Toward Scalable Neural Dialogue State Tracking Model

https://github.com/elnaaz/GCE-Model

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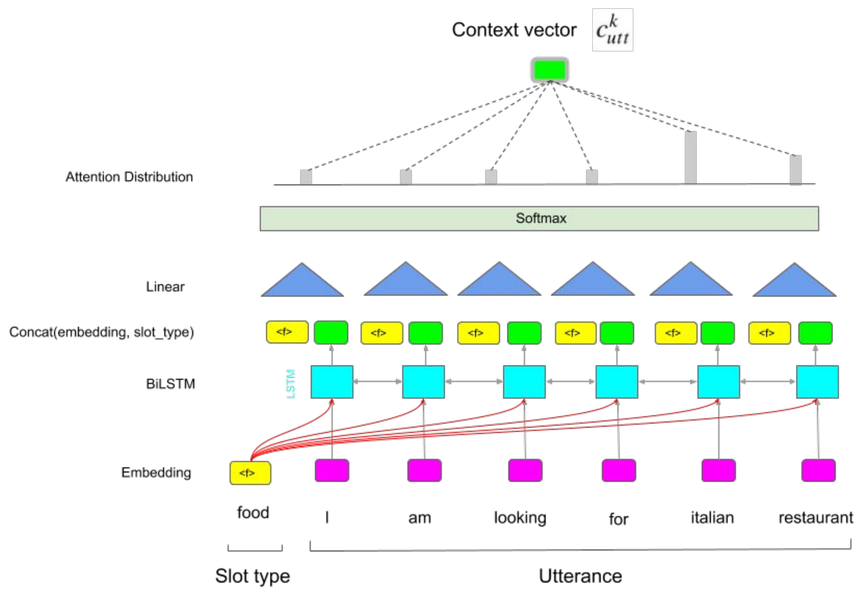
Overview

- Dialog State Tracking (DST) is an important component of task-oriented dialogue systems which keeps track of the goal of the interaction and what has happened in the dialog.
- The latency in the current neural-based dialogue state tracking models prohibits them from being effectively deployed in production systems, albeit their highly accurate performance.
- Recently proposed Global-Local Self-Attention encoder (GLAD) [1] achieves state of arts results on WoZ and DSTC2 datasets.
- GLAD model used dedicated RNN models for each slot type inside three encoders, for user utterance, system action and slots.
- This paper proposes a new scalable and accurate neural dialogue state tracking model, by proposing a Globally Conditioned Encoder (GCE)
- The latency is improved during training and inference by **35%** on average, while preserving accuracy in predicting belief state, **88.51%** on joint goal and **97.38%** on turn request on WoZ dataset.

Proposed Globally-Conditioned Encoder (GCE) Model

- GCE employs the similar approach of learning slot-specific temporal and context representation of utterance and previous system actions
- Reducing the number of recurrent networks from (1 + #slots) to 1 in utterance, system actions and slot encoders



Neural Dialogue State Tracking System

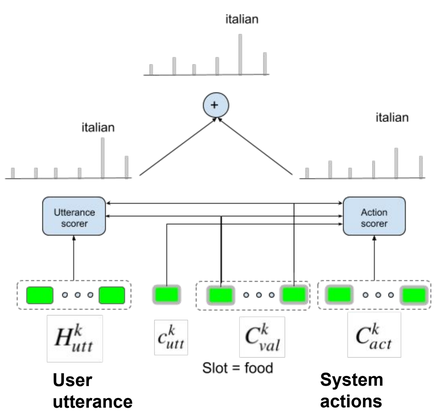
Global-locally self-attentive encoder [1]
Figure indicates system inference based on conditioning on slot-k embedding

H^k_{utt} : user utterance representation

c^k_{utt} : user utterance context vector

C^k_{act} : system action context vector

C^k_{val} : slot-k values context vectors



Evaluation

- The evaluation metric is based on joint goal and turn-level request and joint goal tracking accuracy. The joint goal is the accumulation of turn goals as described [1]
- Table 1: Time complexity for each batch of turn, and train and test epoch. Each batch contains 50 turns. All numbers are in second.
- Table 2: Test accuracy on WoZ dataset (restaurant reservation)
- Table 3: Test accuracy on Multi-WoZ dataset (restaurant, hotel, train, attraction, hospital, taxi, and police)

Table 2
Accuracy on WoZ

Model	Joint Goal	Turn Request
Delex, Model [2]	70.8%	87.1%
Delex. + Semantic Dictionary [2]	83.7%	87.6%
Neural Belief Tracker-DNN [2]	84.4%	91.2%
Neural Belief Tracker - CNN[3]	84.2%	91.6%
GLAD [1]	88.1	97.1
GCE (Ours)	**88.5**	**97.38%**

Table 1: Time Complexity

	Train		Test	
Model	Turn	Total	Turn	Total
GLAD [1]	1.78	89	2.32	76
GCE (Ours)	**1.16**	**60**	**1.92**	**63**

Table 3:
Accuracy on Multi-WoZ

	Train		Test	
Model	split	Turn inform	Joint goal	
GLAD [1]	Dev	66.91	34.83	
	Test	66.89	35.57	
GCE (Ours)	Dev	**67.78**	**37.42**	
	Test	**67.88**	**35.58**	

References

[1] Zhong, Victor, Caiming Xiong and Richard Socher. “Global-Locally Self-Attentive Dialogue State Tracker.” *in ACL* (2018)

[2] Nikola Mrksic, Diarmuid Ó Séaghdha, Tsung-Hsien Wen, Blaise Thomson, and Steve J. Young. 2017. Neural belief tracker: Data-driven dialogue state tracking. In ACL

[3] Tsung-Hsien Wen, Lina Maria Rojas Barahona, Milica Gasic, Nikola Mrksic, Pei hao Su, Stefan Ultes, , Steve J. Young, and David Vandyke. 2017. A network-based end-to-end trainable task oriented dialogue system. In EACL