STEVENS
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Sentiment Analysis and Unsupervised Learning Applied to FOMC Minutes

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Machine Learning in Finance

Text Mining and Sentiment Application in Finance

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Overview of the Problem

FOMC Minutes

- Federal Open Market Committee Minutes provide policy views on the **monetary policy stance** and on the **U.S. economic outlook.**
- Interpretations of FOMC minutes are **more of a art than science.**
- Explore minutes informativeness with **sentiment and topic modelling.**

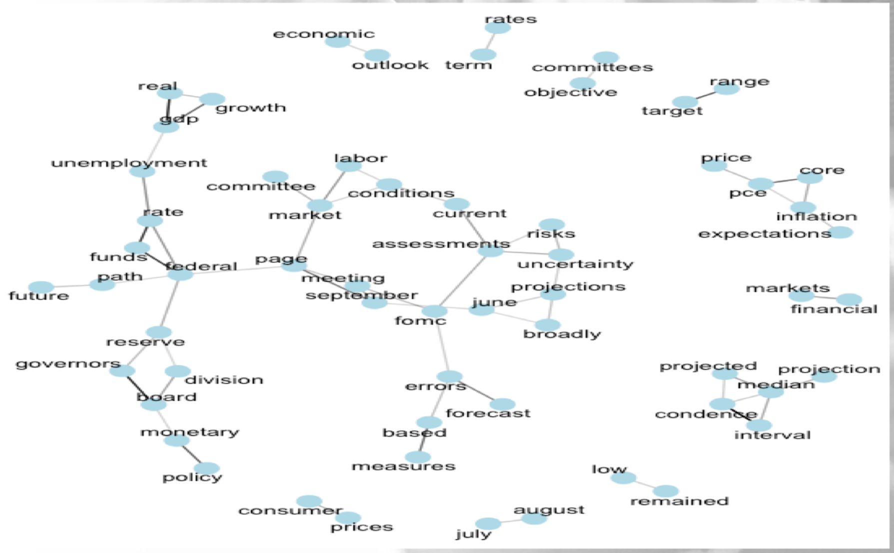
Example Paragraph

Participants' Views on Current Conditions and the Economic Outlook

Participants agreed that over the intermeeting period the labor market had continued to strengthen and that economic activity had been rising at a solid rate. Job gains had been strong, on average, in recent months, and the unemployment rate had remained low. Household spending had continued to grow strongly, while growth of business fixed investment had moderated from its rapid pace earlier last year. On a 12-month basis, both overall inflation and inflation for items other than food and energy had remained near 2 percent. Although market-based measures of inflation compensation had moved lower in recent months, survey-based measures of longer-term inflation expectations were little changed.

Participants continued to view a sustained expansion of economic activity, strong labor market conditions, and inflation near the Committee's symmetric 2 percent objective as the most likely outcomes over the next few years. Participants generally continued to expect the growth rate of real GDP in 2019 to step down somewhat from the pace seen over 2018 to a rate closer to their estimates of longer-run growth, with a few participants commenting that waning fiscal stimulus was expected to contribute to the step-down. Several participants commented that they had nudged down their outlooks for output growth since the December meeting, citing a softening in consumer or business sentiment, a reduction in the outlook for foreign economic growth, or the tightening in financial conditions that had occurred in recent months.

Word Relationships (WordCloud)

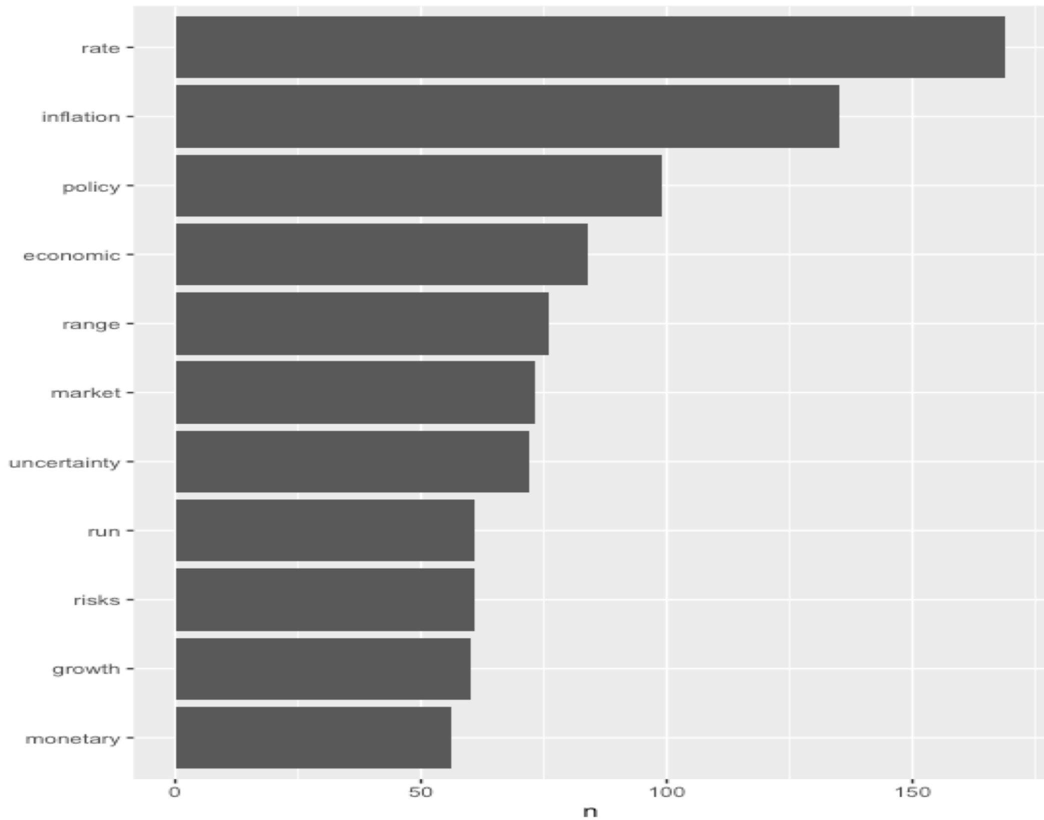


Reference: https://www.federalreserve.gov/monetarypolicy

Sentiment of FOMC Minutes

Sentiment - Preprocessing

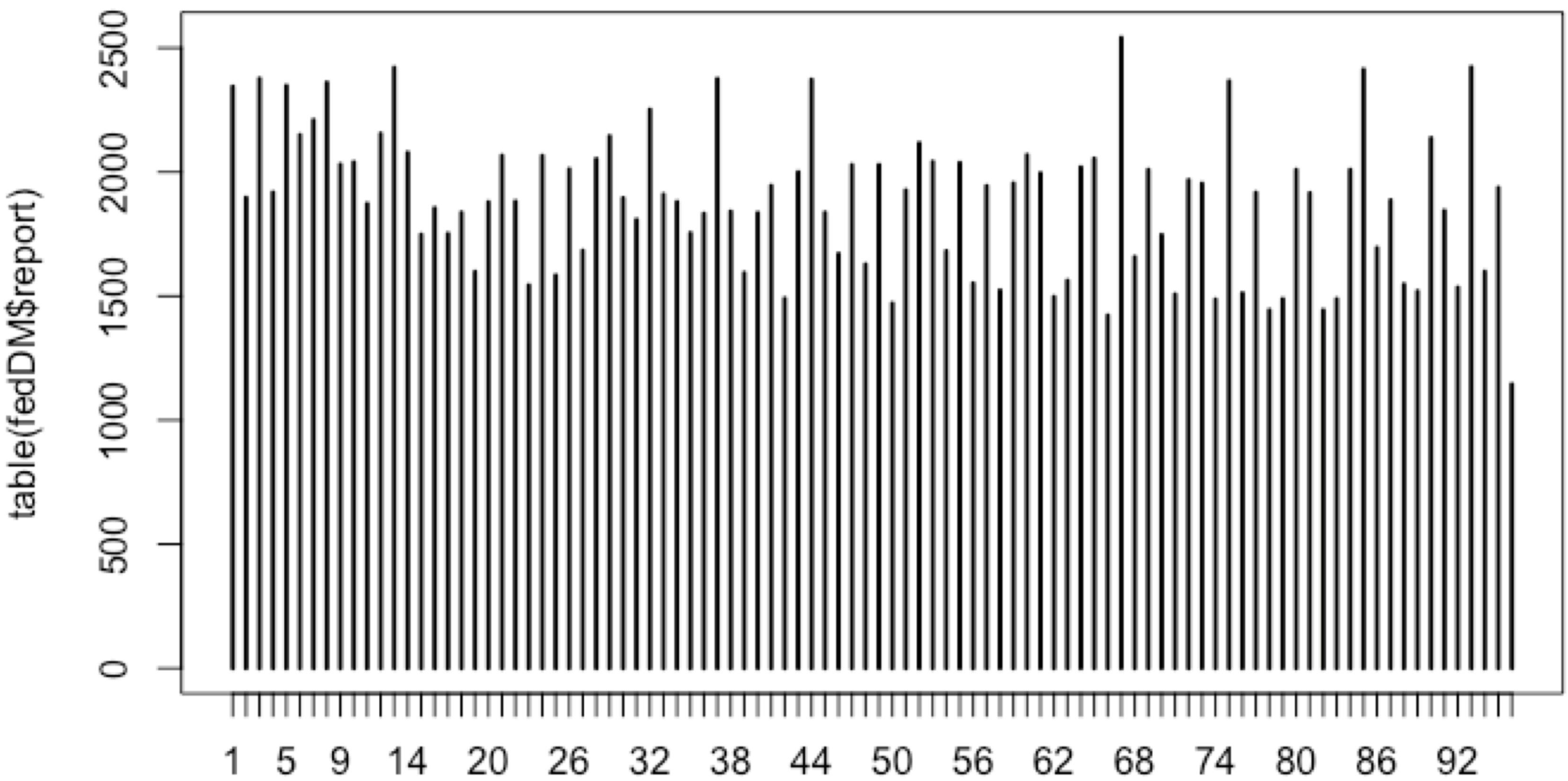
- Remove stop words
- Apply customized word filter
- Convert to lower case
- Take out numbers
- Filter out punctuation
- Lemmatize (not applied)
- Convert to **R-tidy ()*** format
- **Word tokenization**



* https://www.tidyverse.org

Sentiment - Preprocessing

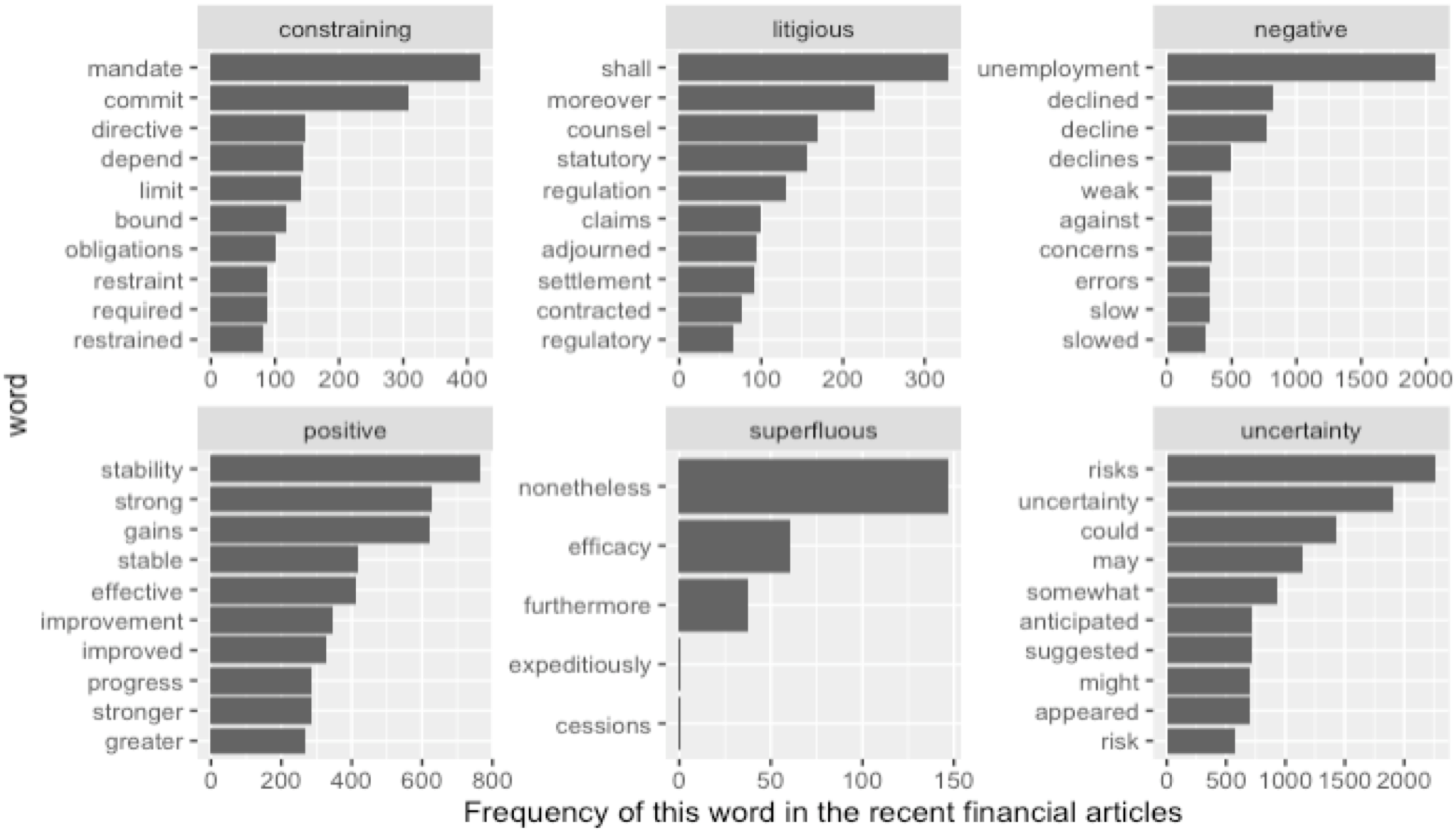
- Average count of words is 1,550 words across documents



document number (1 represents the most meeting)

Financial Dictionary - Sentiment

- **Loughran & McDonald Financial*** Dictionary words into six categories



Reference: *R – Tidytext with Loughran & McDonald financial dictionary

Sentiment

- Sentiment **constructed and validated** via **crowdsourcing**
- Sentiment = **(positive – negative) / (positive + negative)**

report	index	constraining	litigious	negative	positive	superfluous	uncertainty	sentiment
1	1	40	14	194	158	2	198	-0.102272727
2	2	29	11	151	96	3	135	-0.222672065
3	3	41	19	246	119	3	266	-0.347945205
4	4	23	10	253	74	0	111	-0.547400612
5	5	43	42	155	140	3	187	-0.050847458
6	6	16	11	195	77	1	272	-0.433823529
7	7	23	17	212	103	2	207	-0.346031746
8	8	33	10	274	98	3	368	-0.473118280
9	9	29	13	162	107	4	169	-0.204460967
10	10	13	13	213	76	1	358	-0.474048443
11	11	14	10	131	93	1	145	-0.169642857
12	12	23	15	228	97	2	301	-0.403076923
13	13	37	46	173	109	2	186	-0.226950355
14	14	17	9	199	80	2	306	-0.426523297
15	15	16	11	120	92	0	127	-0.132075472
16	16	20	11	144	87	1	281	-0.246753247
17	17	26	14	107	83	2	127	-0.126315789

Sentiment as a Predictor in Machine Learning Model

Control and Experimental Model

- Machine Learning Model: Logistic Classification
- Consider **Control Model** and **Experimental Model** (with sentiment)

Predictor (Lag1)
Carry
2sFF Spread
SPX Index
Oil
MOVE
VIX
Fed Funds Rate
Dollar Index

Target (Classification)
US Treasury Return: 1 (positive), 0 (negative)

Model Results

- Balanced class accuracy increased by ~3% by adding sentiment in machine learning model.

	Control Model	Experimental Model
Balanced Accuracy	0.529	0.558
Sensitivity	0.125	0.250
Specificity	0.933	0.866

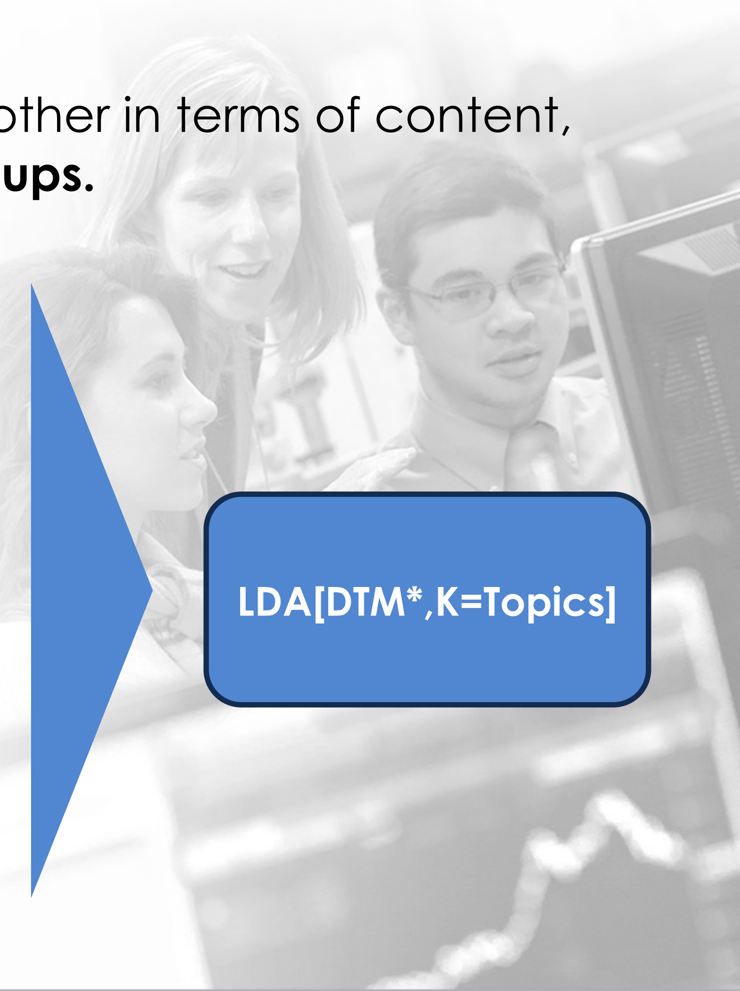
Unsupervised Learning with FOMC Text

Latent Dirichlet Allocation (LDA)

- LDA treats each document as a mixture of topics, and each topic as a mixture of words.
- LDA allows documents to **overlap** with each other in terms of content, rather than being separated into **discrete groups.**

docs	economic	growth	inflation	market	policy	range
0	89	45	129	85	58	59
2	82	44	111	90	66	52
4	96	42	126	82	93	56
6	93	47	127	79	81	62
8	89	45	125	74	55	58
9	33	18	93	65	21	18
12	89	35	99	77	57	53
14	77	47	100	61	55	57
16	77	54	82	58	58	61
20	87	58	123	69	53	55

* Document Term Matrix (TF)

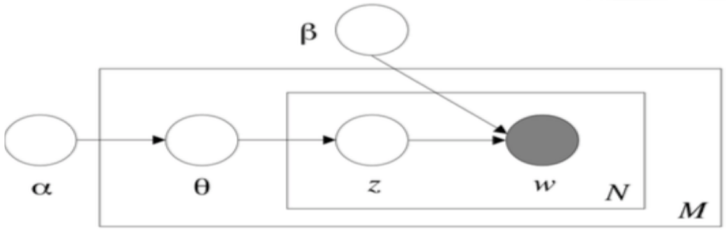


LDA[DTM*,K=Topics]

Latent Dirichlet Allocation (LDA)

- LDA computes **per-topic-per-word probabilities** and **per-document-per-topic probabilities**.

- Documents are probability distributions over topics and topics are probability distributions over words.



Graphical model representation of LDA. The boxes are "plates" representing replicates. The outer plate represents documents, while the inner plate represents the repeated choice of topics and words within a document.

$$p(\theta,\mathbf{z},\mathbf{w}\mid\alpha,\beta)=p(\theta\mid\alpha)\prod_{n=1}^{N}p(z_n\mid\theta)\,p(w_n\mid z_n,\beta)$$

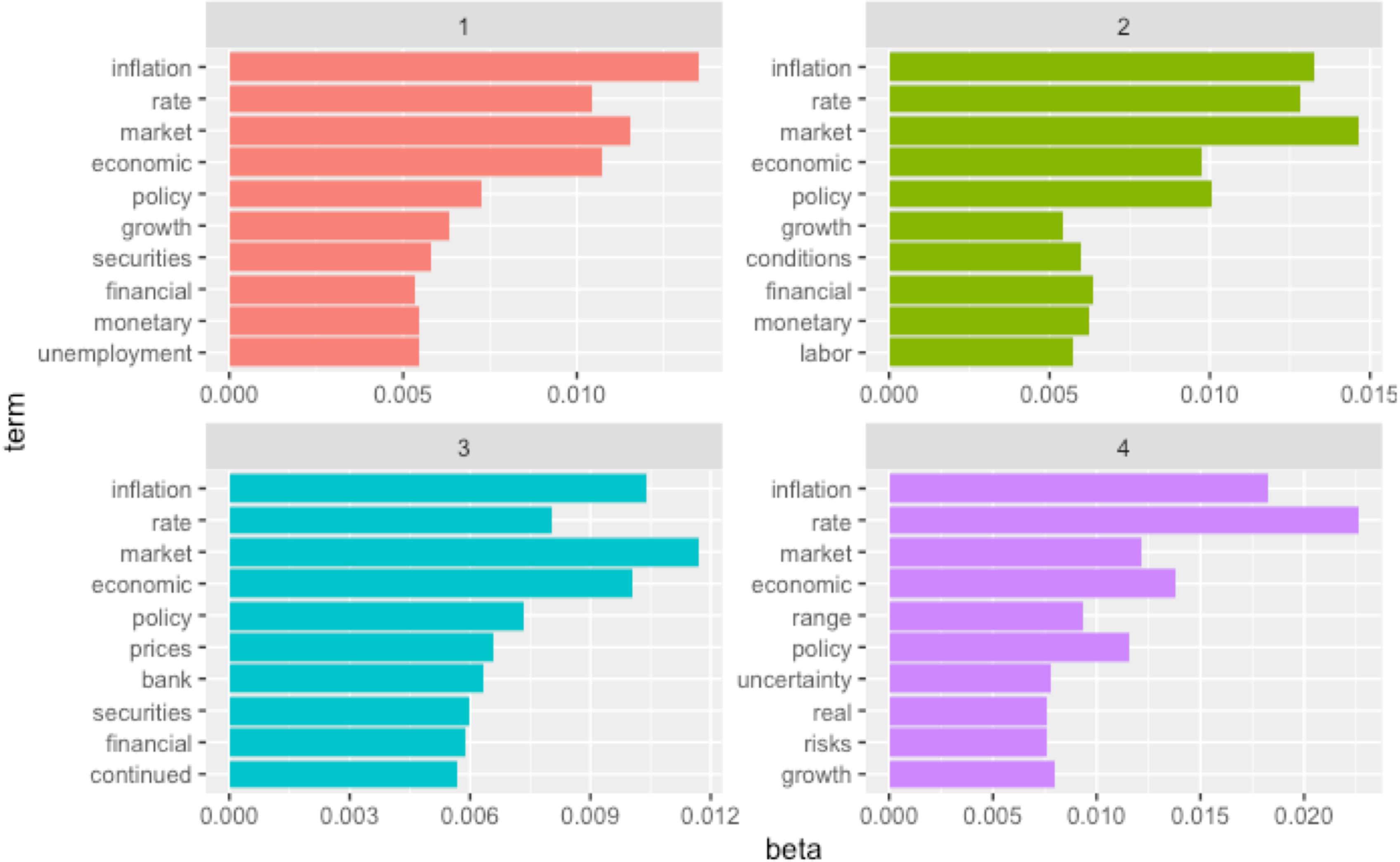
LDA assumes the following generative process for each document $\mathbf{w}$ in a corpus D:

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

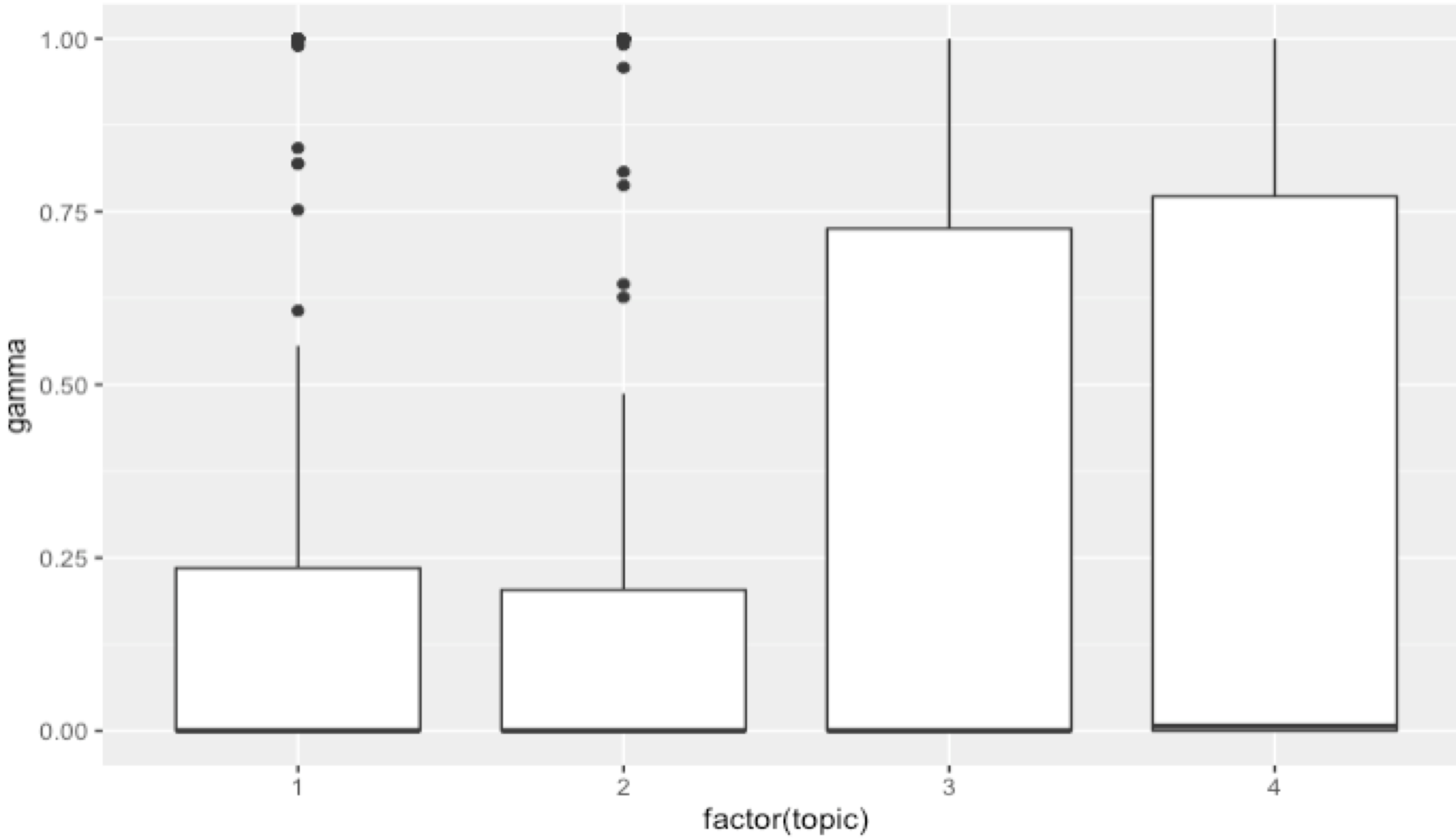
Note: β is the word probabilities per topic, a $k \times V$ matrix, $\beta_{ij} = p(w_j = 1 \mid z_i = 1)$. β is a parameter to be estimated.

Reference: https://www.youtube.com=DWJYZq_fQ2A/watch?v

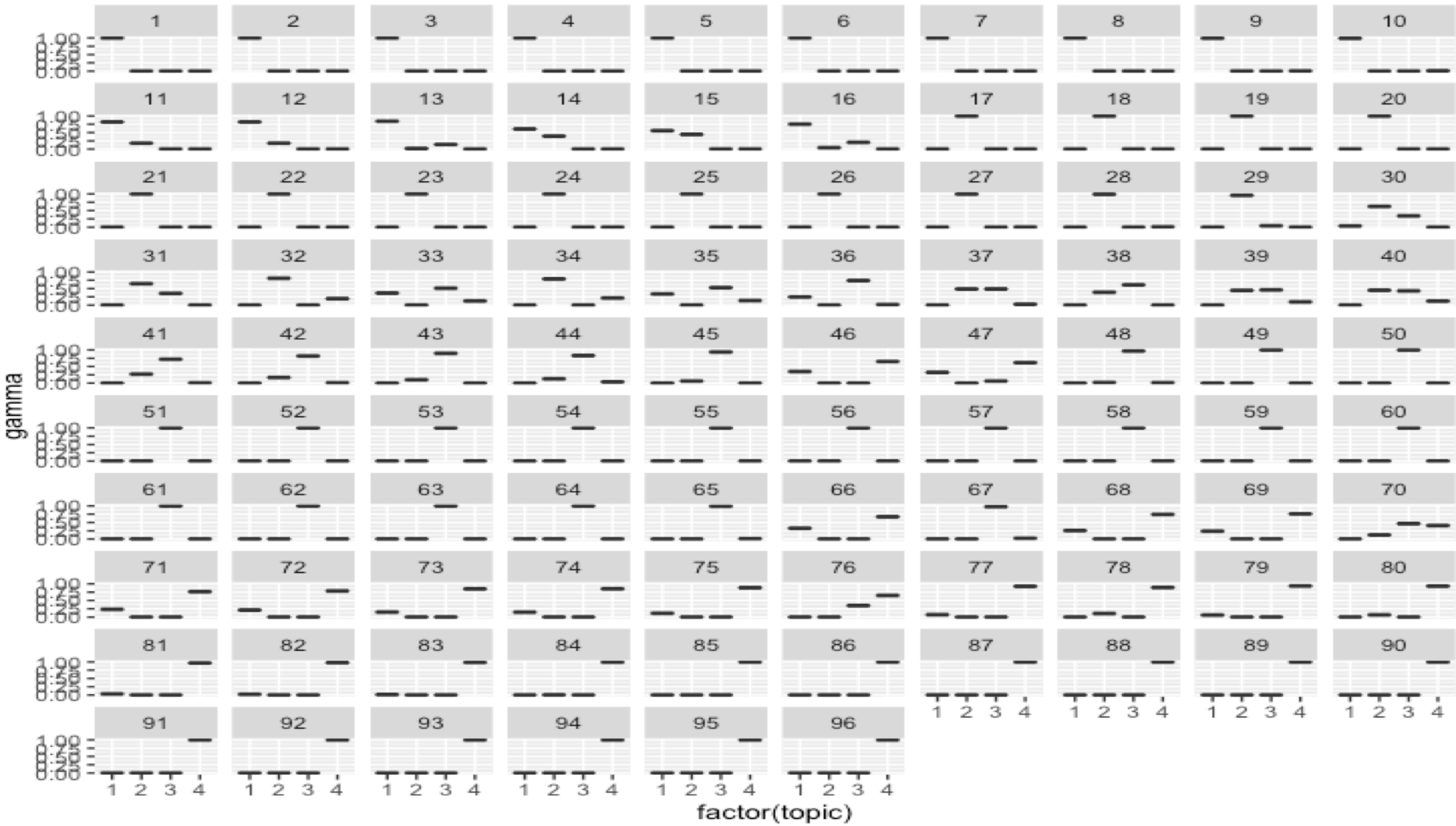
The Most Common Words in Topics



Topic Probability Distribution Across Documents



Topic Probabilities Across Documents



Conclusions and Next Steps

Conclusions

- Adding **sentiment** in machine learning model is **informative** based on the accuracy being improved by **few percentage points**.
- **Word embeddings (contextual NLP)** has potential to improve sentiment (e.g. "unemployment declined" is net positive outcome while simple word tokenization will not capture contextual information).
- LDA represents **reduced dimension of text data**, so **topic sentiment** might be more intuitive as it is few topics driving the FOMC content.
- LDA can potentially used as "quick" **summary tool.**
- **Combining LDA** and **traditional sentiment** is a potential application.