Microblog Conversation Recommendation via Joint Modeling of Topics and Discourse

Xingshan Zeng[1], Jing Li[2], Lu Wang[3],
Nicholas Beauchamp[3], Sarah Shugars[3], Kam-Fai Wong[1]

[1]The Chinese University of Hong Kong
[2]Tencent AI Lab
[3]Northeastern University

Outline

- Introduction
- Model
- Datasets
- Evaluation and Results
- Further Analysis
- Conclusion

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Motivation

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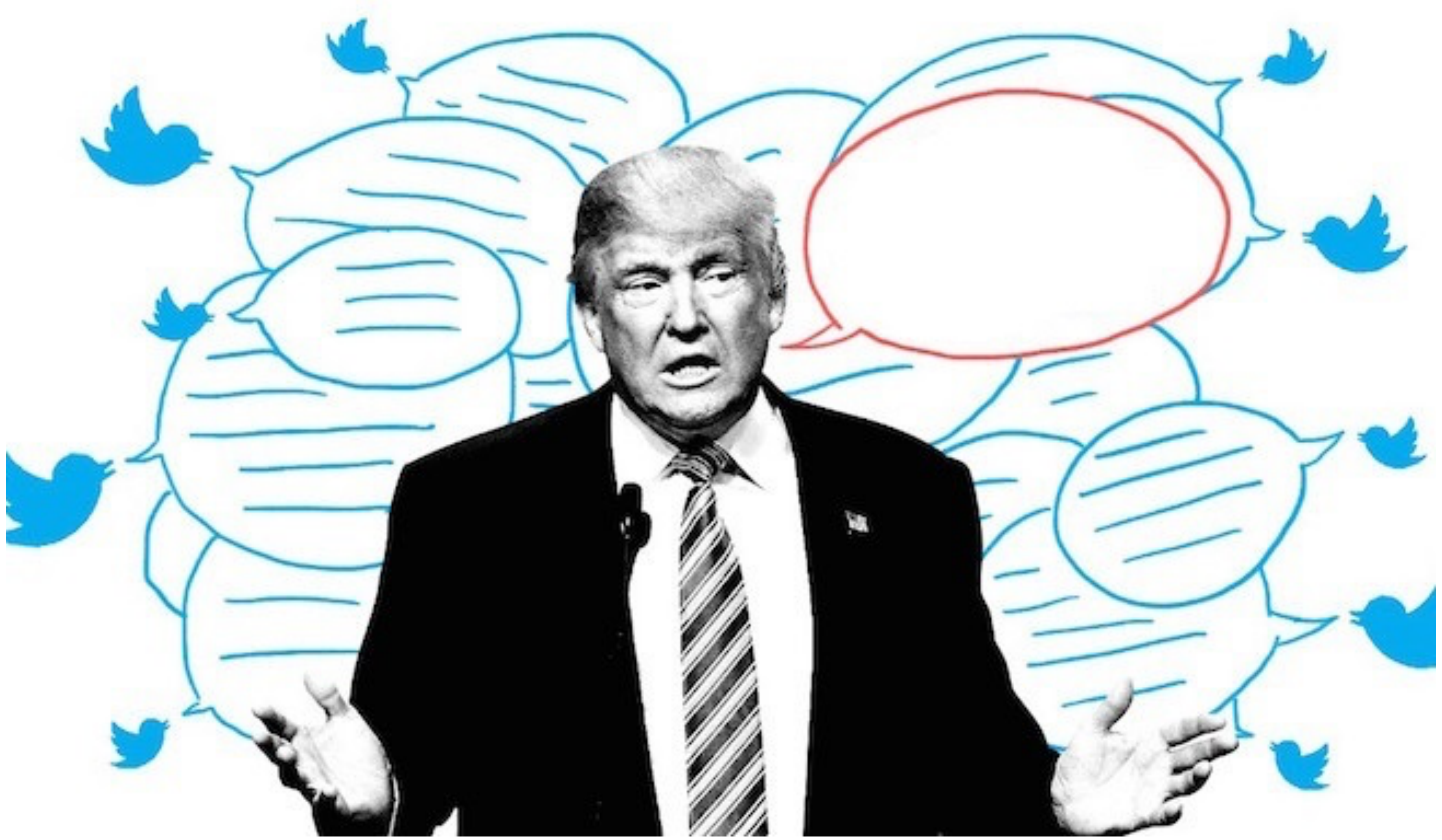

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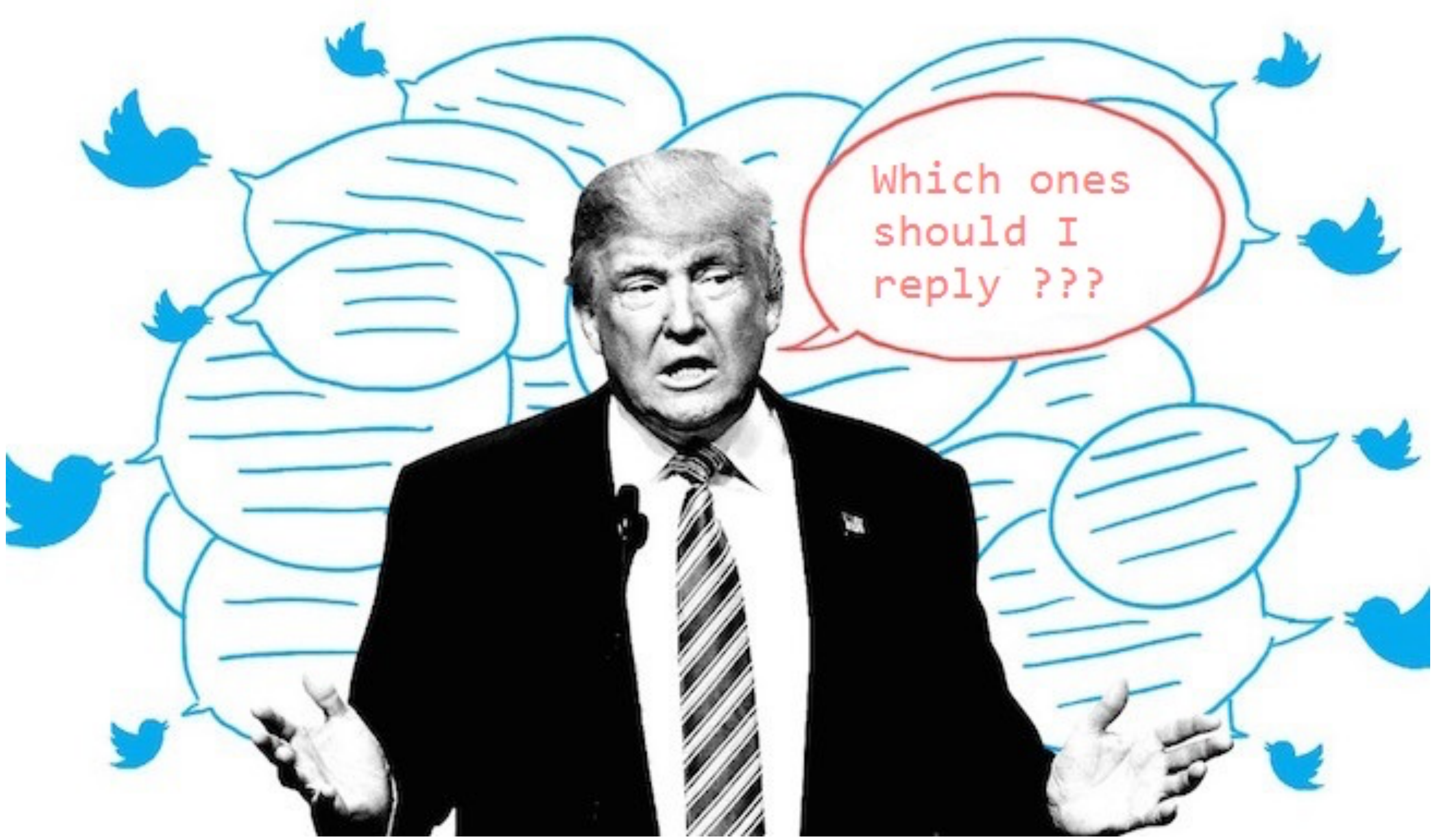

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So many discussions!

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Which conversations to engage in?

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- For ordinary people:

So many discussions!

Which conversations to engage in?

Conversation Recommendation!

Related Work

Related Work

- Conventional Recommender Systems:

Collaborative filtering! *(Pan et al. 2008; McAuley and Leskovec 2013*)

- Recommendation on Social Media:

Post-level recommendation! Can't handle conversations! *(Yan et al. 2012; Chen et al. 2012; Pan et al. 2013; Yu et al. 2016*)

- Conversation Modeling:

Unsupervised; Word distribution! *(Ritter et al. 2010*)

Introduction

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- Objective:

Post recommendation → Conversation recommendation

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New Task!

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Post recommendation → Conversation recommendation

New Task!

- Features:

①Reply history

②Conversation context
(Discourse behaviors / Dialog acts: agreement, argument, etc.)

Introduction

- Our thinking:

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Conversation 1

Sam: My paper has been accepted by ACL!
Tom: Congrats!
Amy: Congrats!
.....

Conversation 2

Jack: Python is the best programming language in the world!
Tom: Nonsense! Java is the best!
Jack: What? Writing Java is a waste of time!
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Introduction

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Which conversation is Tom more likely to return?

Joint effect of **topics** and **discourse**!

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Model Description

- Overall Idea:

Collaborative Filtering + Probabilistic Graphical Model

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$$\min \mathcal{L} + \mu \cdot NLL(\mathcal{C} \,|\, \mathbf{\Theta})$$

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(Reply preference)

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(Corpus Likelihood)

$$\min \boxed{\mathcal{L}} + \mu \cdot \boxed{NLL(\mathcal{C} \mid \boldsymbol{\Theta})}$$

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Collaborative Filtering + Probabilistic Graphical Model

(Reply preference)

(Corpus Likelihood)

$$\min \boxed{\mathcal{L}} + \mu \cdot \boxed{NLL(\mathcal{C} \mid \boldsymbol{\Theta})}$$

(Control the trade-off between the two effects)

Model Description

- Reply Preference:

- One-Class Collaborative Filtering

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$$\mathcal{L} = \sum_{u=1}^{|\mathcal{U}|} \sum_{c=1}^{|\mathcal{C}|} f_{u,c} \cdot (p_{u,c} - r_{u,c})^2$$

Model Description

- Reply Preference:

- One-Class Collaborative Filtering

Predicting score

$$\mathcal{L} = \sum_{u=1}^{|\mathcal{U}|} \sum_{c=1}^{|\mathcal{C}|} f_{u,c} \cdot (p_{u,c} - r_{u,c})^2$$

Real score

$$f_{u,c} = \begin{cases} s & \text{if } r_{u,c} = 1 \text{ (i.e., user replied)} \\ 1 & \text{if } r_{u,c} = 0 \end{cases}$$

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Computed according to both topic and discourse effect!

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$$p_{u,c} = \lambda \cdot \gamma_u^U \cdot \gamma_c^C + (1 - \lambda) \cdot \delta_u^U \cdot \delta_c^C + b_u + b_c + a$$

Model Description

- Reply Preference:

- Predicting score:

Computed according to both topic and discourse effect!

$$p_{u,c} = \underbrace{\lambda}_{\text{trade-off}} \cdot \underbrace{\gamma_u^U \cdot \gamma_c^C}_{\text{topic vectors}} + (1-\lambda) \cdot \underbrace{\delta_u^U \cdot \delta_c^C}_{\text{discourse vectors}} + \underbrace{b_u + b_c}_{\text{bias}} + \underbrace{a}_{\text{offset}}$$

Model Description

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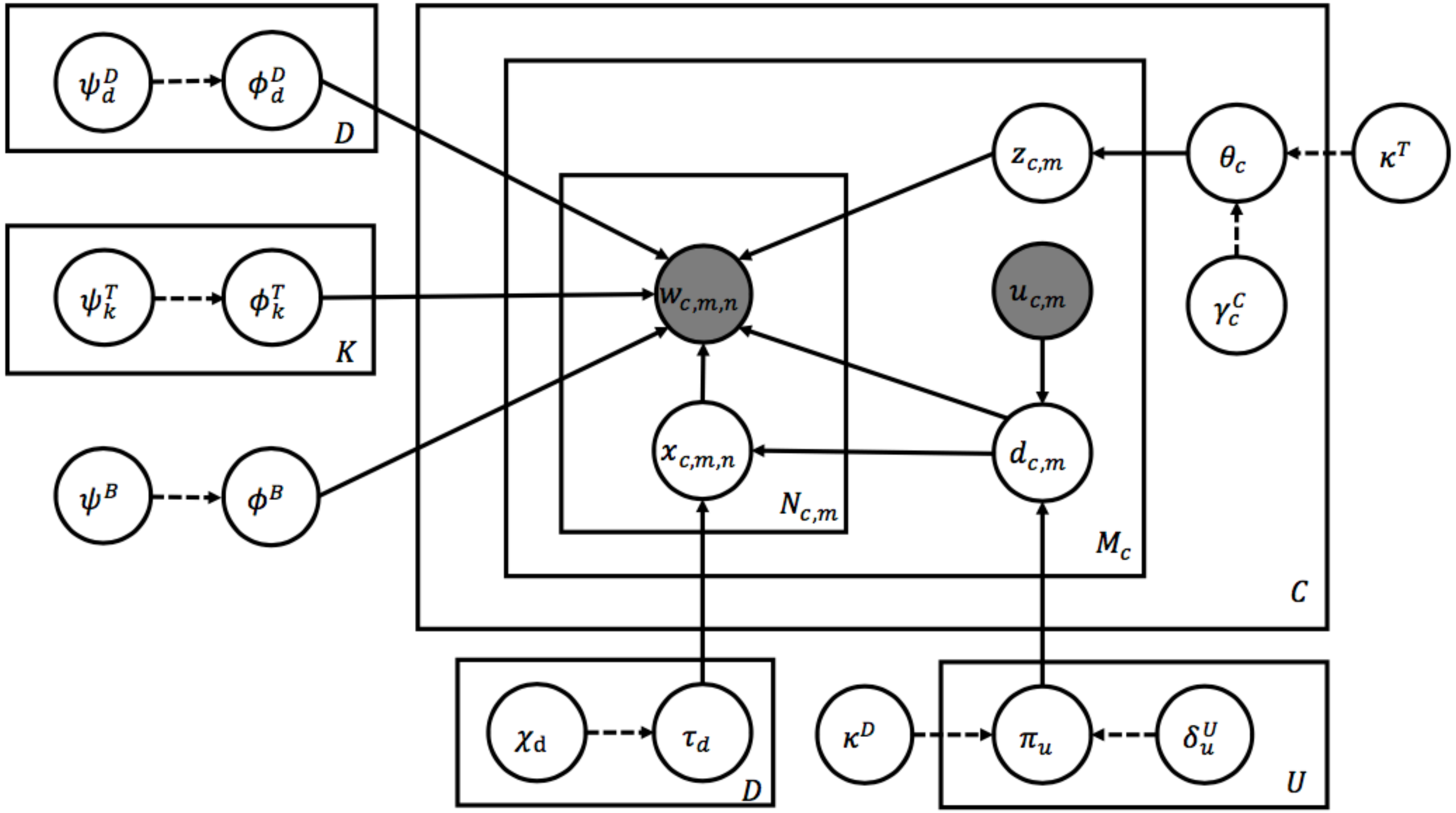
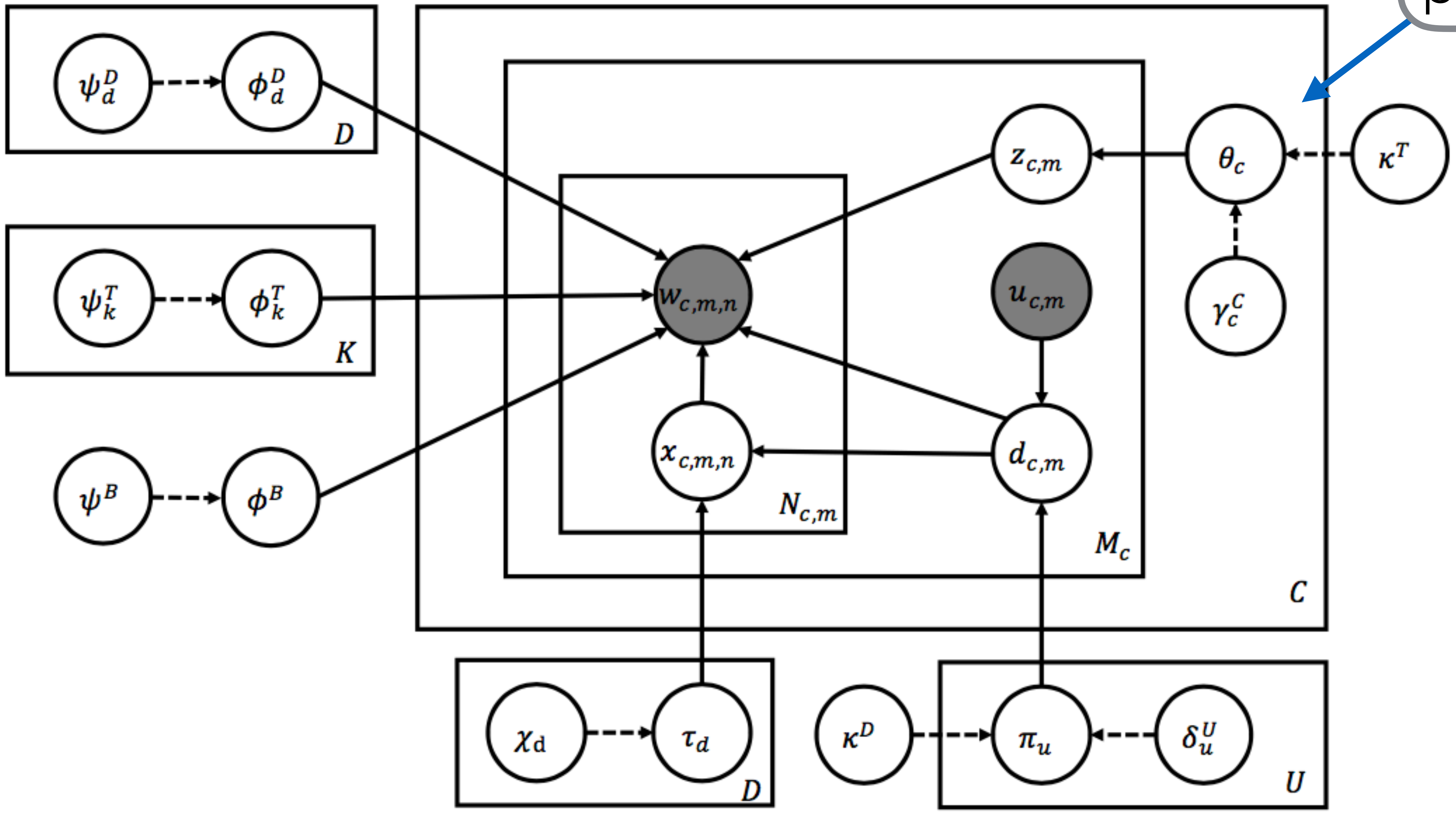


Generative Graph

Model Description

- Corpus Likelihood:

Connecting conversation topics and user preferences



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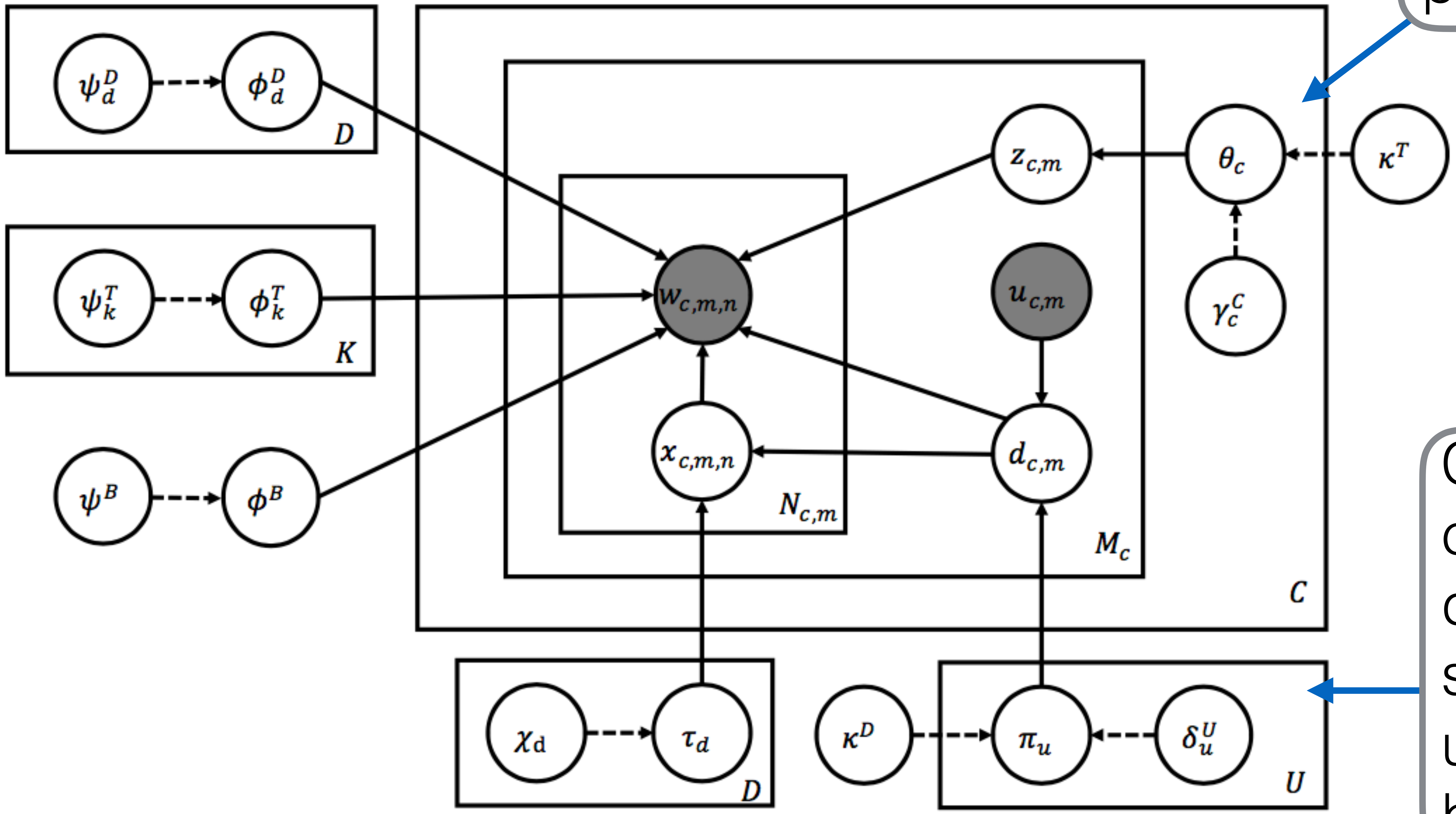


Generative Graph

Connecting conversation topics and user preferences

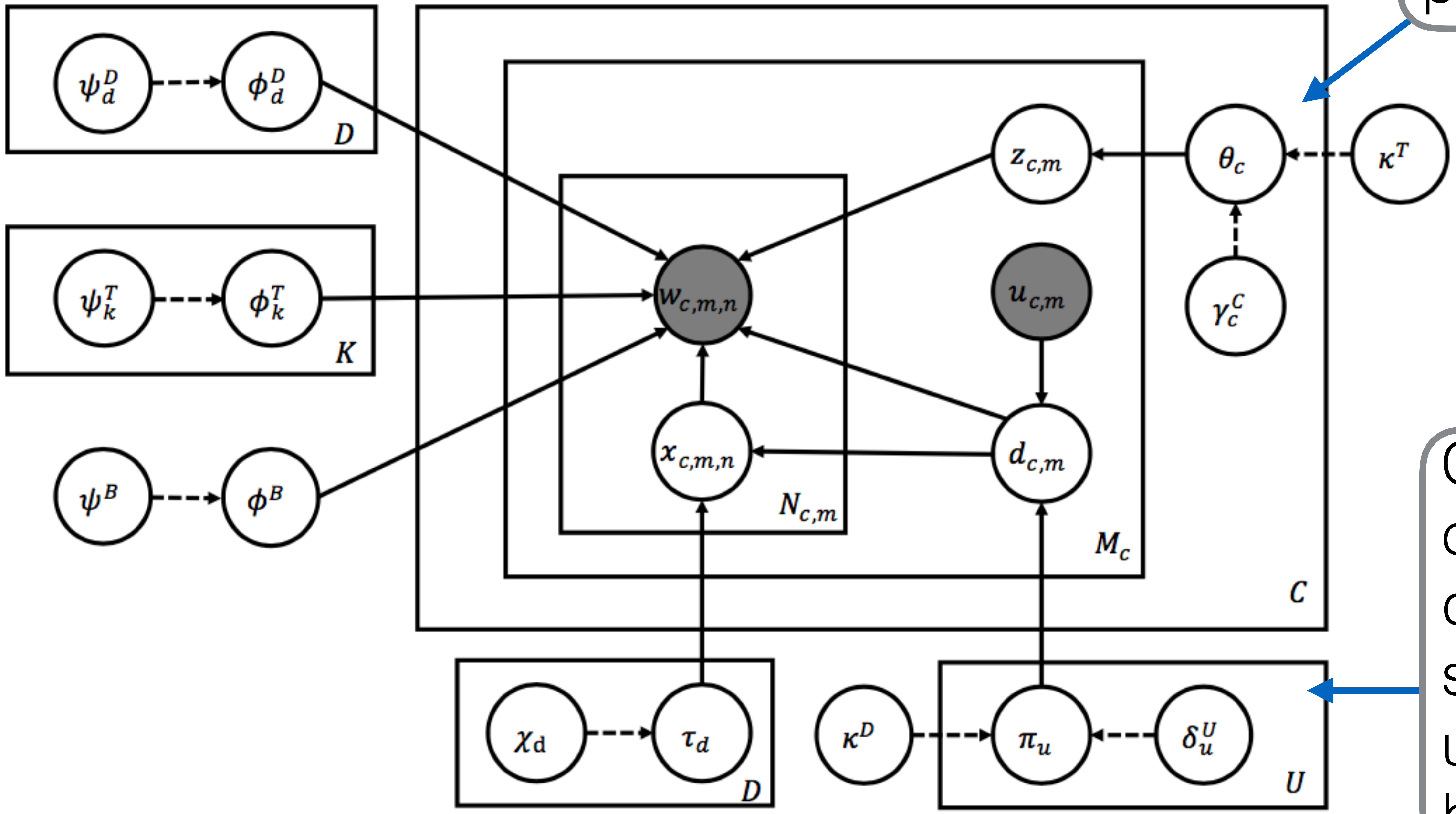
Connecting conversation discourse structure and user discourse behaviors

Model Description

- Corpus Likelihood:

Word distributions

Connecting conversation topics and user preferences



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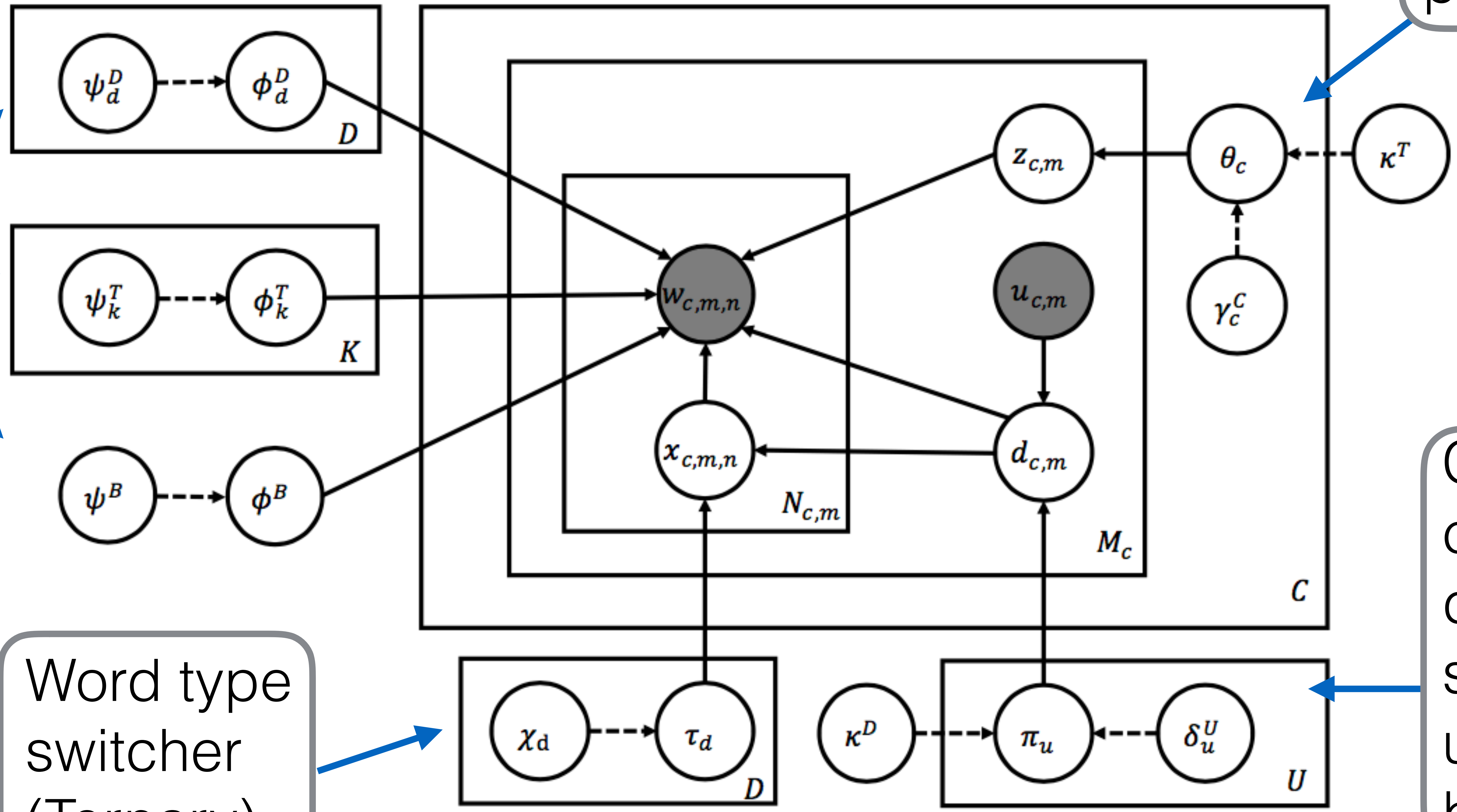

Word type switcher (Ternary)

Connecting conversation discourse structure and user discourse behaviors

Generative Graph

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Datasets

- US Election
- TREC

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Dataset	# of user	# of conv	# of msg
US Election	4,300	2,013	22,092
TREC	10,122	7,500	38,999

Statistics of two datasets

Datasets

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Statistics of two datasets

Experiment setup:

The first 75% of each conversation as training history;

50% for development, 50% for test.

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Evaluation

- Evaluation:

Conversation recommendation: a ranking problem!

- MAP (Mean Average Precision)
- Precision@K
- nDCG@K (Normalized Discounted Cumulative Gain @ K)

Comparison

- Baselines:
  - Random
  - Length
  - Popularity
- Comparisons:
  - One-Class Collaborative Filtering (OCCF) *(Pan et al. 2008)*
  - Ranking SVM (RSVM) *(Duan et al. 2010)*
  - Collaborative Personalized Tweet Recommendation (CTR) *(Chen et al. 2012)*
  - CF + LDA (Adapted HFT) *(McAuley and Leskovec 2013)*

Results

	Models	US Election			TREC		
		MAP	P@1	nDCG@5	MAP	P@1	nDCG@5
Baselines	Random	0.018	0.004	0.009	0.006	0.001	0.002
	Length	0.025	0.002	0.003	0.013	0.002	0.004
	Popularity	0.050	0.010	0.025	0.023	0.005	0.010
Comparisons	OCCF	0.637	0.589	0.649	0.410	0.385	0.425
	RSVM	0.687	0.680	0.690	0.554	0.575	0.559
	CTR	0.673	0.649	0.678	0.475	0.431	0.495
	Adapted HFT	0.698	0.652	0.706	0.487	0.447	0.504
	Our Model	**0.762**	**0.750**	**0.757**	**0.591**	**0.591**	**0.600**

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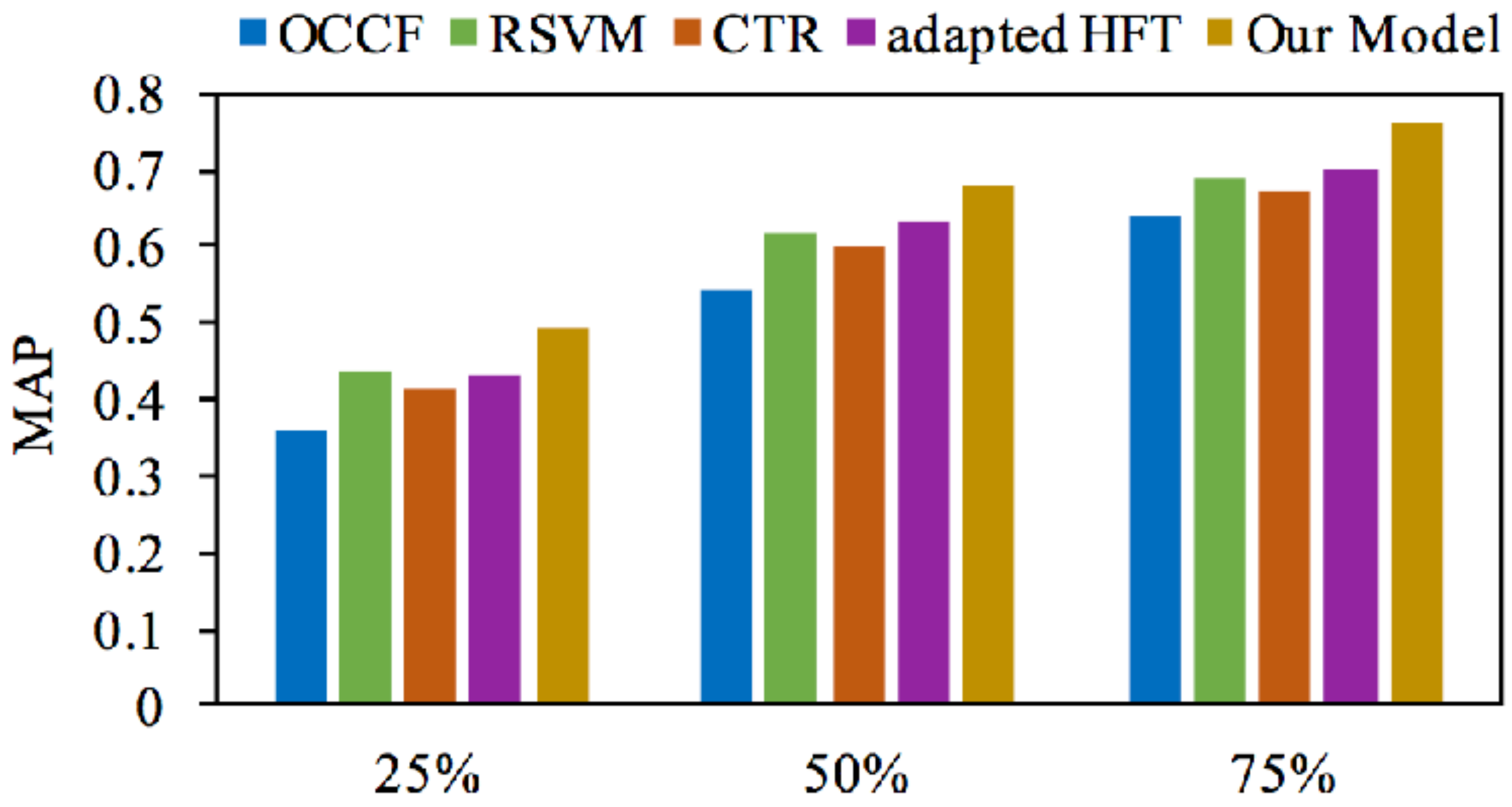
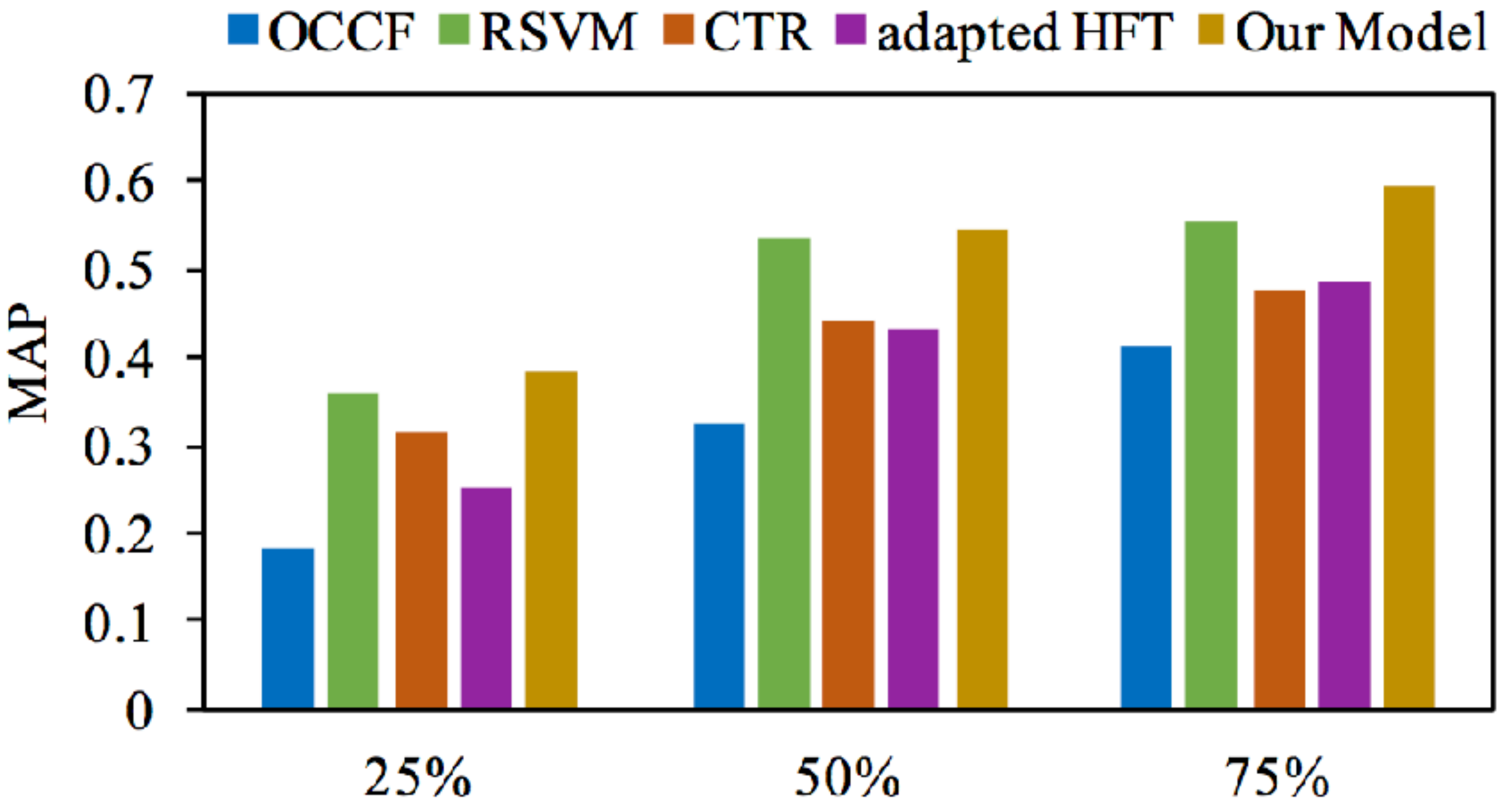
How’s the performance when trained on different conversation history?

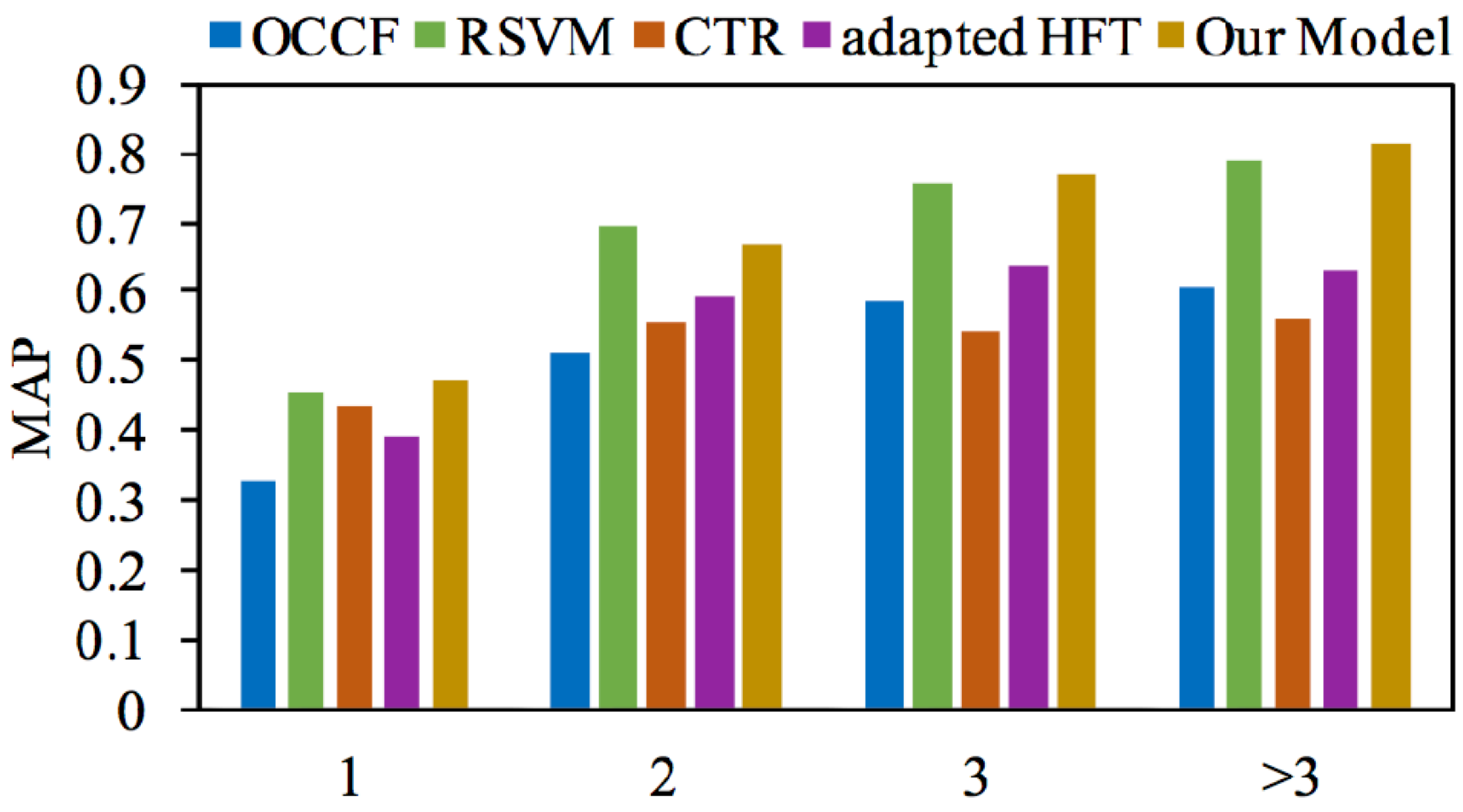


US Election dataset

TREC dataset



How’s the performance for different user sparsity?



# of conversations that users have participated in training

TREC dataset

What if only considering topic or discourse?

Models	US Election	TREC
Adapted HFT (content based)	0.698	0.487
Our Model (topic only)	0.711	0.491
Our Model (discourse only)	0.705	0.483
Our Model (full)	**0.762**	**0.591**

(MAP scores)

What if only considering topic or discourse?

$\lambda = 1$

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What if only considering topic or discourse?

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λ = 0

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What if only considering first time replies?

Models	US Election	TREC
OCCF	0.035	0.033
RSVM	0.023	0.002
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A difficult task!

- Only use features of history and context!
- Discourse behavior history is important!

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Conclusion

- A new task: conversation recommendation
- A novel framework for microblog conversation recommendation (CF + Graphical Model)
- A probabilistic graphical model that can capture both topics and discourse information
- Experiment results show the effectiveness of the model

Thank you!

Datasets:
http://www.ccs.neu.edu/home/luwang/datasets/microblog_conversation.zip