Unsupervised Part-of-Speech Tagging

Background

Bayesian HMM

Natural Language Understanding

Lecture 10: Introduction to Unsupervised Part-of-Speech Tagging

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Part-of-Speech Tagging

Task: take a sentence, assign each word a label indicating its syntactic category (part of speech).

Example:

Campbell, Soup, not surprisingly, does n't have any plans to advertise in the magazine.

Uses Penn Treebank PoS tag set.

Penn Treebank PoS Tagset

DT  Determiner
IN  Preposition or subord. conjunction
NN  Noun, singular or mass
NNS Noun, plural
NNP Proper noun, singular
RB  Adverb
TO  to
VB  Verb, base form
VBZ Verb, 3rd person singular present

Total of 36 tags, plus punctuation. English-specific.
Unsupervised Part-of-Speech Tagging

Current PoS taggers are highly accurate (97% accuracy on Penn Treebank). But they require *manually labelled* training data, which for many major language is not available. Examples:

<table>
<thead>
<tr>
<th>Language</th>
<th>Speakers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Punjabi</td>
<td>109M</td>
</tr>
<tr>
<td>Vietnamese</td>
<td>69M</td>
</tr>
<tr>
<td>Polish</td>
<td>40M</td>
</tr>
<tr>
<td>Oriya</td>
<td>32M</td>
</tr>
<tr>
<td>Malay</td>
<td>37M</td>
</tr>
<tr>
<td>Azerbaijani</td>
<td>20M</td>
</tr>
<tr>
<td>Haitian</td>
<td>7.7M</td>
</tr>
</tbody>
</table>

[From: Das and Petrov, ACL 2011 talk.]

We need models that do not require annotated training data: *unsupervised PoS tagging.*

Hidden Markov Models

The parameters are sets of *multinomial distributions.* For tag types $t = 1 \ldots T$ and word types $w = 1 \ldots W$:

- $\omega = \omega^{(1)} \ldots \omega^{(T)}$: the output distributions for each tag;
- $\tau = \tau^{(1)} \ldots \tau^{(T)}$: the transition distributions for each tag;
- $\omega^{(t)} = \omega^{(1)} \ldots \omega^{(T)}$: the output distribution from tag $t$;
- $\tau^{(t)} = \tau^{(1)} \ldots \tau^{(T)}$: the transition distribution from tag $t$.

Goal of this lecture: *introduce clever ways of estimating $\omega$ and $\tau$.*
Example: $\omega^{(\text{NN})}$ is the output distribution for tag NN:

<table>
<thead>
<tr>
<th>$\omega^{(\text{NN})}_w$</th>
<th>0.1</th>
<th>John</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.0</td>
<td>Mary</td>
</tr>
<tr>
<td></td>
<td>0.2</td>
<td>running</td>
</tr>
<tr>
<td></td>
<td>0.0</td>
<td>jumping</td>
</tr>
</tbody>
</table>

**Key idea:** define priors over the multinomials that are suitable for NLP tasks.

Another way to write the model, often used in statistics and machine learning:

- $t_i|t_{i-1} = t \sim \text{Multinomial}(\tau^{(t)})$
- $w_i|t_i = t \sim \text{Multinomial}(\omega^{(t)})$

This is read as: “Given that $t_{i-1} = t$, the value of $t_i$ is drawn from a multinomial distribution with parameters $\tau^{(t)}$.”

For *inference* (i.e., decoding, applying the model at test time), we need to know $\theta$ and then we can compute $P(t, w)$:

$$P(t, w) = \prod_{i=1}^{n} P(t_i|t_{i-1})P(w_i|t_i) = \prod_{i=1}^{n} \tau_{t_{i-1}}^{(t_i)} \omega^{(t_i)}_w$$

With this, can compute $P(w)$, i.e., a language model:

$$P(w) = \sum_t P(t, w)$$

And also $P(t|w)$, i.e., a PoS tagger:

$$P(t|w) = \frac{P(t, w)}{P(w)}$$
Parameter Estimation for HMMs

For estimation (i.e., training the model, determining its parameters), we need a procedure to set \( \theta \) based on data.

For this, we can rely on Bayes Rule:

\[
P(\theta | w) = \frac{P(w | \theta)P(\theta)}{P(w)} \propto P(w | \theta)P(\theta)
\]

Maximum Likelihood Estimation

Choose the \( \theta \) that makes the data most probable:

\[
\hat{\theta} = \arg\max_{\theta} P(w | \theta)
\]

Basically, we ignore the prior. In most cases, this is equivalent to assuming a uniform prior.

In supervised systems, the relative frequency estimate is equivalent to the maximum likelihood estimate. In the case of HMMs:

\[
\tau_t^{(t')} = \frac{n(t,t')}{n(t)} \quad \omega_t^{(t,w)} = \frac{n(t,w)}{n(t)}
\]

where \( n(e) \) is the number of times \( e \) occurs in the training data.

Estimation Maximization sometimes works well:

- word alignments for machine translation;
- anaphora and coreference.

But it often fails:

- probabilistic context-free grammars: highly sensitive to initialization; F-scores reported are generally low;
- for HMMs, even very small amounts of training data have been show to work better than EM;
- similar picture for many other tasks.
Bayesian Estimation

We said: to train our model, we need to estimate $\theta$ from the data. But is this really true?

- for language modeling, we estimate $P(w_{n+1}|\theta)$, but what we actually need is $P(w_{n+1}|w)$;
- for PoS tagging, we estimate $P(t|\theta, w)$, but we actually need is $P(t|w)$.

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Bayesian Integration

This approach is called Bayesian integration.

Integrating over $\theta$ gives us an average over all possible parameters values. Advantages:

- accounts for uncertainty as to the exact value of $\theta$;
- models the shape of the distribution over $\theta$;
- increases robustness: there may be a range of good values of $\theta$;
- we can use priors favoring sparse solutions (more on this later).

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- for PoS tagging, we estimate $P(t|\theta, w)$, but we actually need is $P(t|w)$.

So we are not actually interested in the value of $\theta$. We could simply do this:

$$P(w_{n+1}|w) = \int \Delta P(w_{n+1}|\theta)P(\theta|w)d\theta$$ (1)

$$P(t|w) = \int \Delta P(t|w, \theta)P(\theta|w)d\theta$$ (2)

We don’t estimate $\theta$, we integrate it out.

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Bayesian Integration

Example: we want to predict: will spinner result be “a” or not?

- Parameter $\theta$ indicates spinner result: $P(\theta = a) = .45$,
  $P(\theta = b) = .35$, $P(\theta = c) = .2$;
- define $t = 1$: result is “a”, $t = 0$: result is not “a”;
- make a prediction about one random variable ($t$) based on the value of another random variable ($\theta$).

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**Bayesian Integration**

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**Maximum likelihood approach:** choose most probable $\theta$:

$\hat{\theta} = a$, and $P(t = 1|\hat{\theta}) = 1$, so we predict $t = 1$.

**Bayesian approach:** average over $\theta$:

$P(t = 1) = \sum_{\theta} P(t = 1|\theta)P(\theta) = 1(.45) + 0(.35) + 0(.2) = .45$, so we predict $t = 0$.

**Dirichlet Distribution**

Choosing the right prior can make integration easier.

This is where the **Dirichlet distribution** comes in. A $K$-dimensional Dirichlet with parameters $\alpha = \alpha_1 \ldots \alpha_K$ is defined as:

$$P(\theta) = \frac{1}{Z} \prod_{j=1}^{K} \theta_j^{\alpha_j-1}$$

We usually only use symmetric Dirichlets, where $\alpha_1 \ldots \alpha_K$ are all equal to $\beta$. We write Dirichlet($\beta$) to mean Dirichlet($\beta, \ldots, \beta$).
**Bayesianizing the HMM**

To Bayesianize the HMM, we augment with it with symmetric Dirichlet priors:

\[
\begin{align*}
    t_i | t_{i-1} &= t, \tau^{(t)} \sim \text{Multinomial}(\tau^{(t)}) \\
    w_i | t_i &= t, \omega^{(t)} \sim \text{Multinomial}(\omega^{(t)}) \\
    \tau^{(t)} | \alpha &\sim \text{Dirichlet}(\alpha) \\
    \omega^{(t)} | \beta &\sim \text{Dirichlet}(\beta)
\end{align*}
\]

To simplify things, we will present a bigram version of the Bayesian HMM; Goldwater and Griffiths (2007) use trigrams.

**Dirichlet Distribution**

If we integrate out the parameters \( \theta = (\tau, \omega) \), we get:

\[
\begin{align*}
P(t_{n+1}|t, \alpha) &= \frac{n(t_n, t_{n+1}) + \alpha}{n(t_n) + T\alpha} \\
P(w_{n+1}|t_{n+1}, t, w, \beta) &= \frac{n(t_{n+1}, w_{n+1}) + \beta}{n(t_{n+1}) + W\beta}
\end{align*}
\]

with \( T \) possible tags and \( W \) possible words with tag \( t \).

We can use these distributions to find \( P(t|w) \) using an estimation method called Gibbs sampling.

**Evaluation**


- use a dictionary that lists possible tags for each word:
  - run: NN, VB, VBN
- the dictionary is actually derived from WSJ corpus;
- train and test on the unlabeled corpus (24,000 words of WSJ):
  - 53.6% of word tokens have multiple possible tags.
  - Average number of tags per token = 2.3.

Goldwater and Griffiths (2007) evaluate tagging accuracy against the gold-standard WSJ tags and compare to:

- HMM with maximum-likelihood estimation using EM (MLHMM);
- Conditional Random Field with contrastive estimation (CRF/CE).

They also experiment with reducing/eliminating dictionary information.
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Results

<table>
<thead>
<tr>
<th>Model</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLHMM</td>
<td>74.7</td>
</tr>
<tr>
<td>BHMM ($\alpha = 1, \beta = 1$)</td>
<td>83.9</td>
</tr>
<tr>
<td>BHMM (best: $\alpha = 0.003, \beta = 1$)</td>
<td>86.8</td>
</tr>
<tr>
<td>CRF/CE (best)</td>
<td>90.1</td>
</tr>
</tbody>
</table>

Integrating over parameters is useful in itself, even with uninformative priors ($\alpha = \beta = 1$); better priors can help even more, though do not reach the state of the art.

Syntactic clustering: input are the words only, no dictionary is used:

- collapse 45 treebank tags onto smaller set of 17;
- hyperparameters ($\alpha, \beta$) are inferred automatically using Metropolis-Hastings sampler;
- standard accuracy measure requires labeled classes, so measure accuracy using best matching of classes.

MLHMM groups instances of the same lexical item together;
BHMM clusters are more coherent, more variable in size.

BHMM transition matrix is sparse, MLHMM is not.
Unsupervised PoS tagging is useful to build lexica and taggers for new language or domains;
maximum likelihood HMM with EM performs poorly;
Bayesian HMM with Gibbs sampling can be used instead;
the Bayesian HMM improves performance by averaging out uncertainty;
it also allows us to use priors that favor sparse solutions as they occur in language data.
Recent work on unsupervised tagging uses HMMs with logistic regression and HMMs with word embeddings: next lecture.

References