Text Analytics

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Documents: What to Do?

- Sometimes your data is a collection of documents
 - social media posts
 - collections of documents (panama papers)
- Text doesn't behave quite the same
- But still need to analyse at scale

An Analysis Approach: Similarity

Given a document collection, present a visualisation that represents the degree of similarity between documents.

- Discard grammar and use only vocabulary for scalability
- Documents that are similar should be close to each other
- Documents that are not similar should be further away
- Sounds familiar...



One way to model: Bag of Words

my document: Aardvarks play with zebra...

- Model the document as a collection of words and count frequencies
- Transform the data into a high dimensional data set
- In this data set, documents will be close if vocabulary is the same
- Get rid of words with little meaning (a, an, the...) stop words
- Need an appropriate distance measure...

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TF-IDF: Not all words are equal

- Measurement of how unique a word is given a collection of documents
- term-frequency $tf = \frac{w}{n}$: n words in document, w number of times word occurs
- inverse document frequency $idf = \log \frac{N}{N_w}$: N number of documents, N_w number of documents with the word counted in w
- TF-IDF : tf · idf measure of how unique word is in documents
- Can be used for normalisation in bag of words models

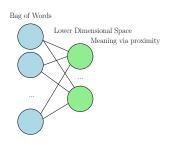


word2vec

- Bag of Words can produce very high dimensional spaces
- Many of these dimensions do not contribute much
- Can we collapse the dimensionality down so that we have similar information but fewer dimensions?
- Yes we can through machine learning

word2vec

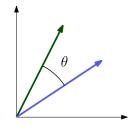
- Compute an embedding of words in a lower dimensional space
- Words used in the same way are in similar areas of the lower dimensional space



- train neural network to convert vectors to lower dimensional space
- context can be document or collection of sentences

Cosine Similarity

- Turns out that straight line distance is not good in these spaces
- But, angle between vectors is a good measure



- Take the cosine of the angle to make between [0, 1]
 - $\cos \theta = 1$ vocabulary (vectors) is the same
 - $\cos \theta = 0$ vocabulary (vectors) are orthogonal
- Problem, how to measure cosine in d dimensions?



Dot product gives you $\cos \theta$

- The dot product gives you $\cos \theta$
- You can express in d dimensions

$$\vec{a} \cdot \vec{b} = ||\vec{a}||||\vec{b}|| \cos \theta$$
$$\cos \theta = \frac{\sum_{i=1}^{d} a_i b_i}{||\vec{a}||||\vec{b}||}$$

- measure close to zero for dissimilar documents
- measure close to one for similar documents

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Similar documents, Different documents

a: Aardvarks play with zebra... b: Tokyo and Olympics...

c: No aardvarks or zebra in Tokyo ...

| | Aardvarks | [1] | ۲٥٦ | | | Aardvarks | ۲1 ⁻ |] | [1] | |
|------------------------|--------------|-----|-------|-----|------------------------|--------------|-----------------|-------|-------|-----|
| | Olympics | 0 | 1 | | | Olympics | 0 | | 0 | |
| $\vec{a}\cdot\vec{b}=$ | play | 1 | 0 | = 0 | $\vec{a}\cdot\vec{c}=$ | play | 0 | | 0 | ≈ 1 |
| | Tokyo | 0 | 1 | | | Tokyo | 0 | - 1 1 | 1 | |
| | zebra | 1 | 0 | | | zebra | 1 | | 1 | |

How to convert distances to two dimensions?

- The cosine similarity can be computed for every pair of vectors
- Loaded into a distance matrix
- Use any dimensionality reduction technique
 - e.g. multidimensional scaling will work

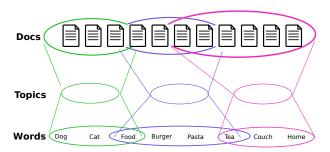
Latent Dirichlet allocation (LDA)

- How to group documents together?
- Each document can belong to many topics
- Topic description should be minimal set of words
- Related documents will have similar words
- How to link documents through words efficiently?

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Latent Dirichlet allocation (LDA)

- Can be seen as a fuzzy clustering
- Topics are defined as a distribution of words
- Words are mapped to topics
- Documents are mapped to topics
- Mapping is done probabilistically



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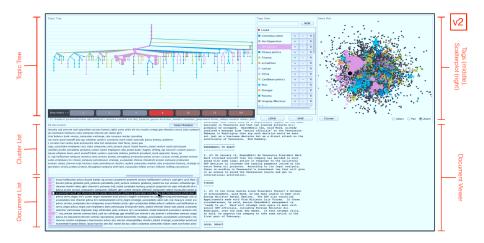
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The standard approach:

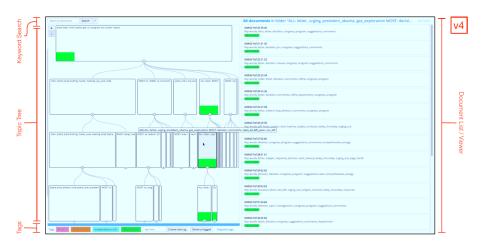
- Encode the documents somehow (TF-IDF)
- Use cosine distance for similarity
- Cluster the documents into topics (hierarchical)
- Visualization to browse topics/documents

M. Brehmer, S. Ingram, J. Stray, and T. Munzner. Overview: The design, adoption, and analysis of a visual document mining tool for investigative journalists.

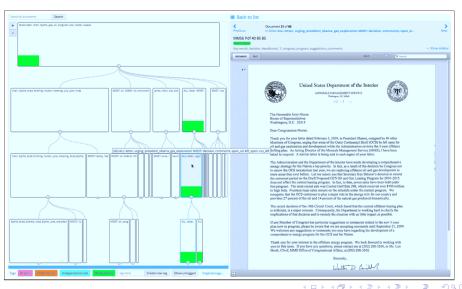
IEEE Transactions on Visualization and Computer Graphics, 20(12):2271-2280, 2014



M. Brehmer, S. Ingram, J. Stray, and T. Munzner. Overview: The design, adoption, and analysis of a visual document mining tool for investigative journalists.



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- What if documents are in more than one topic?
- How do topics correspond to elements in the text?
- Which words are linked to which documents?

Solution

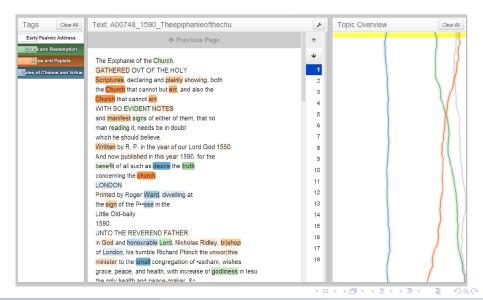
- LDA for topic modelling
- Different views to show different aspects of topics, documents, and words

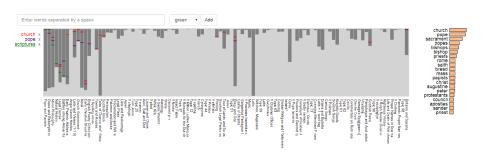
E. Alexander, J. Kohlmann, R. Valenza, M. Witmore, and M. Gleicher. Serendip: Topic model-driven visual exploration of text corpora.

In 2014 IEEE Conference on Visual Analytics Science and Technology (VAST), pages 173-182, October 2014









E. Alexander, J. Kohlmann, R. Valenza, M. Witmore, and M. Gleicher. Serendip: Topic model-driven visual exploration of text corpora.

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Further reading

If you're interested...

- Franz Wanner, Andreas Stoffel, Dominik Jäckle, Bum Chul Kwon, Andreas Weiler, and Daniel A. Keim. State-of-the-art report of visual analysis for event detection in text data streams.
 In R. Borgo, R. Maciejewski, and I. Viola, editors, *EuroVis -*STARs, pages 125–139, Swansea, UK, 2014
- Kostiantyn Kucher, Carita Paradis, and Andreas Kerren. The state of the art in sentiment visualization.
 Computer Graphics Forum, 37(1):71–96, 2018



- [AKV+14] E. Alexander, J. Kohlmann, R. Valenza, M. Witmore, and M. Gleicher. Serendip: Topic model-driven visual exploration of text corpora. In 2014 IEEE Conference on Visual Analytics Science and Technology (VAST), pages 173–182, October 2014.
- [BISM14] M. Brehmer, S. Ingram, J. Stray, and T. Munzner. Overview: The design, adoption, and analysis of a visual document mining tool for investigative journalists. *IEEE Transactions* on Visualization and Computer Graphics, 20(12):2271–2280, 2014.
- [KPK18] Kostiantyn Kucher, Carita Paradis, and Andreas Kerren. The state of the art in sentiment visualization. *Computer Graphics Forum*, 37(1):71–96, 2018.
- [WSJ+14] Franz Wanner, Andreas Stoffel, Dominik Jäckle, Bum Chul Kwon, Andreas Weiler, and Daniel A. Keim. State-of-the-art report of visual analysis for event detection in text data streams. In R. Borgo, R. Maciejewski, and I. Viola, editors, EuroVis - STARs, pages 125–139, Swansea, UK, 2014.