Joint Effects of Context and User History for Predicting Online Conversation Re-entries

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Outline

- Introduction
- Model
- Experimental Setups
- Results
- Conclusion

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Motivation

- We are involved in a wide variety of online discussions every day.

- More and more active users on online platforms!

- Current notification strategy for online platforms: always notify if any new messages come in!

Motivation

Result:

So many messages!

We need an automatic management tool!

1) Help us keep track of the discussions;
2) Predict whether we would like to re-engage in them. Only if yes -> notify!

Introduction

- **Re-entry Prediction:**

Given:

A conversation that one user ever participated in.

Aim:

Forecast whether the user will return to the conversation.

What do we need for the prediction?

Introduction

- Previous Work:

  ✓ Users' arrival patterns (Backstrom et al., 2013)
  (Need several entry records for the users in ongoing conversations.)

  ✓ Social relations, Group information (Budak and Agrawal, 2013)
  (Not always available!)

- Our Work:

  ✓ Conversation context – what has been discussed in the ongoing conversations (conversation's topics / patterns)

  ✓ User history – what kinds of conversations the users were actively involved in (user's preferences / habits) → Ignored by previous work!

Introduction

Target user: U1

User History of U_1

……

H_1: Is there literally no one on twitter who wants to talk about LET ME IN with me? :(

H_2: I think the change in overall tone was enough to let LMI stand on it's own. Love Giacchino's score too.

H_3: I think if i had seen LMI again before making my top ten it would have made the cut. Oh well.

H_4: it's not as bad as I remembered on the blu-ray. Looks like shit next to Avatar, but so does everything lol

……

U1 likes to discuss about movies !

Conversation 1

$T_1[U_2]$: Instead of focusing on when Oscars got it wrong… Let's talk about when the Oscars got it right…

$T_2[U_1]$: The Hurt Locker, The Departed, NCFOM, LOTR, Schindler's List, Braveheart, Gladiator, The Godfather Part 1 & 2.

……

Just giving a list about Oscars!

Conversation 2

……

$T_1[U_3]$: Almost fell asleep in the first hour of INCEPTION. In the theatre.

$T_2[U_4]$: lol do you not like it?

$T_3[U_5]$: Meh. MEMENTO = far better film.

$T_4[U_1]$: apples and oranges, plain and simple.

……

$T_5[U_1]$: Inception and Memento. Same filmmaker, but completely different scope, themes, ideas, genres, etc.

Hot discussion about two movies!

U1 returns!

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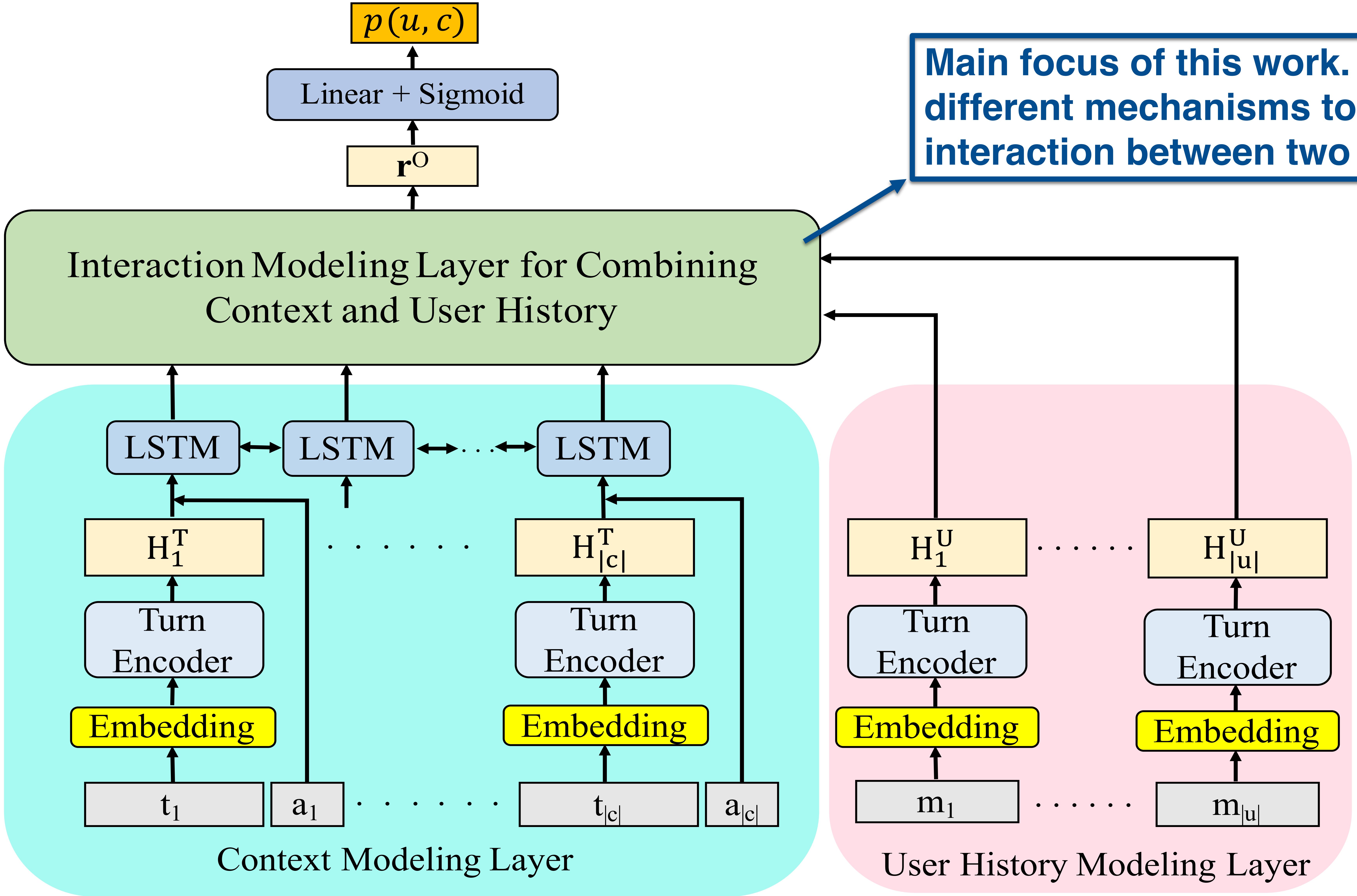
Model



Main focus of this work. We try four different mechanisms to model the interaction between two sources

Model

Interaction Modeling Layer:

- Simple Concatenation

$$r^O = [H^C_{|C|} \; ; \; \sum_j^{|U|} H^U_j / |U| \,]$$

Last state representation of context structure modeling

Average representation of user history modeling

Model

Interaction Modeling Layer:

- Attention over Context

$$\alpha_i = \text{softmax}(H_i^C \cdot \sum_j^{|U|} H_j^U / |U|)$$

$$r^O = \sum_i^{|C|} \alpha_i \cdot H_i^C$$

Model

Interaction Modeling Layer:

- Memory Networks

$$\alpha_j = \text{softmax}(H^{C}_{|C|} \cdot H^{U}_{j})$$

$$r^{O} = \sum_{j}^{|U|} \alpha_j \cdot f_{turn}(H^{U}_{j})$$

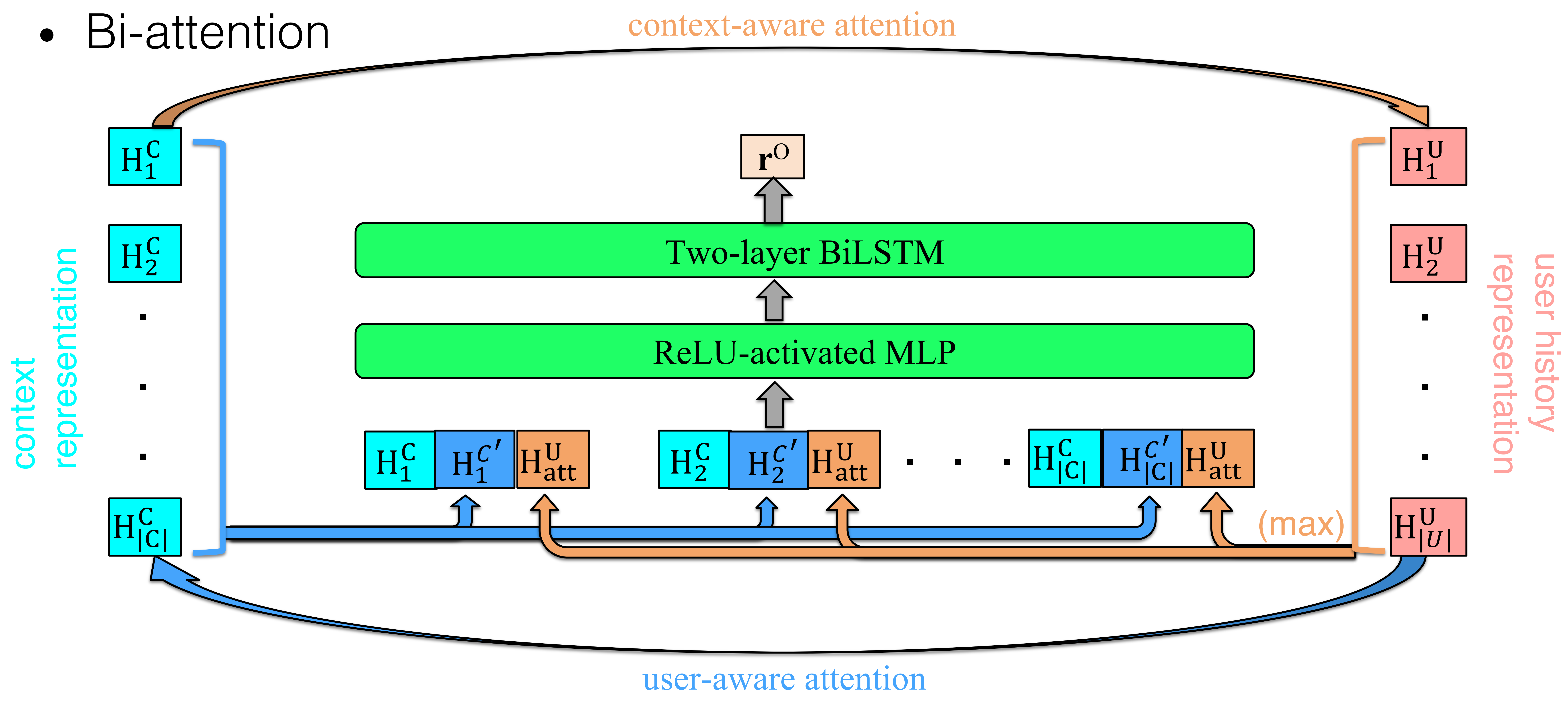
another turn encoder with different parameters

We also adopt multi-hop mechanism, where the output of last hop (r^{O}) is input ($H^{C}_{|C|}$) of next hop!

Model

Interaction Modeling Layer:

- Bi-attention



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Data

Dataset	# of user	# of conv	# of re-entries	# of non re-entries	Avg. # of msgs in user history	Avg. entries per user per conv	Avg. turns per conv
Twitter	10,122	7,500	5,875	8,677	3.9	2.0	5.2
Reddit	13,134	29,477	12,780	39.988	8.4	1.3	3.7

Statistics of two datasets

- Twitter dataset: diverse topics; users tend to re-enter; lack of history.
- Reddit dataset: political topic; users tend to abandon; rich history.

Experiment Setups

- For each dataset: 80%, 10%, 10% --> training, development, test
- Main experiment:
  first re-entry prediction – predict re-entries, given current turns until u's first entry in c as context and u's past chatting messages posted before u engaging in c.
- In-Depth Analysis:
  predicting second and third re-entries;
  results with varying user history;
  ablation study and case study;
  human comparison….

Comparisons

- Baselines:

✓ Random: randomly give a “yes” or “no” answer

✓ History: predict based on users’ history re-entry rate before current conversation

✓ All-Yes: always answers “yes” in re-entry prediction (similar to current policy for online platforms -- always notify!)

- S.O.T.A:

✓ CCCT (Backstrom et al., 2013) (links, arrival patterns, timing effects, etc)

Comparisons

- Variants of our proposed model:

✓ Without history:

Several turn encoders: Avg-Embed, CNN, BiLSTM

(Find a best encoder for rest experiments!)

✓ With History (using best turn encoder):

Four mechanisms to combine history and context –

simple concatenation (Con), attention (Att), memory networks (Mem), and bi-attention (BiA) .

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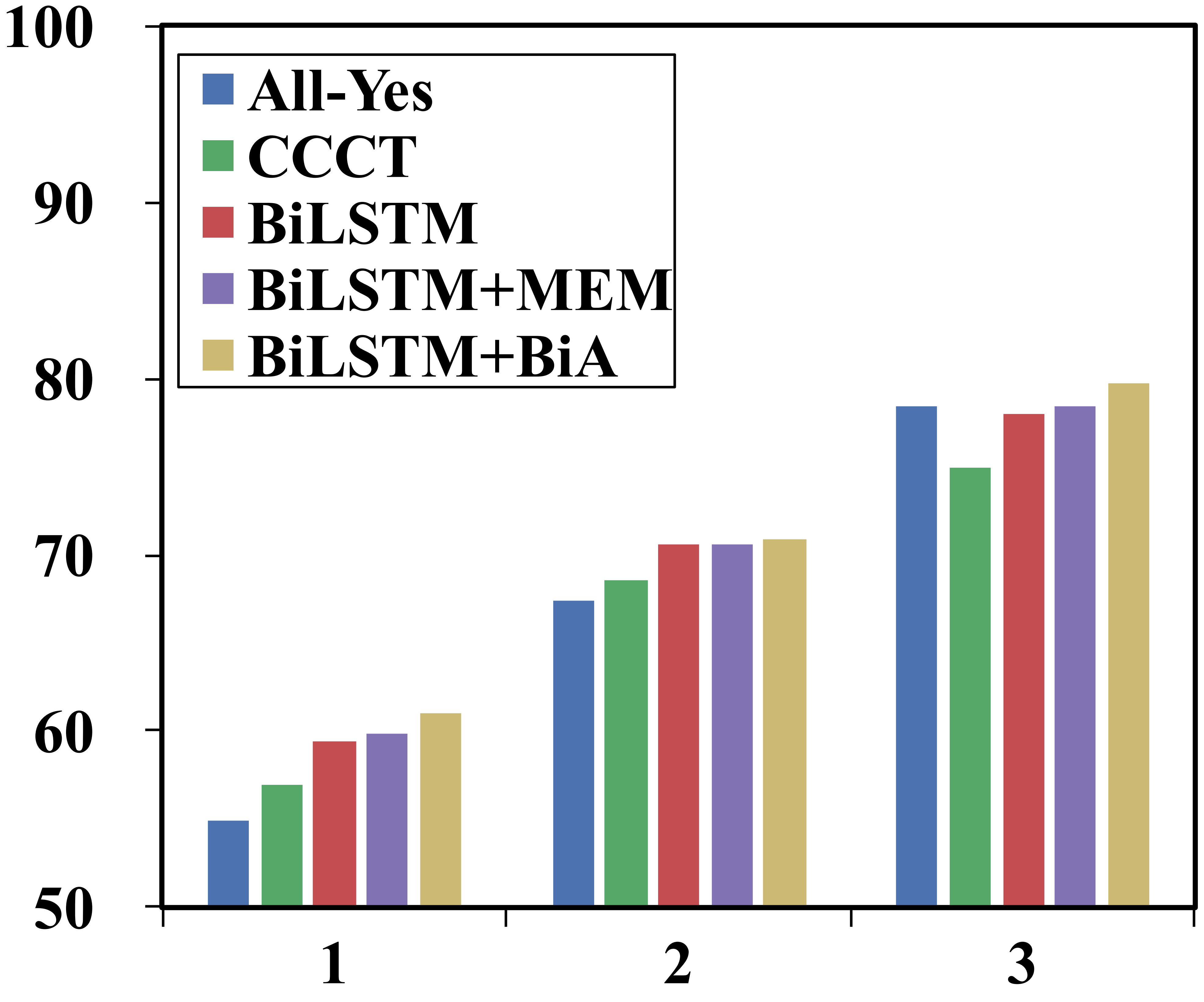
Results

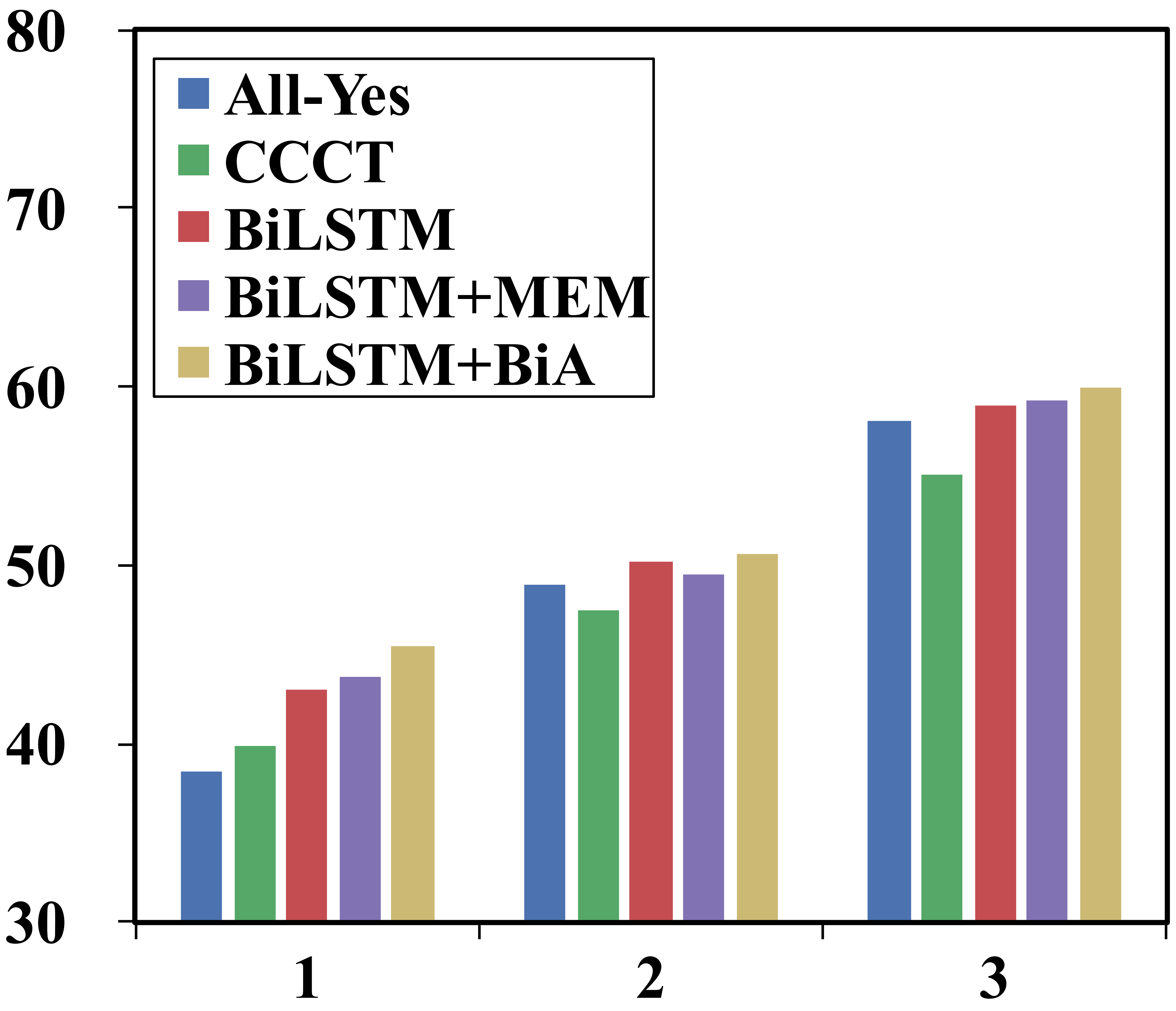
Models	Twitter		Reddit	
	AUC	F1	AUC	F1
Random	51.0	45.0	49.4	32.6
History	50.1	46.4	50.7	35.2
All-Yes	50.0	54.9	50.0	38.5
CCCT	57.7	57.0	59.9	39.8
Avg-Embed	60.4	59.0	63.7	42.4
CNN	58.8	59.1	64.0	42.8
BiLSTM	60.4	59.4	64.1	43.1
BiLSTM + Con	51.0	58.0	50.1	38.6
BiLSTM + Att	58.4	59.0	60.3	41.3
BiLSTM + Mem	61.3	59.9	65.5	43.7
BiLSTM + BiA	**62.7**	**61.1**	**67.1**	**45.4**

Results

- Predicting first, second and third re-entries (F1 scores):



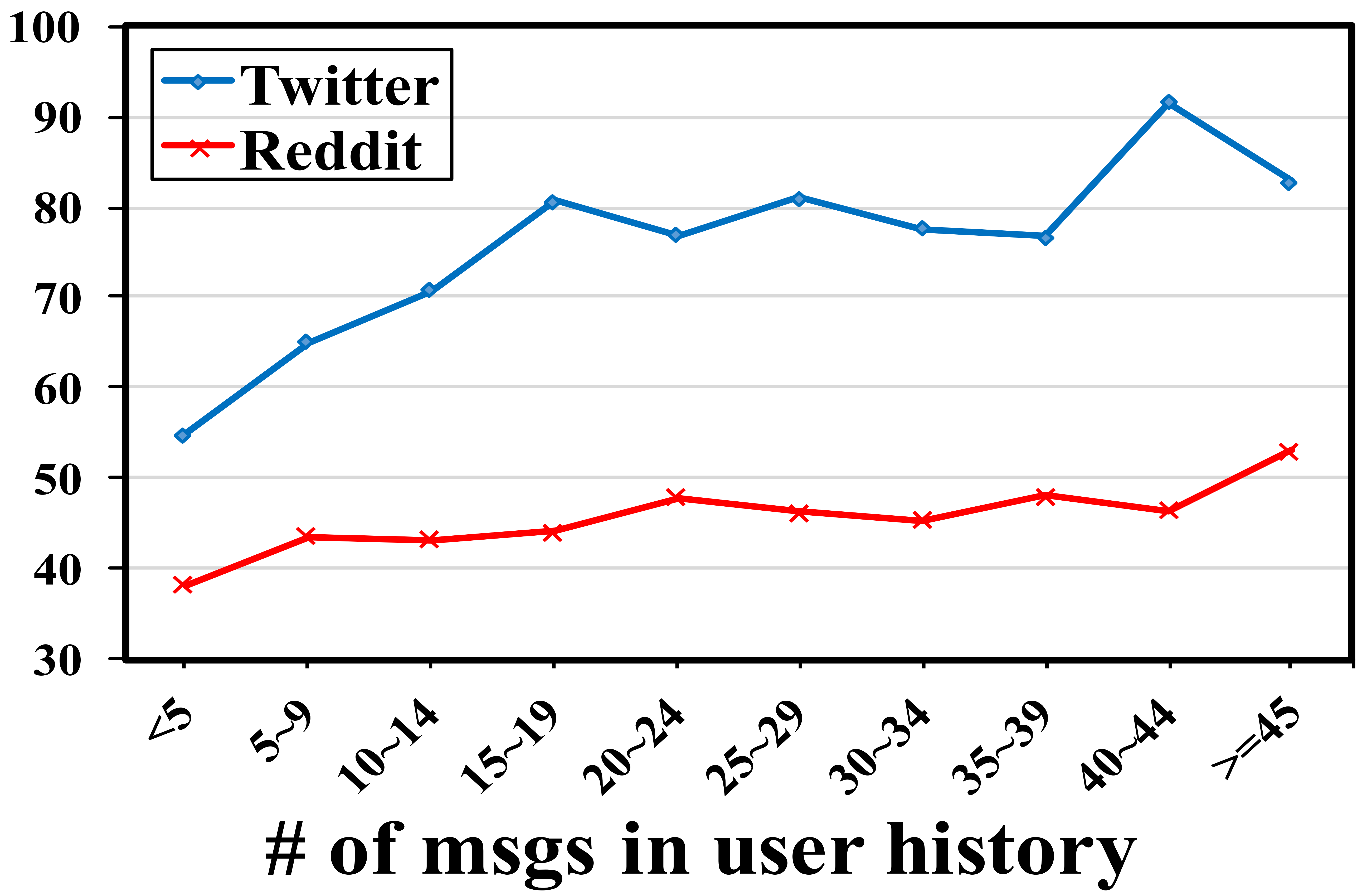
Twitter



Reddit

Results

- Results with varying user history (F1 scores of BiLSTM+BiA) :



Chatting history is useful to signal user re-entries!

Results

- Comparing with Humans:

Setting:
Randomly select 50 users (at least involved in 4 conversations);

Each has one re-entry and one non re-entry conversation (rest for history);

Predict which conversation is given user more likely to return!

Predictor	Twitter	Reddit
Human 1	26 (29)	30 (30)
Human 2	25 (28)	28 (29)
BiLSTM + BiA	**35**	**33**

After reading history

Correctly predicting sample pairs

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Conclusion

- We study the joint effects of conversation context and user chatting history for re-entry prediction with a neural framework.

- Experimental results show that user chatting history indeed benefits the prediction, with well-designed mechanism (bi-attention) for alignment with conversation context.

- Further discussions also show that our model learns meaningful representations and exhibits consistent better performance in different situation, including comparing with humans.

Thank you!