictionary works on different banks
- Multinomial Naïve Bayesian based on dictionary learnt

5. Things To Do Next:

- Noise removal in the dictionary (eg: German, Mervyn)
- KNN, Doc2vec, word2vec for better representation
- LDA noise removal on different time scale
- Use pre-trained model (BERT, XLNET)

Appendix: All relevant tables and graphs

LM dictionary word list

Positive Words

ABUNDANCE	CHARITY	INDEPENDENT#1	PROFITABLE	WORTH#3
ACCRUE	CIVIL#1	INEXPENSIVE	PROSPER	
ADVANTAGE	COMMUNITY	INHERIT	PROSPERITY	
AFFLUENCE	COMPENSATE	INVALUABLE	PROSPEROUS	
AFFLUENT	COMPENSATION	LEGAL	RALLY	
AFLOAT	CONFEDERATION	LIBERAL#2	RECOMPENSE	
ALLIANCE	CONTRIBUTE#1	LIBERALISM	REINSTATE	
ALLIED	CONTRIBUTION	LIBERTY	REWARD#1	
ALLOWANCE	COOPERATIVE#1	LOYAL	RICH#1	
ALLY#1	COUNCIL	LOYALTY	RICH#3	
ARISTOCRACY	COURTLY	LUCRATIVE	RICH#4	
ARISTOCRAT	CRUSADE	LUXURY	RICH#5	
ARISTOCRATIC	CRUSADER	MERITORIOUS	RICH#6	
ASSOCIATE#1	DONATE	NOBILITY	RICHES	
BACKER	DONATION	NOBLEMAN	RICHNESS	
BARGAIN	ECONOMIZE	NOMINATE	SAVINGS	
BENEFACTOR	ENDOW	PARTNER	SECURITY#2	
BENEFICIARY	ENTREPRENEURIAL	PARTNERSHIP	SKILL#1	
BENEFIT#1	EQUALITY	PATRIOT	SUBSIDIZE	
BENEVOLENCE	EQUITY	PATRIOTIC	SUBSIDY	
BENEVOLENT	FELLOWSHIP	PATRON	SUCCESS	
BEQUEATH	FREEDOM	PATRONAGE	SUCCESSFUL	
BETROTH	FRUGAL	PLEDGE	TACTICS	
BETROTHAL	GAIN#2	PRECIOUS	THRIFT	
BONUS	GENEROSITY	PRICELESS	THRIFTY	
BOOM	GIFT	PRIVILEGED	TREASURE#1	
BREADWINNER	GOLD	PRODUCTIVE	TREATISE	
BUY#2	GUIDE#2	PRODUCTIVITY	TREATY	
CAPITALIZE	HUMANITARIAN	PROFIT#1	UNIMPEACHABLE	
CHARITABLE	INDEPENDENCE	PROFIT#2	VALUABLE	

Negative Words

ADVERSARY	DEFAULT	JOBLESS	STEAL#2
ANARCHIST	DEFICIT	LAID#2	TARIFF
ANARCHY	DEPRECIATION	LAY#3	TREASON
ANTITRUST	DEPRESSION#2	LIQUIDATE	TREASONOUS
AUTOCRAT	DESTITUTE	LIQUIDATION	TYRANNY
AUTOCRATIC	DICTATE	MISER	UNDERWORLD
BACKWARD	DICTATORIAL	OWE	UNECONOMICAL
BACKWARDNESS	DISCHARGE#1	POLLUTION	UNEMPLOYED
BANISH#1	DOMINATION	POOR#1	UNPROFITABLE
BANISHMENT	ENSLAVE	POOR#2	USURP
BANKRUPT	ENTANGLE	POOR#3	VAGABOND
BANKRUPTCY	ENTANGLEMENT	POOR#4	VAGRANT
BEGGAR	EXPENSE#1	POOR#5	WAR
BLACKMAIL	EXPENSIVE	POVERTY	WARFARE
BRIBE	EXTRAVAGANT	PROPAGANDA	WARLIKE
BROKE#3	FASCIST	RACE#4	WASTE#1
BUM	FEUDAL	RADICAL	WASTE#2
CHEAP	FINE#6	REACTIONARY	
COLD#3	FINE#7	REBELLIOUS	
COLONY	FIRE#2	RECESSION	
COMBAT#2	GAMBLE#1	REFUGEE	
COMMONER	GAMBLE#2	REVOLT	
CONSPIRACY	GHETTO	REVOLUTION	
CORRUPT	HOLE#2	RUIN#1	
COST#1	HUSTLE	SECEDE	
COST#2	HUSTLER	SECESSION	
COSTLINESS	INFLATION	SEGREGATION	
COSTLY	INTERVENTION	SHORTAGE	
CRISIS	INVADE	SIEGE	
DEBTOR	IRON#3	SQUANDER	

FS dictionary word list

Positive Words			
able	enhancing	profitable	success
absorb	enjoy	rallied	successful
absorbed	excellent	reassuring	successfully
absorbing	favorable	rebound	upgraded
acceptable	favorably	rebounded	upswing
achievement	favourable	rebounding	withstanding
adequately	favourably	recouped	
alleviated	gain	recover	
alleviating	gained	recovered	
beneficial	good	recovering	
benefit	grew	recovery	
benefiting	grow	regained	
benign	healthy	reopening	
better	improve	resilient	
brighter	improved	resolve	
broaden	improvement	sheltered	
buoyancy	improvements	smooth	
calm	improves	smoothly	
calmed	improving	solid	
calming	mitigate	sound	
comfortable	mitigated	sounder	
confident	mitigates	stabilise	
confined	mitigating	stabilised	
contained	mitigation	stabilising	
effective	opportunity	stabilize	
efficient	optimism	stabilized	
enabled	outperformed	stabilizing	
enabling	positive	stable	
enhance	positively	strengthened	
enhanced	preventing	succeeded	

Negative Words									
abnormally	contracting	disappointing	eroding	hampered	jeopardised	poorly	sliding	suffering	unresolved
abrupt	contraction	discouraging	erosion	hampering	jeopardising	poses	slipped	susceptibility	unrest
abundant	corrections	disorderly	escalate	headwinds	jeopardize	posing	slowdown	susceptible	unstable
adverse	costly	disrupt	escalated	hinder	lackluster	problem	slowdowns	tense	unsustainable
adversely	damaging	disrupted	escalating	hindered	lacklustre	problematic	sluggish	tension	volatile
aggravate	danger	disruption	escalation	hindering	lagged	problems	sluggishness	tepid	volatility
aggravated	dangerous	disruptions	exacerbate	hinders	lose	prolonged	slump	threat	vulnerabilities
aggravating	declines	disruptive	exacerbated	hurt	losing	protectionism	slumped	threaten	vulnerability
aggravation	deep	distortions	exacerbating	illiquid	losses	protracted	slumps	threatened	vulnerable
ailing	deeply	distress	excessive	illiquidity	lost	questions	spill	threatening	weaken
alarming	defaults	distressed	exhausted	imbalance	misalignments	recession	spilled	threats	weakened
anxiety	deficient	distrust	expose	imbalances	misconduct	repercussions	spilling	tough	weakening
arrears	deficits	disturbance	exposed	impair	mispricing	restructure	spillover	troubled	weaker
bad	delays	disturbances	exposes	impaired	negative	resurfaced	spillovers	tumbling	weakest
burdened	delinquencies	doubts	exposing	impairing	negatively	riskier	spiral	turbulence	weakness
challenge	dented	downgrade	fail	impairments	nervousness	setback	squeeze	turbulences	weaknesses
challenges	depress	downgraded	failed	impede	nonperforming	setbacks	squeezed	turbulent	worries
challenging	depressed	downgrades	failing	impeded	overcapacity	severely	stagnant	turmoil	worrisome
closure	depressing	downgrading	fails	impediments	overheated	severity	stagnate	unable	worrying
clouded	destabilising	downside	failure	inability	overheating	shaken	stagnated	undermine	worse
compromised	destabilizing	downswing	failures	inadequate	overindebted	shortage	stagnating	undermined	worsen
concern	deteriorate	downturn	faltering	ineffective	overvalued	shortages	stagnation	undermining	worsened
concerns	deteriorated	downward	fear	inefficient	pessimism	shortfall	strain	underperformance	worsening
confronted	deteriorating	drag	fears	insolvencies	pessimistic	shortfalls	strained	underperformed	worst
confronting	deterioration	drastic	forced	insolvency	plummeted	shrank	strains	undesirable	writedowns
constrain	deteriorations	dropped	fragile	insolvent	plummeting	shrink	stresses	unease	
constrained	detrimental	drying	fragilities	instability	plunge	shrinking	struggle	unemployed	
constraining	difficult	endanger	fragility	insufficient	plunged	shrunk	struggling	unexpectedly	
contagion	difficulties	erode	gloomy	insufficiently	poor	slid	suffer	unfavorable	
contracted	difficulty	eroded	hamper	jeopardise	poorer	slide	suffered	unfavourable	

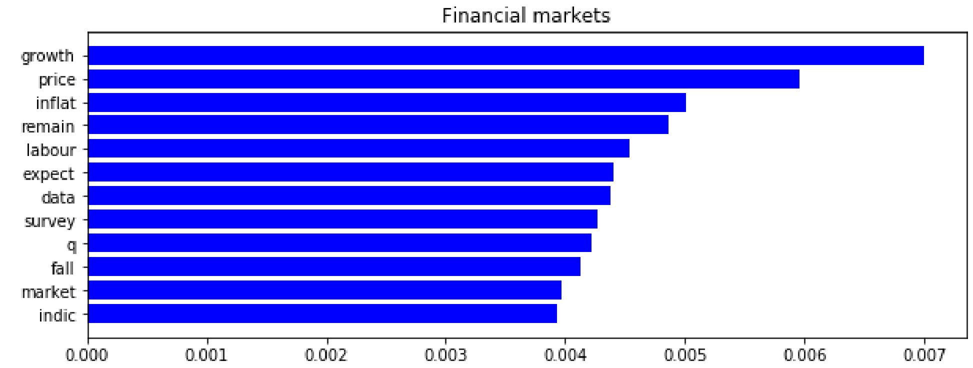
Self-created dictionary word list

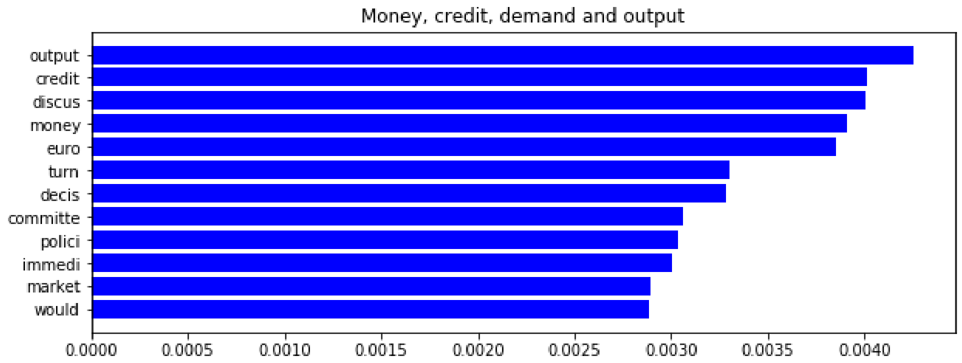
Positive Words

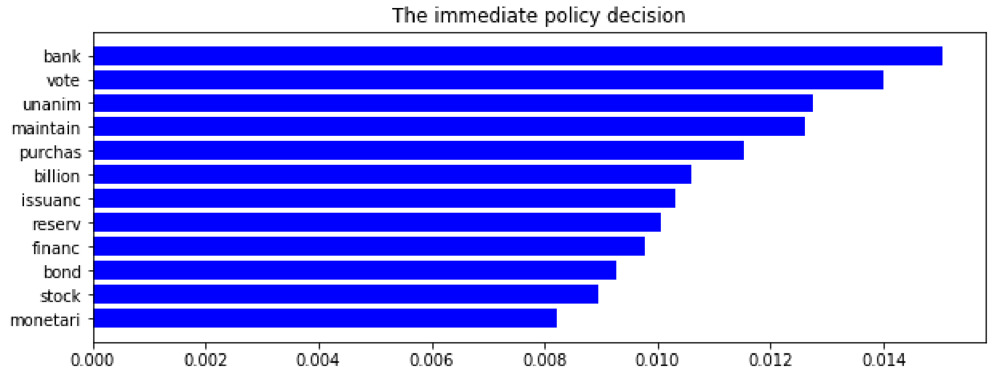
abroad	describ	highest	read	utilis
absenc	differenti	idea	recov	variabl
accept	doubl	ie	recoveri	withdraw
access	east	implement	reform	worker
accommod	effici	improv	resolv	
age	element	instead	restrain	
aris	enjoy	interpret	sensit	
arrang	equilibrium	latter	shortag	
aspect	evolv	leav	singl	
attribut	examin	life	skill	
banker	exceed	link	smooth	
basic	excel	mainli	social	
behaviour	expenditur	mitig	someth	
benefit	fail	narrow	spare	
benign	fast	offici	specif	
better	favour	optim	specul	
book	fed	outperform	spot	
broad	foreign	paid	spring	
buy	furthermor	particip	stabl	
centuri	ga	partli	strengthen	
china	gain	pension	tax	
complet	gap	pick	technic	
complic	gather	pickup	threat	
conduct	gave	pmi	transfer	
consecut	german	posit	twenti	
constant	good	post	unanim	
contain	group	prevent	unchang	
curv	grow	primarili	unexpect	
cyclic	grown	principl	upsw	
date	healthi	profil	upward	

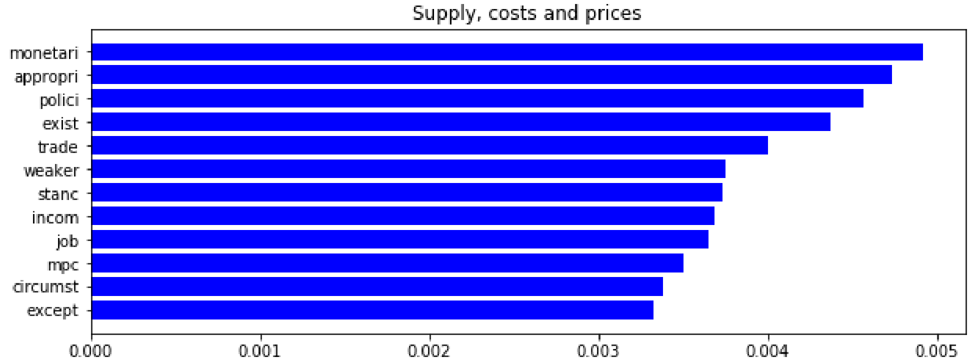
Negative Words

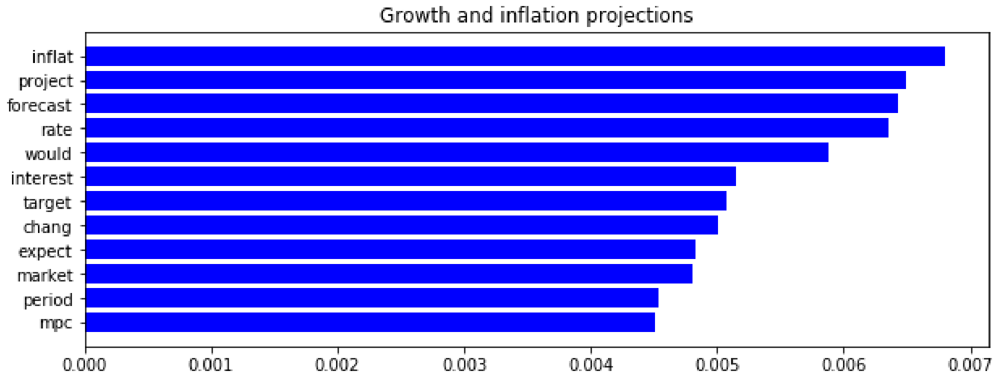
abil	danger	fear	macro	restructur	troubl
abrupt	declin	feed	markedli	riskier	turbul
abund	deep	felt	mervyn	save	turmoil
address	default	financ	mortgag	saw	undermin
adopt	dent	food	neg	sentiment	undesir
advers	deterior	fragil	nervous	setback	unsustain
aggrav	difficult	gfk	notic	sever	upon
alon	difficulti	gloomi	origin	sheet	vulner
alongsid	disrupt	hard	outcom	shortfal	weak
awar	distress	head	overh	shrink	weaken
away	downgrad	illiquid	persist	situat	weaker
bad	downsid	illustr	pessim	slow	weakest
bear	downsw	imbal	pessimist	slowdown	wholesal
becam	downturn	imf	petrol	sluggish	widen
boom	downward	impair	poor	sometim	widespread
challeng	drag	imped	precis	spiral	worri
charter	dri	inadequ	problem	squeez	wors
collaps	driven	insolv	problemat	stabilis	worsen
collater	drop	introduct	prolong	stephen	worst
commerci	ecb	inventori	pronounc	stimul	
consensu	elsewher	judgement	properti	strain	
constraint	ensur	justifi	protract	stress	
contagion	erod	king	question	struggl	
contract	event	lag	react	suffer	
correct	exacerb	learn	recess	summer	
costli	excess	liquid	recognis	surprisingli	
crisi	expo	lose	reinforc	task	
cut	extrem	loss	remark	tension	
damag	failur	lost	resili	threaten	
dampen	falter	lowest	respond	treasuri	

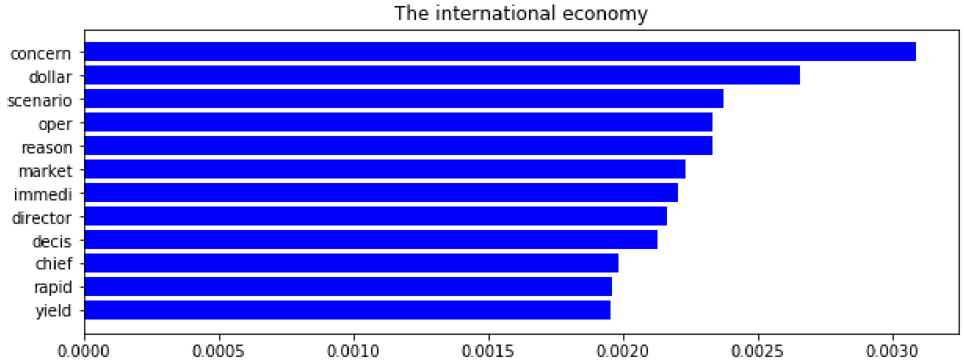

Financial markets
growth
price
inflat
remain
labour
expect
data
survey
q
fall
market
indic
0.000 0.001 0.002 0.003 0.004 0.005 0.006 0.007


Money, credit, demand and output
output
credit
discus
money
euro
turn
decis
committe
polici
immedi
market
would
0.0000 0.0005 0.0010 0.0015 0.0020 0.0025 0.0030 0.0035 0.0040


The immediate policy decision
bank
vote
unanim
maintain
purchas
billion
issuanc
reserv
financ
bond
stock
monetari
0.000 0.002 0.004 0.006 0.008 0.010 0.012 0.014

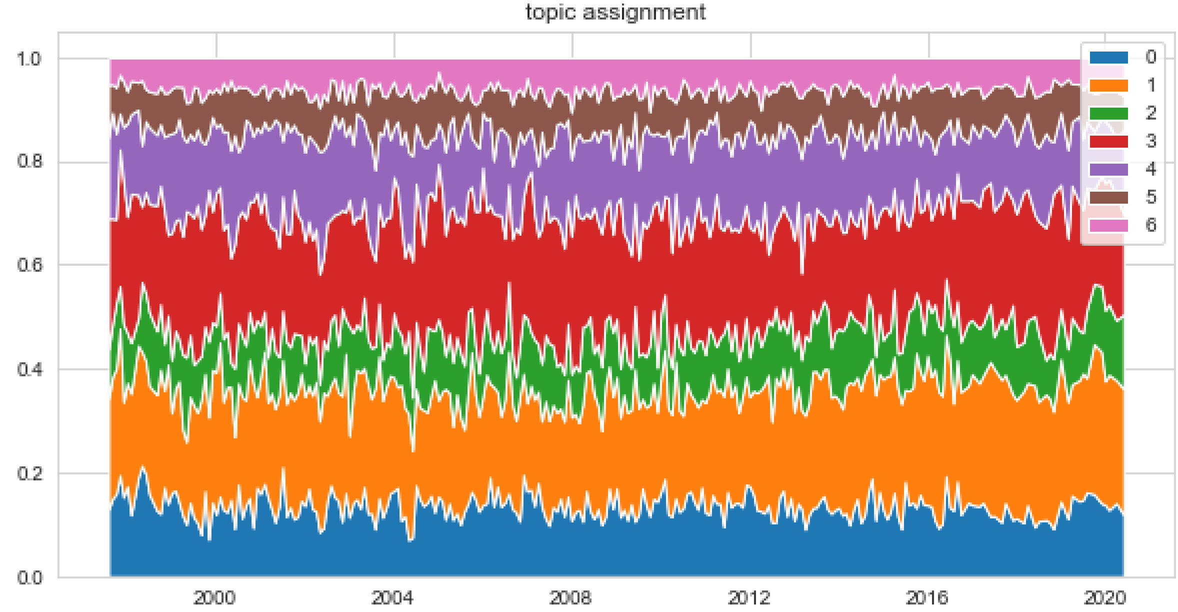

Supply, costs and prices
monetari
appropri
polici
exist
trade
weaker
stanc
incom
job
mpc
circumst
except
0.000 0.001 0.002 0.003 0.004 0.005


Growth and inflation projections
inflat
project
forecast
rate
would
interest
target
chang
expect
market
period
mpc
0.000 0.001 0.002 0.003 0.004 0.005 0.006 0.007


The international economy
concern
dollar
scenario
oper
reason
market
immedi
director
decis
chief
rapid
yield
0.0000 0.0005 0.0010 0.0015 0.0020 0.0025 0.0030

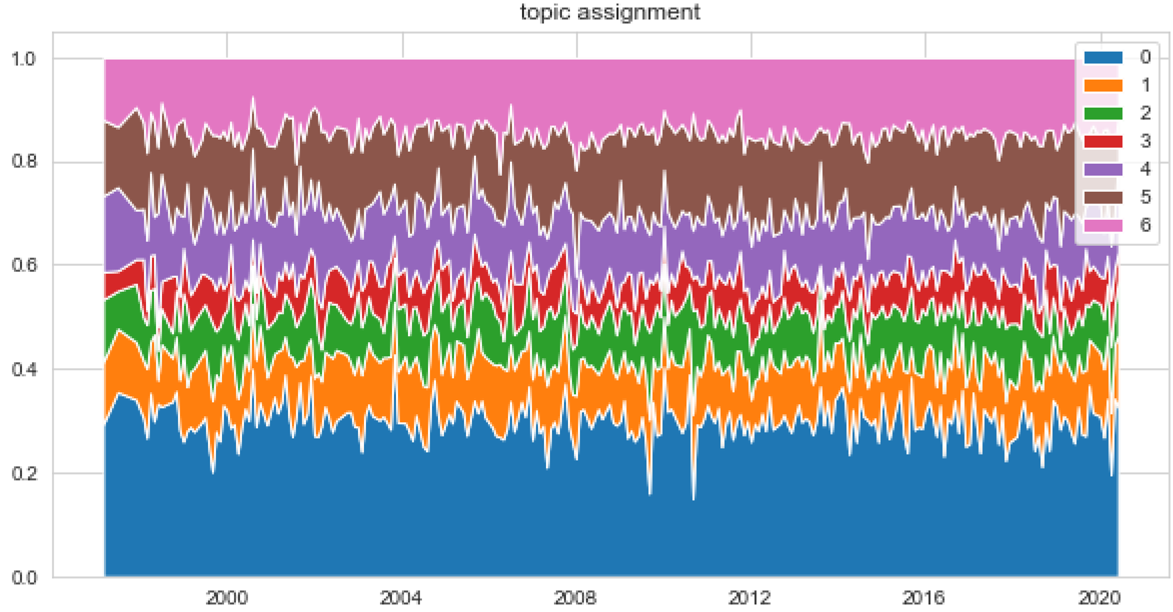
Minutes more consistent

	Baseline Model		Language Filtered		Multinomial NB	
	Minute	Minute OFS	Minute	Minute OFS	Minute	Minute OFS
LIBOR_1Y_change	0.387	0.344	0.387	0.344	0.349	0.310
LIBOR_6M_change	0.456	0.403	0.456	0.403	0.403	0.347
LIBOR_3M_change	0.472	0.376	0.472	0.376	0.417	0.340
LIBOR_1M_change	0.495	0.274	0.495	0.274	0.440	0.238

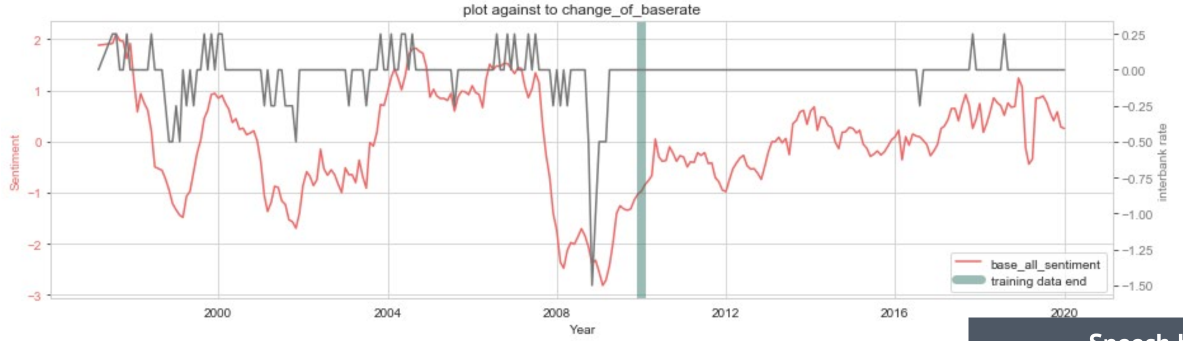


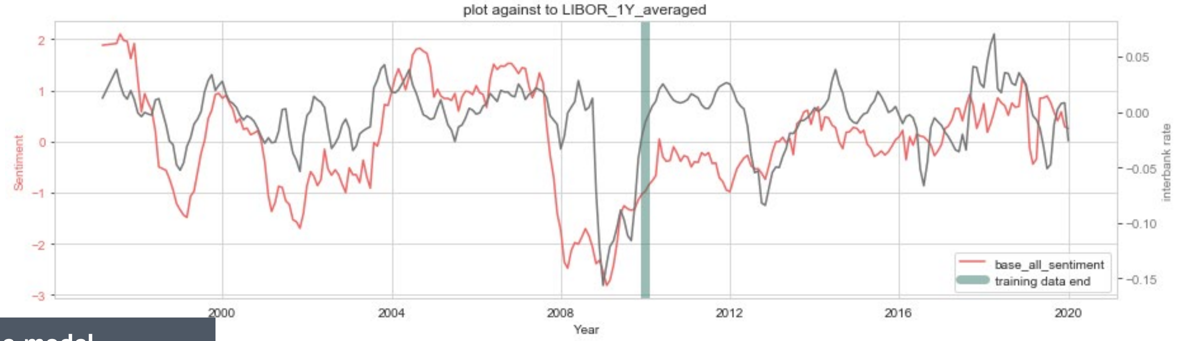
Speech change overtime

	Baseline Model		Language Filtered		Multinomial NB	
	Speech	Speech OFS	Speech	Speech OFS	Speech	Speech OFS
LIBOR_1Y_change	0.345	-0.060	0.346	0.106	0.360	0.039
LIBOR_6M_change	0.381	-0.029	0.369	0.142	0.388	0.097
LIBOR_3M_change	0.373	-0.012	0.335	0.122	0.375	0.113
LIBOR_1M_change	0.361	-0.065	0.325	0.104	0.369	0.080

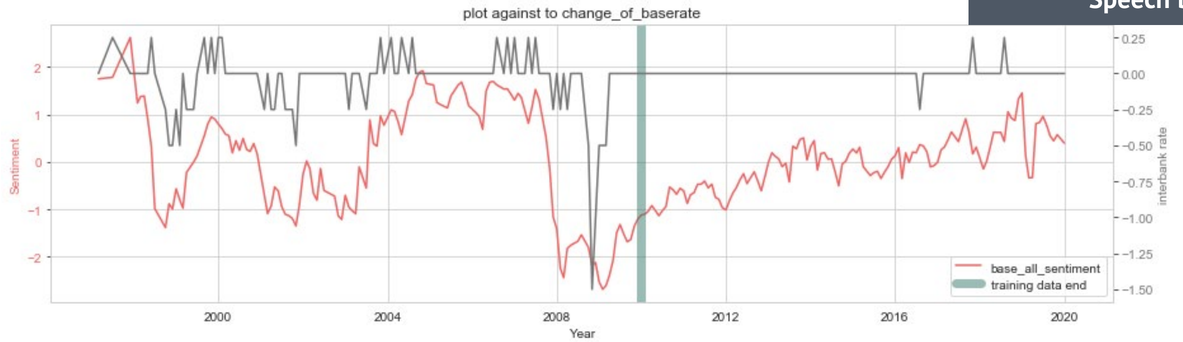


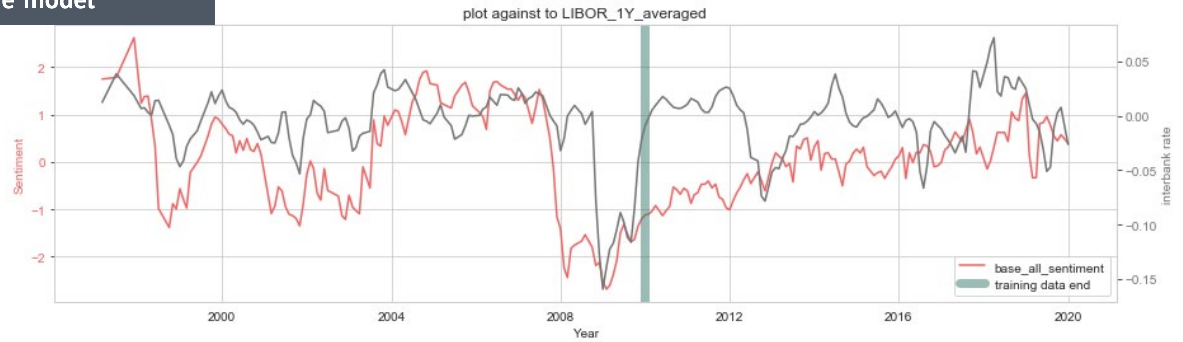
All Text baseline model



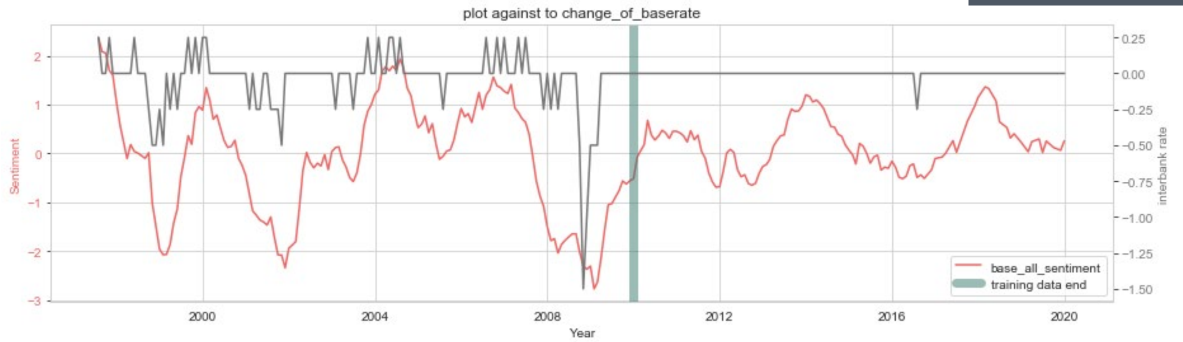


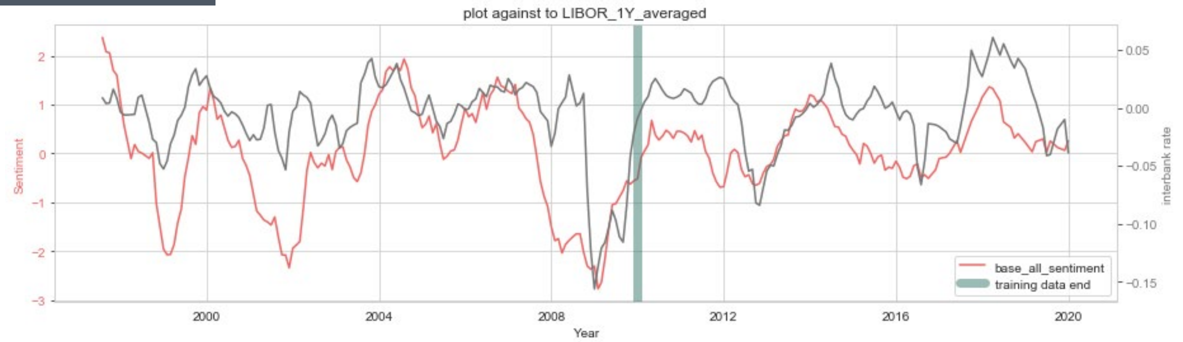
Speech baseline model



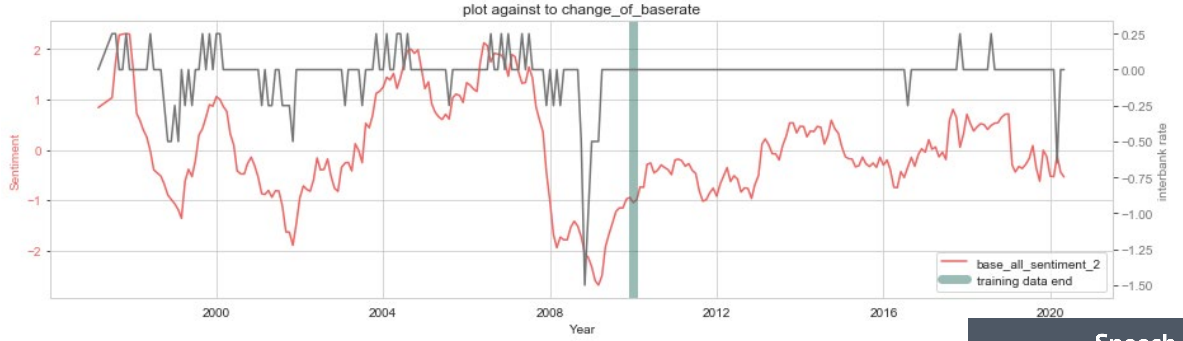


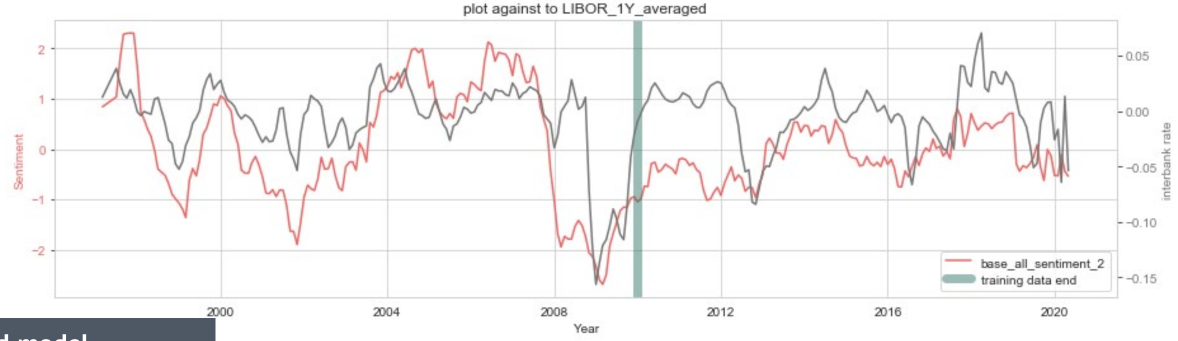
Minutes baseline model



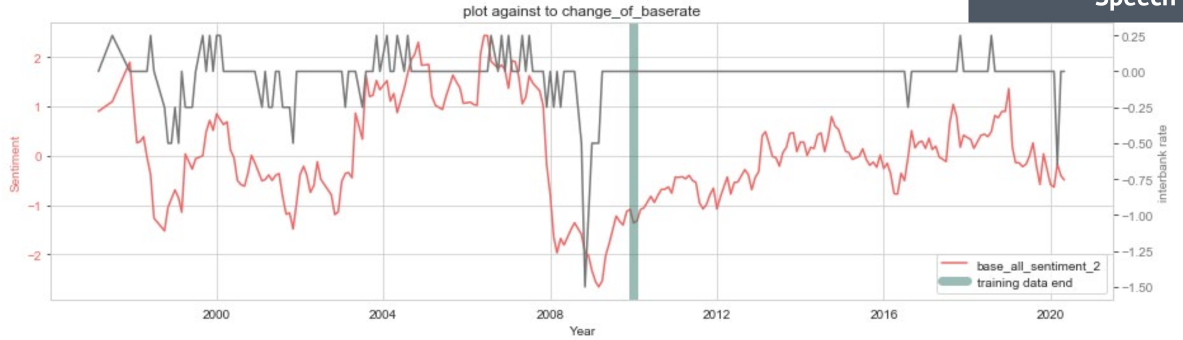


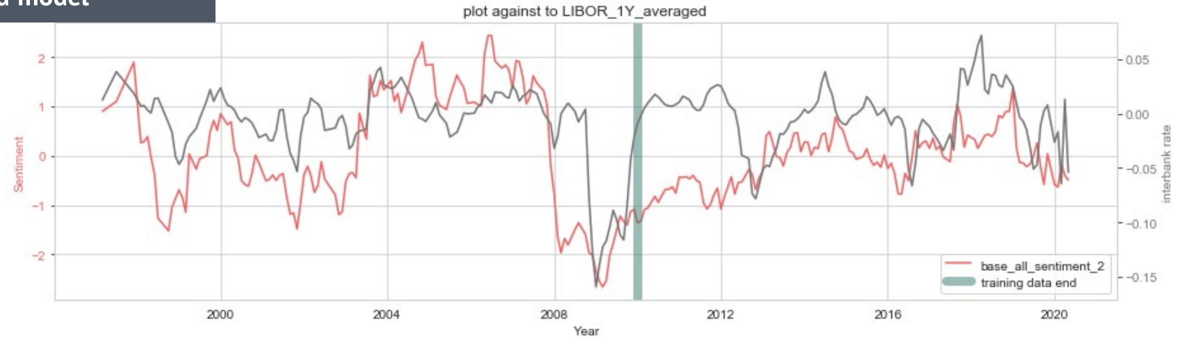
All Text filtered model



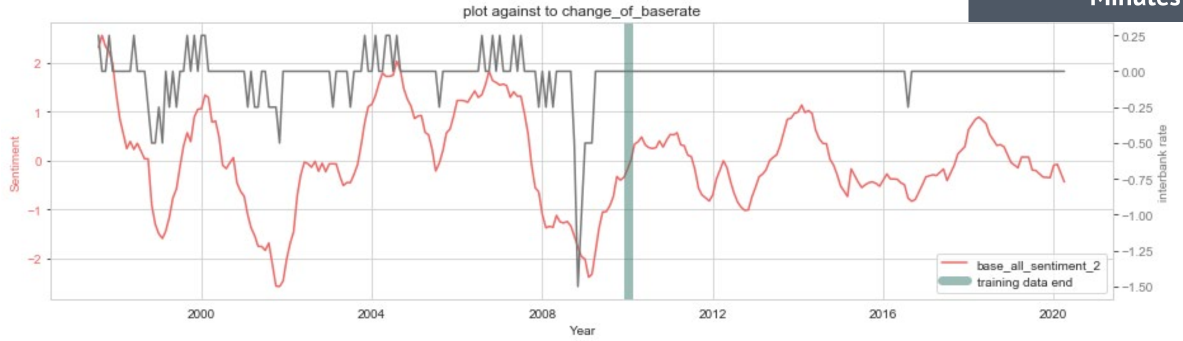


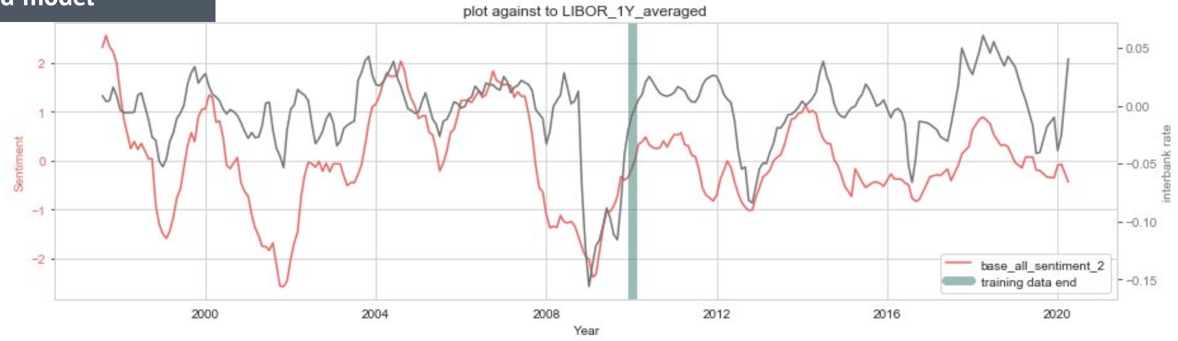
Speech filtered model



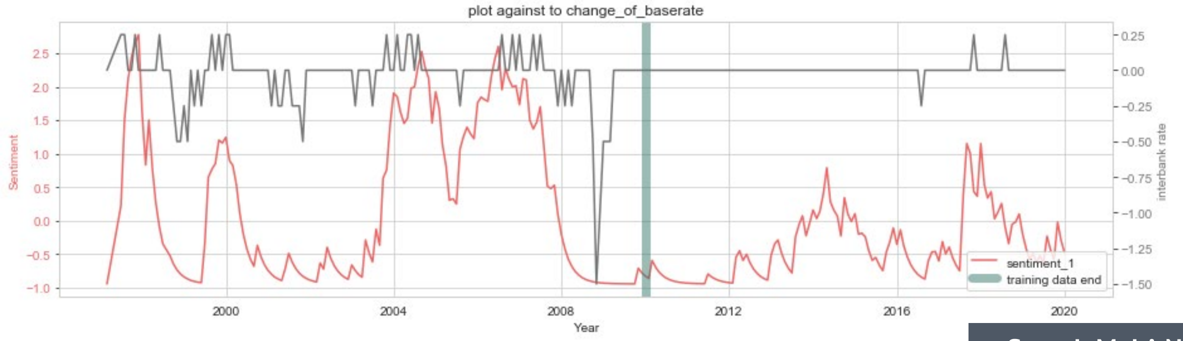


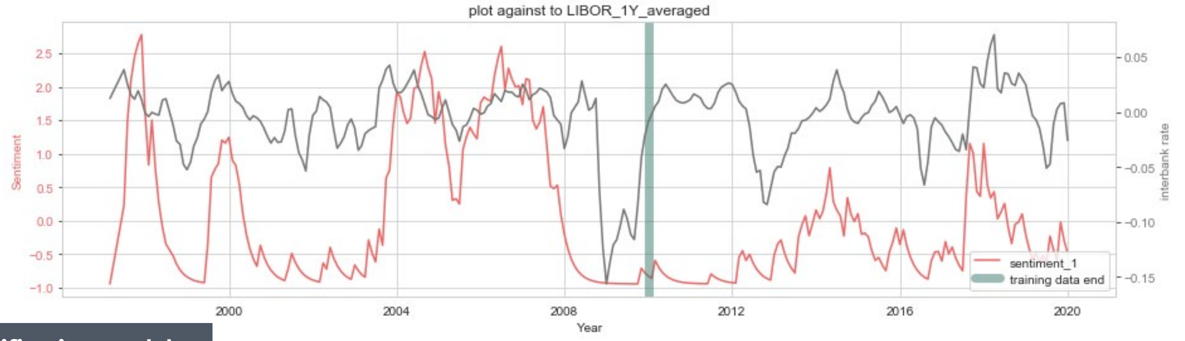
Minutes filtered model



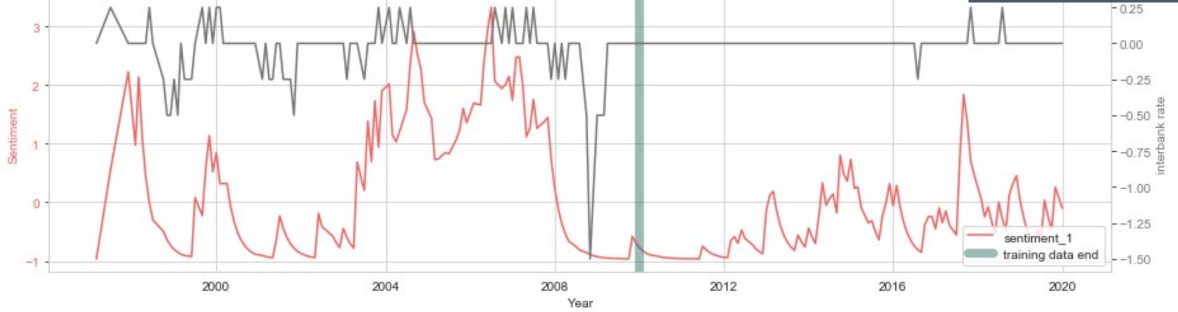


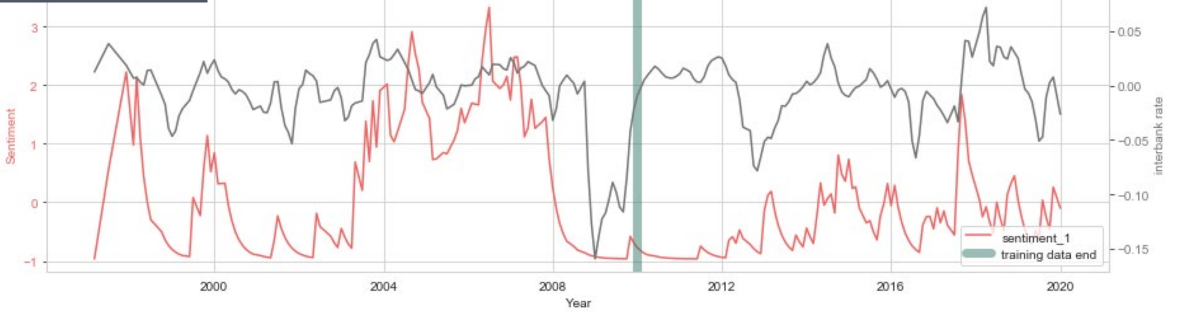
All Text Multi-NB classification model



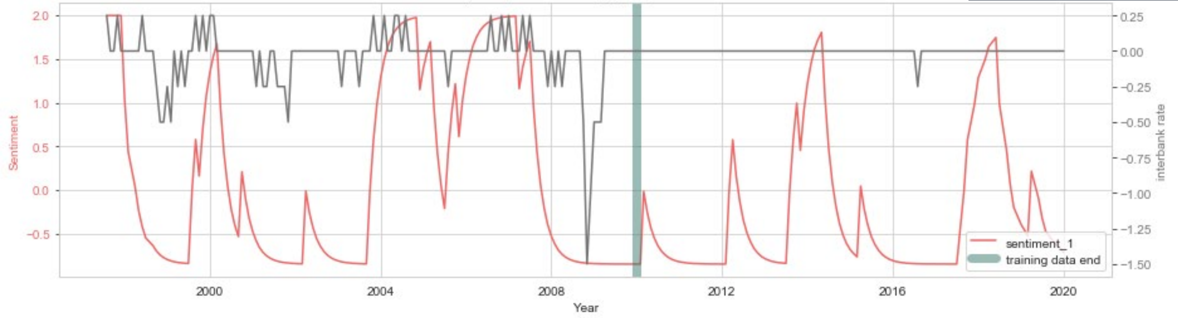


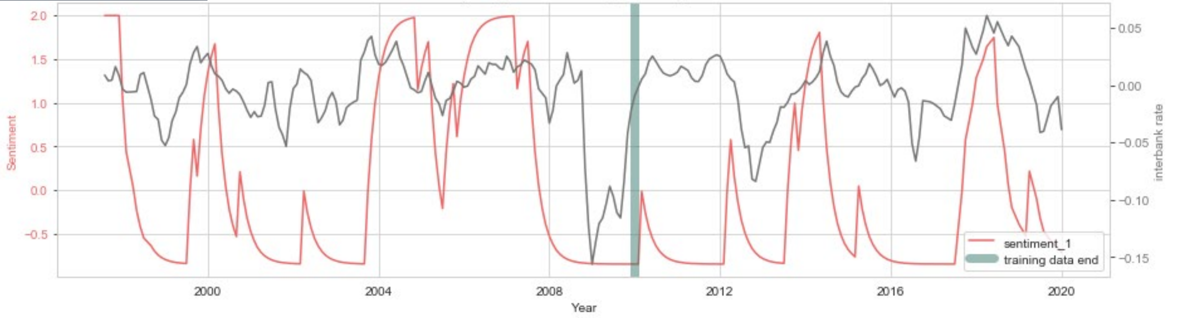
Speech Multi-NB classification model



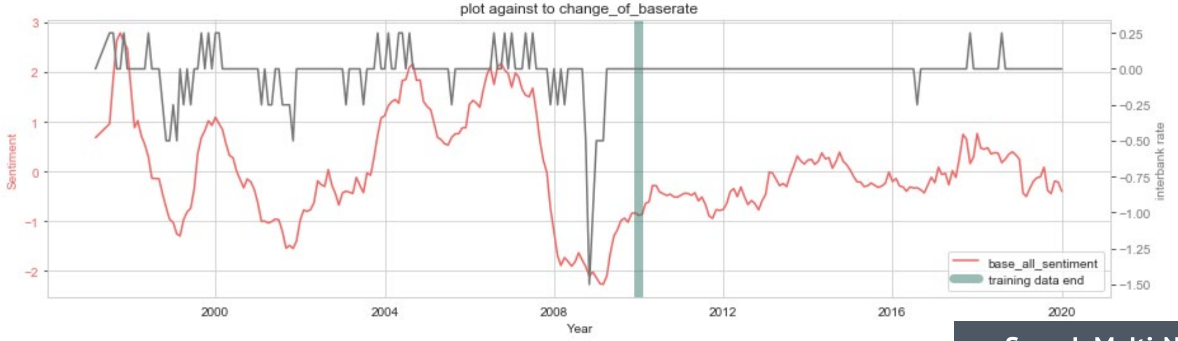


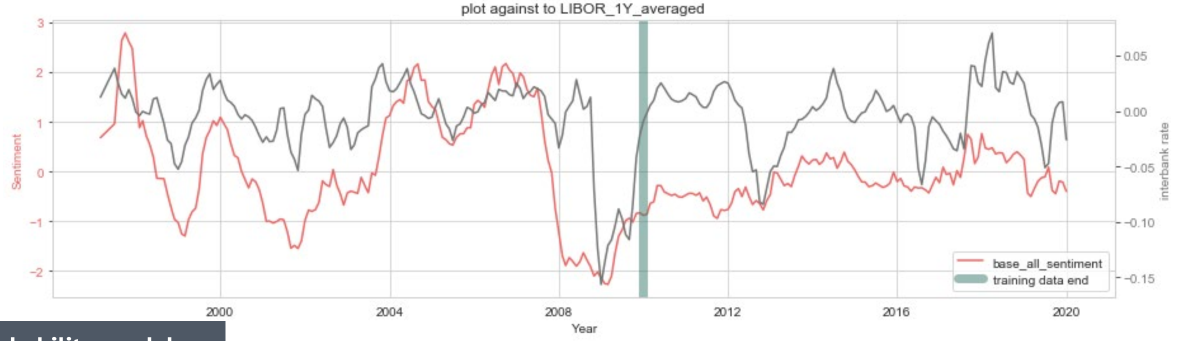
Minutes Multi-NB classification model



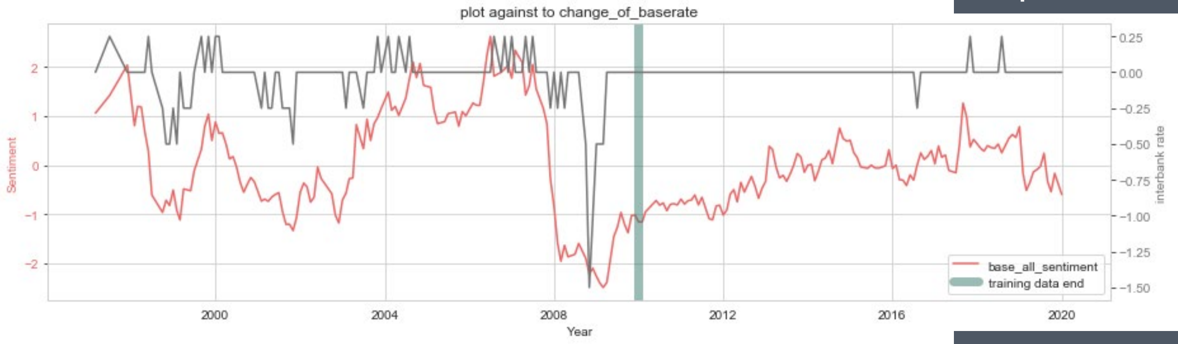


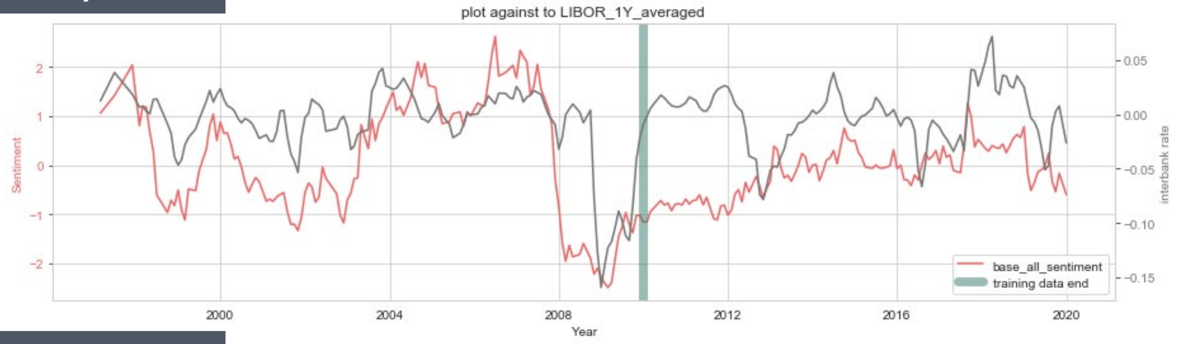
All Text Multi-NB probability model





Speech Multi-NB probability model





Minutes Multi-NB probability model