CSE 5525: Foundations of Speech and Language Processing

Week 3, Lecture 1: Part-Of-Speech Tagging, Sequence Labeling, and Hidden Markov Models (HMMs)

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Many thanks for slides from Prof. Ray Mooney at UT Austin

Logistics

- HW#1 due tonight
- HW#2 OUT
  - 4 weeks (Due on 10/07/2020)
  - BUT, start early!!! (More challenging & lots coming up in OCT)

Reading lecture notes (given in the last column of our course schedule) is necessary to fully understand this week's topics (e.g., HMM/CRF)

Part Of Speech Tagging

- Annotate each word in a sentence with a part-of-speech marker (i.e., syntactic role).
- Lowest level of syntactic analysis.

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.

Penn Treebank Tagset: 45 Tags

Tag	Description	Example	Tag	Description	Example
CC	coordin. conjunction	*and, but, or*	SYM	symbol	+,%, &
CD	cardinal number	*one, two, three*	TO	“to”	*to*
DT	determiner	*a, the*	UH	interjection	*ah, oops*
EX	existential ‘there’	*there*	VB	verb, base form	*eat*
FW	foreign word	*mea culpa*	VBD	verb, past tense	*ate*
IN	preposition/sub-conj	*of, in, by*	VBG	verb, gerund	*eating*
JJ	adjective	*yellow*	VBN	verb, past participle	*eaten*
JJR	adj., comparative	*bigger*	VBP	verb, non-3sg pres	*eat*
JJS	adj., superlative	*wildest*	VBZ	verb, 3sg pres	*eats*
LS	list item marker	*1, 2, One*	WDT	wh-determiner	*which, that*
MD	modal	*can, should*	WP	wh-pronoun	*what, who*
NN	noun, sing. or mass	*llama*	WP$	possessive wh-	*whose*
NNS	noun, plural	*llamas*	WRB	wh-adverb	*how, where*
NNP	proper noun, singular	*IBM*	$	dollar sign	$
NNPS	proper noun, plural	*Carolinas*	#	pound sign	#
PDT	predeterminer	*all, both*	“	left quote	‘ or “
POS	possessive ending	*’s*	”	right quote	’ or ”
PRP	personal pronoun	*I, you, he*	(	left parenthesis	[, (, {, <
PRP$	possessive pronoun	*your, one’s*	)	right parenthesis	],), }, >
RB	adverb	*quickly, never*	,	comma	,
RBR	adverb, comparative	*faster*	.	sentence-final punc	. ! ?
RBS	adverb, superlative	*fastest*	:	mid-sentence punc	: ; ... – -
RP	particle	*up, off*			

Open vs. Closed Class Tags

Open class categories have a large number of words and new ones are easily invented.

– Nouns (Googler, textlish), Verbs (Google), Adjectives (geeky), Abverb (automagically)

Open vs. Closed Class Tags

- **Open class** categories have a large number of words and new ones are easily invented.
  - Nouns (Googler, textlish), Verbs (Google), Adjectives (geeky), Abverb (automagically)

- ***Closed class*** categories are composed of a small, fixed set of grammatical function words for a given language.
  - Pronouns, Prepositions, Modals, Determiners, Particles, Conjunctions
  - e.g., "among" "down"

Ambiguity in POS Tagging

- “Like” can be a verb or a preposition
  - I like/? candy.
  - Time flies like/? an arrow.

Ambiguity in POS Tagging

- "Like" can be a verb or a preposition
  - I like/VBP candy.
  - Time flies like/IN an arrow. (preposition)
- "Around" can be a preposition, particle, or adverb

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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.

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 can give about 90% accuracy
  – Even higher 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 the tokens in a sequence.

There are relationships between the tags!

Noun-Verb is more likely than Verb-Verb

More explanations in Section 7.1, Eisenstein.

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

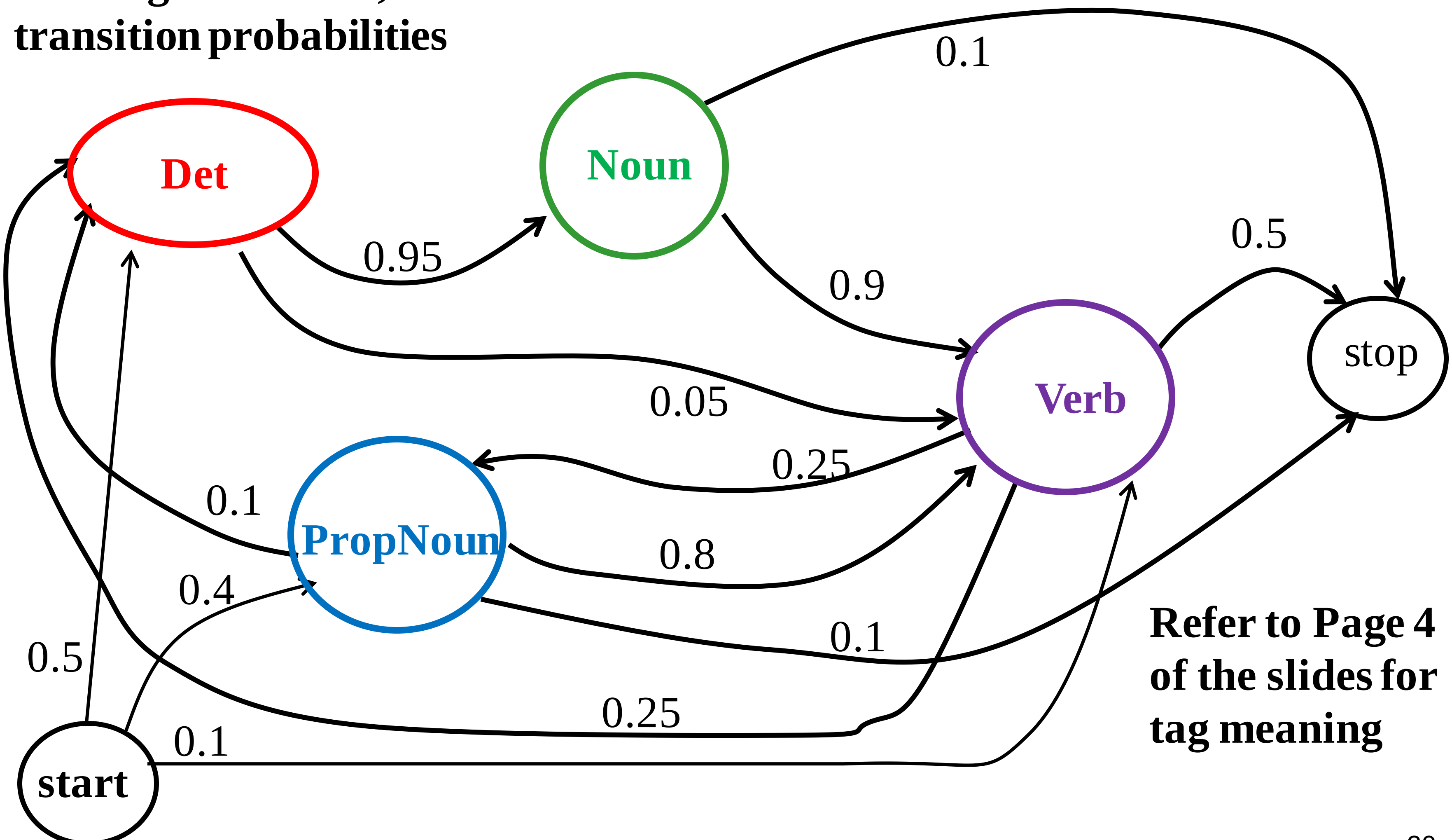
- A finite state machine with probabilistic state transitions.
- Q: What is the Markov assumption?

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

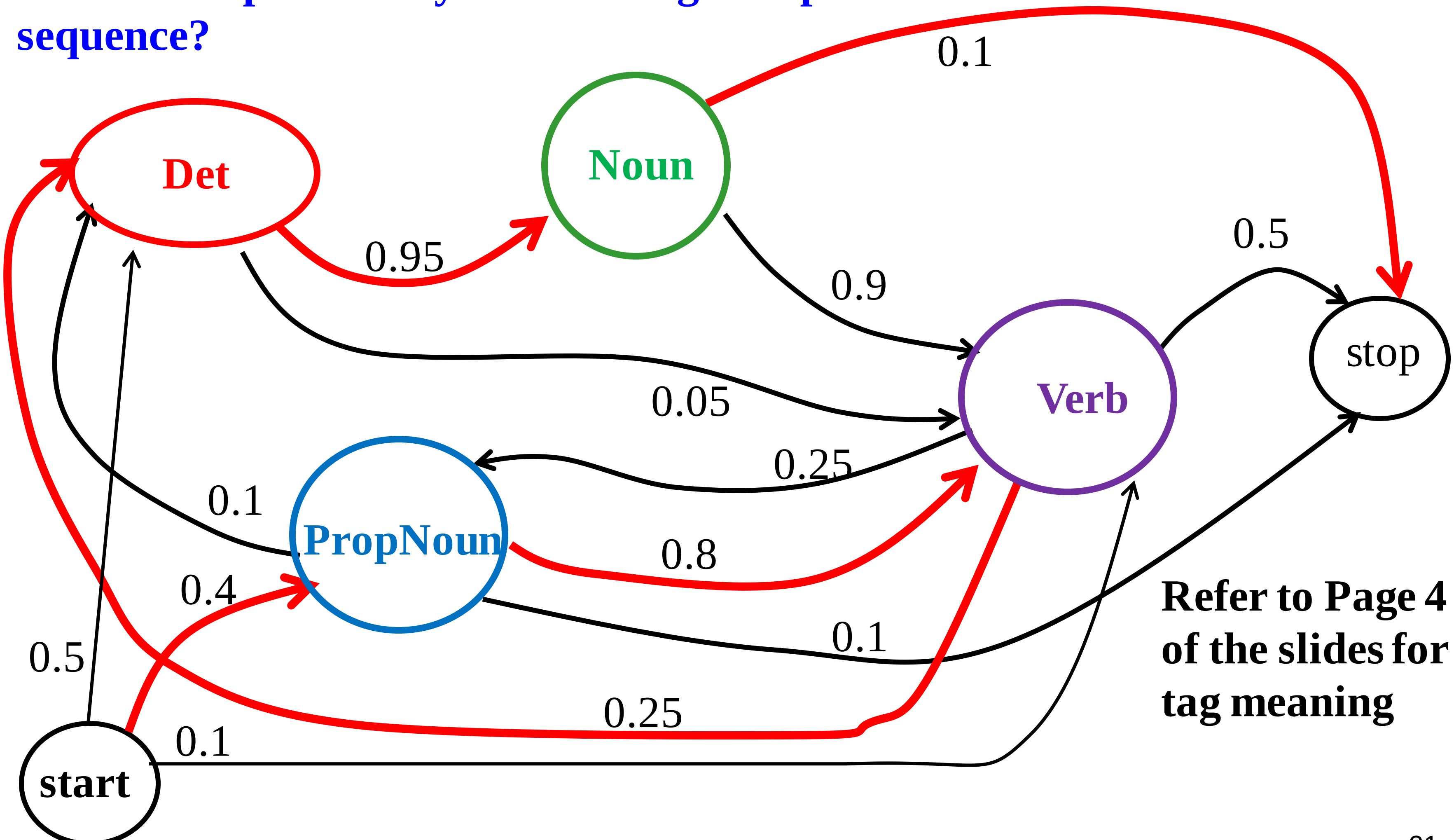
POS tags are states; numbers are state transition probabilities



Refer to Page 4 of the slides for tag meaning

Sample Markov Model for POS

What is the probability of observing "PropNoun Verb Det Noun" as a sequence?



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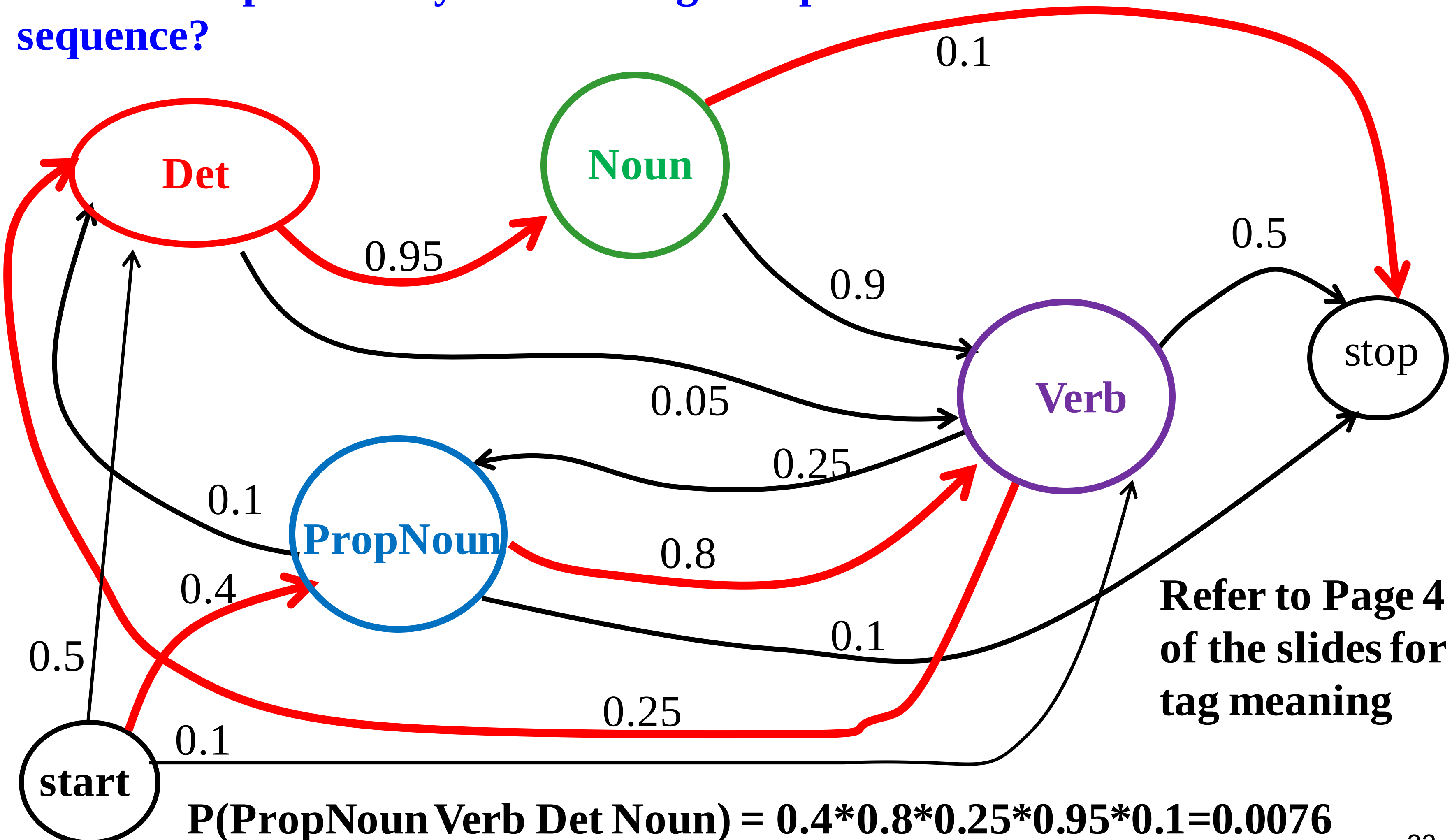

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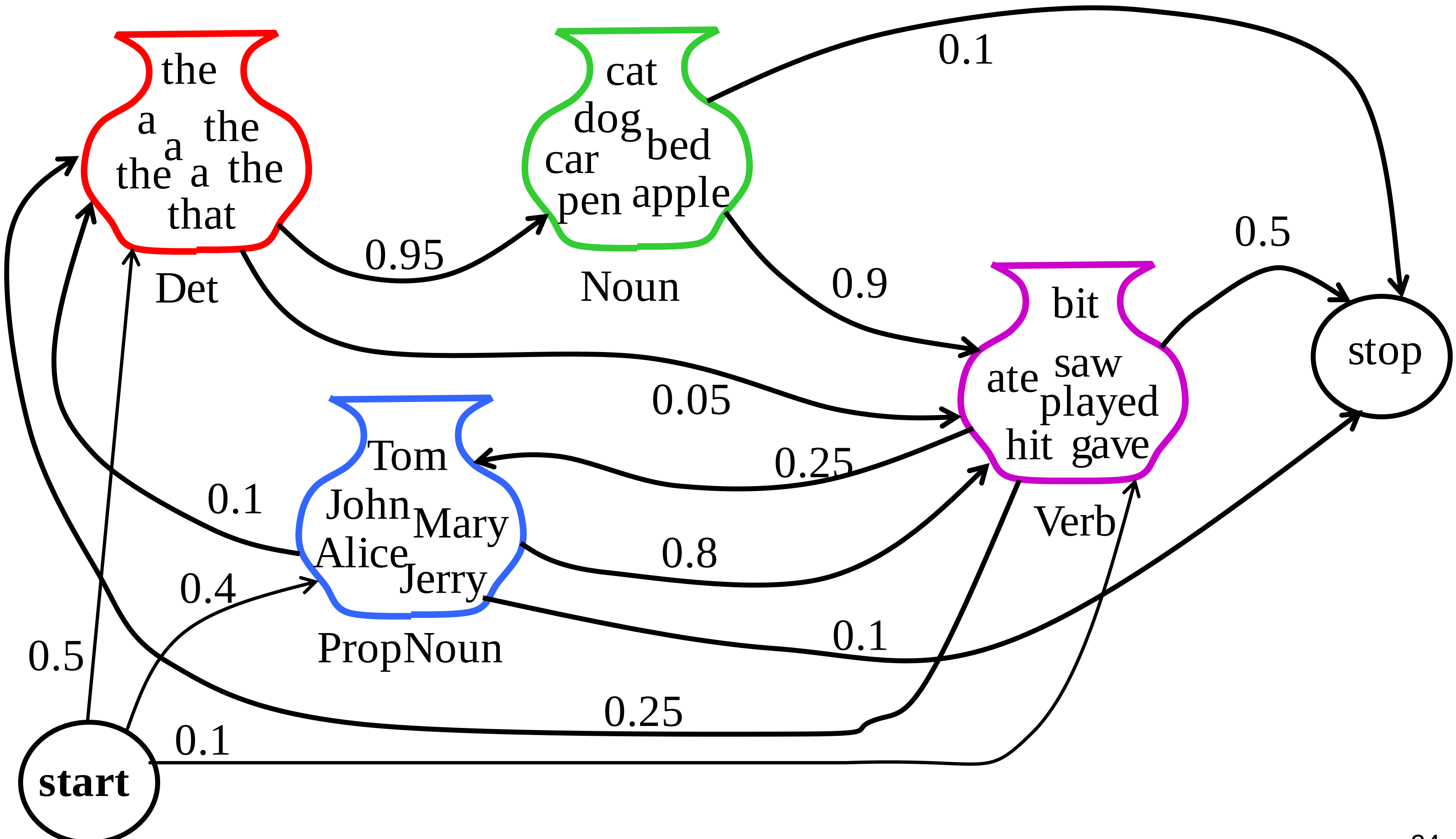
P(PropNoun Verb Det Noun) = 0.4*0.8*0.25*0.95*0.1=0.0076

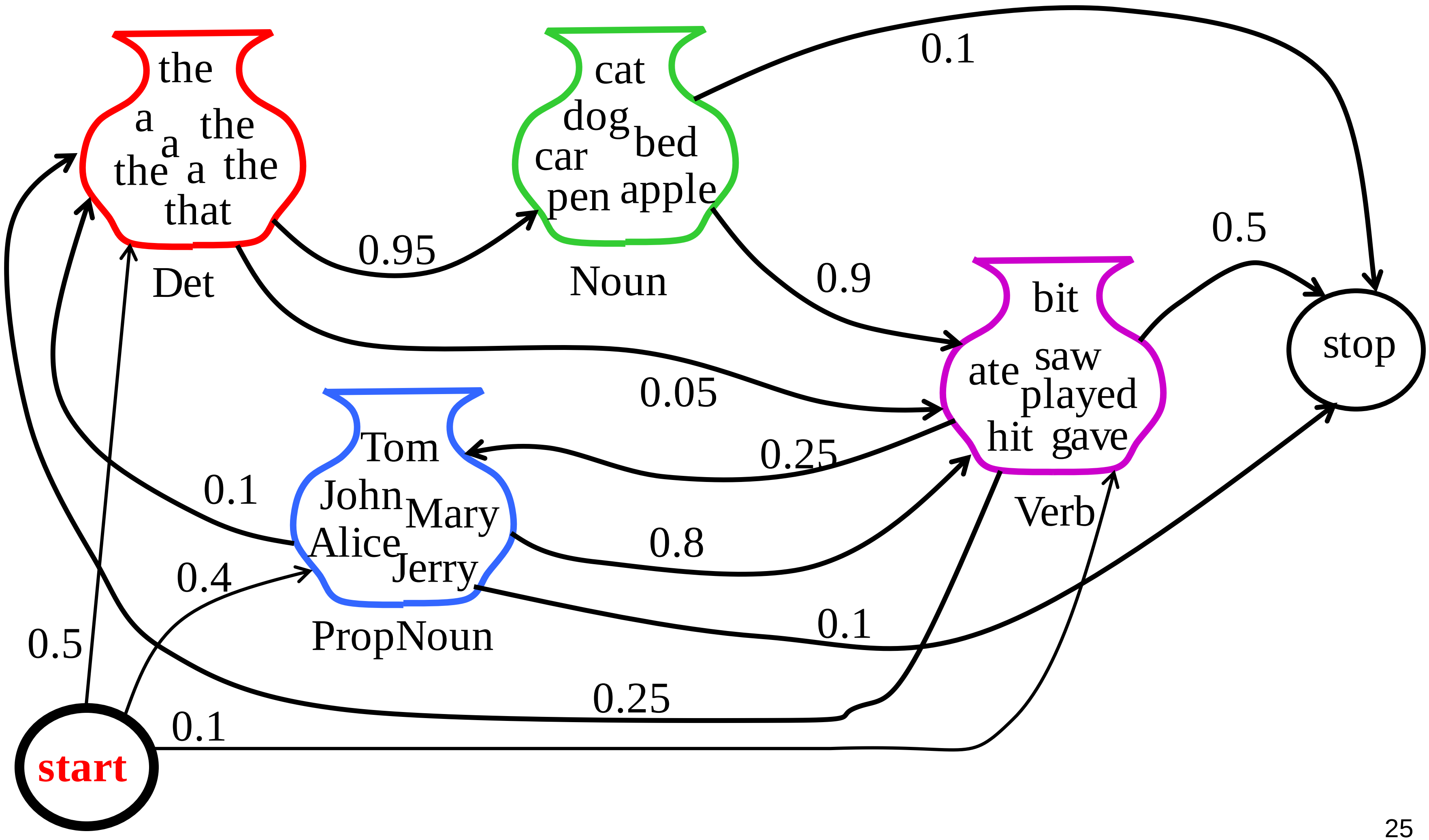
Hidden Markov Model for Sequence Labeling (e.g., POS tagging)

- 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



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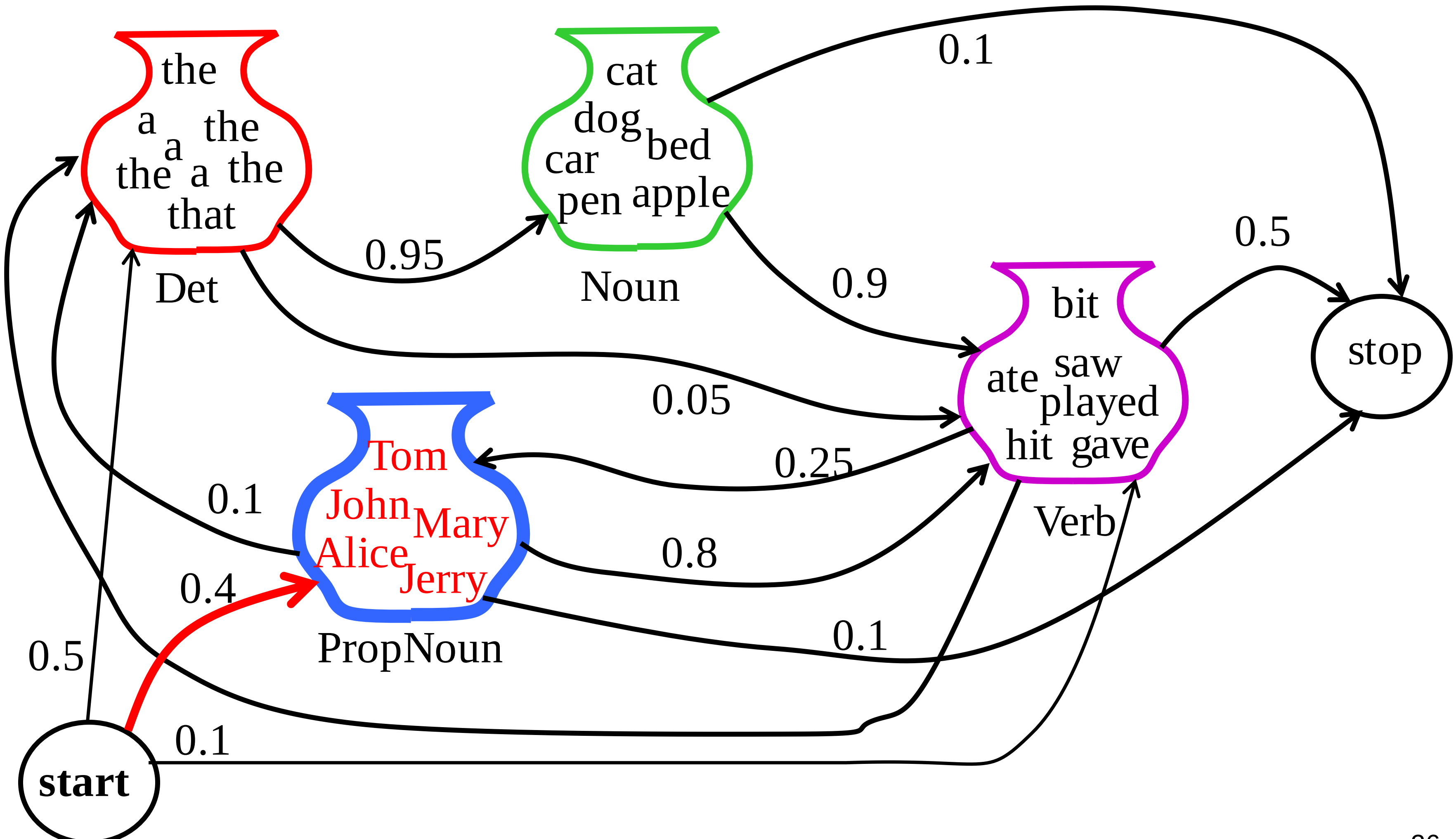

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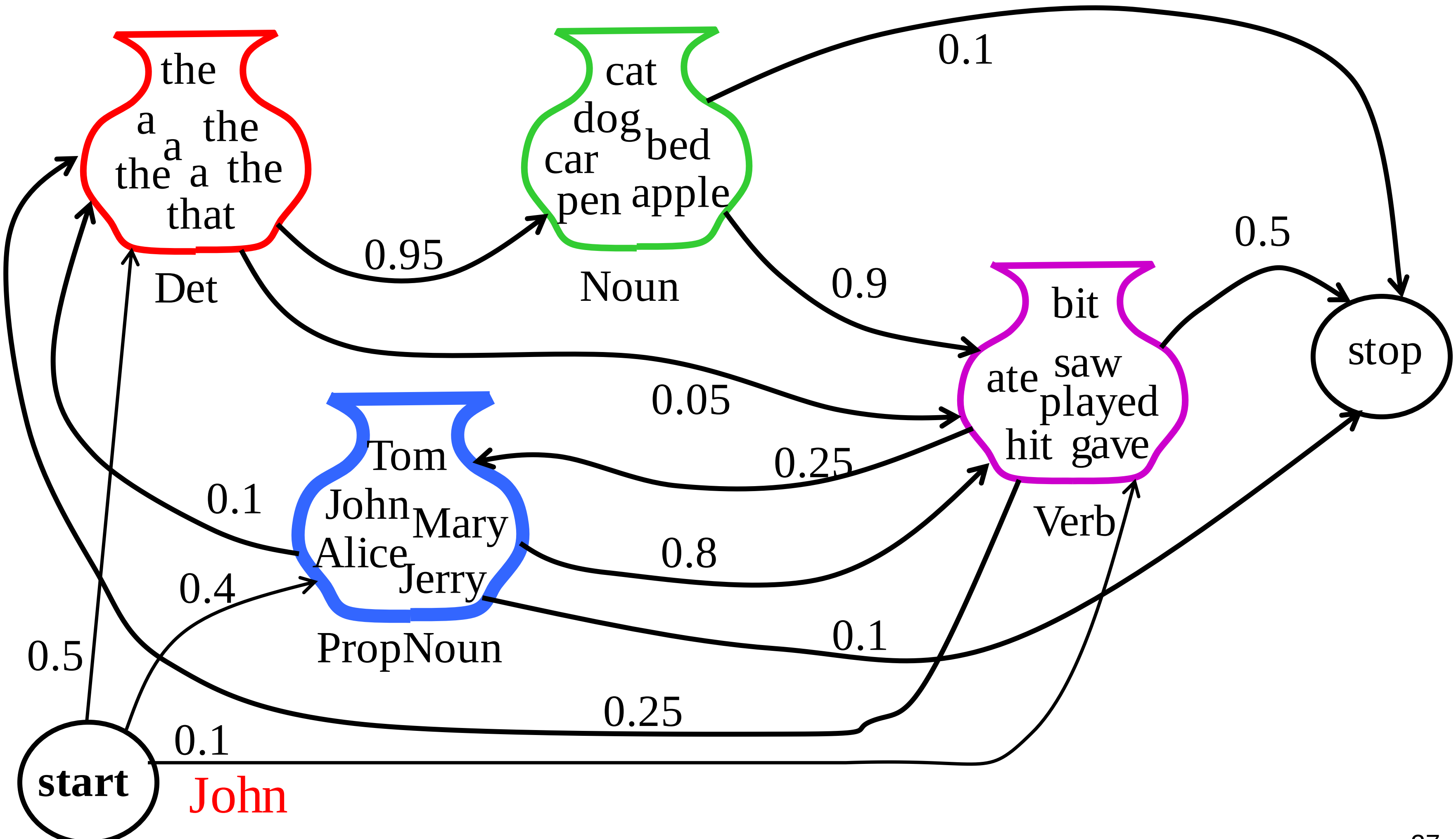

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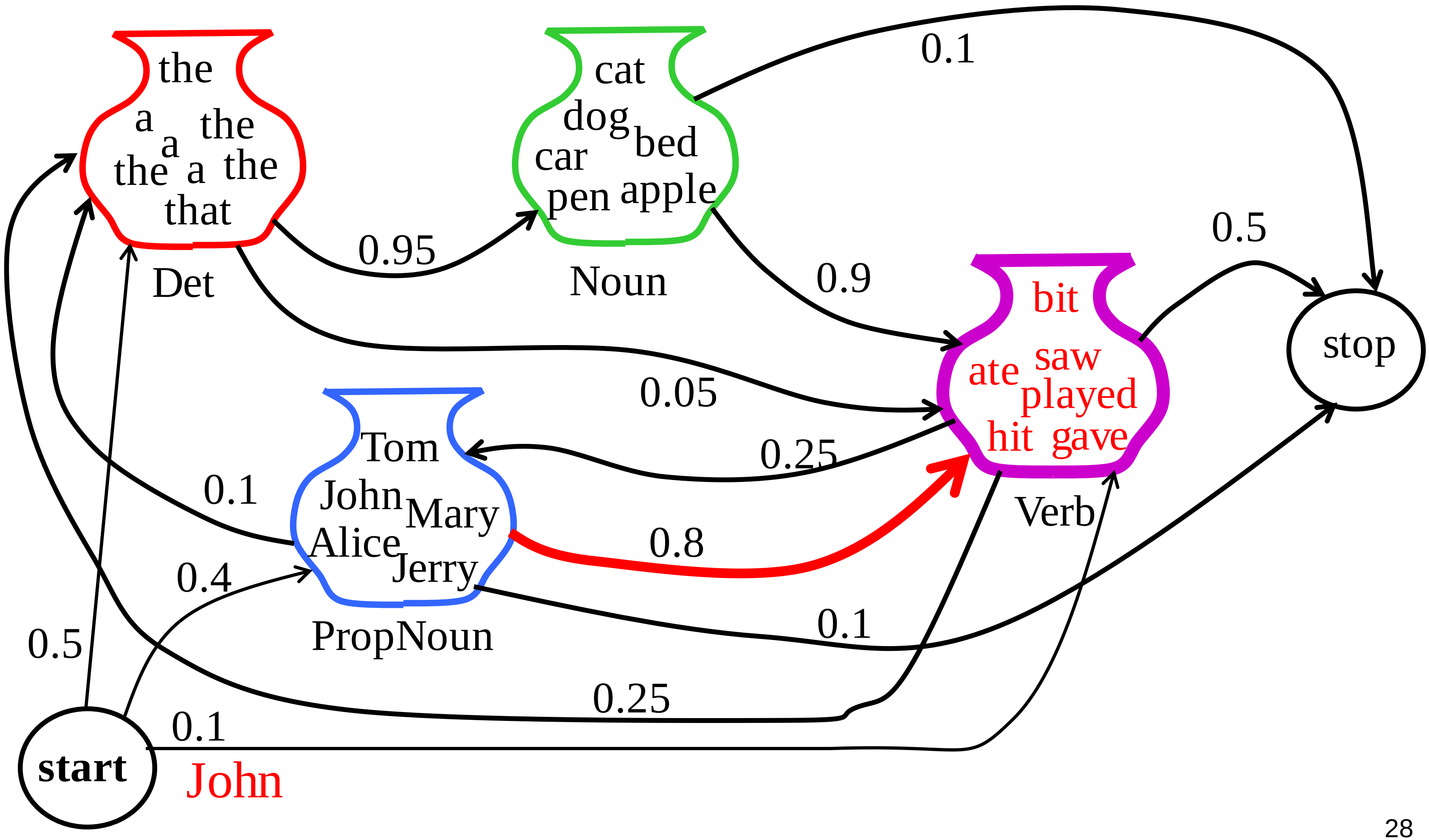

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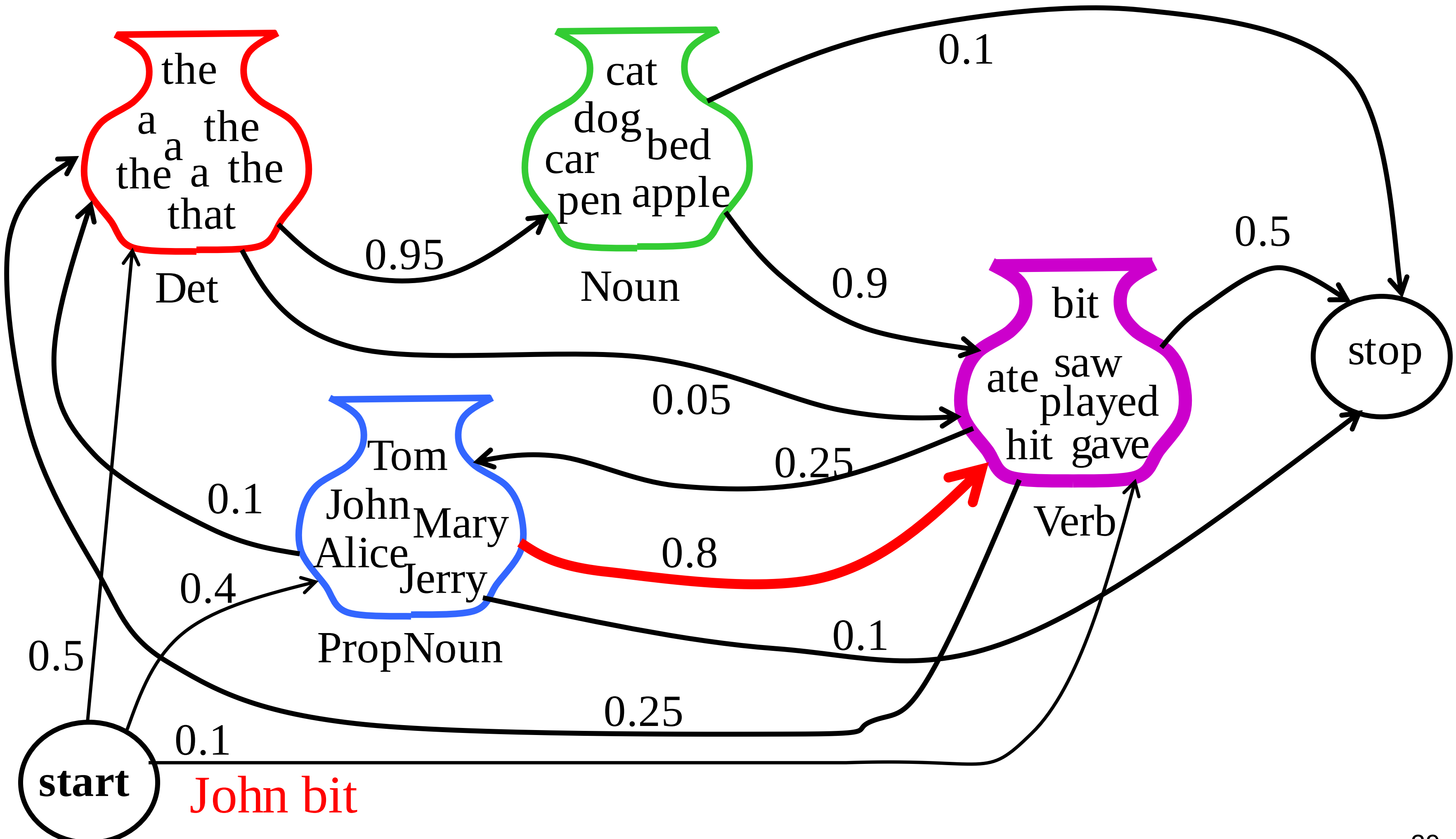

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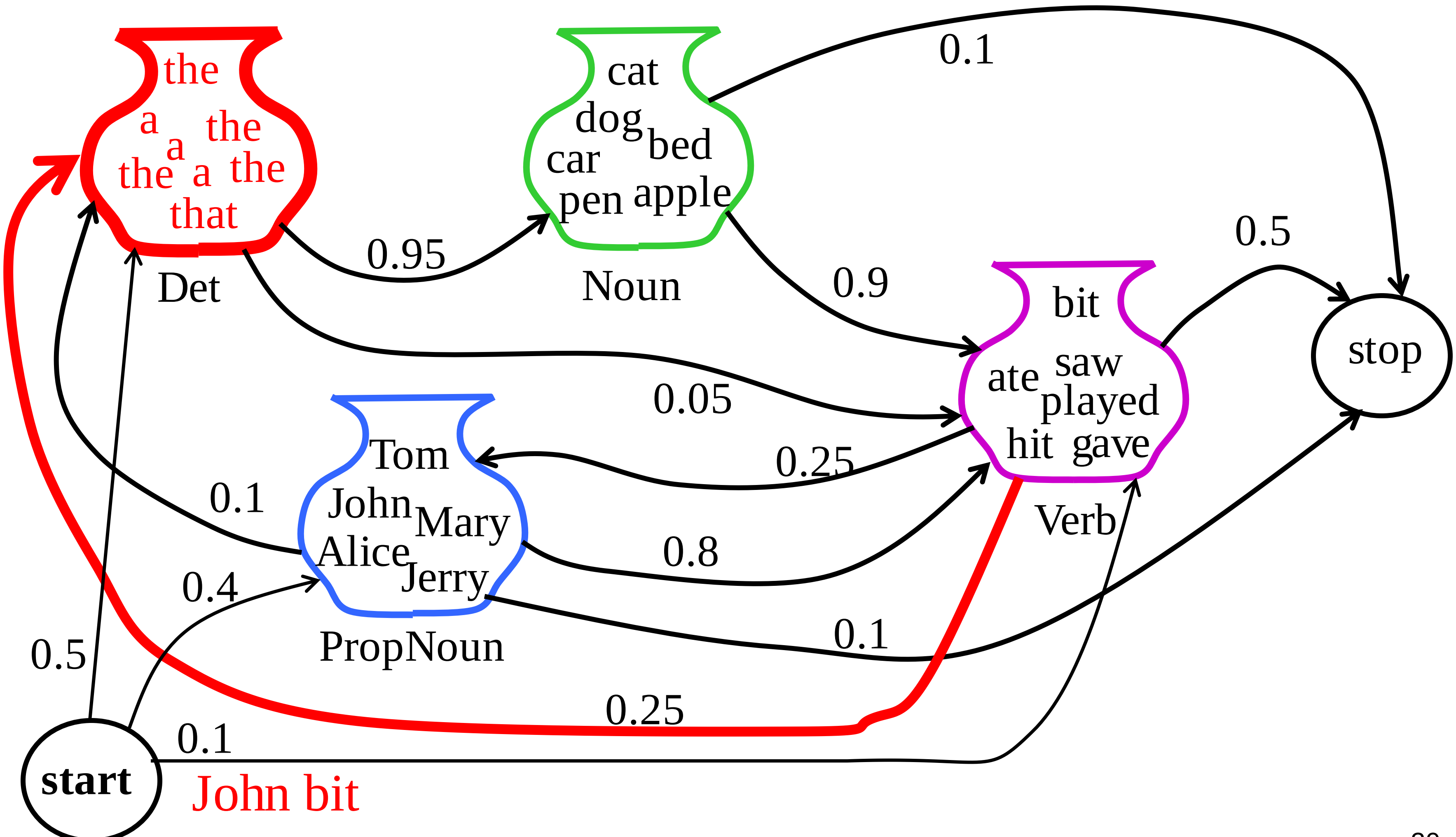

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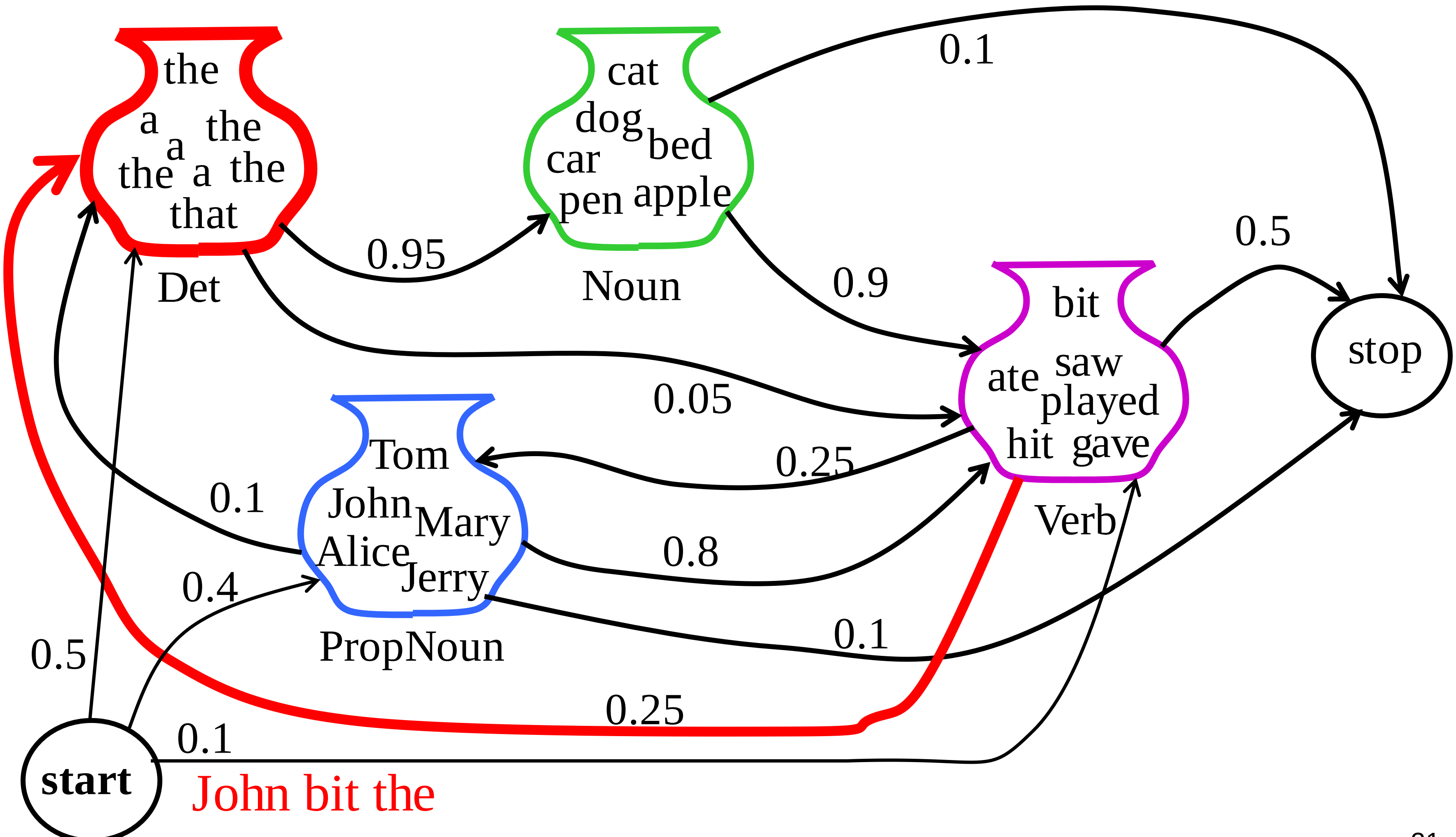

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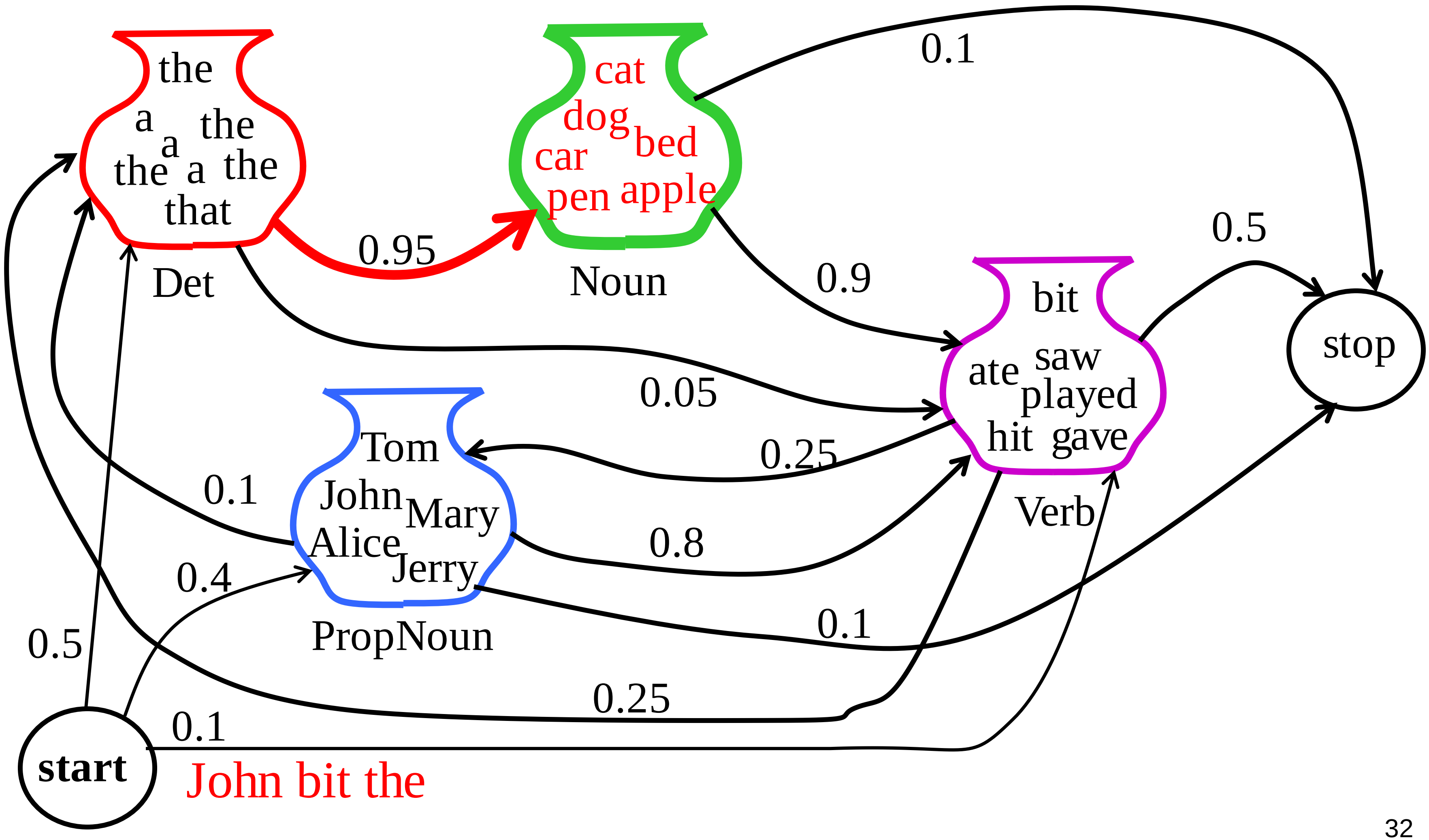

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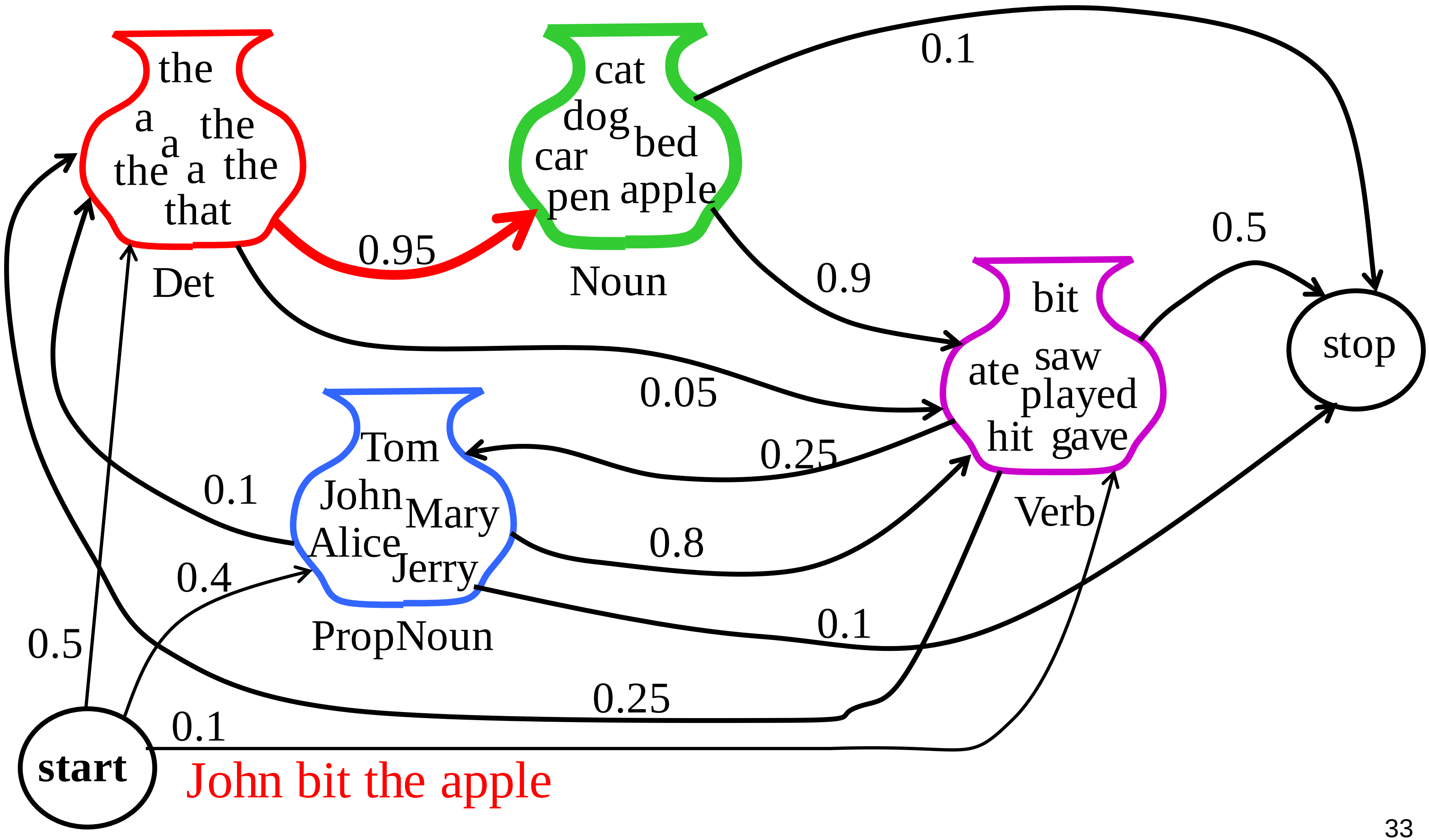

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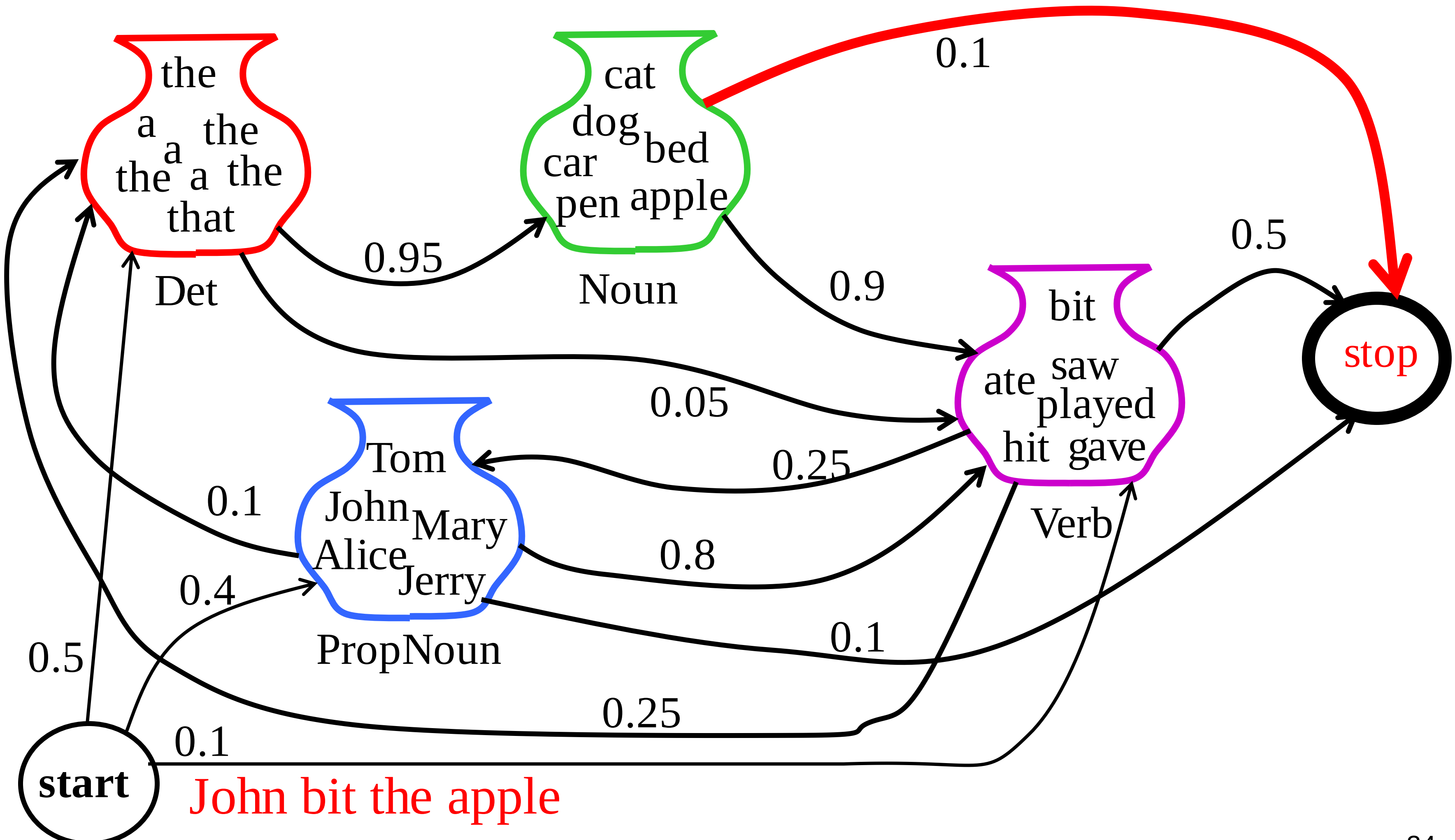


Formal Definition of an HMM

- 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 $A=\{a_{ij}\}$

$$a_{ij} = P(q_{t+1} = s_j \mid q_t = s_i) \qquad 1 \le i, j \le N \text{ and } i = 0, j = F$$

$$\sum_{j=1}^{N} a_{ij} + a_{iF} = 1 \quad 0 \le i \le N$$

- Observation probability distribution for each state j, $B=\{b_j(k)\}$

$$b_j(k) = P(v_k \text{ at } t \mid q_t = s_j) \quad 1 \le j \le N \quad 1 \le \mathrm{k} \le \mathrm{M}$$

- 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

1. Transit to another state $q_{t+1} = s_j$ based on transition distribution a_{ij} for state q_t
2. Pick an observation $o_t = v_k$ based on being in state q_t using distribution $b_{q_t}(k)$

Practice the sample HMM generation in previous slides

Three Useful HMM Tasks

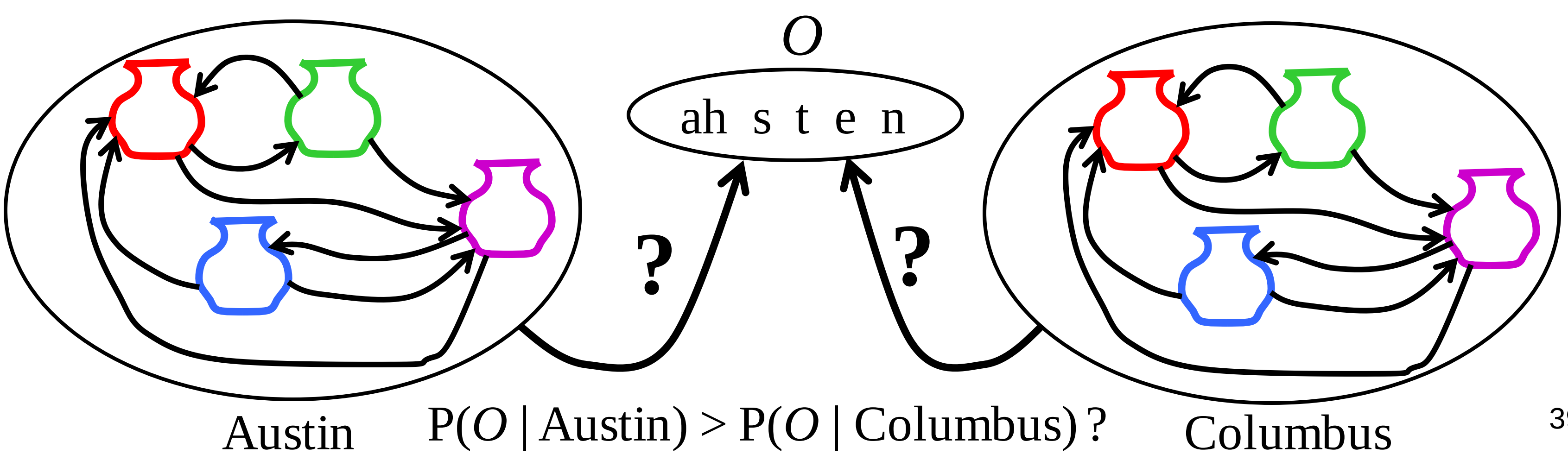
- Observation Likelihood: To classify and order sequences.
- Most likely state sequence (Decoding): To tag each token in a sequence with a label.
- Maximum likelihood training (Learning): To train models to fit empirical training data.

HMM: Observation Likelihood

- Given a sequence of observations, *O*, and a model with a set of parameters $\lambda=\{A, B\}$, 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

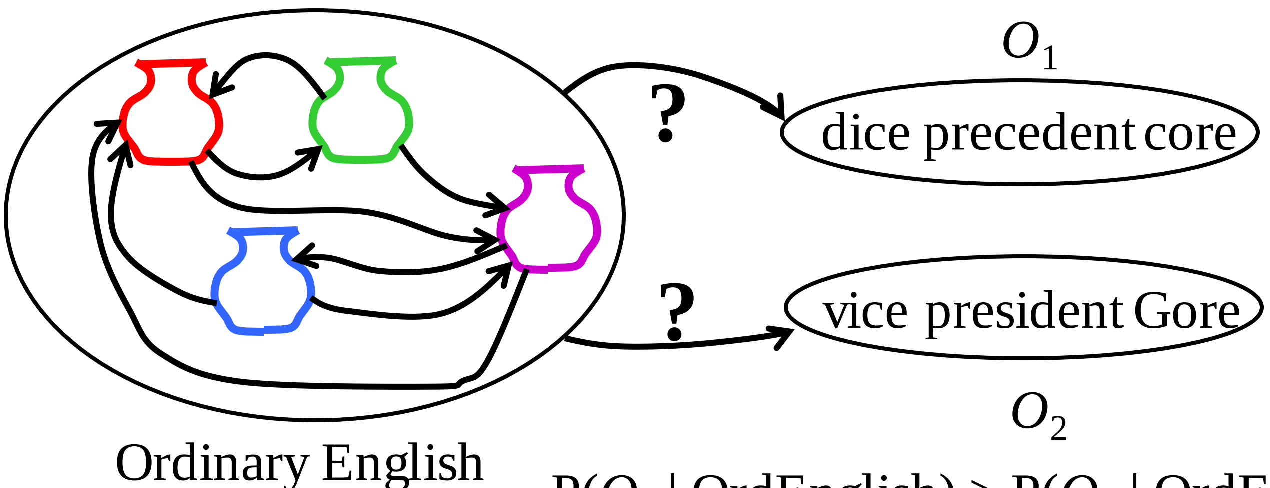
Sequence Classification

- 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.



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 | OrdEnglish) > P(O_1 | 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: ??

HMM: Observation Likelihood Naïve Solution

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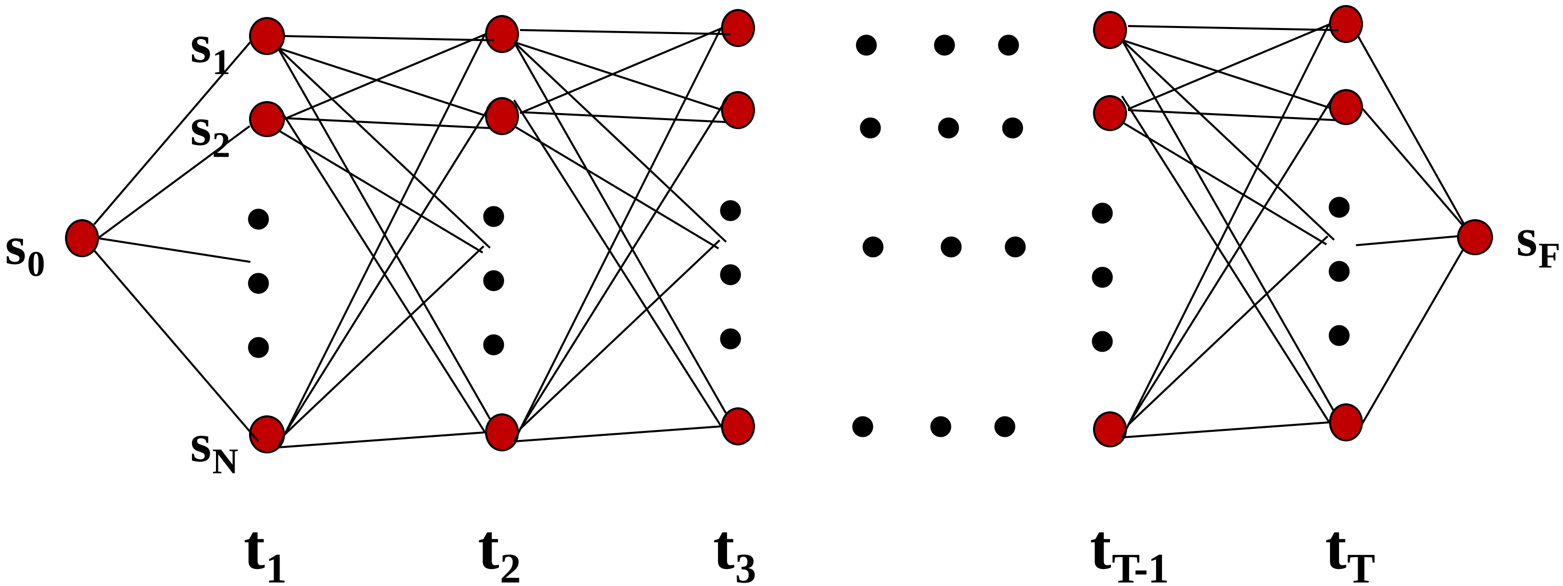
- Compute the probability of a given state sequence from A, and multiply it by the probabilities of generating each of given observations in each of the corresponding states in this sequence to get $P(O,Q|\lambda) = P(O|Q,\lambda)\,P(Q|\lambda)$.
- Sum this over all possible state sequences to get $P(O|\lambda)$.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



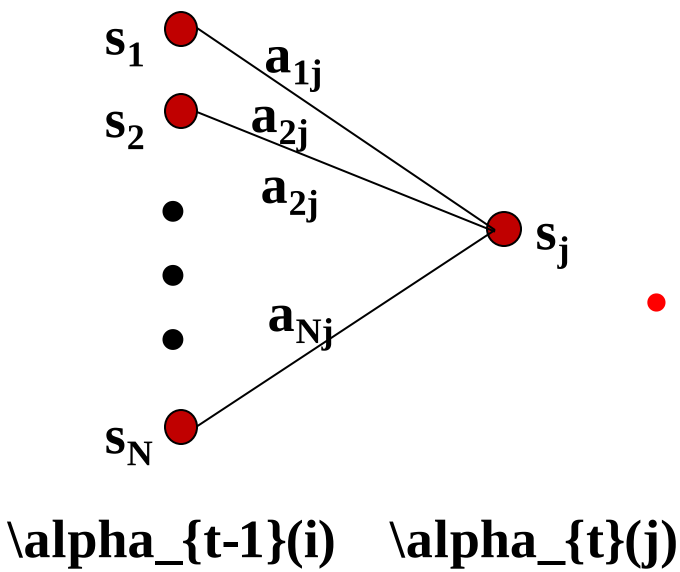
- Continue forward in time until reaching final time point and sum probability of ending in final state.

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*).

$$\alpha_t(j) = P(o_1, o_2, \ldots o_t,\ q_t = s_j \mid \lambda)$$

Forward Step



- 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

$$\alpha_1(j) = a_{0j} b_j(o_1) \quad 1 \le j \le N$$

- Recursion

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

- Termination

$$P(O \mid \lambda) = \alpha_{T+1}(s_F) = \sum_{i=1}^{N} \alpha_T(i) a_{iF}$$

Forward Computational Complexity

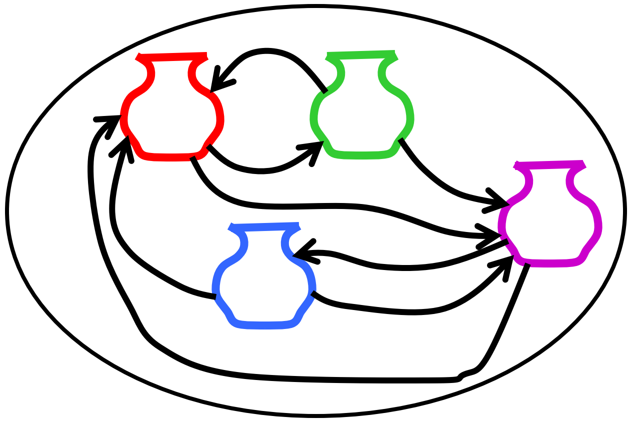
- Requires only $O(TN^2)$ time to compute the probability of an observed sequence given a model. Why?

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, λ, what is the most likely state sequence, $Q=q_1,q_2,\ldots q_T$, that generated this sequence from this model?



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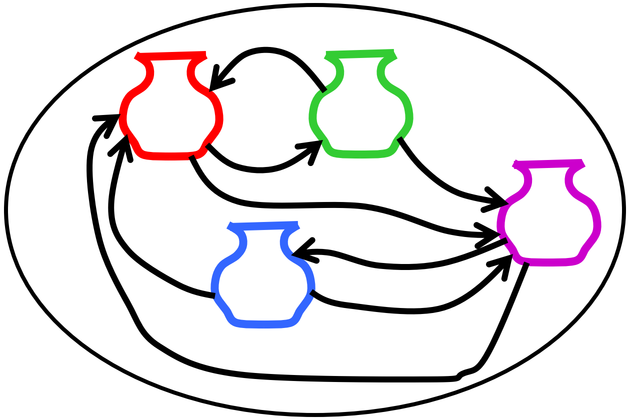

John gave the dog an apple.

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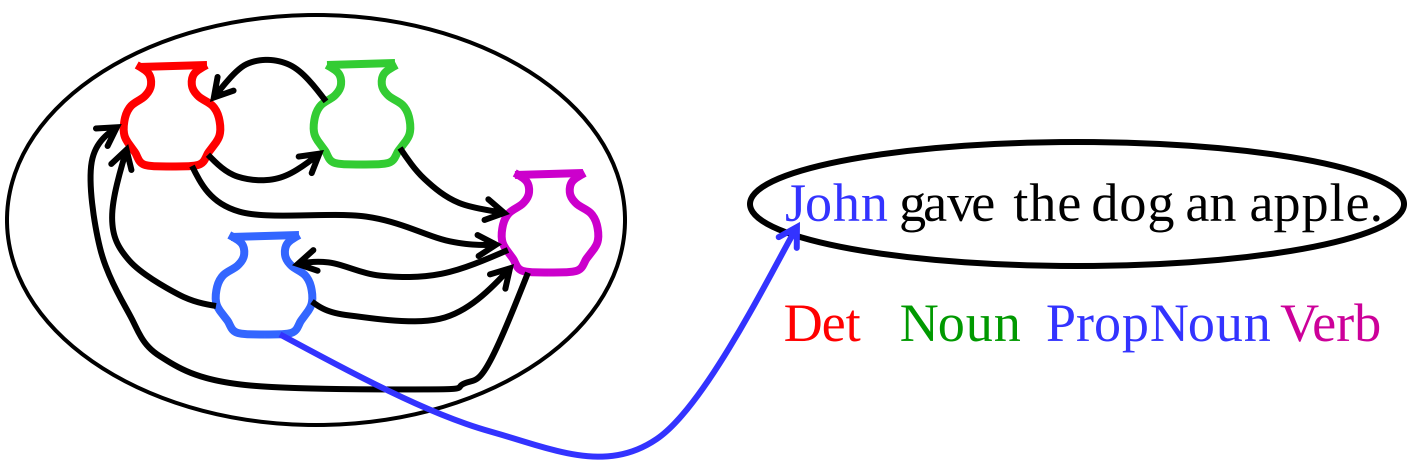

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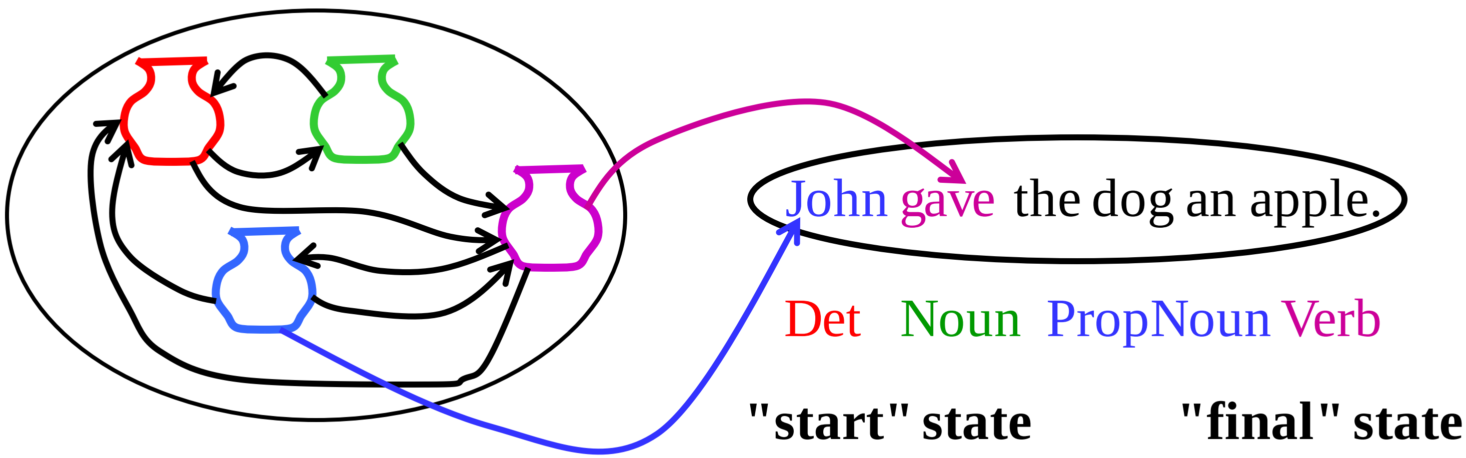

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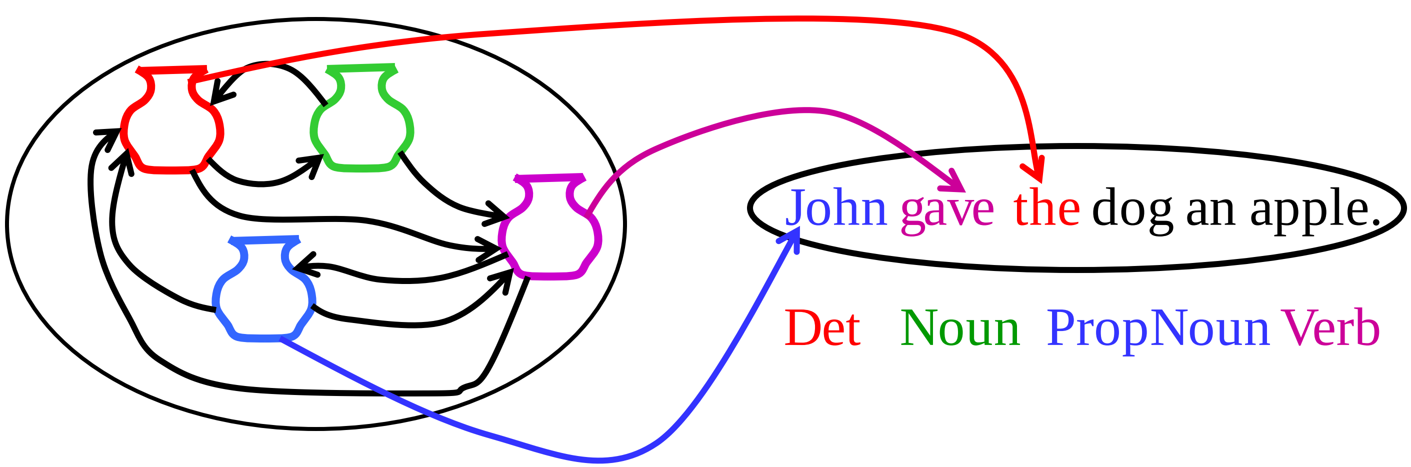

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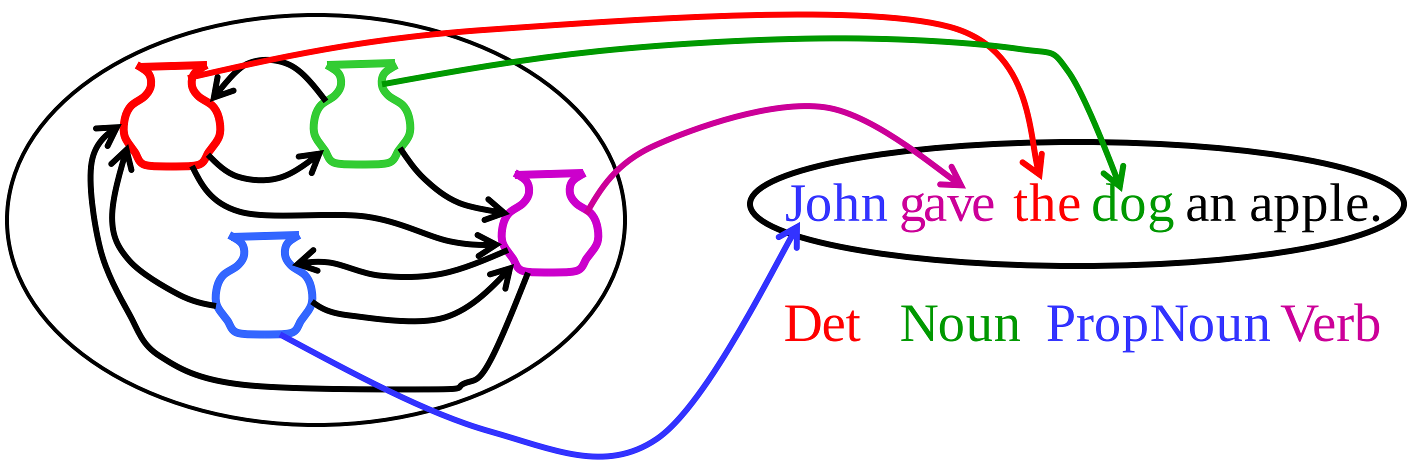

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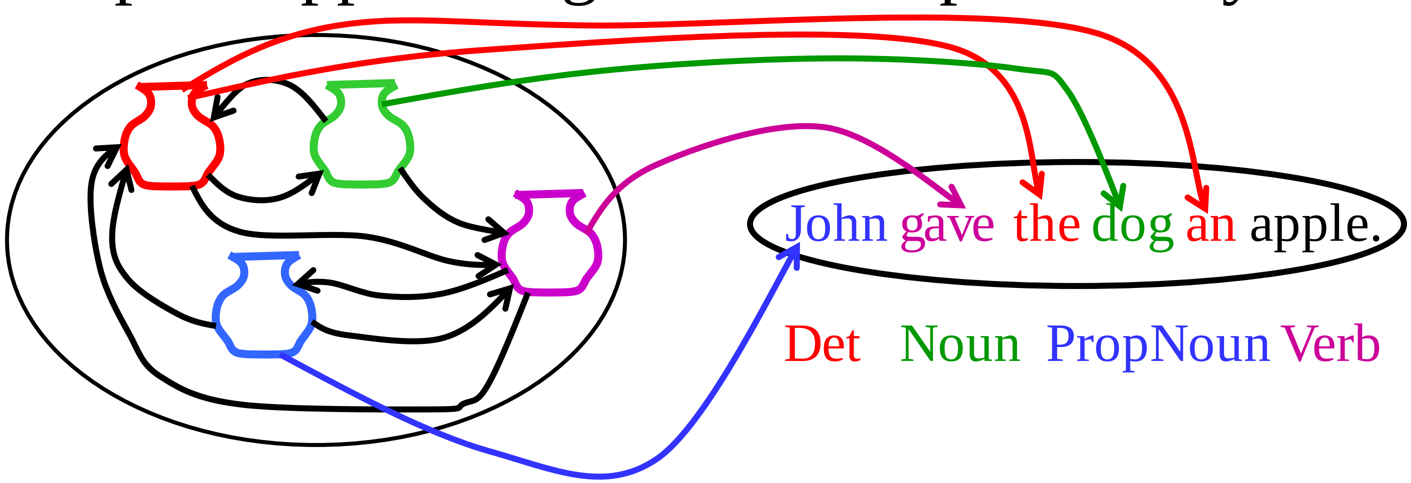

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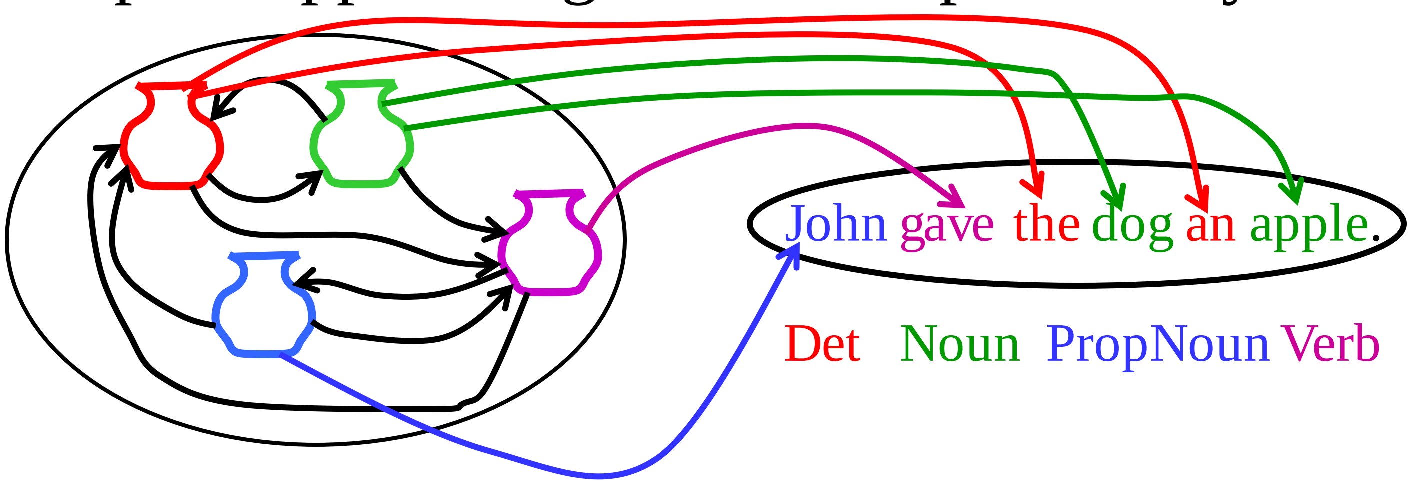


HMM: Most Likely State Sequence Efficient Solution

- 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(TN^2) 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.

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

- 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 first t observations).

Computing the Viterbi Scores

- Initialization

$$v_1(j) = a_{0j} b_j(o_1) \quad 1 \le j \le N$$

- Recursion

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

- Termination

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

Analogous to Forward algorithm except take *max* instead of sum

Computing the Viterbi Backpointers

- Initialization

$$bt_1(j) = s_0 \quad 1 \le j \le N$$

- Recursion

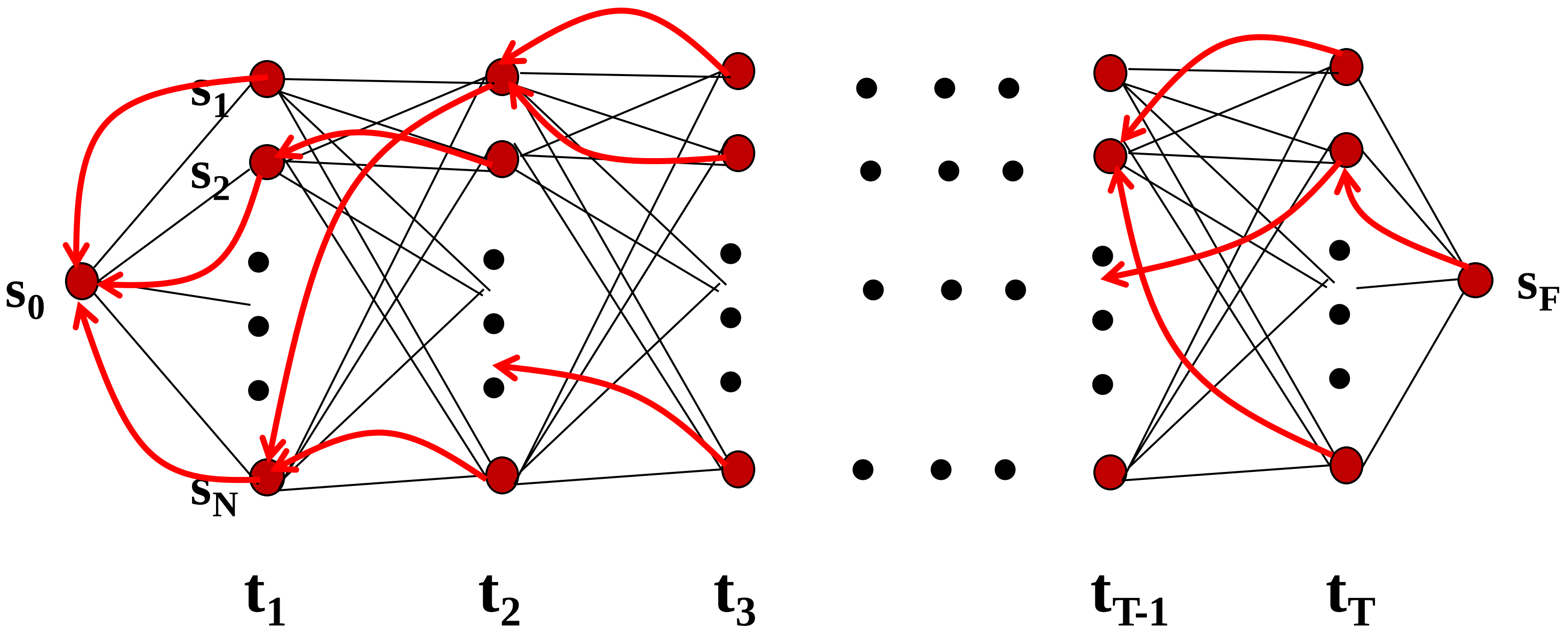
$$bt_t(j) = \operatorname*{argmax}_{i=1}^{N} v_{t-1}(i) a_{ij} b_j(o_t) \quad 1 \le j \le N, \;\; 1 \le t \le T$$

- Termination

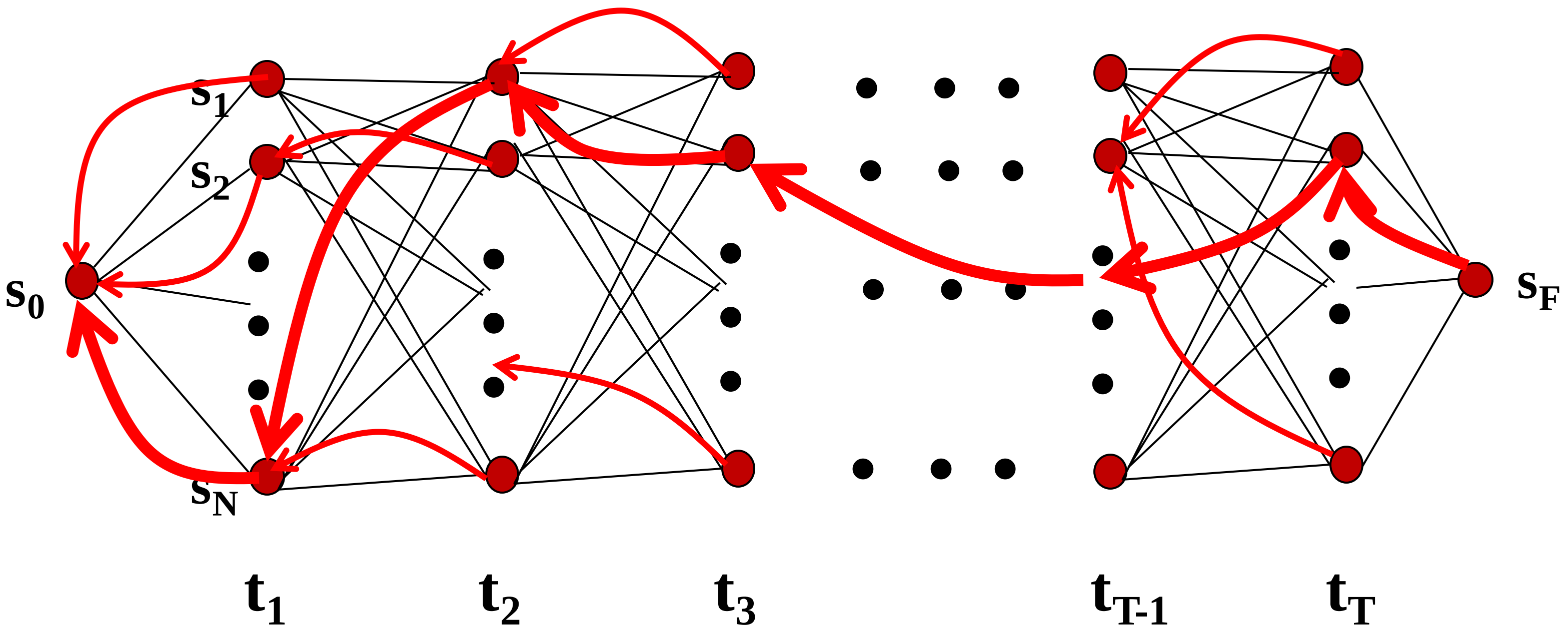
$$q_T{*} = bt_{T+1}(s_F) = \operatorname*{argmax}_{i=1}^{N} v_T(i) a_{iF}$$

Final state in the most probable state sequence. Follow backpointers to initial state to construct full sequence.

Viterbi Backpointers



Viterbi Backtrace



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; e.g., in clustering).
- **Semisupervised Learning**: Some training sequences are labeled, most are unlabeled.

Supervised HMM Training

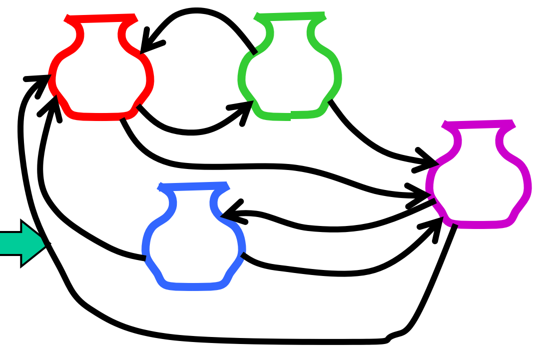
- If training sequences are labeled (tagged) with the underlying state sequences that generated them, then the parameters, $\lambda=\{A,B\}$ can all be estimated directly.

Training Sequences

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

Det Noun PropNoun Verb

Supervised HMM Training



Supervised Parameter Estimation

- Estimate state transition probabilities based on tag bigram and unigram statistics in the labeled data.

$$a_{ij} = \frac{C(q_t = s_i, \mathrm{q}_{\mathrm{t+1}} = s_j)}{C(q_t = s_i)}$$

- 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 (if any) 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.