

# Social Topic Distributions

Hakan Akyürek Mürüvvet Hasanbaşoğlu

May 04, 2020





### Overview

- 1. Project Goal
- 2. Outcomes
- 3. Methodology
- 4. Evaluation
- 5. **Next Tasks -** for the next 2 weeks



### 1. Project Goal: What are we going to do?

**Topic Modeling:** aims to extract topics/clusters from a corpus of texts.



## 1. Project Goal: What are we going to do?

Topic Modeling: aims to extract topics/clusters from a corpus of texts.

- → Derive social topic distributions of:
  - 1- news and social media articles
  - 2- social media users

using their word or sentence vector representations.





# 1. Project Goal: What are we going to do?

Topic Modeling: aims to extract topics/clusters from a corpus of texts.

- → Derive social topic distributions of:
  - 1- news and social media articles
  - 2- social media users

using their word or sentence vector representations.

→ Analyze the topic distributions of different sets of articles and users





## 2. Outcomes: What will we analyze?

- Analyze if news articles attract the users who have similar topics of interest
- Analyze if **relevant users** have more similar topic distributions compared to the **random users**
- Repeat and report the analysis among different news and social media resources





## 2. Outcomes: What will we analyze?

- Analyze if news articles attract the users who have similar topics of interest
- Analyze if **relevant users** have more similar topic distributions compared to the **random users**
- Repeat and report the analysis among different news and social media resources

#### Additionally:

- Group individual social media users that have similar topics of interest
- Group social media and news articles that have similar topics of interest





### **Raw Organic Dataset:**

- Forums, blogs, news sites, social media
- Biased: more strict opinions towards organic food
- Unbiased : less strict opinions towards organic food

	English	German
Number of sentences	441895	487794
Number of comments	140119	94442
Portion of biased (%)	0.465	0.026
Number of tokens	7198582	7752885
Size of vocabulary	141579	262672

Table: Statistics of raw organic dataset



### **Raw Organic Dataset:**

- Forums, blogs, news sites, social media
- Biased: more strict opinions towards organic food
- Unbiased: less strict opinions towards organic food

English	German
441895	487794
140119	94442
0.465	0.026
7198582	7752885
141579	262672
	441895 140119 0.465 7198582

Table: Statistics of raw organic dataset

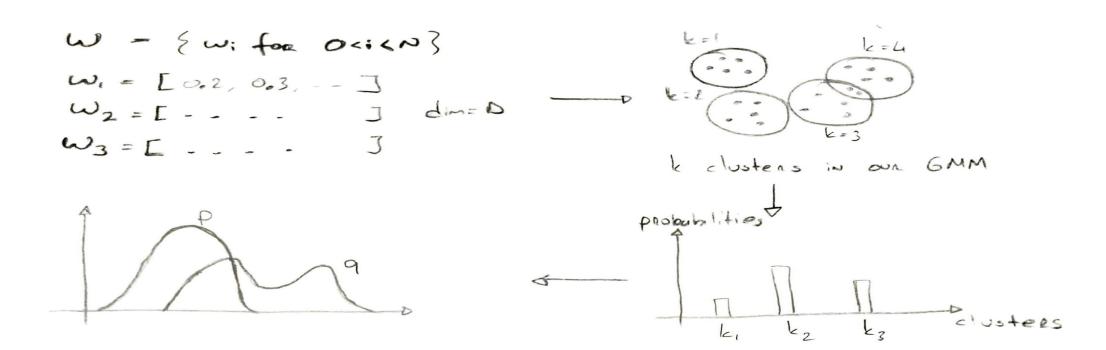
#### **Features:**

- Fine-tune the language model from BERT/GloVe on the whole dataset
- Word and sentence embeddings





Classifier: Gaussian Mixture Model





### **Histogram Generation:**

- Calculate the probability that an article is about topic k
- We are able to get necessary probabilities from our GMM model

$$k^* = \underset{\theta_k}{\operatorname{arg \, max}} p(k|w_1', \cdots, w_N')$$

$$= \underset{\theta_k}{\operatorname{arg \, max}} p(w_1', \cdots, w_N'|k) p(k)$$

$$k^* = \underset{\theta_k}{\operatorname{arg \, max}} p(k) \prod_{i=1}^N p(w_i'|k)$$



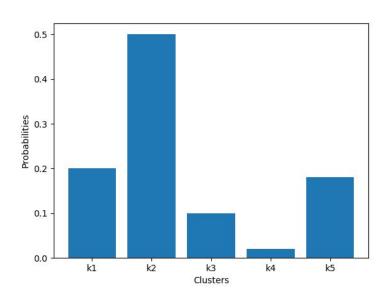
### **Histogram Generation:**

- Calculate the probability that an article is about topic k
- We are able to get necessary probabilities from our GMM model
- Generate a histogram

$$k^* = \underset{\theta_k}{\operatorname{arg max}} p(k|w_1', \dots, w_N')$$

$$= \underset{\theta_k}{\operatorname{arg max}} p(w_1', \dots, w_N'|k) p(k)$$

$$k^* = \underset{\theta_k}{\operatorname{arg max}} p(k) \prod_{i=1}^N p(w_i'|k)$$

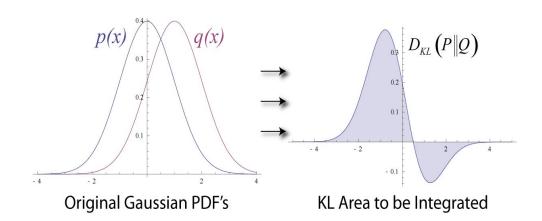




# 4. Evaluation: How are we going to measure our results?

#### **Performance metrics:**

Jensen Shannon or KL divergence to calculate similarity between distributions



How similar are p and q distributions? In our case p would be an article and q, one of it's comments.



### 5. Next Tasks:

- Set up Colab environment
- Prepare the dataset:
  - cleaning
  - preprocessing
  - o create random user dataset
- Get the vector representations for our data
- Further reading about the task



### References

- <u>Document Classification with Distributions of Word Vectors</u>
- <u>Unsupervised Topic Modeling for Short Texts Using Distributed Representations of Words</u>