Lecture 4: Sequence Models I

Alan Ritter

(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

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I ate the spaghetti with chopsticks

Linguistic Structures

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I ate the spaghetti with meatballs

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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)

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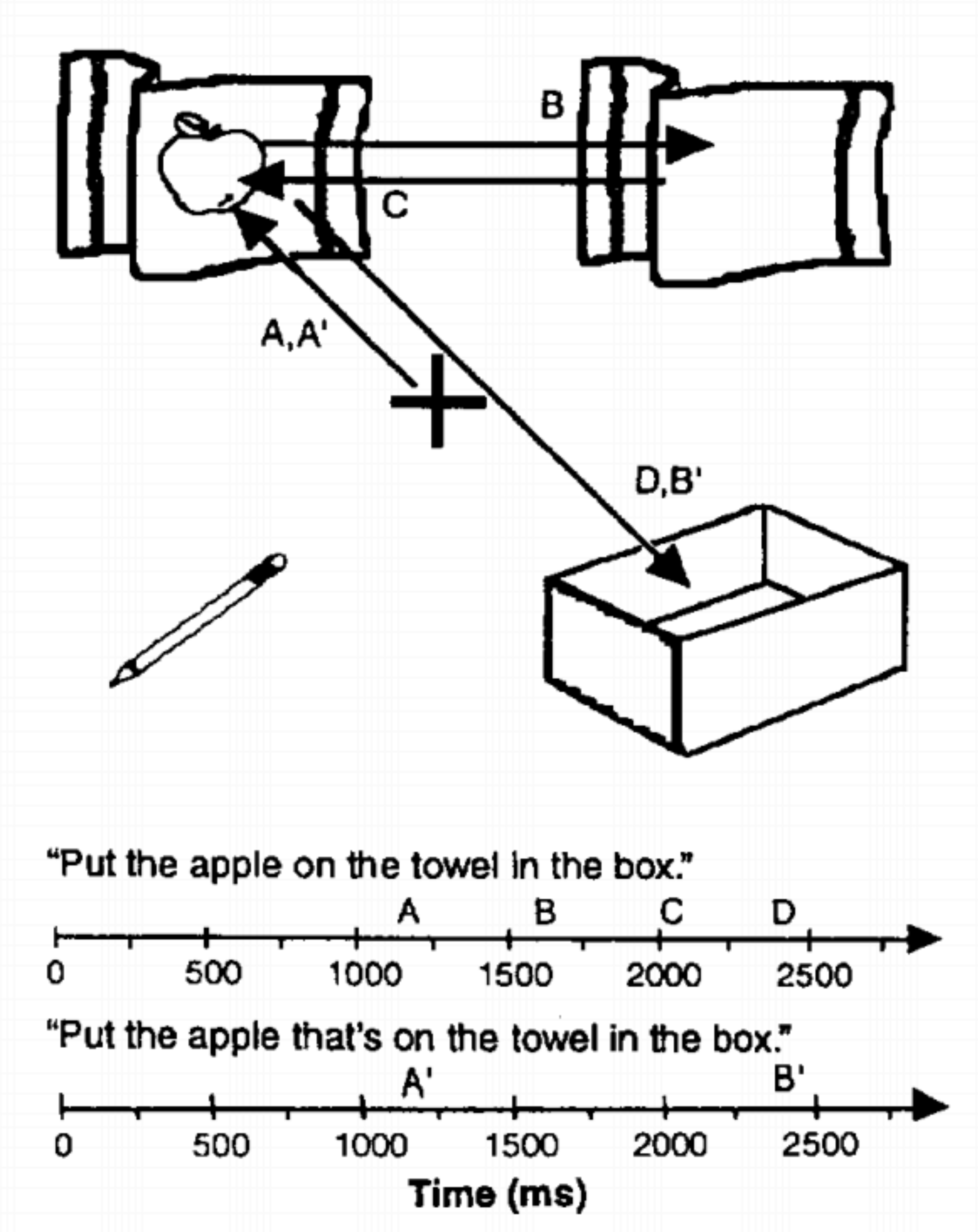

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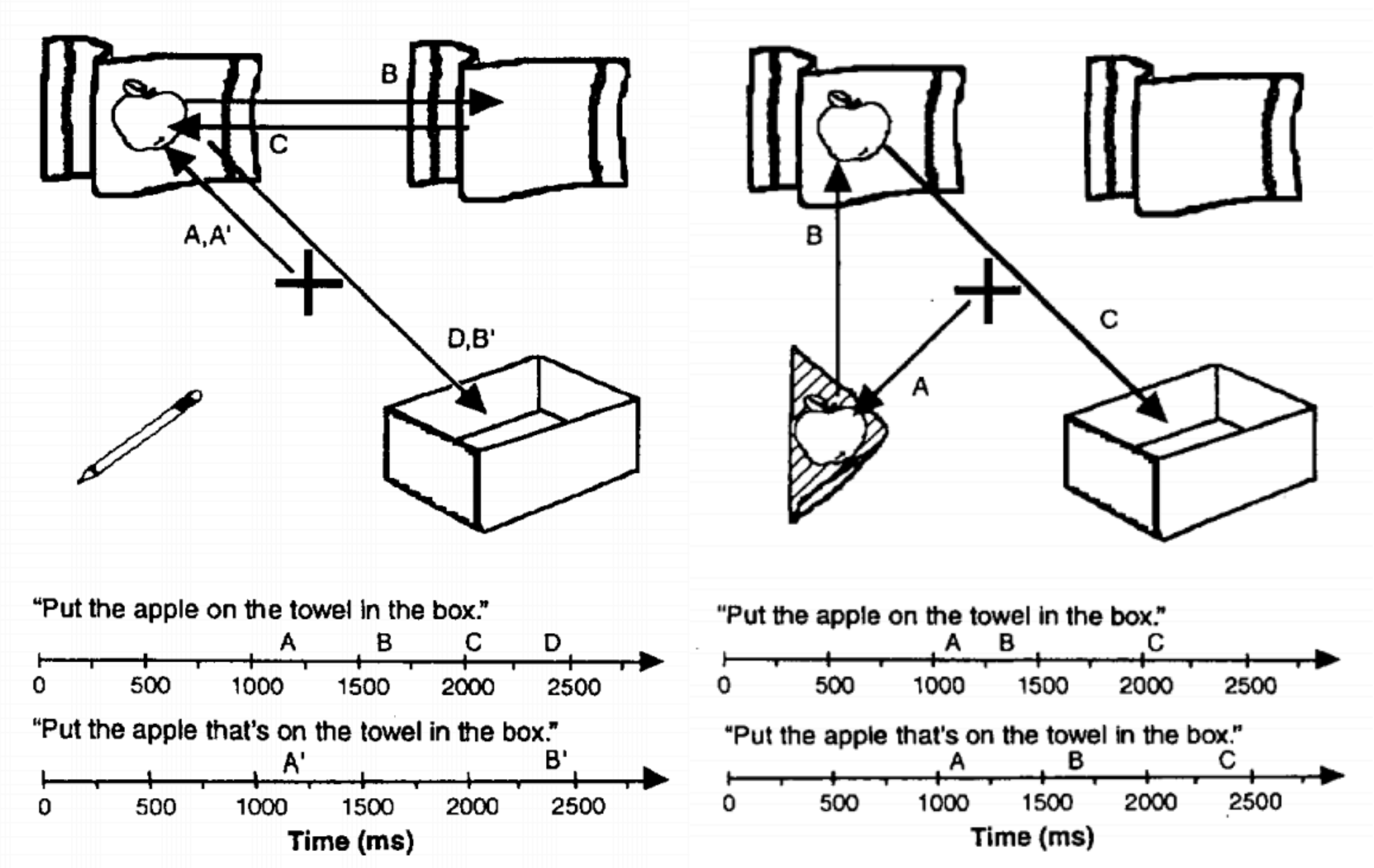

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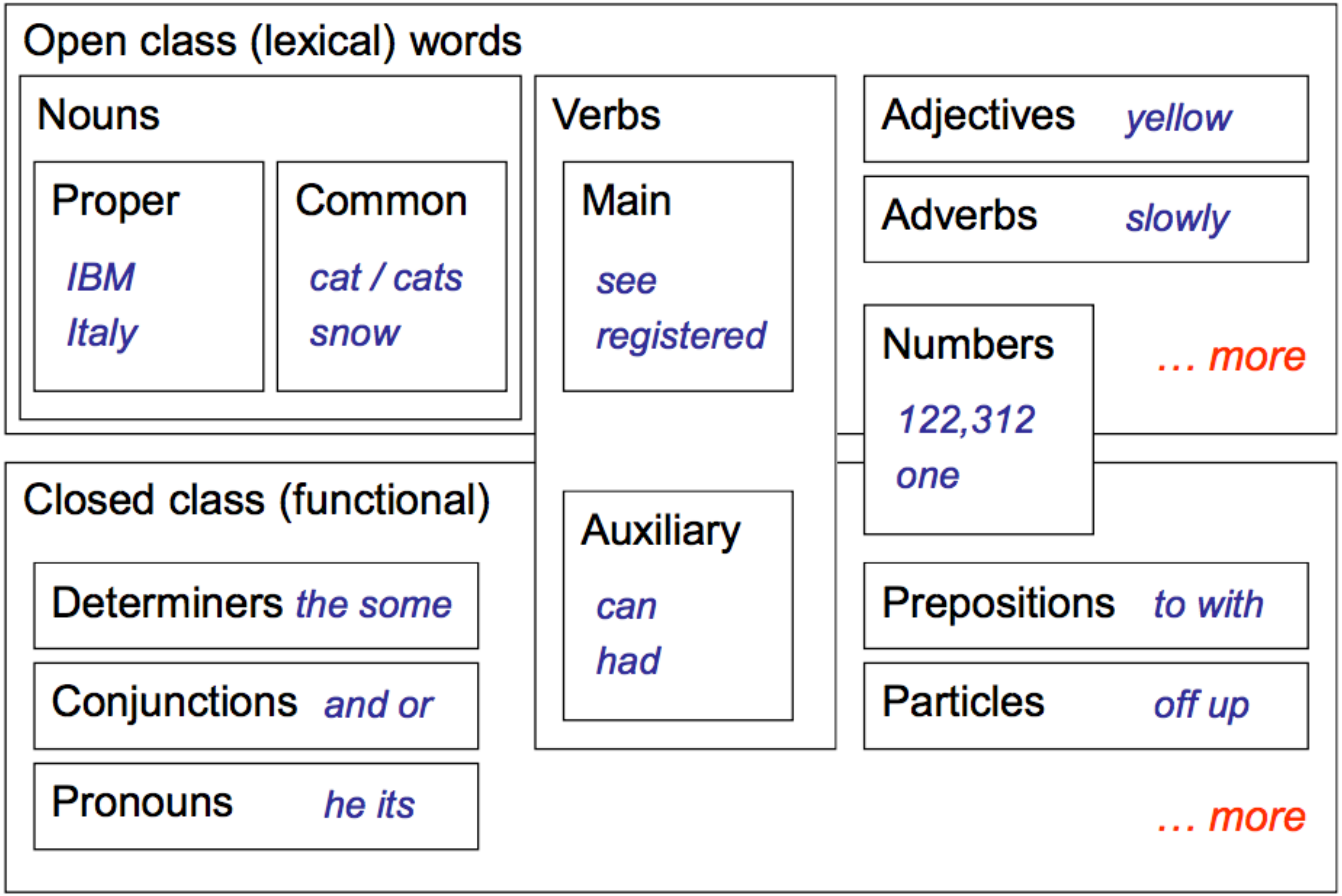
POS Tagging

- 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

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Fed raises interest rates 0.5 percent

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POS Tagging

VBD
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POS Tagging

VBD VB

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- 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

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- Preprocessing step for syntactic parsers
- Domain-independent disambiguation for other tasks
- (Very) shallow information extraction

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

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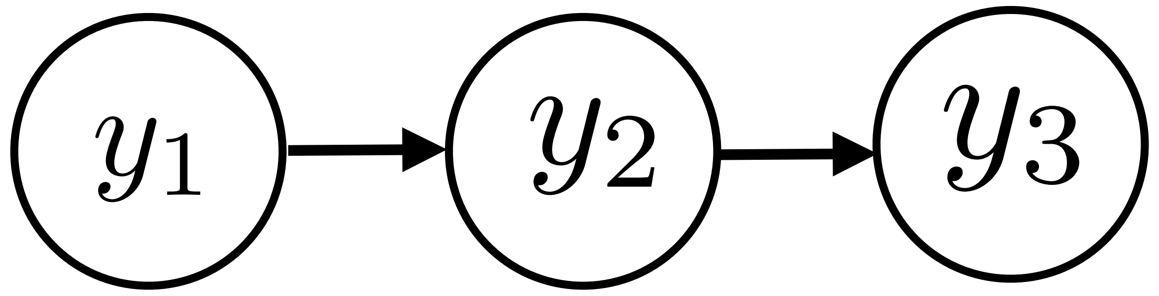

$$P(y_3 | y_1, y_2) = P(y_3 | y_2)$$

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

- Lots of mathematical theory about how Markov chains behave

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- 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

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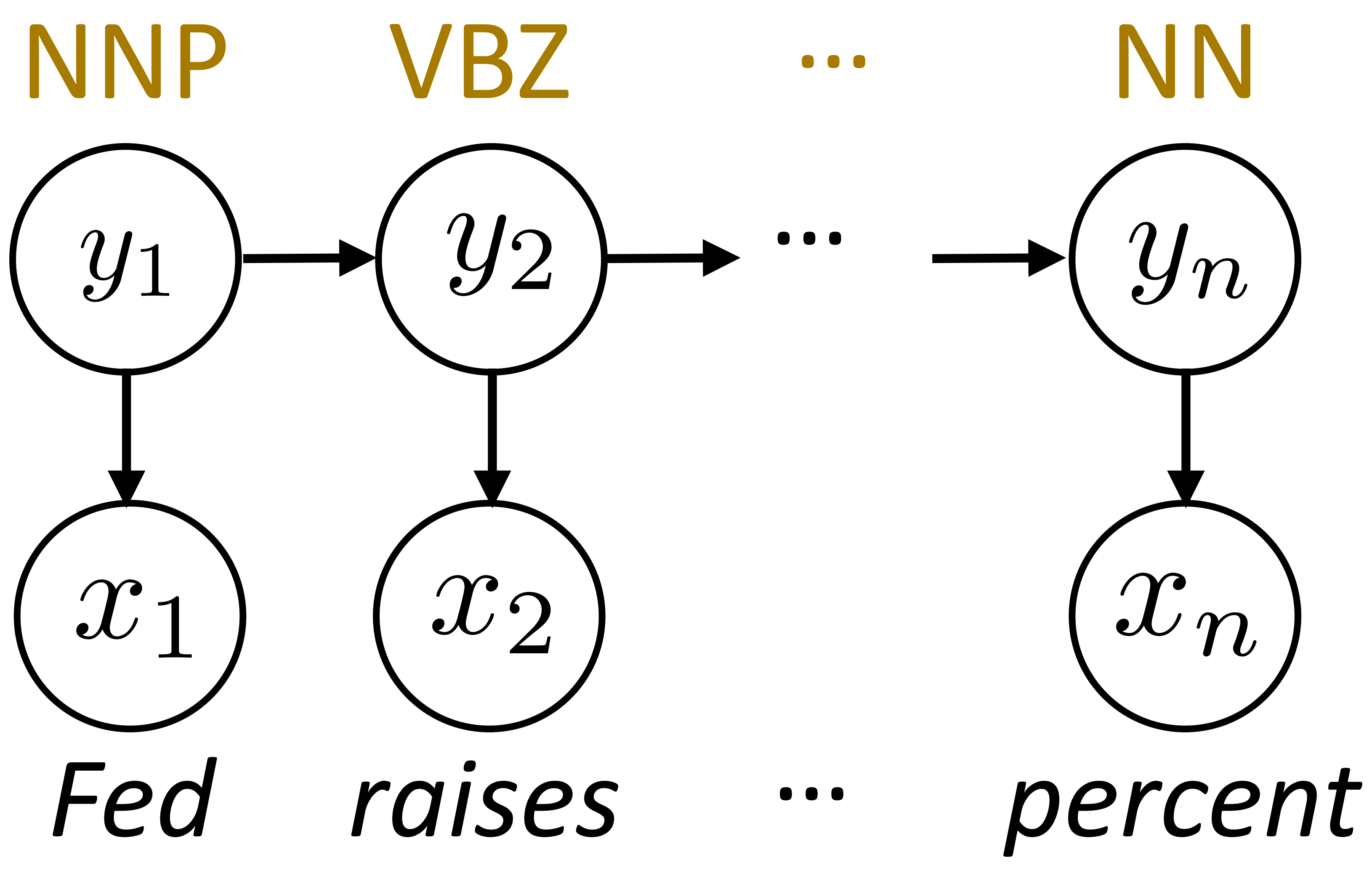

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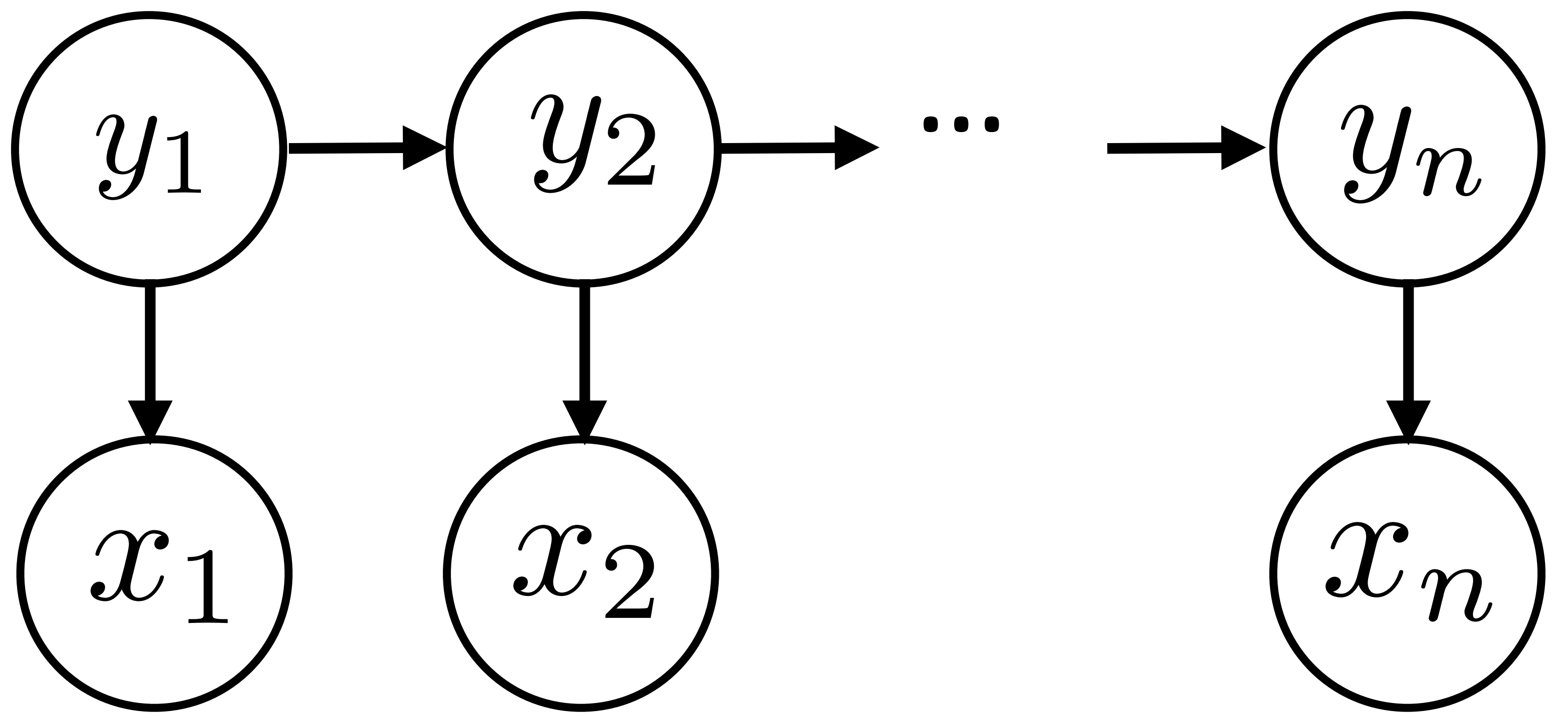

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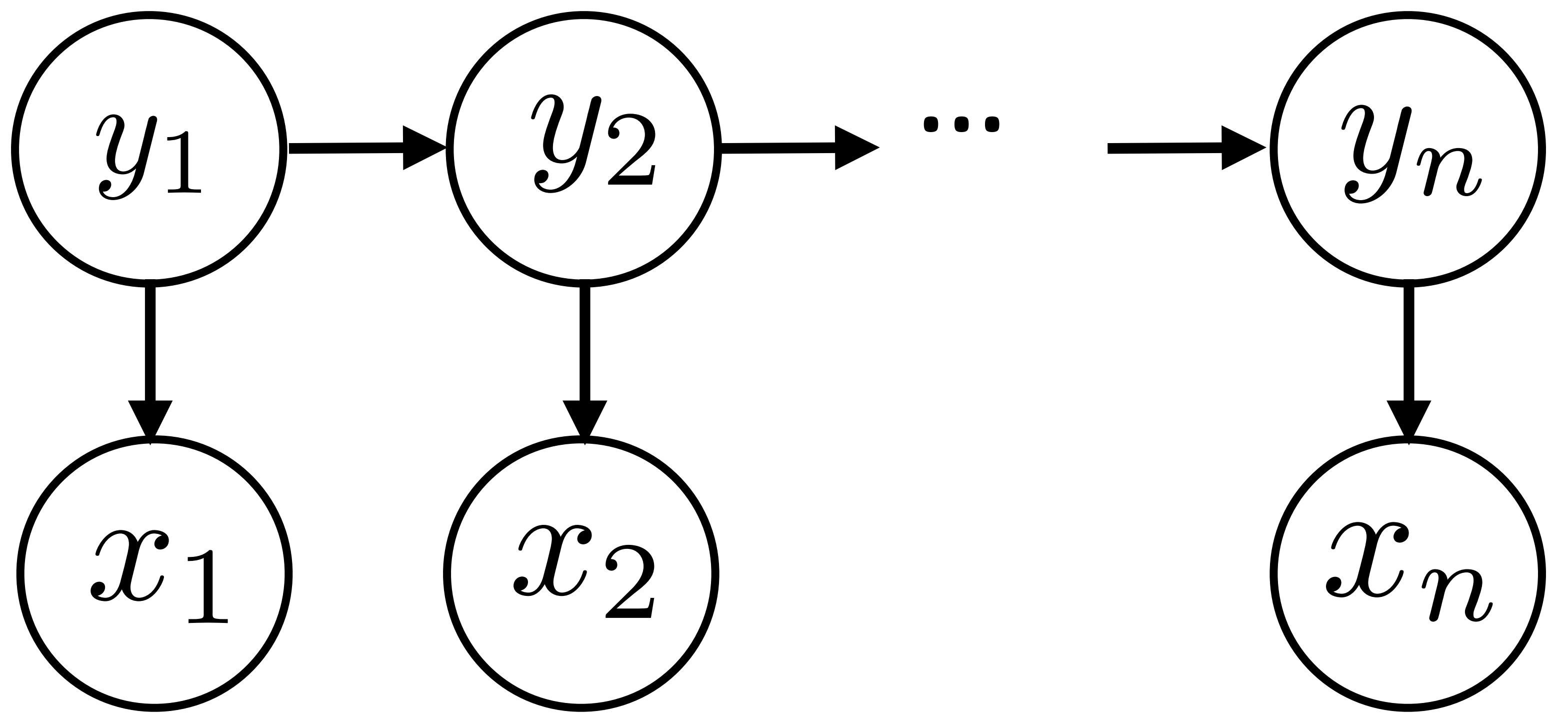

$$P(\mathbf{y}, \mathbf{x}) = P(y_1) \prod_{i=2}^{n} P(y_i | y_{i-1}) \prod_{i=1}^{n} P(x_i | y_i)$$

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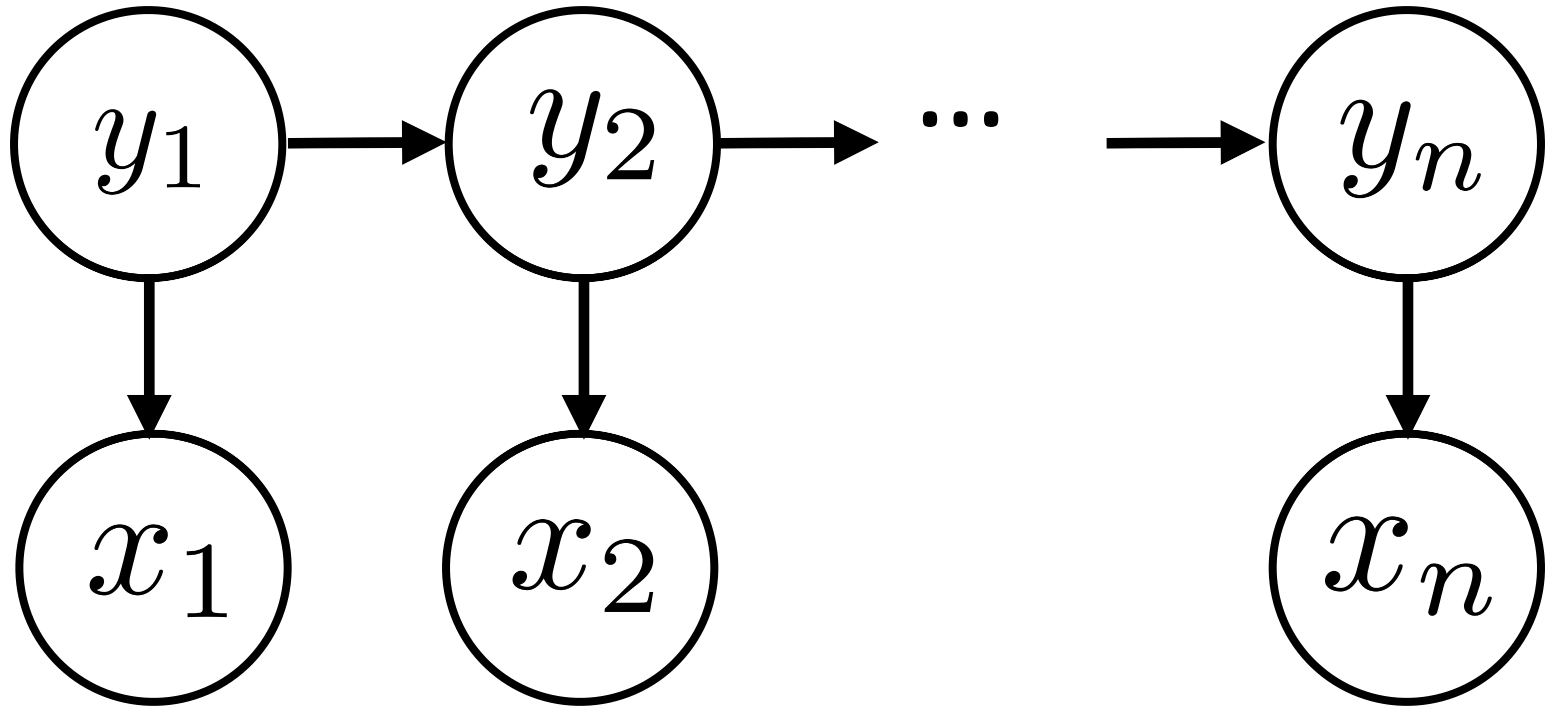

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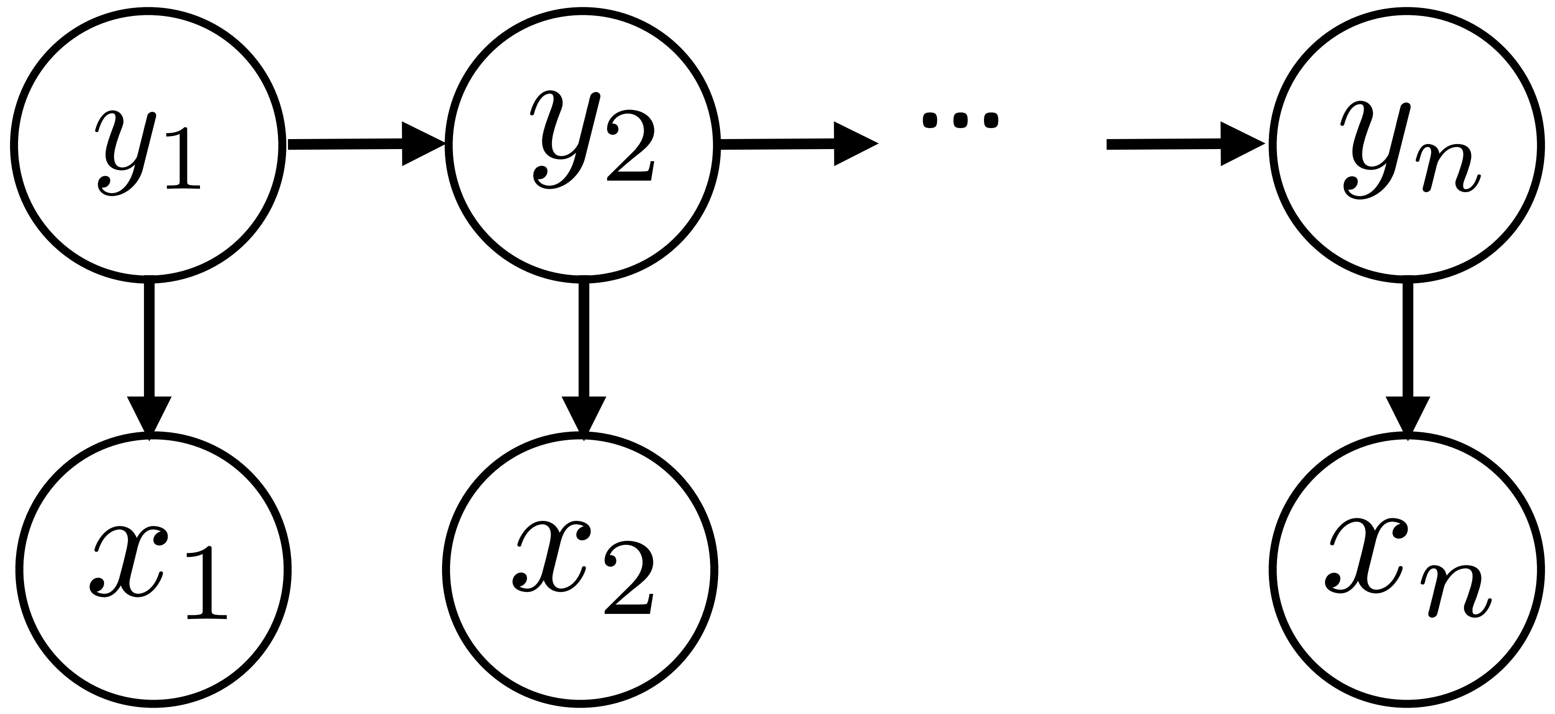

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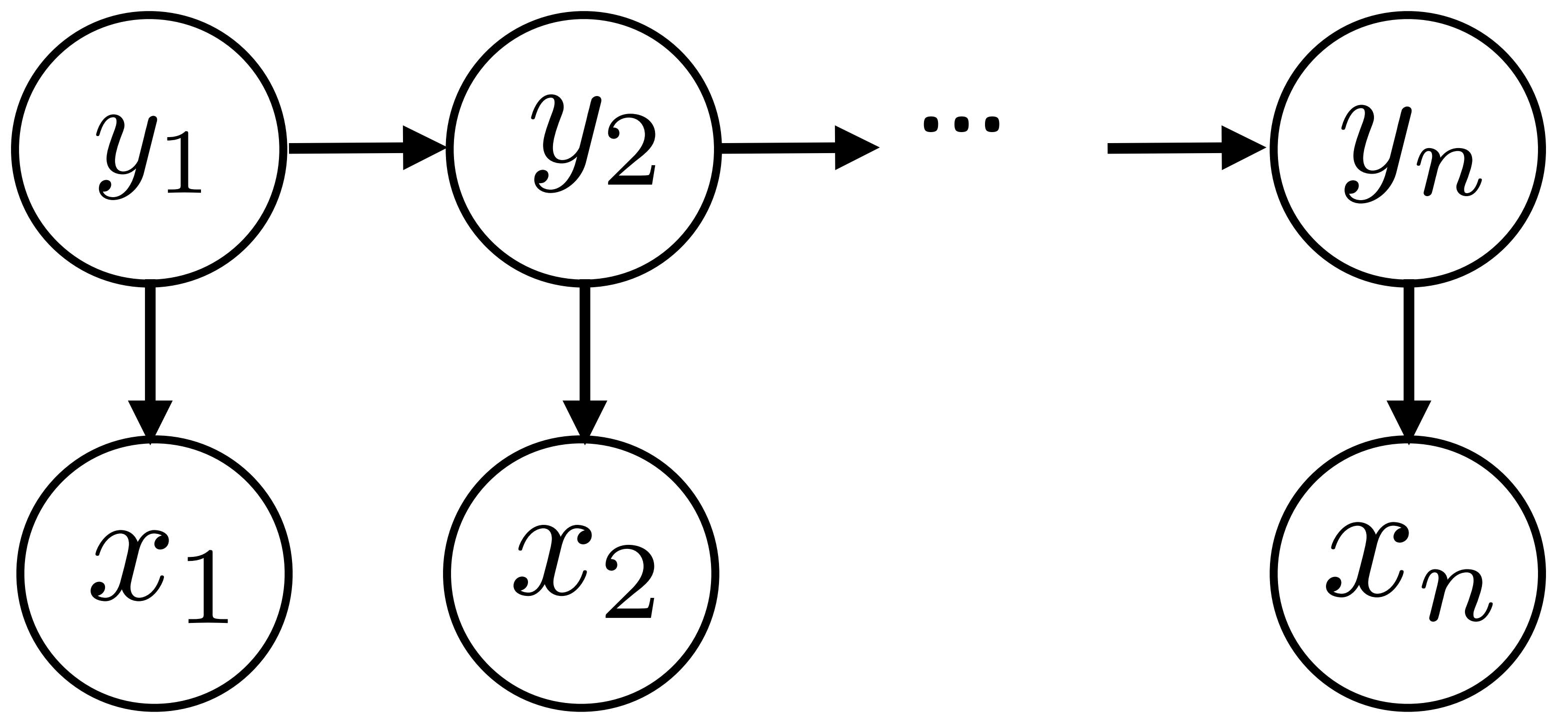

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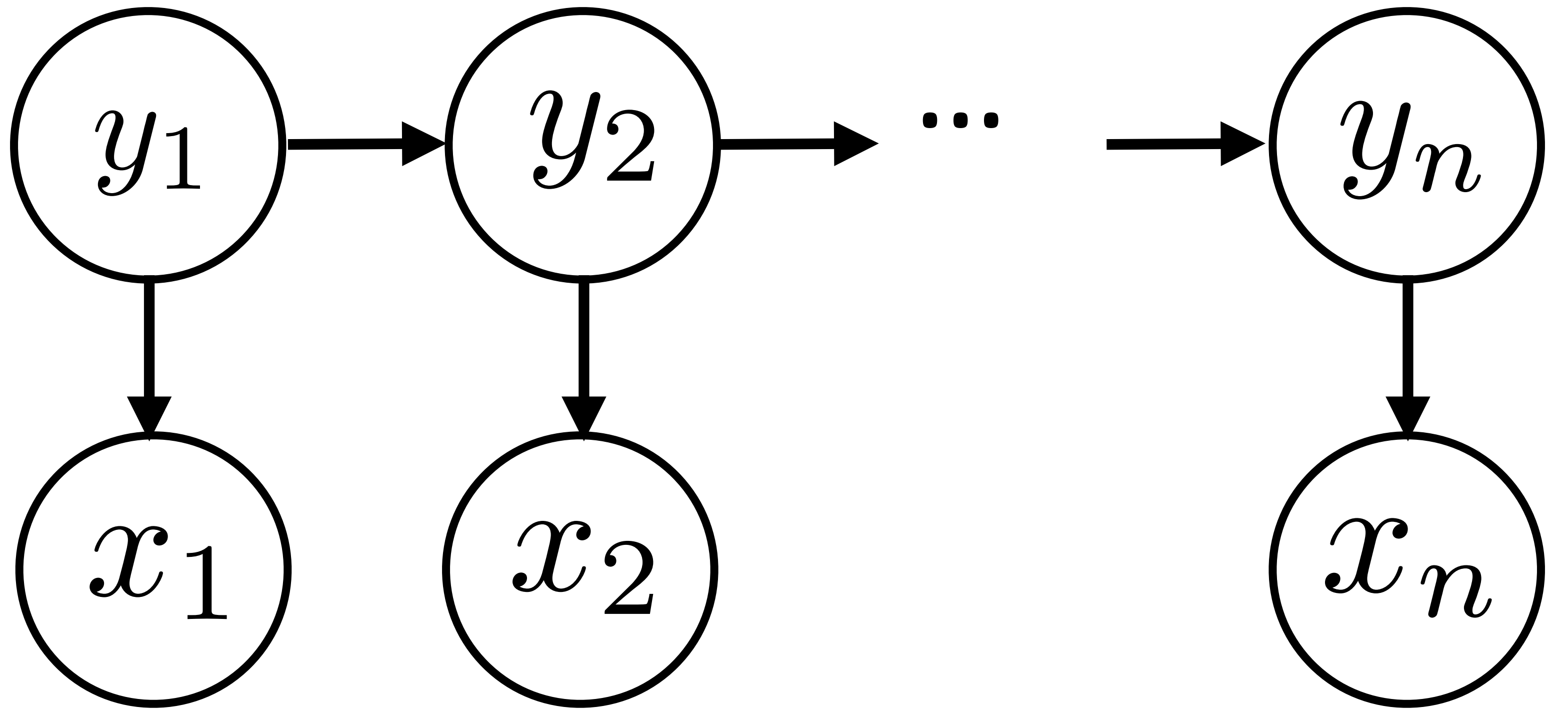

- Observation (*x*) depends only on current state (*y*)

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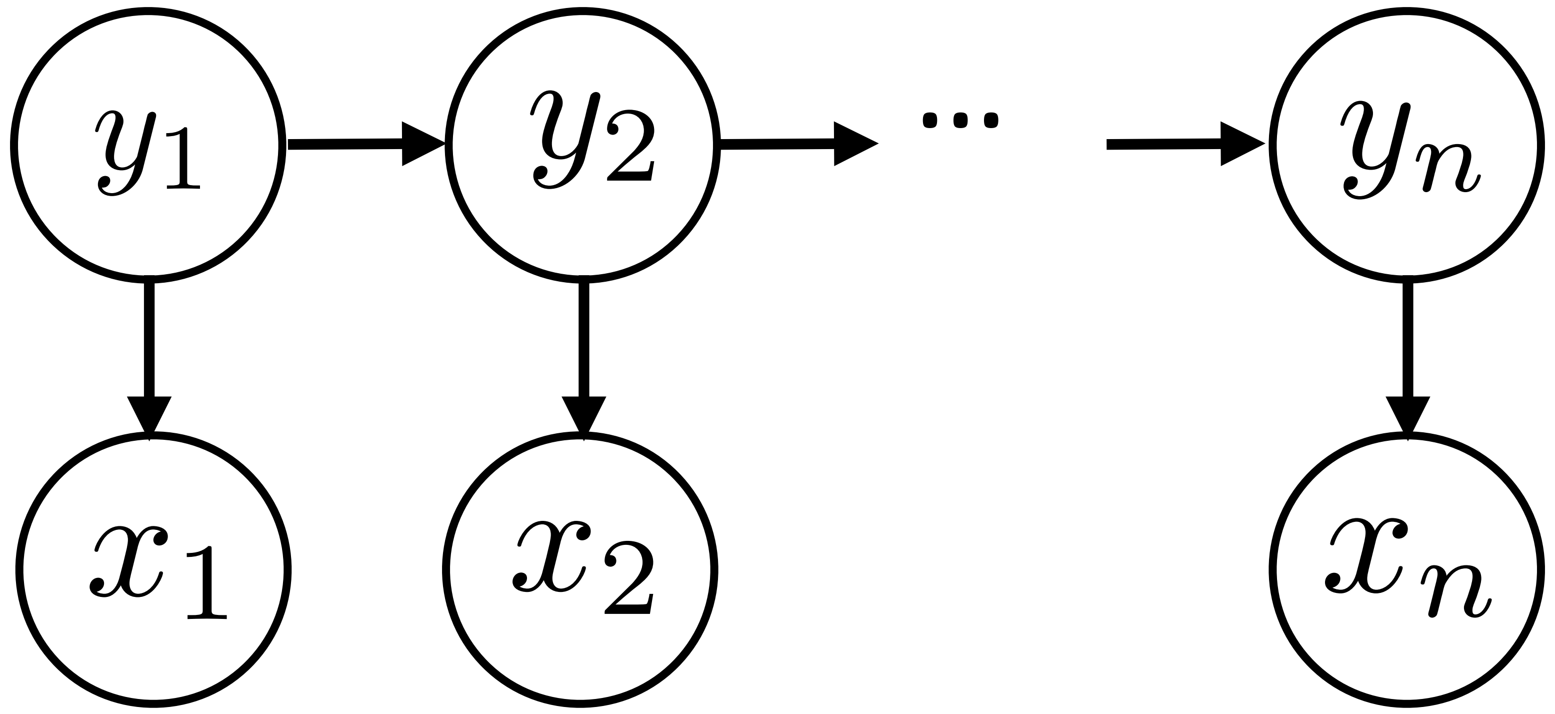

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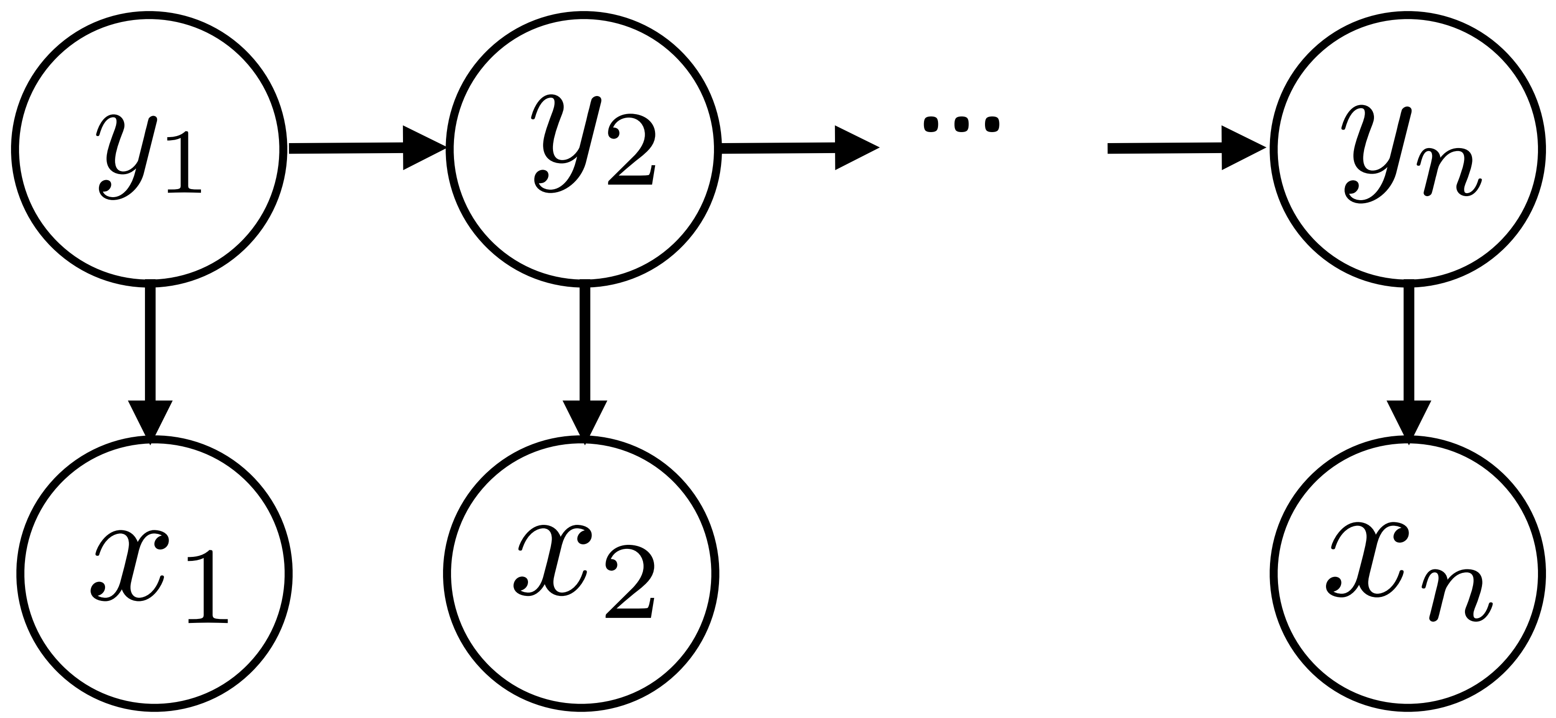

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- Observation (*x*) depends only on current state (*y*)
- Multinomials: tag x tag transitions, tag x word emissions
- P(*x*|*y*) is a distribution over all words in the vocabulary — not a distribution over features (but could be!)

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

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- $P(y_1 = \mathrm{NNP})$ 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!)

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

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- How should we smooth this?

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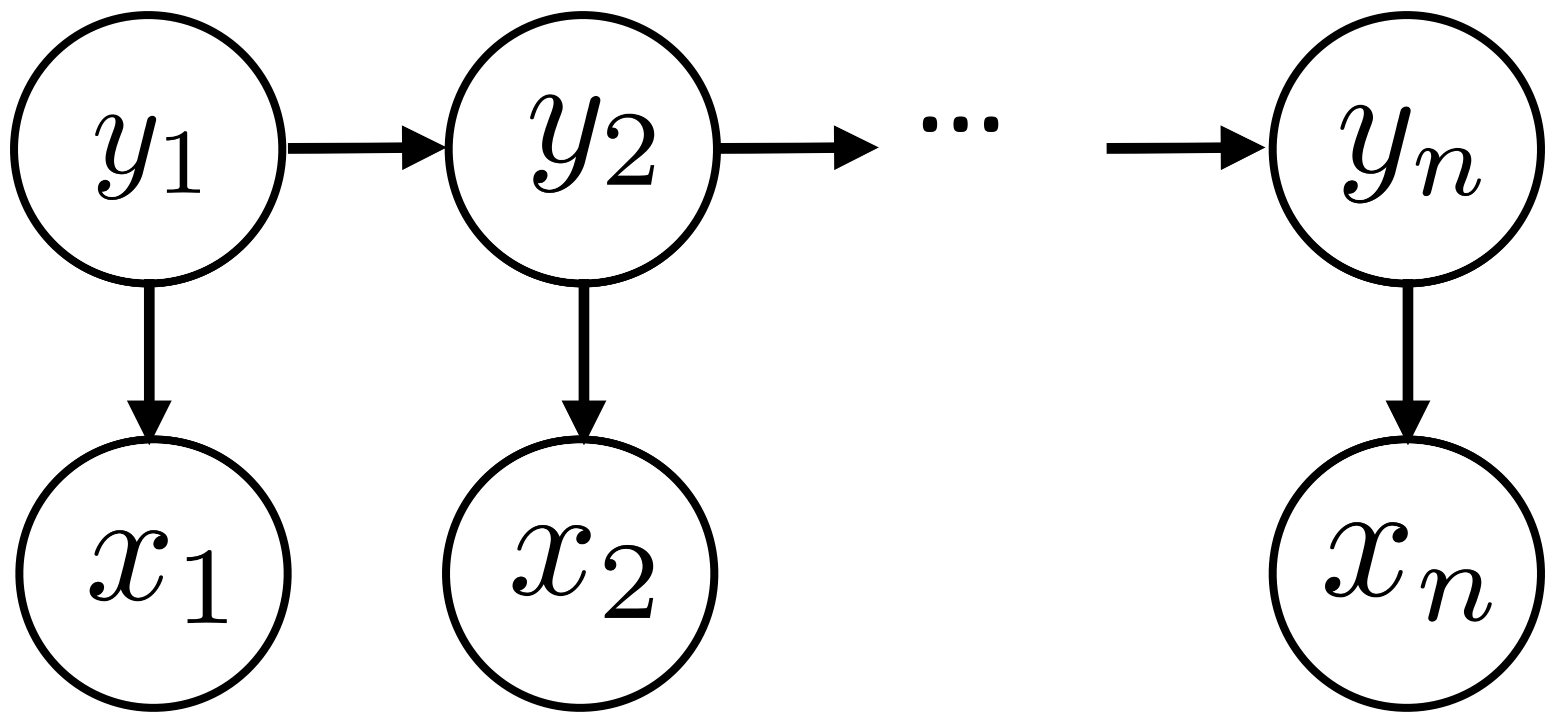
  - Fancy techniques from language modeling, e.g. look at type fertility — P(tag|word) is flatter for some kinds of words than for others)
- P(word|tag) can be a log-linear model — we'll see this in a few lectures

Inference in HMMs

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



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

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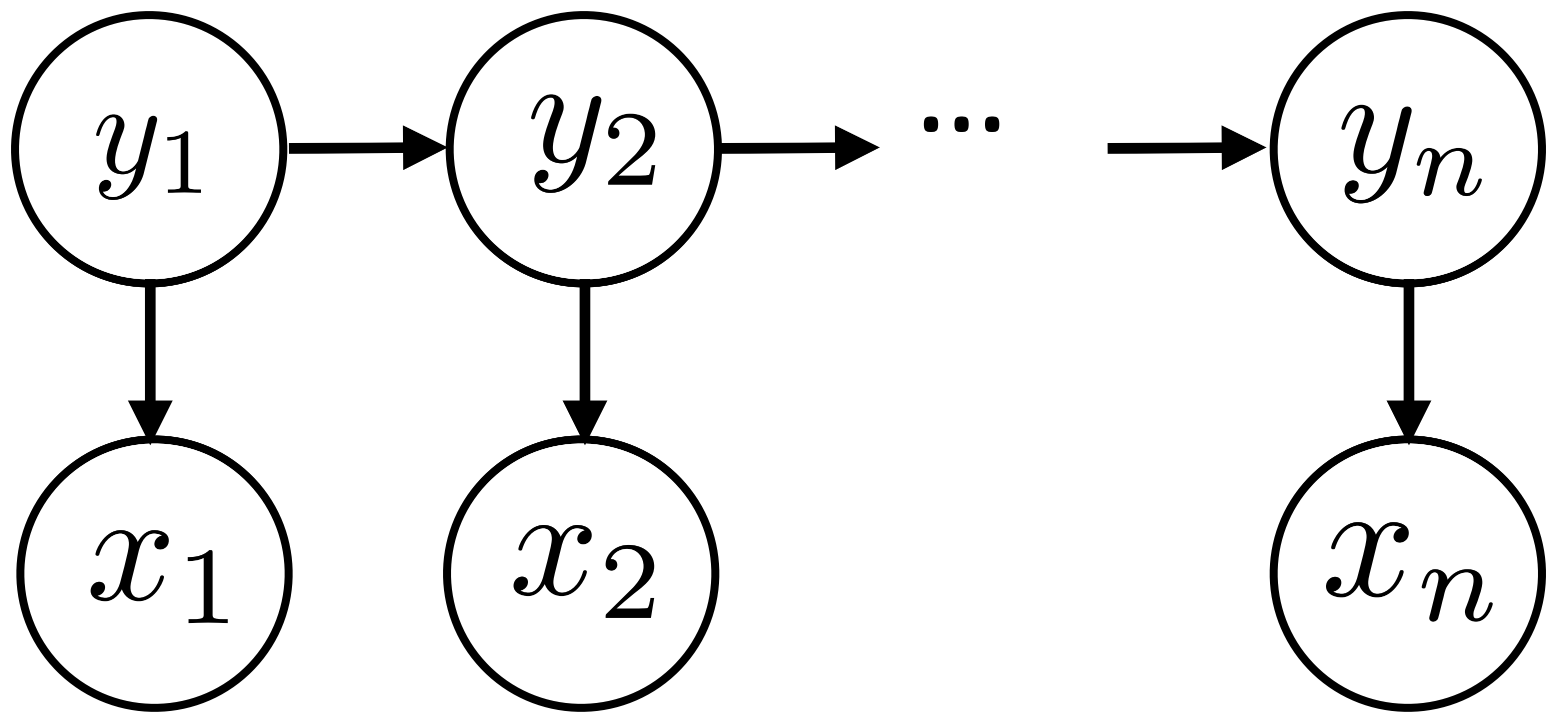

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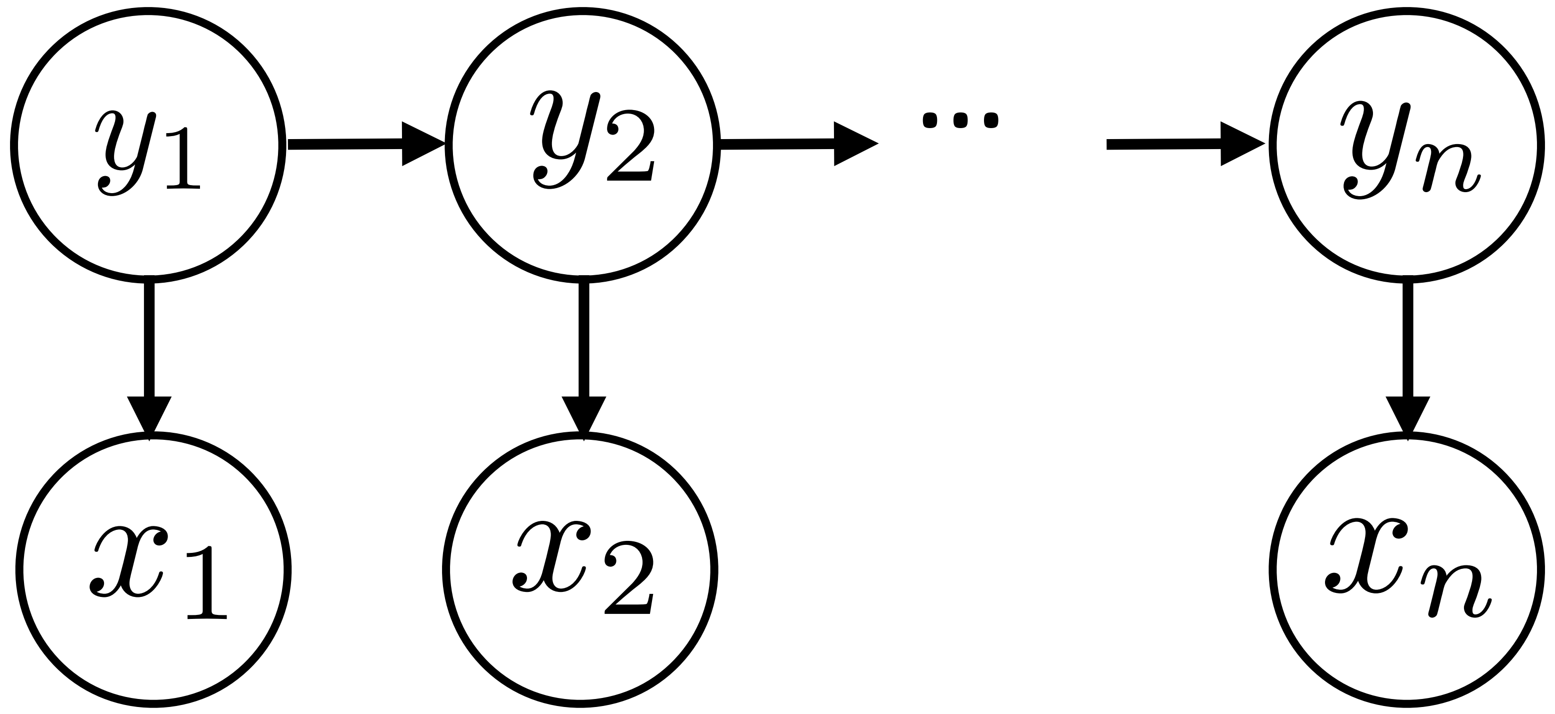

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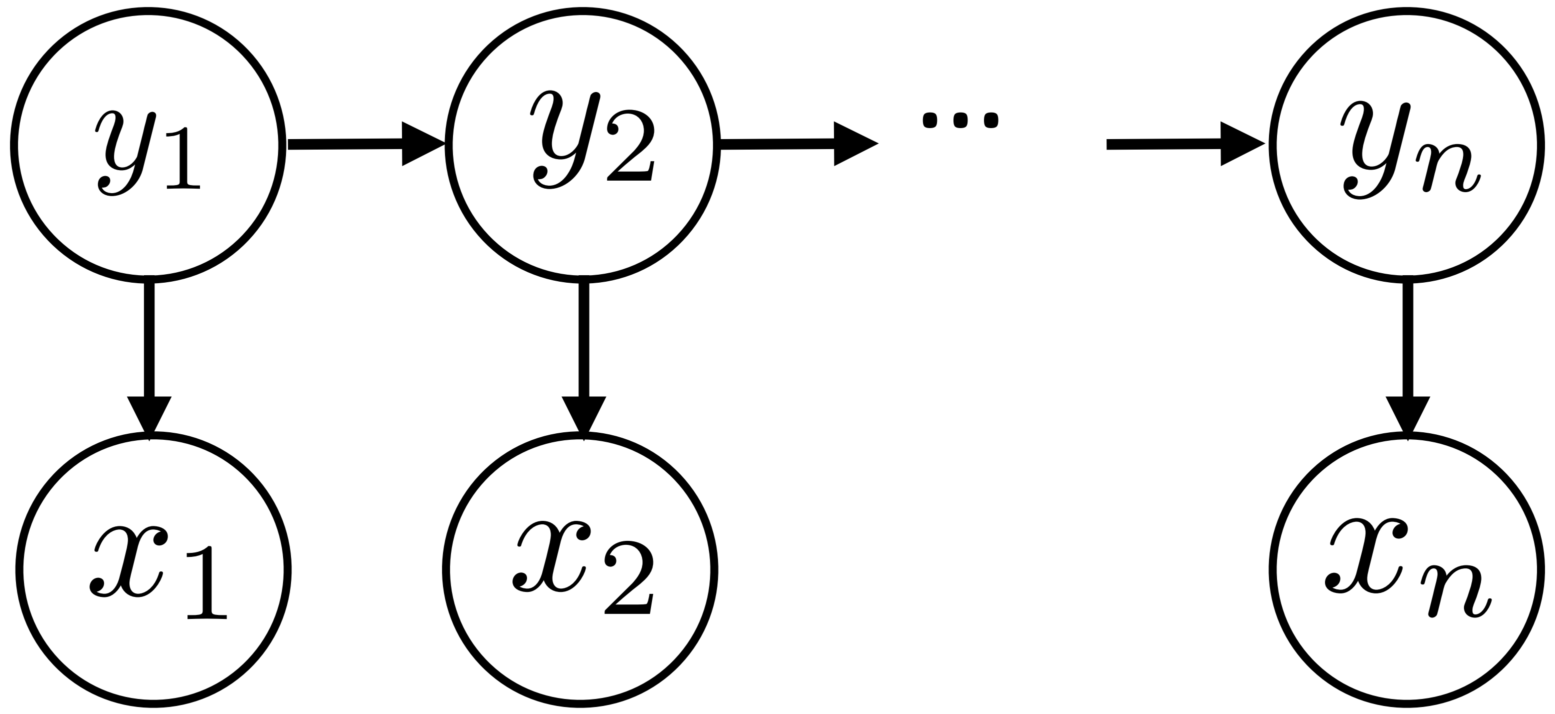

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- Exponentially many possible ***y*** here!

Inference in HMMs

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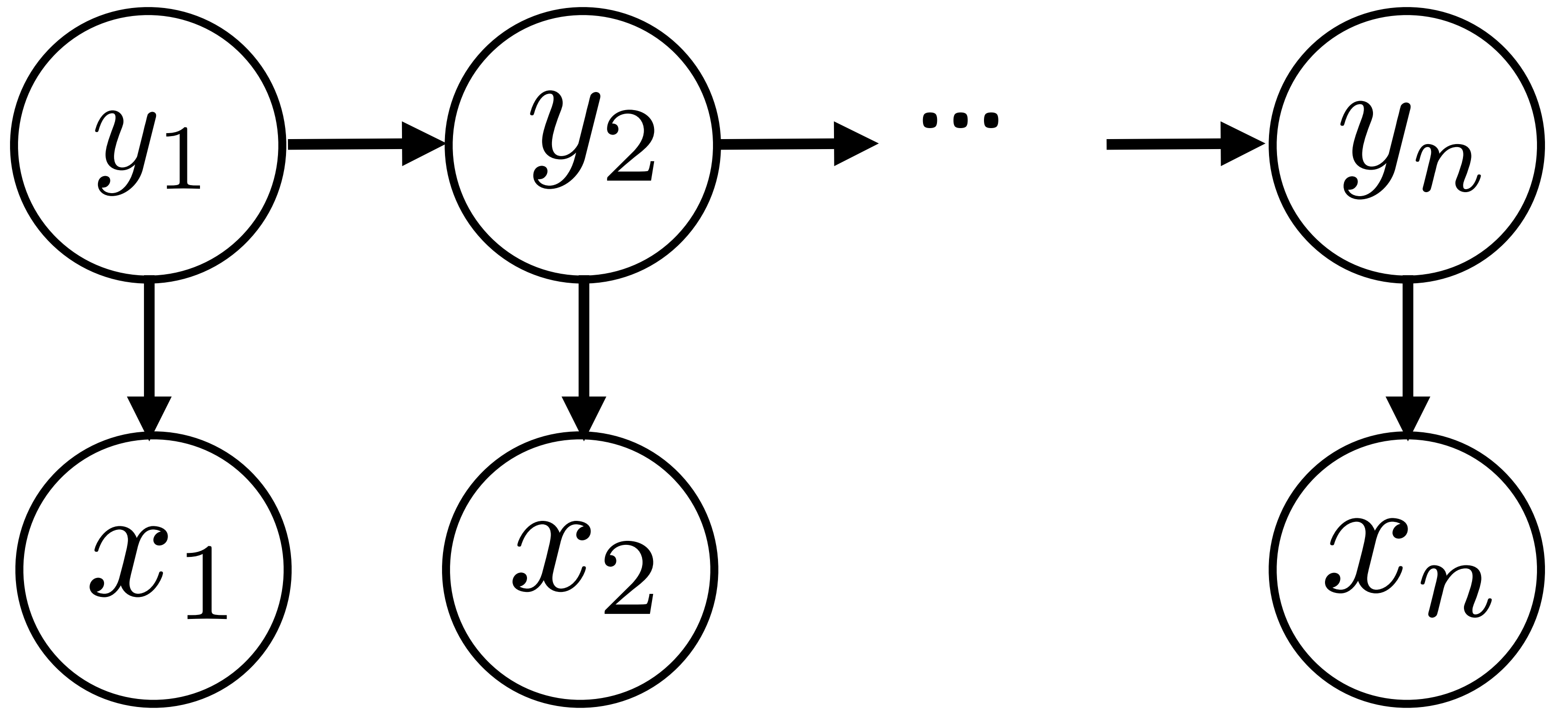

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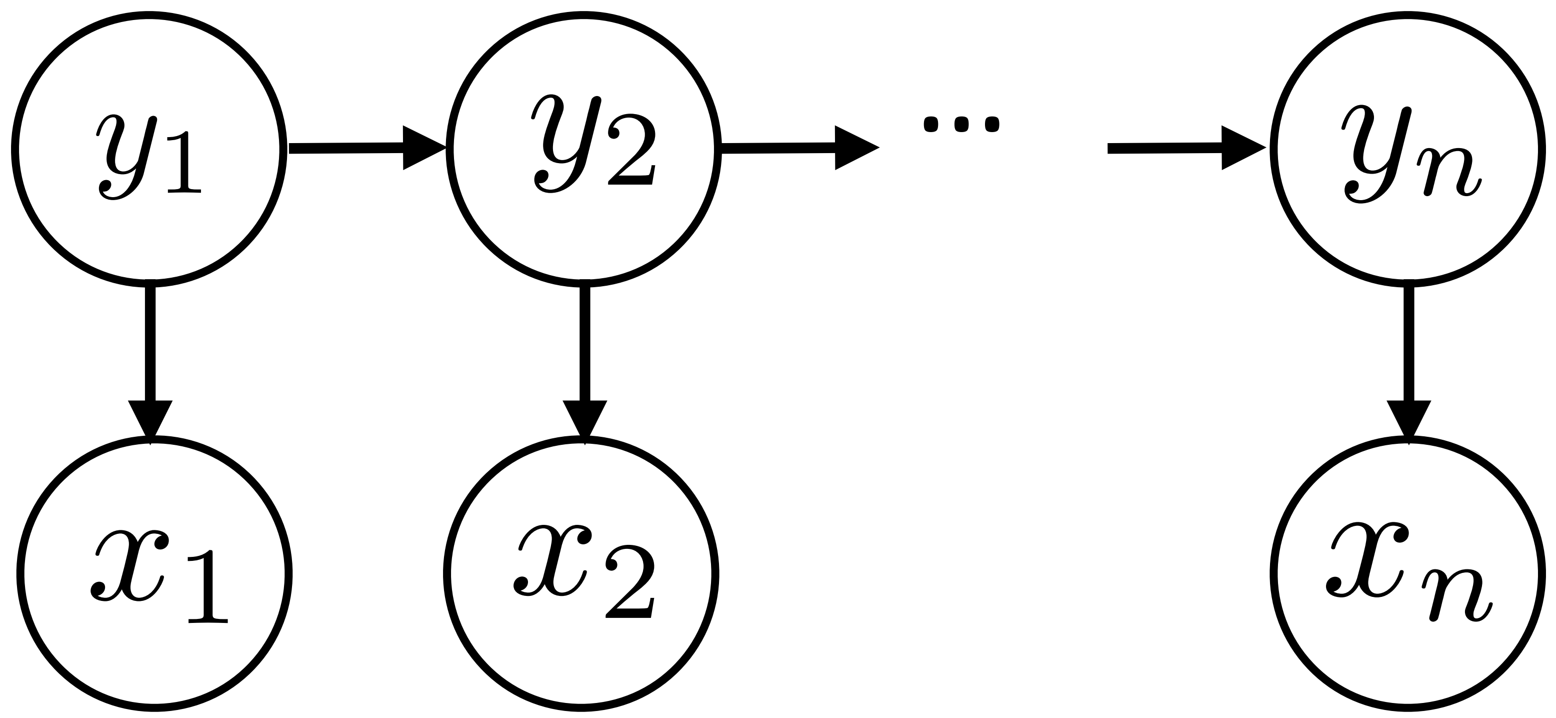

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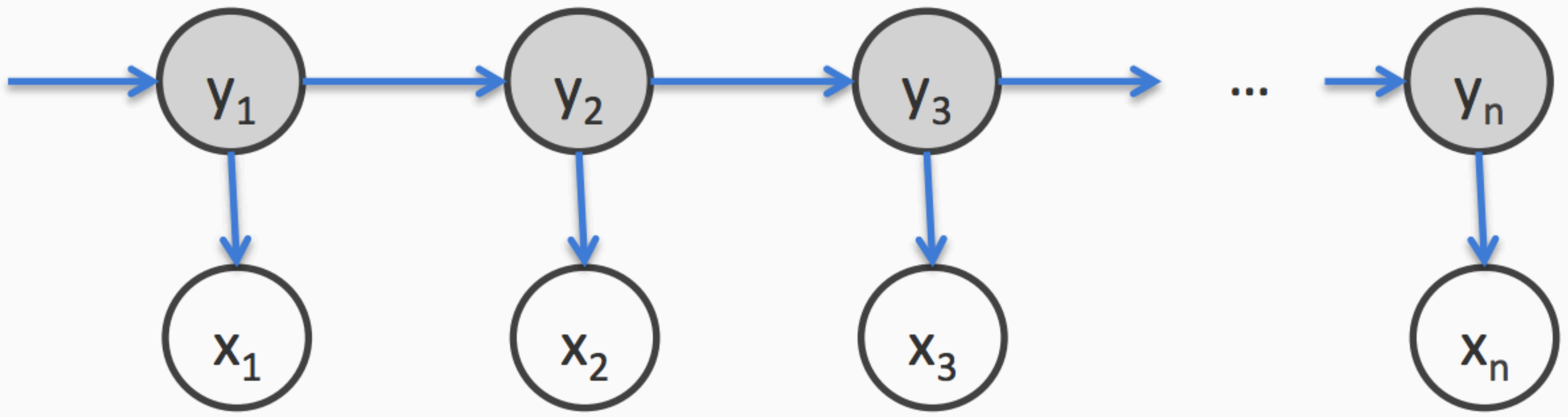
- Exponentially many possible ***y*** here!
- Solution: dynamic programming (possible because of Markov structure!)
  - Many neural sequence models depend on entire previous tag sequence, need to use approximations like beam search

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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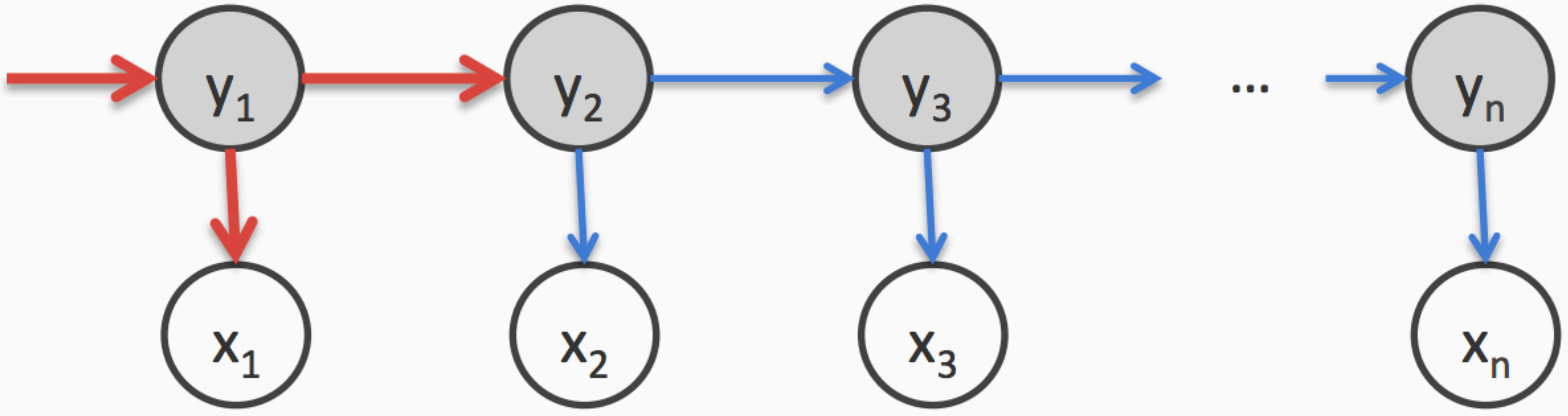
The only terms that depend on y_1



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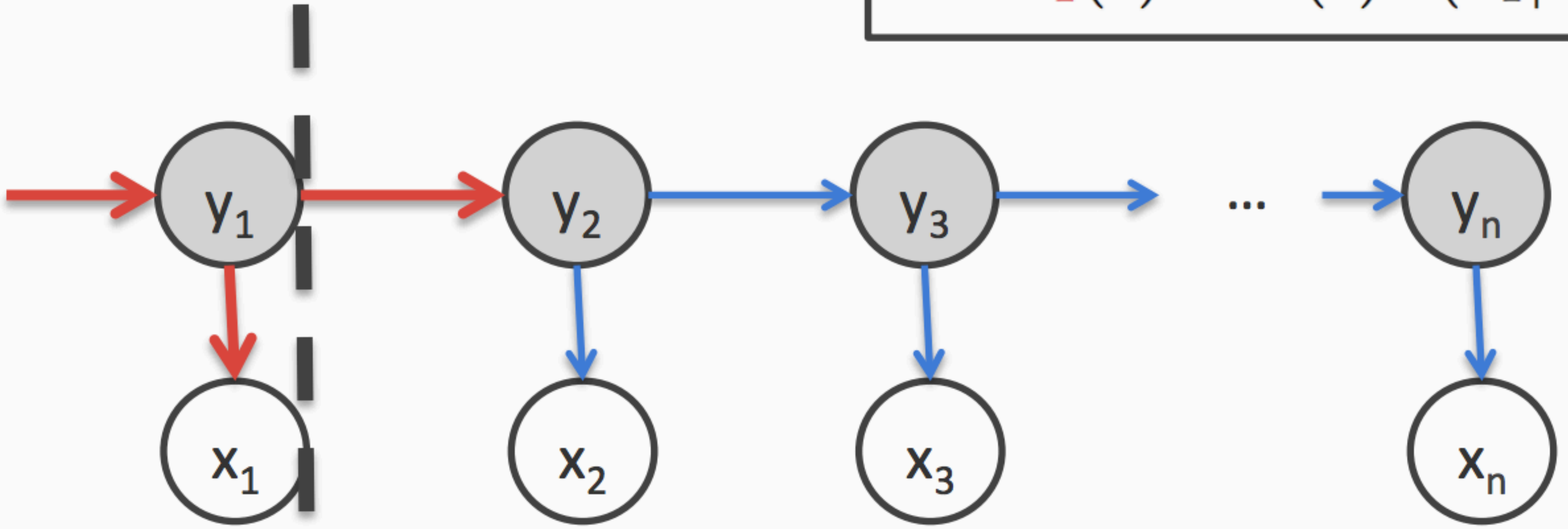
Abstract away the score for all decisions till here into score

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



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

Abstract away the score for all decisions till here into score

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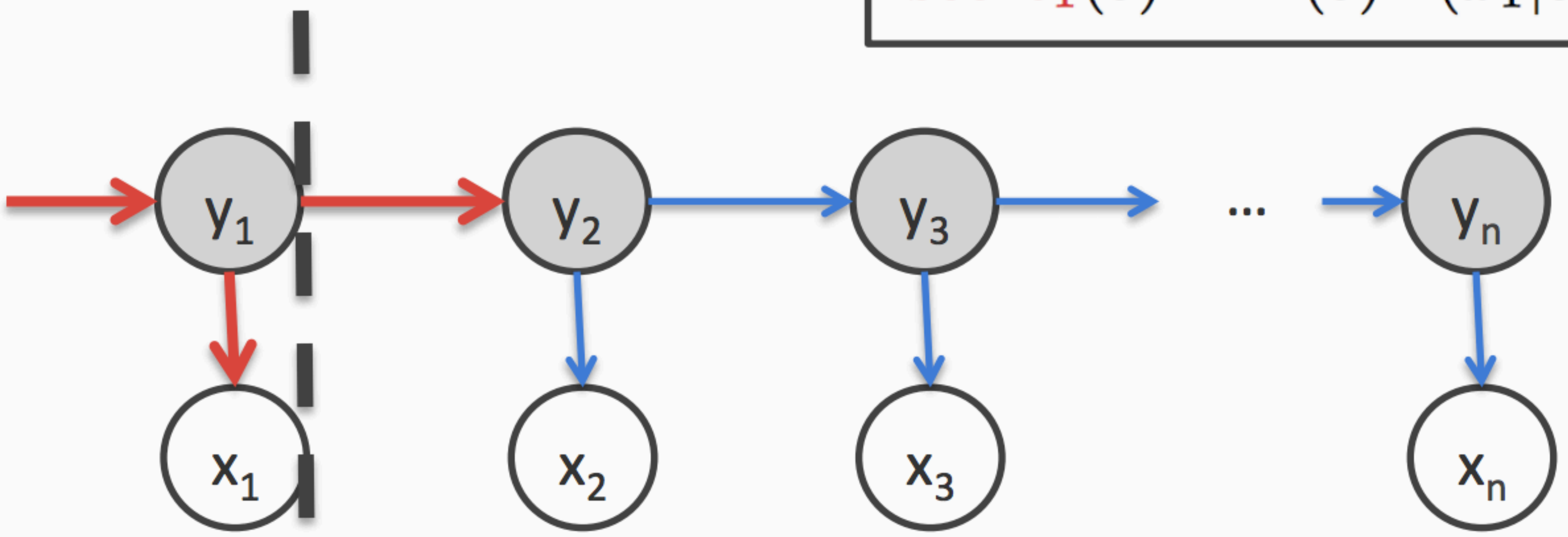

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Viterbi Algorithm

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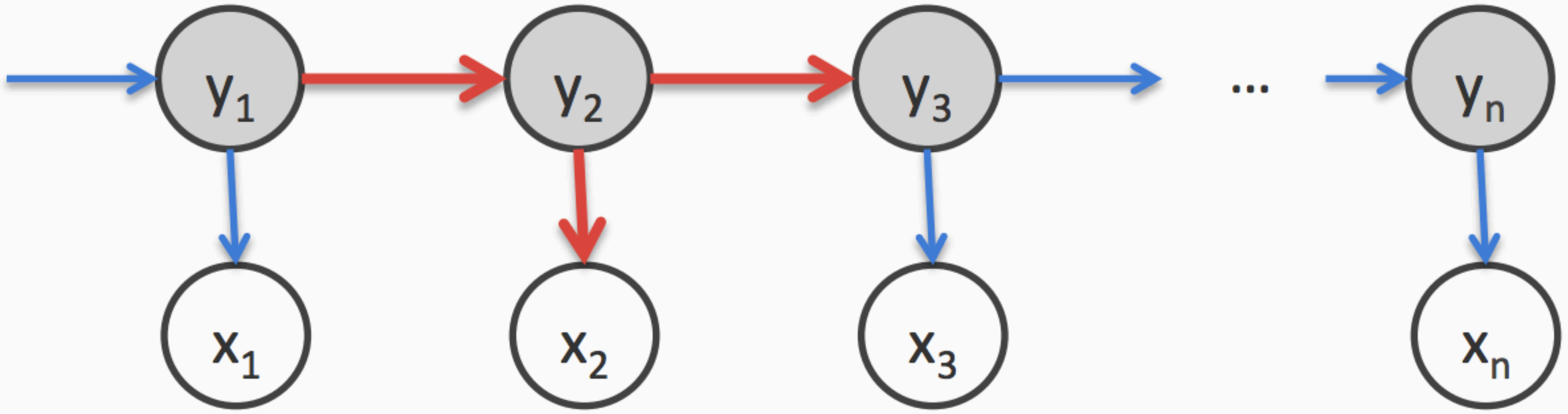
\end{aligned}$$

Only terms that depend on y_2



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Viterbi Algorithm

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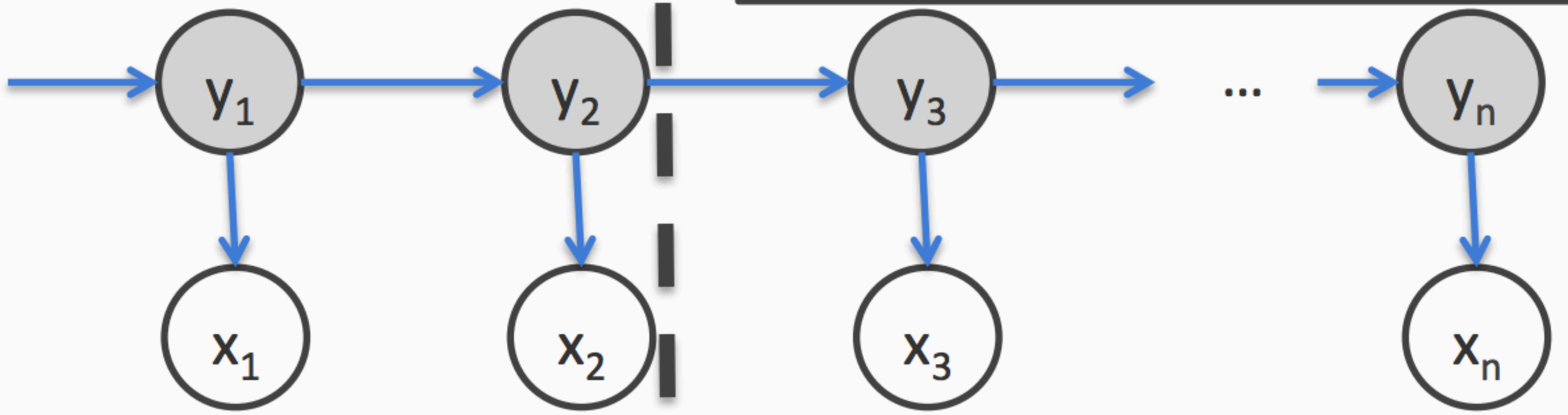
&= \max_{y_2, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots \max_{y_1} P(y_2|y_1)P(x_2|y_2)\mathrm{score}_1(y_1) \\
&= \max_{y_3, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n) \cdots \max_{y_2} P(y_3|y_2)P(x_3|y_3) \max_{y_1} P(y_2|y_1)P(x_2|y_2)\mathrm{score}_1(y_1) \\
&= \max_{y_3, \cdots, y_n} P(y_n|y_{n-1})P(x_n|y_n)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

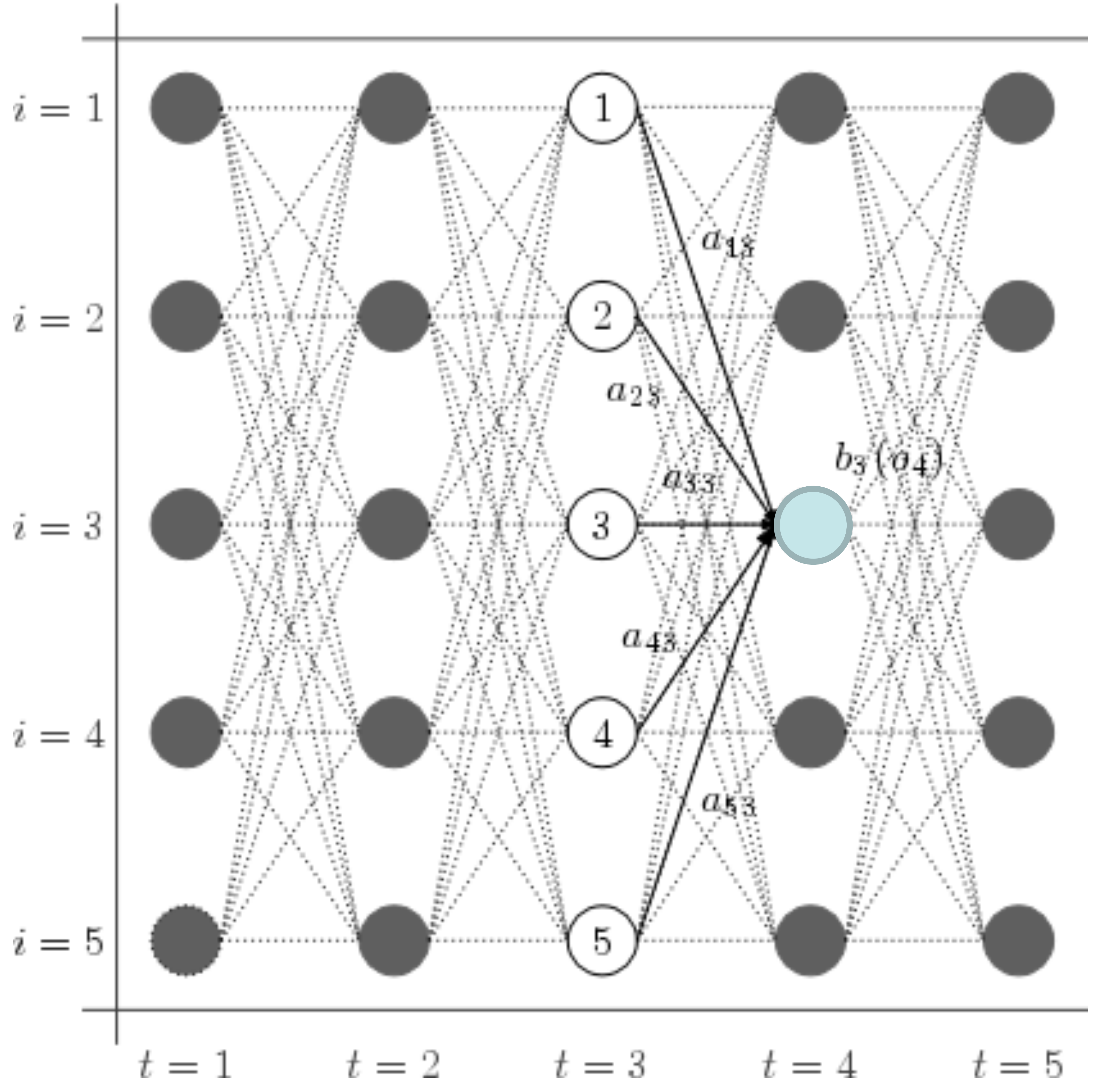
$$\boxed{\mathrm{score}_i(s) = \max_{y_{i-1}} P(s|y_{i-1})P(x_i|s)\mathrm{score}_{i-1}(y_{i-1})}$$



Abstract away the score for all decisions till here into score

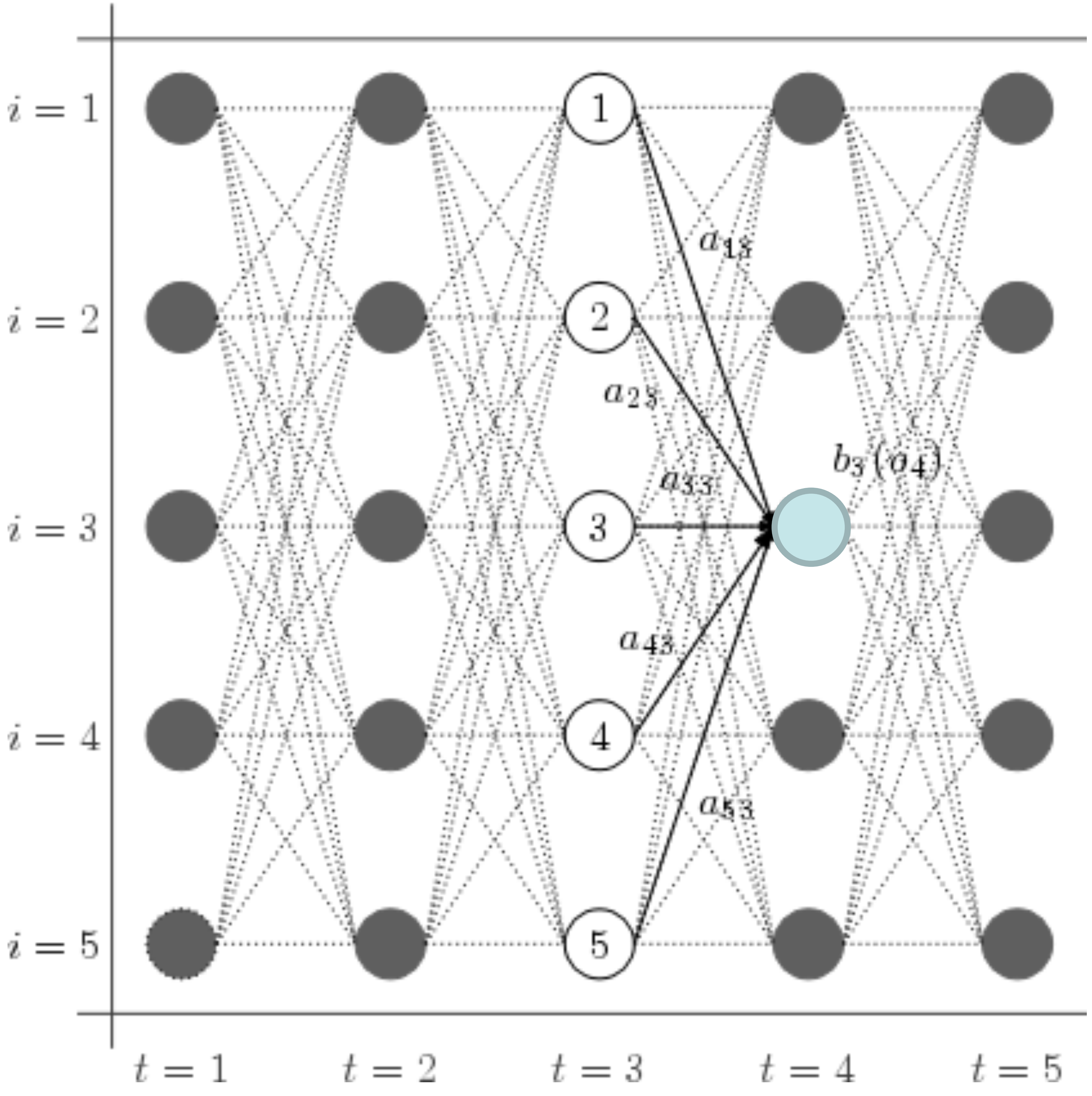
slide credit: Vivek Srikumar

Viterbi Algorithm



slide credit: Dan Klein

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

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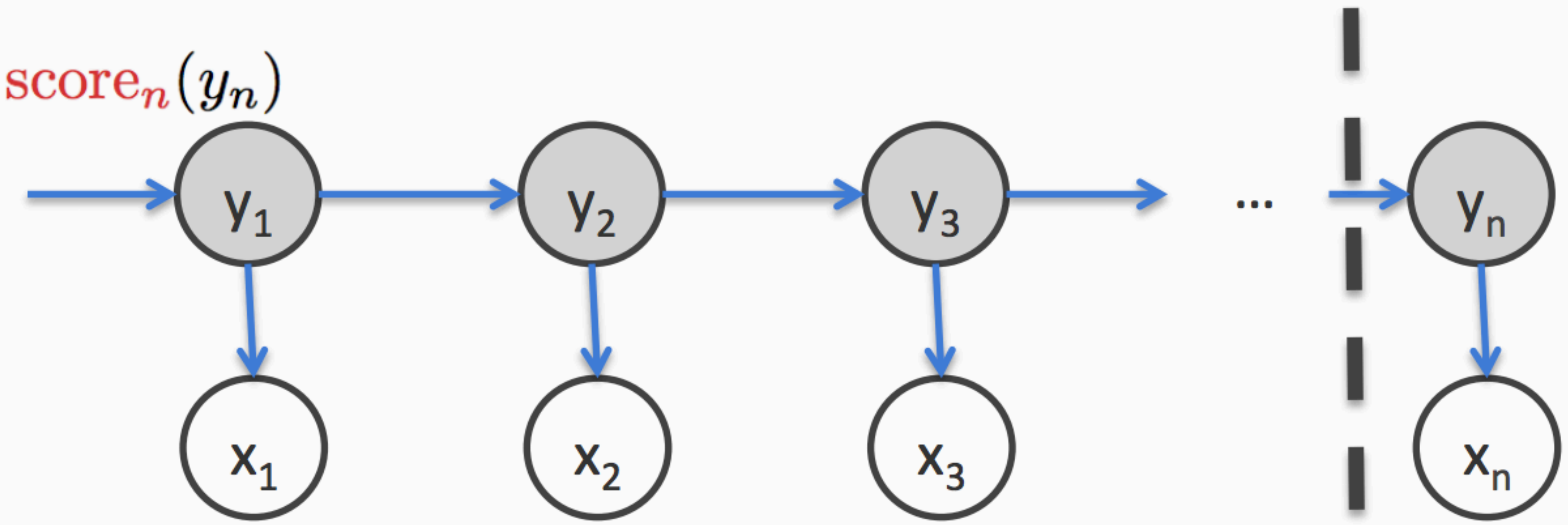
$$\vdots$$

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



Abstract away the score for all decisions till here into score

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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

Forward-Backward Algorithm

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

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

Forward-Backward Algorithm

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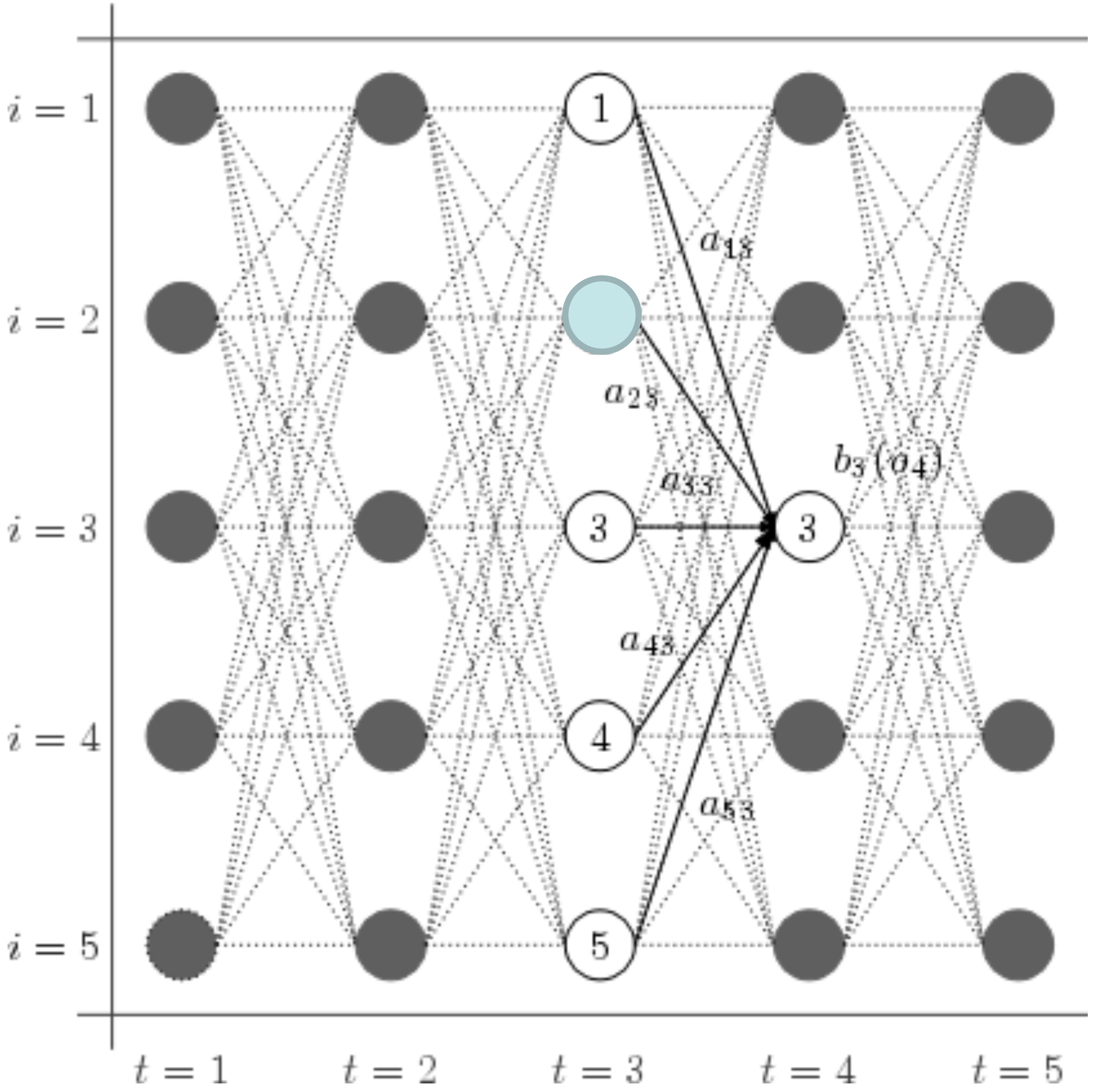
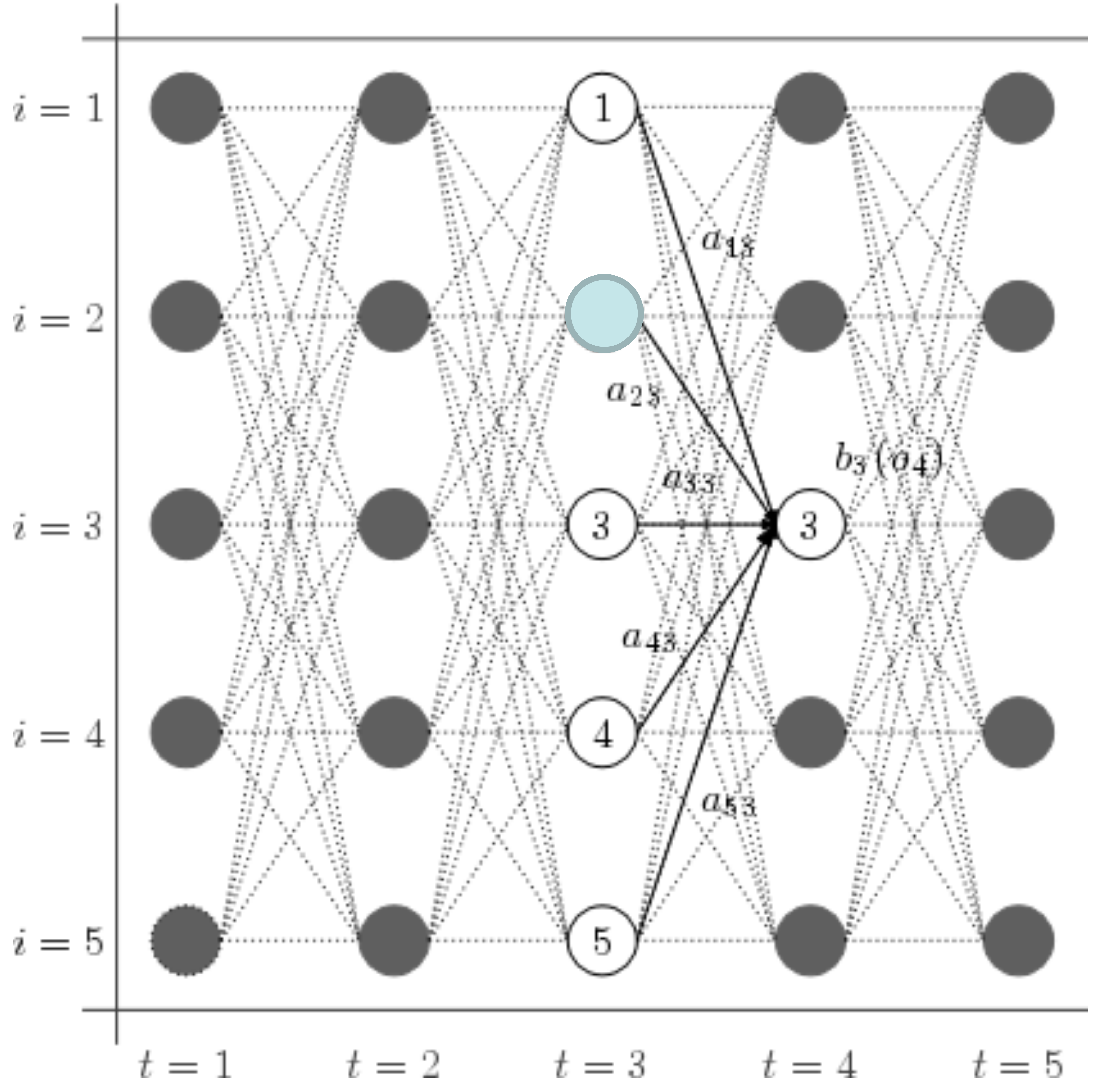
- What did Viterbi compute? $P(\mathbf{y}_{\max}|\mathbf{x}) = \max_{y_1,\ldots,y_n} P(\mathbf{y}|\mathbf{x})$

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

Forward-Backward Algorithm

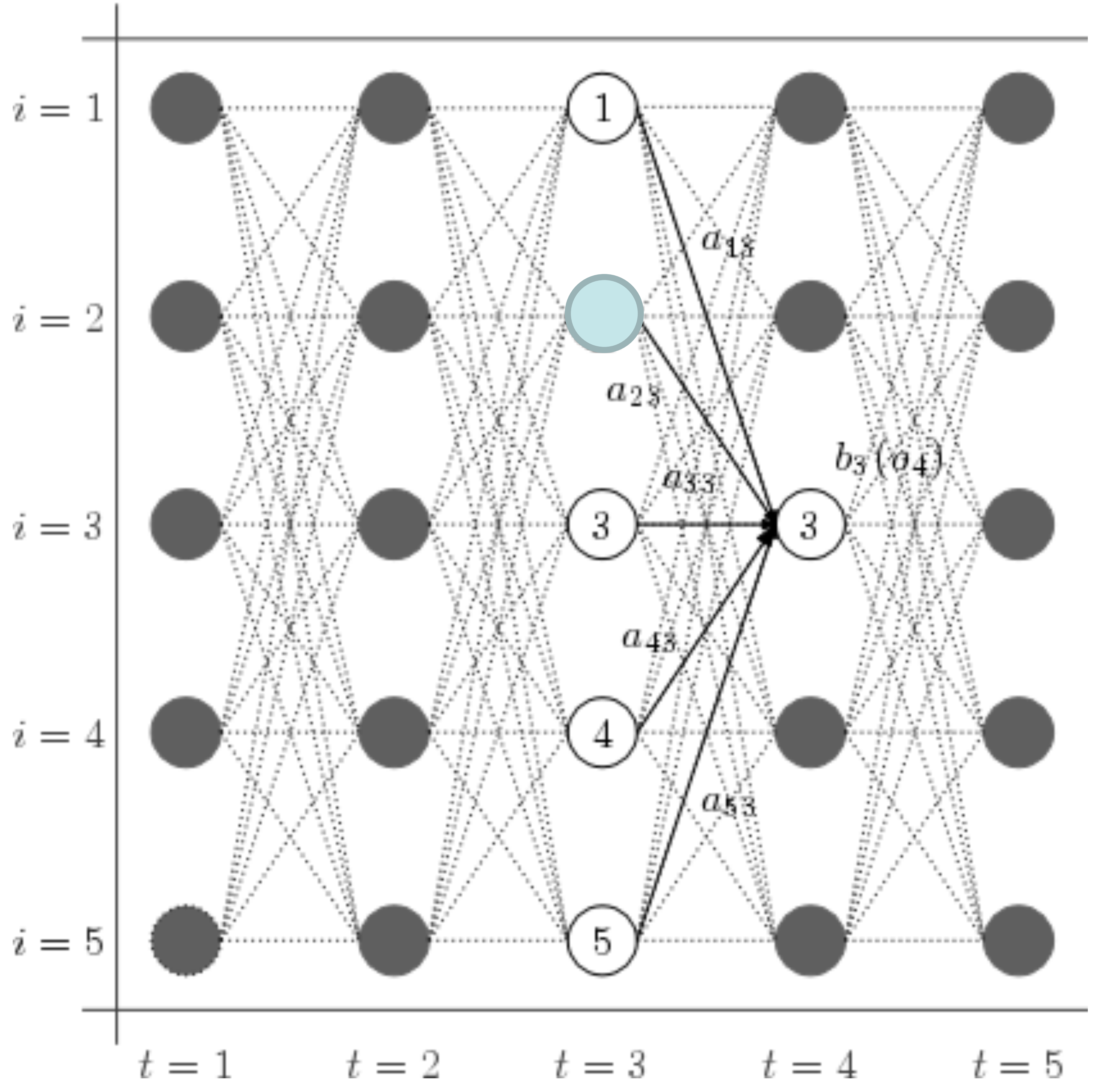


Forward-Backward Algorithm



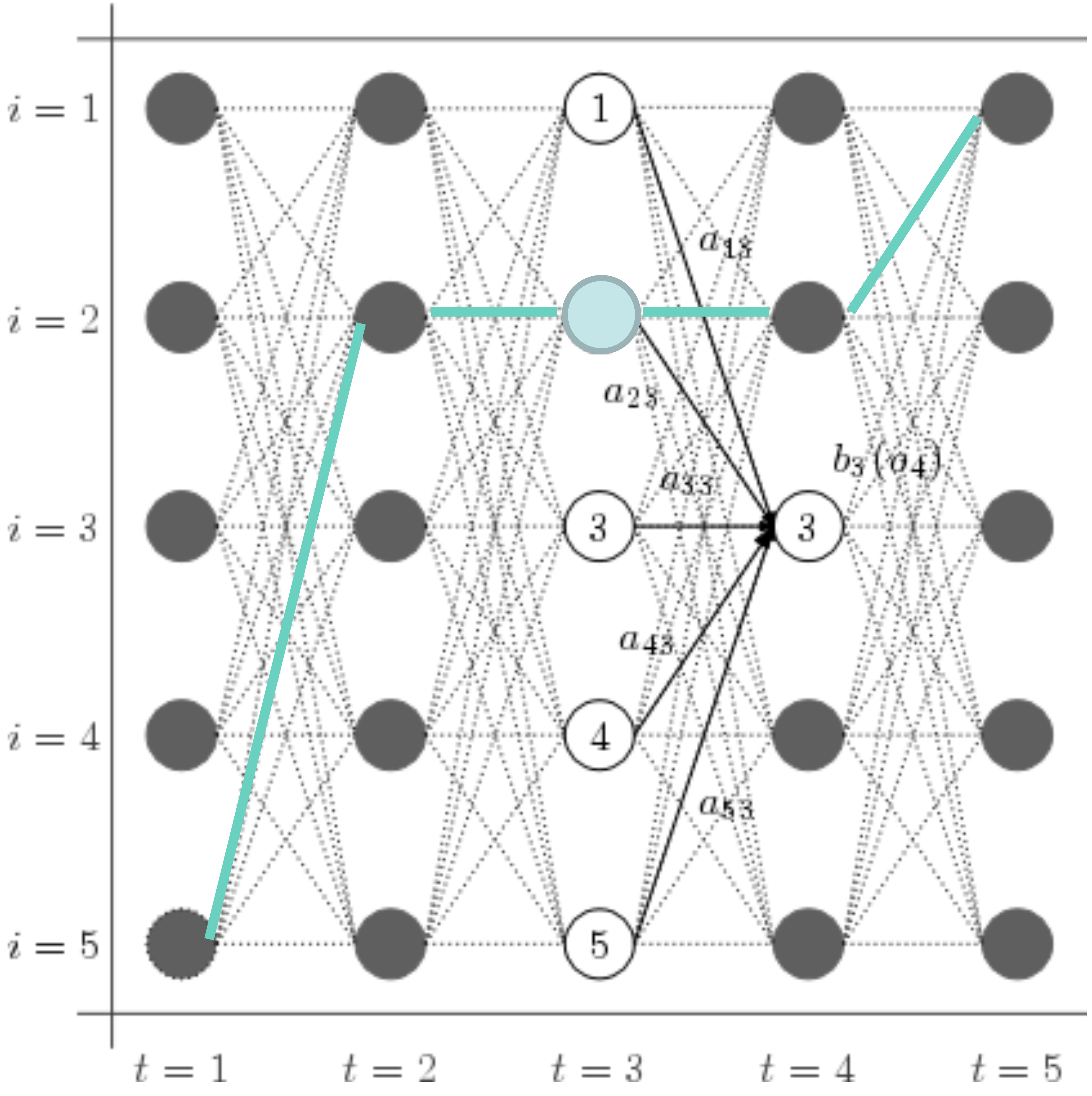
$$P(y_3 = 2|\mathbf{x}) =$$

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



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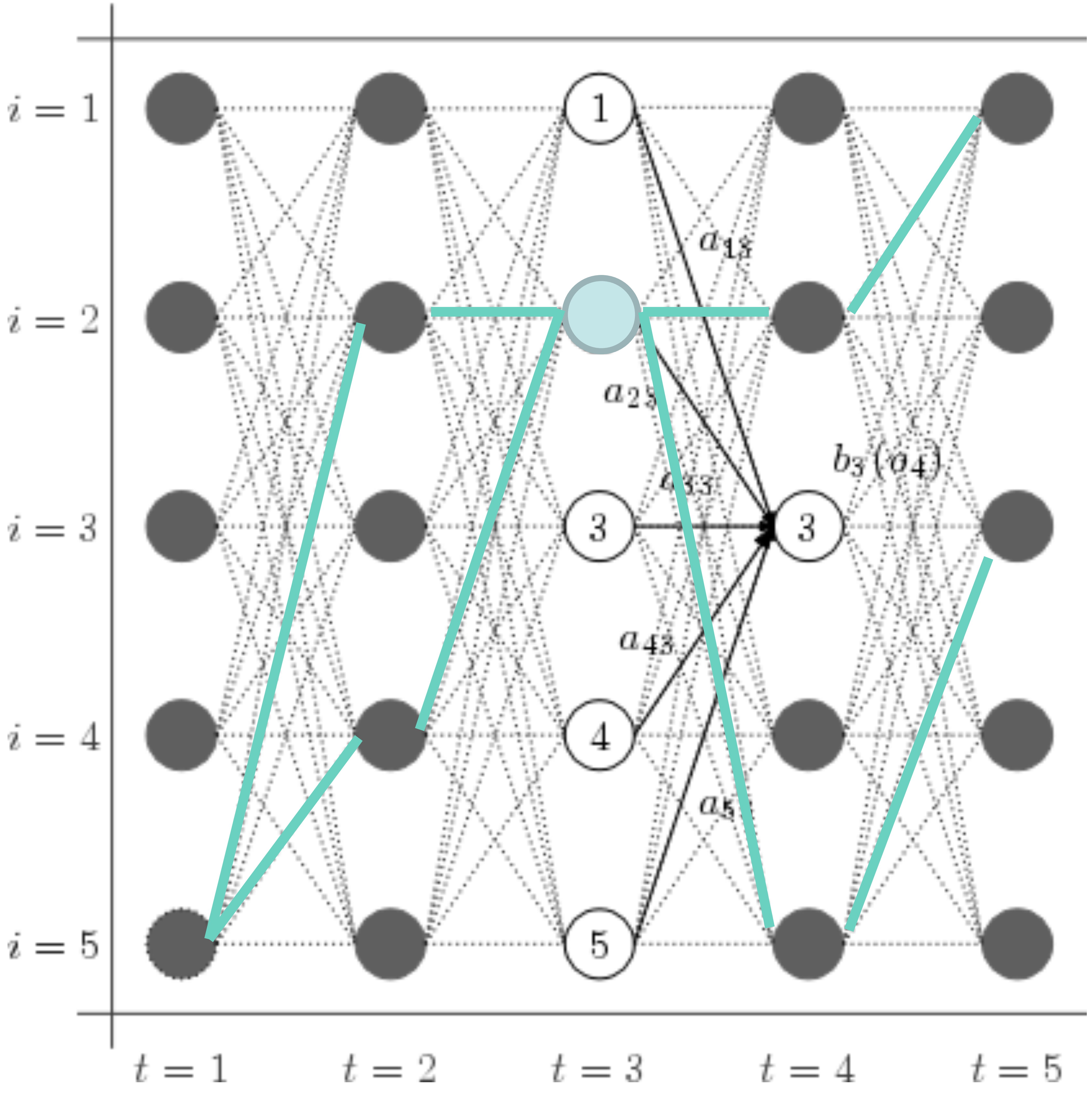
Forward-Backward Algorithm



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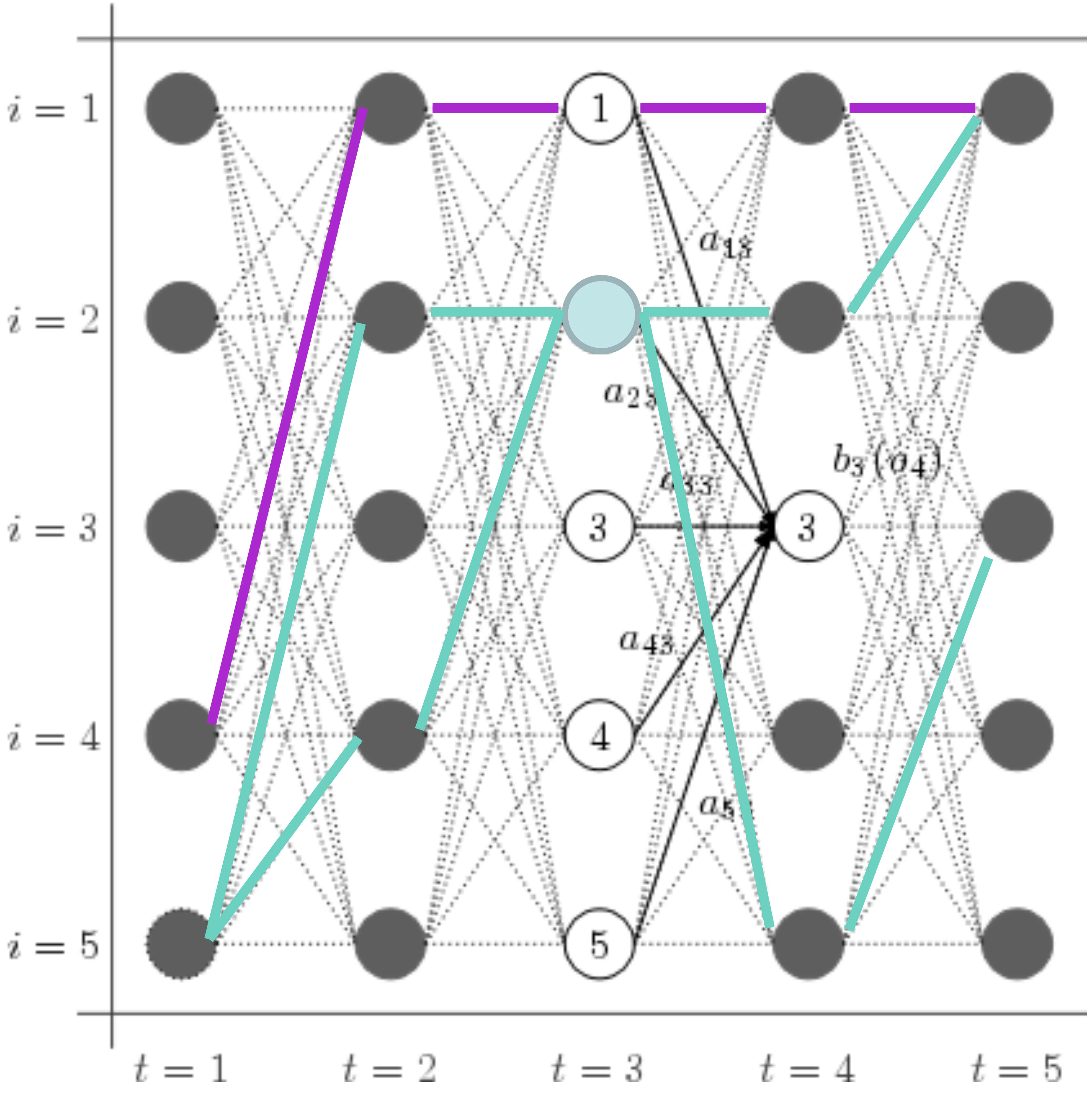
Forward-Backward Algorithm



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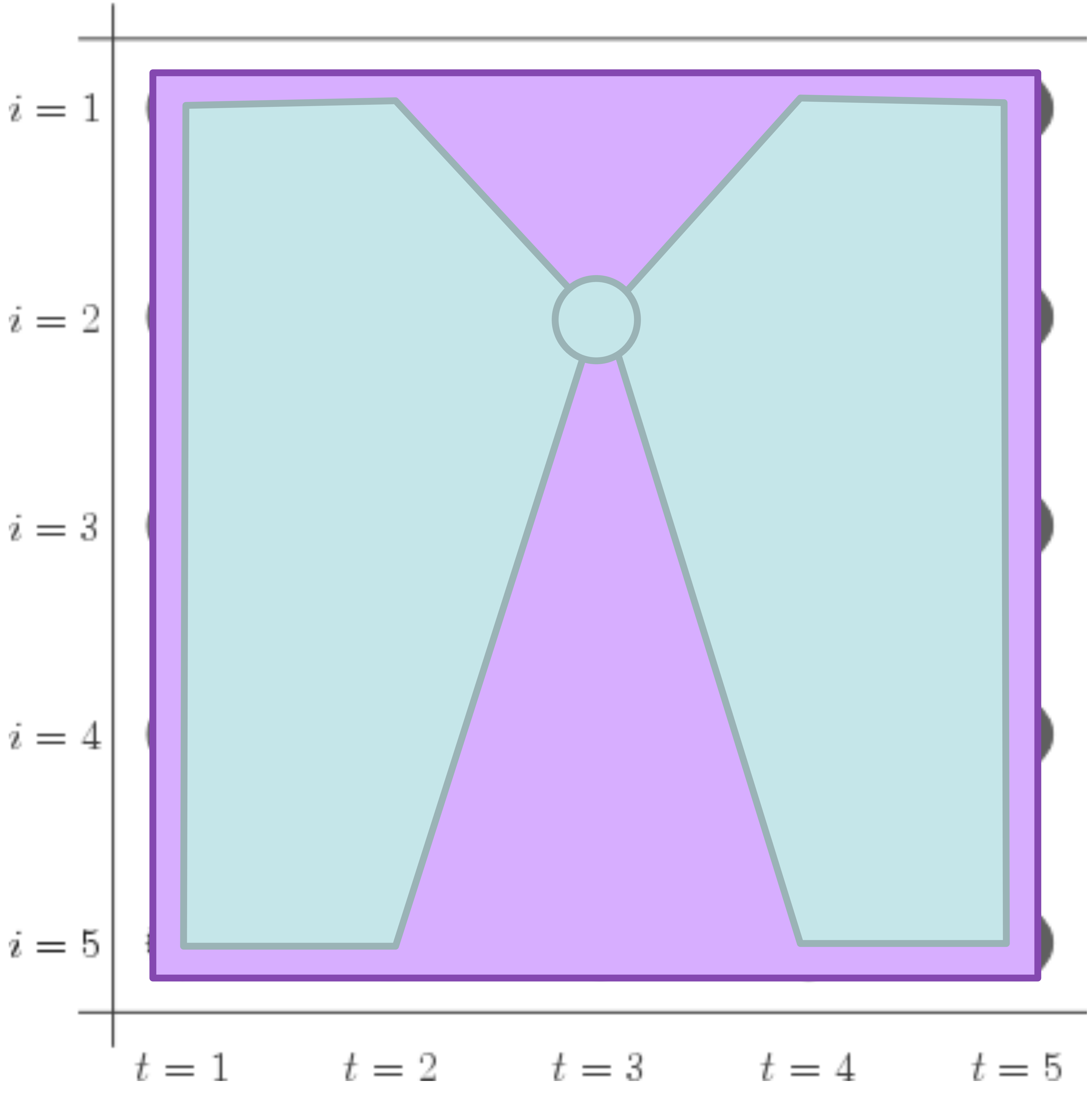
Forward-Backward Algorithm



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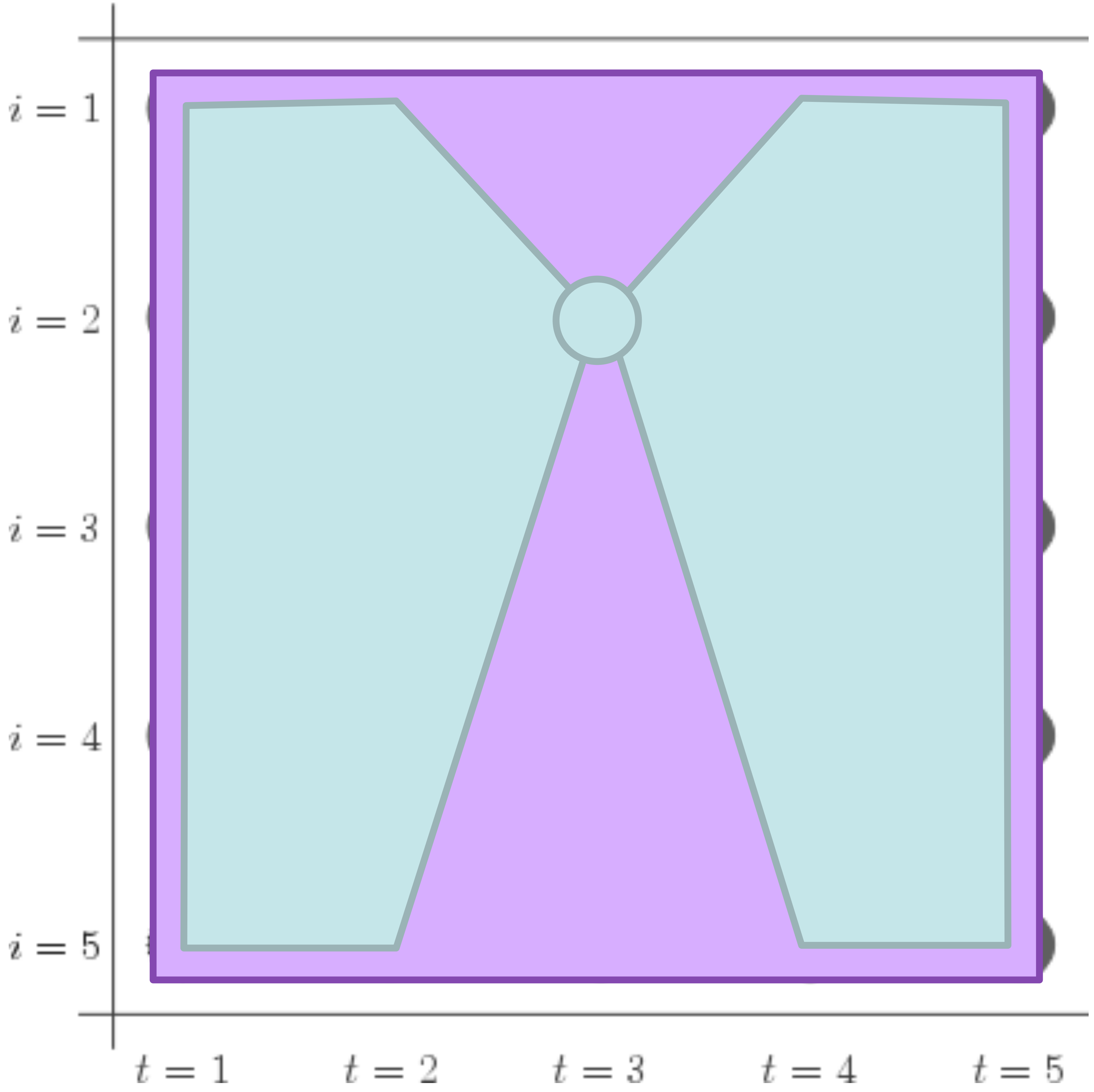
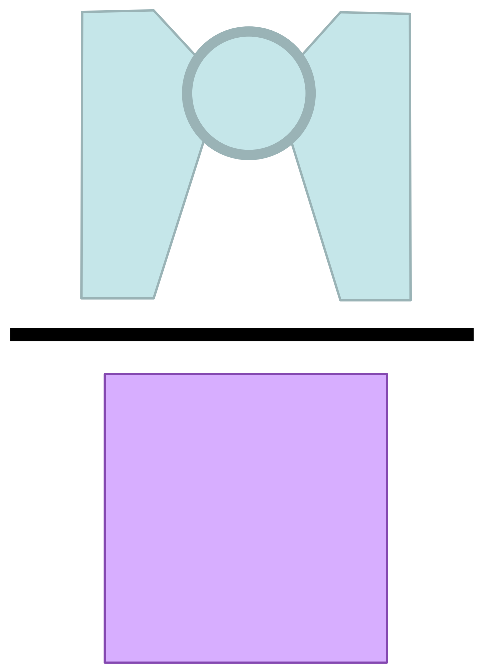
slide credit: Dan Klein

Forward-Backward Algorithm



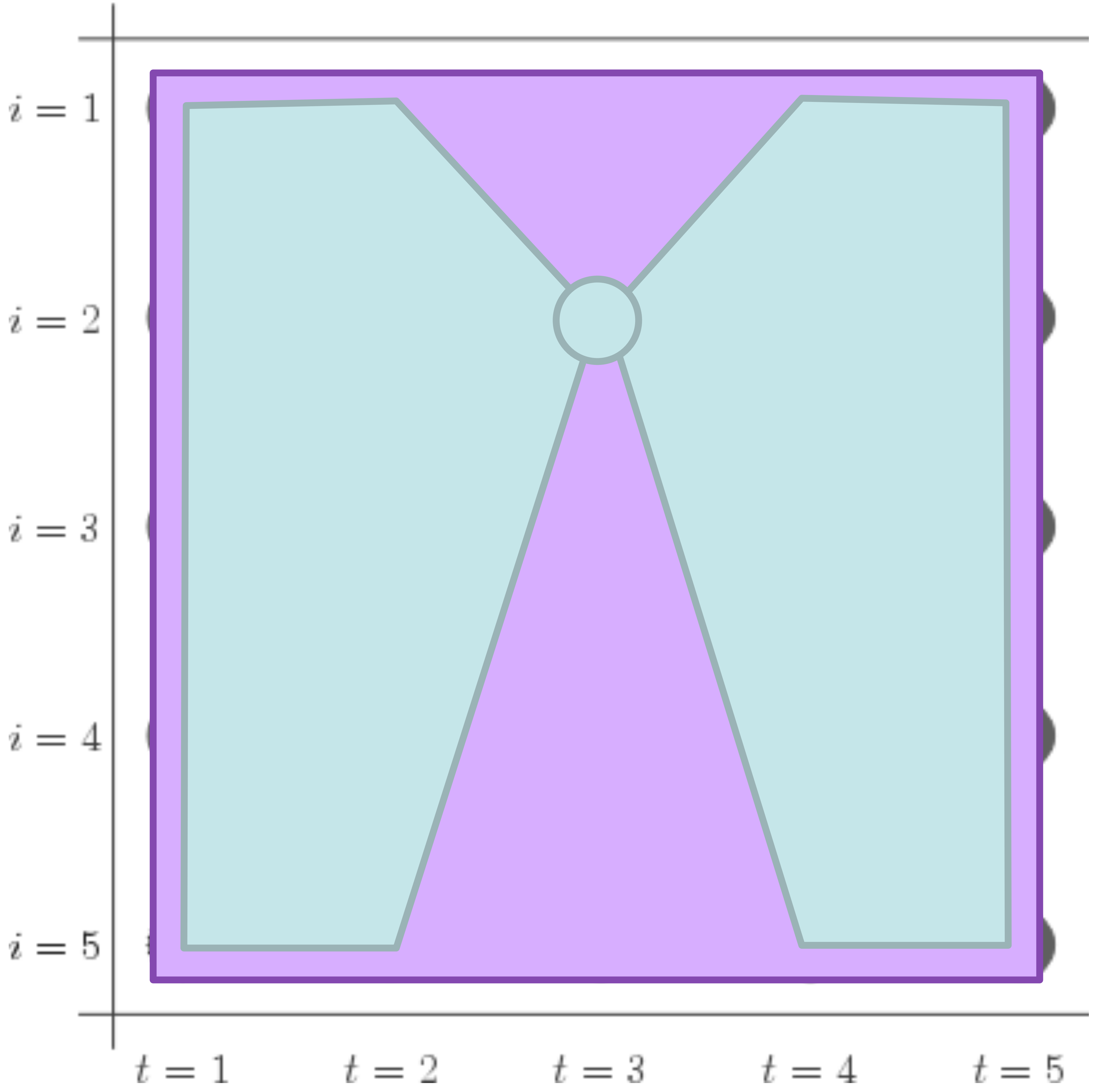
$$P(y_3 = 2|\mathbf{x}) = \frac{\text{sum of all paths through state 2 at time 3}}{\text{sum of all paths}}$$

=



slide credit: Dan Klein

Forward-Backward Algorithm



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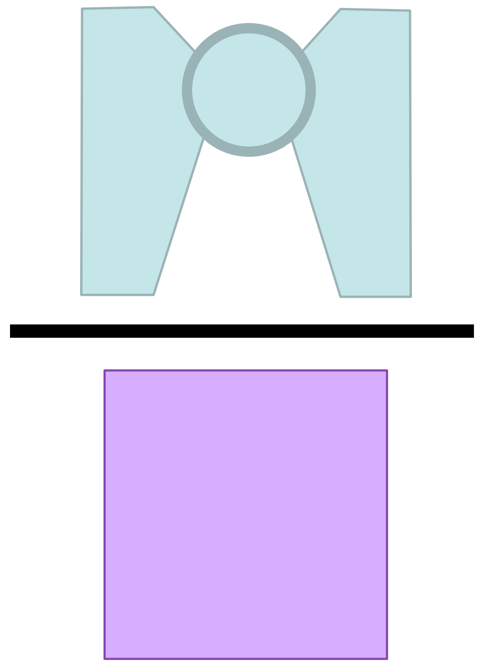
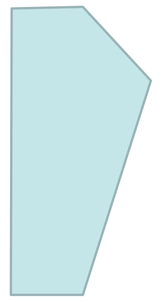
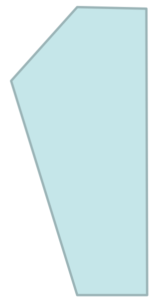


- Easiest and most flexible to do one pass to compute  and one to compute 

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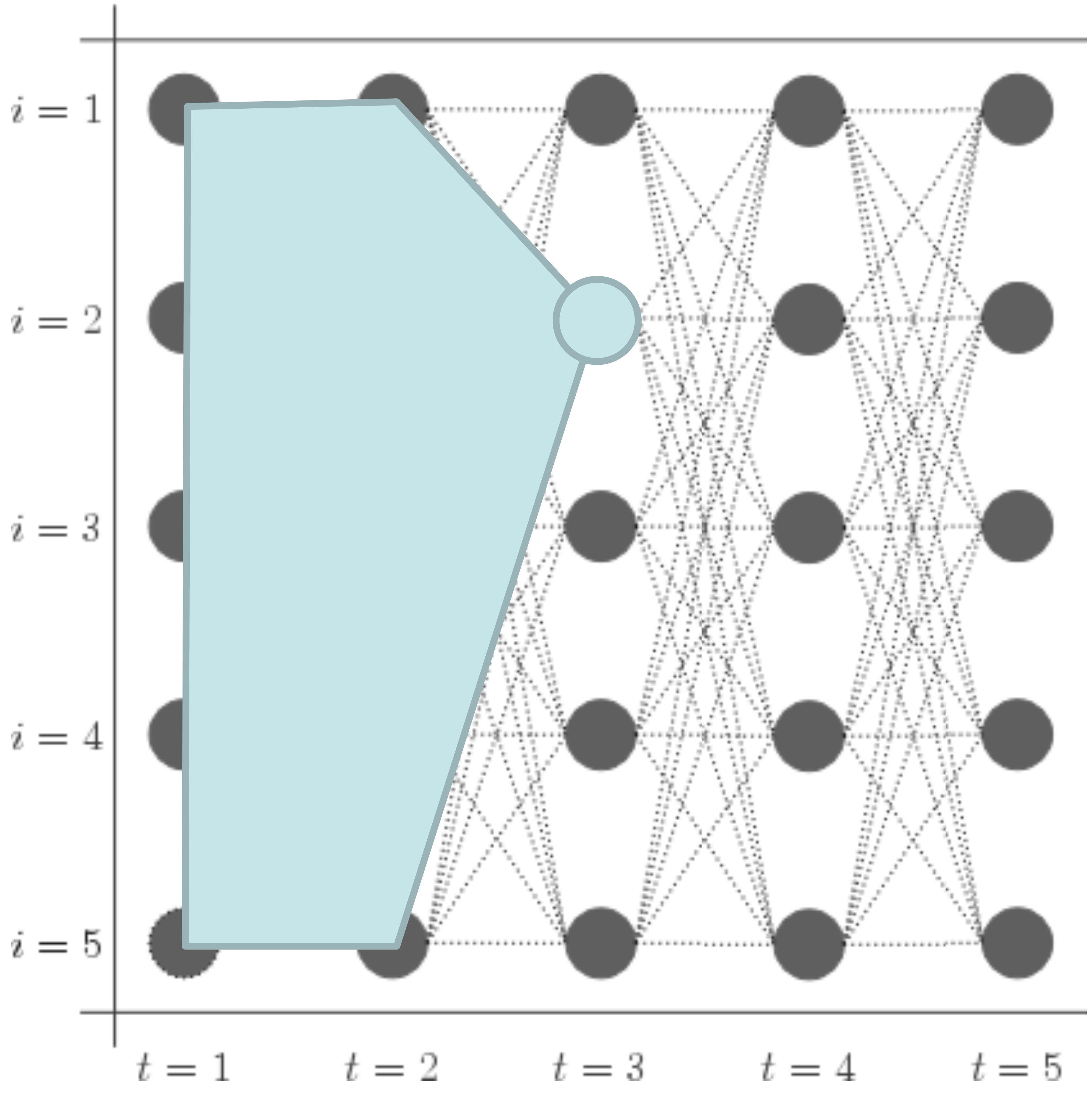

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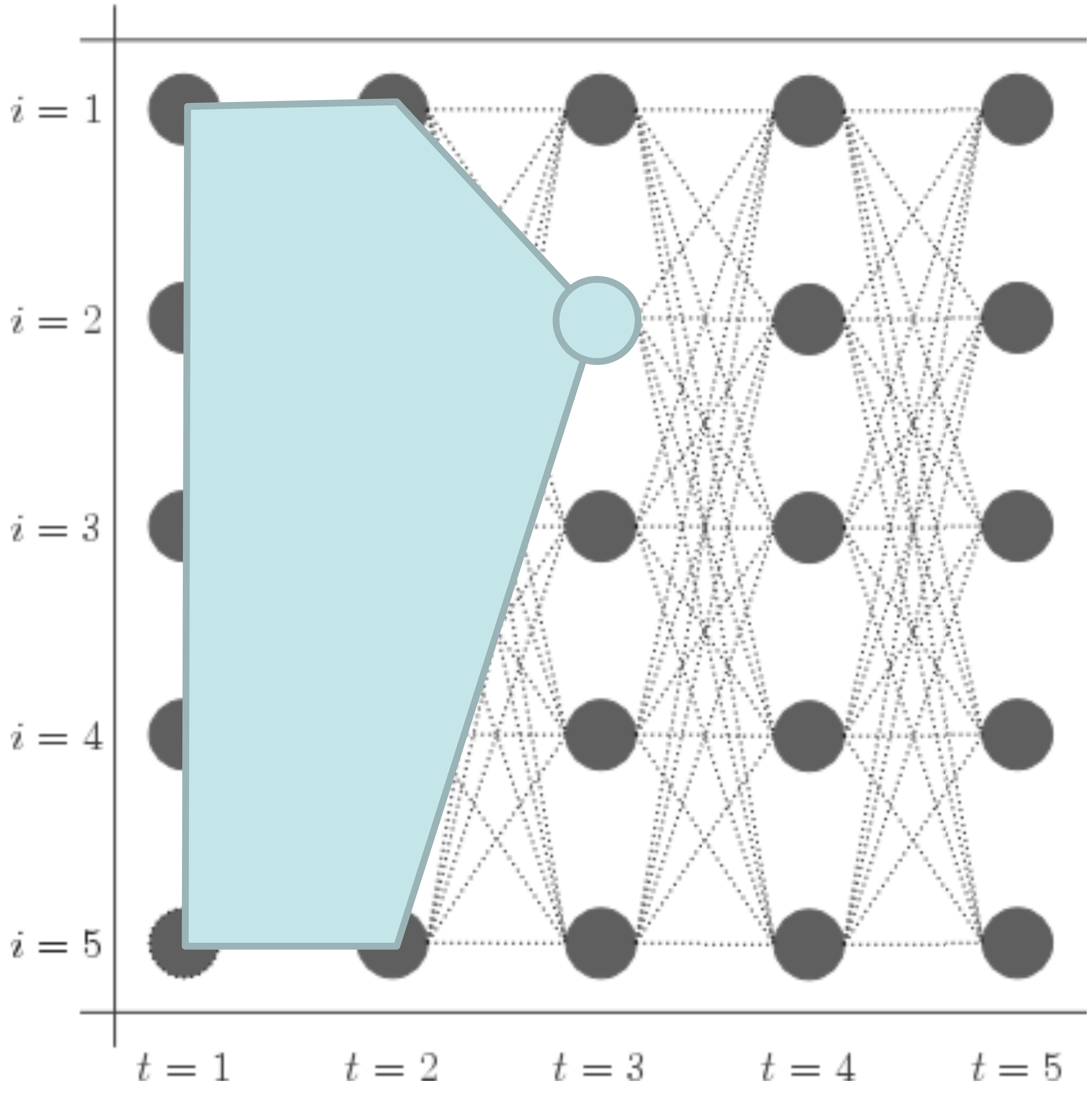

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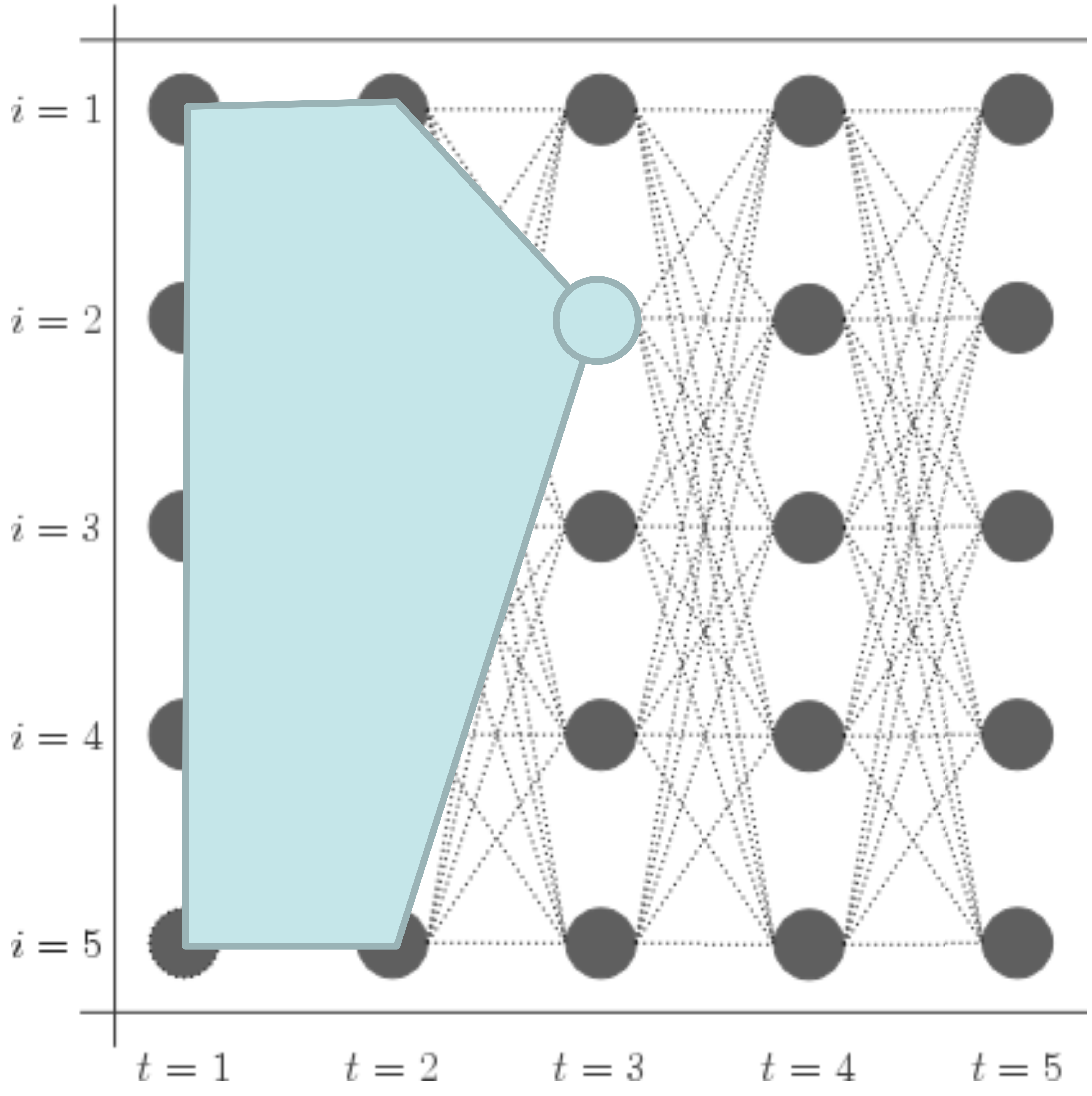
Forward-Backward Algorithm



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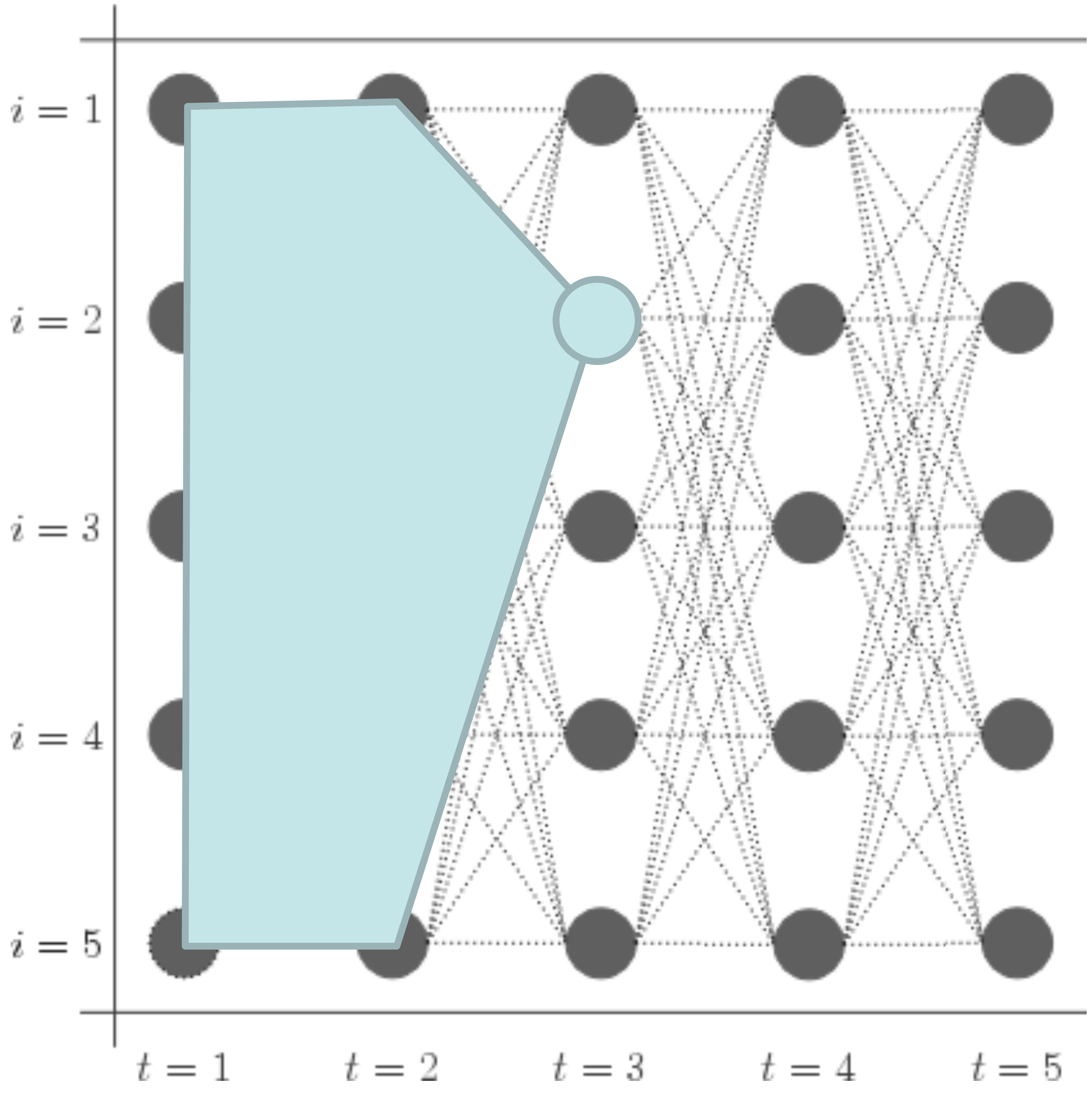

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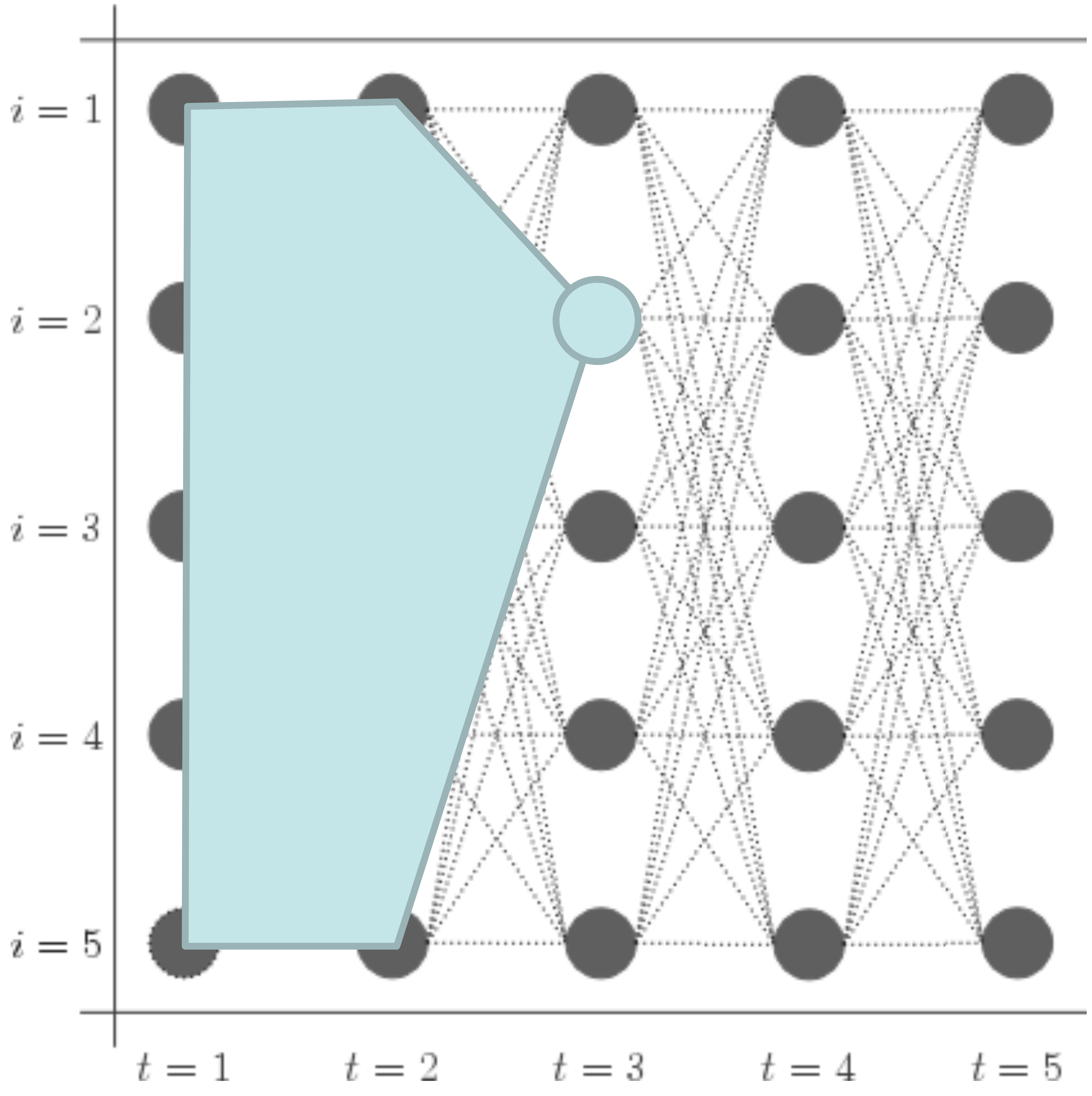

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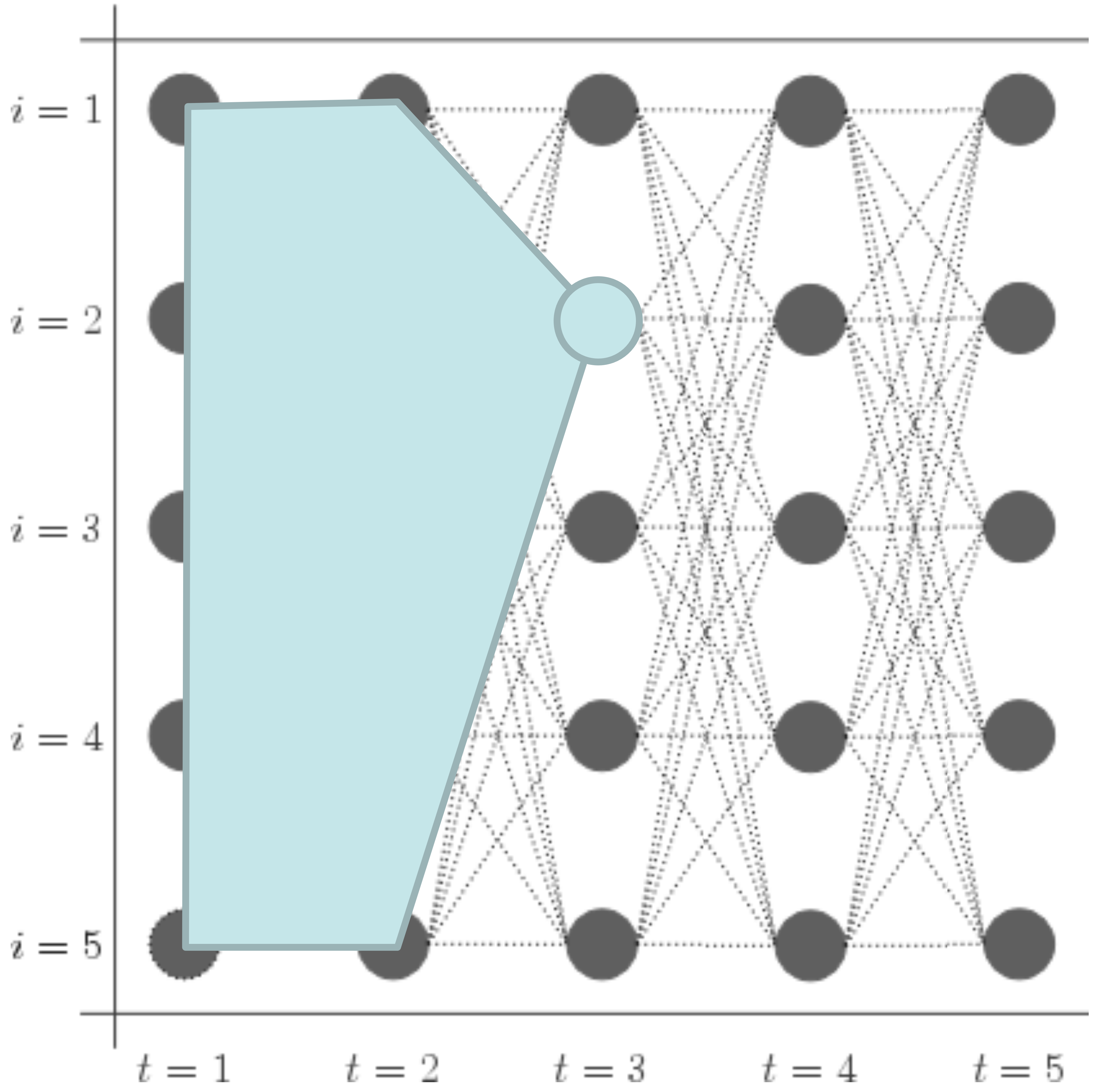

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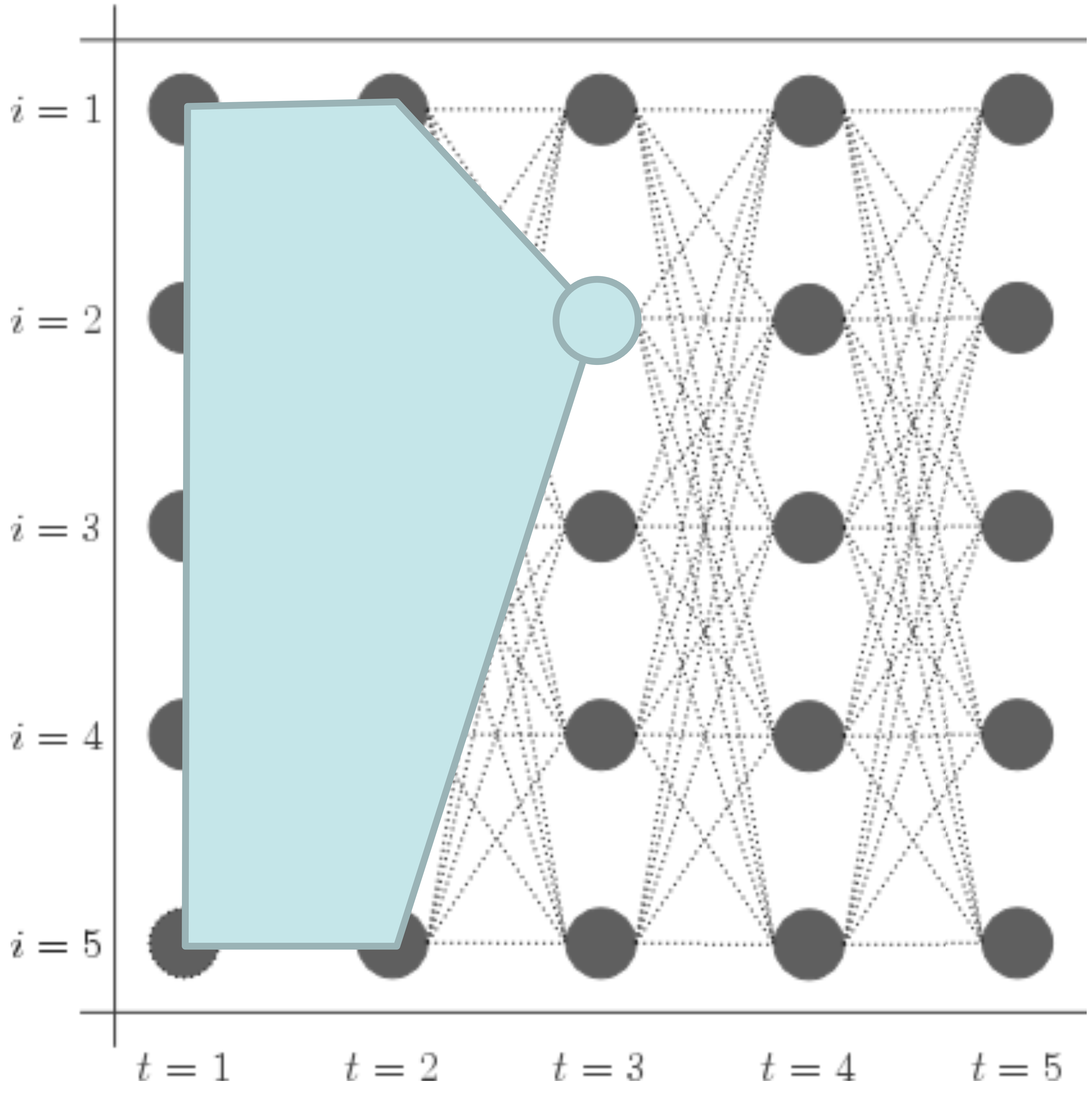

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- These quantities get very small! Store everything as log probabilities

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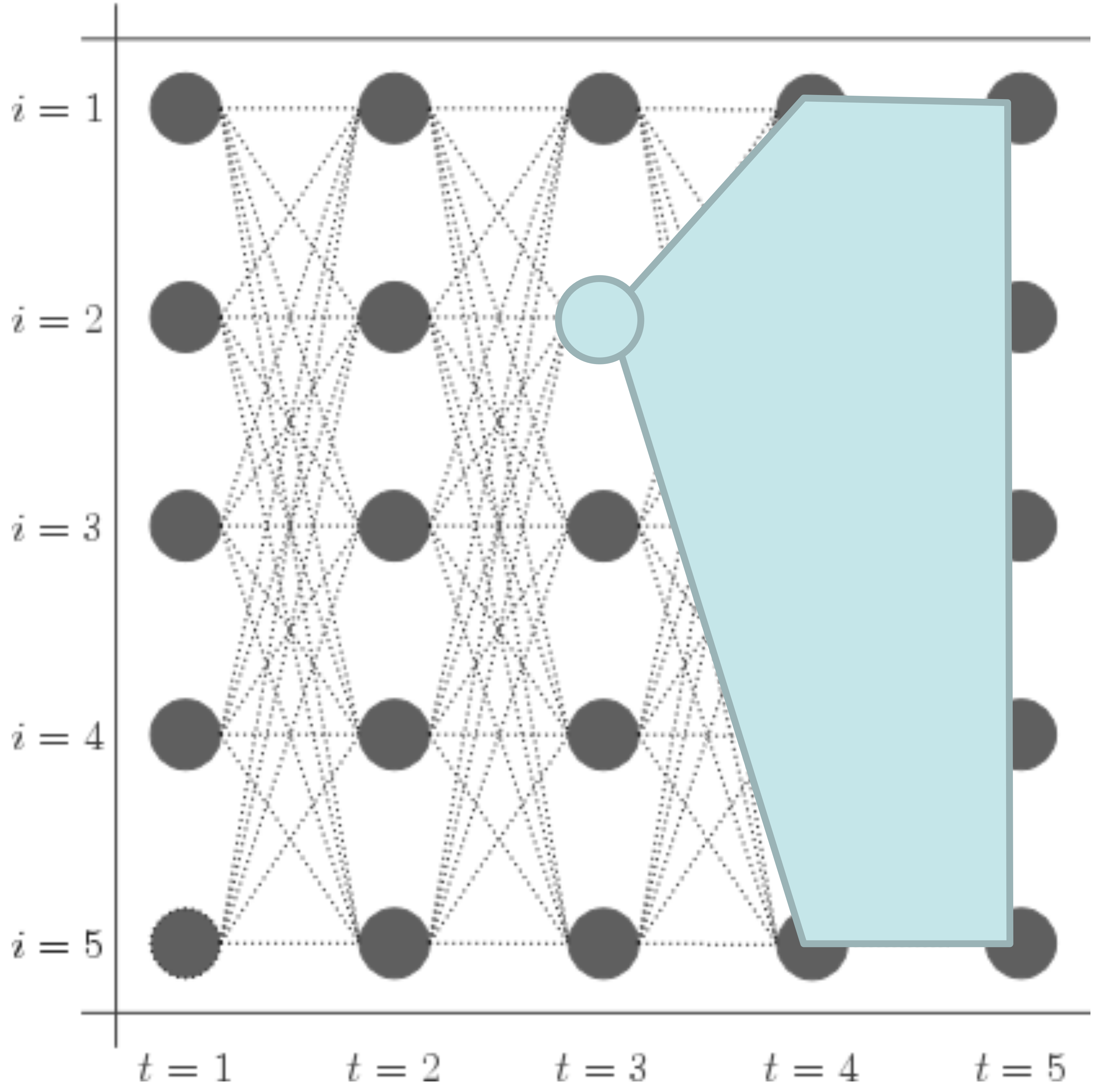

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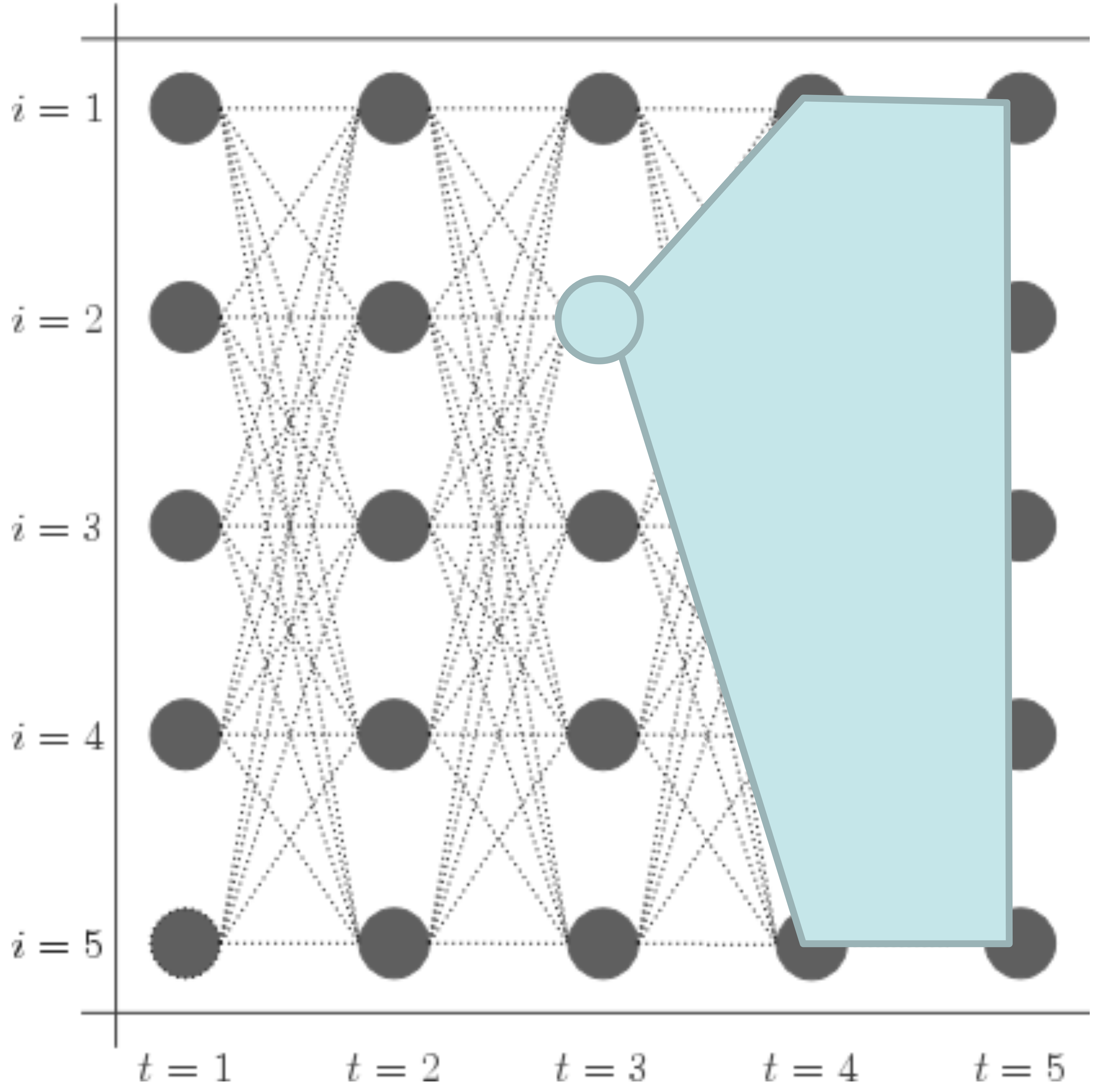

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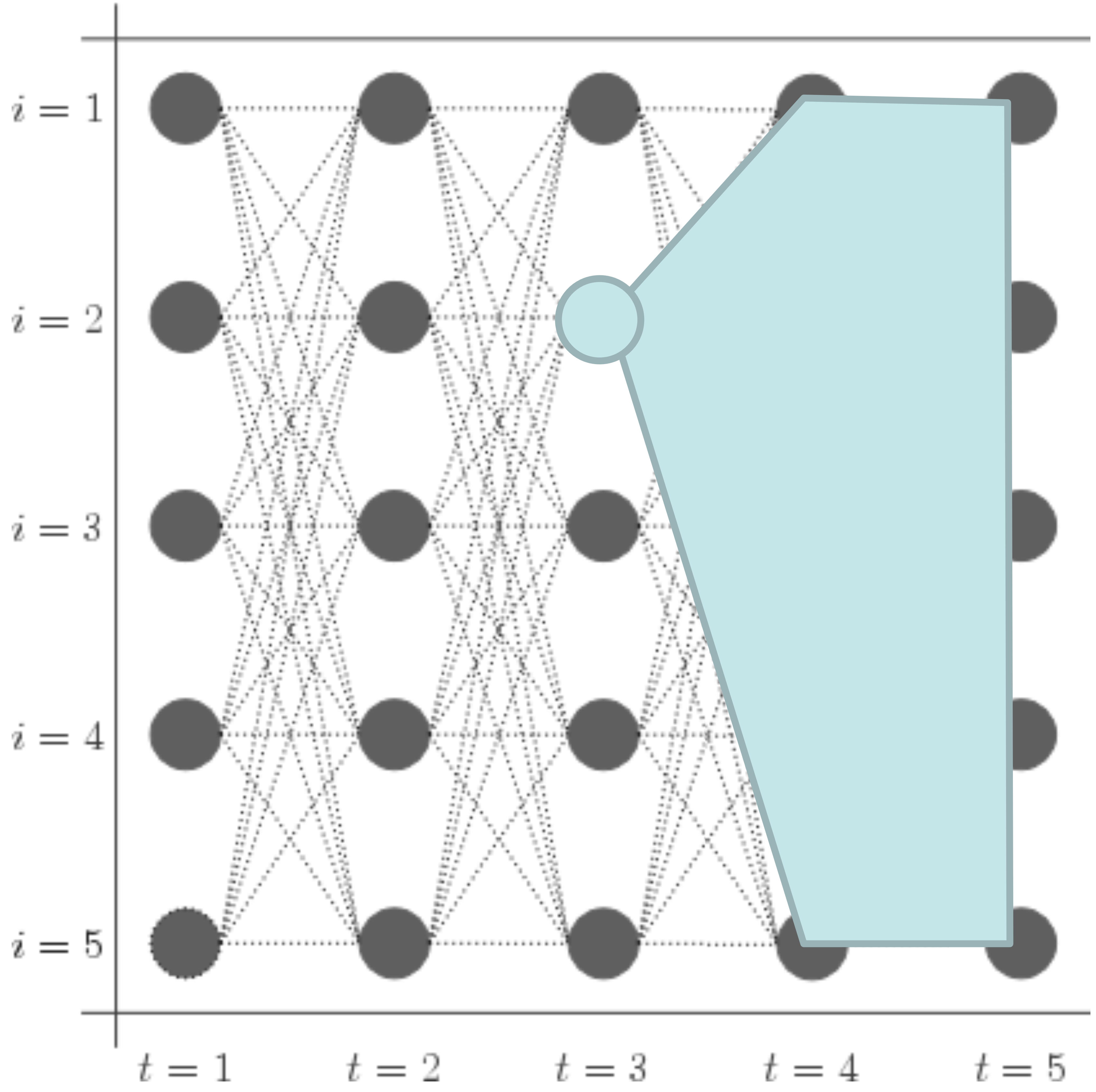

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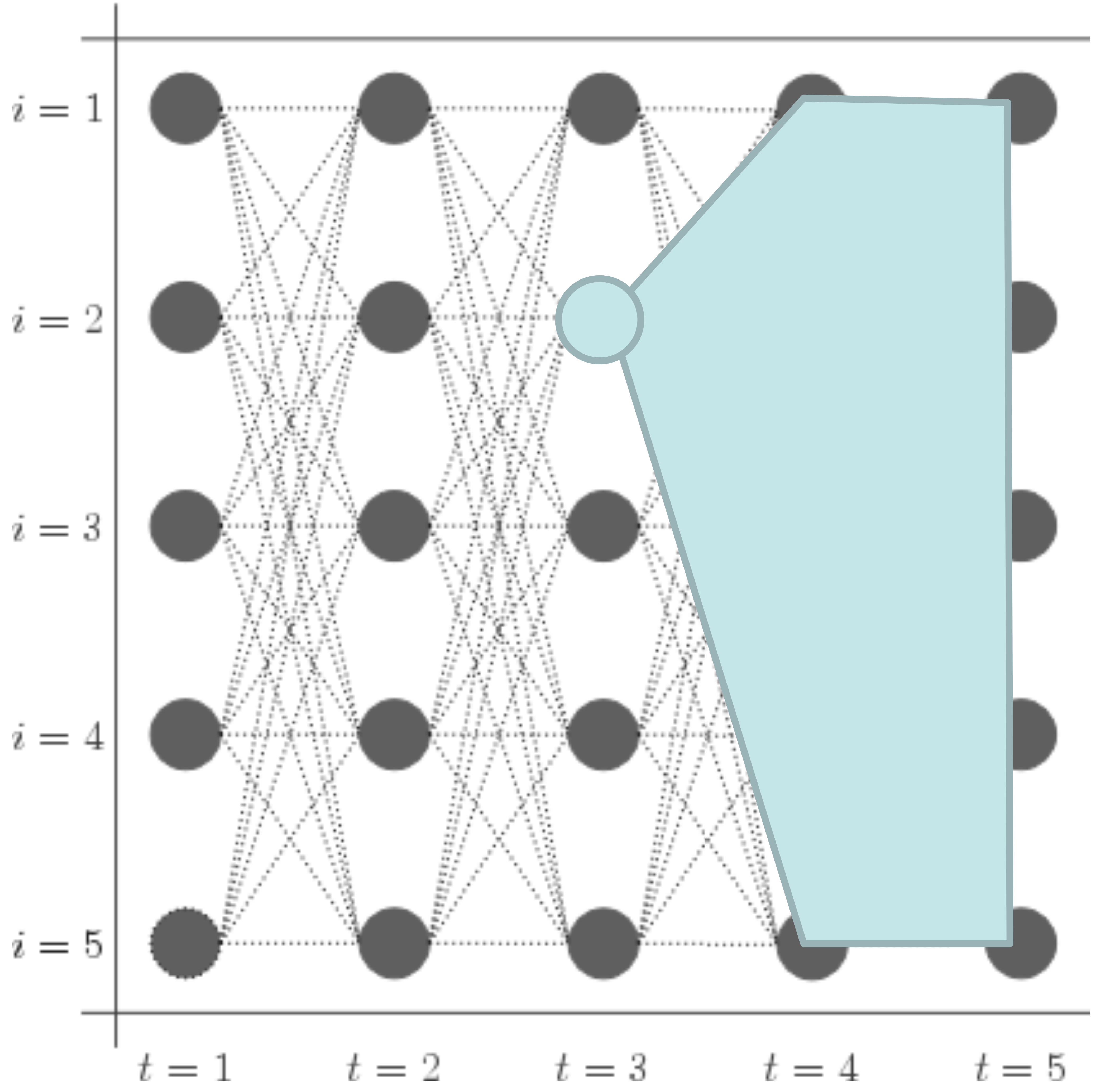
Forward-Backward Algorithm



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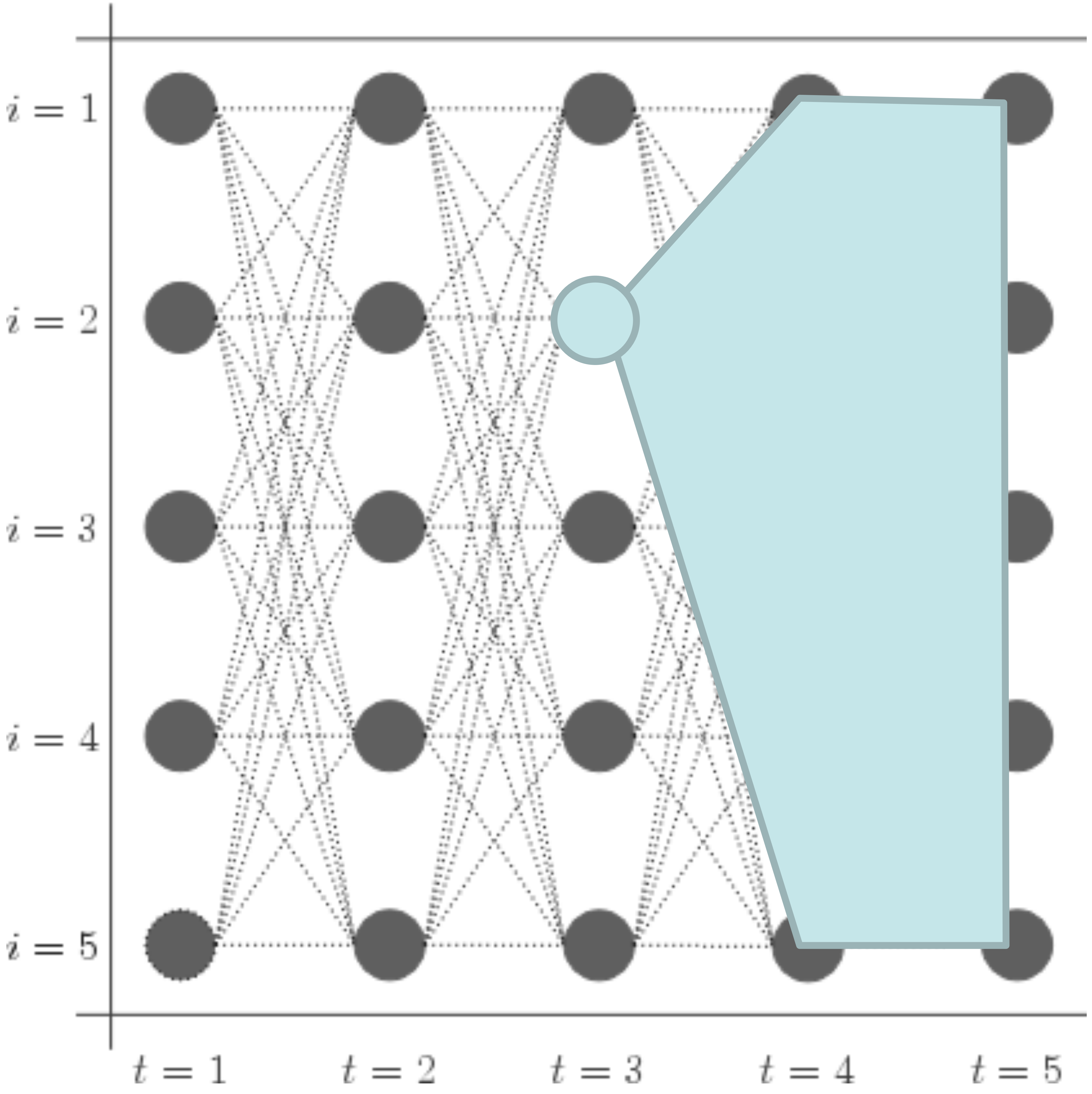

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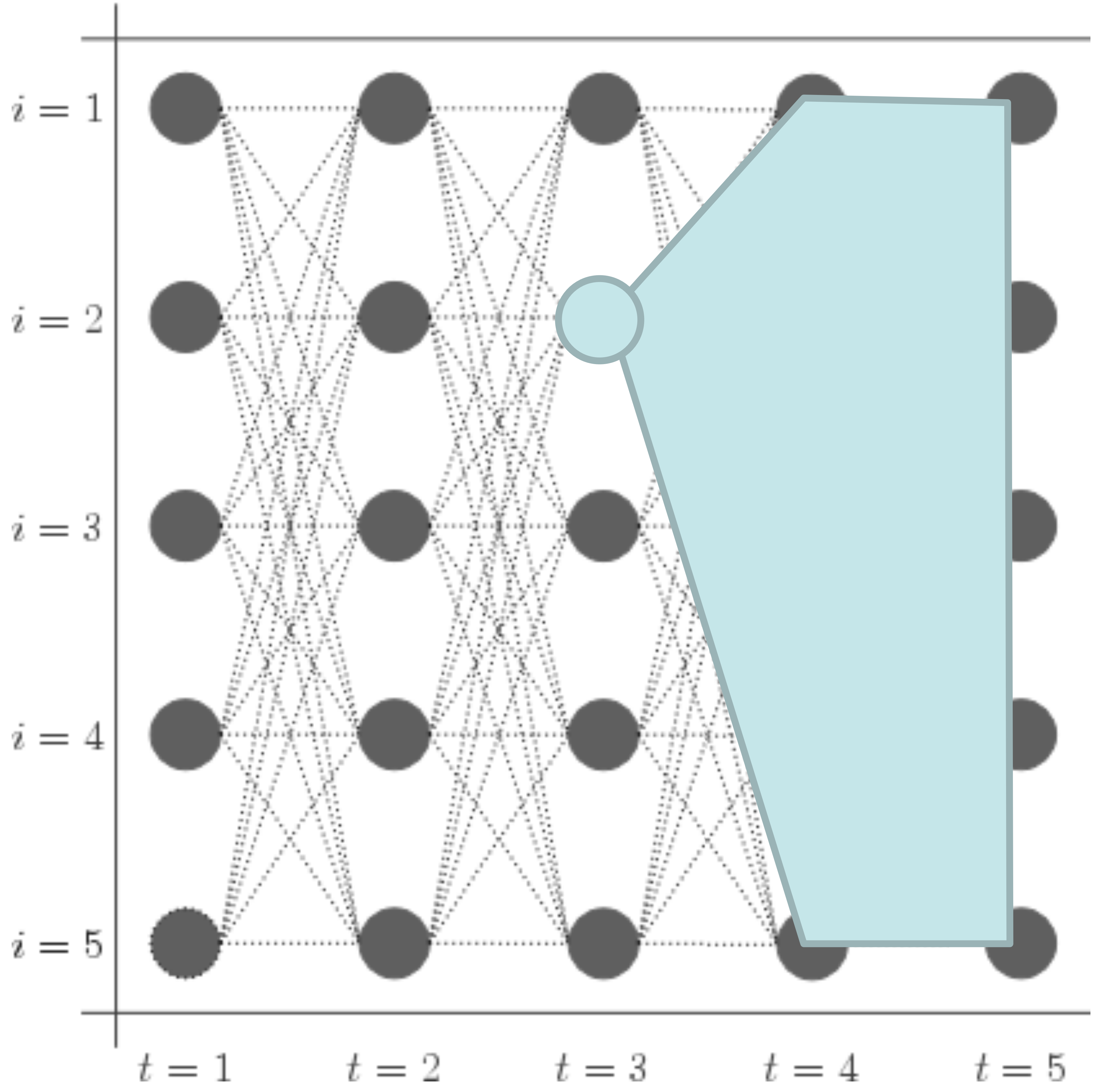

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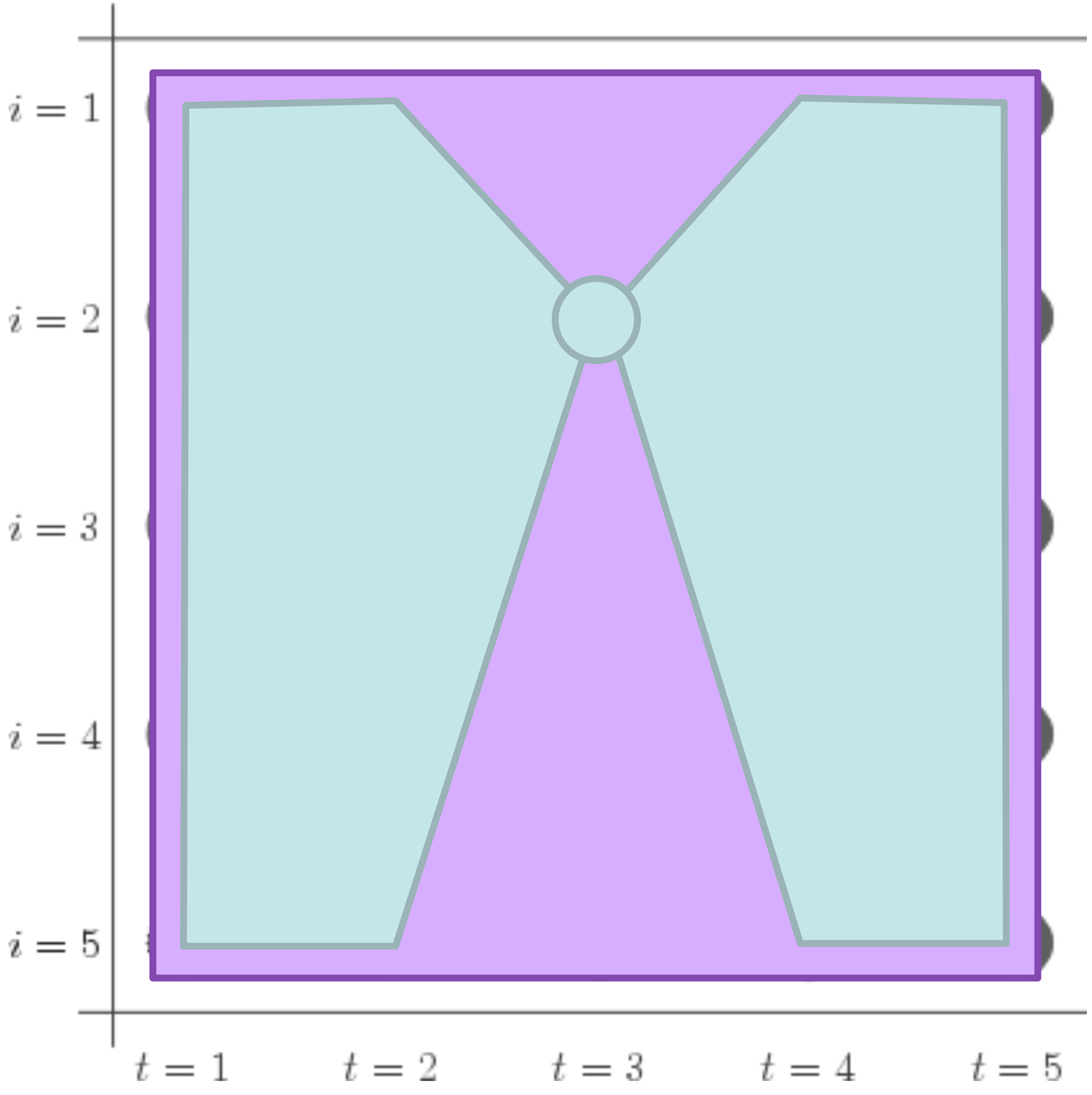

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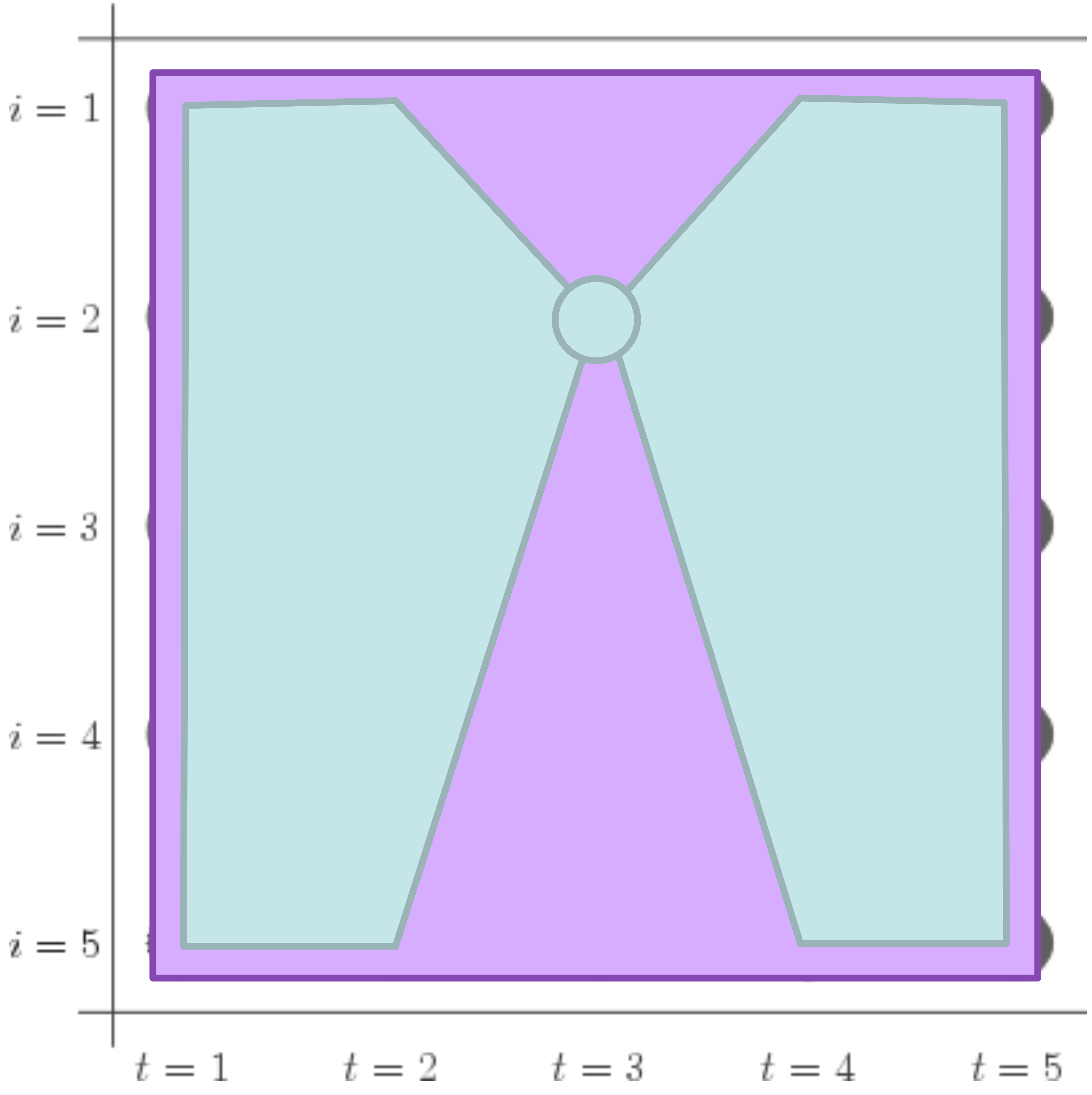

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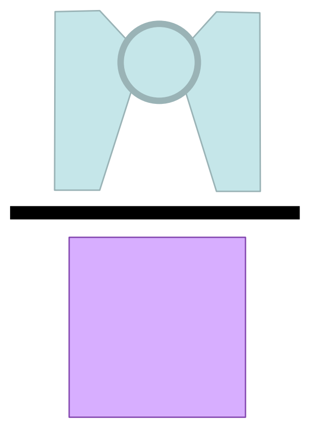
= 

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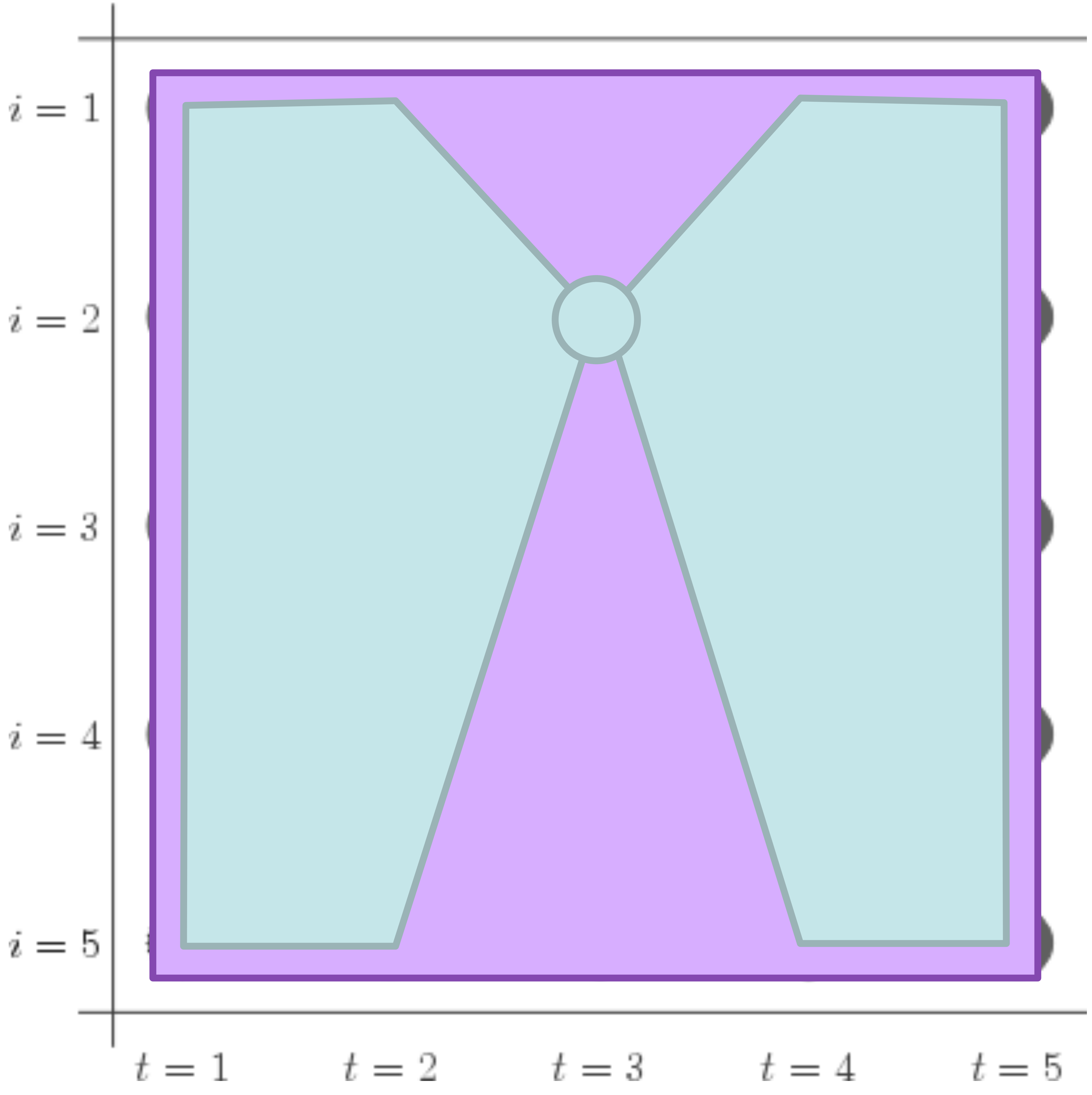

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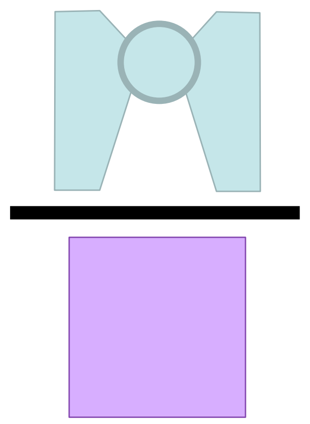

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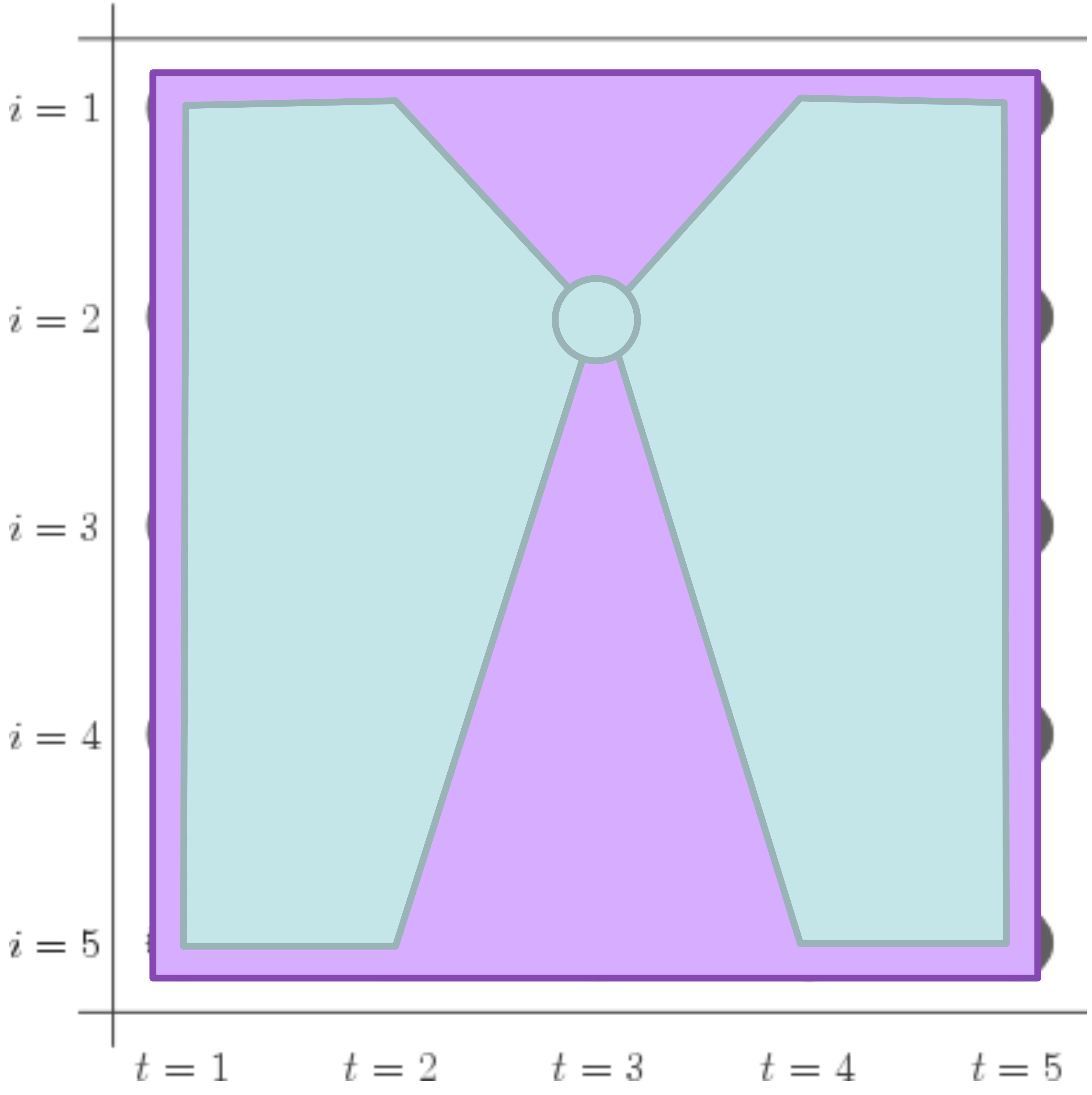

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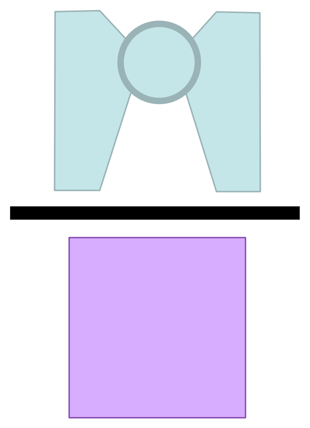

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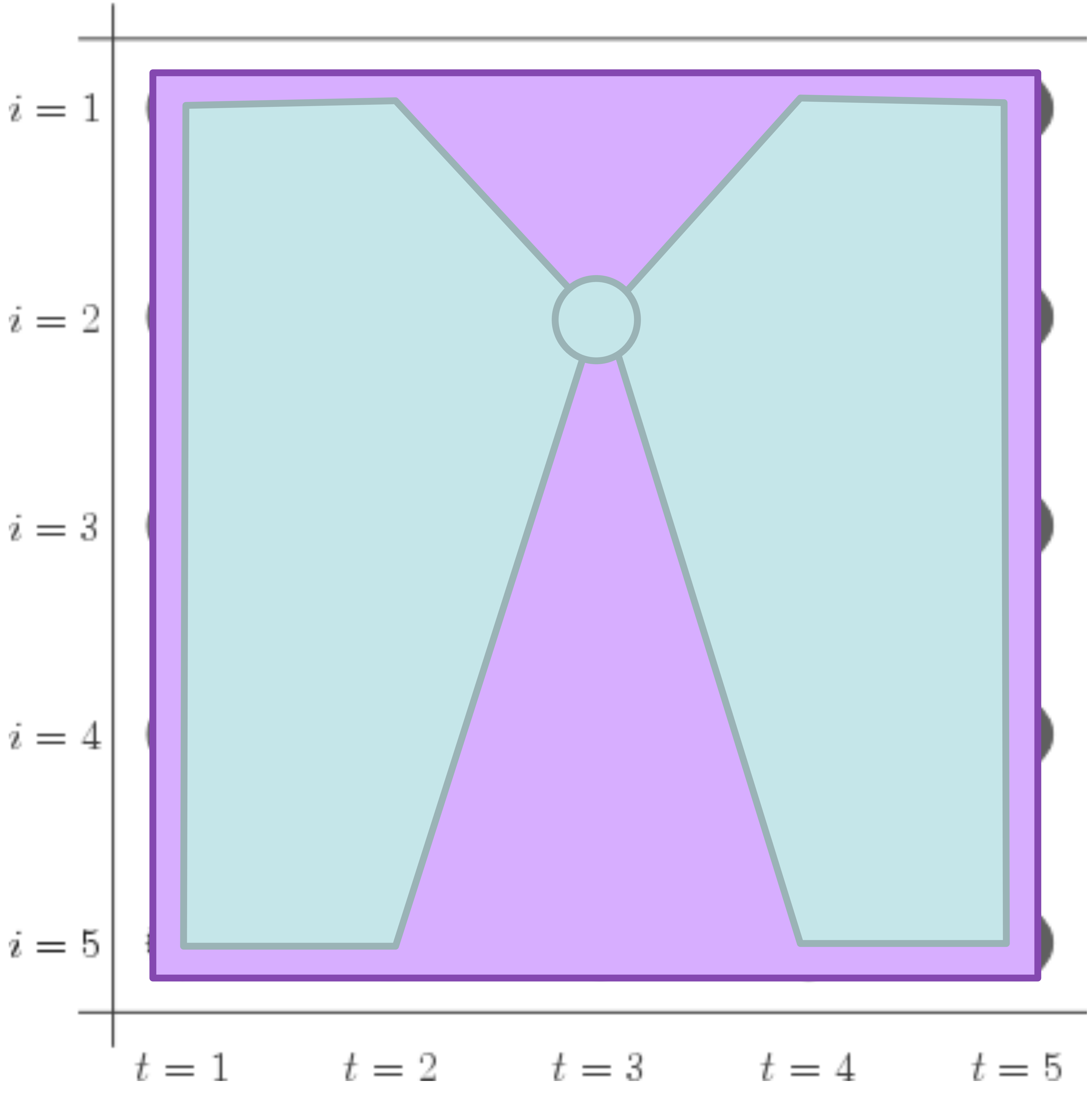
Forward-Backward Algorithm



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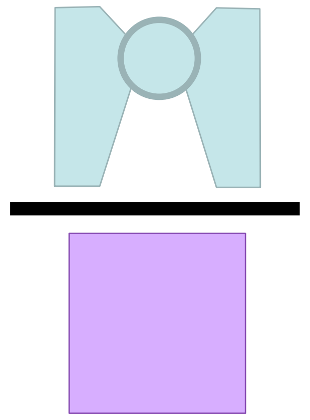

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HMM POS Tagging

Slide credit: Dan Klein

HMM POS Tagging

- Baseline: assign each word its most frequent tag: ~90% accuracy

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NNP VBZ NN NNS CD NN
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- Tradeoff between model capacity and data size — trigrams are a “sweet spot” for POS tagging

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- State-of-the-art (BiLSTM-CRFs): 97.5% / 89%+

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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
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JJ/NN NN

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JJ/NN NN — *official knowledge*

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JJ/NN NN
official knowledge

VBD RP/IN DT NN
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RB VBD/VBN NNS
recently sold shares

(NN NN: *tax cut, art gallery, …*)

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They set up absurd situations, detached from reality

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They set up absurd situations, detached from reality

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

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

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

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- CRFs: feature-based discriminative models

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- CRFs: feature-based discriminative models
- Structured SVM for sequences

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