Word classes and part of speech tagging

Reading: Ch. 5, Jurafsky & Martin (Ch. 10 3rd. Edition)

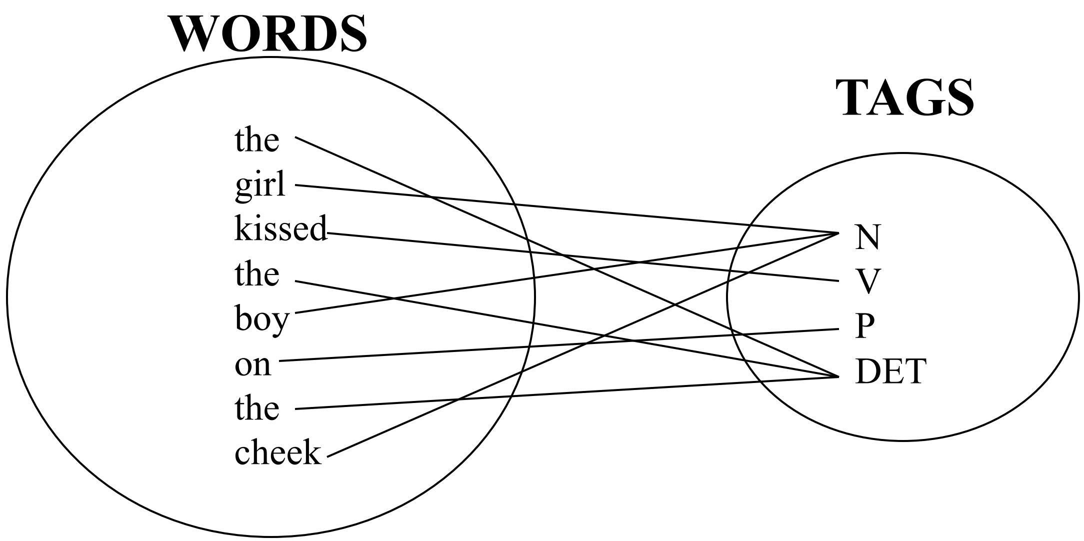
PI Disclosure: This set includes adapted material from Rada Mihalcea, Raymond Mooney and Dan Jurafsky

Outline

- Why part of speech tagging?
- Tag sets and problem definition
- Automatic approaches:
  - HMMs
  - MEMMs

Definition

"The process of assigning a part-of-speech or other lexical class marker to each word in a corpus" (Jurafsky and Martin)



An Example

WORD	LEMMA	TAG
the	the	+DET
girl	girl	+NOUN
kissed	kiss	+VPAST
the	the	+DET
boy	boy	+NOUN
on	on	+PREP
the	the	+DET
cheek	cheek	+NOUN

From: http://www.xrce.xerox.com/competencies/content-analysis/fsnlp/tagger.en.html

Why is POS Tagging Useful?

- First step of a vast number of practical tasks
- Speech synthesis
  - INsult		inSULT
  - OBject		obJECT
  - OVERflow		overFLOW
  - DIScount		disCOUNT
  - CONtent		conTENT
- Parsing
  - Need to know if a word is an N or V before you can parse
- Information extraction
  - Finding names, relations, etc.
- Machine Translation

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POS Tagging: Choosing a Tagset

- Could pick very coarse tagsets
  - N, V, Adj, Adv.
- More commonly used set is finer grained, the "Penn TreeBank tagset", 45 tags
  - PRP$, WRB, WP$, VBG
- Even more fine-grained tagsets exist

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.
- The C5 tagset used for the British National Corpus (BNC) has 61 tags.
- Universal POS tagset includes ~12 tags.

Penn TreeBank POS Tagset

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*			

POS Tagging: The Problem

- Words often have more than one word class:
  - *This* is a nice day = PRP
  - *This* day is nice = DT
  - You can go *this* far = RB
  - The *back* door = JJ
  - On my *back* = NN
  - Win the voters *back* = RB
  - Promised to *back* the bill = VB

POS Tagging: Definition

- The process of assigning a part-of-speech or other lexical class marker to each word in a corpus
- Often applied to punctuation markers as well
- Input: a string of words and a specified tagset
- Output: a single best tag for each word

How Hard is POS Tagging? Measuring Ambiguity

		WSJ		Brown	
Types:					
Unambiguous	(1 tag)	44,432	(**86%**)	45,799	(**85%**)
Ambiguous	(2+ tags)	7,025	(**14%**)	8,050	(**15%**)
Tokens:					
Unambiguous	(1 tag)	577,421	(**45%**)	384,349	(**33%**)
Ambiguous	(2+ tags)	711,780	(**55%**)	786,646	(**67%**)

Consistent Human Annotation is Crucial

- Disambiguating POS tags requires deep knowledge of syntax
- Development of clear heuristics in the form of tagging manuals
  - She told off/RP her friends
  - She told her friends off/RP
  - She stepped off/IN the train
  - *She stepped the train off/IN
- See Manning (2011) for a more in depth discussion

Part-of-Speech Tagging

- Manual Tagging
- Automatic Tagging
  - Two flavors:
    - Rule-based taggers (EngCC ENGTWOL)
    - Stochastic taggers (HMM, Max Ent, CRF-based, Tree-based)
  - Hodge-podge:
    - Transformation–based tagger (Brill, 1995)

Manual Tagging

- Agree on a Tagset after much discussion.
- Chose a corpus, annotate it manually by two or more people.
- Check on inter-annotator agreement.
- Fix any problems with the Tagset (if still possible).

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Classification Learning

- Typical machine learning addresses the problem of classifying a feature-vector description into a fixed number of classes.
- There are many standard learning methods for this task:
  - Decision Trees and Rule Learning
  - Naïve Bayes and Bayesian Networks
  - Logistic Regression / Maximum Entropy (MaxEnt)
  - Perceptron and Neural Networks
  - Support Vector Machines (SVMs)
  - Nearest-Neighbor / Instance-Based

Beyond Classification Learning

- Standard classification problem assumes individual cases are disconnected and independent.
- Many NLP problems do not satisfy this assumption (involve many connected decisions, ambiguity and dependence)

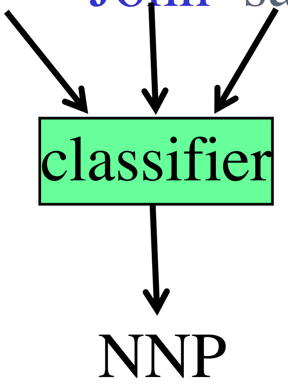
Sequence Labeling Problem

- Many NLP problems can viewed as sequence labeling.
- Each token in a sequence is assigned a label.
- Labels of tokens are dependent on the labels of other tokens in the sequence, particularly their neighbors (not i.i.d).

Sequence Labeling as Classification

- Classify each token independently but use as input features, information about the surrounding tokens (sliding window).

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



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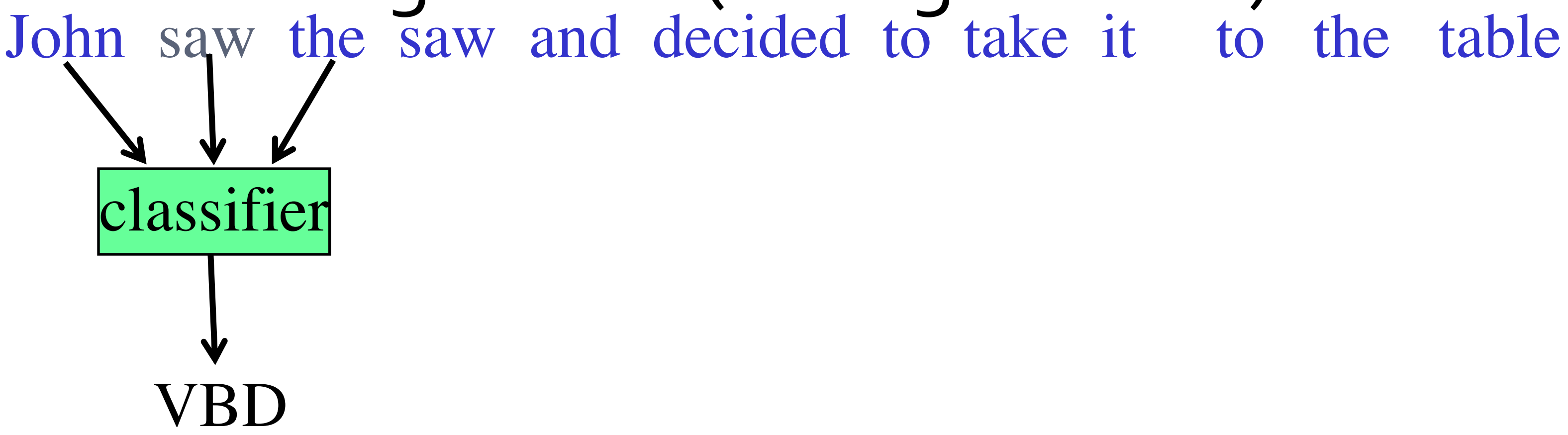

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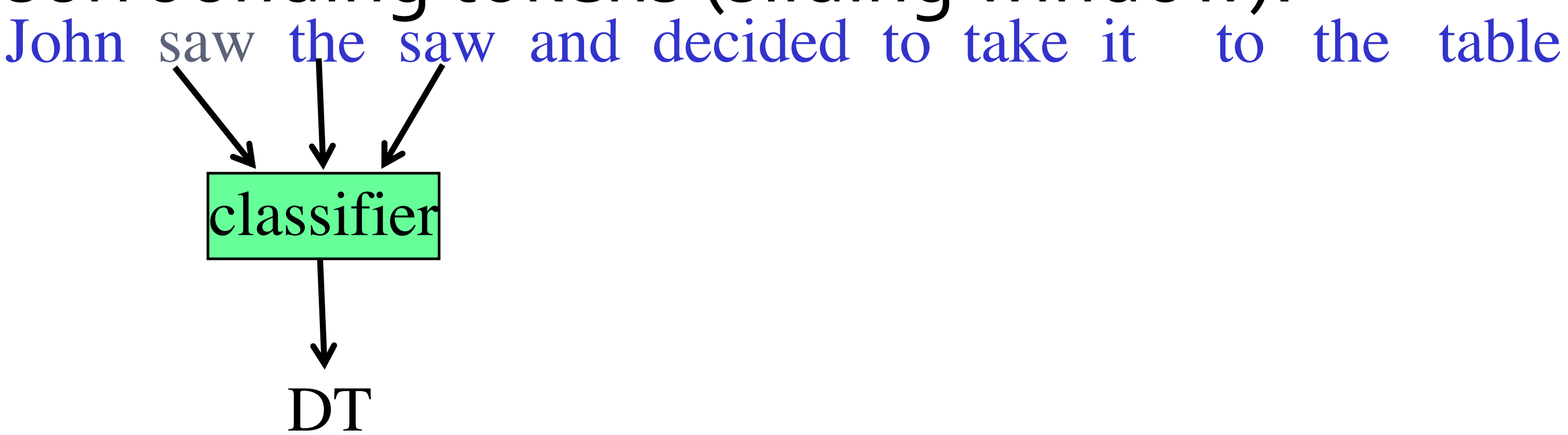

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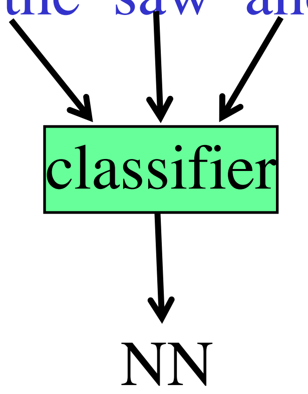

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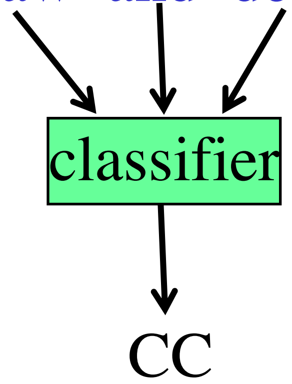

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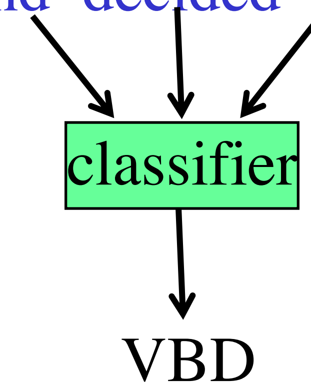

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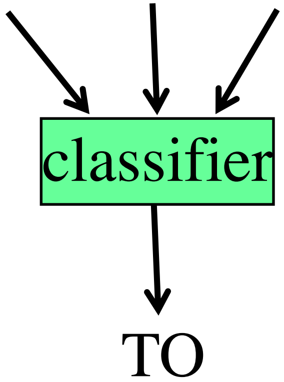

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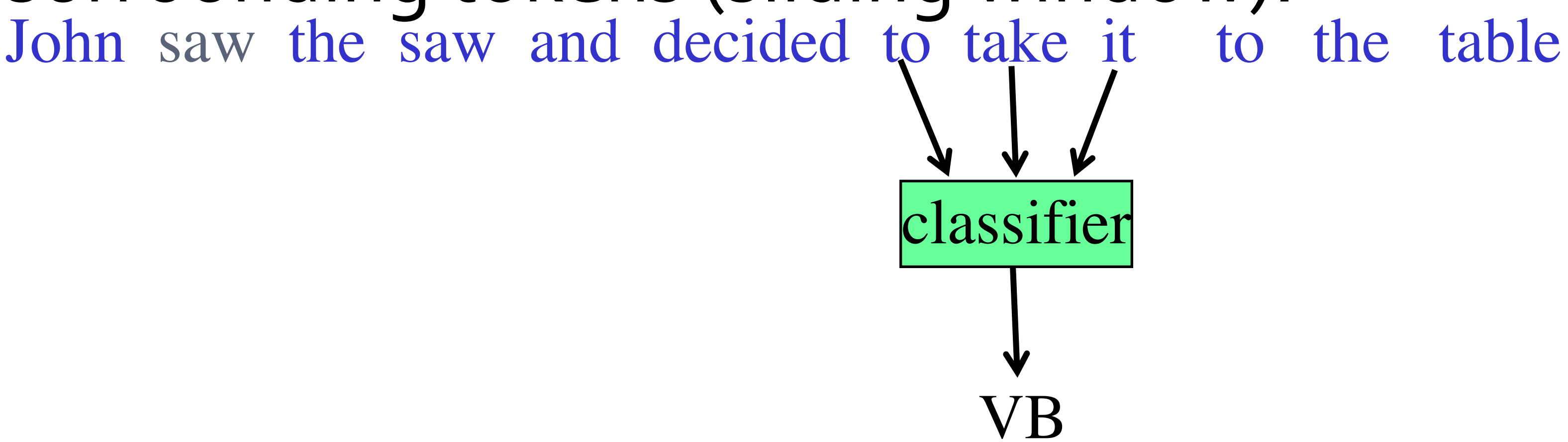

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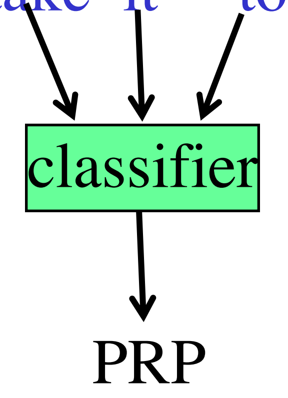

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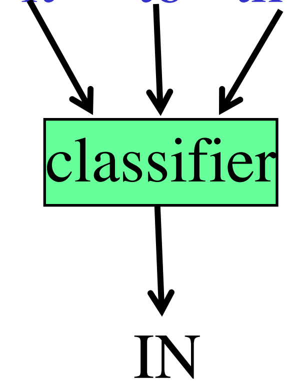

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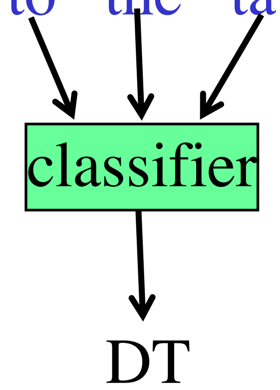

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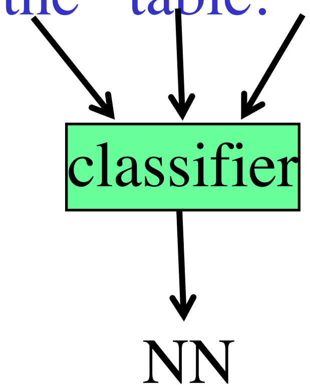


Problems with Sequence Labeling as Classification

- 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 interdependent classifications and collectively determine the most likely global assignment.
- Two standard models
  - Hidden Markov Model (HMM)
  - Conditional Random Field (CRF)

POS Tagging as Sequence Classification

- We are given a sentence (an "observation" or "sequence of observations")
  - *Secretariat is expected to race tomorrow*
- What is the best sequence of tags that corresponds to this sequence of observations?
- Probabilistic view:
  - Consider all possible sequences of tags
  - Out of this universe of sequences, choose the tag sequence which is most probable given the observation sequence of n words $w_1 \ldots w_n$.

Getting to HMMs

- We want, out of all sequences of n tags $t_1 \ldots t_n$ the single tag sequence such that $P(t_1 \ldots t_n | w_1 \ldots w_n)$ is highest.

$$\hat{t}_1^n = \underset{t_1^n}{\operatorname{argmax}} P(t_1^n | w_1^n)$$

- Hat ^ means "our estimate of the best one"
- Argmax_x f(x) means "the x such that f(x) is maximized"

Likelihood and Prior

HMM Taggers choose tag sequence that maximizes this formula:

– P(word|tag) × P(tag|previous n tags)

$$\max_{t_1^n} \overbrace{P(w_1^n|t_1^n)}^{\text{likelihood}} \overbrace{P(t_1^n)}^{\text{prior}}$$

$$P(w_1^n|t_1^n) \approx \prod_{i=1} P(w_i|t_i)$$

$$\prod^{n} P(t_i|t_{i-1})$$

$$\hat{t}_1^n = \underset{t_1^n}{\operatorname{argmax}} P(t_1^n|w_1^n) \approx \underset{t_1^n}{\operatorname{argmax}} \prod_{i=1}^{n} P(w_i|t_i)P(t_i|t_{i-1})$$

Two Kinds of Probabilities

- Tag transition probabilities $p(t_i|t_{i-1})$
  - Determiners likely to precede adjs and nouns
    - That/DT flight/NN
    - The/DT yellow/JJ hat/NN
    - So we expect P(NN|DT) and P(JJ|DT) to be high
    - But P(DT|JJ) to be:
  - Compute P(NN|DT) by counting in a labeled corpus:

$$P(t_i|t_{i-1}) = \frac{C(t_{i-1}, t_i)}{C(t_{i-1})}$$

$$P(NN|DT) = \frac{C(DT, NN)}{C(DT)} = \frac{56,509}{116,454} = .49$$

Two Kinds of Probabilities

- Word likelihood probabilities $p(w_i|t_i)$
  - VBZ (3sg Pres verb) likely to be "is"
  - Compute P(is|VBZ) by counting in a labeled corpus:

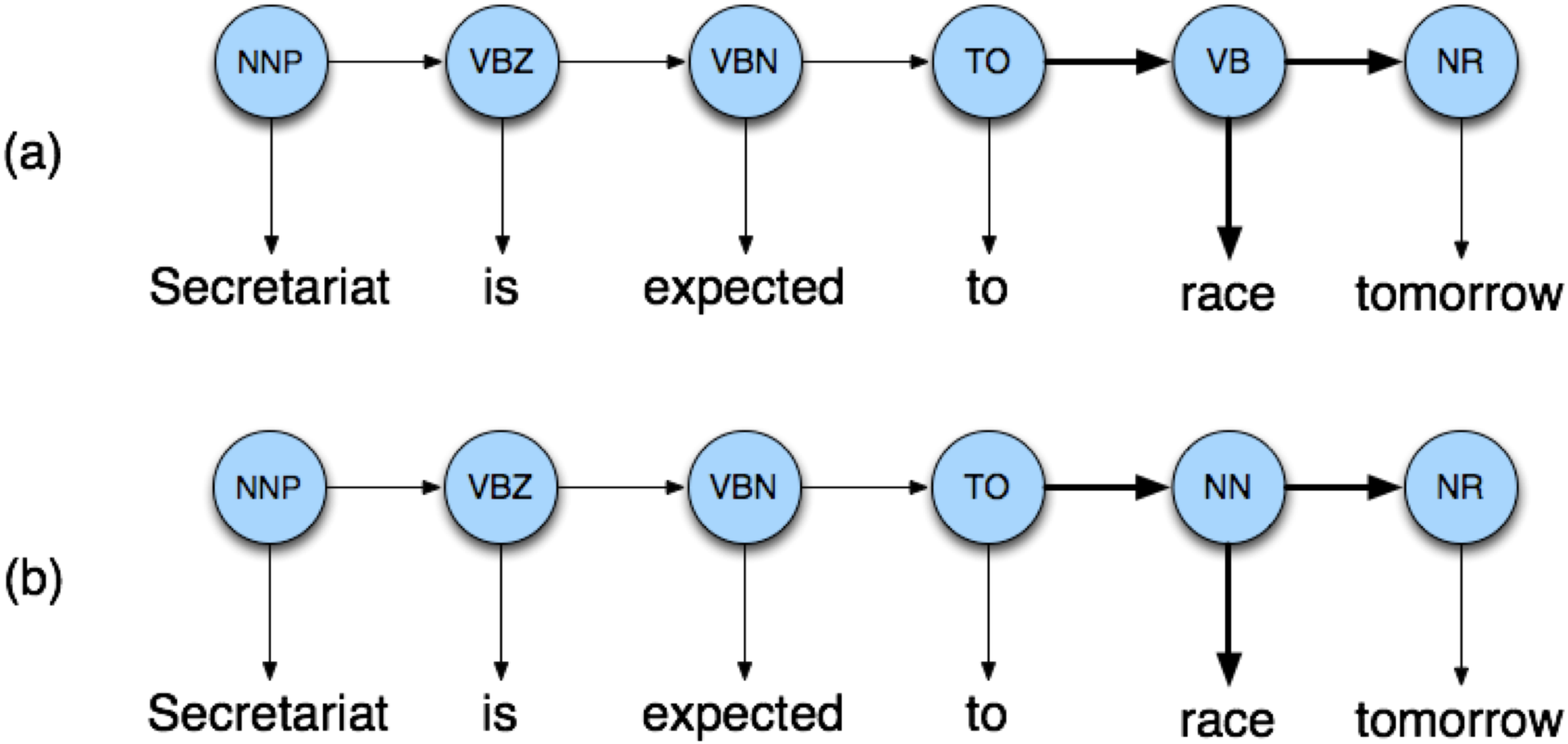
$$P(w_i|t_i) = \frac{C(t_i, w_i)}{C(t_i)}$$

$$P(is|VBZ) = \frac{C(VBZ, is)}{C(VBZ)} = \frac{10,073}{21,627} = .47$$

Example: The Verb "race"

- Secretariat/NNP is/VBZ expected/VBN to/TO **race**/VB tomorrow/NR
- People/NNS continue/VB to/TO inquire/VB the/DT reason/NN for/IN the/DT **race**/NN for/IN outer/JJ space/NN
- How do we pick the right tag?

Disambiguating "race"



Example

- $P(NN|TO) = .00047$
- $P(VB|TO) = .83$
- $P(race|NN) = .00057$
- $P(race|VB) = .00012$
- $P(NR|VB) = .0027$
- $P(NR|NN) = .0012$
- $P(VB|TO)P(NR|VB)P(race|VB) = .00000027$
- $P(NN|TO)P(NR|NN)P(race|NN)=.00000000032$

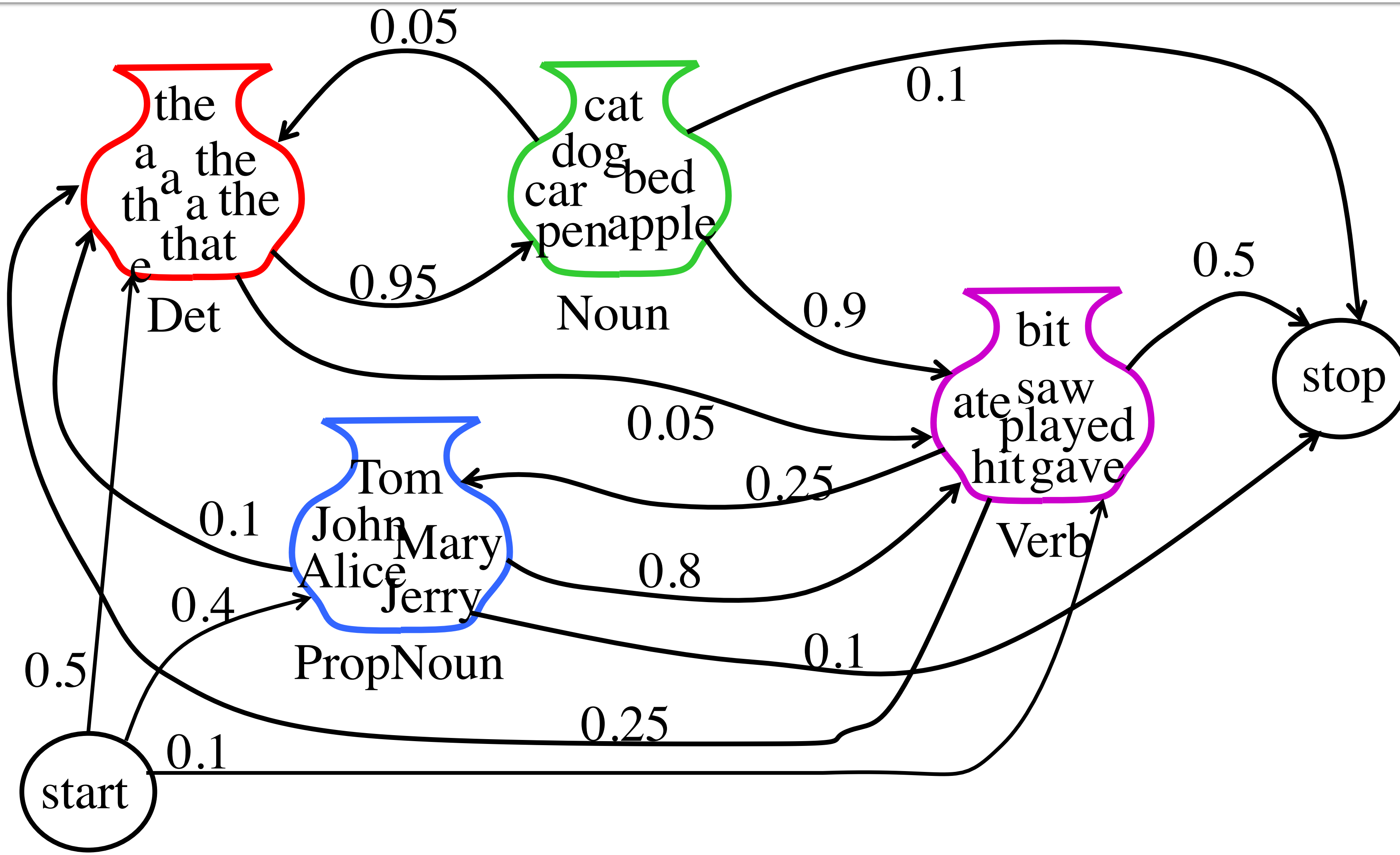
Hidden Markov Models

- What we've described with these two kinds of probabilities is a Hidden Markov Model (HMM)
- MM vs HMM
  - Both use the same algorithms for tagging they differ on the training algorithms

An Early Approach to Statistical POS Tagging

- PARTS tagger (Church, 1988): Stores probability of tag given word instead of word given tag.
  - P(tag|word) × P(tag|previous n tags)
- Compare to:
  - P(word|tag) × P(tag|previous n tags)
- What is the main difference between PARTS tagger (Church) and the HMM tagger?

Sample HMM for POS



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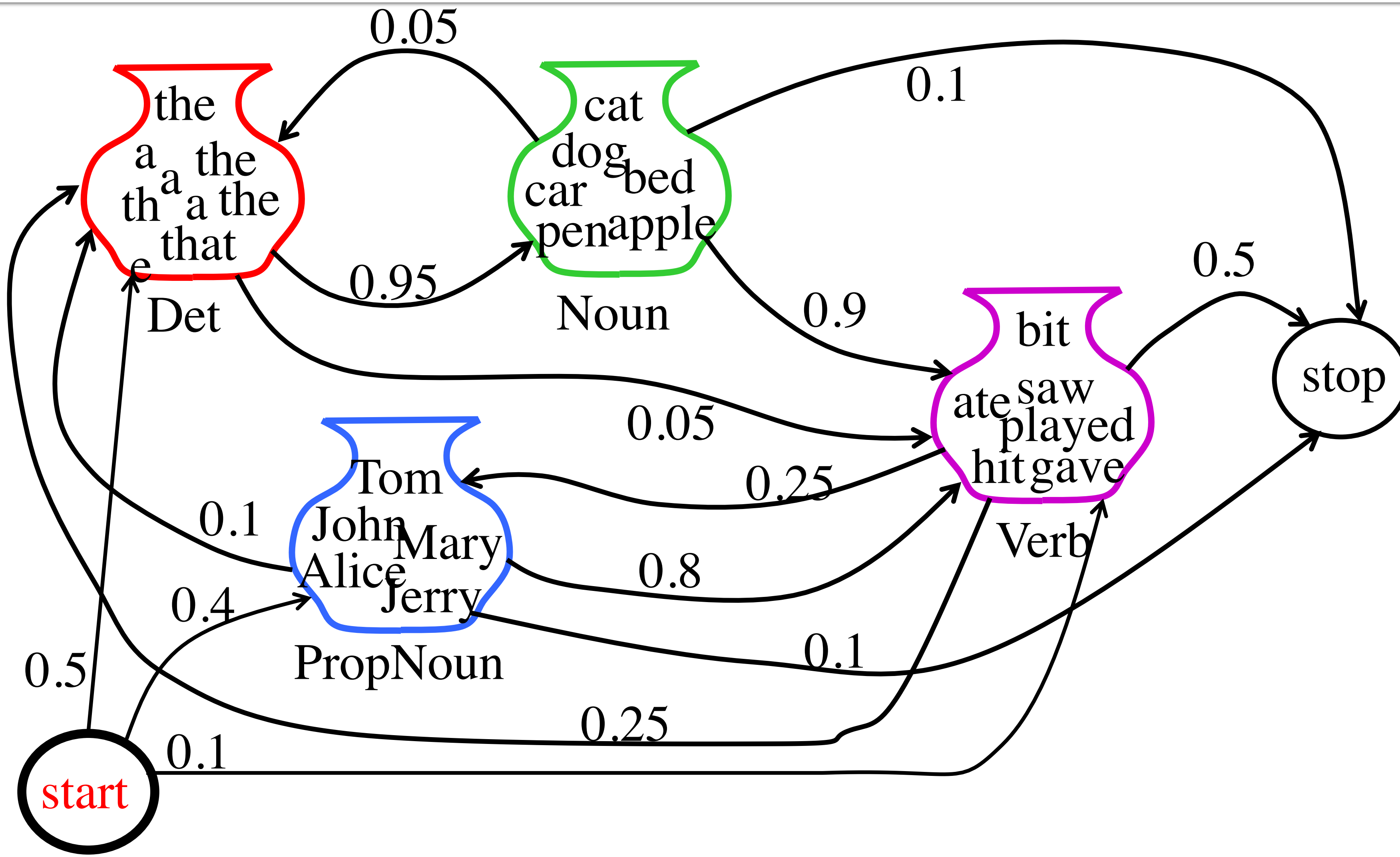

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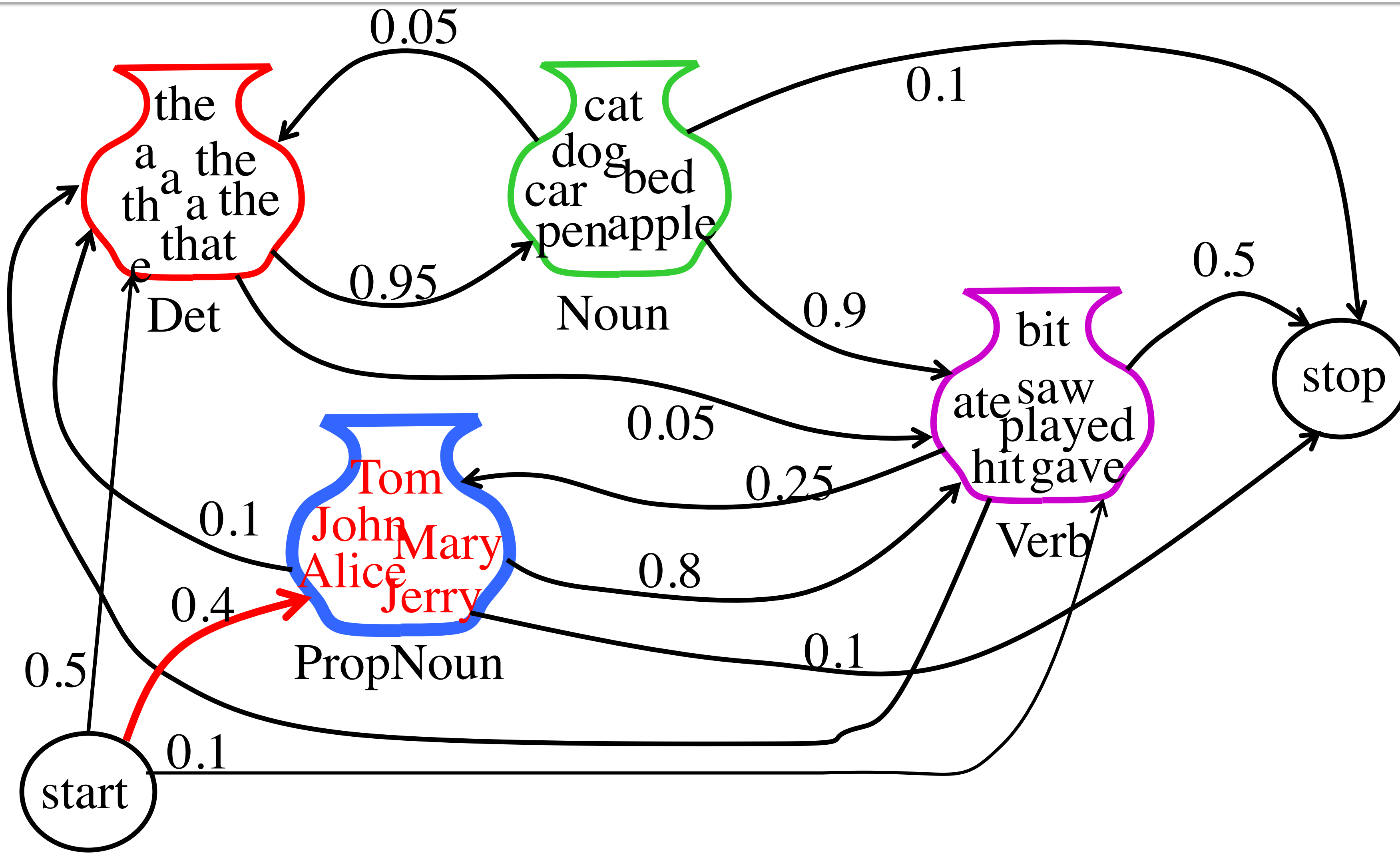

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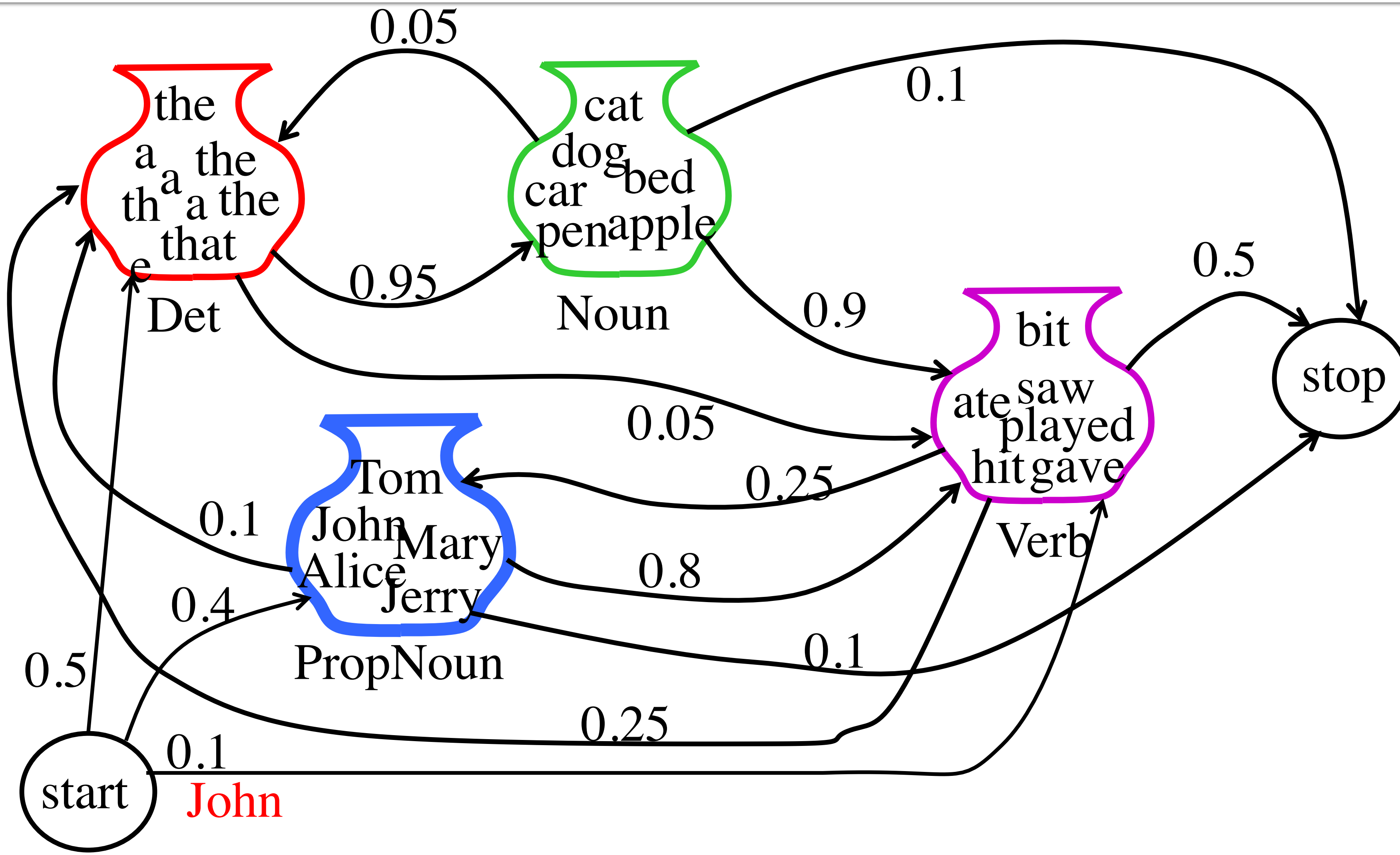

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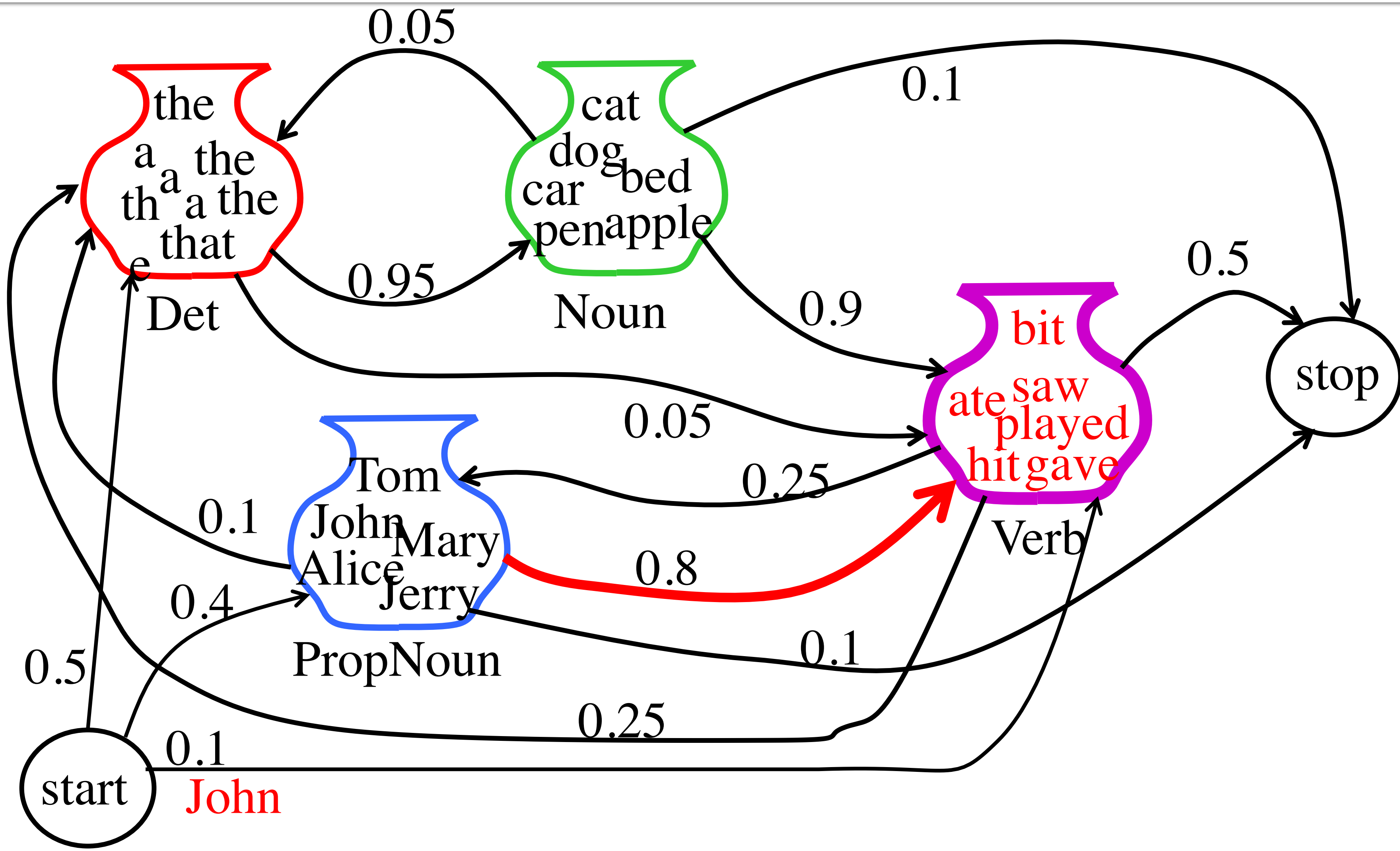

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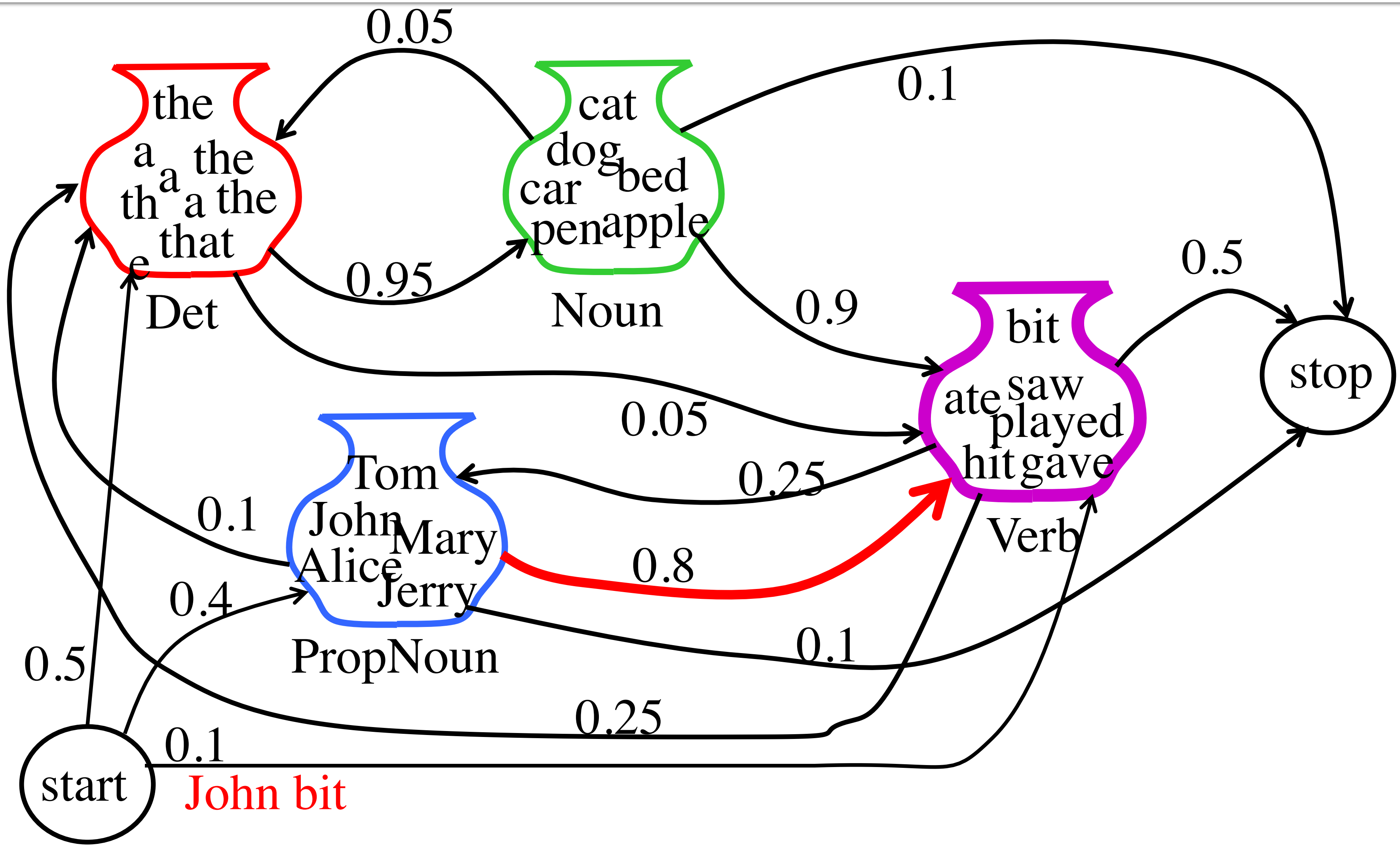

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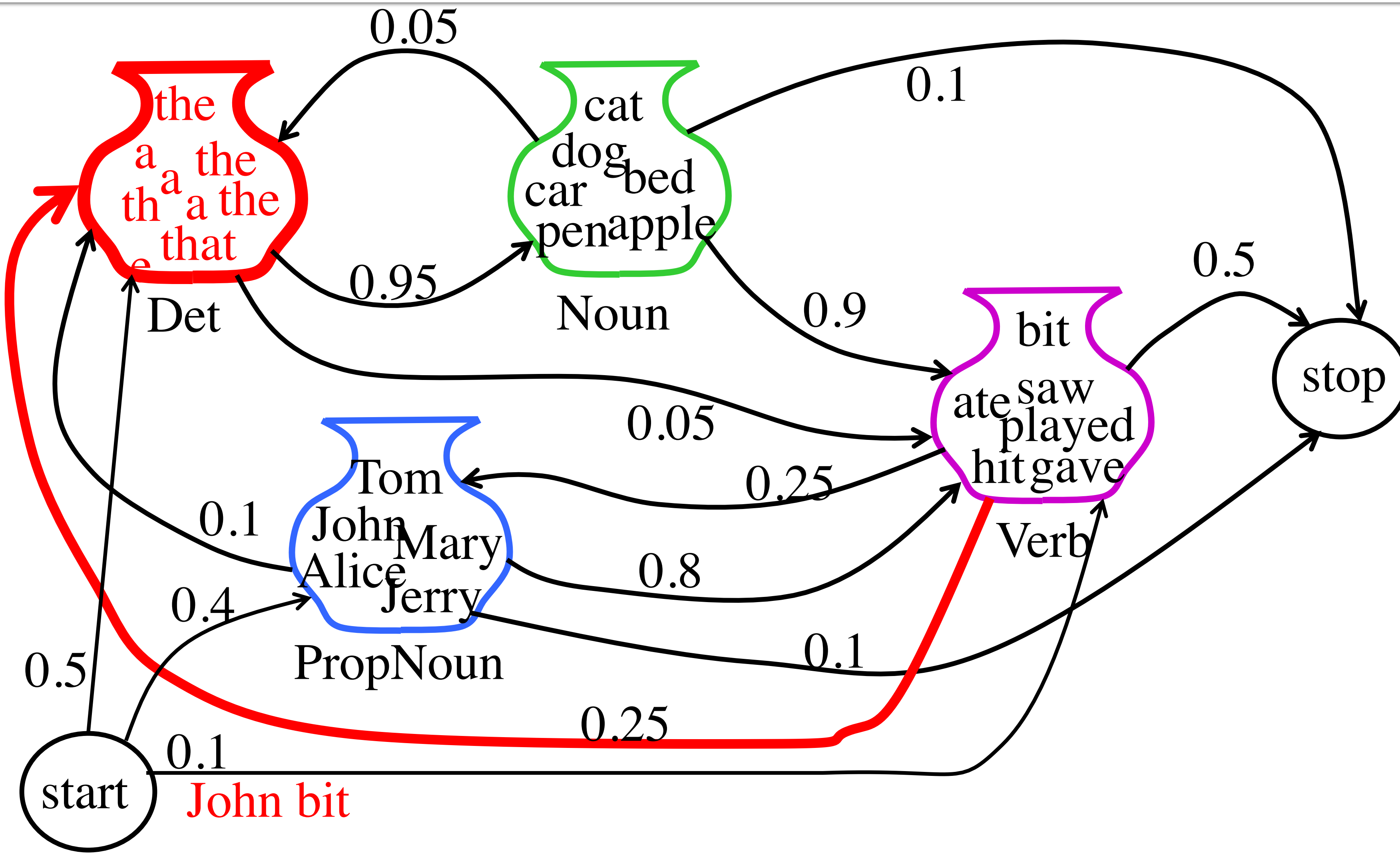

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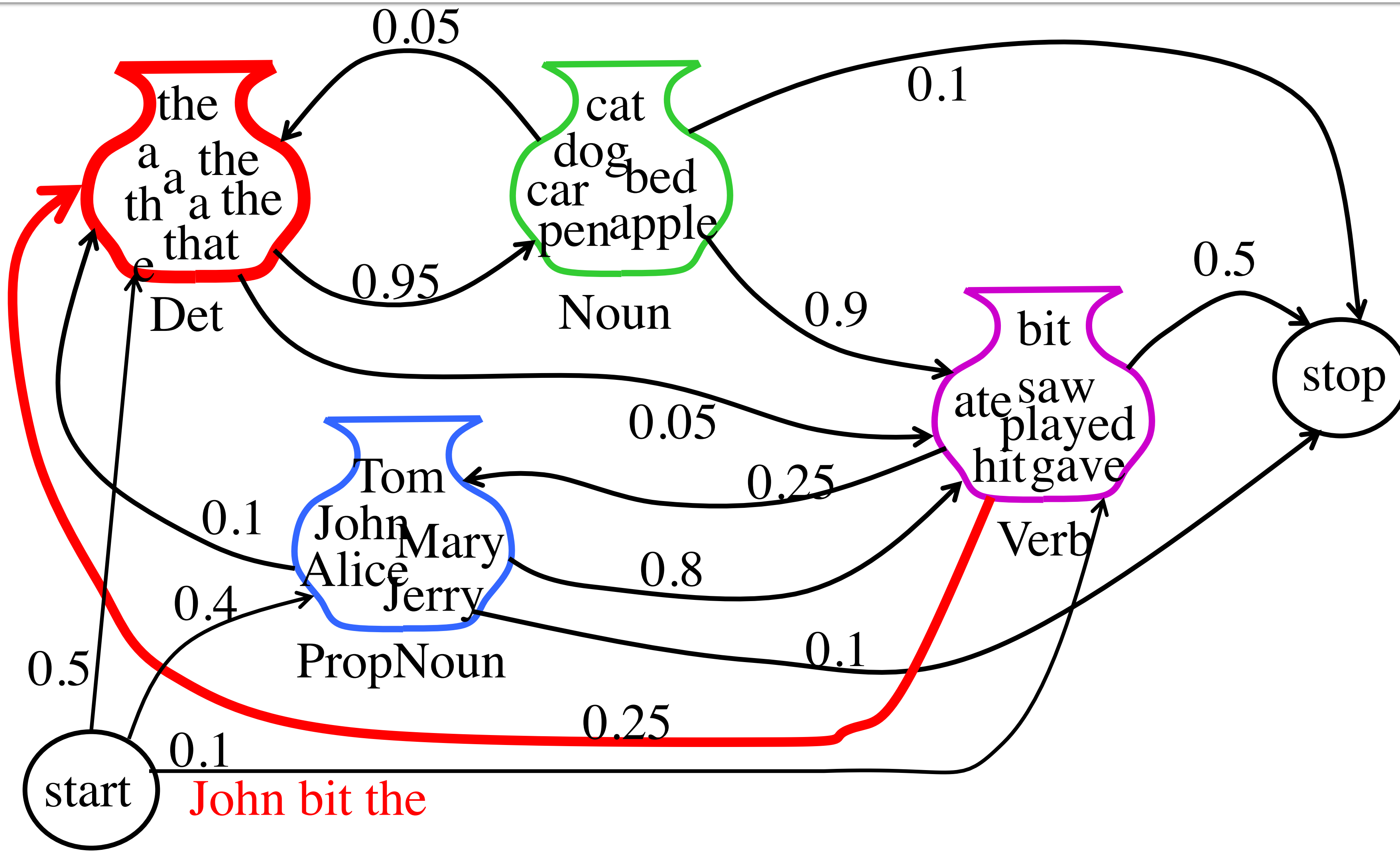

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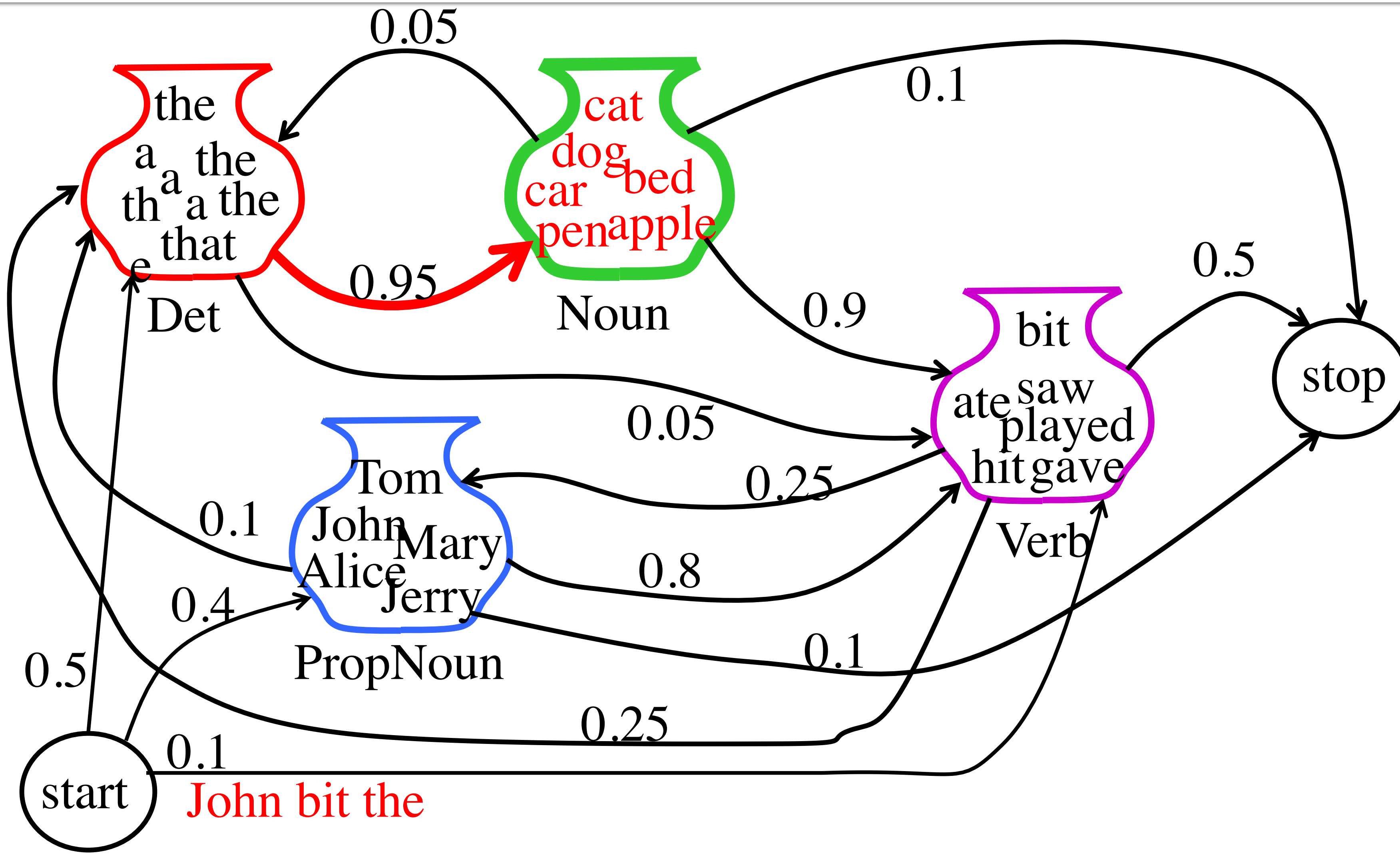

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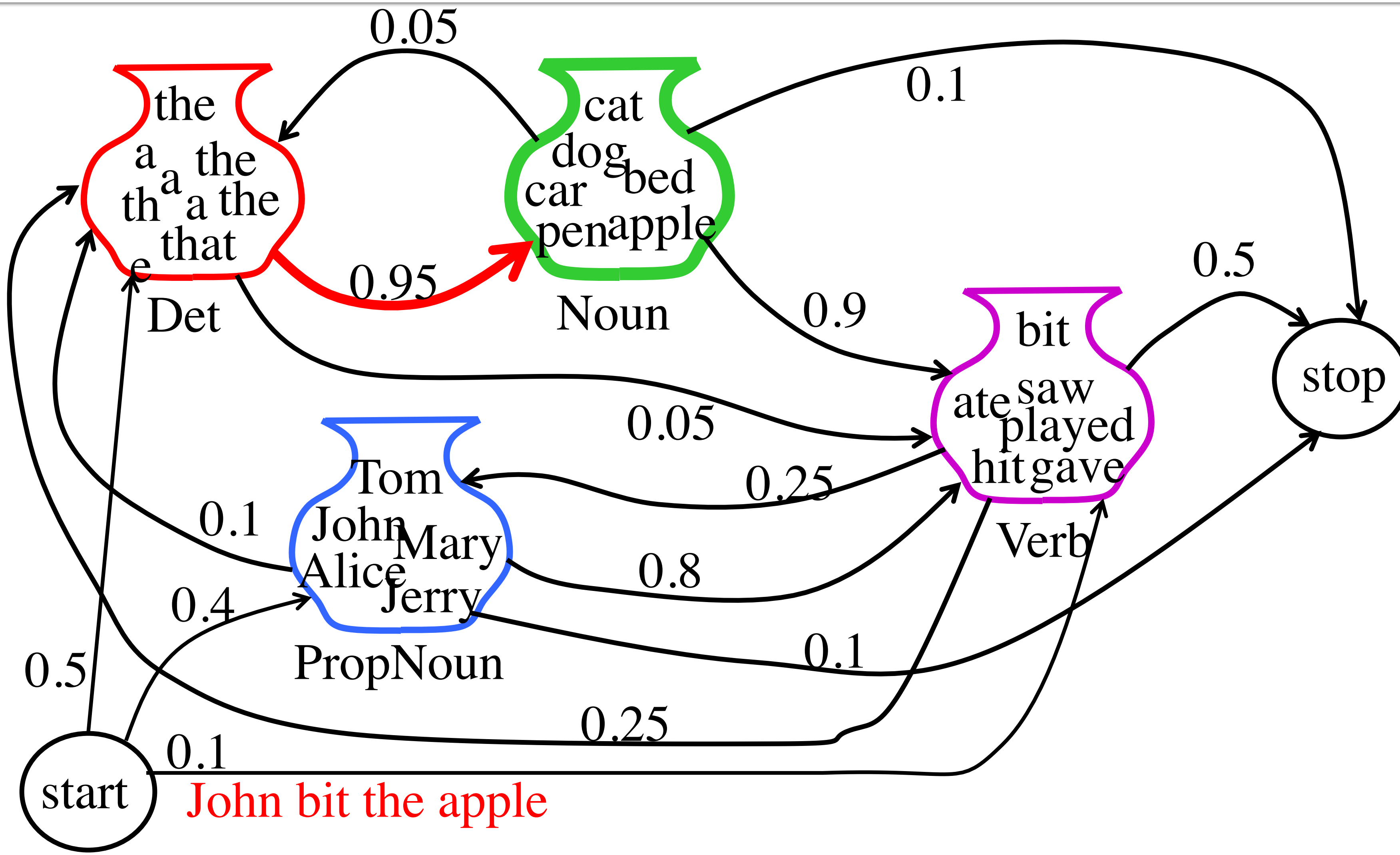
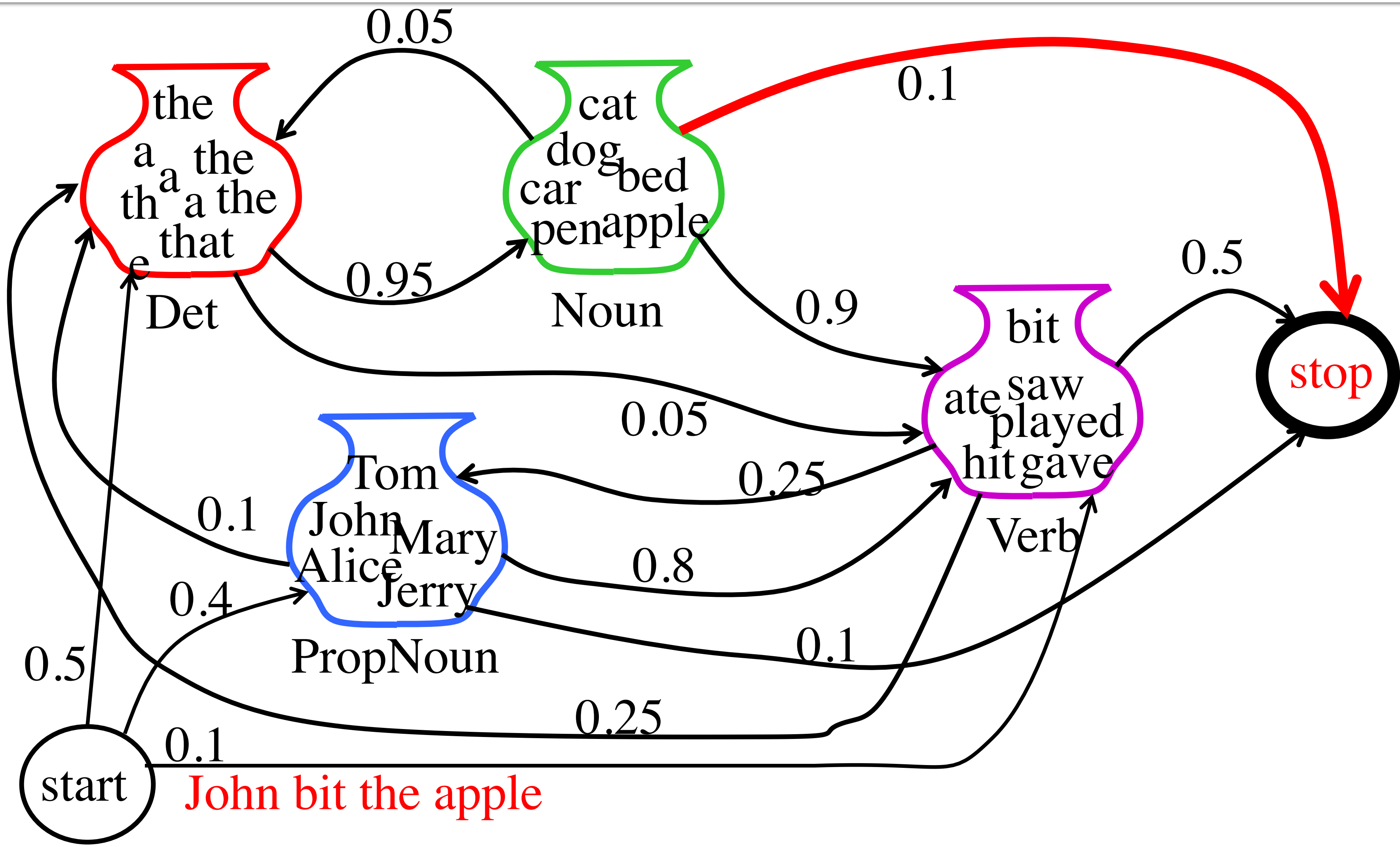


John bit the apple

Sample HMM Generation



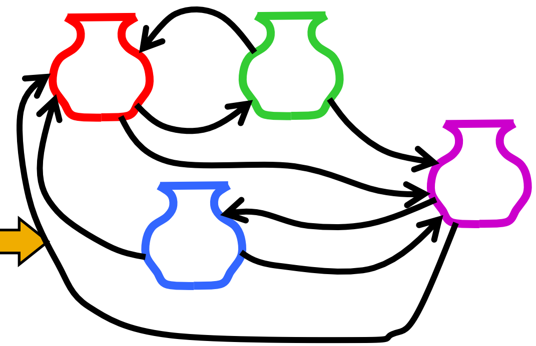
Supervised HMM Training

- If training sequences are labeled (tagged) with the underlying state sequences that generated them, then the parameters, λ={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.
.
.
.

Supervised HMM Training



Det Noun PropNoun Verb

Supervised Parameter Estimation

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

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

- 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.

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) . Most freq. baseline: ~92.4%
  - Generally matching human agreement level.