A Discriminative Topic Model using Document Network Structure

Weiwei Yang[1], Jordan Boyd-Graber[2], and Philip Resnik[1]

[1]University of Maryland College Park and [2]University of Colorado Boulder

August 8, 2016

Paper and Slides

Paper	Slides
http://ter.ps/bv5	http://ter.ps/bv7

Documents are Linked

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Weiwei Yang
Computer Science
University of Maryland
College Park, MD
wwyang@cs.umd.edu

Jordan Boyd-Graber
Computer Science
University of Colorado
Boulder, CO
Jordan.Boyd.Graber@colorado.edu

Philip Resnik
Linguistics and UMIACS
University of Maryland
College Park, MD
resnik@umd.edu

Our Paper

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Our Paper

HIERARCHICAL RELATIONAL MODELS FOR DOCUMENT NETWORKS

BY JONATHAN CHANG[1] AND DAVID M. BLEI[2]

Facebook and Princeton University

Relational Topic Model

[Chang and Blei, 2010]

Latent Dirichlet Allocation

David M. Blei BLEI@CS.BERKELEY.EDU
Computer Science Division
University of California
Berkeley, CA 94720, USA

Andrew Y. Ng ANG@CS.STANFORD.EDU
Computer Science Department
Stanford University
Stanford, CA 94305, USA

Michael I. Jordan JORDAN@CS.BERKELEY.EDU
Computer Science Division and Department of Statistics
University of California
Berkeley, CA 94720, USA

LDA [Blei et al., 2003]

Learning Latent Block Structure in Weighted Networks

CHRISTOPHER AICHER
Department of Applied Mathematics, University of Colorado, Boulder, CO, 80309
christopher.aicher@colorado.edu

ABIGAIL Z. JACOBS
Department of Computer Science, University of Colorado, Boulder, CO, 80309

AARON CLAUSET
Department of Computer Science, University of Colorado, Boulder, CO, 80309
BioFrontiers Institute, University of Colorado, Boulder, CO 80303
Santa Fe Institute, Santa Fe, NM 87501

Weighted Stochastic Block Model

[Aicher et al., 2014]

Links Indicate Topic Similarity

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Our Paper: Topic Model

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Relational Topic Model [Chang and Blei, 2010]: Topic Model

Latent Dirichlet Allocation

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LDA [Blei et al., 2003] : Topic Model

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Weighted Stochastic Block Model [Aicher et al., 2014]

Links Indicate Topic Similarity

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Our Paper: Topic Model, Document Network

⇒

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Relational Topic Model [Chang and Blei, 2010]: Topic Model, Document Network

⇓

Latent Dirichlet Allocation

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LDA [Blei et al., 2003] : Topic Model

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Weighted Stochastic Block Model [Aicher et al., 2014]

Links Indicate Topic Similarity

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Our Paper: Topic Model,

Document Network, Block Detection

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Relational Topic Model

[Chang and Blei, 2010]:

Topic Model, Document Network

Latent Dirichlet Allocation

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LDA [Blei et al., 2003] : Topic Model

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Weighted Stochastic Block Model

[Aicher et al., 2014]: Block Detection

Goal

- Make use of the rich information in document links
  - Improve topic modeling
- Replicate existing links
- Predict held-out links

Outline

1. Block Detection and RTM
2. LBH-RTM
3. Link Prediction Results
4. Conclusions

Paper
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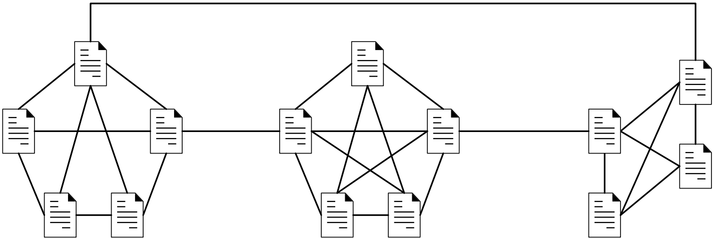
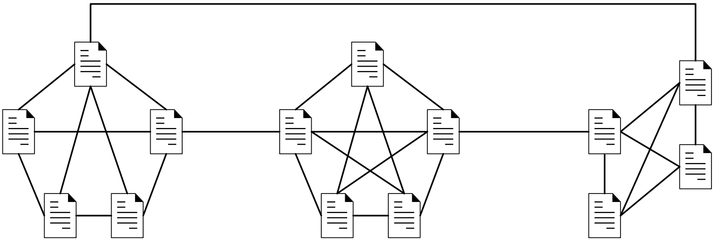
Block Detection

- Find densely-connected blocks in a graph



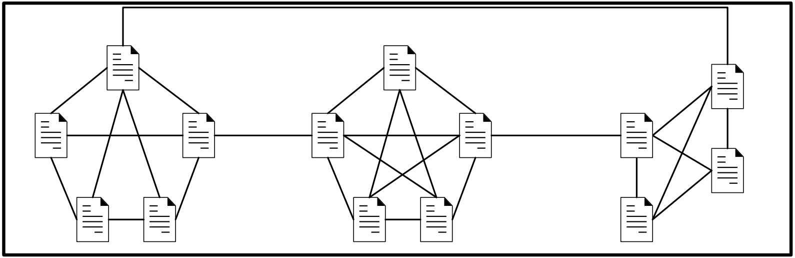
Block Detection

- Find densely-connected blocks in a graph
- Deterministic: Strongly connected components (SCC)



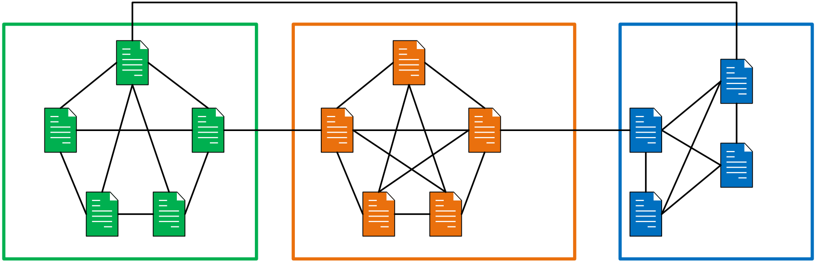
Block Detection

- Find densely-connected blocks in a graph
- Deterministic: Strongly connected components (SCC)
  - Puts any linked nodes into the same component
  - Does not consider link density



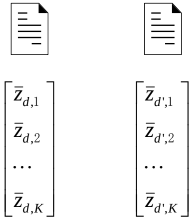
Block Detection

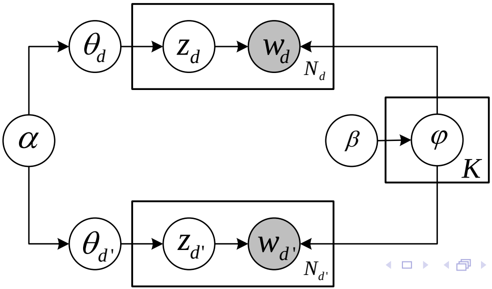
- Find densely-connected blocks in a graph
- Deterministic: Strongly connected components (SCC)
  - Puts any linked nodes into the same component
  - Does not consider link density
- Probabilistic: Weighted stochastic block model (WSBM)



Relational Topic Model [Chang and Blei, 2010]

- A topic model for link prediction
- Jointly models topics and links

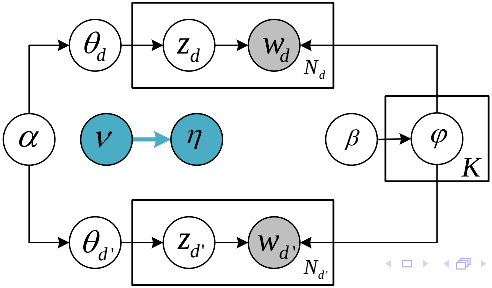




Relational Topic Model [Chang and Blei, 2010]

- A topic model for link prediction
- Jointly models topics and links
- Each topic is assigned a weight
  - Indicate the correlations between topics and links

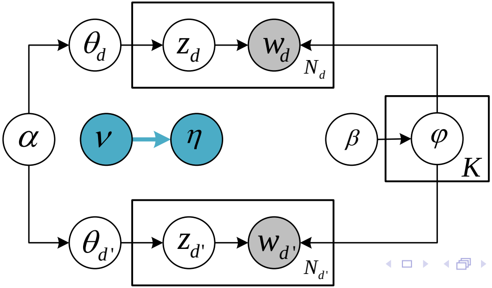
$$\eta^{\mathrm{T}} \begin{bmatrix} \bar{z}_{d,1} \\ \bar{z}_{d,2} \\ \cdots \\ \bar{z}_{d,K} \end{bmatrix} \quad \begin{bmatrix} \bar{z}_{d',1} \\ \bar{z}_{d',2} \\ \cdots \\ \bar{z}_{d',K} \end{bmatrix}$$



Relational Topic Model [Chang and Blei, 2010]

- A topic model for link prediction
- Jointly models topics and links
- Each topic is assigned a weight
  - Indicate the correlations between topics and links
- Composes a regression value $R_{d,d'}$

$$R_{d,d'} = \eta^{\mathrm{T}} \left(\begin{bmatrix} \bar{z}_{d,1} \\ \bar{z}_{d,2} \\ \cdots \\ \bar{z}_{d,K} \end{bmatrix} \circ \begin{bmatrix} \bar{z}_{d',1} \\ \bar{z}_{d',2} \\ \cdots \\ \bar{z}_{d',K} \end{bmatrix} \right)$$



Relational Topic Model [Chang and Blei, 2010]

- A topic model for link prediction
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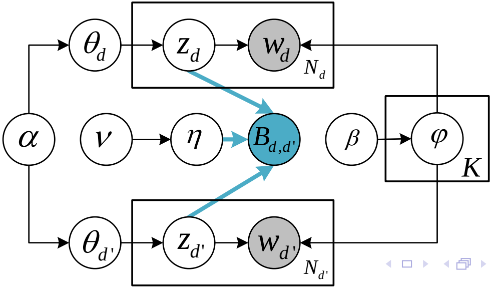
- $\Pr\left(B_{d,d'} = 1\right) = \sigma\left(R_{d,d'}\right)$

$$R_{d,d'} = \eta^{\mathrm{T}} \left(\begin{bmatrix} \bar{z}_{d,1} \\ \bar{z}_{d,2} \\ \cdots \\ \bar{z}_{d,K} \end{bmatrix} \circ \begin{bmatrix} \bar{z}_{d',1} \\ \bar{z}_{d',2} \\ \cdots \\ \bar{z}_{d',K} \end{bmatrix} \right)$$



Outline

1 Block Detection and RTM

2 LBH-RTM

3 Link Prediction Results

4 Conclusions

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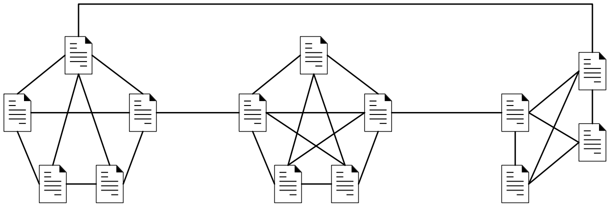
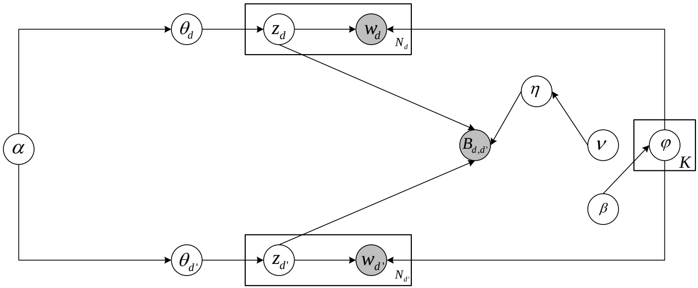
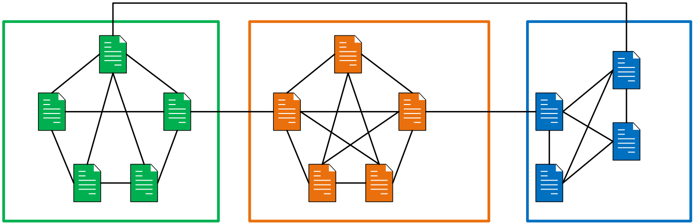
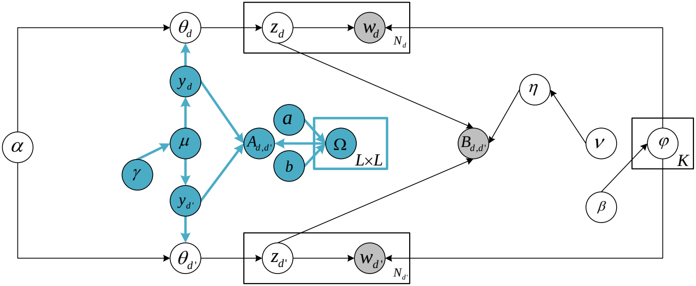
Relational Topic Model



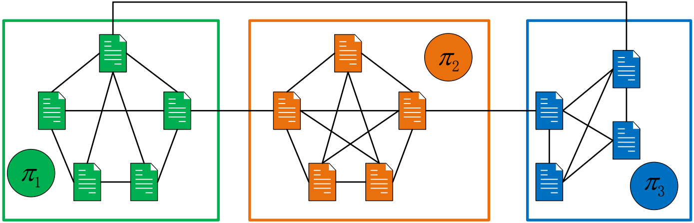


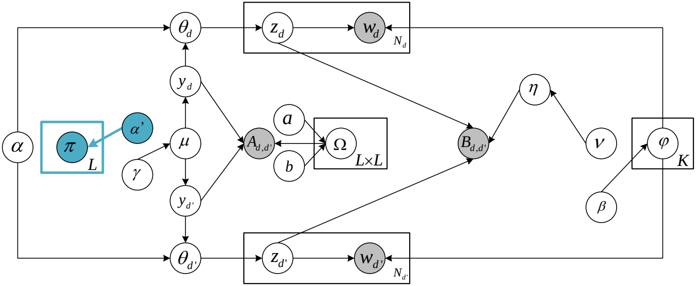
Relational Topic Model with Weighted Stochastic Block Model





Relational Topic Model with Weighted Stochastic Block Model, Block Priors





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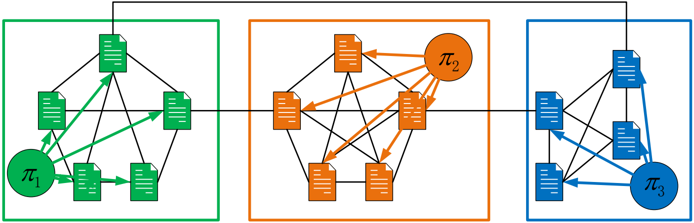
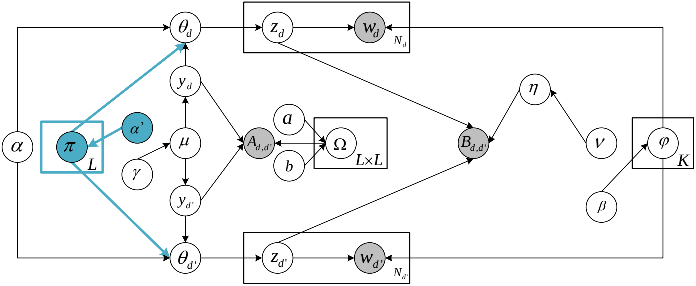
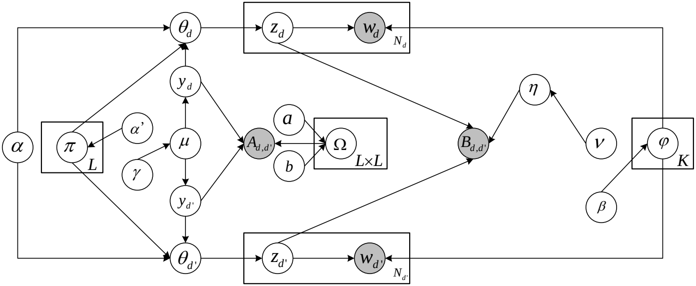




Relational Topic Model with Weighted Stochastic Block Model, Block Priors, Various Features

$$R_{d,d'} = \boldsymbol{\eta}^{\mathsf{T}} \underbrace{\begin{bmatrix} \bar{z}_{d,1} \\ \bar{z}_{d,2} \\ \vdots \\ \bar{z}_{d,K} \end{bmatrix} \circ \begin{bmatrix} \bar{z}_{d',1} \\ \bar{z}_{d',2} \\ \vdots \\ \bar{z}_{d',K} \end{bmatrix}}_{\text{Topical Feature}}$$



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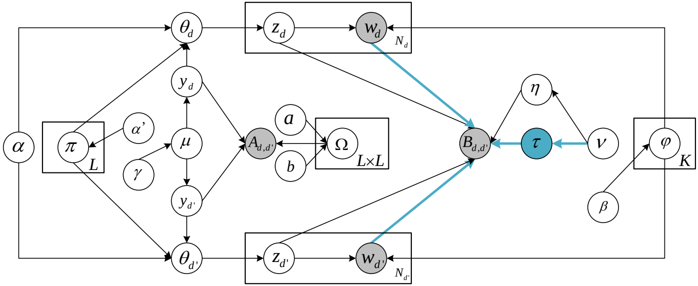

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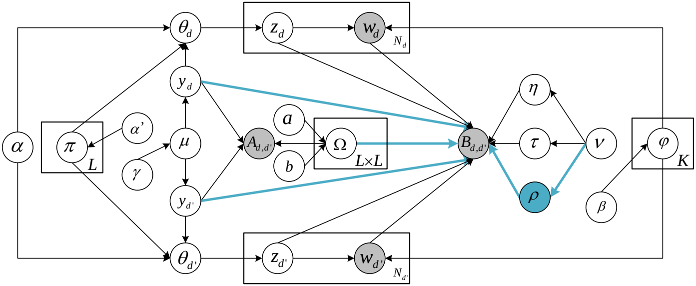

Relational Topic Model with Weighted Stochastic Block Model, Block Priors, Various Features

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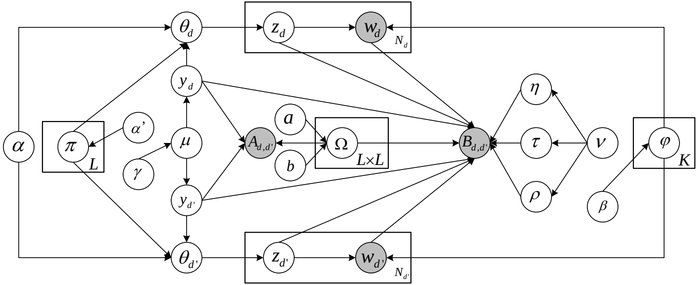
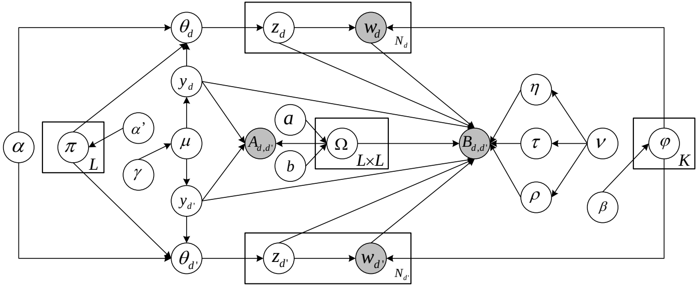
$$\Pr\left(B_{d,d'} = 1\right) = \sigma(R_{d,d'}) \text{ (Sigmoid Loss)}$$



Relational Topic Model with Weighted Stochastic Block Model, Block Priors, Various Features, and Hinge Loss

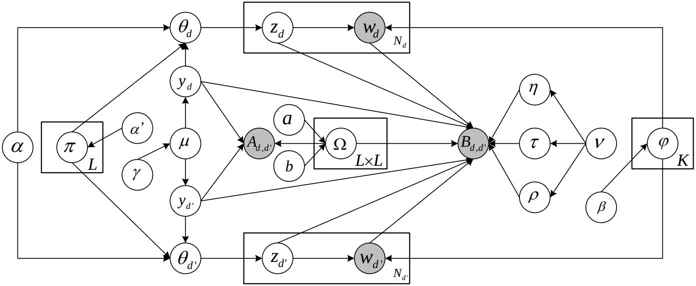
$\Pr(B_{d,d'} = 1) = \sigma(R_{d,d'})$ (Sigmoid Loss)



Relational Topic Model with Weighted Stochastic Block Model, Block Priors, Various Features, and Hinge Loss

$\Pr(B_{d,d'} = 1) = \sigma(R_{d,d'})$ (Sigmoid Loss)

$\rightarrow \quad \Pr(B_{d,d'}) = \exp(-2\max(0, 1 - B_{d,d'}R_{d,d'}))$ (Hinge Loss)



Relational Topic Model with Weighted Stochastic Block Model, Block Priors, Various Features, and Hinge Loss

$$\Pr(B_{d,d'} = 1) = \sigma(R_{d,d'}) \text{ (Sigmoid Loss)}$$

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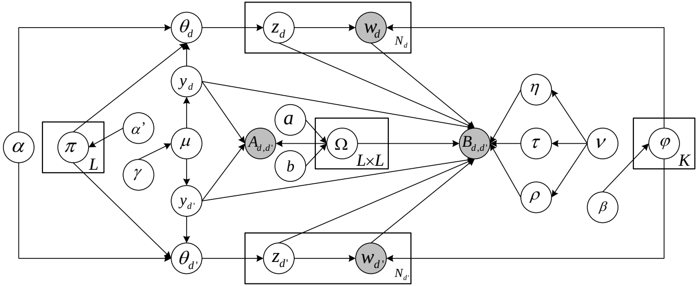
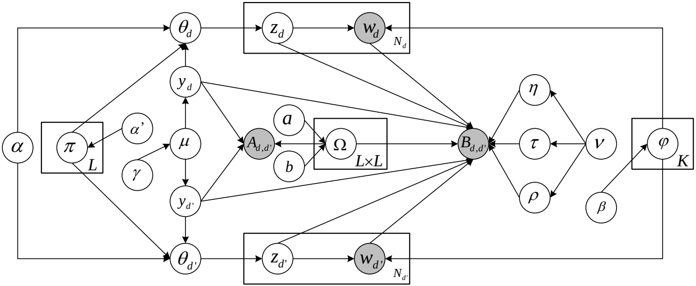
- Make more effective use of side information when inferring topics.



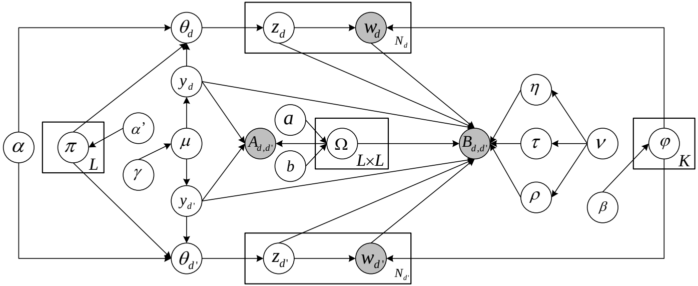
LBH-RTM



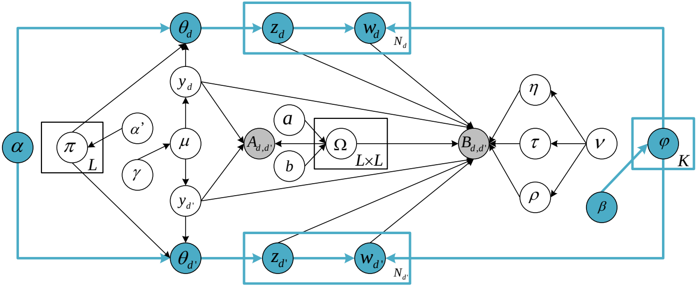
Relational Topic Model with

- **L**exical weights
- **B**lock priors
- **H**inge loss

Baseline Models

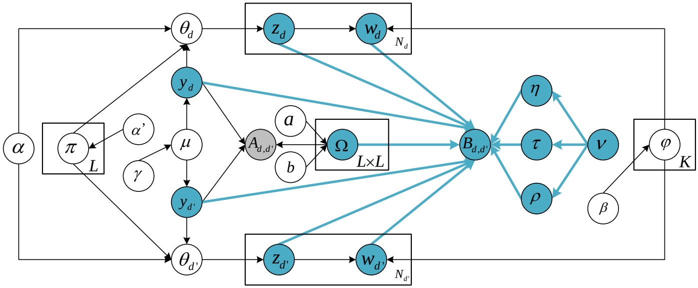


Baseline Models



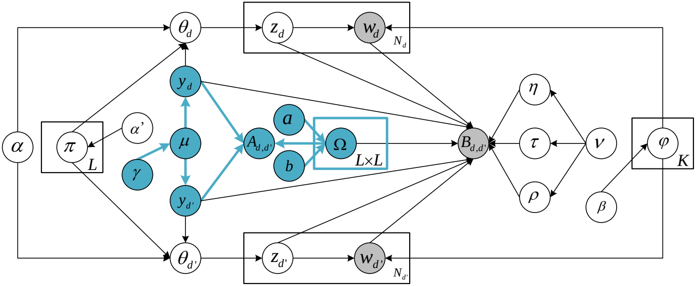
- Vanilla LDA: Infers topics based on words.

Baseline Models



- Vanilla LDA: Infers topics based on words.
- Relational Topic Model with various features:
  - Encourages linked docs to have similar topic distributions.
  - Links indicate topic similarity.

Baseline Models



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- Weighted Stochastic Block Model:
  - Does not understand the content at all.

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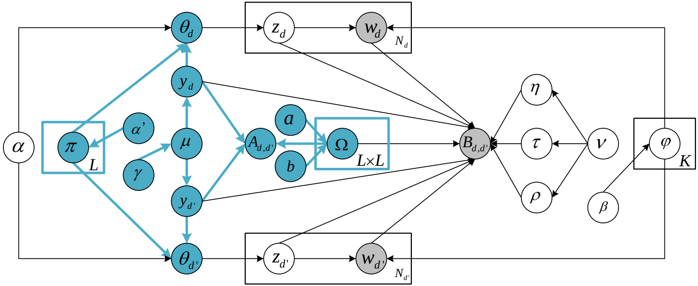

- Vanilla LDA: Infers topics based on words.
- Relational Topic Model with various features:
  - Encourages linked docs to have similar topic distributions.
  - Links indicate topic similarity.
- Weighted Stochastic Block Model:
  - Does not understand the content at all.
  - Finds blocks and provides informative priors.

Outline

1 Block Detection and RTM

2 LBH-RTM

3 Link Prediction Results

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Datasets

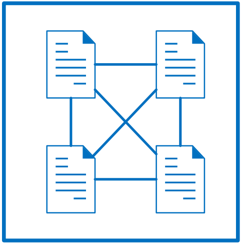
- Cora: Scientific papers and citation links
- WebKB: Web pages and hyperlinks

Corpus	#Docs	#Links	#Vocabulary
Cora	2,362	4,231	1,240
WebKB	877	1,608	1,703

Task

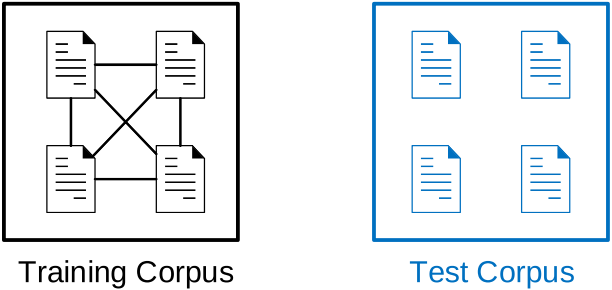
Task

- Training input: Training documents with links



Task

- Training input: Training documents with links
- Test input: Test documents only



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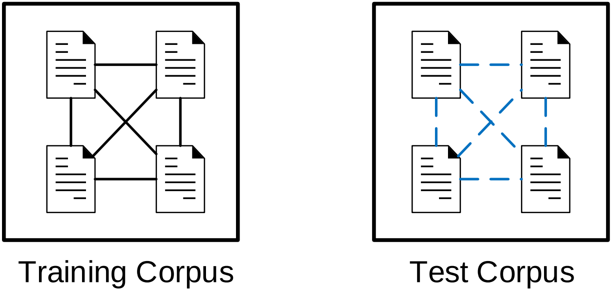
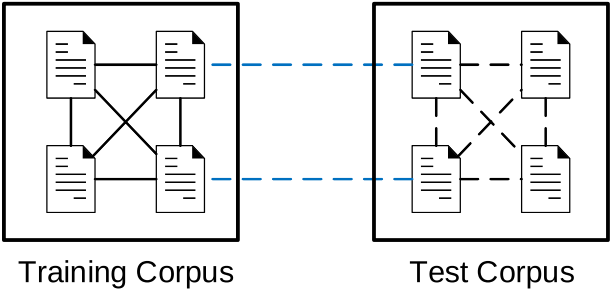
- Training input: Training documents with links
- Test input: Test documents only
- Predict links within test documents



Task

- Training input: Training documents with links
- Test input: Test documents only
- Predict links within test documents
- Predict links from test documents to training documents



Evaluation Metric

- Predictive link rank (PLR)

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  - For a document d, we compute and sort all other documents by their link probabilities to d

Rank	Doc ID	Link Probability
1	5	0.90
2	3	0.85
3	2	0.82
4	4	0.70
5	6	0.63
6	1	0.50

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Rank	**Doc ID**	**Link Probability**	**True Link?**
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Evaluation Metric

- Predictive link rank (PLR)
  - For a document d, we compute and sort all other documents by their link probabilities to d
  - Then compute the average rank of actually linked documents
  - PLR=(2+3+5)/3=3.33

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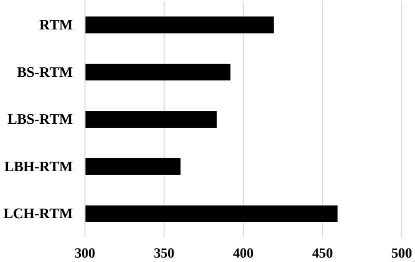
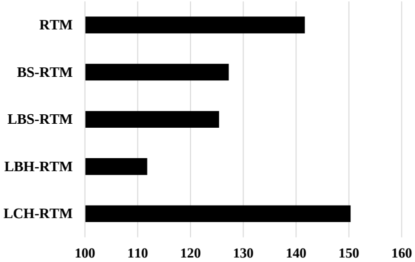
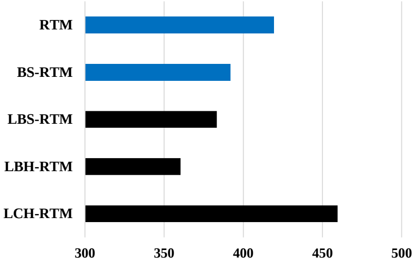
Predictive Link Rank Results

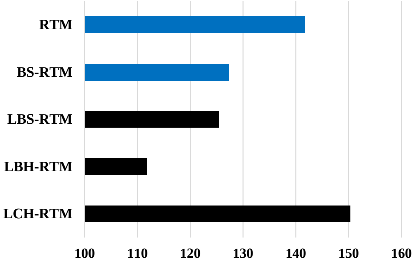




- Incrementally add components on RTM framework

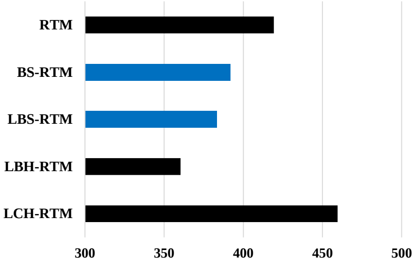
Predictive Link Rank Results

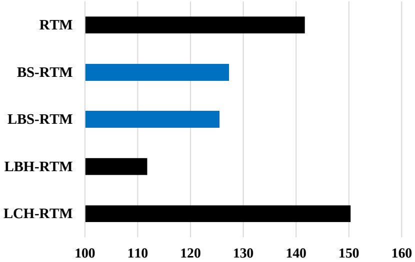




- Incrementally add components on RTM framework
  - Block priors

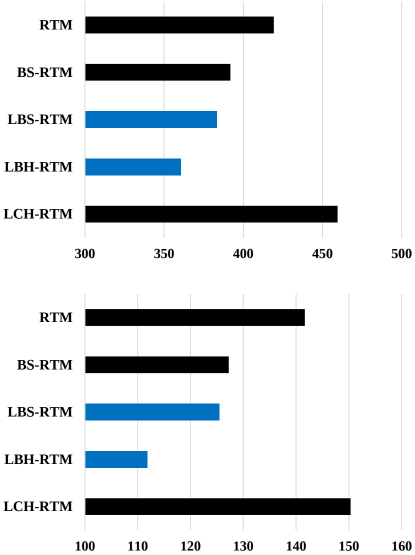
Predictive Link Rank Results





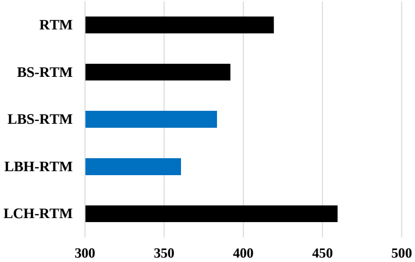
- Incrementally add components on RTM framework
  - Block priors
  - Lexical weights

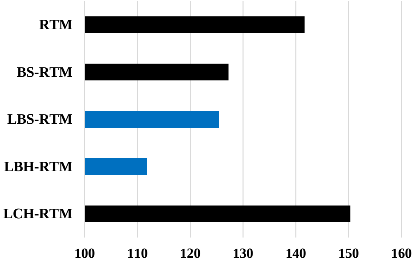
Predictive Link Rank Results



- Incrementally add components on RTM framework
  - Block priors
  - Lexical weights
  - Hinge loss

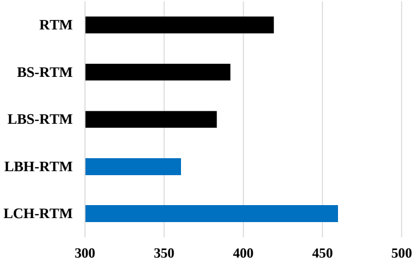
Predictive Link Rank Results

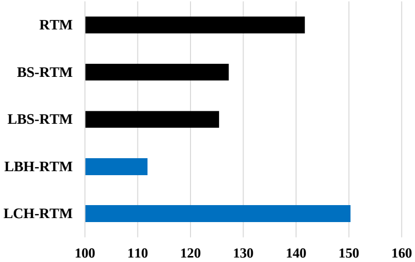




- Incrementally add components on RTM framework
  - Block priors
  - Lexical weights
  - Hinge loss
- Each component contributes to link prediction improvement

Predictive Link Rank Results





- Incrementally add components on RTM framework
  - Block priors
  - Lexical weights
  - Hinge loss
- Each component contributes to link prediction improvement
- Strongly connected components ruin the link prediction

Link Example

Using Fourier-Neural Recurrent Networks
to Fit Sequential Input/Output Data

Renée Koplon
Dept. of Mathematics and Statistics
Wright State University
Dayton, Ohio 45435

Eduardo D. Sontag
Dept. of Mathematics
Rutgers University
New Brunswick, New Jersey 08903

Paper 1 [Koplon and Sontag, 1997]

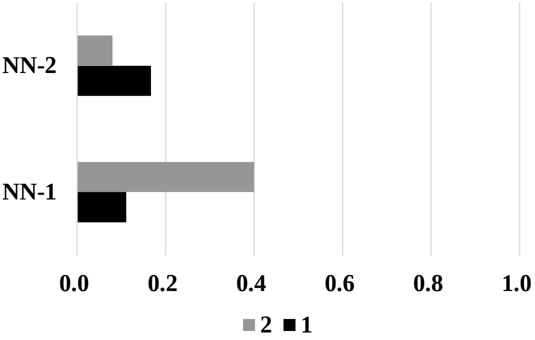
$\Downarrow$

FOR NEURAL NETWORKS, FUNCTION DETERMINES FORM

Francesca Albertini
Eduardo D. Sontag
Department of Mathematics Rutgers University, New Brunswick, NJ 08903
E-mail: albertin@hilbert.rutgers.edu, sontag@hilbert.rutgers.edu

Paper 2 [Albertini and Sontag, 1992]

Link Example — RTM

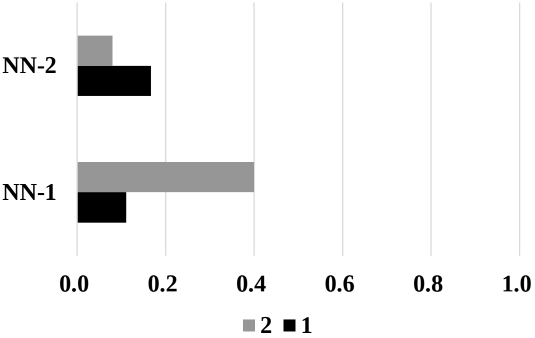


Topic Proportions by RTM

Model	Link Rank
RTM	1,265

NN-1: network, neural, compute, activation, pattern, model
NN-2: network, neural, learn, train, algorithm, local, weight

Link Example — RTM



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NN-1: network, neural, compute, activation, pattern, model
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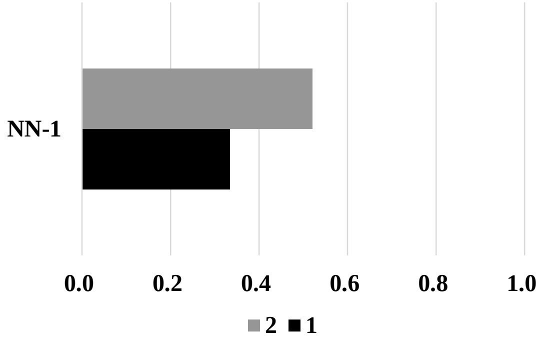
Link Example — BS-RTM

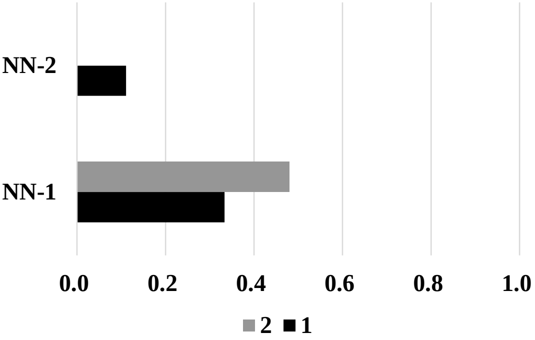


Topic Proportions by BS-RTM

Model	Link Rank
RTM	1,265
BS-RTM	635

NN: network, neural, learn, train, algorithm, weight, input

Link Example — LBS-RTM

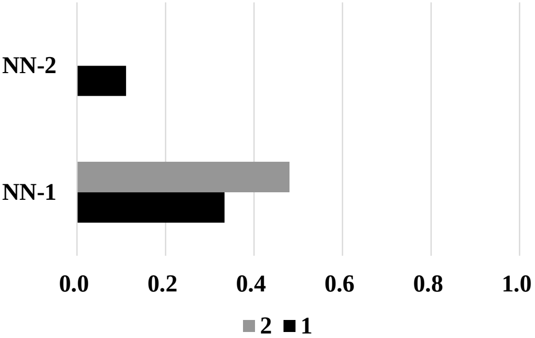


Topic Proportions by LBS-RTM

Model	Link Rank
RTM	1,265
BS-RTM	635
LBS-RTM	132

NN-1: network, neural, learn, train, weight, input, architecture
NN-2: learn, model, agent, reinforce, action, generate, strategy

Link Example — LBS-RTM



Topic Proportions by LBS-RTM

Model	Link Rank
RTM	1,265
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NN-1: network, neural, learn, train, weight, input, architecture

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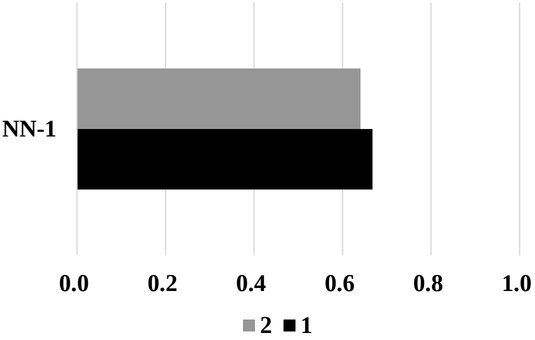
Link Example — LBH-RTM

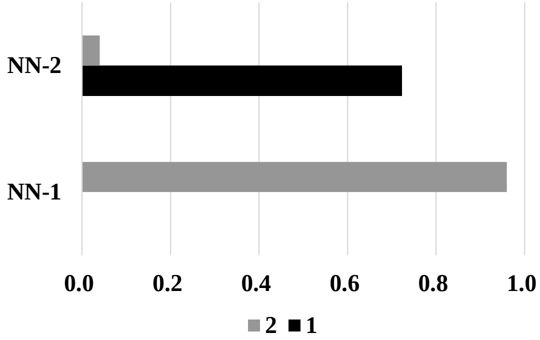


Topic Proportions by LBH-RTM

Model	Link Rank
RTM	1,265
BS-RTM	635
LBS-RTM	132
LBH-RTM	**106**

NN: network, neural, train, learn, function, generate, weight

Link Example — LCH-RTM

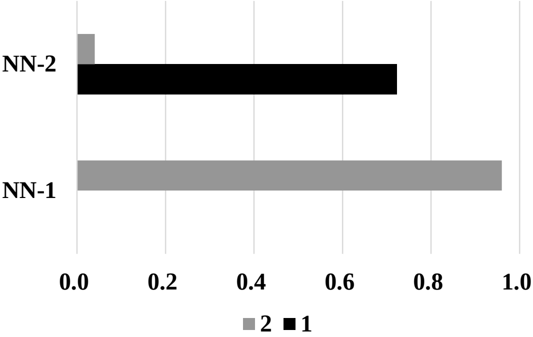


Topic Proportions by LCH-RTM

Model	Link Rank
RTM	1,265
BS-RTM	635
LBS-RTM	132
LBH-RTM	**106**
LCH-RTM	1,385

NN-1: network, model, belief, algorithm, function, approximation
NN-2: network, neural, train, learn, algorithm, weight, result

Link Example — LCH-RTM



Topic Proportions by LCH-RTM

Model	Link Rank
RTM	1,265
BS-RTM	635
LBS-RTM	132
LBH-RTM	**106**
LCH-RTM	1,385

NN-1: network, model, belief, algorithm, function, approximation
NN-2: network, neural, train, learn, algorithm, weight, result

Outline

1 Block Detection and RTM

2 LBH-RTM

3 Link Prediction Results

4 Conclusions

Paper
http://ter.ps/bv5

Slides
http://ter.ps/bv7

Summary

- LBH-RTM
  - Topic model for link prediction
  - Incorporate block priors from links
  - Include lexical weights and hinge loss
- Future directions
  - Directed/undirected links
  - Binary/nonnegative real weight links
  - Link suggestion

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- Jordan Boyd-Graber (UC Boulder)
- Philip Resnik (UMD)

Funders

DARPA

Raytheon
BBN Technologies

NSF

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