Learning the Structures of Online Asynchronous Conversations

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DASFAA

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The enormous online group chat

WeChat

QQ tencent.com

LINE

WhatsApp

snapchat

iMessage

Tango

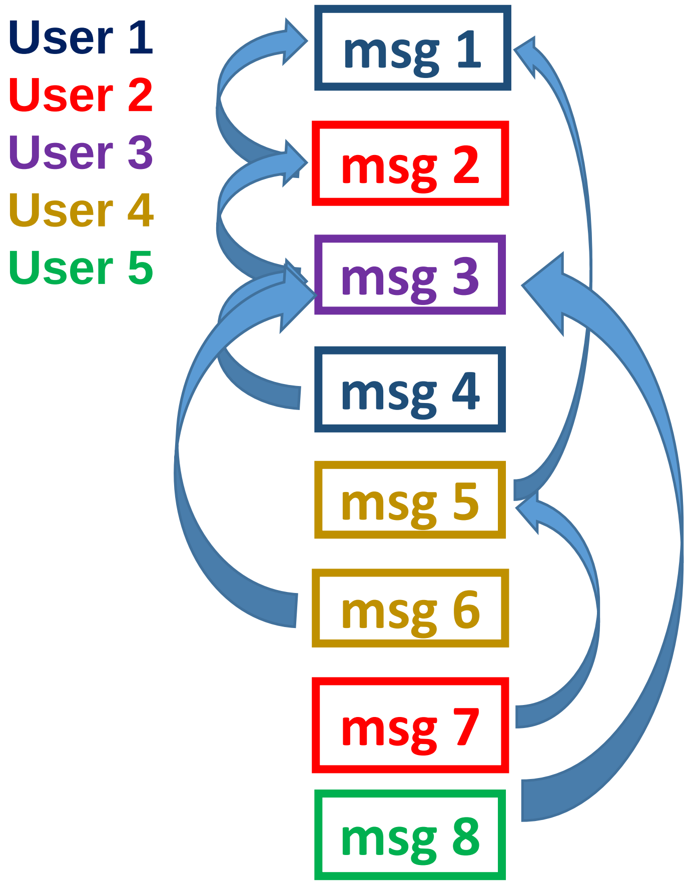
Facebook Messenger

groupme

Learning the structures of online asynchronous conversations.

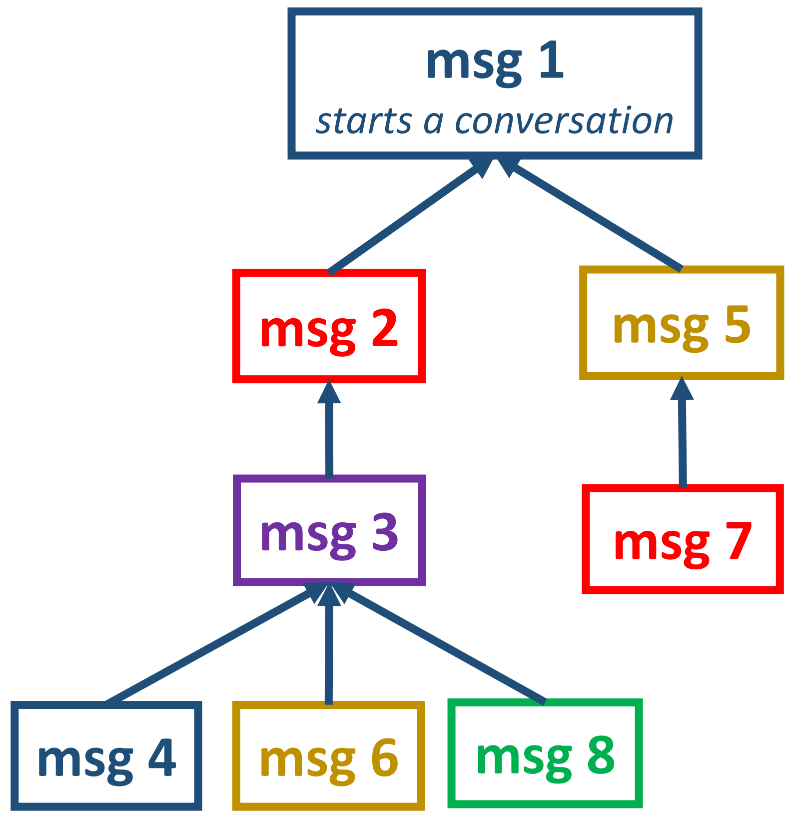
Background

- The structure of a conversation may not be sequential!



Asynchronous conversations

Time order does not represent the logical order

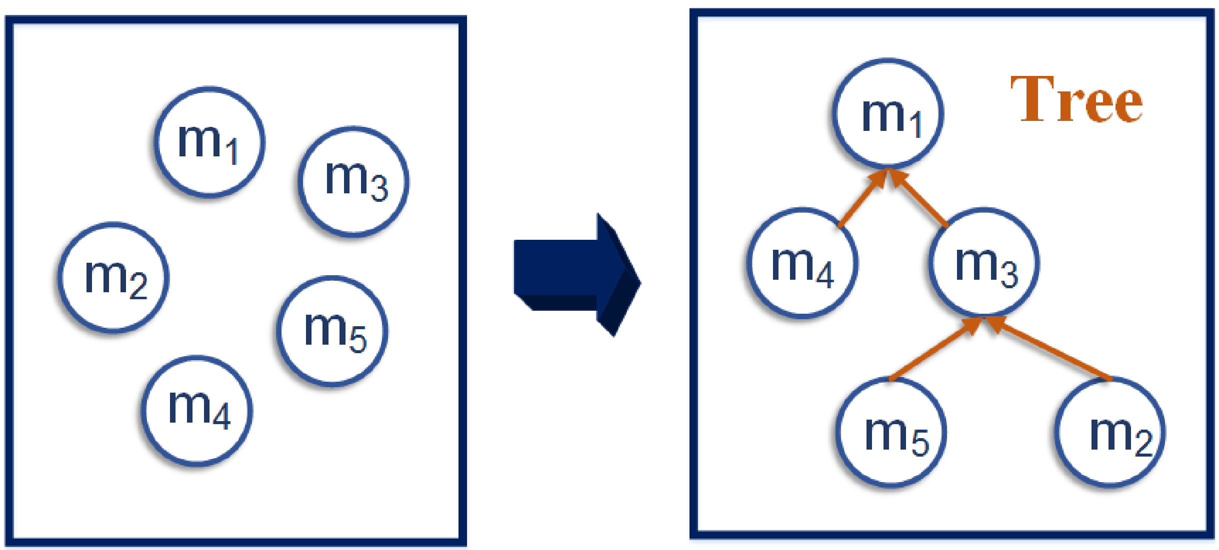


Problem

- Structure learning problem

Goal: reconstruct the *logical order* of a conversation.

Problem: Given a set of messages $M = \{m_1, m_2, \dots m_M\}$ of a conversation, output the structure of this conversation by *identifying the precursor that each message m replies to*.



Conversations Corpus

Recovered Conversation Structure

Related Work

- Conversation Disentanglement & Clustering
  - Chat disentanglement [Elsner, Comput Linguist2010]
  - Topic clustering based on graph [Elsner, ACL2008]
  - Improved topic clustering by enriching TF-IDF [Wang, NAACL2009]
- Dialogue Act
  - The role of a sentence, e.g., *Statement*, *Question*, *Answer*.
  - Dialogue act modeling in conversational speech [Stolcke, Comput Linguist2000]
  - Dialogue act emission in HMM [Ritter, NAACL2010, Joty, IJCAI2011]
- Thread Prediction
  - Recover thread structure in newsgroup conversations [Wang, ICWSM2008]

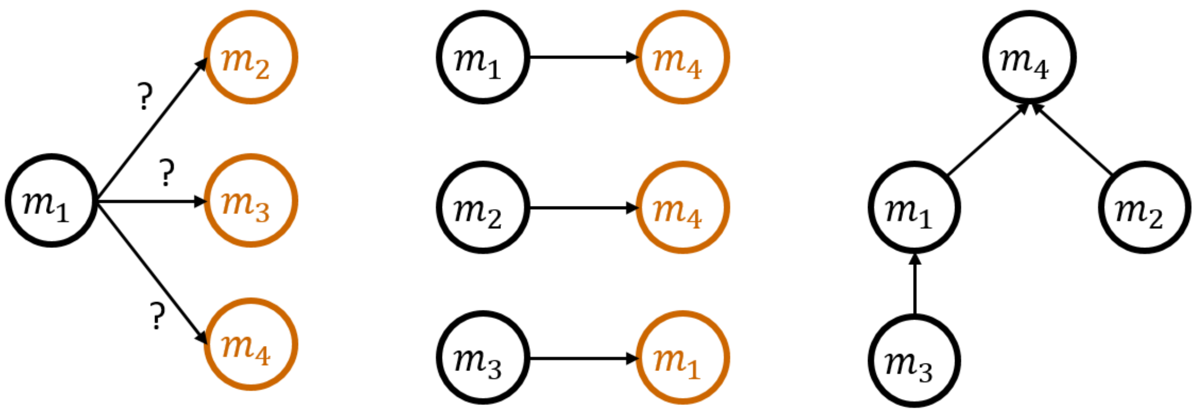
Method

Key problem

- Find the message n that m replies to.

Main steps

- Estimate the probability $P_{n \prec m}$ that m replies to each message n.
- Decide the precursor of m based on $P_{n \prec m}$. (max probability?)
- Recover conversation structure based on the reply-to relations.



(1) (2) (3)

Method

Estimate reply-to probability

- The probability that m_i replies to m_j:

$$p_{m_j \prec m_i} = (1-\gamma)\mathcal{S}(m_i, m_j) + \gamma \mathcal{T}(\mathcal{A}(m_i), \mathcal{A}(m_j)).$$

text similarity

latent dialogue act transferability

Measuring text similarity

- TF-IDF features of messages, $\mathbf{v}_i$, $\mathbf{v}_j$
- Cosine similarity
- Symmetrical measure

$$\mathcal{S}(m_i, m_j) = \frac{\mathbf{v}_i^\top \mathbf{v}_j}{\|\mathbf{v}_i\| \cdot \|\mathbf{v}_j\|}$$

But, reply-to relation is asymmetrical!

- Introduce **latent dialogue act transferability**

Method

Measuring latent dialogue act transferability

- **Dialogue acts** indicate the *roles* played by messages in the conversation (e.g., statement, question, answer)
- **Latent dialogue acts**, represented by *latent features*, can be used to model the *transition* from one message to another.
- Represent m_i by the newly defined **TF-DF feature** $\mathbf{x}_i$ with Top-F **frequent words**:

$$\mathbf{x}_{iw} = n_{w,i} \cdot \frac{1}{1 + \mathrm{e}^{-(1+\ln f_w)}} = n_{w,i} \cdot \frac{f_w}{f_w + \mathrm{e}^{-1}}.$$

- Let $\mathbf{y}_i$ denote the **latent dialogue act feature** of m_i ($\mathbf{A}$: latent matrix),

$$\mathbf{x}_i = \mathbf{A}\mathbf{y}_i$$

- With all messages represented by column vectors,

$$\mathbf{X} = \mathbf{A}\mathbf{Y}$$

$$\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_{|\mathcal{M}|})$$
$$\mathbf{Y} = (\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_{|\mathcal{M}|})$$

Method

Measuring latent dialogue act transferability

- Based on $\mathbf{X} = \mathbf{AY}$, factorize $\mathbf{X}$ to get $\mathbf{Y}$
- Apply Independent Component Analysis (ICA) to get $\mathbf{Y}$
- Whiten $\mathbf{X}$ before performing ICA

Theorem 1. *For* $\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_{|\mathcal{M}|})$, *if random variable* $\mathbf{x} \in \mathbf{X}$ *has zero mean, i.e.* $\mathrm{E}[\mathbf{x}] = \mathbf{0}$, *and* $\mathbf{X}$ *has singular value decomposition* $\mathbf{X} = \mathbf{U\Sigma V}^\top$, *then let* $\mathbf{z} = \left(\frac{1}{\sqrt{|\mathcal{M}|}}\mathbf{\Sigma}\right)^{-1}\mathbf{U}^\top\mathbf{x}$, *random variable* $\mathbf{z}$ *will be whitened.*

- Define **transferability** from m_i to m_j based on $\mathbf{y}_i$ and $\mathbf{y}_j$:

$$\mathcal{T}(\mathcal{A}(m_i), \mathcal{A}(m_j)) = \mathcal{T}(\mathbf{y}_i, \mathbf{y}_j) = \hat{\mathbf{y}}_i^\top \mathbf{B} \hat{\mathbf{y}}_j$$

  - $\mathbf{B}$ is the latent transition matrix.
- Learn transition matrix $\mathbf{B}$ with supervised learning:

$$\widehat{\mathbf{B}} = \operatorname*{argmin}_{\mathbf{B} \in \mathbb{R}^{K \times K}} \|\mathbf{Y}_p^\top \mathbf{B} - \mathbf{Y}_q\|^2$$

$$\mathbf{Y}_p = \left(\hat{\mathbf{y}}_{p_1}, \hat{\mathbf{y}}_{p_2}, \ldots, \hat{\mathbf{y}}_{p_N}\right)$$

$$\mathbf{Y}_q = \left(\hat{\mathbf{y}}_{q_1}, \hat{\mathbf{y}}_{q_2}, \ldots, \hat{\mathbf{y}}_{q_N}\right)$$

Method

Decide reply-to relation

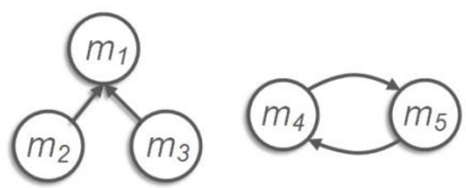
- Decide the precursor of each message based on,

$$p_{m_j \prec m_i} = (1-\gamma)\mathcal{S}(m_i, m_j) + \gamma \mathcal{T}(\mathcal{A}(m_i), \mathcal{A}(m_j)).$$

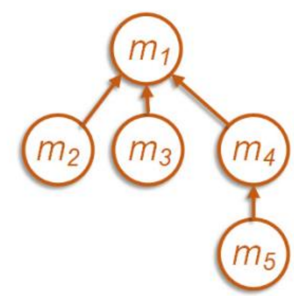
- **The max probability does not always work!**

m_i \ m_j	m_1	m_2	m_3	m_4	m_5
root → m_1		*0.10*	*0.06*	*0.05*	*0.08*
m_2	***0.80***		*0.10*	*0.15*	*0.25*
m_3	***0.75***	*0.02*		*0.01*	*0.04*
m_4	*0.25*	*0.15*	*0.15*		***0.60***
m_5	*0.10*	*0.08*	*0.15*	***0.50***	

(a) Likelihood



(b) Disconnected and cyclic structure



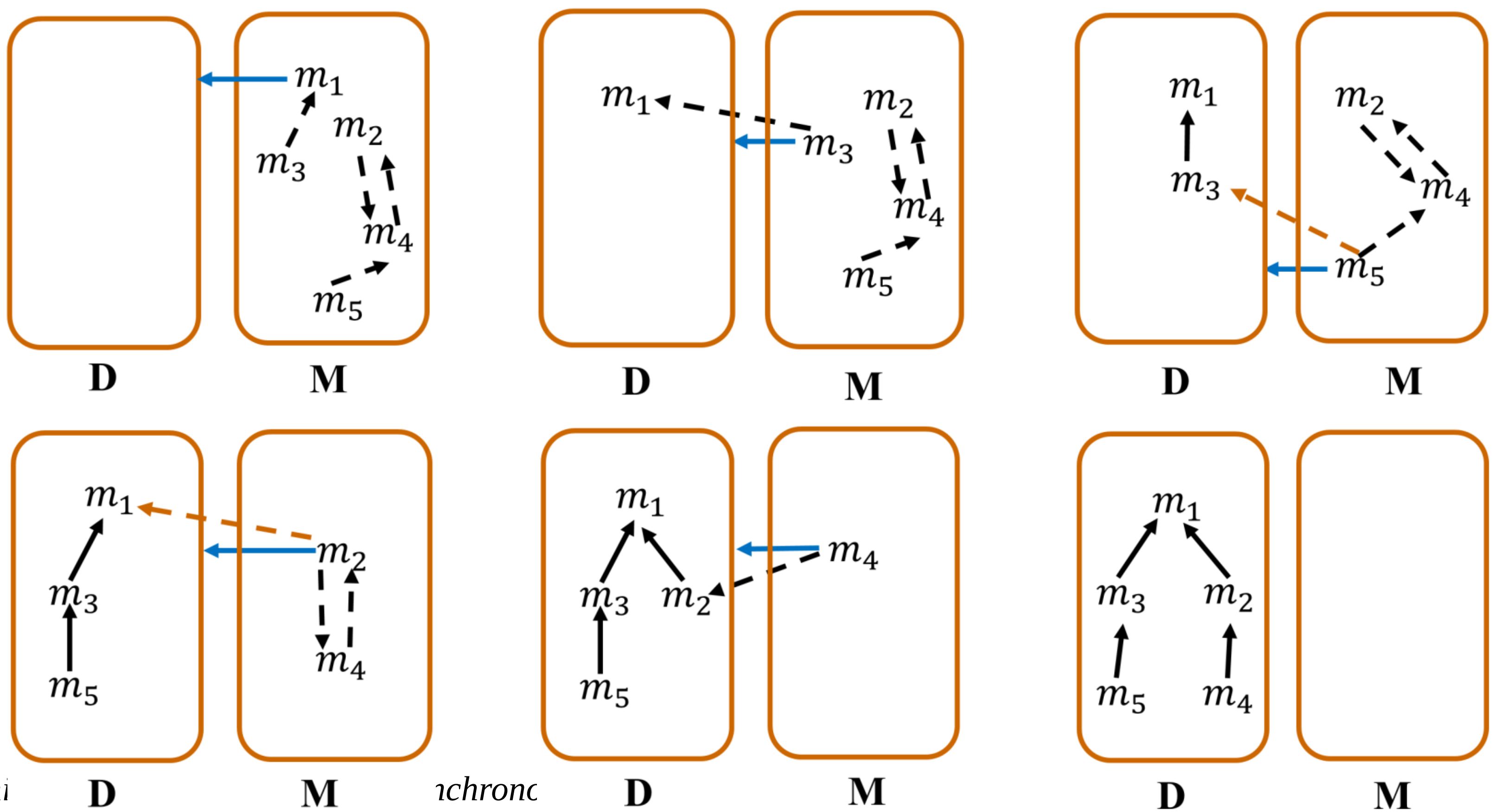
(c) Connected and acyclic structure

- Jointly **decide the precursor** and **recover the structure**.
  - Edmonds' algorithm [Edmonds, 1967]: find the *maximum spanning arborescence* with prescribed root on a *weighted directed graph*

Method

Decide precursor and recover structure

- The Edmonds' algorithm is accurate but time-consuming.
- This paper provides a **heuristic structure recovery method**.



Method

Decide precursor and recover structure

- The Edmonds' algorithm is accurate but time-consuming.
- This paper provides a heuristic structure recovery method.
  1. **M**: unvisited message set (full), **D**: visited message set (empty).
  2. Iteratively move message from **M** to **D** until **M** is empty.
  3. For any $m \in \mathbf{M}$, if $n \in \mathbf{D}$ w.r.t. max $P_{n<m}$, move m to **D**.
  4. Else, move $m \in \mathbf{M}$ that have the largest $P_{n<m}$ to any $n \in \mathbf{D}$ (may not be the max $P_{n<m}$ for m) , and repeat step 3.

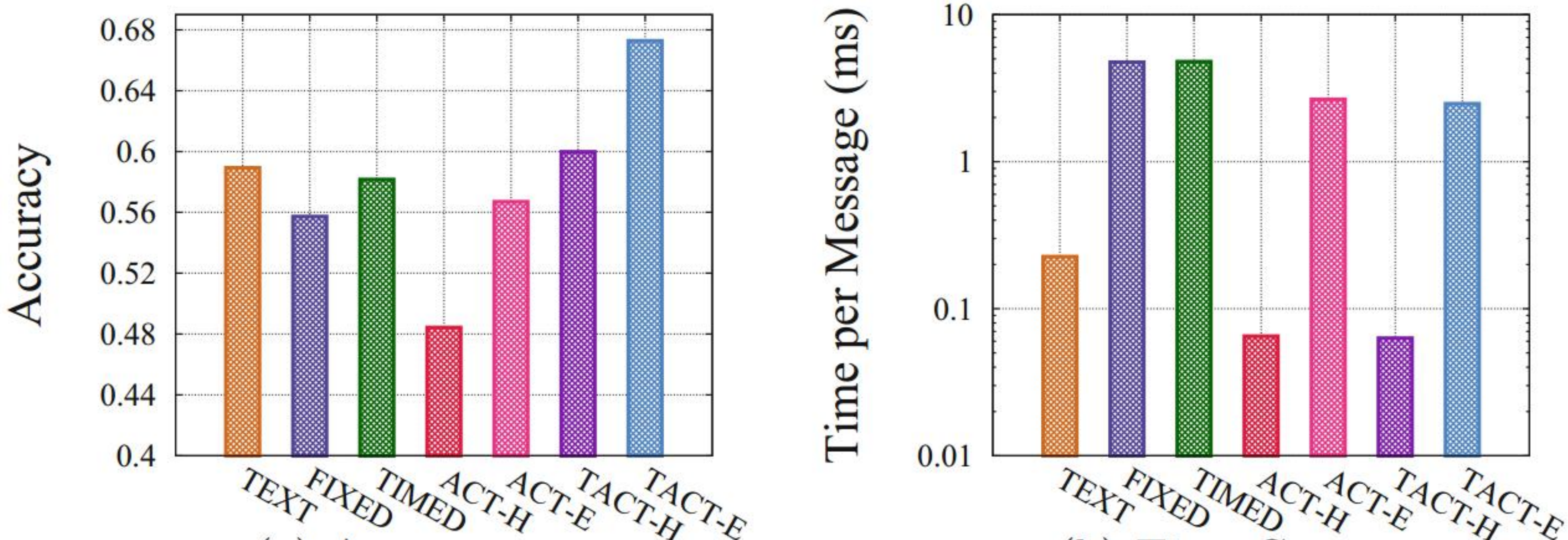
- **Filters**
  - User filter: no self-reply
  - Time filter: reply to message with smaller timestamp

Experiments

- Dataset
  - Crawled web forum discussion from Douban Group.
  - 10,425 conversations, 137,980 messages, in August 2013.
  - Obtain ground-truth by tracking the quoting relations.
  - On average, 12 words in each message after Chinese word-cut.
  - 80% conversations for training, 20% conversations for testing.
  - Numbers are reported as the average of running 5 times.

Experiments

Results



(a) Accuracy (b) Time Cost

- TACT: the proposed method (-E Edmonds', -H Heuristic).
- FIXED & TIMED: thread prediction method [Wang, ICWSM2008]
- **TACT-E** outperforms others on accuracy.
- **TACT-H** outperforms others on efficiency (with the 2nd rank accuracy).

Closing remarks

- Contributions
  - First study on asynchronous conversation structure learning based on online short-text messages.
  - A novel method to extract latent dialogue act features and futher estimate transferability between messages.
  - A novel framework to combine text similarity and latent dialogue act transferability to estimate the reply-to probability.
  - An efficient heuristic method to recover conversation structure that avoids yielding disconnected or cyclic structure.
  - A new online short-text corpus of asynchronous conversations.

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