Data Intensive Linguistics — Lecture 6
Tagging (II): Transformation-Based Learning and Maximum Entropy Models

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Tagging as supervised learning

- Tagging is a **supervised learning problem**
  - given: some annotated data (words annotated with POS tags)
  - build model (based on **features**, i.e. representation of example)
  - predict unseen data (POS tags for words)
- Issues in supervised learning
  - there is no data like more data
  - feature engineering: how best represent the data
  - overfitting to the training data?
- There are many algorithms for supervised learning (naive Bayes, decision trees, maximum entropy, neural networks, support vector machines, ...)

One tagging method: Hidden Markov Models

- HMMs make use of two conditional probability distributions
  - tag sequence model $p(t_n|t_{n-2}, t_{n-1})$
  - tag-word predicition model $p(w_n|t_n)$
- Given these models, we can find the best sequence of tags for a sentence using the Viterbi algorithm

How good is HMM tagging?

- Labeling a sequence is very fast
- Viterbi algorithm outputs best label sequence (previous tags affect labeling of next tag), not just best tag for each word in isolation
- It is easy to get 2nd best sequence, 3rd best sequence, etc.
- But: uses only a *very small window* around word (n previous tags)

More features

- Consider a *larger window*

w_{n-4}	w_{n-3}	w_{n-2}	w_{n-1}	w_n	w_{n+1}	w_{n+2}	w_{n+3}	w_{n+4}
t_{n-4}	t_{n-3}	t_{n-2}	t_{n-1}	t_n	t_{n+1}	t_{n+2}	t_{n+3}	t_{n+4}

- Examples for useful features
  - if one of the previous tags is *MD*, then *VB* is likelier than *VBP* (basic verb form instead of verb in singular present)
  - if next tag is *JJ*, then *RBR* is likelier than *JJR* (adverb instead of adjective)

More features (2)

- Lexical features
  - if one of the previous tags is *not*, then *VB* is likelier than *VBP*
- Morphological features
  - if word ends in *-tion* it is most likely an *NN*
  - if word ends in *-ly* it is most likely an adverb

Using additional features

- Using more features in a conditional probability distribution?

$$p(t_i|w_i, f_0, ..., f_n)$$

⇒ sparse data problems
(insufficient statistics for reliable estimation of the distribution)

- Idea: First apply HMM, then fix errors with additional features

Applying the model to training data

- We can use the HMM tagger to tag the *training data*
- Then, we can compare *predicted tags* to *true tags*

words:	the	old	man	the	boat
predicted:	DET	JJ	NN	DET	NN
true tag:	DET	NN	VB	DET	NN

- How can we fix these errors? Possible **transformation** rules:
  - change *NN* to *VB* if no verb in sentence
    predicted: DET JJ VB DET NN
  - change *JJ* to *NN* if followed by *VB*
    predicted: DET NN VB DET NN

Transformation based learning

- First, **baseline tagger**
  - most frequent tag for word: $\text{argmax}_t\ p(t|w)$
  - Hidden Markov Model tagger
- Then apply transformations that fix the errors
  - go through the sequence word by word
  - if a feature is present in a current example,

  $\rightarrow$ apply rule (change tag)

Learning transformations

- Given: words with their true tags
- Tag sentence with baseline tagger
- Repeat
  - find transformation that minimizes error
  - apply transformation to sentence
  - add transformation to list
- Output: ordered list of transformations

Applying the learned transformations

- Given: a new sentence that we want to tag
- Tag words with baseline tagger
- For each transformation rule (in the sequence they were learned):
  - For each word (in sentence order):
    - apply transformation, if it matches
- Output: tags

Goal: minimizing error

- We need some metric to measure the error
- Here: number of wrongly assigned tags

$$error(D, M) = 1 - \frac{\sum_{i=1}^{N} \delta(t_i^{predicted}, t_i)}{N}$$

- General considerations for **error functions**:
  - Some errors are more costly than others
  - Detecting *cancer*, if *healthy* vs. detecting *healthy* when *cancer*
  - Sometimes error is difficult to assess (machine translation output different from human translation may be still correct)

Overfitting

- It may be possible to fix *all* errors in training
- The last transformations learned may fix only one error each
- Transformations that work in training may not work elsewhere, or may even be generally harmful
- To avoid **overfitting**: stop early

Generative modeling vs. discriminative training

- HMMs are an example for **generative modeling**
  - a model M is created that predicts the training data D
  - the model is broken up into smaller steps
  - for each step, a probability distribution is learned
  - model is optimized on $p(D|M)$, how well it predicts the data
- Transformation-based learning is an example for **discriminative training**
  - a method M is created to predict the training data D
  - it is improved by reducing prediction error
  - look for features that *discriminate* between faulty predictions and truth
  - model is optimized on $error(M, D)$, also called the **loss function**

Probabilities vs. rules

- HMMs: probabilities allow for *graded decisions*, instead of just yes/no
- Transformation based learning: *more features* can be considered
- We would like to combine both

$\Rightarrow$ **Maximum Entropy models**

Maximum Entropy

- Each example (here: word w) is represented by a set of features $\{f_i\}$, here:
  - the word itself
  - morphological properties of the word
  - other words and tags surrounding the word
- The task is the classify the word into a class c_j (here: the POS tag)
- How well a feature f_i predicts a class c_j is defined by a parameter $\alpha(f_i, c_j)$
- Maximum entropy model:

$$p(c_j|w) = \prod_{f_i \in w} \alpha(f_i, c_j)$$

Maximum Entropy training

- Feature selection
  - given the large number of possible features, which ones will be part of the model?
  - we do not want unreliable and rarely occurring features (avoid overfitting)
  - good features help us to reduce the number of classification errors
- Setting the parameter values $\alpha(f_i, c_j)$
  - $\alpha(f_i, c_j)$ are real numbered values, similar to probabilities
  - we want to ensure that the expected co-occurrence of features and classes matches between the training data and the model
  - otherwise we want to have no bias in the model (maintain *maximum entropy*)
  - training algorithm: **generalized iterative scaling**

POS tagging tools

- Three commonly used, freely available tools for tagging:
  - **TnT** by Thorsten Brants (2000): Hidden Markov Model
    `http://www.coli.uni-saarland.de/ thorsten/tnt/`
  - **Brill tagger** by Eric Brill (1995): transformation based learning
    `http://www.cs.jhu.edu/~brill/`
  - **MXPOST** by Adwait Ratnaparkhi (1996): maximum entropy model
    `ftp://ftp.cis.upenn.edu/pub/adwait/jmx/jmx.tar.gz`
- All have similar performance (~96% on Penn Treebank English)