# Part-of-Speech Tagging

Berlin Chen 2004

References:
1. Speech and Language Processing, chapter 8
2. Foundations of Statistical Natural Language Processing, chapter 10

# Review

- Tagging (part-of-speech tagging)
  - The process of assigning (labeling) a part-of-speech or other lexical class marker to each word in a sentence (or a corpus)
    - Decide whether each word is a noun, verb, adjective, or whatever

The/AT representative/NN put/VBD chairs/NNS on/IN the/AT table/NN ✓

Or

The/AT representative/JJ put/NN chairs/VBZ on/IN the/AT table/NN

  - An intermediate layer of representation of syntactic structure
    - When compared with syntactic parsing
  - Above 96% accuracy for most successful approaches

Tagging can be viewed as a kind of syntactic disambiguation

# Introduction

- Parts-of-speech
  - Known as POS, word classes, lexical tags, morphology classes
- Tag sets
  - Penn Treebank : 45 word classes used (Francis, 1979)
    - Penn Treebank is a parsed corpus
  - Brown corpus: 87 word classes used (Marcus et al., 1993)
  - ….

The/DT grand/JJ jury/NN commented/VBD on/IN a/DT number/NN of/IN other/JJ topics/NNS ./.

# The Penn Treebank POS Tag Set

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

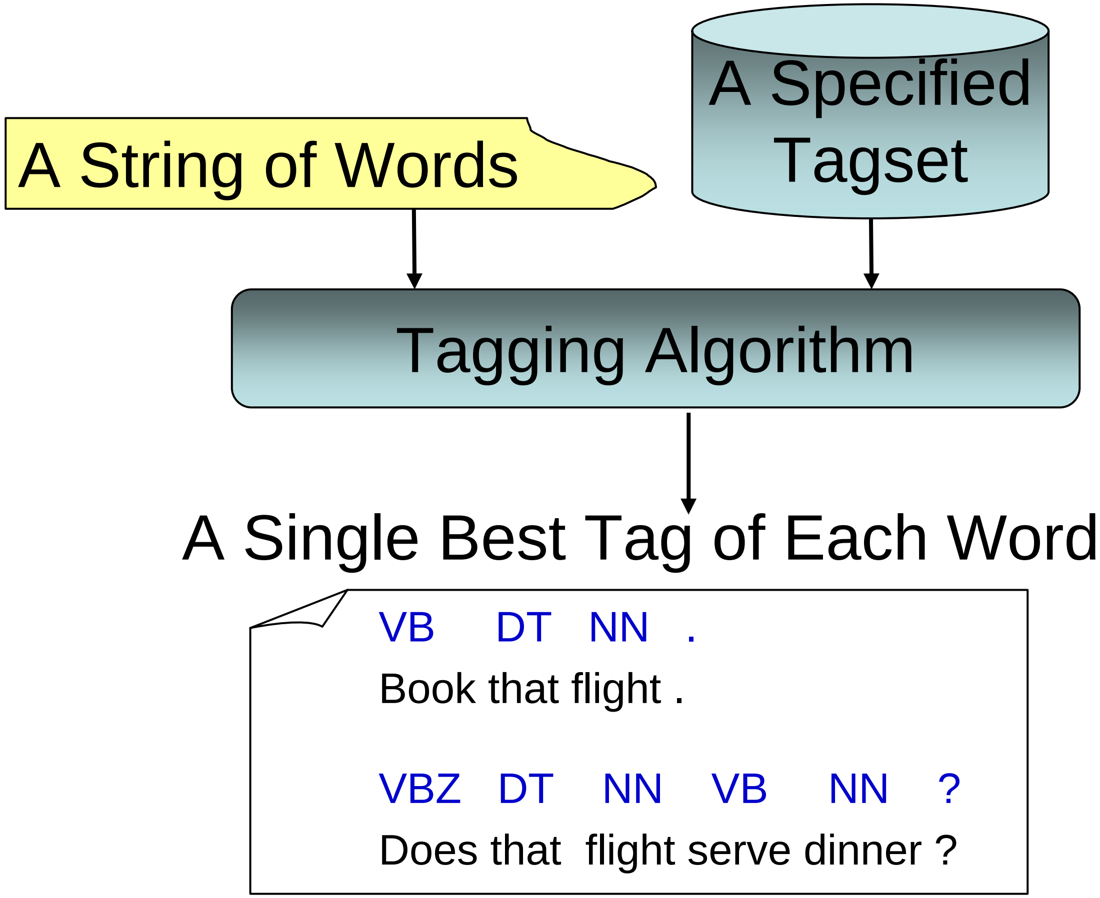
# Disambiguation

- Resolve the ambiguities and chose the proper tag for the context
- Most English words are unambiguous (have only one tag) but many of the most common words are ambiguous
  - E.g.: “*can*” can be a (an auxiliary) verb or a noun
  - E.g.: statistics of Brown corpus

| | | |
|---|---|---|
| **Unambiguous (1 tag)** | **35,340** | |
| **Ambiguous (2–7 tags)** | **4,100** | |
| 2 tags | 3,760 | |
| 3 tags | 264 | |
| 4 tags | 61 | |
| 5 tags | 12 | |
| 6 tags | 2 | |
| 7 tags | 1 | (“still”) |

- 11.5% word types are ambiguous
- But 40% tokens are ambiguous
(However, the probabilities of tags associated a word are not equal → many ambiguous tokens are easy to disambiguate)

# Process of POS Tagging




**Use two information sources:**

- Syntagmatic information (looking at information about tag sequences)
- Lexical information (predicting a tag based on the word concerned)

# POS Tagging Algorithms

Fall into One of Two Classes

- Rule-based Tagger
  - Involve a large database of hand-written disambiguation rules
    - E.g. a rule specifies that an ambiguous word is a noun rather than a verb if it follows a determiner
    - ENGTWOL: a simple rule-based tagger based on the **constraint grammar** architecture

"a new play"

$P(\text{NN}|\text{JJ}) \approx 0.45$

$P(\text{VBP}|\text{JJ}) \approx 0.0005$

- Stochastic/Probabilistic Tagger
  - Use a training corpus to compute the probability of a given word having a given context
  - E.g.: the HMM tagger chooses the best tag for a given word

(maximize the product of **word likelihood** and **tag sequence probability**)

# POS Tagging Algorithms

- Transformation-based/Brill Tagger
  - A hybrid approach
  - Like rule-based approach, determine the tag of an ambiguous word based on rules
  - Like stochastic approach, the rules are automatically induced from previous tagged training corpus with the machine learning technique
    - Supervised learning

# Rule-based POS Tagging

- Two-stage architecture
  - **First stage**: Use a dictionary to assign each word a list of potential parts-of-speech
  - **Second stage**: Use large lists of hand-written disambiguation rules to winnow down this list to a single part-of-speech for each word

| Pavlov | had shown that salivation … | |
|---|---|---|
| Pavlov | **PAVLOV N NOM SG PROPER** | |
| had | **HAVE V PAST VFIN SVO** | (preterit) |
| | HAVE PCP2 SVO | (past participle) |
| shown | **SHOW PCP2 SVOO SVO SV** | |
| that | ADV | |
| | PRON DEM SG | |
| | DET CENTRAL DEM SG | |
| | **CS** | (complementizer) |
| salivation | **N NOM SG** | |

An example for
The ENGTOWL tagger

A set of 1,100 constraints can be applied to the input sentence

# Rule-based POS Tagging

- Simple lexical entries in the ENGTWOL lexicon

| Word | POS | Additional POS features |
|---|---|---|
| smaller | ADJ | COMPARATIVE |
| entire | ADJ | ABSOLUTE ATTRIBUTIVE |
| fast | ADV | SUPERLATIVE |
| that | DET | CENTRAL DEMONSTRATIVE SG |
| all | DET | PREDETERMINER SG/PL QUANTIFIER |
| dog's | N | GENITIVE SG |
| furniture | N | NOMINATIVE SG NOINDEFDETERMINER |
| one-third | NUM | SG |
| she | PRON | PERSONAL FEMININE NOMINATIVE SG3 |
| show | V | IMPERATIVE VFIN |
| show | V | PRESENT -SG3 VFIN |
| show | N | NOMINATIVE SG |
| shown | PCP2 | SVOO SVO SV |
| occurred | PCP2 | SV |
| occurred | V | PAST VFIN SV |

past participle

# Rule-based POS Tagging

ADVERBIAL-THAT RULE
**Given input**: "that"
**if**
(+1 A/ADV/QUANT); /* *if next word is adj, adverb, or quantifier* */
(+2 SENT-LIM); /* *and following which is a sentence boundary,* */
(NOT -1 SVOC/A); /* *and the previous word is not a verb like* */
/* *'consider' which allows adjs as object complements* */
**then** eliminate non-ADV tags
**else** eliminate ADV tag

Example:

one
It isn't **that** odd! A
ADV

I consider **that** odd. NUM
Compliment

# HMM-based Tagging

- Also called *Maximum Likelihood Tagging*
  - Pick the most-likely tag for a word

- For a given sentence or words sequence , an HMM tagger chooses the tag sequence that maximizes the following probability

For a word at position $i$:

$$\text{tag}_i = \arg\max_j P\left(\text{word}_i \middle| \text{tag}_j\right) \cdot P\left(\text{tag}_j \middle| \text{previous } n-1 \text{ tags}\right)$$

word/lexical likelihood    tag sequence probability

N-gram HMM tagger

# HMM-based Tagging

For a word $w_i$ at position $i$, follow Bayes' theorem :

$$t_i = \arg\max_j P\left(t_j \middle| w_i, t_{i-1}, t_{i-2}, \ldots, t_1\right)$$

$$= \arg\max_j \frac{P\left(w_i, t_j \middle| t_{i-1}, t_{i-2}, \ldots, t_1\right)}{P\left(w_i \middle| t_{i-1}, t_{i-2}, \ldots, t_1\right)}$$

$$= \arg\max_j P\left(w_i, t_j \middle| t_{i-1}, t_{i-2}, \ldots, t_1\right)$$

$$= \arg\max_j P\left(w_i \middle| t_j, t_{i-1}, t_{i-2}, \ldots, t_1\right) P\left(t_j \middle| t_{i-1}, t_{i-2}, \ldots, t_1\right)$$

$$\approx \arg\max_j P\left(w_i \middle| t_j\right) P\left(t_j \middle| t_{i-1}, t_{i-2}, \ldots, t_{i-n+1}\right)$$

# HMM-based Tagging

- Assumptions made here
  - Words are independent of each other
    - A word's identity only depends on its tag
  - "Limited Horizon" and "Time Invariant" ("Stationary")
    - Limited Horizon: a word's tag only depends on the previous tag (limited horizon) and the dependency does not change over time (time invariance)
    - Time Invariant: time invariance means the tag dependency won't change as tag sequence appears different positions of a sentence

      Do not model long-distance relationships well !

      - e.g., Wh-extraction,…

# HMM-based Tagging

- Apply bigram-HMM tagger to choose the best tag for a given word
  - Choose the tag $t_i$ for word $w_i$ that is most probable given the previous tag $t_{i-1}$ and current word $w_i$

$$t_i = \arg\max_j P\left(t_j \middle| t_{i-1}, w_i\right)$$

  - Through some simplifying Markov assumptions

$$t_i = \arg\max_j \underbrace{P\left(t_j \middle| t_{i-1}\right)}_{\text{tag sequence probability}} \underbrace{P\left(w_i \middle| t_j\right)}_{\text{word/lexical likelihood}}$$

# HMM-based Tagging

- Apply bigram-HMM tagger to choose the best tag for a given word

$$t_i = \arg\max_j P\left(t_j \middle| t_{i-1}, w_i\right)$$

$$= \arg\max_j \frac{P\left(t_j, w_i \middle| t_{i-1}\right)}{\boxed{P\left(w_i \middle| t_{i-1}\right)}}$$

The same for all tags

$$= \arg\max_j P\left(t_j, w_i \middle| t_{i-1}\right)$$

$$= \arg\max_j P\left(w_i \middle| t_{i-1}, t_j\right) P\left(t_j \middle| t_{i-1}\right)$$

The probability of a word only depends on its tag

$$= \arg\max_j P\left(w_i \middle| t_j\right) P\left(t_j \middle| t_{i-1}\right) = \arg\max_j P\left(t_j \middle| t_{i-1}\right) P\left(w_i \middle| t_j\right)$$

# HMM-based Tagging

- Example: Choose the best tag for a given word

Secretariat/NNP is /VBZ expected/VBN to/TO race/VB tomorrow/NN

to/TO race/???

$$\overset{0.34}{P(VB|TO)}\ \overset{0.00003}{P(race|VB)}=0.00001$$

$$\overset{0.021}{P(NN|TO)}\ \overset{0.00041}{P(race|NN)}=0.000007$$

Pretend that the previous word has already tagged

# HMM-based Tagging

- Apply bigram-HMM tagger to choose the best sequence of tags for a given sentence

$$
\begin{aligned}
\hat{T} &= \arg\max_{T} P(T|W) \\
&= \arg\max_{T} \frac{P(T)P(W|T)}{\cancel{P(W)}} \\
&= \arg\max_{T} P(T)P(W|T) \\
&= \arg\max_{t_1,t_2,\ldots,t_n} P(t_1,t_2,\ldots,t_n)P(w_1,w_1,\ldots,w_n|t_1,t_2,\ldots,t_n) \\
&= \arg\max_{t_1,t_2,\ldots,t_n} \prod_{i=1}^{n}\left[P(t_i|t_1,t_2,\ldots,t_{i-1})P(w_i|t_1,t_2,\ldots,t_n)\right] \\
&= \arg\max_{t_1,t_2,\ldots,t_n} \prod_{i=1}^{n}\left[P(t_i|t_{i-m+1},t_{i-m+2},\ldots,t_{i-1})P(w_i|t_i)\right]
\end{aligned}
$$

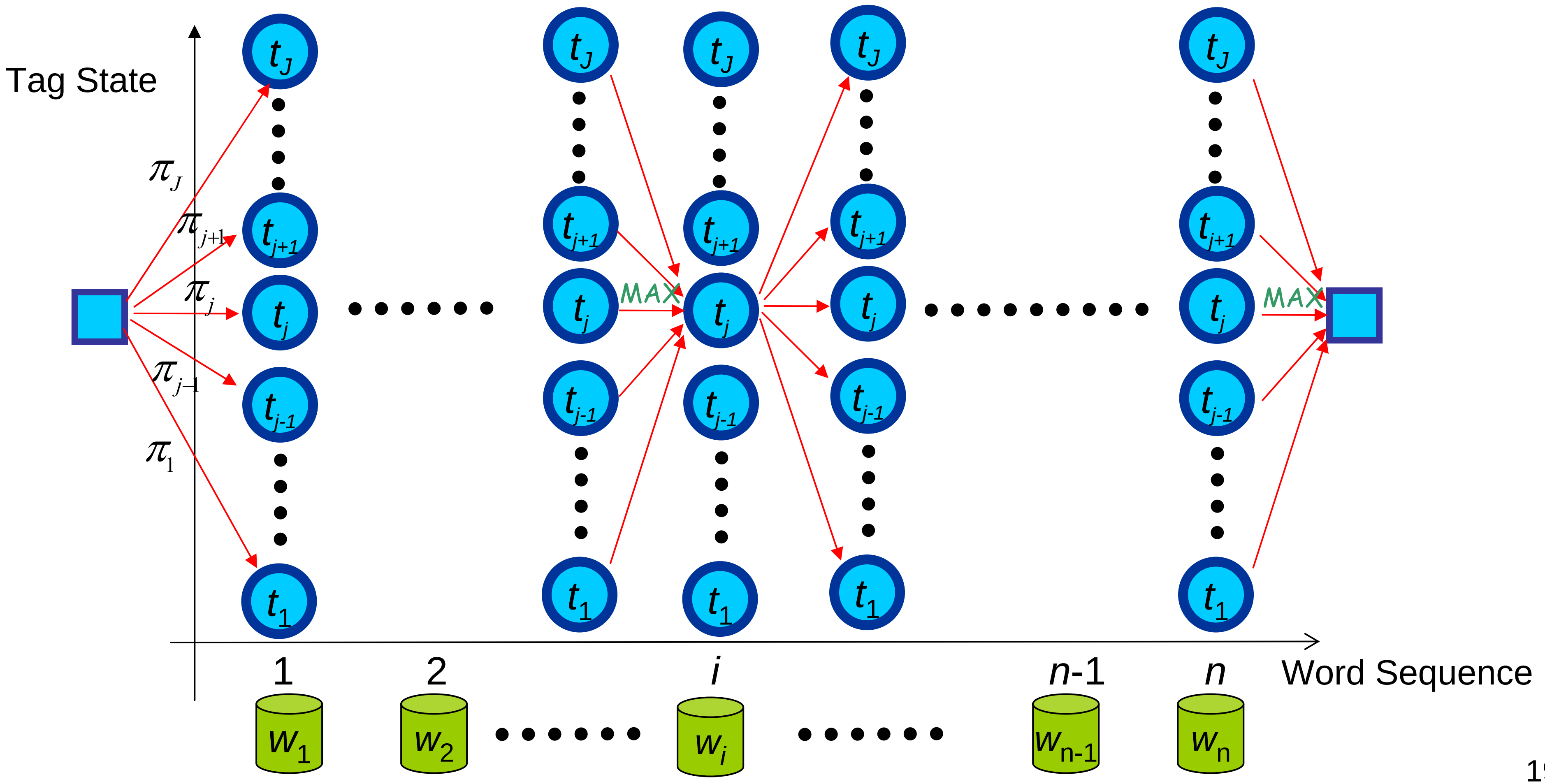
Assumptions:
- words are independent of each other
- a word's identity only depends on its tag

Tag M-gram assumption

The probability of a word only depends on its tag

# HMM-based Tagging

- The Viterbi algorithm for the bigram-HMM tagger
  - States: distinct tags
  - Observations: input word generated by each state



# HMM-based Tagging

- The Viterbi algorithm for the bigram-HMM tagger

$$1.\ \text{Initialization}\ \delta_1(j) = \pi_k P(w_1 | t_j),\ 1 \le j \le J$$

$$2.\ \text{Induction}\ \delta_i(j) = \left[\max_k \delta_{i-1}(k) P(t_j | t_k)\right] P(w_i | t_j),\ \ 2 \le i \le n,\ 1 \le j \le J$$

$$\psi_i(j) = \underset{1 \le k \le J}{\text{argmax}} \left[\delta_{i-1}(k) P(t_j | t_k)\right]$$

$$3.\text{Termination}\ \ X_n = \underset{1 \le j \le J}{\text{argmax}}\, \delta_n(j)$$

$$\text{for i} := n\text{-1 to 1 step -1 do}$$

$$X_i = \psi_i(X_{i+1})$$

$$\text{end}$$

# HMM-based Tagging

- Apply trigram-HMM tagger to choose the best sequence of tags for a given sentence
  - **When trigram model is used**

$$\hat{T} = \arg\max_{t_1, t_2, \ldots, t_n} \left[ P(t_1) P(t_2 | t_1) \prod_{i=3}^{n} P(t_i | t_{i-2}, t_{i-1}) \right] \left[ \prod_{i=1}^{n} P(w_i | t_i) \right]$$

- Maximum likelihood estimation based on the relative frequencies observed in the pre-tagged training corpus (labeled data)

$$P_{ML}(t_i | t_{i-2}, t_{i-1}) = \frac{c(t_{i-2} t_{i-1} t_i)}{\sum_j c(t_{i-2} t_{i-1} t_j)}$$

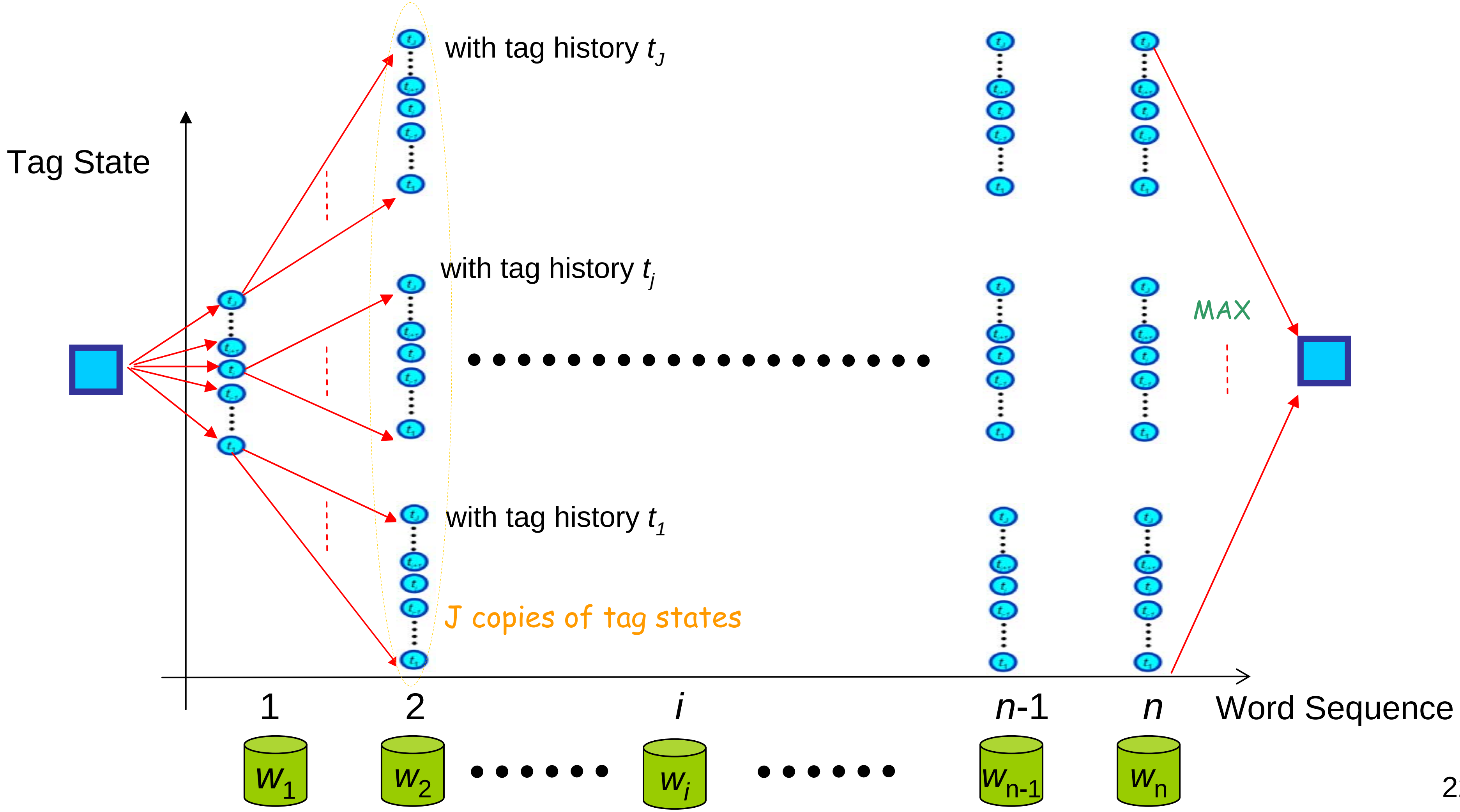
$$P_{ML}(w_i | t_i) = \frac{c(w_i, t_i)}{\sum_j c(w_j, t_i)}$$

Smoothing or linear interpolation are needed !

$$P_{smoothed}(t_i | t_{i-2}, t_{i-1}) = \alpha \cdot P_{ML}(t_i | t_{i-2}, t_{i-1}) + \beta \cdot P_{ML}(t_i | t_{i-1}) + (1 - \alpha - \beta) \cdot P_{ML}(t_i | t_{i-1})$$

# HMM-based Tagging

- Apply trigram-HMM tagger to choose the best sequence of tags for a given sentence



# HMM-based Tagging

| First tag | AT | BEZ | IN | NN | VB | PERIOD |
|---|---|---|---|---|---|---|
| | Second tag | | | | | |
| AT | 0 | 0 | 0 | 48636 | 0 | 19 |
| BEZ | 1973 | 0 | 426 | 187 | 0 | 38 |
| IN | 43322 | 0 | 1325 | 17314 | 0 | 185 |
| NN | 1067 | 3720 | 42470 | 11773 | 614 | 21392 |
| VB | 6072 | 42 | 4758 | 1476 | 129 | 1522 |
| PERIOD | 8016 | 75 | 4656 | 1329 | 954 | 0 |

**Table 10.3** Idealized counts of some tag transitions in the Brown Corpus. For example, NN occurs 48636 times after AT.

$$P\left(t_i \middle| t_{i-1}\right) = \frac{c\left(t_{i-1} t_i\right)}{\sum_j c\left(t_{i-1} t_j\right)}$$

| | AT | BEZ | IN | NN | VB | PERIOD |
|---|---|---|---|---|---|---|
| *bear* | 0 | 0 | 0 | 10 | 43 | 0 |
| *is* | 0 | 10065 | 0 | 0 | 0 | 0 |
| *move* | 0 | 0 | 0 | 36 | 133 | 0 |
| *on* | 0 | 0 | 5484 | 0 | 0 | 0 |
| *president* | 0 | 0 | 0 | 382 | 0 | 0 |
| *progress* | 0 | 0 | 0 | 108 | 4 | 0 |
| *the* | 69016 | 0 | 0 | 0 | 0 | 0 |
| . | 0 | 0 | 0 | 0 | 0 | 48809 |

**Table 10.4** Idealized counts for the tags that some words occur with in the Brown Corpus. For example, 36 occurrences of *move* are with the tag NN.

$$P\left(w_i \middle| t_i\right) = \frac{c\left(w_i, t_i\right)}{\sum_j c\left(w_j, t_i\right)}$$

# HMM-based Tagging

- Probability re-estimation based on unlabeled data
  - EM (Expectation-Maximization) algorithm is applied
    - Start with a dictionary that lists which tags can be assigned to which words
      - » word likelihood function cab be estimated
      - » tag transition probabilities set to be equal
    - EM algorithm learns (re-estimates) the word likelihood function for each tag and the tag transition probabilities

- However, a tagger trained on hand-tagged data worked better than one trained via EM
  - Treat the model as a Markov Model in training but treat them as a Hidden Markov Model in tagging

# Transformation-based Tagging

- Also called Brill tagging
  - An instance of Transformation-Based Learning (TBL)
- **Spirits**
  - Like the rule-based approach, TBL is based on rules that specify what tags should be assigned to what word
  - Like the stochastic approach, rules are automatically induced from the data by the machine learning technique
- Note that TBL is a supervised learning technique
  - It assumes a pre-tagged training corpus

# Transformation-based Tagging

- How the TBL rules are learned
  - Three major stages
    1. Label every word with its most-likely tag using a set of tagging rules (use the broadest rules at first)

    2. Examine every possible transformation (rewrite rule), and select the one that results in the most improved tagging (supervised! should compare to the pre-tagged corpus )

    3. Re-tag the data according this rule
  - The above three stages are repeated until some stopping criterion is reached
    - Such as insufficient improvement over the previous pass
  - An ordered list of transformations (rules) can be finally obtained

# Transformation-based Tagging

- Example

1 $P$(NN|race)=0.98
$P$(VB|race)=0.02

So, race will be initially coded as NN
(label every word with its most-likely tag)

2

(a). is/VBZ expected/VBN to/To race/NN tomorrow/NN

(b). the/DT race/NN for/IN outer/JJ space/NN

Refer to the correct tag
Information of each word,
and find the tag of *race*
in (a) is wrong

3

Learn/pick a most suitable transformation rule: (by examining every possible transformation)

*Change* NN *to* VB *while the previous tag is* TO

Rewrite rule: expected/VBN to/To race/NN → expected/VBN to/To race/VB

# Transformation-based Tagging

- Templates (abstracted transformations)
  - The set of possible transformations may be infinite
  - Should limit the set of transformations
  - The design of a small set of templates (abstracted transformations) is needed

E.g., a strange rule like:
transform NN to VB if the previous word was "IBM" and
the word "the" occurs between 17 and 158 words before that

# Transformation-based Tagging

- Possible templates (abstracted transformations)

- The preceding (following) word is tagged **z**.
  The word two before (after) is tagged **z**.
  One of the two preceding (following) words is tagged **z**.
  One of the three preceding (following) words is tagged **z**.
  The preceding word is tagged **z** and the following word is tagged **w**.
  The preceding (following) word is tagged **z** and the word
  two before (after) is tagged **w**.

Brill's templates.
Each begins with
"Change tag a to tag
b when ...."

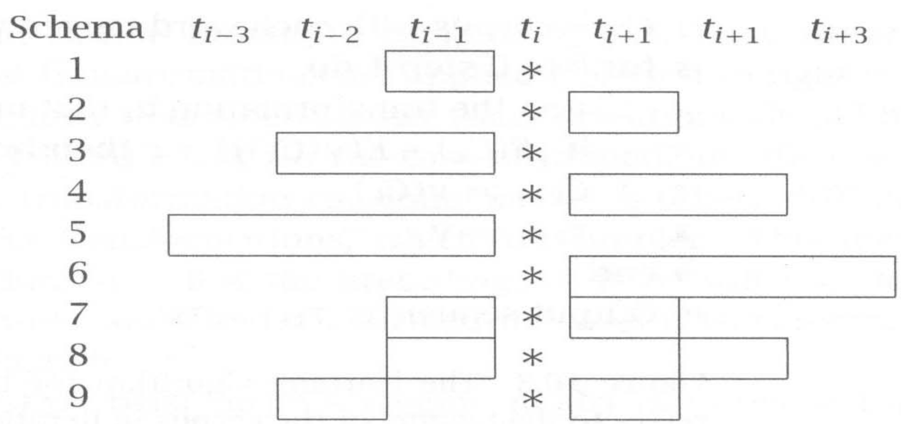



**Table 10.7** Triggering environments in Brill's transformation-based tagger. Examples: Line 5 refers to the triggering environment "Tag $t^j$ occurs in one of the three previous positions"; Line 9 refers to the triggering environment "Tag $t^j$ occurs two positions earlier and tag $t^k$ occurs in the following position."

# Transformation-based Tagging

- Learned transformations

Verb, 3sg, past tense

Modal verbs (should, can,…)

| # | Change tags From | To | Condition | Example |
|---|---|---|---|---|
| 1 | NN | VB | Previous tag is TO | to/TO race/NN → VB |
| 2 | VBP | VB | One of the previous 3 tags is MD | might/MD vanish/VBP → VB |
| 3 | NN | VB | One of the previous 2 tags is MD | might/MD not reply/NN → VB |
| 4 | VB | NN | One of the previous 2 tags is DT | |
| 5 | VBD | VBN | One of the previous 3 tags is VBZ | |

Rules learned by Brill's original tagger

Verb, past participle

Verb, 3sg, Present

**Table 10.7** Triggering environments in Brill's transformation-based tagger. Examples: Line 5 refers to the triggering environment "Tag $t^j$ occurs in one of the three previous positions"; Line 9 refers to the triggering environment "Tag $t^j$ occurs two positions earlier and tag $t^k$ occurs in the following position."

| Source tag | Target tag | Triggering environment |
|---|---|---|
| NN | VB | previous tag is TO |
| VBP | VB | one of the previous three tags is MD |
| JJR | RBR | next tag is JJ |
| VBP | VB | one of the previous two words is *n't* |

**more** valuable player

Constraints for tags

Constraints for words

**Table 10.8** Examples of some transformations learned in transformation-based tagging.

# Transformation-based Tagging

- Reference for tags used in the previous slide

| Tag | Part Of Speech |
|---|---|
| AT | article |
| BEZ | the word *is* |
| IN | preposition |
| JJ | adjective |
| JJR | comparative adjective |
| MD | modal |
| NN | singular or mass noun |
| NNP | singular proper noun |
| NNS | plural noun |
| PERIOD | . : ? ! |
| PN | personal pronoun |
| RB | adverb |
| RBR | comparative adverb |
| TO | the word *to* |
| VB | verb, base form |
| VBD | verb, past tense |
| VBG | verb, present participle, gerund |
| VBN | verb, past participle |
| VBP | verb, non-3rd person singular present |
| VBZ | verb, 3rd singular present |
| WDT | *wh-* determiner (*what, which*) |

**Table 10.1** Some part-of-speech tags frequently used for tagging Englis

# Transformation-based Tagging

- Algorithm

```
function TBL(corpus) returns transforms-queue
 INTIALIZE-WITH-MOST-LIKELY-TAGS(corpus)
 until end condition is met do
   templates ← GENERATE-POTENTIAL-RELEVANT-TEMPLATES
   best-transform ← GET-BEST-TRANSFORM(corpus, templates)
   APPLY-TRANSFORM(best-transform, corpus)
   ENQUEUE(best-transform-rule, transforms-queue)
 end
 return(transforms-queue)
```

append to the rule list

```
function GET-BEST-TRANSFORM(corpus, templates) returns transform
  for each template in templates
    (instance, score) ← GET-BEST-INSTANCE(corpus, template)
    if (score > best-transform.score) then best-transform ← (instance, score)
  return(best-transform)
```

Get best instance for each transformation

```
function GET-BEST-INSTANCE(corpus, template) returns transform
  for from-tag ← from tag−1 to tag−n do
    for to-tag ← from tag−1 to tag−n do
      for pos ← from 1 to corpus-size do
        if (correct-tag(pos) == to-tag && current-tag(pos) == from-tag)
            num-good-transforms(current-tag(pos−1))++
        elseif (correct-tag(pos)==from-tag && current-tag(pos)==from-tag)
            num-bad-transforms(current-tag(pos−1))++
      end
      best-Z ← ARGMAX_t(num-good-transforms(t) - num-bad-transforms(t))
      if(num-good-transforms(best-Z) - num-bad-transforms(best-Z)
                > best-instance.Z) then
        best-instance ← "Change tag from from-tag to to-tag
                        if previous tag is best-Z"
  return(best-instance)
```

for all combinations of tags

traverse corpus

Y

X

Z

Check if it is better than the best instance achieved in previous iterations

```
procedure APPLY-TRANSFORM(transform, corpus)
for pos ← from 1 to corpus-size do
  if (current-tag(pos)==best-rule-from)
       && (current-tag(pos−1)==best-rule-prev))
    current-tag(pos) = best-rule-to
```

The **GET_BEST_INSTANCE** procedure in the example algorithm is "Change tag from X to Y if the previous tag is Z".

# Multiple Tags and Multi-part Words

- Multiple tags
  - A word is ambiguous between multiple tags and it is impossible or very difficult to disambiguate, so multiple tags is allowed, e.g.
    - adjective versus preterite versus past participle (JJ/VBD/VBN)
    - adjective versus noun as prenominal modifier (JJ/NN)

- Multi-part words
  - Certain words are split or some adjacent words are treated as a single word

would/MD n't/RB Children/NNS 's/POS **treated as separate words**

in terms of (in/II31 terms/II32 of/II33) **treated as a single word**

# Tagging of Unknown Words

- Unknown words are a major problem for taggers
  - Different accuracy of taggers over different corpora is often determined by the proportion of unknown words

- How to guess the part of speech of unknown words?
  - Simplest unknown-word algorithm
  - Slightly more complex algorithm
  - Most-powerful unknown-word algorithm

# Tagging of Unknown Words

- Simplest unknown-word algorithm
  - Pretend that each unknown word is ambiguous among all possible tags, with equal probability
    - Lose/ignore lexical information for unknown words
  - Must rely solely on the contextual POS-trigram (syntagmatic information) to suggest the proper tag

$$\hat{T} = \arg\max_{t_1, t_2, \ldots, t_n} \left[ P(t_1) P(t_2 | t_1) \prod_{i=3}^{n} P(t_i | t_{i-2}, t_{i-1}) \right] \left[ \prod_{i=1}^{n} P(w_i | t_i) \right]$$

- Slightly more complex algorithm
  - Based on the idea that the probability distribution of tags over unknown words is very similar to the distribution of tags over words that occurred only once in a training set
  - The likelihood for an unknown word is determined by the average of the distribution over all singleton in the training set (similar to Good-Turing? )

Nouns or Verbs $P(w_i | t_i)$?

# Tagging of Unknown Words

- Most-powerful unknown-word algorithm
  - Hand-designed features
    - The information about how the word is spelled (inflectional and derivational features), e.g.:
      - Words end with s ($\rightarrow$plural nouns)
      - Words end with ed ($\rightarrow$past participles)
    - The information of word capitalization (initial or non-initial) and hyphenation

$$P(w_i|t_i) = p(\text{unknown} - \text{word}|t_i)\cdot p(\text{captial}|t_i)\cdot p(\text{endings/hyph}|t_i)$$

Assumption: independence between features

  - Features induced by machine learning
    - E.g.: TBL algorithm uses templates to induce useful English inflectional and derivational features and hyphenation

The first N letters of the word
The last N letters of the word

# Tagging of Unknown Words

| Feature | Value | NNP | NN | NNS | VBG | VBZ |
|---|---|---|---|---|---|---|
| unknown word | yes | 0.05 | 0.02 | 0.02 | 0.005 | 0.005 |
| | no | 0.95 | 0.98 | 0.98 | 0.995 | 0.995 |
| capitalized | yes | 0.95 | 0.10 | 0.10 | 0.005 | 0.005 |
| | no | 0.05 | 0.90 | 0.90 | 0.995 | 0.995 |
| ending | *-s* | 0.05 | 0.01 | 0.98 | 0.00 | 0.99 |
| | *-ing* | 0.01 | 0.01 | 0.00 | 1.00 | 0.00 |
| | *-tion* | 0.05 | 0.10 | 0.00 | 0.00 | 0.00 |
| | other | 0.89 | 0.88 | 0.02 | 0.00 | 0.01 |

**Table 10.5** Table of probabilities for dealing with unknown words in tagging. For example, $P(\text{unknown word} = \text{yes}|\text{NNP}) = 0.05$ and $P(\text{ending} = \textit{-ing}|\text{VBG}) = 1.0$.

# Evaluation of Taggers

- Compare the tagged results with a human labeled **Gold Standard** test set in percentages of correction
  - Most tagging algorithms have an accuracy of around 96~97% for the sample tagsets like the Penn Treebank set
  - Upper bound (ceiling) and lower bound (baseline)
    - *Ceiling*: is achieved by seeing how well humans do on the task
      - A 3~4% margin of error
    - Baseline: is achieved by using the unigram most-like tags for each word
      - 90~91% accuracy can be attained

# Error Analysis

- Confusion matrix

| | IN | JJ | NN | NNP | RB | VBD | VBN |
|---|---|---|---|---|---|---|---|
| **IN** | - | .2 | | | .7 | | |
| **JJ** | .2 | - | **3.3** | 2.1 | 1.7 | .2 | **2.7** |
| **NN** | | **8.7** | - | | | | .2 |
| **NNP** | .2 | **3.3** | **4.1** | - | .2 | | |
| **RB** | **2.2** | 2.0 | .5 | | - | | |
| **VBD** | | .3 | .5 | | | - | **4.4** |
| **VBN** | | **2.8** | | | | **2.6** | - |

- Major problems facing current taggers
  - NN (noun) versus NNP (proper noun) and JJ (adjective)
  - RP (particle) versus RB (adverb) versus JJ
  - VBD (past tense verb) versus VBN (past participle verb) versus JJ

# Applications of POS Tagging

- Tell what words are likely to occur in a word's vicinity
  - E.g. the vicinity of the possessive or person pronouns
- Tell the pronunciation of a word
  - DIScount (noun) and disCOUNT (verb) …
- Advanced ASR language models
  - Word-class N-grams
- Partial parsing
  - A simplest one: find the noun phrases (names) or other phrases in a sentence

# Applications of POS Tagging

- Information retrieval
  - Word stemming
  - Help select out nouns or important words from a doc
  - Phrase-level information

    United, States, of, America → "United States of America"

    secondary, education → "secondary education"

    - Phrase normalization

      Book publishing, publishing of books

- Information extraction
  - Semantic tags or categories

# Applications of POS Tagging

- Question Answering
  - Answer a user query that is formulated in the form of a question by return an appropriate noun phrase such as a location, a person, or a date
    - E.g. "Who killed President Kennedy?"

In summary, the role of taggers appears to be a fast lightweight component that gives sufficient information for many applications

- But not always a desirable preprocessing stage for all applications
- Many probabilistic parsers are now good enough !

# Class-based N-grams

- Use the lexical tag/category/class information to augment the *N*-gram models

$$P\left(w_n \middle| w_{n-N+1}^{n-1}\right) = P\left(w_n \middle| c_n\right) P\left(c_n \middle| c_{n-N+1}^{n-1}\right)$$

prob. of a word given the tag

prob. of a tag given the previous *N*-1 tags

  – Maximum likelihood estimation

$$P\left(w_i \middle| c_j\right) = \frac{C(w)}{C(c)}$$

$$P\left(c_j \middle| c_k\right) = \frac{C(c_k c_j)}{\sum_l C(c_l c_j)}$$

Constraints: a word may only belong to one lexical category

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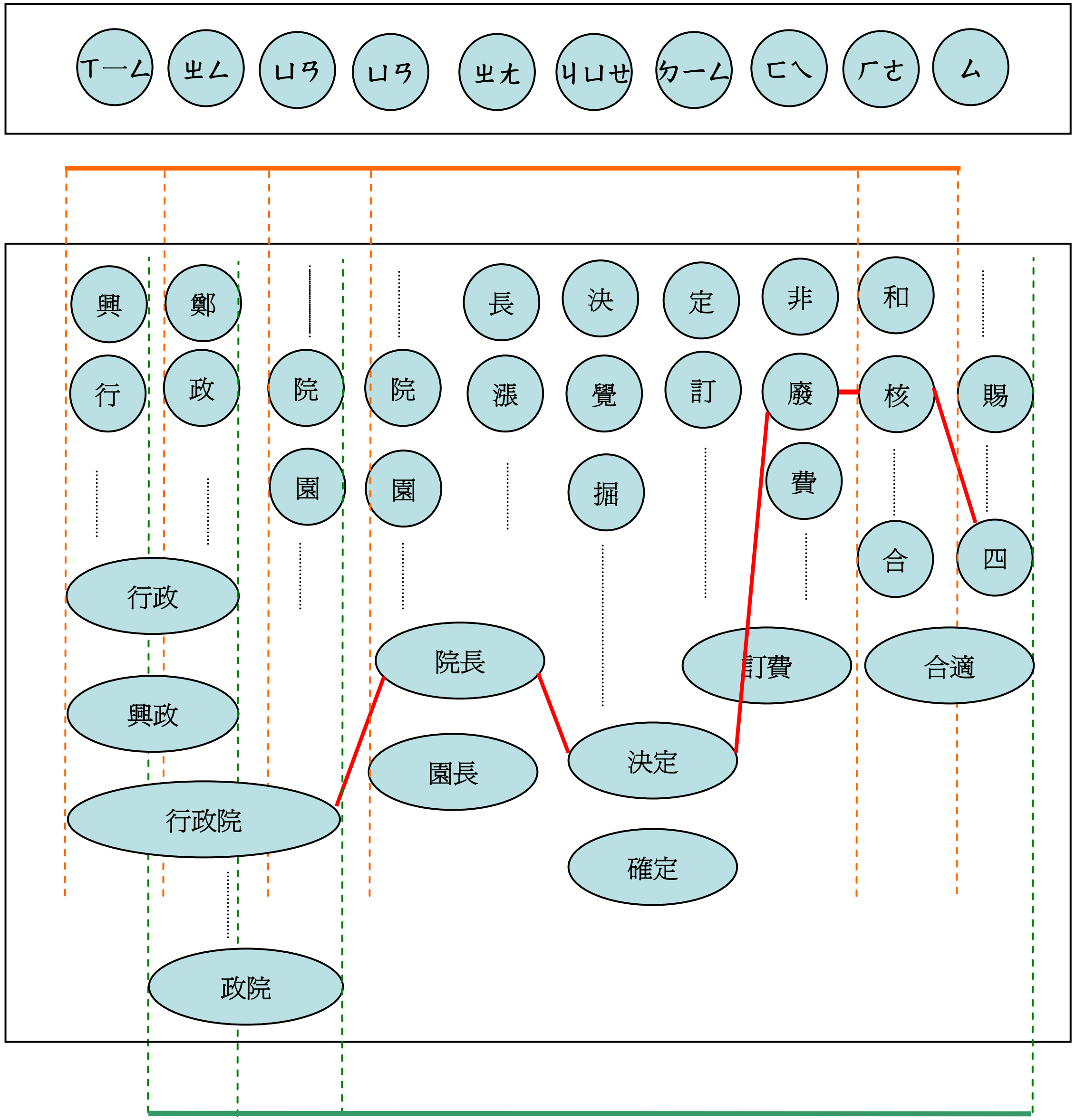

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