Lecture 17: Unsupervised Learning

Alan Ritter

(many slides from Greg Durrett)

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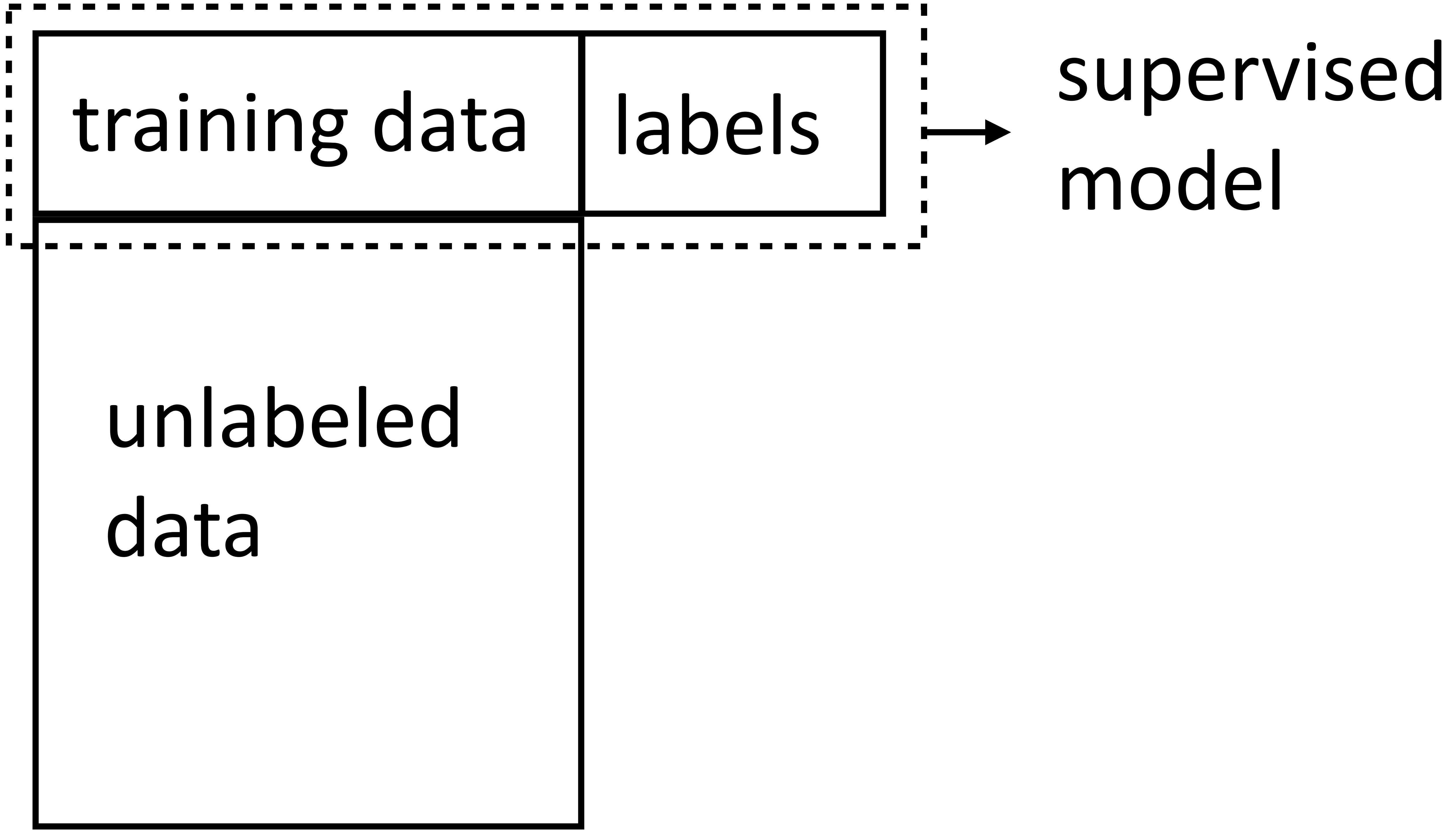

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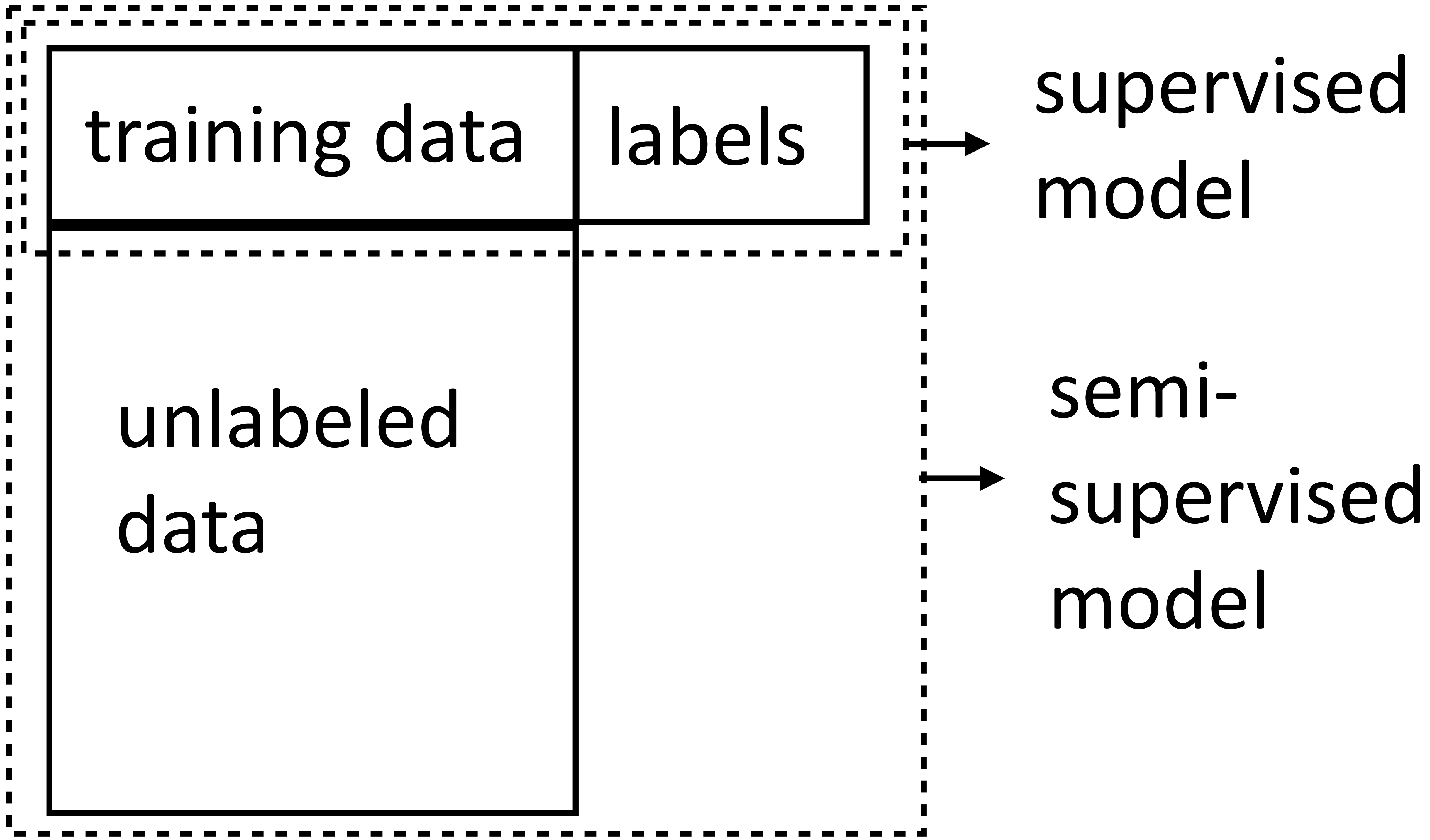

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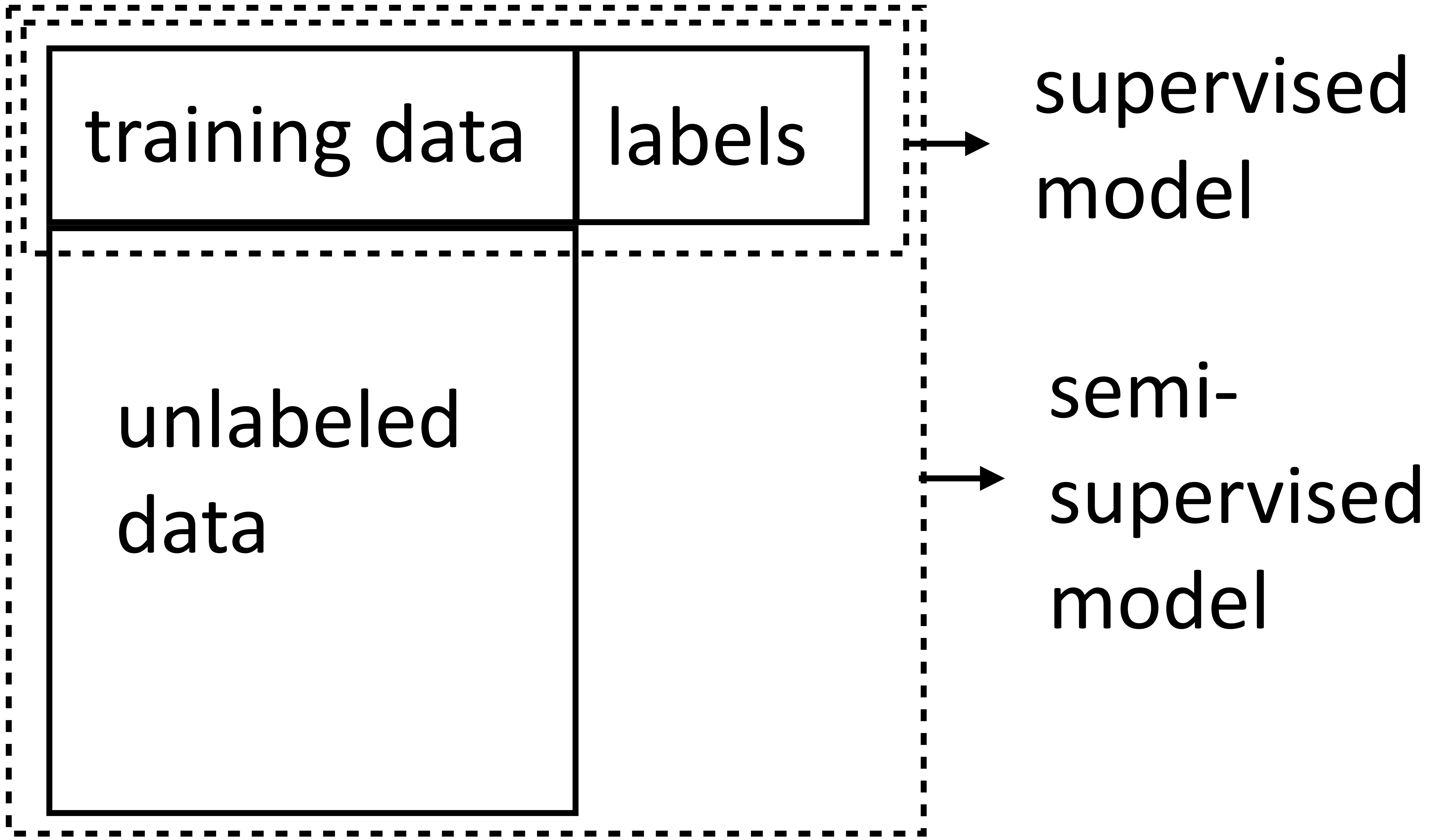

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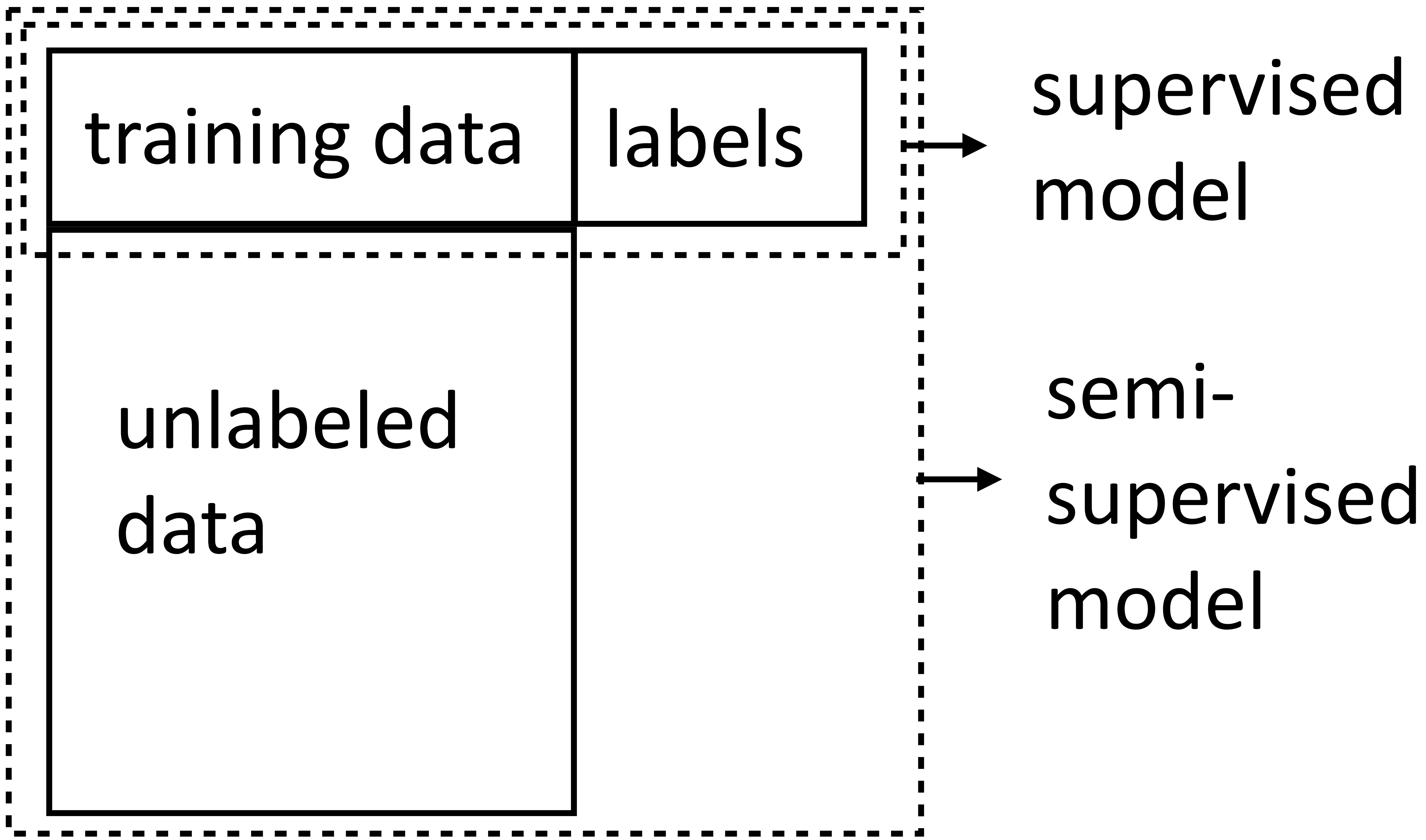

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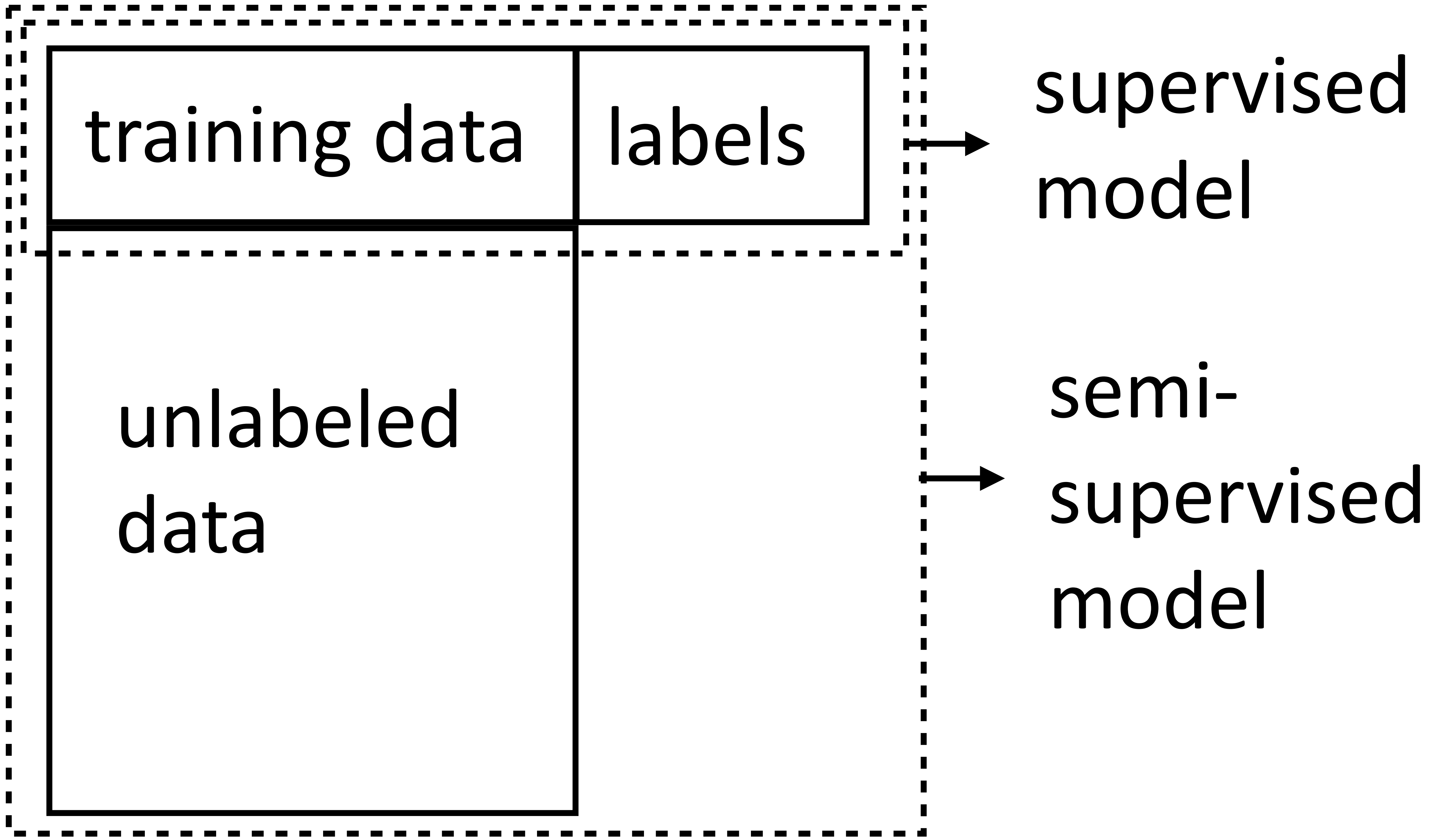

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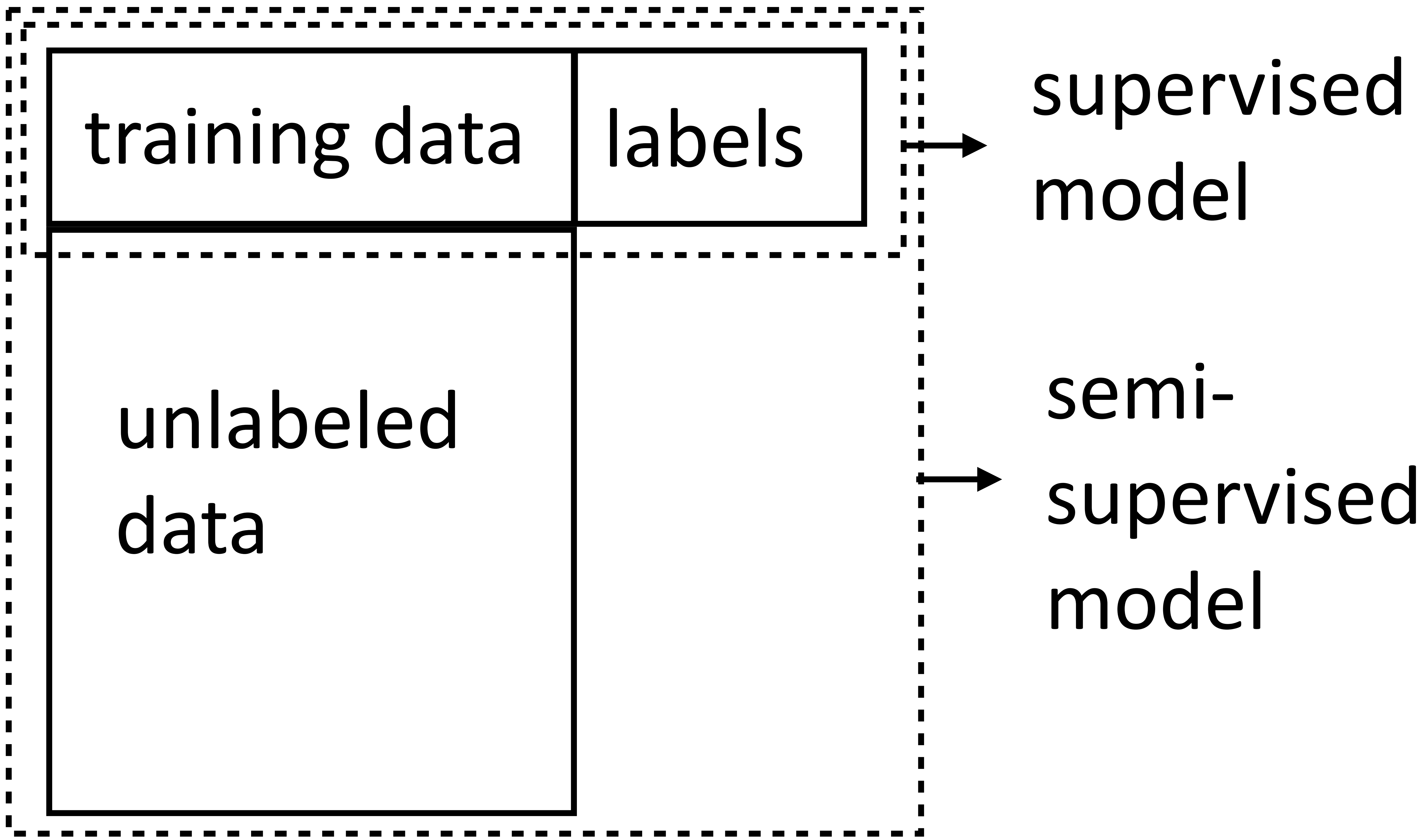
  - Learn linguistic structure from unlabeled data and use it?



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  - Expectation maximization for learning HMMs
- Continuous structure with generative models: variational autoencoders
- Continuous structure with “discriminative” models: transfer learning

EM for HMMs

Recall: Hidden Markov Models

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

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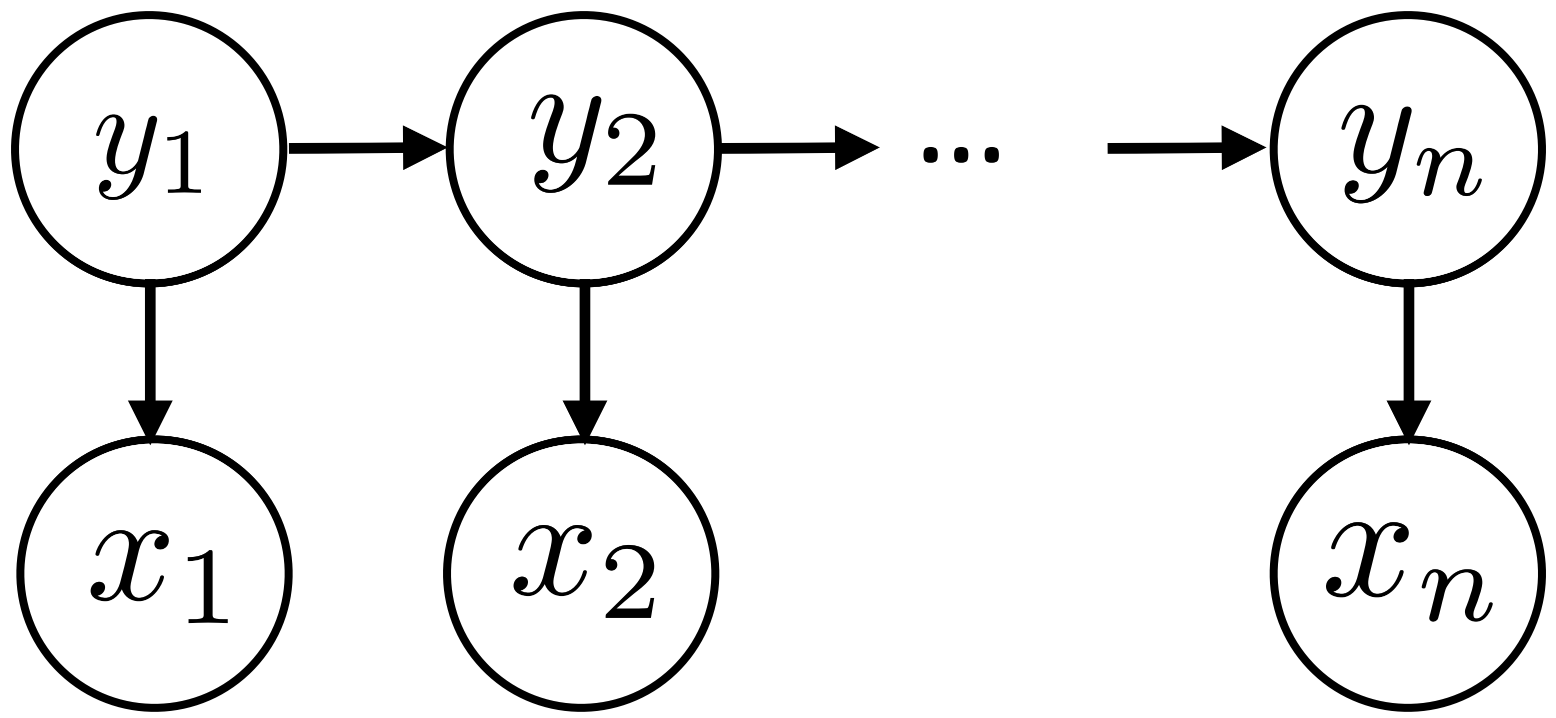

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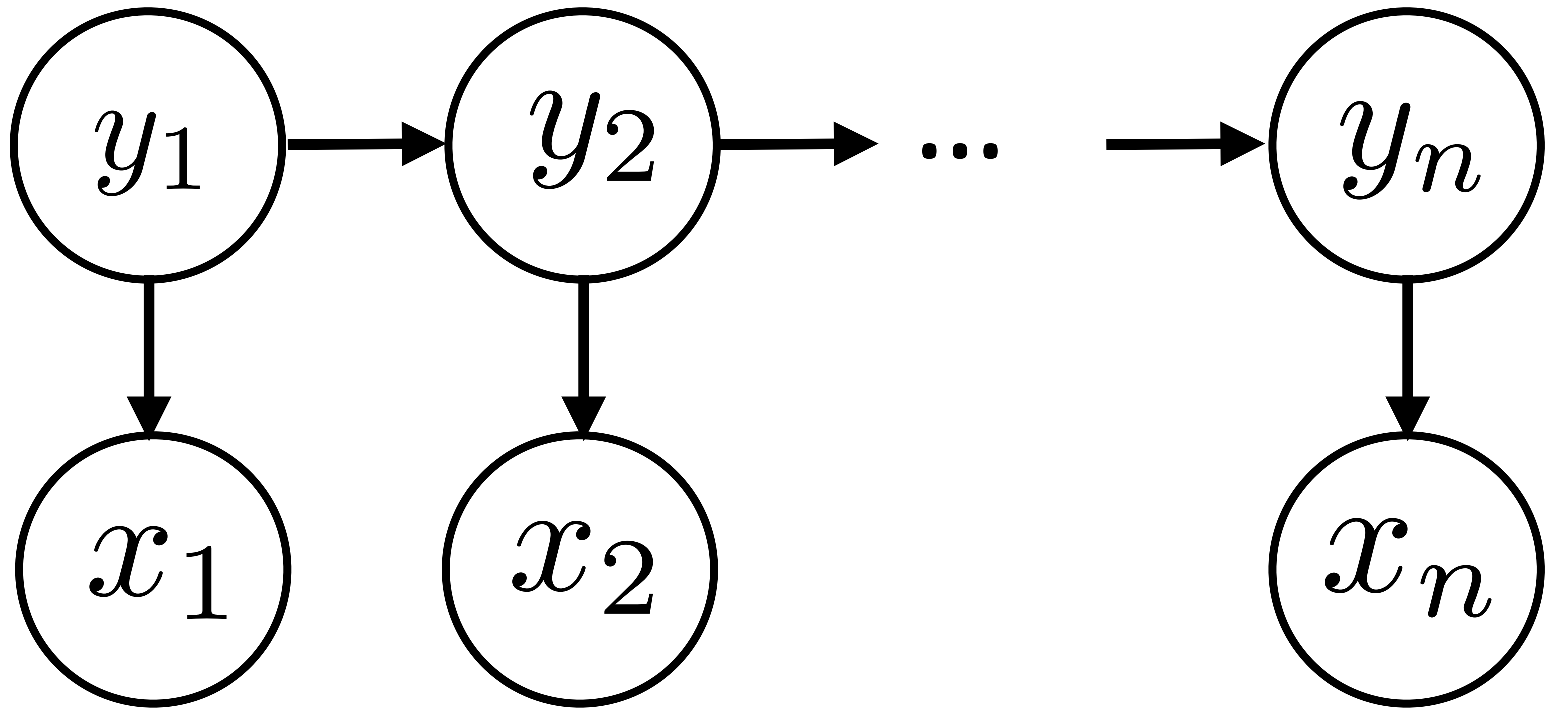

$$P(\mathbf{y}, \mathbf{x}) = P(y_1) \prod_{i=2}^{n} P(y_i | y_{i-1}) \prod_{i=1}^{n} P(x_i | y_i)$$

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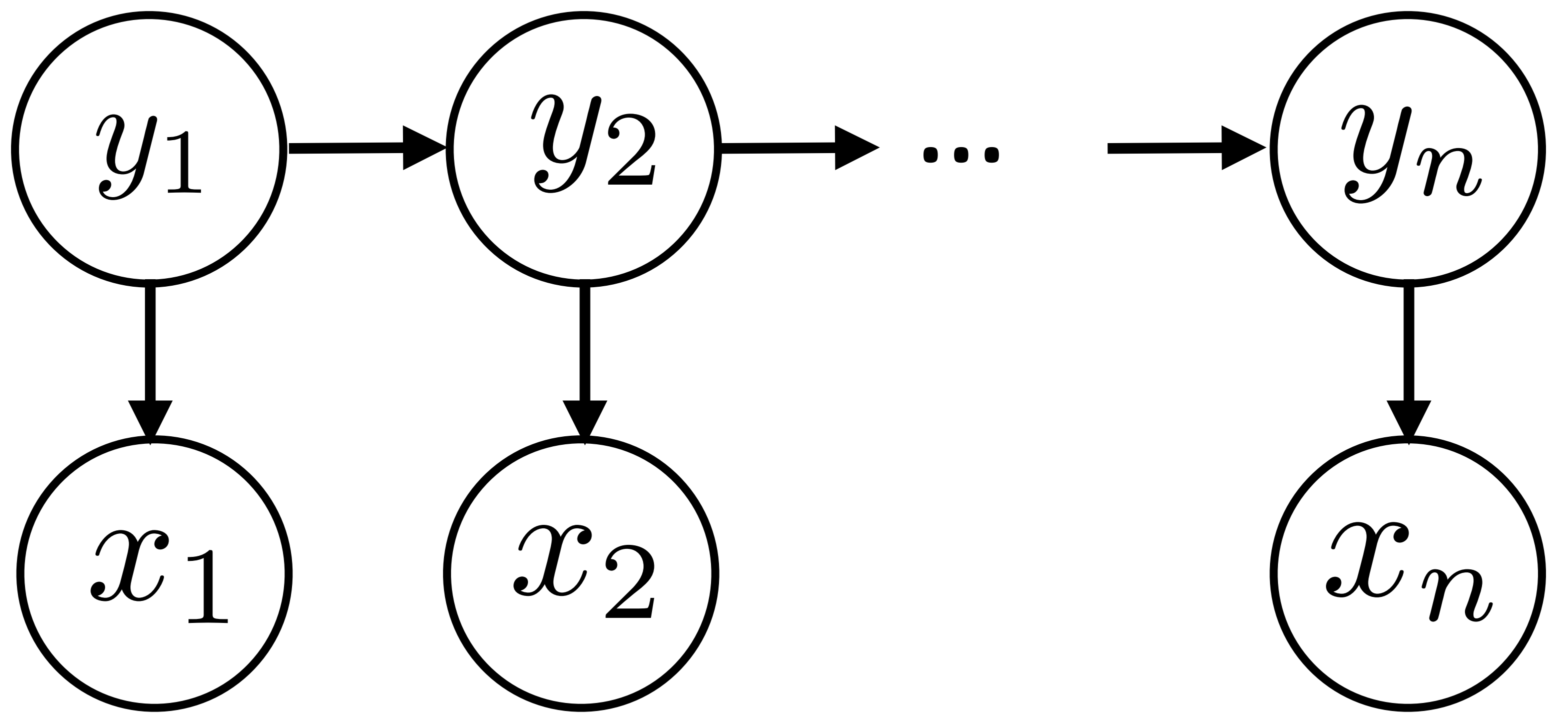

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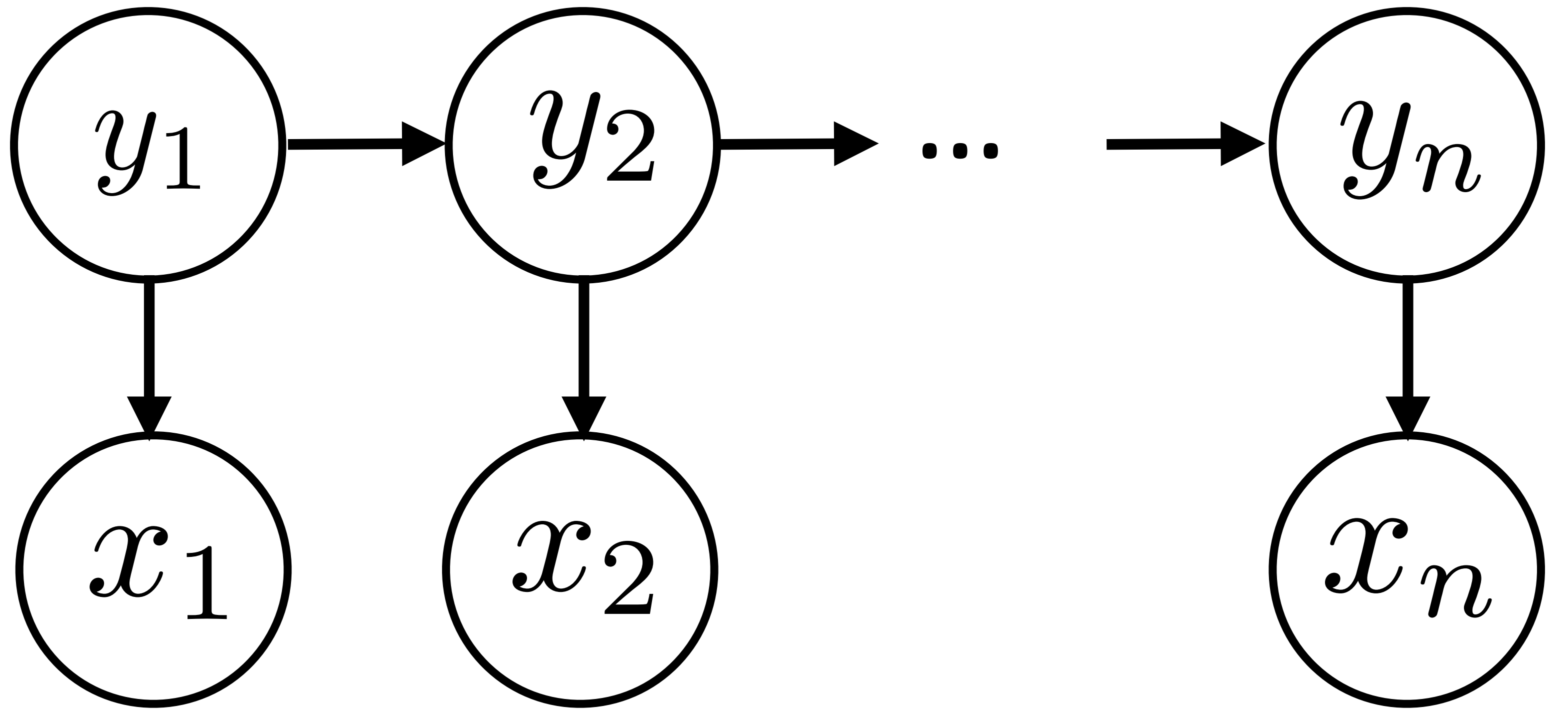

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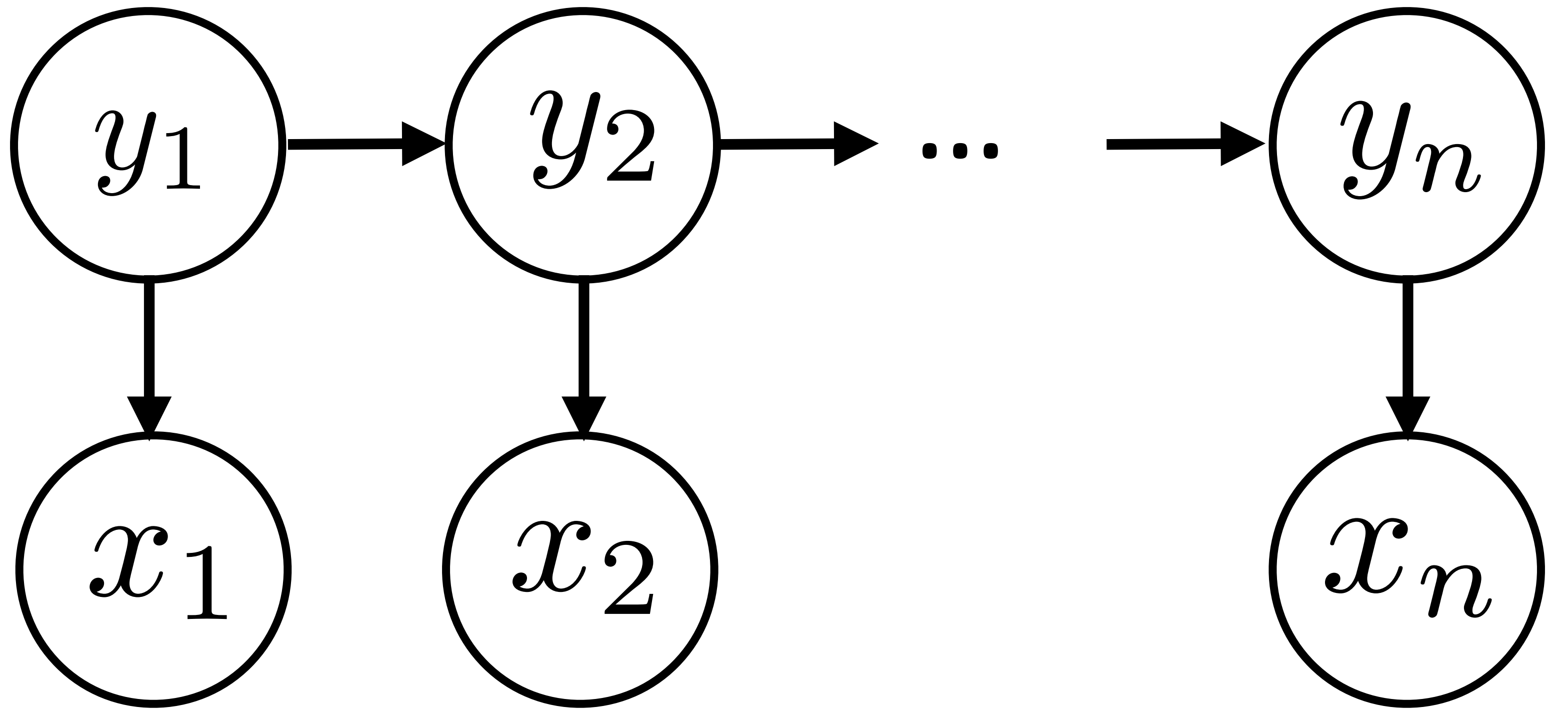

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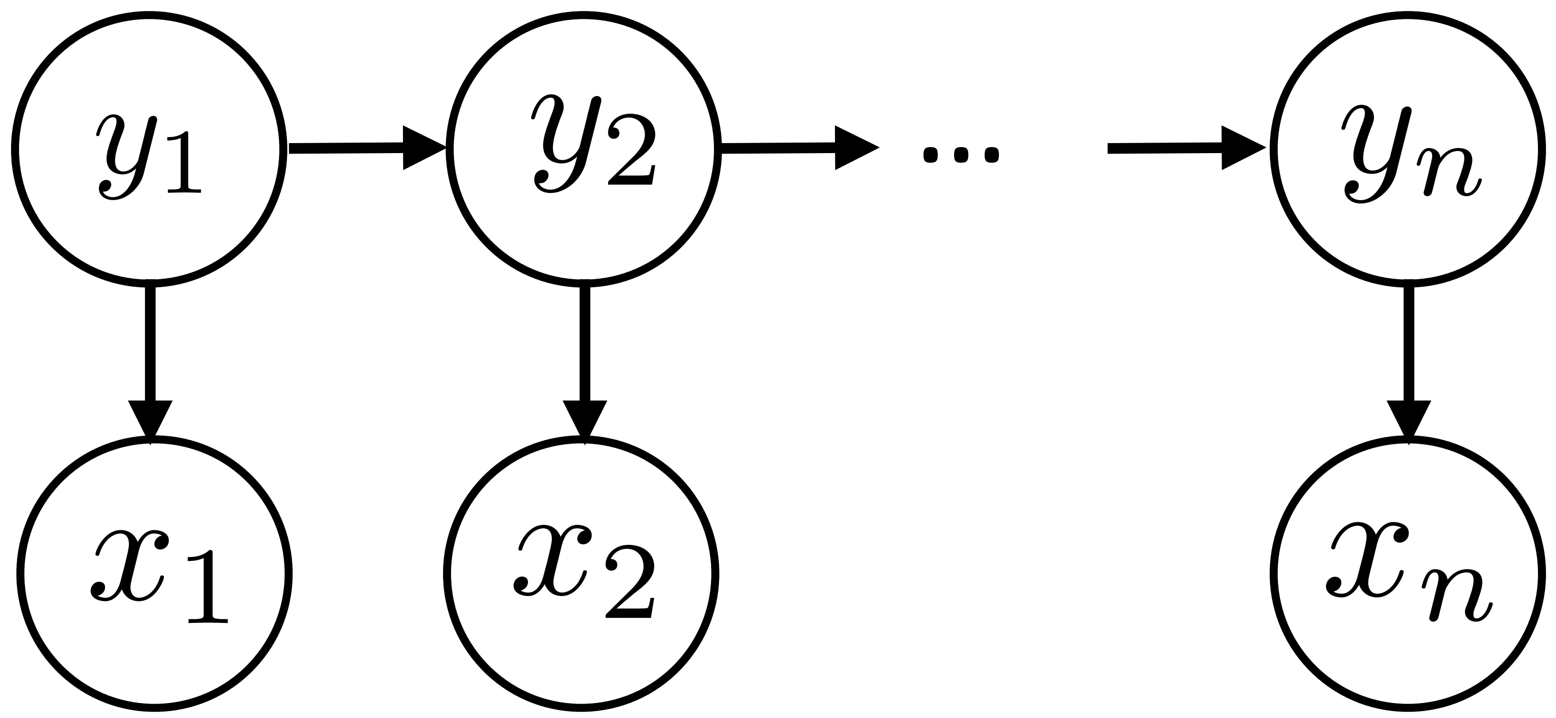

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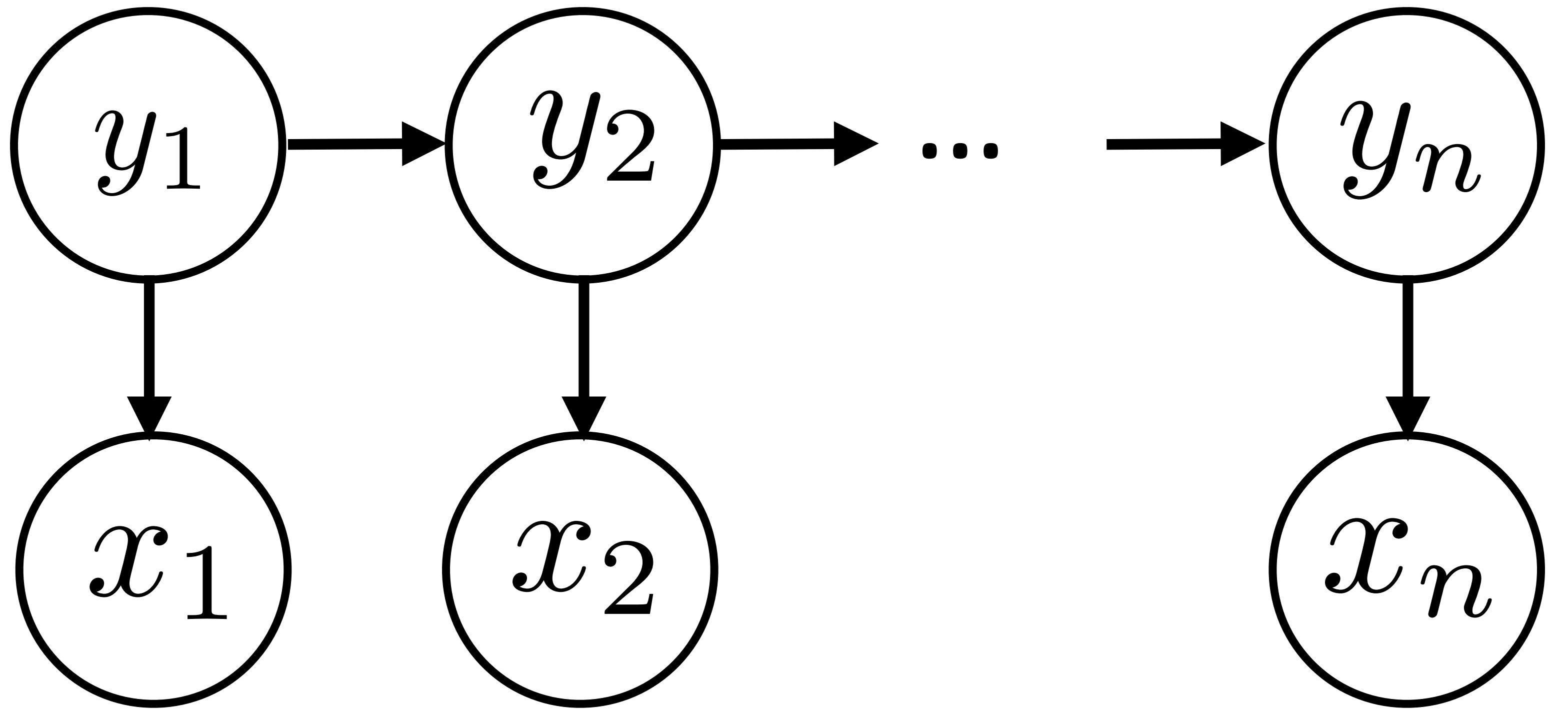

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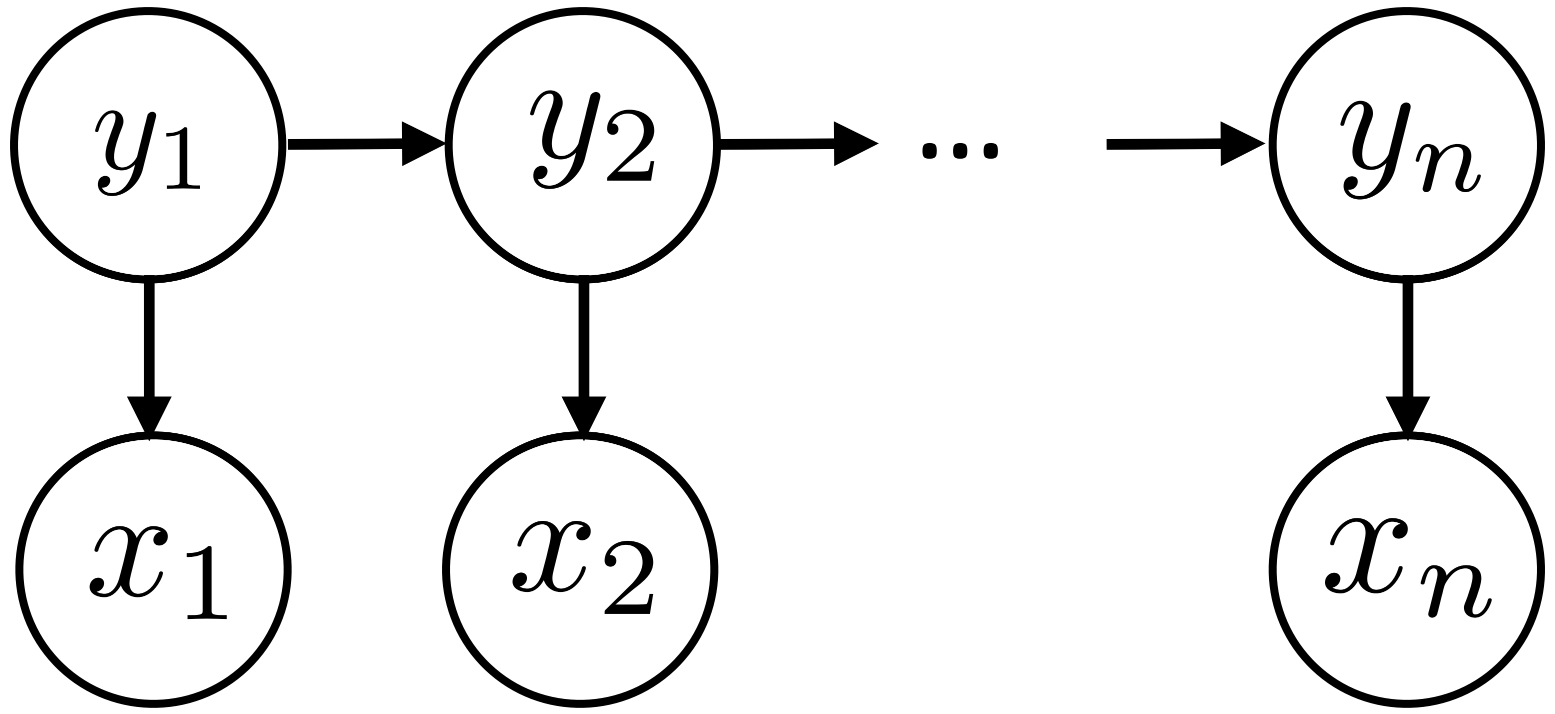

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- P(*x*|*y*) is a distribution over all words in the vocabulary — not a distribution over features (but could be!)

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- What did you do? Use current model parameters + data to refine your model. This is what EM will do

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- non-convex optimization problem

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- What's the point of this? Model has inductive bias and so should learn some useful latent structure ***y*** (clustering effect)
- EM is just one procedure for optimizing this kind of objective

Expectation Maximization

Adapted from Leon Gu

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- Can optimize this lower-bound on log likelihood instead of log-likelihood

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- Compute $P(y_i = s|\mathbf{x}, \theta^{t-1}),\ P(y_i = s_1, y_{i+1} = s_2|\mathbf{x}, \theta^{t-1})$

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tag marginals at each position	tag pair marginals at each position

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  tag pair marginals at each position
- M-step: set parameters to optimize the crazy argmax term

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the	*dog*

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$\longrightarrow$

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count(DT, dog) = 0

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DT *the*	NN *dog*	→	count(DT, the) = 1 count(DT, dog) = 0 count(NN, the) = 0 count(NN, dog) = 1	→	P(the|DT) = 1 P(dog|DT) = 0 P(the|NN) = 0 P(dog|NN) = 1

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the *dog*		count(DT, dog) = 0		P(dog|DT) = 0
		count(NN, the) = 0		P(the|NN) = 0
		count(NN, dog) = 1		P(dog|NN) = 1

- Same procedure, but maximizing P(**x**,**y**) in expectation under *q* means that *q* specifies *fractional counts*

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- Same procedure, but maximizing P(**x**,**y**) in expectation under *q* means that *q* specifies *fractional counts*

the *dog*

M-Step

- Recall how we maximized log P(**x**,**y**): read counts off data

DT NN	→	count(DT, the) = 1	→	P(the|DT) = 1
the dog		count(DT, dog) = 0		P(dog|DT) = 0
		count(NN, the) = 0		P(the|NN) = 0
		count(NN, dog) = 1		P(dog|NN) = 1

- Same procedure, but maximizing P(**x**,**y**) in expectation under *q* means that *q* specifies *fractional counts*

q	**DT: 0.9**	DT: 0.3
	NN: 0.1	**NN: 0.7**
	the	*dog*

M-Step

- Recall how we maximized log P(**x**,**y**): read counts off data

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the dog		count(DT, dog) = 0		P(dog|DT) = 0
		count(NN, the) = 0		P(the|NN) = 0
		count(NN, dog) = 1		P(dog|NN) = 1

- Same procedure, but maximizing P(**x**,**y**) in expectation under *q* means that *q* specifies *fractional counts*

q	*the*	*dog*
	DT: 0.9	DT: 0.3
	NN: 0.1	**NN: 0.7**

→

count(DT, the) = 0.9

count(DT, dog) = 0.3

count(NN, the) = 0.1

count(NN, dog) = 0.7

M-Step

- Recall how we maximized log P(**x**,**y**): read counts off data

DT	NN	→	count(DT, the) = 1 count(DT, dog) = 0 count(NN, the) = 0 count(NN, dog) = 1	→	P(the|DT) = 1 P(dog|DT) = 0 P(the|NN) = 0 P(dog|NN) = 1
the	*dog*				

- Same procedure, but maximizing P(**x**,**y**) in expectation under *q* means that *q* specifies *fractional counts*

q	**DT: 0.9** NN: 0.1	DT: 0.3 **NN: 0.7**	→	count(DT, the) = 0.9 count(DT, dog) = 0.3 count(NN, the) = 0.1 count(NN, dog) = 0.7	→	P(the|DT) = 0.75 P(dog|DT) = 0.25 P(the|NN) = 0.125 P(dog|NN) = 0.875
	the	*dog*				

M-Step

M-Step

- Same for transition probabilities

M-Step

- Same for transition probabilities

q

DT—NN: 0.6
DT—DT: 0.1
NN—DT: 0.2
NN—NN: 0.1

the *dog*

M-Step

- Same for transition probabilities

q	**DT—NN: 0.6** DT—DT: 0.1 NN—DT: 0.2 NN—NN: 0.1	→
	the *dog*	

P(DT|DT) = 1/7

P(NN|DT) = 6/7

P(DT|NN) = 2/3

P(NN|NN) = 1/3

How does EM learn things?

How does EM learn things?

the *dog* *the* *marsupial*

How does EM learn things?

- Initialize (M-step 0):
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the *dog* *the* *marsupial*

How does EM learn things?

- Initialize (M-step 0):
  - Emissions

    P(the|DT) = **0.9**

    P(dog|DT) = 0.05

    P(marsupial|DT) = 0.05

the *dog* *the* *marsupial*

How does EM learn things?

- Initialize (M-step 0):
  - Emissions

P(the|DT) = **0.9**
P(dog|DT) = 0.05
P(marsupial|DT) = 0.05

P(the|NN) = 0.05
P(dog|NN) = **0.9**
P(marsupial|NN) = 0.05

the *dog* *the* *marsupial*

How does EM learn things?

- Initialize (M-step 0):
  - Emissions

    P(the|DT) = **0.9** P(the|NN) = 0.05

    P(dog|DT) = 0.05 P(dog|NN) = **0.9**

    P(marsupial|DT) = 0.05 P(marsupial|NN) = 0.05

  - Transition probabilities: uniform

the *dog* *the* *marsupial*

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- Initialize (M-step 0):
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    P(the|DT) = **0.9** P(the|NN) = 0.05

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  - Transition probabilities: uniform
- E-step 1: (all values are approximate)

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- Initialize (M-step 0):
  - Emissions

    P(the|DT) = **0.9** P(the|NN) = 0.05

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  - Transition probabilities: uniform
- E-step 1: (all values are approximate)

DT: 0.95	DT: 0.05		
NN: 0.05	**NN: 0.95**		
the	*dog*	*the*	*marsupial*

How does EM learn things?

- Initialize (M-step 0):
  - Emissions

P(the|DT) = **0.9**	P(the|NN) = 0.05
P(dog|DT) = 0.05	P(dog|NN) = **0.9**
P(marsupial|DT) = 0.05	P(marsupial|NN) = 0.05

  - Transition probabilities: uniform
- E-step 1: (all values are approximate)

DT: 0.95	DT: 0.05	**DT: 0.95**	DT: 0.5
NN: 0.05	**NN: 0.95**	NN: 0.05	NN: 0.5
the	*dog*	*the*	*marsupial*

How does EM learn things?

- Initialize (M-step 0):
  - Emissions

    P(the|DT) = **0.9** P(the|NN) = 0.05
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  - Transition probabilities: uniform
- E-step 1: (all values are approximate)

DT: 0.95	DT: 0.05	**DT: 0.95**	DT: 0.5
NN: 0.05	**NN: 0.95**	NN: 0.05	NN: 0.5
the	*dog*	*the*	*marsupial*

- uniform

How does EM learn things?

- E-step 1:

DT: 0.95	DT: 0.05	**DT: 0.95**	DT: 0.5
NN: 0.05	**NN: 0.95**	NN: 0.05	NN: 0.5
the	*dog*	*the*	*marsupial*

How does EM learn things?

- E-step 1:

DT: 0.95	DT: 0.05	**DT: 0.95**	$\boxed{\text{DT: 0.5}}$
NN: 0.05	**NN: 0.95**	NN: 0.05	$\boxed{\text{NN: 0.5}}$
the	*dog*	*the*	*marsupial*

- M-step 1:
  - Emissions aren't so different

How does EM learn things?

- E-step 1:

DT: 0.95	DT: 0.05	**DT: 0.95**	DT: 0.5
NN: 0.05	**NN: 0.95**	NN: 0.05	NN: 0.5
the	*dog*	*the*	*marsupial*

- M-step 1:
  - Emissions aren't so different
  - Transition probabilities (approx): P(NN|DT) = 3/4, P(DT|DT) = 1/4

How does EM learn things?

- E-step 2:

DT: 0.95	DT: 0.05	**DT: 0.95**	DT: 0.30
NN: 0.05	**NN: 0.95**	NN: 0.05	**NN: 0.70**
the	*dog*	*the*	*marsupial*

- M-step 1:
  - Emissions aren't so different
  - Transition probabilities (approx): P(NN|DT) = 3/4, P(DT|DT) = 1/4

How does EM learn things?

- E-step 2:

DT: 0.95	DT: 0.05	**DT: 0.95**	DT: 0.30
NN: 0.05	**NN: 0.95**	NN: 0.05	**NN: 0.70**
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How does EM learn things?

- E-step 2:

DT: 0.95	DT: 0.05	**DT: 0.95**	$\boxed{\text{DT: 0.30}}$
NN: 0.05	**NN: 0.95**	NN: 0.05	$\boxed{\textbf{NN: 0.70}}$
the	*dog*	*the*	*marsupial*

- M-step 2:
  - Emission P(marsupial|NN) > P(marsupial|DT)

How does EM learn things?

- E-step 2:

DT: 0.95	DT: 0.05	**DT: 0.95**	DT: 0.30
NN: 0.05	**NN: 0.95**	NN: 0.05	**NN: 0.70**
the	*dog*	*the*	*marsupial*

- M-step 2:
  - Emission P(marsupial|NN) > P(marsupial|DT)
  - Remember to tag marsupial as NN in the future!

How does EM learn things?

- E-step 2:

DT: 0.95	DT: 0.05	**DT: 0.95**	DT: 0.30
NN: 0.05	**NN: 0.95**	NN: 0.05	**NN: 0.70**
the	*dog*	*the*	*marsupial*

- M-step 2:
  - Emission P(marsupial|NN) > P(marsupial|DT)
  - Remember to tag marsupial as NN in the future!
  - Context constrained what we learned! That’s how data helped us

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How does EM learn things?

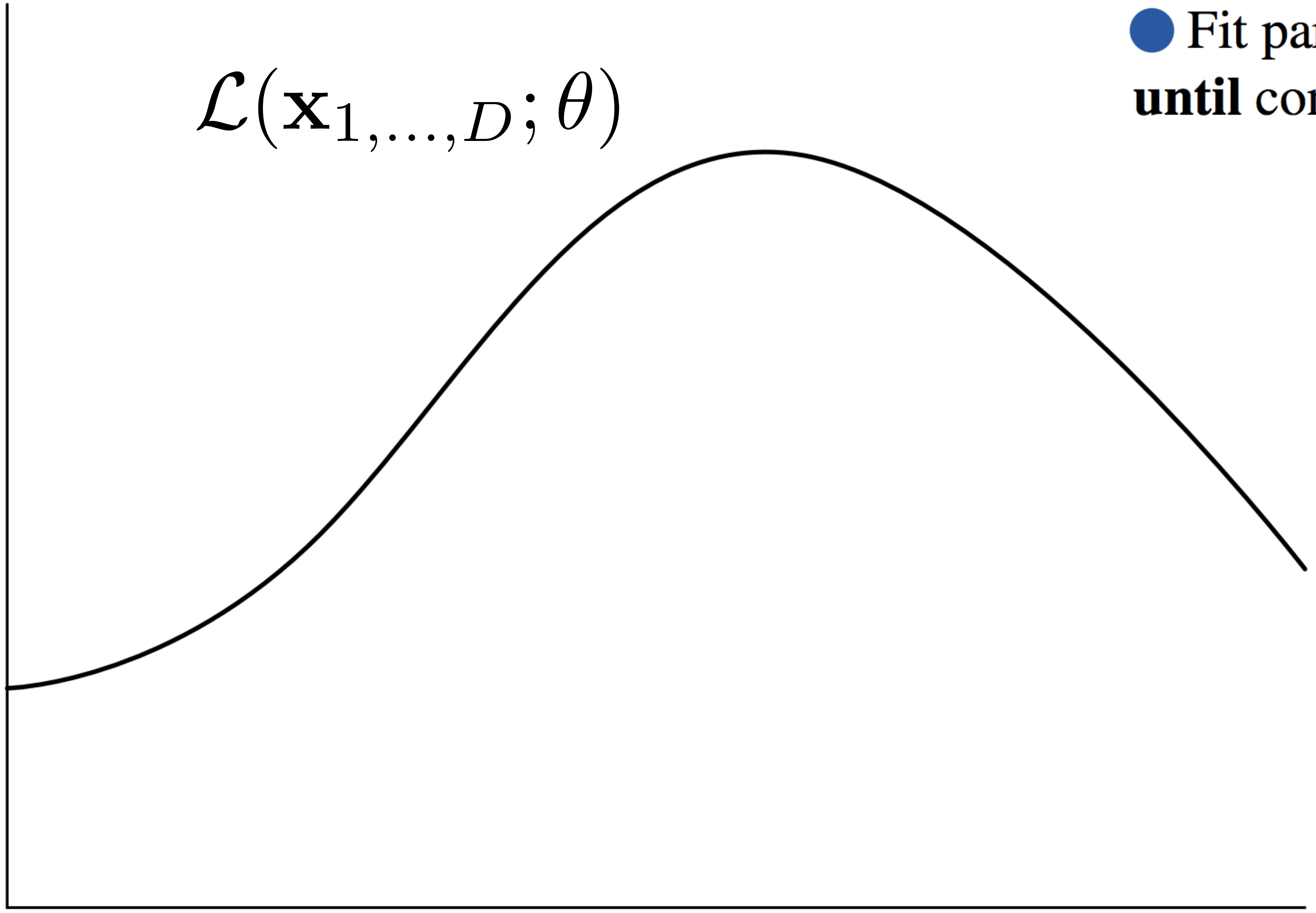
- Can think of *q* as a kind of "fractional annotation"
- E-step: compute annotations (posterior under current model)
- M-step: supervised learning with those fractional annotations
- Initialize with some reasonable weights, alternate E and M until convergence

EM's Lower Bound

$$\mathcal{L}(\mathbf{x}_{1,\dots,D}) = \sum_{i=1}^{D} \log \sum_{\mathbf{y}} P(\mathbf{y}, \mathbf{x}_i)$$

Initialize probabilities $\boldsymbol{\theta}$
repeat
- Compute expected counts $\mathbf{e}$
- Fit parameters $\boldsymbol{\theta}$

until convergence



slide credit: Taylor Berg-Kirkpatrick

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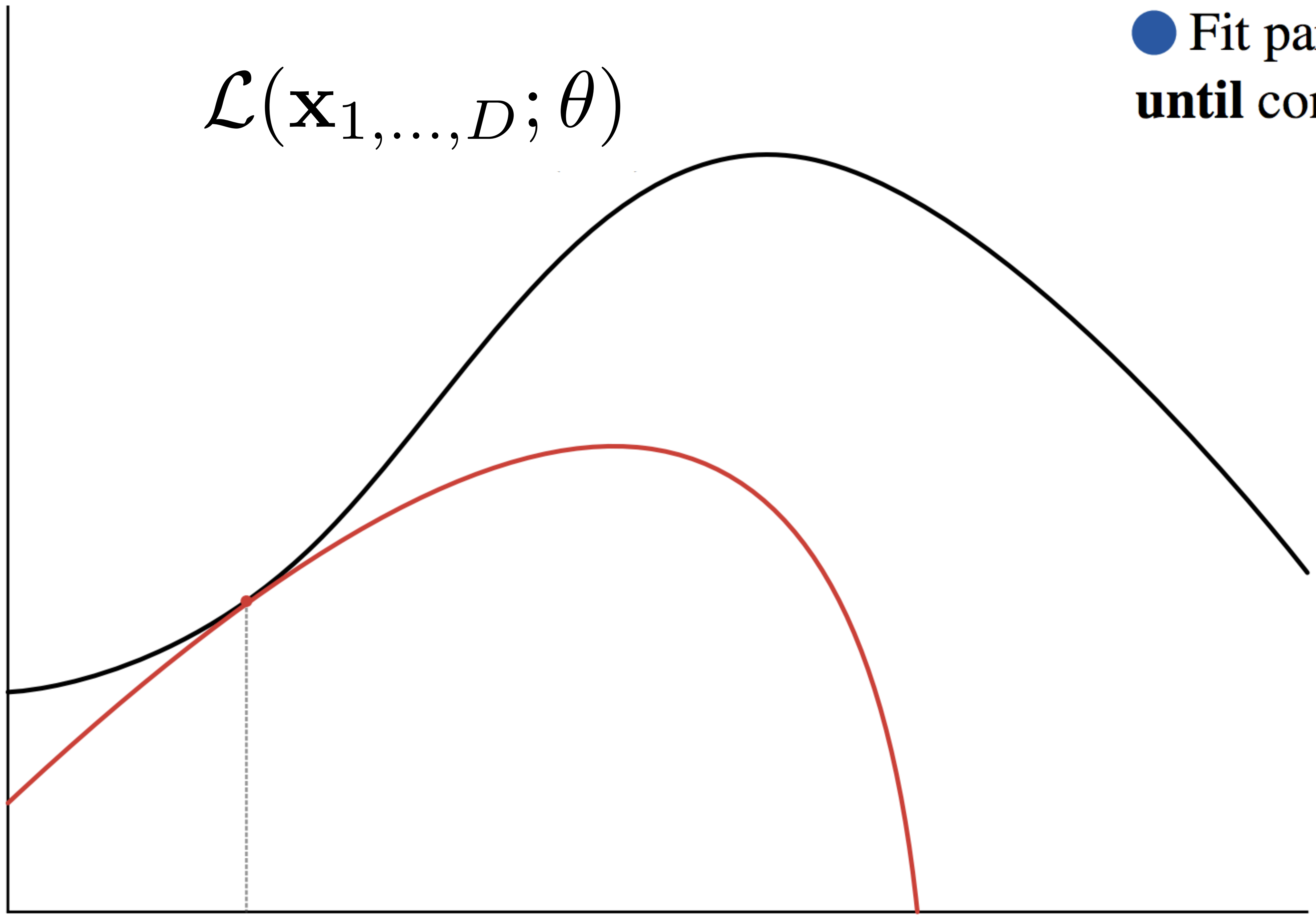

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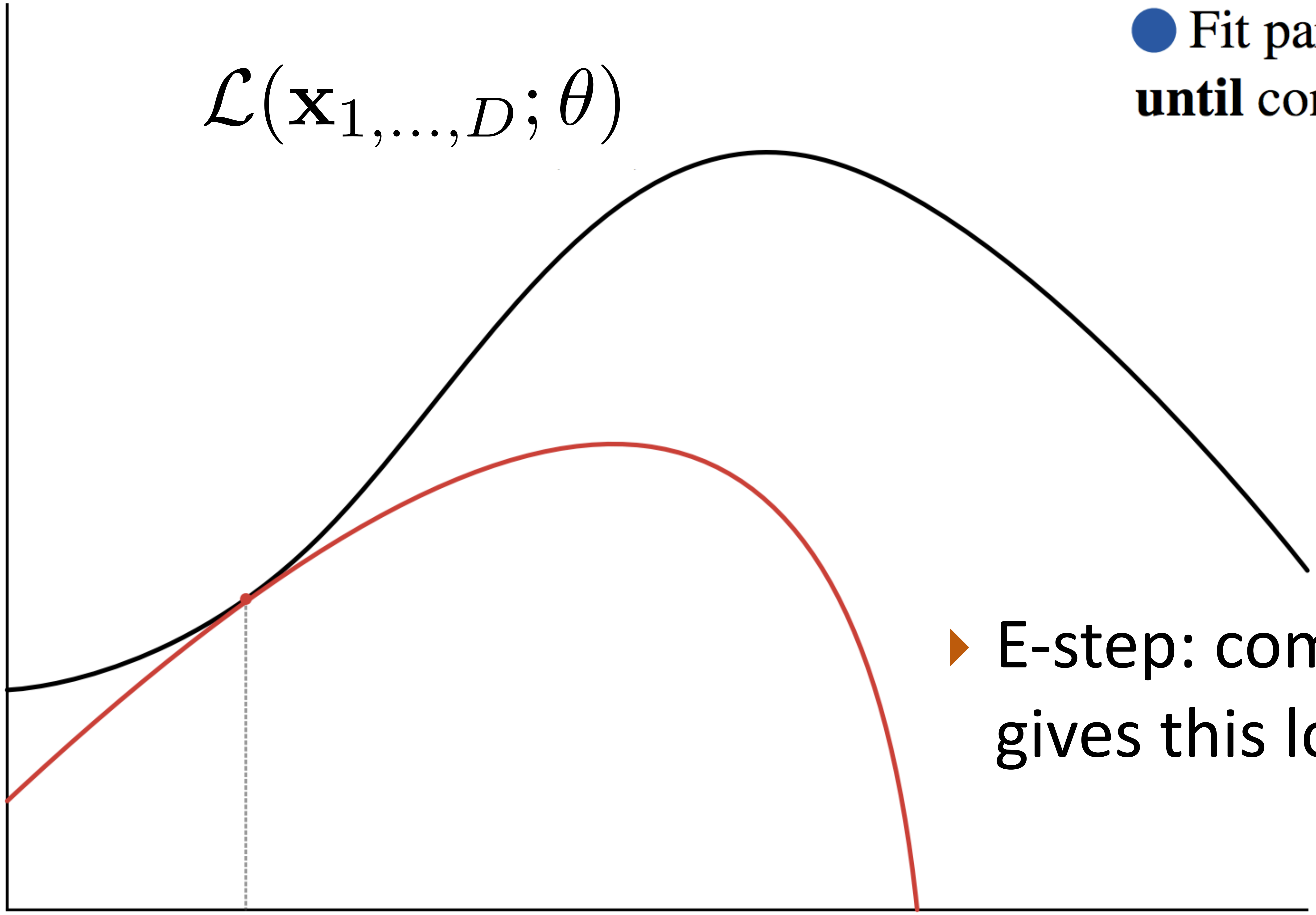

- E-step: compute *q* which gives this lower bound

slide credit: Taylor Berg-Kirkpatrick

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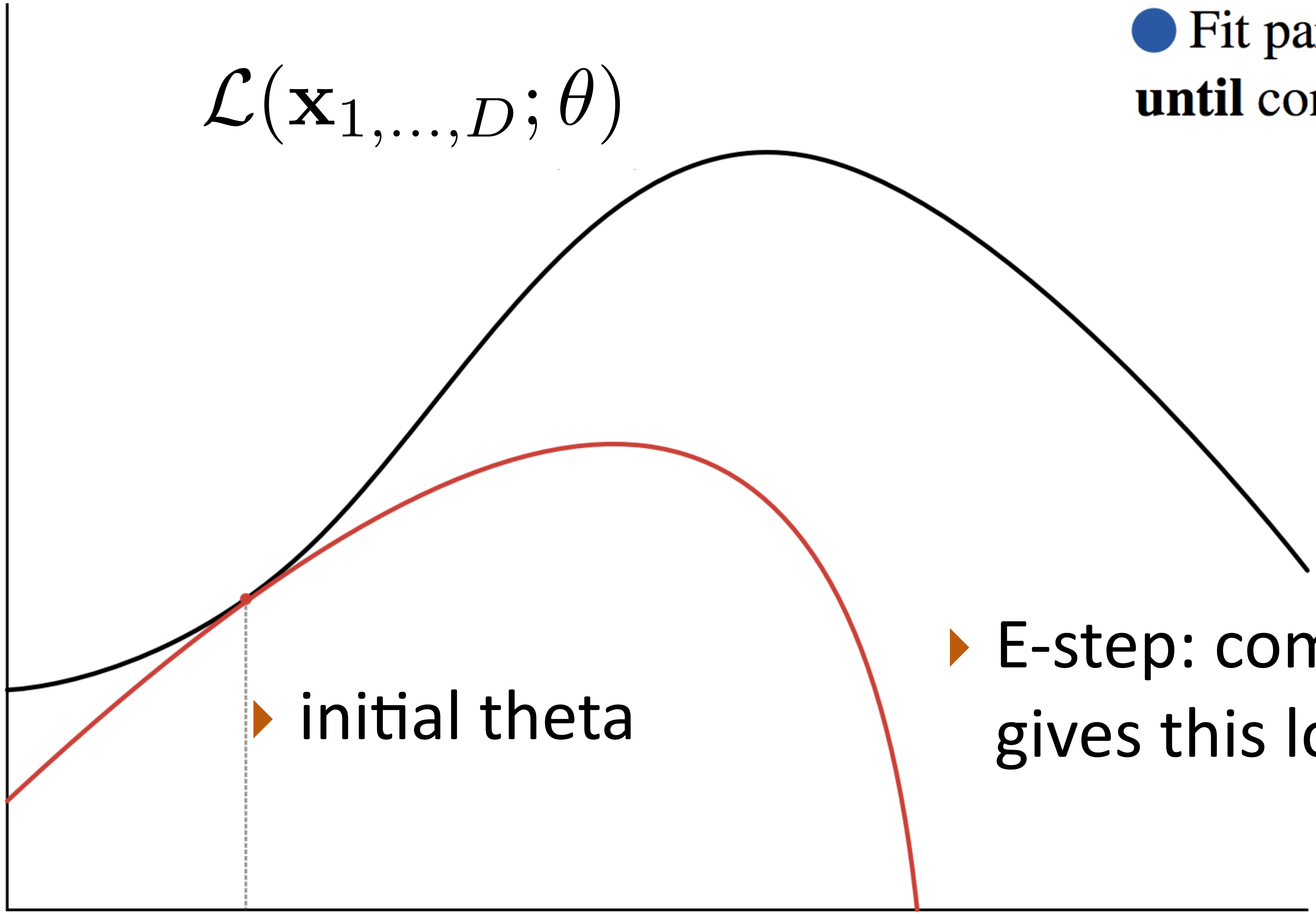

- initial theta
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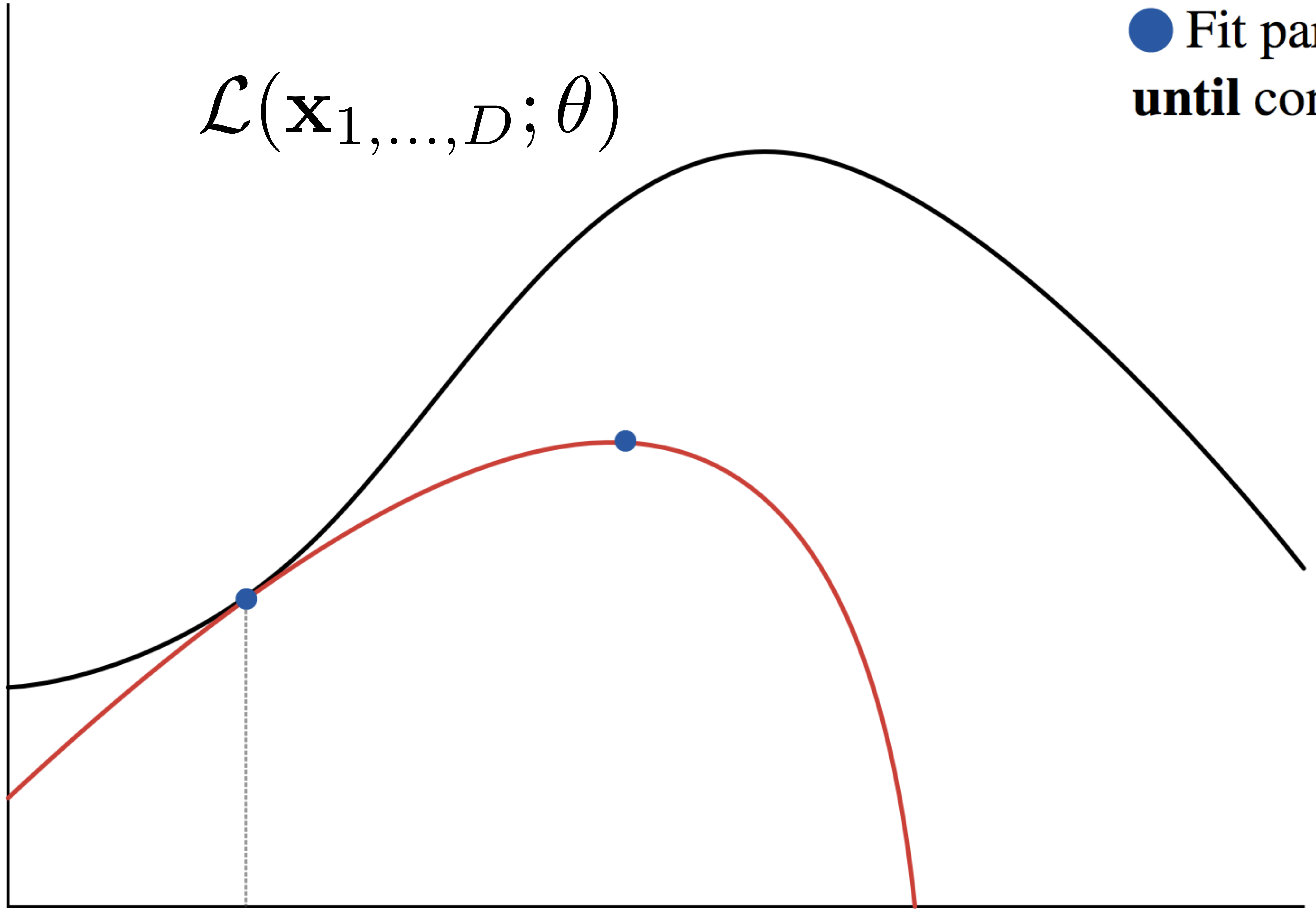

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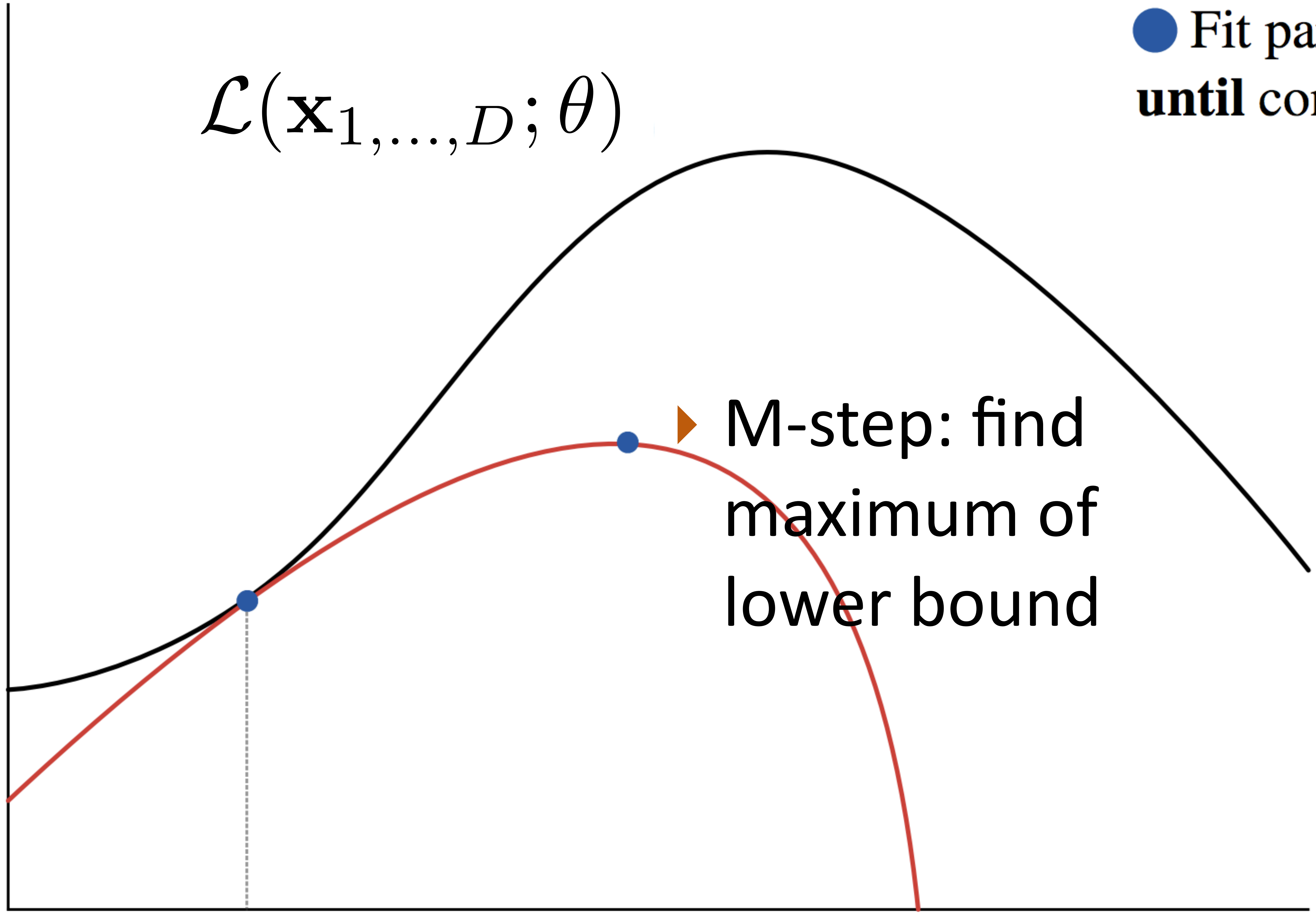

- M-step: find maximum of lower bound

slide credit: Taylor Berg-Kirkpatrick

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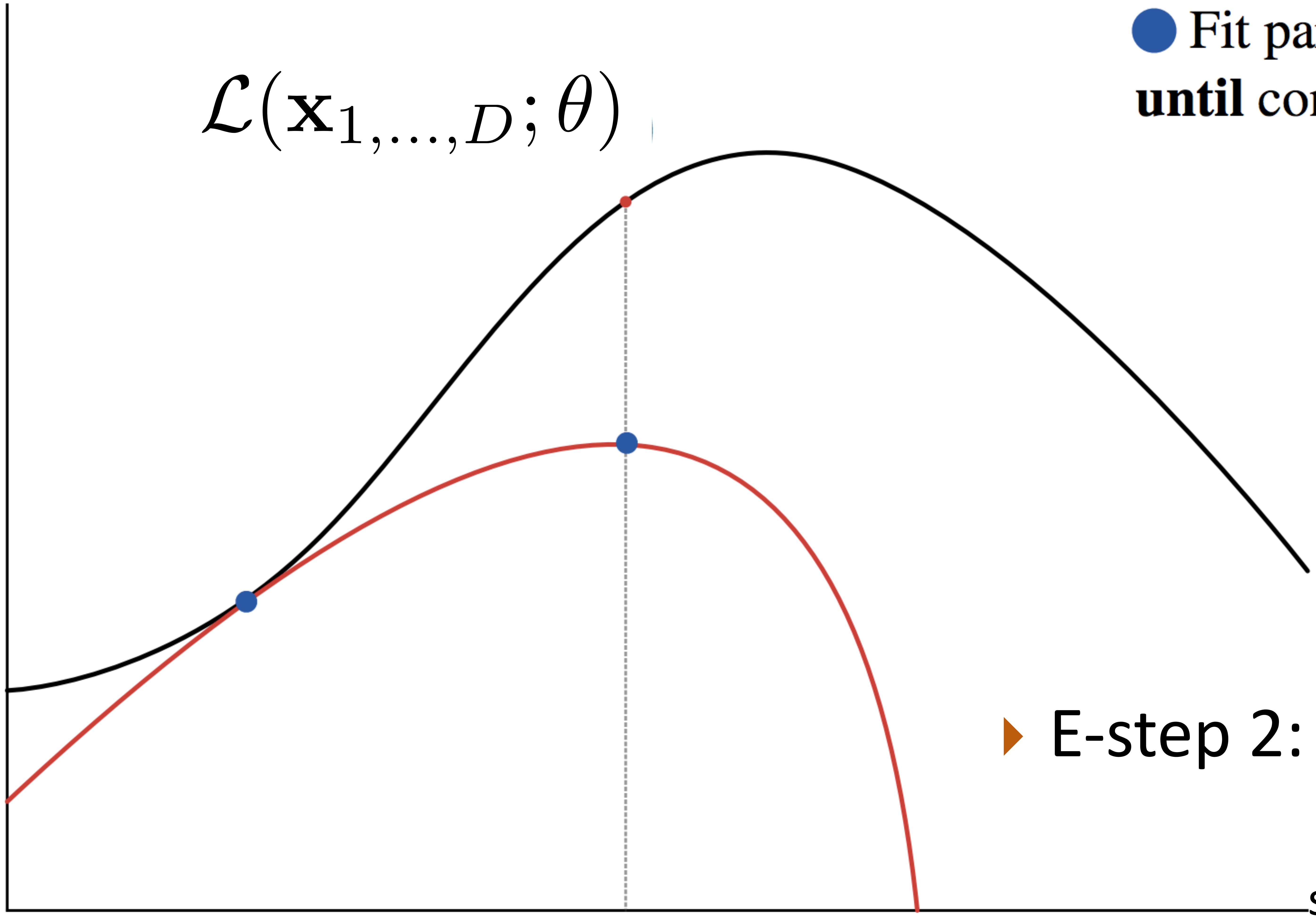

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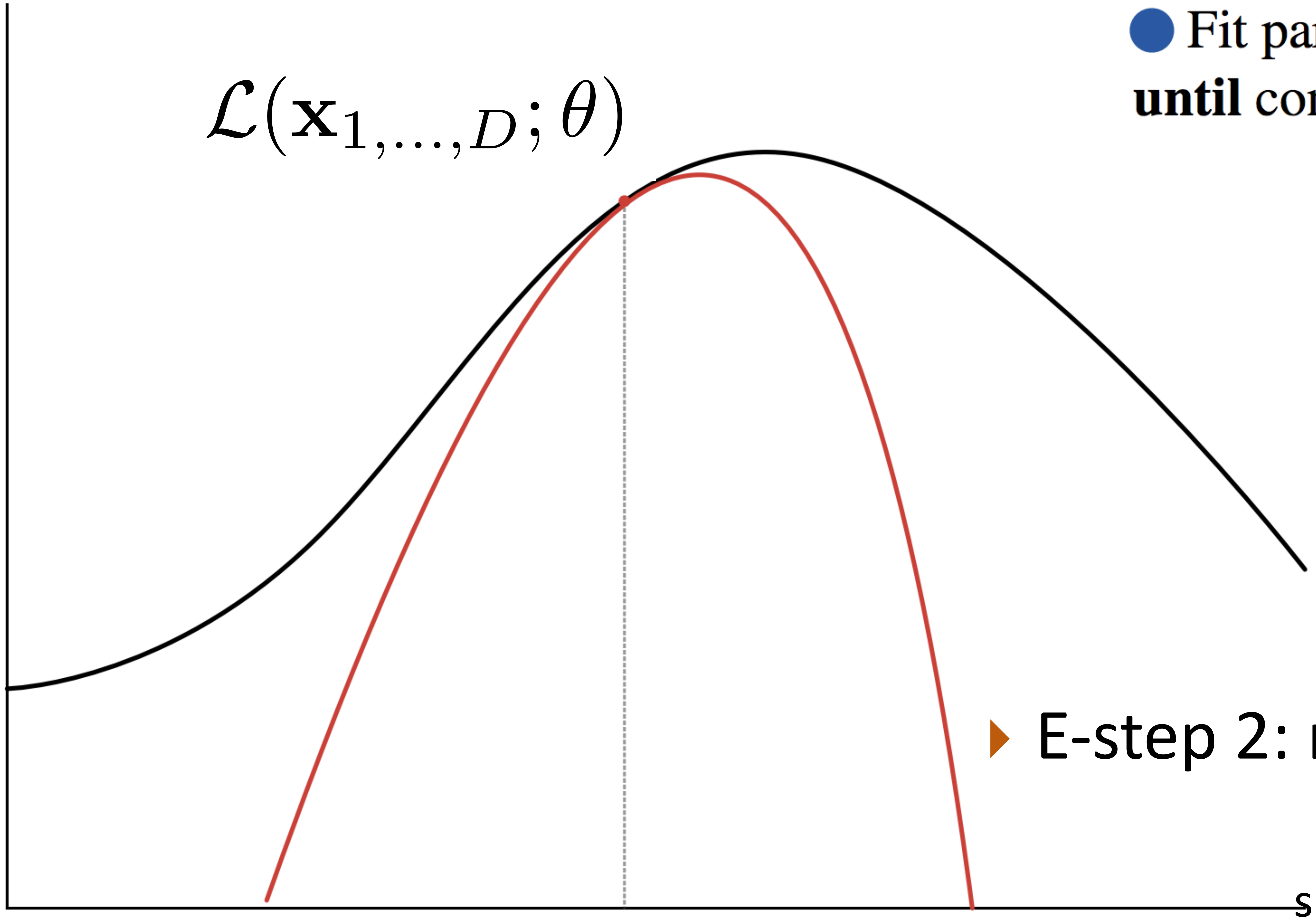

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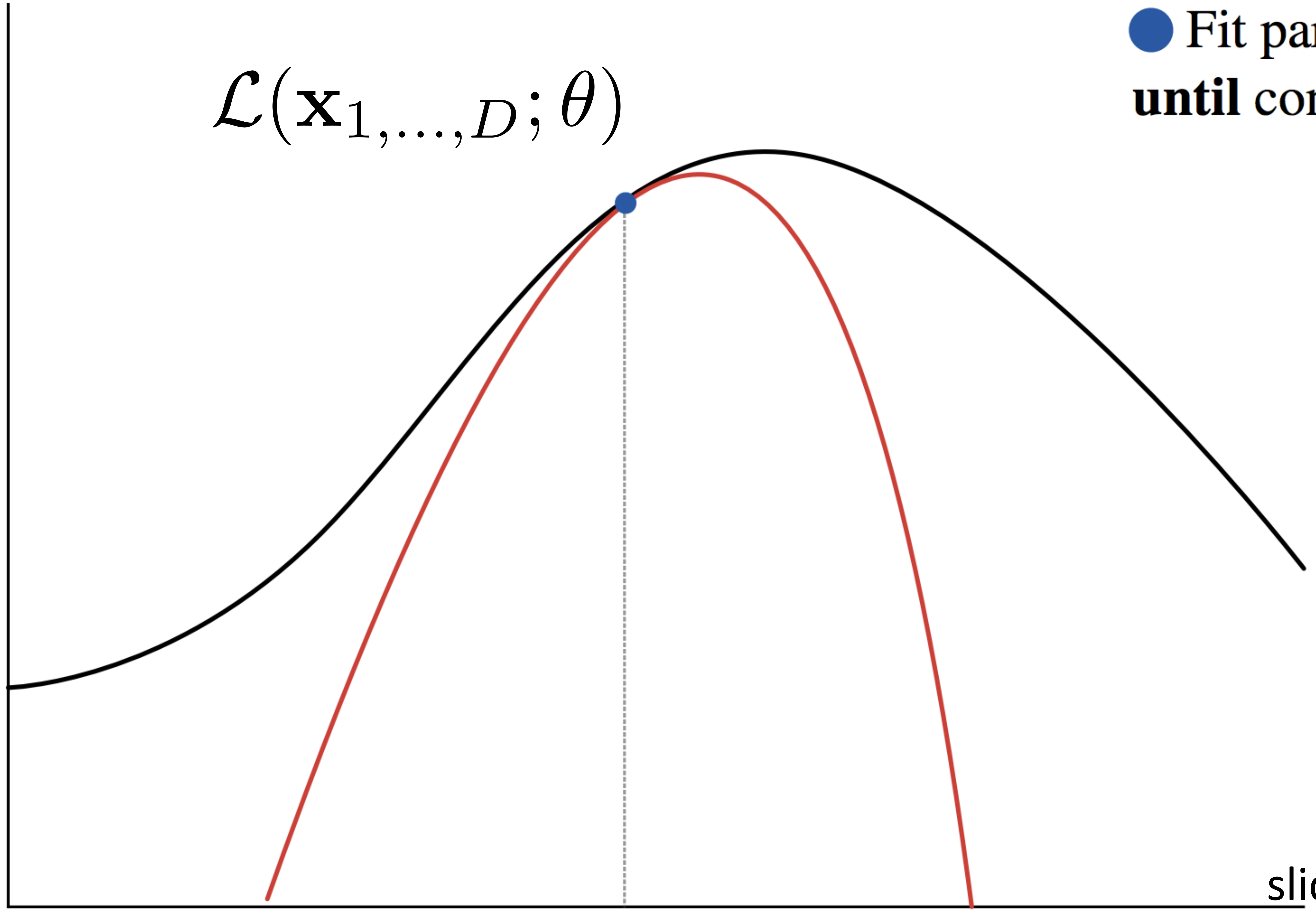

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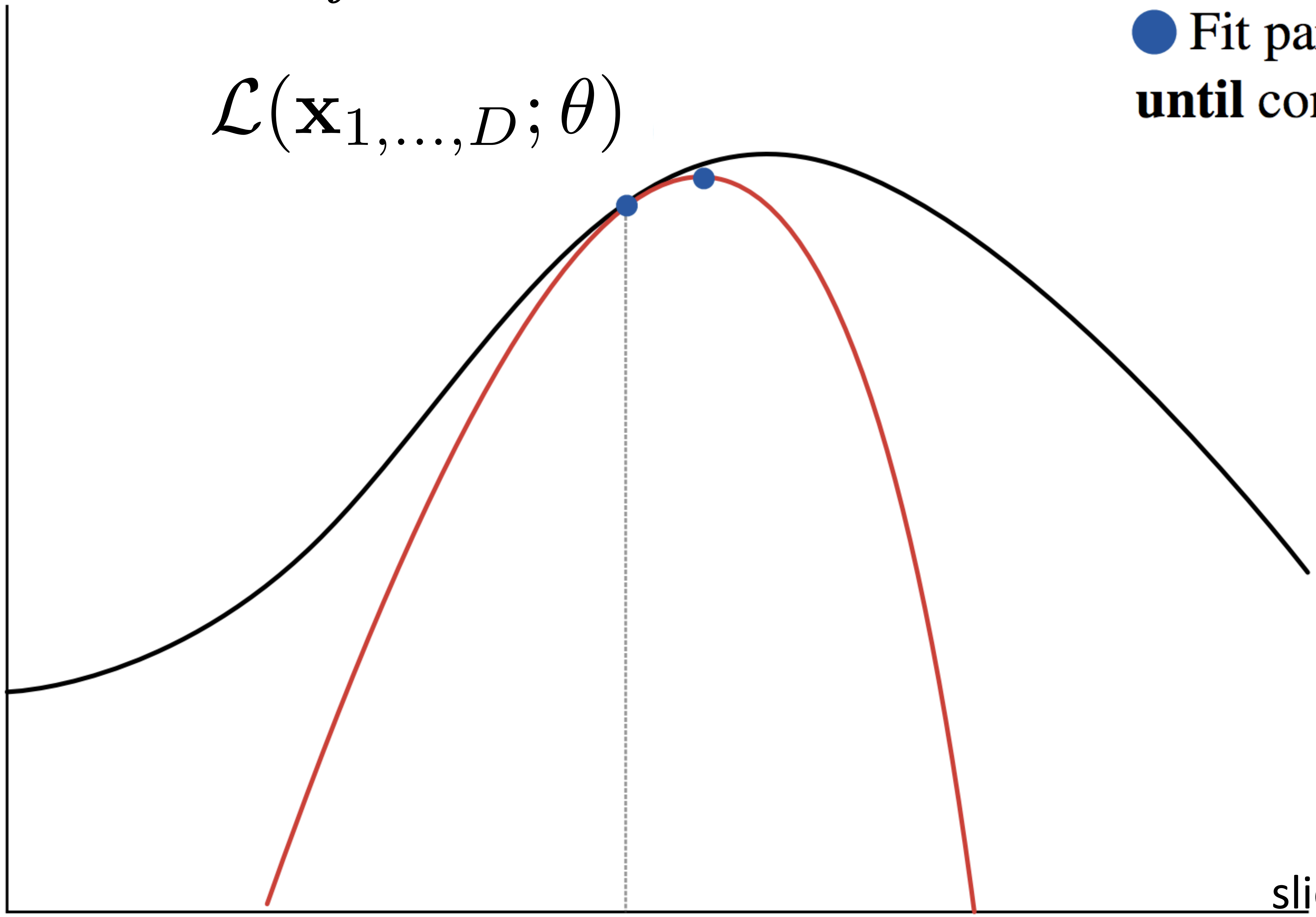

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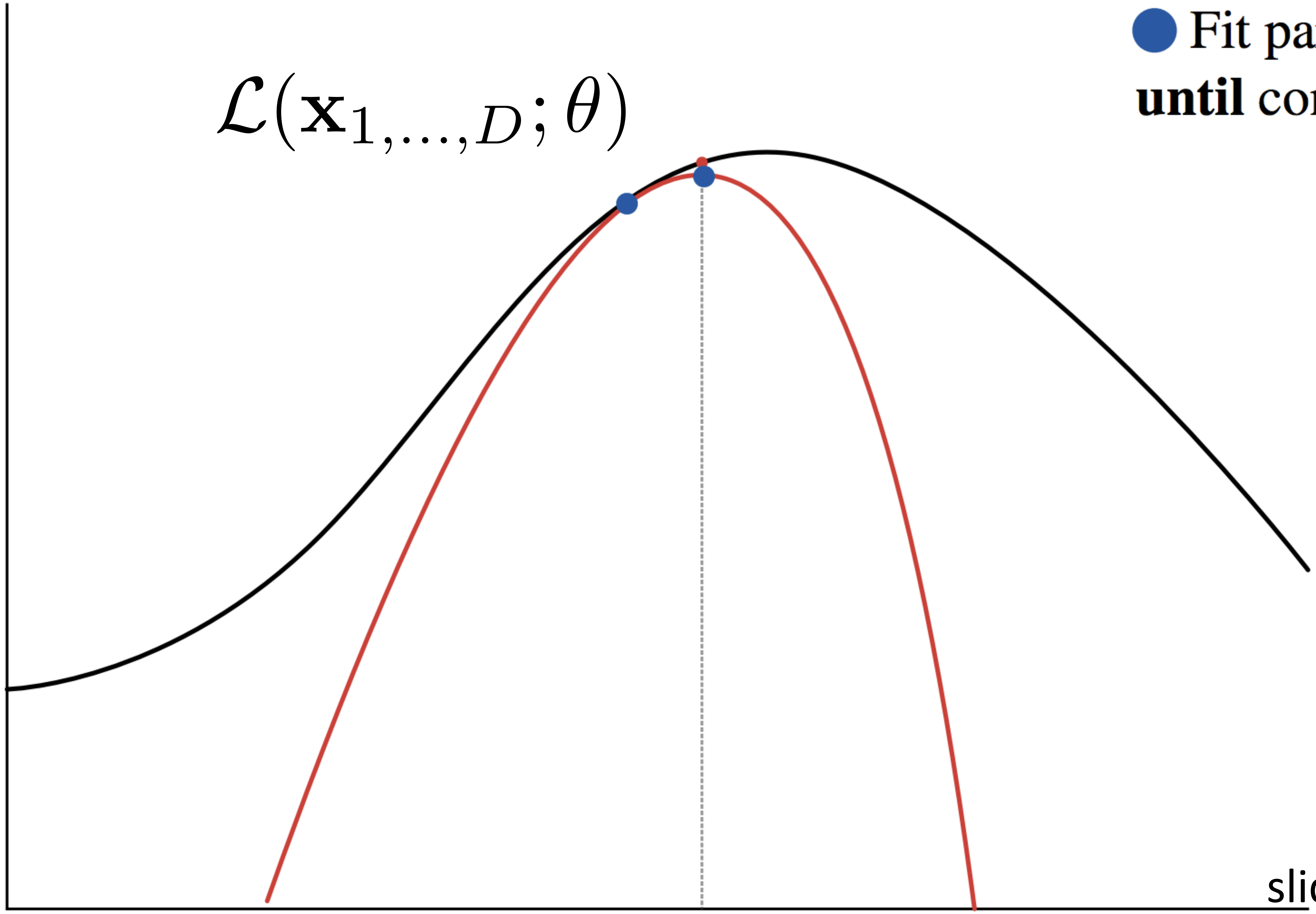

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Part-of-speech Induction

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Part-of-speech Induction

- Merialdo (1994): you have a whitelist of tags for each word
- Learn parameters on *k* examples to start, use those to initialize EM, run on 1 million words of unlabeled data
- Tag dictionary + data should get us started in the right direction…

Part-of-speech Induction

	Number of tagged sentences used for the initial model						
	0	100	2000	5000	10000	20000	all
Iter	Correct tags (% words) after ML on 1M words						
0	77.0	90.0	95.4	96.2	96.6	96.9	97.0
1	80.5	92.6	95.8	96.3	96.6	96.7	96.8
2	81.8	93.0	95.7	96.1	96.3	96.4	96.4
3	83.0	93.1	95.4	95.8	96.1	96.2	96.2
4	84.0	93.0	95.2	95.5	95.8	96.0	96.0
5	84.8	92.9	95.1	95.4	95.6	95.8	95.8
6	85.3	92.8	94.9	95.2	95.5	95.6	95.7
7	85.8	92.8	94.7	95.1	95.3	95.5	95.5
8	86.1	92.7	94.6	95.0	95.2	95.4	95.4
9	86.3	92.6	94.5	94.9	95.1	95.3	95.3
10	86.6	92.6	94.4	94.8	95.0	95.2	95.2

Merialdo (1994)

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7	85.8	92.8	94.7	95.1	95.3	95.5	95.5
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- Small amounts of data > large amounts of unlabeled data
- Running EM *hurts* performance once you have labeled data

Merialdo (1994)

Two Hours of Annotation

Human Annotations	0. No EM			1. EM only			2. With LP		
Initial data	T	K	U	T	K	U	T	K	U
KIN tokens A	**72**	90	58	55	82	32	71	86	58
KIN types A				63	77	32	78	83	69
MLG tokens B	74	89	49	68	87	39	74	89	49
MLG types B				71	87	46	72	81	57
ENG tokens A	63	83	38	62	83	37	**72**	85	55
ENG types A				66	76	37	75	81	56
ENG tokens B	70	87	44	70	87	43	**78**	90	60
ENG types B				69	83	38	75	82	61

Garrette and Baldridge (2013)

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ENG tokens A	63	83	38	62	83	37	**72**	85	55
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- Kinyarwanda and Malagasy (two actual low-resource languages)

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ENG tokens A	63	83	38	62	83	37	**72**	85	55
ENG types A				66	76	37	75	81	56
ENG tokens B	70	87	44	70	87	43	**78**	90	60
ENG types B				69	83	38	75	82	61

- Kinyarwanda and Malagasy (two actual low-resource languages)
- Label propagation (technique for using dictionary labels) helps a lot, with data that was collected in two hours

Garrette and Baldridge (2013)

Variational Autoencoders

Continuous Latent Variables

- For discrete latent variables ***y***, we optimized: $P(\mathbf{x}) = \sum_{\mathbf{y}} P(\mathbf{y}, \mathbf{x})$

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$$P(\mathbf{x}) = \int P(z)P(\mathbf{x}|z)\partial z$$

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$$P(\mathbf{x}) = \int P(z)P(\mathbf{x}|z)\partial z$$

- Can use EM here when P(*z*) and P(***x***|z) are Gaussians

Continuous Latent Variables

- For discrete latent variables ***y***, we optimized: $P(\mathbf{x}) = \sum_{\mathbf{y}} P(\mathbf{y}, \mathbf{x})$
- What if we want to use continuous latent variables?

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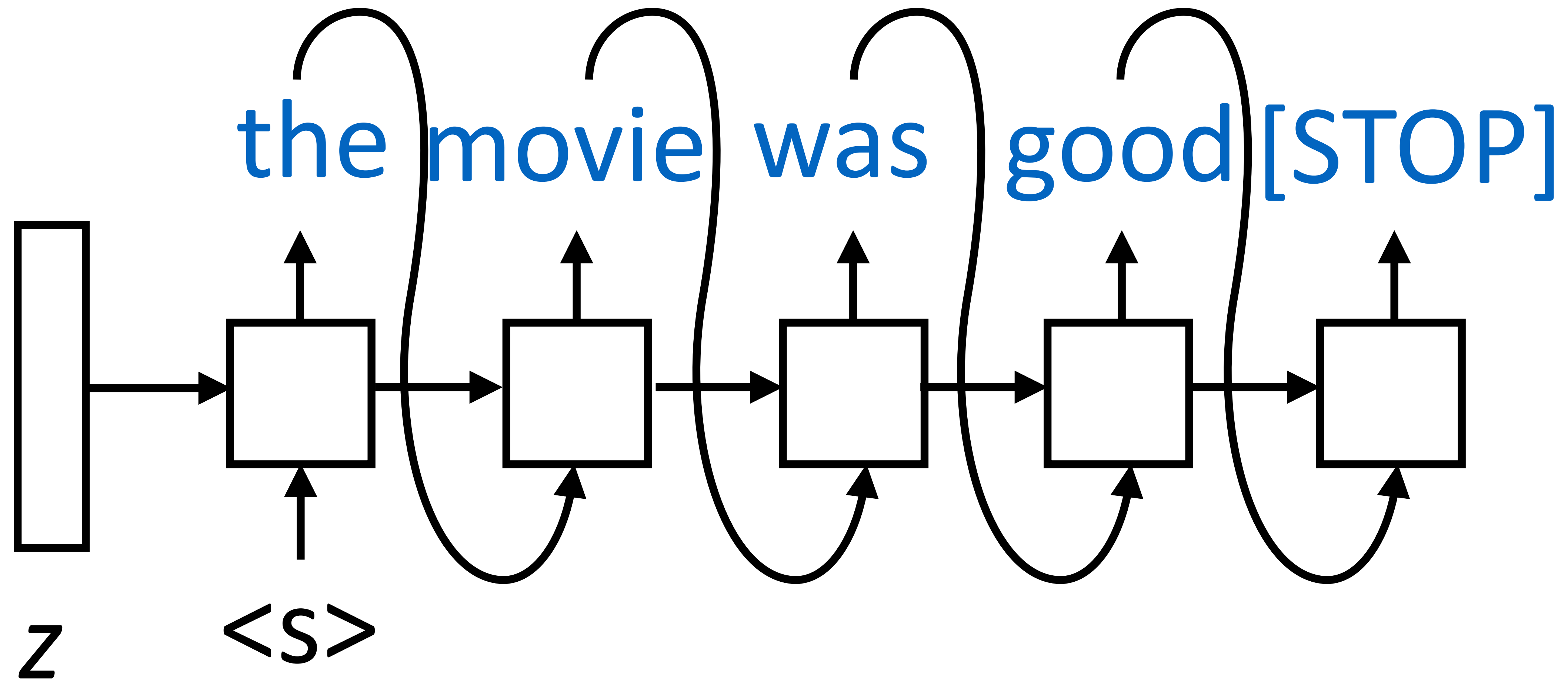
- Can use EM here when P(*z*) and P(***x***|z) are Gaussians
- What if we want P(***x***|*z*) to be something more complicated, like an LSTM with *z* as the initial state?

Deep Generative Models

$$P(z, \mathbf{x}) = P(z)P(\mathbf{x}|z)$$



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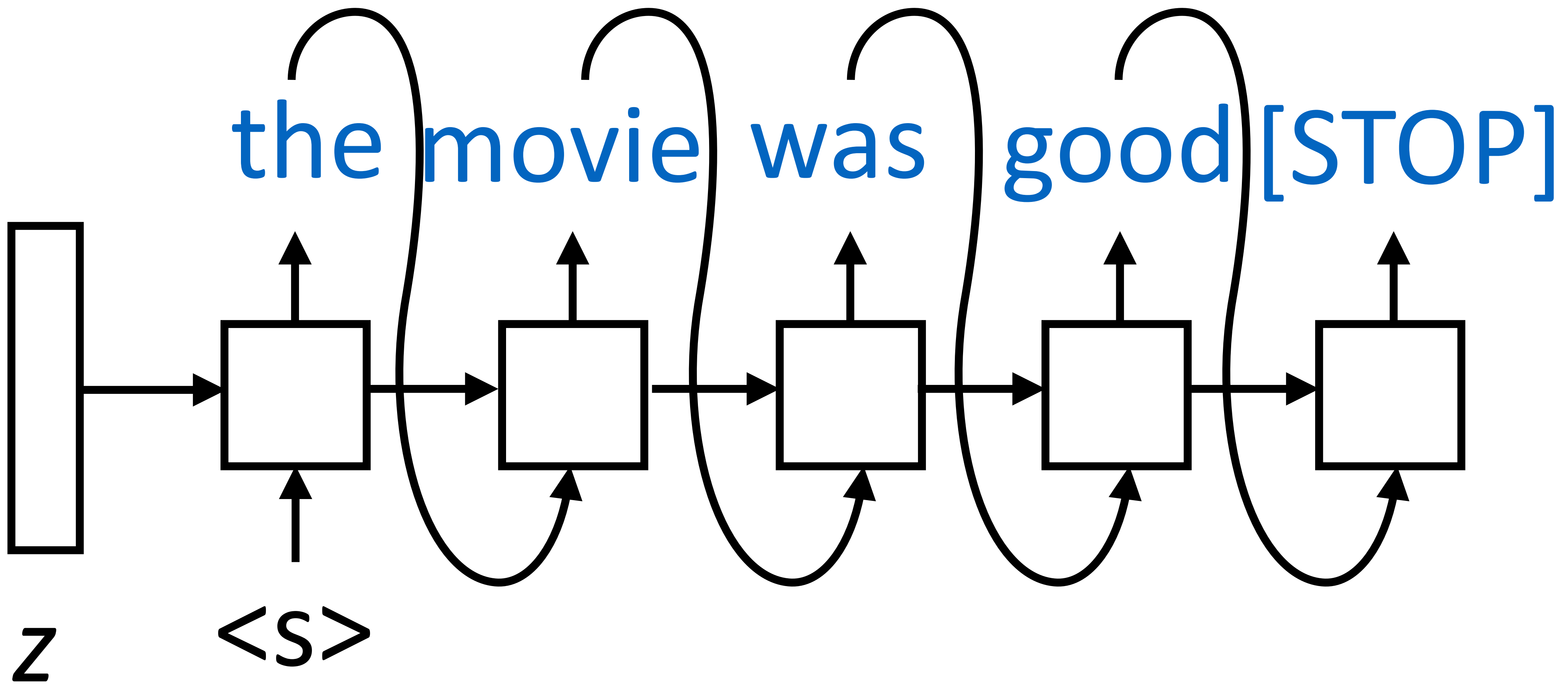

- *z* is a latent variable which should control the generation of the sentence, maybe capture something about its topic

Deep Generative Models

$$\log \int_z P(\mathbf{x}, z|\theta)$$

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$$\log \int_z P(\mathbf{x}, z|\theta) = \log \int_z q(z) \frac{P(\mathbf{x}, z|\theta)}{q(z)}$$

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"make the data likely under q" "make q close to the prior"

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Miao et al. (2015)

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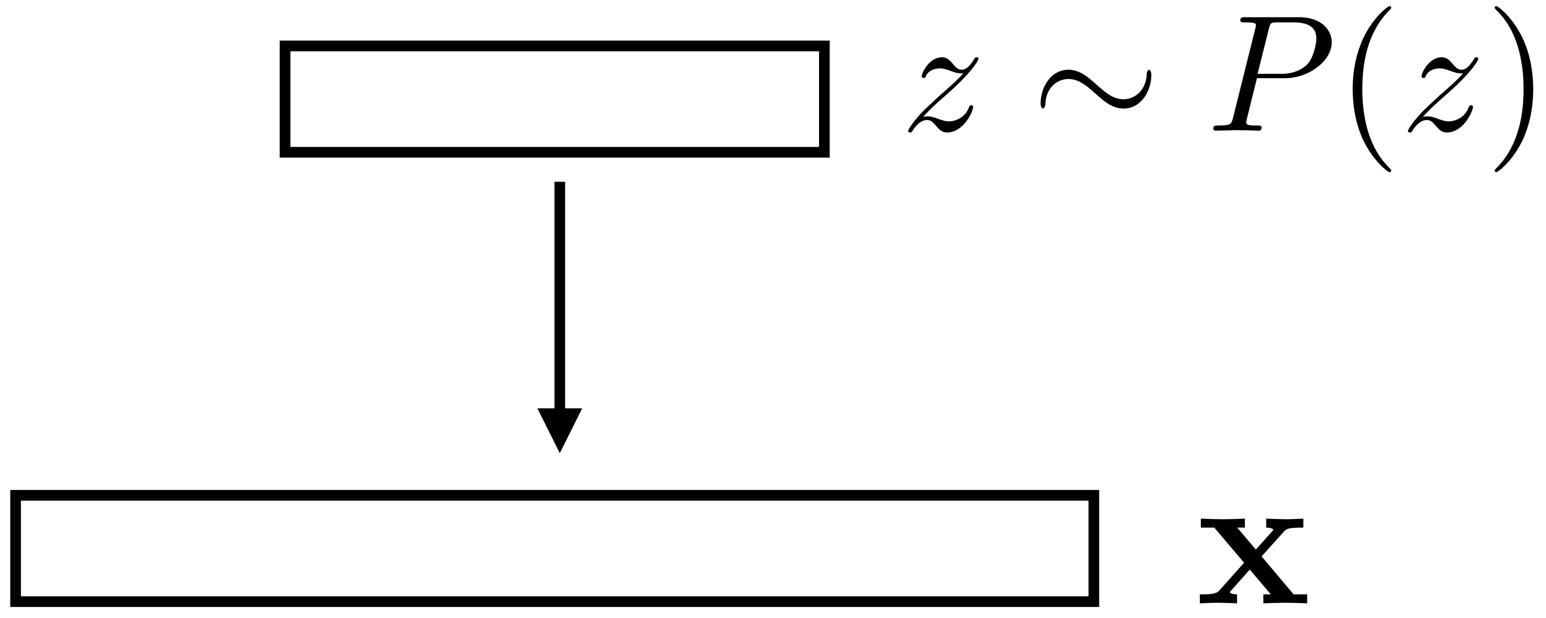

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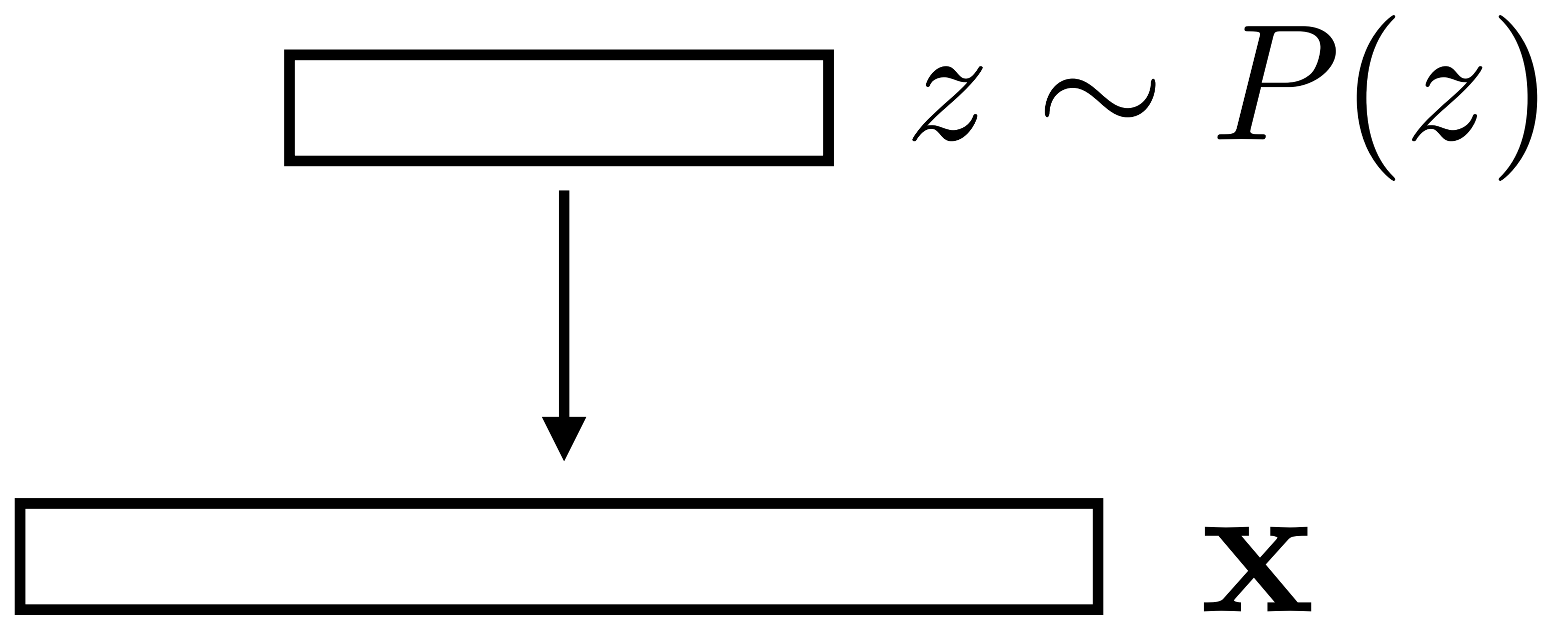

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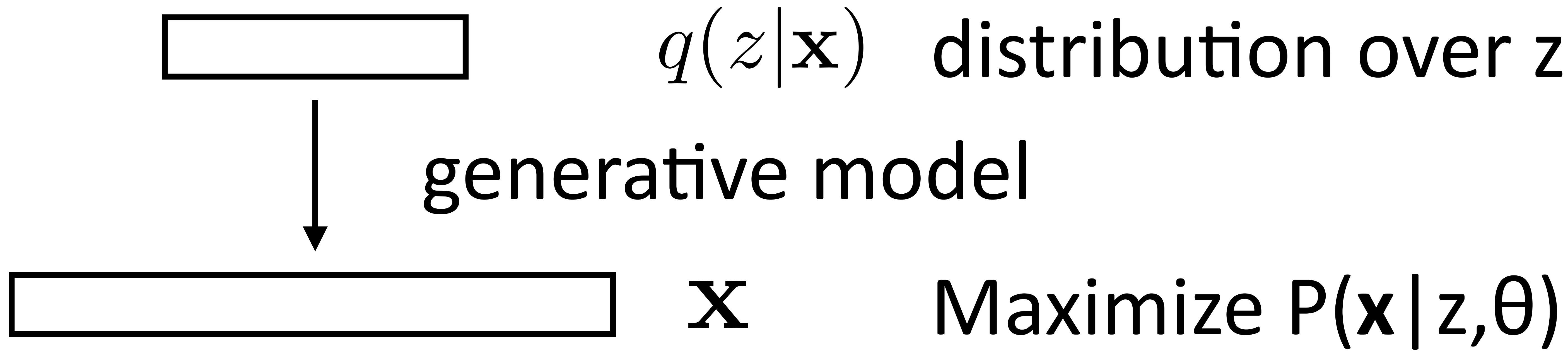

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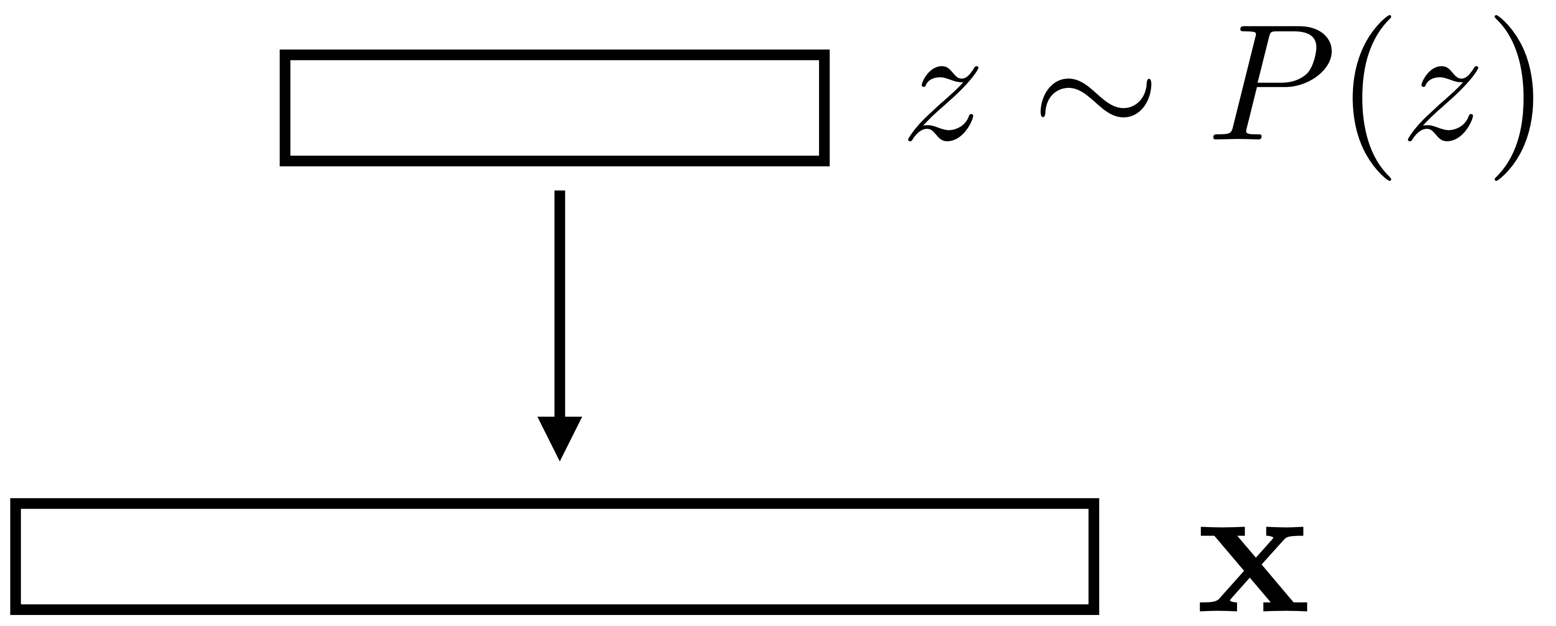

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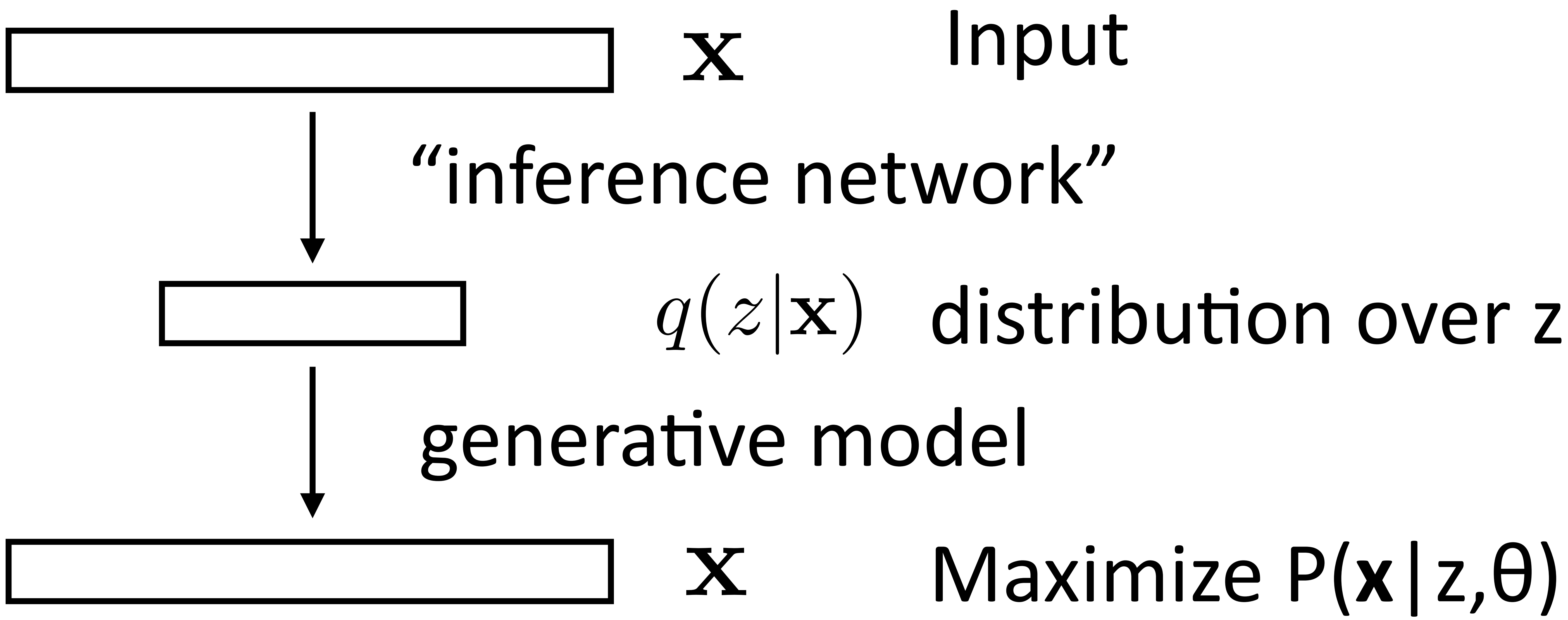

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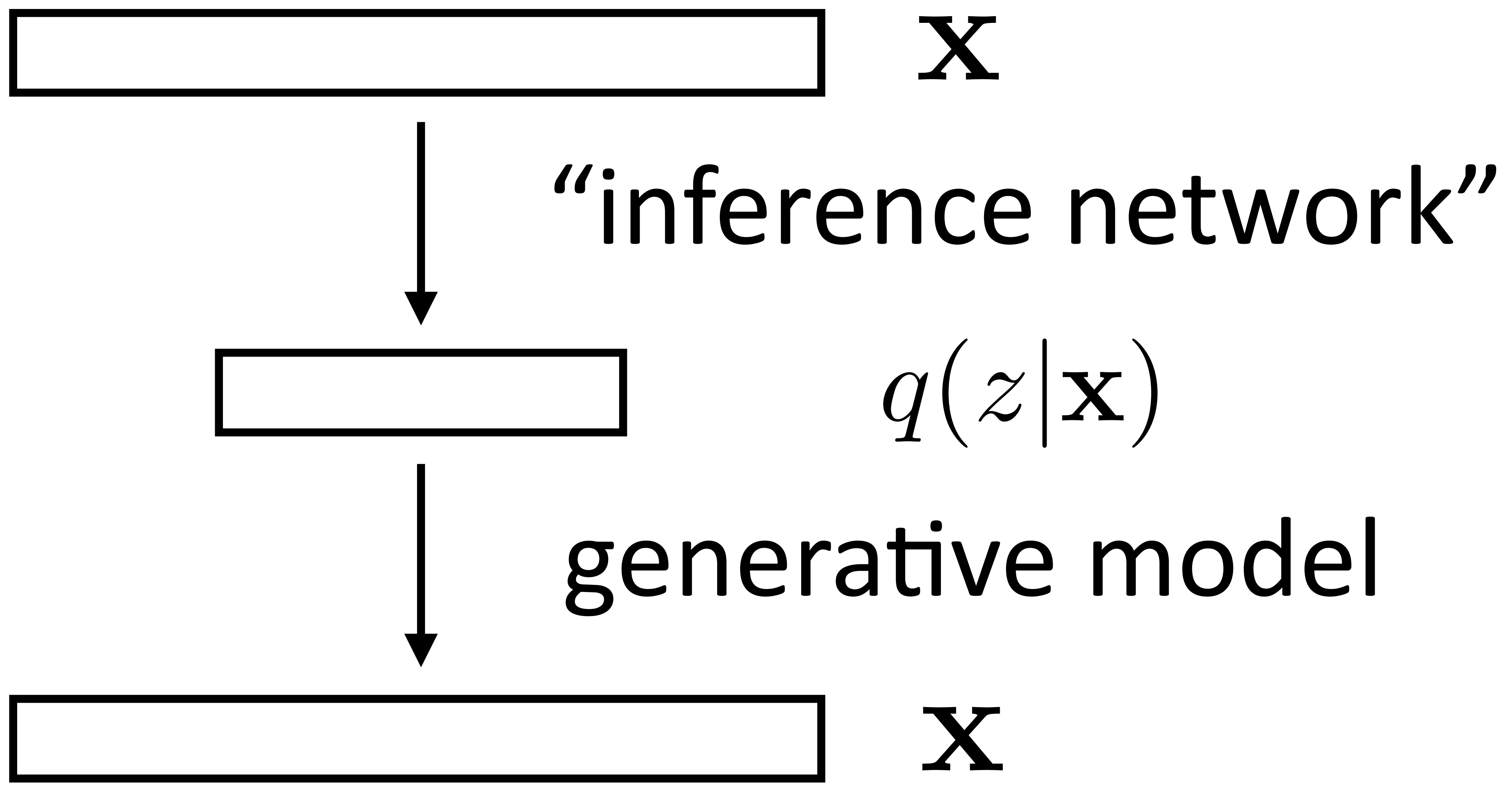

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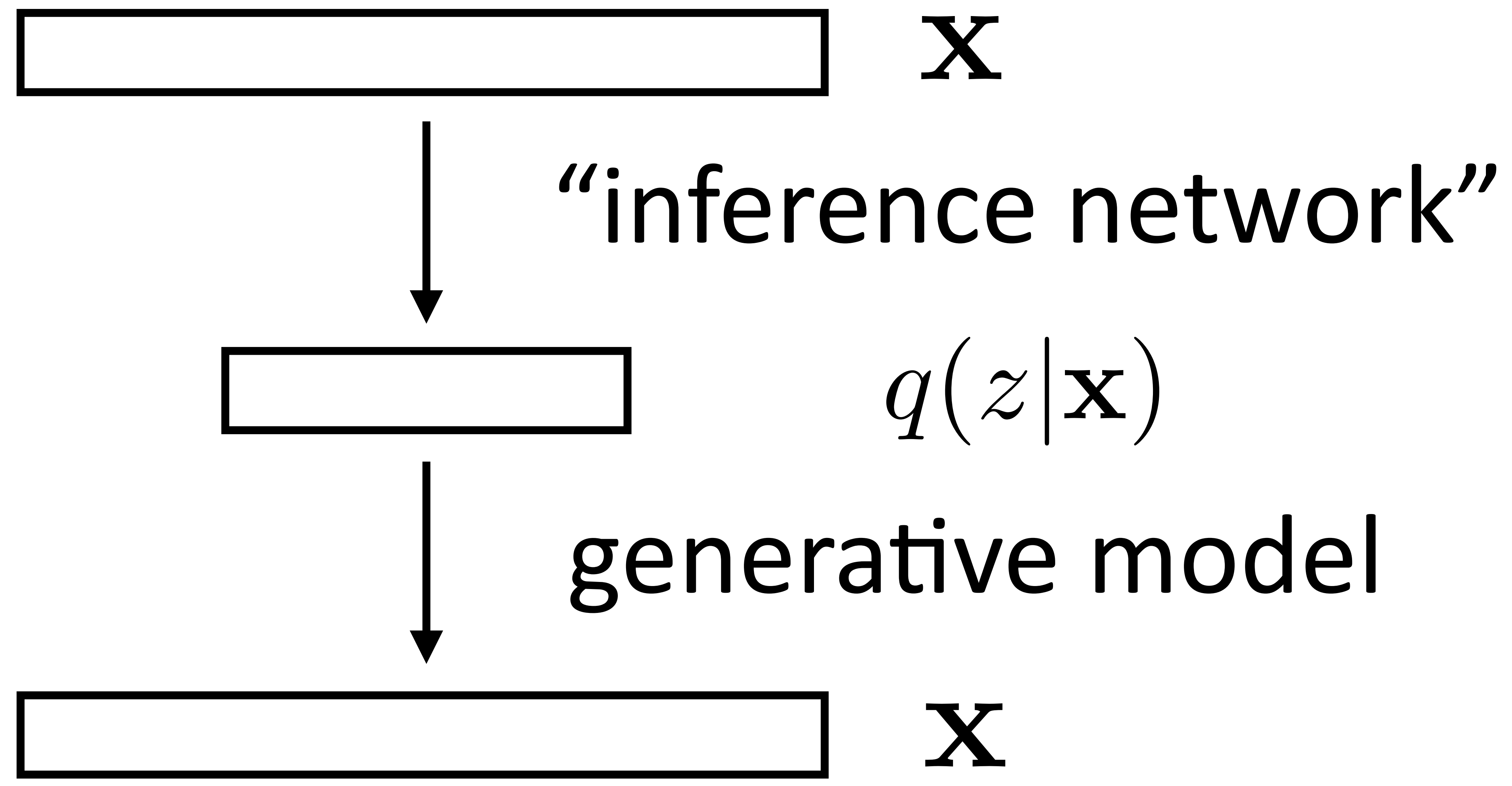

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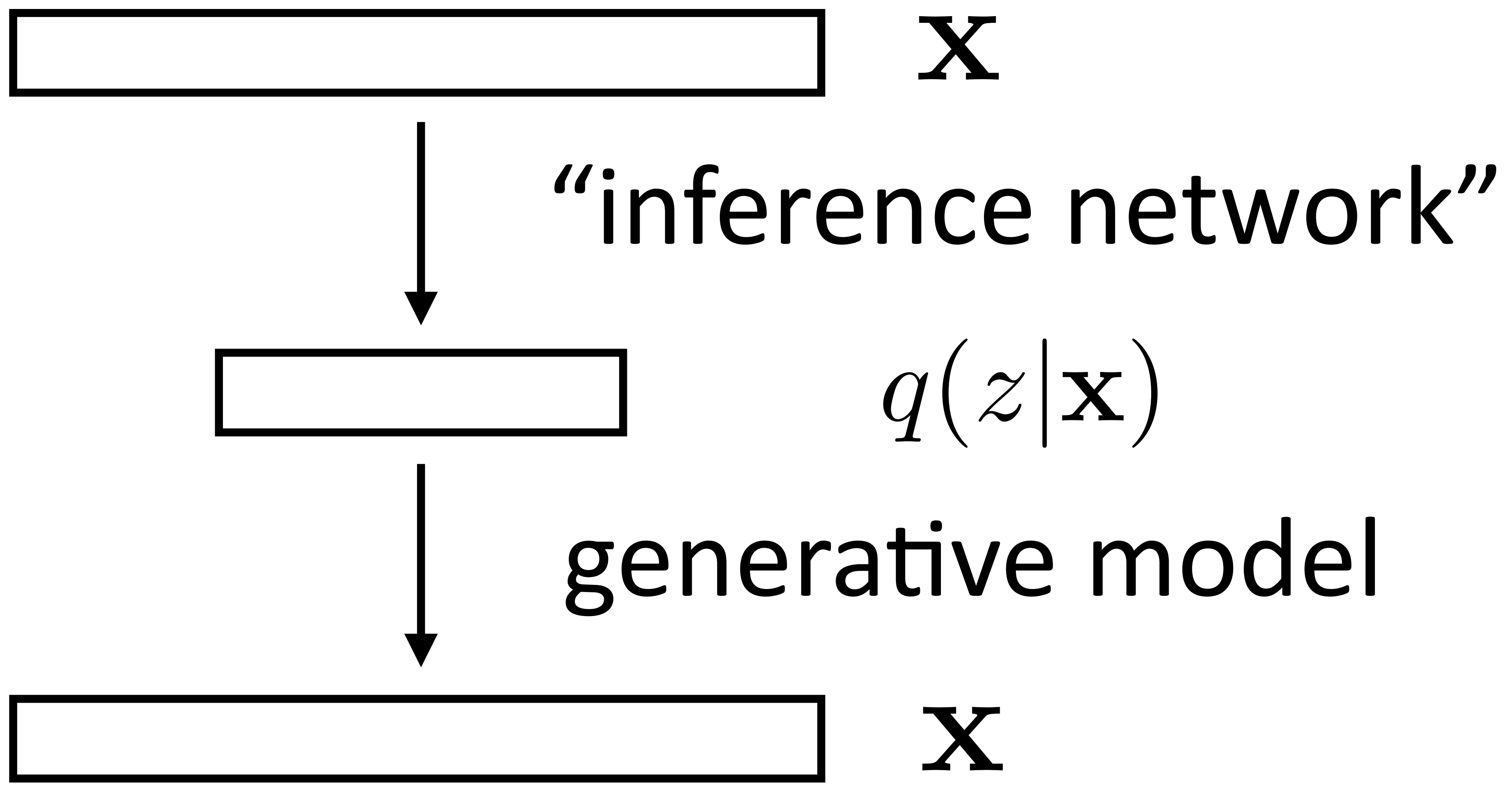

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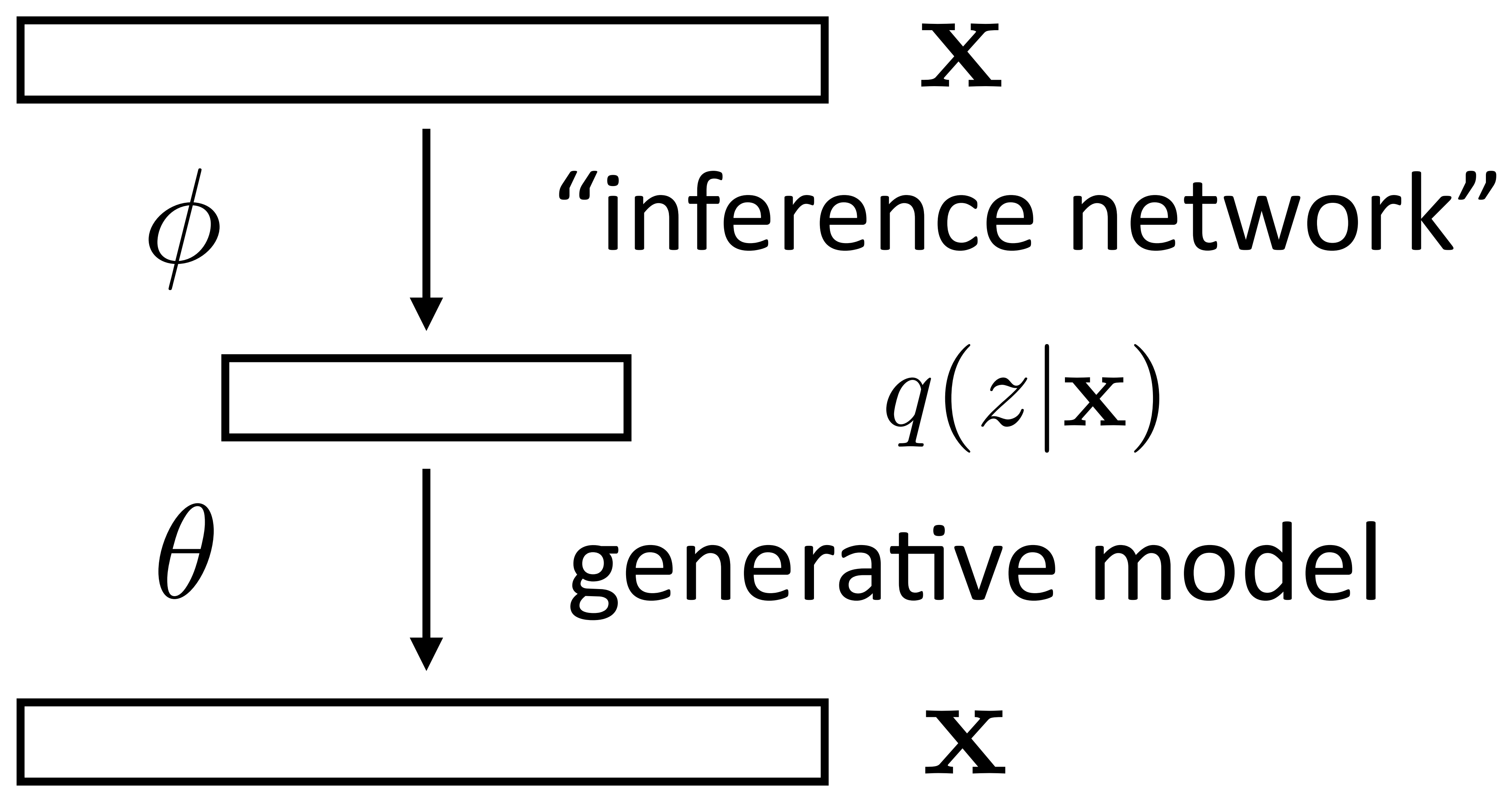

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- How to handle the expectation? Sampling

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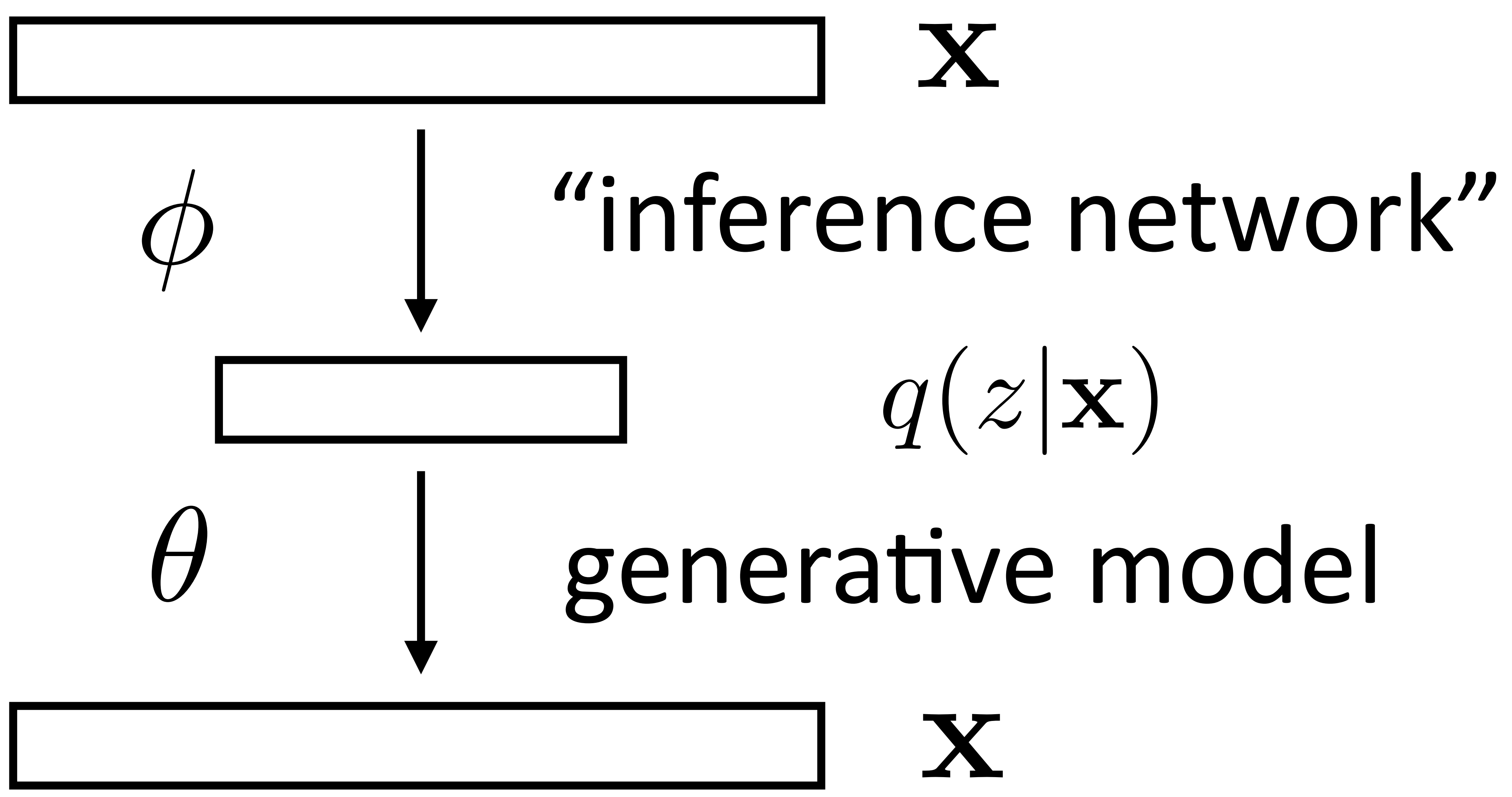

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For each example **x**

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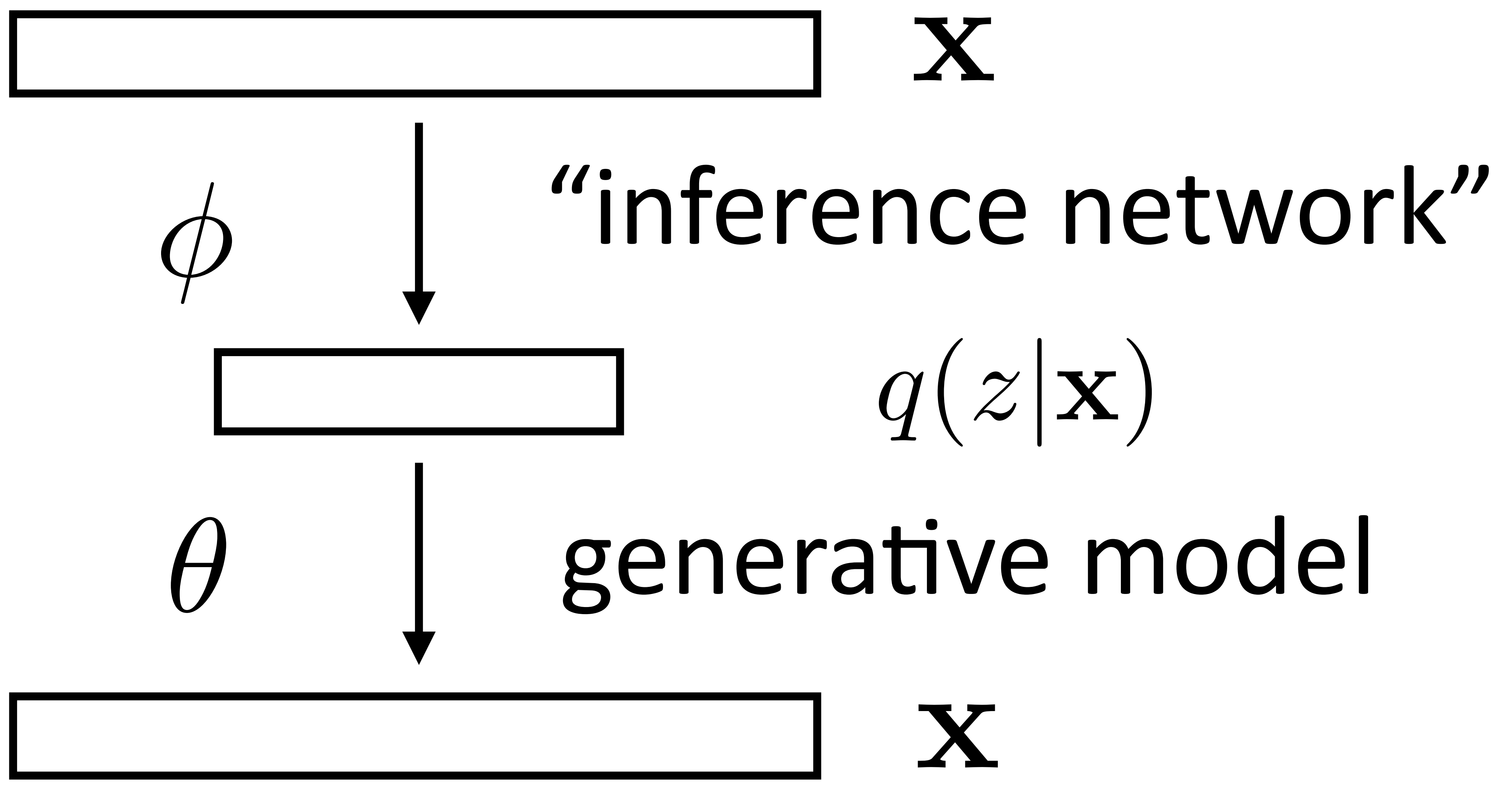

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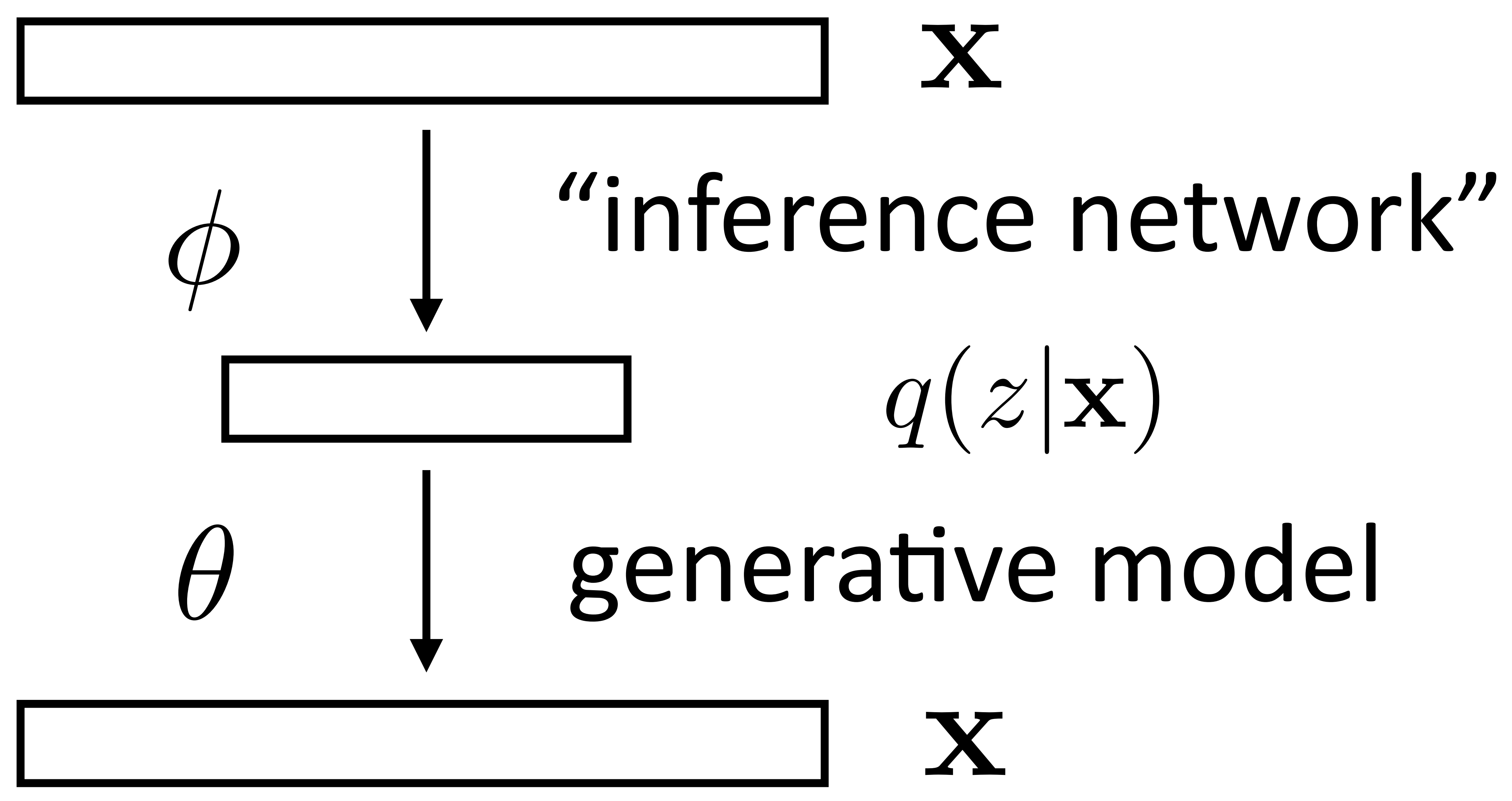

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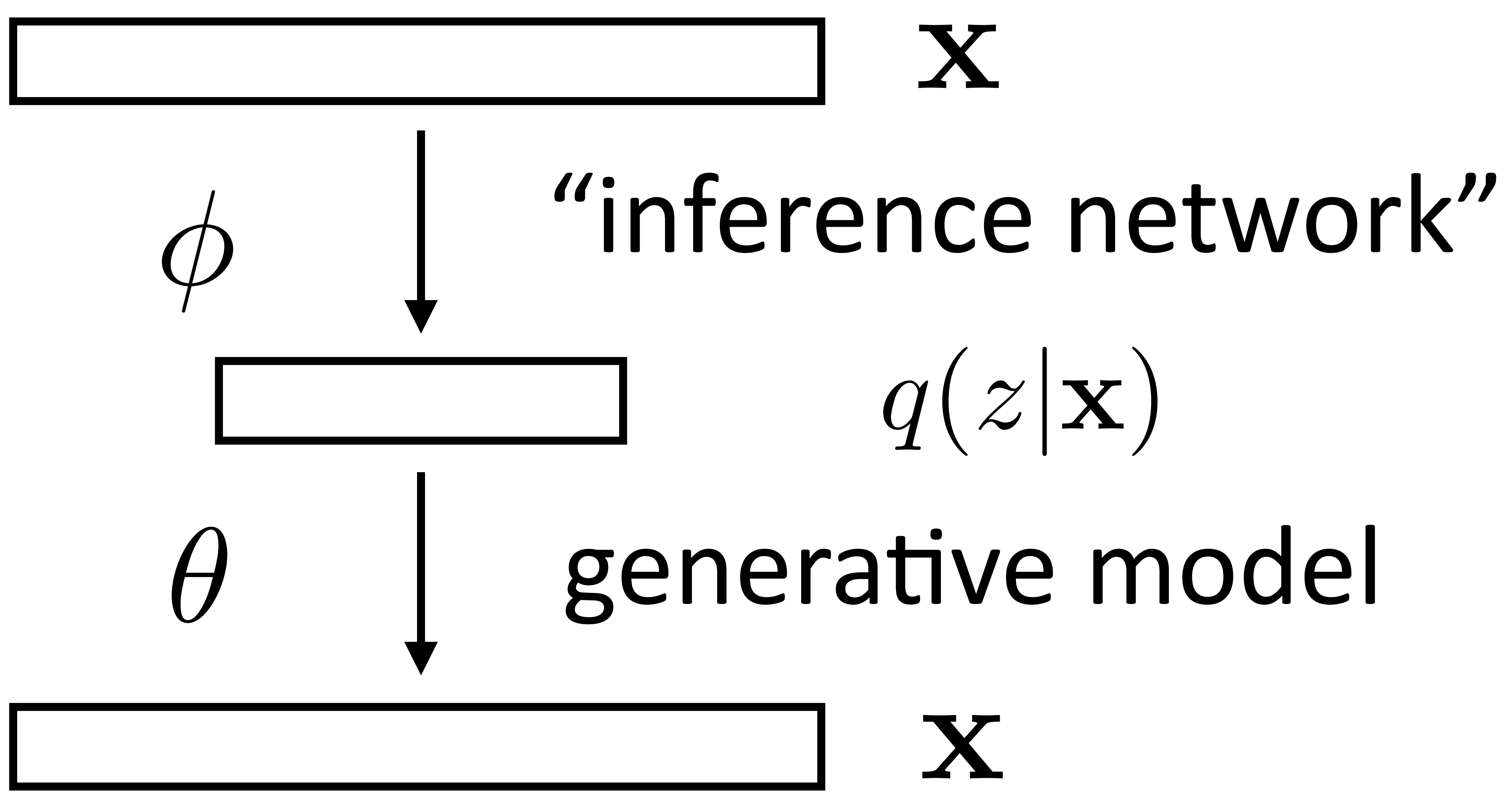

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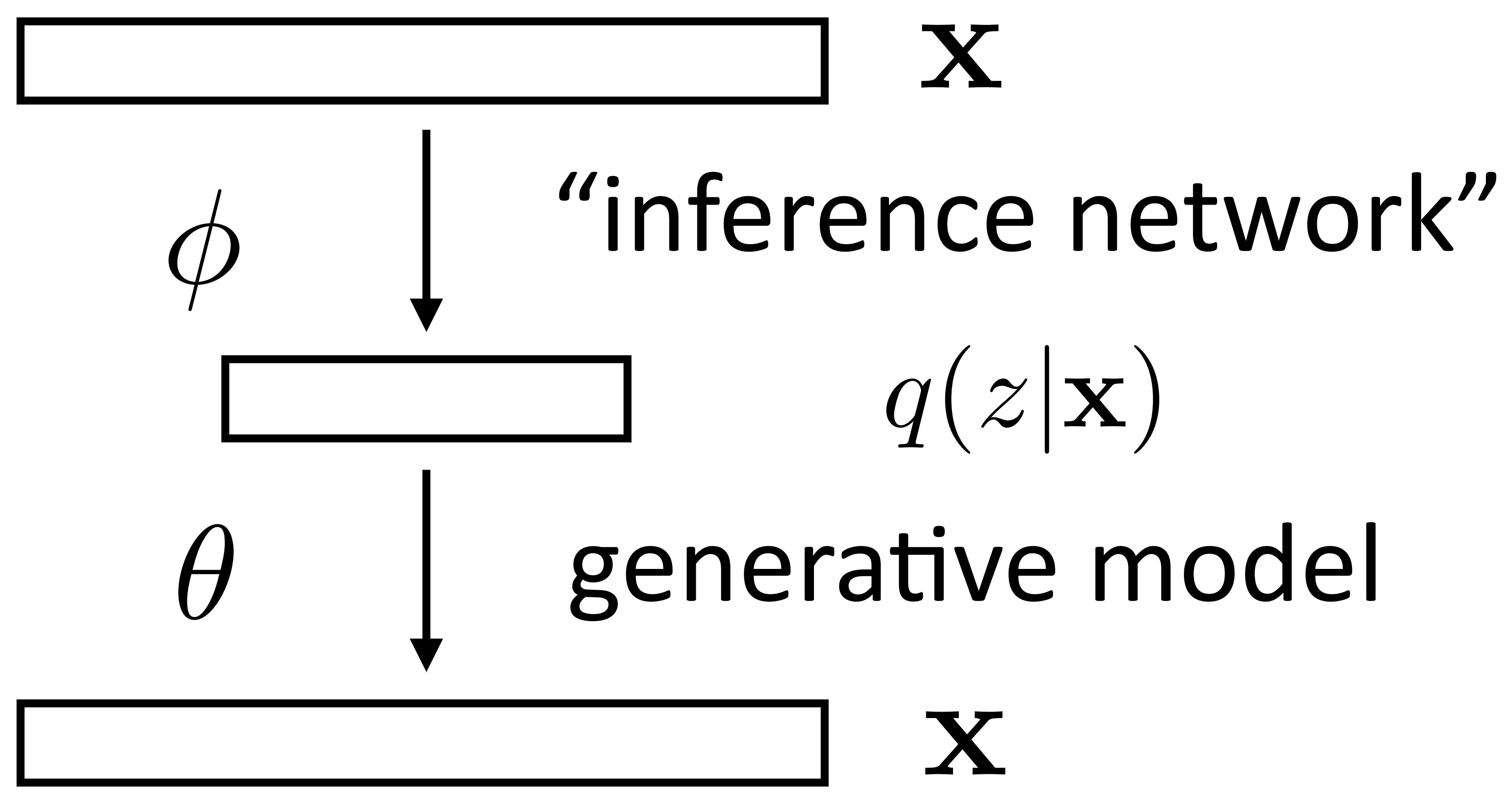

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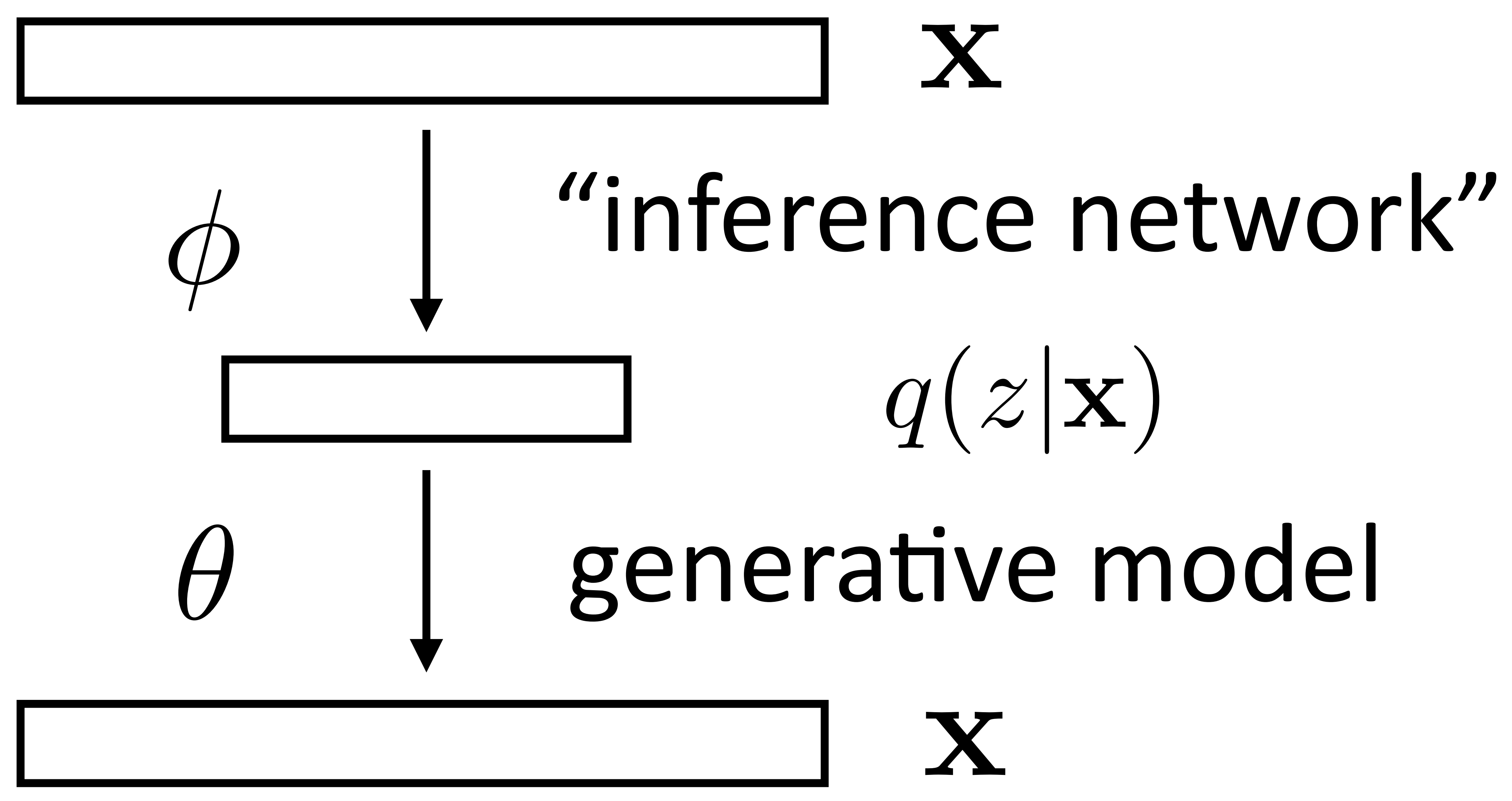

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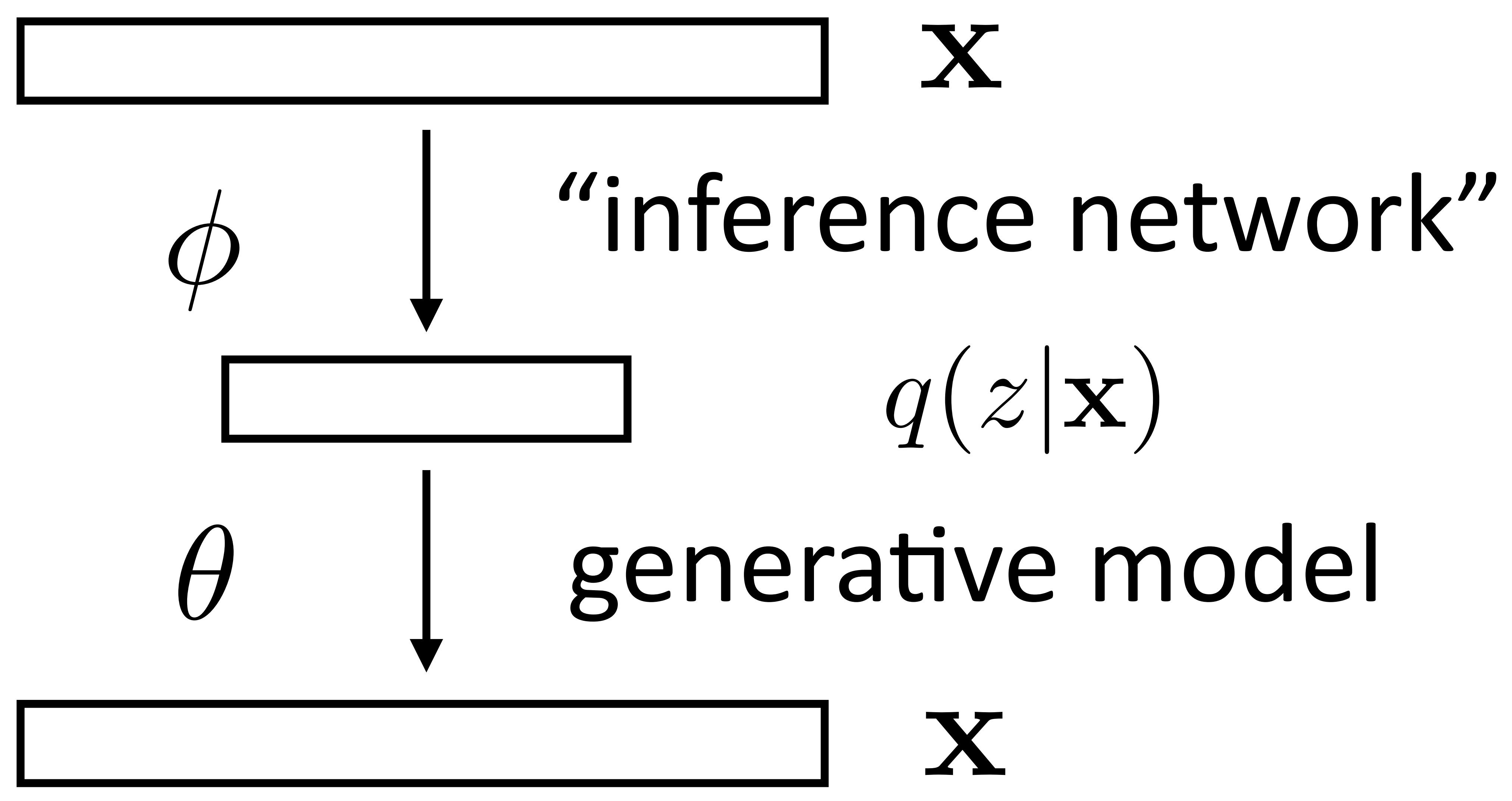
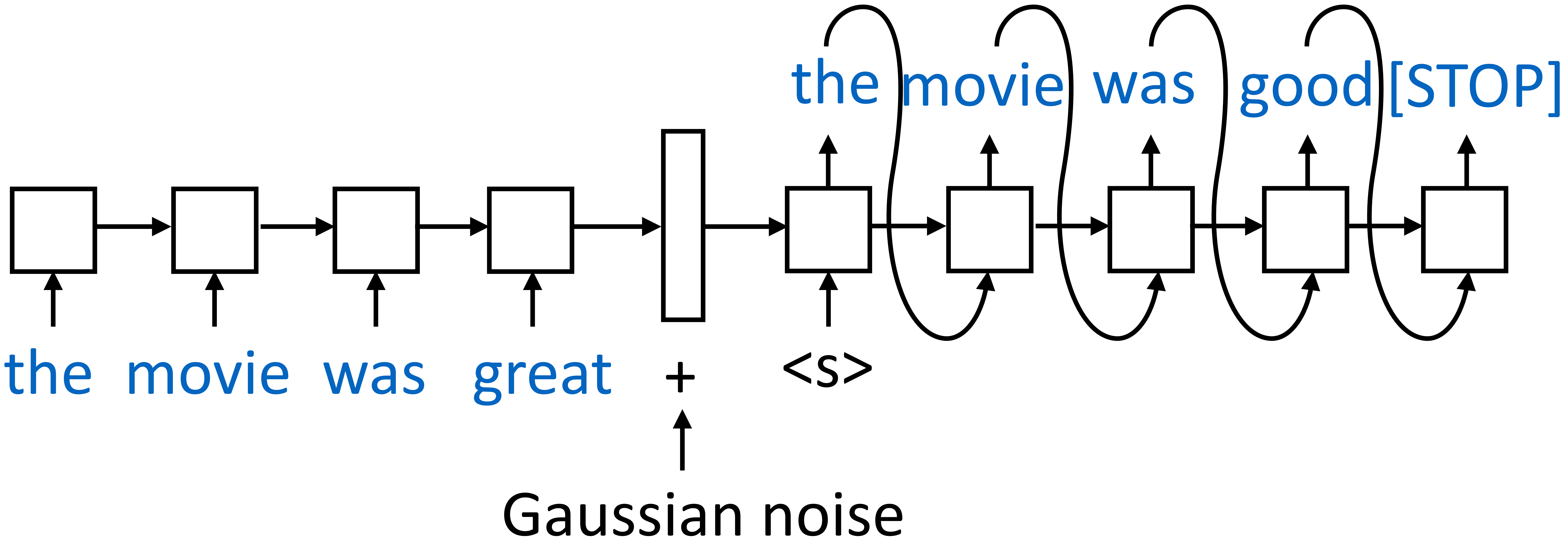


Autoencoders



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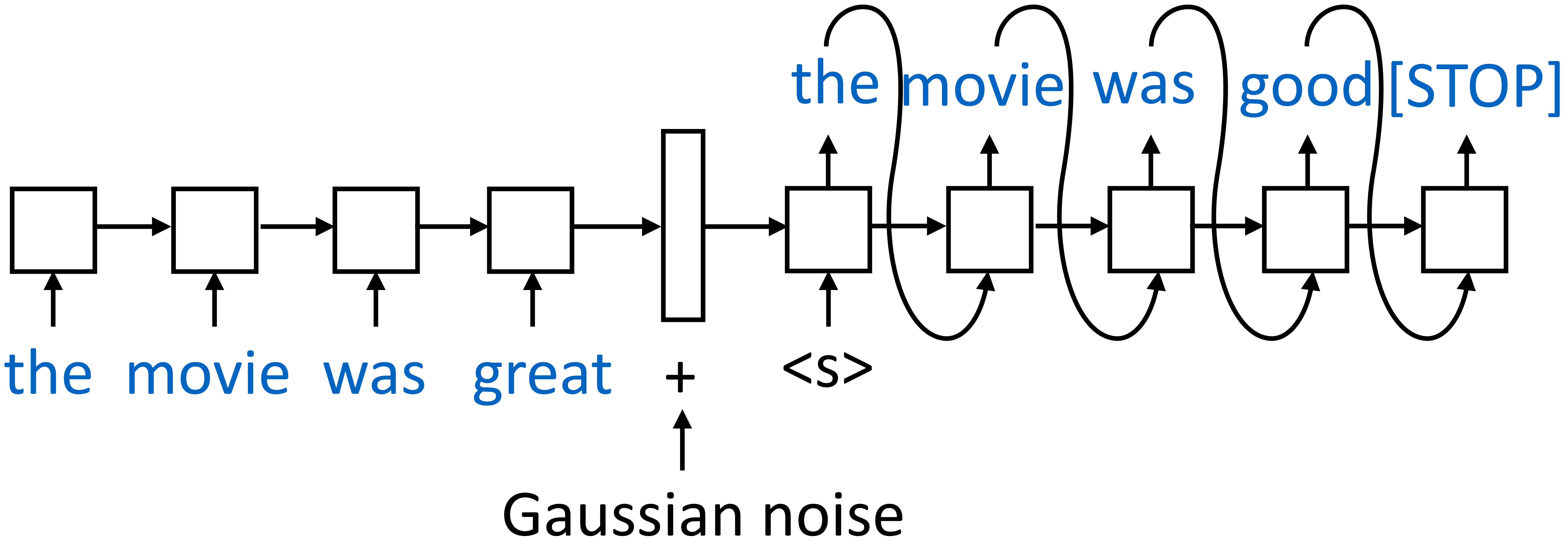

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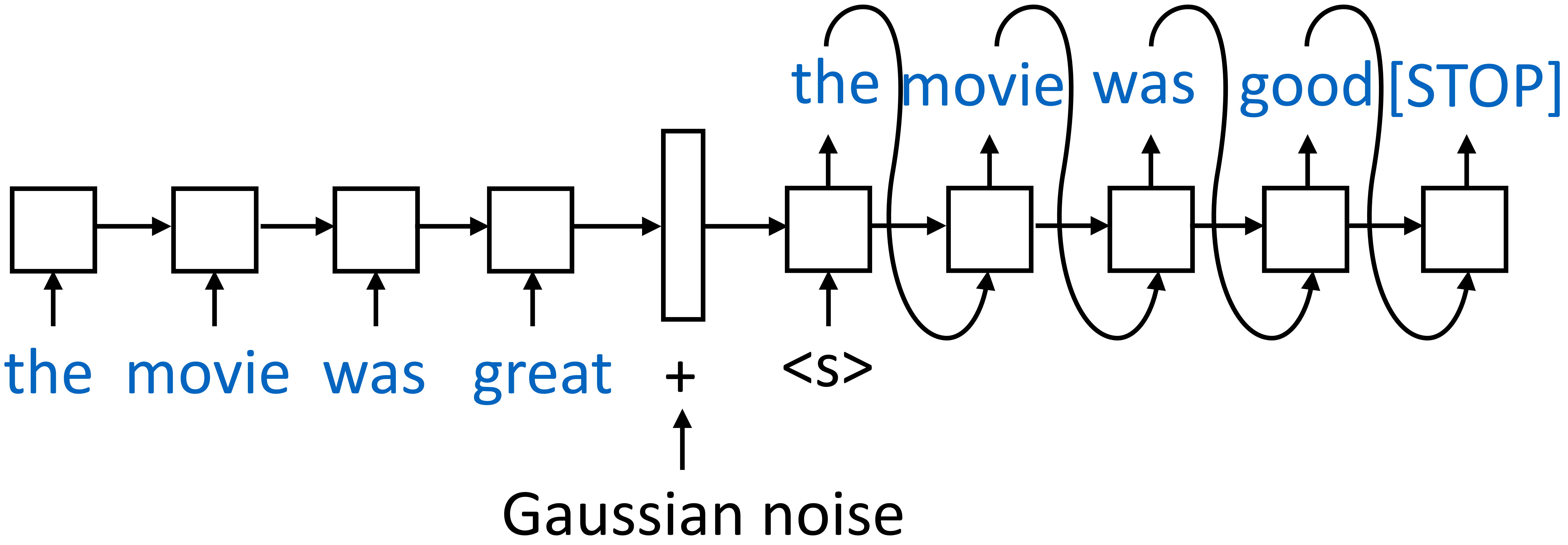

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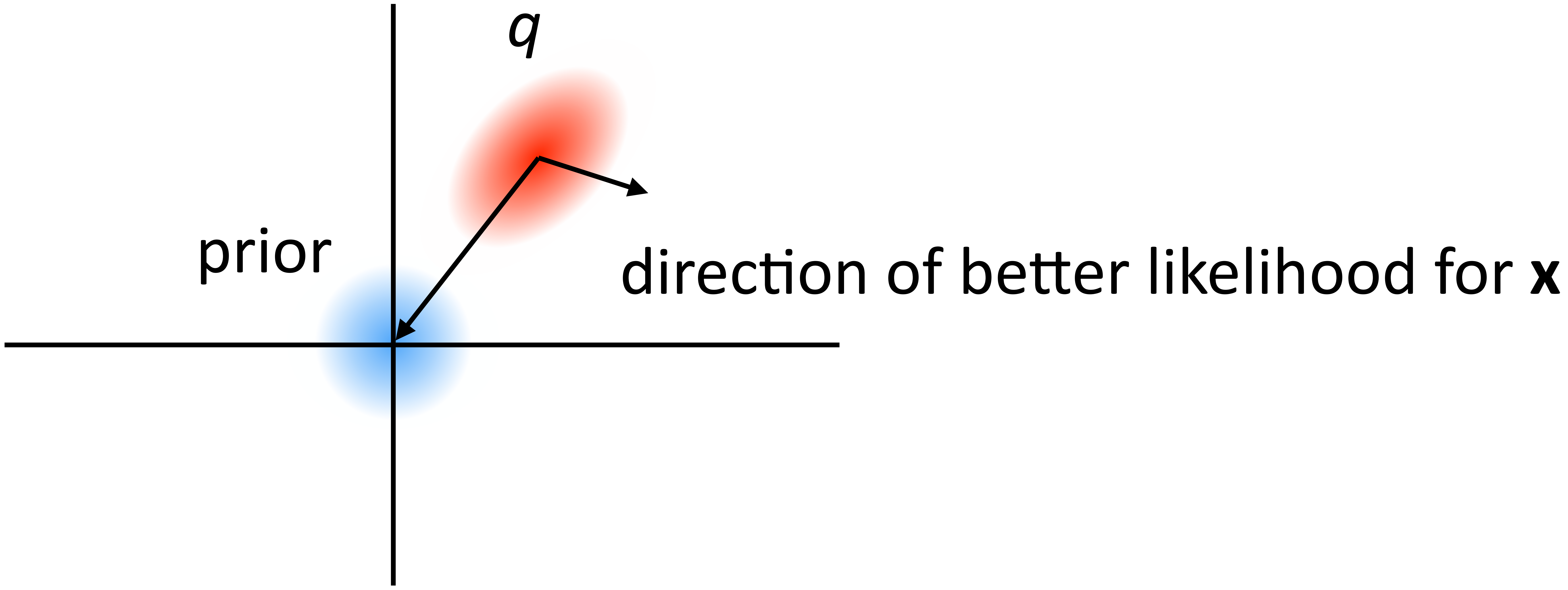
Visualization

$$\mathbb{E}_{q(z|\mathbf{x})}[\log P(\mathbf{x}|z,\theta)] + \mathrm{KL}(q(z|\mathbf{x})\|P(z))$$

- What does gradient encourage latent space to do?



What do VAEs do?

Bowman et al. (2016), Zhao et al. (2017)

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MEAN	*they were laughing at the same time .*	*i went to the kitchen .*	*what are you doing ?*
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- …or use the latent representations for semi-supervised learning

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Self-Supervision / Transfer Learning

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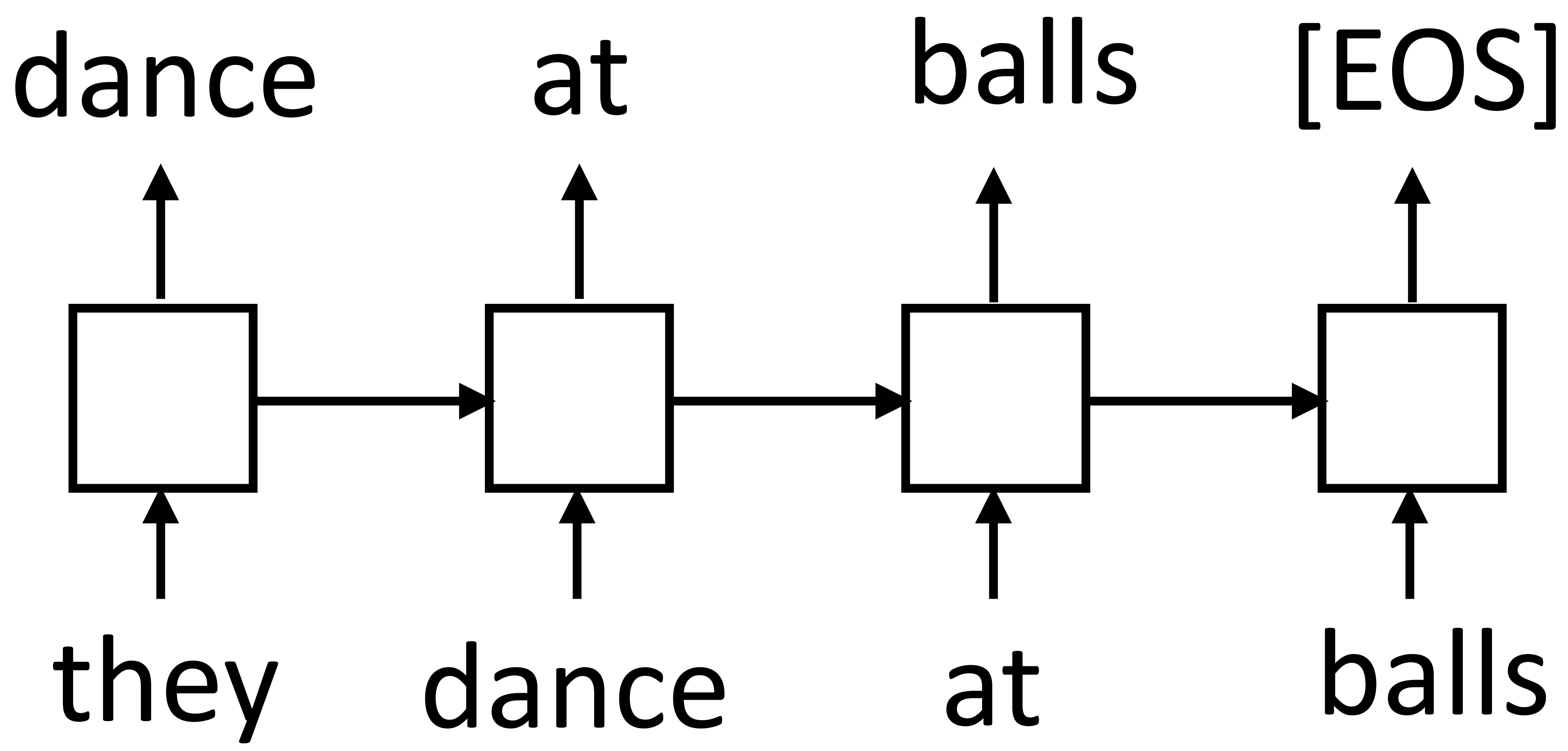
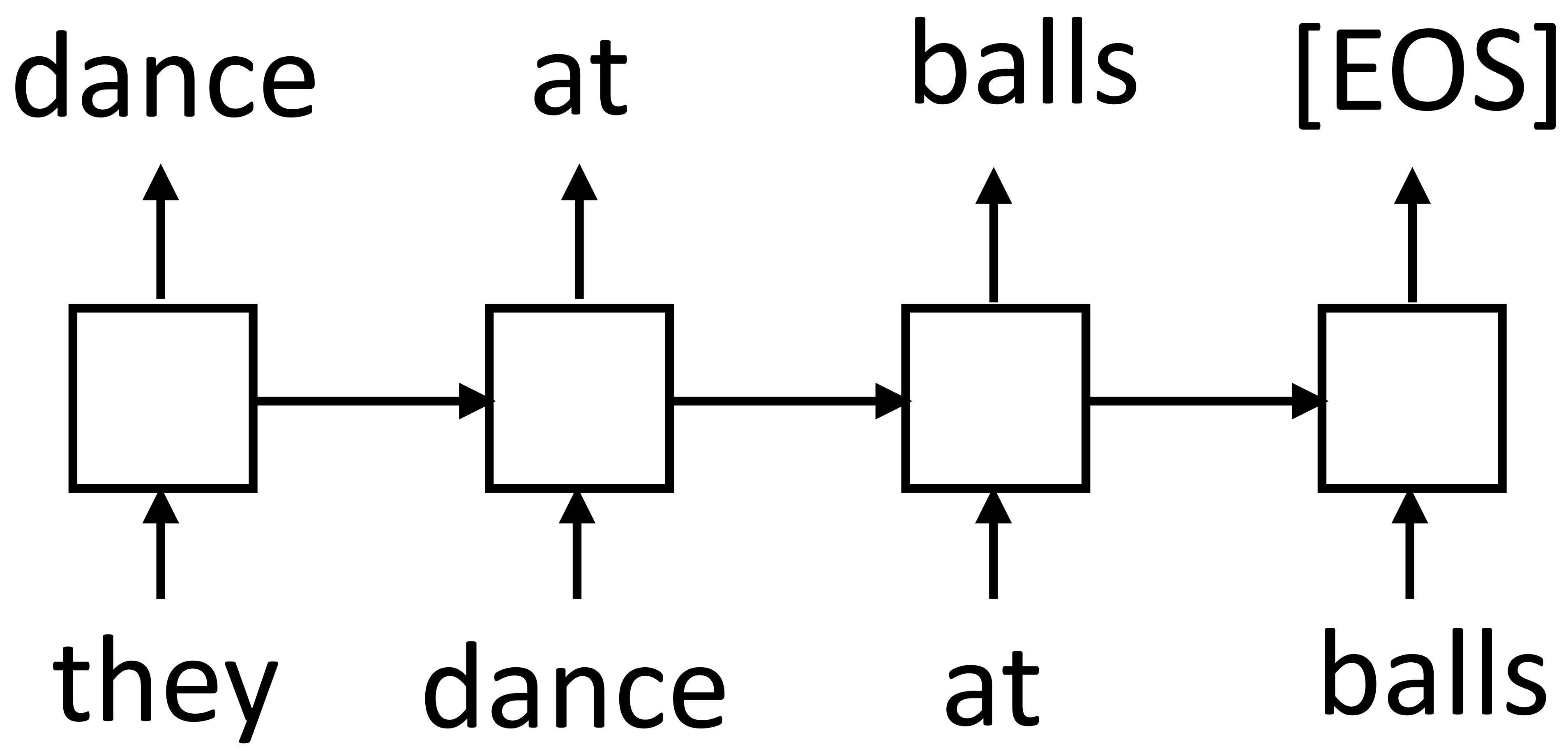
- Language modeling is a "more contextualized" form of word2vec

ELMo



ELMo



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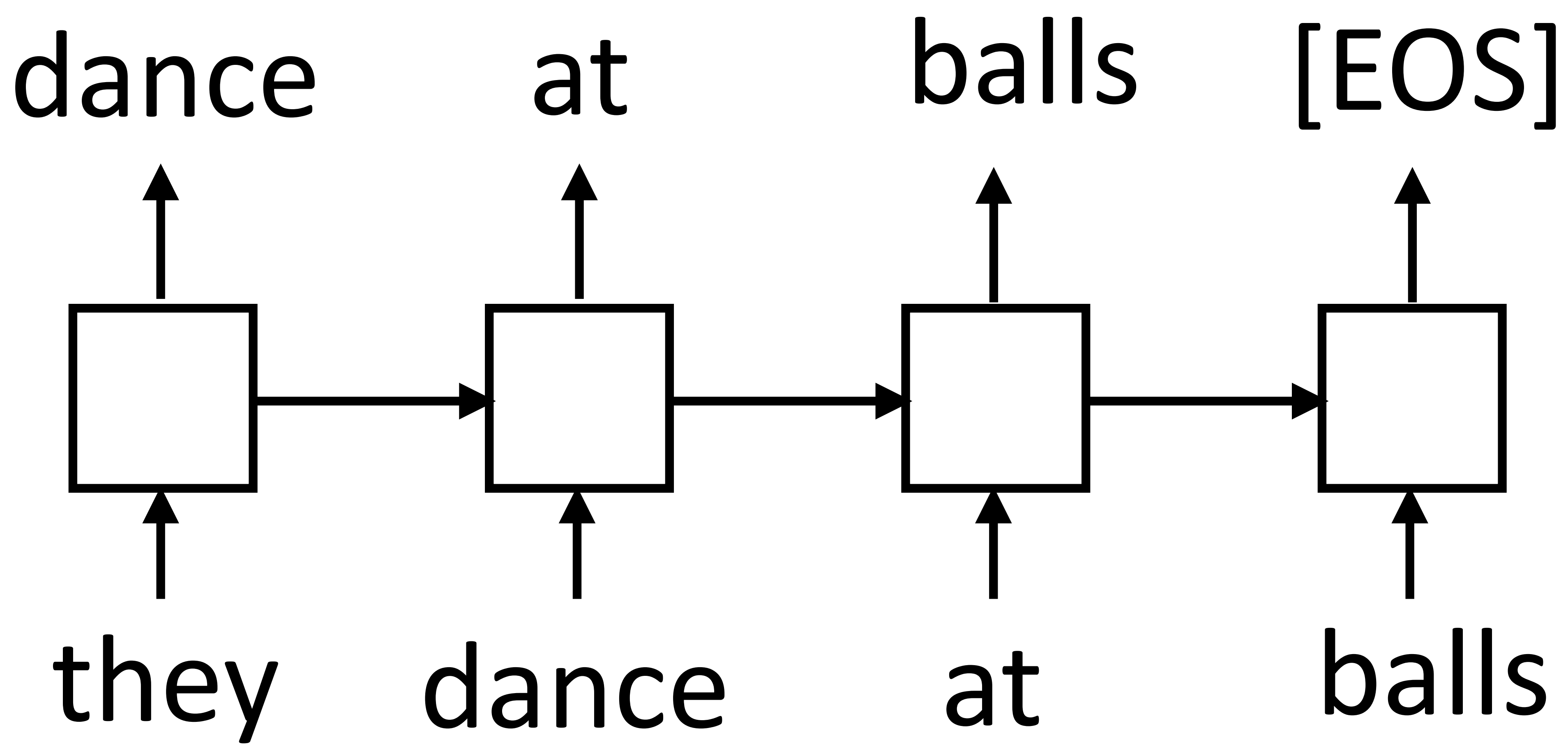

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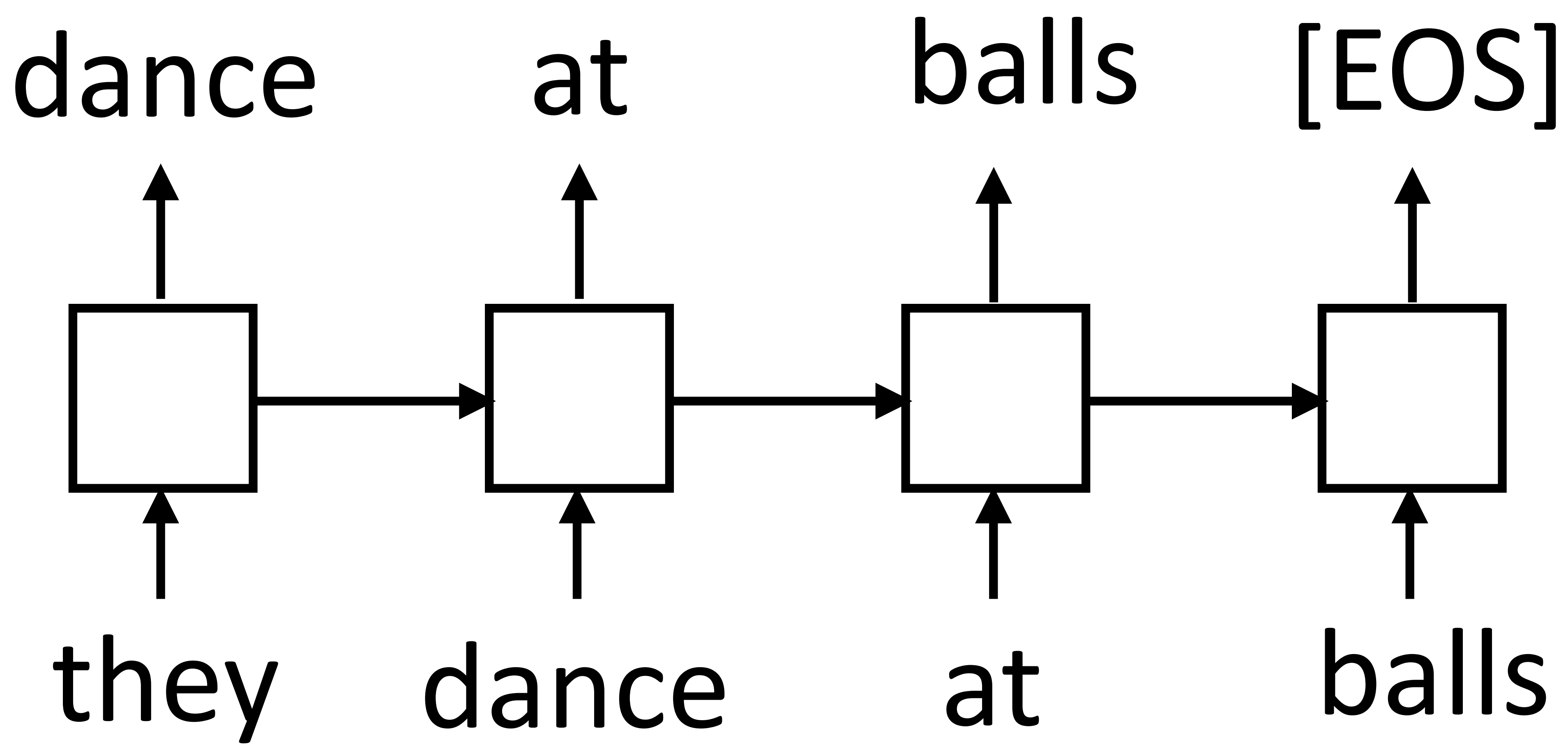

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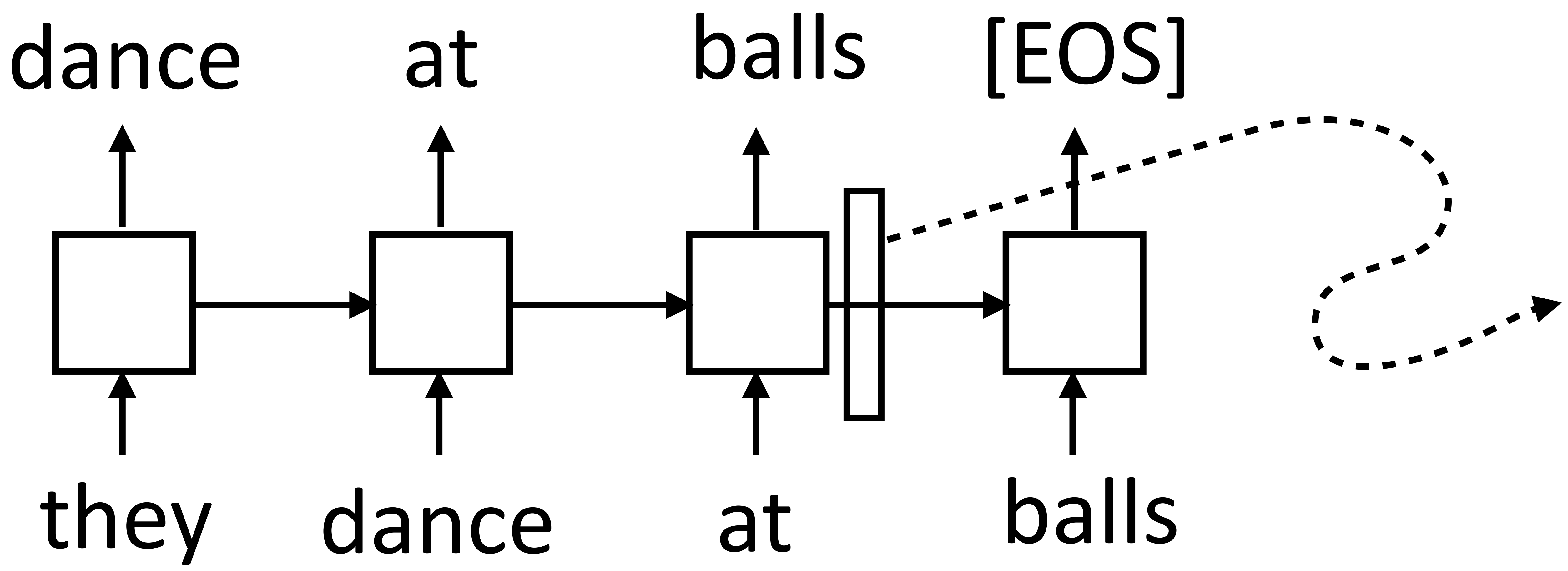

learn a linear classifier on top of this vector to get a POS tagger with 97.3% accuracy (~SOTA)

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Results

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.9	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	88.1	91.3	45.4	80.0	82.3	56.0	75.2
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.1	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**91.1**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**81.9**

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- Dramatic gains on a range of sentence pair / single sentence tasks: paraphrase identification, entailment, sentiment, textual similarity, …
- Not a generative model! But learns really effective representations…

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- Continuous structure with "discriminative" models
  - ELMo / BERT seem extremely useful

Takeaways

- EM sort of works for POS induction
- VAE can learn sentence representations
- Language modeling or text infilling as pretraining seems best — arguably not "unsupervised" but the annotation is free
- Using unlabeled data effectively seems like one of the most important directions in NLP right now
- Next time: Jessy Li guest lecture on discourse