

POS tagging

LING 570

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Outline

- The POS tagging task
- Rule-based approach
- Statistical approach
 - N-gram model: HMM
 - MaxEnt model: later in ling570
 - Other models: in Ling572 and beyond

The task

- Training data: a tagged corpus
- Build a system:
 - Input: $w_1 \ w_2 \ \dots \ w_n$
 - Output: $w_1/t_1 \ w_2/t_2 \ \dots \ w_n/t_n$
- POS tags:
 - Open class: noun, verb, adj, adv
 - Closed class: prep, det, pron, conj, particles, ...
- Tagsets:
 - 30 tags or more is pretty common.
 - Ex: how many tags for verbs?

Why POS tagging?

- As a preprocessing step for parsing, chunking, etc.
 - Chunking: /Det? Adj* N* N/
 - Parsing: VP → V NP vs. VP → buy NP
- Text-to-speech: Please record the lecture
- Morphological analysis:
 - Ex: saw → see +V +past
 - saw → saw +N + PL

Main problem: ambiguity

- Example: **book** a flight; buy a **book**
- How hard is the tagging problem?
 - Many frequent words are ambiguous.
 - Penn English Treebank (PTB):
 - Unigram: 91%
 - Trigram: 93%
 - Best result: 97-98%
 - Upper bound: 97-98% (?)
 - The tagging problem may be harder for
 - other domains
 - other languages

Main approaches

- Rule-based approach:
 - Stochastic approach: Choose $t_1 t_2 \dots t_n$ that maximizes $P(t_1^n | w_1^n)$
 - N-gram models:
 - Use a classifier with beam search
 - Ex: Decision Tree, MaxEnt, Boosting, SVM, ...
 - Use sequence labeling algorithms
 - Ex: HMM, CRF, TBL
- ➔ Most of the algorithms will be covered in LING 572.
- ➔ Today we will focus on N-gram models.

Evaluation

- Train your model on the training data
- Test on unseen test data to obtain the best tag sequence.
- Accuracy: the percentage of words in the test data that are correctly tagged:
 - System: John/N called/V this/PN number/N
 - Gold: John/N called/V this/DT number/N
 - Accuracy is 3/4

Rule-based approach

POS tagger for English

- Human knowledge
- Annotated data:
 - John/NNP will/MD book/VB the/DT flight/NN tomorrow/NN
 - Mary/NNP bought/VBD a/DT book/NN
- Rules:
 - NN => VB if the word follows a MD
- Transformation-based learning (TBL)

N-gram tagger

Building a statistical system

- Collect data and divide it into training, development, and testing or use n-fold cross validation
- Modeling:
 - What is the function to optimize? e.g., $P(y | x)$, $P(x, y)$
 - How to decompose it to something that can be estimated?
- Training: estimate the parameters from the training data
- Decoding: run the model on the test data
- Evaluation: compare the system output with the gold standard

Notation

$$w_1^n: w_1 \ w_2 \ \dots \ w_n$$

$$t_1^n: t_1 \ t_2 \ \dots \ t_n$$

$$\max_y P(y|x)$$

$$y^* = \arg \max_y P(y|x)$$

N-gram POS tagger: modeling

$$\begin{aligned} & \arg \max_{t_1^n} P(t_1^n | w_1^n) \\ &= \arg \max_{t_1^n} \frac{P(t_1^n) * P(w_1^n | t_1^n)}{P(w_1^n)} \\ &= \arg \max_{t_1^n} P(t_1^n) * P(w_1^n | t_1^n) \end{aligned}$$

$$P(t_1^n) \approx \prod_i P(t_i | t_{i-N+1}^{i-1})$$

$$P(w_1^n | t_1^n) = \prod_i P(w_i | t_1^n, w_1^{i-1}) \approx \prod_i P(w_i | t_i)$$

N-gram POS tagger (cont)

$$\operatorname{argmax}_{t_1^n} P(t_1^n | w_1^n)$$

$$\approx \operatorname{argmax}_{t_1^n} \prod_i P(w_i | t_i) P(t_i | t_{i-N+1}^{i-1})$$

Bigram model: $\prod_i P(w_i | t_i) P(t_i | t_{i-1})$

Trigram model: $\prod_i P(w_i | t_i) P(t_i | t_{i-2}, t_{i-1})$

Bigram model: training

$$\prod_i P(w_i | t_i) P(t_i | t_{i-1})$$

Training: How to estimate $P(w_i | t_i)$ and $P(t_i | t_{i-1})$?

- Supervised learning (tags in the training data are known): ML estimation
- Unsupervised learning (tags in the training data are unknown): forward-backward algorithm

Bigram training: ML estimation

$$P(w_i | t_i) = \frac{Cnt(w_i, t_i)}{Cnt(t_i)}$$

$$P(t_i | t_{i-1}) = \frac{Cnt(t_{i-1}, t_i)}{Cnt(t_{i-1})}$$

Bigram model: decoding

- Given $P(w_i | t_i)$ and $P(t_i | t_{i-1})$, how to find the best tag sequence for a sentence?

→ Use Viterbi algorithm for HMM

- The task of determining which sequence of variables is the underlying source of observations is called the **decoding** task.

Coming next

- Hidden Markov Model (HMM)
- Use a classifier