

Addressee and Response Selection in Multi-Party Conversations with Speaker Interaction RNNs

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Abstract

In this paper, we study the problem of addressee and response selection in multi-party conversations. Understanding multi-party conversations is challenging because of complex speaker interactions: multiple speakers exchange messages with each other, playing different roles (sender, addressee, observer), and these roles vary across turns. To tackle this challenge, we propose the Speaker Interaction Recurrent Neural Network (SI-RNN). Whereas the previous state-of-the-art system updated speaker embeddings only for the sender, SI-RNN uses a novel dialog encoder to update speaker embeddings in a role-sensitive way. Additionally, unlike the previous work that selected the addressee and response separately, SI-RNN selects them jointly by viewing the task as a sequence prediction problem. Experimental results show that SI-RNN significantly improves the accuracy of addressee and response selection, particularly in complex conversations with many speakers and responses to distant messages many turns in the past.

1 Introduction

Real-world conversations often involve more than two speakers. In the Ubuntu Internet Relay Chat channel (IRC), for example, one user can initiate a discussion about an Ubuntu-related technical issue, and many other users can work together to solve the problem. Dialogs can have complex speaker interactions: at each turn, users play one of three roles (sender, addressee, observer), and those roles vary across turns.

In this paper, we study the problem of addressee and response selection in multi-party conversations: given a responding speaker and a dialog context, the task is to select an addressee and a response from a set of candidates for the responding speaker. The task requires modeling multi-party conversations and can be directly used to build retrieval-based dialog systems (Lu and Li 2013; Hu et al. 2014; Ji, Lu, and Li 2014; Wang et al. 2015).

The previous state-of-the-art DYNAMIC-RNN model from Ouchi and Tsuboi (2016) maintains speaker embeddings to track each speaker status, which dynamically changes across time steps. It then produces the context embedding from the speaker embeddings and selects the ad-

dressee and response based on embedding similarity. However, this model updates only the sender embedding, not the embeddings of the addressee or observers, with the corresponding utterance, and it selects the addressee and response separately. In this way, it only models *who* says *what* and fails to capture addressee information. Experimental results show that the separate selection process often produces inconsistent addressee-response pairs.

To solve these issues, we introduce the Speaker Interaction Recurrent Neural Network (SI-RNN). SI-RNN re-designs the dialog encoder by updating speaker embeddings in a role-sensitive way. Speaker embeddings are updated in different GRU-based units depending on their roles (sender, addressee, observer). Furthermore, we note that the addressee and response are mutually dependent and view the task as a joint prediction problem. Therefore, SI-RNN models the conditional probability (of addressee given the response and vice versa) and selects the addressee and response pair by maximizing the joint probability.

On a public standard benchmark data set, SI-RNN significantly improves the addressee and response selection accuracy, particularly in complex conversations with many speakers and responses to distant messages many turns in the past. Our code and data set are available online ¹.

2 Related Work

We follow a data-driven approach to dialog systems. Singh et al. (1999), Henderson, Lemon, and Georgila (2008), and Young et al. (2013) optimize the dialog policy using Reinforcement Learning or the Partially Observable Markov Decision Process framework. In addition, Henderson, Thomson, and Williams (2014) propose to use a predefined ontology as a logical representation for the information exchanged in the conversation. The dialog system can be divided into different modules, such as Natural Language Understanding (Yao et al. 2014; Mesnil et al. 2015), Dialog State Tracking (Henderson, Thomson, and Young 2014; Williams, Raux, and Henderson 2016), and Natural Language Generation (Wen et al. 2015). Furthermore, Wen et al. (2016) and Bordes and Weston (2017) propose end-to-end trainable goal-oriented dialog systems.

¹The released code: <https://github.com/ryanzhumich/sirnn>

Recently, short text conversation has been popular. The system receives a short dialog context and generates a response using statistical machine translation or seq-to-seq networks (Ritter, Cherry, and Dolan 2011; Vinyals and Le 2015; Shang, Lu, and Li 2015; Serban et al. 2016; Li et al. 2016; Mei, Bansal, and Walter 2017). In contrast to response generation, the retrieval-based approach uses a ranking model to select the highest scoring response from candidates (Lu and Li 2013; Hu et al. 2014; Ji, Lu, and Li 2014; Wang et al. 2015). However, these models are single-turn responding machines and thus still are limited to short contexts with only two speakers. As for larger context, Lowe et al. (2015) propose the Next Utterance Classification (NUC) task for multi-turn two-party dialogs. Ouchi and Tsuboi (2016) extend NUC to multi-party conversations by integrating the addressee detection problem. Since the data is text based, they use only textual information to predict addressees as opposed to relying on acoustic signals or gaze information in multimodal dialog systems (Jovanović, Akker, and Nijholt 2006; op den Akker and Traum 2009).

Furthermore, several other papers are recently presented focusing on modeling role-specific information given the dialogue contexts (Meng, Mou, and Jin 2017; Chi et al. 2017; Chen et al. 2017). For example, Meng, Mou, and Jin (2017) combine content and temporal information to predict the utterance speaker. By contrast, our SIRNN explicitly utilizes the speaker interaction to maintain speaker embeddings and predicts the addressee and response by joint selection.

3 Preliminaries

3.1 Addressee and Response Selection

Ouchi and Tsuboi (2016) propose the addressee and response selection task for multi-party conversation. Given a responding speaker a_{res} and a dialog context \mathcal{C} , the task is to select a response and an addressee. \mathcal{C} is a list ordered by time step:

$$\mathcal{C} = [(a_{sender}^{(t)}, a_{addressee}^{(t)}, u^{(t)})]_{t=1}^T$$

where $a_{sender}^{(t)}$ says $u^{(t)}$ to $a_{addressee}^{(t)}$ at time step t , and T is the total number of time steps before the response and addressee selection. The set of speakers appearing in \mathcal{C} is denoted $\mathcal{A}(\mathcal{C})$. As for the output, the addressee is selected from $\mathcal{A}(\mathcal{C})$, and the response is selected from a set of candidates \mathcal{R} . \mathcal{R} contains the ground-truth response and one or more false responses. We provide some examples in Table 4 (Section 6).

3.2 DYNAMIC-RNN Model

In this section, we briefly review the state-of-the-art DYNAMIC-RNN model (Ouchi and Tsuboi 2016), which our proposed model is based on. DYNAMIC-RNN solves the task in two phases: 1) the dialog encoder maintains a set of speaker embeddings to track each speaker status, which dynamically changes with time step t ; 2) then DYNAMIC-RNN produces the context embedding from the speaker embeddings and selects the addressee and response based on embedding similarity among context, speaker, and utterance.

	Data	Notation
Input	Responding Speaker	a_{res}
	Context	\mathcal{C}
Output	Candidate Responses	\mathcal{R}
	Addressee Response	$a \in \mathcal{A}(\mathcal{C})$ $r \in \mathcal{R}$
	Sender ID at time t	$a_{sender}^{(t)}$
	Addressee ID at time t	$a_{addressee}^{(t)}$
	Utterance at time t	$u^{(t)}$
	Utterance embedding at time t	$\mathbf{u}^{(t)}$
	Speaker embedding of a_i at time t	$\mathbf{a}_i^{(t)}$

Table 1: Notations for the task and model.

Dialog Encoder. Figure 1 (Left) illustrates the dialog encoder in DYNAMIC-RNN on an example context. In this example, a_2 says $u^{(1)}$ to a_1 , then a_1 says $u^{(2)}$ to a_3 , and finally a_3 says $u^{(3)}$ to a_2 . The context \mathcal{C} will be:

$$\mathcal{C} = [(a_2, a_1, u^{(1)}), (a_1, a_3, u^{(2)}), (a_3, a_2, u^{(3)})] \quad (1)$$

with the set of speakers $\mathcal{A}(\mathcal{C}) = \{a_1, a_2, a_3\}$.

For a speaker a_i , the bold letter $\mathbf{a}_i^{(t)} \in \mathbb{R}^{d_s}$ denotes its embedding at time step t . Speaker embeddings are initialized as zero vectors and updated recurrently as hidden states of GRUs (Cho et al. 2014; Chung et al. 2014). Specifically, for each time step t with the sender a_{sdr} and the utterance $u^{(t)}$, the sender embedding \mathbf{a}_{sdr} is updated recurrently from the utterance:

$$\mathbf{a}_{sdr}^{(t)} = \text{GRU}(\mathbf{a}_{sdr}^{(t-1)}, \mathbf{u}^{(t)}),$$

where $\mathbf{u}^{(t)} \in \mathbb{R}^{d_u}$ is the embedding for utterance $u^{(t)}$. Other speaker embeddings are updated from $\mathbf{u}^{(t)} = \mathbf{0}$. The speaker embeddings are updated until time step T .

Selection Model. To summarize the whole dialog context \mathcal{C} , the model applies element-wise max pooling over all the speaker embeddings to get the context embedding $\mathbf{h}_\mathcal{C}$:

$$\mathbf{h}_\mathcal{C} = \max_{a_i=a_1, \dots, a_{|\mathcal{A}(\mathcal{C})|}} \mathbf{a}_i^{(T)} \in \mathbb{R}^{d_s} \quad (2)$$

The probability of an addressee and a response being the ground truth is calculated based on embedding similarity. To be specific, for addressee selection, the model compares the candidate speaker a_p , the dialog context \mathcal{C} , and the responding speaker a_{res} :

$$\mathbb{P}(a_p|\mathcal{C}) = \sigma([\mathbf{a}_{res}; \mathbf{h}_\mathcal{C}]^\top \mathbf{W}_a \mathbf{a}_p) \quad (3)$$

where \mathbf{a}_{res} is the final speaker embedding for the responding speaker a_{res} , \mathbf{a}_p is the final speaker embedding for the candidate addressee a_p , σ is the logistic sigmoid function, $[\cdot; \cdot]$ is the row-wise concatenation operator, and $\mathbf{W}_a \in \mathbb{R}^{2d_s \times d_s}$ is a learnable parameter. Similarly, for response selection,

$$\mathbb{P}(r_q|\mathcal{C}) = \sigma([\mathbf{a}_{res}; \mathbf{h}_\mathcal{C}]^\top \mathbf{W}_r \mathbf{r}_q) \quad (4)$$

where $\mathbf{r}_q \in \mathbb{R}^{d_u}$ is the embedding for the candidate response r_q , and $\mathbf{W}_r \in \mathbb{R}^{2d_s \times d_u}$ is a learnable parameter.

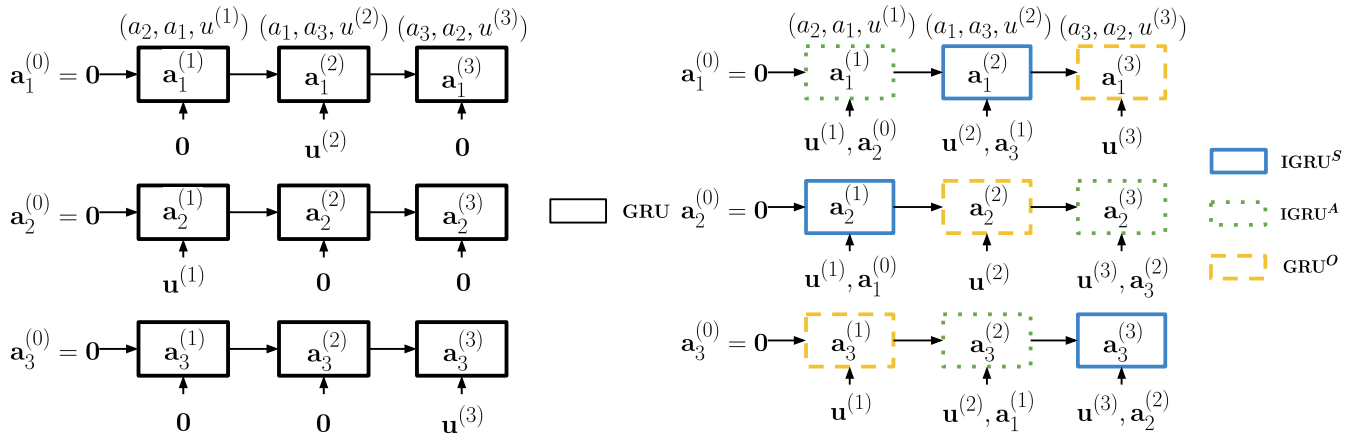


Figure 1: Dialog encoders in DYNAMIC-RNN (Left) and SI-RNN (Right) for an example context at the top. Speaker embeddings are initialized as zero vectors and updated recurrently as hidden states along the time step. In SI-RNN, the same speaker embedding is updated in different units depending on the role (IGRU^S for sender, IGRU^A for addressee, GRU^O for observer).

The model is trained end-to-end to minimize a joint cross-entropy loss for the addressee selection and the response selection with equal weights. At test time, the addressee and the response are separately selected to maximize the probability in Eq 3 and Eq 4.

4 Speaker Interaction RNN

While DYNAMIC-RNN can track the speaker status by capturing *who* says *what* in multi-party conversation, there are still some issues. First, at each time step, only the sender embedding is updated from the utterance. Therefore, other speakers are blind to what is being said, and the model fails to capture addressee information. Second, while the addressee and response are mutually dependent, DYNAMIC-RNN selects them independently. Consider a case where the responding speaker is talking to two other speakers in separate conversation threads. The choice of addressee is likely to be either of the two speakers, but the choice is much less ambiguous if the correct response is given, and vice versa. DYNAMIC-RNN often produces inconsistent addressee-response pairs due to the separate selection. See Table 4 for examples.

In contrast to DYNAMIC-RNN, the dialog encoder in SI-RNN updates embeddings for all the speakers besides the sender at each time step. Speaker embeddings are updated depending on their roles: the update of the sender is different from the addressee, which is different from the observers. Furthermore, the update of a speaker embedding is not only from the utterance, but also from other speakers. These are achieved by designing variations of GRUs for different roles. Finally, SI-RNN selects the addressee and response jointly by maximizing the joint probability.

4.1 Utterance Encoder

To encode an utterance $u = (w_1, w_2, \dots, w_N)$ of N words, we use a RNN with Gated Recurrent Units (Cho et al. 2014; Chung et al. 2014):

$$\mathbf{h}_j = \text{GRU}(\mathbf{h}_{j-1}, \mathbf{x}_j)$$

where \mathbf{x}_j is the word embedding for w_j , and \mathbf{h}_j is the GRU hidden state. \mathbf{h}_0 is initialized as a zero vector, and the utterance embedding is the last hidden state, i.e. $\mathbf{u} = \mathbf{h}_N$.

4.2 Dialog Encoder

Figure 1 (Right) shows how SI-RNN encodes the example in Eq 1. Unlike DYNAMIC-RNN, SI-RNN updates all speaker embeddings in a role-sensitive manner. For example, at the first time step when a_2 says $u^{(1)}$ to a_1 , DYNAMIC-RNN only updates a_2 using $\mathbf{u}^{(1)}$, while other speakers are updated using $\mathbf{0}$. In contrast, SI-RNN updates each speaker status with different units: IGRU^S updates the sender embedding a_2 from the utterance embedding $\mathbf{u}^{(1)}$ and the addressee embedding a_1 ; IGRU^A updates the addressee embedding a_1 from $\mathbf{u}^{(1)}$ and a_2 ; GRU^O updates the observer embedding a_3 from $\mathbf{u}^{(1)}$.

Algorithm 1 gives a formal definition of the dialog encoder in SI-RNN. The dialog encoder is a function that takes as input a dialog context \mathcal{C} (lines 1-5) and returns speaker embeddings at the final time step (lines 28-30). Speaker embeddings are initialized as d_s -dimensional zero vectors (lines 6-9). Speaker embeddings are updated by iterating over each line in the context (lines 10-27).

4.3 Role-Sensitive Update

In this subsection, we explain in detail how IGRU^S/IGRU^A/GRU^O update speaker embeddings according to their roles at each time step (Algorithm 1 lines 19-26).

As shown in Figure 2, IGRU^S/IGRU^A/GRU^O are all GRU-based units. IGRU^S updates the sender embedding from the previous sender embedding $\mathbf{a}_{sdr}^{(t-1)}$, the previous addressee embedding $\mathbf{a}_{adr}^{(t-1)}$, and the utterance embedding $\mathbf{u}^{(t)}$:

$$\mathbf{a}_{sdr}^{(t)} \leftarrow \text{IGRU}^S(\mathbf{a}_{sdr}^{(t-1)}, \mathbf{a}_{adr}^{(t-1)}, \mathbf{u}^{(t)})$$

Algorithm 1 Dialog Encoder in SI-RNN

```

1: Input
2: Dialog context  $\mathcal{C}$  with speakers  $\mathcal{A}(\mathcal{C})$ :
3:  $\mathcal{C} = [(a_{sender}^{(t)}, a_{addressee}^{(t)}, u^{(t)})]_{t=1}^T$ 
4:  $\mathcal{A}(\mathcal{C}) = \{a_1, a_2, \dots, a_{|\mathcal{A}(\mathcal{C})|}\}$ 
5: where  $a_{sender}^{(t)}, a_{addressee}^{(t)} \in \mathcal{A}(\mathcal{C})$ 
6: // Initialize speaker embeddings
7: for  $a_i = a_1, a_2, \dots, a_{|\mathcal{A}(\mathcal{C})|}$  do
8:    $\mathbf{a}_i^{(0)} \leftarrow \mathbf{0} \in \mathbb{R}^{d_s}$ 
9: end for
10: // Update speaker embeddings
11: for  $t = 1, 2, \dots, T$  do
12:   // Update sender, addressee, observers
13:    $a_{sdr} \leftarrow a_{sender}^{(t)}$ 
14:    $a_{adr} \leftarrow a_{addressee}^{(t)}$ 
15:    $\mathcal{O} \leftarrow \mathcal{A}(\mathcal{C}) - \{a_{sdr}, a_{adr}\}$ 
16:   // Compute utterance embedding
17:    $\mathbf{u}^{(t)} \leftarrow \text{UtteranceEncoder}(u^{(t)})$ 
18:    $\mathbf{u}^{(t)} \leftarrow \text{Concatenate}(\mathbf{a}_{sdr}^{(t-1)}, \mathbf{u}^{(t)})$ 
19:   // Update sender embedding
20:    $\mathbf{a}_{sdr}^{(t)} \leftarrow \text{IGRU}^S(\mathbf{a}_{sdr}^{(t-1)}, \mathbf{a}_{adr}^{(t-1)}, \mathbf{u}^{(t)})$ 
21:   // Update addressee embedding
22:    $\mathbf{a}_{adr}^{(t)} \leftarrow \text{IGRU}^A(\mathbf{a}_{adr}^{(t-1)}, \mathbf{a}_{sdr}^{(t-1)}, \mathbf{u}^{(t)})$ 
23:   // Update observer embeddings
24:   for  $a_{obr}$  in  $\mathcal{O}$  do
25:      $\mathbf{a}_{obr}^{(t)} \leftarrow \text{GRU}^O(\mathbf{a}_{obr}^{(t-1)}, \mathbf{u}^{(t)})$ 
26:   end for
27: end for
28: // Return final speaker embeddings
29: Output
30: return  $\mathbf{a}_i^{(T)}$  for  $a_i = a_1, a_2, \dots, a_{|\mathcal{A}(\mathcal{C})|}$ 

```

The update, as illustrated in the upper part of Figure 2, is controlled by three gates. The $\mathbf{r}_S^{(t)}$ gate controls the previous sender embedding $\mathbf{a}_{sdr}^{(t-1)}$, and $\mathbf{p}_S^{(t)}$ controls the previous addressee embedding $\mathbf{a}_{adr}^{(t-1)}$. Those two gated interactions together produce the sender embedding proposal $\tilde{\mathbf{a}}_{sdr}^{(t)}$. Finally, the update gate $\mathbf{z}_S^{(t)}$ combines the proposal $\tilde{\mathbf{a}}_{sdr}^{(t)}$ and the previous sender embedding $\mathbf{a}_{sdr}^{(t-1)}$ to update the sender embedding $\mathbf{a}_{sdr}^{(t)}$. The computations in IGRU^S (including gates $\mathbf{r}_S^{(t)}$, $\mathbf{p}_S^{(t)}$, $\mathbf{z}_S^{(t)}$, the proposal embedding $\tilde{\mathbf{a}}_{sdr}^{(t)}$, and the final updated embedding $\mathbf{a}_{sdr}^{(t)}$) are formulated as:

$$\begin{aligned}
\mathbf{r}_S^{(t)} &= \sigma(\mathbf{W}_S^r \mathbf{u}^{(t)} + \mathbf{U}_S^r \mathbf{a}_{sdr}^{(t-1)} + \mathbf{V}_S^r \mathbf{a}_{adr}^{(t-1)}) \\
\mathbf{p}_S^{(t)} &= \sigma(\mathbf{W}_S^p \mathbf{u}^{(t)} + \mathbf{U}_S^p \mathbf{a}_{sdr}^{(t-1)} + \mathbf{V}_S^p \mathbf{a}_{adr}^{(t-1)}) \\
\mathbf{z}_S^{(t)} &= \sigma(\mathbf{W}_S^z \mathbf{u}^{(t)} + \mathbf{U}_S^z \mathbf{a}_{sdr}^{(t-1)} + \mathbf{V}_S^z \mathbf{a}_{adr}^{(t-1)}) \\
\tilde{\mathbf{a}}_{sdr}^{(t)} &= \tanh(\mathbf{W}_S \mathbf{u}^{(t)} + \mathbf{U}_S(\mathbf{r}_S^{(t)} \odot \mathbf{a}_{sdr}^{(t-1)} \\
&\quad + \mathbf{V}_S(\mathbf{p}_S^{(t)} \odot \mathbf{a}_{adr}^{(t-1)})) \\
\mathbf{a}_{sdr}^{(t)} &= \mathbf{z}_S^{(t)} \odot \mathbf{a}_{sdr}^{(t-1)} + (1 - \mathbf{z}_S^{(t)}) \odot \tilde{\mathbf{a}}_{sdr}^{(t)}
\end{aligned}$$

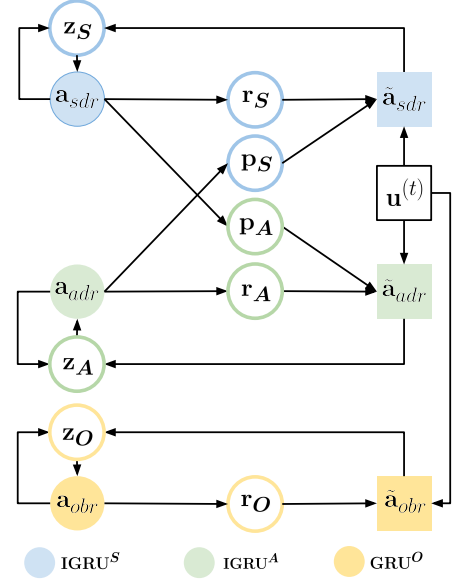


Figure 2: Illustration of IGRU^S (upper, blue), IGRU^A (middle, green), and GRU^O (lower, yellow). Filled circles are speaker embeddings, which are recurrently updated. Unfilled circles are gates. Filled squares are speaker embedding proposals.

where $\{\mathbf{W}_S^r, \mathbf{W}_S^p, \mathbf{W}_S^z, \mathbf{U}_S^r, \mathbf{U}_S^p, \mathbf{U}_S^z, \mathbf{V}_S^r, \mathbf{V}_S^p, \mathbf{V}_S^z, \mathbf{W}_S, \mathbf{U}_S, \mathbf{V}_S\}$ are learnable parameters. IGRU^A uses the same formulation with a different set of parameters, as illustrated in the middle of Figure 2. In addition, we update the observer embeddings from the utterance. GRU^O is implemented as the traditional GRU unit in the lower part of Figure 2. Note that the parameters in $\text{IGRU}^S/\text{IGRU}^A/\text{GRU}^O$ are not shared. This allows SI-RNN to learn role-dependent features to control speaker embedding updates. The formulations of IGRU^A and GRU^O are similar.

4.4 Joint Selection

The dialog encoder takes the dialog context \mathcal{C} as input and returns speaker embeddings at the final time step, $\mathbf{a}_i^{(T)}$. Recall from Section 3.2 that DYNAMIC-RNN produces the context embedding \mathbf{h}_C using Eq 2 and then selects the addressee and response separately using Eq 3 and Eq 4.

In contrast, SI-RNN performs addressee and response selection jointly: the response is dependent on the addressee and vice versa. Therefore, we view the task as a sequence prediction process: given the context and responding speaker, we first predict the addressee, and then predict the response given the addressee. (We also use the reversed prediction order as in Eq 7.)

In addition to Eq 3 and Eq 4, SI-RNN is also trained to model the conditional probability as follows. To predict the addressee, we calculate the probability of the candidate speaker a_p to be the ground-truth *given* the ground-truth re-

sponse r (available during training time):

$$\mathbb{P}(a_p|\mathcal{C}, r) = \sigma([\mathbf{a}_{res}; \mathbf{h}_C; \mathbf{r}]^\top \mathbf{W}_{ar} \mathbf{a}_p) \quad (5)$$

The key difference from Eq 3 is that Eq 5 is conditioned on the correct response r with embedding \mathbf{r} . Similarly, for response selection, we calculate the probability of a candidate response r_q given the ground-truth addressee a_{adr} :

$$\mathbb{P}(r_q|\mathcal{C}, a_{adr}) = \sigma([\mathbf{a}_{res}; \mathbf{h}_C; \mathbf{a}_{adr}]^\top \mathbf{W}_{ra} \mathbf{r}_q) \quad (6)$$

At test time, SI-RNN selects the addressee-response pair from $\mathcal{A}(\mathcal{C}) \times \mathcal{R}$ to maximize the joint probability $\mathbb{P}(r_q, a_p|\mathcal{C})$:

$$\begin{aligned} \hat{a}, \hat{r} &= \arg \max_{a_p, r_q \in \mathcal{A}(\mathcal{C}) \times \mathcal{R}} \mathbb{P}(r_q, a_p|\mathcal{C}) \\ &= \arg \max_{a_p, r_q \in \mathcal{A}(\mathcal{C}) \times \mathcal{R}} \mathbb{P}(r_q|\mathcal{C}) \cdot \mathbb{P}(a_p|\mathcal{C}, r_q) \\ &\quad + \mathbb{P}(a_p|\mathcal{C}) \cdot \mathbb{P}(r_q|\mathcal{C}, a_p) \end{aligned} \quad (7)$$

In Eq 7, we decompose the joint probability into two terms: the first term selects the response given the context, and then selects the addressee given the context and the selected response; the second term selects the addressee and response in the reversed order.²

5 Experimental Setup

Data Set. We use the Ubuntu Multiparty Conversation Corpus (Ouchi and Tsuboi 2016) and summarize the data statistics in Table 3. The whole data set (including the Train/Dev/Test split and the false response candidates) is publicly available.³ The data set is built from the Ubuntu IRC chat room where a number of users discuss Ubuntu-related technical issues. The log is organized as one file per day corresponding to a document \mathcal{D} . Each document consists of (Time, SenderID, Utterance) lines. If users explicitly mention addressees at the beginning of the utterance, the addresseeID is extracted. Then a sample, namely a unit of input (the dialog context and the current sender) and output (the addressee and response prediction) for the task, is created to predict the ground-truth addressee and response of this line. Note that samples are created only when the addressee is explicitly mentioned for clear, unambiguous ground-truth labels. False response candidates are randomly chosen from all other utterances *within the same document*. Therefore, distractors are likely from the same sub-conversation or even from the same sender but at different time steps. This makes it harder than Lowe et al. (2015) where distractors are randomly chosen from all documents. If no addressee is explicitly mentioned, the addressee is left blank and the line is marked as a part of the context.

Baselines. Apart from DYNAMIC-RNN, we also include several other baselines. RECENT+TF-IDF always selects

²Detail: We also considered an alternative decomposition of the joint probability as $\log \mathbb{P}(r_q, a_p|\mathcal{C}) = \frac{1}{2}[\log \mathbb{P}(r_q|\mathcal{C}) + \log \mathbb{P}(a_p|\mathcal{C}, r_q) + \log \mathbb{P}(a_p|\mathcal{C}) + \log \mathbb{P}(r_q|\mathcal{C}, a_p)]$, but the performance was similar to Eq 7.

³<https://github.com/hiroki13/response-ranking/tree/master/data/input>

the most recent speaker (except the responding speaker a_{res}) as the addressee and chooses the response to maximize the tf-idf cosine similarity with the context. We improve it by using a slightly different addressee selection heuristic (DIRECT-RECENT+TF-IDF): select the most recent speaker that *directly talks to* a_{res} by an explicit addressee mention. We select from the previous 15 utterances, which is the longest context among all the experiments. This works much better when there are multiple concurrent sub-conversations, and a_{res} responds to a distant message in the context. We also include another GRU-based model STATIC-RNN from Ouchi and Tsuboi (2016). Unlike DYNAMIC-RNN, speaker embeddings in STATIC-RNN are based on the order of speakers and are fixed. Furthermore, inspired by Zhou et al. (2016) and Serban et al. (2016), we implement STATIC-HIER-RNN, a hierarchical version of STATIC-RNN. It first builds utterance embeddings from words and then uses high-level RNNs to process utterance embeddings.

6 Results and Discussion

For fair and meaningful quantitative comparisons, we follow Ouchi and Tsuboi (2016)’s evaluation protocols. SI-RNN improves the overall accuracy on the addressee and response selection task. Two ablation experiments further analyze the contribution of role-sensitive units and joint selection respectively. We then confirm the robustness of SI-RNN with the number of speakers and distant responses. Finally, in a case study we discuss how SI-RNN handles complex conversations by either engaging in a new sub-conversation or responding to a distant message.

Overall Result. As shown in Table 2, SI-RNN significantly improves upon the previous state-of-the-art. In particular, addressee selection (ADR) benefits most, with different number of candidate responses (denoted as RES-CAND): around 12% in RES-CAND = 2 and more than 10% in RES-CAND = 10. Response selection (RES) is also improved, suggesting role-sensitive GRUs and joint selection are helpful for response selection as well. The improvement is more obvious with more candidate responses (2% in RES-CAND = 2 and 4% in RES-CAND = 10). These together result in significantly better accuracy on the ADR-RES metric as well.

Ablation Study. We show an ablation study in the last rows of Table 2. First, we share the parameters of IGRU^S/IGRU^A/GRU^O. The accuracy decreases significantly, indicating that it is crucial to learn role-sensitive units to update speaker embeddings. Second, to examine our joint selection, we fall back to selecting the addressee and response separately, as in DYNAMIC-RNN. We find that joint selection improves ADR and RES individually, and it is particularly helpful for pair selection ADR-RES.

Number of Speakers. Numerous speakers create complex dialogs and increased candidate addressee, thus the task becomes more challenging. In Figure 3 (Upper), we investigate how ADR accuracy changes with the number of speakers in the context of length 15, corresponding to the rows with T=15 in Table 2. RECENT+TF-IDF always chooses the most recent speaker and the accuracy

	T	RES-CAND = 2				RES-CAND = 10			
		DEV	TEST			DEV	TEST		
		ADR-RES	ADR-RES	ADR	RES	ADR-RES	ADR-RES	ADR	RES
Chance	-	0.62	0.62	1.24	50.00	0.12	0.12	1.24	10.00
Recent+TF-IDF	15	37.11	37.13	55.62	67.89	14.91	15.44	55.62	29.19
Direct-Recent+TF-IDF	15	45.83	45.76	67.72	67.89	18.94	19.50	67.72	29.40
Static-RNN	5	47.08	46.99	60.39	75.07	21.96	21.98	60.26	33.27
(Ouchi and Tsuboi 2016)	10	48.52	48.67	60.97	77.75	22.78	23.31	60.66	35.91
	15	49.03	49.27	61.95	78.14	23.73	23.49	60.98	36.58
Static-Hier-RNN	5	49.19	49.38	62.20	76.70	23.68	23.75	62.24	34.51
(Zhou et al. 2016)	10	51.37	51.76	64.61	78.28	25.46	25.83	64.86	36.94
(Serban et al. 2016)	15	52.78	53.04	65.84	79.08	26.31	26.62	65.89	37.85
Dynamic-RNN	5	49.38	49.80	63.19	76.07	23.44	23.72	63.28	33.62
(Ouchi and Tsuboi 2016)	10	52.76	53.85	66.94	78.16	25.44	25.95	66.70	36.14
	15	54.45	54.88	68.54	78.64	26.73	27.19	68.41	36.93
SI-RNN (Ours)	5	60.57	60.69	74.08	78.14	30.65	30.71	72.59	36.45
	10	65.34	65.63	78.76	80.34	34.18	34.09	77.13	39.20
	15	67.01	67.30	80.47	80.91	35.50	35.76	78.53	40.83
SI-RNN w/ shared IGRUs	15	59.50	59.47	74.20	78.08	28.31	28.45	73.35	36.00
SI-RNN w/o joint selection	15	63.13	63.40	77.56	80.38	32.24	32.53	77.61	39.73

Table 2: Addressee and response selection results on the Ubuntu Multiparty Conversation Corpus. Metrics include accuracy of addressee selection (ADR), response selection (RES), and pair selection (ADR-RES). RES-CAND: the number of candidate responses. T : the context length.

	Total	Train	Dev	Test
# Docs	7,355	6,606	367	382
# Utters	2.4M	2.1M	132.4k	151.3k
# Samples	-	665.6k	45.1k	51.9k
Adr Mention Freq	-	0.32	0.34	0.34
# Speakers / Doc	26.8	26.3	30.7	32.1
# Utters / Doc	326.3	317.9	360.8	396.1
# Words / Utter	11.1	11.1	11.2	11.3

Table 3: Data Statistics. “Adr Mention Freq” is the frequency of explicit addressee mention.

drops dramatically as the number of speakers increases. DIRECT-RECENT+TF-IDF shows better performance, and DYNAMIC-RNN is marginally better. SI-RNN is much more robust and remains above 70% accuracy across all bins. The advantage is more obvious for bins with more speakers.

Addressing Distance. Addressing distance is the time difference from the responding speaker to the ground-truth addressee. As the histogram in Figure 3 (Lower) shows, while the majority of responses target the most recent speaker, many responses go back five or more time steps. It is important to note that for those distant responses, DYNAMIC-RNN sees a clear performance decrease, even worse than DIRECT-RECENT+TF-IDF. In contrast, SI-RNN handles distant responses much more accurately.

Case Study. Examples in Table 4 show how SI-RNN can handle complex multi-party conversations by selecting from 10 candidate responses. In both examples, the responding speakers participate in two or more concurrent sub-conversations with other speakers.

Example (a) demonstrates the ability of SI-RNN to engage in a new sub-conversation. The responding speaker “wafflejock” is originally involved in two sub-conversations:

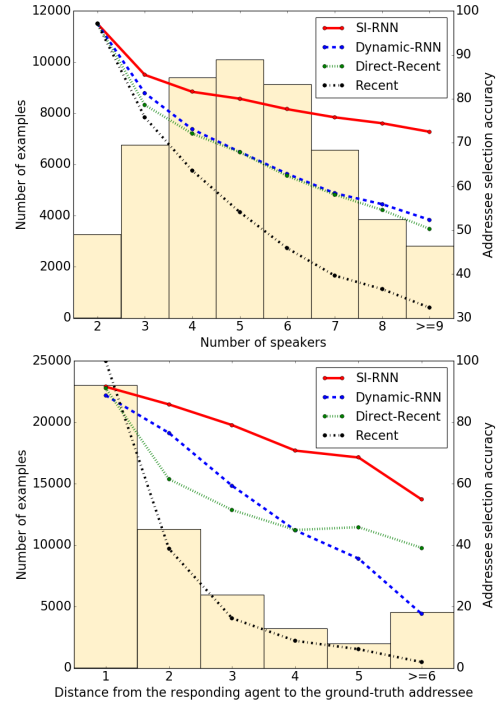


Figure 3: Effect of the number of speakers in the context (Upper) and the addressee distance (Lower). Left axis: the histogram shows the number of test examples. Right axis: the curves show ADR accuracy on the test set.

the sub-conversation 1 with “codepython”, and the ubuntu installation issue with “theoletom”. While it is reasonable to address “codepython” and “theoletom”, the responses from other baselines are not helpful to solve corresponding issues.

	Sender	Addressee	Utterance
1	codepython	wafflejock	thanks
1	wafflejock	codepython	yup np
2	wafflejock	theoletom	you can use sudo apt-get install packagename – reinstall, to have apt-get install reinstall some package/metapackage and redo the configuration for the program as well
3	codepython	-	i installed ubuntu on a separate external drive. now when i boot into mac, the external drive does not show up as bootable. the blue light is on. any ideas?
4	Guest54977	-	hello there. wondering to anyone who knows, where an ubuntu backup can be retrieved from.
2	theoletom	wafflejock	it's not a program. it's a desktop environment.
4	Guest54977	-	did some searching on my system and googling, but couldn't find an answer
2	theoletom	-	be a trace of it left yet there still is.
2	theoletom	-	i think i might just need a fresh install of ubuntu. if there isn't a way to revert to default settings
5	releaf	-	what's your opinion on a \$500 laptop that will be a dedicated ubuntu machine?
5	releaf	-	are any of the pre-loaded ones good deals?
5	releaf	-	if not, are there any laptops that are known for being oem-heavy or otherwise ubuntu friendly?
3	codepython	-	my usb stick shows up as bootable (efi) when i boot my mac. but not my external hard drive on which i just installed ubuntu. how do i make it bootable from mac hardware?
3	Jordan_U	codepython	did you install ubuntu to this external drive from a different machine?
5	Umeaboy	releaf	what country you from?
5	wafflejock		
Model Prediction		Addressee	Response
Direct-Recent+TF-IDF		theoletom	ubuntu install fresh
Dynamic-RNN		codepython	no prime is the replacement
SI-RNN		★ releaf	★ there are a few ubuntu dedicated laptop providers like umeaboy is asking depends on where you are

(a) SI-RNN chooses to engage in a new sub-conversation by suggesting a solution to “releaf” about Ubuntu dedicated laptops.

	Sender	Addressee	Utterance
1	VeryBewitching	nicomachus	anything i should be concerned about before i do it?
1	nicomachus	VeryBewitching	always back up before partitioning.
1	VeryBewitching	nicomachus	i would have assumed that, i was wondering more if this is something that tends to be touch and go, want to know if i should put coffee on :)
2	TechMonger	-	it was hibernating. i can ping it now
2	TechMonger	-	why does my router pick up disconnected devices when i reset my device list? or how
2	Ionic	-	because the dhcp refresh interval hasn't passed yet?
2	TechMonger	-	so dhcp refresh is different than device list refresh?
2	D33p	TechMonger	what an enlightenment @techmonger :)
2	BuzzardBuzz	-	dhcp refresh for all clients is needed when you change your subnet ip
2	BuzzardBuzz	-	if you want them to work together
2	Ionic	BuzzardBuzz	uhm, no.
2	chingao	TechMonger	nicomachus asked this way at the beginning: is the machine that you 're trying to ping turned on?
1	nicomachus		
Model Prediction		Addressee	Response
Direct-Recent+TF-IDF		★ VeryBewitching	i have tried with this program y-ppa manager, yet still doesn't work.
Dynamic-RNN		chingao	install the package “linux-generic”, that will install the kernel and the headers if they are not installed
SI-RNN		★ VeryBewitching	★ if it's the last partition on the disk, it won't take long. if gparted has to copy data to move another partition too, it can take a couple hours.

(b) SI-RNN remembers the distant sub-conversation 1 and responds to “VeryBewitching” with a detailed answer.

Table 4: Case Study. ★ denotes the ground-truth. Sub-conversations are coded with different numbers for the purpose of analysis (sub-conversation labels are not available during training or testing).

TF-IDF prefers the response with the “install” key-word, yet the response is repetitive and not helpful. DYNAMIC-RNN selects an irrelevant response to “codepython”. SI-RNN chooses to engage in a new sub-conversation by suggesting a solution to “releaf” about Ubuntu dedicated laptops.

Example (b) shows the advantage of SI-RNN in responding to a distant message. The responding speaker “nico-

machus” is actively engaged with “VeryBewitching” in the sub-conversation 1 and is also loosely involved in the sub-conversation 2: “chingao” mentions “nicomachus” in the most recent utterance. SI-RNN remembers the distant sub-conversation 1 and responds to “VeryBewitching” with a detailed answer. DIRECT-RECENT+TF-IDF selects the ground-truth addressee because “VeryBewitching” talks to “nicomachus”, but the response is not helpful. DYNAMIC-

RNN is biased to the recent speaker “chingao”, yet the response is not relevant.

7 Conclusion

SI-RNN jointly models *who* says *what* to *whom* by updating speaker embeddings in a role-sensitive way. It provides state-of-the-art addressee and response selection, which can instantly help retrieval-based dialog systems. In the future, we also consider using SI-RNN to extract sub-conversations in the unlabeled conversation corpus and provide a large-scale disentangled multi-party conversation data set.

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