Probabilistic Topic Models: Mixture of Unigram Language Models

ChengXiang "Cheng" Zhai
Department of Computer Science
University of Illinois at Urbana-Champaign

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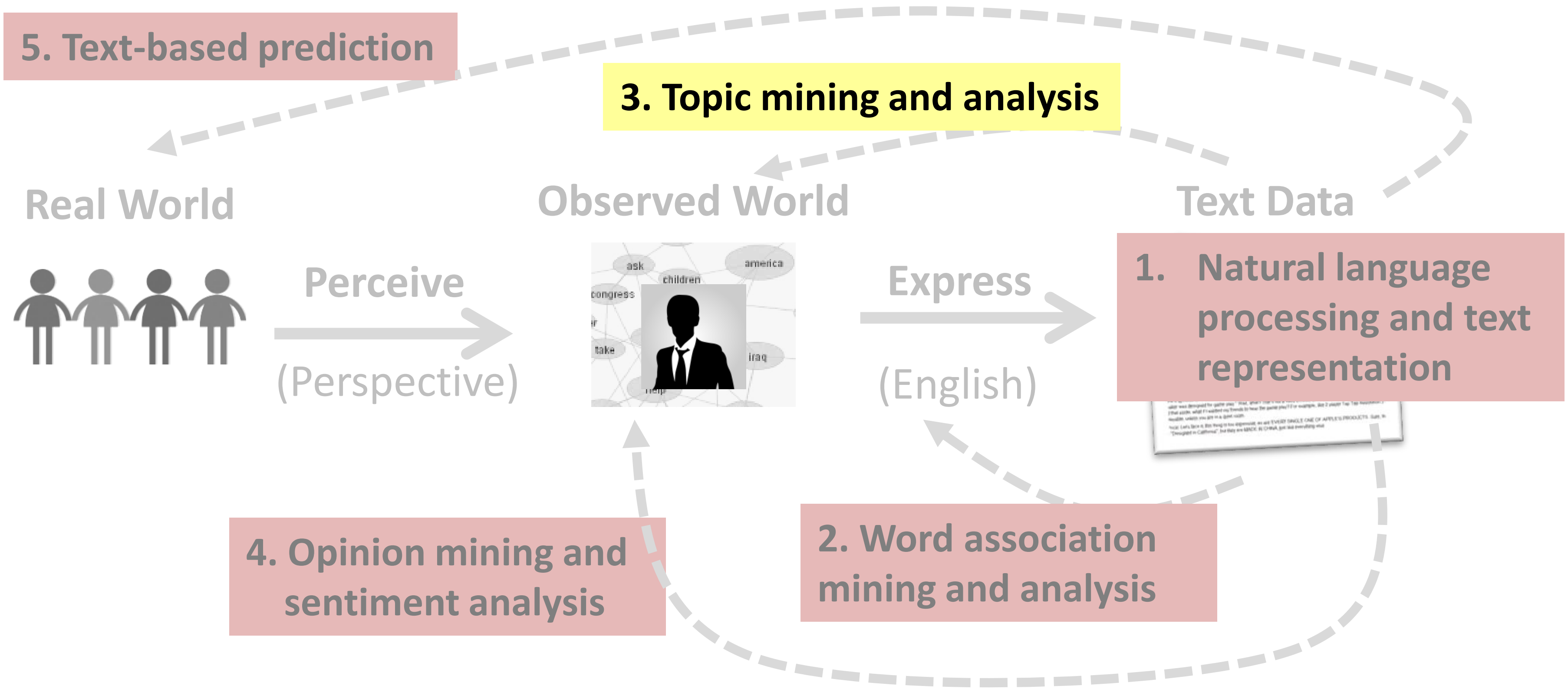


Factoring out Background Words

d

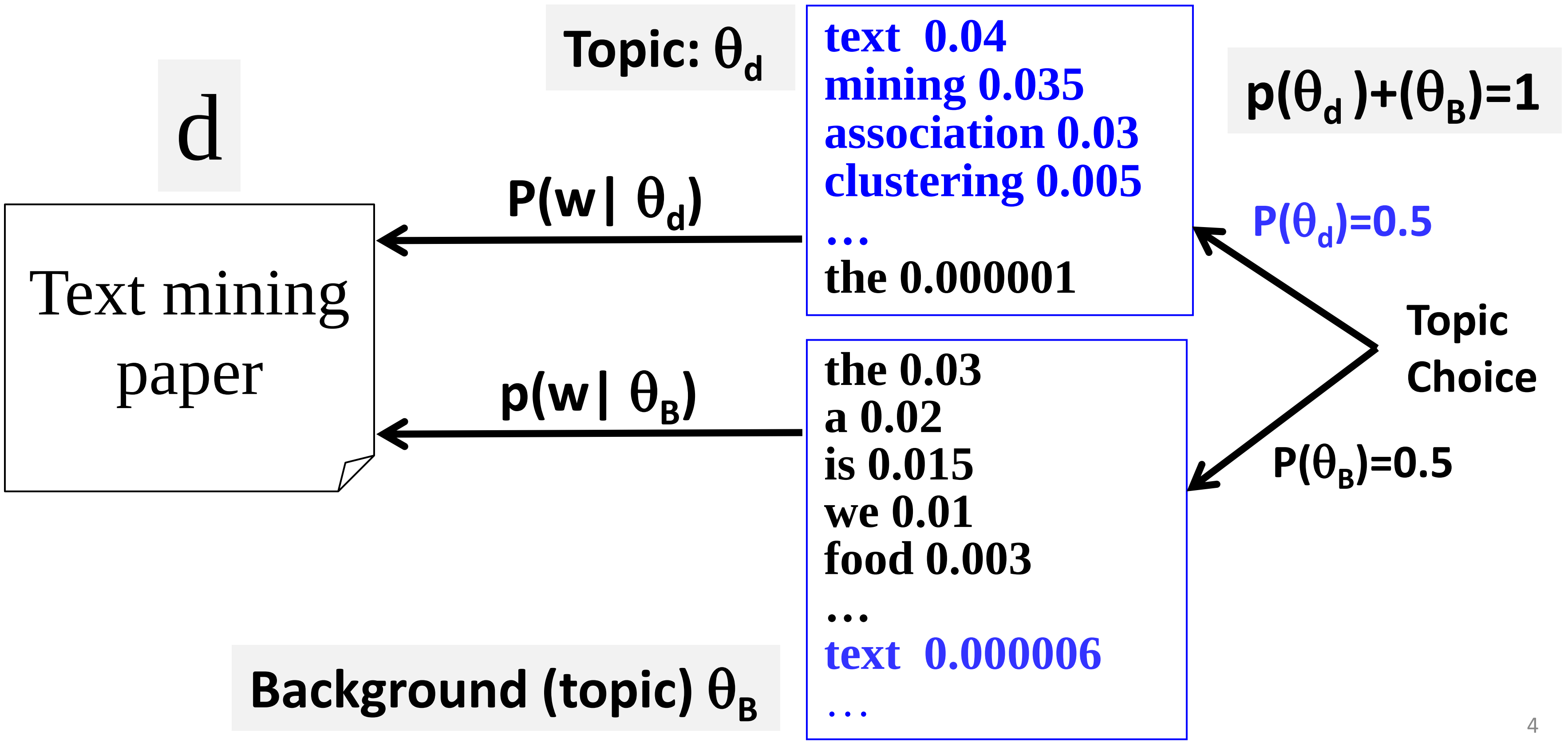
Text mining paper

p(w| θ)

the 0.031
a 0.018
…
text 0.04
mining 0.035
association 0.03
clustering 0.005
computer 0.0009
…
food 0.000001
…

How can we get rid of these common words?

Generate d Using Two Word Distributions



What's the probability of observing a word w?

Topic: θ_d

text 0.04
mining 0.035

$p(\theta_d)+(\theta_B)=1$

d

P("the")=$p(\theta_d)p(\text{"the"}|\theta_d) + p(\theta_B)p(\text{"the"}|\theta_B)$
= 0.5*0.000001+0.5*0.03

=0.5

"the"?

the 0.000001

Topic
hoice

"text"?

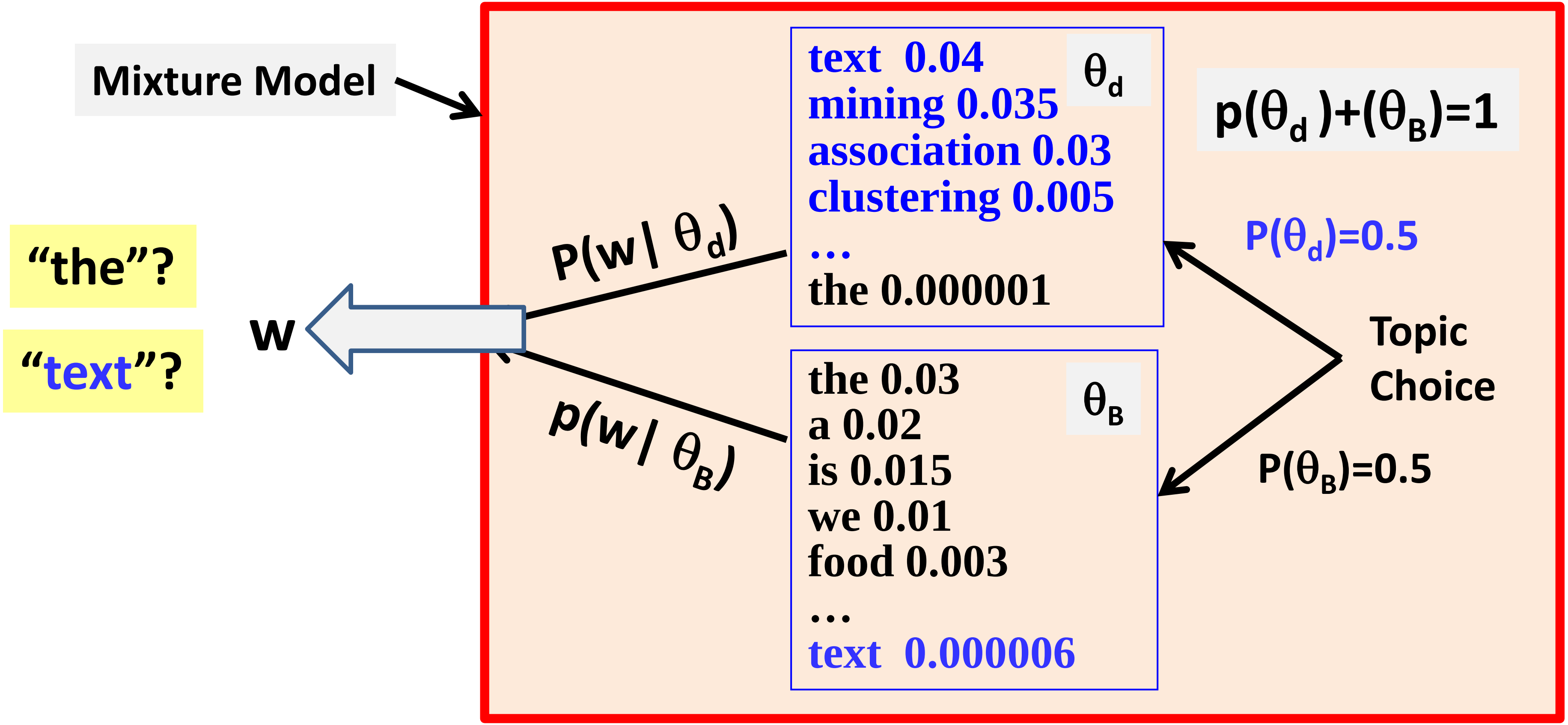
P("text")=$p(\theta_d)p(\text{"text"}|\theta_d) + p(\theta_B)p(\text{"text"}|\theta_B)$
= 0.5*0.04+0.5*0.000006

.5

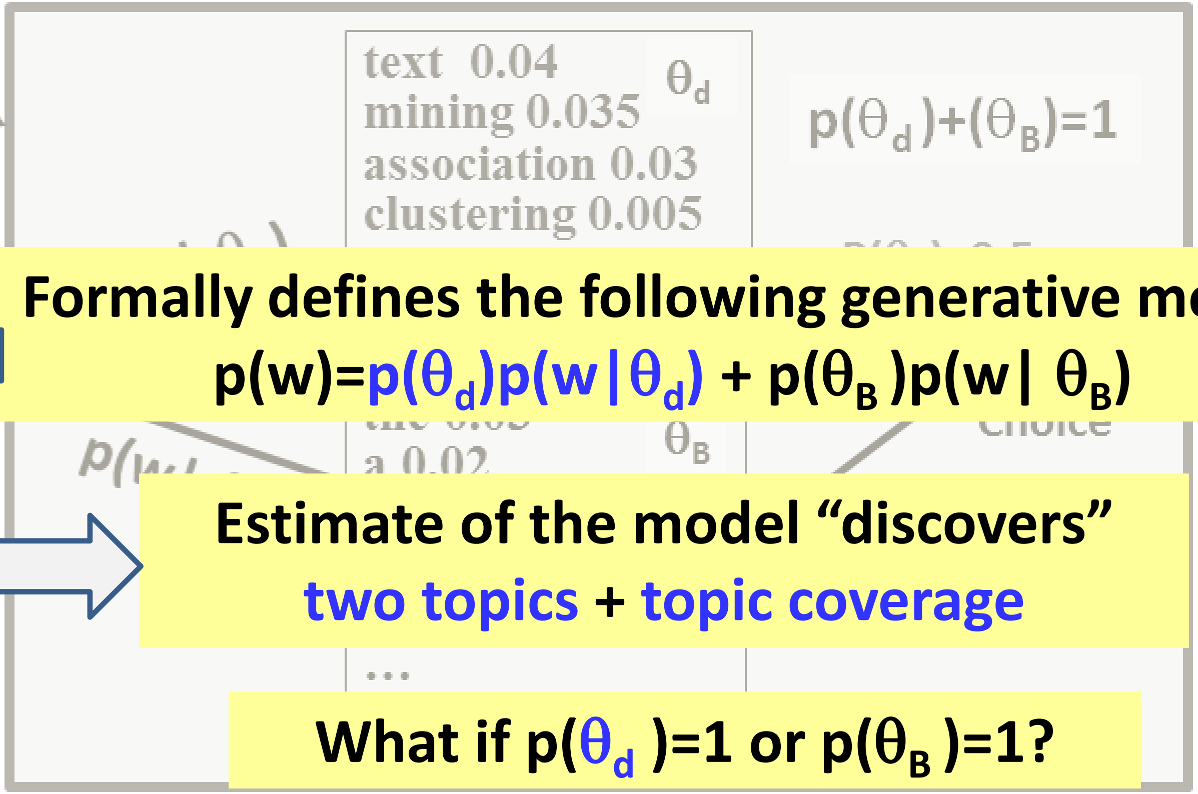
we 0.01
food 0.003
…
text 0.000006
…

Background (topic) θ_B

The Idea of a Mixture Model



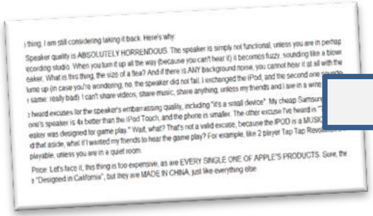
As a Generative Model…



w

Formally defines the following generative model:

$$p(w)=p(\theta_d)p(w|\theta_d) + p(\theta_B)p(w|\theta_B)$$



Estimate of the model "discovers"

two topics + topic coverage

What if $p(\theta_d)=1$ or $p(\theta_B)=1$?

Mixture of Two Unigram Language Models

- **Data**: Document d
- Mixture **Model**: **parameters** $\Lambda=(\{p(w|\theta_d)\}, \{p(w|\theta_B)\}, p(\theta_B), p(\theta_d))$
  - Two unigram LMs: θ_d **(the topic of d);** θ_B **(background topic)**
  - Mixing weight (topic choice): $\mathbf{p(\theta_d)+p(\theta_B)=1}$
- **Likelihood** function:

$$p(d|\Lambda)=\prod_{i=1}^{|d|}p(x_i|\Lambda)=\prod_{i=1}^{|d|}[p(\theta_d)p(x_i|\theta_d)+p(\theta_B)p(x_i|\theta_B)]$$

$$=\prod_{i=1}^{M}[p(\theta_d)p(w_i|\theta_d)+p(\theta_B)p(w_i|\theta_B)]^{c(w,d)}$$

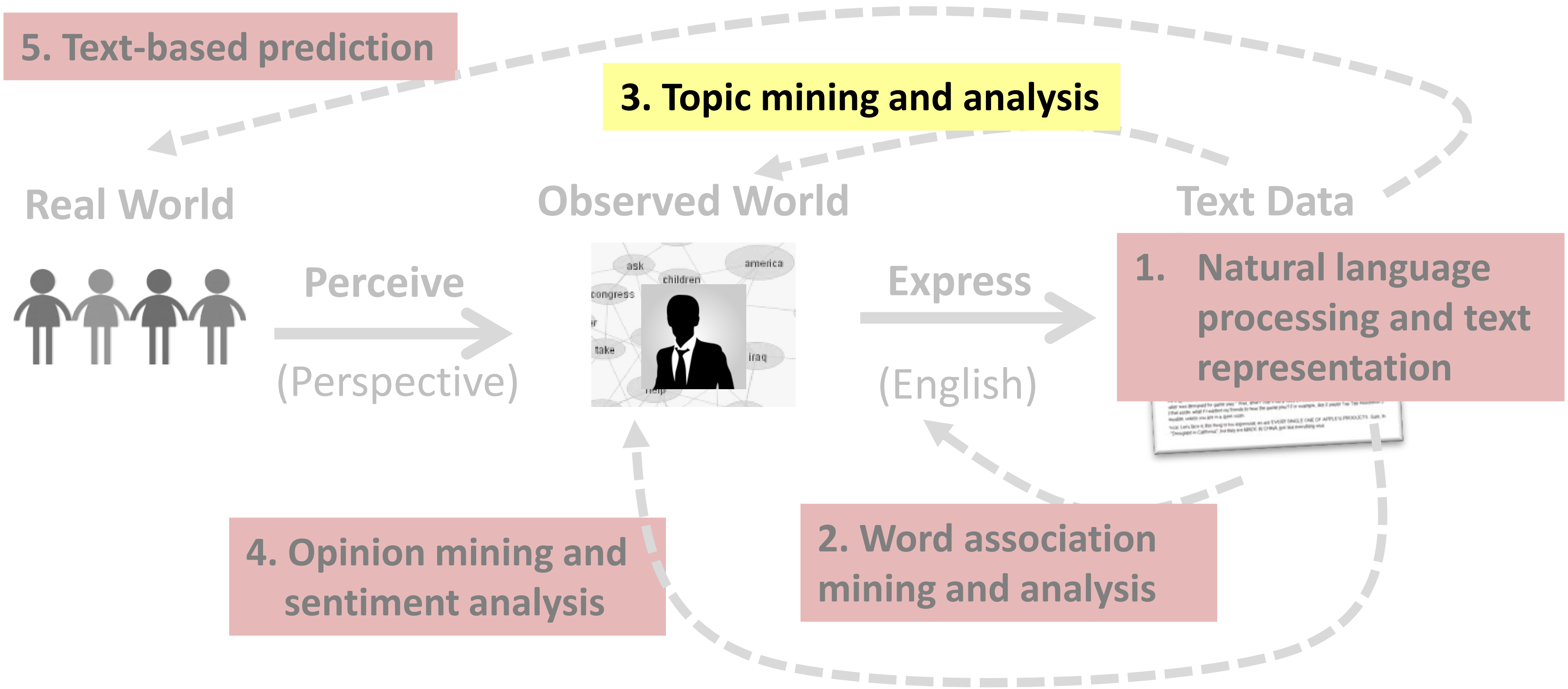
- ML **Estimate:** $\Lambda^*=\arg\max_{\Lambda} p(d|\Lambda)$

Subject to $\sum_{i=1}^{M}p(w_i|\theta_d)=\sum_{i=1}^{M}p(w_i|\theta_B)=1 \qquad p(\theta_d)+p(\theta_B)=1$

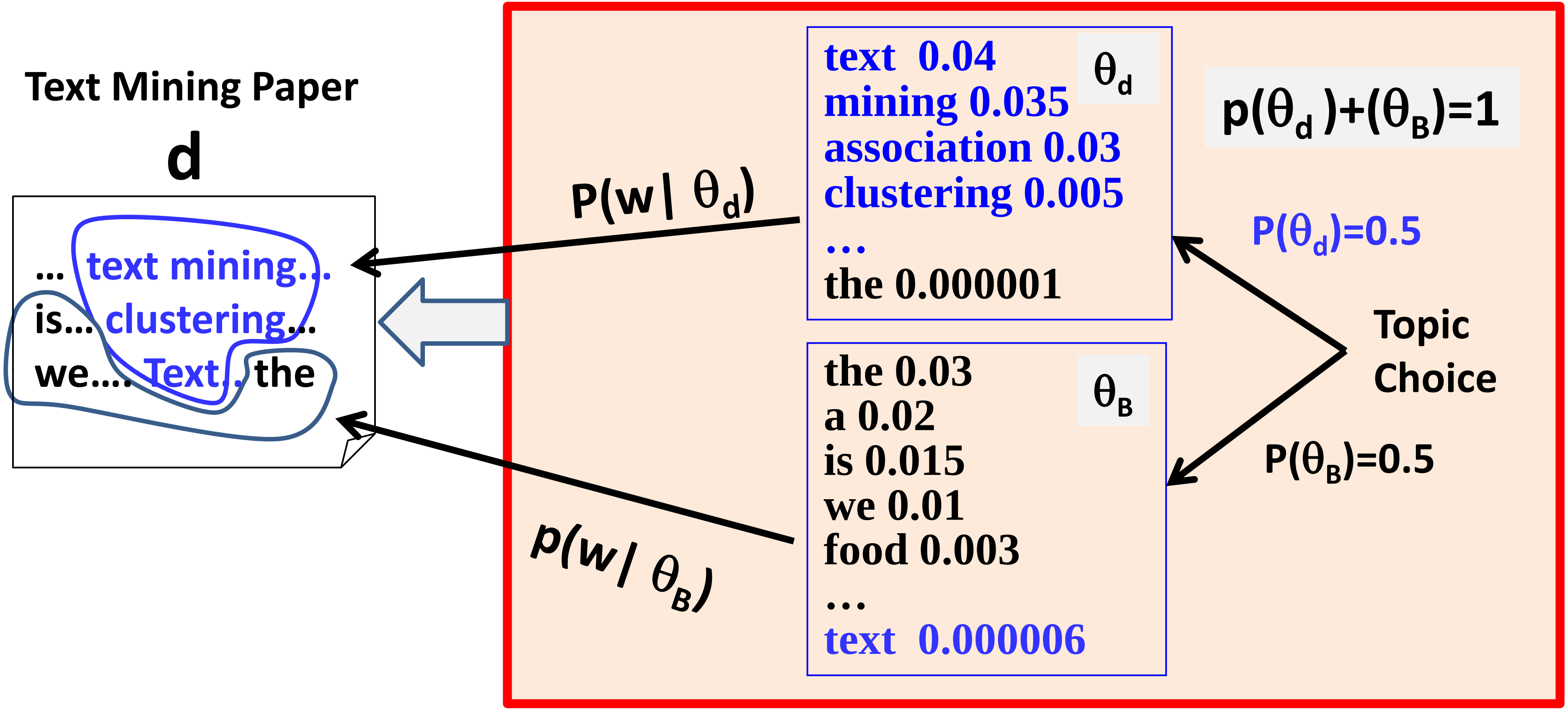
Probabilistic Topic Models: Mixture Model Estimation

ChengXiang "Cheng" Zhai
Department of Computer Science
University of Illinois at Urbana-Champaign

Probabilistic Topic Models: Mixture Model Estimation



Back to Factoring out Background Words



Estimation of One Topic: $P(w|\theta_d)$

Adjust θ_d to maximize $p(d|\Lambda)$
(all other parameters are known)

Would the ML estimate <u>demote</u> background words in θ_d ?

d

… text mining…
is… clustering…
we…. Text.. the

θ_d

text ?
mining ?
association ?
clustering ?
…
the ?

θ_B

the 0.03
a 0.02
is 0.015
we 0.01
food 0.003
…
text 0.000006

$p(\theta_d)+(\theta_B)=1$

$P(\theta_d)=0.5$

Topic Choice

$P(\theta_B)=0.5$

Behavior of a Mixture Model

d = text the

Likelihood:

$$P(\text{“text”}) = p(\theta_d)p(\text{“text”}|\theta_d) + p(\theta_B)p(\text{“text”}|\theta_B)$$
$$= 0.5*p(\text{“text”}|\theta_d) + 0.5*0.1$$

$$P(\text{“the”}) = 0.5*p(\text{“the”}|\theta_d) + 0.5*0.9$$

$$p(d|\Lambda) = p(\text{“text”}|\Lambda)\, p(\text{“the”}|\Lambda)$$
$$= [0.5*p(\text{“text”}|\theta_d) + 0.5*0.1] \times$$
$$[0.5*p(\text{“the”}|\theta_d) + 0.5*0.9]$$

θ_d: text ?, the ?

$P(\theta_d)=0.5$

$P(\theta_B)=0.5$

θ_B: the 0.9, text 0.1

How can we set $p(\text{“text”}|\theta_d)$ & $p(\text{“text”}|\theta_d)$ to maximize it?

Note that $p(\text{“text”}|\theta_d) + p(\text{“the”}|\theta_d) = 1$

"Collaboration" and "Competition" of θ_d and θ_B

$p(d|\Lambda)=p(\text{"text"}|\Lambda)\, p(\text{"the"}|\Lambda)$

$= [0.5*p(\text{"text"}|\theta_d) + 0.5*0.1] \times$

$[0.5*p(\text{"the"}|\theta_d) + 0.5*0.9]$

d = text the

text ?
the ?
θ_d

$P(\theta_d)=0.5$

$P(\theta_B)=0.5$

the 0.9
text 0.1
θ_B

Note that $p(\text{"text"}|\theta_d) + p(\text{"the"}|\theta_d) = 1$

If $x + y = constant$, then xy reaches maximum when $x = y$.

$0.5*p(\text{"text"}|\theta_d) + 0.5*0.1 = 0.5*p(\text{"the"}|\theta_d) + 0.5*0.9$

→ $p(\text{"text"}|\theta_d)=0.9 \;>>\; p(\text{"the"}|\theta_d) = 0.1$!

Behavior 1: if $p(w1|\theta_B) > p(w2|\theta_B)$, then $p(w1|\theta_d) < p(w2|\theta_d)$

Response to Data Frequency

d = text the

$p(d|\Lambda) = [0.5*p(\text{"text"}|\theta_d) + 0.5*0.1]$
$\times [0.5*p(\text{"the"}|\theta_d) + 0.5*0.9]$

$\rightarrow p(\text{"text"}|\theta_d)=0.9 \quad >> \quad p(\text{"the"}|\theta_d) =0.1$!

d' = text the the the the ...the

$p(d'|\Lambda) = [0.5*p(\text{"text"}|\theta_d) + 0.5*0.1]$
$\times [0.5*p(\text{"the"}|\theta_d) + 0.5*0.9]$
$\times [0.5*p(\text{"the"}|\theta_d) + 0.5*0.9]$
$\times [0.5*p(\text{"the"}|\theta_d) + 0.5*0.9]$
...
$\times [0.5*p(\text{"the"}|\theta_d) + 0.5*0.9]$

What if we increase $p(\theta_B)$?

What's the optimal solution now? $p(\text{"the"}|\theta_d) > 0.1$? or $p(\text{"the"}|\theta_d) < 0.1$?

Behavior 2: high frequency words get higher $p(w|\theta_d)$

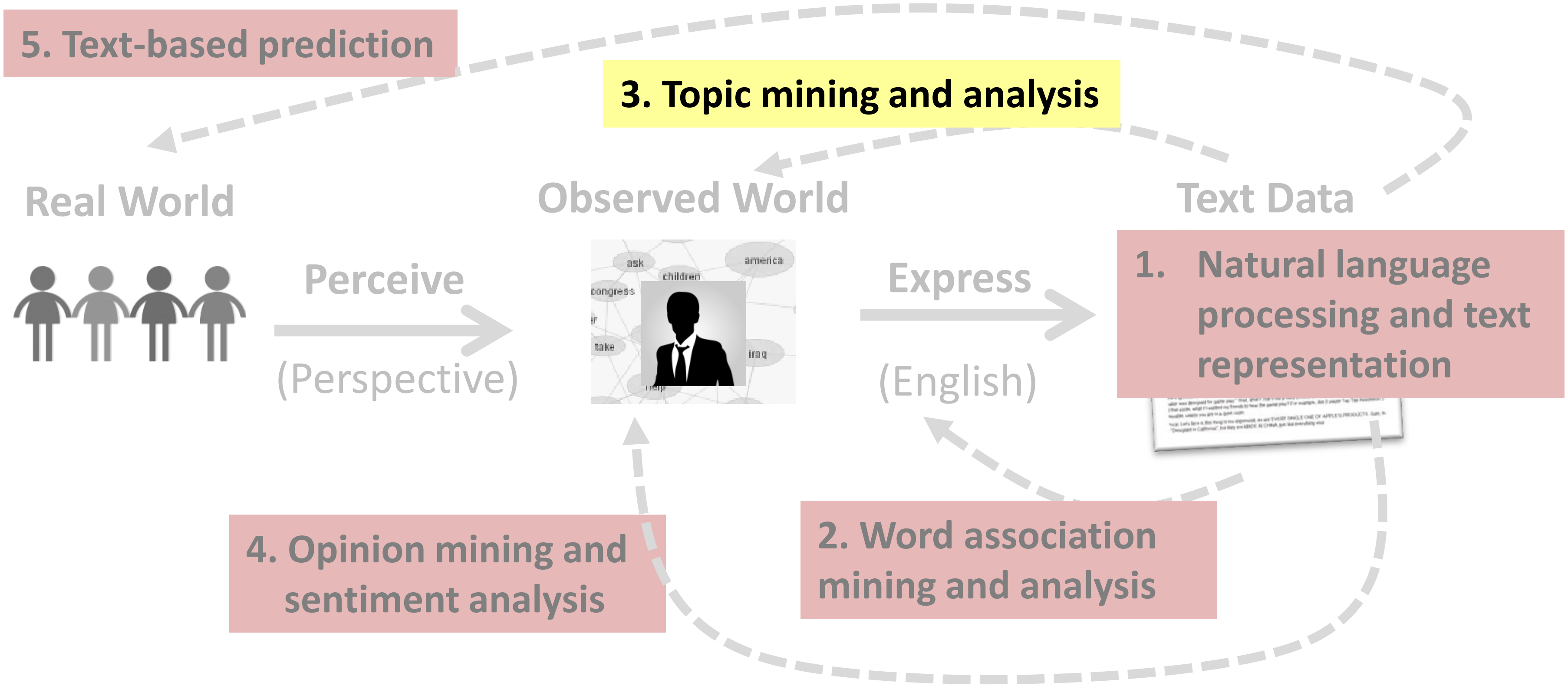
Summary

- General behavior of a mixture model:
  - Every component model attempts to assign high probabilities to highly frequent words in the data (to “collaboratively maximize likelihood”)
  - Different component models tend to “bet” high probabilities on different words (to avoid “competition” or “waste of probability”)
  - The probability of choosing each component “regulates” the collaboration/competition between the component models
- Fixing one component to a background word distribution (i.e., background language model):
  - Helps “get rid of background words” in other component
  - Is an example of imposing a prior on the model parameters (prior = one model must be exactly the same as the background LM)

Probabilistic Topic Models: Expectation-Maximization Algorithm

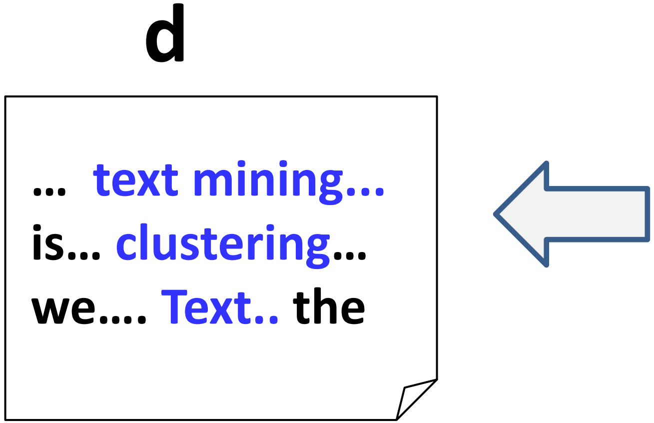
ChengXiang "Cheng" Zhai
Department of Computer Science
University of Illinois at Urbana-Champaign

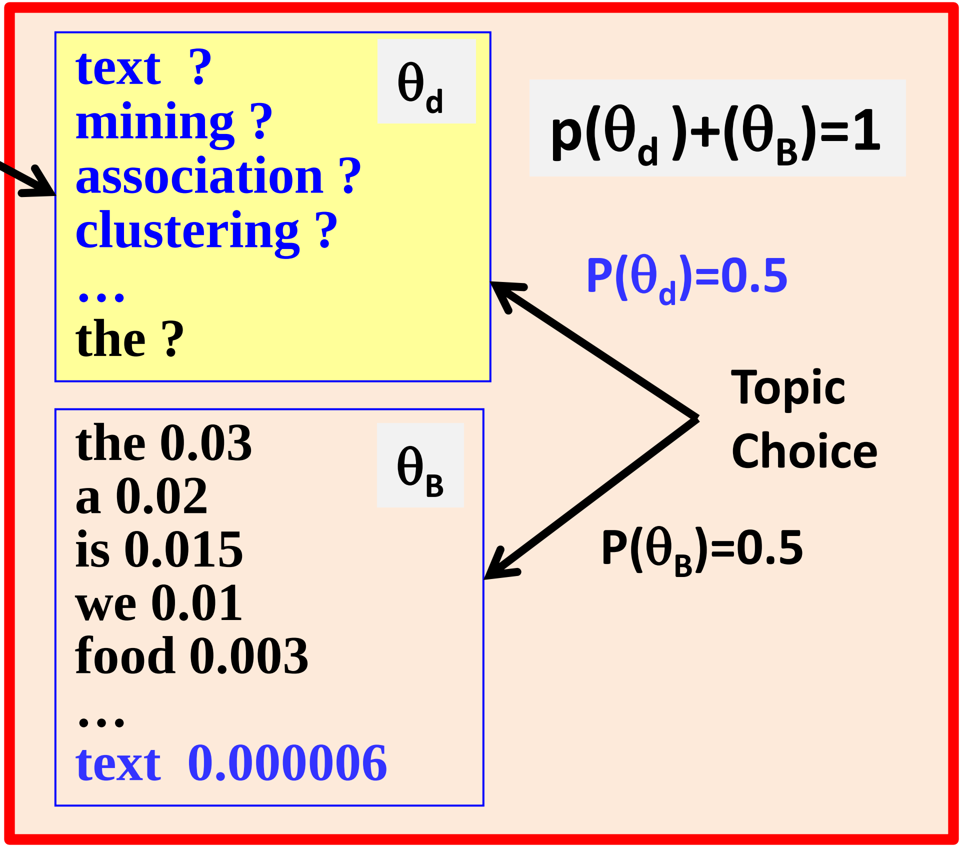
Probabilistic Topic Models: Expectation-Maximization (EM) Algorithm



Estimation of One Topic: $P(w|\theta_d)$

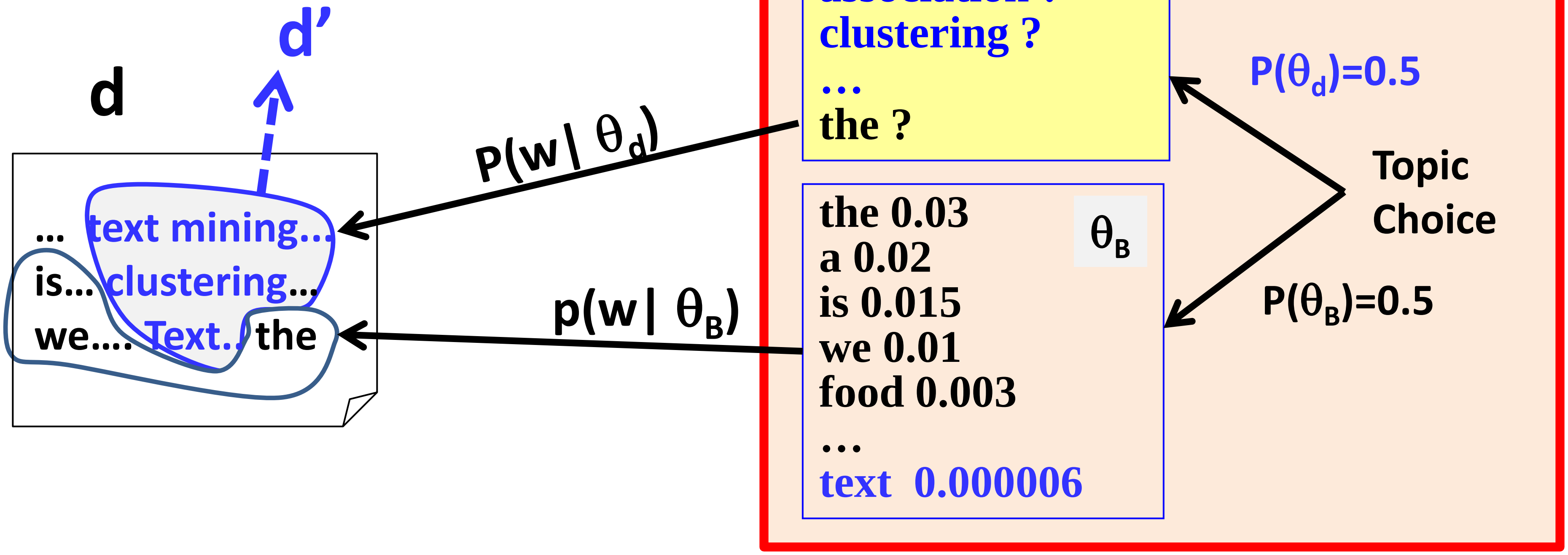
How to set θ_d to maximize $p(d|\Lambda)$?
(all other parameters are known)





If we know which word is from which distribution…

$$p(w_i \mid \theta_d) = \frac{c(w_i, d')}{\sum_{w' \in V} c(w', d')}$$



Given all the parameters, infer the distribution a word is from…

Is "text" more likely from θ_d or θ_B ?

From θ_d (Z=0)?

$p(\theta_d)p(\text{"text"}|\theta_d)$

From θ_B (Z=1)?

$p(\theta_B)p(\text{"text"}|\theta_B)$

$P(w|\ \theta_d)$

$p(w|\ \theta_B)$

θ_d

text 0.04
mining 0.035
association 0.03
clustering 0.005
…
the 0.000001

θ_B

the 0.03
a 0.02
is 0.015
we 0.01
food 0.003
…
text 0.000006

$p(\theta_d)+p(\theta_B)=1$

$P(\theta_d)=0.5$

Topic Choice

$P(\theta_B)=0.5$

$$p(z=0\,|\,w=\text{"text"}) = \frac{p(\theta_d)p(\text{"text"}|\theta_d)}{p(\theta_d)p(\text{"text"}|\theta_d)+p(\theta_B)p(\text{"text"}|\theta_B)}$$

The Expectation-Maximization (EM) Algorithm

Hidden Variable:
$z \in \{0, 1\}$

	z
the	**1**
paper	**1**
presents	**1**
a	**1**
text	**0**
mining	**0**
algorithm	**0**
for	**1**
clustering	**0**
...	**...**

Initialize p(w|θ_d) with random values.
Then iteratively improve it using E-step & M-step.
Stop when likelihood doesn't change.

$$p^{(n)}(z=0 \mid w) = \frac{p(\theta_d)p^{(n)}(w \mid \theta_d)}{p(\theta_d)p^{(n)}(w \mid \theta_d) + p(\theta_B)p(w \mid \theta_B)}$$

E-step

How likely w is from θ_d

$$p^{(n+1)}(w \mid \theta_d) = \frac{c(w,d)p^{(n)}(z=0 \mid w)}{\sum_{w' \in V} c(w',d)p^{(n)}(z=0 \mid w')}$$

M-step

EM Computation in Action

E-step
$$p^{(n)}(z=0\,|\,w)=\frac{p(\theta_d)p^{(n)}(w\,|\,\theta_d)}{p(\theta_d)p^{(n)}(w\,|\,\theta_d)+p(\theta_B)p(w\,|\,\theta_B)}$$

M-step
$$p^{(n+1)}(w\,|\,\theta_d)=\frac{c(w,d)p^{(n)}(z=0\,|\,w)}{\sum_{w'\in V}c(w',d)p^{(n)}(z=0\,|\,w')}$$

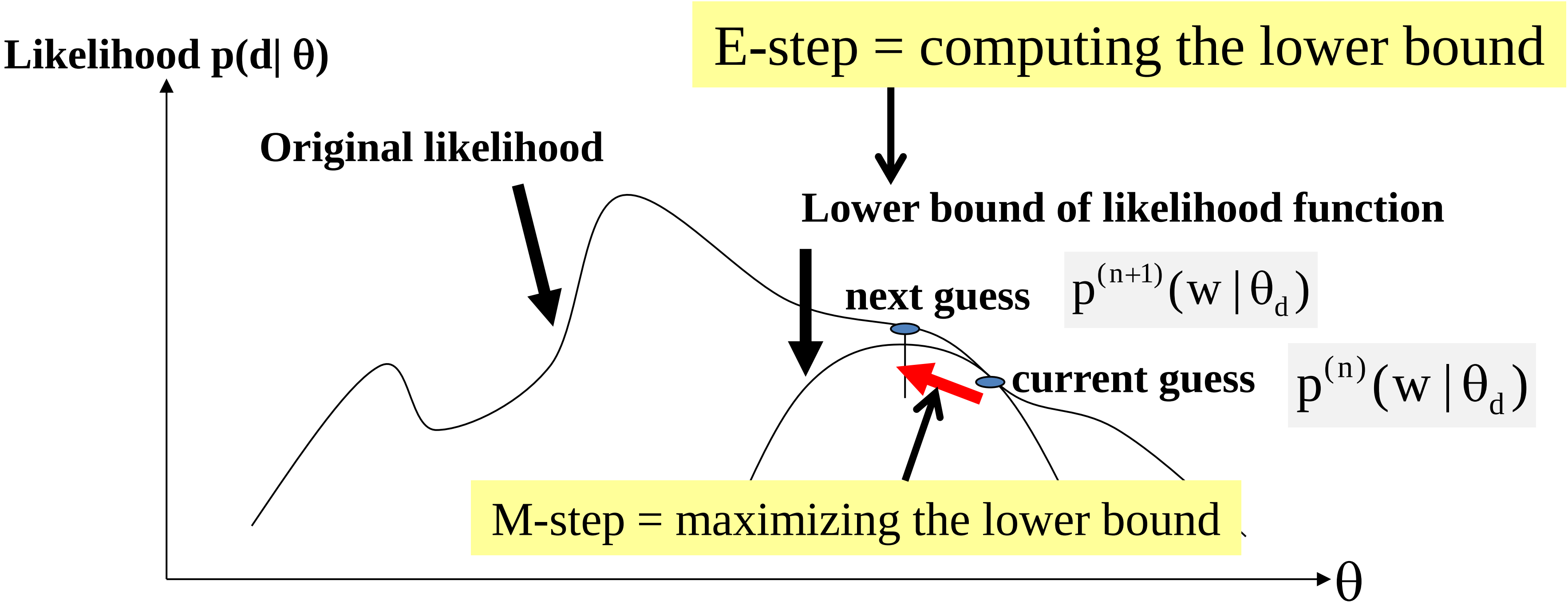
Assume
$p(\theta_d)=p(\theta_B)=0.5$
and $p(w|\theta_B)$ is known

Word	#	$p(w\|\theta_B)$	Iteration 1		Iteration 2		Iteration 3	
			$P(w\|\theta)$	$p(z=0\|w)$	$P(w\|\theta)$	$P(z=0\|w)$	$P(w\|\theta)$	$P(z=0\|w)$
The	4	0.5	**0.25**	0.33	**0.20**	0.29	**0.18**	0.26
Paper	2	0.3	**0.25**	0.45	**0.14**	0.32	**0.10**	0.25
Text	4	0.1	**0.25**	0.71	**0.44**	0.81	**0.50**	0.93
Mining	2	0.1	**0.25**	0.71	**0.22**	0.69	**0.22**	0.69
Log-Likelihood			-16.96		-16.13		-16.02	

Likelihood increasing

"By products": Are they also useful?

EM As Hill-Climbing ➔ Converge to Local Maximum



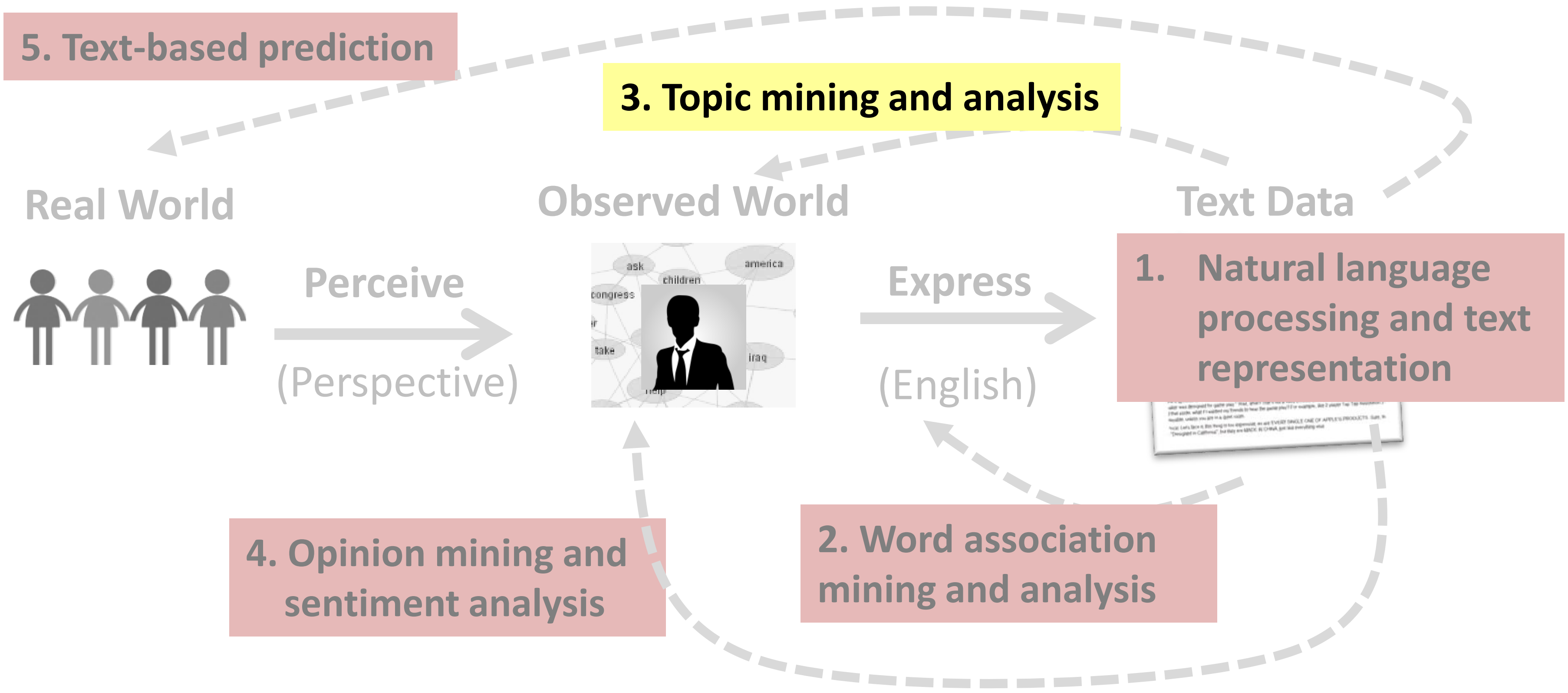
Summary

- Expectation-Maximization (EM) algorithm
  - General algorithm for computing ML estimate of mixture models
  - Hill-climbing, so can only converge to a local maximum (depending on initial points)
- E-step: "augment" data by predicting values of useful hidden variables
- M-step: exploit the "augmented data" to improve estimate of parameters ("improve" is guaranteed in terms of likelihood)
- "Data augmentation" is probabilistic ➔ Split counts of events probabilistically

Probabilistic Latent Semantic Analysis (PLSA)

ChengXiang "Cheng" Zhai
Department of Computer Science
University of Illinois at Urbana-Champaign

Probabilistic Latent Semantic Analysis (PLSA)



Document as a Sample of Mixed Topics

Topic θ_1

government 0.3
response 0.2
...

Topic θ_2

city 0.2
new 0.1
orleans 0.05
...

. . .

Topic θ_k

donate 0.1
relief 0.05
help 0.02
...

Background θ_B

the 0.04
a 0.03
...

Blog article about "Hurricane Katrina"

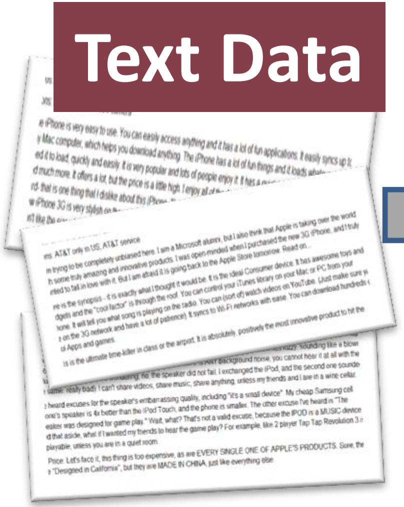
[Criticism of government response to the hurricane primarily consisted of criticism of its response to the approach of the storm and its aftermath, specifically in the delayed response] to the [flooding of New Orleans. … 80% of the 1.3 million residents of the greater New Orleans metropolitan area evacuated] …[Over seventy countries pledged monetary donations or other assistance]. …

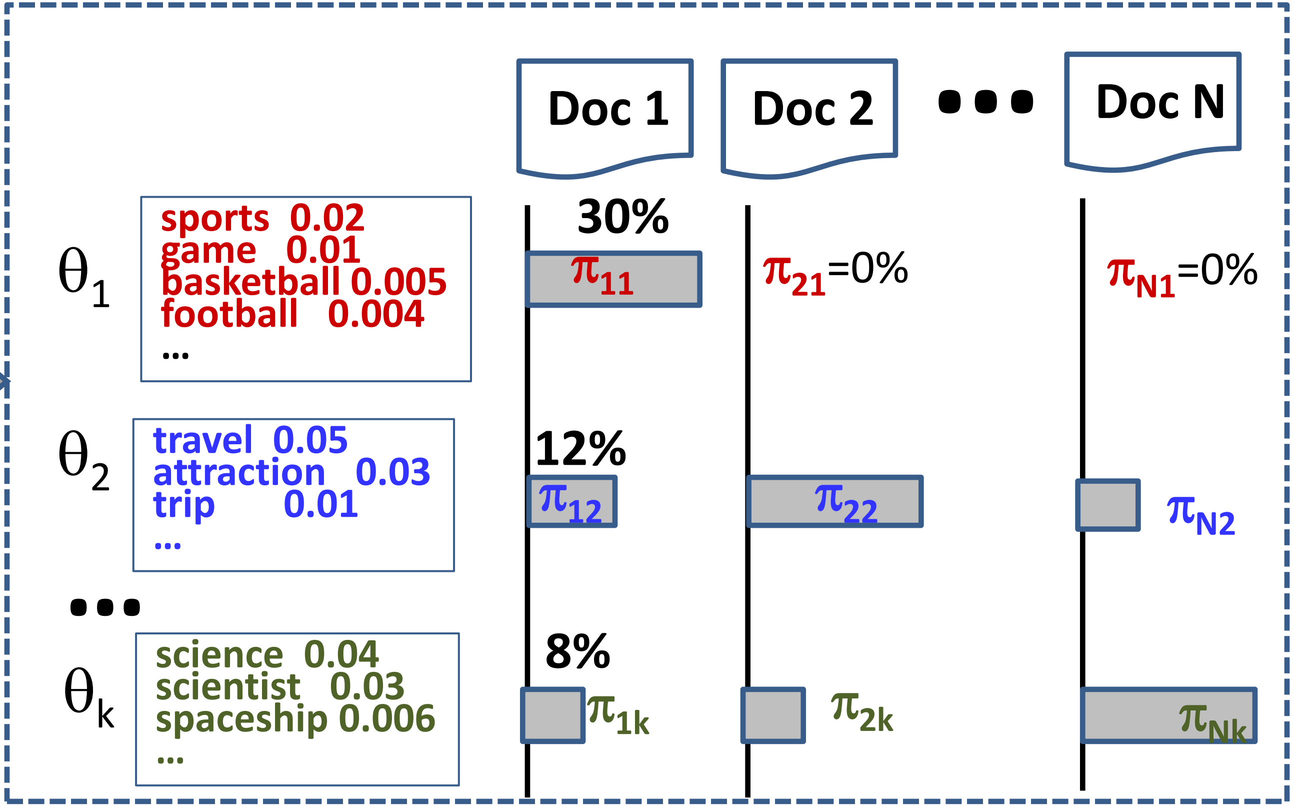
Many applications are possible if we can "decode" the topics in text…

Mining Multiple Topics from Text

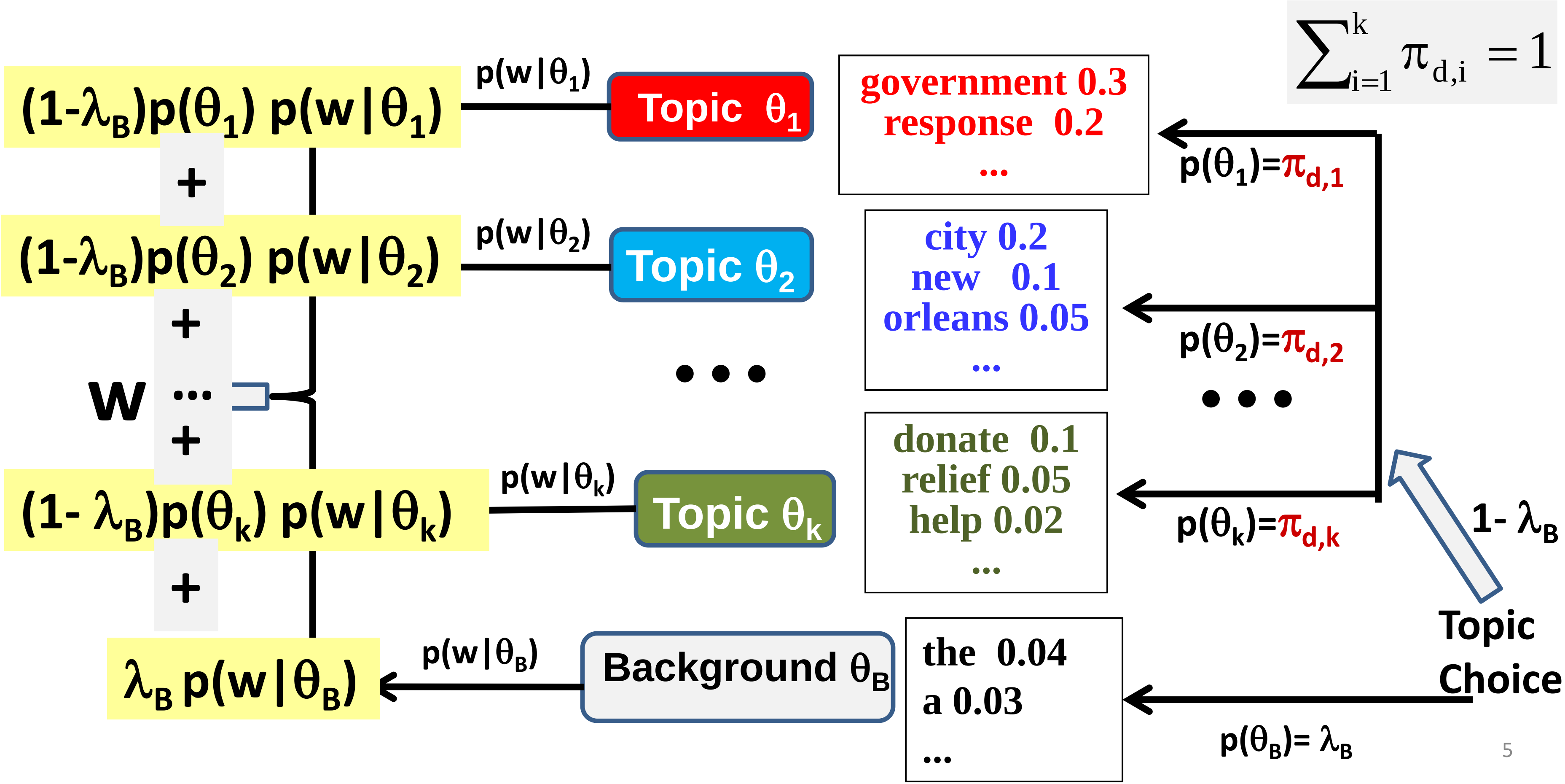
INPUT: C, k, V

OUTPUT: { θ_1, …, θ_k }, { π_{i1}, …, π_{ik} }





Generating Text with Multiple Topics: p(w)=?



Probabilistic Latent Semantic Analysis (PLSA)

Percentage of background words (known)

Background LM (known)

Coverage of topic θ_j in doc d

Prob. of word w in topic θ_j

$$p_d(w) = \lambda_B p(w|\theta_B) + (1-\lambda_B)\sum_{j=1}^{k} \pi_{d,j}\, p(w|\theta_j)$$

$$\log p(d) = \sum_{w \in V} c(w,d) \log[\lambda_B p(w|\theta_B) + (1-\lambda_B)\sum_{j=1}^{k} \pi_{d,j}\, p(w|\theta_j)]$$

$$\log p(C|\Lambda) = \sum_{d \in C}\sum_{w \in V} c(w,d) \log[\lambda_B p(w|\theta_B) + (1-\lambda_B)\sum_{j=1}^{k} \pi_{d,j}\, p(w|\theta_j)]$$

Unknown Parameters: $\Lambda=(\{\pi_{d,j}\}, \{\theta_j\})$, j=1, …, k

How many unknown parameters are there in total?

ML Parameter Estimation

$$p_d(w) = \lambda_B p(w \mid \theta_B) + (1-\lambda_B)\sum_{j=1}^{k} \pi_{d,j}\, p(w \mid \theta_j)$$

$$\log p(d) = \sum_{w \in V} c(w,d) \log[\lambda_B p(w \mid \theta_B) + (1-\lambda_B)\sum_{j=1}^{k} \pi_{d,j}\, p(w \mid \theta_j)]$$

$$\log p(C \mid \Lambda) = \sum_{d \in C}\sum_{w \in V} c(w,d) \log[\lambda_B p(w \mid \theta_B) + (1-\lambda_B)\sum_{j=1}^{k} \pi_{d,j}\, p(w \mid \theta_j)]$$

Constrained Optimization: $\Lambda^* = \arg\max_{\Lambda} p(C \mid \Lambda)$

$\forall j \in [1,k], \sum_{i=1}^{M} p(w_i \mid \theta_j) = 1$

$\forall d \in C, \sum_{j=1}^{k} \pi_{d,j} = 1$

EM Algorithm for PLSA: E-Step

Hidden Variable (=topic indicator): $z_{d,w} \in \{B, 1, 2, \ldots, k\}$

Probability that **w in doc d** is generated from **topic θ_j**

Use of Bayes Rule

$$p(z_{d,w} = j) = \frac{\pi_{d,j}^{(n)} p^{(n)}(w \mid \theta_j)}{\sum_{j'=1}^{k} \pi_{d,j'}^{(n)} p^{(n)}(w \mid \theta_{j'})}$$

$$p(z_{d,w} = B) = \frac{\lambda_B p(w \mid \theta_B)}{\lambda_B p(w \mid \theta_B) + (1-\lambda_B) \sum_{j=1}^{k} \pi_{d,j}^{(n)} p^{(n)}(w \mid \theta_j)}$$

Probability that **w in doc d** is generated from **background θ_B**

EM Algorithm for PLSA: M-Step

Hidden Variable (=topic indicator): $z_{d,w} \in \{B, 1, 2, \ldots, k\}$

ML Estimate based on "allocated" word counts to topic θ_j

Re-estimated **probability** of **doc d** covering **topic θ_j**

$$\pi_{d,j}^{(n+1)} = \frac{\sum_{w \in V} \boxed{c(w,d)(1-p(z_{d,w}=B))p(z_{d,w}=j)}}{\sum_{j'}\sum_{w \in V} c(w,d)(1-p(z_{d,w}=B))p(z_{d,w}=j')}$$

$$p^{(n+1)}(w \mid \theta_j) = \frac{\sum_{d \in C} \boxed{c(w,d)(1-p(z_{d,w}=B))p(z_{d,w}=j)}}{\sum_{w' \in V}\sum_{d \in C} c(w',d)(1-p(z_{d,w'}=B))p(z_{d,w'}=j)}$$

Re-estimated **probability** of **word w** for **topic θ_j**

Computation of the EM Algorithm

- Initialize all unknown parameters randomly
- Repeat until likelihood converges
  - E-step $p(z_{d,w} = j) \propto \pi_{d,j}^{(n)} p^{(n)}(w \mid \theta_j)$ $\quad \sum_{j=1}^{k} p(z_{d,w} = j) = 1$

    $p(z_{d,w} = B) \propto \lambda_B p(w \mid \theta_B) \leftarrow$ What's the normalizer for this one?
  - M-step

$$\pi_{d,j}^{(n+1)} \propto \sum_{w \in V} c(w,d)(1 - p(z_{d,w} = B)) p(z_{d,w} = j) \qquad \forall d \in C, \sum_{j=1}^{k} \pi_{d,j} = 1$$

$$p^{(n+1)}(w \mid \theta_j) \propto \sum_{d \in C} c(w,d)(1 - p(z_{d,w} = B)) p(z_{d,w} = j) \qquad \forall j \in [1,k], \sum_{w \in V} p(w \mid \theta_j) = 1$$

In general, accumulate counts, and then normalize

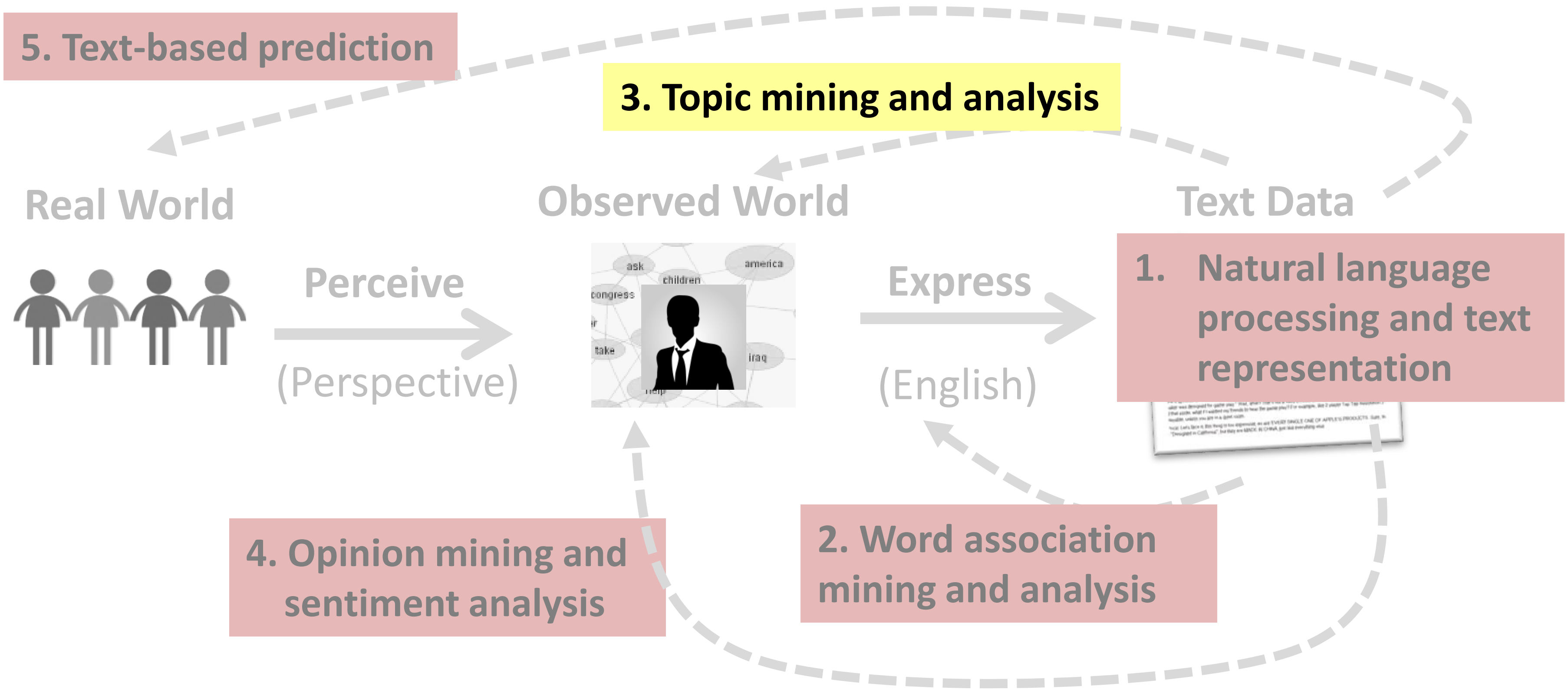
Summary

- PLSA = mixture model with k unigram LMs (k topics)
- Adding a pre-determined background LM helps discover discriminative topics
- ML estimate "discovers" topical knowledge from text data
  – k word distributions (k topics)
  – proportion of each topic in each document
- The output can enable many applications!
  – Clustering of terms and docs (treat each topic as a cluster)
  – Further associate topics with different contexts (e.g., time periods, locations, authors, sources, etc.)

Latent Dirichlet Allocation (LDA)

ChengXiang "Cheng" Zhai
Department of Computer Science
University of Illinois at Urbana-Champaign

Latent Dirichlet Allocation (LDA)



Extensions of PLSA

- PLSA with prior knowledge ➔ User-controlled PLSA
- PLSA as a generative model ➔ Latent Dirichlet Allocation

PLSA with Prior Knowledge

- Users may have expectations about which topics to analyze:
  - We expect to see “retrieval models” as a topic in IR
  - We want to see aspects such as “battery” and “memory” for opinions about a laptop
- Users may have knowledge about what topics are (or are NOT) covered in a document
  - Tags = topics ➔ A doc can only be generated using topics corresponding to the tags assigned to the document
- We can incorporate such knowledge as priors of PLSA model

Maximum a Posteriori (MAP) Estimate

$$\Lambda^* = \arg\max_{\Lambda} p(\Lambda) p(Data \mid \Lambda)$$

- We may use p(Λ) to encode all kinds of preferences and constraints, e.g.,
  - p(Λ)>0 if and only if one topic is precisely “background”: p(w|θ_B)
  - p(Λ)>0 if and only if for a particular doc d, $\pi_{d,3}$=0 and $\pi_{d,1}$=1/2
  - p(Λ) favors a Λ with topics that assign high probabilities to some particular words
- The MAP estimate (with conjugate prior) can be computed using a similar EM algorithm to the ML estimate with smoothing to reflect prior preferences

EM Algorithm with Conjugate Prior on $p(w|\theta_i)$

$$p(z_{d,w}=j)=\frac{\pi_{d,j}^{(n)}p^{(n)}(w|\theta_j)}{\sum_{j'=1}^{k}\pi_{d,j'}^{(n)}p^{(n)}(w|\theta_{j'})}$$

$$p(z_{d,w}=B)=\frac{\lambda_B p(w|\theta_B)}{\lambda_B p(w|\theta_B)+(1-\lambda_B)\sum_{j=1}^{k}\pi_{d,j}^{(n)}p^{(n)}(w|\theta_j)}$$

$$\pi_{d,j}^{(n+1)}=\frac{\sum_{w\in V}c(w,d)(1-p(z_{d,w}=B))p(z_{d,w}=j)}{\sum_{j'}\sum_{w\in V}c(w,d)(1-p(z_{d,w}=B))p(z_{d,w}=j')}$$

$$p^{(n+1)}(w|\theta_j)=\frac{\sum_{d\in C}c(w,d)(1-p(z_{d,w}=B))p(z_{d,w}=j)+\mu p(w|\theta'_j)}{\sum_{w'\in V}\sum_{d\in C}c(w',d)(1-p(z_{d,w'}=B))p(z_{d,w'}=j)+\mu}$$

Prior: $p(w|\theta'_j)$

battery 0.5
life 0.5

Pseudo counts of w from prior θ'

Sum of all pseudo counts

What if $\mu=0$? What if $\mu=+\infty$?

We may also set any parameter to a constant (including 0) as needed

Deficiency of PLSA

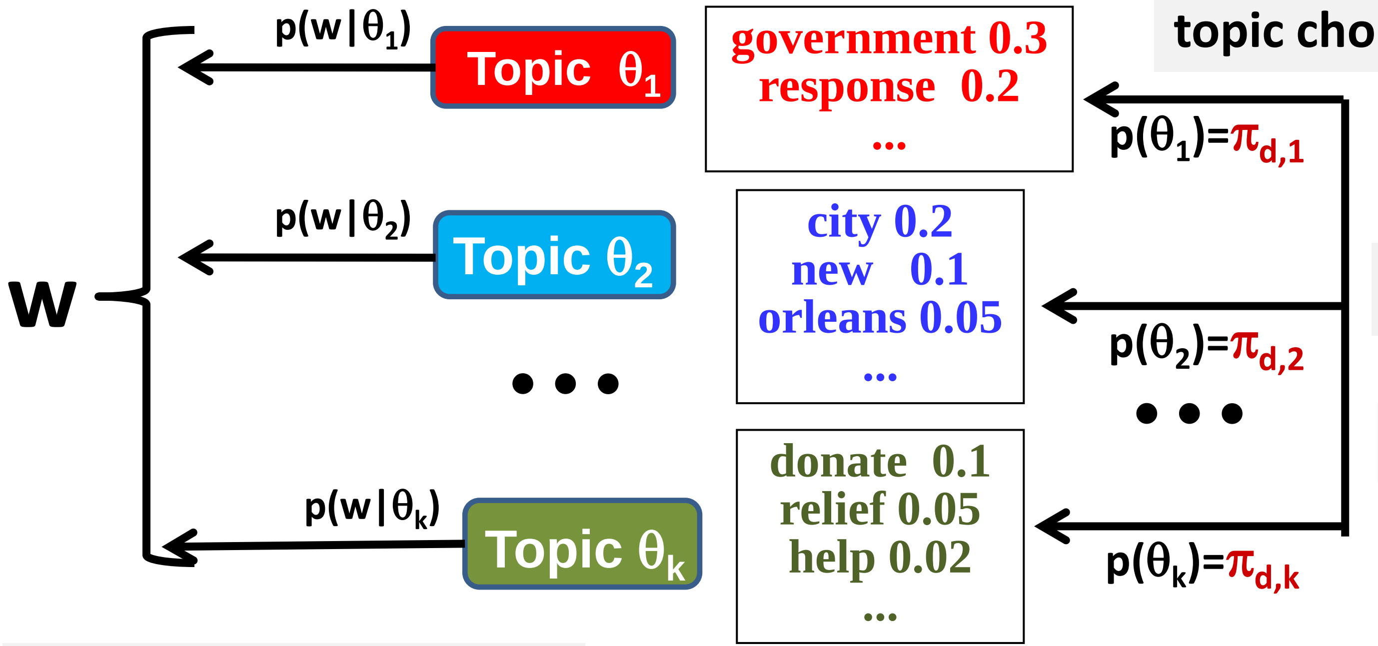
- Not a generative model
  - Can't compute probability of a new document
  - Heuristic workaround is possible, though
- Many parameters ➔ high complexity of models
  - Many local maxima
  - Prone to overfitting
- Not necessarily a problem for text mining (only interested in fitting the "training" documents)

Latent Dirichlet Allocation (LDA)

- Make PLSA a generative model by imposing a Dirichlet prior on the model parameters ➔
  - LDA = Bayesian version of PLSA
  - Parameters are regularized
- Can achieve the same goal as PLSA for text mining purposes
  - Topic coverage and topic word distributions can be inferred using Bayesian inference

8

PLSA → LDA



Both word distributions and topic choices are free in PLSA

$$\vec{\pi}_d = (\pi_{d,1}, \ldots, \pi_{d,k})$$

$$p(\vec{\pi}_d) = \text{Dirichlet}(\vec{\alpha})$$

$$\vec{\alpha} = (\alpha_1, \ldots, \alpha_k), \alpha_i > 0$$

$$\vec{\theta}_i = (p(w_1 \mid \theta_i), \ldots, p(w_M \mid \theta_i))$$

$$p(\vec{\theta}_i) = \text{Dirichlet}(\vec{\beta})$$

$$\vec{\beta} = (\beta_1, \ldots, \beta_M), \beta_i > 0$$

LDA imposes a prior on both

Likelihood Functions for PLSA vs. LDA

PLSA

$$p_d(w|\{\theta_j\},\{\pi_{d,j}\}) = \underline{\sum_{j=1}^{k} \pi_{d,j}\, p(w|\theta_j)}$$

$$\log p(d|\{\theta_j\},\{\pi_{d,j}\}) = \sum_{w\in V} c(w,d)\log[\sum_{j=1}^{k} \pi_{d,j}\, p(w|\theta_j)]$$

$$\log p(C|\{\theta_j\},\{\pi_{d,j}\}) = \sum_{d\in C} \log p(d|\{\theta_j\},\{\pi_{d,j}\})$$

Core assumption in all topic models

LDA

$$p_d(w|\{\theta_j\},\{\pi_{d,j}\}) = \underline{\sum_{j=1}^{k} \pi_{d,j}\, p(w|\theta_j)}$$

PLSA component

$$\log p(d|\vec{\alpha},\{\theta_j\}) = \int \boxed{\sum_{w\in V} c(w,d)\log[\sum_{j=1}^{k} \pi_{d,j}\, p(w|\theta_j)]}\; \underline{p(\vec{\pi}_d|\vec{\alpha})\,d\vec{\pi}_d}$$

$$\log p(C|\vec{\alpha},\vec{\beta}) = \int \sum_{d\in C} \log p(d|\vec{\alpha},\{\theta_j\}) \underline{\prod_{j=1}^{k} p(\theta_j|\vec{\beta})\,d\theta_1 \ldots d\theta_k}$$

Added by LDA

Parameter Estimation and Inferences in LDA

- Parameters can be estimated using ML estimator

$$(\hat{\vec{\alpha}}, \hat{\vec{\beta}}) = \arg\max_{\vec{\alpha}, \vec{\beta}} \log p(C \mid \vec{\alpha}, \vec{\beta})$$

How many parameters in LDA vs. PLSA?

- However, **$\{\theta_j\}$ and $\{\pi_{d,j}\}$** must now be computed using posterior inference
  - Computationally intractable
  - Must resort to approximate inference
  - Many different inference methods are available

Summary of Probabilistic Topic Models

- Probabilistic topic models provide a general principled way of mining and analyzing topics in text with many applications
- Basic task setup:
  - Input: Text data
  - Output: k topics + proportions of these topics covered in each document
- PLSA is the basic topic model, often adequate for most applications
- LDA improves over PLSA by imposing priors
  - Theoretically more appealing
  - Practically, LDA and PLSA perform similarly for many tasks

Suggested Readings

- Blei, D. 2012. “Probabilistic Topic Models.” *Communications of the ACM* 55 (4): 77–84. doi: 10.1145/2133806.2133826.
- Qiaozhu Mei, Xuehua Shen, and ChengXiang Zhai. “Automatic Labeling of Multinomial Topic Models.” *Proceedings of ACM KDD 2007*, pp. 490-499, DOI=10.1145/1281192.1281246.
- Yue Lu, Qiaozhu Mei, and Chengxiang Zhai. 2011. Investigating task performance of probabilistic topic models: an empirical study of PLSA and LDA. *Information Retrieval*, 14, 2 (April 2011), 178-203. DOI=10.1007/s10791-010-9141-9.