



DISCUSSION: WHATEVER IT TAKES TO UNDERSTAND A  
CENTRAL BANK - EMBEDDING THEIR WORDS USING  
NEURAL NETWORKS  
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## Overview

# Summary

## This paper:

- Presents a language model for quantifying text on central bank communication.
- Uses 23,000 central bank communication documents from over 130 central banks.
- Provides four different applications of the model.
- ★ Brings an impressive methodological contribution to text analysis on central bank communication.

## Methodology

# Model

⇒ Embedding is based on the understanding that the meaning of a word depends on the environment in which the word appears, surrounding words, and the overall context.

Table 2: Model Overview

Model	Word	Document	Corpus
Word2Vec Skipgram	x		CB corpus
Word2Vec BOW	x		CB corpus
Word2Vec Le and Mikolov (2014)	x		Google News
GloVe	x		CB corpus
GloVe Pennington et al. (2014)	x		Wikipedia/Gigaword
Doc2Vec D-BOW	x	x	CB corpus
Doc2Vec D-BOW Pre	x	x	CB corpus
Doc2Vec DM	x	x	CB corpus
Doc2Vec DM Pre	x	x	CB corpus
LDA	x	x	CB corpus

*Note:* The columns 'Word' and 'Document' refer to the model language model's ability to generate word- and document-embeddings and 'CB' is used as an abbreviation for 'Central Bank'.

# Model Evaluation

## Extrinsic evaluation

- ⇒ Embeddings from each model are classified using two ML techniques, K-Nearest-Neighbor(KNN) and random forest on the task of predicting each speech's central bank and publication year.
- ★ Winner: *Doc2Vec* at the document level.

## Intrinsic evaluation

- ⇒ Using cosine similarity metric :
  - ✓ Find most similar words to the relevant words used by central banks (e.g. unemployment).
  - ✓ Estimate similarity of central banks at the document level.

# Applications

## Application 1

Similarity to the ECB increases when countries adopt an inflation target.

## Application 2

When uncertainty is high, Draghi's speech and other similar speeches to his, lower the spread of government bonds.

## Application 3

Male and female pronouns are associated with different profession.

## Application 4

Explores the relation between speech embeddings and different policy shocks.

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- ⇒ What is the purpose of the intrinsic evaluation?
  - ✓ Wouldn't embeddings of any model when evaluated on cosine similarity produce some results of similarity between banks - when do you say the result is wrong?
  - ✓ How about using different metric - euclidean distance?

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## On applications:

- ⇒ Embeddings require large dataset for model training, but several applications are based on the ECB's communication - small fraction of the overall corpus - is this problematic?
- ⇒ Application 3: On what data did the model produce embeddings of professions and pronouns?
  - ✓ This exercise uses word embeddings, the most accurate model was the model on document level, does this have any implications?