# Variational Hierarchical User-based Conversation Model KAIST

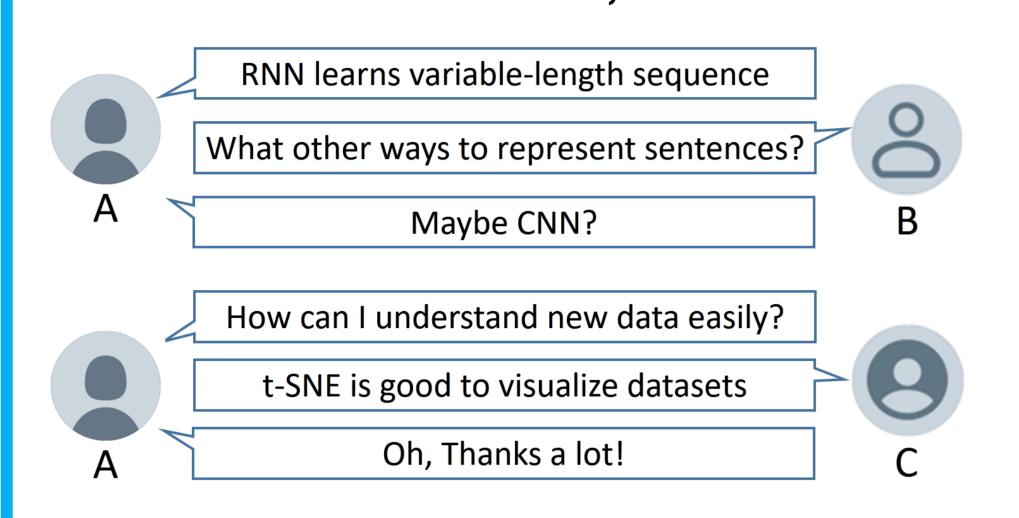
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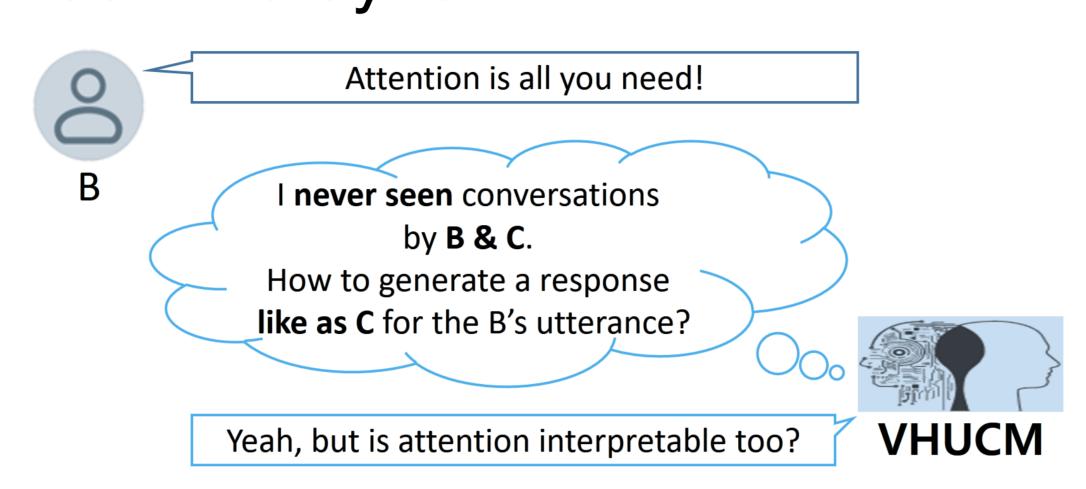
# School of Computing

# Motivation

### **Cold Start Problem**

- New speaker: no conversations in the training data
- New dyad: both speakers in the training data with conversations with other users, but none between the dyad





### Main Idea

- Conversational context depends on the speakers
- Conversational partners minimize social difference among them
- We infer the new speakers' representation from the partners

# Contributions

- Developed a conversation model that includes the speakers for
- Inferring conversational context from their former conversations
- Generating personalized response
- Solving new speakers and dyads problem
- Made a large, longitudinal open-domain conversation corpus
- Showed a significant performance gain on appropriate responses

# Twitter Conversation Corpus

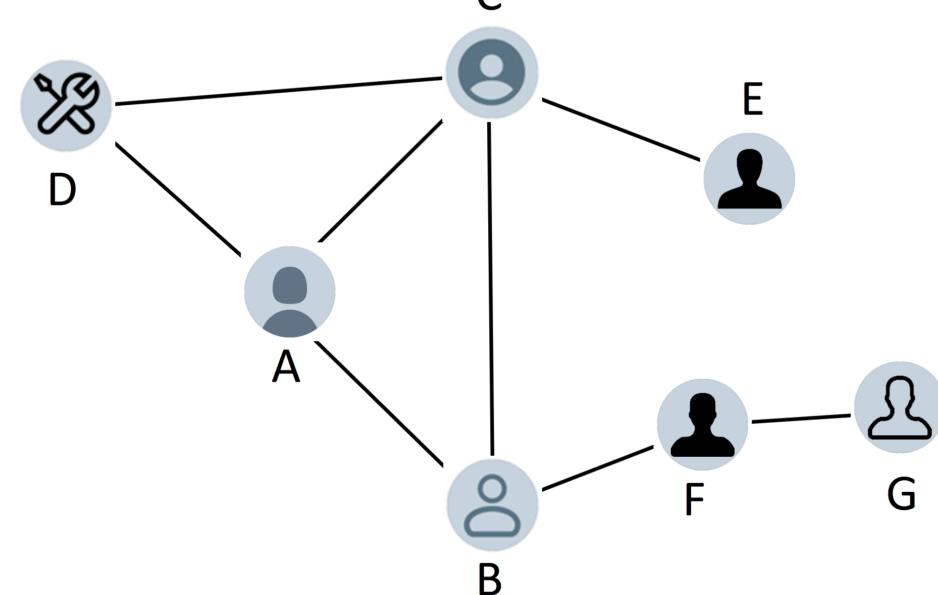
## Open-domain naturally occurring conversations

- Personal casual conversations
- Naturally-occurring, as opposed to authored (e.g., movie scripts)
- Open-domain, as opposed to specific topics (e.g., discussions)

### **Conversation Network**

Node: user (speaker)

• Edge: # conversations between users



<Example of conversation network>

### **Corpus Statistics**

Users	Dyads	Convs	Utterances	Days (period)
27K	107K	770K	6,109K	2.6K

# Response Quality

### **Automatic Metrics**

	BLEU	<b>Emb-Avg</b>	<b>Emb-Gre</b>	<b>ROUGE-L</b>	Dist-2
VHCR (NAACL 2018)	0.137	0.599	0.381	0.075	0.076
DialogWAE (ICLR 2019)	0.127	0.586	0.369	0.080	0.104
VHUCM	0.120	0.633	0.394	0.079	0.108
VHUCM-PUE	0.161	0.643	0.400	0.087	0.123

### **Examples of Personalized Responses**

### VHUCM-PUE generates

- Consistent demographic answers for the same speaker (User A)
- Different answers based on the dyads  $(A \sim B \text{ and } A \sim C \neq A \sim D)$

### Questioner Answerer Where is your hometown? Do you love me?

User B	User A	north carolina!	i love you .
User C	User A	north carolina .	yes i do!
User D	User A	north carolina.	no i do not
User A	User B	minesota . <unk></unk>	because i love you
User A	User C	manchester:) xx	i love you too :) xx
User A	User D	i live in <unk></unk>	no . i don't .

# WHUCM $\mathbf{z}^{a}$ $\mathbf{z}^{conv}$ $\mathbf{z}^{t}$ $\mathbf{z}^{utt}$ $\mathbf{z}^{utt}$ $\mathbf{z}^{utt}$ $\mathbf{z}^{t+1}$ $\mathbf{z}^{t+1}$ $\mathbf{z}^{t}$ $\mathbf{z}^{t}$ $\mathbf{z}^{t+1}$ $\mathbf{z}^{t}$ $\mathbf{z}^{t+1}$ $\mathbf{z}^{t}$ $\mathbf{z}^{t}$ $\mathbf{z}^{t}$ $\mathbf{z}^{t}$ $\mathbf{z}^{t}$ $\mathbf{z}^{t}$

### Structure

- Conversational context variable  $z^{conv}$
- Takes two speakers  $s^a$  and  $s^b$
- Infers the context of the conversation
- Personalized utterance variable  $z_t^{utt}$
- Takes the conversational context and the speaker  $S_t$
- Goes to decoder to generate a response  $x_t$

# VHUCM-PUE

### Pre-trained User Embedding

- Train user embedding from the conversation network by node2vec
- Initialize the user embedding in VHUCM

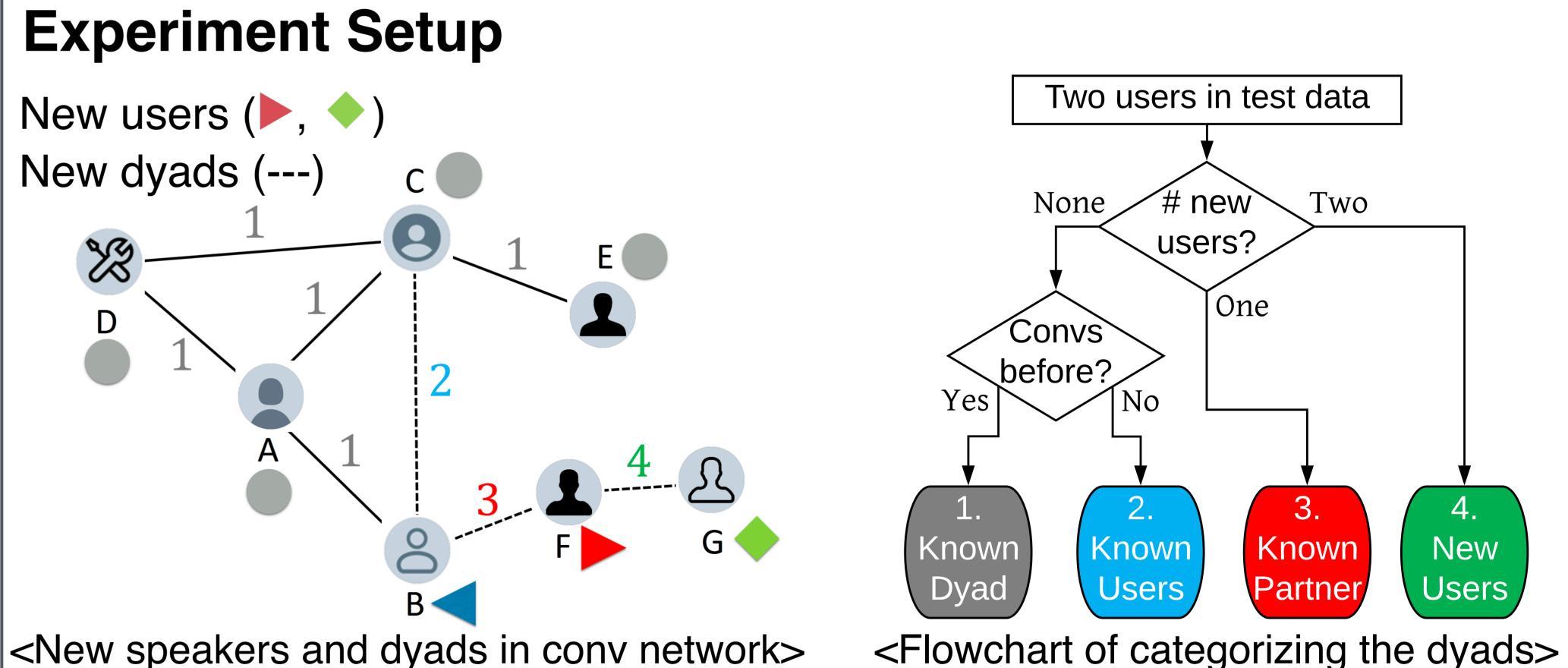
### New User Embedding

- Average the new user's friends  $s^F = \sum s^i + \epsilon$  if F is
- Add small Gaussian noise

*i*∈friends of F

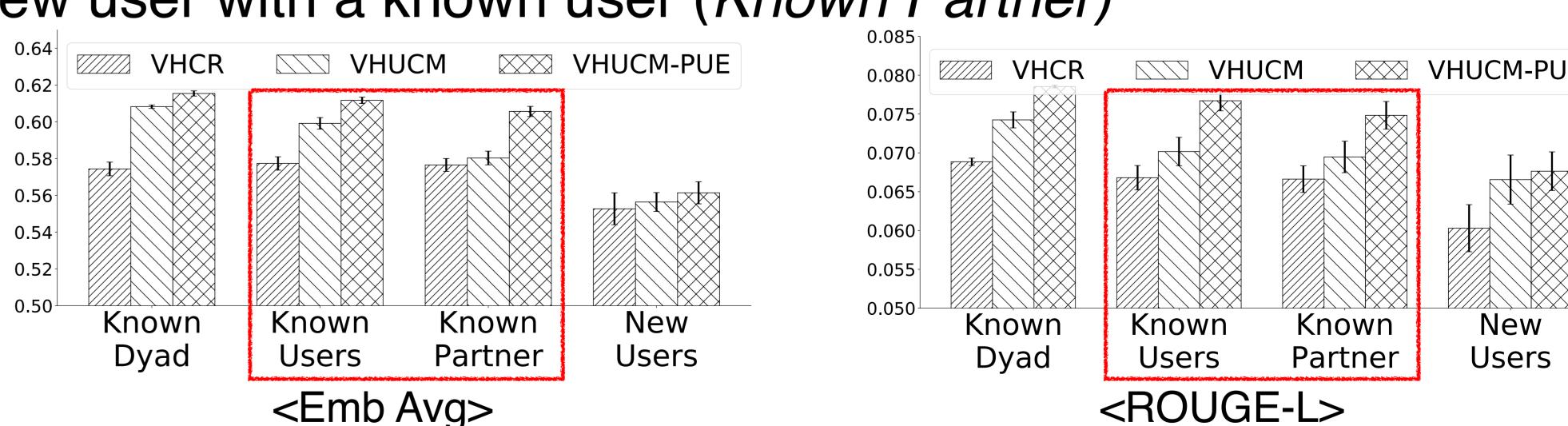
a new user

# New Speakers & Dyads



### Results

• VHUCM-PUE outperforms the other models in cases involving new user with a known user (*Known Partner*)



 Conversation partners ( ■ & ►) are close in the embedding space of VHUCM-PUE, but not VHUCM

