EECS 498-004: Introduction to Natural Language Processing

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Outline

- What is part-of-speech (POS) and POS tagging?
- Hidden Markov Model (HMM) for POS tagging
- Learning an HMM
- Prediction with an learned HMM (inference)

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Parts of Speech

- Perhaps starting with Aristotle in the West (384–322 BCE), there was the idea of having parts of speech (POS)
  - a.k.a lexical categories, word classes, "tags"
- Lowest level of syntactic analysis

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English Parts of Speech (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 the slides.
  - Reduced from the Brown set for use in the context of a parsed corpus (i.e. Penn Treebank).

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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)

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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)

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Open vs. Closed classes

- Open vs. Closed classes
  - Closed:
    - determiners: ***a, an, the***
    - pronouns: ***she, he, I***
    - prepositions: ***on, under, over, near, by, …***
    - Why "closed"?
  - Open:
    - Nouns, Verbs, Adjectives, Adverbs.

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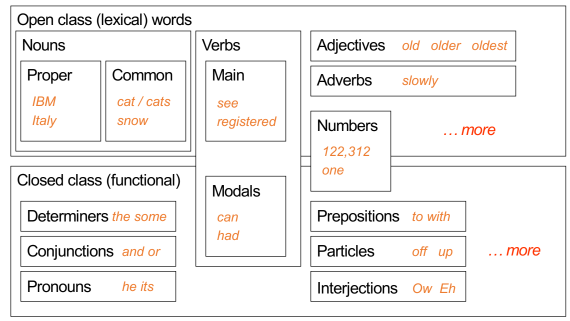

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Ambiguity in POS Tagging

- "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.

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POS Tagging

- The POS tagging problem is to determine the POS tag for a particular instance of a word.

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POS Tagging

NN*: noun
VB*: verb
UH: interjection
JJ: adjective
RB: adverb
IN: preposition

- Input: plays well with others
- Ambiguity: NNS/VBZ UH/JJ/NN/RB IN NNS
- Output: Plays/VBZ well/RB with/IN others/NNS
- Uses:
  - Text-to-speech (how do we pronounce "lead"?)
  - Can write regexps over the output for phrase extraction
    - Noun phrase: (Det) Adj* N+
  - As input to or to speed up a full parser

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POS tagging performance

- How many tags are correct? (Tag accuracy)
  - About 97% currently

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POS tagging performance

- How many tags are correct? (Tag accuracy)
  - About 97% currently
  - But baseline is already 90%
    - Baseline is performance of stupidest possible method
      - Take an annotated corpus (or a dictionary), tag every word with its most frequent tag
      - Tag unknown words as nouns
  - Partly easy because
    - Many words are unambiguous
    - You get points for them (*the*, *a*, etc.) and for punctuation marks!

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How difficult is POS tagging?

- Word types: roughly speaking, unique words
- About 11% of the word types in the Brown corpus are ambiguous with regard to part of speech
- But they tend to be very common words. E.g., *that*
  - I know *that* he is honest = IN (preposition)
  - Yes, *that* play was nice = DT (determiner)
  - You can't go *that* far = RB (adverb)
- 40% of the word tokens are ambiguous

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Sources of information

- What are the main sources of information for POS tagging? *"Bill saw that man yesterday"*

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Sources of information

- What are the main sources of information for POS tagging? *"Bill saw that man yesterday"*
  - **Contextual**: Knowledge of neighboring words
    - Bill saw that man yesterday
    - NNP NN DT NN NN
    - VB VB(D) IN VB NN
  - **Local**: Knowledge of word probabilities
    - *man* is rarely used as a verb….
- The latter proves the most useful, but the former also helps
- Sometimes these preferences are in conflict:
  - *The trash can is in the garage*

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More and Better Features → Feature-based tagger

- Can do surprisingly well just looking at a word by itself:
  - Word the: the → DT
  - Lowercased word Importantly: importantly → RB
  - Prefixes unfathomable: un- → JJ
  - Suffixes Importantly: -ly → RB
  - Capitalization Meridian: CAP → NNP
  - Word shapes 35-year: d-x → JJ

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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) – **this lecture!**, 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), Transformers
- Generally, learning-based approaches have been found to be more effective overall, taking into account the total amount of human expertise and effort involved.

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Hidden Markov Model

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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.

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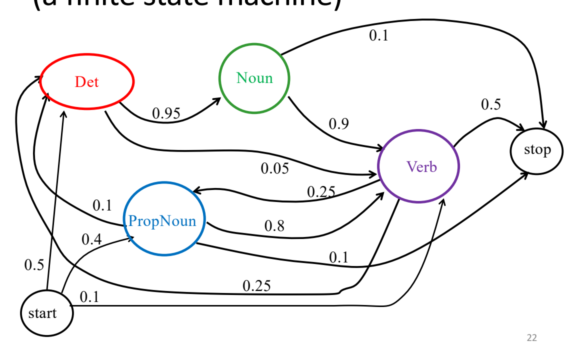
Sample Markov Model for POS (a finite state machine)



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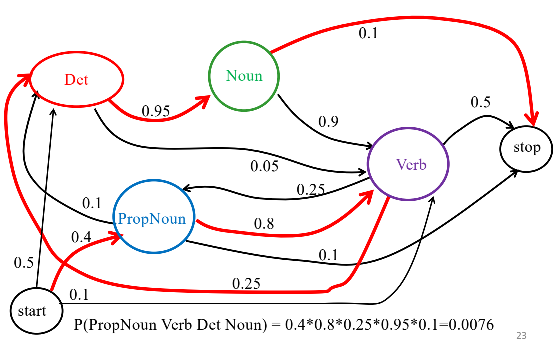
Sample Markov Model for POS



P(PropNoun Verb Det Noun) = 0.4*0.8*0.25*0.95*0.1=0.0076

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Hidden Markov Model

- Probabilistic generative model for sequences.
- Assume an underlying set of ***hidden*** (unobserved) states in which the model can be (e.g. part-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).

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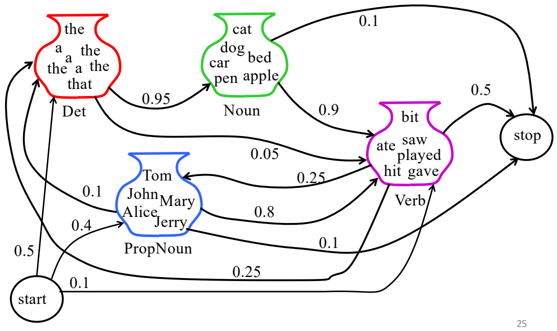
Sample HMM Generation



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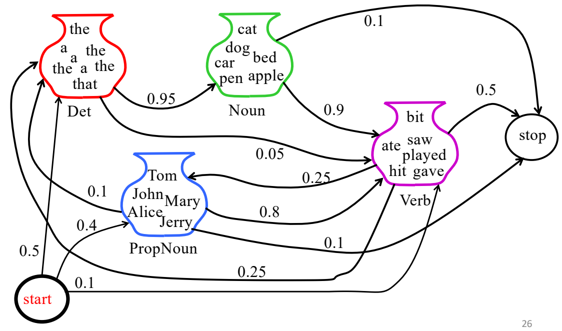

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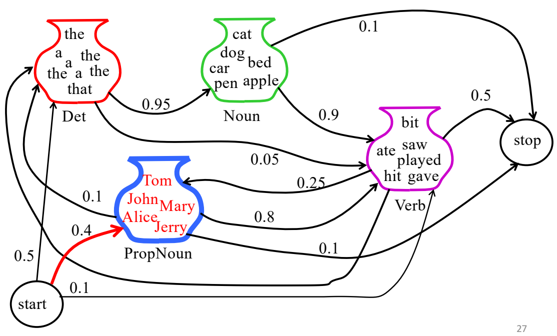

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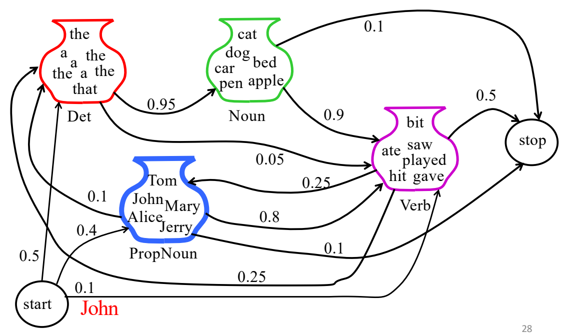

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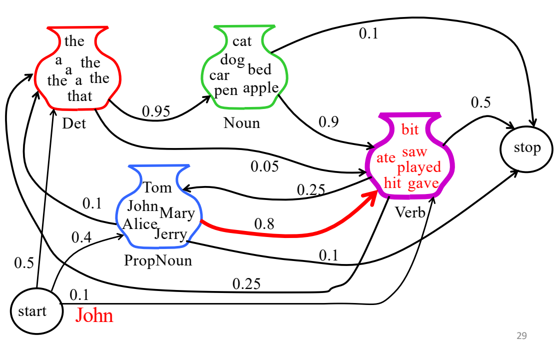

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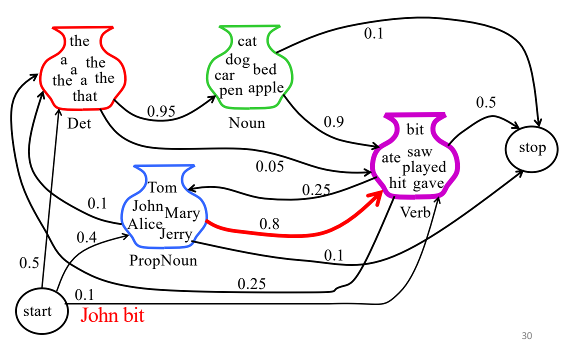

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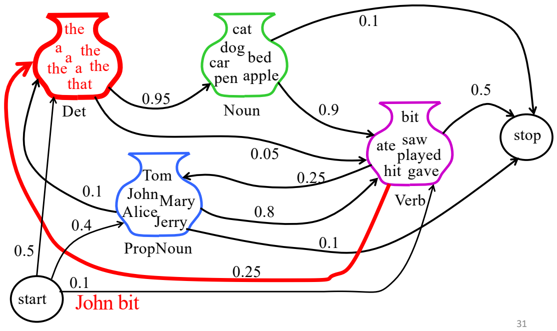

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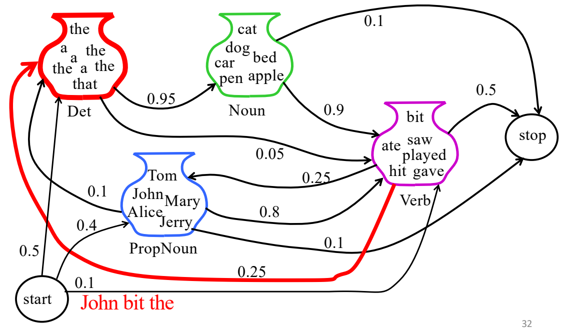

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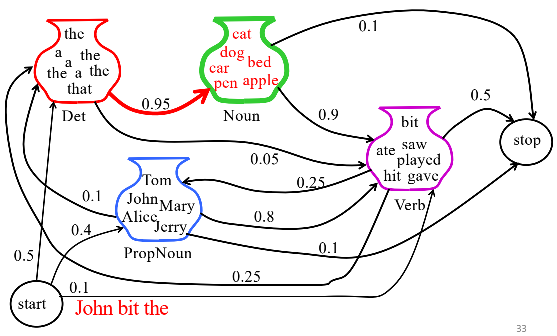

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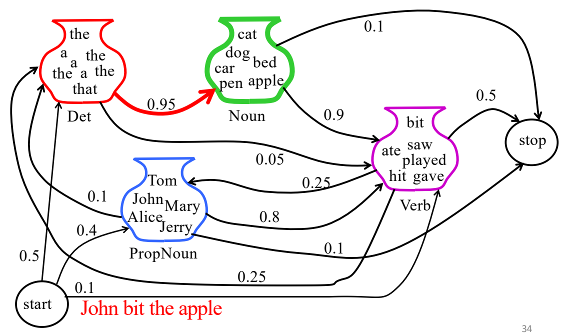

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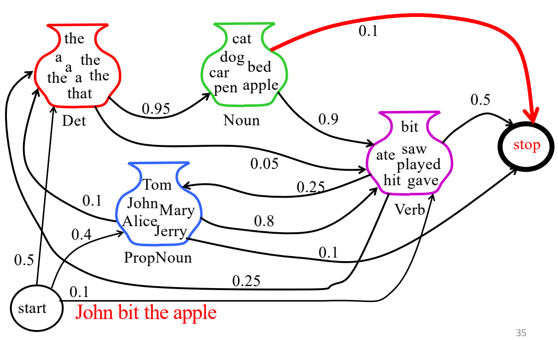

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Formally, Markov Sequences

- Consider a sequence of random variables $X_1, X_2, \ldots, X_m$ where m is the length of the sequence
- Each variable X_i can take any value in $\{1, 2, \ldots, k\}$
- How do we model the joint distribution

$$P(X_1 = x_1, X_2 = x_2, \ldots, X_m = x_m)$$

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The Markov Assumption

$$
\begin{aligned}
& P(X_1 = x_1, X_2 = x_2, \ldots, X_m = x_m) \\
= \; & P(X_1 = x_1) \prod_{j=2}^{m} P(X_j = x_j | X_1 = x_1, \ldots, X_{j-1} = x_{j-1}) \\
= \; & P(X_1 = x_1) \prod_{j=2}^{m} P(X_j = x_j | X_{j-1} = x_{j-1})
\end{aligned}
$$

- The first equality is exact (by the chain rule).
- The second equality follows from *the Markov assumption*: for all $j = 2 \ldots m$,

$$P(X_j = x_j | X_1 = x_1, \ldots, X_{j-1} = x_{j-1}) = P(X_j = x_j | X_{j-1} = x_{j-1})$$

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Homogeneous Markov Chains

- In a *homogeneous* Markov chain, we make an additional assumption, that for $j = 2 \ldots m$,

$$P(X_j = x_j | X_{j-1} = x_{j-1}) = q(x_j | x_{j-1})$$

where $q(x'|x)$ is some function

- Idea behind this assumption: the transition probabilities do not depend on the position in the Markov chain (do not depend on the index j)

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$$P(X_j = x_j | X_{j-1} = x_{j-1}) = q(x_j | x_{j-1})$$

where $q(x'|x)$ is some function

- Idea behind this assumption: the transition probabilities do not depend on the position in the Markov chain (do not depend on the index j)

"the Markov Chains follows the Markov assumption"

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Markov Models

- Our model is then as follows:

$$p(x_1, x_2, \ldots x_m; \underline{\theta}) = q(x_1) \prod_{j=2}^{m} q(x_j | x_{j-1})$$

- Parameters in the model:
  - $q(x)$ for $x = \{1, 2, \ldots, k\}$
    Constraints: $q(x) \geq 0$ and $\sum_{x=1}^{k} q(x) = 1$
  - $q(x'|x)$ for $x = \{1, 2, \ldots, k\}$ and $x' = \{1, 2, \ldots, k\}$
    Constraints: $q(x'|x) \geq 0$ and $\sum_{x'=1}^{k} q(x'|x) = 1$

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Probabilistic Models for Sequence Pairs – words and POS tags

- We have two sequences of random variables: $X_1, X_2, \ldots, X_m$ and $S_1, S_2, \ldots, S_m$
- Intuitively, each X_i corresponds to an "observation" and each S_i corresponds to an underlying "state" that generated the observation. Assume that each S_i is in $\{1, 2, \ldots k\}$, and each X_i is in $\{1, 2, \ldots o\}$
- How do we model the joint distribution

$$P(X_1 = x_1, \ldots, X_m = x_m, S_1 = s_1, \ldots, S_m = s_m)$$

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Probabilistic Models for Sequence Pairs – words and POS tags

- We have two sequences of random variables: $X_1, X_2, \ldots, X_m$ and $S_1, S_2, \ldots, S_m$

  Words **Part-of-Speech tags**
- Intuitively, each X_i corresponds to an "observation" and each S_i corresponds to an underlying "state" that generated the observation. Assume that each S_i is in $\{1, 2, \ldots k\}$, and each X_i is in $\{1, 2, \ldots o\}$
- How do we model the joint distribution

$$P(X_1 = x_1, \ldots, X_m = x_m, S_1 = s_1, \ldots, S_m = s_m)$$

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Firstly, why would we want to model the joint distribution?

$$P(X_1 = x_1, \ldots, X_m = x_m, S_1 = s_1, \ldots, S_m = s_m)$$

Words **Part-of-Speech tags**

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Hidden Markov Models (HMMs)

- In HMMs, we assume that:

Words **Part-of-Speech tags**

$$P(X_1 = x_1, \ldots, X_m = x_m, S_1 = s_1, \ldots, S_m = s_m)$$
$$= P(S_1 = s_1) \prod_{j=2}^{m} P(S_j = s_j | S_{j-1} = s_{j-1}) \prod_{j=1}^{m} P(X_j = x_j | S_j = s_j)$$

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Independence Assumptions in HMMs

- By the chain rule, the following equality is exact:

$$P(X_1 = x_1, \ldots, X_m = x_m, S_1 = s_1, \ldots, S_m = s_m)$$
$$= P(S_1 = s_1, \ldots, S_m = s_m) \times P(X_1 = x_1, \ldots, X_m = x_m | S_1 = s_1, \ldots, S_m = s_m)$$

- Assumption 1: the state sequence forms a Markov chain

e.g. Part-of-Speech tags

$$P(S_1 = s_1, \ldots, S_m = s_m) = P(S_1 = s_1) \prod_{j=2}^{m} P(S_j = s_j | S_{j-1} = s_{j-1})$$

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- By the chain rule, the following equality is exact:

$$P(X_1 = x_1, \ldots, X_m = x_m | S_1 = s_1, \ldots, S_m = s_m)$$
$$= \prod_{j=1}^{m} P(X_j = x_j | S_1 = s_1, \ldots, S_m = s_m, X_1 = x_1, \ldots X_{j-1} = x_{j-1})$$

- Assumption 2: each observation depends only on the underlying state

$$P(X_j = x_j | S_1 = s_1, \ldots, S_m = s_m, X_1 = x_1, \ldots X_{j-1} = x_{j-1})$$
$$= P(X_j = x_j | S_j = s_j)$$

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Formally

- The model takes the following form:

$$p(x_1 \ldots x_m, s_1 \ldots s_m; \underline{\theta}) = t(s_1) \prod_{j=2}^{m} t(s_j | s_{j-1}) \prod_{j=1}^{m} e(x_j | s_j)$$

- Parameters in the model:

1. Initial state parameters $t(s)$ for $s \in \{1, 2, \ldots, k\}$
2. Transition parameters $t(s'|s)$ for $s, s' \in \{1, 2, \ldots, k\}$
3. Emission parameters $e(x|s)$ for $s \in \{1, 2, \ldots, k\}$ and $x \in \{1, 2, \ldots, o\}$

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HMM

- Parameter estimation
  - Learning the probabilities from training data
  - P(verb|noun)?, P(*apples*|noun)?
- Inference: Viterbi algorithm (dynamic programming)
  - Given a new sentence, what are the POS tags for the words?

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HMM

- Parameter estimation
- Inference: Viterbi algorithm (dynamic programming)

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Parameter Estimation with Fully Observed Data

- We'll now discuss parameter estimates in the case of *fully observed data*: for $i = 1 \ldots n$, we have pairs of sequences $x_{i,j}$ for $j = 1 \ldots m$ and $s_{i,j}$ for $j = 1 \ldots m$. (i.e., we have n training examples, each of length m.)

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Parameter Estimation: Transition Parameters

- P(verb|noun)?

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- Assume we have fully observed data: for $i = 1 \ldots n$, we have pairs of sequences $x_{i,j}$ for $j = 1 \ldots m$ and $s_{i,j}$ for $j = 1 \ldots m$
- Define count$(i, s \rightarrow s')$ to be the number of times state s' follows state s in the i'th training example. More formally:

$$\text{count}(i, s \rightarrow s') = \sum_{j=1}^{m-1} [[s_{i,j} = s \wedge s_{i,j+1} = s']]$$

(We define $[[\pi]]$ to be 1 if π is true, 0 otherwise.)

- The maximum-likelihood estimates of transition probabilities are then

$$t(s'|s) = \frac{\sum_{i=1}^{n} \text{count}(i, s \rightarrow s')}{\sum_{i=1}^{n} \sum_{s'} \text{count}(i, s \rightarrow s')}$$

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Parameter Estimation: Emission Parameters

- P(*apples*|noun)?

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- Assume we have fully observed data: for $i = 1 \ldots n$, we have pairs of sequences $x_{i,j}$ for $j = 1 \ldots m$ and $s_{i,j}$ for $j = 1 \ldots m$
- Define $\text{count}(i, s \rightsquigarrow x)$ to be the number of times state s is paired with emission x. More formally:

$$\text{count}(i, s \rightsquigarrow x) = \sum_{j=1}^{m} [[s_{i,j} = s \wedge x_{i,j} = x]]$$

- The maximum-likelihood estimates of emission probabilities are then

$$e(x|s) = \frac{\sum_{i=1}^{n} \text{count}(i, s \rightsquigarrow x)}{\sum_{i=1}^{n} \sum_{x} \text{count}(i, s \rightsquigarrow x)}$$

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Parameter Estimation: Initial State Parameters

- Assume we have fully observed data: for $i = 1 \ldots n$, we have pairs of sequences $x_{i,j}$ for $j = 1 \ldots m$ and $s_{i,j}$ for $j = 1 \ldots m$
- Define $\text{count}(i, s)$ to be 1 if state s is the initial state in the sequence, and 0 otherwise:

$$\text{count}(i, s) = [[s_{i,1} = s]]$$

- The maximum-likelihood estimates of initial state probabilities are:

$$t(s) = \frac{\sum_{i=1}^{n} \text{count}(i, s)}{n}$$

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HMM

- Parameter estimation
- Inference: Viterbi algorithm (dynamic programming)

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The Viterbi Algorithm

- Goal: for a given input sequence $x_1, \ldots, x_m$, find

$$\arg\max_{s_1, \ldots, s_m} p(x_1 \ldots x_m, s_1 \ldots s_m; \underline{\theta})$$

- This is the most likely state sequence $s_1 \ldots s_m$ for the given input sequence $x_1 \ldots x_m$

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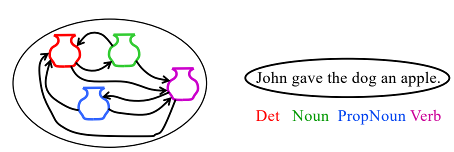
Most Likely State Sequence

- Given an observation sequence, *X*, and a model, what is the most likely state sequence, $S=s_1,s_2,\ldots s_m$, 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.



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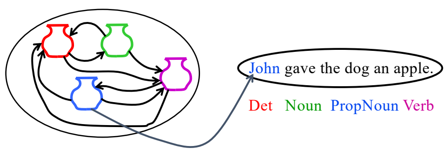

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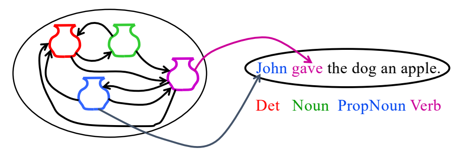

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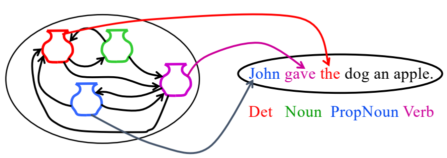

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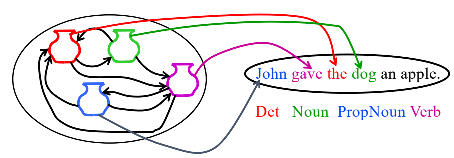

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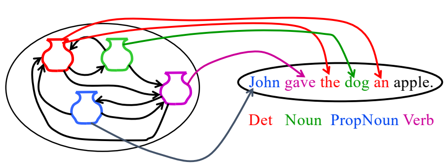

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Most Likely State Sequence

- Given an observation sequence, X, and a model, what is the most likely state sequence, $S = s_1, s_2, \ldots s_m$, that generated this sequence from this model?
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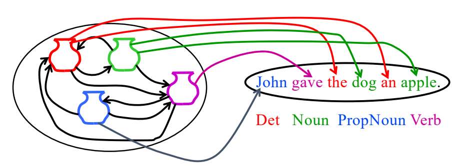

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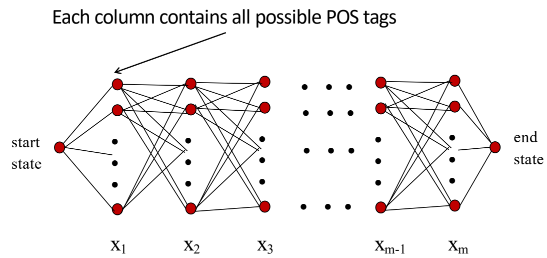

- Continue forward in time until reaching final time point.
- **The goal**: find a path with highest probability

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The Viterbi Algorithm

- Goal: for a given input sequence $x_1, \ldots, x_m$, find

$$\arg \max_{s_1,\ldots,s_m} p(x_1 \ldots x_m, s_1 \ldots s_m; \underline{\theta})$$

- The *Viterbi algorithm* is a dynamic programming algorithm. Basic data structure:

$$\pi[j, s]$$

will be a table entry that stores the maximum probability for any state sequence ending in state s at position j. More formally: $\pi[1, s] = t(s)e(x_1|s)$, and for $j > 1$,

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$$\pi[j, s]$$ *Why do we need this data structure?*

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The Viterbi Algorithm

- Initialization: for $s = 1 \ldots k$

$$\pi[1, s] = t(s)e(x_1|s)$$

- For $j = 2 \ldots m$, $s = 1 \ldots k$:

$$\pi[j, s] = \max_{s' \in \{1 \ldots k\}} [\pi[j-1, s'] \times t(s|s') \times e(x_j|s)]$$

- We then have

$$\max_{s_1 \ldots s_m} p(x_1 \ldots x_m, s_1 \ldots s_m; \underline{\theta}) = \max_{s} \pi[m, s]$$

- The algorithm runs in $O(mk^2)$ time

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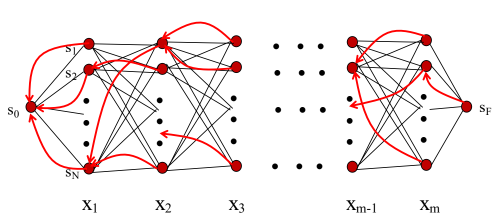
Viterbi Backpointers



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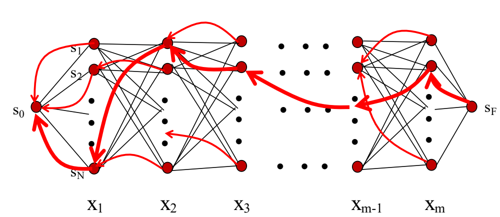
Viterbi Backtrace



Most likely Sequence: $s_0\ s_N\ s_1\ s_2 \ldots s_2\ s_F$

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The Viterbi Algorithm: Backpointers

- Initialization: for $s = 1 \dots k$

$$\pi[1, s] = t(s)e(x_1|s)$$

- For $j = 2 \dots m$, $s = 1 \dots k$:

$$\pi[j, s] = \max_{s' \in \{1 \dots k\}} [\pi[j-1, s'] \times t(s|s') \times e(x_j|s)]$$

and

$$bp[j, s] = \arg \max_{s' \in \{1 \dots k\}} [\pi[j-1, s'] \times t(s|s') \times e(x_j|s)]$$

- The bp entries are backpointers that will allow us to recover the identity of the highest probability state sequence

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- Highest probability for any sequence of states is

$$\max_s \pi[m, s]$$

- To recover identity of highest-probability sequence:

$$s_m = \arg \max_s \pi[m, s]$$

and for $j = m \dots 2$,

$$s_{j-1} = bp[j, s_j]$$

- The sequence of states $s_1 \dots s_m$ is then

$$\arg \max_{s_1, \dots, s_m} p(x_1 \dots x_m, s_1 \dots s_m; \underline{\theta})$$

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Homework

- Reading J&M Ch5.1-5.5, Ch6.1-6.5
- For 3rd Edition:

https://web.stanford.edu/~jurafsky/slp3/8.pdf

- HMM notes
  - http://www.cs.columbia.edu/~mcollins/hmms-spring2013.pdf

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