CS 6501 Natural Language Processing

Sequence Labeling (I)

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September 12, 2018

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Overview

1. Problem Formulation
2. Sequential Modeling
3. Viterbi Decoding
4. Parameter Estimation
5. Applications

Problem Formulation

Part of Speech (POS)

- A way to categorize words with similar *grammatical* properties
- Common English POS tags
  - NOUN: used to name persons, things, animals, places etc.

    e.g., `Tom Hanks`, `yesterday`, `Grounds`
  - VERB: show an action or state

    e.g., `fight`, `was`
  - PRONOUN: replacement of nouns

    e.g., `she`, `his`, `it`, `theirs`
  - ADJECTIVE: used to describe a noun or a pronoun

    e.g., `large`, `beautiful`

Part of Speech (II)

- Common English POS tags (cont.)
  - ADVERB: used to describe adjectives, verbs, or another adverb

    e.g., `gracefully`, `yesterday`, `very`
  - PREPOSITION: specify location or a location in time

    e.g., `above`, `near`, `since`
  - CONJUNCTION: join words, phrases, or clauses together

    e.g., `and`, `for`
  - INTERJECTION: convey strong emotions

    e.g., `Ouch`, `Hey`

POS Tagging

Example

Teacher Strikes Idle Children

- Teacher$_{\texttt{Noun}}$ Strikes$_{\texttt{Noun}}$ Idle$_{\texttt{Verb}}$ Children$_{\texttt{Noun}}$
- Teacher$_{\texttt{Noun}}$ Strikes$_{\texttt{Verb}}$ Idle$_{\texttt{Adj}}$ Children$_{\texttt{Noun}}$

[Eisenstein, 2018, Chap 8]

Goal

From a training set, to learn a mapping f,

$$f : x \rightarrow y \tag{1}$$

where

- x: a sentence
- y: the POS tag sequence of x

Sequence Labeling as Classification

$$f : \boldsymbol{x} \rightarrow \boldsymbol{y} \tag{2}$$

For example

- $\boldsymbol{x}$: entire sentence
- $\boldsymbol{y}$: entire sequence
- $P(\boldsymbol{y}|\boldsymbol{x})$

Example

Teacher$_{\texttt{Noun}}$ Strikes$_{\texttt{Verb}}$ Idle$_{\texttt{Adj}}$ Children$_{\texttt{Noun}}$

Sequence Labeling as Classification

$$f : x \to y \tag{2}$$

For example

- x: only one token
- y: only the corresponding tag
- $P(y_i|x_i)$

Example

Teacher$_{\texttt{Noun}}$ Strikes$_{\texttt{Verb}}$ Idle$_{\texttt{Adj}}$ Children$_{\texttt{Noun}}$

Sequence Labeling as Classification

Example

`The trash can is in the garage`

- f: logistic regression
- x: the target token (e.g., `can`) and its surroundings (e.g., `trash, is`)
  - MODAL VERB: can be
  - NOUN
- y: the corresponding tag

Sequential Decision

Example

`they can fish`

- $\texttt{they}_{\texttt{Pronoun}}$ $\texttt{can}_{\texttt{Modal\_Verb}}$ $\texttt{fish}_{\texttt{Verb}}$
- $\texttt{they}_{\texttt{Pronoun}}$ $\texttt{can}_{\texttt{Verb}}$ $\texttt{fish}_{\texttt{Noun}}$

[Eisenstein, 2018]

Sequential Decision

Example

`they can fish`

- they$_{\texttt{Pronoun}}$ can$_{\texttt{Modal_Verb}}$ fish$_{\texttt{Verb}}$
- they$_{\texttt{Pronoun}}$ can$_{\texttt{Verb}}$ fish$_{\texttt{Noun}}$

The dependency between $\{y_i\}$

[Eisenstein, 2018]

Sequential Modeling

Generative Models

- observation $\boldsymbol{x}$
- target variable $\boldsymbol{y}$

$$P(\boldsymbol{x}, \boldsymbol{y}) = P(\boldsymbol{x}|\boldsymbol{y}) \cdot P(\boldsymbol{y}) \tag{3}$$

Inference: Bayes rule

$$P(\boldsymbol{y}|\boldsymbol{x}) = \frac{P(\boldsymbol{x}|\boldsymbol{y}) \cdot P(\boldsymbol{y})}{P(\boldsymbol{x})} \tag{4}$$

$P(\boldsymbol{y})$

$$P(\boldsymbol{x}, \boldsymbol{y}) = P(\boldsymbol{x}|\boldsymbol{y}) \cdot P(\boldsymbol{y}) \tag{5}$$

$P(\boldsymbol{y})$

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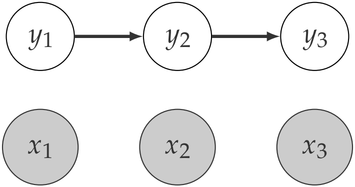
Factorization

$$P(\boldsymbol{y}) = \prod_{i=1} \underbrace{P(y_i|y_{i-1})}_{\text{Transition probability, Markov chain}} \tag{6}$$

Graphical model



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$$P(\boldsymbol{x}, \boldsymbol{y}) = P(\boldsymbol{x}|\boldsymbol{y}) \cdot P(\boldsymbol{y}) \tag{7}$$

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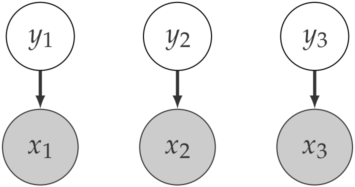
Factorization

$$P(\boldsymbol{x}|\boldsymbol{y}) = \prod_{i=1} \underbrace{P(x_i|y_i)}_{\text{Emission probability}} \tag{8}$$

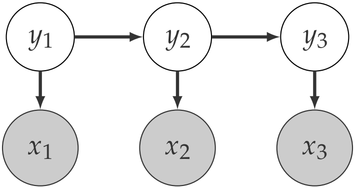
Graphical model



Hidden Markov Models

$$P(\boldsymbol{x}, \boldsymbol{y}) = \prod_{i=1} \left\{ P(y_i | y_{i-1}) P(x_i | y_i) \right\} \tag{9}$$

Graphical model



- $\boldsymbol{x}$: observation (e.g., sentences)
- $\boldsymbol{y}$: hidden variables (e.g., POS sequences)

Viterbi Decoding

Formulation

$$\hat{\boldsymbol{y}} = \arg\max_{\boldsymbol{y}} P(\boldsymbol{x}, \boldsymbol{y}) \tag{10}$$

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Dependency

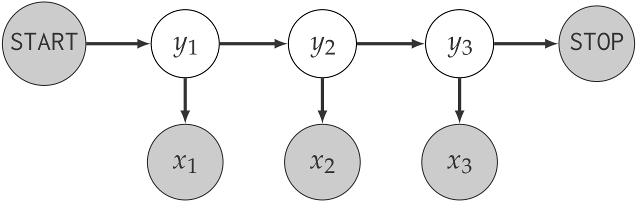
$$P(\boldsymbol{x}, \boldsymbol{y}) = \prod_{i=1} \left\{ P(y_i | y_{i-1}) P(x_i | y_i) \right\} \tag{11}$$

The value of y_i depends on

- y_{i-1} via $P(y_i | y_{i-1})$
- y_{i+1} via $P(y_{i+1} | y_i)$
- x_i via $P(x_i | y_i)$

START and STOP

Graphical model



Factorization

Factorize $P(\boldsymbol{x}, \boldsymbol{y})$ with respect to (x_i, y_i)

$$
\begin{aligned}
P(\boldsymbol{x}, \boldsymbol{y}) =& P(\boldsymbol{x}_{\leq i-1}, \boldsymbol{y}_{\leq i-1}) \cdot P(x_i, y_i | \boldsymbol{y}_{\leq i-1}) \cdot P(\boldsymbol{x}_{\geq i+1}, \boldsymbol{y}_{\geq i+1} | y_i) \\
=& P(\boldsymbol{x}_{\leq i-1}, \boldsymbol{y}_{\leq i-1}) \cdot P(x_i | y_i) \cdot P(y_i | y_{i-1}) \\
& \cdot P(\boldsymbol{x}_{\geq i+1}, \boldsymbol{y}_{\geq i+1} | y_i)
\end{aligned}
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\end{aligned}
$$

Three components

$$
\underbrace{P(\boldsymbol{x}_{\leq i-1}, \boldsymbol{y}_{\leq i-1})}_{\text{past}} \cdot \underbrace{P(x_i | y_i) \cdot P(y_i | y_{i-1})}_{\text{present}} \cdot \underbrace{P(\boldsymbol{x}_{\geq i+1}, \boldsymbol{y}_{\geq i+1} | y_i)}_{\text{future}} \tag{12}
$$

Basic Idea of Decoding

Three components

$$\underbrace{P(\boldsymbol{x}_{\leq i-1}, \boldsymbol{y}_{\leq i-1})}_{\text{past}} \cdot \underbrace{P(x_i | y_i) \cdot P(y_i | y_{i-1})}_{\text{present}} \cdot \underbrace{P(\boldsymbol{x}_{\geq i+1}, \boldsymbol{y}_{\geq i+1} | y_i)}_{\text{future}} \tag{13}$$

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- Forward enumerating:
  - Start from y_1, for every possible value of y_i, from the best path from y_{i-1}
  - $\arg\max_{y_{i-1}} P(\boldsymbol{x}_{\leq i-1}, \boldsymbol{y}_{\leq i-1}) \cdot P(x_i|y_i) \cdot P(y_i|y_{i-1})$
  - Depends on past and present states $\{\boldsymbol{y}_{\leq i}\}$

Basic Idea of Decoding

Three components

$$\underbrace{P(\boldsymbol{x}_{\leq i-1}, \boldsymbol{y}_{\leq i-1})}_{\text{past}} \cdot \underbrace{P(x_i|y_i) \cdot P(y_i|y_{i-1})}_{\text{present}} \cdot \underbrace{P(\boldsymbol{x}_{\geq i+1}, \boldsymbol{y}_{\geq i+1}|y_i)}_{\text{future}} \tag{13}$$

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  - $\arg\max_{y_{i-1}} P(\boldsymbol{x}_{\leq i-1}, \boldsymbol{y}_{\leq i-1}) \cdot P(x_i|y_i) \cdot P(y_i|y_{i-1})$
  - Depends on past and present states $\{\boldsymbol{y}_{\leq i}\}$
- Backward tracing:
  - Start from $y_T = \texttt{STOP}$, for a given y_{i+1} find the best y_i
  - Depends on future states $\boldsymbol{y}_{\geq i+1}$

A Few More Notations

- v_{i-1}: score function associated with the past states
- s_i: score function associated with the present state

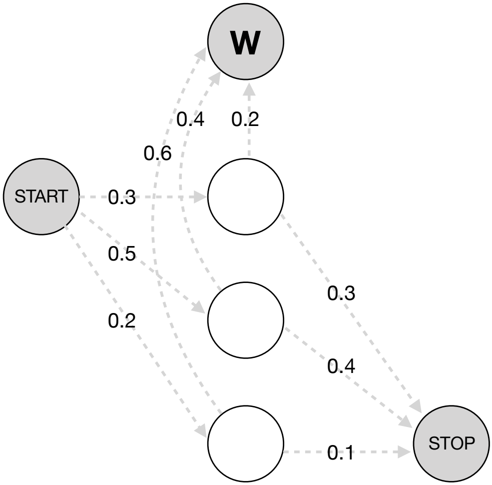
From

$$\arg\max_{y_{i-1}} P(\boldsymbol{x}_{\leq i-1}, \boldsymbol{y}_{\leq i-1}) \cdot P(x_i|y_i) \cdot P(y_i|y_{i-1})$$

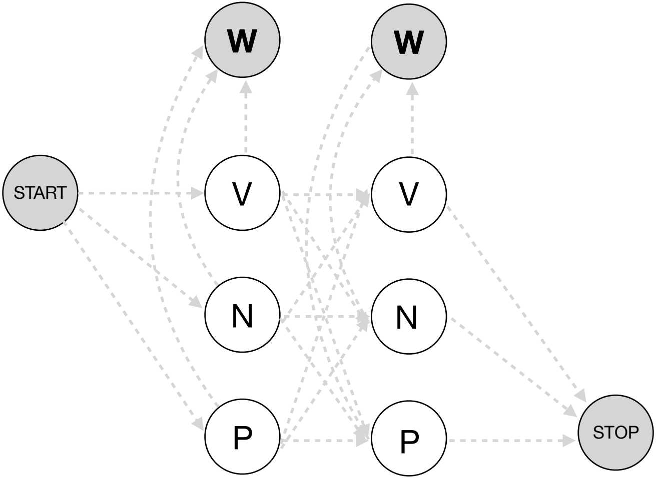
to

$$\arg\max_{y_{i-1}} s_i(y_i, y_{i-1}) + v_{i-1}(y_{i-1})$$

Example (I)



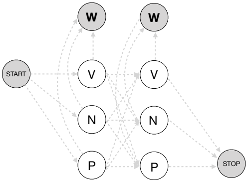
Example (II)



Viterbi Algorithm

Algorithm 11 The Viterbi algorithm. Each $s_m(k, k')$ is a local score for tag $y_m = k$ and $y_{m-1} = k'$.

> **for** $k \in \{0, \ldots K\}$ **do**
> $v_1(k) = s_1(k, \Diamond)$
> **for** $m \in \{2, \ldots, M\}$ **do**
>   **for** $k \in \{0, \ldots, K\}$ **do**
> $v_m(k) = \max_{k'} s_m(k, k') + v_{m-1}(k')$
> $b_m(k) = \mathrm{argmax}_{k'} s_m(k, k') + v_{m-1}(k')$
> $y_M = \mathrm{argmax}_k s_{M+1}(\blacklozenge, k) + v_M(k)$
> **for** $m \in \{M - 1, \ldots 1\}$ **do**
> $y_m = b_m(y_{m+1})$
> **return** $\boldsymbol{y}_{1:M}$



[Eisenstein, 2018]

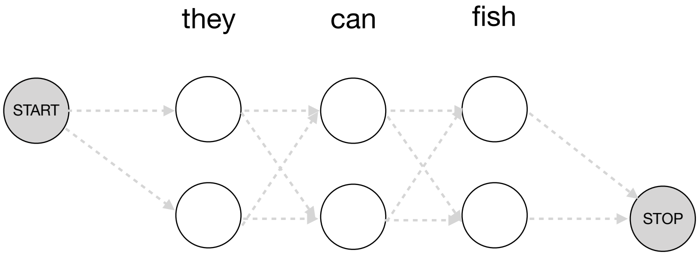
Example (III)

	they	*can*	*fish*
N	-2	-3	-3
V	-10	-1	-3

(a) Emission scores

	N	V	$\blacklozenge$
$\lozenge$	-1	-2	$-\infty$
N	-3	-1	-1
V	-1	-3	-1

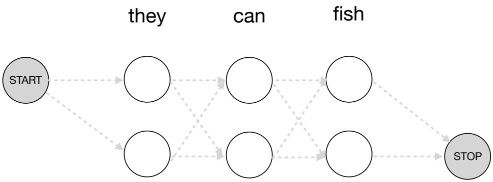
(b) Transition scores



(c) Trellis

Complexity

- T: sentence length
- K: possible tags



- $T \cdot K$ slots on trellis
- K computations for each slot

Therefore, total time complexity is $\mathcal{O}(TK^2)$

Parameter Estimation

Training Corpus

$$
\begin{aligned}
P(x_i|y_i) &=? \\
P(y_i|y_{i-1}) &=?
\end{aligned}
\tag{14}
$$

Training corpus

- $\texttt{they}_{\text{PRON}}$ $\texttt{can}_{\text{VERB}}$ $\texttt{fish}_{\text{NOUN}}$
- $\texttt{teacher}_{\text{NOUN}}$ $\texttt{strikes}_{\text{VERB}}$ $\texttt{idle}_{\text{ADJ}}$ $\texttt{children}_{\text{NOUN}}$
- ...

MLE

Transition probability

$$P(y_i|y_{i-1}) \approx \frac{c(y_i, y_{i-1})}{c(y_{i-1})} \tag{15}$$

Emission probability

$$P(x_i|y_i) \approx \frac{c(x_i, y_i)}{c(y_i)} \tag{16}$$

Applications

Parts of Speech

- *"Open classes"*
  - Nouns
  - Verbs
  - Adjectives
  - Adverbs
  - Numbers
- *"Closed classes"*
  - Modal verbs (e.g., `can, should`)
  - Prepositions (e.g., `on, to`)
  - Particles (e.g., `off, up`)
  - Determiners (e.g., `the, some`)
  - Pronouns (e.g., `she, they`)
  - Conjunctions (e.g., `and, or`)

[Smith, 2018]

Penn Treebank Tagset

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 ”)
PRP	Personal pronoun	*I, you, he*	(	Left parenthesis	([, (, {, <)
PRP$	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*			

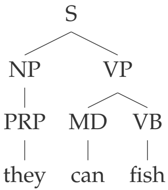
45 taggs, about 40 pages of guidelines [Marcus et al., 1993]

Why We Need POS?

- Disambiguation
  - they$_{\text{PRP}}$ can$_{\text{MD}}$ fish$_{\text{VB}}$

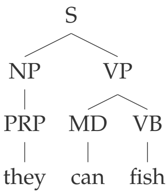
Why We Need POS?

- Disambiguation
  - they$_{PRP}$ can$_{MD}$ fish$_{VB}$
- Basic component for syntactic parsing



Why We Need POS?

- Disambiguation
  - $\texttt{they}_{\texttt{PRP}}\ \texttt{can}_{\texttt{MD}}\ \texttt{fish}_{\texttt{VB}}$
- Basic component for syntactic parsing



- Word prediction in speech recognition
  - Personal pronouns (`I`, `you`, `he`) are likely to be followed by verbs

Another Application: Named Entity Recognition

Example

`Atlantis touched down at Kennedy Space Center`

Another Application: Named Entity Recognition

Example

[Atlantis]$_{\text{MSIC}}$ touched down at [Kennedy Space Center]$_{\text{LOC}}$

Another Application: Named Entity Recognition

Example

`[Atlantis]`$_{\text{MSIC}}$ `touched down at` `[Kennedy Space Center]`$_{\text{LOC}}$

Tag set

- B: beginning
- I: inside
- O: outside

Category

- Person
- Location
- Organization
- Msic

Another Application: Named Entity Recognition

Example

`[Atlantis]`$_{\text{MSIC}}$ `touched down at [Kennedy Space Center]`$_{\text{LOC}}$

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- B: beginning
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Category

- Person
- Location
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Atlantis	touched	down	at	Kennedy	Space	Center	.
B_{MSIC}	O	O	O	B_{LOC}	I_{LOC}	I_{LOC}	O

Summary

- Sequence labeling problems
  - Part-of-Speech tagging
  - Named entity recognition
- Viterbi decoding
- Parameter estimation

Reference

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