A Tutorial on

Graph-based Semi-Supervised Learning Algorithms for NLP

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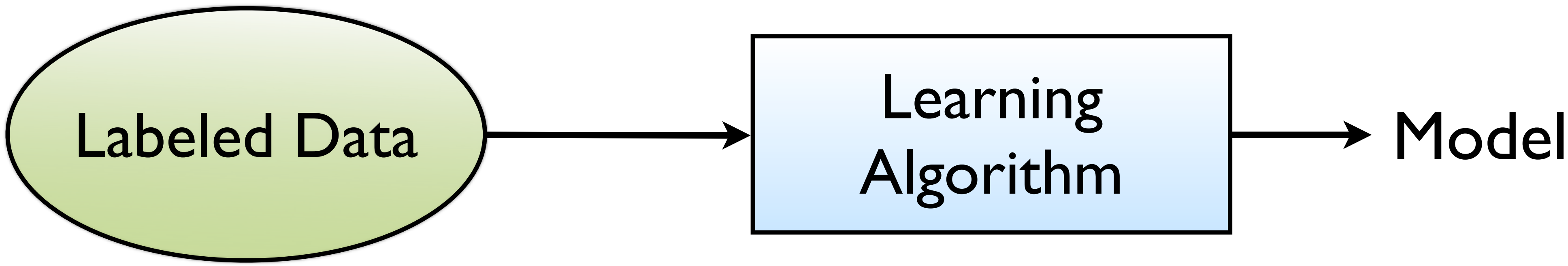
ACL 2012, South Korea

http://graph-ssl.wikidot.com/

Supervised Learning



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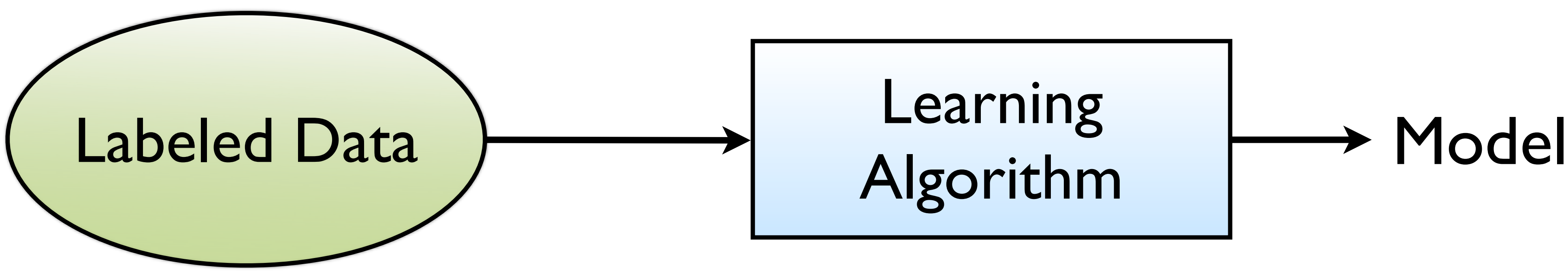


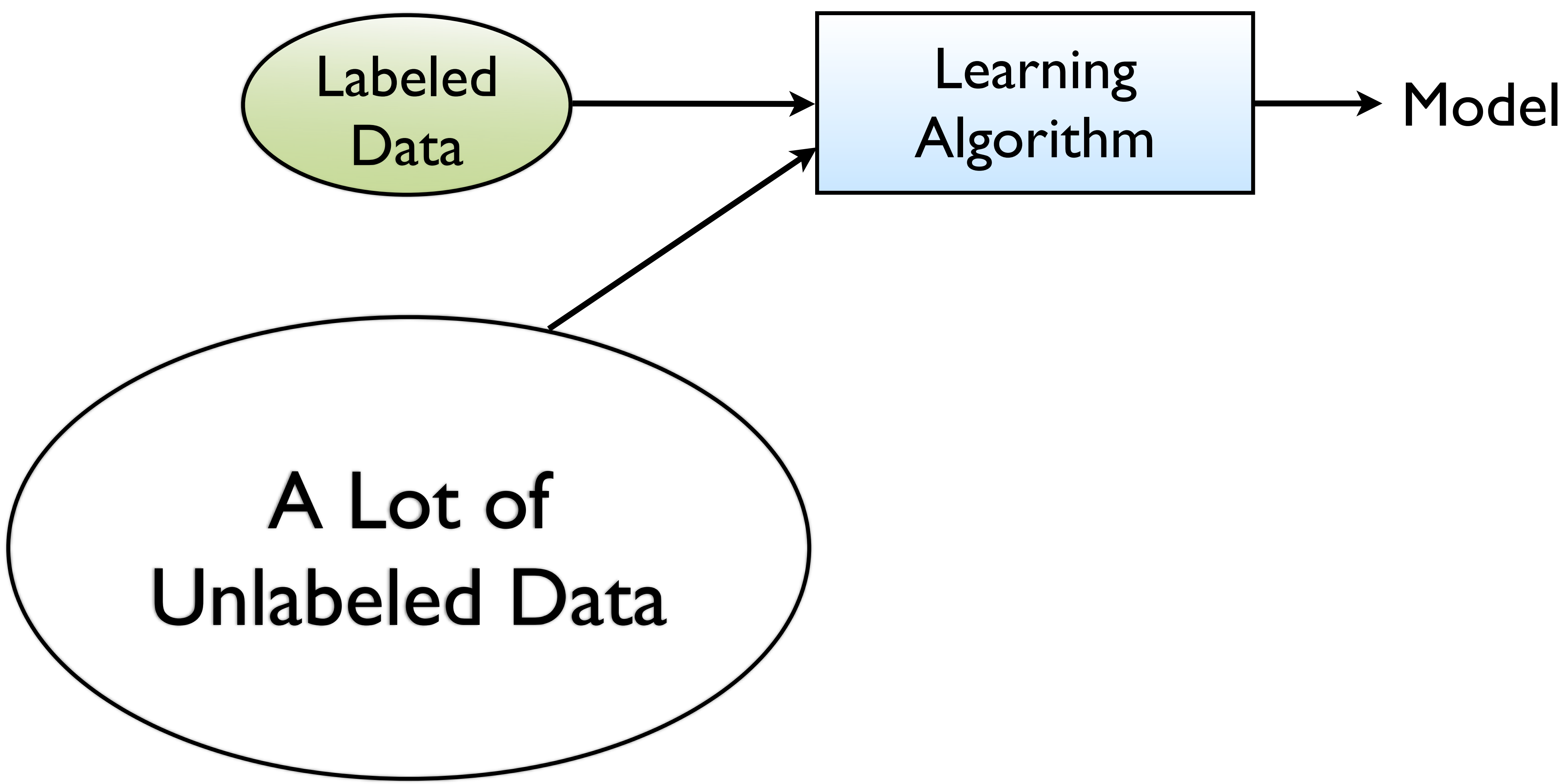
Examples:

Decision Trees

Support Vector Machine (SVM)

Maximum Entropy (MaxEnt)

Semi-Supervised Learning (SSL)



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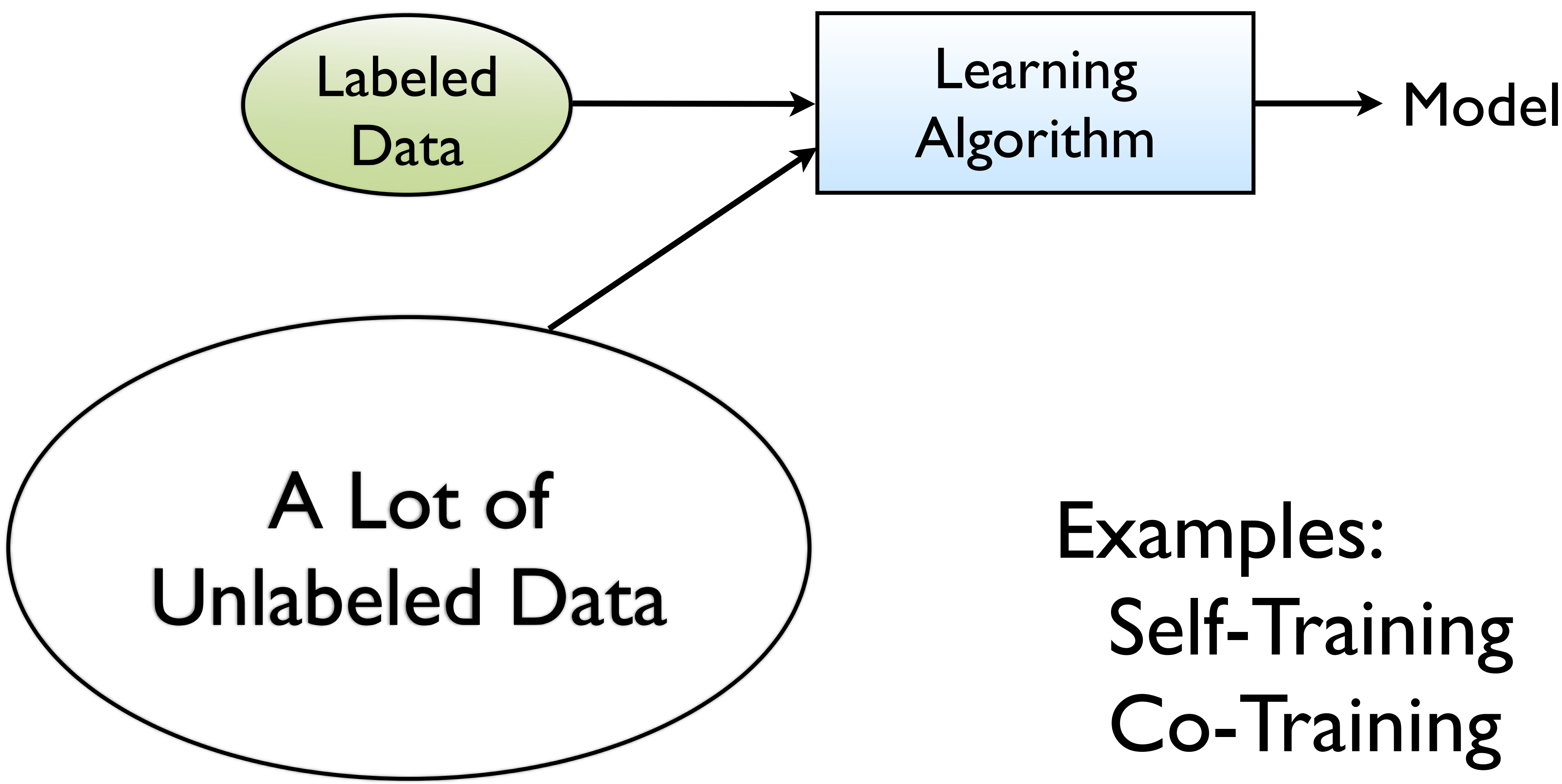

Examples:
- Self-Training
- Co-Training

Why SSL?

How can unlabeled data be helpful?

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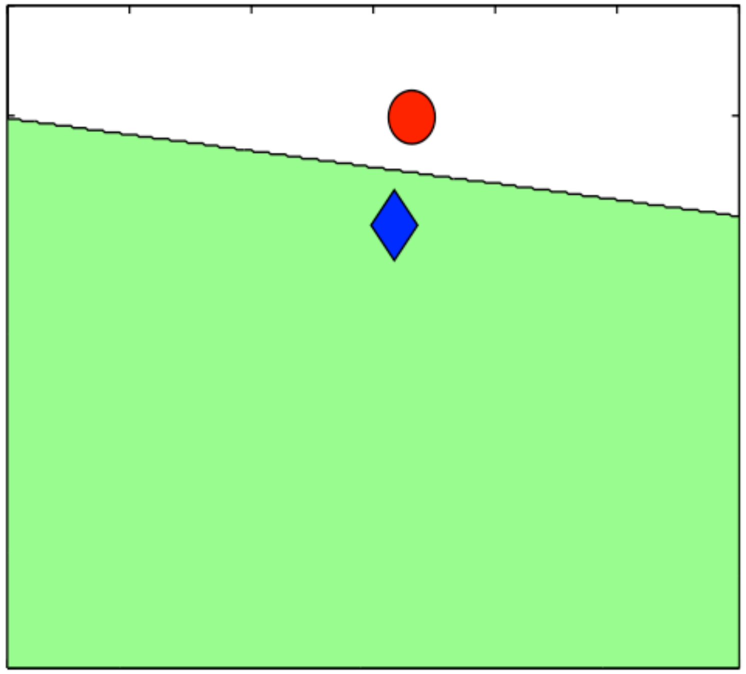

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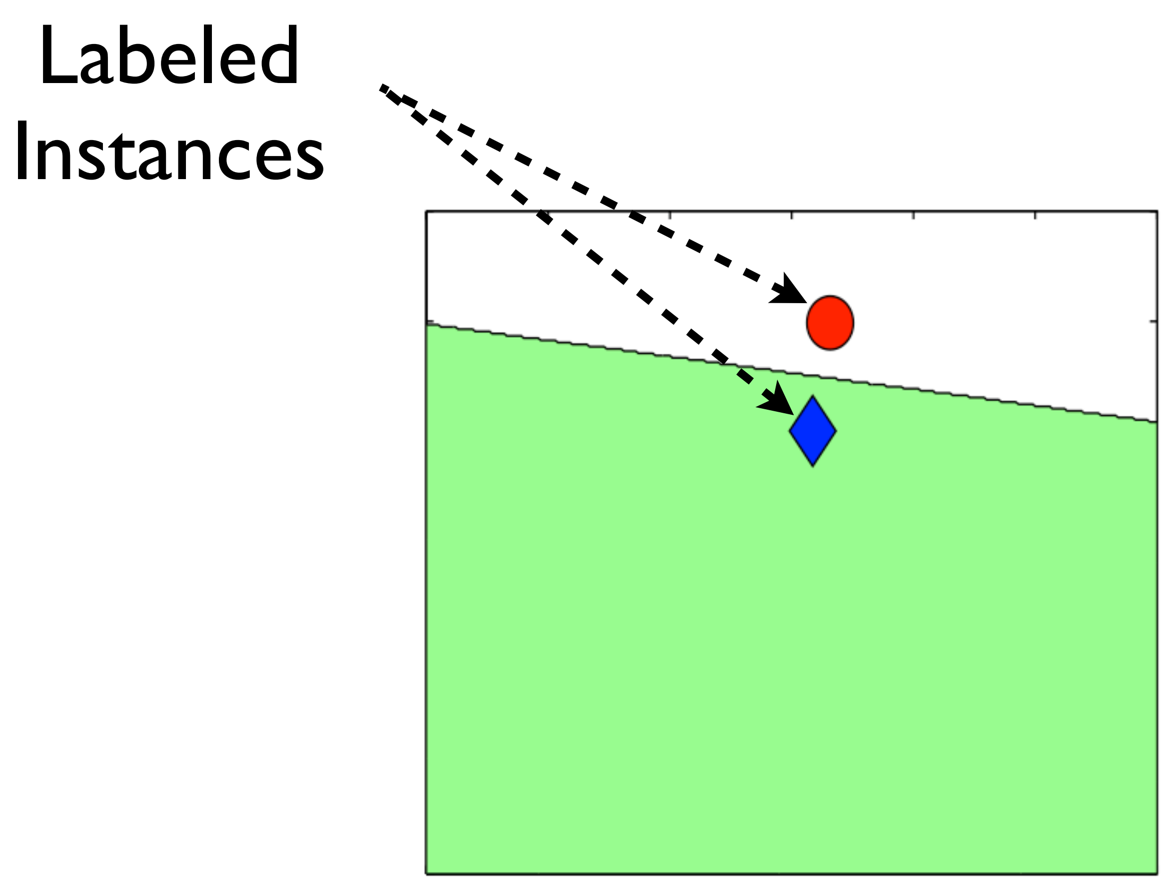

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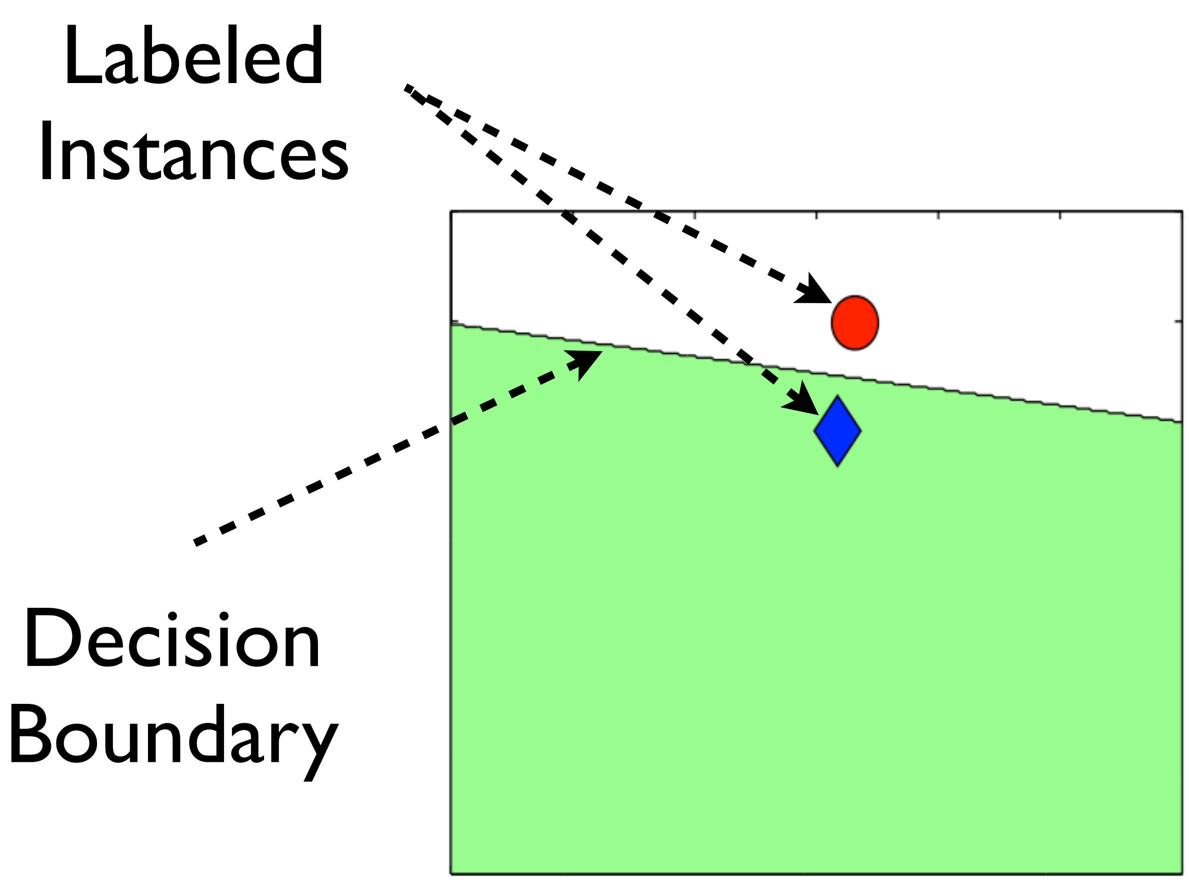

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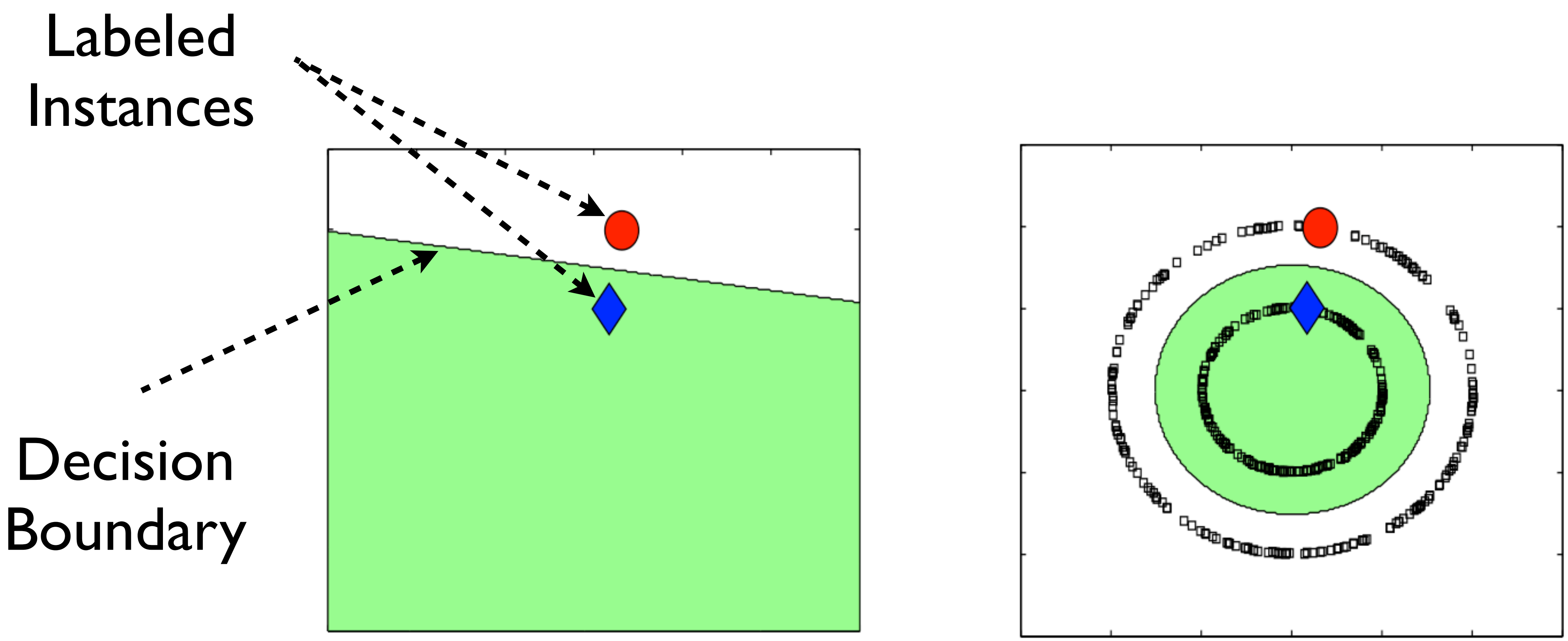

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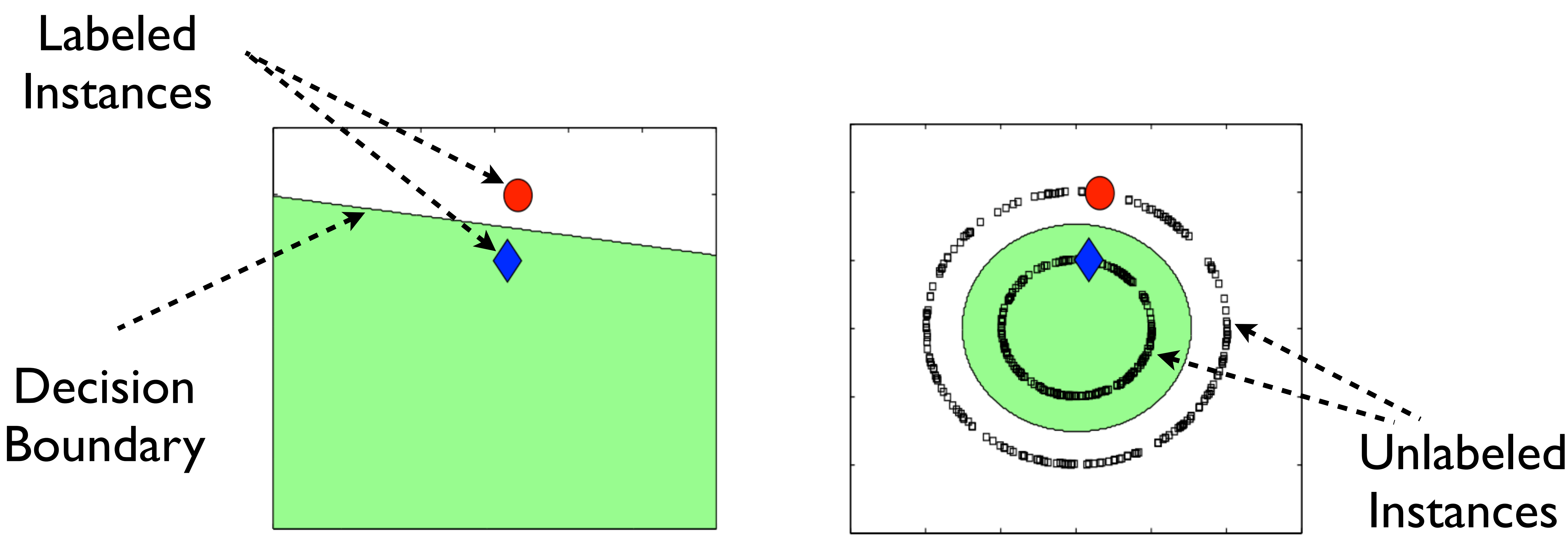

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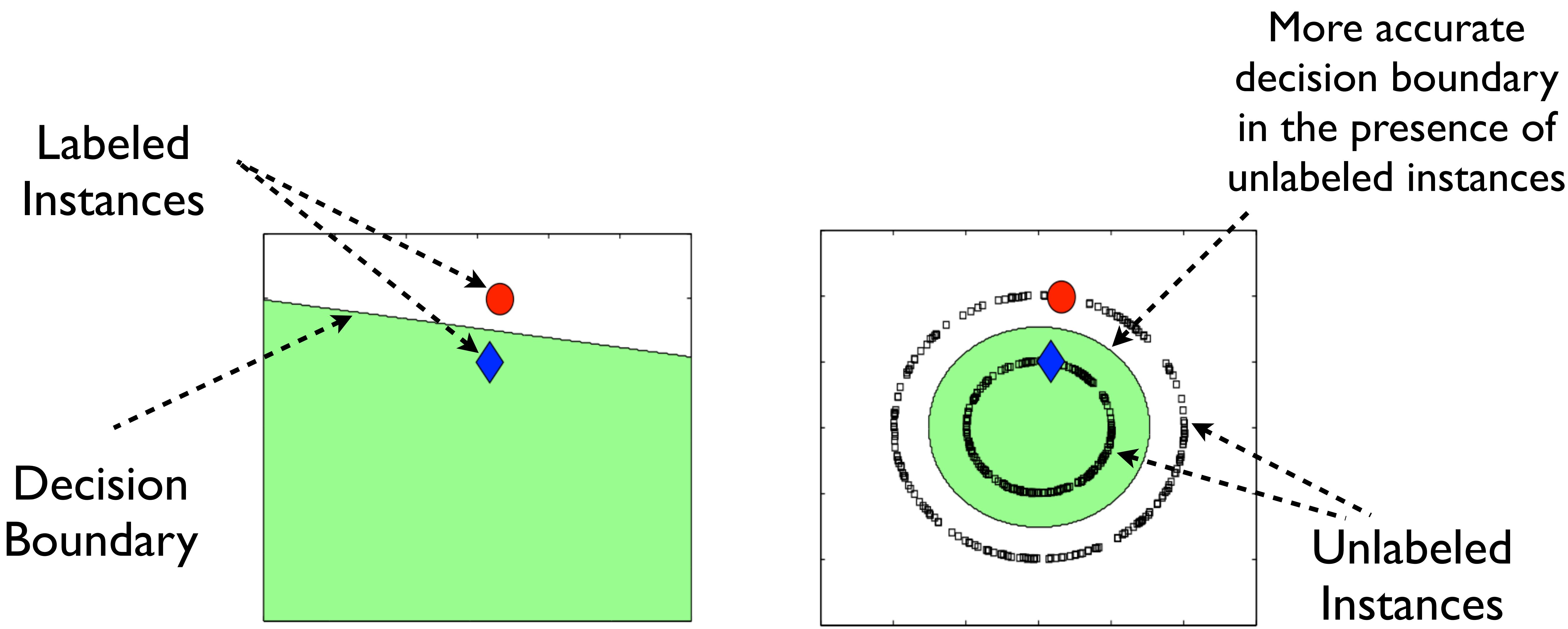

Without Unlabeled Data With Unlabeled Data

Example from [Belkin et al., JMLR 2006]

Inductive vs Transductive

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Supervised
(Labeled)

Semi-supervised
(Labeled + Unlabeled)

Inductive vs Transductive

	Inductive (Generalize to Unseen Data)	Transductive (Doesn't Generalize to Unseen Data)
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See Chapter 25 of SSL Book: http://olivier.chapelle.cc/ssl-book/discussion.pdf

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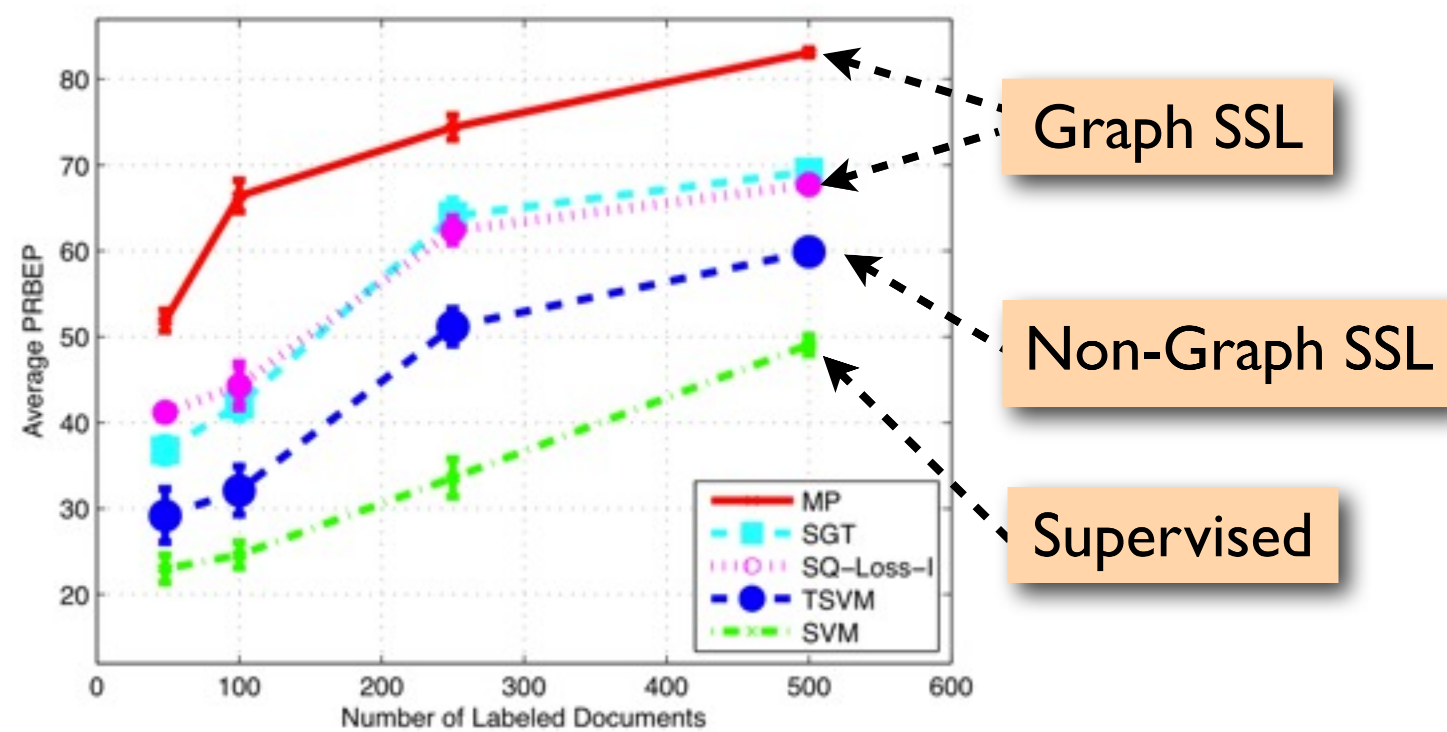
Text Classification



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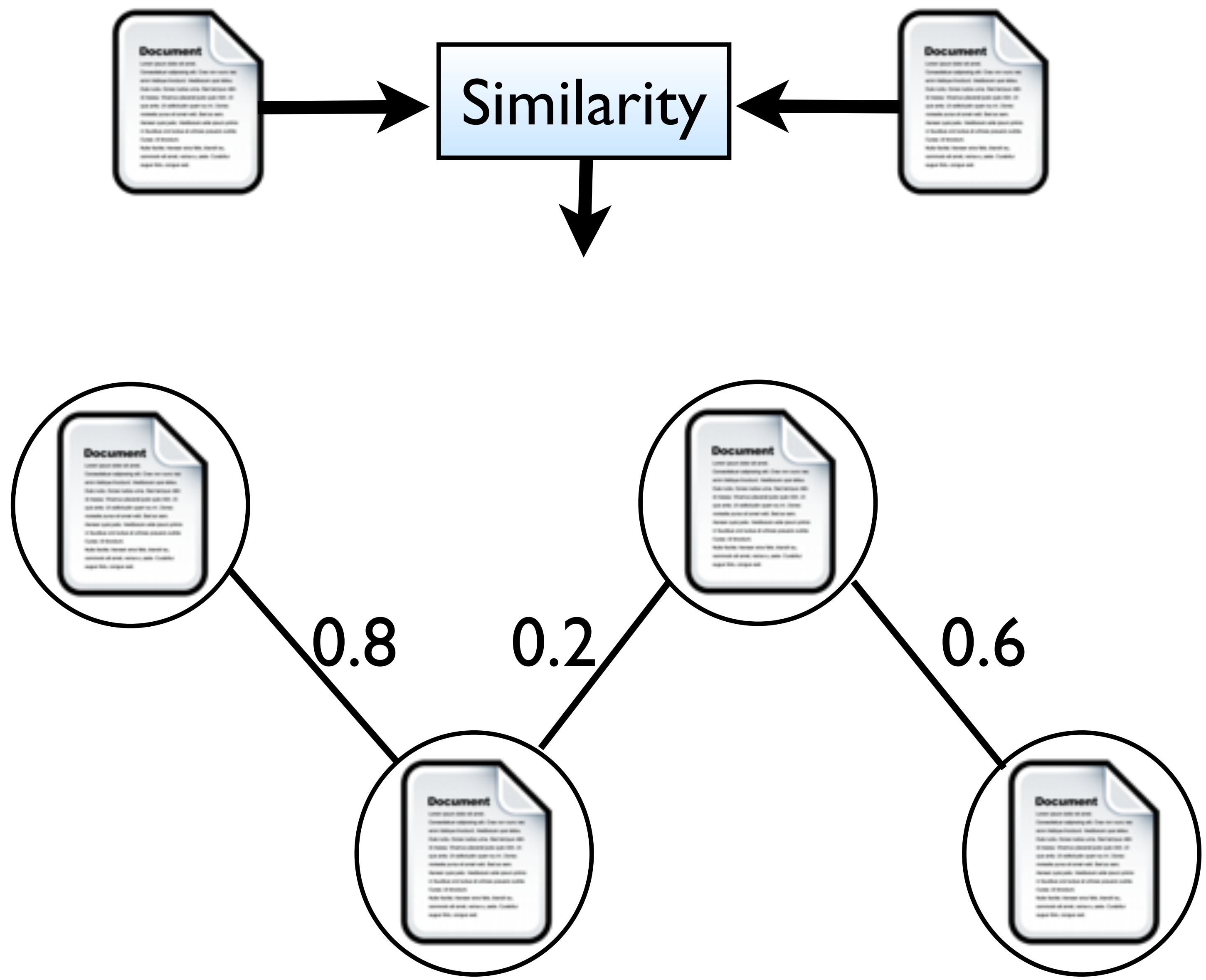

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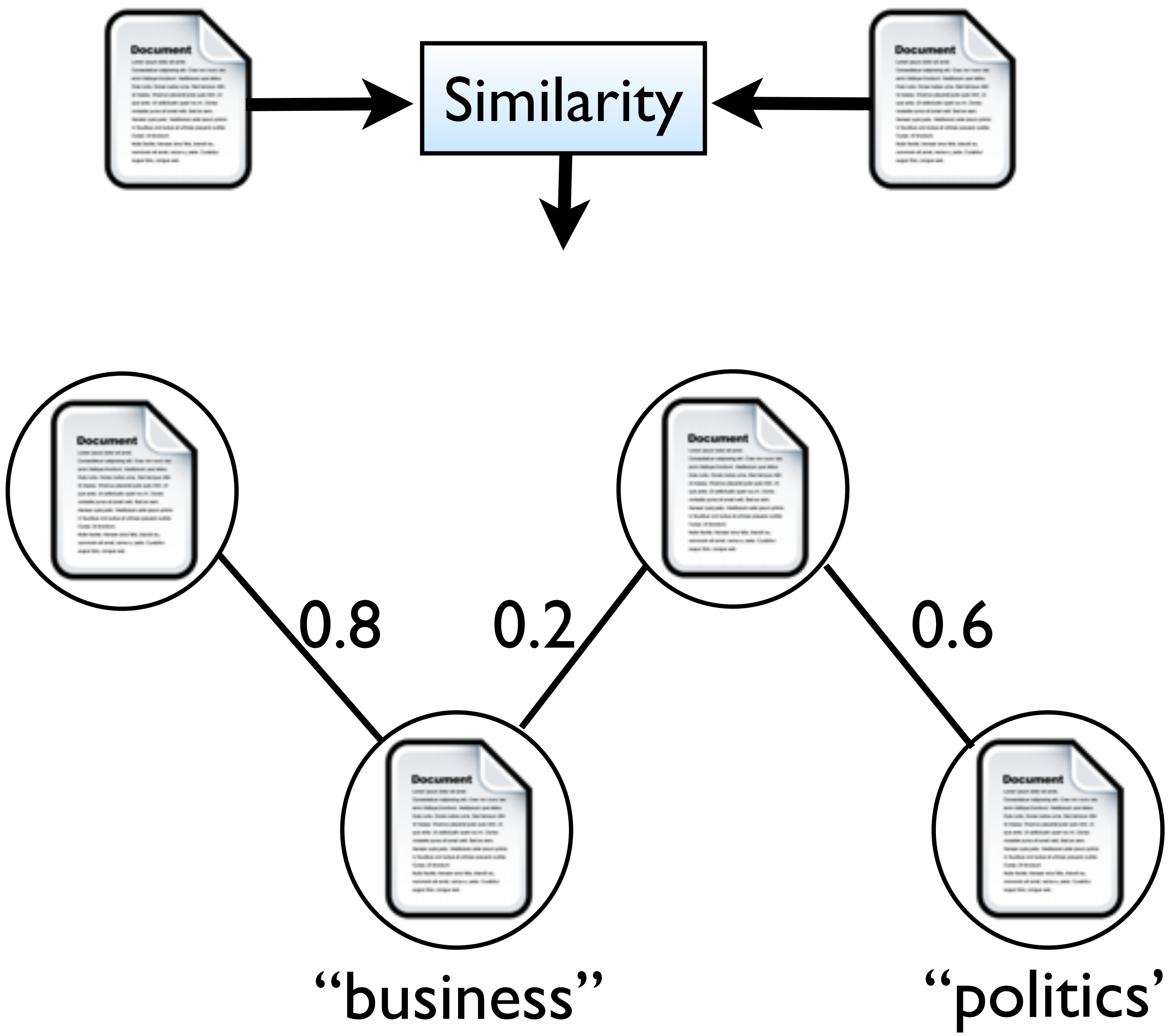

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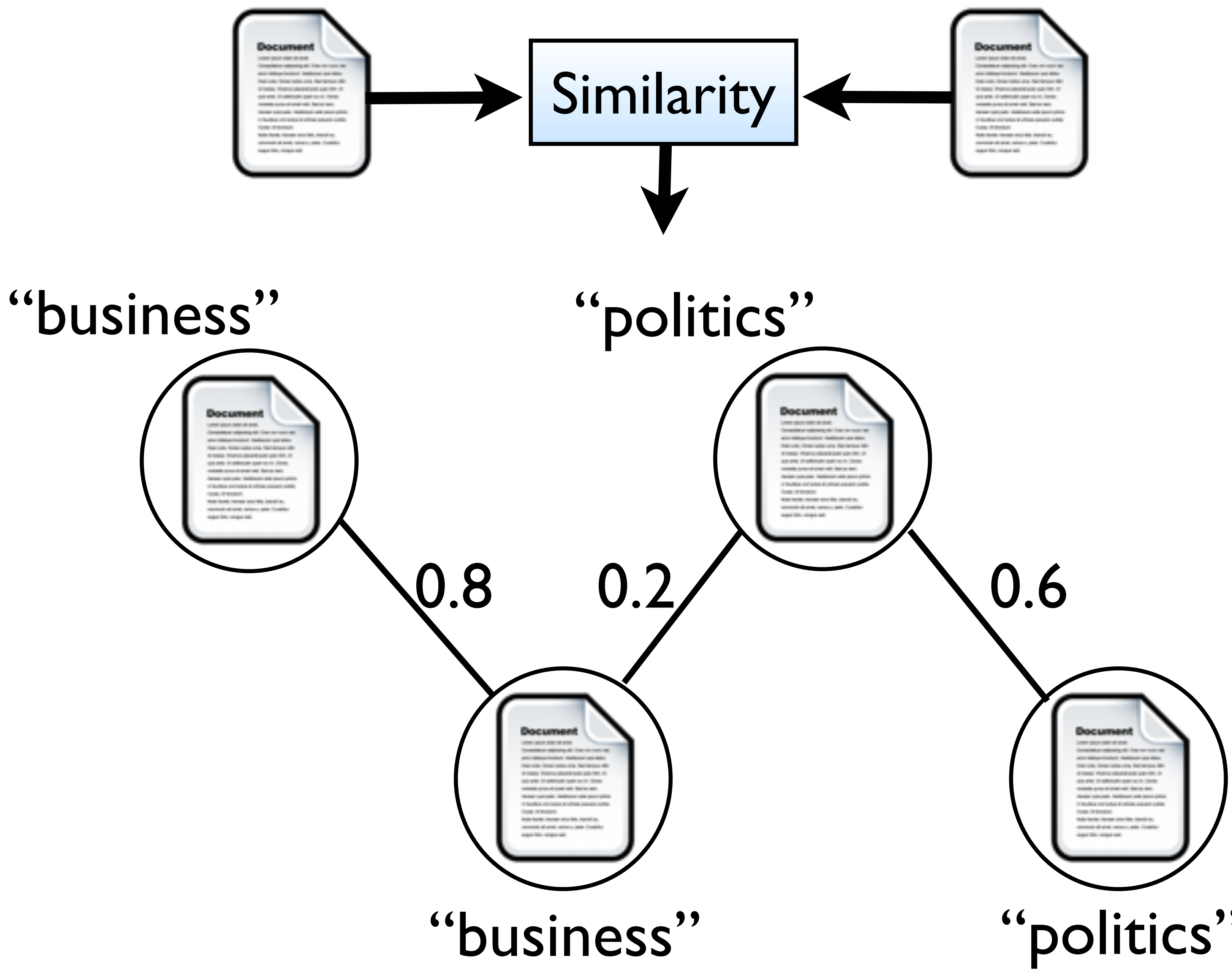

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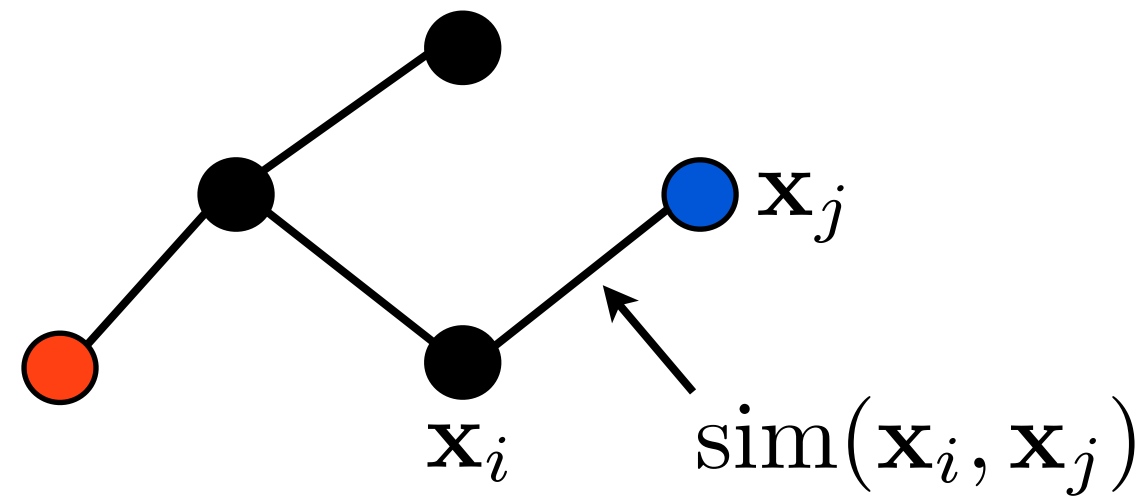

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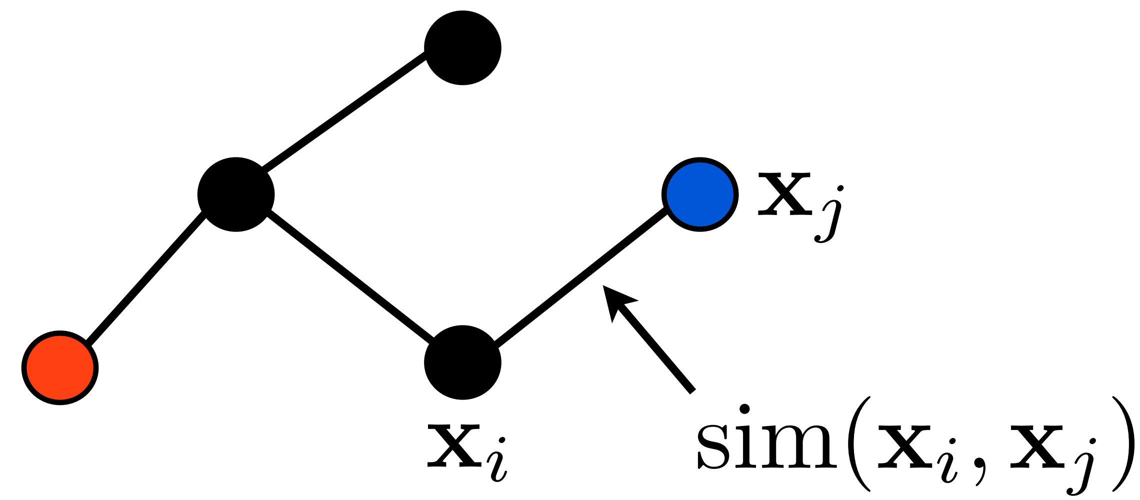

- Two stages
  - Graph construction (if not already present)
  - Label Inference

Outline

- Motivation
- Graph Construction
- Inference Methods
- Scalability
- Applications
- Conclusion & Future Work

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Graph Construction

- Neighborhood Methods
  - k-NN Graph Construction (k-NNG)
  - e-Neighborhood Method
- Metric Learning
- Other approaches

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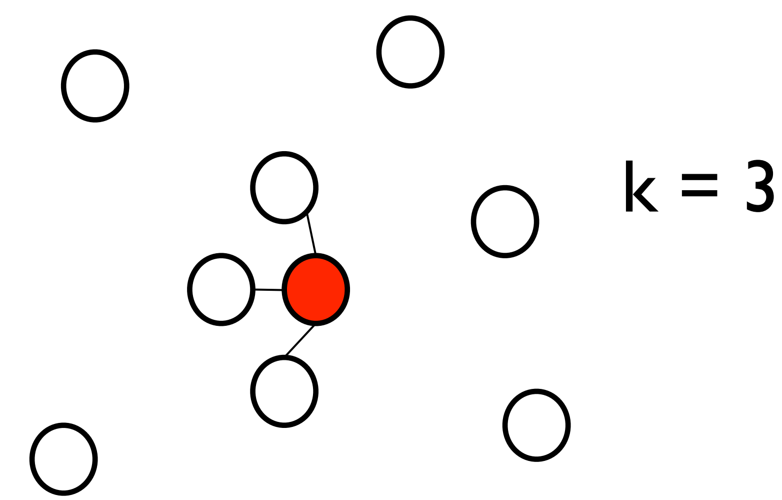

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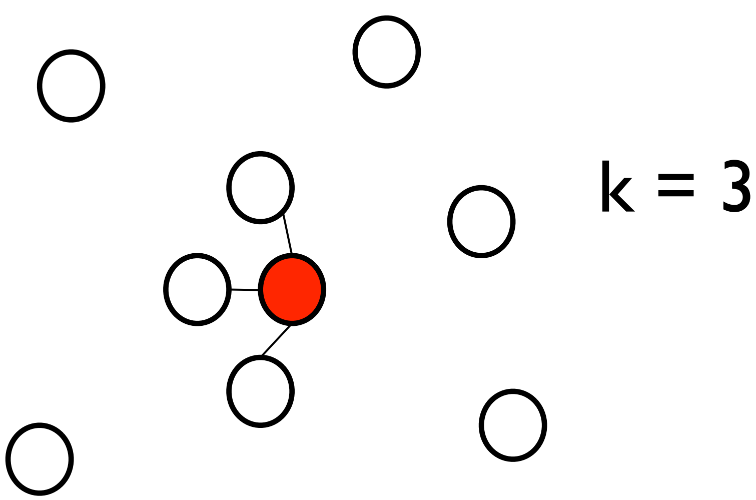

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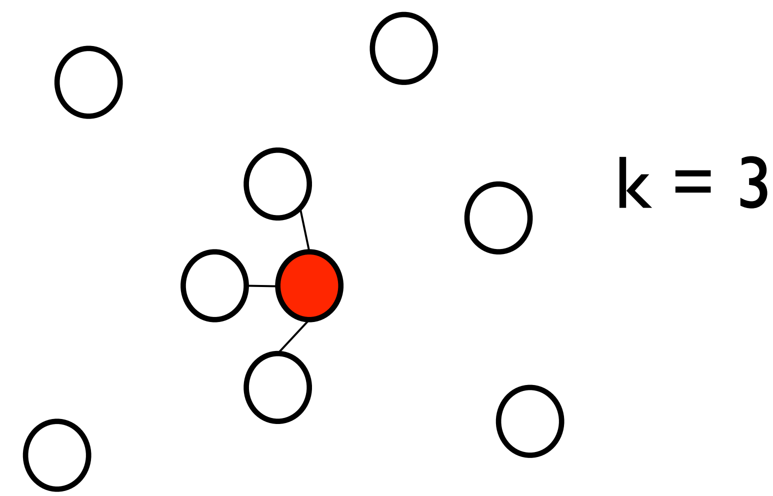

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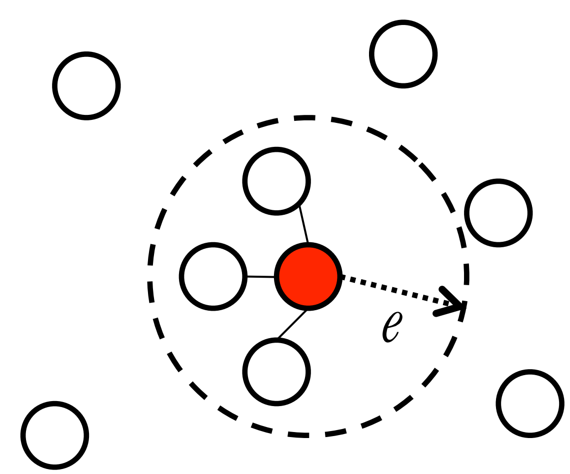

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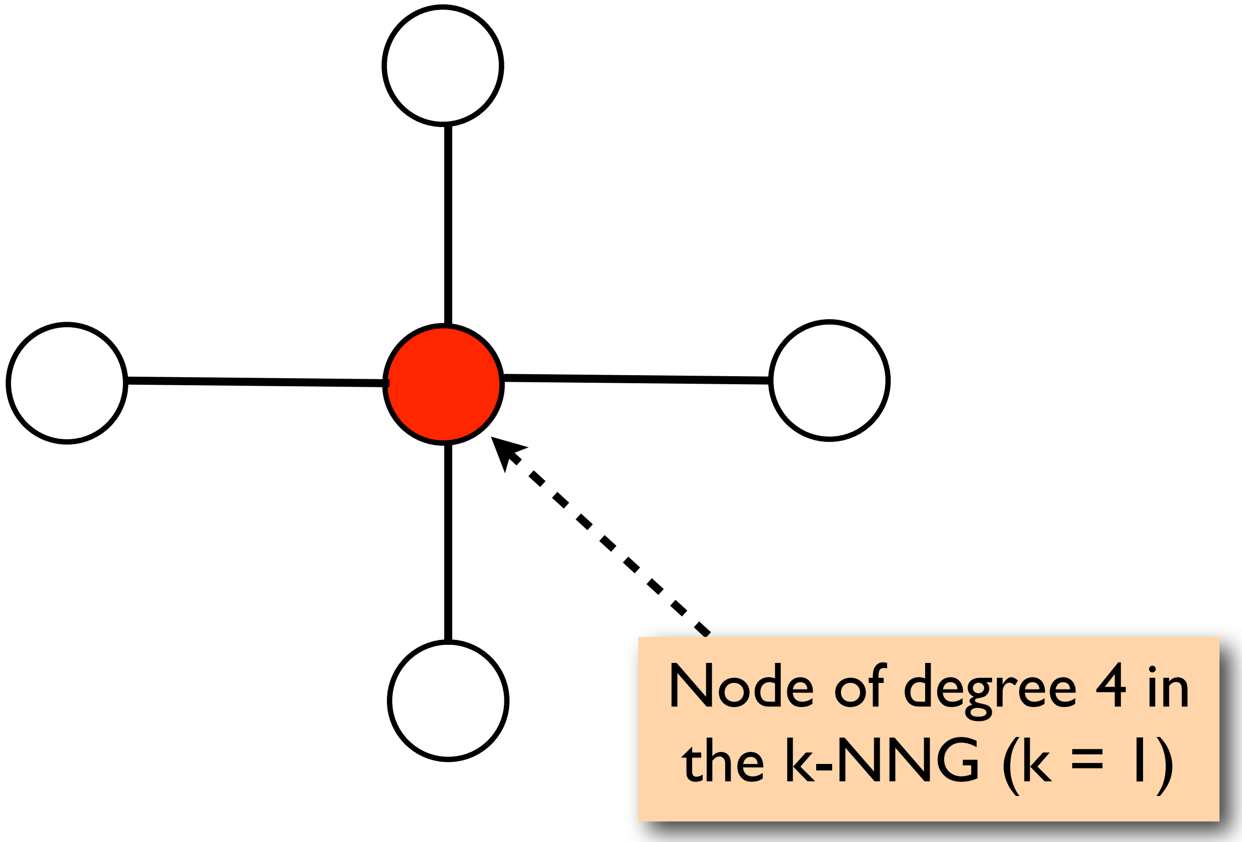

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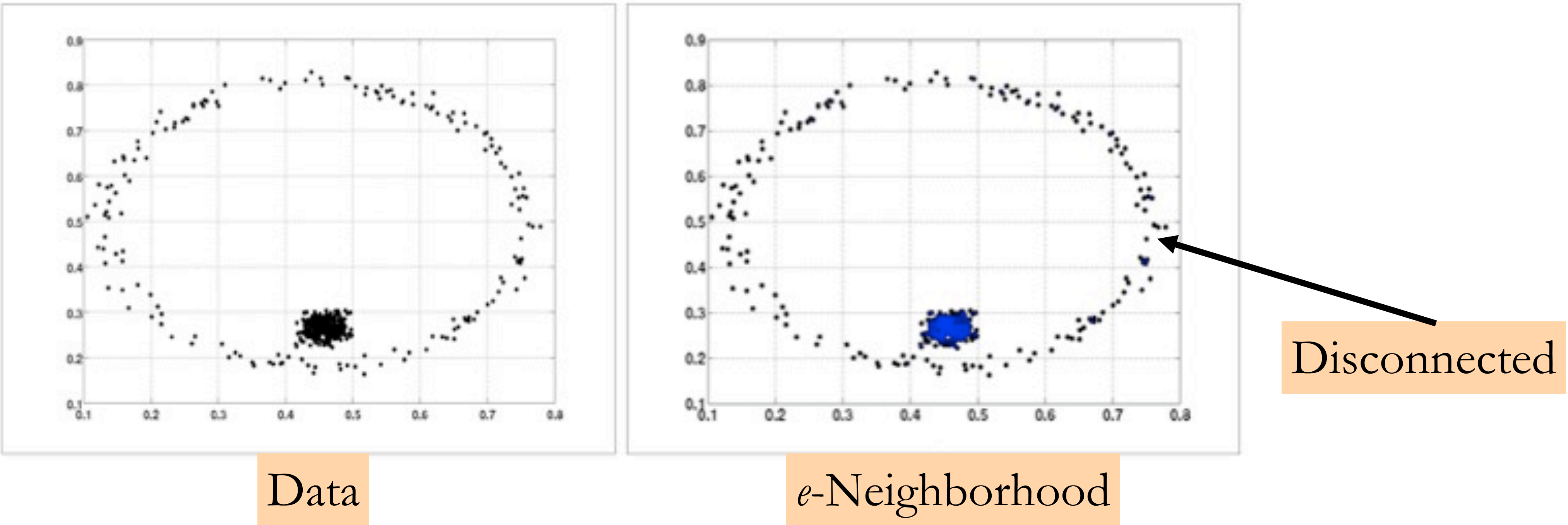

Figure from [Jebara et al., ICML 2009]

Graph Construction using Metric Learning

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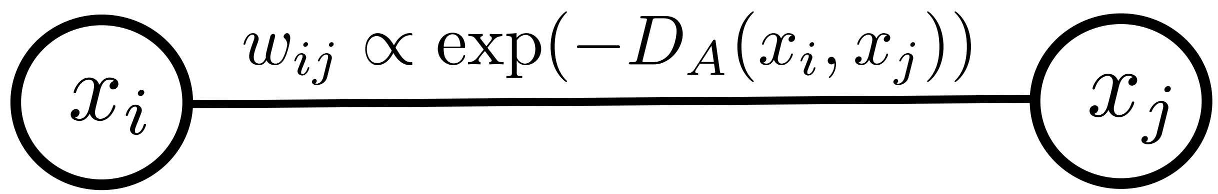

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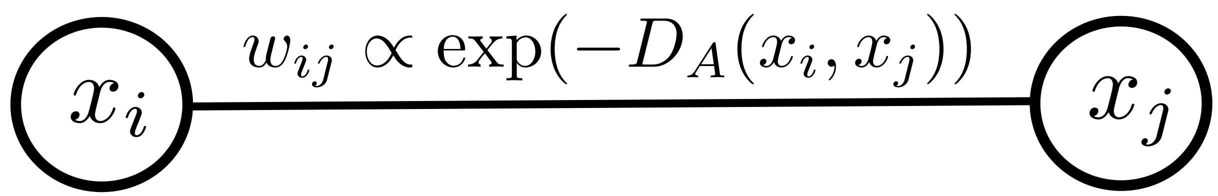

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Estimated using Mahalanobis metric learning algorithms

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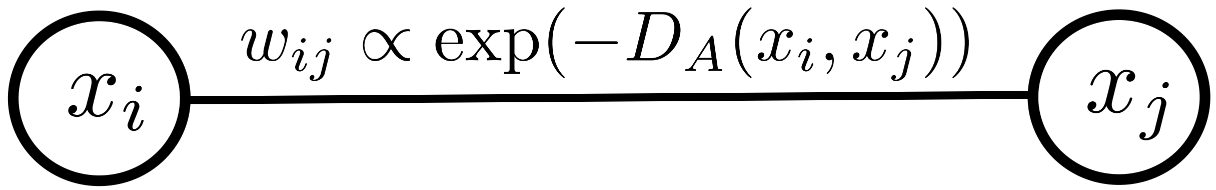

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- Supervised Metric Learning
  - ITML [Kulis et al., ICML 2007]
  - LMNN [Weinberger and Saul, JMLR 2009]
- Semi-supervised Metric Learning
  - IDML [Dhillon et al., UPenn TR 2010]

Benefits of Metric Learning for Graph Construction

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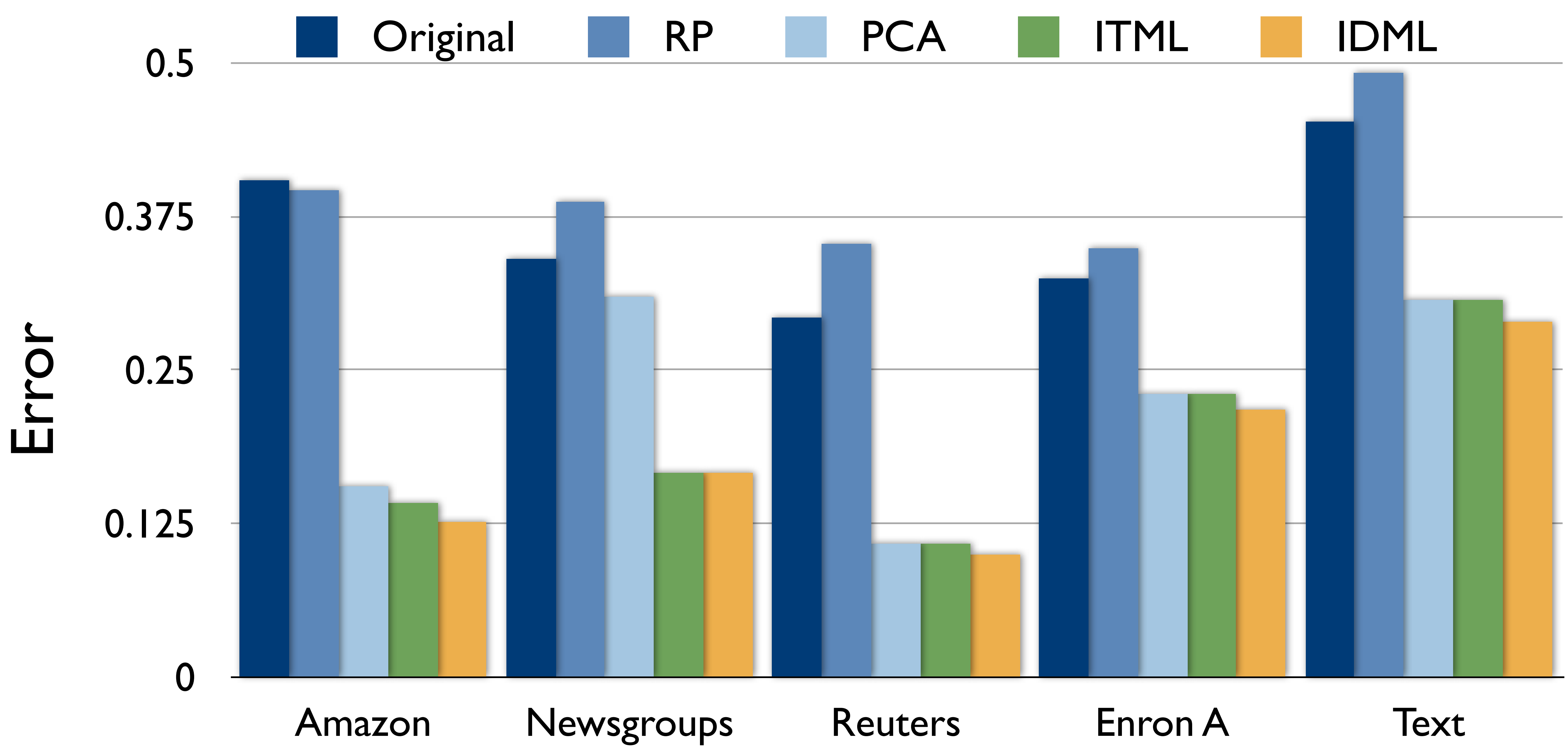

100 seed and1400 test instances, all inferences using LP

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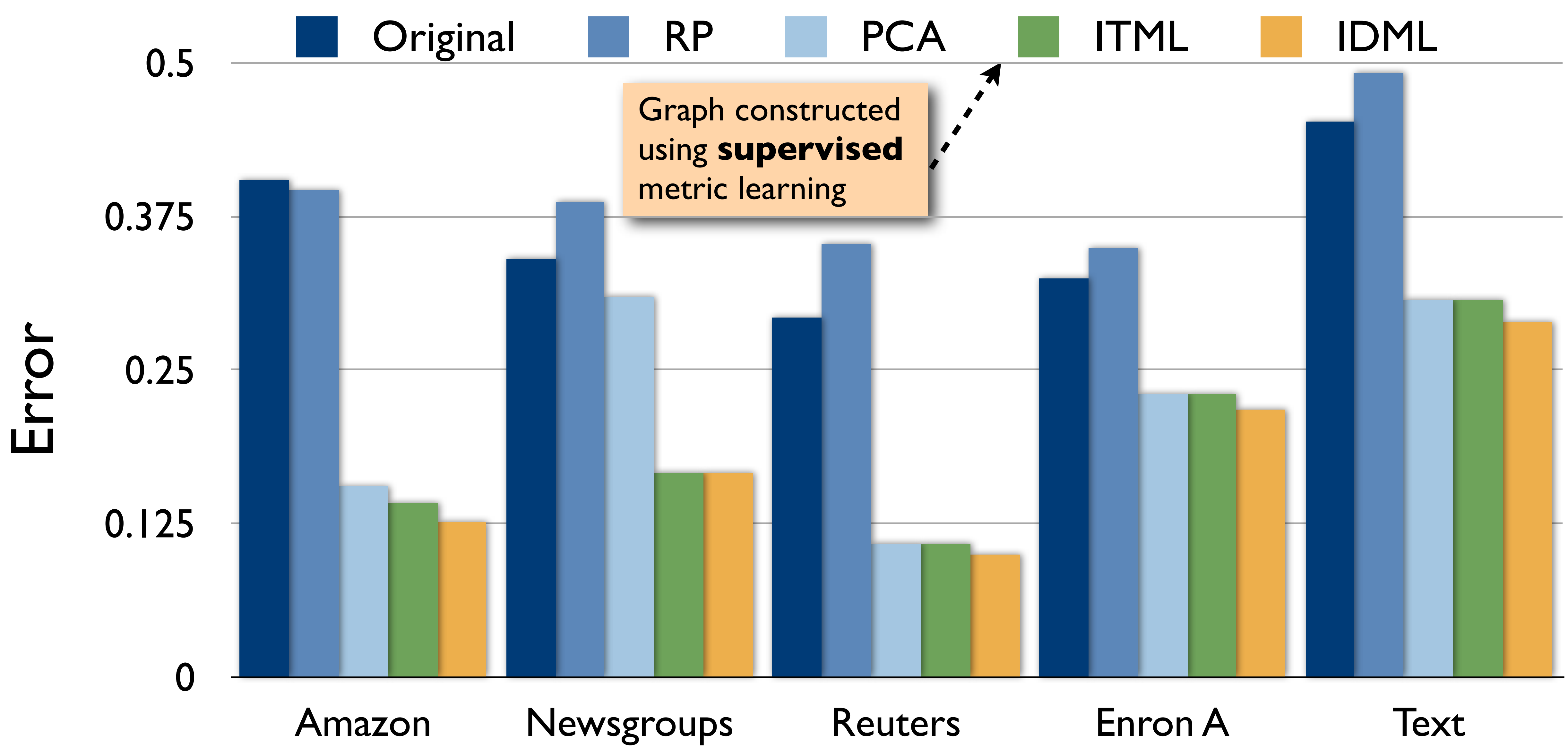

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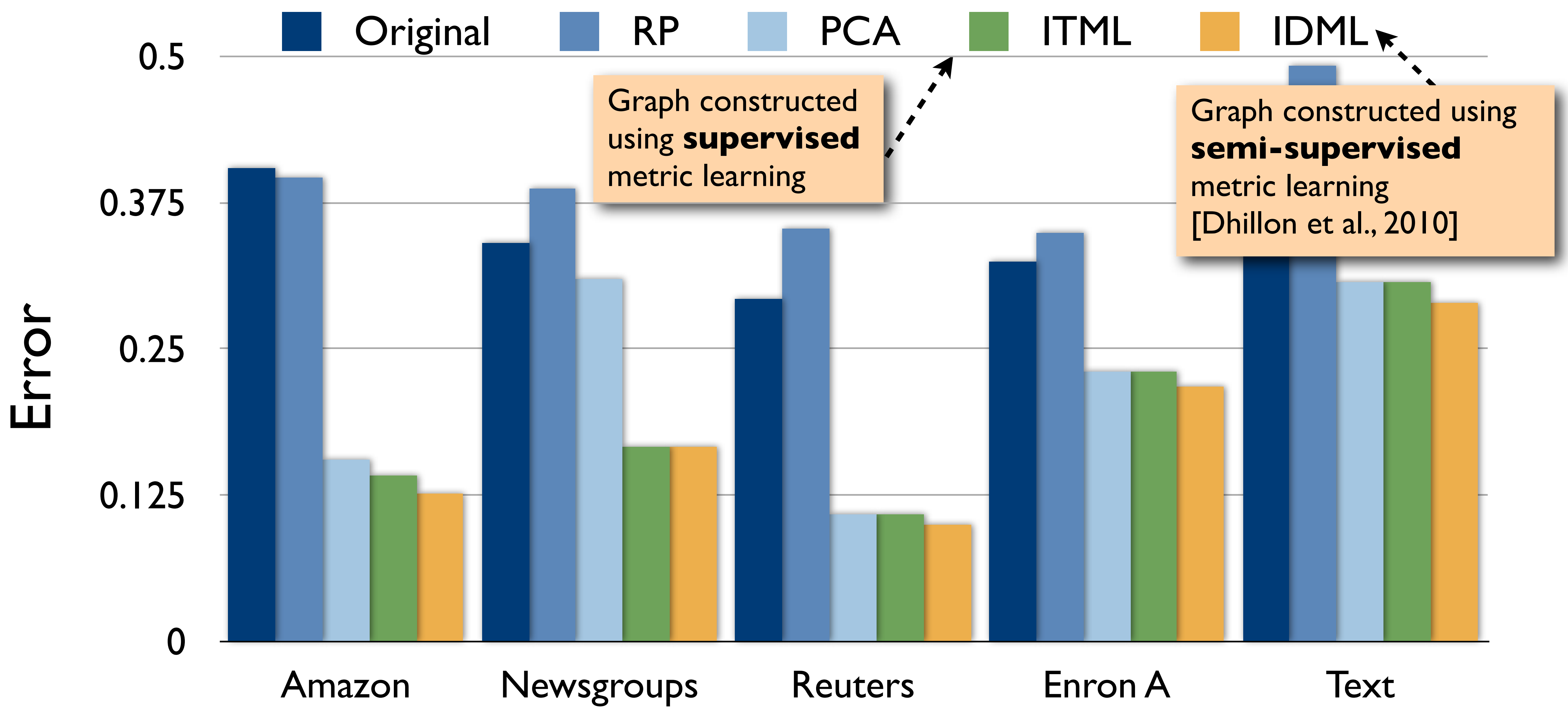

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[Dhillon et al., UPenn TR 2010]

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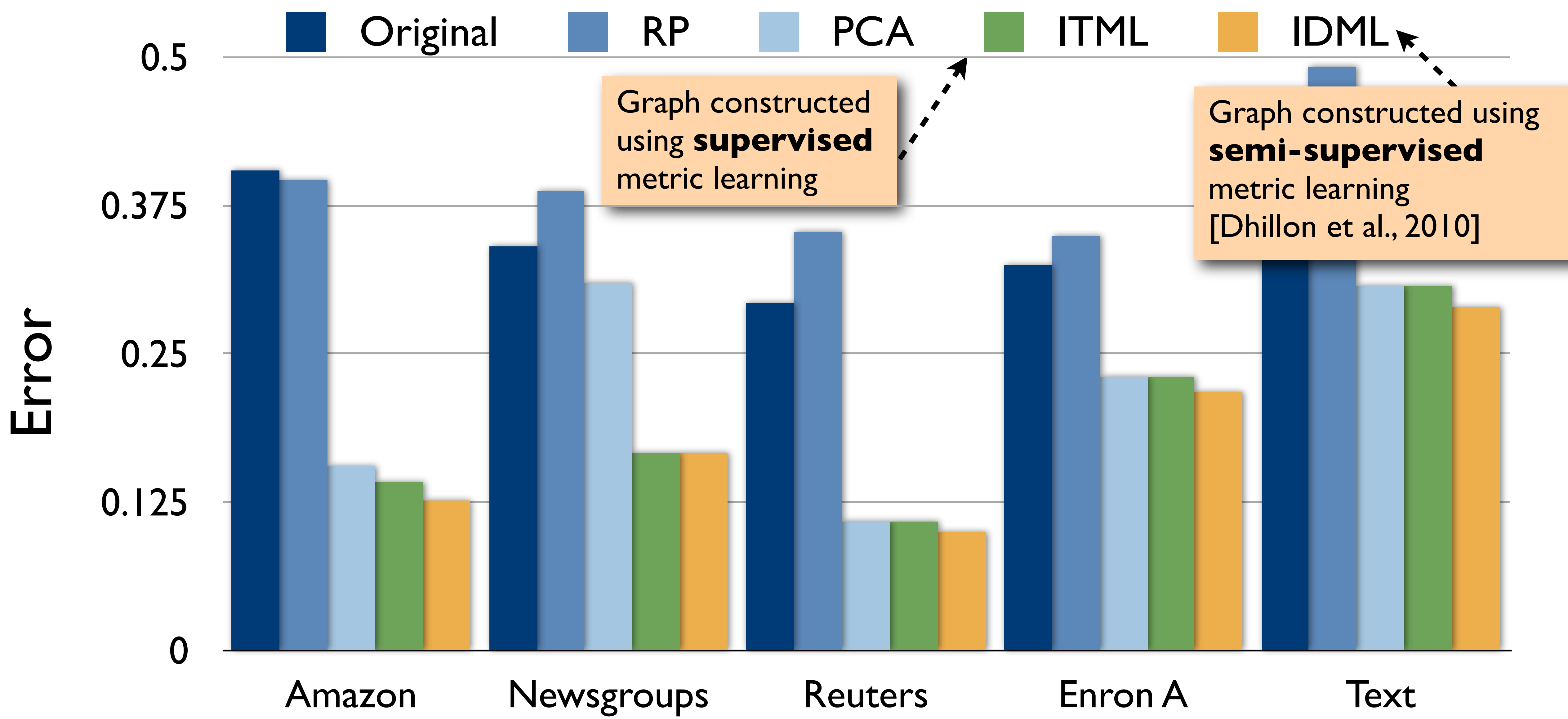

100 seed and1400 test instances, all inferences using LP

Careful graph construction is critical!

[Dhillon et al., UPenn TR 2010]

Other Graph Construction Approaches

- Local Reconstruction
  - Linear Neighborhood [Wang and Zhang, ICML 2005]
  - Regular Graph: b-matching [Jebara et al., ICML 2008]
  - Fitting Graph to Vector Data [Daitch et al., ICML 2009]
- Graph Kernels
  - [Zhu et al., NIPS 2005]

Outline

- Motivation
- Graph Construction
- Inference Methods
  - Label Propagation
  - Modified Adsorption
  - Measure Propagation
  - Sparse Label Propagation
  - Manifold Regularization
  - Spectral Graph Transduction
- Scalability
- Applications
- Conclusion & Future Work

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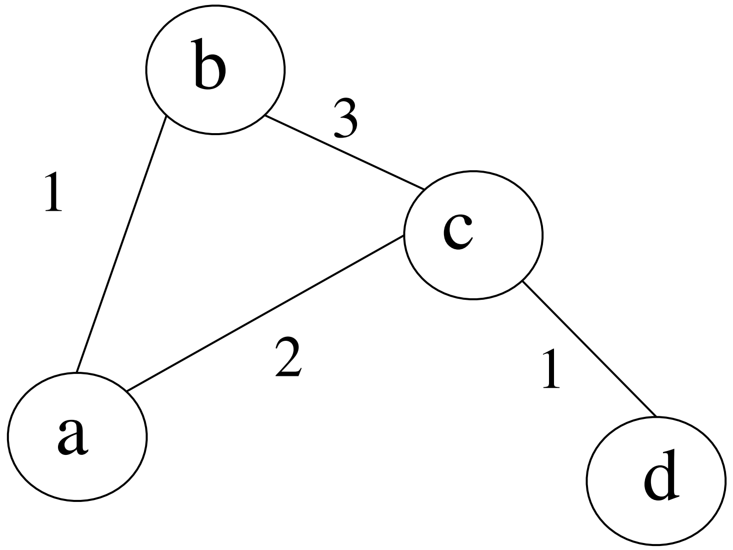

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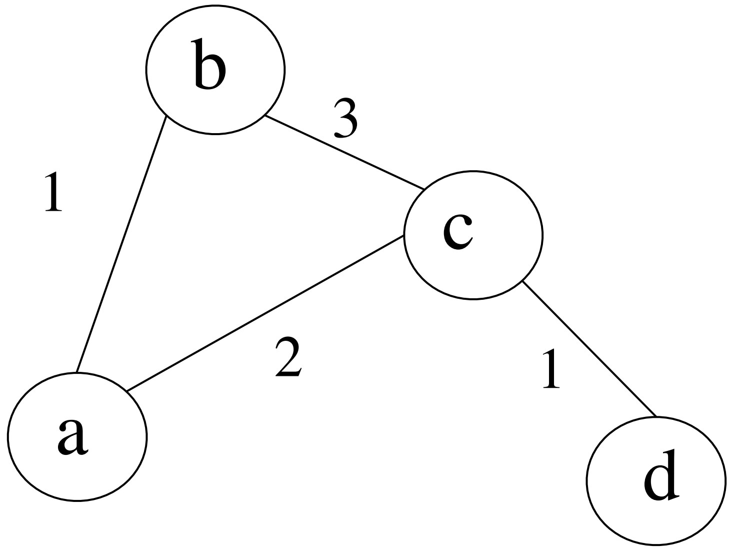

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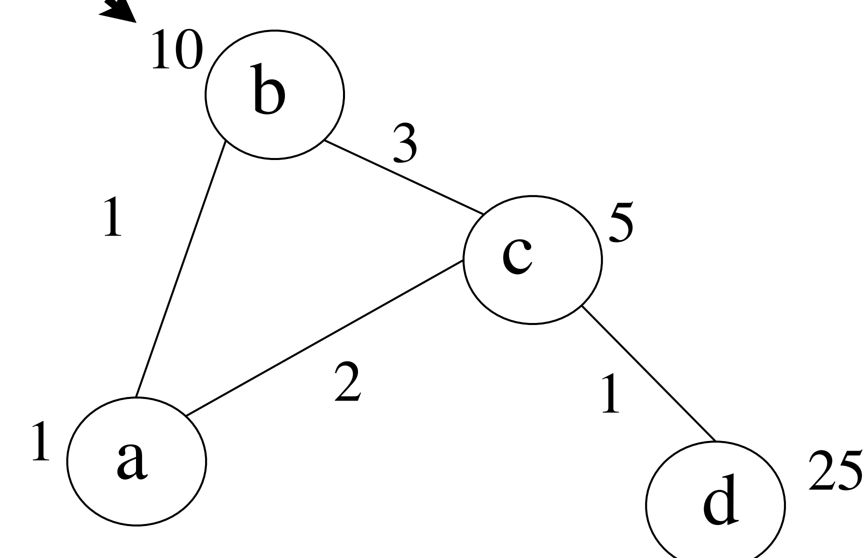

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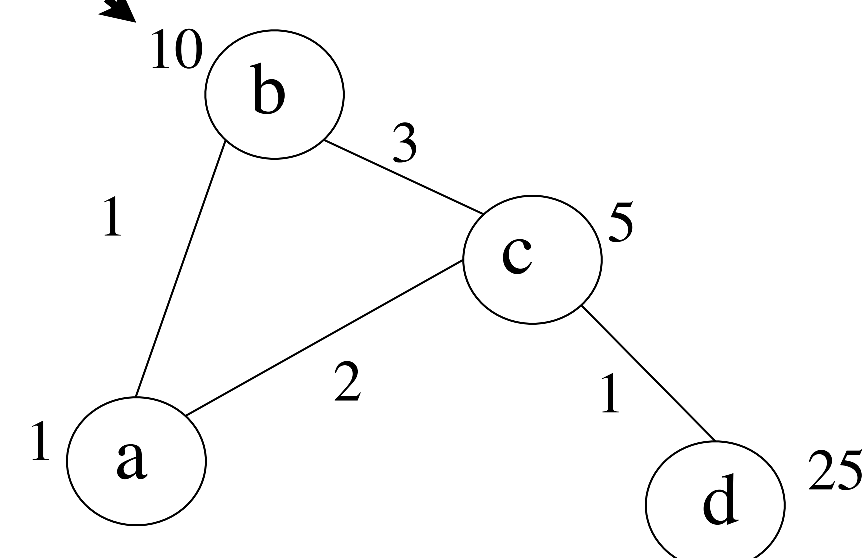

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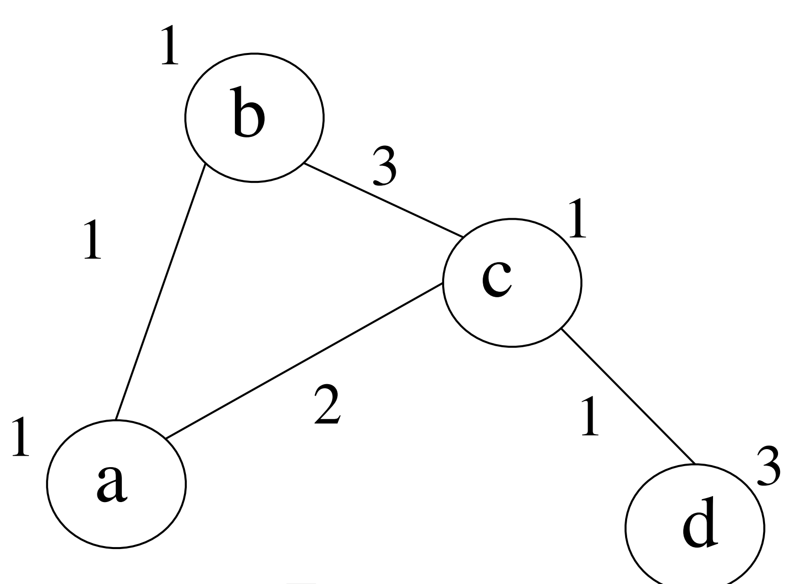

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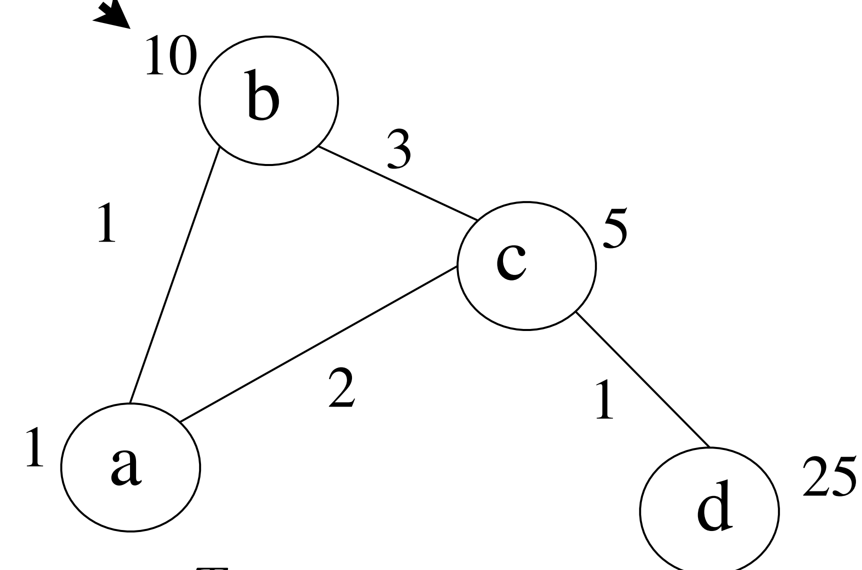

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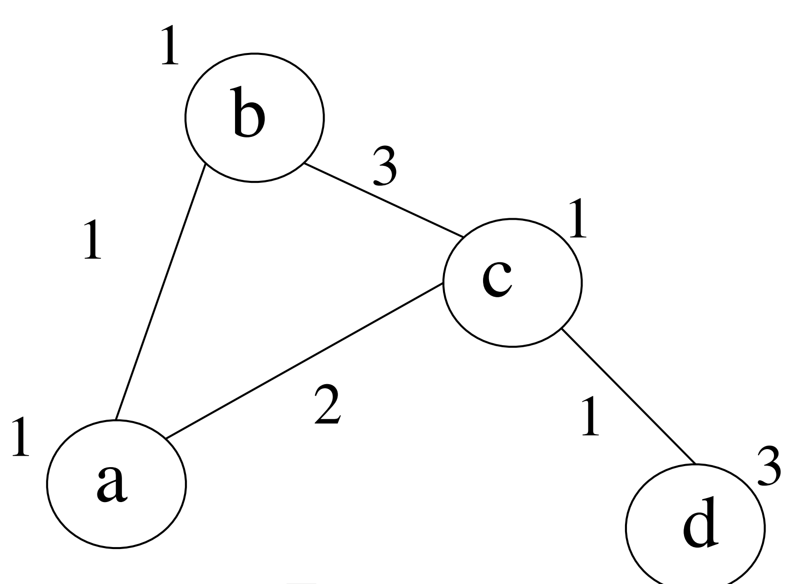

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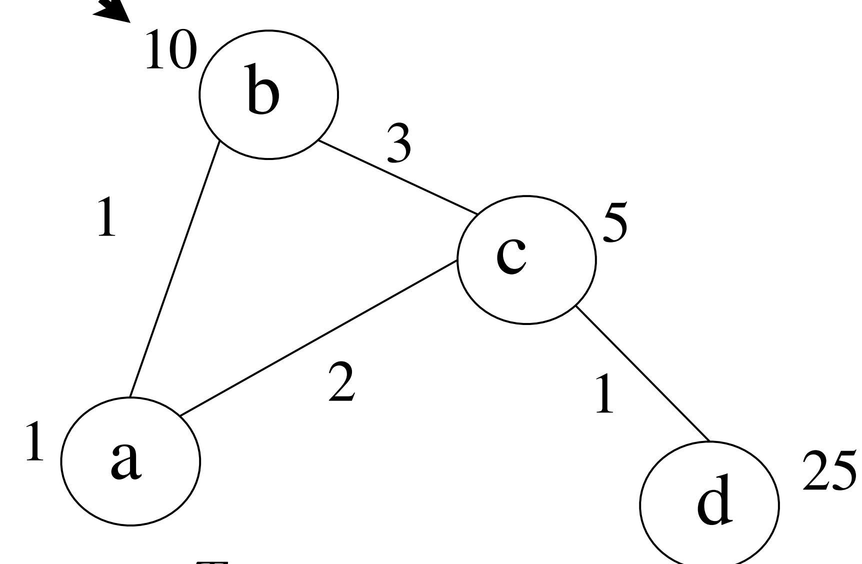

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Not Smooth

Relationship between Eigenvalues of the Laplacian and Smoothness

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Measure of Non-Smoothness (previous slide)

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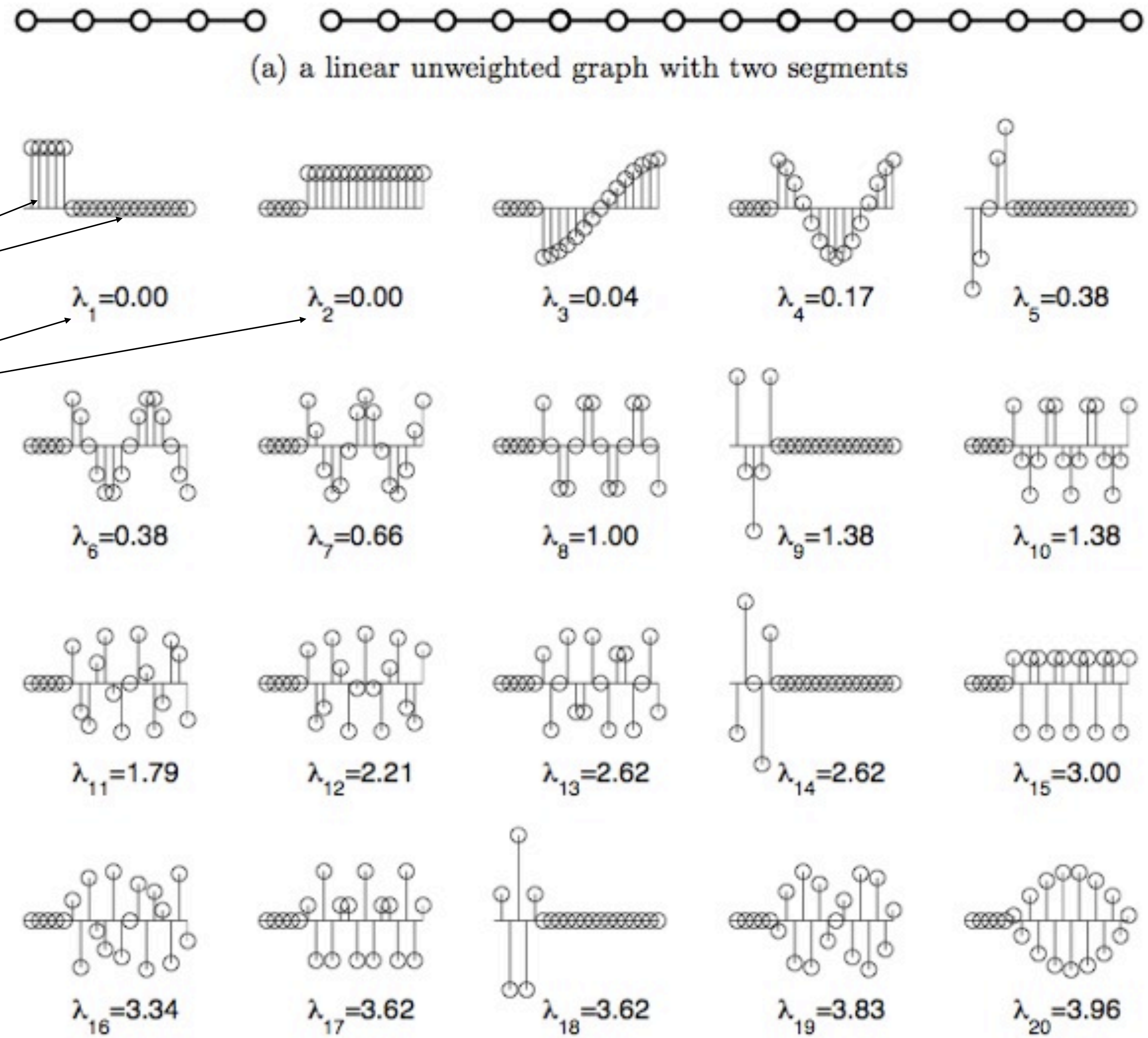
Measure of Non-Smoothness (previous slide)

If an eigenvector is used to classify nodes, then the corresponding eigenvalue gives the measure of non-smoothness

Spectrum of the Graph Laplacian

Constant within component

Number of connected components = Number of 0 eigenvalues



(a) a linear unweighted graph with two segments

(b) the eigenvectors and eigenvalues of the Laplacian L

Higher Eigenvalue, Irregular Eigenvector, Less smoothness

Figure from [Zhu et al., 2005]

Outline

- Motivation
- Graph Construction
- Inference Methods
    - Label Propagation
    - Modified Adsorption
    - Measure Propagation
    - Sparse Label Propagation
    - Manifold Regularization
- Scalability
- Applications
- Conclusion & Future Work

Notations

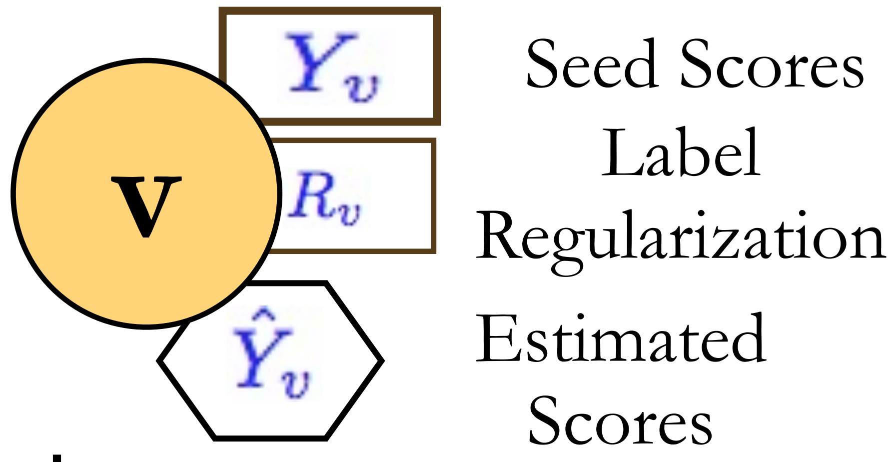
$\hat{Y}_{v,l}$: score of estimated label l on node v

$Y_{v,l}$: score of seed label l on node v

$R_{v,l}$: regularization target for label l on node v

S : seed node indicator (diagonal matrix)

W_{uv} : weight of edge (u, v) in the graph



LP-ZGL [Zhu et al., ICML 2003]

$$\arg\min_{\hat{Y}} \sum_{l=1}^{m} W_{uv}(\hat{Y}_{ul} - \hat{Y}_{vl})^2 = \sum_{l=1}^{m} \hat{Y}_l^T L \hat{Y}_l$$

such that $Y_{ul} = \hat{Y}_{ul}, \ \forall S_{uu} = 1$

Graph Laplacian

LP-ZGL [Zhu et al., ICML 2003]

Smooth

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Match Seeds (hard)

Graph Laplacian

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Graph Laplacian

- **Smoothness**
  - two nodes connected by an edge with high weight should be assigned similar labels

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Match Seeds (hard)

Graph Laplacian

- **Smoothness**
  - two nodes connected by an edge with high weight should be assigned similar labels
- Solution satisfies harmonic property

Outline

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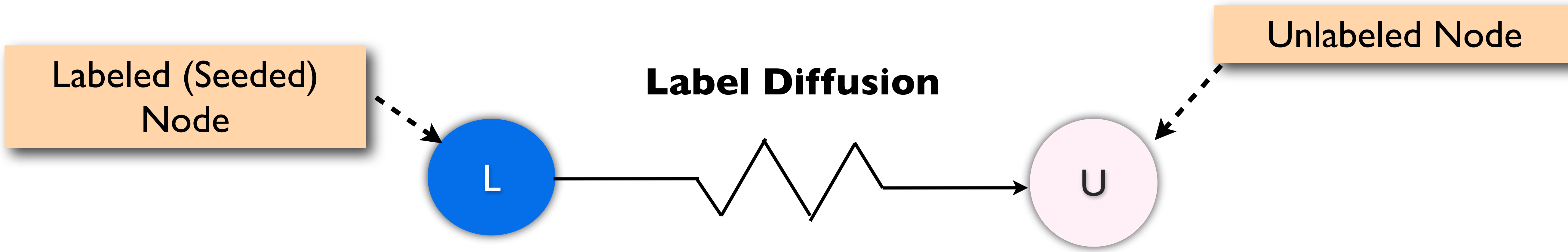
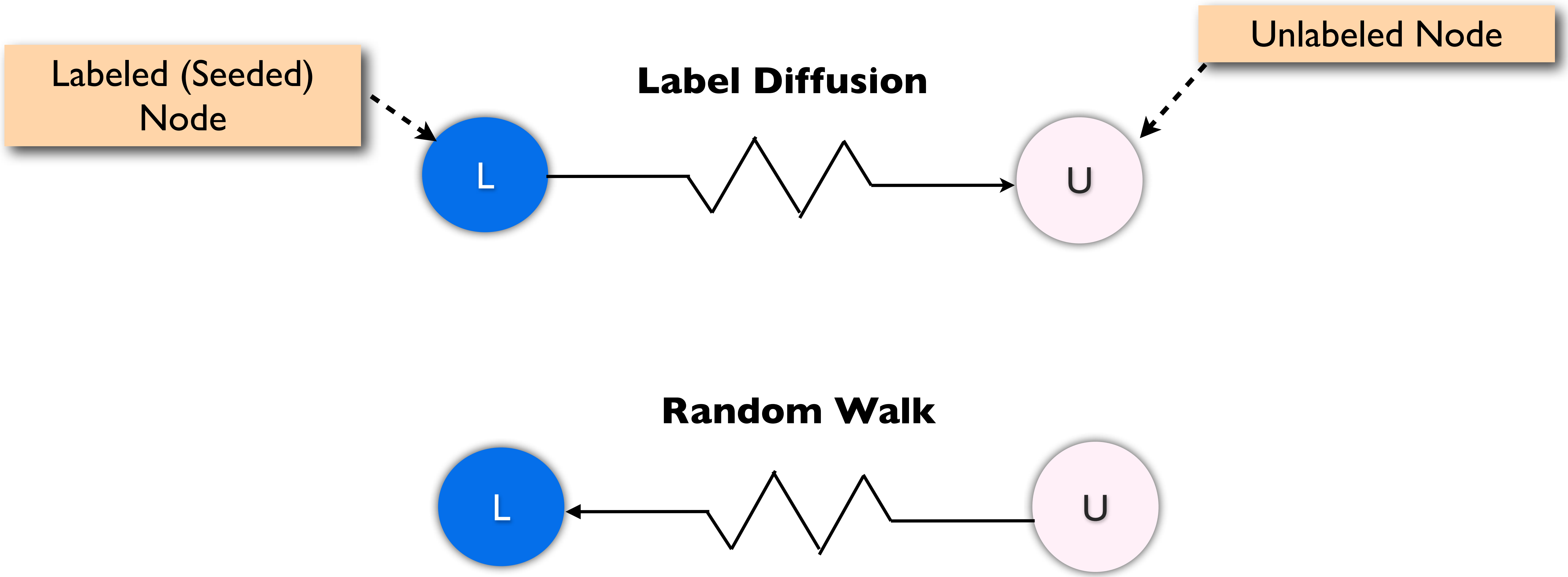
Two Related Views

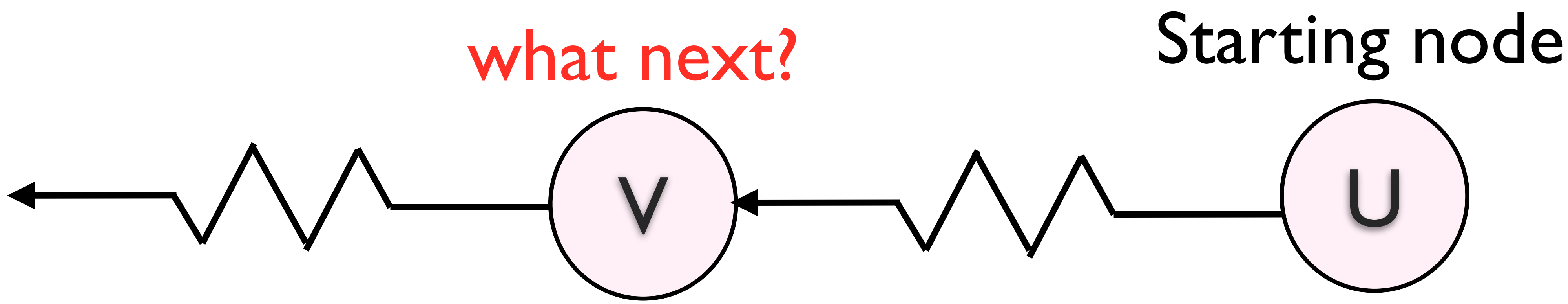


Two Related Views



Random Walk View

Random Walk View



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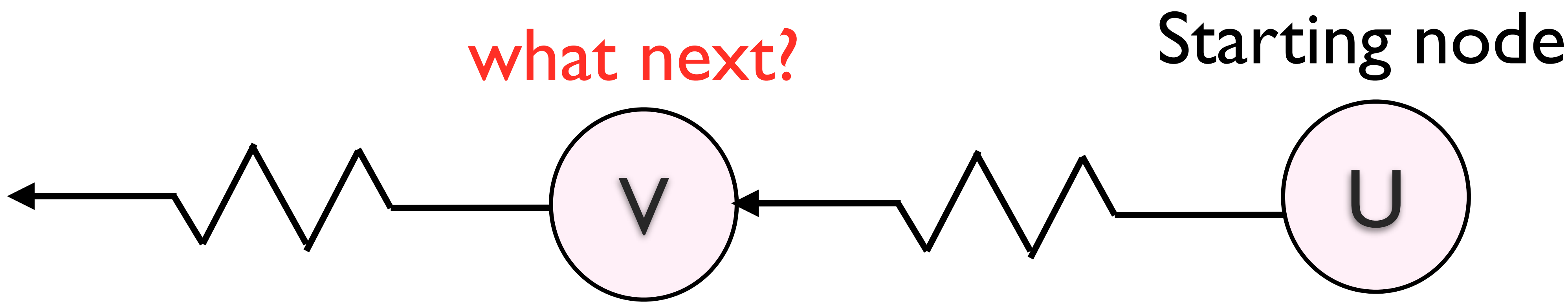

- Continue walk with probability $\mathbf{p_v^{cont}}$
- Assign V's seed label to U with probability $\mathbf{p_v^{inj}}$
- Abandon random walk with probability $\mathbf{p_v^{abnd}}$
  - assign U a dummy label

Discounting Nodes

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- Certain nodes can be unreliable (e.g., high degree nodes)
    - do not allow propagation/walk through them

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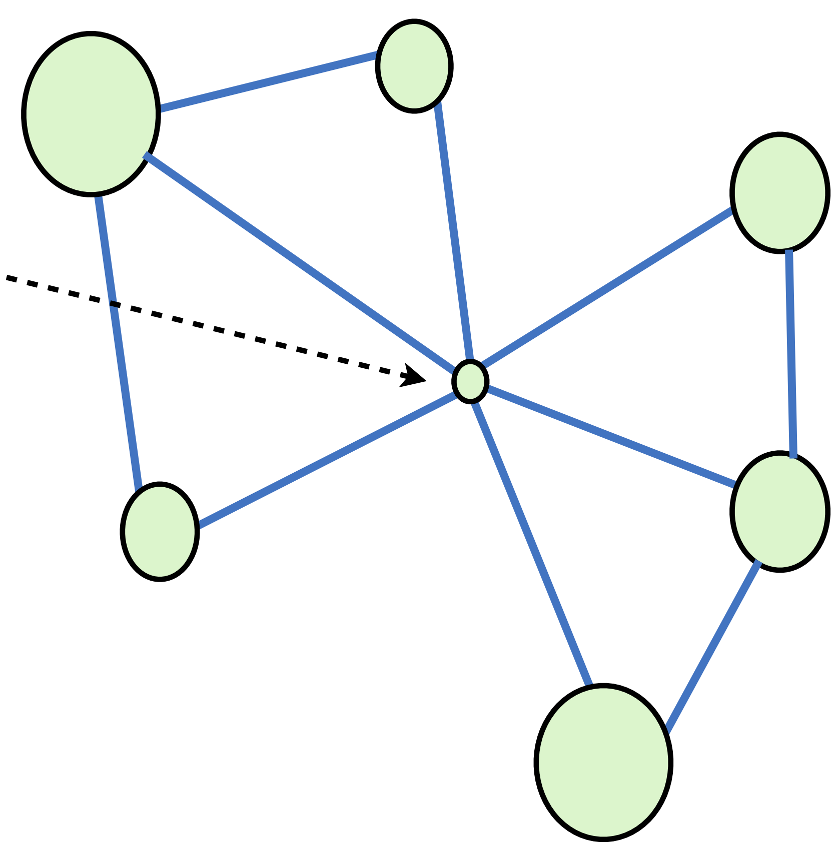
    - do not allow propagation/walk through them
- Solution: increase abandon probability on such nodes:

$$\mathbf{p_v^{abnd}} \propto \mathrm{degree(v)}$$



Redefining Matrices

$$W'_{uv} = p_u^{cont} \times W_{uv}$$

New Edge Weight

$$S_{uu} = \sqrt{p_u^{inj}}$$

$R_{u\top} = p_u^{abnd}$, and 0 for non-dummy labels

Dummy Label

Modified Adsorption (MAD)

[Talukdar and Crammer, ECML 2009]

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$$\arg\min_{\hat{\boldsymbol{Y}}} \sum_{l=1}^{m+1} \left[\|\boldsymbol{S}\hat{\boldsymbol{Y}}_l - \boldsymbol{S}\boldsymbol{Y}_l\|^2 + \mu_1 \sum_{u,v} \boldsymbol{M}_{uv}(\hat{\boldsymbol{Y}}_{ul} - \hat{\boldsymbol{Y}}_{vl})^2 + \mu_2 \|\hat{\boldsymbol{Y}}_l - \boldsymbol{R}_l\|^2 \right]$$

- m labels, +1 dummy label
- $\boldsymbol{M} = \boldsymbol{W}'^{\top} + \boldsymbol{W}'$ is the symmetrized weight matrix
- $\hat{\boldsymbol{Y}}_{vl}$: weight of label l on node v
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- $\boldsymbol{S}$: diagonal matrix, nonzero for seed nodes
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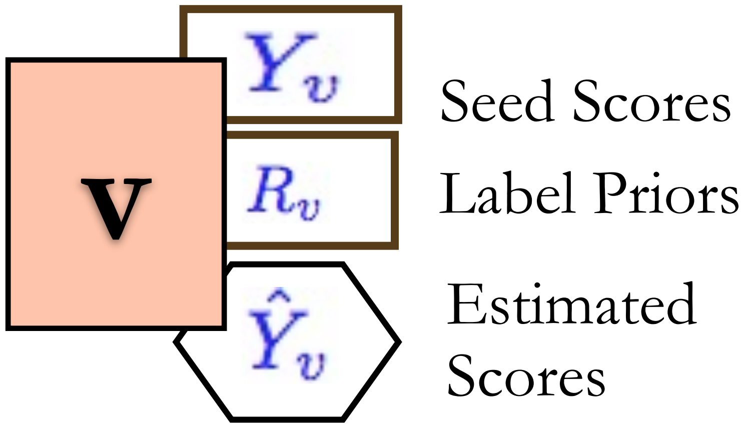

Modified Adsorption (MAD)

[Talukdar and Crammer, ECML 2009]

Match Seeds (soft)

$$\arg\min_{\hat{\boldsymbol{Y}}} \sum_{l=1}^{m+1} \left[\boxed{\|\boldsymbol{S}\hat{\boldsymbol{Y}}_l - \boldsymbol{S}\boldsymbol{Y}_l\|^2} + \mu_1 \sum_{u,v} \boldsymbol{M}_{uv}(\hat{\boldsymbol{Y}}_{ul} - \hat{\boldsymbol{Y}}_{vl})^2 + \mu_2 \|\hat{\boldsymbol{Y}}_l - \boldsymbol{R}_l\|^2 \right]$$

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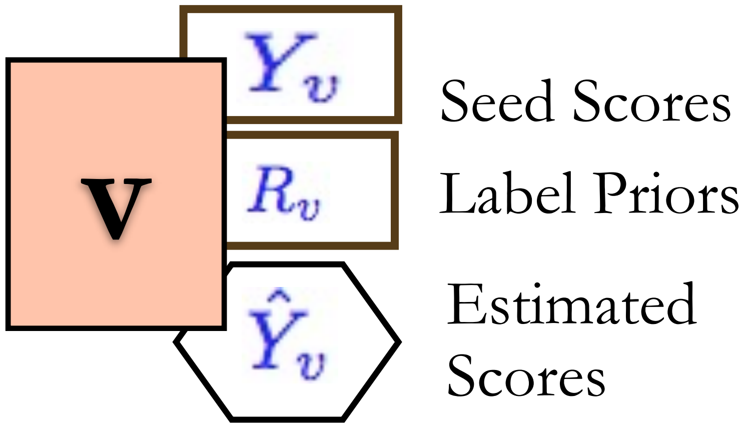

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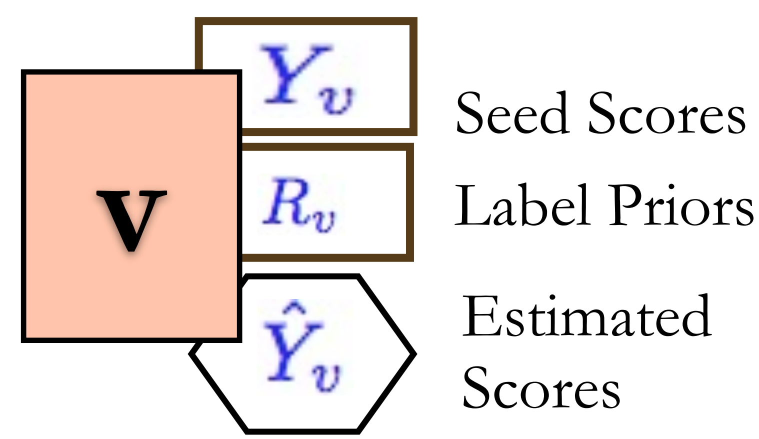

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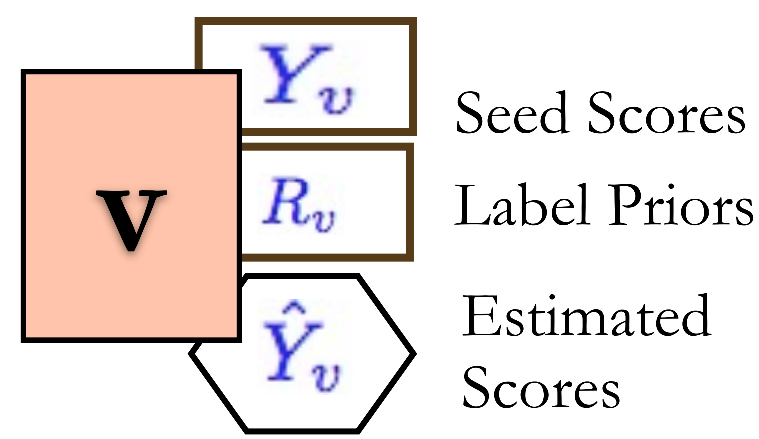

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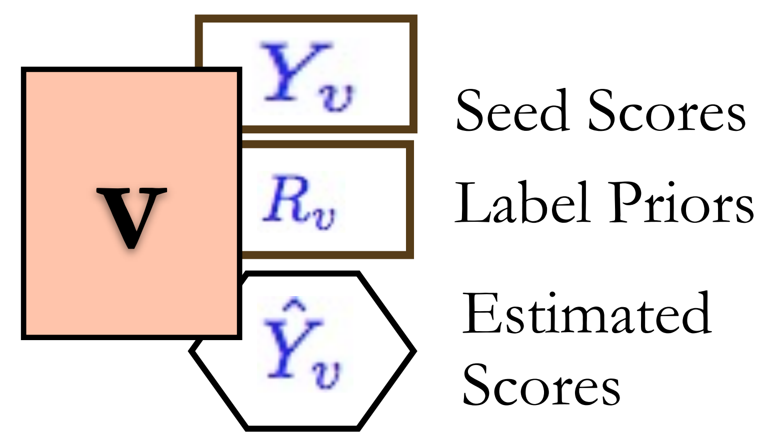

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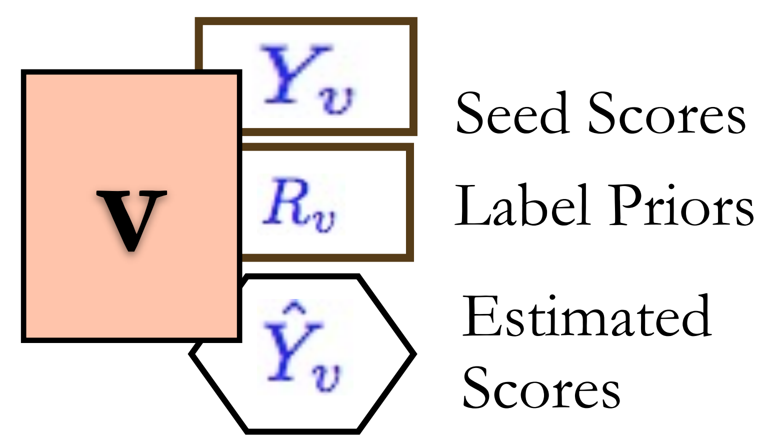

MAD has extra regularization compared to LP-ZGL [Zhu et al, ICML 03]; similar to QC [Bengio et al, 2006]

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[Talukdar and Crammer, ECML 2009]

Match Seeds (soft) — Smooth — Match Priors (Regularizer)

$$\arg\min_{\hat{\boldsymbol{Y}}} \sum_{l=1}^{m+1} \left[\boxed{\|\boldsymbol{S}\hat{\boldsymbol{Y}}_l - \boldsymbol{S}\boldsymbol{Y}_l\|^2} + \mu_1 \boxed{\sum_{u,v} \boldsymbol{M}_{uv}(\hat{\boldsymbol{Y}}_{ul} - \hat{\boldsymbol{Y}}_{vl})^2} + \boxed{\mu_2 \|\hat{\boldsymbol{Y}}_l - \boldsymbol{R}_l\|^2} \right]$$

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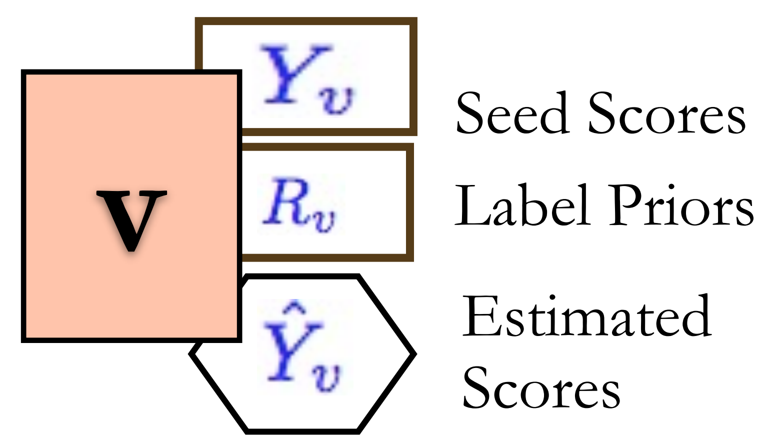

MAD's Objective is Convex

MAD has extra regularization compared to LP-ZGL [Zhu et al, ICML 03]; similar to QC [Bengio et al, 2006]

Solving MAD Objective

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- Can be solved using matrix inversion (like in LP)
  - but matrix inversion is expensive

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- Can be solved using matrix inversion (like in LP)
  - but matrix inversion is expensive
- Instead solved exactly using a system of linear equations ($Ax = b$)
  - solved using Jacobi iterations
  - results in iterative updates
  - guaranteed convergence
  - see [Bengio et al., 2006] and
    [Talukdar and Crammer, ECML 2009] for details

Solving MAD using Iterative Updates

Inputs $\boldsymbol{Y}, \boldsymbol{R} : |V| \times (|L|+1)$, $\boldsymbol{W} : |V| \times |V|$, $\boldsymbol{S} : |V| \times |V|$ diagonal

$\hat{\boldsymbol{Y}} \leftarrow \boldsymbol{Y}$

$\boldsymbol{M} = \boldsymbol{W}' + \boldsymbol{W}^{\dagger}$

$Z_v \leftarrow \boldsymbol{S}_{vv} + \mu_1 \sum_{u \neq v} \boldsymbol{M}_{vu} + \mu_2 \quad \forall v \in V$

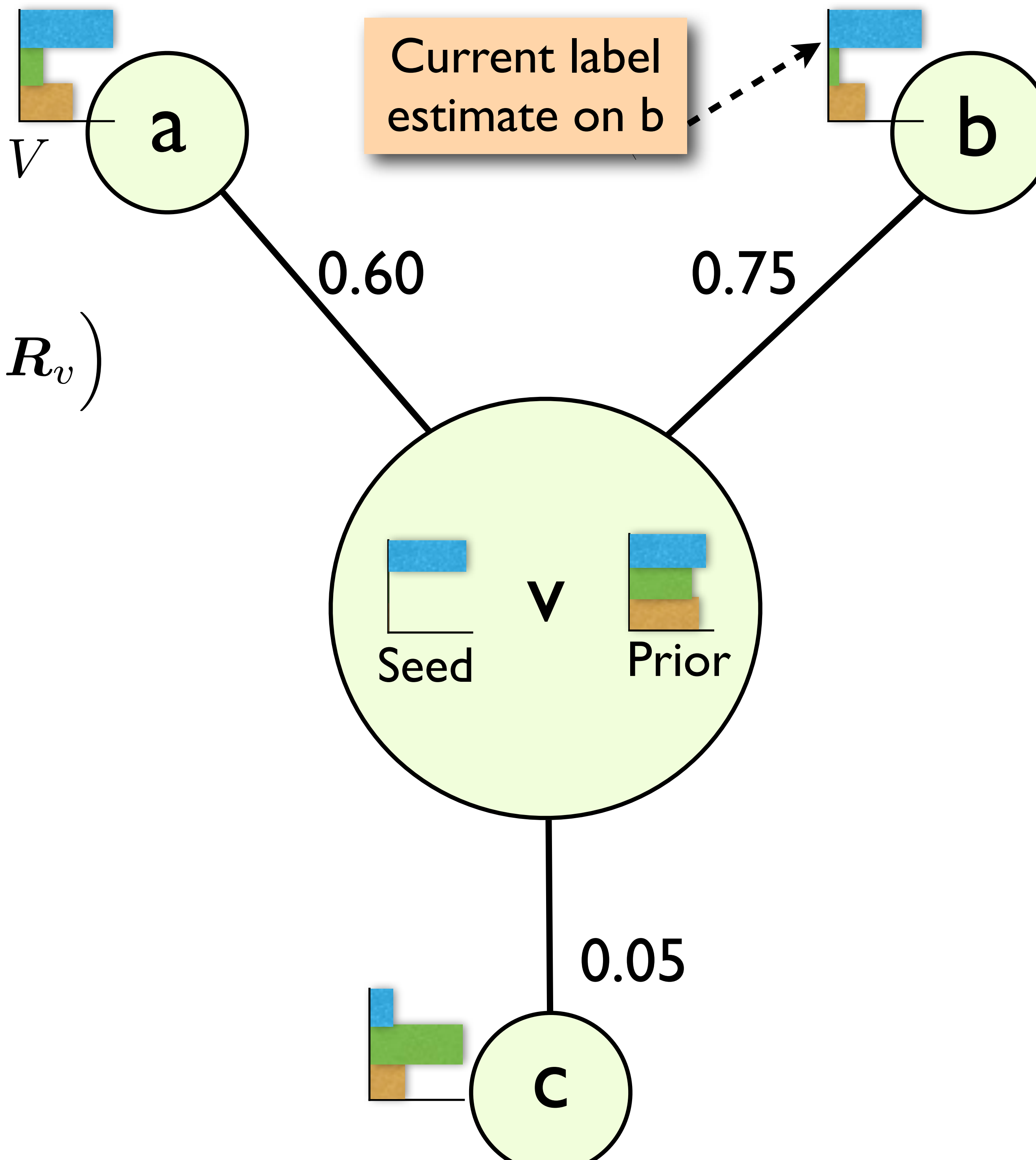
repeat

  for all $v \in V$ **do**

    $\hat{\boldsymbol{Y}}_v \leftarrow \frac{1}{Z_v} \left((\boldsymbol{S}\boldsymbol{Y})_v + \mu_1 \boldsymbol{M}_{v\cdot} \hat{\boldsymbol{Y}} + \mu_2 \boldsymbol{R}_v \right)$

  end for

until convergence



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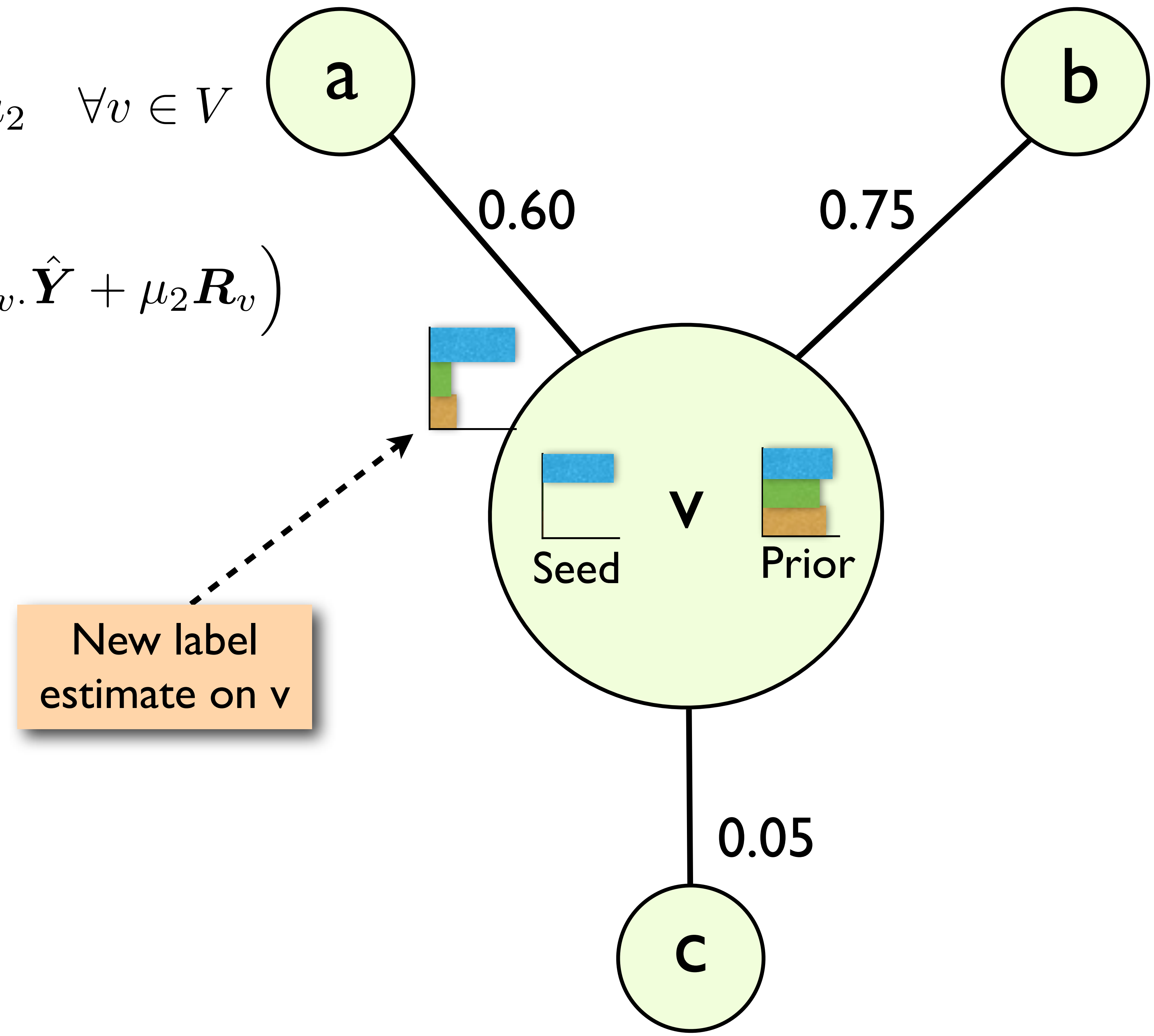

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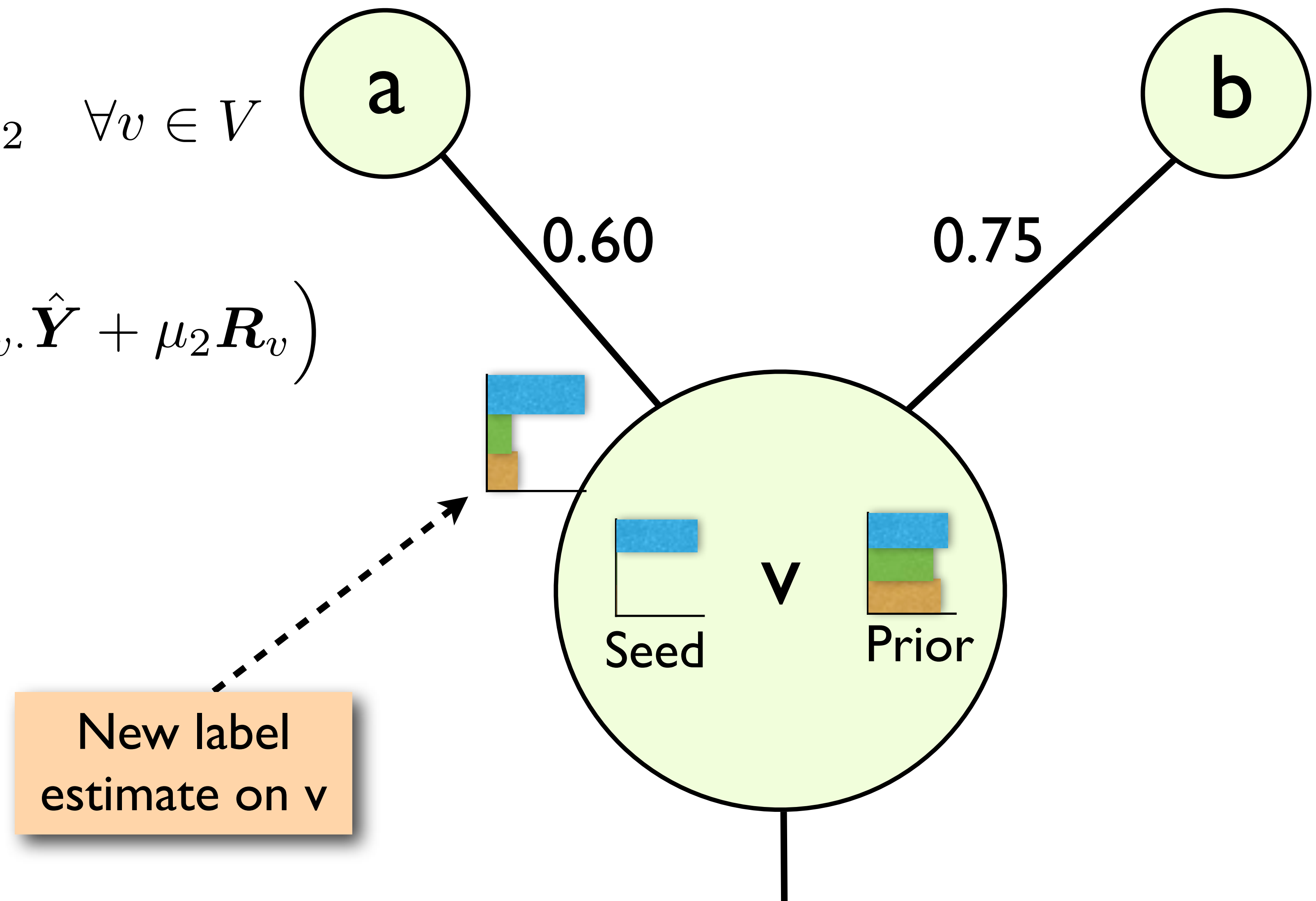

- Importance of a node can be discounted
- Easily Parallelizable: Scalable (more later)

When is MAD most effective?

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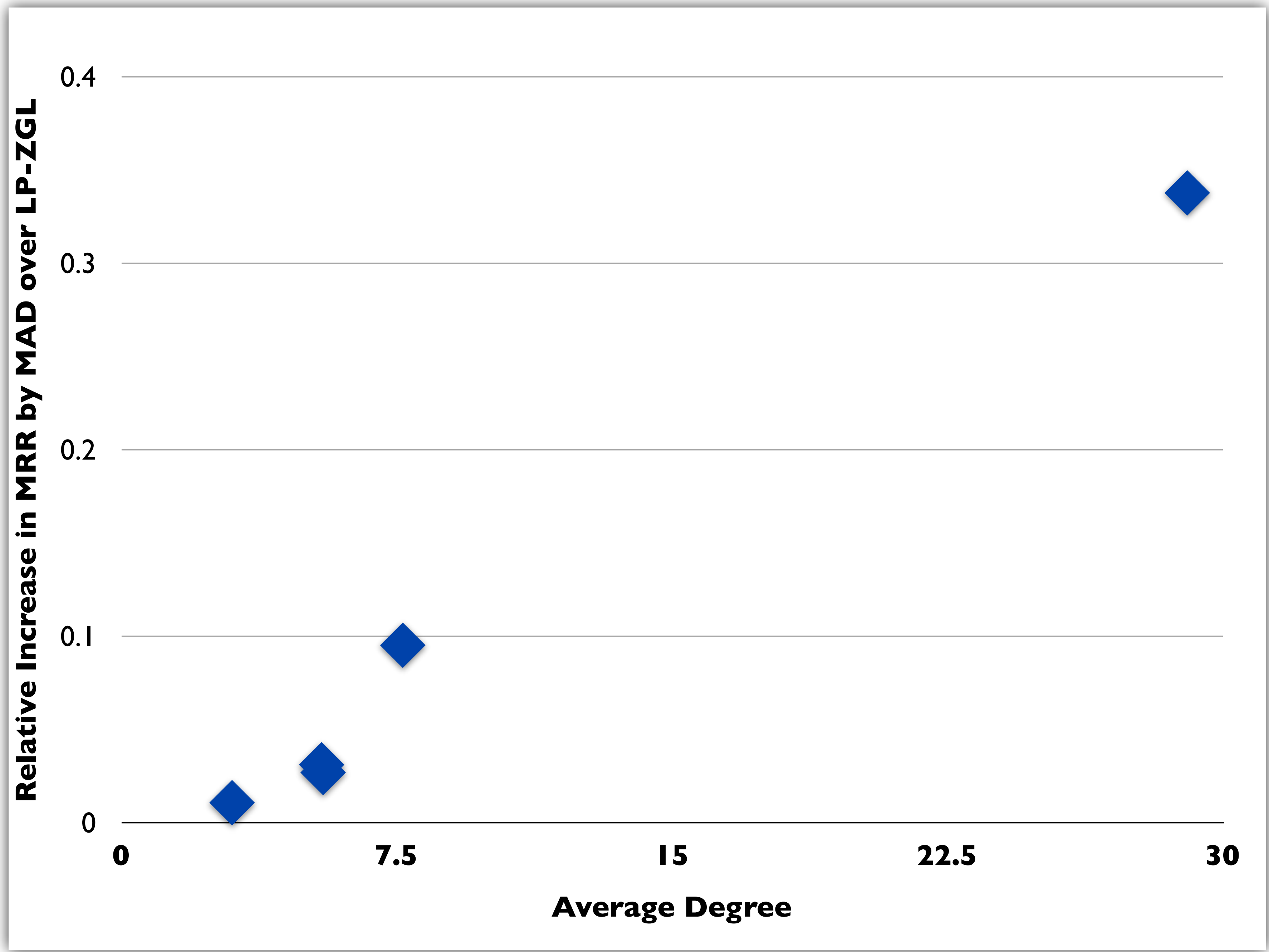
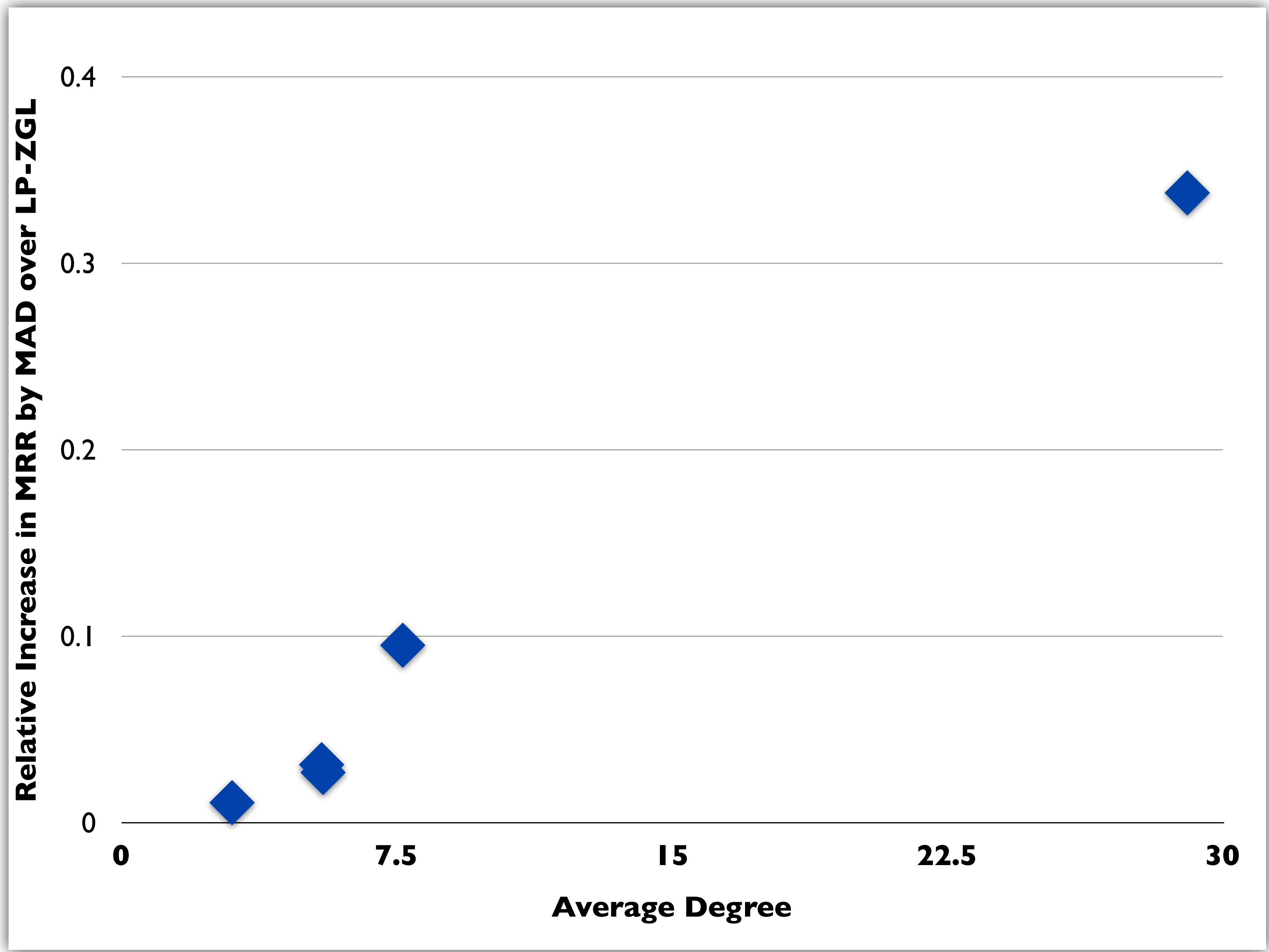


When is MAD most effective?



MAD is particularly effective in denser graphs, where there is greater need for regularization.

Extension to Dependent Labels

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Labels are not always mutually exclusive

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Label Similarity in Sentiment Classification

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Modified Adsorption with Dependent Labels (MADDL) [Talukdar and Crammer, ECML 2009]

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- Can take label similarities into account
- Convex Objective

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Labels are not always mutually exclusive

Label Similarity in Sentiment Classification

Modified Adsorption with Dependent Labels (MADDL) [Talukdar and Crammer, ECML 2009]

- Can take label similarities into account
- Convex Objective
- Efficient iterative/parallelizable updates as in MAD

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Measure Propagation (MP)

[Subramanya and Bilmes, EMNLP 2008, NIPS 2009, JMLR 2011]

CKL

$$\arg\min_{\{p_i\}} \sum_{i=1}^{l} D_{KL}(r_i||p_i) + \mu \sum_{i,j} w_{ij} D_{KL}(p_i||p_j) - \nu \sum_{i=1}^{n} H(p_i)$$

$$\text{s.t.} \ \sum_{y} p_i(y) = 1, \ p_i(y) \geq 0, \ \forall y, i$$

Measure Propagation (MP)

[Subramanya and Bilmes, EMNLP 2008, NIPS 2009, JMLR 2011]

C_{KL}

Divergence on seed nodes

$$\arg\min_{\{p_i\}} \sum_{i=1}^{l} \boxed{D_{KL}(r_i||p_i)} + \mu \sum_{i,j} w_{ij} D_{KL}(p_i||p_j) - \nu \sum_{i=1}^{n} H(p_i)$$

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Seed and estimated label distributions (normalized) on node *i*

Measure Propagation (MP)

[Subramanya and Bilmes, EMNLP 2008, NIPS 2009, JMLR 2011]

CKL

Divergence on seed nodes

Smoothness (divergence across edge)

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Seed and estimated label distributions (normalized) on node *i*

KL Divergence

$$D_{KL}(p_i || p_j) = \sum_y p_i(y) \log \frac{p_i(y)}{p_j(y)}$$

Measure Propagation (MP)

[Subramanya and Bilmes, EMNLP 2008, NIPS 2009, JMLR 2011]

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Smoothness (divergence across edge)

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Entropy

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Measure Propagation (MP)

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Smoothness (divergence across edge)

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Seed and estimated label distributions (normalized) on node *i*

Normalization Constraint

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$$D_{KL}(p_i \| p_j) = \sum_{y} p_i(y) \log \frac{p_i(y)}{p_j(y)}$$

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Entropy

$$H(p_i) = -\sum_y p_i(y) \log p_i(y)$$

C_{KL} is convex (with non-negative edge weights and hyper-parameters)

MP is related to Information Regularization [Corduneanu and Jaakkola, 2003]

Solving MP Objective

- For ease of optimization, reformulate MP objective:

CMP

$$\arg\min_{\{p_i, q_i\}} \sum_{i=1}^{l} D_{KL}(r_i || q_i) + \mu \sum_{i,j} w'_{ij} D_{KL}(p_i || q_j) - \nu \sum_{i=1}^{n} H(p_i)$$

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Encourages agreement between p_i and q_i

$$\operatorname*{argmin}_{\mathrm{p} \in \Delta^n} C_{KL}(\mathrm{p}) = \lim_{\alpha \to \infty} \operatorname*{argmin}_{\mathrm{p},\mathrm{q} \in \Delta^n} C_{MP}(\mathrm{p}, \mathrm{q})$$

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C_{MP} is also convex

(with non-negative edge weights and hyper-parameters)

Solving MP Objective

- For ease of optimization, reformulate MP objective:

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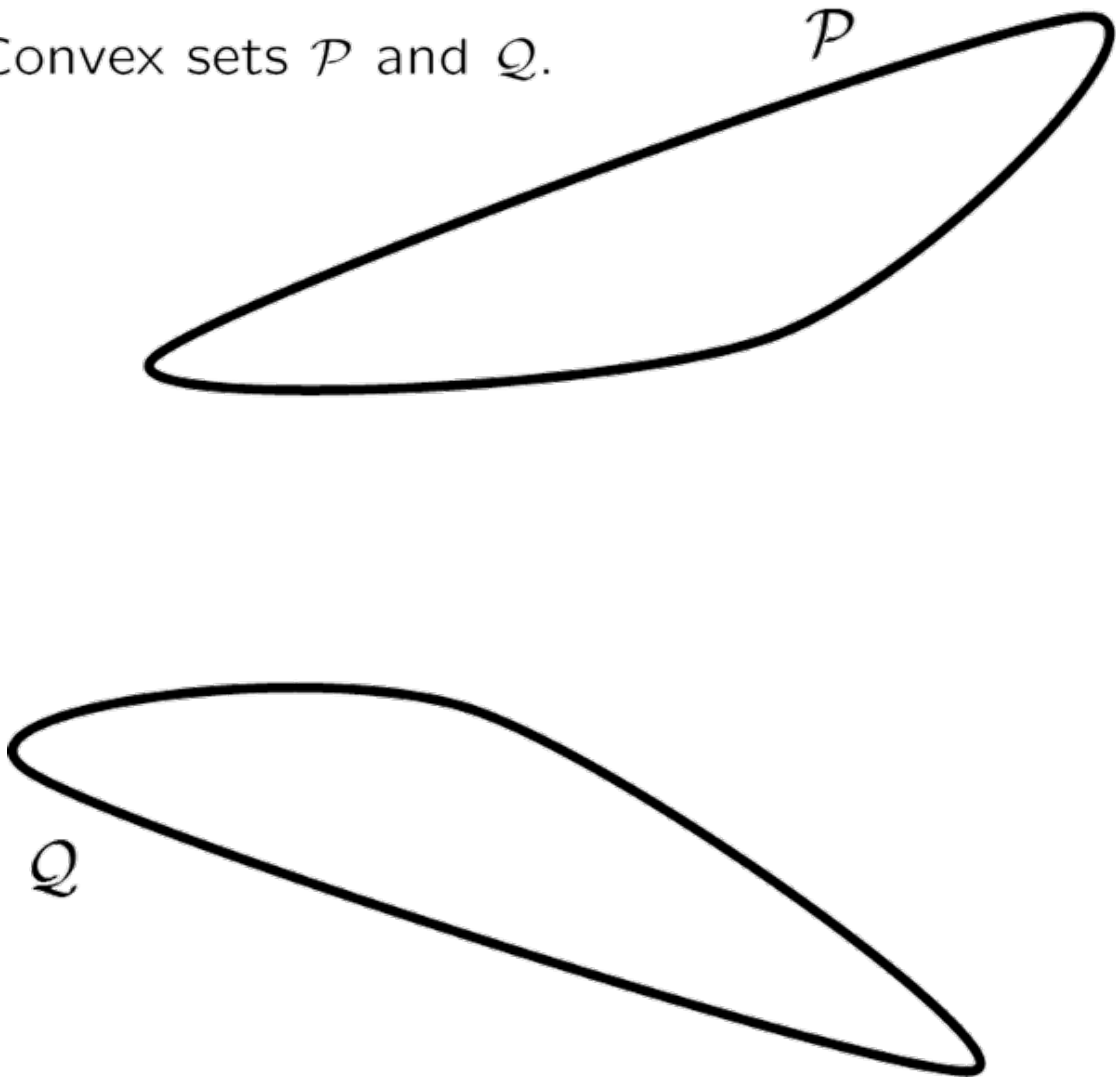
(with non-negative edge weights and hyper-parameters)

C_{MP} can be solved using Alternating Minimization (AM)

Alternating Minimization

Convex sets $\mathcal{P}$ and $\mathcal{Q}$.

Given distance $d(P, Q)$ with $P \in \mathcal{P}$ and $Q \in \mathcal{Q}$.



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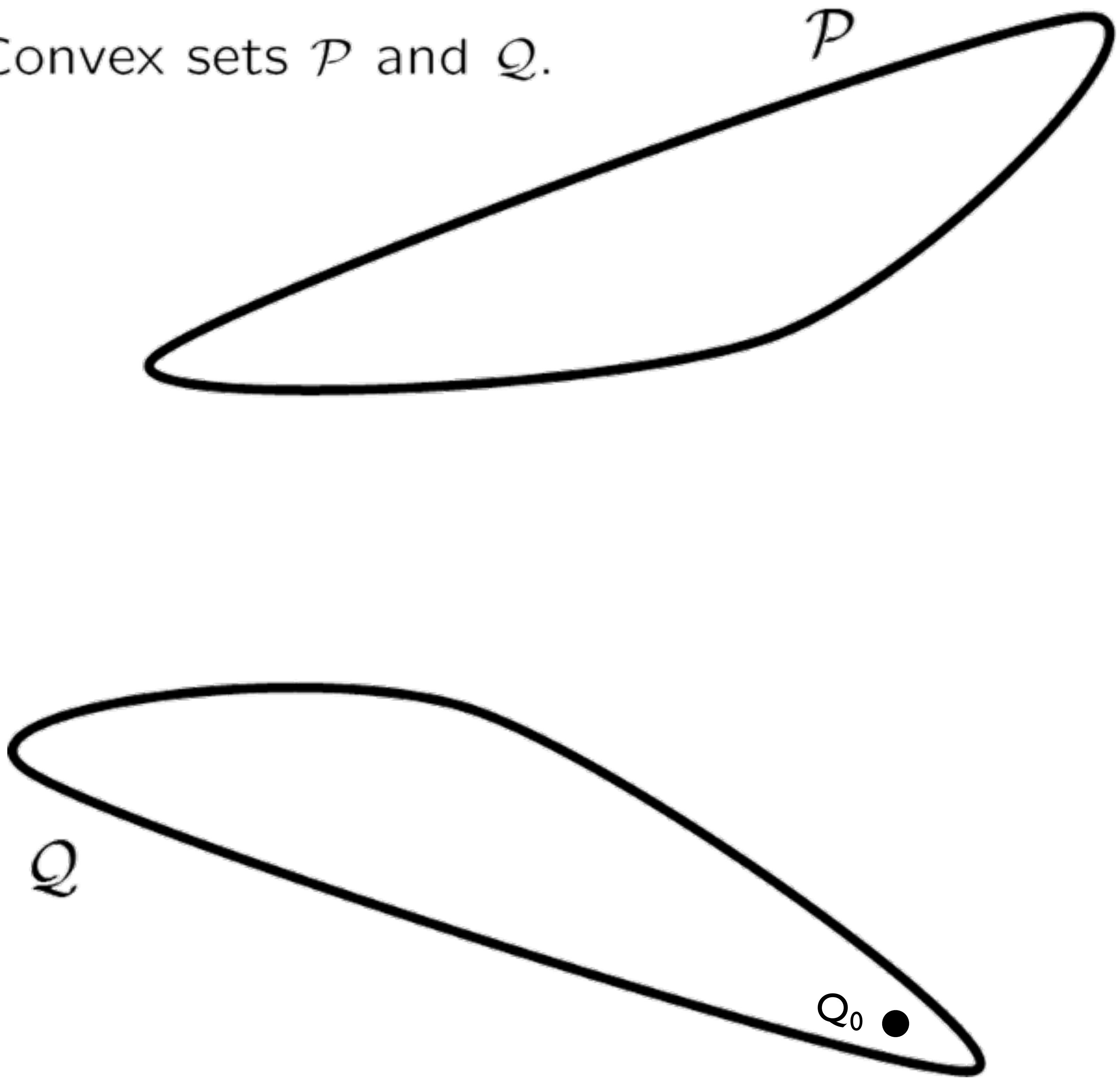

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Start with $Q_0 \in \mathcal{Q}$

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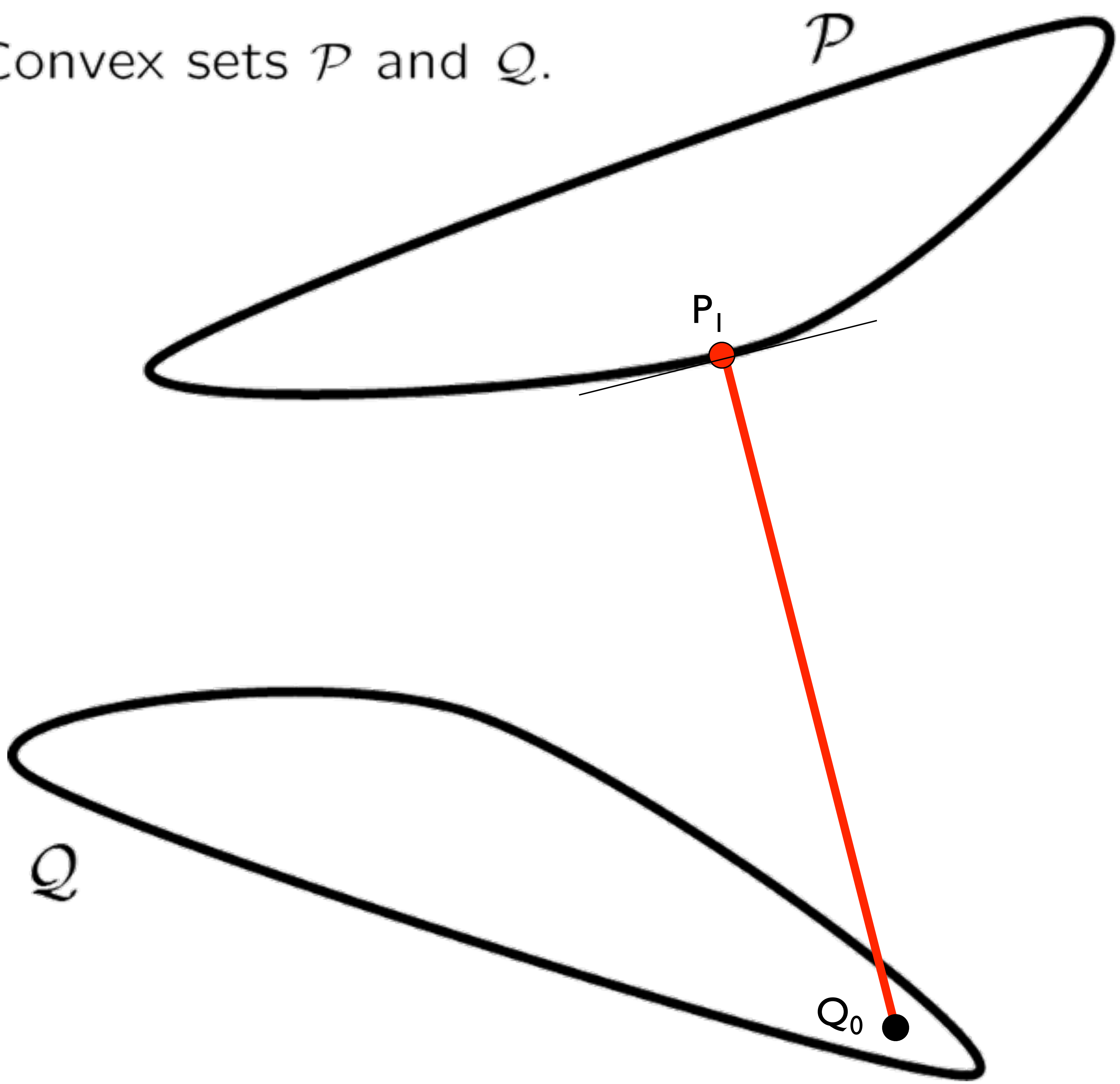

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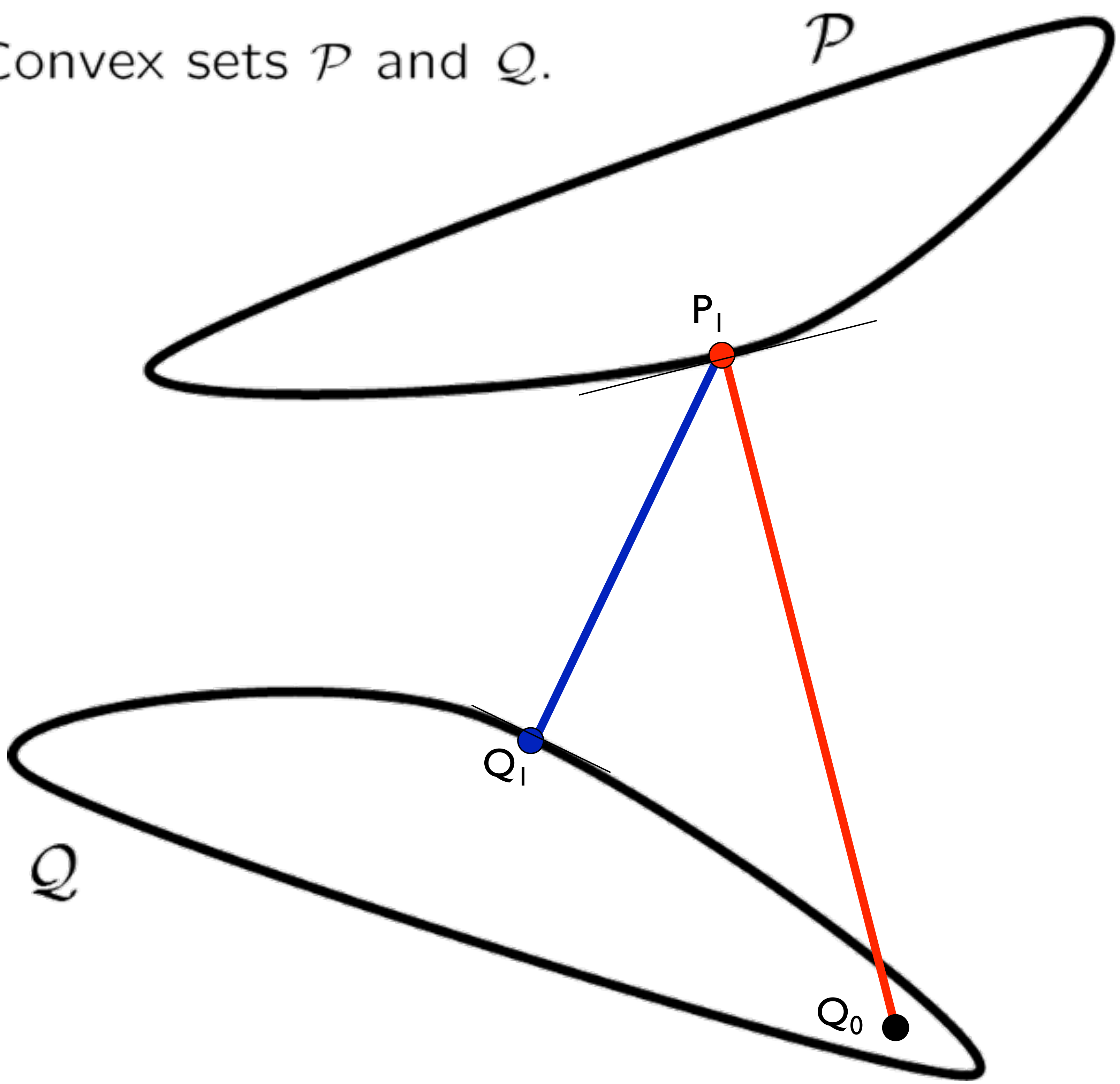

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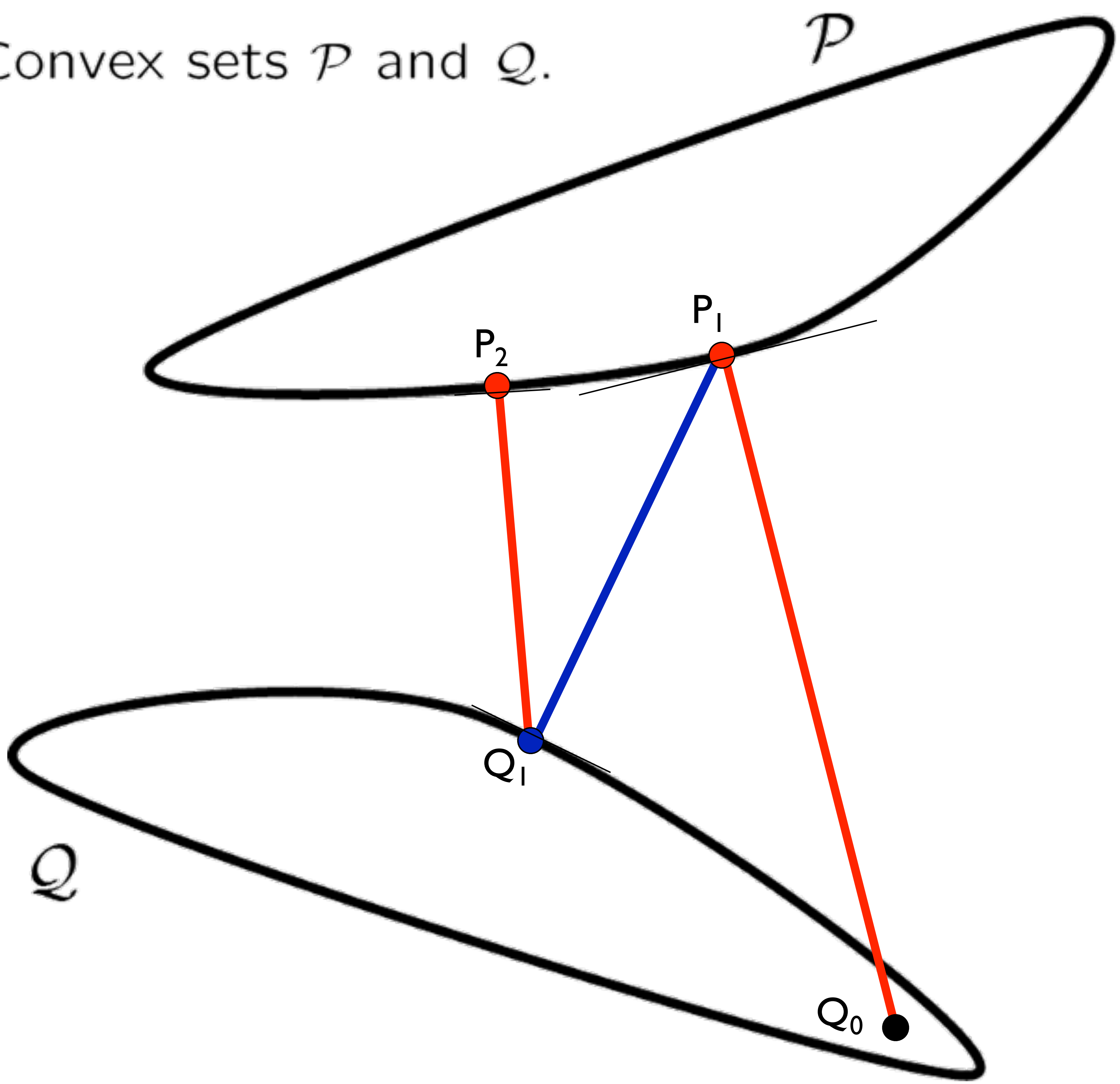

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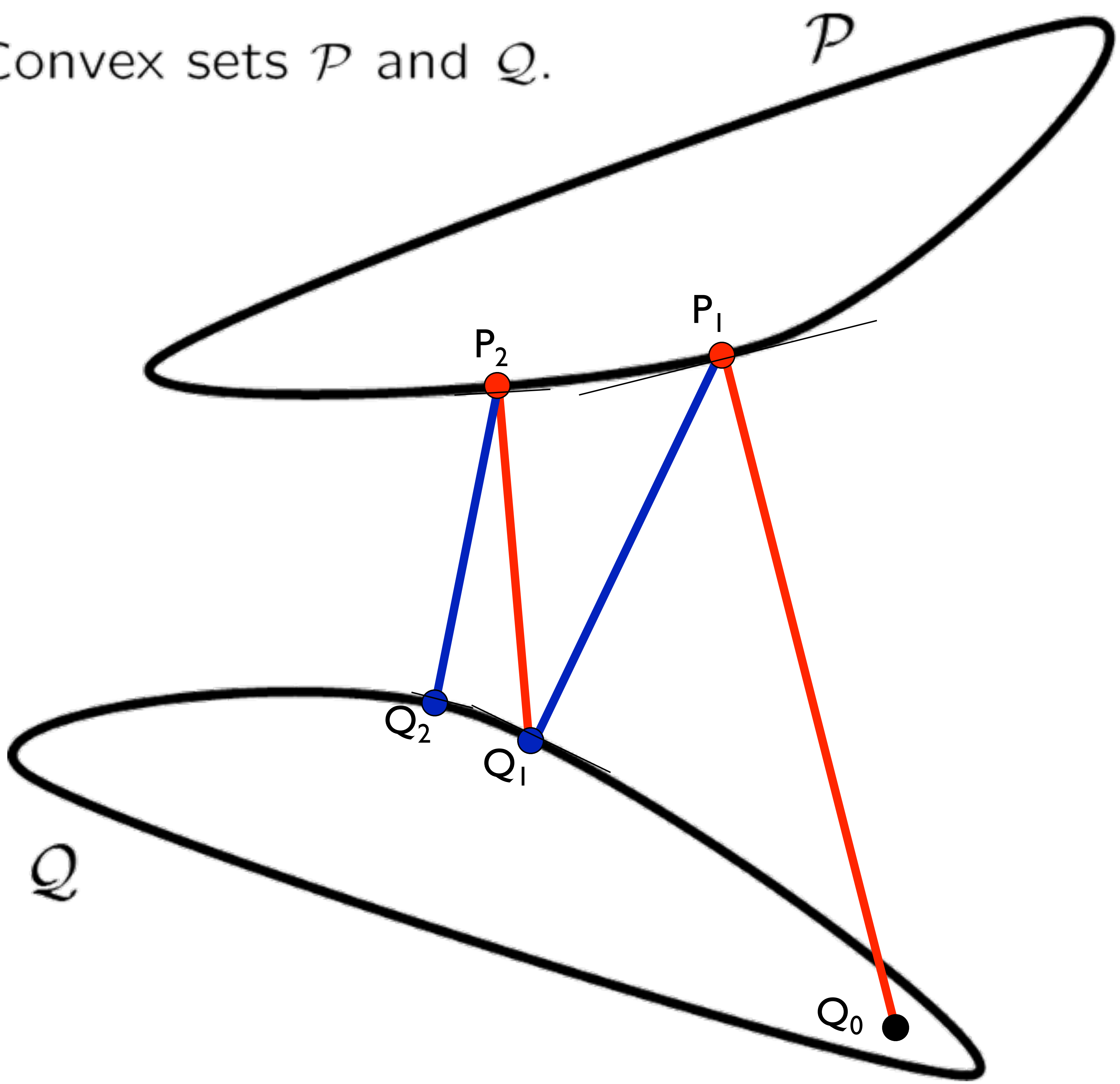

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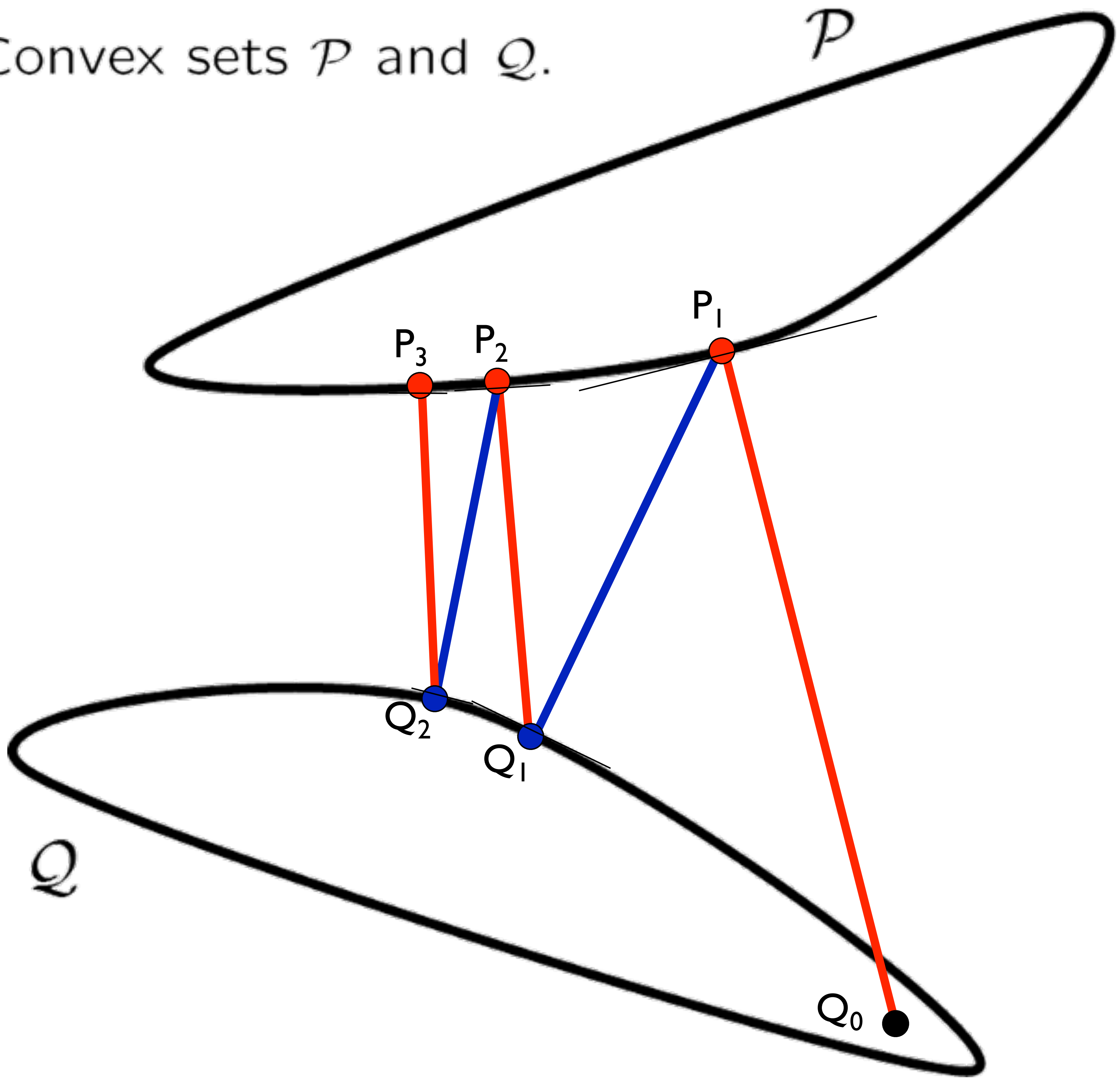

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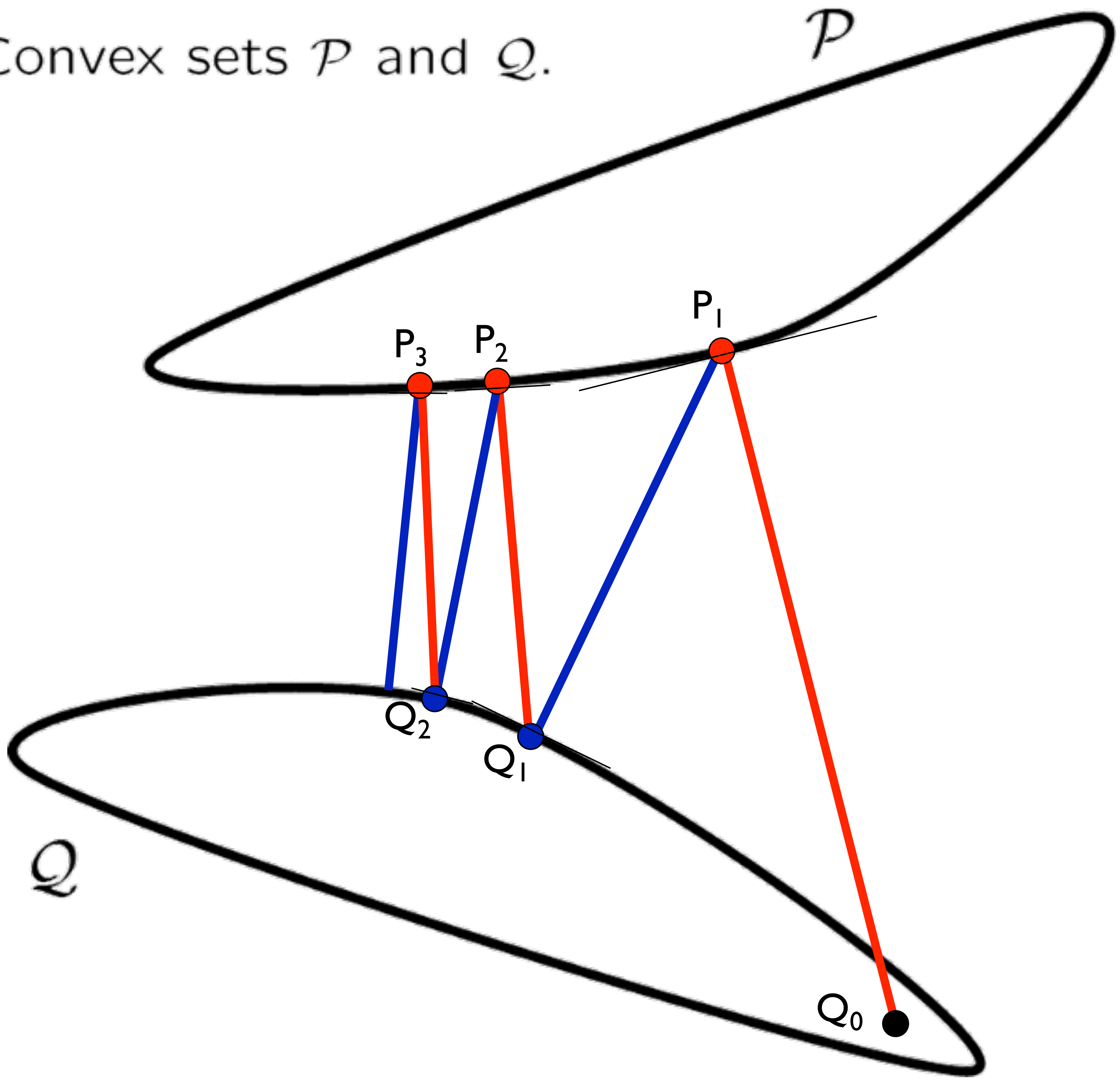

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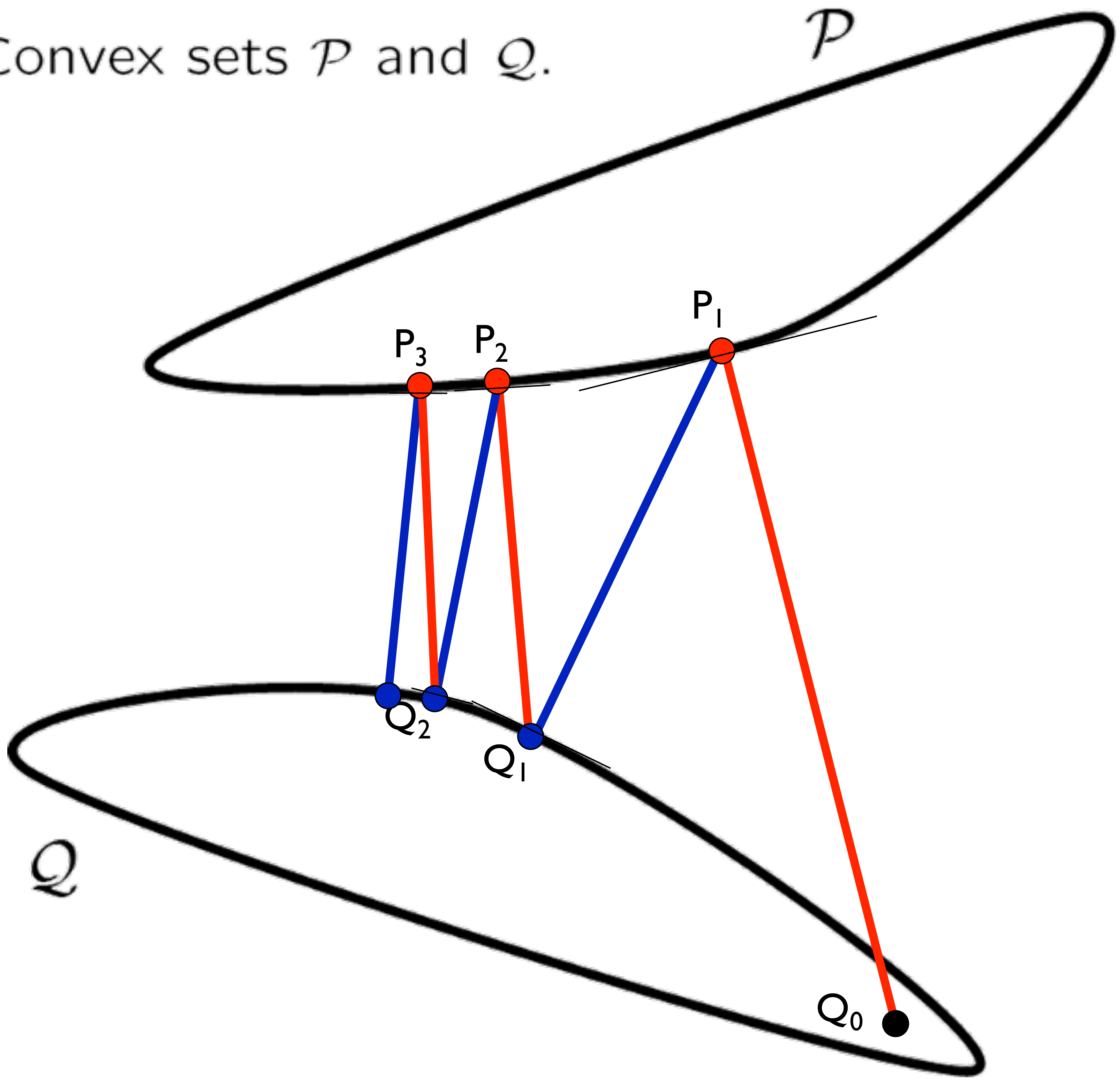

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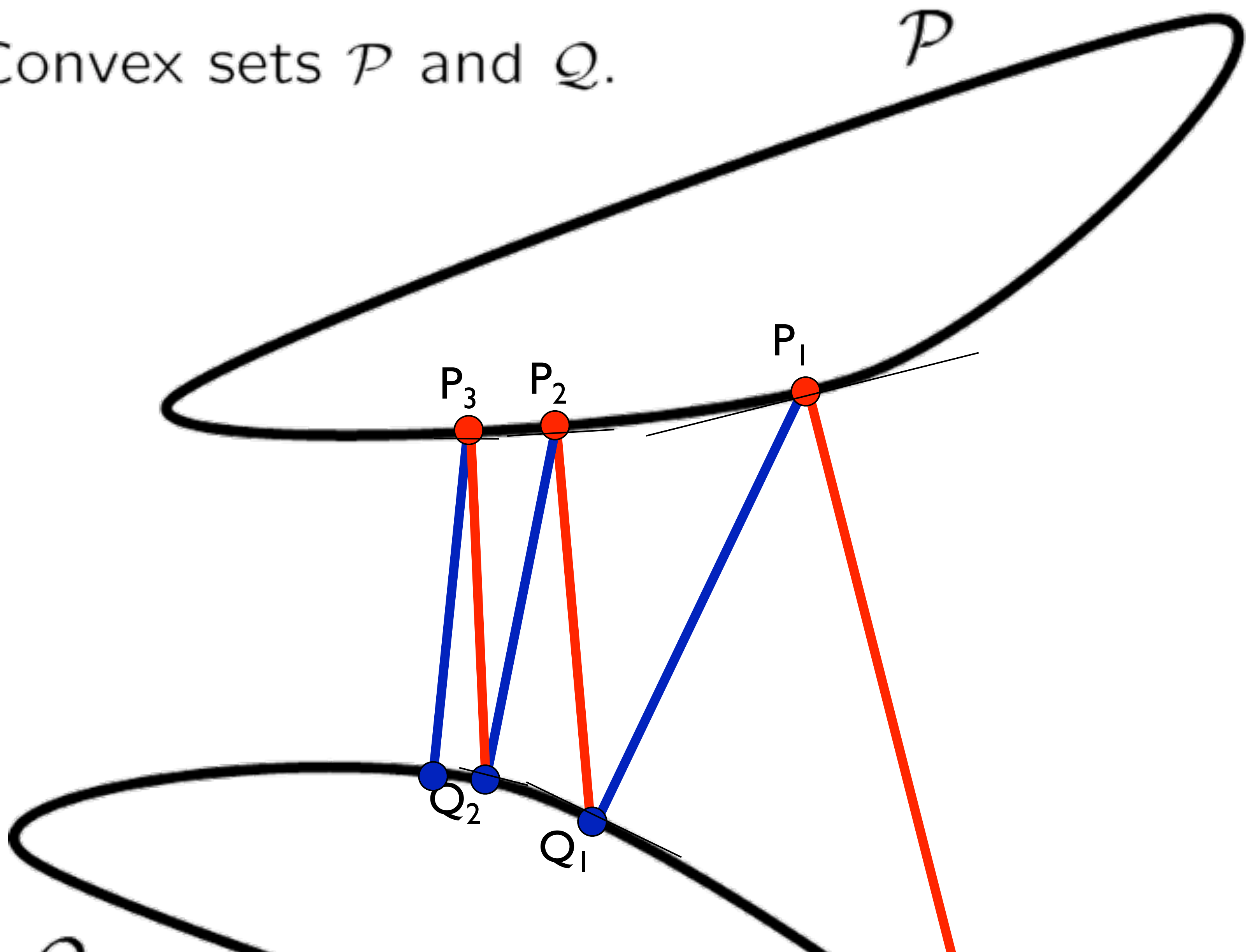

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$$P_1 = \operatorname*{argmin}_P d(P, Q_0)$$

$$Q_1 = \operatorname*{argmin}_Q d(P_1, Q)$$

$$P_2 = \operatorname*{argmin}_P d(P, Q_1)$$

$$Q_2 = \operatorname*{argmin}_Q d(P_2, Q)$$

C$_{\text{MP}}$ satisfies the necessary conditions for AM to converge [Subramanya and Bilmes, JMLR 2011]

Why AM?

Why AM?

Criteria	MOM	AM
Iterative	YES	YES
Learning Rate	Armijo Rule	None
Number of Hyper-parameters	7	1 (α)
Test for Convergence	Requires Tuning	Automatic
Update Equations	Not Intuitive	Intuitive and easily Parallelized

Table 1: There are two ways to solving the proposed objective, namely, the popular numerical optimization tool method of multipliers (MOM), and the proposed approach based on alternating minimization (AM). This table compares the two approaches on various fronts.

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$$p_i^{(n)}(y) = \frac{\exp\{\frac{\mu}{\gamma_i}\sum_j w'_{ij}\log q_j^{(n-1)}(y)\}}{\sum_y \exp\{\frac{\mu}{\gamma_i}\sum_j w'_{ij}\log q_j^{(n-1)}(y)\}}$$

$$q_i^{(n)}(y) = \frac{r_i(y)\delta(i \le l) + \mu\sum_j w'_{ji} p_j^{(n)}(y)}{\delta(i \le l) + \mu\sum_j w'_{ji}}$$

$$\text{where } \gamma_i = \nu + \mu\sum_j w'_{ij}$$

Performance of SSL Algorithms

	COIL						OPT					
l	10	20	50	80	100	150	10	20	50	80	100	150
k-NN	34.5	53.9	66.9	77.9	79.2	83.5	79.6	83.9	85.5	90.5	92.0	93.8
SGT	40.1	61.2	78.0	88.5	89.0	89.9	90.4	90.6	91.4	94.7	**97.4**	**97.4**
LapRLS	**49.2**	61.4	78.4	80.1	84.5	87.8	89.7	**91.2**	92.3	96.1	**97.6**	**97.3**
SQ-Loss-I	**48.9**	63.0	**81.0**	87.5	89.0	90.9	**92.2**	90.2	**95.9**	**97.2**	**97.3**	**97.7**
MP	47.7	**65.7**	78.5	**89.6**	**90.2**	**91.1**	90.6	**90.8**	94.7	**96.6**	**97.0**	**97.1**

Comparison of accuracies for different number of labeled samples across COIL (6 classes) and OPT (10 classes) datasets

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Graph SSL can be effective when the data satisfies manifold assumption. More results and discussion in Chapter 21 of the SSL Book (Chapelle et al.)

Outline

- Motivation
- Graph Construction
- Inference Methods
  - Label Propagation
  - Modified Adsorption
  - Measure Propagation
  - Sparse Label Propagation
  - Manifold Regularization
- Scalability
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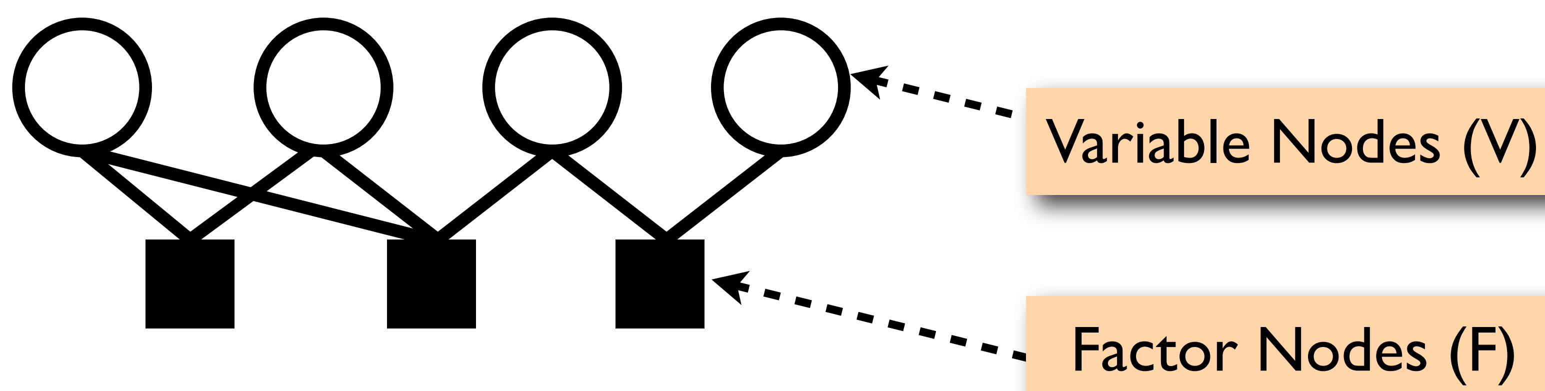
Background: Factor Graphs
[Kschischang et al., 2001]

Factor Graph

- bipartite graph
- variable nodes (e.g., label distribution on a node)
- factor nodes: fitness function over variable assignment



Distribution over all variables' values

$$\log P\left(\{v\}_{v\in V}\right) \quad = \quad -\log Z + \sum_{f\in F} \log \alpha_f \left(\{v\}_{(v,f)\in E}\right)$$

variables connected to factor f

Factor Graph Interpretation of Graph SSL [Zhu et al., ICML 2003] [Das and Smith, NAACL 2012]

3-term Graph SSL Objective (common to many algorithms)

min Seed Matching Loss (if any) + Edge Smoothness Loss + Regularization Loss

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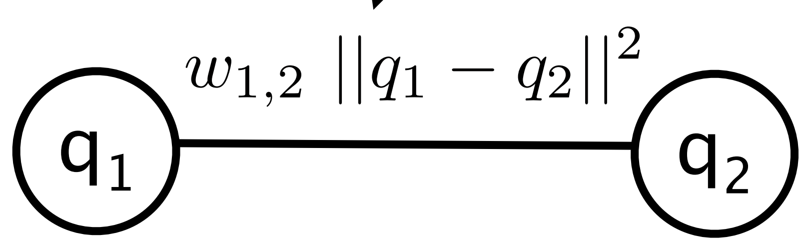

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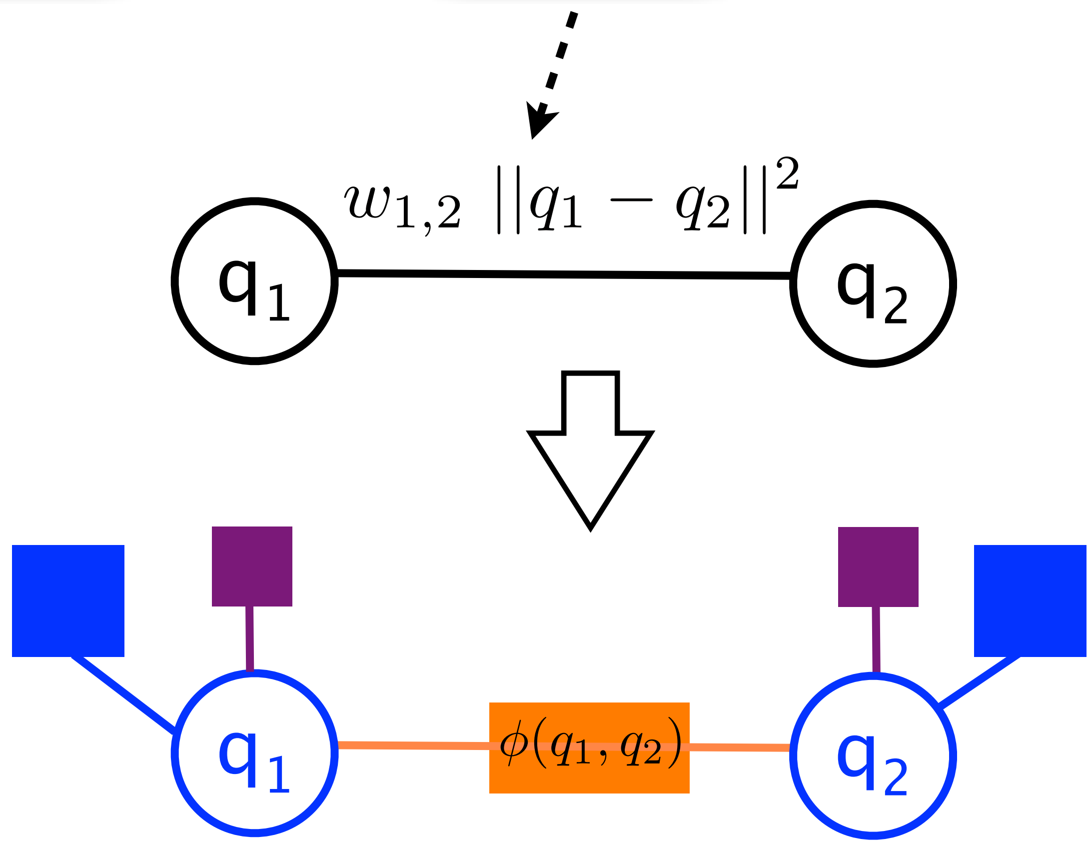

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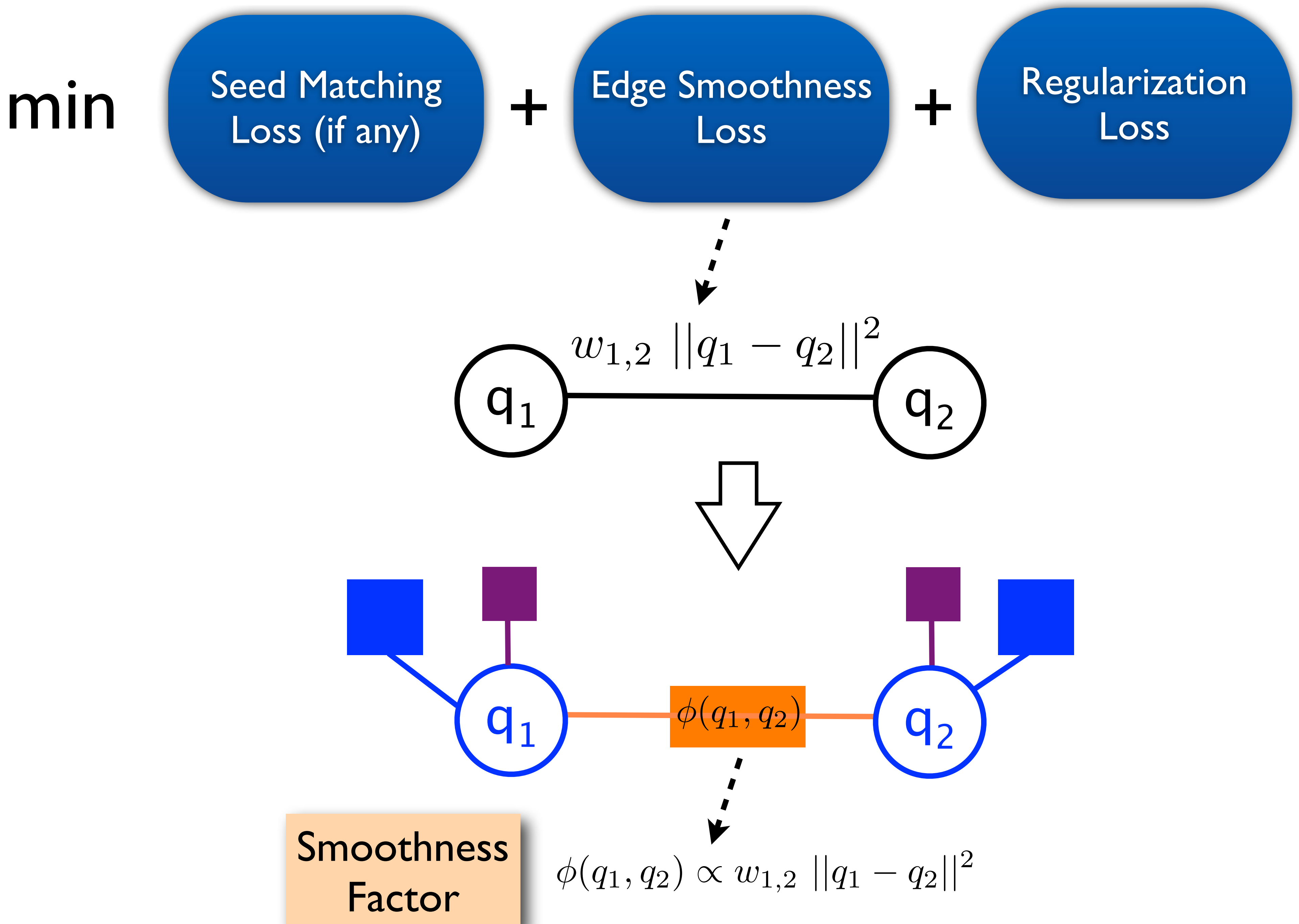

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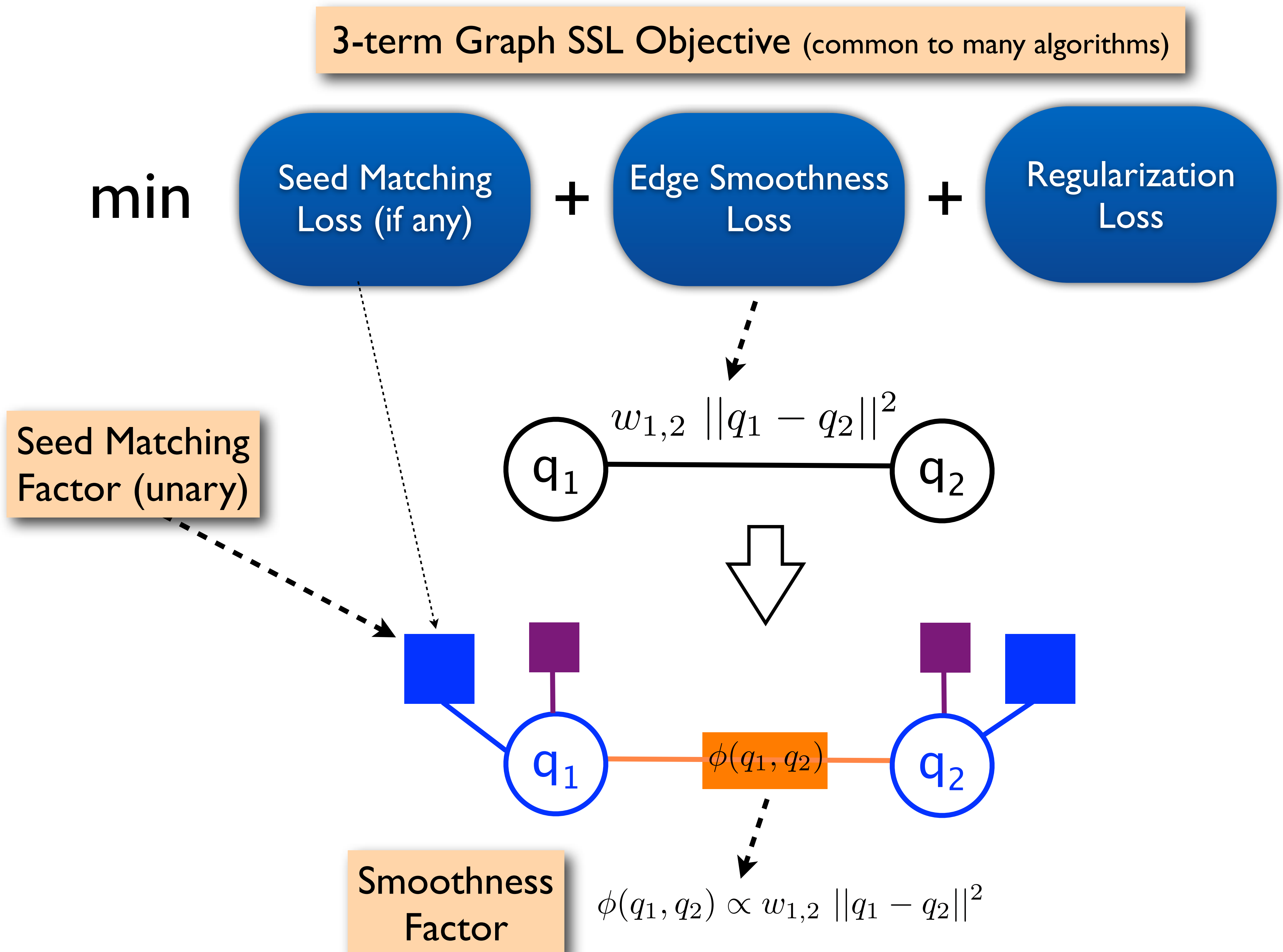

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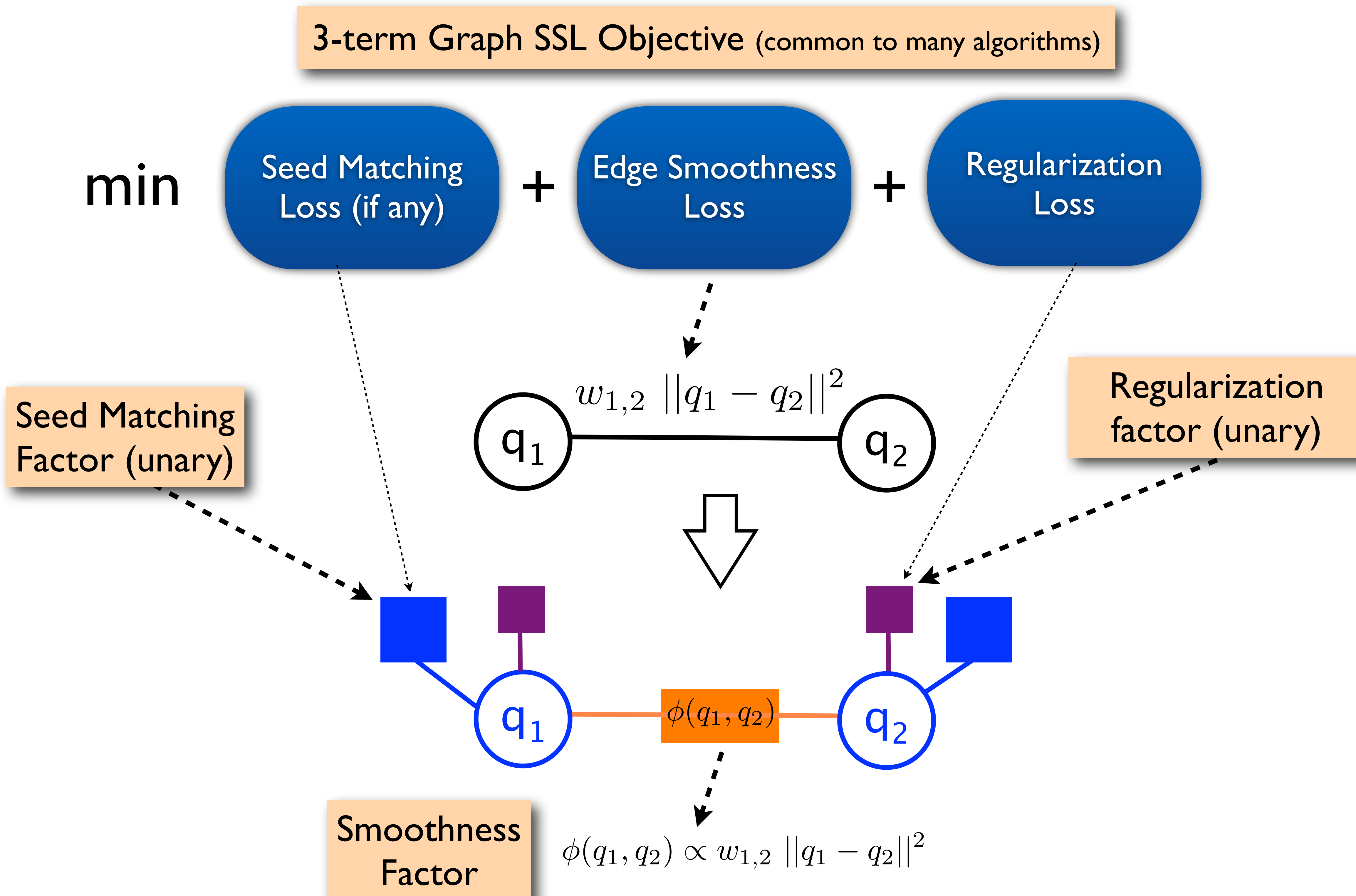
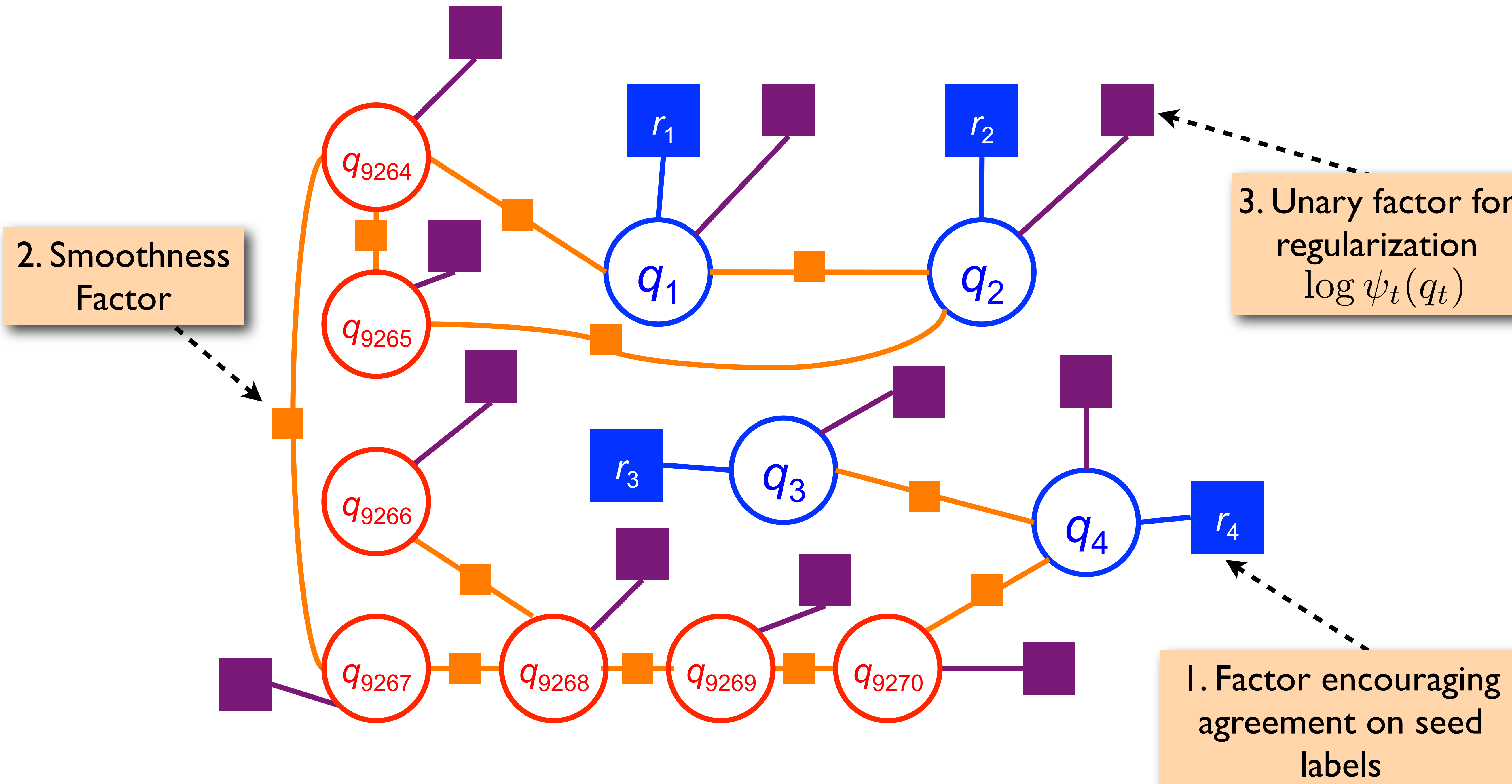


Factor Graph Interpretation

[Zhu et al., ICML 2003][Das and Smith, NAACL 2012]



Label Propagation with Sparsity

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Enforce through sparsity inducing unary factor

Label Propagation with Sparsity

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Lasso (Tibshirani, 1996) $\log \psi_t(q_t) = -\lambda \left\| q_t \right\|_1$

Elitist Lasso (Kowalski and Torrésani, 2009)

$$\log \psi_t(q_t) = -\lambda \left(\left\| q_t \right\|_1 \right)^2$$

Label Propagation with Sparsity

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For more details, see [Das and Smith, NAACL 2012]

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Manifold Regularization

[Belkin et al., JMLR 2006]

$$f^* = \arg\min_f \frac{1}{l} \sum_{i=1}^{l} V(y_i, f(x_i)) + \beta \ f^T L f + \gamma ||f||_K^2$$

Manifold Regularization
[Belkin et al., JMLR 2006]

Training Data
Loss

$$f^* = \arg\min_f \frac{1}{l} \sum_{i=1}^{l} \boxed{V(y_i, f(x_i))} + \beta\ f^T L f + \gamma ||f||_K^2$$

Loss Function
(e.g., soft margin)

Manifold Regularization

[Belkin et al., JMLR 2006]

Training Data Loss

Smoothness Regularizer

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Loss Function (e.g., soft margin)

Laplacian of graph over labeled and unlabeled data

Manifold Regularization

[Belkin et al., JMLR 2006]

Training Data Loss

Smoothness Regularizer

Regularizer (e.g., L2)

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Loss Function (e.g., soft margin)

Laplacian of graph over labeled and unlabeled data

Trains an <u>inductive</u> classifier which can generalize to unseen instances

Other Graph-based SSL Methods

- SSL on Directed Graphs
  - [Zhou et al, NIPS 2005], [Zhou et al., ICML 2005]
- Learning with dissimilarity edges
  - [Goldberg et al., AISTATS 2007]
- Spectral Graph Transduction [Joachims, ICML 2003]
- Graph Transduction using Alternating Minimization
  - [Wang et al., ICML 2008]
- Graph as regularizer for Multi-Layered Perceptron
  - [Karlen et al., ICML 2008], [Malkin et al., Interspeech 2009]

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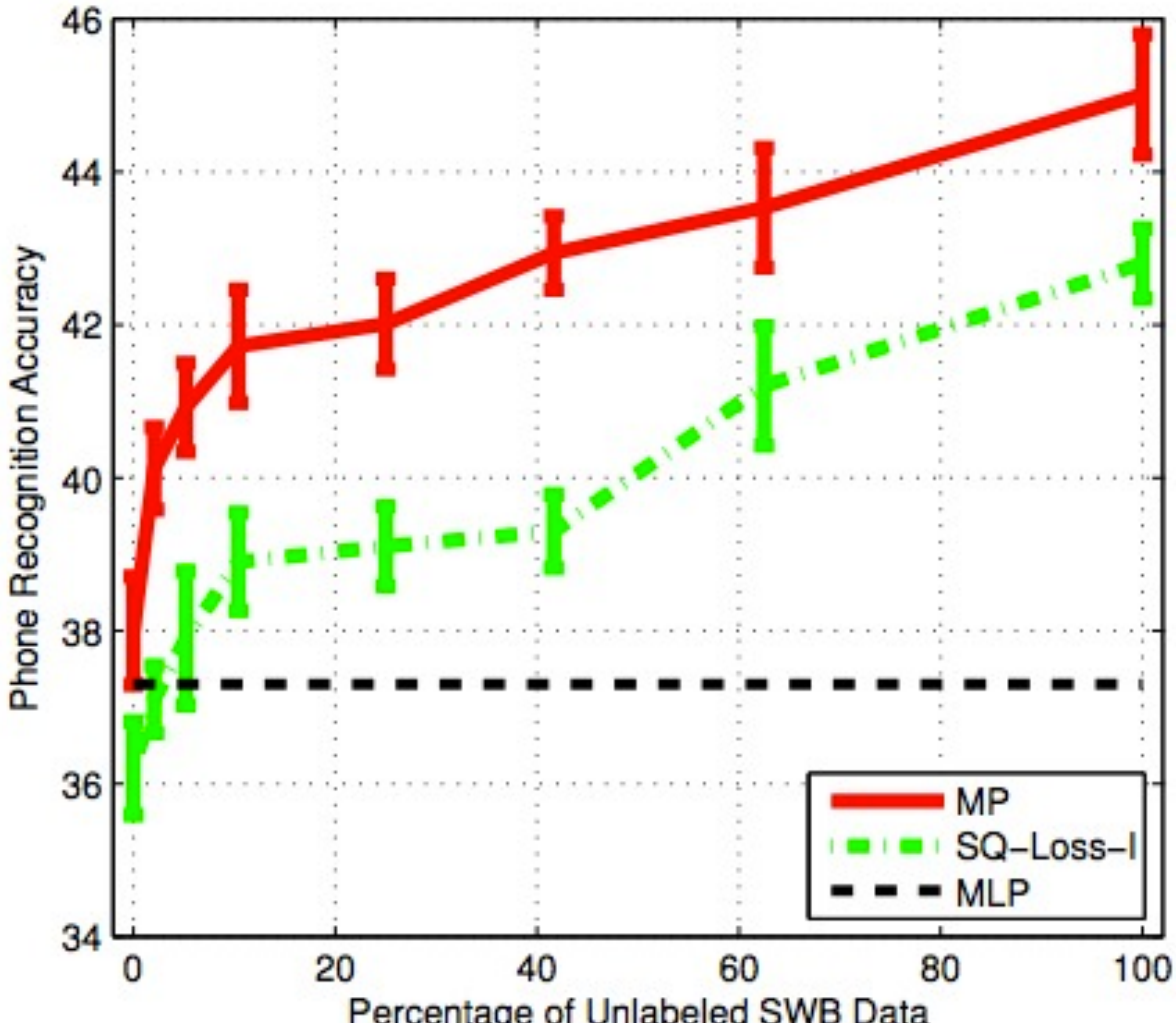
More (Unlabeled) Data is Better Data



[Subramanya & Bilmes, JMLR 2011]

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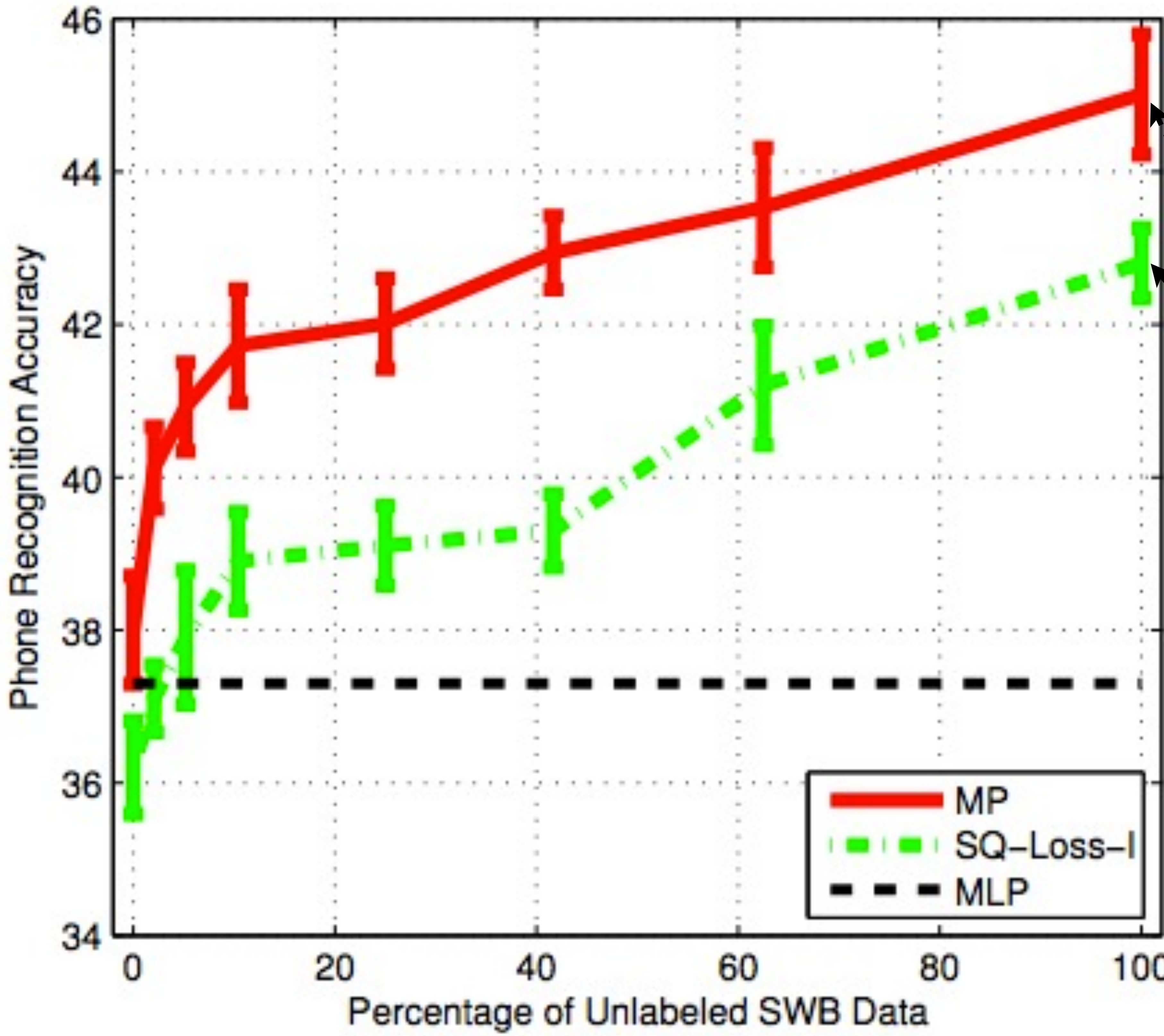

Graph with
120m
vertices

[Subramanya & Bilmes, JMLR 2011]

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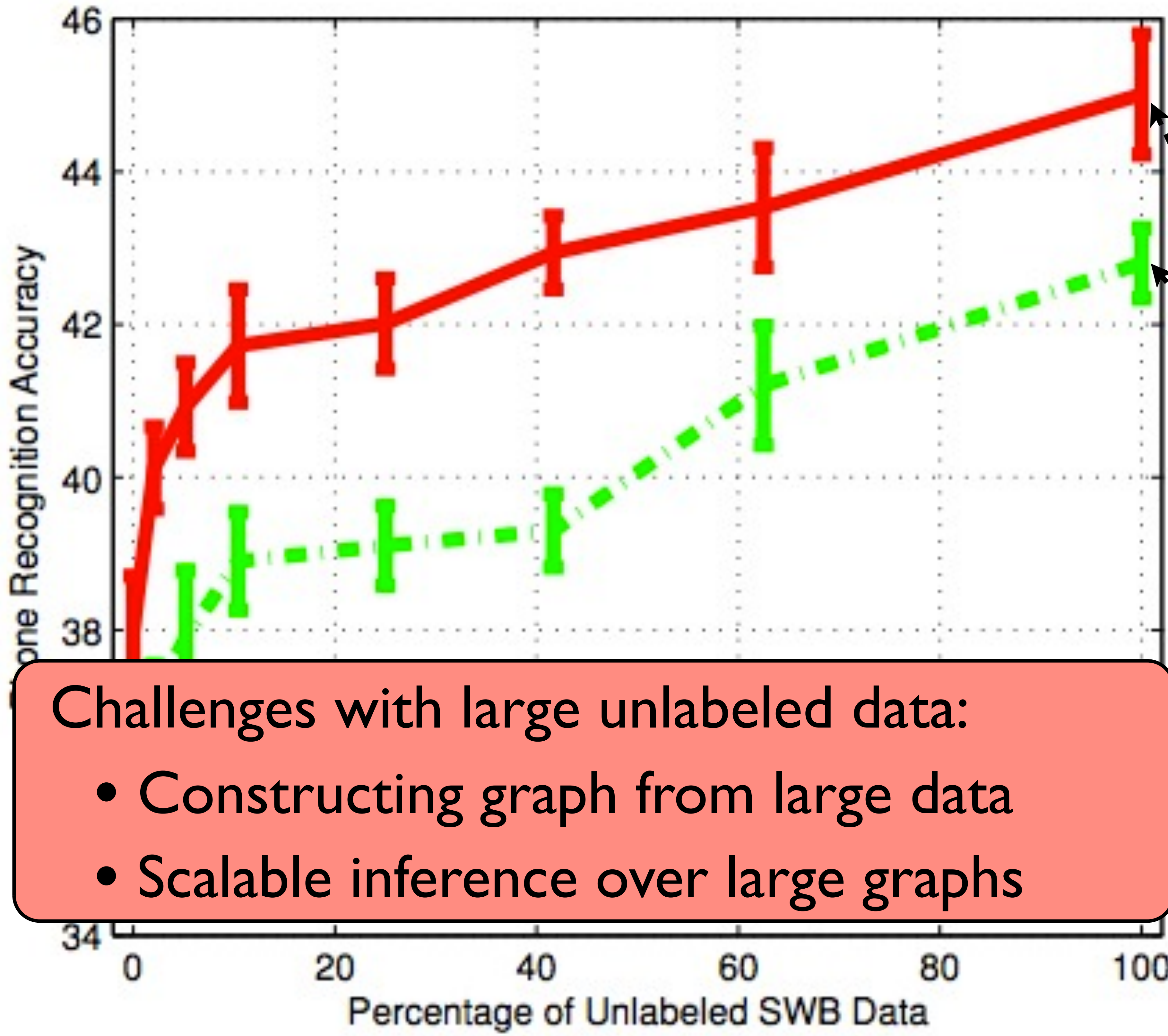

Graph with **120m** vertices

Challenges with large unlabeled data:

- Constructing graph from large data
- Scalable inference over large graphs

[Subramanya & Bilmes, JMLR 2011]

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Scalability Issues (I)

Graph Construction

Scalability Issues (I)

Graph Construction

- Brute force (exact) k-NNG too expensive (quadratic)

Scalability Issues (I)
Graph Construction

- Brute force (exact) k-NNG too expensive (quadratic)
  - Approximate nearest neighbor using kd-tree [Friedman et al., 1977, also see http://www.cs.umd.edu/˜mount/]

Scalability Issues (II)

Label Inference

- Sub-sample the data
  - Construct graph over a subset of a unlabeled data [Delalleau et al., AISTATS 2005]
  - Sparse Grids [Garcke & Griebel, KDD 2001]

Scalability Issues (II)

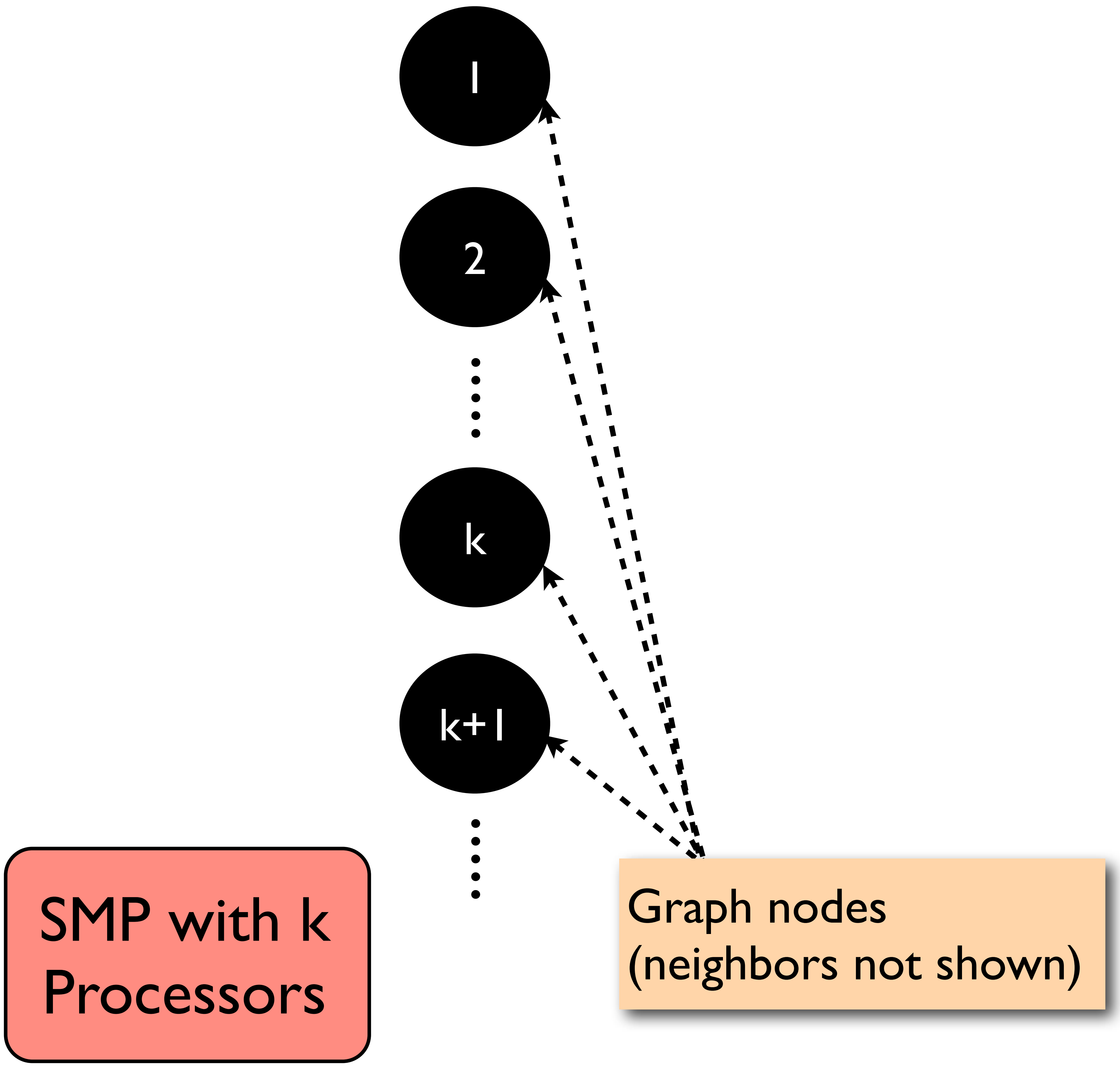
Label Inference

- Sub-sample the data
  - Construct graph over a subset of a unlabeled data [Delalleau et al., AISTATS 2005]
  - Sparse Grids [Garcke & Griebel, KDD 2001]
- How about using <u>more computation</u>? (next section)
  - Symmetric multi-processor (SMP)
  - Distributed Computer

Outline

- Motivation
- Graph Construction
- Inference Methods
- Scalability
  - Scalability Issues
  - Node reordering [Subramanya & Bilmes, JMLR 2011; Bilmes & Subramanya, 2011]
  - MapReduce Parallelization
- Applications
- Conclusion & Future Work

Parallel computation on a SMP



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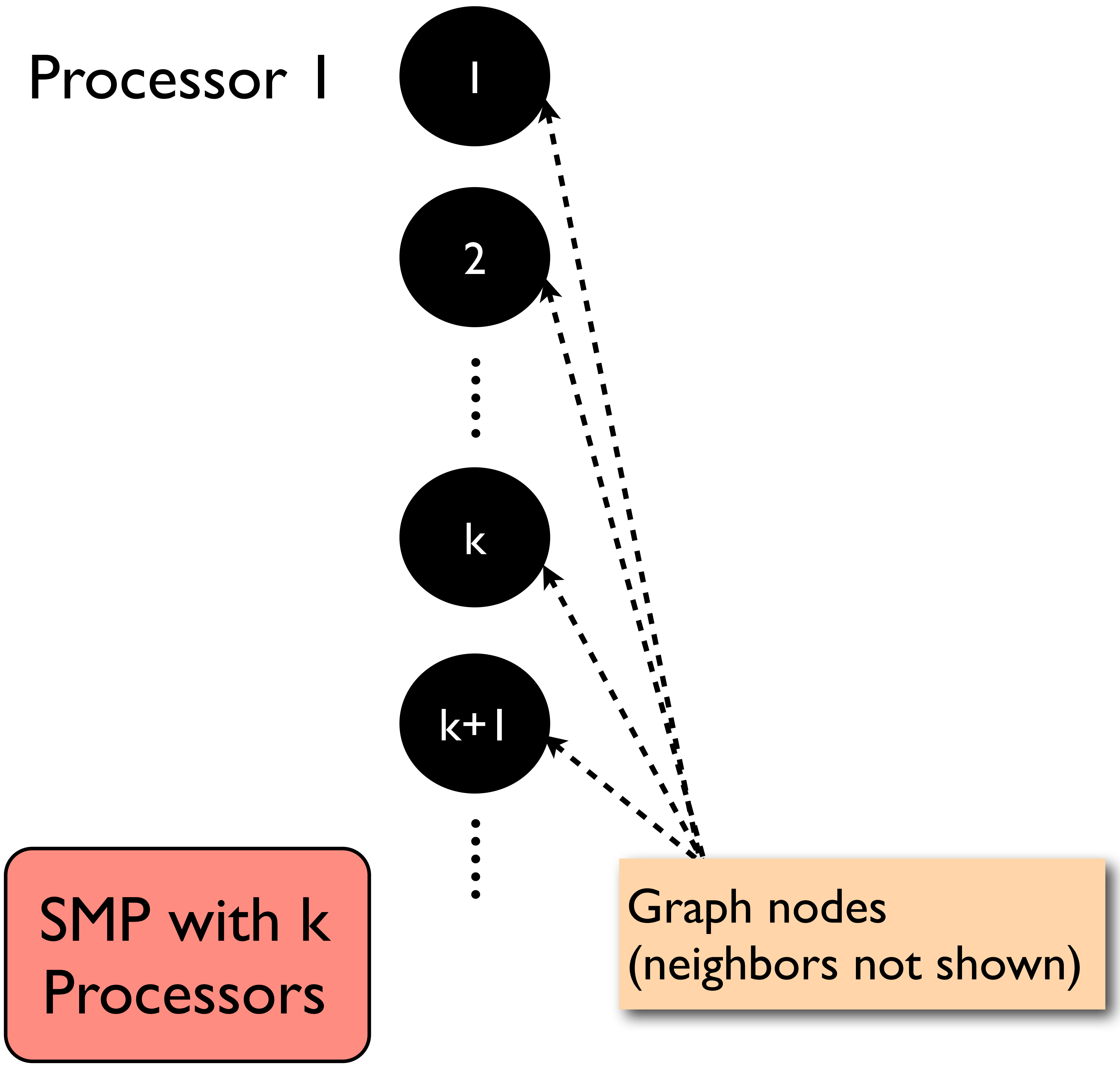

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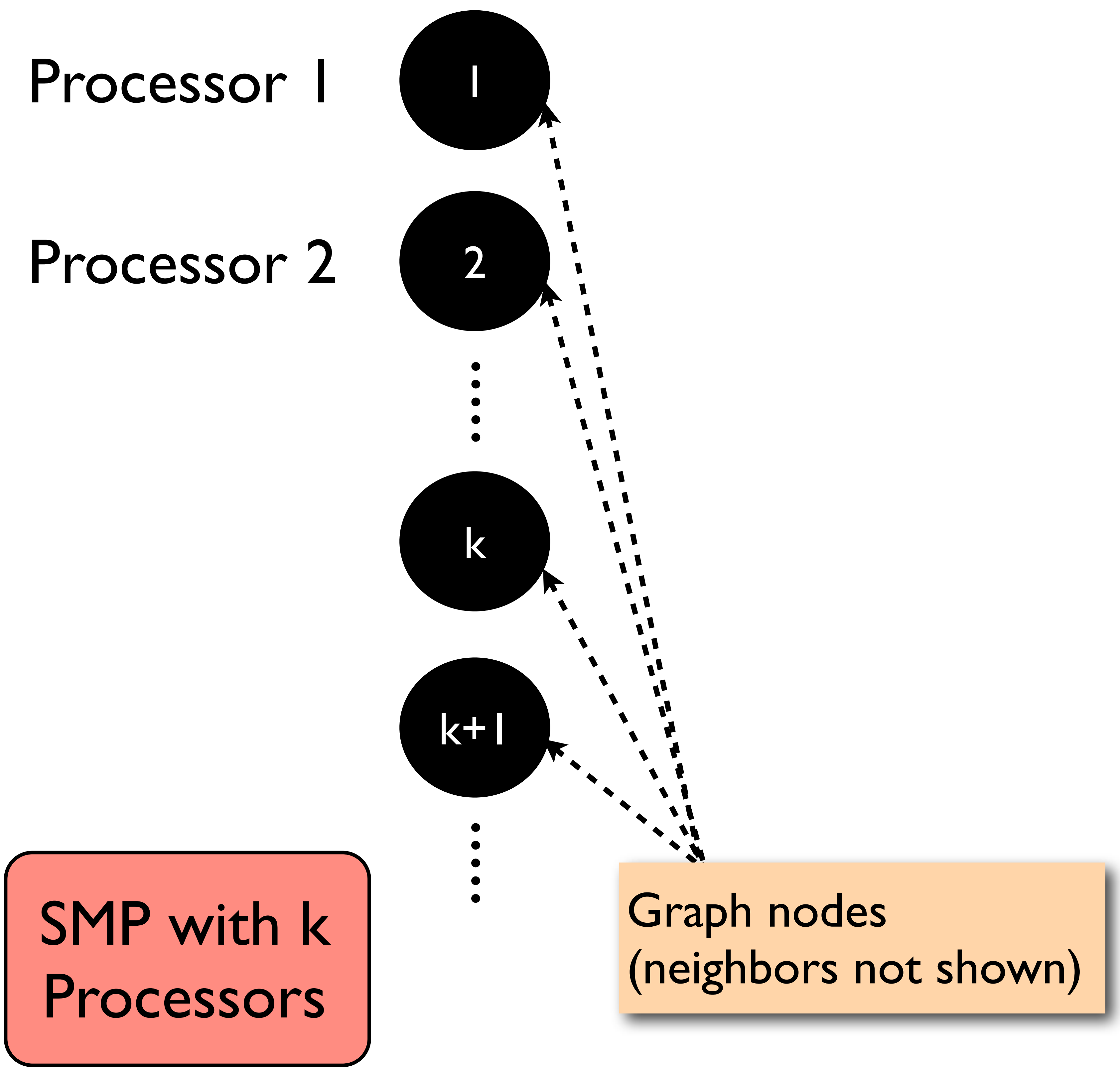

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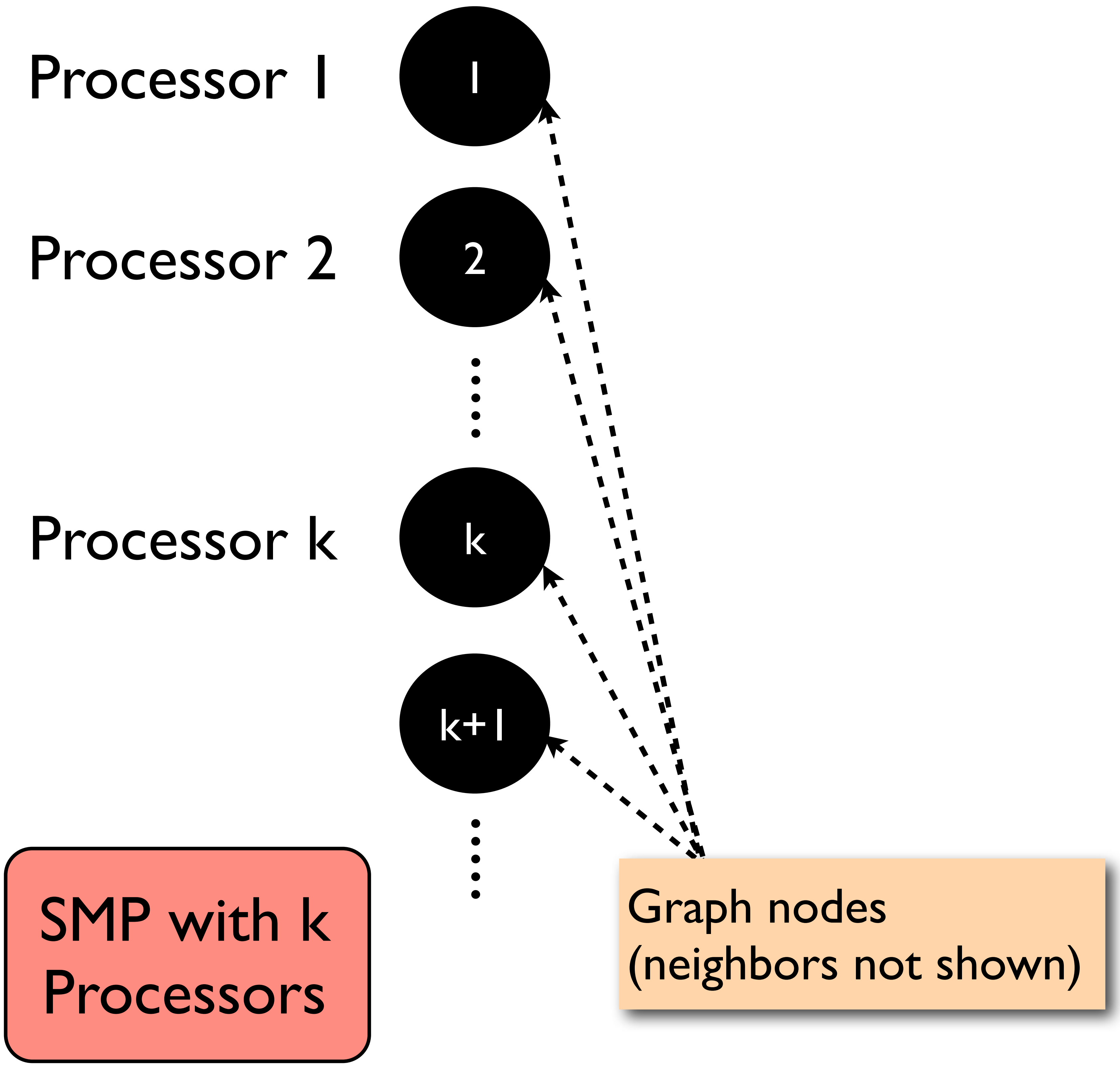

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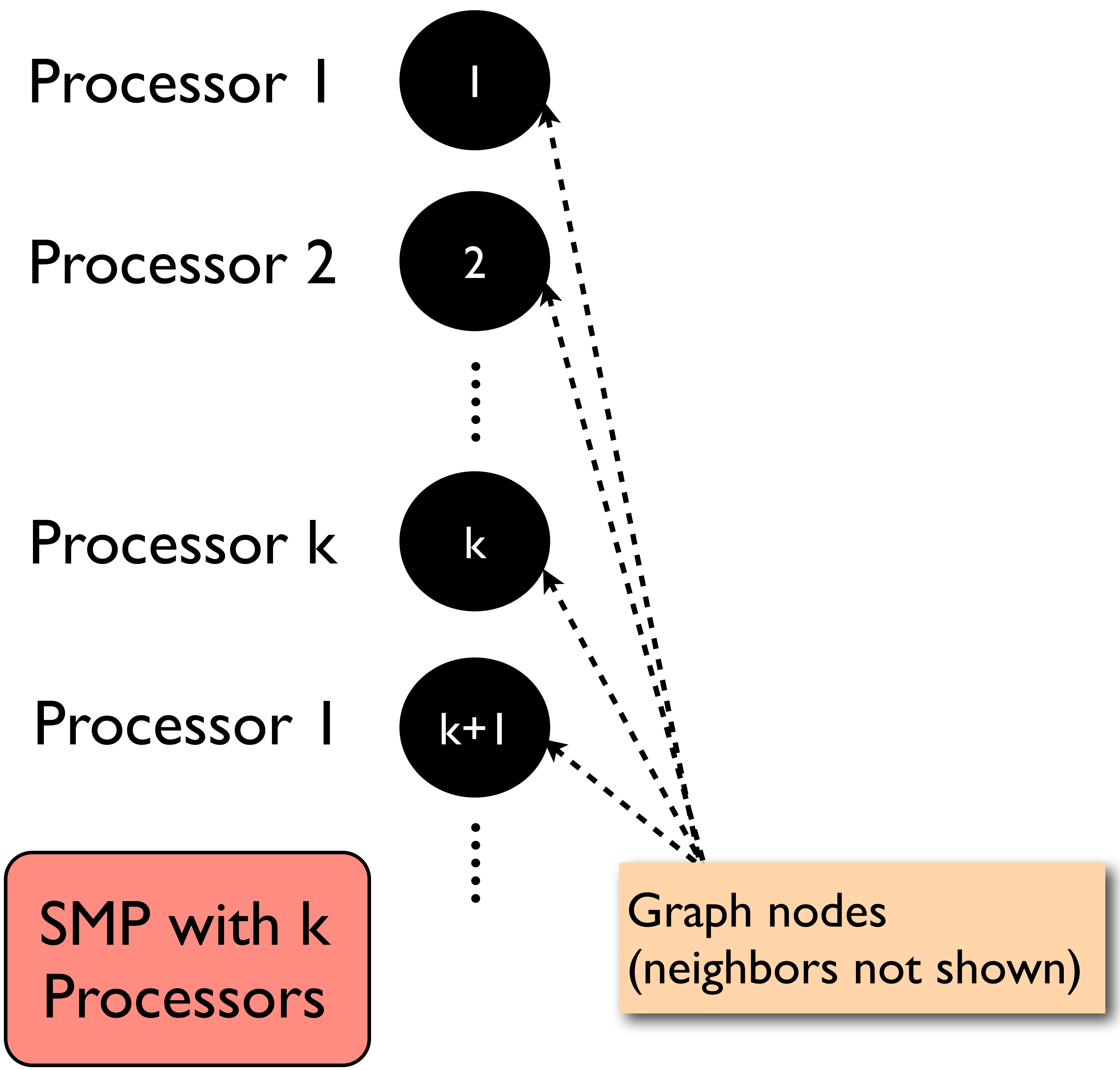
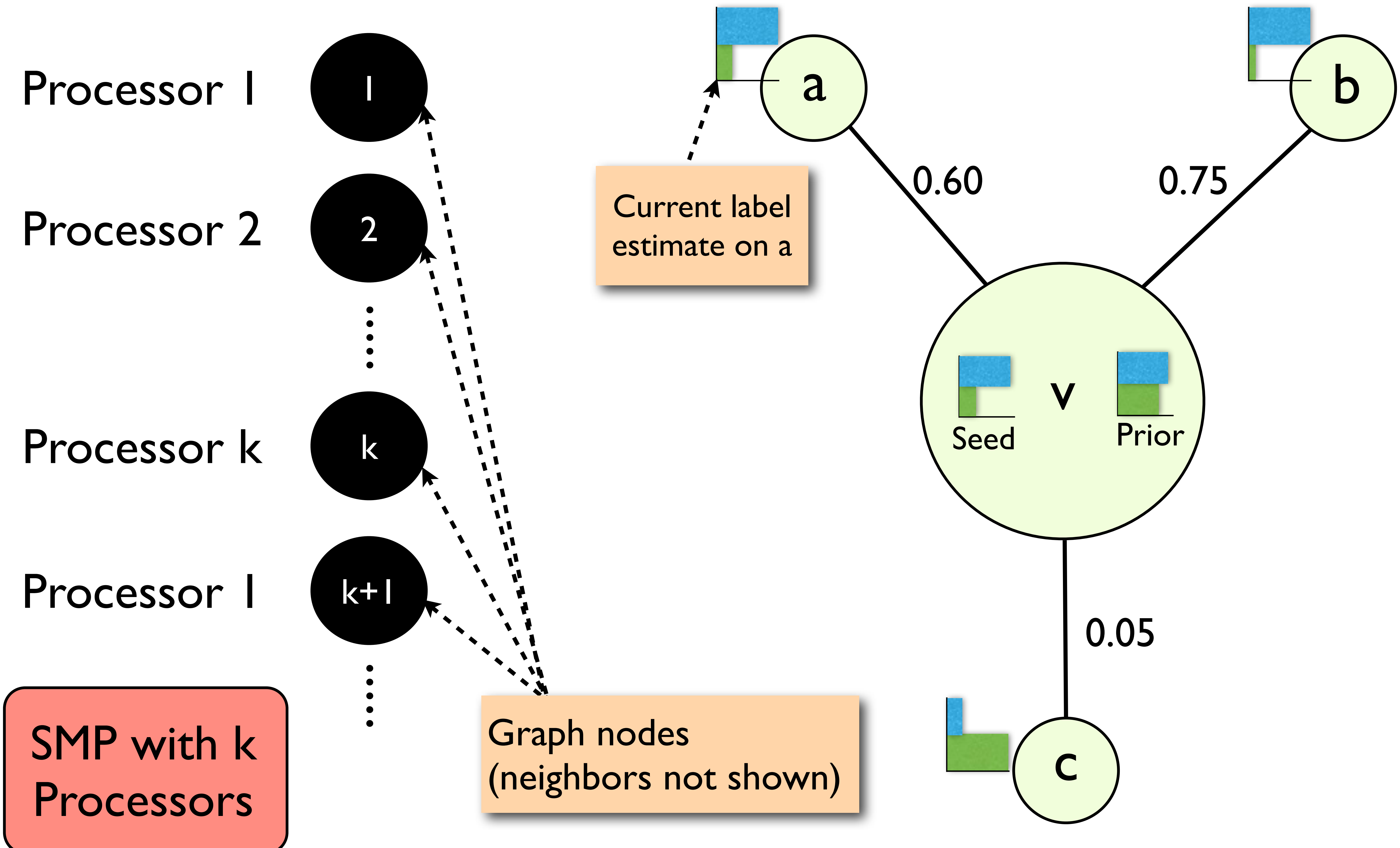


Label Update using Message Passing



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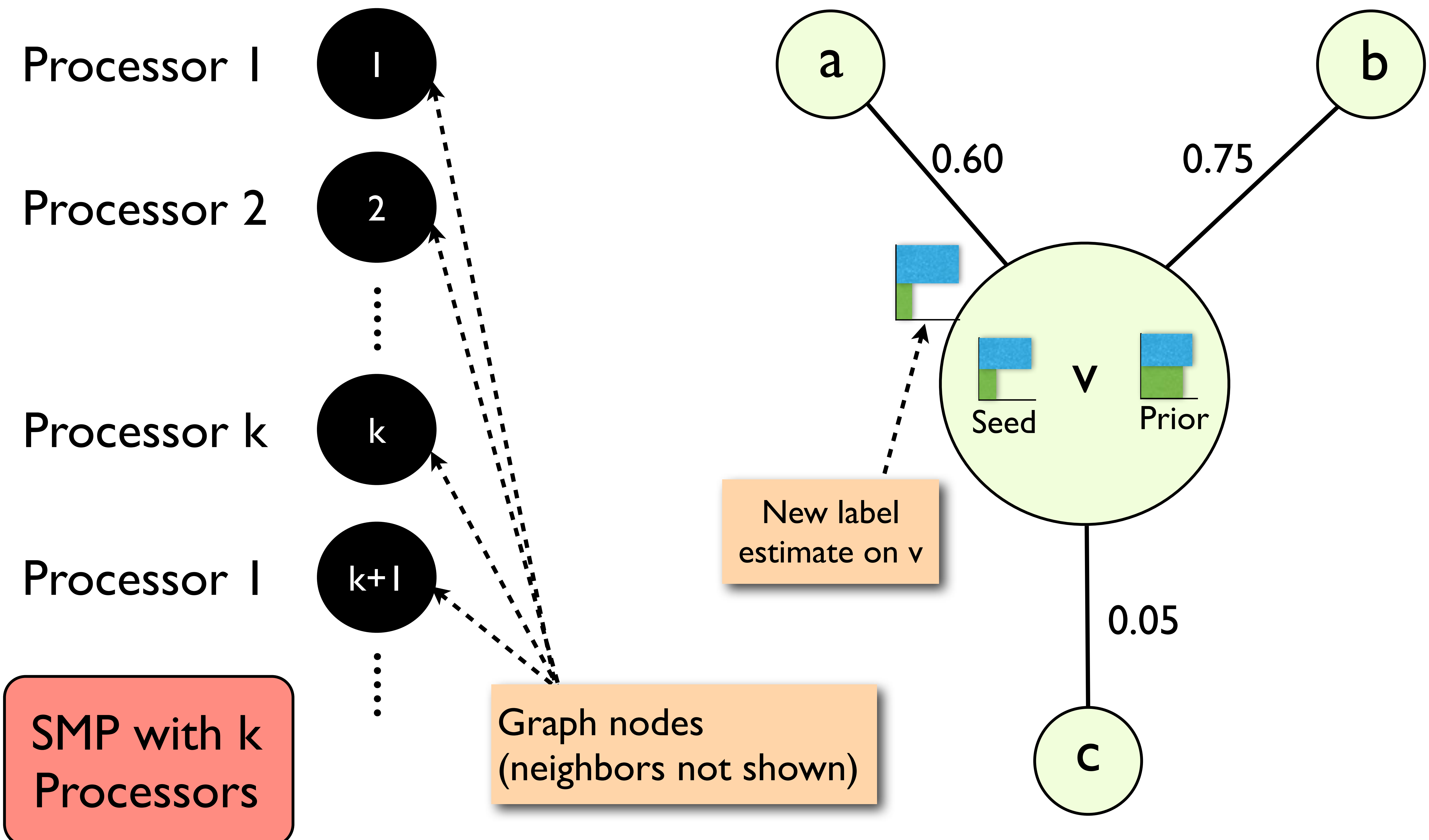
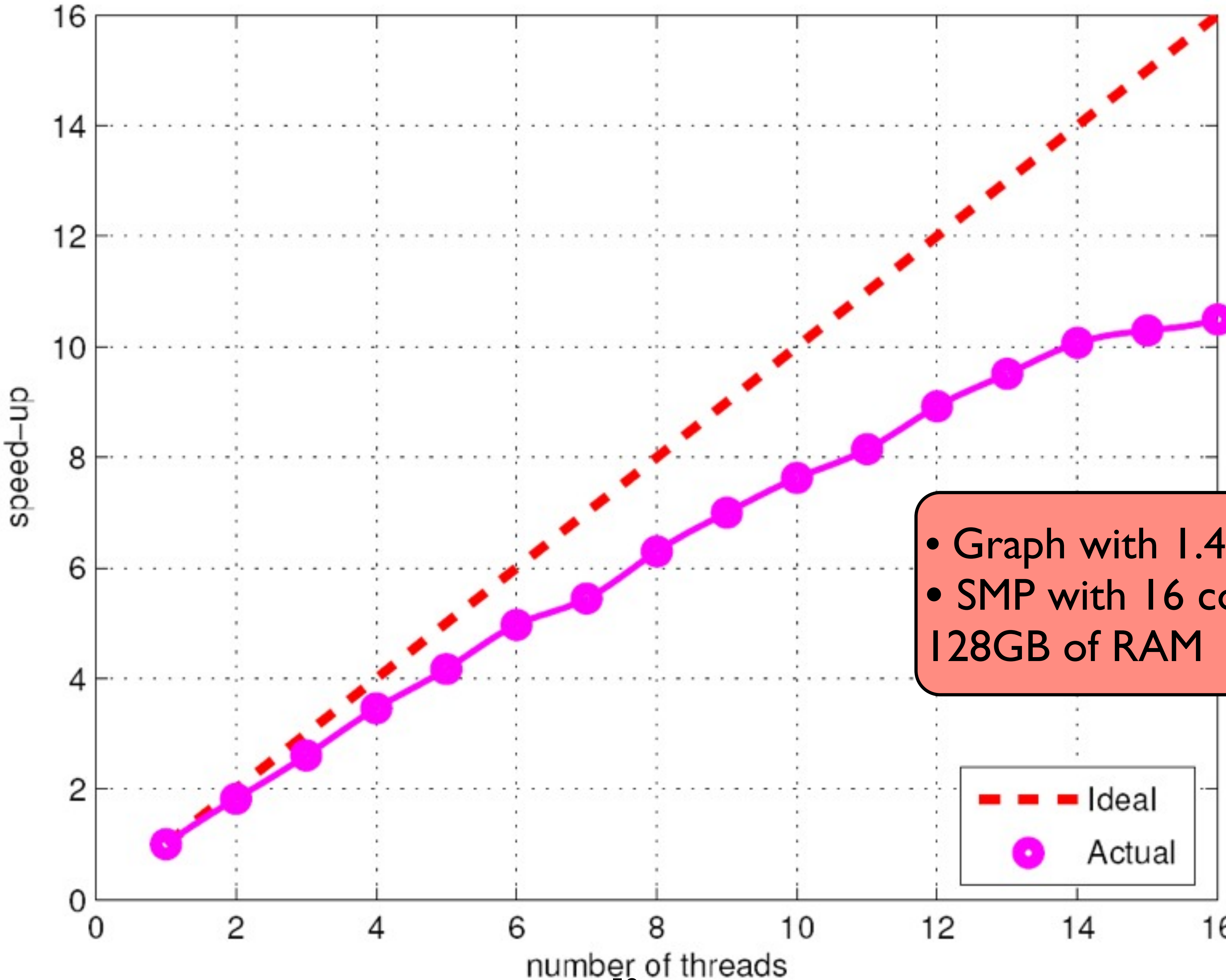


Speed-up on SMP



• Graph with 1.4M nodes
• SMP with 16 cores and 128GB of RAM

[Subramanya & Bilmes, JMLR, 2011]

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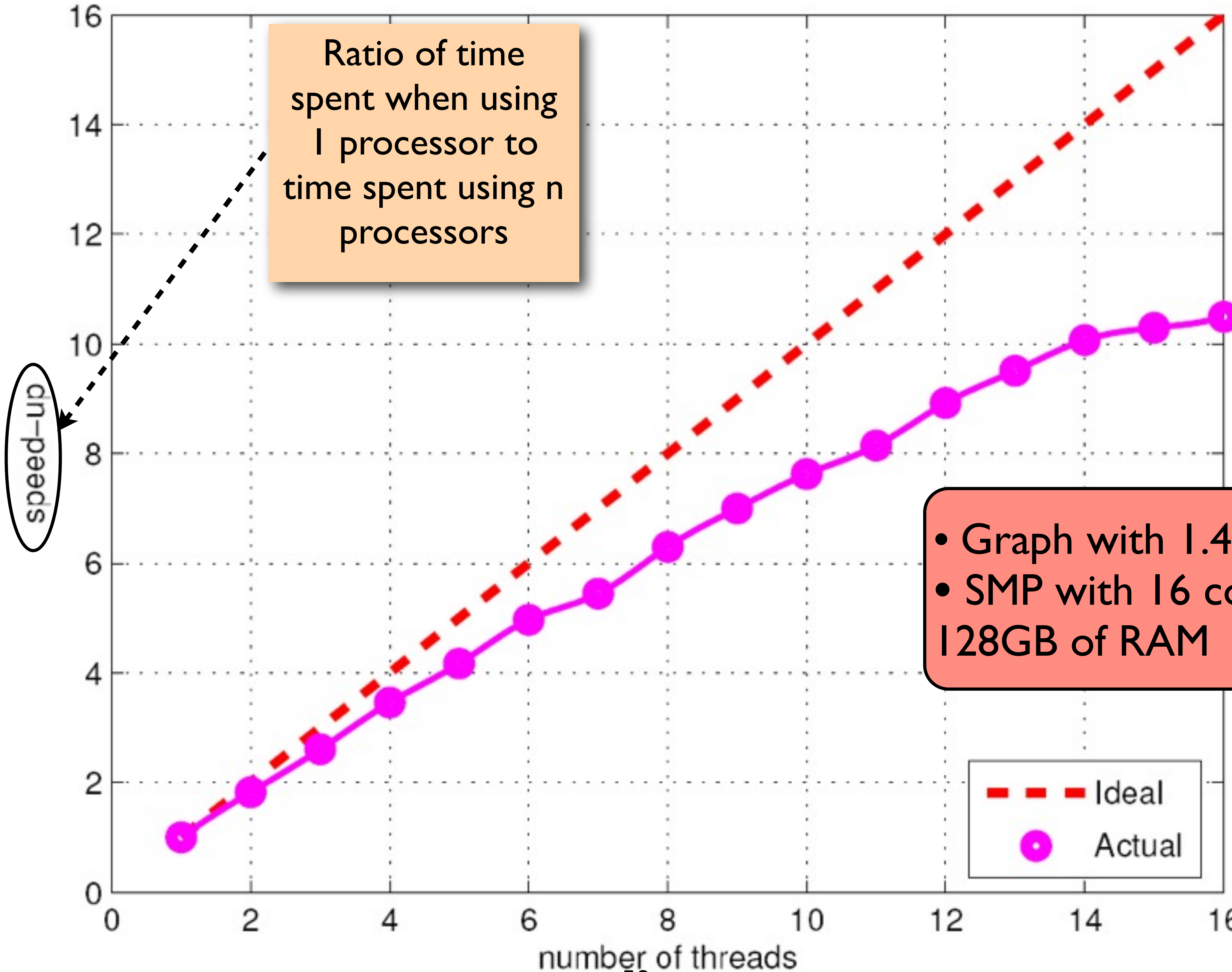

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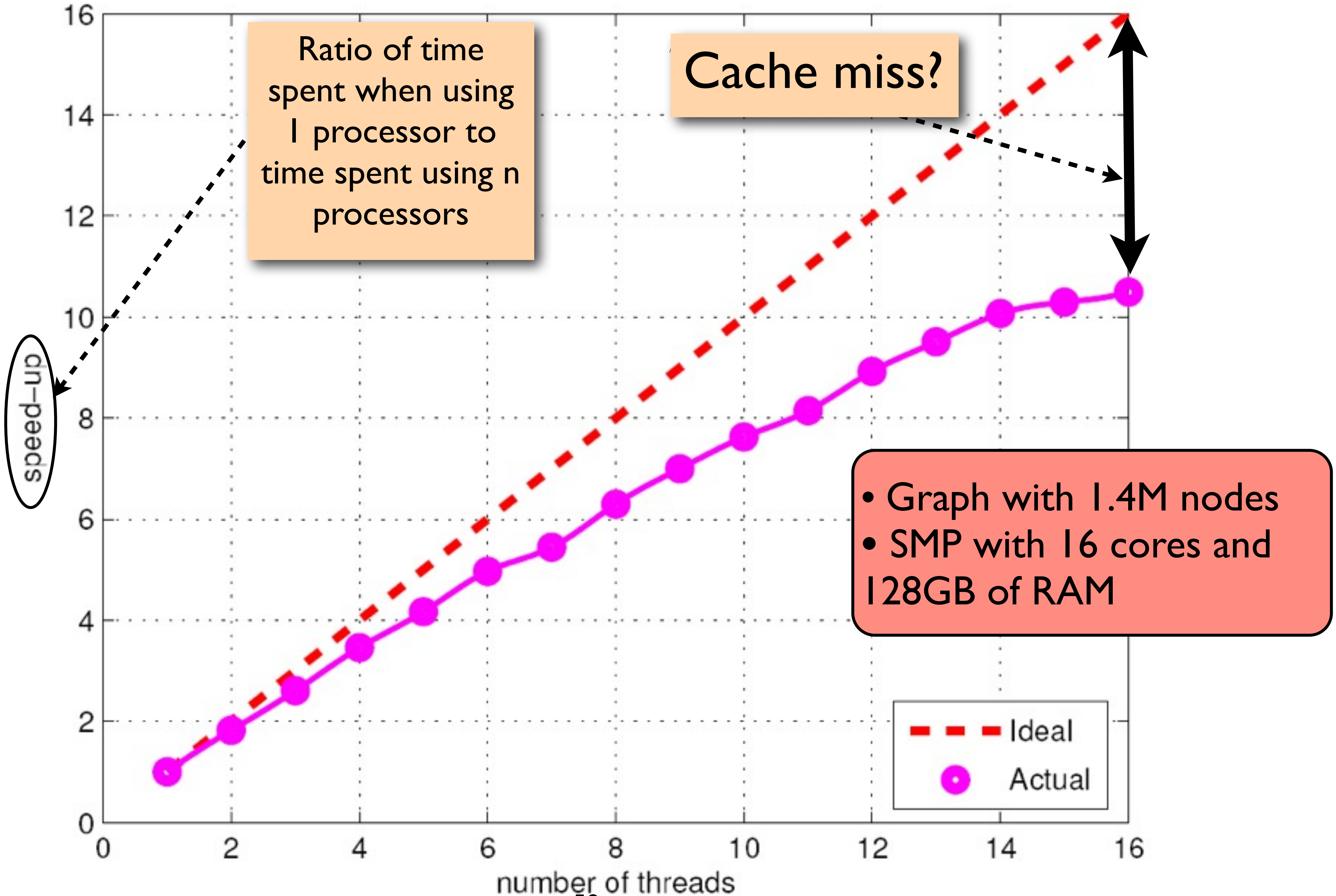

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Node Reordering Algorithm

Input: Graph G = (V, E)

Result: Node ordered graph

1. Select an arbitrary node v
2. while unselected nodes remain do

    2.1. select an unselected node v` from among the neighbors' neighbors of v that has maximum overlap with v` neighbors

    2.2. mark v` as selected

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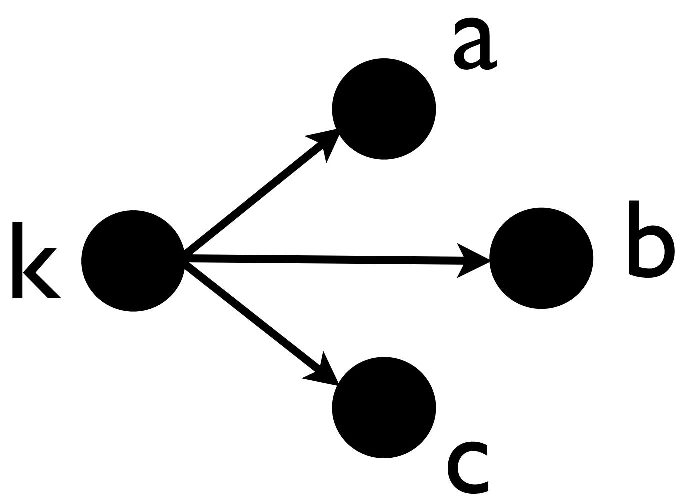
Exhaustive for sparse (e.g., k-NN) graphs

[Subramanya & Bilmes, JMLR, 2011]

Node Reordering Algorithm : Intuition



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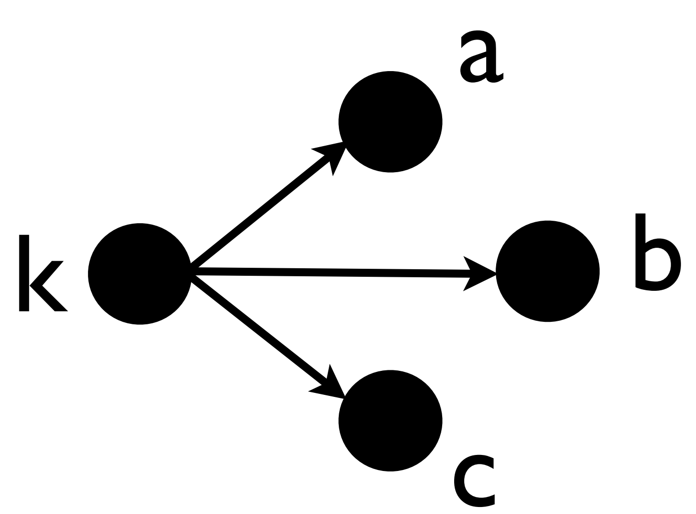

Which node should be placed after k to optimize cache performance?

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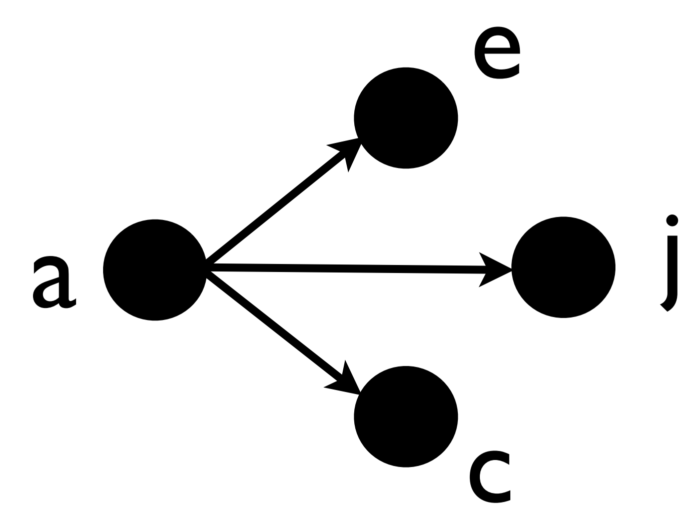

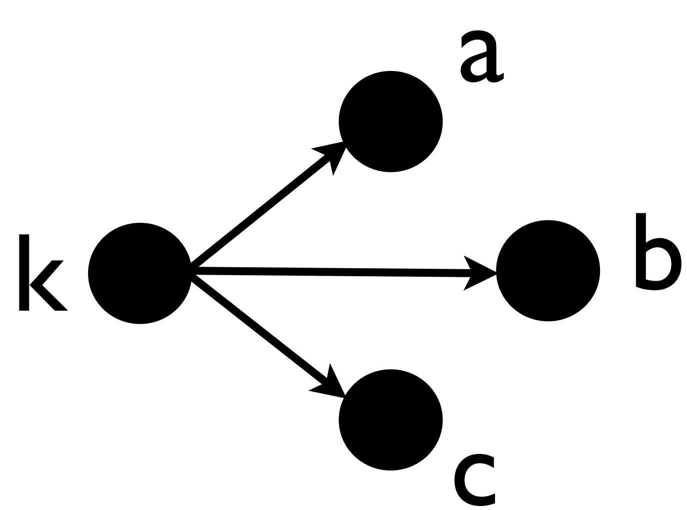

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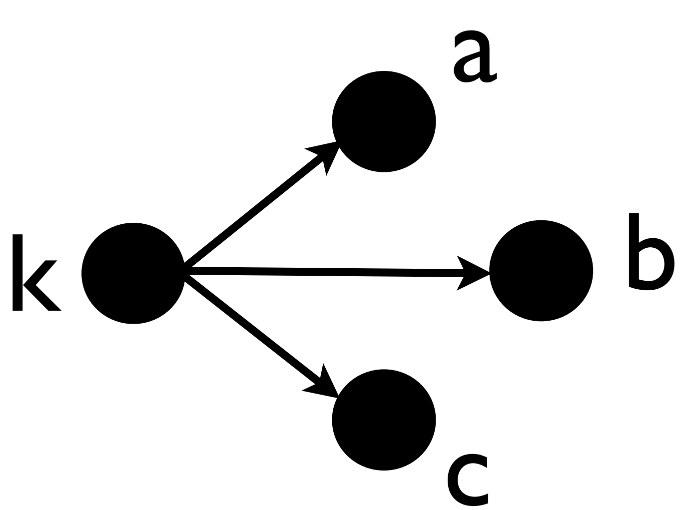

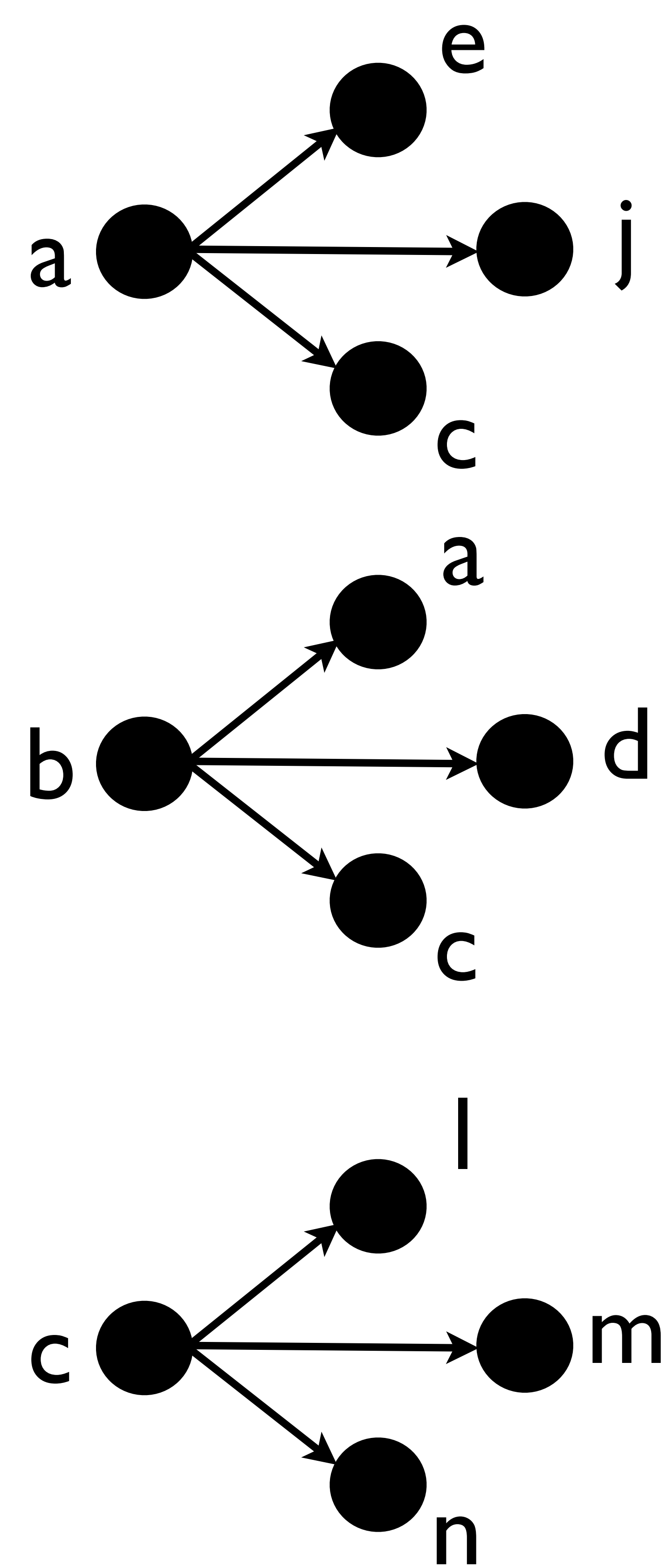

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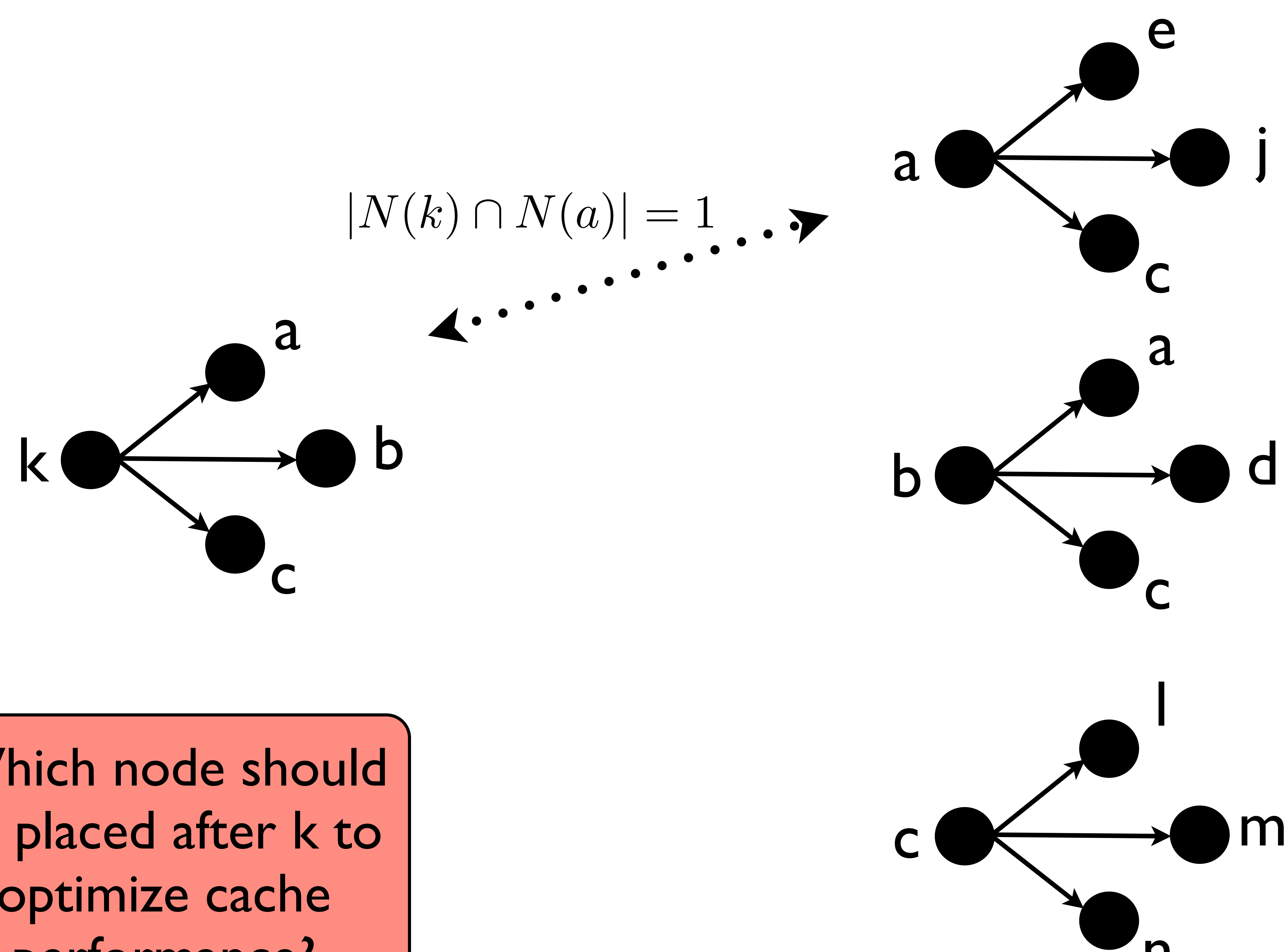

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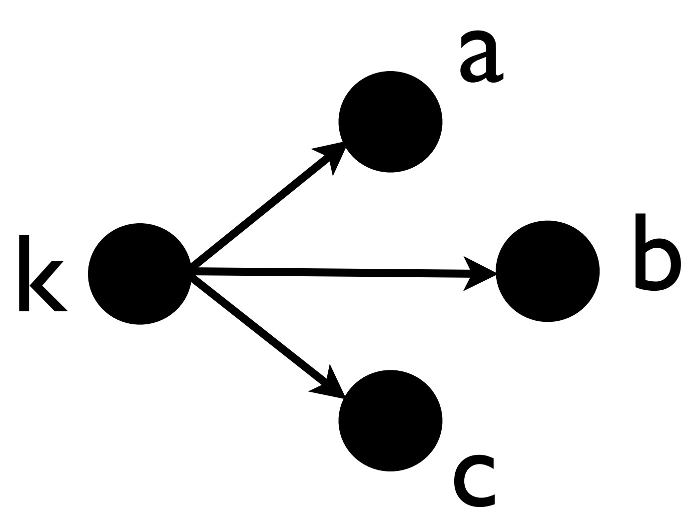
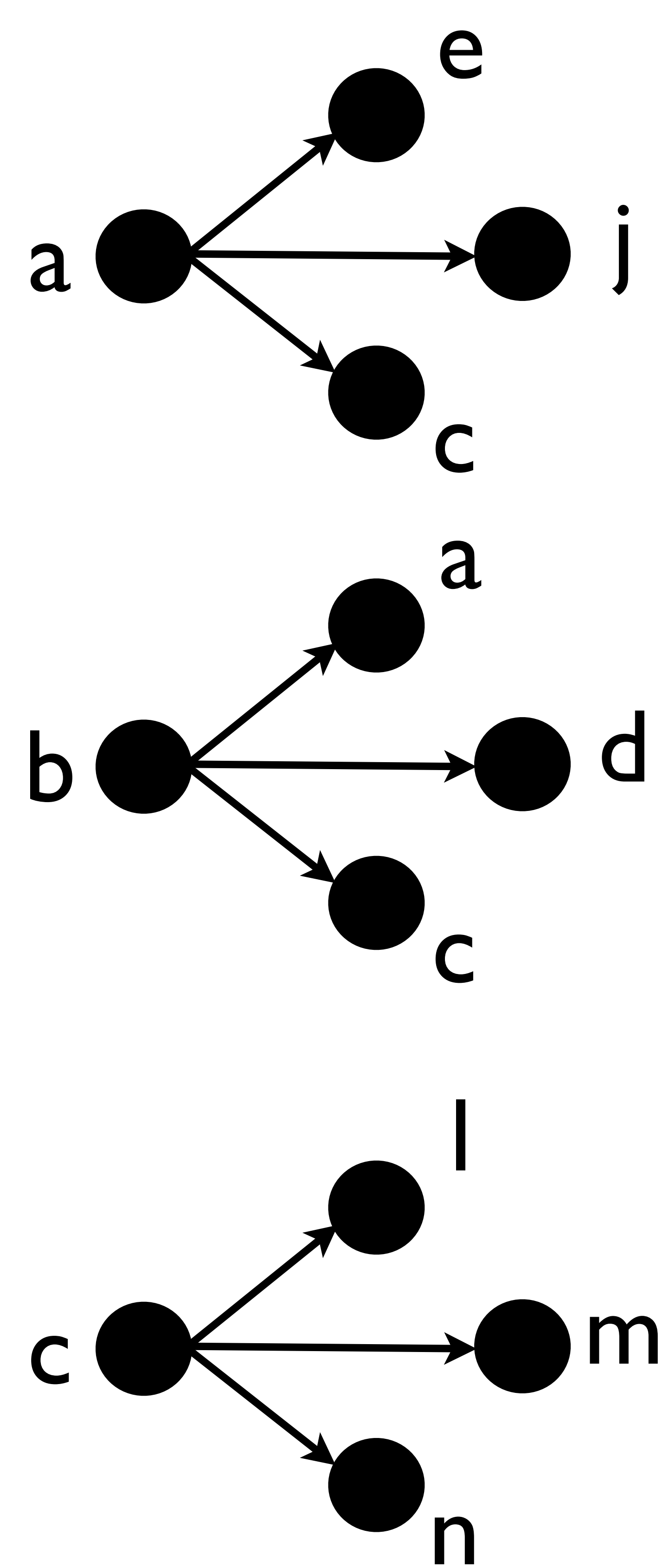
Node Reordering Algorithm : Intuition

Cardinality of Intersection

$|N(k) \cap N(a)| = 1$





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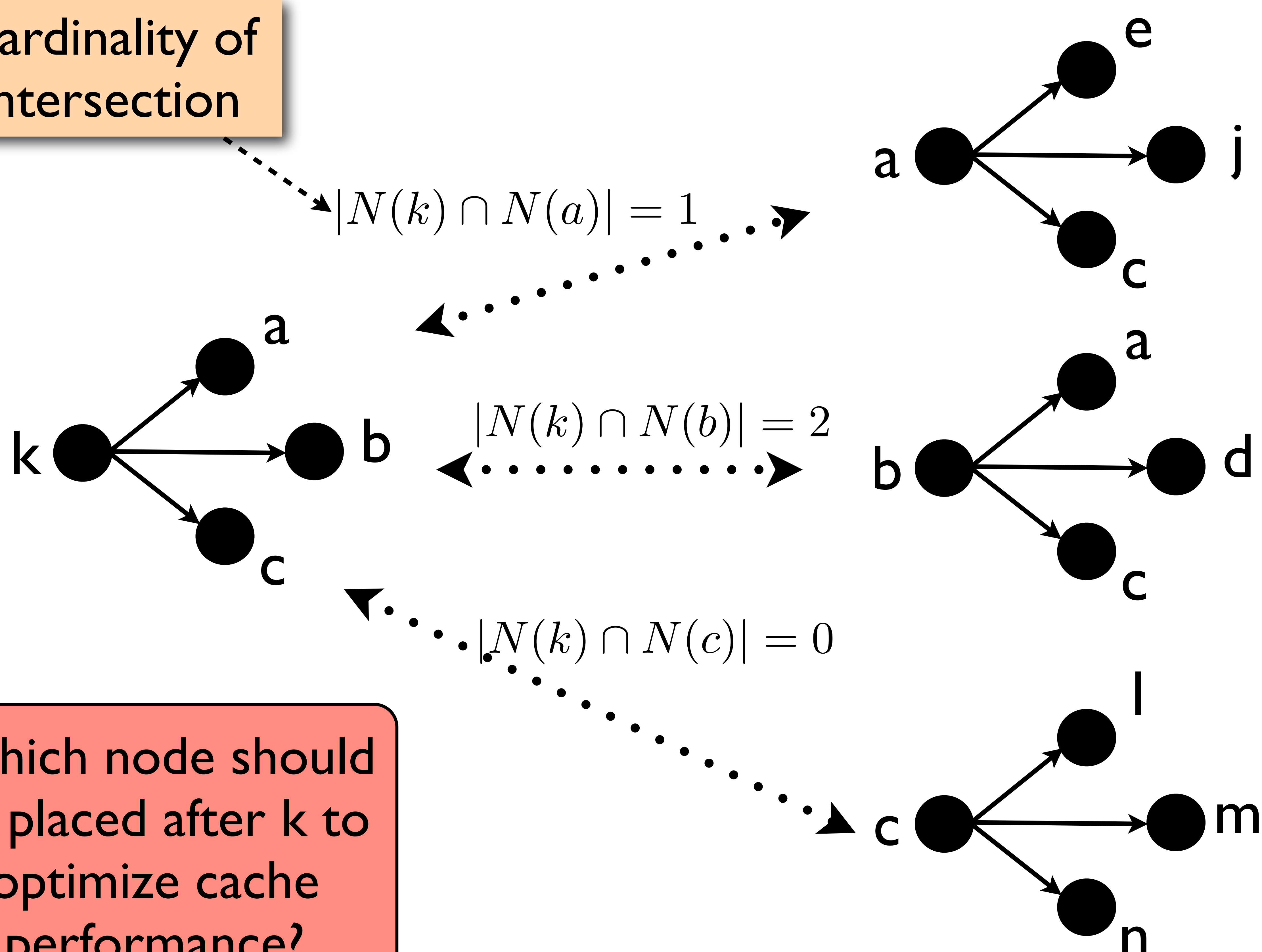

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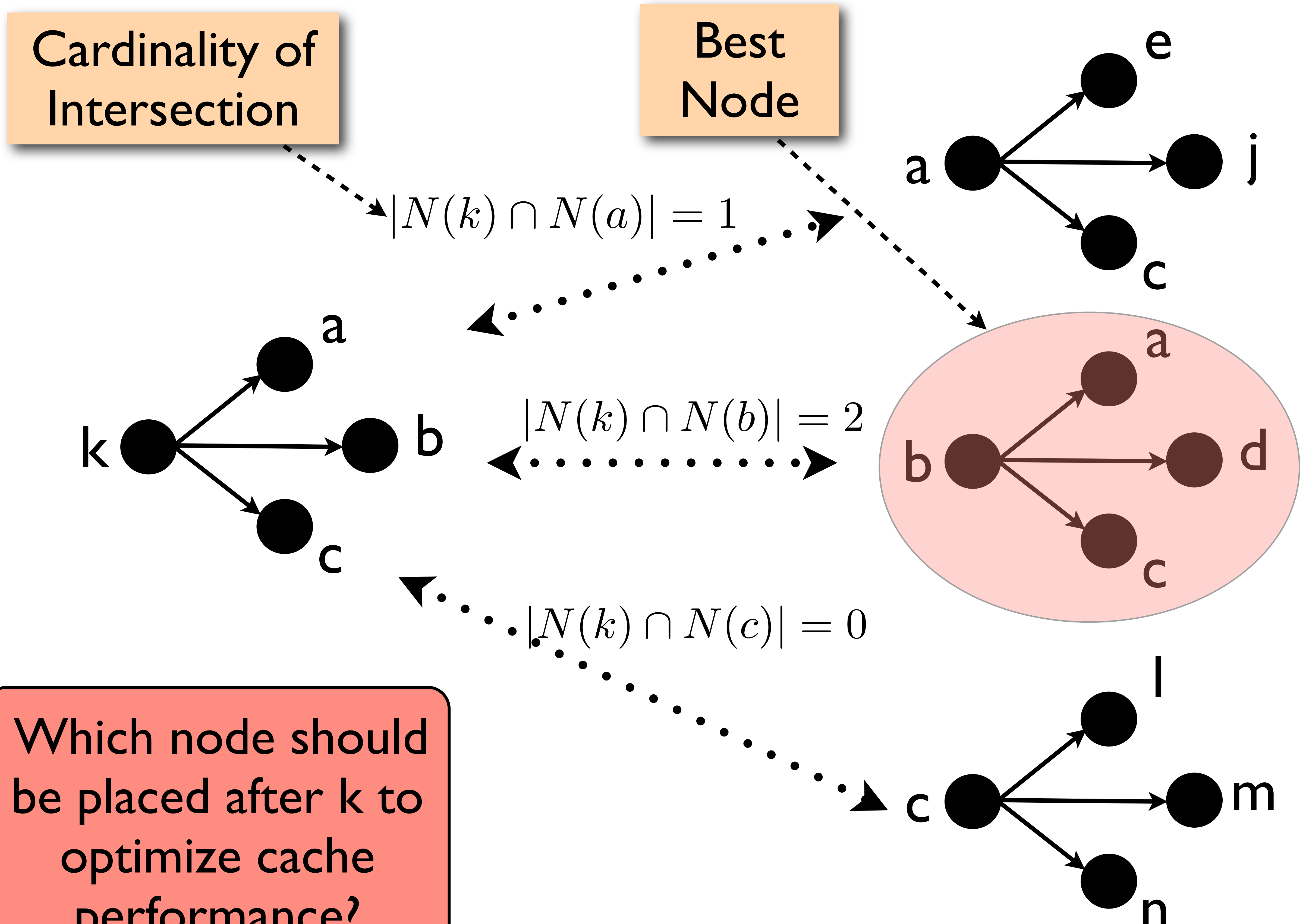

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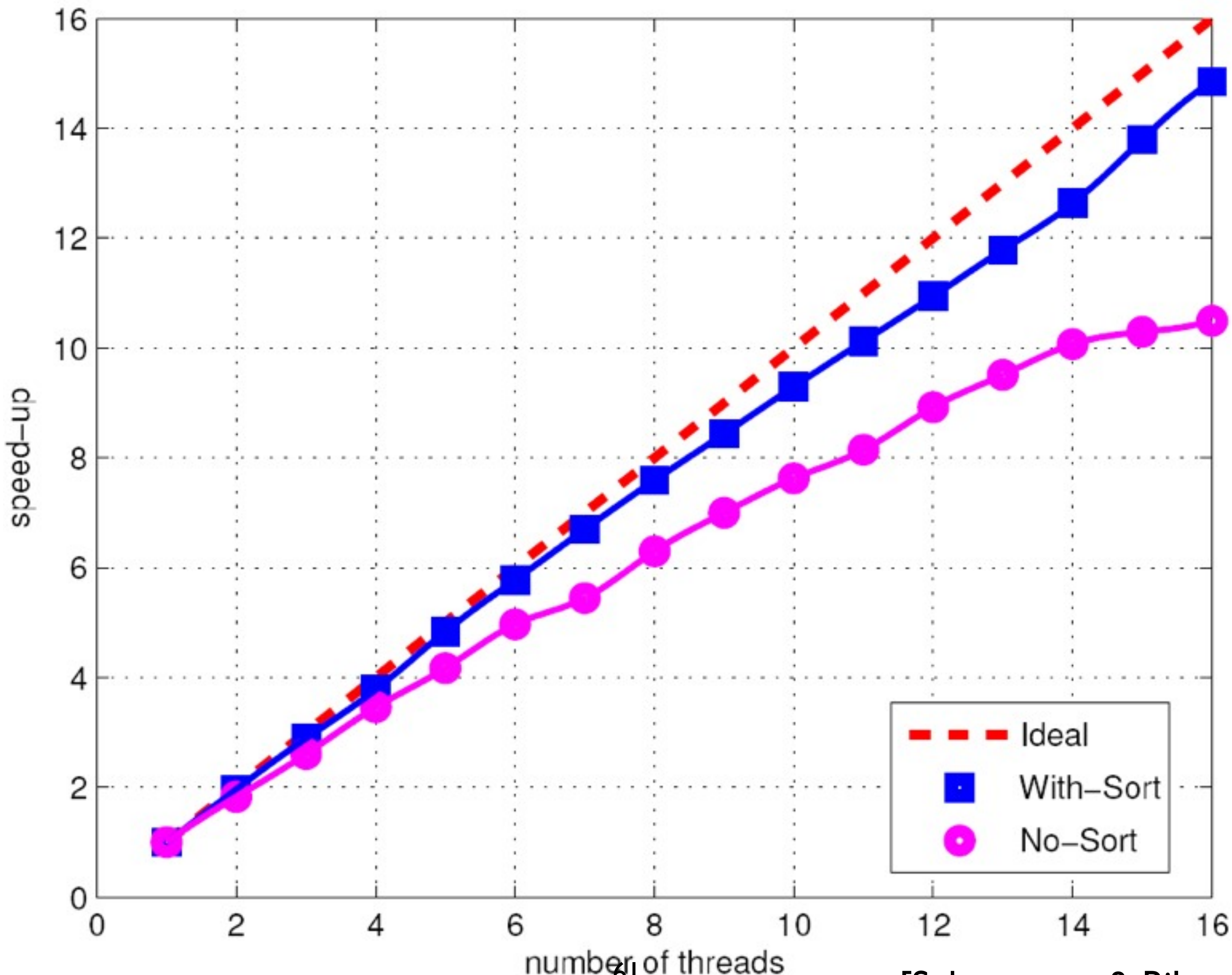
Speed-up on SMP after Node Ordering

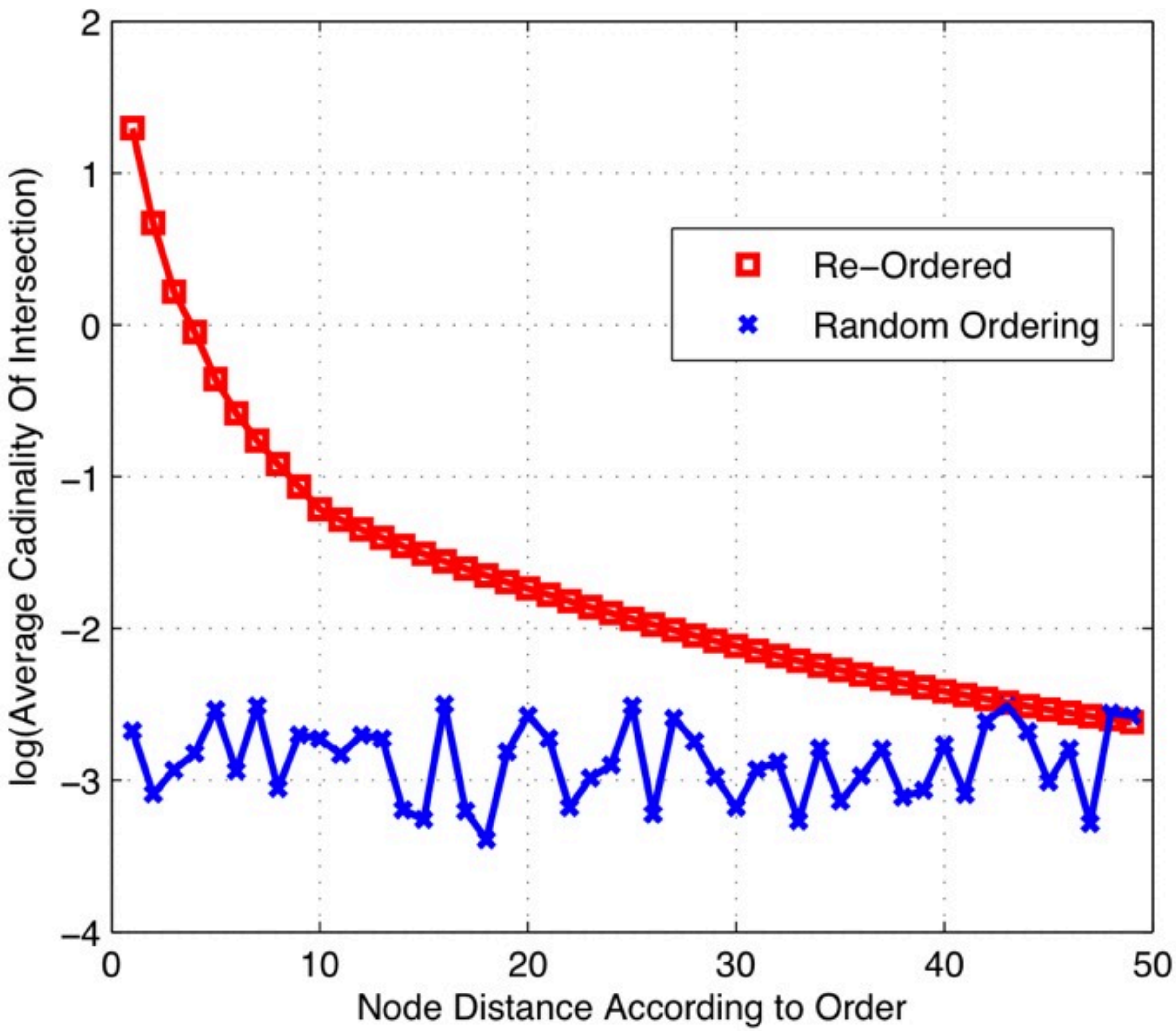


[Subramanya & Bilmes, JMLR, 2011]

Distributed Processing

- **Maximize** overlap between consecutive nodes within the same machine
- **Minimize** overlap across machines (reduce inter machine communication)

Distributed Processing



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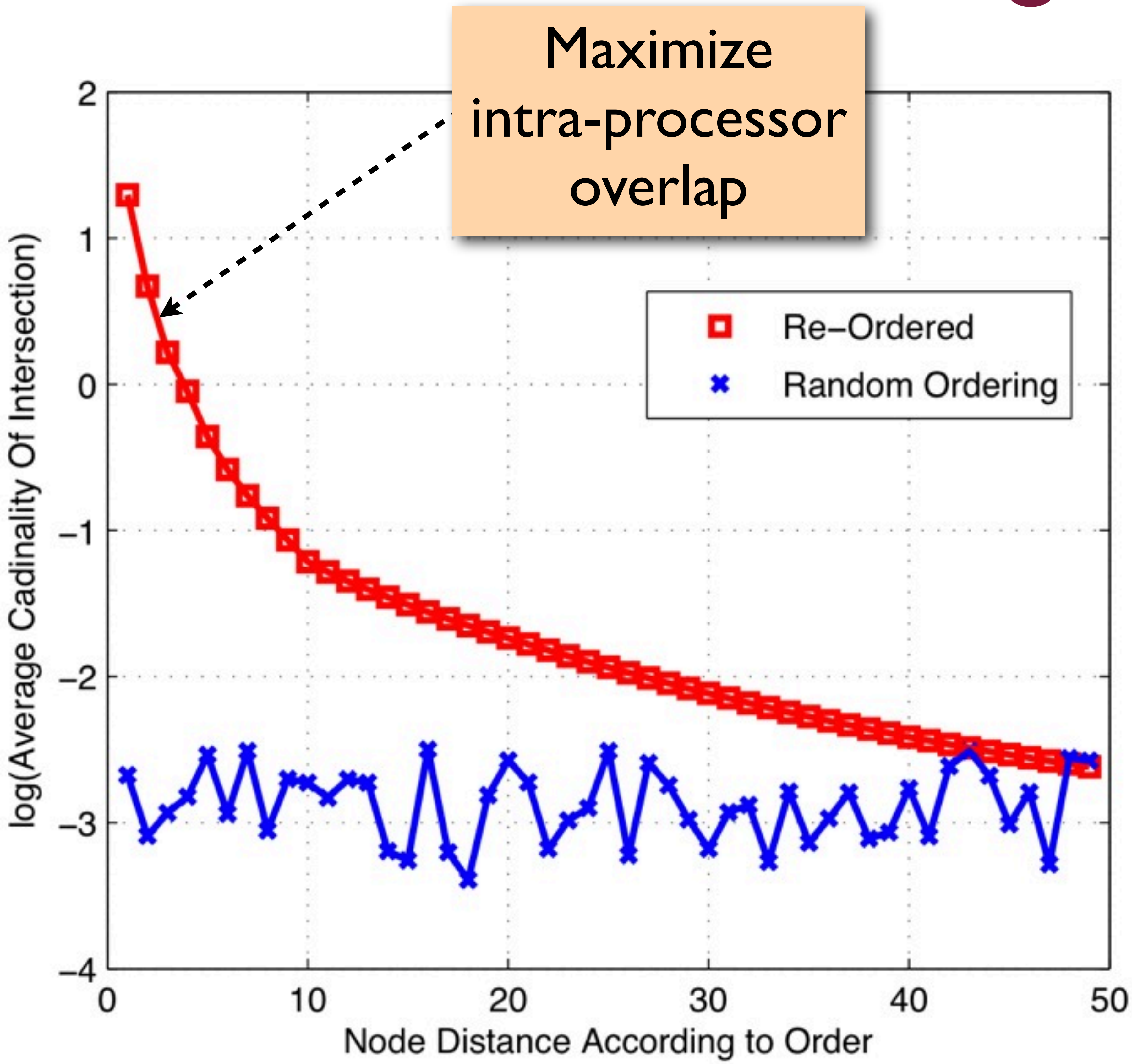

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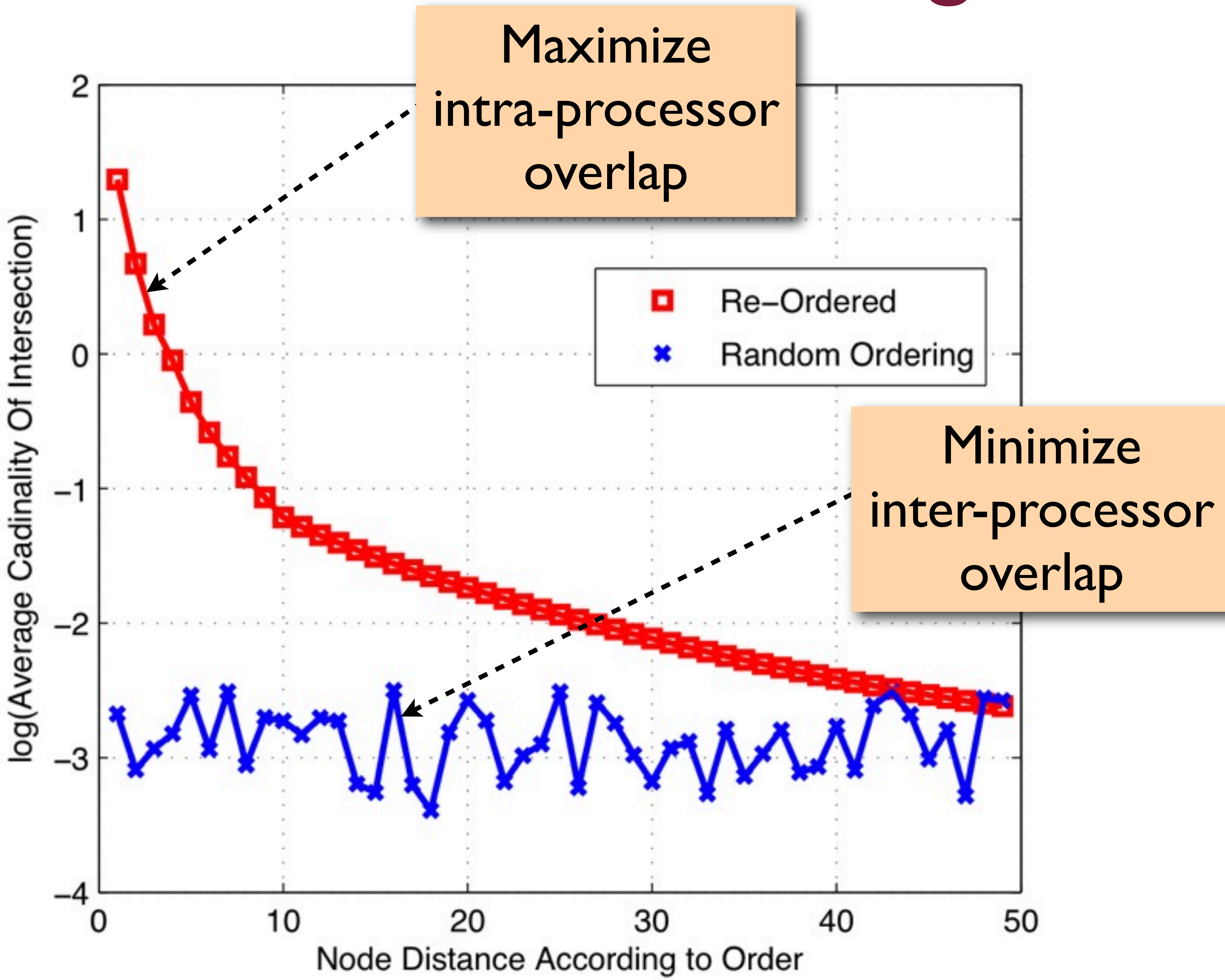

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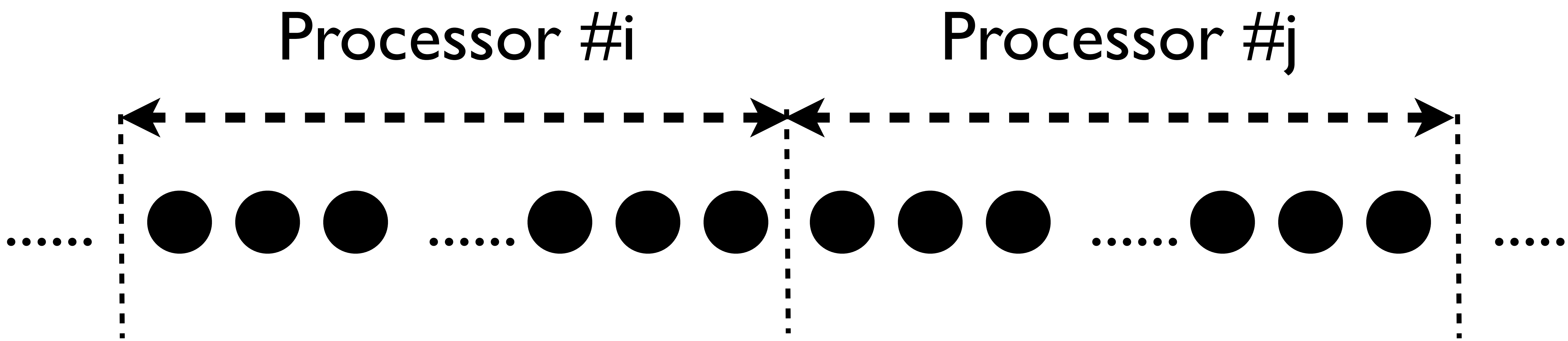
Node reordering for Distributed Computer



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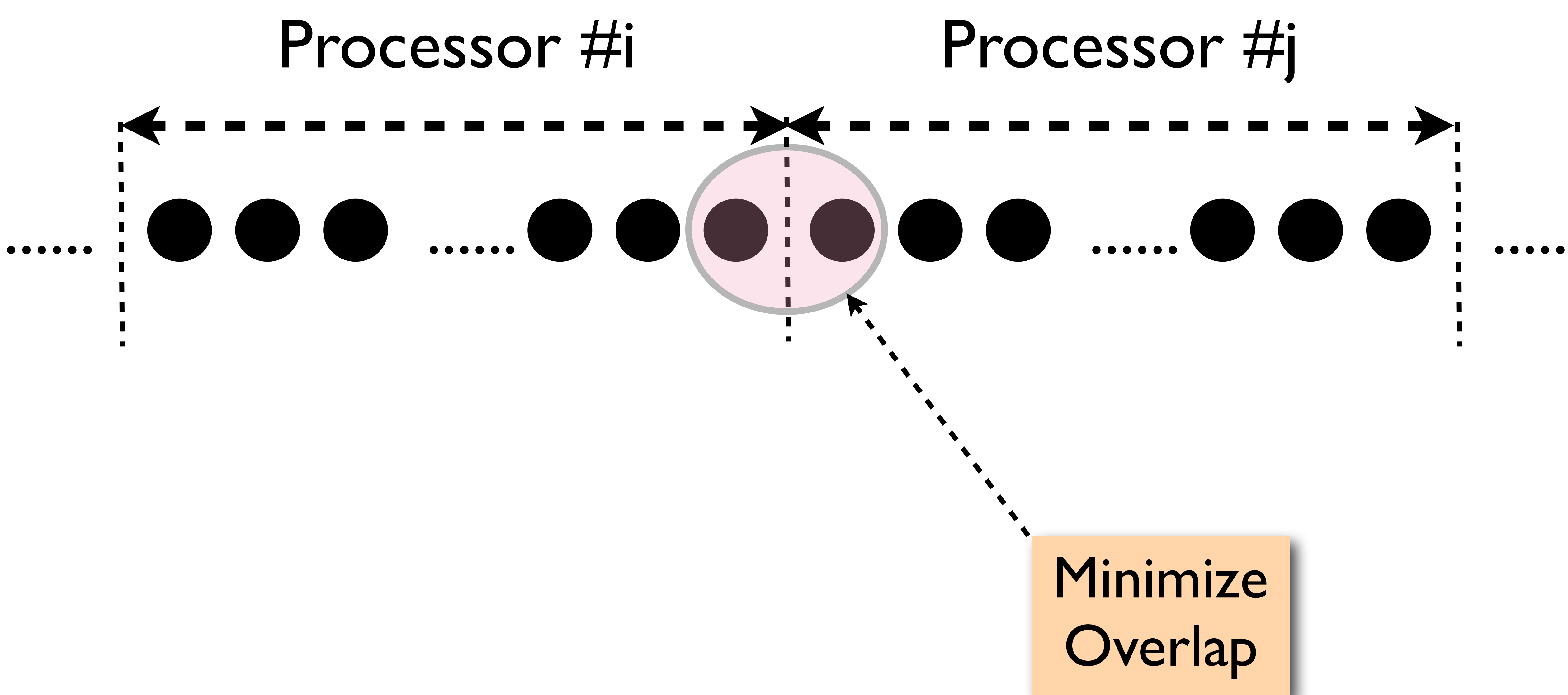

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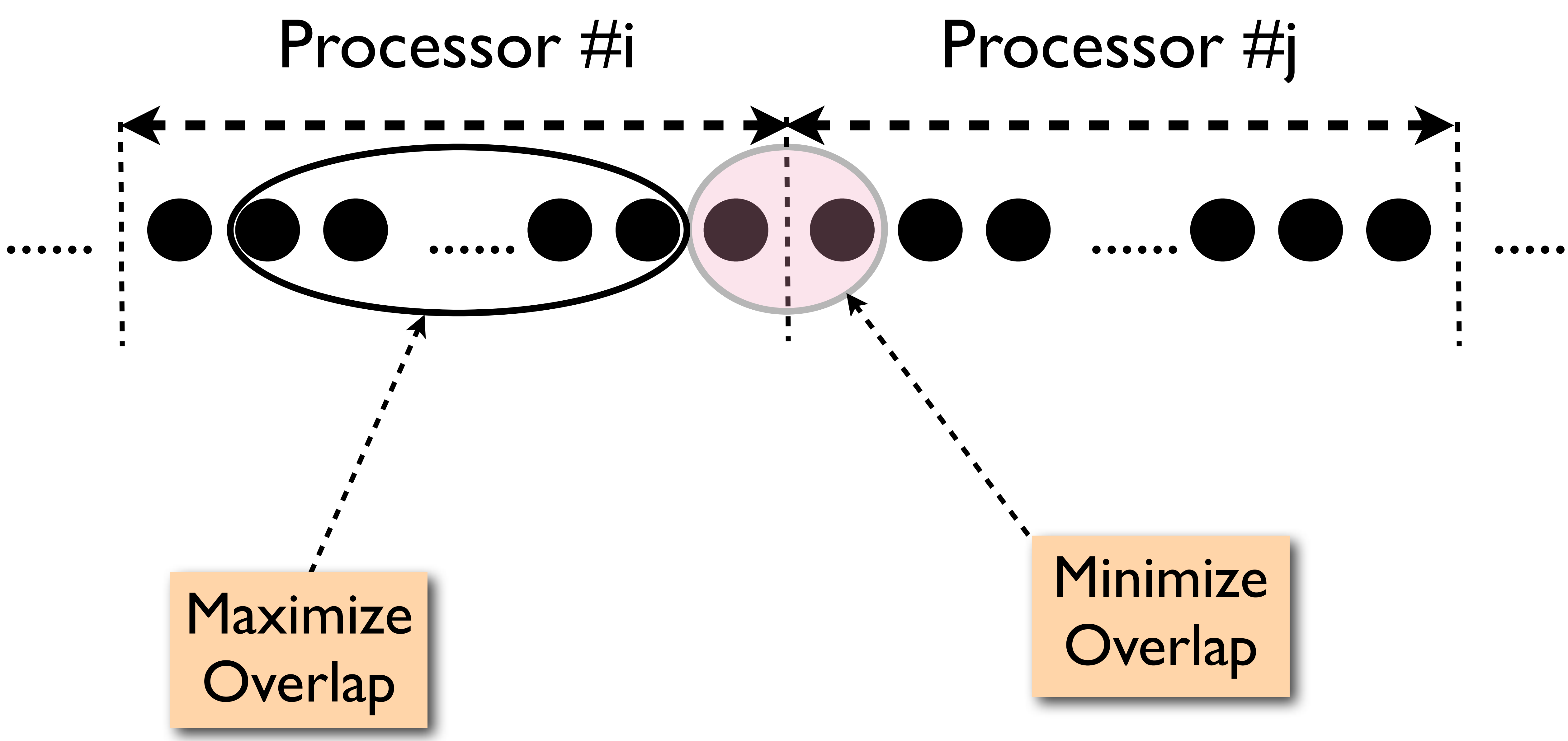
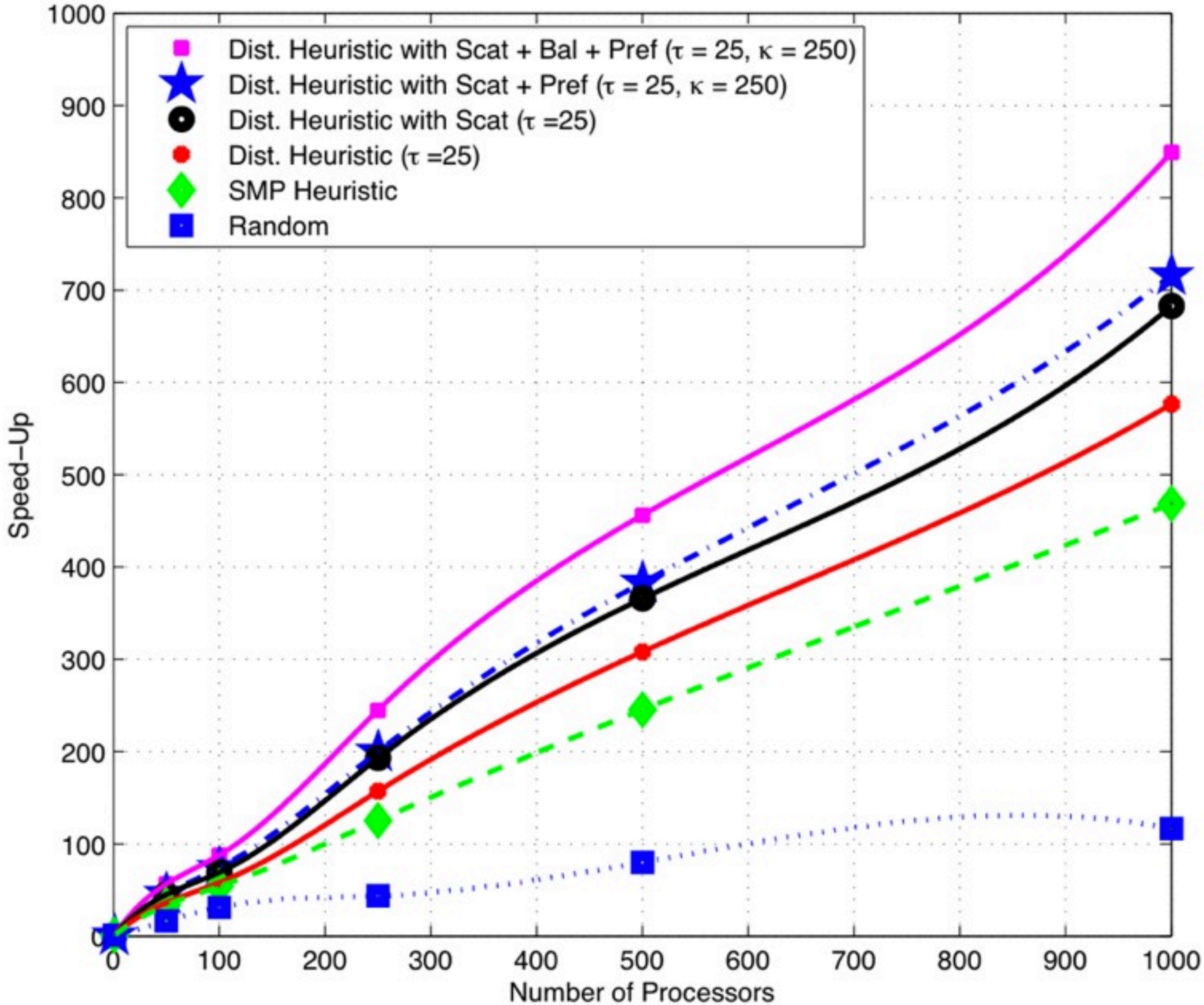


Distributed Processing Results



[Bilmes & Subramanya, 2011]

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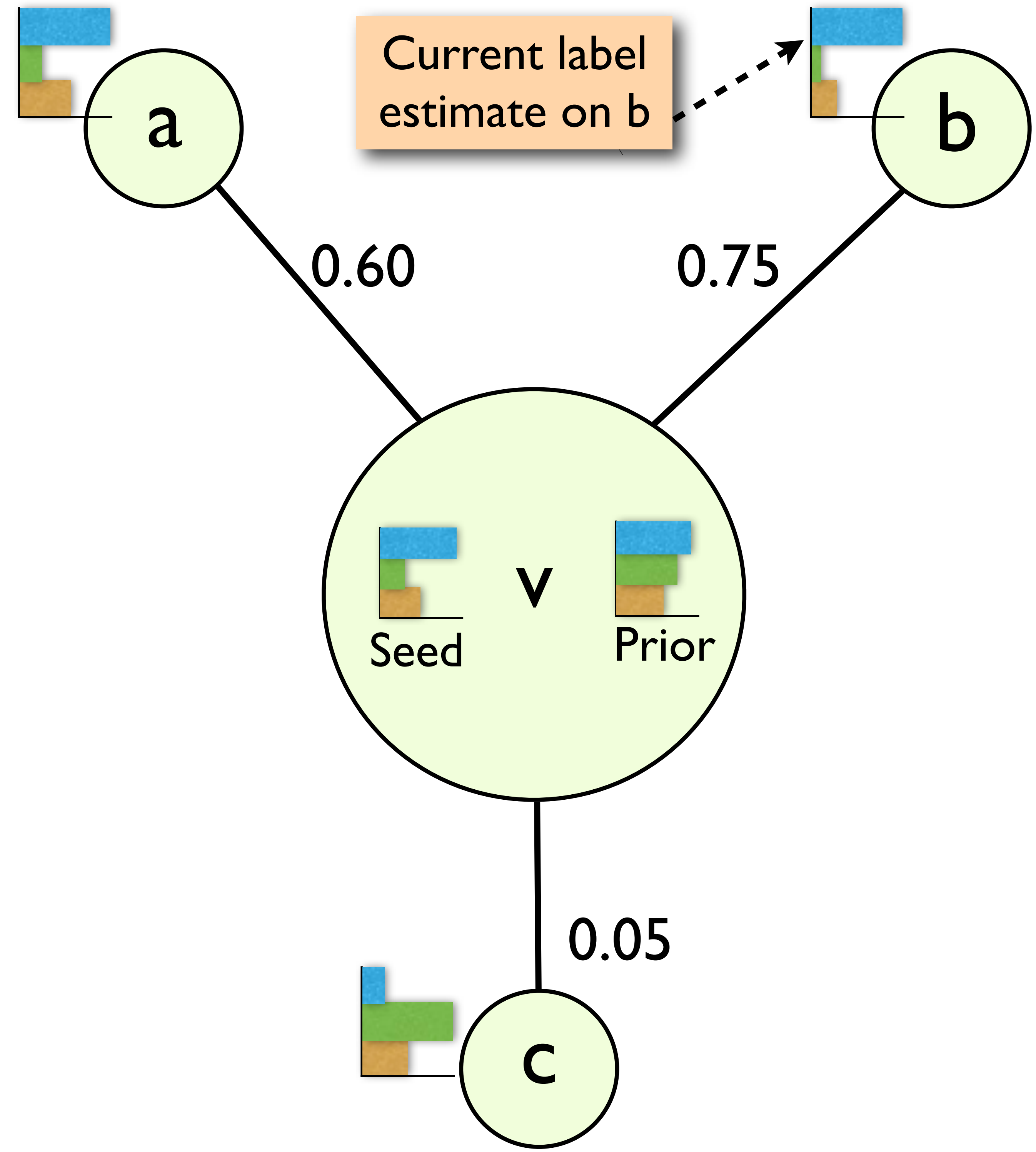
MapReduce Implementation of MAD



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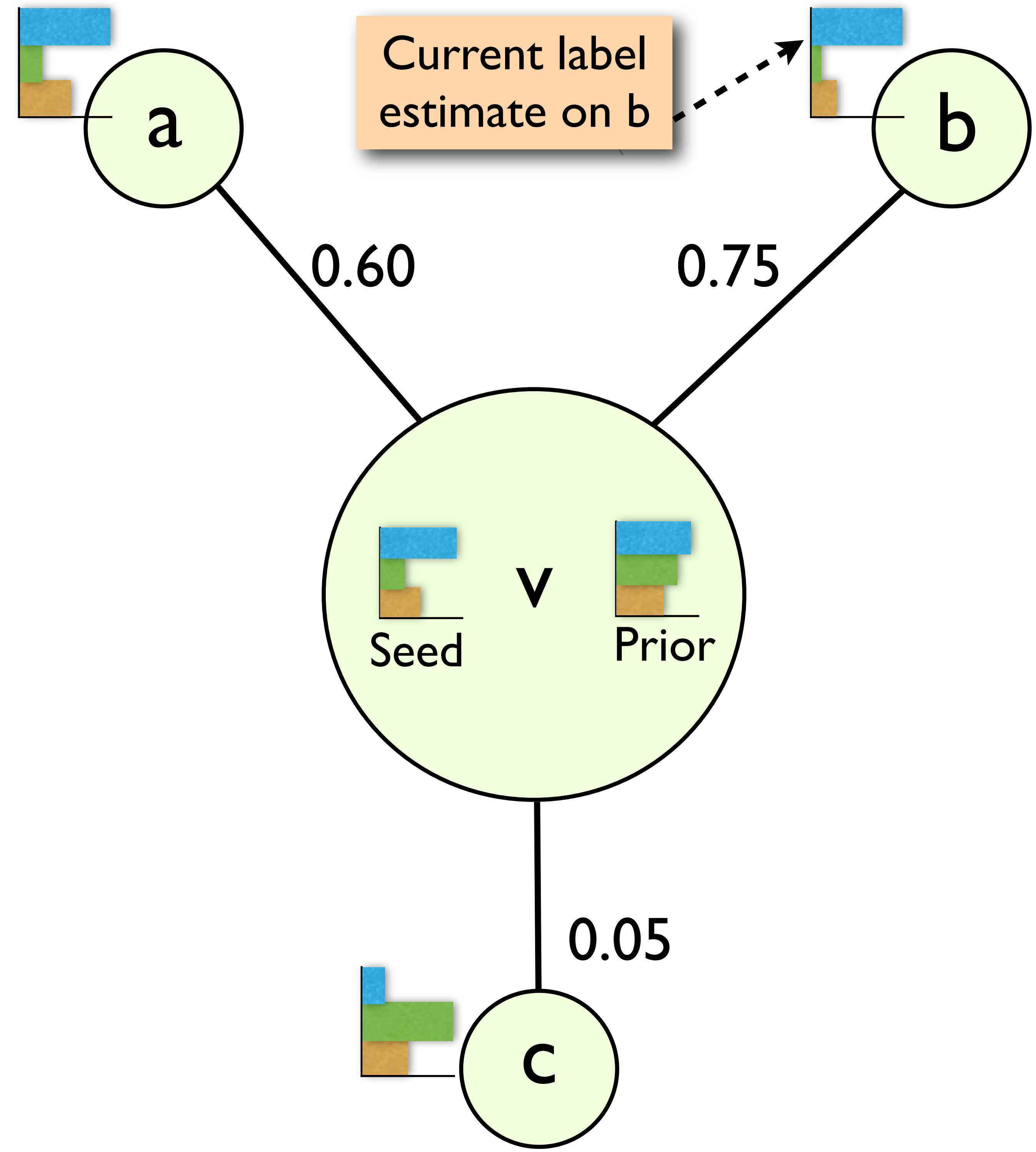
  - Each node send its current label assignments to its neighbors



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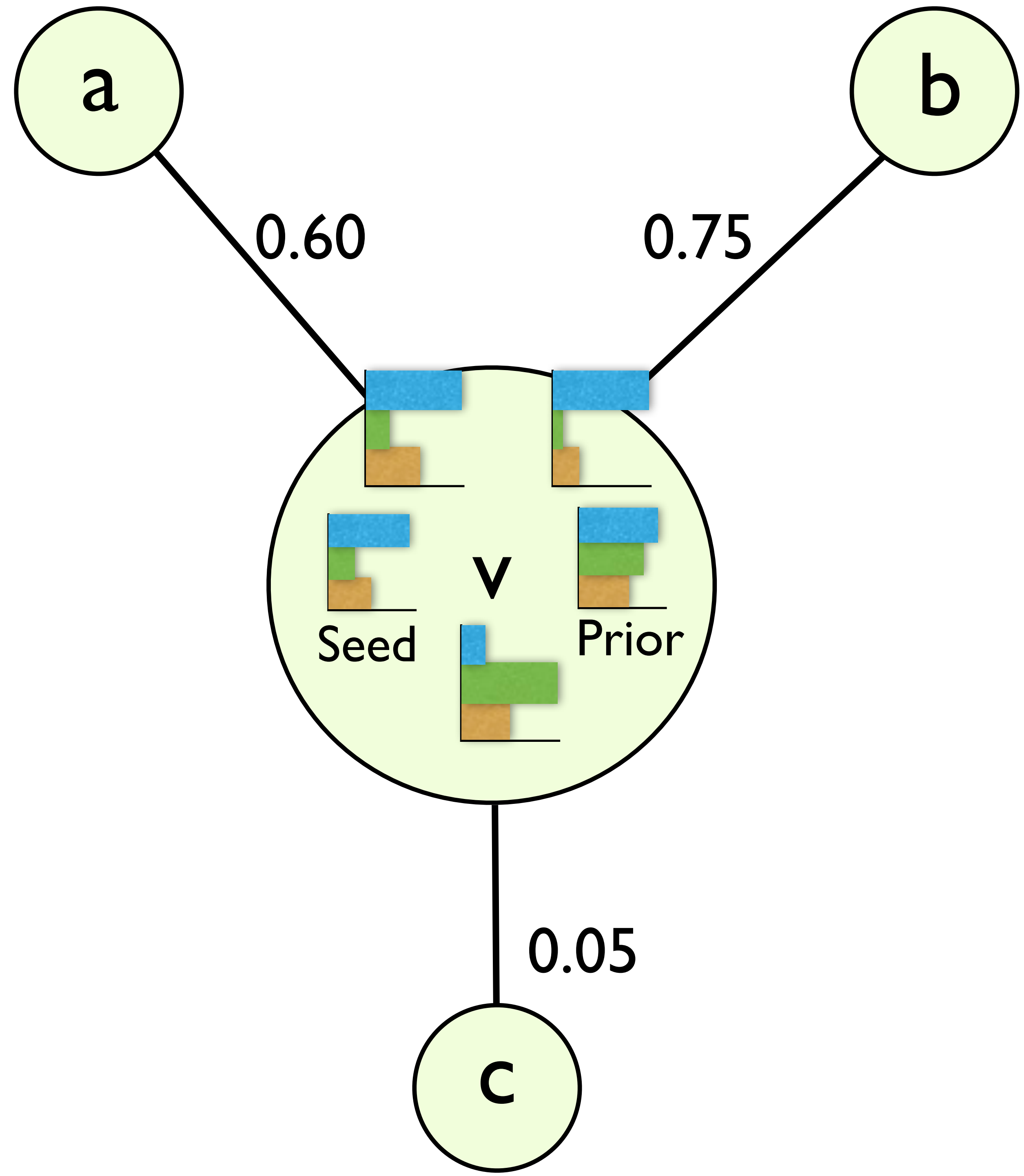

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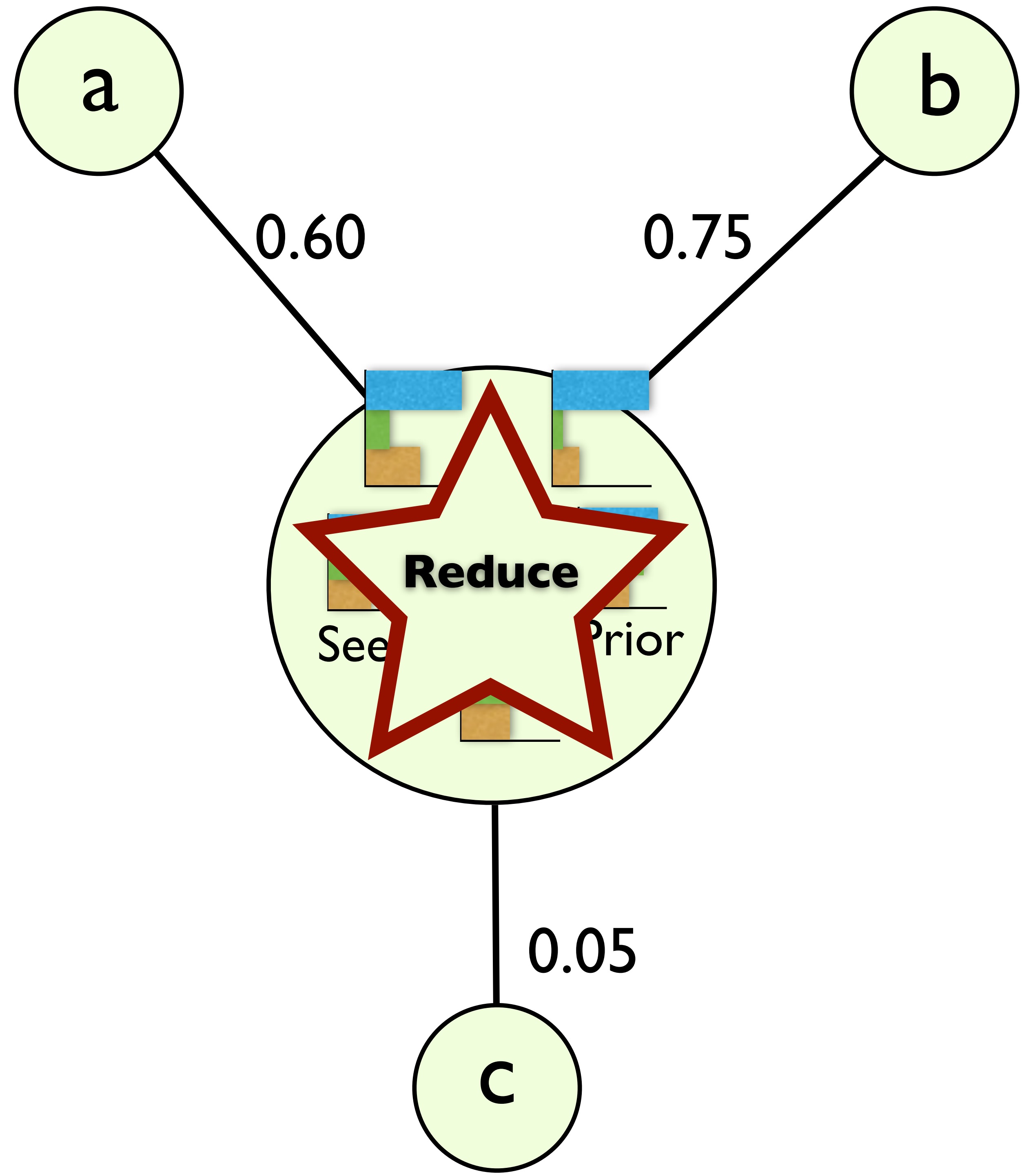

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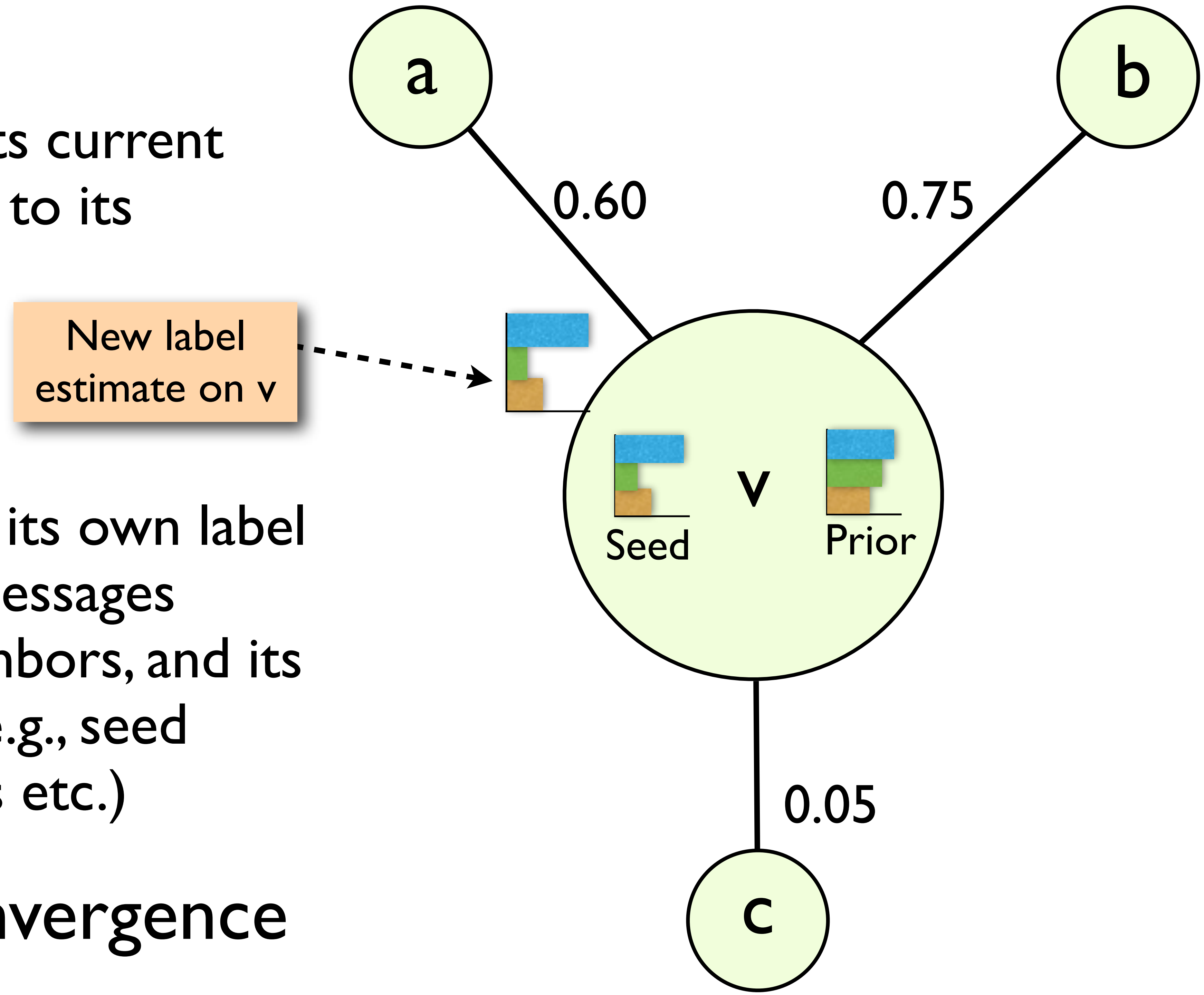

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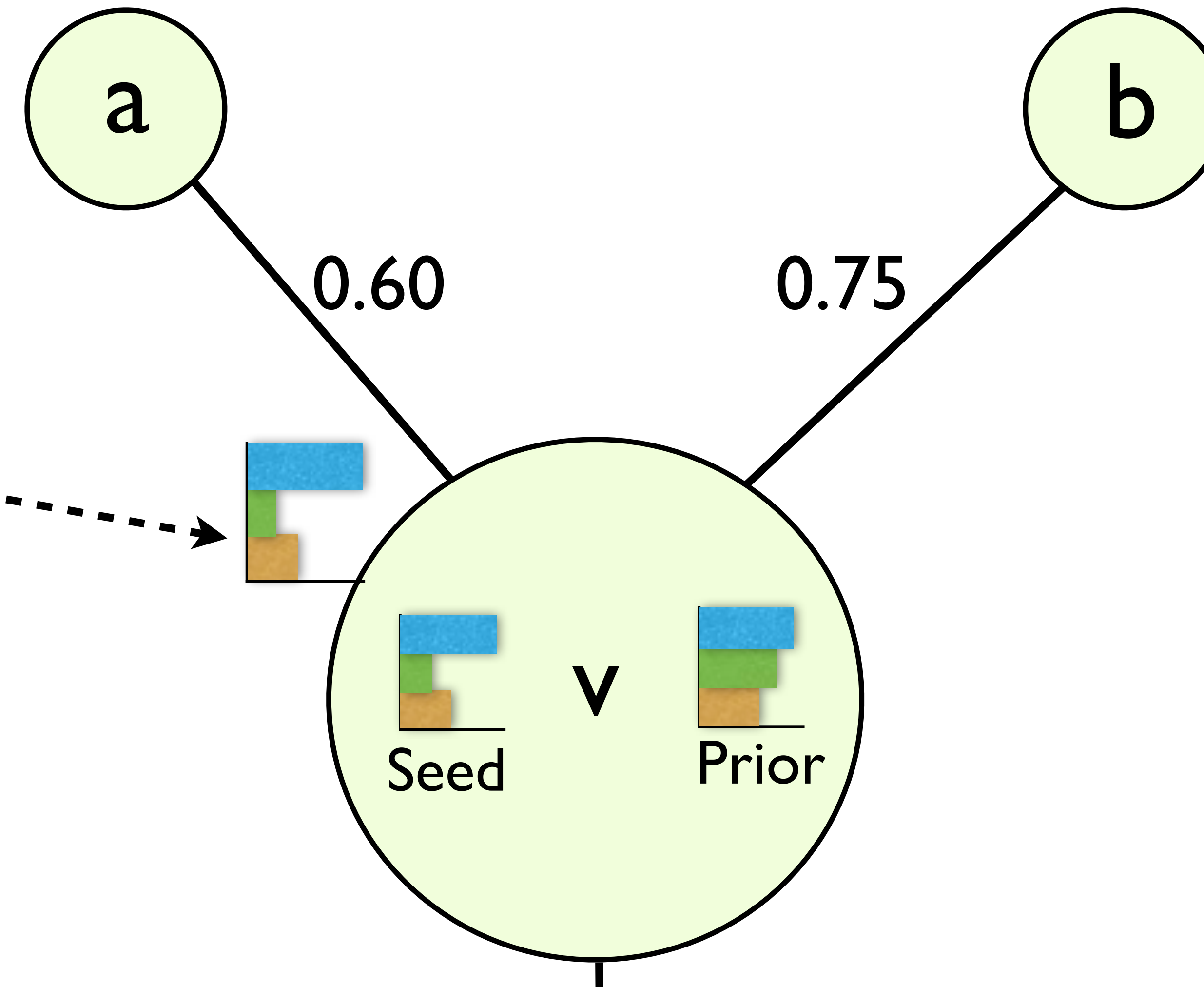

Code in Junto Label Propagation Toolkit
(includes Hadoop-based implementation)
http://code.google.com/p/junto/

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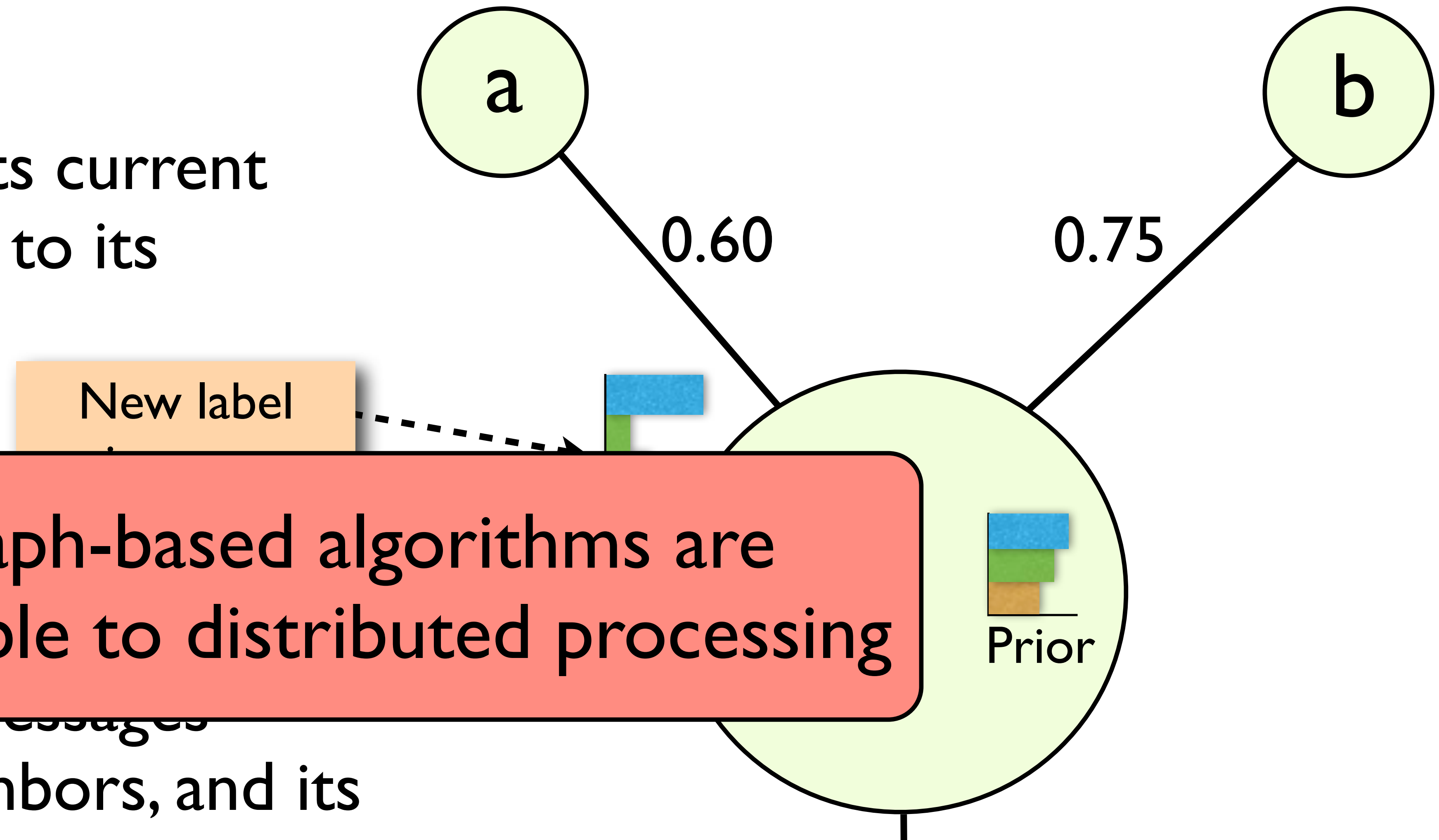

Graph-based algorithms are amenable to distributed processing

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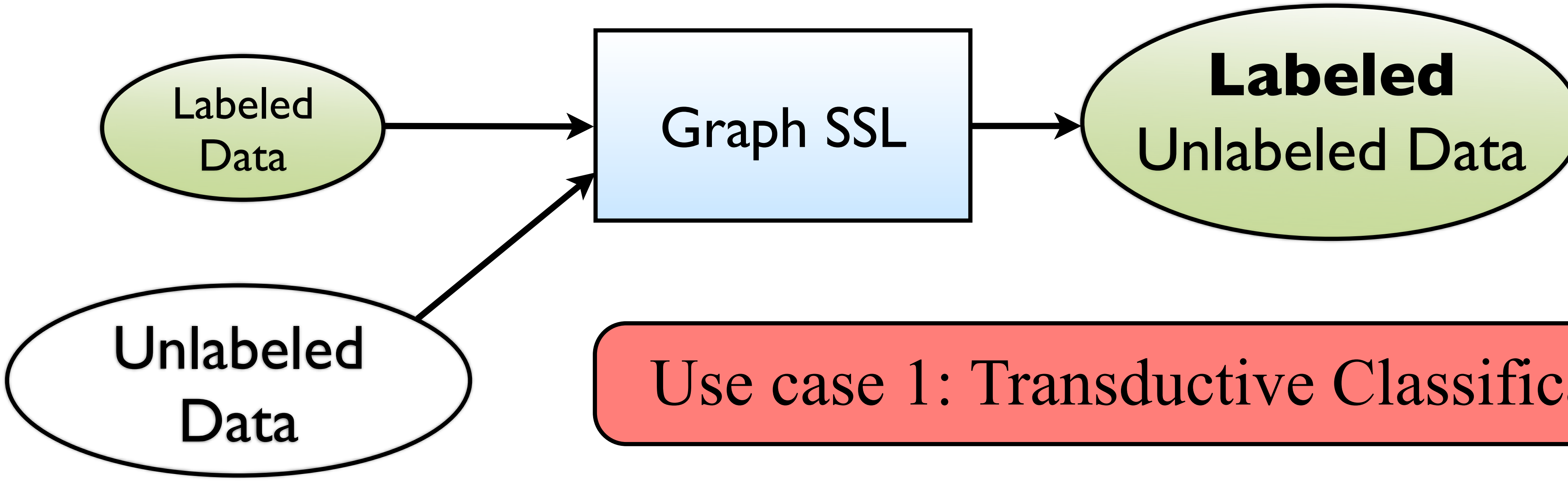
Graph-SSL : How is it used?



Use case 1: Transductive Classification

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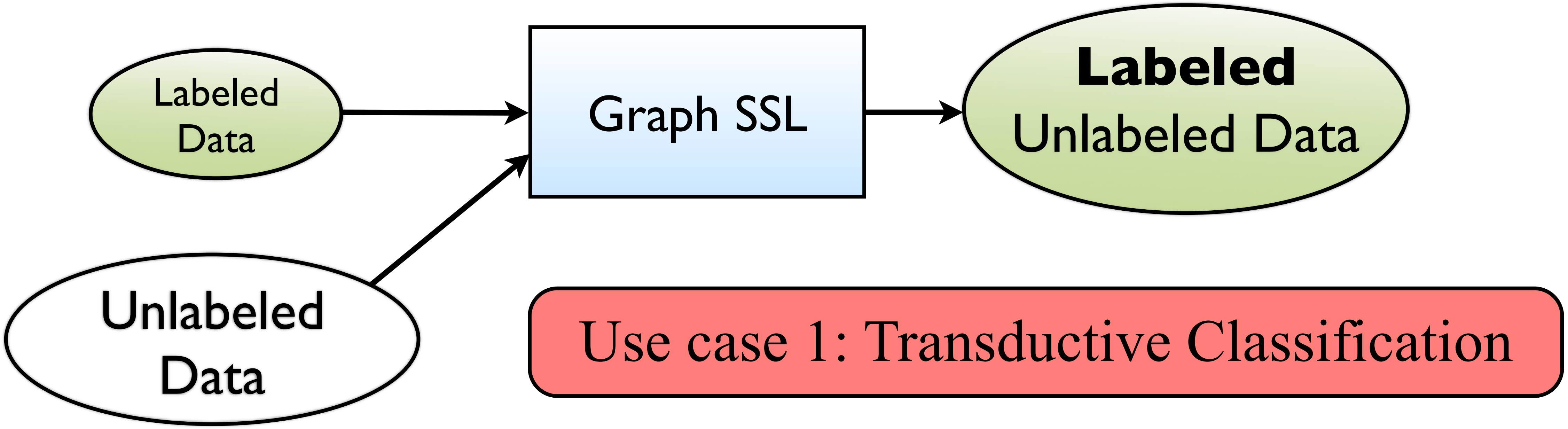

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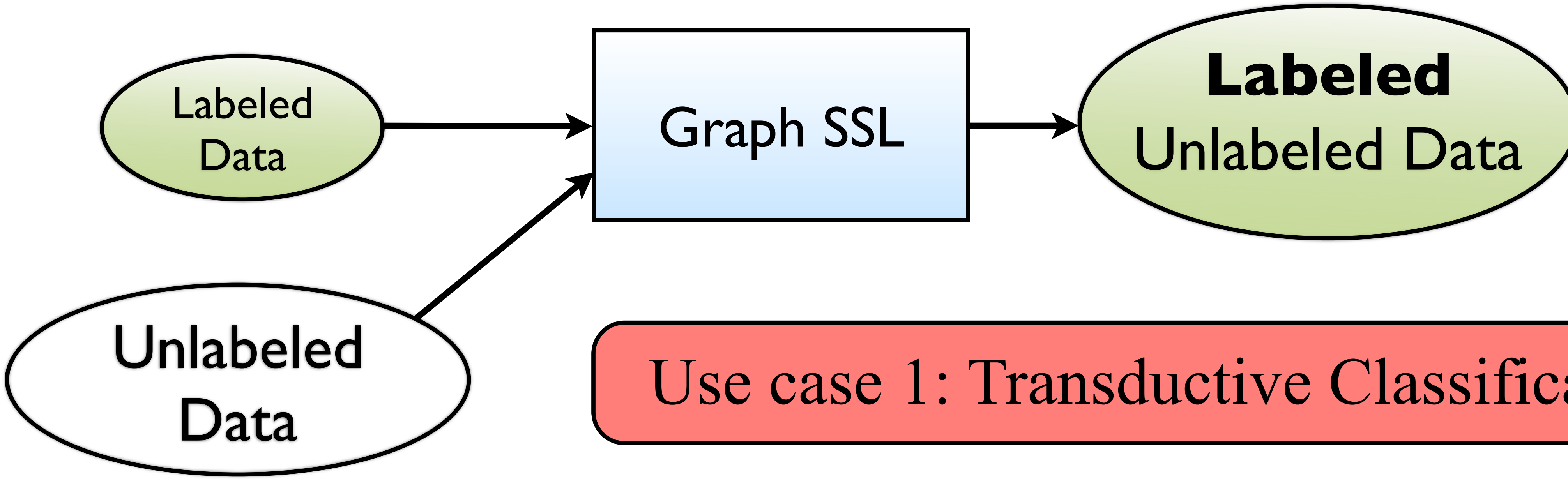

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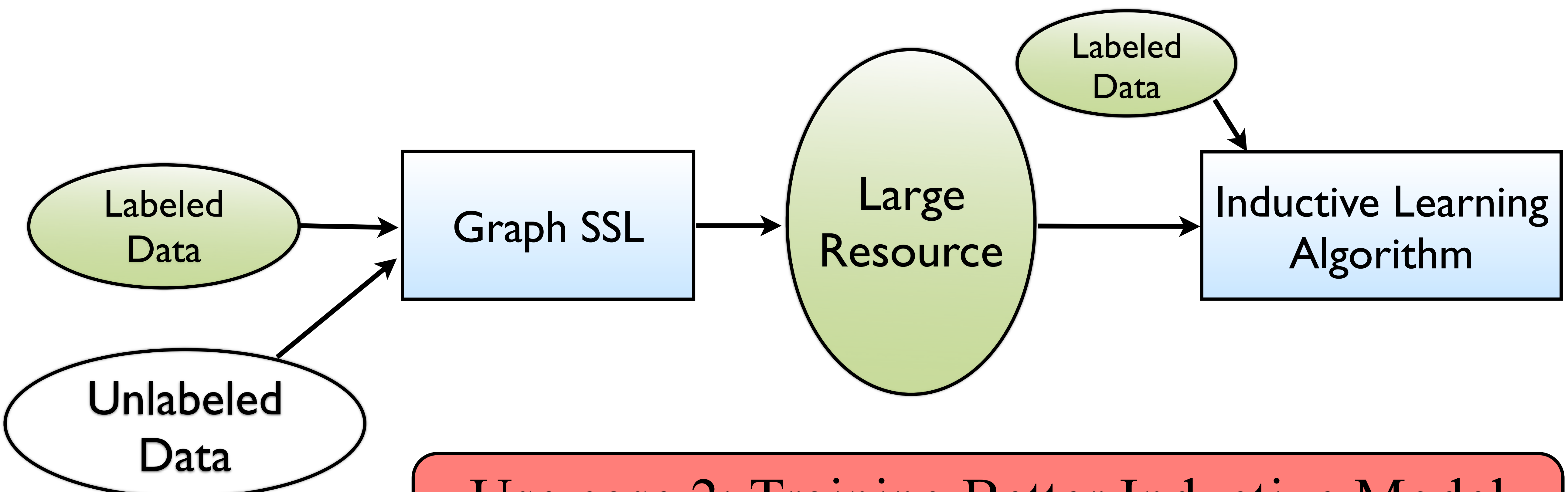

Use case 2: Training Better Inductive Model

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- Training supervised models requires large amounts of labeled data [Dumais et al., 1998]

Corpora

- **Reuters** [Lewis, et al., 1978]
  - Newswire
  - About 20K document with 135 categories. Use top 10 categories (e.g., "earnings", "acquistions", "wheat", "interest") and label the remaining as "other"

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- **WebKB** [Bekkerman, et al., 2003]
  - 8K webpages from 4 academic domains
  - Categories include "course", "department", "faculty" and "project"

Feature Extraction

Showers continued throughout the week in the Bahia cocoa zone, alleviating the drought since early January and improving prospects for the coming temporao, ...

Document
[Lewis, et al., 1978]

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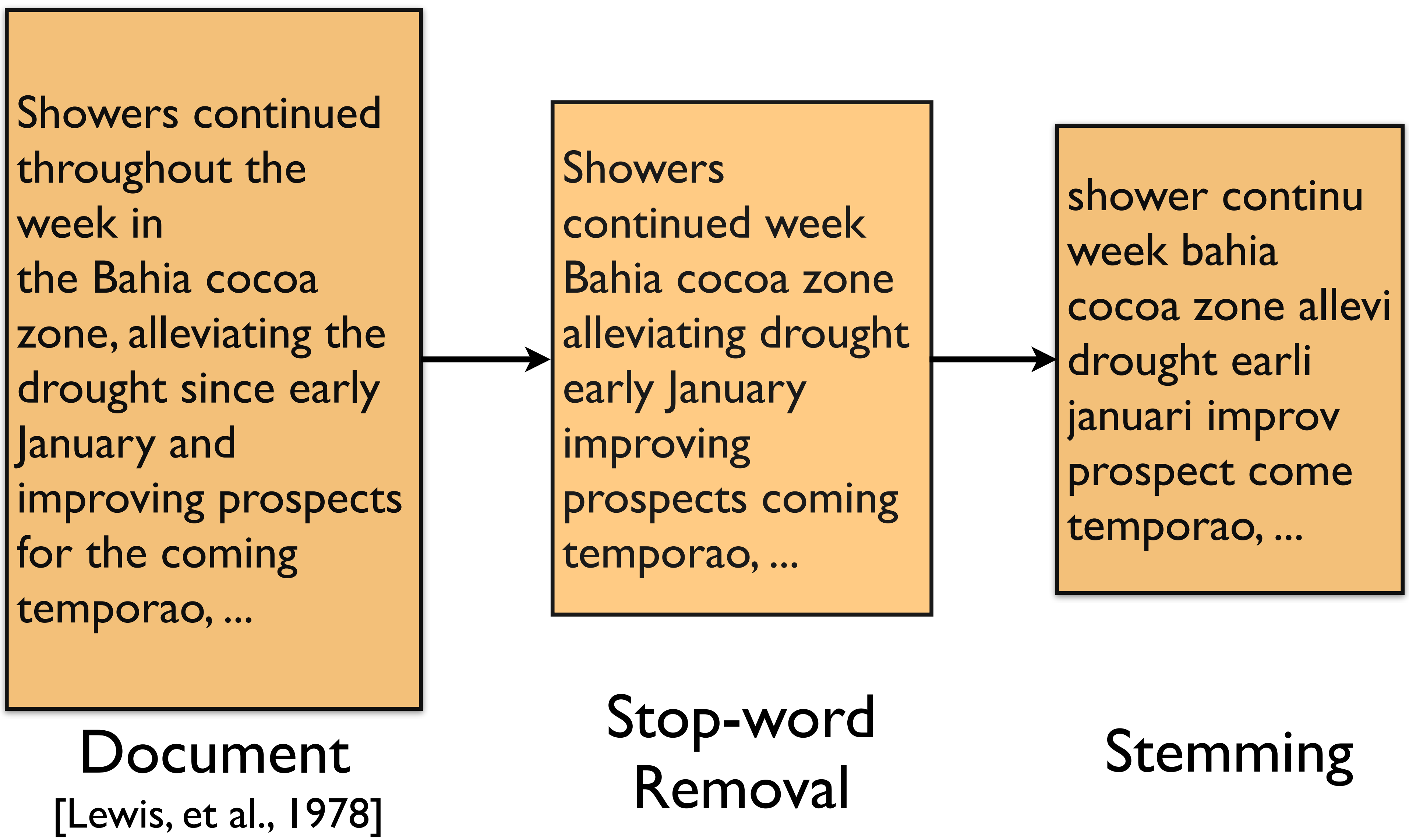
Stop-word Removal

Feature Extraction



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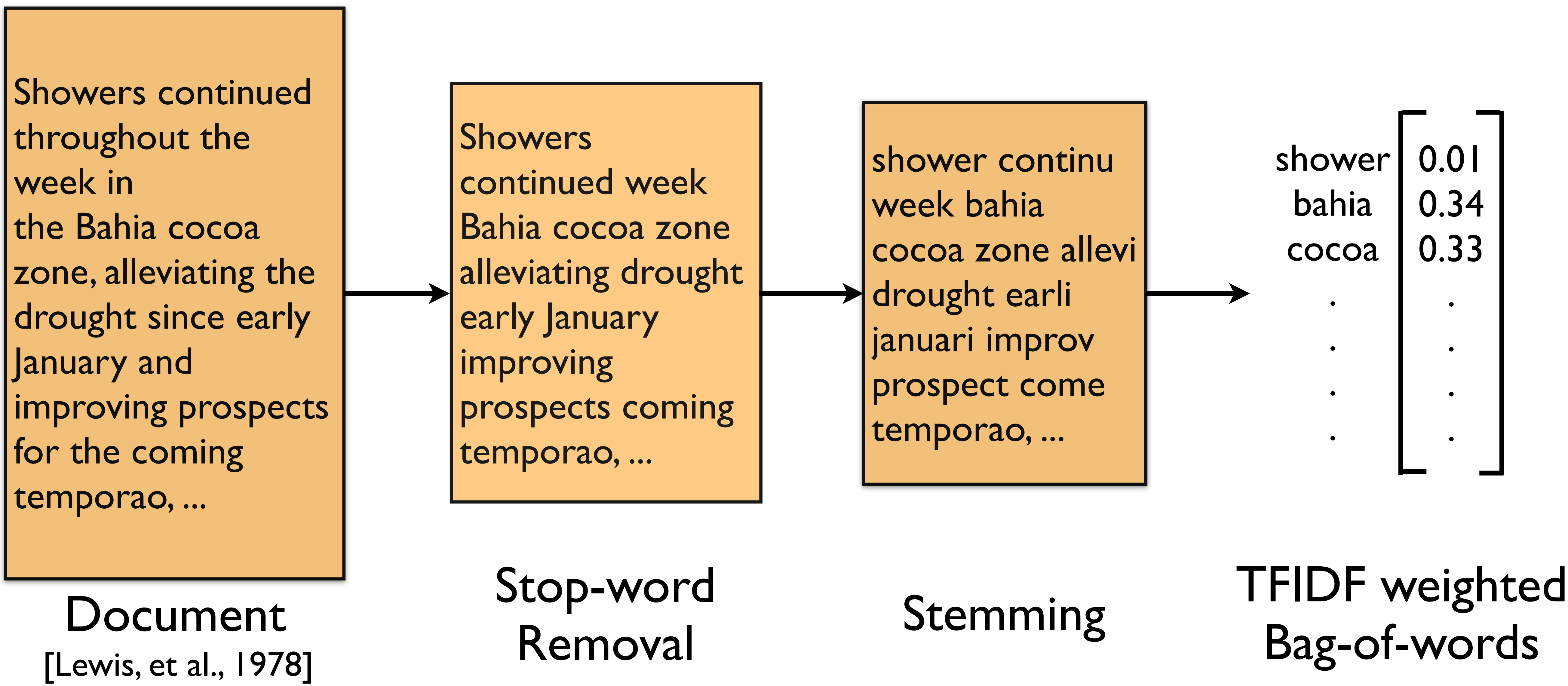

Results

Average PRBEP	SVM	TSVM	SGT	LP	MP	MAD
Reuters	48.9	59.3	60.3	59.7	**66.3**	-
WebKB	23.0	29.2	36.8	41.2	51.9	**53.7**

Precision-recall break even point (PRBEP)

Results

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Transductive SVM
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Support Vector Machine (Supervised)

Transductive SVM [Joachims 1999]

Spectral Graph Transduction (SGT) [Joachims 2003]

Label Propagation [Zhu & Ghahramani 2002]

Measure Propagation [Subramanya & Bilmes 2008]

Modified Adsorption [Talukdar & Crammer 2009]

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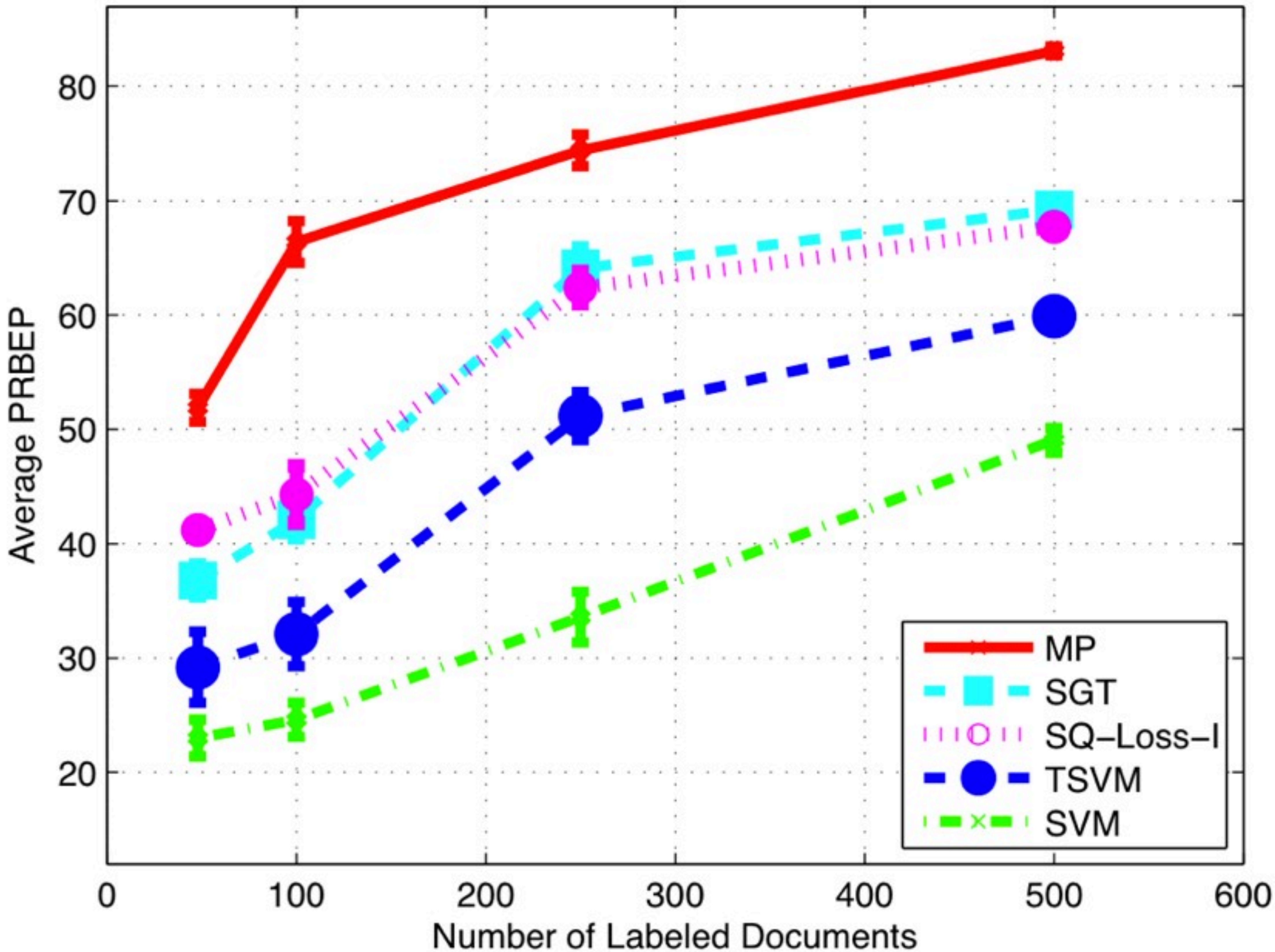
Results on WebKB



[Subramanya & Bilmes, EMNLP 2008]

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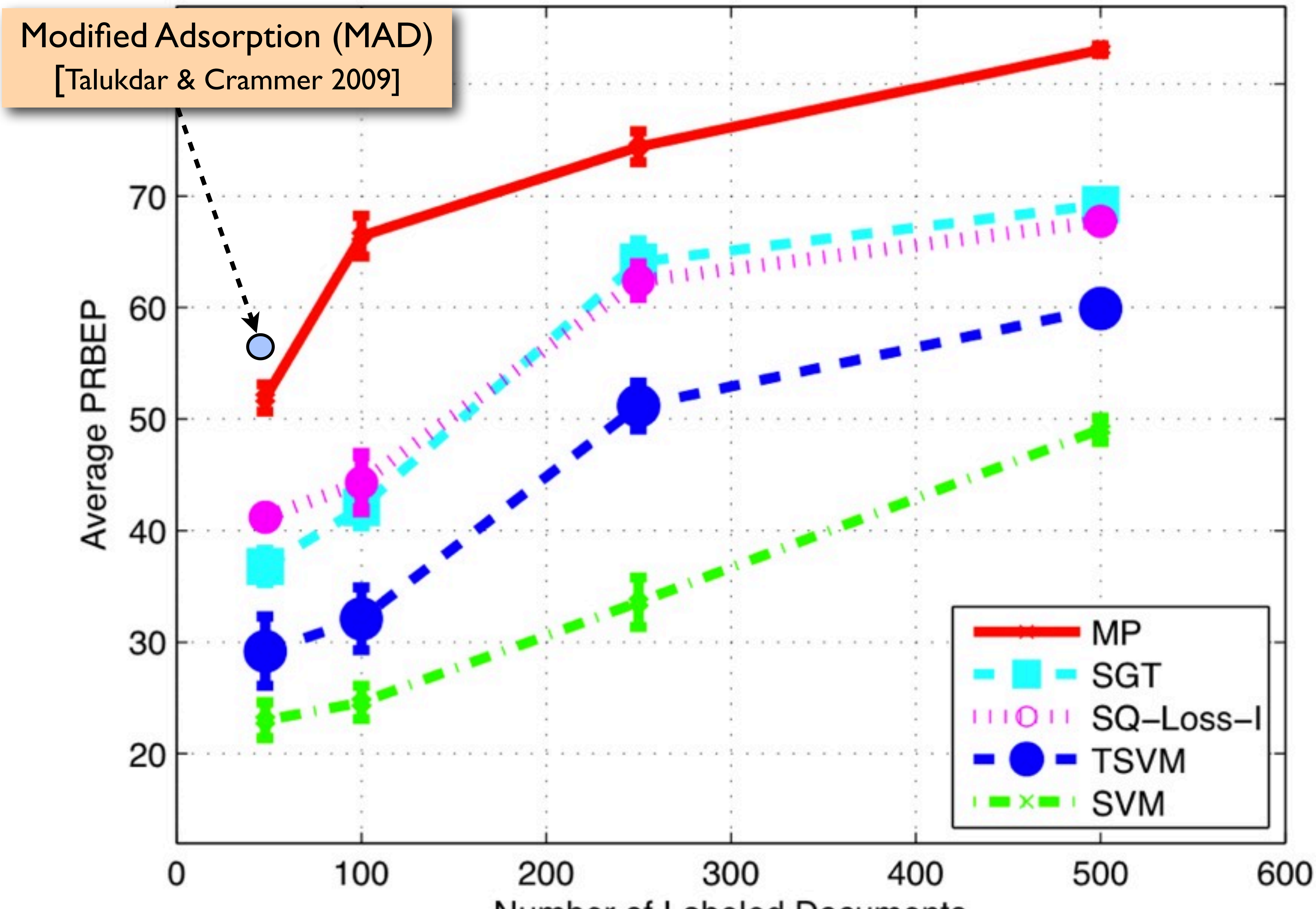

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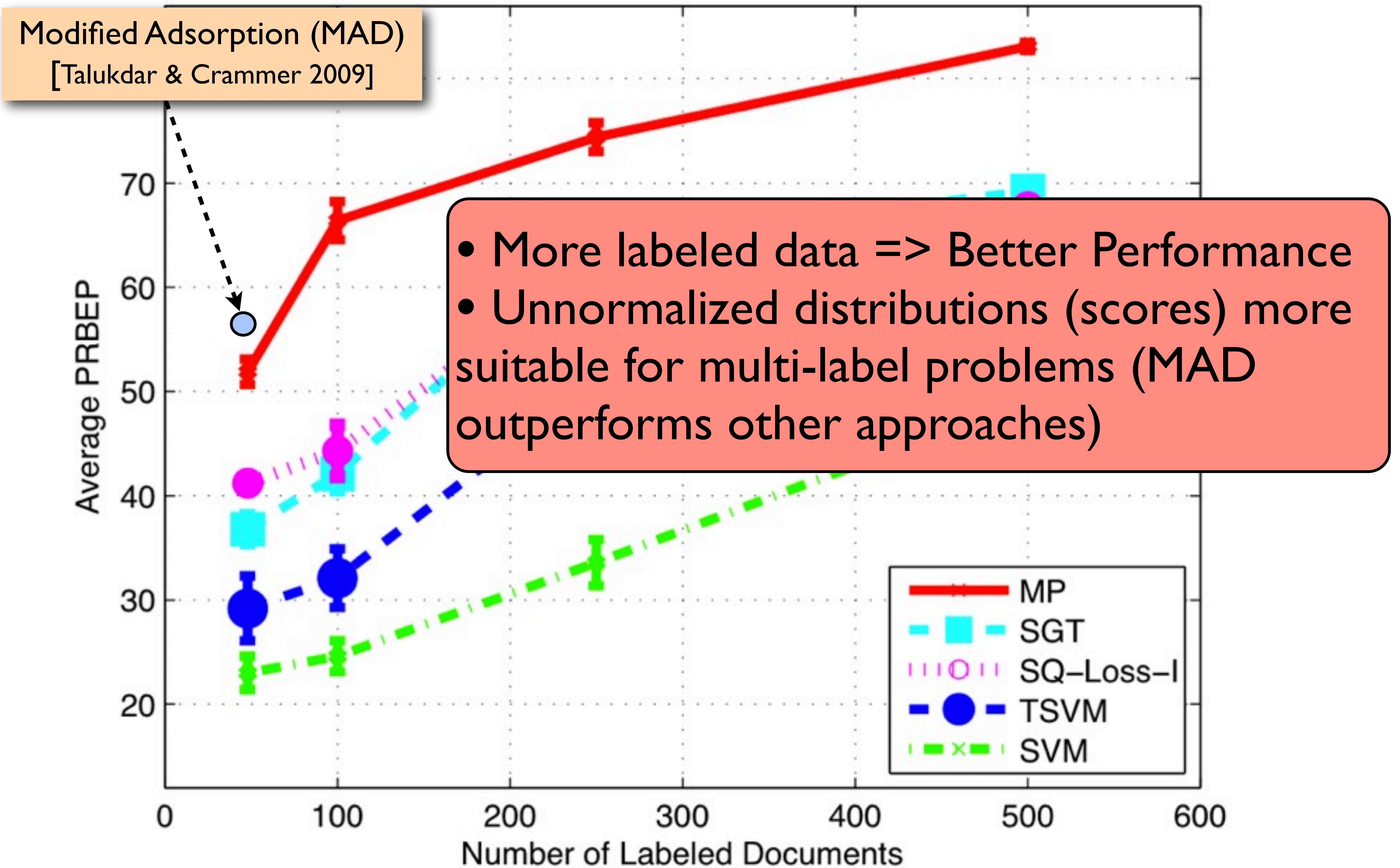

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Big Picture

Use case 1: Transductive Classification

Use case 2: Training Better Inductive Model

	Use case 1	Use case 2
Text Categorization		

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Use case 1: Transductive Classification

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- Given a document either
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  - assign a star rating
- Similar to text categorization
  - Can be solved using standard machine learning approaches [Pang, Lee & Vaidyanathan, EMNLP 2002]

Problem Description

- fortunately, they managed to do it in an interesting and funny way.
- he is one of the most exciting martial artists on the big screen.
- the romance was enchanting.

Movie review dataset [Pang et al. EMNLP 2002]

Problem Description

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- he is one of the most exciting martial artists on the big screen.
- the romance was enchanting.

- A woman in peril. A confrontation. An explosion. The end. Yawn. Yawn. Yawn.
- don't go see this movie

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  - Negative polarity: “bad”, “humorless”, “unbearable”, “out of touch”, “bumps in the road”

Polarity Lexicons (I)

- Large lists of phrases that encode the polarity (positive or negative) of each phrase
  - Positive polarity: “enjoyable”, “breathtakingly”, “once in a life time”
  - Negative polarity: “bad”, “humorless”, “unbearable”, “out of touch”, “bumps in the road”
- Best results obtained by combining with machine learning approaches [Wilson et al., HLT-EMNLP 05; Blair-Goldensohn et al. 08; Choi & Cardie EMNLP 09]

Polarity Lexicons (II)

- Common strategy: start with two **small** seed sets
  - P: positive phrases, e.g., “great” “fantastic”
  - N: negative phrases, e.g., “awful”, “dreadful”
- Grow lexicons with graph propagation algorithms

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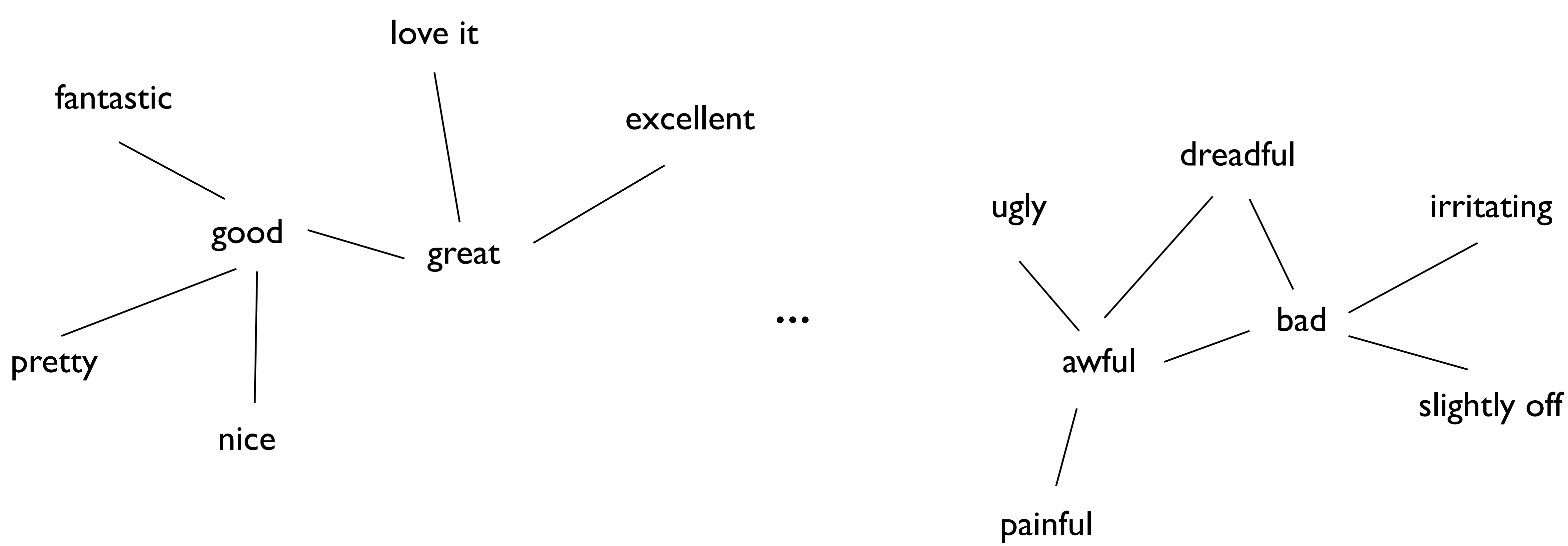

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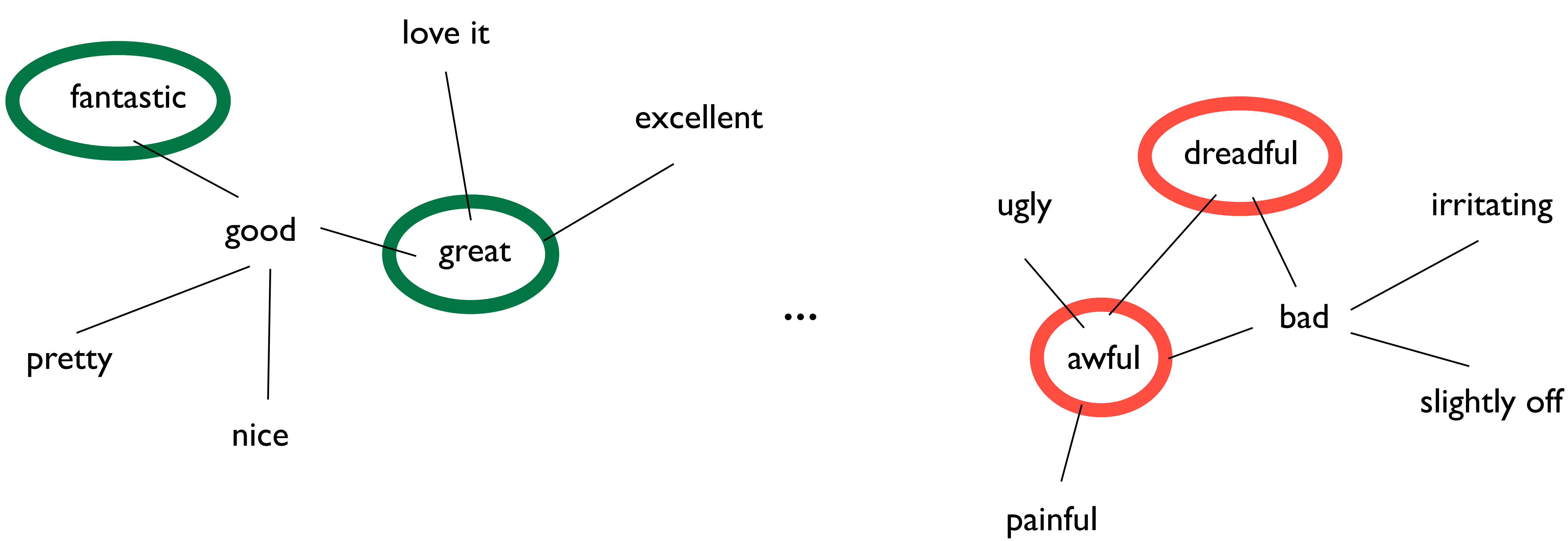

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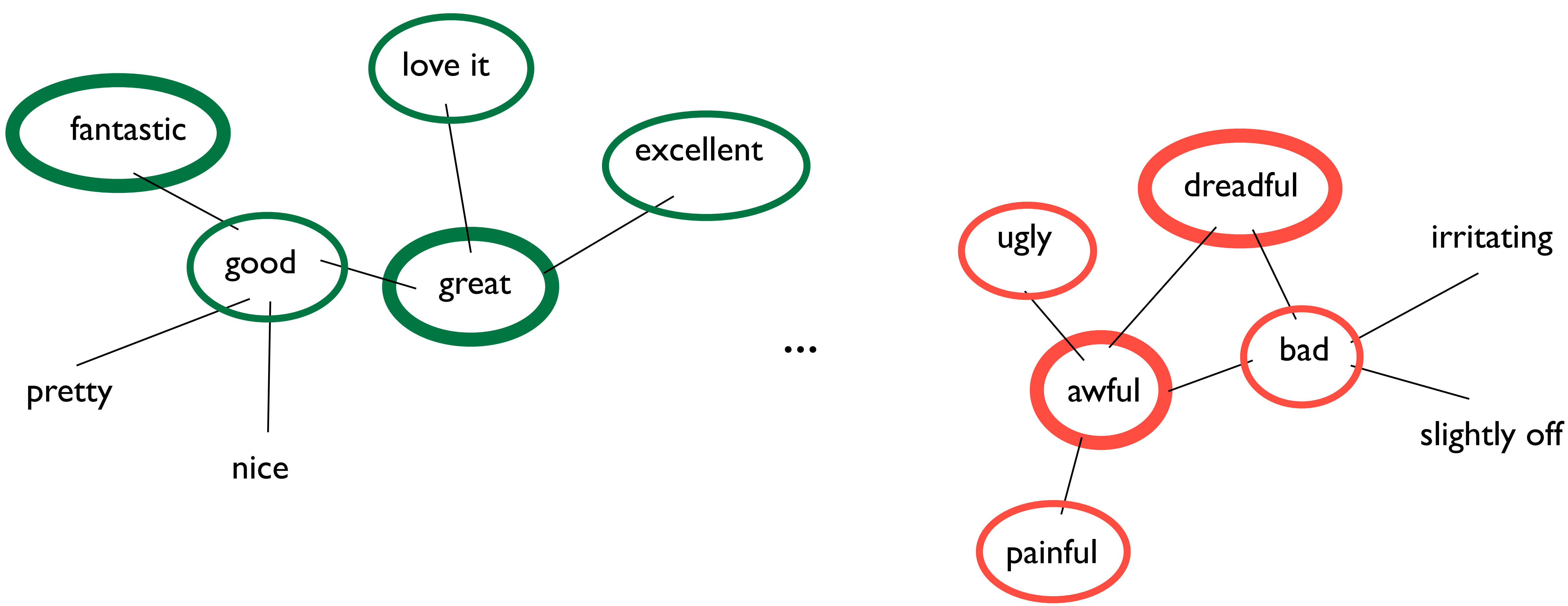

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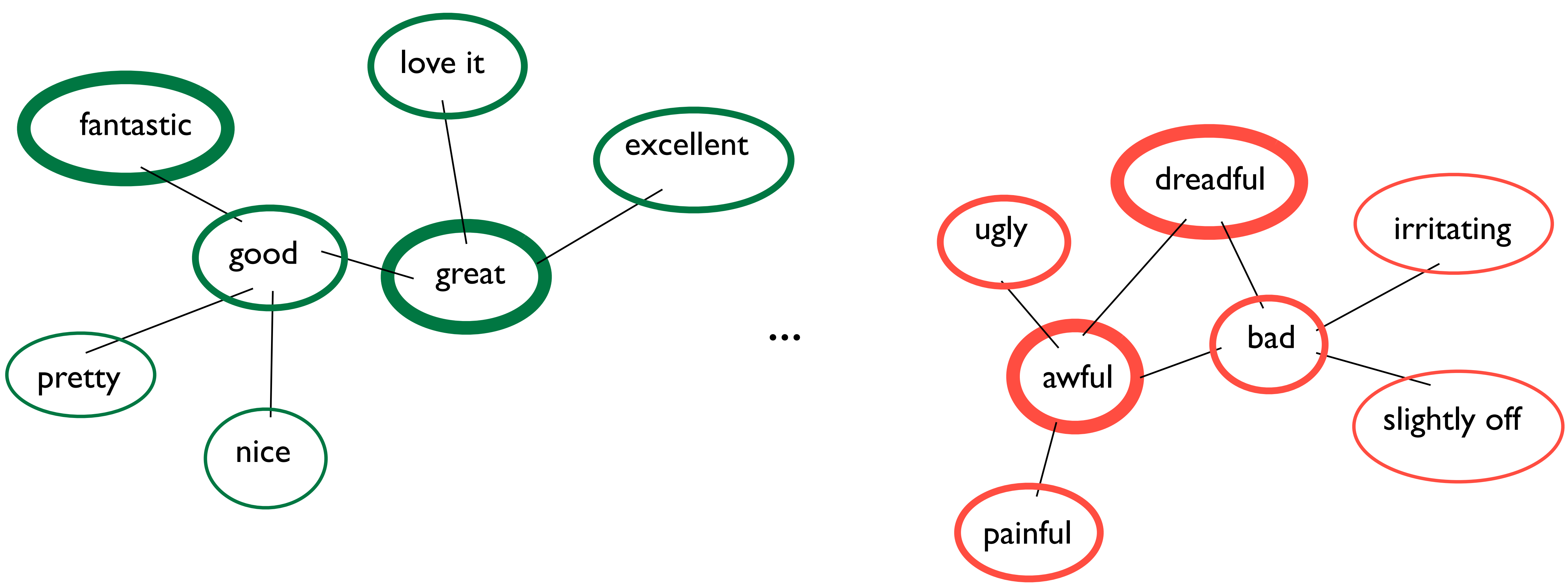


Graph Construction (I)

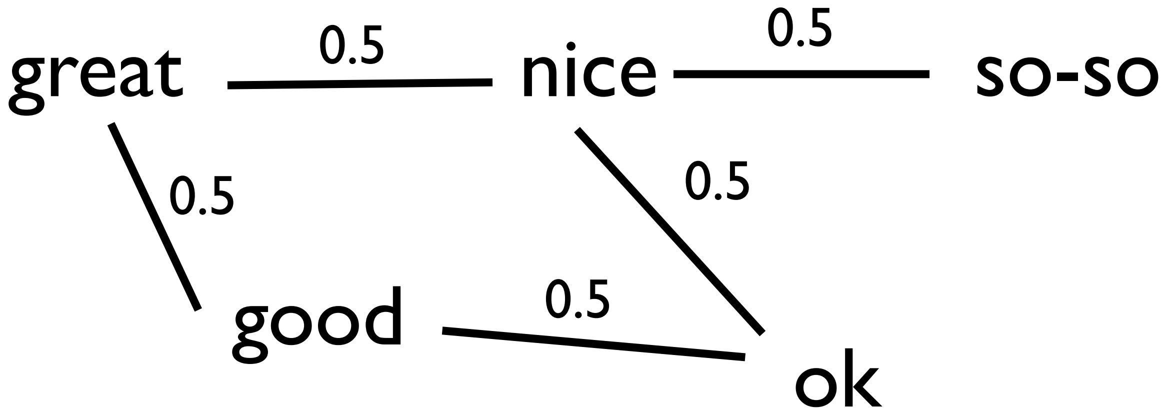
- WordNet [Hu & Liu, KDD 04; Kim & Hovy, ICCL 04; Blair-Goldensohn 08; Rao & Ravichandran EACL 09]
  - Defines synonyms, antonyms, hypernyms, etc.
  - Make edges between synonyms
  - Enforce constraints between antonyms
  - Issues
    - coverage
    - hard to find resources for all languages

Graph Construction (II)

- Use web data!
- All n-grams (phrases) up to length 10 from 4 billion web pages
  - Pruned down to 20 million candidate phrases
  - Feature vector obtained by aggregating words that occurred in **local** context

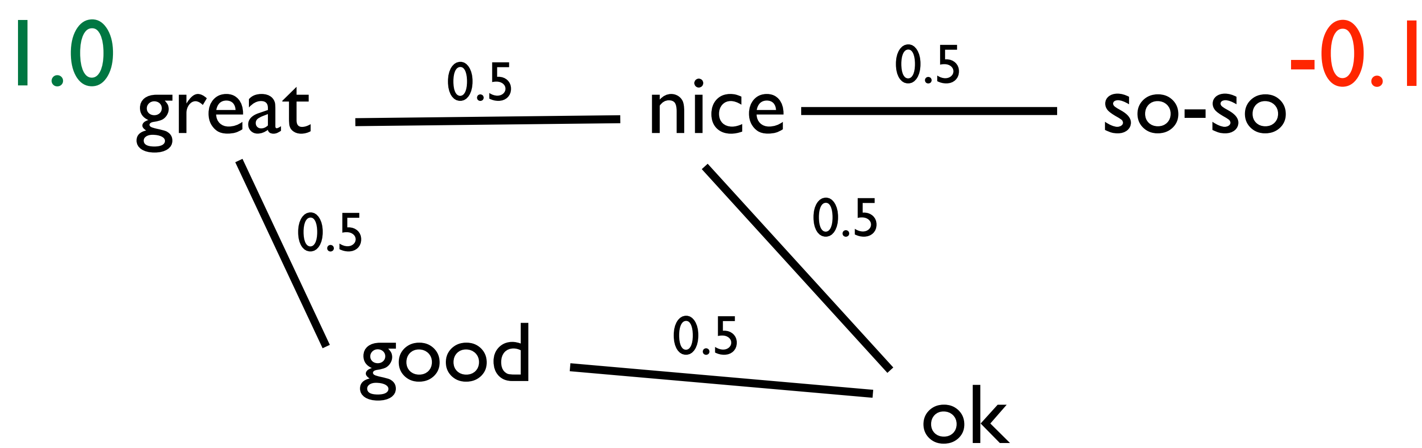
[Velikovich, et al., NAACL 2010]

Graph Propagation (I)



[Zhu & Ghahramani 2002]

Graph Propagation (I)



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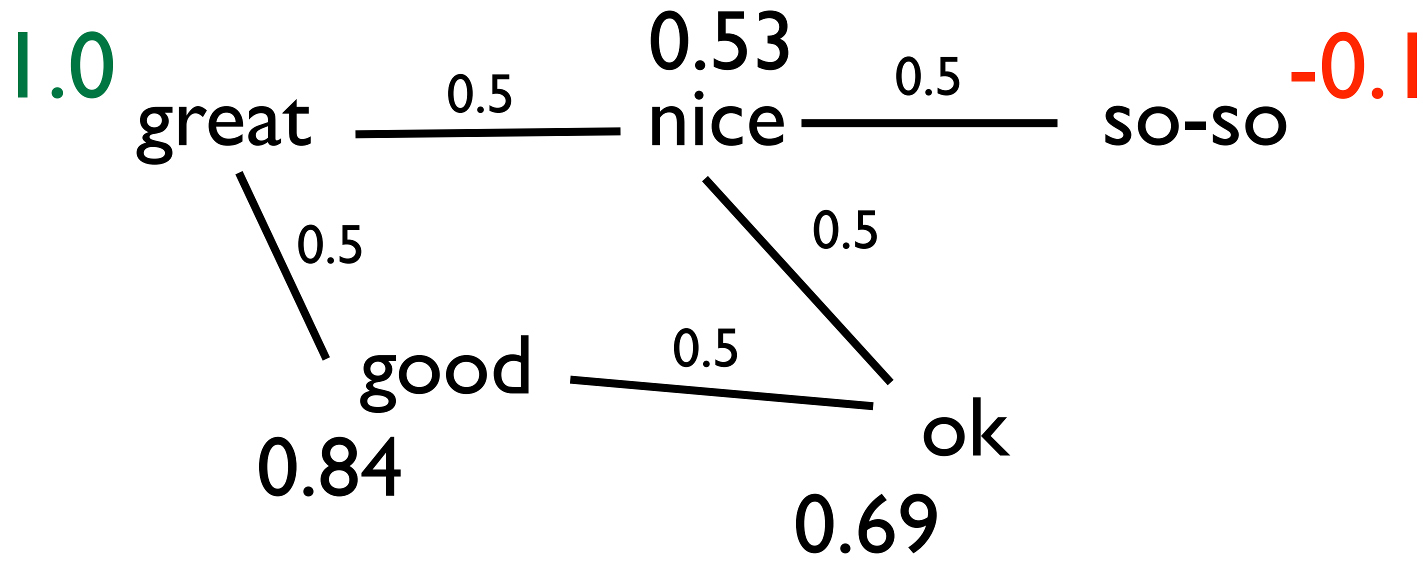

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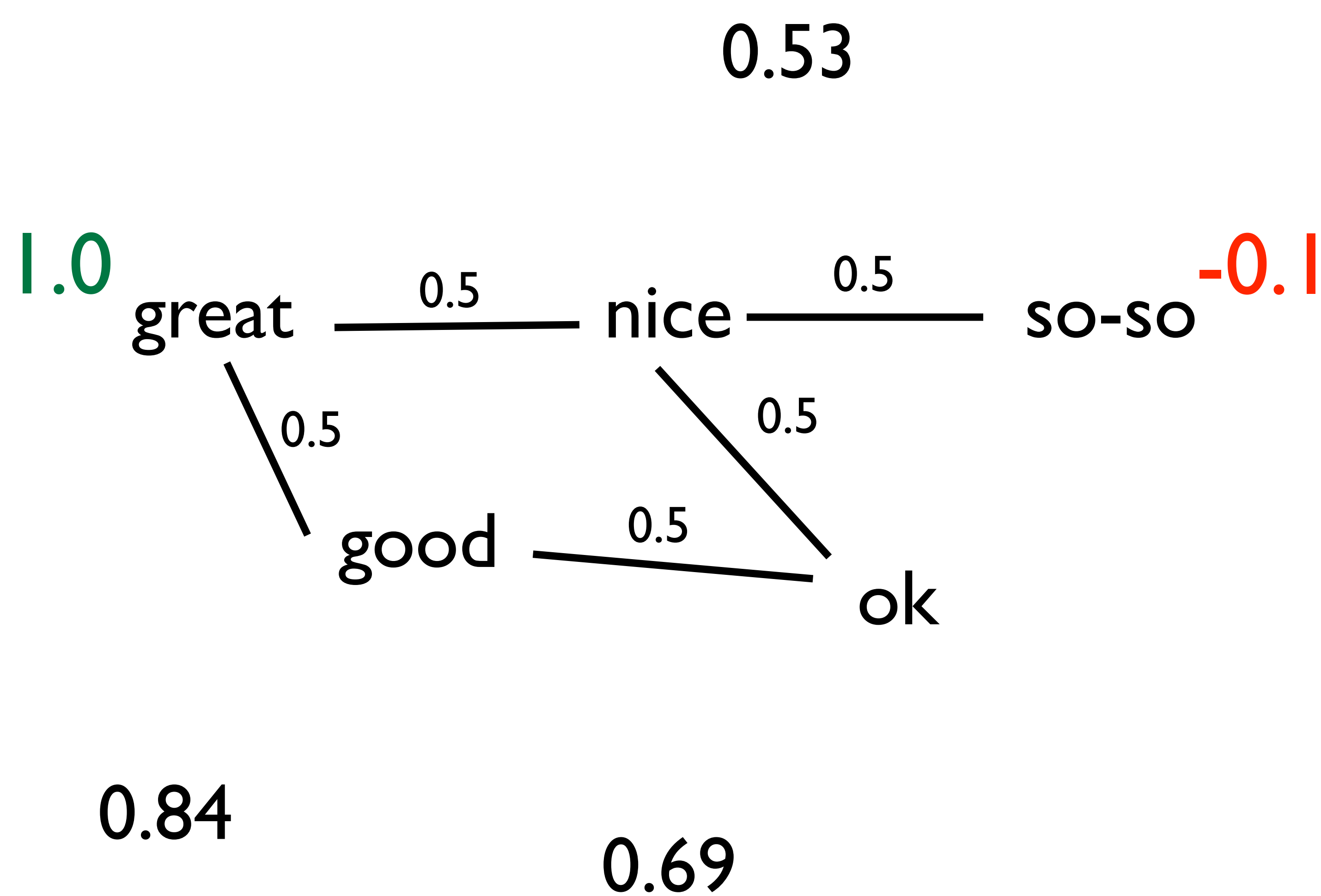

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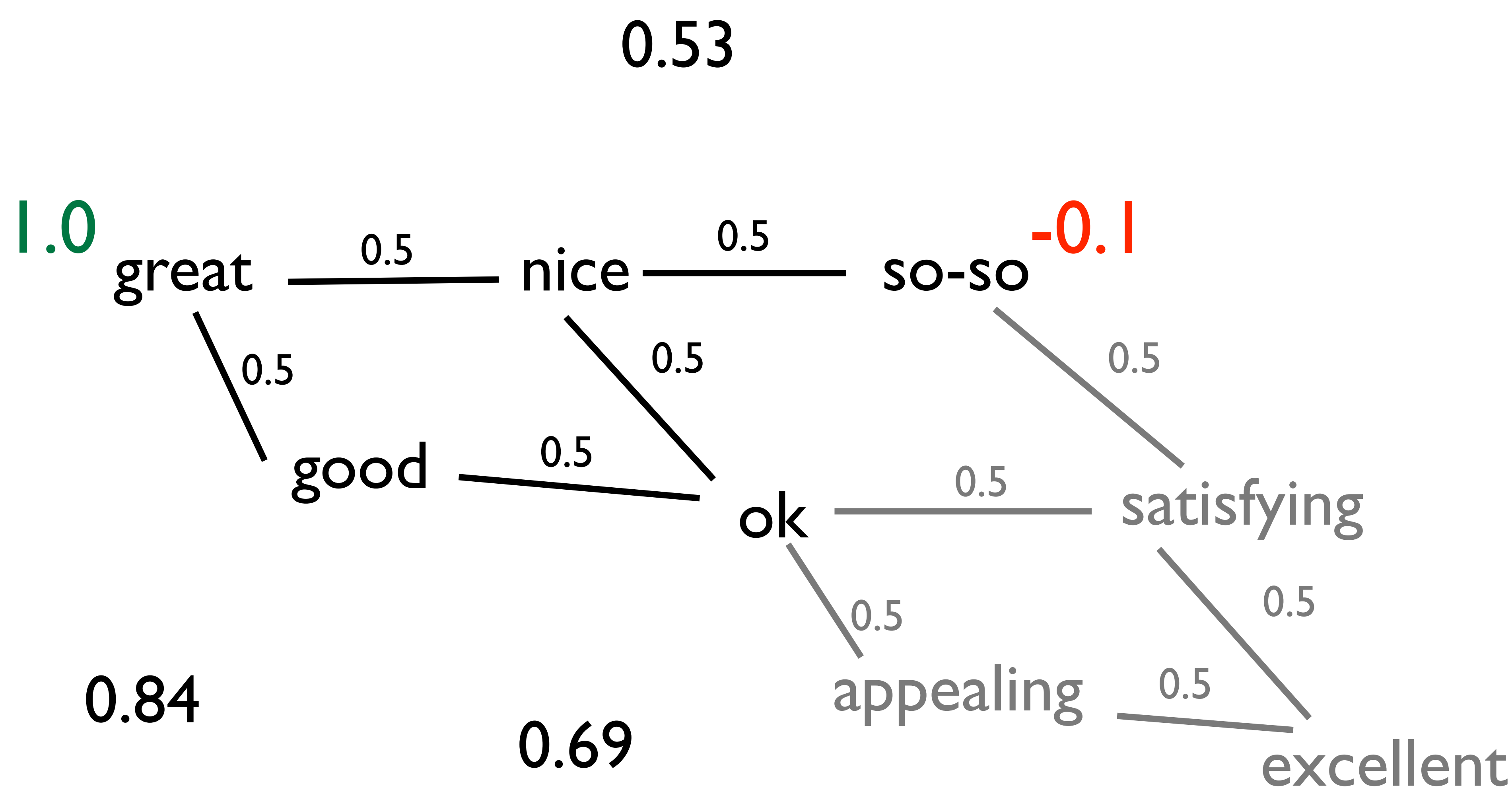

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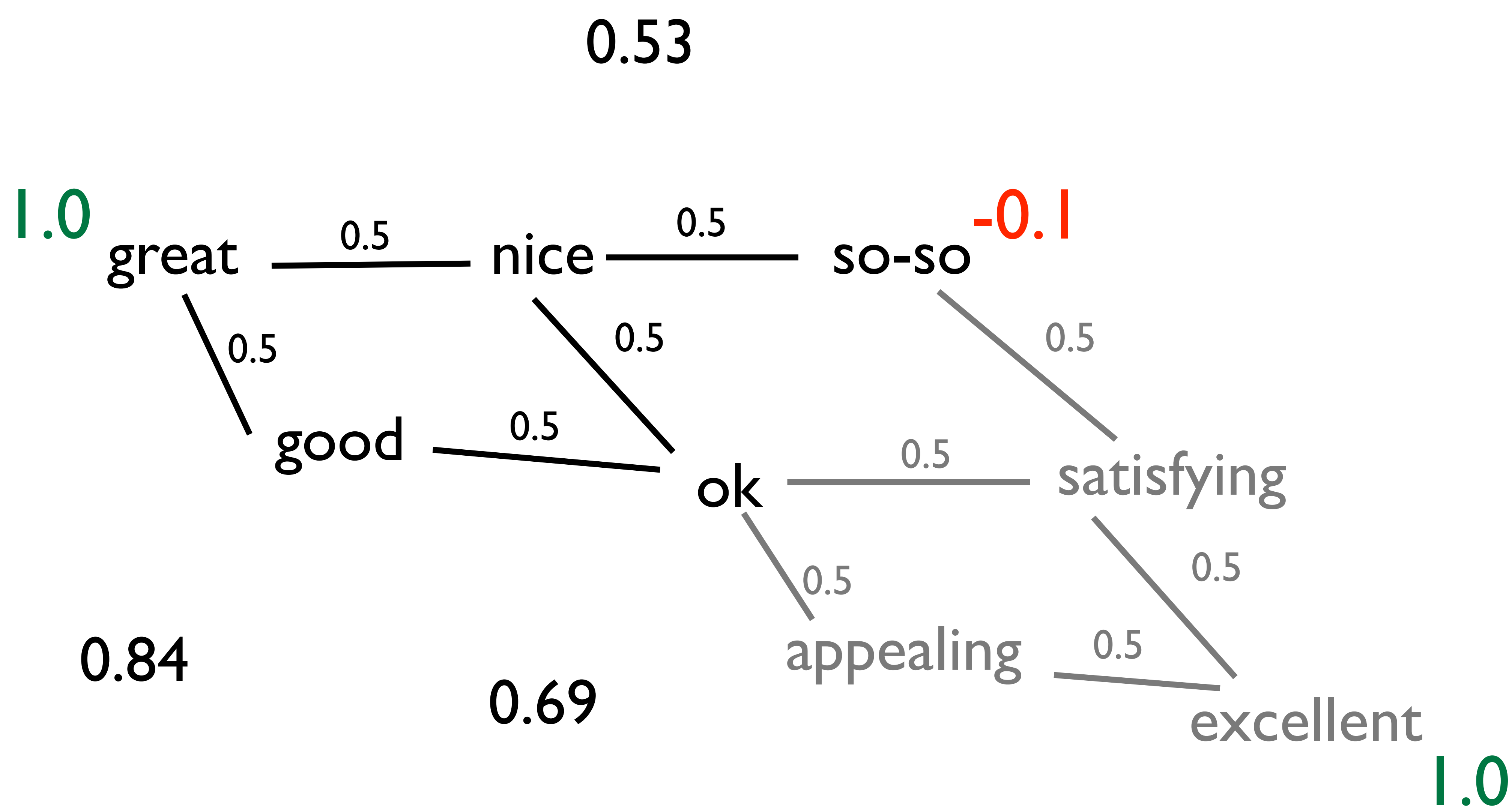

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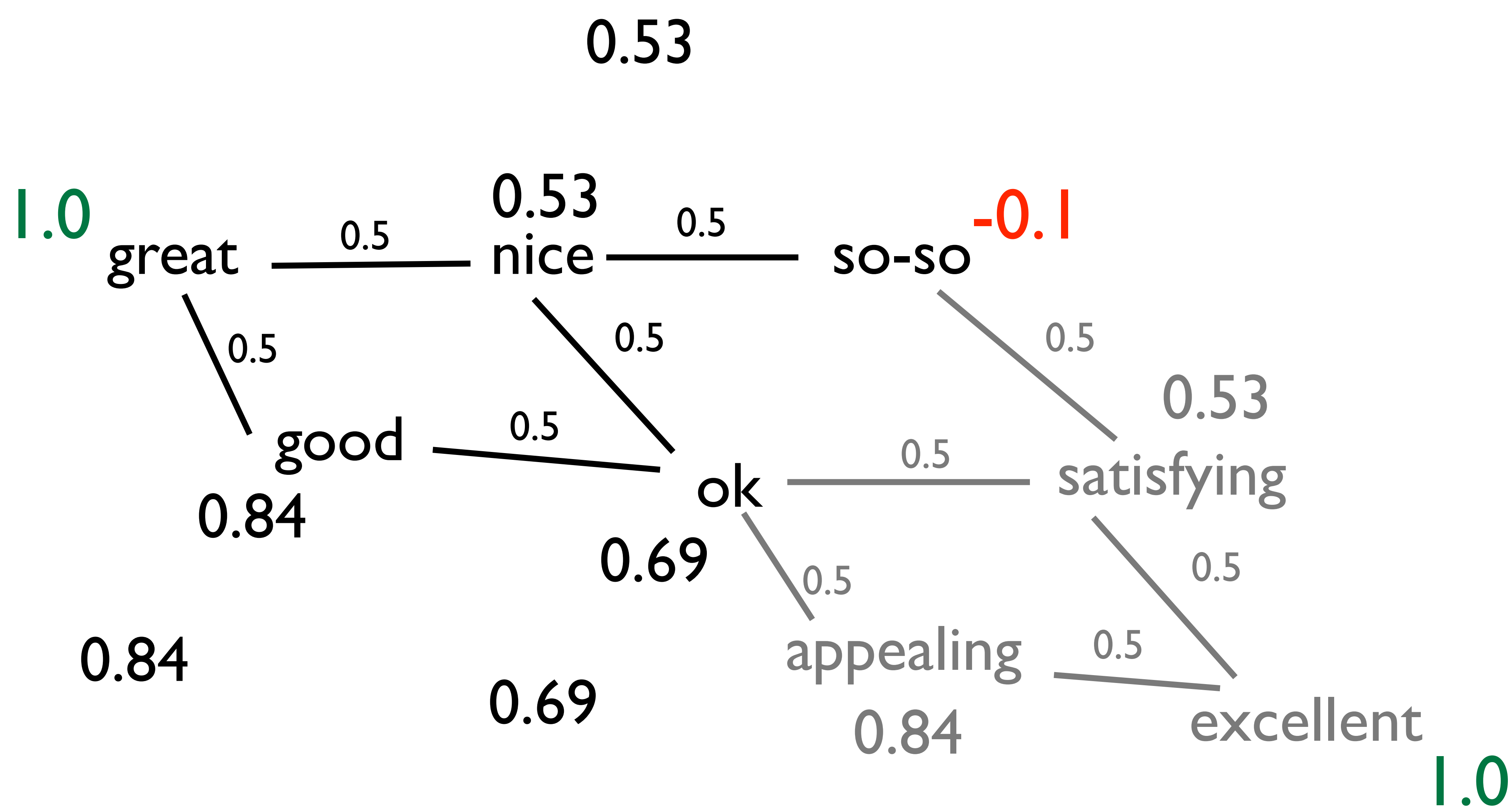

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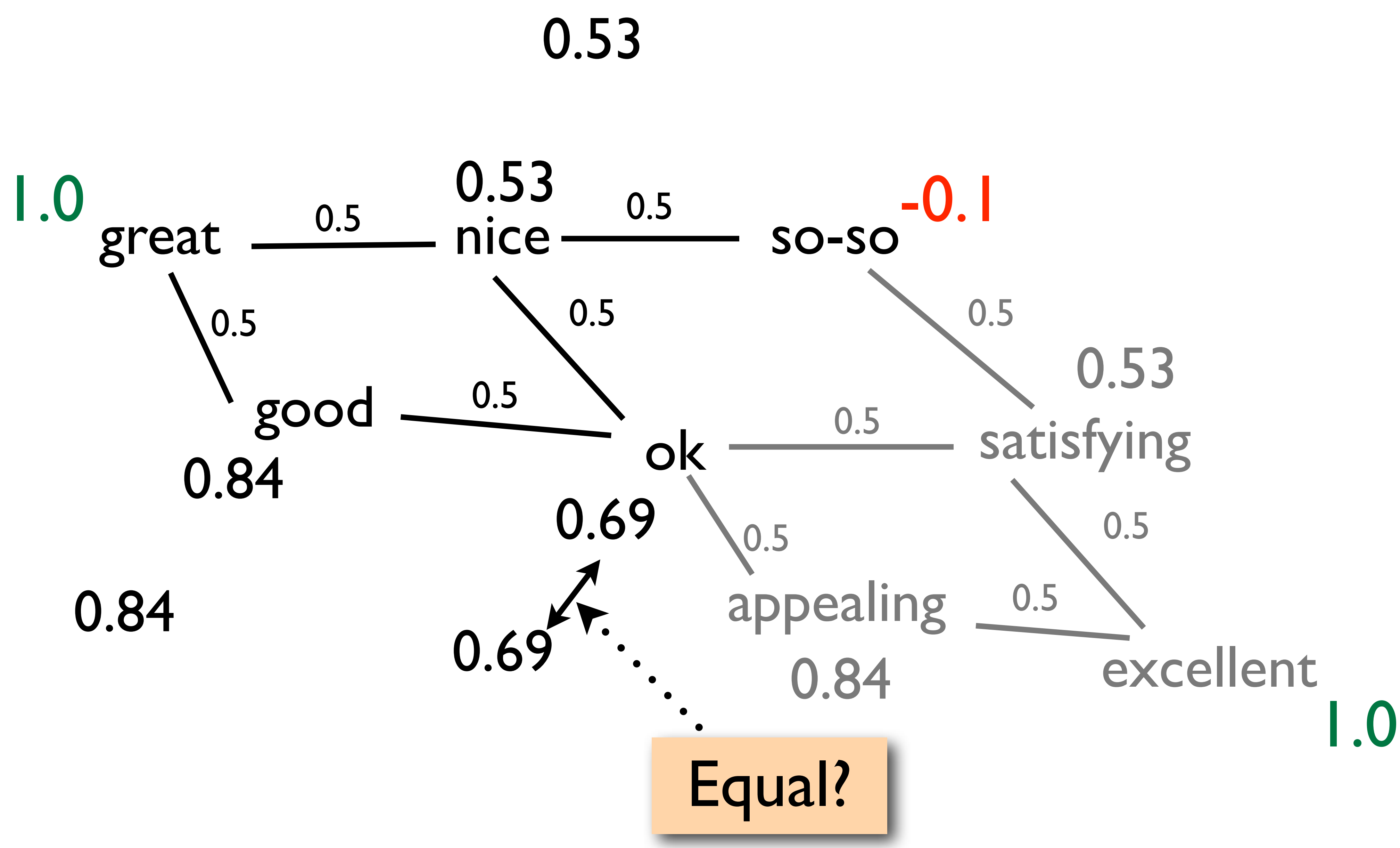

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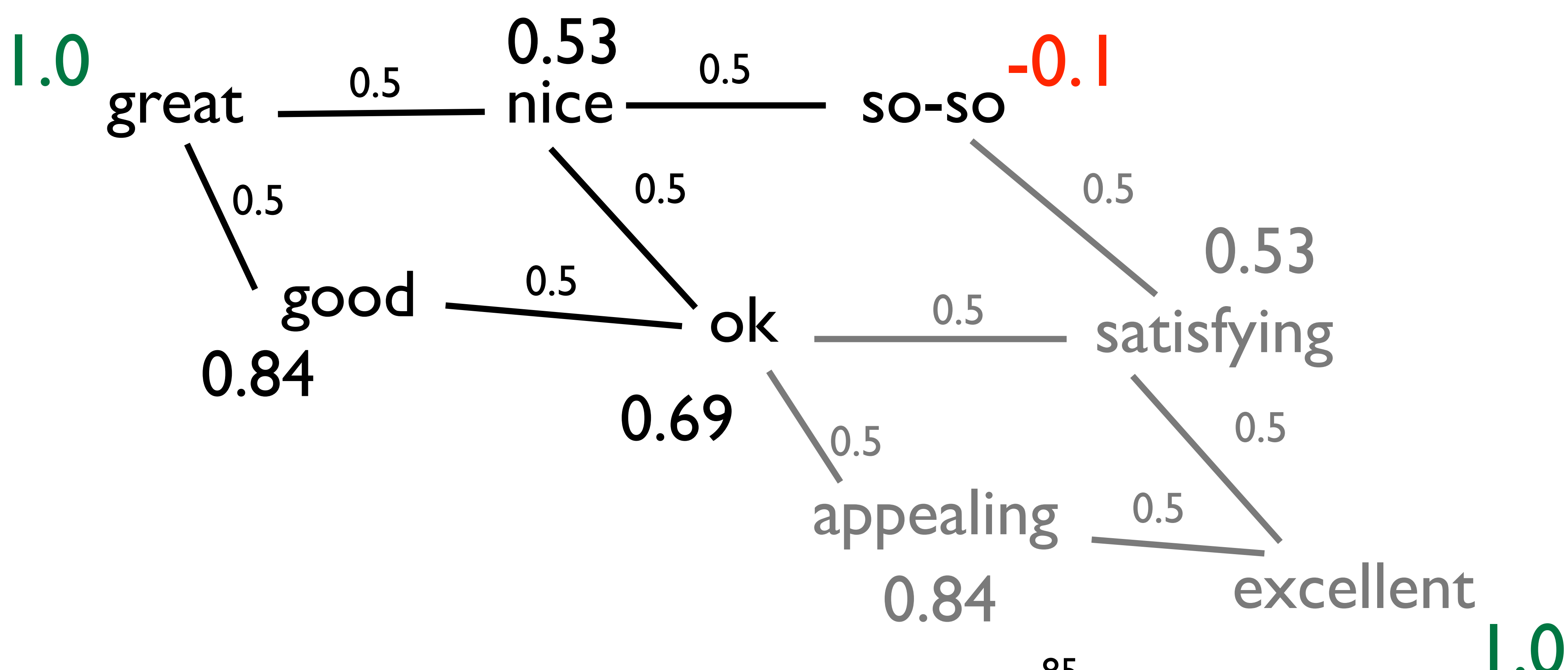

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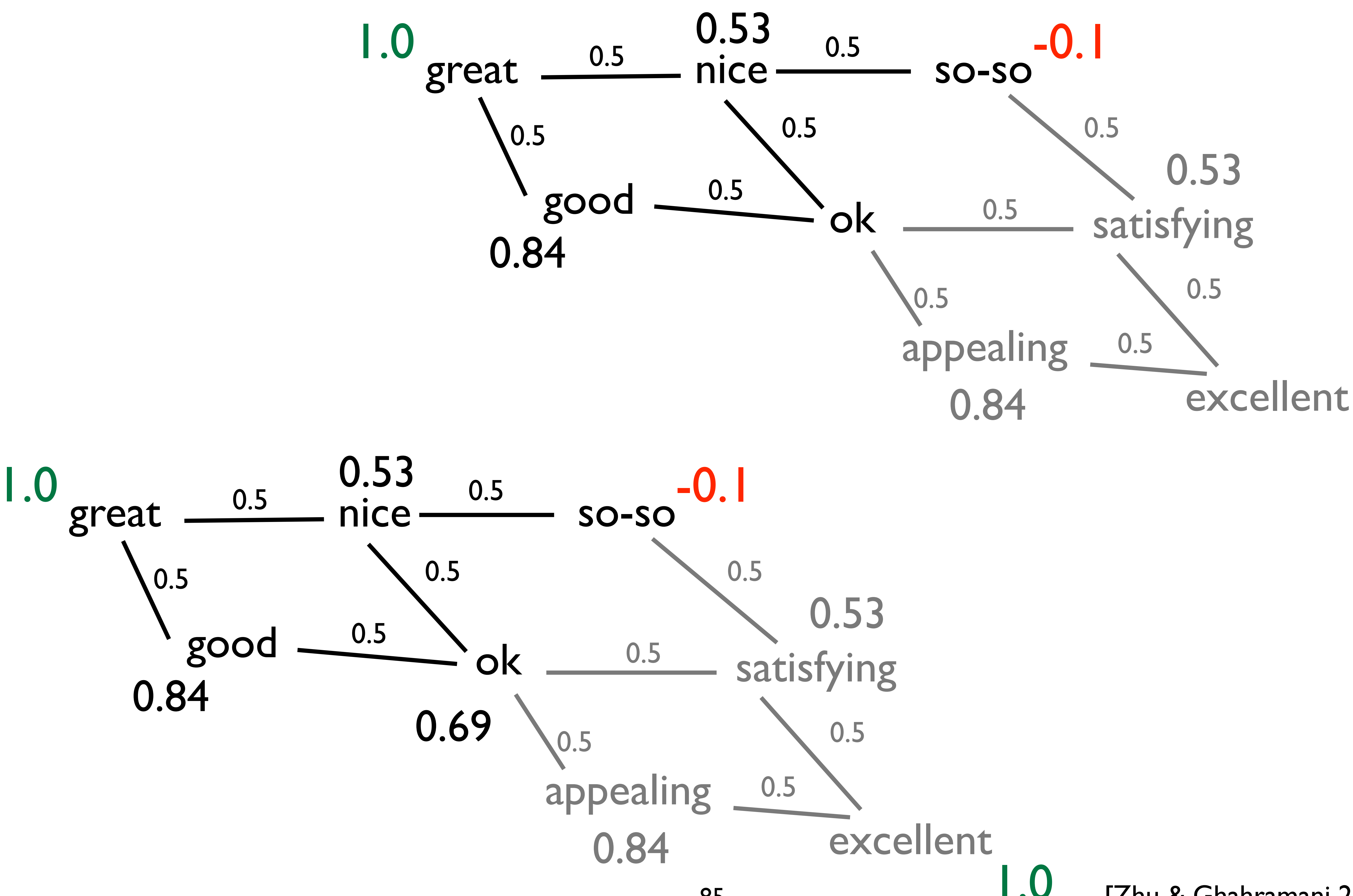

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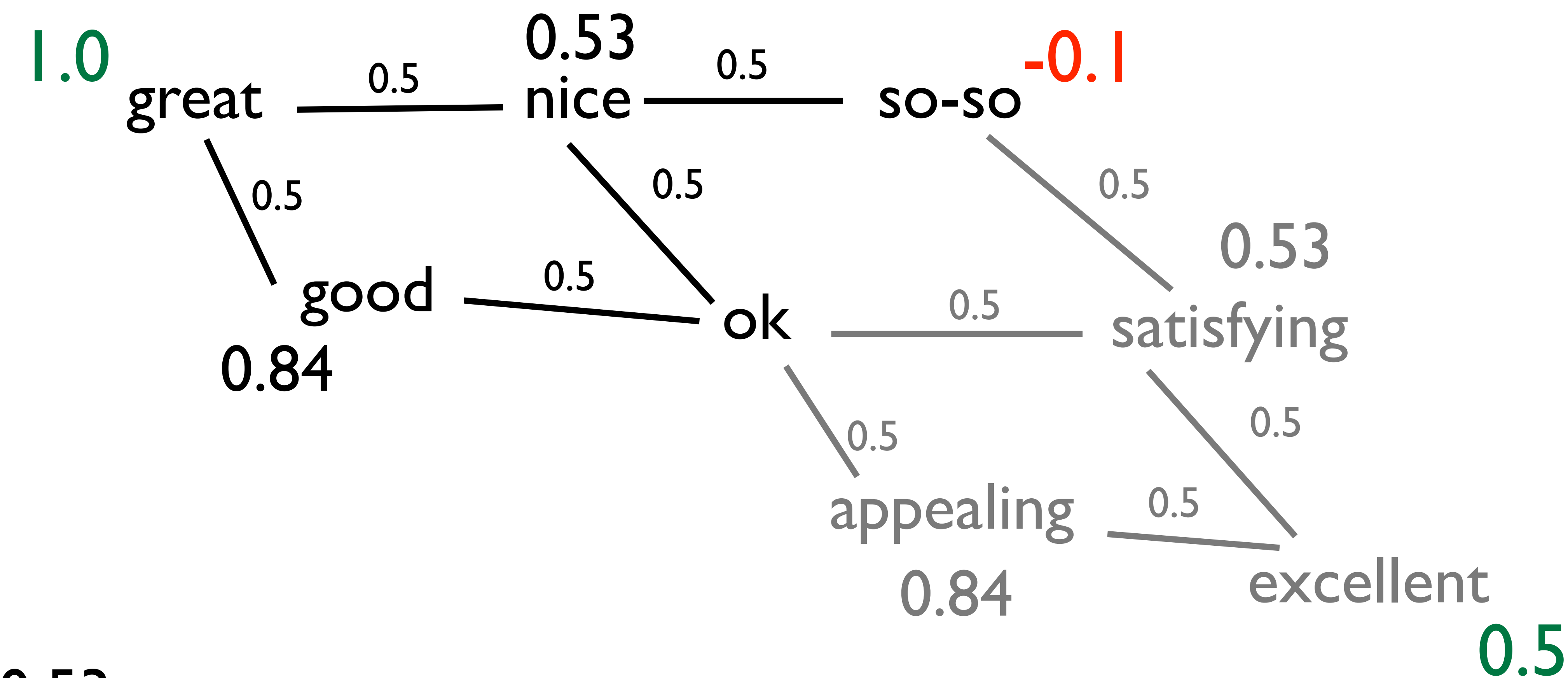

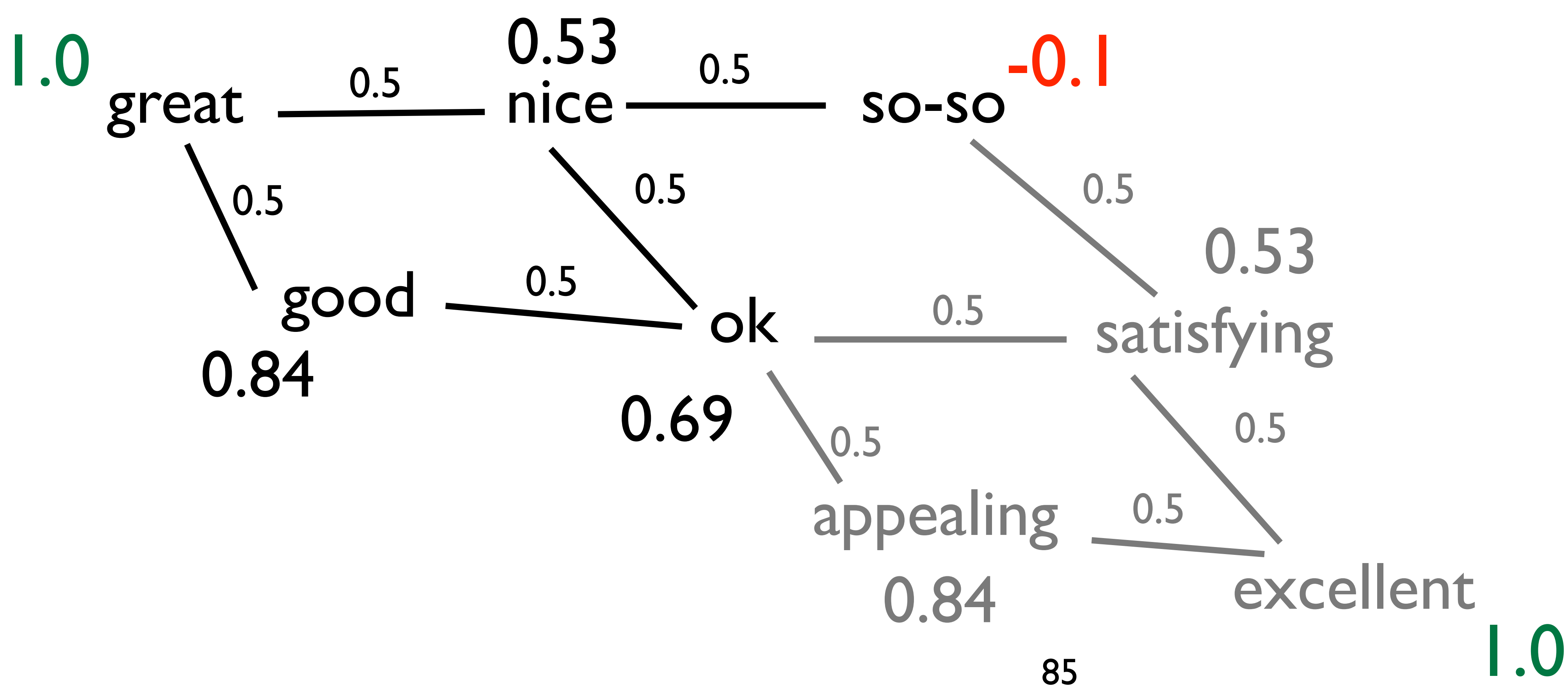

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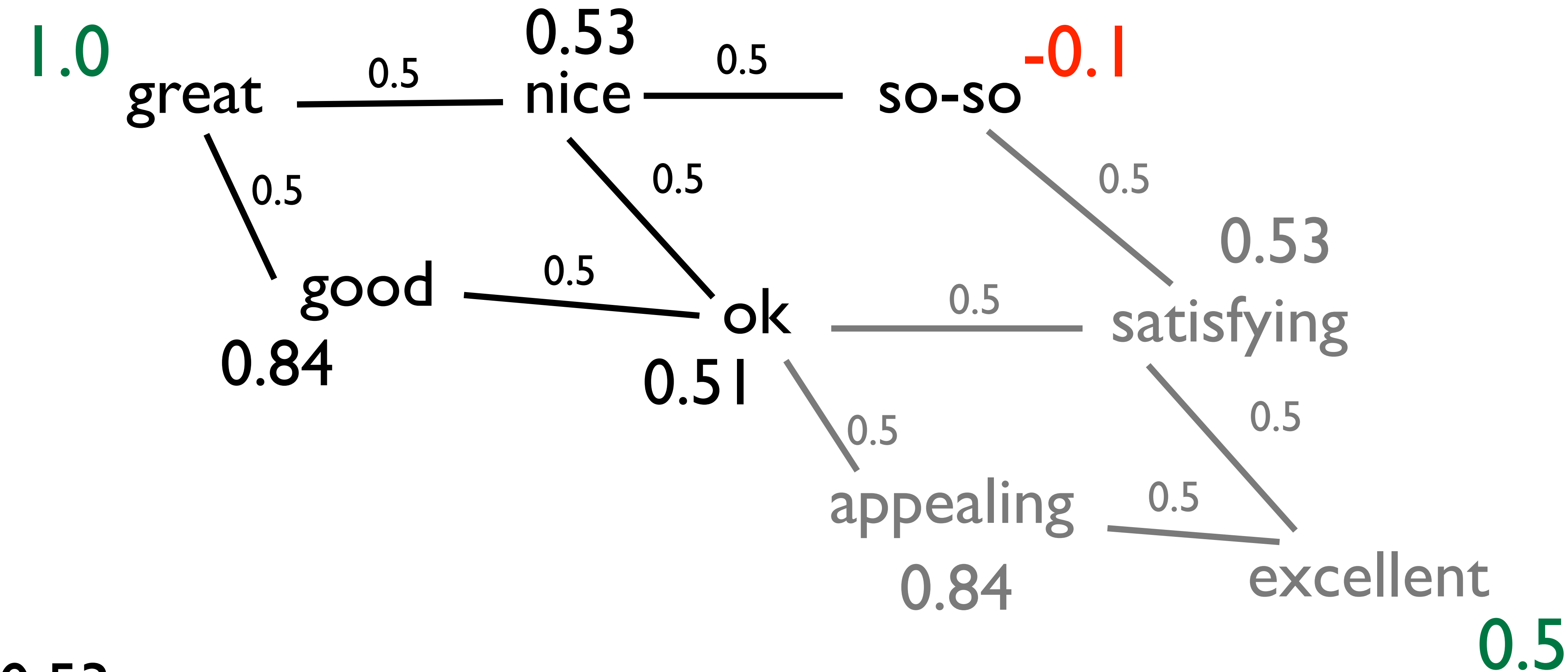

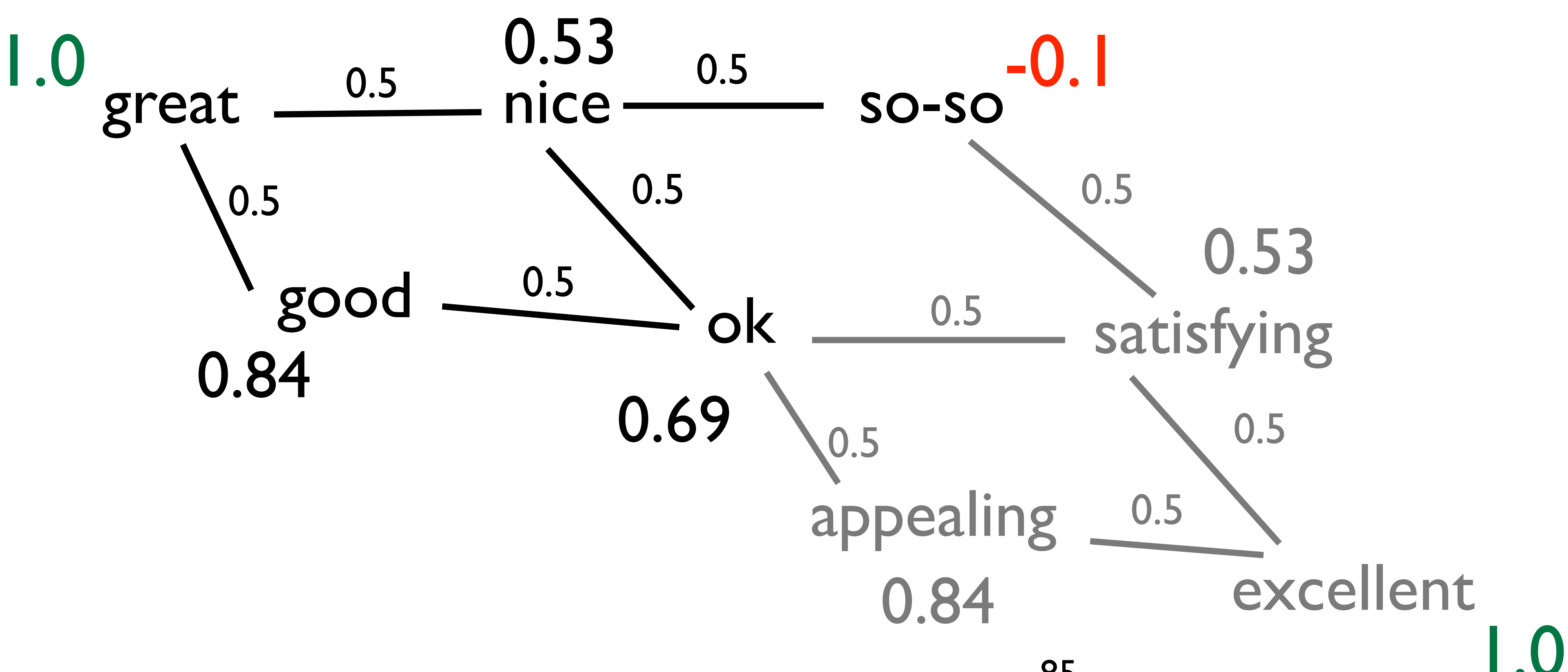

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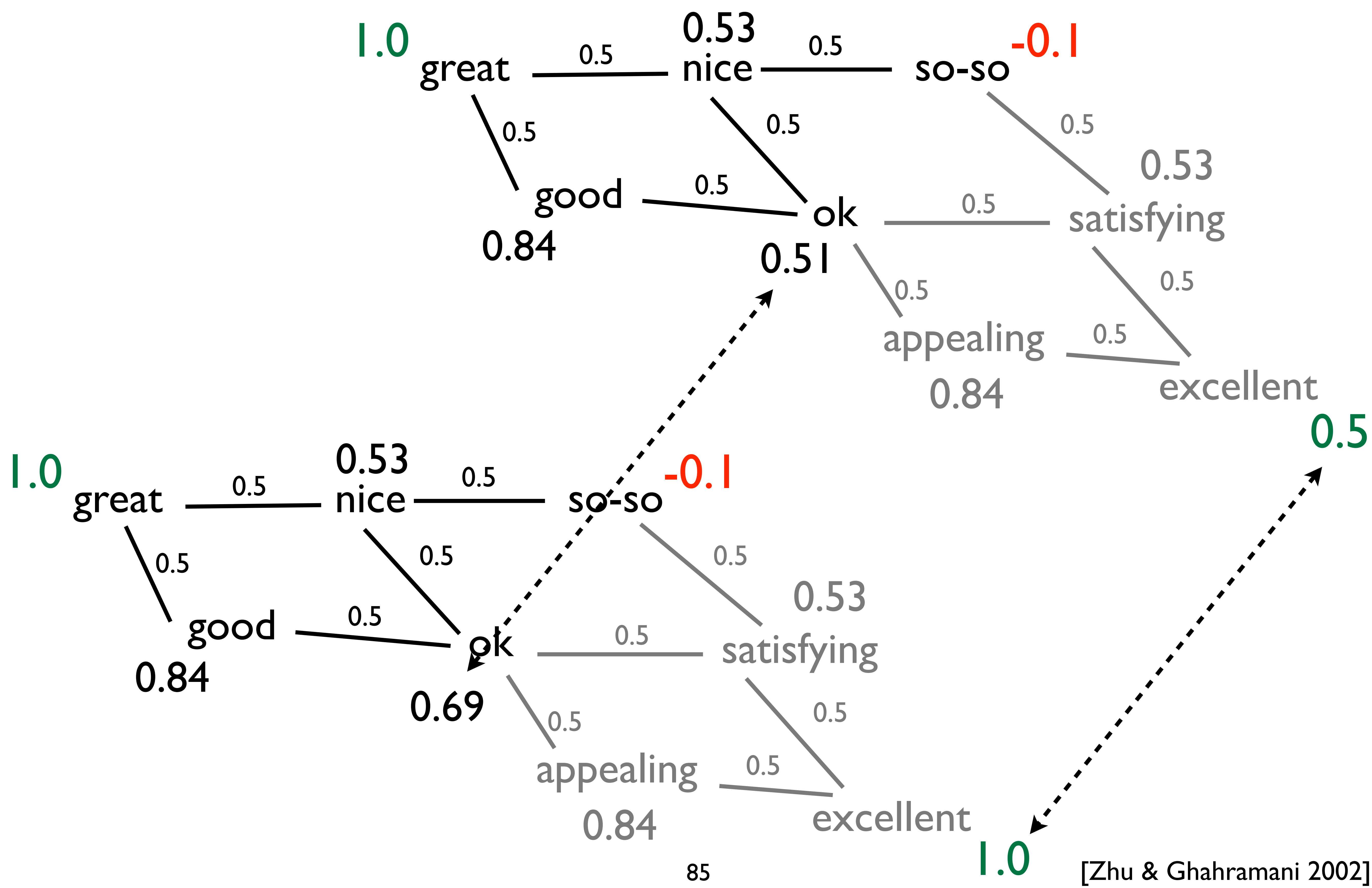
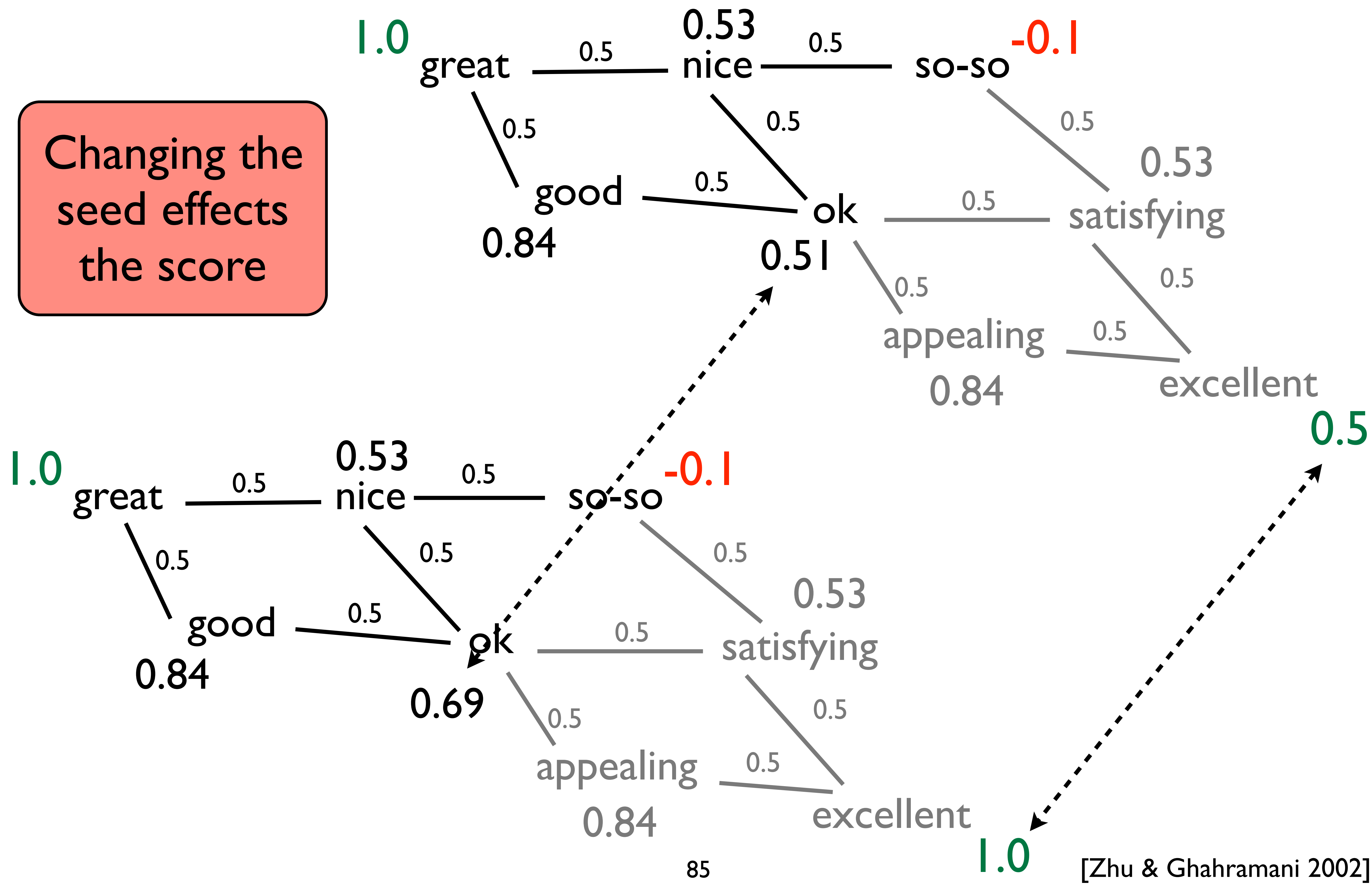


[Zhu & Ghahramani 2002]

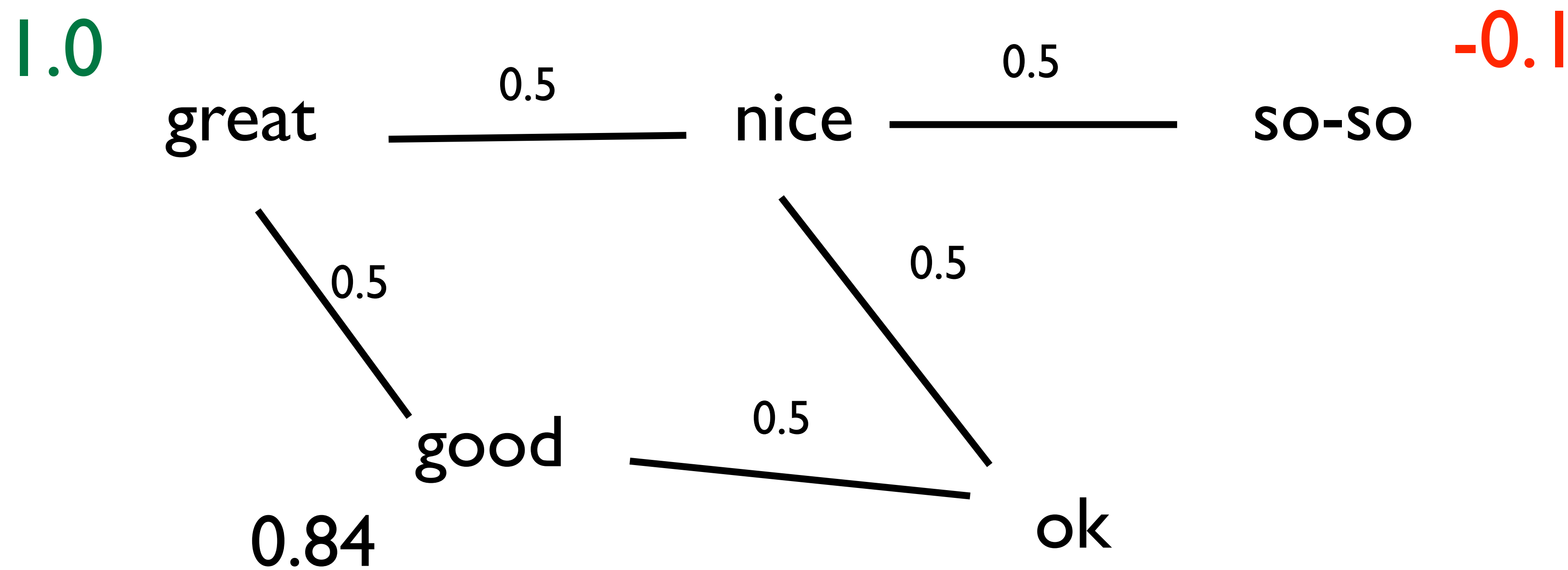
Graph Propagation (II)

Changing the seed effects the score



[Zhu & Ghahramani 2002]

Graph Propagation (III)



[Zhu & Ghahramani 2002]

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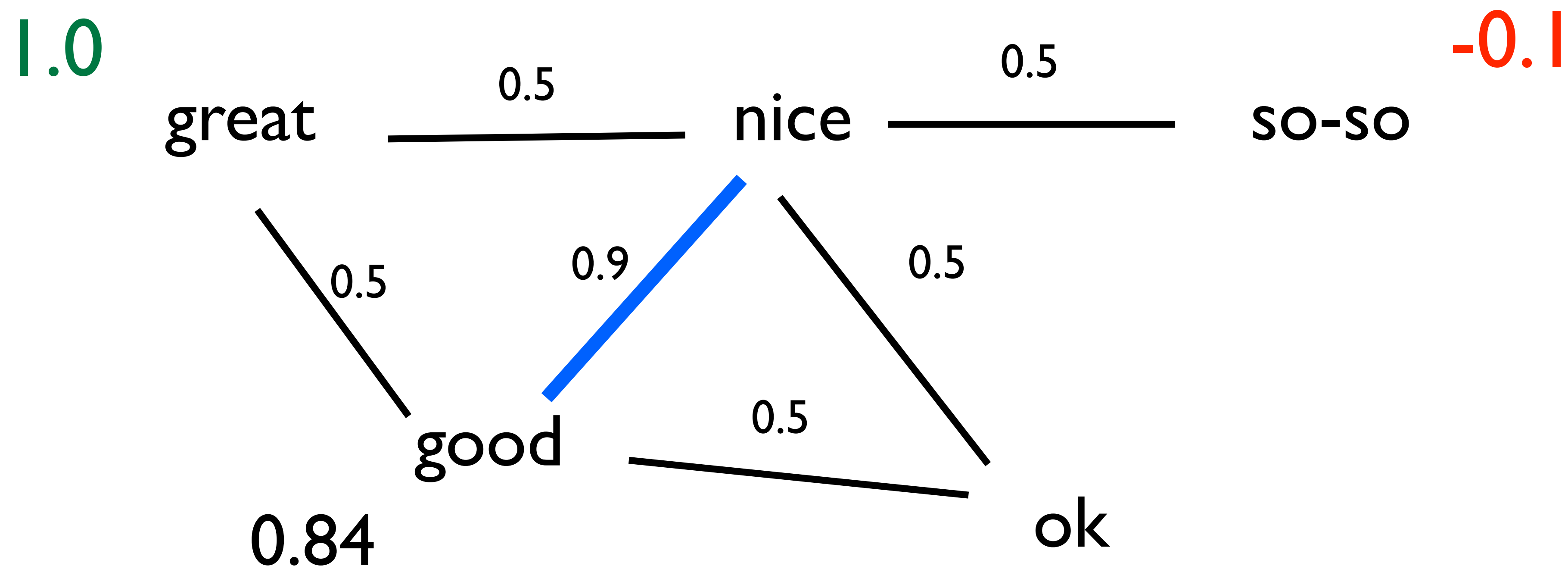

[Zhu & Ghahramani 2002]

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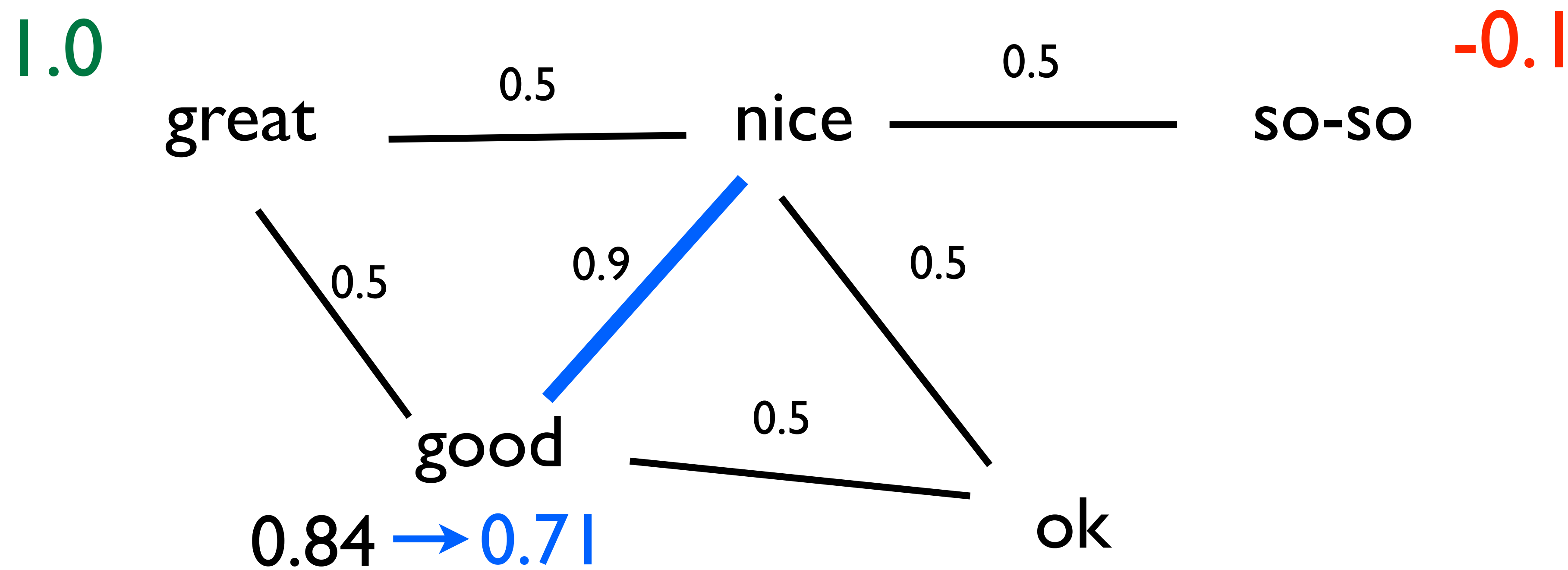

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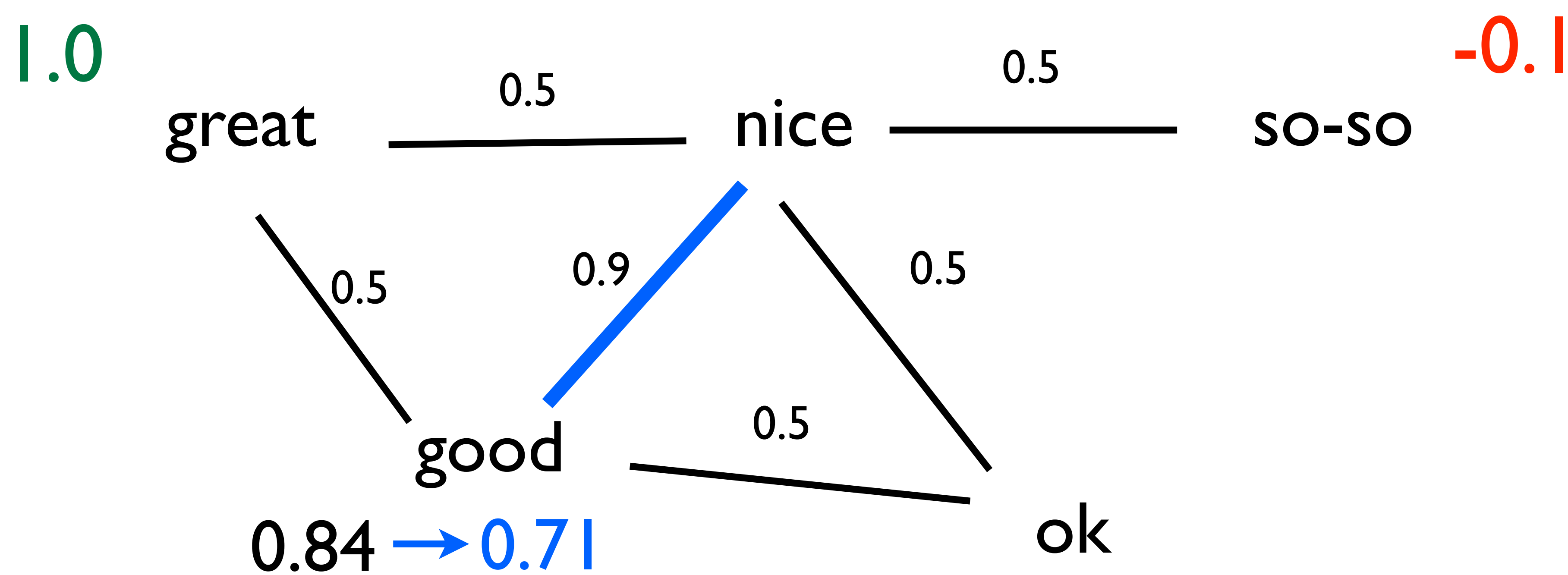
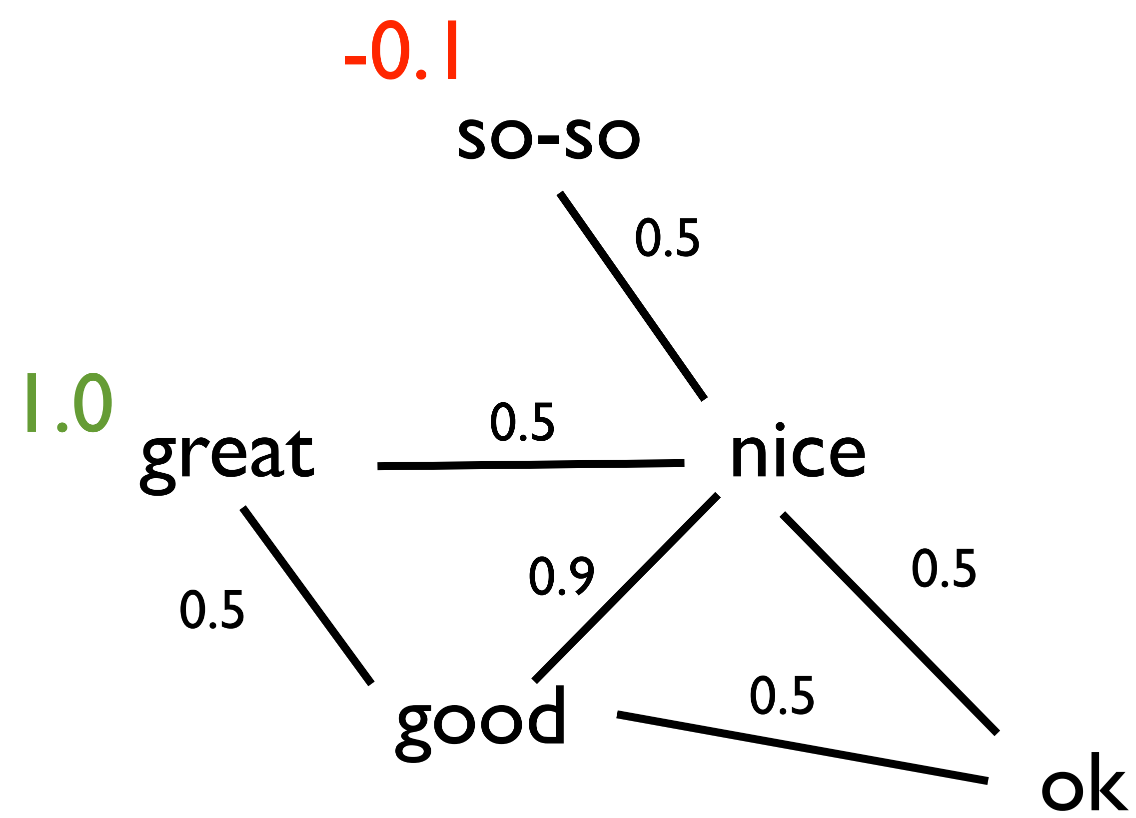


Single edge difference causes a change in the score

[Zhu & Ghahramani 2002]

“Best Path to Seed” Propagation



[Velikovich, et al., NAACL 2010]

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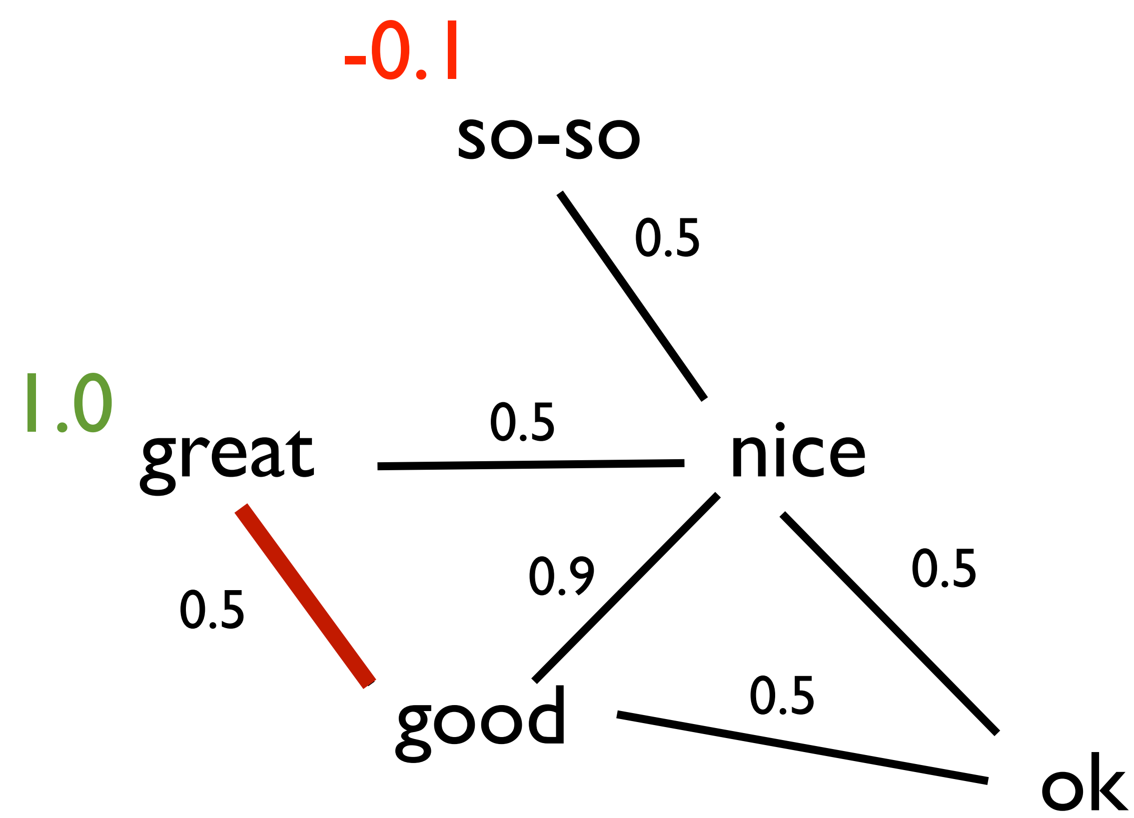

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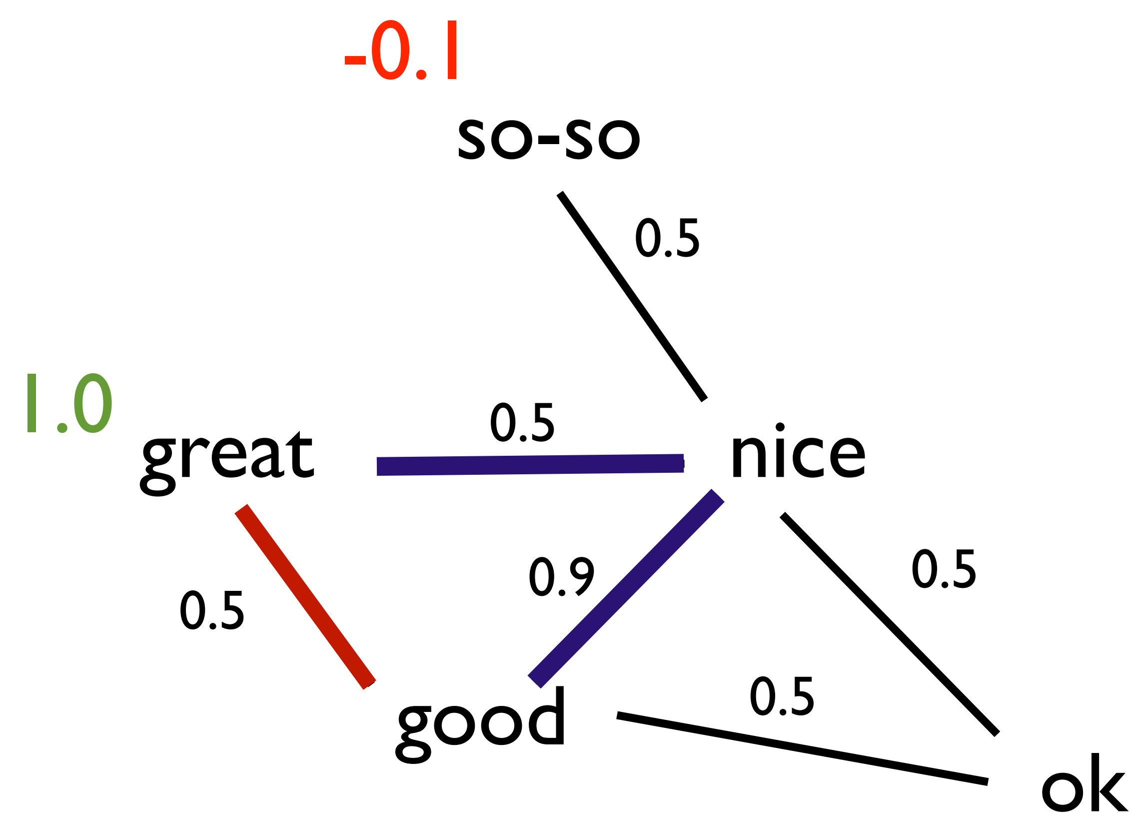

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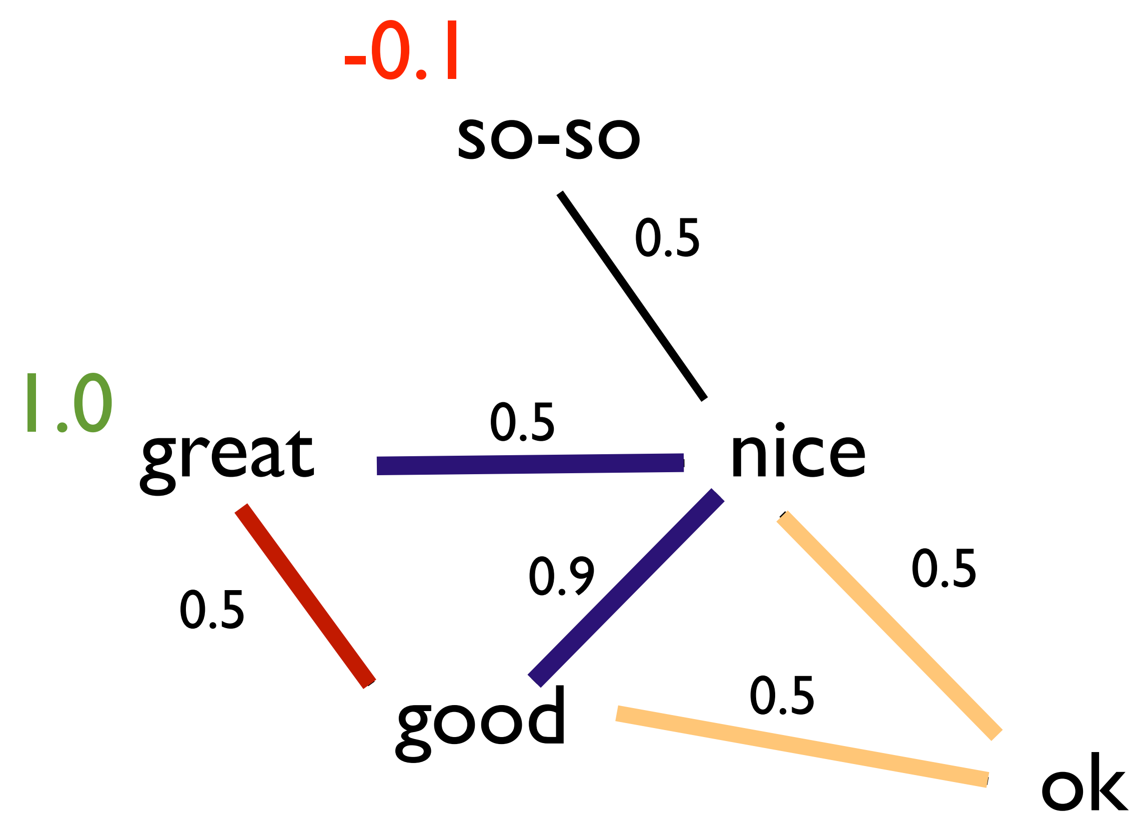

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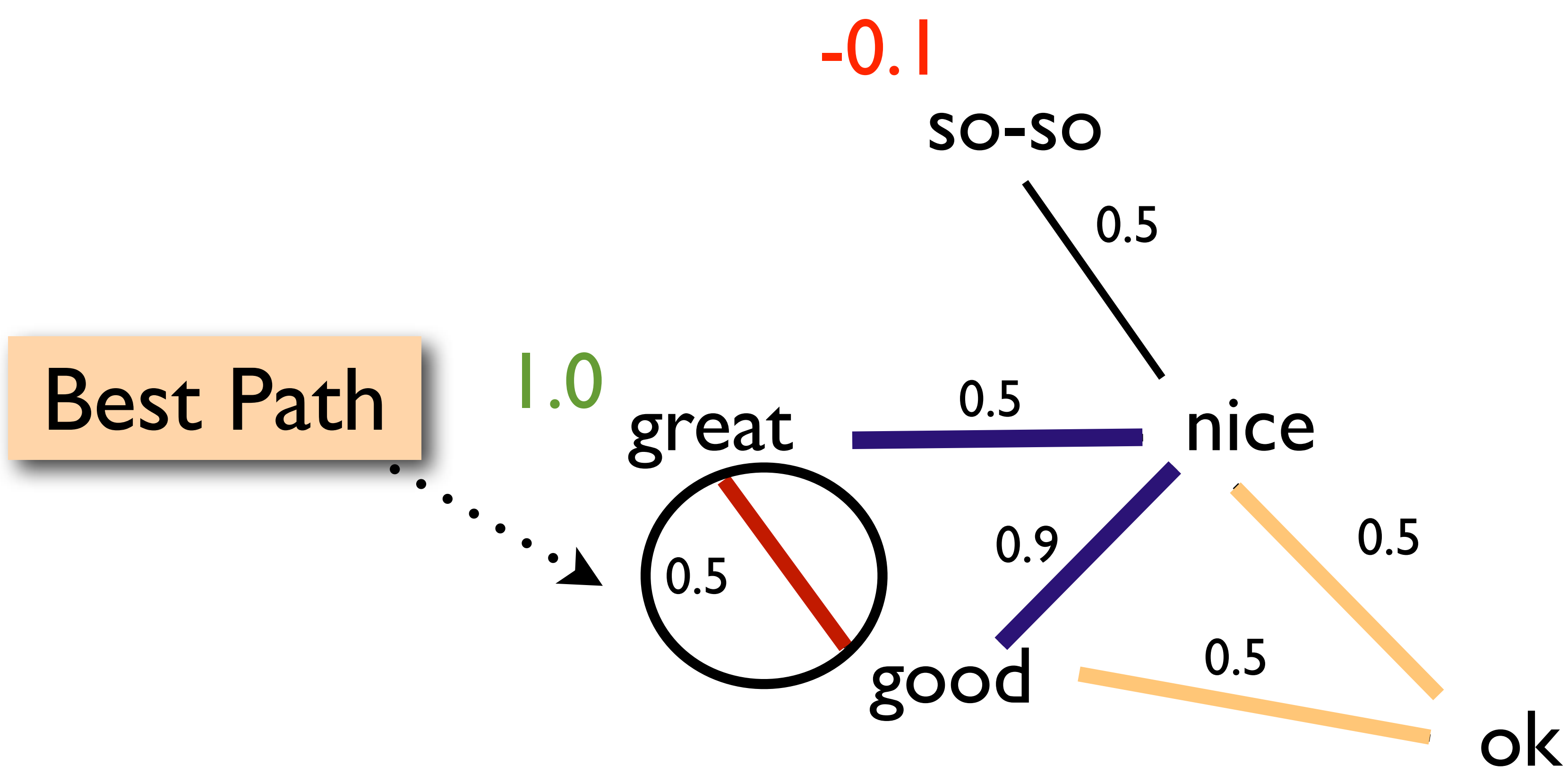

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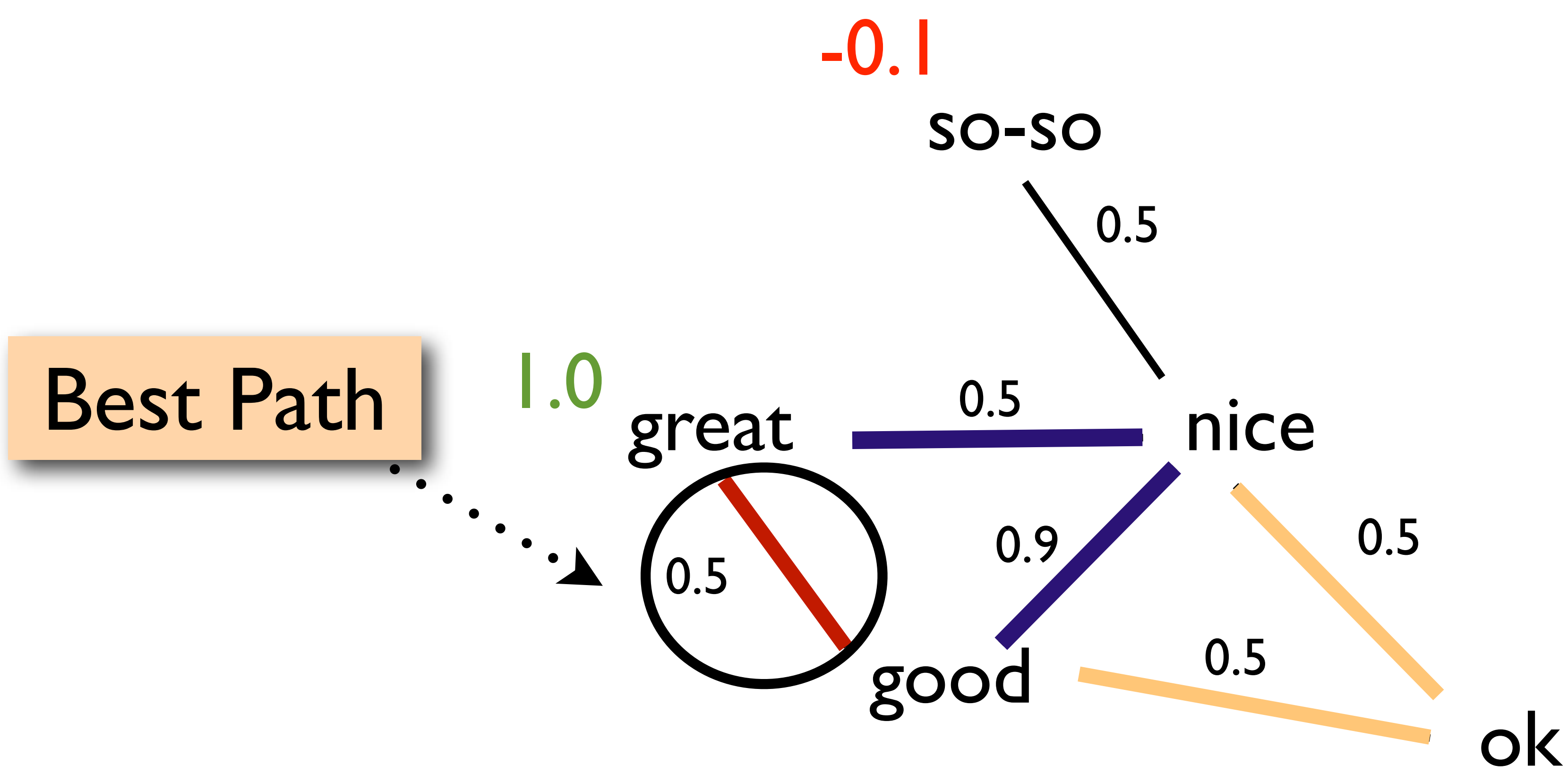


Key observation: **sentiment phrases** are those that have **short highly weighted paths** to **seed nodes**

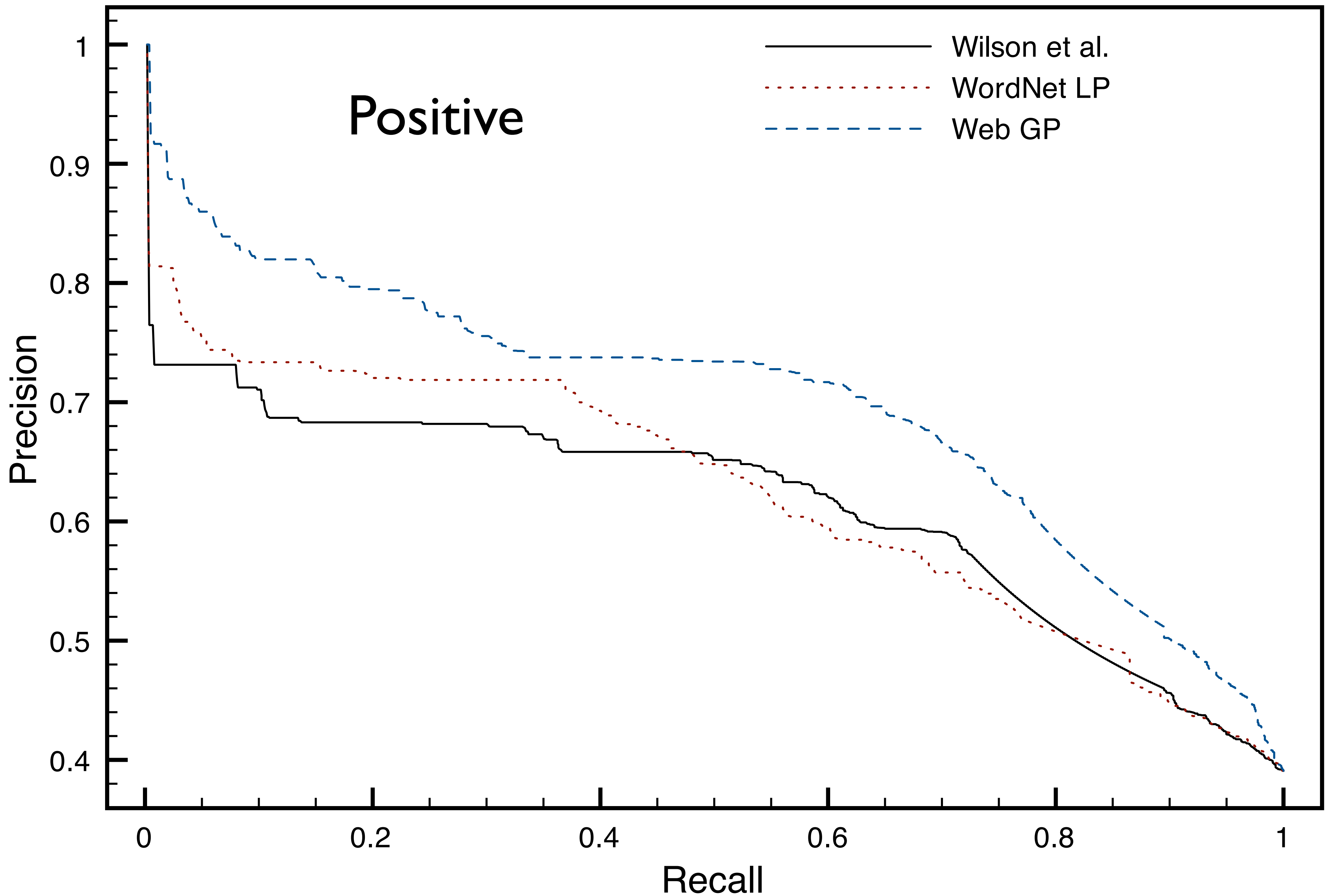
[Velikovich, et al., NAACL 2010]

Results

Lexicon	Phrases	Positive	Negative
Wilson et al. 2005	7,618	2,718	4,900
WordNet LP [Blair-Goldensohn et al. 07]	12,310	5,705	6,605
Web GP [Velikovich et al. 2010]	**178,104**	**90,337**	**87,767**

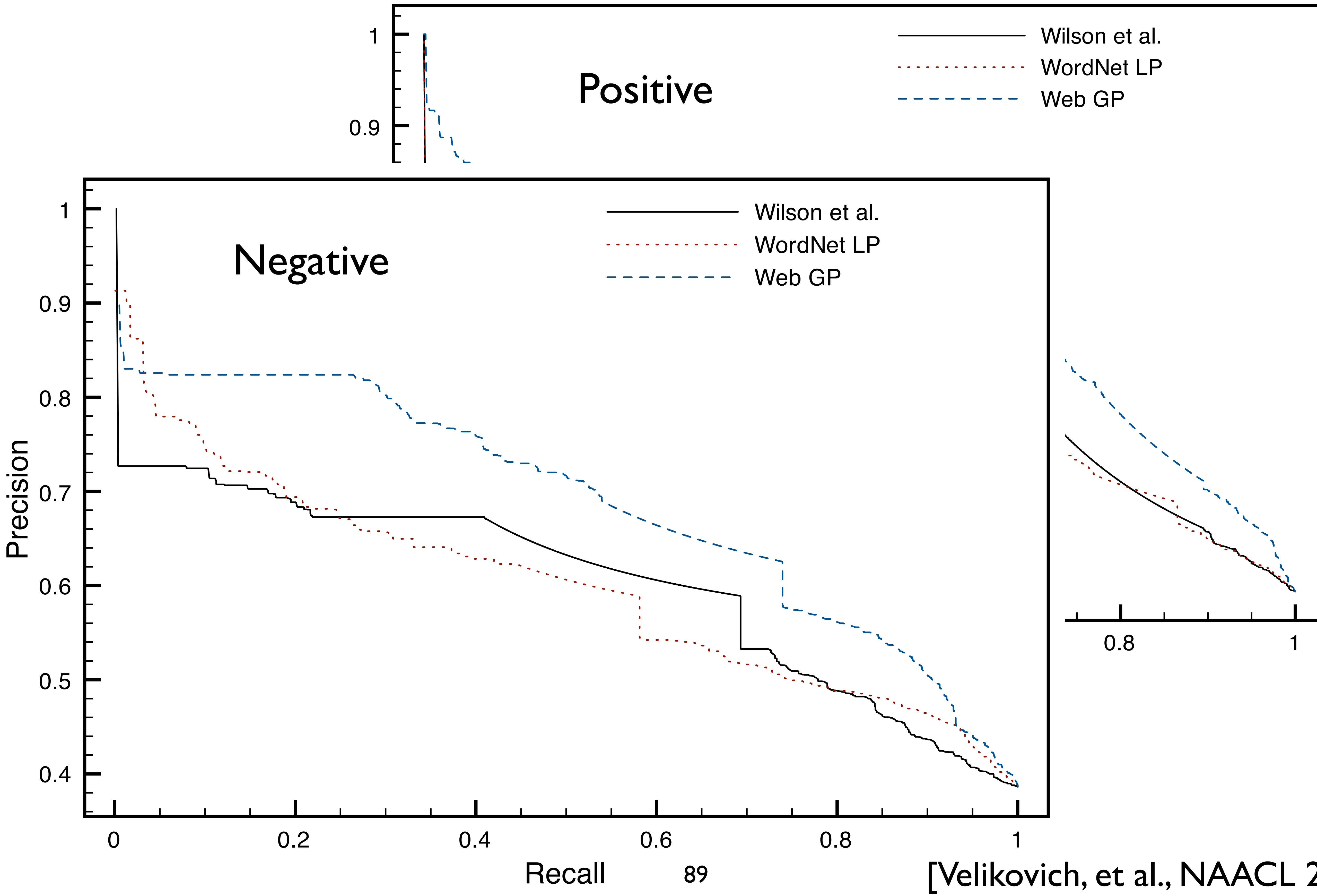
Size of the output lexicon

Results



[Velikovich, et al., NAACL 2010]

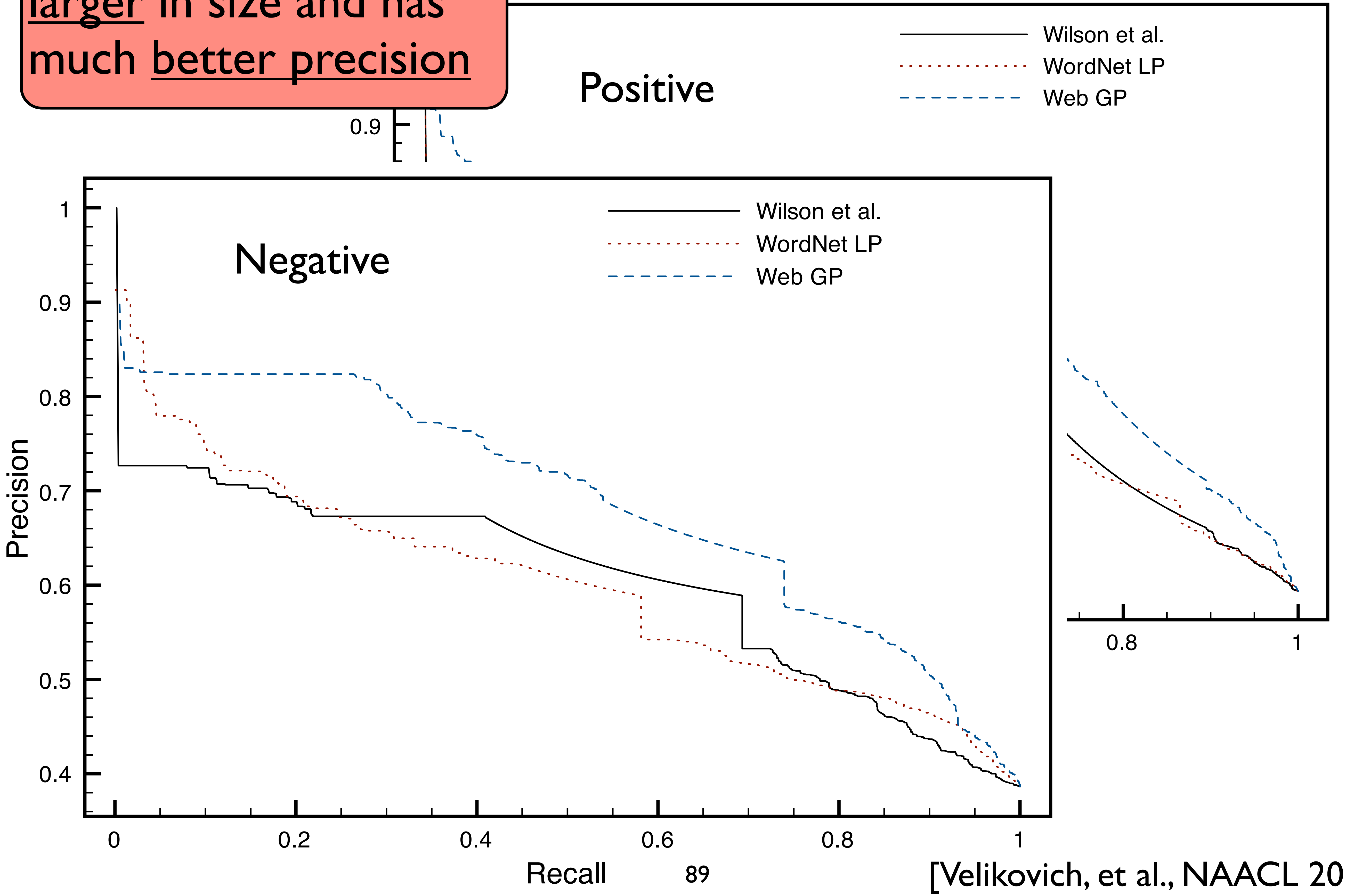
Results



[Velikovich, et al., NAACL 2010]

Results

Resulting lexicon is larger in size and has much better precision



[Velikovich, et al., NAACL 2010]

Results

excellent, fabulous, beautiful, inspiring,
loveable, nicee, niice, cooool, coooool,
once in a life time, state-of-the-art, fail-safe operation,
just what you need, just what the doctor ordered

bad, awful, terrible, dirty, $#%! face, $#%!ed up, shut your $#%!ing mouth, run of the mill, out of touch, over the hill

[Velikovich, et al., NAACL 2010]

Results

Spelling Variations

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excellent, fabulous, beautiful, inspiring, loveable, nicee, niice, cooool, coooool, once in a life time, state-of-the-art, fail-safe operation, just what you need, just what the doctor ordered

Multi-word expressions

bad, awful, terrible, dirty, $#%! face, $#%!ed up, shut your $#%!ing mouth, run of the mill, out of touch, over the hill

[Velikovich, et al., NAACL 2010]

Big Picture

Use case 1: Transductive Classification

Use case 2: Training Better Inductive Model

	Use case 1	Use case 2
Text Categorization	✓	
Sentiment Analysis		

Big Picture

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Big Picture

Use case 1: Transductive Classification

Use case 2: Training Better Inductive Model

	Use case 1	Use case 2
Text Categorization	✓	
Sentiment Analysis	✓	✓

Outline

- Motivation
- Graph Construction
- Inference Methods
- Scalability
- Applications
    - Text Categorization
    - Sentiment Analysis
    - Class Instance Acquisition [Talukdar et al., EMNLP 2008]
    - POS Tagging
    - MultiLingual POS Tagging
    - Semantic Parsing
- Conclusion & Future Work

Problem Description

- Given an entity, assign human readable descriptors to it
  - *Toyota* is a *car manufacturer*, *japanese company*, *multinational company*
  - *African countries* such as *Uganda* and *Angola*
- Large scale, open domain (1000's of classes)
- Applications
  - web search, advertising, etc.

Extraction Techniques

Extraction Techniques

....
What Other Musicians Would Fans of the Album Listen to:
Storytelling musicians come to mind. Musicians *such as* Johnny Cash, and Woodie Guthrie.

What is Distinctive About this Release?:
Every song on the album has its own unique sound. From the fast paced *That Texas Girl* to the acoustic ....

[van Durme and Pasca, AAAI 2008]

- Uses "<Class> *such as* <Instance>" patterns
- Extracts both class (musician) and instance (Johnny Cash)

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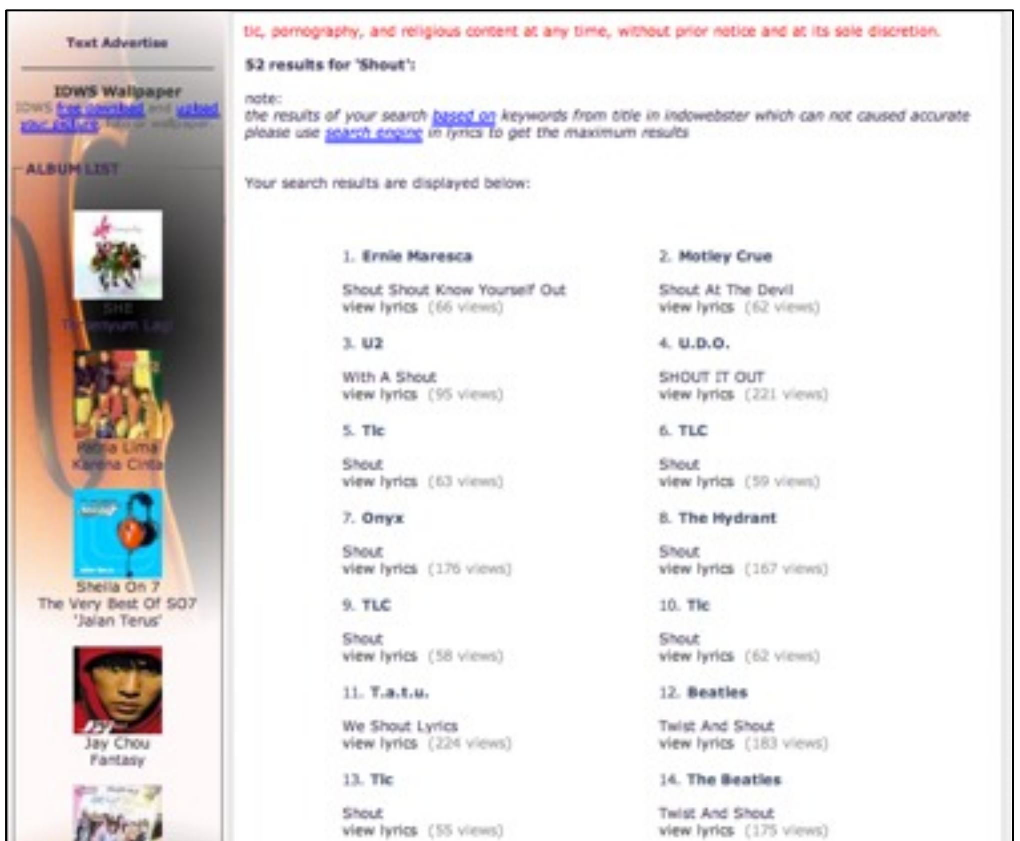

Extractions from HTML lists and tables

- [Wang and Cohen, ICDM 2007]
- WebTables [Cafarella et al., VLDB 2008], 154 million HTML tables

Extraction Techniques

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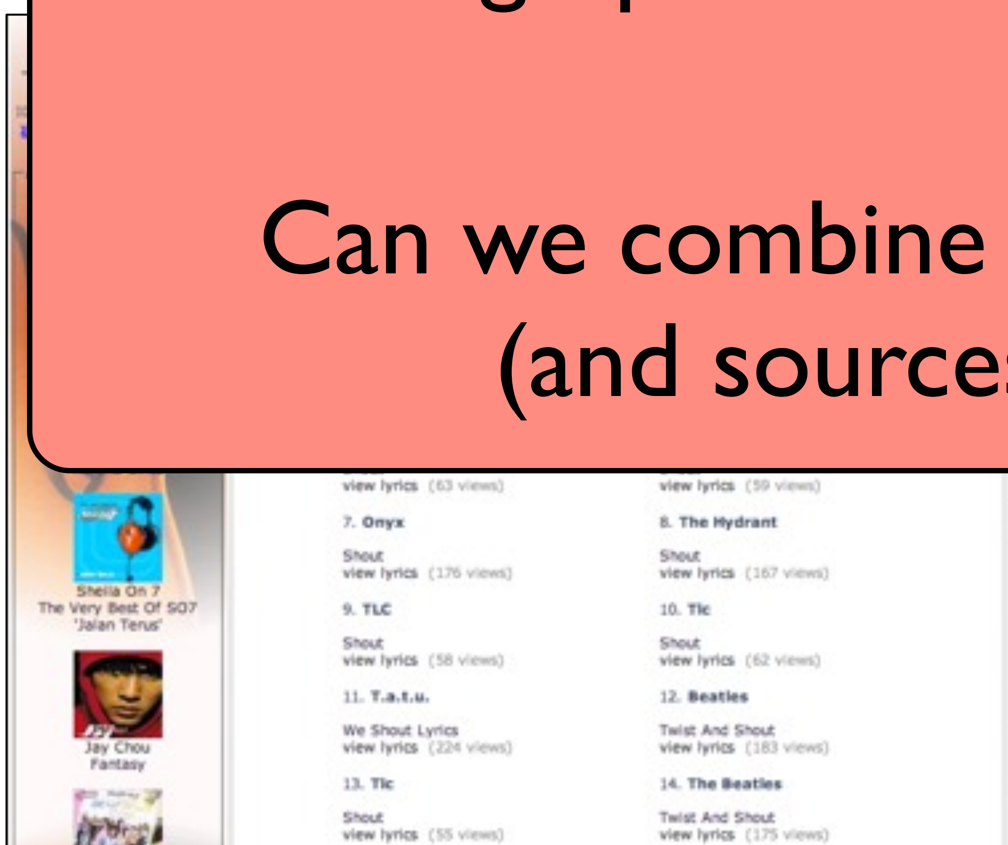


[van Durme and Pasca, AAAI 2008]

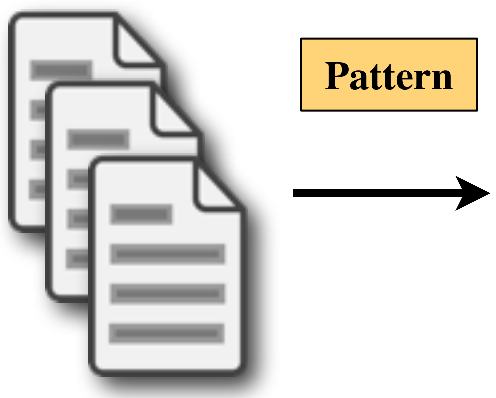
- Uses "<Class> *such as* <Instance>" patterns

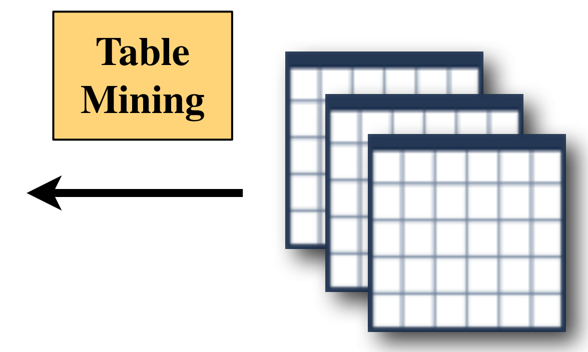
Pattern-based methods are usually tuned for high-precision, resulting in low coverage

Can we combine extractions from all methods (and sources) to improve coverage?

- WebTables [Cafarella et al., VLDB 2008], 154 million HTML tables

Graph Construction





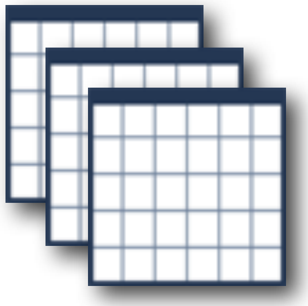
Graph Construction

Pattern

Set 1
Bob Dylan (0.95)
Johnny Cash (0.87)
Billy Joel (0.82)

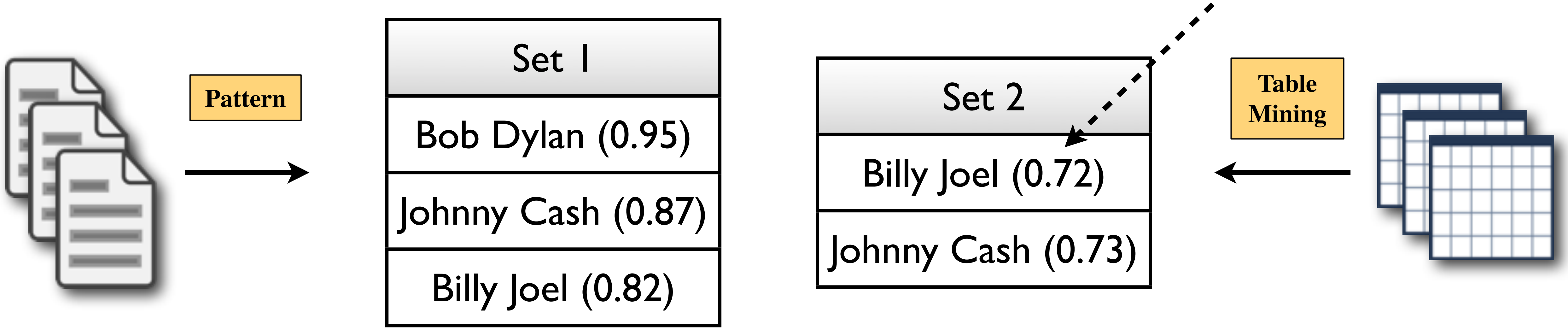
Set 2
Billy Joel (0.72)
Johnny Cash (0.73)

Table Mining



Graph Construction

Extraction Confidence



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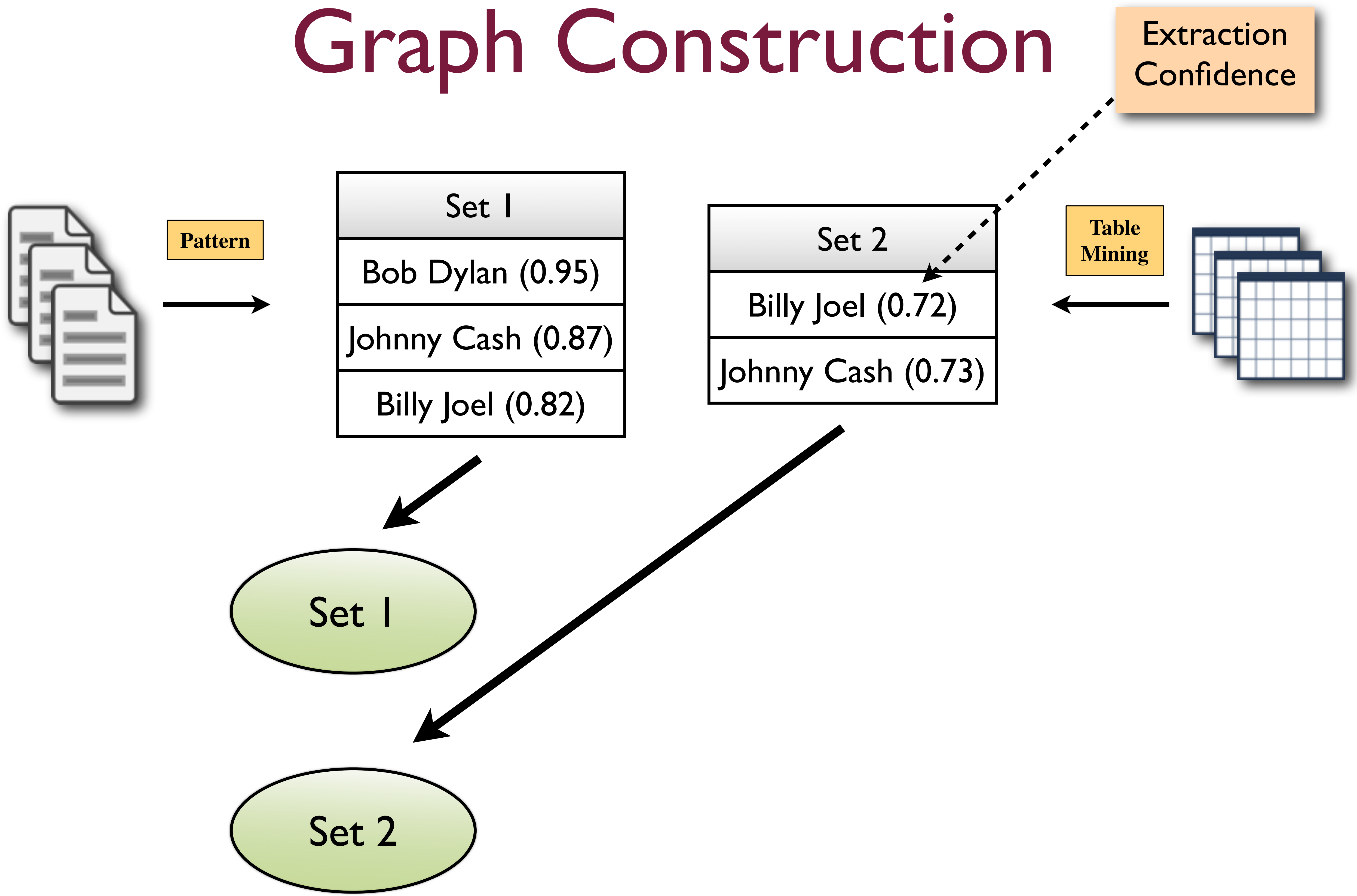

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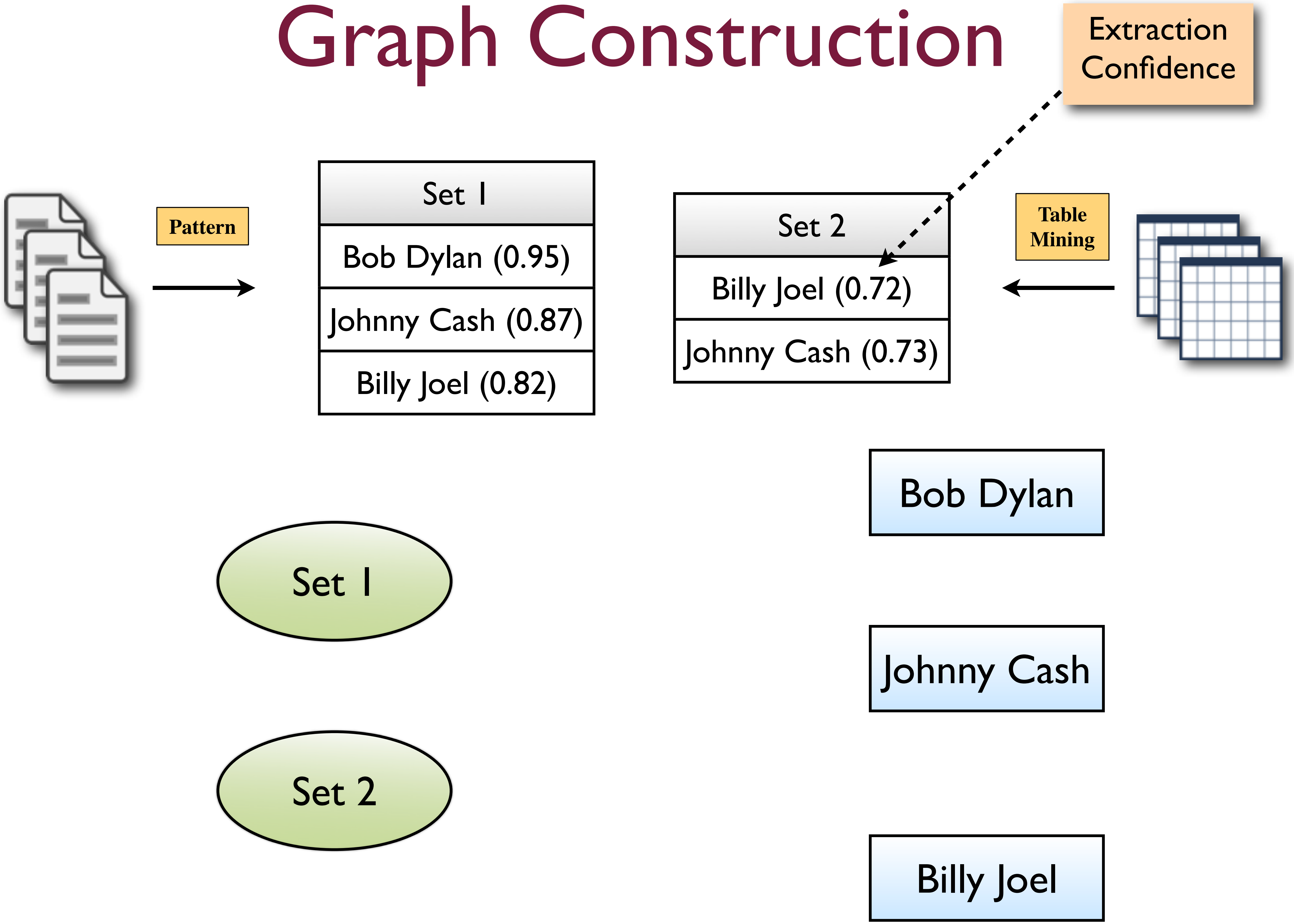

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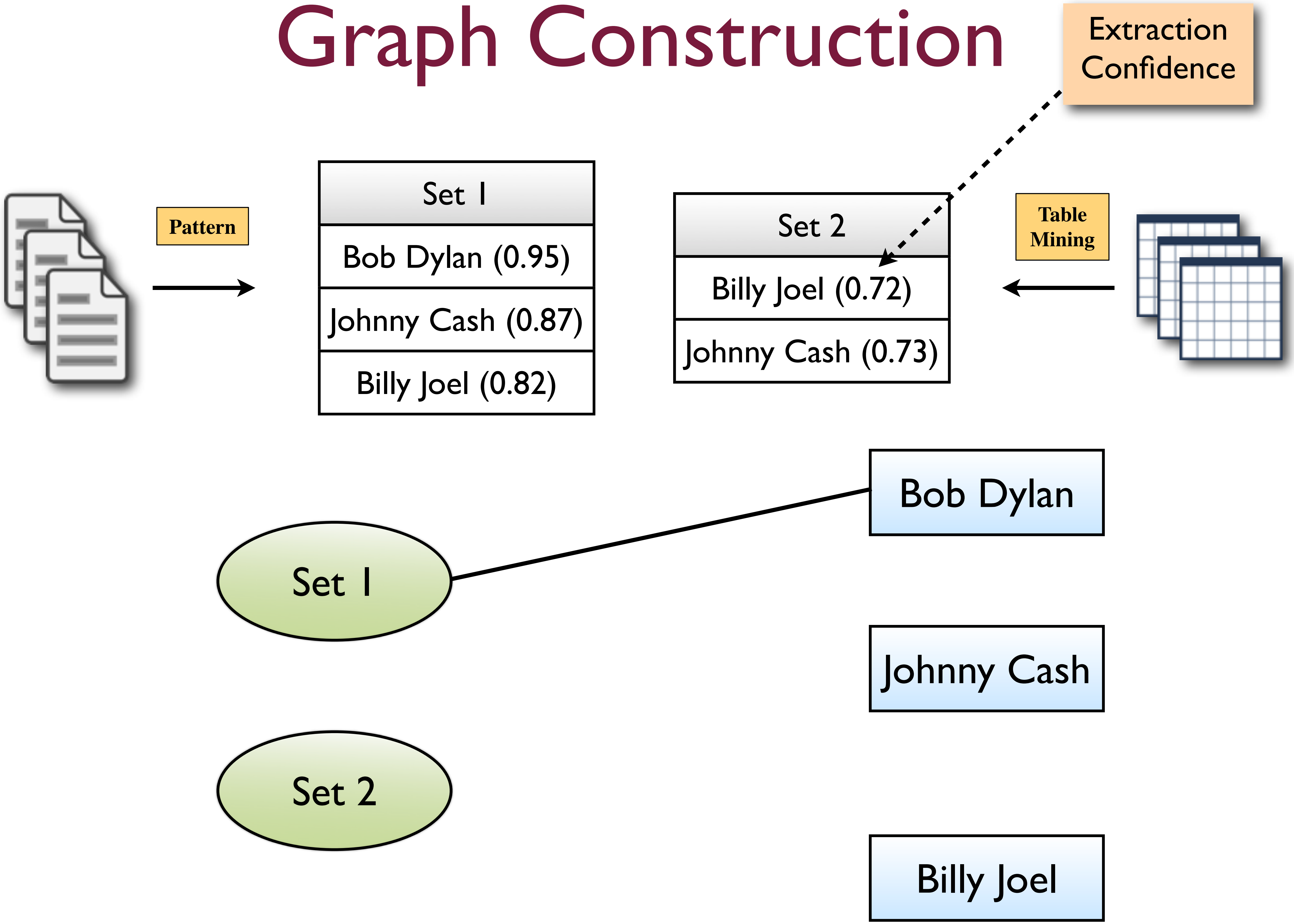

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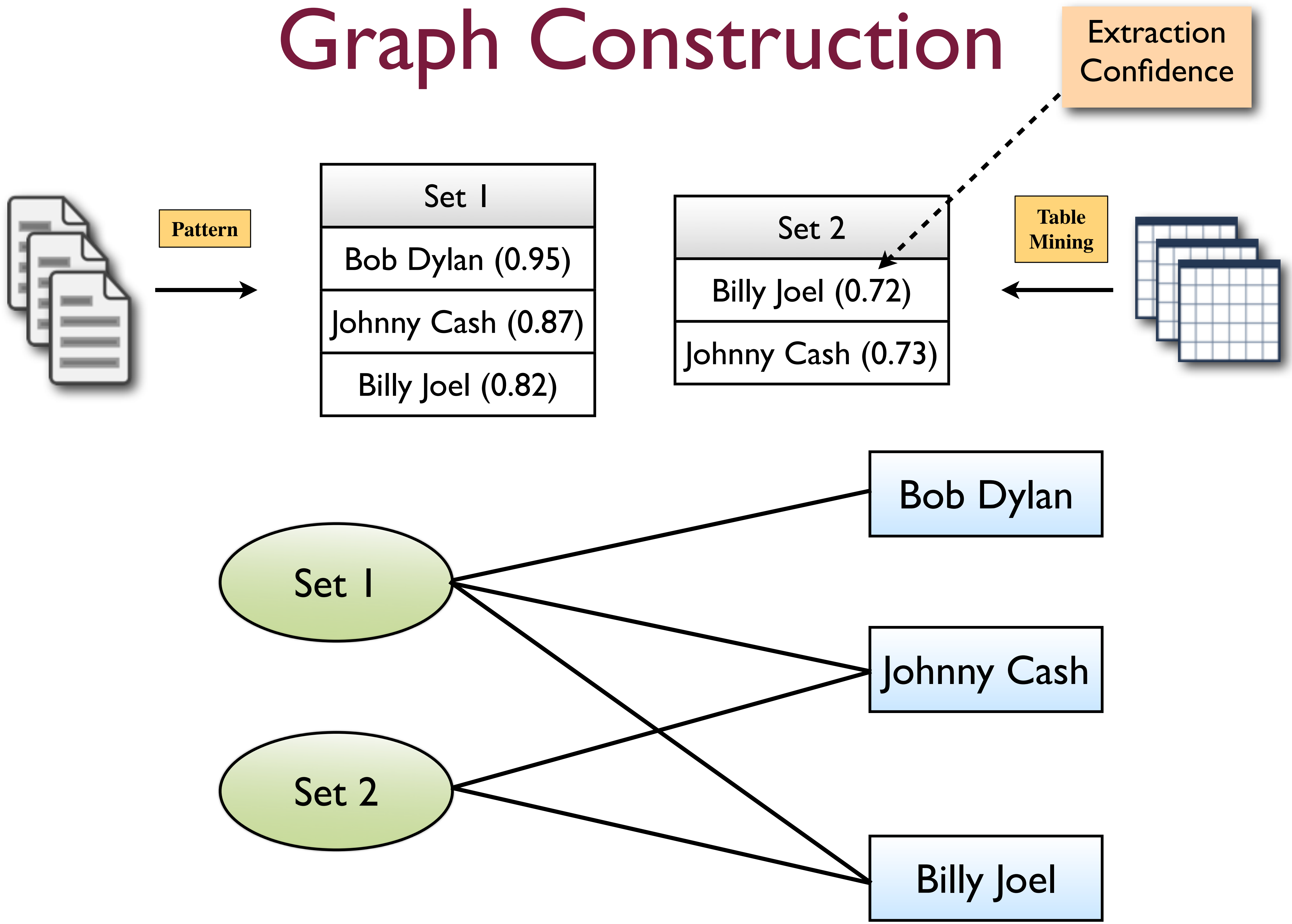

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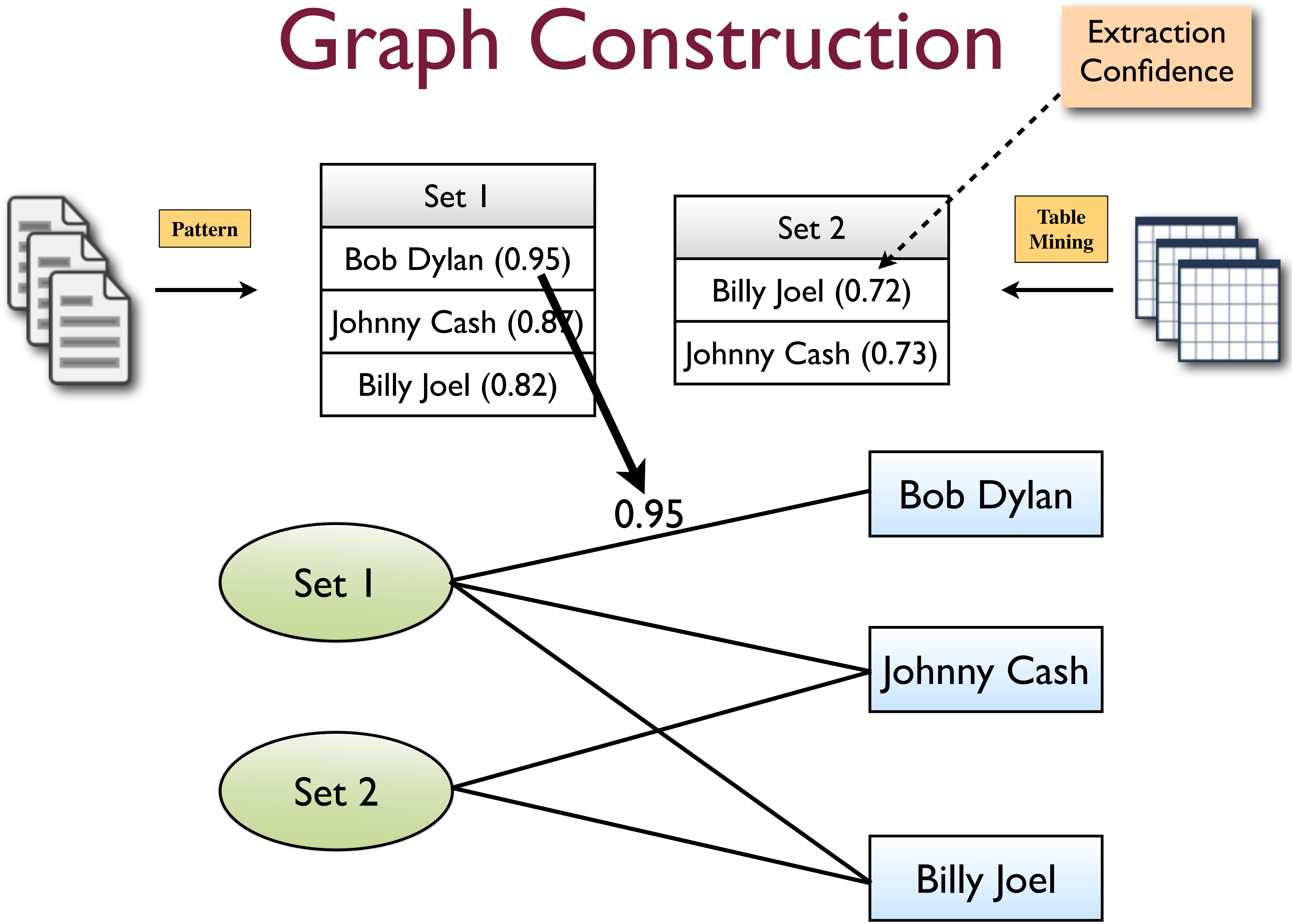

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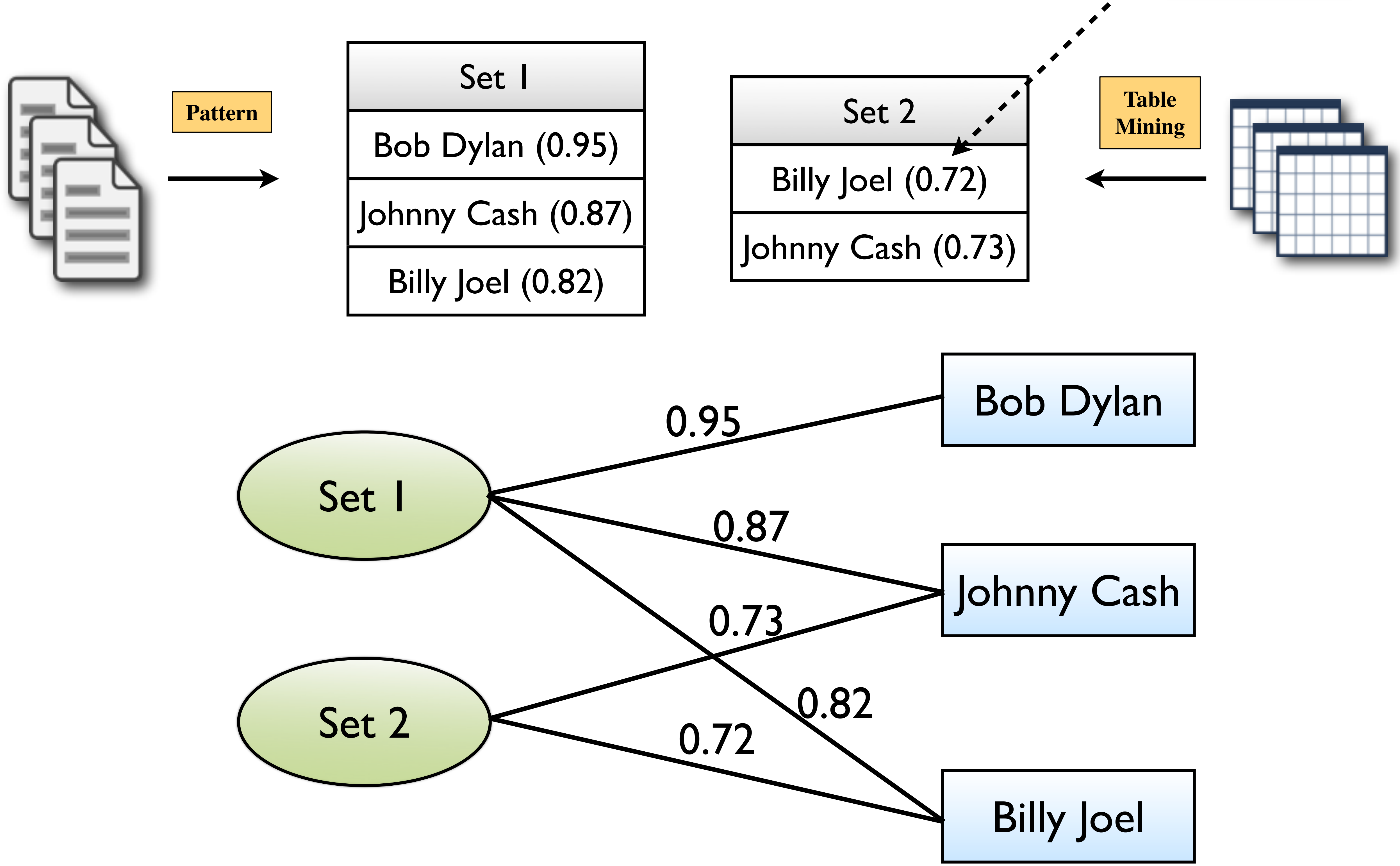

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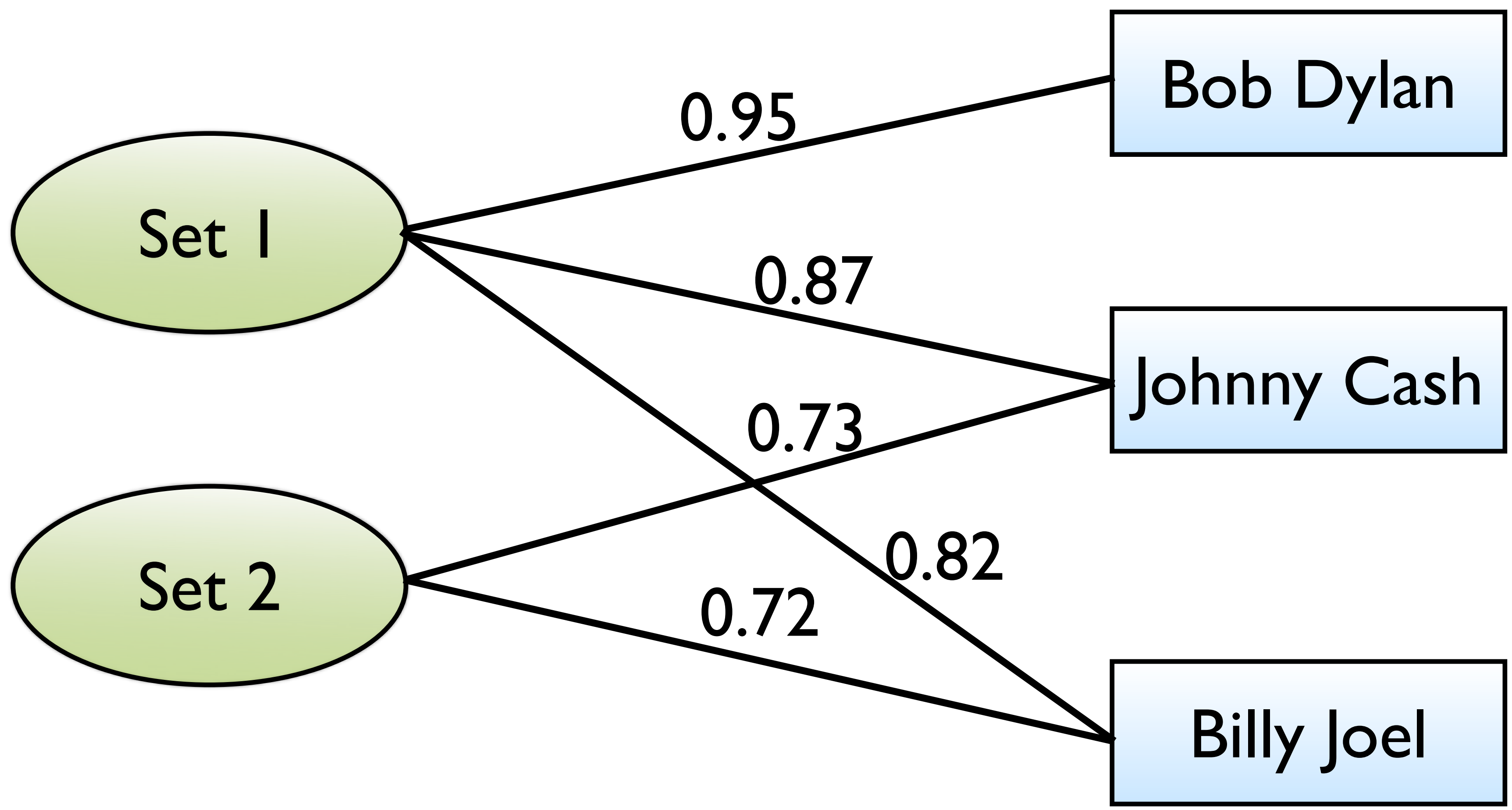

- Bi-partite graph (not a k-NNG)
- "Set" nodes encourage members of the set to have similar labels
- Natural way to represent extractions from many sources and methods

Goal

Pattern

Set 1
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Johnny Cash (0.87)
Billy Joel (0.82)

Set 2
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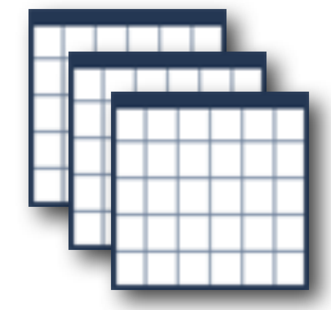
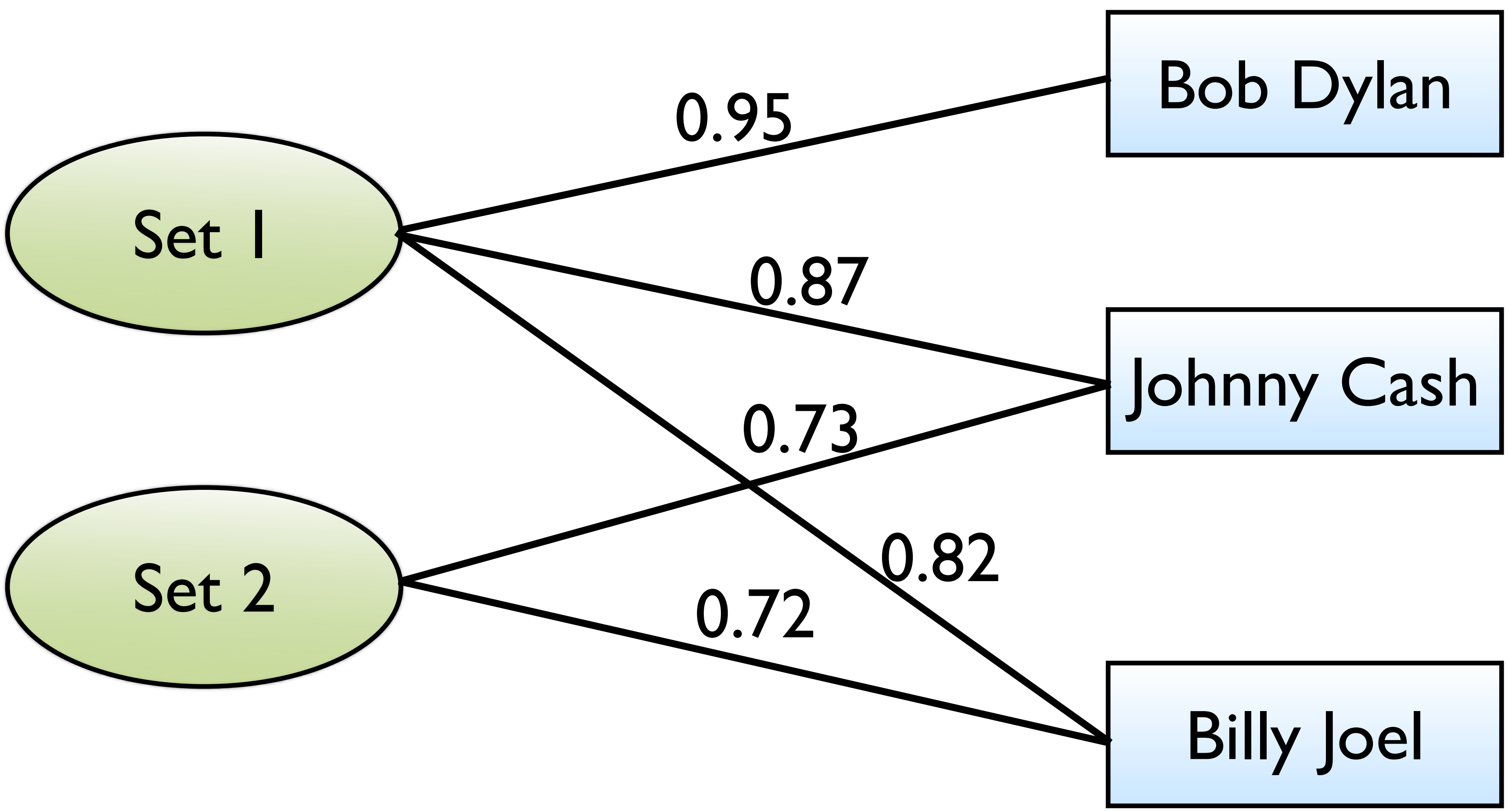
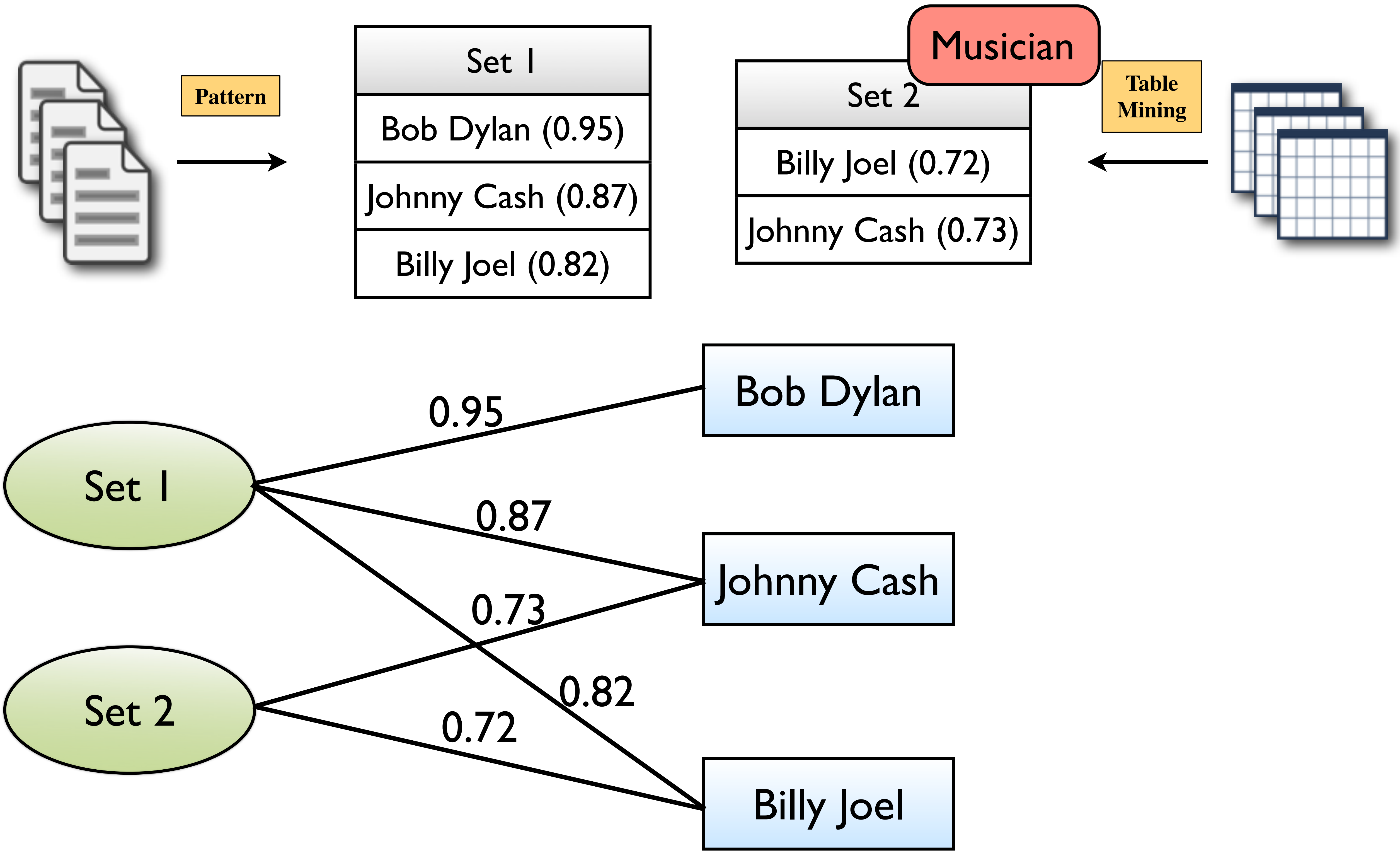




Goal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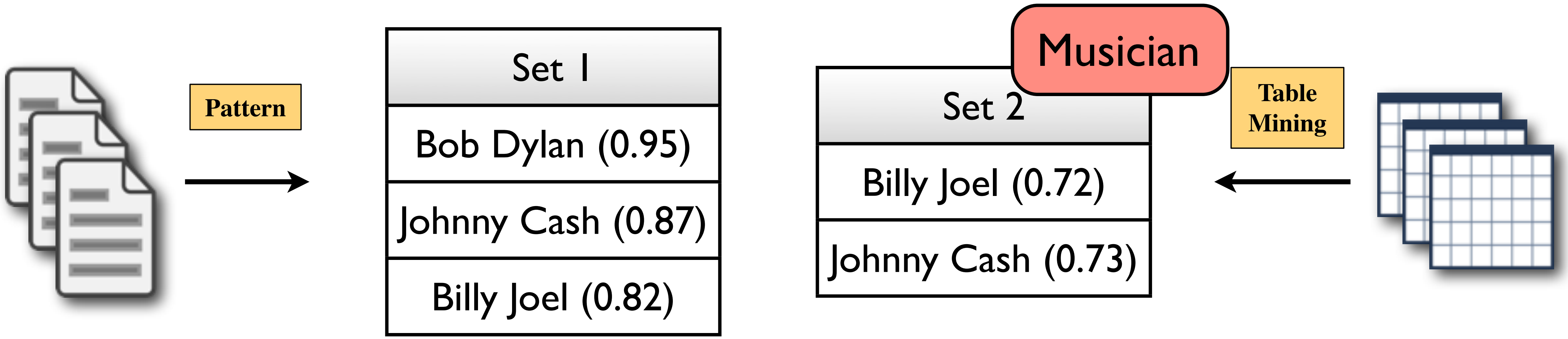
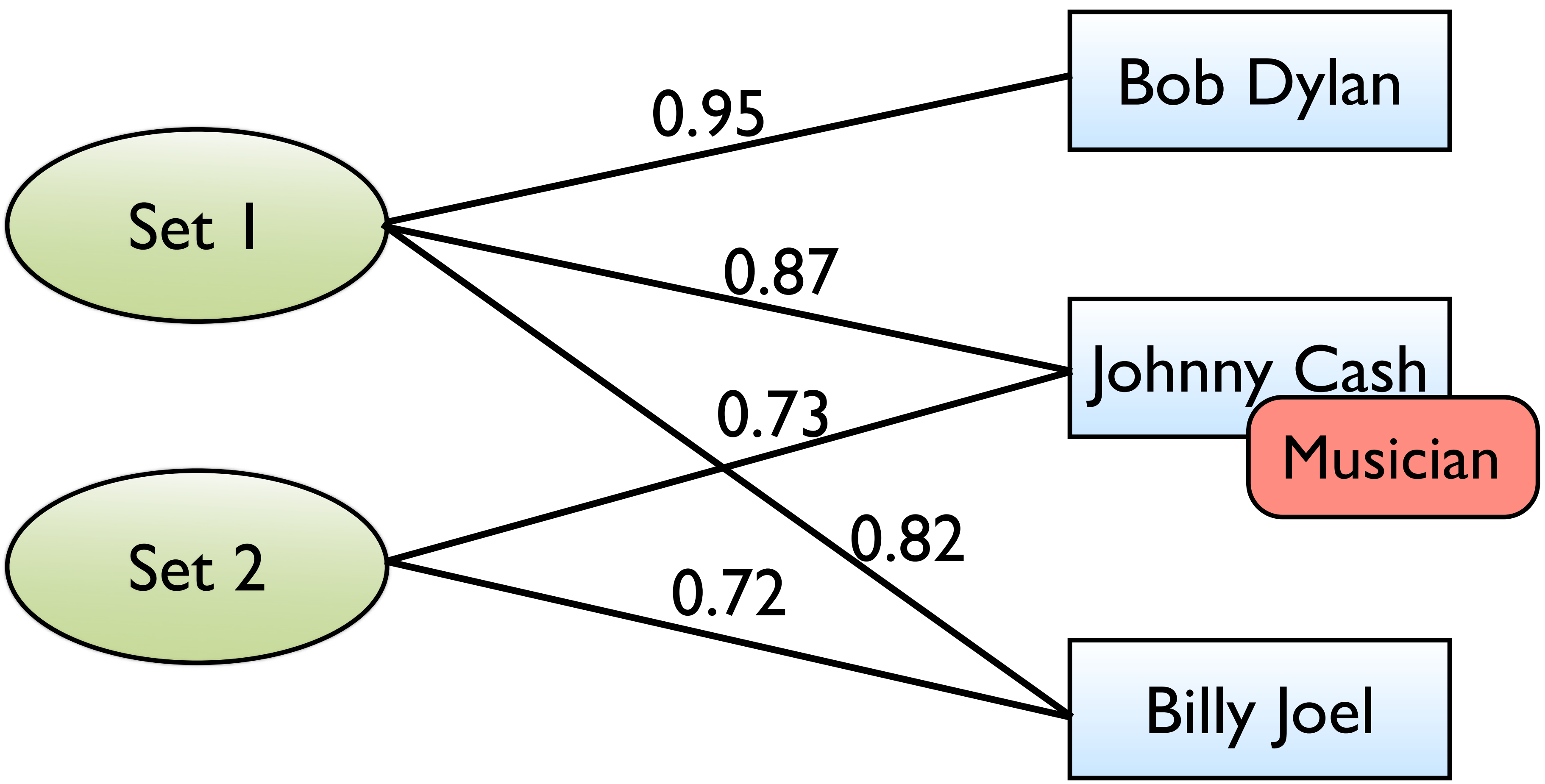
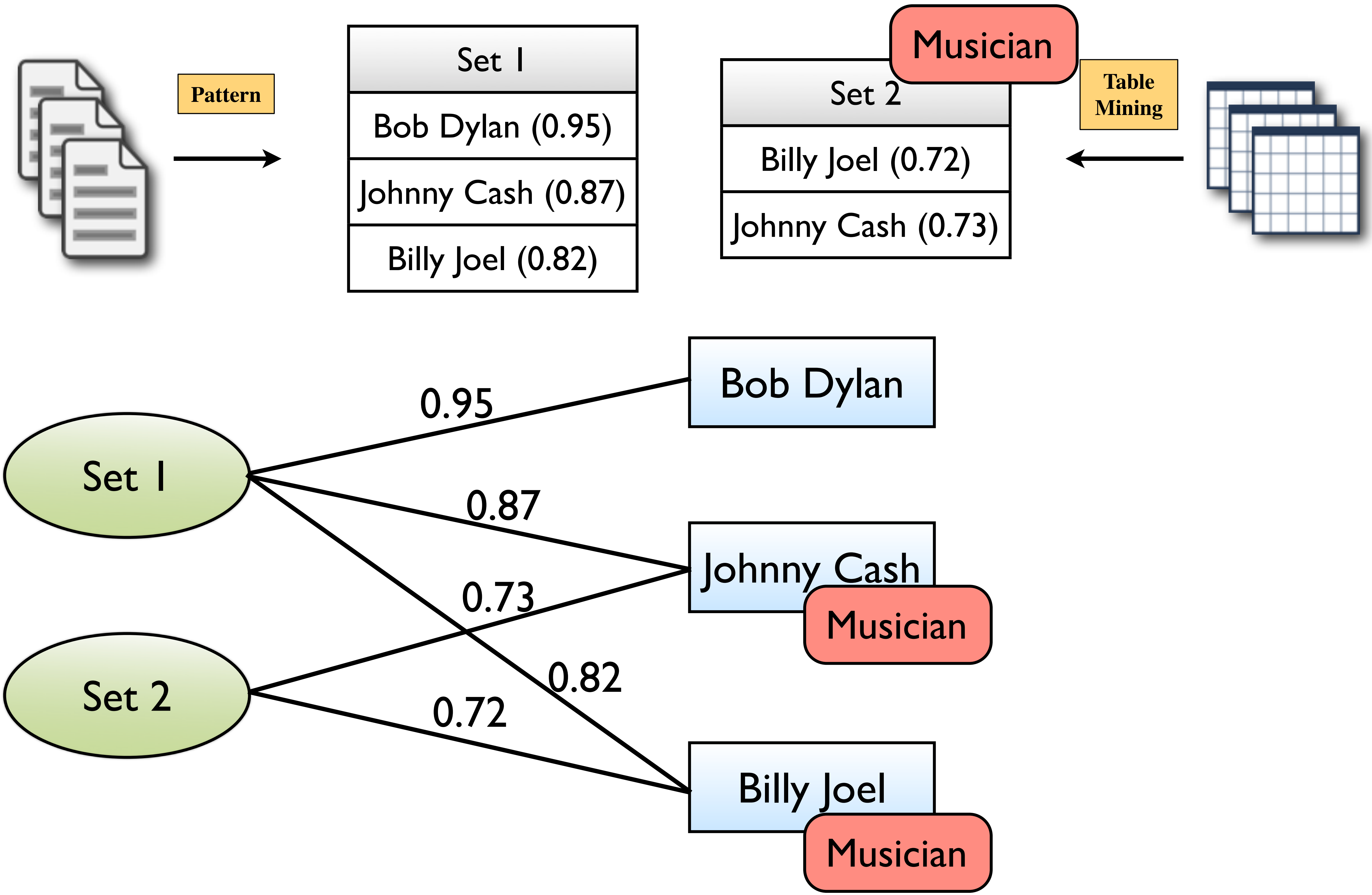
Johnny Cash (0.87)
Billy Joel (0.82)
Musician
Set 2
Billy Joel (0.72)
Johnny Cash (0.73)
Table Mining
Set 1
Set 2
0.95
0.87
0.73
0.82
0.72
Bob Dylan
Johnny Cash
Billy Joel

Goal


Pattern
Set 1
Bob Dylan (0.95)
Johnny Cash (0.87)
Billy Joel (0.82)
Musician
Set 2
Billy Joel (0.72)
Johnny Cash (0.73)
Table Mining


Set 1
Set 2
0.95
0.87
0.73
0.82
0.72
Bob Dylan
Johnny Cash
Musician
Billy Joel

Goal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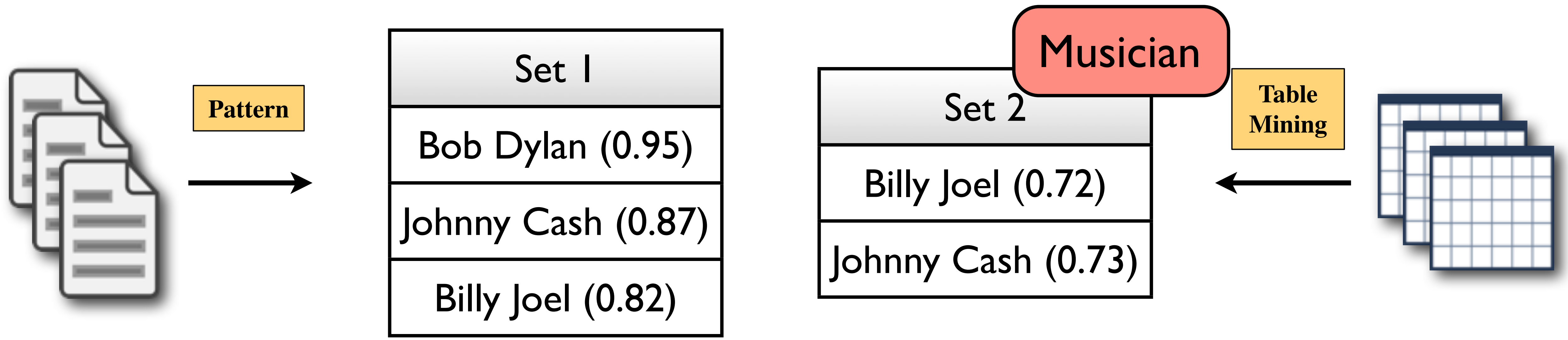
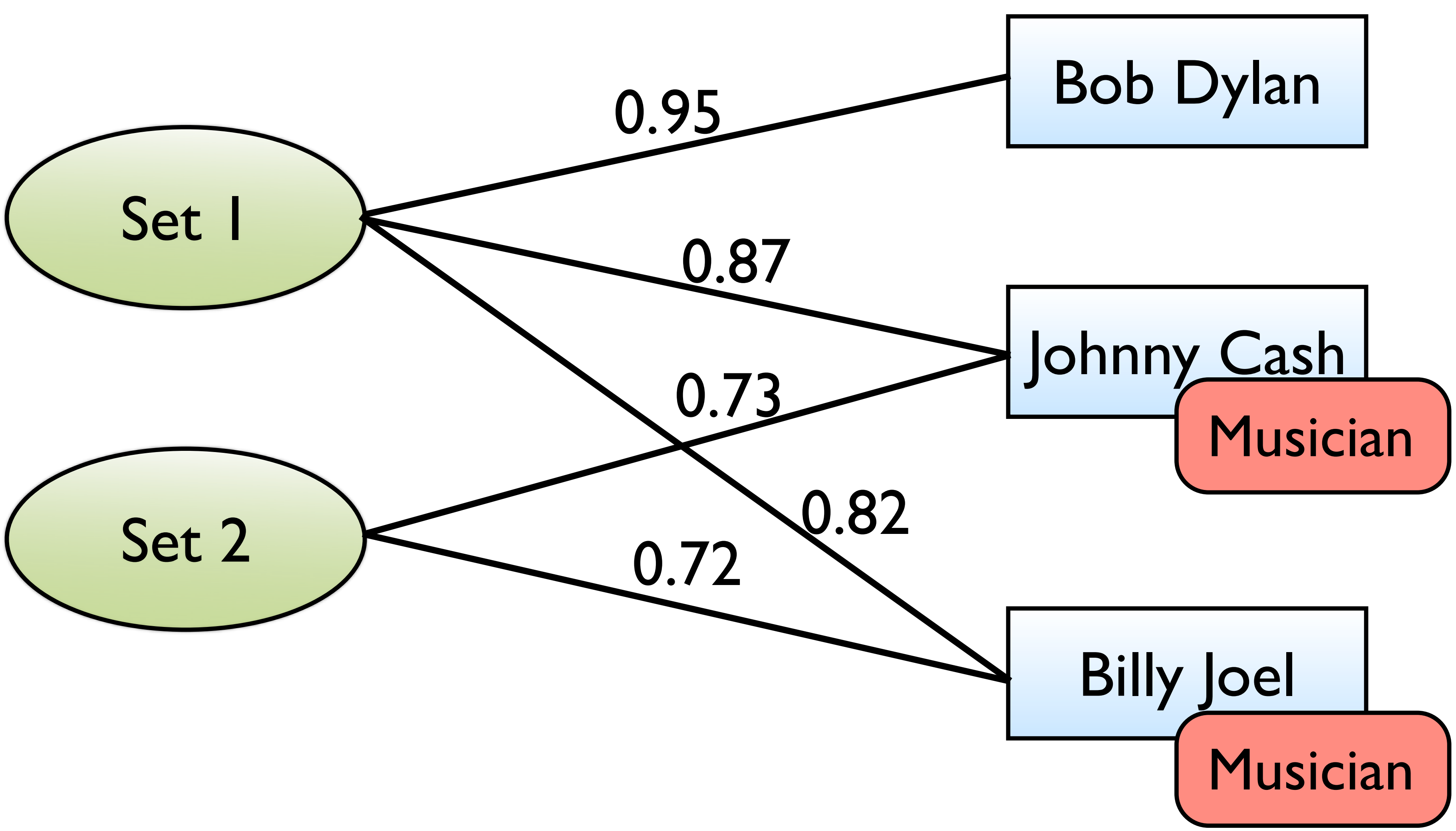
Musician

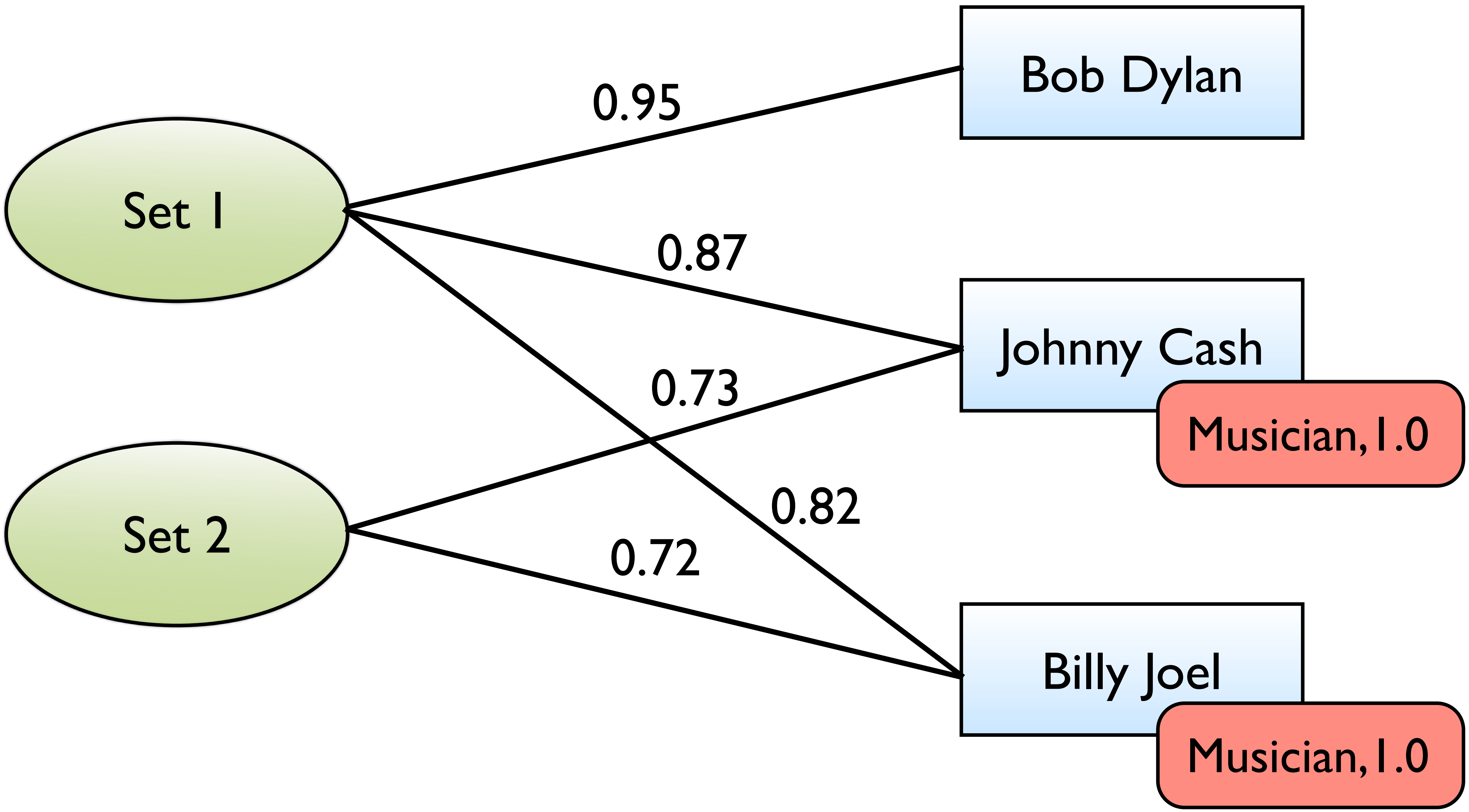
Goal



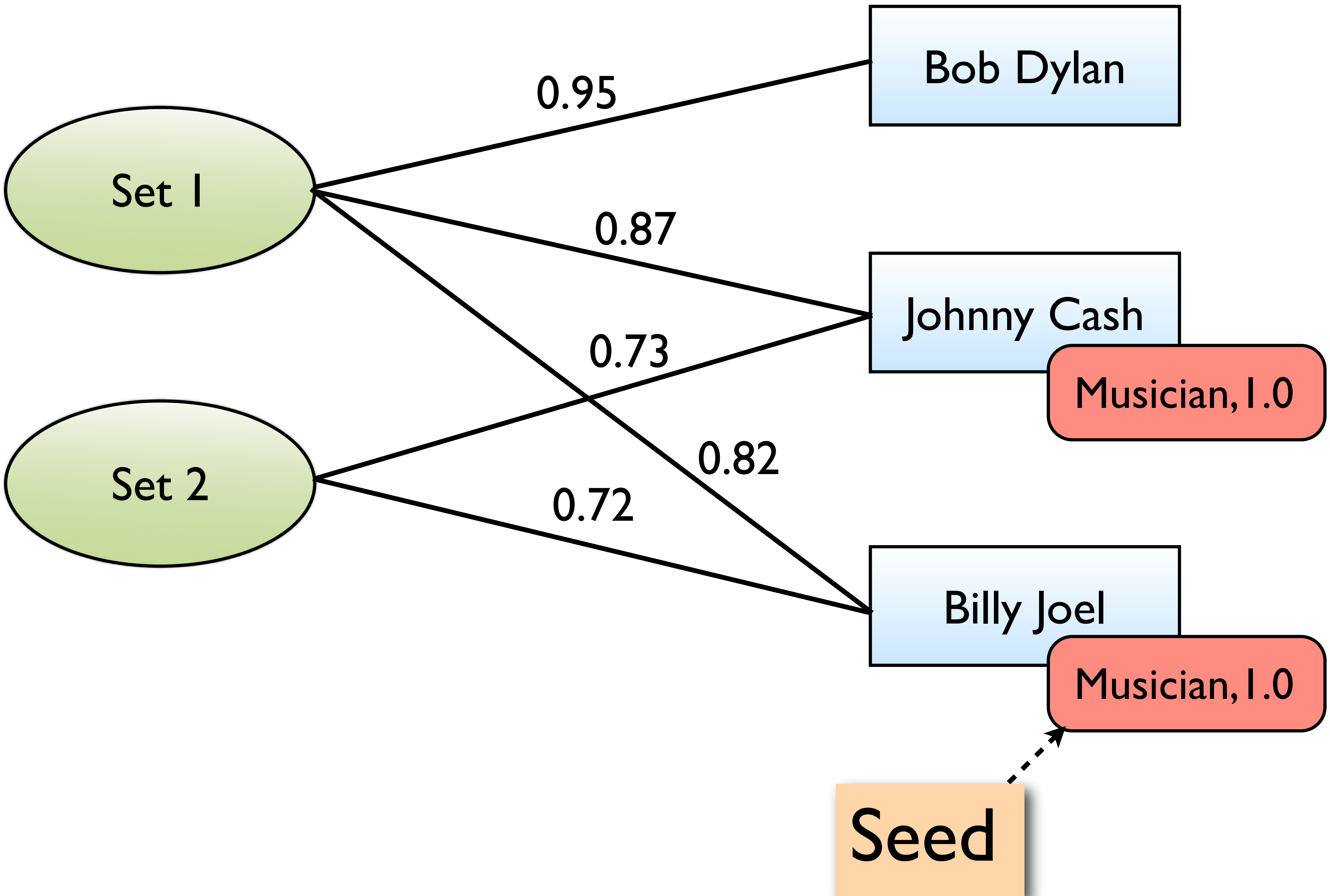


Can we infer that **Bob Dylan** is also a musician?

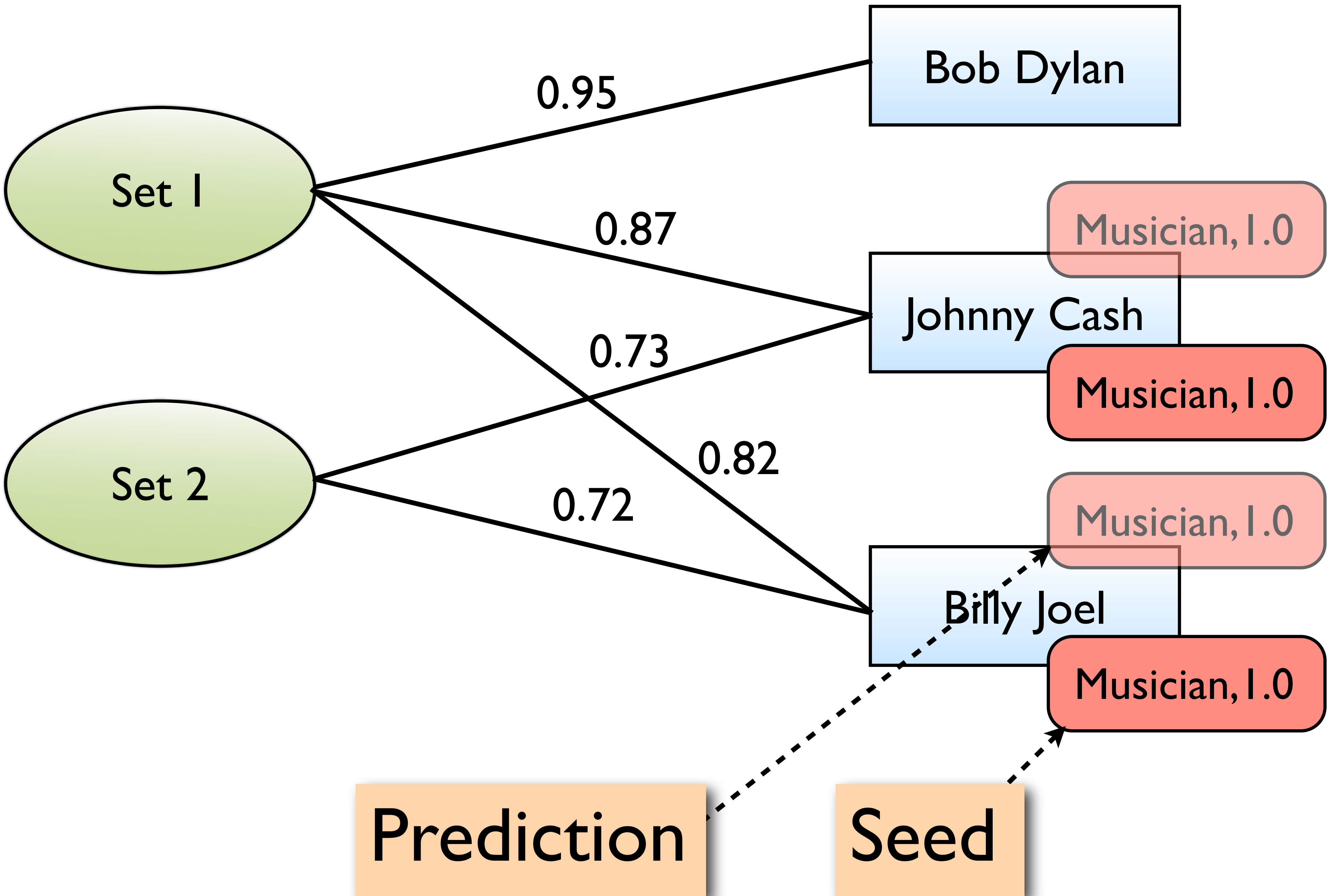
Graph Propagation



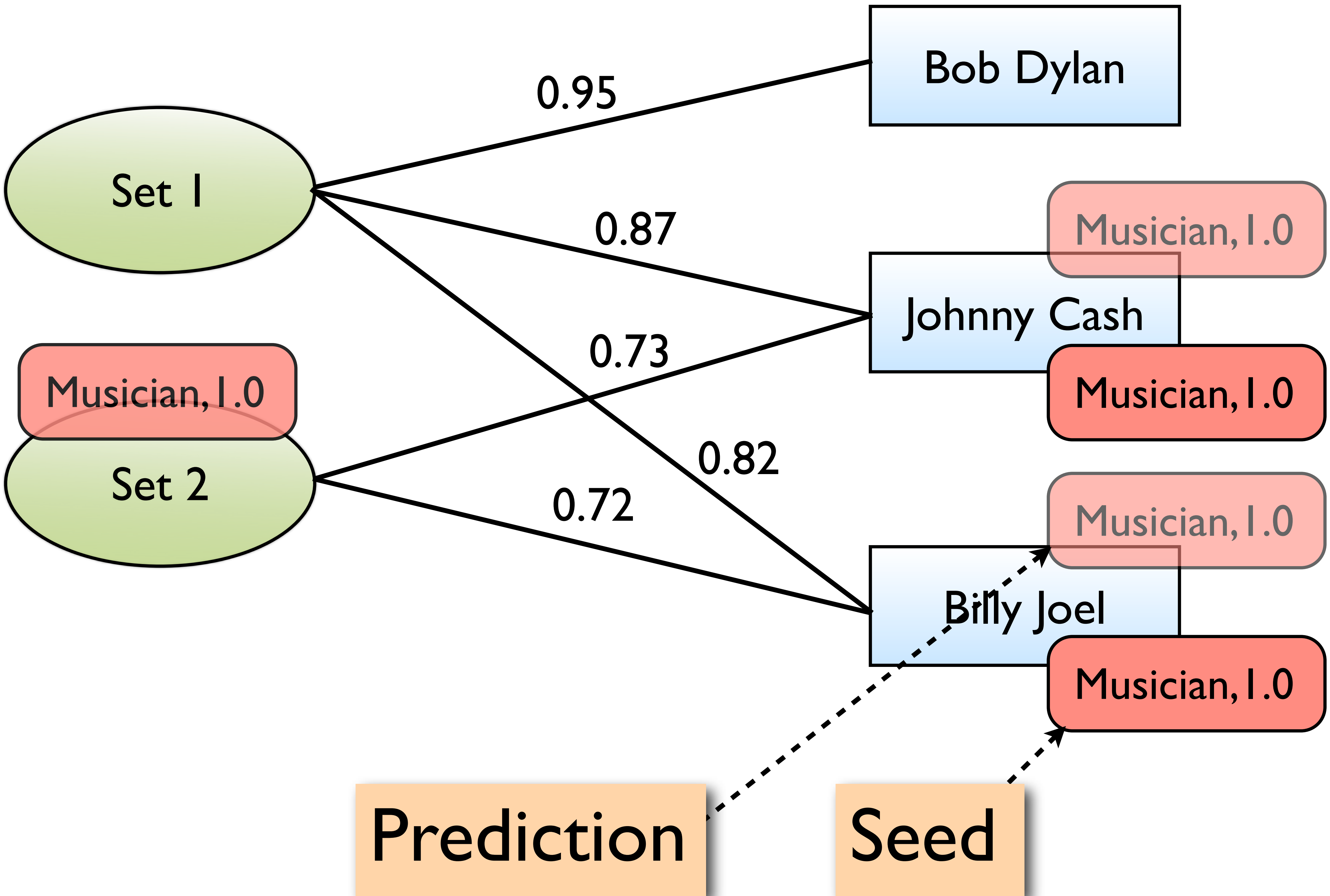
Graph Propagation



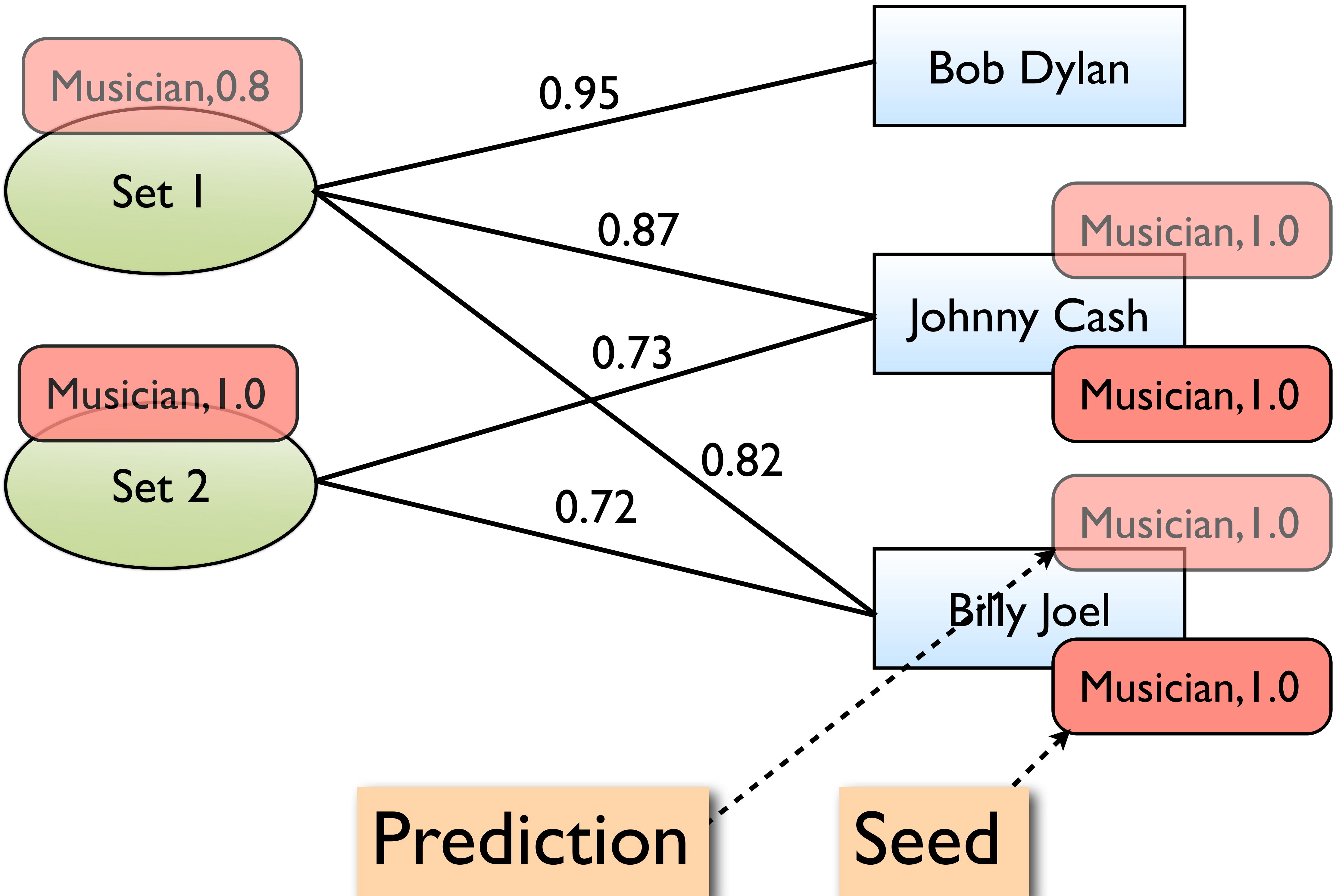
Graph Propagation



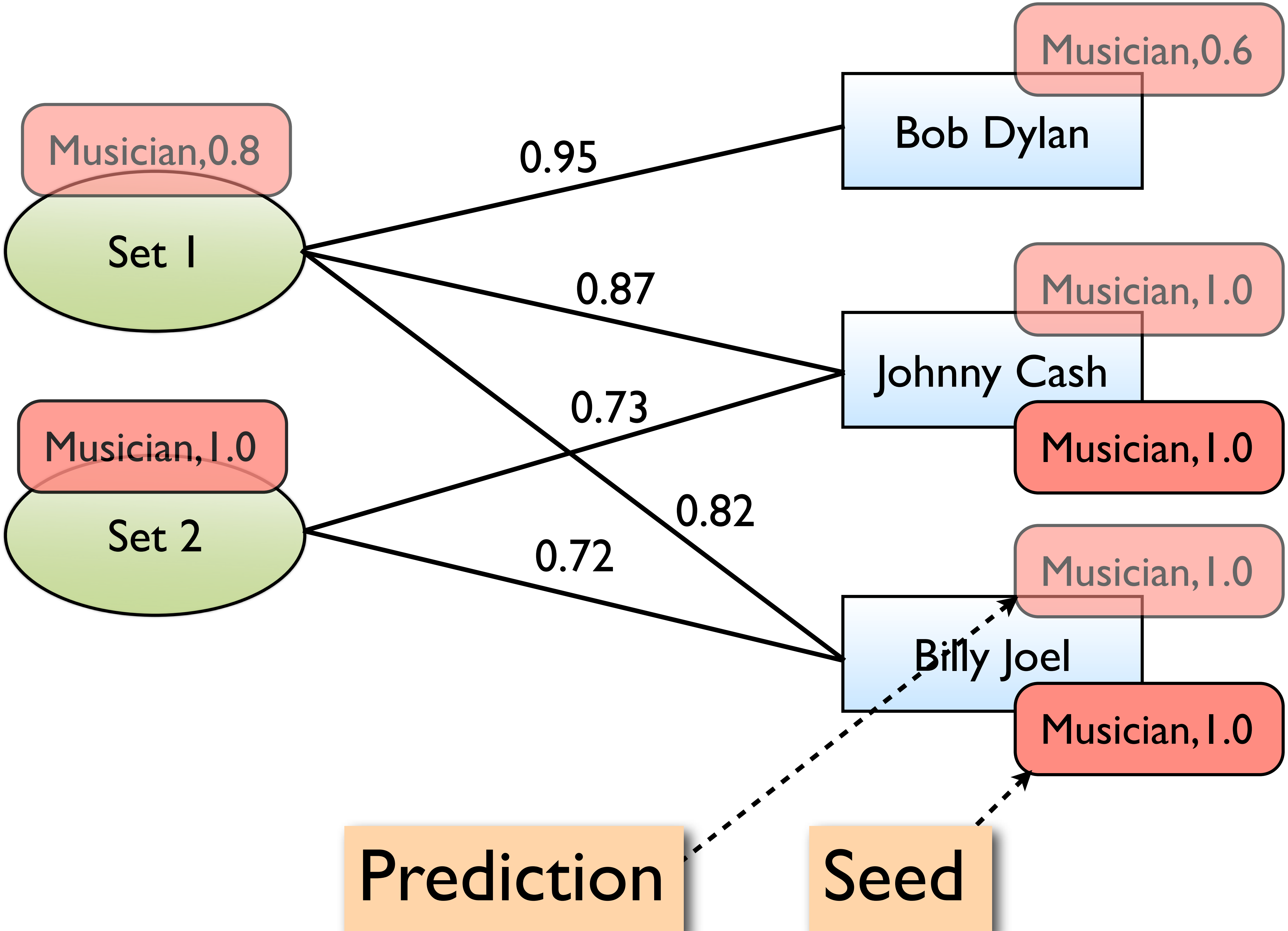
Graph Propagation



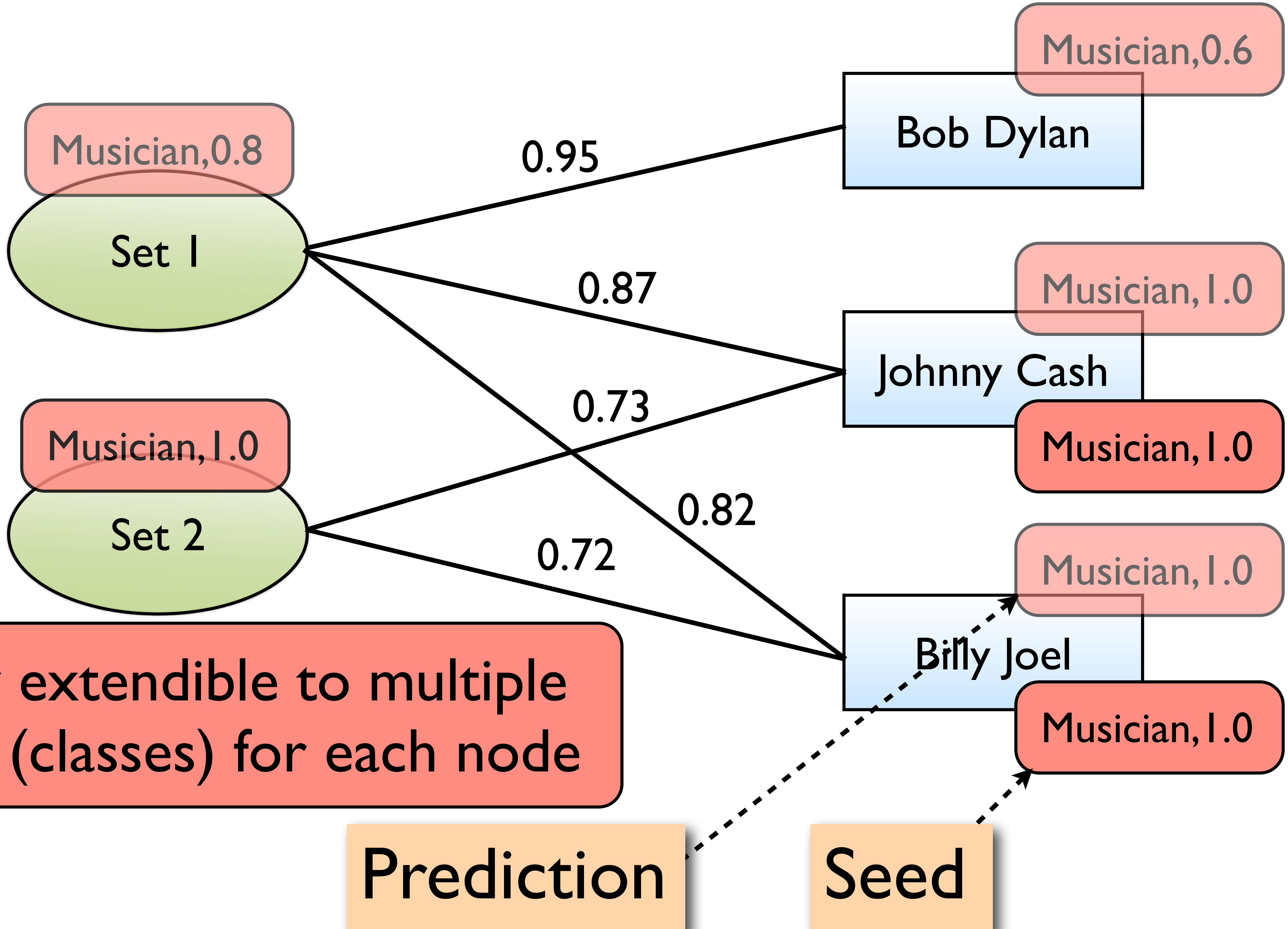
Graph Propagation



Graph Propagation



Graph Propagation



Easily extendible to multiple seeds (classes) for each node

Evaluation Metric

Mean Reciprocal Rank

$$\mathrm{MRR} = \frac{1}{|\text{test-set}|} \sum_{v \in \text{test-set}} \frac{1}{\text{rank}_v(\text{class}(v))}$$

Evaluation Metric

Mean Reciprocal Rank

$$\mathrm{MRR} = \frac{1}{|\text{test-set}|} \sum_{v \in \text{test-set}} \frac{1}{\mathrm{rank}_v(\mathrm{class}(v))}$$

Linguist, 0.6

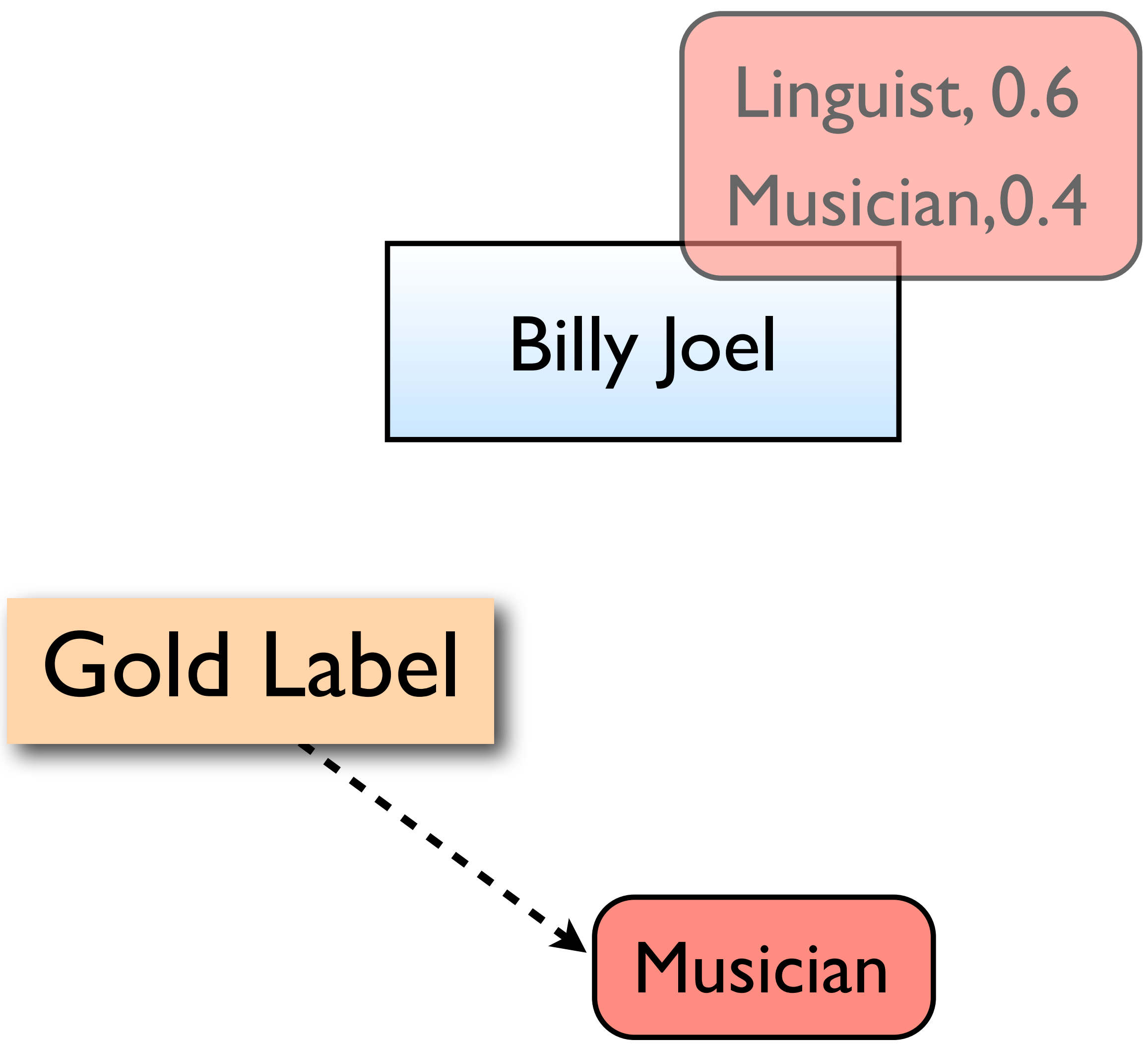
Musician,0.4

Billy Joel

Evaluation Metric

Mean Reciprocal Rank

$$\mathrm{MRR} = \frac{1}{|\text{test-set}|} \sum_{v \in \text{test-set}} \frac{1}{\mathrm{rank}_v(\mathrm{class}(v))}$$



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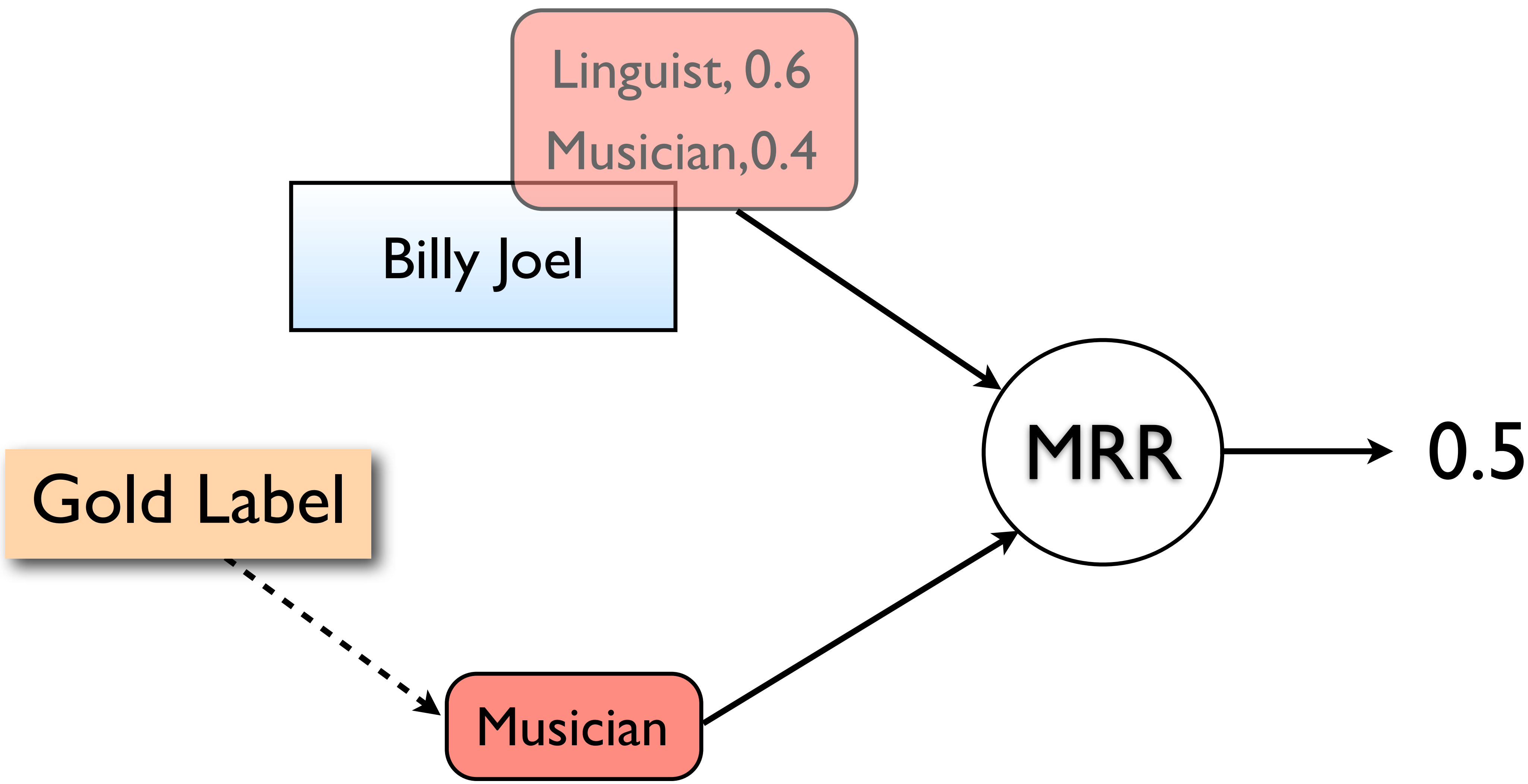
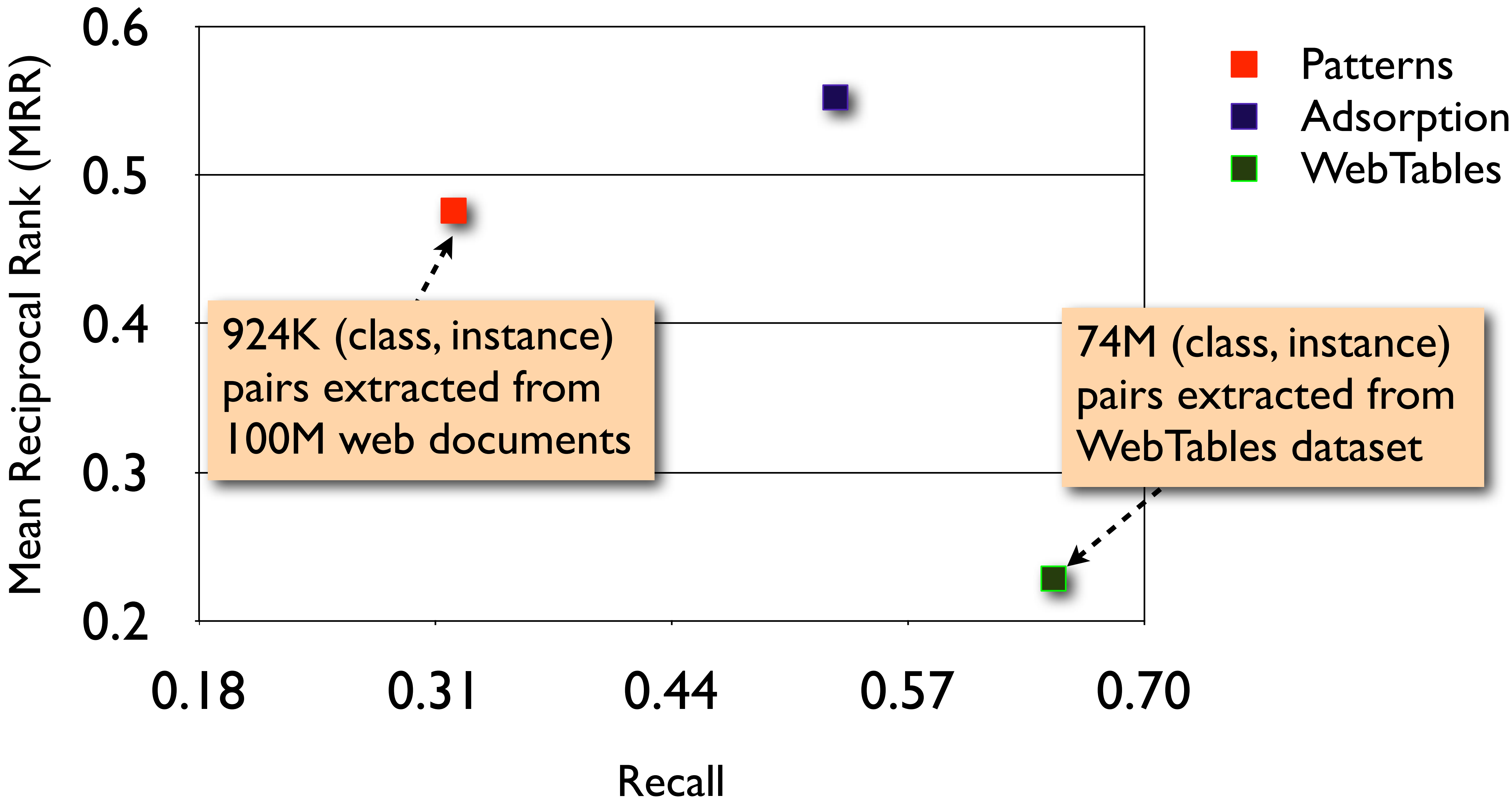


Extraction for Known Instances

Graph with
1.4m nodes,
75m edges used.

Evaluation against WordNet Dataset (38 classes, 8910 instances)

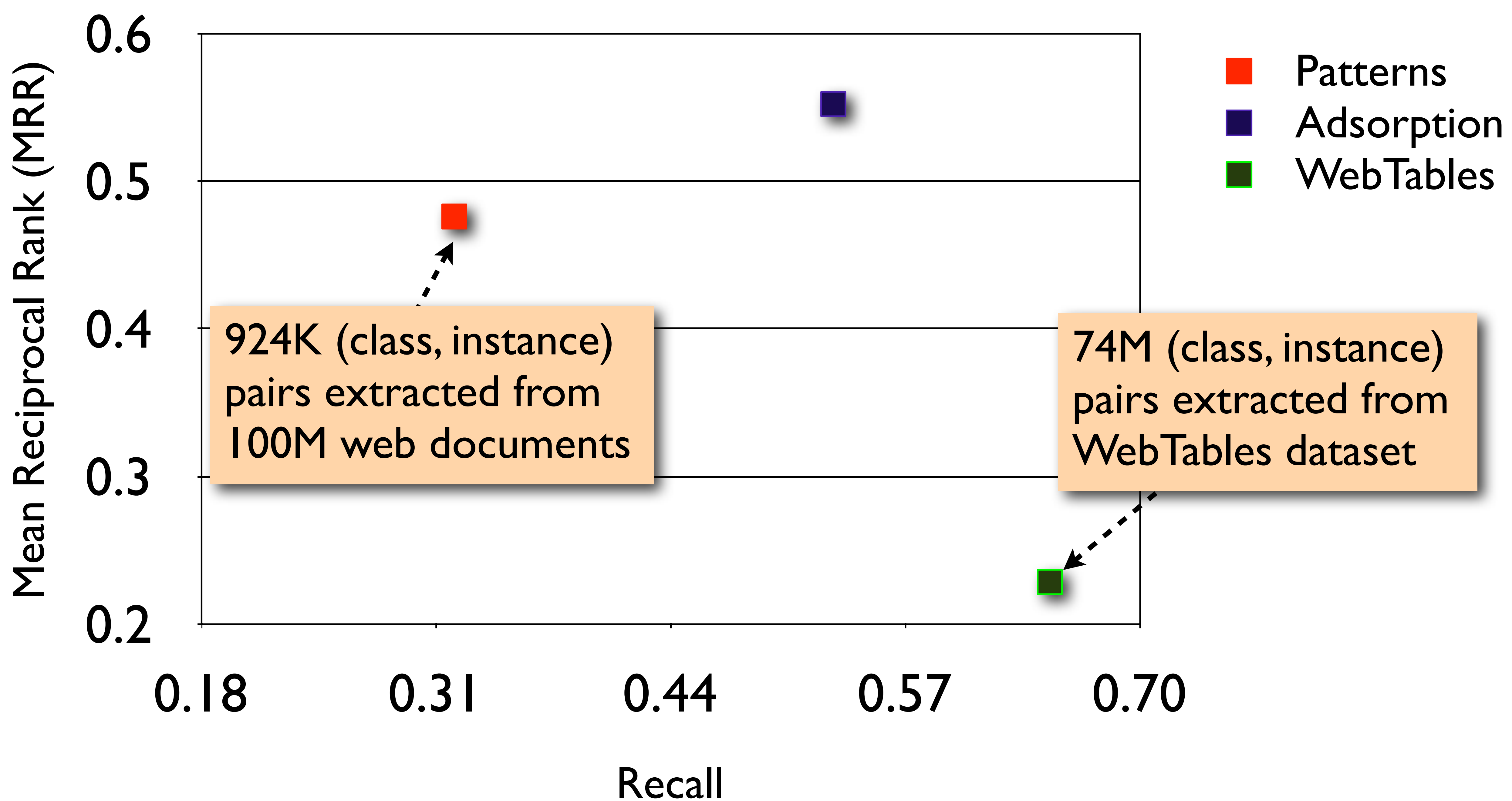


Extraction for Known Instances

Adsorption is able to assign ***better*** class labels to ***more*** instances.

Graph with 1.4m nodes, 75m edges used.

Evaluation against WordNet Dataset (38 classes, 8910 instances)



Extracted Pairs

Total classes: **9081**

Class	**Some non-seed Instances found by Adsorption**
Scientific Journals	Journal of Physics, Nature, Structural and Molecular Biology, Sciences Sociales et sante, Kidney and Blood Pressure Research, American Journal of Physiology-Cell Physiology, …
NFL Players	Tony Gonzales, Thabiti Davis, Taylor Stubblefield, Ron Dixon, Rodney Hannan, …
Book Publishers	Small Night Shade Books, House of Ansari Press, Highwater Books, Distributed Art Publishers, Cooper Canyon Press, …

Extracted Pairs

Total classes: **9081**

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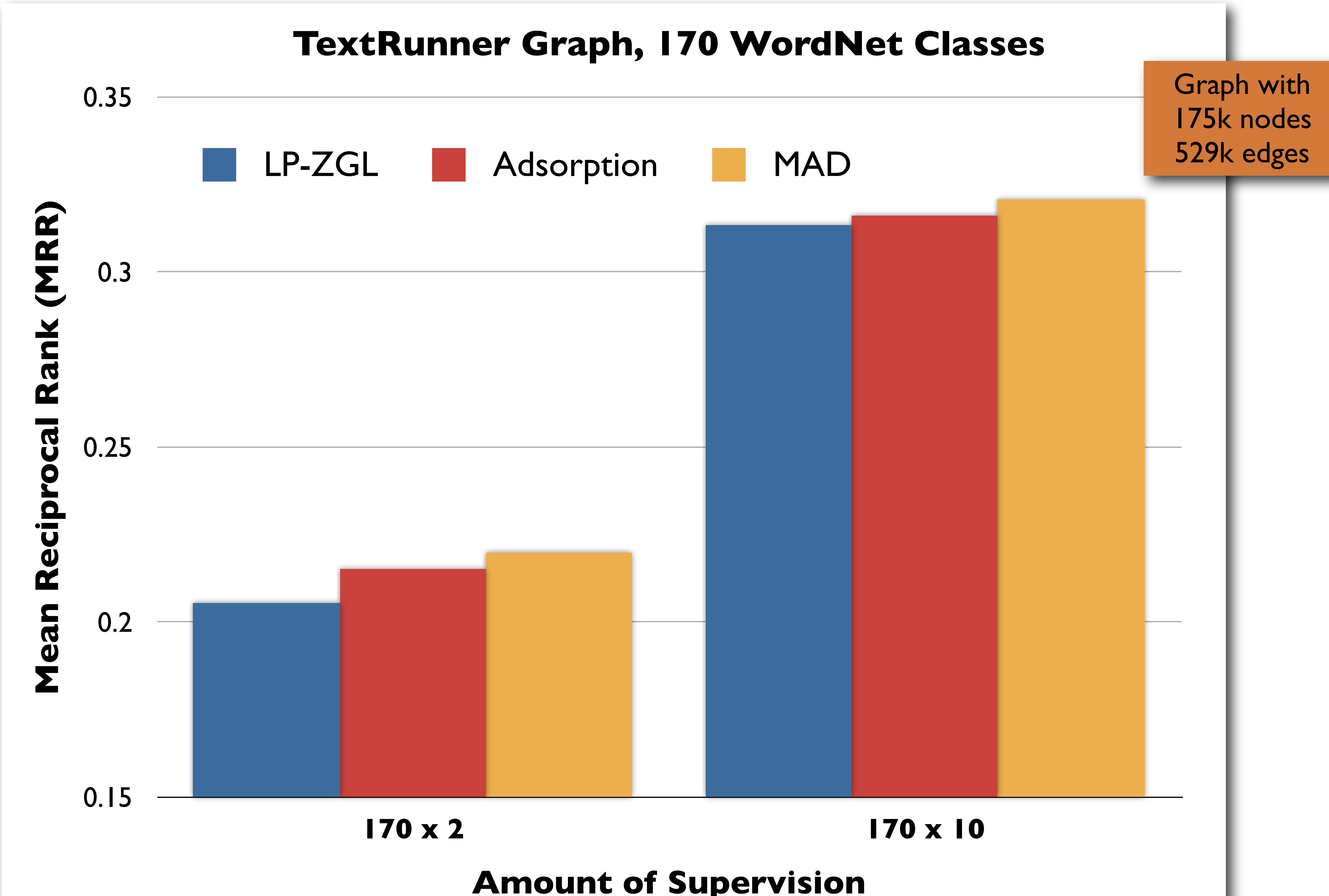
Book Publishers	Small Night Shade Books, House of Ansari Press, Highwater Books, Distributed Art Publishers, Cooper Canyon Press, …

Graph-based methods can easily handle large number of classes

Results

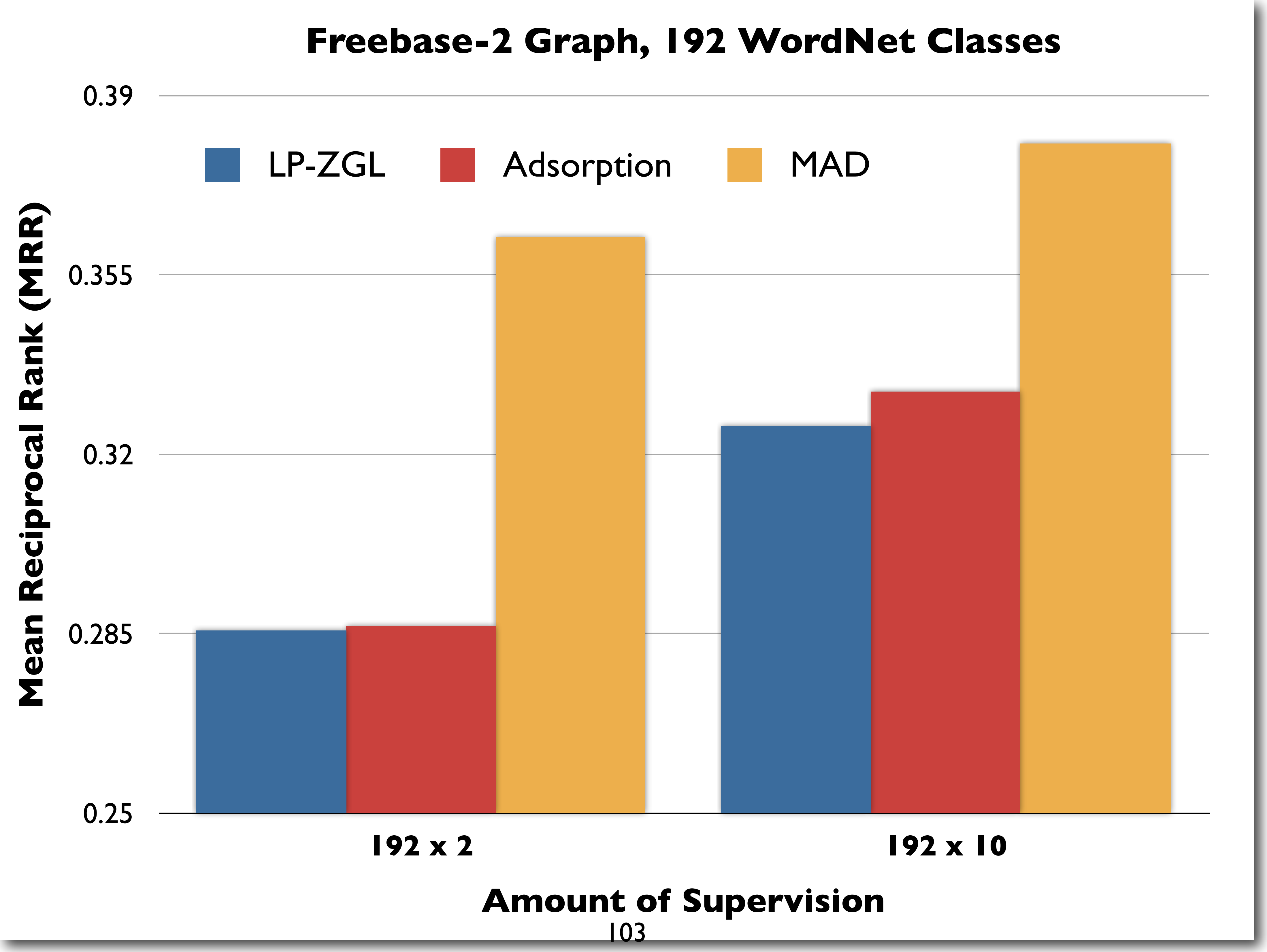
Data available @ http://www.talukdar.net/datasets/class_inst/



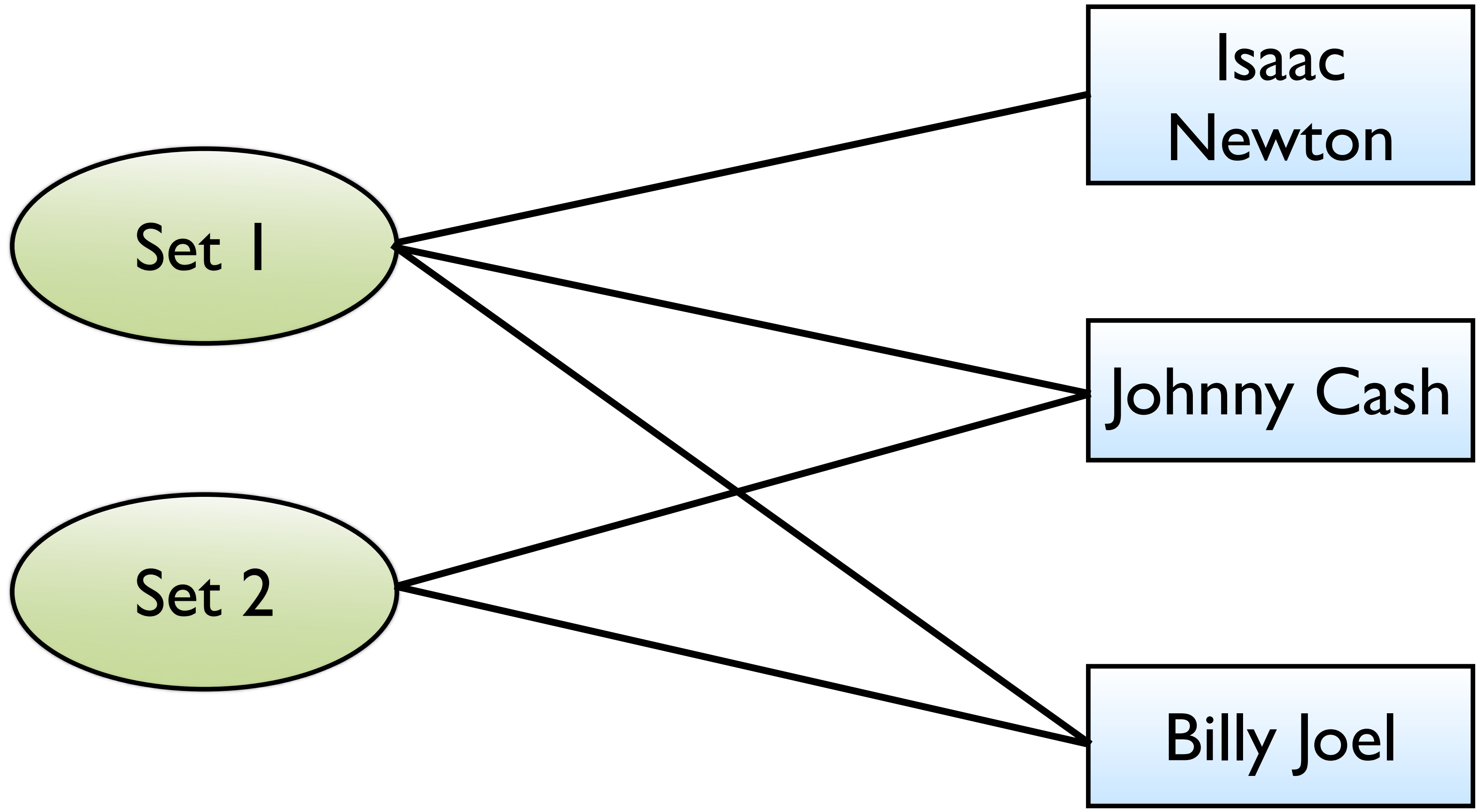
Results

Graph with
303k nodes
2.3m edges

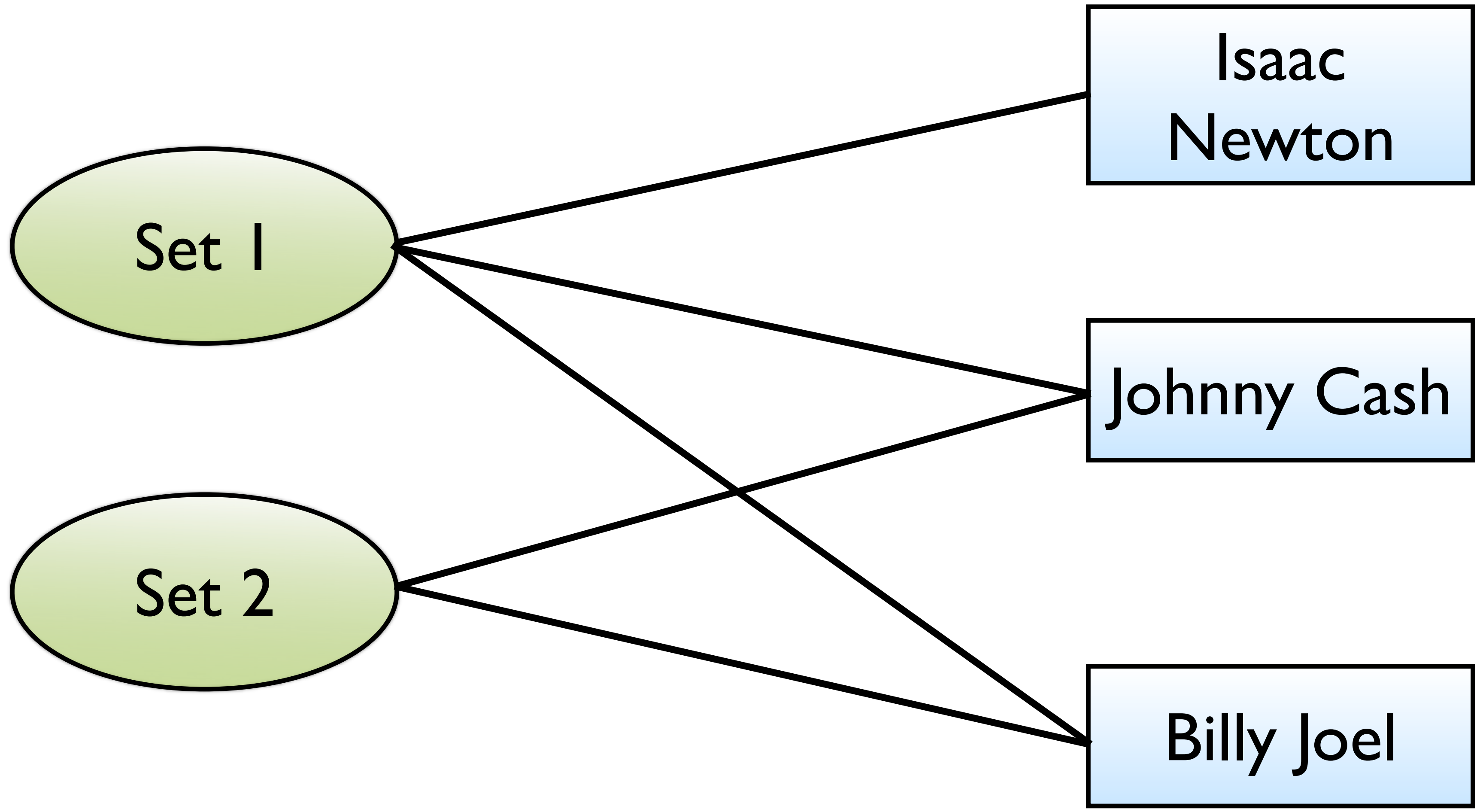
Data available @ http://www.talukdar.net/datasets/class_inst/



Semantic Constraints



Semantic Constraints

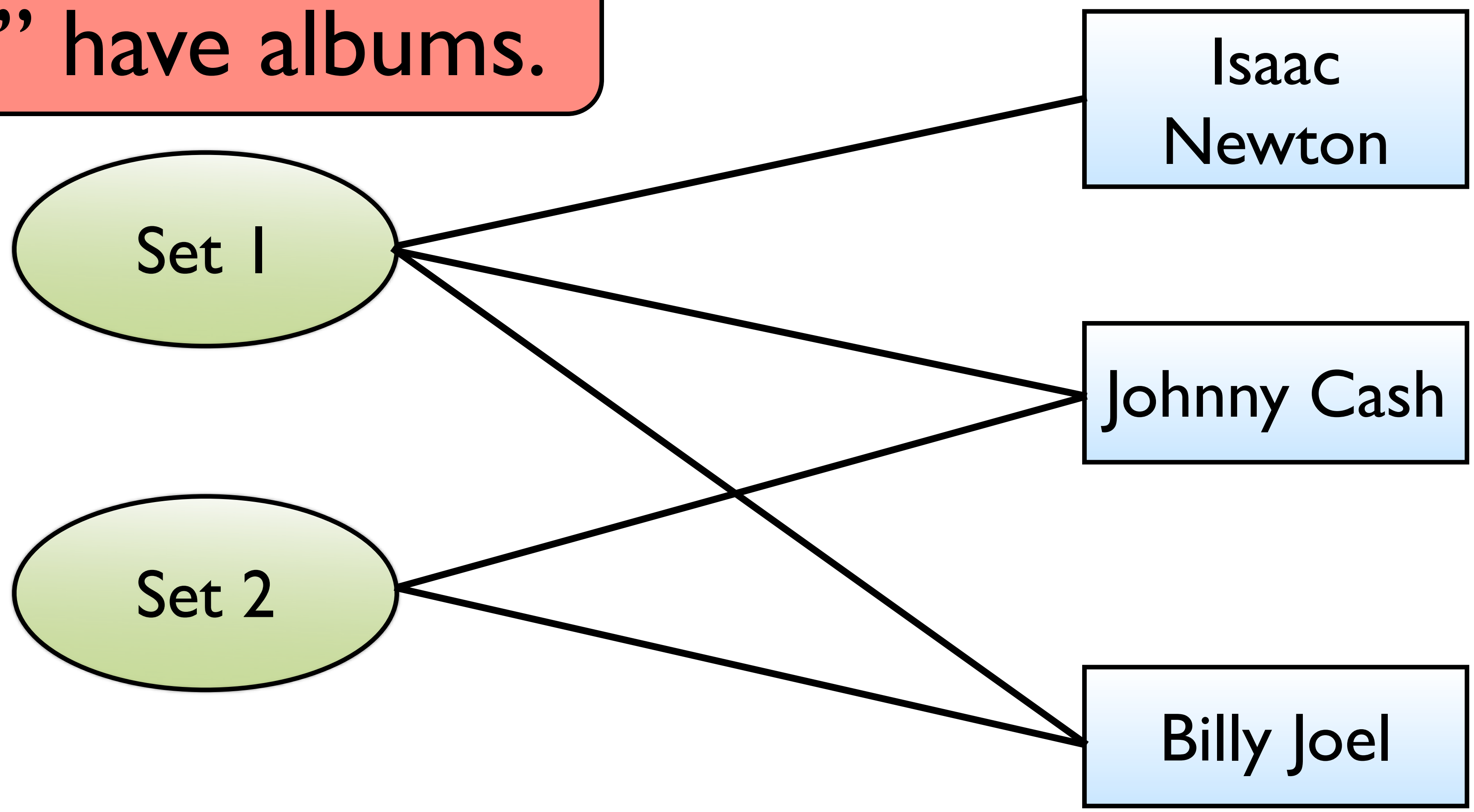


Suppose we knew that both “Johnny Cash” and “Billy Joel” have albums.

How do we encode this constraint?

Solution (I)

Both "Johnny Cash" and "Billy Joel" have albums.



Solution (I)

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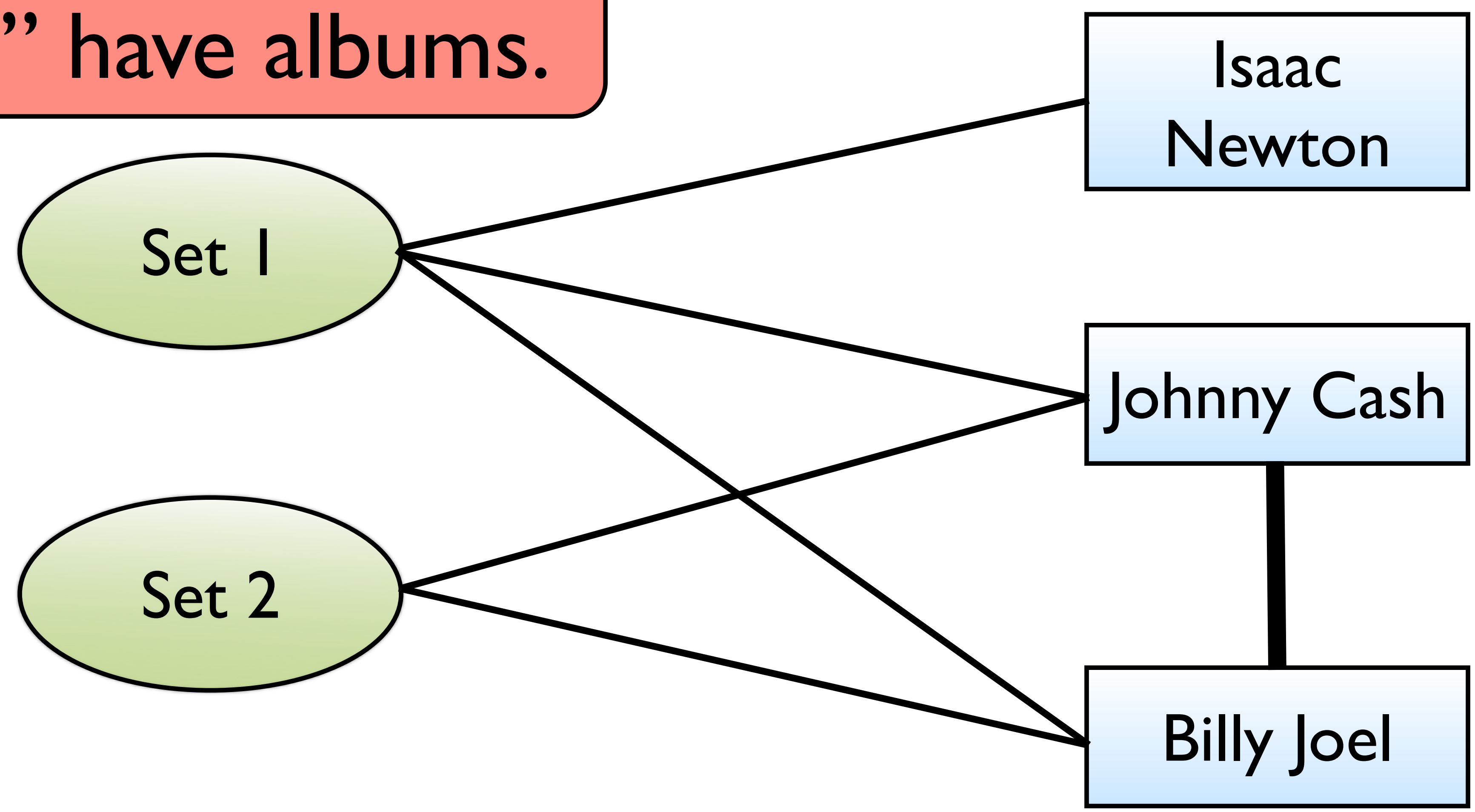

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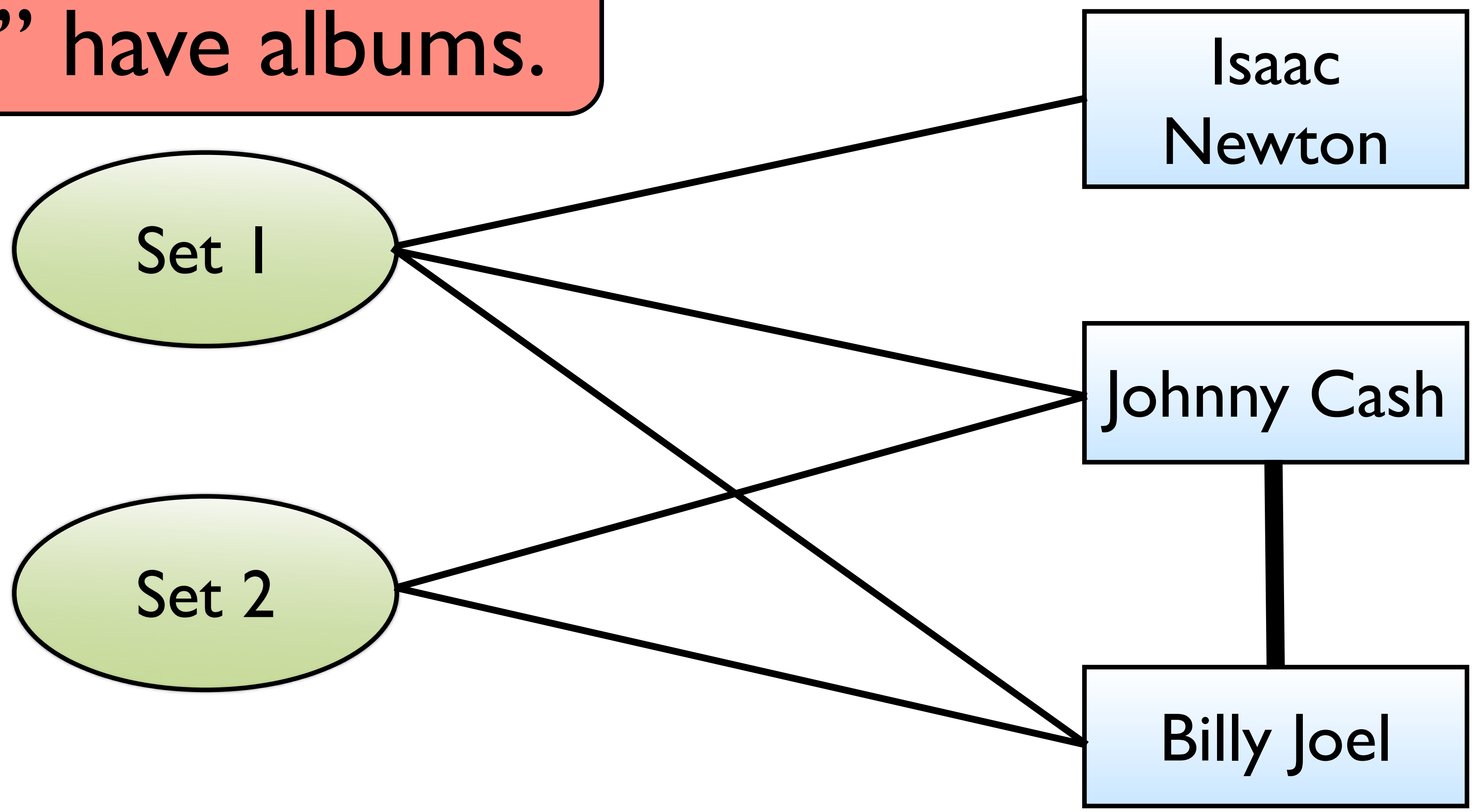
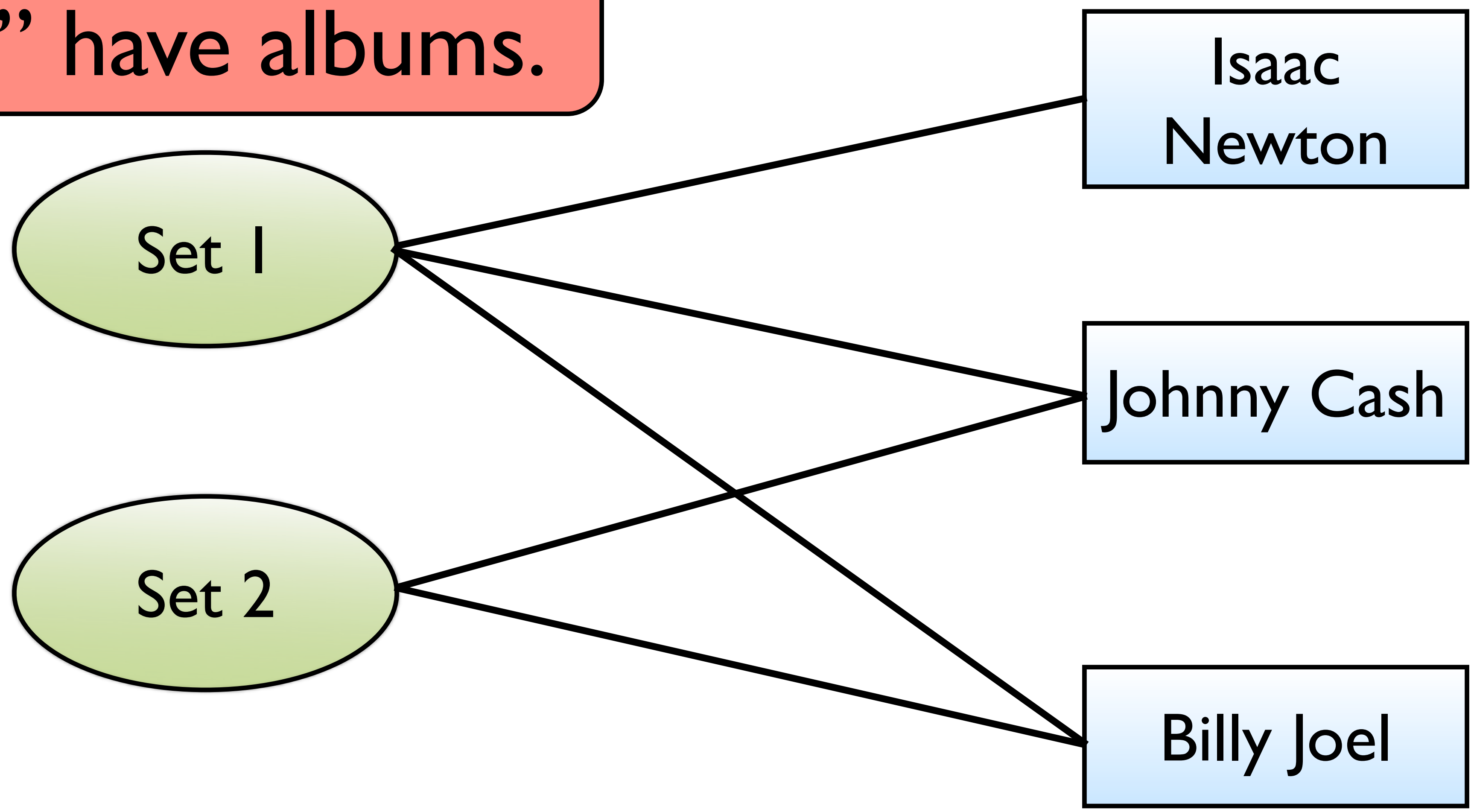


- Graph is no longer bi-partite (not necessarily bad)
- Can lead to cliques of size of number of instances in the constraint (bad)

Solution (II)

Both "Johnny Cash" and "Billy Joel" have albums.



[Talukdar & Periera, ACL 2010]

Solution (II)

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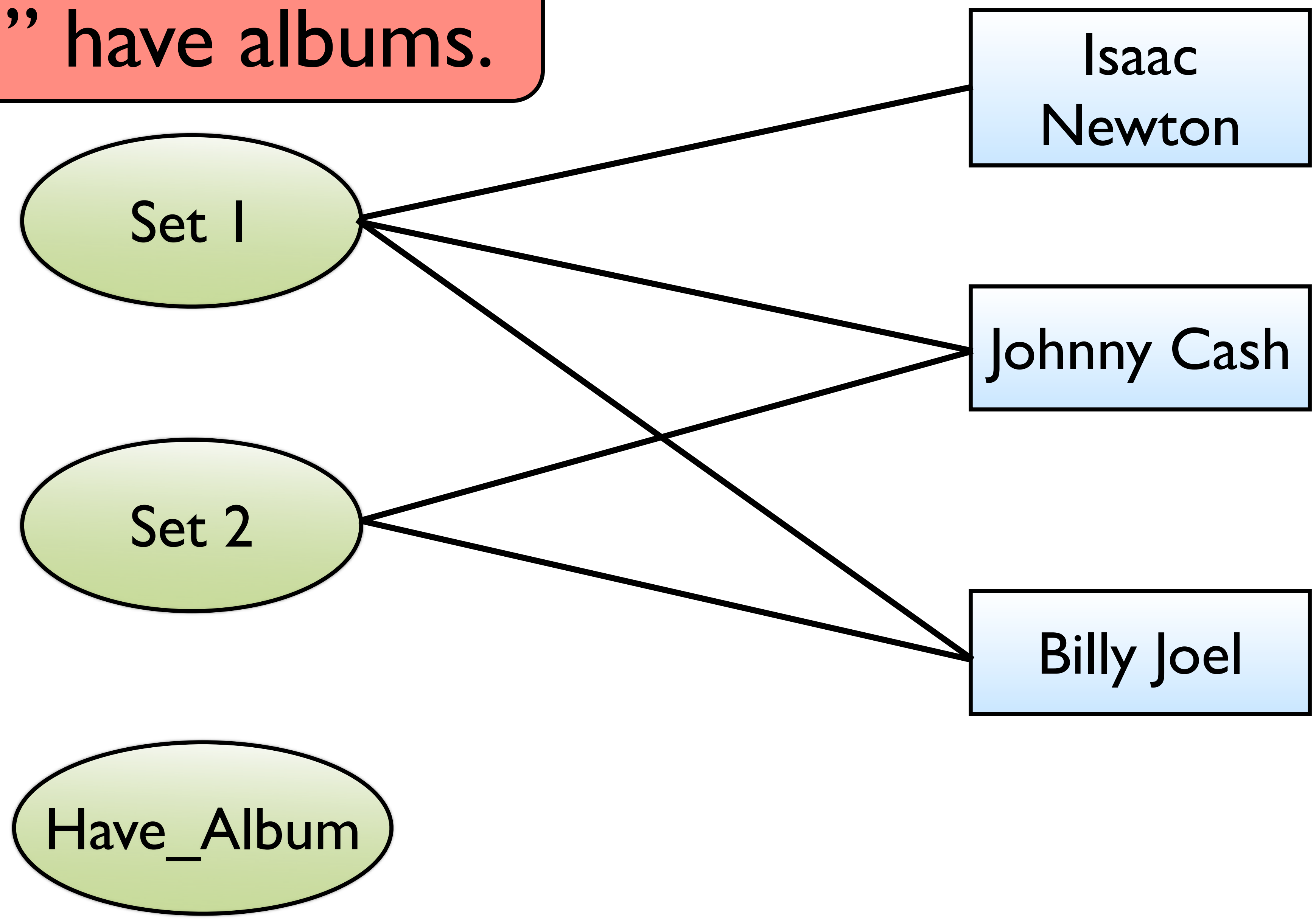

[Talukdar & Periera, ACL 2010]

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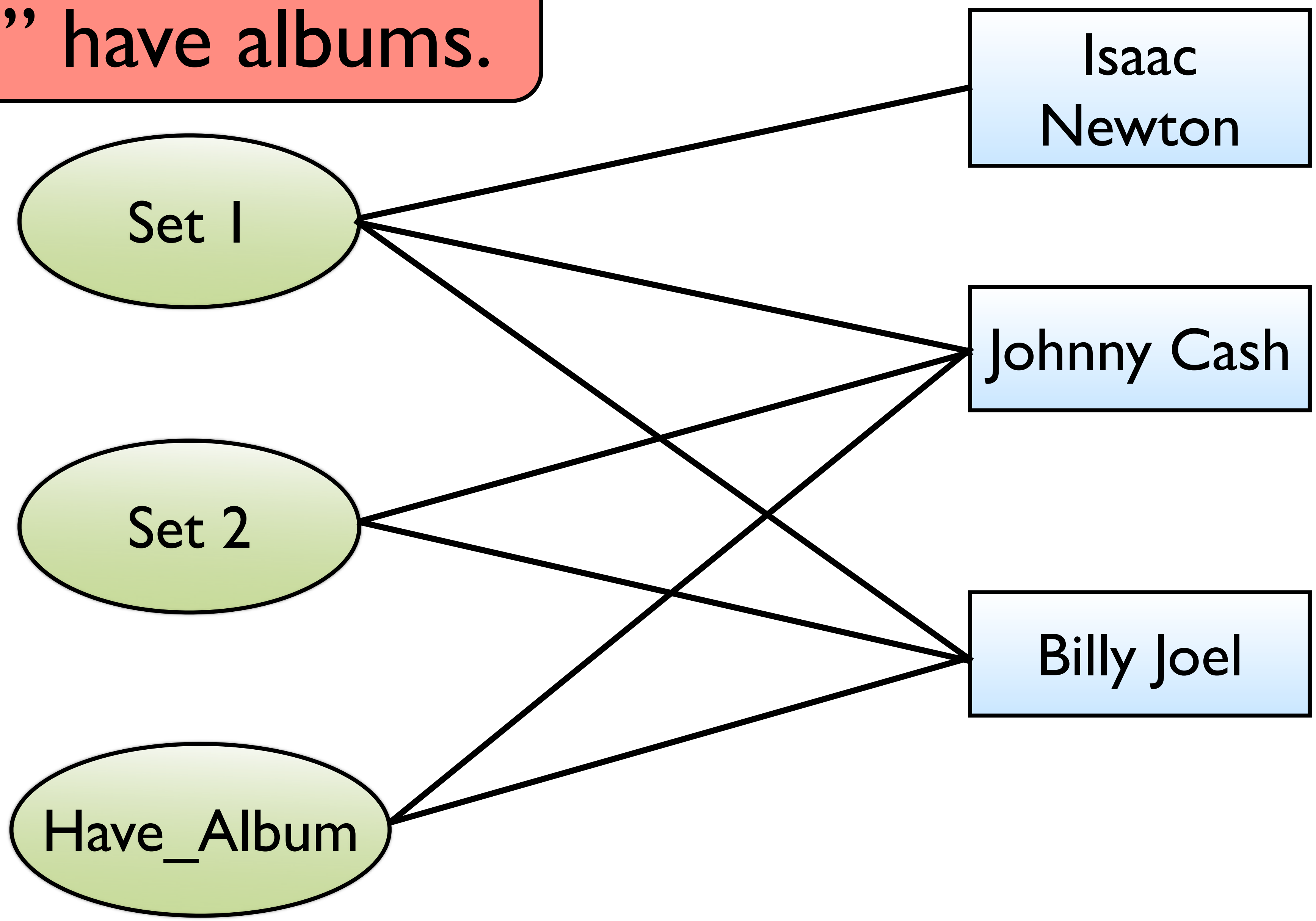

[Talukdar & Periera, ACL 2010]

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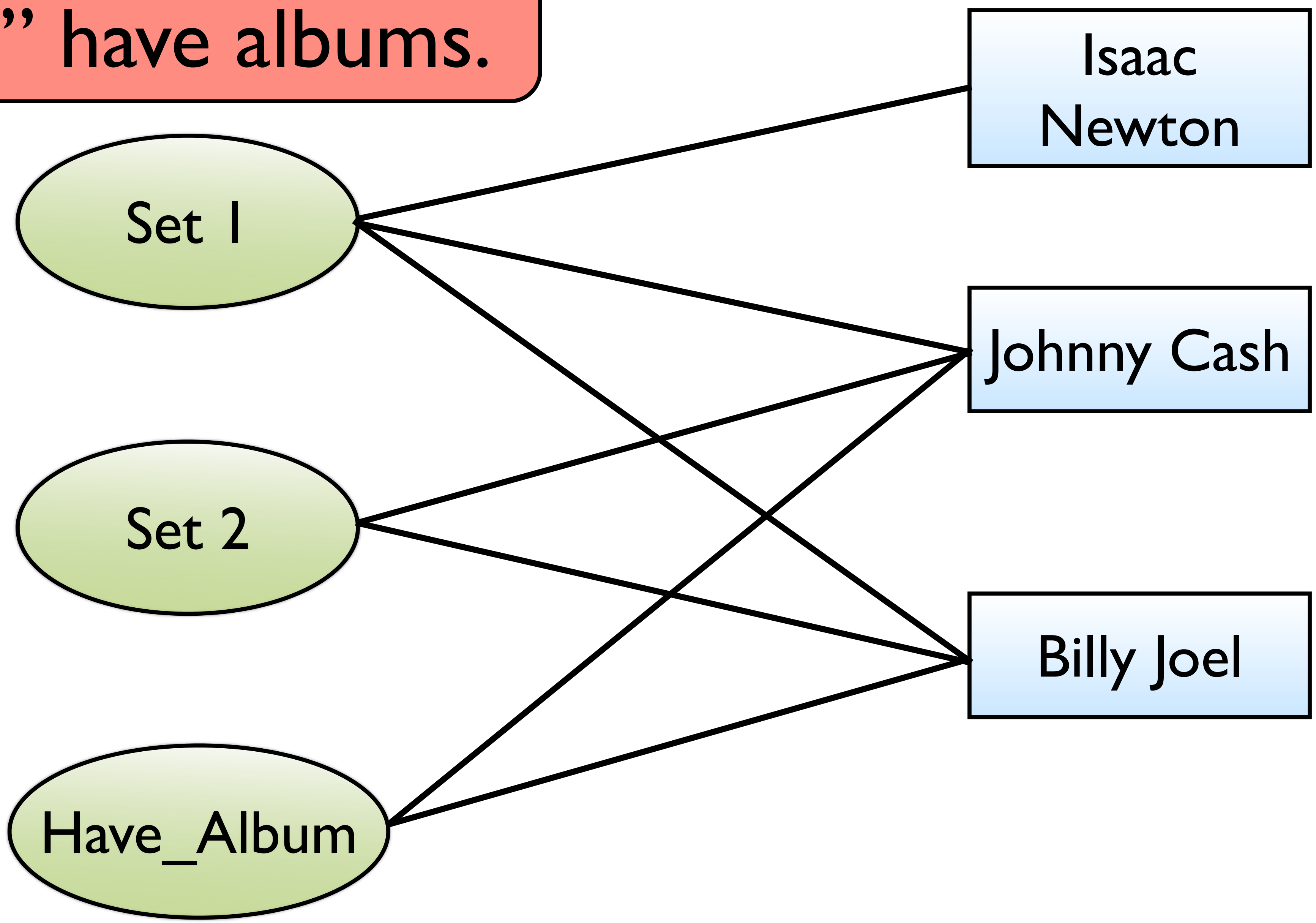
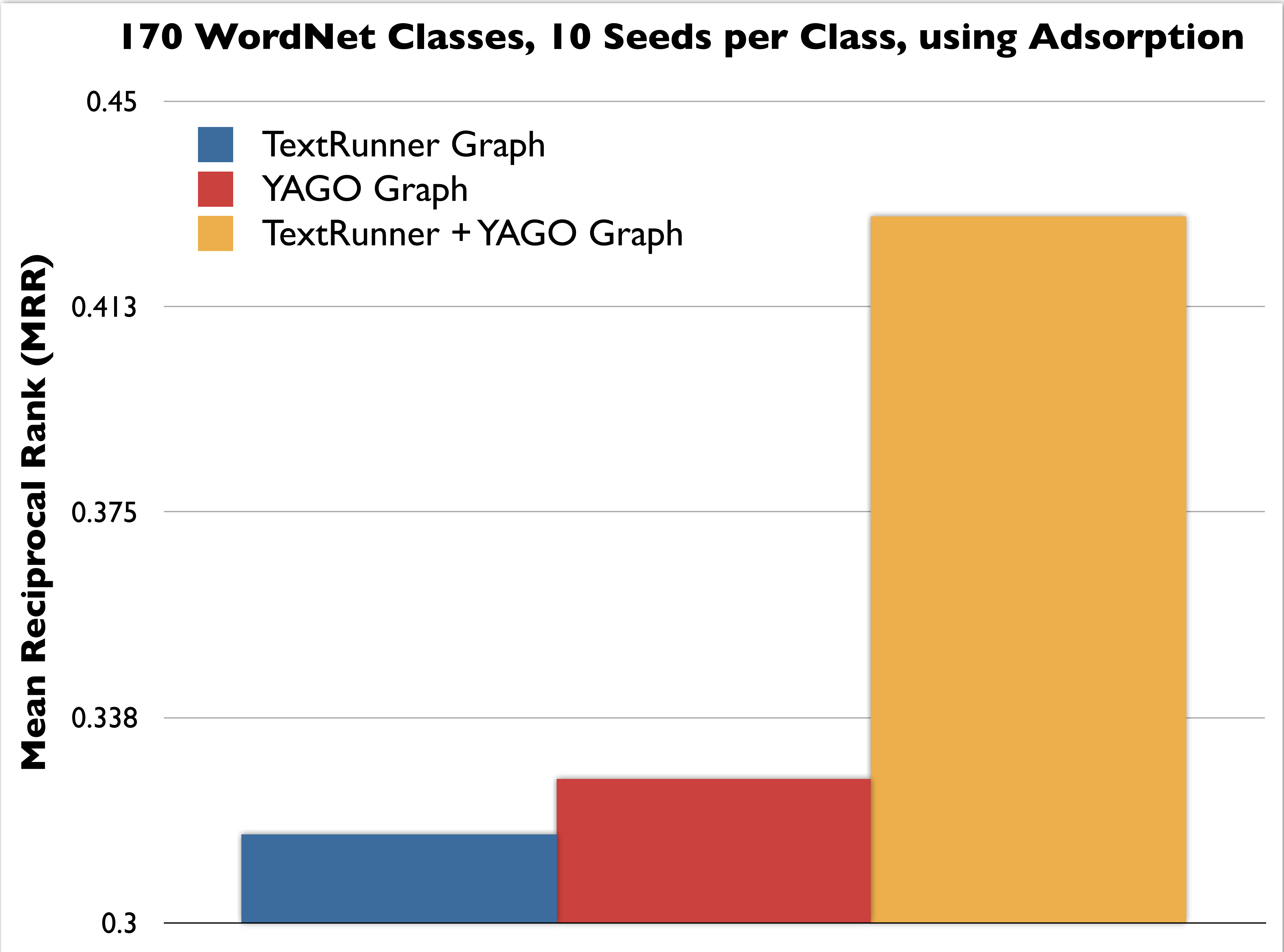


Semantic Constraints may be easily encoded

[Talukdar & Periera, ACL 2010]

Results with Semantic Constraints



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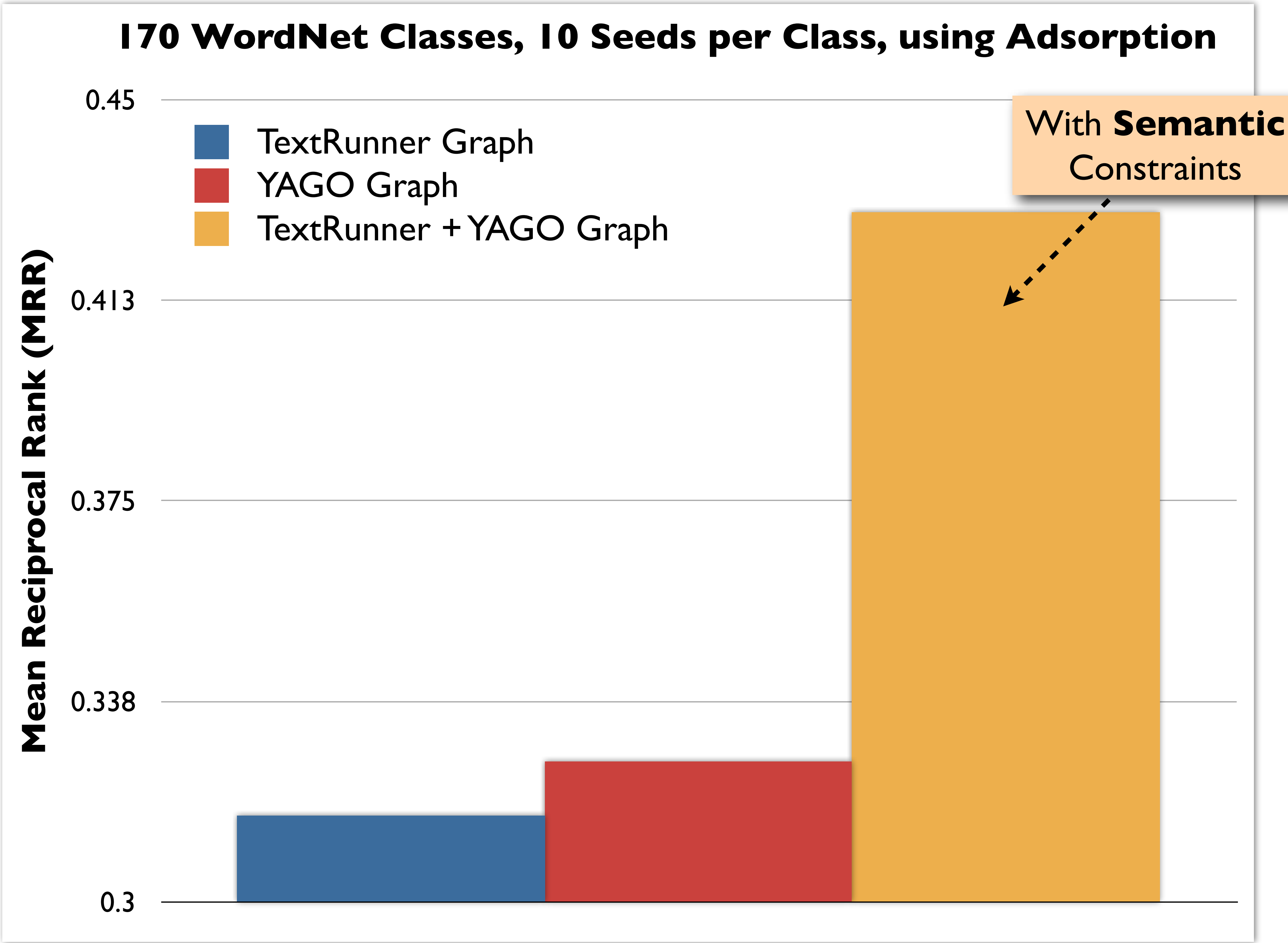
[Talukdar & Periera, ACL 2010]

Results with Semantic Constraints



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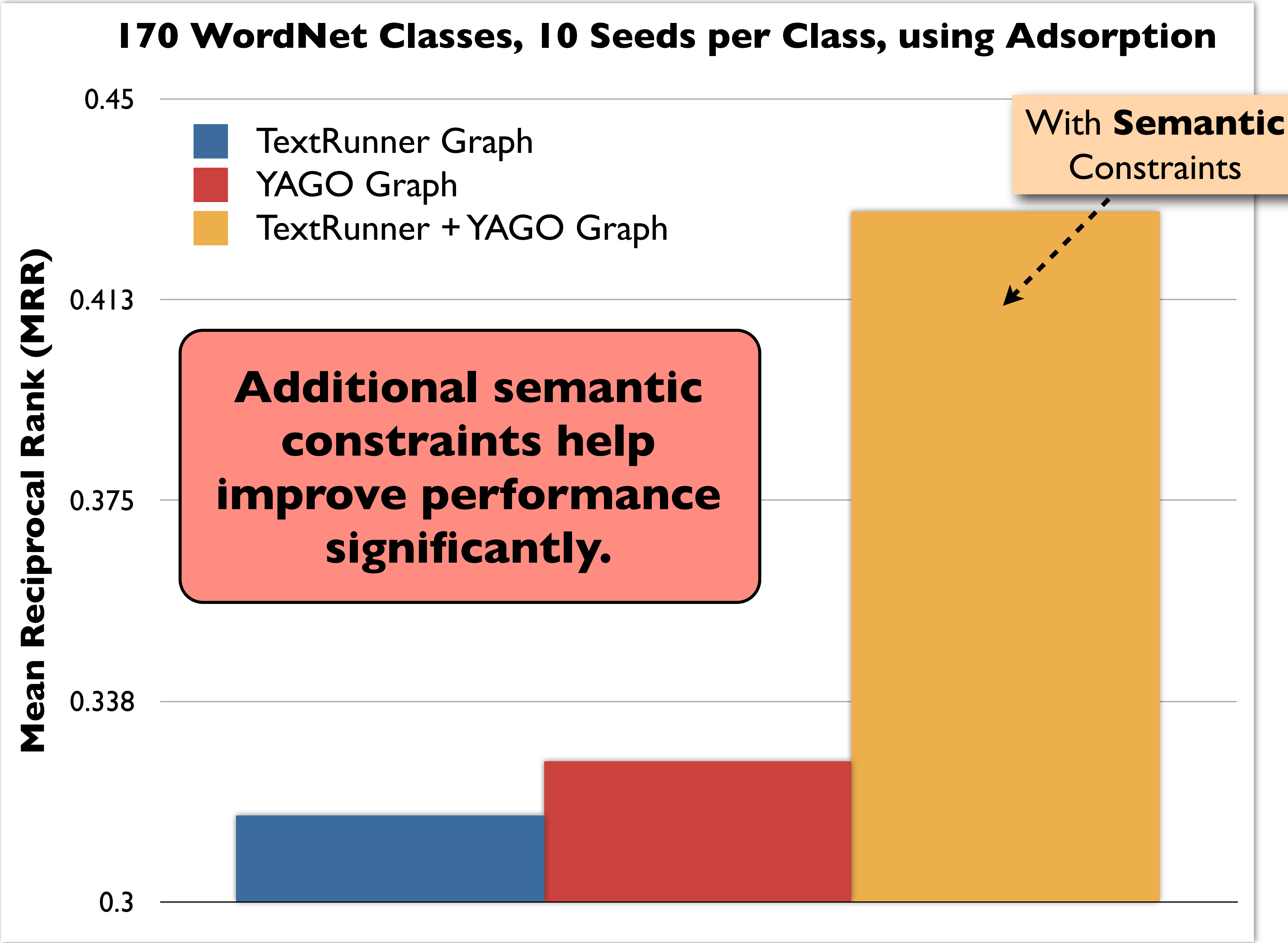
[Talukdar & Periera, ACL 2010]

Results with Semantic Constraints



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[Talukdar & Periera, ACL 2010]

Big Picture

Use case 1: Transductive Classification

Use case 2: Training Better Inductive Model

	Use case 1	Use case 2
Text Categorization	✓	
Sentiment Analysis	✓	✓
Class Instance Acquisition		

Big Picture

Use case 1: Transductive Classification

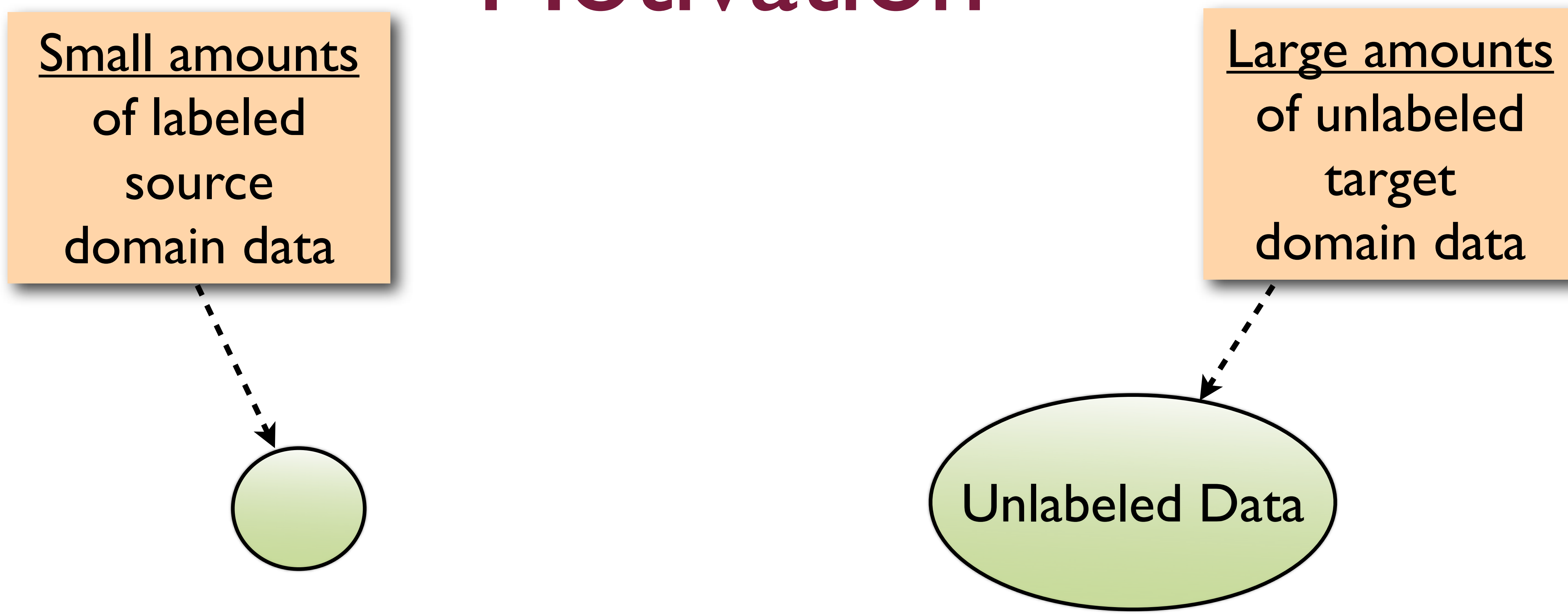
Use case 2: Training Better Inductive Model

	Use case 1	Use case 2
Text Categorization	✓	
Sentiment Analysis	✓	✓
Class Instance Acquisition	✓	

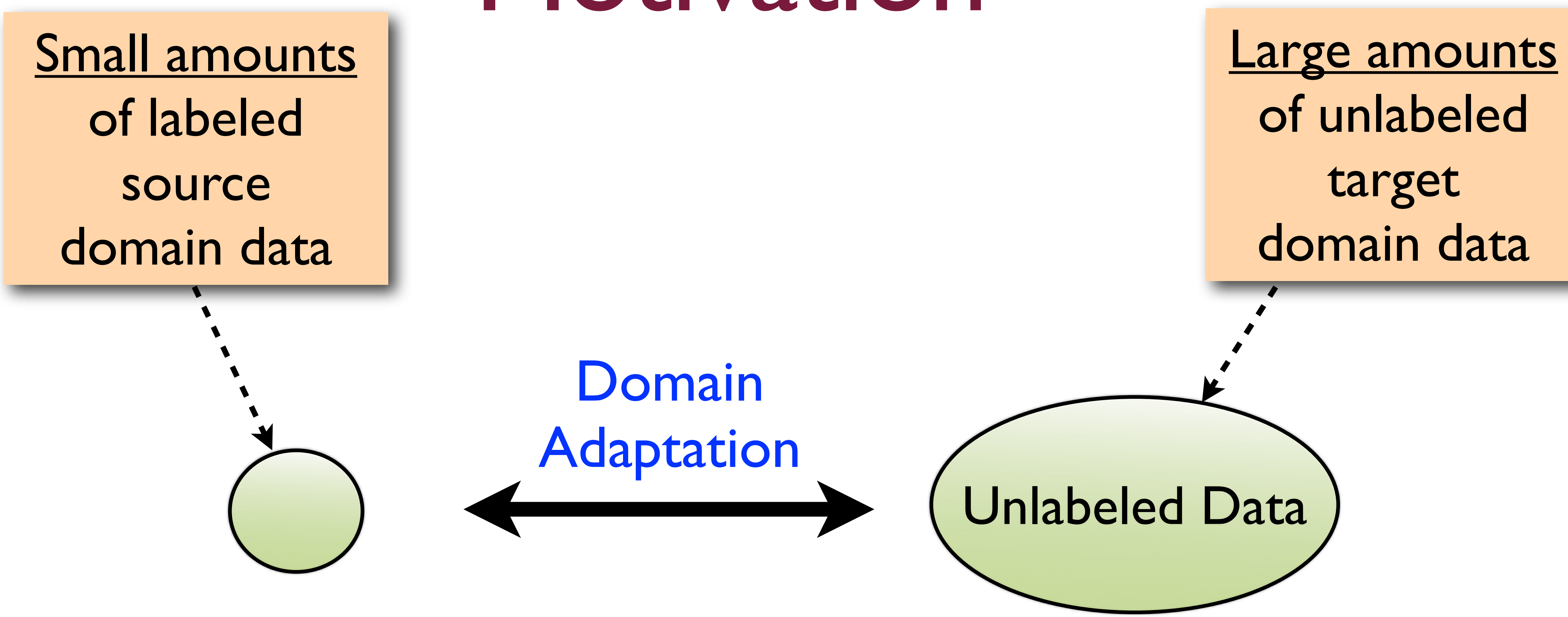
Outline

- Motivation
- Graph Construction
- Inference Methods
- Scalability
- Applications
  - Text Categorization
  - Sentiment Analysis
  - Class Instance Acquisition
  - POS Tagging [Subramanya et. al., EMNLP 2008]
  - MultiLingual POS Tagging
  - Semantic Parsing
- Conclusion & Future Work

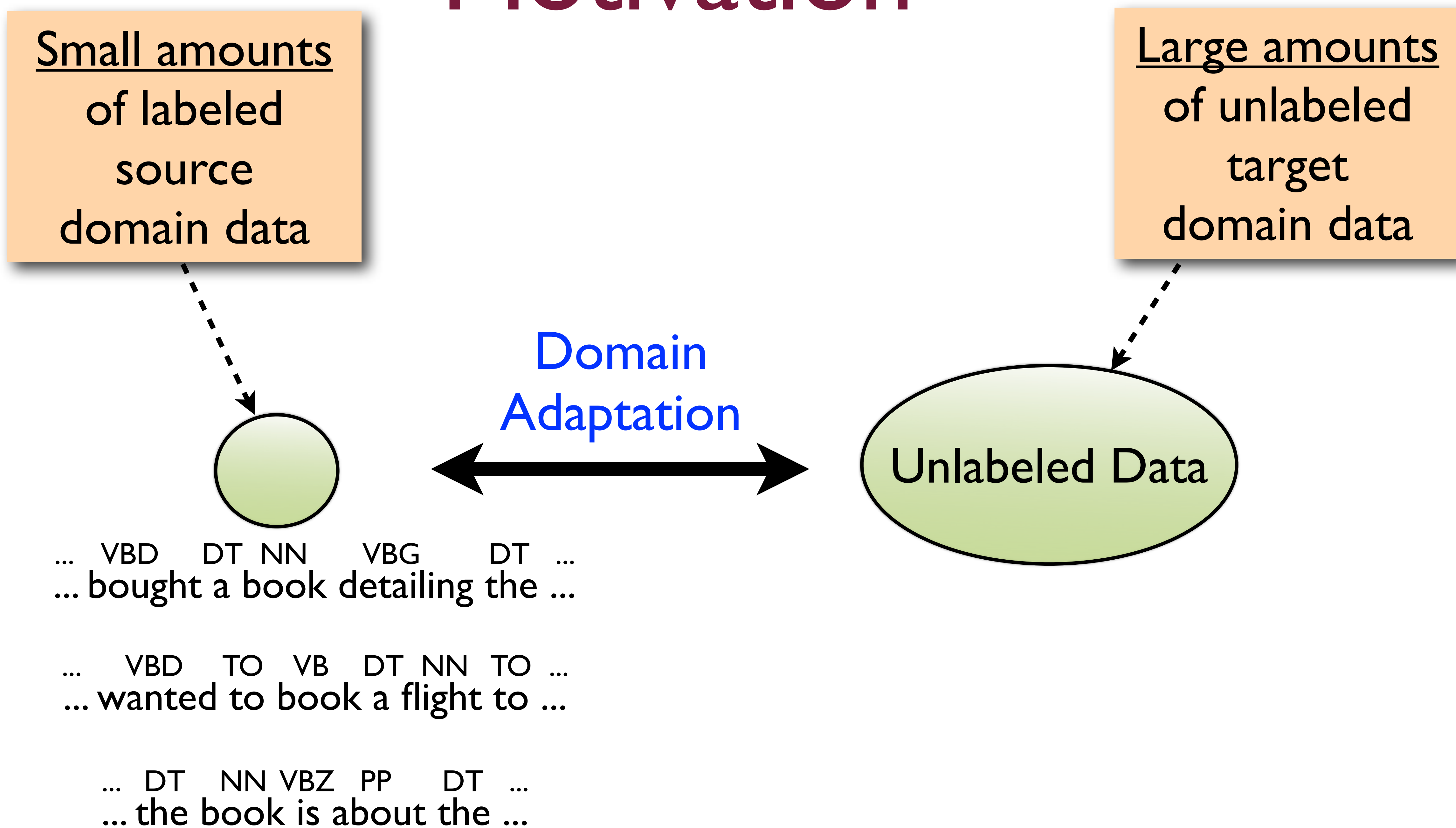
Motivation


Small amounts of labeled source domain data
Large amounts of unlabeled target domain data
Unlabeled Data

Motivation

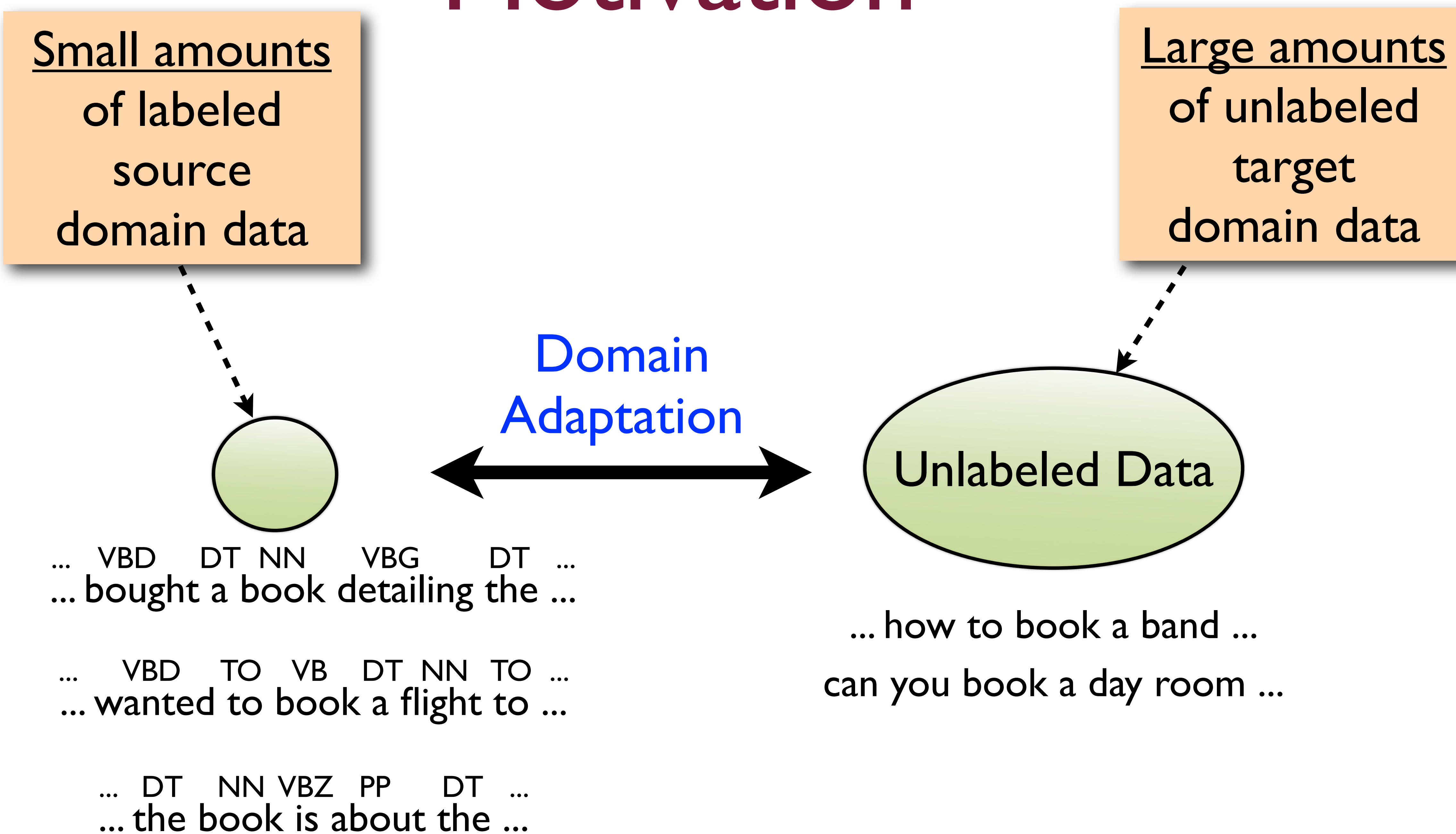

Small amounts of labeled source domain data
Large amounts of unlabeled target domain data
Domain Adaptation
Unlabeled Data

Motivation



Small amounts of labeled source domain data
Large amounts of unlabeled target domain data
Domain Adaptation
Unlabeled Data
... VBD DT NN VBG DT ...
... bought a book detailing the ...
... VBD TO VB DT NN TO ...
... wanted to book a flight to ...
... DT NN VBZ PP DT ...
... the book is about the ...

Motivation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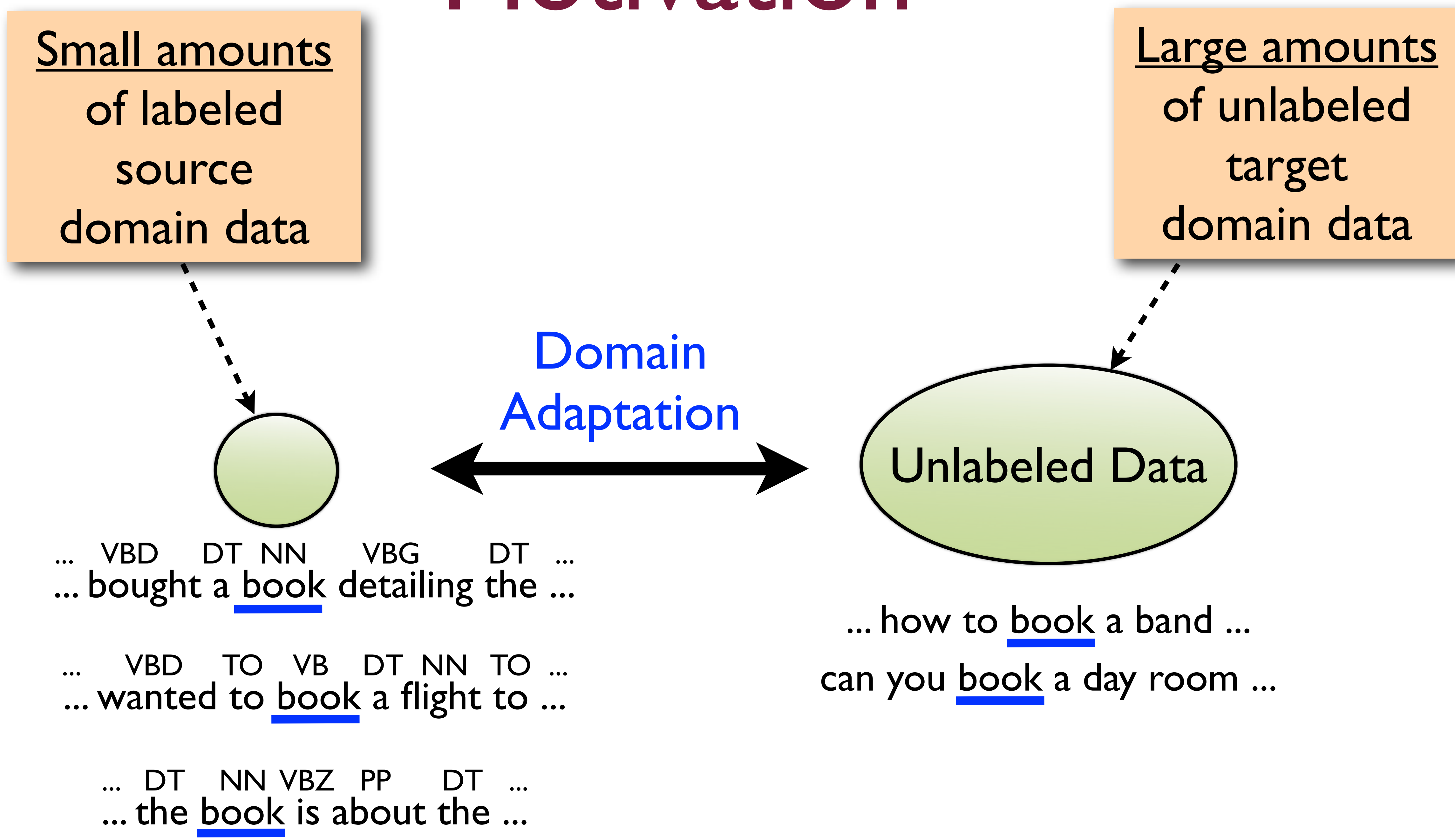
... the book is about the ...
... how to book a band ...
can you book a day room ...

Motivation



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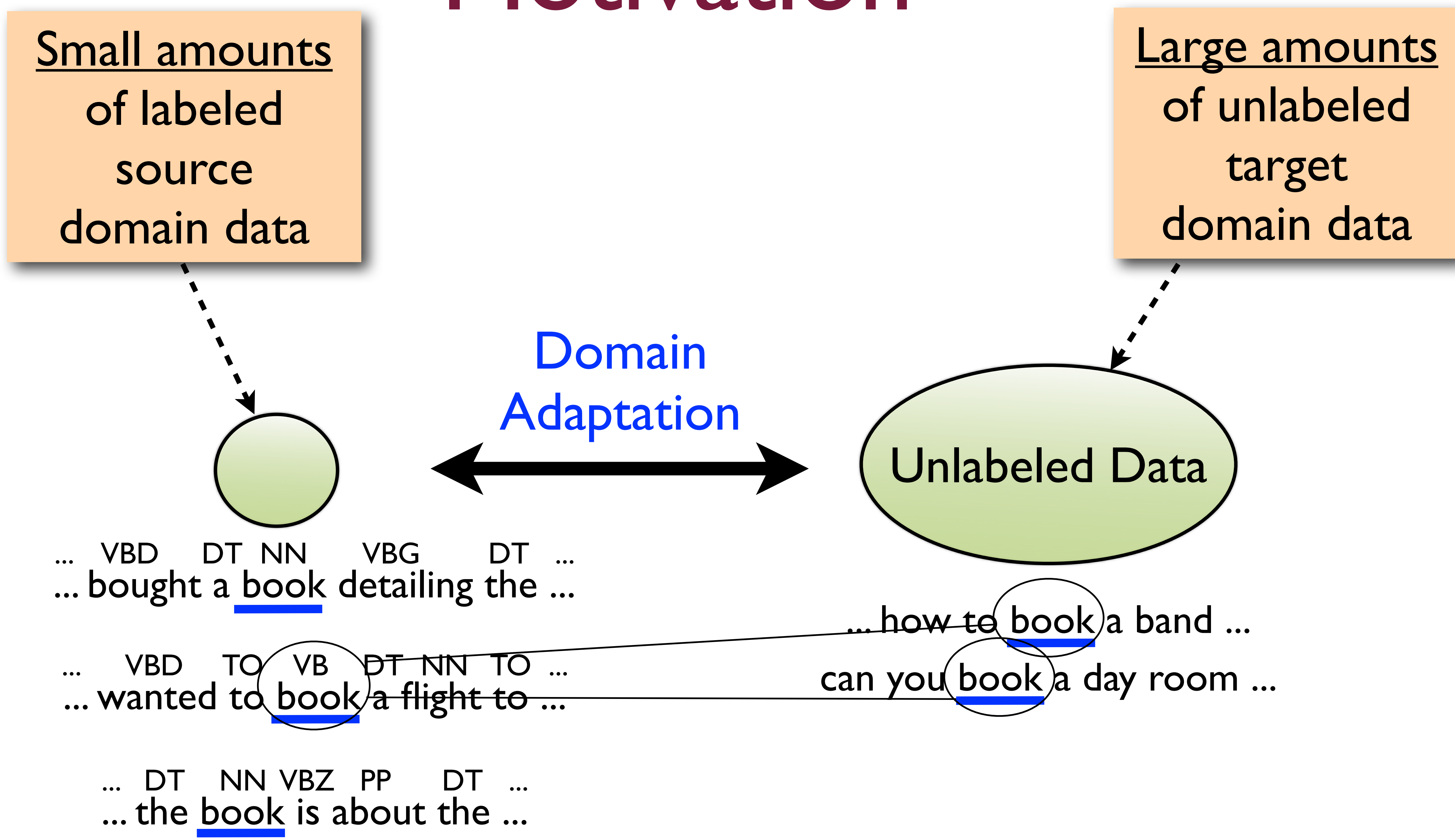

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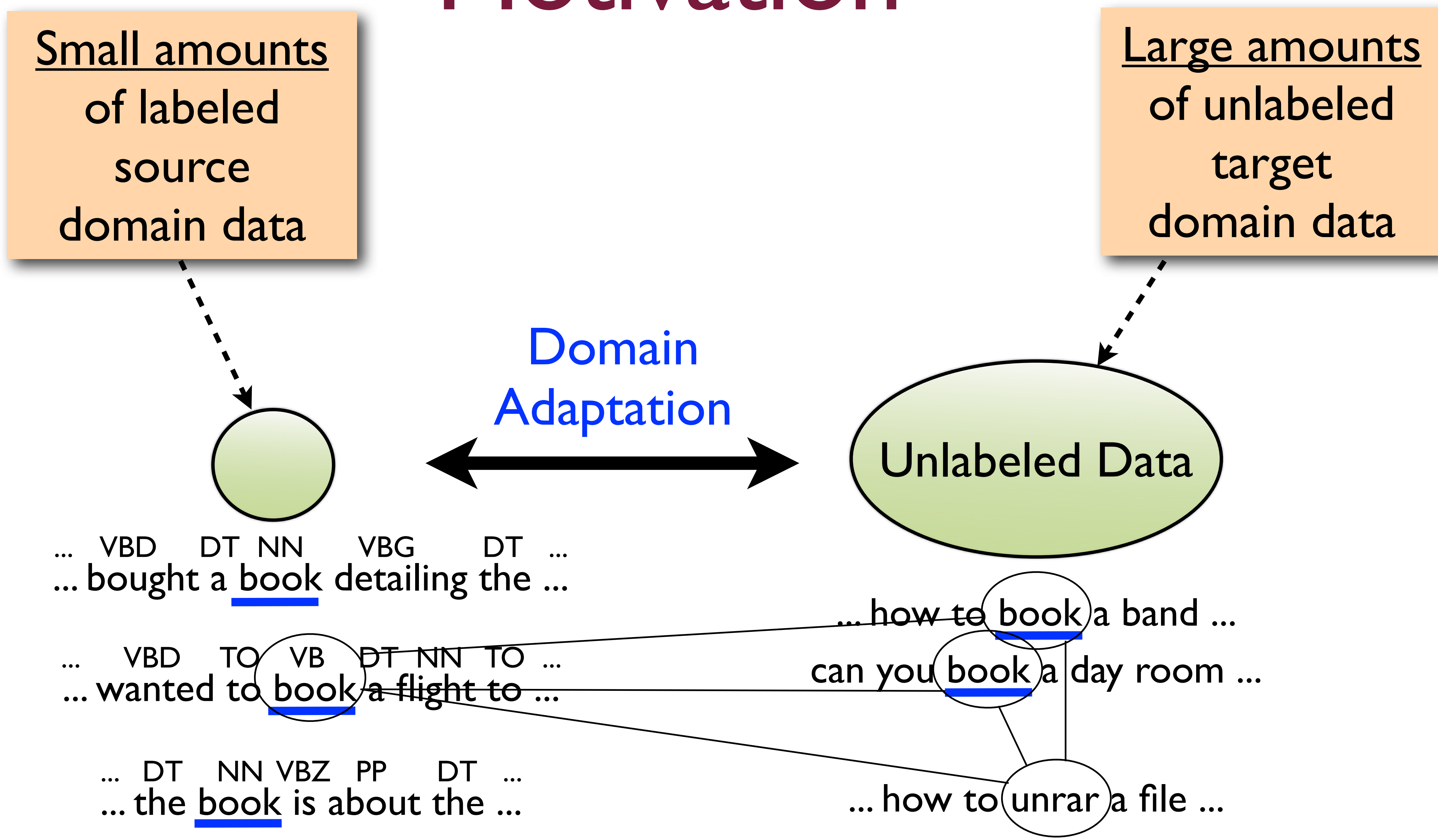

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domain data
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Domain
Adaptation
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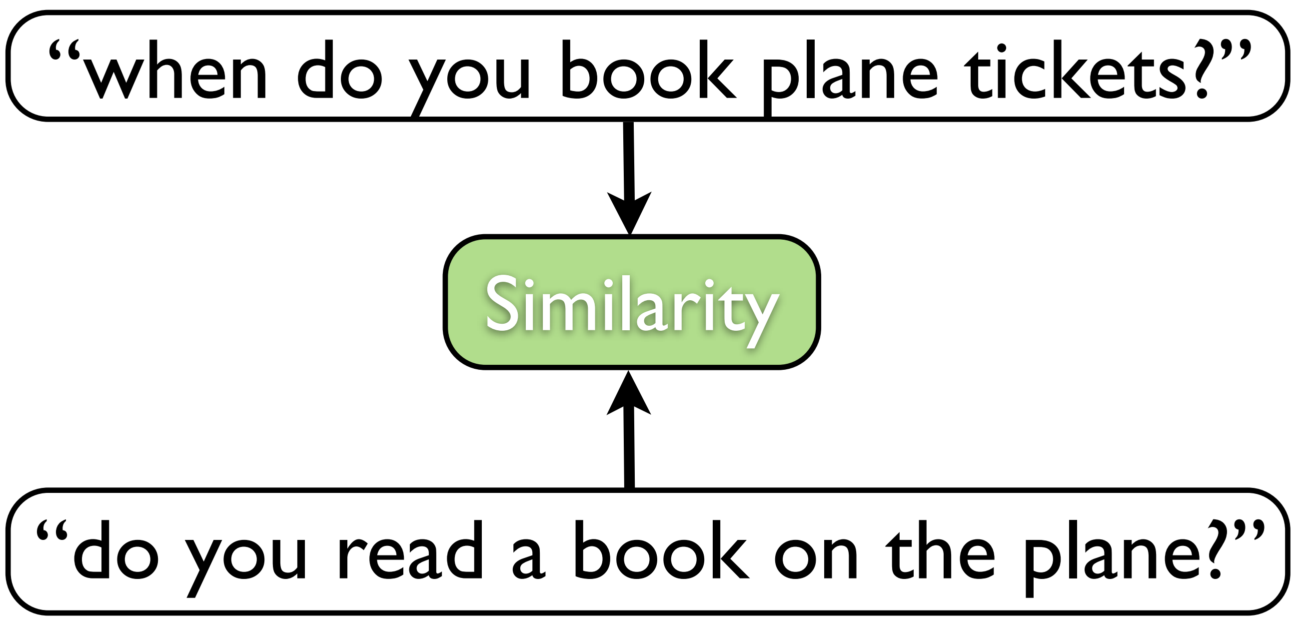
... wanted to book a flight to ...
... DT NN VBZ PP DT ...
... the book is about the ...
... how to book a band ...
can you book a day room ...
... how to unrar a file ...

Graph Construction (I)

“when do you book plane tickets?”

“do you read a book on the plane?”

Graph Construction (I)



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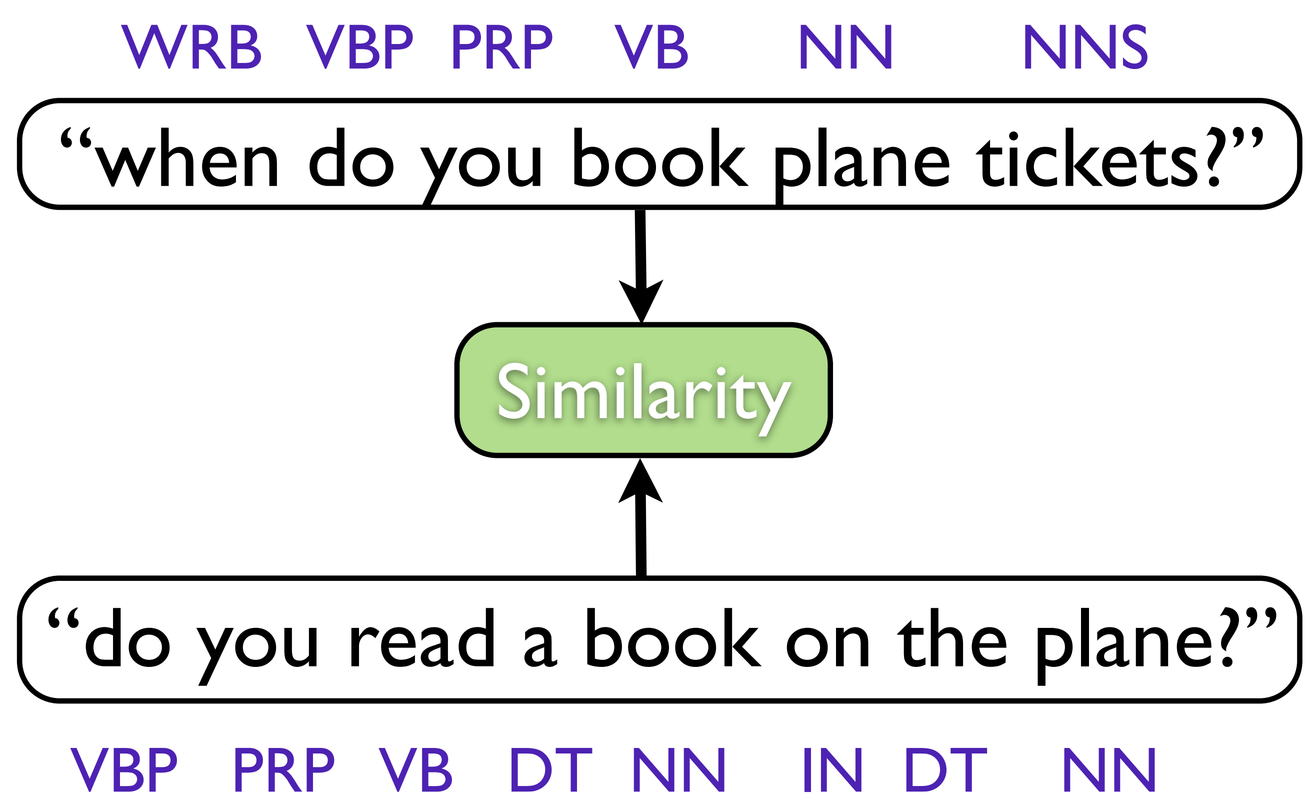

Graph Construction (II)

can you book a day room at hilton hawaiian village ?

what was the book that has no letter e ?

how much does it cost to book a band ?

how to get a book agent ?

Graph Construction (II)

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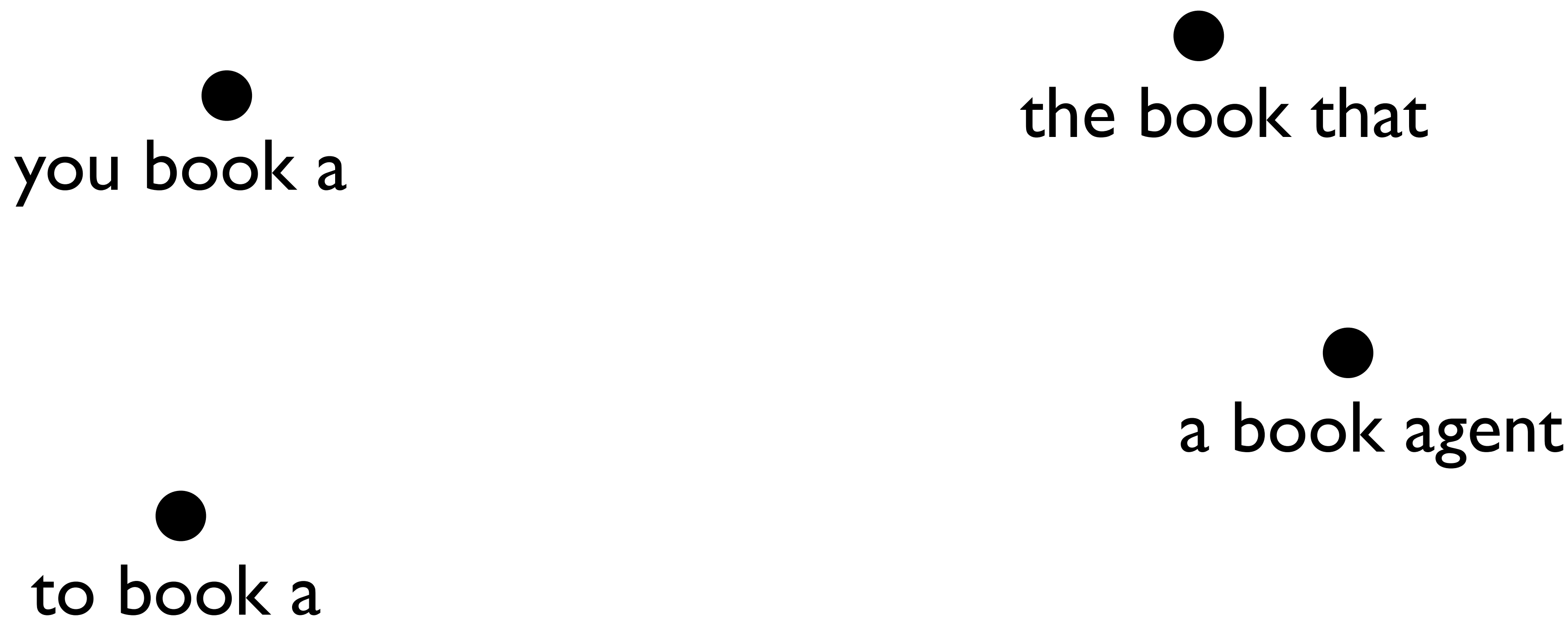

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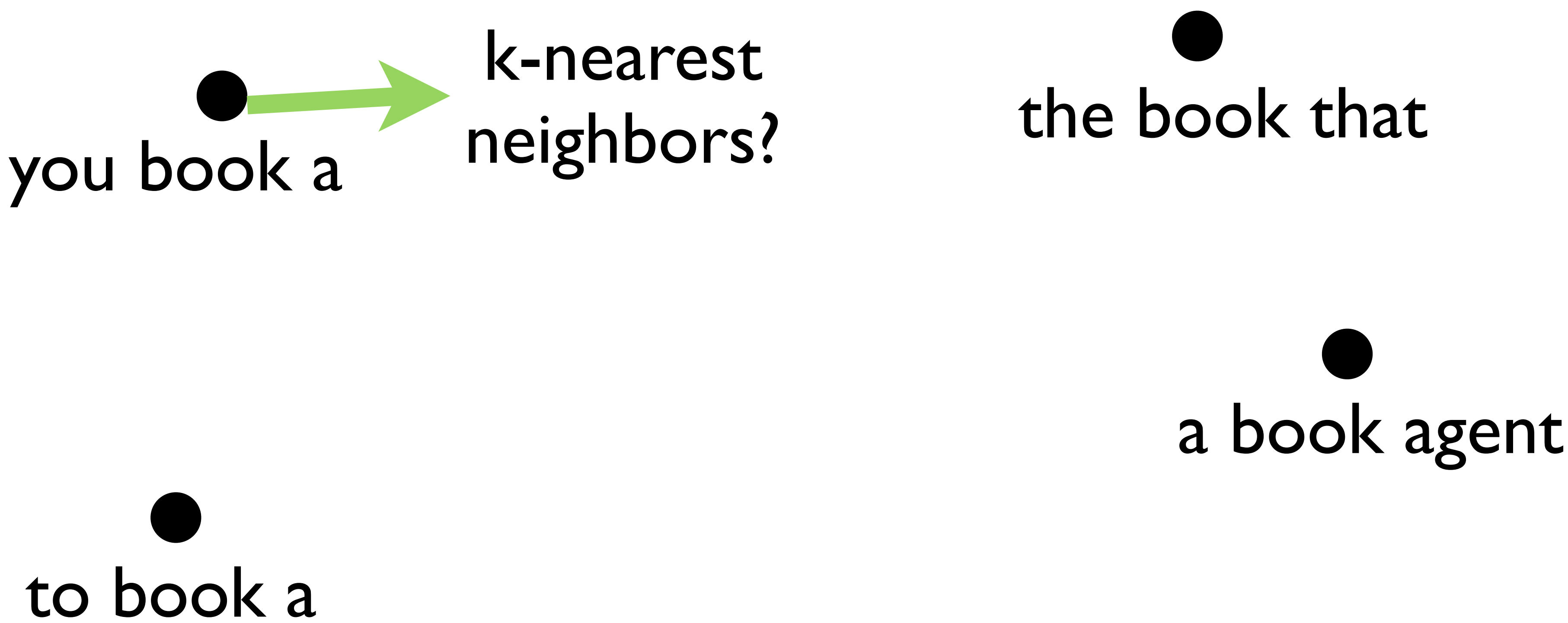
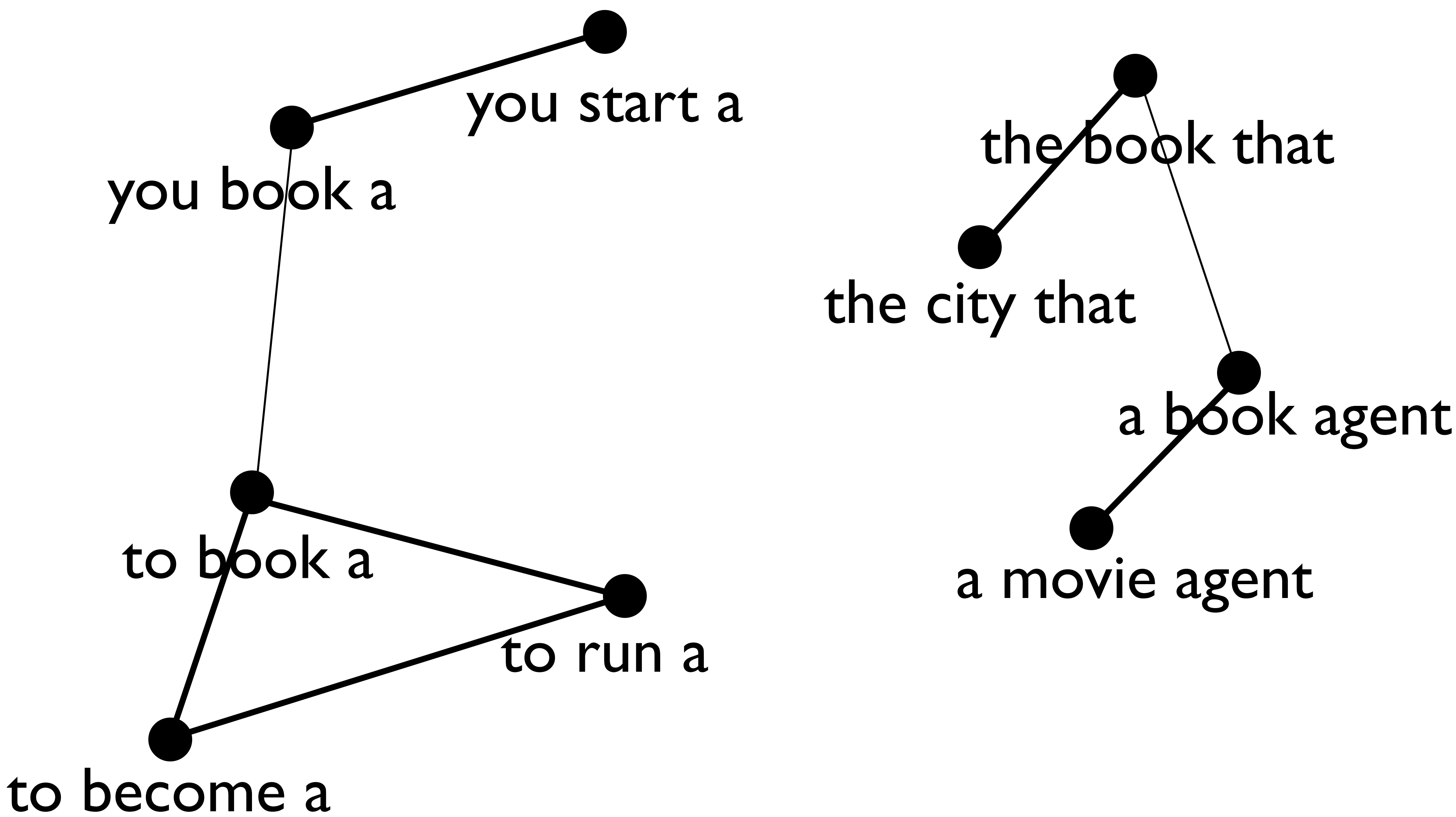
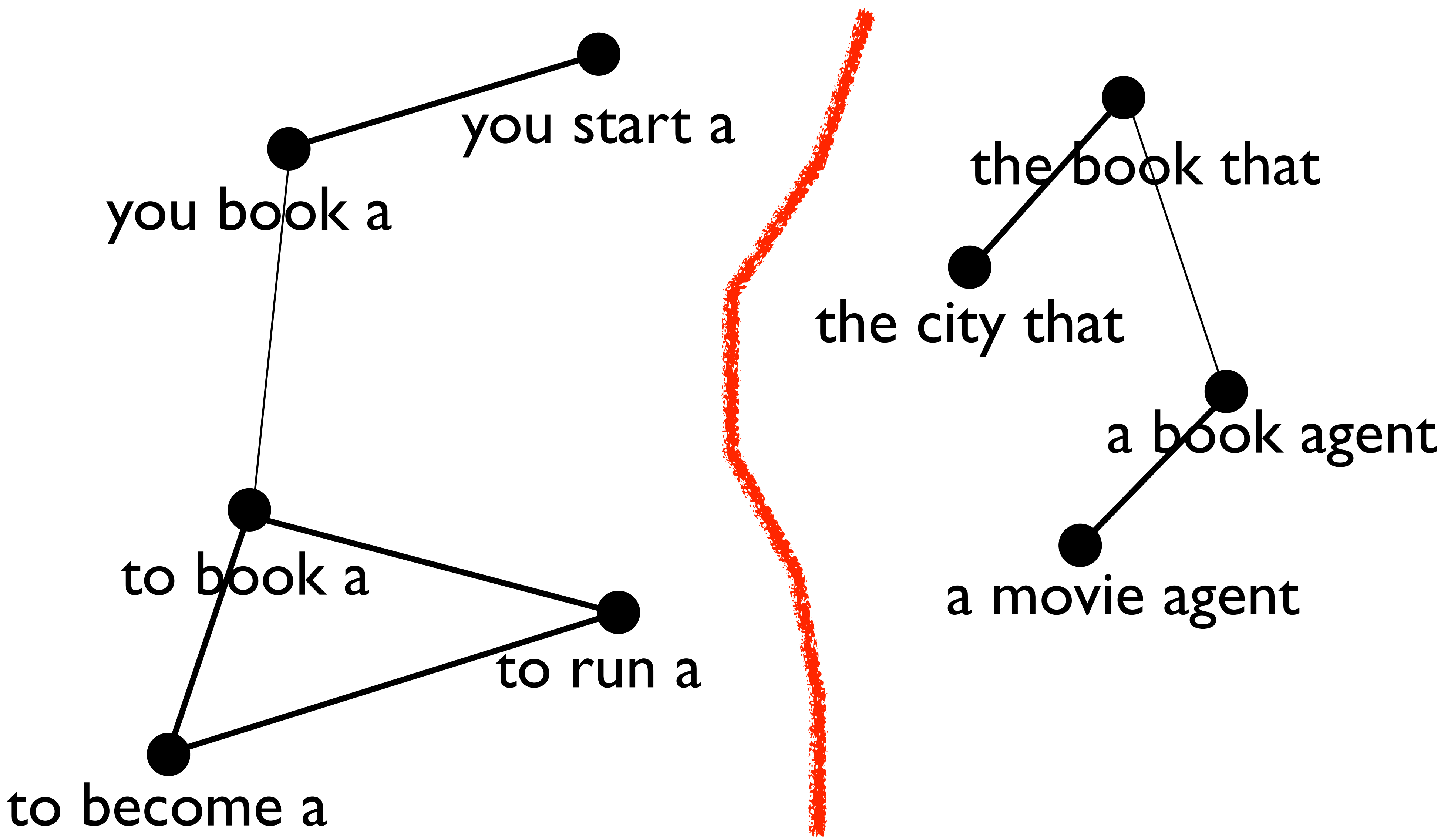


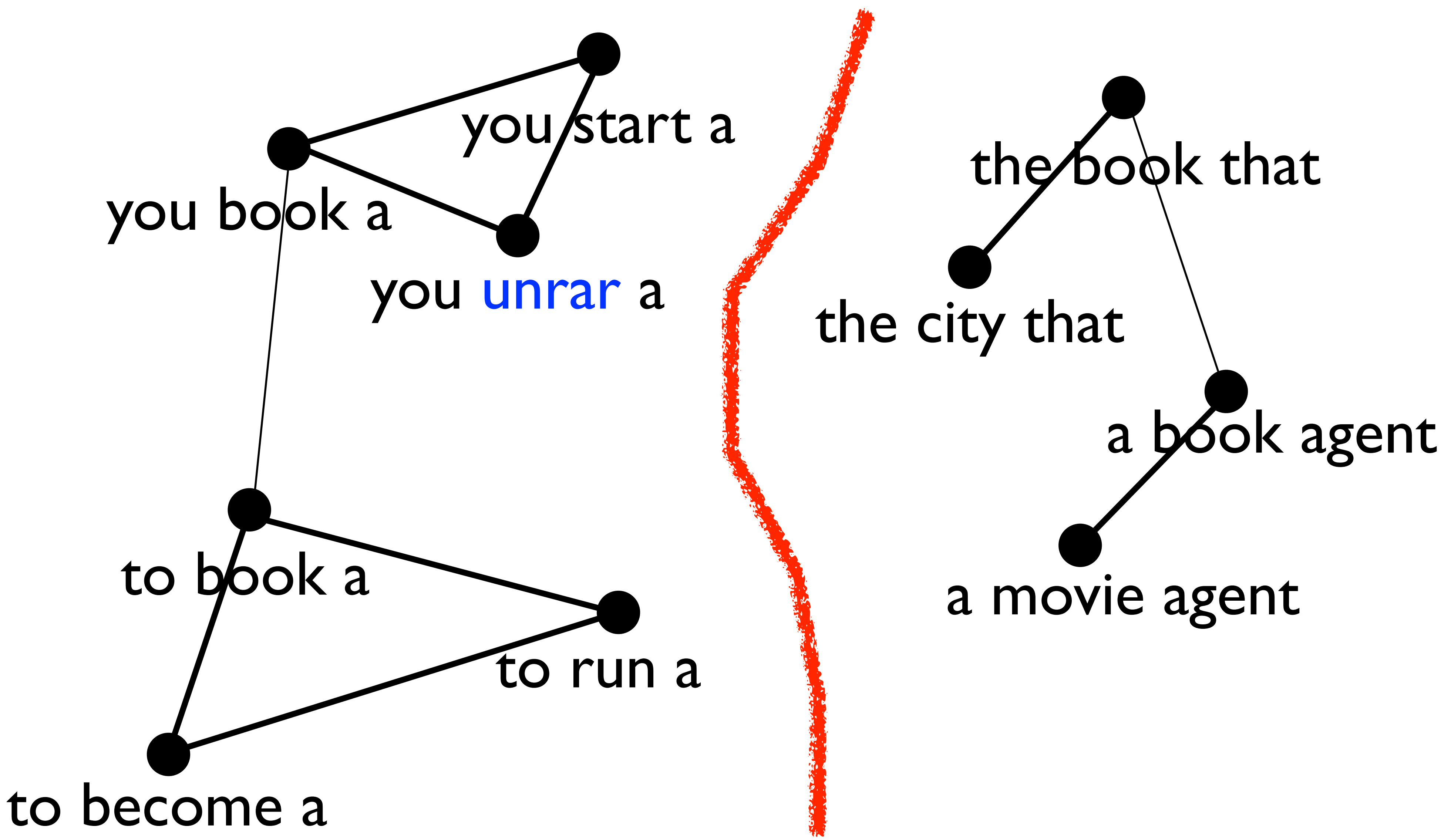
Graph Construction (III)



Graph Construction (III)



Graph Construction (III)



Graph Construction - Features

how much does it cost to book a band ?

Graph Construction - Features

how much does it cost to book a band ?

Graph Construction - Features

how much does it cost to book a band ?

Trigram + Context	cost to book a band

Graph Construction - Features

how much does it cost to book a band ?

Trigram + Context	cost to book a band
Left Context	cost to

Graph Construction - Features

how much does it cost to book a band ?

Trigram + Context	cost to book a band
Left Context	cost to
Right Context	a band

Graph Construction - Features

how much does it cost to book a band ?

Trigram + Context	cost to book a band
Left Context	cost to
Right Context	a band
Center Word	book

Graph Construction - Features

how much does it cost to book a band ?

Trigram + Context	cost to book a band
Left Context	cost to
Right Context	a band
Center Word	book
Trigram - Center Word	to _____ a
Left Word + Right Context	to _____ a band
Left Context + Right Word	cost to _____ a
Suffix	none

Graph Construction - Features

how much to book a flight to paris?

how much does it cost to book a band ?

Graph Construction - Features

how much to book a flight to paris?

how much does it cost to book a band ?

Graph Construction - Features

how much to <u>book</u> a flight to paris?

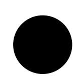
how much does it cost to <u>book</u> a band ?

Graph Construction - Features

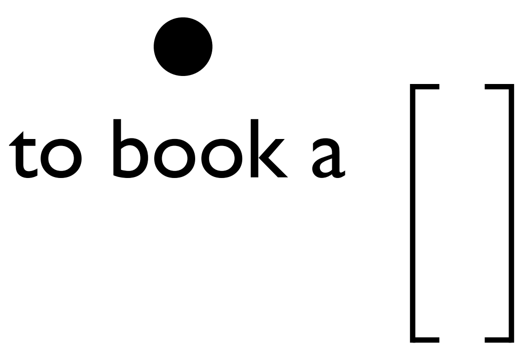
how much to book a flight to paris?

how much does it cost to book a band ?

Graph Construction - Features

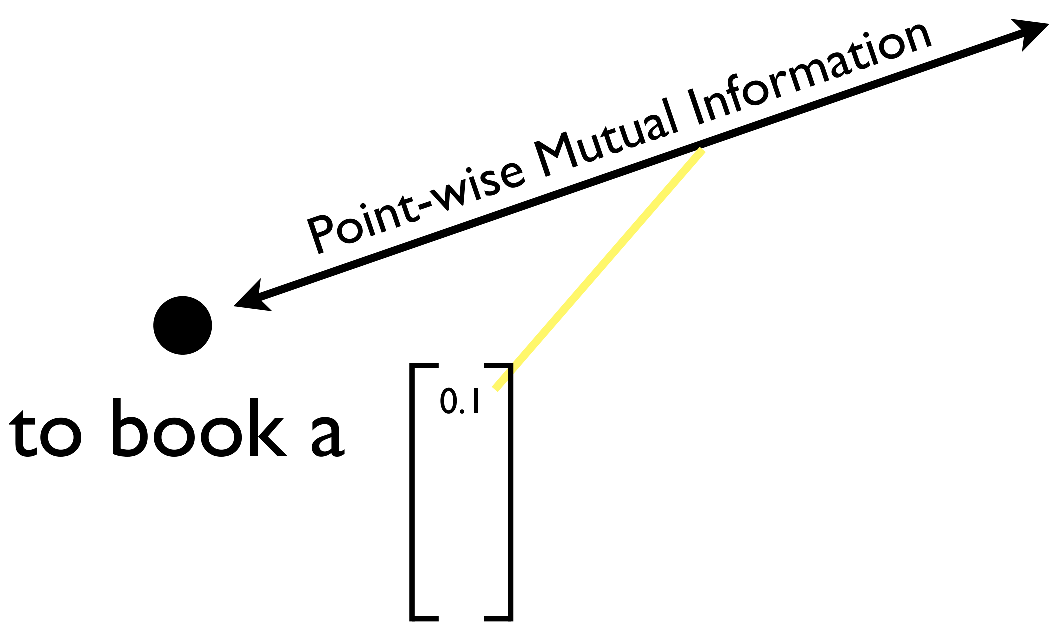


Graph Construction - Features



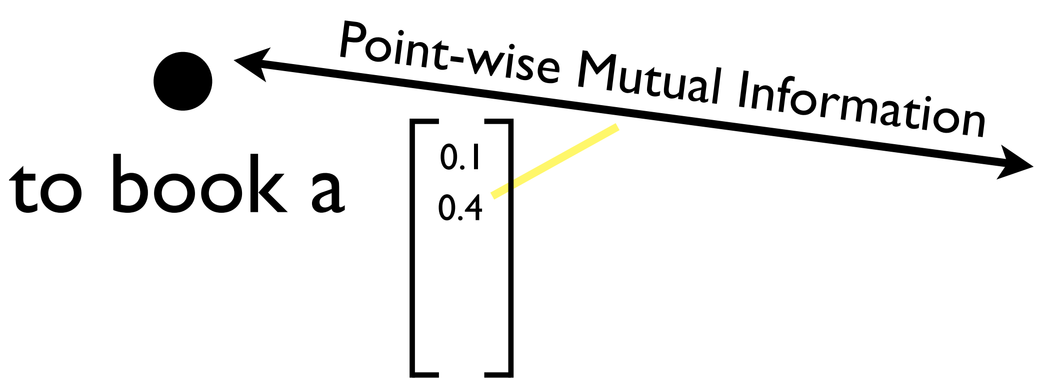
Trigram + Context
Left Context
Right Context
Center Word
Trigram - Center Word
Left Word + Right Context
Left Context + Right Word
Suffix

Graph Construction - Features



Trigram + Context
Left Context
Right Context
Center Word
Trigram - Center Word
Left Word + Right Context
Left Context + Right Word
Suffix

Graph Construction - Features



Trigram + Context
Left Context
Right Context
Center Word
Trigram - Center Word
Left Word + Right Context
Left Context + Right Word
Suffix

Graph Construction - Features

to book a $\begin{bmatrix} 0.1 \\ 0.4 \\ \vdots \end{bmatrix}$

Trigram + Context
Left Context
Right Context
Center Word
Trigram - Center Word
Left Word + Right Context
Left Context + Right Word
Suffix

Similarity Function

to book a $\begin{bmatrix} 0.1 \\ 0.4 \\ \cdot \\ \cdot \\ \cdot \end{bmatrix}$

Cosine Similarity (,) = 0.56

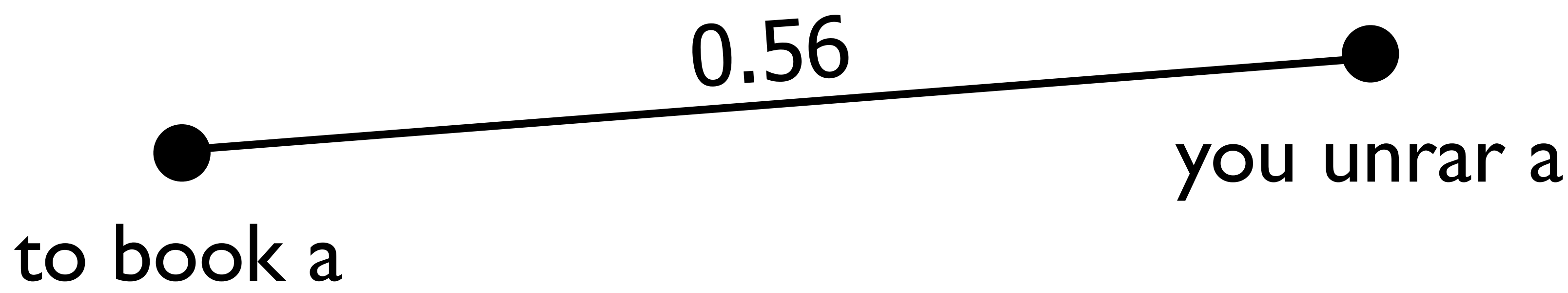
Similarity Function

you unrar a

to book a $\begin{bmatrix} 0.1 \\ 0.4 \\ \cdot \\ \cdot \\ \cdot \end{bmatrix}$

Cosine Similarity (,) = 0.56

Similarity Function



$$\text{Cosine Similarity}\left(\begin{bmatrix} 0.1 \\ 0.4 \\ \vdots \end{bmatrix} , \begin{bmatrix} 0.2 \\ 0.3 \\ \vdots \end{bmatrix} \right) = 0.56$$

Approach (I)

1. Train a CRF on labeled data
2. While not converged do:
   2.1. Posterior decode **unlabeled data** using CRF

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CRF

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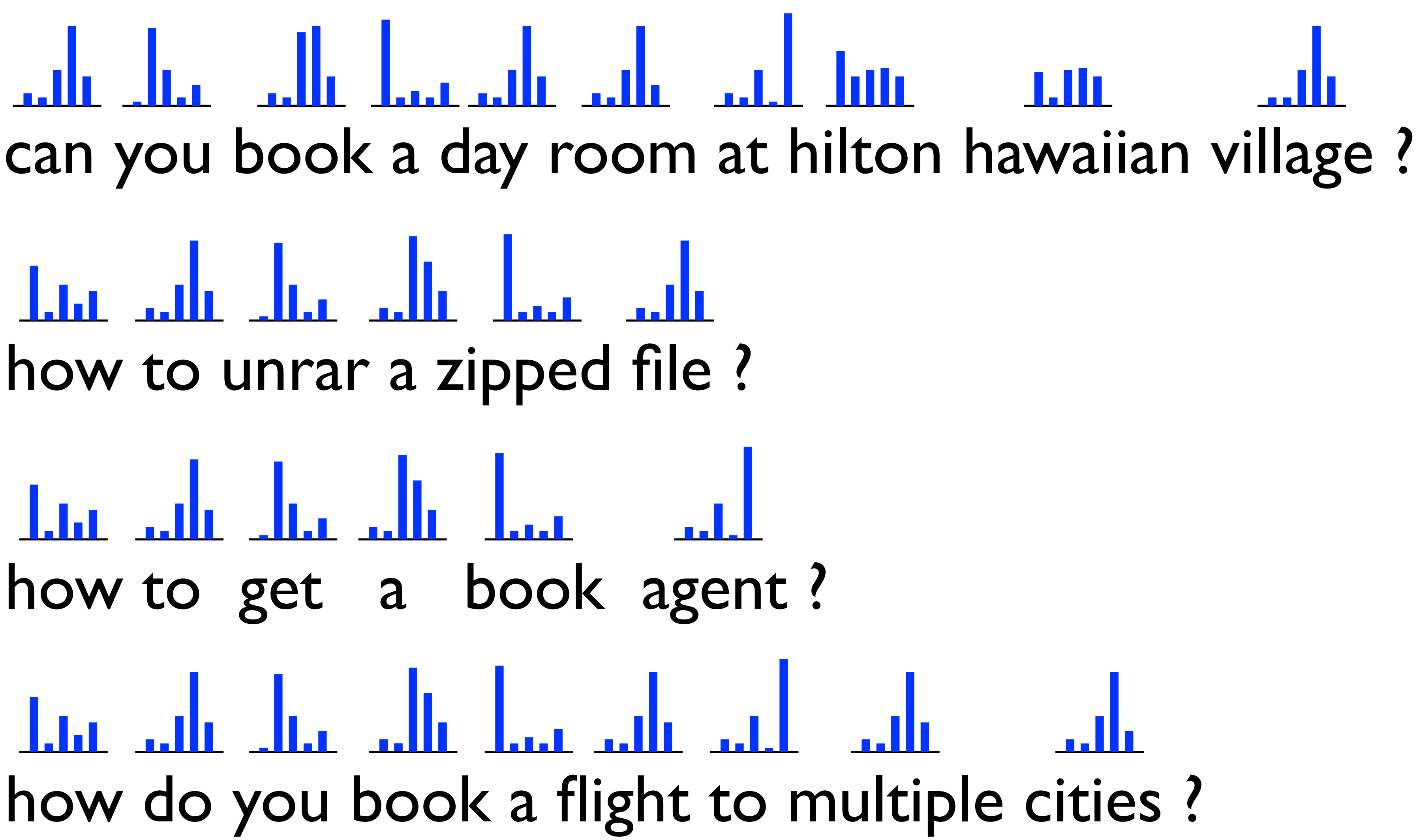

Approach (II)

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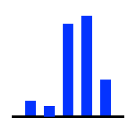

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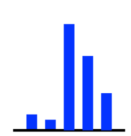

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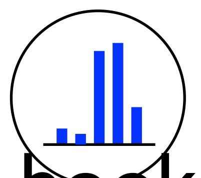

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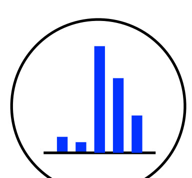
- you book a



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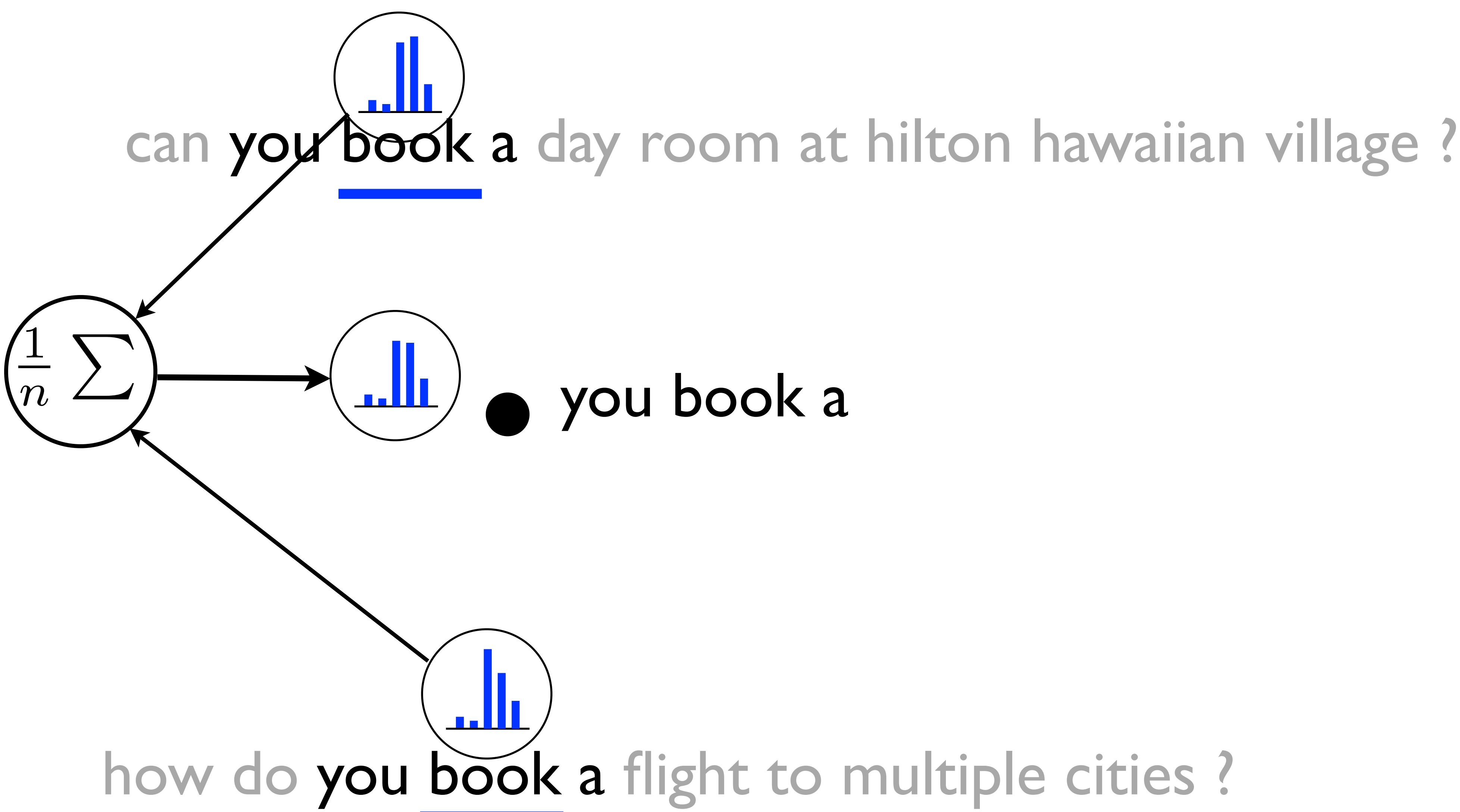

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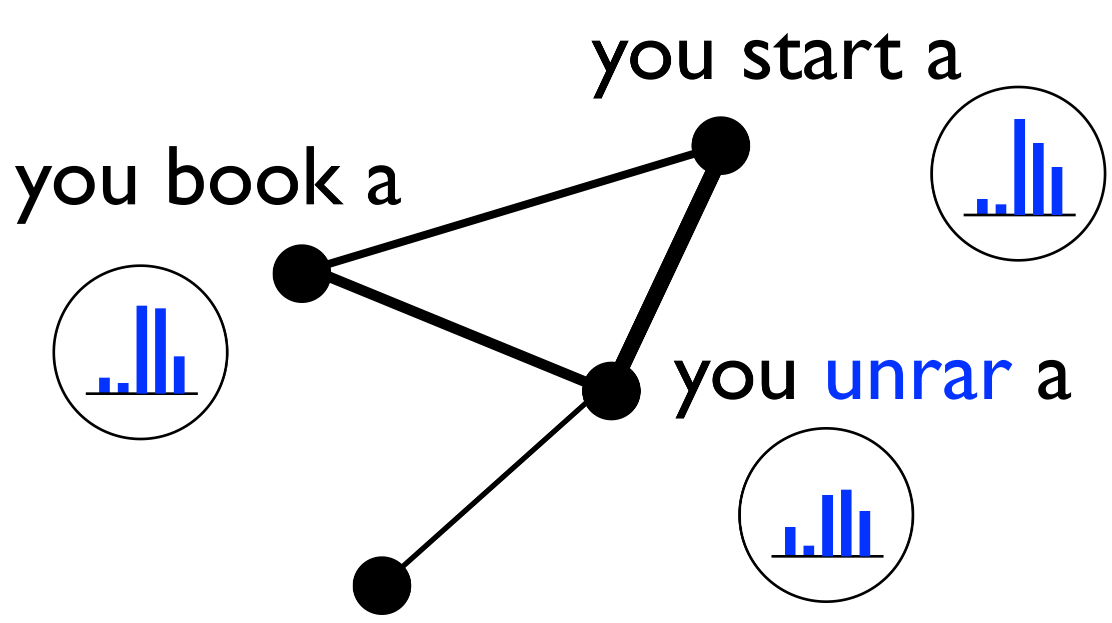

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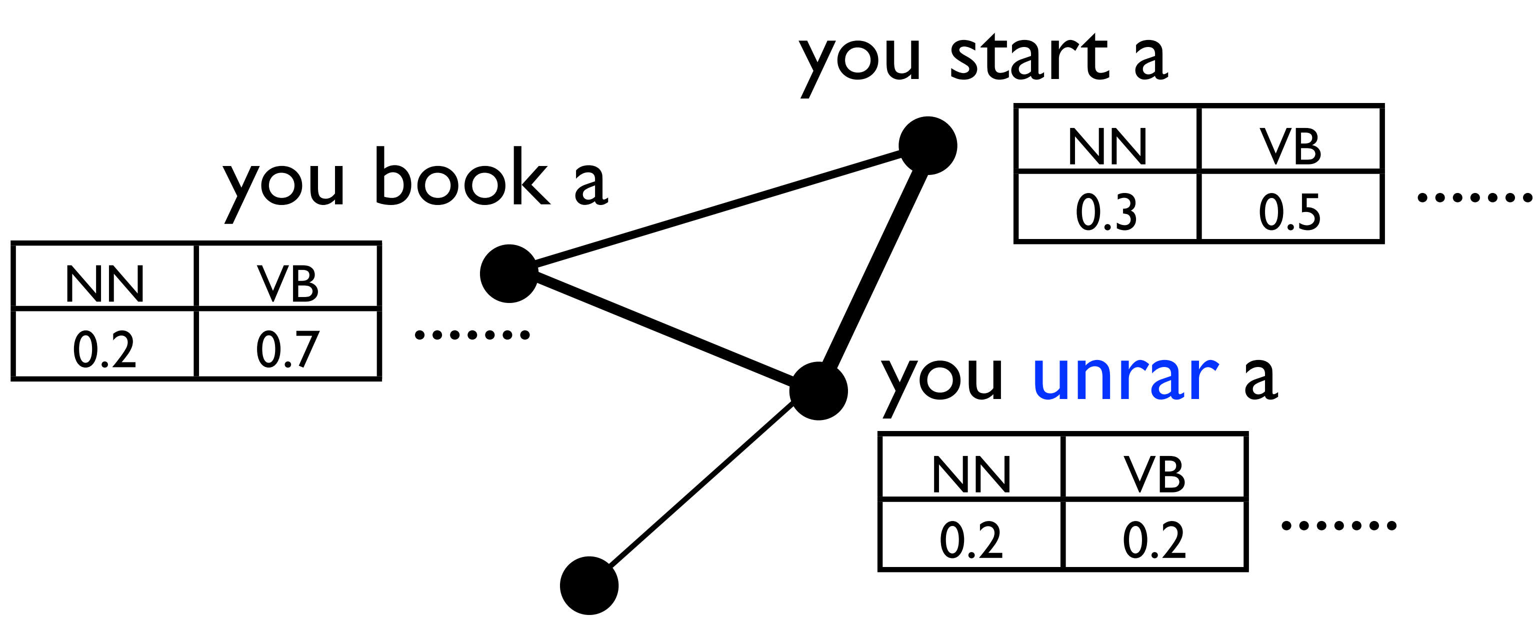

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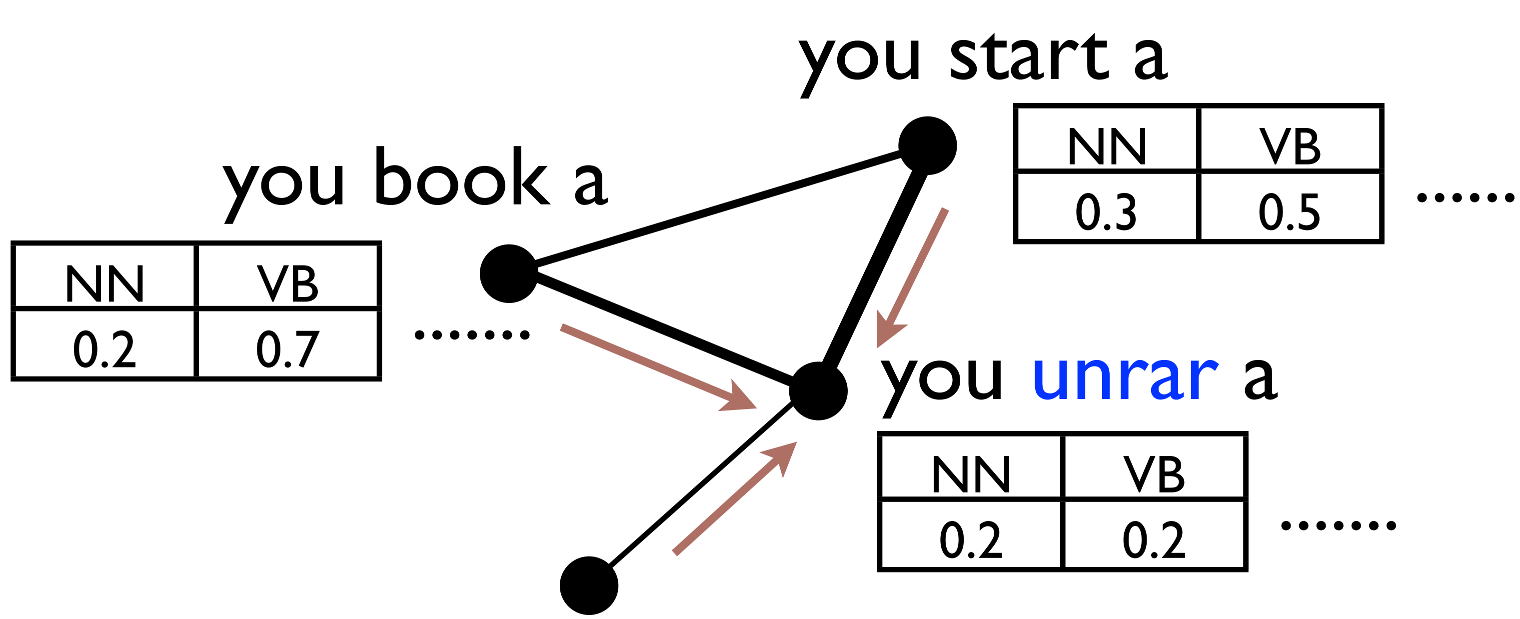

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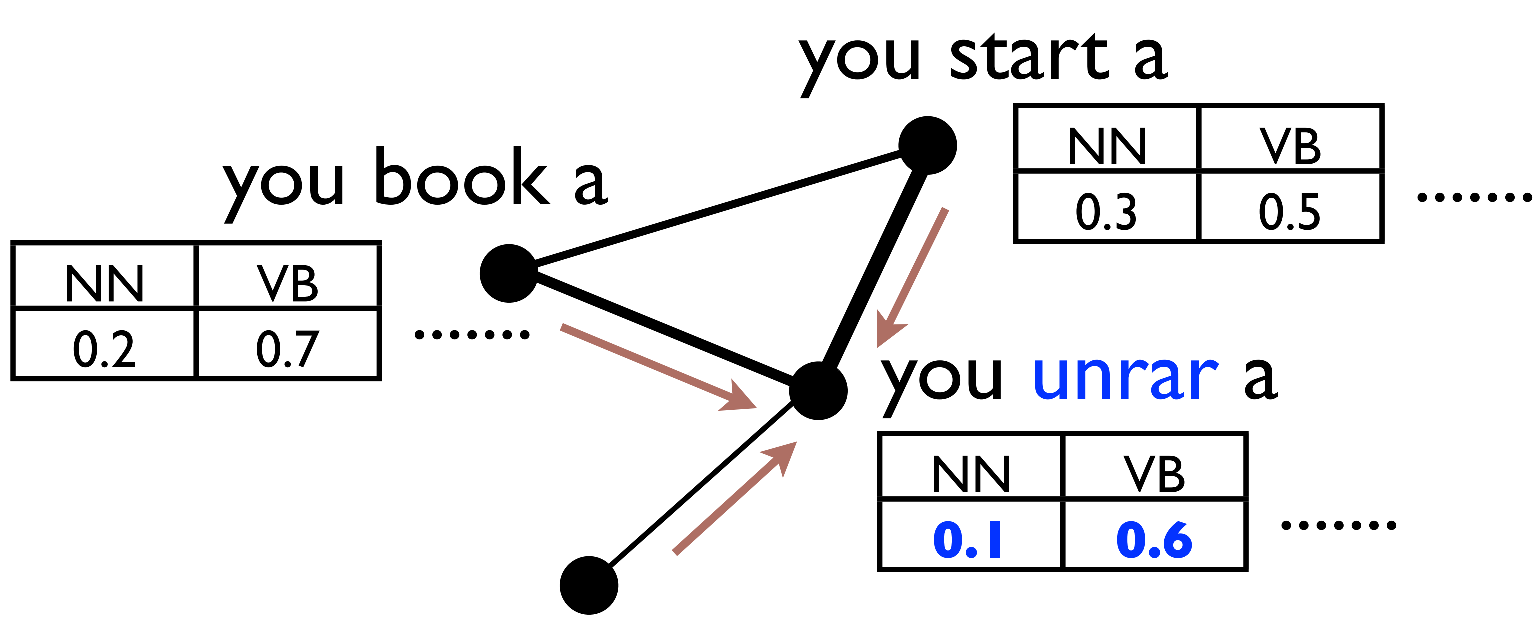

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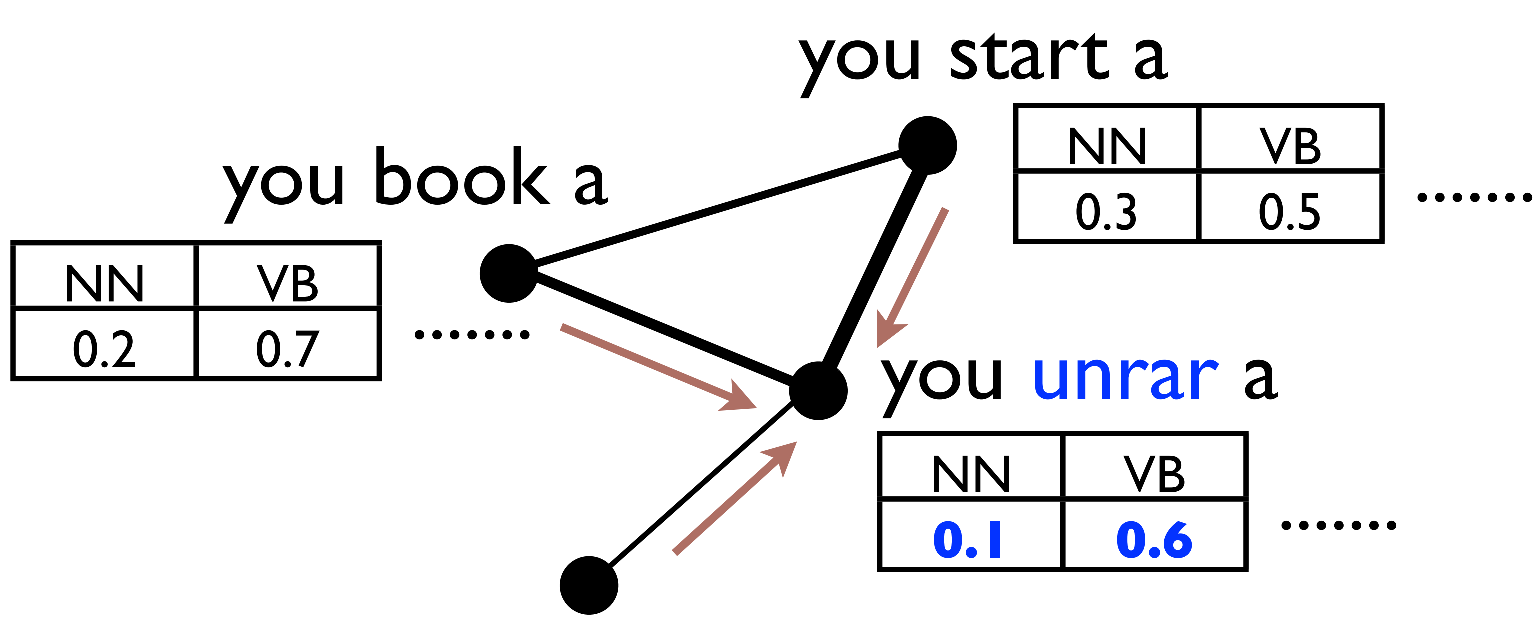

If two n-grams are similar according to the graph then their output distributions should be similar

Approach (IV)

1. Train a CRF on labeled data
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   2.4. Viterbi Decode

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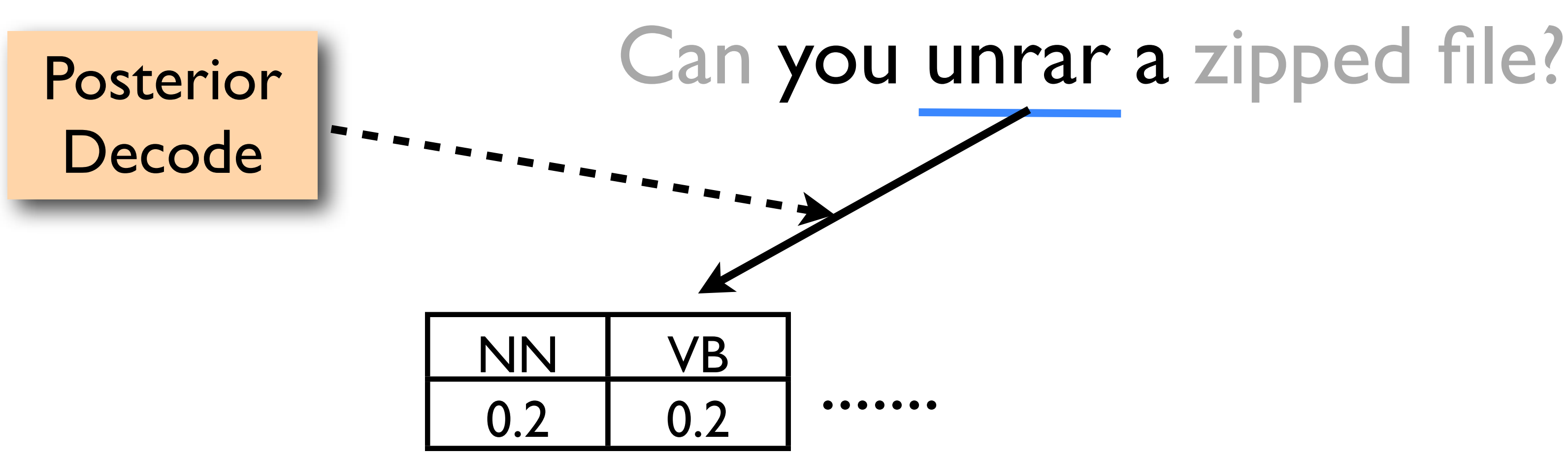

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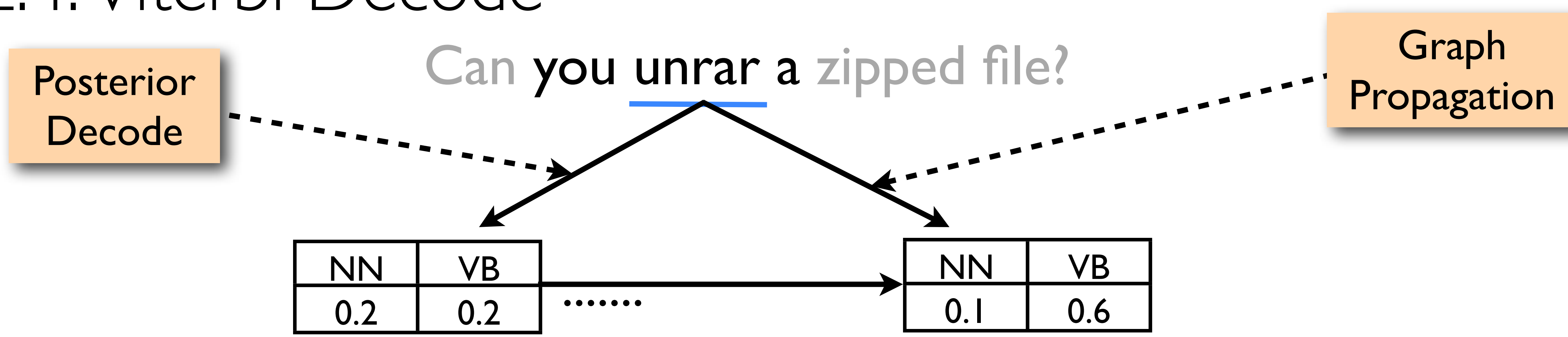

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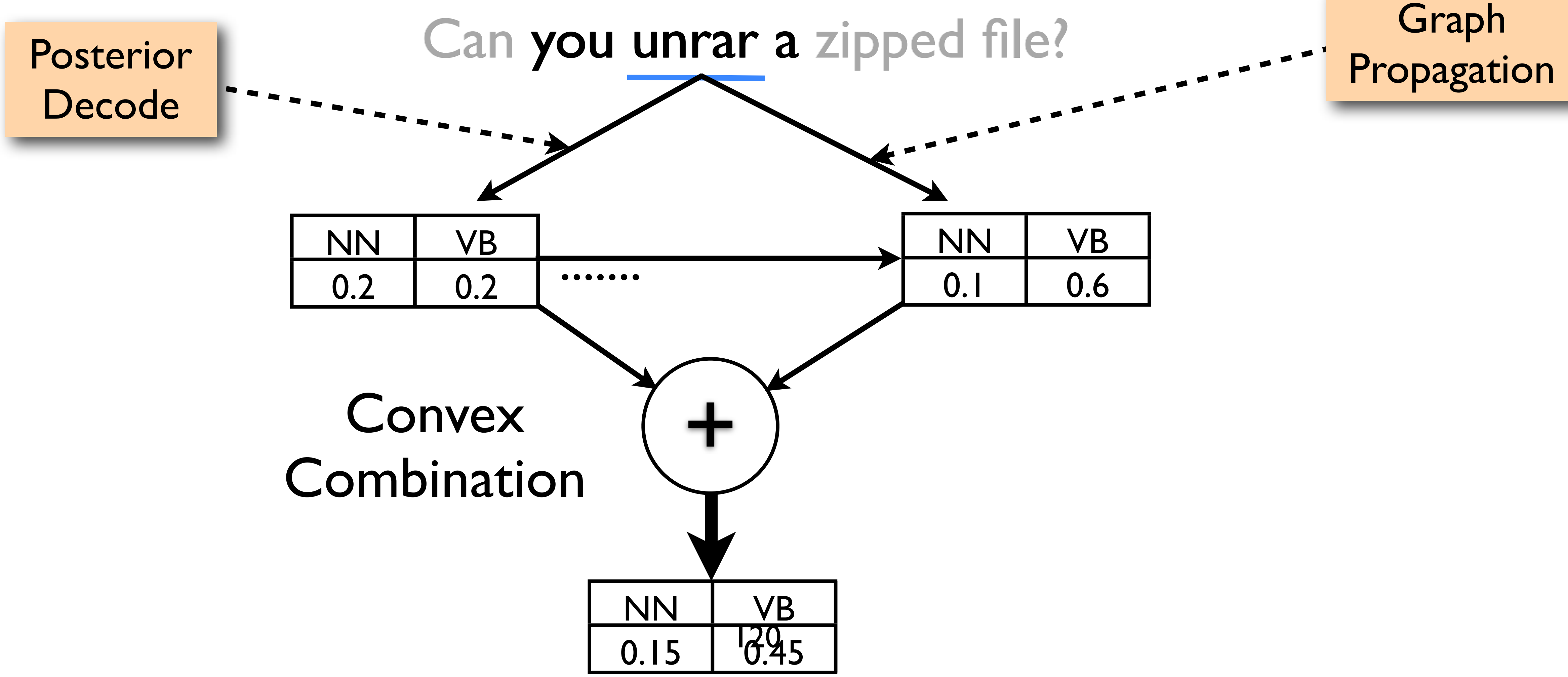

Approach (V)

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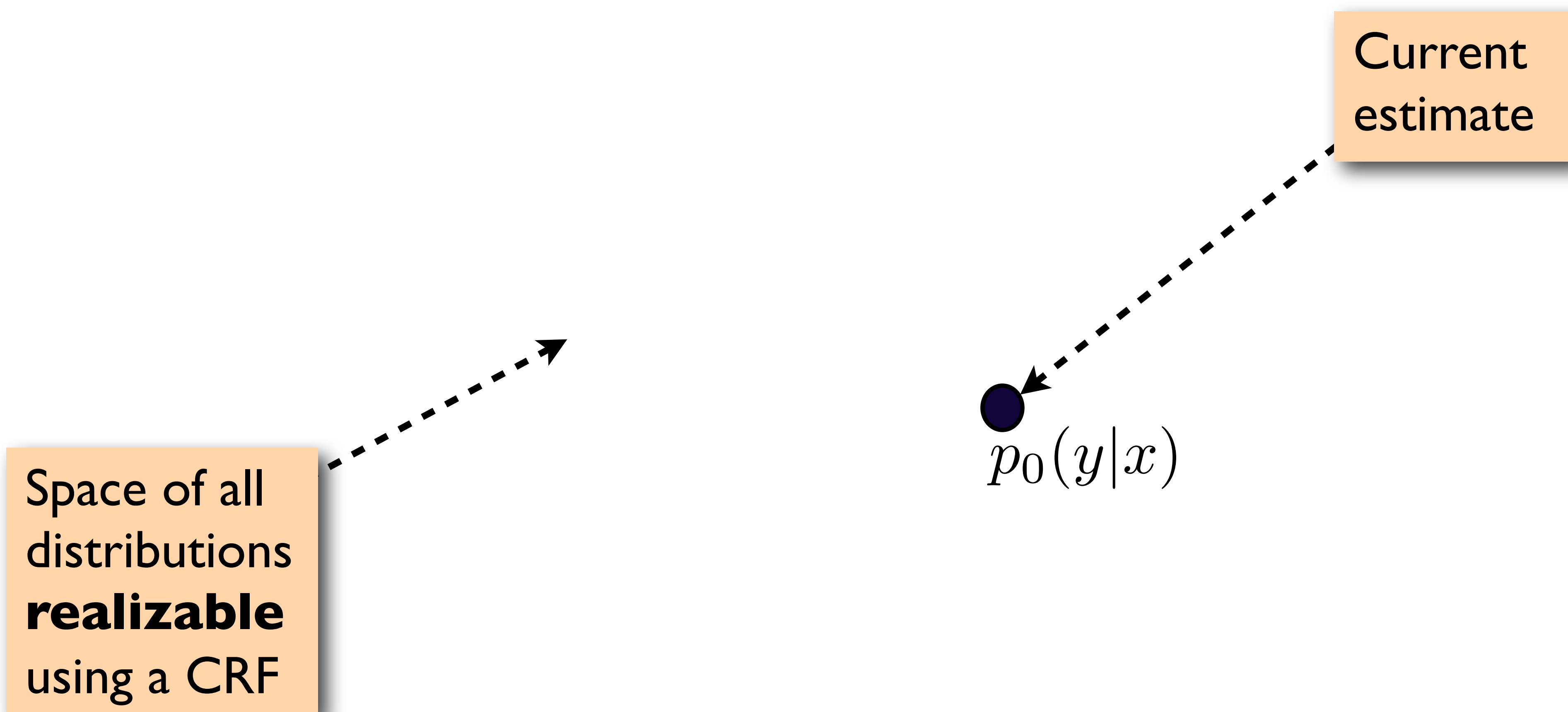
   2.4. Viterbi Decode
   2.5. Retrain CRF on labeled & **automatically labeled** unlabeled data

Viterbi Decoding : Intuition



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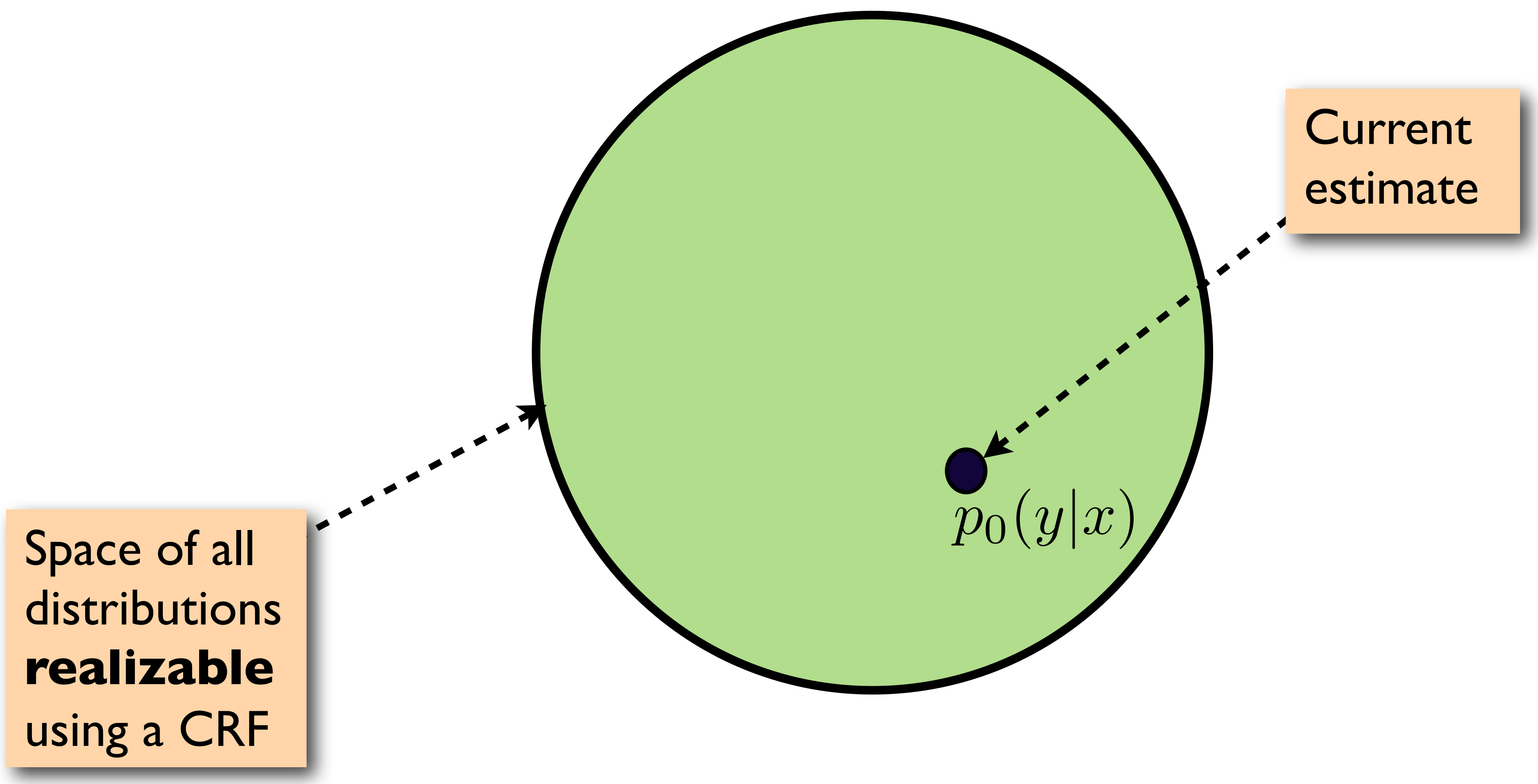

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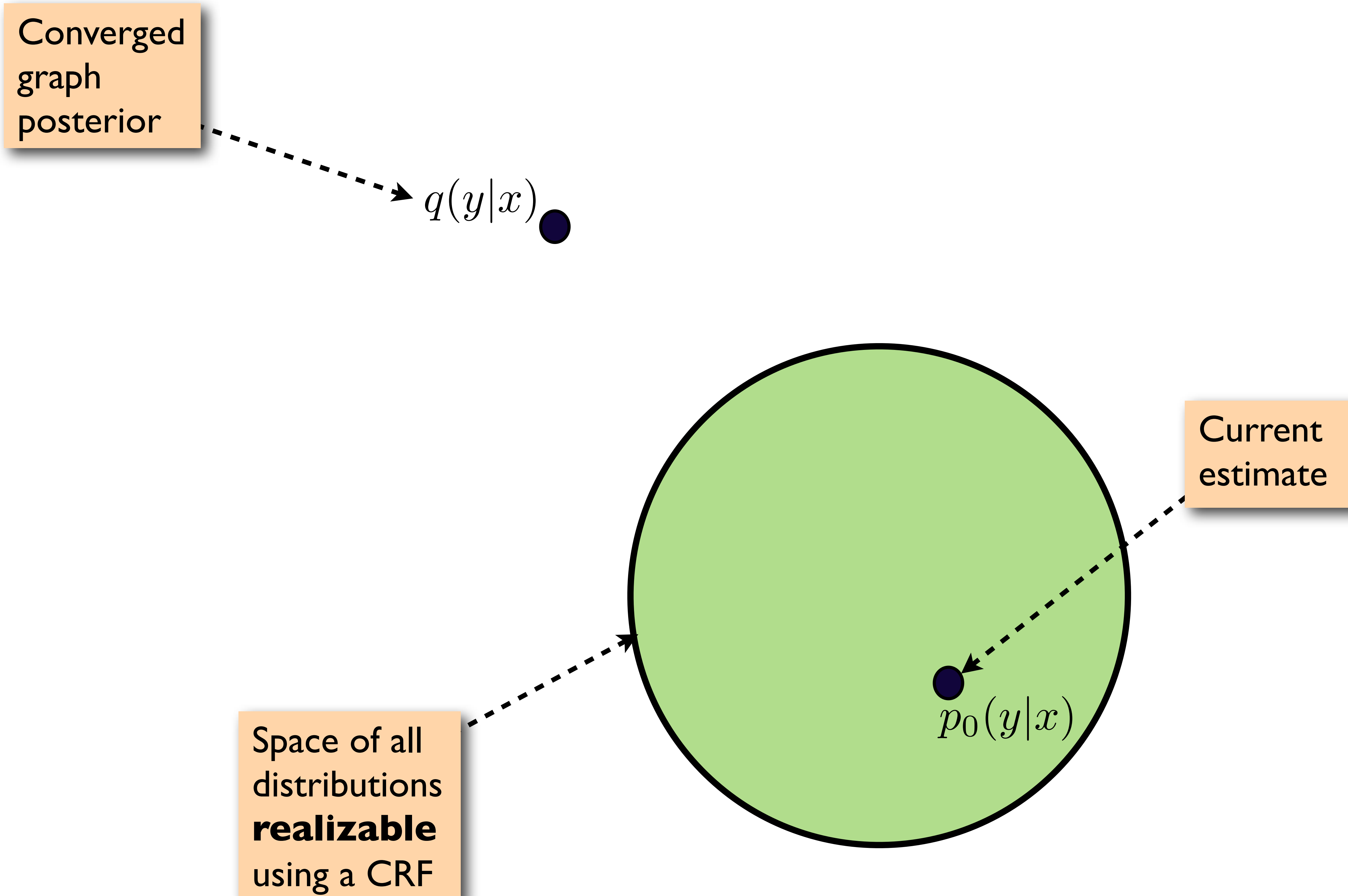

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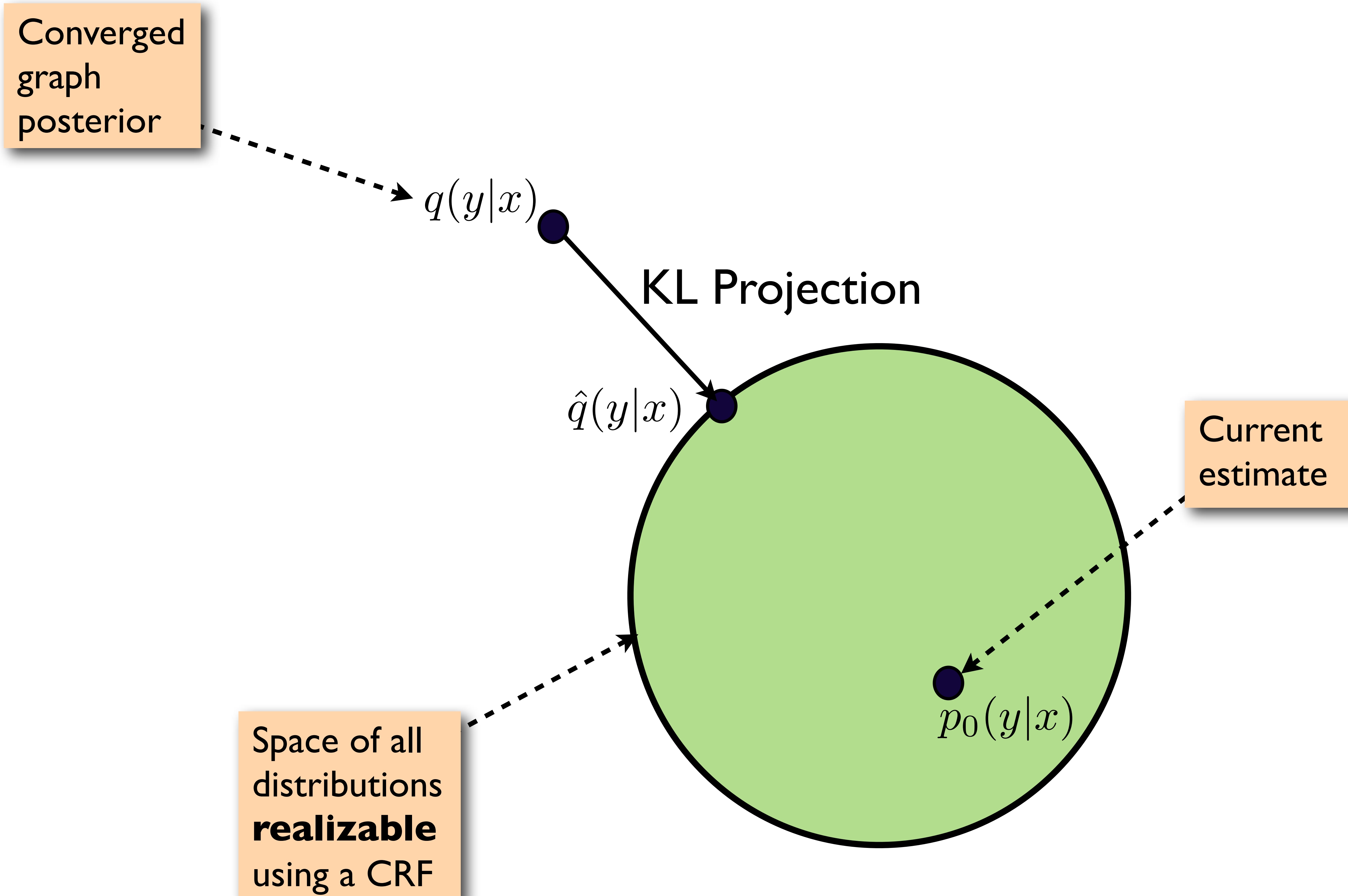

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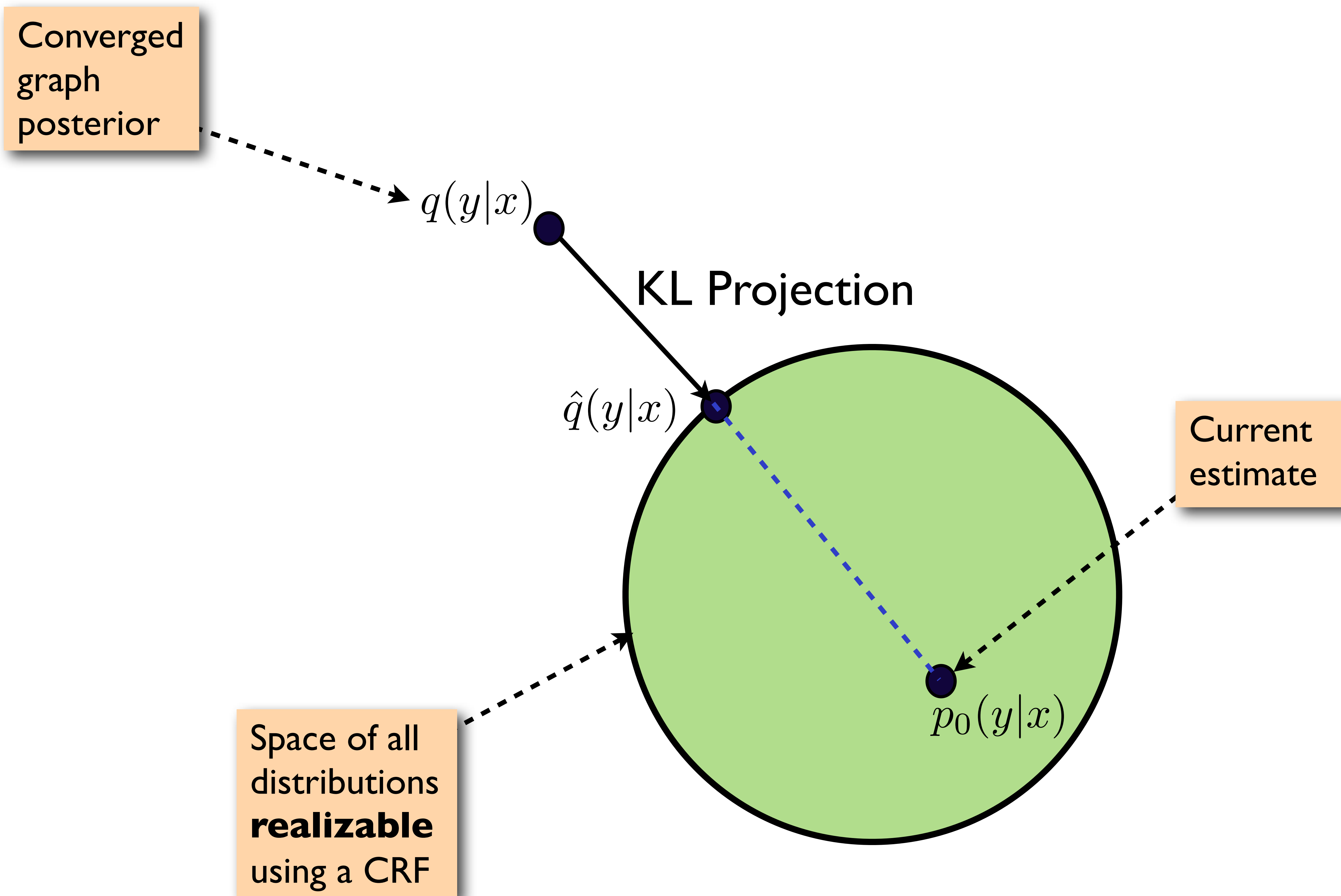

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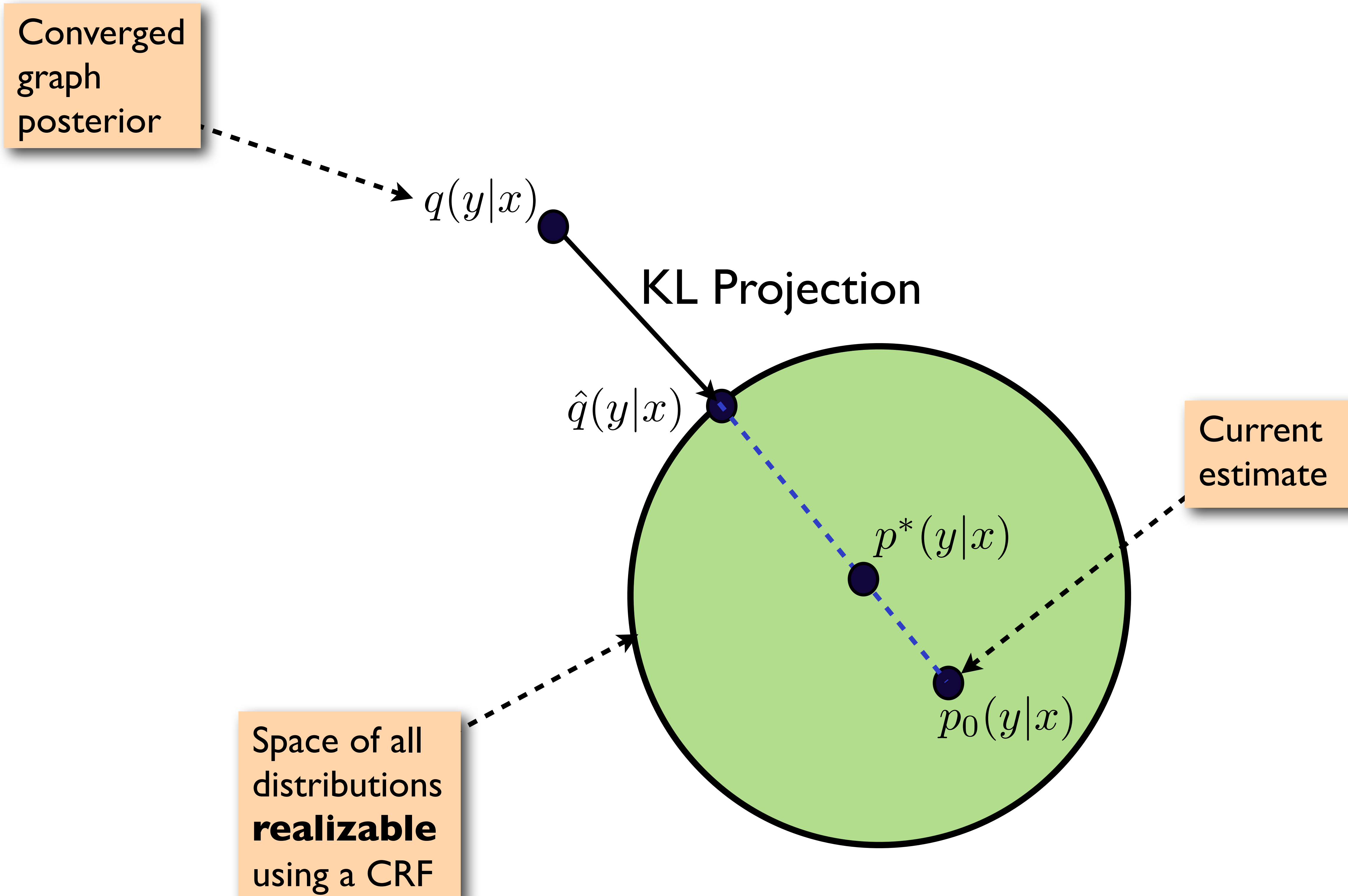

Corpora

- Source Domain (labeled): Wall Street Journal (WSJ) section of the Penn Treebank.
- Target Domain:
  - QuestionBank: 4000 labeled sentences
  - Penn BioTreebank: 1061 labeled sentences

Graph Construction: Question Bank

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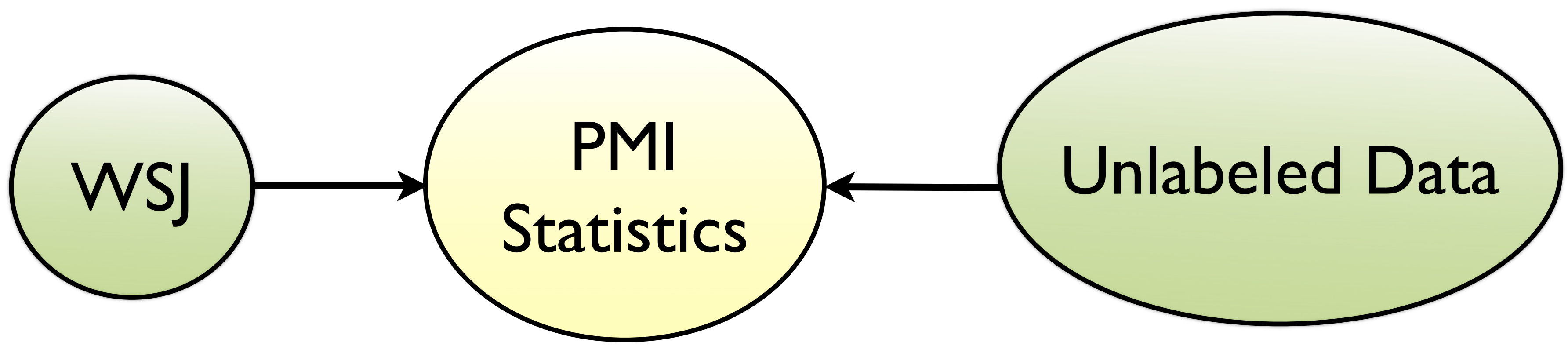

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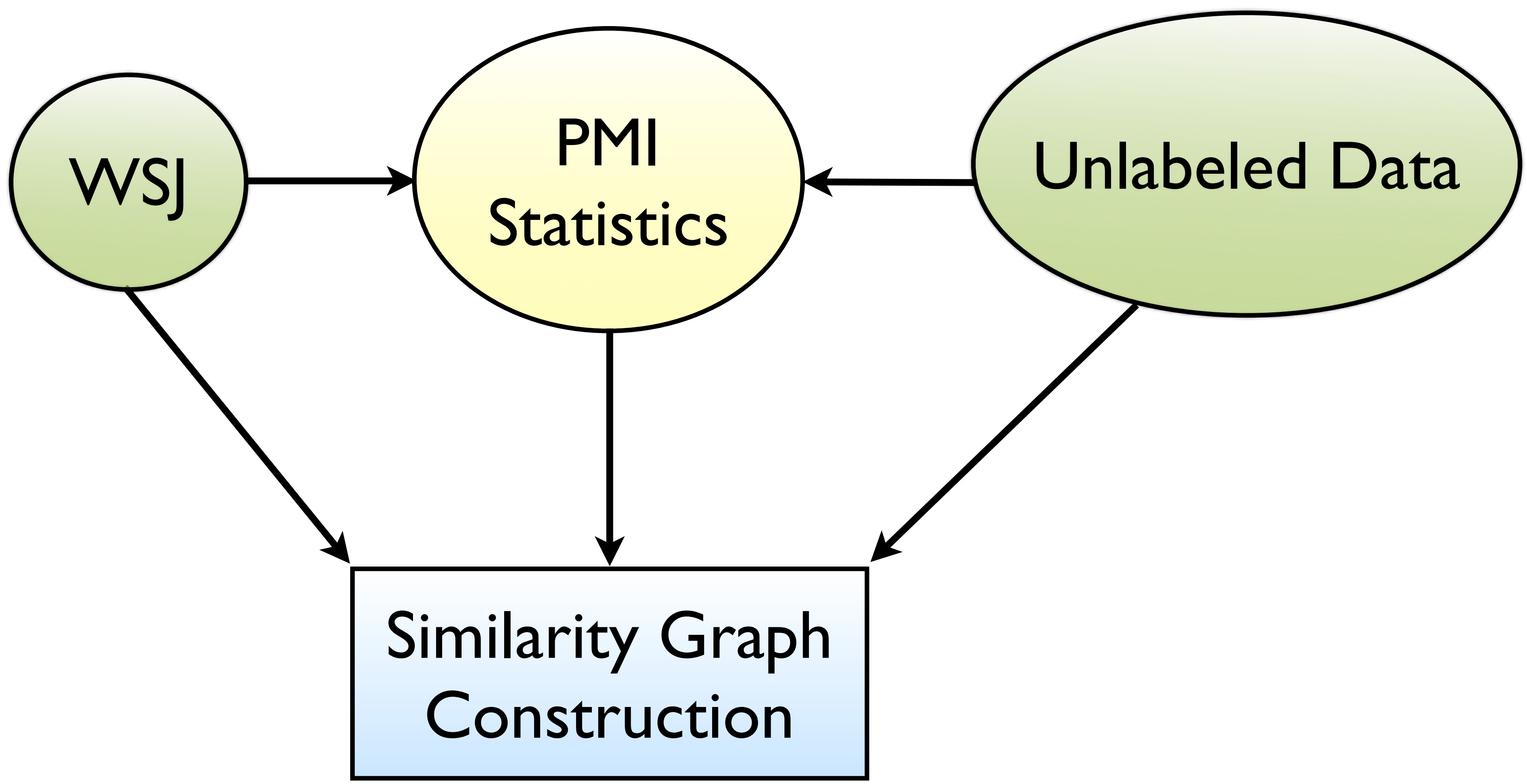

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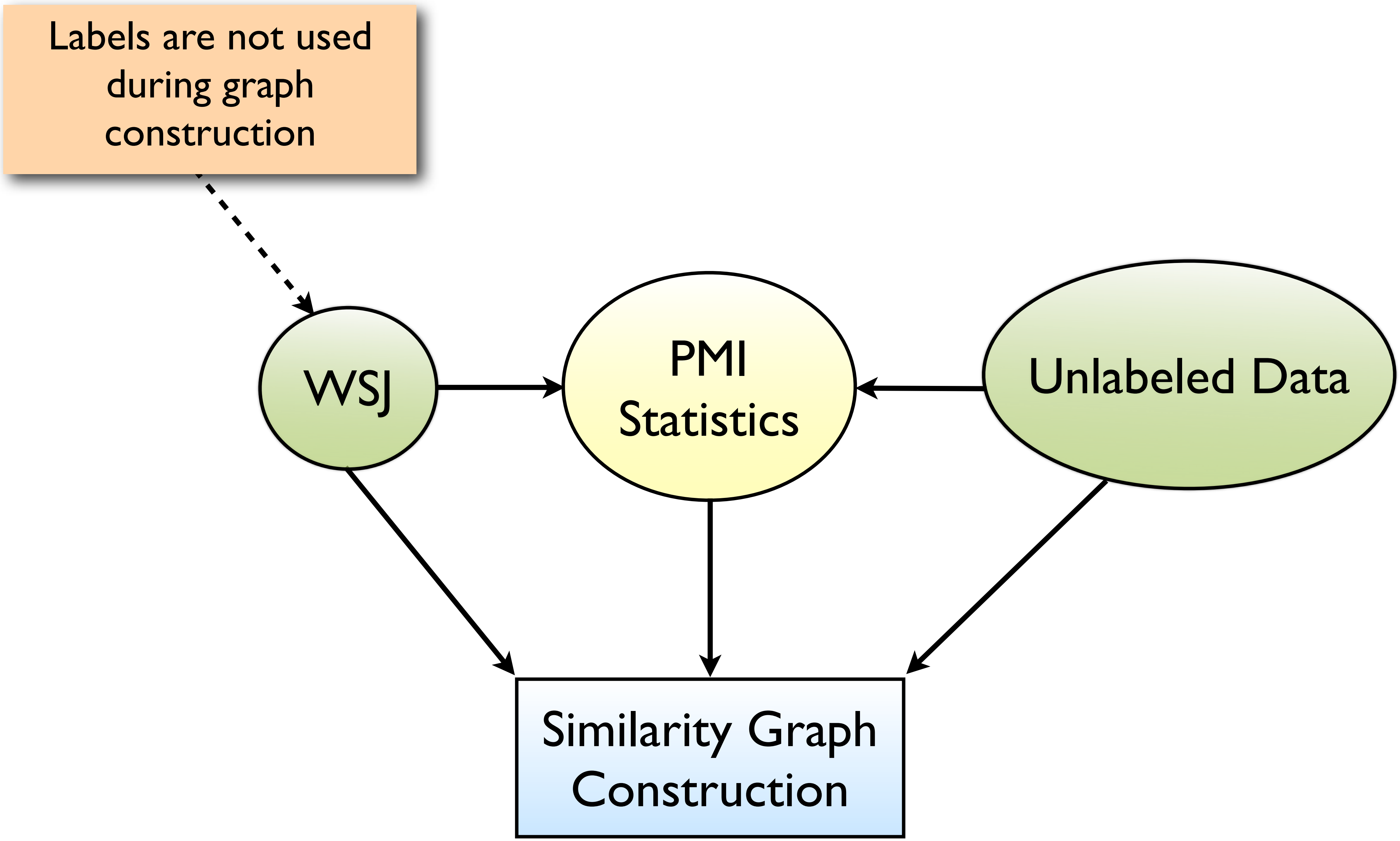

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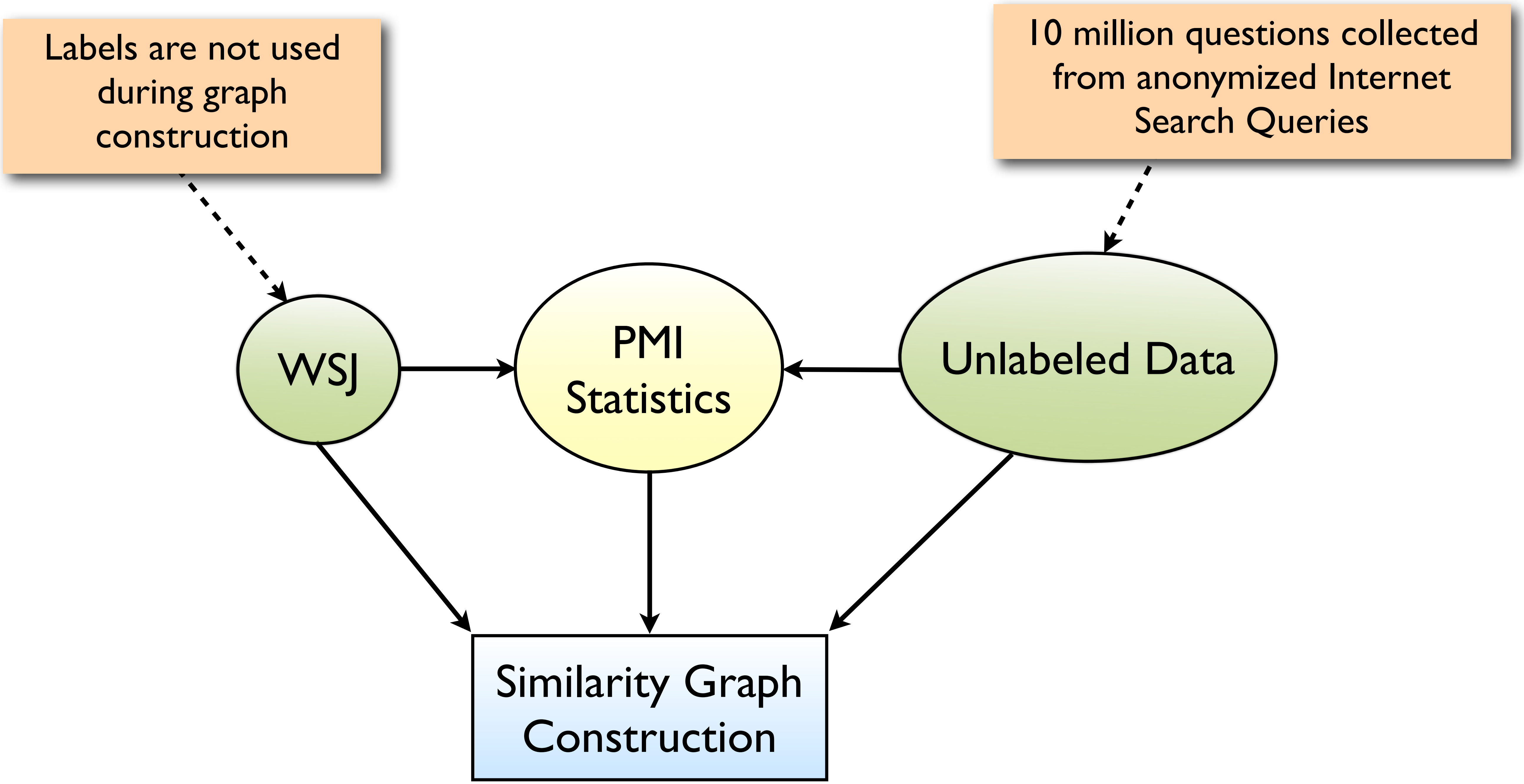
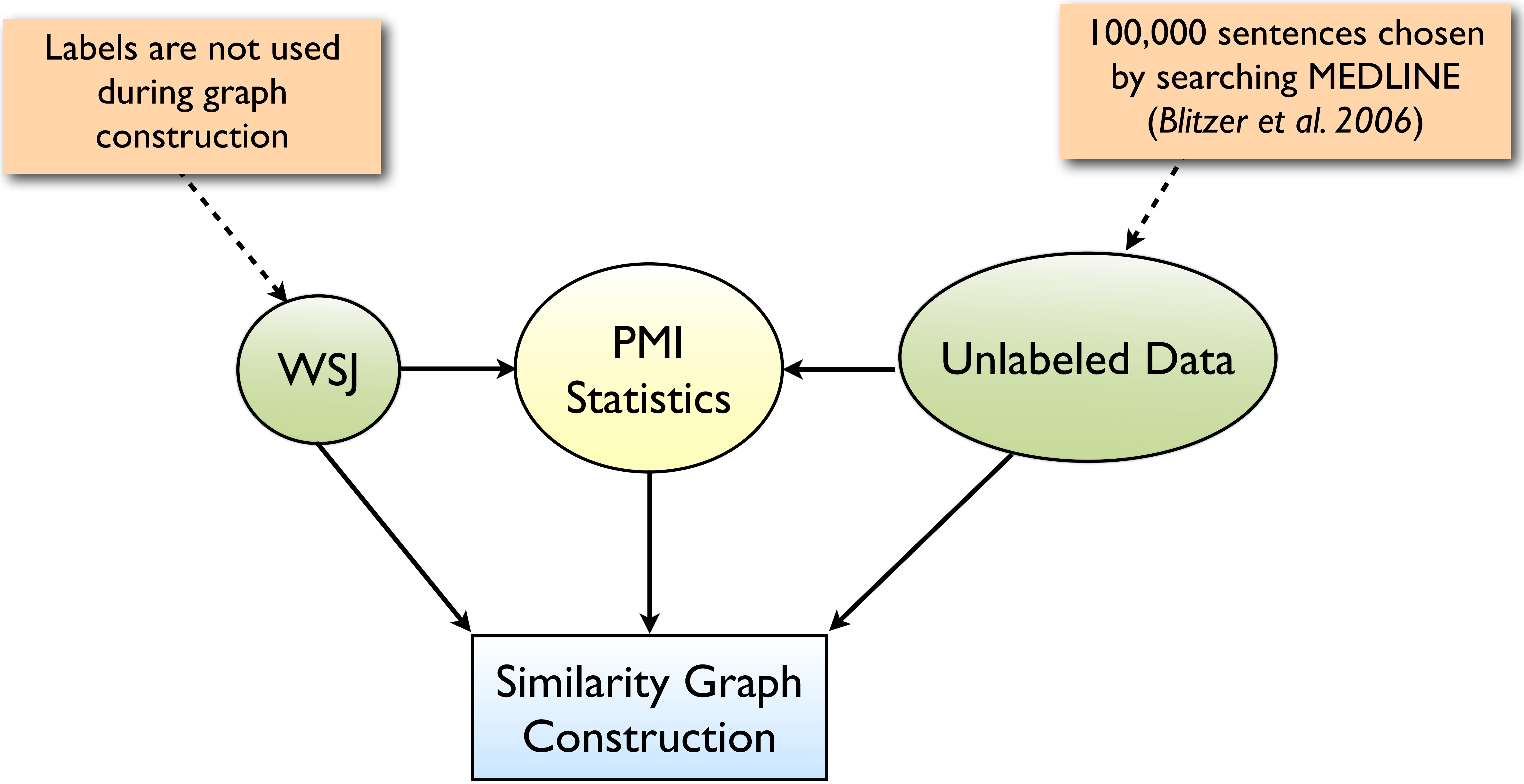


Graph Construction: Bio



Baseline (Supervised)

Not the same as features used using graph construction

- Features: word identity, suffixes, prefixes & special character detectors (dashes, digits, etc.).
- Achieves 97.17% accuracy on WSJ development set.

Results

	Questions	Bio
Baseline	83.8	86.2
Self-training	84.0	87.1
Semi-supervised CRF	**86.8**	**87.6**

Analysis

	Questions	Bio
percentage of unlabeled trigrams not connected to and any labeled trigram	12.4	46.8
average path length between an unlabeled trigram and its nearest labeled trigram	9.4	22.4

Analysis

Sparse Graph

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Analysis

- Pros
  - Inductive
  - Produces a CRF (standard CRF inference infrastructure may be used)
- Issues
  - Graph construction
  - Graph is not integrated with CRF training

Big Picture

Use case 1: Transductive Classification

Use case 2: Training Better Inductive Model

	Use case 1	Use case 2
Text Categorization	✓	
Sentiment Analysis	✓	✓
Class Instance Acquisition	✓	
POS Tagging		

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- Motivation
- Graph Construction
- Inference Methods
- Scalability
- Applications
  - Text Categorization
  - Sentiment Analysis
  - Class Instance Acquisition
  - POS Tagging
  - MultiLingual POS Tagging [Das & Petrov, ACL 2011]
  - Semantic Parsing
- Conclusion & Future Work

Motivation

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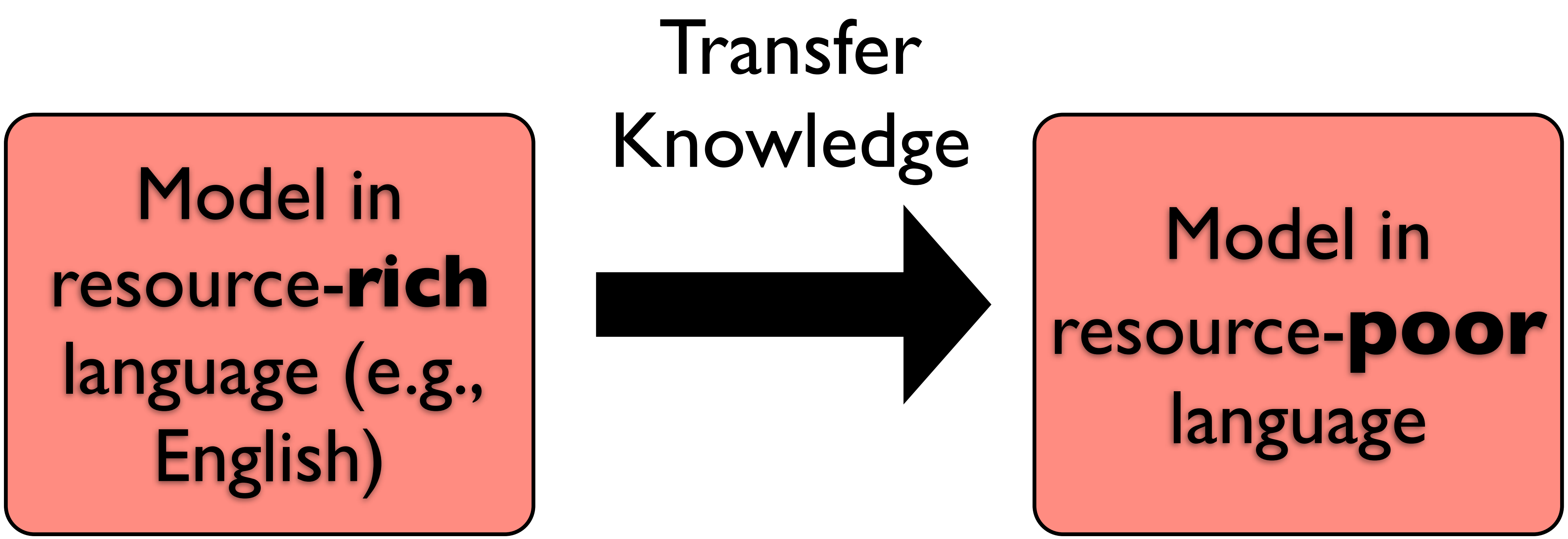

Cross-Lingual Projection

The food at Google is good .

Cross-Lingual Projection

96% Accuracy

DET	NOUN	ADP	NOUN	VERB	ADJ	.
The	food	at	Google	is	good	.

Cross-Lingual Projection

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Das Essen ist gut bei Google .

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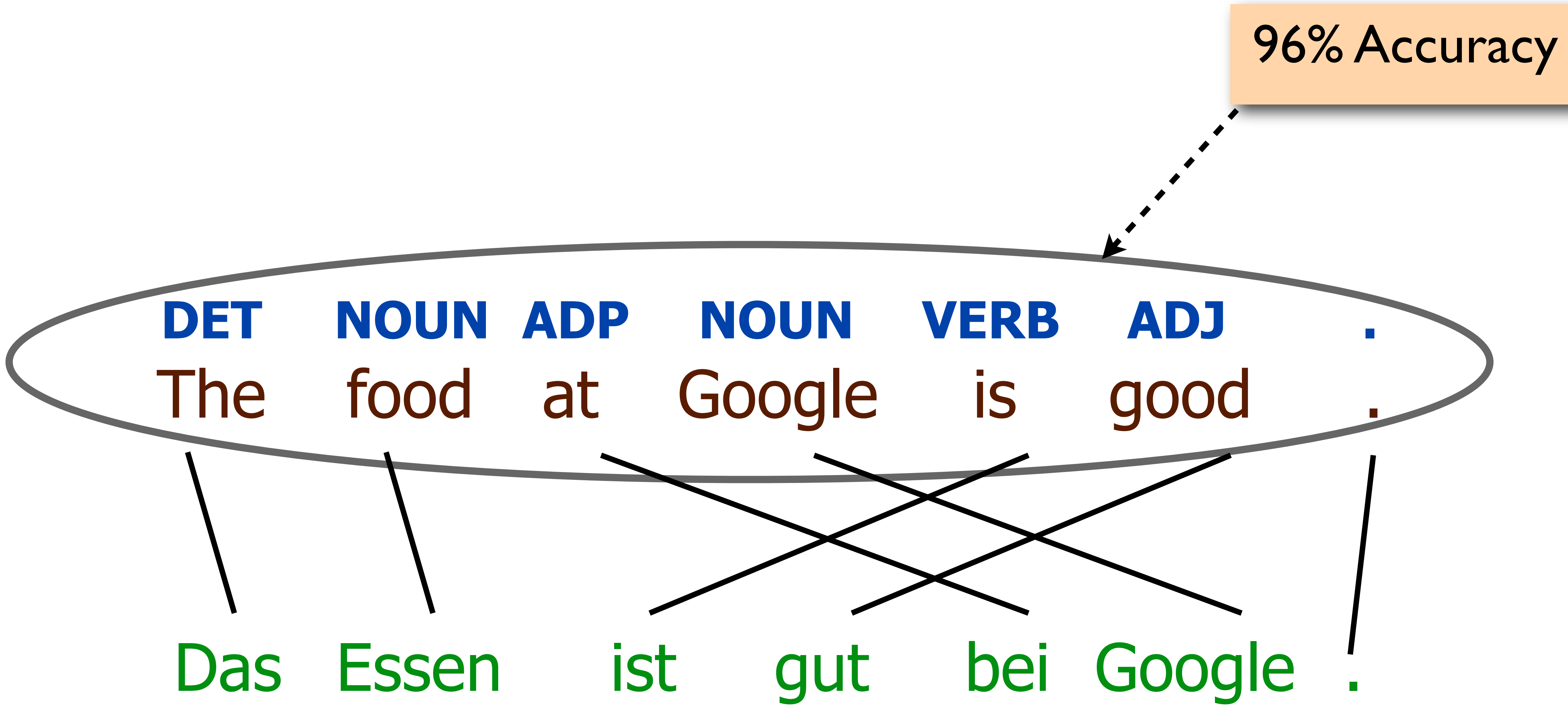
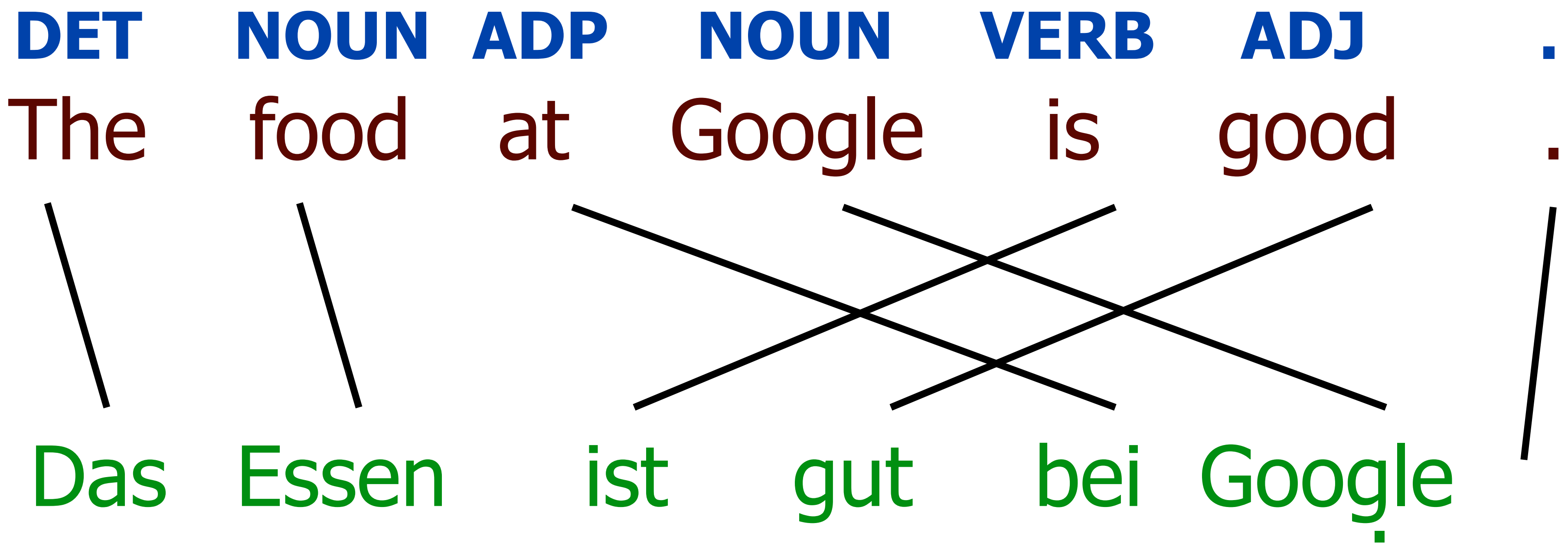


Automatic alignments from translation data

(available for more than 50 languages)

Cross-Lingual Projection



Cross-Lingual Projection

NOUN
food

DET
The

Essen

Das

VERB
is

ADJ
good

ist

gut

.

bei

Google

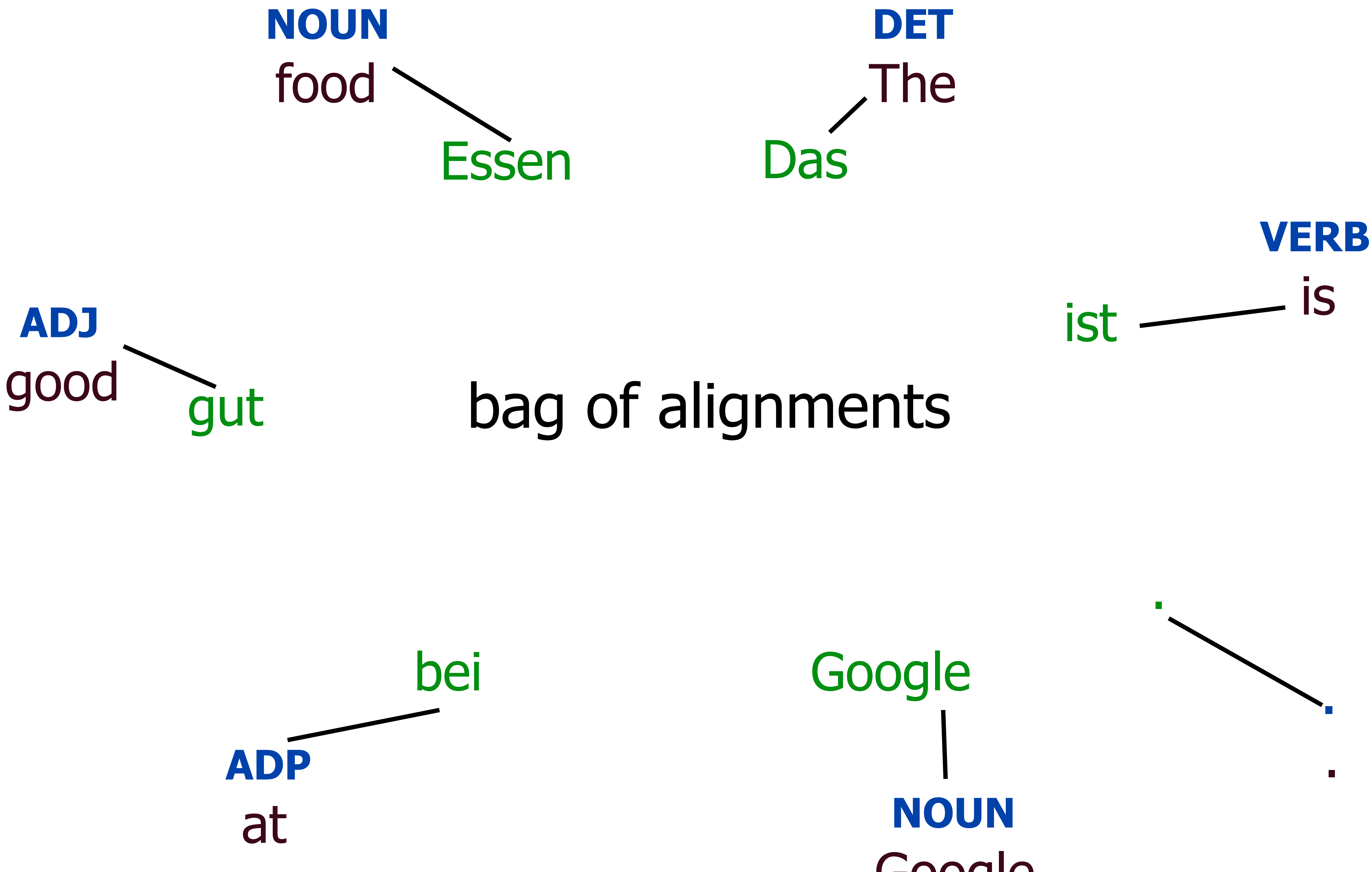
.

.

ADP
at

NOUN
Google

Cross-Lingual Projection



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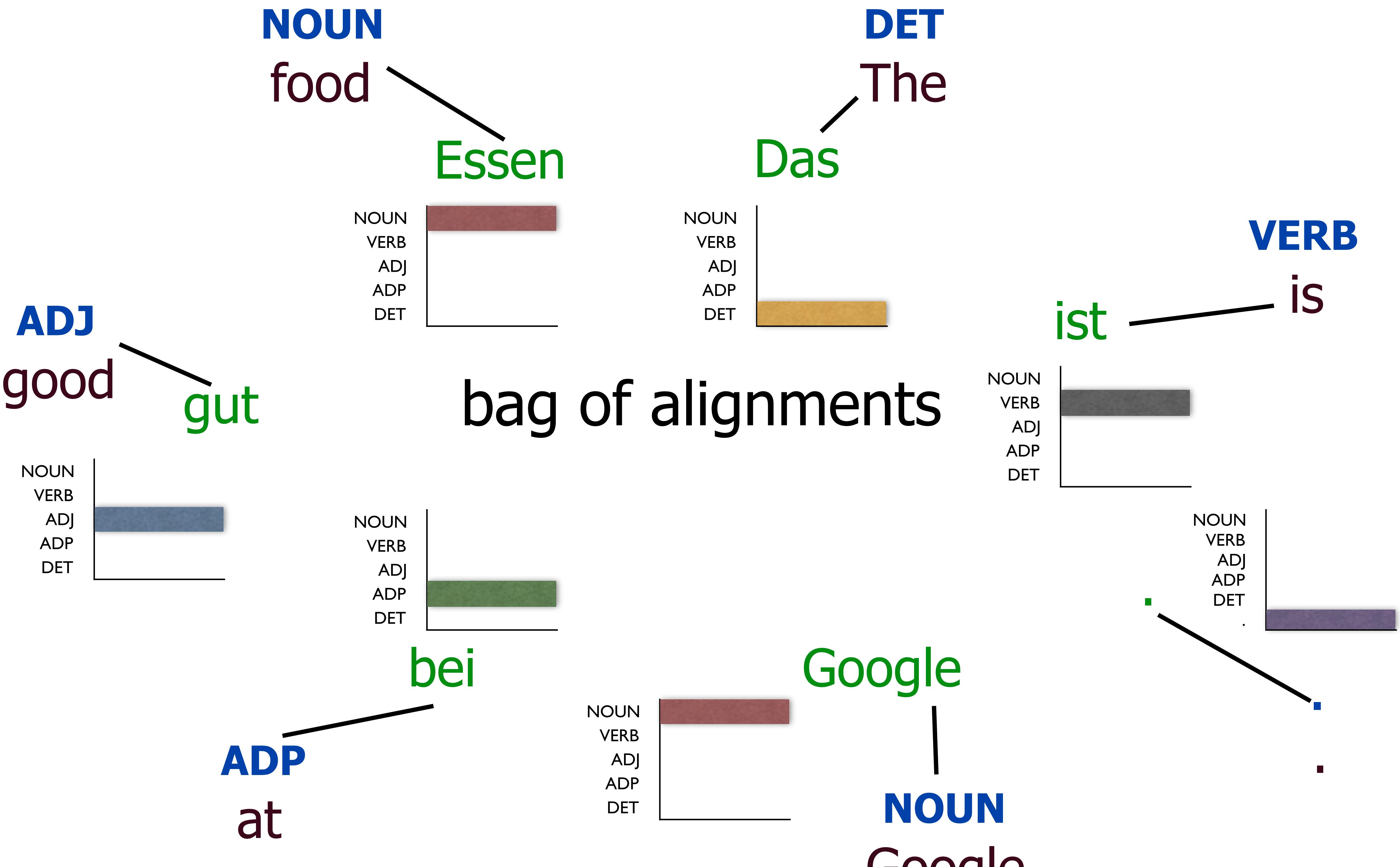

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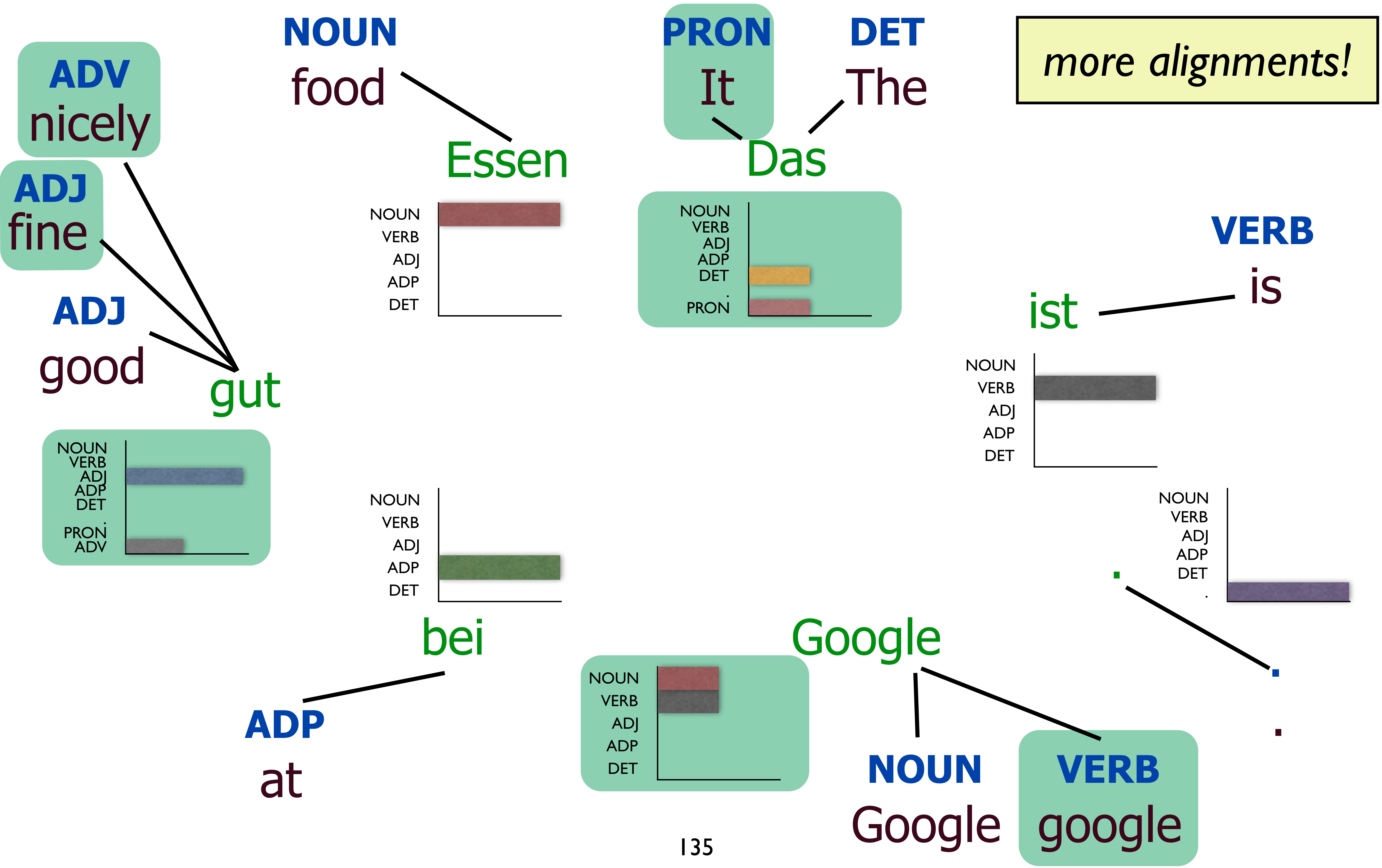

Cross-Lingual Projection Results

	Danish	Dutch	German	Greek	Italian	Portuguese	Spanish	Swedish	Average
Feature-HMM	69.1	65.1	81.3	71.8	68.1	78.4	80.2	70.1	73.0

Feature-HMM [Berg-Kirkpatrick, NAACL 2010]

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Feature-HMM [Berg-Kirkpatrick, NAACL 2010]

Graph Regularization

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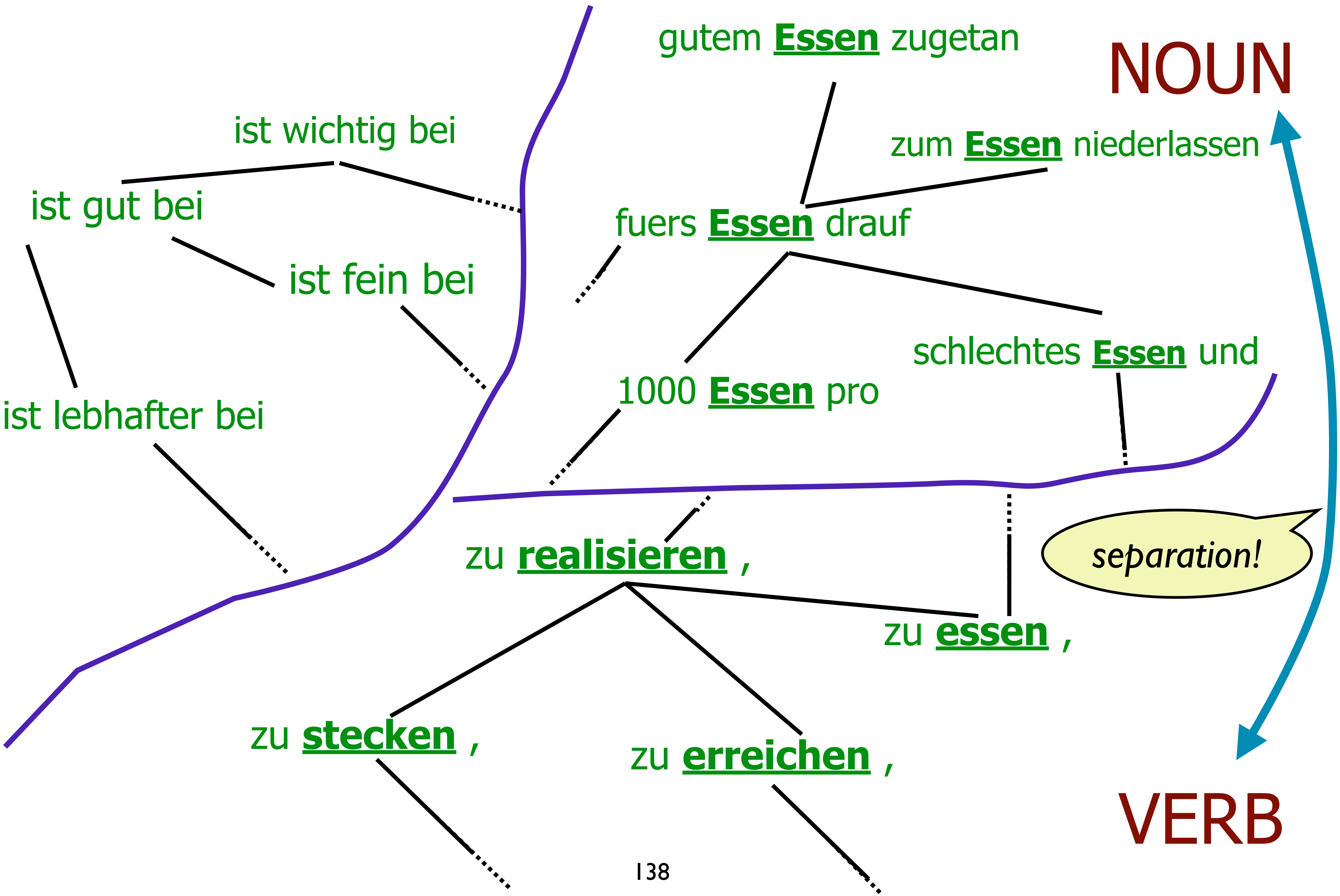

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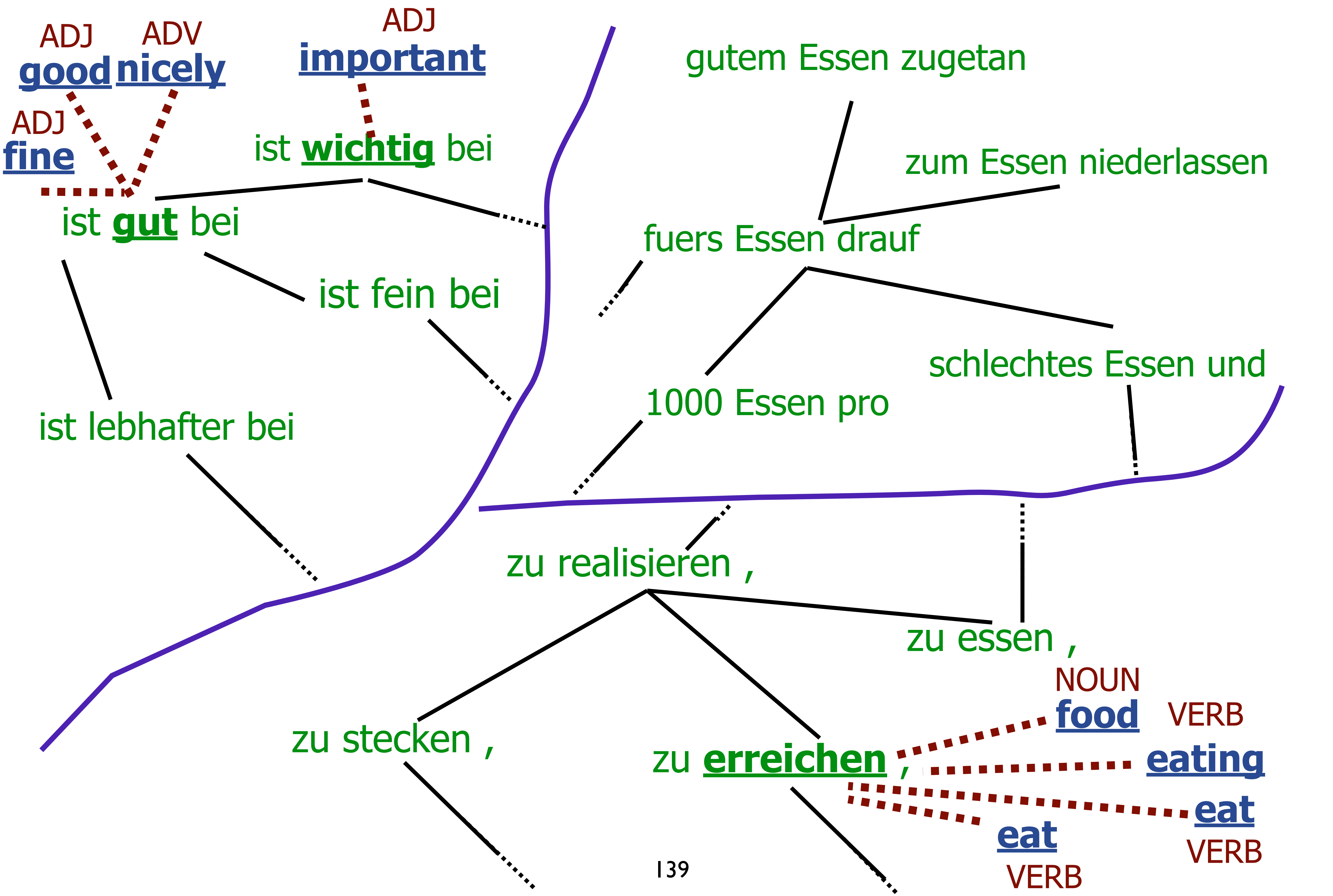

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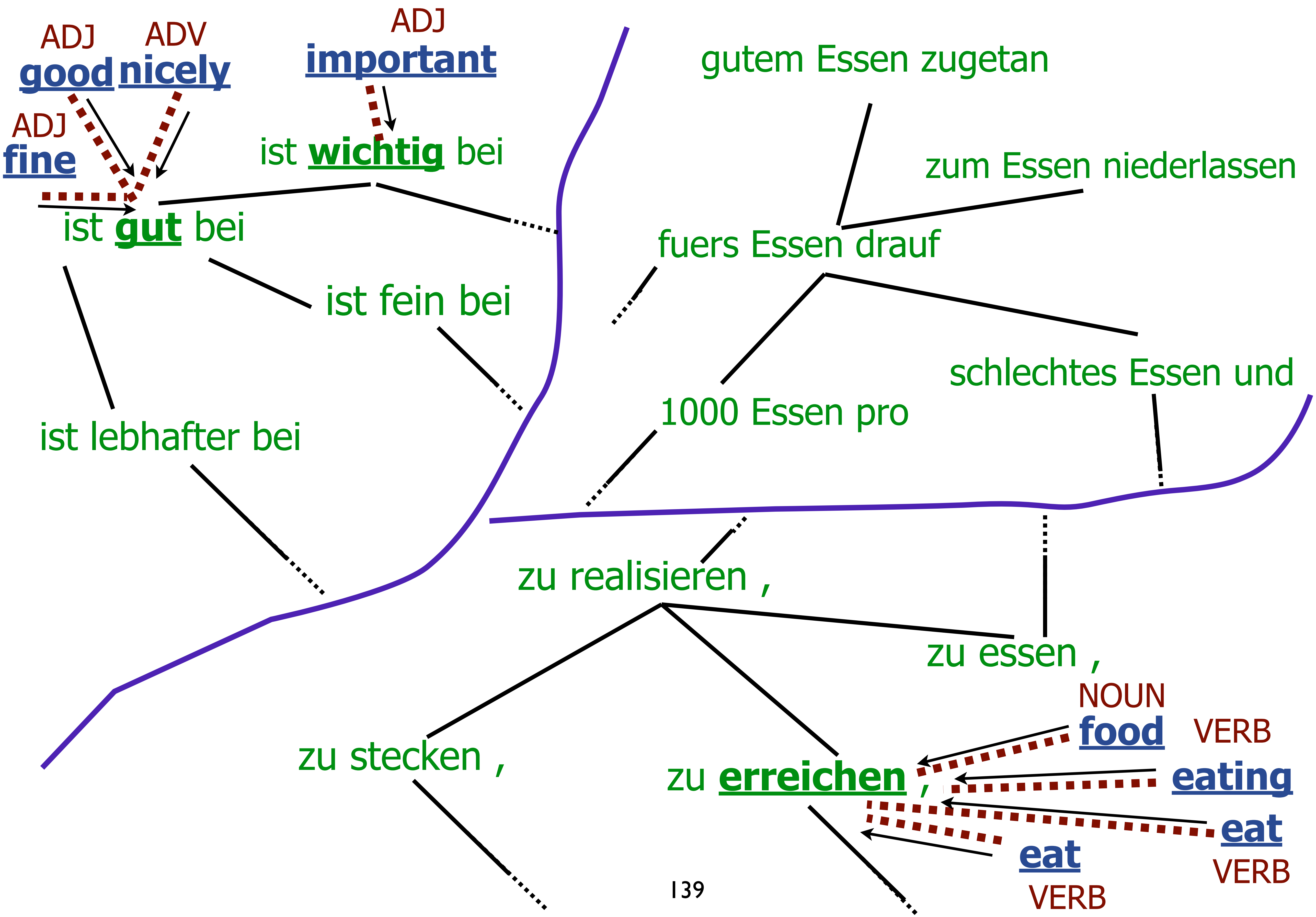

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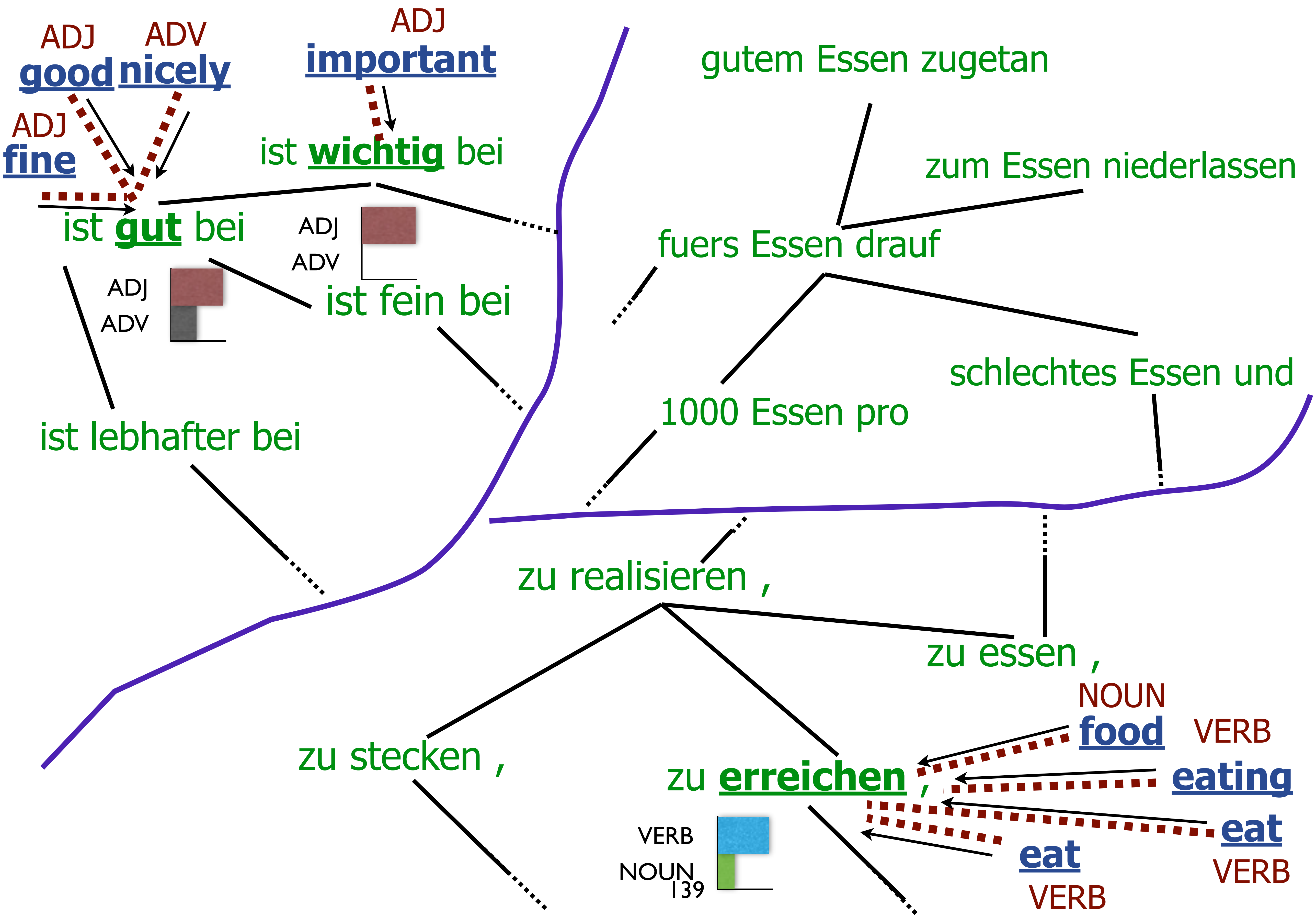

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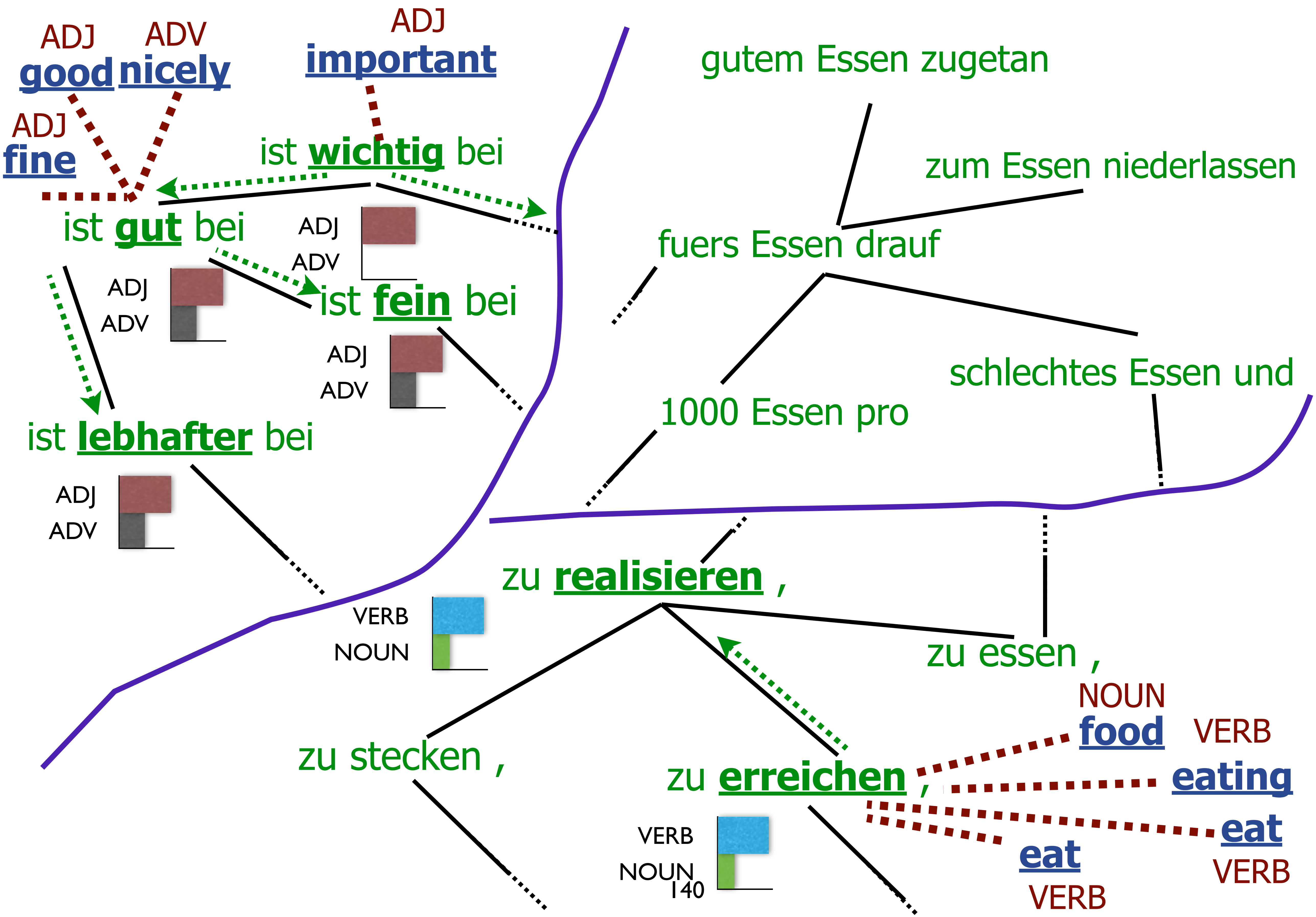

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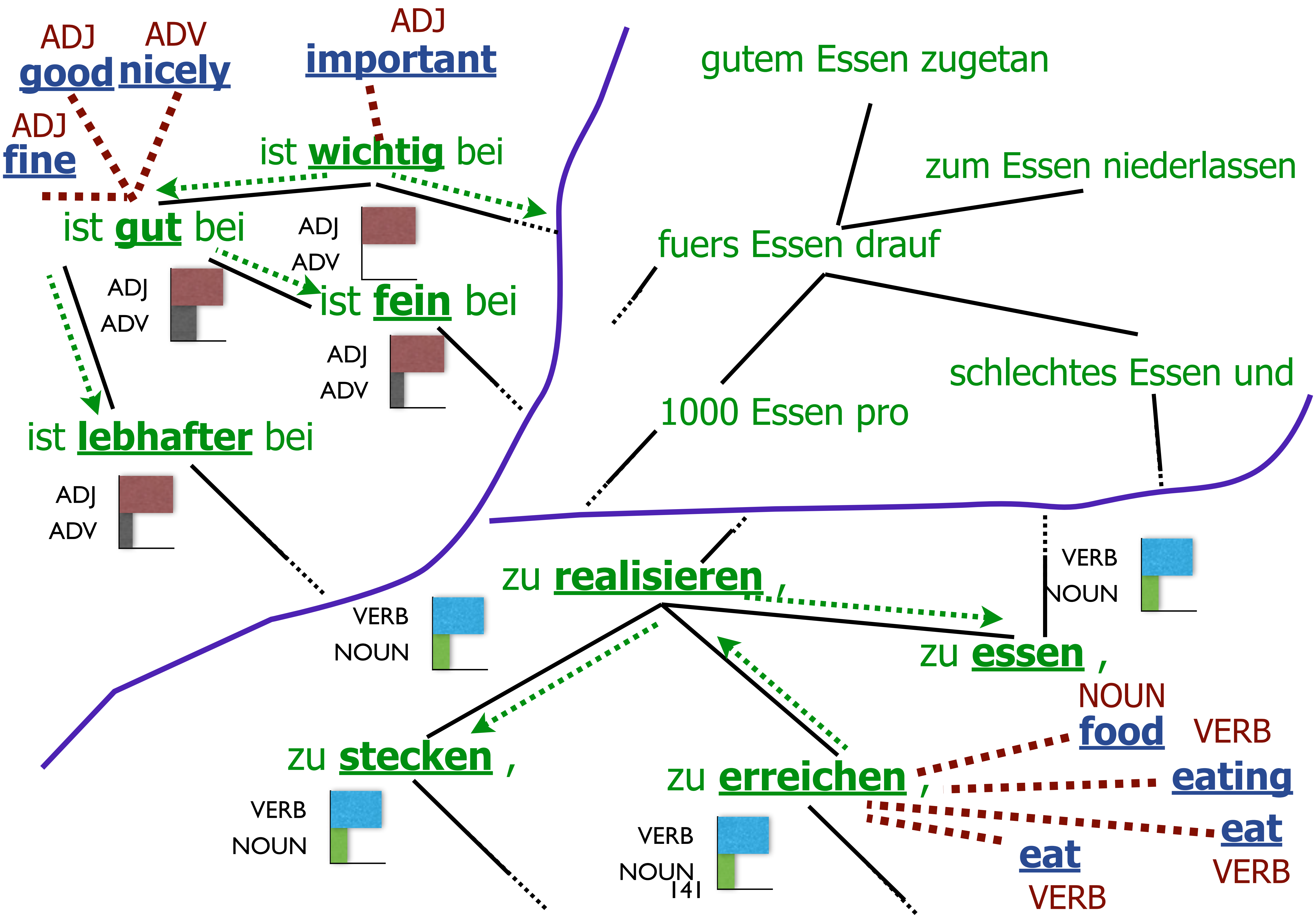

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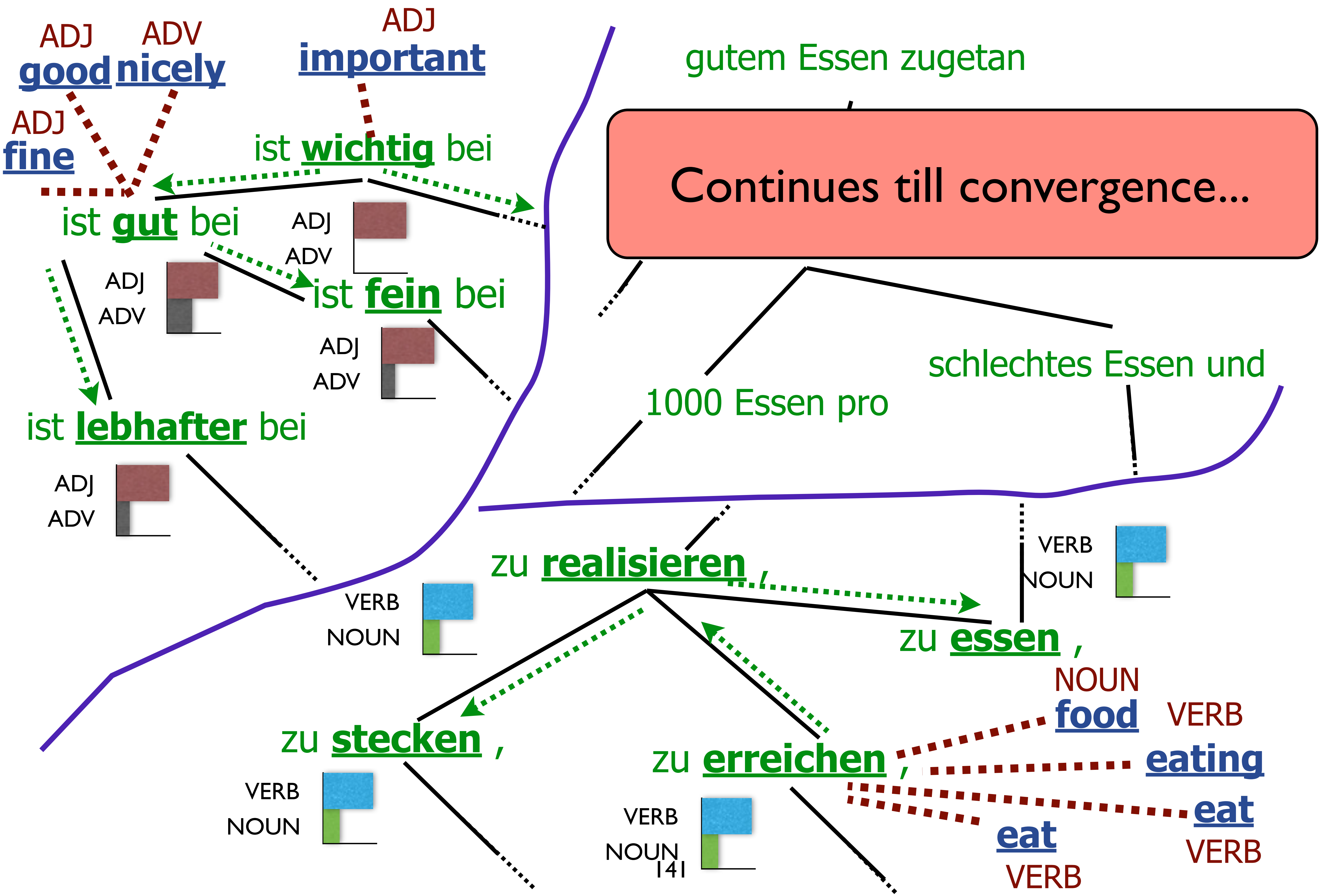

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Oracle (Supervised)	96.9	94.9	98.2	97.8	95.8	97.2	96.8	94.8	96.6

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Problem Description

- Extract shallow semantic structure: **Frames** and **Roles**

I want to go to Jeju Island on Sunday

Problem Description

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I want to go to Jeju Island on Sunday

Predicate

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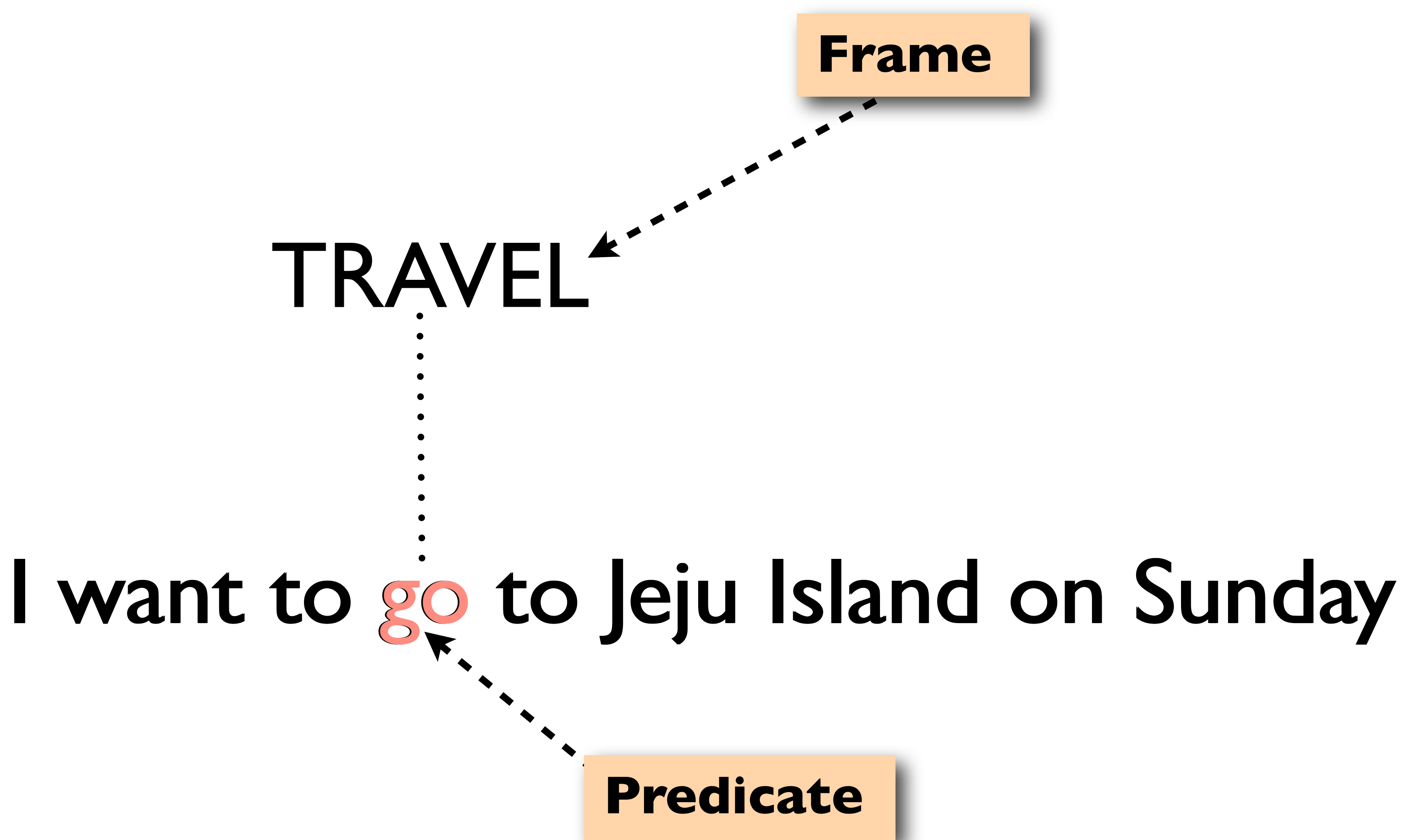

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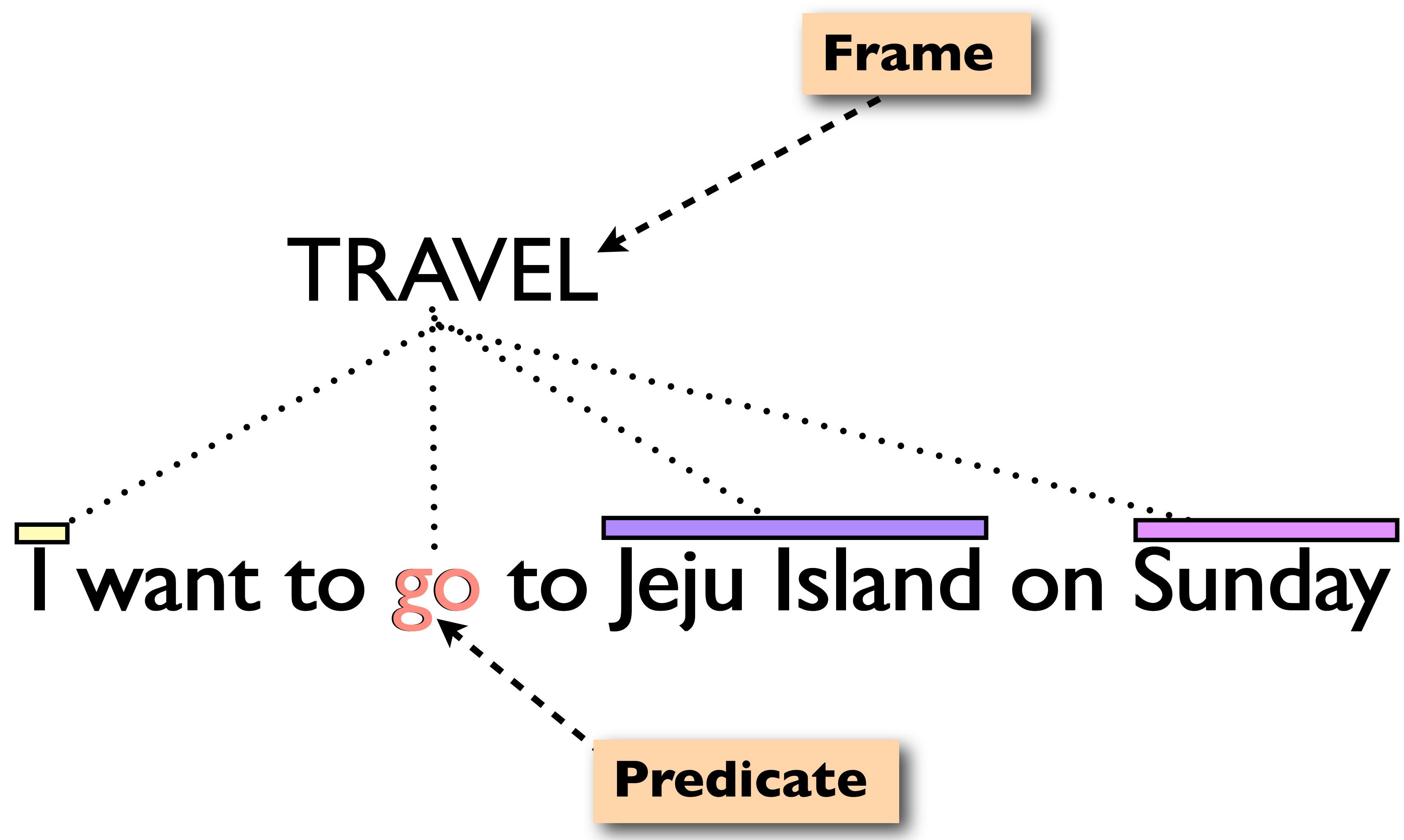

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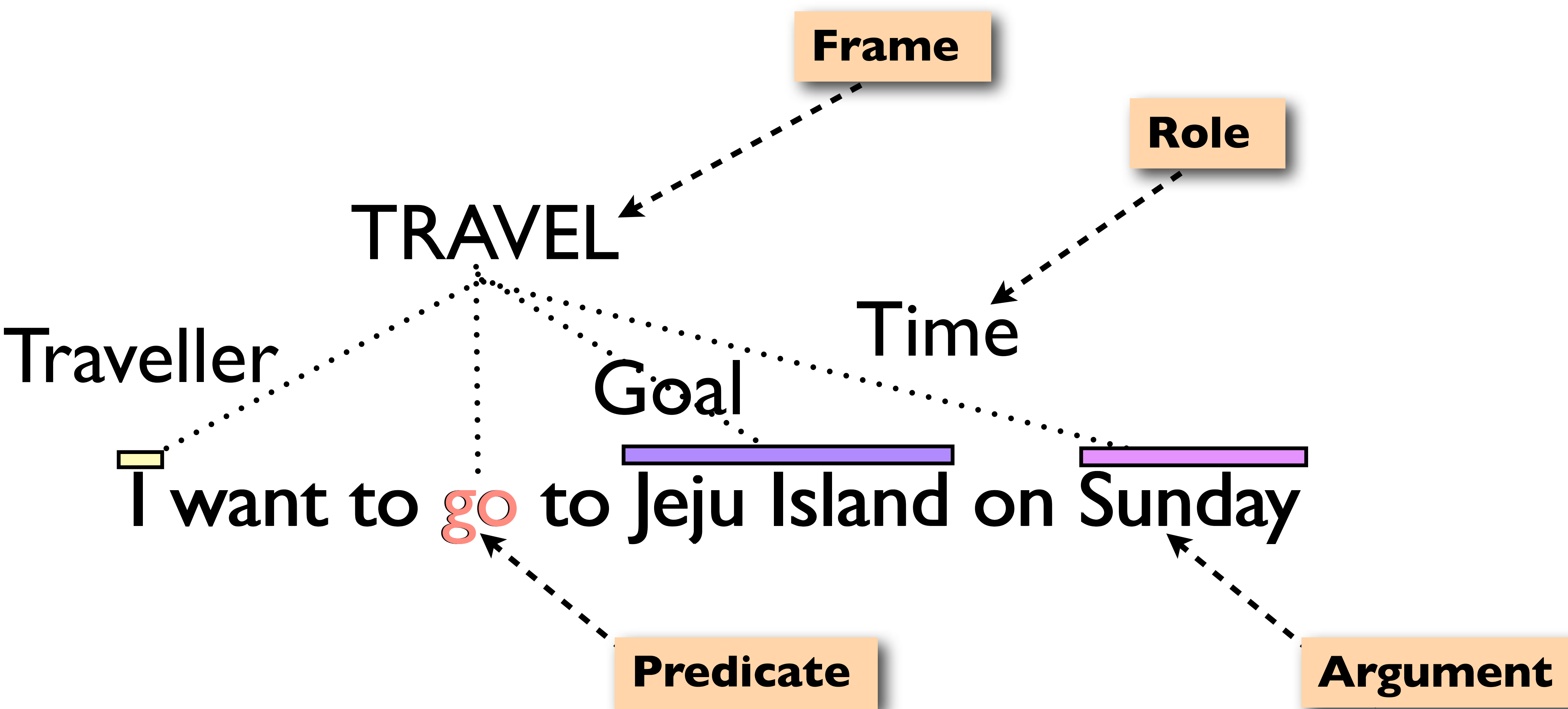
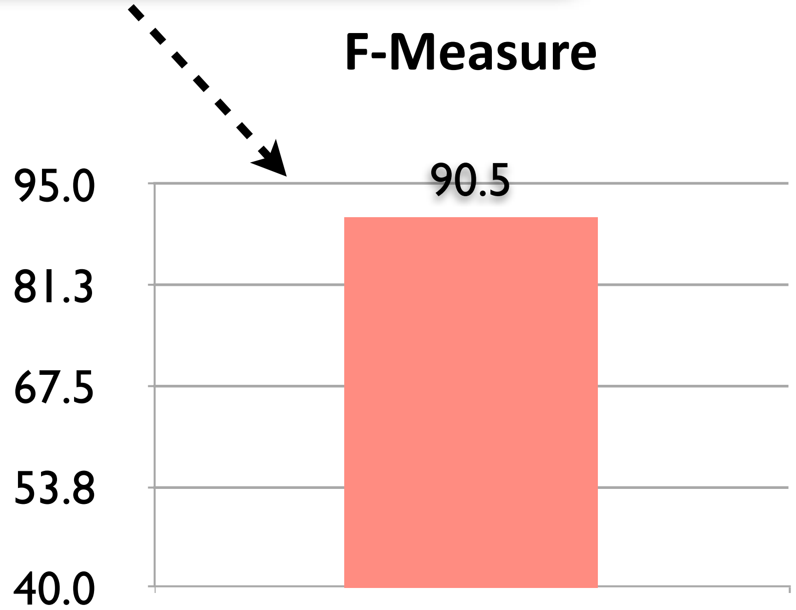


Problem Description

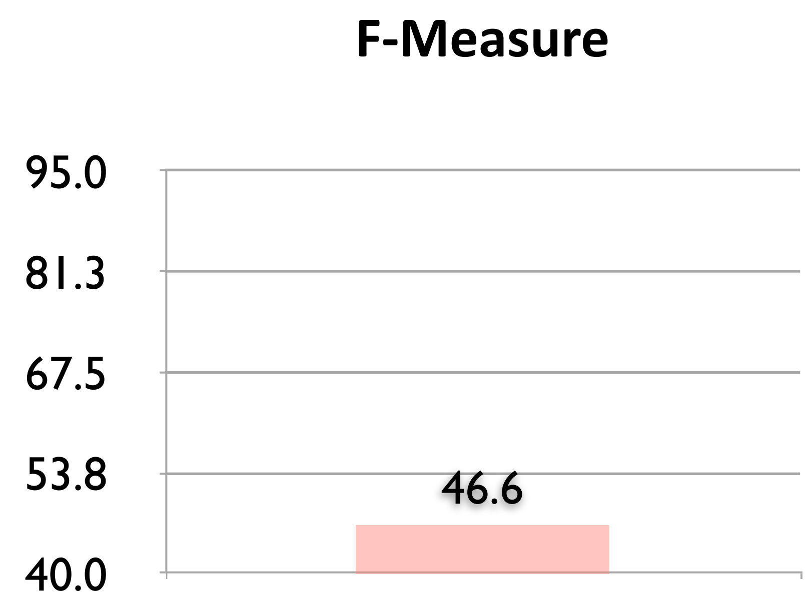
- Predicate identification
  - Most approaches assume this is given
- Frame identification
- Argument identification

Motivation

Frame Identification



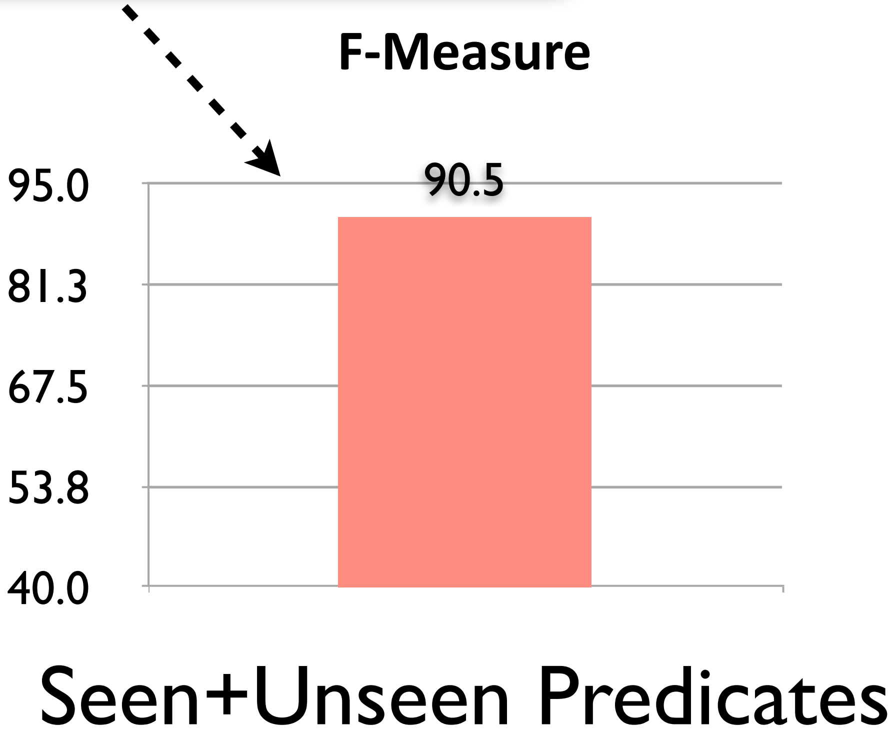
Seen+Unseen Predicates

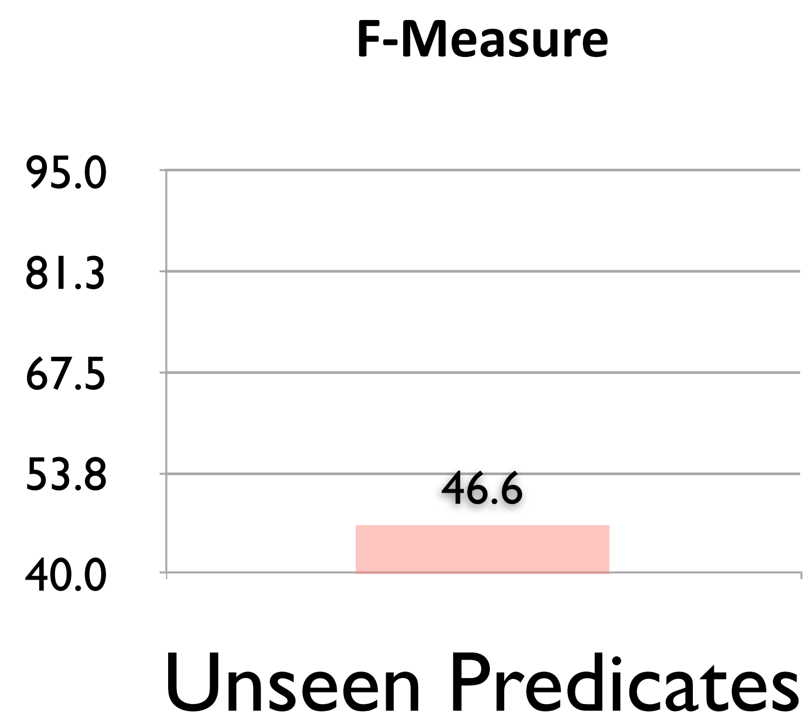


Unseen Predicates

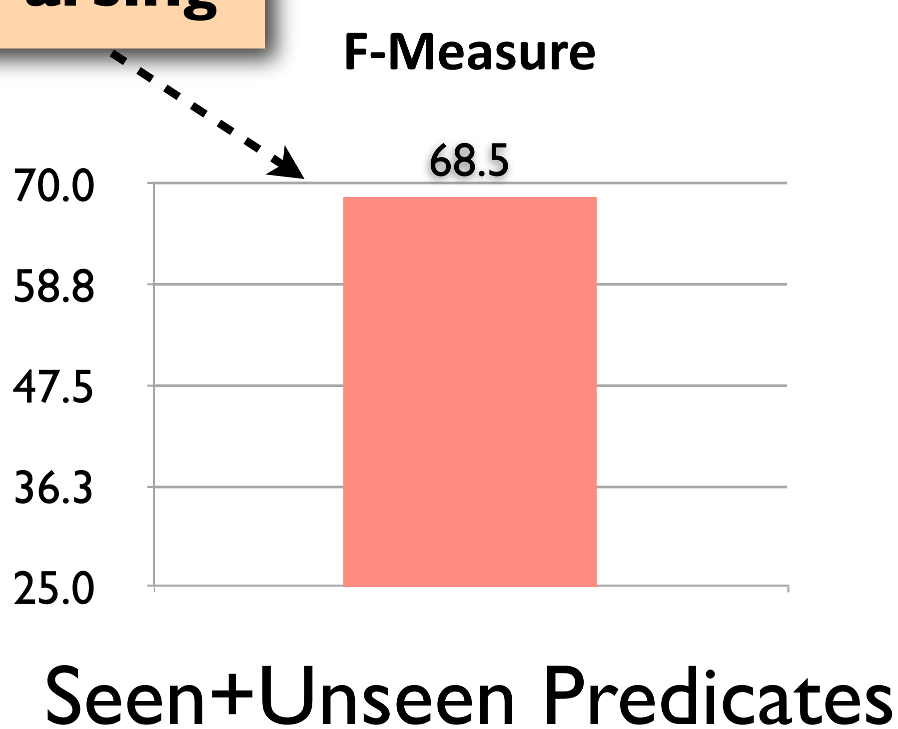
Motivation

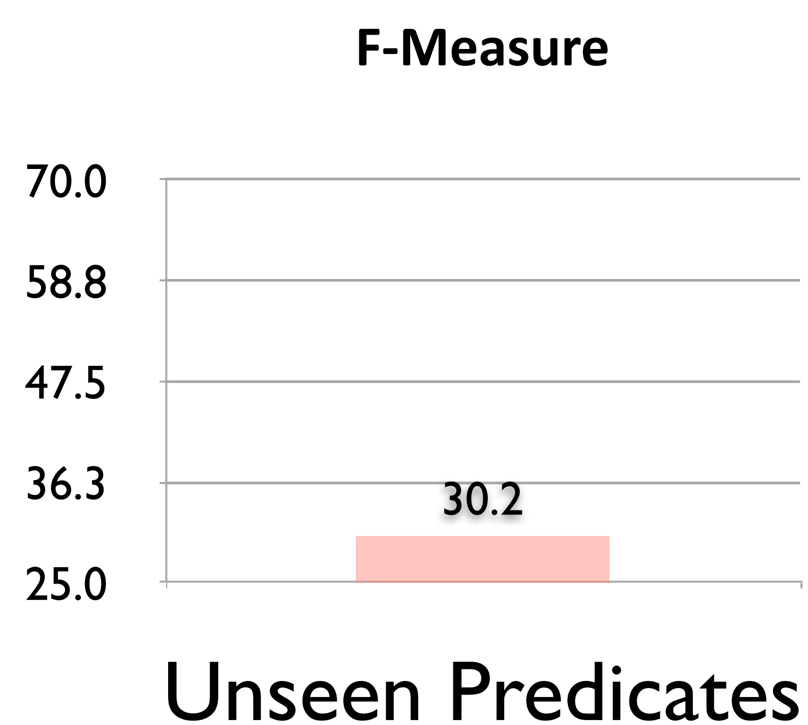
Frame Identification





Full Parsing





Sparse label data

- Labeled data has only about 9,263 labeled predicates (targets)
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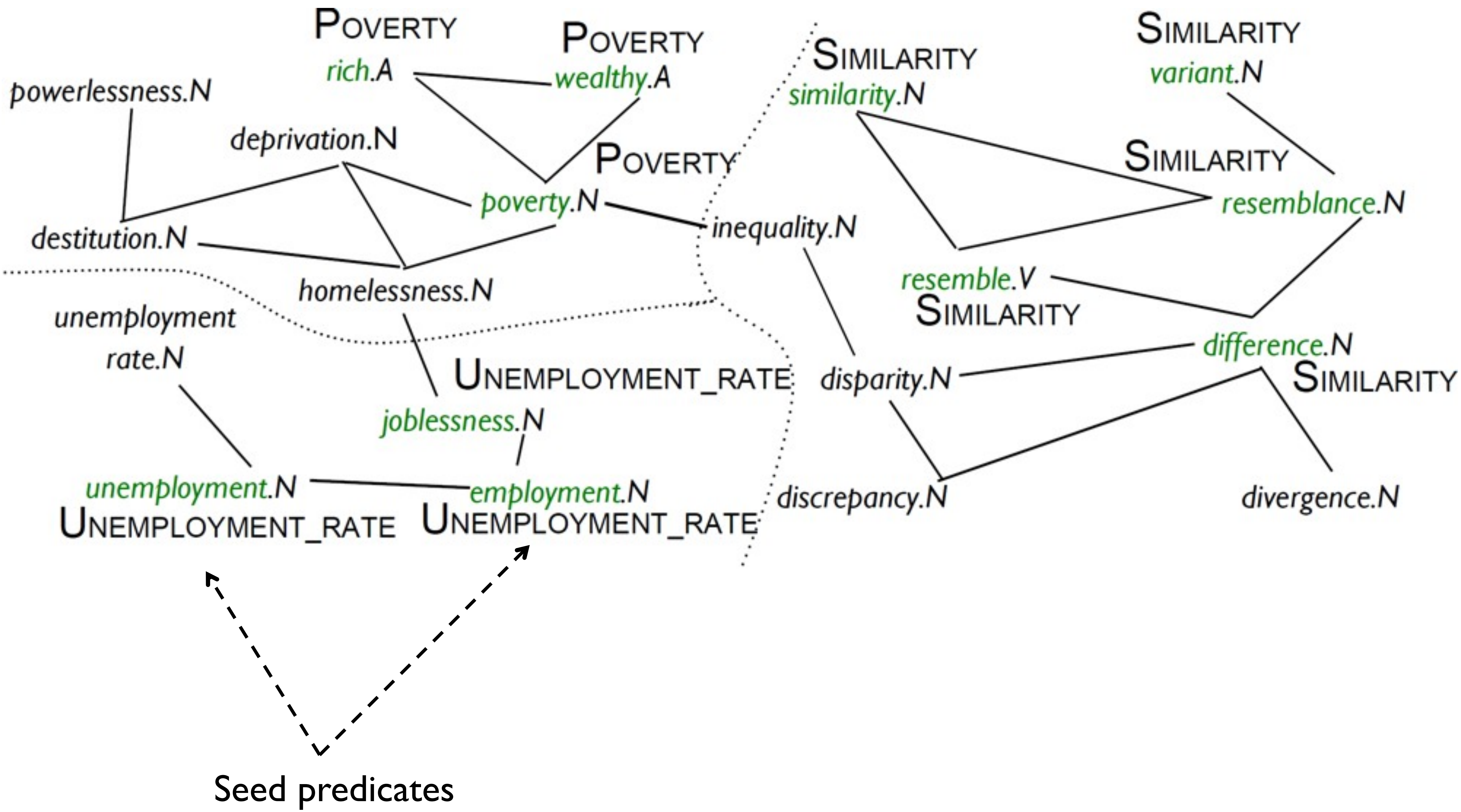
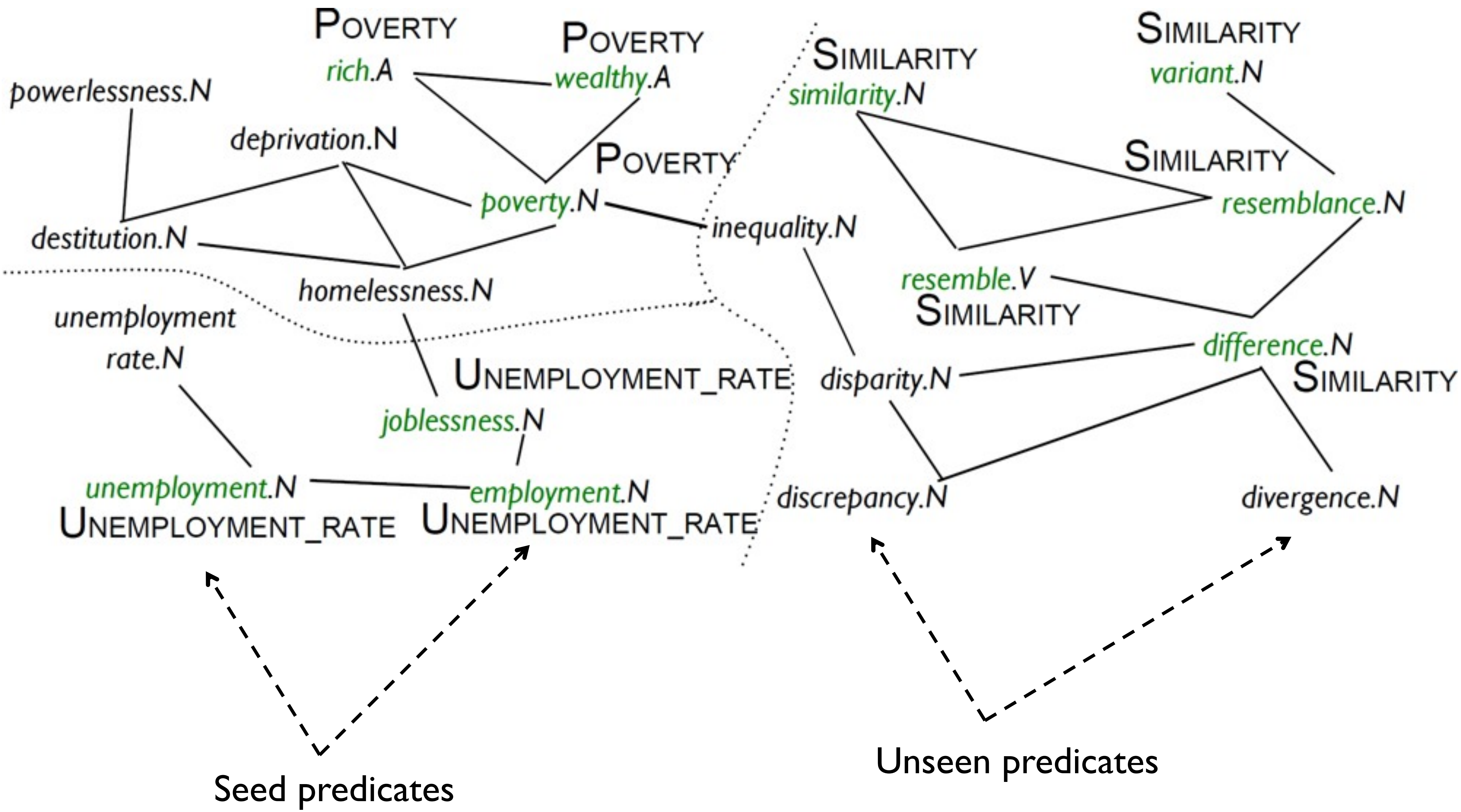
- Construct a graph with potential predicates as vertices

- Expand the lexicon by using graph-based SSL

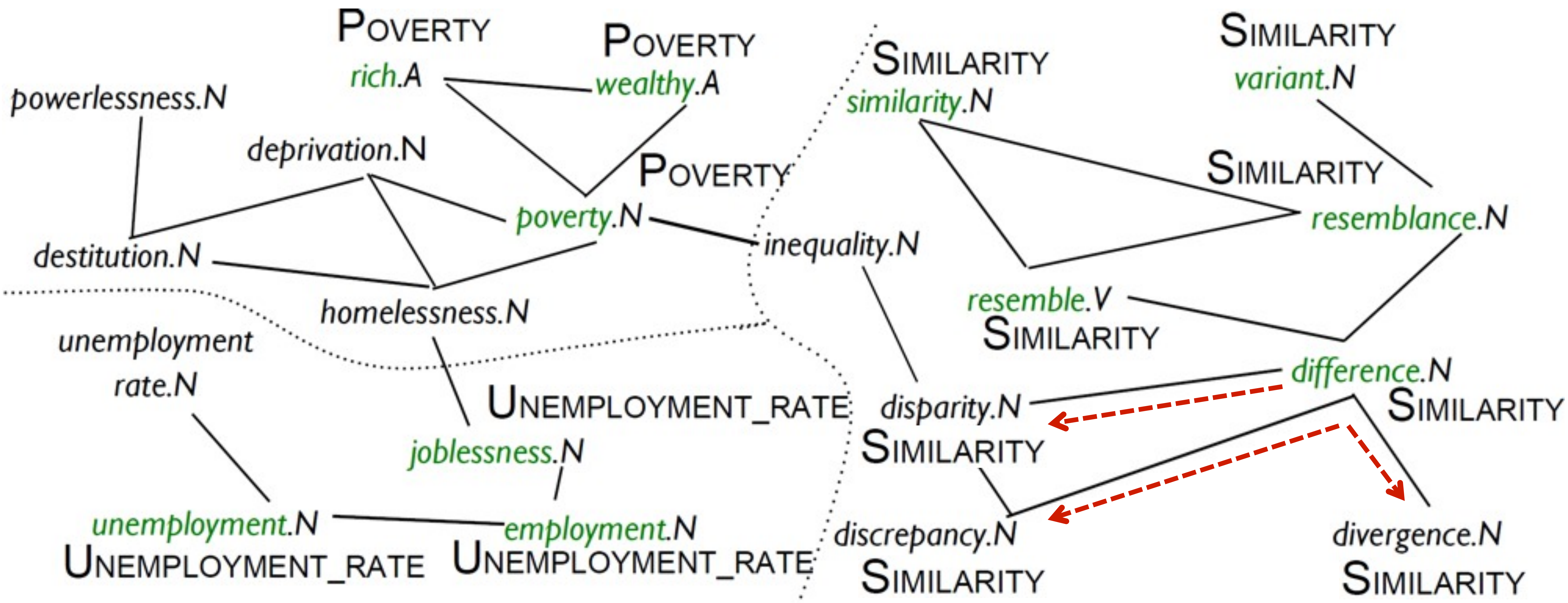
Graph Propagation (I)



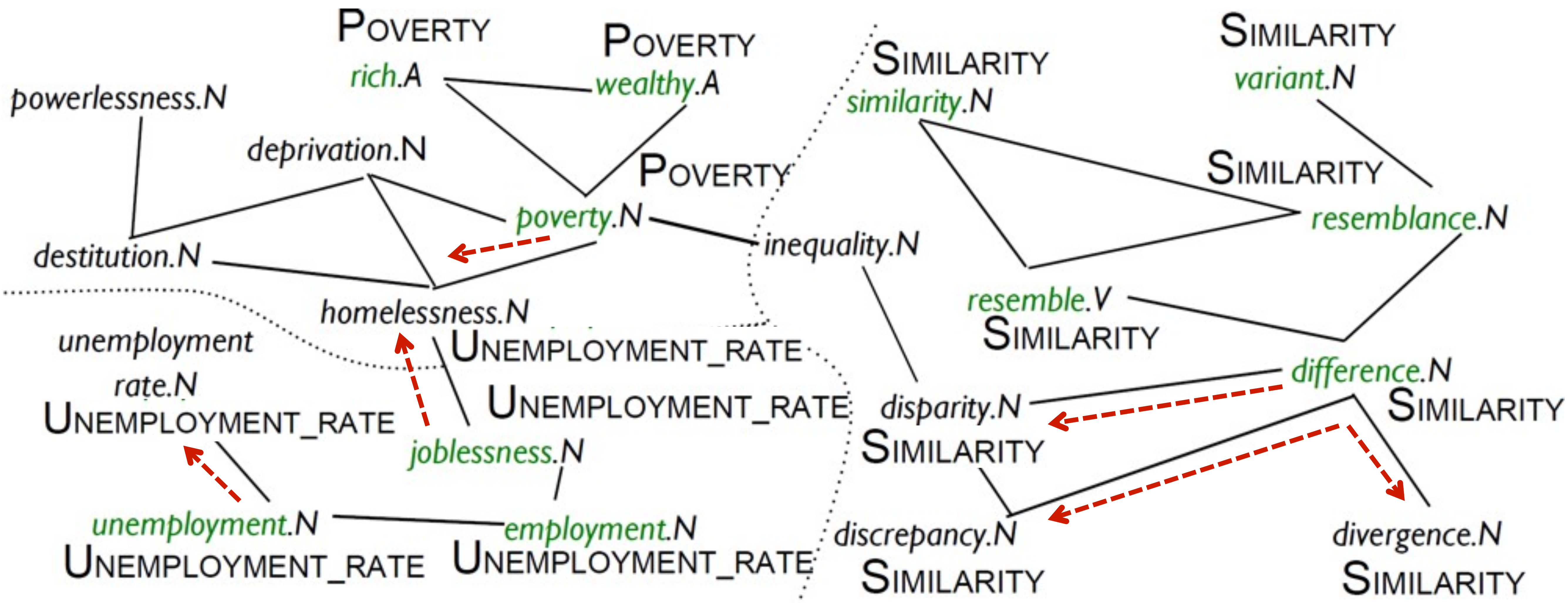
Graph Propagation (II)



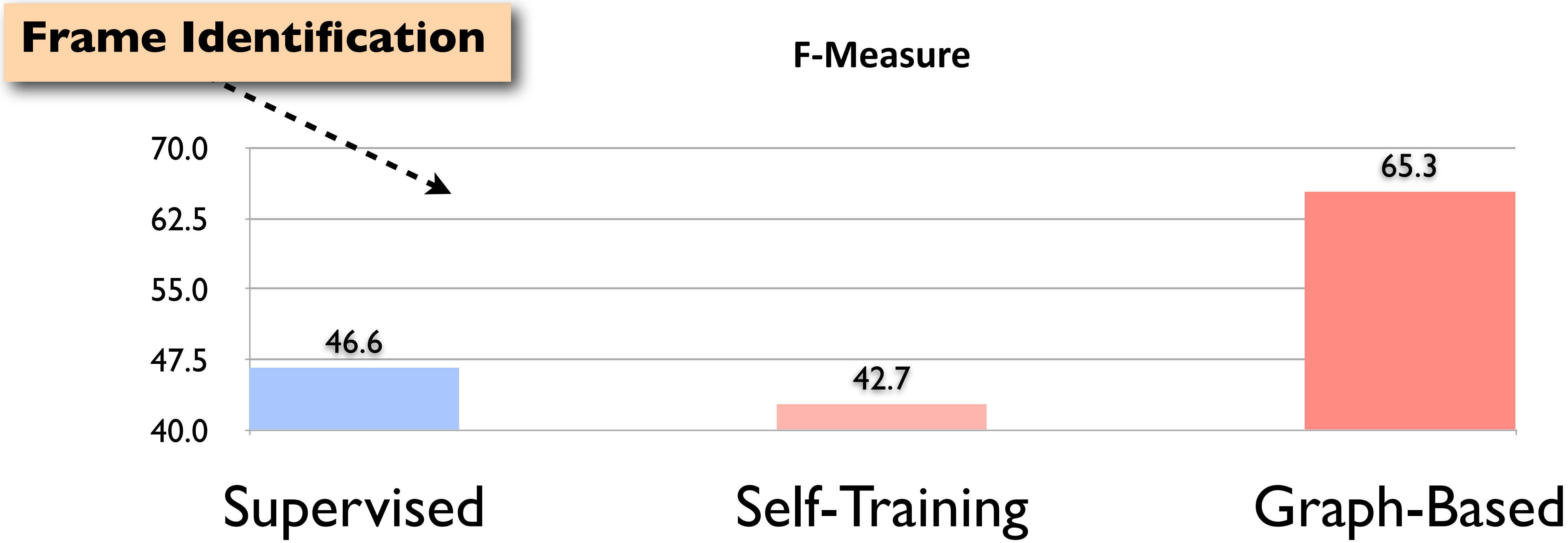
Graph Propagation (III)



Graph Propagation (IV)

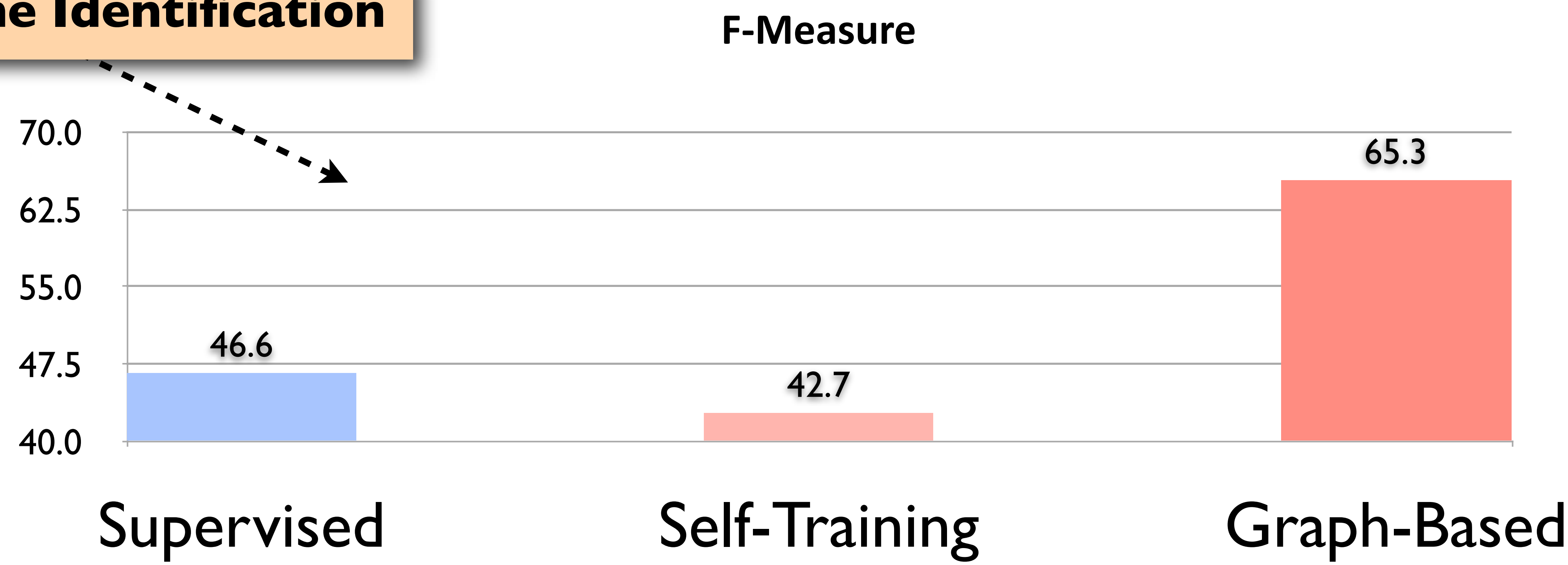


Results on Unseen Predicates



Results on Unseen Predicates

Frame Identification



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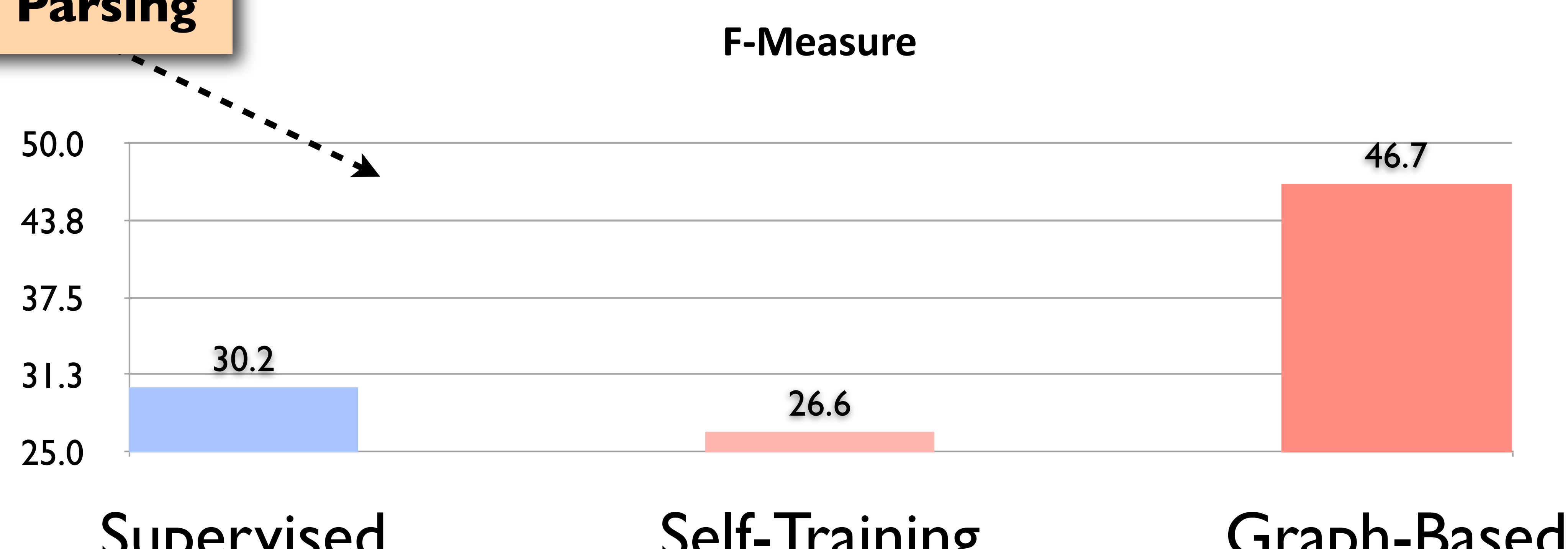

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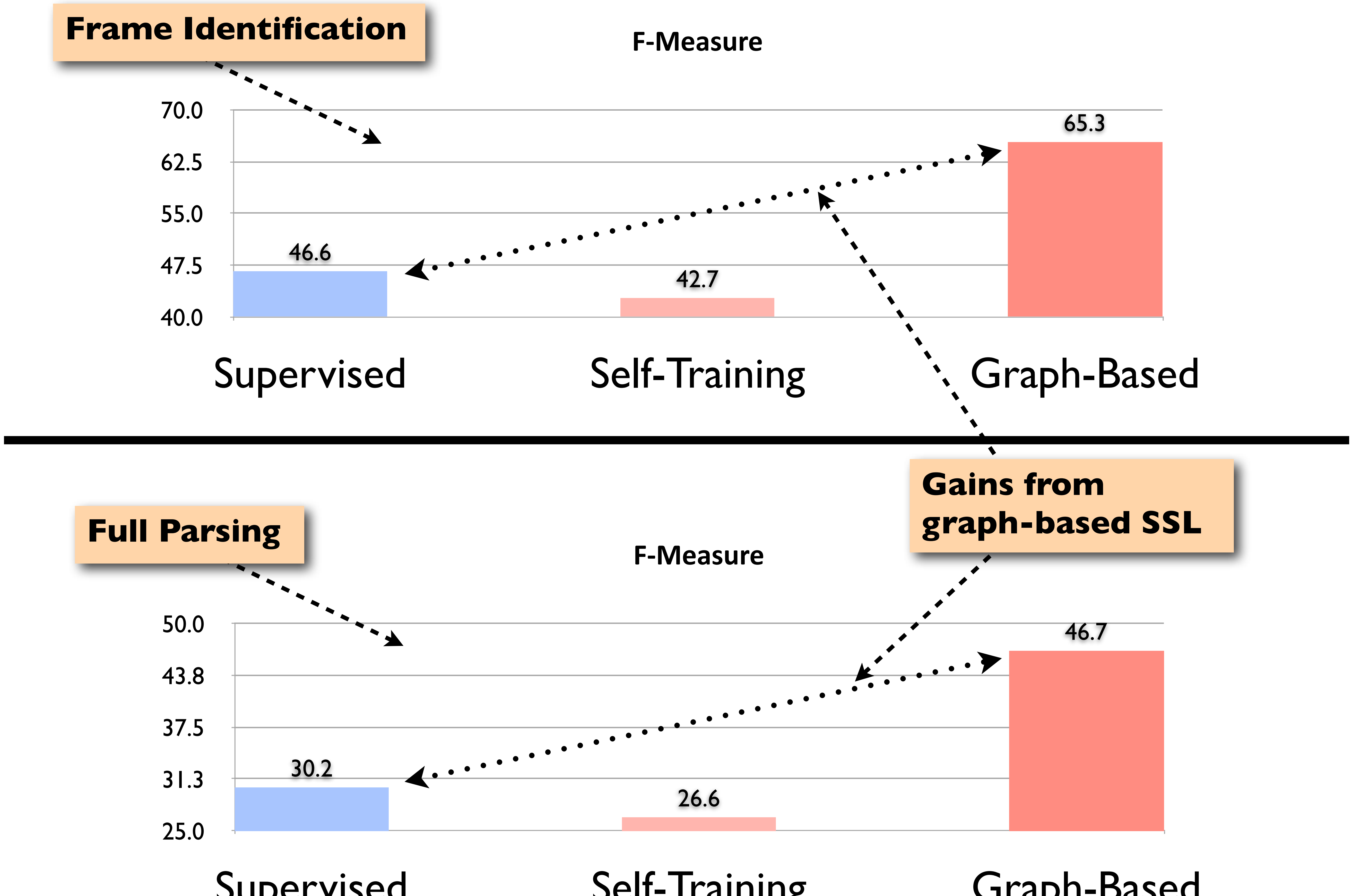

Big Picture

Use case 1: Transductive Classification

Use case 2: Training Better Inductive Model

	Use case 1	Use case 2
Text Categorization	✓	
Sentiment Analysis	✓	✓
Class Instance Acquisition	✓	
POS Tagging		✓
Multilingual POS Tagging	✓	✓
Semantic Parsing		

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  - for probabilistic interpretation
- Manifold Regularization
  - for generalization to unseen data (induction)

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- Effective in practice

Open Challenges

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- Graph-based SSL for Structured Prediction
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  - Algorithms: Combining Inductive and graph-based methods
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- Scalable graph construction, especially with multi-modal data
- Extensions with other loss functions, sparsity, etc.
- Using side information

Acknowledgments

- National Science Foundation (NSF) IIS-0447972
- DARPA HRO1107-1-0029, FA8750-09-C-0179
- Google Research Award
- Dipanjan Das (Google), Ryan McDonald (Google), Fernando Pereira (Google), Slav Petrov (Google), Noah Smith (CMU)

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Thanks!

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