07 – Topic identification, topic modelling

IA161 Natural Language Processing in Practice

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Outline

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

4.2 AROMA 9/10 APPEARANCE 4/5 TASTE 8/10 PALATE 4/5 OVERALL 17/20
viktorvee (33) - Greater London, ENGLAND - APR 12, 2013

Treacle like, viscous, thick, a dark brown or black with cream brown head. Can't think of much to improve here, bitter and sweet and mineral all in one in perfect harmony.

3.9 AROMA 8/10 APPEARANCE 3/5 TASTE 8/10 PALATE 4/5 OVERALL 16/20
Hermod (2155) - Vantaa, FINLAND - APR 9, 2013

33cl bottle from AlesByMail. Bottled on 09.01.13. Poured black in color with a brown, thin head. Aroma has milk chocolate and roasted malt at first, later strong black coffee and tar hits you. Flavor has roasted, almost burnt malt, strong coffee, dark chocolate notes and light ashyness. Very dry finish, ash and tar notes here as well. Interesting, fresh and tasty. Great stuff!

3.8 AROMA 8/10 APPEARANCE 4/5 TASTE 7/10 PALATE 4/5 OVERALL 15/20
Lowenbrau (927) - Asturias, Oviedo, SPAIN - APR 6, 2013

330ml bottle @Cimmeria, Oviedo. Intense coffee aromas, along with some nut ones. Pours very dark, opaque, with nice creamy tan head, persistent, good lacing. Medium body, soft carbonation, sticky texture. Taste is coffee, cacao, some nuts, raisins. Very well balanced. Artertaste is long, warm and dry. Very enjoyable.

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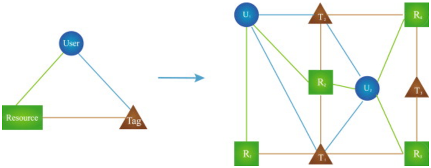
Water	Hops	Malt	Yeast
golden	citrus	caramel	banana
white	hops	amber	clove
grassy	grapefruit	malt	bubblegum
light	orange	sweet	bubble
head	pine	copper	gum

Topic modelling

- organize and understand large collections of documents
- text mining
- discover uknown 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
- vs. topic classification – categorize documents into set of topics

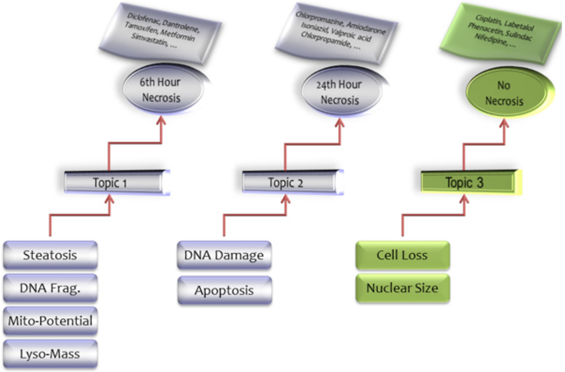
Recommender systems

- 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*

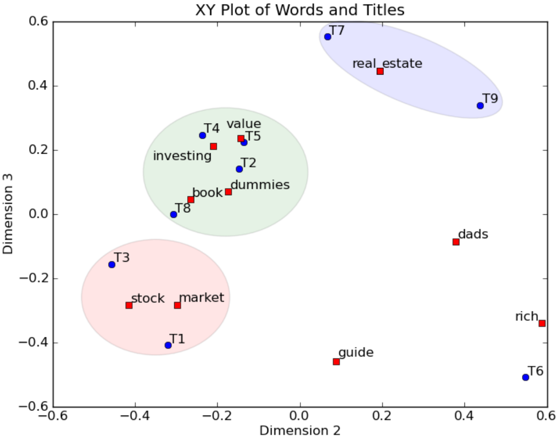
Terms	Documents													
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14
abnormalities	0	0	0	0	0	0	0	1	0	1	0	0	0	0
age	1	0	0	0	0	0	0	0	0	0	0	1	0	0
behavior	0	0	0	0	1	1	0	0	0	0	0	0	0	0
blood	0	0	0	0	0	0	0	1	0	0	1	0	0	0
close	0	0	0	0	0	0	1	0	0	0	1	0	0	0
culture	1	1	0	0	0	0	0	1	1	0	0	0	0	0
depressed	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

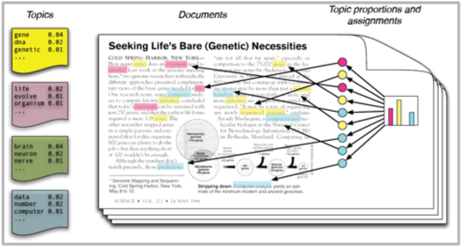
LSA – step 3

- 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

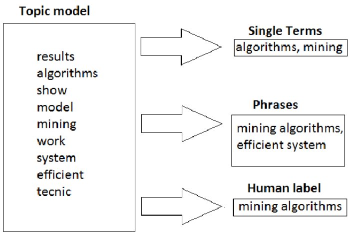
LDA process

- 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*
    - $p(\textit{topic } t | \textit{document } d)$ – how many words in document have topic?
    - $p(\textit{word } w | \textit{topic } t)$ – how many assignments to topic for word?
    - new topic: probability $p(\textit{topic } t | \textit{document } d) \times p(\textit{word } w | \textit{topic } t)$
- repeat and reach almost steady state

Topic Labeling

represent topic with human-friendly label

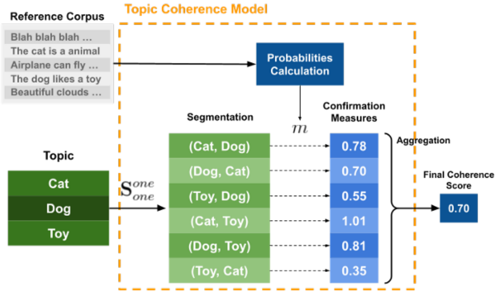
- top N words from the list
- find Wikipedia article based on word list
- document summarization from topic documents



Topic Coherence

measuring score for single topic quality by semantic similarity between words in topic

- Segmentation – segment topic into word pairs
- Probability Estimation – probability of words in documents, based on reference corpus
- Confirmation Measure – "quality" of word subsets based on probabilities
- Aggregation – compute single score



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)

Gensim – LDA parameters

- `Alpha` – similarity of documents.
  Low value: documents are mixture of few topics.
  High value: documents are represented by more topics, i.e. more similar.
- `Beta` – similarity of topics.
  Low value: topics are created by more unique words.
  High value: topics contains more words in common.

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