CS 388: Natural Language Processing: Part-Of-Speech Tagging, Sequence Labeling, and Hidden Markov Models (HMMs)

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Part Of Speech Tagging

• Annotate each word in a sentence with a part-of-speech marker.
• Lowest level of syntactic analysis.

John saw the saw and decided to take it to the table.

John saw the saw and decided to take it to the table.
NNP VBD DT NN CC VBD TO VB PRP IN DT NN

• Useful for subsequent syntactic parsing and word sense disambiguation.
English POS Tagsets

- Original Brown corpus used a large set of 87 POS tags.
- Most common in NLP today is the Penn Treebank set of 45 tags.
  - Tagset used in these slides.
  - Reduced from the Brown set for use in the context of a parsed corpus (i.e. treebank).
- The C5 tagset used for the British National Corpus (BNC) has 61 tags.
English Parts of Speech

- **Noun (person, place or thing)**
  - Singular (NN): dog, fork
  - Plural (NNS): dogs, forks
  - Proper (NNP, NNPS): John, Springfields
  - Personal pronoun (PRP): I, you, he, she, it
  - Wh-pronoun (WP): who, what

- **Verb (actions and processes)**
  - Base, infinitive (VB): eat
  - Past tense (VBD): ate
  - Gerund (VBG): eating
  - Past participle (VBN): eaten
  - Non 3rd person singular present tense (VBP): eat
  - 3rd person singular present tense: (VBZ): eats
  - Modal (MD): should, can
  - To (TO): to (to eat)
English Parts of Speech (cont.)

- **Adjective (modify nouns)**
  - Basic (JJ): red, tall
  - Comparative (JJR): redder, taller
  - Superlative (JJS): reddest, tallest

- **Adverb (modify verbs)**
  - Basic (RB): quickly
  - Comparative (RBR): quicker
  - Superlative (RBS): quickest

- **Preposition (IN):** on, in, by, to, with

- **Determiner:**
  - Basic (DT) a, an, the
  - WH-determiner (WDT): which, that

- **Coordinating Conjunction (CC):** and, but, or,

- **Particle (RP):** off (took off), up (put up)
Closed vs. Open Class

- **Closed class** categories are composed of a small, fixed set of grammatical function words for a given language.
  - Pronouns, Prepositions, Modals, Determiners, Particles, Conjunctions
- Open class categories have large number of words and new ones are easily invented.
  - Nouns (Googler, textlish), Verbs (Google), Adjectives (geeky), Abverb (automagically)
Ambiguity in POS Tagging

• “Like” can be a verb or a preposition
  – I like/VBP candy.
  – Time flies like/IN an arrow.

• “Around” can be a preposition, particle, or adverb
  – I bought it at the shop around/IN the corner.
  – I never got around/RP to getting a car.
  – A new Prius costs around/RB $25K.
POS Tagging Process

• Usually assume a separate initial tokenization process that separates and/or disambiguates punctuation, including detecting sentence boundaries.

• Degree of ambiguity in English (based on Brown corpus)
  – 11.5% of word types are ambiguous.
  – 40% of word tokens are ambiguous.

• Average POS tagging disagreement amongst expert human judges for the Penn treebank was 3.5%
  – Based on correcting the output of an initial automated tagger, which was deemed to be more accurate than tagging from scratch.

• Baseline: Picking the most frequent tag for each specific word type gives about 90% accuracy
  – 93.7% if use model for unknown words for Penn Treebank tagset.
POS Tagging Approaches

• **Rule-Based**: Human crafted rules based on lexical and other linguistic knowledge.

• **Learning-Based**: Trained on human annotated corpora like the Penn Treebank.
  
  – **Statistical models**: Hidden Markov Model (HMM), Maximum Entropy Markov Model (MEMM), Conditional Random Field (CRF)
  
  – **Rule learning**: Transformation Based Learning (TBL)
  
  – **Neural networks**: Recurrent networks like Long Short Term Memory (LSTMs)

• Generally, learning-based approaches have been found to be more effective overall, taking into account the total amount of human expertise and effort involved.
Problems with Sequence Labeling as Classification

• Not easy to integrate information from category of tokens on both sides.
• Difficult to propagate uncertainty between decisions and “collectively” determine the most likely joint assignment of categories to all of the tokens in a sequence.
Probabilistic Sequence Models

• Probabilistic sequence models allow integrating uncertainty over multiple, interdependent classifications and collectively determine the most likely global assignment.

• Two standard models
  – Hidden Markov Model (HMM)
  – Conditional Random Field (CRF)
Markov Model / Markov Chain

- A finite state machine with probabilistic state transitions.
- Makes Markov assumption that next state only depends on the current state and independent of previous history.
Sample Markov Model for POS

- **Det**
  - Transition to **Noun**: 0.95
  - Transition to **PropNoun**: 0.4
  - Transition to **Verb**: 0.5
  - Transition to **stop**: 0.1

- **Noun**
  - Transition to **PropNoun**: 0.05
  - Transition to **Verb**: 0.8
  - Transition to **stop**: 0.5

- **PropNoun**
  - Transition to **Verb**: 0.25
  - Transition to **Det**: 0.1
  - Transition to **stop**: 0.1

- **Verb**
  - Transition to **stop**: 0.1

- **stop**
  - Transition to **Det**: 0.1
  - Transition to **Noun**: 0.9
  - Transition to **PropNoun**: 0.4
  - Transition to **Verb**: 0.5
Sample Markov Model for POS

\[ P(\text{PropNoun Verb Det Noun}) = 0.4 \times 0.8 \times 0.25 \times 0.95 \times 0.1 = 0.0076 \]
Hidden Markov Model

• Probabilistic generative model for sequences.
• Assume an underlying set of *hidden* (unobserved, latent) states in which the model can be (e.g. parts of speech).
• Assume probabilistic transitions between states over time (e.g. transition from POS to another POS as sequence is generated).
• Assume a *probabilistic* generation of tokens from states (e.g. words generated for each POS).
Sample HMM for POS
Sample HMM Generation
Sample HMM Generation
Sample HMM Generation

The HMM model consists of the following states:

- **Start**
- **Det**
- **PropNoun**
- **Noun**
- **Verb**

The transitions between states are as follows:

- **Start** to **Det** with probability 0.5
- **Det** to **PropNoun** with probability 0.5
- **PropNoun** to **Noun** with probability 0.4
- **Noun** to **Verb** with probability 0.5
- **Verb** to **Stop** with probability 0.5

The emission probabilities are:

- **Det**:
  - "the" with probability 0.95
  - "a" with probability 0.1
  - "that" with probability 0.1

- **PropNoun**:
  - "Tom" with probability 0.1
  - "John" with probability 0.5
  - "Mary" with probability 0.4

- **Noun**:
  - "cat" with probability 0.9
  - "dog" with probability 0.1

- **Verb**:
  - "ate" with probability 0.05
  - "saw" with probability 0.8
  - "played" with probability 0.25
  - "hit" with probability 0.25
  - "gave" with probability 0.1

The model also includes self-loops with probability 0.1 for each state.
Sample HMM Generation
Sample HMM Generation

John bit
Sample HMM Generation

```
John bit
```
John bit the
Sample HMM Generation

John bit the.

Diagram showing the transitions and emissions in an HMM model.
John bit the apple
Sample HMM Generation

John bit the apple
Formal Definition of an HMM

• A set of \( N + 2 \) states \( S = \{ s_0, s_1, s_2, \ldots, s_N, s_F \} \)
  – Distinguished start state: \( s_0 \)
  – Distinguished final state: \( s_F \)

• A set of \( M \) possible observations \( V = \{ v_1, v_2, \ldots, v_M \} \)

• A state transition probability distribution \( A = \{ a_{ij} \} \)
  \[
  a_{ij} = P(q_{t+1} = s_j \mid q_t = s_i) \quad 1 \leq i, j \leq N \text{ and } i = 0, j = F
  \]
  \[
  \sum_{j=1}^{N} a_{ij} + a_{iF} = 1 \quad 0 \leq i \leq N
  \]

• Observation probability distribution for each state \( j \)
  \( B = \{ b_j(k) \} \)
  \[
  b_j(k) = P(v_k \text{ at } t \mid q_t = s_j) \quad 1 \leq j \leq N, 1 \leq k \leq M
  \]

• Total parameter set \( \lambda = \{ A, B \} \)
HMM Generation Procedure

• To generate a sequence of $T$ observations:

$$O = o_1 \ o_2 \ \ldots \ o_T$$

Set initial state $q_1 = s_0$
For $t = 1$ to $T$
  Transit to another state $q_{t+1} = s_j$ based on transition
distribution $a_{ij}$ for state $q_t$
  Pick an observation $o_t = v_k$ based on being in state $q_t$ using
distribution $b_{q_t}(k)$
Three Useful HMM Tasks

- **Observation Likelihood**: To classify and order sequences.
- **Most likely state sequence (Decoding)**: To tag each token in a sequence with a label.
- **Maximum likelihood training (Learning)**: To train models to fit empirical training data.
HMM: Observation Likelihood

• Given a sequence of observations, $O$, and a model with a set of parameters, $\lambda$, what is the probability that this observation was generated by this model: $P(O|\lambda)$?

• Allows HMM to be used as a language model: A formal probabilistic model of a language that assigns a probability to each string saying how likely that string was to have been generated by the language.

• Useful for two tasks:
  – Sequence Classification
  – Most Likely Sequence
Sequence Classification

- Assume an HMM is available for each category (i.e. language).
- What is the most likely category for a given observation sequence, i.e. which category’s HMM is most likely to have generated it?
- Used in speech recognition to find most likely word model to have generate a given sound or phoneme sequence.

\[
P(O \mid \text{Austin}) > P(O \mid \text{Boston})
\]
Most Likely Sequence

• Of two or more possible sequences, which one was most likely generated by a given model?

• Used to score alternative word sequence interpretations in speech recognition.

\[
P(O_2 \mid \text{OrdEnglish}) > P(O_1 \mid \text{OrdEnglish}) ?
\]
HMM: Observation Likelihood
Naïve Solution

• Consider all possible state sequences, $Q$, of length $T$ that the model could have traversed in generating the given observation sequence.

• Compute the probability of a given state sequence from $A$, and multiply it by the probabilities of generating each of given observations in each of the corresponding states in this sequence to get $P(O,Q|\lambda) = P(O|Q,\lambda)P(Q|\lambda)$.

• Sum this over all possible state sequences to get $P(O|\lambda)$.

• Computationally complex: $O(TN^T)$. 
HMM: Observation Likelihood
Efficient Solution

• Due to the Markov assumption, the probability of being in any state at any given time \( t \) only relies on the probability of being in each of the possible states at time \( t-1 \).

• **Forward Algorithm**: Uses dynamic programming to exploit this fact to efficiently compute observation likelihood in \( O(TN^2) \) time.
  
  – Compute a *forward trellis* that compactly and implicitly encodes information about all possible state paths.
Forward Trellis

- Continue forward in time until reaching final time point and sum probability of ending in final state.
Forward Probabilities

• Let $\alpha_t(j)$ be the probability of being in state $j$ after seeing the first $t$ observations (by summing over all initial paths leading to $j$).

$$\alpha_t(j) = P(o_1, o_2, ..., o_t, q_t = s_j \mid \lambda)$$
Consider all possible ways of getting to $s_j$ at time $t$ by coming from all possible states $s_i$ and determine probability of each.

Sum these to get the total probability of being in state $s_j$ at time $t$ while accounting for the first $t-1$ observations.

Then multiply by the probability of actually observing $o_t$ in $s_j$. 
Computing the Forward Probabilities

- **Initialization**
  \[ \alpha_1(j) = a_{0j} b_j(o_1) \quad 1 \leq j \leq N \]

- **Recursion**
  \[
  \alpha_t(j) = \left[ \sum_{i=1}^{N} \alpha_{t-1}(i) a_{ij} \right] b_j(o_t) \quad 1 \leq j \leq N, \quad 1 < t \leq T
  \]

- **Termination**
  \[
  P(O \mid \lambda) = \alpha_{T+1}(s_F) = \sum_{i=1}^{N} \alpha_T(i) a_{iF}
  \]
Forward Computational Complexity

- Requires only $O(TN^2)$ time to compute the probability of an observed sequence given a model.
- Exploits the fact that all state sequences must merge into one of the $N$ possible states at any point in time and the Markov assumption that only the last state effects the next one.
Most Likely State Sequence (Decoding)

• Given an observation sequence, $O$, and a model, $\lambda$, what is the most likely state sequence, $Q = q_1, q_2, \ldots q_T$, that generated this sequence from this model?

• Used for sequence labeling, assuming each state corresponds to a tag, it determines the globally best assignment of tags to all tokens in a sequence using a principled approach grounded in probability theory.

John gave the dog an apple.
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HMM: Most Likely State Sequence Efficient Solution

- Obviously, could use naïve algorithm based on examining every possible state sequence of length $T$.
- Dynamic Programming can also be used to exploit the Markov assumption and efficiently determine the most likely state sequence for a given observation and model.
- Standard procedure is called the Viterbi algorithm (Viterbi, 1967) and also has $O(N^2T)$ time complexity.
Viterbi Scores

- Recursively compute the probability of the most likely subsequence of states that accounts for the first $t$ observations and ends in state $s_j$.

$$v_t(j) = \max_{q_0, q_1, \ldots, q_{t-1}, o_1, \ldots, o_t, q_t = s_j | \lambda} P(q_0, q_1, \ldots, q_{t-1}, o_1, \ldots, o_t, q_t = s_j | \lambda)$$

- Also record “backpointers” that subsequently allow backtracing the most probable state sequence.
  - $bt_t(j)$ stores the state at time $t-1$ that maximizes the probability that system was in state $s_j$ at time $t$ (given the observed sequence).
Computing the Viterbi Scores

- Initialization
  \[ v_1(j) = a_{0j} b_j(o_1) \quad 1 \leq j \leq N \]

- Recursion
  \[ v_t(j) = \max_{i=1}^N v_{t-1}(i) a_{ij} b_j(o_t) \quad 1 \leq j \leq N, \quad 1 < t \leq T \]

- Termination
  \[ P^* = v_{T+1}(s_F) = \max_{i=1}^N v_T(i) a_{iF} \]

Analogous to Forward algorithm except take \textit{max} instead of \textit{sum}
Computing the Viterbi Backpointers

• Initialization

\[ bt_1(j) = s_0 \quad 1 \leq j \leq N \]

• Recursion

\[ bt_t(j) = \arg\max_{i=1}^{N} \nu_{t-1}(i) a_{ij} b_j(o_t) \quad 1 \leq j \leq N, \quad 1 \leq t \leq T \]

• Termination

\[ q_T^* = bt_{T+1}(s_F) = \arg\max_{i=1}^{N} \nu_T(i) a_{iF} \]

Final state in the most probable state sequence. Follow backpointers to initial state to construct full sequence.
Viterbi Backpointers
Most likely Sequence: $s_0 \ s_N \ s_1 \ s_2 \ \ldots \ s_2 \ s_F$
HMM Learning

- **Supervised Learning**: All training sequences are completely labeled (tagged).
- **Unsupervised Learning**: All training sequences are unlabelled (but generally know the number of tags, i.e. states).
- **Semisupervised Learning**: Some training sequences are labeled, most are unlabeled.
Supervised HMM Training

• If training sequences are labeled (tagged) with the underlying state sequences that generated them, then the parameters, $\lambda=\{A,B\}$ can all be estimated directly.

Training Sequences

John ate the apple
A dog bit Mary
Mary hit the dog
John gave Mary the cat.

Det  Noun  PropNoun  Verb
Supervised Parameter Estimation

• Estimate state transition probabilities based on tag bigram and unigram statistics in the labeled data.
  \[ a_{ij} = \frac{C(q_t = s_i, q_{t+1} = s_j)}{C(q_t = s_i)} \]

• Estimate the observation probabilities based on tag/word co-occurrence statistics in the labeled data.
  \[ b_j(k) = \frac{C(q_i = s_j, o_i = v_k)}{C(q_i = s_j)} \]

• Use appropriate smoothing if training data is sparse.
Learning and Using HMM Taggers

- Use a corpus of labeled sequence data to easily construct an HMM using supervised training.
- Given a novel unlabeled test sequence to tag, use the Viterbi algorithm to predict the most likely (globally optimal) tag sequence.
Evaluating Taggers

- Train on *training set* of labeled sequences.
- Possibly tune parameters based on performance on a *development set*.
- Measure accuracy on a disjoint *test set*.
- Generally measure *tagging accuracy*, i.e. the percentage of tokens tagged correctly.
- Accuracy of most modern POS taggers, including HMMs is 96–97% (for Penn tagset trained on about 800K words).
  - Generally matching human agreement level.