# Sequence Models I

Wei Xu

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

# 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*

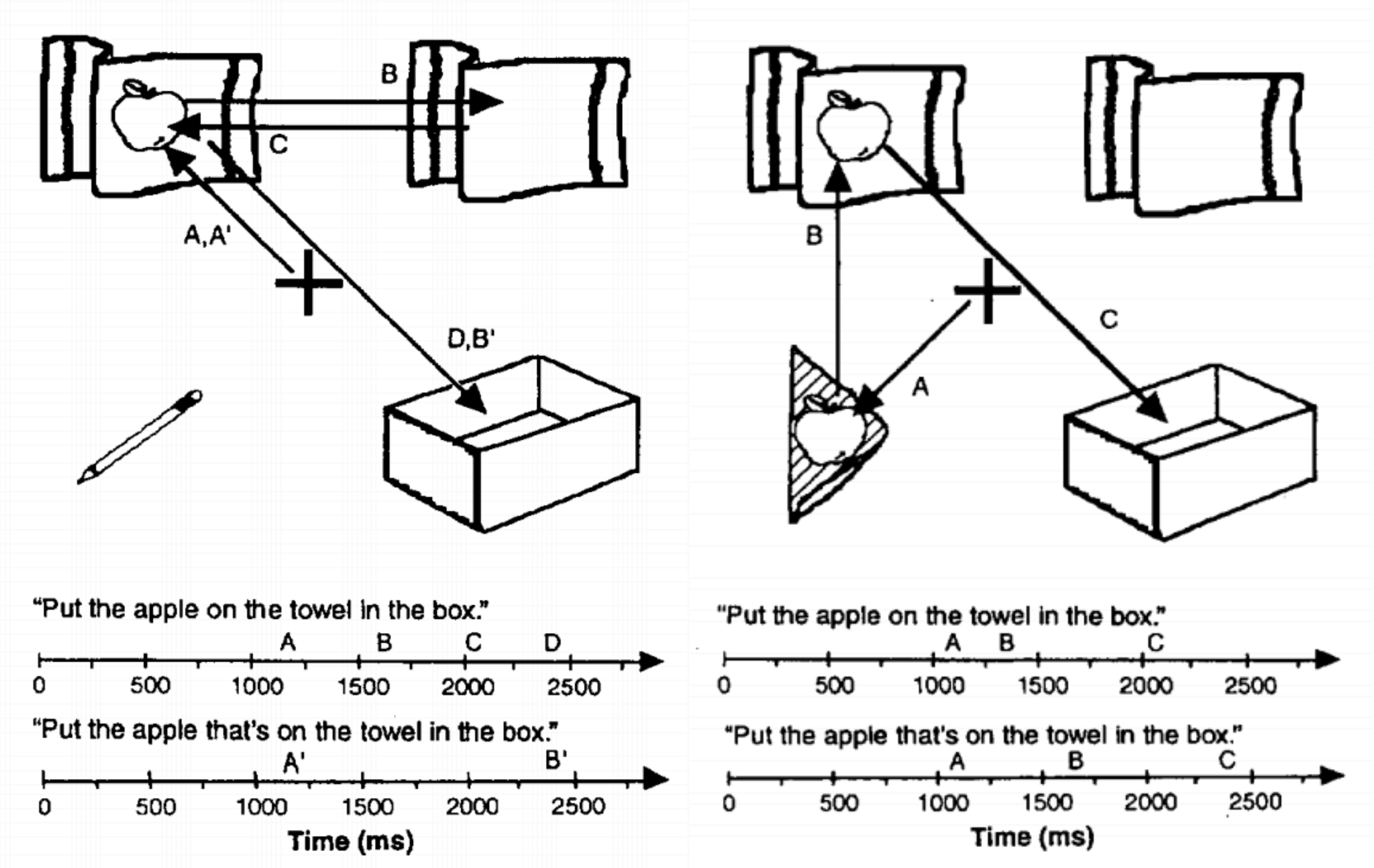
- Understanding syntax fundamentally requires trees — the sentences have the same shallow analysis

| 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



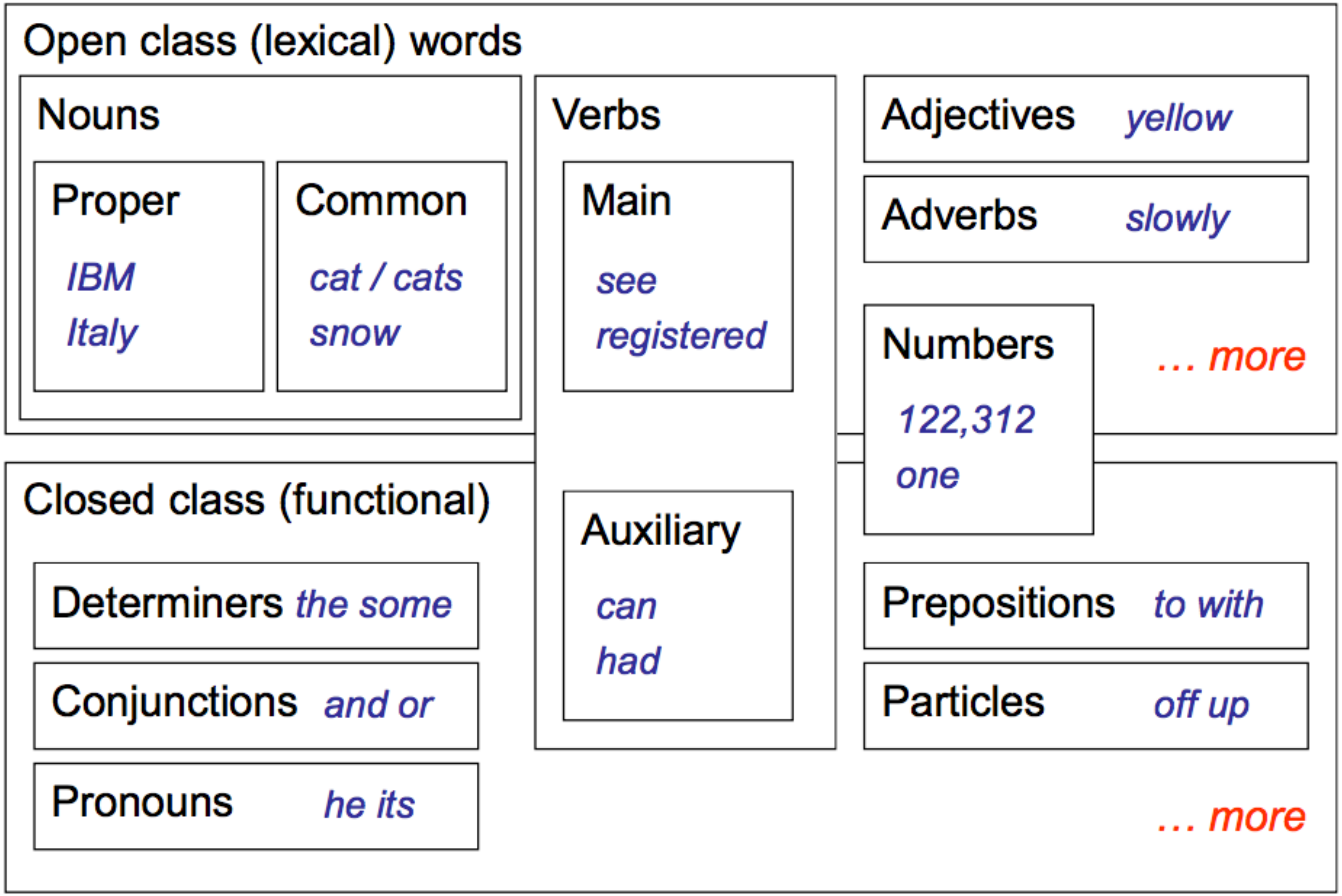

Tanenhaus et al. (1995)

# 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

| | | |
|---|---|---|
| **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 |

# POS Tagging

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

| | | | | | |
|---|---|---|---|---|---|
| VBD | | VB | | | |
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| NNP | NNS | NN | NNS | CD | NN |
| *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.

# 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

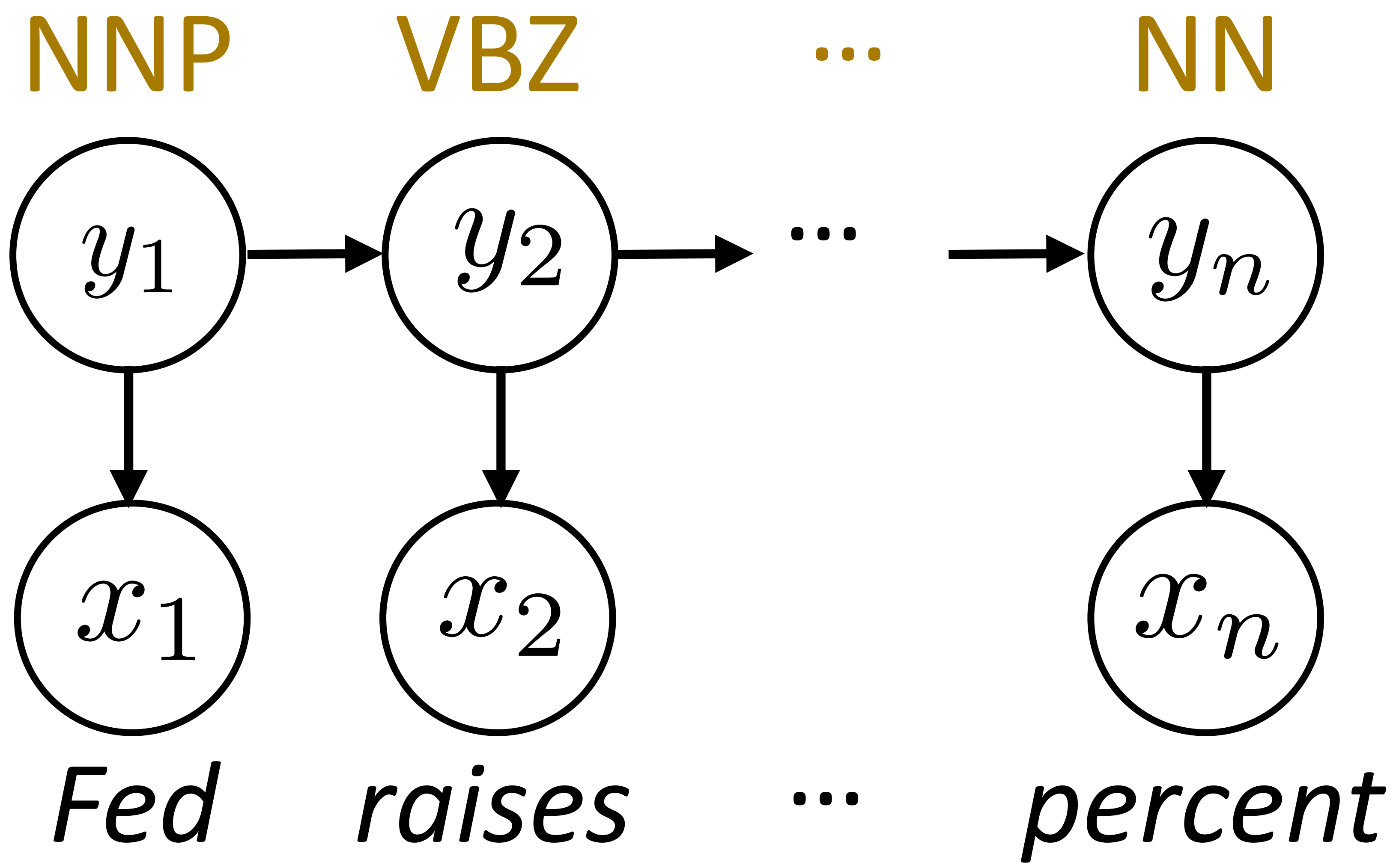
- Input $\mathbf{x} = (x_1, ..., x_n)$ Output $\mathbf{y} = (y_1, ..., y_n)$
- Model the sequence of *y* as a Markov process
- Markov property: future is conditionally independent of the past given the present

$$y_1 \rightarrow y_2 \rightarrow y_3 \qquad P(y_3|y_1, y_2) = P(y_3|y_2)$$

- 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

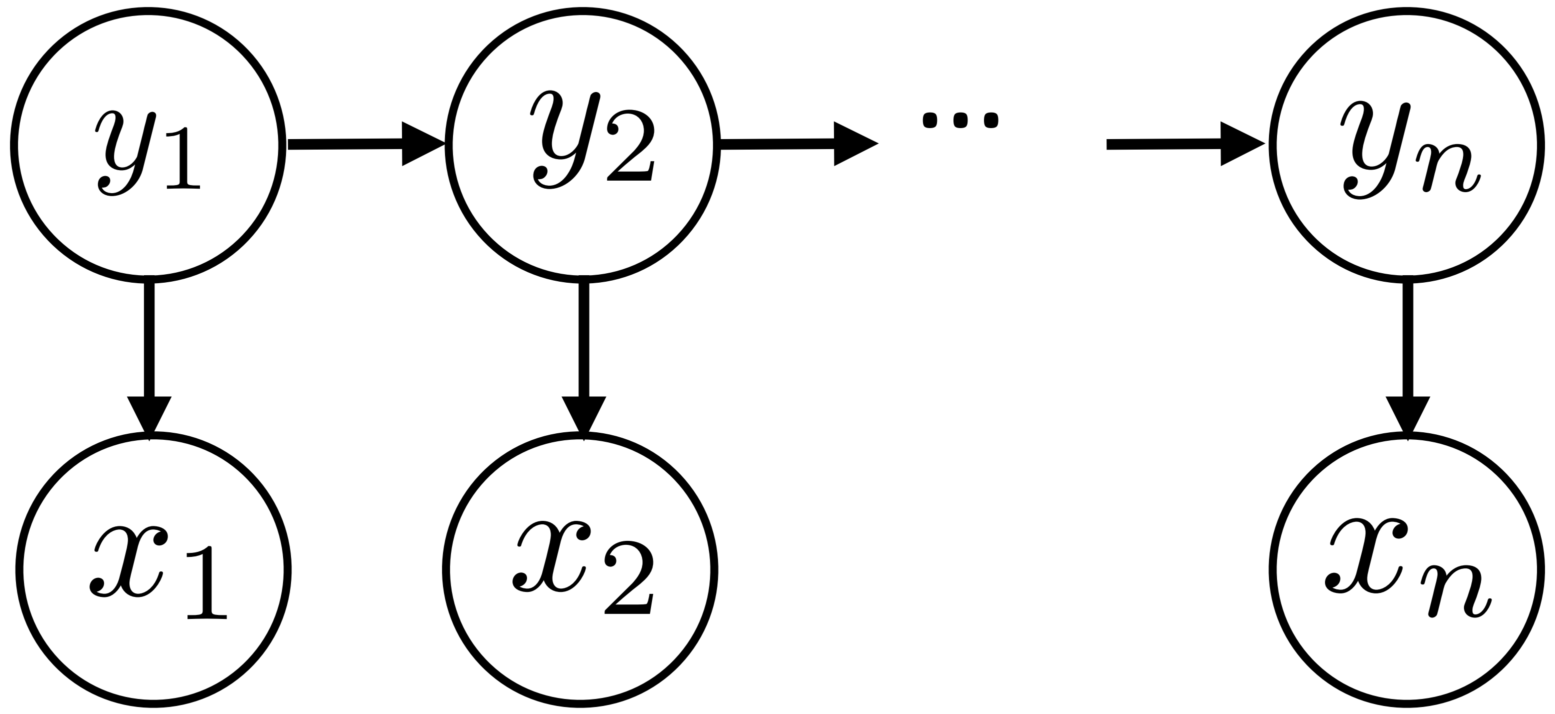
# Hidden Markov Models

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



# Hidden Markov Models

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




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

- 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

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

$\hat{P}$ = 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

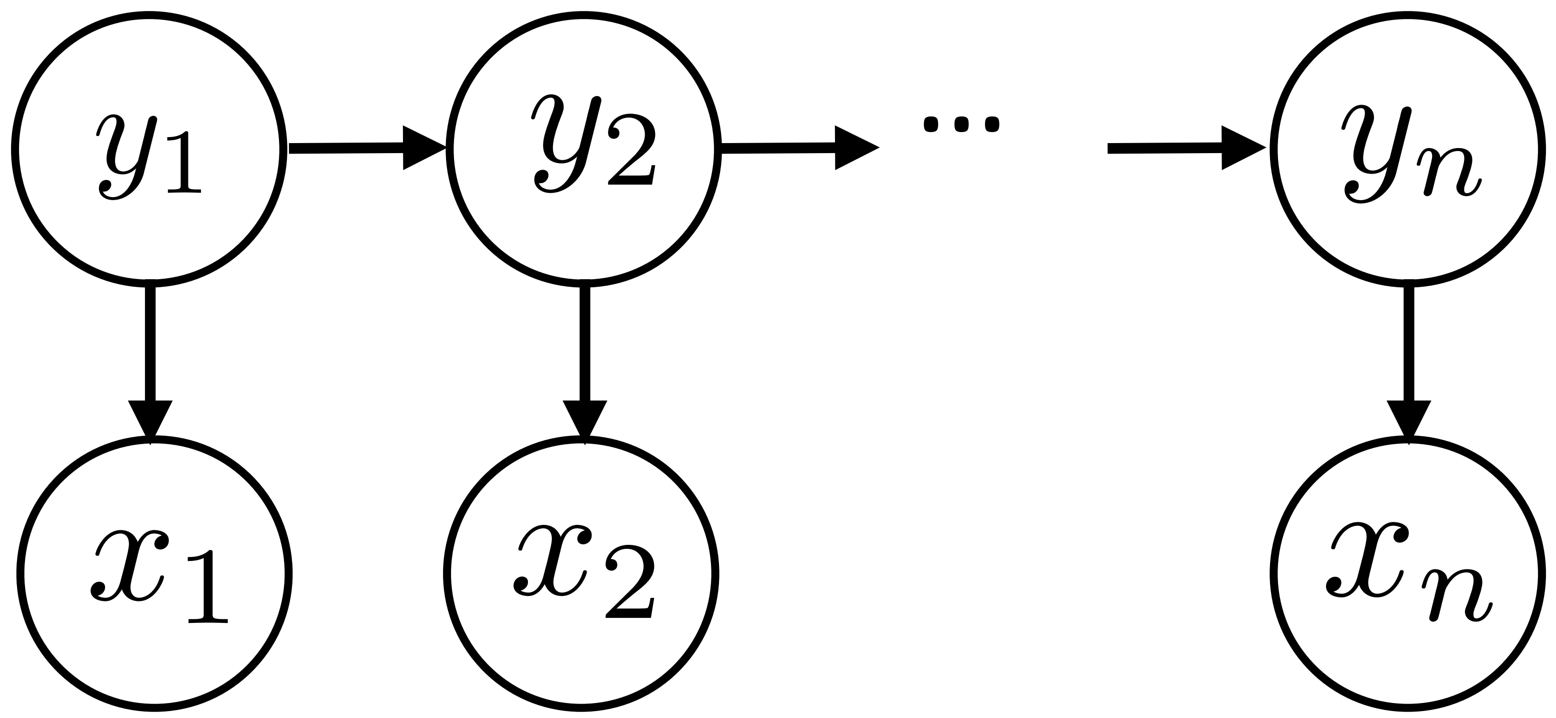
- P(word | NN) = (0.5 *interest*, 0.5 *percent*) — hard to smooth!
- Can interpolate with distribution looking at word shape P(word shape | tag) (e.g., P(capitalized word of len >= 8 | tag))
- Alternative: use Bayes' rule

$$P(\text{word}|\text{tag}) = \frac{P(\text{tag}|\text{word})P(\text{word})}{P(\text{tag})}$$

  - 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 $\mathbf{y} = (y_1, ..., y_n)$




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

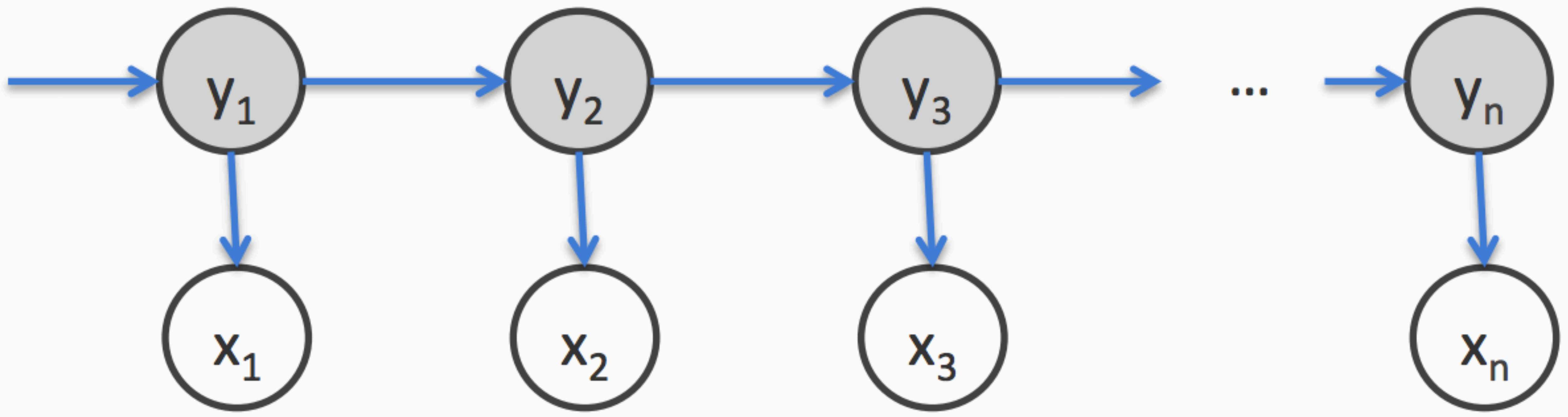
- Inference problem: $\text{argmax}_{\mathbf{y}} P(\mathbf{y} | \mathbf{x}) = \text{argmax}_{\mathbf{y}} \frac{P(\mathbf{y}, \mathbf{x})}{\cancel{P(\mathbf{x})}}$
- Exponentially many possible ***y*** here!
- Solution: dynamic programming (possible because of Markov structure!)
  - Many neural sequence 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

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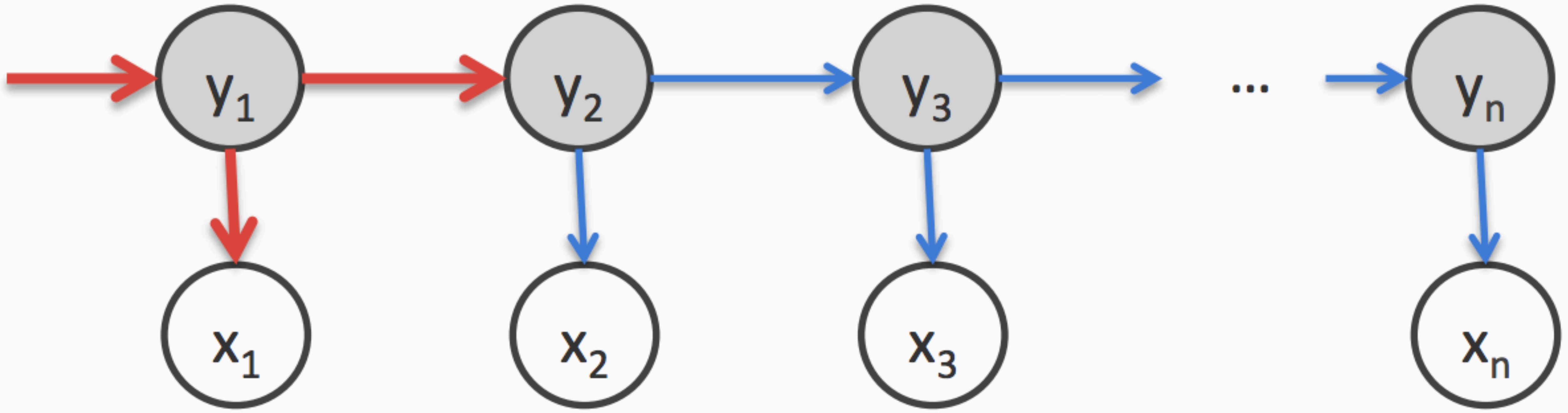
$$= \max_{y_2, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots \max_{y_1} P(y_2|y_1)P(x_2|y_2)P(y_1)P(x_1|y_1)$$

The only terms that depend on $y_1$

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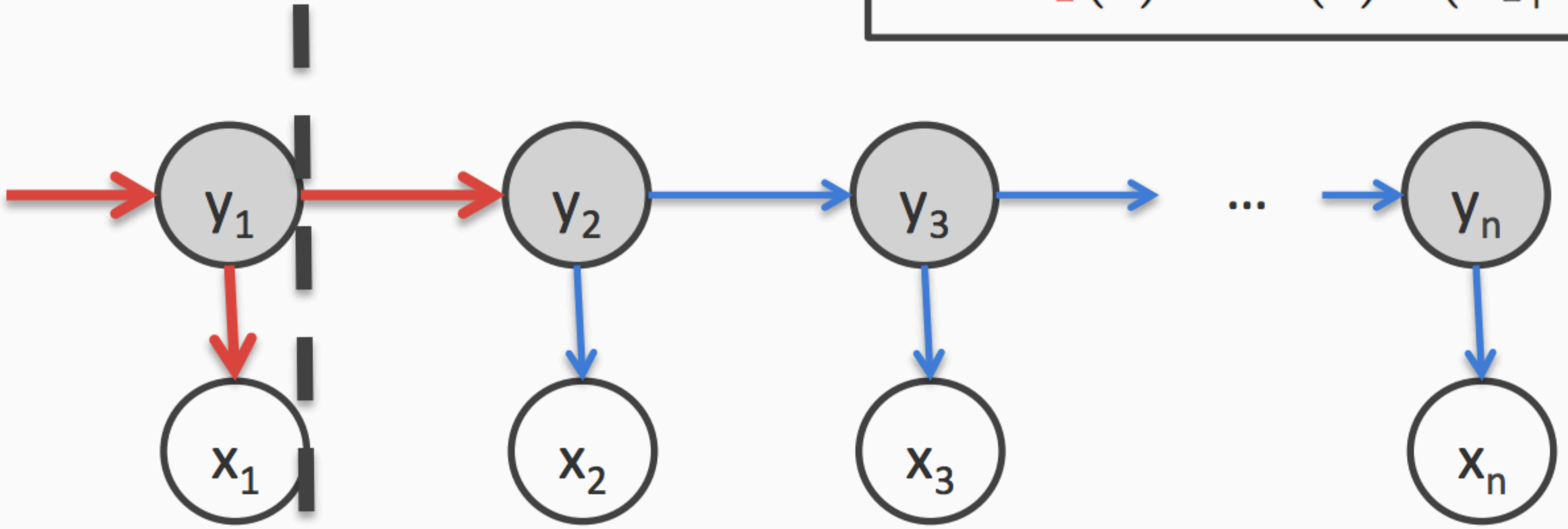
$$= \max_{y_2, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots \max_{y_1} P(y_2|y_1)P(x_2|y_2)\text{score}_1(y_1)$$

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

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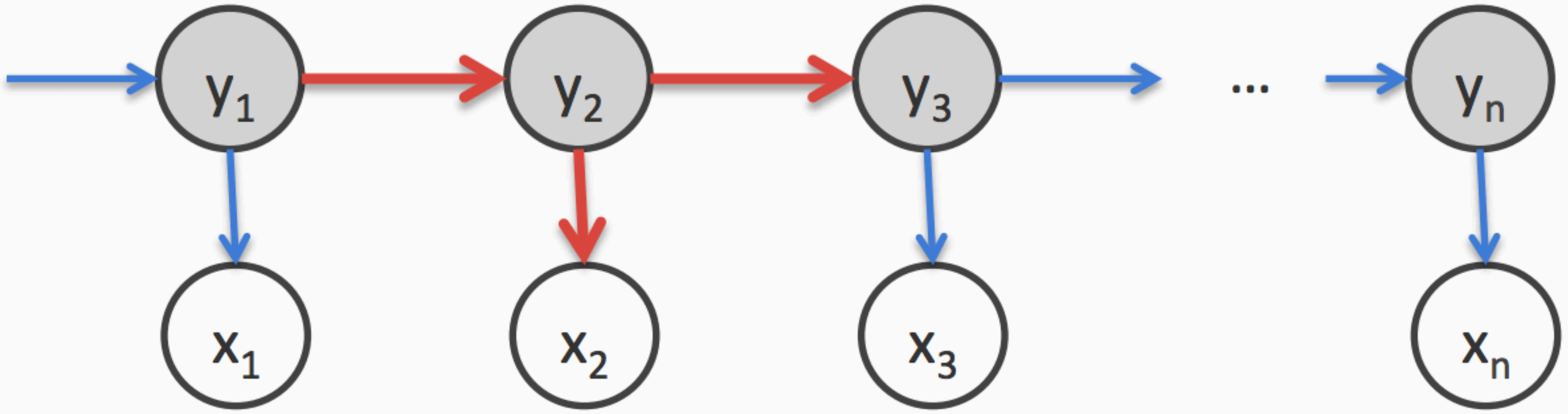
$$= \max_{y_3, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots \max_{y_2} P(y_3|y_2)P(x_3|y_3) \max_{y_1} P(y_2|y_1)P(x_2|y_2)\mathrm{score}_1(y_1)$$

Only terms that depend on $y_2$

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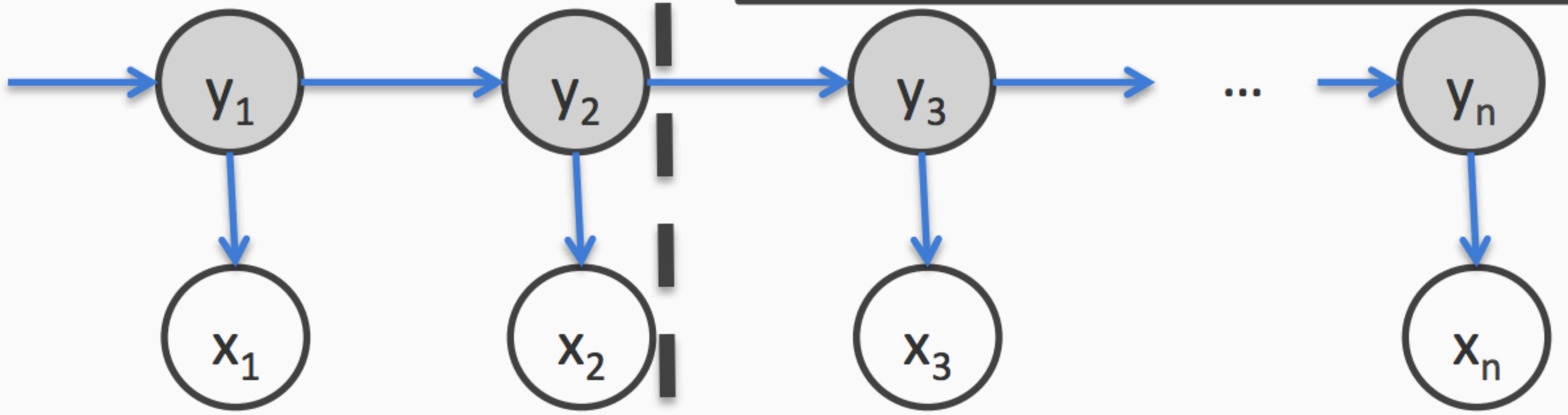
$$\begin{aligned}
&\max_{y_1, y_2, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots P(y_2|y_1)P(x_2|y_2)P(y_1)P(x_1|y_1) \\
&= \max_{y_2, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots \max_{y_1} P(y_2|y_1)P(x_2|y_2)P(y_1)P(x_1|y_1) \\
&= \max_{y_2, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots \max_{y_1} P(y_2|y_1)P(x_2|y_2)\text{score}_1(y_1)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

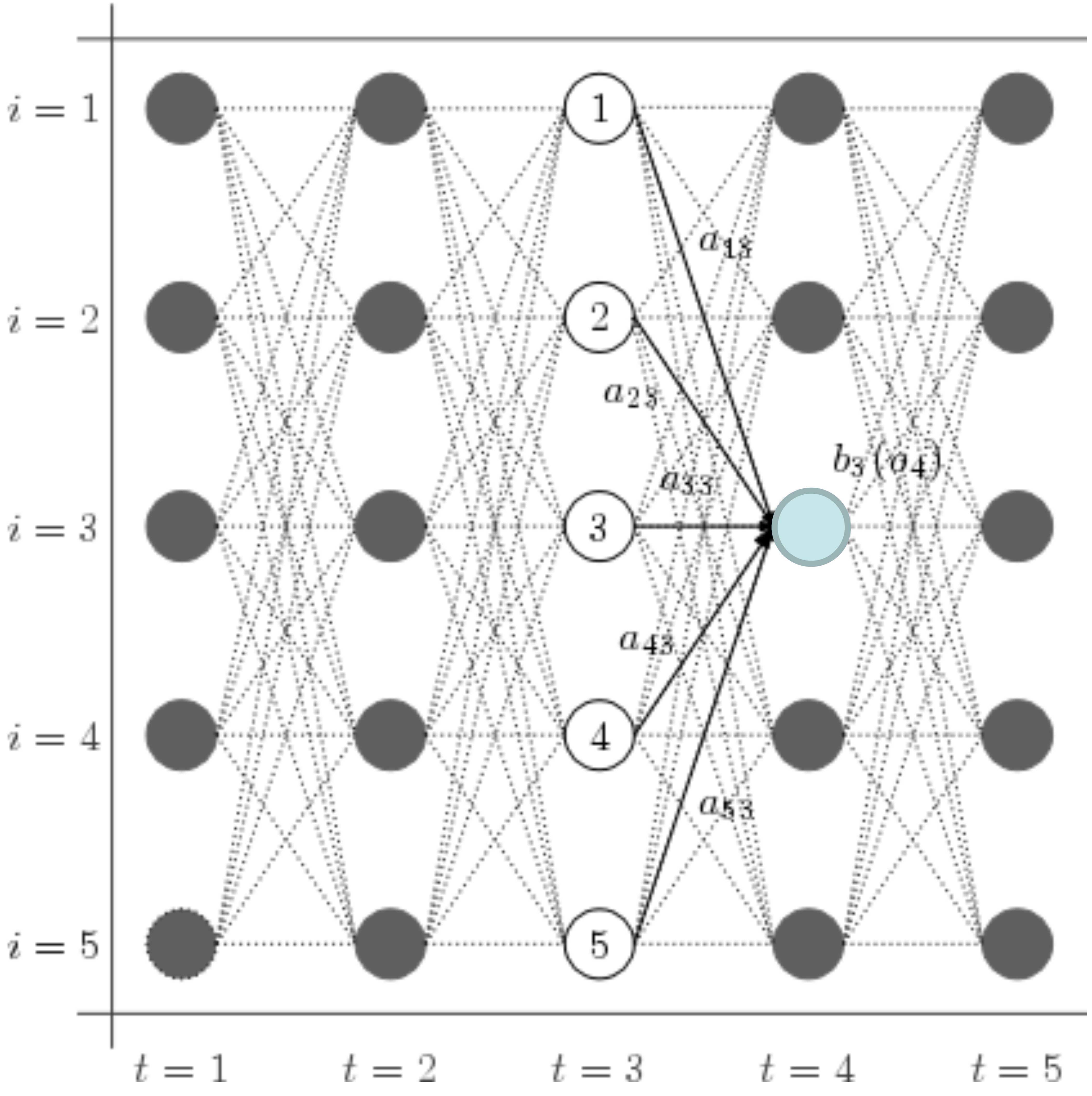
$$\boxed{\text{score}_i(s) = \max_{y_{i-1}} P(s|y_{i-1})P(x_i|s)\text{score}_{i-1}(y_{i-1})}$$




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

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

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

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

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

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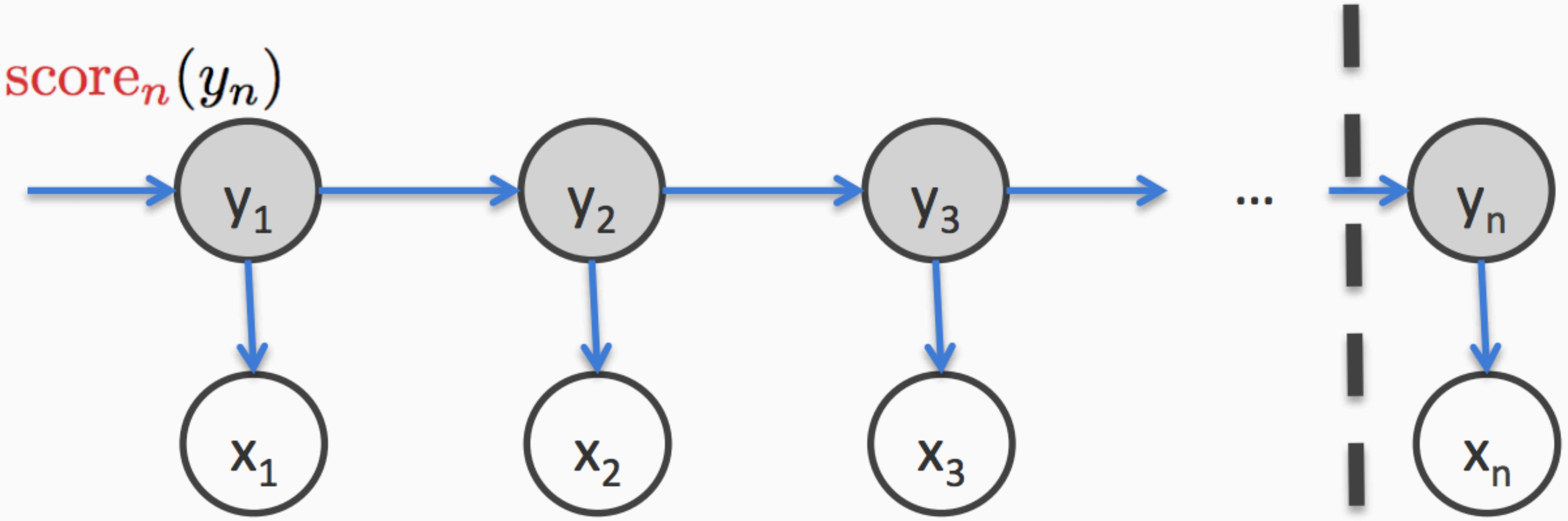
$$\vdots$$

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

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$$\begin{aligned}
&\max_{y_1, y_2, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots P(y_2|y_1)P(x_2|y_2)P(y_1)P(x_1|y_1) \\
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&\vdots \\
&= \max_{y_n} \text{score}_n(y_n)
\end{aligned}$$

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

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



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

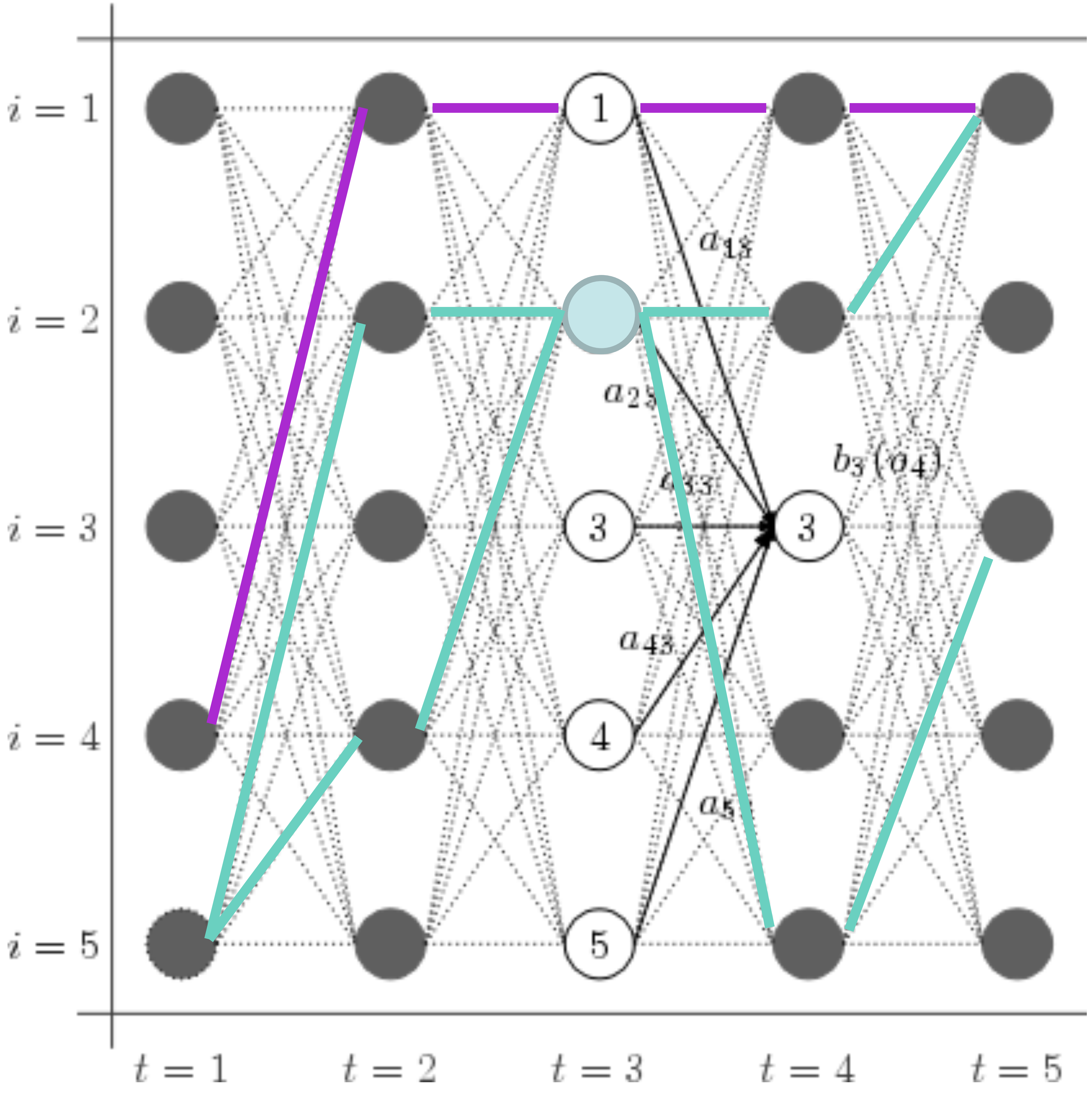
- In addition to finding the best path, we may want to compute marginal probabilities of paths $P(y_i = s|\mathbf{x})$

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

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

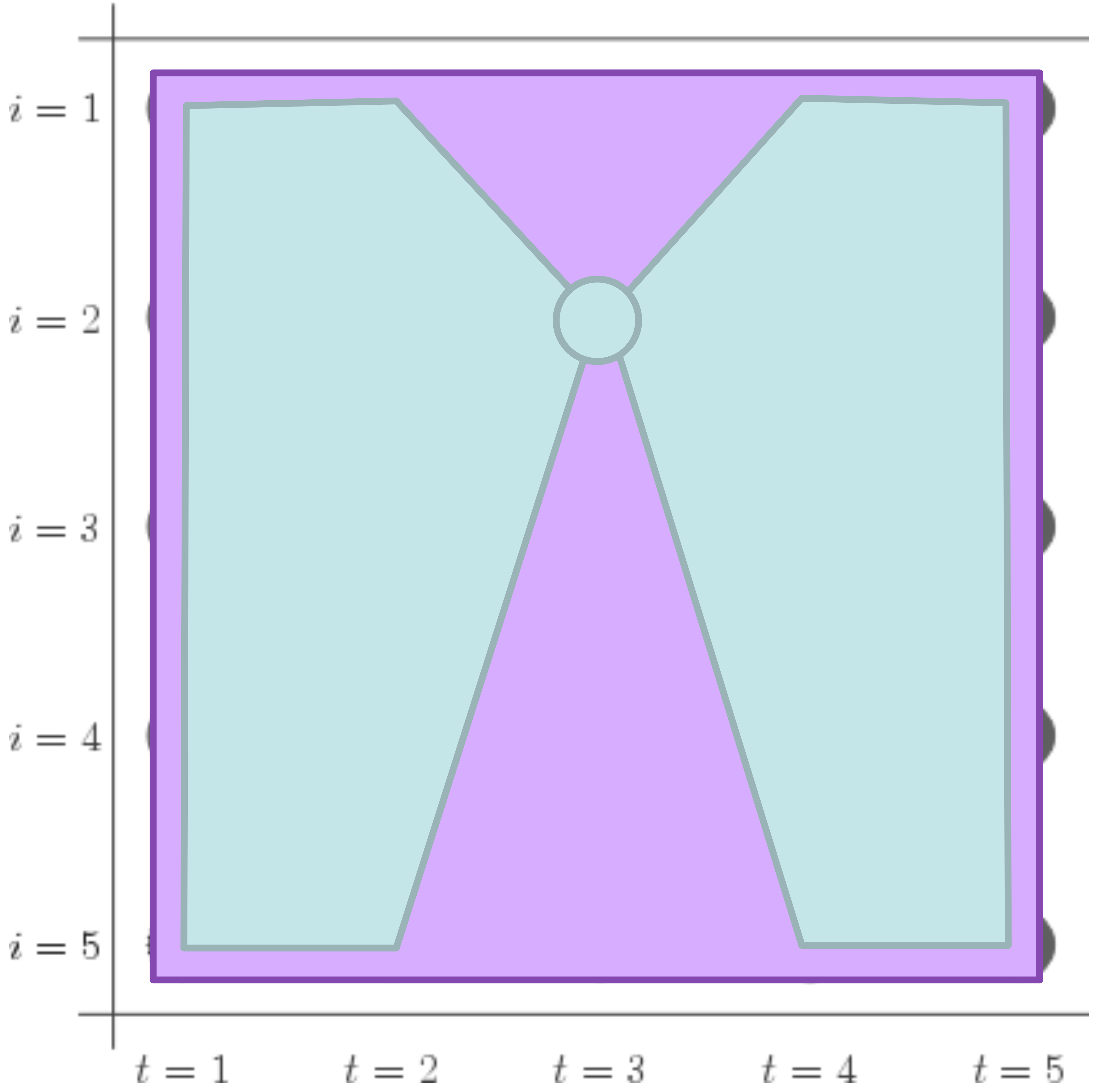
- Can compute marginals with dynamic programming as well using an algorithm called forward-backward

# Forward-Backward Algorithm

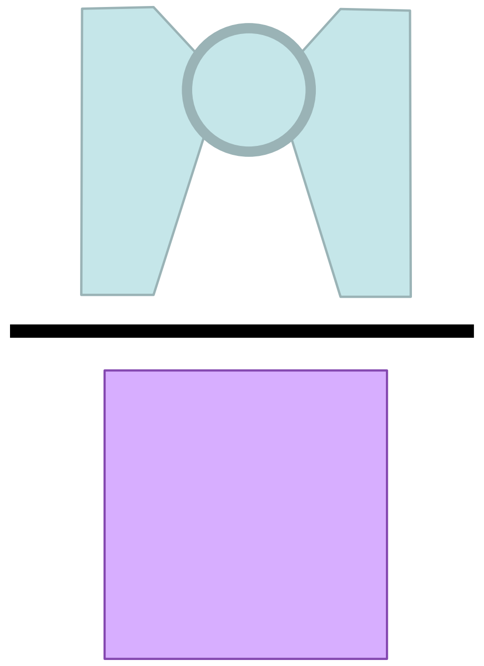


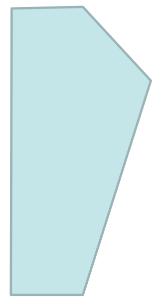
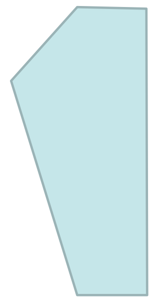

$$P(y_3 = 2|\mathbf{x}) = \frac{\text{sum of all paths through state 2 at time 3}}{\text{sum of all paths}}$$

# Forward-Backward Algorithm



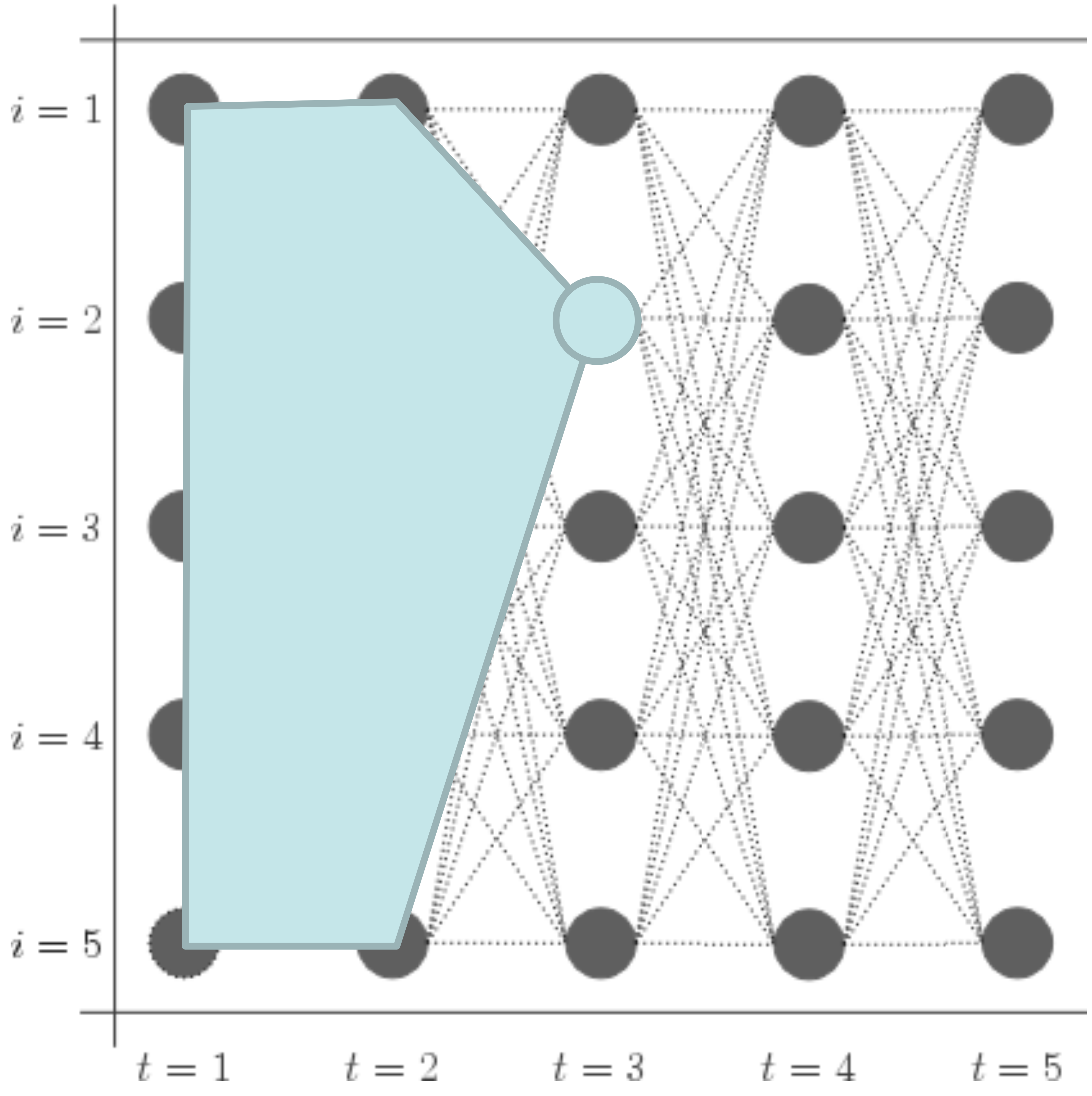

$$P(y_3 = 2|\mathbf{x}) = \frac{\text{sum of all paths through state 2 at time 3}}{\text{sum of all paths}}$$

= 

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

slide credit: Dan Klein

# Forward-Backward Algorithm




- Initial:

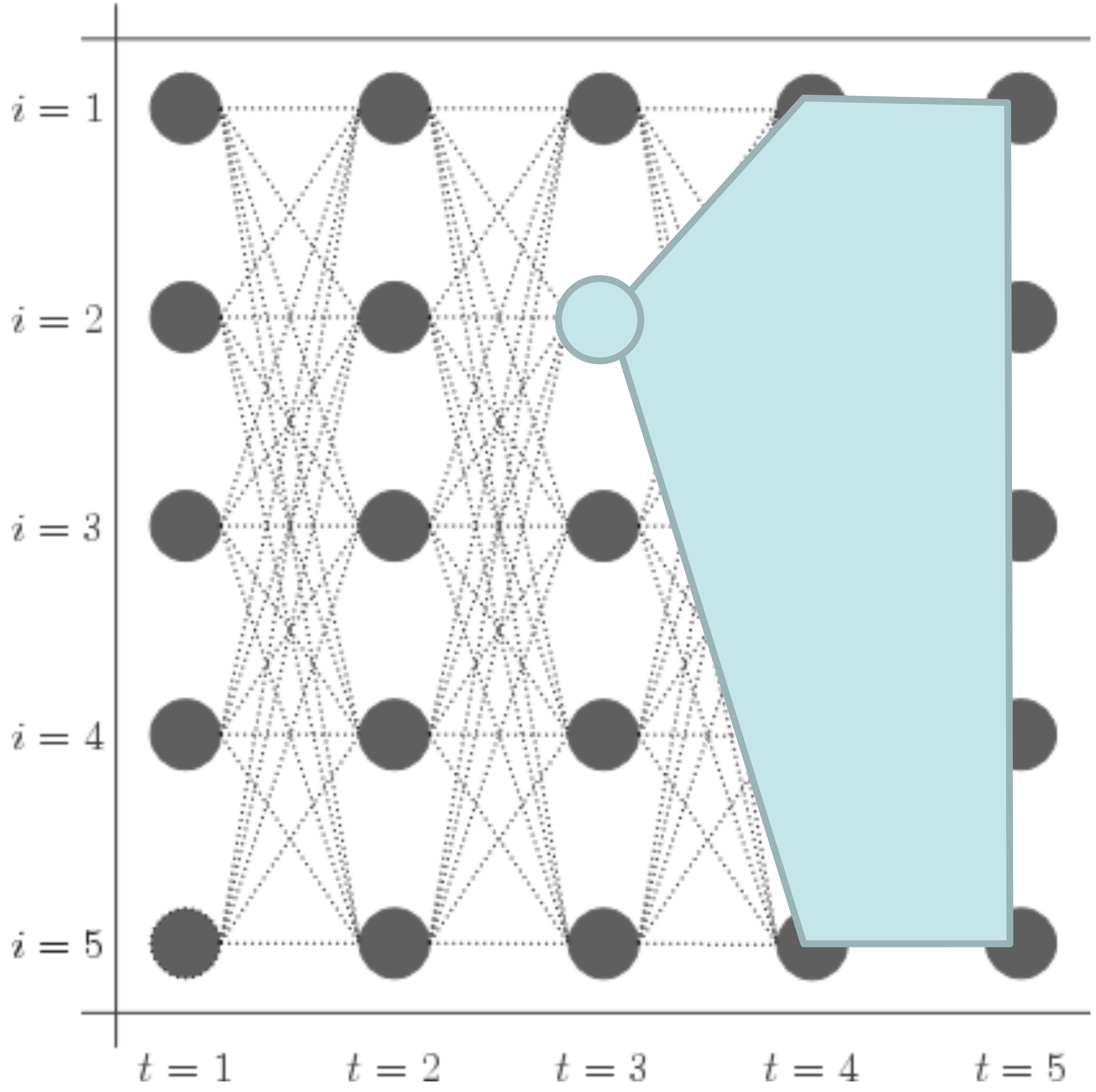
$$\alpha_1(s) = P(s)P(x_1|s)$$

- 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:

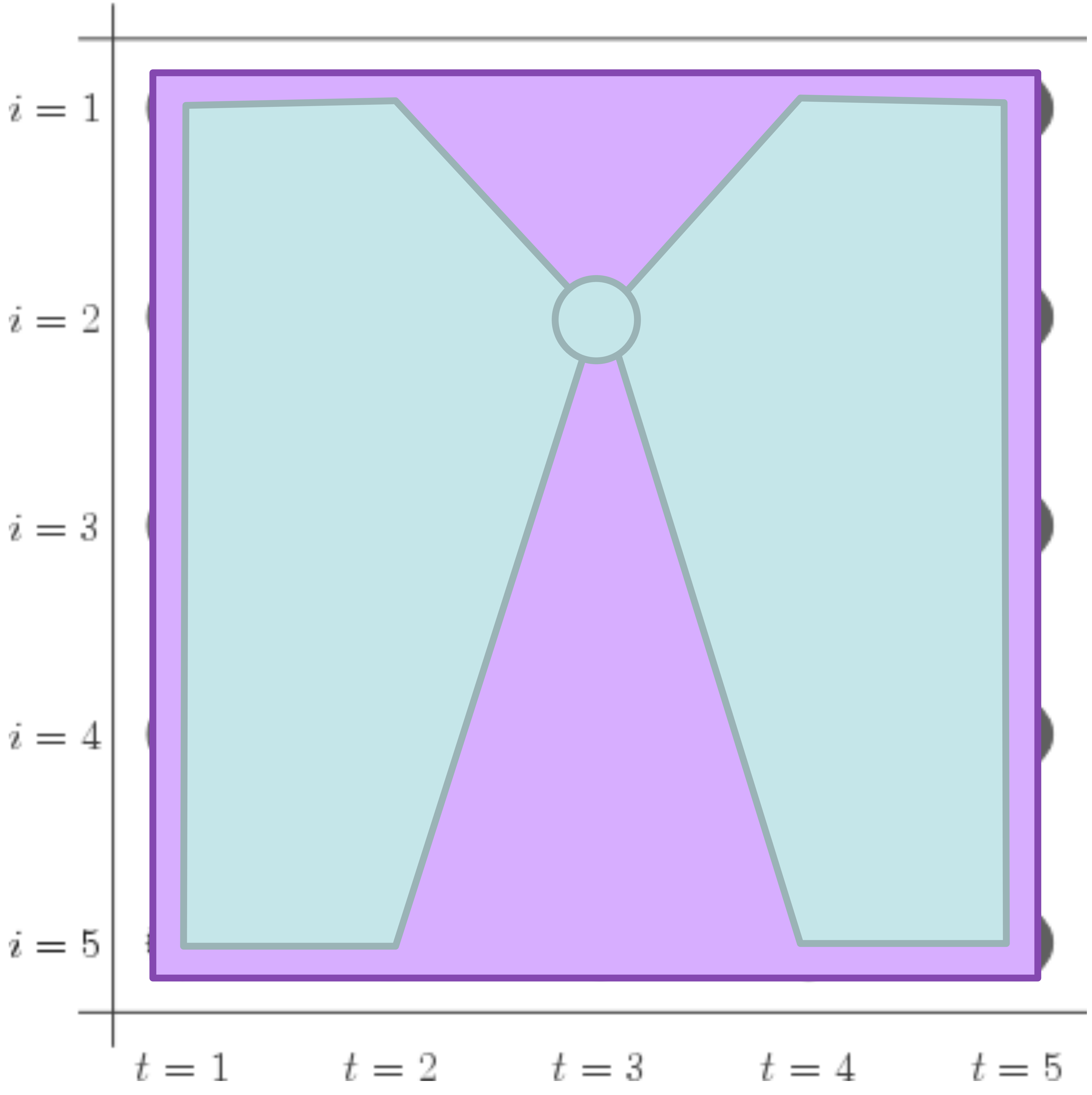
$$\beta_n(s) = 1$$

- 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




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

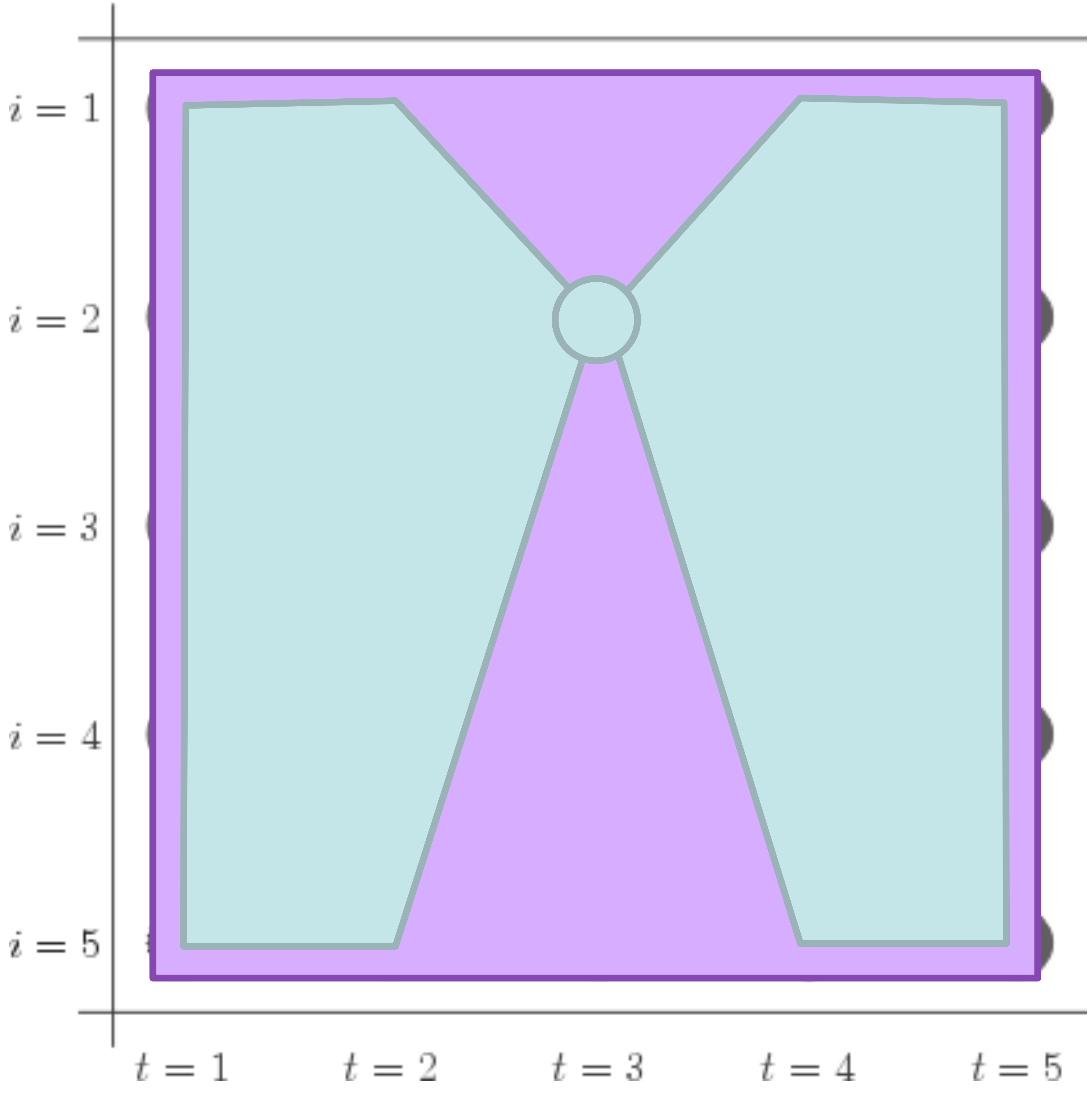
$$\alpha_t(s_t) = \sum_{s_{t-1}} \alpha_{t-1}(s_{t-1})P(s_t|s_{t-1})P(x_t|s_t)$$

$$\beta_n(s) = 1$$

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

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

# Forward-Backward Algorithm



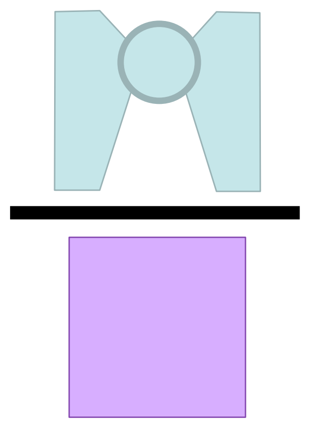

$$\alpha_1(s) = P(s)P(x_1|s)$$

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

$$\beta_n(s) = 1$$

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

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



- 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