CS 6120/CS4120: Natural Language Processing

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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

English Parts of Speech (POS) Tagsets

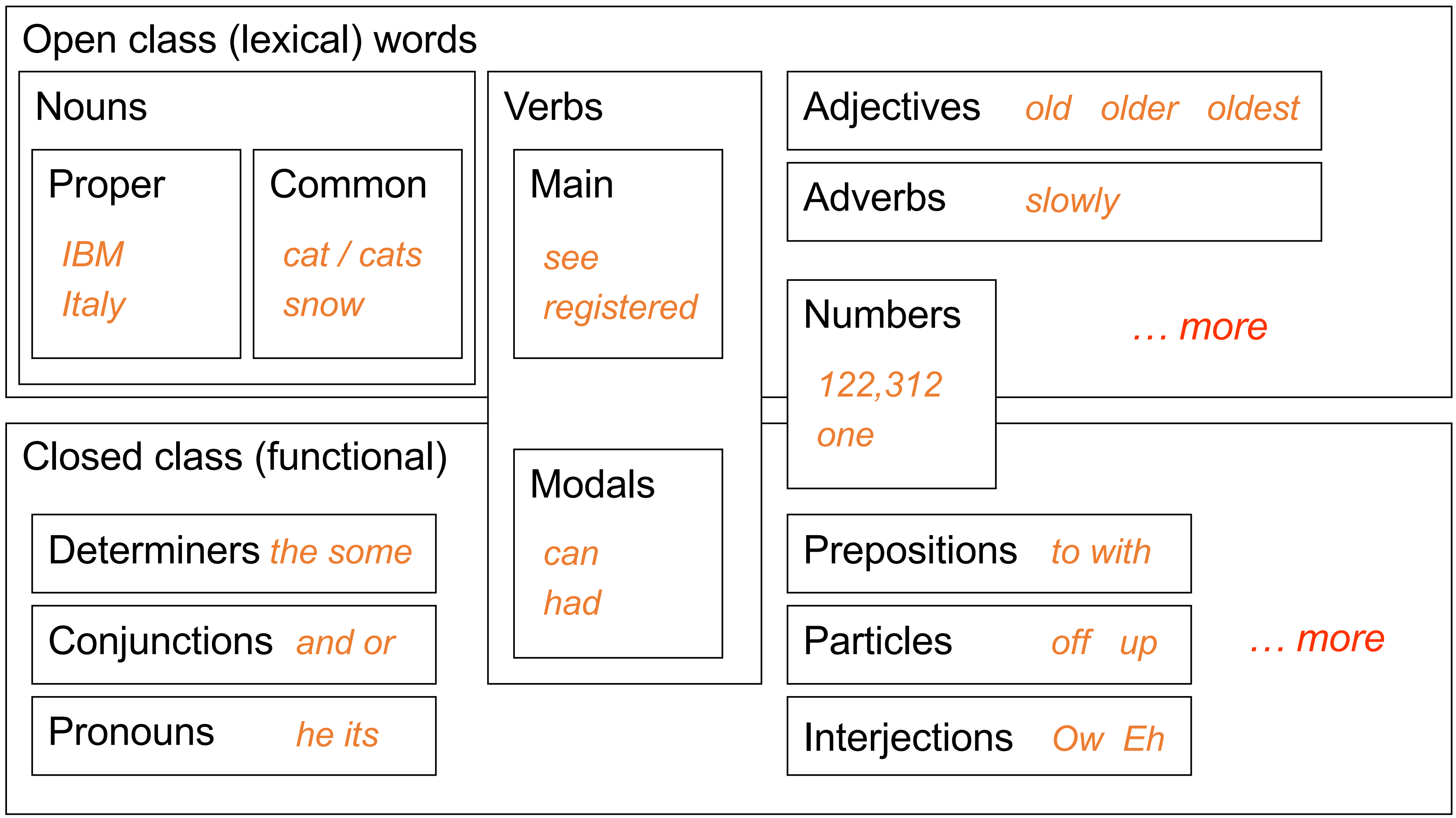
- Original Brown corpus used a large set of 87 POS tags.
- Most common in NLP today is the Penn Treebank set of 45 tags.
  - Tagset used in the slides.
  - Reduced from the Brown set for use in the context of a parsed corpus (i.e. Penn Treebank).

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)



Open class (lexical) words
Nouns
Proper
IBM
Italy
Common
cat / cats
snow
Verbs
Main
see
registered
Modals
can
had
Adjectives old older oldest
Adverbs slowly
Numbers
122,312
one
… more
Closed class (functional)
Determiners the some
Conjunctions and or
Pronouns he its
Prepositions to with
Particles off up
Interjections Ow Eh
… more

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.

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

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

POS Tagging

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

- 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

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!

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

Sources of information

- What are the main sources of information for POS tagging?
  - **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*

More and Better Features ➔ Feature-based tagger

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

POS Tagging Approaches

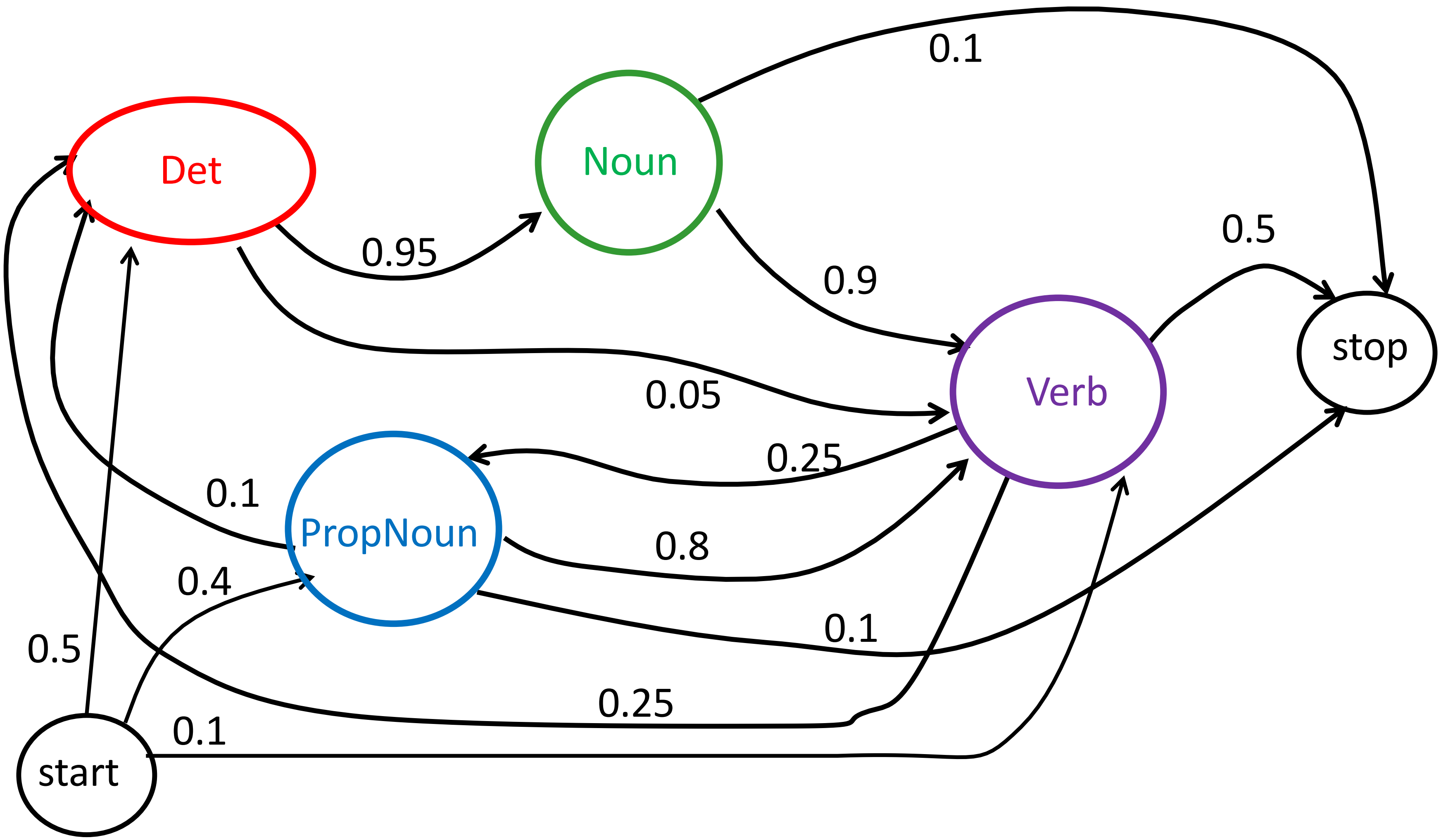
- **Rule-Based**: Human crafted rules based on lexical and other linguistic knowledge.
- **Learning-Based**: Trained on human annotated corpora like the Penn Treebank.
  - **Statistical models**: Hidden Markov Model (HMM) – **this lecture!**, Maximum Entropy Markov Model (MEMM), Conditional Random Field (CRF)
  - **Rule learning**: Transformation Based Learning (TBL)
  - **Neural networks**: Recurrent networks like Long Short Term Memory (LSTMs)
- Generally, learning-based approaches have been found to be more effective overall, taking into account the total amount of human expertise and effort involved.

Hidden Markov Model

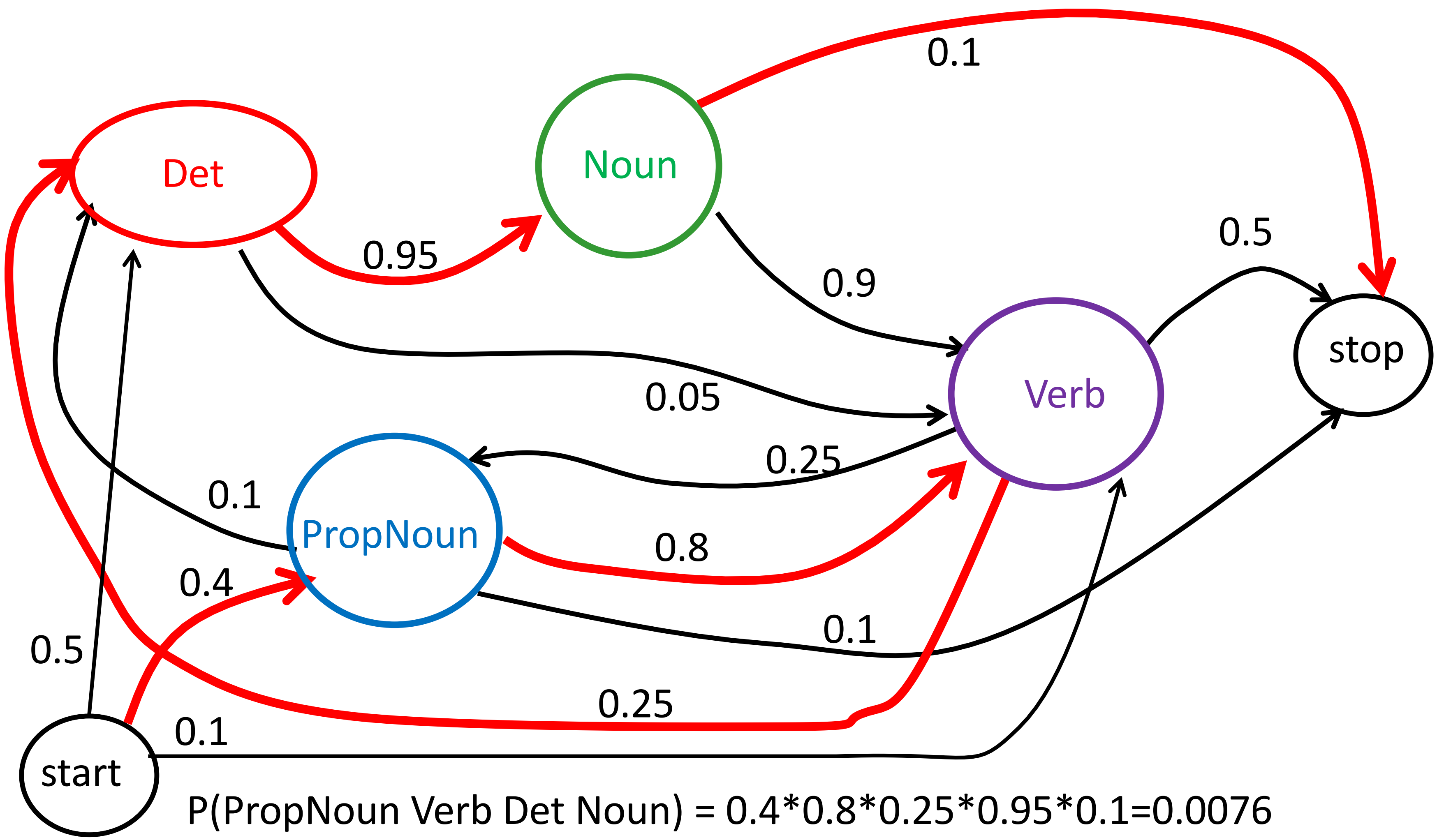
Markov Model / Markov Chain

- 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
(a finite state machine)



Sample Markov Model for POS

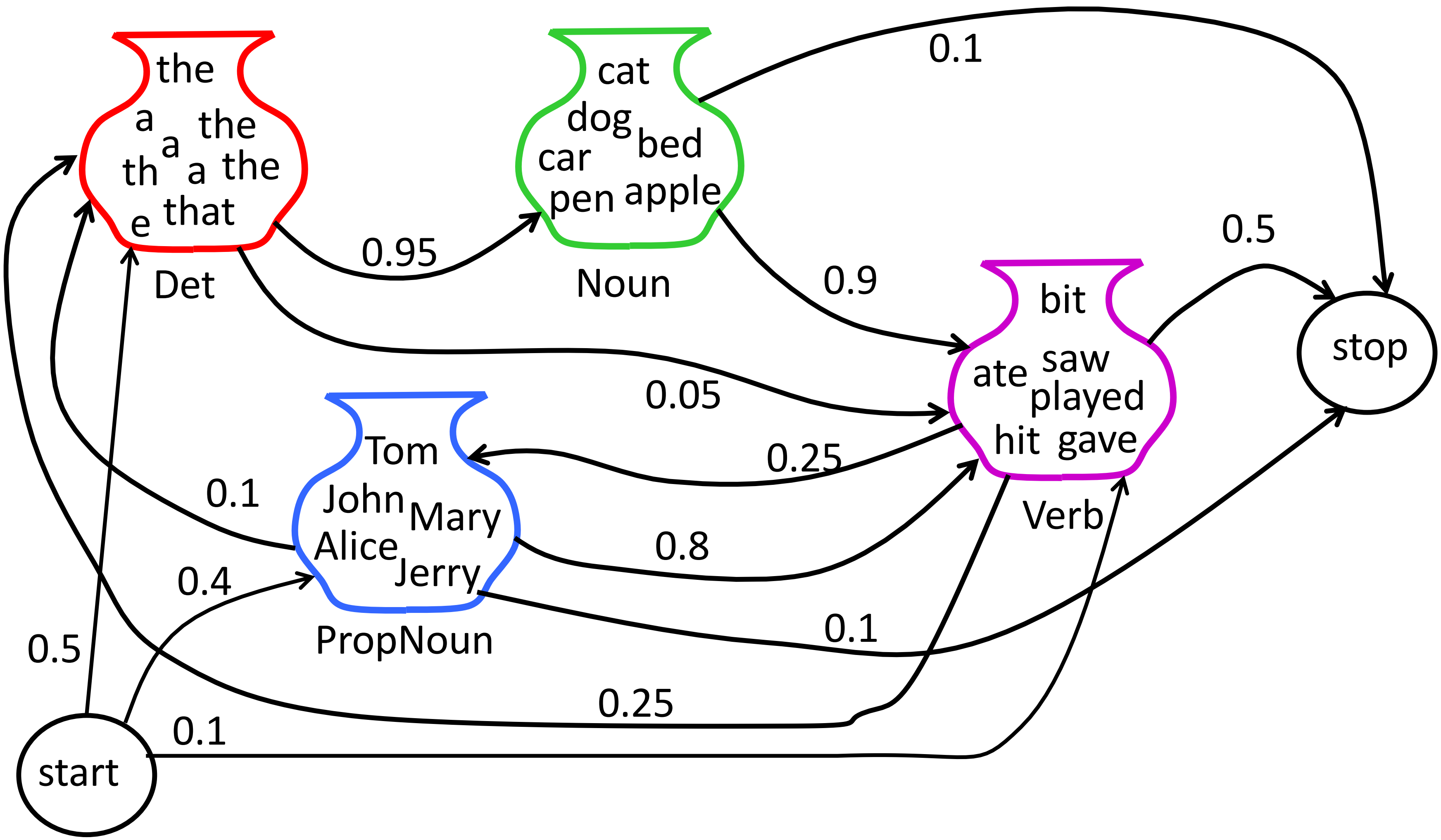


P(PropNoun Verb Det Noun) = 0.4*0.8*0.25*0.95*0.1=0.0076

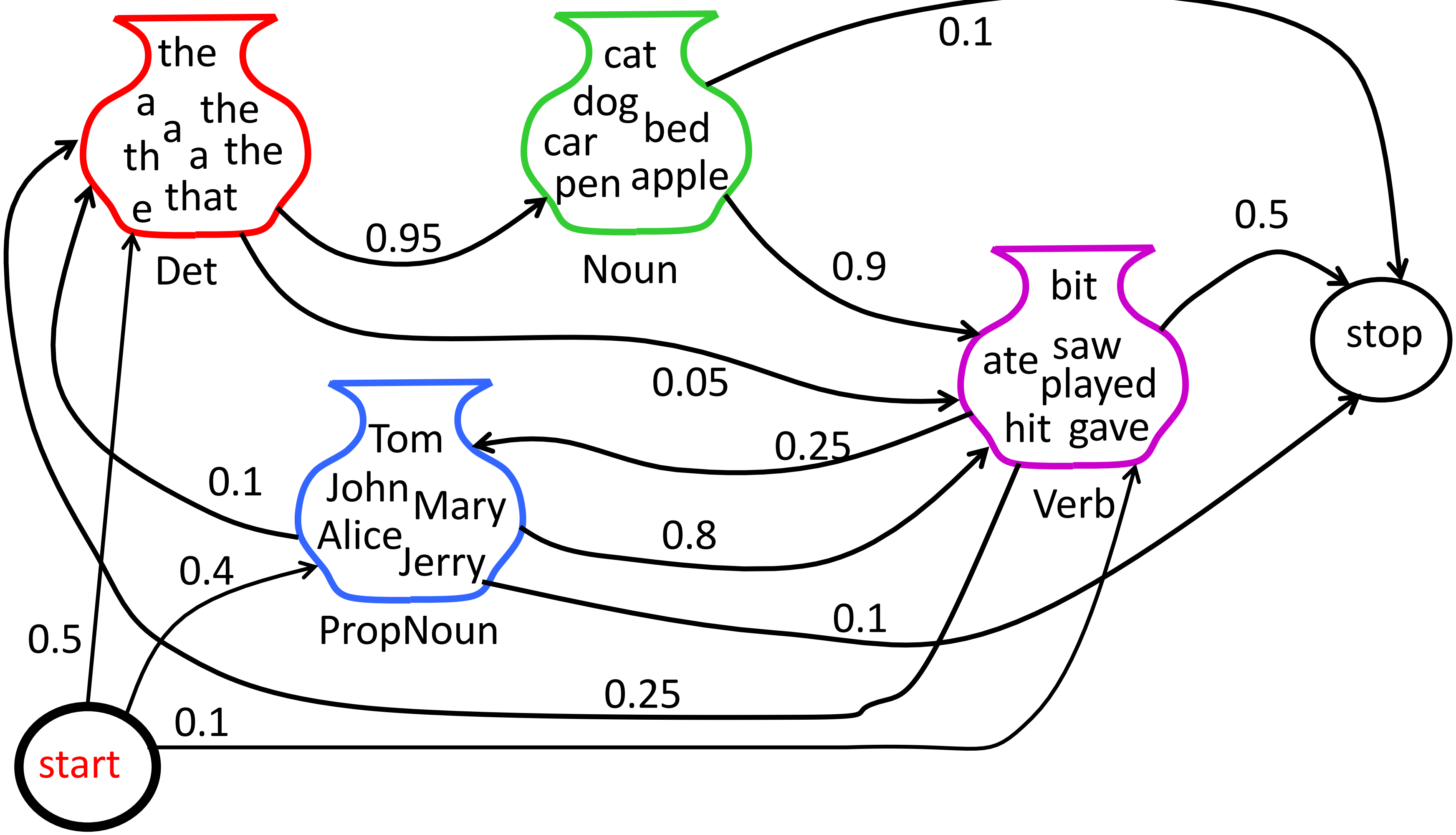
Hidden Markov Model

- 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).

Sample HMM for POS



Sample HMM Generation



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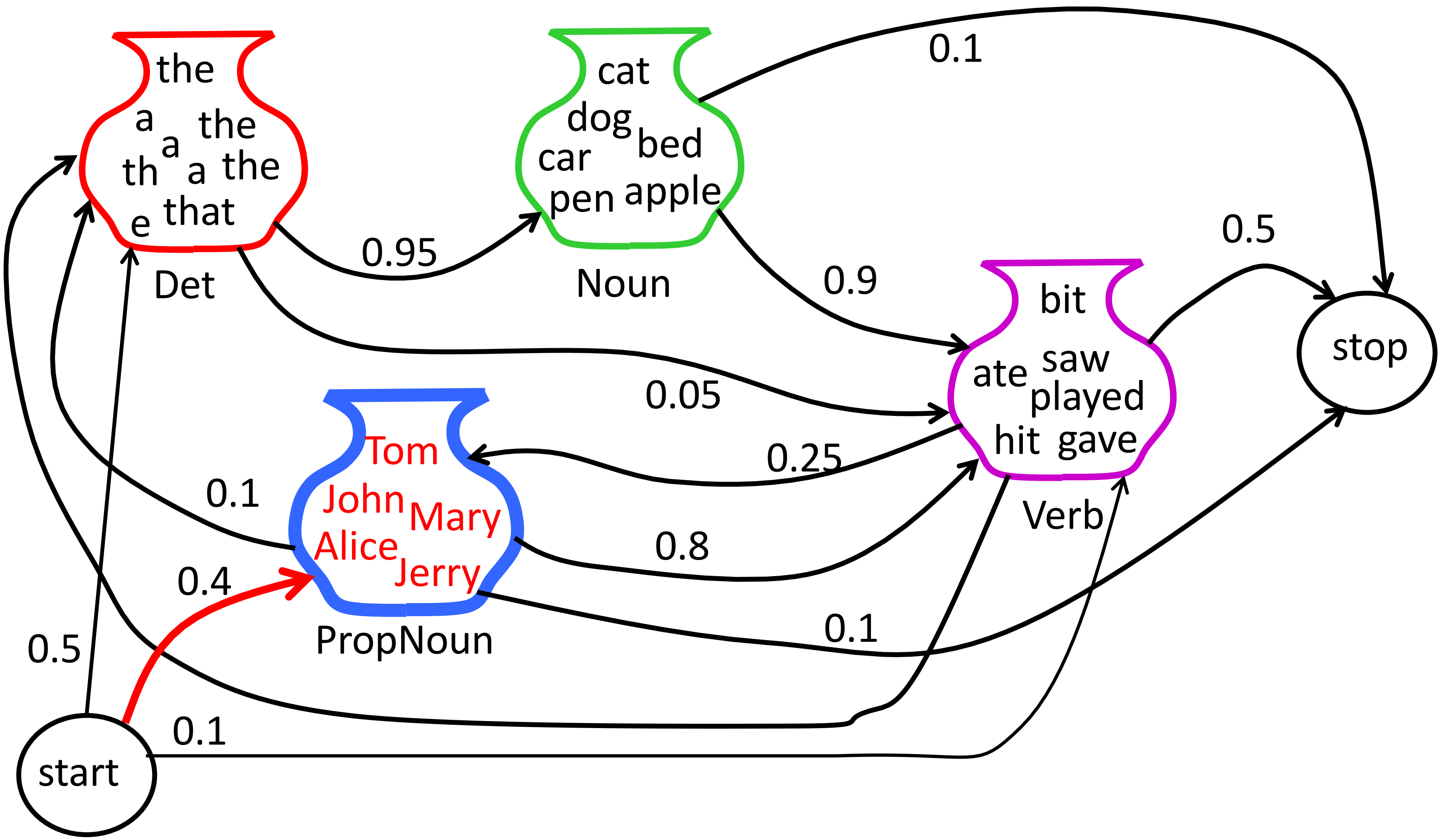

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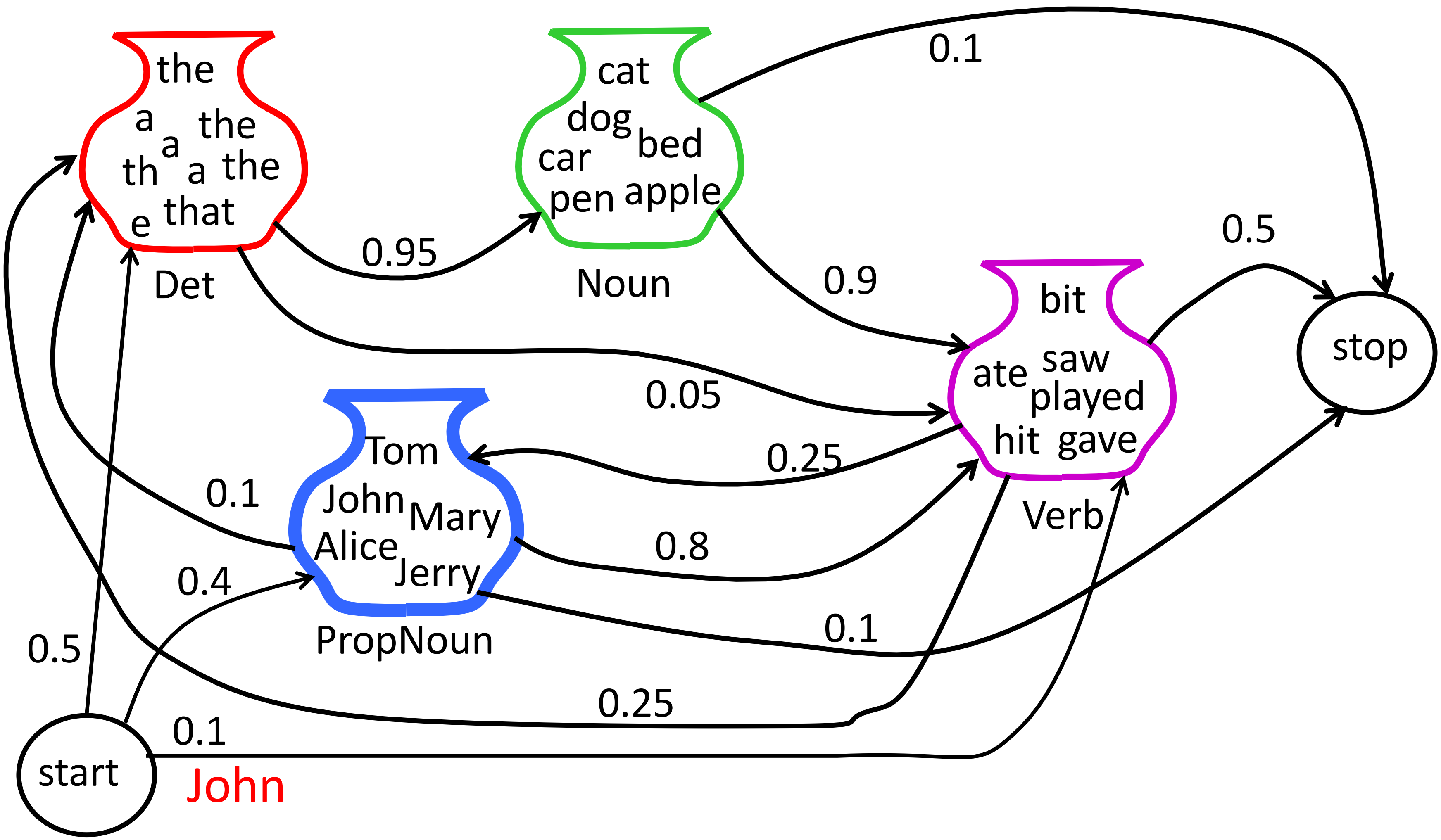

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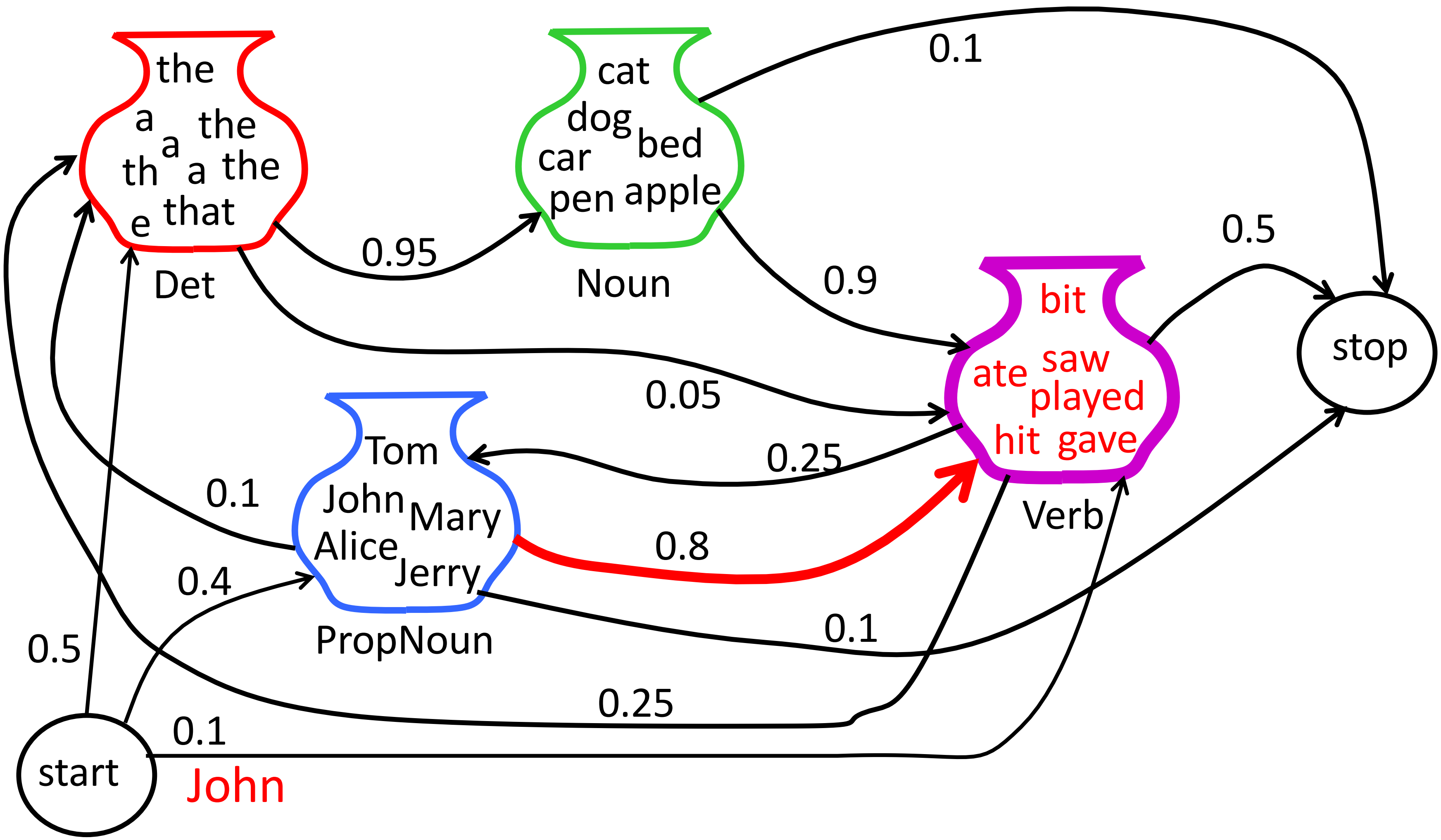

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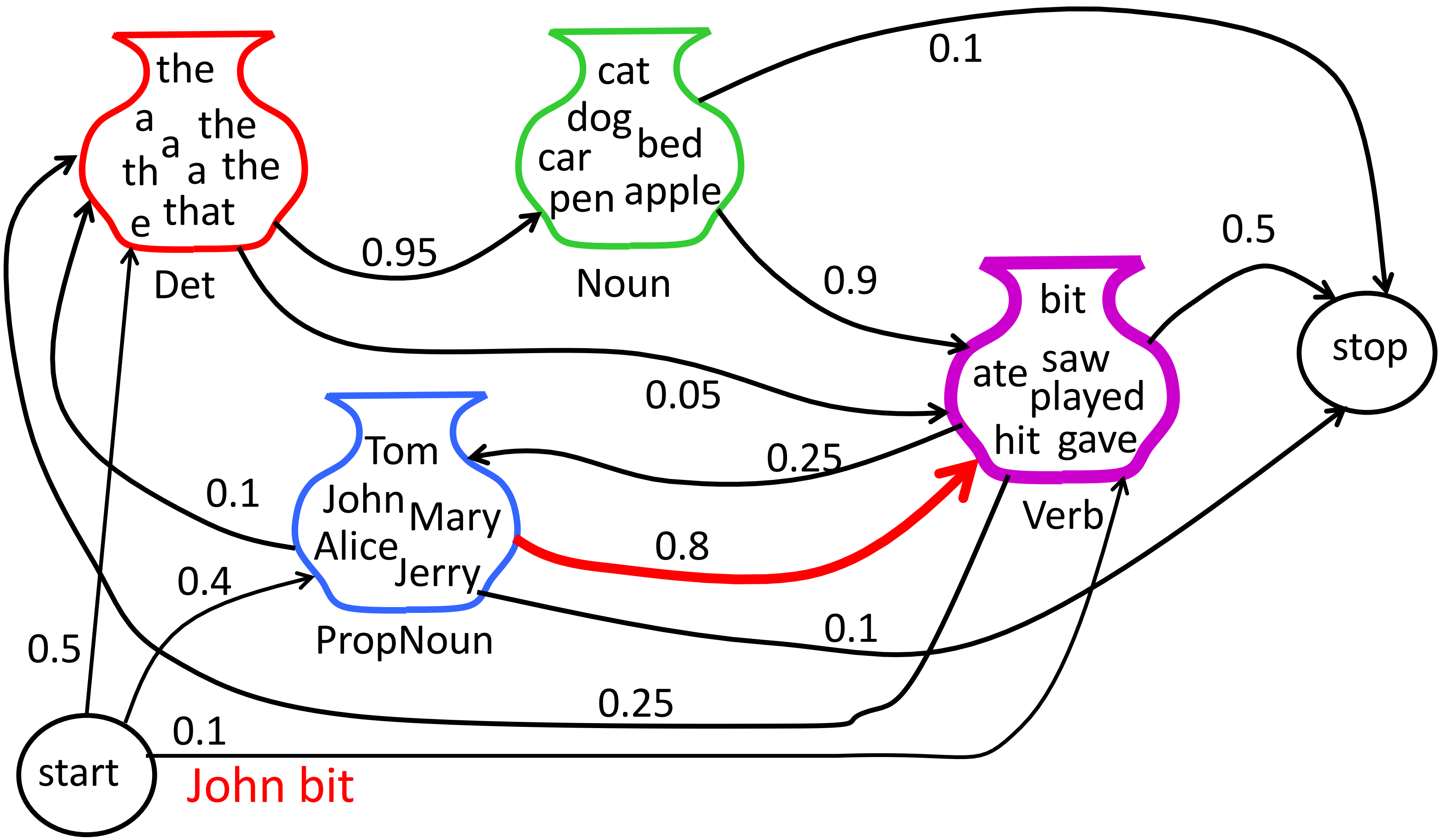

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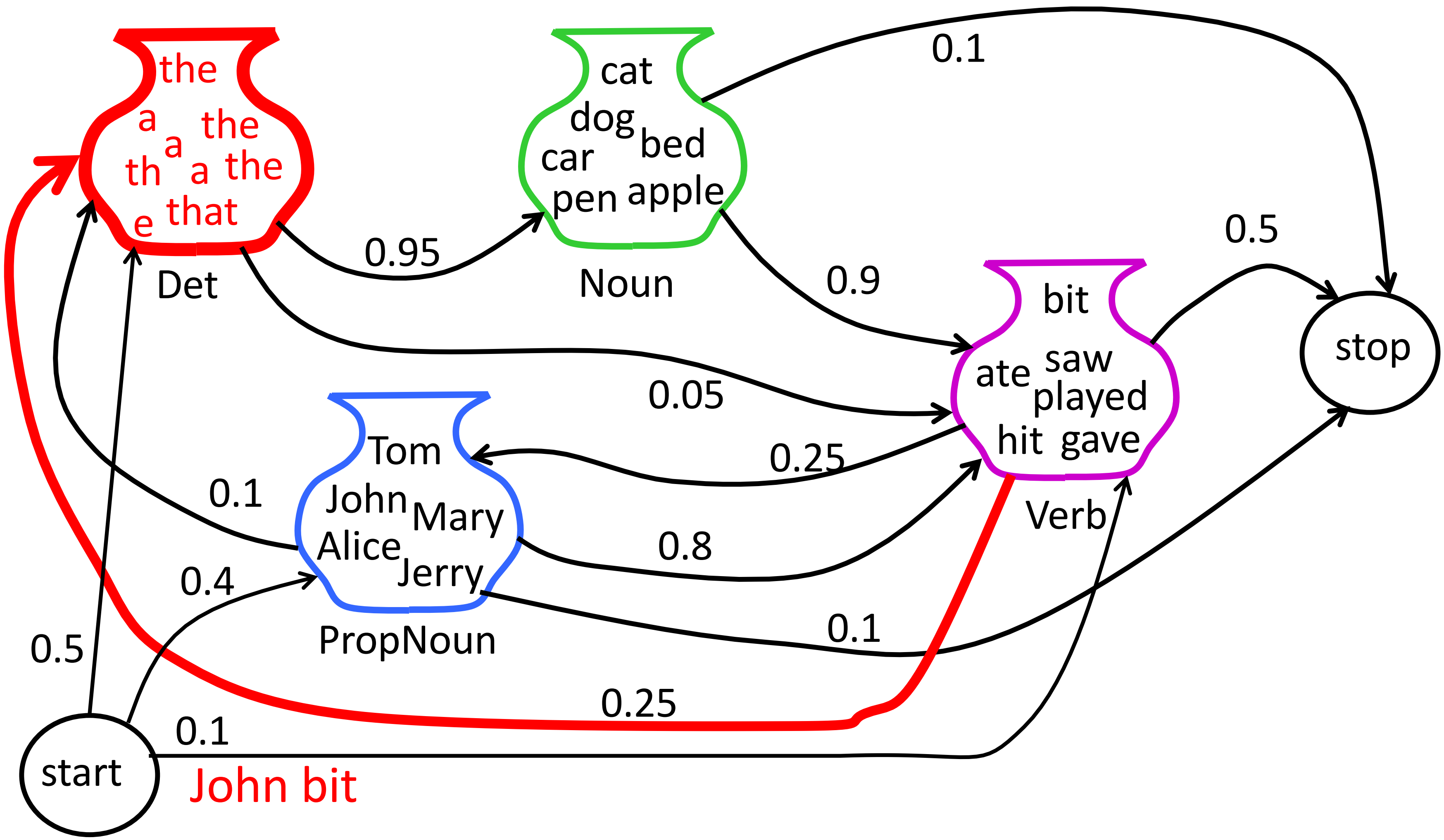

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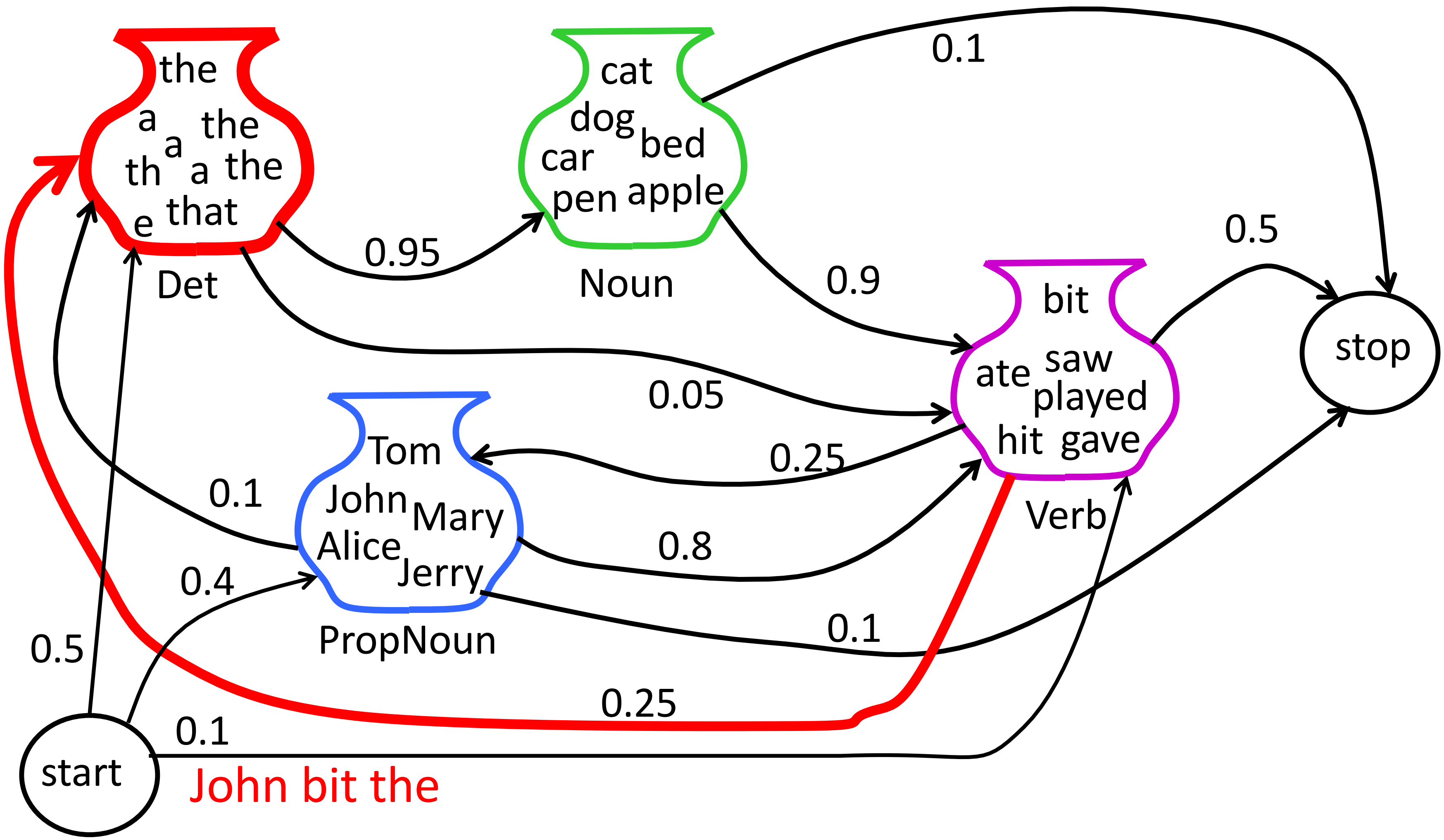

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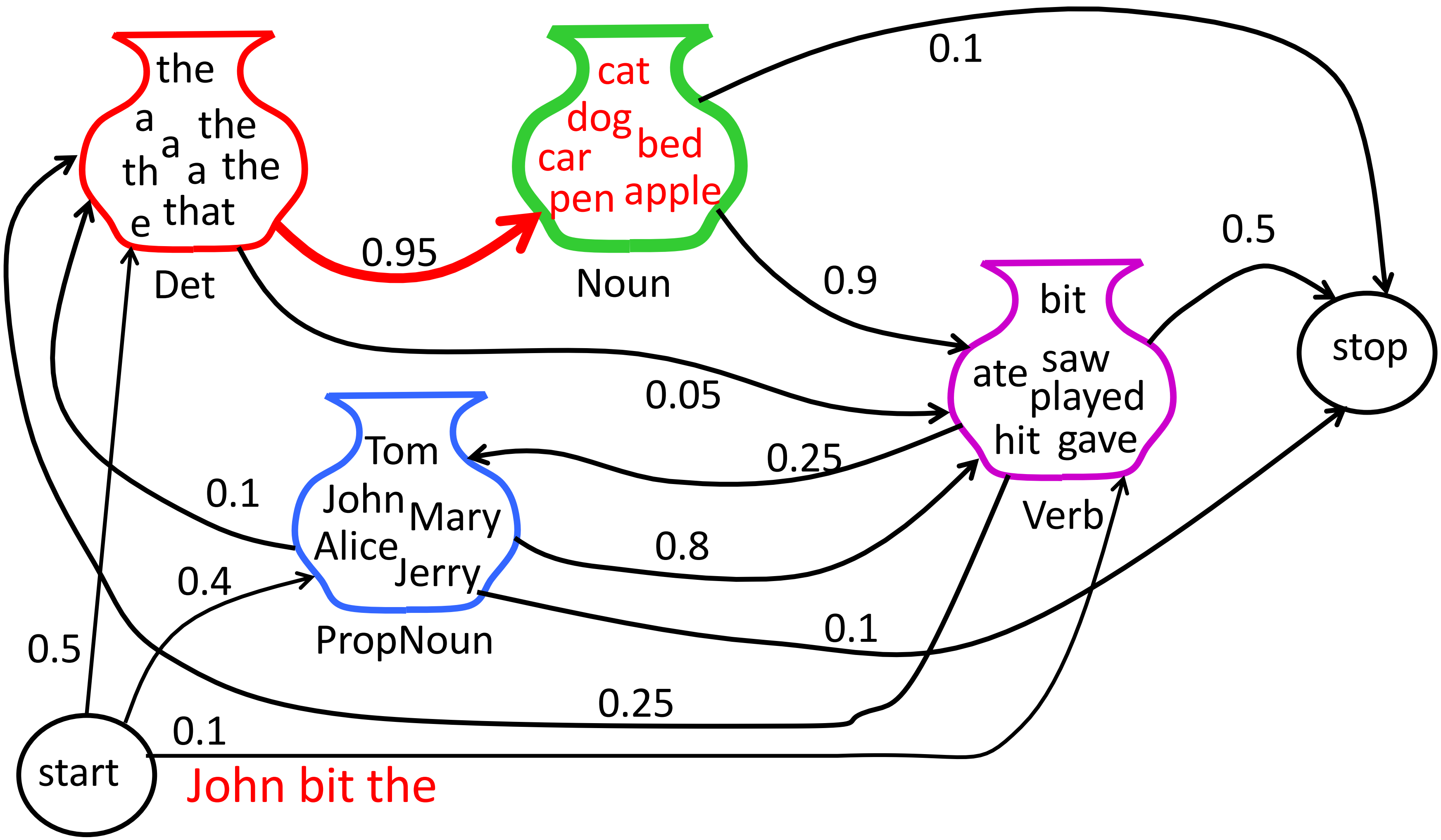

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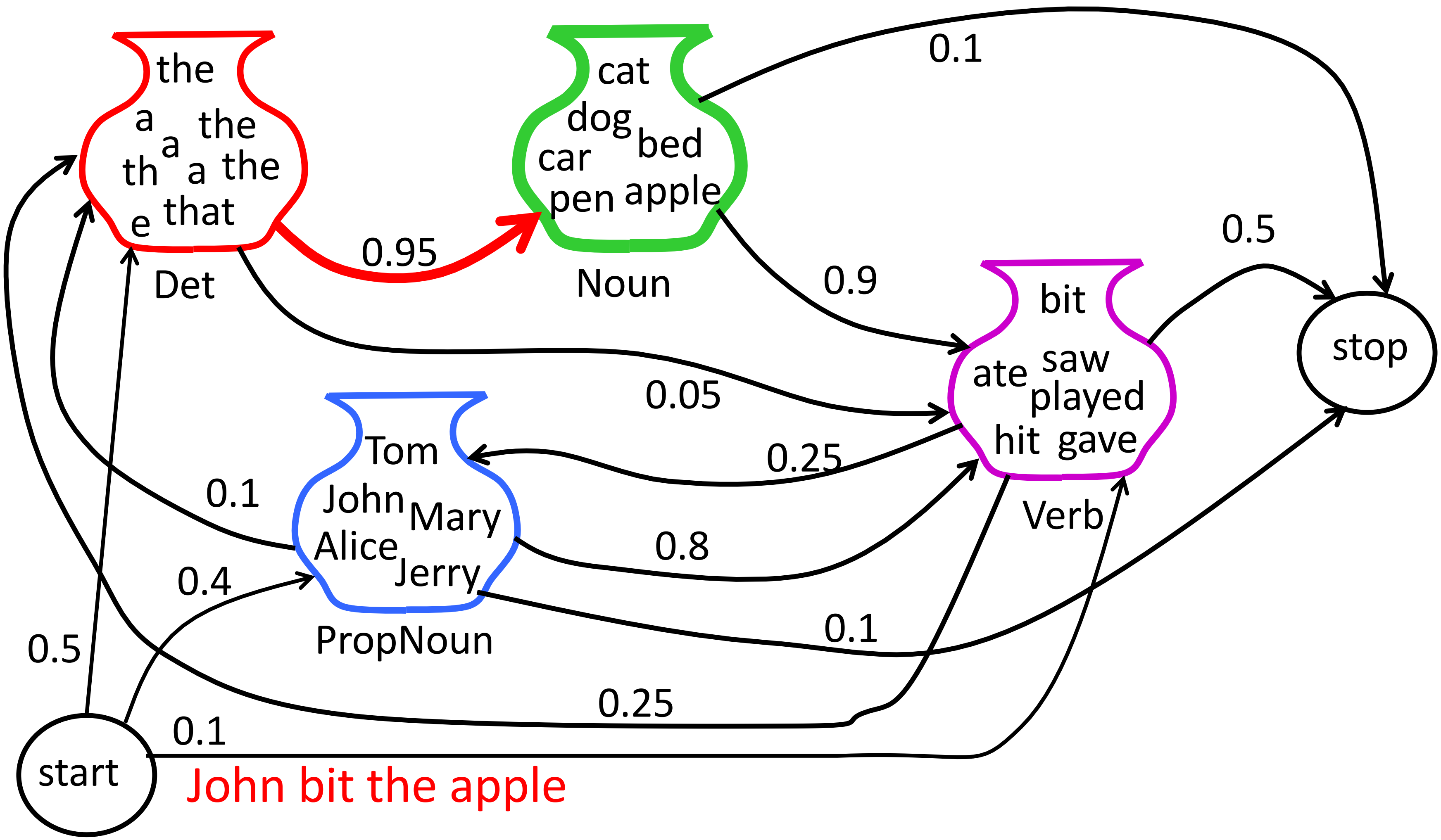

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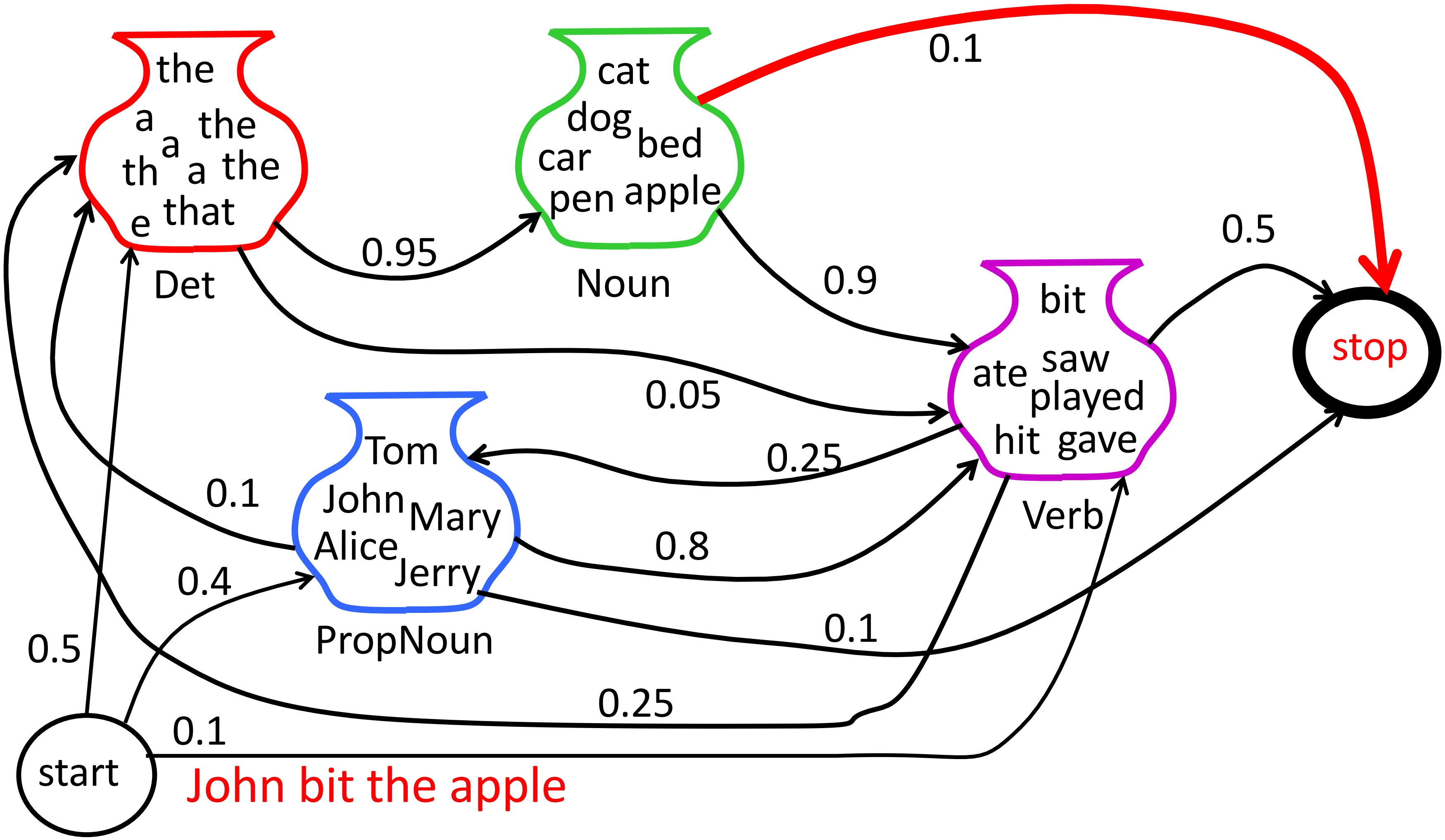

Formally, Markov Sequences

- 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

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

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 $j = 2 \ldots m$,

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

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)

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 $\sum_{x'=1}^{k} q(x'|x) = 1$

Probabilistic Models for Sequence Pairs

- 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

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

Probabilistic Models for Sequence Pairs

- 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**

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- How do we model the joint distribution

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

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**

Supervised Learning Problems

- We have training examples $x^{(i)}, y^{(i)}$ for $i = 1 \ldots m$. Each $x^{(i)}$ is an input, each $y^{(i)}$ is a label.
- Task is to learn a function f mapping inputs x to labels $f(x)$

Generative Models

- We have training examples $x^{(i)}, y^{(i)}$ for $i = 1 \ldots m$. Task is to learn a function f mapping inputs x to labels $f(x)$.

- Generative models:
  - Learn a distribution $p(x, y)$ from training examples
  - Often we have $p(x, y) = p(y)p(x|y)$

- Note: we then have

$$p(y|x) = \frac{p(y)p(x|y)}{p(x)}$$

where $p(x) = \sum_y p(y)p(x|y)$

Prediction with Generative Models

- We have training examples $x^{(i)}, y^{(i)}$ for $i = 1 \dots m$. Task is to learn a function f mapping inputs x to labels $f(x)$.
- Generative models:
  - Learn a distribution $p(x, y)$ from training examples
  - Often we have $p(x, y) = p(y)p(x|y)$
- Output from the model:

$$
\begin{aligned}
f(x) &= \arg\max_y p(y|x) \\
&= \arg\max_y \frac{p(y)p(x|y)}{p(x)} \\
&= \arg\max_y p(y)p(x|y)
\end{aligned}
$$

Probabilistic Models for Sequence Pairs

- 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

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

Hidden Markov Models (HMMs)

- In HMMs, we assume that:

Words **Part-of-Speech tags**

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

$$= P(S_1 = s_1) \prod_{j=2}^{m} P(S_j = s_j | S_{j-1} = s_{j-1}) \prod_{j=1}^{m} P(X_j = x_j | S_j = s_j)$$

Independence Assumptions in HMMs

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

$$
\begin{aligned}
& P(X_1 = x_1, \ldots, X_m = x_m, S_1 = s_1, \ldots, S_m = s_m) \\
= \quad & P(S_1 = s_1, \ldots, S_m = s_m) \times \\
& P(X_1 = x_1, \ldots, X_m = x_m | S_1 = s_1, \ldots, S_m = s_m)
\end{aligned}
$$

- 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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& 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)
\end{aligned}
$$

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

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

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 $x \in \{1, 2, \ldots, o\}$

HMM

- Parameter estimation
  - Learning the probabilities from training data
  - P(verb|noun)?, P(apple|noun)?

- Inference: Viterbi algorithm (dynamic programming)
  - Given a new sentence, what are the POS tags for the words?

HMM

- Parameter estimation

- Inference: Viterbi algorithm (dynamic programming)

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.)

Parameter Estimation: Transition Parameters

- $P(\text{verb}|\text{noun})$?

- 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

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

Parameter Estimation: Emission Parameters

- P(apple|noun)?

- 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

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

Parameter Estimation: Initial State Parameters

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

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

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

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

HMM

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

The Viterbi Algorithm

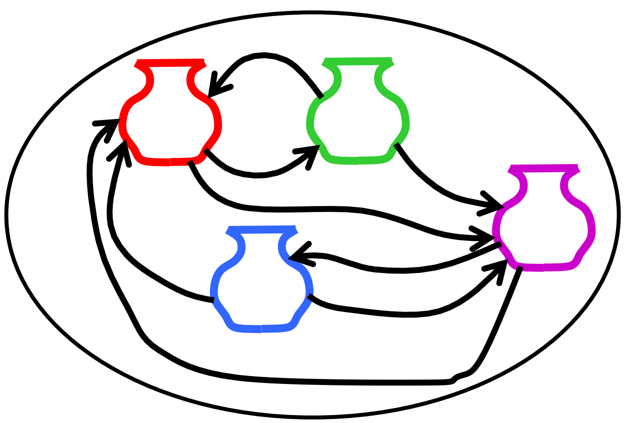
- Goal: for a given input sequence $x_1, \ldots, x_m$, find

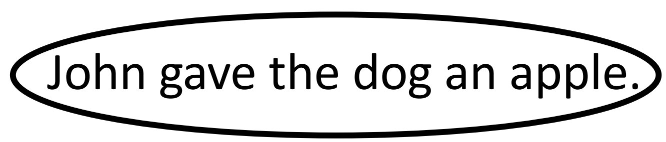
$$\arg \max_{s_1, \ldots, s_m} p(x_1 \ldots x_m, s_1 \ldots s_m; \underline{\theta})$$

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

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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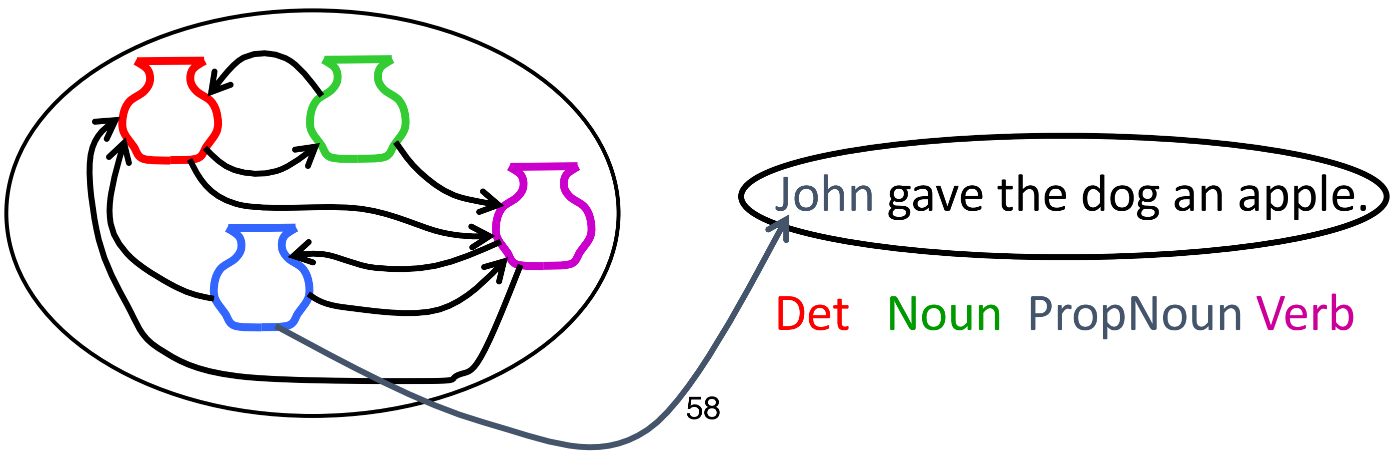

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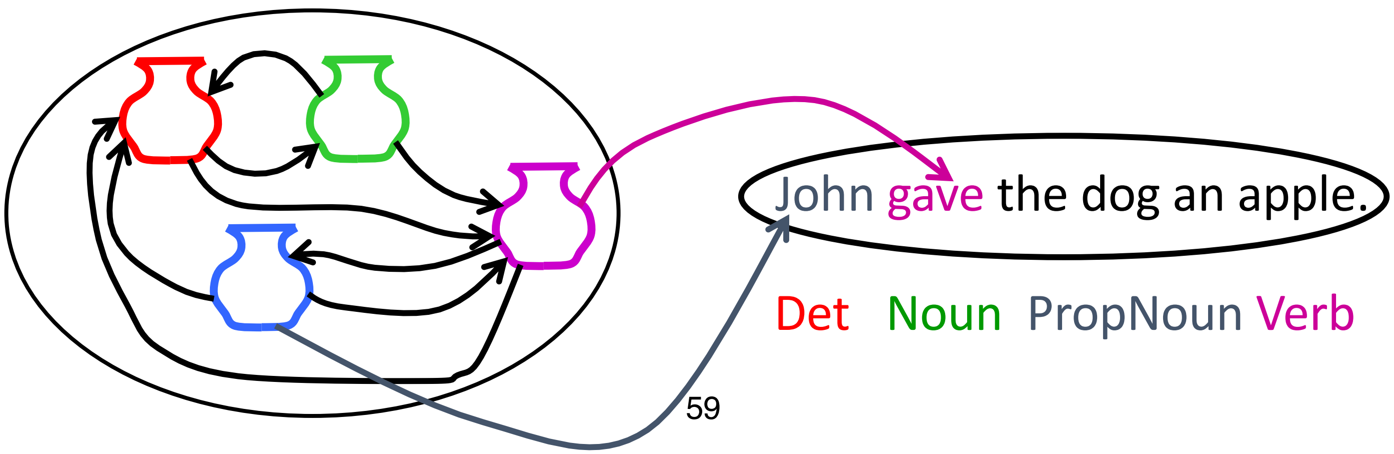

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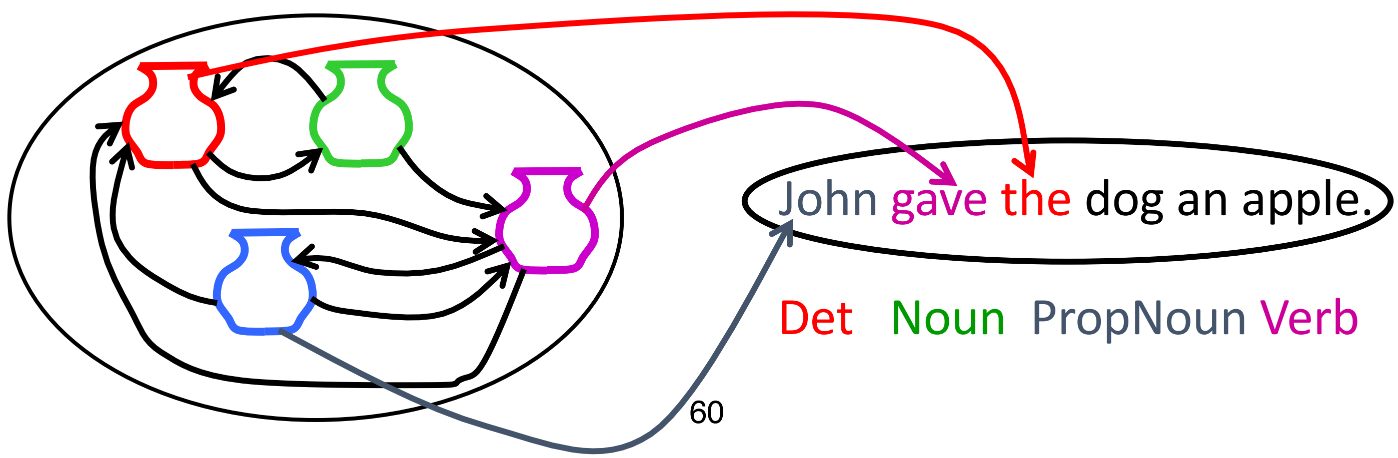

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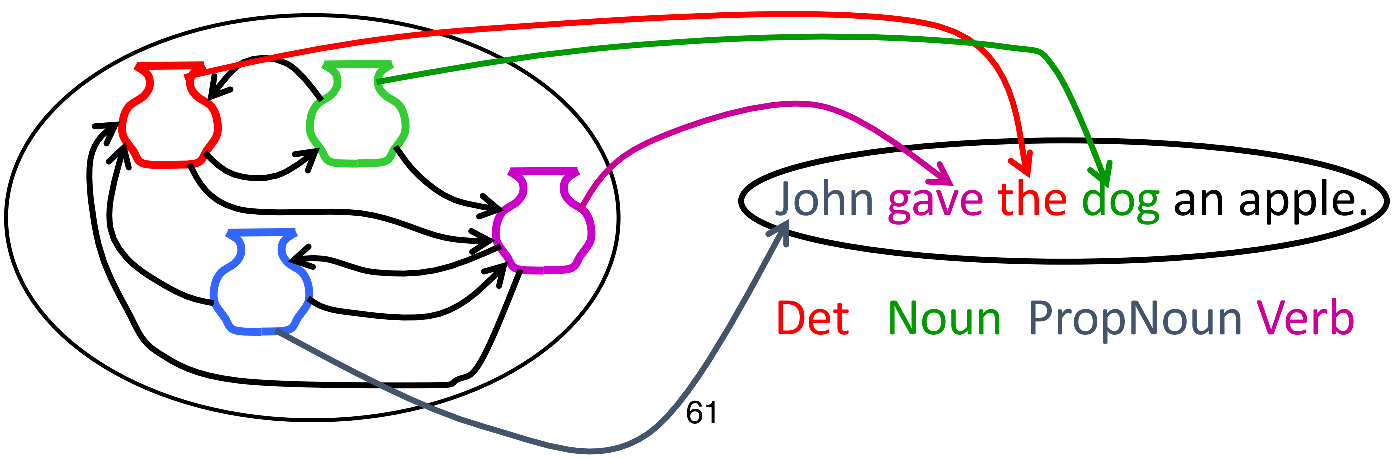
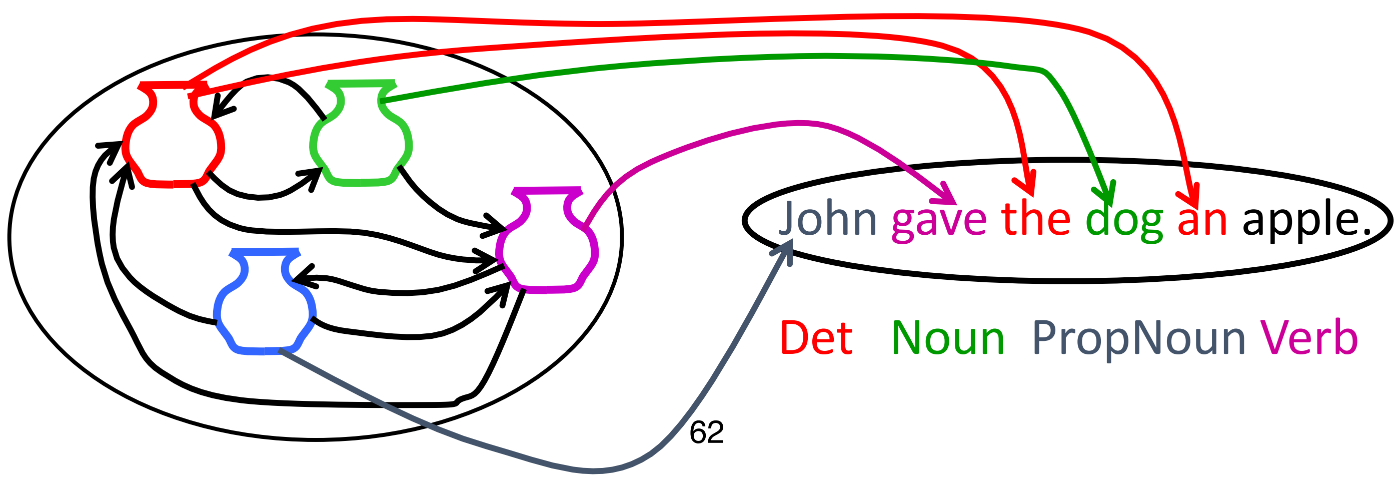


Most Likely State Sequence

- 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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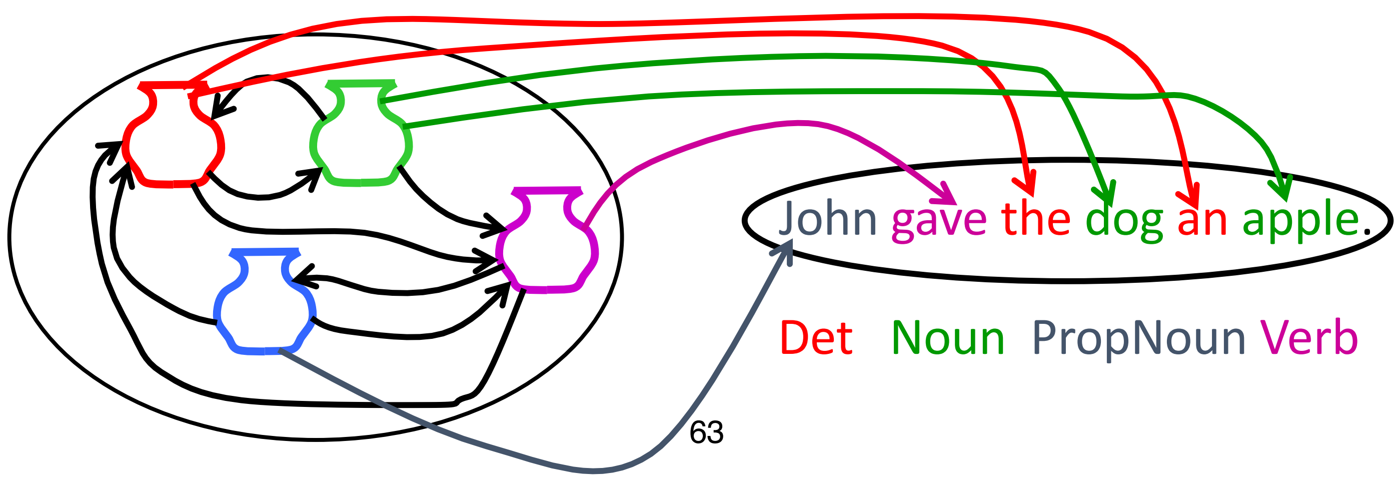
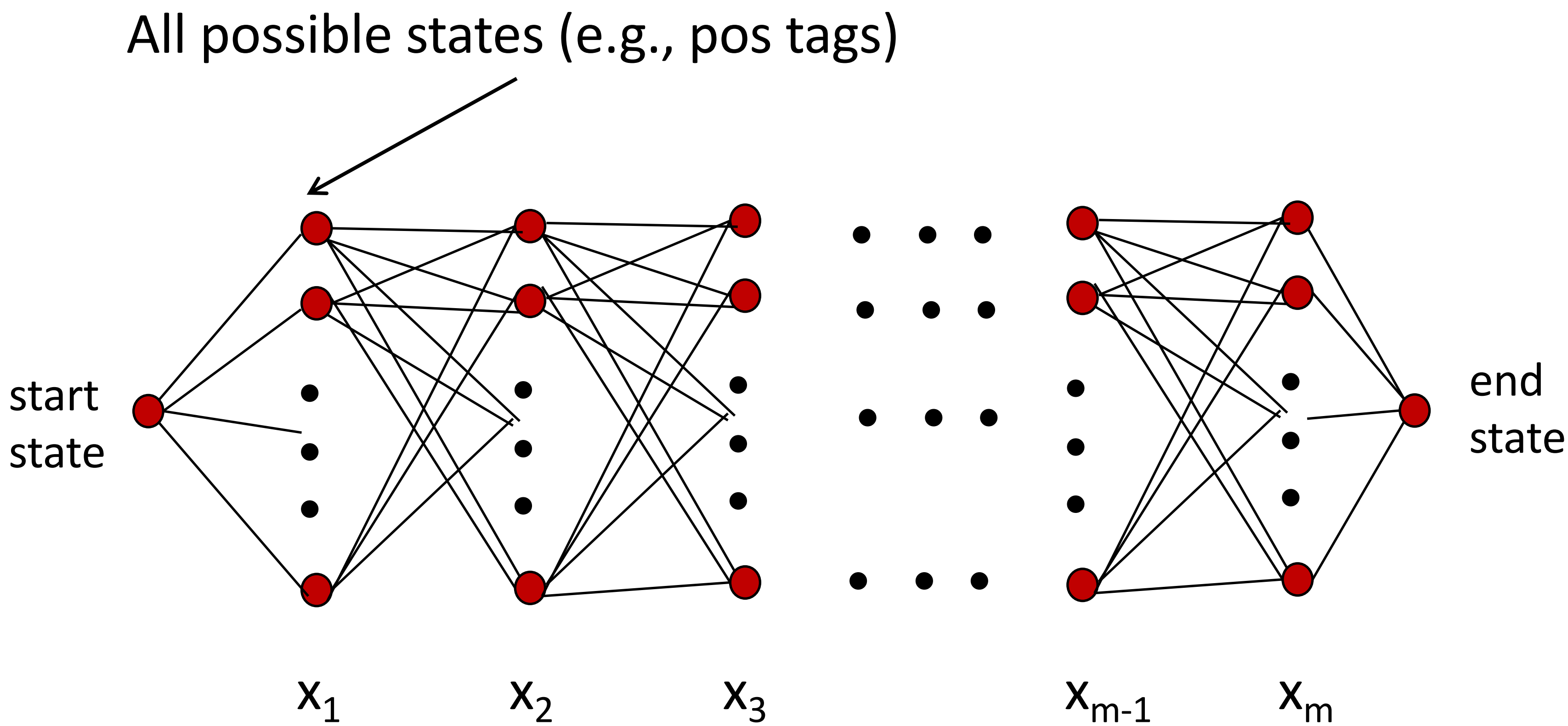




- Continue forward in time until reaching final time point.
- **The goal**: find a path with highest probability

The Viterbi Algorithm

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

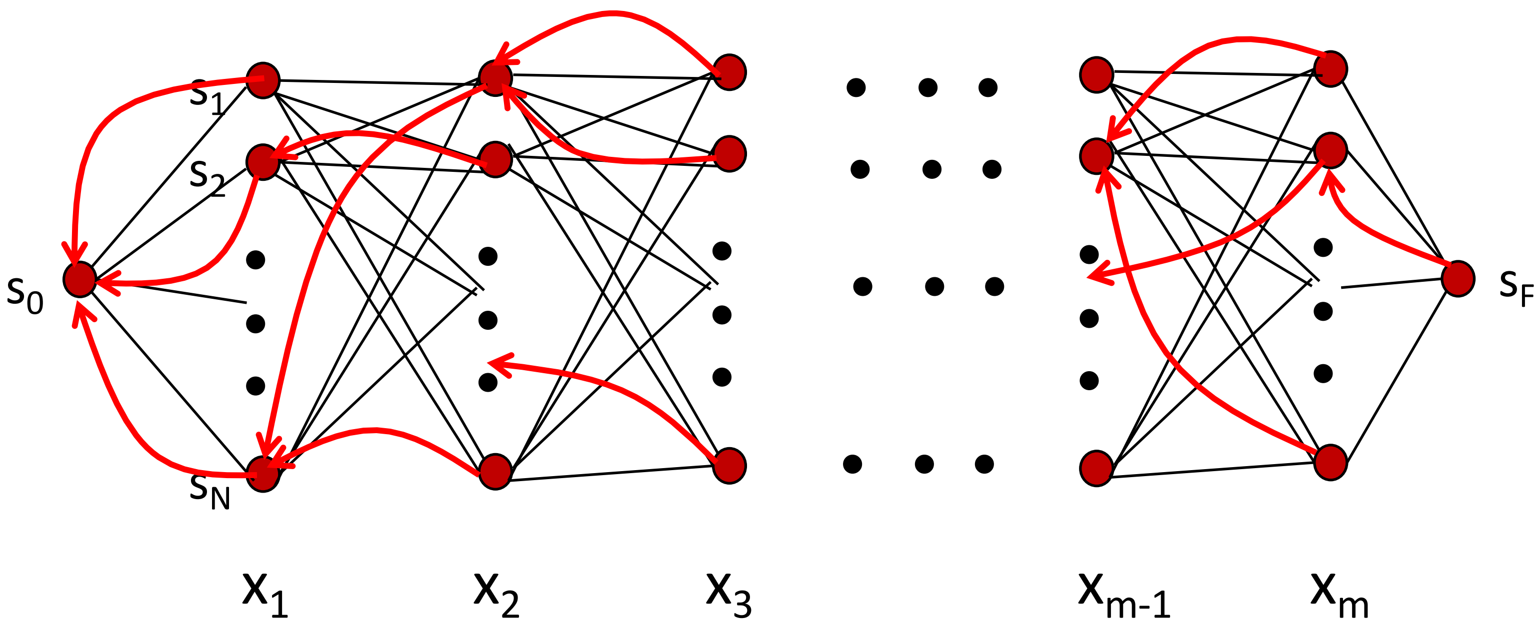
$$\arg \max_{s_1, \ldots, s_m} p(x_1 \ldots x_m, s_1 \ldots s_m; \underline{\theta})$$

- 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 $j > 1$,

$$\pi[j, s] = \max_{s_1 \ldots s_{j-1}} \left[t(s_1)e(x_1|s_1) \left(\prod_{k=2}^{j-1} t(\overset{\substack{\textbf{Transition}\\ \downarrow}}{s_k}|s_{k-1})e(\overset{\substack{\textbf{Emission}\\ \downarrow}}{x_k}|s_k) \right) \overset{\substack{\textbf{State s}\\ \downarrow}}{t}(s|s_{j-1})e(\overset{\substack{\textbf{Emission}\\ \textbf{from}\\ \textbf{state s}\\ \downarrow}}{x_j}|s) \right]$$



s_0
s_1
s_2
s_N
s_F
x_1
x_2
x_3
x_{m-1}
x_m

The Viterbi Algorithm

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

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

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

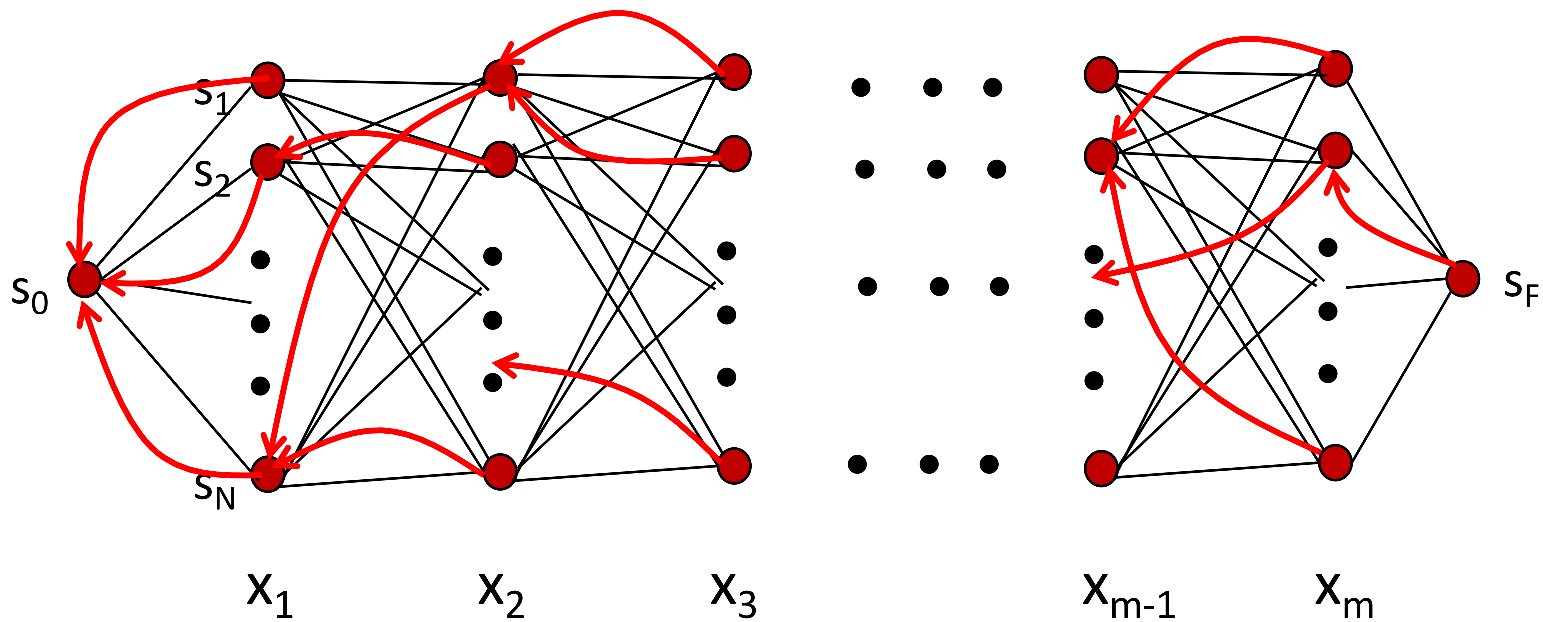
$$\pi[j, s] = \max_{s' \in \{1 \ldots k\}} \left[\pi[j-1, s'] \times t(s|s') \times e(x_j|s)\right]$$

- We then have

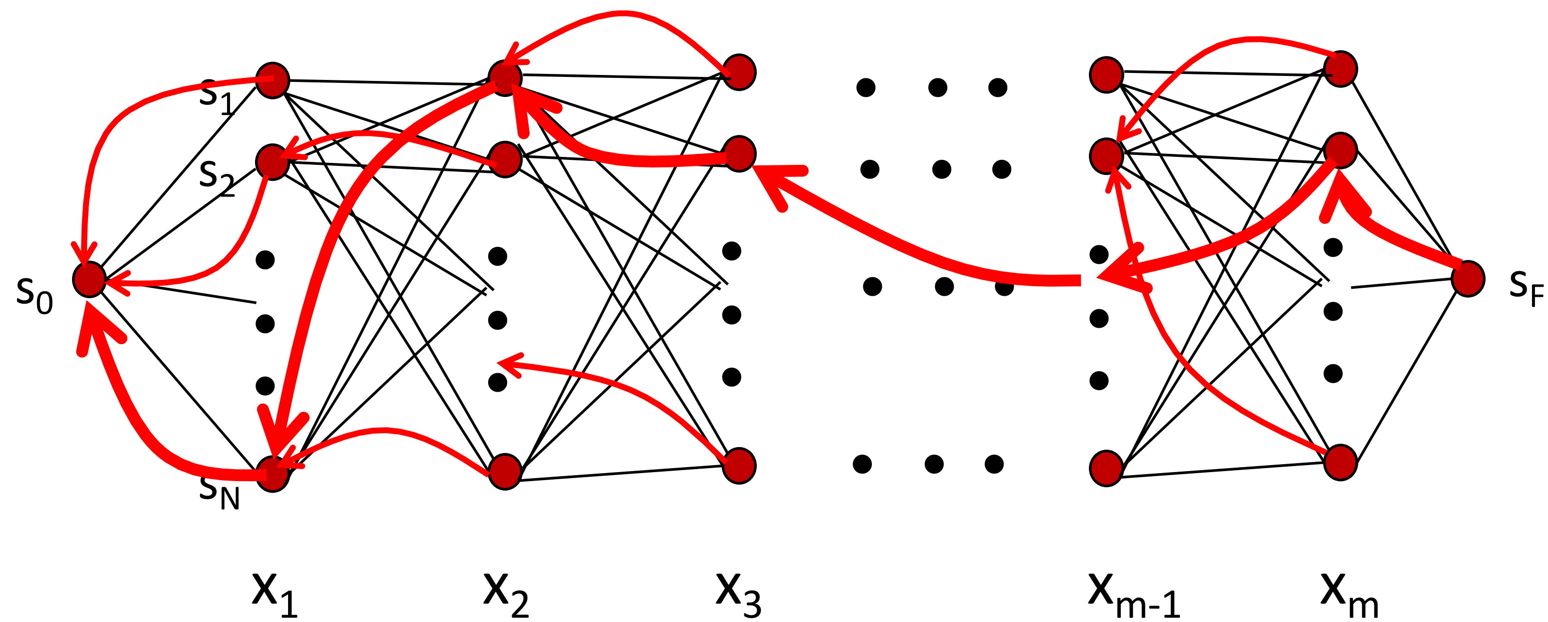
$$\max_{s_1 \ldots s_m} p(x_1 \ldots x_m, s_1 \ldots s_m; \underline{\theta}) = \max_s \pi[m, s]$$

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

Viterbi Backpointers



Viterbi Backtrace



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

The Viterbi Algorithm: Backpointers

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

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

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

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

and

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

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

- 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 $j = m \ldots 2$,

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

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

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

Homework

- Reading J&M ch5&6
- Reading ch6 at https://web.stanford.edu/~jurafsky/slp3/6.pdf
- HMM notes
  - http://www.cs.columbia.edu/~mcollins/hmms-spring2013.pdf

- Assignment 1 is out. Due Feb 6.

- Start thinking about course project and find a team.