# Monte Carlo MCMC
## Efficient Inference by Approximate Sampling

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# Overview

- MCMC is a popular choice for inference in NLP
  - But is often slow in practice
- Existing work has focused on:
  - Modifying the model for faster sampling
  - Generating multiple samples simultaneously
  - Improving quality of each sample
- Instead, we generate “approximate samples”
  - But each sample is much faster
- Results in up to 13 times speedup!

# Background

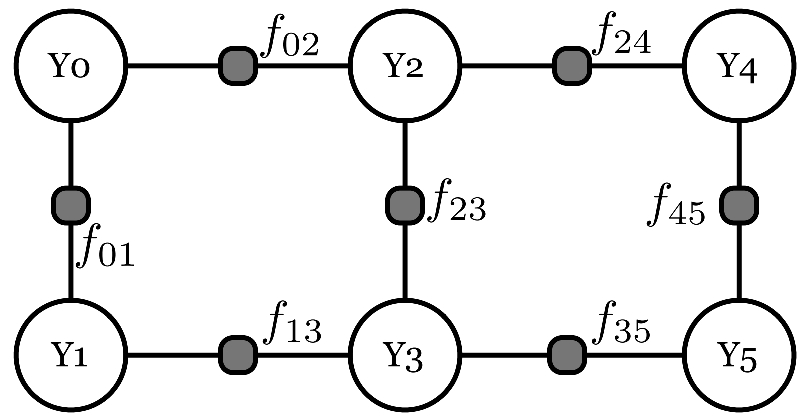
# Graphical Models

- Factor Graphs
- Variables **Y**
- Factors **F**
- Score of a configuration:

$$\psi(\mathbf{Y}{=}\mathbf{y}) = \sum_{f \in \mathbf{F}} f(\mathbf{y}_f)$$

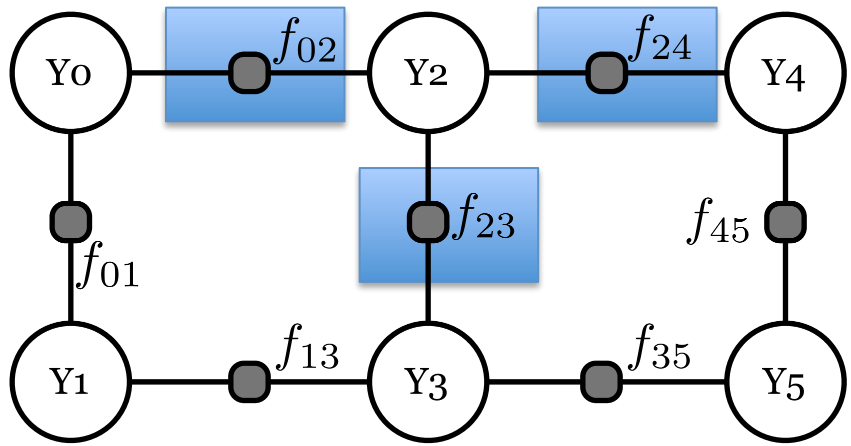
- Probability:

$$p(\mathbf{Y}{=}\mathbf{y}) = \frac{1}{Z} \exp \psi(\mathbf{y})$$



# Markov Chain Monte Carlo

1. Current Sample, **y**
2. Propose a move: **y** → **y'**
3. Accept with Probability α




$$\alpha(\mathbf{y},\mathbf{y'}) = \frac{p(\mathbf{y'})}{p(\mathbf{y})}$$

$$= \exp\ \psi(\mathbf{y'}) - \psi(\mathbf{y})$$

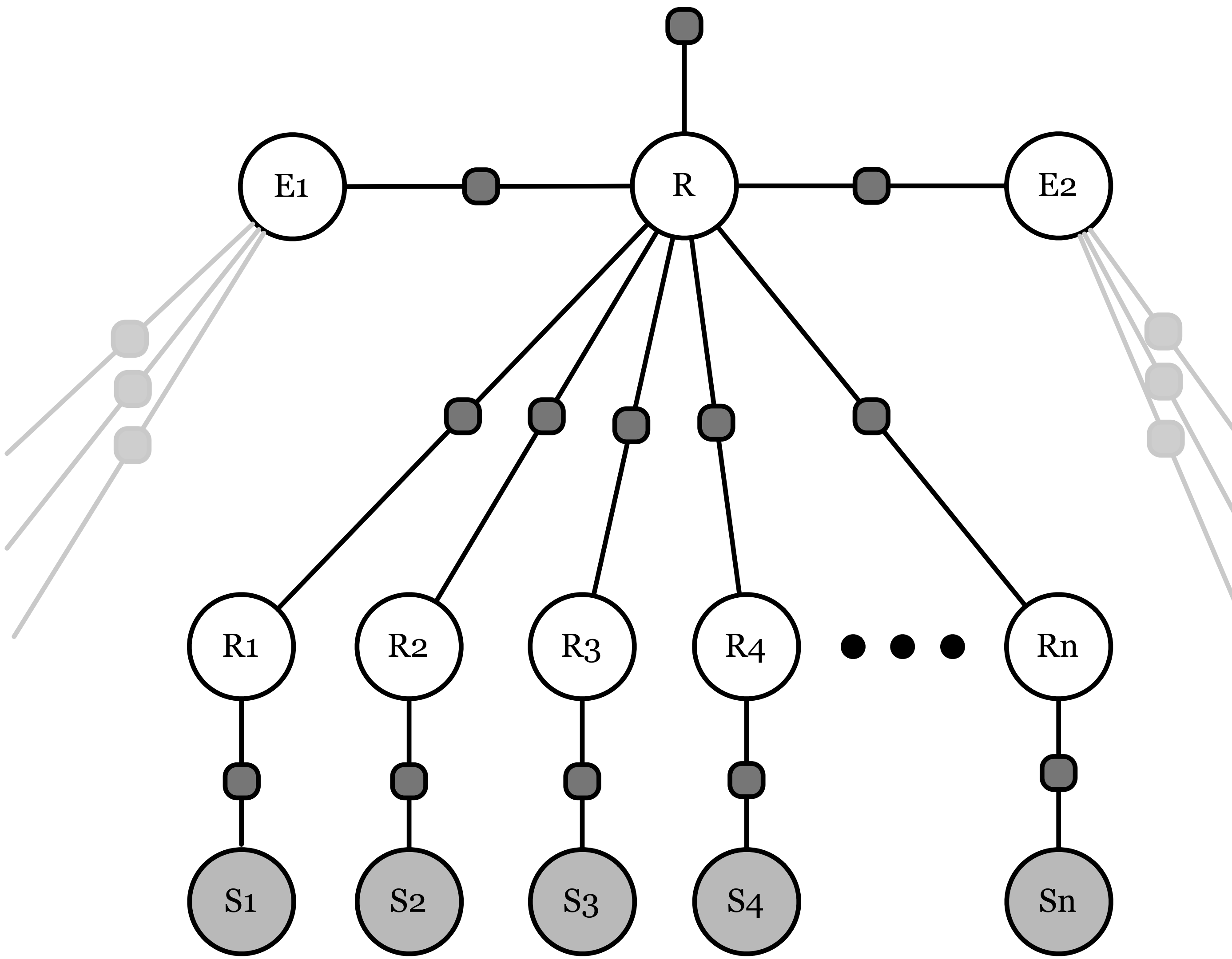
$$= \exp\ \psi(\mathbf{y'}/\mathbf{y}) - \psi(\mathbf{y}/\mathbf{y'})$$

4. Current sample ← **y'**

# Markov Chain Monte Carlo

- **Pros**: Low memory requirement, etc.
- Generating a sample is often fast
  – Depends only on factors involved in a proposal
- Unfortunately, sometimes this is a bottleneck
  1. If a variable neighbors many factors
  2. A proposal changes many variables
  3. Scoring a factor is slow (expensive features)

# Example: Relation Extraction



# Monte Carlo MCMC

# Approximating Sampling

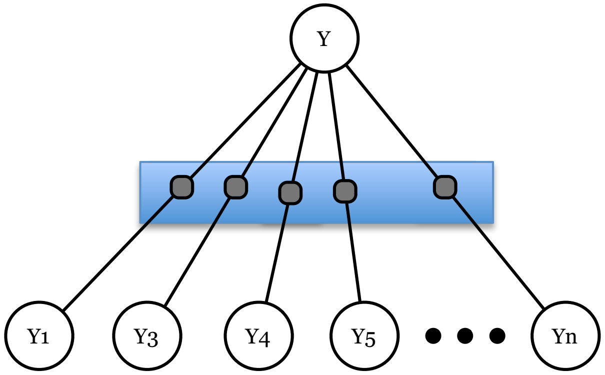
- Acceptance ratio involves partial model scores

$$\alpha(\mathbf{y},\mathbf{y}') = \exp\ \psi(\mathbf{y}'/\mathbf{y}) - \psi(\mathbf{y}/\mathbf{y}')$$

$$\psi(\mathbf{y}/\mathbf{y}') = \sum_{f\in\mathbf{F}'} f(\mathbf{y}) = |\mathbf{F}'|\mathbb{E}_{\mathbf{F}'} f(\mathbf{y})$$

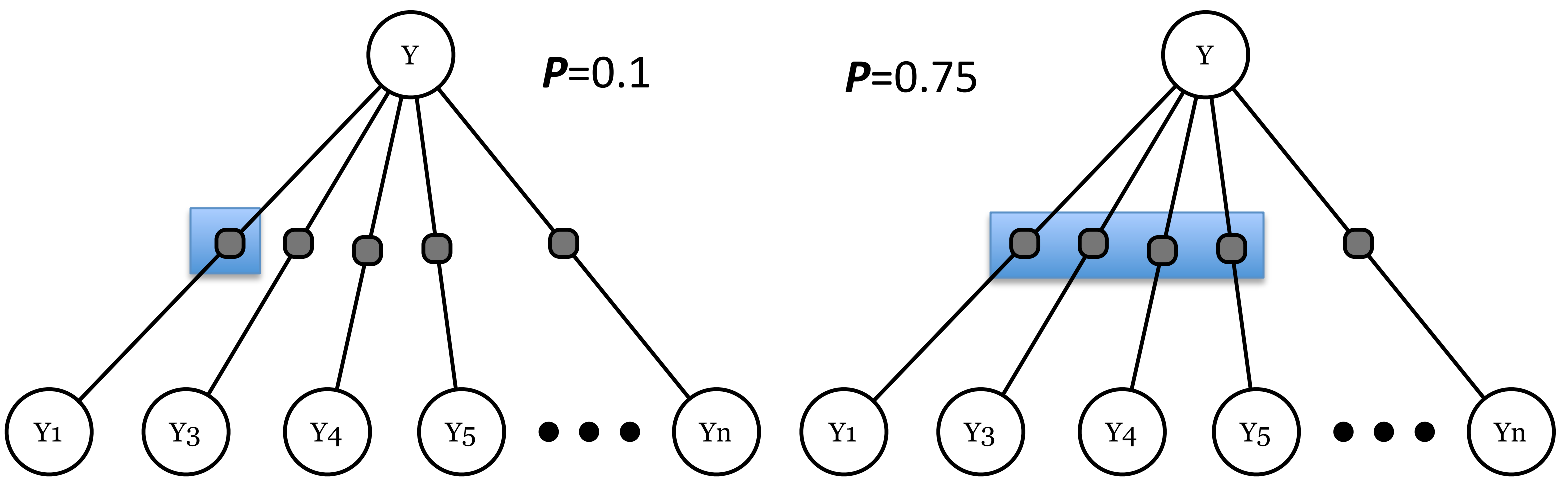
- Estimate the scores by sub-sampling the factors:

$$\mathbf{S} \subseteq \mathbf{F}';\ \psi_{\mathbf{S}}(\mathbf{y}/\mathbf{y}') = |\mathbf{F}'|\mathbb{E}_{\mathbf{S}} f(\mathbf{y})$$



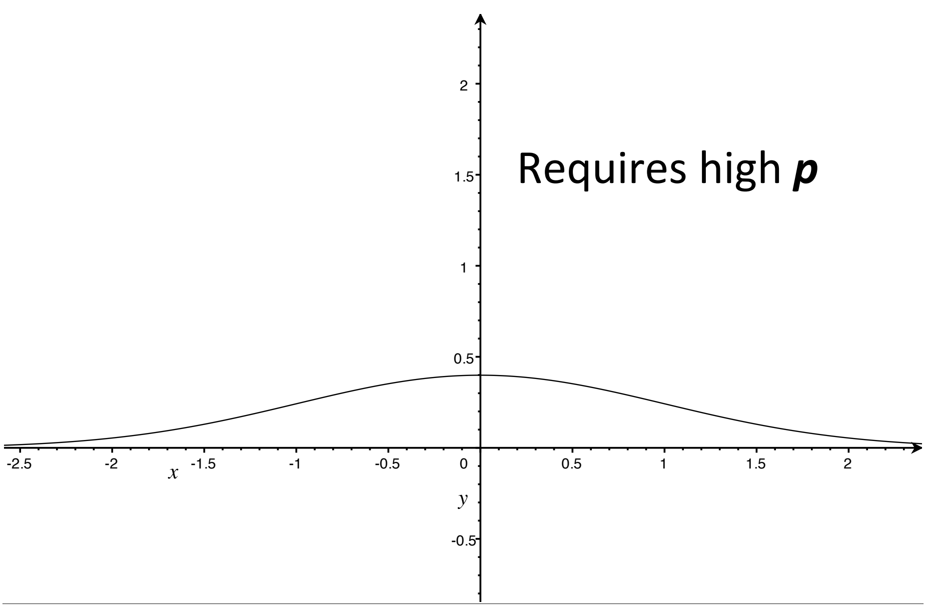
# Uniform Sampling

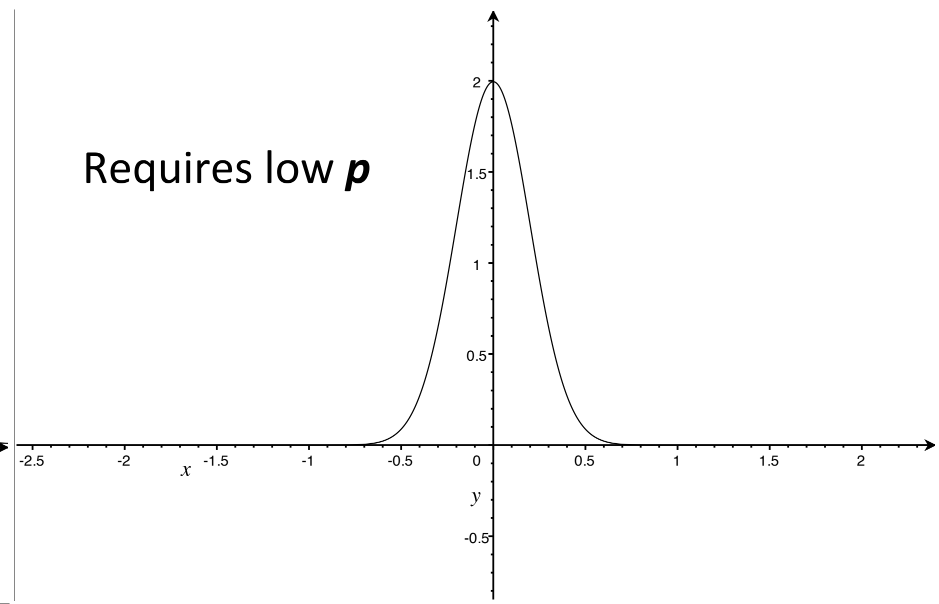
- Pick the subset **S** uniformly
  - Proportion of factors to pick is ***p***
- Scoring is ***1/p*** times faster
  - But with lower ***p***, more samples are needed



# Limitations of Uniform Sampling

- Performance is sensitive to parameter ***p***
  - Which has to be manually specified
- Different proposals may prefer different ***p***'s
  - Depends on the variance of the factor scores

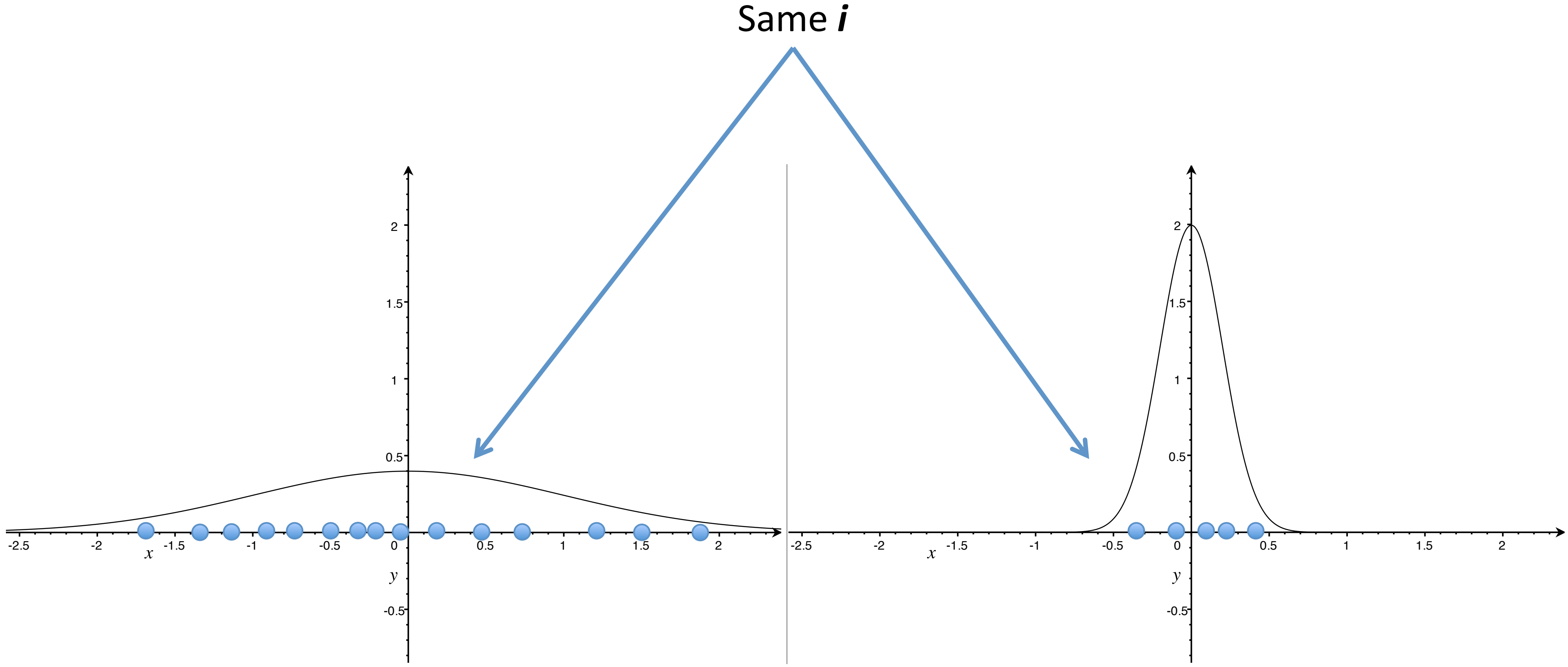


# Confidence-Based Stopping

- Sample uniformly as before
  - Compute 95% confidence interval around mean
- We want to sample till reasonably confident
  - If, width of interval < ***i***, stop.
  - Else, continue sampling
- Need to include finite population control (fpc)
  - Since ***S*** is a substantial subset of ***F'***

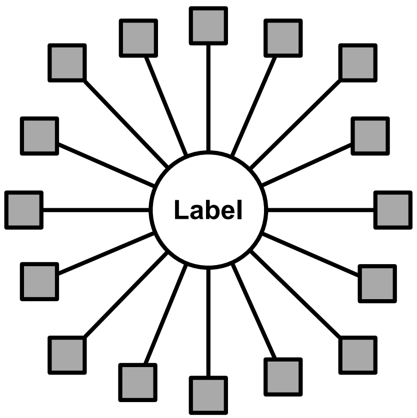
# Confidence-Based Stopping

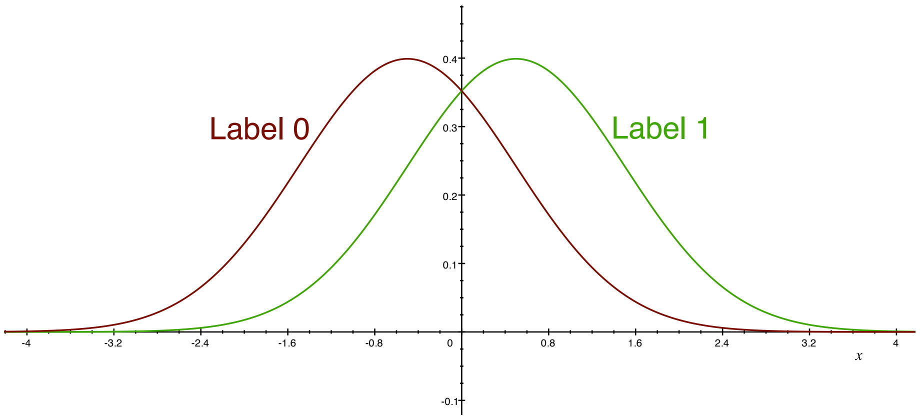


# Experiments

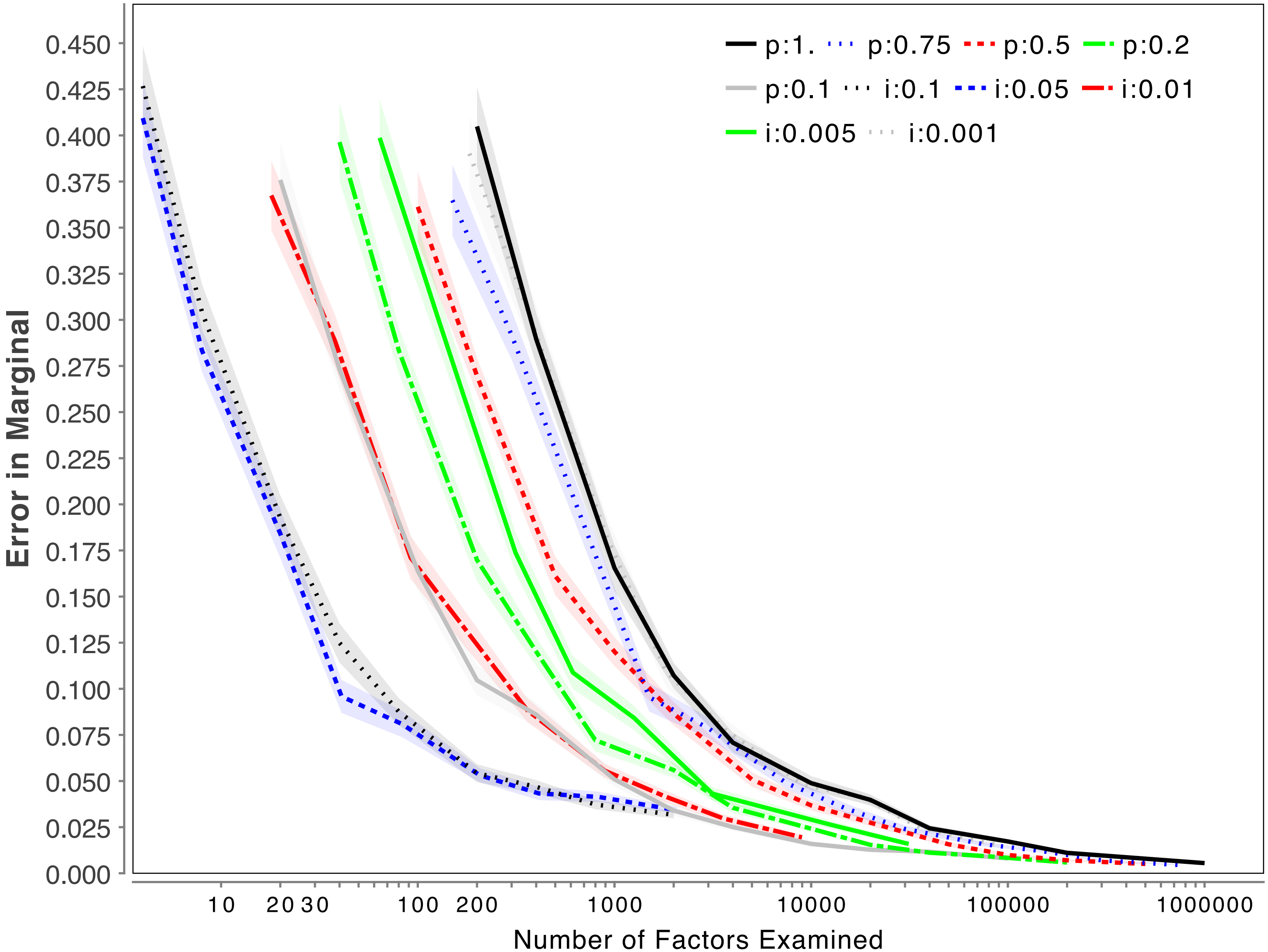
# Synthetic Data

- Binary Classification Model
  - 100 factors
- Generate Samples
  - Compute marginals from them
  - Compare error to exact
- Similar operation as Gibbs
  - Ignore Burn-in and Thinning



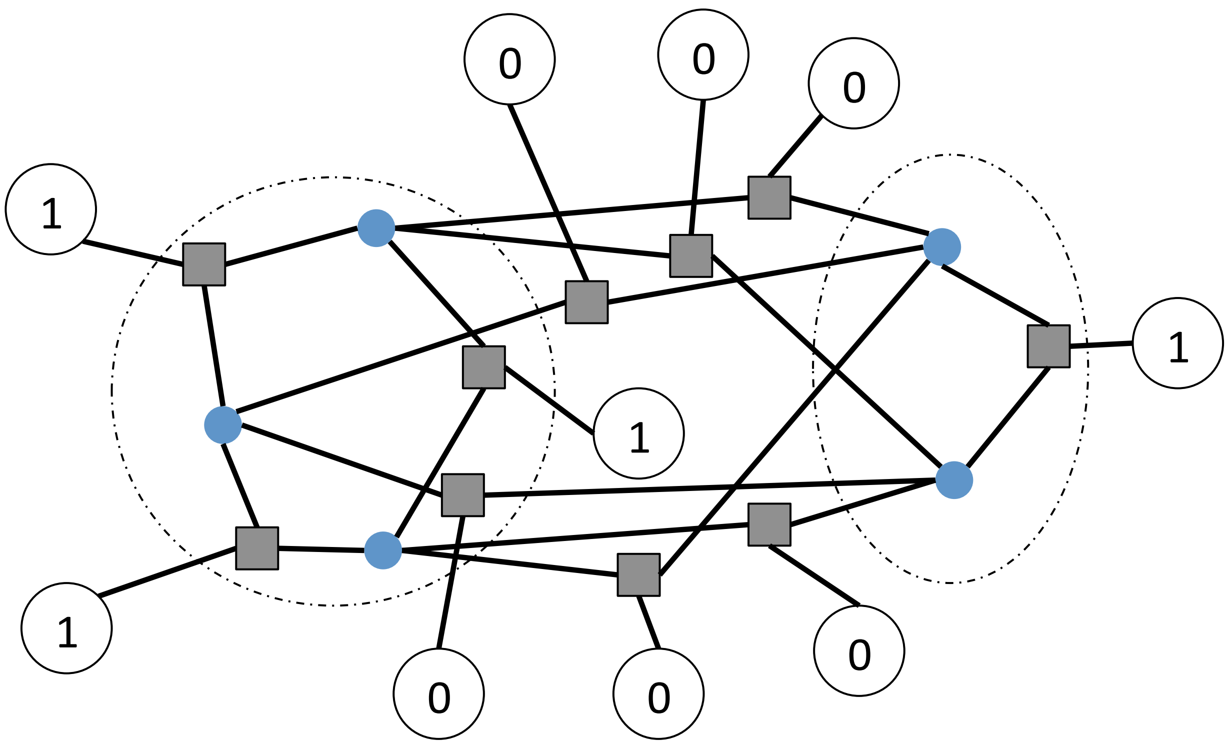



# Synthetic Data



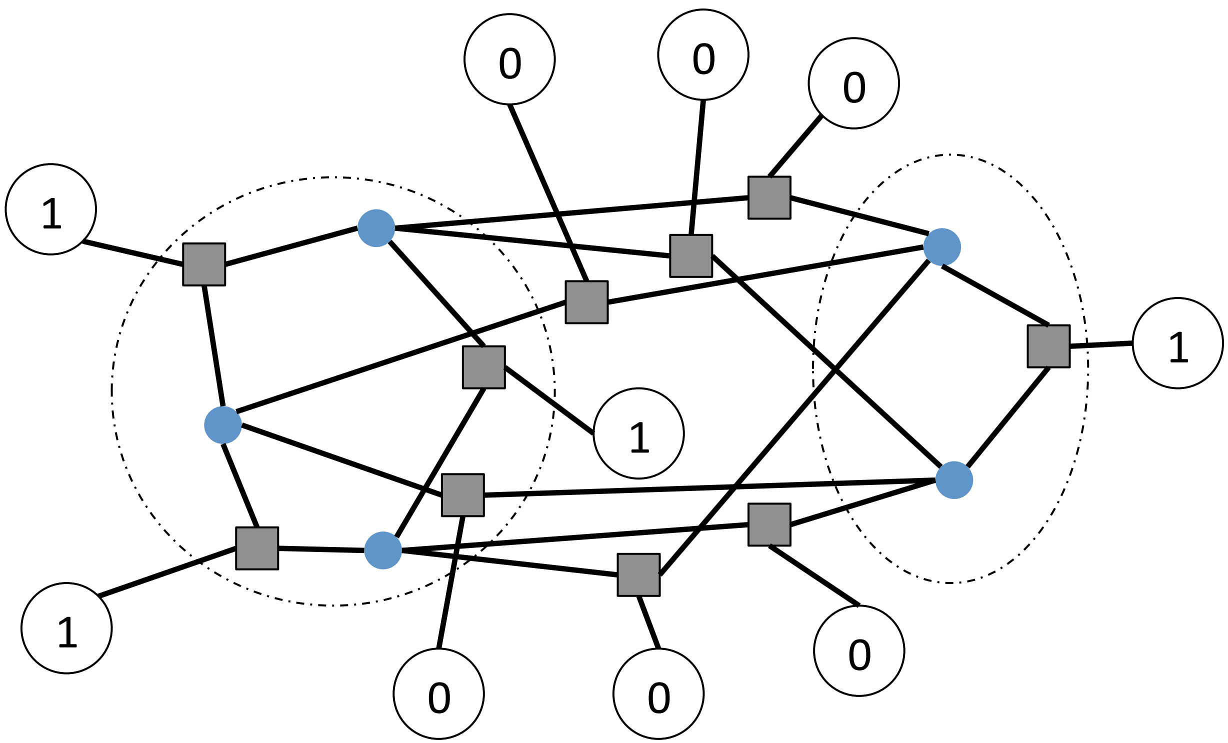
# Entity Resolution Model

- Or Clustering…
- Used for Entity Disambiguation, Coreference Resolution, Record De-duplication, etc.



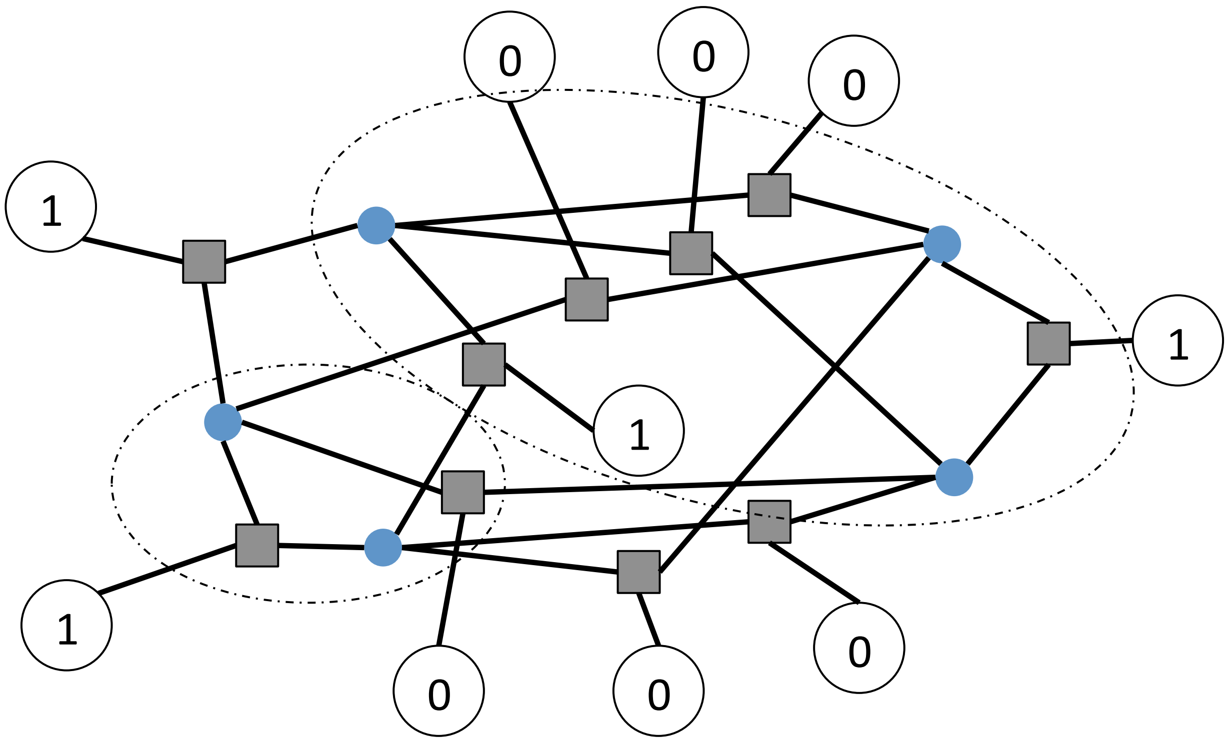
# MCMC for Entity Resolution

- Initialize to any valid configuration



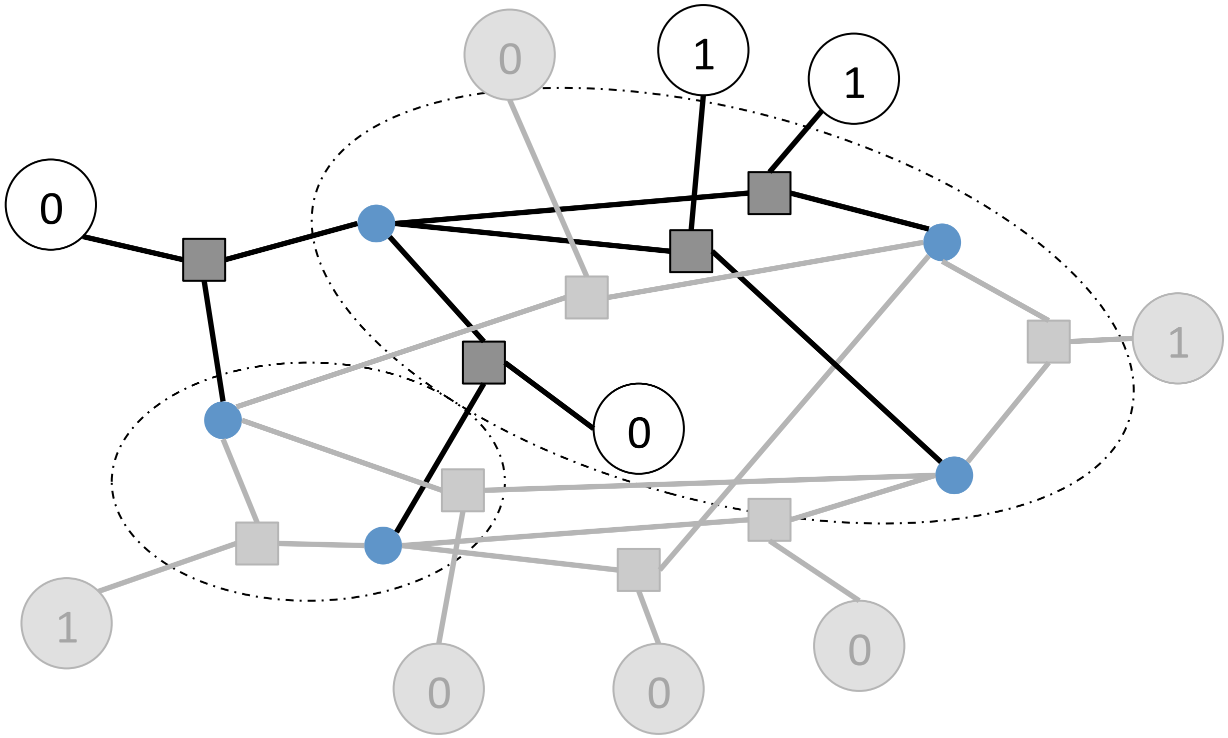
# MCMC for Entity Resolution

- Proposal moves a single data point..



# MCMC for Entity Resolution

- Score factors that neighbor the moved point
  - And the points in the old and new clusters



# MCMC for Entity Resolution

- Pros:
  - Allows us to enforce transitivity implicitly
  - May not compare all pairs of points
  - Scoring a proposal is linear in cluster size
- Cons:
  - Scoring a proposal is linear in cluster size!!!

  (Fortunately, points in a cluster are redundant)

# Cora Citation Matching

- 1295 citation strings that refer to 134 papers

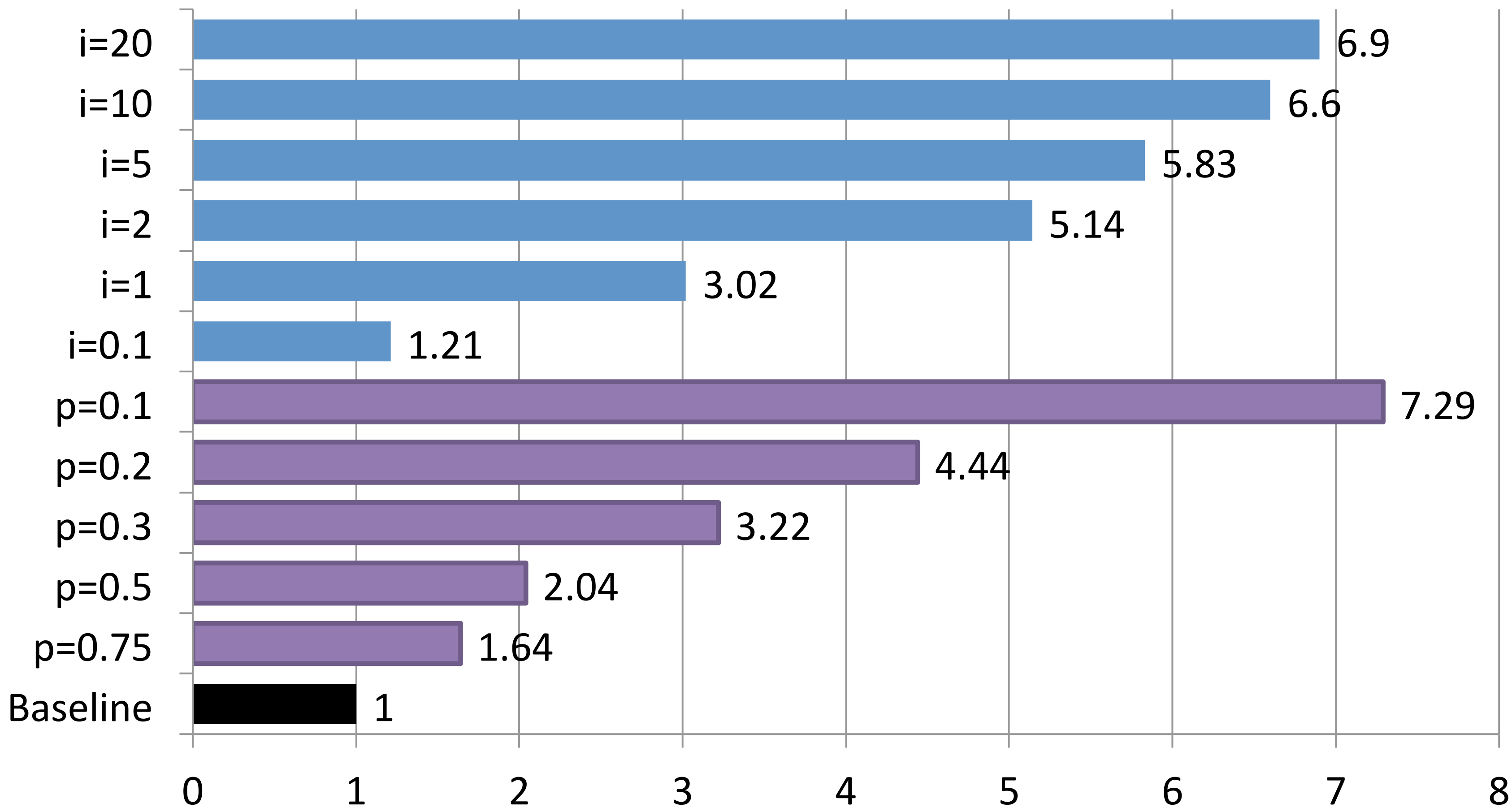
Yoav Freund, H. Sebastian Seung, Eli Shamir, Naftali Tishby. Information, prediction, and query by committee, NIPS92, p. 1993 483-490

Y. freund, H.S seung, E. shamir, and N. tishby. Accelerating learning using query by Committee. Proceedings of the 1992 conf. on neural informations processing systems (to appear), 1993

< 10 citations per paper on average

- Use features based on similarity of fields
  – Author, Title and Venue

# Speedup to obtain 90% $B^3$



# Large-Scale Author Coreference

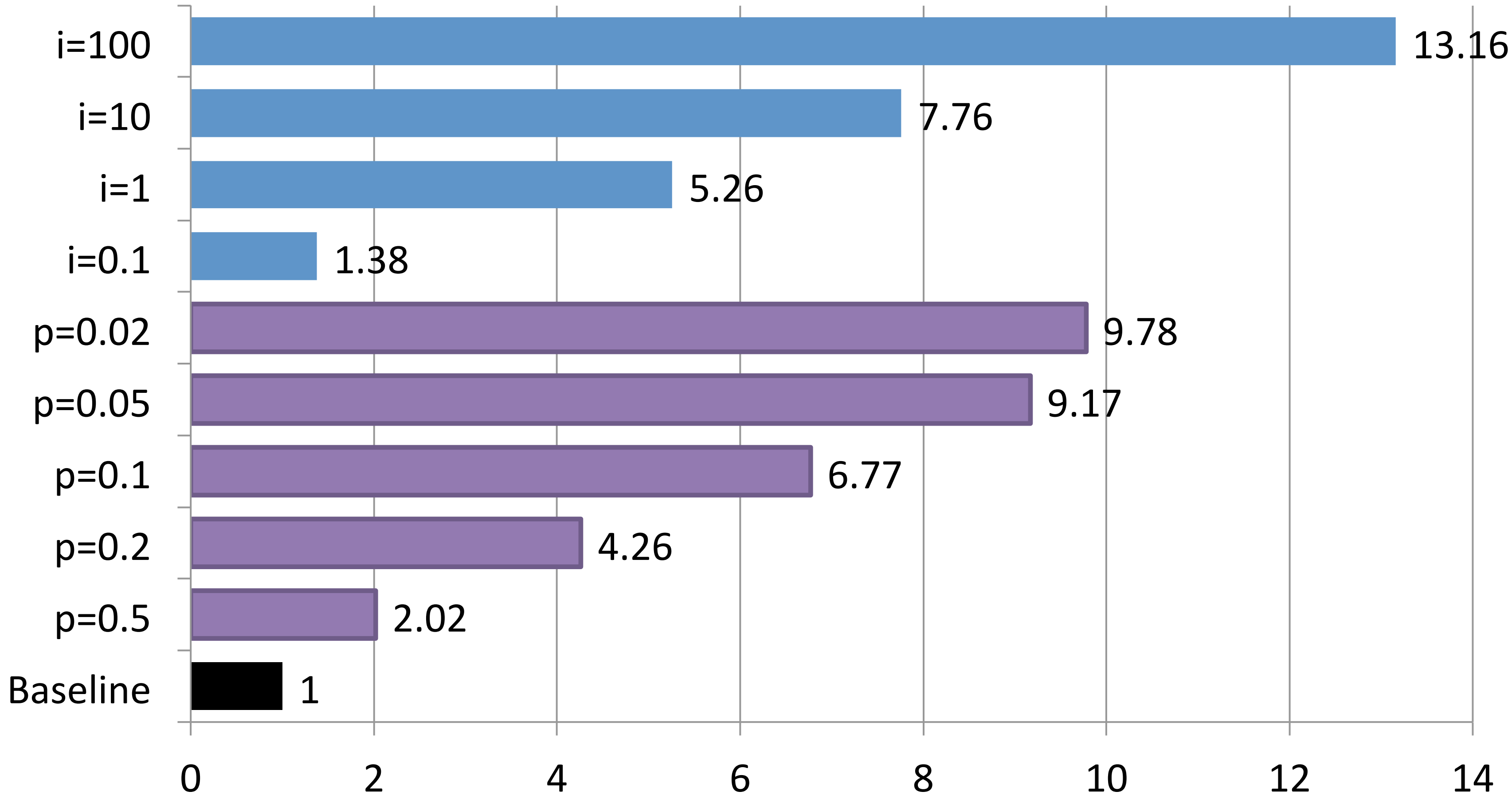
- 5 million authors from DBLP BibTex entries

*@techreport*{
author= S. Palacharia, N.P.Jouppi, **J.E.Smith**,
title= Quantifying the complexity of superscalar processors
institution= University of Wisconsin, year=1996}

@inproceedings{
author= Aggarwal, Ranganathan, Jouppi, and **Smith**,
title= Building High Availability Systems with Commodity Processors,
booktitle=Int. Symposium on Computer Architecture, year=2007}

- Include 2,833 **labeled** mentions from Rexa
- Use BibTex context as the features
  - First/last names, title BOW, title topics, coauthors

# Speedup to obtain 80% $B^3$



# Limitations and Future Work

1. Is fairly naïve about factor selection
   – Assumes factors are distributed normally
   – Does not (re)use factor scores
   – **Future**: Score-aware factor selection
2. Theoretical Issues
   – Unwanted bias in the samples, introduces error
   – **Future**: Reweight samples to remove the bias
3. Dynamic Threshold
   – *Ideal* threshold may depend on the state of inference
   – **Future**: Reduce approximation as inference proceeds
4. Evaluate on more tasks

# Summary

- Examined scenarios where MCMC is slow
- Proposed stochastic evaluation of samples
  - Uniform Sampling
  - Confidence-Based Sampling
- Demonstrated significant speedups
  - For marginal inference on synthetic data
  - Up to 13x speedup on large-scale entity resolution
- Approach is general and easy to code

# Thanks!

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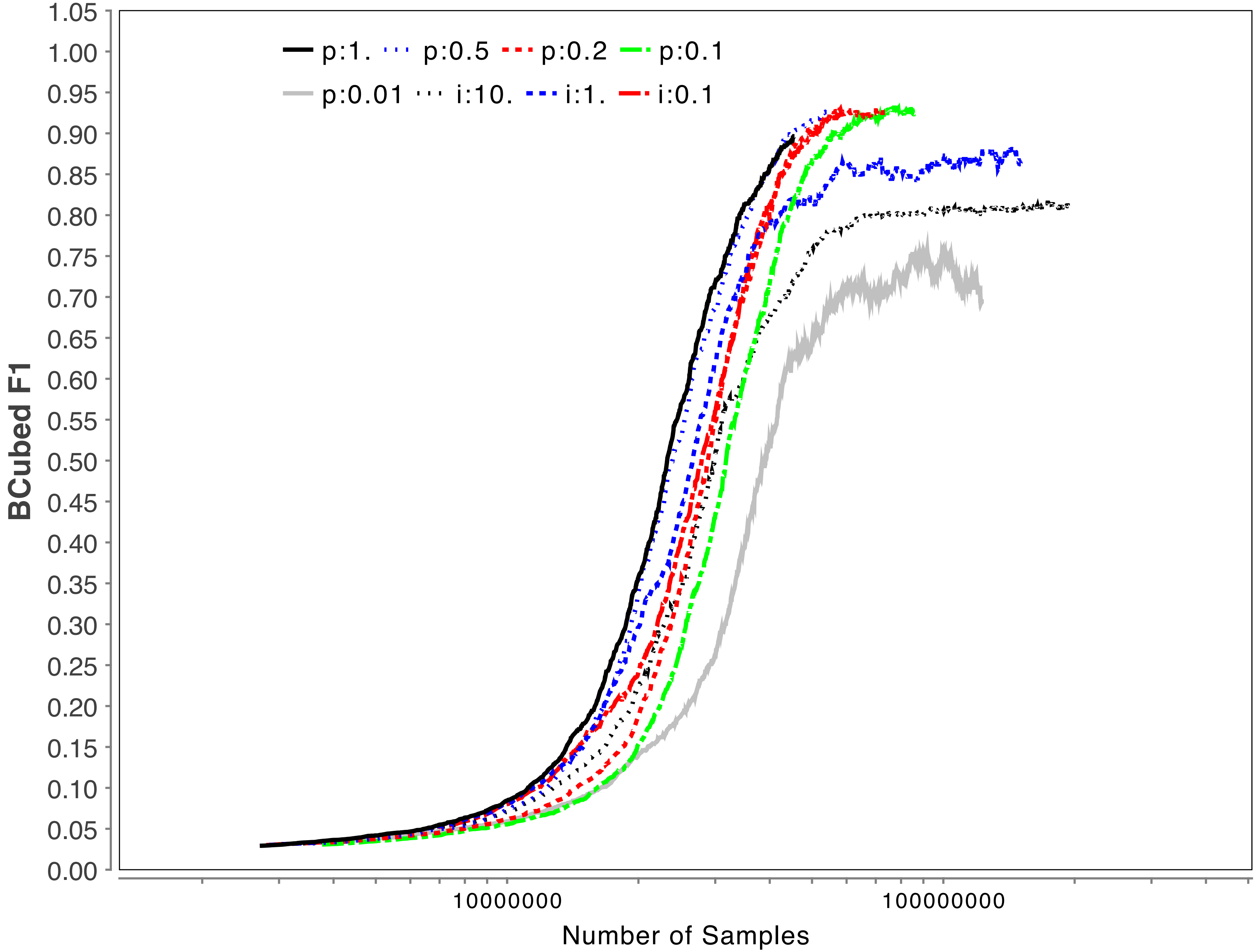
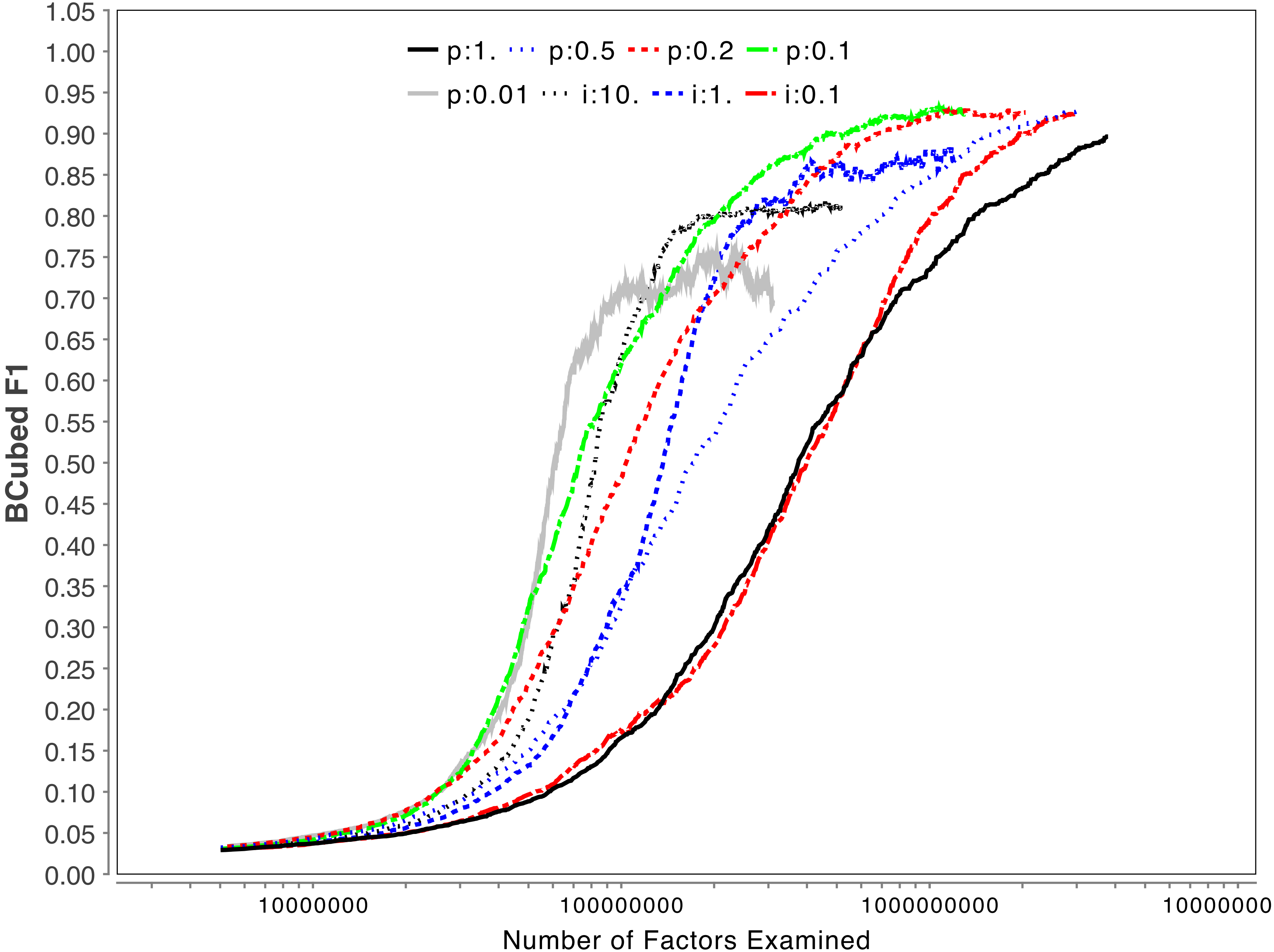
# Appendix



p:1.
p:0.5
p:0.2
p:0.1
p:0.01
i:10.
i:1.
i:0.1
BCubed F1
1.05
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
10000000
100000000
Number of Samples



p:1.
p:0.5
p:0.2
p:0.1
p:0.01
i:10.
i:1.
i:0.1
BCubed F1
1.05
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
0.60
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0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
10000000
100000000
1000000000
Number of Factors Examined