CS 6501 Natural Language Processing

Conditional Random Fields

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Overview

1. Conditional Random Fields
2. Inference
3. Parameter Estimation
4. Applications of Sequence Labeling

Conditional Random Fields

Logistic Regression

A direct application of logistic regression:

$$p(\boldsymbol{y}|\boldsymbol{x}) = \frac{\exp(\boldsymbol{\theta}^\top \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{y}))}{\sum_{\boldsymbol{y}' \in \mathcal{Y}^T} \exp(\boldsymbol{\theta}^\top \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{y}'))} \tag{1}$$

Huge $\mathcal{Y}^T$ causes the problems on

- decoding $\operatorname{argmax}_{\boldsymbol{y}' \in \mathcal{Y}^T} p(\boldsymbol{y}'|\boldsymbol{x})$

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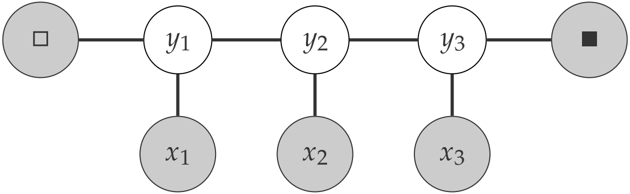
Huge $\mathcal{Y}^T$ causes the problems on

- decoding $\text{argmax}_{\boldsymbol{y}' \in \mathcal{Y}^T} p(\boldsymbol{y}'|\boldsymbol{x})$
- computing the partition function with $|\mathcal{Y}^T| = K^T$ possible values

Conditional Random Fields

Graphical Model:



- Conditional independence
- Undirected graph
- Factorization over cliques

Decomposition of $f(x, y)$

Based on the dependency between x and y, the feature function can be factorized as

$$f(x, y) = \sum_{i=1}^{T} \underbrace{f_i(x_i, y_i, y_{i-1})}_{\text{local feature function}} \quad (2)$$

where

- i: the position to be tagged
- $y_i \in \mathcal{Y}$: POS tag at position i
- $y_{i-1} \in \mathcal{Y}$: POS tag at position $i-1$
- x_i: observation (word) at position i
- $f_i(x_i, y_i, y_{i-1})$ captures the dependency of (y_{i-1}, y_i) and (x_i, y_i)

Local Feature Function: Example

- standard features

[Lafferty et al., 2001]

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- standard features
- whether a spelling begins with upper case letter,
  - `IBM`, `Virginia`: PROPER NOUN

[Lafferty et al., 2001]

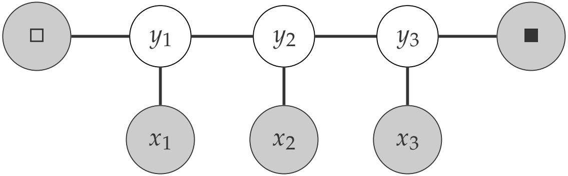
Local Feature Function: Example

- standard features
- whether a spelling begins with upper case letter,
  - `IBM`, `Virginia`: PROPER NOUN
- whether it ends in one of the following suffixes:
  - `-ies` e.g., `parties`: PROPER NOUN, PLURAL
  - `-ly` e.g., `extremely`, `loudly`: ADVERB
  - `-ing` e.g., : VERB, GERUND OR PRESENT PARTICIPLE
  - ...

[Lafferty et al., 2001]

Graphical Model Representation

Conditional Random Fields:



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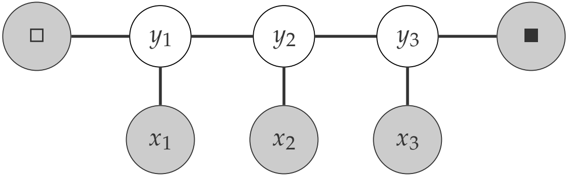
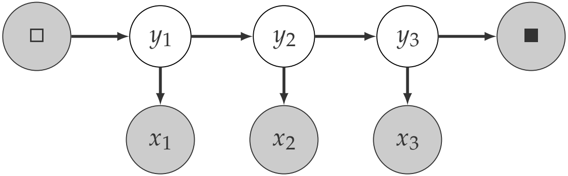


Hidden Markov Models:



Inference

Decode $p(\boldsymbol{y}|\boldsymbol{x})$

With this local feature function:

$$\boldsymbol{f}(\boldsymbol{x}, \boldsymbol{y}) = \sum_{i=1}^{T} \boldsymbol{f}_i(x_i, y_i, y_{i-1}) \tag{3}$$

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\end{aligned}$$

Factorization

Factorize $\boldsymbol{\theta}^\top \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{y})$ with respect to timestep i

$$\begin{aligned}\sum_{i=1}^{T} \boldsymbol{\theta}^\top \boldsymbol{f}_i(x_i, y_i, y_{i-1}) = & \underbrace{\sum_{j \le i-1} \boldsymbol{\theta}^\top \boldsymbol{f}_j(x_j, y_j, y_{j-1})}_{\text{past}} \\ & + \underbrace{\boldsymbol{\theta}^\top \boldsymbol{f}_i(x_i, y_i, y_{i-1})}_{\text{present}} \\ & + \underbrace{\sum_{k \ge i+1} \boldsymbol{\theta}^\top \boldsymbol{f}_k(x_k, y_k, y_{k-1})}_{\text{future}}\end{aligned} \tag{4}$$

Viterbi Algorithm

$$s_i(k, k') = \boldsymbol{\theta}^\top \boldsymbol{f}_i(x_i, y_{i-1} = k', y_i = k)$$

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

[Eisenstein, 2018]

Parameter Estimation

Parameter Estimation: Logistic regression

When label y is still a random variable

$$p(y|\boldsymbol{x};\boldsymbol{\theta}) = \frac{\exp(\boldsymbol{\theta}^\top \boldsymbol{f}(\boldsymbol{x},y))}{\sum_{y'\in\mathcal{Y}} \exp(\boldsymbol{\theta}^\top \boldsymbol{f}(\boldsymbol{x},y'))} \tag{5}$$

the derivative with respect $\boldsymbol{\theta}$

$$\frac{\partial \log p(y|\boldsymbol{x};\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} = \boldsymbol{f}\left(\boldsymbol{x},y\right) - \mathbb{E}_{Y|X}[\boldsymbol{f}\left(\boldsymbol{x},y\right)] \tag{6}$$

where

$$\mathbb{E}_{Y|X}[\boldsymbol{f}\left(\boldsymbol{x},y\right)] = \sum_{y\in\mathcal{Y}} \left\{p(y|\boldsymbol{x})\boldsymbol{f}(\boldsymbol{x},y)\right\} \tag{7}$$

Parameter Estimation: CRFs

When label $\boldsymbol{y}$ is a sequence

$$\frac{\partial \log p(\boldsymbol{y}|\boldsymbol{x};\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} = \boldsymbol{f}(\boldsymbol{x},\boldsymbol{y}) - \mathbb{E}_{Y|X}[\boldsymbol{f}(\boldsymbol{x},\boldsymbol{y})] \tag{8}$$

where

$$\mathbb{E}_{Y|X}[\boldsymbol{f}(\boldsymbol{x},\boldsymbol{y})] = \sum_{\boldsymbol{y}\in\mathcal{Y}^T} \left\{ p(\boldsymbol{y}|\boldsymbol{x})\boldsymbol{f}(\boldsymbol{x},\boldsymbol{y}) \right\} \tag{9}$$

and

$$\boldsymbol{f}(\boldsymbol{x},\boldsymbol{y}) = \sum_{i=1}^{T} \boldsymbol{f}_i(\boldsymbol{x}, y_{i-1}, y_i) \tag{10}$$

Expectation

$$\begin{aligned}
\mathbb{E}_{Y|X}[\boldsymbol{f}(\boldsymbol{x},\boldsymbol{y})] &= \sum_{\boldsymbol{y}\in\mathcal{Y}^T} \left\{ p(\boldsymbol{y} \mid \boldsymbol{x}) \boldsymbol{f}(\boldsymbol{x},\boldsymbol{y}) \right\} \\
&= \sum_{\boldsymbol{y}\in\mathcal{Y}^T} \left\{ p(\boldsymbol{y} \mid \boldsymbol{x}) \sum_{i=1}^{T} \boldsymbol{f}_i(x_i, y_{i-1}, y_i) \right\} \\
&= \sum_{\boldsymbol{y}\in\mathcal{Y}^T} \sum_{i=1}^{T} \left\{ p(\boldsymbol{y} \mid \boldsymbol{x}) \boldsymbol{f}_i(x_i, y_{i-1}, y_i) \right\} \\
&= \sum_{i=1}^{T} \sum_{\boldsymbol{y}\in\mathcal{Y}^T} \left\{ p(\boldsymbol{y} \mid \boldsymbol{x}) \boldsymbol{f}_i(x_i, y_{i-1}, y_i) \right\} \\
&= \sum_{i=1}^{T} \sum_{y_{i-1}\in\mathcal{Y}; y_i\in\mathcal{Y}} \left\{ p(y_{i-1}, y_i \mid \boldsymbol{x}) \boldsymbol{f}_i(\boldsymbol{x}, y_{i-1}, y_i) \right\}
\end{aligned}$$

Applications of Sequence Labeling

Applications

- Part-of-Speech taggins [Eisenstein, 2018, section 8.1]
- Named entity recognition (NER) [Eisenstein, 2018, section 8.3]
- Dialogue act identification [Eisenstein, 2018, section 8.6]

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, 2017]

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

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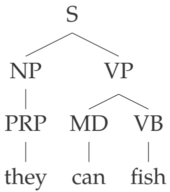
  - they$_{\mathrm{PRP}}$ can$_{\mathrm{MD}}$ fish$_{\mathrm{VB}}$
- Basic component for syntactic parsing



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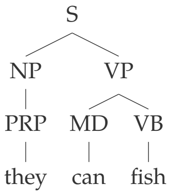

- Word prediction in speech recognition
  - Personal pronouns (`I`, `you`, `he`) are likely to be followed by verbs

Applications

- ✓ Part-of-Speech taggins [Eisenstein, 2018, section 8.1]
- Named entity recognition (NER) [Eisenstein, 2018, section 8.3]
- Dialogue act identification [Eisenstein, 2018, section 8.6]

Named Entity Recognition

Example

```
Atlantis touched down at Kennedy Space Center
```

Named Entity Recognition

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

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

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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BIO Annotation

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

Another Type of NER

For understanding scientific articles and academic papers

Computer Science:
This paper addresses the task of **[named entity recognition]**$_{\text{Task}}$, using **[conditional random fields]**$_{\text{Process}}$. Our method is evlauated on the **[ConLL NER Corpus]**$_{\text{Material}}$.

Physics:
[Local field effects] $_{\text{Process}}$ on spontaneous emission rates within **[nanostructure photonics material]**$_{\text{Material}}$ for example are familiar, and have been well used.

Material Science:
The **[Kelvin probe force microscopy technique]** $_{\text{Process}}$ allows **[detection of local EWF]**$_{\text{Task}}$ between an **[atomic force micorscopy]**$_{\text{Material}}$ and **[metal surface]**$_{\text{Material}}$.

[Luan et al., 2017]

Applications

- ✓ Part-of-Speech taggins [Eisenstein, 2018, section 8.1]
- ✓ Named entity recognition (NER) [Eisenstein, 2018, section 8.3]
- ► Dialogue act identification [Eisenstein, 2018, section 8.6]

Dialog Act Identification

Dialogue acts are labels over utterances in a dialogue, corresponding roughly to the speaker's intention.

Speaker	Dialogue Act	Utterance
A	YES-NO-QUESTION	*So do you go college right now?*
A	ABANDONED	*Are yo-*
B	YES-ANSWER	*Yeah,*
B	STATEMENT	*It's my last year [laughter].*
A	DECLARATIVE-QUESTION	*You're a, so you're a senior now.*
B	YES-ANSWER	*Yeah,*
B	STATEMENT	*I'm working on my projects trying to graduate [laughter]*
A	APPRECIATION	*Oh, good for you.*
B	BACKCHANNEL	*Yeah.*

- Sequence labeling over utterances
- For better understanding a conversation

Reference

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