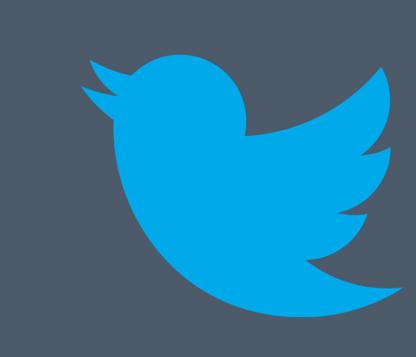




TOPIC MODELING FOR TWITTER ACCOUNTS

Mehmet Akif Çördük Burak Suyunu

Advisor: Assoc. Prof. Ali Taylan Cemgil



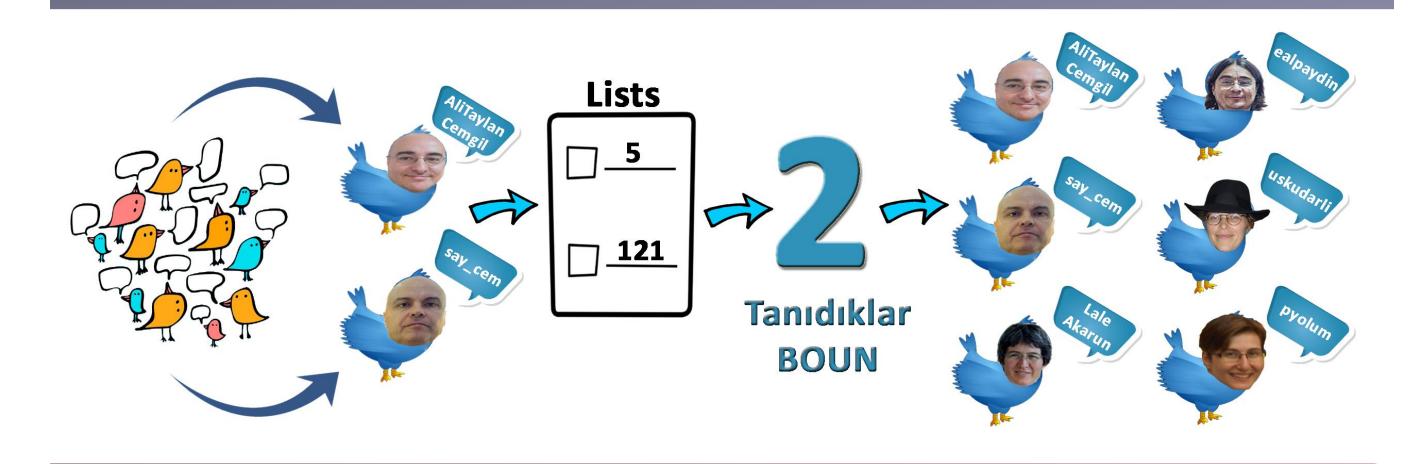




WHAT ARE THEY TWEETING ABOUT

- Makers, scientists, influencers and many other people share their ideas, products and innovations via the most intellectual social network Twitter.
- It is hard to find the information about a **topic** in the giant network of Twitter.
- Our aim is to find users who are tweeting about the same topic. With this aim we want to bring people interested in the same community together.
- In this project, we focused on maker communities and influencers in the context of computer science, such as ML, Robotics, 3D Printing, Arduino.
- We worked on 1.118 users and approximately 3.250.000 tweets.

DATASET - SIMILAR-TWITTER

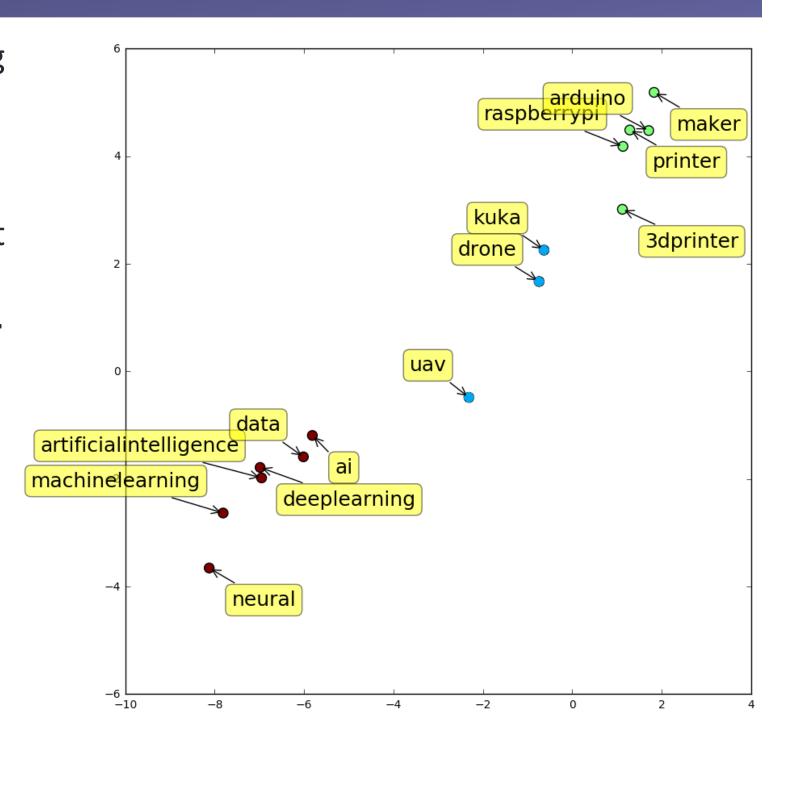


MAINTAINING TWEETS – NLP

- Imagination is more important than knowledge: https://Einstein.co #Einstein
- **Remove URLs**
 - Imagination is more important than knowledge: #Einstein
- **Tokenization**
- **Stop Words**
 - ['imagination', 'important', 'knowledge', 'einstein']
- Remove non-English accounts
- **Stemming**
 - ['imagin', 'import', 'knowledg', 'einstein']
- Remove words that appears at most 10 times in the whole corpus

CLUSTERING WORDS - WORD2VEC

- Word2Vec uses word embedding to map words to a **vector** of real numbers.
- We applied k-means clustering to the vectors to see the relevant words together.
- We chose the word at the **center** of the cluster to represent the other words from the same cluster in the word corpus.
- We **normalized** the number of occurrences in the corpus to handle the problem of less frequent words being more important.

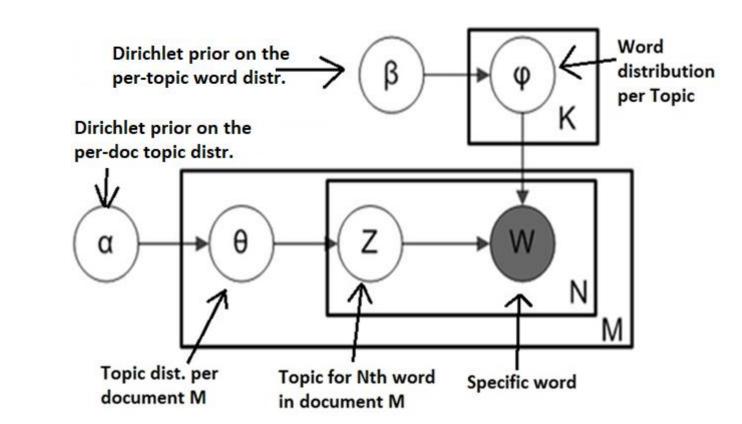


TOPIC MODELING

- In machine learning and natural language processing, a topic model is a type of statistical model for discovering the topics that occur in a collection of documents.
- We know that a document is about a particular topic, we expect particular words to appear more often than others since some words are more related to the subject.
- So we are trying to learn topic distribution over the vocabulary or word distributions of the topics.
- I like to eat broccoli and bananas.
- I ate a banana and spinach smoothie for breakfast.
- Hamsters and kittens are cute.
- My sister adopted a kitten yesterday.
- Look at this cute hamster munching on a piece of broccoli.
- Sentences 1 and 2: 100% Topic A
- Sentences 3 and 4: 100% Topic B
- Sentence 5: 60% Topic A, 40% Topic B
- Topic A: 30% broccoli, 15% bananas, 10% breakfast, 10% munching, ... (Food)
- Topic B: 20% chinchillas, 20% kittens, 20% cute, 15% hamster, ... (cute animals)

LDA (LATENT DIRICHLET ALLOC)

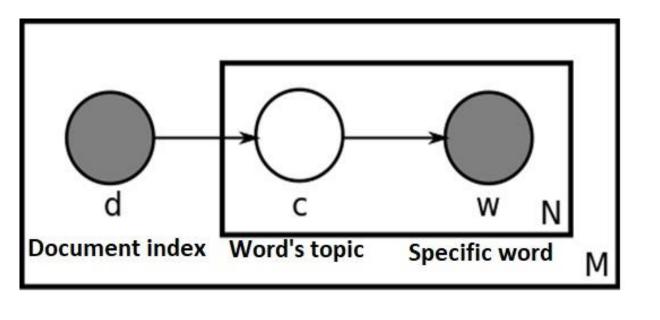
- Assign each word in a document to one of **K topics randomly**
- To obtain a correct distribution, iterate over each document D and for each document iterate over each word W.
- Then, for each topic T reassign the word W to a new topic T':

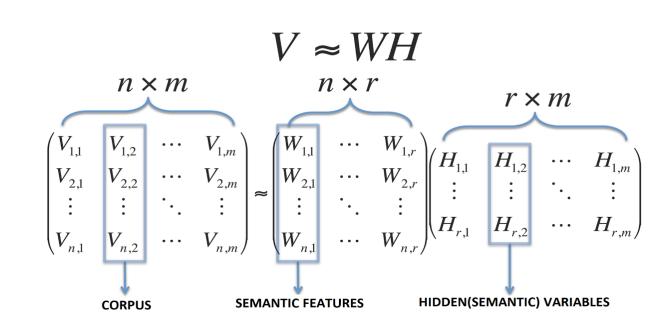


 $P(Word\ W\ |\ Topic\ T)*P(Topic\ T\ |\ Document\ D)$

NMF (NON-NEGATIVE MATRIX FACT)

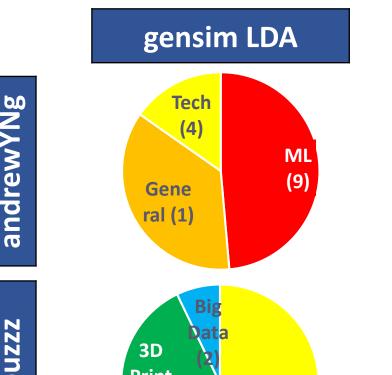
- NMF decomposes the data into two low rank matrices (W, H) whose product constitutes the data matrix.
- At each iteration, update W and H with additive update rules to minimize the squared error to reach a good decomposition.
- NMF + Kullback-Leibler Divergence + Drichlet priors on distributions => **LDA**
- NMF trains much faster than LDA

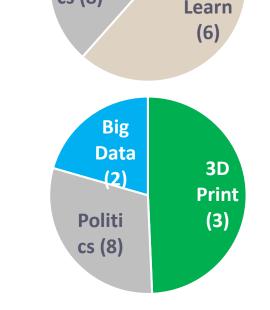




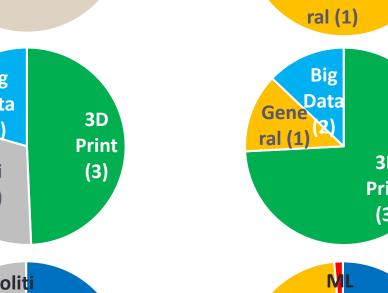
RESULTS

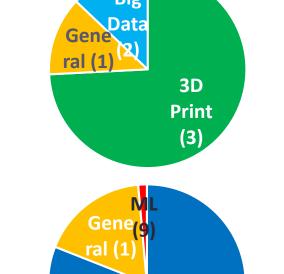
| | Daily (1) | Big Data (2) | 3D Print (3) | Tech (4) | Robotics (5) | Deep Learn (6) | EdTech (7) | Politics (8) | ML (9) | Arduino (10) |
|---------------------|-----------------------|------------------------------|--------------------------|-------------------------------|------------------------------|--------------------------|--------------------------|------------------------|--------------------------|-------------------------------|
| gensim LDA | think work time | data bigdata analytics | 3D print 3Dprint | tech innov wear | robot manufac automat | | stem robot 3dprint | us trump world | datasci data ML | drone arduino robot |
| scikit LDA | work time think | data bigdata ai | 3Dprint 3D print | startup business market | robot manufac us | | stem code learn | | | arduino maker project |
| scikit NMF | work time look | bigdata analytics data | 3Dprint 3D print | | robot drone kuka | learn deep neural | edtech stem edchat | | datasci ML DeepL | pi rasberrypi raspberry |
| gensim LDA (w2v) | love day today | bigdata data ai | 3Dprint 3D printer | market business startup | robot manufac engineer | learn deep machine | stem code learn | trump year us | datasci data ML | arduino robot project |
| scikit LDA (w2v) | love day us | data bigdata analytics | 3Dprint 3D printer | innov join learn | robot ai techn | learn deep machine | code stem learn | trump us science | datasci data ML | arduino project kit |
| scikit NMF (w2v) | time day today | bigdata analytics data | 3Dprint 3D printer | startup bussiness innov | robot kuka automat | learn deep neural | stem science women | trump vote obama | datasci ML bigdata | arduino kit rasp-pi |



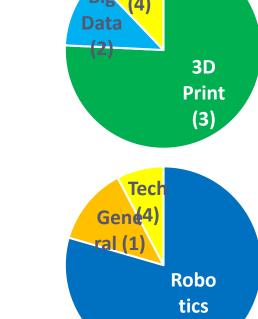


gensim LDA (w2v)

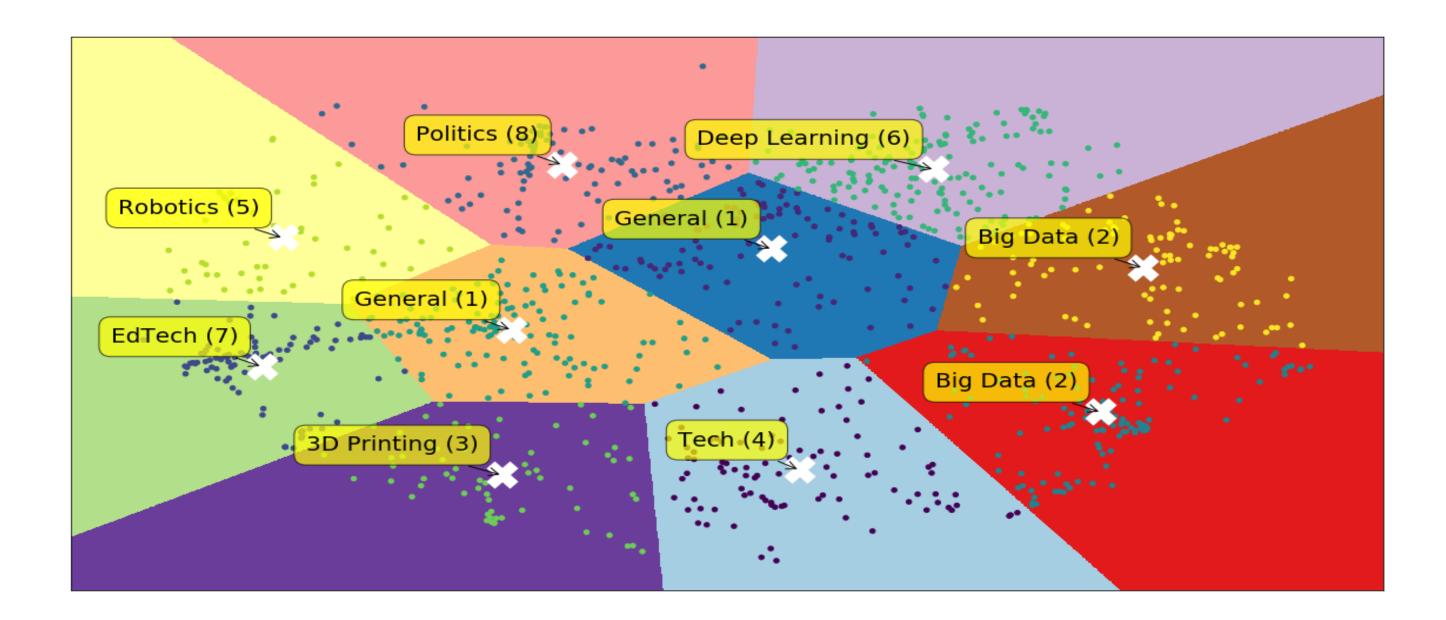




scikit NMF



scikit NMF (w2v)



CONCLUSION

- The hardest part of our project is the evaluation of results. Because all the results we got from topic modeling algorithms needs human interpretation. So, to make those interpretation clear and understandable we came up with the idea of color coded charts. Even it is hard to interpret, we got very promising and comparable results. While NMF generally gives better results than LDA; Word2Vec improved both methods significantly in capturing the general idea.
- All in all, one can find different datasets with Similar-Twitter and analyze them with our **Topic Modeling** approaches to create communities.