Bayesian Symbol-Refined Tree Substitution Grammars for Syntactic Parsing

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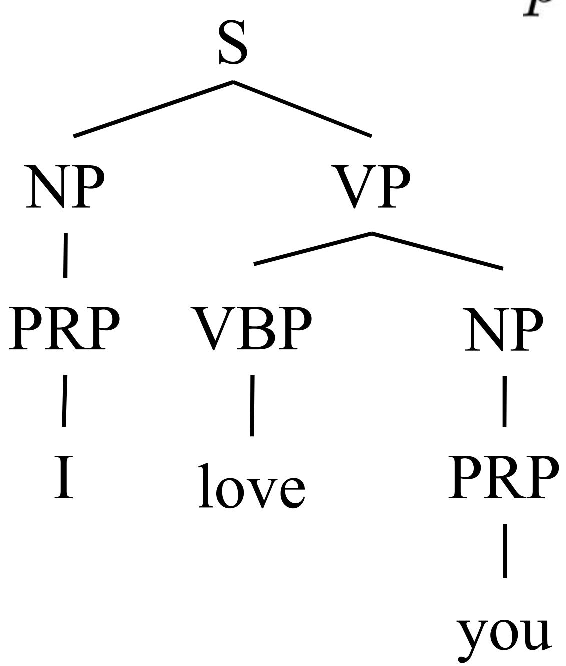
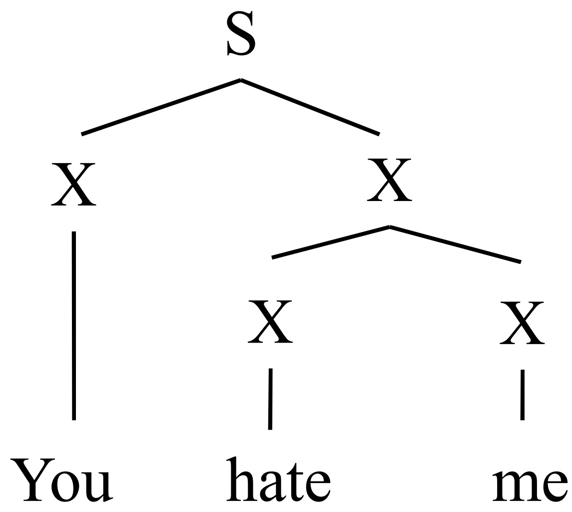
Task: Statistical Constituent Parsing

Training

$p\left(\text{tree}\right)$



Testing



F-score: ?

Previous Work

- Naive CFG-based parser does NOT perform well...
    - Coarse symbol annotations
    - Strong independence assumption

Previous approaches:

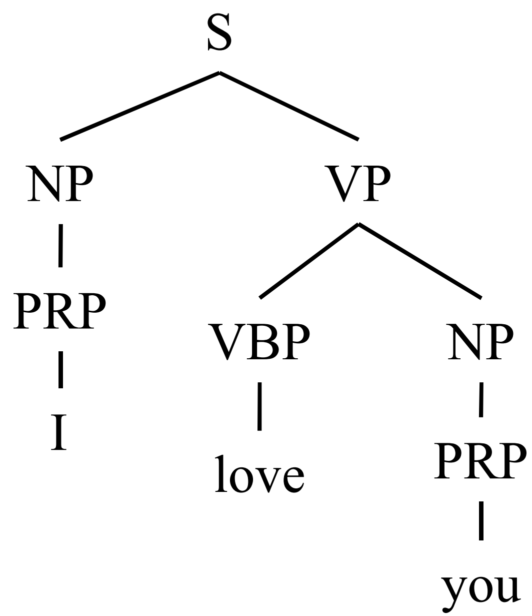
a) CFG with automatic symbol refinement
[Matsuzaki et al. 05, Petrov et al. 06]

b) Tree substitution grammars (TSG)
[Cohn et al. 09, Post et al. 09]

a) CFG with automatic symbol refinement

- Idea: split symbols into subcategories
  (based on the likelihood)

- Inference: EM algorithm



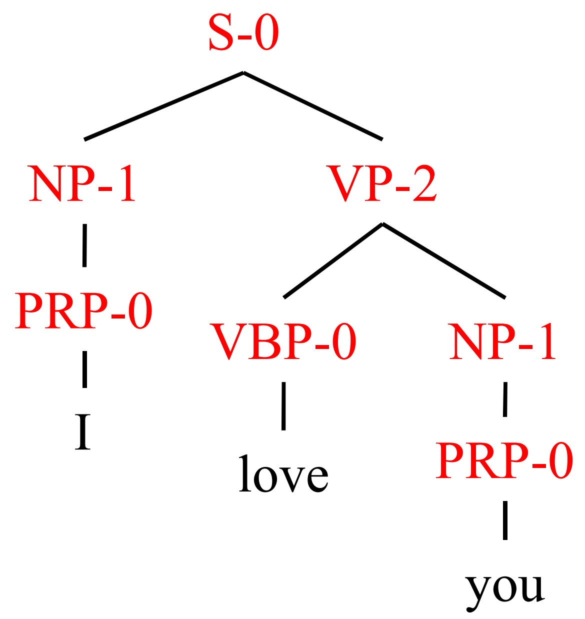
a) CFG with automatic symbol refinement

- Idea: split symbols into subcategories (based on the likelihood)

- Inference: EM algorithm

Refined PCFG rules:

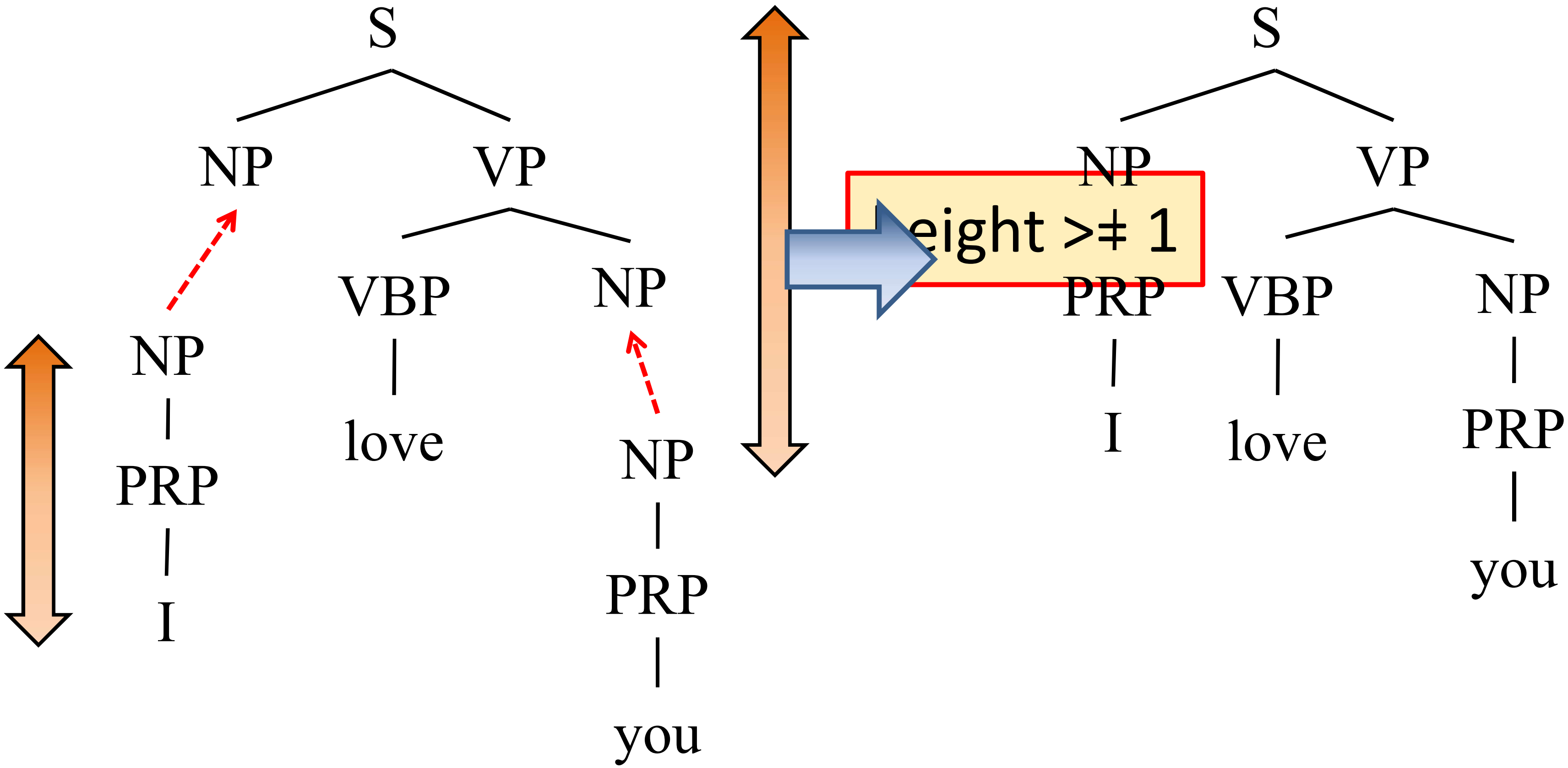
S-0	$\rightarrow$	NP-1 VP-2	p_0
NP-1	$\rightarrow$	PRP-0	p_1
PRP-0	$\rightarrow$	"I"	p_2
VP-2	$\rightarrow$	VBP-0 NP-1	p_3



b) Tree Substitution Grammars (TSG)

- Idea: Allow arbitrarily large tree fragments

- Inference: MCMC sampling



Motivation

Two approaches are complementary

[Cohn et al. 09, Bansal & Klein 10]

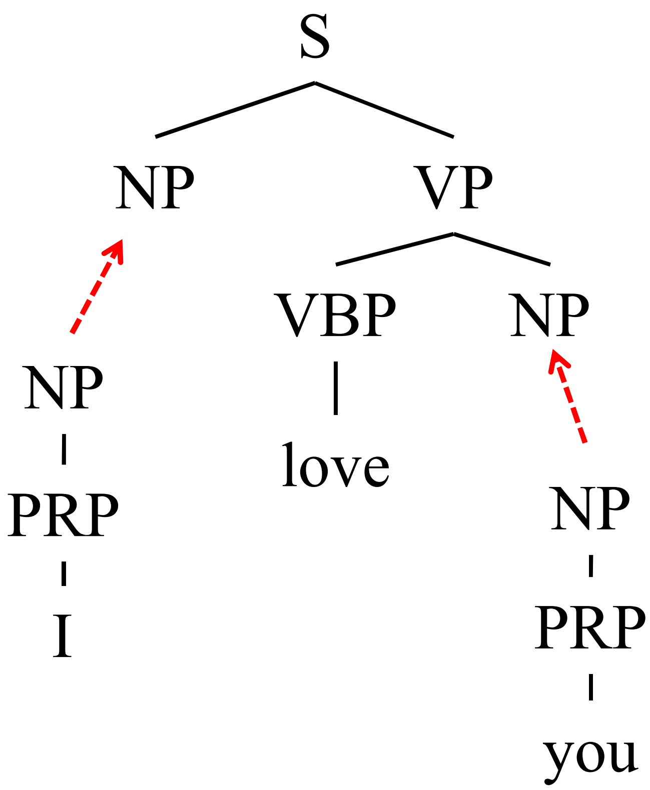
- Clustering context
- Learning structure

Proposal:

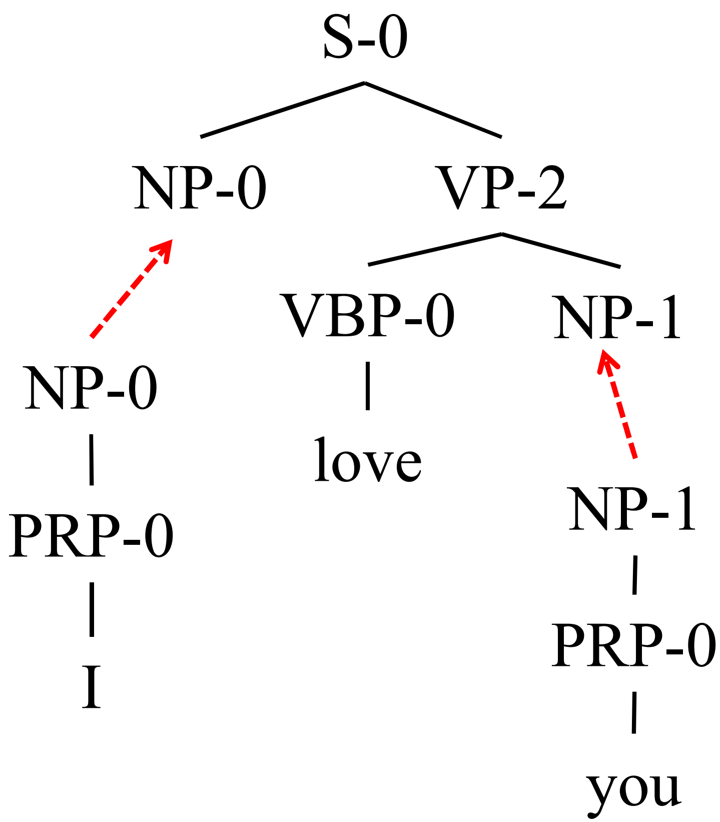
Symbol-Refined TSG (SR-TSG)

SR-TSG

TSG



SR-TSG

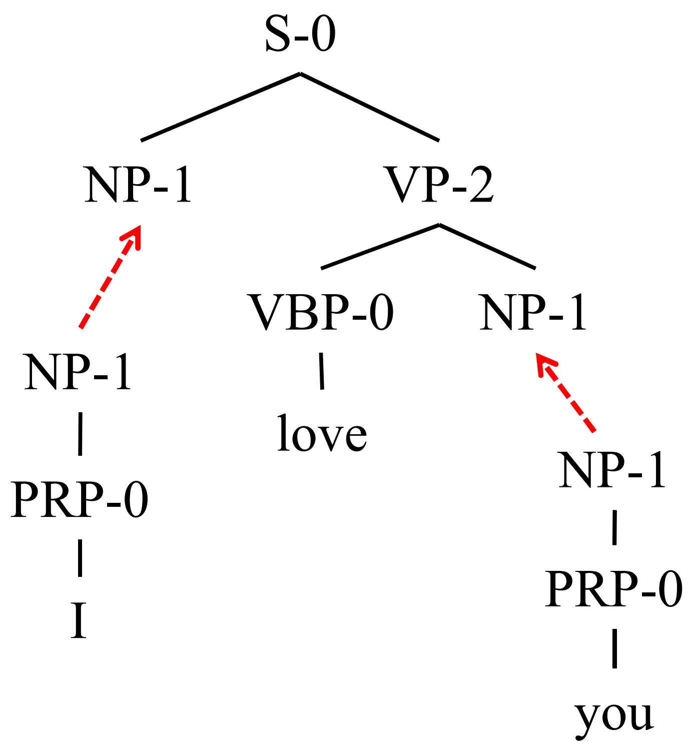


SR-TSG

- Latent variables of SR-TSG:

tree fragments + symbol subcategories

Search space is huge !



Challenge:

<u>Fully automatic learning</u>

⇔ TSG + refinement [Bansal & Klein 10]

Probabilistic model

Inference

Probabilistic Model of SR-TSG

Overview of Probabilistic Model

What we need:

1. Probability distribution over refined tree fragments

   Pitman-Yor process

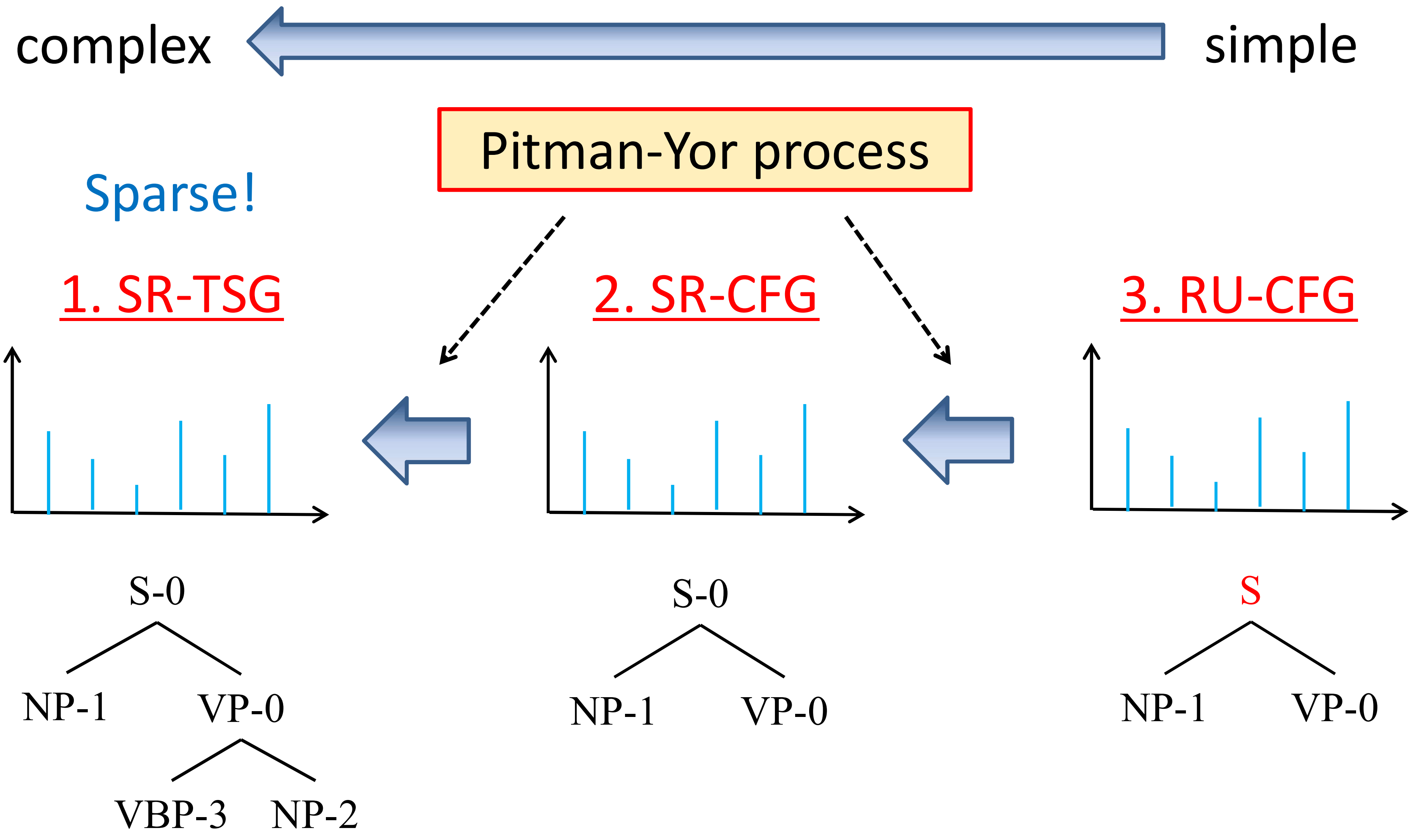
   [Pitman & Yor 96]

2. Framework for back-off smoothing

   Large $\longrightarrow$ small tree fragments

   3-level hierarchy

3-Level Hierarchy



Pitman-Yor Process (PYP)

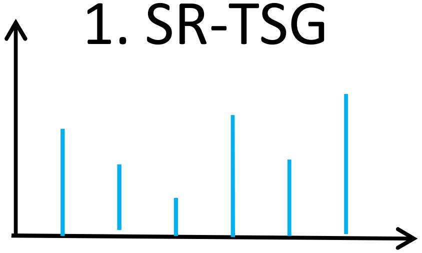
- A prior for non-parametric Bayesian model

- Useful for modeling data with power-law distribution

- Closely related to Chinese Restaurant Process (CRP)

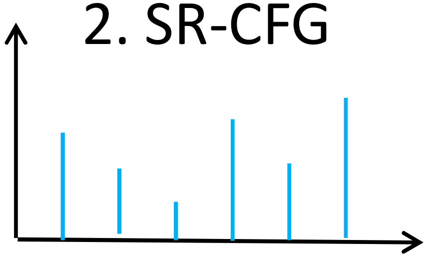
Pitman-Yor Process (PYP)

1. SR-TSG

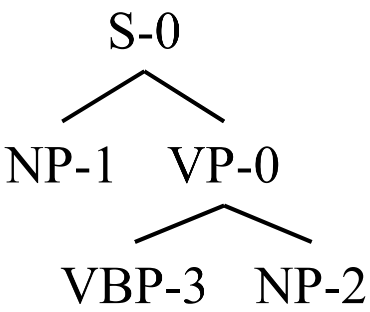


PYP

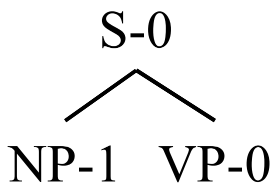
2. SR-CFG



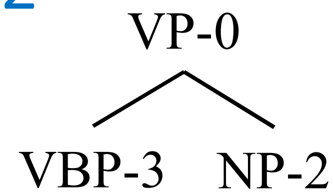
A



A1



A2



Eq. $$\boxed{p\left(A\right) = \alpha \cdot count\left(A\right) + \beta \cdot \underline{P_0\left(A\right)}}$$ Base distr.

"Rich get richer" effect

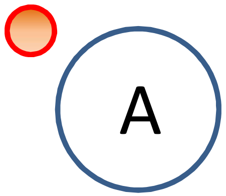
$$\propto p'\left(A1\right) \times p'\left(A2\right)$$

smoothing

Chinese Restaurant Process

Chinese Restaurant Process

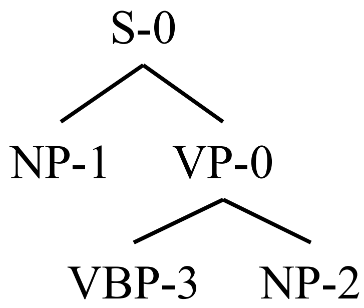
$$\mathrm{PYP}\left(d, \theta, P_0\right)$$



1

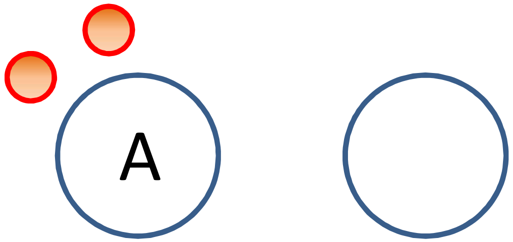
$\times P_0\left(A\right)$

A

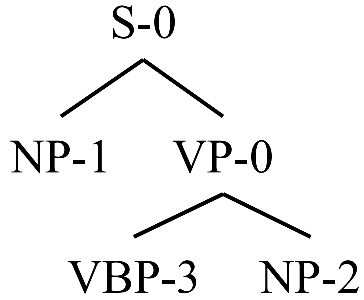


Chinese Restaurant Process

$$\mathrm{PYP}\left(d, \theta, P_0\right)$$

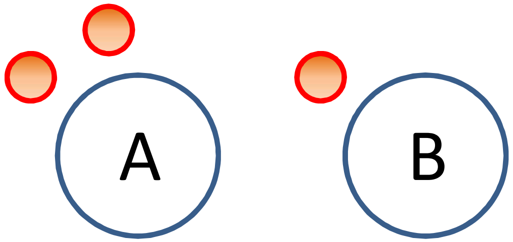


$1 - d$ $\qquad$ $\theta + d$



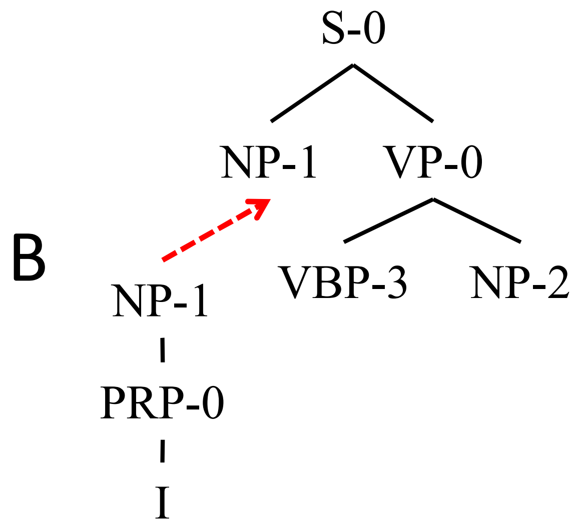
Chinese Restaurant Process

$$\mathrm{PYP}\left(d, \theta, P_0\right)$$



$2 - d$ $\qquad$ $\theta + d$

$\times P_0\left(B\right)$

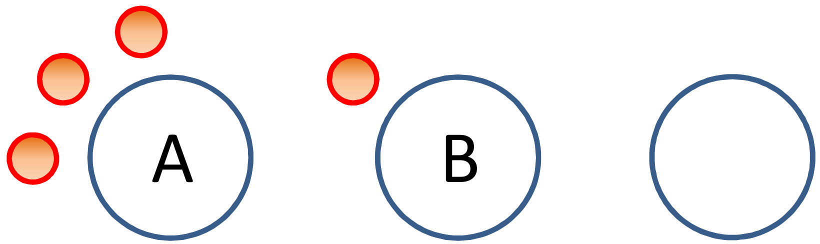


- Prob. of choosing a table $\propto \begin{cases} \mathrm{count}\left(k\right) - d & \text{occupied} \\ \theta + \#\ \mathrm{tables} \cdot d & \text{new table} \end{cases}$

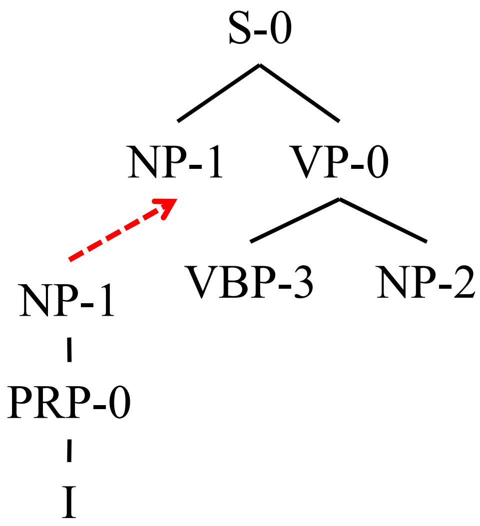
- “Rich get richer” effect

Chinese Restaurant Process

$$\text{PYP}\left(d, \theta, P_0\right)$$



$2 - d$ $\quad 1 - d$ $\quad \theta + 2d$

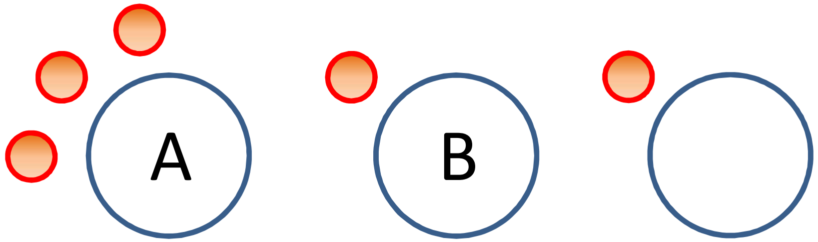


- Prob. of choosing a table $\propto \begin{cases} \text{count}\left(k\right) - d & \text{occupied} \\ \theta + \#\ \text{tables} \cdot d & \text{new table} \end{cases}$

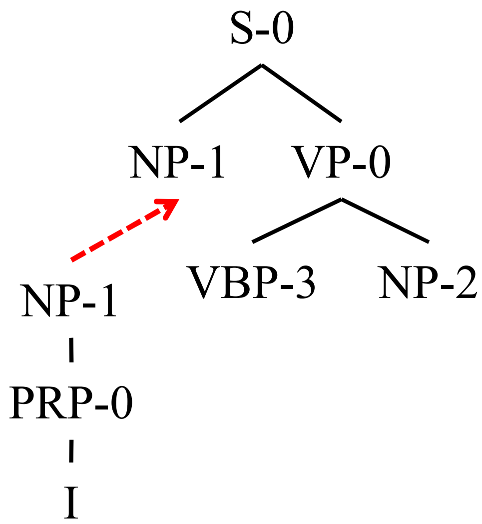
- “Rich get richer” effect

Chinese Restaurant Process

$$\mathrm{PYP}\left(d, \theta, P_0\right)$$



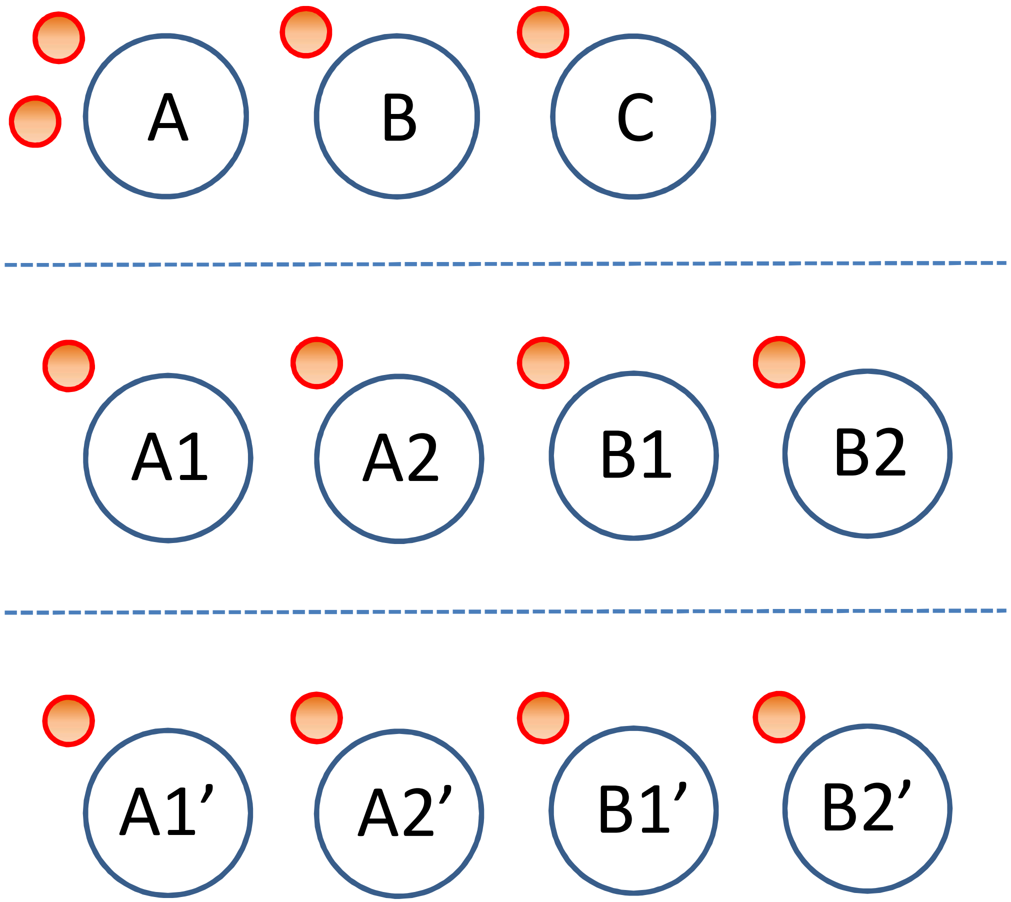
$3 - d$ $\quad 1 - d$ $\quad \theta + 2d$

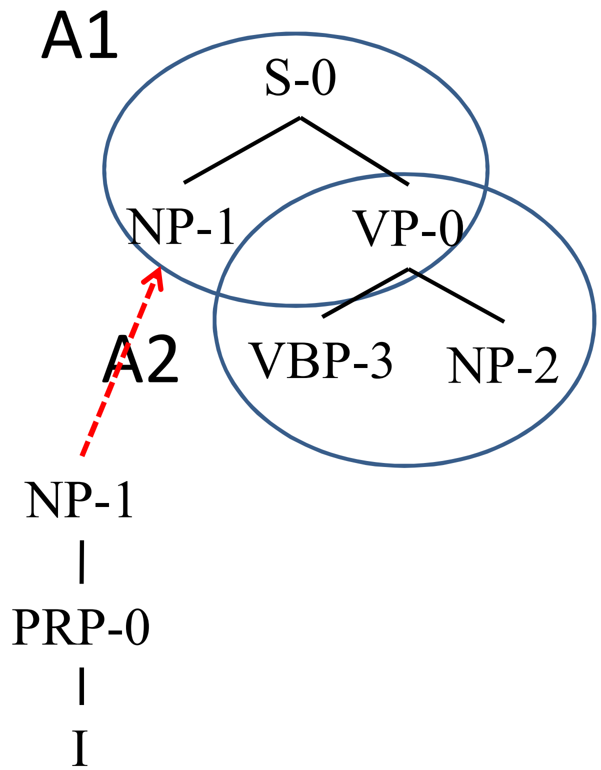


- Prob. of choosing a table $\propto \begin{cases} \mathrm{count}\,(k) - d & \text{occupied} \\ \theta + \#\ \mathrm{tables} \cdot d & \text{new table} \end{cases}$

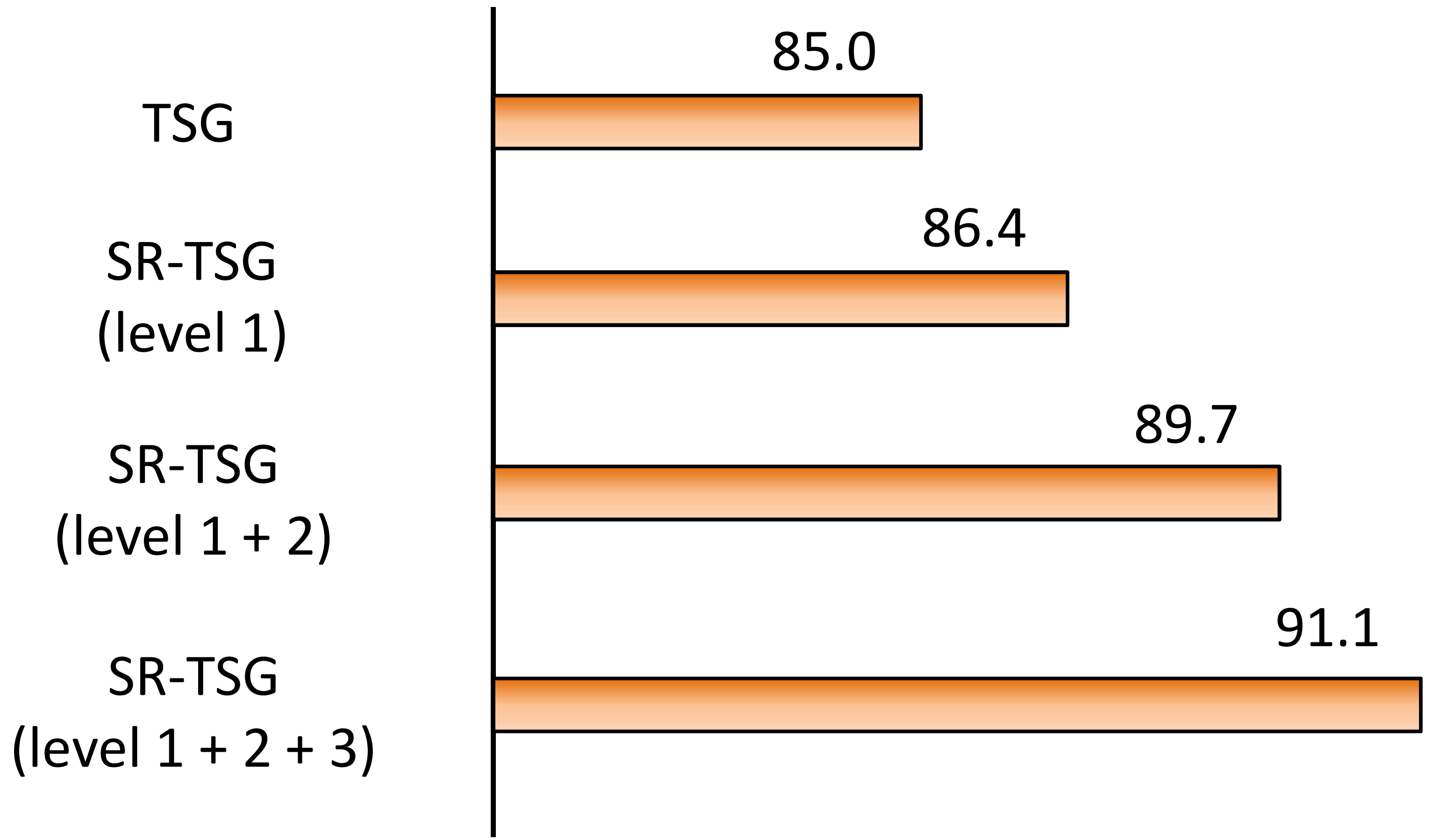
- “Rich get richer” effect

Chinese Restaurant Process





Effect of back-off smoothing



Summary of Probabilistic Model

- Probability distribution over SR-TSG fragments
  - Pitman-Yor process as a prior

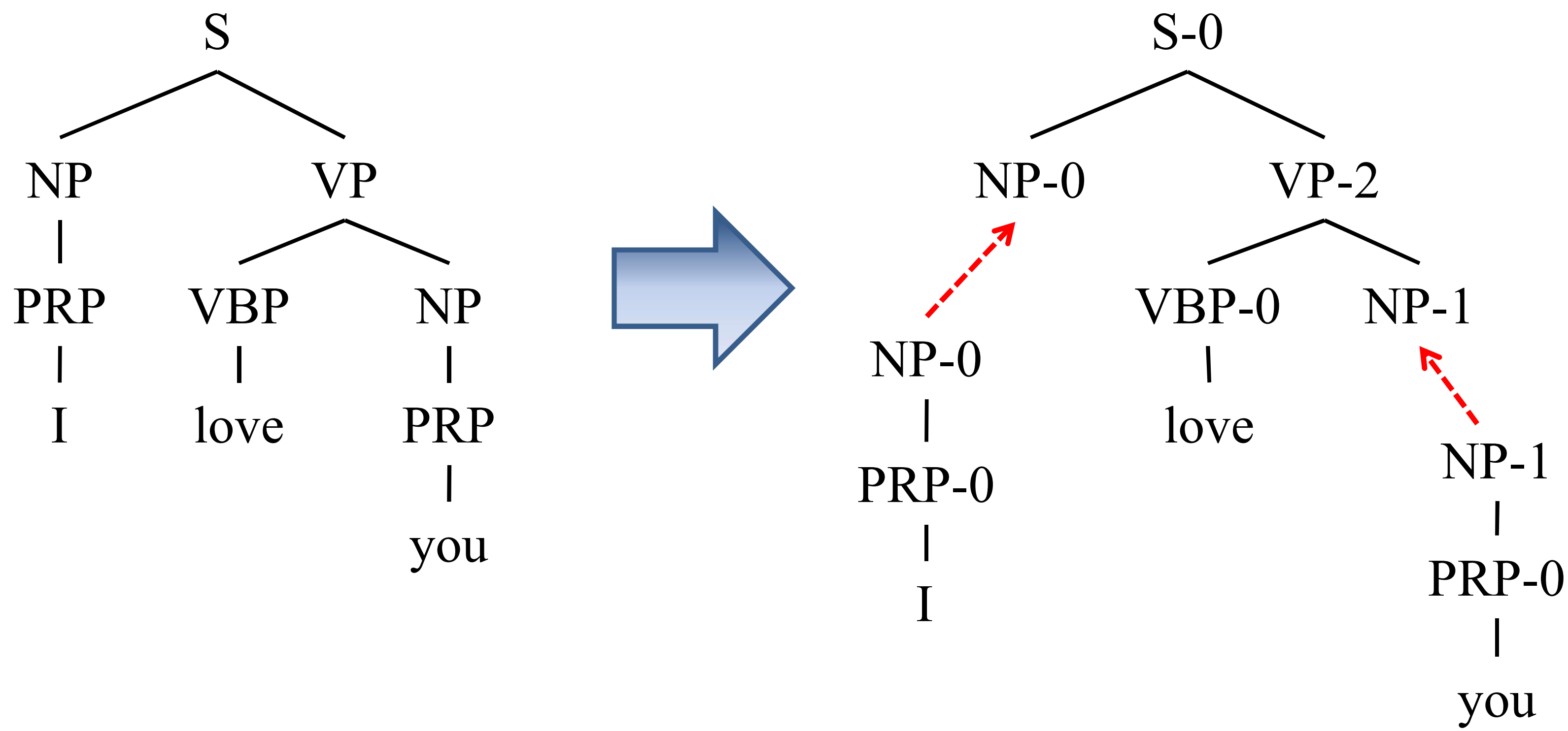
- 3-level hierarchy for back-off smoothing
  - SR-TSG ← SR-CFG ← RU-CFG

- Parsing accuracy(f-score): 91.1% on English PTB

Inference

Overview of Inference

What we want:



Overview of Inference

- MAP estimation: $\underset{\mathbf{Z}}{\text{argmax}}\ p(\mathbf{Z}\,|\,\mathbf{T})$

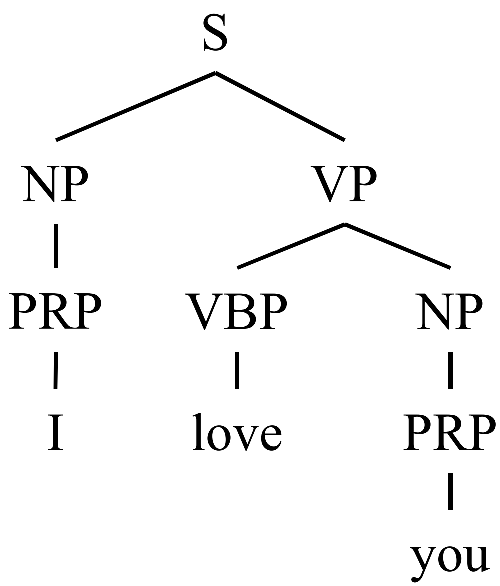
- MCMC sampling for inference

tree fragments	+	symbol subcategories

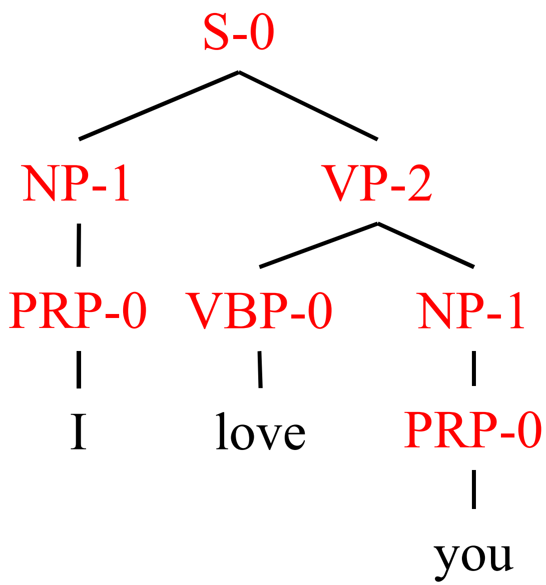
Stepwise training:

	tree fragments	symbol subcategories
1.	Fix	Train
2.	Train	Almost fixed

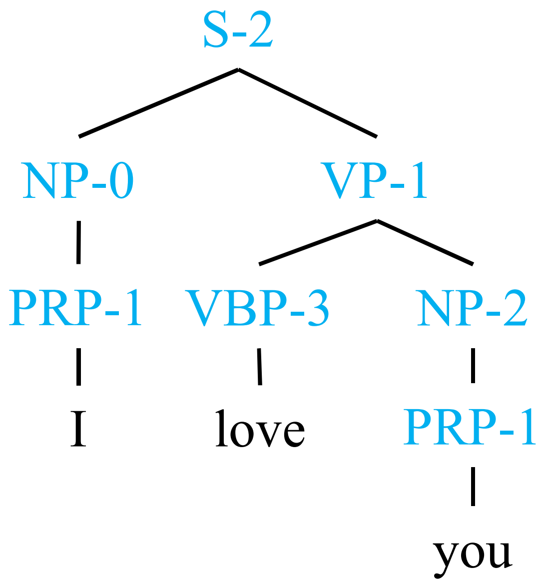
Overview of MCMC Sampling



Overview of MCMC Sampling



Overview of MCMC Sampling



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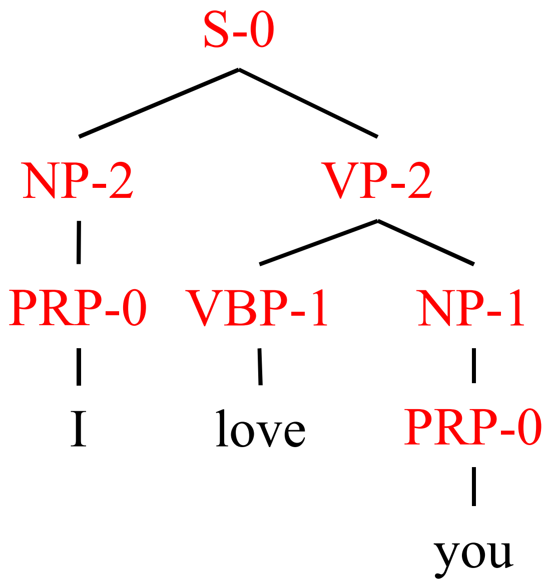

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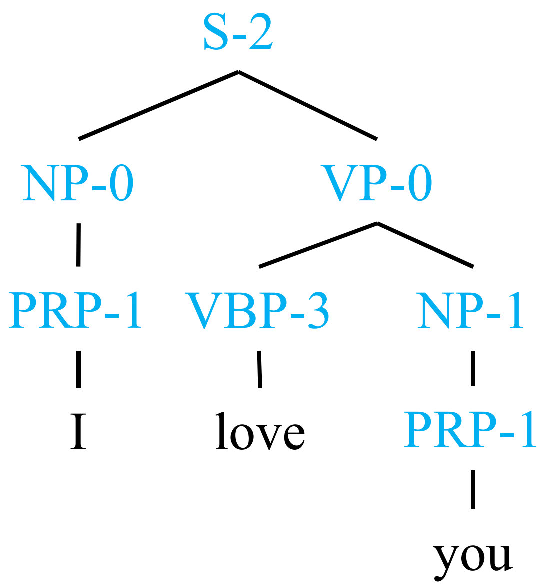
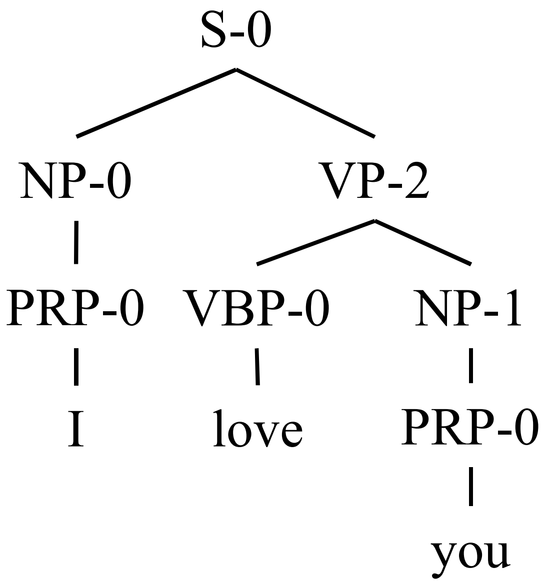
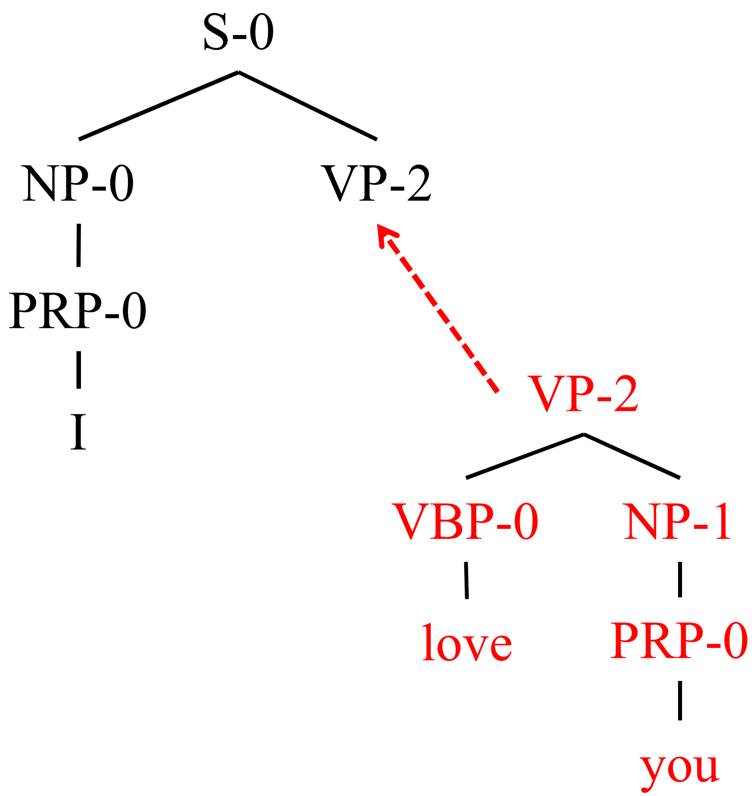


Overview of MCMC Sampling



Overview of MCMC Sampling



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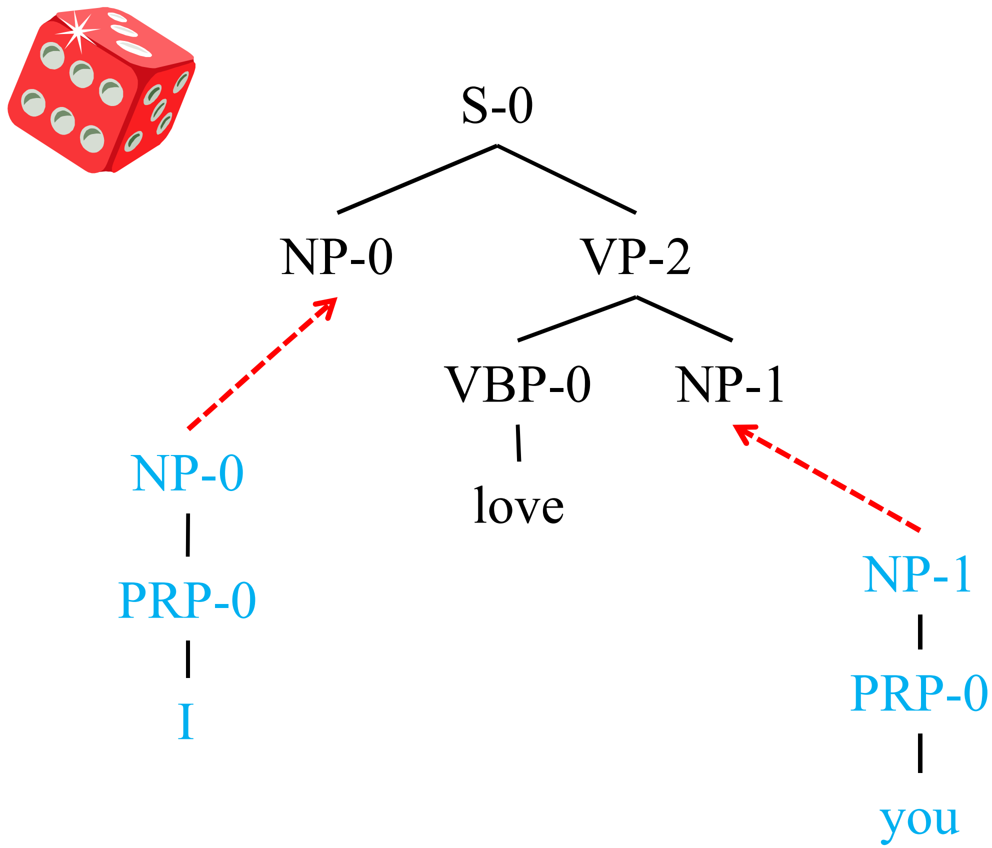

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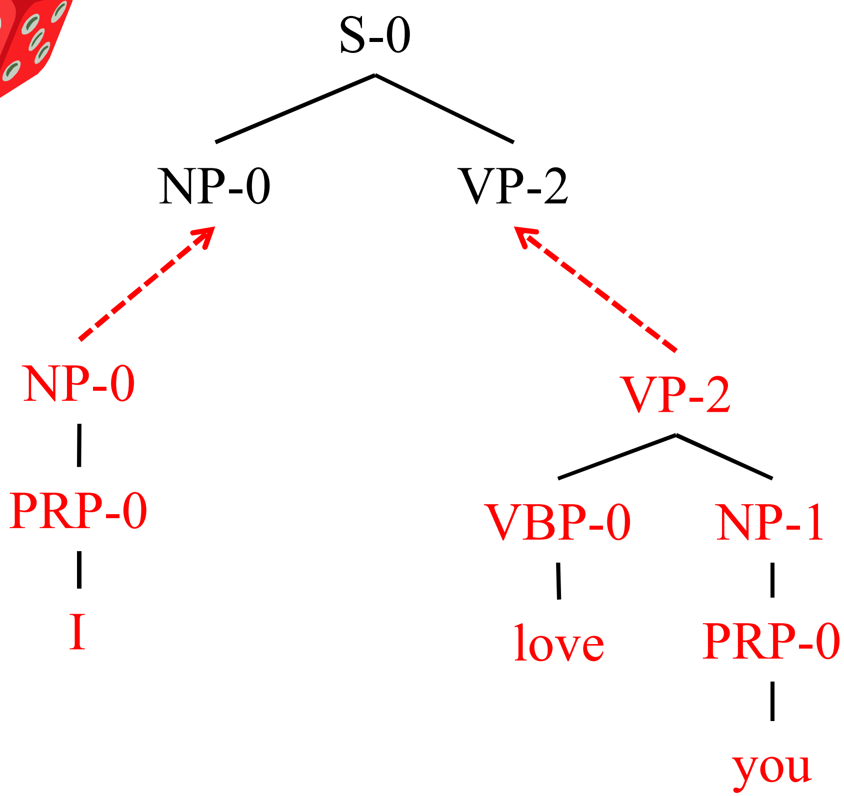
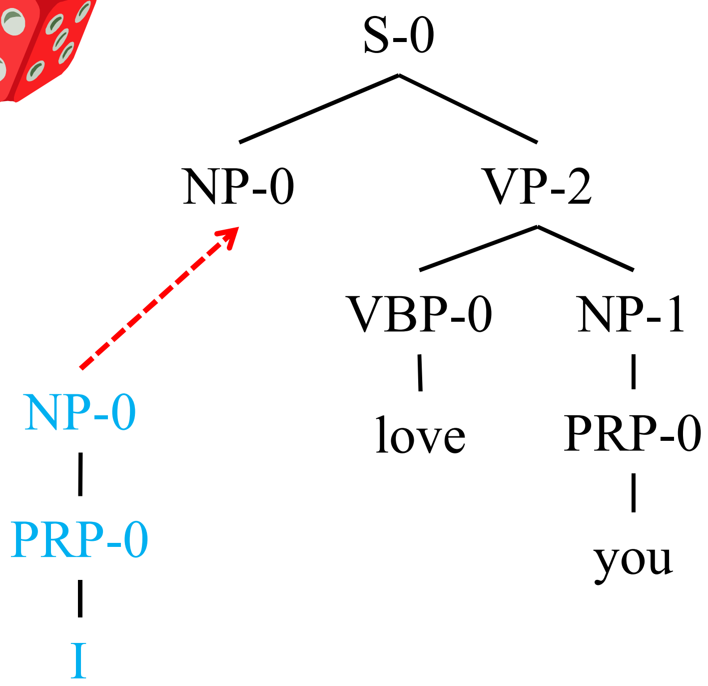
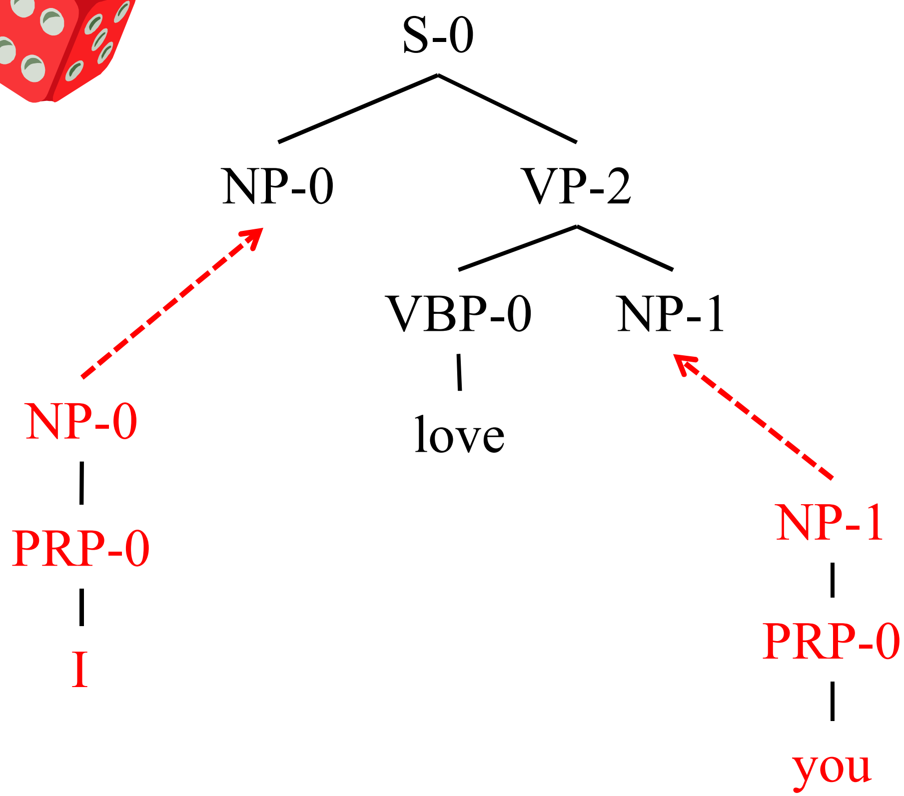


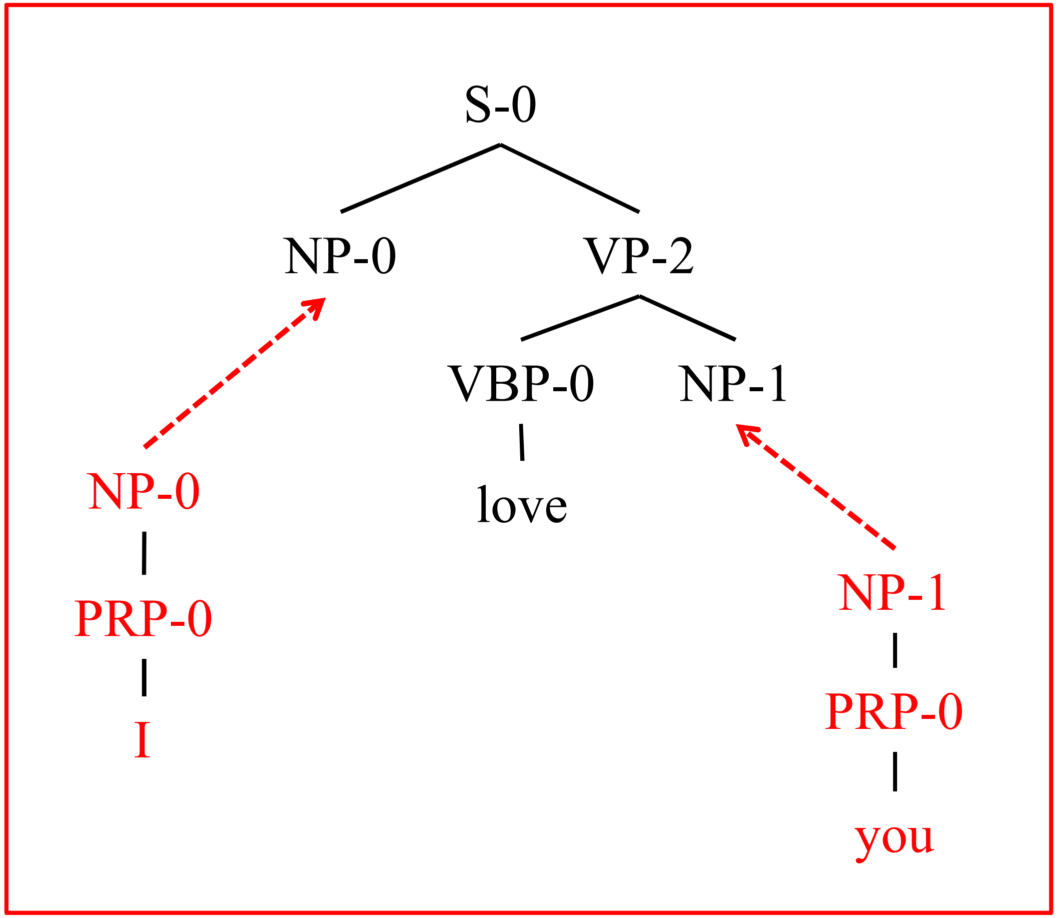
Overview of MCMC Sampling



Overview of MCMC Sampling



Overview of MCMC Sampling

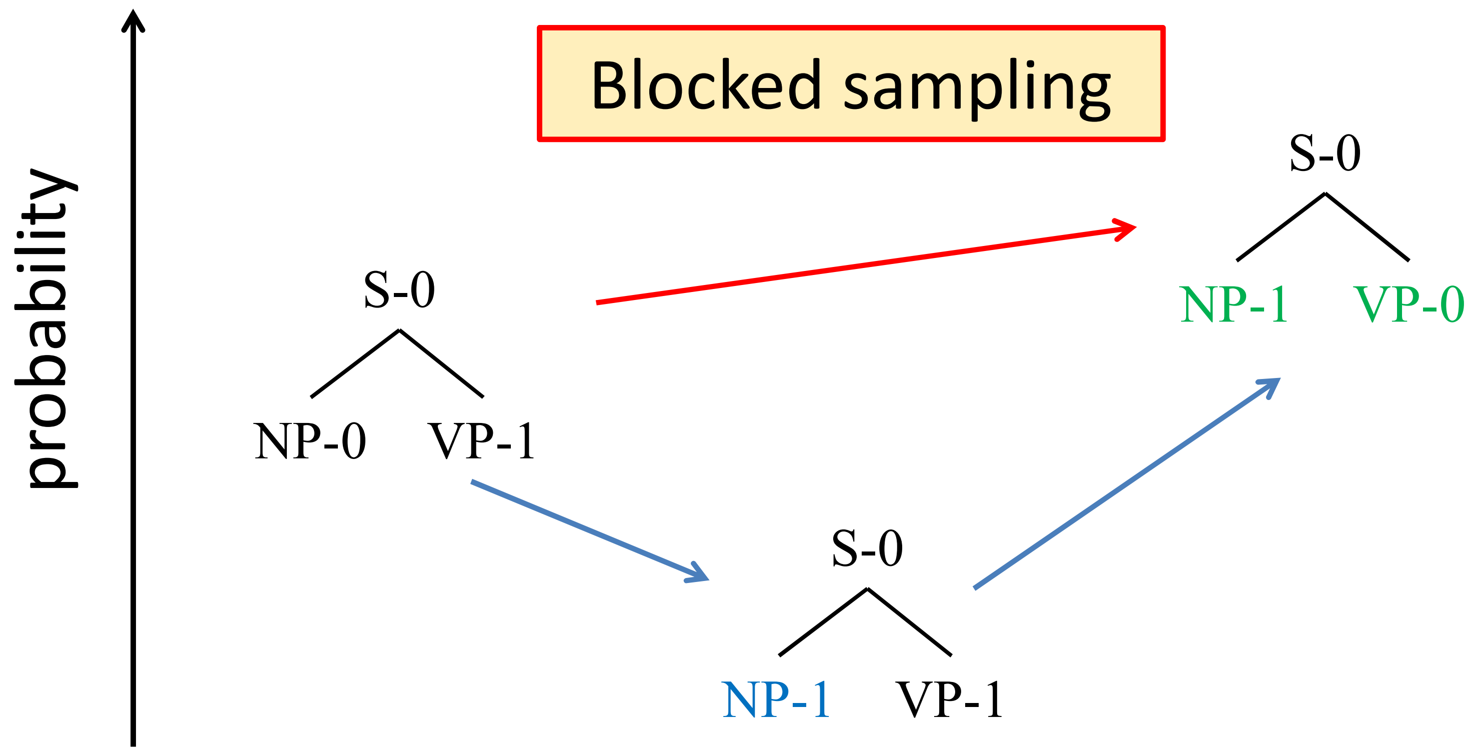


Inference of Symbol Refinement

Problem:

- Gibbs sampler is inefficient

  Update only one variable at a time



Inference of Symbol Refinement

Proposal:

- 3 types of blocked samplers to find better solution

For each MCMC iteration...

a) Run sentence sampler

b) Run subtree sampler

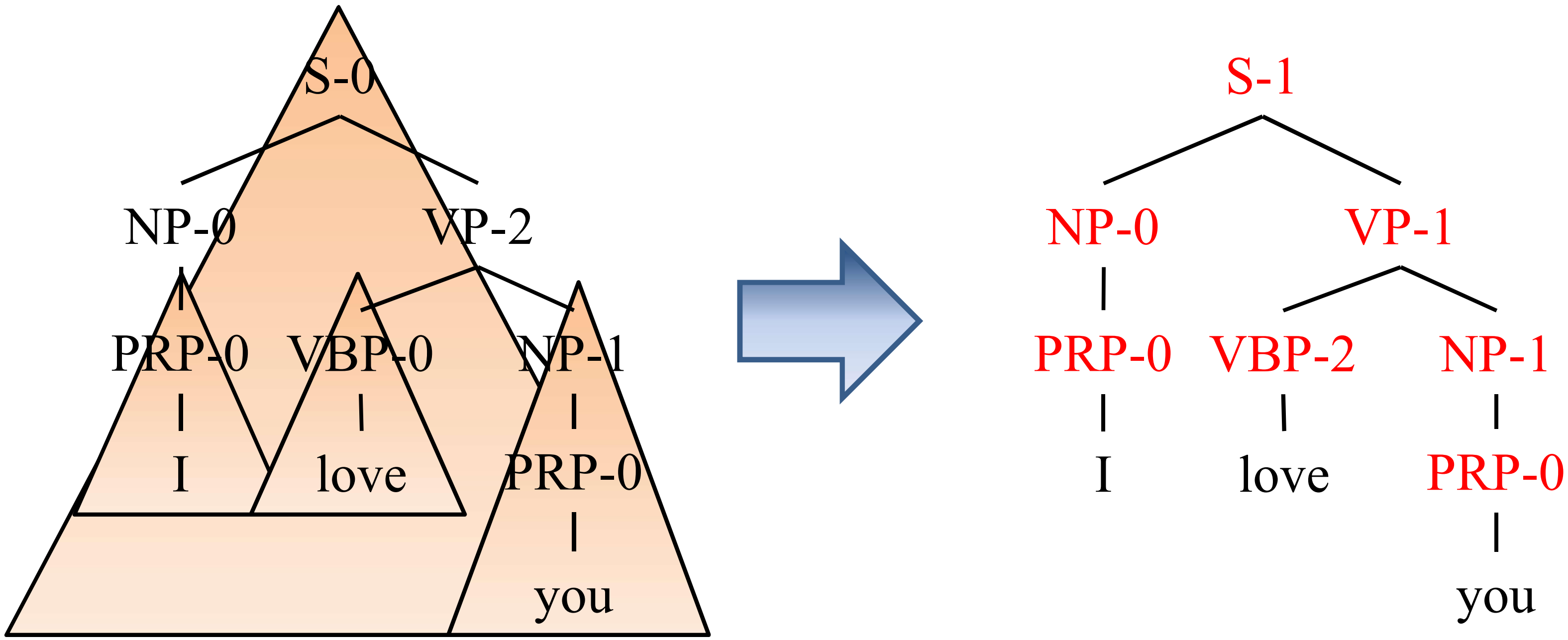
c) Run restaurant sampler

a) Sentence Sampler

- Metropolis-Hastings (MH) algorithm [Johnson et al. 07]

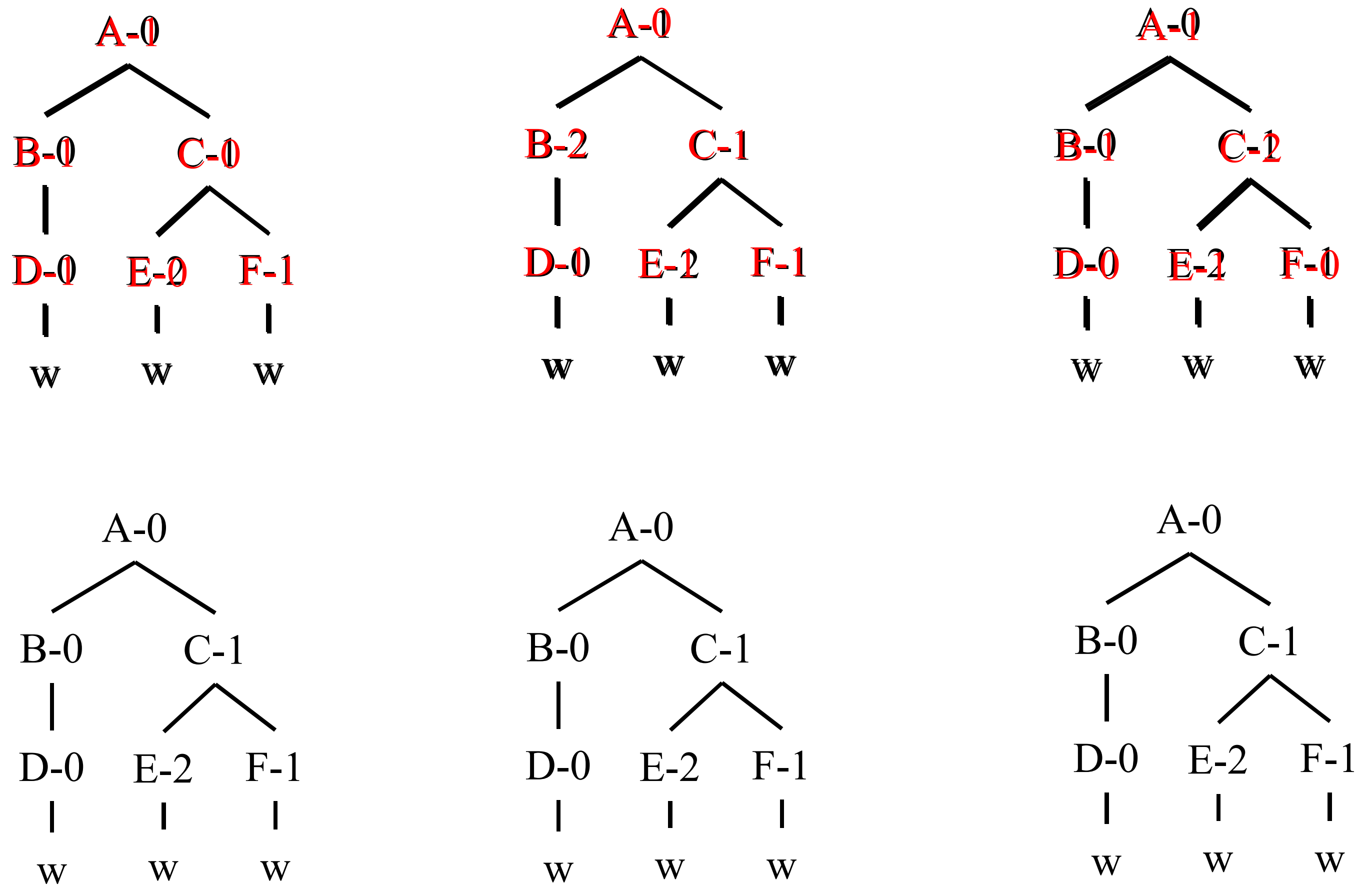
For each sentence...

1. Run inside algorithm
2. Sample a derivation
3. Accept or reject the sample



a) Sentence Sampler

- Update a sentence at a time



b) Subtree Sampler

- Update the same type of subtree simultaneously

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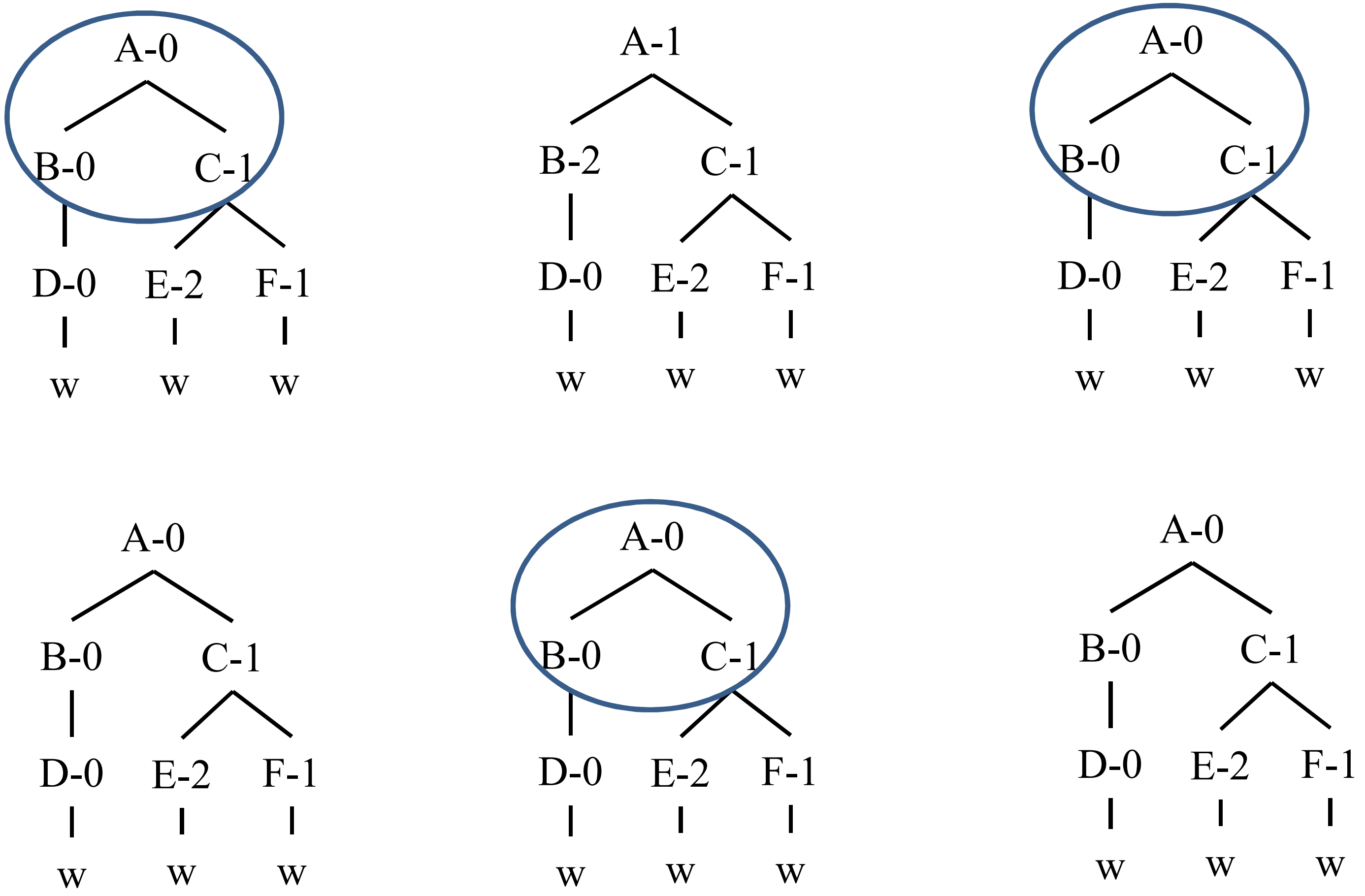

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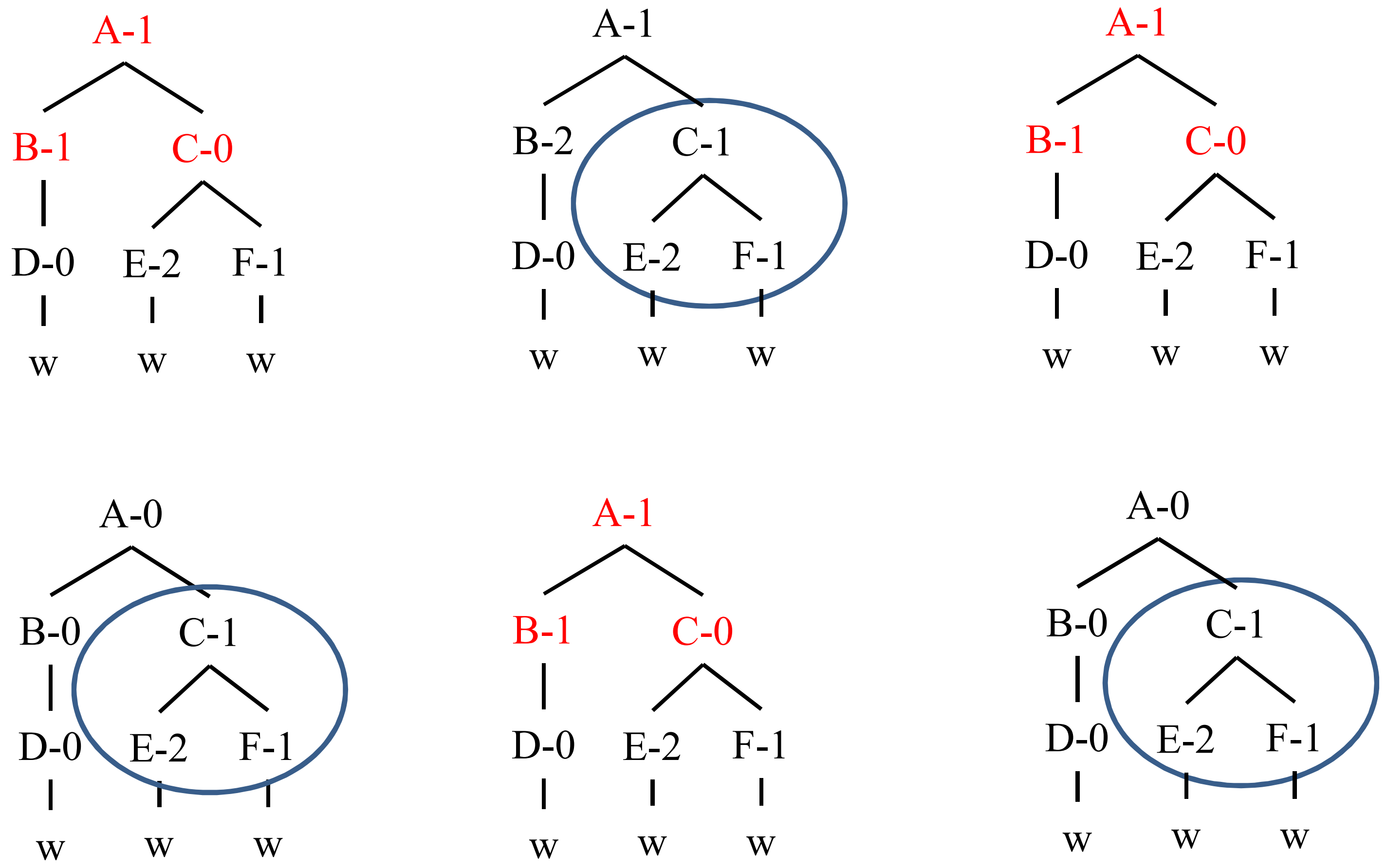

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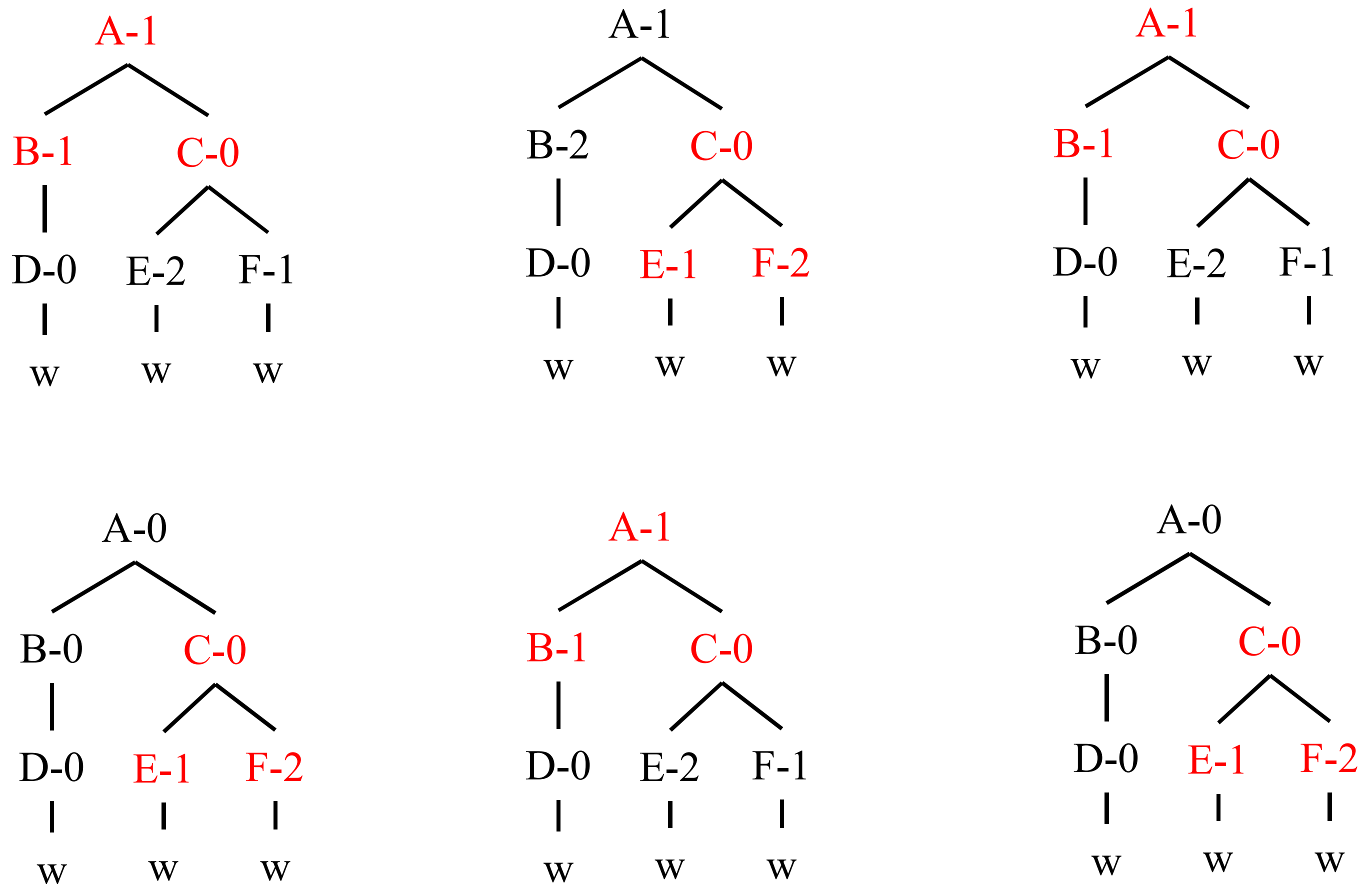

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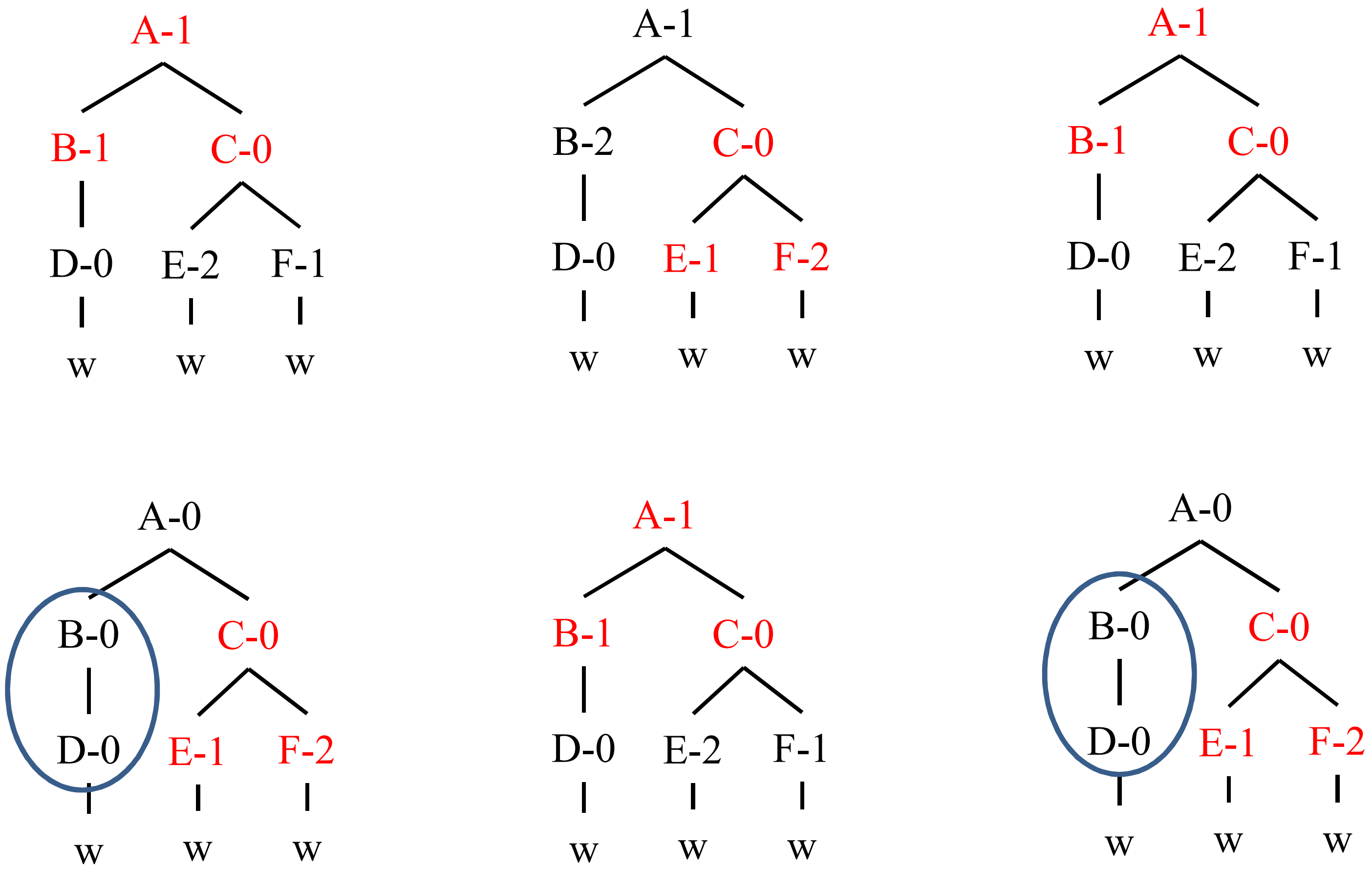

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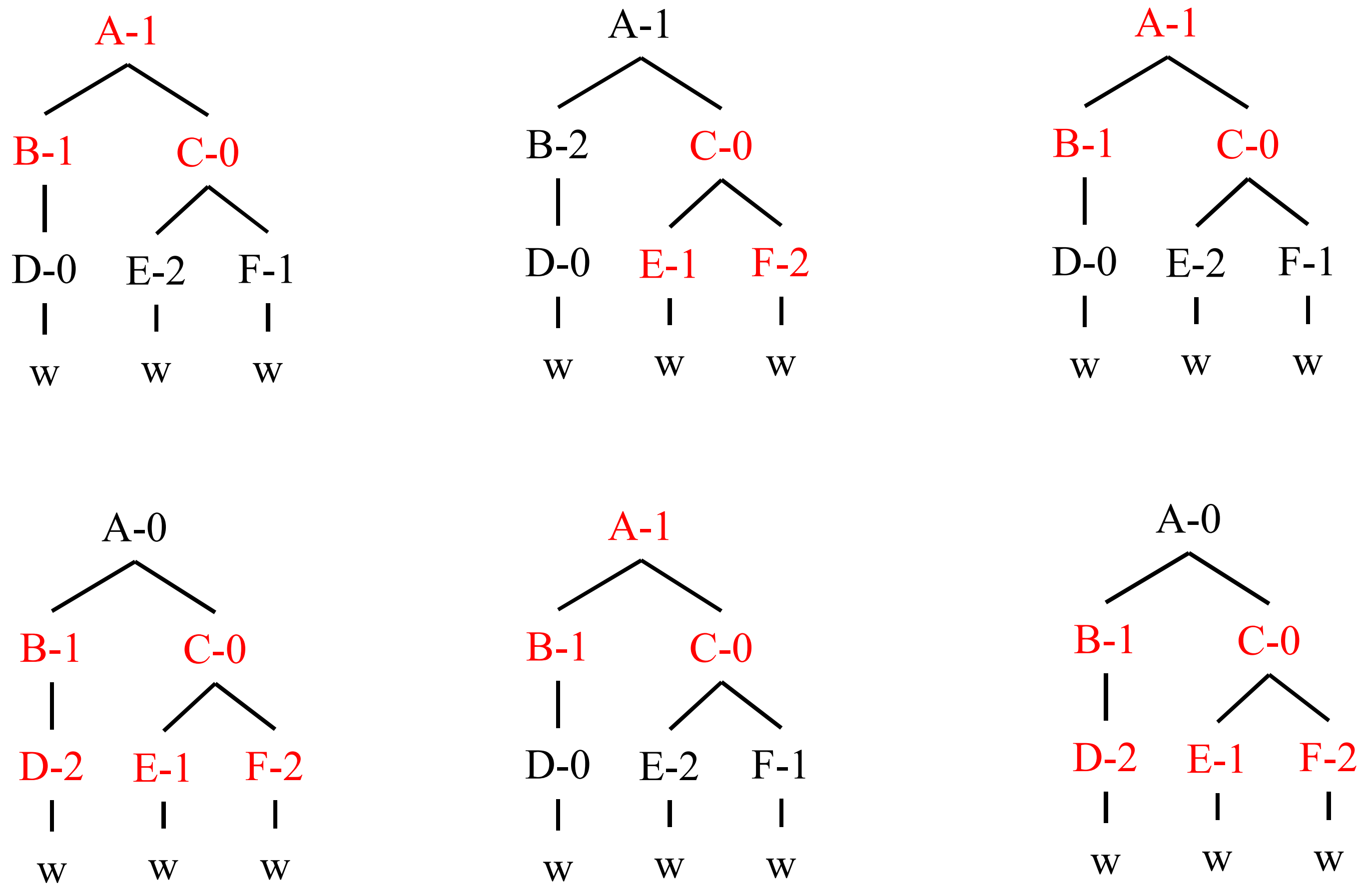
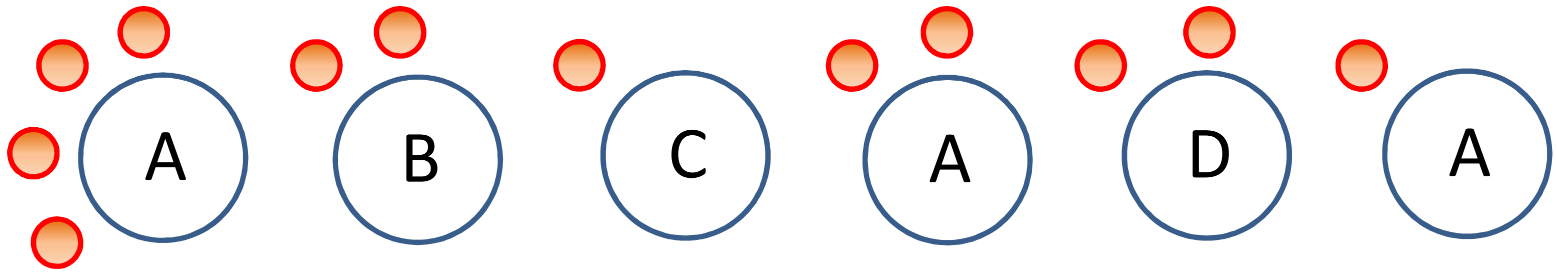


c) Restaurant Sampler

- Update # of tables

c) Restaurant Sampler

- Update # of tables



For each table label ...

- Keep count

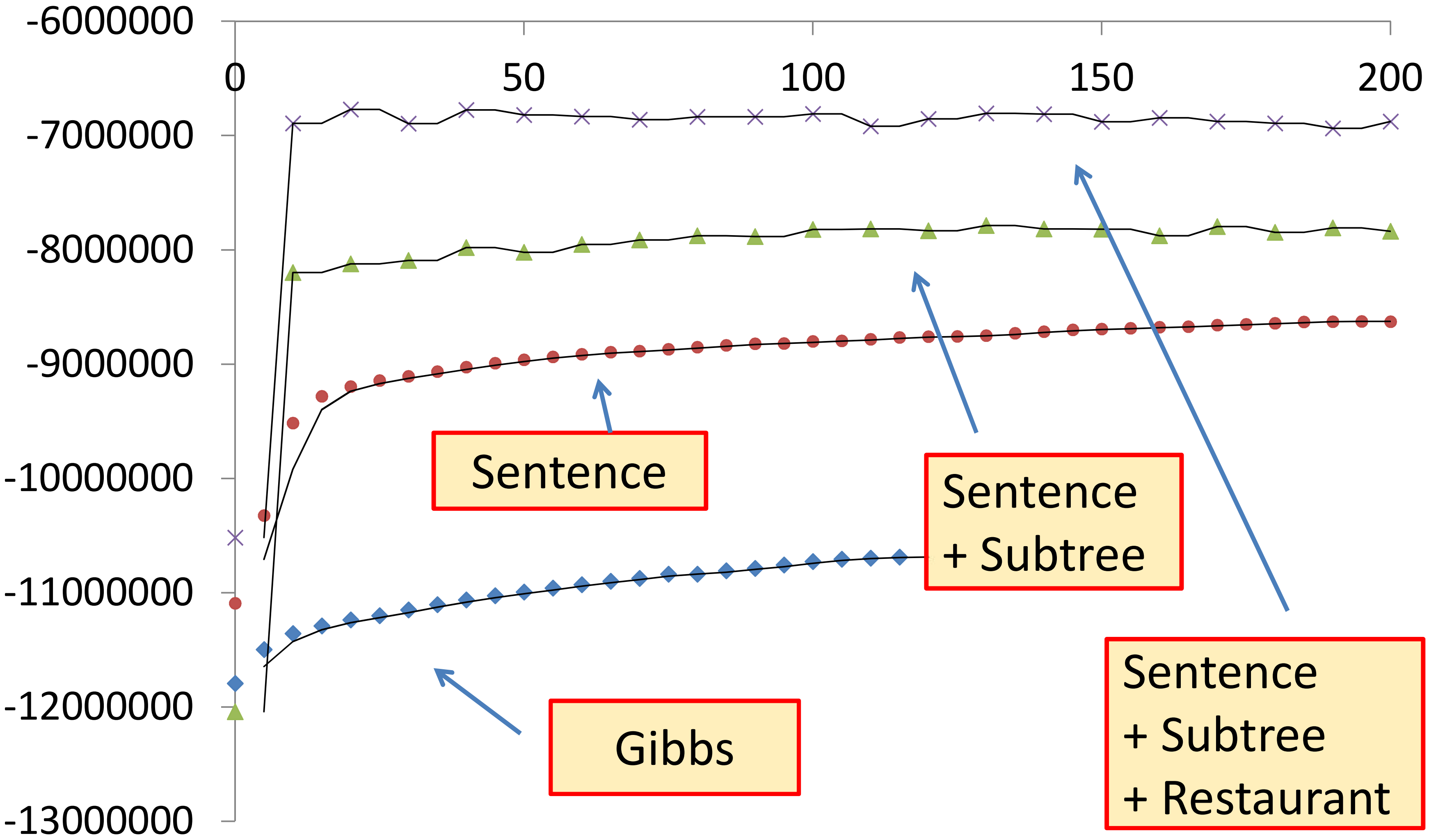
count = 6

- Remove all

- Add one by one

Helpful for optimizing # of tables

Effect of MCMC Samplers



Summary of Inference

- MCMC sampling

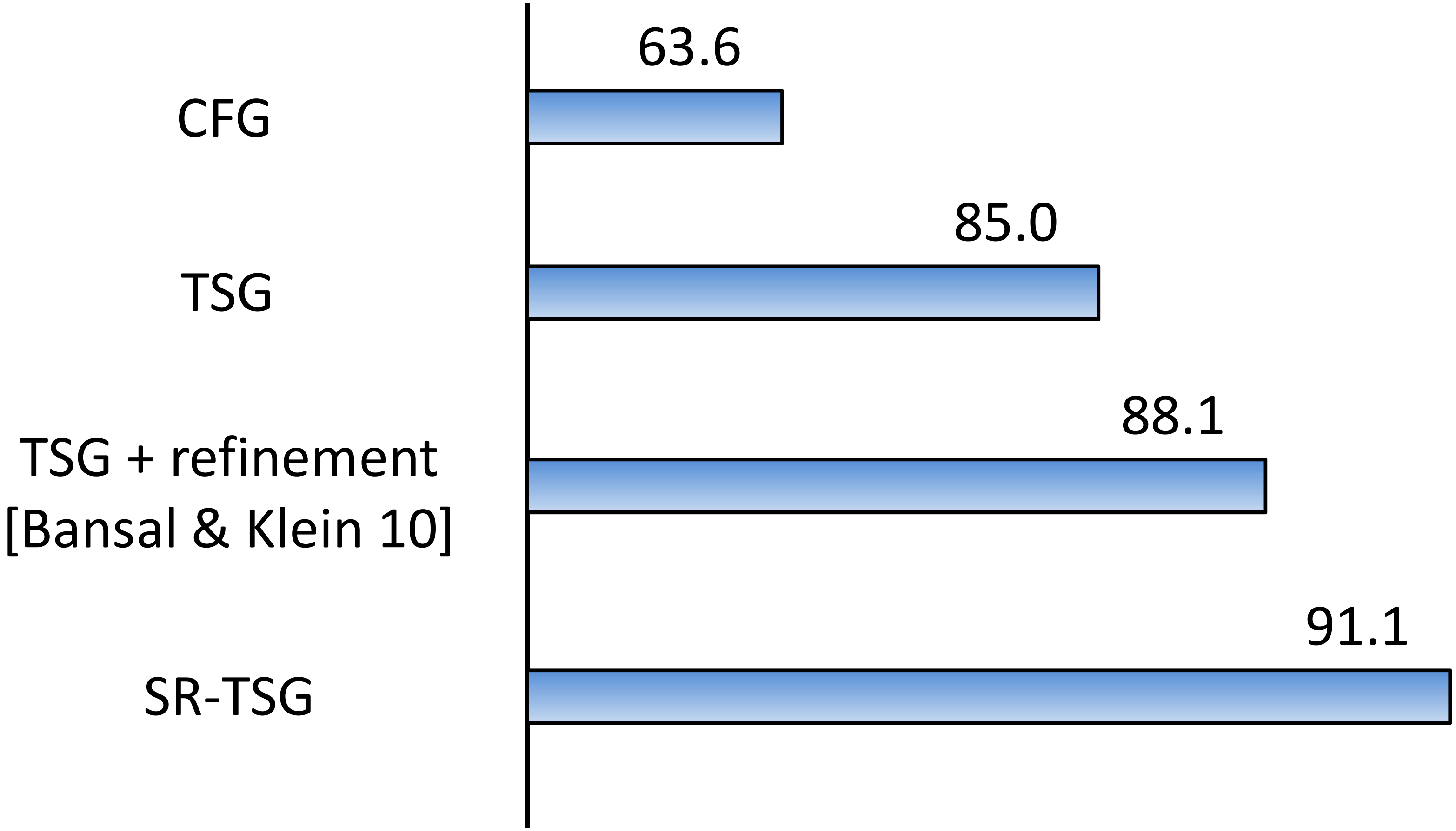
- Stepwise training for the induction of latent variables

- 3 types of blocked samplers

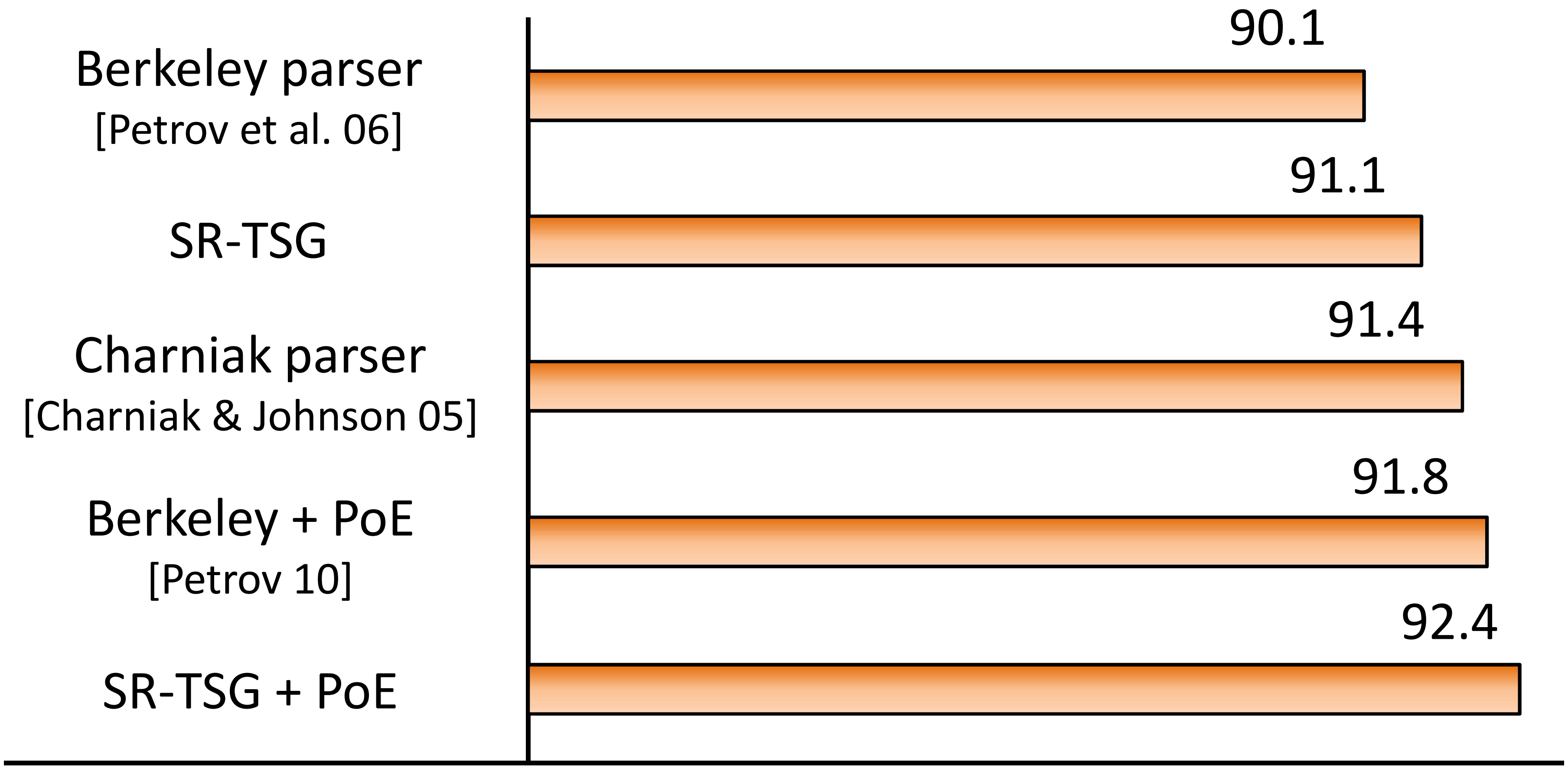
    - Effective for finding better solution

Experiment

Parsing Accuracy



Final Result



- System combination [Zhang et al. 09]
- Self-training [Huang et al. 10]

are better than SR-TSG.

Conclusion

Approach:

SR-TSG = TSG + symbol refinement

- Fully automatic learning

Probabilistic Model:

Pitman-Yor process + 3-level hierarchy

Inference:

3 types of MCMC samplers for efficient training

Result:

State-of-the-art

Thank you.

Internal Subcategory Marginalization

- Encourage the model to find large tree fragments