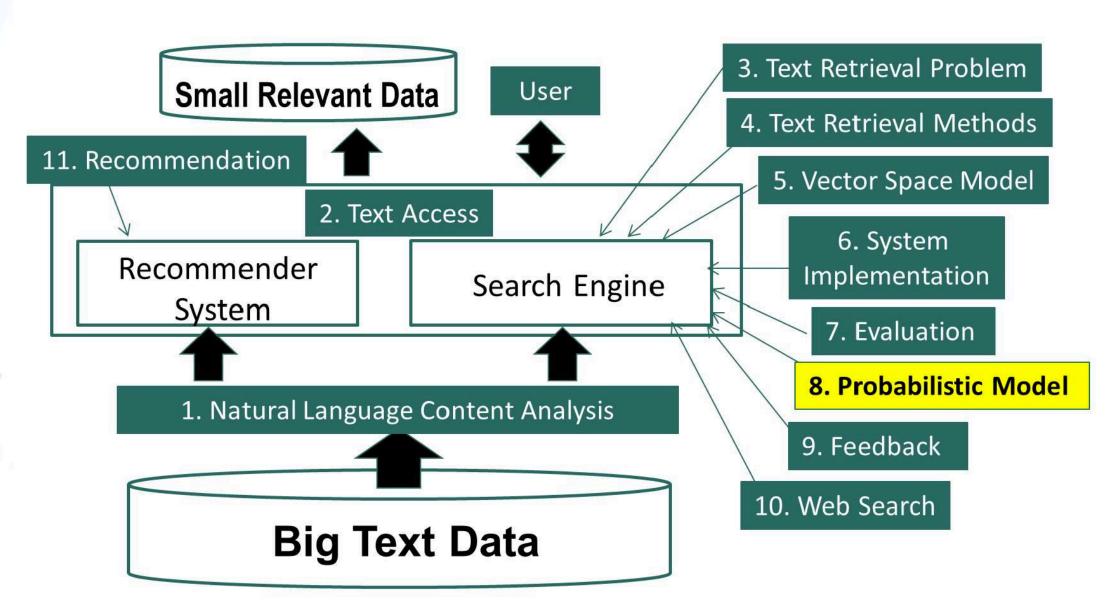
# Information Retrieval & Text Mining

Probabilistic Retrieval Model: Statistical Language Model

Dr. Saeed UI Hassan Information Technology University

#### Probabilistic Retrieval Model: Basic Idea



#### Overview

- What is a Language Model?
- Unigram Language Model
- Uses of a Language Model

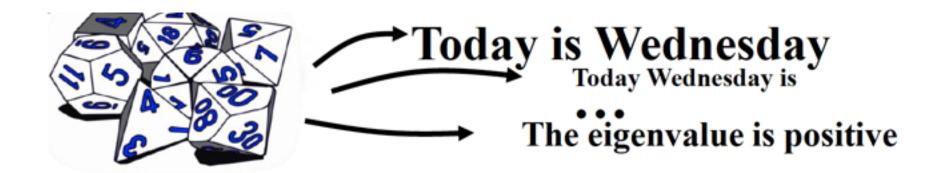
#### What is a Statistical Language Model (LM)?

- A probability distribution over word sequences
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  - p("The eigenvalue is positive")  $\approx$  0.00001
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  - Given that a user is interested in sports news, how likely would the user use "baseball" in a query? (information retrieval)

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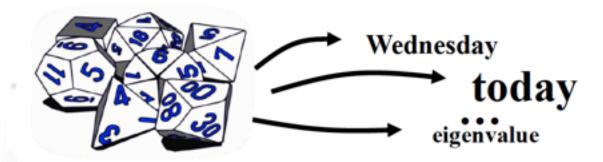
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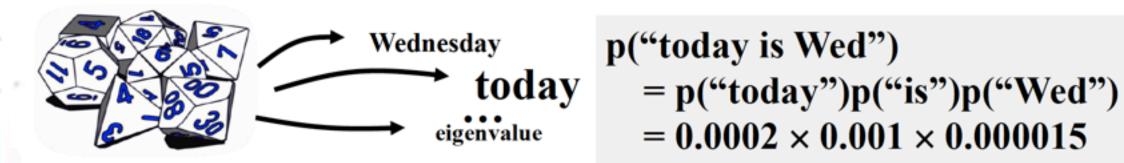
Given probabilities of each word, the sum of all is = 1

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#### Text Generation with Unigram LM

Unigram LM  $p(w|\theta)$ 

Sampling

**Document =?** 

Topic 1:

Text mining in food 0.00001

**text 0.2** mining 0.1 association 0.01 clustering 0.02

Topic 2:

Health

**food 0.25** nutrition 0.1 healthy 0.05 diet 0.02

#### Text Generation with Unigram LM

Sampling Unigram LM  $p(w|\theta)$ **Document =?** text 0.2Text mining mining 0.1 association 0.01 Topic 1: clustering 0.02 paper Text mining in food 0.00001 Food nutrition food 0.25 Topic 2: nutrition 0.1 paper healthy 0.05 Health

diet 0.02

#### **Estimation of Unigram LM**

Unigram LM  $p(w|\theta)=?$ 

Estimation

Text Mining Paper d

Total #words=100

text ?
mining ?
association
?
database ?
...
query ?



text 10 mining 5 association 3 database 3 algorithm 2 .... query 1 efficient 1

#### **Estimation of Unigram LM**

Unigram LM  $p(w|\theta)=?$ 

10/100

5/100

3/100

3/100

1/100

text? mining?

association

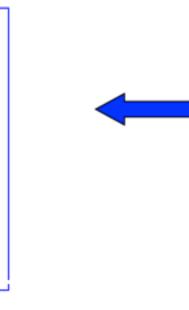
database?

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Estimation

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Text Mining Paper d

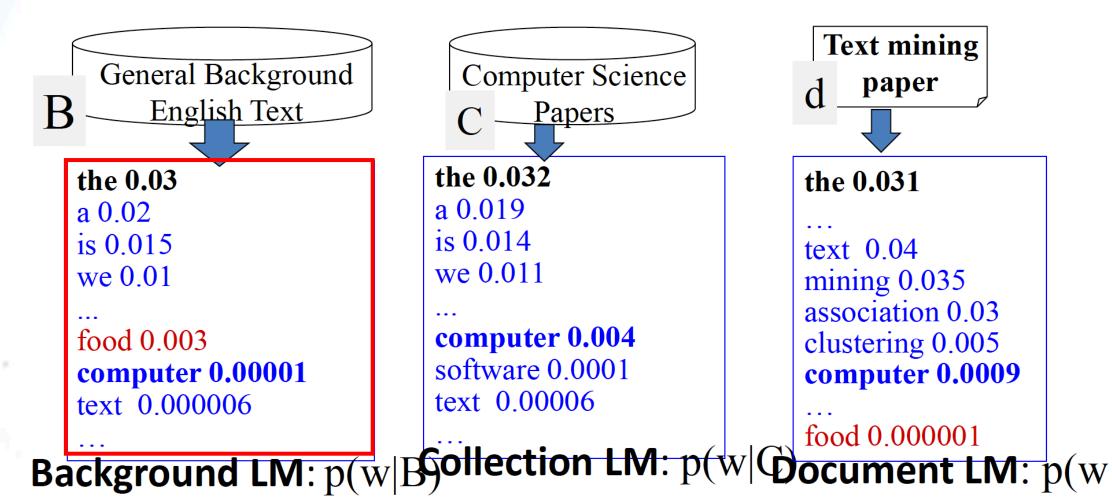
Total #words=100



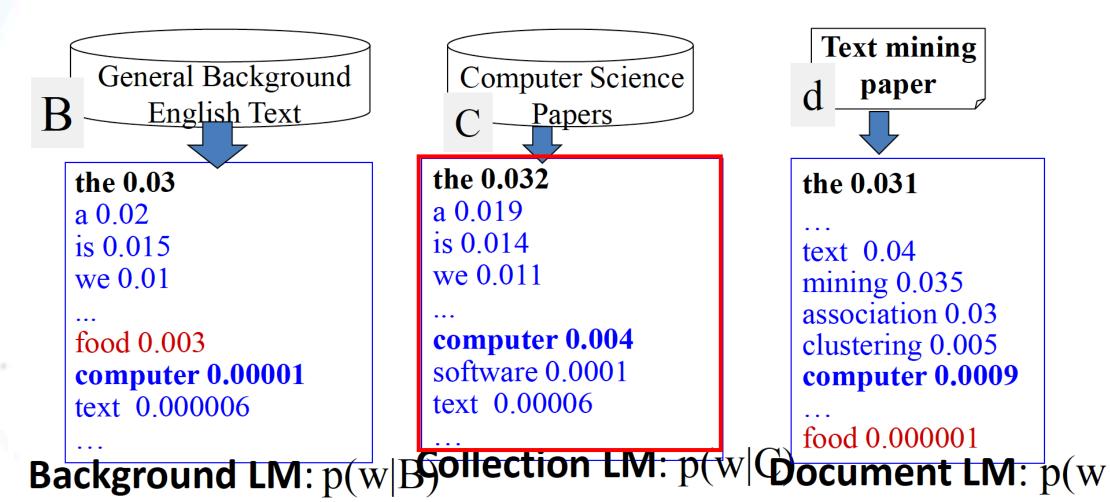


$$p(w \mid \theta) = p(w \mid d) = \frac{c(w, d)}{|d|}$$

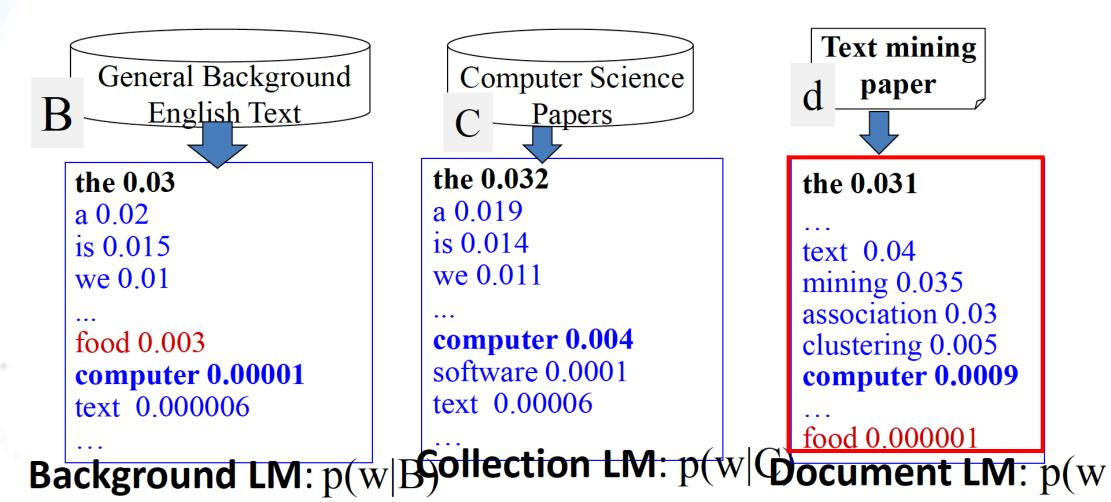
#### LMs for Topic Representation

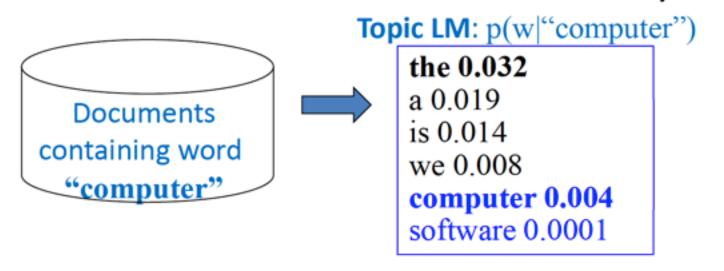


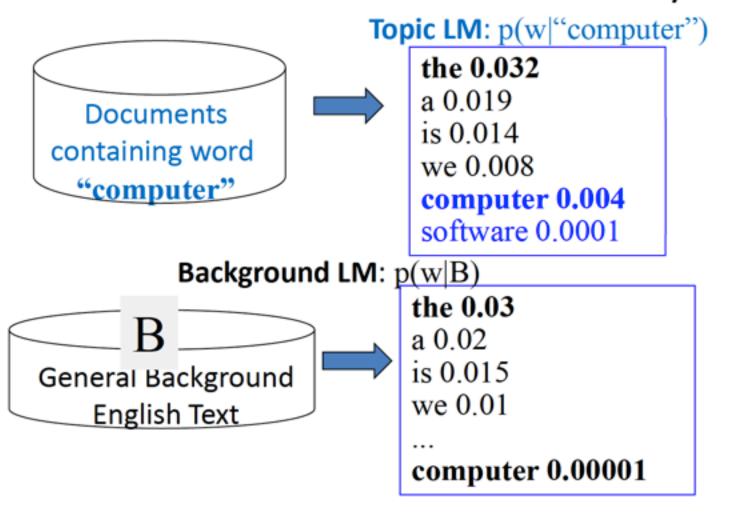
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Documents
containing word
"computer"

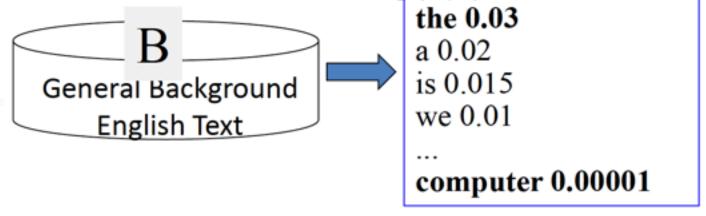
Topic LM: p(w|"computer")

the 0.032
a 0.019
is 0.014
we 0.008
computer 0.004
software 0.0001

Normalized Topic LM:

p(w|"computer")/p(w|B)

**Background LM**: p(w|B)



**Topic LM**: p(w|"computer") **Normalized Topic LM:** the 0.032 p(w|"computer")/p(w|B) a 0.019 Documents is 0.014 computer 400 containing word we 0.008 software 150 "computer" computer 0.004 program 104 software 0.0001 **Background LM**: p(w|B)text 3.0 the 0.03 the 1.1 a 0.02 is 0.015 a 0.99 General Background is 0.9 we 0.01**English Text** we 0.8 **computer 0.00001** 10

# Summary

- Language Model = probability distribution over text
- Unigram Language Model = word distribution
- Uses of a Language Model
  - Representing topics
  - Discovering word associations

# Additional Readings

- Chris Manning and Hinrich Schütze, Foundations of Statistical Natural Language Processing, MIT Press.
   Cambridge, MA: May 1999.
- Rosenfeld, R., "Two decades of statistical language modeling: where do we go from here?," *Proceedings of the IEEE*, vol.88, no.8, pp.1270,1278, Aug. 2000