

Large-Scale Multi-Domain Belief Tracking with Knowledge Sharing

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- Semantic decoding and belief tracking require different type of labelled data
- Combining these two units, reduces the amount of labelled data required and avoid possibility of information loss in the SD stage.

Belief Tracking

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Turn 2:

System: There are nine guesthouse hotels in various areas. What part of town are you hoping for? **User:** I just need it booked for 6 people for a total of 4 nights starting from sunday.

Labels: hotel:{internet=yes, type=guesthouse, parking=yes, pricerange=cheap Book=day, Book=people, Book=stay}

Turn 3:

. . .

System: You're booked at the Alexander Bed and Breakfast, 517a coldham lane, for 6 people for four nights starting Sunday. **User:** Thank you! I'm also looking for a restaurant. Ideally an Italian place in the same price range in the centre.

```
Labels: hotel:{internet=yes, type=guesthouse, parking=yes pricerange=cheap
Book=day, Book=people, Book=stay}, restaurant: {area=centre, food=Italian,
pricerange=cheap}
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This causes a **bottleneck in scaling** the belief tracker to larger domains and complex dialogues

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- 4. How do we track the dialogue context?
- 5. How do we handle many domains?





3 Bidirectional LSTMs (domain, slot, value)









Belief State Update

• Use a statistical belief update mechanism modelled by a RNN

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Datasets

- Wizard of Oz framework for collecting data for belief tracking
- Amazon MTurk users given tasks to complete, access to the database
- They produce dialogues and annotate them
- Single-domain dataset WOZ 2.0 (Wen et al 2016)
- New multi-domain dataset MultiWOZ

Datasets

	WOZ 2.0	New Dataset
# of dialogues	1200	9855
# of domains	1	5
Avg. # of turns	7.45	14.30
# of slots	7	27
# of values	99	663

Results

1. Single-domain Dialogues:

	WOZ 2.0		MultiWOZ (only restaurants)			
Slot	NBT-CNN	Bi-LSTM	CNN	NBT-CNN	Bi-LSTM	CNN
Food	88.9	96.1	96.4	78.3	84.7	85.3
Price range	93.7	98. 0	97.9	92.6	95.6	93.6
Area	94.3	97.8	98.1	78.3	82.6	86.4
Joint goals	84.2	85.1	85.5	57.7	59.9	63.7

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1. Single-domain Dialogues:

2. Multi-Domain Dialogues:

MultiWOZ (multi-domain)				
Model	F1 score	Accuracy %		
Uniform Sampling	0.108	10.8		
Bi-LSTM	0.876	93.7		
CNN	0.878	93.2		

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