Variational Decoding for Statistical Machine Translation

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Spurious Ambiguity

- Statistical models in MT exhibit **spurious ambiguity**
  - Many different derivations (e.g., trees or segmentations) generate the same translation string

- Regular phrase-based MT systems
  - phrase segmentation ambiguity
- Tree-based MT systems
  - derivation tree ambiguity

Spurious Ambiguity in Phrase Segmentations

Spurious Ambiguity in Phrase Segmentations

机器 翻译 软件

Spurious Ambiguity in Phrase Segmentations

机器 翻译 软件

machine translation software

Spurious Ambiguity in Phrase Segmentations

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machine translation software

machine translation

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machine translation software

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machine translation software

机器

machine

Spurious Ambiguity in Phrase Segmentations

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machine translation

Spurious Ambiguity in Phrase Segmentations

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Spurious Ambiguity in Phrase Segmentations

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machine translation software

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机器 翻译 软件

machine translation software

机器 翻译 软件

machine translation software

machine translation software

- Same output: "machine translation software"
- Three different phrase segmentations

Spurious Ambiguity in Phrase Segmentations

机器 翻译 软件

machine translation software

machine translation software

机器 翻译 软件

machine translation software

机器 翻译 软件

machine translation software

machine translation software

- Same output: "machine translation software"
- Three different phrase segmentations

machine transfer software

Spurious Ambiguity in Derivation Trees

Spurious Ambiguity in Derivation Trees

机器 翻译 软件

Spurious Ambiguity in Derivation Trees

机器 翻译 软件

S->(机器, machine)

Spurious Ambiguity in Derivation Trees

机器 翻译 软件

S->(机器, machine) S->(翻译, translation)

Spurious Ambiguity in Derivation Trees

机器 翻译 软件

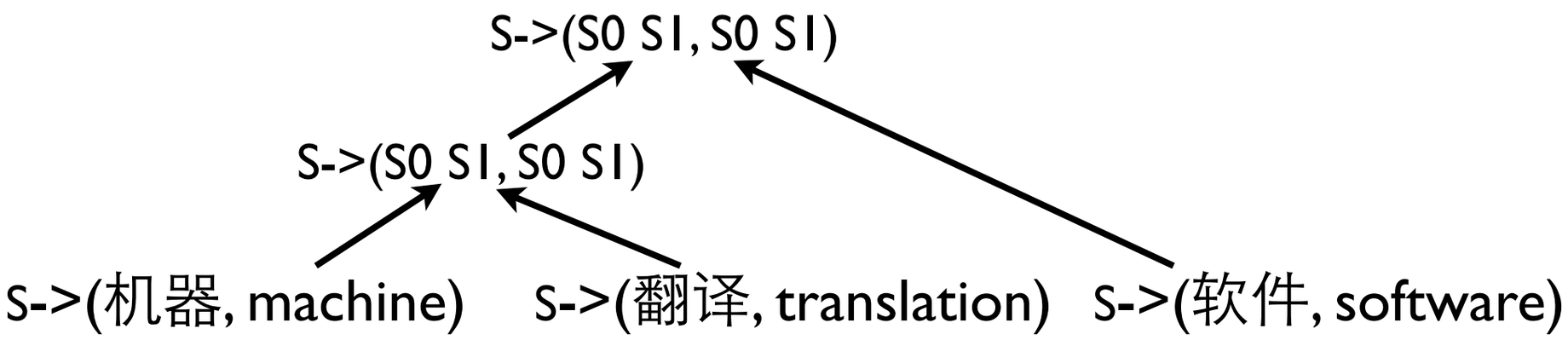
S->(机器, machine) S->(翻译, translation) S->(软件, software)

Spurious Ambiguity in Derivation Trees

机器 翻译 软件

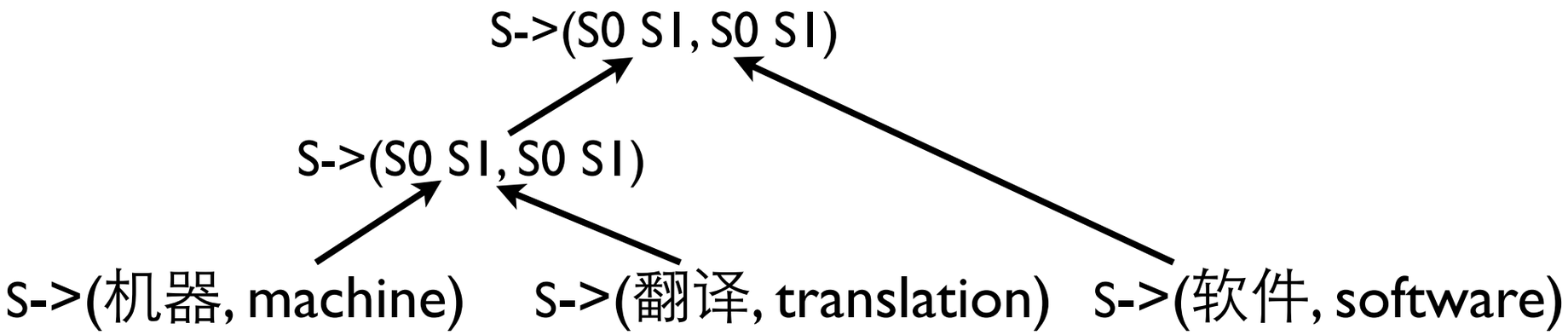
Spurious Ambiguity in Derivation Trees

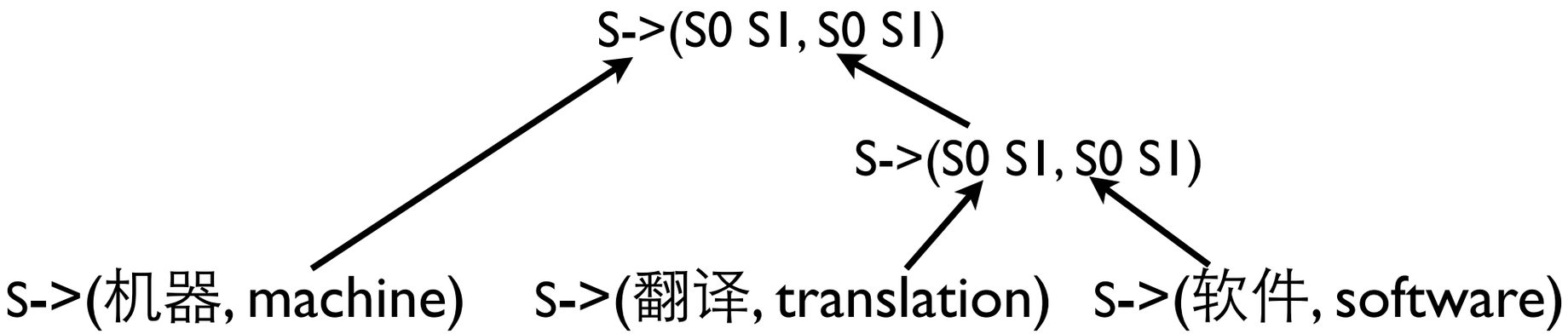
机器 翻译 软件



Spurious Ambiguity in Derivation Trees

机器 翻译 软件





Spurious Ambiguity in Derivation Trees

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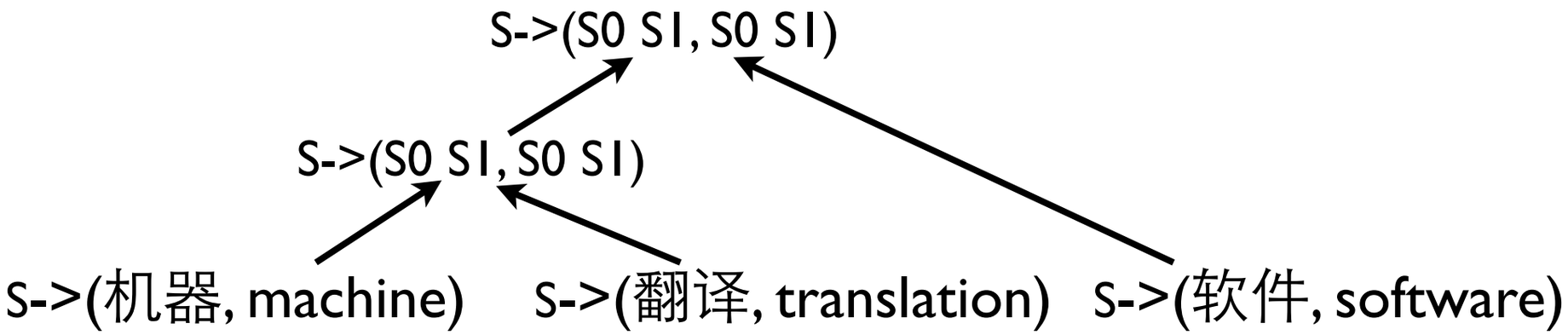
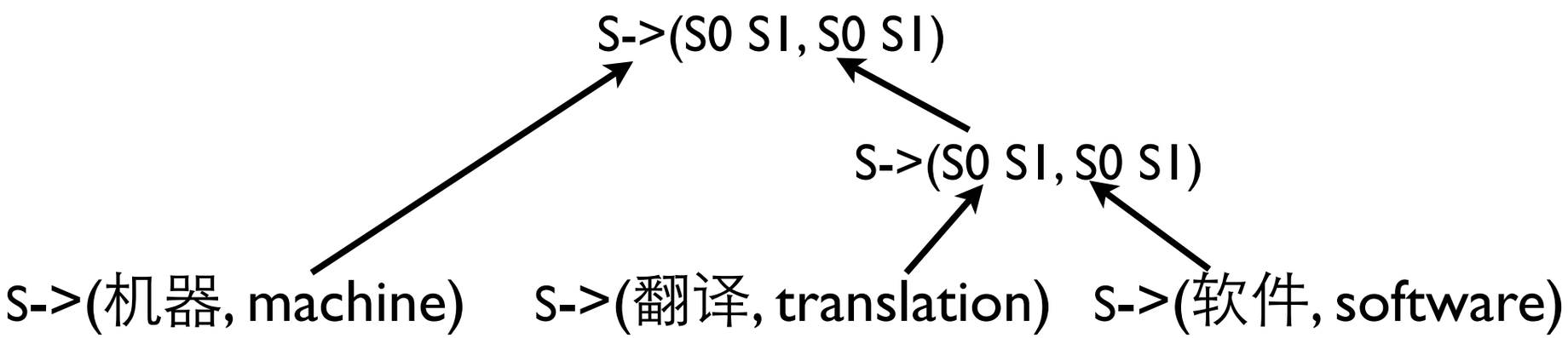
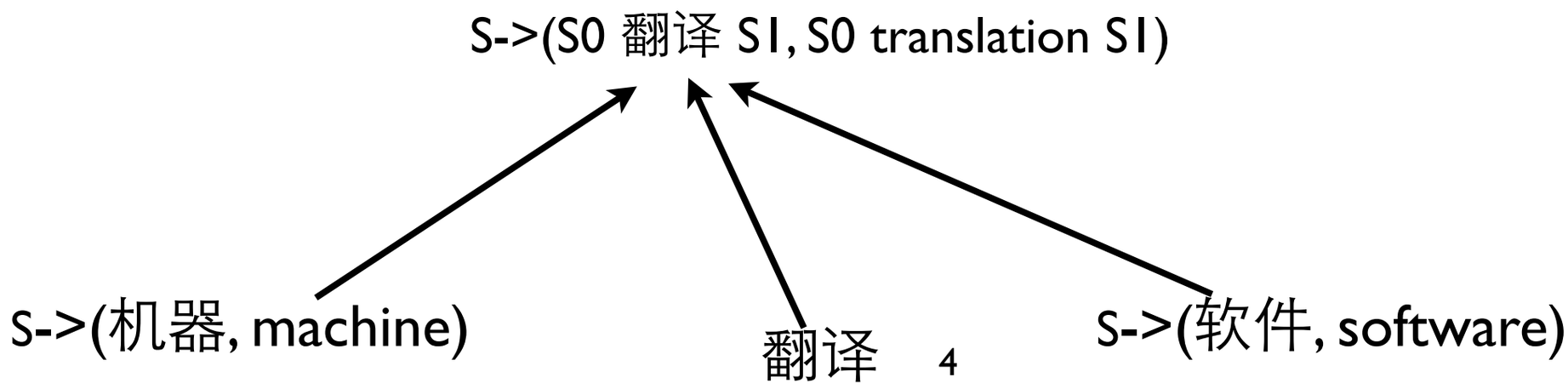


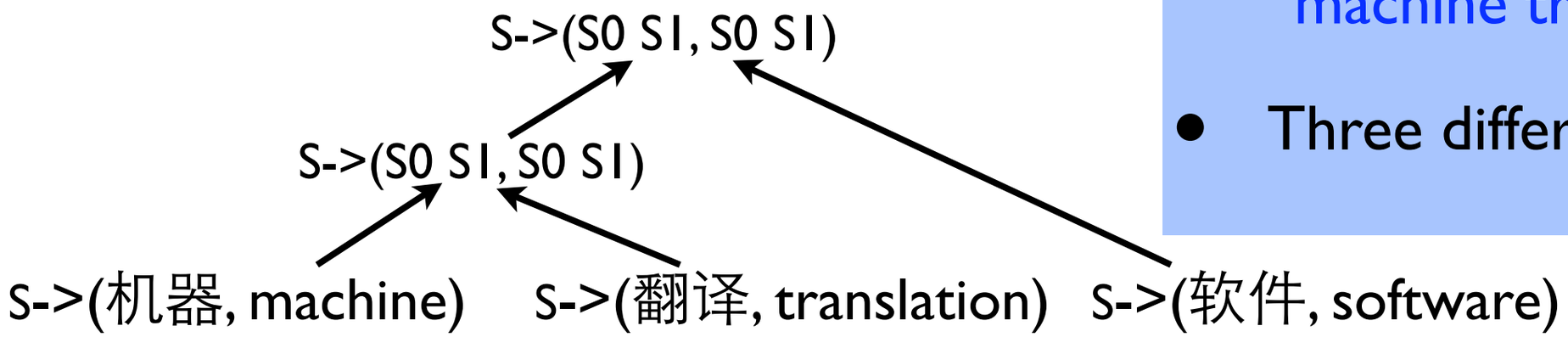


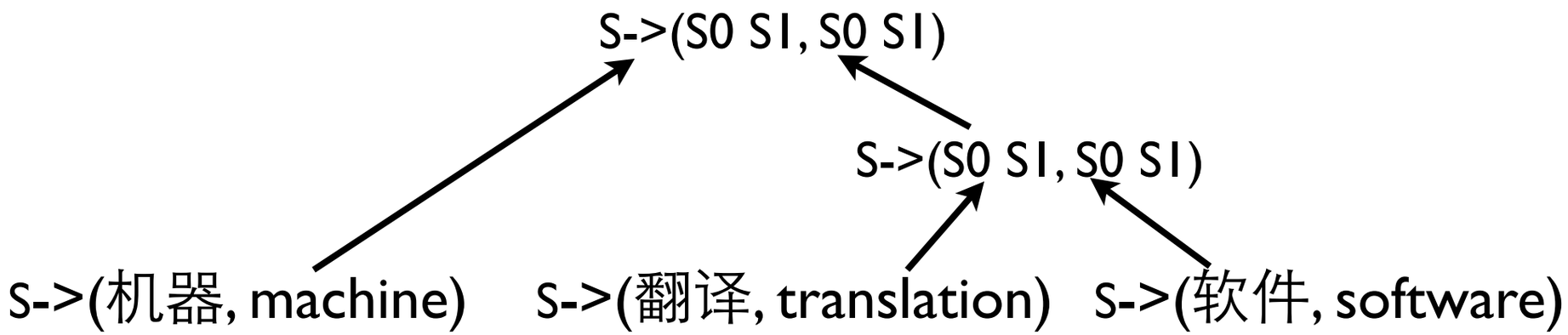


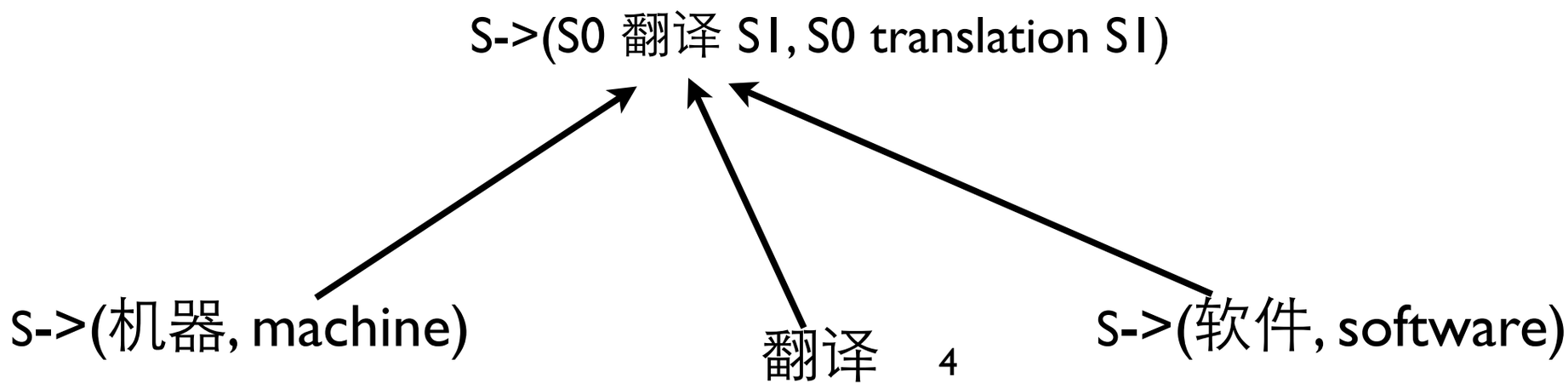
Spurious Ambiguity in Derivation Trees

机器 翻译 软件

- Same output:
  "machine translation software"
- Three different derivation trees







Maximum A Posterior (MAP) Decoding

Maximum A Posterior (MAP) Decoding

translation string

red translation

blue translation

green translation

Maximum A Posterior (MAP) Decoding

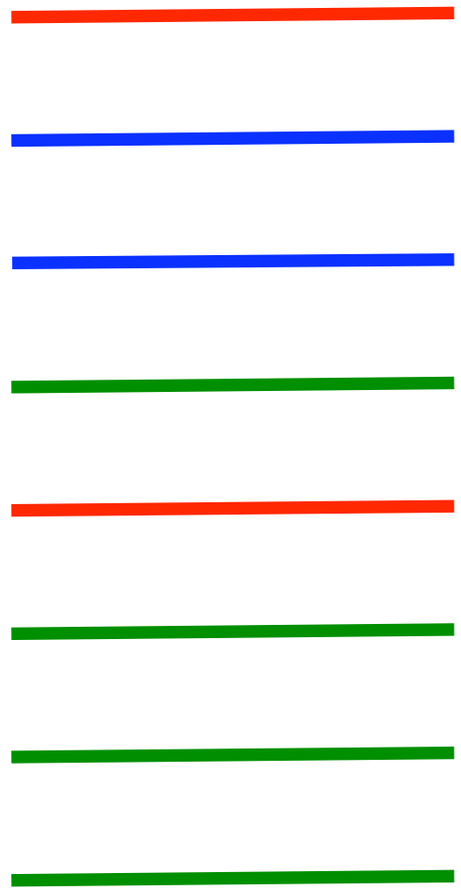
translation string

derivation

red translation

blue translation

green translation



Maximum A Posterior (MAP) Decoding

translation string	derivation	probability
red translation		0.16
		0.14
blue translation		0.14
		0.13
green translation		0.12
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		0.10
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- Exact MAP decoding

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- Exact MAP decoding

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\begin{aligned}
y^* &= \arg \max_{y \in \mathrm{Trans}(x)} p(y|x) \\
&= \arg \max_{y \in \mathrm{Trans}(x)} \sum_{d \in \mathrm{D}(x,y)} p(y, d|x)
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- d: derivation

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\end{aligned}
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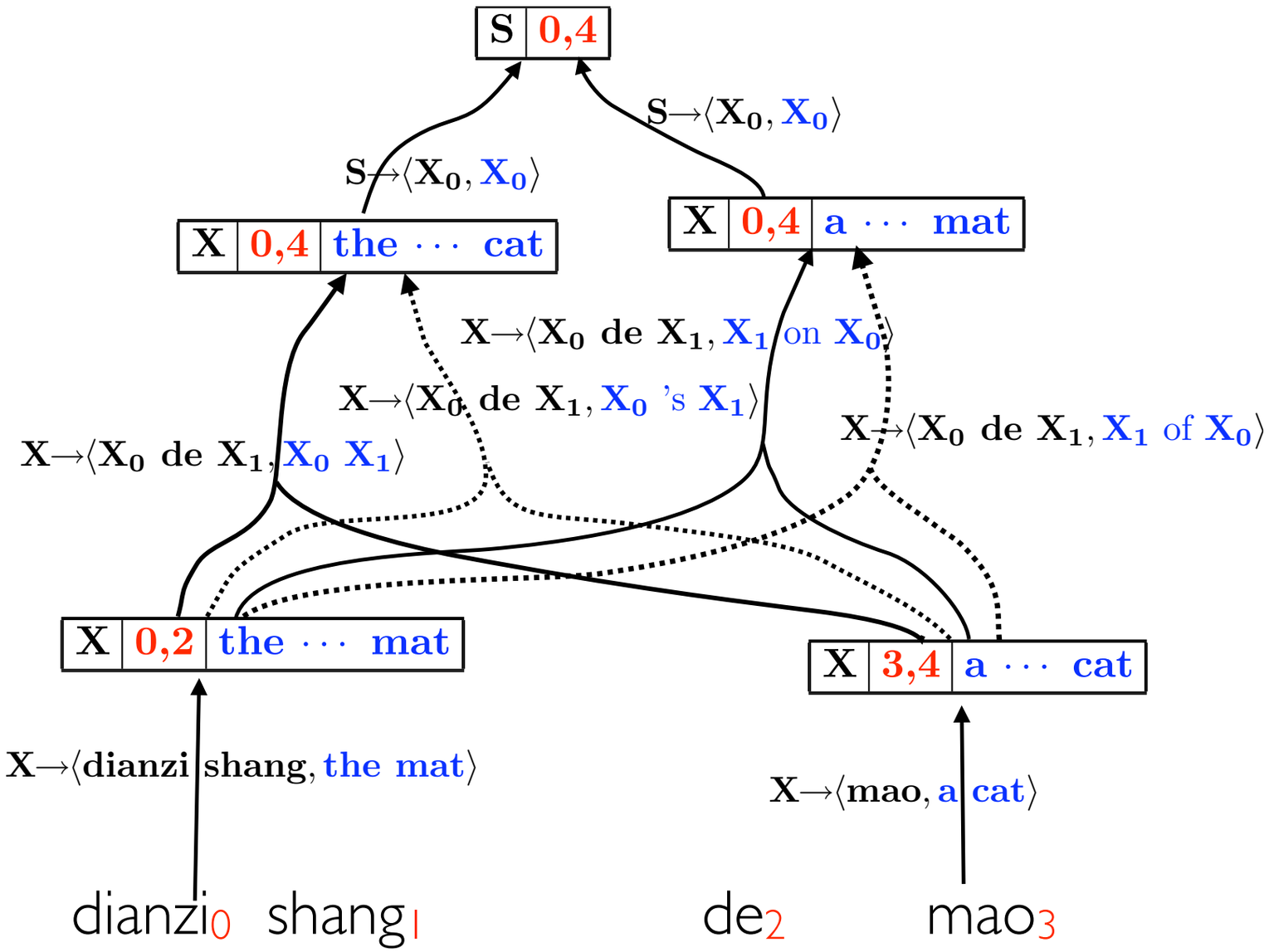
- x: Foreign sentence
- y: English sentence
- d: derivation

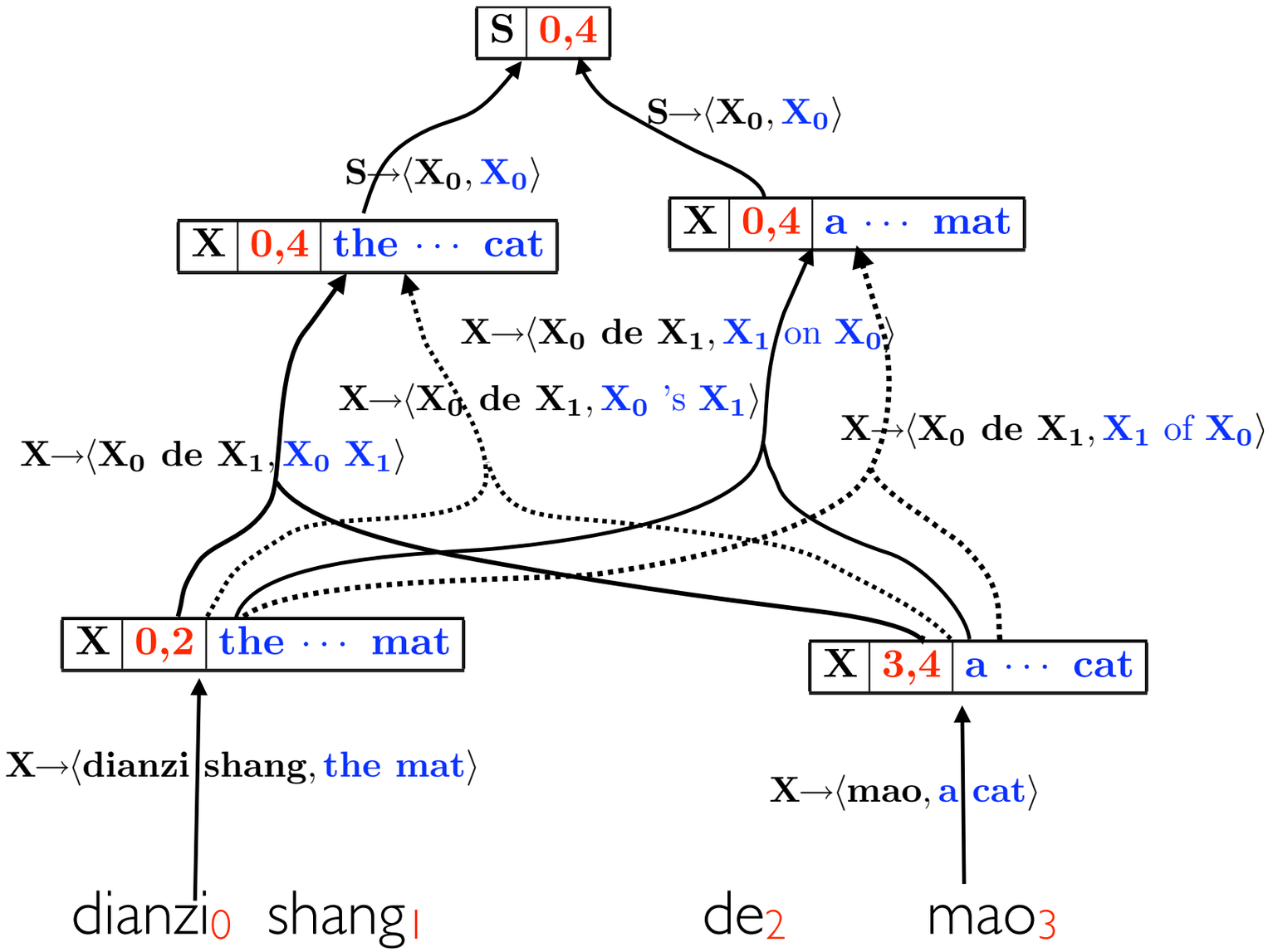
Hypergraph as a search space

Hypergraph as a search space

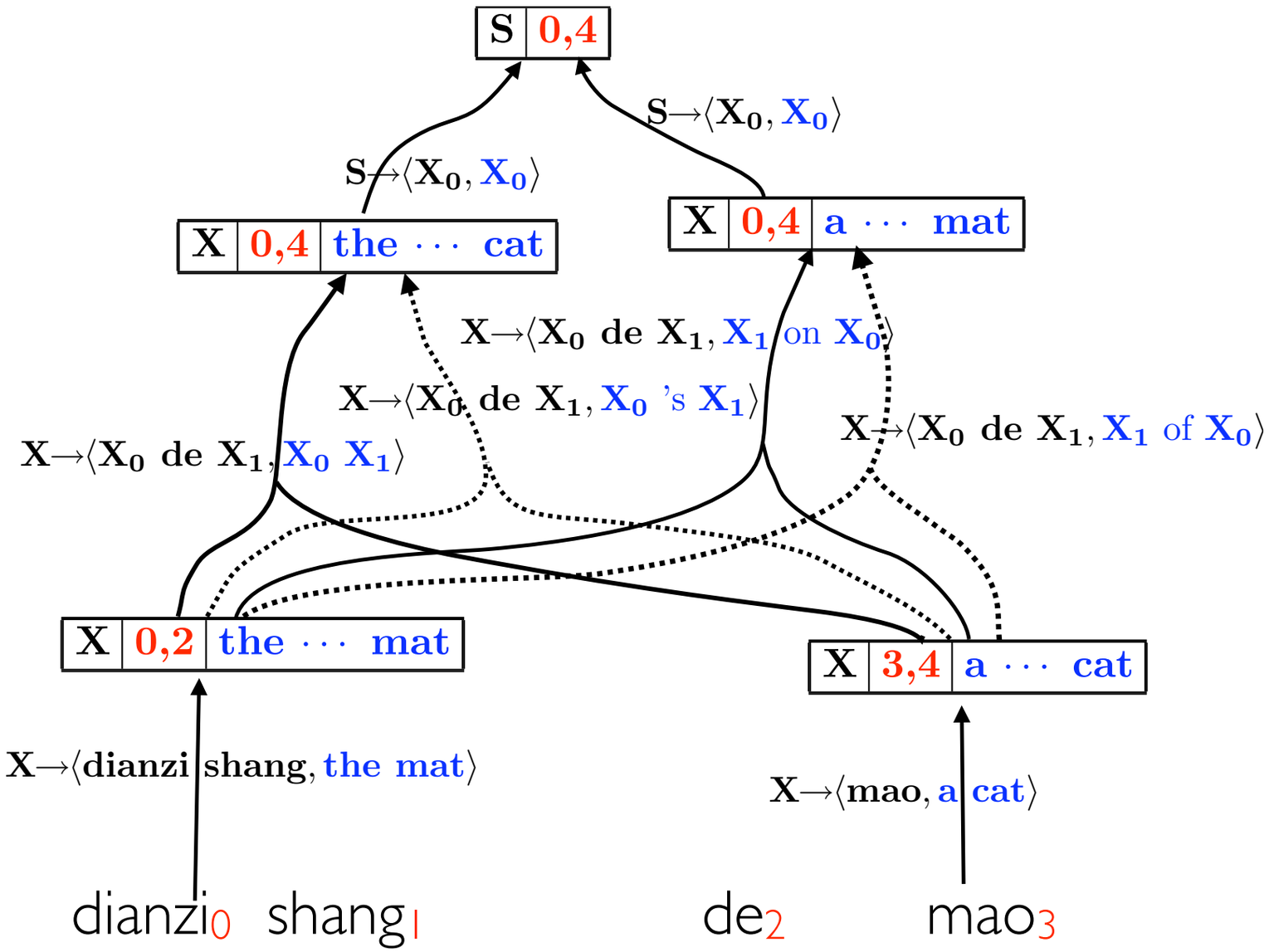


Hypergraph as a search space

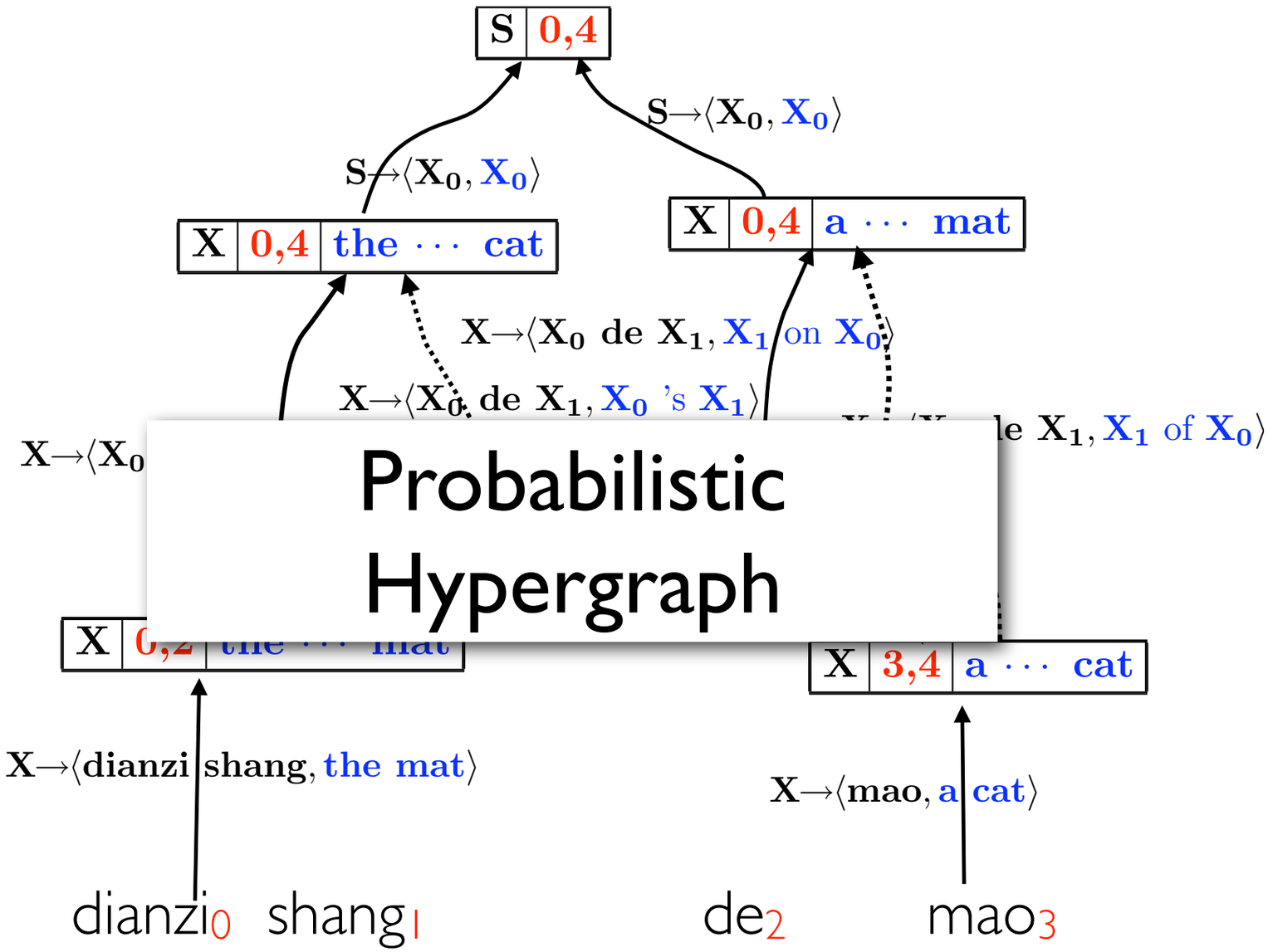
A hypergraph is a compact structure to encode exponentially many trees.



Hypergraph as a search space

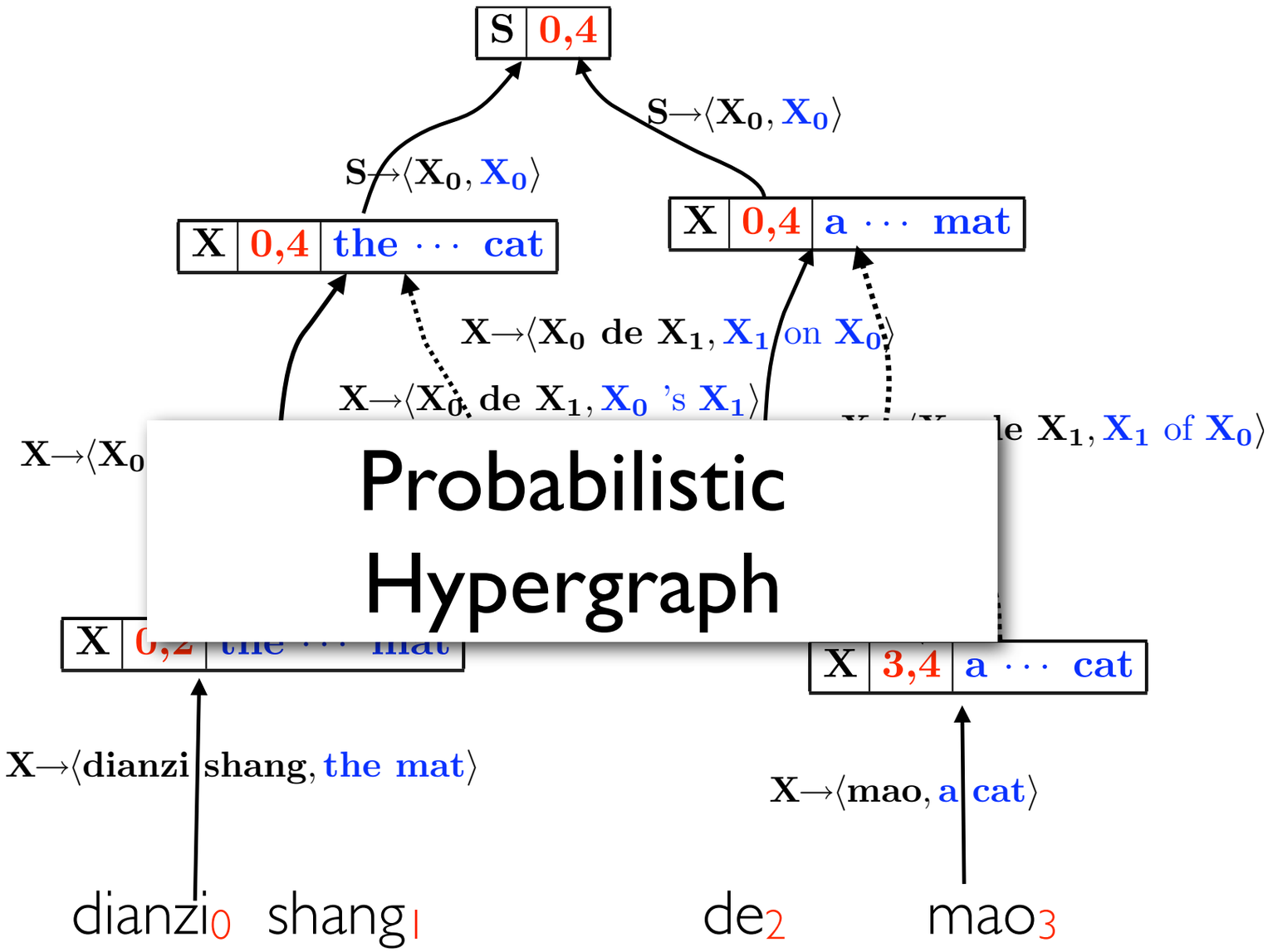


Hypergraph as a search space



Hypergraph as a search space

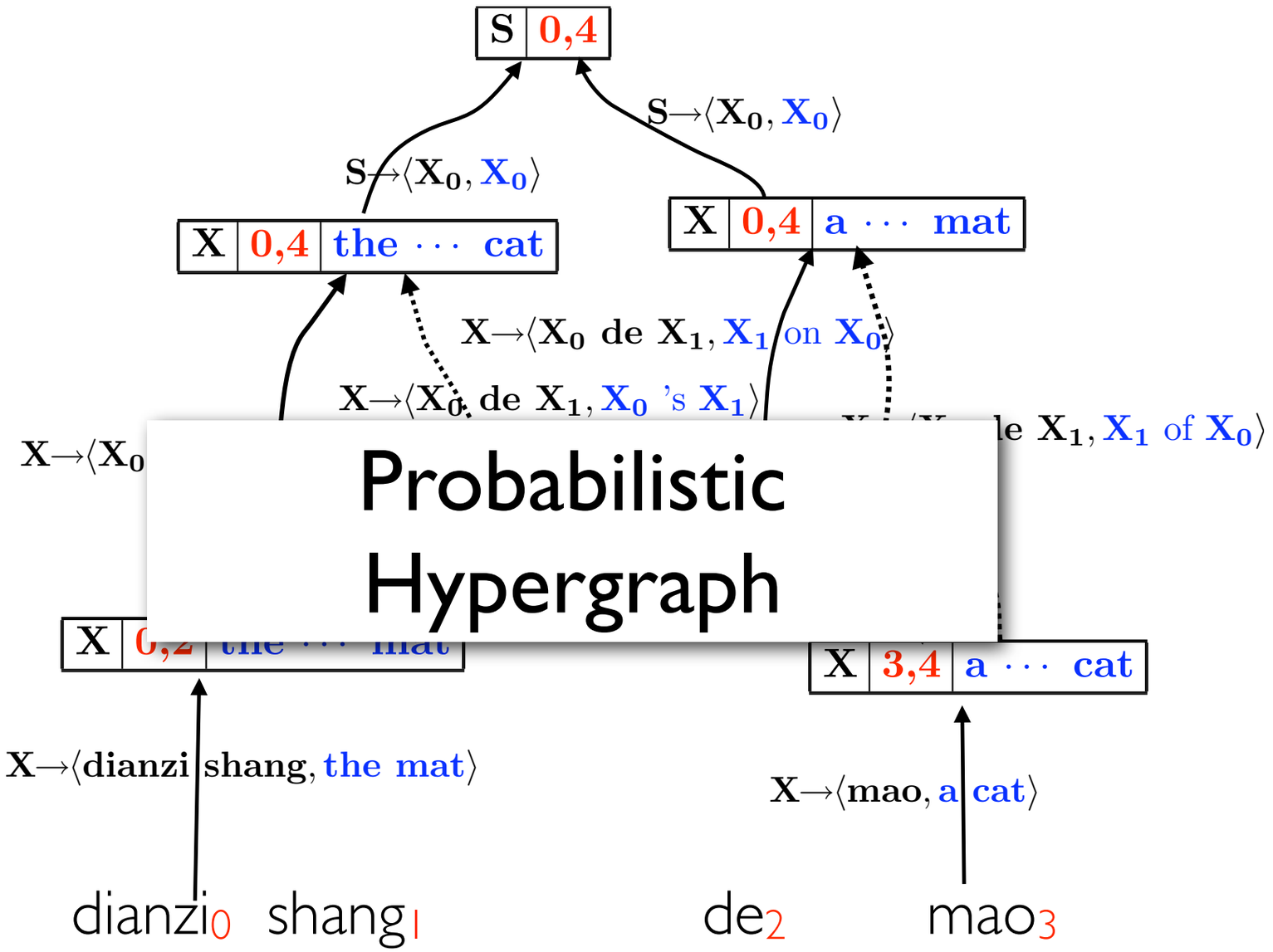
The hypergraph defines a probability distribution over **derivation trees**, i.e. p(y, d | x),



Hypergraph as a search space

The hypergraph defines a probability distribution over **derivation trees**, i.e. p(y, d | x),

and also a distribution (implicit) over **strings**, i.e. p(y | x).



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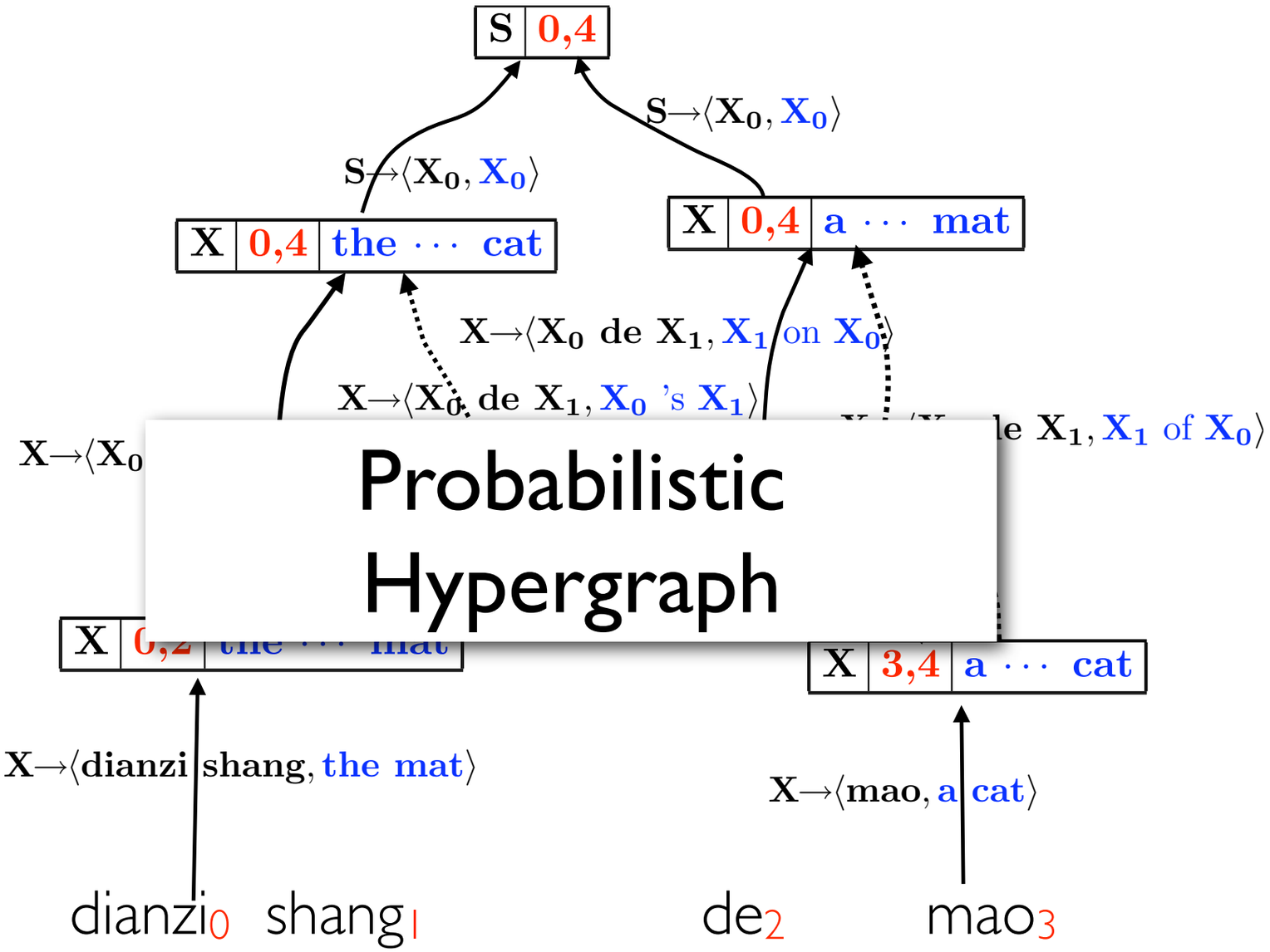

Probabilistic Hypergraph

- Exact MAP decoding

$$y^* = \arg\max_{y \in \mathrm{HG}(x)} p(y|x)$$

$$= \arg\max_{y \in \mathrm{HG}(x)} \sum_{d \in \mathrm{D}(x,y)} p(y, d|x)$$

exponential size

NP-hard (Sima'an 1996)

Decoding with spurious ambiguity?

- Maximum a posterior (MAP) decoding

- Viterbi approximation

- N-best approximation (crunching) (May and Knight 2006)

Viterbi Approximation

translation string	MAP	derivation	probability
red translation	0.28		0.16
			0.14
blue translation	0.28		0.14
green translation	0.44		0.13
			0.12
			0.11
			0.10
			0.10

- Viterbi approximation

$$
\begin{aligned}
y^* &= \arg \max_{y \in \mathrm{Trans}(x)} \max_{d \in \mathrm{D}(x,y)} p(y, d|x) \\
&= \mathrm{Y}(\arg \max_{d \in \mathrm{D}(x)} p(y, d|x))
\end{aligned}
$$

Viterbi Approximation

translation string	MAP	Viterbi	derivation	probability
red translation	0.28			0.16
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blue translation	0.28	
green translation	0.44	

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N-best Approximation

translation string	MAP	Viterbi
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derivation	probability
	0.16
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- N-best approximation (crunching) (May and Knight 2006)

$$y^* = \arg \max_{y \in \mathrm{Trans}(x)} \sum_{d \in \mathrm{D}(x,y) \cap \mathrm{ND}(x)} p(y, d|x)$$

N-best Approximation

translation string	MAP	Viterbi	4-best crunching	derivation	probability
red translation	0.28	0.16			0.16
blue translation	0.28	0.14			0.14
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- N-best approximation (crunching) (May and Knight 2006)

$$y^* = \arg \max_{y \in \mathrm{Trans}(x)} \sum_{d \in \mathrm{D}(x,y) \cap \mathrm{ND}(x)} p(y, d|x)$$

MAP vs. Approximations

translation string	MAP	Viterbi	4-best crunching	derivation	probability
red translation	0.28	0.16	0.16		0.16
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- Exact MAP decoding under spurious ambiguity is intractable
- Viterbi and crunching are efficient, but ignore most derivations
- Our goal: develop an approximation that considers all the derivations but still allows tractable decoding

Variational Decoding

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Decoding using **Variational** approximation

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Decoding using a sentence-specific **approximate** distribution

Variational Decoding for MT: an Overview

Variational Decoding for MT: an Overview

Sentence-specific decoding

Variational Decoding for MT: an Overview

Sentence-specific decoding

Three steps:

Variational Decoding for MT: an Overview

Sentence-specific decoding

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Variational Decoding for MT: an Overview

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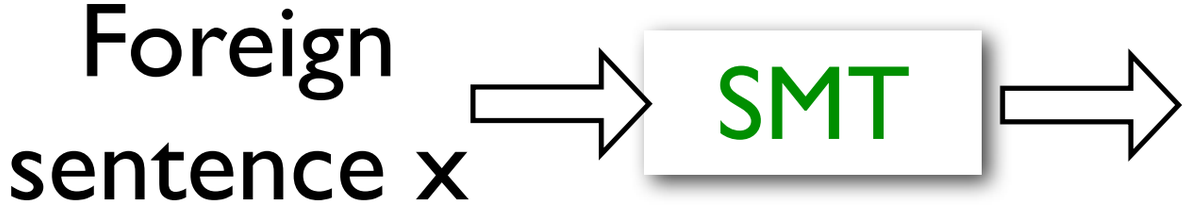

Variational Decoding for MT: an Overview

Sentence-specific decoding

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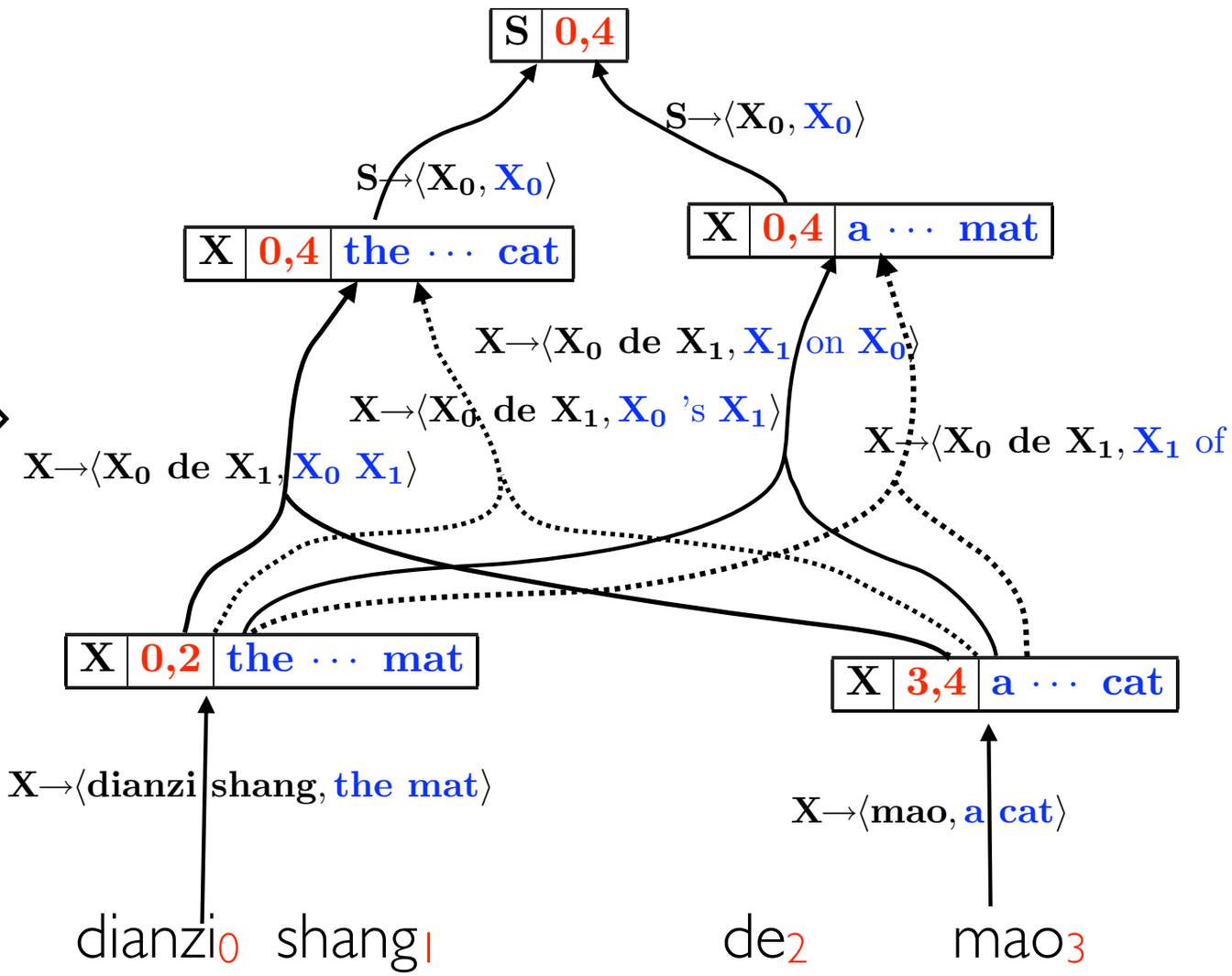

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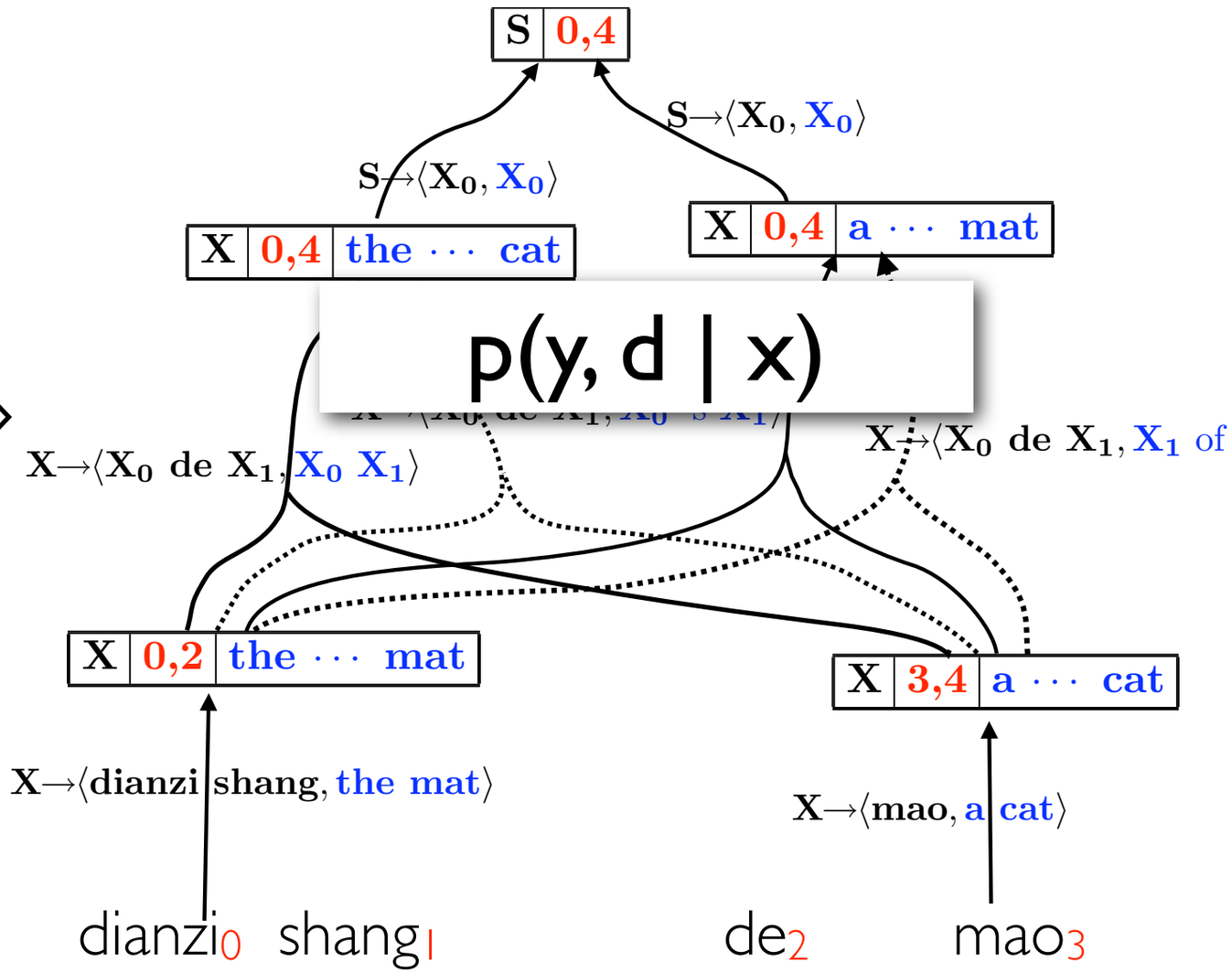

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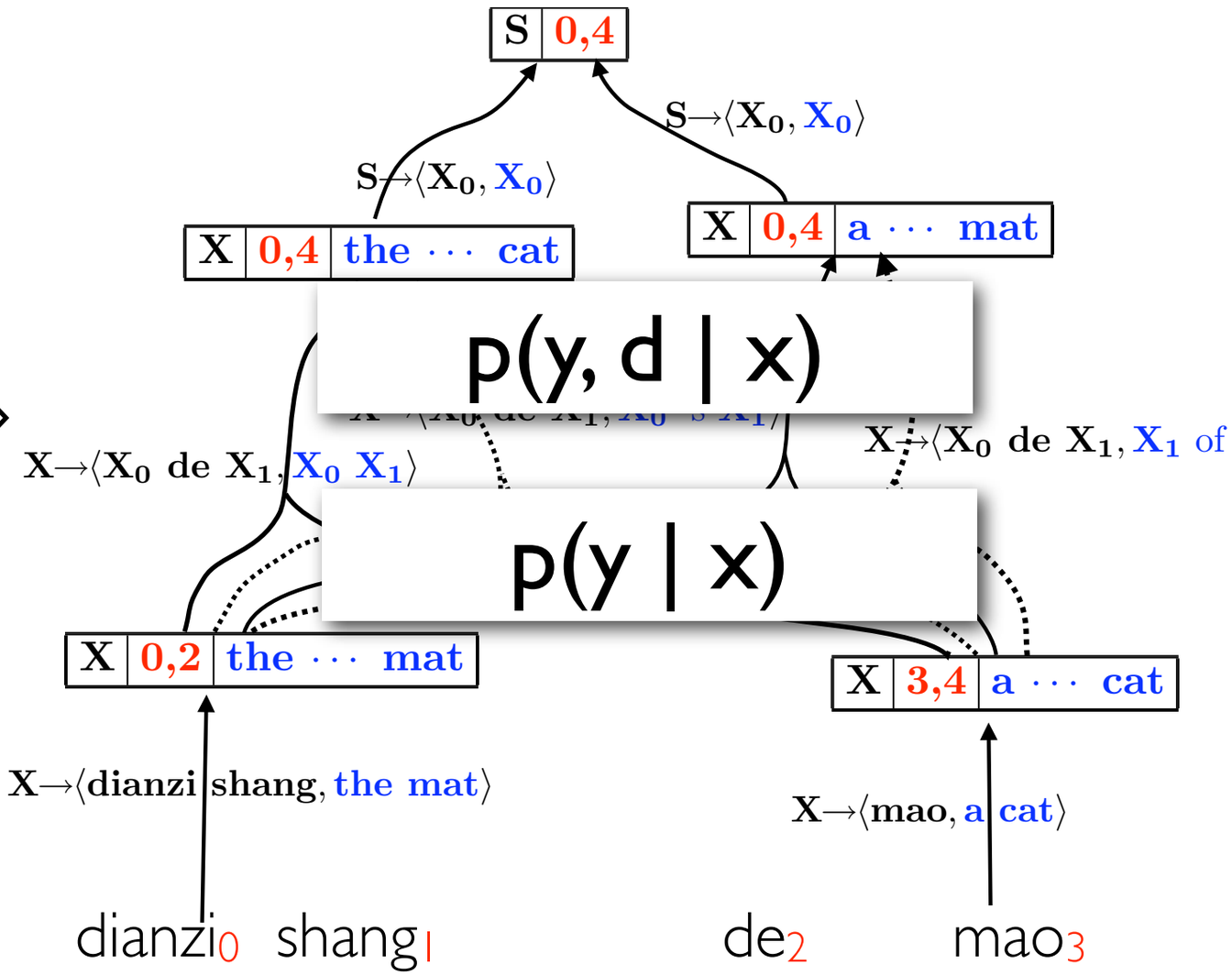

Variational Decoding for MT: an Overview

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MAP decoding under P is intractable

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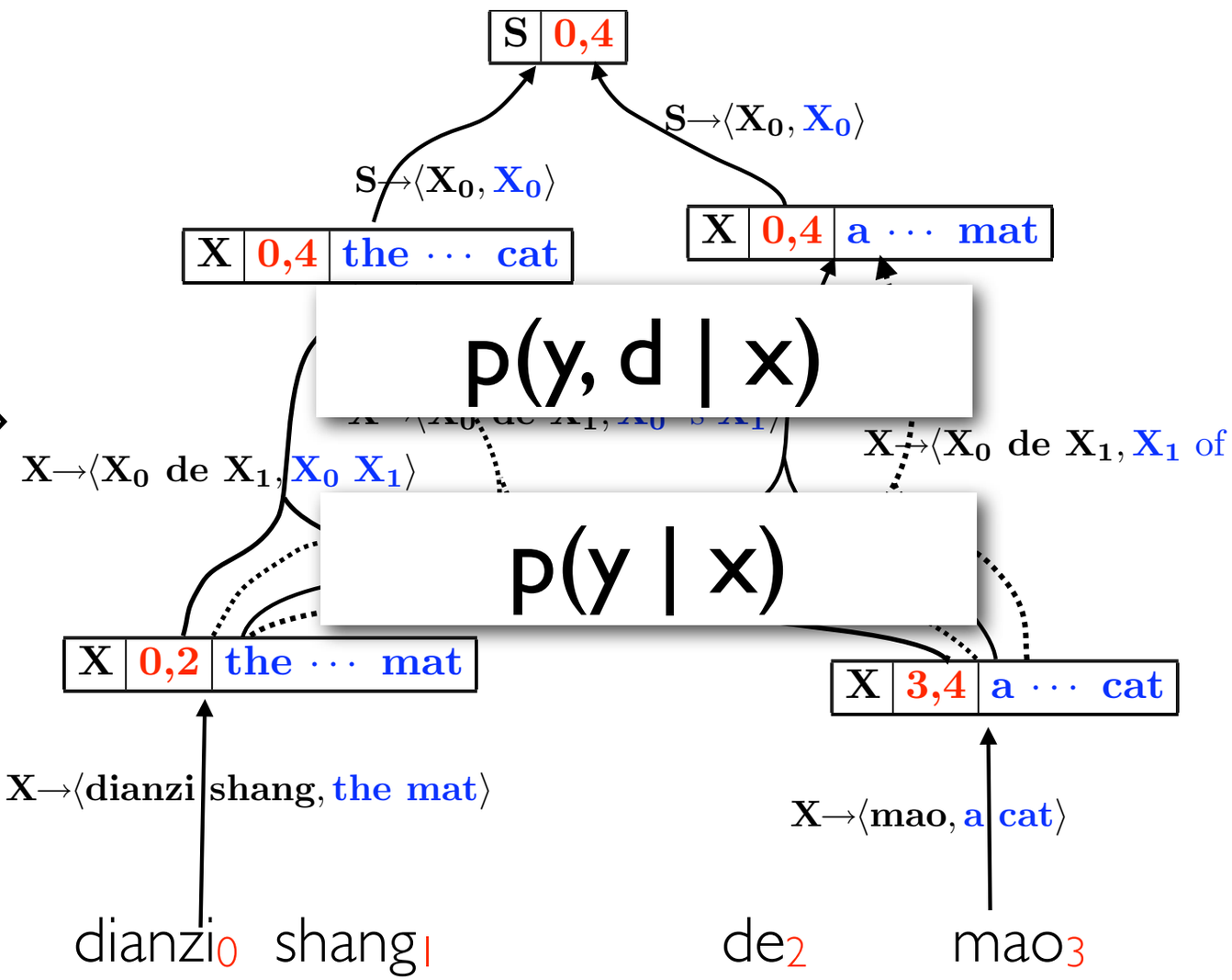

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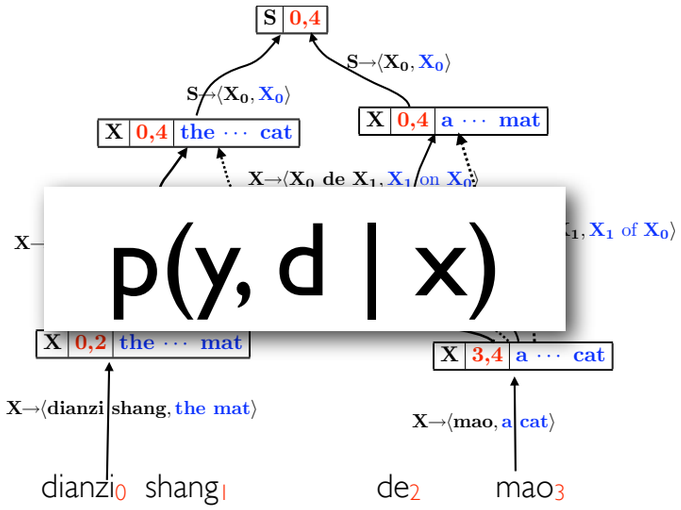

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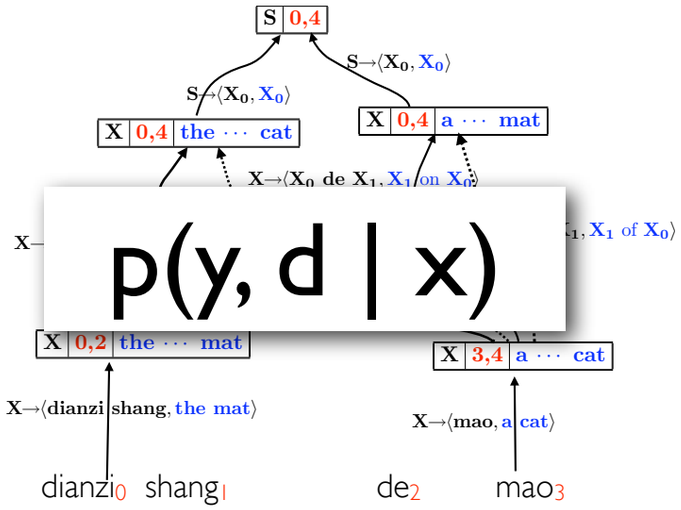

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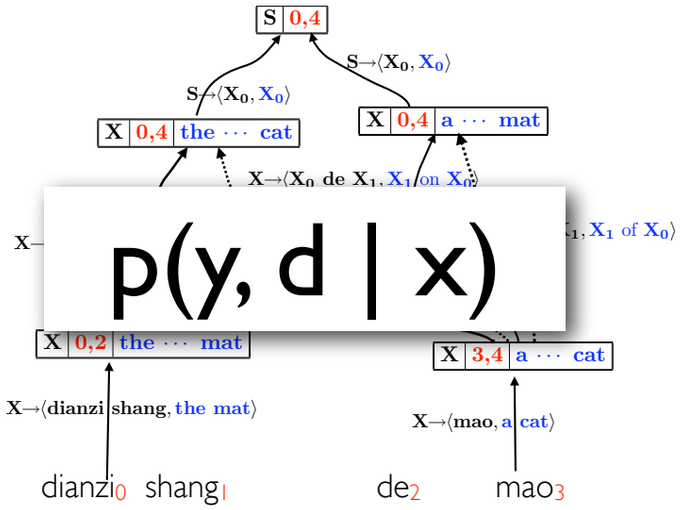
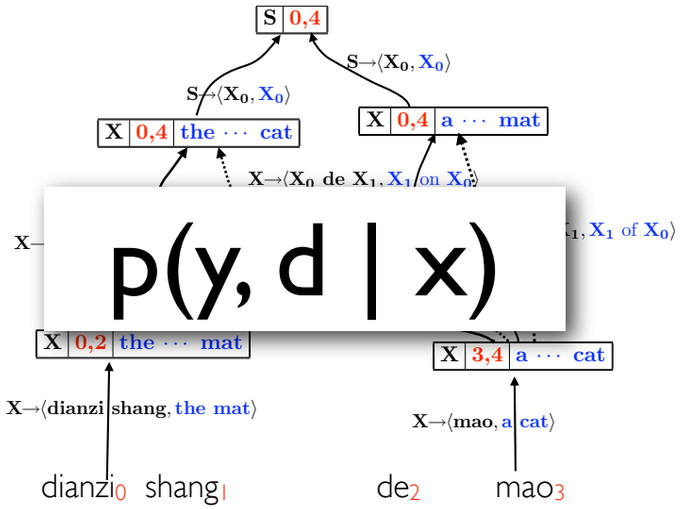


Generate a hypergraph

2

1



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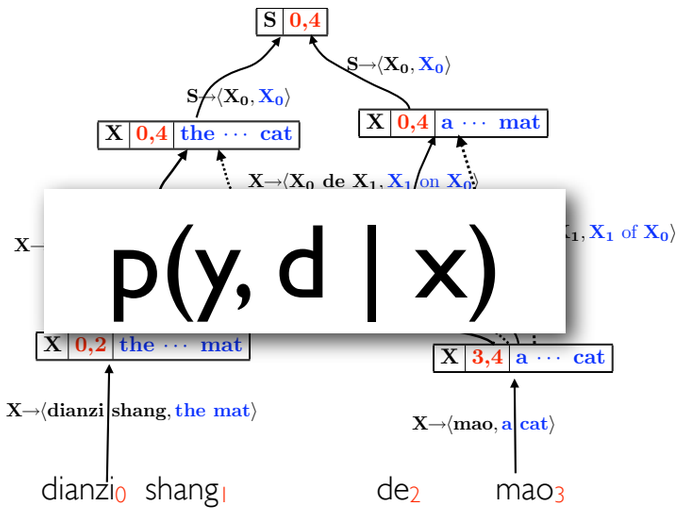

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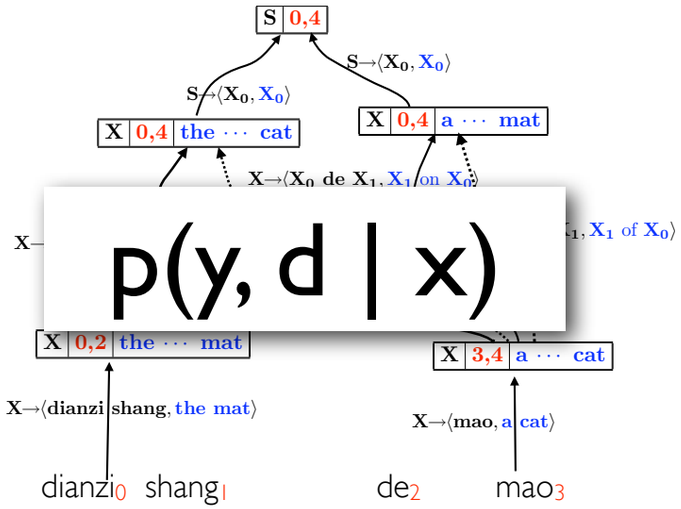

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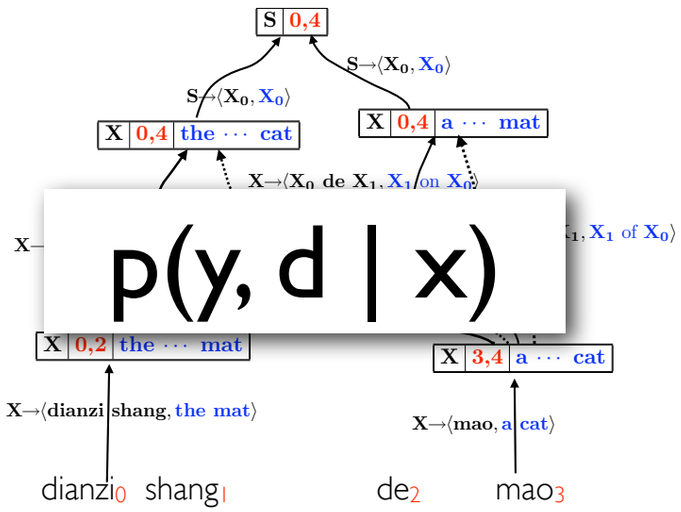

Estimate a model
from the hypergraph

q*(y | x)

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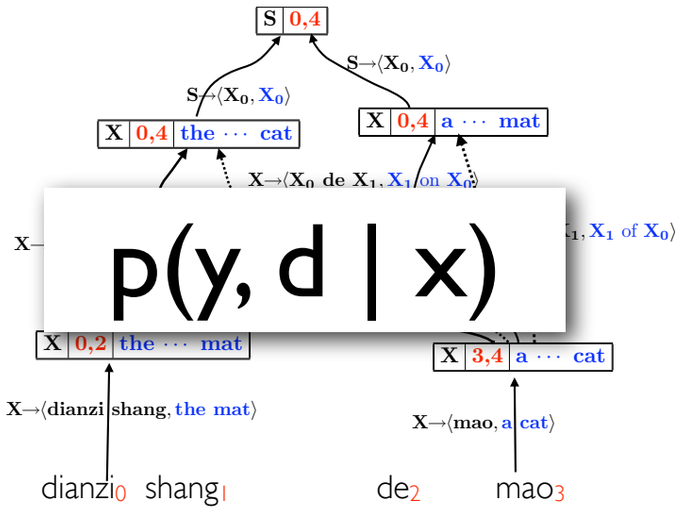

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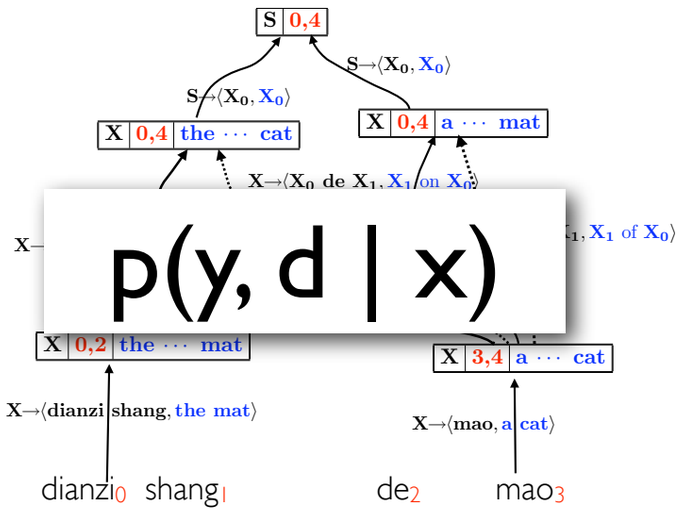

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q* is an n-gram model over output strings.

$$q^*(y \mid x)$$

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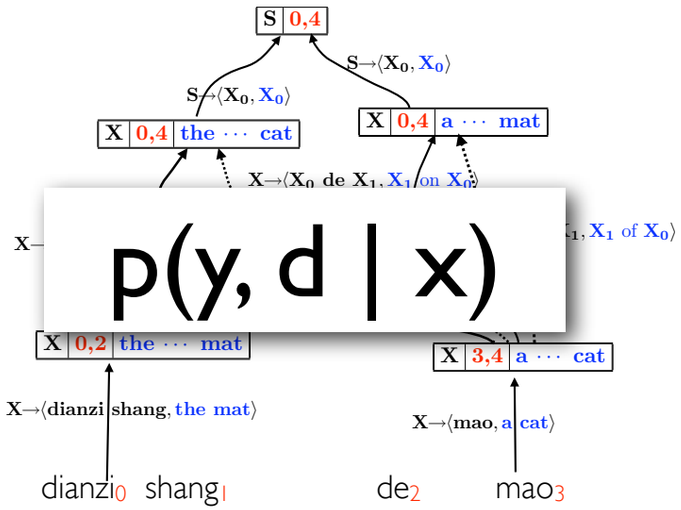

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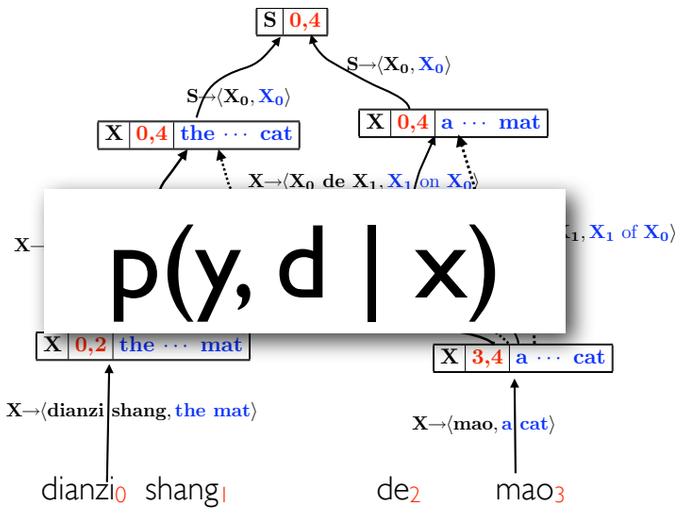

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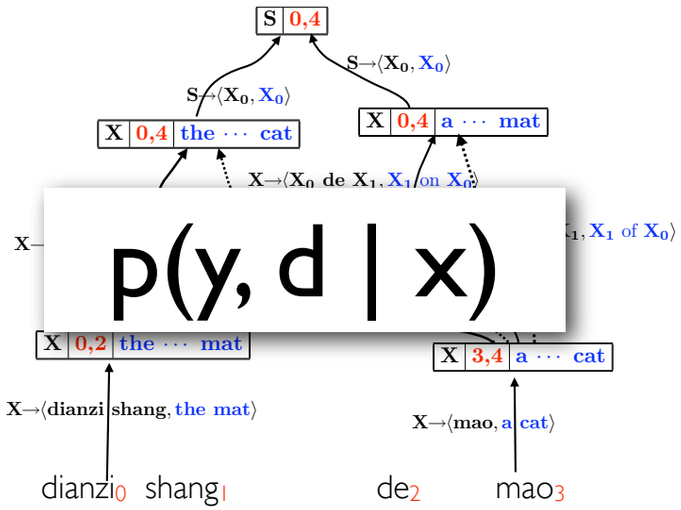

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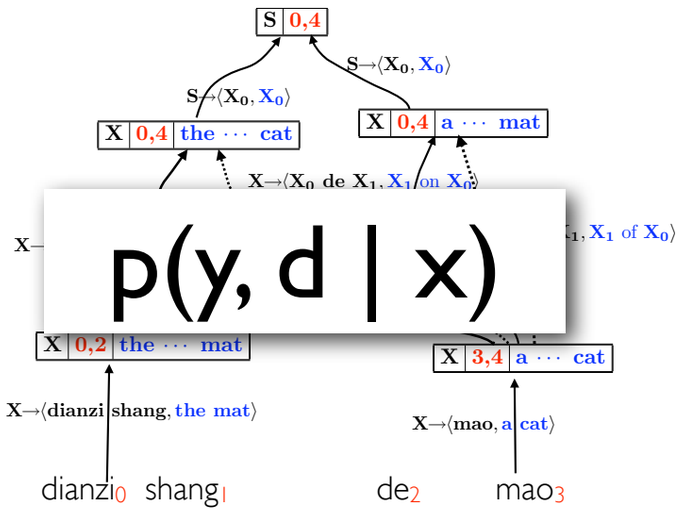

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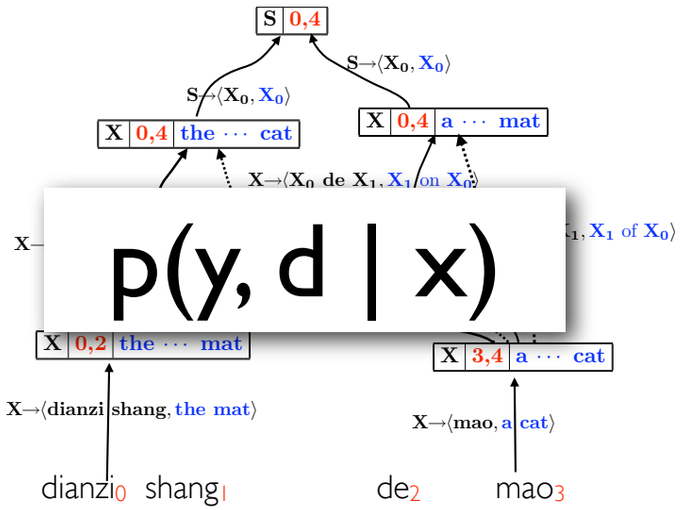

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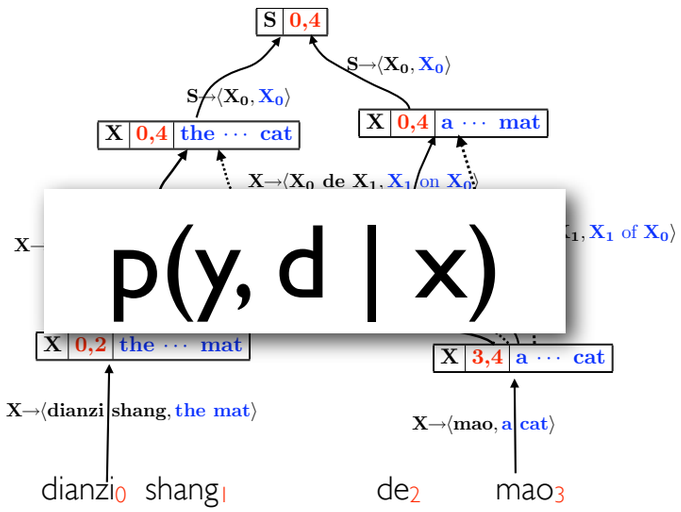

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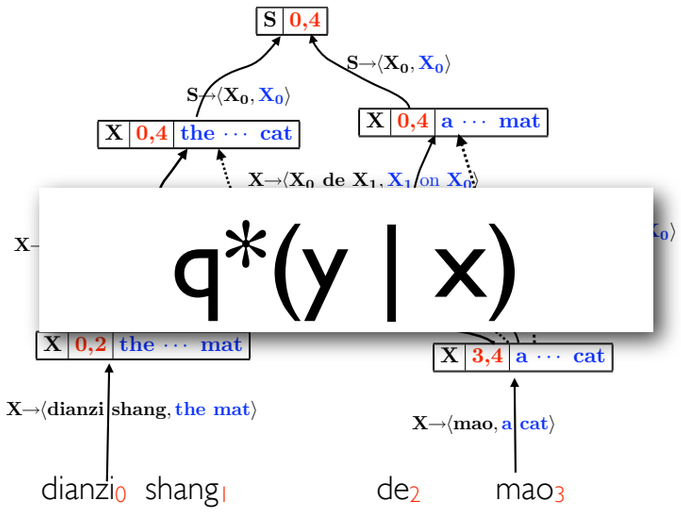

Decode using q* on the hypergraph

Variational Inference

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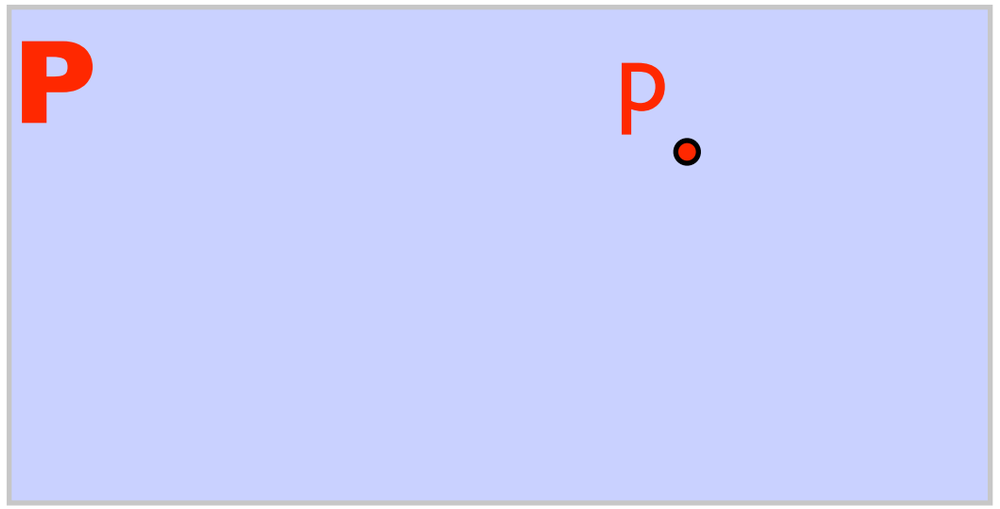

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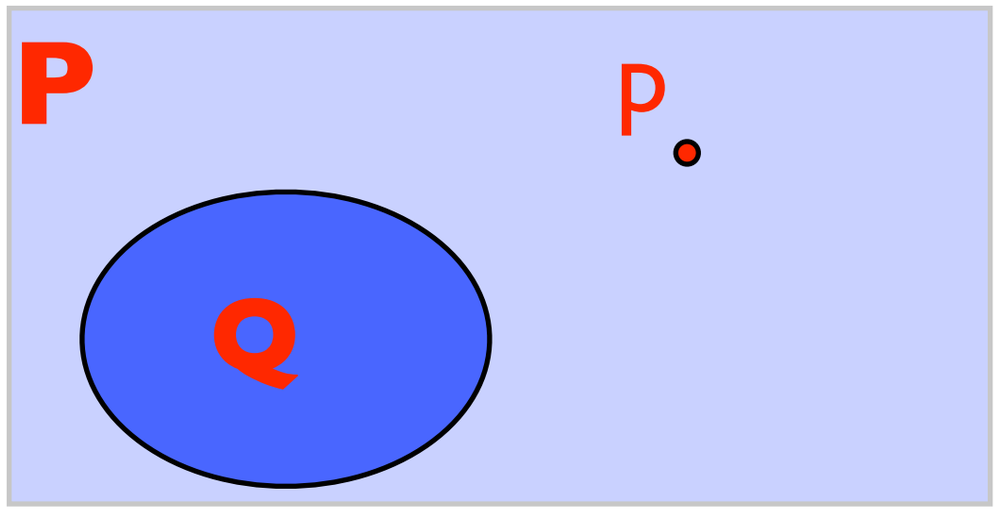

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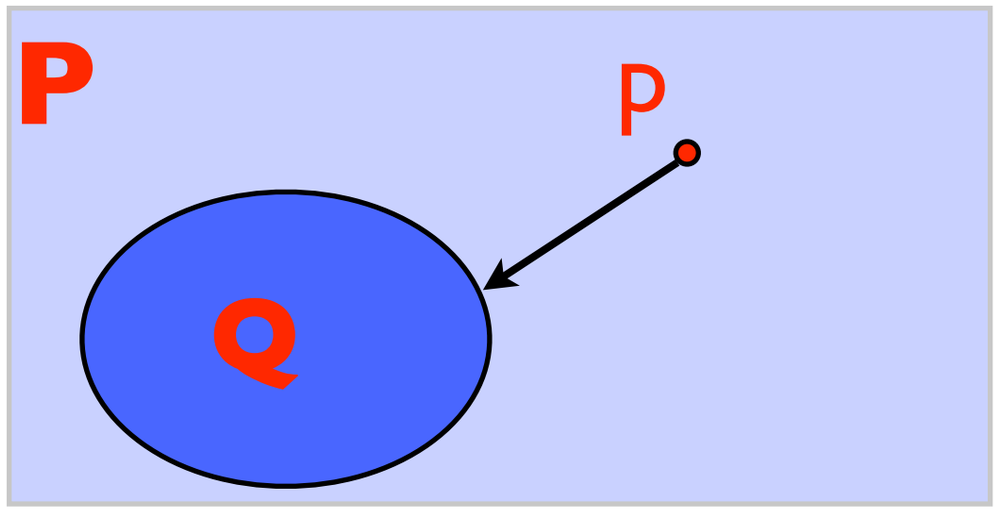

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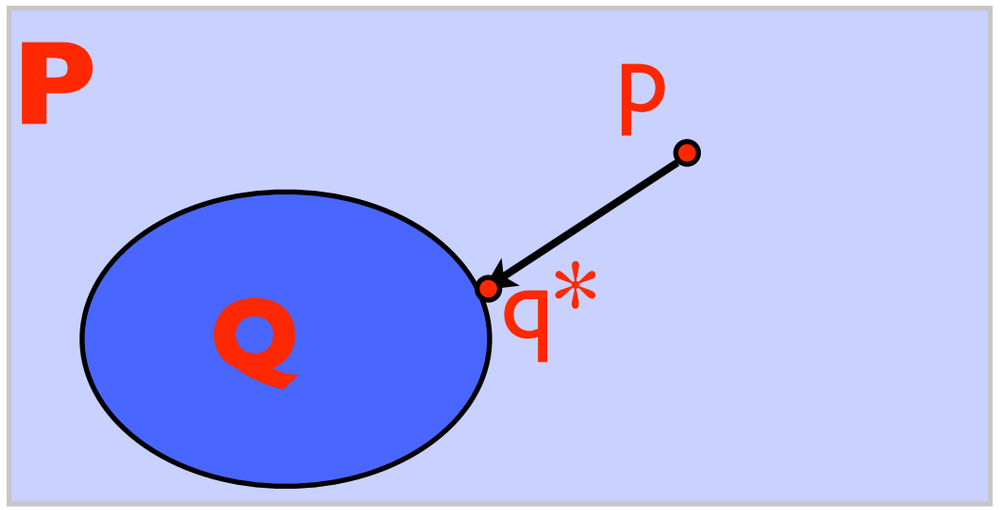

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Variational Approximation

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Other ways of parameterizations are possible!

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how to estimate these n-gram probabilities?

Estimation of q*∈Q

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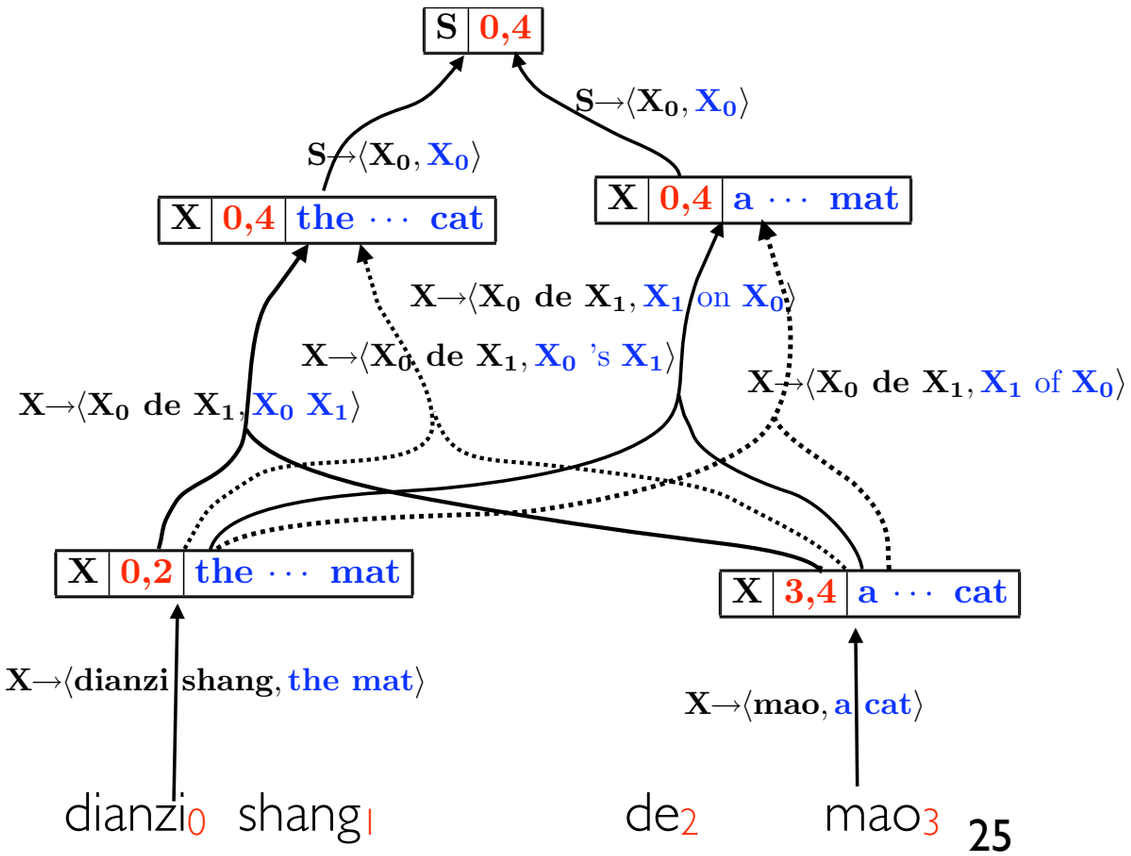

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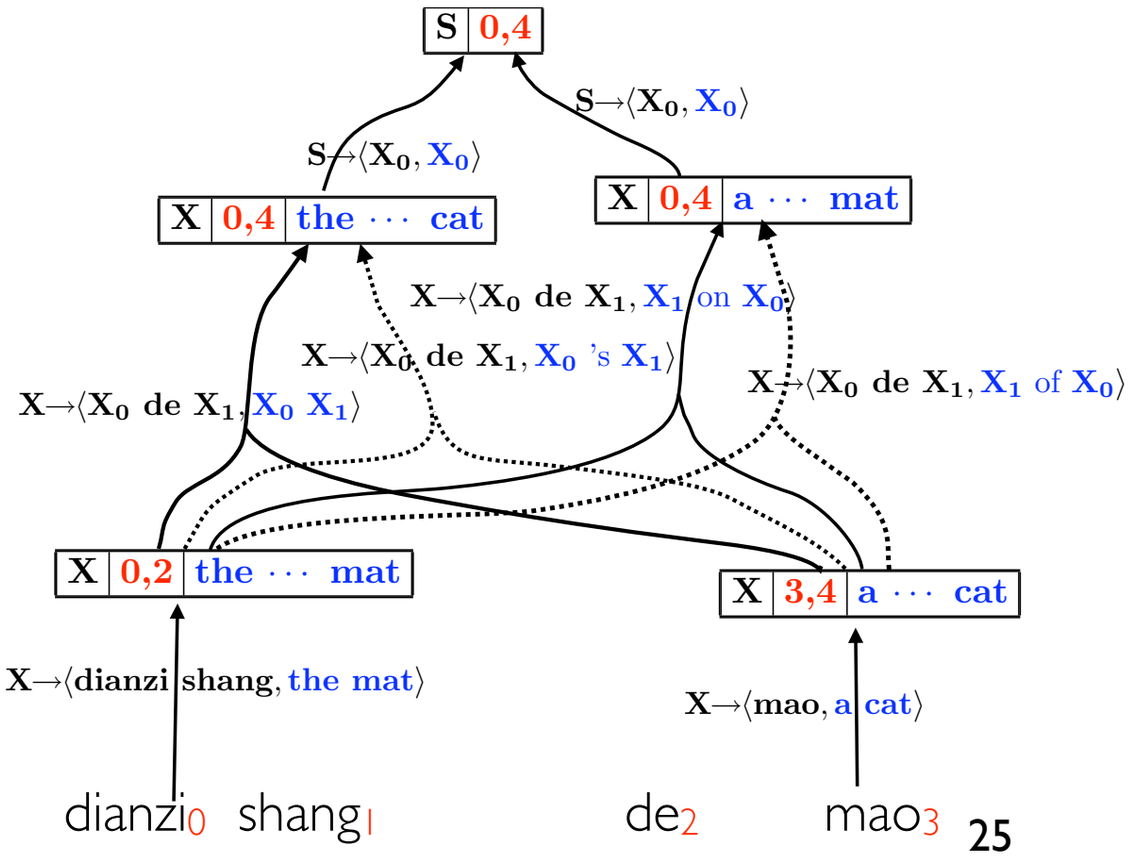
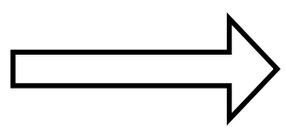


estimate



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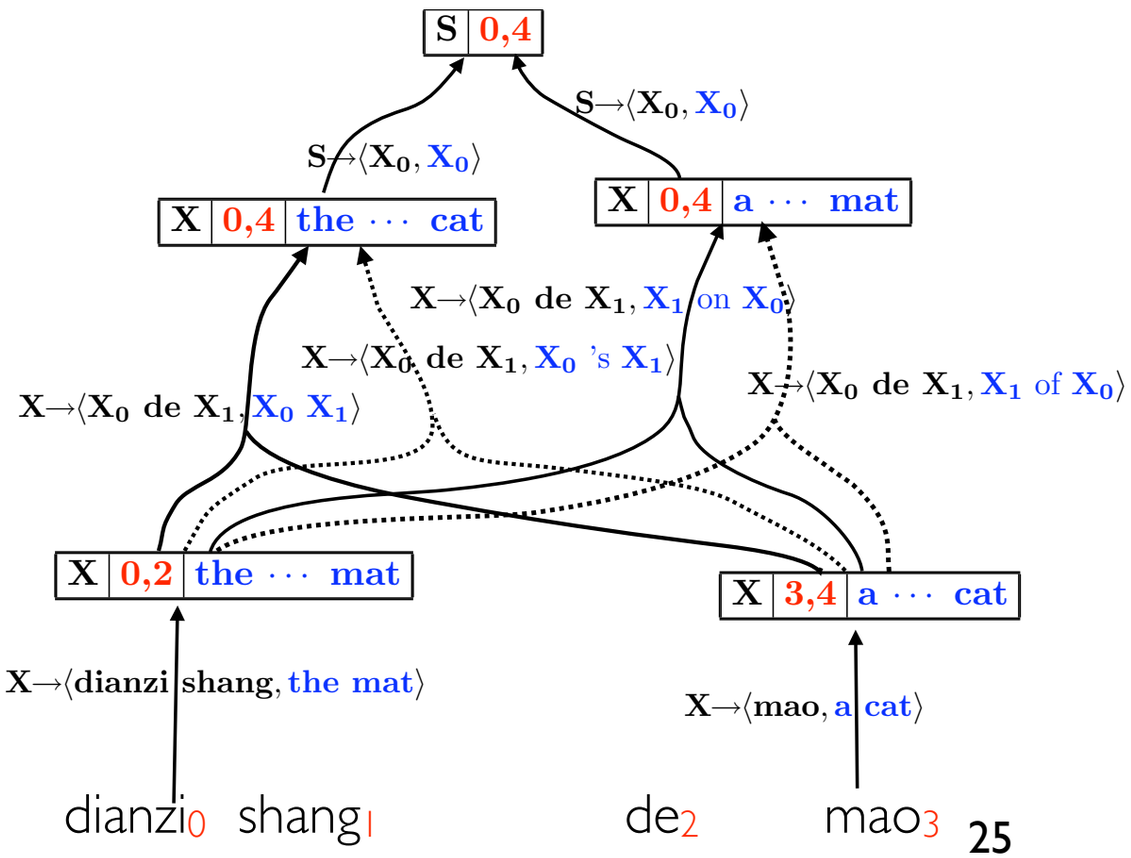

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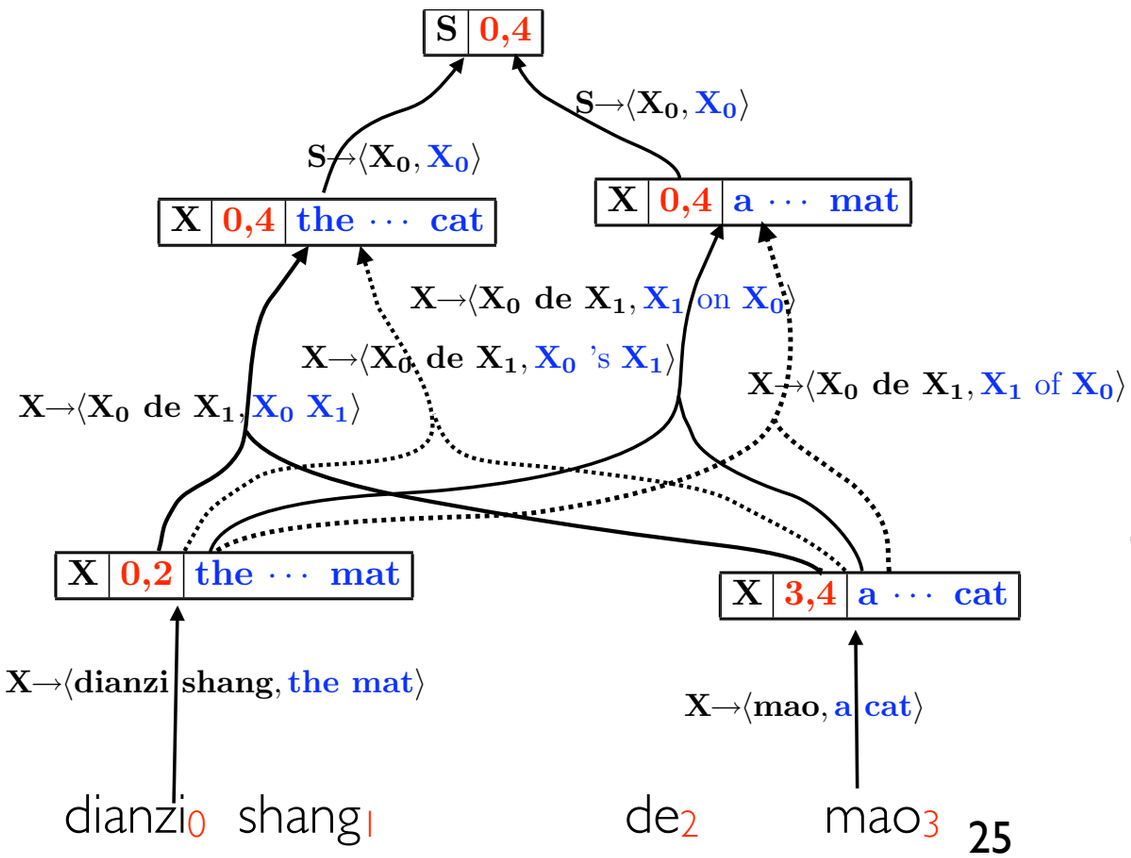

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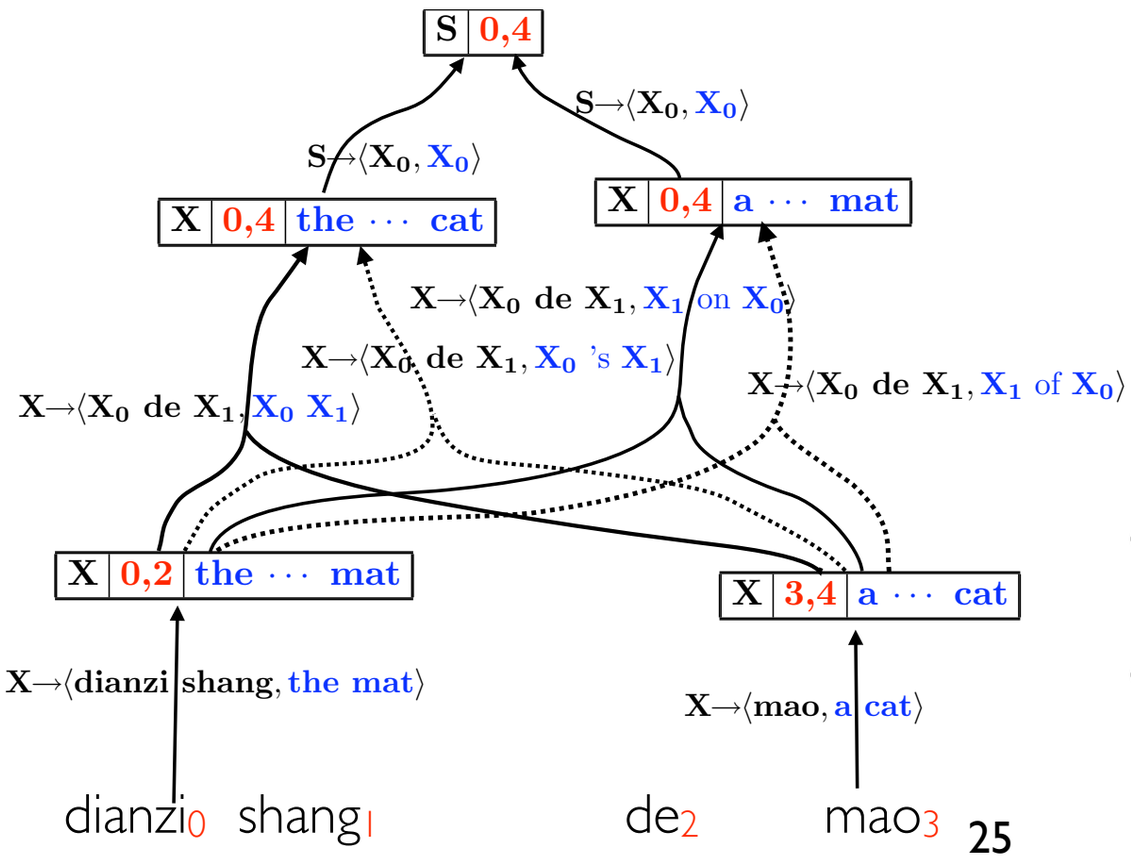

estimate

⟹ bi-gram model

- brute force
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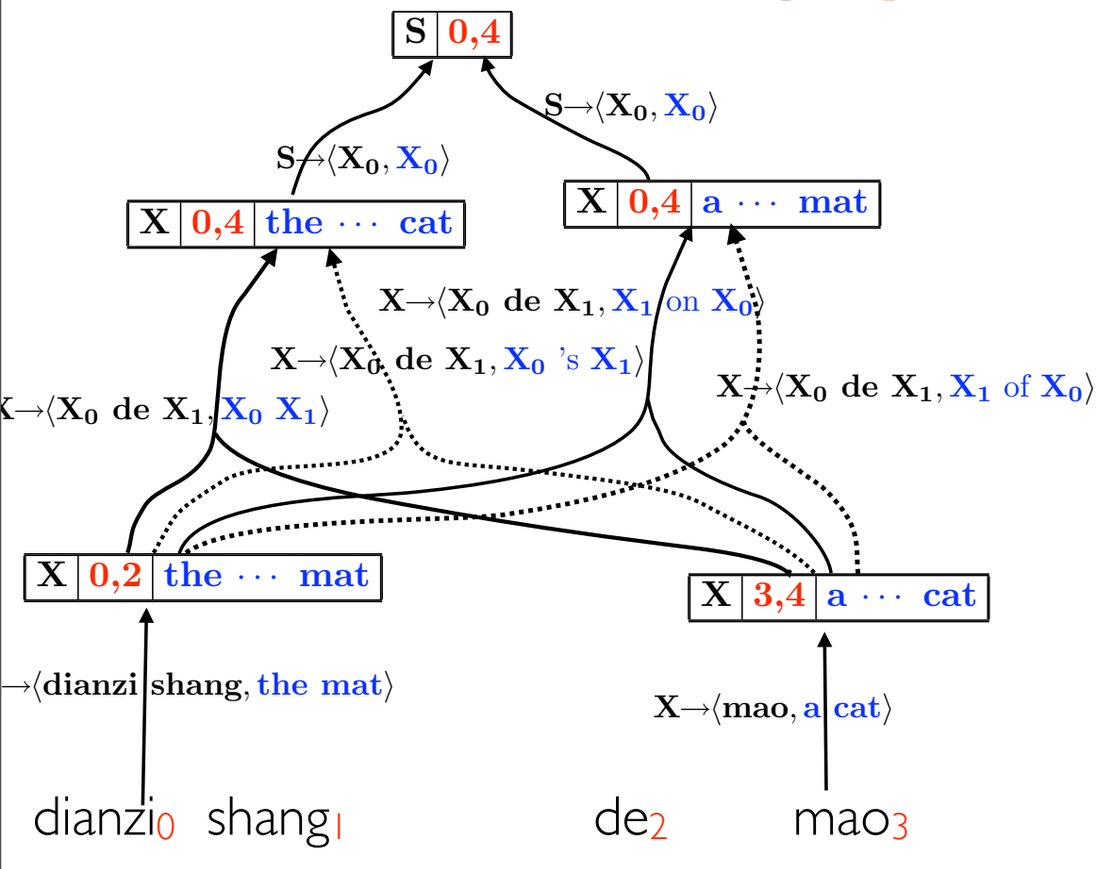
Estimating q* from a hypergraph: brute force



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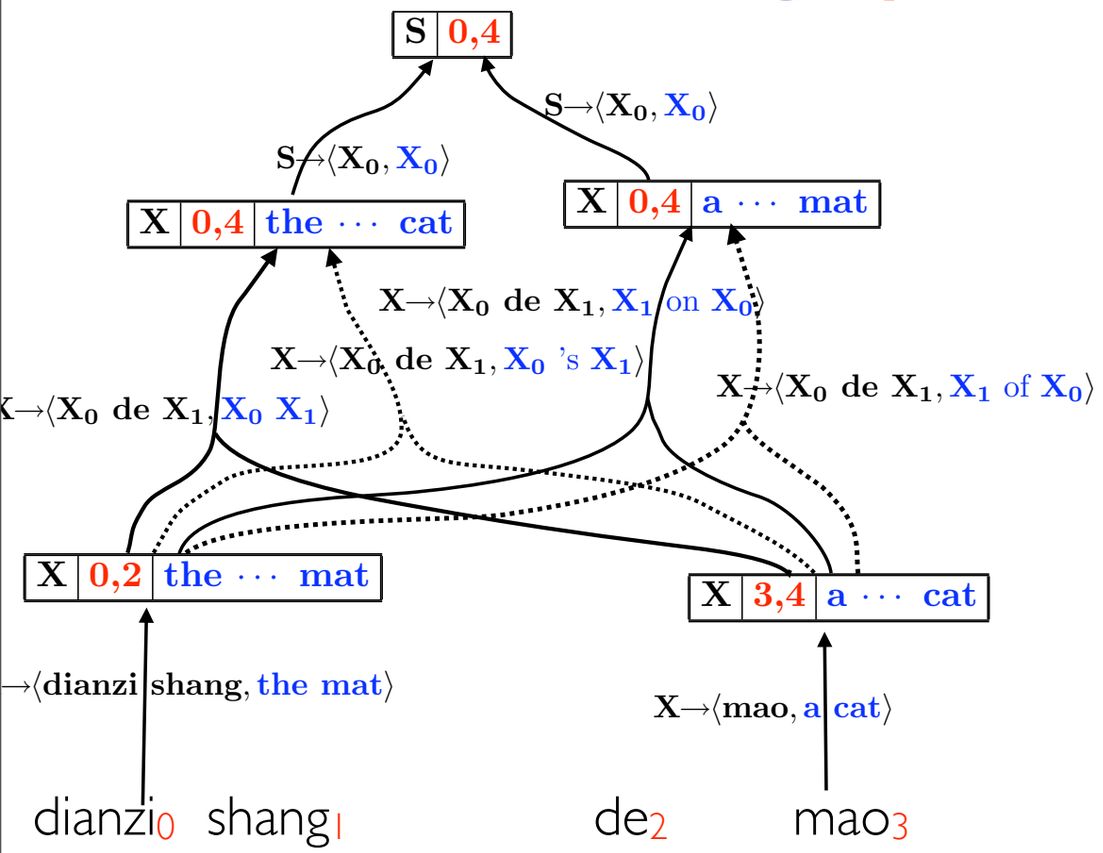
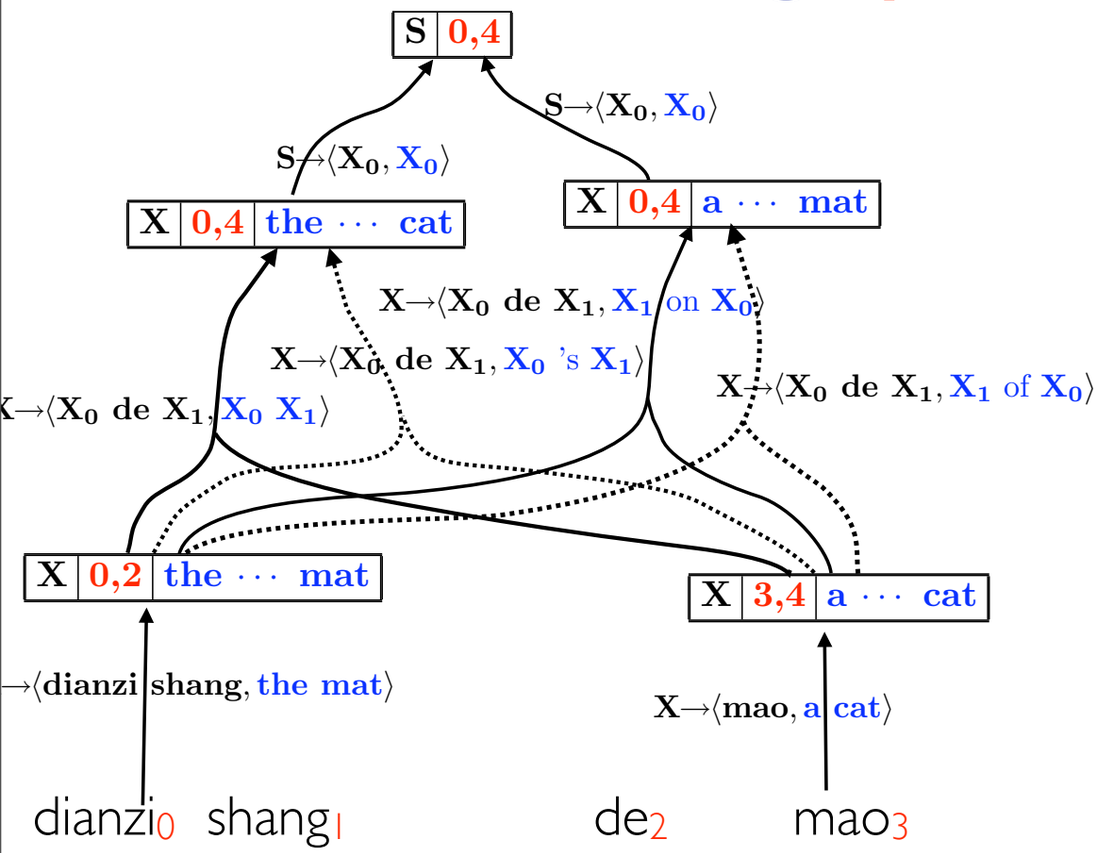


Bi-gram estimation:

Estimating q* from a hypergraph: brute force



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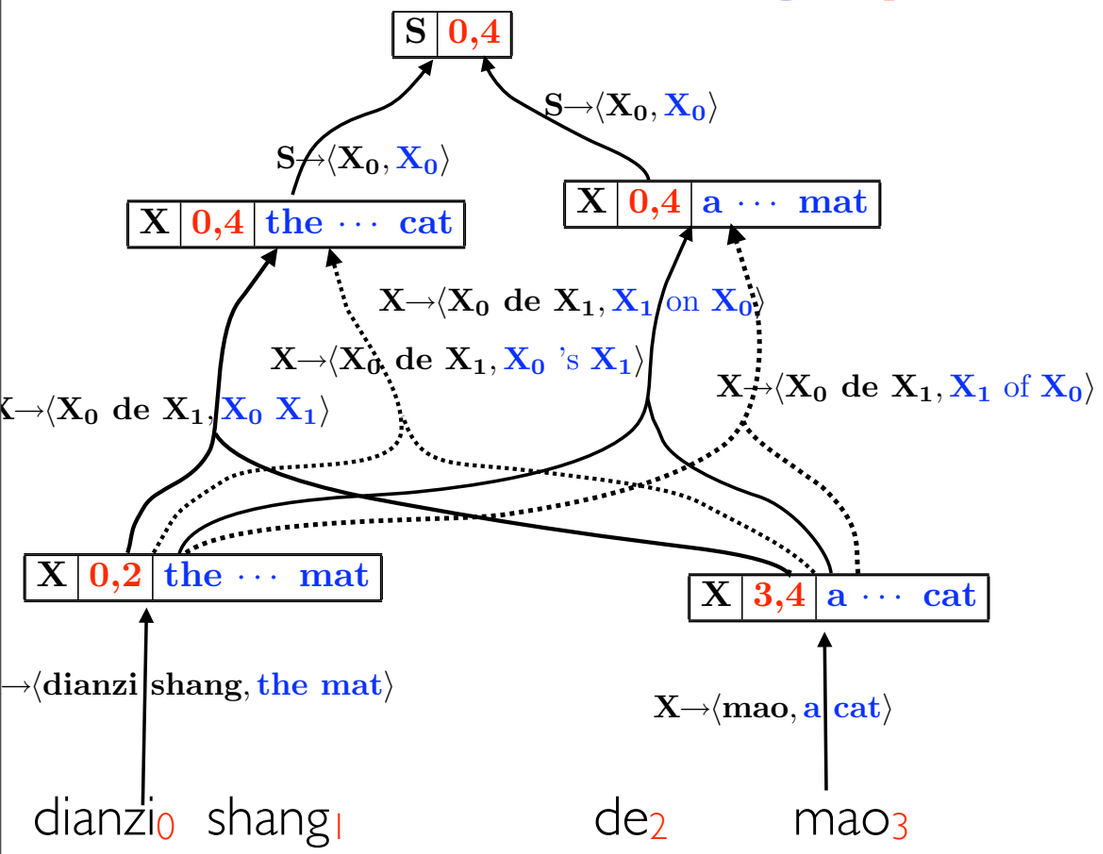

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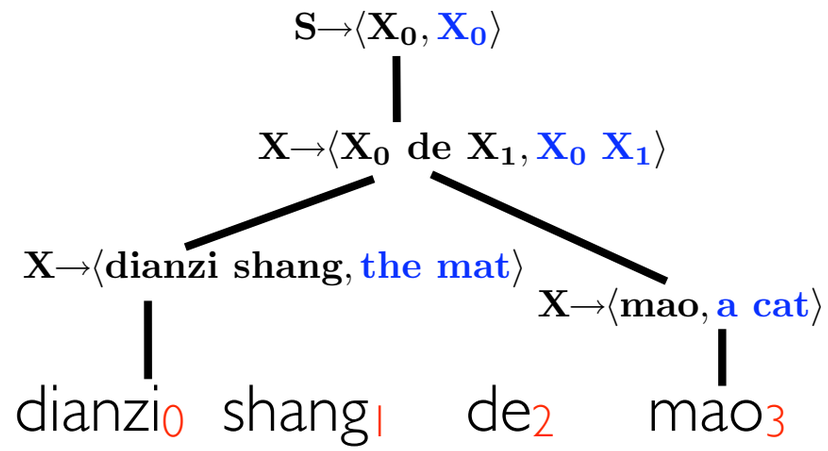

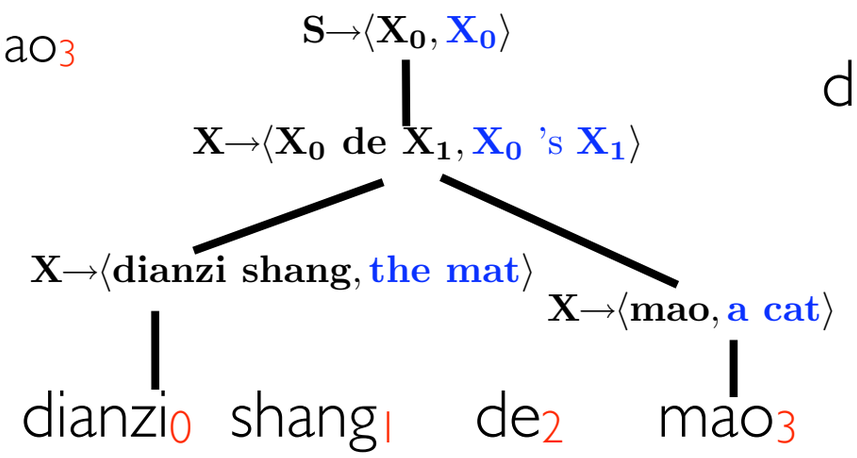

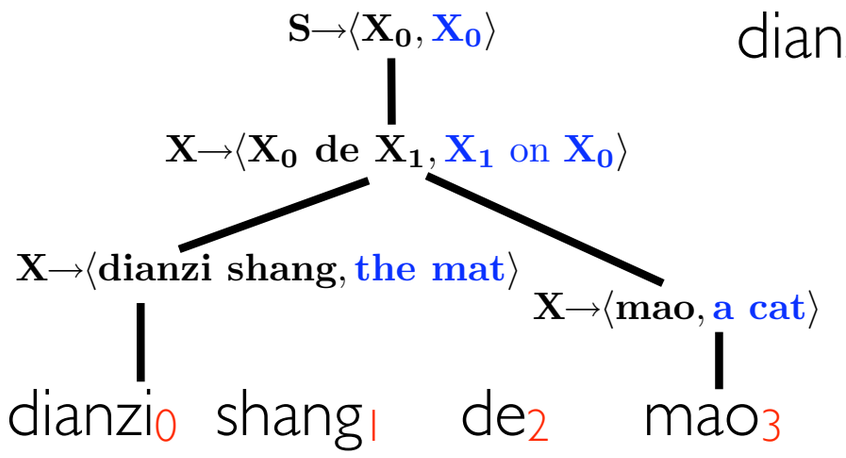

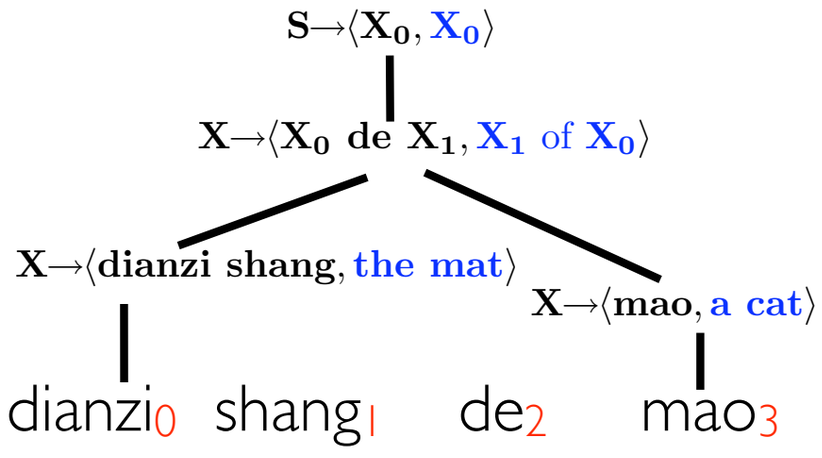

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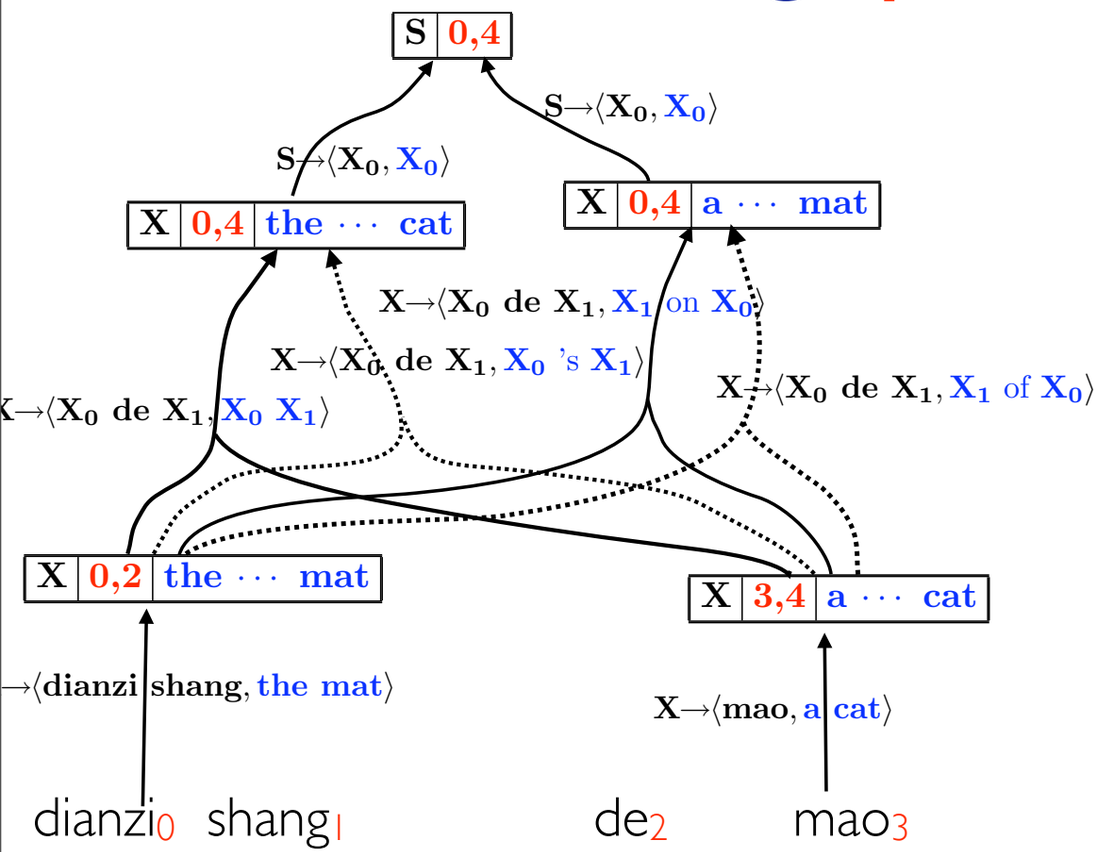

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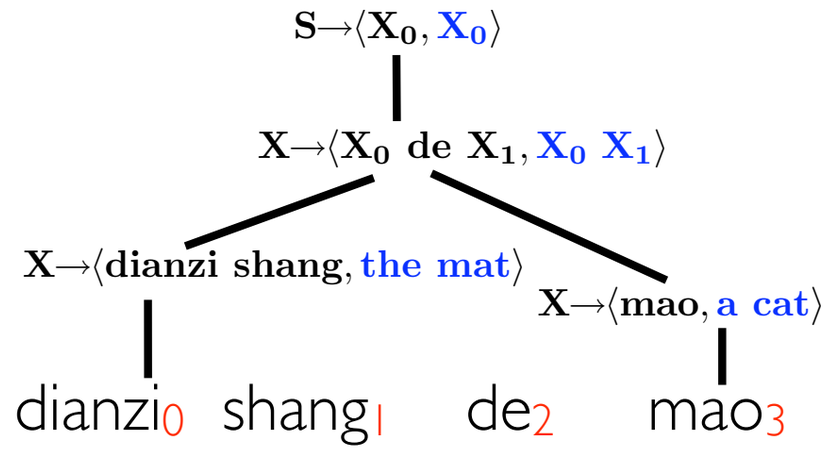
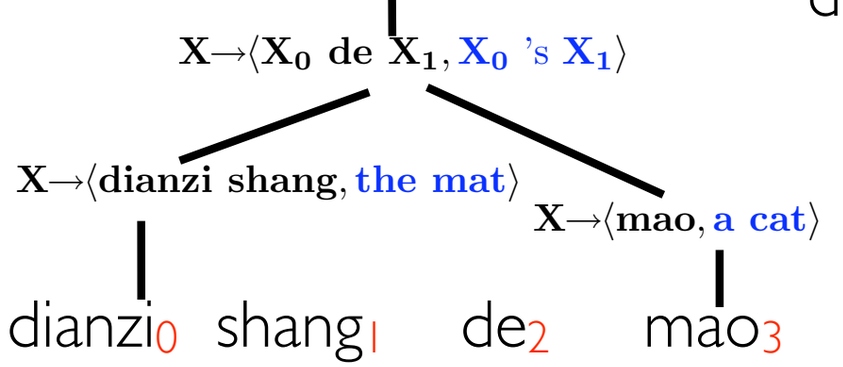


the mat a cat



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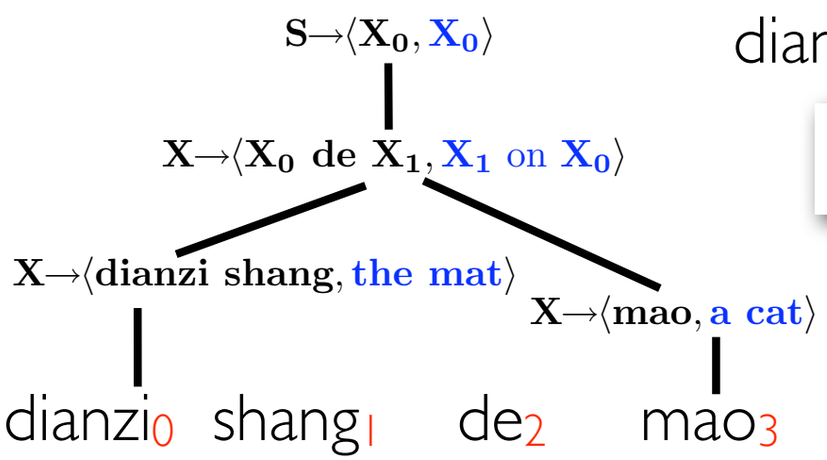

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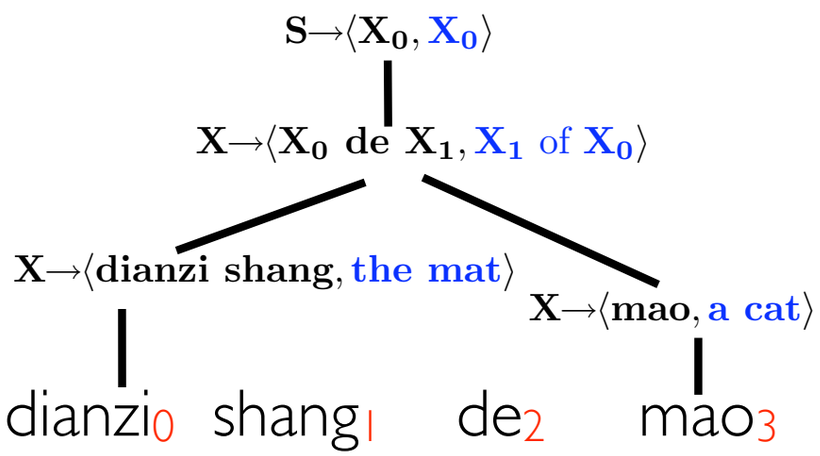

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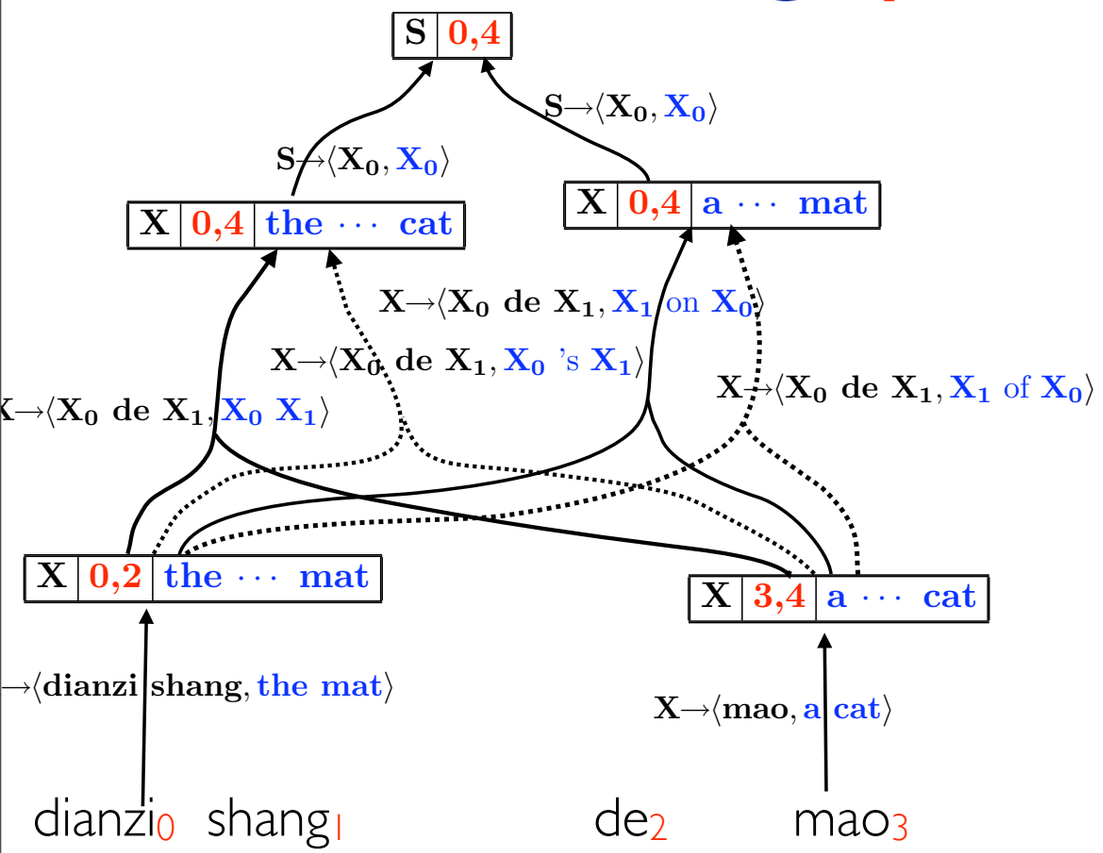

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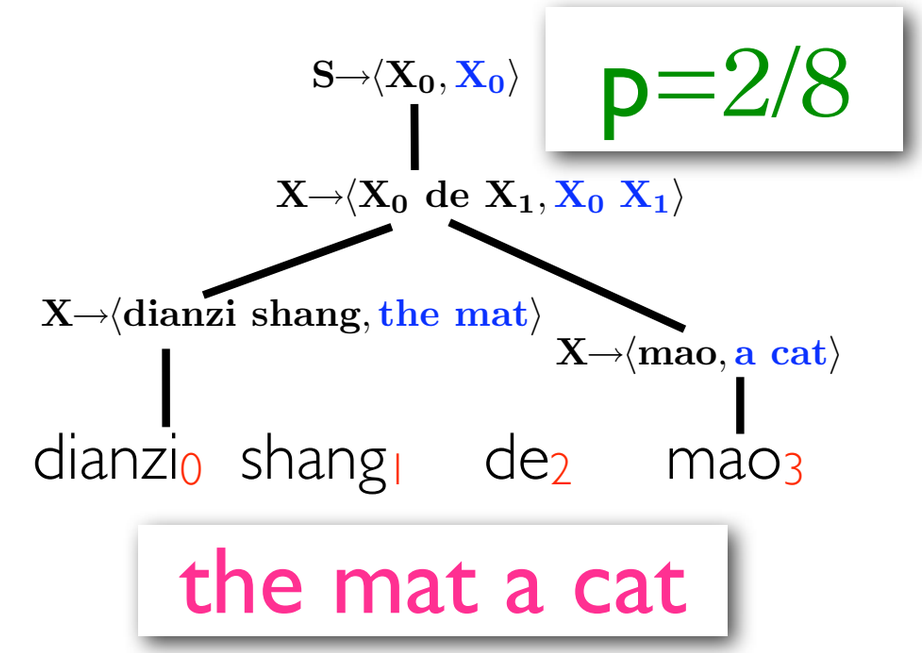

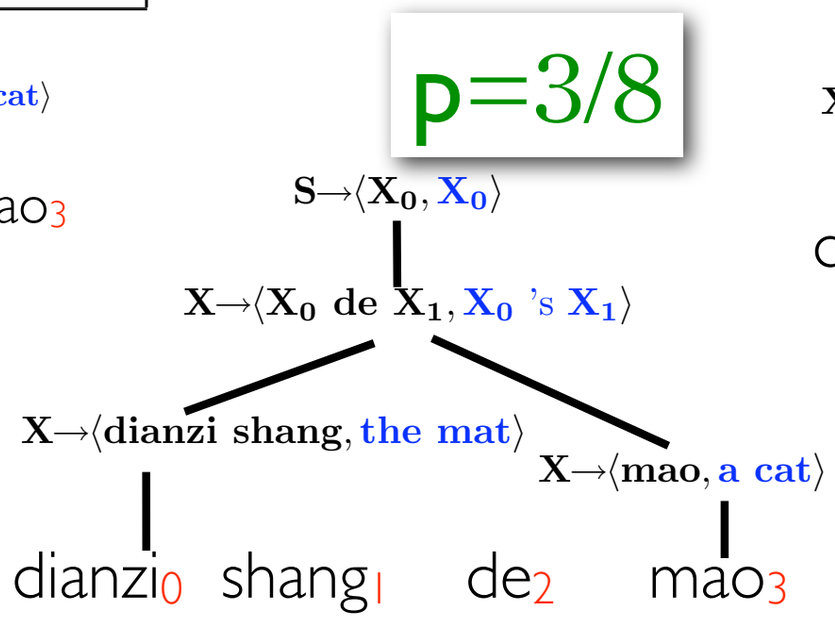

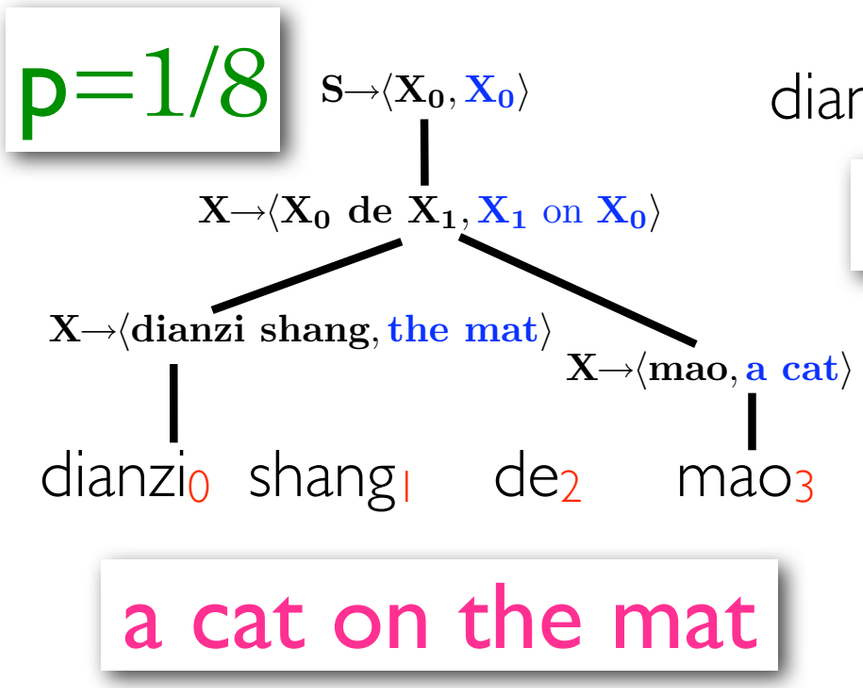

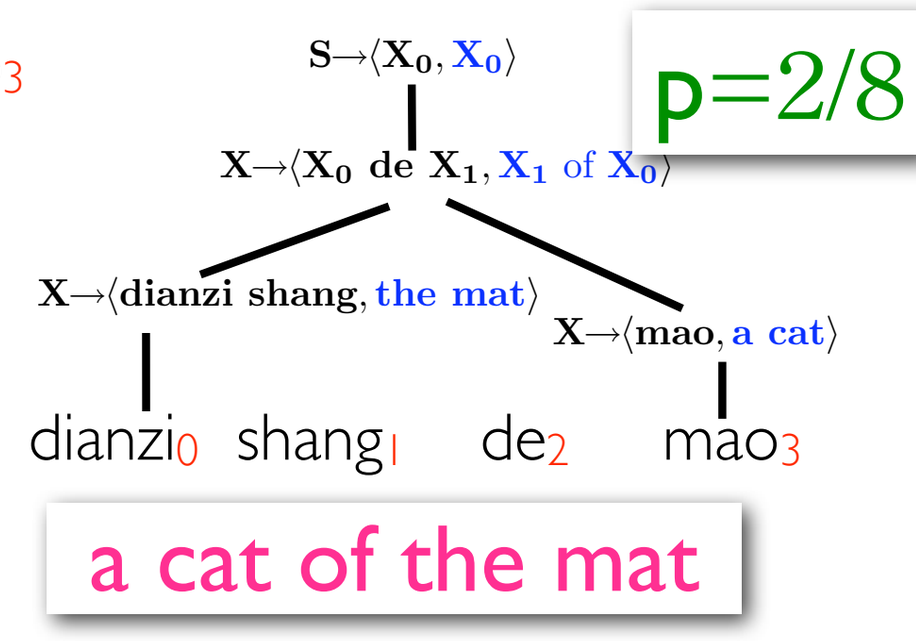

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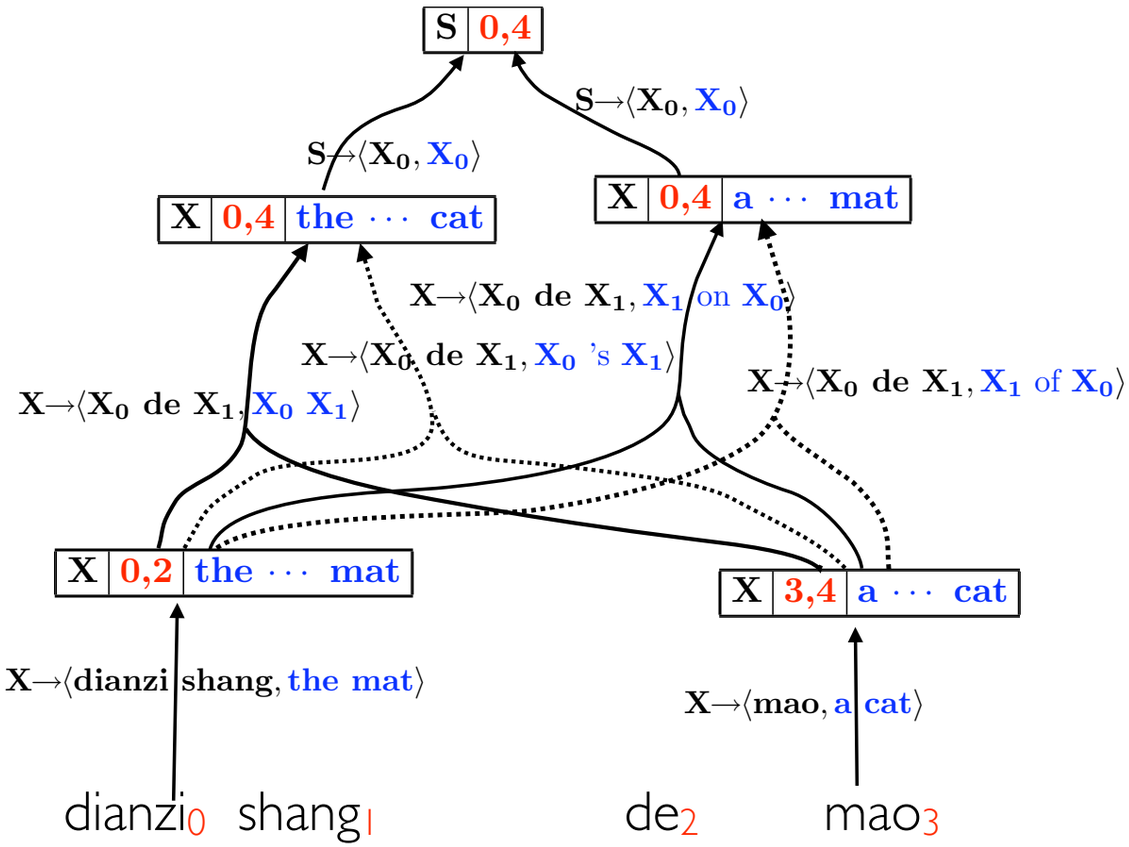

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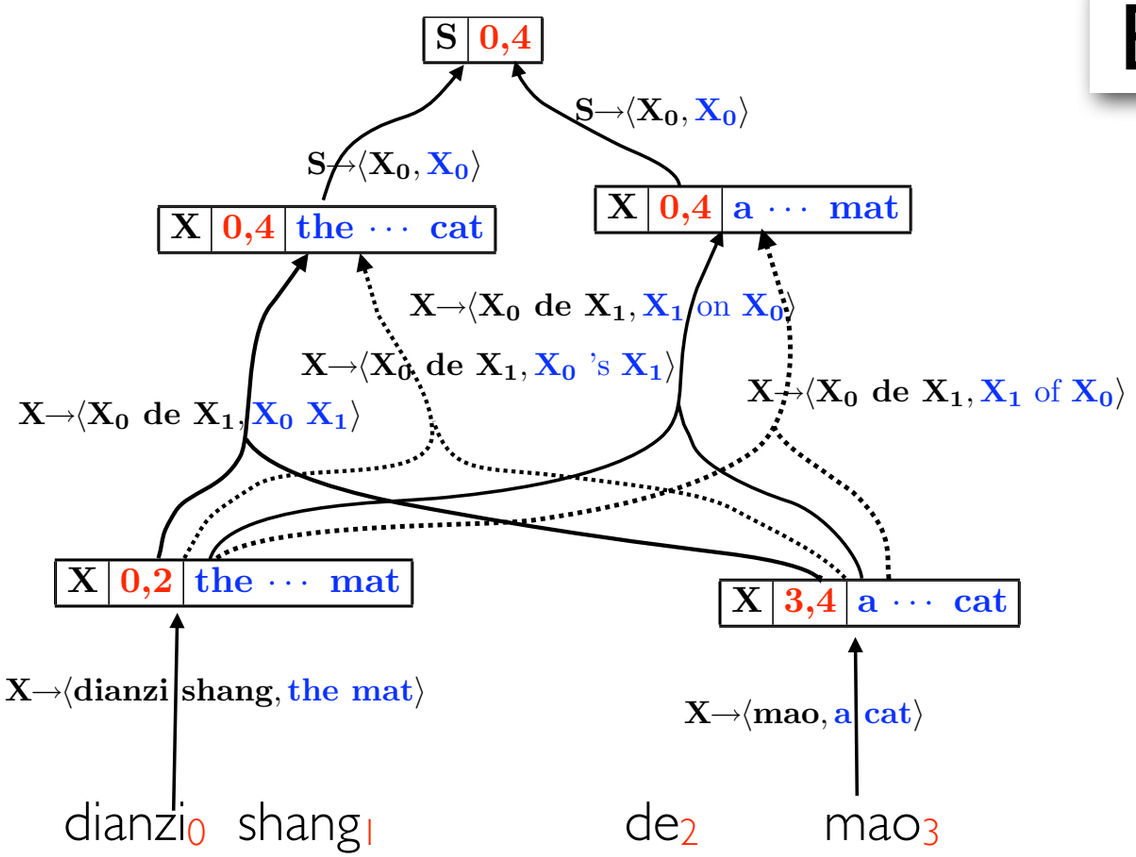

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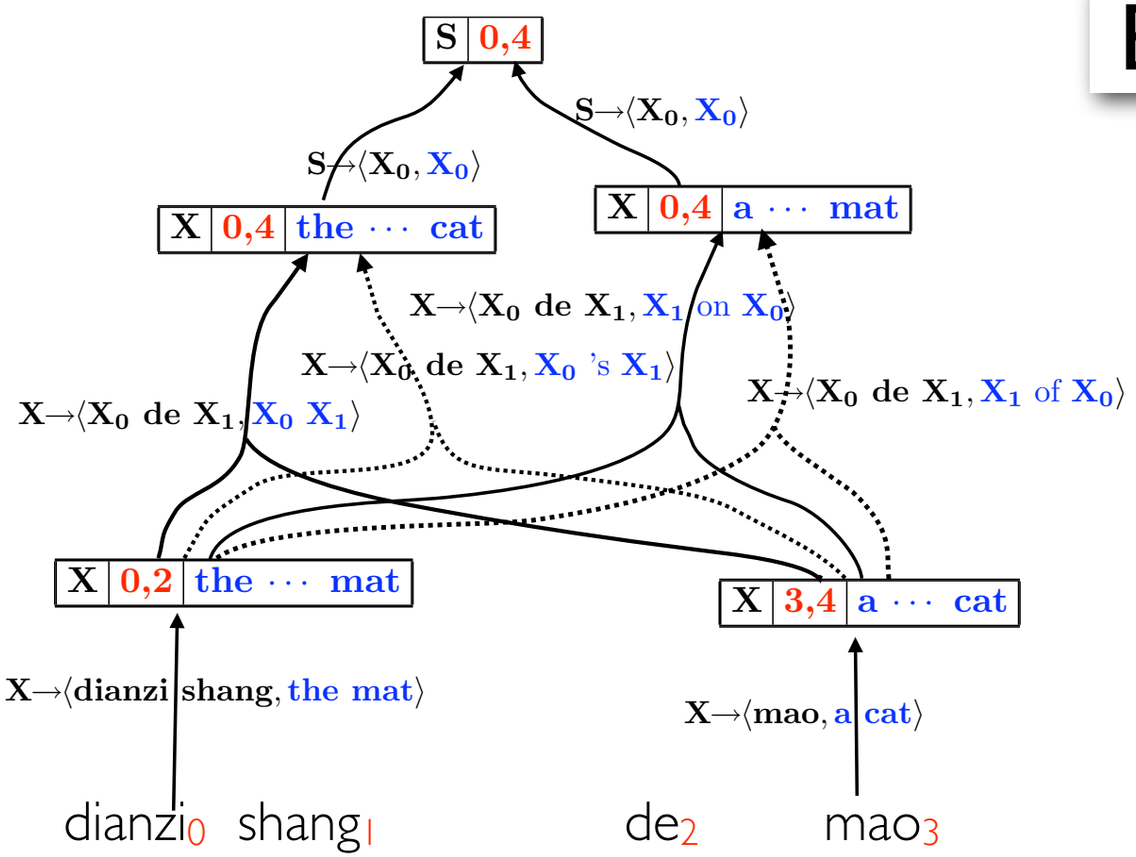

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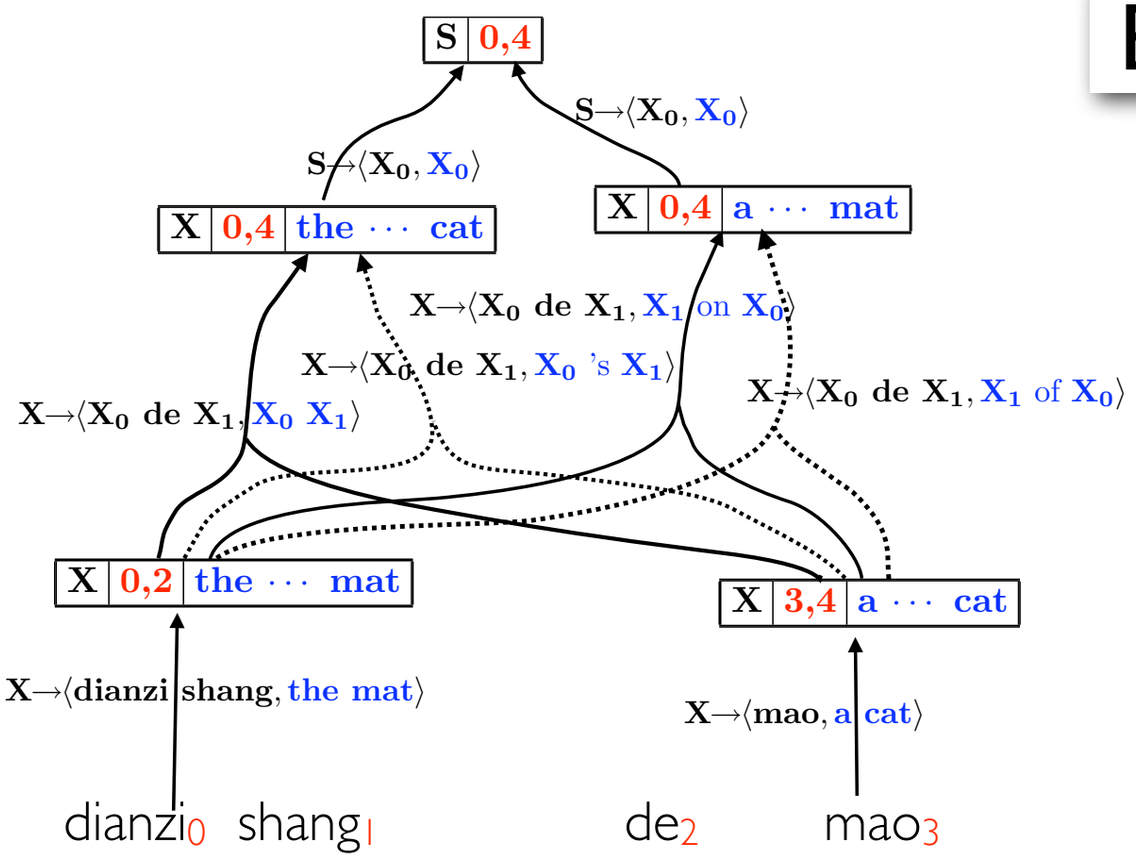

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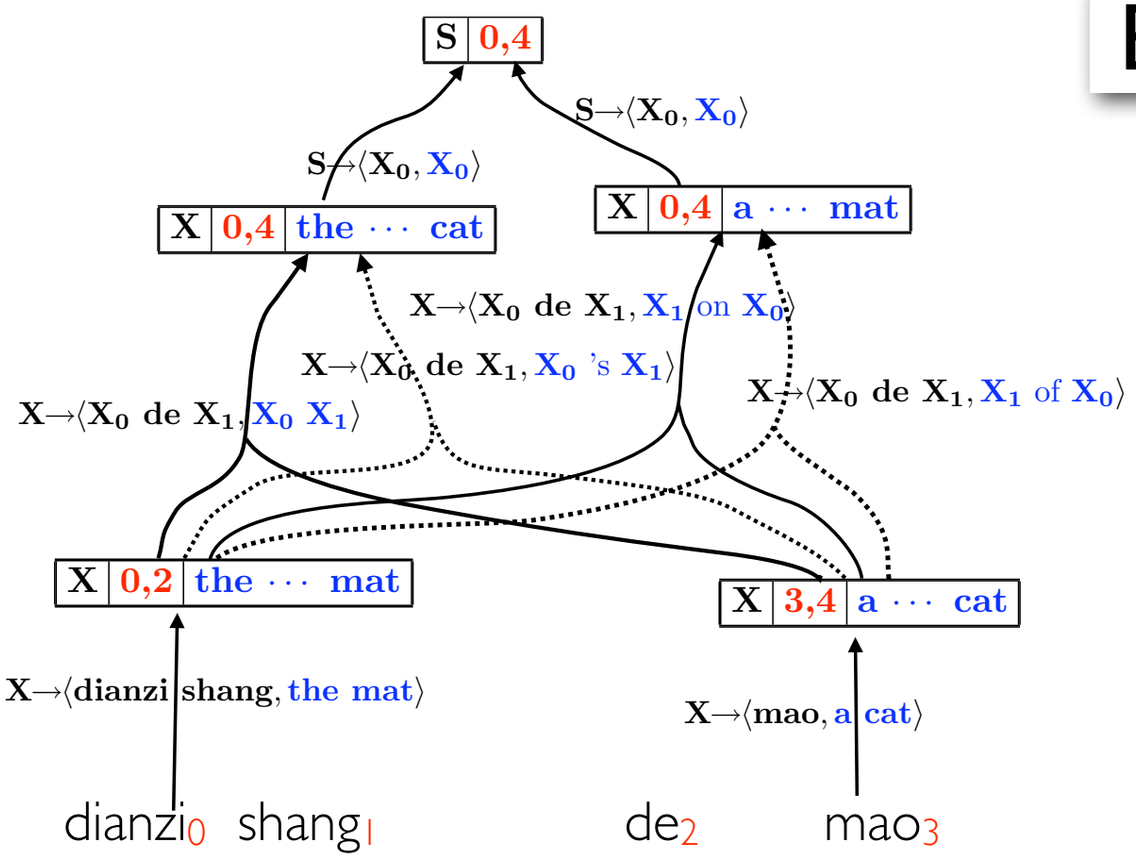

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John already told you how to do this ☺

KL divergences under different variational models

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Measure bits/word	$\overline{\mathrm{H}}(p)$	$\overline{\mathrm{KL}}(p\|\|\cdot)$			
		q_1^*	q_2^*	q_3^*	q_4^*
MT'04	1.36	0.97	0.32	0.21	0.17
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- The larger the order n is, the smaller the KL divergence is!
- The reduction of KL divergence happens mostly when switching from unigram to bigram

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How to compute them on a **hypergraph**?

see (Li and Eisner, EMNLP'09)

BLEU scores when using a single variational n-gram model

Decoding scheme	MT'04	MT'05
Viterbi	35.4	32.6
1gram	25.9	24.5
2gram	**36.1**	**33.4**
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modeling error in p

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Minimum Bayes Risk (MBR) decoding?

(Tromble et al. 2008)

(Denero et al. 2009)

Minimum Risk Decoding

- Maximum A Posterior (MAP) decoding
  - find the most **probable** translation string

$$y^* = \arg \max_{y \in \mathrm{HG}(x)} p(y|x)$$

- Minimum risk decoding
  - find the **consensus** translation string

$$y^* = \arg \min_{y \in \mathrm{HG}(x)} \mathrm{Risk}(y)$$

$$\mathrm{Risk}(y) = \sum_{y'} L(y, y')p(y'|x)$$

Variational Decoding(VD) vs. MBR (Tromble et al. 2008)

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spurious ambiguity

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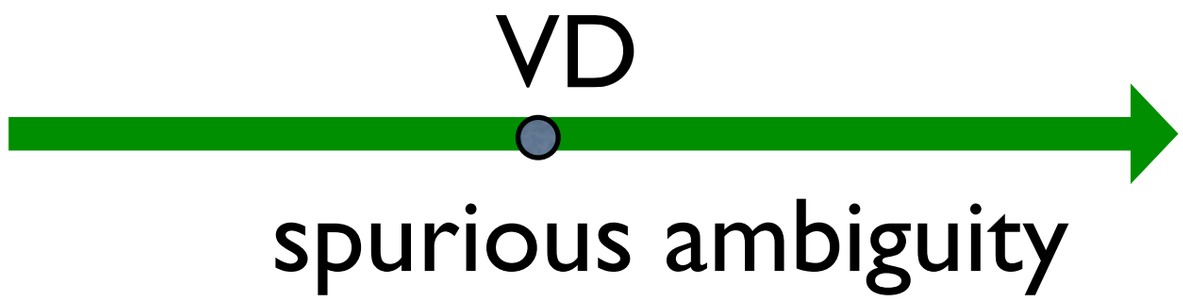

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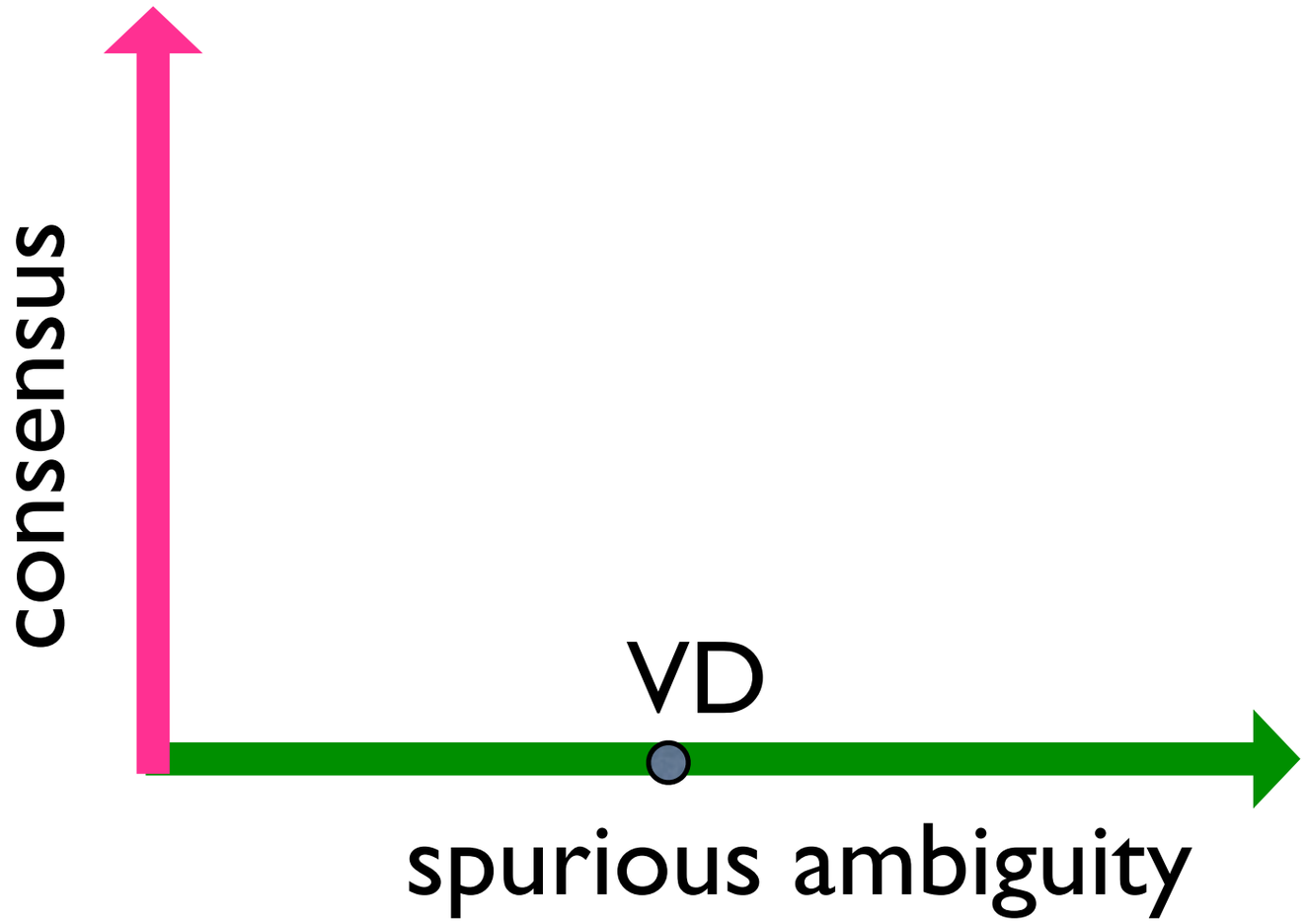

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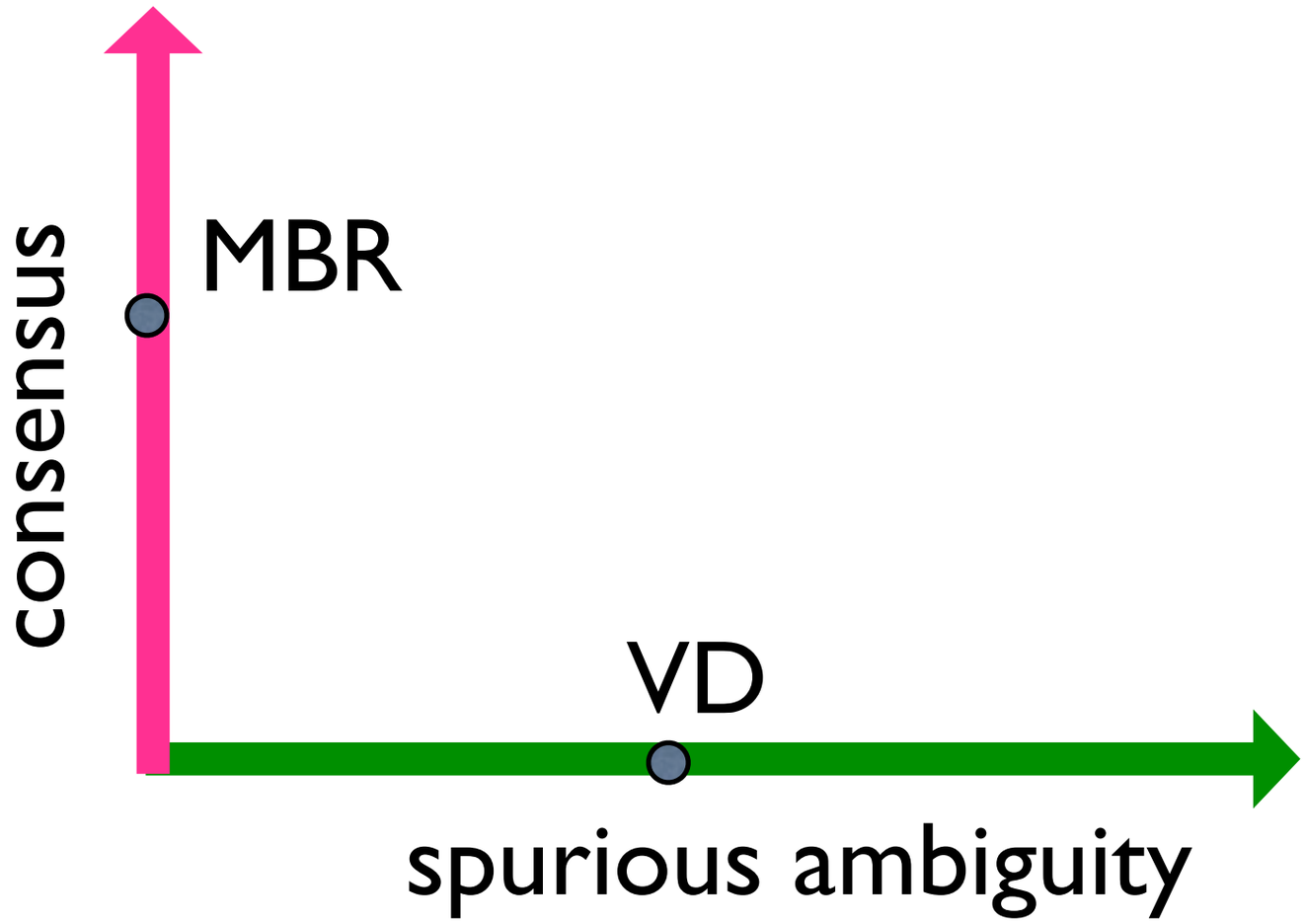

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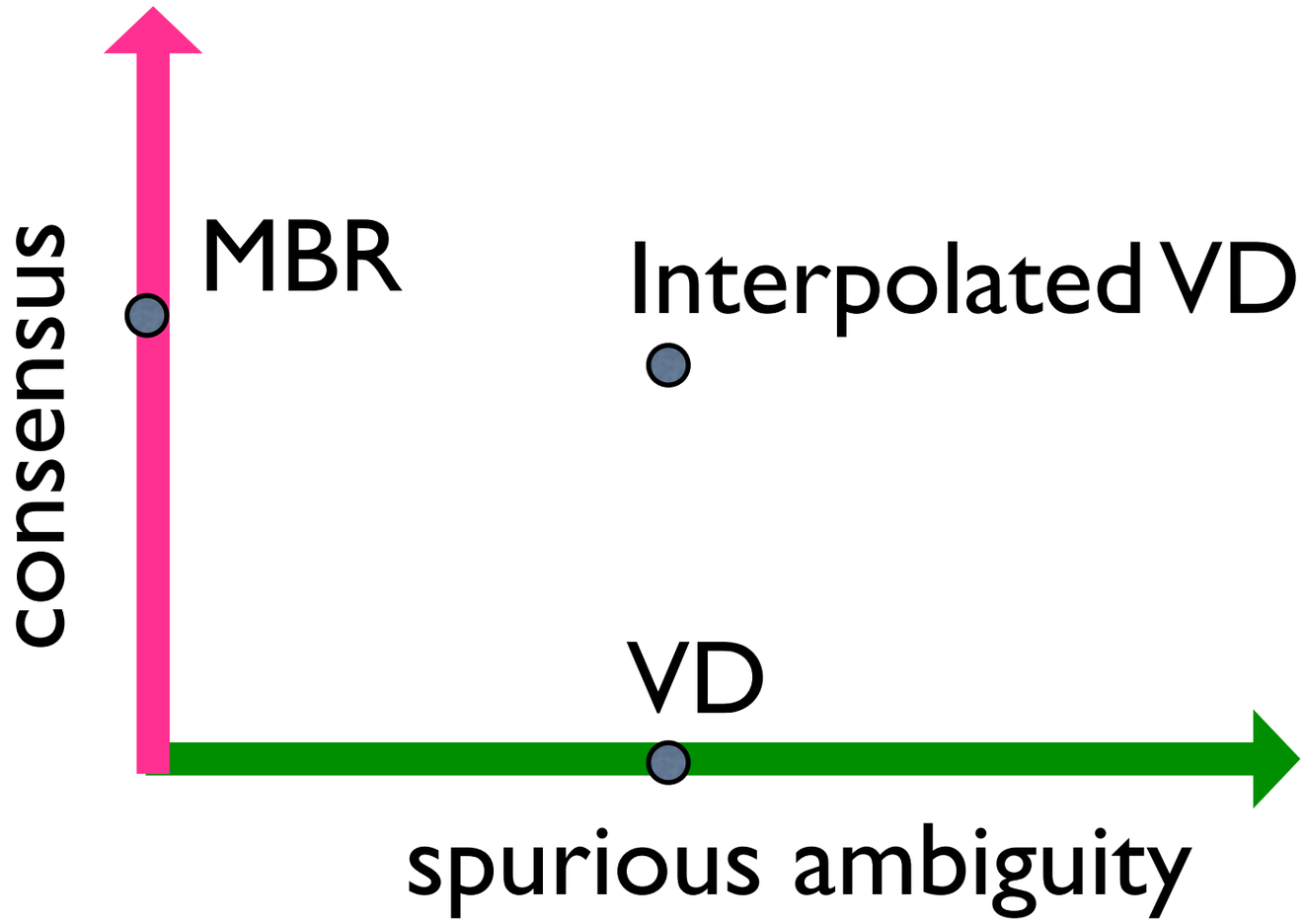

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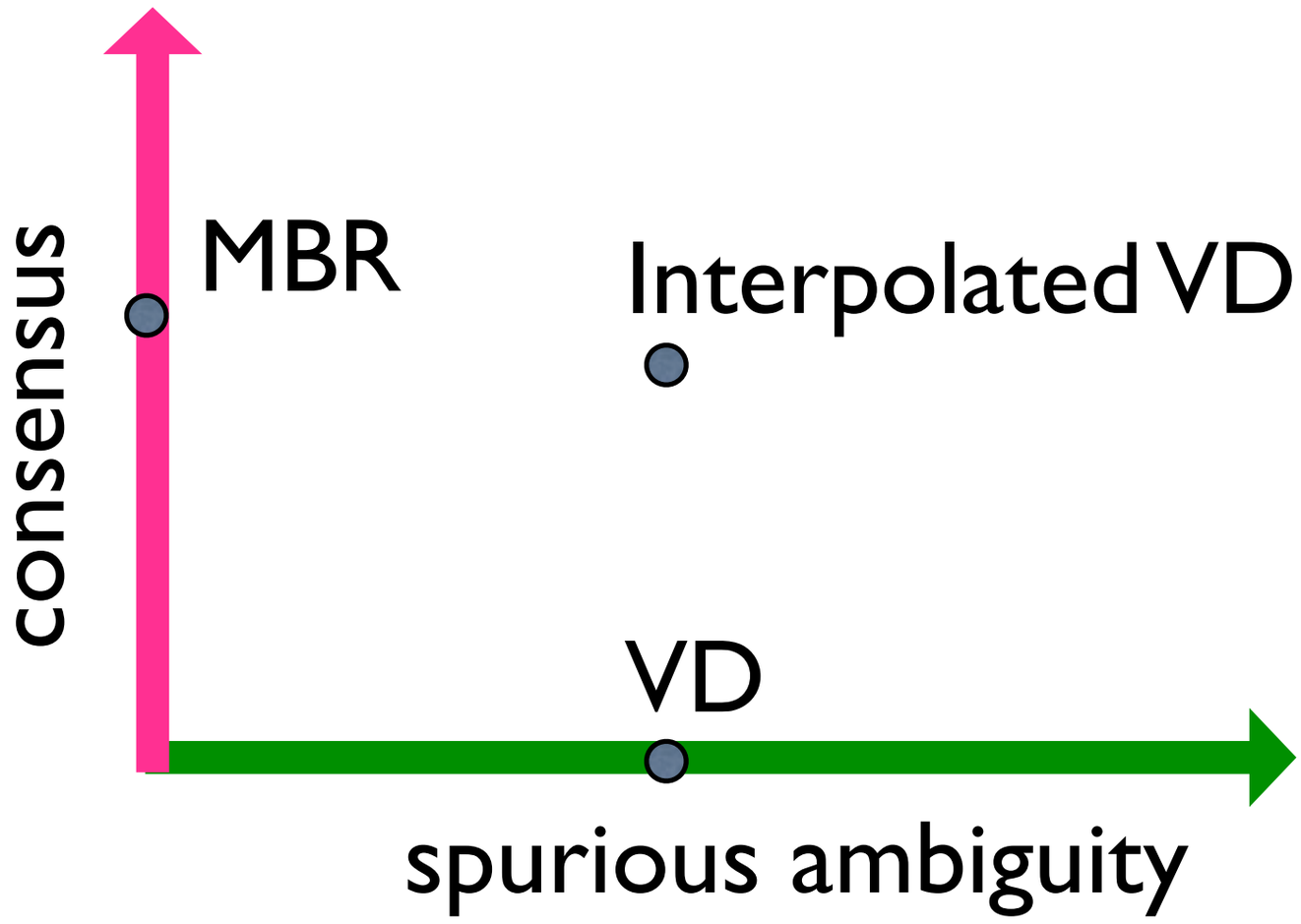

Both BLEU metric and our variational distributions happen to use n-gram dependencies.

- Variational decoding with interpolation

$$y^* = \arg \max_{y \in \mathrm{HG}(x)} \sum_n \theta_n \cdot \log q_n^*(y \mid x)$$

$$q_n(y \mid x) = \prod_{w \in W_n} q(r(w) \mid h(w), x)^{c_w(y)}$$

$$q(r(w) \mid h(w), x) = \frac{\sum_{y'} c_w(y') p(y' \mid x)}{\sum_{y'} c_{h(w)}(y') p(y' \mid x)}$$

- Minimum risk decoding (Tromble et al. 2008)

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→ non-probabilistic

$$g(w \mid x) = \sum_{y'} \delta_w(y') p(y' \mid x)$$

→ very expensive to compute

BLEU Results on Chinese-English NIST MT Tasks

Decoding scheme	MT'04	MT'05
Viterbi	35.4	32.6
MBR (K=1000)	35.8	32.7
Crunching (N=10000)	35.7	32.8
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- variational decoding improves over Viterbi, MBR, and crunching

Conclusions

- Exact MAP decoding with spurious ambiguity is intractable
- Viterbi or N-best approximations are efficient, but ignore most derivations
- We developed a variational approximation, which considers all derivations but still allows tractable decoding
- Our variational decoding improves a state of the art baseline

Future directions

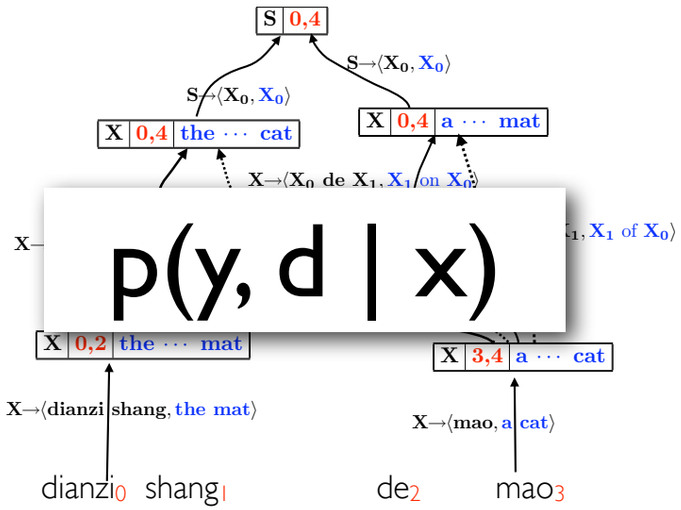
- The MT pipeline is full of intractable problems
  - variational approximation is a principled way to tackle these problems
- Decoding with spurious ambiguity is a common problem in many other NLP applications
  - Models with latent variables
  - Data oriented parsing (DOP)
  - Hidden Markov Models (HMM)
  - .....

Thank you!

谢谢!

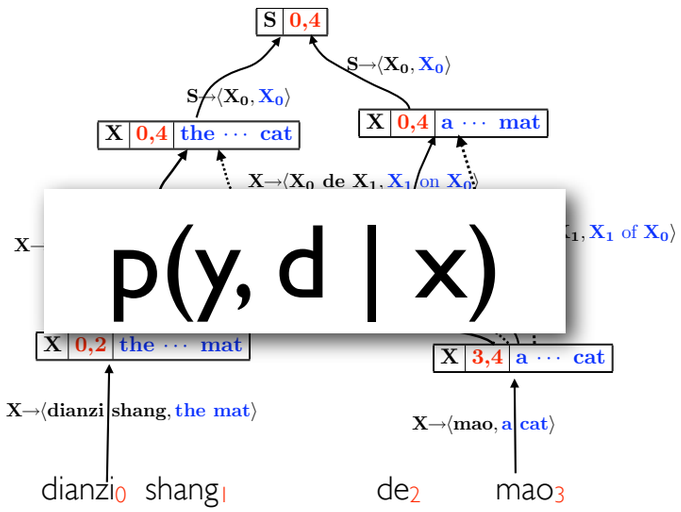

Joshua

1



Generate a hypergraph

2



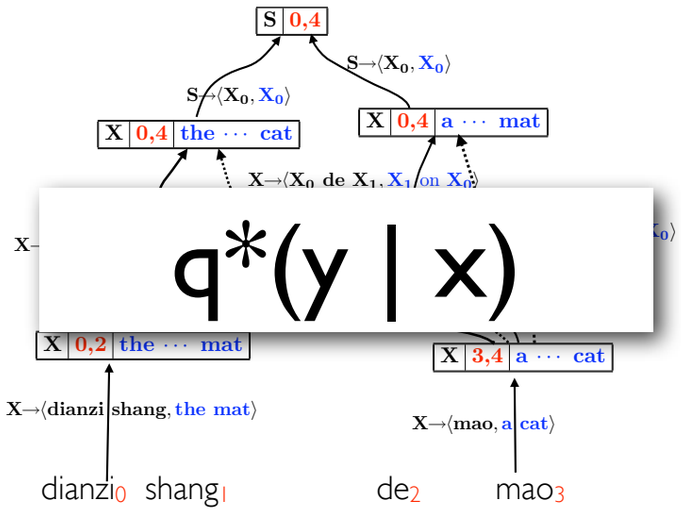
Estimate a model from the hypergraph

q* is an n-gram model over output strings.

$$q^*(y \mid x)$$

$$\approx \sum_{d \in D(x,y)} p(y,d|x)$$

3



Decode using q* on the hypergraph