Blocked Inference in Bayesian Tree Substitution Grammars

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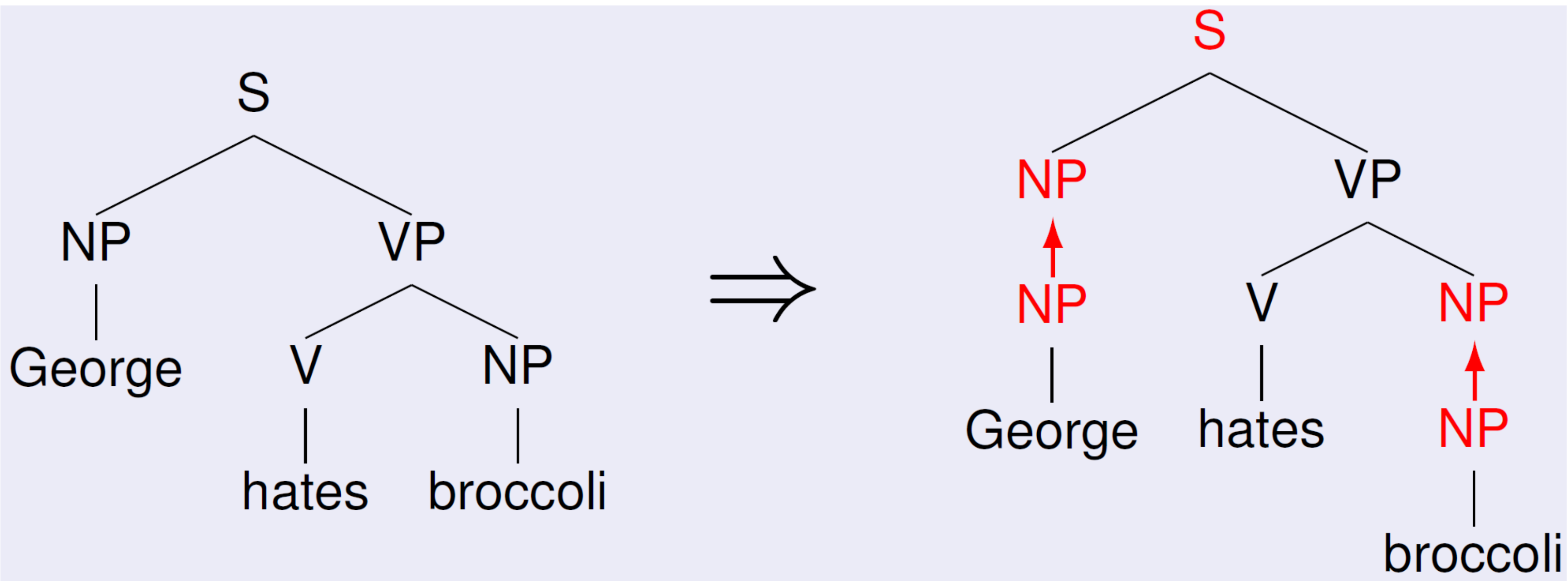
Overview

- Builds on work of Cohn, Goldwater, & Blunsom (2009)
  - Infinite Bayesian model for learning a tree substitution grammar from parsed corpus.
  - There: used a Gibbs sampler for inference.
    - Samples a single variable at a time.
    - Simple, but slow to converge.
  - Here: develop a blocked Metropolis-Hastings sampler.
    - Samples groups of variables at a time.
    - Technical challenges, but faster convergence and better F1.
- General point: in models with strong dependencies between variables (e.g. structured models), need to sample groups of variables together.

Task: supervised TSG parsing

Training input:

Inferred TSG:



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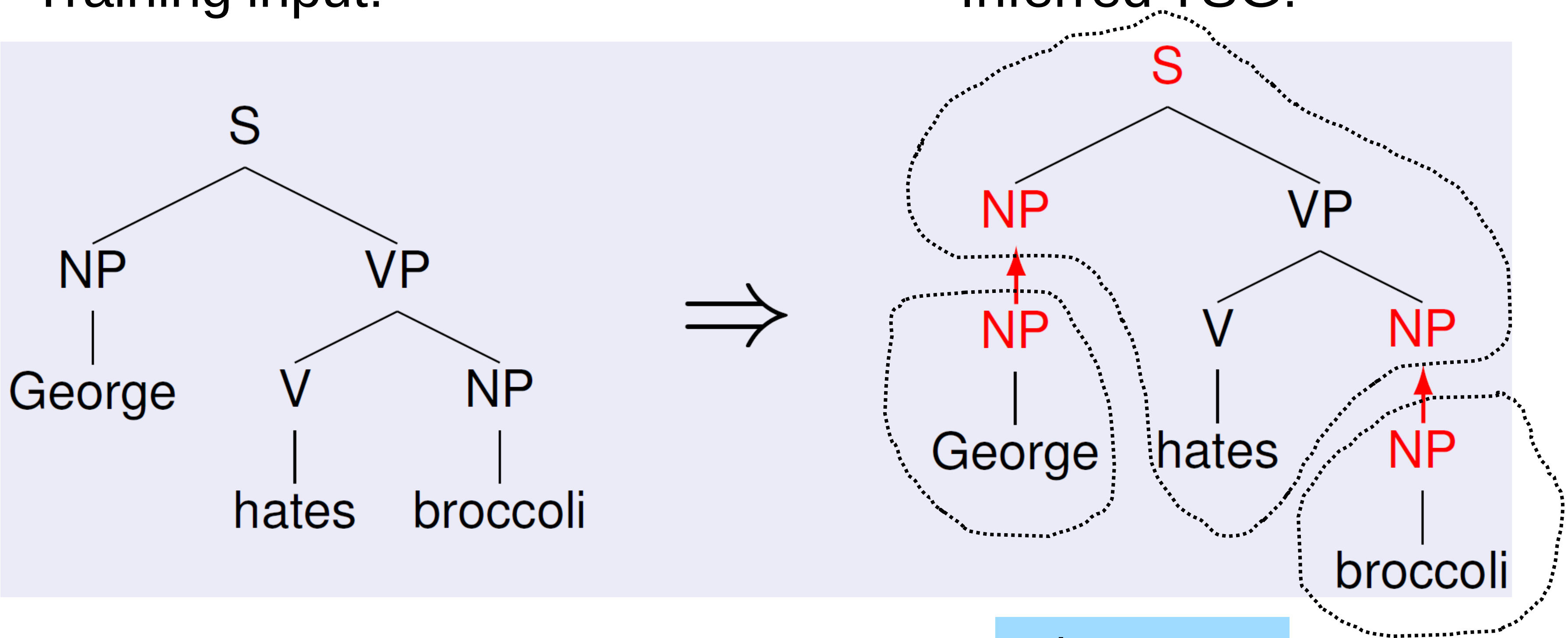

Elementary trees

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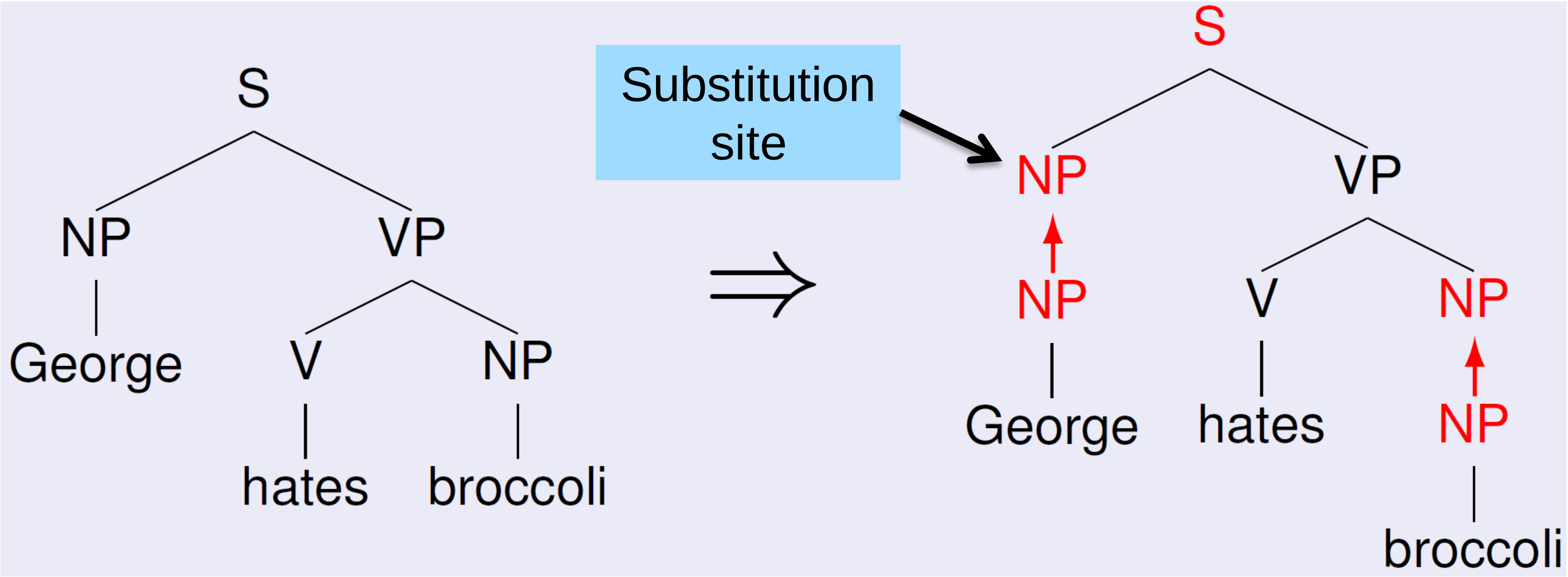

Model: probabilistic TSG

- Weighted grammar; productions are elementary trees.
- Infinite model uses Dirichlet process prior over productions for each non-terminal c.
  - For elementary trees $e_1 \ldots e_n$:

$$P(e_i \mid e_1 \ldots e_{i-1}, c, \alpha_c, P_0) \propto n_{e_i,c} + \alpha_c P_0(e_i \mid c)$$

(Cohn, Goldwater, & Blunsom, NAACL '09;
also Post & Gildea '09, O'Donnell, Goodman, & Tenenbaum '09)

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previous # of
e_i rooted at c

Prob. of elem. tree roughly proportional to # of previous occurrences.

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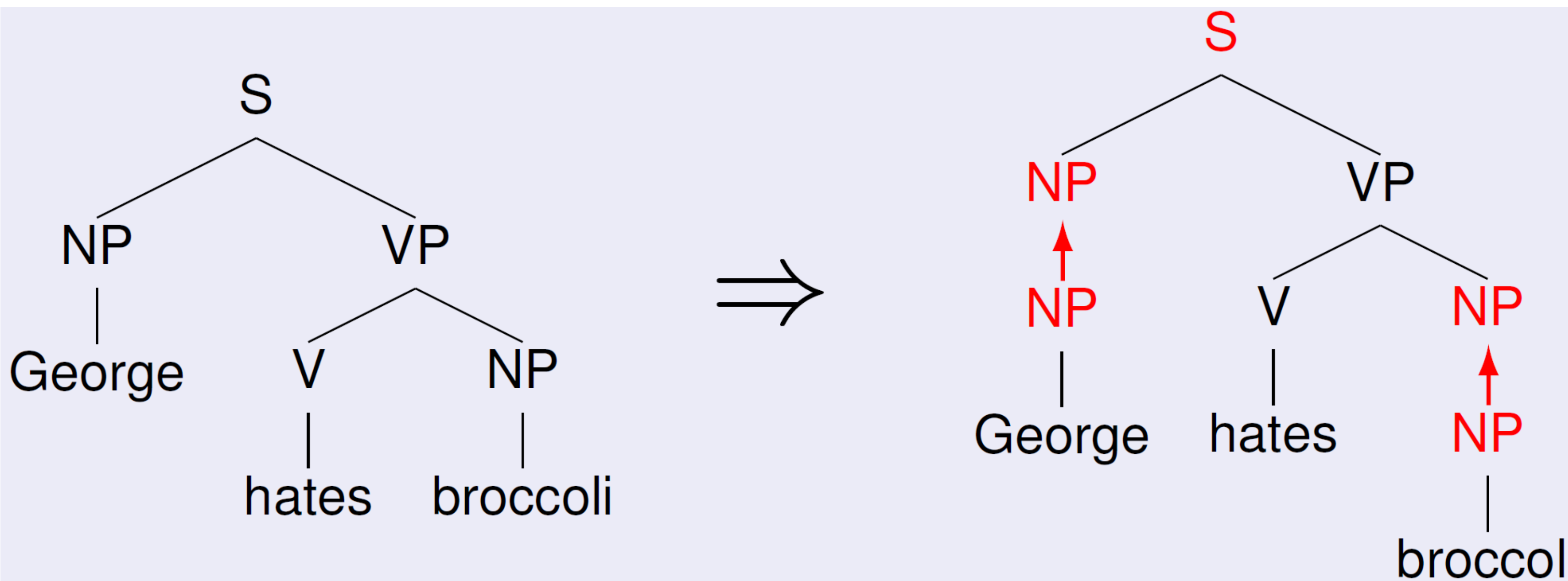
base distribution over all possible elem. trees

But all elem. trees have non-zero prob.
(P_0 uses PCFG rules to generate elem. trees)

Inference

- Segment treebank into high probability $e_1 \ldots e_n$:
    - Which nodes are substitution sites?



Inference

- Use Markov Chain Monte Carlo.
  - Sample a few hidden variables (nodes) at a time, conditioned on values of all others.
  - Iterate to convergence: Samples from posterior $P(e_1 ... e_n | d)$.

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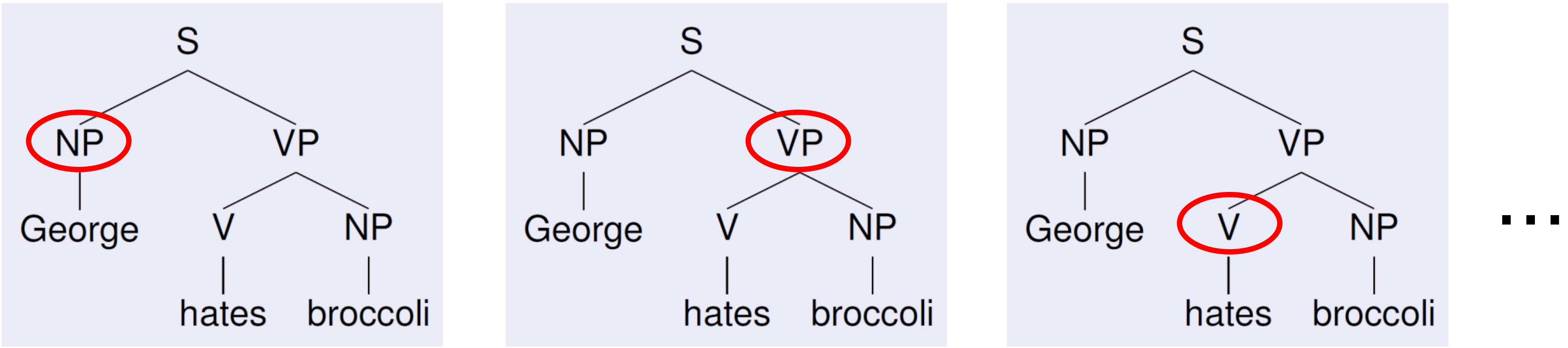
- Easy method: Gibbs sampler.



- But: poor mixing!

Inference

- Use Markov Chain Monte Carlo.
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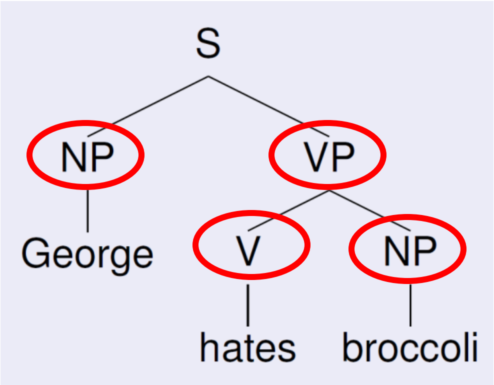
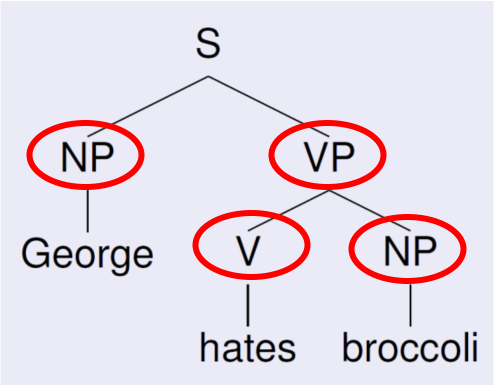
- Better method: blocked sampler.



- But: tricky to compute!

Problems with blocked sampling

- Exponentially many segmentations of each tree.



- Dynamic programming is possible using Metropolis-Hastings sampler (Johnson et al., 2007).
  - ...But only for finite PCFG.

MH for Bayesian TSG

- TSG model is infinite; how to apply dynamic programming?

$$P(e_i \mid e_1 \ldots e_{i-1}, c, \alpha_c, P_0) \propto n_{e_i,c} + \alpha_c P_0(e_i \mid c)$$

Non-zero prob. for any tree generated by PCFG rules.

- Key insight: Infinite grammar can be represented as a finite PCFG!

Grammar transform

- Convert infinite TSG to finite PCFG:
  - Sub-grammar A contains PCFG productions for all elem. trees with count > 0.
  - Sub-grammar B is a PCFG representing P_0 .
  - Rule with prob. proportional to α_c connects the two sub-grammars.

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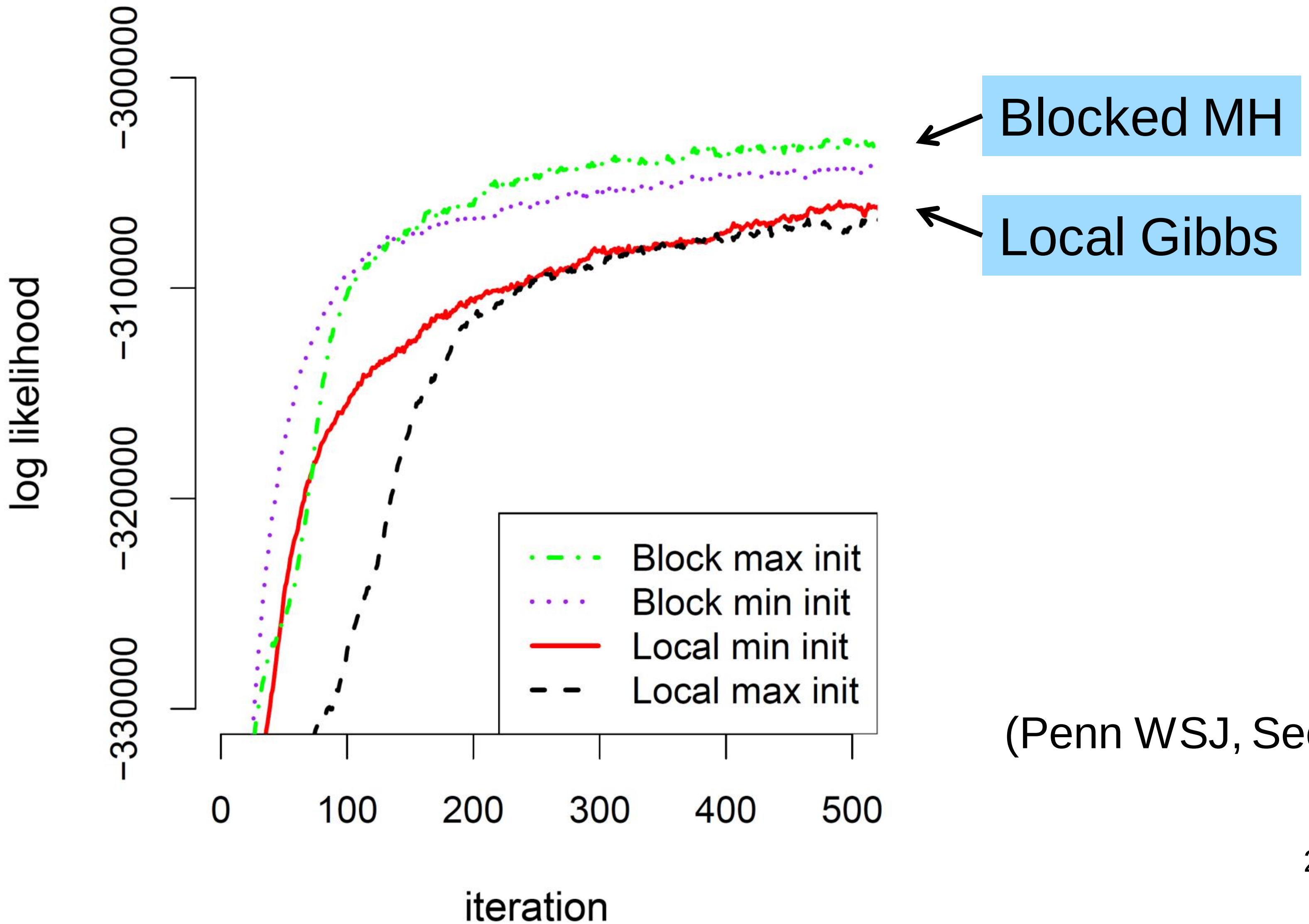
- Now can use MH for Bayesian PCFG.
- Bonus: can use for unsupervised training.

Faster convergence



(Penn WSJ, Sec. 2)

Higher parsing accuracy

- Improved F-score on small and large training sets:

Training set	’09 best	New best
WSJ sec. 2	77.6	78.4
WSJ sec. 2-21	84.0	85.3

Conclusions

- Local Gibbs sampling mixes poorly for structured prediction models; better to use blocked sampling.
- Grammar transform represents infinite TSG as finite PCFG, making blocked sampling possible.
- Blocked sampler: faster training and better parsing.
- See poster or paper for more details/results.

- Future extensions:
    - Use Pitman-Yor process instead of Dirichlet process.
    - Unsupervised dependency grammar TSG induction.