# HMM and Part of Speech Tagging

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# Outline

- Parts of Speech Tagsets
- Rule-based POS Tagging
- HMM POS Tagging
- Transformation-based POS Tagging

# Part of Speech Tags Standards

- There is no standard set of parts of speech that is used by all researchers for all languages.
- The most commonly used English tagset is that of the Penn Treebank at the University of Pennsylvania:
  - pdf of POS annotation guidelines at class website
    - http://cs.nyu.edu/courses/spring12/CSCI-GA.2590-001/ptb_tagguide.pdf
- To map several POS tagsets to each other, see Table 1 in:
  - http://nlp.cs.nyu.edu/meyers/Annotation%20Compatibility%20Working%20Group%20Report%202006.html
- POS tagsets:
  - Assume Particular Tokenizations, e.g., ***Mary's*** **→** ***Mary*** **+** ***'s***
  - Distinguish inflectional morphology: e.g., *eat*/**VB**, *eats*/**VBZ**, *ate*/**VBD**
  - Are exceptionless – there are tags for all possible tokens

# The Penn Treebank II POS tagset

- Verbs: VB, VBP, VBZ, VBD, VBG, VBN
  - base, present-non-3rd, present-3rd, past, -ing, -en
- Nouns: NNP, NNPS, NN, NNS
  - proper/common, singular/plural (singular includes mass + generic)
- Adjectives: JJ, JJR, JJS (base, comparative, superlative)
- Adverbs: RB, RBR, RBS, RP (base, comparative, superlative, particle)
- Pronouns: PRP, PP$ (personal, possessive)
- Interogatives: WP, WP$, WDT, WRB (compare to: PRP, PP$, DT, RB)
- Other Closed Class: CC, CD, DT, PDT, IN, MD
- Punctuation: **# $ . , : ( ) “ ” " ' `**
- Weird Cases: FW(***deja vu***), SYM (**@**), LS (***1, 2, a, b***), TO (***to***), POS(***'s, '***), UH (***no, OK, well***), EX (***it/there***)
- Newer tags: HYPH, PU

# Part of Speech Tagging

- POS taggers assign 1 POS tag to each input token
  - *The*/DT *silly*/**JJ** *man*/**NN** *is*/**VBZ** *a*/**DT** *professor*/**NN** ./**PU**
- Different ways of breaking down POS tagging:
  - Use separate “tokenizer”, program that divides string into list of tokens – POS tagger processes output
  - Incorporate tokenizer into POS tagger
- Different ways of breaking down parsing:
  - Use separate POS tagger – output of tagger is input to parser
  - Assign POS tags as part of parsing (assumed previously)
- Accurate POS tagging is “easier” than accurate parsing
  - POS tags may be sufficient information for some tasks

# Some Tokenization Rules for English

- 1) Divide at spaces and hyphens.
- 2) Divide before punctuation that is followed by: a space or the end of the line
  - Define punctuation as any non-letter/non-number:
    - `!@#$%^&*()-_+={[}]\|:;'"<,>.?/
  - Punctuation followed by a space, other punctuation, or at the end of line should be separated from words:
    - ***...and he left.") → and he left . " )***
- 3) Break off the following as separate tokens when followed by a space or end of line:
  - ***'s***, ***n't***, ***'d***, ***'ve***, ***'m***, ***'ll***, ***'re***, … (a short list)
- 4) Abbreviations are exceptions to rule 2:
  - Period after abbreviations should not be separate from words
    - Most cases covered by list of 100 items (or if sentence end is known)
  - Final periods are not duplicated after abbreviations (consistency issues)

# Rule-based POS Tagger

- Method
  - Assign lists of potential POS tags to each word based on dictionary
  - Manual rules for Out of Vocabulary (OOV) words
    - Ex: Non-initial capital → NNP; ends in S → VBZ|NNS; default → NN|JJ; etc.
  - Apply hand-written constraints until each word has only one possible POS
- Sample Constraints:
  - 1) DT cannot immediately precede a verb
  - 2) No verb can immediately precede a tensed verb (VBZ,VBP,VBD)
- Example:
  - The/DT book/{NN|VB|VBP} is/VBZ on/IN the/DT table{NN|VB|VBP}
  - The/DT book/NN is/VBZ on/IN the/DT table/NN
    - DT cannot precede VB or VBP
    - VBZ cannot be preceded by VB or VBP

# Introduction to Probability

- Estimate of probability of future event based on past observations

$$P(event) = \frac{\text{num of events}}{\text{num of trials}}$$

- Conditional Probability: probability of X given Y

$$P(X|Y) = \frac{P(X,Y)}{P(Y)}$$

- Examples:
  - If out of 1000 words, ***the*** occurs 200 times, we predict:
    - a random word is 20% likely to be ***the***
  - If the word after ***the*** is a noun 120 times and an adjective 60 times:
    - A word following ***the*** is
      - 120/200 = 60% likely to be a noun
      - 60/200 = 30% likely to be an adjective

# More Math Terminology

- N instances of a variable looked at individually:

  $X_1^n$ is the same as $\{X_{1,} X_{2,} X_{3,} .. X_n\}$ in sequence

- For example,

  $$\prod_{i=1}^{n} P(X_i)$$

  means the product of instances of X from 1 to n
- Max = the maximum number in a set
- Argmax = the formula that maximizes a particular argument of the formula

# Probabilistic Models of POS tagging

- For tokens $w_1$, ..., $w_n$, find the most probable corresponding sequence of possible tags $t_1$, ..., $t_n$
  - We assume that *probable* means something like “most frequently observed in some manually tagged corpus of words”.
- Penn Treebank II (a common training corpus)
  - 1 million words from the Wall Street Journal
  - Tagged for POS (and other attributes)
- The specific sequence (sentence) is not in the training corpus
  - Therefore the actual “probability” is 0
  - Common practice: estimate probability given assumptions, e.g.,
    - Choose the most frequent possible sequence of tags independently of how frequently each tag is assigned to each token

# Probabilistic Assumptions of HMM Tagging

- $\hat{t} = \underset{t_1^n}{argmax}\, P(t_1^n | w_1^n)$
  - Choose the tag sequence of length n that is most probable given the input token sequence
- Bayes Rule:
  - $P(x|y) = \frac{P(y|x)P(x)}{P(y)}$
  - Way to derive the probability of x given y when you know the probability of y given x
- Applying Bayes Rule to Tag Probability
  - $\hat{t} = \underset{t_1^n}{argmax}\, \frac{P(w_1^n|t_1^n)P(t_1^n)}{P(w_1^n)}$

# Simplifying Assumptions for HMMs

- Simplification: Drop the denominator
  - Denominator is same for all the tag sequences
  - $\hat{t} = \underset{t_1^n}{argmax} P(w_1^n | t_1^n) P(t_1^n)$
  - For each tag sequence calculate the product of:
    - The probability of the word sequence given the tag sequence (**likelihood**)
    - The probability of the tag sequence (**prior probability**)
  - Still too hard
- 2 simplifying assumptions make it possible to estimate the probability of tag sequences given word sequences:
  - 1) If the probability of a word is only dependent on its own POS tag,
    - $P(w_1^n | t_1^n) \approx \prod_{i=1}^{n} P(w_i | t_i)$
  - 2) If the probability of a POS tag is only dependent on the previous POS tag,
    - $P(t^n) \approx \prod_{i=1}^{n} P(t_i | t_{i-1})$
- The result of these assumptions: $\hat{t} \approx \underset{t_1^n}{argmax} \prod_{i=1}^{n} P(w_i | t_i) P(t_i | t_{i-1})$
- HMM taggers are fast and achieve precision/recall scores of about 93-95%

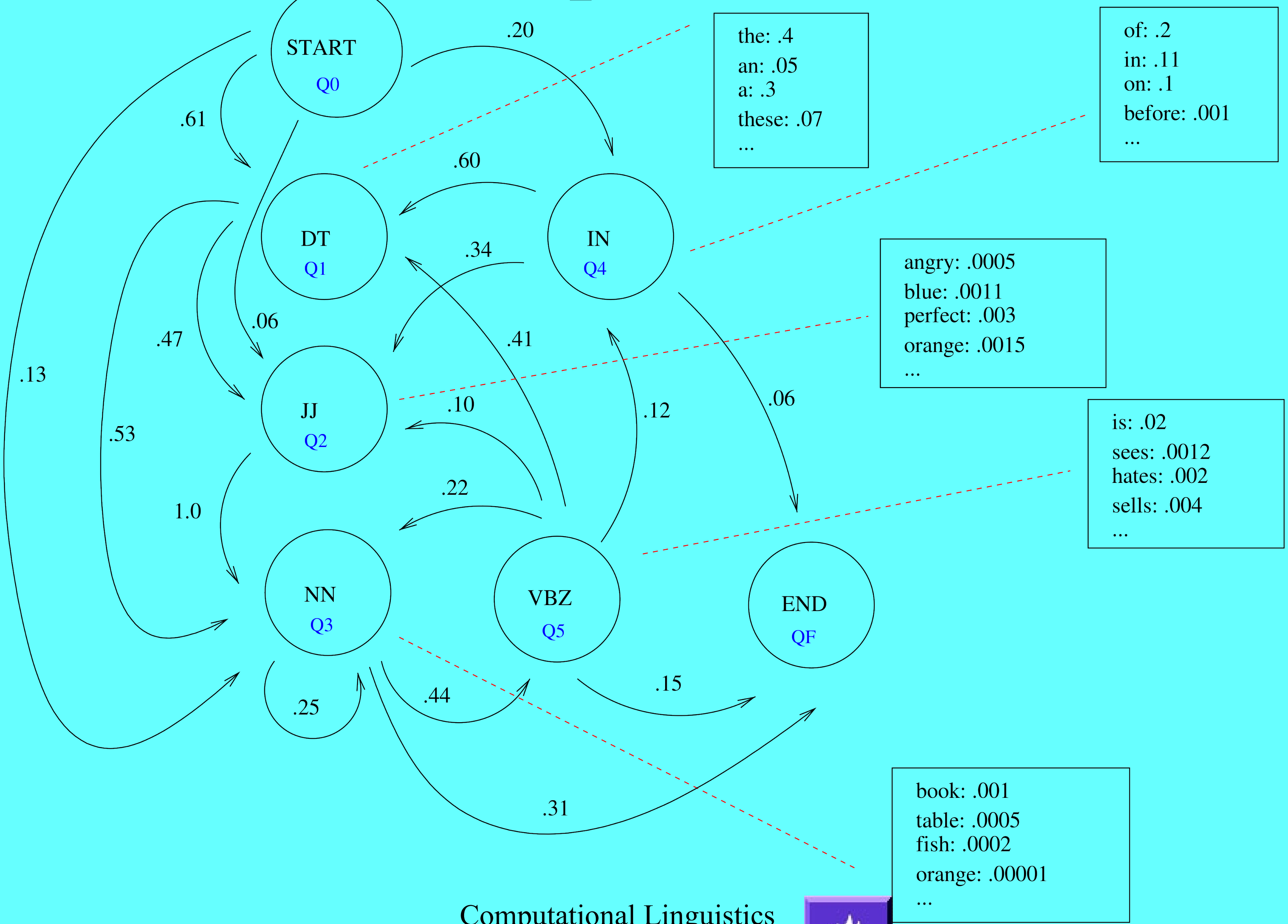
# Estimating Probability of $\hat{t}$

- We assume that: $\hat{t} \approx \underset{t_1^n}{argmax} \prod_{i=1}^{n} P(w_i|t_i) P(t_i|t_{i-1})$
- Acquire frequencies from a training corpus:
  - Word Frequency with given POS
    - suppose ***book*** occurs 14 times in a corpus: 10 times (.001) as **NN (**there are 10000 instances of **NN** in the corpus); 3 times (.003) as **VBP** (the corpus has 1000 **VBP**s**)**, and 1 instance of book (.005) as **VB (**the corpus has 500 **VB**s).
  - Given the previous tag, how often does each tag occur
    - suppose **DT is** followed by **NN** 80,000 times (.53), **JJ** 30,000 times (.2), **NNS** 20,000 times (.13), **VBN** 3,000 (.02) times, … out of a total of 150,000 occurrences of **DT**
- All possible tags for sequence:
  - *The*/**DT** *book*/**{NN|VB|VBP}** *is*/**VBZ** *on*/**IN** *the*/**DT** *table*/**{NN|VB|VBP}**
- Hypothetical probabilities for highest scoring tag sequence:
  - *The*/**DT** *book*/**NN** *is*/**VBZ** *on*/**IN** *the*/**DT** *table*/**NN**
  - *The*/**DT=.4,** *book*/**NN=.001,** *is*/**VBZ=.02,** *on*/**IN=.1,** *the*/**DT=.4***,* *table*/**NN=.0005,**
  - **B DT = .61, DT NN = .53, NN VBZ =.44, VBZ IN = .12, IN DT = .05, DT NN = .53 NN E .31**
  - $\prod_{i=1}^{n} P(w_i|t_i) P(t_i|t_{i-1}) = (.4 \times .61)(.001 \times .53)(.02 \times .44)(.1 \times .12)(.4 \times .05)(.005 \times .53)(1 \times .31) \approx 2.4 \times 10^{-13}$

# Defining an HMM

- A Weighted Finite-state Automaton (WFSA)
  - Each transition arc is associated with a probability
  - The sum of all arcs outgoing from a single node is 1
- Markov chain is a WFSA in which an input string uniquely determine path through the Automaton
- Hidden Markov Model (HMM) is a slightly different case because some information (previous POS tags) is unknown (or hidden)
- HMM consists of the following:
  - **Q** = set of states: $\mathbf{q_0}$ (start state), …, $\mathbf{q_F}$ (final state)
  - **A** = transition probability matrix of **n X n** probabilities of transitioning between any pair of **n** states (**n** = **F**+1). Called: ***prior probability*** or ***transition probability*** of a tag sequence
  - **O** = sequence of **T** observations (**words**) from a vocabulary **V**
  - **B** = sequence of observation likelihoods (probability of observation generated at state) – Called ***likelihood*** (of word sequence given tag sequence), aka ***emission probability***

# Example HMM



START
Q0
DT
Q1
JJ
Q2
NN
Q3
IN
Q4
VBZ
Q5
END
QF
.20
.61
.60
.34
.06
.47
.13
.53
.41
.10
.12
.06
.22
1.0
.25
.44
.15
.31
the: .4
an: .05
a: .3
these: .07
...
of: .2
in: .11
on: .1
before: .001
...
angry: .0005
blue: .0011
perfect: .003
orange: .0015
...
is: .02
sees: .0012
hates: .002
sells: .004
...
book: .001
table: .0005
fish: .0002
orange: .00001
...

# Viterbi Algorithm for HMM

Observed_Words = $\mathbf{w_1} \ldots \mathbf{w_T}$

- States = $\mathbf{q_o}, \mathbf{q_1} \ldots \mathbf{q_N}, \mathbf{q_F}$

**A** = **N** × **N** matrix such that $\mathbf{a_{i,j}}$ is the probability of the transition from $\mathbf{q_i}$ to $\mathbf{q_j}$

**B** = lookup table such that $\mathbf{b_i(w_t)}$ is the probability that POS **i** is realized as word **t**

**viterbi** = (**N**+2) × **T** matrix # columns are states, rows are words

**backpointer** = (**N**+2) × **T** matrix # highest scoring previous cells for viterbi

for states **q** from 1 to **N**:

initialize **viterbi[q,1]** to $\mathbf{a_{0,q}}$ * $\mathbf{b_q(w_1)}$ # score transition 0→q given $w_1$

initialize **backpointer[q,1]** to 0 (start state)

for word **w** from 2 to **T**:

for state **q** from 1 to **N**: # for T-1 × N (w,q) pairs

**viterbi[q,w]**$\leftarrow \max_{q'=1}^{N} viterbi[q',t-1] * a_{q',q} * b_q(w_t)$ # score = maximum previous * prior * likelihood

**backpointer[q.w]** $\leftarrow \operatorname{argmax}_{q'=1}^{N} viterbi[q',t-1] * a_{q',q}$ # backpointer = maximum previous

viterbi[qF,T]$\leftarrow \max_{q=1}^{N} viterbi[q,T] * a_{q,qF}$ # score = maximum previous * prior * likelihood

backpointer[qF,T]$\leftarrow \operatorname{argmax}_{q=1}^{N} viterbi[q,T] * a_{q,qF}$ # backpointer = maximum previous

- return(best_path) # derive by following backpointers from (qF,T) to $q_0$

# *Walk Through: The book fell off the table.* (ignoring period)

$$1 * .4 * .61 * .00001 * .53 * .02 * .33 * .1 * .12 * .4 * .6 * .54 * .0005 * .33 * 1 = 2.19 * 10^{-15}$$

| | 0 | 1: *The* | 2:orange | 3: *is* | 4: *on* | 5: *the* | 6: *table* | 7 |
|---|---|---|---|---|---|---|---|---|
| **Start** | 1 | | | | | | | |
| **DT** | | .4 * .61 | | | | .4*.6 | | |
| **IN** | | | | | .1*.12 | | | |
| **JJ** | | | .0015 * .47 | | | | | |
| **VBZ** | | | | | | | | |
| **NN** | | | .00001 * .53 | .02*.44 | | | .53*.0005 | |
| **End** | | | | | | | | .33 * 1 |

# Comments on Viterbi Trace

- Initialize scores for first column: transitions from 0 to each possible state given: ***the***
  - The probability of reaching Q1 matching the first item on the tape (***the***) will be .4 X .61 = .244 (this is also the only possibility)
- The adjective sense of *orange* is more likely locally, but leads to a dead end
- The transitions from B and the transition to E are necessary parts of the process.

# Go to Ralph's Viterbi Demo for ***Fish Sleep***

# N-grams

- Prior Probability in our HMM was estimated as:
  - freq(currentPOS, previousPOS) / freq(previousPOS)
  - This is a bigram
- Trigram: freq(POS-2, POS-1, POS) / freq(POS-2,POS-1)
- N-gram: freq(POS-N…POS)/freq(POS-N…POS-1)
- N-grams
  - Used a lot in computational linguistics
  - N-grams can be calculated for: words, POS, other attributes
  - Chapter 4 has more info on N-grams
- J & M show how to extend HMM to tri-grams by calculating the prior based on two previous POS tags instead of one
  - They also show a way of combining unigram, bigram and trigrams

# Unknown (OOV) Words

- Possibility 1
  - Assume they are equally ambiguous between all POS
    - Refinements:
      - Assume distribution of unknown = overall POS distribution
      - Assume distribution of unknown = distribution of 1 time words
  - Use N-grams to predict the correct tag
- Possibility 2
  - Use morphology (prefixes, suffixes), orthography (uppercase/lowercase), hyphenation
- Possibility 3: Some combination

# Homework

- http://cs.nyu.edu/courses/spring16/CSCI-UA.0480-011/homework4.html