A Discriminative Topic Model using Document Network Structure

Weiwei Yang\textsuperscript{1}, Jordan Boyd-Graber\textsuperscript{2}, and Philip Resnik\textsuperscript{1}

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August 8, 2016
Paper and Slides

Paper
http://ter.ps/bv5

Slides
http://ter.ps/bv7
Documents are Linked

A Discriminative Topic Model using Document Network Structure

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Our Paper
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HIERARCHICAL RELATIONAL MODELS FOR DOCUMENT NETWORKS

BY JONATHAN CHANG¹ AND DAVID M. BLEI²

Facebook and Princeton University

Relational Topic Model
[Chang and Blei, 2010]

Learning Latent Block Structure in Weighted Networks

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Weighted Stochastic Block Model
[Aicher et al., 2014]
A Discriminative Topic Model using Document Network Structure

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Our Paper: Topic Model

Latent Dirichlet Allocation

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

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Relational Topic Model
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Topic Model

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1. Introduction

Network data, such as citation networks of documents, have been a rich source of information for researchers. For example, citation networks of articles also contain text and abstracts of the papers, which can be used to infer the topics of the papers. The basic methodology proposed by Blei et al. (2003) is Latent Dirichlet Allocation (LDA), a generative probabilistic model for collections of documents.

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key words and phrases. Mixed-membership models, variational methods, text analysis, network models.

124

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Facebook and Princeton University

Relational Topic Model

[Chang and Blei, 2010]:

Topic Model, Document Network

Learning Latent Block Structure in Weighted Networks

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Weighted Stochastic Block Model

[Aicher et al., 2014]
Links Indicate Topic Similarity

A Discriminative Topic Model using Document Network Structure

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Our Paper: Topic Model, Document Network, Block Detection

Latent Dirichlet Allocation

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HIERARCHICAL RELATIONAL MODELS FOR DOCUMENT NETWORKS

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Relational Topic Model
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Weighted Stochastic Block Model
[Aicher et al., 2014]: Block Detection

LDA [Blei et al., 2003]: Topic Model
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 http://ter.ps/bv5
Slides http://ter.ps/bv7
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

![Diagram of Relational Topic Model]

\[ \eta^T \]

\[ \begin{bmatrix}
  \bar{z}_{d,1} \\
  \bar{z}_{d,2} \\
  \vdots \\
  \bar{z}_{d,K}
\end{bmatrix} \]
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 $R_{d,d'}$

$$R_{d,d'} = \eta^T \circ \begin{bmatrix} z_{d,1} \\ z_{d,2} \\ \vdots \\ z_{d,K} \\ z'_{d,1} \\ z'_{d,2} \\ \vdots \\ z'_{d,K} \end{bmatrix}$$
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 $R_{d,d'}$
- $\Pr (B_{d,d'} = 1) = \sigma (R_{d,d'})$

$$R_{d,d'} = \eta^T \begin{bmatrix} \bar{z}_{d,1} \\ \bar{z}_{d,2} \\ \vdots \\ \bar{z}_{d,K} \end{bmatrix}$$
Outline

1. Block Detection and RTM
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Relational Topic Model with Weighted Stochastic Block Model
Relational Topic Model with Weighted Stochastic Block Model, Block Priors
Relational Topic Model with Weighted Stochastic Block Model, Block Priors
Relational Topic Model with Weighted Stochastic Block Model, Block Priors, Various Features

\[ R_{d,d'} = \eta^T \begin{bmatrix} Z_{d,1} \\ Z_{d,2} \\ \vdots \\ Z_{d,K} \end{bmatrix} \circ \begin{bmatrix} Z'_{d,1} \\ Z'_{d,2} \\ \vdots \\ Z'_{d,K} \end{bmatrix} \]

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

$$R_{d,d'} = \eta^T \begin{bmatrix} \bar{z}_{d,1} \\ \bar{z}_{d,2} \\ \vdots \\ \bar{z}_{d,K} \end{bmatrix} \circ \begin{bmatrix} \bar{z}_{d',1} \\ \bar{z}_{d',2} \\ \vdots \\ \bar{z}_{d',K} \end{bmatrix}$$

Topical Feature

$$+ \tau^T \begin{bmatrix} \bar{w}_{d,1} \\ \bar{w}_{d,2} \\ \vdots \\ \bar{w}_{d,V} \end{bmatrix} \circ \begin{bmatrix} \bar{w}_{d',1} \\ \bar{w}_{d',2} \\ \vdots \\ \bar{w}_{d',V} \end{bmatrix}$$

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

\[ R_{d,d'} = \eta^T \circ \begin{bmatrix} \bar{Z}_{d,1} \\ \bar{Z}_{d,2} \\ \vdots \\ \bar{Z}_{d,K} \end{bmatrix} + \tau^T \circ \begin{bmatrix} \bar{W}_{d,1} \\ \bar{W}_{d,2} \\ \vdots \\ \bar{W}_{d',V} \end{bmatrix} + \rho_{l,l'} \Omega_{l,l'} \]

**Topical Feature**

**Lexical Feature**

**Block Feat.**
Relational Topic Model with Weighted Stochastic Block Model, Block Priors, Various Features

\[ R_{d,d'} = \eta^T \left[ \begin{array}{c} \bar{Z}_{d,1} \\ \bar{Z}_{d,2} \\ \vdots \\ \bar{Z}_{d,K} \end{array} \right] \circ \left[ \begin{array}{c} \bar{Z}'_{d,1} \\ \bar{Z}'_{d,2} \\ \vdots \\ \bar{Z}'_{d,K} \end{array} \right] + \tau^T \left[ \begin{array}{c} \bar{W}_{d,1} \\ \bar{W}_{d,2} \\ \vdots \\ \bar{W}_{d,V} \end{array} \right] \circ \left[ \begin{array}{c} \bar{W}'_{d,1} \\ \bar{W}'_{d,2} \\ \vdots \\ \bar{W}'_{d,V} \end{array} \right] + \rho_{l,l'} \Omega_{l,l'} \]

Topical Feature

Lexical Feature

Embedding of Block Feature

Block Feat.

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

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

\[ \rightarrow \Pr (B_{d,d'}) = \exp (-2 \max (0, 1 - B_{d,d'}R_{d,d'})) \text{ (Hinge Loss)} \]
Relational Topic Model with Weighted Stochastic Block Model, Block Priors, Various Features, and Hinge Loss

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

\[
\Rightarrow \quad \Pr (B_{d,d'}) = \exp (-2 \max (0, 1 - B_{d,d'} R_{d,d'})) \quad \text{(Hinge Loss)}
\]

- Make more effective use of side information when inferring topics.
Relational Topic Model with

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

Weighted Stochastic Block Model:
- Does not understand the content at all.
- Finds blocks and provides informative priors.
Baseline Models

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Baseline Models

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Outline

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

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

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

<table>
<thead>
<tr>
<th>Corpus</th>
<th>#Docs</th>
<th>#Links</th>
<th>#Vocabulary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cora</td>
<td>2,362</td>
<td>4,231</td>
<td>1,240</td>
</tr>
<tr>
<td>WebKB</td>
<td>877</td>
<td>1,608</td>
<td>1,703</td>
</tr>
</tbody>
</table>
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
Task

- Training input: Training documents with links

Training Corpus
Task

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

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

Training Corpus

Test Corpus
**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)

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.

\[ \text{PLR} = \frac{2 + 3 + 5}{3} = 3.33 \]
**Evaluation Metric**

- Predictive link rank (PLR)
  - For a document $d$, we compute and sort all other documents by their link probabilities to $d$

<table>
<thead>
<tr>
<th>Rank</th>
<th>Doc ID</th>
<th>Link Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5</td>
<td>0.90</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>0.85</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>0.82</td>
</tr>
<tr>
<td>4</td>
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</tr>
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Evaluation Metric

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Evaluate 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

- RTM
- BS-RTM
- LBS-RTM
- LBH-RTM
- LCH-RTM

Incrementally add components on RTM framework
Predictive Link Rank Results

- Incrementally add components on RTM framework
- Block priors
Predictive Link Rank Results

![Bar chart showing the results of Predictive Link Rank.](chart)

- **RTM**
- **BS-RTM**
- **LBS-RTM**
- **LBH-RTM**
- **LCH-RTM**

Each component contributes to link prediction improvement:
- Block priors
- Lexical weights

Incrementally add components on RTM framework.
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
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
Using Fourier-Neural Recurrent Networks to Fit Sequential Input/Output Data

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Eduardo D. Sontag
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New Brunswick, New Jersey 08903

Paper 1 [Koplon and Sontag, 1997]

FOR NEURAL NETWORKS, FUNCTION DETERMINES FORM

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Paper 2 [Albertini and Sontag, 1992]
Link Example — RTM

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

<table>
<thead>
<tr>
<th>Model</th>
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<tbody>
<tr>
<td>RTM</td>
<td>1,265</td>
</tr>
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</table>

Topic Proportions by RTM
Link Example — RTM

NN-1: network, neural, compute, activation, pattern, model
NN-2: network, neural, learn, train, algorithm, local, weight
Link Example — BS-RTM

NN-1

2 1

Topic Proportions by BS-RTM

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

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<tr>
<td>BS-RTM</td>
<td>635</td>
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</tbody>
</table>
Link Example — LBS-RTM

Topic Proportions by LBS-RTM

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

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**Link Example — LBS-RTM**

**Topic Proportions by LBS-RTM**

| NN-1: network, neural, learn, train, weight, input, architecture |
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**Link Example — LBH-RTM**

**Topic Proportions by LBH-RTM**

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

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<td>LBH-RTM</td>
<td><strong>106</strong></td>
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Link Example — LCH-RTM

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<tr>
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</tr>
<tr>
<td>LCH-RTM</td>
<td>1,385</td>
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NN-1: network, model, belief, algorithm, function, approximation
NN-2: network, neural, train, learn, algorithm, weight, result
Link Example — LCH-RTM

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

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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
Thanks

Collaborators

- Jordan Boyd-Graber (UC Boulder)
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Funders

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