



Natural Language Processing

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Part 1: Classification tasks in NLP

Classification tasks in NLP

Naive Bayes Classifier

Log linear models

Tagging tasks in NLP

Log-linear models for Tagging

Prepositional Phrases

- ▶ noun attach: *I bought the shirt with pockets*
- ▶ verb attach: *I washed the shirt with soap*
- ▶ As in the case of other attachment decisions in parsing: it depends on the meaning of the entire sentence – needs world knowledge, etc.
- ▶ Maybe there is a simpler solution: we can attempt to solve it using heuristics or associations between words

Ambiguity Resolution: Prepositional Phrases in English

- Learning Prepositional Phrase Attachment: Annotated Data

v	n_1	p	n_2	Attachment
join	board	as	director	V
is	chairman	of	N.V.	N
using	crocidolite	in	filters	V
bring	attention	to	problem	V
is	asbestos	in	products	N
making	paper	for	filters	N
including	three	with	cancer	N
⋮	⋮	⋮	⋮	⋮

Prepositional Phrase Attachment

Method	Accuracy
Always noun attachment	59.0
Most likely for each preposition	72.2
Average Human (4 head words only)	88.2
Average Human (whole sentence)	93.2

Back-off Smoothing

- ▶ Random variable a represents attachment.
- ▶ $a = n_1$ or $a = v$ (two-class classification)
- ▶ We want to compute probability of noun attachment:
 $p(a = n_1 \mid v, n_1, p, n_2)$.
- ▶ Probability of verb attachment is $1 - p(a = n_1 \mid v, n_1, p, n_2)$.

Back-off Smoothing

1. If $f(v, n_1, p, n_2) > 0$ and $\hat{p} \neq 0.5$

$$\hat{p}(a_{n_1} \mid v, n_1, p, n_2) = \frac{f(a_{n_1}, v, n_1, p, n_2)}{f(v, n_1, p, n_2)}$$

2. Else if $f(v, n_1, p) + f(v, p, n_2) + f(n_1, p, n_2) > 0$
and $\hat{p} \neq 0.5$

$$\hat{p}(a_{n_1} \mid v, n_1, p, n_2) = \frac{f(a_{n_1}, v, n_1, p) + f(a_{n_1}, v, p, n_2) + f(a_{n_1}, n_1, p, n_2)}{f(v, n_1, p) + f(v, p, n_2) + f(n_1, p, n_2)}$$

3. Else if $f(v, p) + f(n_1, p) + f(p, n_2) > 0$

$$\hat{p}(a_{n_1} \mid v, n_1, p, n_2) = \frac{f(a_{n_1}, v, p) + f(a_{n_1}, n_1, p) + f(a_{n_1}, p, n_2)}{f(v, p) + f(n_1, p) + f(p, n_2)}$$

4. Else if $f(p) > 0$ (try choosing attachment based on preposition alone)

$$\hat{p}(a_{n_1} \mid v, n_1, p, n_2) = \frac{f(a_{n_1}, p)}{f(p)}$$

5. Else $\hat{p}(a_{n_1} \mid v, n_1, p, n_2) = 1.0$

Prepositional Phrase Attachment: Results

- ▶ **Results (Collins and Brooks 1995):** 84.5% accuracy with the use of some limited word classes for dates, numbers, etc.
 - ▶ **Toutanova, Manning, and Ng, 2004:**
use sophisticated smoothing model for PP attachment
86.18% with words & stems; with word classes: 87.54%
 - ▶ **Merlo, Crocker and Berthouzoz, 1997:**
test on multiple PPs, generalize disambiguation of 1 PP to 2-3 PPs
1PP: 84.3% 2PP: 69.6% 3PP: 43.6%
- Note that this is still not the real problem faced in parsing natural language**

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Part 2: Probabilistic Classifiers

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Log-linear models for Tagging

Naive Bayes Classifier

- ▶ \mathbf{x} is the input that can be represented as d independent features f_j , $1 \leq j \leq d$
- ▶ y is the output classification
- ▶ $P(y | \mathbf{x}) = \frac{P(y) \cdot P(\mathbf{x}|y)}{P(\mathbf{x})}$ (Bayes Rule)
- ▶ $P(\mathbf{x} | y) = \prod_{j=1}^d P(f_j | y)$
- ▶ $P(y | \mathbf{x}) = P(y) \cdot \prod_{j=1}^d P(f_j | y)$

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Log linear model

- ▶ Let there be m features, $f_k(\mathbf{x}, y)$ for $k = 1, \dots, m$
- ▶ Define a parameter vector $\mathbf{w} \in \mathbb{R}^m$
- ▶ Each (\mathbf{x}, y) pair is mapped to score:

$$s(\mathbf{x}, y) = \sum_k w_k \cdot f_k(\mathbf{x}, y)$$

- ▶ Using inner product notation:

$$\begin{aligned}\mathbf{w} \cdot \mathbf{f}(\mathbf{x}, y) &= \sum_k w_k \cdot f_k(\mathbf{x}, y) \\ s(\mathbf{x}, y) &= \mathbf{w} \cdot \mathbf{f}(\mathbf{x}, y)\end{aligned}$$

- ▶ To get a probability from the score: Renormalize!

$$\Pr(y \mid \mathbf{x}, \mathbf{w}) = \frac{\exp(s(\mathbf{x}, y))}{\sum_{y'} \exp(s(\mathbf{x}, y'))}$$

Log linear model

- ▶ The name 'log-linear model' comes from:

$$\log \Pr(y \mid \mathbf{x}, \mathbf{w}) = \underbrace{\mathbf{w} \cdot \mathbf{f}(\mathbf{x}, y)}_{\text{linear term}} - \underbrace{\log \sum_{y'} \exp(\mathbf{w} \cdot \mathbf{f}(\mathbf{x}, y'))}_{\text{normalization term}}$$

- ▶ Once the weights are learned, we can perform predictions using these features.
- ▶ The goal: to find \mathbf{w} that maximizes the log likelihood $L(\mathbf{w})$ of the labeled training set containing (\mathbf{x}_i, y_i) for $i = 1 \dots n$

$$\begin{aligned} L(\mathbf{w}) &= \sum_i \log \Pr(y_i \mid \mathbf{x}_i, \mathbf{w}) \\ &= \sum_i \mathbf{w} \cdot \mathbf{f}(\mathbf{x}_i, y_i) - \sum_i \log \sum_{y'} \exp(\mathbf{w} \cdot \mathbf{f}(\mathbf{x}_i, y')) \end{aligned}$$

Log linear model

- Maximize:

$$L(\mathbf{w}) = \sum_i \mathbf{w} \cdot \mathbf{f}(\mathbf{x}_i, y_i) - \sum_i \log \sum_{y'} \exp(\mathbf{w} \cdot \mathbf{f}(\mathbf{x}_i, y'))$$

- Calculate gradient:

$$\begin{aligned} & \left. \frac{dL(\mathbf{w})}{d\mathbf{w}} \right|_{\mathbf{w}} \\ &= \sum_i \mathbf{f}(\mathbf{x}_i, y_i) - \sum_i \frac{1}{\sum_{y''} \exp(\mathbf{w} \cdot \mathbf{f}(\mathbf{x}_i, y''))} \\ & \quad \sum_{y'} \mathbf{f}(\mathbf{x}_i, y') \cdot \exp(\mathbf{w} \cdot \mathbf{f}(\mathbf{x}_i, y')) \\ &= \sum_i \mathbf{f}(\mathbf{x}_i, y_i) - \sum_i \sum_{y'} \mathbf{f}(\mathbf{x}_i, y') \frac{\exp(\mathbf{w} \cdot \mathbf{f}(\mathbf{x}_i, y'))}{\sum_{y''} \exp(\mathbf{w} \cdot \mathbf{f}(\mathbf{x}_i, y''))} \\ &= \underbrace{\sum_i \mathbf{f}(\mathbf{x}_i, y_i)}_{\text{Observed counts}} - \underbrace{\sum_i \sum_{y'} \mathbf{f}(\mathbf{x}_i, y') \Pr(y' | \mathbf{x}_i, \mathbf{w})}_{\text{Expected counts}} \end{aligned}$$

Log linear model

- ▶ Init: $\mathbf{w}^{(0)} = \mathbf{0}$
- ▶ $t \leftarrow 0$
- ▶ Iterate until convergence:
 - ▶ Calculate: $\Delta = \left. \frac{dL(\mathbf{w})}{d\mathbf{w}} \right|_{\mathbf{w}=\mathbf{w}^{(t)}}$
 - ▶ Find $\beta^* = \arg \max_{\beta} L(\mathbf{w}^{(t)} + \beta \Delta)$
 - ▶ Set $\mathbf{w}^{(t+1)} \leftarrow \mathbf{w}^{(t)} + \beta^* \Delta$

Learning the weights: \mathbf{w} : Generalized Iterative Scaling

$$f^\# = \max_{x,y} \sum_j f_j(x,y)$$

(the maximum possible feature value; needed for scaling)

Initialize $\mathbf{w}^{(0)}$

For each iteration t

 expected[j] \leftarrow 0 for $j = 1 \dots \#$ of features

 For $i = 1$ to |training data|

 For each feature f_j

$$\text{expected}[j] += f_j(x_i, y_i) \cdot P(y_i | x_i, \mathbf{w}^{(t)})$$

 For each feature $f_j(x, y)$

$$\text{observed}[j] = f_j(x, y) \cdot \frac{c(x,y)}{|\text{training data}|}$$

 For each feature $f_j(x, y)$

$$w_j^{(t+1)} \leftarrow w_j^{(t)} \cdot \sqrt{\frac{\text{observed}[j]}{\text{expected}[j]}}$$

cf. Goodman, NIPS '01

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Part 3: Linear models for Tagging

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Tagging Tasks

Tagged Sequences

a b e e a f h j \Rightarrow a/Y b/Z e/Y e/Y a/Z f/X h/Z j/Y

Example 1: Part-of-speech tagging

Profits/N soared/V at/P Boeing/N Co./N ,/, easily/ADV
topping/V forecasts/N on/P Wall/N Street/N ,/, as/P
their/POSS CEO/N Alan/N Mulally/N announced/V first/ADJ
quarter/N results/N ./.

Example 2: Named Entity Recognition

Profits/O soared/O at/O Boeing/B-CO Co./I-CO ,/O easily/O
topping/O forecasts/O on/O Wall/B-LOC Street/I-LOC ,/O as/O
their/O CEO/O Alan/B-PER Mulally/I-PER announced/O first/O
quarter/O results/O ./O

Notation for Tagging Tasks

- ▶ Set of possible input words: \mathcal{V}
- ▶ Set of possible tags: \mathcal{T}
- ▶ Word sequence: $x_{[1:n]} = [x_1, \dots, x_n]$
- ▶ Tag sequence: $t_{[1:n]} = [t_1, \dots, t_n]$
- ▶ Training data is N tagged sentences, the i^{th} sentence has length n_i :

$$(x_{[1:n]}^{(i)}, t_{[1:n]}^{(i)}) \text{ for } i = 1, \dots, N$$

Independence Assumptions for Tagging

Chain Rule

$$P(t_{[1:n]} \mid x_{[1:n]}) = \prod_{j=1}^n P(t_j \mid t_{j-1}, \dots, t_1, x_{[1:n]}, j)$$

Make independence assumptions

$$P(t_{[1:n]} \mid x_{[1:n]}) \approx \prod_{j=1}^n P(t_j \mid t_{j-1}, x_{[1:n]}, j)$$

j is the word being tagged.

We model the conditional probability directly: no Bayes Rule here.

Questions

- ▶ Split up $P(t_j \mid t_{j-1}, x_{[1:n]}, j)$ into parameters?
- ▶ How to find $\arg \max_{t_{[1:n]}} P(t_{[1:n]} \mid x_{[1:n]})$?

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Representation: finding the right parameters

Problem: Predict ?? using context, $P(?? \mid \text{context})$

Profits/**N** soared/**V** at/**P** Boeing/**??** Co. , easily topping forecasts on Wall Street , as their CEO Alan Mulally announced first quarter results .

Representation: history

- ▶ A history is a 3-tuple: $(t_{-1}, x_{[1:n]}, i)$
- ▶ t_{-1} is the previous tag (we are assuming a bigram model)
- ▶ $x_{[1:n]}$ are the n words in the input
- ▶ i is the index of the word being tagged
- ▶ For example, for $x_4 = \text{Boeing}$:
 - ▶ $t_{-1} = \text{P}$
 - ▶ $x_{[1:n]} = (\text{Profits}, \text{soared}, \dots, \text{results}, .)$
 - ▶ $i = 4$

Feature-vectors over history-tag pairs

Take a history, tag pair (h, t)

$f_k(h, t)$ for $k = 1, \dots, m$ are **feature functions** representing the tagging decision.

Example: Part-of-speech tagging [Ratnaparkhi 1996]

$$f_{100}(h, t) = \begin{cases} 1 & \text{if current word } x_i \text{ is } \texttt{Boeing} \text{ and } t = \texttt{N} \\ 0 & \text{otherwise} \end{cases}$$

$$f_{101}(h, t) = \begin{cases} 1 & \text{if } t_{-1} \text{ is } \texttt{P} \text{ and } t = \texttt{N} \\ 0 & \text{otherwise} \end{cases}$$

Log linear model for Tagging

- ▶ Let there be m features, $f_k(\mathbf{x}, \mathbf{y})$ for $k = 1, \dots, m$
- ▶ $\mathbf{x} = x_{[1:n]}$ and $\mathbf{y} = t_{[1:n]}$
- ▶ Define a parameter vector $\mathbf{w} \in \mathbb{R}^m$
- ▶ Each (\mathbf{x}, \mathbf{y}) pair is mapped to score:

$$s(\mathbf{x}, \mathbf{y}) = \sum_k w_k \cdot f_k(\mathbf{x}, \mathbf{y})$$

- ▶ Using inner product notation:

$$\begin{aligned}\mathbf{w} \cdot \mathbf{f}(\mathbf{x}, \mathbf{y}) &= \sum_k w_k \cdot f_k(\mathbf{x}, \mathbf{y}) \\ s(\mathbf{x}, \mathbf{y}) &= \mathbf{w} \cdot \mathbf{f}(\mathbf{x}, \mathbf{y})\end{aligned}$$

- ▶ To get a probability from the score: Renormalize!

$$\Pr(\mathbf{y} \mid \mathbf{x}, \mathbf{w}) = \frac{\exp(s(\mathbf{x}, \mathbf{y}))}{\sum_{\mathbf{y}'} \exp(s(\mathbf{x}, \mathbf{y}'))}$$

Feature functions for Tagging

Problem

- ▶ We have defined a log-linear model using feature functions: $\mathbf{f}(\mathbf{x}, \mathbf{y})$
- ▶ We have defined parameters using a history h so feature functions are: $\mathbf{f}(h, t)$

Locally normalized log-linear taggers

Conditional Distribution over history, tag pair (h, t)

$$\log \Pr(t \mid h) = \mathbf{w} \cdot \mathbf{f}(h, t) - \log \sum_{t'} \exp(\mathbf{w} \cdot \mathbf{f}(h, t'))$$

- ▶ $\mathbf{f}(h, t)$ is a vector of feature functions
- ▶ \mathbf{w} is the weight vector

Local normalization for tagging

- ▶ Word sequence: $x_{[1:n]}$ and tag sequence: $t_{[1:n]}$
- ▶ Histories $h_i = (t_{i-1}, x_{[1:n]}, i)$

$$\log \Pr(t_{[1:n]} \mid x_{[1:n]}) = \sum_{i=1}^n \log \Pr(t_i \mid h_i)$$

Globally normalized log-linear taggers

Global feature function $\Phi(\mathbf{x}, \mathbf{y})$

- ▶ Word sequence: $\mathbf{x} = x_{[1:n]}$ and tag sequence: $\mathbf{y} = t_{[1:n]}$
- ▶ From *local* histories $h_i = (t_{i-1}, x_{[1:n]}, i)$ to global Φ values:

$$\Phi_k(x_{[1:n]}, t_{[1:n]}) = \sum_{i=1}^n f_k(h_i, t_i)$$

- ▶ $\Phi(\mathbf{x}, \mathbf{y}) = (\Phi_1, \Phi_2, \dots, \Phi_m)$ is a *global* feature vector
- ▶ \mathbf{w} is the weight vector for Φ

Global normalization for tagging

$$\log \Pr(\mathbf{y} \mid \mathbf{x}, \mathbf{w}) = \mathbf{w} \cdot \Phi(\mathbf{x}, \mathbf{y}) - \log \sum_{\mathbf{y}'} \exp(\mathbf{w} \cdot \Phi(\mathbf{x}, \mathbf{y}'))$$

Conditional Random Field

Global normalization for tagging

$$\log \Pr(\mathbf{y} \mid \mathbf{x}, \mathbf{w}) = \mathbf{w} \cdot \Phi(\mathbf{x}, \mathbf{y}) - \log \sum_{\mathbf{y}'} \exp(\mathbf{w} \cdot \Phi(\mathbf{x}, \mathbf{y}'))$$

- ▶ This model is also called a conditional random field (CRF)

Algorithms for training and decoding

- ▶ Global normalization could be expensive: requires sum over exponentially many terms \mathbf{y}'
- ▶ Finding $\arg \max_{\mathbf{y}} \log \Pr(\mathbf{y} \mid \mathbf{x})$ can be accomplished using the Viterbi algorithm.
- ▶ Training: finding the weight vector \mathbf{w} can be done using a variant of the Forward algorithm.

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