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

Guest Lecture on Oct 11

Chenhao Tan (https://chenhaot.com/)
University of Chicago
9th floor Coda Atrium

Meet TAs at 11:45am (Oct 11) in the Coda Lobby

No class at the regular time

Linguistic Structures

- Language is tree-structured

Linguistic Structures

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I ate the spaghetti with chopsticks

Linguistic Structures

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

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

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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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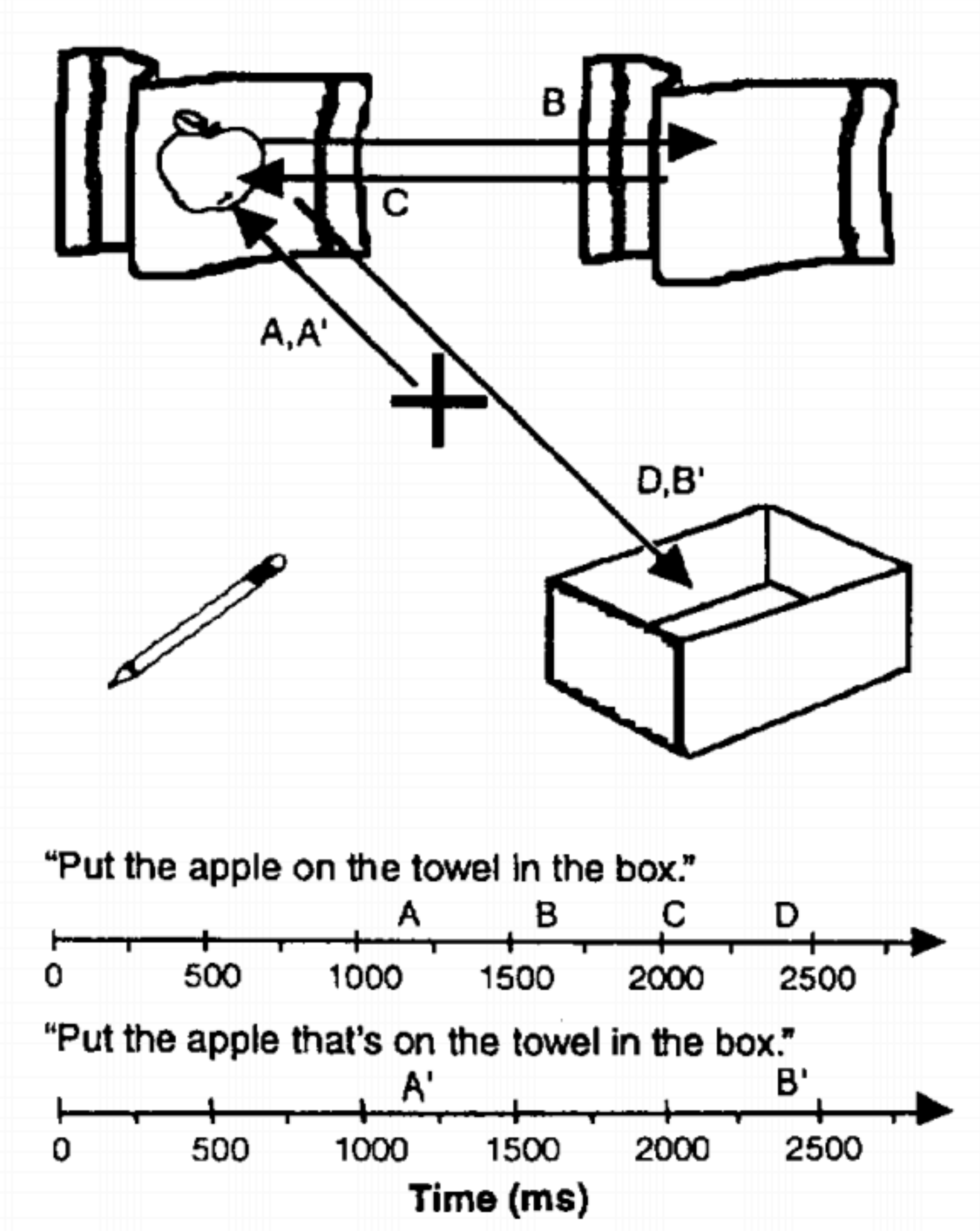

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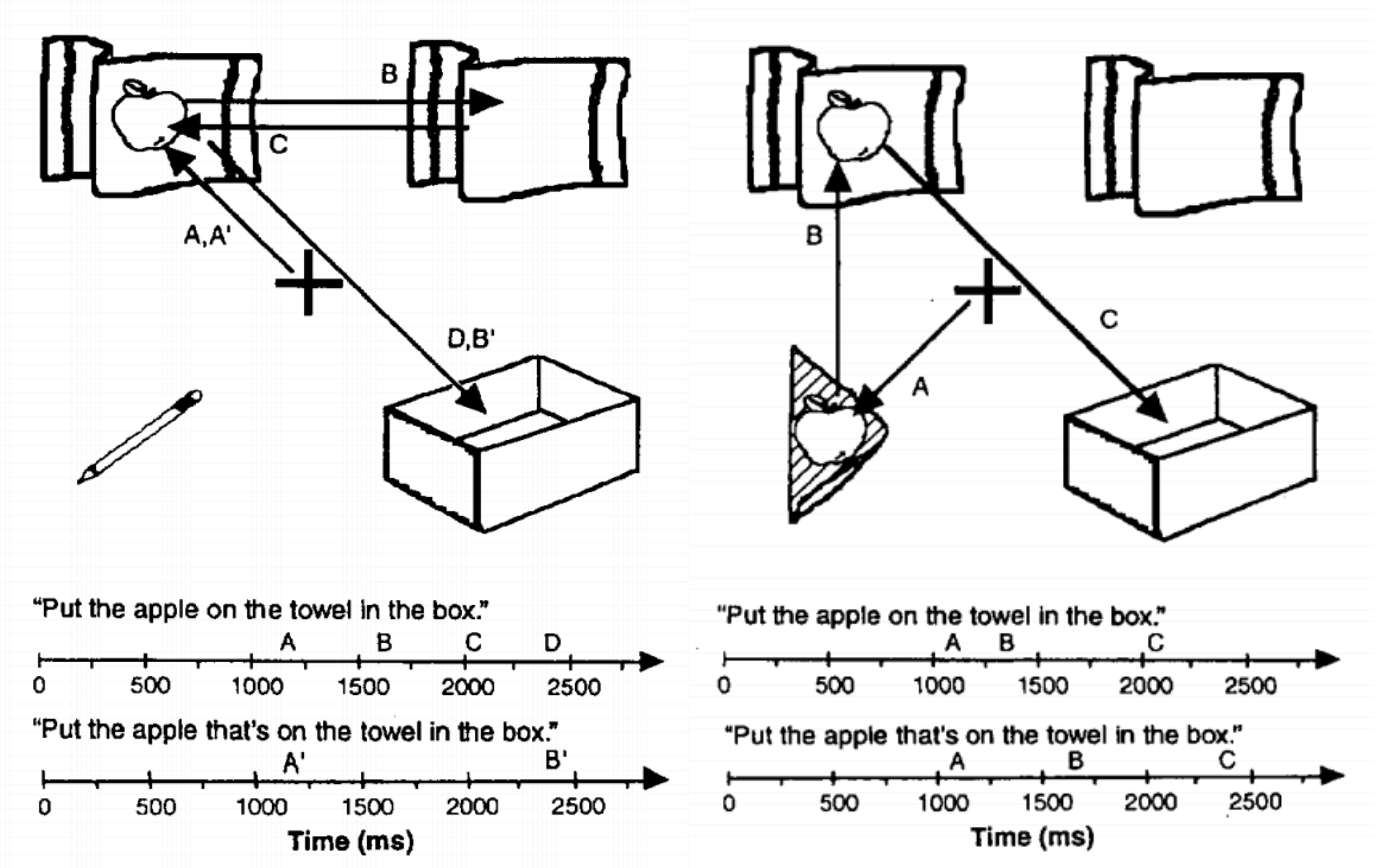


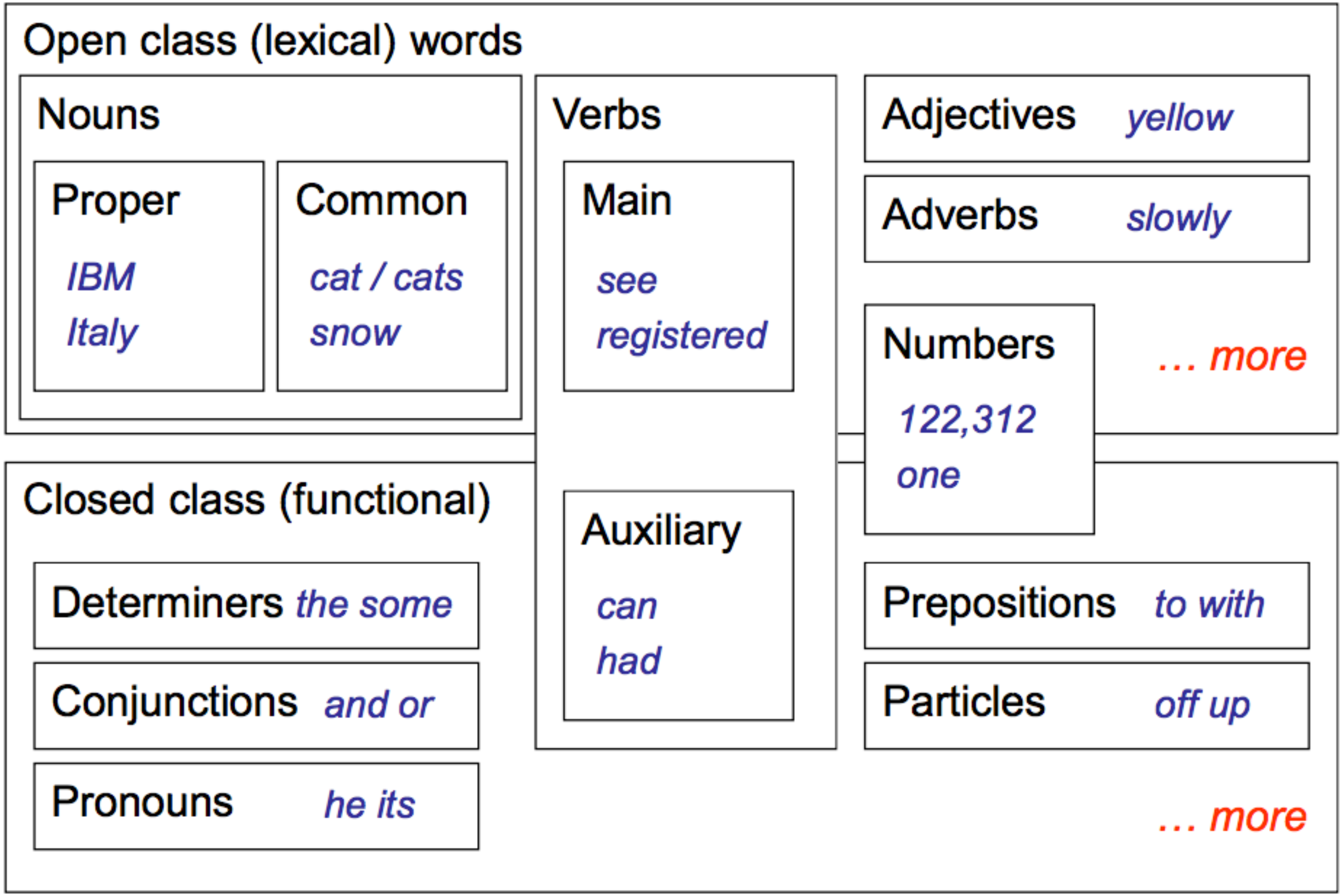
Tanenhaus et al. (1995)

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

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Fed raises interest rates 0.5 percent

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POS Tagging

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NNP
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POS Tagging

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POS Tagging

VBD VB
VBN VBZ VBP
NNP NNS NN

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

Sequence Models

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

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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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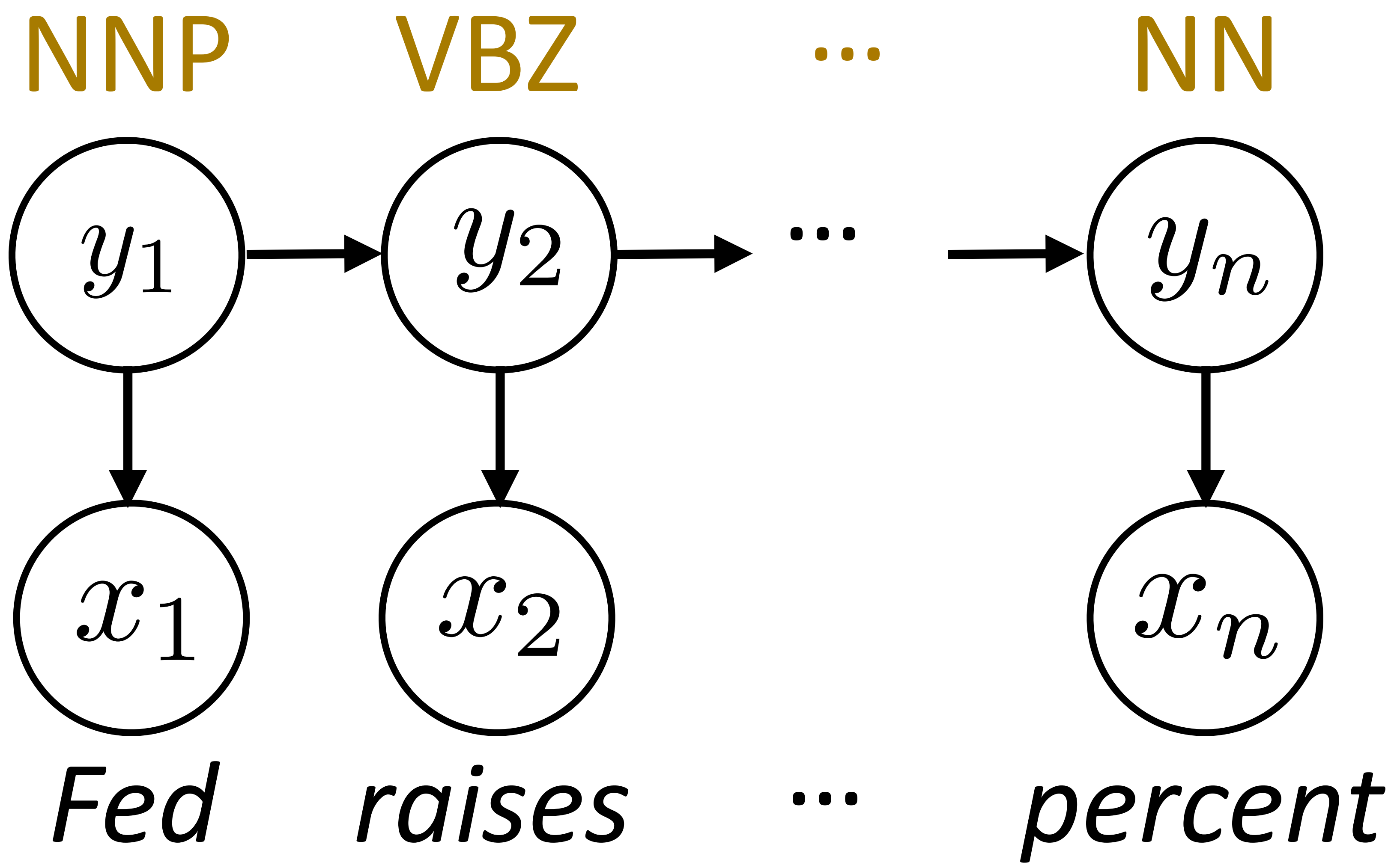

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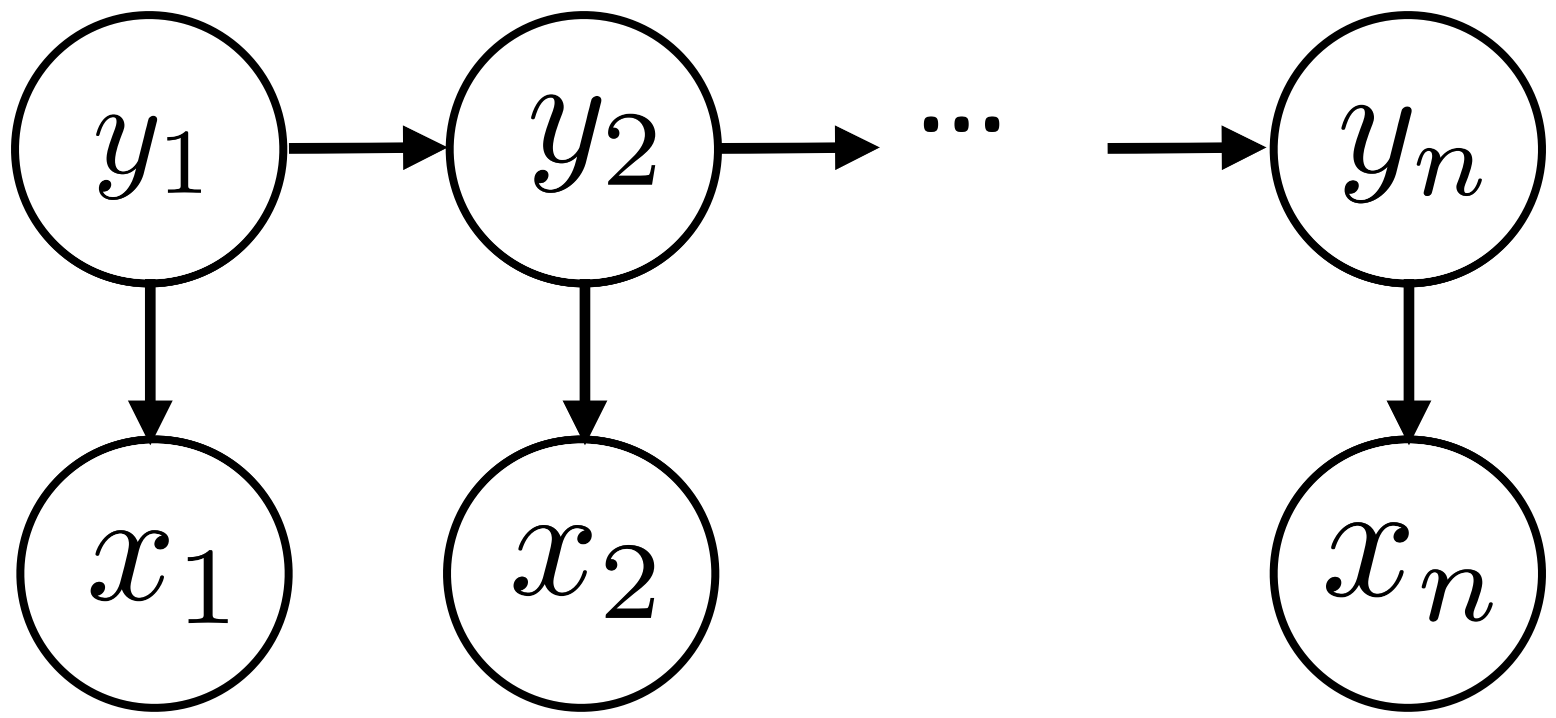

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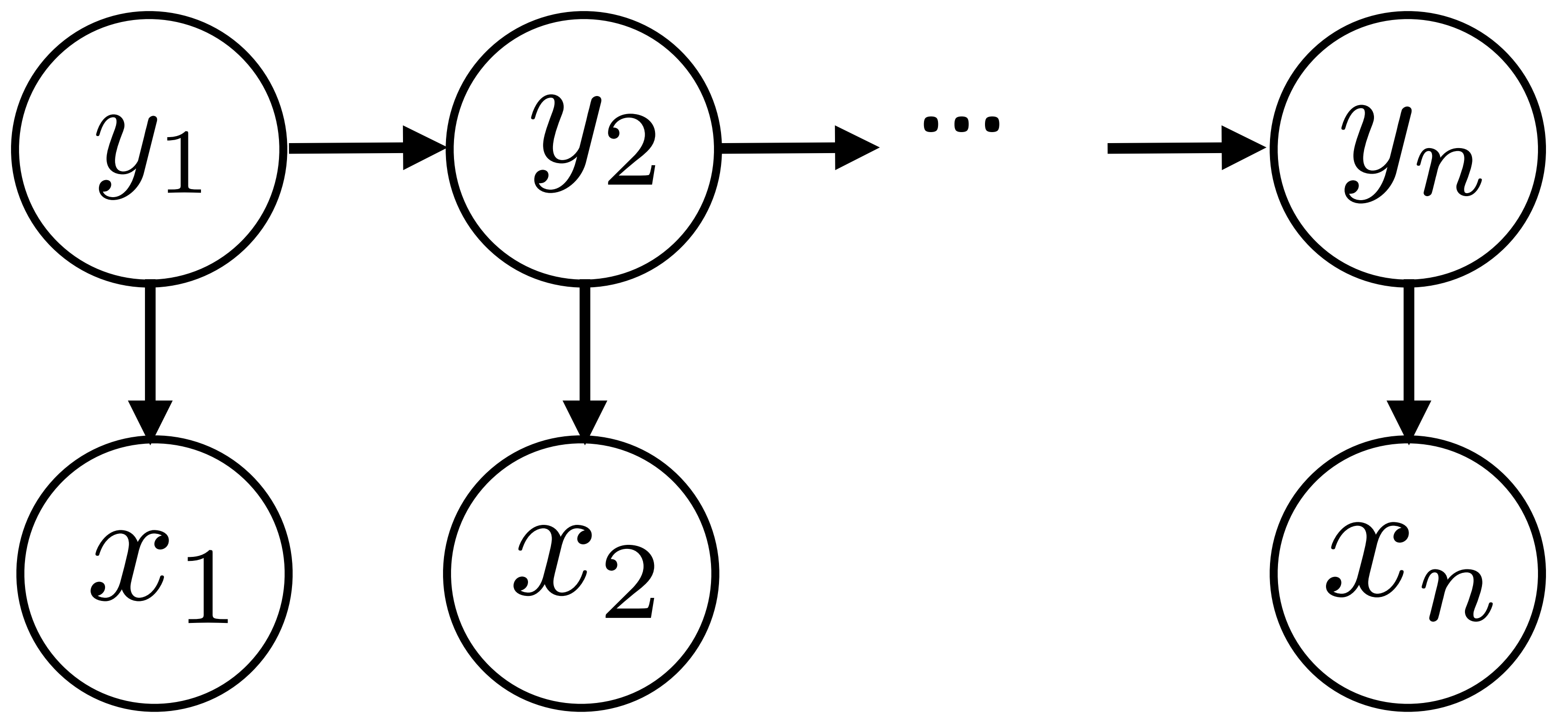

$$P(\mathbf{y}, \mathbf{x}) = P(y_1) \prod_{i=2}^{n} P(y_i | y_{i-1}) \prod_{i=1}^{n} P(x_i | y_i)$$

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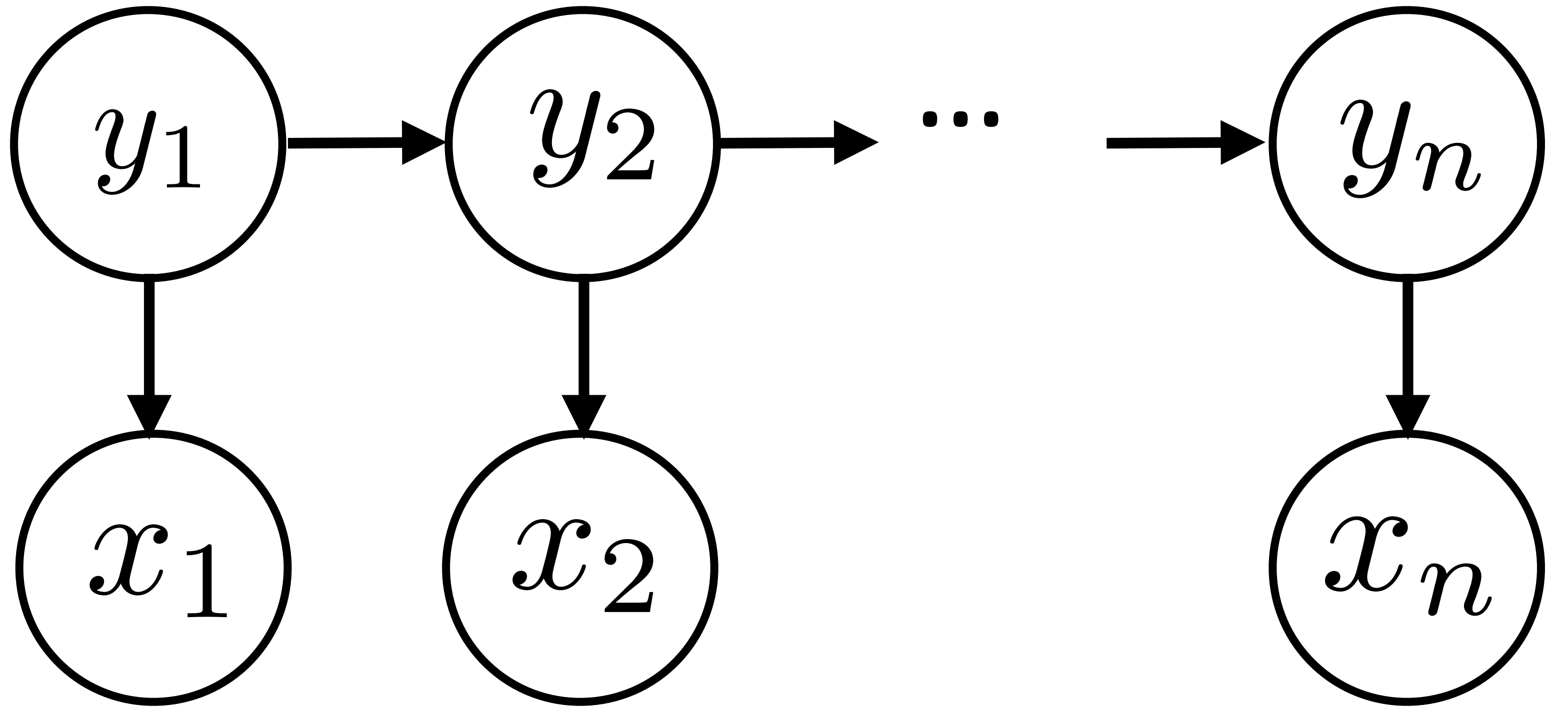

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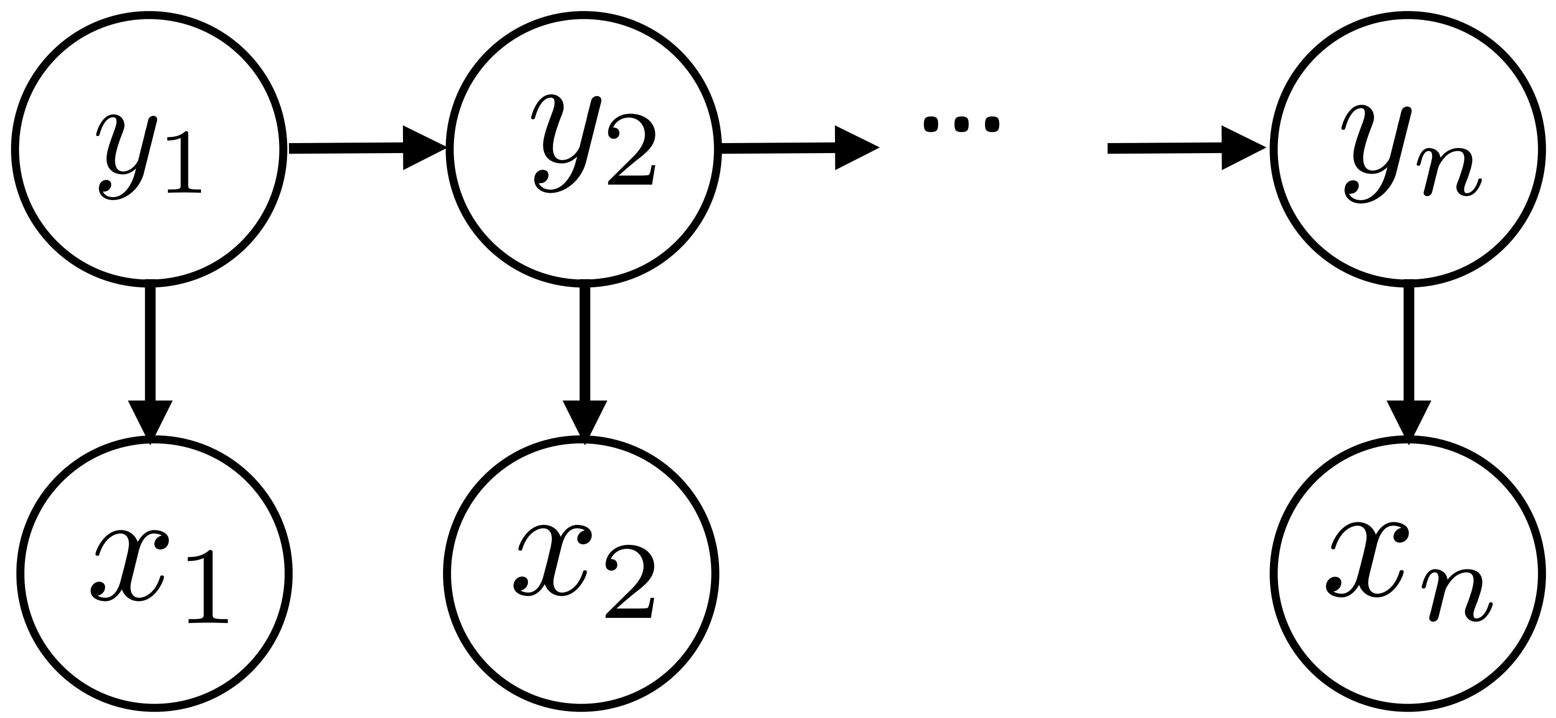

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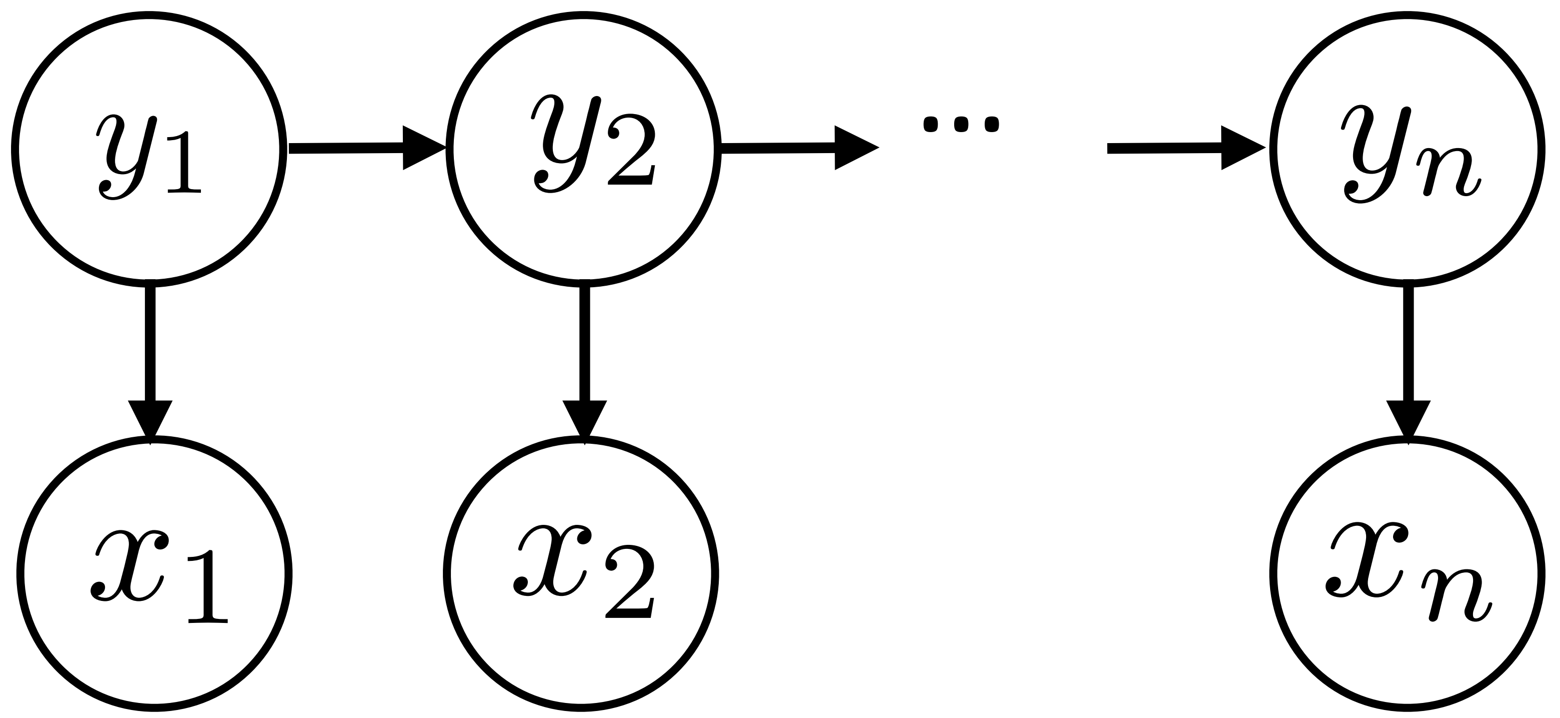

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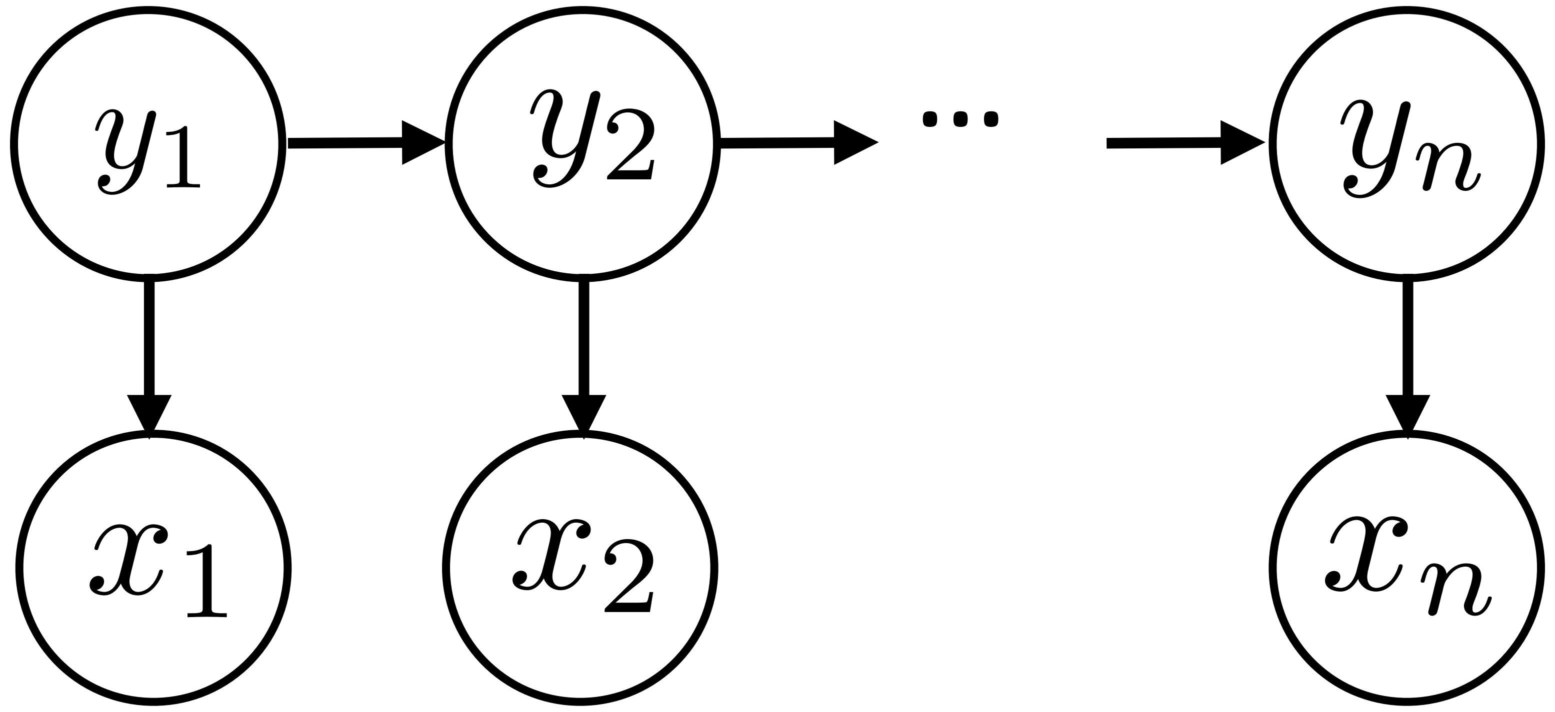

- Observation (*x*) depends only on current state (*y*)

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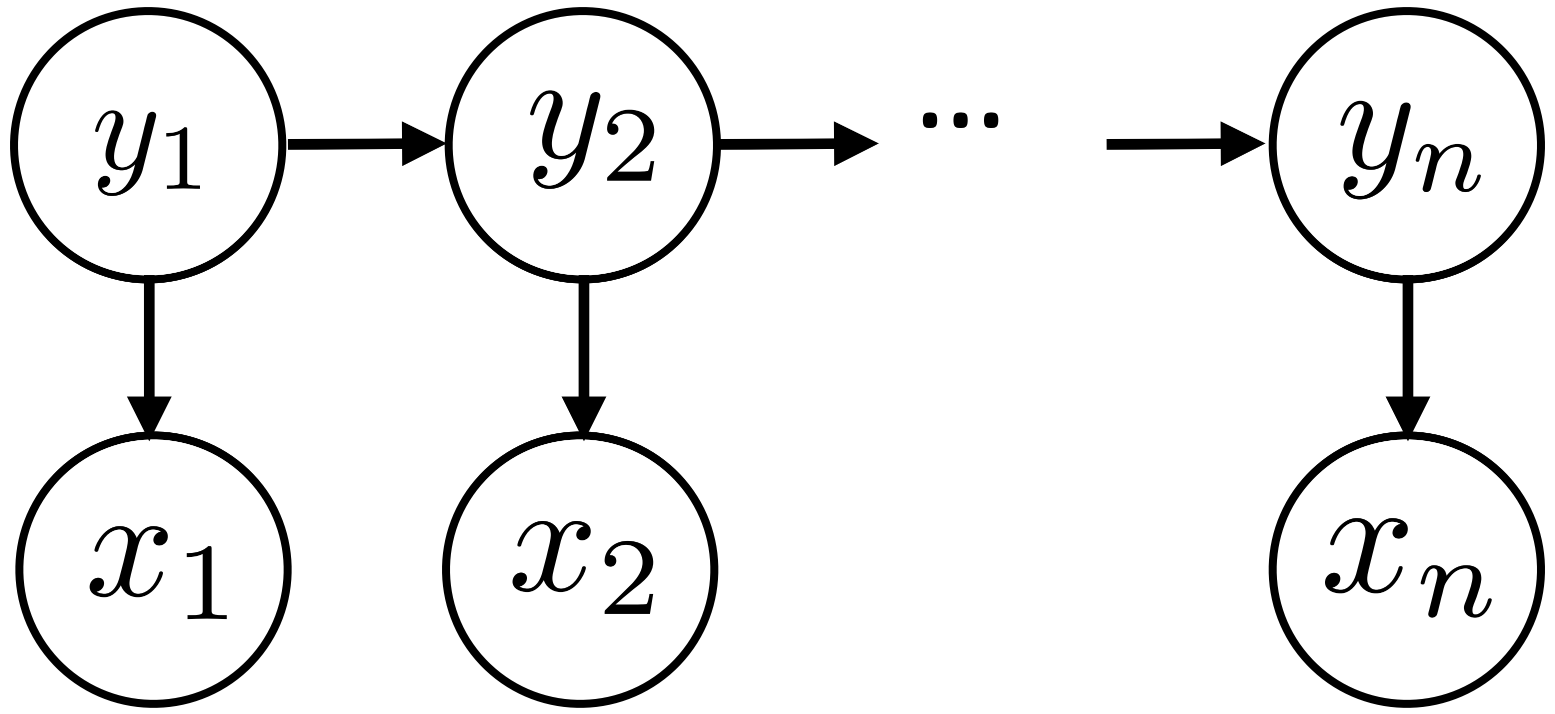

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$$
\begin{array}{ccccccc}
y_1 & \rightarrow & y_2 & \rightarrow & \cdots & \rightarrow & y_n \\
\downarrow & & \downarrow & & & & \downarrow \\
x_1 & & x_2 & & & & x_n
\end{array}
$$

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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!)

Estimating Transitions

NNP VBZ NN NNS CD NN .

Fed raises interest rates 0.5 percent .

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- P(tag | NN)

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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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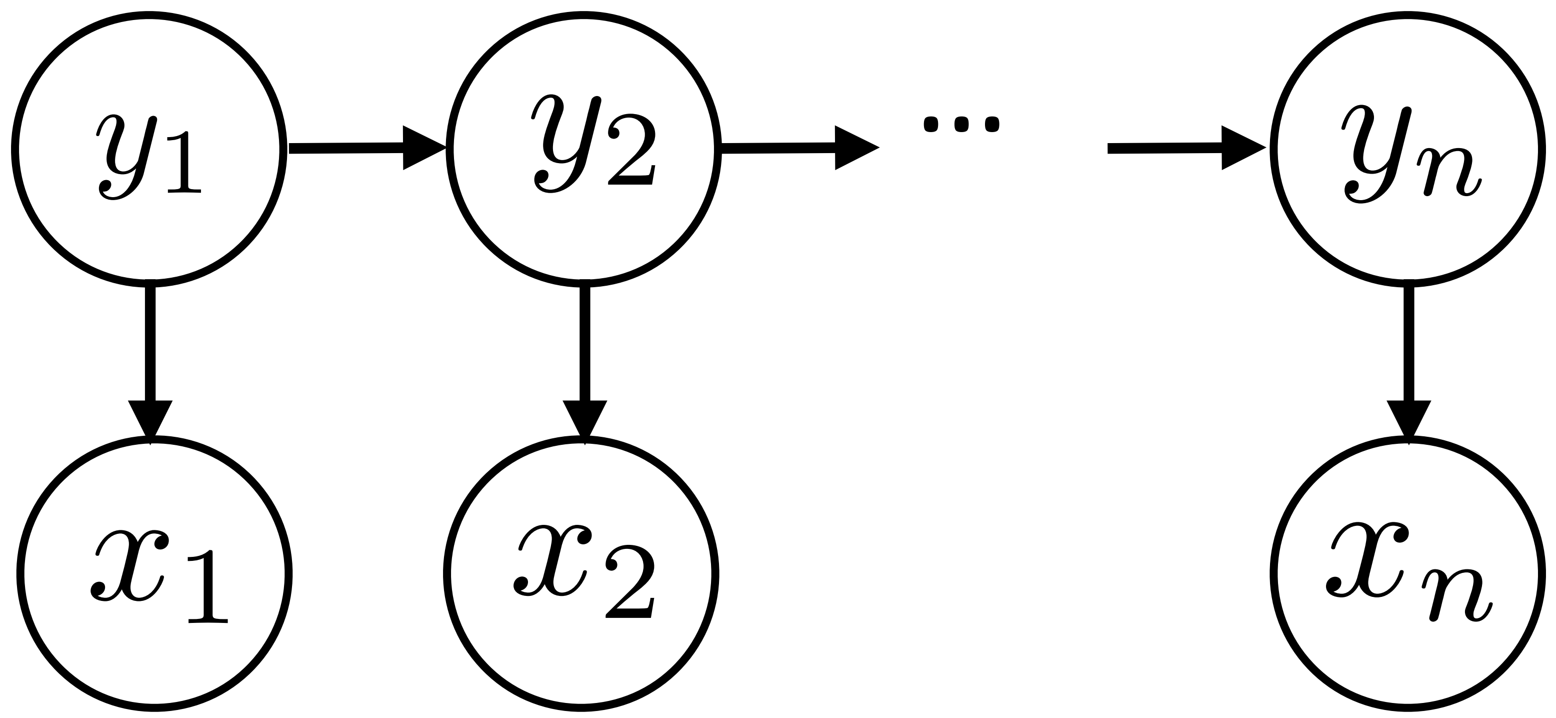
- P(word|tag) can be a log-linear model — we'll see this in a few lectures

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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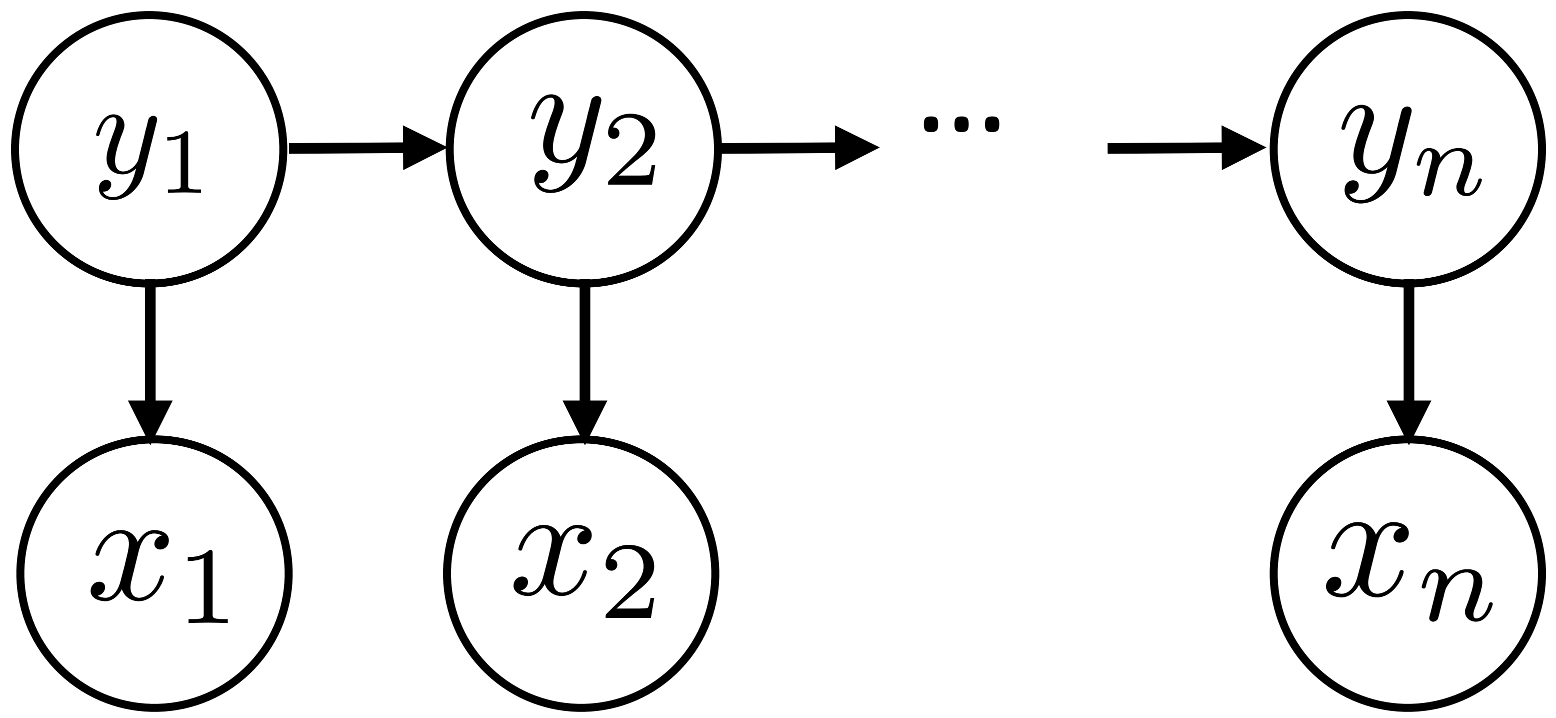

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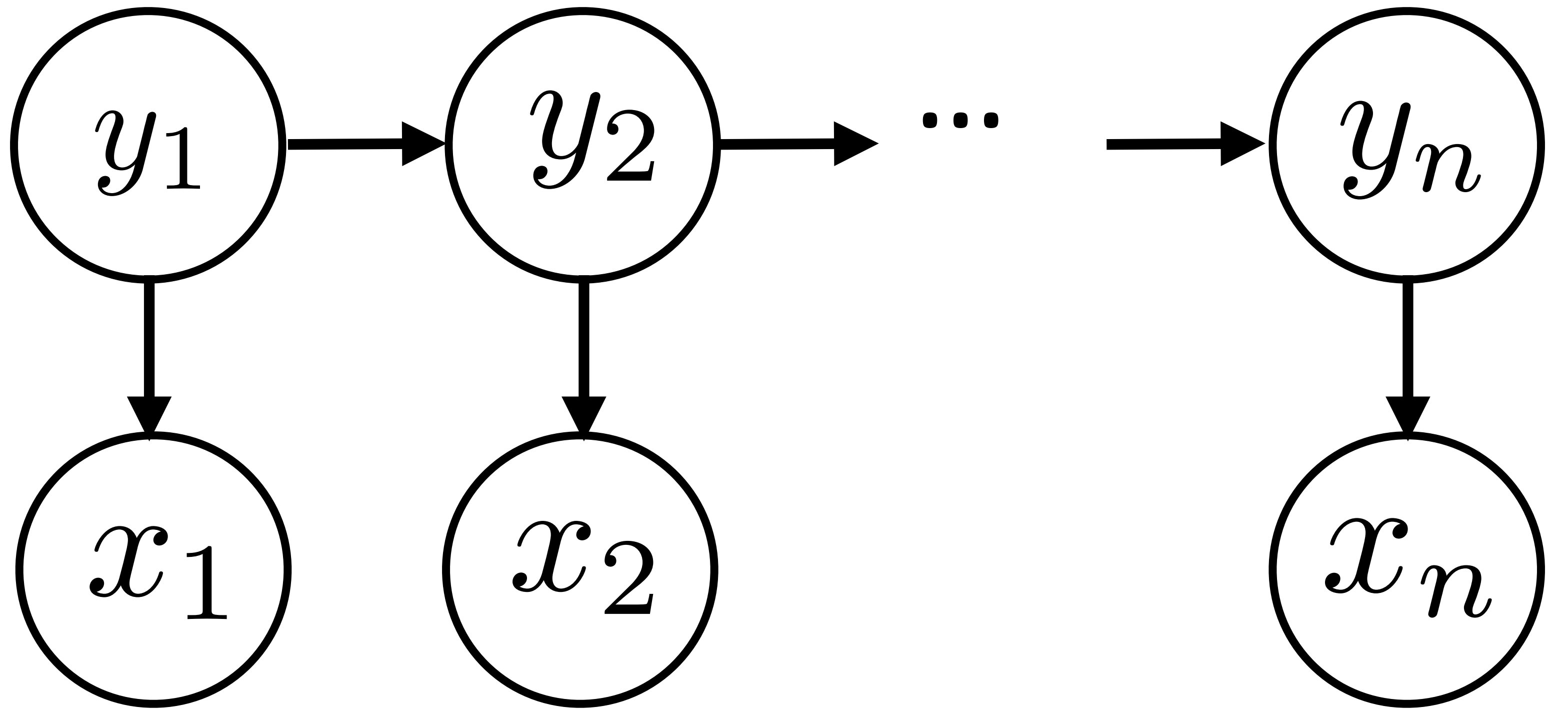

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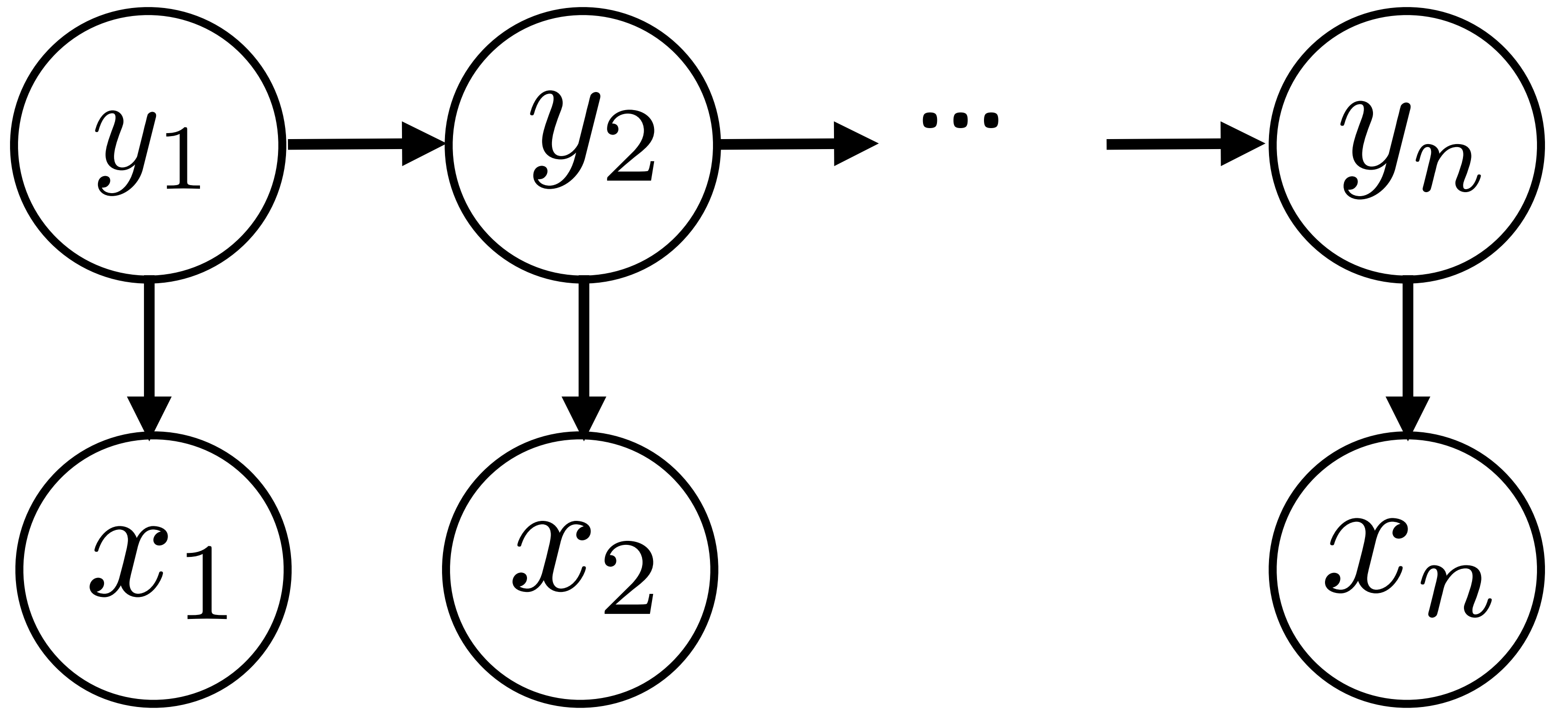

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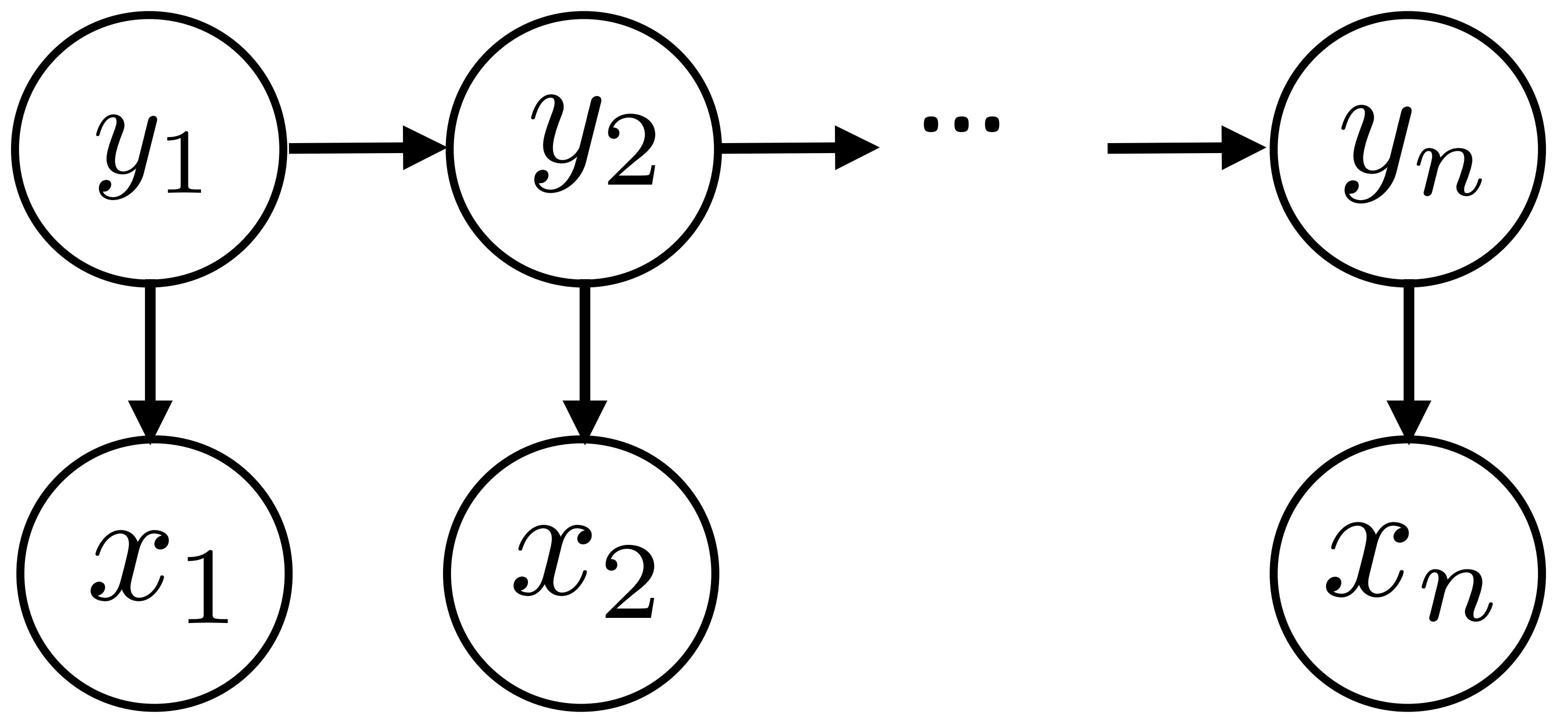

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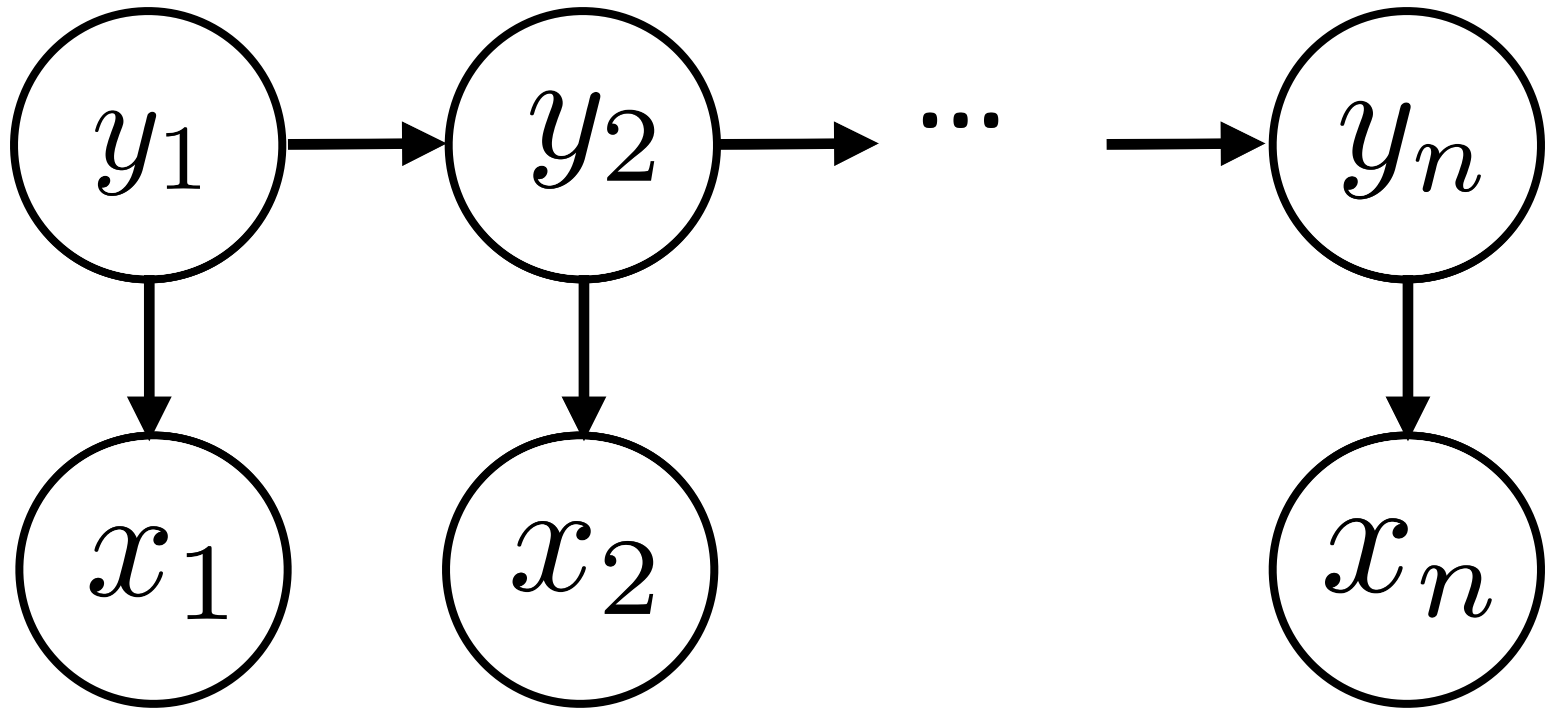

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- Exponentially many possible ***y*** here!
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  - Many neural sequence models depend on entire previous tag sequence, need to use approximations like beam search

Viterbi Algorithm

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

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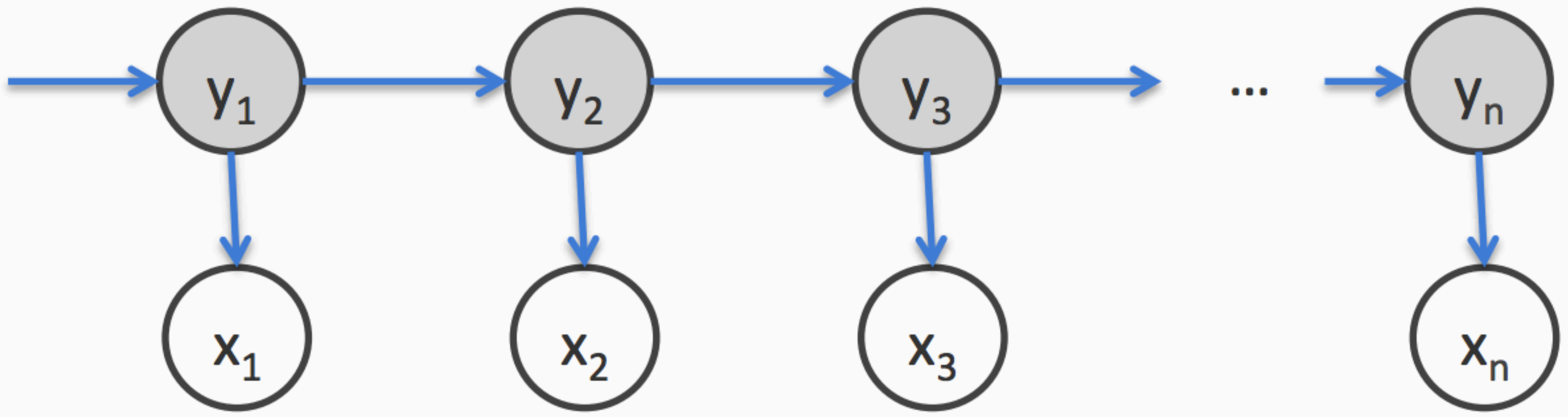
Transition probabilities　Emission probabilities　Initial probability



slide credit: Vivek Srikumar

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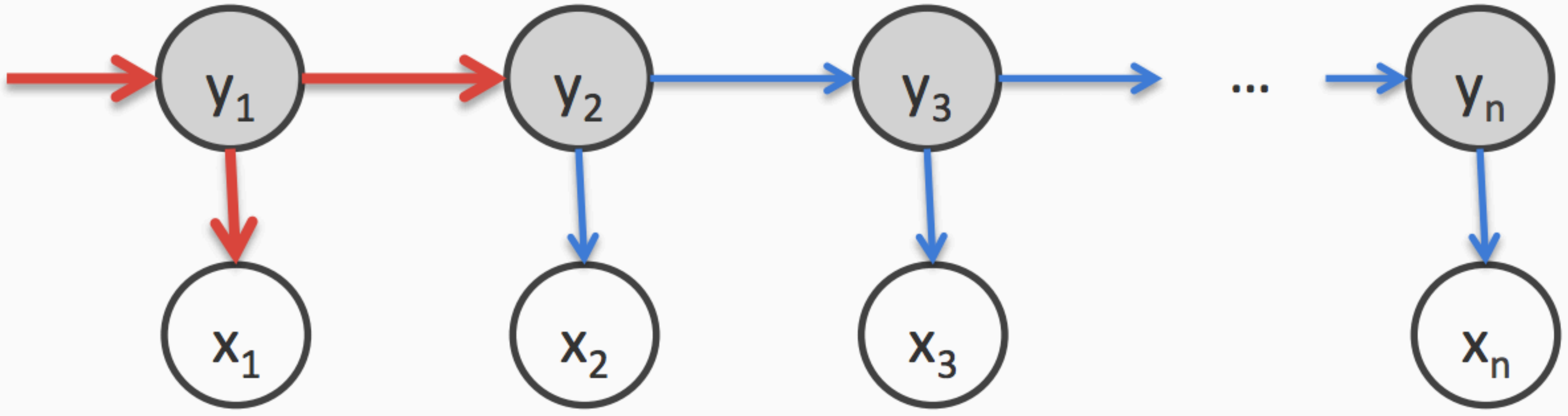
The only terms that depend on y_1



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Abstract away the score for all decisions till here into score

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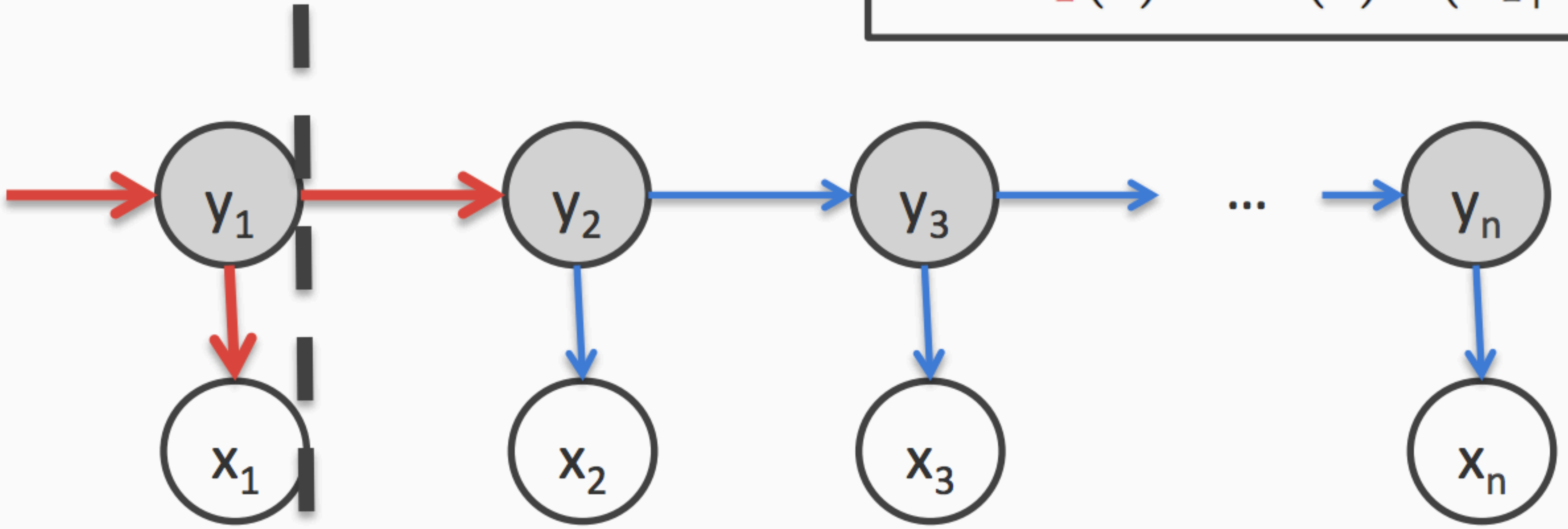

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best (partial) score for
a sequence ending in state *s*

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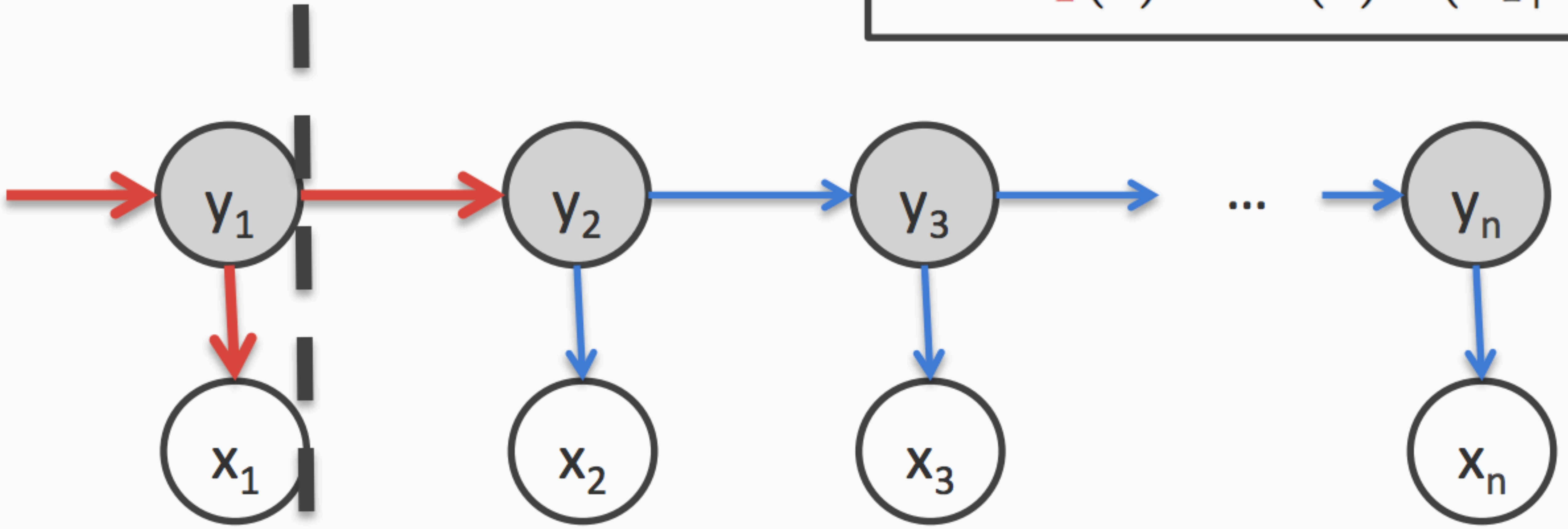

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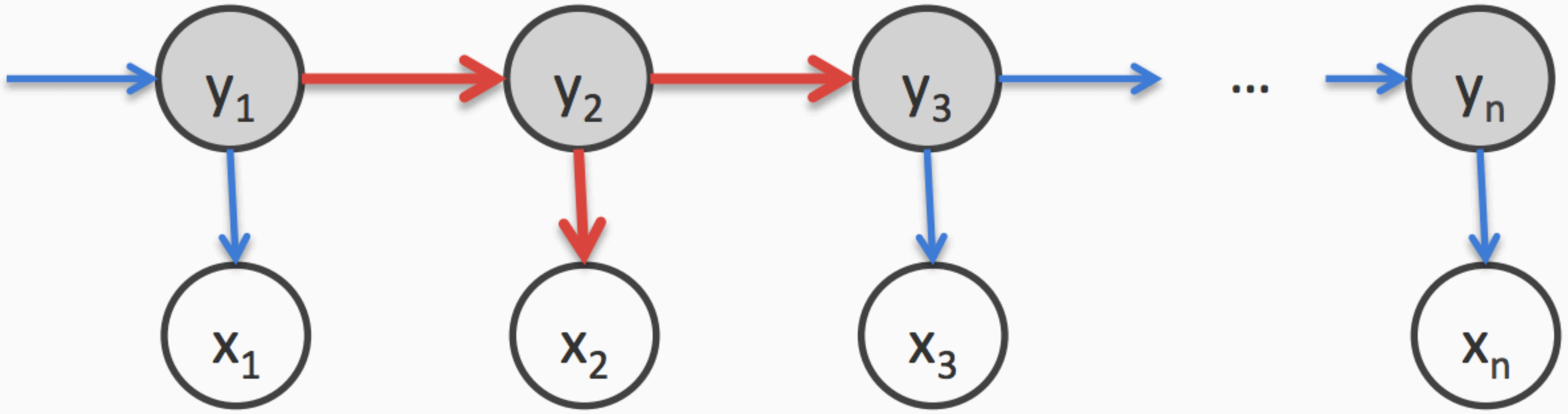
Only terms that depend on y_2



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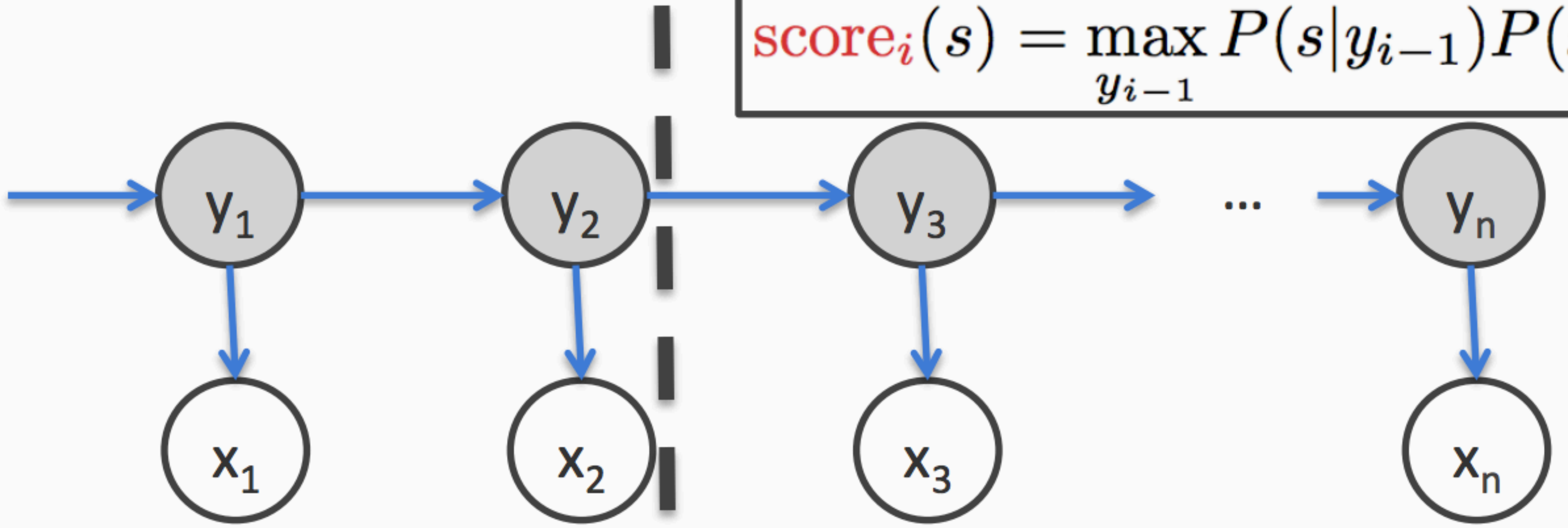
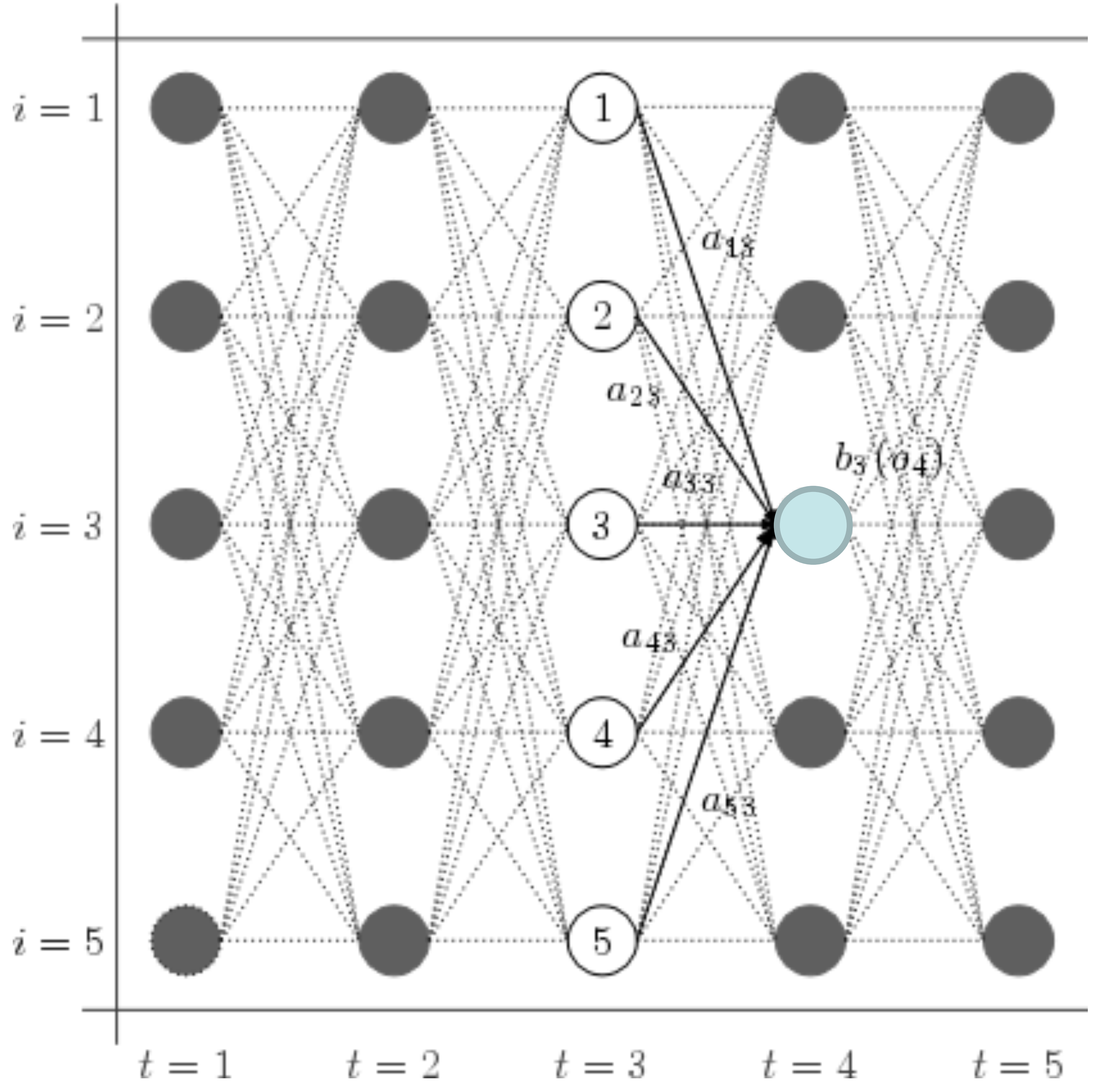


Abstract away the score for all decisions till here into score

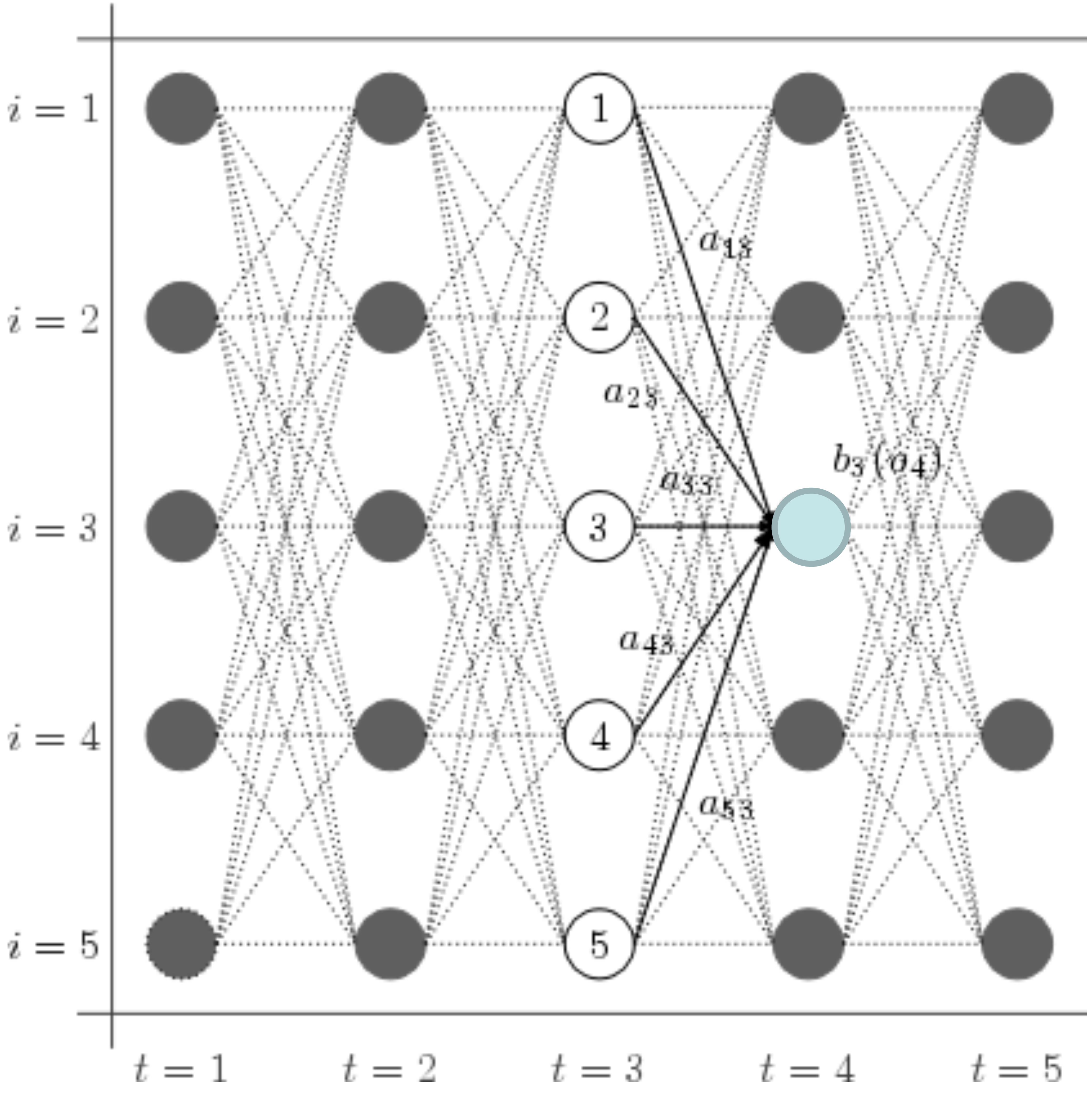
slide credit: Vivek Srikumar

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

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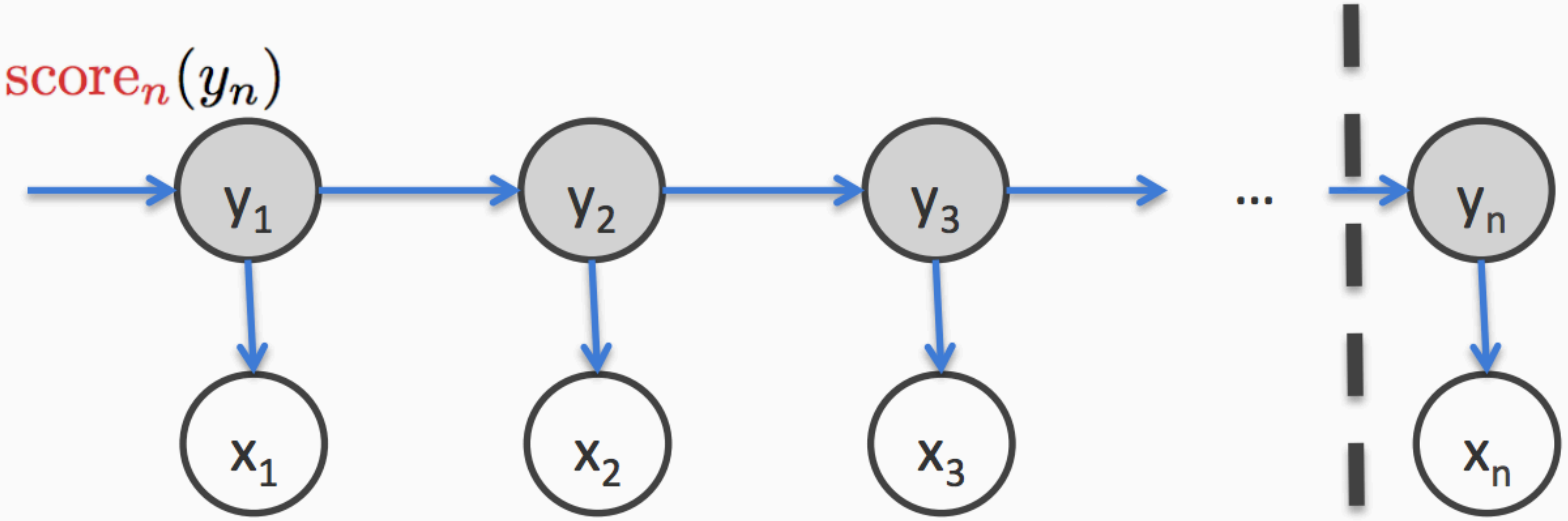
$$\vdots$$

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



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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

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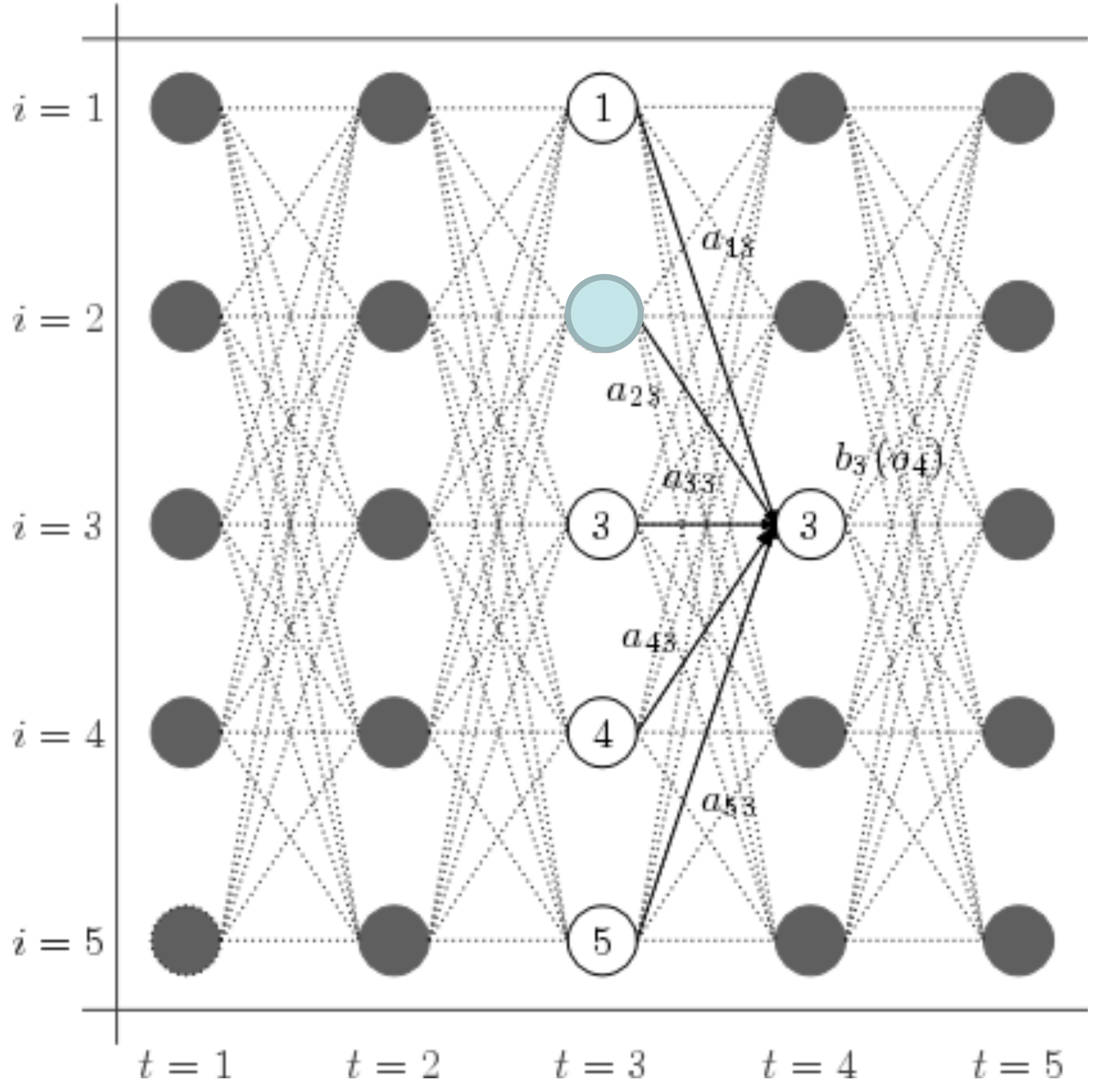
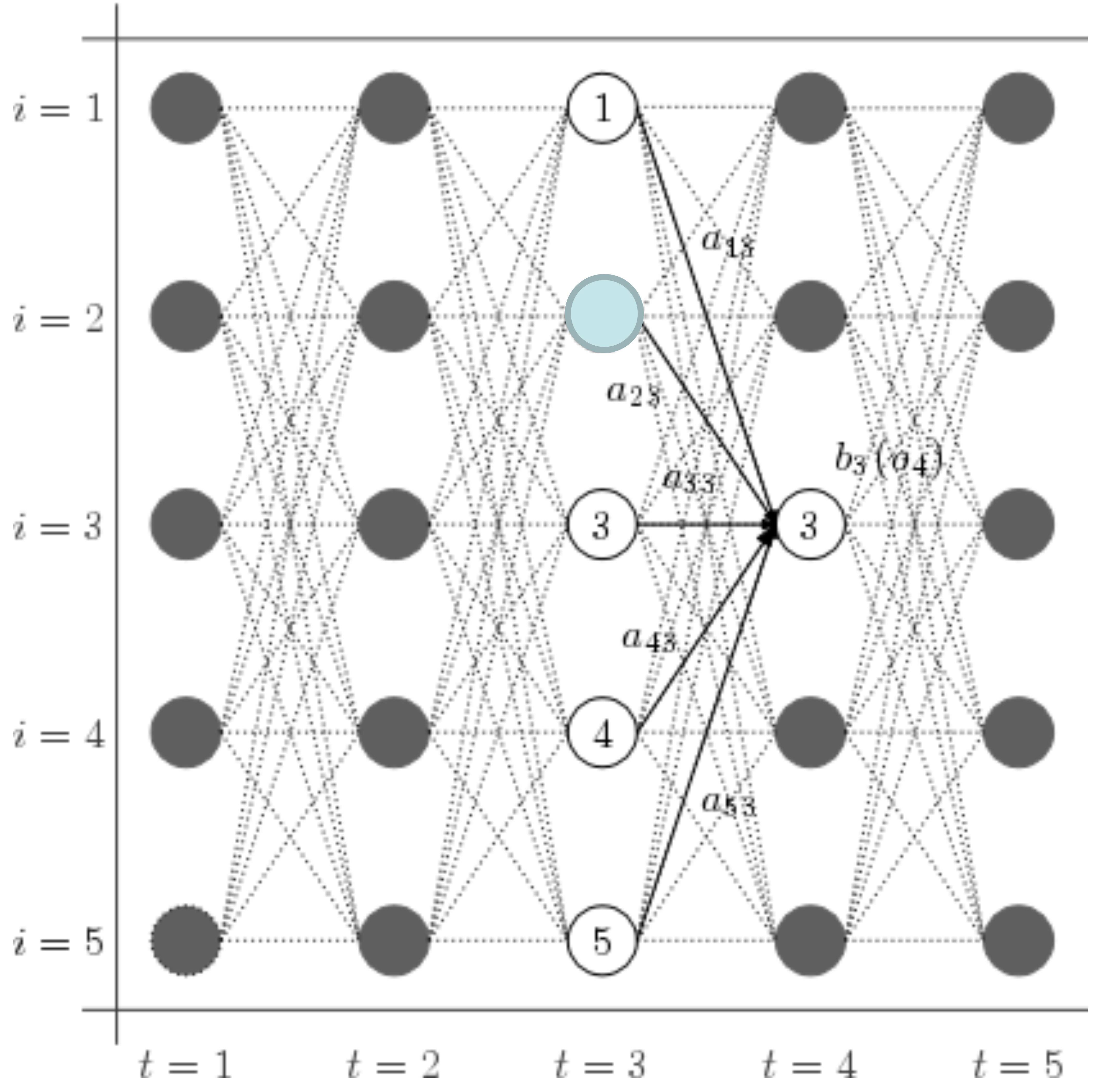
- Can compute marginals with dynamic programming as well using an algorithm called forward-backward

Forward-Backward Algorithm

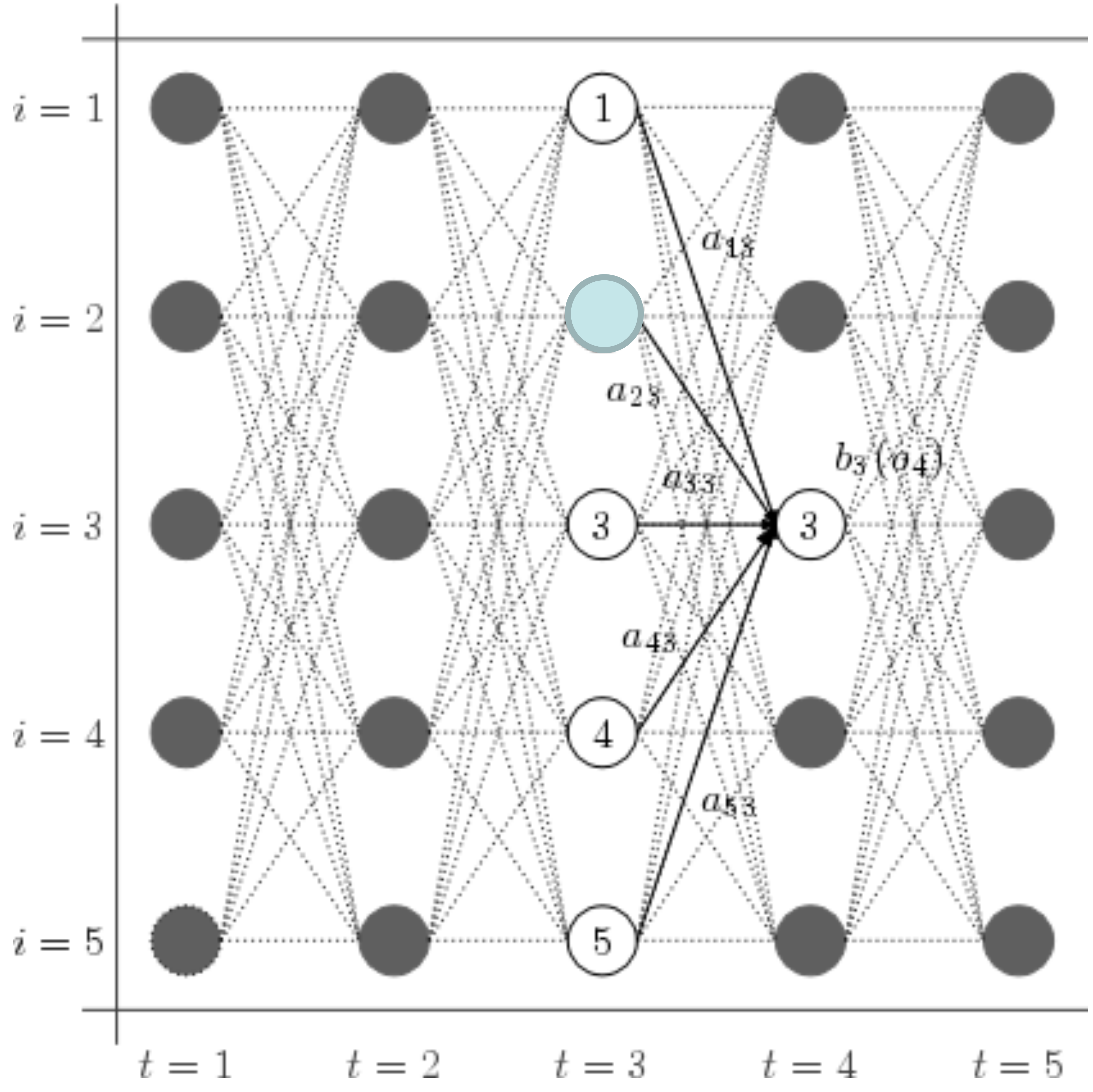


Forward-Backward Algorithm



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

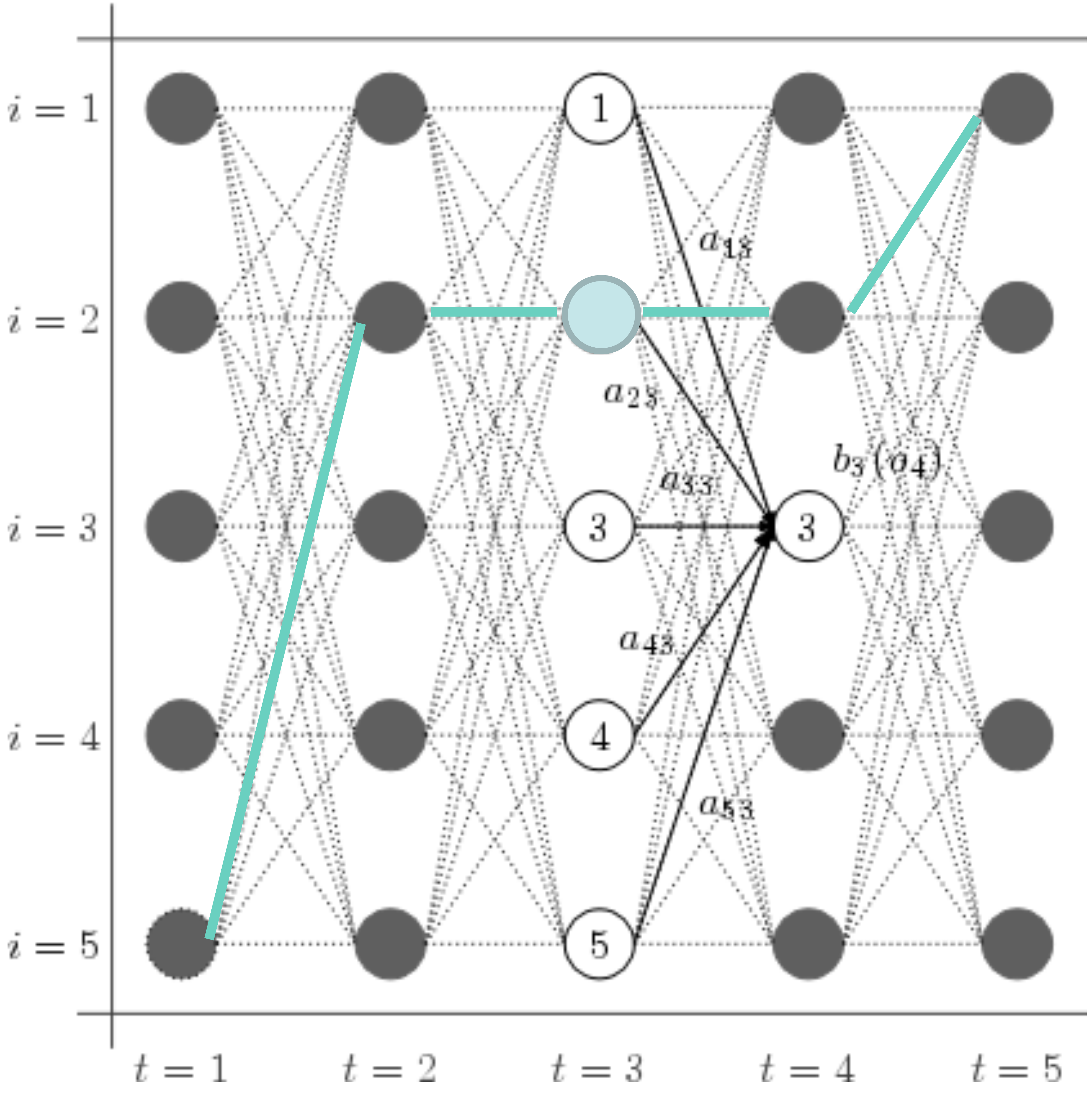
Forward-Backward Algorithm



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

$$\frac{\text{sum of all paths through state 2 at time 3}}{\text{sum of all paths}}$$

Forward-Backward Algorithm



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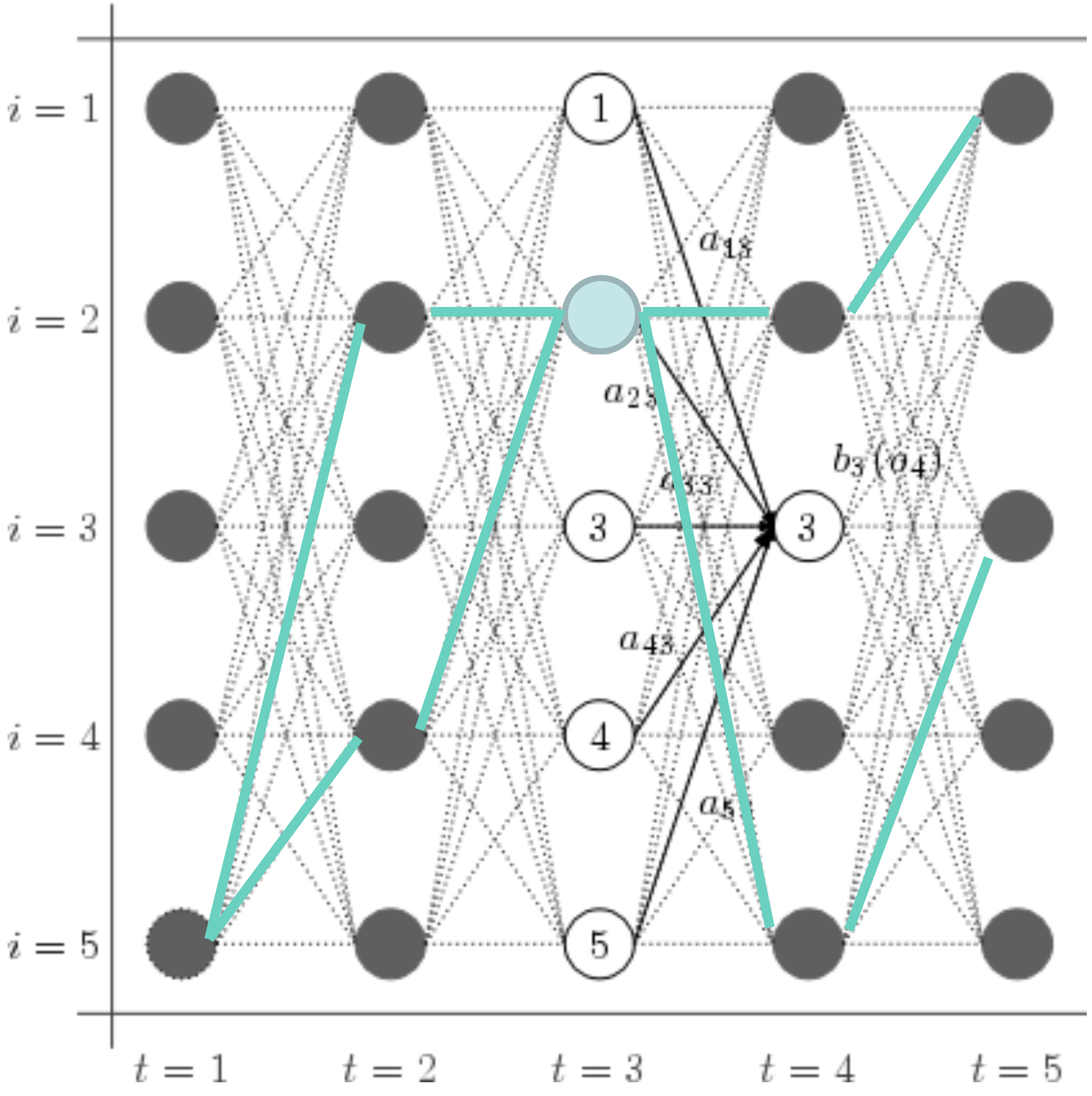

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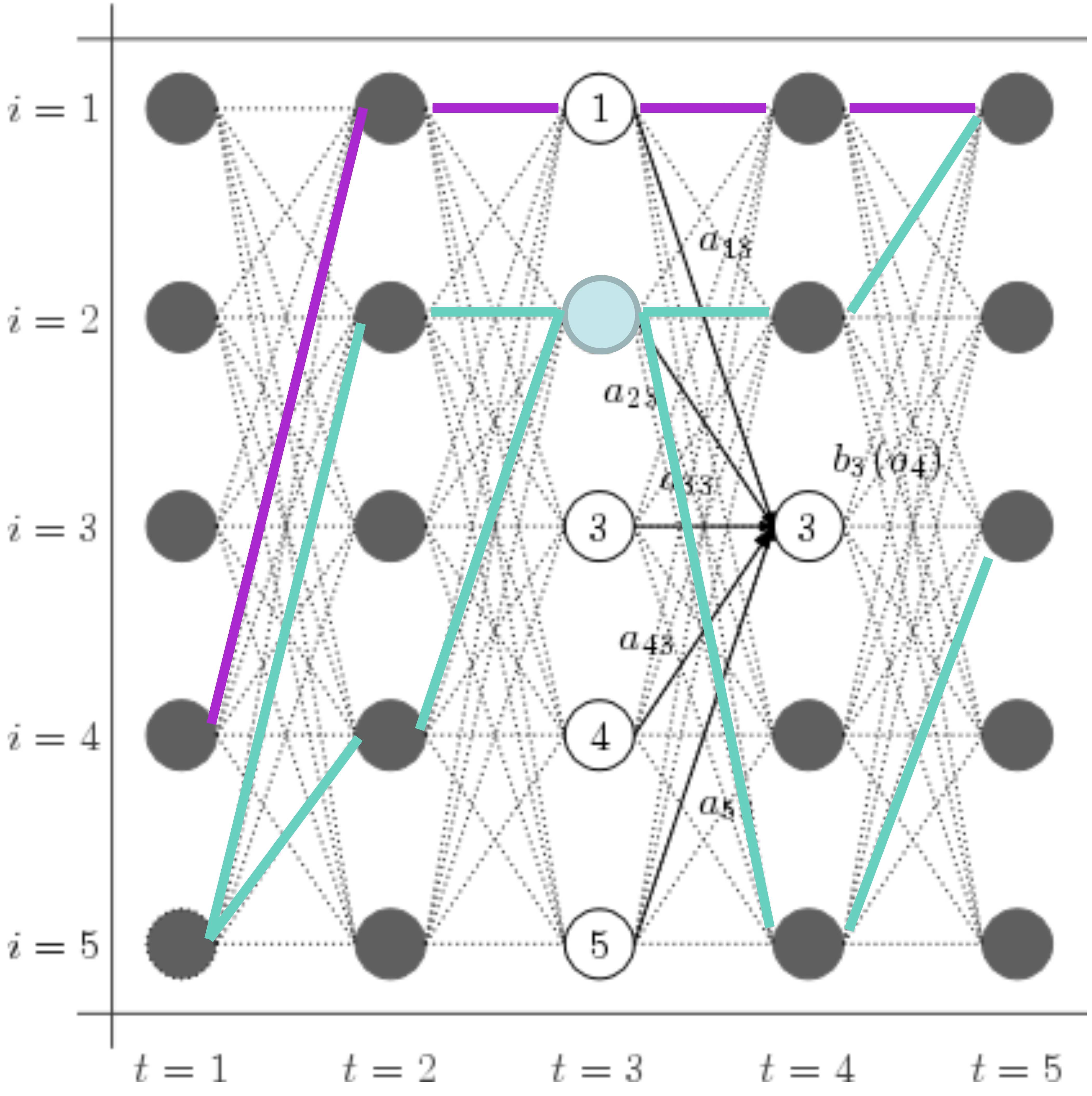

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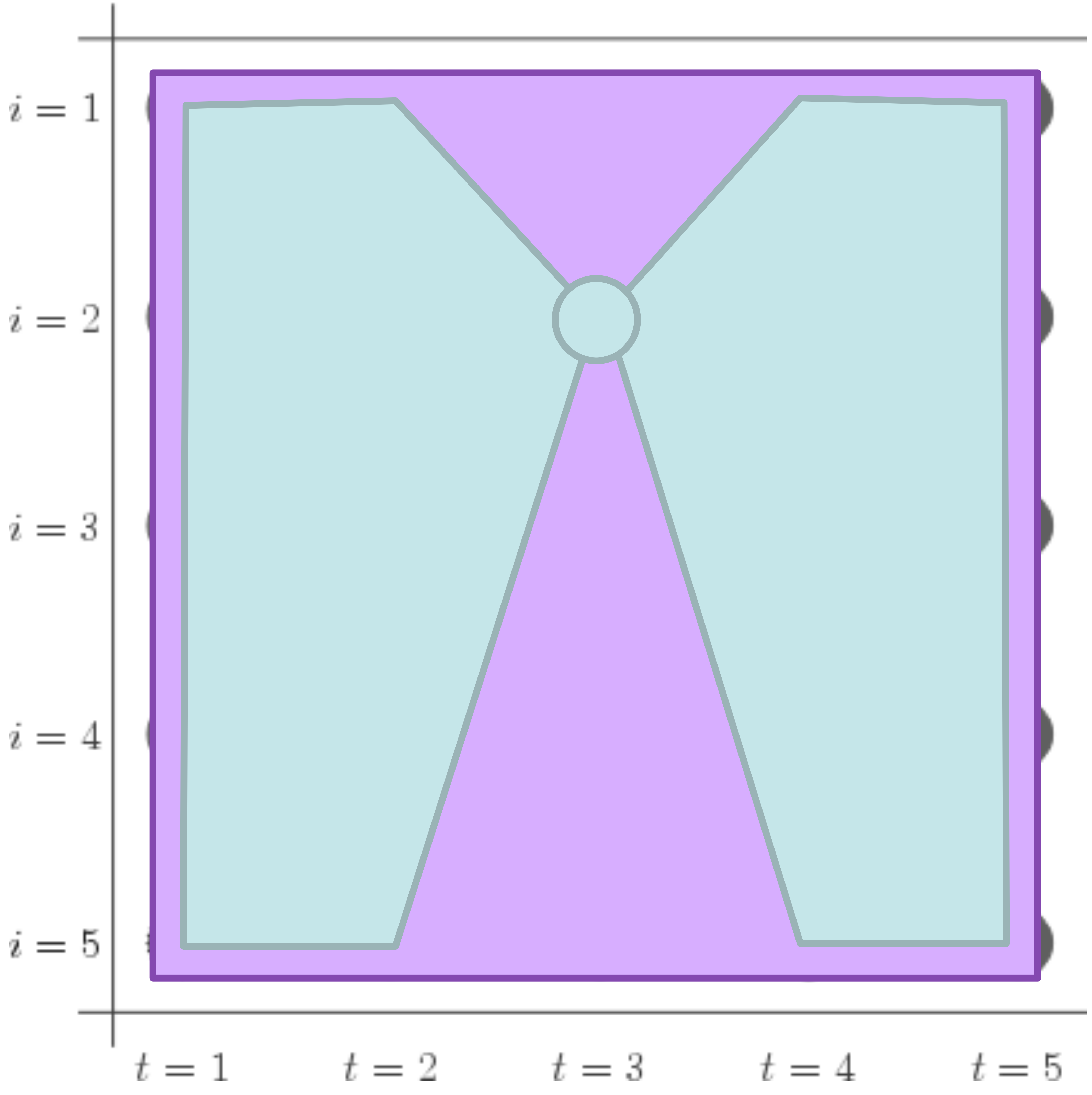
Forward-Backward Algorithm



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slide credit: Dan Klein

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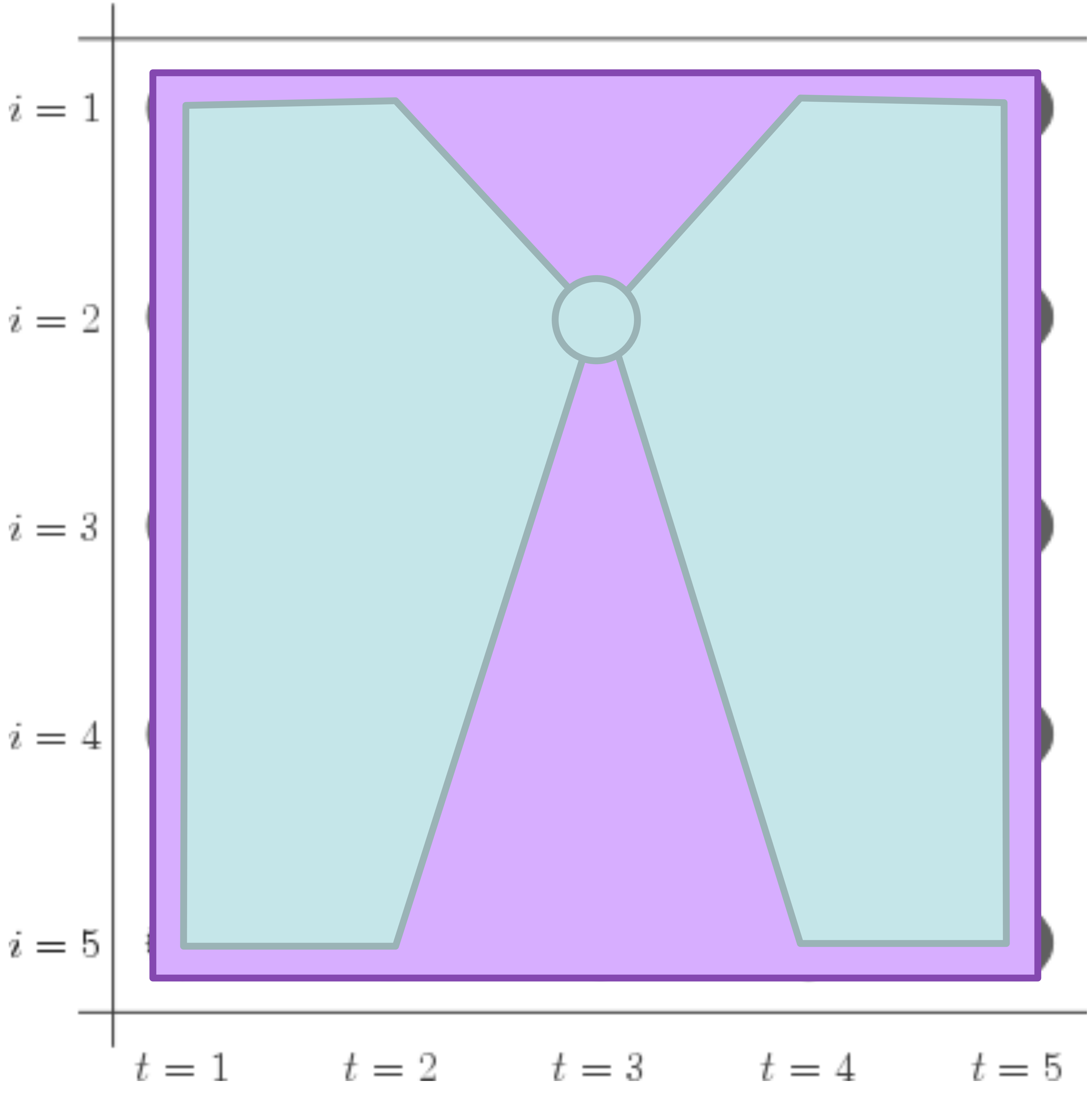

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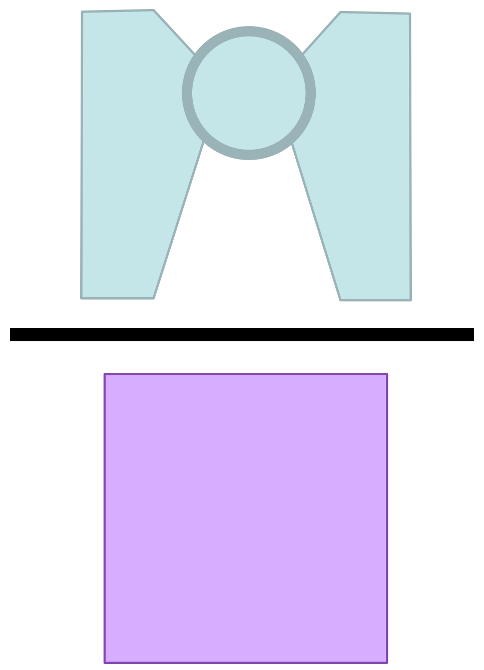
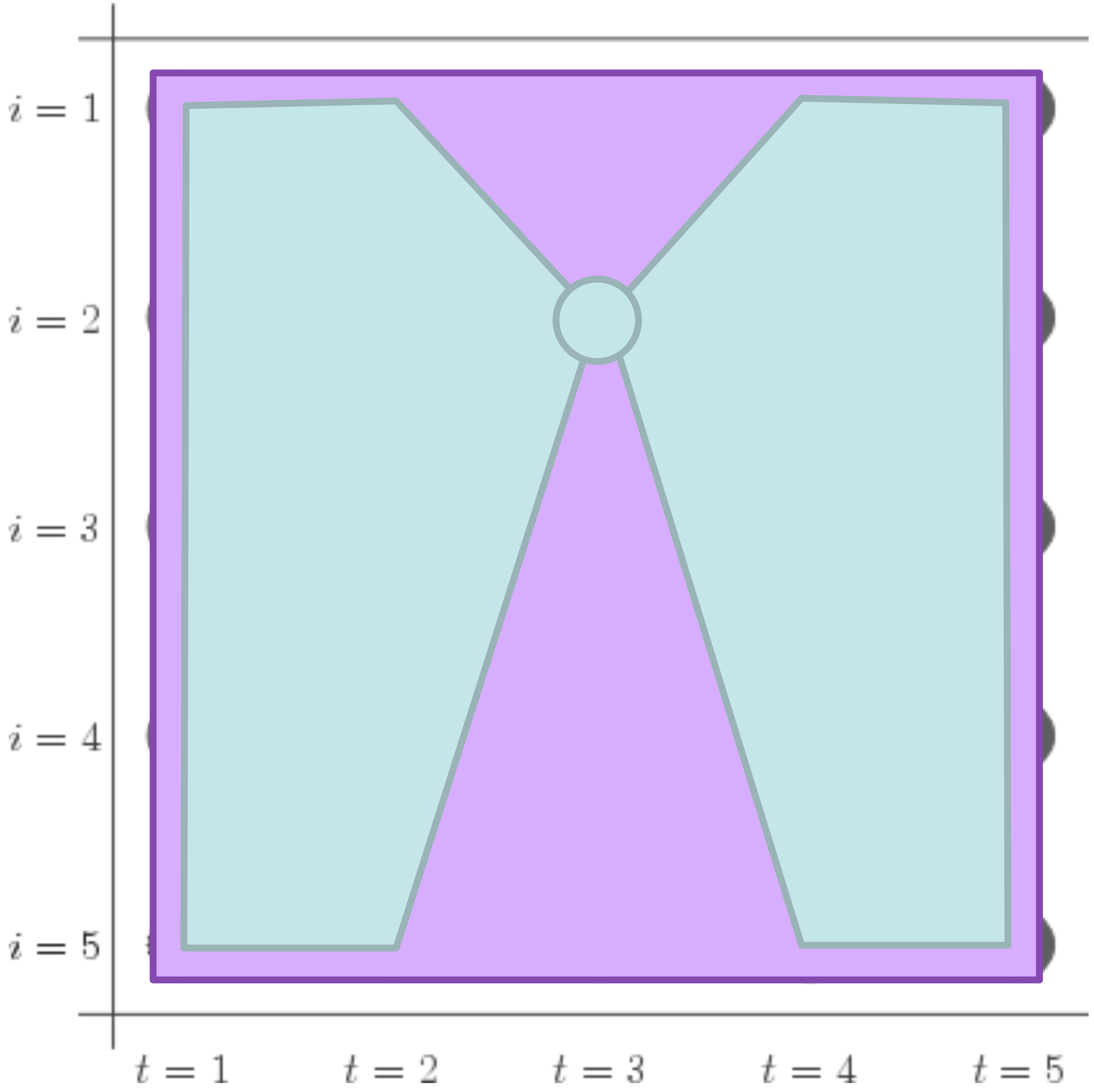
=



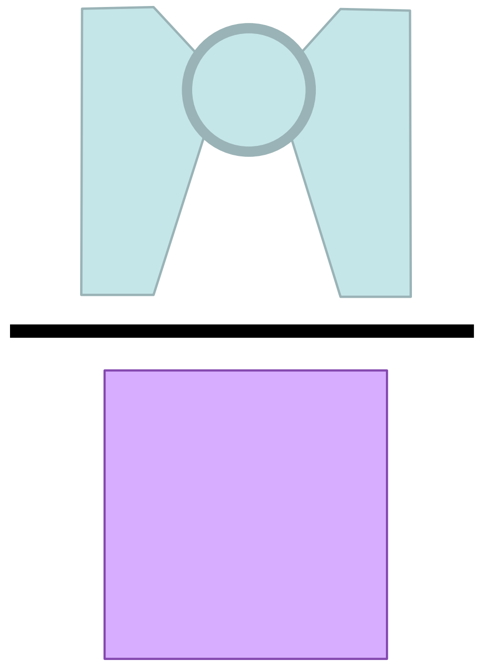
slide credit: Dan Klein

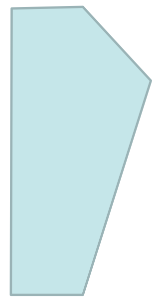
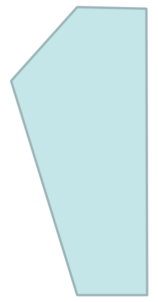
Forward-Backward Algorithm



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

=



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

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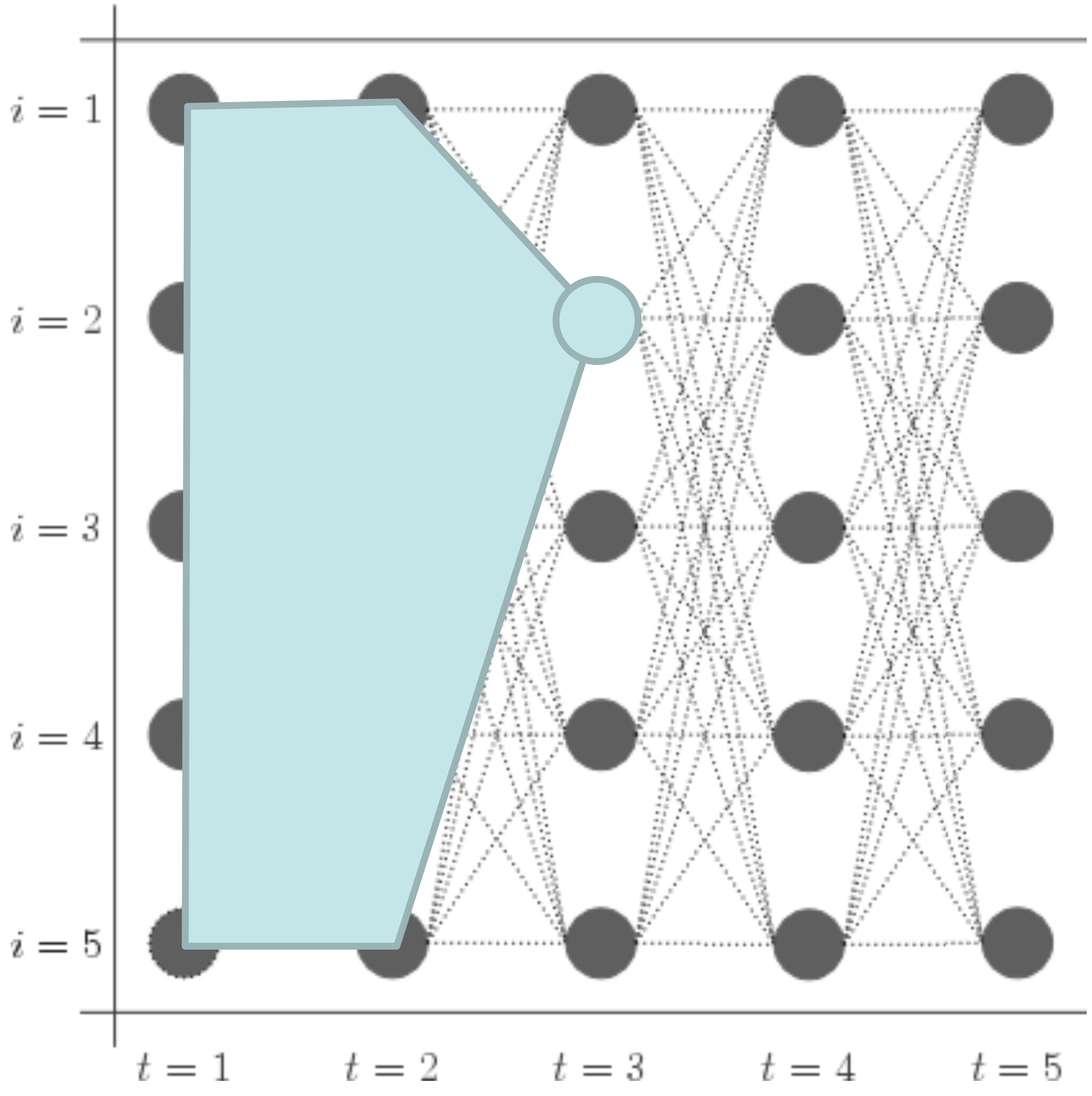

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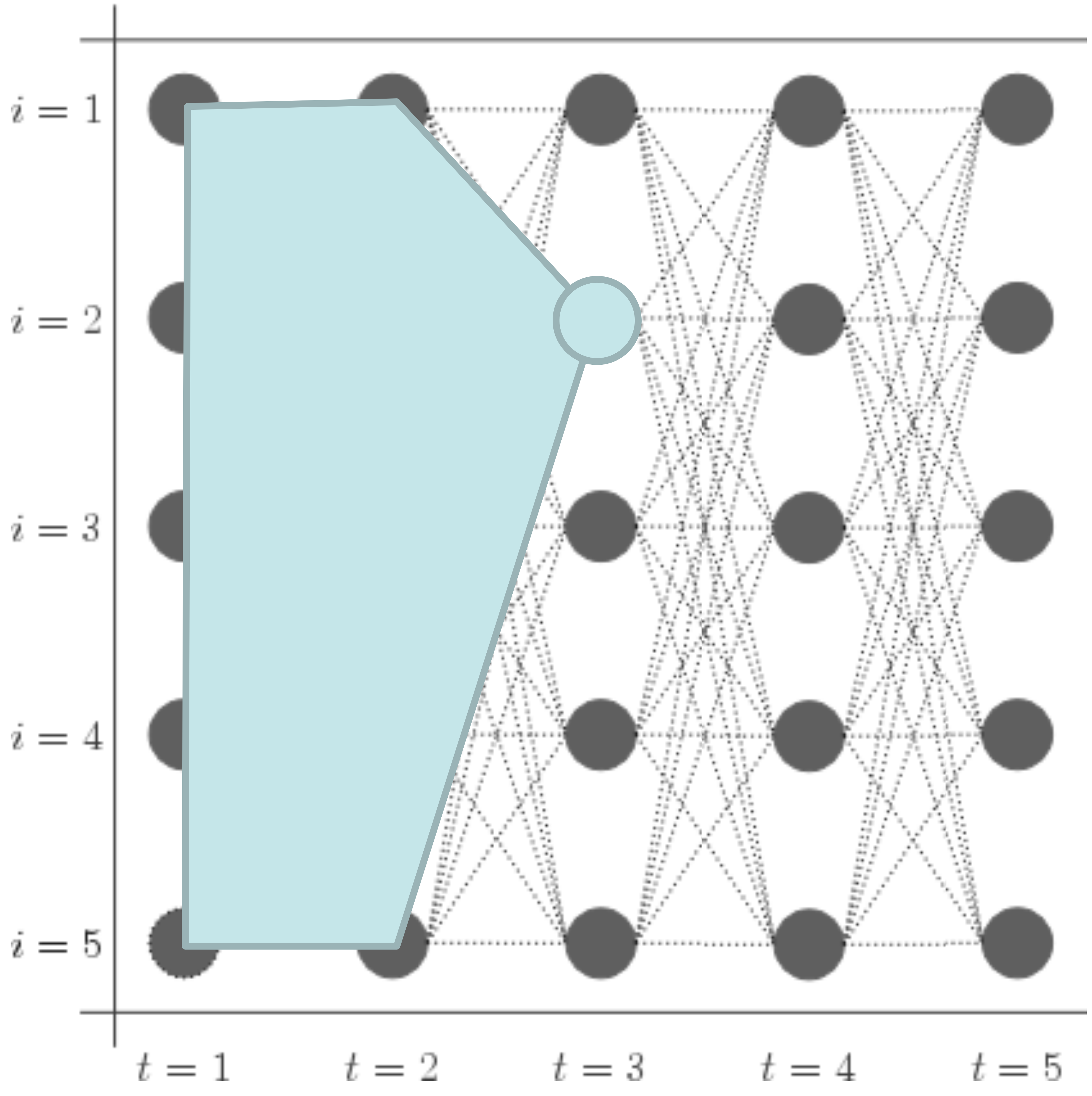

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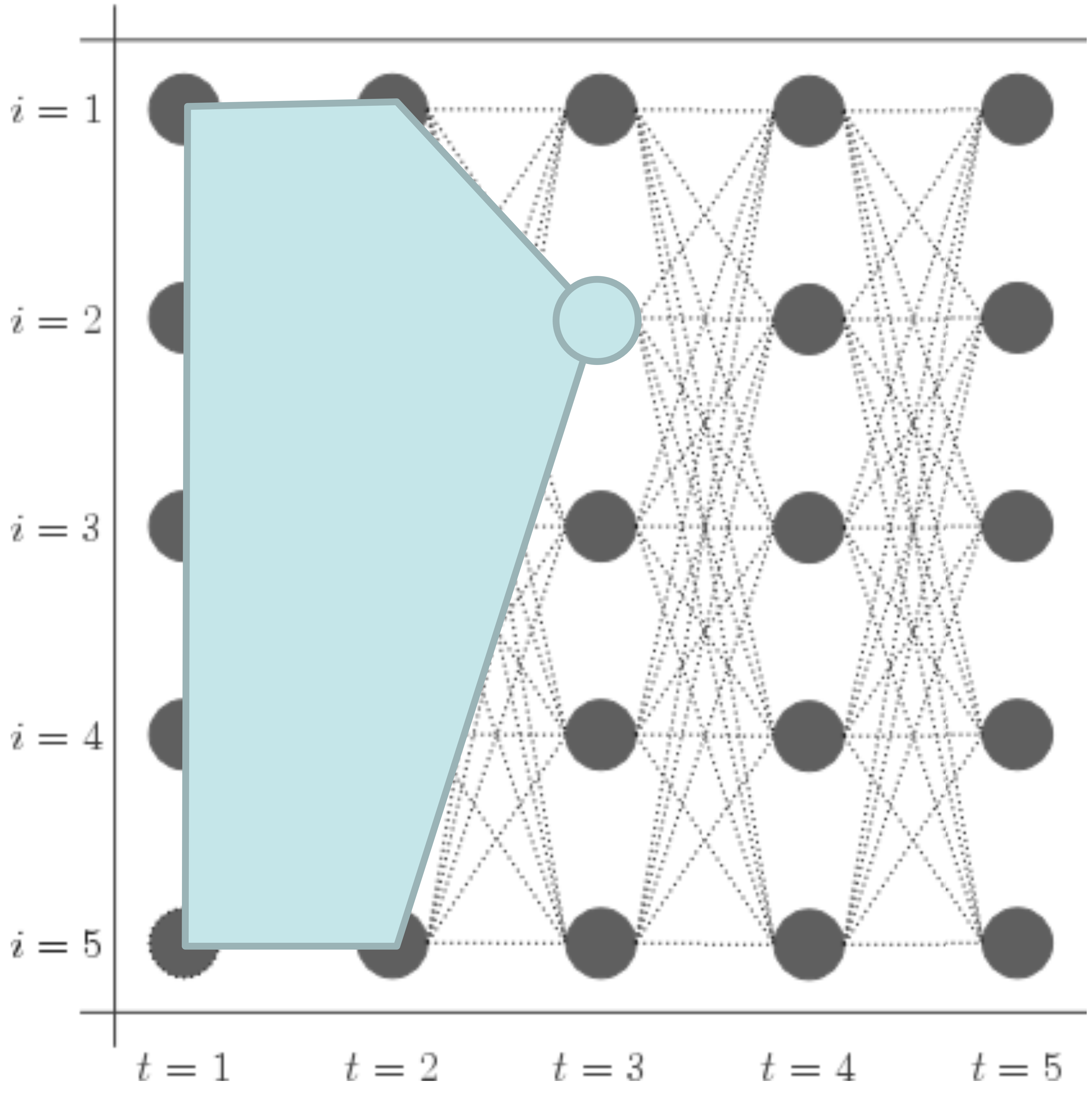
Forward-Backward Algorithm



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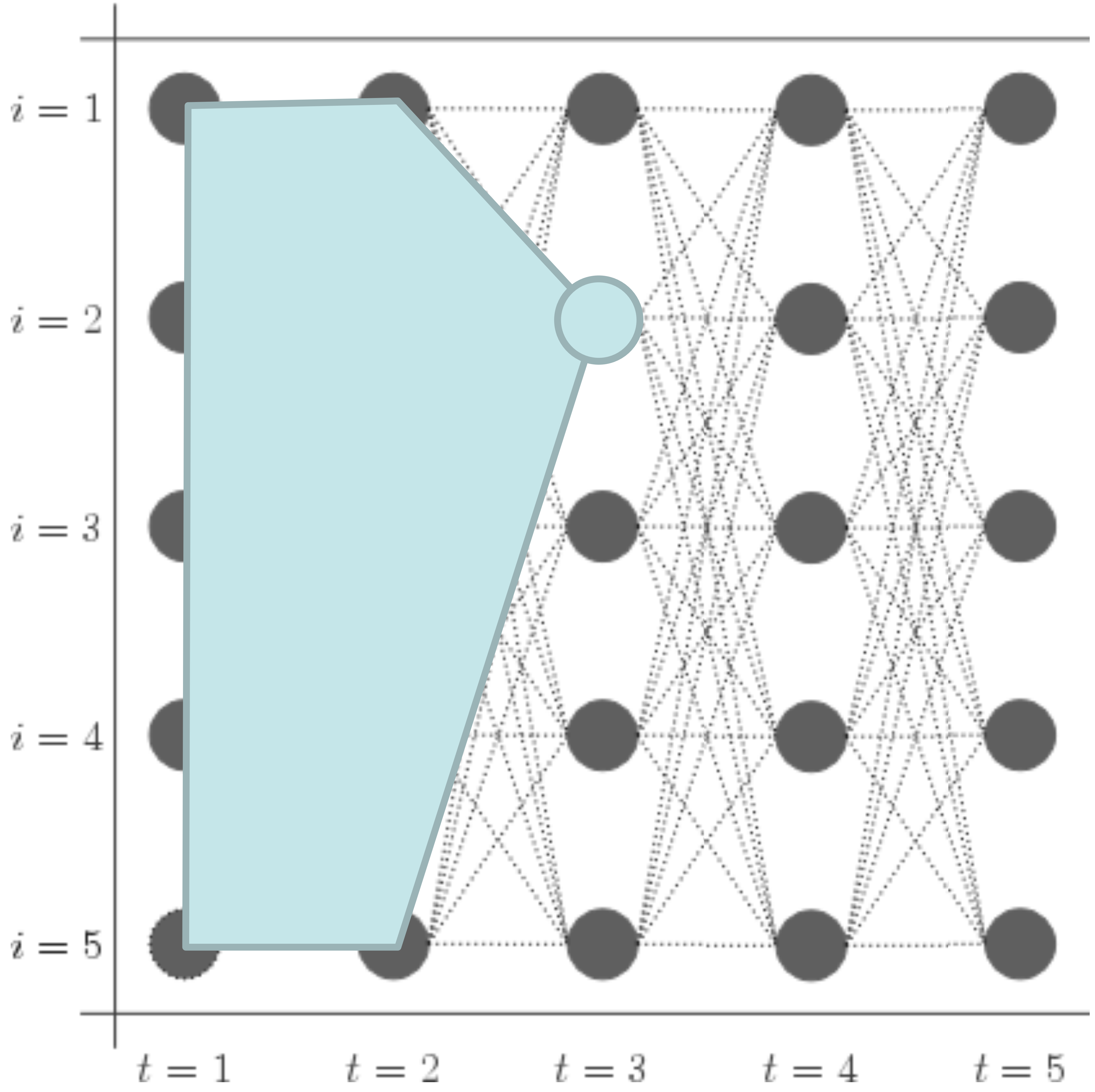
Forward-Backward Algorithm



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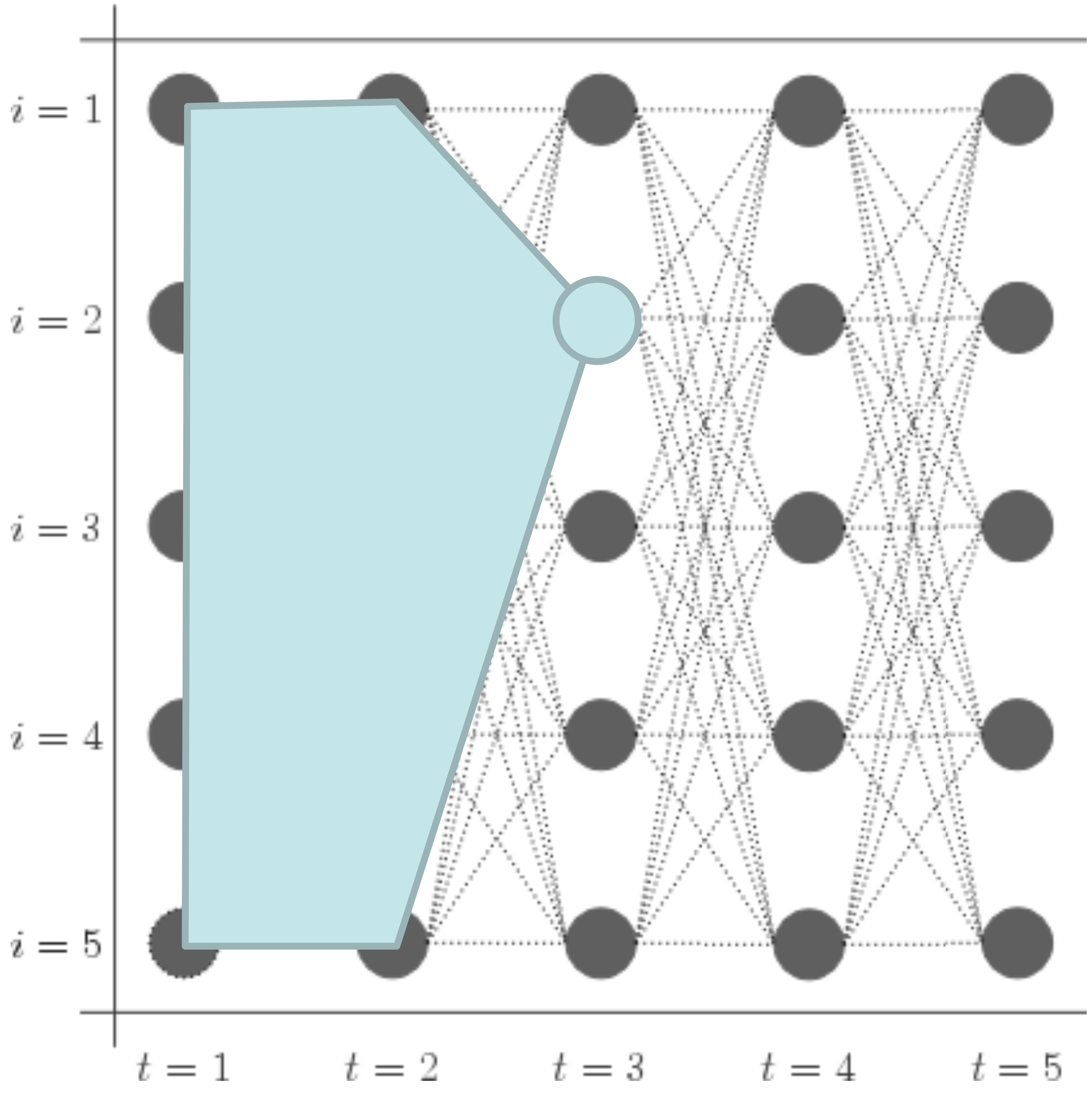
Forward-Backward Algorithm



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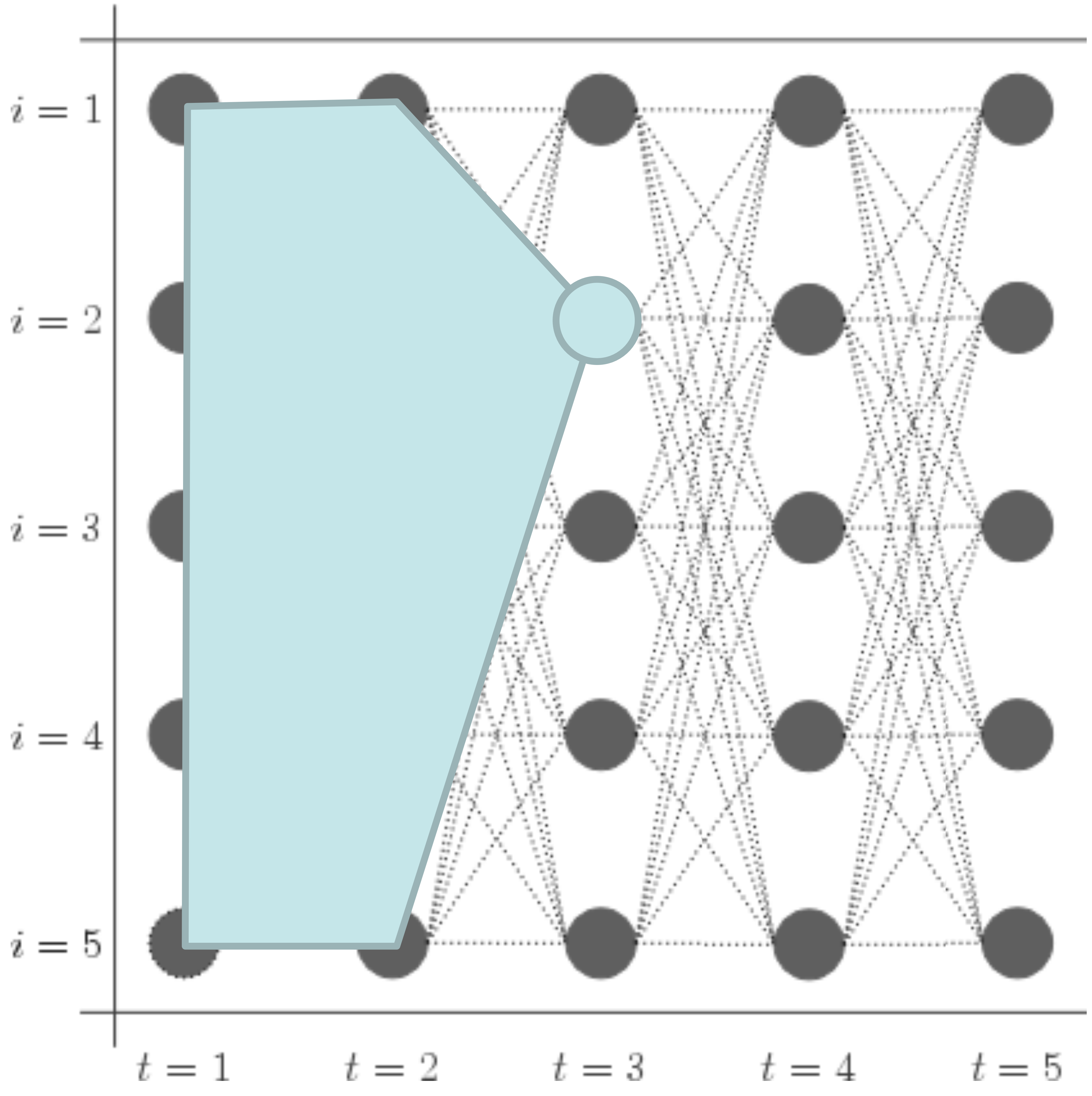

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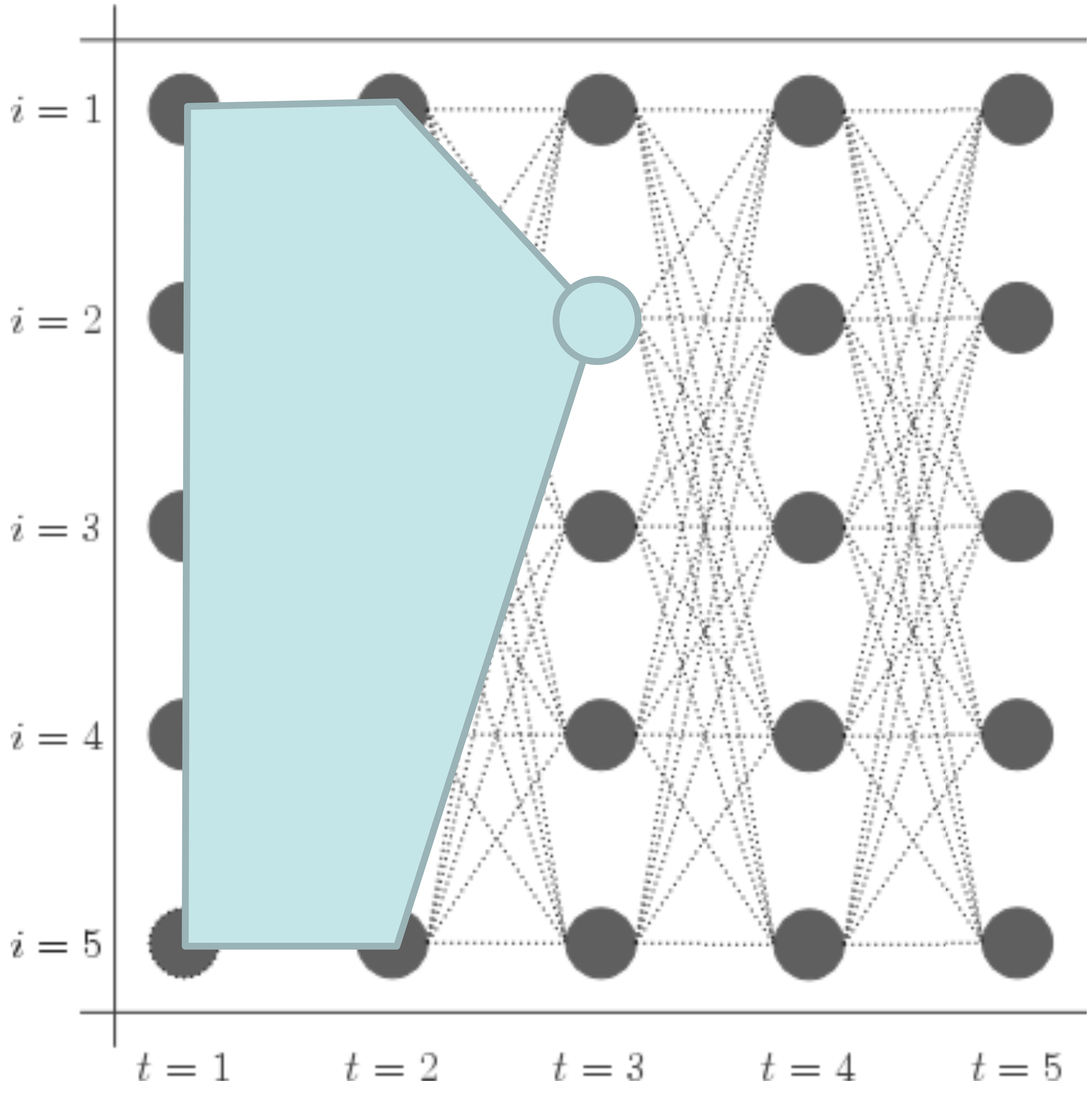

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- These quantities get very small! Store everything as log probabilities

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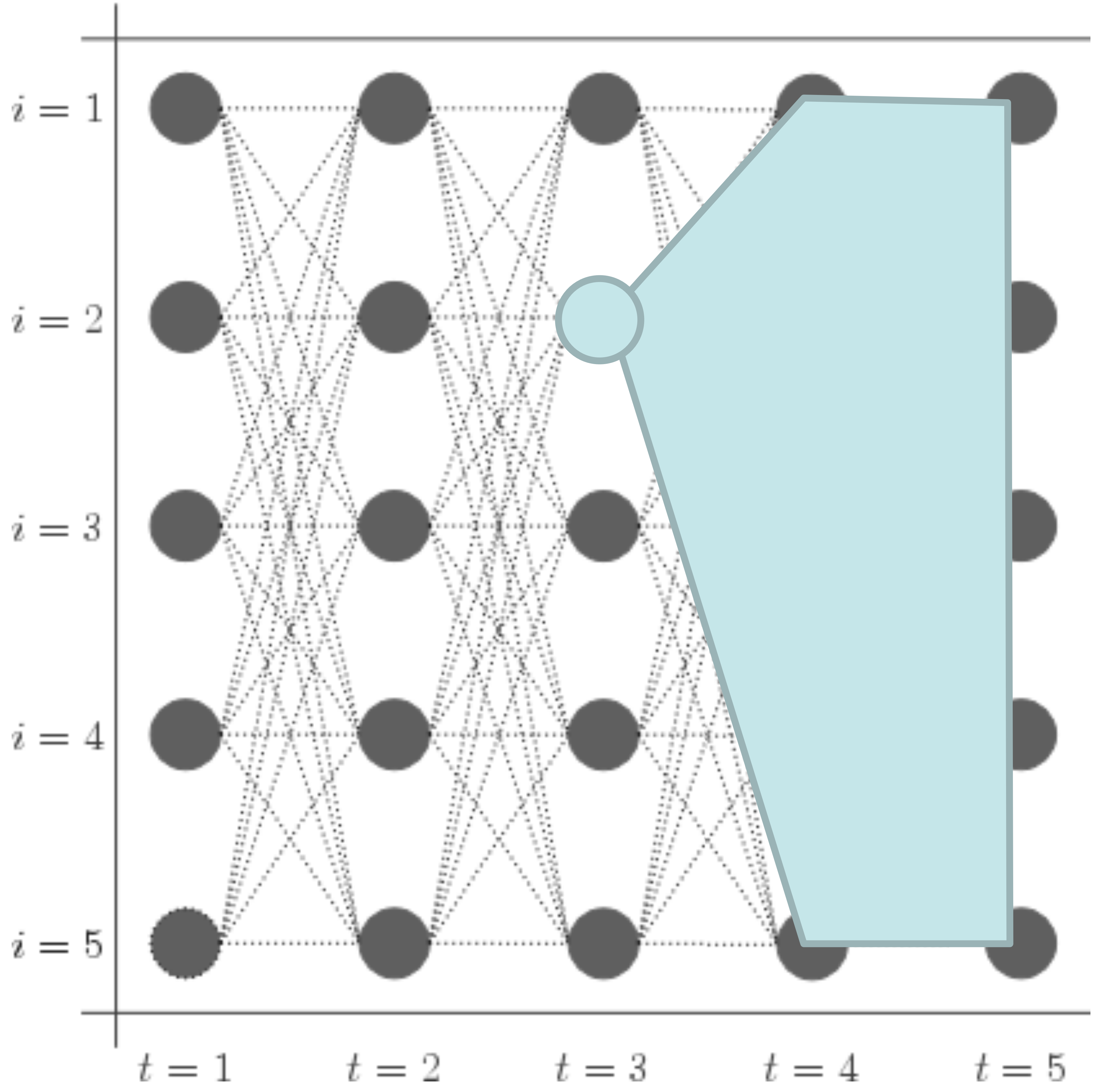

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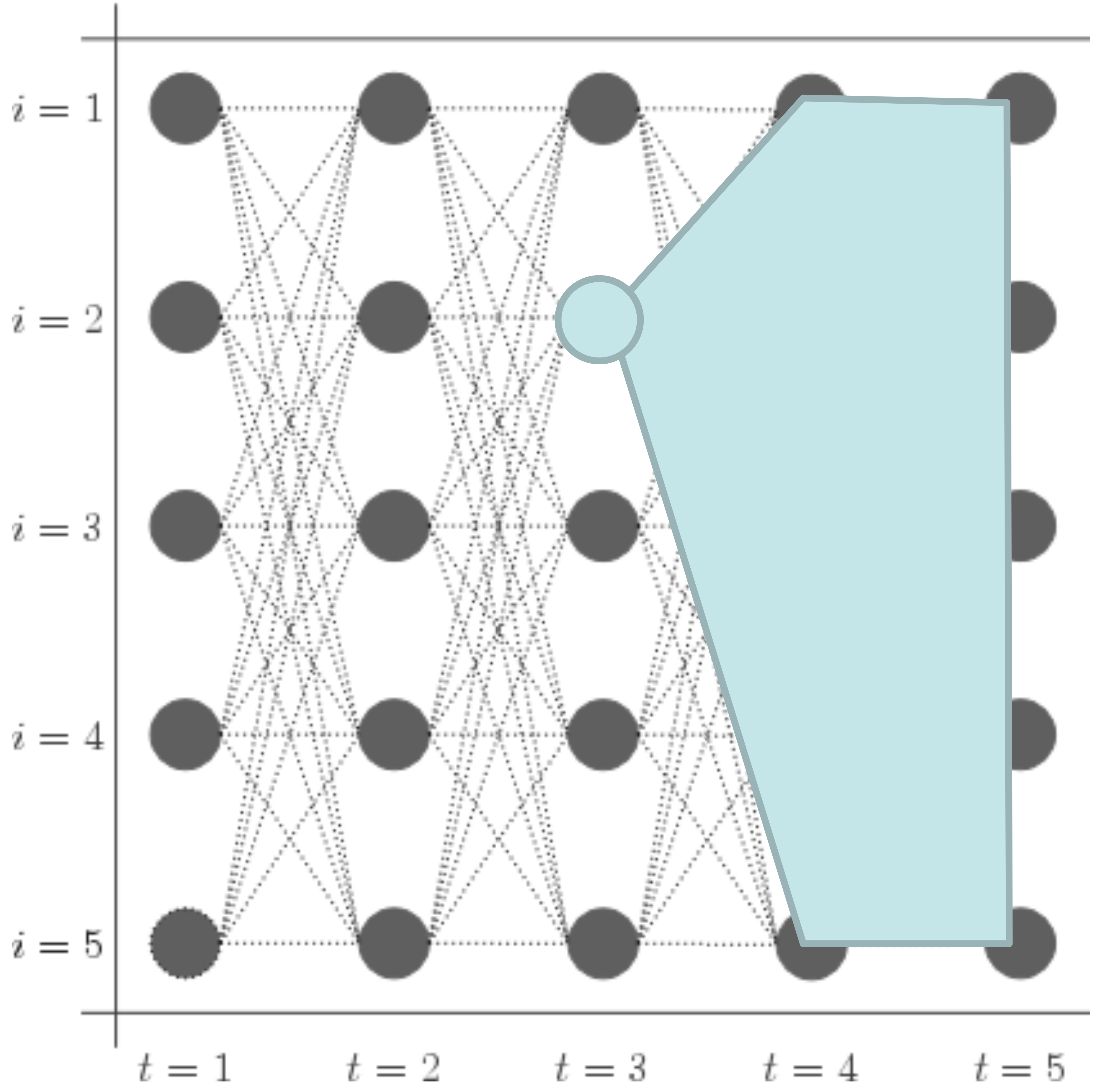

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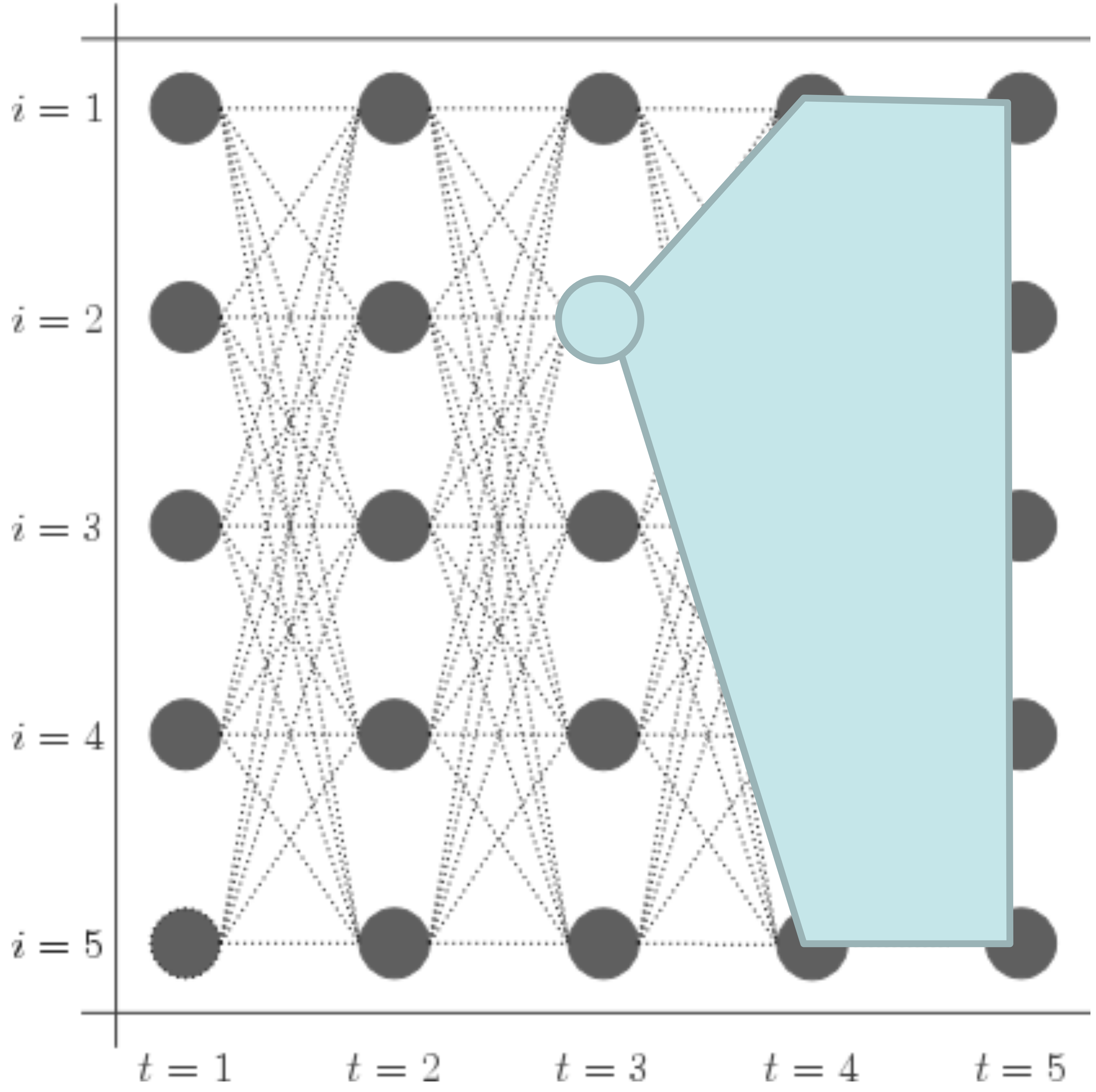

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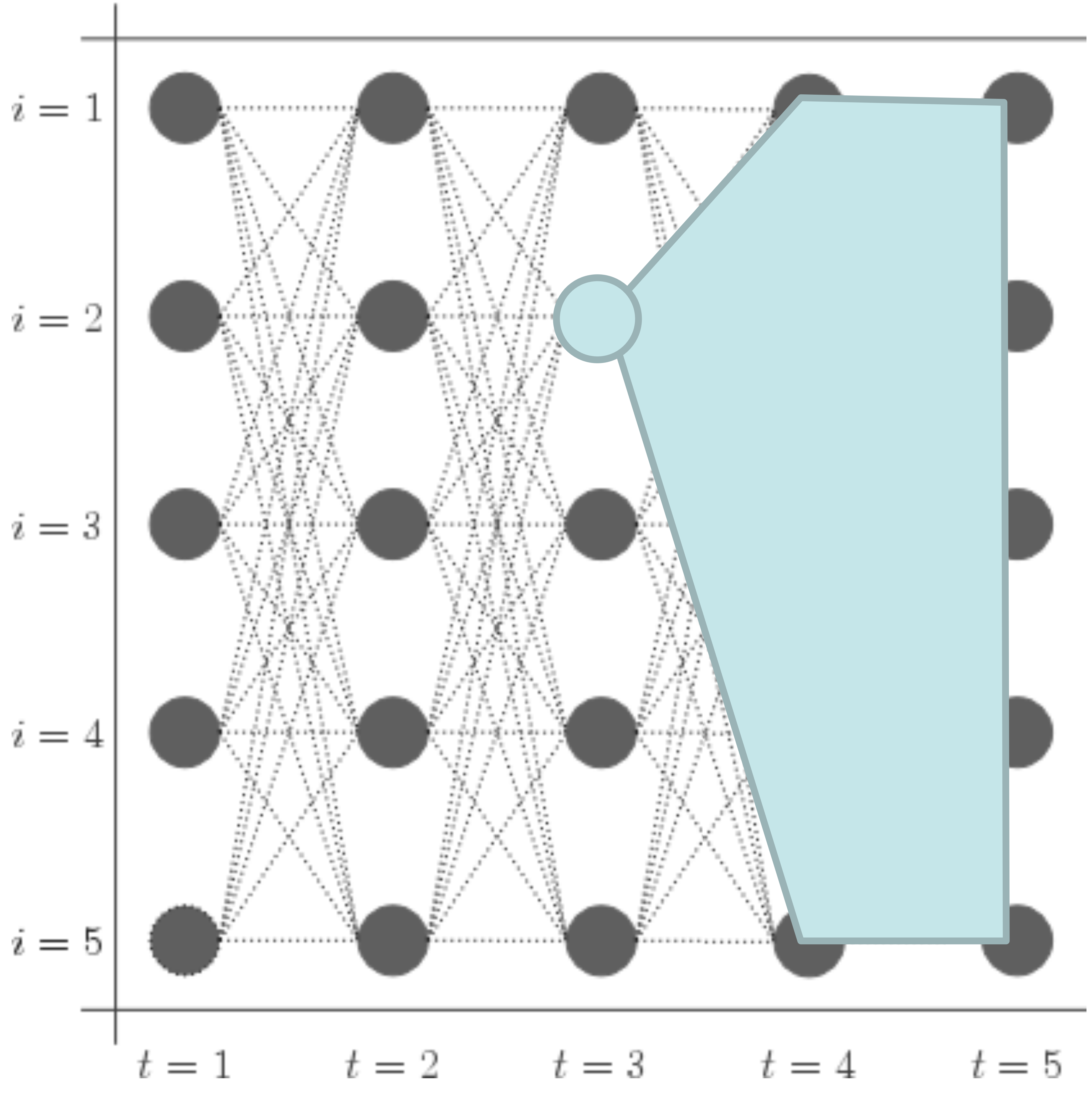
Forward-Backward Algorithm



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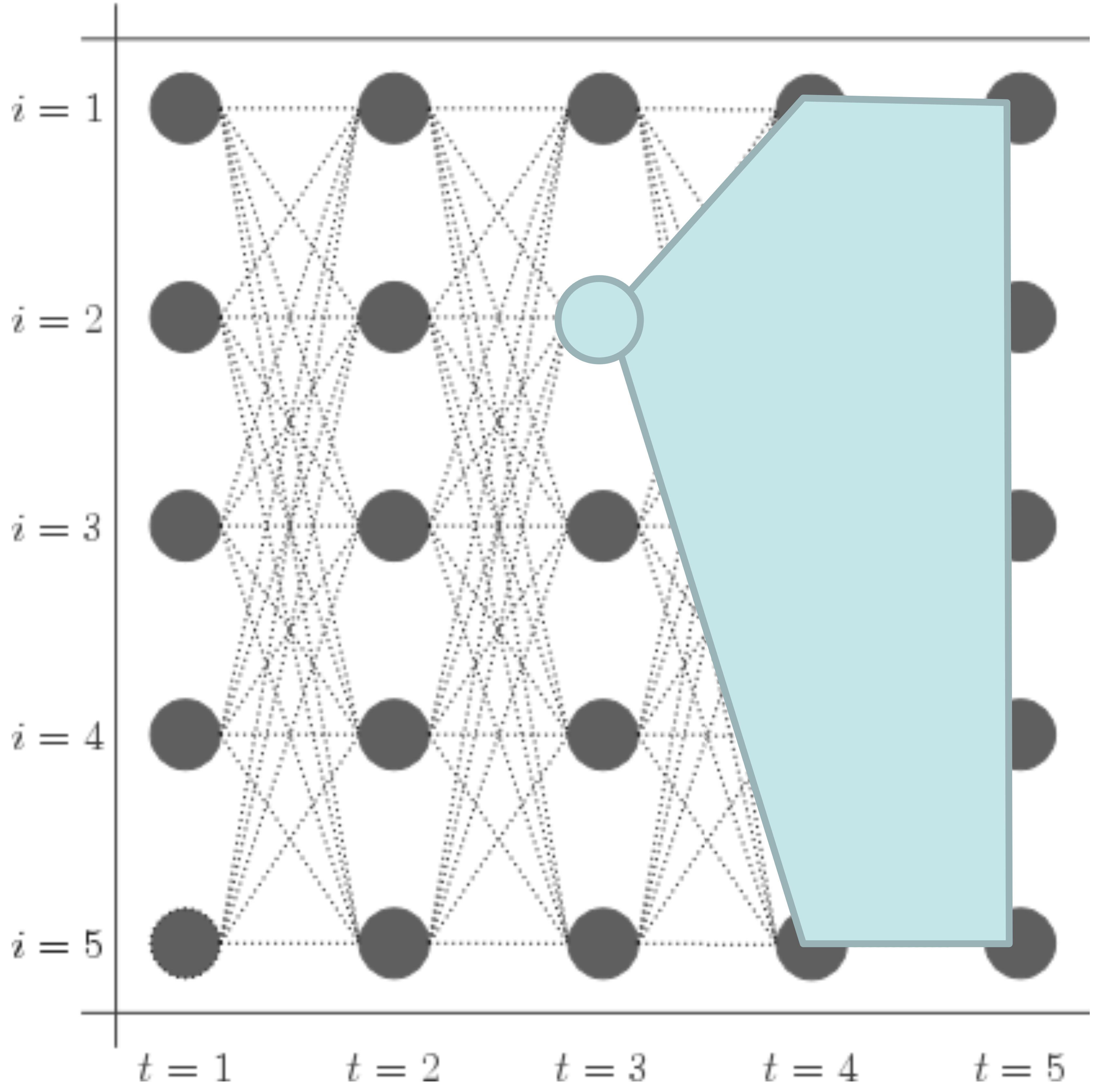

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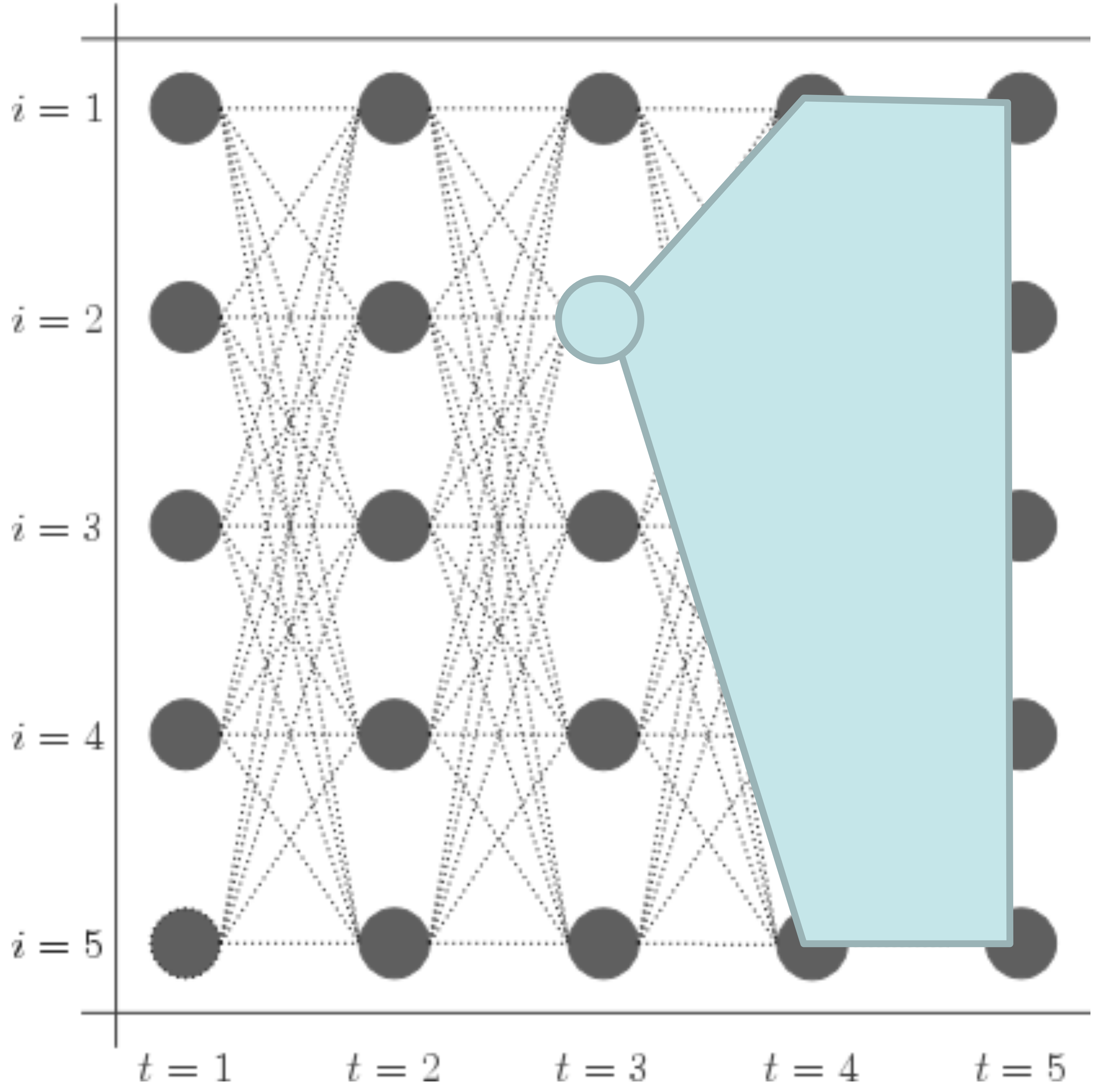

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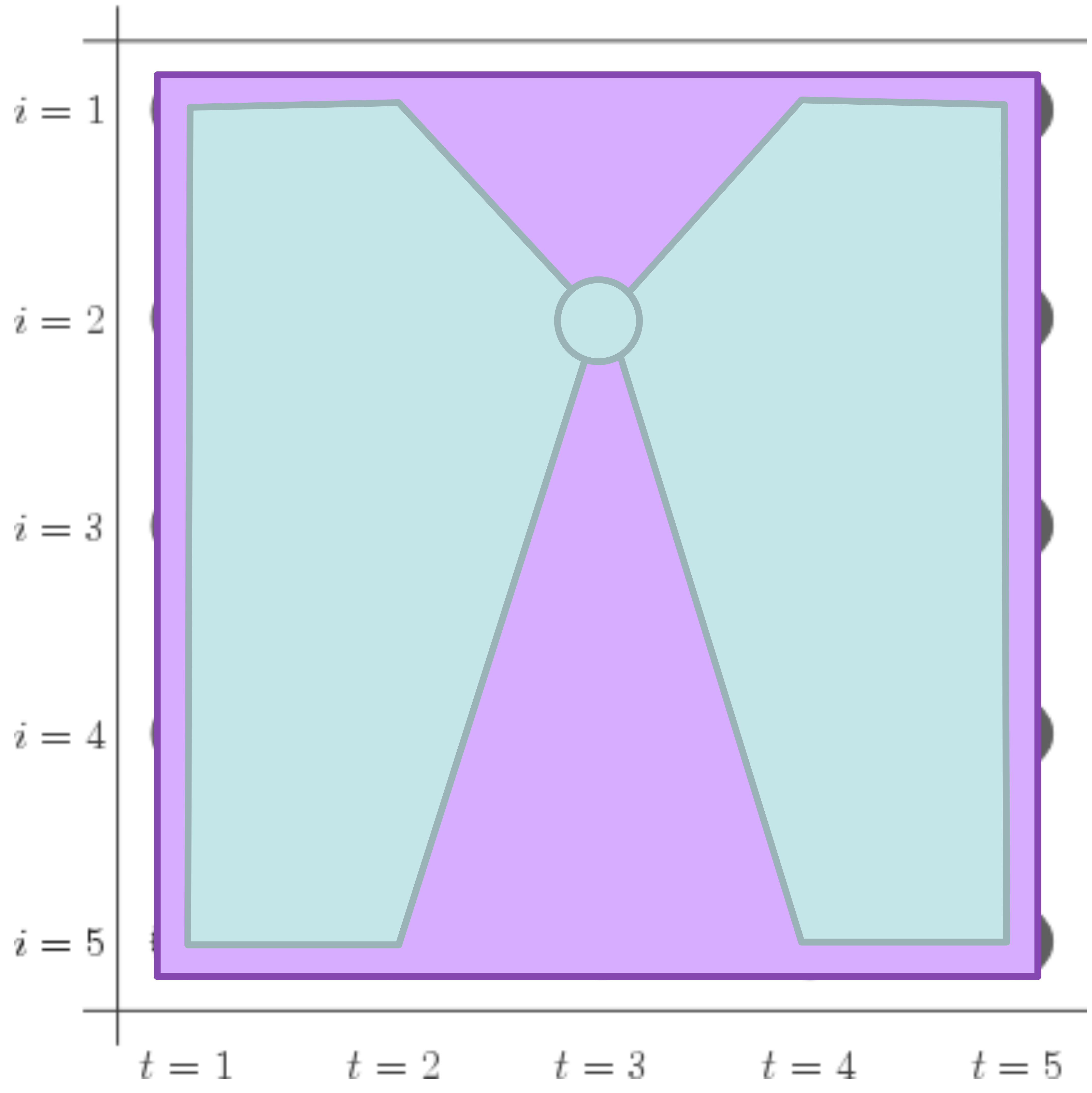

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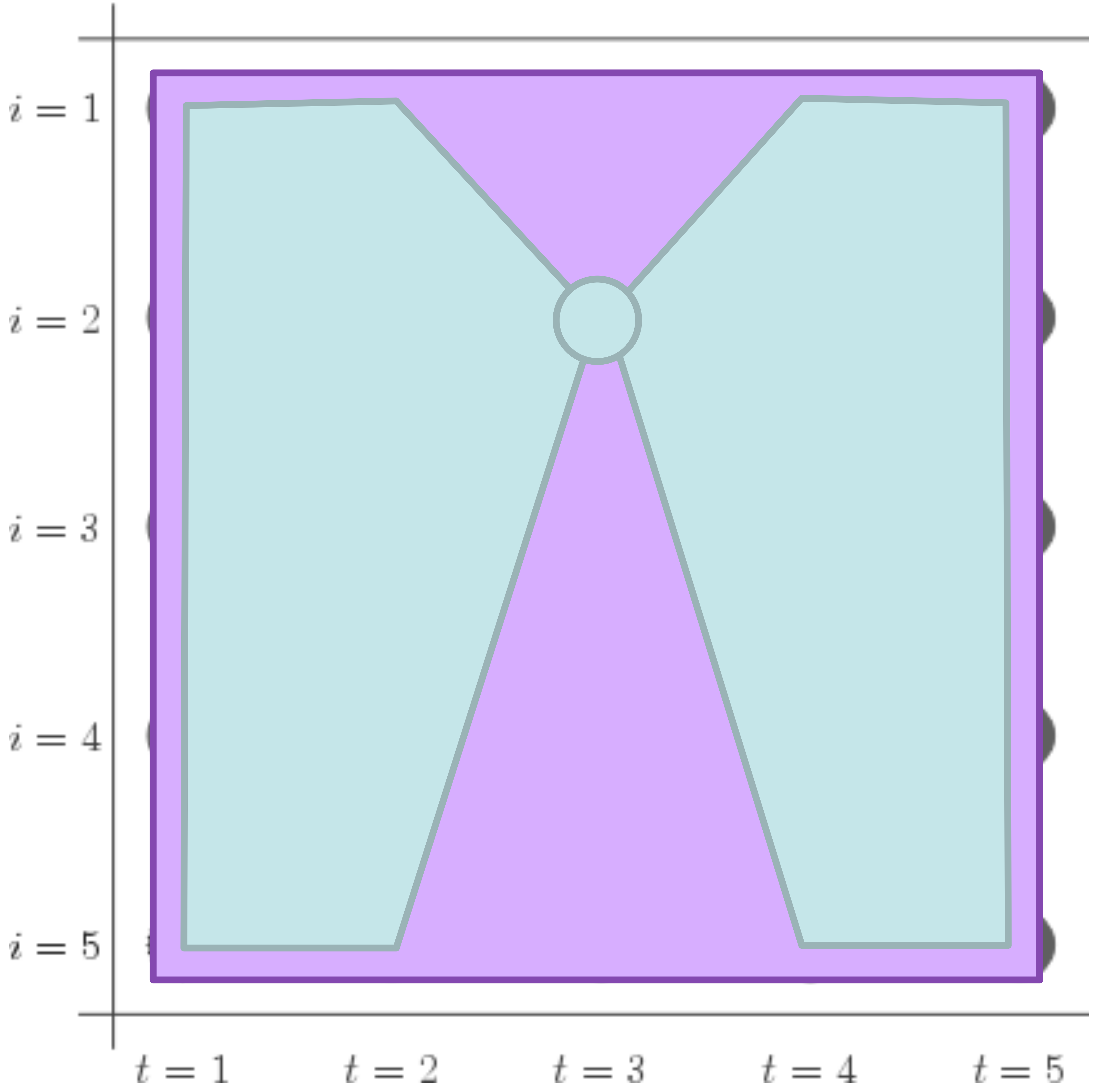

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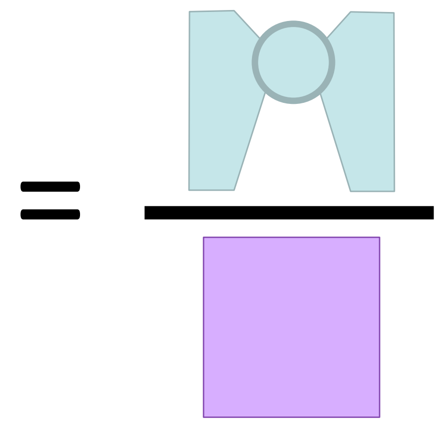

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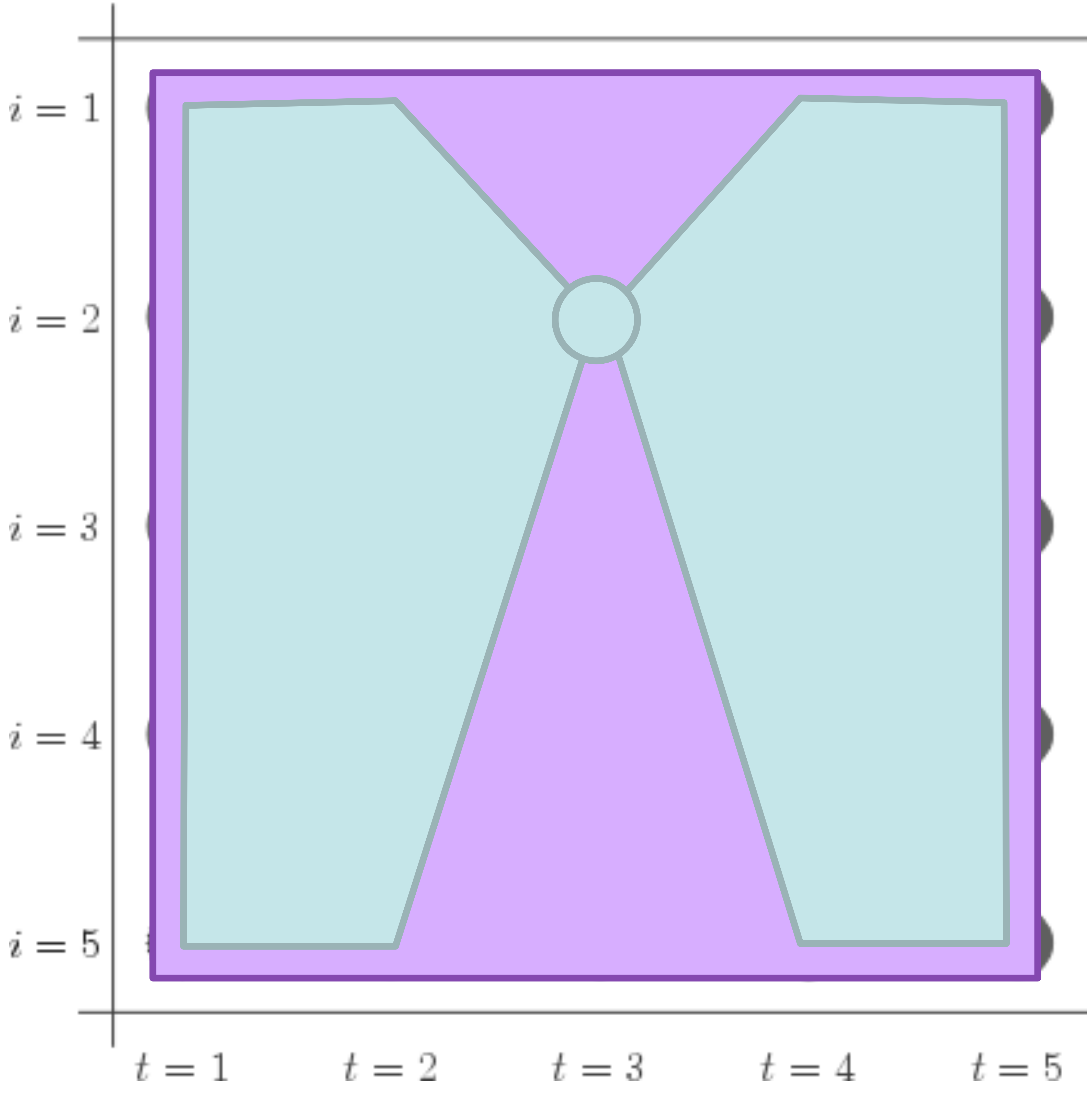

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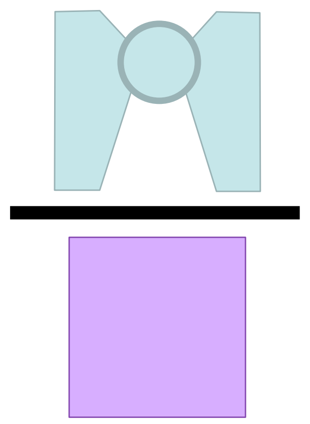

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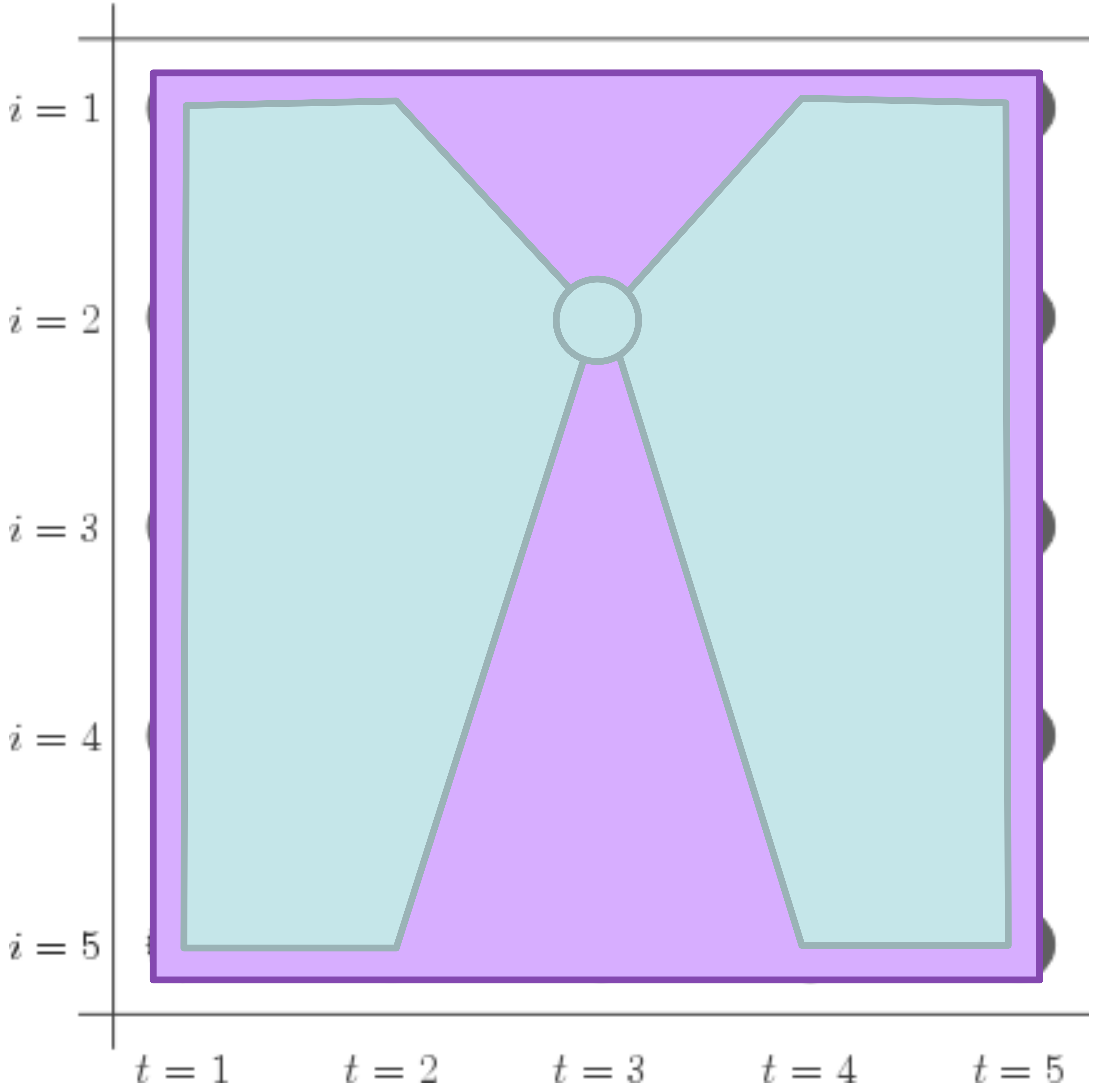

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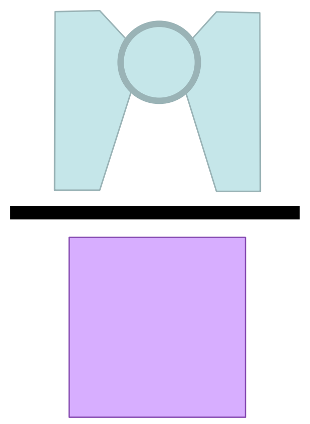

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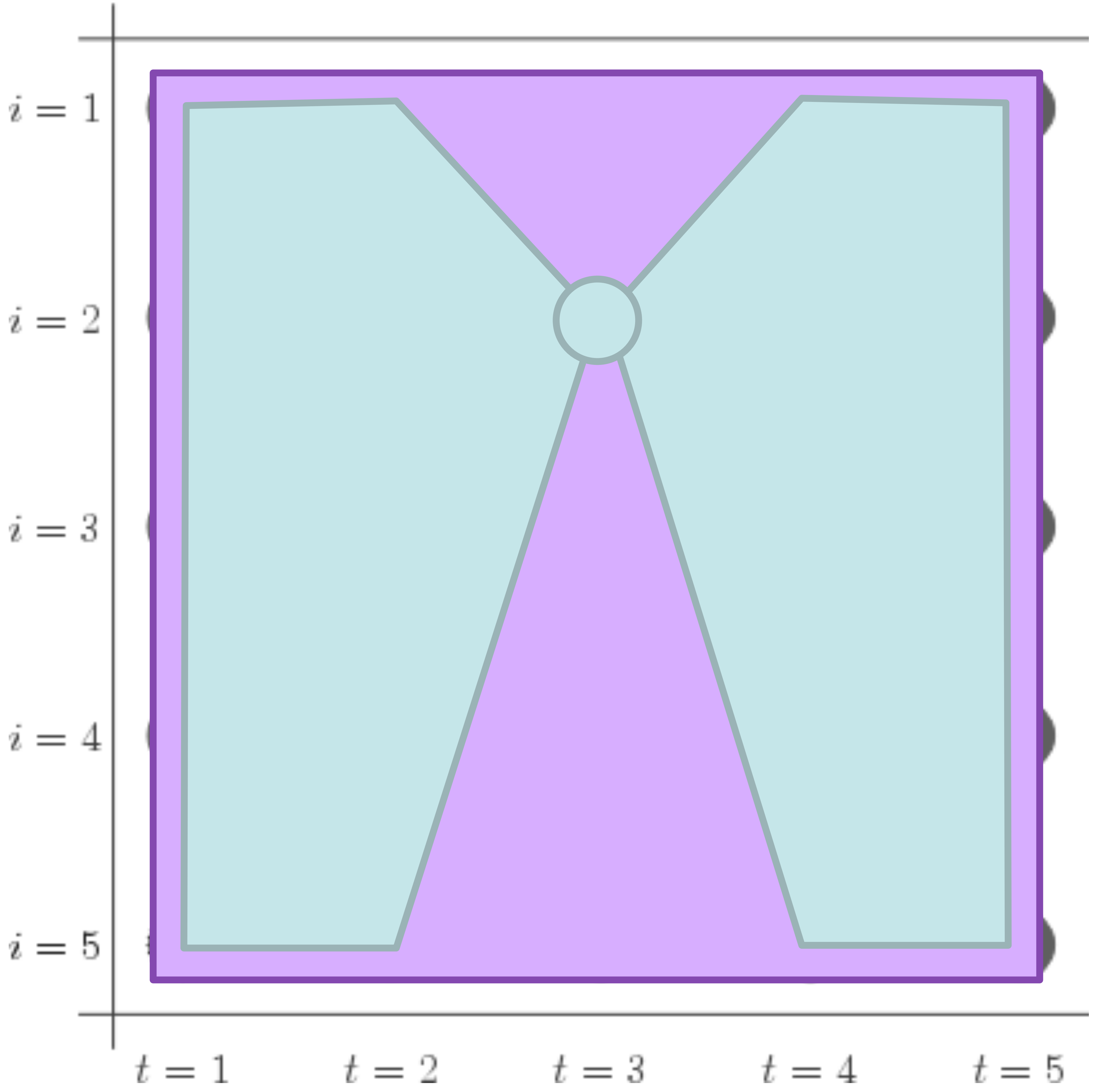
Forward-Backward Algorithm



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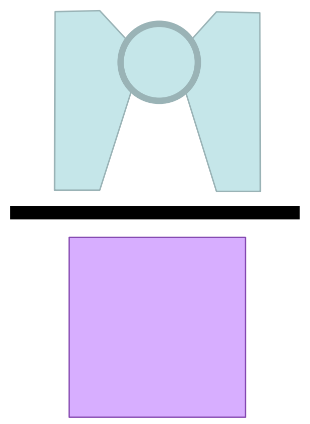

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HMM POS Tagging

Slide credit: Dan Klein

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

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Trigram Taggers

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

HMM 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
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
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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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Remaining Errors

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

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adjective or verbal participle? JJ / VBN?

a $ 10 million fourth-quarter charge against discontinued operations

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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

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Next Time

Next Time

- CRFs: feature-based discriminative models

Next Time

- CRFs: feature-based discriminative models

- Structured SVM for sequences

Next Time

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