Latent Semantic Analysis & Topic Models

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Review

- Recall
- Precision
- Mean Average Precision (MAP)
- Normalized Discounting Cumulated Gain (NDCG)

Introduction

- Classic IR might lead to poor retrieval due to:
  - Relevant documents that do not contain at least one index term are not retrieved
  - Synonymy (同義詞) and polysemy (一詞多義) are crucial for IR
    - Car vs. Automobile

      The prevalence of synonyms tends to decrease the **recall** performance of retrieval systems

    - Bank

      Polysemy is one factor underlying poor **precision**

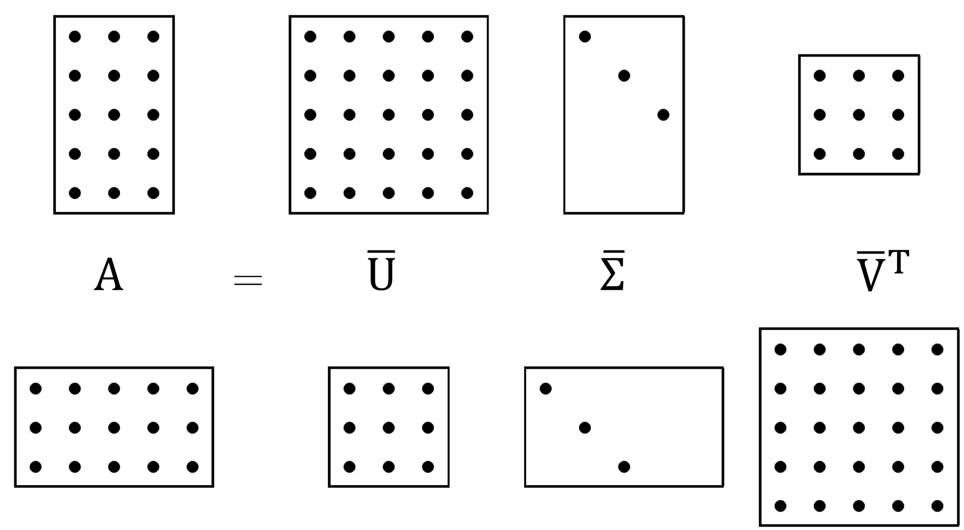
  - Retrieval based on index terms is vague and noisy
    - The user information need is more related to **concepts** and ideas than to **index terms**

Latent Semantic Analysis

Singular Value Decomposition

- In linear algebra, the singular-value decomposition (SVD) is a factorization of a real or complex matrix

- Formally, the SVD of an $m \times n$ matrix A is a factorization of the form $\overline{\mathrm{U}}\overline{\Sigma}\overline{\mathrm{V}}^{\mathrm{T}}$
  – $\overline{\mathrm{U}}$ is an $m \times m$ unitary matrix (i.e.,$\overline{\mathrm{U}}\overline{\mathrm{U}}^{\mathrm{T}} = \mathrm{I} = \overline{\mathrm{U}}^{\mathrm{T}}\overline{\mathrm{U}}$)
  – $\overline{\Sigma}$ is an $m \times n$ rectangular diagonal matrix with non-negative real numbers on the diagonal
  – $\overline{\mathrm{V}}$ is an $n \times n$ unitary matrix



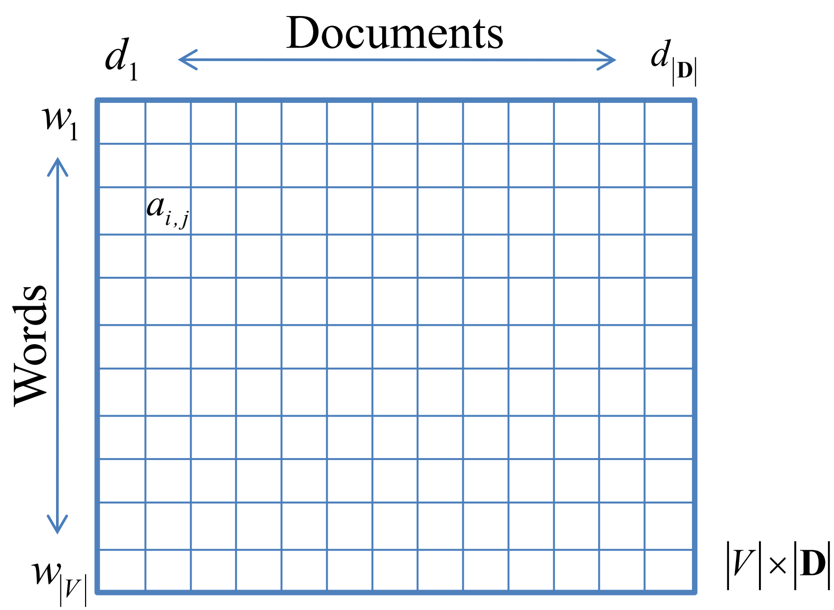
Introduction - LSA

- **Latent Semantic Analysis** also called
  - Latent Semantic Indexing (LSI)
  - Latent Semantic Mapping (LSM)
  - Two-Mode Factor Analysis

- The LSA paradigm operates under the assumption that there is some underlying **latent semantic structure** in the data
  - Algebraic and/or statistical techniques are brought to bear to estimate this latent structure and get rid of the obscuring "noise"

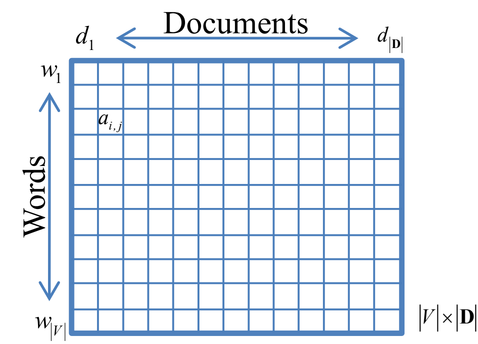
Latent Semantic Analysis – 1

- A given document collection can be represented as a word-document matrix
  - Row: composed of **words** (terms), which are the individual components making up a document
  - Column: composed of **documents** which are of a predetermined size of text such as paragraphs, collections of paragraphs, sentences, etc.



Latent Semantic Analysis – 2.

- In the word-by-document, each element $a_{i,j}$ is represented the importance of word w_i in document d_j
  - The TF-IDF score
  - The Entropy-based method



$$a_{i,j} = (1 - \varepsilon_i) \frac{c(w_i, d_j)}{|d_j|}$$

$$\varepsilon_i = -\frac{1}{log\,|\mathbf{D}|} \sum_{j=1}^{|\mathbf{D}|} \left(\frac{c(w_i, d_j)}{\sum_{j'=1}^{|\mathbf{D}|} c(w_i, d_{j'})} log \frac{c(w_i, d_j)}{\sum_{j'=1}^{|\mathbf{D}|} c(w_i, d_{j'})} \right)$$

- $0 \leq \varepsilon_i \leq 1$
  - $\varepsilon_i = 1 \Rightarrow \forall d_j,\ \ c\left(w_i, d_j\right) = \frac{\sum_{j'=1}^{|\mathbf{D}|} c(w_i, d_{j'})}{|\mathbf{D}|}$: the word distributed across many documents throughout the corpus
  - $\varepsilon_i = 0 \Rightarrow \exists d_j,\ \ c\left(w_i, d_j\right) \approx \sum_{j'=1}^{|\mathbf{D}|} c(w_i, d_{j'})$: the word is present only in a few specific documents

$$a_{i,j} = (1-\varepsilon_i)\frac{c(w_i,d_j)}{|d_j|}$$

Latent Semantic Analysis – 2..

$$\varepsilon_i = -\frac{1}{log\,|\mathbf{D}|}\sum_{j=1}^{|\mathbf{D}|}\left(\frac{c(w_i,d_j)}{\sum_{j'=1}^{|\mathbf{D}|}c(w_i,d_{j'})}\,log\,\frac{c(w_i,d_j)}{\sum_{j'=1}^{|\mathbf{D}|}c(w_i,d_{j'})}\right)$$

- $\varepsilon_i = 1 \Rightarrow \forall d_j,\ \ c\left(w_i,d_j\right) = \frac{\sum_{j'=1}^{|\mathbf{D}|}c(w_i,d_{j'})}{|\mathbf{D}|}$: the word distributed across many documents throughout the corpus

$$\begin{aligned}\varepsilon_i &= -\frac{1}{log|\mathbf{D}|}\sum_{j=1}^{|\mathbf{D}|}\left(\frac{c\left(w_i,d_j\right)}{\sum_{j'=1}^{|\mathbf{D}|}c\left(w_i,d_{j'}\right)}\,log\,\frac{c\left(w_i,d_j\right)}{\sum_{j'=1}^{|\mathbf{D}|}c\left(w_i,d_{j'}\right)}\right)\\ &= -\frac{1}{log|\mathbf{D}|}\sum_{j=1}^{|\mathbf{D}|}\left(\frac{\frac{\sum_{j'=1}^{|\mathbf{D}|}c\left(w_i,d_{j'}\right)}{|\mathbf{D}|}}{\sum_{j'=1}^{|\mathbf{D}|}c\left(w_i,d_{j'}\right)}\,log\,\frac{\frac{\sum_{j'=1}^{|\mathbf{D}|}c\left(w_i,d_{j'}\right)}{|\mathbf{D}|}}{\sum_{j'=1}^{|\mathbf{D}|}c\left(w_i,d_{j'}\right)}\right)\\ &= -\frac{1}{log|\mathbf{D}|}\sum_{j=1}^{|\mathbf{D}|}\left(\frac{1}{|\mathbf{D}|}\,log\,\frac{1}{|\mathbf{D}|}\right) = -\frac{1}{log|\mathbf{D}|}\left(log\,\frac{1}{|\mathbf{D}|}\right) = -\frac{1}{log|\mathbf{D}|}(-\,log|\mathbf{D}|) = 1\end{aligned}$$

$$a_{i,j} = (1-\varepsilon_i)\frac{c(w_i,d_j)}{|d_j|}$$

Latent Semantic Analysis – 2…

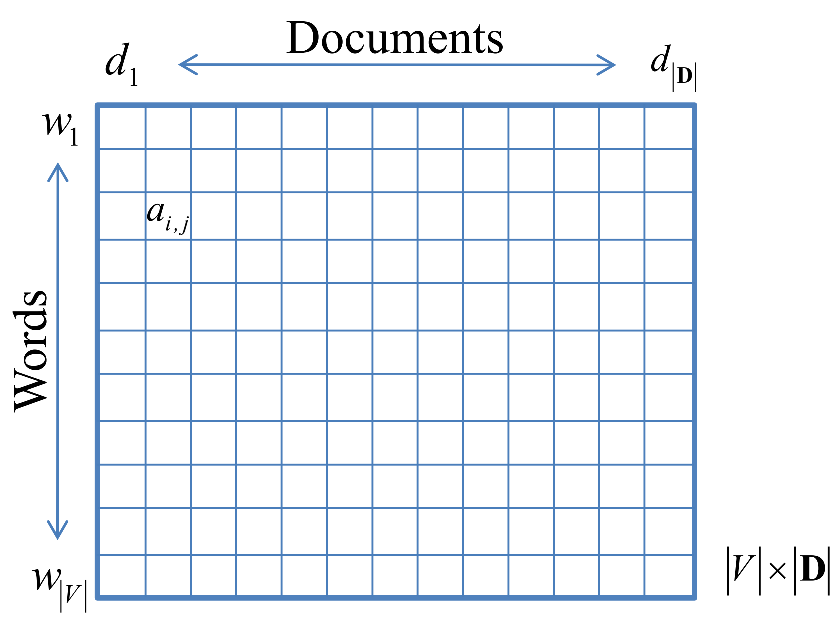
$$\varepsilon_i = -\frac{1}{log\,|\mathbf{D}|}\sum_{j=1}^{|\mathbf{D}|}\left(\frac{c(w_i,d_j)}{\sum_{j'=1}^{|\mathbf{D}|}c(w_i,d_{j'})}\,log\,\frac{c(w_i,d_j)}{\sum_{j'=1}^{|\mathbf{D}|}c(w_i,d_{j'})}\right)$$

- $\varepsilon_i = 0 \Rightarrow \exists d_j,\ \ c(w_i,d_j) \approx \sum_{j'=1}^{|\mathbf{D}|}c(w_i,d_{j'})$: the word is present only in a few specific documents

$$\begin{aligned}
\varepsilon_i &= -\frac{1}{\log|\mathbf{D}|}\sum_{j=1}^{|\mathbf{D}|}\left(\frac{c(w_i,d_j)}{\sum_{j'=1}^{|\mathbf{D}|}c(w_i,d_{j'})}\,log\,\frac{c(w_i,d_j)}{\sum_{j'=1}^{|\mathbf{D}|}c(w_i,d_{j'})}\right)\\
&= -\frac{1}{\log|\mathbf{D}|}\times(|\mathbf{D}|-1)\times\left(\frac{0}{\sum_{j'=1}^{|\mathbf{D}|}c(w_i,d_{j'})}\,log\,\frac{0}{\sum_{j'=1}^{|\mathbf{D}|}c(w_i,d_{j'})}\right)\\
&\quad -\frac{1}{\log|\mathbf{D}|}\times\left(\frac{\sum_{j'=1}^{|\mathbf{D}|}c(w_i,d_{j'})}{\sum_{j'=1}^{|\mathbf{D}|}c(w_i,d_{j'})}\,log\,\frac{\sum_{j'=1}^{|\mathbf{D}|}c(w_i,d_{j'})}{\sum_{j'=1}^{|\mathbf{D}|}c(w_i,d_{j'})}\right)\\
&= 0
\end{aligned}$$

Latent Semantic Analysis – 3

- For the word-by-document matrix, it should be noted that
  - the dimensions and can be extremely large
  - the vectors and are typically very sparse
  - the two spaces (for words and documents) are distinct from one other

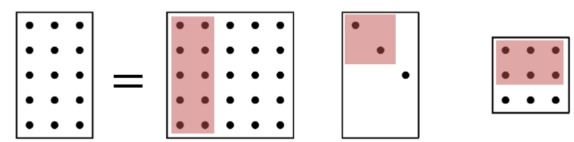


Latent Semantic Analysis – 4

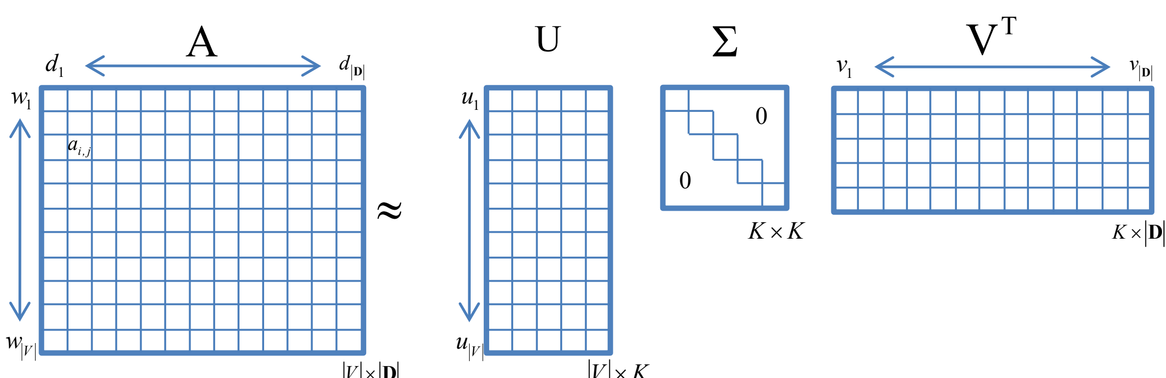
- In order to explore the latent semantic space, to project word and document vectors in the space, and to reduce the size of the vectors, the **Singular Value Decomposition** (SVD) can be employed
  - $K \leq \min(|V|, |\mathbf{D}|)$: **low-rank approximation**

$$\mathrm{A}_{|V|\times|\mathbf{D}|} = \overline{\mathrm{U}}_{|V|\times|V|}\overline{\Sigma}_{|V|\times|\mathbf{D}|}\overline{\mathrm{V}}^{\mathrm{T}}_{|\mathbf{D}|\times|\mathbf{D}|} \approx \mathrm{U}_{|V|\times K}\Sigma_{K\times K}\mathrm{V}^{\mathrm{T}}_{K\times|\mathbf{D}|} = \mathrm{A}'_{|V|\times|\mathbf{D}|}$$

  - The objective function is



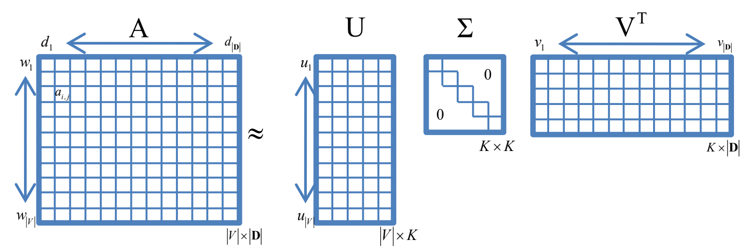
$$min\|\mathrm{A} - \mathrm{A}'\|_F^2, \text{for a given } K$$



$$\|\mathrm{B}\|_F^2 = \sum_i \sum_j b_{i,j}^2$$

Latent Semantic Analysis – 5

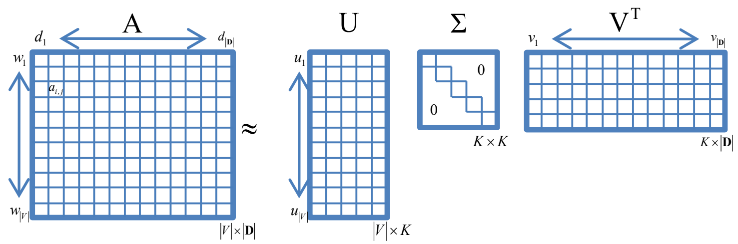
- Properties of SVD decomposition
  - Both left and right singular matrices and are column-orthonormal
    - $U^T U = V^T V = I$
  - Values (nonnegative real numbers) in diagonal matrix are square roots of the eigenvalues of $A^T A$
    - $\Sigma^2 = \mathrm{diag}\{\lambda_1, \lambda_2, \dots, \lambda_K\}$
    - $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_K \geq 0$



  - The column vectors of U define an orthonormal basis for d_j
    - $A \approx U\Sigma V^T \Rightarrow A^T U \approx \left(U\Sigma V^T\right)^T U = V\Sigma U^T U = V\Sigma \Rightarrow U^T A = \Sigma V^T$
  - The column vectors of V define an orthonormal basis for w_i
    - $A \approx U\Sigma V^T \Rightarrow AV \approx \left(U\Sigma V^T\right) V = U\Sigma V^T V = U\Sigma \Rightarrow V^T A^T = \Sigma U^T$

Latent Semantic Analysis – 6

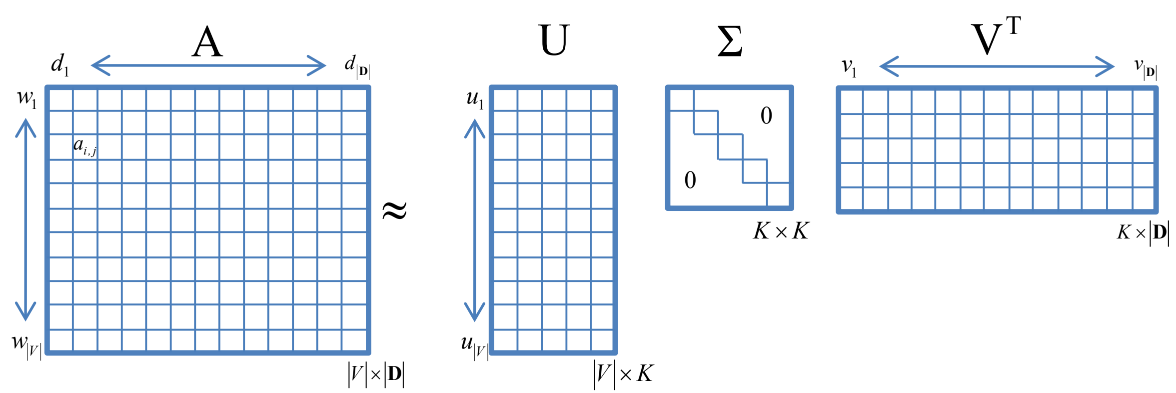
- New representations
  - For each words, the new vector representation is Σu_i^{T}
  - For each document, the new vector representation is Σv_i^{T}



- While the original high-dimensional vectors are sparse, the corresponding low-dimensional latent vectors will typically not be sparse
  - It is possible to compute meaningful association values between pairs of documents, even if the documents do not have any terms in common
    - The hope is that terms having a common meaning (synonyms), are roughly mapped to the same direction in the latent space

Latent Semantic Analysis – 7

- By using the decomposition
  - Compare two words
    - $A \approx U\Sigma V^T \Rightarrow AA^T \approx U\Sigma V^T(U\Sigma V^T)^T = U\Sigma V^T V\Sigma^T U^T = U\Sigma(U\Sigma)^T$
  - Compare two documents
    - $A \approx U\Sigma V^T \Rightarrow A^T A \approx (U\Sigma V^T)^T U\Sigma V^T = V\Sigma^T U^T U\Sigma V^T = V\Sigma(V\Sigma)^T$
  - Compare words and documents
    - $A \approx U\Sigma V^T$



Latent Semantic Analysis – 8

- For a given query (as a document), a low-dimensional representation should be inferred
  - The low-dimensional representation can be obtained by using the **fold-in** strategy

$$(\vec{q}'^{\mathrm{T}})_{1\times K} = \underbrace{(\vec{q}^{\mathrm{T}})_{1\times|V|}\mathrm{U}_{|V|\times K}}_{\text{Weighted sum of the word vectors}}\underbrace{\Sigma^{-1}_{K\times K}}_{\text{Each dimension has its own weight}}$$

$\mathrm{B} = \mathrm{U}\Sigma\mathrm{V}^{\mathrm{T}}$
$\Rightarrow \mathrm{B}^{\mathrm{T}} = (\mathrm{U}\Sigma\mathrm{V}^{\mathrm{T}})^{\mathrm{T}} = \mathrm{V}\Sigma^{\mathrm{T}}\mathrm{U}^{\mathrm{T}}$
$\Rightarrow \mathrm{B}^{\mathrm{T}}\mathrm{U} = \mathrm{V}\Sigma^{\mathrm{T}}$
$\Rightarrow \mathrm{B}^{\mathrm{T}}\mathrm{U}\Sigma^{-1} = \mathrm{V}\Sigma\Sigma^{-1} = \mathrm{V}$

  - For a new document, the representation can also be derived by the fold-in strategy
  - Consequently, the relevance degree can be computed:

$$sim(q, d_j) = cos(\Sigma\vec{q}', \Sigma\vec{d}_j') = \frac{\Sigma\vec{q}' \cdot \Sigma\vec{d}_j'}{|\Sigma\vec{q}||\Sigma\vec{d}_j'|}$$

$$sim(q, d_j) = cos(\vec{q}', \vec{d}_j')$$

Example – 1.

$A =$

	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

$U =$

	1	2
ship	−0.44	−0.30
boat	−0.13	−0.33
ocean	−0.48	−0.51
voyage	−0.70	0.35
trip	−0.26	0.65

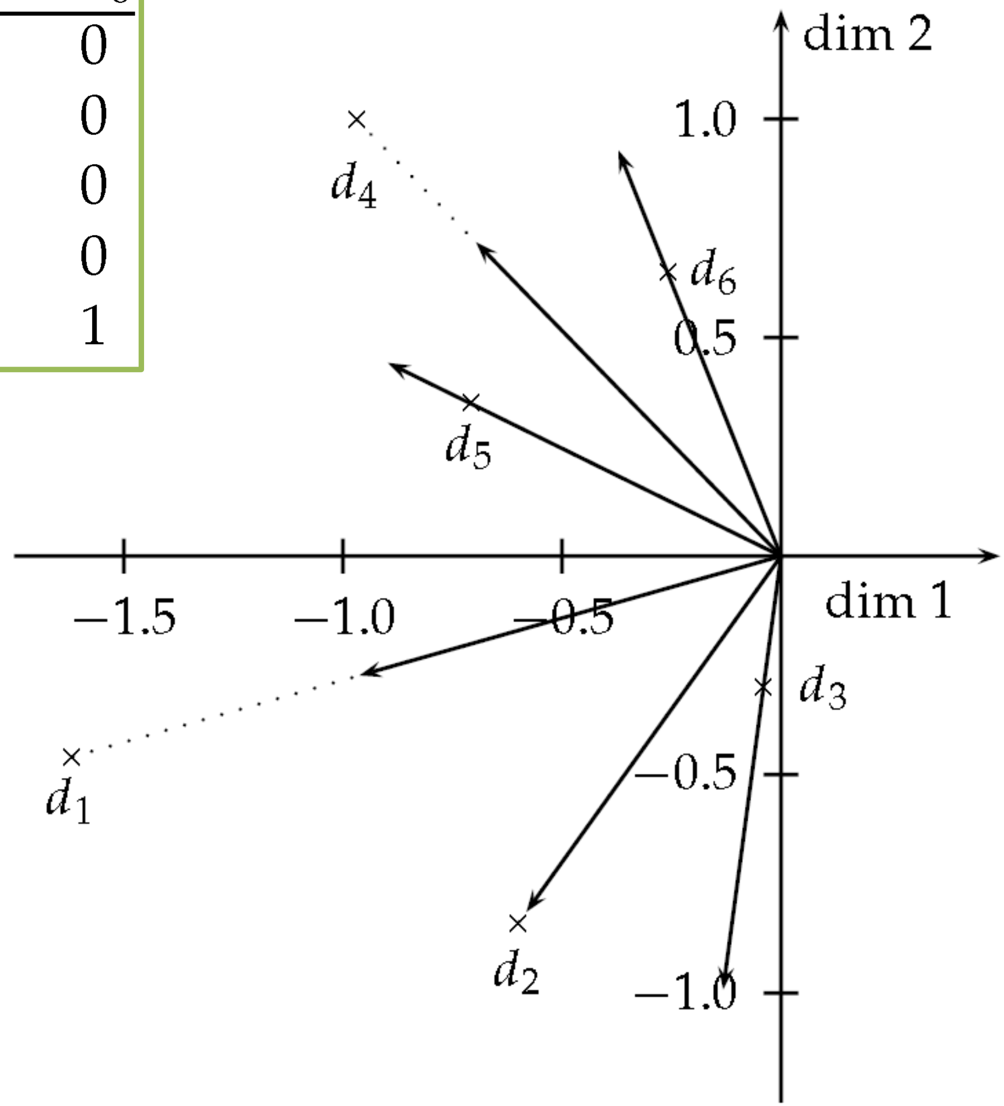
$$\Sigma = \begin{matrix} 2.16 & 0.00 \\ 0.00 & 1.59 \end{matrix}$$

$V^T =$

	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

Example – 1..

	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



Example – 2.

c1: *Human* machine *interface* for Lab ABC *computer* applications
c2: A *survey* of *user* opinion of *computer system response time*
c3: The *EPS user interface* management *system*
c4: *System* and *human system* engineering testing of *EPS*
c5: Relation of *user*-perceived *response time* to error measurement

m1: The generation of random, binary, unordered *trees*
m2: The intersection *graph* of paths in *trees*
m3: *Graph minors* IV: Widths of *trees* and well-quasi-ordering
m4: *Graph minors*: A *survey*

	Terms	**Documents**								
		c1	c2	c3	c4	c5	m1	m2	m3	m4
1	*human*	1	0	0	1	0	0	0	0	0
2	*interface*	1	0	1	0	0	0	0	0	0
3	*computer*	1	1	0	0	0	0	0	0	0
4	*user*	0	1	1	0	1	0	0	0	0
5	*system*	0	1	1	2	0	0	0	0	0
6	*response*	0	1	0	0	1	0	0	0	0
7	*time*	0	1	0	0	1	0	0	0	0
8	*EPS*	0	0	1	1	0	0	0	0	0
9	*survey*	0	1	0	0	0	0	0	0	1
10	*trees*	0	0	0	0	0	1	1	1	0
11	*graph*	0	0	0	0	0	0	1	1	1
12	*minors*	0	0	0	0	0	0	0	1	1

Example – 2..

Query="human computer interaction"

c1: *Human* machine *interface* for Lab ABC *computer* applications
c2: A *survey* of *user* opinion of *computer system response time*
c3: The *EPS user interface* management *system*
c4: *System* and *human system* engineering testing of *EPS*
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m1: The generation of random, binary, unordered *trees*
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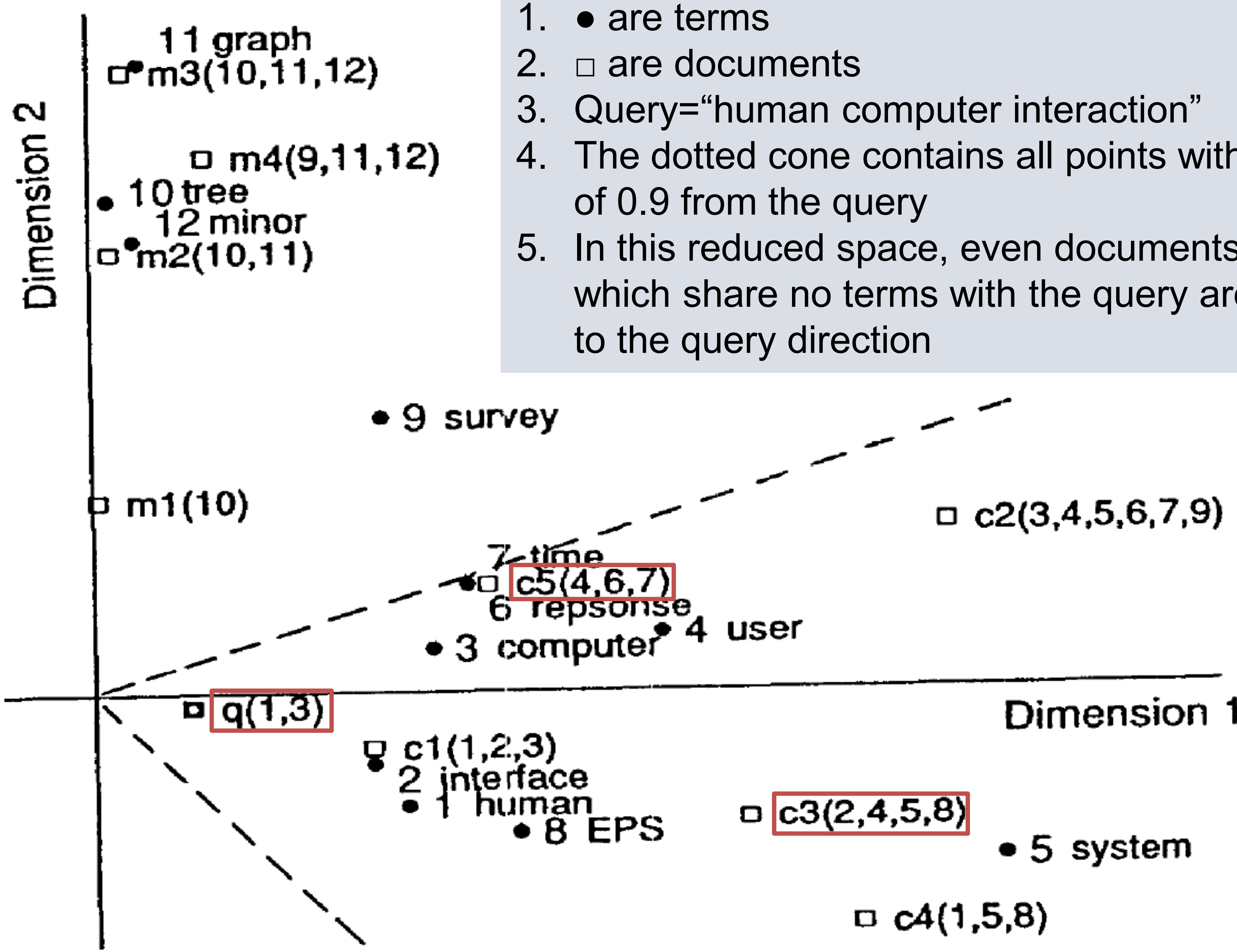
	Terms	Documents								
		c1	c2	c3	c4	c5	m1	m2	m3	m4
1	*human*	1	0	0	1	0	0	0	0	0
2	*interface*	1	0	1	0	0	0	0	0	0
3	*computer*	1	1	0	0	0	0	0	0	0
4	*user*	0	1	1	0	1	0	0	0	0
5	*system*	0	1	1	2	0	0	0	0	0
6	*response*	0	1	0	0	1	0	0	0	0
7	*time*	0	1	0	0	1	0	0	0	0
8	*EPS*	0	0	1	1	0	0	0	0	0
9	*survey*	0	1	0	0	0	0	0	0	1
10	*trees*	0	0	0	0	0	1	1	1	0
11	*graph*	0	0	0	0	0	0	1	1	1
12	*minors*	0	0	0	0	0	0	0	1	1

Example – 2..

1. ● are terms
2. □ are documents
3. Query="human computer interaction"
4. The dotted cone contains all points within a cosine of 0.9 from the query
5. In this reduced space, even documents c3 and c5, which share no terms with the query are very close to the query direction



Pros and Cons

- Advantages
  - As we reduce K, **recall tends to increase**, as expected
  - Most surprisingly, a value of K in the low hundreds can actually **increase precision** on some query benchmarks
  - Finding a new space for words and documents

- Disadvantages
  - The computational cost of the SVD is significant
  - Irrelevant or Antonymous
  - The reconstruction has negative entities

LSA-based Language Modeling – 1

- A goal of statistical language modeling is to learn the joint probability function of sequences of words in a language
  - By using n-gram model

$$P(w_1, w_2, \dots, w_T) \approx \prod_{t=1}^{T} P(w_t | w_{t-n+1}, \dots, w_{t-1})$$

  - By incorporating n-gram model and LSA-based model

$$P(w_1, w_2, \dots, w_T) \approx \prod_{t=1}^{T} P\left(w_t | H_{t-1}^{n,l}\right) = \prod_{t=1}^{T} P\left(w_t | \underbrace{H_{t-1}^{n}}_{\text{Lexical Information}}, \underbrace{H_{t-1}^{l}}_{\text{Semantic Information}}\right)$$

LSA-based Language Modeling – 2

- The probability can further be decomposed:

$$P\left(w_t|H_{t-1}^n, H_{t-1}^l\right) = \frac{P\left(w_t, H_{t-1}^l|H_{t-1}^n\right)}{\sum_{w_i \in V} P\left(w_i, H_{t-1}^l|H_{t-1}^n\right)}$$

- Expanding and rearranging, the numerator is seen to be:

$$\begin{aligned}
P\left(w_t, H_{t-1}^l|H_{t-1}^n\right) &= \frac{P\left(w_t, H_{t-1}^l, H_{t-1}^n\right)}{P(H_{t-1}^n)} \\
&= \frac{P\left(w_t, H_{t-1}^l, H_{t-1}^n\right)P(w_t, H_{t-1}^n)}{P(H_{t-1}^n)P(w_t, H_{t-1}^n)} \\
&= P(w_t|H_{t-1}^n)P\left(H_{t-1}^l|w_t, H_{t-1}^n\right) \\
&= P(w_t|w_{t-n+1}, \dots, w_{t-1})P\left(H_{t-1}^l\middle|w_{t-n+1}, \dots, w_{t-1}, w_t\right) \\
&= P(w_t|w_{t-n+1}, \dots, w_{t-1})P\left(H_{t-1}^l\middle|w_t\right)
\end{aligned}$$

We assume the probability of the document history given the current word is not affected by other context words

LSA-based Language Modeling – 3

- Consequently, we can obtain:

$$P\left(w_t|H_{t-1}^{n,l}\right) = P\left(w_t|H_{t-1}^{n}, H_{t-1}^{l}\right) = \frac{P(w_t|w_{t-n+1}, \dots, w_{t-1})P\left(H_{t-1}^{l}|w_t\right)}{\sum_{w_i \in V} P(w_i|w_{t-n+1}, \dots, w_{t-1})P\left(H_{t-1}^{l}|w_i\right)}$$

$$= \frac{P(w_t|w_{t-n+1}, \dots, w_{t-1})\frac{P(w_t|H_{t-1}^{l})}{P(w_t)}}{\sum_{w_i \in V} P(w_i|w_{t-n+1}, \dots, w_{t-1})\frac{P(w_i|H_{t-1}^{l})}{P(w_i)}}$$

- H_{t-1}^{l} can be represented by a vector in the semantic space

$$\left(\overrightarrow{H_{t-1}^{l}}'^{\mathrm{T}}\right)_{1\times K} = \left(\overrightarrow{H_{t-1}^{l}}^{\mathrm{T}}\right)_{1\times|V|} \mathrm{U}_{|V|\times K}\Sigma_{K\times K}^{-1}$$

- Thus, the semantic smoothing factor can be estimated by:

$$P(w_t|H_{t-1}^{l}) \propto \cos(\Sigma^{\frac{1}{2}}\overrightarrow{H_{t-1}^{l}}', \Sigma^{\frac{1}{2}}u_{w_t}^{\mathrm{T}})$$

LSA-based Language Modeling – Appendix

- By using the entropy-based method to score each element in the vector, a fast strategy can be derived for sequential data

$$\overrightarrow{H_t^l} = \frac{|H_t^l| - 1}{|H_t^l|} \overrightarrow{H_{t-1}^l} + \frac{1 - \varepsilon_{w_t}}{|H_t^l|} \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$a_{i,j} = (1 - \varepsilon_i) \frac{c(w_i, d_j)}{|d_j|}$$

Statistical Topic Models

From LSA to Probabilistic Topic Models

- Three important claims made for LSA
  - The semantic information can derived from a word-document co-occurrence matrix
  - The dimension reduction is an essential part of its derivation
  - Words and documents can be represented as points in the Euclidean space
- Probabilistic topic models are consistent with the first two claims, but differs in the third one
  - The semantic properties of words and documents are expressed in terms of probabilistic topics

Probabilistic Latent Semantic Analysis

- **Probabilistic Latent Semantic Analysis** also called
  - Probabilistic Latent Semantic Indexing (PLSI)
  - Aspect Model

- PLSA is a probabilistic counterpart of LSA
  - $P(d_j)$: the probability of selecting document d_j
  - $P(w_i|T_k)$: the probability of word w_i condition on a latent factor/topic T_k
    - **Aspect!**
  - $P(T_k|d_j)$: the probability of a latent factor/topic T_k generated by document d_j

PLSA – 1

- The PLSA model is a latent variable model for co-occurrence data (i.e., each pair of word w_i and document d_j) which associates an unobserved class variable (i.e., latent factor T_k)

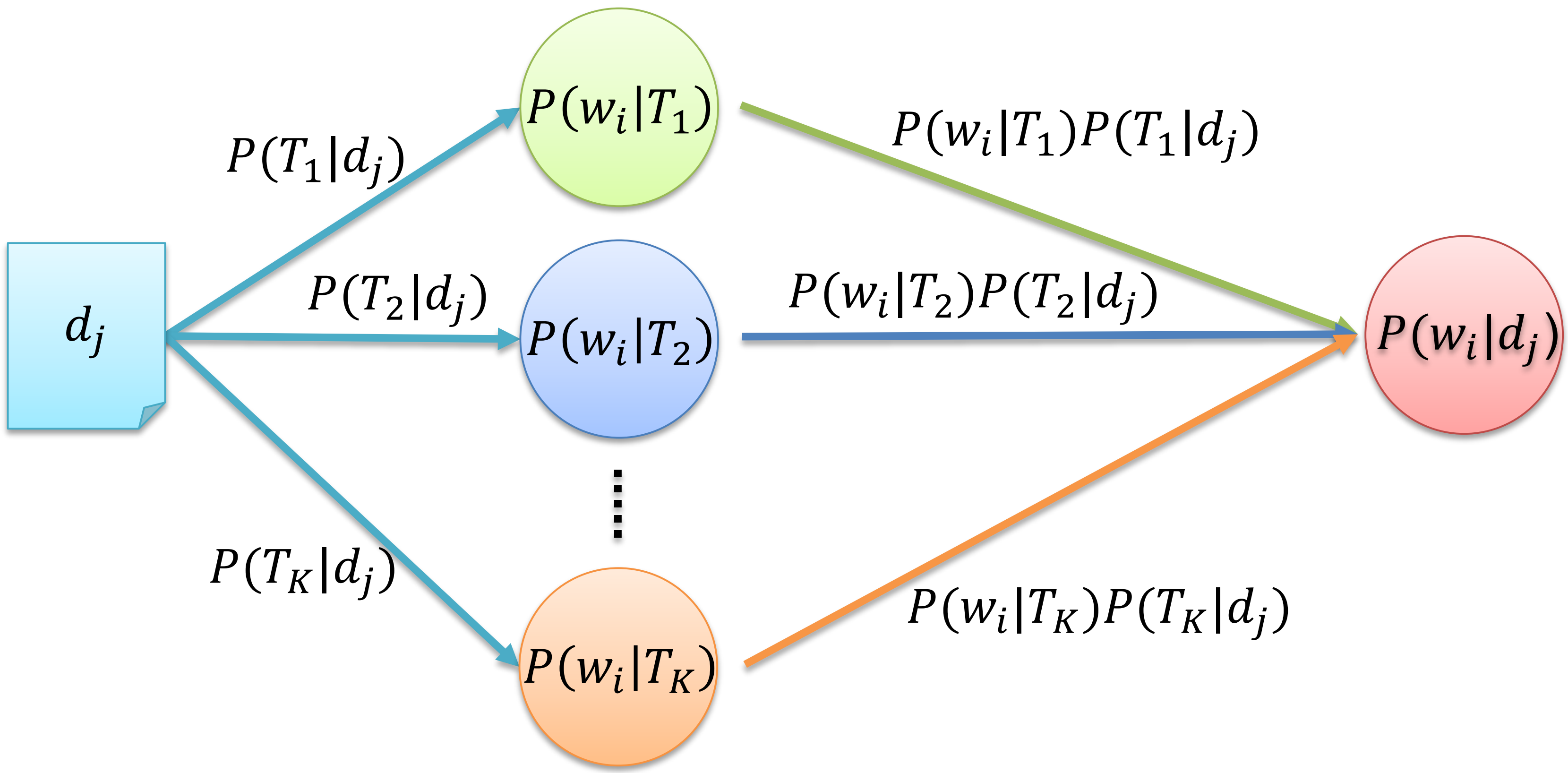
$$P(w_i, d_j) = P(d_j)P(w_i|d_j) = P(d_j)\sum_{k=1}^{K} P(w_i|T_k)P(T_k|d_j)$$

$$\begin{aligned}
P(w_i|d_j) &= \sum_{k=1}^{K} P(w_i, T_k|d_j) = \sum_{k=1}^{K} \frac{P(w_i, T_k, d_j)}{P(d_j)} \\
&= \sum_{k=1}^{K} \frac{P(w_i, d_j|T_k)P(T_k)}{P(d_j)} \\
&= \sum_{k=1}^{K} \frac{P(w_i\,|T_k)P(d_j|T_k)P(T_k)}{P(d_j)} \\
&= \sum_{k=1}^{K} \frac{P(w_i\,|T_k)P(d_j, T_k)}{P(d_j)} = \sum_{k=1}^{K} P(w_i\,|T_k)P(T_k|d_j)
\end{aligned}$$

Conditional Independence Assumption
document and word are independent conditioned on the state of the associated latent variable

PLSA – 2

- Thus, the modeling goal is to identify conditional probability mass functions $P(w_i|T_k)$ such that the document-specific word distributions $P(w_i|d_j)$ are as faithfully as possible approximated by convex combinations of these aspects



PLSA – 3

- The training objective is defined to maximize the total log-likelihood of a given training collection
  - The model parameters are $P(d_j)$, $P(w_i|T_k)$, and $P(T_k|d_j)$

$$
\begin{aligned}
\mathcal{L} &= \sum_{w_i \in V} \sum_{d_j \in \mathbf{D}} c(w_i, d_j) log P(w_i, d_j) \\
&= \sum_{w_i \in V} \sum_{d_j \in \mathbf{D}} c(w_i, d_j) log \left(P(d_j) \sum_{k=1}^{K} P(w_i|T_k) P(T_k|d_j) \right)
\end{aligned}
$$

PLSA – 4

- By using the Expectation-Maximization algorithm
  - E-step

$$P\left(T_k \middle| w_i, d_j\right) = \frac{P(w_i|T_k)P\left(T_k \middle| d_j\right)}{\sum_{k=1}^{K} P(w_i|T_k)P\left(T_k \middle| d_j\right)}$$

  - M-step

$$P(w_i|T_k) = \frac{\sum_{d_j \in \mathbf{D}} c(w_i, d_j)P\left(T_k \middle| w_i, d_j\right)}{\sum_{i'=1}^{|V|} \sum_{d_j \in \mathbf{D}} c(w_{i'}, d_j)P\left(T_k \middle| w_{i'}, d_j\right)}$$

$$P(T_k|d_j) = \frac{\sum_{i=1}^{|V|} c(w_i, d_j)P\left(T_k \middle| w_i, d_j\right)}{\sum_{i'=1}^{|V|} c(w_{i'}, d_j)}$$

PLSA – 5

- Consequently, for a given pair of query and document, the relevance degree can be determined by combining unigram model and PLSA model

$$P(w_i|d_j) = \frac{c(w_i, d_j)}{|d_j|}$$

$$\begin{aligned} P(q|d_j) &\approx \prod_{i=1}^{|q|} P(w_i|d_j) \\ &= \prod_{i=1}^{|q|} \left(\alpha \cdot P(w_i|d_j) + (1-\alpha) \cdot P_{PLSA}(w_i|d_j)\right) \\ &= \prod_{i=1}^{|q|} \left[\alpha \cdot P(w_i|d_j) + (1-\alpha) \cdot \left(\sum_{k=1}^{K} P(w_i|T_k) P(T_k|d_j)\right)\right] \end{aligned}$$

  - In order to incorporate the general information, the background model can also be integrated

$$P(q|d_j) = \prod_{i=1}^{|q|} \left[\alpha \cdot P(w_i|d_j) + \beta \cdot \left(\sum_{k=1}^{K} P(w_i|T_k) P(T_k|d_j)\right) + (1-\alpha-\beta) \cdot P_{BG}(w_i)\right]$$

PLSA – 6

- For a new document d_m, the **fold-in** strategy can be perform to obtain the topic distribution $P(T_k|d_m)$ for the document
  - The word distribution for each topic $P(w_i|T_k)$ is fixed
  - E-step

$$P(T_k|w_i, d_m) = \frac{P(w_i|T_k)P(T_k|d_m)}{\sum_{k=1}^{K} P(w_i|T_k)P(T_k|d_m)}$$

  - M-step

$$P(T_k|d_m) = \frac{\sum_{i=1}^{|V|} c(w_i, d_m)P(T_k|w_i, d_m)}{\sum_{i'=1}^{|V|} c(w_{i'}, d_m)}$$

PLSA – 7

- In addition to the query likelihood measure, we can combine PLSA with the vector-space model
  - Query can be treated as a document, thus the fold-in strategy can be perform to obtain $P(T_k|q)$
  - The topic distributions for document and query are vector representations
  - The similarity degree can be estimated under the semantic space

$$sim(q, d_j) = \cos(\vec{q}, \vec{d}_j) = \frac{\sum_{k=1}^{K} P(T_k|q) P(T_k|d_j)}{\sqrt{\sum_{k=1}^{K} P(T_k|q)^2} \sqrt{\sum_{k=1}^{K} P(T_k|d_j)^2}}$$

Link PLSA and LSA

- Another derivation of PLSA model

$$\boldsymbol{P(w_i, d_j)} = \sum_{k=1}^{K} P(w_i, d_j, T_k)$$

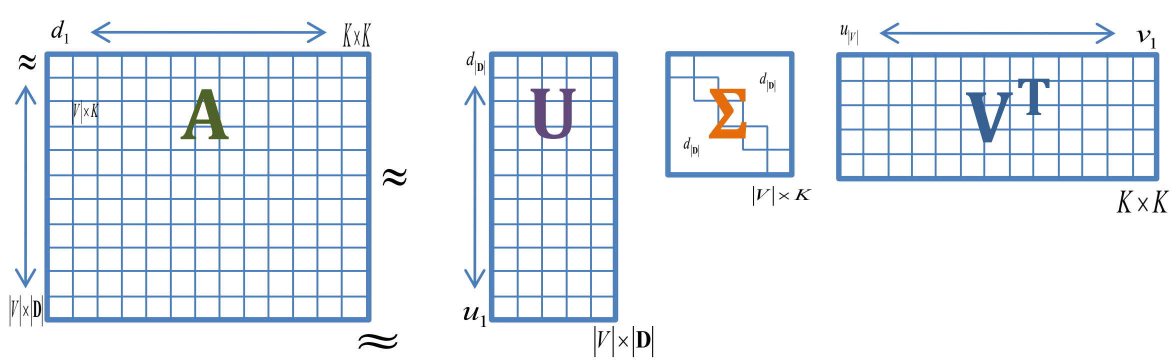
$$= \sum_{k=1}^{K} P(w_i | d_j, T_k) P(d_j, T_k)$$

$$= \sum_{k=1}^{K} P(w_i | T_k) P(d_j, T_k)$$

$$= \sum_{k=1}^{K} \boldsymbol{P(w_i | T_k) P(T_k) P(d_j | T_k)}$$

Conditional Independence Assumption
document and word are independent conditioned on the state of the associated latent variable

$$P(T_k)P(d_j|T_k) = P(T_k)\frac{P(d_j, T_k)}{P(T_k)}$$
$$= P(d_j, T_k) = P(T_k|d_j)P(d_j)$$



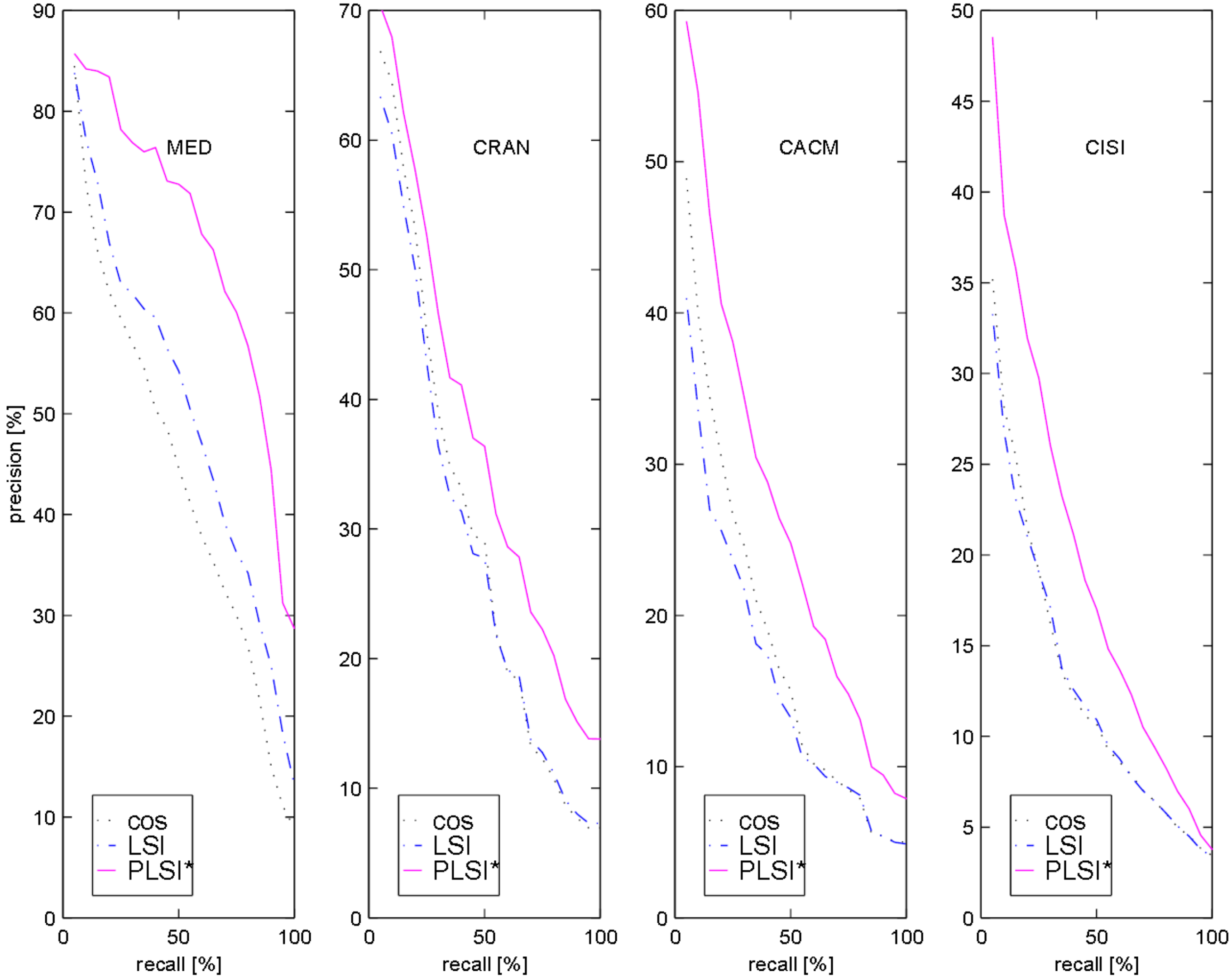
Comparisons – PLSA & LSA

- Decomposition/Approximation
  - LSA: least-squares criterion measured on the L2- or Frobenius norms of the word-by-document matrix
  - PLSA: maximization of the collection likelihood, which implies to minimize the KL-divergence measure

- Computational complexity
  - LSA: SVD decomposition
  - PLSA: EM training
  - The model complexity of Both LSA and PLSA grows linearly with the number of training documents
  - There is no general way to estimate or predict the vector representation (of LSA) or the model parameters (of PLSA) for a newly observed document
    - Fold-in strategy

Comparisons – Experiments

- All of the results are based on cosine similarity measure



Comparisons – Factors/Topics

- Factors from a 128 factor decomposition of the TDT-1 corpus
  - Factors are represented by their 10 most probable words, i.e., the words are ordered according to $P(w_i|T_k)$

- There is no obvious interpretation of the directions in the LSA latent space, while the directions in the PLSA space are interpretable as multinomial word distributions

"plane"	"space shuttle"	"family"	"Hollywood"	"Bosnia"	"Iraq"	"Rwanda"	"Kobe"
plane	space	home	film	un	iraq	refugees	building
airport	shuttle	family	movie	bosnian	iraqi	aid	city
crash	mission	like	music	serbs	sanctions	rwanda	people
flight	astronauts	love	new	bosnia	kuwait	relief	rescue
safety	launch	kids	best	serb	un	people	buildings
aircraft	station	mother	hollywood	sarajevo	council	camps	workers
air	crew	life	love	nato	gulf	zaire	kobe
passenger	nasa	happy	actor	peacekeepers	saddam	camp	victims
board	satellite	friends	entertainment	nations	baghdad	food	area
airline	earth	cnn	star	peace	hussein	rwandan	earthquake

Comparisons – Polysemy

- Many words in natural language are polysemous, having multiple senses; their semantic ambiguity can only be resolved by other words in the context
  - For example, the word PLAY is given relatively high probability related to the different senses of the word ([illegible]

Topic 77

word	prob.
MUSIC	.090
DANCE	.034
SONG	.033
PLAY	.030
SING	.026
SINGING	.026
BAND	.026
PLAYED	.023
SANG	.022
SONGS	.021
DANCING	.020
PIANO	.017
PLAYING	.016
RHYTHM	.015
ALBERT	.013
MUSICAL	.013

Topic 82

word	prob.
LITERATURE	.031
POEM	.028
POETRY	.027
POET	.020
PLAYS	.019
POEMS	.019
PLAY	.015
LITERARY	.013
WRITERS	.013
DRAMA	.012
WROTE	.012
POETS	.011
WRITER	.011
SHAKESPEARE	.010
WRITTEN	.009
STAGE	.009

Topic 166

word	prob.
PLAY	.136
BALL	.129
GAME	.065
PLAYING	.042
HIT	.032
PLAYED	.031
BASEBALL	.027
GAMES	.025
BAT	.019
RUN	.019
THROW	.016
BALLS	.015
TENNIS	.011
HOME	.010
CATCH	.010
FIELD	.010

Revisiting the Objective Function

$$KL(T||E) = \sum\nolimits_{x \in \mathbf{X}} T(x) log \frac{T(x)}{E(x)}$$

$$\mathcal{L} = \sum_{w_i \in V} \sum_{d_j \in \mathbf{D}} c(w_i, d_j) log P(w_i, d_j)$$

$$= \sum_{w_i \in V} \sum_{d_j \in \mathbf{D}} c(w_i, d_j) log \left(P(d_j) \sum_{k=1}^{K} P(w_i|T_k) P(T_k|d_j) \right)$$

$$= \sum_{d_j \in \mathbf{D}} \sum_{w_i \in V} c(w_i, d_j) \left[log P(d_j) + log \left(\sum_{k=1}^{K} P(w_i|T_k) P(T_k|d_j) \right) \right]$$

$$= \sum_{d_j \in \mathbf{D}} \sum_{w_i \in V} |d_j| \frac{c(w_i, d_j)}{|d_j|} \left[log P(d_j) + log \left(\sum_{k=1}^{K} P(w_i|T_k) P(T_k|d_j) \right) \right]$$

$$= \sum_{d_j \in \mathbf{D}} |d_j| \sum_{w_i \in V} P(w_i|d_j) [log P(d_j) + log P_{PLSA}(w_i|d_j)]$$

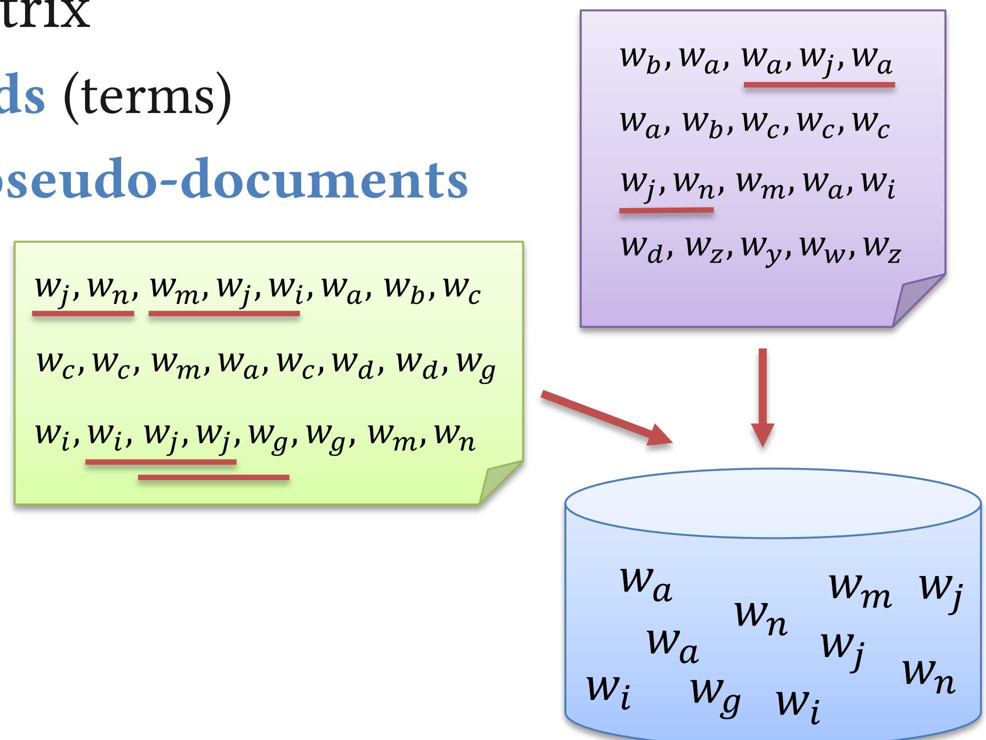
$$= \sum_{d_j \in \mathbf{D}} |d_j| \sum_{w_i \in V} \Big(\underbrace{P(w_i|d_j) log P(d_j)}_{\text{Constant}} + \underbrace{P(w_i|d_j) log P_{PLSA}(w_i|d_j)}_{\text{KL-Divergence}} \Big)$$

Word Topic Modeling – 1

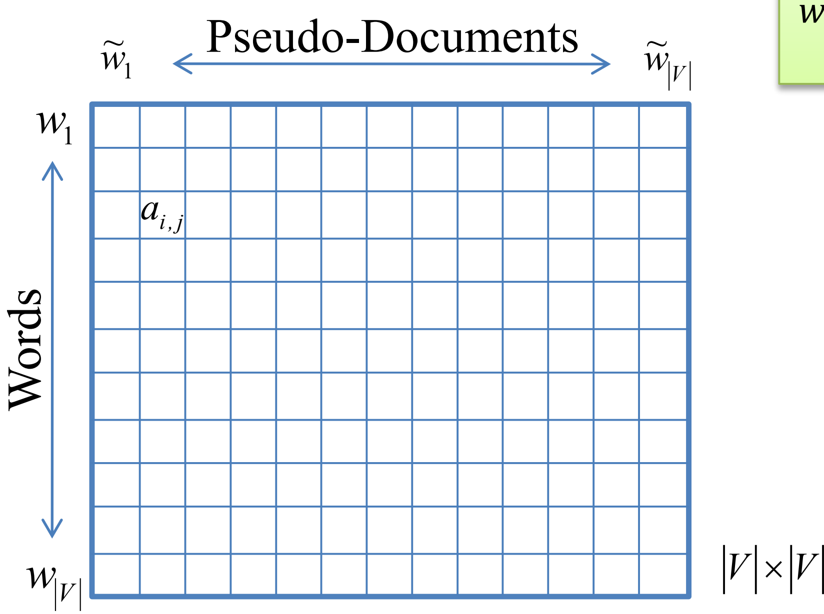
- WTM is a novel extension of the PLSA model
  - The model parameters of PLSA grow linearly with the size of the corpus
    - For WTM, the number of parameters is fixed
  - PLSA explores the co-occurrence relationship between words and documents
    - WTM focuses on the word-word co-occurrence relationship
  - For a new document, fold-in strategy is time consuming
    - For WTM, a linear combination technique can be applied

Word Topic Modeling – 2

- A given document collection can be represented as a word-by-pseudo-document matrix
  - Row: composed of **words** (terms)
  - Column: composed of **pseudo-documents**



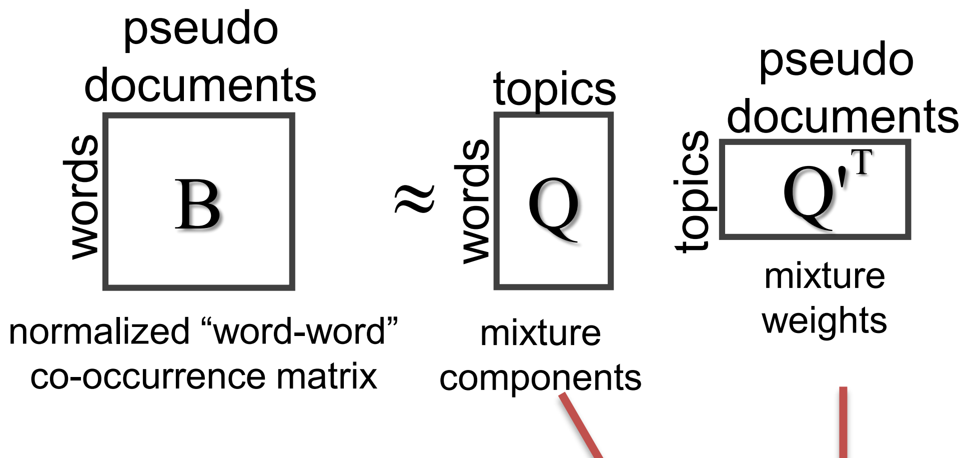
pseudo-document $\tilde{w}_j$



- The window size is set to 3
- $a_{i,j} = 2 \quad a_{m,j} = 1$

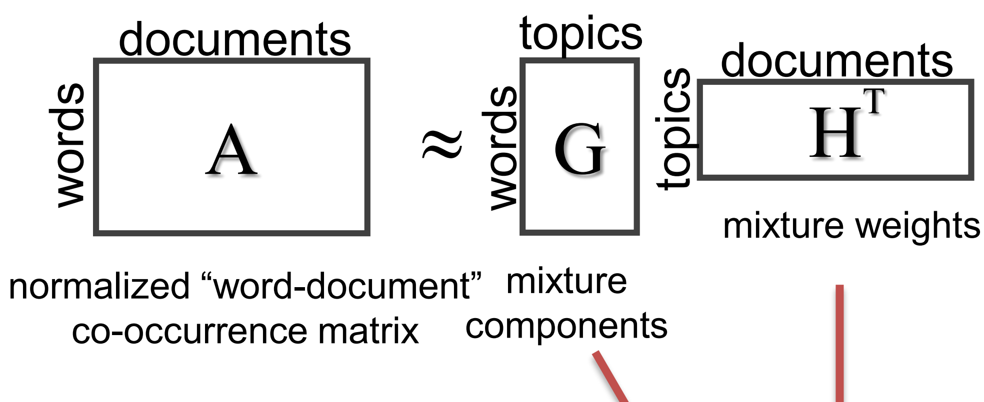
Word Topic Modeling – 3

- WTM



$$P_{\mathrm{WTM}}\left(w_i \middle| \widetilde{w}_j\right) = \sum_{k=1}^{K} P(w_i|T_k)P\left(T_k \middle| \widetilde{w}_j\right)$$

- PLSA



$$P_{\mathrm{PLSA}}\left(w_i \middle| d_j\right) = \sum_{k=1}^{K} P(w_i|T_k)P\left(T_k \middle| d_j\right)$$

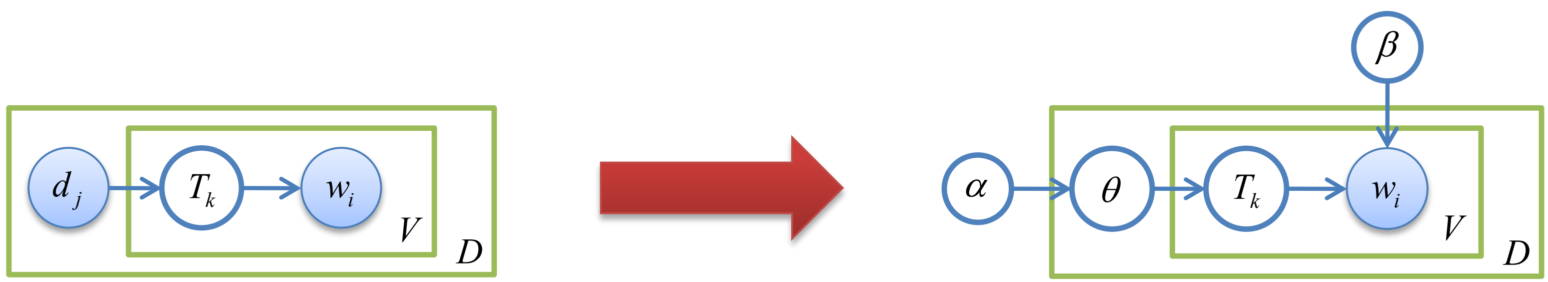
Word Topic Modeling – 4

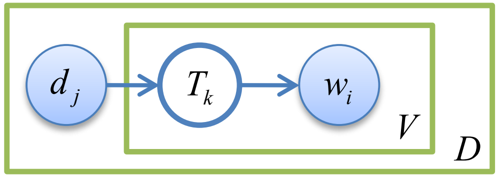
- For a new document, we can linearly combine the associated WTM models of the words occurring in the document to form a composite WTM model

$$
\begin{aligned}
P_{\mathrm{WTM}}\left(w_i \middle| d_j\right) &= \frac{1}{|d_j|} \sum_{j'=1}^{|d_j|} \sum_{k=1}^{K} P(w_i|T_k) P\left(T_k \middle| \widetilde{w}_{j'}\right) \\
&= \sum_{k=1}^{K} P(w_i|T_k) \sum_{j'=1}^{|d_j|} \frac{P\left(T_k \middle| \widetilde{w}_{j'}\right)}{|d_j|} \\
&= \sum_{k=1}^{K} P(w_i|T_k) \hat{P}\left(T_k \middle| d_j\right)
\end{aligned}
$$

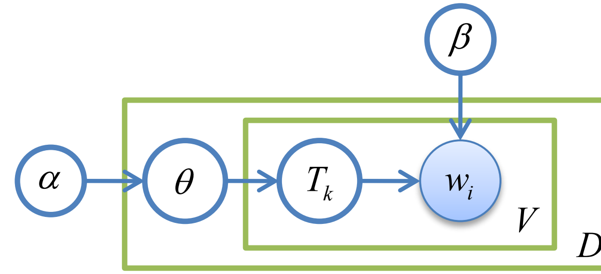
From PLSA to Latent Dirichelet Allocation

- In traditional topic models, there are several problems:
  - The model parameters grow linearly with the size of the corpus
    - EM is time-consuming
  - It is not clear how to assign probability to a document outside of the training set
    - Fold-in is a compromising strategy
    - Retrain the model is time-consuming





PLSA & LDA – 1



- PLSA
  - PLSA assumes that the model parameters are fixed and unknown

$$\mathcal{L} = \prod_{w_i \in V} \prod_{d_j \in \mathbf{D}} P(w_i, d_j)^{c(w_i, d_j)} = \prod_{d_j \in \mathbf{D}} \prod_{i=1}^{|d_j|} P(w_i, d_j)$$

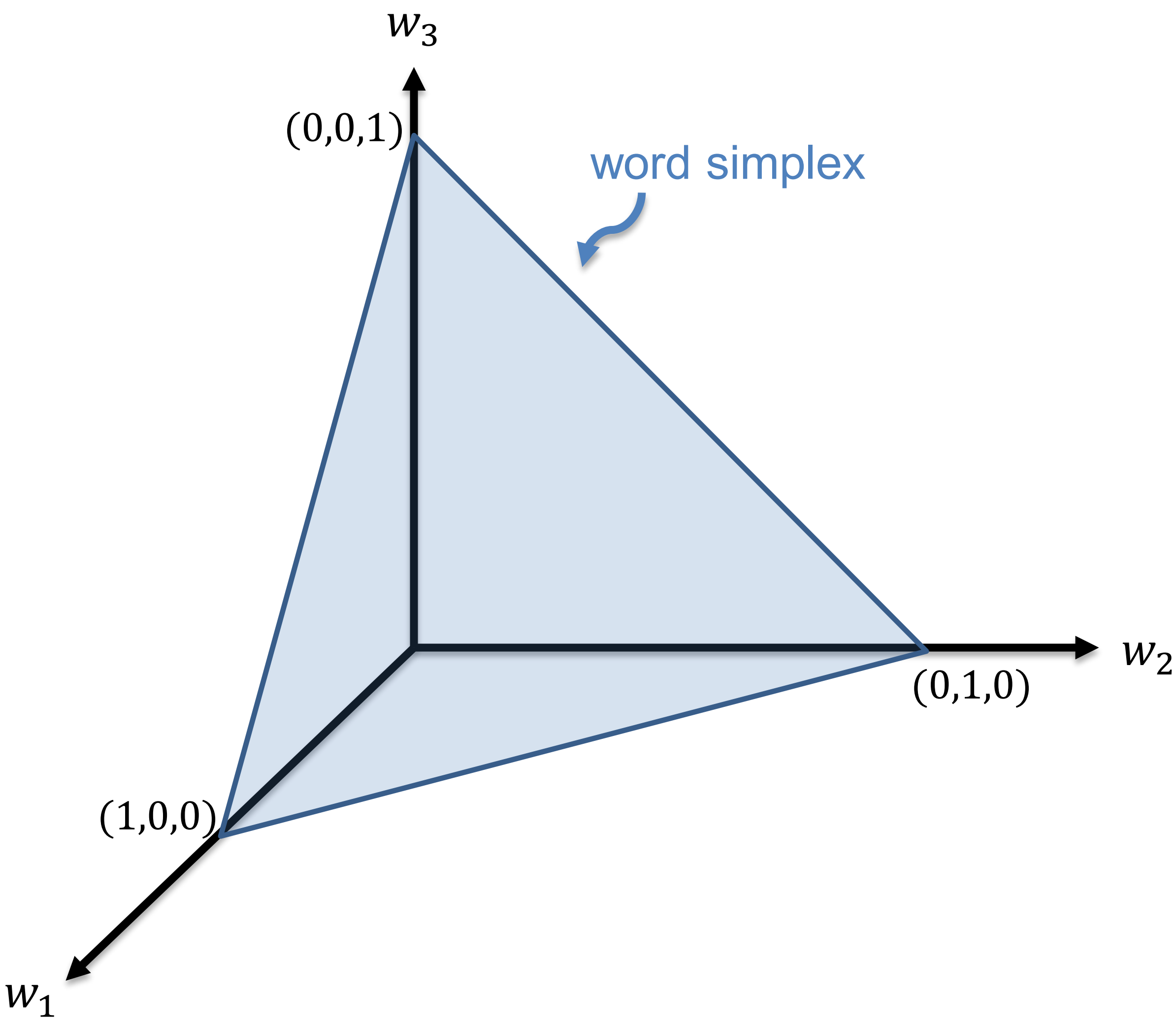
$$= \prod_{d_j \in \mathbf{D}} \prod_{i=1}^{|d_j|} \left(P(d_j) \sum_{k=1}^{K} P(w_i|T_k) P(T_k|d_j) \right)$$

- LDA
  - LDA places a priori constraints on the model parameters
    - Dirichelet distribution

$$\mathcal{L} = \prod_{d_j \in \mathbf{D}} \int P(\theta_{d_j}|\alpha) \left(\prod_{i=1}^{|d_j|} \left(\sum_{k=1}^{K} P(w_i|T_k, \beta) P\left(T_k \middle| \theta_{d_j}\right) \right) \right) d\theta_{d_j}$$

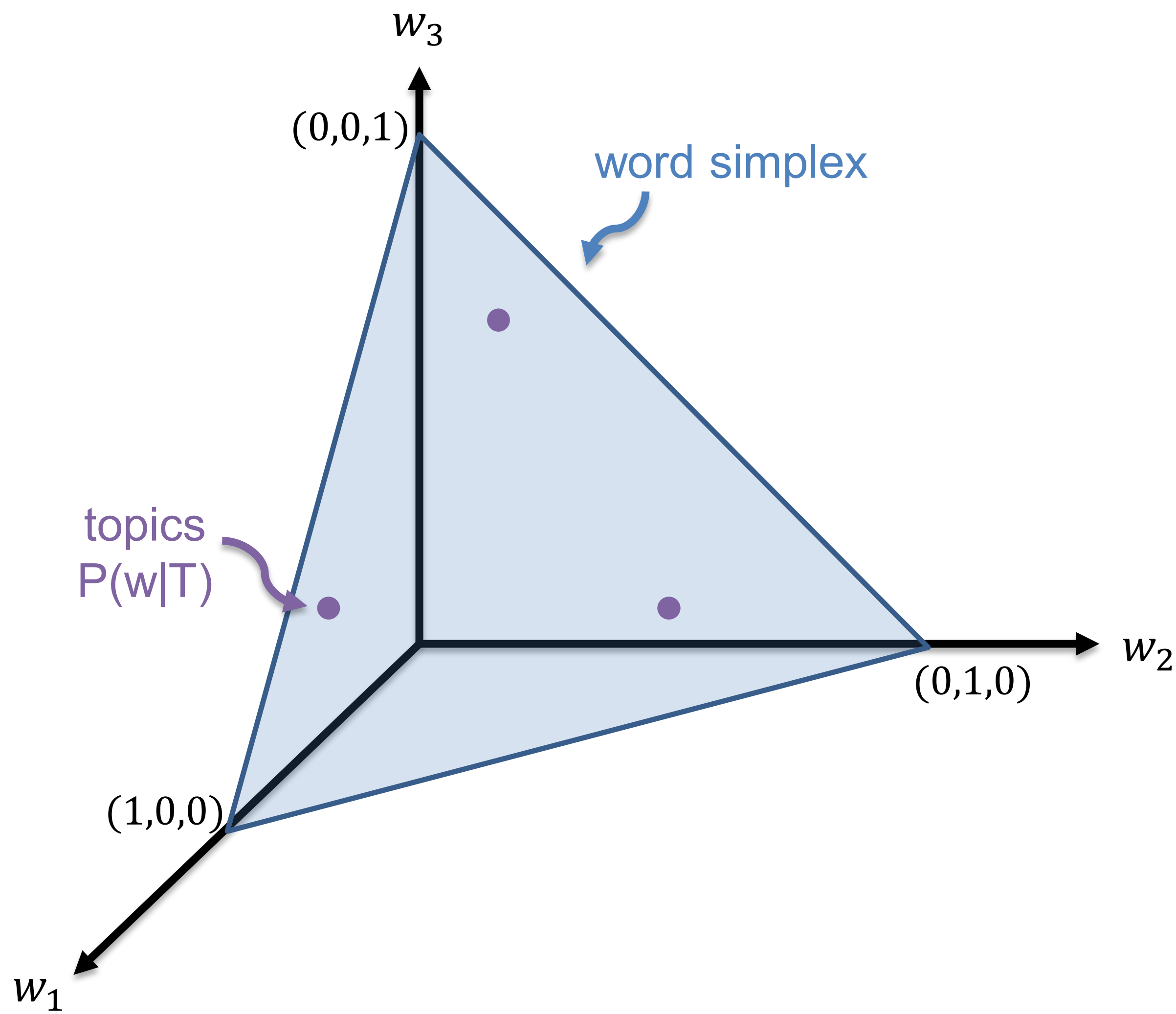
PLSA & LDA – 2

- The topic simplex for three topics embedded in the word simplex for three words



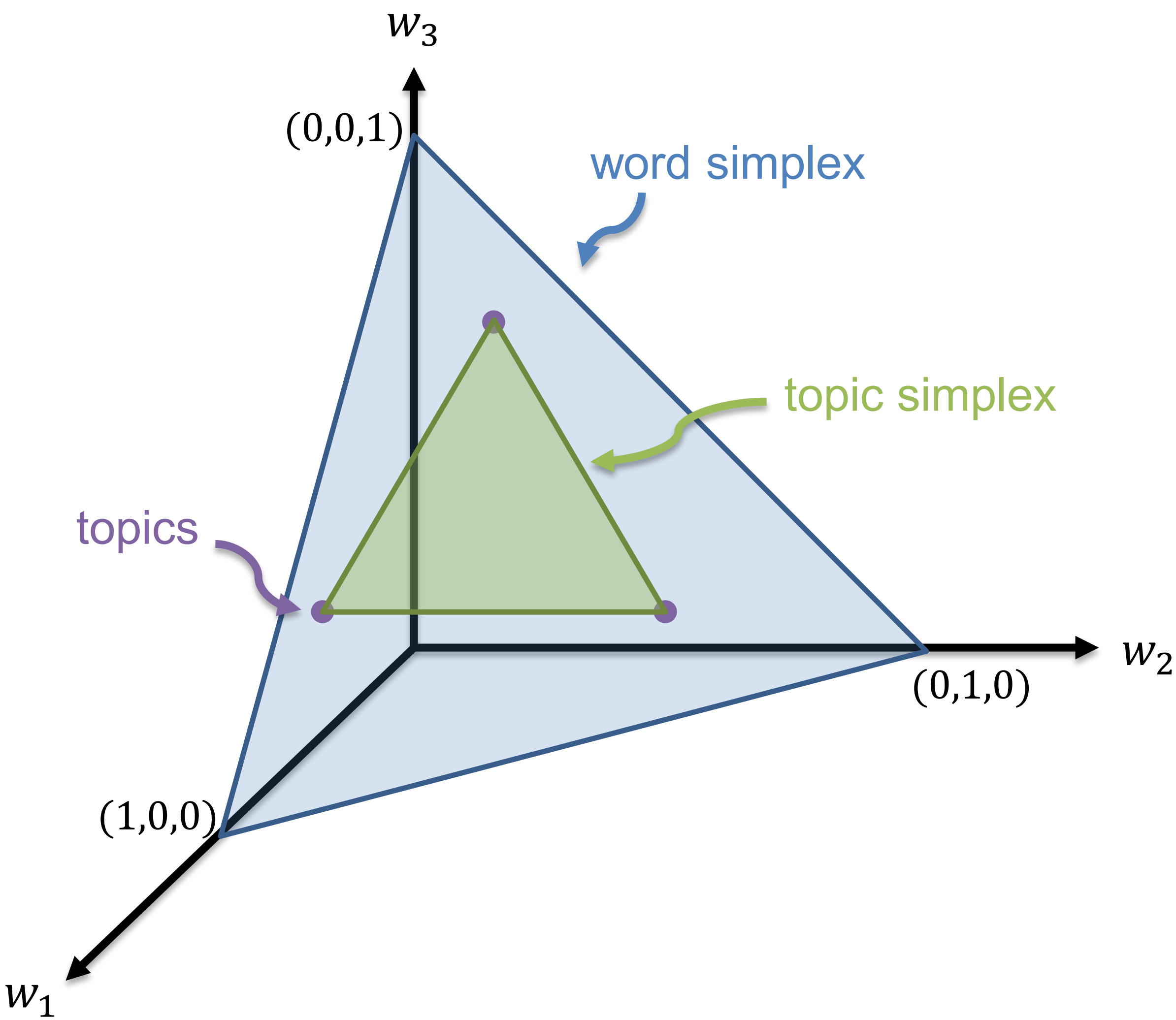
PLSA & LDA – 3

- The topic simplex for three topics embedded in the word simplex for three words



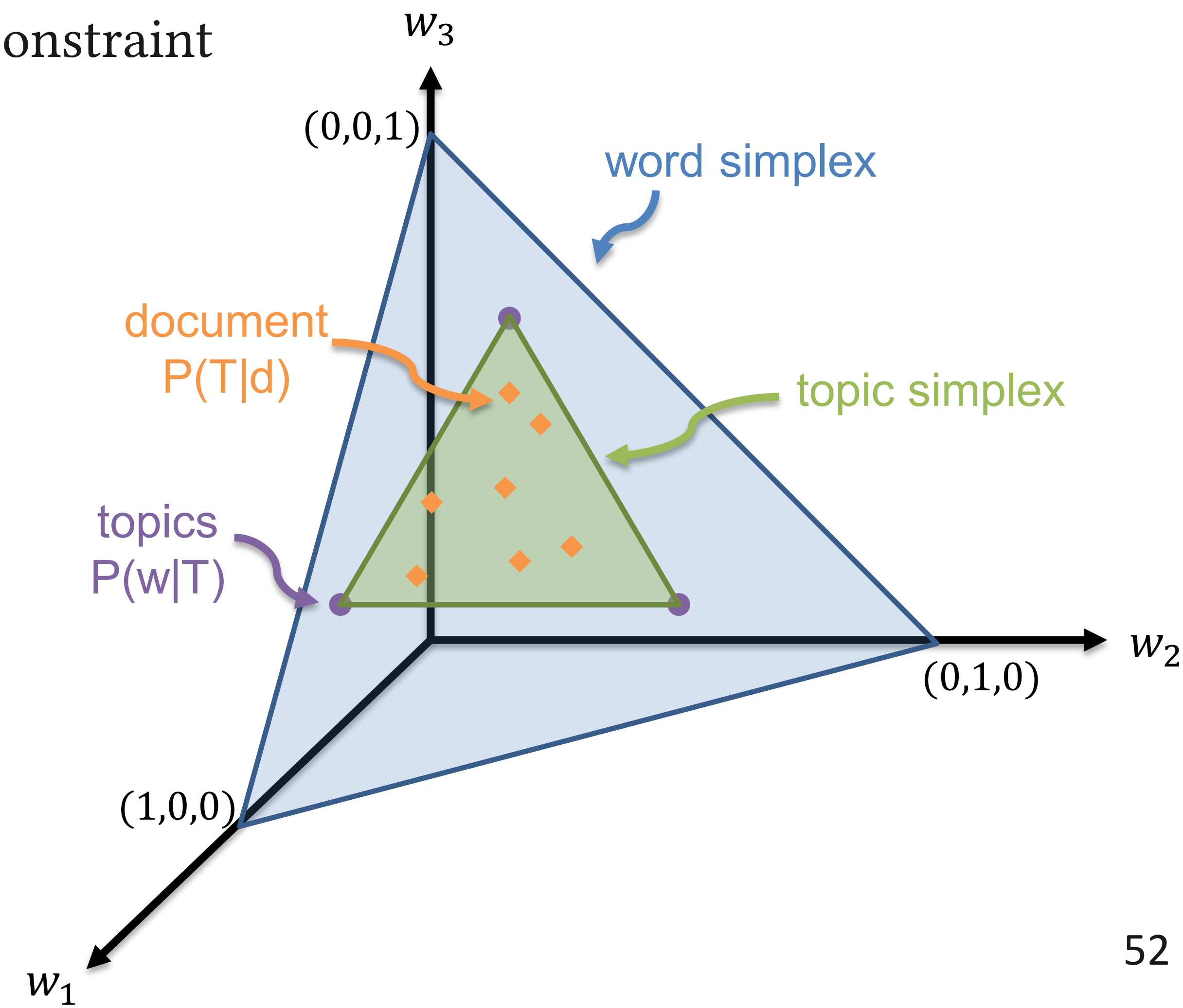
PLSA & LDA – 4

- The topic simplex for three topics embedded in the word simplex for three words



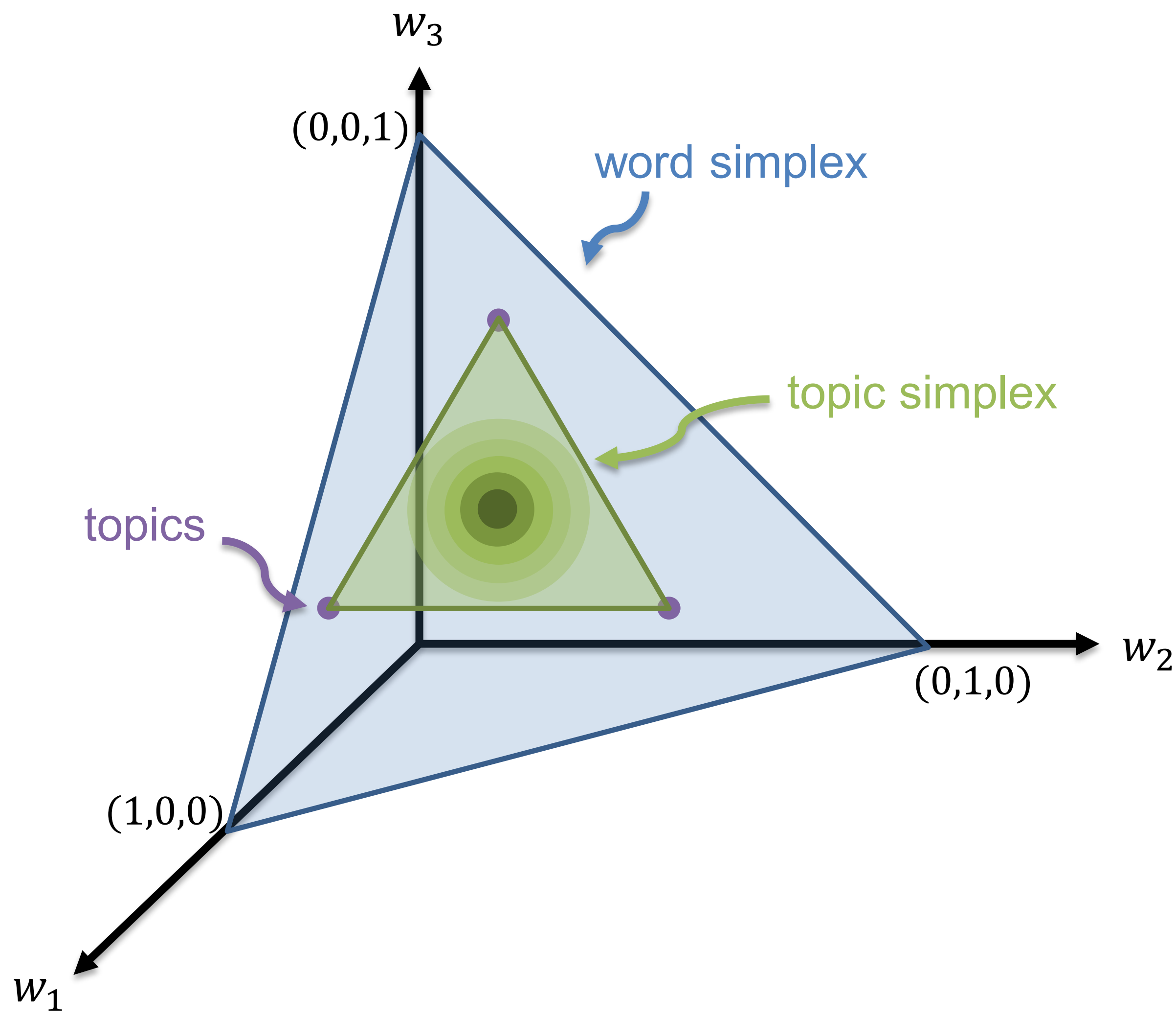
PLSA & LDA – 5

- The topic simplex for three topics embedded in the word simplex for three words
  - PLSA: no prior constraint



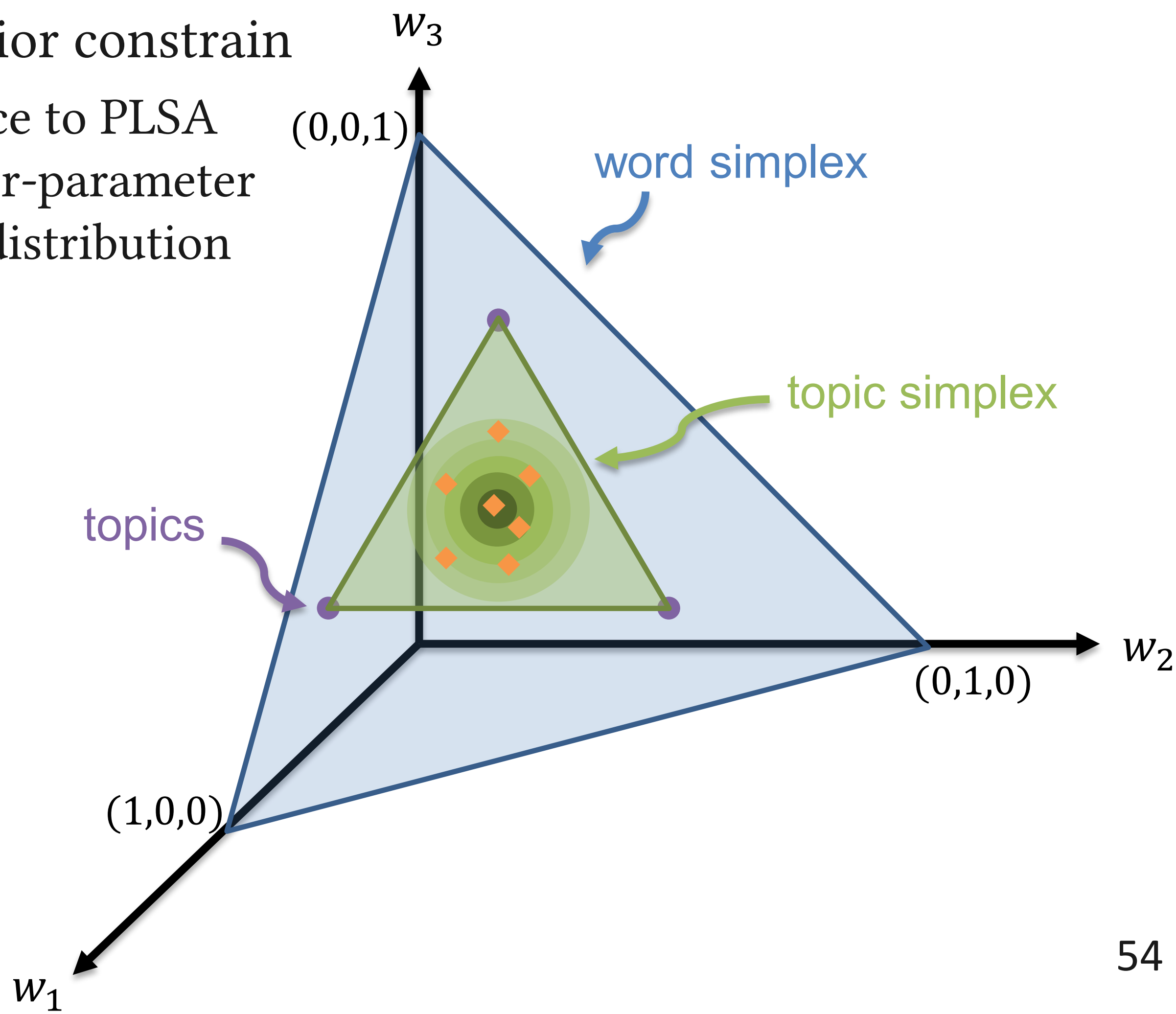
PLSA & LDA – 6

- The topic simplex for three topics embedded in the word simplex for three words

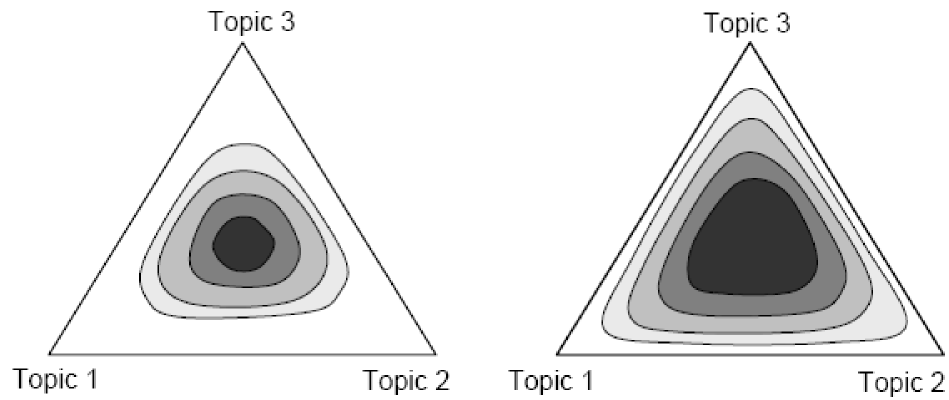


PLSA & LDA – 7

- The topic simplex for three topics embedded in the word simplex for three words
  - LDA: follow a prior constrain
    - LDA will reduce to PLSA when the hyper-parameter for Dirichelet distribution sets to 1



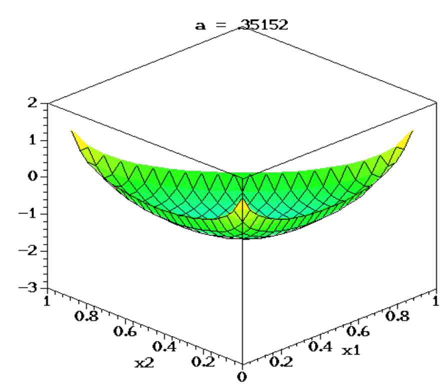
PLSA & LDA – 8



$\alpha = 4.0$ $\alpha = 2.0$

- Dirichlet priors on the topic distributions can be interpreted as forces on the topic combinations with higher α moving the topics away from the corners of the simplex, leading to more smoothing

$$P(\boldsymbol{\theta}|\boldsymbol{\alpha}) = \frac{1}{B(\boldsymbol{\alpha})}\prod_{k=1}^{K}\theta_k^{\alpha_k - 1} = \frac{\Gamma(\sum_{k=1}^{K}\alpha_k)}{\prod_{k=1}^{K}\Gamma(\alpha_k)}\prod_{k=1}^{K}\theta_k^{\alpha_k - 1}$$



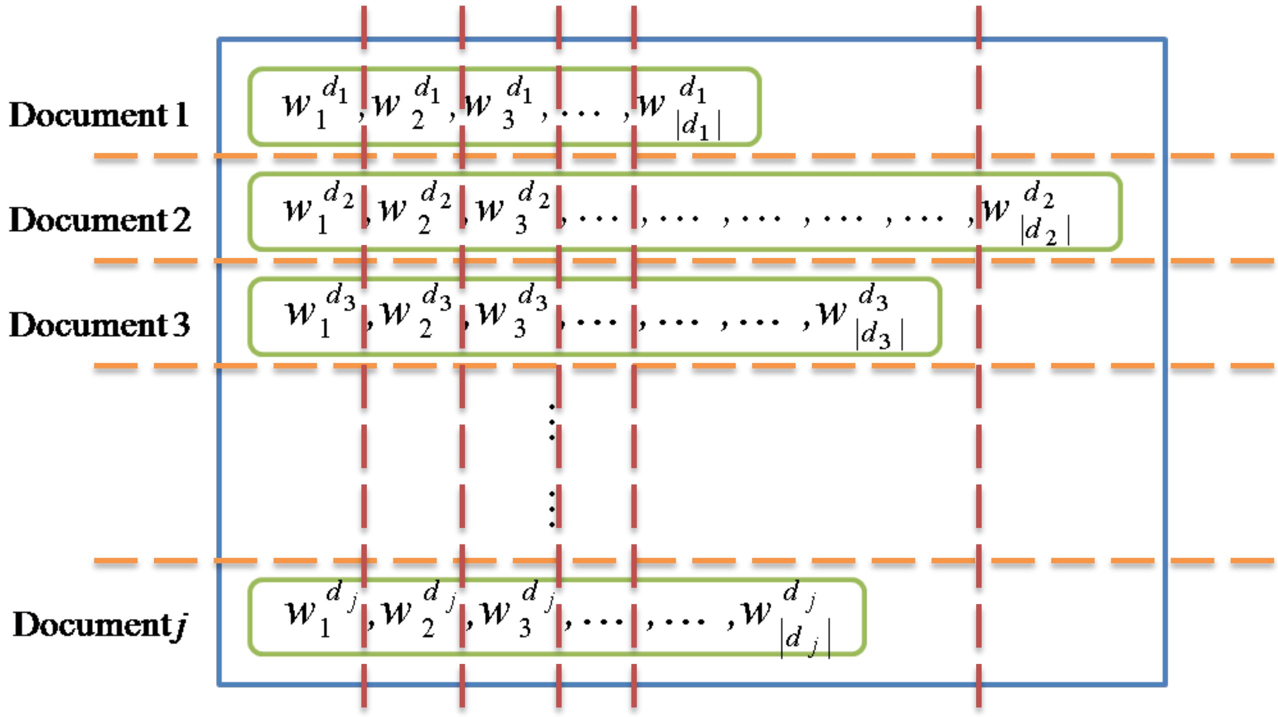
LDA – Experiments

- QL: query likelihood measure
- CBDM: cluster-based model (simplified variant of PLSA)
- LBDM: LDA model

Collection	QL	CBDM	LBDM	%chg over QL	%chg over CBDM
AP	0.2179	0.2326	0.2651	+21.64*	+13.97*
FT	0.2589	0.2713	0.2807	+7.54*	+3.46*
SJMN	0.2032	0.2171	0.2307	+13.57*	+6.26*
LA	0.2468	0.2590	0.2666	+8.02[2]	+2.93
WSJ	0.2958	0.2984	0.3253	+9.97*	+9.01*

PLSA, LDA and WTM – 1

- PLSA, LDA and WTM can be analyzed from several perspectives
  - Explore the latent information from different points of view
    - “between words and documents” vs. “between words”



PLSA, LDA and WTM – 2

- Use different methods when calculating the topic mixture weights
  - "time-consuming" vs. "simple combination"

- Model parameters

Model	PLSA	LDA	WTM
Relationships	doc-word	doc-word	word-word
No. of parameters	$\lvert V \rvert \times K + \lvert \mathbf{D} \rvert \times K$	$K + \lvert V \rvert \times K$	$2 \times \lvert V \rvert \times K$

Homework 3 – Description

- In this project, you will have
  - 16 Short Queries
  - 2265 Documents
  - A Background Language Model (BGLM.txt)
  - A Set of Documents for Topic Model Training (Collection.txt)

- Our goal is to implement the PLSA model, and incorporate the PLSA and query likelihood measure for retrieval
  - Thus, the ultimate goal is to enhance the estimation of each document language model

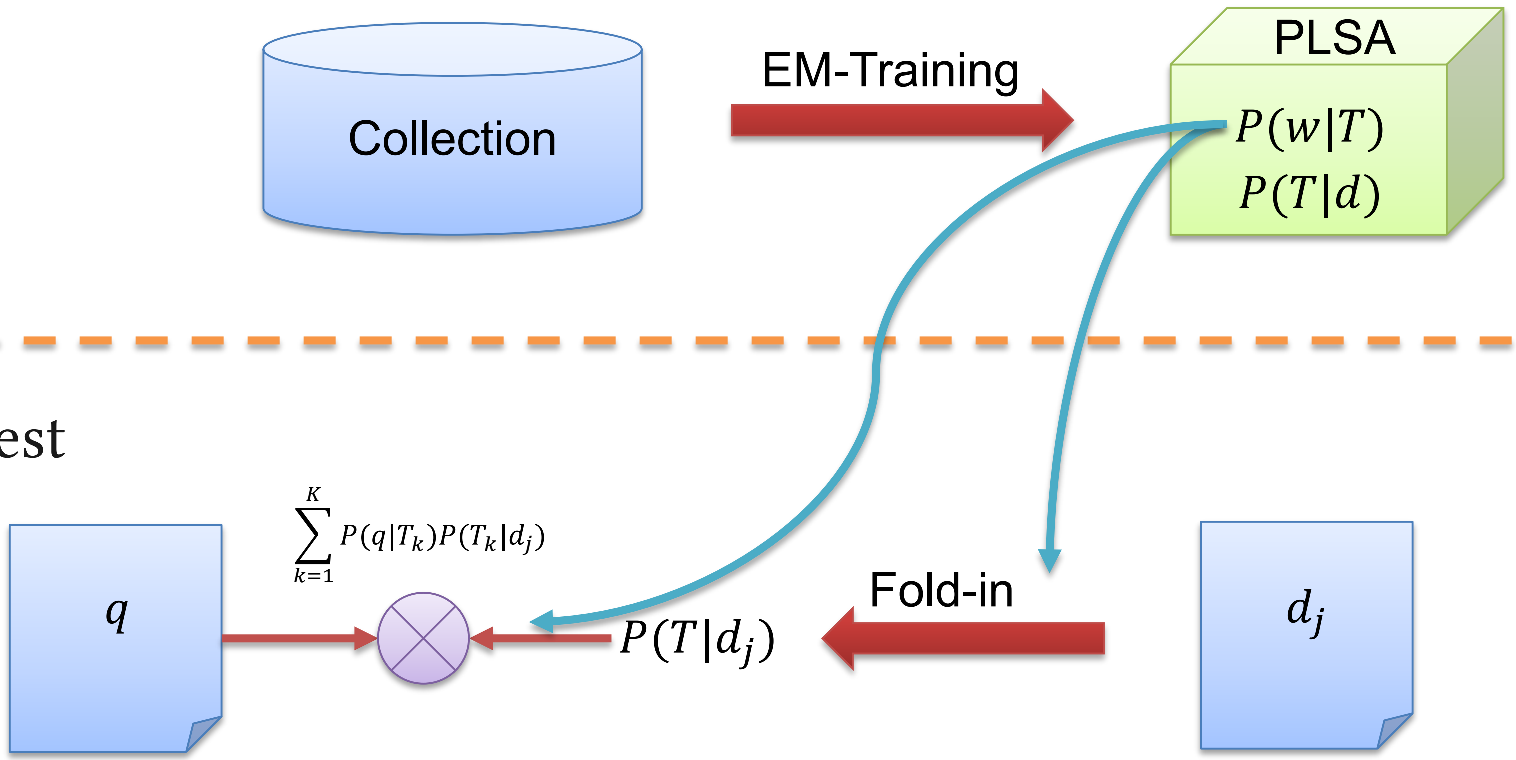
$$P(q|d_j) \approx \prod_{i=1}^{|q|} P'(w_i|d_j)$$

Obtained by using fold-in strategy

$$P'(w_i|d_j) = \alpha \cdot P(w_i|d_j) + \beta \cdot \sum_{k=1}^{K} P(w_i|T_k)P(T_k|d_j) + (1-\alpha-\beta) \cdot P(w_i|BG)$$

Homework 3 – Flowchart

- Training



- Test

Homework 3 – BGLM

- The vocabulary size is 51253
  - The word id starts from 0 to 51252

BGLM.txt - 記事本

檔案(F) 編輯(E) 格式(O) 檢視(V) 說明(H)

word id	$lnP(w_i)$
51215	-22.42474748728176700000
51216	-22.42474748728176700000
51217	-22.42474748728176700000
51218	-22.42474748728176700000
51219	-22.42474748728176700000
51220	-22.42474748728176700000
51221	-22.42474748728176700000
51222	-22.42474748728176700000
51223	-15.53506750127963300000
51224	-22.42474748728176700000
51225	-22.42474748728176700000
51226	-22.42474748728176700000
51227	-22.42474748728176700000
51228	-22.42474748728176700000
51229	-22.42474748728176700000
51230	-10.73104836924566800000
51231	-22.42474748728176700000
51232	-13.13717380611637800000
51233	-22.42474748728176700000
51234	-22.42474748728176700000
51235	-22.42474748728176700000
51236	-22.42474748728176700000
51237	-22.42474748728176700000
51238	-22.42474748728176700000
51239	-22.42474748728176700000
51240	-22.42474748728176700000
51241	-22.42474748728176700000
51242	-22.42474748728176700000
51243	-22.42474748728176700000
51244	-22.42474748728176700000
51245	-22.42474748728176700000
51246	-22.42474748728176700000
51247	-22.42474748728176700000
51248	-14.84192031073563500000
51249	-22.42474748728176700000
51250	-22.42474748728176700000
51251	-15.53506750127963300000
51252	-22.42474748728176700000

Homework 3 – Collection

- In the collection file, each line refers to a document
  - Thus, we have about 18 thousand documents

Collection.txt

```
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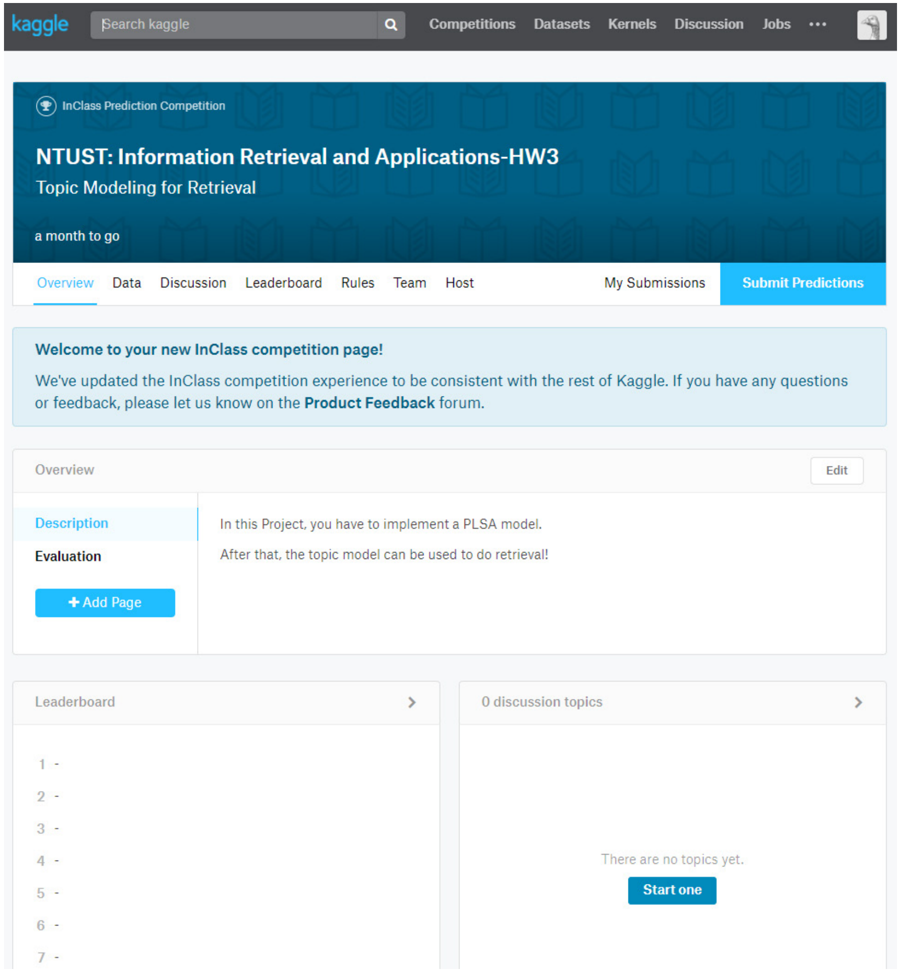
Homework 3 – Kaggle

- Please login our competition page at Kaggle
  - https://www.kaggle.com/t/3a0b466580294899a666e4c088be1074
- **Your team name is ID_Name**
  - M123456_陳冠宇



Homework 3 – Submission Format

submission.txt

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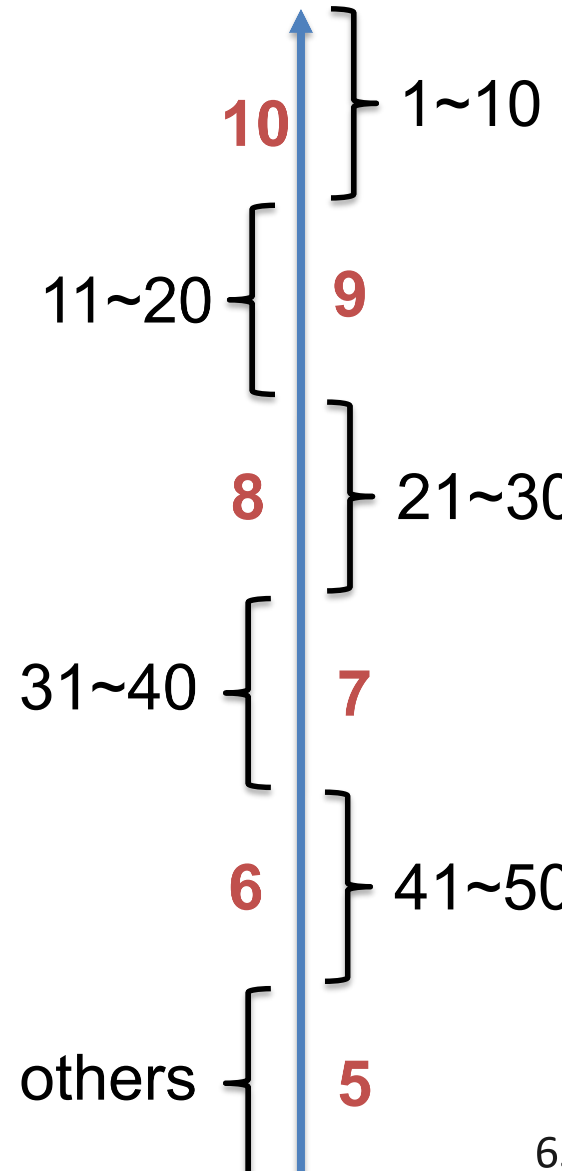
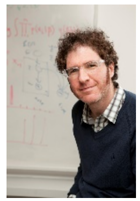
Homework 3 – Scoring

- The evaluation measure is MAP
- You can upload **ten** results each day
  - Turning the parameters
  - Please **Do Not** register several teams
- The **hard** deadline is 11/9 11:00
- You should also upload source codes and a mini report to moodle
  - TA will ask you to demo your program
  - In this HW, you can only leverage PLSA to do retrieval
  - If you use other models, you will get 0



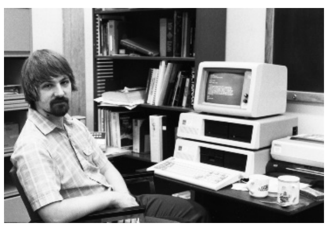
The Evolution

David M. Blei
Columbia University, USA



Thomas Hofmann
ETH Zurich, Switzerland

Scott Deerwester



2003 Latent Dirichlet Allocation

1999 Probabilistic Latent Semantic Analysis

1998 Language Modeling Approaches

1994 Best Match Models (Okapi Systems)

1988 Latent Semantic Analysis

1976 Probabilistic Model

1975 Vector Space Model

1973 Boolean Model

1972 Inverse Document Frequency

1957 Term Frequency

Questions?

kychen@mail.ntust.edu.tw