Information Retrieval 1

Semantic-based Retrieval

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Document representation and matching

Evaluation	**Document representation & matching**	Conversational search
Learning to rank	IR—user interaction	Recommender systems

Outline

1. Topic modeling
2. Latent semantic indexing/analysis

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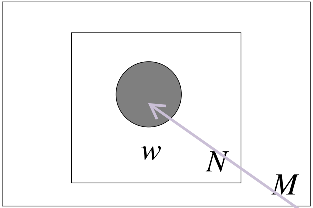
Unigram language model



$$w_{ij} \sim Mult(d_i)$$
$$i \in \{1, \dots, M\}$$
$$j \in \{1, \dots, N_i\}$$

we have M docs
Each doc has length N.means a doc has N words
Each word w can occur maximally N times, in a doc.

shaded circle: we observe the word w
empty circle: we dont observe the word w

Mixture of unigrams

we have 4 unigrams: Arts, budgets, children, education. we want to represent a word by the combination of these 4 unigrams

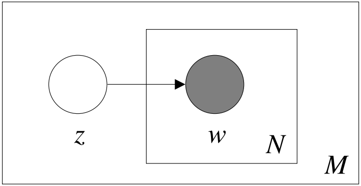
越往上的排位的word
拥有越高的prob

"Arts"	"Budgets"	"Children"	"Education"
NEW	MILLION	CHILDREN	SCHOOL
FILM	TAX	WOMEN	STUDENTS
SHOW	PROGRAM	PEOPLE	SCHOOLS
MUSIC	BUDGET	CHILD	EDUCATION
MOVIE	BILLION	YEARS	TEACHERS
PLAY	FEDERAL	FAMILIES	HIGH
MUSICAL	YEAR	WORK	PUBLIC
BEST	SPENDING	PARENTS	TEACHER
ACTOR	NEW	SAYS	BENNETT
FIRST	STATE	FAMILY	MANIGAT
YORK	PLAN	WELFARE	NAMPHY
OPERA	MONEY	MEN	STATE
THEATER	PROGRAMS	PERCENT	PRESIDENT
ACTRESS	GOVERNMENT	CARE	ELEMENTARY
LOVE	CONGRESS	LIFE	HAITI

film has high rank in Arts, low rank in children

Blei et al., "Latent Dirichlet Allocation"

Mixture of unigrams



$$z_i \sim Mult(\theta)$$
$$w_{ij} \sim Mult(\phi_{z_i})$$

Blei et al., "Latent Dirichlet Allocation"

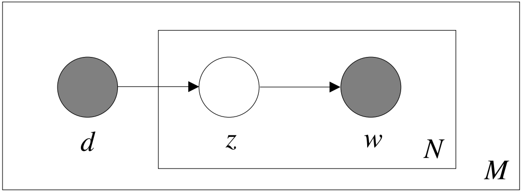
Probabilistic latent semantic analysis (pLSA)

every word comes from
a certain doc. we

The William Randolph Hearst Foundation will give $1.25 million to Lincoln Center, Metropolitan Opera Co., New York Philharmonic and Juilliard School. "Our board felt that we had a real opportunity to make a mark on the future of the performing arts with these grants an act every bit as important as our traditional areas of support in health, medical research, education and the social services," Hearst Foundation President Randolph A. Hearst said Monday in announcing the grants. Lincoln Center's share will be $200,000 for its new building, which will house young artists and provide new public facilities. The Metropolitan Opera Co. and New York Philharmonic will receive $400,000 each. The Juilliard School, where music and the performing arts are taught, will get $250,000. The Hearst Foundation, a leading supporter of the Lincoln Center Consolidated Corporate Fund, will make its usual annual $100,000 donation, too.

Blei et al., "Latent Dirichlet Allocation"

pLSA



multinomial distr

$$z_{ij} \sim Mult(\theta_i)$$
$$w_{ij} \sim Mult(\phi_{z_{ij}})$$

prob that the topic z is chosen
from the doc d.
=how important the topic z is in
the doc d
note: one doc might have several
topics. what is the prob that this
topic is selected.

before,
prob of word given the doc
= tf(w,d)/doc len

prob of a word in the topic

$$P(w \mid d) = \sum_z P(w \mid \phi_z) P(z \mid \theta_d)$$

sum over all topics

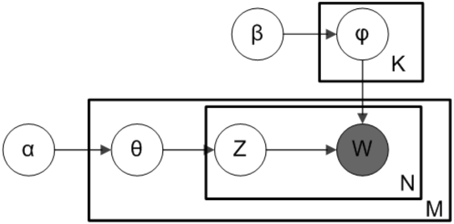
how important a word is in
a topic * how important a
topic is in a doc

., “Latent Diri

Latent Dirichlet allocation (LDA)

与LSA不同的是：LDA adds prior to word and prior to doc

隐含狄利克雷分布



a doc theta is drawn from a multinomial dist prior (with parameter alpha)

1. Choose $\theta_i \sim Dir(\alpha)$, where $i \in \{1, \dots, M\}$
2. Choose $\phi_k \sim Dir(\beta)$, where $k \in \{1, \dots, K\}$
3. For each position j, where $j \in \{1, \dots, N_i\}$
   (a) Choose a topic $z_{ij} \sim Mult(\theta_i)$
   (b) Choose a word $w_{ij} \sim Mult(\phi_{z_{ij}})$

https://en.wikipedia.org/wiki/Latent_Dirichlet_allocation

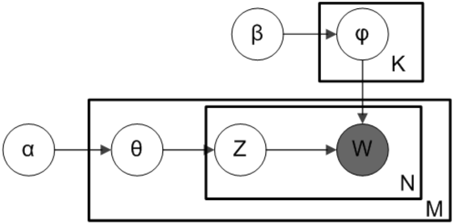
Documents as distributions

- Documents and queries are distributions over words

$$P(w \mid d) = \sum_{z} P(w \mid \phi_z) P(z \mid \theta_d)$$

- $P(w \mid \phi_z)$ and $P(z \mid \theta_d)$ are estimated through topic modeling (discussed next)
- Match documents and queries using QLM or KL-divergence

Estimating LDA

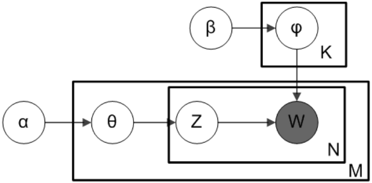


every doc is a distri of topics
every topic is a distri of words
we need to estimate these two distri

$$z_{ij} \sim Mult(\theta_i)$$
$$w_{ij} \sim Mult(\phi_{z_{ij}})$$

We need to find θ_d for every document and ϕ_z for every topic

Estimating LDA: notation



observed

unobserved

W	Words in documents (observed)
Z	Topics for words (not observed)
$\boldsymbol{\theta}$	Distributions of topics in documents (parameters)
$\boldsymbol{\phi}$	Distributions of words in topics (parameters)
$L(\boldsymbol{\theta}, \boldsymbol{\phi}; \mathrm{W}, \mathrm{Z}) = p(\mathrm{X}, \mathrm{Z} \mid \boldsymbol{\theta}, \boldsymbol{\phi})$	Log-likelihood of observed data W and unobserved random variables Z, given parameters $\boldsymbol{\theta}, \boldsymbol{\phi}$

Estimating LDA: expectation-maximization

- E-step: define the expected value of the log-likelihood function, with respect to the current estimates of the parameters $\boldsymbol{\theta}^{(t)}, \boldsymbol{\phi}^{(t)}$:

$$Q(\boldsymbol{\theta}, \boldsymbol{\phi} \mid \boldsymbol{\theta}^{(t)}, \boldsymbol{\phi}^{(t)}) = \mathrm{E}_{\mathrm{Z}|\mathrm{W}, \boldsymbol{\theta}^{(t)}, \boldsymbol{\phi}^{(t)}} [\log L(\boldsymbol{\theta}, \boldsymbol{\phi}; \mathrm{W}, \mathrm{Z})]$$

- M-step: find the parameters that maximize this quantity

$$\boldsymbol{\theta}^{(t+1)}, \boldsymbol{\phi}^{(t+1)} = \arg\max_{\boldsymbol{\theta}, \boldsymbol{\phi}} Q(\boldsymbol{\theta}, \boldsymbol{\phi} \mid \boldsymbol{\theta}^{(t)}, \boldsymbol{\phi}^{(t)})$$

- Repeat until convergence

https://en.wikipedia.org/wiki/Expectation-maximization_algorithm

Outline

1. Topic modeling
2. Latent semantic indexing/analysis

LSI

Vector space model

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
Anthony	1	1	0	0	0	1	
Brutus	1	1	0	1	0	0	
Caesar	1	1	0	1	1	1	
Calpurnia	0	1	0	0	0	0	
Cleopatra	1	0	0	0	0	0	
mercy	1	0	1	1	1	1	
worser	1	0	1	1	1	0	
...							

Manning et al., "Introduction to Information Retrieval"

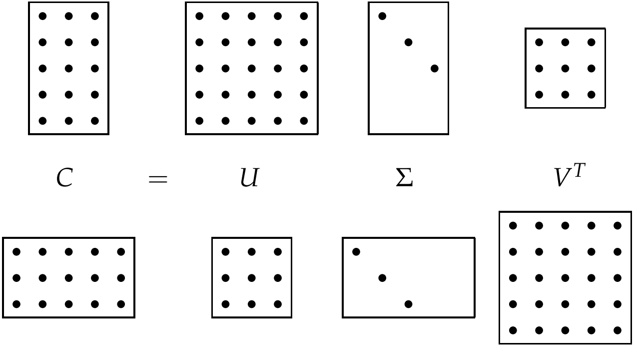
Singular value decomposition

- C is a $m \times n$ matrix (term-document)
- C can be decomposed as

$$C = U \Sigma V^T$$

- U is a $m \times m$ unitary matrix
- Σ is a diagonal $m \times n$ matrix with singular values
- V^T is a $n \times n$ unitary matrix

Singular value decomposition



Manning et al., "Introduction to Information Retrieval"

SVD example: original matrix

d1,d2,d3 talk about ship, boat and ocean

d4,d5,d6 talks about voyage and trip

	d_1	d_2	d_3	d_4	d_5	d_6
ship	1	0	1	0	0	0
boat	0	1	0	0	0	0
ocean	1	1	0	0	0	0
voyage	1	0	0	1	1	0
trip	0	0	0	1	0	1

if my query =trip,
then i will not only want to get doc 4 and 6, i also want to take a look on doc 5. because vector of d4 is similar to d5, vector of d6 is similar to d5.

doc 5 is similar to d4 and d6

al., "Introduction to Information Retrieval"

SVD example: decomposition

	1	2	3	4	5
ship	−0.44	−0.30	0.57	0.58	0.25
boat	−0.13	−0.33	−0.59	0.00	0.73
ocean	−0.48	−0.51	−0.37	0.00	−0.61
voyage	−0.70	0.35	0.15	−0.58	0.16
trip	−0.26	0.65	−0.41	0.58	−0.09

largest singular value

$\times$

2.16	0.00	0.00	0.00	0.00
0.00	1.59	0.00	0.00	0.00
0.00	0.00	1.28	0.00	0.00
0.00	0.00	0.00	1.00	0.00
0.00	0.00	0.00	0.00	0.39

second largest singular value

the second element distinguishes two groups:
group 1:d1,d2,d3 2nd element<0
group 2: d4,d5,d6 2nd element>0

$\times$

	d_1	d_2	d_3	d_4	d_5	d_6
1	−0.75	−0.28	−0.20	−0.45	−0.33	−0.12
2	−0.29	−0.53	−0.19	0.63	0.22	0.41
3	0.28	−0.75	0.45	−0.20	0.12	−0.33
4	0.00	0.00	0.58	0.00	−0.58	0.58
5	−0.53	0.29	0.63	0.19	0.41	−0.22

Manning et al., “Introduction to Information Retrieval”

Low-rank approximation

$$C = U\Sigma V^T = \sum_{i=1}^{\min(m,n)} \sigma_i \vec{u}_i \vec{v}_i^T$$

$$\approx \sum_{i=1}^{k} \sigma_i \vec{u}_i \vec{v}_i^T = U_k \Sigma_k V_k^T$$

LSI/LSA example: low-rank approximation

2.16	0.00	0.00	0.00	0.00
0.00	1.59	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00

$\times$

	d_1	d_2	d_3	d_4	d_5	d_6
1	−1.62	−0.60	−0.44	−0.97	−0.70	−0.26
2	−0.46	−0.84	−0.30	1.00	0.35	0.65

Manning et al., "Introduction to Information Retrieval"

Latent semantic indexing/analysis

$$
\begin{array}{ccccccccc}
 & & \begin{array}{c} C \\ (\mathbf{d}_j) \\ \downarrow \end{array} & & & \begin{array}{c} U_k \end{array} & \begin{array}{c} \Sigma_k \end{array} & & \begin{array}{c} V_k^T \\ (\hat{\mathbf{d}}_j) \\ \downarrow \end{array} \\
(\mathbf{t}_i^T) \rightarrow & & \begin{bmatrix} x_{1,1} & \dots & x_{1,n} \\ \vdots & \ddots & \vdots \\ x_{m,1} & \dots & x_{m,n} \end{bmatrix} & = & (\hat{\mathbf{t}}_i^T) \rightarrow & \begin{bmatrix} \begin{bmatrix} \\ \mathbf{u}_1 \\ \\ \end{bmatrix} \dots \begin{bmatrix} \\ \mathbf{u}_k \\ \\ \end{bmatrix} \end{bmatrix} \cdot & \begin{bmatrix} \sigma_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sigma_k \end{bmatrix} & \cdot & \begin{bmatrix} [& \mathbf{v}_1 &] \\ & \vdots & \\ [& \mathbf{v}_k &] \end{bmatrix}
\end{array}
$$

we want semantically similar docs to be close to each other in the semantic space

$$d_j = U_k \Sigma_k \hat{d}_j \Longrightarrow \hat{d}_j = \Sigma_k^{-1} U_k^T d_j$$

dj=[0,1,0,0,1,...] a binary verctor= a doc

new representation of a doc

https://en.wikipedia.org/wiki/Latent_semantic_analysis

Documents as vectors

we represent a doc as a vec, a query as a vec

- Given a collection of documents, perform SVD and low-rank approximation to obtain Σ_k and U_k
- Given a document and a query, represent them as a vectors in the obtained "semantic" vector space

$$\hat{d} = \Sigma_k^{-1} U_k^T d$$
$$\hat{q} = \Sigma_k^{-1} U_k^T q$$

- Match the obtained "semantic" vector representations $\hat{d}$ and $\hat{q}$ using cosine similarity

Semantic retrieval summary

- Documents as distributions
  - Topic modeling (pLSA, LDA)
- Documents as vectors
  - Latent semantic indexing/analysis

Materials

- Manning et al., Chapter 18
- Blei et al.
  Latent Dirichlet Allocation
  Journal of Machine Learning Research, 2003

Materials

- Mikolov et al.
  Distributed Representations of Words and Phrases and their Compositionality
  Advances in neural information processing systems, 2013
- Le and Mikolov
  Distributed Representations of Sentences and Documents
  Proceedings of JMLR, 2014