

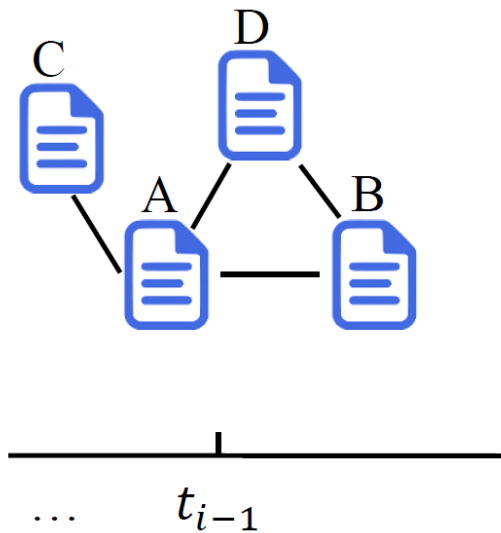
# Dynamic Topic Models for Temporal Document Networks

Delvin Ce Zhang and Hady W. Lauw  
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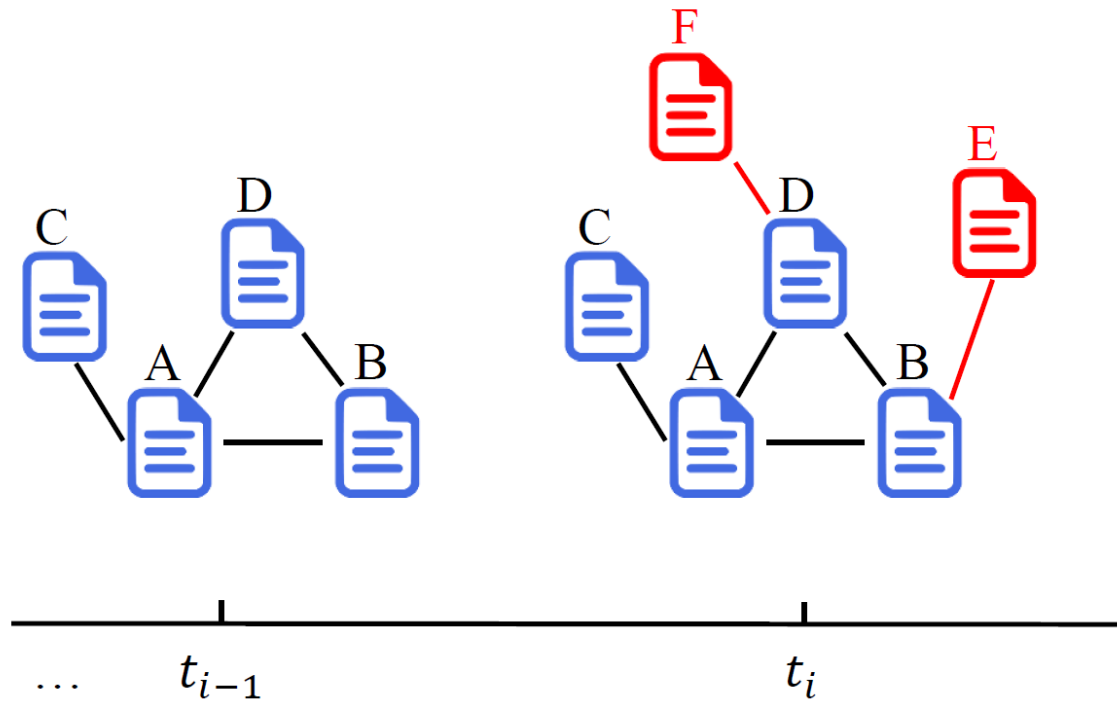
# Motivation

- **Temporal Document Networks**
  - Examples: Paper citation network, Web page hyperlink network, etc.
  - Illustration:



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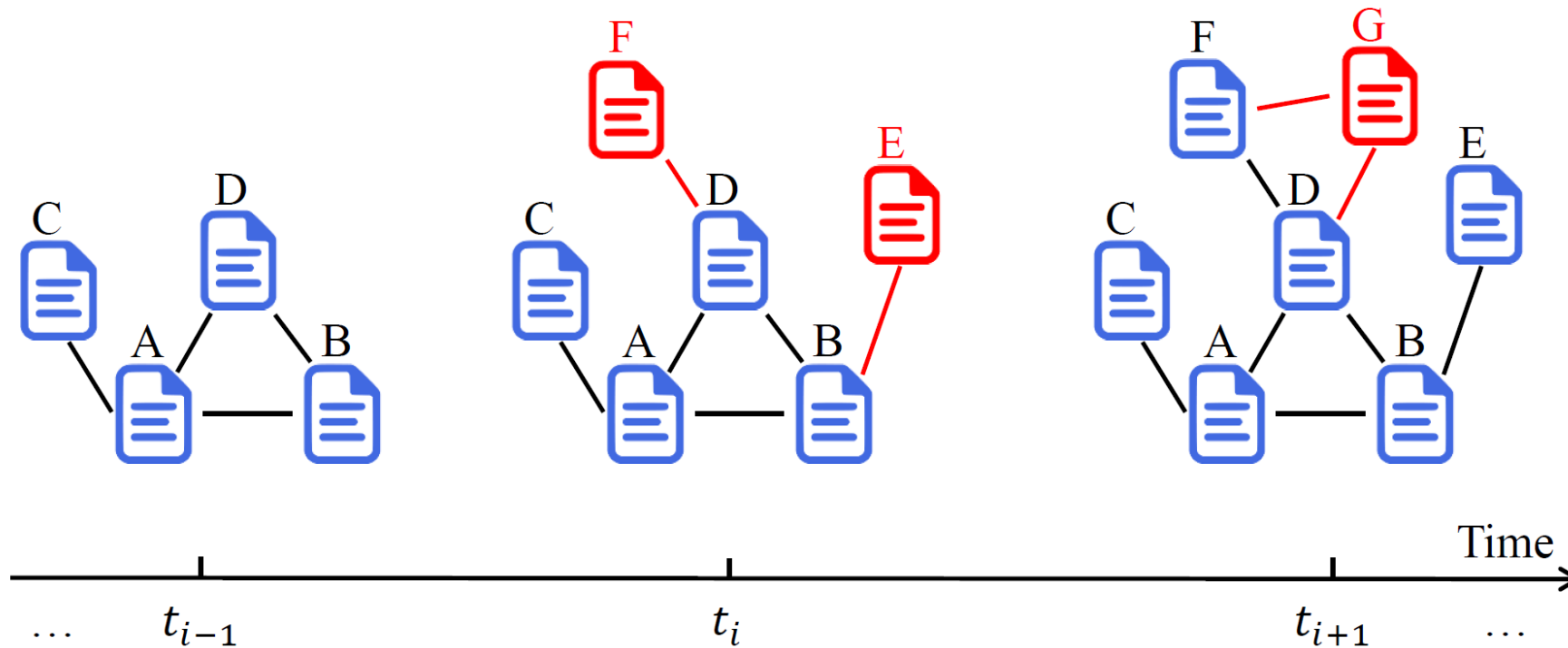
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# Motivation

- Temporal Document Networks**

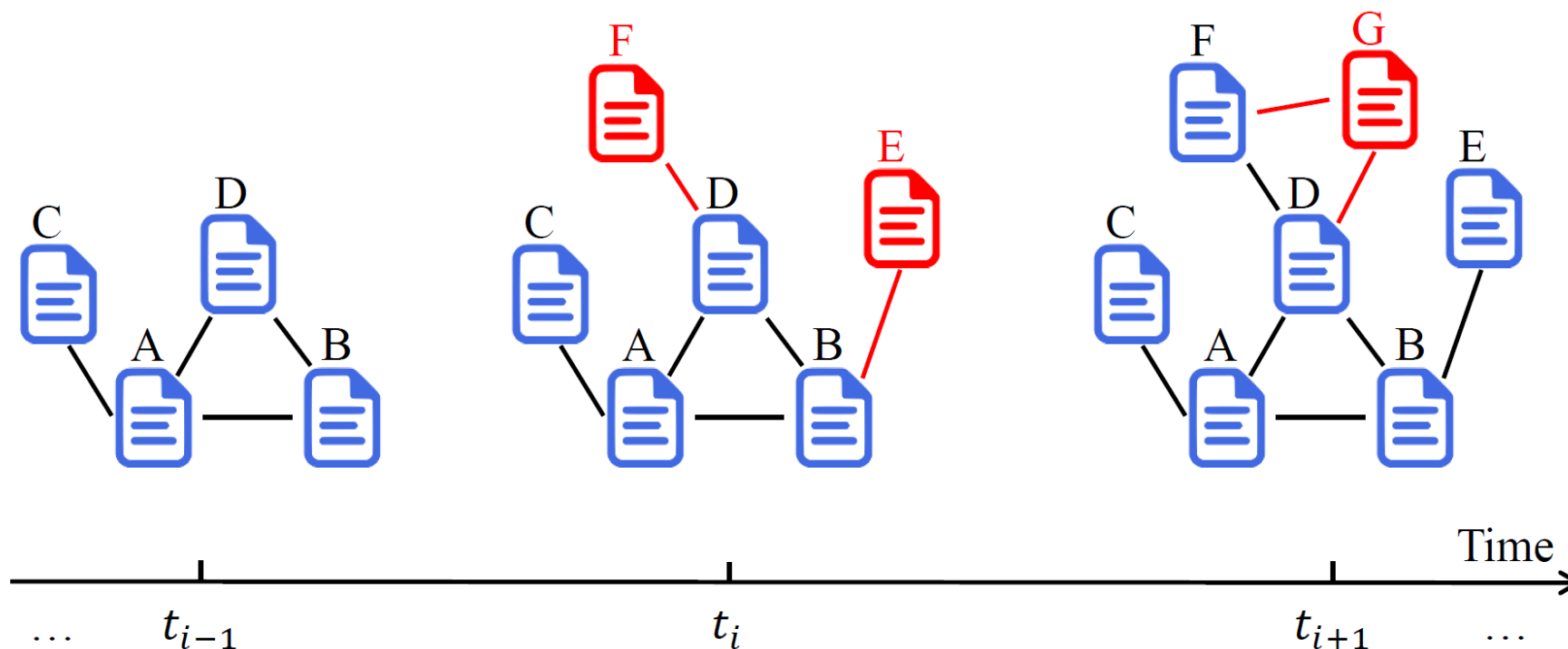
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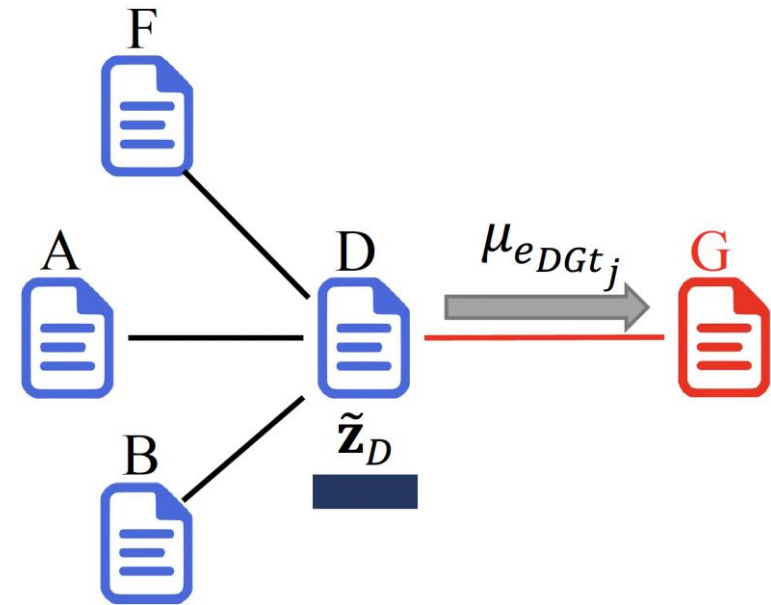
- **Temporal Document Networks**

- Examples: Paper citation network, Web page hyperlink network, etc.
- Illustration:



Existing research [1] considers network connectivity only, ignoring document dynamics.

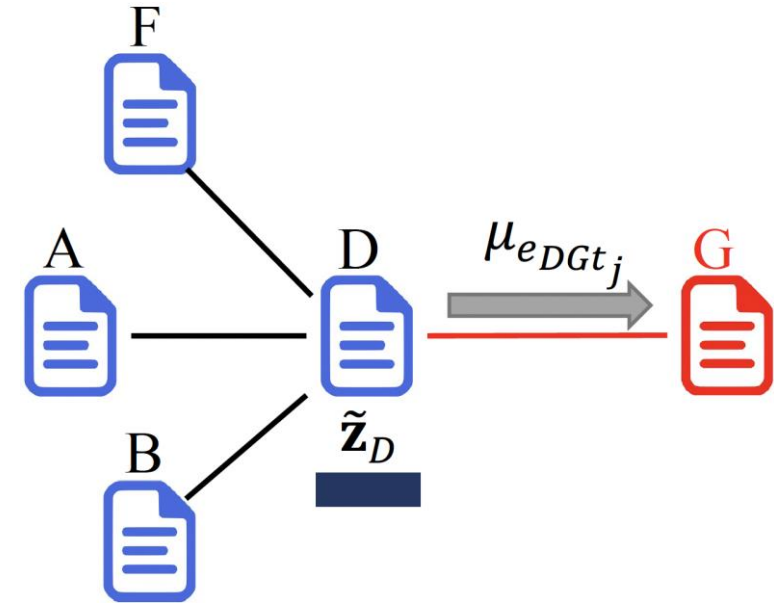
# Model Architecture



# Model Architecture

- We design a Time-Aware Optimal Transport to predict each link.

$$d_C(\tilde{\mathbf{z}}_i, \mathbf{d}_j, t_i, t_j) = \min_{\mathbf{P} \in U(\tilde{\mathbf{z}}_i, \mathbf{d}_j, t_i, t_j)} \sum_{t=t_i}^{t_j} \sum_{k=1}^K \sum_{w=1}^{|\mathcal{V}|} p_{tkw} c_{tkw}$$

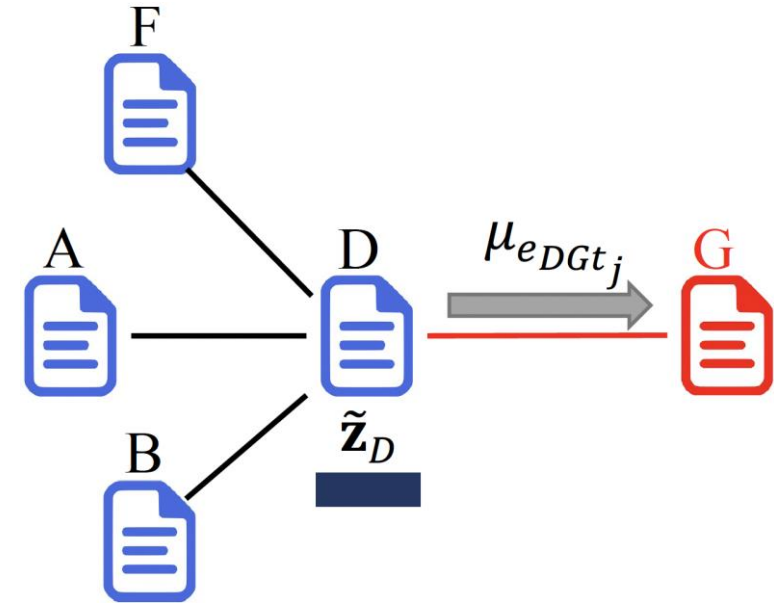


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Time dimension

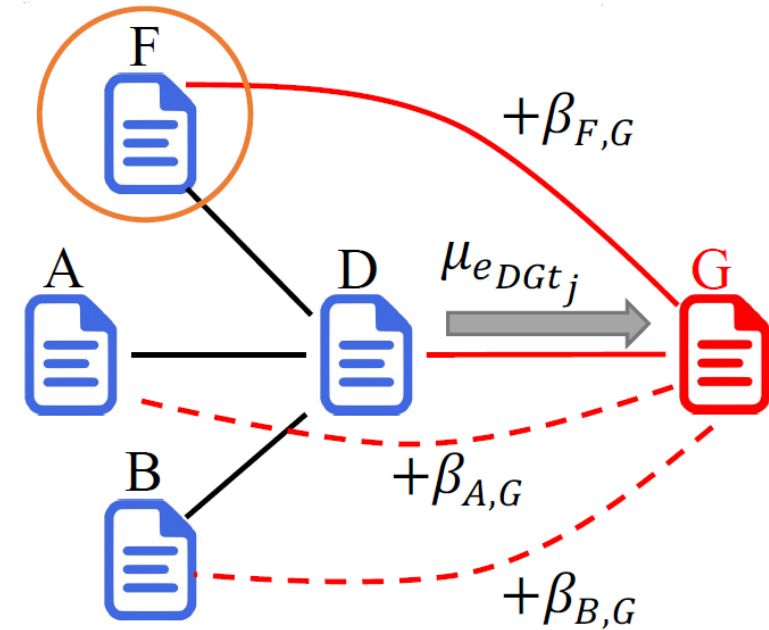




# Model Architecture

- We further introduce Hawkes Process to capture higher-order neighbors.

$$\lambda_{e_{ijt}} = \underbrace{\mu_{e_{ijt}}}_{\text{semantic modeling}} + \eta_{HP} \underbrace{\sum_{p \in \mathcal{N}_t(i)} \beta_{pj} a_{ip}}_{\text{network modeling}}$$

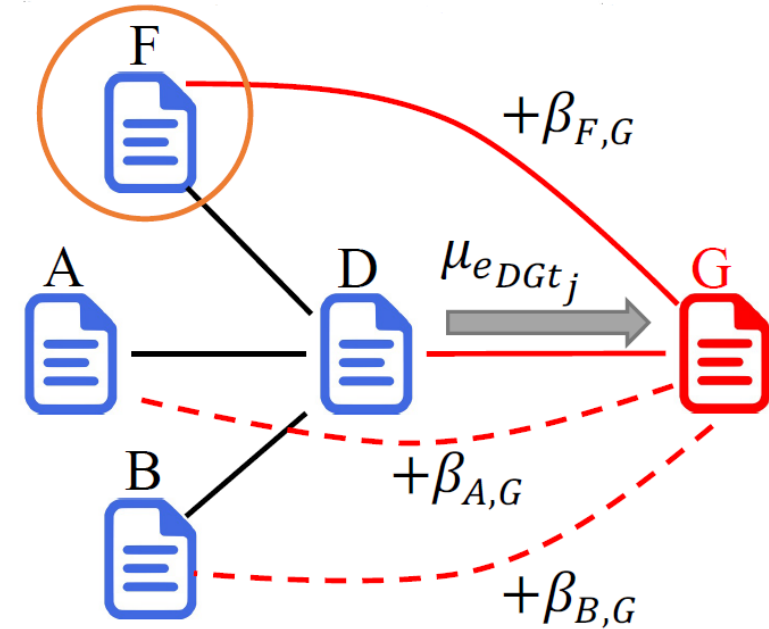


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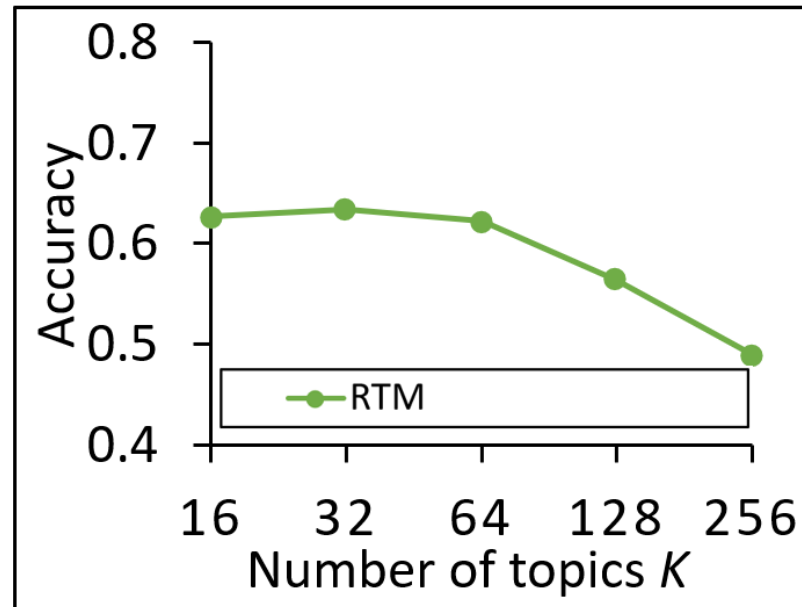
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Influence of higher-order neighbors



# Experiments

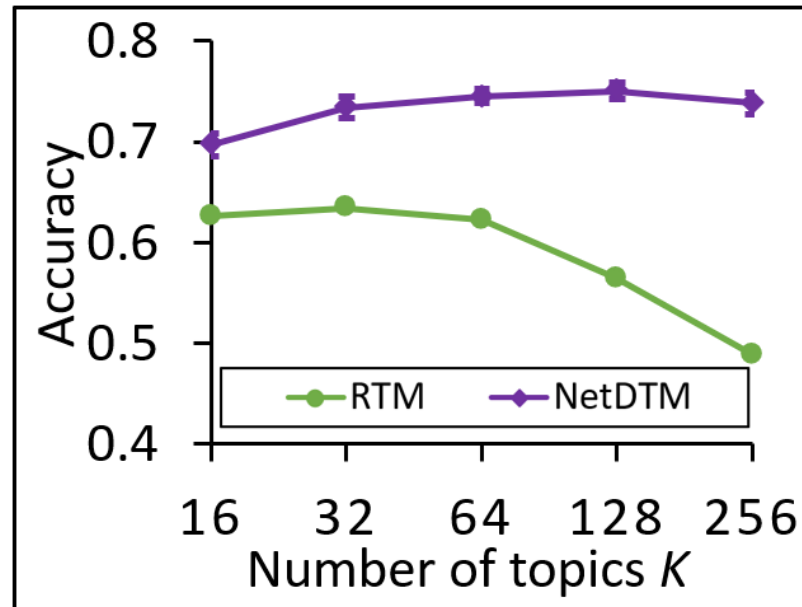
- Document classification against RTM, a static model.



(a) Classification accuracy on A corpus

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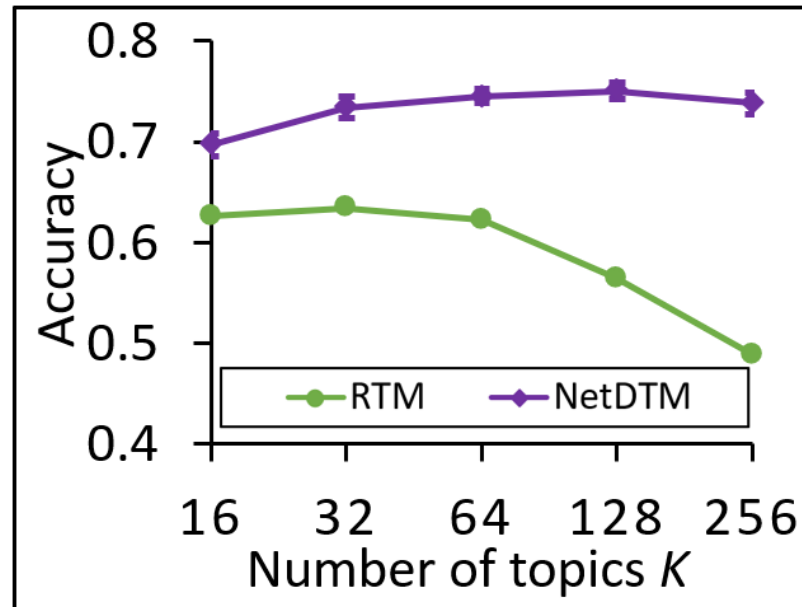
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(a) Classification accuracy on A corpus

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- Document classification against RTM, a static model.
- Modeling both network structure and dynamics improves topic quality.

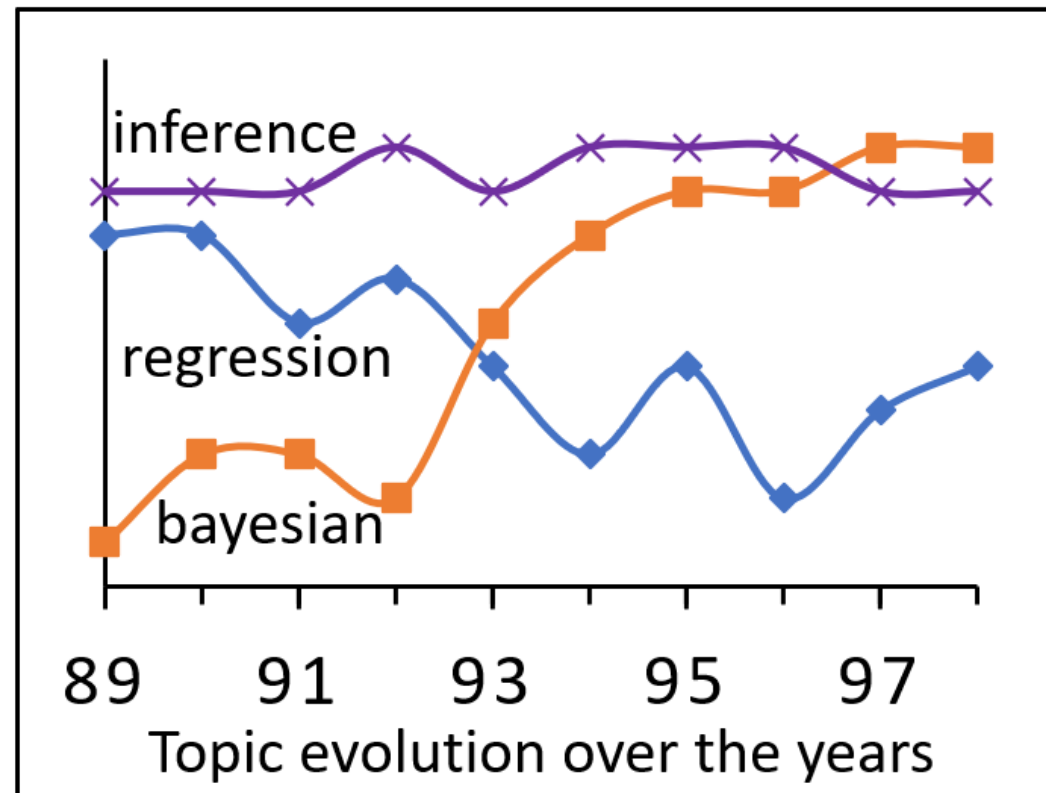


(a) Classification accuracy on A corpus

# Experiments

- Our model can capture topic evolution, while static RTM can not.

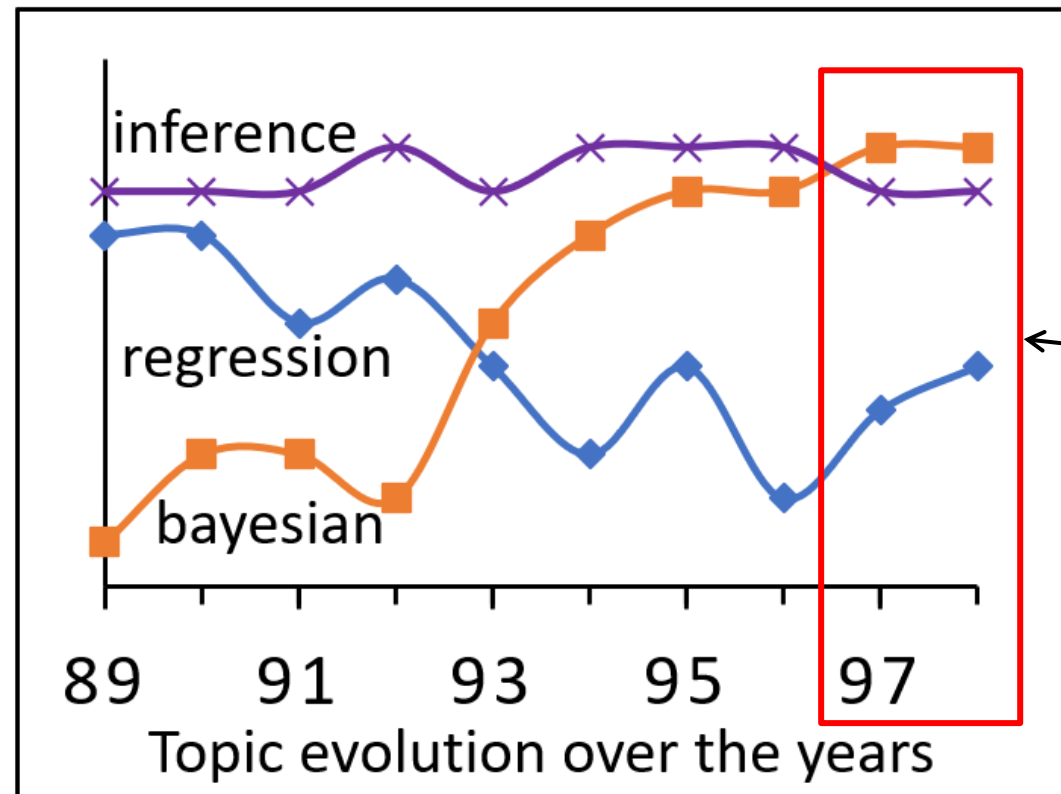
Topic “Bayesian Inference”



# Experiments

- Our model can capture topic evolution, while static RTM can not.

Topic “Bayesian Inference”



The most recent  
topic popularity

# Delvin Ce Zhang is looking for a postdoc place!

- **Graduation date:** **July 2023**
- **Research interests (Data Mining and Machine Learning)**
  - Graph Representation Learning, Graph Neural Networks
  - Text Mining
  - Recommender Systems
- **First-authored publications**
  - ICML-22, KDD-22, AAAI-20, CIKM-21, 2 × ECML/PKDD-21
  - NeurIPS (being reviewed), TKDE (being reviewed)
- **PC member**
  - NeurIPS, ICML, KDD, ACL, WWW, etc.
- **Homepage:** [delvincezhang.com](http://delvincezhang.com)
- **Email:** [cezhang.2018@smu.edu.sg](mailto:cezhang.2018@smu.edu.sg)