Probabilistic Topic Models: Mixture of Unigram Language Models

ChengXiang “Cheng” Zhai
Department of Computer Science
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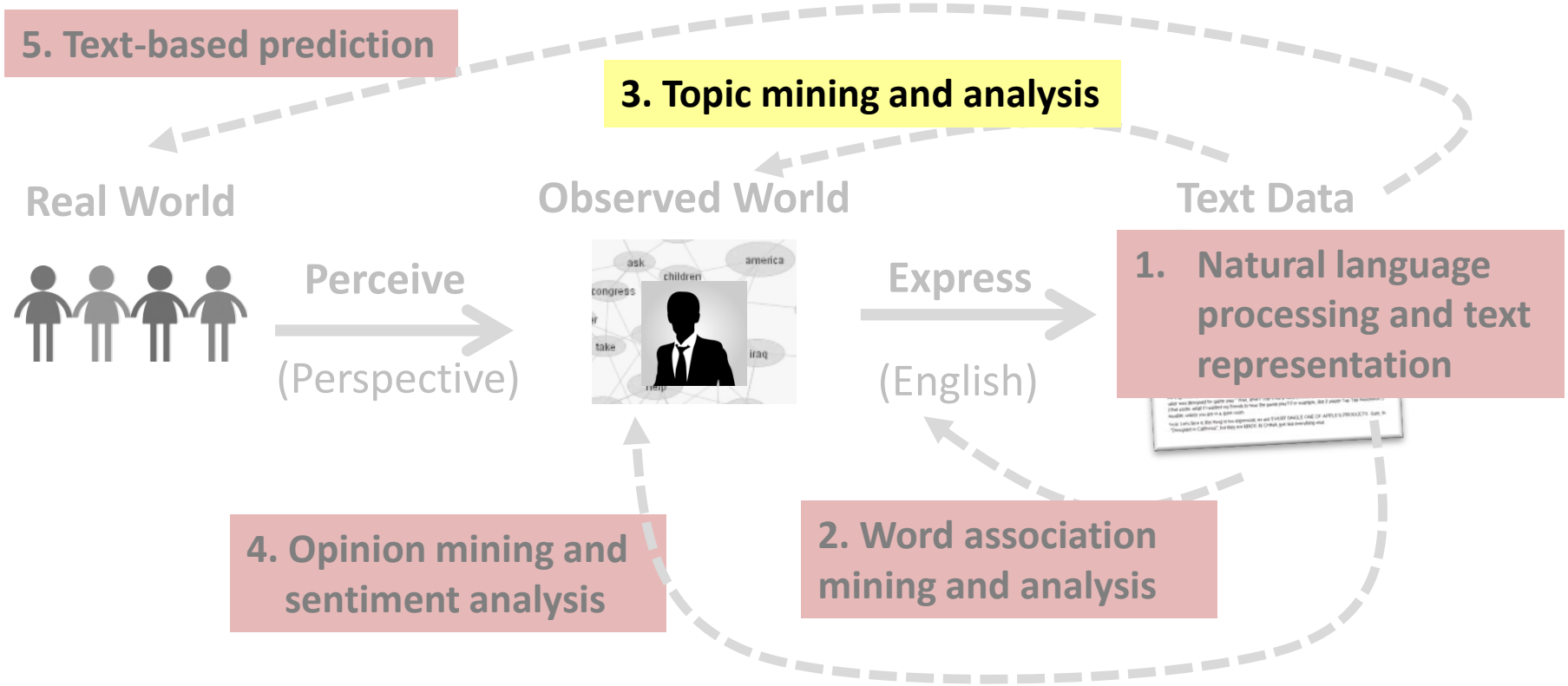
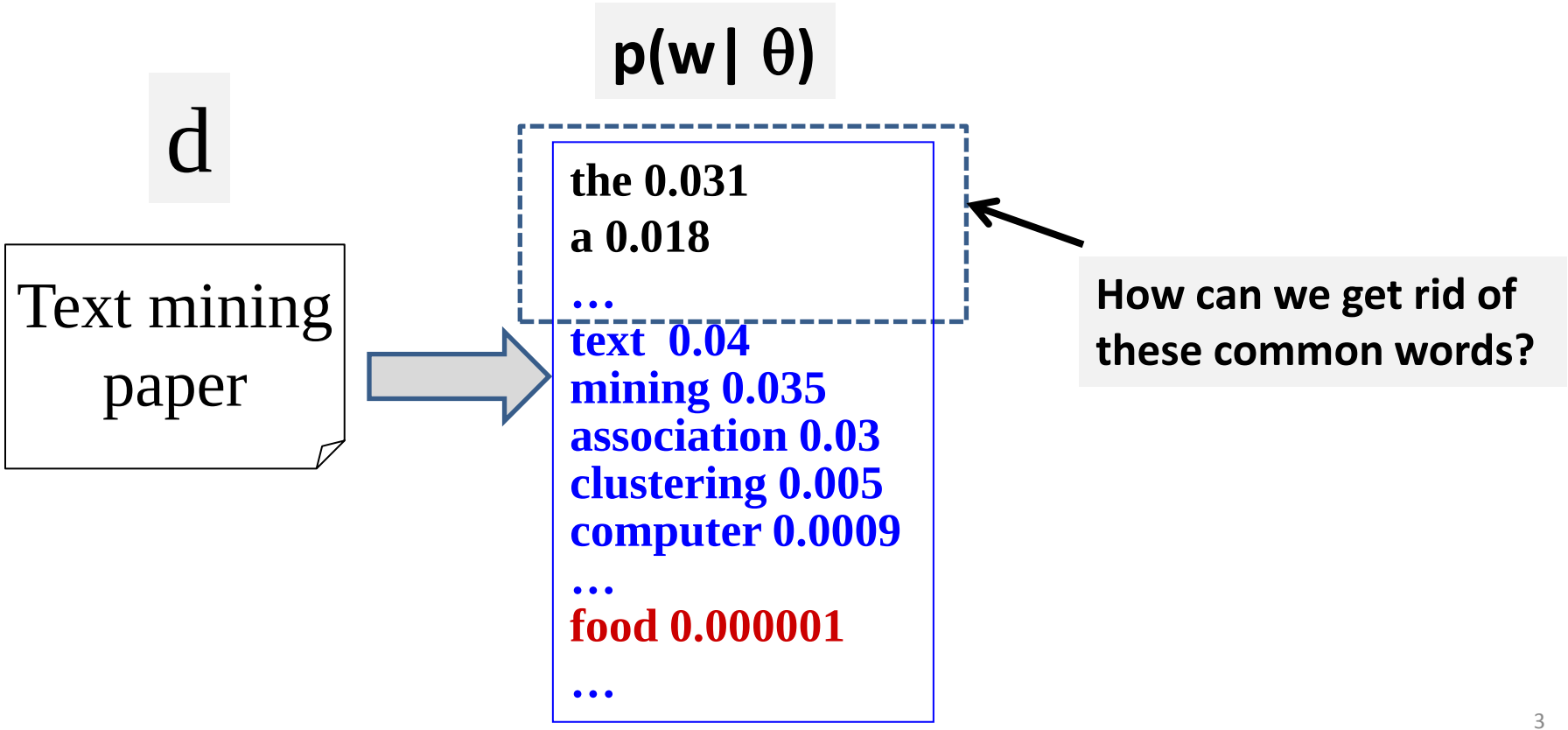
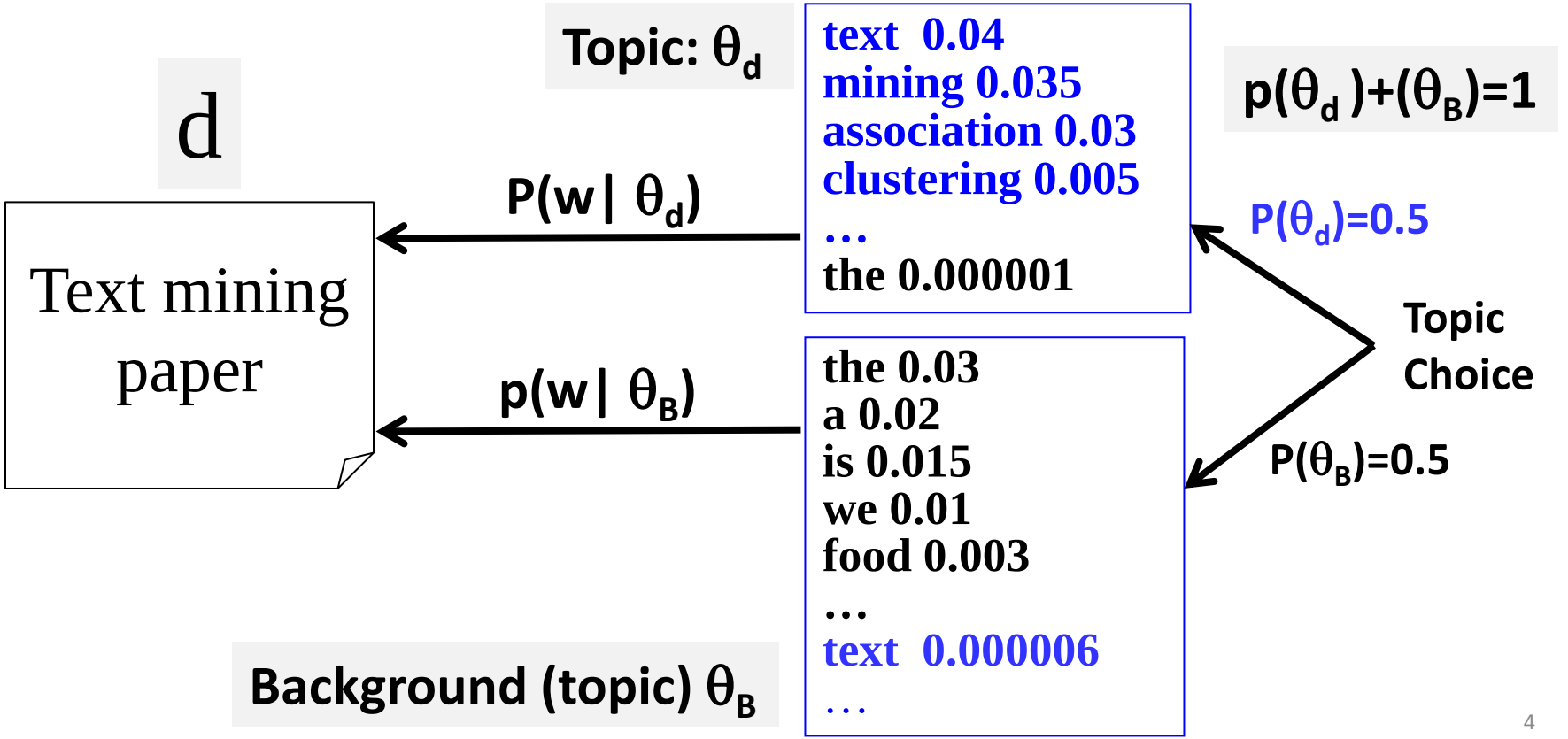


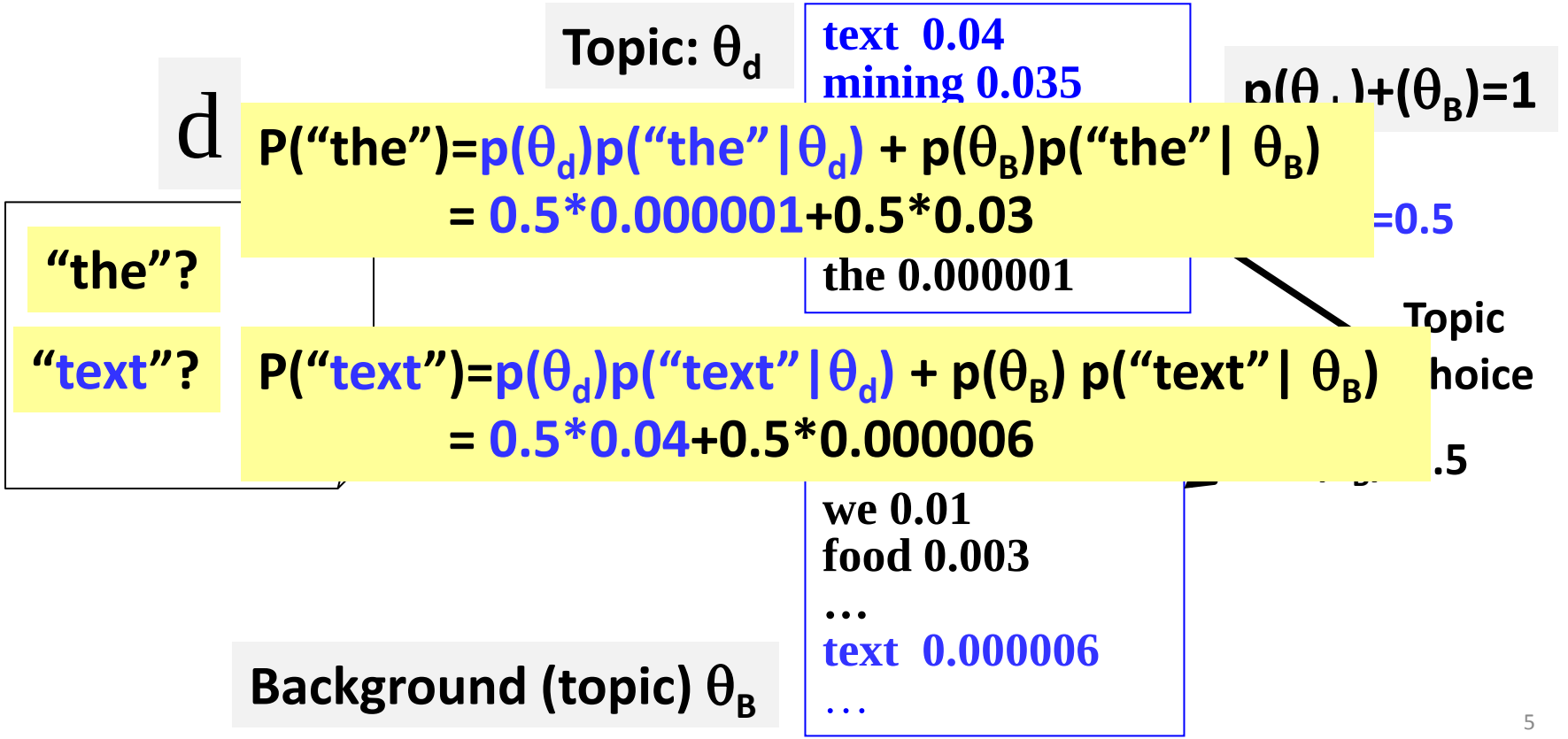
Factoring out Background Words



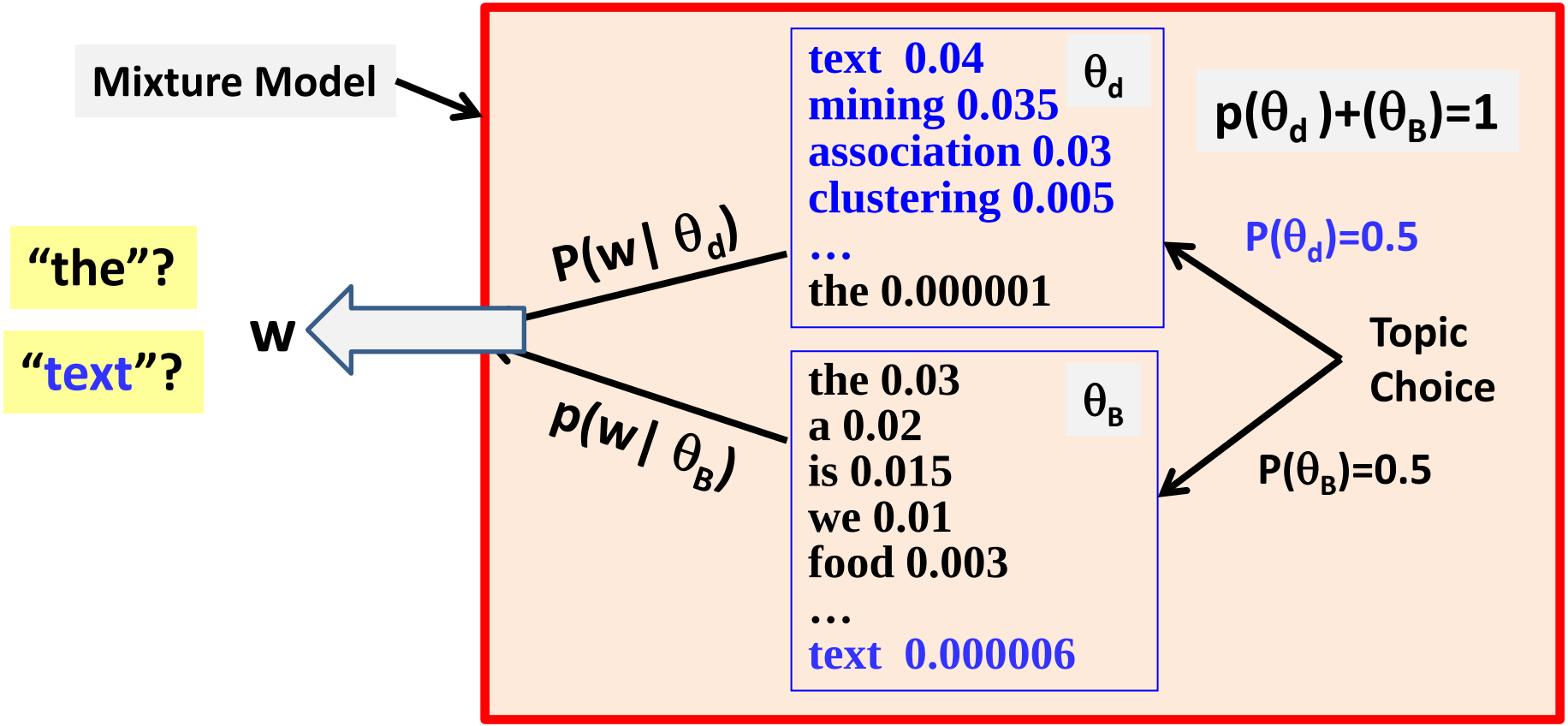
Generate d Using Two Word Distributions



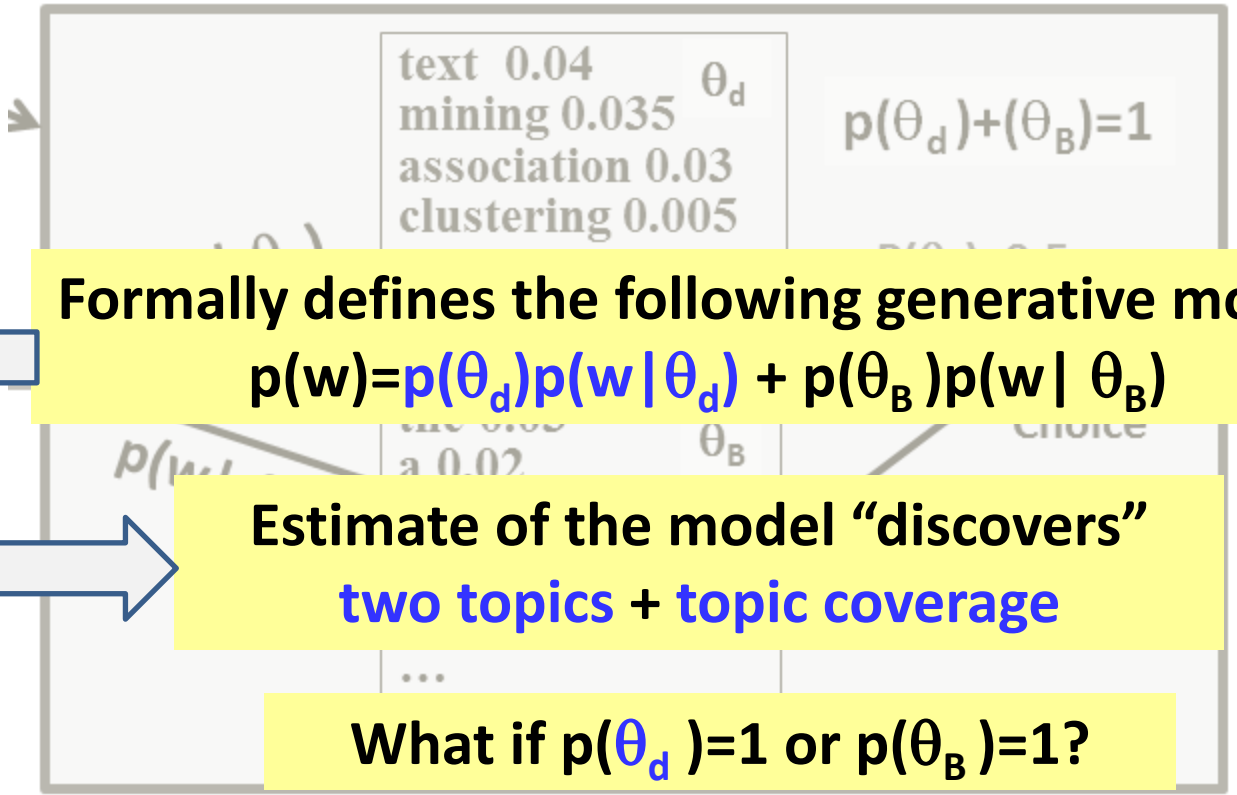
What's the probability of observing a word w?



The Idea of a Mixture Model



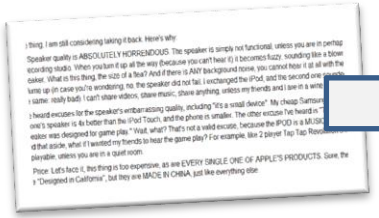
As a Generative Model…



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

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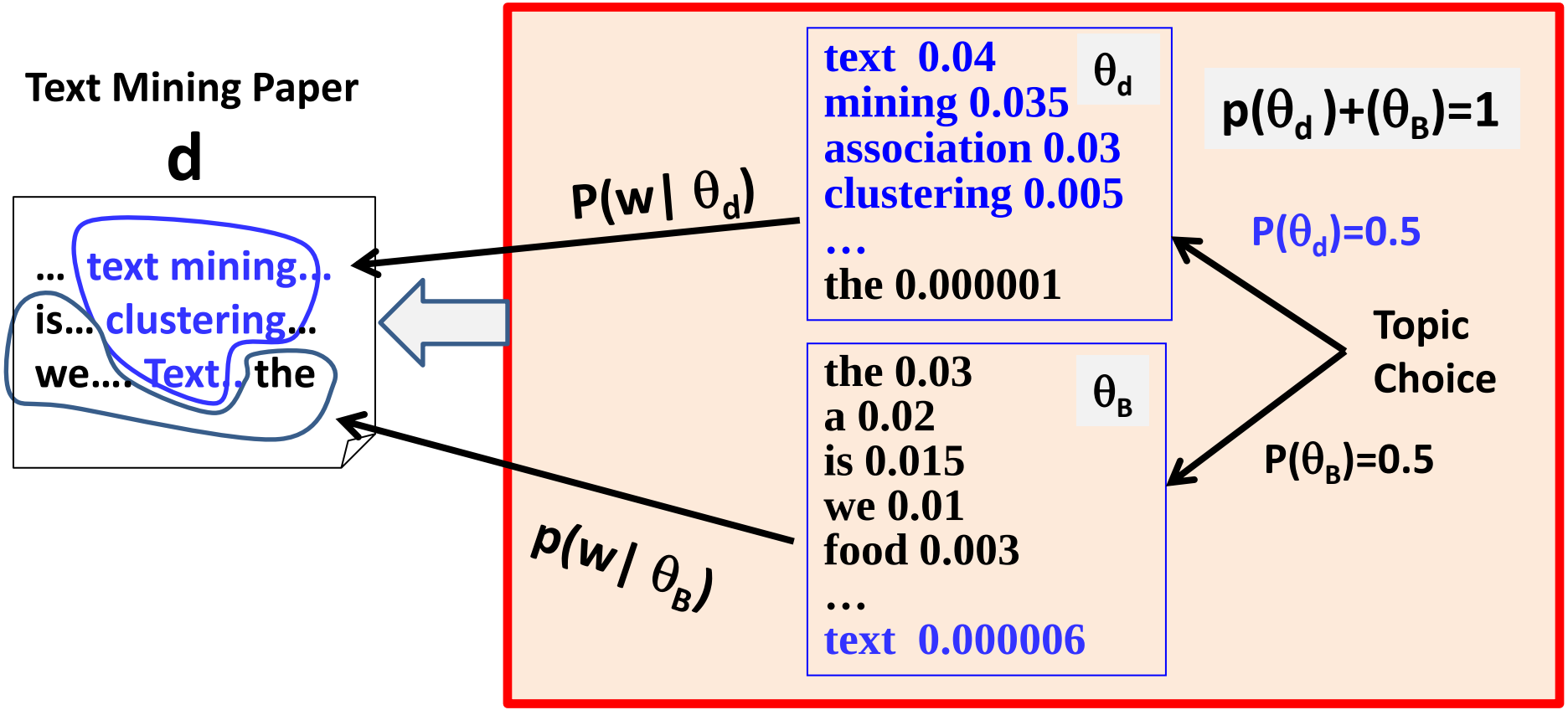


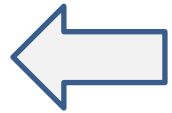
Estimation of One Topic: $P(w|\theta_d)$

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

Would the ML estimate demote background words in θ_d ?

d

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



Behavior of a Mixture Model

d = text the

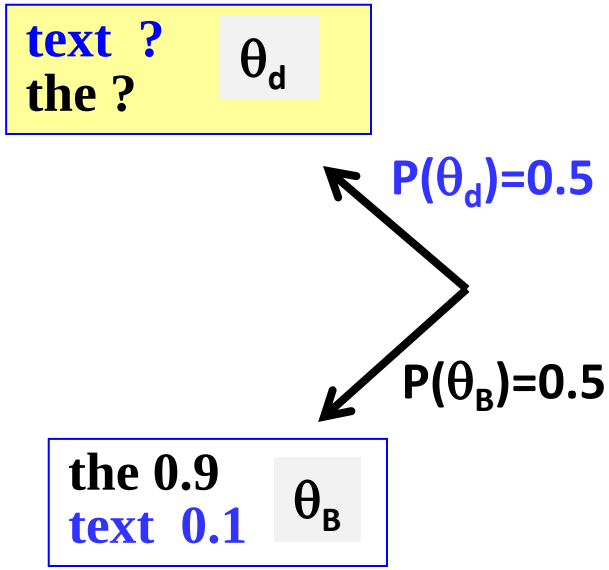
Likelihood:

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

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

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

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



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

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

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text ? θ_d
the ?

$P(\theta_d)=0.5$

$P(\theta_B)=0.5$

the 0.9 θ_B
text 0.1

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

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

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

➔ $p(\text{"text"}|\theta_d)=0.9 \gg p(\text{"the"}|\theta_d)=0.1$!

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

Response to Data Frequency

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$p(d|\Lambda)$ = [0.5*p("text"|θ_d) + 0.5*0.1]
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Behavior 2: high frequency words get higher $p(w|\theta_d)$

Summary

- General behavior of a mixture model:
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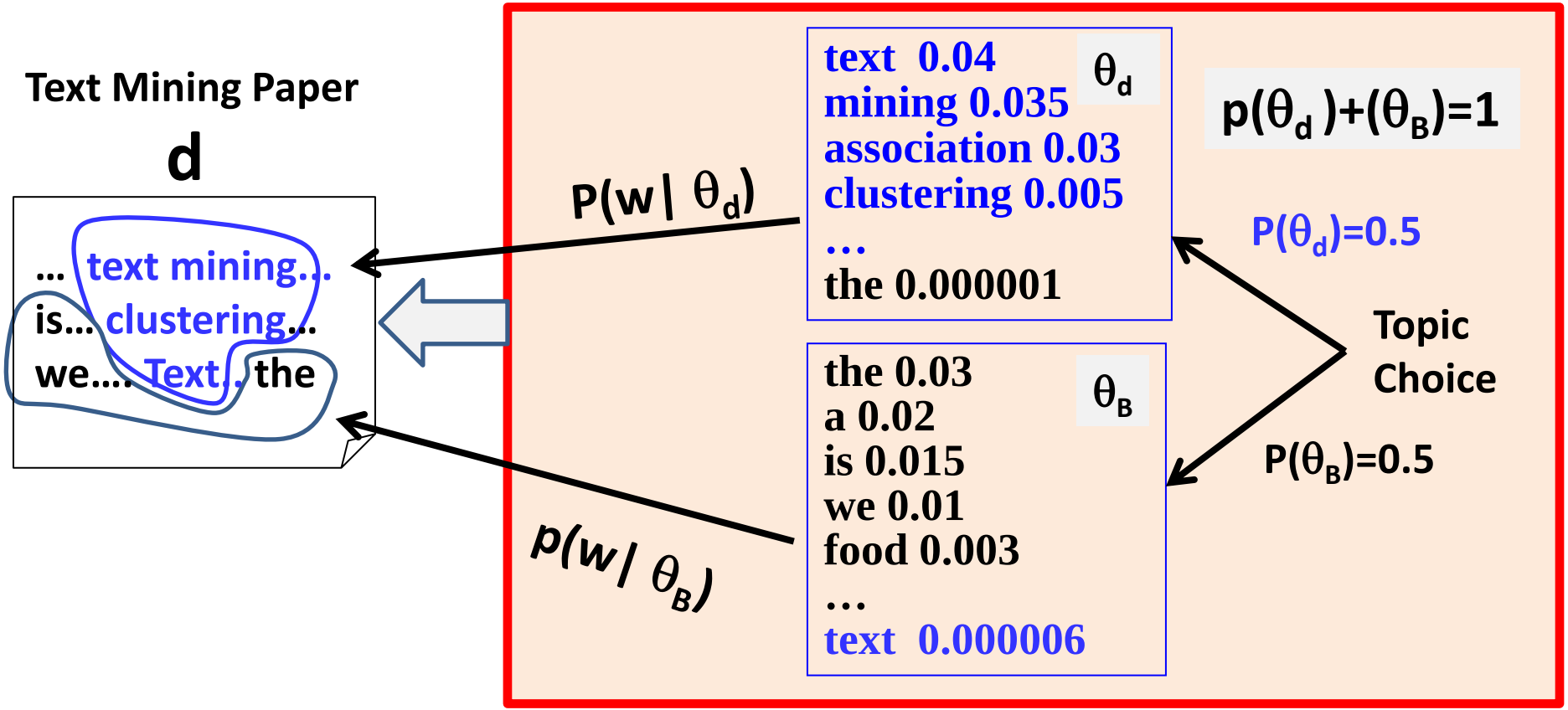

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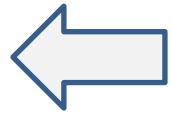

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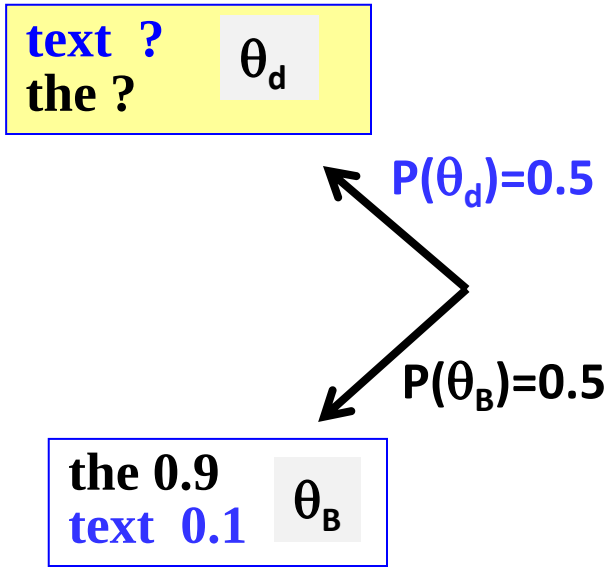

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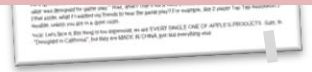

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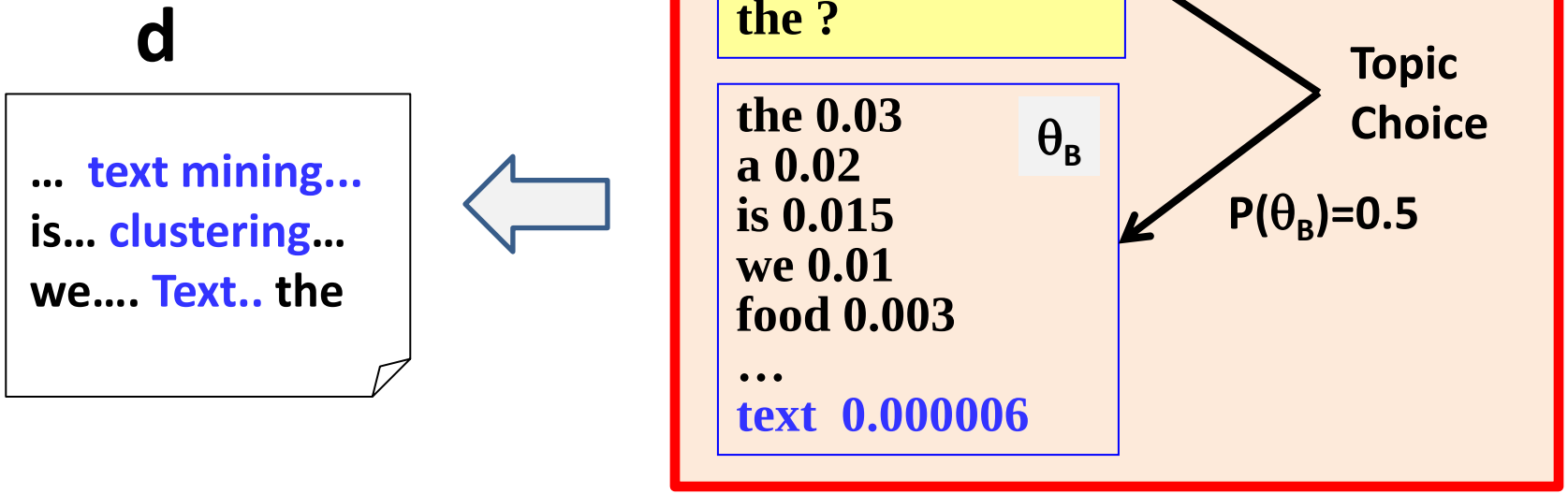

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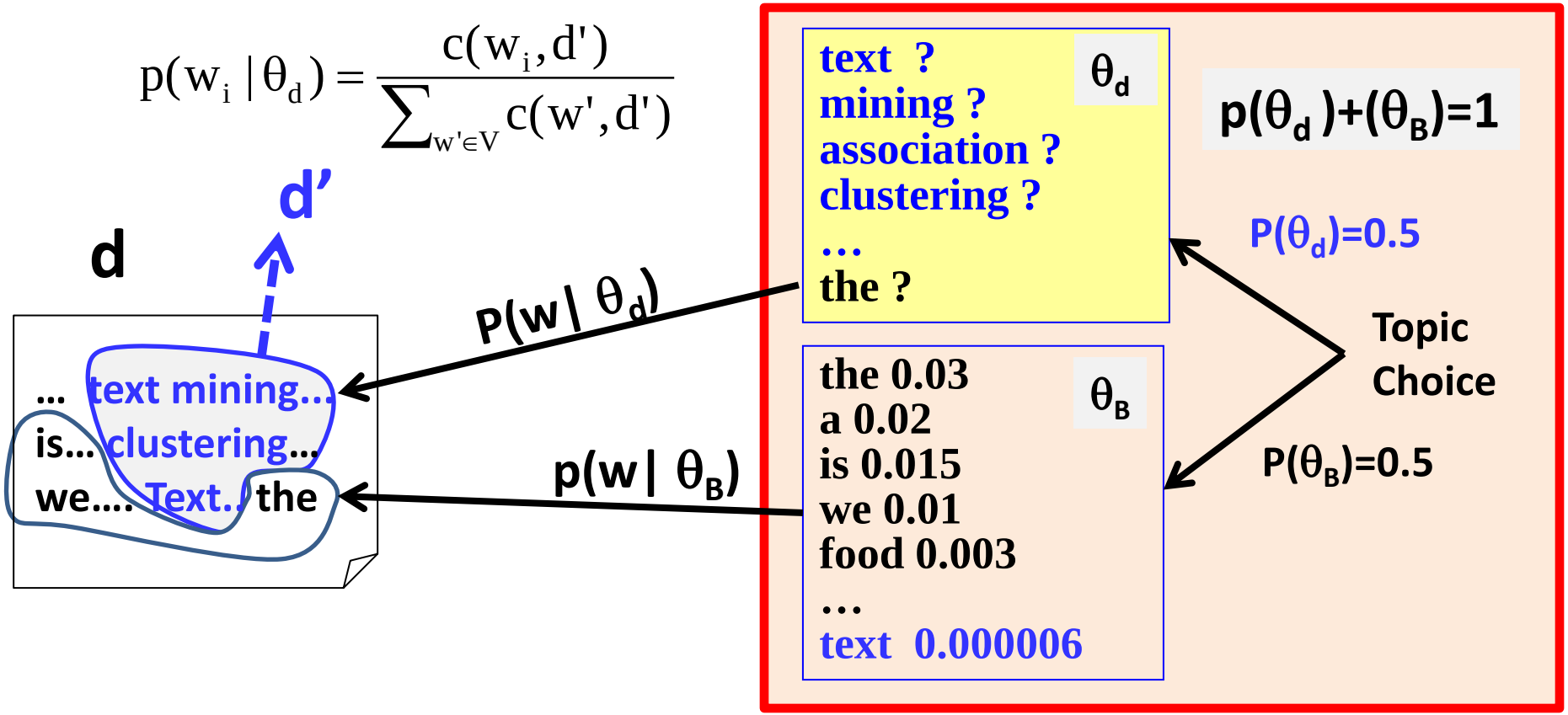
$$p(w_i \mid \theta_d) = \frac{c(w_i, d')}{\sum_{w' \in V} c(w', d')}$$



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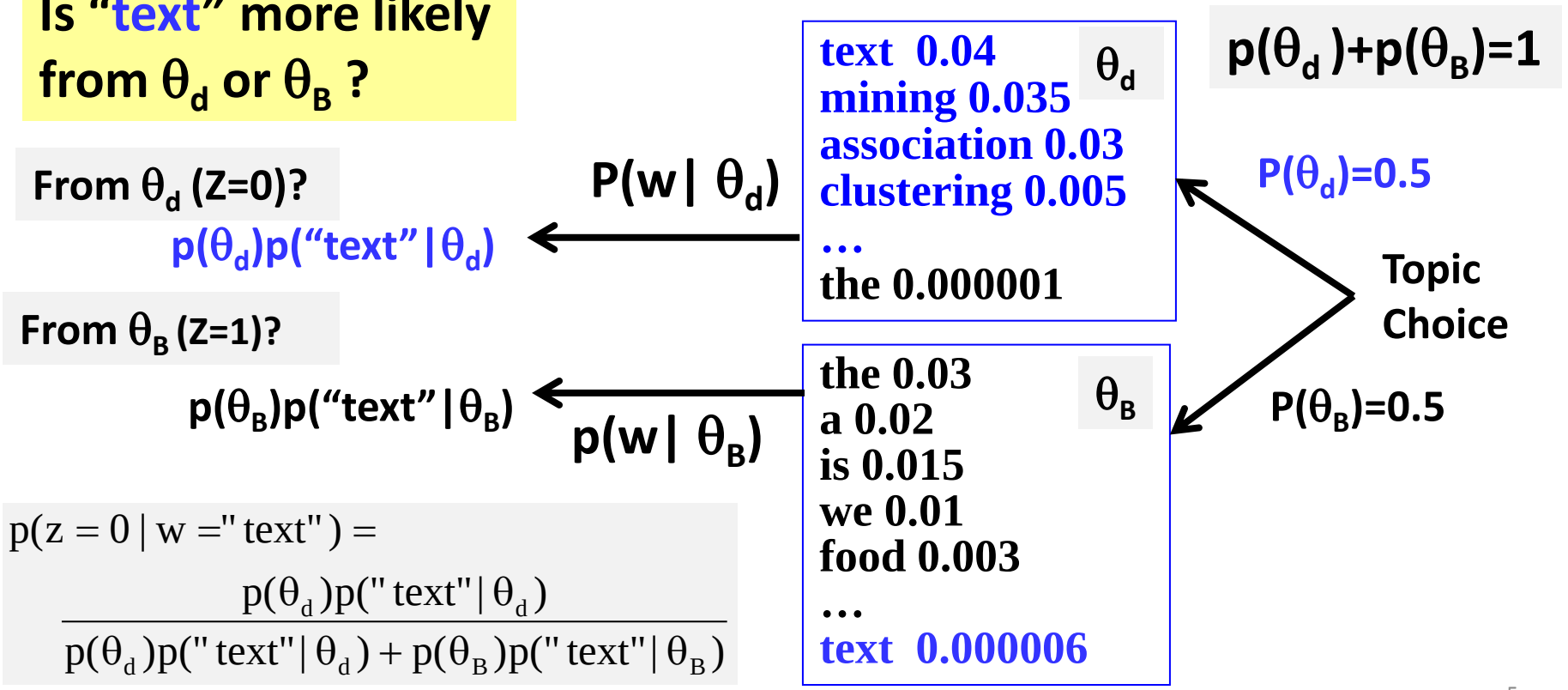


$$p(z=0 \mid w=\text{"text"}) = \frac{p(\theta_d)p(\text{"text"}|\theta_d)}{p(\theta_d)p(\text{"text"}|\theta_d)+p(\theta_B)p(\text{"text"}|\theta_B)}$$

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

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

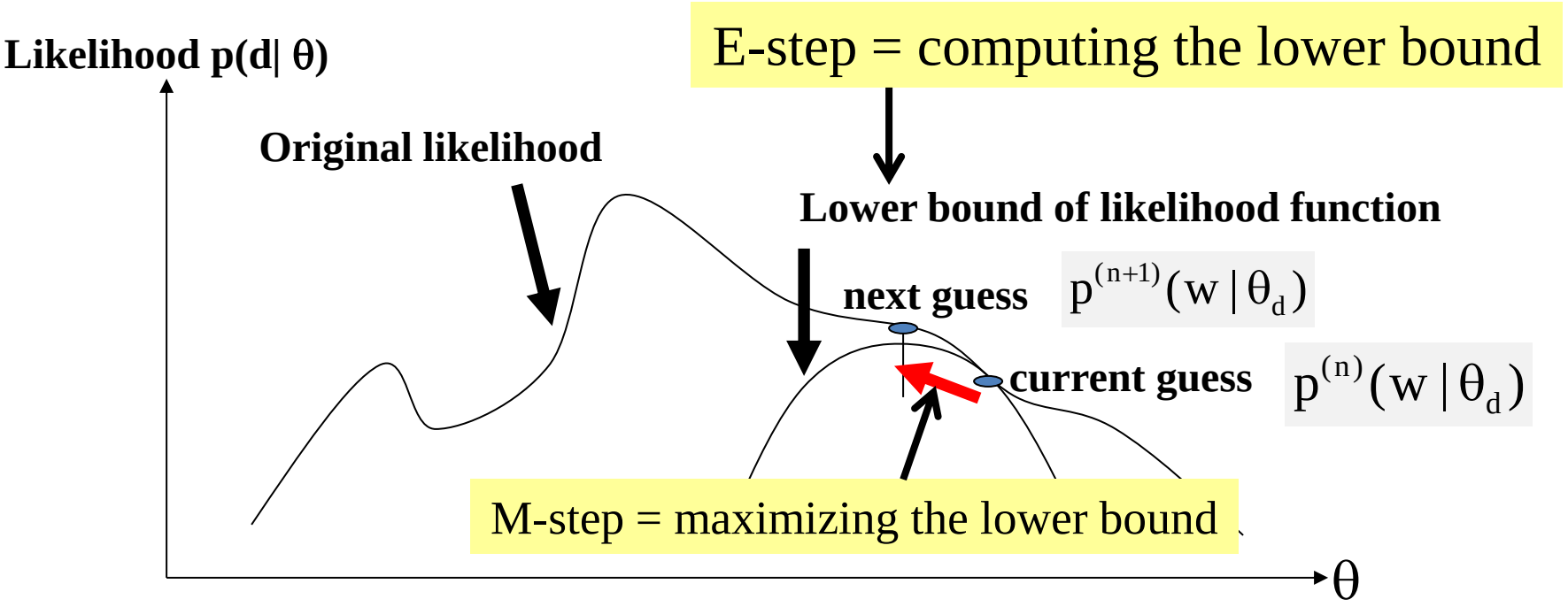
Assume $p(\theta_d)=p(\theta_B)=0.5$ and $p(w\mid\theta_B)$ is known

Word	#	$p(w\mid\theta_B)$	Iteration 1		Iteration 2		Iteration 3	
			$P(w\mid\theta)$	$p(z=0\mid w)$	$P(w\mid\theta)$	$P(z=0\mid w)$	$P(w\mid\theta)$	$P(z=0\mid w)$
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

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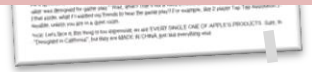

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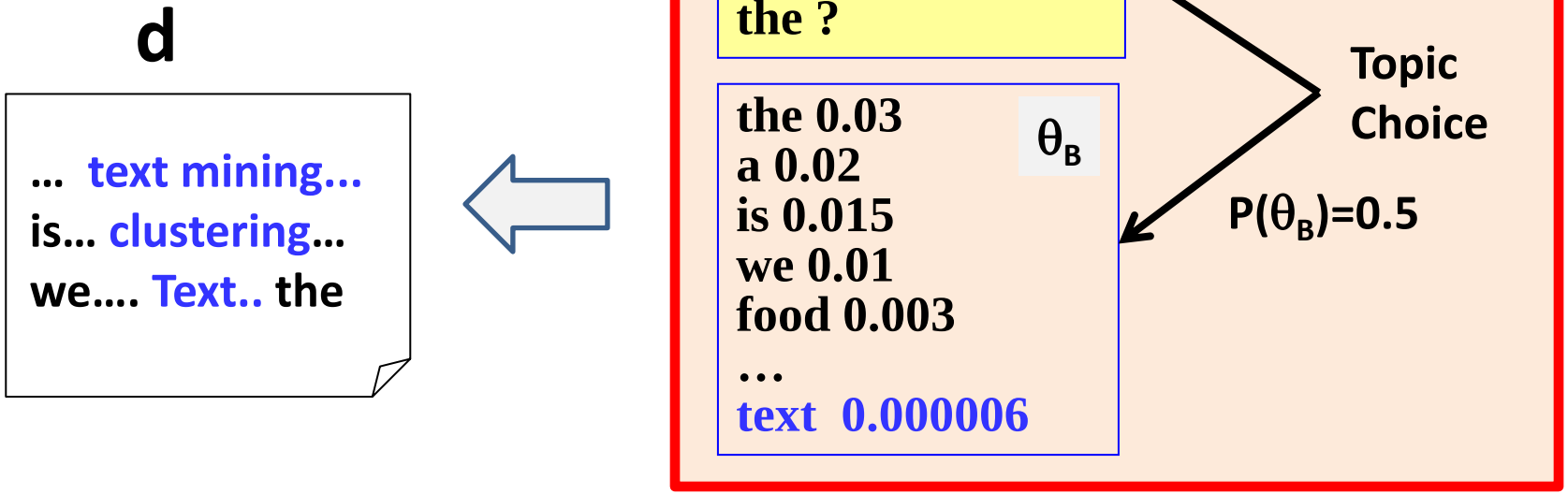

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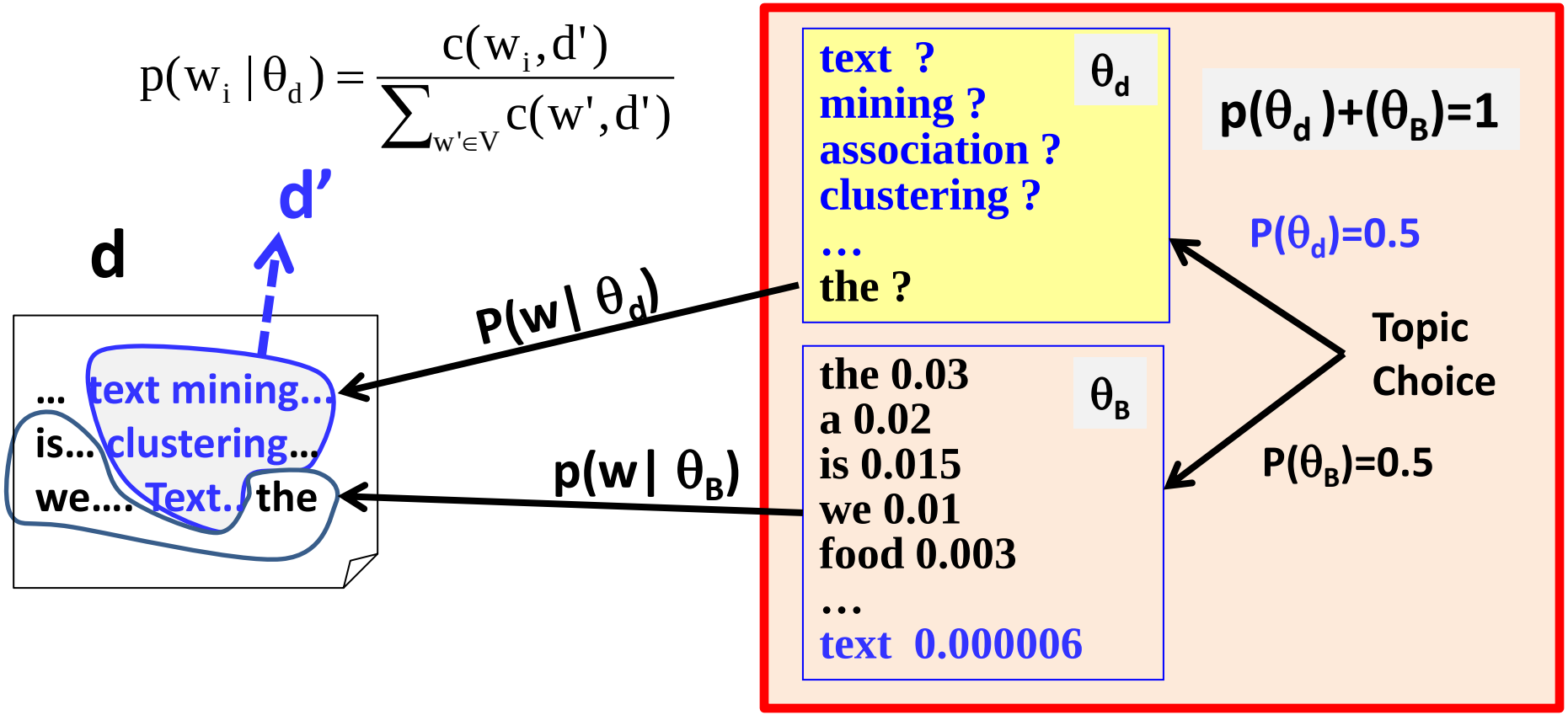

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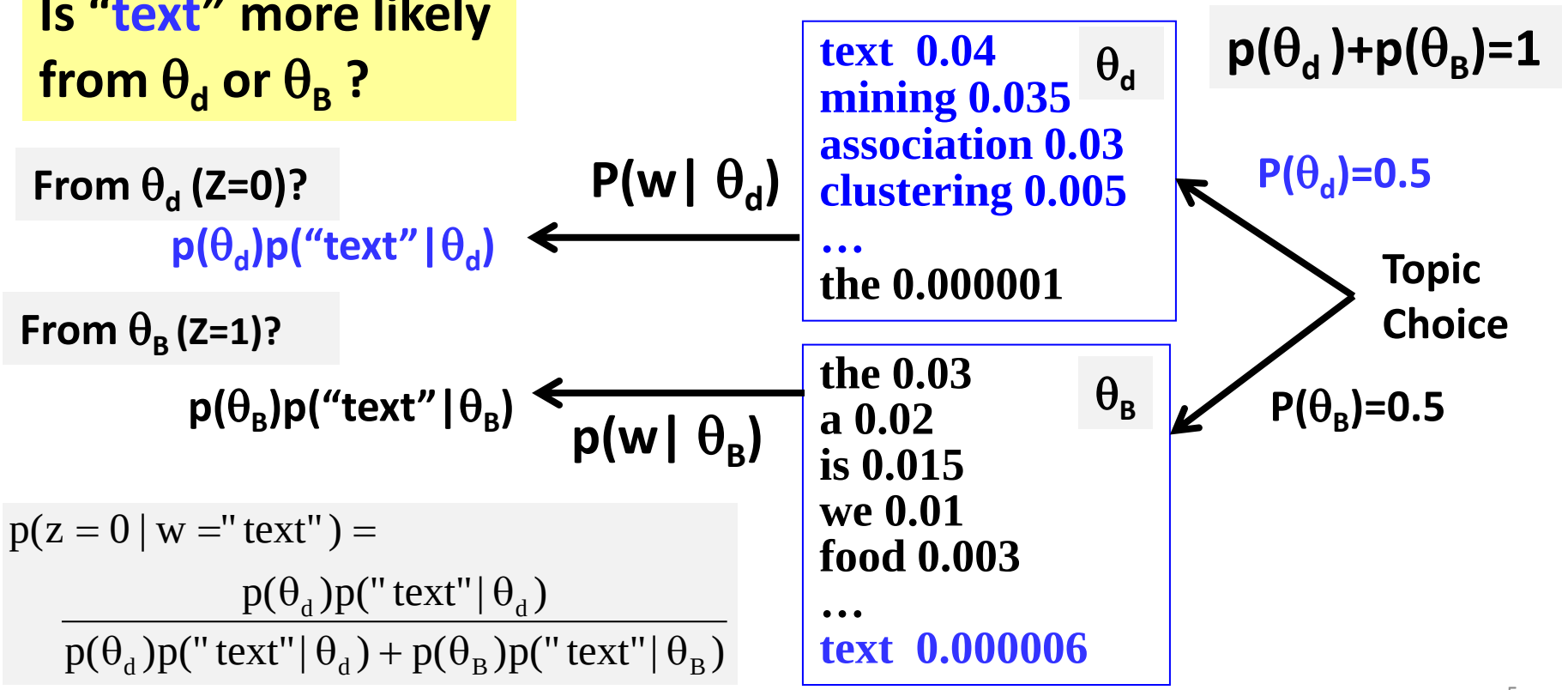

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Word	#	$p(w\mid\theta_B)$	Iteration 1		Iteration 2		Iteration 3	
			$P(w\mid\theta)$	$p(z=0\mid w)$	$P(w\mid\theta)$	$P(z=0\mid w)$	$P(w\mid\theta)$	$P(z=0\mid w)$
The	4	0.5	**0.25**	0.33	**0.20**	0.29	**0.18**	0.26
Paper	2	0.3	**0.25**	0.45	**0.14**	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
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Likelihood increasing →

"By products": Are they also useful?

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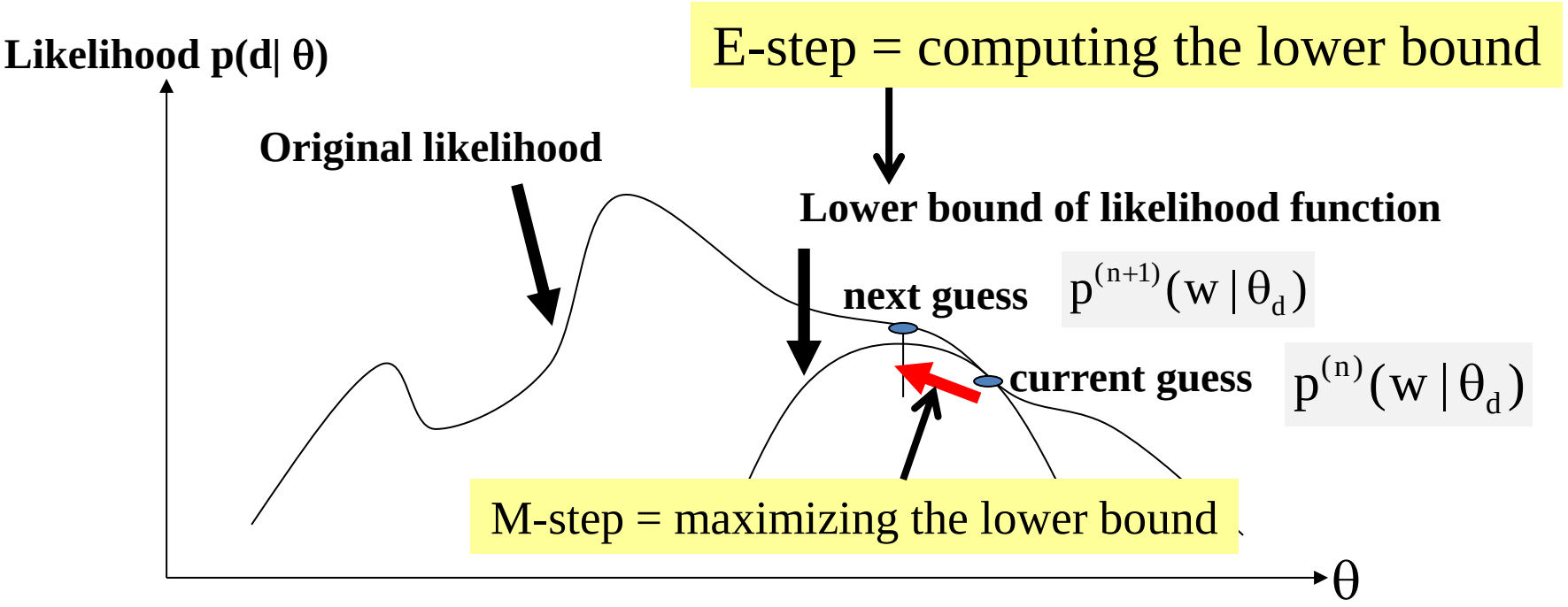

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Probabilistic Topic Models: Expectation-Maximization Algorithm

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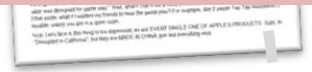

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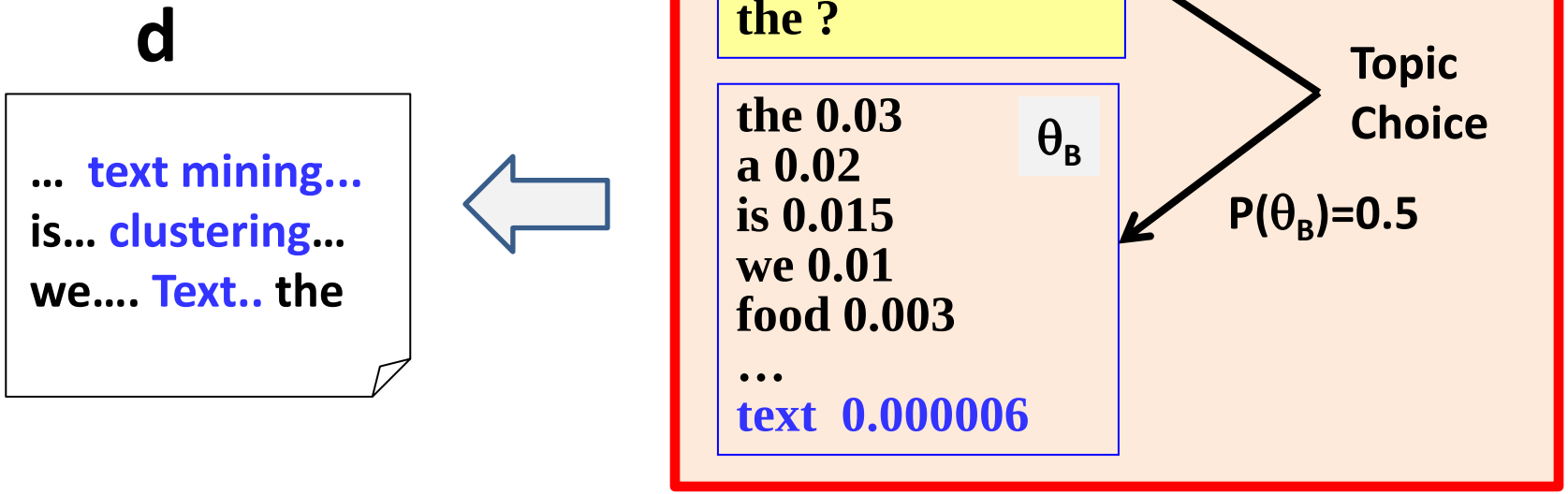
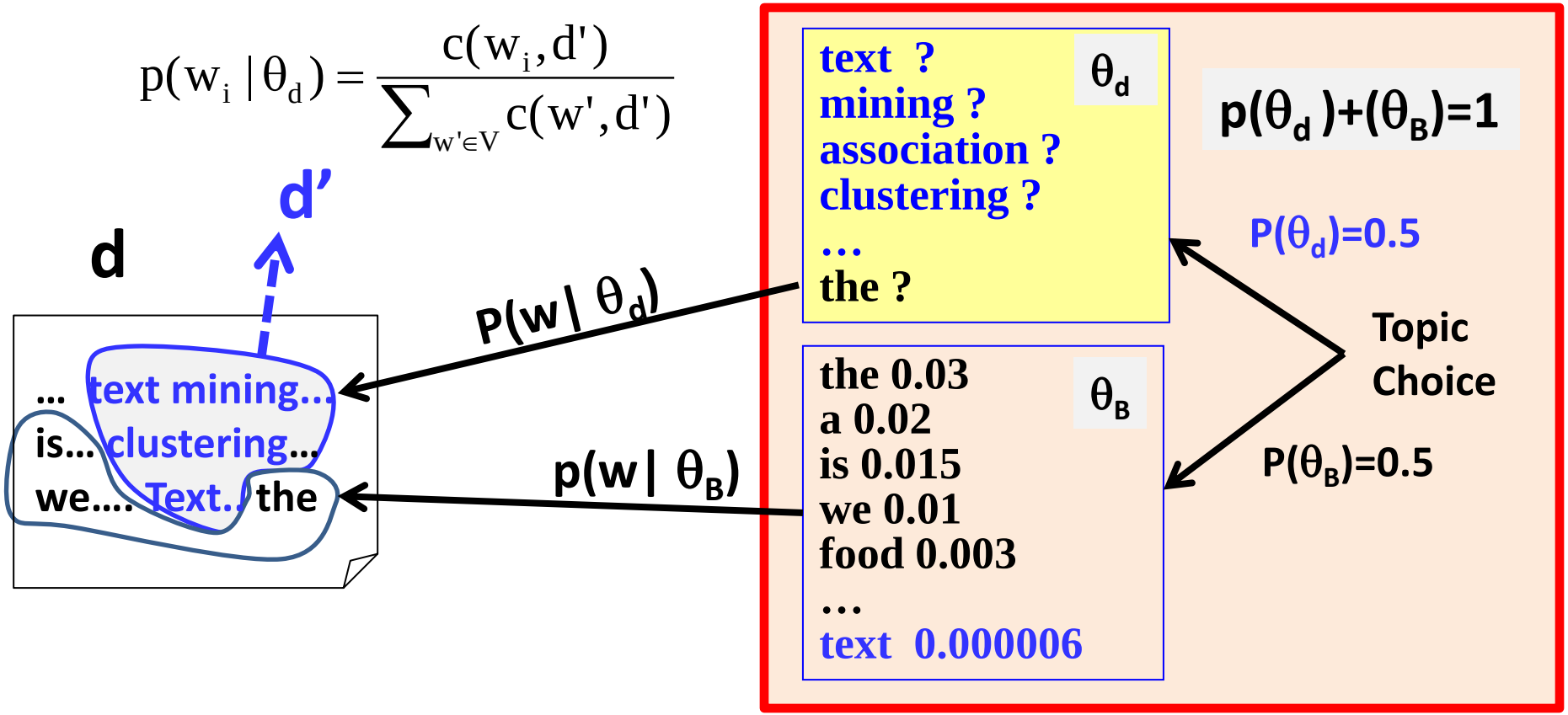
Estimation of One Topic: $P(w|\theta_d)$

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



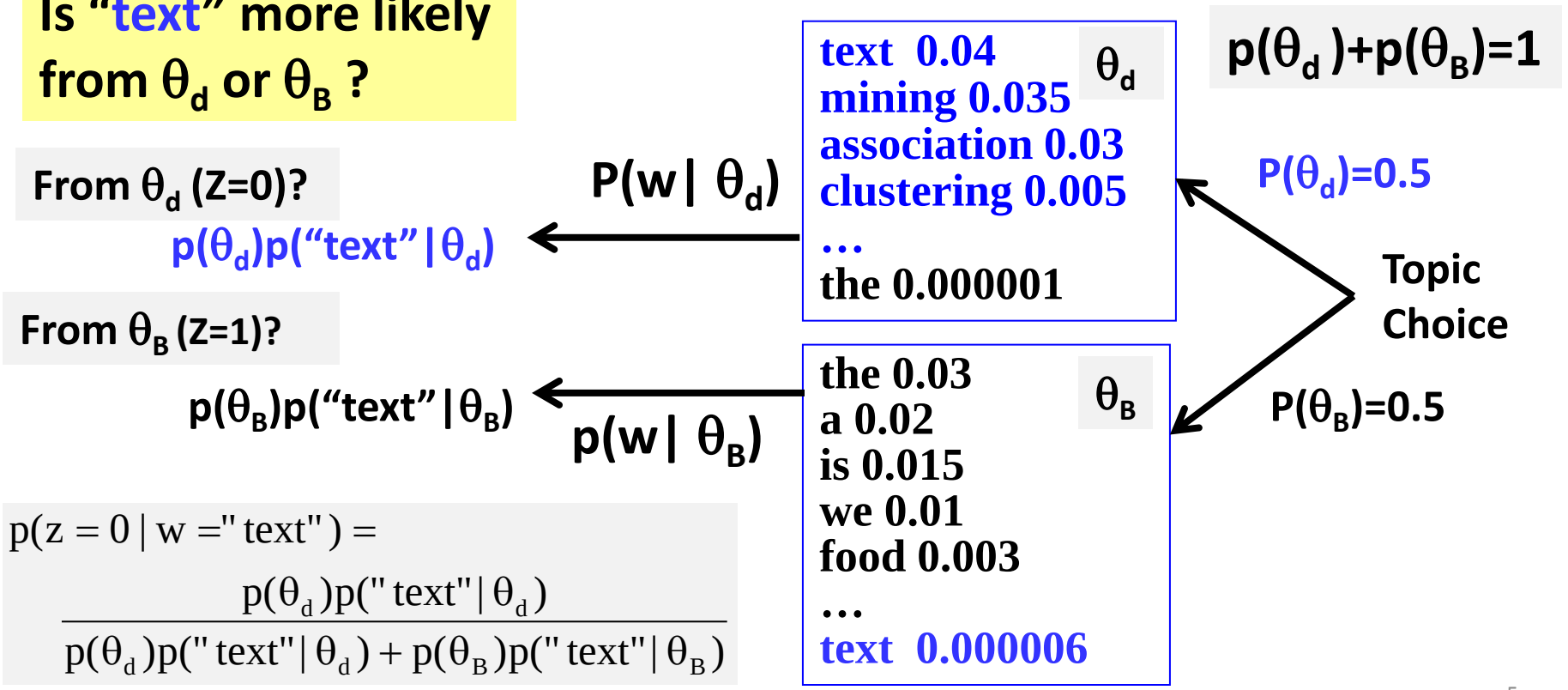
If we know which word is from which distribution…

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



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

Is "text" more likely from θ_d or θ_B ?



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

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
...	...

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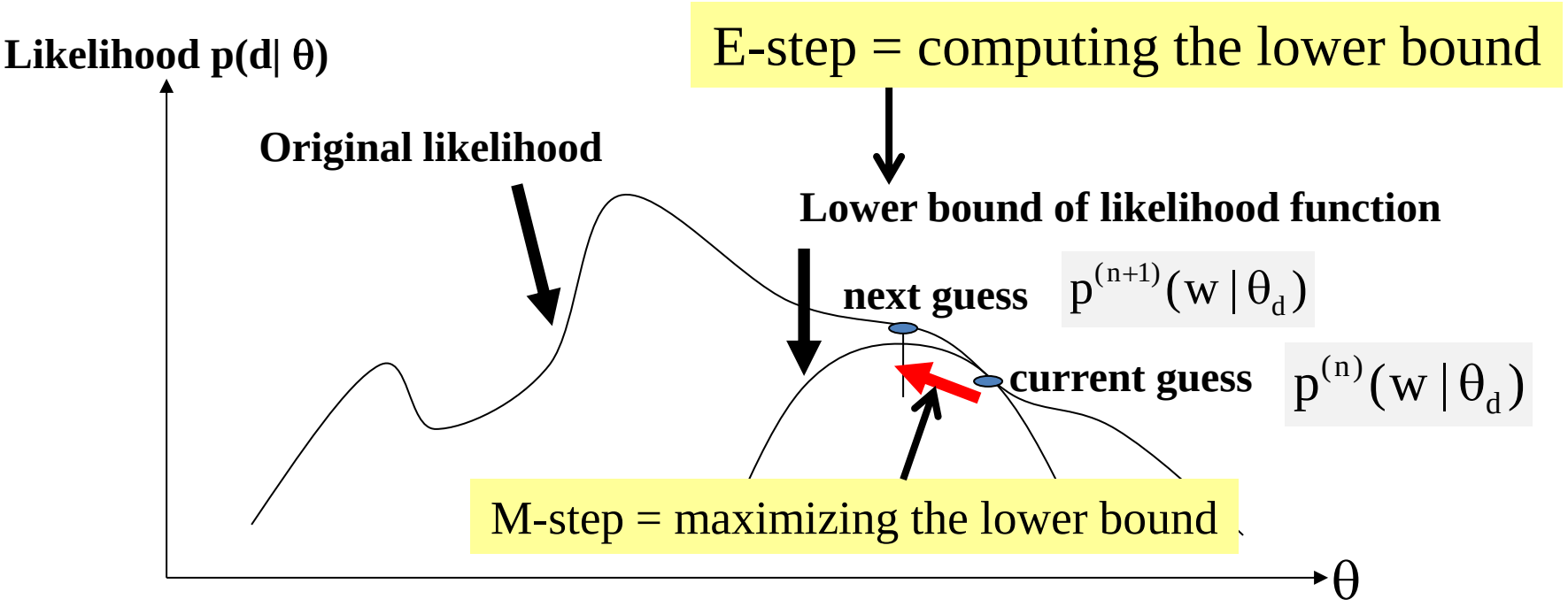

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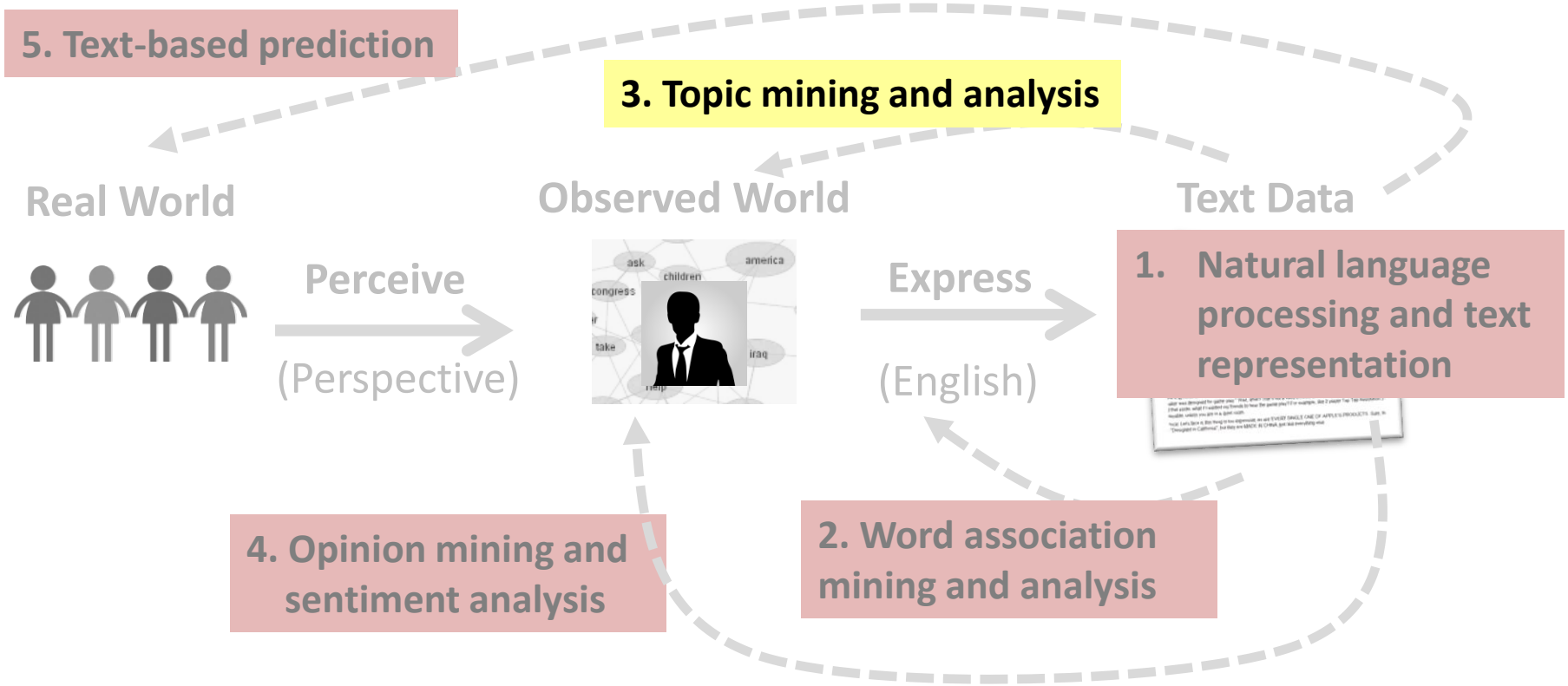

Document as a Sample of Mixed Topics

Topic θ_1	government 0.3 response 0.2 ...
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. . .	
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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…

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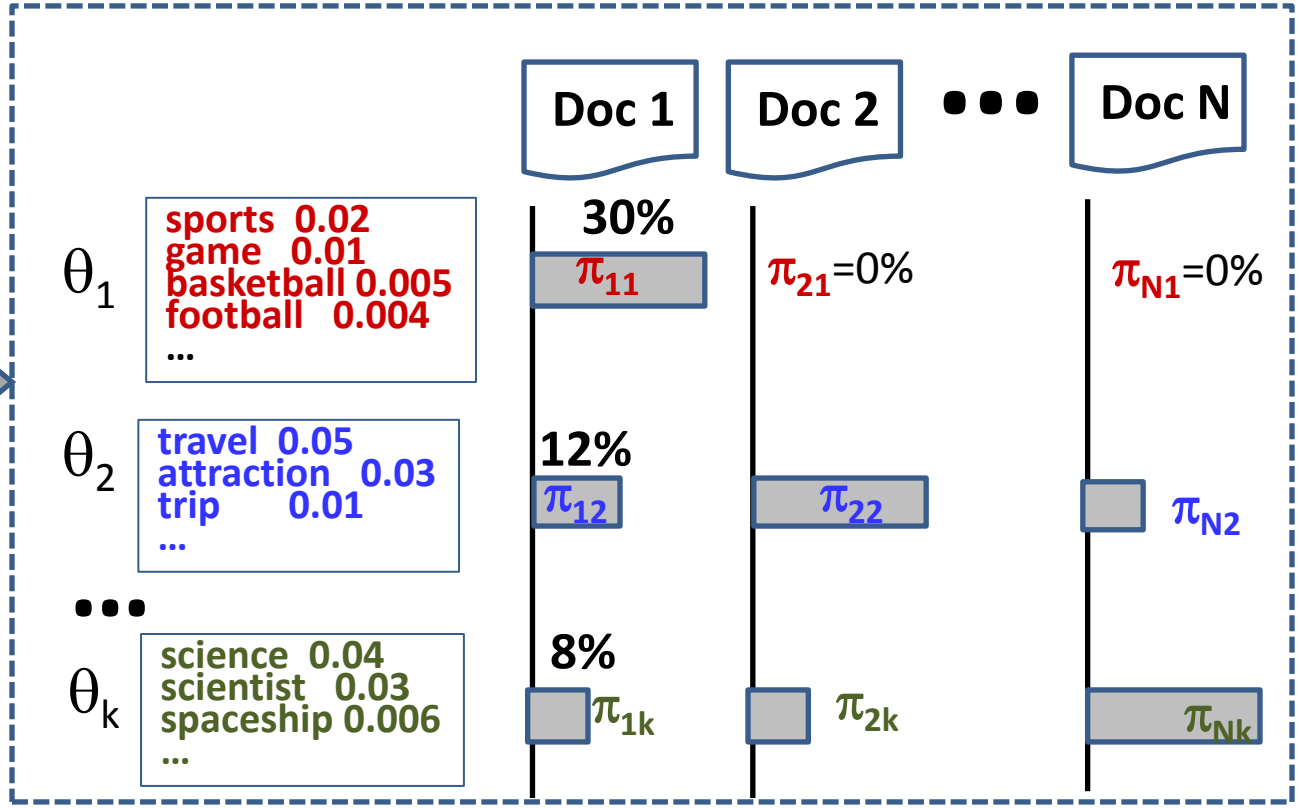

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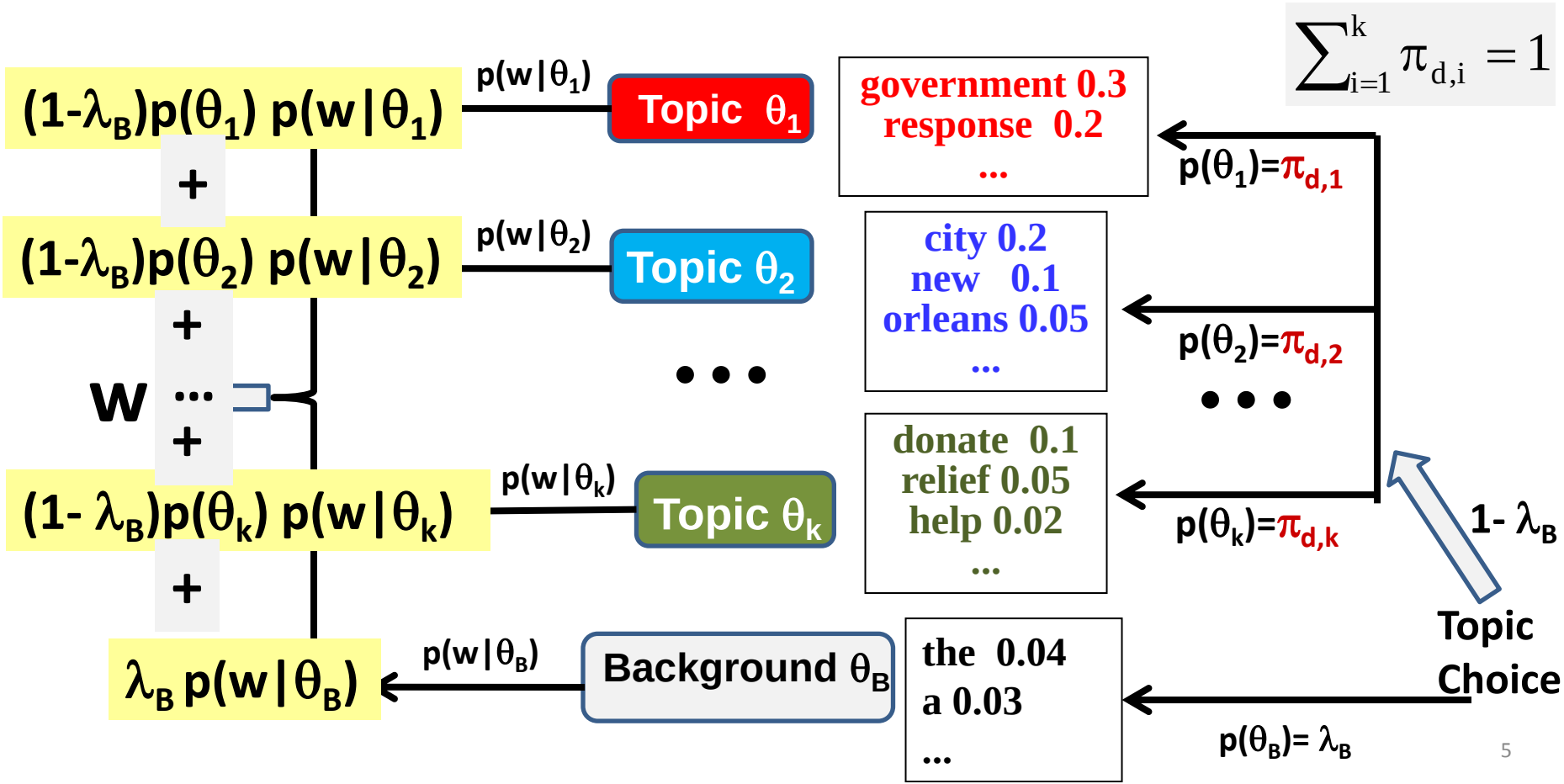

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Percentage of background words (known)

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Coverage of topic θ_j in doc d

Prob. of word w in topic θ_j

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

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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

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

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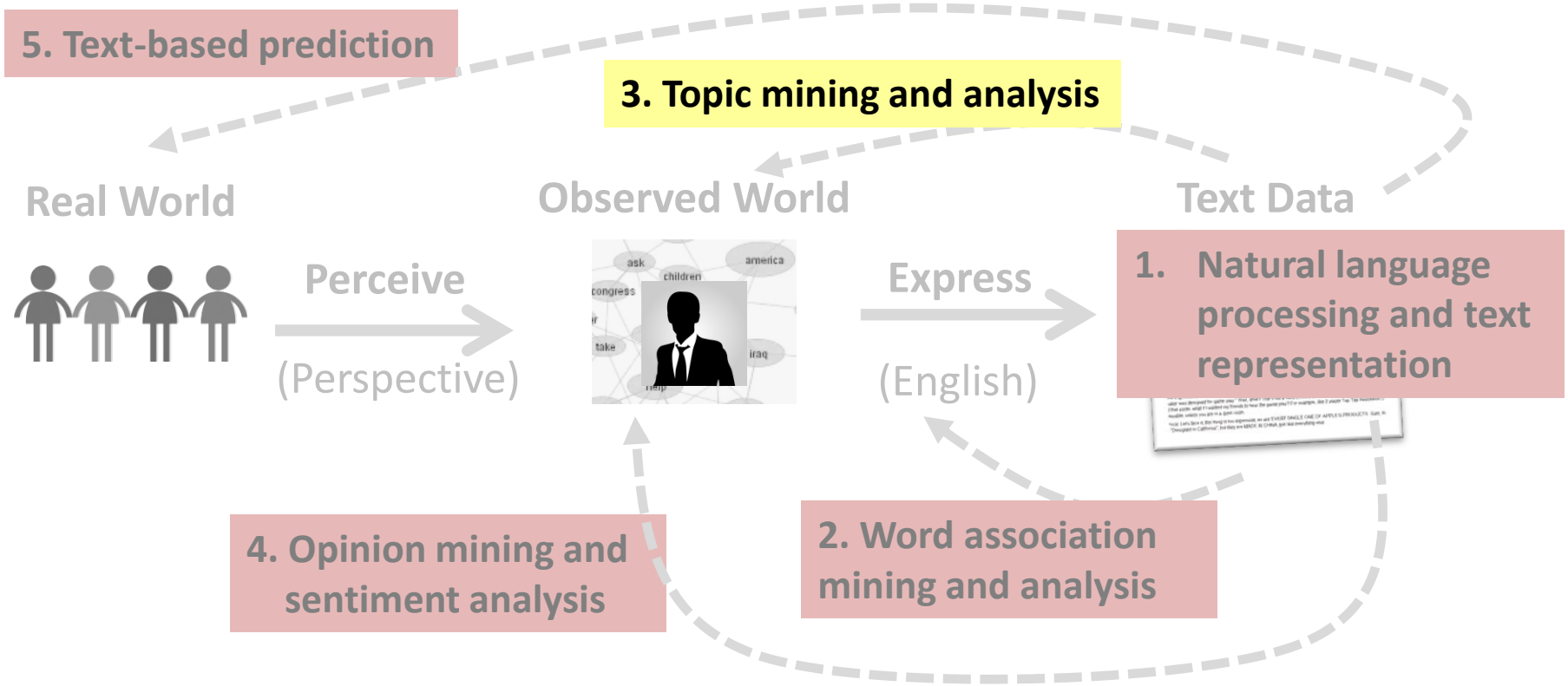

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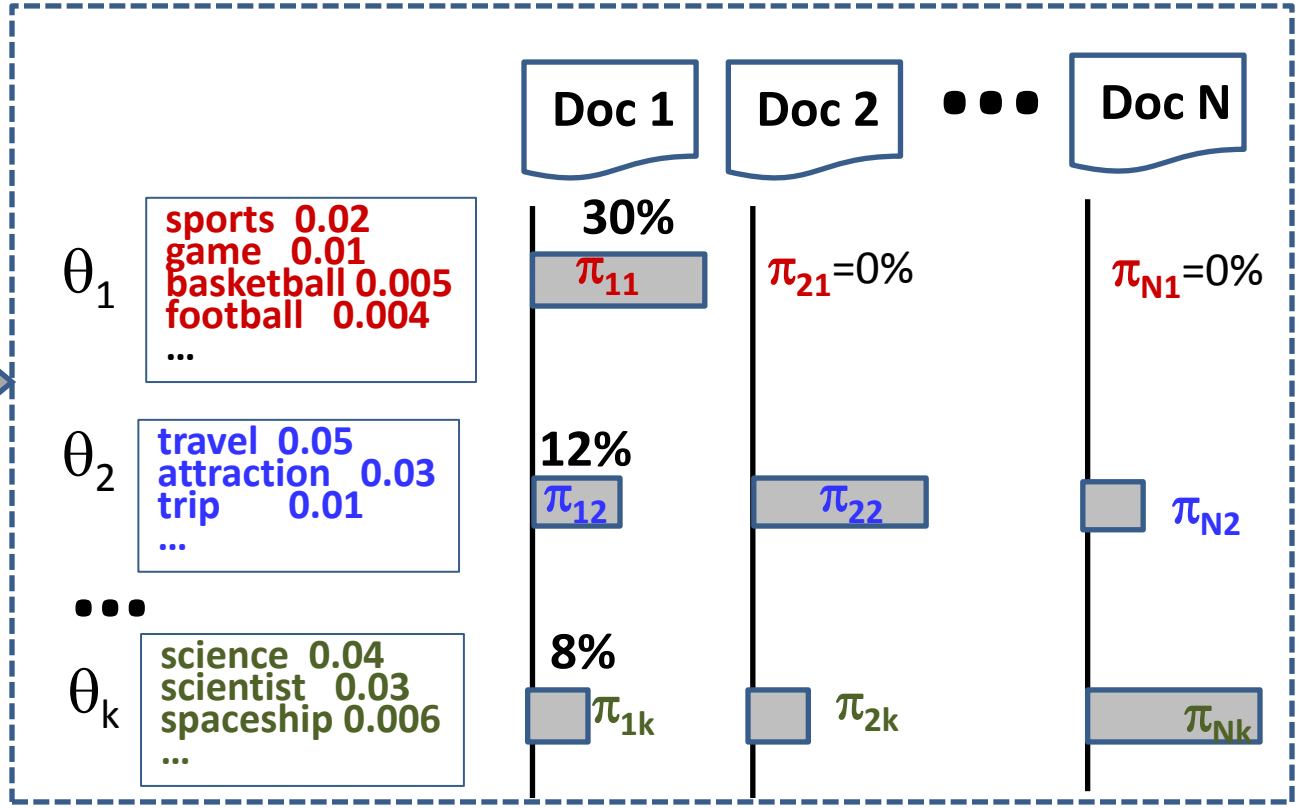

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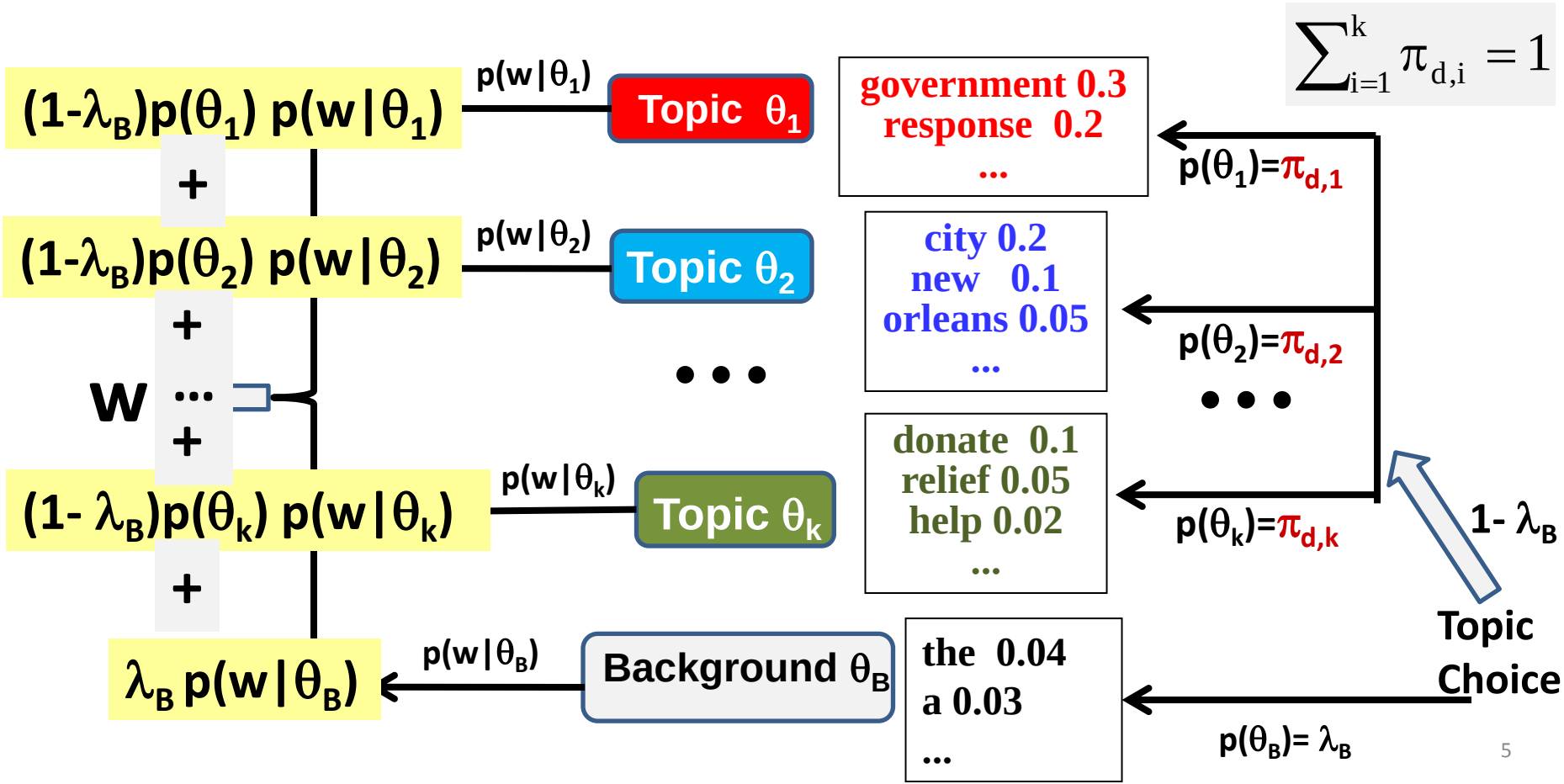

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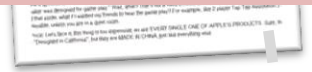

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Extensions of PLSA

- 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)
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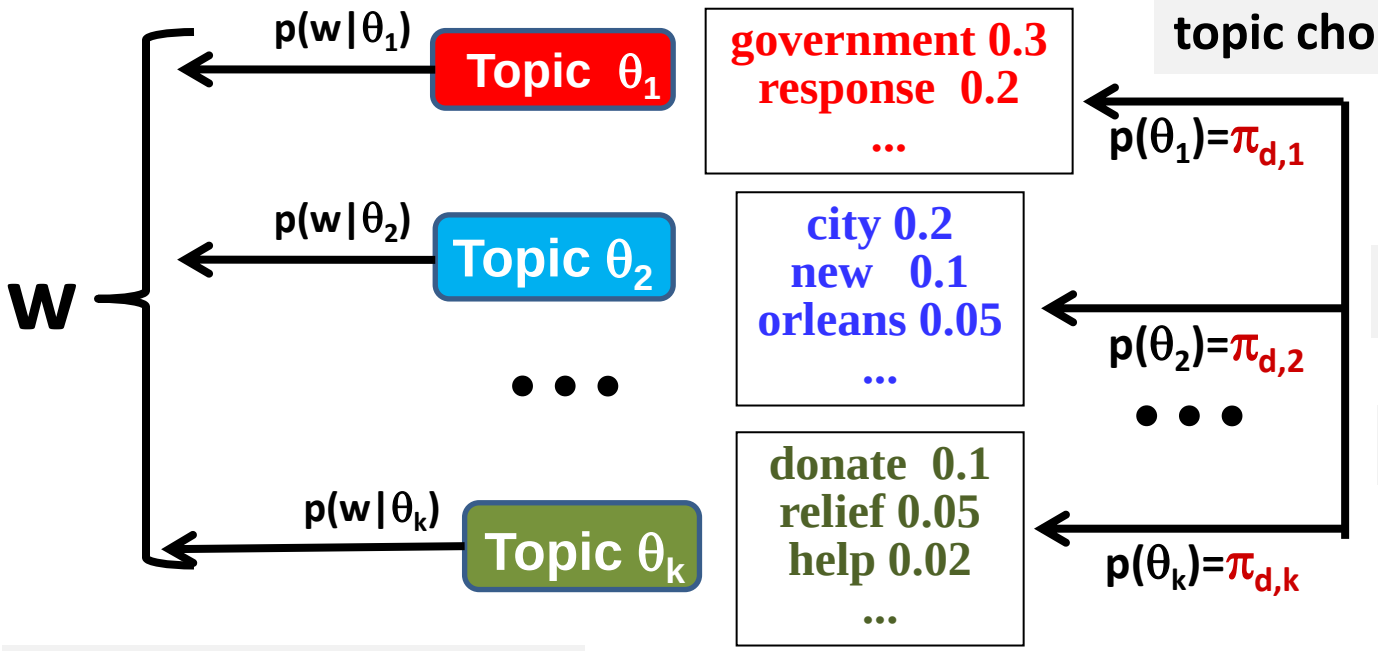

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PLSA

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Core assumption in all topic models

PLSA component

Added by LDA

Parameter Estimation and Inferences in LDA

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Latent Dirichlet Allocation (LDA)

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Department of Computer Science
University of Illinois at Urbana-Champaign

Latent Dirichlet Allocation (LDA)

5. Text-based prediction

3. Topic mining and analysis

Real World

Observed World

Text Data

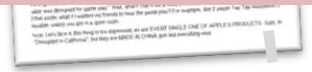
Perceive

(Perspective)

Express

(English)

1. Natural language processing and text representation



2. Word association mining and analysis

4. Opinion mining and sentiment analysis

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

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

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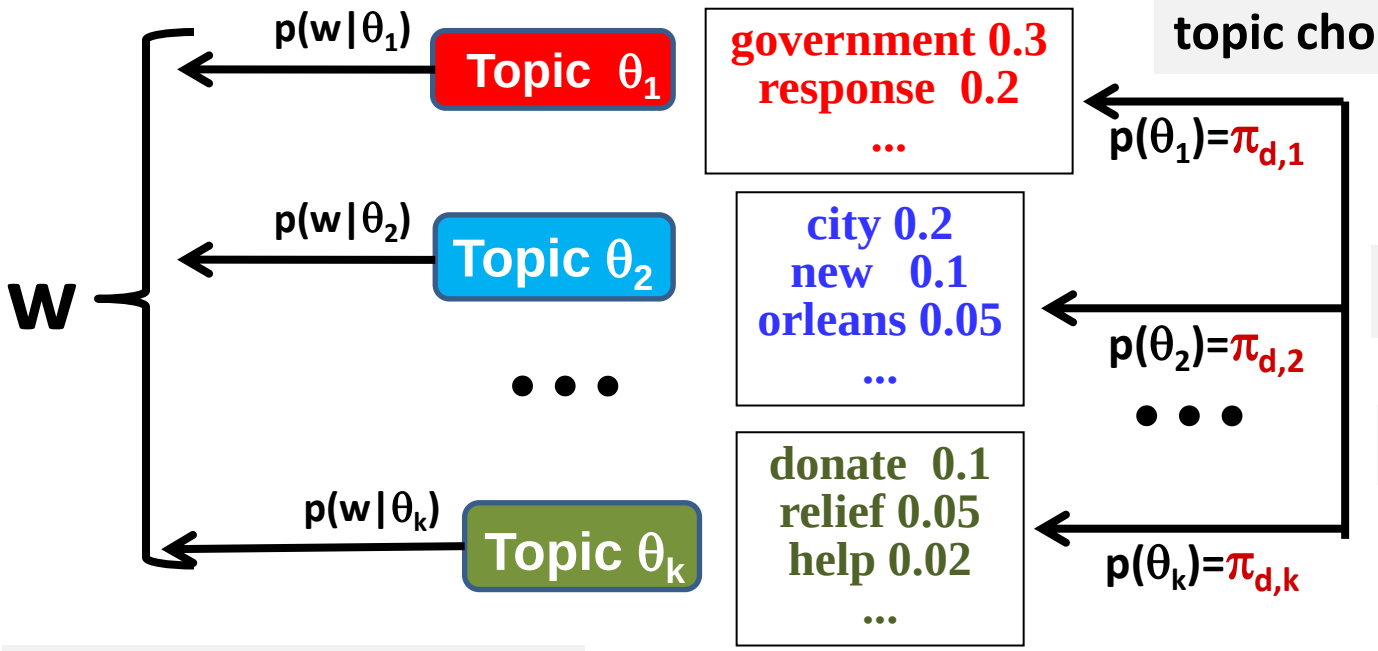

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