Topic Modelling



About the Module

- What are Topics
- Introduction to topic modelling
- Latent dirichlet allocation
- Implementation of topic modelling



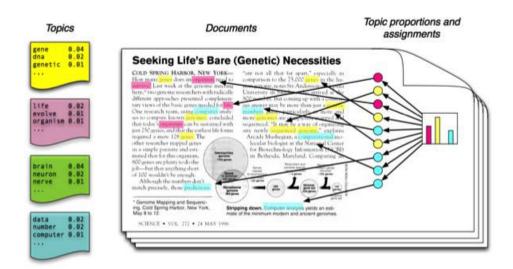
Topics

- A repeating group of statistically significant tokens or words in a corpus
- Statistical Significance
 - Group of words occurring together in the documents
 - Similar term and inverse document frequencies intervals
 - Frequently occurring together

Topic 1		Topic 2		Topic 3	
term	weight	term	weight	term	weight
game	0.014	space	0.021	drive	0.021
team	0.011	nasa	0.006	card	0.015
hockey	0.009	earth	0.006	system	0.013
play	0.008	henry	0.005	scsi	0.012
games	0.007	launch	0.004	hard	0.011



Topic Modelling



- Process to find the topics form documents in an unsupervised manner
- Text mining approach to find recurring patterns in the text documents



Importance of Topic Modelling

- Document Categorization
- Document Summarization
- Dimensionality Reduction
- Information Retrieval
- Recommendation Engines



Topic Modelling Techniques

- LDA Latent Dirichlet Allocation
- NNMF Non-Negative Matrix Factorization
- LSA Latent Semantic Allocation



- Document 1: I want to have fruits for my breakfast. Document 2: I like to eat almonds, eggs and fruits.
- Document 3: I will take fruits and biscuits with me while going to Zoo
- Document 4: The zookeeper feeds the lion very carefully
- Document 5: One should give good quality biscuits to their dogs

LDA Output

- Topic 1: 30% fruits, 15% eggs, 10% biscuits... (... food)
- Topic 2: 20% lion, 10% dogs, 5% zoo... (... animals)
- Documents 1 and 2: 100% Topic 1
- Documents 3: 100% Topic 2
- Document 4 and Document 5: 70% Topic 1, 30% Topic 2



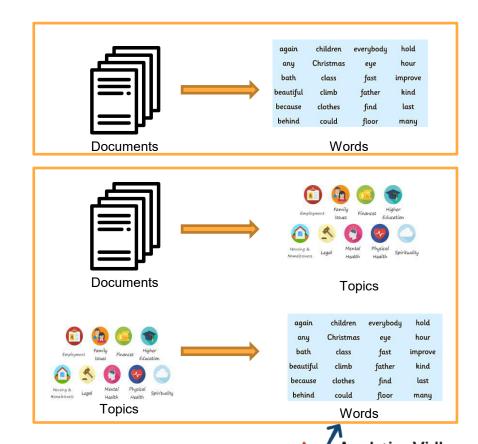
Generative probabilistic model

Finds topics from a corpus Annotates documents with topics

LDA Assumptions

Documents = mixture of topics Topics = mixture of words

Documents: Probability Distributions of Topics
 Topics: Probability Distributions of Words



- Corpus : Document Word Matrix
- Document Word Matrix = Document Topic Matrix + Topic Word Matrix

4					
		W1	W2	W3	Wn
	D1	0	2	1	3
	D2	1	4	0	0
	D3	0	2	3	1
	Ωn	1	1	3	0

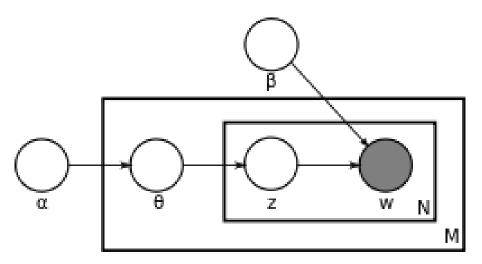
	K1	K2	К3	K
D1	1	0	0	1
D2	1	1	0	0
D3	1	0	0	1
<u>Dn</u>	1	0	1	0

	W1	W2	W3	<u>Wm</u>
K1	0	1	1	1
K2	1	1	1	0
К3	1	0	0	1
K	1	1	0	0

• Goal – Optimize representations

Document Topic distributions
Topic Terms distributions





• M: Total Documents in Corpus

N: No of words in a Document

w: Word in a document

z: Latent topic assigned to the word

theta: Topic Distribution

Alpha, Beta – LDA model parameters



• Corpus:

```
D1 = (w1, w2, w3, w4, ...... wn)

D2 = (w'1, w'2, w'3, w'4, ..... w'n)

D3 = (w"1, w"2, w"3, w"4, ..... w"n)

...

Dm = (w1, w2, w3, w4, ..... wn)
```

First step: Assign random topics to each word

```
D1 = (w1 (k4), w2 (k2), w3 (k2), w4 (k2), ...... wn (k3))

D2 = (w'1 (k1), w'2 (k7), w'3 (k3), w'4 (k6), ...... w'n (k2))

D3 = (w"1(k5), w"2 (k4), w"3 (k1), w"4 (k5), ...... w"n (k1))

...

Dm = (w1 (k4), w2 (k2), w3 (k6), w4 (k1), ..... wn (k2))
```



```
D1 = (w1 (k4), w2 (k2), w3 (k2), w4 (k2), ...... wn (k3))
D2 = (w'1 (k1), w'2 (k7), w'3 (k3), w'4 (k6), ...... w'n (k2))
D3 = (w''1(k5), w''2(k4), w''3(k1), w''4(k5), ...... w''n(k1))
Documents: Mixture of Topics:
D1 = k4 + k2 + k2 + k2 + ... k3
D2 = k1 + k7 + k3 + k6 + ... k2
D3 = k5 + k4 + k1 + k5 + ... k1
Dn = ...
Topics : Mixture of Terms:
k1 = w'1 + w''3
k2 = w2 + w3 + w4 + ...
kn = wi + ...
```



Optimization Steps:

Iterate: each document d

Iterate: each word w

- Assume that all topic assignments except the current word are correct
- compute p1, p2

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p1 = proportion (topic t / document d) p2 = proportion (word w / topic t)
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p1 -> proportion of words in document d that are currently assigned to topic t p2 -> proportion of assignments to topic t that come from w, over all documents



- Reassign word w of document d a new topic k'
 - Where we choose topic k' with a new probability = p1 * p2
- Repeated large number of times until steady state

