CS 6501 Natural Language Processing

Sequence Labeling (I)

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Overview

1. Final Project Suggestion
2. Problem Definition
3. Hidden Markov Models
4. Parameter Estimation
5. Viterbi Decoding

Final Project Suggestion

Text Classification and Sentiment Analysis

Projects from last year:

- A Deeper Look into Social Media-focused Sentiment Analysis
- Citation Recommendation by Abstract

Convation Modeling

Projects from last year:

- Neural Dialog System with Personality
- Chit-chat Bot Modeling

Text Generaiton

Projects from last year:

- A Deep Learning Approach for Meme Generation
- Variational Image Captioning Using Deterministic Attention
- Neural Style Transfer for Natural Language
- Generating Subject Line from Email Text

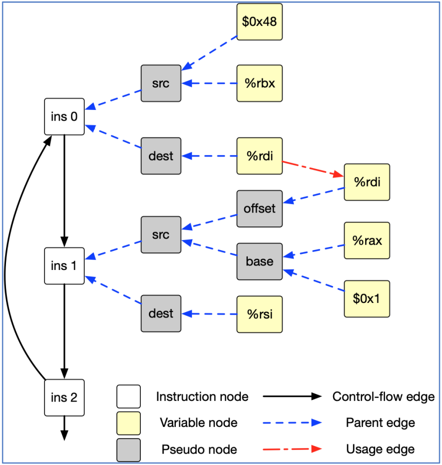
Interpretability and Adversarial Learning

Projects from last year:

- Incorporating Textual Data from Reviews for Explainable Recommendation
- Label Flipping Attacks on Sentiment Analysis Systems
- Topic-based Interpretability Improvement on Citation Recommendation System

Sequential Modeling for Computer Architecture

- Using neural network and NLP models to analyze machine code



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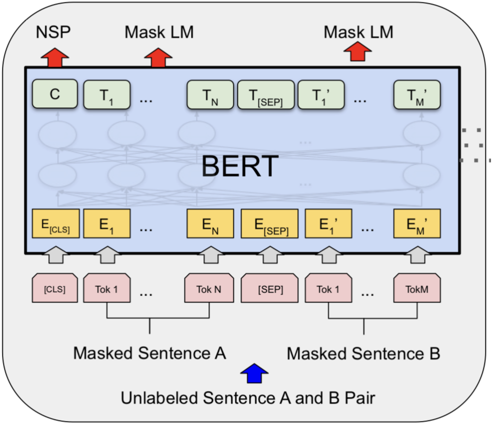
Running BERT on Edge Devices



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Problem Definition

Part of Speech

- 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]

Sequence Labeling

From a training set, to learn a mapping $p(\boldsymbol{y} \mid \boldsymbol{x})$,

$$\hat{y} = \underset{y}{\operatorname{argmax}}\, p(\boldsymbol{y} \mid \boldsymbol{x}) \tag{1}$$

where

- $\boldsymbol{x}$: a sentence (a sequence of words)
- $\boldsymbol{y}$: the POS tag sequence of $\boldsymbol{x}$ (a sequence of POS tags)

Example

$\boldsymbol{x}$	x_1 Teacher	x_2 Strikes	x_3 Idle	x_4 Children
$\boldsymbol{y}$	y_1 NOUN	y_2 NOUN	y_3 VERB	y_4 NOUN

Label Classification

$$\hat{y} = \operatorname*{argmax}_{y} p(\boldsymbol{y} \mid \boldsymbol{x}) \tag{2}$$

- $\boldsymbol{x}$: entire sentenceonly one token
- $\boldsymbol{y}$: entire sequenceonly the corresponding tag
- $P(\boldsymbol{y}|\boldsymbol{x})P(y_i|x_i)$

Example

$\boldsymbol{x}$	x_1 Teacher	x_2 Strikes	x_3 Idle	x_4 Children
$\boldsymbol{y}$	y_1 NOUN	y_2 NOUN	y_3 VERB	y_4 NOUN

Label Classification

Example

$\boldsymbol{x}$	x_1	x_2	x_3	x_4
	Teacher	Strikes	Idle	Children
$\boldsymbol{y}$	y_1	y_2	y_3	y_4
	NOUN	NOUN	VERB	NOUN
	NOUN	VERB	ADJ	NOUN

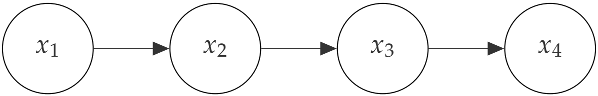
Limitations [`TODO: revise the following description`]

- No constraint from the previous POS tag
  - Solution: sequence labeling (e.g., hidden Markove models, conditional random fields)
- No information from the surrounding words
  - Solution: conditional random fields

Markov Chain

Modeling the dependency between $\{y_i\}$ as

$$p(\boldsymbol{y}) = p(y_1)p(y_2 \mid y_1)p(y_3 \mid y_2)p(y_4 \mid y_3) \tag{3}$$



Question

How to merge the conditional dependence from $p(\boldsymbol{y})$ into $p(\boldsymbol{y} \mid \boldsymbol{x})$?

Hidden Markov Models

Generative Models

- Observation $\boldsymbol{x}$
- Target variable $\boldsymbol{y}$

Bayes rule

$$\begin{aligned} p(\boldsymbol{y}|\boldsymbol{x}) &= \frac{p(\boldsymbol{x}|\boldsymbol{y}) \cdot p(\boldsymbol{y})}{p(\boldsymbol{x})} \\ &\approx \underbrace{p(\boldsymbol{y})}_{\text{prior}} \cdot \underbrace{p(\boldsymbol{x}|\boldsymbol{y})}_{\text{likelihood}} \end{aligned} \tag{4}$$

Prior $p(\boldsymbol{y})$

$$p(\boldsymbol{y} \mid \boldsymbol{x}) \approx p(\boldsymbol{y}) \cdot p(\boldsymbol{x} \mid \boldsymbol{y}) \tag{5}$$

Factorization

$$p(\boldsymbol{y}) = \prod_{i=1} \underbrace{p(y_i \mid y_{i-1})}_{\text{Transition probability}} \tag{6}$$

Graphical model

$$y_1 \longrightarrow y_2 \longrightarrow y_3 \longrightarrow y_4$$

$$p(\boldsymbol{y}) = p(y_1) \cdot p(y_2 \mid y_1) \cdot (y_3 \mid y_2) \cdot p(y_4 \mid y_3)$$

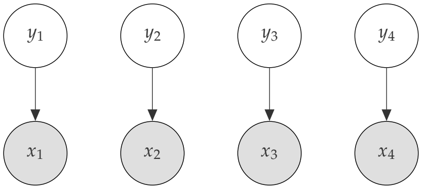
Likelihood $P(x|y)$

$$p(\boldsymbol{y} \mid \boldsymbol{x}) = p(\boldsymbol{y}) \cdot p(\boldsymbol{x} \mid \boldsymbol{y}) \tag{7}$$

Factorization

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

Graphical model

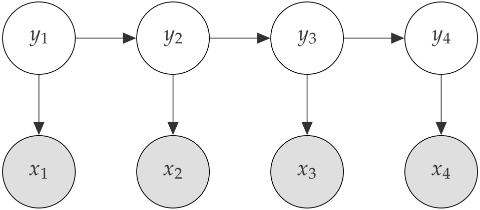


$$p(\boldsymbol{x} \mid \boldsymbol{y}) = p(x_1 \mid y_1) \cdot p(x_2 \mid y_2) \cdot p(x_3 \mid y_3) \cdot p(x_4 \mid y_4)$$

Hidden Markov Models

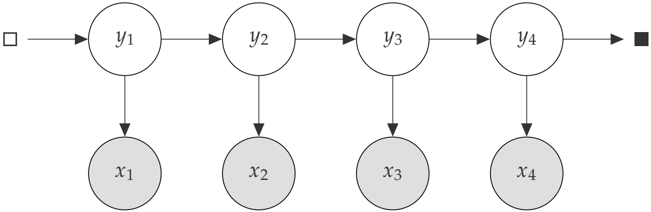
$$P(\boldsymbol{x}, \boldsymbol{y}) = \prod_{i=1} \left\{ P(y_i | y_{i-1}) P(x_i | y_i) \right\} \tag{9}$$

Graphical model



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

Two Special Tokens



$$P(\boldsymbol{x}, \boldsymbol{y}) = P(y_1 \mid \square) \prod_{i=1} \left\{ P(y_i | y_{i-1}) P(x_i | y_i) \right\} p(\blacksquare \mid y_4) \quad (10)$$

Two Questions

- Learning: parameter estimation
  - $p(y_n \mid y_{n-1}) =?$
  - $p(x_n \mid y_n) =?$
- Prediction: inference/decoding
  - $\hat{\boldsymbol{y}} = \operatorname{argmax}_{\boldsymbol{y}} p(\boldsymbol{y} \mid \boldsymbol{x})$

Parameter Estimation

Training Corpus

Training corpus

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

How to estimate the following probabilities?

$$\begin{aligned} P(x_i|y_i) &= ? \\ P(y_i|y_{i-1}) &= ? \end{aligned} \tag{11}$$

MLE

Transition probability

$$P(y_i|y_{i-1}) = \frac{\#(y_i, y_{i-1})}{\#(y_{i-1})} \tag{12}$$

Emission probability

$$P(x_i|y_i) = \frac{\#(x_i, y_i)}{\#(y_i)} \tag{13}$$

Viterbi Decoding

Decoding by Brute-force Search

Given a sentence

```
The dog barks
```

and the possible POS tags {D,N,V}. A brute-force algorithm will try every possible combination as

$$\begin{array}{ccc} D & D & D \\ D & D & N \\ D & D & V \\ D & N & D \\ D & N & N \\ D & N & N \\ \vdots & \vdots & \vdots \end{array}$$

There are $3^3 = 27$ possible sequences in this case.

Decoding y_i

$$\hat{\boldsymbol{y}} = \operatorname*{argmax}_{\boldsymbol{y}} p(\boldsymbol{y} \mid \boldsymbol{x}) \tag{14}$$

$$= \operatorname*{argmax}_{\boldsymbol{y}} p(\boldsymbol{x}, \boldsymbol{y}) \tag{15}$$

$$\tag{16}$$

With conditional dependency

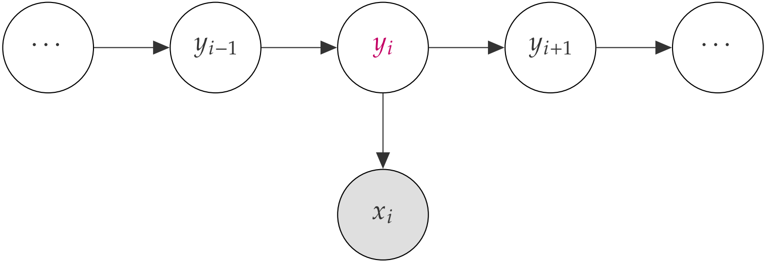
$$p(\boldsymbol{x}, \boldsymbol{y}) = \prod_{i=1} \left\{ p(y_i \mid y_{i-1}) p(x_i \mid y_i) \right\} \tag{17}$$

$$= \cdots \underbrace{p(y_i \mid y_{i-1}) \cdot p(y_{i+1} \mid y_i) \cdot p(x_i \mid y_i)}_{\text{items related to } y_i} \cdots \tag{18}$$

Decoding y_i (II)

$$p(\boldsymbol{x}, \boldsymbol{y}) = \prod_{i=1} \left\{ p(y_i \mid y_{i-1}) p(x_i \mid y_i) \right\} \tag{19}$$

$$= \cdots \underbrace{p(y_i \mid y_{i-1}) \cdot p(y_{i+1} \mid y_i) \cdot p(x_i \mid y_i)}_{\text{items related to } y_i} \cdots \tag{20}$$



Factorization

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

$$
\begin{aligned}
p(\boldsymbol{x}, \boldsymbol{y}) &= p(\boldsymbol{x}_{\leq i-1}, \boldsymbol{y}_{\leq i-1}) \cdot p(x_i, y_i | \boldsymbol{y}_{\leq i-1}) \cdot p(\boldsymbol{x}_{\geq i+1}, \boldsymbol{y}_{\geq i+1} | y_i) \\
&= p(\boldsymbol{x}_{\leq i-1}, \boldsymbol{y}_{\leq i-1}) \cdot p(x_i | y_i) \cdot p(y_i | y_{i-1}) \qquad (21) \\
&\quad \cdot p(\boldsymbol{x}_{\geq i+1}, \boldsymbol{y}_{\geq i+1} | y_i) \qquad (22)
\end{aligned}
$$

Three components

$$
\underbrace{p(\boldsymbol{x}_{\leq i-1}, \boldsymbol{y}_{\leq i-1})}_{\leq i-1} \cdot \underbrace{p(x_i | y_i) \cdot p(y_i | y_{i-1})}_{i} \cdot \underbrace{p(\boldsymbol{x}_{\geq i+1}, \boldsymbol{y}_{\geq i+1} | y_i)}_{> i} \qquad (23)
$$

Principle of Optimality

Assume we have the optimal decoded sequence $\hat{\boldsymbol{y}}$, such that

$$\hat{\boldsymbol{y}} = \operatorname*{argmax}_{\boldsymbol{y}} p(\boldsymbol{x}, \boldsymbol{y}), \tag{24}$$

then, $\boldsymbol{y}_{\geq i}$ is the also the optimal subsequence of the following subproblem

$$\hat{\boldsymbol{y}}_{\geq i} = \operatorname*{argmax}_{\boldsymbol{y}_{\geq i}} p(\boldsymbol{x}_{\geq i}, \boldsymbol{y}_{\geq i} \mid \hat{y}_i) \tag{25}$$

Justification:

$$\begin{aligned} p(\boldsymbol{x}, \boldsymbol{y}) = p(&\boldsymbol{x}_{\leq i-1}, \hat{\boldsymbol{y}}_{\leq i-1}) \\ &\cdot p(x_i \mid y_i) \cdot p(y_i \mid \hat{y}_{i-1}) \\ &\cdot p(\boldsymbol{x}_{\geq i+1}, \boldsymbol{y}_{\geq i+1} | y_i) \end{aligned} \tag{26}$$

Basic Idea of Decoding

$$\underbrace{p(\boldsymbol{x}_{\leq i-1}, \boldsymbol{y}_{\leq i-1})}_{\leq i-1} \cdot \underbrace{p(x_i|y_i) \cdot p(y_i|y_{i-1})}_{i} \cdot \underbrace{p(\boldsymbol{x}_{\geq i+1}, \boldsymbol{y}_{\geq i+1}|y_i)}_{>i} \tag{27}$$

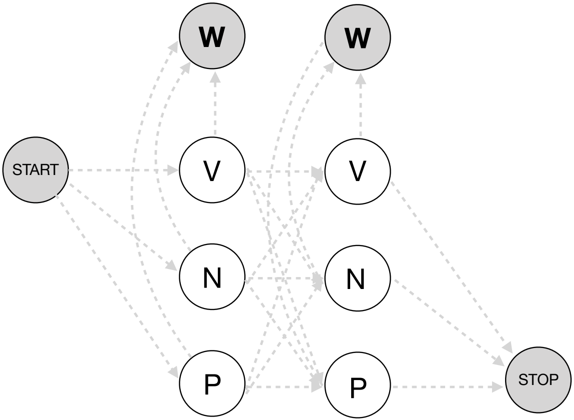
- Forward computation: start from y_1, for every possible value of y_i, from the best path from y_{i-1}

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

  depending on past and present states $\{\boldsymbol{y}_{\leq i}\}$
- Backward tracing: start from $y_T = \blacksquare$, for a given y_{i+1} find the best y_i

Example

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



Reference

Eisenstein, J. (2018).
Natural Language Processing.
MIT Press.