SEntNet: Source-aware Recurrent Entity Network for Dialogue Response Selection

Jiahuan Pei[1] Arent Stienstra[1] Julia Kiseleva[2] Maarten de Rijke[1]

[1]University of Amsterdam
[2]Microsoft Research AI

Overview

- **Goal**. Select an appropriate response from candidates given a dialogue context for Task-oriented Dialogue Systems (TDSs).
- **Problem**. Obtaining key information from a complex, long dialogue context is challenging, especially when different sources of information are available.
- **Solution**. Employ source-specific memories to exploit differences in the usage of words and syntactic structure from different information sources, i.e., user, system, and knowledge base (KB).

System Response Selection in TDSs

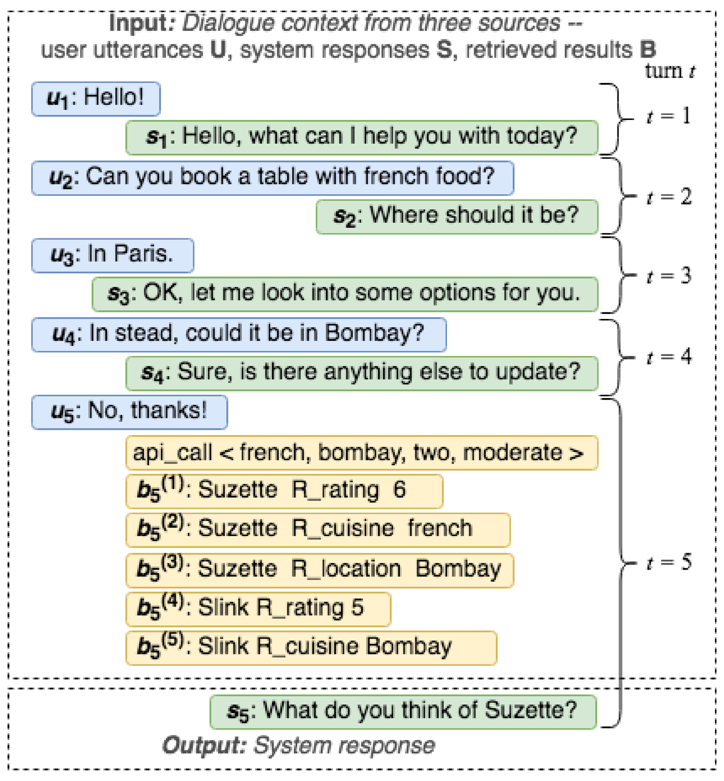


Figure: An example of response selection for booking a restaurant. The top box contains the input for response selection; the bottom box shows the selected response.

- **Given**: a dialogue context $(\mathbb{U}_t, \mathbb{S}_{t-1}, \mathbb{B}_t)$
  - $\mathbb{U}_t = (u_1, u_2, \ldots, u_t)$ are user utterances;
  - $\mathbb{S}_{t-1} = (s_1, s_2, \ldots, s_{t-1})$ are system responses; and
  - $\mathbb{B}_t = (b_t^1, b_t^2, \ldots, b_t^{\lambda})$ is λ-best retrieved results from an external KB.
- **Goal**: select a response s_t from candidates by

$$\psi_\Theta(\mathbb{U}_t, \mathbb{S}_{t-1}, \mathbb{B}_t) \rightarrow s_t. \quad (1)$$

Source-aware Recurrent Entity Network (SEntNet)

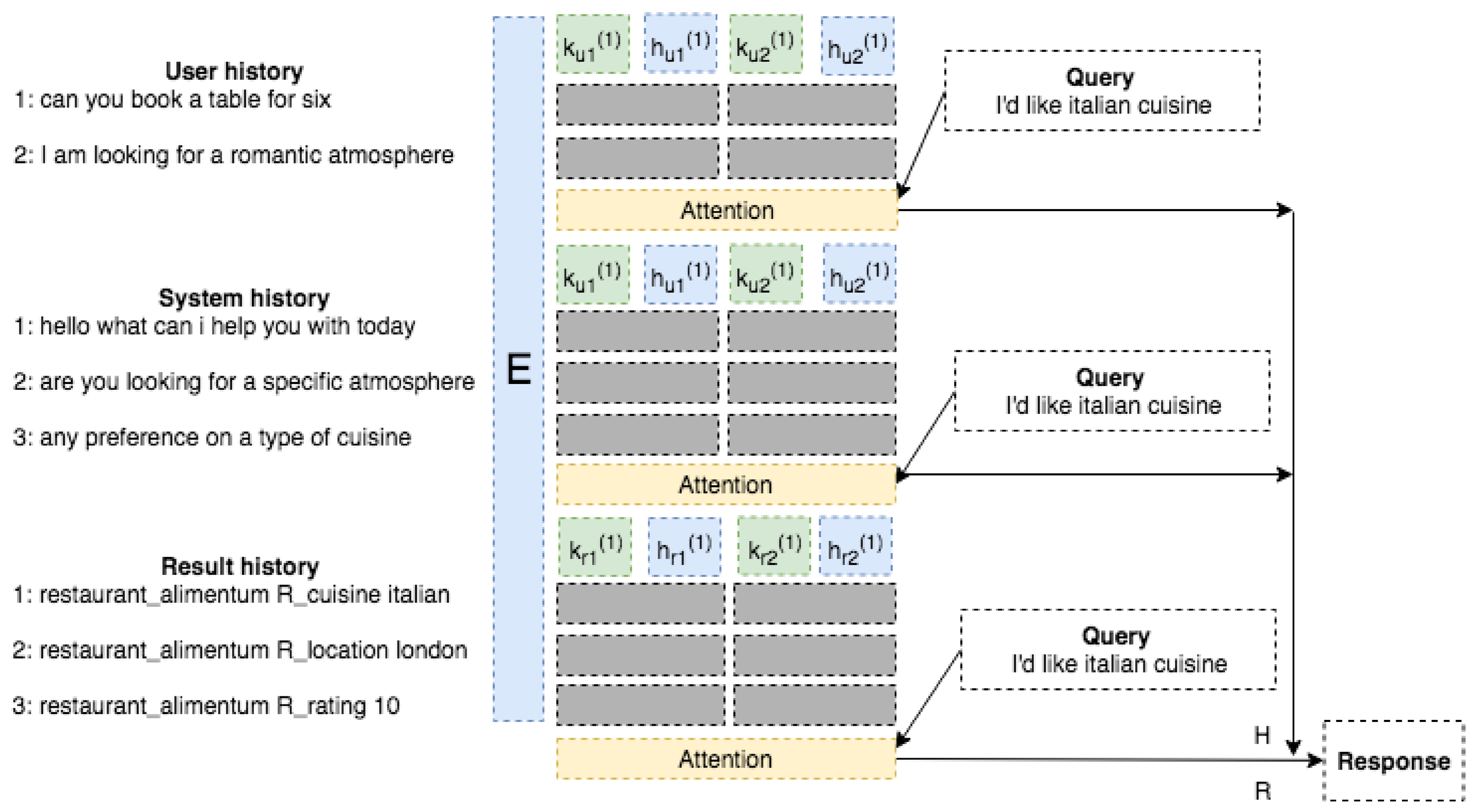


Figure: Schematic representation of SEntNet architecture with separate source-specific memory modules.

SEntNet's functions depend on three modules described below.

- **Input module**. The embedding of the i-th utterance $e_{i(\mathcal{S})}$ for source $\mathcal{S}$ is:

$$e_{i(\mathcal{S})} = \Sigma_x f_x \odot w_x^i + l_x^i \in \mathbb{R}^d. \quad (2)$$

- **Dynamic memory module**. For the i-th utterance from $\mathcal{S}$ in the dialogue, the memory block for the j-th entity is updated as:

$$g_{j(\mathcal{S})}^i = \sigma(e_{i(\mathcal{S})}^T h_{j(\mathcal{S})}^{i-1} + e_{i(\mathcal{S})}^T k_{j(\mathcal{S})}^{i-1}) \in \mathbb{R}^d \quad (3)$$
$$\tilde{h}_{j(\mathcal{S})}^i = \phi(G_{\mathcal{S}} h_{j(\mathcal{S})}^{i-1} + V_{\mathcal{S}} k_{j(\mathcal{S})}^{i-1} + W_{\mathcal{S}} e_{i(\mathcal{S})}) \in \mathbb{R}^d \quad (4)$$
$$h_{j(\mathcal{S})}^i = \frac{h_{j(\mathcal{S})}^{i-1} + g_{j(\mathcal{S})}^i \odot \tilde{h}_{j(\mathcal{S})}^i}{\| h_{j(\mathcal{S})}^{i-1} + g_{j(\mathcal{S})}^i \odot \tilde{h}_{j(\mathcal{S})}^i \|} \in \mathbb{R}^d \quad (5)$$
$$h_{j(\mathcal{S})} = h_{j(\mathcal{S})}^1 \oplus h_{j(\mathcal{S})}^2 \oplus \cdots \oplus h_{j(\mathcal{S})}^n. \quad (6)$$

- **Output module**. Let $q \in \mathbb{R}^d$ be the embedding of the user utterance u_t for the current turn t. The output module is defined as:

$$p_{j(\mathcal{S})} = \text{softmax}(q^T h_{j(\mathcal{S})}) \quad (7)$$
$$z_{\mathcal{S}} = \Sigma_j h_{j(\mathcal{S})} p_{j(\mathcal{S})} \in \mathbb{R}^d \quad (8)$$
$$z = z_{\mathcal{S}_{\mathbb{U}}} \oplus z_{\mathcal{S}_{\mathbb{S}}} \oplus z_{\mathcal{S}_{\mathbb{B}}} \in \mathbb{R}^{3d} \quad (9)$$
$$\tilde{y} = L\phi(q + Hz) \in \mathbb{R}^r \quad (10)$$
$$y = \text{softmax}(\tilde{y}_j). \quad (11)$$

Experimental Setup

Research questions

RQ1: How well does SEntNet predict appropriate responses?
RQ2: How do different embeddings affect SEntNet's performance?
RQ3: How well does SEntNet perform in the case of limited data? And
RQ4: How does lexical diversity affect SEntNet's performance?

- **Datasets**. Dialog bAbI (Bordes&Weston,2017); DSTC2 (Henderson et al.,2014).
- **Evaluation**. Turn-level accuracy – the fraction of correct responses out of all.

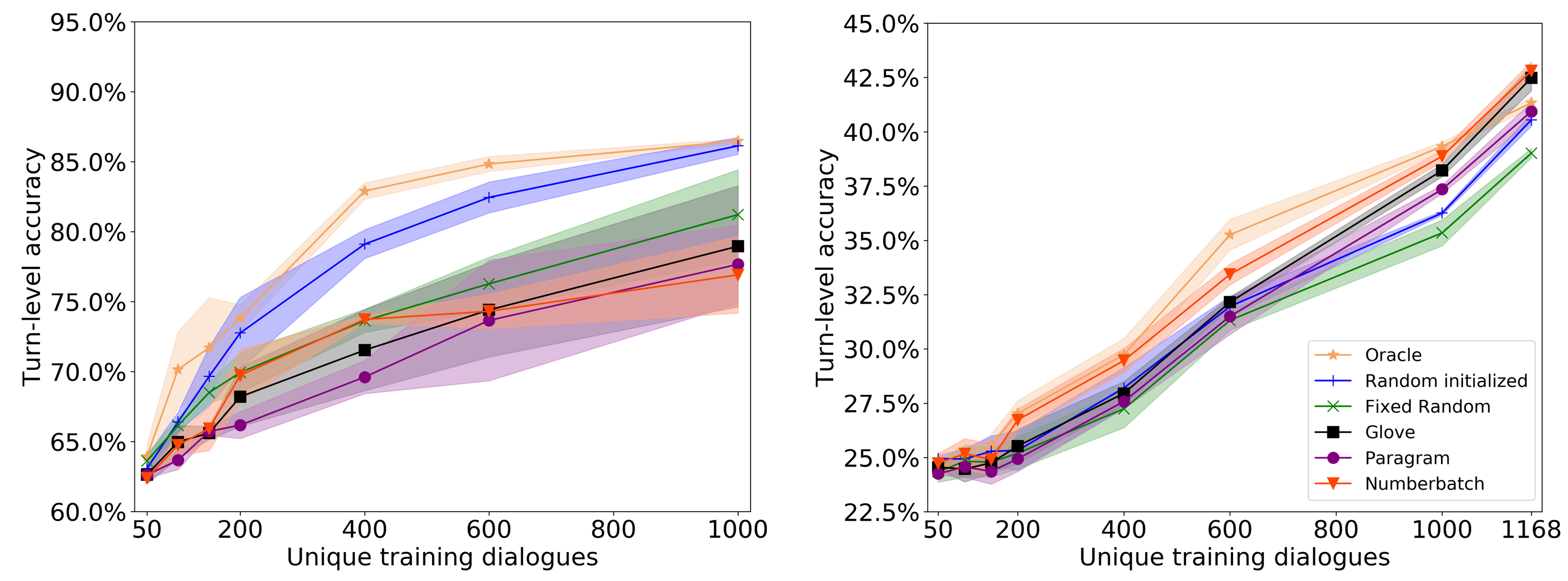
Results

Model	bAbI	DSTC2
TF-IDF	0.040	0.030
Q2A	0.570	0.220
EntNet	0.850	0.388
DQMemNN	0.863	–
HHCN	–	**0.661**
SEntNet	**0.910**	0.412

Table: Comparison with baselines on the bAbI and DSTC2 datasets (**RQ1**).

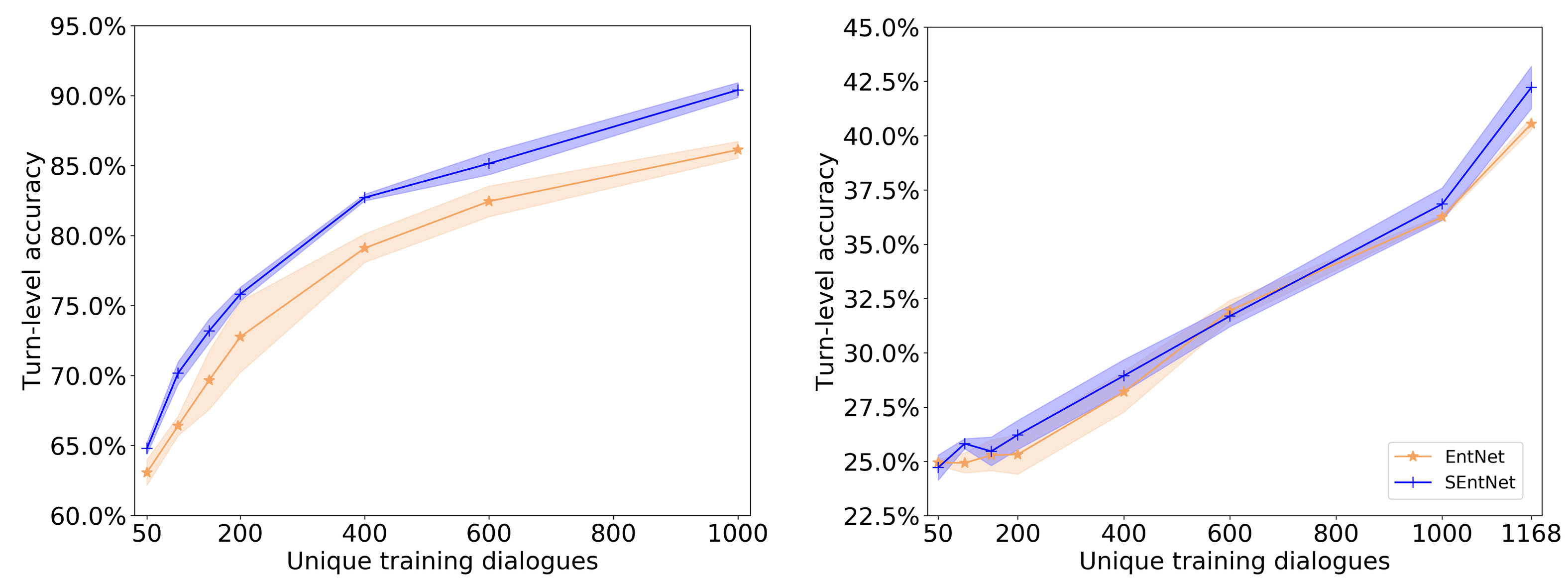
Model	bAbI	DSTC2
EntNet	0.850	0.388
EntNet+POS	0.850	0.398
SEntNet	**0.910**	**0.412**
SEntNet+POS	0.890	0.409

Table: The effect of lexical diversity on EntNet and SEntNet, on the bAbI and DSTC2 datasets (**RQ4**).



(a) bAbI (b) DSTC2

Figure: Turn-level accuracy of SEntNet for different embedding spaces on both datasets. (**RQ2**).



(a) bAbI (b) DSTC2

Figure: Turn-level accuracy of SEntNet on both datasets, when trained with different volumes of training dialogues (**RQ3**).

Conclusion

We propose **SEntNet**, a dialogue response selection model in memory network architecture:

- Select responses aware of source-specific history and consistently outperforms the baselines for end-to-end TDSs.
- Optimizing embeddings while training is useful for the performance.
- Tolerant of sparse data and able to handle different degrees of lexical diversity.
- Increase of learnable parameters by introducing extra memory modules can be addressed with parallel update mechanism design inherited from EntNet.

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University of Amsterdam

 j.pei@uva.nl