Sequence Models I

Wei Xu

(many slides from Greg Durrett, Dan Klein, Vivek Srikumar, Chris Manning, Yoav Artzi)

Administrivia

- Homework 2 is released, due on February 18 (start early!).
- Reading: Eisenstein 7.0-7.4, Jurafsky+Martin Chapter 8

This Lecture

- Sequence modeling
- HMMs for POS tagging
- HMM parameter estimation
- Viterbi, forward-backward

Linguistic Structures

- Language is tree-structured

I ate the spaghetti with chopsticks   *I ate the spaghetti with meatballs*

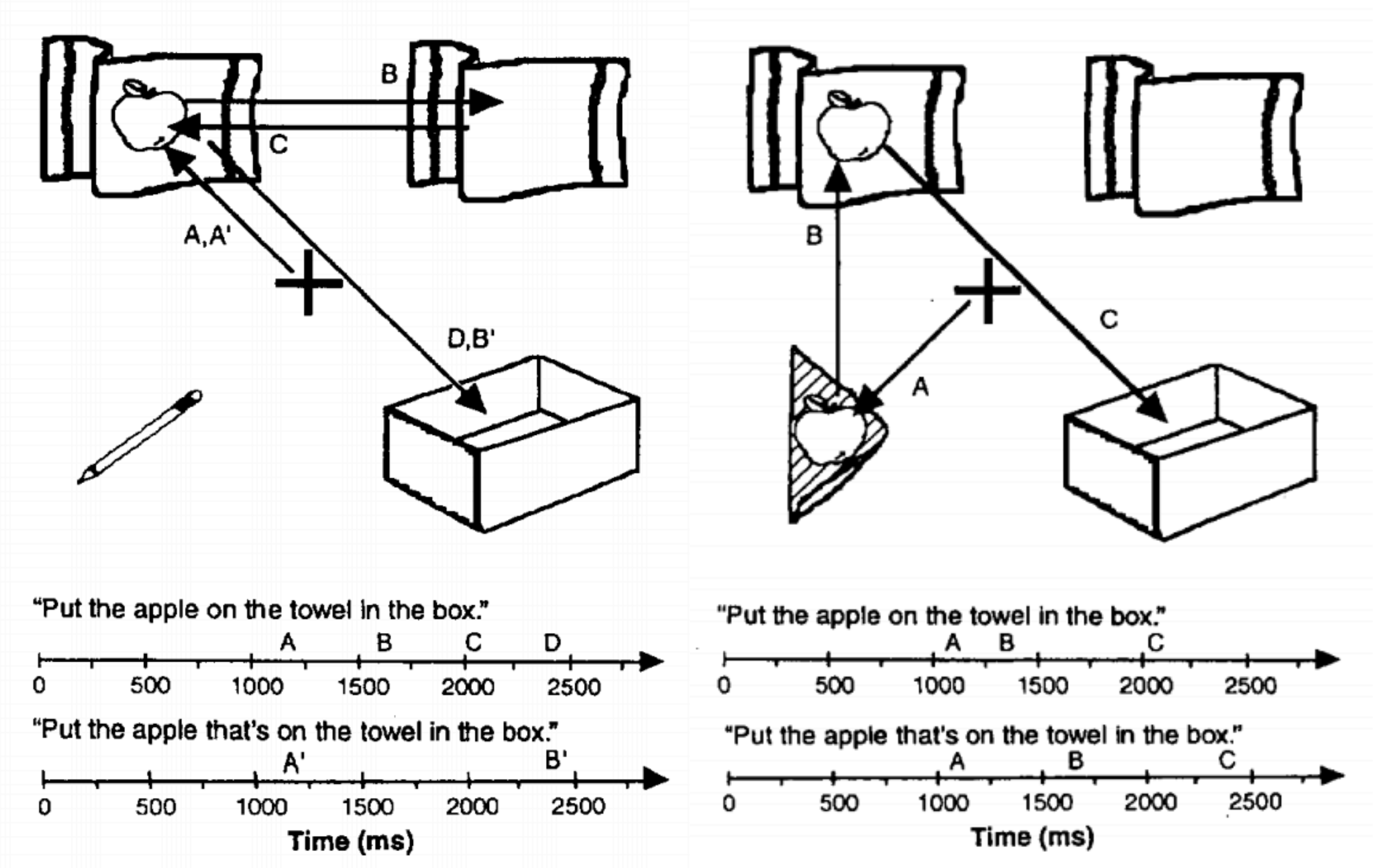
- Understanding syntax fundamentally requires trees — the sentences have the same shallow analysis

PRP VBZ DT NN IN NNS
I ate the spaghetti with chopsticks

PRP VBZ DT NN IN NNS
I ate the spaghetti with meatballs

Linguistic Structures

- Language is sequentially structured: interpreted in an online way



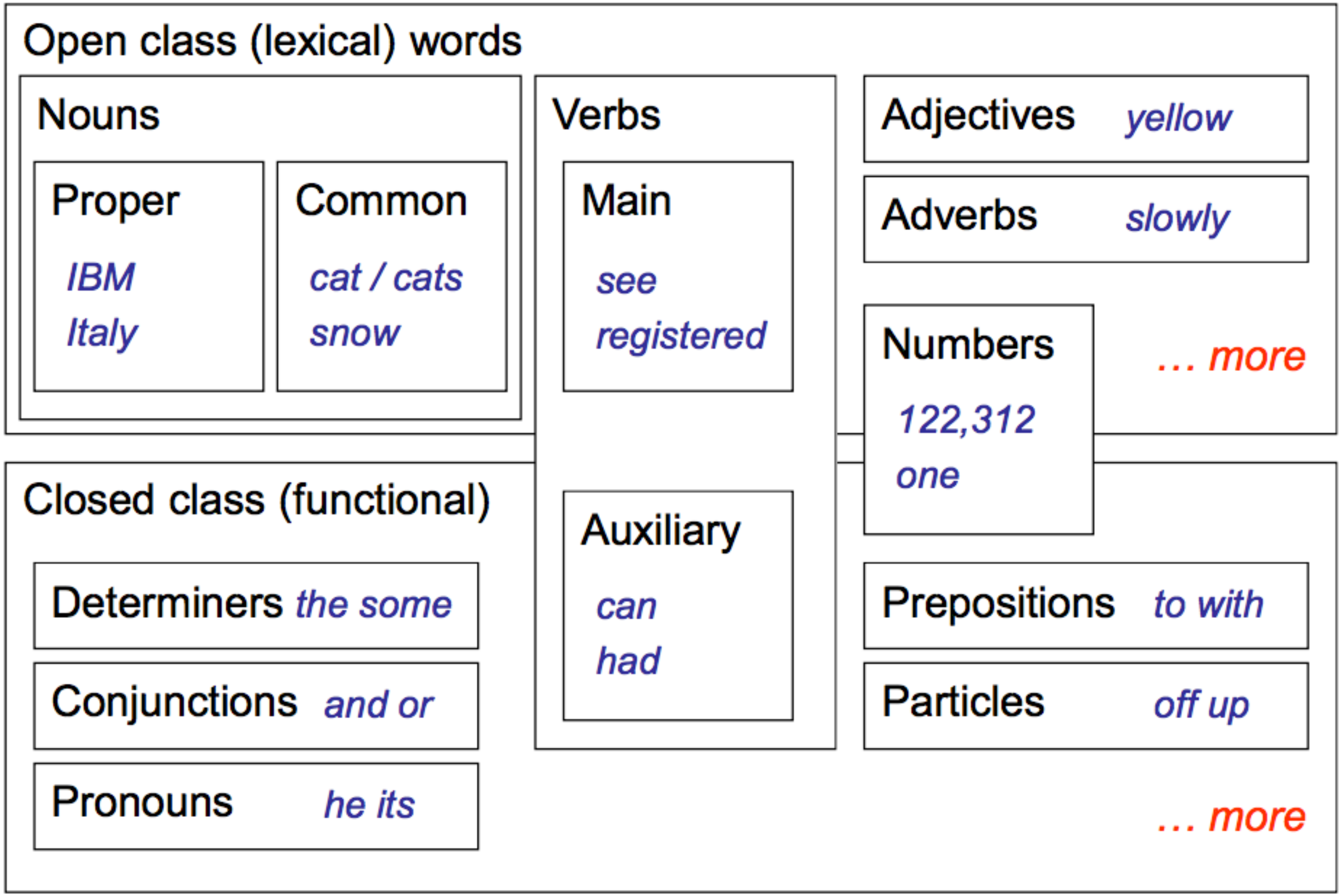
Tanenhaus et al. (1995)

POS Tagging

- What tags are out there?

Ghana 's ambassador should have set up the big meeting in DC yesterday .

POS Tagging



Slide credit: Dan Klein

POS Tagging

Fed	raises	interest	rates	0.5	percent
VBD		VB			
VBN	VBZ	VBP	VBZ		
NNP	NNS	NN	NNS	CD	NN

Fed raises interest rates 0.5 percent

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Fed raises interest rates 0.5 percent

I hereby increase interest rates 0.5%

I'm 0.5% interested in the Fed's raises!

- Other paths are also plausible but even more semantically weird…
- What governs the correct choice? Word + context
  - Word identity: most words have <=2 tags, many have one (*percent*, *the*)
  - Context: nouns start sentences, nouns follow verbs, etc.

POS Tagging

CC	conjunction, coordinating	and both but either or
CD	numeral, cardinal	mid-1890 nine-thirty 0.5 one
DT	determiner	a all an every no that the
EX	existential there	there
FW	foreign word	gemeinschaft hund ich jeux
IN	preposition or conjunction, subordinating	among whether out on by if
JJ	adjective or numeral, ordinal	third ill-mannered regrettable
JJR	adjective, comparative	braver cheaper taller
JJS	adjective, superlative	bravest cheapest tallest
MD	modal auxiliary	can may might will would
NN	noun, common, singular or mass	cabbage thermostat investment subhumanity
NNP	noun, proper, singular	Motown Cougar Yvette Liverpool
NNPS	noun, proper, plural	Americans Materials States
NNS	noun, common, plural	undergraduates bric-a-brac averages
POS	genitive marker	' 's
PRP	pronoun, personal	hers himself it we them
PRP$	pronoun, possessive	her his mine my our ours their thy your
RB	adverb	occasionally maddeningly adventurously
RBR	adverb, comparative	further gloomier heavier less-perfectly
RBS	adverb, superlative	best biggest nearest worst
RP	particle	aboard away back by on open through
TO	"to" as preposition or infinitive marker	to
UH	interjection	huh howdy uh whammo shucks heck
VB	verb, base form	ask bring fire see take
VBD	verb, past tense	pleaded swiped registered saw
VBG	verb, present participle or gerund	stirring focusing approaching erasing
VBN	verb, past participle	dilapidated imitated reunifed unsettled
VBP	verb, present tense, not 3rd person singular	twist appear comprise mold postpone
VBZ	verb, present tense, 3rd person singular	bases reconstructs marks uses
WDT	WH-determiner	that what whatever which whichever
WP	WH-pronoun	that what whatever which who whom
WP$	WH-pronoun, possessive	whose
WRB	Wh-adverb	however whenever where why

What is this good for?

- Text-to-speech: *record*, *lead*
- Preprocessing step for syntactic parsers
- Domain-independent disambiguation for other tasks
- (Very) shallow information extraction

Sequence Models

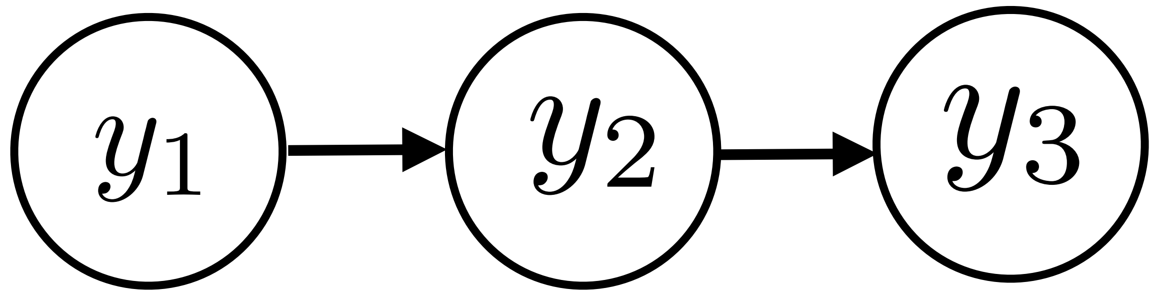
- Input $\mathbf{x} = (x_1, ..., x_n)$ Output $\mathbf{y} = (y_1, ..., y_n)$

- POS tagging: ***x*** is a sequence of words, ***y*** is a sequence of tags

- Today: generative models P(***x, y***); discriminative models next time

Hidden Markov Models

- Input $\mathbf{x} = (x_1, ..., x_n)$ Output $\mathbf{y} = (y_1, ..., y_n)$
- Model the sequence of *y* as a Markov process (dynamics model)
- Markov property: future is conditionally independent of the past given the present

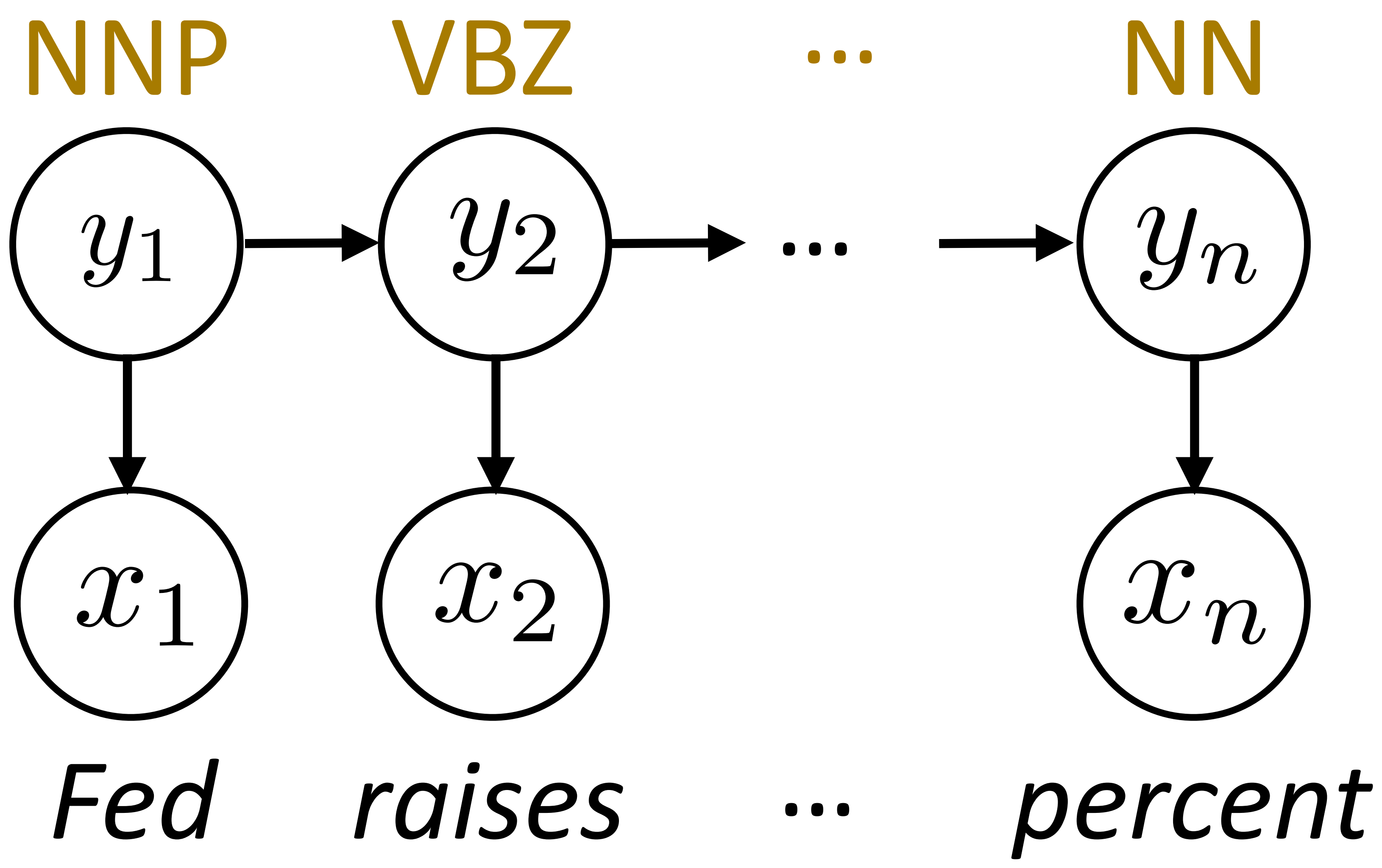


$$P(y_3|y_1, y_2) = P(y_3|y_2)$$

- Lots of mathematical theory about how Markov chains behave
- If *y* are tags, this roughly corresponds to assuming that the next tag only depends on the current tag, not anything before

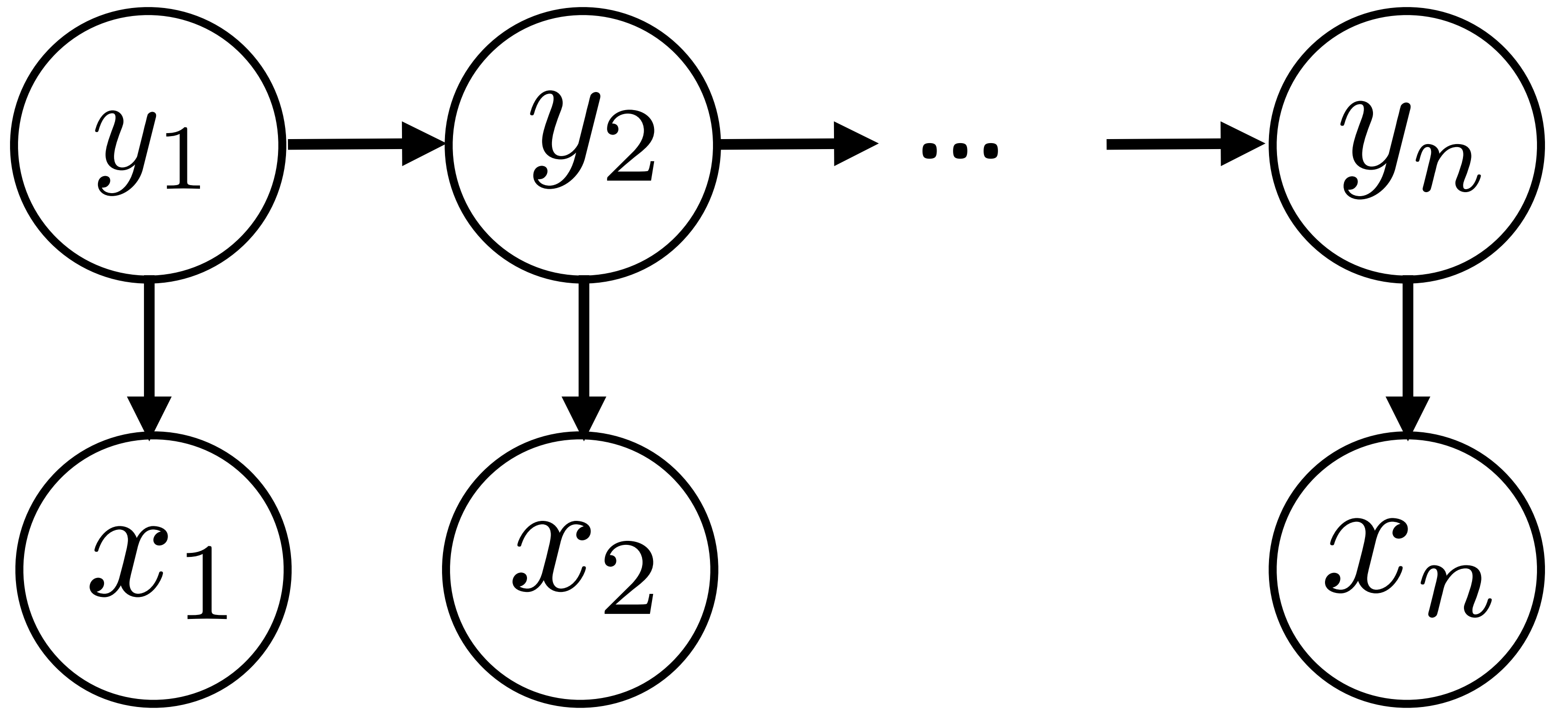
Hidden Markov Models

- Input $\mathbf{x} = (x_1, \ldots, x_n)$ Output $\mathbf{y} = (y_1, \ldots, y_n)$



Hidden Markov Models

- Input $\mathbf{x} = (x_1, ..., x_n)$ Output $\mathbf{y} = (y_1, ..., y_n)$



$$P(\mathbf{y}, \mathbf{x}) = \underbrace{P(y_1)}_{\text{Initial distribution}} \underbrace{\prod_{i=2}^{n} P(y_i | y_{i-1})}_{\text{Transition probabilities}} \underbrace{\prod_{i=1}^{n} P(x_i | y_i)}_{\text{Emission probabilities}}$$

- Observation (*x*) depends only on current state (*y*)
- Multinomials: tag x tag transitions, tag x word emissions
- P(*x*|*y*) is a distribution over all words in the vocabulary — not a distribution over features (but could be!)

Transitions in POS Tagging

- Dynamics model $P(y_1)\prod_{i=2}^{n} P(y_i|y_{i-1})$

VBD		VB				
VBN	VBZ	VBP	VBZ			
NNP	NNS	NN	NNS	CD	NN	.
Fed	*raises*	*interest*	*rates*	*0.5*	*percent*	*.*

NNP - proper noun, singular
VBZ - verb, 3rd ps. sing. present
NN - noun, singular or mass

- $P(y_1 = \mathrm{NNP})$ likely because start of sentence
- $P(y_2 = \mathrm{VBZ}|y_1 = \mathrm{NNP})$ likely because verb often follows noun
- $P(y_3 = \mathrm{NN}|y_2 = \mathrm{VBZ})$ direct object follows verb, other verb rarely follows past tense verb (main verbs can follow modals though!)

Estimating Transitions

NNP VBZ NN NNS CD NN .

Fed raises interest rates 0.5 percent .

- Similar to Naive Bayes estimation: maximum likelihood solution = normalized counts (with smoothing) read off supervised data
- P(tag | NN) = (0.5 ., 0.5 NNS)
- How to smooth?
- One method: smooth with unigram distribution over tags

$$P(\text{tag}|\text{tag}_{-1}) = (1-\lambda)\hat{P}(\text{tag}|\text{tag}_{-1}) + \lambda\hat{P}(\text{tag})$$

$\hat{P}$ = empirical distribution (read off from data)

Emissions in POS Tagging

NNP VBZ NN NNS CD NN .
Fed raises interest rates 0.5 percent .

- Emissions P(*x* | *y*) capture the distribution of words occurring with a given tag
- P(word | NN) = (0.05 *person*, 0.04 *official*, 0.03 *interest*, 0.03 *percent* …)
- When you compute the posterior for a given word's tags, the distribution favors tags that are more likely to generate that word
- How should we smooth this?

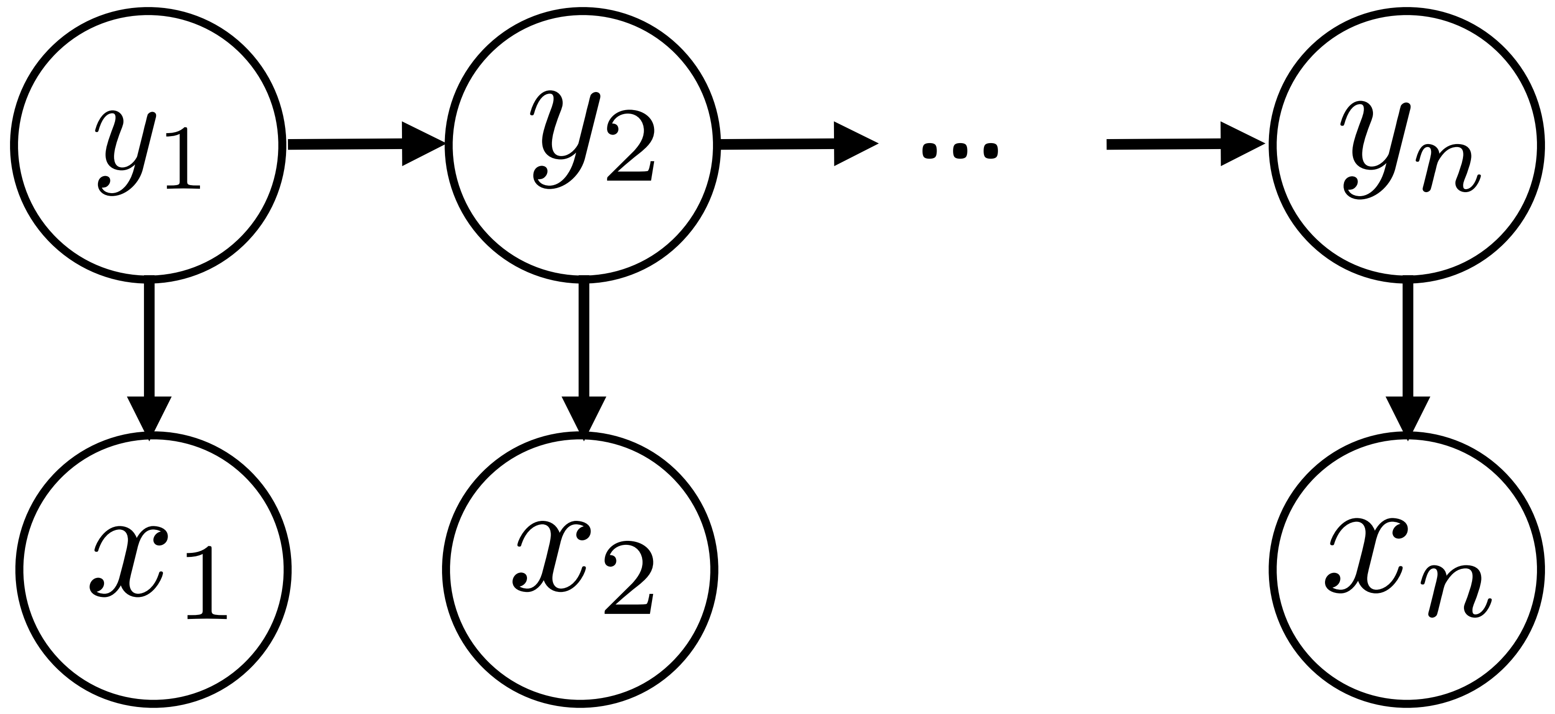
Estimating Emissions

NNP VBZ NN NNS CD NN
Fed raises interest rates 0.5 percent

- P(word | NN) = (0.5 *interest*, 0.5 *percent*) — hard to smooth!
- Can interpolate with distribution looking at word shape P(word shape | tag) (e.g., P(capitalized word of len >= 8 | tag))
- Alternative: use Bayes' rule $$P(\mathrm{word}|\mathrm{tag}) = \frac{P(\mathrm{tag}|\mathrm{word})P(\mathrm{word})}{P(\mathrm{tag})}$$
  - Fancy techniques from language modeling, e.g. look at type fertility — P(tag|word) is flatter for some kinds of words than for others)
- P(word|tag) can be a log-linear model — we'll see this in a few lectures

Inference in HMMs

- Input $\mathbf{x} = (x_1, ..., x_n)$ Output $\mathbf{y} = (y_1, ..., y_n)$



$$P(\mathbf{y}, \mathbf{x}) = P(y_1) \prod_{i=2}^{n} \boxed{P(y_i|y_{i-1})} \prod_{i=1}^{n} P(x_i|y_i)$$

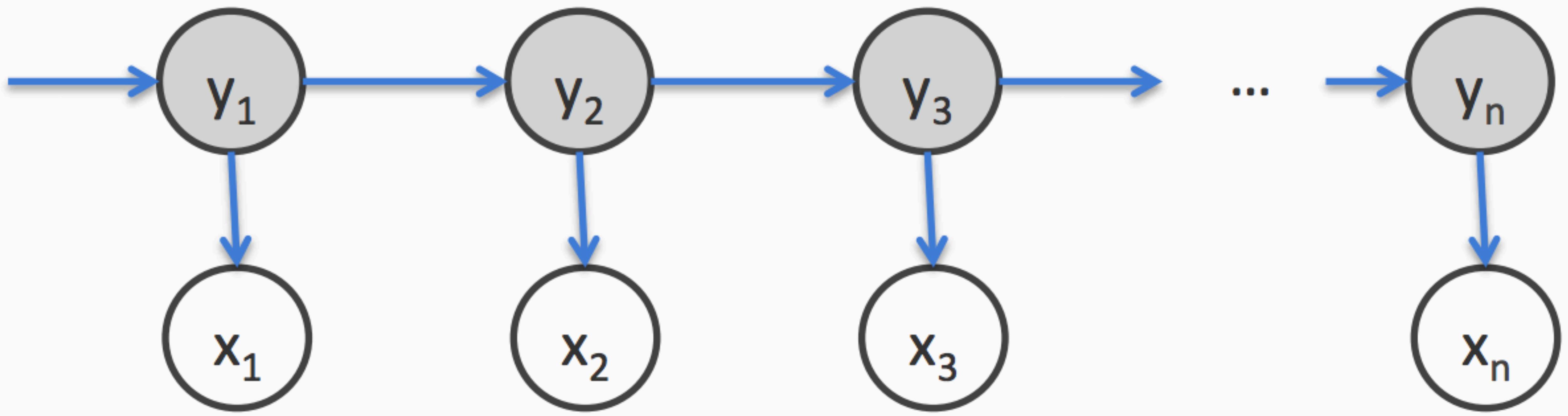
- Inference problem: $\text{argmax}_{\mathbf{y}} P(\mathbf{y}|\mathbf{x}) = \text{argmax}_{\mathbf{y}} \frac{P(\mathbf{y}, \mathbf{x})}{\cancel{P(\mathbf{x})}}$
- Exponentially many possible ***y*** here!
- Solution: dynamic programming (possible because of Markov structure!)
  - Many neural sequence models depend on entire previous tag sequence, need to use approximations like beam search

Viterbi Algorithm

$$P(x_1, x_2, \cdots, x_n, y_1, y_2, \cdots y_n) = P(y_1) \prod_{i=1}^{n-1} P(y_{i+1}|y_i) \prod_{i=1}^{n} P(x_i|y_i)$$

$$\max_{y_1, y_2, \cdots, y_n} P(y_n|y_{n-1}) P(x_n|y_n) \cdots P(y_2|y_1) P(x_2|y_2) P(y_1) P(x_1|y_1)$$

Transition probabilities   Emission probabilities   Initial probability



slide credit: Vivek Srikumar

Viterbi Algorithm

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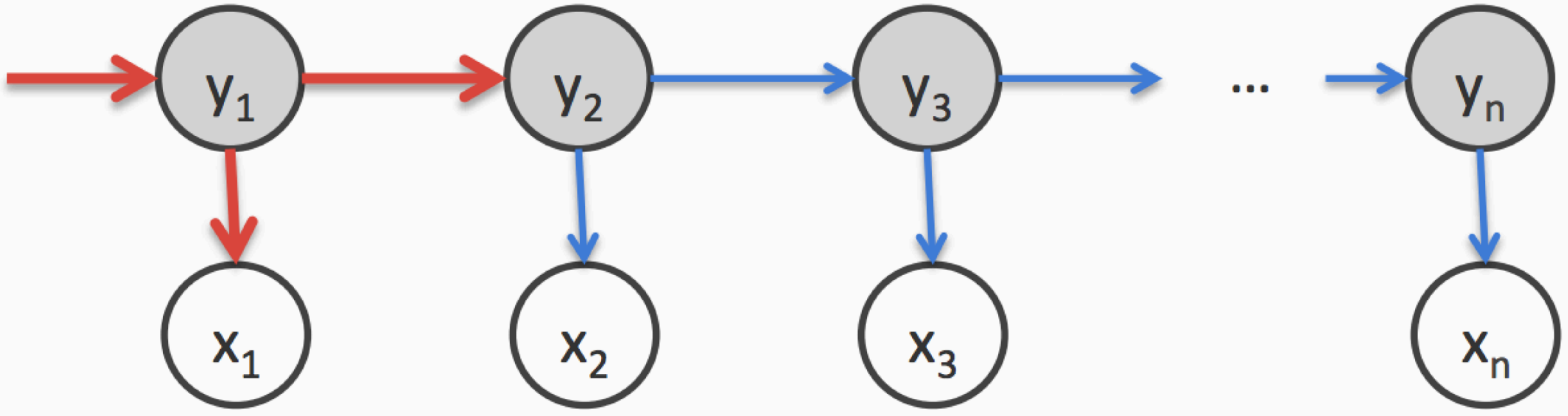
$$\max_{y_1, y_2, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots P(y_2|y_1)P(x_2|y_2)P(y_1)P(x_1|y_1)$$

$$= \max_{y_2, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots \max_{y_1} P(y_2|y_1)P(x_2|y_2)P(y_1)P(x_1|y_1)$$

The only terms that depend on y_1



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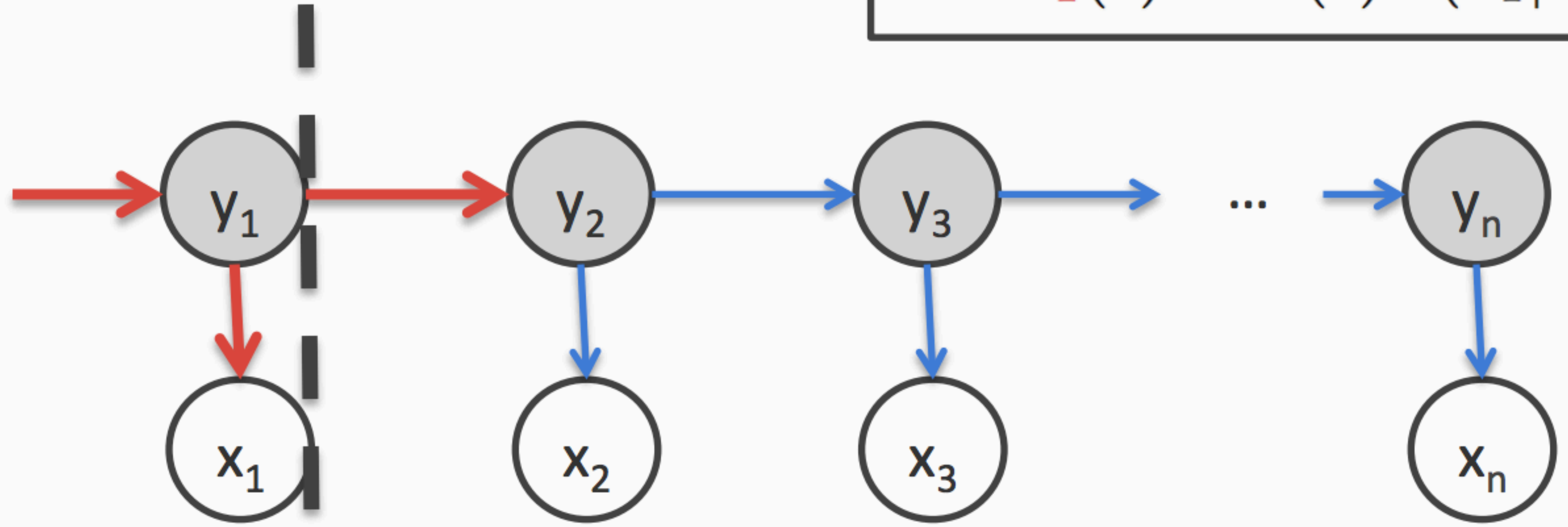
$$= \max_{y_2, \cdots, y_n} P(y_n|y_{n-1}) P(x_n|y_n) \cdots \max_{y_1} P(y_2|y_1) P(x_2|y_2) \text{score}_1(y_1)$$

best (partial) score for
a sequence ending in state *s*

Abstract away the score for all
decisions till here into score

$$\boxed{\text{score}_1(s) = P(s) P(x_1|s)}$$



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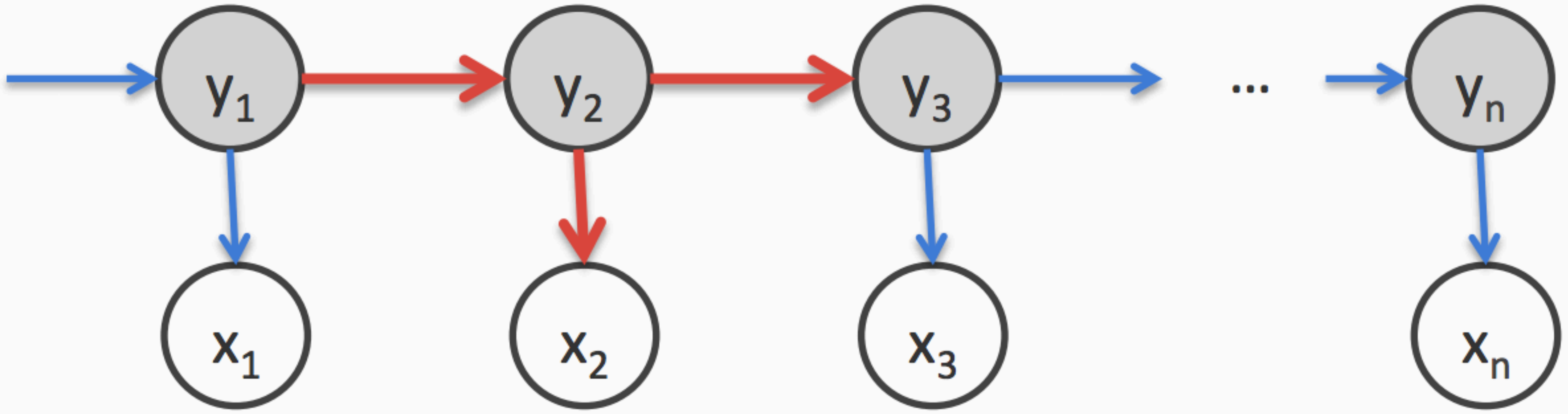
$$\begin{aligned}
&\max_{y_1, y_2, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots P(y_2|y_1)P(x_2|y_2)P(y_1)P(x_1|y_1) \\
&= \max_{y_2, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots \max_{y_1} P(y_2|y_1)P(x_2|y_2)P(y_1)P(x_1|y_1) \\
&= \max_{y_2, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots \max_{y_1} P(y_2|y_1)P(x_2|y_2)\mathrm{score}_1(y_1) \\
&= \max_{y_3, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots \max_{y_2} P(y_3|y_2)P(x_3|y_3) \max_{y_1} P(y_2|y_1)P(x_2|y_2)\mathrm{score}_1(y_1)
\end{aligned}$$

Only terms that depend on y_2



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Viterbi Algorithm

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$$\begin{aligned}
&\max_{y_1, y_2, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots P(y_2|y_1)P(x_2|y_2)P(y_1)P(x_1|y_1) \\
&= \max_{y_2, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots \max_{y_1} P(y_2|y_1)P(x_2|y_2)P(y_1)P(x_1|y_1) \\
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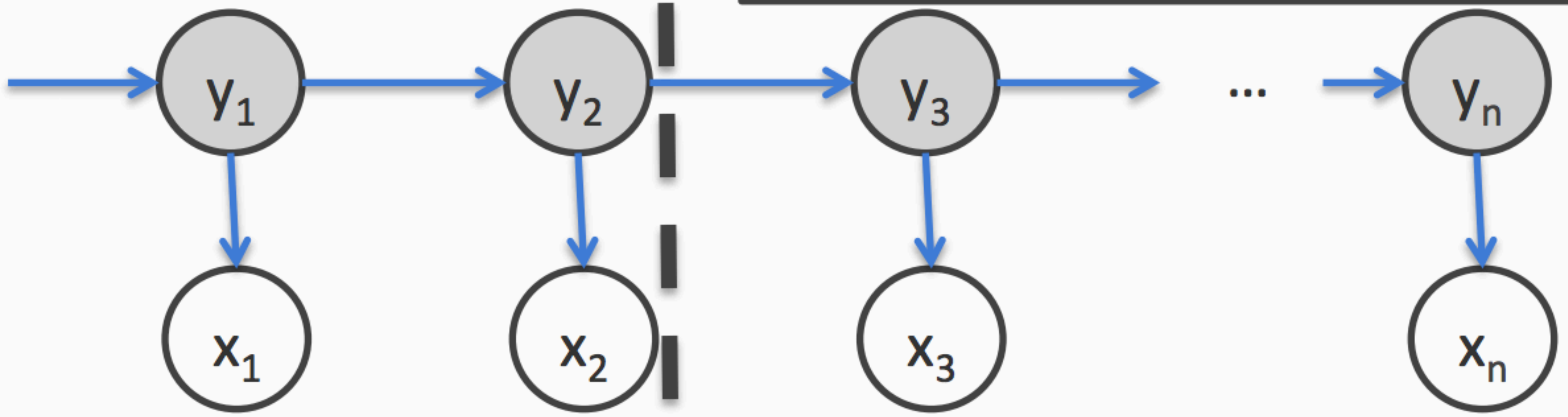
&= \max_{y_3, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots \max_{y_2} P(y_3|y_2)P(x_3|y_3) \max_{y_1} P(y_2|y_1)P(x_2|y_2)\mathrm{score}_1(y_1) \\
&= \max_{y_3, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots \max_{y_2} P(y_3|y_2)P(x_3|y_3)\mathrm{score}_2(y_2)
\end{aligned}$$

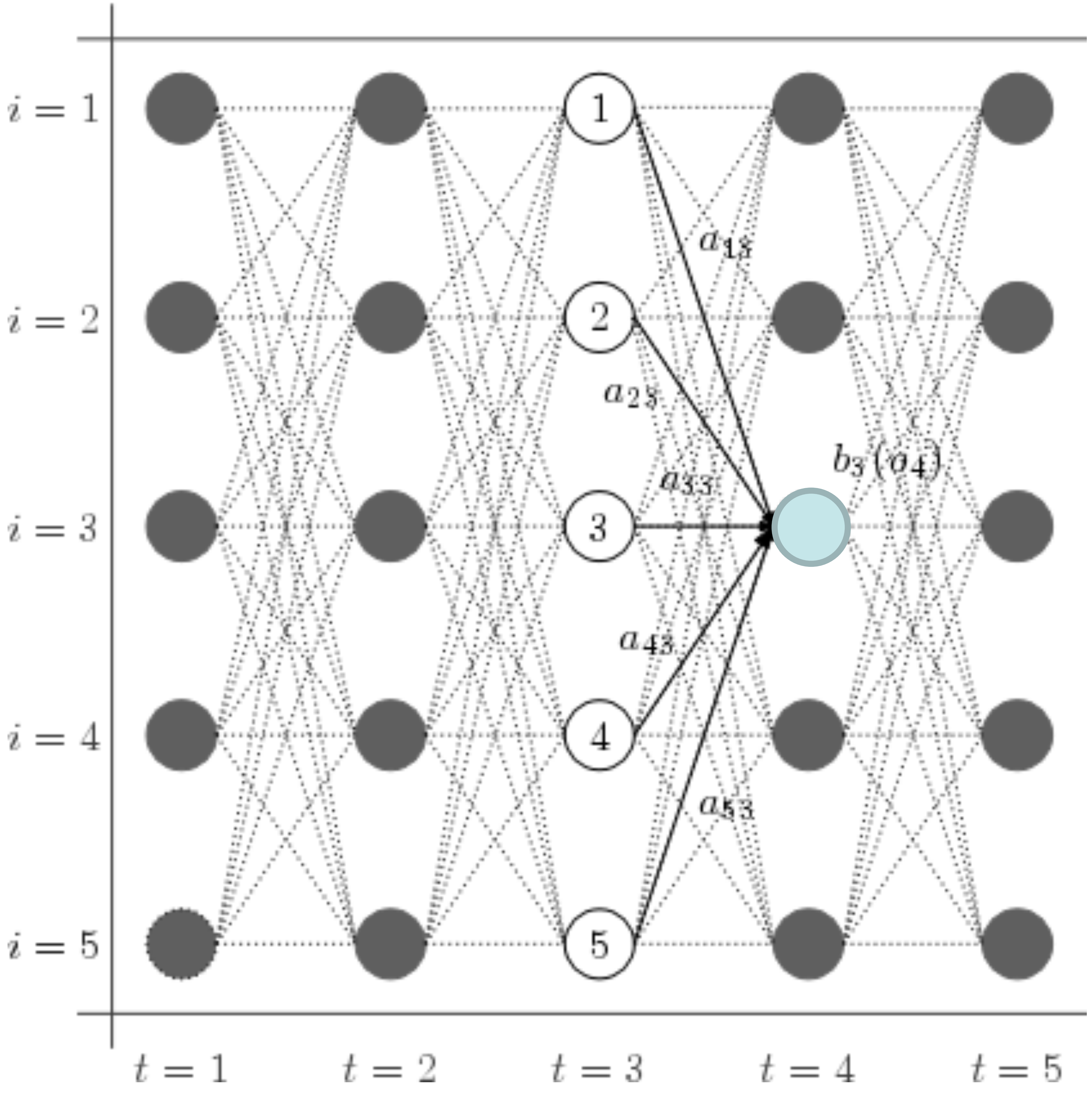
$$\boxed{\mathrm{score}_i(s) = \max_{y_{i-1}} P(s|y_{i-1})P(x_i|s)\mathrm{score}_{i-1}(y_{i-1})}$$



Abstract away the score for all decisions till here into score

slide credit: Vivek Srikumar

Viterbi Algorithm



- “Think about” all possible immediate prior state values. Everything before that has already been accounted for by earlier stages.

slide credit: Dan Klein

Viterbi Algorithm

$$P(x_1, x_2, \cdots, x_n, y_1, y_2, \cdots y_n) = P(y_1) \prod_{i=1}^{n-1} P(y_{i+1}|y_i) \prod_{i=1}^{n} P(x_i|y_i)$$

$$\max_{y_1, y_2, \cdots, y_n} P(y_n|y_{n-1}) P(x_n|y_n) \cdots P(y_2|y_1) P(x_2|y_2) P(y_1) P(x_1|y_1)$$

$$= \max_{y_2, \cdots, y_n} P(y_n|y_{n-1}) P(x_n|y_n) \cdots \max_{y_1} P(y_2|y_1) P(x_2|y_2) P(y_1) P(x_1|y_1)$$

$$= \max_{y_2, \cdots, y_n} P(y_n|y_{n-1}) P(x_n|y_n) \cdots \max_{y_1} P(y_2|y_1) P(x_2|y_2) \mathrm{score}_1(y_1)$$

$$= \max_{y_3, \cdots, y_n} P(y_n|y_{n-1}) P(x_n|y_n) \cdots \max_{y_2} P(y_3|y_2) P(x_3|y_3) \max_{y_1} P(y_2|y_1) P(x_2|y_2) \mathrm{score}_1(y_1)$$

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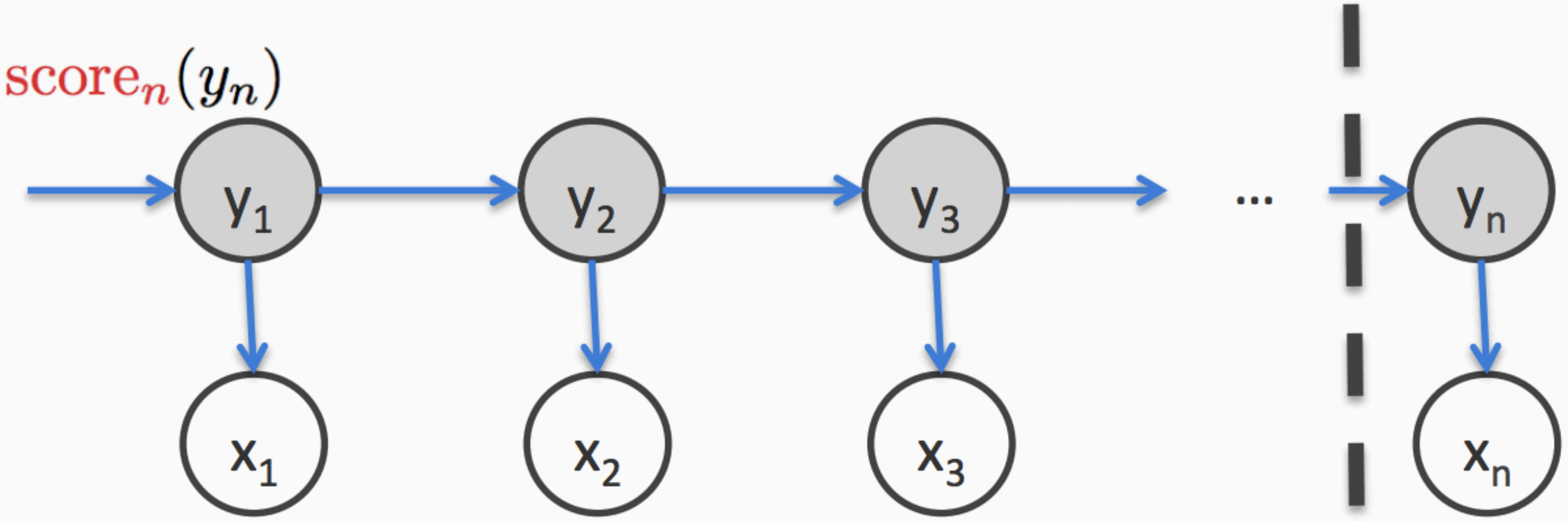
$$\vdots$$

$$= \max_{y_n} \mathrm{score}_n(y_n)$$



Abstract away the score for all decisions till here into score

slide credit: Vivek Srikumar

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$$\vdots$$

$$= \max_{y_n} \mathrm{score}_n(y_n)$$

$$\mathrm{score}_1(s) = P(s)P(x_1|s)$$

$$\mathrm{score}_i(s) = \max_{y_{i-1}} P(s|y_{i-1})P(x_i|s)\mathrm{score}_{i-1}(y_{i-1})$$

slide credit: Vivek Srikumar

Viterbi Algorithm

1. Initial: For each state s, calculate

$$\text{score}_1(s) = P(s)P(x_1|s) = \pi_s B_{x_1,s}$$

2. Recurrence: For i = 2 to n, for every state s, calculate

$$\text{score}_i(s) = \max_{y_{i-1}} P(s|y_{i-1})P(x_i|s)\text{score}_{i-1}(y_{i-1})$$
$$= \max_{y_{i-1}} A_{y_{i-1},s} B_{s,x_i} \text{score}_{i-1}(y_{i-1})$$

3. Final state: calculate

$$\max_{\mathbf{y}} P(\mathbf{y}, \mathbf{x}|\pi, A, B) = \max_{s} \text{score}_n(s)$$

π: Initial probabilities
A: Transitions
B: Emissions

This only calculates the max. To get final answer (*argmax*),

- keep track of which state corresponds to the max at each step
- build the answer using these back pointers

slide credit: Vivek Srikumar

Forward-Backward Algorithm

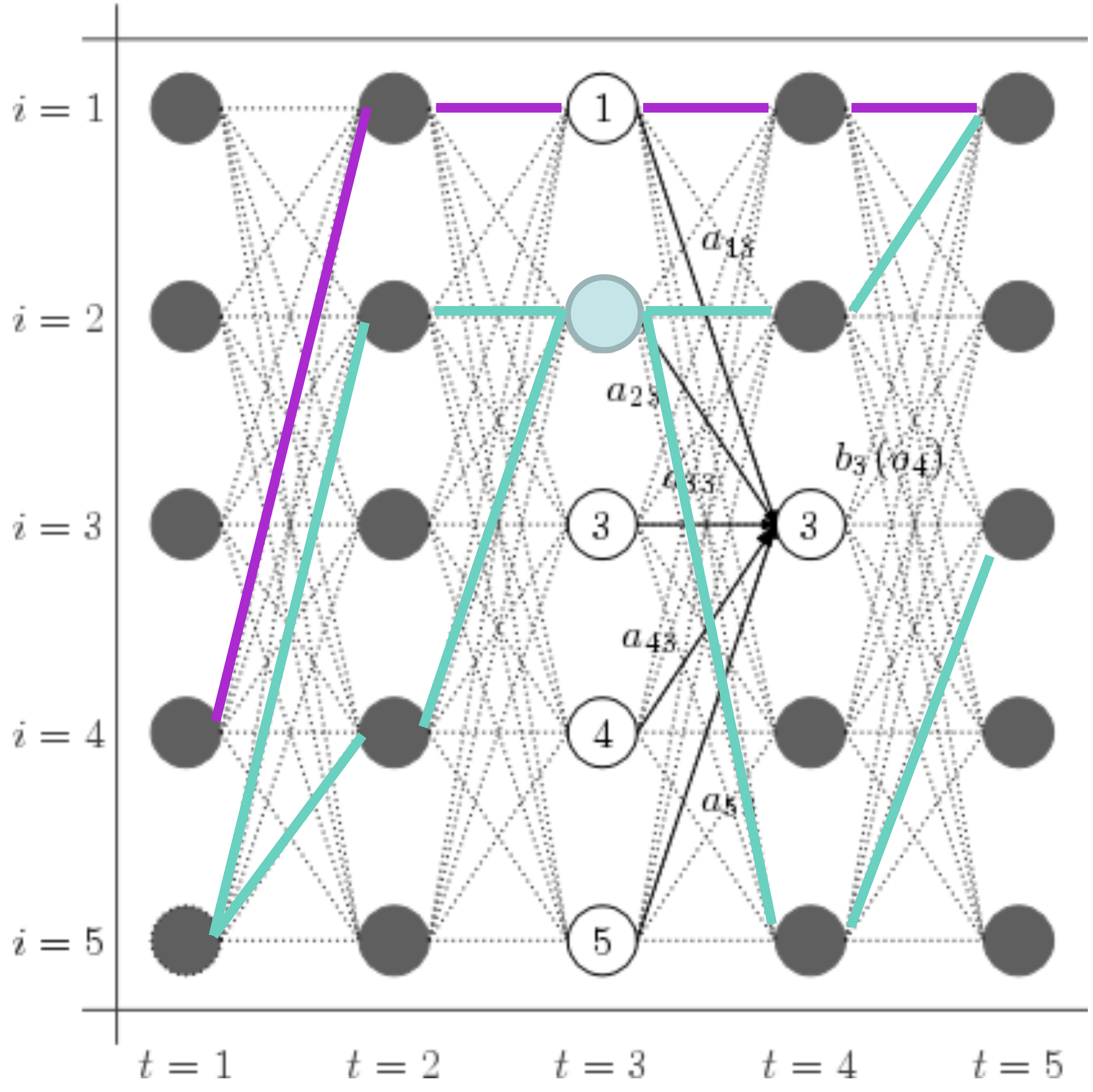
- In addition to finding the best path, we may want to compute marginal probabilities of paths $P(y_i = s|\mathbf{x})$

$$P(y_i = s|\mathbf{x}) = \sum_{y_1,\ldots,y_{i-1},y_{i+1},\ldots,y_n} P(\mathbf{y}|\mathbf{x})$$

- What did Viterbi compute? $P(\mathbf{y}_{\max}|\mathbf{x}) = \max_{y_1,\ldots,y_n} P(\mathbf{y}|\mathbf{x})$

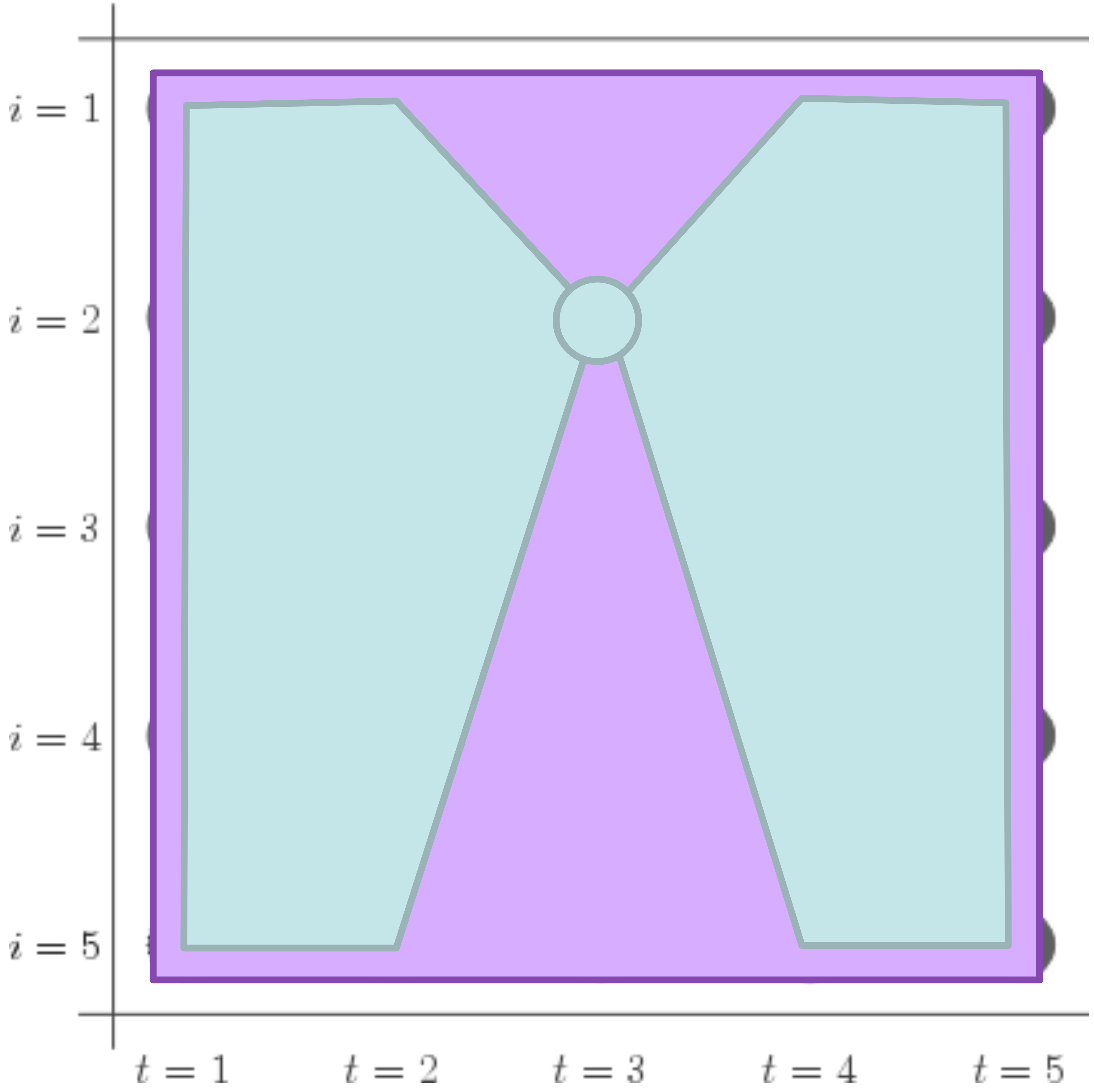
- Can compute marginals with dynamic programming as well using an algorithm called forward-backward

Forward-Backward Algorithm



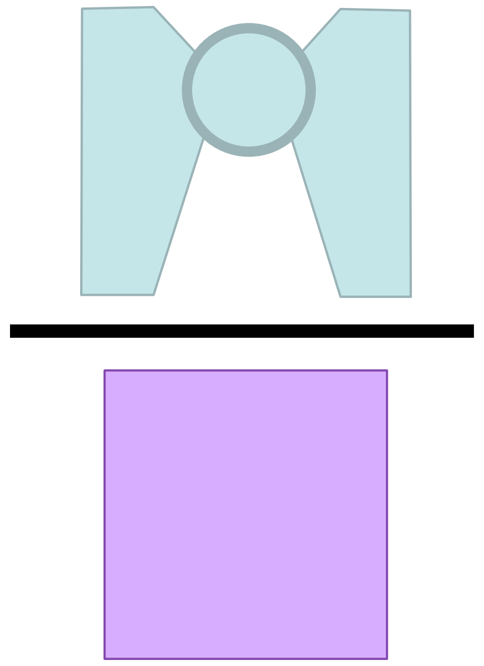
$$P(y_3 = 2|\mathbf{x}) = \frac{\text{sum of all paths through state 2 at time 3}}{\text{sum of all paths}}$$

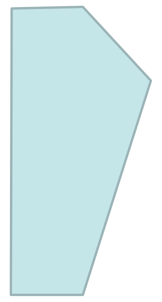
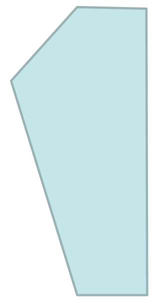
Forward-Backward Algorithm



$$P(y_3 = 2|\mathbf{x}) = \frac{\text{sum of all paths through state 2 at time 3}}{\text{sum of all paths}}$$

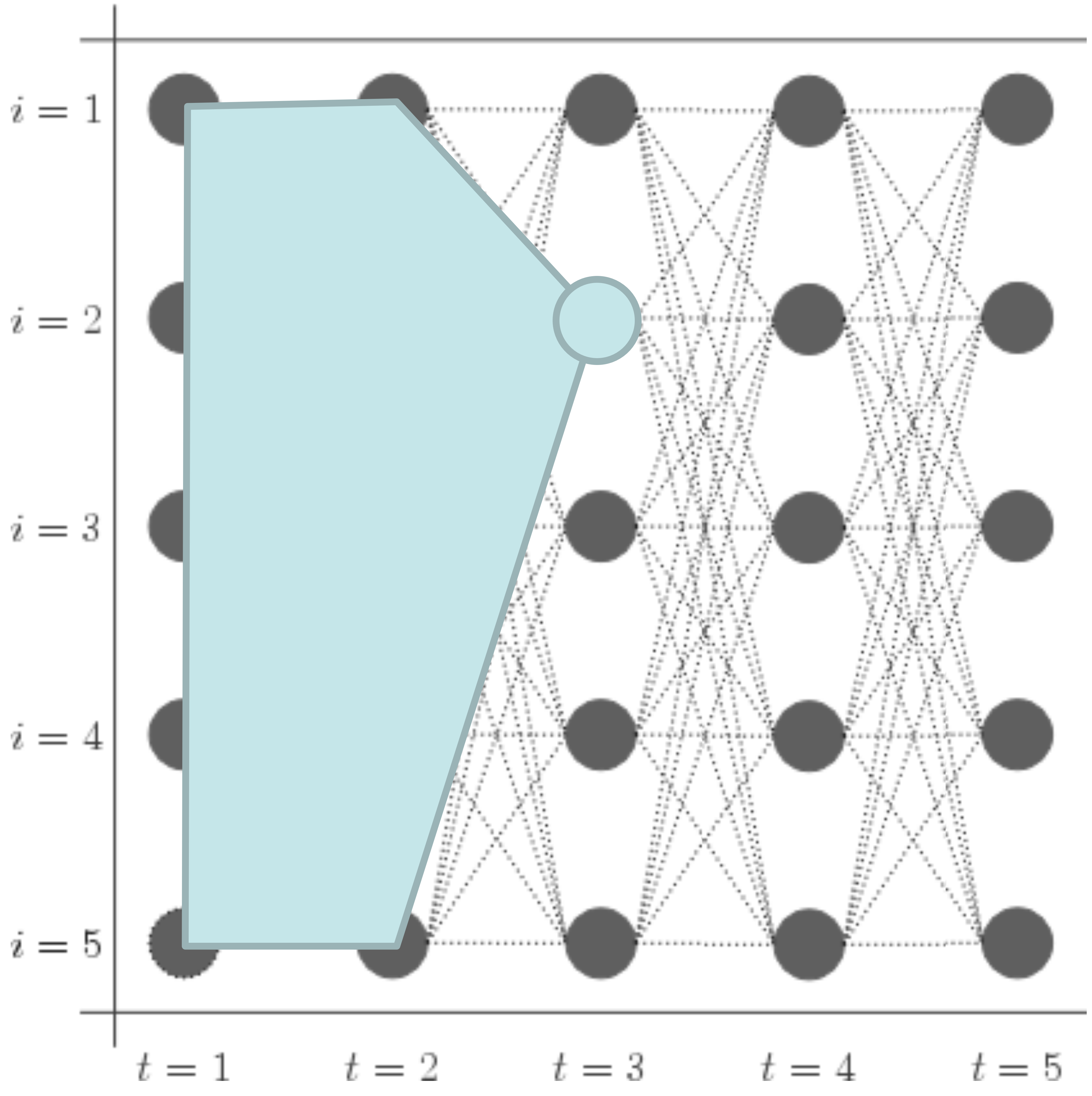
=



- Easiest and most flexible to do one pass to compute  and one to compute 

slide credit: Dan Klein

Forward-Backward Algorithm



- Initial:

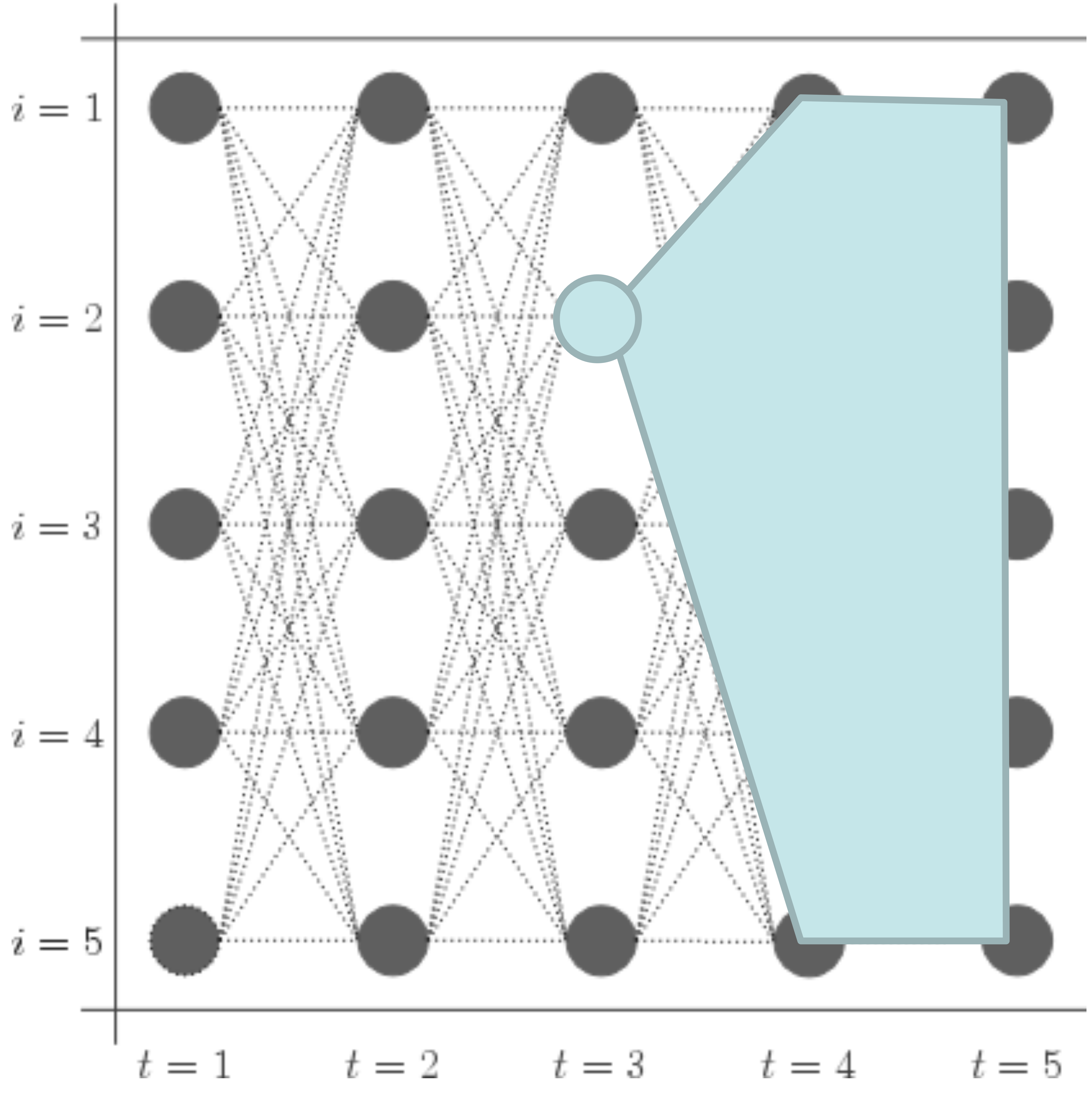
$$\alpha_1(s) = P(s)P(x_1|s)$$

- Recurrence:

$$\alpha_t(s_t) = \sum_{s_{t-1}} \alpha_{t-1}(s_{t-1})P(s_t|s_{t-1})P(x_t|s_t)$$

- Same as Viterbi but summing instead of maxing!
- These quantities get very small! Store everything as log probabilities

Forward-Backward Algorithm



- Initial:

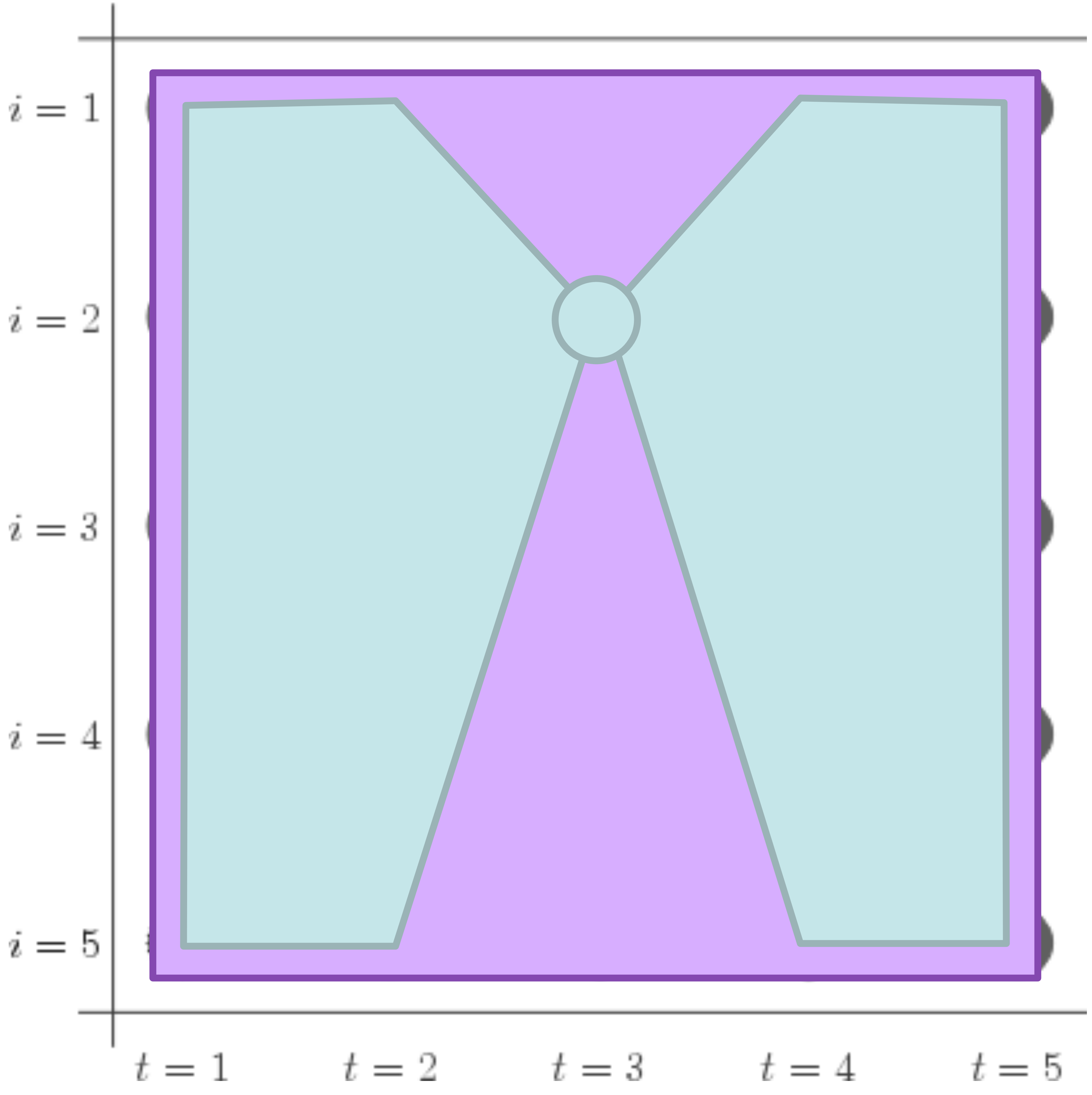
$$\beta_n(s) = 1$$

- Recurrence:

$$\beta_t(s_t) = \sum_{s_{t+1}} \beta_{t+1}(s_{t+1}) P(s_{t+1}|s_t) \boxed{P(x_{t+1}|s_{t+1})}$$

- Big differences: count emission for the *next* timestep (not current one)

Forward-Backward Algorithm



$$\alpha_1(s) = P(s)P(x_1|s)$$

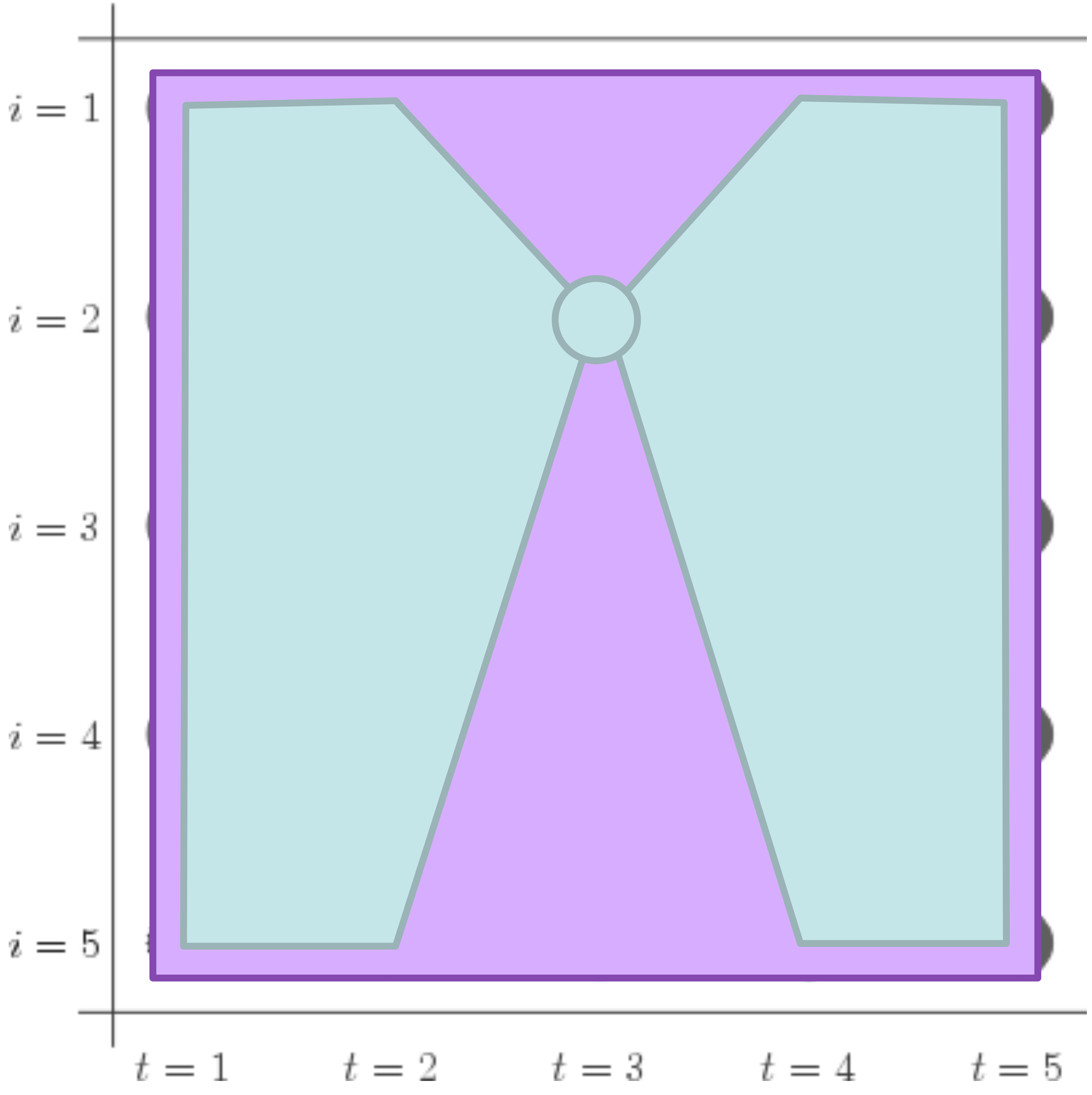
$$\alpha_t(s_t) = \sum_{s_{t-1}} \alpha_{t-1}(s_{t-1})P(s_t|s_{t-1})P(x_t|s_t)$$

$$\beta_n(s) = 1$$

$$\beta_t(s_t) = \sum_{s_{t+1}} \beta_{t+1}(s_{t+1})P(s_{t+1}|s_t)\boxed{P(x_{t+1}|s_{t+1})}$$

- Big differences: count emission for the *next* timestep (not current one)

Forward-Backward Algorithm

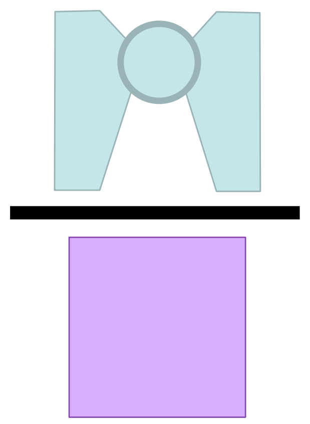


$$\alpha_1(s) = P(s)P(x_1|s)$$

$$\alpha_t(s_t) = \sum_{s_{t-1}} \alpha_{t-1}(s_{t-1})P(s_t|s_{t-1})P(x_t|s_t)$$

$$\beta_n(s) = 1$$

$$\beta_t(s_t) = \sum_{s_{t+1}} \beta_{t+1}(s_{t+1})P(s_{t+1}|s_t)P(x_{t+1}|s_{t+1})$$

$$P(s_3 = 2|\mathbf{x}) = \frac{\alpha_3(2)\beta_3(2)}{\sum_i \alpha_3(i)\beta_3(i)} =$$ 

- What is the denominator here? $P(\mathbf{x})$

HMM POS Tagging

- Baseline: assign each word its most frequent tag: ~90% accuracy
- Trigram HMM: ~95% accuracy / 55% on unknown words

Slide credit: Dan Klein

Trigram Taggers

NNP VBZ NN NNS CD NN
Fed raises interest rates 0.5 percent

- Trigram model: y_1 = (<S>, NNP), y_2 = (NNP, VBZ), …
- P((VBZ, NN) | (NNP, VBZ)) — more context! Noun-verb-noun S-V-O
- Tradeoff between model capacity and data size — trigrams are a "sweet spot" for POS tagging

HMM POS Tagging

- Baseline: assign each word its most frequent tag: ~90% accuracy
- Trigram HMM: ~95% accuracy / 55% on unknown words
- TnT tagger (Brants 1998, tuned HMM): 96.2% accuracy / 86.0% on unks
- State-of-the-art (BiLSTM-CRFs): 97.5% / 89%+

Slide credit: Dan Klein

Errors

	JJ	NN	NNP	NNPS	RB	RP	IN	VB	VBD	VBN	VBP	Total
JJ	0	**177**	**56**	0	**61**	2	5	10	15	**108**	0	488
NN	**244**	0	**103**	0	12	1	1	29	5	6	19	525
NNP	**107**	**106**	0	**132**	5	0	7	5	1	2	0	427
NNPS	1	0	**110**	0	0	0	0	0	0	0	0	142
RB	**72**	21	7	0	0	16	**138**	1	0	0	0	295
RP	0	0	0	0	**39**	0	**65**	0	0	0	0	104
IN	11	0	1	0	**169**	**103**	0	1	0	0	0	323
VB	17	**64**	9	0	2	0	1	0	4	7	**85**	189
VBD	10	5	3	0	0	0	0	3	0	**143**	2	166
VBN	**101**	3	3	0	0	0	0	3	**108**	0	1	221
VBP	5	34	3	1	1	0	2	**49**	6	3	0	104
Total	626	536	348	144	317	122	279	102	140	269	108	3651

JJ/NN NN
official knowledge

VBD RP/IN DT NN
made up the story

RB VBD/VBN NNS
recently sold shares

(NN NN: *tax cut, art gallery, …*)

Slide credit: Dan Klein / Toutanova + Manning (2000)

Remaining Errors

- Lexicon gap (word not seen with that tag in training) 4.5%
- Unknown word: 4.5%
- Could get right: 16% (many of these involve parsing!)
- Difficult linguistics: 20%

VBD / VBP? (past or present?)

They set up absurd situations, detached from reality

- Underspecified / unclear, gold standard inconsistent / wrong: **58%**

adjective or verbal participle? JJ / VBN?

a $ 10 million fourth-quarter charge against discontinued operations

Manning 2011 “Part-of-Speech Tagging from 97% to 100%: Is It Time for Some Linguistics?”

Other Languages

Language	Source	# Tags	O/O	U/U	O/U
Arabic	PADT/CoNLL07 (Hajič et al., 2004)	21	96.1	96.9	97.0
Basque	Basque3LB/CoNLL07 (Aduriz et al., 2003)	64	89.3	93.7	93.7
Bulgarian	BTB/CoNLL06 (Simov et al., 2002)	54	95.7	97.5	97.8
Catalan	CESS-ECE/CoNLL07 (Martí et al., 2007)	54	98.5	98.2	98.8
Chinese	Penn ChineseTreebank 6.0 (Palmer et al., 2007)	34	91.7	93.4	94.1
Chinese	Sinica/CoNLL07 (Chen et al., 2003)	294	87.5	91.8	92.6
Czech	PDT/CoNLL07 (Böhmová et al., 2003)	63	99.1	99.1	99.1
Danish	DDT/CoNLL06 (Kromann et al., 2003)	25	96.2	96.4	96.9
Dutch	Alpino/CoNLL06 (Van der Beek et al., 2002)	12	93.0	95.0	95.0
English	PennTreebank (Marcus et al., 1993)	45	96.7	96.8	97.7
French	FrenchTreebank (Abeillé et al., 2003)	30	96.6	96.7	97.3
German	Tiger/CoNLL06 (Brants et al., 2002)	54	97.9	98.1	98.8
German	Negra (Skut et al., 1997)	54	96.9	97.9	98.6
Greek	GDT/CoNLL07 (Prokopidis et al., 2005)	38	97.2	97.5	97.8
Hungarian	Szeged/CoNLL07 (Csendes et al., 2005)	43	94.5	95.6	95.8
Italian	ISST/CoNLL07 (Montemagni et al., 2003)	28	94.9	95.8	95.8
Japanese	Verbmobil/CoNLL06 (Kawata and Bartels, 2000)	80	98.3	98.0	99.1
Japanese	Kyoto4.0 (Kurohashi and Nagao, 1997)	42	97.4	98.7	99.3
Korean	Sejong (http://www.sejong.or.kr)	187	96.5	97.5	98.4
Portuguese	Floresta Sintá(c)tica/CoNLL06 (Afonso et al., 2002)	22	96.9	96.8	97.4
Russian	SynTagRus-RNC (Boguslavsky et al., 2002)	11	96.8	96.8	96.8
Slovene	SDT/CoNLL06 (Džeroski et al., 2006)	29	94.7	94.6	95.3
Spanish	Ancora-Cast3LB/CoNLL06 (Civit and Martí, 2004)	47	96.3	96.3	96.9
Swedish	Talbanken05/CoNLL06 (Nivre et al., 2006)	41	93.6	94.7	95.1
Turkish	METU-Sabanci/CoNLL07 (Oflazer et al., 2003)	31	87.5	89.1	90.2

Petrov et al. 2012

Next Time

- CRFs: feature-based discriminative models
- Structured SVM for sequences
- Named entity recognition