06 – Topic identification, topic modelling

IA161 Advanced Techniques of Natural Language Processing

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Outline

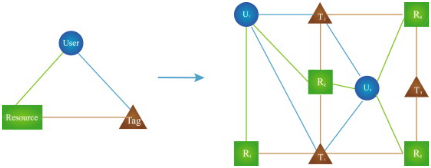
- Introduction to topic modelling
- Latent Semantic Analysis
- Latent Dirichlet Allocation
- Gensim

Topic modelling

- organize and understand large collections of documents
- text mining
- discover topical patterns in documents
- topic – group of words representing the information
- applications
  - recommender systems
  - document/book classification
  - bio-informatics (interpret biological data)
  - opinion/sentiment analysis
  - chatbots, topic tracking
  - text categorization

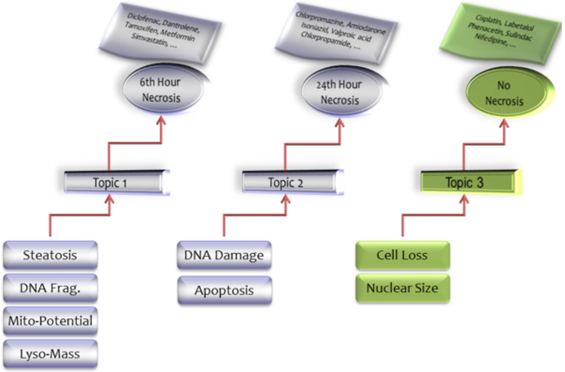
Recommender systems

- recommend the best product for user
- clusters of users, based on preference
- clusters of products
- Netflix prize



Bio-informatics

- categorize patients to risk groups, based on text protocols
- detect common genomic features, based on gene sequence data
- group drugs by diagnosis



Latent Semantic Analysis

- vector representation of documents
- compare by vector distance
- document = bag of words
- topic = set of words
- applications:
  - data clustering, document classification
  - term relations (synonymy, polysemy)
  - cross language document retrieval
  - word relations in text
  - similarity in multi choice questions
  - prior art in patents

LSA – step 1

- count term-document matrix (word frequency in documents)
- rows = words, columns = documents
- *sparse matrix*

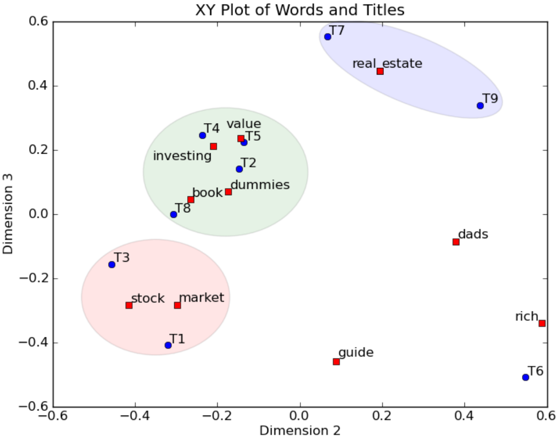
Terms	Documents													
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14
abnormalities	0	0	0	0	0	0	0	1	0	1	0	0	0	0
age	1	0	0	0	0	0	0	0	0	0	0	1	0	0
behavior	0	0	0	0	1	1	0	0	0	0	0	0	0	0
blood	0	0	0	0	0	0	0	1	0	0	1	0	0	0
close	0	0	0	0	0	0	1	0	0	0	1	0	0	0
culture	1	1	0	0	0	0	0	1	1	0	0	0	0	0
depressed	1	0	1	1	1	0	0	0	0	0	0	0	0	0
discharge	1	1	0	0	0	1	0	0	0	0	0	0	0	0
disease	0	0	0	0	0	0	0	0	1	0	1	0	0	0
fast	0	0	0	0	0	0	0	0	0	1	0	1	1	1
generation	0	0	0	0	0	0	0	0	1	0	0	0	1	0
oestrogen	0	0	1	1	0	0	0	0	0	0	0	0	0	0
patients	1	1	0	1	0	0	0	1	0	0	0	0	0	0
pressure	0	0	0	0	0	0	0	0	0	0	1	0	0	1
rats	0	0	0	0	0	0	0	0	0	0	0	0	1	1
respect	0	0	0	0	0	0	0	1	0	0	0	1	0	0
rise	0	0	0	1	0	0	0	0	0	0	0	0	0	1
study	1	0	1	0	0	0	0	0	1	0	0	0	0	0

LSA – step 2

- weighting matrix elements
- most popular tf–idf
- term occuring in many documents is not interesting for analysis

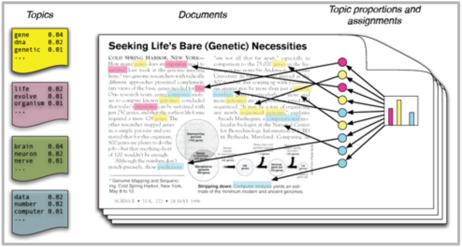
LSA – step 3

- Singular Value Decomposition
- matrix factorization (reduce dimensions, throw away noise)
- cluster close vectors (documents and terms)



Latent Dirichlet Allocation

- statistical model
- each document is a mix of topics
- LDA discovers topics and their ratio
- each word in document was generated by one of the topics
- applications:
  - topic relations
  - content recommendation
  - group/community overlapping
  - document topic changes
  - genetics (ancestral populations)



Example

Document 1: I like to eat broccoli and bananas.
Document 2: I ate a banana and spinach smoothie for breakfast.
Document 3: Chinchillas and kittens are cute.
Document 4: My sister adopted a kitten yesterday.
Document 5: Look at this cute hamster munching on a piece of broccoli.

Example

Topic A: 30% broccoli, 15% bananas, 10% breakfast, 10% munching
Topic B: 20% chinchillas, 20% kittens, 20% cute, 15% hamster

Example

Document 1 and 2: 100% Topic A
Document 3 and 4: 100% Topic B
Document 5: 60% Topic A, 40% Topic B

LDA process

- pick fixed number of topics
- for each document, randomly assign topic to each word
- improve, for each document d:
  - for each word w and topic t count:
  - *all topic assignments are correct, except for current word*
  - $p(\mathit{topic}\ t | \mathit{document}\ d)$ – how many words in document have topic?
  - $p(\mathit{word}\ w | \mathit{topic}\ t)$ – how many assignments to topic for word?
  - new topic: probability $p(\mathit{topic}\ t | \mathit{document}\ d) \times p(\mathit{word}\ w | \mathit{topic}\ t)$
- repeat and reach almost steady state

Topic Labeling

represent topic with human-friendly label

- top N words from the list
- find Wikipedia article based on word list
- document summarization from topic documents

Gensim

```
>>> from gensim import corpora, models, similarities
>>>
>>> # Load corpus iterator from a Matrix Market file on disk.
>>> corpus = corpora.MmCorpus('/path/to/corpus.mm')
>>>
>>> # Initialize Latent Semantic Indexing with 200 dimensions.
>>> lsi = models.LsiModel(corpus, num_topics=200)
>>>
>>> # Convert another corpus to the latent space and index it.
>>> index = similarities.MatrixSimilarity(lsi[another_corpus])
>>>
>>> # Compute similarity of a query vs. indexed documents
>>> sims = index[query]
```

Gensim – LSA

```
gensim.models.lsimodel.LsiModel(corpus=None,
num_topics=200, id2word=None, chunksize=20000, decay=1.0,
distributed=False, onepass=True, power_iters=2,
extra_samples=100)
```

- `chunksize` – number of documents in memory (more documents, more memory)
- `decay` – newly added documents are more important?
- `power_iters` – more iterations improve accuracy, but lower performance
- `onepass` – False to use multi-pass algorithm, for static data increase accuracy

Gensim – LDA

```
gensim.models.ldamodel.LdaModel(corpus=None,
num_topics=100, id2word=None, distributed=False,
chunksize=2000, passes=1, update_every=1,
alpha='symmetric', eta=None, decay=0.5, offset=1.0,
eval_every=10, iterations=50, gamma_threshold=0.001,
minimum_probability=0.01, random_state=None, ns_conf=None,
minimum_phi_value=0.01, per_word_topics=False)
```

- `chunksize` – number of documents in memory (more documents, more memory)
- `update_every` – number of chunks before moving to next step
- chunksize=100k, update_every=1 equals to chunksize=50k, update_every=2 (saves memory)
- `decay` – newly added documents are more important?
- `alpha, eta` – preset expected topics and word probability for start
- `eval_every` – log perplexity is estimated after x updates (lower number, slower training)

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