sequence modeling:

part-of-speech tagging with hidden Markov models

CS 585, Fall 2018

Introduction to Natural Language Processing

http://people.cs.umass.edu/~miyyer/cs585/

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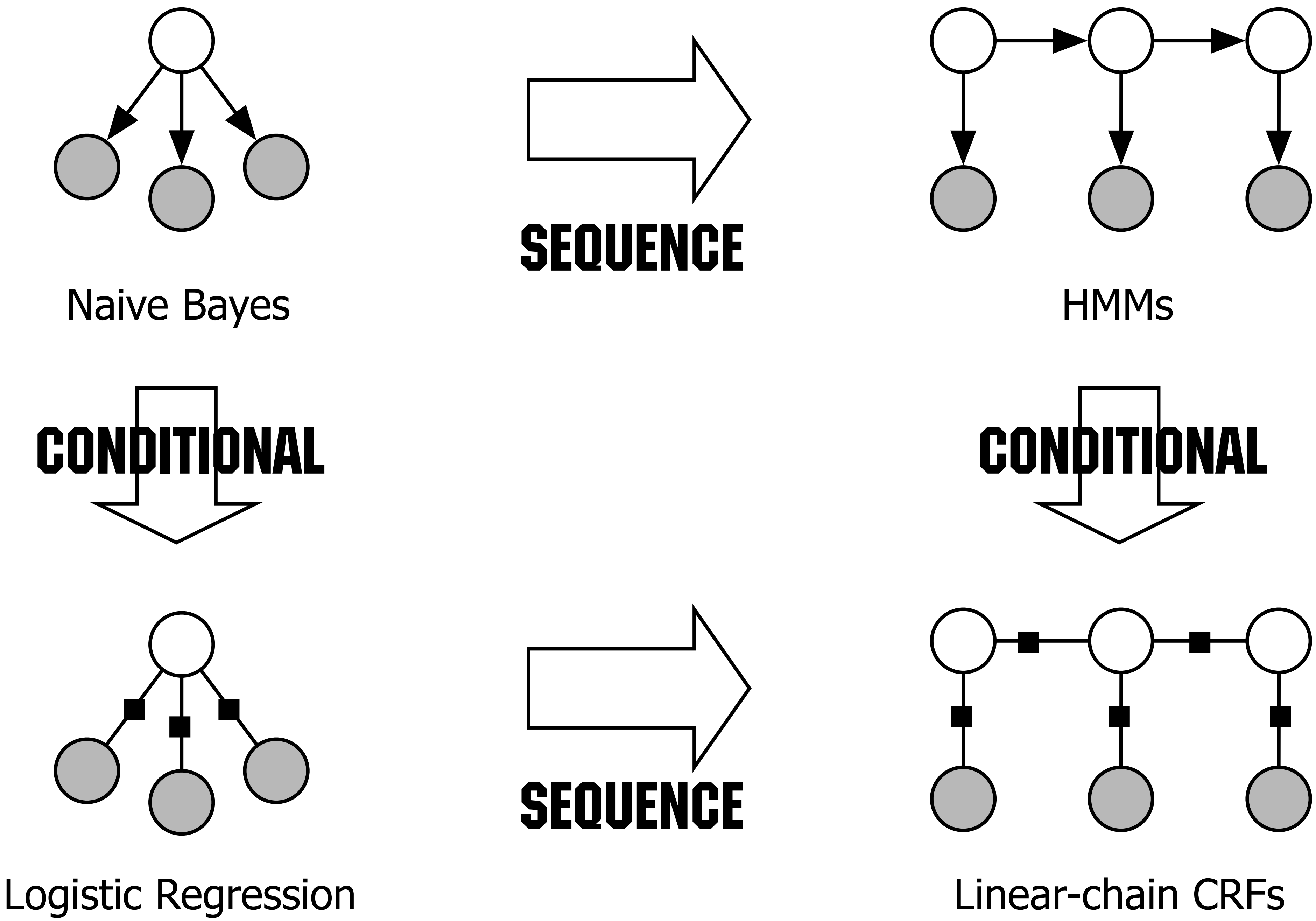
many slides from Brendan O'Connor & Jordan Boyd-Graber

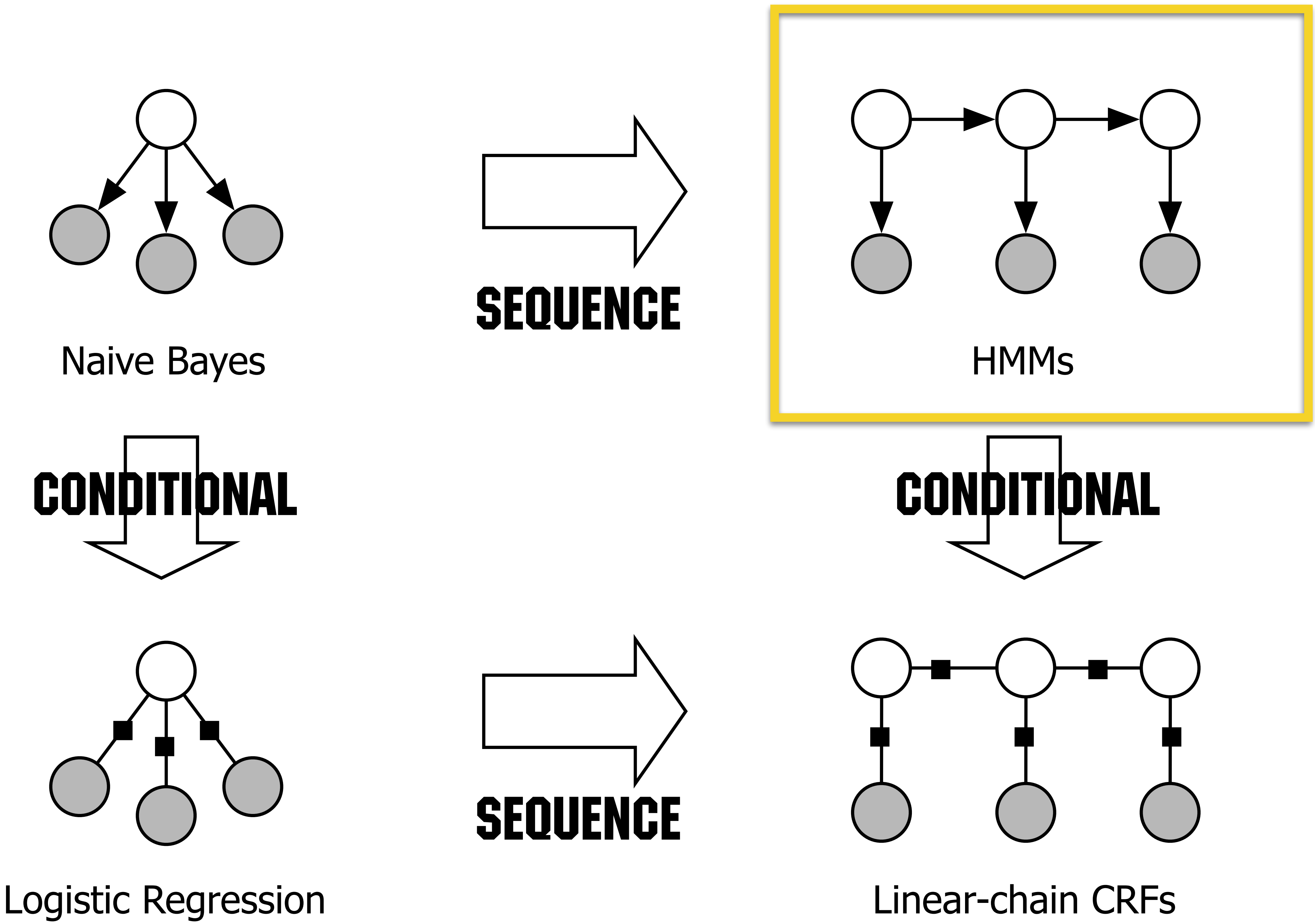
questions from last time…

- literally none :(
- submit more questions! or feedback! or complaints!

These are all **log-linear** models



These are all **log-linear** models



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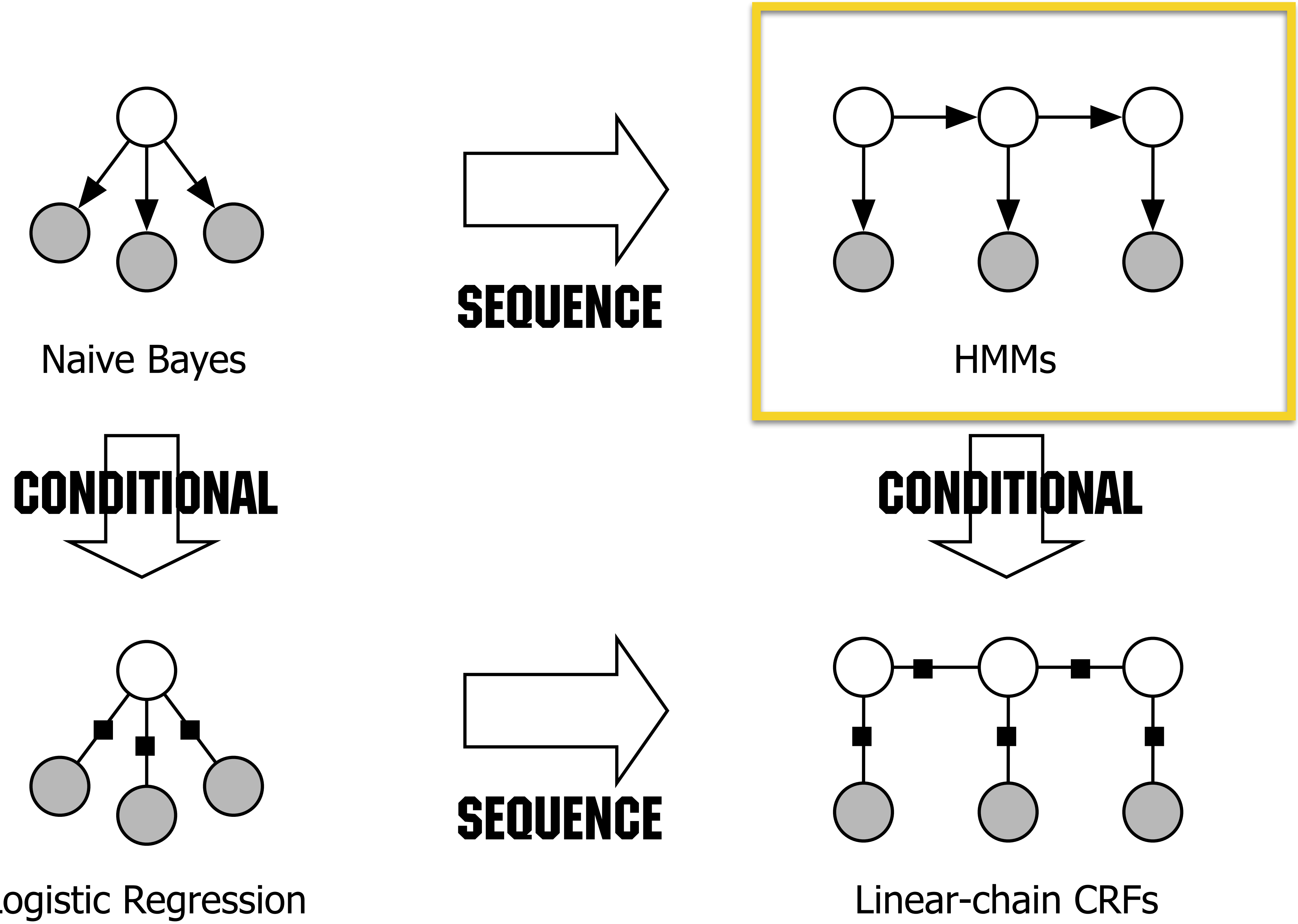


are neural networks log-linear models?

Where are we going with this?

- Text classification: bags of words
- Language Modeling: n-grams
- Sequence tagging:
  - Parts of Speech
  - Named Entity Recognition
  - Other areas: bioinformatics (gene prediction), etc…

Tagging (Sequence Labeling)

- Given a sequence (in NLP, words), assign appropriate labels to each word.
- Many NLP problems can be viewed as sequence labeling:
  - POS Tagging
  - Chunking
  - Named Entity Tagging
- Labels of tokens are dependent on the labels of other tokens in the sequence, particularly their neighbors

Plays	well	with	others.
VBZ	RB	IN	NNS

What’s a part-of-speech (POS)?

- Syntax = how words compose to form larger meaning bearing units

- POS = syntactic categories for words (a.k.a word class)
  - You could substitute words within a class and have a syntactically valid sentence

    I saw the **dog**

    I saw the **cat**

    I saw the ___

  - Gives information how words combine into larger phrases

Why do we want POS?

- Useful for many syntactic and other NLP tasks.
  - Phrase identification (“chunking”)
  - Named entity recognition
  - Full parsing
  - Sentiment
- Especially when there’s a low amount of training data

POS patterns: sentiment

- Turney (2002): identify bigram phrases, from unlabeled corpus, useful for sentiment analysis.

Table 1. Patterns of tags for extracting two-word phrases from reviews.

	First Word	Second Word	Third Word (Not Extracted)
1.	JJ	NN or NNS	anything
2.	RB, RBR, or RBS	JJ	not NN nor NNS
3.	JJ	JJ	not NN nor NNS
4.	NN or NNS	JJ	not NN nor NNS
5.	RB, RBR, or RBS	VB, VBD, VBN, or VBG	anything

→

Table 2. An example of the processing of a review that the author has classified as *recommended*.[6]

Extracted Phrase	Part-of-Speech Tags	Semantic Orientation
online experience	JJ NN	2.253
low fees	JJ NNS	0.333
local branch	JJ NN	0.421
small part	JJ NN	0.053
online service	JJ NN	2.780
printable version	JJ NN	-0.705
direct deposit	JJ NN	1.288
well other	RB JJ	0.237
inconveniently located	RB VBN	-1.541
other bank	JJ NN	-0.850
true service	JJ NN	-0.732

POS patterns: simple noun phrases

- Quick and dirty noun phrase identification

Tag Pattern	Example
A N	*linear function*
N N	*regression coefficients*
A A N	*Gaussian random variable*
A N N	*cumulative distribution function*
N A N	*mean squared error*
N N N	*class probability function*
N P N	*degrees of freedom*

Table 5.2 Part of speech tag patterns for collocation filtering. These patterns were used by Justeson and Katz to identify likely collocations among frequently occurring word sequences.

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*, …**
    - Q: why called "closed"?
  - Open:
    - Nouns, Verbs, Adjectives, Adverbs.

Many Tagging Standards

- Penn Treebank (45 tags) … this is the most common one
- Brown corpus (85 tags)
- Coarse tagsets
  - Universal POS tags (Petrov et. al. https://github.com/slavpetrov/universal-pos-tags)
  - Motivation: cross-linguistic regularities

Penn Treebank POS

- 45 possible tags
- 34 pages of tagging guidelines

https://catalog.ldc.upenn.edu/docs/LDC99T42/tagguid1.pdf

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*			

Ambiguity in POS Tagging

- Words often have more than one POS: *back*
  - The *back* door = JJ
  - On my *back* = NN
  - Win the voters *back* = RB
  - Promised to *back* the bill = VB
- The POS tagging problem is to determine the POS tag for a particular instance of a word.

POS Tagging

- Input: Plays well with others
- Ambiguity: NNS/VBZ UH/JJ/NN/RB IN NNS
- Output: Plays/VBZ well/RB with/IN others/NNS

Penn Treebank POS tags

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
      - 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?

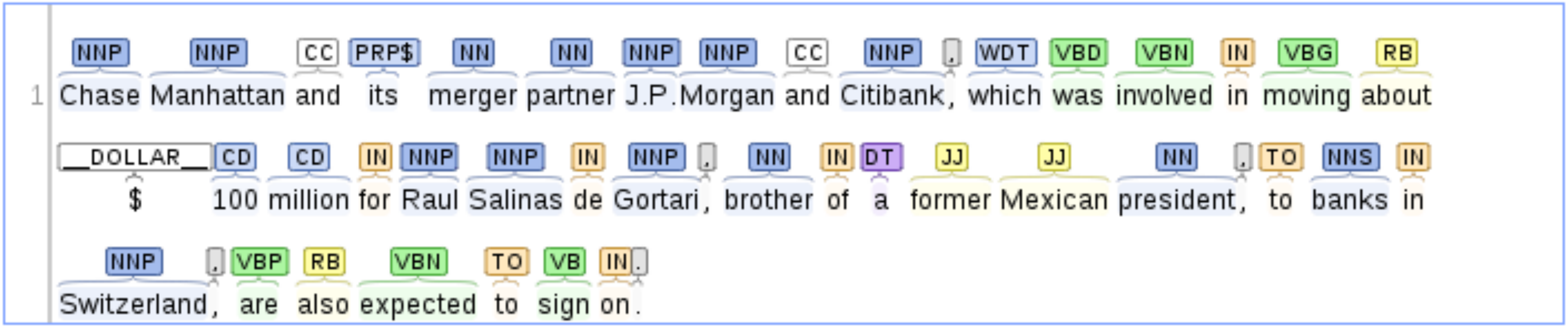
- About 11% of the **word types** in the Brown corpus are ambiguous with regard to part of speech
- But they tend to be very common words. E.g., *that*
  - I know *that* he is honest = IN
  - Yes, *that* play was nice = DT
  - You can't go *that* far = RB
- 40% of the **word tokens** are ambiguous

Token vs. Type

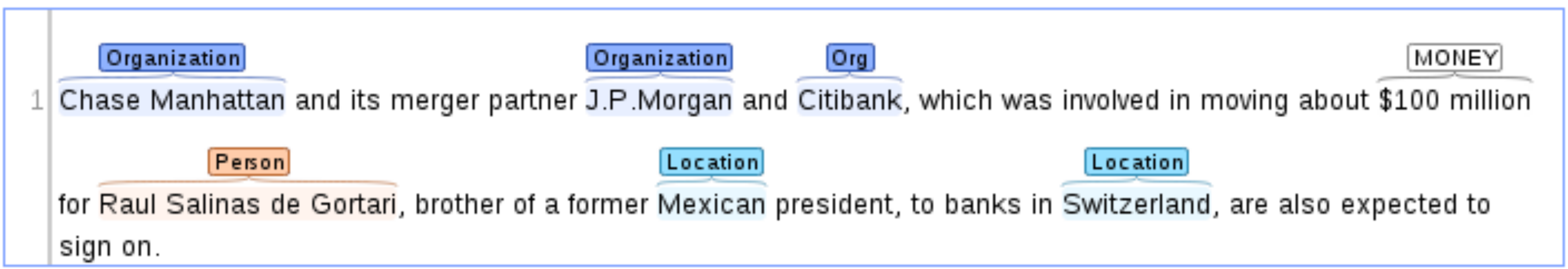
Token is instance or individual occurrence of a type.

Stanford CoreNLP Toolkit

Part-of-Speech:



Named Entity Recognition:



Two Types of Constraints

Influential/JJ members/NNS of/IN the/DT House/NNP Ways/NNP and/CC Means/NNP Committee/NNP introduced/VBD legislation/NN that/WDT would/MD restrict/VB how/WRB the/DT new/JJ savings-and-loan/NN bailout/NN agency/NN can/MD raise/VB capital/NN ./.

- "Local": e.g., *can* is more likely to be a modal verb MD rather than a noun NN
- "Contextual": e.g., a noun is much more likely than a verb to follow a determiner
- Sometimes these preferences are in conflict:

  The trash can is in the garage

Hidden Markov Models

- We have an input sentence $x = x_1, x_2, \ldots, x_n$ (x_i is the i'th word in the sentence)
- We have a tag sequence $y = y_1, y_2, \ldots, y_n$ (y_i is the i'th tag in the sentence)
- We'll use an HMM to define

$$p(x_1, x_2, \ldots, x_n, y_1, y_2, \ldots, y_n)$$

for any sentence $x_1 \ldots x_n$ and tag sequence $y_1 \ldots y_n$ of the same length.

- Then the most likely tag sequence for x is

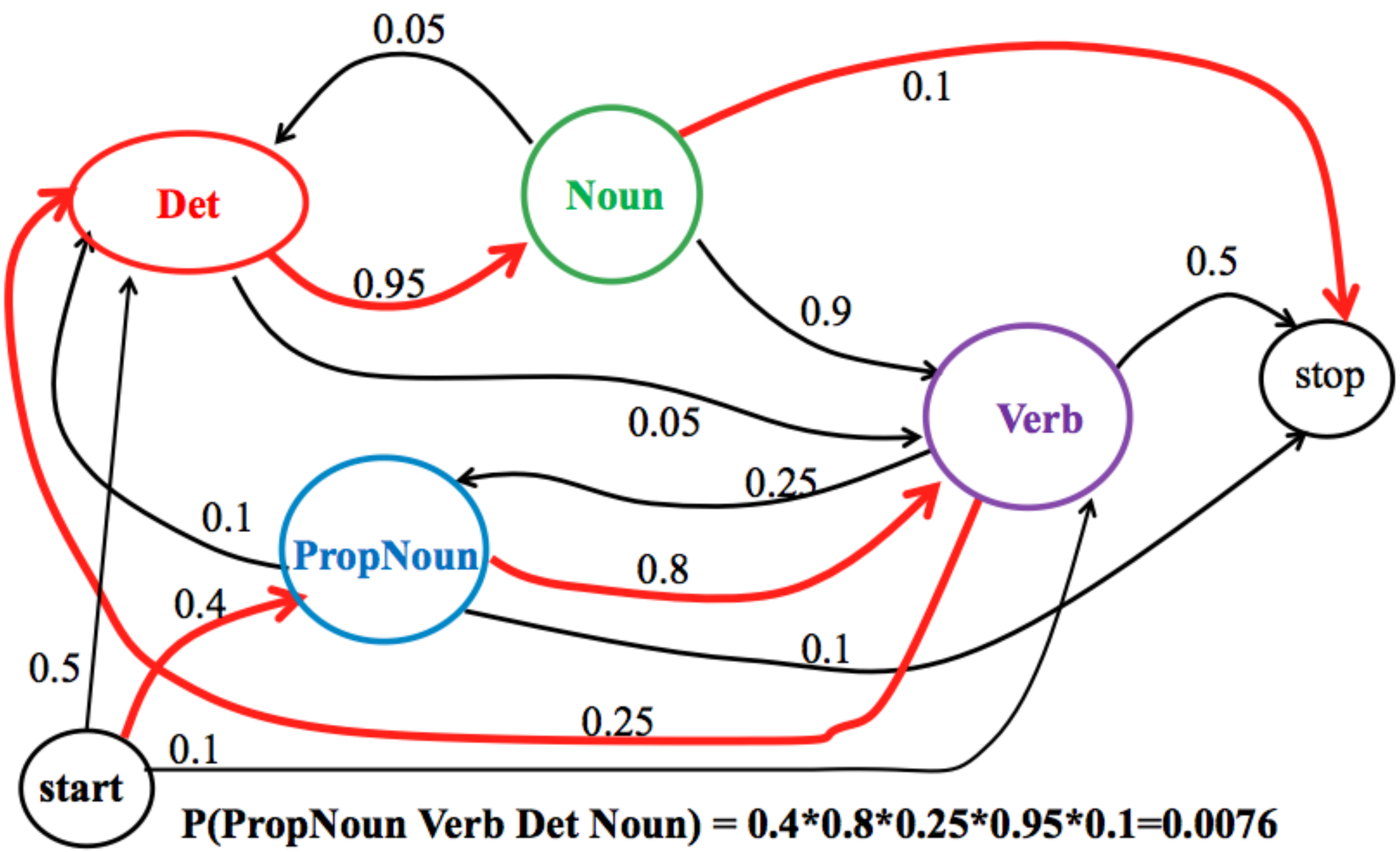
$$\arg\max_{y_1 \cdots y_n} p(x_1 \ldots x_n, y_1, y_2, \ldots, y_n)$$

are HMMs generative or discriminative models?

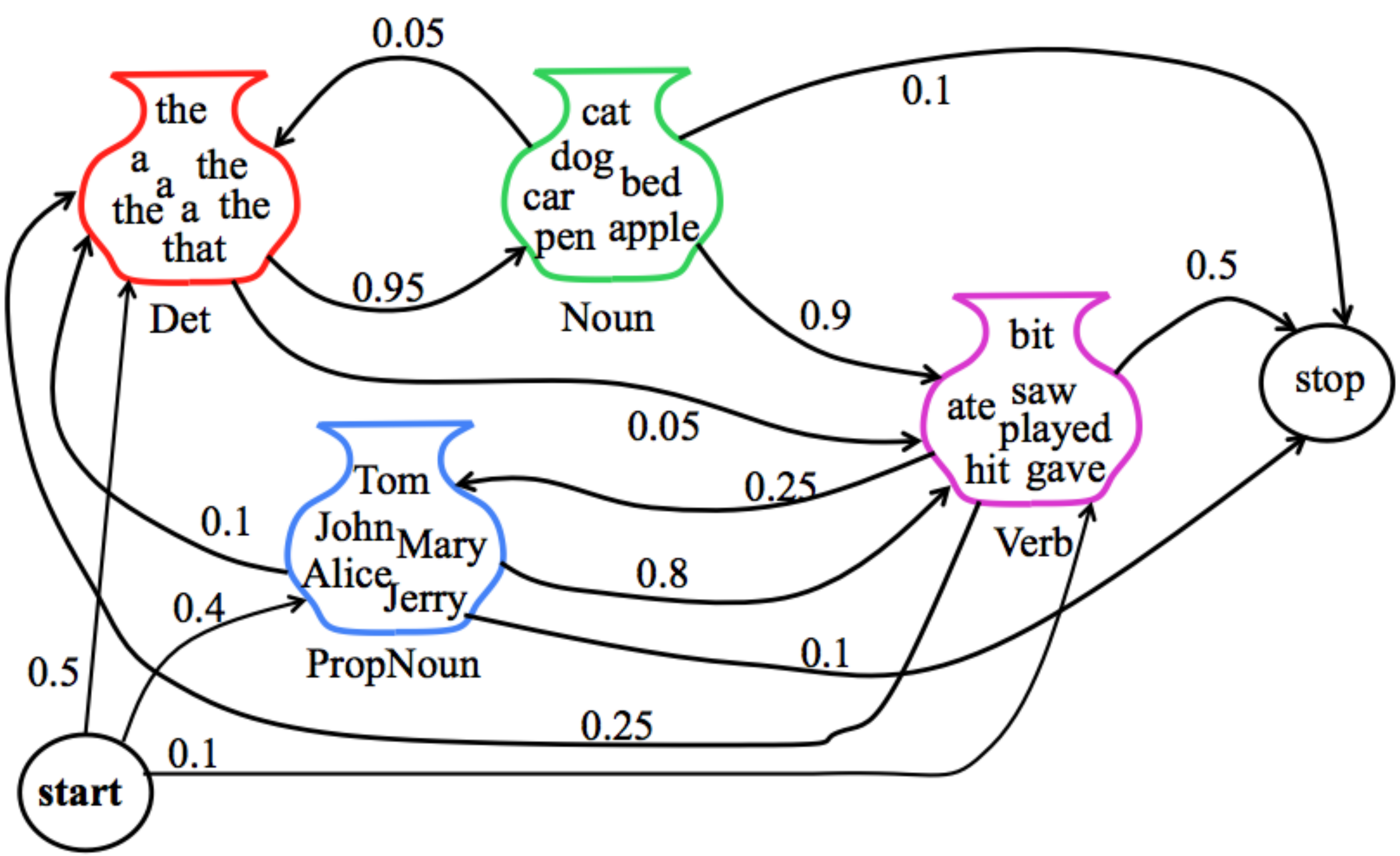
Generative Model

- Probabilistic generative model for sequences.
- Assume an underlying set of hidden (unobserved) states in which the model can be (e.g. parts of speech). different from RNN hidden states!
- 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).

Cartoon


0.05
0.1
Det
Noun
0.95
0.9
0.5
stop
Verb
0.05
0.25
0.1
PropNoun
0.8
0.4
0.1
0.5
0.25
start
0.1
P(PropNoun Verb Det Noun) = 0.4*0.8*0.25*0.95*0.1=0.0076

Cartoon



0.05
0.1
the
a
the
a
the
a
the
that
Det
cat
dog
bed
car
pen
apple
Noun
0.95
0.9
0.5
bit
ate
saw
played
hit
gave
Verb
stop
0.05
0.25
Tom
John
Mary
Alice
Jerry
PropNoun
0.1
0.8
0.4
0.1
0.5
0.25
0.1
start

HMM Definition

Assume K parts of speech, a lexicon size of V, a series of observations $\{x_1, \ldots, x_N\}$, and a series of unobserved states $\{z_1, \ldots, z_N\}$.

- π A distribution over start states (vector of length K): $\pi_i = p(z_1 = i)$
- θ Transition matrix (matrix of size K by K): $\theta_{i,j} = p(z_n = j | z_{n-1} = i)$ Markov assumption!
- β An emission matrix (matrix of size K by V): $\beta_{j,w} = p(x_n = w | z_n = j)$

HMM Definition

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Two problems: How do we move from data to a model? (Estimation) How do we move from a model and unlabled data to labeled data? (Inference)

today: estimation

Reminder: How do we estimate a probability?

- For a multinomial distribution (i.e. a discrete distribution, like over words):

$$\theta_i = \frac{n_i + \alpha_i}{\sum_k n_k + \alpha_k} \tag{1}$$

- α_i is called a smoothing factor, a pseudocount, etc.

just like in naive Bayes, we'll be counting to estimate these probabilities!

Training Sentences

x = tokens
z = POS tags

x	here	come	old	flattop
z	MOD	V	MOD	N

a	crowd	of	people	stopped	and	stared
DET	N	PREP	N	V	CONJ	V

gotta	get	you	into	my	life
V	V	PRO	PREP	PRO	V

and	I	love	her
CONJ	PRO	V	PRO

Initial Probability π

POS	Frequency	Probability
MOD	1.1	0.234
DET	1.1	0.234
CONJ	1.1	0.234
N	0.1	0.021
PREP	0.1	0.021
PRO	0.1	0.021
V	1.1	0.234

let's use add-alpha smoothing with alpha = 0.1

Training Sentences

here	come	old	flattop
MOD	V	MOD	N

a	crowd	of	people	stopped	and	stared
DET	N	PREP	N	V	CONJ	V

gotta	get	you	into	my	life
V	V	PRO	PREP	PRO	N

and	I	love	her
CONJ	PRO	V	PRO

Training Sentences

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Training Sentences

here	come	old	flattop			
MOD	V	MOD	N			

a	crowd	of	people	stopped	and	stared
DET	N	PREP	N	V	CONJ	V

gotta	get	you	into	my	life
V	V	PRO	PREP	PRO	N

and	I	love	her
CONJ	PRO	V	PRO

Transition Probability θ

- We can ignore the words; just look at the parts of speech. Let's compute one row, the row for verbs.
- We see the following transitions: V $\rightarrow$ MOD, V $\rightarrow$ CONJ, V $\rightarrow$ V, V $\rightarrow$ PRO, and V $\rightarrow$ PRO

POS	Frequency	Probability
MOD	1.1	0.193
DET	0.1	0.018
CONJ	1.1	0.193
N	0.1	0.018
PREP	0.1	0.018
PRO	2.1	0.368
V	1.1	0.193

how many transition probability distributions do we have?

Training Sentences

here	come	old	flattop
MOD	V	MOD	N

a	crowd	of	people	stopped	and	stared
DET	N	PREP	N	V	CONJ	V

gotta	get	you	into	my	life
V	V	PRO	PREP	PRO	N

and	I	love	her
CONJ	PRO	V	PRO

Training Sentences

here	come	old	flattop
MOD	V	MOD	N

a	crowd	of	people	stopped	and	stared
DET	N	PREP	N	V	CONJ	V

gotta	get	you	into	my	life
V	V	PRO	PREP	PRO	N

and	I	love	her
CONJ	PRO	V	PRO

Emission Probability β

Let's look at verbs . . .

Word	a	and	come	crowd	flattop
Frequency	0.1	0.1	1.1	0.1	0.1
Probability	0.0125	0.0125	0.1375	0.0125	0.0125

Word	get	gotta	her	here	i
Frequency	1.1	1.1	0.1	0.1	0.1
Probability	0.1375	0.1375	0.0125	0.0125	0.0125

Word	into	it	life	love	my
Frequency	0.1	0.1	0.1	1.1	0.1
Probability	0.0125	0.0125	0.0125	0.1375	0.0125

Word	of	old	people	stared	stopped
Frequency	0.1	0.1	0.1	1.1	1.1
Probability	0.0125	0.0125	0.0125	0.1375	0.1375

how many emission probability distributions do we have?

Next time . . .

- Viterbi algorithm: dynamic algorithm discovering the most likely POS sequence given a sentence

what if we don't have any labeled data to estimate an HMM? we can still learn a model using the expectation-maximization algorithm. but we won't cover this in class :(