EMNLP

Sequence Tagging II – Linear Models

韩喆

fengyansong@pku.edu.cn

Institute of Computer Science and Technology

Peking University

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Recap: The HMM POS Tagger

- We represent
  - a sentence of any length n: $x_1, x_2, x_3, ...x_n$
  - its corresponding POS tag sequence; $y_1, y_2, y_3, ...y_n$
- We care the joint probability of a sentence and its POS tag sequence:

$$p(x_1, x_2, x_3, ...x_n, y_1, y_2, y_3, ...y_n)$$

(Generative Model)

- Then the most likely POS tag sequence for $x_1, x_2, x_3, ...x_n$:

$$\arg\max_{y_1...y_n} p(y_1, y_2, y_3, ...y_n) p(x_1, x_2, x_3, ...x_n | y_1, y_2, y_3, ...y_n)$$

- Make Markov Assumptions (e.g., Trigram)

$$\arg\max_{y_1...y_n} \prod_i p(y_i | y_{i-2}, y_{i-1}) \prod_i p(x_i | y_i)$$

Elements in Our HMM POS Tagger

- Elements
  - a sequence of words
  - a sequence of POS tags
  - the beginning and end of a sentence
- Parameters
  - Sequences of POS tags
  - Co-occurrences of words and POS tags

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Anything else useful?

- if the current word ending with *ing*, *ed*, *se*, *ly*, *ical*, or ....
- if the previous word is *the*
- if the next word is *.*
- ...

A Naive Way to Incorporate

…… many p_{ML}s

- $p_{ML}(POS_{w_i} = \text{VB}|w_i \text{ ending with } \textit{ing})$
- $p_{ML}(POS_{w_i} = \text{VB}|w_i \text{ ending with } \textit{ed})$
- $p_{ML}(POS_{w_i} = \text{VB}|w_i \text{ ending with } \textit{se})$
- $p_{ML}(POS_{w_i} = \text{VB}|w_i \text{ ending with } \textit{ly})$
- $p_{ML}(POS_{w_i} = \text{VB} w_i \text{ ending with } \textit{ical})$
- $p_{ML}(POS_{w_i} = \text{VB} w_{i-1} = \textit{the})$
- $p_{ML}(POS_{w_i} = \text{VB} w_{i+1} = \text{. (a period)})$
- …

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- $p_{ML}(POS_{w_i} = \text{VB} | w_i$ ending with *ing*$)$
- $p_{ML}(POS_{w_i} = \text{VB} | w_i$ ending with *ed*$)$
- $p_{ML}(POS_{w_i} = \text{VB} | w_i$ ending with *se*$)$
- $p_{ML}(POS_{w_i} = \text{VB} | w_i$ ending with *ly*$)$
- $p_{ML}(POS_{w_i} = \text{VB} w_i$ ending with *ical*$)$
- $p_{ML}(POS_{w_i} = \text{VB} w_{i-1} =$ *the*$)$
- $p_{ML}(POS_{w_i} = \text{VB} w_{i+1} =$. (a period)$)$
- ...

This gives you lots of λs to tune.

Another View: Features

Features: pieces of evidences describing some aspects of observed data x, usually with respect to the predicted label y

- computer vision
  - the shape, color, texture, size.....of an object
  - other objects nearby, relative postions
  - number of objects available
  - ...
- natural language process, e.g., POS tagging
  - the target word itself, prefix, suffix, capital or not, ...
  - context: words before/after the target, their morphology
  - number of those indications

Features in NLP

Features in NLP: pieces of evidences describing some aspects of observed data x with respect to the predicted label y, usually with the purpose of providing a conditional probability $p(y|x)$

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Often

- A feature is a function $f_i(x, y) \in \mathcal{R}$
- more often , it is a binary or indicator function
- for example,

$$f_i(x, y) = \begin{cases} 1 & \text{if } x = \text{Beijing and } y\text{=NNP} \\ 0 & \text{otherwise} \end{cases}$$

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- if we have m aspects to describe an instance, i.e., m features:

Features based Linear Models

Linear classifiers with the form like, $\lambda_i f_i(x, y)$

- need a linear function to map $f_i(x, y)$ to lable y
- possibly need a weight λ_i for each feature $f_i(x, y)$
- then, for each possible label y of instance x, we can compute a score:

$$score(x, y) = \sum_i \lambda_i f_i(x, y)$$

- the classifier should choose y^*:

$$y^* = \arg\max_y \sum_i \lambda_i f_i(x, y)$$

Features based Linear Models: An Example

Tagging *Beijing* with a trained model:

I love Beijing .

- aspects: the target word, previous words, suffix, prefix, capitalized, ...
- curwd_Beijing_NNP, pre1word_love_NNP, pref_Be_NNP, cap_1_NNP, curwd_Beijing_VB, pref_Be_VB...
- for each possible labels (NNP, VB, DT, ...), coupled aspects with lables
- obtain λs using some algorithm, $\lambda_{curwd\_Beijing\_NNP} = 10$, $\lambda_{pref\_Be\_NNP} = 5$, $\lambda_{cap\_1\_DT} = -10$, ...
- compute score(Beijing, NNP), score(Beijing, VB), score(Beijing, DT), ...
- choose the largest one: score(Beijing, NNP)

Features based Linear Models: Algorithms

The key is to choose proper weights λs for features

- the Perceptron algorithm
- Margin-based models (the Support Vector Machines, SVM)
- Exponential Models:
  - log-linear models, maximum entropy models, logistic models, ...
  - basically, produce a probabilistic model according to score(x, y)

$$p(y|x) = \frac{\exp score(x, y)}{\sum_{y'} \exp score(x, y')} = \frac{\exp \sum_i \lambda_i f_i(x, y)}{\sum_{y'} \exp \sum_i \lambda_i f_i(x, y')}$$

  - numerator: positive score for label y
  - denominator: normalization

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  - numerator: positive score for label y
  - denominator: normalization
  - a powerful tool! (covered in later lectures)

The Perceptron Algorithm

- Classic: Rosenblatt 1958
- Modern: Freund and Schapire 1999
  - proof for convergence
  - very competitive performances in classifications
- NLP: Michael Collins 2002, 2004, ...
  - modificatioins with respect to NLP applications
  - serves as alternative parameter estimation methods for many ML models
  - You SHOULD read at least the 2002 paper

A Variant of The Perceptron Algorithm

- **Inputs**:
  - Training set (x_k, y_k) for $k = 1, 2, ..., n$
  - x_k the data, and y_k the label
- Initialization:
  - $\lambda = [0, 0, 0.....],\ T$
- Define:
  - follow Collins: GEN enumerates possible candidate lable ys for data x
  - $z = \arg\max_{y \in GEN(x)} \sum_i \lambda_i f_i(x, y)$
- Loop:
  - For $t = 1, 2, 3..., T,\ k = 1, 2, 3, ..., n$
    compute $z_k = \arg\max_{y \in GEN(x_k)} \sum_i \lambda_i f_i(x_k, y)$
    update λs
    - if $z_k \neq y_k$: $\lambda = \lambda + f(x_k, y_k) - f(x_k, z_k)$
- Output:
  - λs

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    compute $z_k = \arg\max_{y \in GEN(x_k)} \sum_i \lambda_i f_i(x_k, y)$ (Key: decode z)
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    - if $z_k \neq y_k$: $\lambda = \lambda + f(x_k, y_k) - f(x_k, z_k)$
- Output:
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Structured Perceptron for POS Tagging (A simple case)

training data: *China*/N *Mobile*/N *is*/V *a*/DT *communication*/N *giant*/N *in*/P *east*/ADJ *Asia*/N

- in a step during training:
  China/N *Mobile*/N ... *communication*/N *giant*/**??** *in east Asia*
  - word *giant* may have many choices of tags : **N, V, DT, P, ADJ, ...**

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  - word *giant* may have many choices of tags : **N, V, DT, P, ADJ, ...**
  - for each choice, .e.g, N, we extract m features :
    - $f_1(x, y) = 1$ if current word is *giant* and $y = N$. $\rightarrow f_1(x, y) = 1$
    - $f_{11}(x, y) = 1$ if current word is *giant* and $y = ADJ$. $\rightarrow f_{11}(x, y) = 0$
    - $f_2(x, y) = 1$ if previous word is *the* and $y = N$. $\rightarrow f_2(x, y) = 0$
    - $f_{22}(x, y) = 1$ if previous word is *the* and $y = ADJ$. $\rightarrow f_{22}(x, y) = 0$
    - $f_3(x, y) = 1$ if sufix of current word is *ant* and $y = N$. $\rightarrow f_3(x, y) = 1$
    - $f_{33}(x, y) = 1$ if sufix of current word is *ant* and $y = ADJ$. $\rightarrow f_{33}(x, y) = 0$
    - ...
  - compute score$(giant, N) = \sum_i \lambda_i f_i(giant, N)$, score$(giant, ADJ)$, ...

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    - ...
  - compute score$(giant, N) = \sum_i \lambda_i f_i(giant, N)$, score$(giant, ADJ)$, ...

Structured Perceptron for POS Tagging (A simple case)

- the resulting sequence is
  China/N *Mobile*/N *is*/V *a*/DT *communication*/N *giant*/ADJ *in*/DT *east*/ADJ *Asia*/N
- the gold-standard one
  China/N *Mobile*/N *is*/V *a*/DT *communication*/N *giant*/N *in*/P *east*/ADJ *Asia*/N

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- we compare them, and find the differences:

Structured Perceptron for POS Tagging (A simple case)

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  China/N *Mobile*/N *is*/V *a*/DT *communication*/N *giant*/ADJ *in*/DT *east*/ADJ *Asia*/N
- the gold-standard one

  China/N *Mobile*/N *is*/V *a*/DT *communication*/N *giant*/N *in*/P *east*/ADJ *Asia*/N
- we compare them, and find the differences:
- if necessary, we **update** the features related to the correct/wrong predictions
  - $\lambda^*_{f_1(x,y)} = \lambda_{f_1(x,y)} + 1$
  - $\lambda^*_{f_3(x,y)} = \lambda_{f_3(x,y)} + 1$
  - $\lambda^*_{f_{11}(x,y)} = \lambda_{f_{11}(x,y)} - 1$
  - $\lambda^*_{f_{33}(x,y)} = \lambda_{f_{33}(x,y)} - 1$
  -

A Bit Complex

If we want to include features like

- $f_{100}(x, y) = 1$ if previous tag is *N* and $y = N$. $\rightarrow f_100(giant, N) = 1$
- $f_{101}(x, y) = 1$ if the previous two tags are *DT_N* and $y = N$. $\rightarrow$ $f_{101}(giant, N) = 1$
- ...
- we can not directly compute score$(giant, N)$, score$(giant, ADJ)$, ...

A Bit Complex

If we want to include features like

- $f_{100}(x, y) = 1$ if previous tag is *N* and $y = N$. $\rightarrow f_1 00(giant, N) = 1$
- $f_{101}(x, y) = 1$ if the previous two tags are *DT_N* and $y = N$. $\rightarrow$ $f_{101}(giant, N) = 1$
- ...
- we can not directly compute score$(giant, N)$, score$(giant, ADJ)$, ...
- we need to decode the best tag sequence for the whole sentence using Dynamic Programming

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- $f_{101}(x, y) = 1$ if the previous two tags are *DT_N* and $y = N$. $\rightarrow$ $f_{101}(giant, N) = 1$
- ...
- we can not directly compute score$(giant, N)$, score$(giant, ADJ)$, ...
- we need to decode the best tag sequence for the whole sentence using Dynamic Programming

  $\rightarrow$ **the Viterbi Algorithm**
-
$$\arg\max_{y \in GEN(x)} \sum_{w \in x} \sum_i \lambda_i f_i(\text{history}(w), y)$$

Decoding: the Viterbi Algorithm

- for sentence of length n
- define the score of tag sequence $t_1, t_2, ... t_j$:

  score$(t_1, t_2, ... t_j) = \sum_{w \in x} \sum_i \lambda_i f_i'(w, t_{w-2}, t_{w-1}, t_w)$
- define the dynamic programming table

  $\pi(j, u, v)$ = maximum probability of a tag sequence ending with tags u, v at position j
- so,

$$\pi(j, u, v) = \max_{<t_1, t_2, ... t_{j-2}>} \text{score}(t_1, t_2, ... t_{j-2}, u, v)$$

- Recursively:

  base with $\pi(0, \text{START}, \text{START}) = 0$

  for any $j \in 1, 2, ..., n$, for possible u and v:

$$\pi(j, u, v) = \max_t (\pi(j-1, t, u) + \sum_i \lambda_i f_i'(word_v, t, u, v))$$

More about Perceptron

- Voted Perceptron (Collins 2002)
- Averaged Perceptron (Collins 2002)
- Early Update (Collins and Roak 2004)

  Questions

- can this model take features like:

  how many times we see a verb in this sentence ?

Readings

1999 Large Margin Classification using the Perceptron Algorithm, Machine Learning, 1999

2002 Discriminative Training Methods for Hidden Markov Models: Theory and Experiments with Perceptron Algorithms. Michael Collins, EMNLP, 2002