S → NP VP
NP → PRP
VP → VBD NP
NP → DT NN
PRP → she
VBD → heard
DT → the
NN → noise

The Infinite PCFG using Hierarchical Dirichlet Processes

EMNLP 2007 Prague, Czech Republic

June 29, 2007

Percy Liang Slav Petrov

Michael I. Jordan Dan Klein

How do we choose the grammar complexity?

Grammar induction:

How many grammar symbols (NP, VP, etc.)?

?

She heard the noise

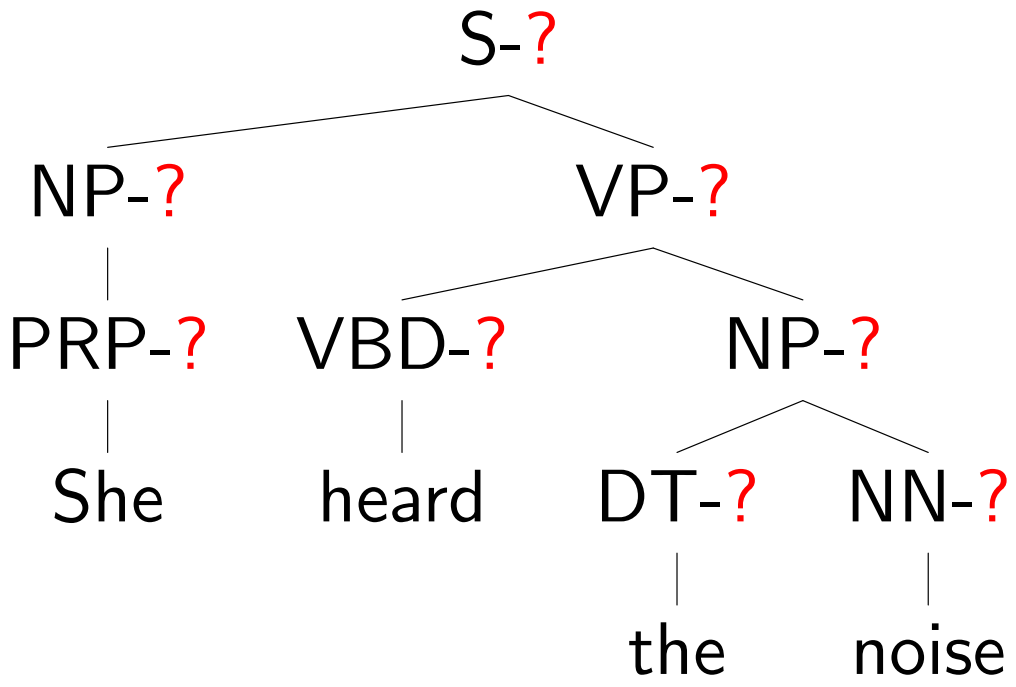
How do we choose the grammar complexity?

Grammar induction:

How many grammar symbols (NP, VP, etc.)?

Grammar refinement:

How many grammar subsymbols (NP-loc, NP-subj, etc.)?



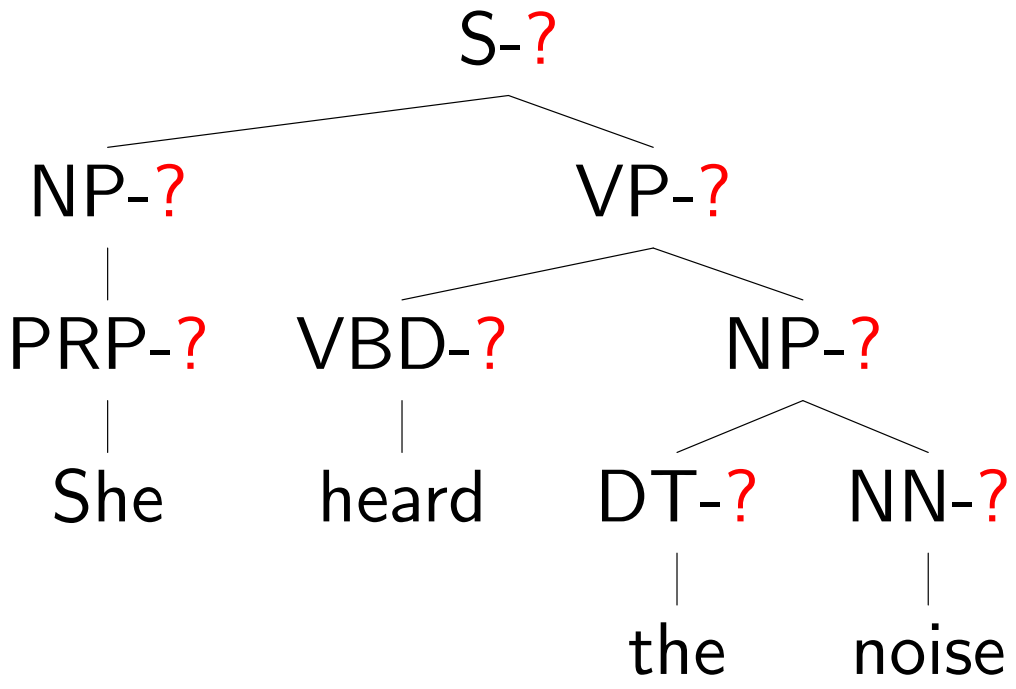
How do we choose the grammar complexity?

Grammar induction:

How many grammar symbols (NP, VP, etc.)?

Grammar refinement:

How many grammar subsymbols (NP-loc, NP-subj, etc.)?



Our solution: the HDP-PCFG allows number of (sub)symbols to adapt to data

A motivating example

True grammar:

$S \rightarrow A\,A \mid B\,B \mid C\,C \mid D\,D$

$A \rightarrow a_1 \mid a_2 \mid a_3$

$B \rightarrow b_1 \mid b_2 \mid b_3$

$C \rightarrow c_1 \mid c_2 \mid c_3$

$D \rightarrow d_1 \mid d_2 \mid d_3$

A motivating example

True grammar:

$S \rightarrow A\,A \mid B\,B \mid C\,C \mid D\,D$

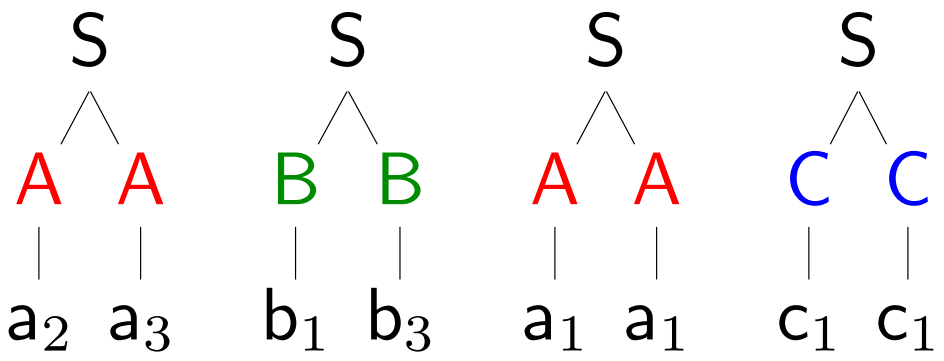
$A \rightarrow a_1 \mid a_2 \mid a_3$

$B \rightarrow b_1 \mid b_2 \mid b_3$

$C \rightarrow c_1 \mid c_2 \mid c_3$

$D \rightarrow d_1 \mid d_2 \mid d_3$

Generate examples:



A motivating example

True grammar:

$S \rightarrow A\,A \mid B\,B \mid C\,C \mid D\,D$

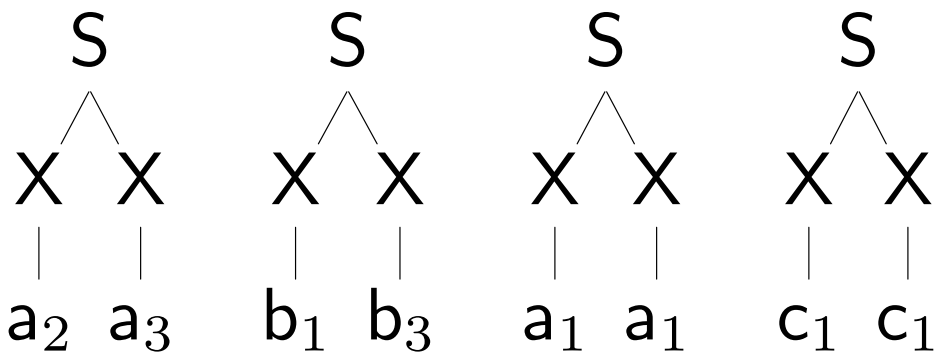
$A \rightarrow a_1 \mid a_2 \mid a_3$

$B \rightarrow b_1 \mid b_2 \mid b_3$

$C \rightarrow c_1 \mid c_2 \mid c_3$

$D \rightarrow d_1 \mid d_2 \mid d_3$

Collapse A,B,C,D $\Rightarrow$ X:



A motivating example

True grammar:

$S \rightarrow A\,A \mid B\,B \mid C\,C \mid D\,D$

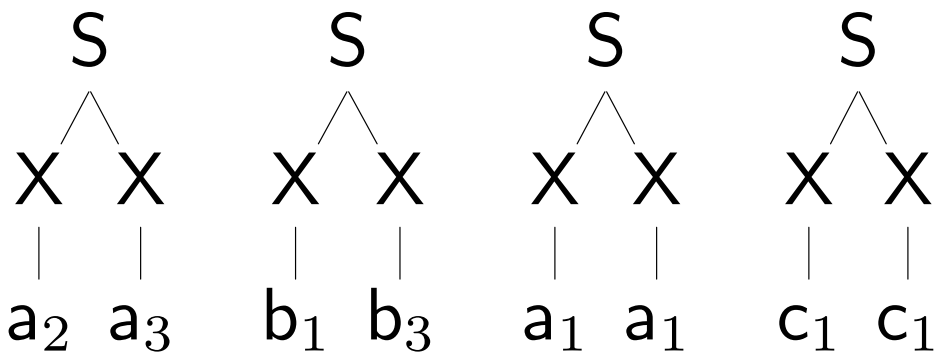
$A \rightarrow a_1 \mid a_2 \mid a_3$

$B \rightarrow b_1 \mid b_2 \mid b_3$

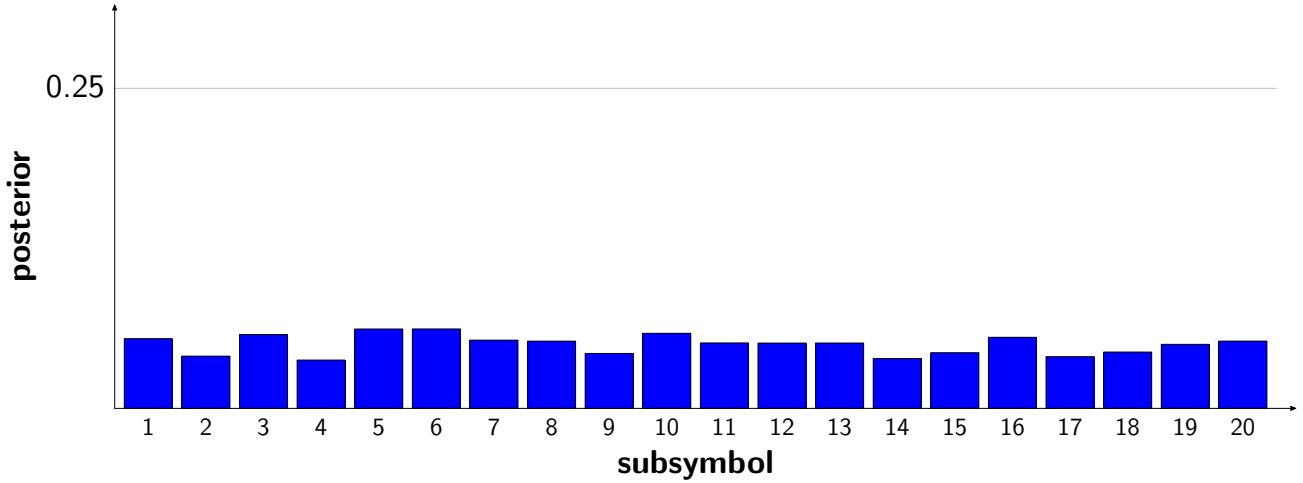
$C \rightarrow c_1 \mid c_2 \mid c_3$

$D \rightarrow d_1 \mid d_2 \mid d_3$

Collapse A,B,C,D $\Rightarrow$ X:



Results:



standard PCFG

A motivating example

True grammar:

$S \rightarrow A\,A \mid B\,B \mid C\,C \mid D\,D$

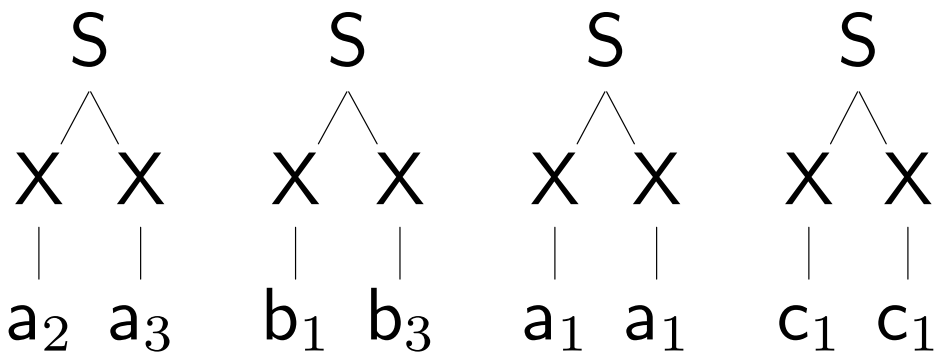
$A \rightarrow a_1 \mid a_2 \mid a_3$

$B \rightarrow b_1 \mid b_2 \mid b_3$

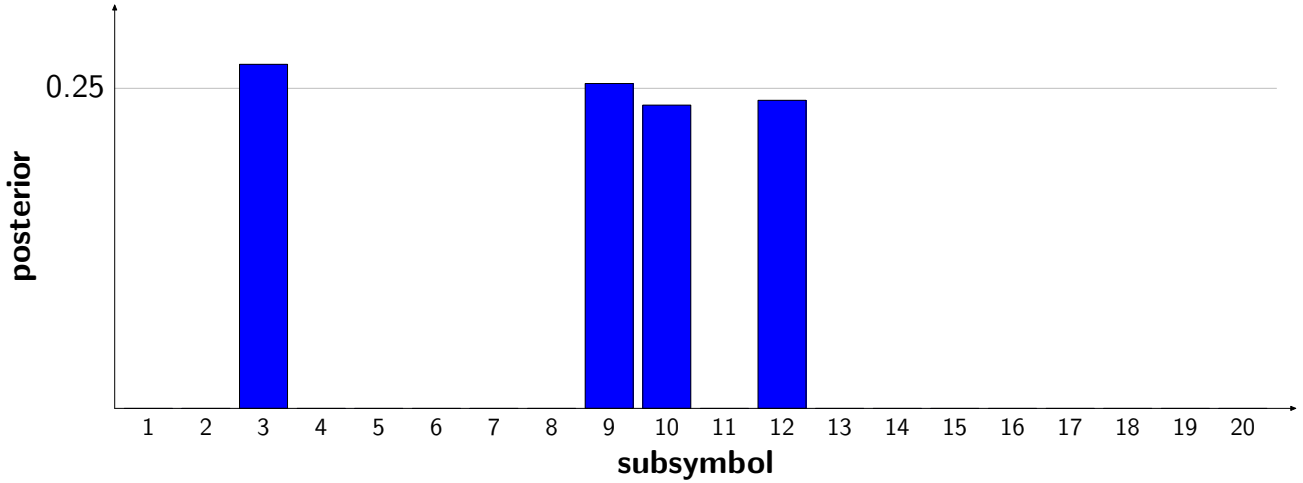
$C \rightarrow c_1 \mid c_2 \mid c_3$

$D \rightarrow d_1 \mid d_2 \mid d_3$

Collapse A,B,C,D $\Rightarrow$ X:



Results:



HDP-PCFG

The meeting of two fields

Grammar learning 

Lexicalized

[Charniak, 1996]

[Collins, 1999]

Manual refinement

[Johnson, 1998]

[Klein, Manning, 2003]

Automatic refinement

[Matsuzaki, et al., 2005]

[Petrov, et al., 2006]

The meeting of two fields

Grammar learning 

Lexicalized

[Charniak, 1996]

[Collins, 1999]

Manual refinement

[Johnson, 1998]

[Klein, Manning, 2003]

Automatic refinement

[Matsuzaki, et al., 2005]

[Petrov, et al., 2006]

Bayesian nonparametrics ○○○○⋯

Basic theory

[Ferguson, 1973]

[Antoniak, 1974]

[Sethuraman, 1994]

[Escobar, West, 1995]

[Neal, 2000]

More complex models

[Teh, et al., 2006]

[Beal, et al., 2002]

[Goldwater, et al., 2006]

[Sohn, Xing, 2007]

The meeting of two fields

Grammar learning 

Lexicalized

[Charniak, 1996]

[Collins, 1999]

Manual refinement

[Johnson, 1998]

[Klein, Manning, 2003]

Automatic refinement

[Matsuzaki, et al., 2005]

[Petrov, et al., 2006]

Bayesian nonparametrics 

Basic theory

[Ferguson, 1973]

[Antoniak, 1974]

[Sethuraman, 1994]

[Escobar, West, 1995]

[Neal, 2000]

More complex models

[Teh, et al., 2006]

[Beal, et al., 2002]

[Goldwater, et al., 2006]

[Sohn, Xing, 2007]

Nonparametric grammars

[Johnson, et al., 2006]

[Finkel, et al., 2007]

[Liang, et al., 2007]

The meeting of two fields

Grammar learning 

Lexicalized

[Charniak, 1996]

[Collins, 1999]

Bayesian nonparametrics 

Basic theory

[Ferguson, 1973]

[Antoniak, 1974]

Ma

Auto

[

[N

Our contribution

- Definition of the HDP-PCFG
- Simple and efficient variational inference algorithm
- Empirical comparison with finite models on a full-scale parsing task

Nonparametric grammars

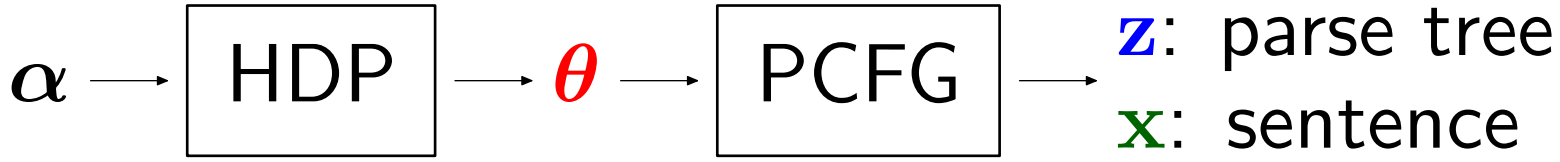
[Johnson, et al., 2006]

[Finkel, et al., 2007]

[Liang, et al., 2007]

Bayesian paradigm

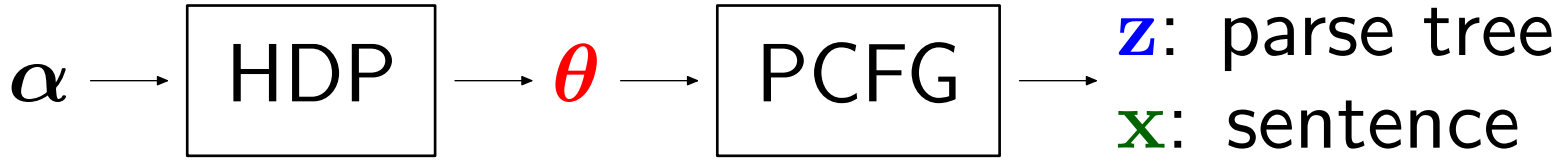
Generative model:



hyperparameters grammar

Bayesian paradigm

Generative model:

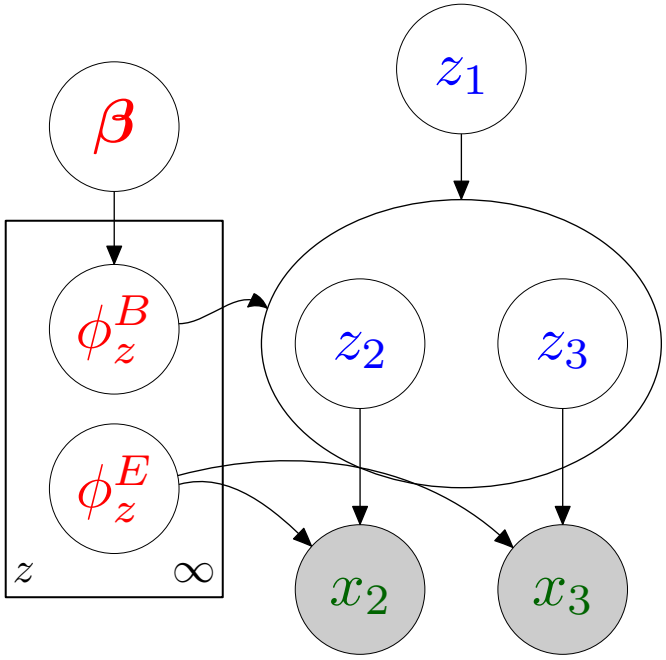


Bayesian posterior inference:

Observe $\mathbf{x}$.

What's $\boldsymbol{\theta}$ and $\mathbf{z}$?

HDP probabilistic context-free grammars



HDP-PCFG

$\boldsymbol{\beta} \sim \text{GEM}(\alpha)$ [generate distribution over symbols]

For each symbol $z \in \{1, 2, \ldots\}$:

$\phi_z^E \sim \text{Dirichlet}(\alpha^E)$ [generate emission probs]

$\phi_z^B \sim \text{DP}(\alpha^B, \boldsymbol{\beta}\boldsymbol{\beta}^T)$ [binary production probs]

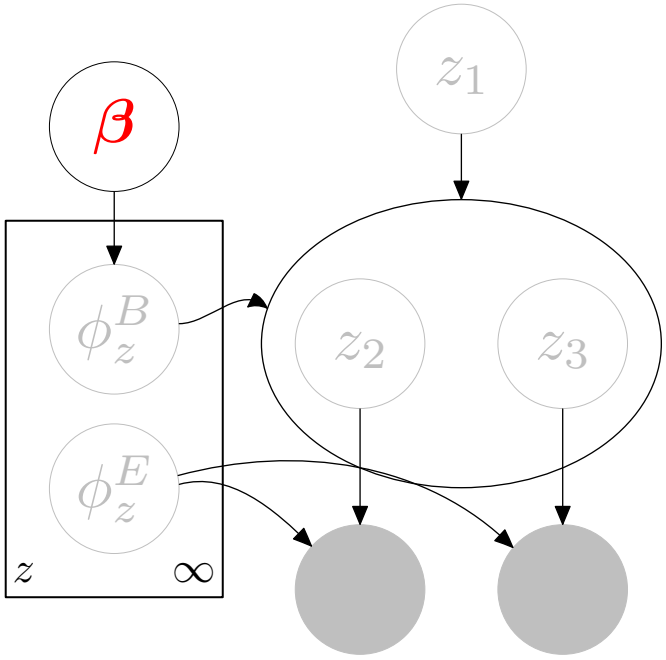
For each nonterminal node i:

$(z_{L(i)}, z_{R(i)}) \sim \text{Multinomial}(\phi_{z_i}^B)$ [child symbols]

For each preterminal node i:

$x_i \sim \text{Multinomial}(\phi_{z_i}^E)$ [terminal symbol]

HDP probabilistic context-free grammars



HDP-PCFG

$\boldsymbol{\beta} \sim \text{GEM}(\alpha)$ [generate distribution over symbols]

For each symbol $z \in \{1, 2, \dots\}$:

$\phi_z^E \sim \text{Dirichlet}(\alpha^E)$ [generate emission probs]

$\phi_z^B \sim \text{DP}(\alpha^B, \boldsymbol{\beta}\boldsymbol{\beta}^T)$ [binary production probs]

For each nonterminal node i:

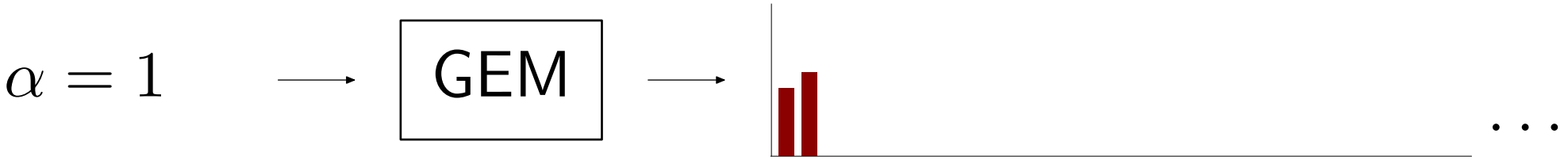
$(z_{L(i)}, z_{R(i)}) \sim \text{Multinomial}(\phi_{z_i}^B)$ [child symbols]

For each preterminal node i:

$x_i \sim \text{Multinomial}(\phi_{z_i}^E)$ [terminal symbol]

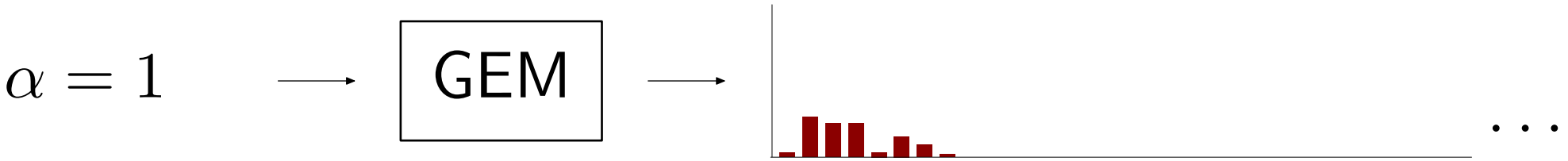
HDP-PCFG: prior over symbols

$$\boldsymbol{\beta} \sim \text{GEM}(\alpha)$$



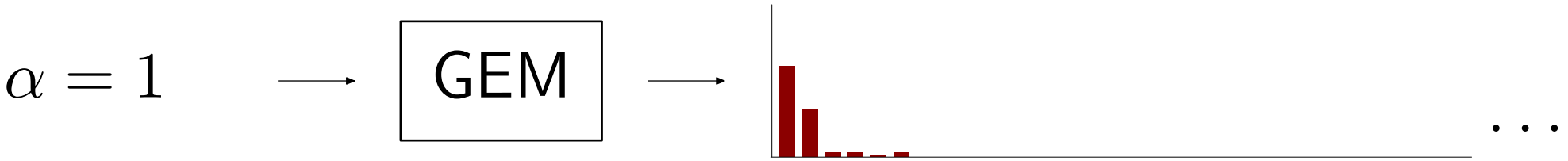
HDP-PCFG: prior over symbols

$$\boldsymbol{\beta} \sim \text{GEM}(\alpha)$$



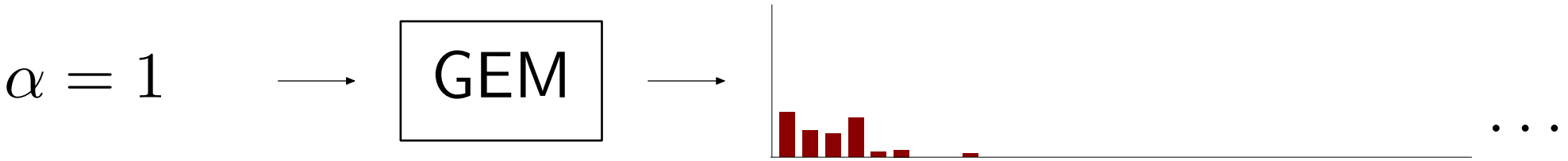
HDP-PCFG: prior over symbols

$$\boldsymbol{\beta} \sim \text{GEM}(\alpha)$$



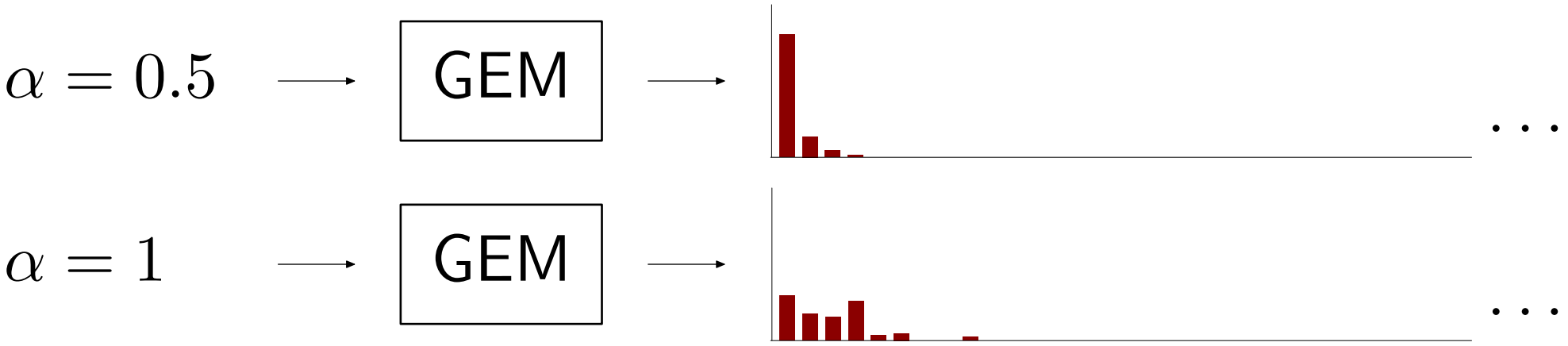
HDP-PCFG: prior over symbols

$$\boldsymbol{\beta} \sim \text{GEM}(\alpha)$$



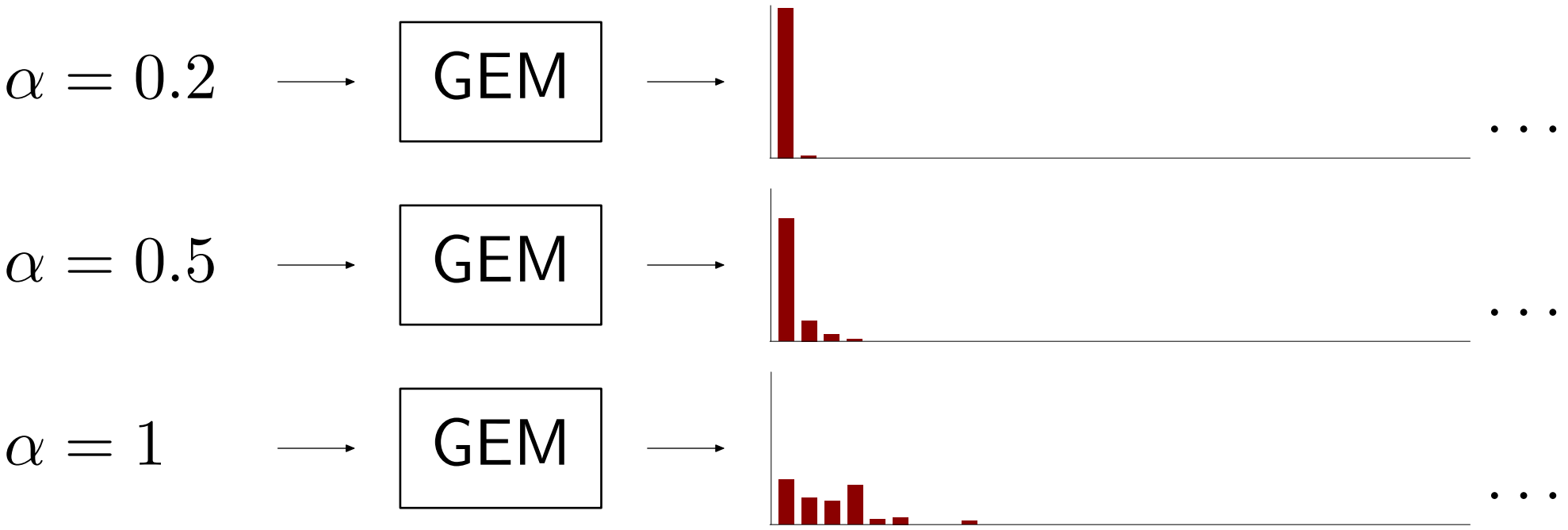
HDP-PCFG: prior over symbols

$$\boldsymbol{\beta} \sim \text{GEM}(\alpha)$$



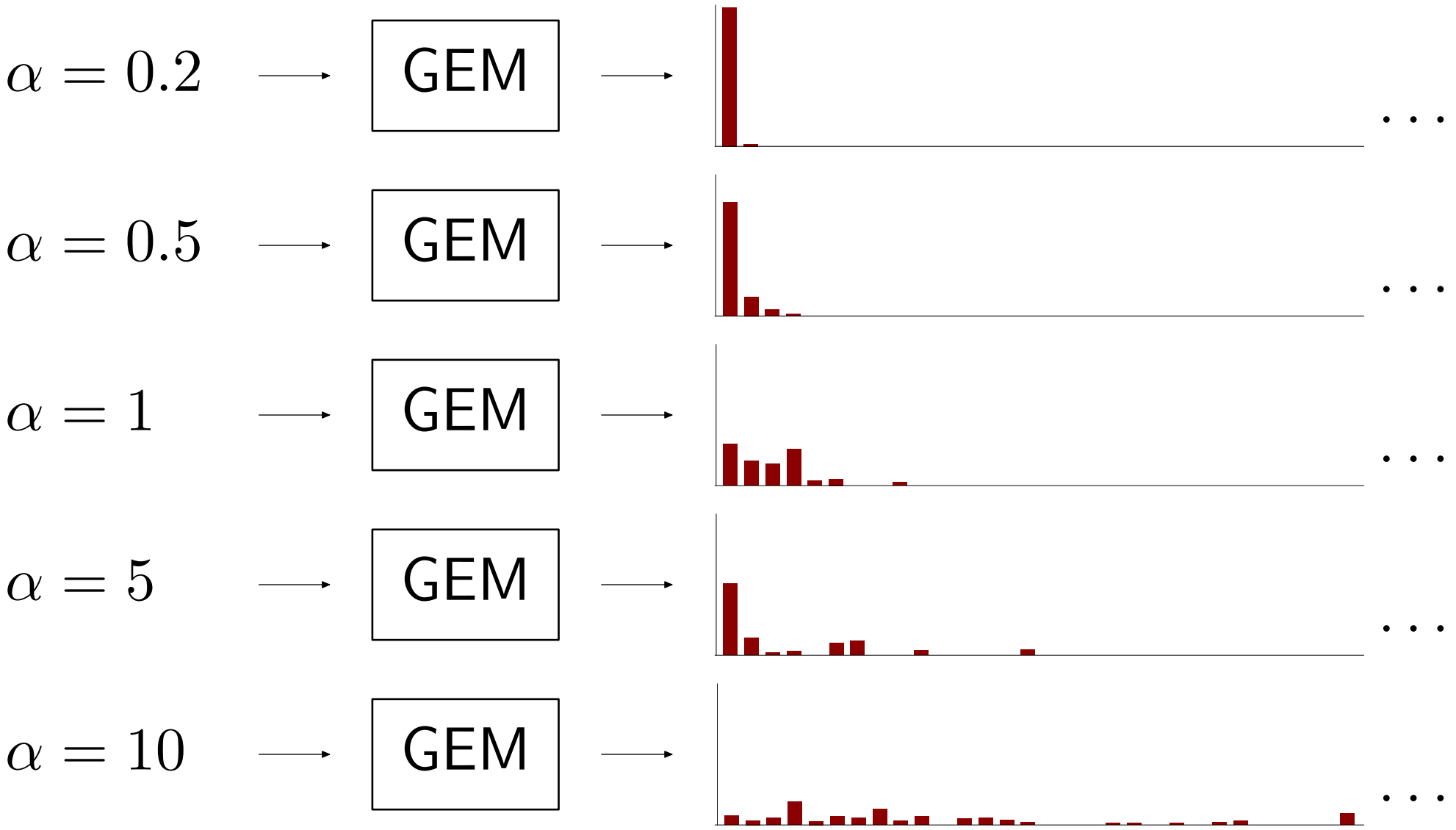
HDP-PCFG: prior over symbols

$$\boldsymbol{\beta} \sim \text{GEM}(\alpha)$$

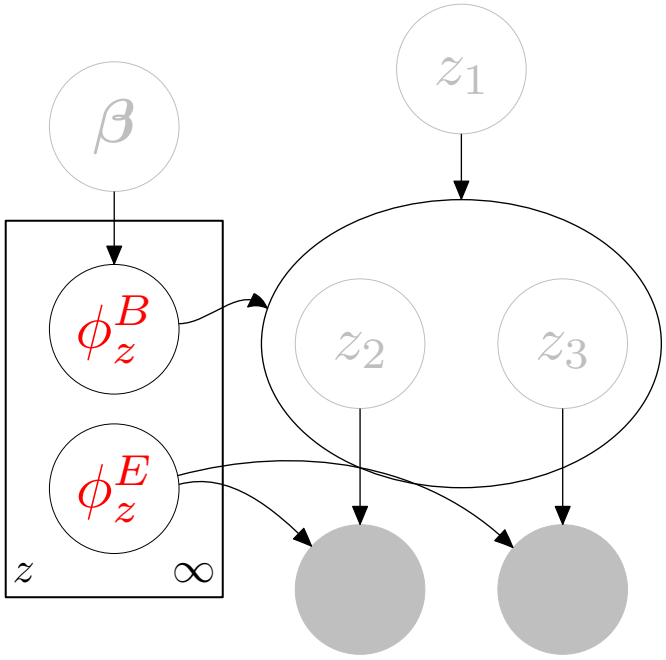


HDP-PCFG: prior over symbols

$$\boldsymbol{\beta} \sim \text{GEM}(\alpha)$$



HDP probabilistic context-free grammars



HDP-PCFG

$\beta \sim \text{GEM}(\alpha)$ [generate distribution over symbols]

For each symbol $z \in \{1, 2, \dots\}$:

$\phi_z^E \sim \text{Dirichlet}(\alpha^E)$ [generate emission probs]

$\phi_z^B \sim \text{DP}(\alpha^B, \beta\beta^T)$ [binary production probs]

For each nonterminal node i:

$(z_{L(i)}, z_{R(i)}) \sim \text{Multinomial}(\phi_{z_i}^B)$ [child symbols]

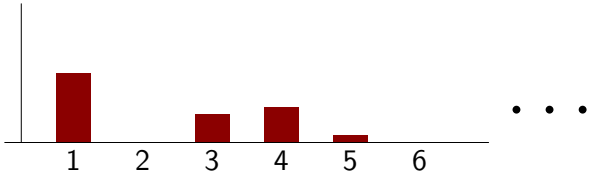
For each preterminal node i:

$x_i \sim \text{Multinomial}(\phi_{z_i}^E)$ [terminal symbol]

HDP-PCFG: binary productions

Distribution over symbols (top-level):

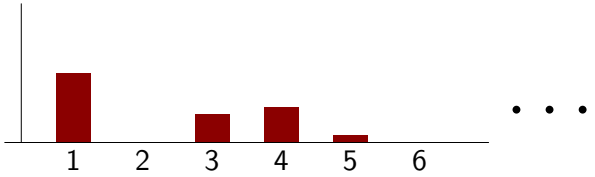
$$\boldsymbol{\beta} \sim \text{GEM}(\alpha)$$



HDP-PCFG: binary productions

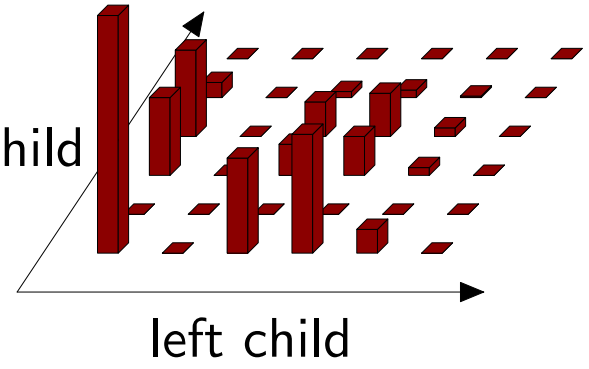
Distribution over symbols (top-level):

$$\boldsymbol{\beta} \sim \text{GEM}(\alpha)$$



Mean distribution over child symbols:

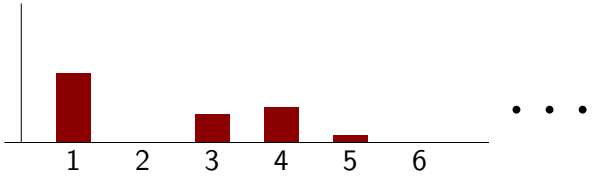
$$\boldsymbol{\beta}\boldsymbol{\beta}^T$$



HDP-PCFG: binary productions

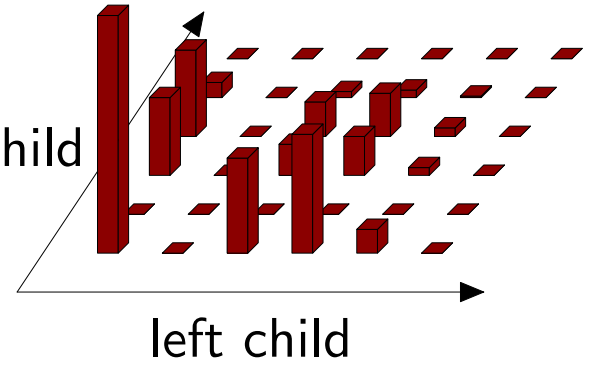
Distribution over symbols (top-level):

$$\boldsymbol{\beta} \sim \text{GEM}(\alpha)$$



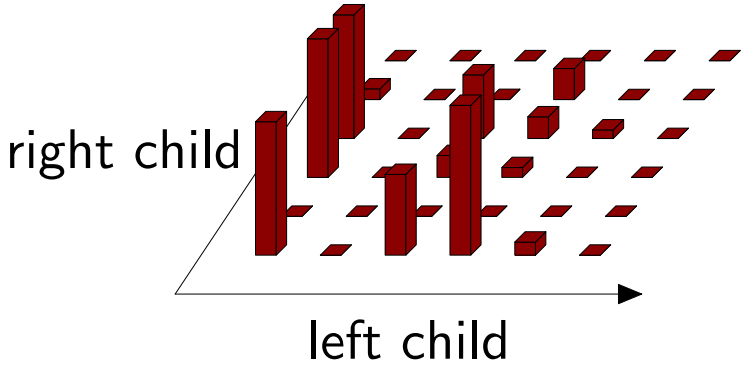
Mean distribution over child symbols:

$$\boldsymbol{\beta}\boldsymbol{\beta}^T$$



Distribution over child symbols (per-state):

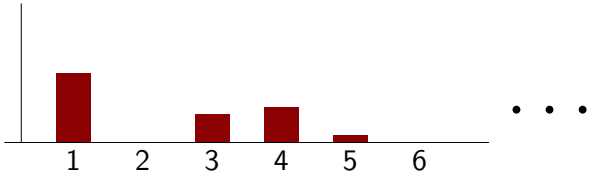
$$\phi_z^B \sim \text{DP}(\alpha^B, \boldsymbol{\beta}\boldsymbol{\beta}^T)$$



HDP-PCFG: binary productions

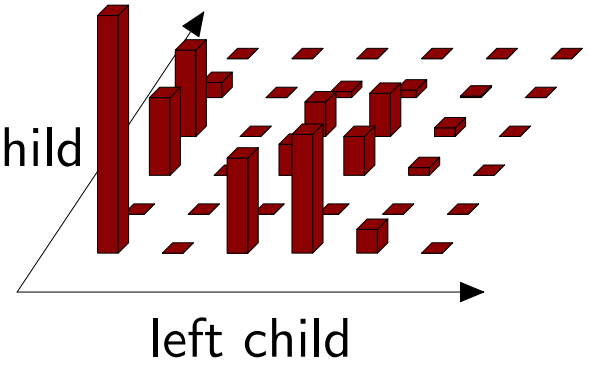
Distribution over symbols (top-level):

$$\boldsymbol{\beta} \sim \text{GEM}(\alpha)$$



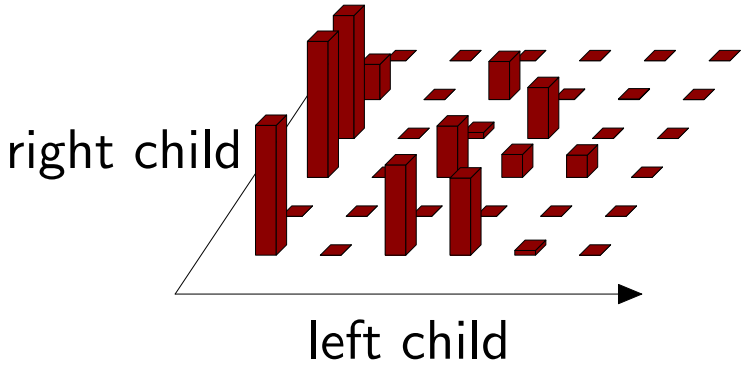
Mean distribution over child symbols:

$$\boldsymbol{\beta}\boldsymbol{\beta}^T$$



Distribution over child symbols (per-state):

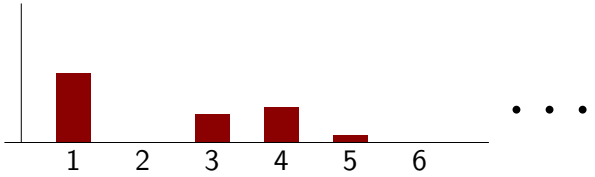
$$\phi_z^B \sim \text{DP}(\alpha^B, \boldsymbol{\beta}\boldsymbol{\beta}^T)$$



HDP-PCFG: binary productions

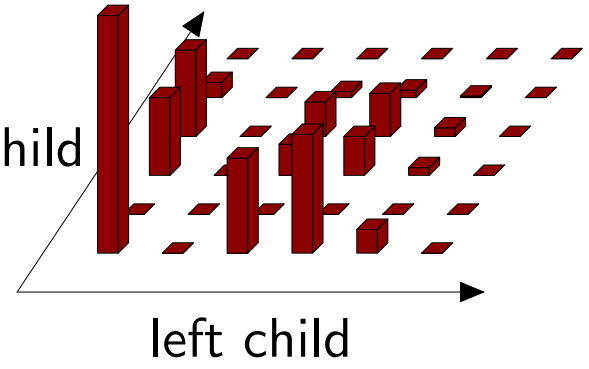
Distribution over symbols (top-level):

$$\boldsymbol{\beta} \sim \text{GEM}(\alpha)$$



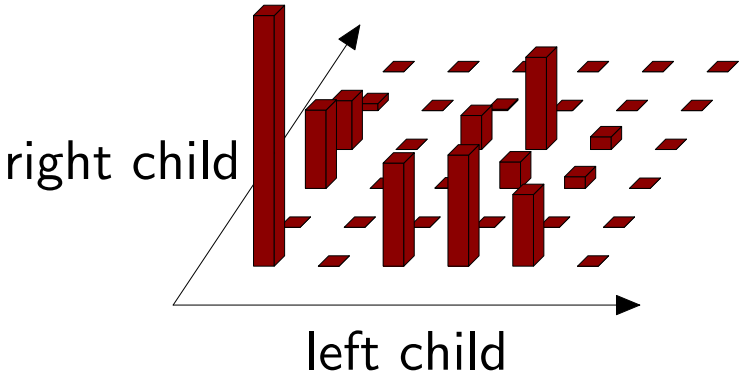
Mean distribution over child symbols:

$$\boldsymbol{\beta}\boldsymbol{\beta}^T$$



Distribution over child symbols (per-state):

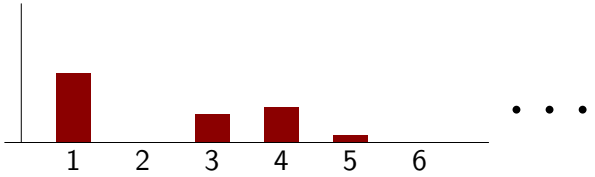
$$\phi_z^B \sim \text{DP}(\alpha^B, \boldsymbol{\beta}\boldsymbol{\beta}^T)$$



HDP-PCFG: binary productions

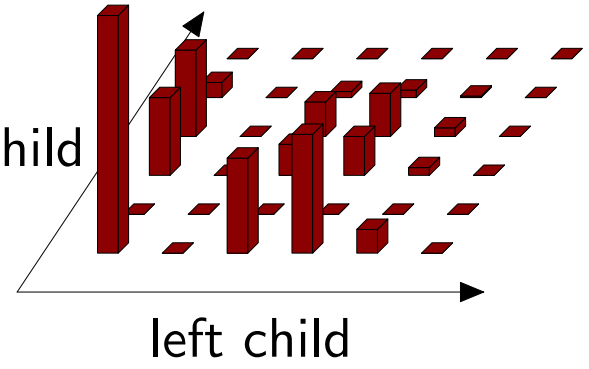
Distribution over symbols (top-level):

$$\boldsymbol{\beta} \sim \text{GEM}(\alpha)$$



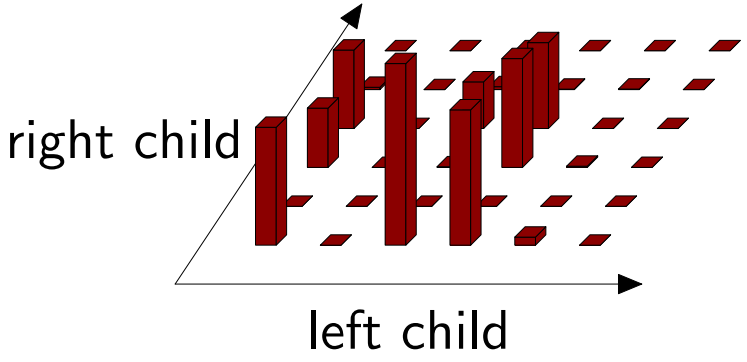
Mean distribution over child symbols:

$$\boldsymbol{\beta}\boldsymbol{\beta}^T$$

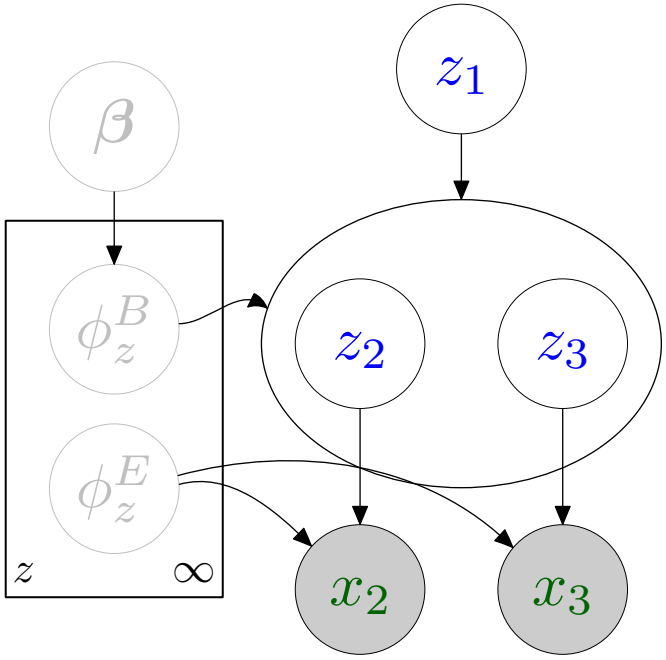


Distribution over child symbols (per-state):

$$\phi_z^B \sim \text{DP}(\alpha^B, \boldsymbol{\beta}\boldsymbol{\beta}^T)$$



HDP probabilistic context-free grammars



HDP-PCFG

$\beta \sim \text{GEM}(\alpha)$ [generate distribution over symbols]

For each symbol $z \in \{1, 2, \ldots\}$:

$\phi_z^E \sim \text{Dirichlet}(\alpha^E)$ [generate emission probs]

$\phi_z^B \sim \text{DP}(\alpha^B, \beta\beta^T)$ [binary production probs]

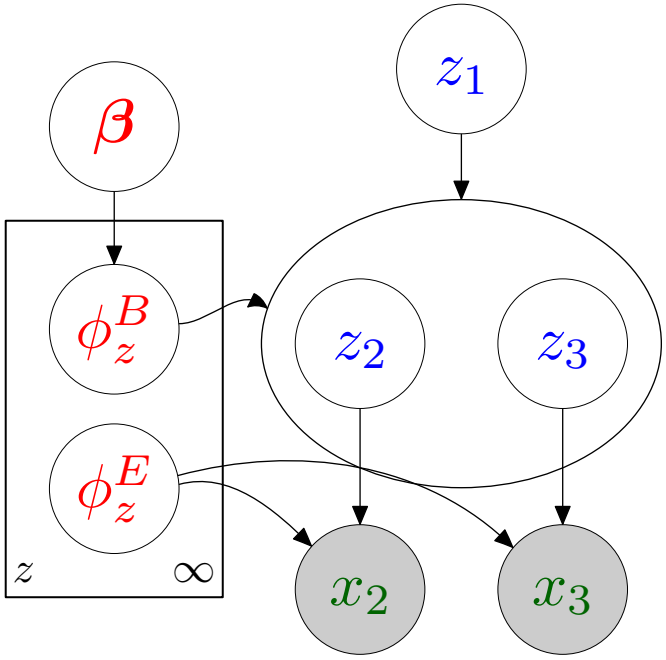
For each nonterminal node i:

$(z_{L(i)}, z_{R(i)}) \sim \text{Multinomial}(\phi_{z_i}^B)$ [child symbols]

For each preterminal node i:

$x_i \sim \text{Multinomial}(\phi_{z_i}^E)$ [terminal symbol]

HDP probabilistic context-free grammars



HDP-PCFG

$\boldsymbol{\beta} \sim \text{GEM}(\alpha)$ [generate distribution over symbols]

For each symbol $z \in \{1, 2, \ldots\}$:

$\phi_z^E \sim \text{Dirichlet}(\alpha^E)$ [generate emission probs]

$\phi_z^B \sim \text{DP}(\alpha^B, \boldsymbol{\beta}\boldsymbol{\beta}^T)$ [binary production probs]

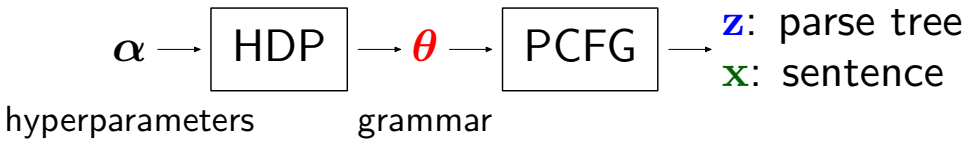
For each nonterminal node i:

$(z_{L(i)}, z_{R(i)}) \sim \text{Multinomial}(\phi_{z_i}^B)$ [child symbols]

For each preterminal node i:

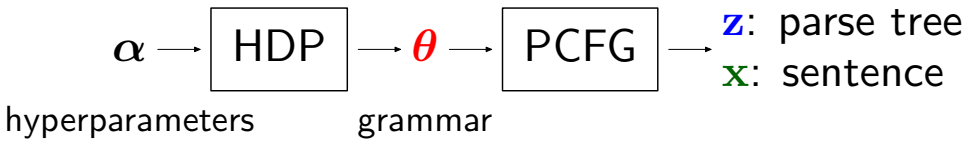
$x_i \sim \text{Multinomial}(\phi_{z_i}^E)$ [terminal symbol]

Variational Bayesian inference



Goal: compute posterior $p(\boldsymbol{\theta}, \mathbf{z} \mid \mathbf{x})$

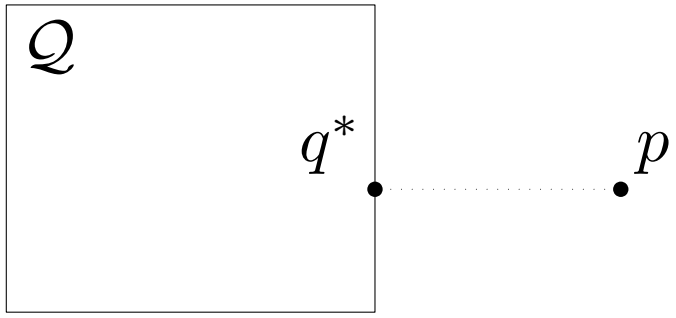
Variational Bayesian inference



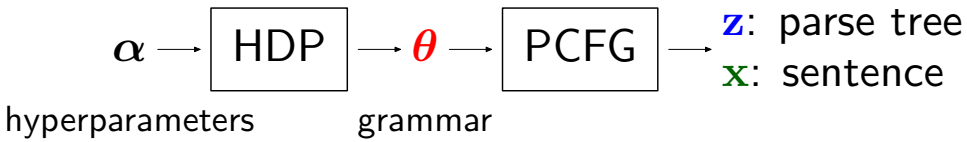
Goal: compute posterior $p(\boldsymbol{\theta}, \mathbf{z} \mid \mathbf{x})$

Variational inference:
approximate posterior with best from a set of tractable distributions $\mathcal{Q}$:

$$q^* = \operatorname*{argmin}_{q \in \mathcal{Q}} \mathrm{KL}(q \,||\, p)$$



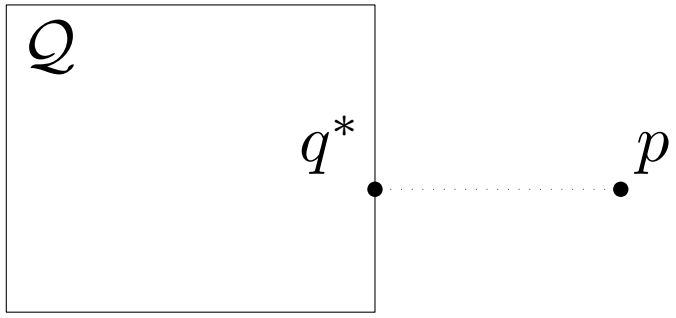
Variational Bayesian inference



Goal: compute posterior $p(\boldsymbol{\theta}, \mathbf{z} \mid \mathbf{x})$

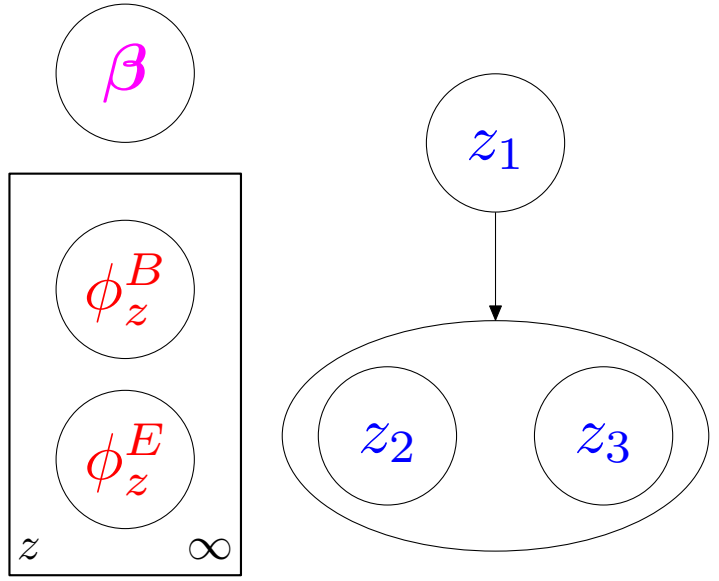
Variational inference:
approximate posterior with best from a set of tractable distributions $\mathcal{Q}$:

$$q^* = \operatorname*{argmin}_{q \in \mathcal{Q}} \mathrm{KL}(q \,||\, p)$$



Mean-field approximation:

$$\mathcal{Q} = \left\{ q : q = q(\mathbf{z}) q(\boldsymbol{\beta}) q(\boldsymbol{\phi}) \right\}$$



Coordinate-wise descent algorithm

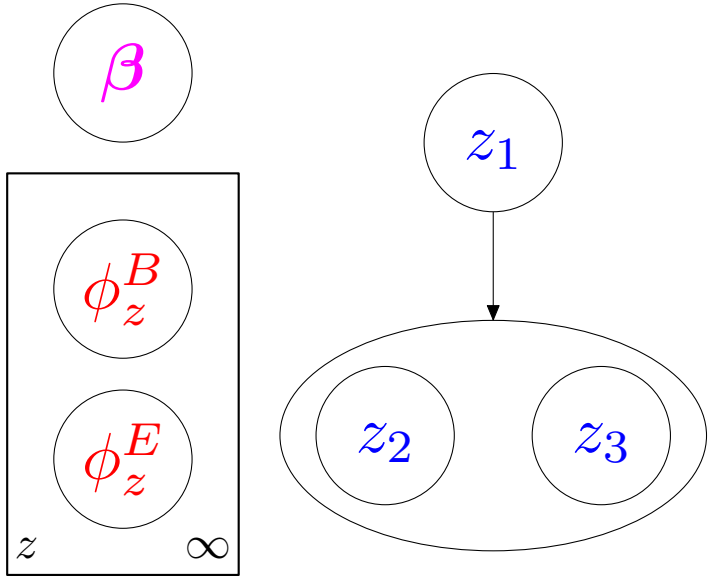
Goal: $\operatorname{argmin}_{q \in \mathcal{Q}} \mathrm{KL}(q \,||\, p)$

$$q = q(\mathbf{z})q(\boldsymbol{\phi})q(\boldsymbol{\beta})$$

$\mathbf{z}$ = parse tree

$\boldsymbol{\phi}$ = rule probabilities

$\boldsymbol{\beta}$ = inventory of symbols



Coordinate-wise descent algorithm

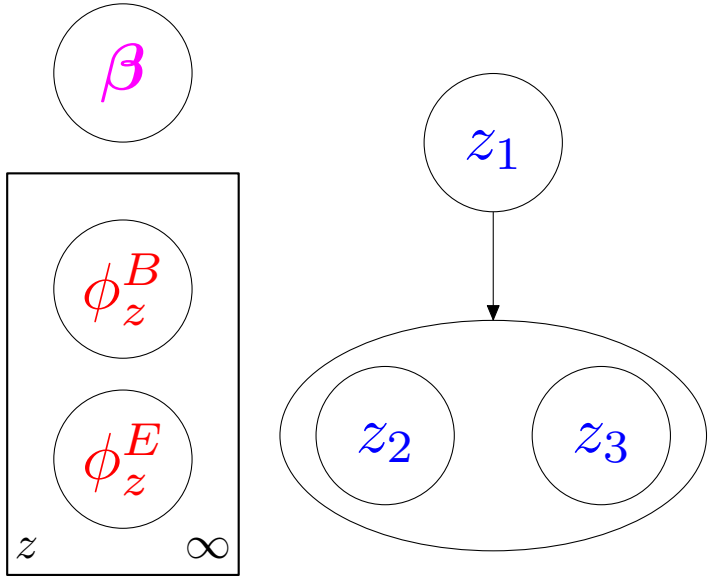
Goal: $\operatorname{argmin}_{q \in \mathcal{Q}} \mathrm{KL}(q \,||\, p)$

$q = q(\mathbf{z})q(\boldsymbol{\phi})q(\boldsymbol{\beta})$

$\mathbf{z}$ = parse tree

$\boldsymbol{\phi}$ = rule probabilities

$\boldsymbol{\beta}$ = inventory of symbols



Iterate:

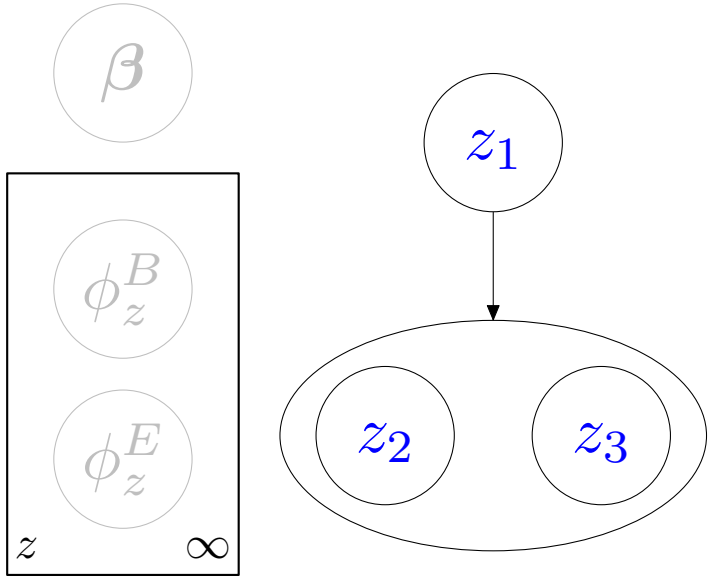
- Optimize $q(\mathbf{z})$ (E-step):
- Optimize $q(\boldsymbol{\phi})$ (M-step):
- Optimize $q(\boldsymbol{\beta})$ (no equivalent in EM):

Coordinate-wise descent algorithm

Goal: $\operatorname{argmin}_{q \in \mathcal{Q}} \mathrm{KL}(q \,||\, p)$

$$q = q(\mathbf{z})q(\boldsymbol{\phi})q(\boldsymbol{\beta})$$

$\mathbf{z}$ = parse tree
$\boldsymbol{\phi}$ = rule probabilities
$\boldsymbol{\beta}$ = inventory of symbols



Iterate:

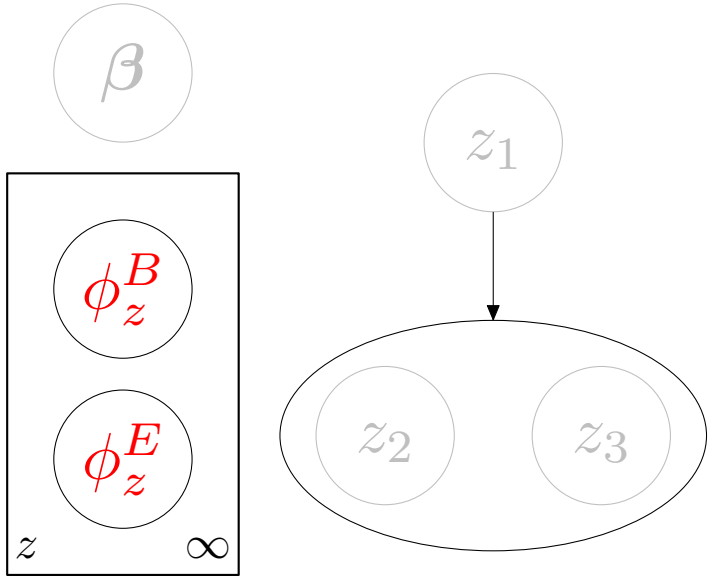
- Optimize $q(\mathbf{z})$ (E-step):
  - Inside-outside with rule weights $W(r)$
  - Gather expected rule counts $C(r)$
- Optimize $q(\boldsymbol{\phi})$ (M-step):
- Optimize $q(\boldsymbol{\beta})$ (no equivalent in EM):

Coordinate-wise descent algorithm

Goal: $\operatorname{argmin}_{q \in \mathcal{Q}} \mathrm{KL}(q \,||\, p)$

$$q = q(\mathbf{z})q(\boldsymbol{\phi})q(\boldsymbol{\beta})$$

$\mathbf{z}$ = parse tree
$\boldsymbol{\phi}$ = rule probabilities
$\boldsymbol{\beta}$ = inventory of symbols



Iterate:

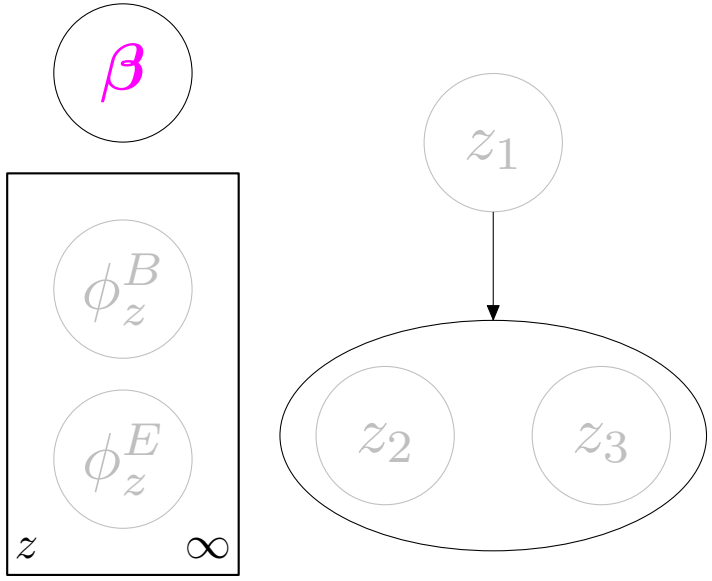
- Optimize $q(\mathbf{z})$ (E-step):
  - Inside-outside with rule weights $W(r)$
  - Gather expected rule counts $C(r)$
- Optimize $q(\boldsymbol{\phi})$ (M-step):
  - Update Dirichlet posteriors (expected rule counts + pseudocounts)
  - Compute rule weights $W(r)$
- Optimize $q(\boldsymbol{\beta})$ (no equivalent in EM):

Coordinate-wise descent algorithm

Goal: $\operatorname{argmin}_{q \in \mathcal{Q}} \mathrm{KL}(q \,||\, p)$

$$q = q(\mathbf{z})q(\boldsymbol{\phi})q(\boldsymbol{\beta})$$

$\mathbf{z}$ = parse tree
$\boldsymbol{\phi}$ = rule probabilities
$\boldsymbol{\beta}$ = inventory of symbols



Iterate:

- Optimize $q(\mathbf{z})$ (E-step):
  - Inside-outside with rule weights $W(r)$
  - Gather expected rule counts $C(r)$
- Optimize $q(\boldsymbol{\phi})$ (M-step):
  - Update Dirichlet posteriors (expected rule counts + pseudocounts)
  - Compute rule weights $W(r)$
- Optimize $q(\boldsymbol{\beta})$ (no equivalent in EM):
  - Truncate at level K (set the maximum number of symbols)
  - Use projected gradient to adapt number of symbols

Rule weights

- Weight $W(r)$ of rule r similar to probability $p(r)$
- $W(r)$ unnormalized $\Rightarrow$ extra degree of freedom

Rule weights

- Weight $W(r)$ of rule r similar to probability $p(r)$
- $W(r)$ unnormalized $\Rightarrow$ extra degree of freedom

EM (maximum likelihood):

$$W(r) = \frac{C(r)}{\sum_{r'} C(r')}$$

Rule weights

- Weight $W(r)$ of rule r similar to probability $p(r)$
- $W(r)$ unnormalized $\Rightarrow$ extra degree of freedom

EM (maximum likelihood):

$$W(r) = \frac{C(r)}{\sum_{r'} C(r')}$$

EM (maximum a posteriori):

$$W(r) = \frac{\text{prior}(r) - 1 + C(r)}{\sum_{r'} \text{prior}(r') - 1 + C(r')}$$

Rule weights

- Weight $W(r)$ of rule r similar to probability $p(r)$
- $W(r)$ unnormalized $\Rightarrow$ extra degree of freedom

EM (maximum likelihood):

$$W(r) = \frac{C(r)}{\sum_{r'} C(r')}$$

EM (maximum a posteriori):

$$W(r) = \frac{\text{prior}(r) - 1 + C(r)}{\sum_{r'} \text{prior}(r') - 1 + C(r')}$$

Mean-field (with DP prior):

$$W(r) = \frac{\exp \Psi(\text{prior}(r) + C(r))}{\exp \Psi(\sum_{r'} \text{prior}(r') + C(r'))}$$

Rule weights

- Weight $W(r)$ of rule r similar to probability $p(r)$
- $W(r)$ unnormalized $\Rightarrow$ extra degree of freedom

EM (maximum likelihood):

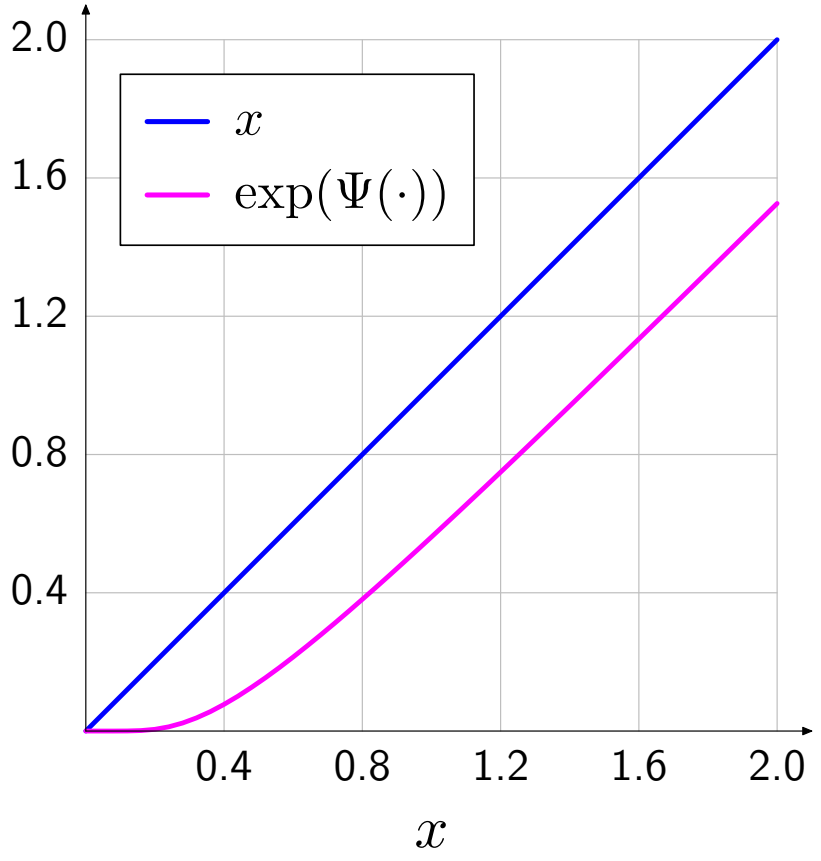
$$W(r) = \frac{C(r)}{\sum_{r'} C(r')}$$

EM (maximum a posteriori):

$$W(r) = \frac{\text{prior}(r) - 1 + C(r)}{\sum_{r'} \text{prior}(r') - 1 + C(r')}$$

Mean-field (with DP prior):

$$W(r) = \frac{\exp \Psi(\text{prior}(r) + C(r))}{\exp \Psi(\sum_{r'} \text{prior}(r') + C(r'))}$$



Rule weights

- Weight $W(r)$ of rule r similar to probability $p(r)$
- $W(r)$ unnormalized $\Rightarrow$ extra degree of freedom

EM (maximum likelihood):

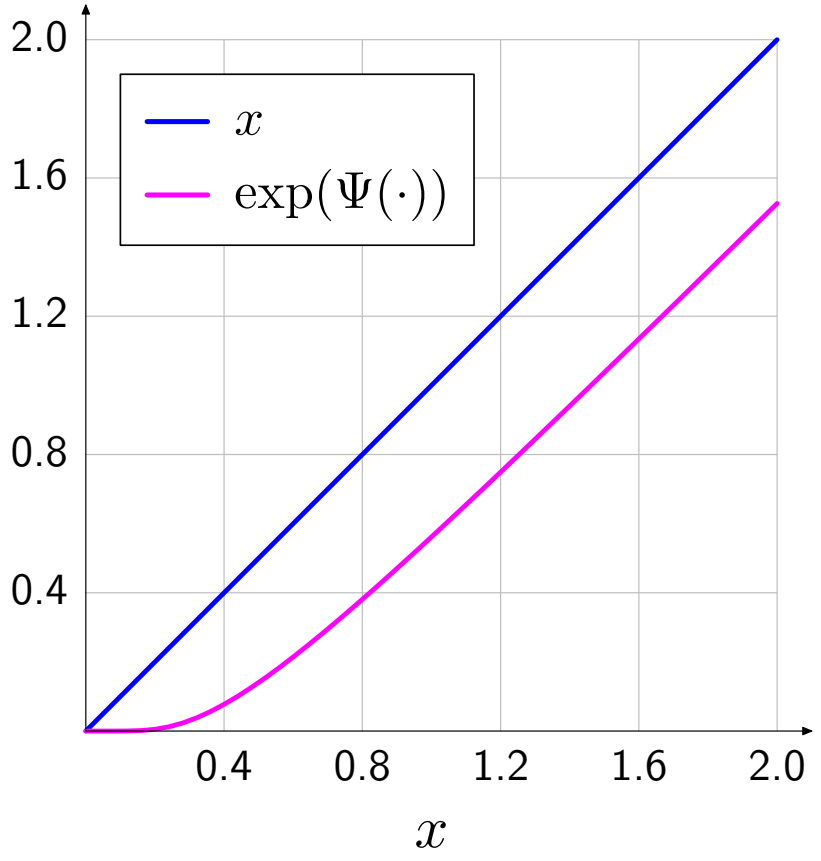
$$W(r) = \frac{C(r)}{\sum_{r'} C(r')}$$

EM (maximum a posteriori):

$$W(r) = \frac{\text{prior}(r) - 1 + C(r)}{\sum_{r'} \text{prior}(r') - 1 + C(r')}$$

Mean-field (with DP prior):

$$W(r) = \frac{\exp \Psi(\text{prior}(r) + C(r))}{\exp \Psi(\sum_{r'} \text{prior}(r') + C(r'))} \approxeq \frac{C(r) - 0.5}{\sum_{r'} C(r') - 0.5}$$



Rule weights

- Weight $W(r)$ of rule r similar to probability $p(r)$
- $W(r)$ unnormalized $\Rightarrow$ extra degree of freedom

EM (maximum likelihood):

$$W(r) = \frac{C(r)}{\sum_{r'} C(r')}$$

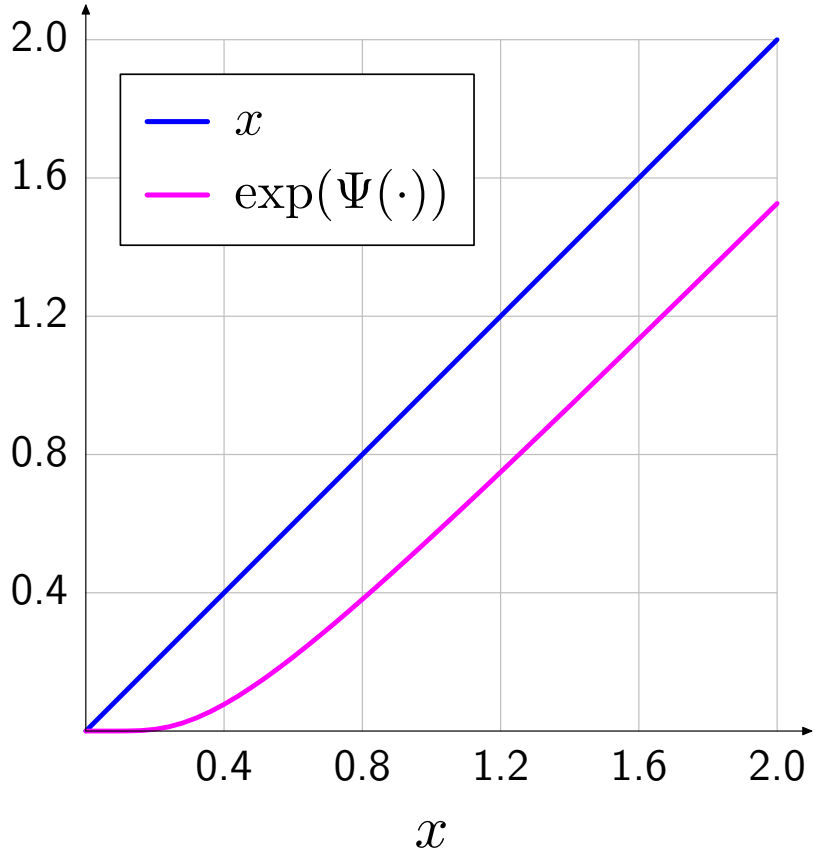
EM (maximum a posteriori):

$$W(r) = \frac{\text{prior}(r) - 1 + C(r)}{\sum_{r'} \text{prior}(r') - 1 + C(r')}$$

Mean-field (with DP prior):

$$W(r) = \frac{\exp \Psi(\text{prior}(r) + C(r))}{\exp \Psi(\sum_{r'} \text{prior}(r') + C(r'))}$$

$$\approx \frac{C(r) - 0.5}{\sum_{r'} C(r') - 0.5}$$



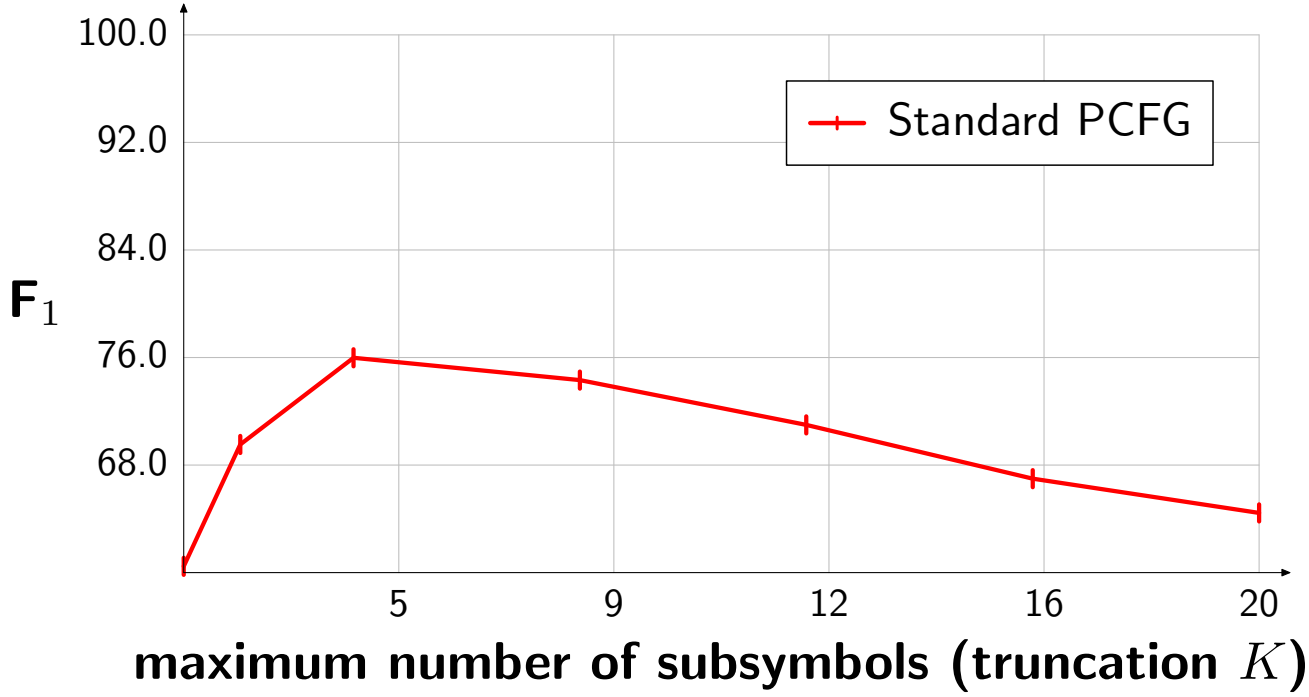
Subtract 0.5 $\Rightarrow$ small counts hurt more than large counts

$\Rightarrow$ rich gets richer $\Rightarrow$ controls number of symbols

Parsing the WSJ Penn Treebank

Setup: grammar refinement (split symbols into subsymbols)

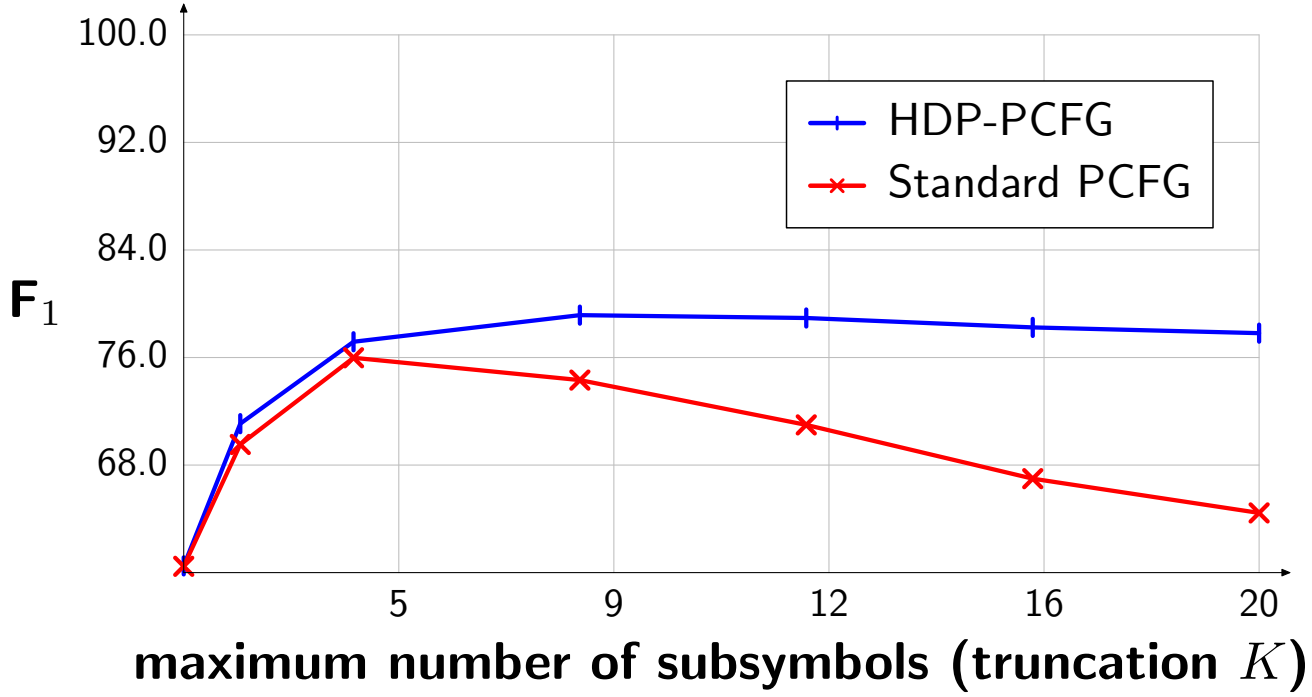
Training on one section:



Parsing the WSJ Penn Treebank

Setup: grammar refinement (split symbols into subsymbols)

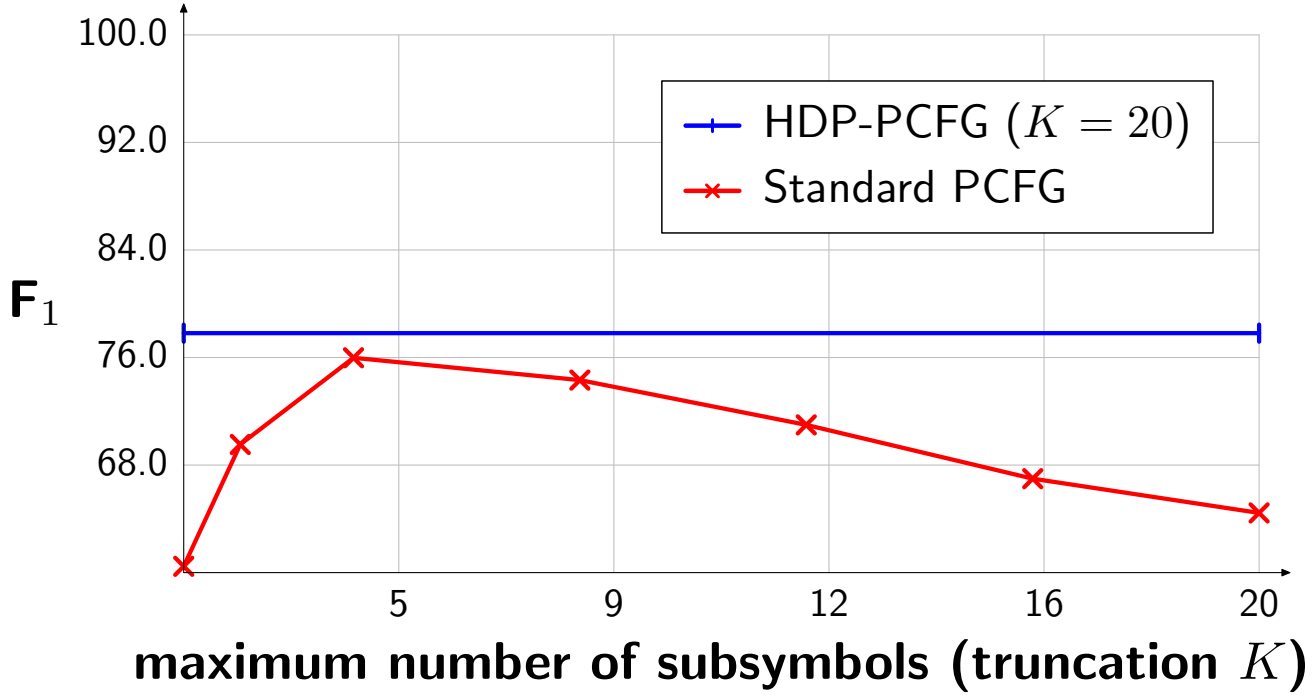
Training on one section:



Parsing the WSJ Penn Treebank

Setup: grammar refinement (split symbols into subsymbols)

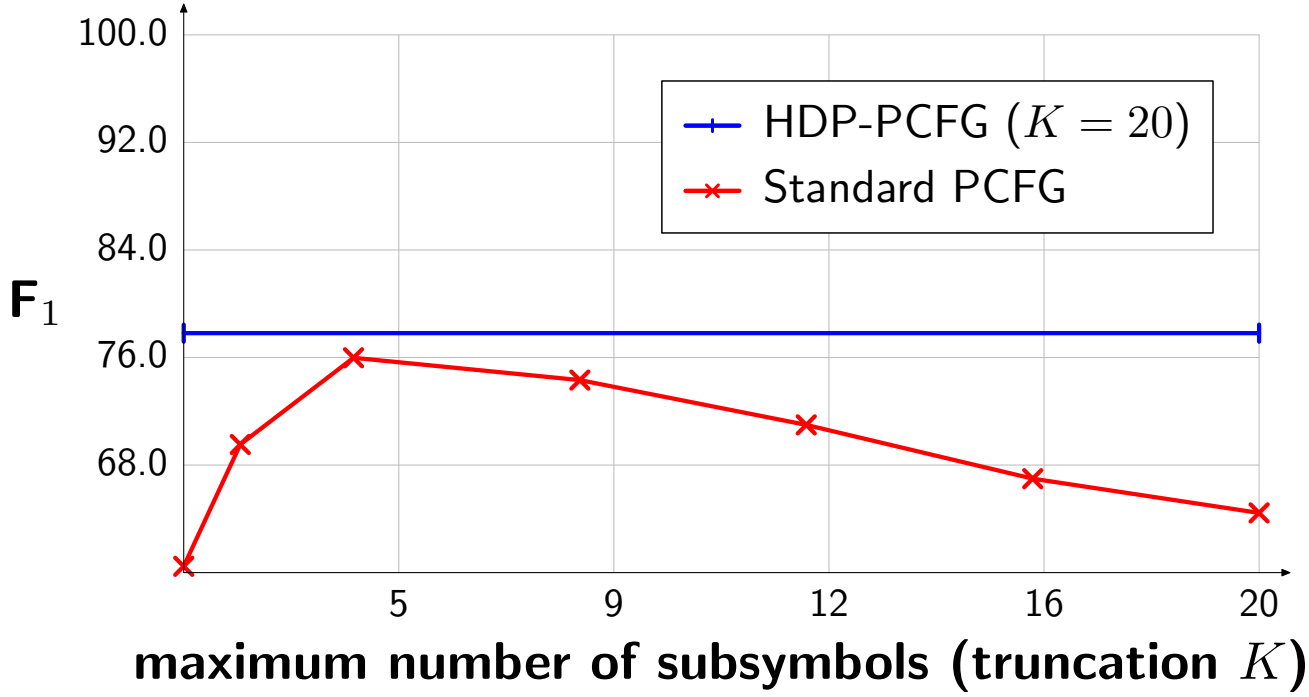
Training on one section:



Parsing the WSJ Penn Treebank

Setup: grammar refinement (split symbols into subsymbols)

Training on one section:



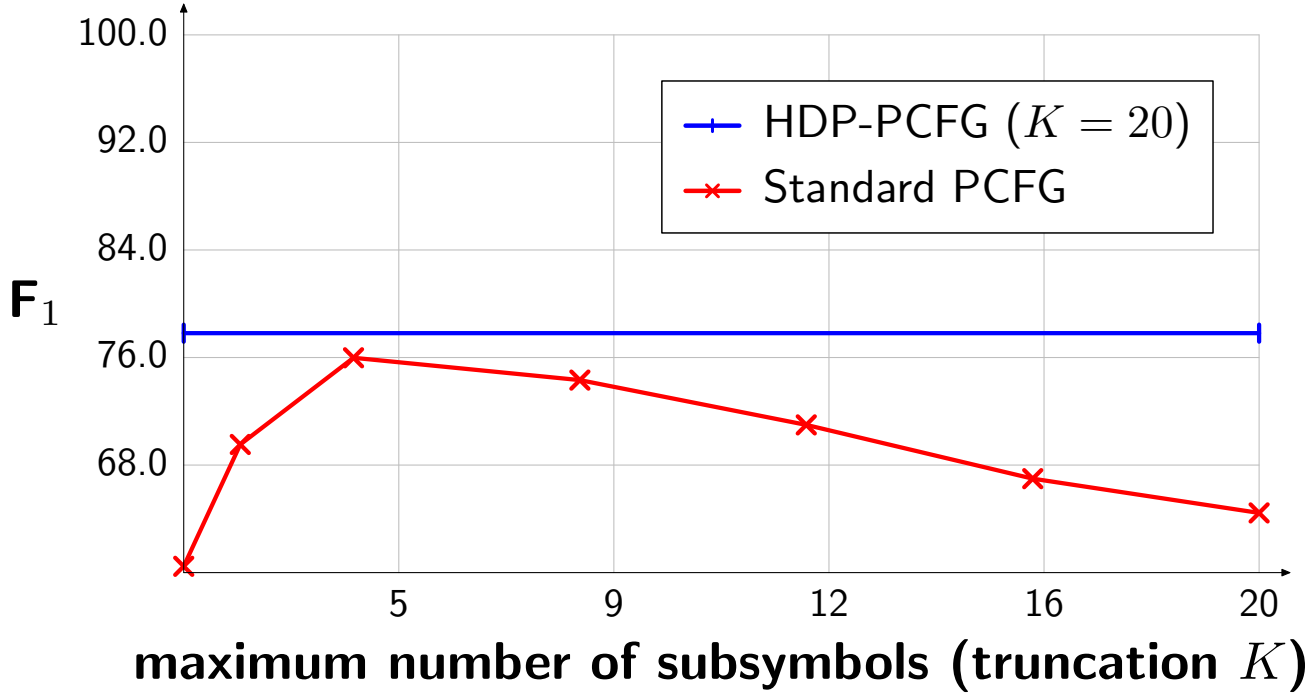
Training on 20 sections: $(K = 16)$

Standard PCFG: 86.23 HDP-PCFG: 87.08

Parsing the WSJ Penn Treebank

Setup: grammar refinement (split symbols into subsymbols)

Training on one section:



Training on 20 sections: $(K = 16)$

Standard PCFG: 86.23 HDP-PCFG: 87.08

Results:

- HDP-PCFG overfits less than standard PCFG
- If have large amounts of data, HDP-PCFG $\approxeq$ standard PCFG

Conclusions

- What? HDP-PCFG model
  allows number of grammar symbols to adapt to data
- How? Mean-field algorithm (variational inference)
  simple, efficient, similar to EM
- When? Have small amounts of data
  overfits less than standard PCFG
- Why? Declarative framework
  Grammar complexity specified declaratively in model
  rather than in learning procedure

S → NP VP
NP → PRP
VP → VBD NP
NP → DT NN
PRP → she
VBD → heard
DT → the
NN → noise
S → NP VP
NP → PRP
VP → VBD NP
NP → DT NN
PRP → she
VBD → heard
DT → the
NN → noise
S → NP VP
NP → PRP
VP → VBD NP
NP → DT NN
PRP → she
VBD → heard
DT → the
NN → noise
S → NP VP
NP → PRP
VP → VBD NP
NP → DT NN
PRP → she
VBD → heard
DT → the
NN → noise
S → NP VP
NP → PRP
VP → VBD NP
NP → DT NN
PRP → she
VBD → heard
DT → the
NN → noise
S → NP VP
NP → PRP
VP → VBD NP
NP → DT NN
PRP → she
VBD → heard
DT → the
NN → noise