Part of Speech Tagging

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(Slides adapted from Joakim Nivre)

Part-of-Speech Tagging

- Given a word sequence $w_1 \cdots w_m$, determine the corresponding part-of-speech (tag) sequence $t_1 \cdots t_m$.
- Probabilistic view of the problem:

$$\begin{aligned}
\arg\max_{t_1 \cdots t_m} P(t_1 \cdots t_m \mid w_1 \cdots w_m) &= \\
\arg\max_{t_1 \cdots t_m} \frac{P(t_1 \cdots t_m) P(w_1 \cdots w_m \mid t_1 \cdots t_m)}{P(w_1 \cdots w_m)} &= \\
\arg\max_{t_1 \cdots t_m} P(t_1 \cdots t_m) P(w_1 \cdots w_m \mid t_1 \cdots t_m) &
\end{aligned}$$

Independence Assumptions

- Contextual model: Tags are dependent only on $n-1$ preceding tags (tag n-grams, n-classes):

$$P(t_1 \cdots t_m) = \prod_{i=1}^{m} P(t_i \mid t_{i-(n-1)} \cdots t_{i-1})$$

For biclass models ($n = 2$),

$$P(t_1 \cdots t_m) = \prod_{i=1}^{m} P(t_i \mid t_{i-1})$$

- Lexical model: Word forms are dependent only on their own part-of-speech:

$$P(w_1 \cdots w_m \mid t_1 \cdots t_m) = \prod_{i=1}^{m} P(w_i \mid t_i)$$

For biclass models ($n = 2$),

$$
\begin{aligned}
\arg\max_{t_1 \cdots t_m} P(t_1 \cdots t_m) P(w_1 \cdots w_m \mid t_1 \cdots t_m) &= \\
\arg\max_{t_1 \cdots t_m} \prod_{i=1}^{m} P(t_i \mid t_{i-1}) \prod_{i=1}^{m} P(w_i \mid t_i) &= \\
\arg\max_{t_1 \cdots t_m} \prod_{i=1}^{m} P(t_i \mid t_{i-1}) P(w_i \mid t_i) &=
\end{aligned}
$$

Example

- Tagging *the can smells* using the triclass model:

$$
\begin{aligned}
P(\mathrm{dt\ nn\ vb} \mid \textit{the can smells}) \quad = \quad & P(\mathrm{dt} \mid \#\ \#) \cdot P(\mathrm{nn} \mid \#\ \mathrm{dt}) \cdot \\
& P(\mathrm{vb} \mid \mathrm{dt\ nn}) \cdot P(\textit{the} \mid \mathrm{dt}) \cdot \\
& P(\textit{can} \mid \mathrm{nn}) \cdot P(\textit{smells} \mid \mathrm{vb})
\end{aligned}
$$

- Compare:

$$
\begin{array}{rcl}
P(\textit{can} \mid \mathrm{vb}) & > & P(\textit{can} \mid \mathrm{nn}) \\
P(\textit{smells} \mid \mathrm{vb}) & > & P(\textit{smells} \mid \mathrm{nn}) \\
P(\mathrm{nn} \mid \#\ \mathrm{dt}) & >> & P(\mathrm{vb} \mid \#\ \mathrm{dt}) \\
P(\mathrm{vb} \mid \mathrm{dt\ nn}) & > & P(\mathrm{nn} \mid \mathrm{dt\ nn})\ (?)
\end{array}
$$

Hidden Markov Models 1

- Markov models are probabilistic finite automata that are used for many kinds of (sequential) disambiguation tasks such as:
  1. Speech recognition
  2. Spell checking
  3. Part-of-speech tagging
  4. Named entity recognition
- A (discrete) Markov model runs through a sequence of states emitting signals. If the state sequence cannot be determined from the sequence of emitted signals, the model is said to be hidden.

Hidden Markov Models 2

- A Markov model consists of five elements:
  1. A finite set of states $\Omega = \{s^1, \ldots, s^k\}$.
  2. A finite signal alphabet $\Sigma = \{\sigma^1, \ldots, \sigma^m\}$.
  3. Initial probabilities $P(s)$ (for every $s \in \Omega$) defining the probability of starting in state s.
  4. Transition probabilities $P(s^i \mid s^j)$ (for every $(s^i, s^j) \in \Omega^2$) defining the probability of going from state s^j to state s^i.
  5. Emission probabilities $P(\sigma \mid s)$ (for every $(\sigma, s) \in \Sigma \times \Omega$) defining the probability of emitting symbol σ in state s.

Hidden Markov Models 3

- State transitions are assumed to be independent of everything except the current state:

$$P(s_1 \cdots s_n) = P(s_1) \prod_{i=2}^{n} P(s_i \mid s_{i-1})$$

- Signal emissions are assumed to be independent of everything except the current state:

$$P(s_1 \cdots s_n, \sigma_1 \cdots \sigma_n) = P(s_1)\, P(\sigma_1 \mid s_1) \prod_{i=2}^{n} P(s_i \mid s_{i-1})\, P(\sigma_i \mid s_i)$$

Hidden Markov Models 4

- If we want, we can simplify things by adding a dummy state s^0 such that $P(s) = P(s \mid s^0)$ (for every $s \in \Omega$)
- State transitions:

$$P(s_1 \cdots s_n) = \prod_{i=1}^{n} P(s_i \mid s_{i-1})$$

- Signal emissions:

$$P(s_1 \cdots s_n, \sigma_1 \cdots \sigma_n) = \prod_{i=1}^{n} P(s_i \mid s_{i-1})\, P(\sigma_i \mid s_i)$$

Hidden Markov Models 5

- The probability of a signal sequence is obtained by summing over all state sequences that could have produced that signal sequence:

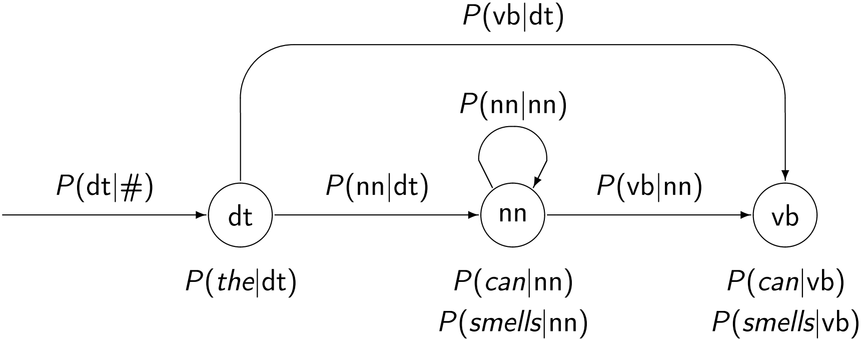
$$P(\sigma_1 \cdots \sigma_n) = \sum_{s_1 \cdots s_n \in \Omega^n} \prod_{i=1}^{n} P(s_i \mid s_{i-1}) \, P(\sigma_i \mid s_i)$$

- Problems for HMMs:
  1. Optimal state sequence: $\arg\max_{s_1 \cdots s_n} P(s_1 \cdots s_n \mid \sigma_1 \cdots \sigma_n)$.
  2. Signal probability: $P(\sigma_1 \cdots \sigma_n)$.
  3. Parameter estimation: $\hat{P}(s)$, $\hat{P}(s_i \mid s_j)$, $\hat{P}(\sigma \mid s)$.

HMM Tagging

- Contextual model:
  1. The biclass model can be represented by a first-order Markov model, where each state represents one tag; $s_i = t_i$
  2. The triclass model can be represented by a second-order Markov model, where each state represents a pair of tags; $s_i = \langle t_i, t_{i-1} \rangle$
  3. In both cases, transition probabilities represent contextual probabilities.
- Lexical model:
  1. Signals represented word forms; $\sigma_i = w_i$
  2. Emission probabilities represent lexical probabilities; $P(\sigma_i \mid s_i) = P(w_i \mid t_i)$
  3. (t_0 written as $\#$ for biclass model)

Example: First-Order HMM



Parameter Estimation

- Two different methods for estimating probabilities (lexical and contextual):
    1. Supervised learning: Probabilities can be estimated using frequency counts in a (manually) tagged training corpus.
    2. Unsupervised learning: Probabilities can be estimated from an untagged training corpus using expectation-maximization.
- Experiments have shown that supervised learning yields superior results even with limited amounts of training data.

Supervised Learning

- Maximum likelihood estimation:
  1. Contextual probabilities:

$$\hat{P}(t_i \mid t_{i-2}t_{i-1}) = \frac{C(t_{i-2}t_{i-1}t_i)}{C(t_{i-2}t_{i-1})}$$

  2. Lexical probabilities:

$$\hat{P}(w \mid t) = \frac{C(w,t)}{C(t)}$$

- Maximum likelihood estimates need to be smoothed because of sparse data (cf. language modeling).

Supervised Learning Algorithm

for all tags t^j **do**
  for all tags t^k **do**
    $\hat{P}(t^k \mid t^j) := \frac{C(t^j t^k)}{C(t^j)}$
  end for
end for
for all tags t^j **do**
  for all words w^l do **do**
    $\hat{P}(w^l \mid t^j) := \frac{C(w^l : t^j)}{C(t^j)}$
  end for
end for

Supervised Learning

	Second tag						
First tag	AT	BEZ	IN	NN	VB	PER	$\sum$
AT	0	0	0	48636	0	19	48 655
BEZ	1973	0	426	187	0	38	2624
IN	43322	0	1325	17314	0	185	62146
NN	1067	3720	42470	11773	614	21392	81036
VB	6072	42	4758	1476	129	1522	
PER	8016	75	4656	1329	954	0	15030

- $\hat{P}(\text{AT} \mid \text{PER}) = \frac{C(\text{PER AT})}{C(\text{PER}} = \frac{8016}{15030} = 0.5333$

Supervised Learning

	AT	BEZ	IN	NN	VB	PER
bear	0	0	0	10	43	0
is	0	10065	0	0	0	0
move	0	0	0	36	133	0
on	0	0	5484	0	0	0
president	0	0	0	382	0	0
progress	0	0	0	108	4	0
the	0	0	0	0	0	0
.	0	0	0	0	0	48809
total (all words)	120991	10065	130534	134171	20976	49267

- $\hat{P}(\text{bear} \mid \text{NN}) = \frac{C(\text{bear:NN})}{C(\text{NN}} = \frac{10}{134171} = 0.7453 \cdot 10^{-4}$

Computing probabilities, example

Compute and compare the following two probabilities:

- P(AT NN BEZ IN AT NN | The bear is on the move.)
- P(AT NN BEZ IN AT VB | The bear is on the move.)

For this, we need P(AT | PER), P(NN | AT), P(BEZ | NN), P(IN | BEZ), P(AT | IN), and P(PER | NN), P(bear | NN), P(is | BEZ), P(on | IN), P(the | AT), P(move | NN), P(move | VB)
We assume that the sentence is preceded by ".".

Smoothing for Part-of-Speech Tagging

- Contextual probabilities are structurally similar to n-gram probabilities in language modeling and can be smoothed using the same methods.
- Smoothing of lexical probabilities breaks down into two sub-problems:
  1. Known words are usually handled with standard methods.
  2. Unknown words are often treated separately to take into account information about suffixes, capitalization, etc.

Viterbi Tagging

- HMM tagging amounts to finding the optimal path (state sequence) through the model for a given signal sequence.
- The number of possible paths grows exponentially with the length of the input.
- The Viterbi algorithm is a dynamic programming algorithm that finds the optimal state sequence in polynomial time.
- Running time is $O(ms^2)$, where m is the length of the input and s is the number of states in the model.

Viterbi algorithm

$\delta_0(\text{PERIOD}) = 1.0$
$\delta_0(\text{t}) = 0.0$ for $t \neq$PERIOD
for $i := 0$ to $n-1$ step 1 **do**
  for all tags t^j **do**
    $\delta_{i+1} := \max_{1 \leq k \leq T}[\delta_i(t^k) \times P(t^j \mid t^k) \times P(w_{i+1} \mid t^j)]$
    $\psi_{i+1} := \arg\max_{1 \leq k \leq T}[\delta_i(t^k) \times P(t^j \mid t^k) \times P(w_{i+1} \mid t^j)]$
  end for
end for
$X_n = \arg\max_{1 \leq j \leq T} \delta_n(t^j)$
for $j := n-1$ to 1 step -1 **do**
  $X_j = \psi_{j+1}(X_{j+1})$
end for
$P(t^{X_1}, \ldots, t^{X_n}) = \delta_n(t^{X_n})$

Tagset (part of full tagset) with indices

- t^1=AT
- t^2=BEZ
- t^3=IN
- t^4=NN
- t^5=VB
- t^6=PERIOD (PER)

Viterbi algorithm: first induction iteration

$i := 0$
for all tags t^j do **do**
  $\delta_1 := \max_{1 \leq k \leq T}[\delta_0(t^k) \times P(t^j \mid t^k) \times P(w_1 \mid t^j)]$
  $\psi_1 := \arg\max_{1 \leq k \leq T}[\delta_i(t^k) \times P(t^j \mid t^k) \times P(w_1 \mid t^j)]$
end for

We have $t^1 =$AT.

First tag:

$t^j :=$ AT
$\delta_1 := \max_{1 \leq k \leq T}[\delta_0(t^k) \times P(\text{AT} \mid t^k) \times P(w_1 \mid \text{AT})]$
$\psi_1 := \arg\max_{1 \leq k \leq T}[\delta_0(t^k) \times P(\text{AT} \mid t^k) \times P(w_1 \mid \text{AT})]$

Unsupervised Learning

- Expectation-Maximization (EM) is a method for approximating optimal probability estimates :
  1. Guess an estimate $\hat{\theta}$.
  2. Expectation: Compute expected frequencies based on training data and current value of $\hat{\theta}$.
  3. Maximization: Adjust $\hat{\theta}$ based on expected frequencies.
  4. Iterate steps 2 and 3 until convergence.
- Special case for HMM known as the Baum-Welch algorithm.
- Problem: Local maxima.

Example: Expectation-Maximization 1

- Lexicon:

the	dt
car	nn
can	nn vb

- Training corpus:

the can
the car

- Initial estimates:

$$\hat{P}(\text{nn}|\text{dt}) = \hat{P}(\text{vb}|\text{dt}) = 0.5$$

Example: Expectation-Maximization 2

Expectation	Maximization
$E[C(\text{nn}\|\text{dt})] = 1.5$	
$E[C(\text{vb}\|\text{dt})] = 0.5$	
	$\hat{P}(\text{nn}\|\text{dt}) = 0.75$
	$\hat{P}(\text{vb}\|\text{dt}) = 0.25$
$E[C(\text{nn}\|\text{dt})] = 1.75$	
$E[C(\text{vb}\|\text{dt})] = 0.25$	
	$\hat{P}(\text{nn}\|\text{dt}) = 0.875$
	$\hat{P}(\text{vb}\|\text{dt}) = 0.125$
$E[C(\text{nn}\|\text{dt})] = 1.875$	
$E[C(\text{vb}\|\text{dt})] = 0.125$	
	$\hat{P}(\text{nn}\|\text{dt}) = 0.9375$
	$\hat{P}(\text{vb}\|\text{dt}) = 0.0625$

Statistical Evaluation

- Many aspects of natural language processing systems can be evaluated by performing series of (more or less controlled) experiments.
- The results of such experiments are often quantitative measurements which can be summarized and analyzed using statistical methods.
- Evaluation methods are (in principle) independent of whether the systems evaluated are statistical or not.

Emprical Evaluation of Accuracy

- Most natural language processing systems make errors even when they function perfectly.
- Accuracy can be tested by running systems on representative samples of inputs.
- Three kinds of statistical methods are relevant:
  1. Descriptive statistics: Measures
  2. Estimation: Confidence intervals
  3. Hypothesis testing: Significant differences

Test Data

- Requirements on test data set:
  1. Distinct from any training data
  2. Unbiased (random sample)
  3. As large as possible
- These requirements are not always met.
- Testing may be supervised or unsupervised depending on whether the test data set contains solutions or not.
- Gold standard: Solutions provided by human experts.

Descriptive Statistics

- Descriptive measures such as sample means and proportions are used to summarize test results.
- Examples:

  1. Accuracy rate (percent correct): $\frac{1}{n}\sum_{i=1}^{n} x_i$
  2. Recall: $\frac{\text{true positives}}{\text{true positives}+\text{false negatives}}$
  3. Precision: $\frac{\text{true positives}}{\text{true positives}+\text{false positives}}$
  4. Logprob: $\frac{1}{n}\sum_{i=1}^{n} \log_2 \hat{P}(x_i)$

Example 1: Language Modeling

- Evaluation of language models as such are always unsupervised (no gold standards for string probabilities).
- Evaluation measures:
  1. Corpus probability
  2. Corpus entropy (logprob)
  3. Corpus perplexity

Example 2: PoS Tagging and WSD

- Supervised evaluation with gold standard is the norm.
- Evaluation measures:
    1. Percent correct
    2. Recall
    3. Precision

Example 3: Syntactic Parsing

- Supervised evaluation with gold standard (treebank).
- Evaluation measures:
  1. Percent correct
  2. Labeled/bracketed recall
  3. Labeled/bracketed precision
  4. Zero crossing