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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Presentation Overview

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Named Entities

Named entity, in its core usage, means anything that can be referred to with a proper name. Most common 4 tags:

- PER (Person): "Marie Curie"
- LOC (Location): "New York City"
- ORG (Organization): "Stanford University"
- GPE (Geo-Political Entity): "Boulder, Colorado"

Named Entities

- Often multi-word phrases
- But the term is also extended to things that aren't entities: dates, times, prices

Named Entity tagging

The task of named entity recognition (NER):

- Find spans of text that constitute proper names
- Tag the type of the entity.

NER output

Citing high fuel prices, [**ORG** United Airlines] said [**TIME** Friday] it has increased fares by [**MONEY** $ 6] per round trip on flights to some cities also served by lower-cost carriers. [**ORG** American Airlines] , a unit of [**ORG** AMR Corp.] , immediately matched the move, spokesman [**PER** Tim Wagner] said. [**ORG** United], a unit of [**ORG** UAL Corp.], said the increase took effect [**TIME** Thursday] and applies to most routes where it competes against discount carriers, such as [**LOC** Chicago] to [**LOC** Dallas] and [**LOC** Denver] to [**LOC** San Francisco].

Why NER?

Sentiment analysis: consumer's sentiment toward a particular company or person?

Question Answering: answer questions about an entity?

Information Extraction: Extracting facts about entities from text.

Why NER is hard

Segmentation

- In POS tagging, no segmentation problem since each word gets one tag.
- In NER we have to find and segment the entities!

Type ambiguity

[**PER** Washington] was born into slavery on the farm of James Burroughs.
[**ORG** Washington] went up 2 games to 1 in the four-game series.
Blair arrived in [**LOC** Washington] for what may well be his last state visit.
In June, [**GPE** Washington] passed a primary seatbelt law.

BIO Tagging

[**PER** Jane Villanueva] of [**ORG** United], a unit of [**ORG** United Airlines Holding], said the fare applies to the [**LOC** Chicago]route.

Words	BIO Label
Jane	B-PER
Villanueva	I-PER
of	O
United	B-ORG
Airlines	I-ORG
Holding	I-ORG
discussed	O
the	O
Chicago	B-LOC
route	O
.	O

BIO Tagging

* B: token that begins a span
* I: tokens inside a span
* O: tokens outside of any span
* of tags (where n is entity types):
* 1 O tag,
* n B tags,
* n I tags
* total of 2n+1

Words	BIO Label
Jane	B-PER
Villanueva	I-PER
of	O
United	B-ORG
Airlines	I-ORG
Holding	I-ORG
discussed	O
the	O
Chicago	B-LOC
route	O
.	O

BIO Tagging variants: IO and BIOES

[**PER** Jane Villanueva] of [**ORG** United], a unit of [**ORG** United Airlines Holding], said the fare applies to the [**LOC** Chicago]route.

Words	IO Label	BIO Label	BIOES Label
Jane	I-PER	B-PER	B-PER
Villanueva	I-PER	I-PER	E-PER
of	O	O	O
United	I-ORG	B-ORG	B-ORG
Airlines	I-ORG	I-ORG	I-ORG
Holding	I-ORG	I-ORG	E-ORG
discussed	O	O	O
the	O	O	O
Chicago	I-LOC	B-LOC	S-LOC
route	O	O	O
.	O	O	O

Standard algorithms for NER

Supervised Machine Learning given a human-labeled training set of text annotated with tags

- Hidden Markov Models
- Conditional Random Fields (CRF)/ Maximum Entropy Markov Models (MEMM)
- Neural sequence models (RNNs or Transformers)
- Large Language Models (like BERT), finetuned

Presentation Overview

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
- Speech recognition
- Optical Character Recognition (OCR)
- Bioinformatics

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

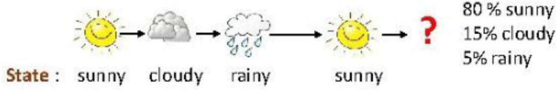
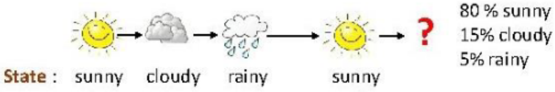


Figure: AA. Markov

Markov assumption

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



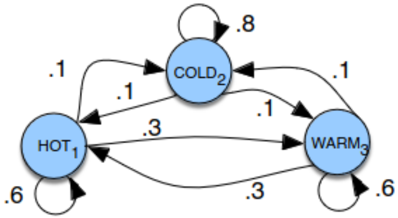
Markov assumption: $P(q_i = a | q_1 ... q_{i-1}) = P(q_1 = a | q_{i-1})$

Markov chains

Components of the Markov chains

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

Markov chains



(a)

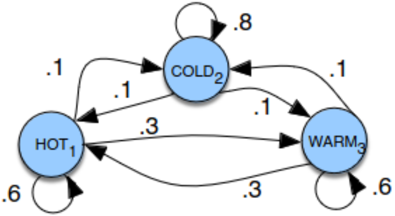
Markov Chain in Figure (a)

- $Q = \{HOT, COLD, WARM\}$
- Transition probability matrix A:

	π	HOT	COLD	WARM
HOT	0.1	0.6	0.1	0.3
COLD	0.7	0.1	0.8	0.1
WARM	0.2	0.3	0.1	0.6

- Initial probability distribution

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



(a)

Calculate the probabilities of

1. hot hot hot hot
2. cold hot cold hot

Markov Chain in Figure (a)

- $Q = \{HOT, COLD, WARM\}$
- Transition probability matrix A:

	π	HOT	COLD	WARM
HOT	0.1	0.6	0.1	0.3
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- Initial probability distribution

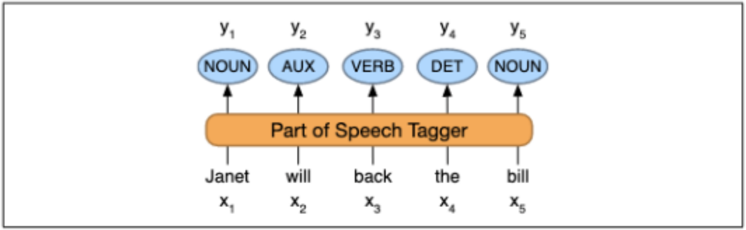
  $\pi = [0.1, 0.7, 0.2]$

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

$Q = q_1 q_2 \ldots q_N$	a set of N **states**
$A = a_{11} \ldots a_{ij} \ldots a_{NN}$	a **transition probability matrix** A, each a_{ij} representing the probability of moving from state i to state j, s.t. $\sum_{j=1}^{N} a_{ij} = 1 \quad \forall i$
$O = o_1 o_2 \ldots o_T$	a sequence of T **observations**, each one drawn from a vocabulary $V = v_1, v_2, \ldots, v_V$
$B = b_i(o_t)$	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
$\pi = \pi_1, \pi_2, \ldots, \pi_N$	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: $P(q_i|q_1,...q_{i-1}) = P(q_i|q_{i-1})$

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

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

The Hidden Markov Model

A sample HMM for the ice cream task.

- The two hidden states (H and C) correspond to **hot** and **cold** weather,
- The observations $O = 1, 2, 3$: number of ice creams eaten by Jason on a given day

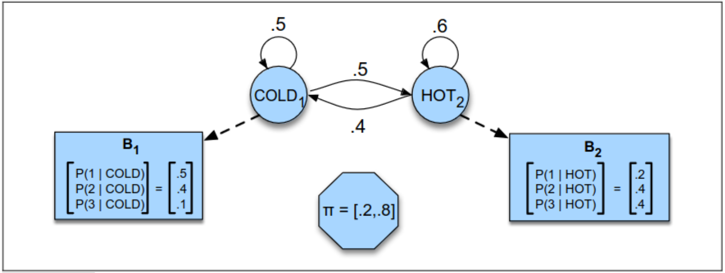


Figure: A hidden Markov model for relating numbers of ice creams eaten by Jason (the observations) to the weather (H or C, the hidden variables).

HMM Tagger

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

HMM Tagger

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:

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

HMM Tagger

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:

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

Reference

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