I. Introduction

- In goal-oriented dialog systems, belief trackers estimate the probability distribution of slot-values at every dialog turn.
- Previous neural approaches have modeled domain- and slot-dependent belief trackers, and have difficulty in adding new slot-values, resulting in lack of flexibility of domain ontology configurations.
- We propose a new approach to universal and scalable belief tracker, called slot-utterance matching belief tracker (SUMBT).
- SUMBT learns the relations between domain-slot-types and slot-values appearing in utterances through attention mechanisms based on contextual semantic vectors.
- Furthermore, SUMBT predicts slot-value labels in a non-parametric way.

II. SUMBT: Slot-Utterance Matching Belief Tracker

1) Contextual Semantic Encoder

   - Encode pairs of system $x_s^{sp}$ and user utterance $x_u^{sp}$, using the pretrained BERT:
     $$U_t = BERT([x_s^{sp}, x_u^{sp}])$$
   - Also, literally encode domain-slot-type $s$ and slot-values $t_r$ at turn $r$:
     $$q^s = BERT_s(x^s), \ y^t_r = BERT_s(x^t_r)$$
   - The slot-value BERT encoder is not fine-tuned.

2) Slot-Utterance Matching

   - Retrieve the relevant information corresponding to the domain-slot-type from the utterances using attention mechanism:
     $$h^t = \text{MultiHead}(Q, K, V)$$
   - Belief Tracker
     - Model dialog flows using an RNN
     $$d^t_r = \text{RNN}(d^t_{r-1}, h^t)$$
     - Additionally, normalize the RNN output
     $$y^t_r = \text{LayerNorm}(d^t_r)$$

4) Training Criteria

   - Distance metric based classifier
     $$p \left( q^s, x_s^{sp}, x_u^{sp}, s \right) = \exp \left( -d(y^t_r, y^t_r') \right)$$
   - Training loss
     $$L(\theta) = -\sum_{s \in \mathcal{D}} \sum_{r=1}^{T} \log p \left( q^s, x_s^{sp}, x_u^{sp}, s \right)$$

   - By training all domain-slot-types together, the model can learn general relations between slot-types and slot-values, which helps to improve performance.

IV. Conclusion

- SUMBT achieved the state-of-the-art joint accuracy performance in WOZ 2.0 and MultiWOZ corpora.
- Sharing knowledge by learning from multiple domain data helps to improve performance.
- As future work, we plan to explore whether SUMBT can continually learn new domain when ontology is updated.

- Our implementation is open-published in https://github.com/SKTBrain/SUMBT.

V. References


