

CHAPTER 8: Sequence Labeling for Parts of Speech and Named Entities

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Group 5: 8.3 - 8.4.3

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① 8.3 Named Entities and Named Entity Tagging

② 8.4 HMM Part-of-Speech Tagging

8.4.1 Markov Chains

8.4.2 The Hidden Markov Model

The components of an HMM tagger

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The components of an HMM tagger

Introducing HMM

The Hidden Markov Model - HMM

- A statistical model with unknown parameters that must be determined from known parameters.
- Extends from the mathematical model: **Markov Chains**.

Applications

- Sequence labeling: NER, POS tagging
- Optical Character Recognition (OCR)
- Speech recognition
- Bioinformatics

Markov chains

Markov chains

A model that tells us something about the probabilities of sequences of random variables, states

- Sequence of states with a temporal order
- States can take values from any discrete set of values.
- **Markov assumption:** When predicting the future, the past doesn't matter

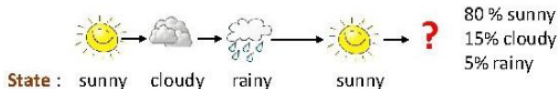
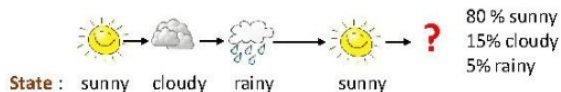


Figure: AA. Markov

Markov assumption

When predicting the future, the past doesn't matter, only the present



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

Components of the Markov chains

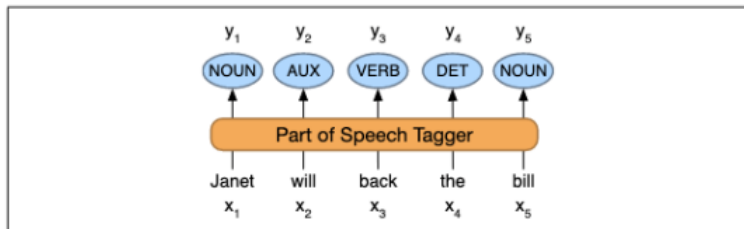
- $Q = q_1 q_2 \dots q_n$: a set of N **states**
- $A = a_{11} a_{12} \dots a_{N1} \dots a_{NN}$: a **transition probability matrix** A , each a_{ij} representing the probability of moving from state i to state j
- $\pi = \pi_1, \pi_2, \dots, \pi_n$: an **initial probability distribution** over states. π_i is the probability that the Markov chain will start in state i .

The Hidden Markov Model

A hidden Markov model (HMM) allows us to talk about both observed events and hidden events.

Unobservable Events:

- Part-of-speech
- Entity type



The Hidden Markov Model

$Q = q_1 q_2 \dots q_N$	a set of N states
$A = a_{11} \dots a_{ij} \dots a_{NN}$	a transition probability matrix A , each a_{ij} representing the probability of moving from state i to state j , s.t. $\sum_{j=1}^N a_{ij} = 1 \quad \forall i$
$O = o_1 o_2 \dots o_T$	a sequence of T observations , each one drawn from a vocabulary $V = v_1, v_2, \dots, v_V$
$B = b_i(o_t)$	a sequence of observation likelihoods , also called emission probabilities , each expressing the probability of an observation o_t being generated from a state q_i
$\pi = \pi_1, \pi_2, \dots, \pi_N$	an initial probability distribution over states. π_i is the probability that the Markov chain will start in state i . Some states j may have $\pi_j = 0$, meaning that they cannot be initial states. Also, $\sum_{i=1}^n \pi_i = 1$

Figure: Components of Hidden Markov Model

First order Hidden Markov Model

A first-order HMM instantiates two simplifying assumptions

- 1 The probability of a particular state depends only on the previous state

Markov Assumption: $P(q_i | q_1, \dots, q_{i-1}) = P(q_i | q_{i-1})$

- 2 The probability of an output observation depends only on the state that produced it and not on any other states.

Independence: $P(o_i | q_1, \dots, q_i, \dots, q_T, o_1, \dots, o_i, \dots, o_T) = P(o_i | q_i)$

A model in Natural Language Processing based on HMM, used for labeling elements in a sequence.

HMM Tagger consists of 2 components:

- ① A: The probability of a tag occurring given the previous tag
- ② B: The probability, given a tag, that it will be associated with a given word

The probability of a tag occurring given the previous tag

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

Example - In the WSJ corpus:

- MD occurs **13124** times
- MD is followed by VB **10471** times

Tag transition probability MD - VB:

$$P(VB | MD) = \frac{C(MD, VB)}{C(MD)} = \frac{10471}{13124} = 0.8$$

The probability of a word occurring associated with a tag

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

Example - In the WSJ corpus:

- MD occurs **13124** times
- MD is associated with *will* **4046** times

Tag transition probability MD - VB:

$$P(\textit{will}|\textit{MD}) = \frac{C(\textit{MD}, \textit{will})}{C(\textit{MD})} = \frac{4046}{13124} = 0.31$$



Speech and Language Processing (3rd ed. draft)

Dan Jurafsky and James H. Martin

Part I: Fundamental Algorithms, *Chapter 8: Sequence Labeling for Parts of Speech and Named Entities*

Thanks for listening!

Q&A section