



上海外国语大学  
SHANGHAI INTERNATIONAL STUDIES UNIVERSITY

# New Media Data Analytics and Application

Lecture 9: Basic Statistics for  
Natural Language Processing

Ting Wang

- The Foundation of Statistics
- Bayes' Theorem
- Markov Model
- N-gram
- Chinese Word Segmentation



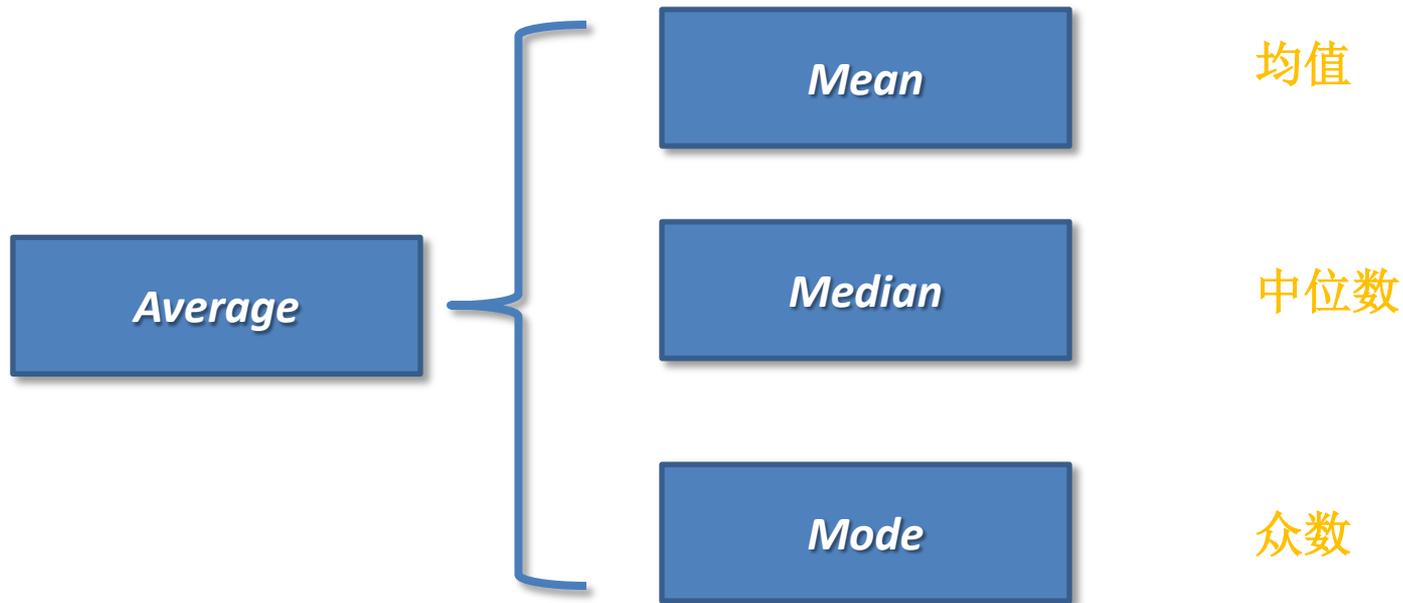


introduce some basic statistical metrics to you

# The Foundation of Statistics

# The Foundation of Statistics

## *Average* 平均数



# The Foundation of Statistics

## Mean 均值

Supposing:  $X = (x_1, x_2, \dots, x_n)$

$$\bar{X} = \frac{\sum X}{n}$$



# The Foundation of Statistics

## *Median* 中位数

the value separating the higher half of a data sample, a population, or a probability distribution, from the lower half.

Supposing:  $X = (x_1, x_2, \dots, x_n)$

Sort  $X$  from small number to large number,

–if  $n$  is an odd number, then the Median of  $X$  is the middle one,

–if  $n$  is an even number, then the Median of  $X$  is the **mean** of the two middle numbers.

1, 3, 3, **6**, 7, 8, 9

Median = 6

1, 2, 3, **4**, **5**, 6, 8, 9

Median =  $(4 + 5) \div 2$   
= 4.5



# The Foundation of Statistics

## *Mode* 众数

the value that appears most often in a set of data

Comparison of common averages of values { 1, 2, 2, 3, 4, 7, 9 }

Type	Description	Example	Result
Arithmetic mean	Sum of values of a data set divided by number of values: $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$	(1+2+2+3+4+7+9) / 7	4
Median	Middle value separating the greater and lesser halves of a data set	1, 2, 2, <b>3</b> , 4, 7, 9	3
Mode	Most frequent value in a data set	1, <b>2, 2</b> , 3, 4, 7, 9	2

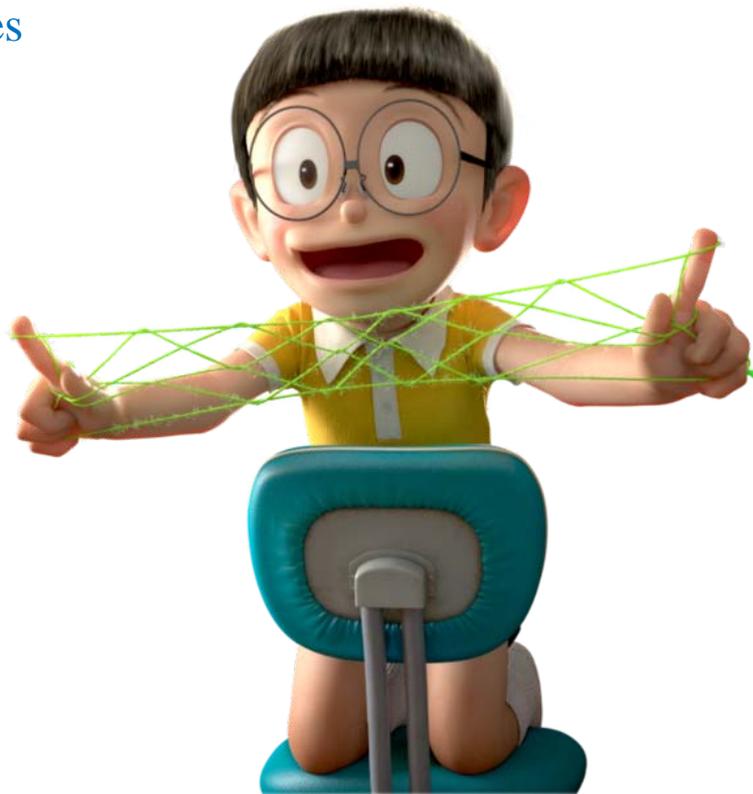


# The Foundation of Statistics

## *Range* 极差

the difference between the largest and smallest values

$$r = \text{Max} - \text{Min}$$



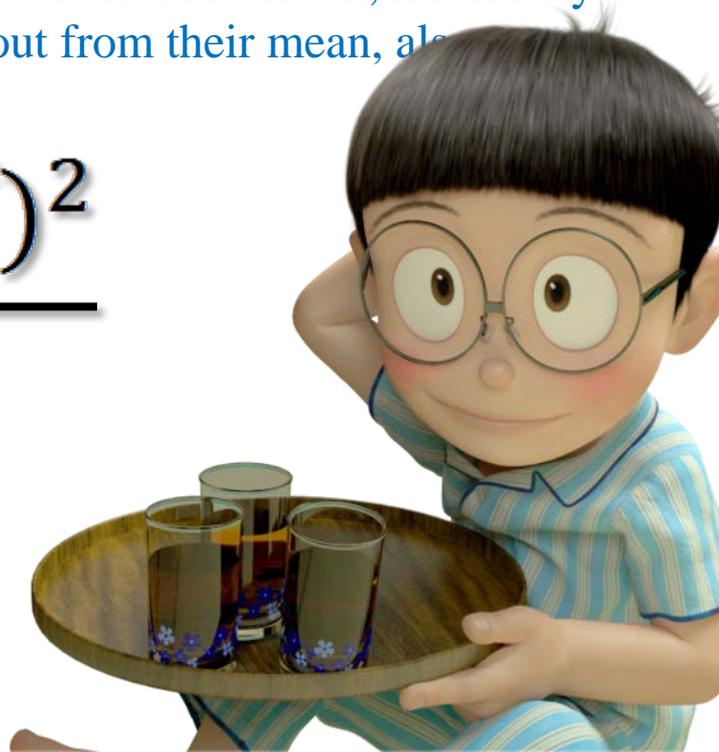
# The Foundation of Statistics

## Variance 方差

the expectation of the squared deviation of a random variable from its mean, informally measures how far a set of (random) numbers are spread out from their mean, also known as  $D(X)$ ,  $Var(X)$

$$s^2 = \frac{\sum (X - \bar{X})^2}{n - 1}$$

Why  $n-1$ ?



# The Foundation of Statistics

## *Standard Deviation* 标准差

$$s = \sqrt{\frac{\sum (X - \bar{X})^2}{n - 1}}$$



# The Foundation of Statistics

*Expected Value* 数学期望

$$E[X] = \bar{X} = \sum_{i=1}^n x_i P_i$$

Where:  $P_i$  is the weight of  $x_i$   
in Statistics,  $P$  is the probability.



# The Foundation of Statistics

## *Properties of Expected Value*

- If  $C$  is a constant,  $E[C]=C$
- If  $X$  and  $Y$  are random variables such that  $X \leq Y$ , then  $E[X] \leq E[Y]$
- $E[X+C]=E[X]+C$
- $E[X+Y]=E[X]+E[Y]$
- $E[CX]=CE[X]$
- $D[X]=E[X^2]-(E[X])^2$





very useful for natural language processing

# Bayes' Theorem

# Bayes' Theorem

## Probability 概率



$$P(x_i) = 1/6$$

Sample Space:

$\{1, 2, 3, 4, 5, 6\}$



$$P(x_i) = 1/2$$

$\{H, T\}$

## *Properties of Probability*

$$P(x_i) \geq 0$$

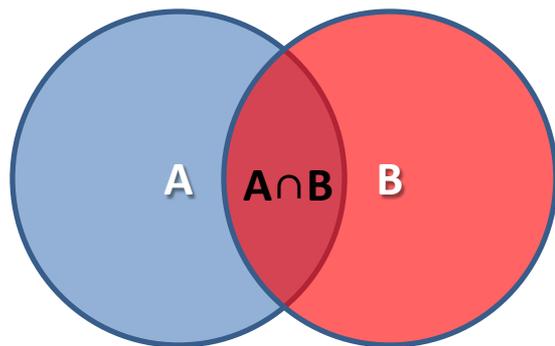
$$P(x_i) \in [0,1]$$

$$\sum_{i=1}^n P(x_i) = 1$$

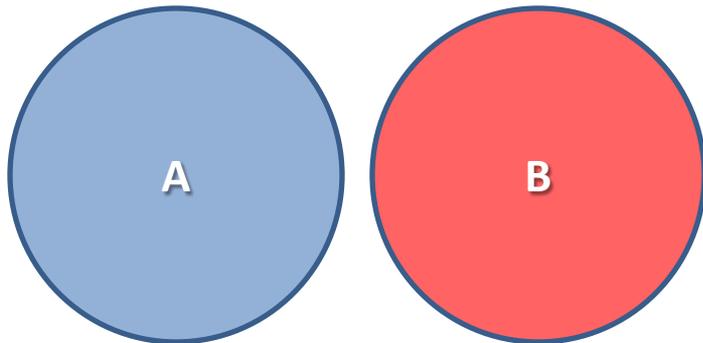


# Bayes' Theorem

## *Independence* 独立性



*Dependent*



*Independent*

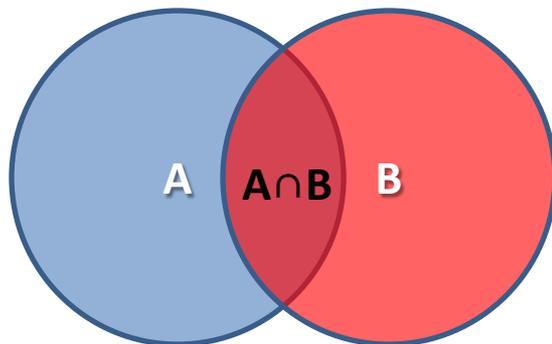


# Bayes' Theorem

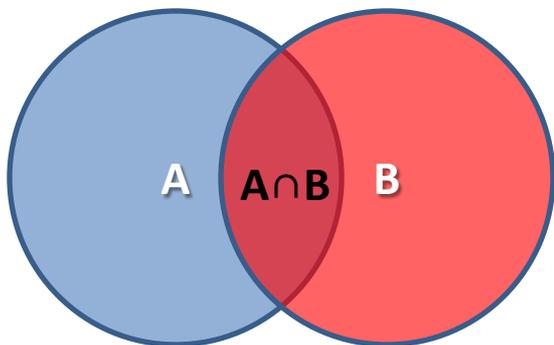
## *Conditional Probability* 条件概率

$P(A | B)$ , is the probability of observing event A given that B is true

$$P(A|B) = P(A \cap B) / P(B)$$



## Bayes' Theorem 贝叶斯定理



$$P(A|B) = P(A \cap B) / P(B)$$

$$P(A \cap B) = P(A|B)P(B)$$

$$P(A \cap B) = P(B|A)P(A)$$

$$P(A|B)P(B) = P(B|A)P(A)$$

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

# Bayes' Theorem

Bayes' Theorem plays an very important role in statistical NLP.

- We can predict what you will say!
  - **Uncle Sam:** How are you?
  - **Chinese student:** Fine, Thank you, and you?
  - **Chinese student's Predictive Answer:** I am fine, too!
  - **Uncle Sam:** Nothing much.
  - **Chinese student:** 。 。 。 （不多??）



一脸懵逼



# Bayes' Theorem

- Because, for Chinese students:

$P(\text{Fine, Thank you, and you?} \mid \text{How are you?})$  ↗

$P(\text{I am fine, too!} \mid \text{Fine, Thank you, and you?})$  ↗

$P(\text{Nothing much} \mid \text{Fine, Thank you, and you?})$  ↘

In the corpus of Chinese students,

$P(\text{I am fine, too!} \mid \text{Fine, Thank you, and you?}) > P(\text{Nothing much} \mid \text{Fine, Thank you, and you?})$



## *Another Example:*

I ate a red \_\_\_\_\_ .

A. telephone    B. light    C. swim    D. tomato

# Bayes' Theorem

## *No Grammar! But the Frequency of use!*

- The most successful Chinglish:  
*Long time no see!*
- Chinglish Future Star:  
*Good Good Study, Day Day UP!*





your future is decided by now, not the past

# Markov Model

*Stochastic Process* 随机过程

*Markov Chain* 马尔科夫链



$$X = (x_1, x_2, \dots, x_n)$$

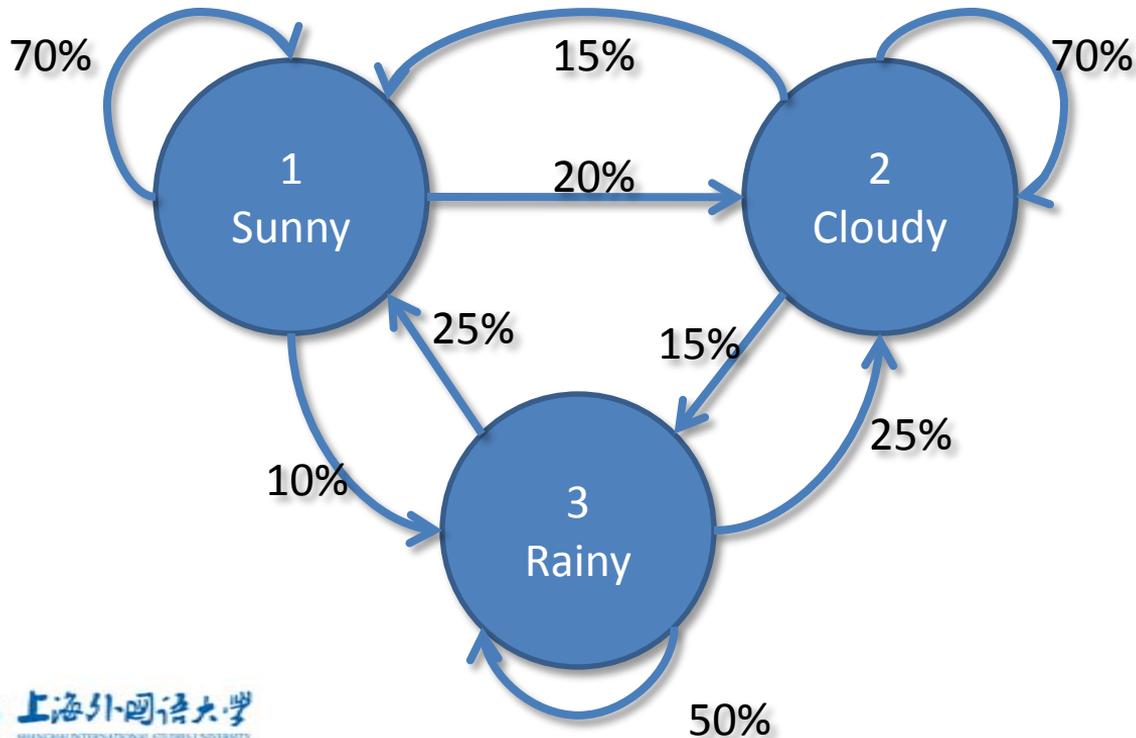
$x_i$  is a *Stochastic Process*

1,3,5,2,1,4,2,6,3,.....

$X$  is a *Markov Chain*

# Markov Model

## Transition Probability 转移概率



$$\begin{bmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{bmatrix} =$$

$$\begin{bmatrix} 0.7 & 0.2 & 0.1 \\ 0.15 & 0.7 & 0.15 \\ 0.25 & 0.25 & 0.5 \end{bmatrix}$$

Stochastic Matrix  
概率转移矩阵

出度之和100%

## *Markov Model* 马尔科夫模型

$$P(x_{t+1}|x_1, x_2, \dots, x_t) = P(x_{t+1}|x_t)$$

First-Order Markov Model

***Your future is not decided by your past, but now!***

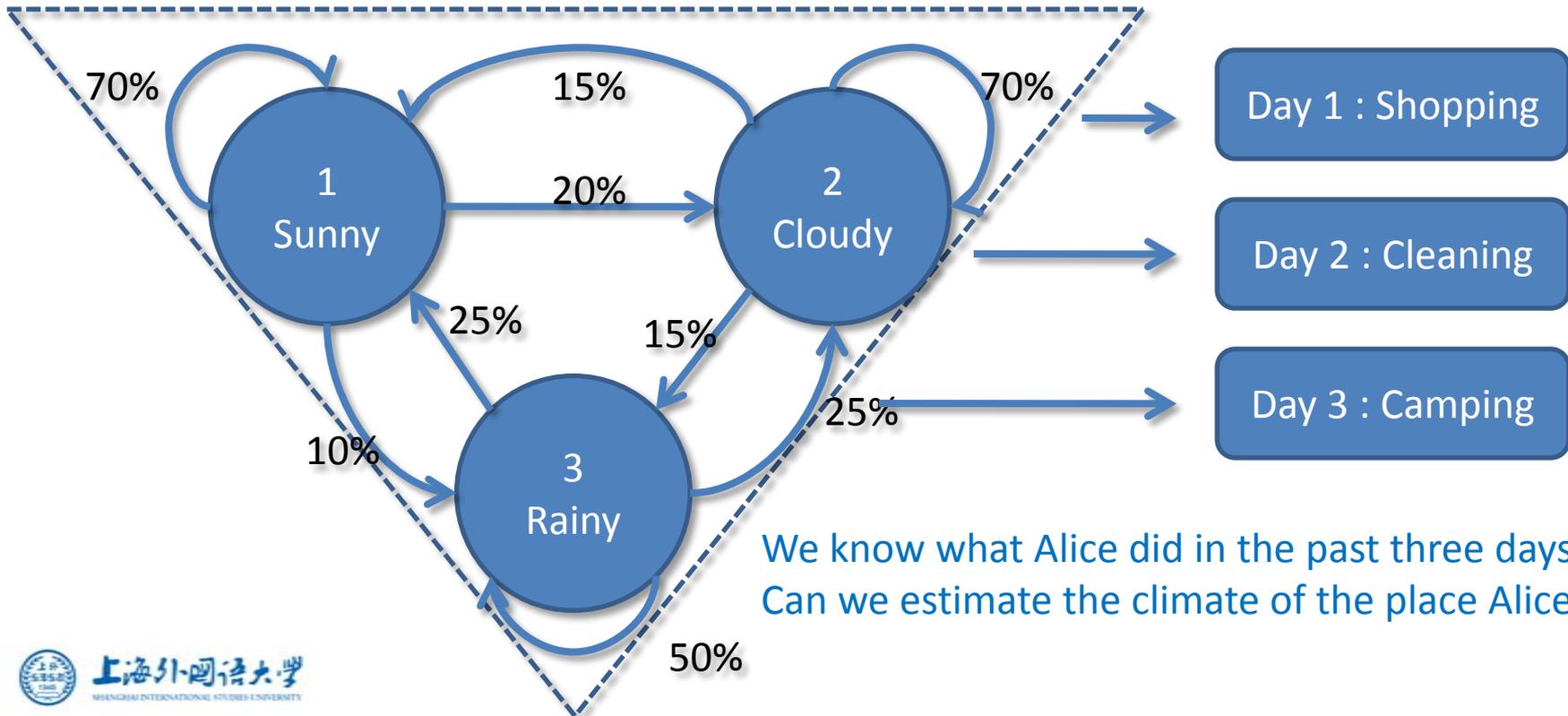
Second-Order Markov Model

$$P(x_{t+1}|x_1, x_2, \dots, x_t) = P(x_{t+1}|x_t x_{t-1})$$



# Markov Model

## Hidden Markov Model 隐马尔科夫模型



## *The Applications of Markov Model in NLP*

- Machine Translation
- Word Segmentation
- Speech Recognition
- Part-of-speech Tagging
- Natural Language Generation
- ...





one of the most important statistical computational linguistic models

# N-gram

## Definition of N-gram *N*元文法

An n-gram model is a type of probabilistic language model for predicting the next item in such a sequence in the form of a  $(n - 1)$ -order Markov model.

N	N-gram	$(N - 1)$ -order Markov model	Example
1	1-gram(unigram)	Independent from history	One Word
2	2-gram(bigram)	1-order (HMM-1)	Two Words
3	3-gram(trigram)	2-order (HMM-2)	Three Words
...	...	...	...



## *Unigram* 上下文无关文法

- Only consider the probability of the word itself
- Hypothesis: Every word is independent.

$$P(X) = P(x_1, x_2, \dots, x_N) = \prod_{i=1}^N P(x_i)$$

$$P(x_i) = \frac{\text{Number of } x_i \text{ in the artical}}{\text{Number of all words in the artical}}$$



## Bigram 二元文法

The current word is influenced by the previous one word

$$\begin{aligned} P(X) &= P(x_1, x_2, \dots, x_N) = P(x_1)P(x_2|x_1)P(x_3|x_2) \cdots P(x_N|x_{N-1}) \\ &= P(x_1) \prod_{i=2}^N P(x_i|x_{i-1}) \end{aligned}$$

$$P(x_i|x_{i-1}) = \frac{\text{Number of } (x_{i-1}x_i) \text{ in the artical}}{\text{Number of all } x_{i-1} \text{ in the artical}}$$



## Trigram 三元文法

The current word is influenced by the previous two words

$$\begin{aligned} P(X) &= P(x_1, x_2, \dots, x_N) = P(x_1)P(x_2|x_1)P(x_3|x_2x_1)P(x_4|x_3x_2) \cdots P(x_N|x_{N-1}x_{N-2}) \\ &= P(x_1)P(x_2|x_1) \prod_{i=3}^N P(x_i|x_{i-1}x_{i-2}) \end{aligned}$$

$$P(x_i|x_{i-1}x_{i-2}) = \frac{\text{Number of } (x_{i-2}x_{i-1}x_i) \text{ in the artical}}{\text{Number of all } (x_{i-2}x_{i-1}) \text{ in the artical}}$$



## *Tips*

1. Previous studies showed that trigram and four-gram often have better performance
2. The larger of  $N$ , the more complex of the computation
3. N-gram needs training data set, while it is impossible for a training data set to contain all the matches of a word

## *Smoothing* 平滑

- Zero Probability 零概率
- Small Probability 小概率
- Laplace Smoothing 拉普拉斯平滑

$$P(x_i|x_1, x_2, \dots, x_{i-1}) = \frac{\text{Number of } (x_1 \dots x_i) \text{ in the article} + 1}{\text{Number of all } (x_1 \dots x_{i-1}) \text{ in the article} + \text{Number of words in dictionary}}$$



## *Commonly used Smoothing Approaches*

- Linear interpolation (e.g., taking the weighted mean of the unigram, bigram, and trigram)
- Good–Turing discounting
- Witten–Bell discounting
- Lidstone's smoothing
- Katz's back-off model (trigram)
- Kneser–Ney smoothing

Ref. <https://en.wikipedia.org/wiki/N-gram>





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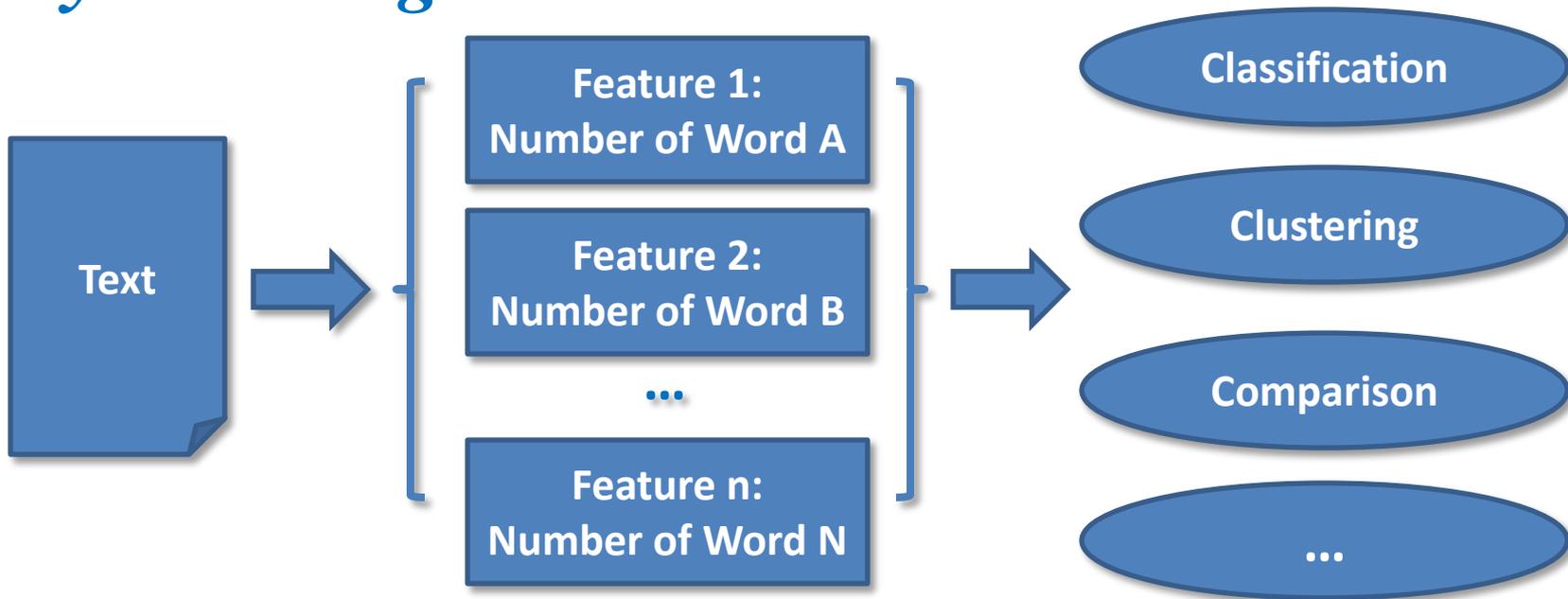
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the first step for Chinese information processing

# Chinese Word Segmentation

# Chinese Word Segmentation

## *Why Word Segmentation?*



**However, it is difficult to extract words from Chinese text.**

# Chinese Word Segmentation

## *Difficulties: Disambiguation*

乒乓球拍卖完了

乒乓|球拍|卖完了

乒乓球|拍卖|完了

一脸懵逼



# Chinese Word Segmentation

## *Forward Max. matching method, FMM*

### 正向最大匹配

准备工作：需要分词词典D

设MaxLen表示最大词长度

算法：

1. 从生语料N中取长度为MaxLen的字串str, 令Len= MaxLen
2. 把str与D中的词相匹配
3. 若匹配成功, 则认为str为词, N中去掉str (指针前移Len个单位), 返回1
4. 若匹配不成功,
  - ◆ 若Len>1则Len--, 从生语料N中取长度为Len的字串str返回2;
  - ◆ 否则, 得到单字词, N中去掉str (指针前移1个单位), 返回1

若4中得到的单字不是词, 则要进行未登录词处理

若待切分的语料字符串长度小于MaxLen, 则取str为待切分语料



# Chinese Word Segmentation

## *Backward Max. matching method, BMM*

### 逆向最大匹配

1. Similar to FMM, but the text is scanned from the right side
2. Often jointly use with FMM



# Chinese Word Segmentation

## • Statistical Matching Method

FMM and BMM

```
Begin initialize Path← {}, AmbiguousString, SubString← {}
While (AmbiguousString.Length>0)
{
    //只考虑以当前HMM第一个状态开始的匹配序列
    SubString←以AmbiguousString中的第一个字为基准，取出所有可能的匹配字符串
    Foreach SubString
    {
        //提供当前情况下所有的概率，为判断歧义作参考
        计算当前每一种可能情况的概率P(SubString) //unigram, bigram, trigram with smoothing
    }
    //选择概率最大的SubString添加到Path
    将argmax (P(SubString))添加到Path
    //准备考察除去最大概率的SubString后的AmbiguousString，从HMM序列首部开始，除去所有的匹配状态
    AmbiguousString.Remove(0, argmax (P(SubString)).Length)
}
Return Path
End
```



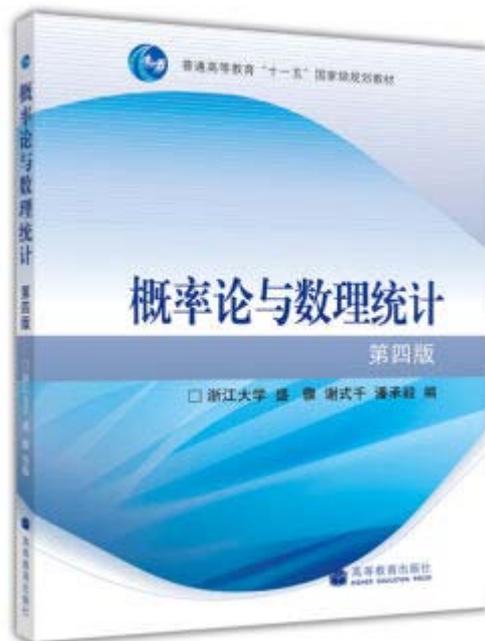


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# Reference

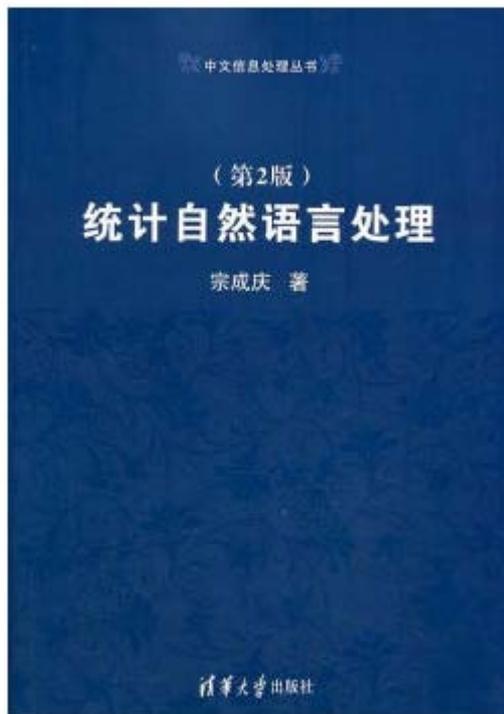
# Reference

- <https://item.jd.com/11701113.html>



# Reference

- <https://item.jd.com/1040675628.html>





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# Homework

# Homework

- Data Collection for your group.
- Try your best to write a Chinese word segmentation algorithm and run it.
- How work will be presented group by group on Dec. 21 and report should be handed before Jan. 6.





# The End of Lecture 9

Thank You

<http://www.wangting.ac.cn>

