# Analyzing Errors of Unsupervised Learning

ACL 2008 Columbus, Ohio

June 18, 2008

Percy Liang Dan Klein

# Unsupervised grammar induction

Goal: induce hidden syntax

The man ate a tasty sandwich

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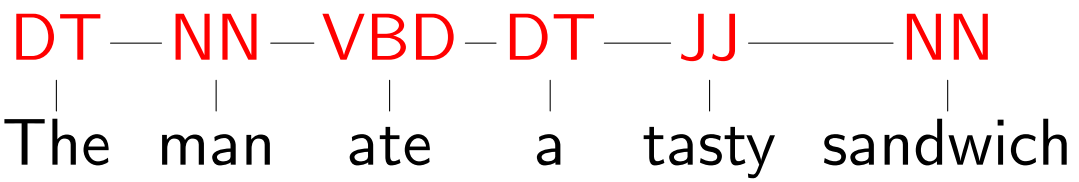


POS tagging

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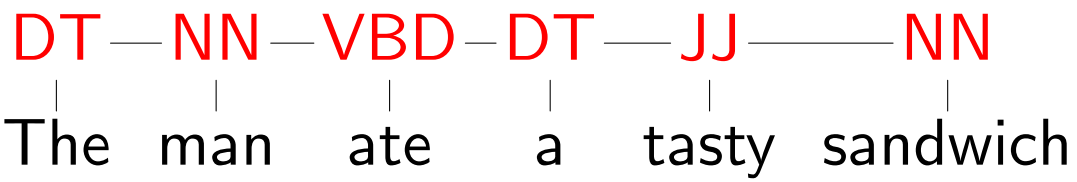


DT NN VBD

DT

JJ NN

POS tagging

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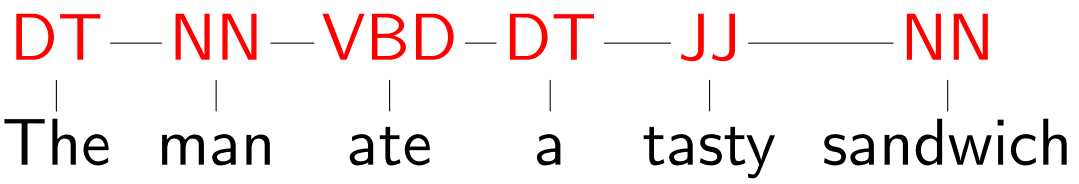


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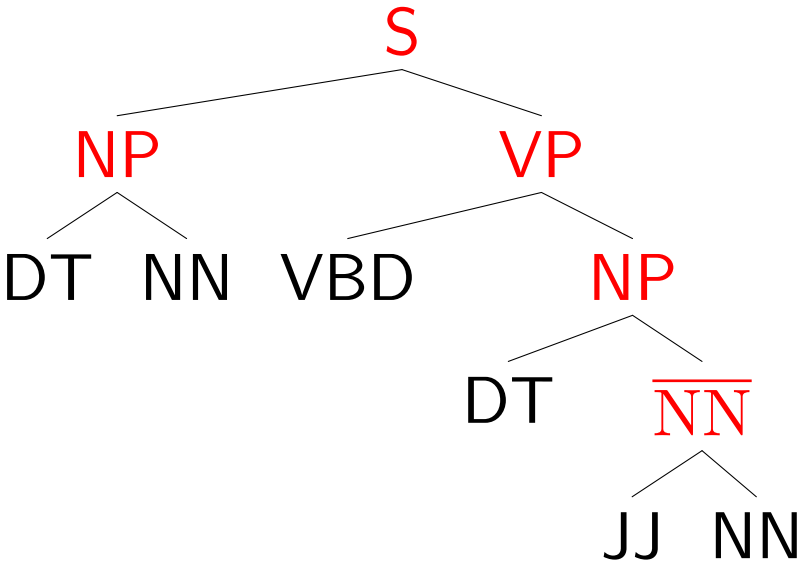


Constituency parsing

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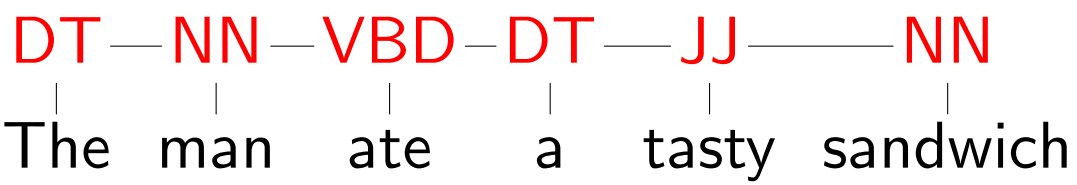


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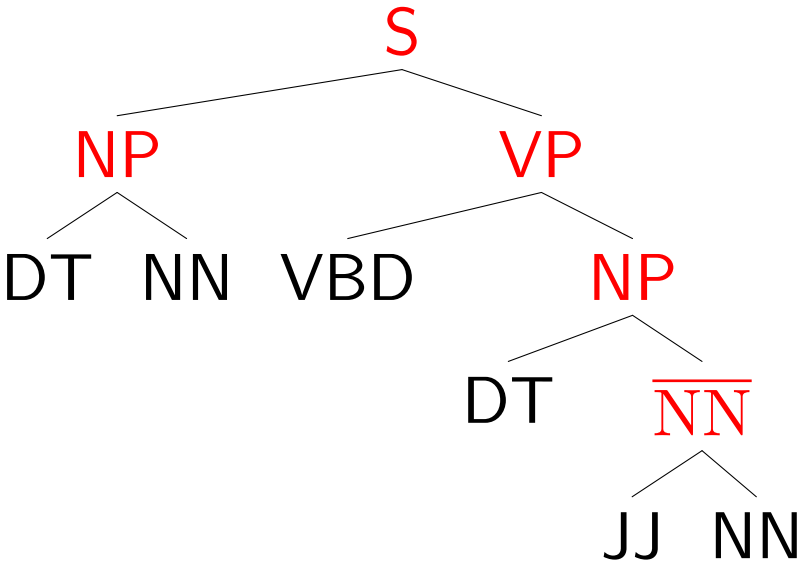


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For example, on POS tagging using HMMs:

Unsupervised using EM $\approxeq 60\%$

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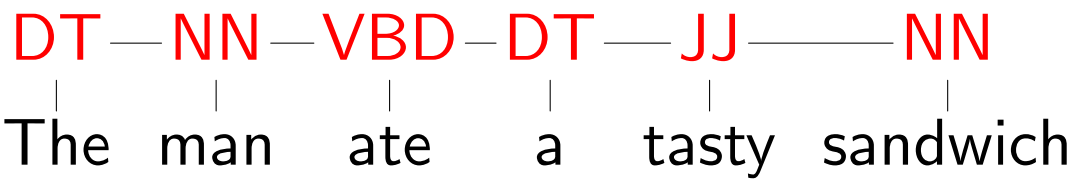


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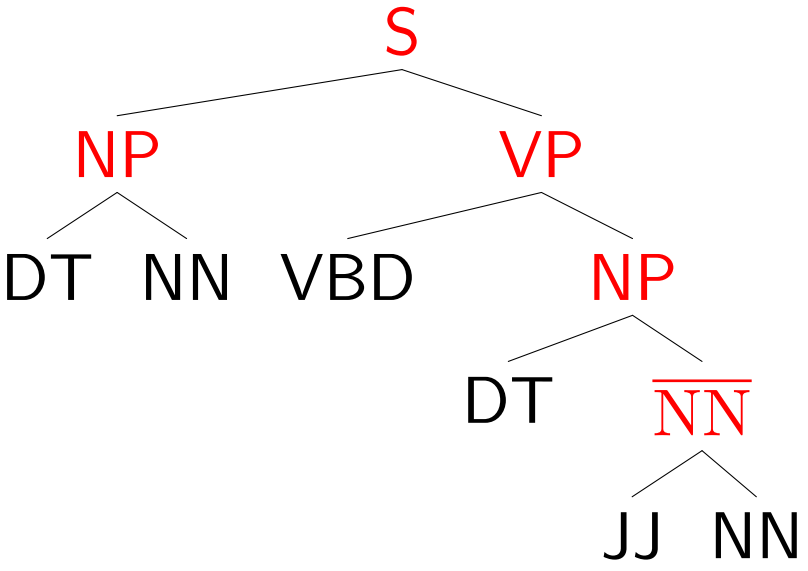


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- Supervised $\geq 90\%$

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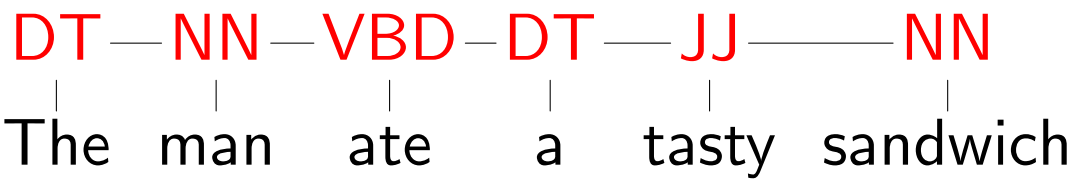


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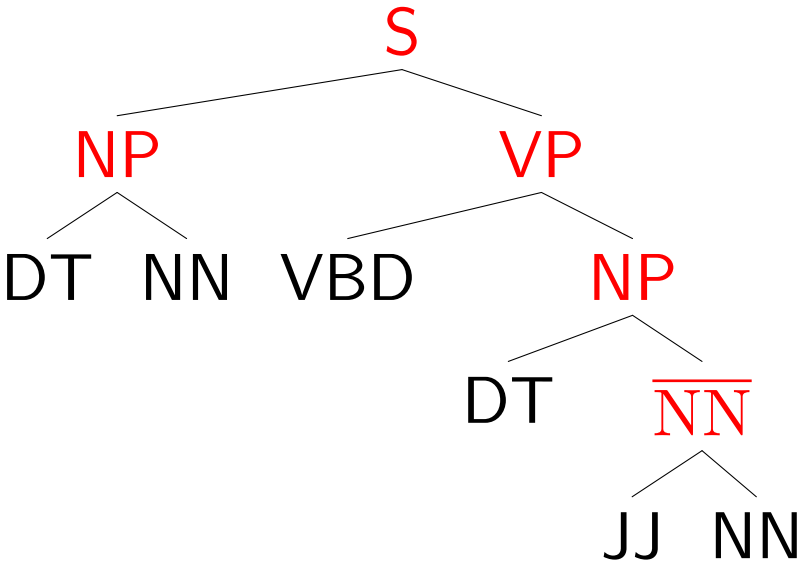


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**Why does EM fail?**

# Four types of errors:

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- Optimization error
  - Local optima

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# Four types of errors:

## Optimization error

Local optima

## Estimation error

Limited data

## Approximation error

Likelihood objective $\not\Leftrightarrow$ accuracy

## Identifiability error

Different parameter settings $\longrightarrow$ same objective

# Approximation error

Problem: model likelihood $\not\Leftrightarrow$ prediction accuracy

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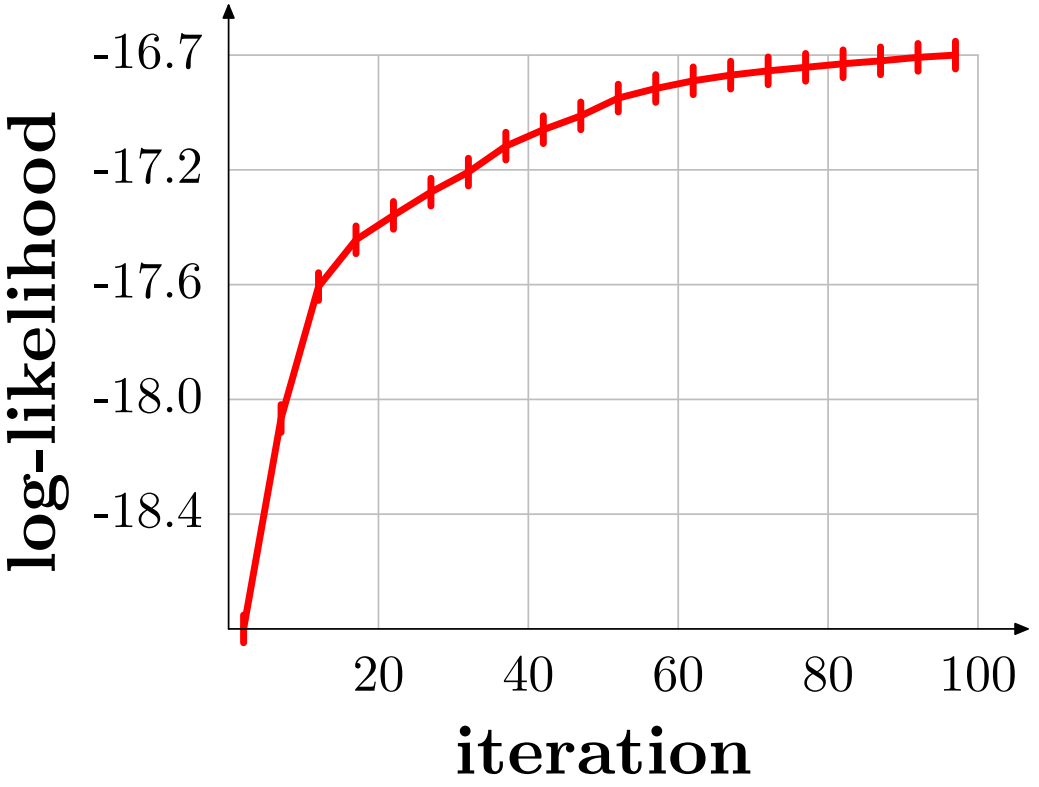
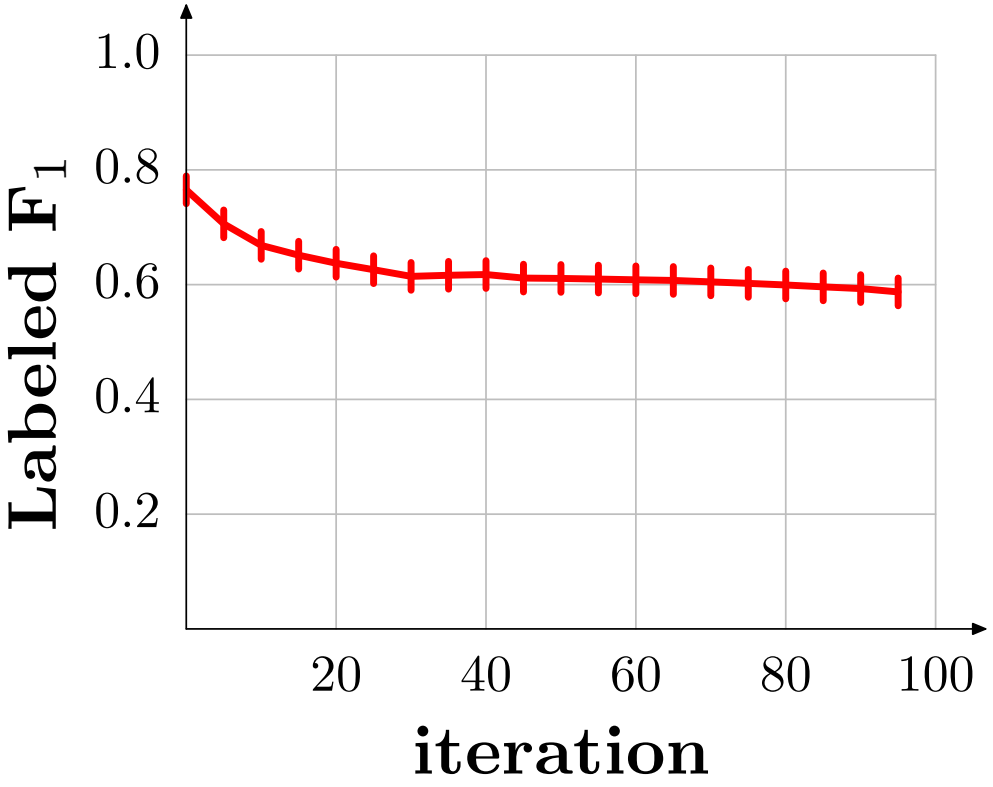
PCFG (EM starting from supervised parameter estimate):



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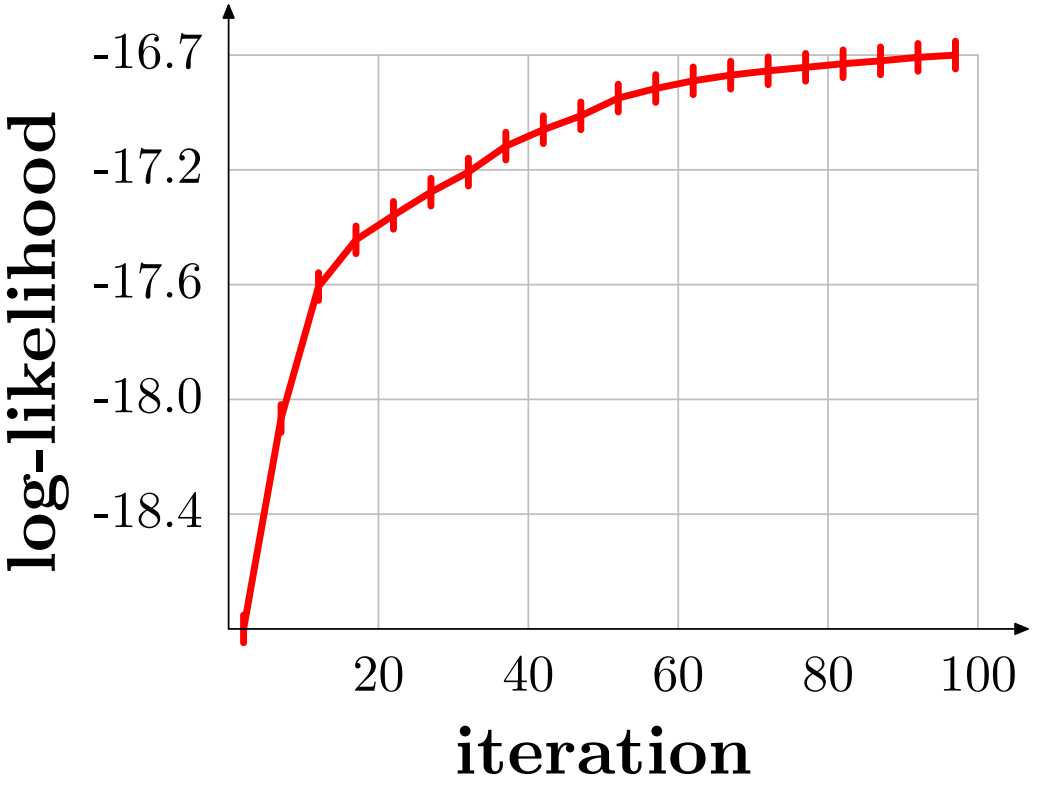


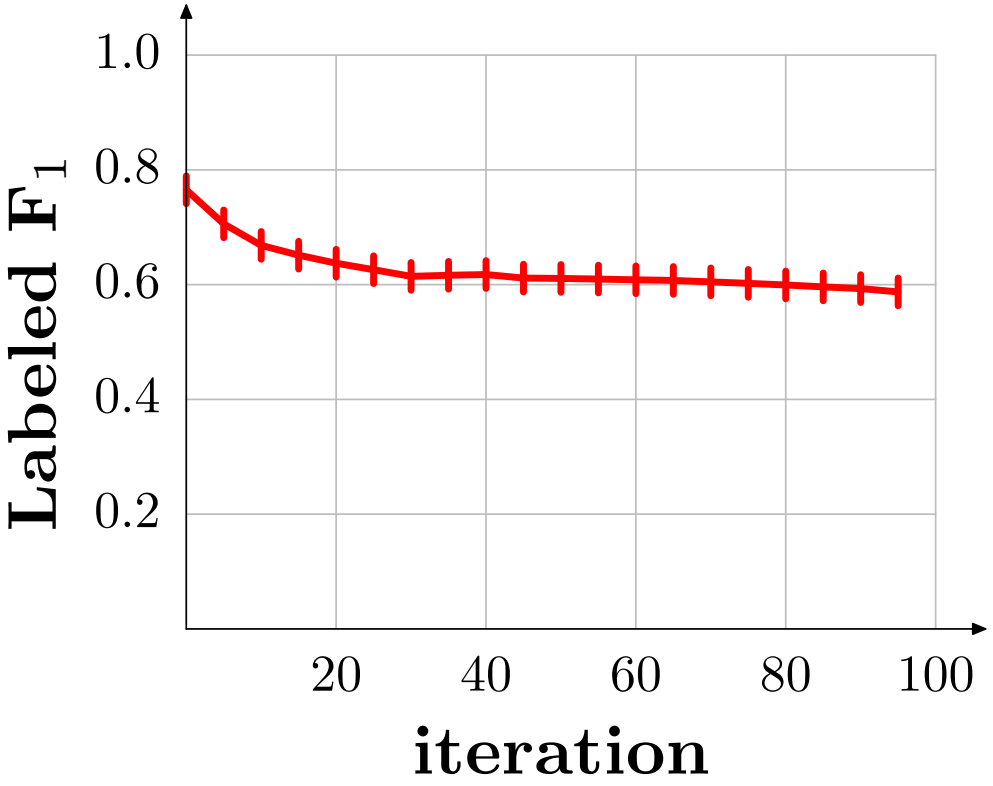


**What qualitative changes is EM making?**

# Migrations

For the HMM:

Truth

DT NN NN RB VBD NNS
The chief executive allegedly made contributions

Iteration 1

DT JJ NN RB VBN NNS
The chief executive allegedly made contributions

# Migrations

For the HMM:

| | | | | | | |
|---|---|---|---|---|---|---|
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Summarize changes by a set of migrations:

NN → JJ

VBD → VBN

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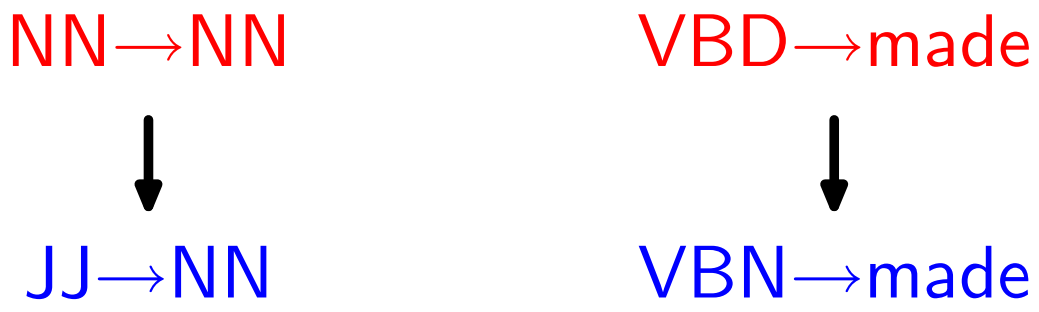


**What are the prominent migrations over the entire corpora?**

# Top HMM migrations

**Iteration 1**

START → ~~NN~~ **NNP**

Sentence-initial nouns are often proper

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**Iteration 2**

~~NN~~ **JJ** → NN

(same as above)

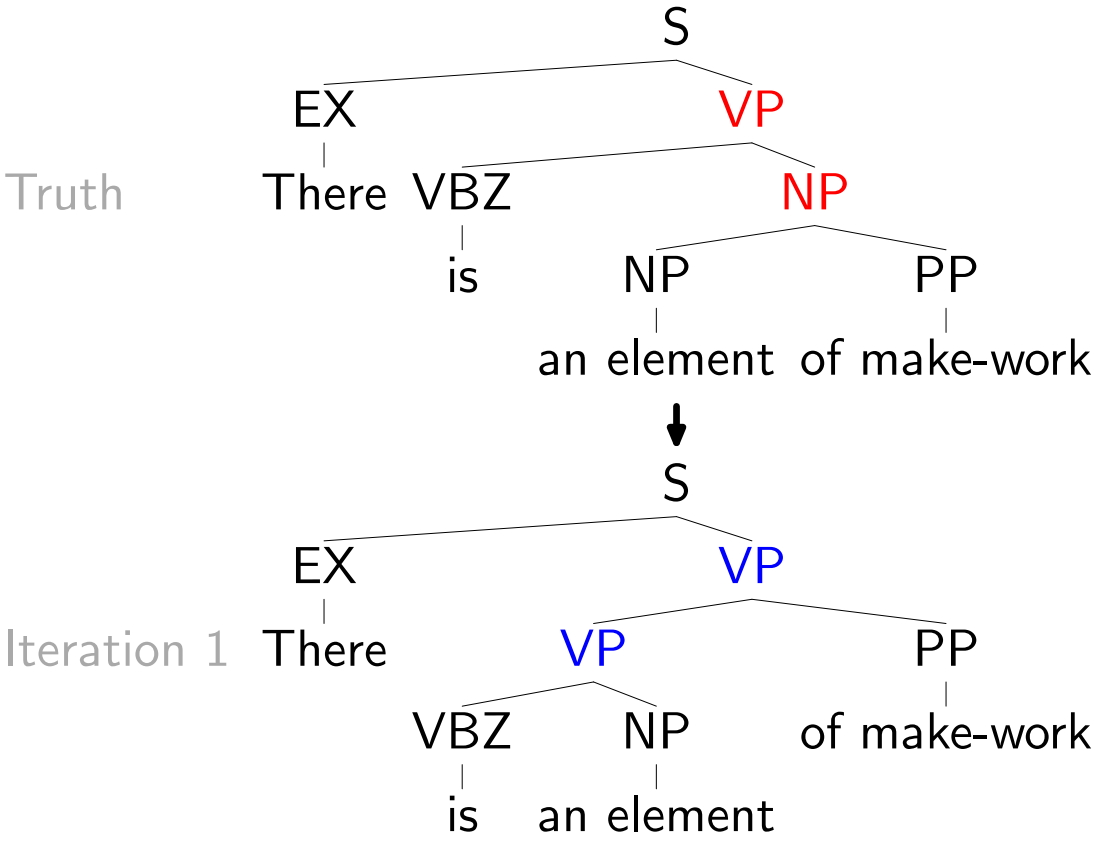
START → ~~NN~~ **NNP**

(same as above)

~~JJ~~ **RB** → TO

Inconsistent gold tags
*contribute much/JJ/RB to*

# Meta-modeling for PCFGs



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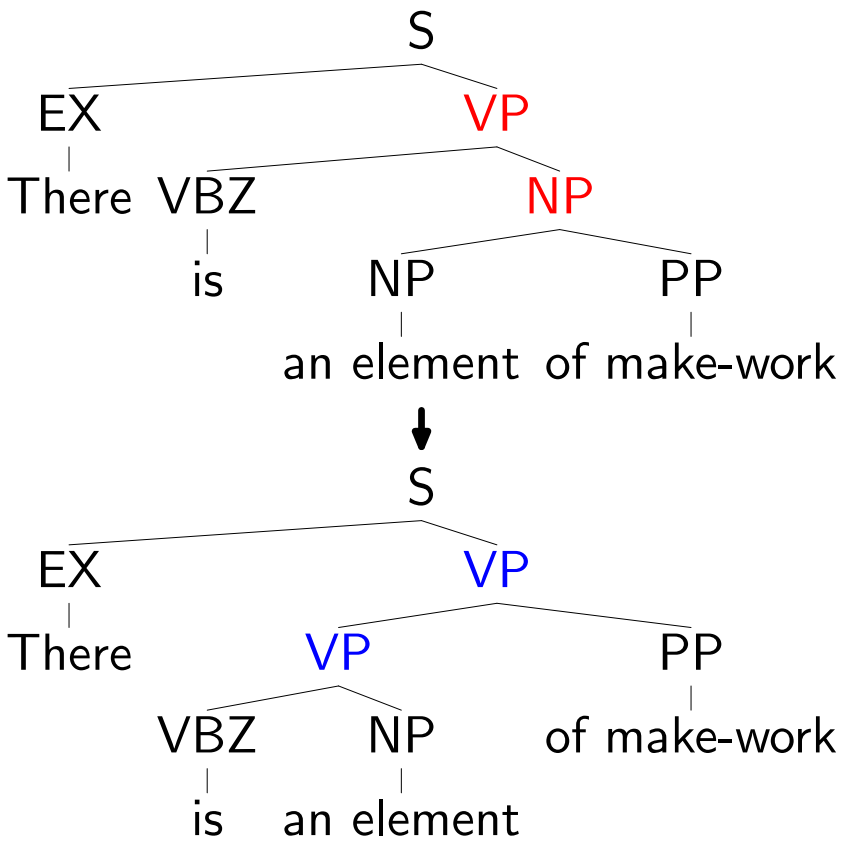


Truth

NP→NP PP

VP→VBZ NP

Iteration 1

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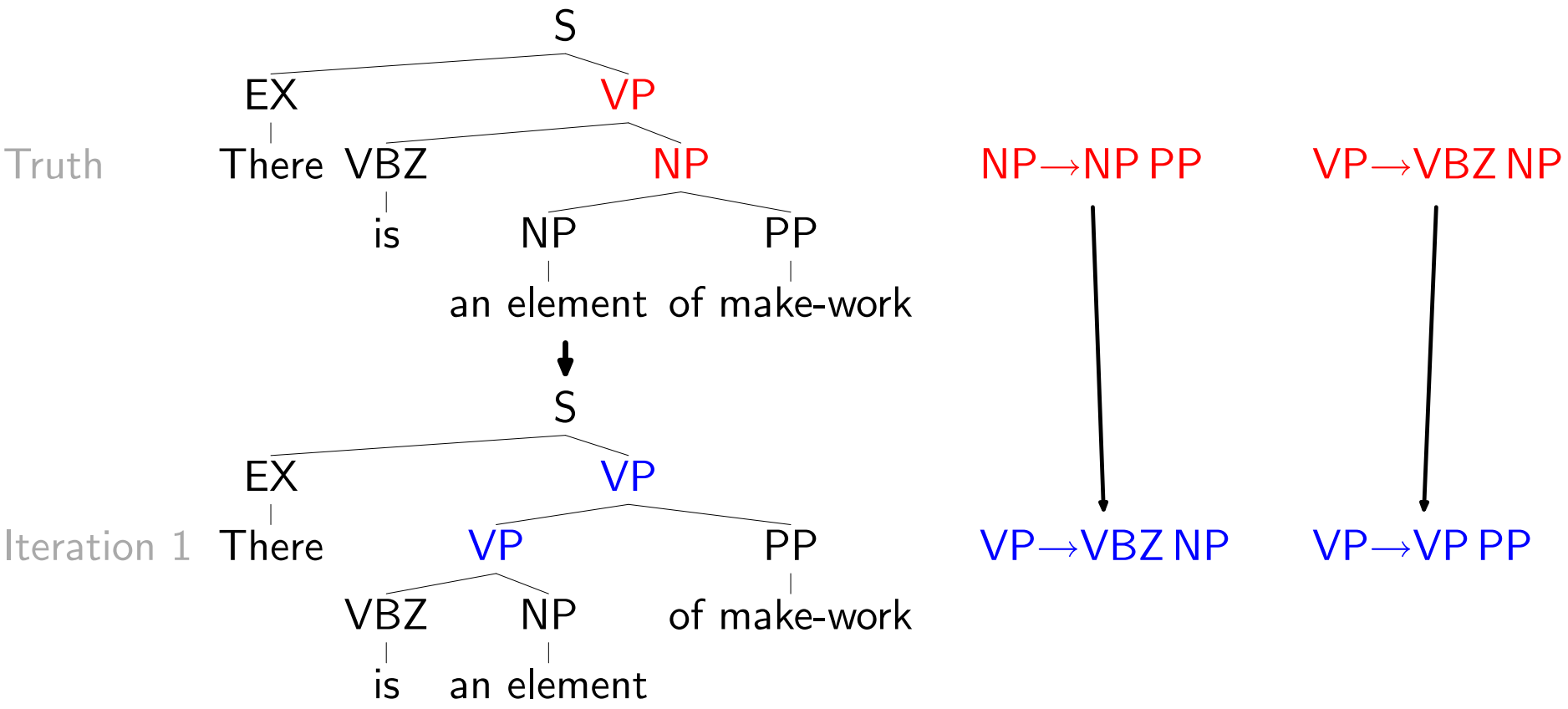


Migrations less clear due to uncertainty in tree structure...

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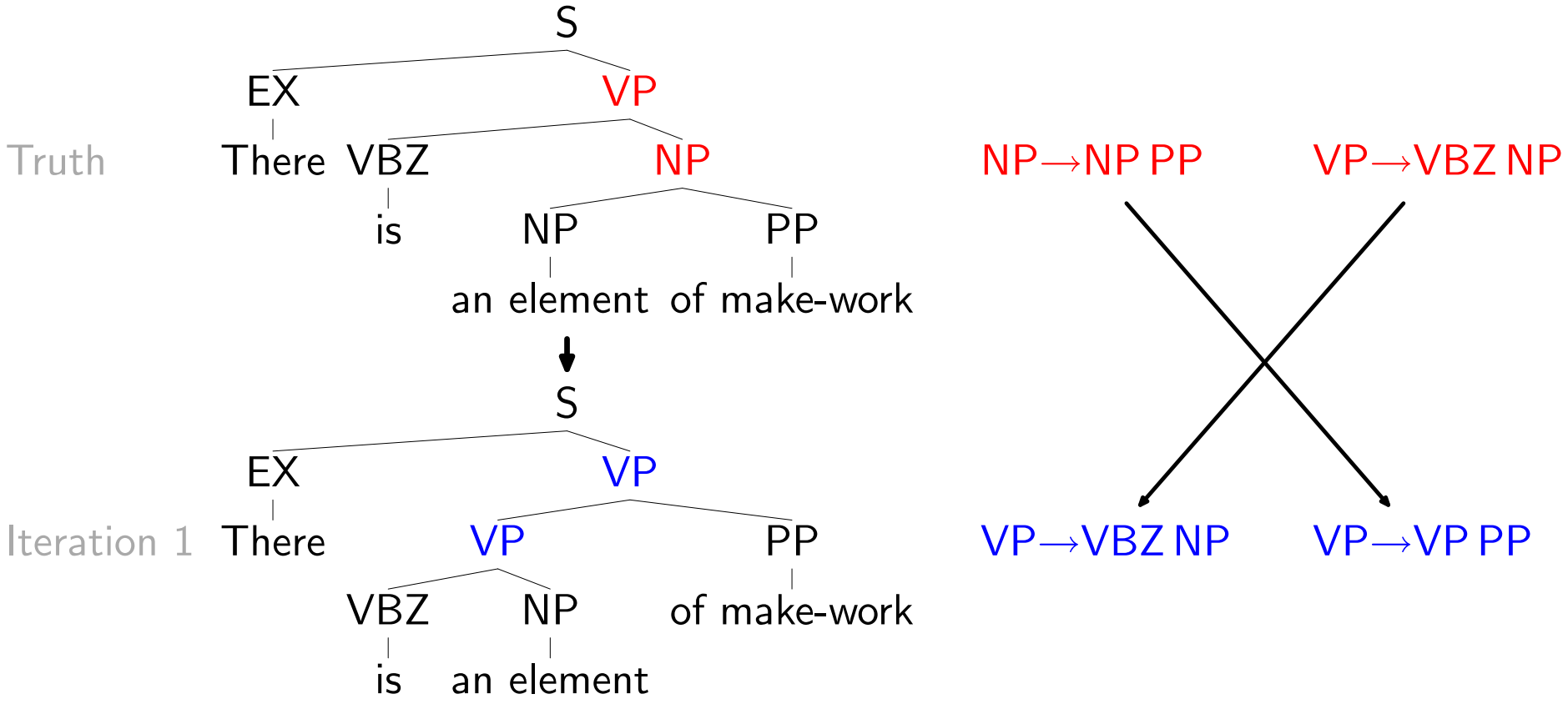


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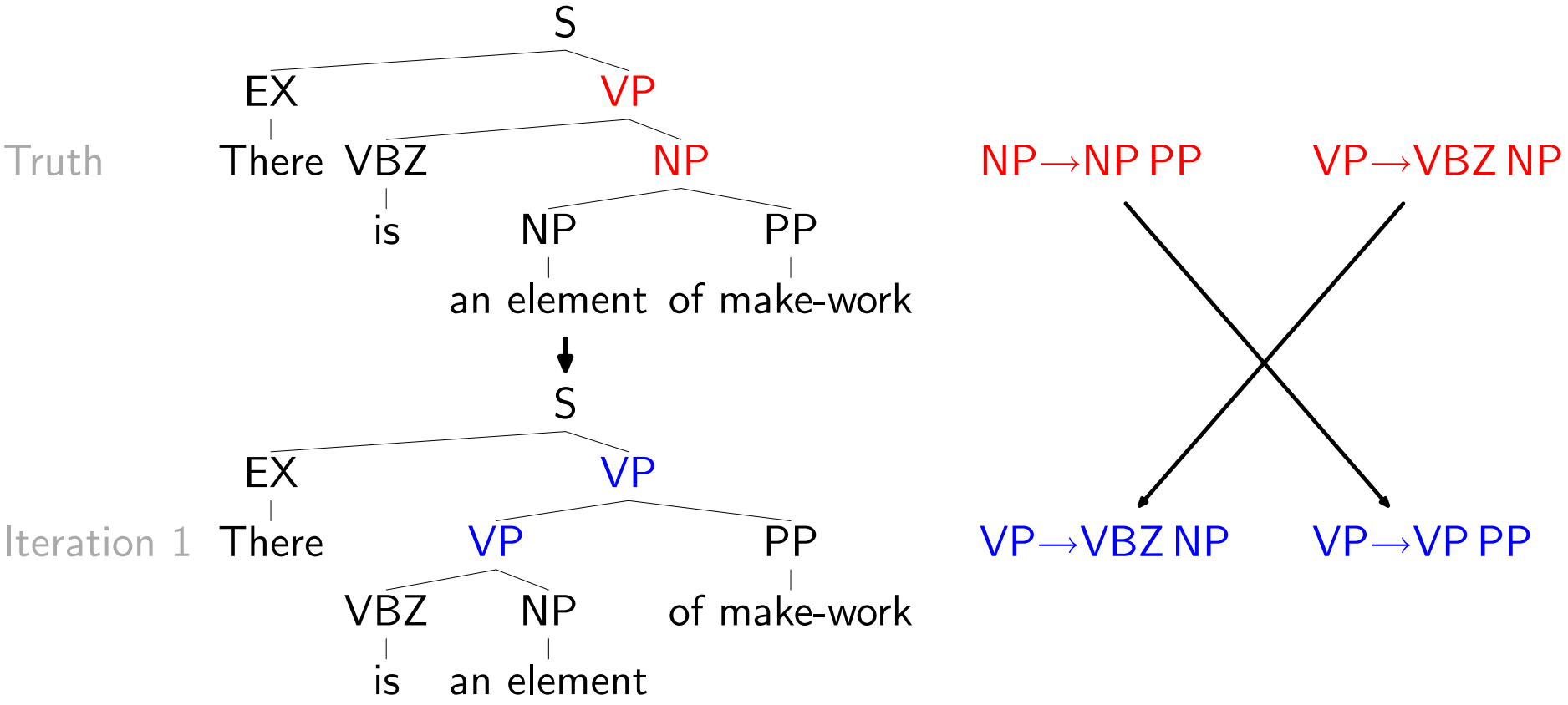


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## Our approach: use a meta-model

- Migrations are hidden alignments to be learned
- Fit using EM

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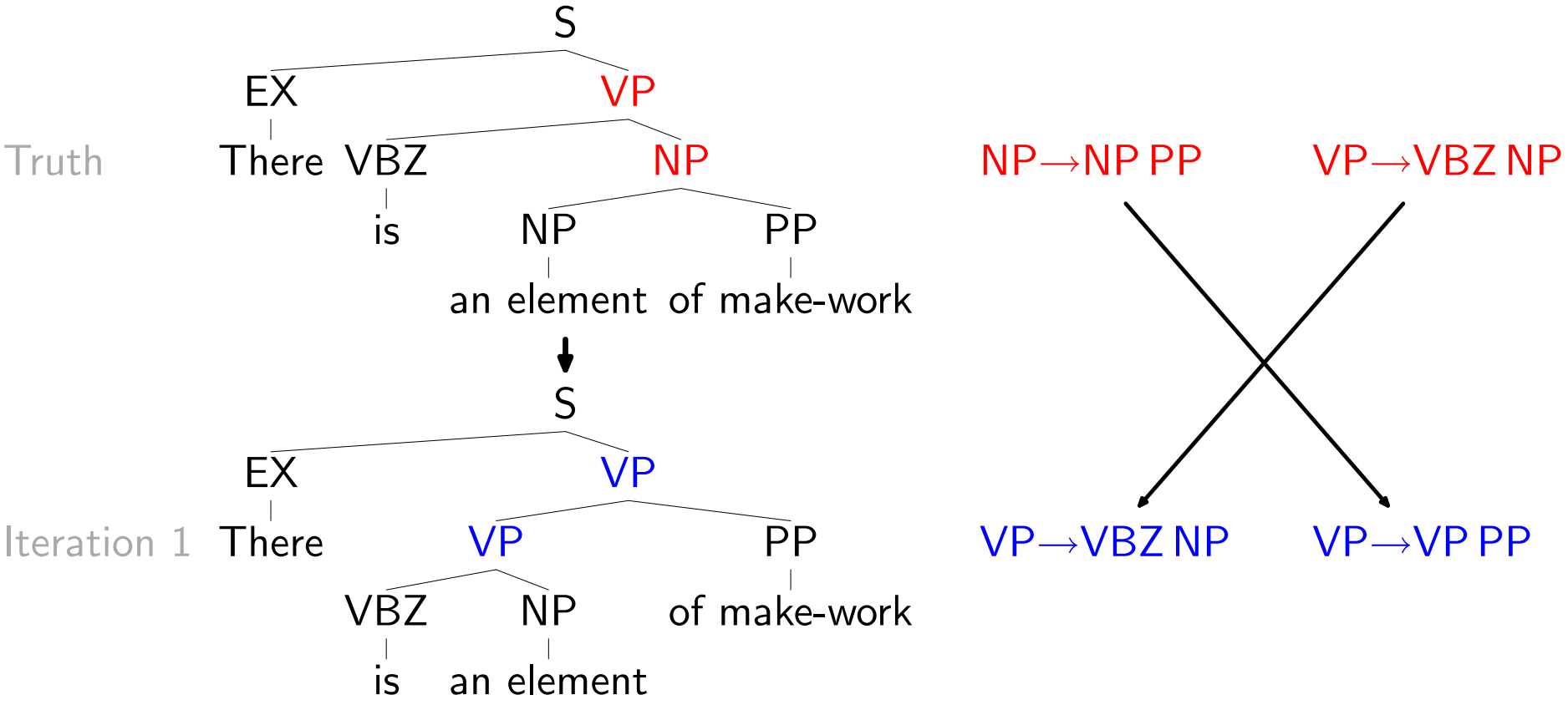


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# Top PCFG migrations learned by meta-model

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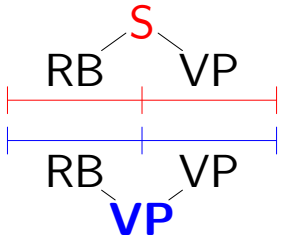


Sentential adverbs → VP adverbs

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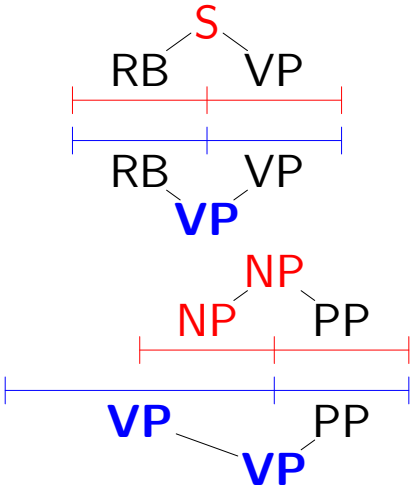


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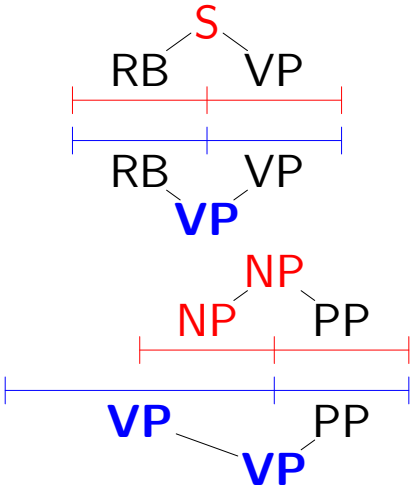


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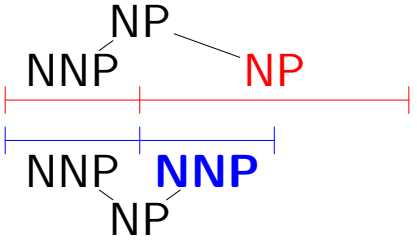


Right-branching → left-branching structures

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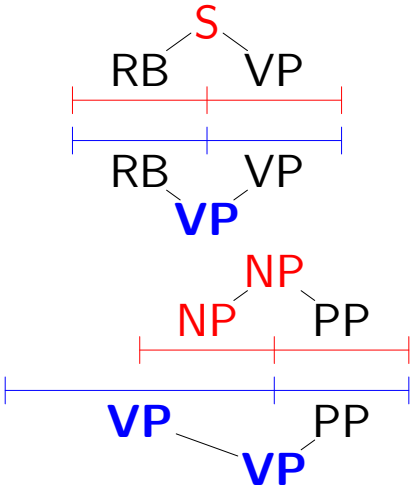


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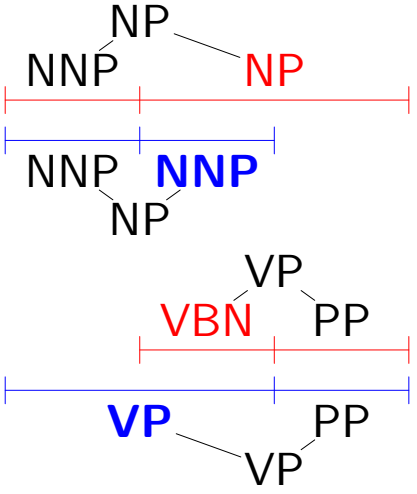


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# Meta-modeling summary

- Meta-model: a diagnostic tool to analyze errors systematically

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✓ Approximation error
Identifiability error
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$\mathbf{x}$: input sentence

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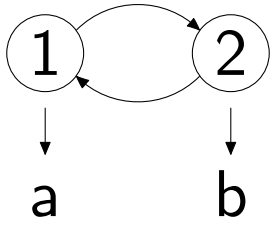
$\boxed{\theta_1} \;?\; \boxed{\theta_2}$

but matters to prediction (bad!) $p_{\theta_1}(\mathbf{y} \mid \mathbf{x}) \neq p_{\theta_2}(\mathbf{y} \mid \mathbf{x})$

# Examples of non-identifiability

- Label symmetries

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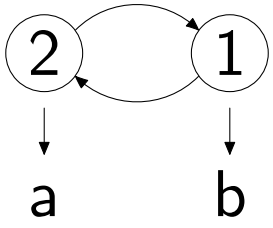


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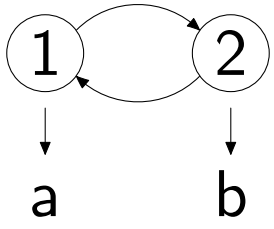


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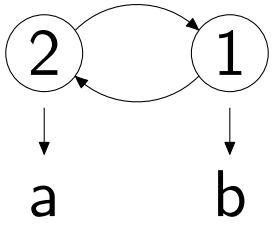


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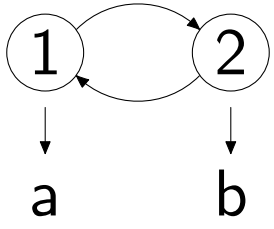


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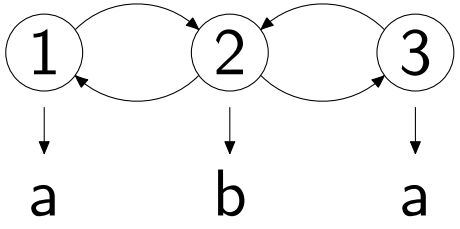


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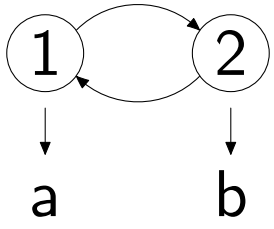


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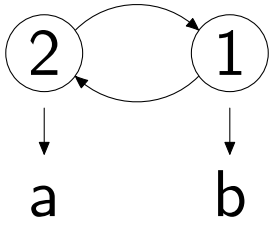


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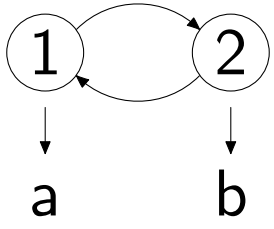


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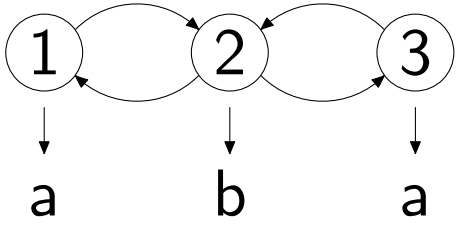


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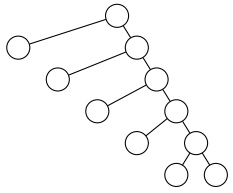

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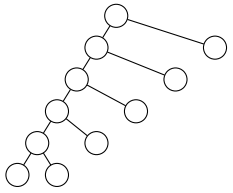

can both simulate the HMM

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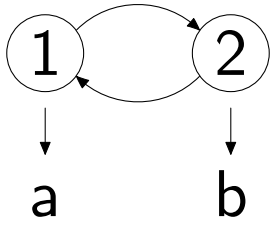

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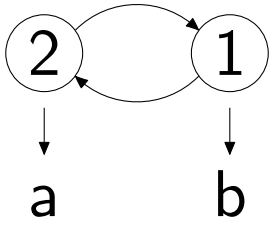

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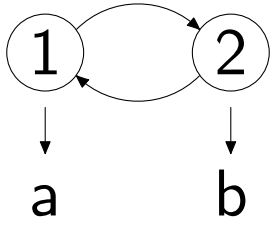

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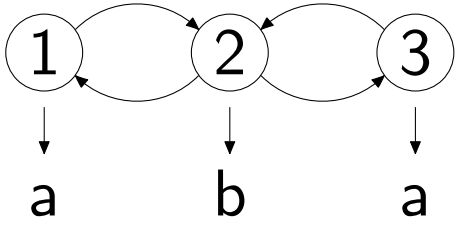

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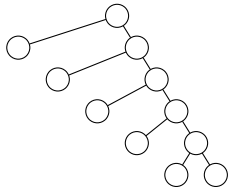
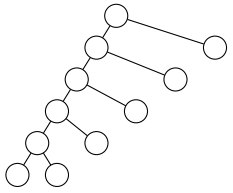
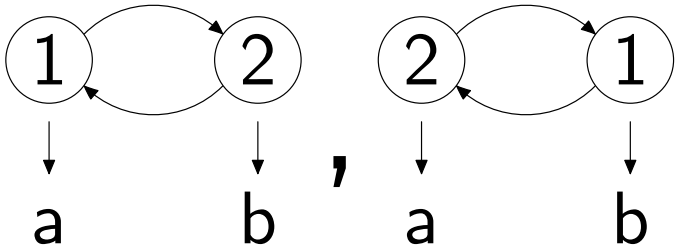
- PCFG (if true distribution is HMM)


and

can both simulate the HMM

Real data is complex, so last two are not an issue

# Identifiability and distance

Given $\theta_1$ and $\theta_2$, how to measure distance between them?

Want distance $\left( \right.$ 

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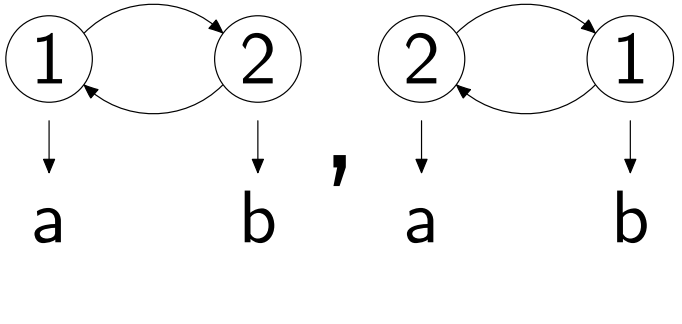
Want distance $\left( \right.$ 

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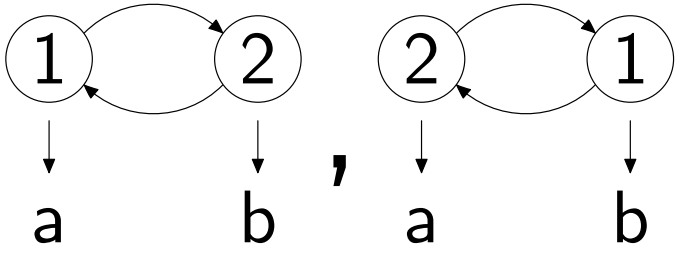
Want distance $\left( \right.$ 

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✓ Approximation error
✓ Identifiability error
Estimation error
Optimization error

# Estimation and optimization errors

Experiment setup:

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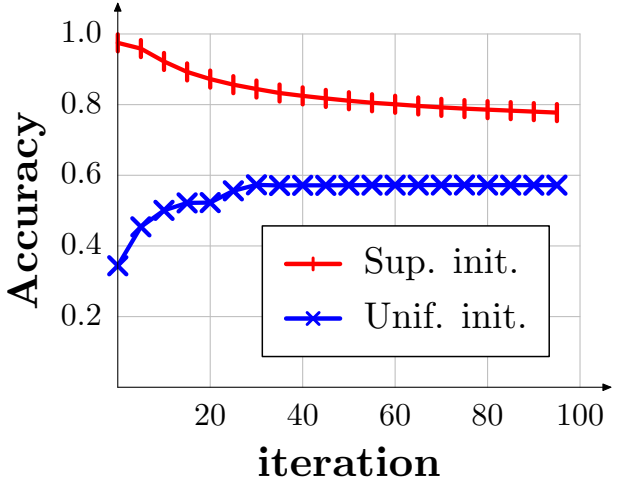
$\theta^*$ ← estimation error → global optimum ← optimization error → EM solution

HMM on 5K examples:



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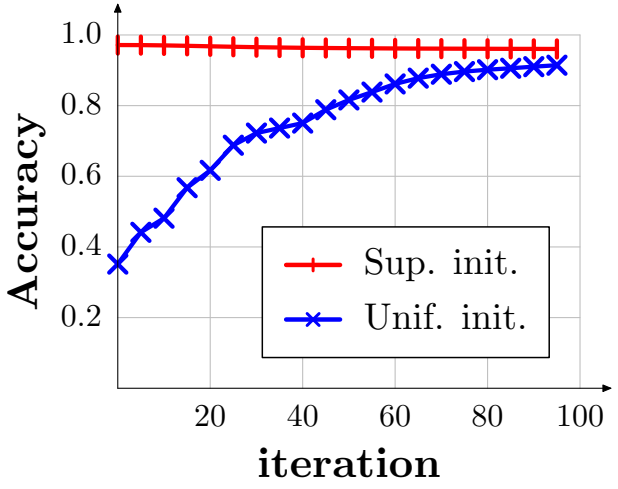
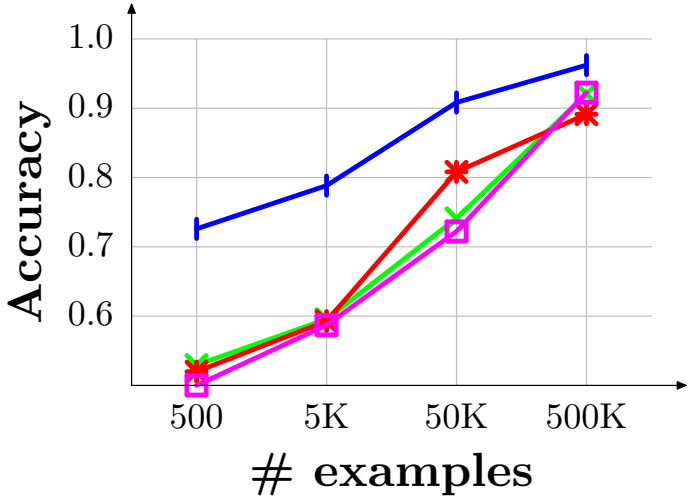


# Optimization error decreases with more data

On HMM model (similar for PCFG and a dependency model):




Synthetic data

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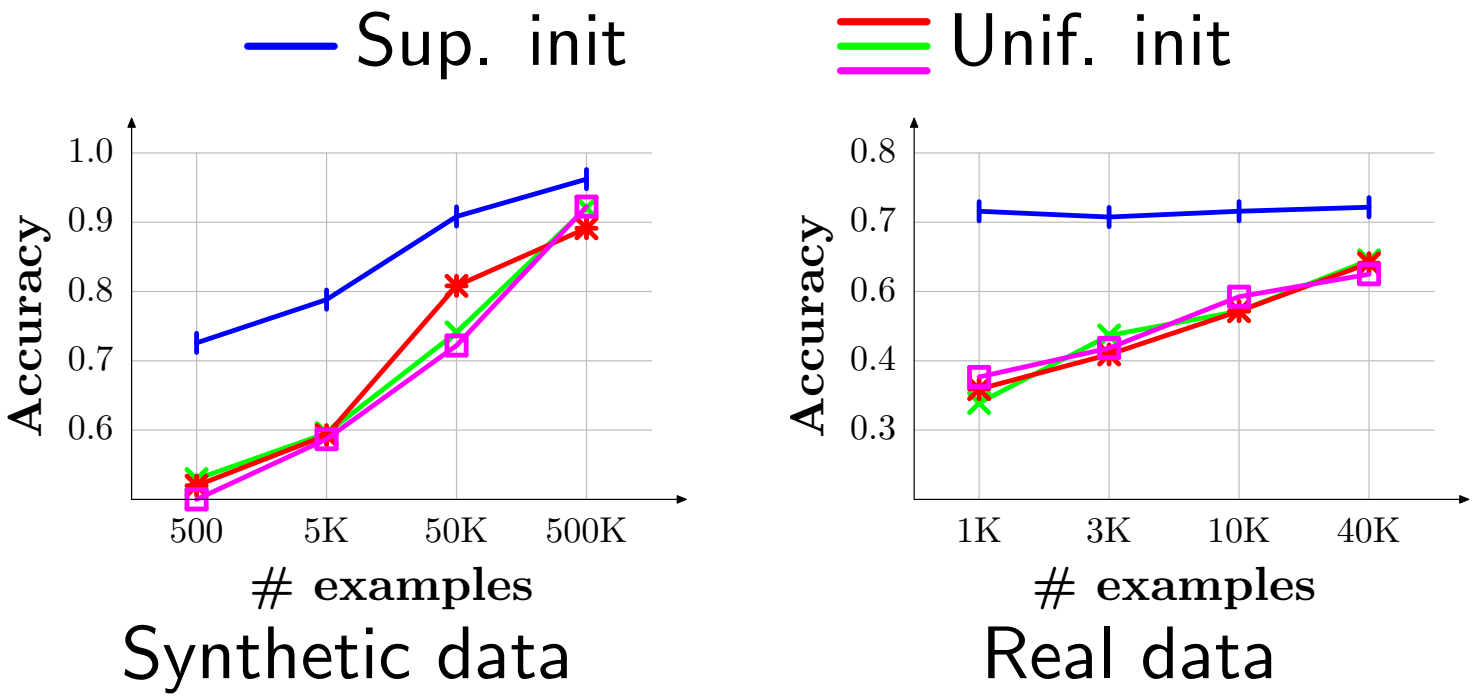

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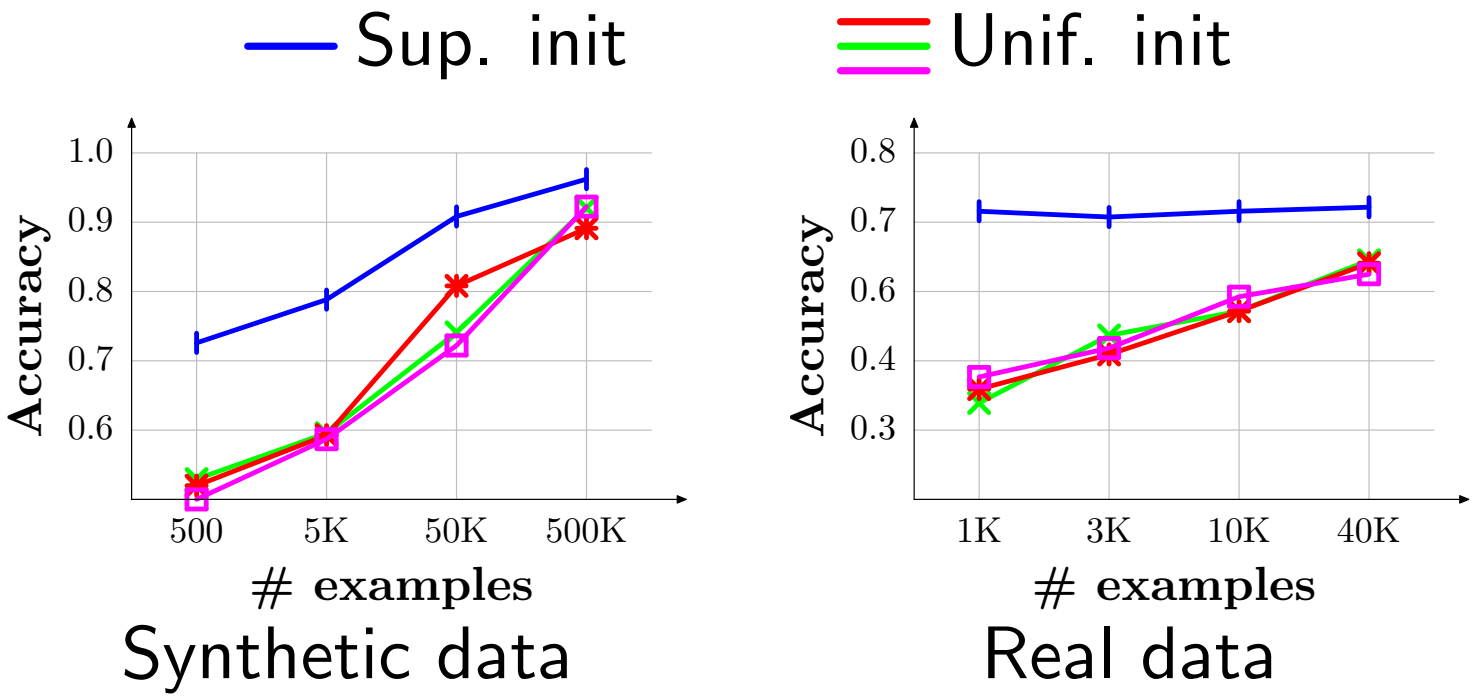


Why does this phenomenon happen?

- Intuition: with more data, EM can pick up the salient patterns more easily
- Was also shown for mixture of Gaussians [Srebro, 2006]

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