



Natural Language Processing

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Part 1: Classification tasks in NLP

Classification tasks in NLP

Naive Bayes Classifier

Log linear models

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%

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Part 2: Probabilistic Classifiers

Classification tasks in NLP

Naive Bayes Classifier

Log linear models

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)
- ▶ $P(\mathbf{x} | y) = \prod_{j=1}^d P(f_j | y)$
- ▶ $P(y | \mathbf{x}) = P(y) \cdot \prod_{j=1}^d P(f_j | y)$

Classification tasks in NLP

Naive Bayes Classifier

Log linear models

Log linear model

- ▶ The model classifies input into output labels $y \in \mathcal{Y}$
- ▶ Let there be m features, $f_k(\mathbf{x}, y)$ for $k = 1, \dots, m$
- ▶ Define a parameter vector $\mathbf{v} \in \mathbb{R}^m$
- ▶ Each (\mathbf{x}, y) pair is mapped to score:

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

- ▶ Using inner product notation:

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

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

$$\Pr(y \mid \mathbf{x}; \mathbf{v}) = \frac{\exp(s(\mathbf{x}, y))}{\sum_{y' \in \mathcal{Y}} \exp(s(\mathbf{x}, y'))}$$

Log linear model

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

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

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

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

Log linear model

- Maximize:

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

- Calculate gradient:

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

Gradient ascent

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

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

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

(the maximum possible feature value; needed for scaling)

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

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

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

 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 $f_j(x, y)$

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

cf. Goodman, NIPS '01

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