A Measure of deliberation quality of FOMC meetings

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ABSTRACT

Since 1993, transcripts of the Federal Open Market Committee (FOMC) meetings are published for deliberation transparency by the US Federal Reserve. These meetings have a direct influence on monetary policies in the US, as well as they are key in the decision process of interest rates. The Federal Reserve has leverage on the financial market and on US economy, its objective is to maintain stable prices and sustain economic growth.

In this context, we explore decision process through the analysis of the meetings' transcripts using Natural Language Processing methods such as Latent Dirichlet Allocation (LDA). Using statistical tools, we break out the process of decision-making and seek to quantify the role and influence each interlocutor has in these meetings.

Keywords

Latent Dirichlet Allocation, Speech analysis, Natural Language Processing, FOMC

1. LDA FOR TOPIC MODELLING

In this paper, we mainly use a statistical approach called Latent Dirichlet Allocation for topic modelling which consists in discovering the underlying "topics" occurring during the speeches of every meetings. Those topics are generally semantically linked and give us a way to synthetize information as well as discover underlying links between subject that come into discussion.

1.1 Processing transcripts

Transcripts are published online every year by the Federal Reserve at FOMC_historical_year. We continued the work of Etienne Lenaour, proposing a Python script that automatically webscraps the newest published transcripts given a start date and computing a selection of sentiment analysis scores based on Loughran, MacDonald, and Harvard's dictionaries. We process textual data using classical meth-

ods of tokenization, lemmatization, and cleaning, removing stopwords, symbols and punctuation.

Unname		interlocutor_name	stateme	statement	statement_numb							score_			
0		CHAIR YELLEN.		Good morning everybody. As you kno	statement_0	CHAIR YELLEN	0.5	-0.00576			0.0	0.0	0.01440		
1		MR. FISCHER.		So moved Madam Chair.	statement_1	CHAIR YELLEN				0.0	0.0	0.0	0.0		0.0
2	annannan a	CHAIR YELLEN.	17	Thank you. Without objection. I am go	statement_2	CHAIR YELLEN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	***************************************	MR. POTTER.	1467	1 Thank you Madam Chair. We will be	statement_3	CHAIR YELLEN	-0.565217	-0.02354	0.04147	-1.0	0.0	0.0	0.00784	0.0134	0.0
- 4	***************************************	CHAIR YELLEN.	3	Questions? President Kocherlakota.	statement_4	CHAIR YELLEN	0.0	0.0	0.0	0.0	0.0	0.0	0.0		0.0
5	***************************************	MR. KOCHERLAKOTA.		Yes. Actually it is more of a comment t		CHAIR YELLEN				0.0	0.0	0.0	0.06666		0.0
6		MR. POTTER.	50	In the p ast week that is true. The TIPS	statement_6	CHAIR YELLEN				0.0	0.0	0.0	0.0		0.0
7	***************************************	CHAIR YELLEN.	6	Other questions for Simon? President	statement_7	CHAIR YELLEN	-1.0			0.0	0.0	0.0	0.0		0.0
8	***************************************	MR. EVANS.	145	In t able 4 exhibit 1 you have expectat	statement_8	CHAIR YELLEN	1.0	0.0	0.05797	0.0	0.0	0.0	0.02898	0.0	0.0
9	***************************************	MR. POTTER.	25	If the Committee released details on w	statement_9	CHAIR YELLEN	0.0	0.0	0.07692	0.0	0.0	0.0	0.07692	0.0	0.0
10	***************************************	MR. EVANS.	7	Yes. In terms of the informational con	statement_10	CHAIR YELLEN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
11	***************************************	MR. POTTER.	94	I do think that the core inflation numl	statement_11	CHAIR YELLEN	0.0	-0.02325	0.06976	0.0	0.0	0.0	0.0	0.0	0.0
12	***************************************	MR. EVANS.	40	Another question I had in looking at y	statement_12	CHAIR YELLEN	-1.0	-0.05555	0.05555	0.0	0.0	0.0	0.0	0.0	0.0
13	***************************************	MR. POTTER.	35	Market participants freely give you a le	statement_13	CHAIR YELLEN	0.0	0.0	0.05882	0.0	0.0	0.0	0.0	0.0	0.0
14	***************************************	MR. EVANS.	15	Well I guess I am wondering about the	statement_14	CHAIR YELLEN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
15	***************************************	MR, POTTER.	130	When we just ask them for the point	statement_15	CHAIR YELLEN	0.0	-0.01694	0.03389	0.0	0.0	0.0	0.0	0.0169	0.0
16	***************************************	MR. EVANS.	2	Thank you.	statement_16	CHAIR YELLEN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
17	***************************************	CHAIR YELLEN.	18	Further questions for Simon? No resp	statement_17	CHAIR YELLEN	-1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
18	***************************************	MS. LOGAN.	1954	2 III discuss testing of tools for norms	statement_18	CHAIR YELLEN	-0.047619	-0.01612	0.02716	-1.0	0.0	0.0	0.01018	0.0025	0.0
19	***************************************	CHAIR YELLEN.	7	Thank you. Are there questions? Presi	statement_19	CHAIR YELLEN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
20	annan	MR. LACKER.	101	I just have a comment. I have argued a	statement 20	CHAIR YELLEN	-1.0	-0.02040	0.0	0.0	0.0	0.0	0.02040	0.0	0.0
21	ammunu	MS. LOGAN.	85	Doing it now in advance versus April v	statement_21	CHAIR YELLEN	0.0	0.0	0.06060	0.0	0.0	0.0	0.03030	0.0	0.0
22	annanana a	MR. LACKER.	9	So y ou are appealing to some technic	statement_22	CHAIR YELLEN	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0
23	annanana a	MS. LOGAN.	10	F or it to be perceived as a technical a	statement_23	CHAIR YELLEN	0.0	0.0	0.25	0.0	0.0	0.0	0.0	0.0	0.0
24	***************************************	MD LACKED	20	No one thinks we are going to mire ra	statement 24	CHAIR VELLEN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Figure 1: Excerpt of the processed dataset

The variable of interests and especially the cleaned statements are stored in a dataset (see fig. 1) and each statement corresponds to a speech. All meetings are concatenated and we are also interested in the influence of an eventual change of chair in the way speeches may evolve, thus we keep that information as variable of interest as well.

1.2 Motivation

Latent Dirichlet Allocation is an unsupervised statistical method for topic modelling. In our setting, we are interested in using topic modelling to analyze the content of the speeches during the meetings, the evolution of speeches and the role of people interacting during those speeches. A first general overview on all meetings available to this date shows no topic seems to appear significantly more than others overall when looking at 30 topics. However, when we break out topic frequency for each year and per chair, it seems that a shift in dominating topics is occuring (see table 1). Should we expect more novelty in the last tenures?

Chair person					
CHAIRMAN BURNS	20	23	16	27	21
CHAIRMAN MILLER	16	23	20	27	18
CHAIRMAN VOLCKER	16	18	23	21	27
CHAIRMAN GREENSPAN	19	6	7	22	9
CHAIRMAN BERNANKE	13	2	5	29	26
CHAIR YELLEN	11	4	24	26	3

Table 1: Top 5 topics per chair person (chronological order): in red, topics occurring three times, in orange and in green, topics occurring twice

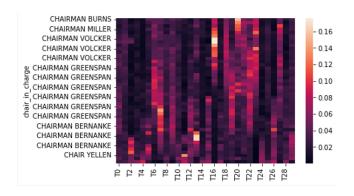


Figure 2: LDA on all meetings from 1976 to 2015 with 30 topics of 100 words: topic frequency for every chair

1.3 Theoretical of LDA

The Latent Dirichlet Allocation method is a generative probabilistic method: observations (β) are words and group of words collected into text documents denoted M. For each document M containing N words, we assume a mixture θ of a smaller number of topics z generated from documents using a Dirichlet prior of parameter $\alpha < 1$. Similarly, we then assume that each words w comes from a distribution of topics z of our documents that we estimate using a Dirichlet prior of parameter $\beta < 1$. This is shown in figure 3 and explained in table 2.

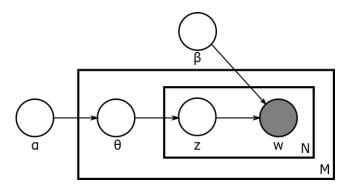


Figure 3: Representation of parameters intervening in a LDA

LDA algorithm

Choose α of Dirichlet prior document-wise Choose β of Dirichlet prior topic-wise for each document

Draw mixture distribution $\theta \sim Dir(\alpha)$ for each topic, each document

Draw word-to-topic distribution $\sim Dir(\beta)$ for each document and each word draw a topic $z \sim Multinomial(\theta)$ draw a word in this topic using a multinomial

Table 2: Description of the generative algorithm of LDA

2. SPEECH EVOLUTION IN FOMC MEET-INGS

2.1 LDA on transcripts



Figure 4: LDA with 30 topics, 100 keywords on all transcripts

We compare

We first introduce the notion of novelty, transience and resonance following A. Barron's article [1].

2.2 Measures of Novelty, Transience and Resonance

Given speech mixtures $S=(s_i^{(t)})_{1\leq i\leq K}^{0\leq t\leq T}$, with t indexing the chronological order, i indexing the topic, we use Kullback-Leibler divergence to model "surprise", meaning the appearance of a new topic in a frame of topic mixtures set with parameter w which defines a window of past speeches. The novelty of the t-th speech taken as center speech is given by :

$$\mathcal{N}_w(t) = \frac{1}{w} \sum_{d=1}^{w} \text{KLD}(s^{(t)}|s^{(t-d)})$$
 (1)

We also refer to transience as the persistance of a speech's subject in the discussion using similar notations:

$$\mathcal{T}_w(t) = \frac{1}{w} \sum_{d=1}^w \text{KLD}(s^{(t)}|s^{(t+d)})$$
 (2)

Which allows us to introduce the notion of resonance: $\mathcal{R}_w(t) = \mathcal{N}_w(t) - \mathcal{T}_w(t)$ This metrics tell us about the quality of a speech in terms of its reception: a transience speech means the content is heavily propagated, and novelty accounts for disruption in a stream of ideas. We expect, based on Barron's article, that novelty, transience and resonance are role reflective of the speaker.

We show in fig. 5 the density plot of transience, resonance and novelty in all statements after processing. On the left, the density plot of transience v. novelty per speech is given at scale w=7. This density plot shows that overall, there is a concentration of speeches around the symmetry line of transience v. novelty but also a large scatter. Temporal asymmetry can be seen in resonance v. novelty density plot: novel speeches are more likely to be resonant speeches as well which means that differing from the past and influencing future speeches increases with novelty. These results

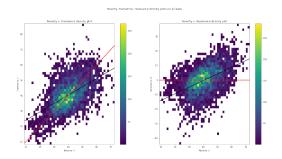


Figure 5: Transience v. Novelty and Resonance v. Novelty on $30\ \text{topics}$

are similar to Barron's in his study of French Revolution's deliberation speeches. Similarly, we compute for each interlocutor taking part in debates and discussions at the FOMC a score of novelty and resonance.

2.3 Measuring discrepancy per speakers

- 3. PARAMETERS TÜNING AND ROBUST-NESS
- 4. CONCLUSIONS
- 5. REFERENCES
- A. T. J. Barron and al. Individuals, institutions, and innovation in the debates of the french revolution. Proceedings of the National Academy of Sciences, 115 (18):4607–4612, May 2018.