

# Information Extraction

Dr. Cao Truong Tran,  
Computer Science Department, Faculty of Information Technology, Le Quy Don  
Technical University, Hanoi, Vietnam  
Email: [truongct@lqdtu.edu.vn](mailto:truongct@lqdtu.edu.vn)

# Contents

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- Information Extraction
- Sequence labeling
  - POS tagging
  - Named Entity Recognition
- Hidden Markov Models
- Conditional Random Fields (CRFs)
- Using CRFs tools for IE

# Information Extraction

# Information Extraction

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- Information extraction is the problem of automatically extracting structured information from unstructured documents.
- Organize the information systematically, the extracted information can be put into the database as input for other algorithms (data mining).

Firm XYZ is a full service advertising agency specializing in direct and interactive marketing. Located in Bigtown CA, Firm XYZ is looking for an Assistant Account Manager to help manage and coordinate interactive marketing initiatives for a marquee automotive account. Experience in online marketing, automotive and/or the advertising field is a plus. Assistant Account Manager Responsibilities Ensures smooth implementation of programs and initiatives Helps manage the delivery of projects and key client deliverables . . . Compensation: \$50,000-\$80,000 Hiring Organization: Firm XYZ

**INDUSTRY**

Advertising

**POSITION**

Assistant Account Manager

**LOCATION**

Bigtown, CA.

**COMPANY**

Firm XYZ

**SALARY**

\$50,000-\$80,000

# Information Extraction

Updating data into the database by extracting information from text fragments

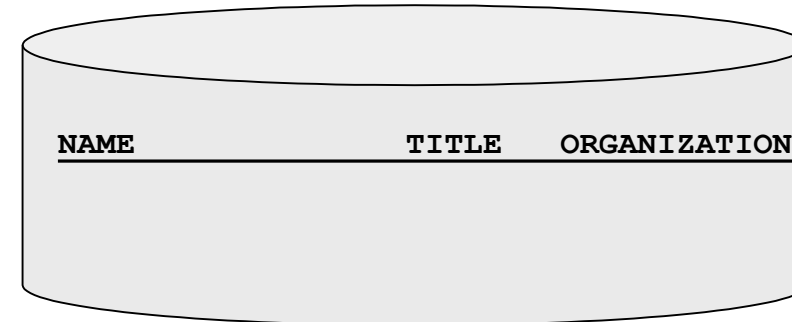
October 14, 2002, 4:00 a.m. PT

For years, Microsoft Corporation CEO Bill Gates railed against the economic philosophy of open-source software with Orwellian fervor, denouncing its communal licensing as a "cancer" that stifled technological innovation.

Today, Microsoft claims to "love" the open-source concept, by which software code is made public to encourage improvement and development by outside programmers. Gates himself says Microsoft will gladly disclose its crown jewels--the coveted code behind the Windows operating system--to select customers.

"We can be open source. We love the concept of shared source," said Bill Veghte, a Microsoft VP. "That's a super-important shift for us in terms of code access."

Richard Stallman, founder of the Free Software Foundation, countered saying...



# Information Extraction

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| NAME             | TITLE   | ORGANIZATION |
|------------------|---------|--------------|
| Bill Gates       | CEO     | Microsoft    |
| Bill Veghte      | VP      | Microsoft    |
| Richard Stallman | founder | Free Soft..  |

# The complexity of the problem

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## Closed set

### U.S. states

He was born in Alabama...

The big Wyoming sky...

## Regular set

### U.S. phone numbers

Phone: (413) 545-1323

The CALD main office is 412-268-1299

## Complex pattern

### U.S. postal addresses

University of Arkansas  
P.O. Box 140

Hope, AR Headquarters:  
1128 Main Street, 4th Floor  
Cincinnati, Ohio 45210

## Ambiguous patterns, needing context and many sources of evidence

### Person names

...was among the six houses sold  
by Hope Feldman that year.

Pawel Opalinski, Software  
Engineer at WhizBang Labs.



# Relation Extraction

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Jack Welch will retire as CEO of General Electric tomorrow. The top role at the Connecticut company will be filled by Jeffrey Immelt.

## Single entity

**Person:** Jack Welch

**Person:** Jeffrey Immelt

**Location:** Connecticut

## Binary relationship

**Relation:** Person-Title

**Person:** Jack Welch

**Title:** CEO

**Relation:** Company-Location

**Company:** General Electric

**Location:** Connecticut

## N-ary record

**Relation:** Succession

**Company:** General Electric

**Title:** CEO

**Out:** Jack Welsh

**In:** Jeffrey Immelt

*“Named entity” extraction*

# Sub Problems

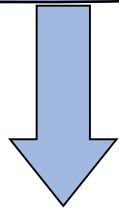
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- Named Entity Recognition (NER)
- Coreference Resolution
- Entity Linking
- Relation Extraction
- Event Extraction

# Relation Extraction: Disease Outbreaks

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May 19 1995, Atlanta -- The Centers for Disease Control and Prevention, which is in the front line of the world's response to the deadly Ebola epidemic in Zaire, is finding itself hard pressed to cope with the crisis...



**Information  
Extraction System**



| <i>Date</i> | <i>Disease Name</i> | <i>Location</i> |
|-------------|---------------------|-----------------|
| Jan. 1995   | Malaria             | Ethiopia        |
| July 1995   | Mad Cow Disease     | U.K.            |
| Feb. 1995   | Pneumonia           | U.S.            |

# Relation Extraction: Protein Interactions

---

“We show that CBF-A and CBF-C interact with each other to form a CBF-A-CBF-C complex and that CBF-B does not interact with CBF-A or CBF-C individually but that it associates with the CBF-A-CBF-C complex.”

CBF-A  $\xleftrightarrow[\text{complex}]{\text{interact}}$  CBF-C

CBF-B  $\xrightarrow{\text{associates}}$  CBF-A-CBF-C complex

# Resolving coreference (both within and across documents)

John Fitzgerald Kennedy was born at 83 Beals Street in Brookline, Massachusetts on Tuesday, September 29, 1917, at 3:00 pm,[7] the second son of Joseph P. Kennedy, Sr., and Rose Fitzgerald; Rose Kennedy, in turn, was the eldest child of John "Honey Fitz" Fitzgerald, a prominent Boston political figure who was the city's mayor and a three-term member of Congress. Kennedy lived in Brookline for his first five years and attended Edward Devotion School, Noble and Greenough Lower School, and the Dexter School, through 4th grade. In 1927, the family moved to 5040 Independence Avenue in the Bronx, New York City; two years later, they moved to 294 Pondfield Road in Bronxville, New York, where Kennedy was a member of Scout Troop 2 (and was the first Boy Scout to become President).[8] Kennedy spent summers with his family at their home in Hyannisport, Massachusetts, and Christmas and Easter holidays with his family at their winter home in Palm Beach, Florida. For the 5th through 7th grade, Kennedy attended Riverdale Country School, a private school for boys. For 8th grade in September 1930, the 13-year old Kennedy attended Canterbury School in New Milford, Connecticut.



# Sequence labeling

# Sequence labeling

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- Many NLP problems can be reduced to sequence labeling
- Input: a string of words
- Output: string of labeled words

| VBG     | NN          | IN | DT | NN  | IN | NN       |
|---------|-------------|----|----|-----|----|----------|
| Chasing | opportunity | in | an | age | of | upheaval |

**POS tagging**

| PERS    | O         | O      | O  | ORG  | ORG   |
|---------|-----------|--------|----|------|-------|
| Murdoch | discusses | future | of | News | Corp. |

**Named entity recognition**

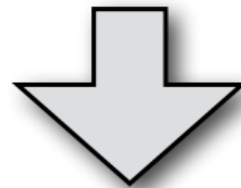
| B | B | I | I | B | I | B | I | B | B |
|---|---|---|---|---|---|---|---|---|---|
| 而 | 相 | 对 | 于 | 这 | 些 | 品 | 牌 | 的 | 价 |

**Word segmentation**

# Sequence labeling

---

She      promised      to      back      the      bill  
 $\mathbf{w} =$     $w^{(1)}$             $w^{(2)}$             $w^{(3)}$             $w^{(4)}$     $w^{(5)}$     $w^{(6)}$



$\mathbf{t} =$     $t^{(1)}$             $t^{(2)}$             $t^{(3)}$             $t^{(4)}$     $t^{(5)}$     $t^{(6)}$   
**PRP    VBD    TO    VB   DT   NN**

- Given a sequence of words  $\mathbf{w}=w(1)...w(n)$ , find the sequence of tags with the highest probability  $\mathbf{t}=t(1)...t(n)$

$$\mathbf{t}^* = \operatorname{argmax}_{\mathbf{t}} P(\mathbf{t} \mid \mathbf{w})$$



# Part of Speech tagging

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- Part of Speech tagging – POS tagging
- Each word in the sentence is labeled with its corresponding word tag
- Input: 1 word delimited text + label set
- Output: the most accurate way of labeling

# Part of Speech tagging

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- Applications:
  - Speech synthesis: record - N: ['reko:d], V: [ri'ko:d];
  - Preprocessor for parsing.
  - Speech recognition, search, etc.

# Part of Speech tagging

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- Brown corpus: 87 labels
- 3 commonly used sets:
  - Small: 45 longan - Penn treebank
  - Average: 61 labels, British national corpus
  - Large: 146 labels, C7

| Tag   | Description           | Example                | Tag  | Description           | Example              |
|-------|-----------------------|------------------------|------|-----------------------|----------------------|
| CC    | Coordin. Conjunction  | <i>and, but, or</i>    | SYM  | Symbol                | <i>+, %, &amp;</i>   |
| CD    | Cardinal number       | <i>one, two, three</i> | TO   | “to”                  | <i>to</i>            |
| DT    | Determiner            | <i>a, the</i>          | UH   | Interjection          | <i>ah, oops</i>      |
| EX    | Existential ‘there’   | <i>there</i>           | VB   | Verb, base form       | <i>eat</i>           |
| FW    | Foreign word          | <i>mea culpa</i>       | VBD  | Verb, past tense      | <i>ate</i>           |
| IN    | Preposition/sub-conj  | <i>of, in, by</i>      | VBG  | Verb, gerund          | <i>eating</i>        |
| JJ    | Adjective             | <i>yellow</i>          | VCN  | Verb, past participle | <i>eaten</i>         |
| JJR   | Adj., comparative     | <i>bigger</i>          | VBP  | Verb, non-3sg pres    | <i>eat</i>           |
| JJS   | Adj., superlative     | <i>wildest</i>         | VBZ  | Verb, 3sg pres        | <i>eats</i>          |
| LS    | List item marker      | <i>1, 2, One</i>       | WDT  | Wh-determiner         | <i>which, that</i>   |
| MD    | Modal                 | <i>can, should</i>     | WP   | Wh-pronoun            | <i>what, who</i>     |
| NN    | Noun, sing. or mass   | <i>llama</i>           | WP\$ | Possessive wh-        | <i>whose</i>         |
| NNS   | Noun, plural          | <i>llamas</i>          | WRB  | Wh-adverb             | <i>how, where</i>    |
| NNP   | Proper noun, singular | <i>IBM</i>             | \$   | Dollar sign           | <i>\$</i>            |
| NNPS  | Proper noun, plural   | <i>Carolinas</i>       | #    | Pound sign            | <i>#</i>             |
| PDT   | Predeterminer         | <i>all, both</i>       | “    | Left quote            | <i>‘ or “</i>        |
| POS   | Possessive ending     | <i>'s</i>              | ”    | Right quote           | <i>’ or ”</i>        |
| PRP   | Personal pronoun      | <i>I, you, he</i>      | (    | Left parenthesis      | <i>[, (, {, &lt;</i> |
| PRP\$ | Possessive pronoun    | <i>your, one's</i>     | )    | Right parenthesis     | <i>], ), }, &gt;</i> |
| RB    | Adverb                | <i>quickly, never</i>  | ,    | Comma                 | <i>,</i>             |
| RBR   | Adverb, comparative   | <i>faster</i>          | .    | Sentence-final punc   | <i>. ! ?</i>         |
| RBS   | Adverb, superlative   | <i>fastest</i>         | :    | Mid-sentence punc     | <i>: ; ... - -</i>   |
| RP    | Particle              | <i>up, off</i>         |      |                       |                      |

# Example

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- **There/EX** are/VBP 70/CD children/NNS **there/RB**
- EX: word for existence there
- RB: adverb
- Difficulty in labeling from categories: ambiguous.

# Part of Speech tagging for Vietnamese

|   |   |
|---|---|
| Câu tiếng Việt đã tách từ               | Qua những lần từ Sài_Gòn về Quảng_Ngãi kiểm_tra công_việc , Sophie và Jane thường trò_chuyện với Mai , cảm_nhận ngọn_lửa_sống và niềm_tin mãnh_liệt từ người phụ_nữ VN này .  |
| Câu tiếng Việt đã được gán nhãn từ loại | Qua <b>những</b> lần từ Sài_Gòn về Quảng_Ngãi <b>kiểm_tra</b> <b>công_việc</b> , Sophie và Jane thường <b>trò_chuyện</b> với Mai , <b>cảm_nhận</b> ngọn_lửa_sống và niềm_tin <b>mãnh_liệt</b> từ người phụ_nữ VN <b>này</b> . |
| Chú thích từ loại                       | <div> DANH TỪ ■ DANH TỪ ■ THÁN TỪ ■<br/> ĐỘNG TỪ ■ PHỤ TỪ ■ TRỢ TỪ ■<br/> TÍNH TỪ ■ GIỚI TỪ ■ TỪ ĐƠN LẺ ■<br/> ĐẠI TỪ ■ CẢM TỪ ■ TỪ VIẾT TẮT ■<br/> ĐỊNH TỪ ■ LIÊN TỪ ■ KHÔNG XÁC ĐỊNH ■ </div>                               |

# Named-entity recognition

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- Important subproblem of information extraction
- An entity is an object or collection of objects in the natural world described in language
- Classify:
  - Name
  - Place name
  - Organization Name
  - Numeric value
  - Time

# Named-entity recognition

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- Identify in text groups of entities with predefined names such as names of people, organizations, places, times, etc.
- tags
  - PERS
  - ORG
  - LOC
  - DATE





# Named-entity recognition

---

Pierre Vinken , 61 years old , will join IBM 's board  
as a nonexecutive director Nov. 29 .



[PERS Pierre Vinken] , 61 years old , will join  
[ORG IBM] 's board as a nonexecutive director  
[DATE Nov. 2] .

# BIO Labels

---

- Define new tags
  - B-PERS, B-DATE, ...: Mark the start of the named entity (Begin)
  - I-PERS, I-DATE, ...: Highlight the next words of the named entity (Inside)
  - O: Highlight words that do not have a named entity (Outside)

# BIO Labels

---

[PERS Pierre Vinken] , 61 years old , will join  
[ORG IBM] 's board as a nonexecutive director  
[DATE Nov. 2] .



Pierre\_B-PERS Vinken\_I-PERS ,\_O 61\_O years\_O old\_O ,\_O  
will\_O join\_O IBM\_B-ORG 's\_O board\_O as\_O a\_O  
nonexecutive\_O director\_O Nov.\_B-DATE 29\_I-DATE .\_O

# VLSP 2016

---

|           | POS tag | Chunking tag | NE    | Nested NE |
|-----------|---------|--------------|-------|-----------|
| Anh       | N       | B-NP         | O     | O         |
| Thanh     | Np      | I-NP         | I-PER | O         |
| là        | V       | B-VP         | O     | O         |
| cán_bộ    | N       | B-NP         | O     | O         |
| Ủy ban    | N       | B-NP         | B-ORG | O         |
| nhân_dân  | N       | I-NP         | I-ORG | O         |
| Thành_phố | N       | I-NP         | I-ORG | B-LOC     |
| Hà_Nội    | Np      | I-NP         | I-ORG | I-LOC     |
| .         | .       | O            | O     | O         |

# Approaches

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- rule-based approaches
  - Email, Time, Phone Number, URL, Amount
- Statistical Machine Learning
  - Hidden Markov Model - HMM
  - Maximum Entropy Markov Model (MEMM)
  - Conditional Random Field (CRF)
- Deep learning
  - RNN/LSTM
  - BERT

# Libraries

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- NLTK
- Spacy
- Stanford Core NLP
- Allen NLP
- Flair

# Hidden Markov Models

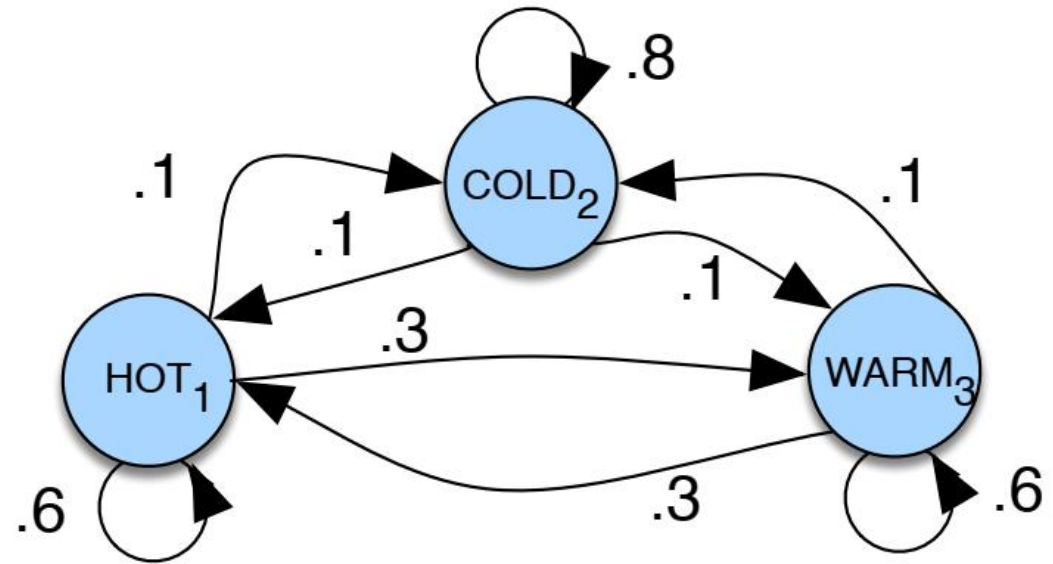
# Markov Models

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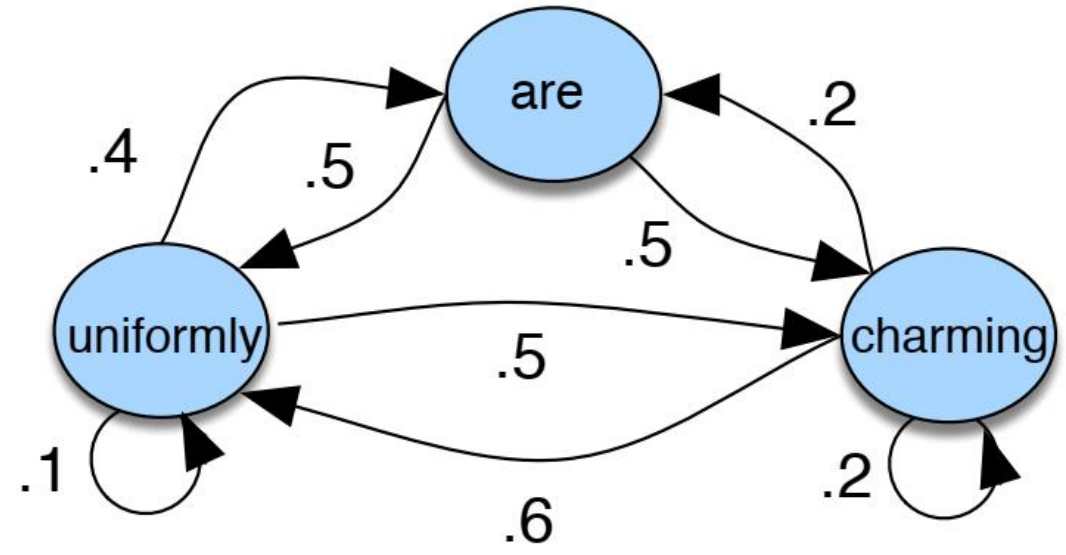
- Hidden Markov model is one of the important machine learning models
- Basic Markov models: Markov chain model and hidden Markov model
- The Markov chain model, also known as the observable Markov model, is the simplest Markov model.
- Hidden Markov and Markov chain models are both extended from **Finite Automat**
- A weighted finite automat whose edges are attached to probabilities, representing the probability of entering that edge. The sum of all probabilities of the edges coming out of a vertex must be 1.
- Markov series is a special case of finite weighted automat, then the input sequence determines the states that the automat will go through.



# Markov Chain



(a)



(b)

Initial distribution  $\pi = [0.1, 0.7, 0.2]$

# Markov Chain

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- Components:

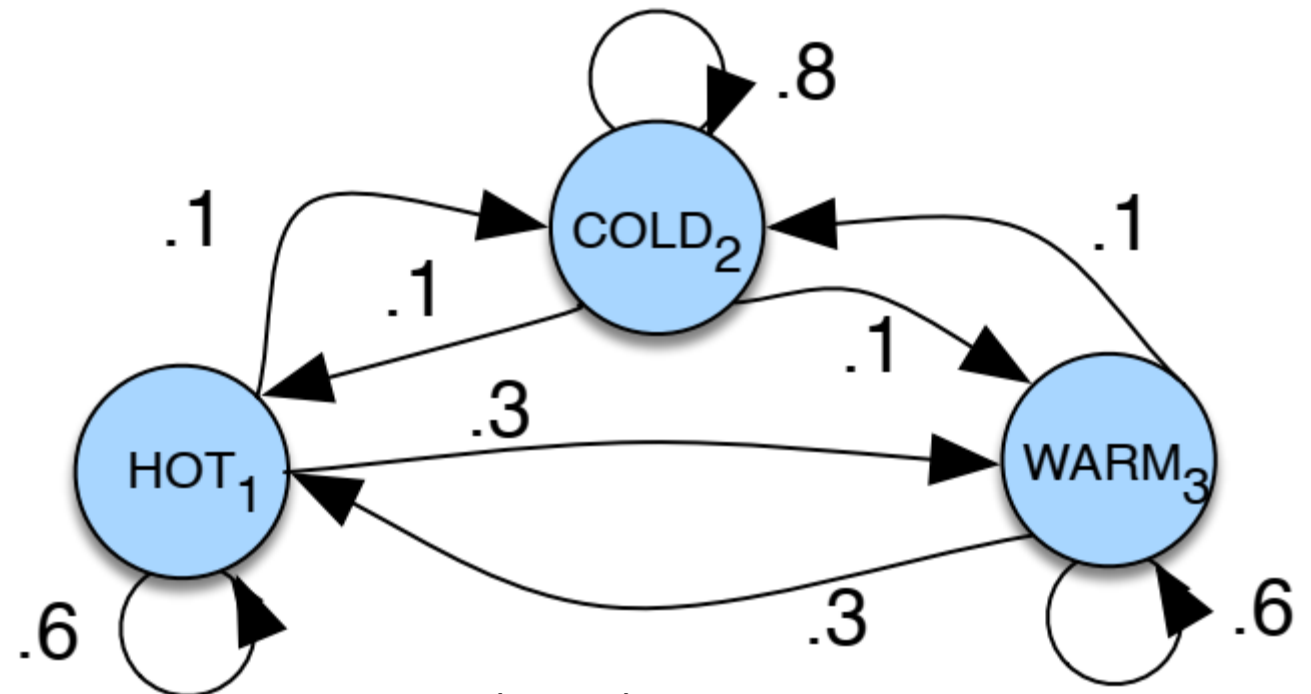
|   |  |
|---|--|
| $Q = q_1 q_2 \dots q_N$                       | set of N states  |
| $A = a_{11} a_{12} \dots a_{N1} \dots a_{NN}$ | matrix transition probability state A, $a_{ij}$ represents the probability of transition from state i to state j $\sum_{j=1}^N a_{ij} = 1 \forall i$ |
| $\pi = \pi_1, \pi_2, \dots, \pi_N$            | initial probability distribution of states $\sum_{i=1}^N \pi_i = 1$  |

- Markov **conjecture**: the probability of a state depends only on the state before it

$$P(q_i = a | q_1 \dots q_{i-1}) = P(q_i = a | q_{i-1})$$

# Example

- Calculate the probability of the following series:
  - hot hot hot hot
  - cold hot cold hot



Phân bố ban đầu  $\pi = [0.1, 0.7, 0.2]$

$$\begin{aligned}
 & \text{1) } P(H) * P(H|H) * \\
 & P(H|H) * P(H|H) \\
 & = 0,1 . 0,6 . 0,6 . 0,6 \\
 & = 0,0216
 \end{aligned}$$

$$\text{2) } P(C) * P(H|C) * P(C|H) * P(H|C) = 0,7 . 0,1 . 0,1 . 0,1 = 0,007$$

# Hidden Markov Model

---

- The Markov series model is used to calculate the probability of an observable sequence of events
- However, in many cases there are events we are interested in that may not be directly observed
- The hidden Markov model allows us to consider both observable and hidden events.

| VBG     | NN          | IN | DT | NN  | IN | NN       |
|---------|-------------|----|----|-----|----|----------|
| Chasing | opportunity | in | an | age | of | upheaval |

**POS tagging**

# Hidden Markov Model

---

- Components:

|   |   |
|---|---|
| $Q = q_1 q_2 \dots q_N$                       | set of N states   |
| $A = a_{11} a_{12} \dots a_{N1} \dots a_{NN}$ | matrix transition probability state A, $a_{ij}$ represents the probability of transition from state i to state j<br>$\sum_{j=1}^N a_{ij} = 1 \quad \forall i$ |
| $O = o_1 o_2 \dots o_T$                       | observable sequence of events   |
| $B = b_i(o_t)$                                | emission probabilities: probability that event $o_t$ is generated from state $q_i$  |
| $\pi = \pi_1, \pi_2, \dots, \pi_N$            | initial probability distribution of states<br>$\sum_{i=1}^N \pi_i = 1$  |

# State transition probability

---

- The state transition probability is calculated by counting the number of occurrences of the labels in the corpus

$$P(t_i|t_{i-1}) = \frac{C(t_{i-1}, t_i)}{C(t_{i-1})}$$

- For example, MD appears 13124 times, of which 10471 times VB appears immediately after it

$$P(VB|MD) = \frac{C(MD, VB)}{C(MD)} = \frac{10471}{13124} = .80$$

# Emission probabilities

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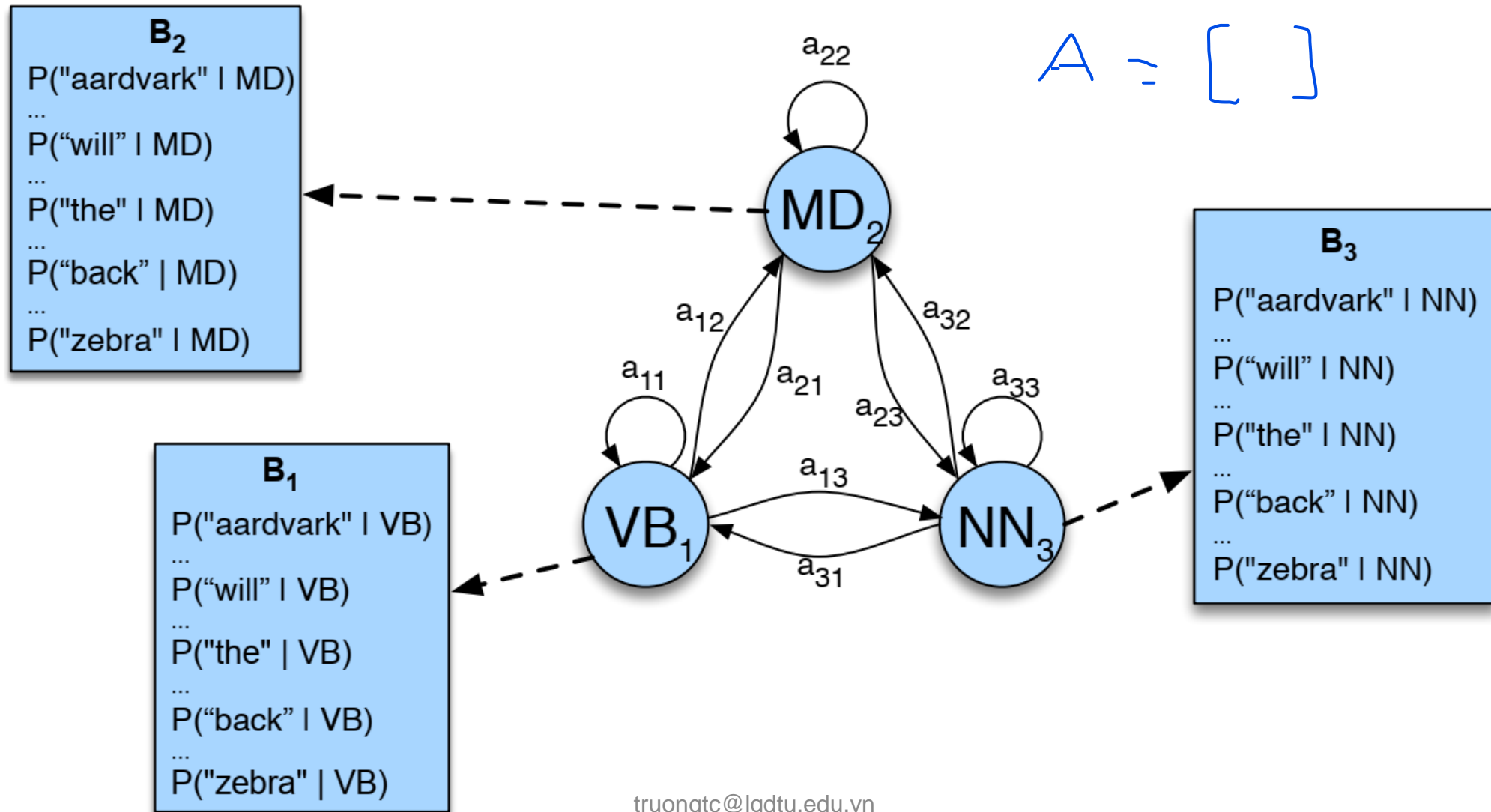
- Probability of event  $o_t$  generated from state  $q_i$
- Probability that a label goes with a word

$$P(w_i|t_i) = \frac{C(t_i, w_i)}{C(t_i)}$$

$$P(\underbrace{will}_{\text{label}}|MD) = \frac{C(MD, will)}{C(MD)} = \frac{4046}{13124} = .31$$

Neu la 1 modal verb, xác suất will là bn ?

# Hidden Markov Model





# HMM cho sequence labeling

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- Determine the hidden state sequence corresponding to the observable sequence, called decoding
- Given as input an HMM  $\lambda=(A,B)$  and an observable sequence  $O = o_1o_2\dots o_T$ , find the sequence of states  $Q = q_1q_2 \dots q_N$

$$\hat{t}_1^n = \operatorname{argmax}_{t_1^n} P(t_1^n | w_1^n)$$

- Bayes theory:

$$\hat{t}_1^n = \operatorname{argmax}_{t_1^n} \frac{P(w_1^n | t_1^n) P(t_1^n)}{P(w_1^n)}$$

# HMM cho sequence labeling

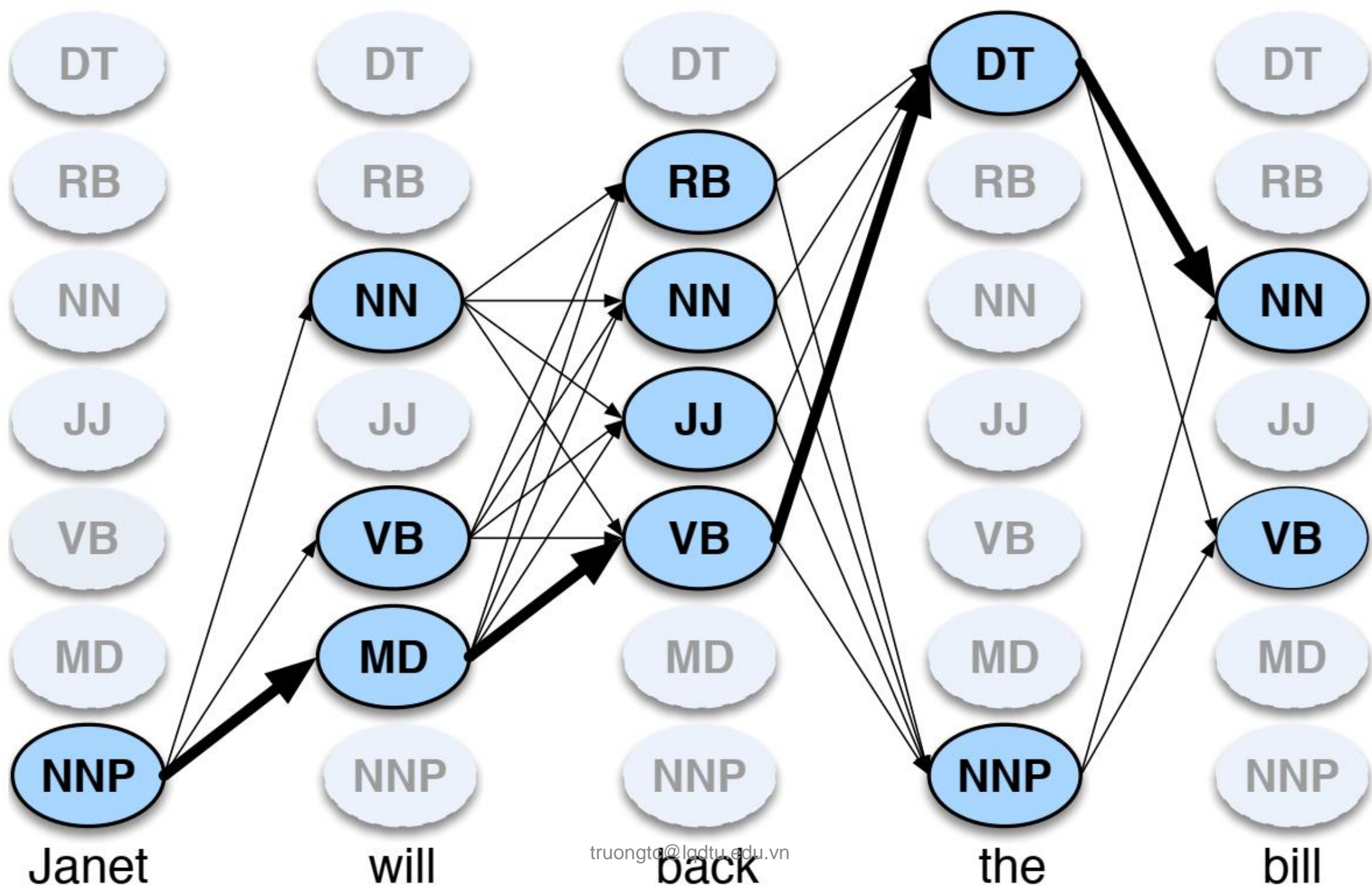
$$\hat{t}_1^n = \operatorname{argmax}_{t_1^n} P(w_1^n | t_1^n) P(t_1^n)$$

$$\hat{t}_1^n = \operatorname{argmax}_{t_1^n} P(t_1^n | w_1^n) \approx \operatorname{argmax}_{t_1^n} \prod_{i=1}^n \overbrace{P(w_i | t_i)}^{\text{emission}} \overbrace{P(t_i | t_{i-1})}^{\text{transition}}$$

- Solve with Viterbi algorithm (dynamic programming)

x S  
xuất hiện của  
1 từ chỉ phụ thuộc  
vào thể của chính nó

phụ thuộc  
vào thể  
trước đó



# Conditional Random Fields (CRFs)

# Conditional Random Fields

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- Lafferty et al. 2001
- Widely applied in many fields from NNTN to machine vision, sequence analysis in biology
- CRF is a statistical method but is often used in conjunction with deep learning models

# Generative and discriminative

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- All try to model the probability distribution on  $(y, x)$
- HMM: generative model of the input sequence  $x$ , describing the distribution that "generates"  $x$  when the label  $y$  is known (using Bayes' theorem)

$$\hat{y} = \operatorname{argmax}_y P(y|x) = \operatorname{argmax}_y P(x|y)P(y)$$

- Discriminative (CRF) models directly model  $P(y|x)$  using feature functions

# Conditional Random Fields

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- The distribution  $P(\mathbf{y}|\mathbf{x})$  in the CRF is defined as follows

$$p(\mathbf{y}|\mathbf{x}) = \frac{1}{Z(\mathbf{x})} \prod_{t=1}^T \exp \left\{ \sum_{k=1}^K \theta_k f_k(y_t, y_{t-1}, \mathbf{x}_t) \right\}$$

- Parameter vector  $\theta = \{\theta_k\} \in \mathbb{R}^K$
- Normalization function

$$Z(\mathbf{x}) = \sum_{\mathbf{y}} \prod_{t=1}^T \exp \left\{ \sum_{k=1}^K \theta_k f_k(y_t, y_{t-1}, \mathbf{x}_t) \right\}$$

# Features

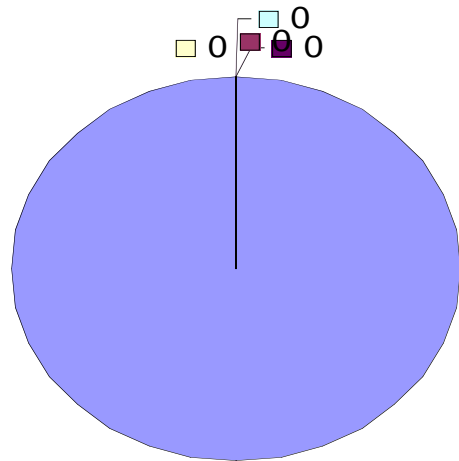
---

- Features of current word, words before and after it, label before it
  - Contains a specific prefix/suffix
  - Contains numbers, capital letters, dashes
  - All caps
  - Word shape
  - Label from category
- Which feature to use depends on the problem and the training data set

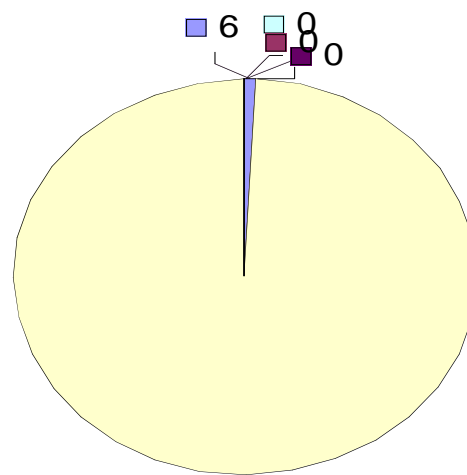


# Features

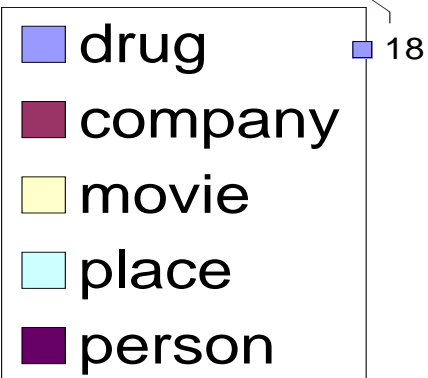
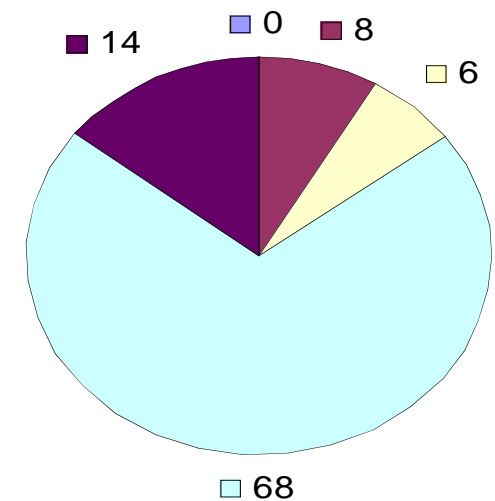
oxa



:



field



Cotrimoxazole

Wethersfield

Alien Fury: Countdown to Invasion

# Word shape

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- Simple word representation by encoding lowercase characters to 'x', uppercase to 'X', numbers to 'd'

|              |              |       |
|--------------|--------------|-------|
| I.M.F        | X.X.X        | X.X.X |
| DC10-30      | XXdd-dd      | Xd-d  |
| well-dressed | xxxx-xxxxxxx | x-x   |

# Training models

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- Determine the parameters of the model  $\theta = \{\theta_k\} \in \mathbb{R}^K$
- Maximum likelihood: the training data has the greatest probability for the selected parameters (similar to logistic regression)

$$\ell(\theta) = \sum_{i=1}^N \sum_{t=1}^T \sum_{k=1}^K \theta_k f_k(y_t^{(i)}, y_{t-1}^{(i)}, \mathbf{x}_t^{(i)}) - \sum_{i=1}^N \log Z(\mathbf{x}^{(i)}) - \sum_{k=1}^K \frac{\theta_k^2}{2\sigma^2}$$

- It is possible to apply optimization algorithms such as gradient descent

# Predictions

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- After training the model, for each input  $x$  it is necessary to predict the corresponding label such that

$$\hat{y} = \operatorname{argmax}_y P(y|x)$$

- It is possible to apply the Viterbi algorithm to find the state series (label series) so that the probability  $P(y|x)$  reaches the maximum value.

# Practice comparing CRF and HMM

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- Lafferty et al. 2001
- Penn treebank POS tagging (45 tags)
- Use spelling features:
  - does it start with a number or a capital letter,
  - contains no dash,
  - contain the following suffixes: -ing, -ogy, -ed, -s, -ly, -ion, -tion, -ity, -ies
- oov = out-of-vocabulary (not observed in the training set)

| <i>model</i>      | <i>error</i> | <i>oov error</i> |
|-------------------|--------------|------------------|
| HMM               | 5.69%        | 45.99%           |
| MEMM              | 6.37%        | 54.61%           |
| CRF               | 5.55%        | 48.05%           |
| MEMM <sup>+</sup> | 4.81%        | 26.99%           |
| CRF <sup>+</sup>  | 4.27%        | 23.76%           |

<sup>+</sup>Using spelling features

# Practice

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- Using the `sklearn_crfsuite` library to train the CRF model for the NER . problem
- Using CRF model to extract information from text



# Q&A

Thank you!