Joint Reasoning on Hybrid-Knowledge sources for Task-Oriented Dialog

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Introduction

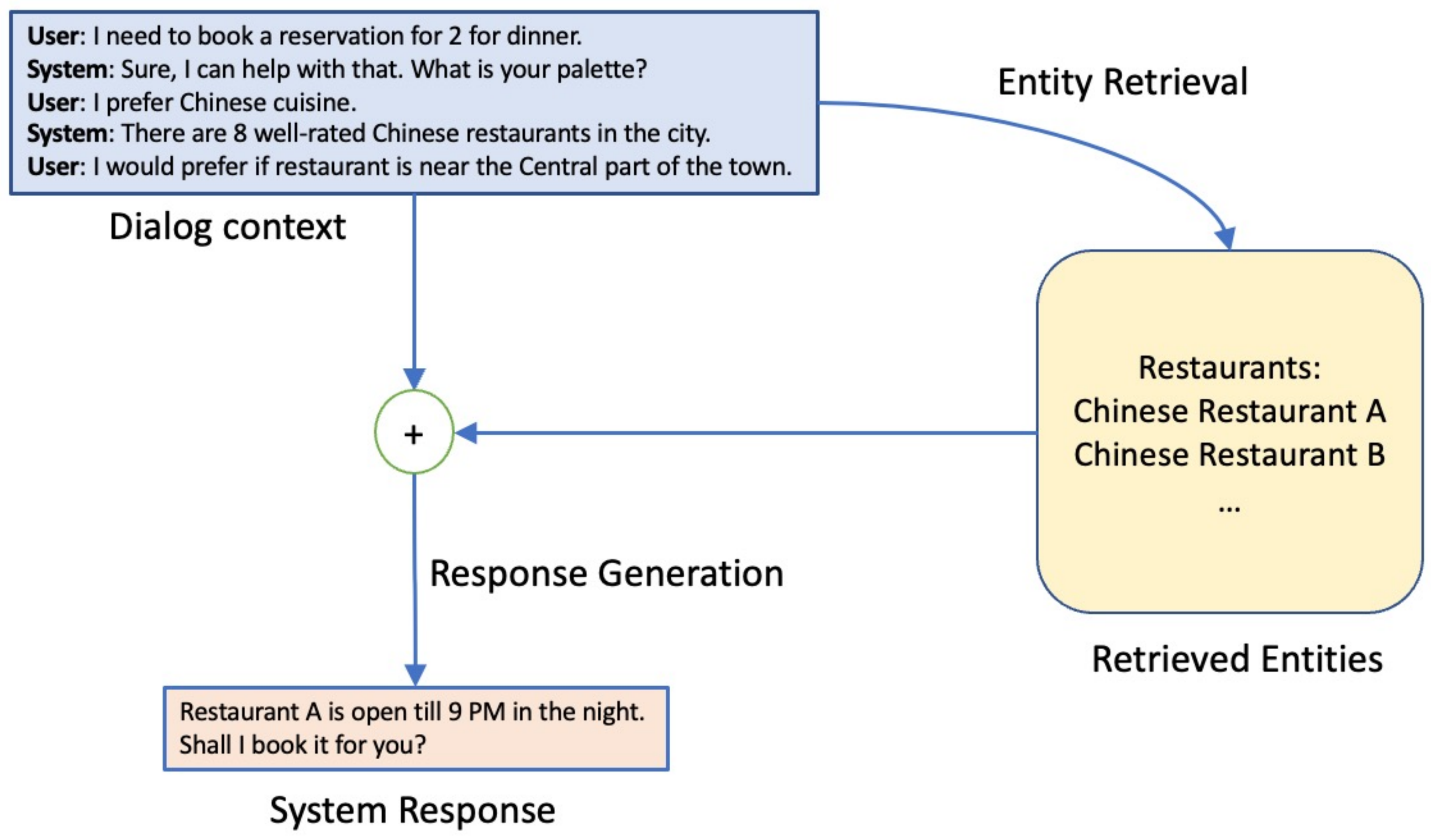
- Traditional ToD systems use structured knowledge for response generation but information may also reside in unstructured sources
- Recent approaches like HyKnow and SeKnow [Gao et al.] have tried to tackle this problem but their models make limiting assumptions
- They assume that certain information is always in structured sources (for eg. Phone number) and certain information is always in unstructured knowledge

HybridToD dataset

- We create a new dataset by systematically modifying the MultiWoZ dataset proposed by SeKnow [Gao et al.]
- We define an entity as the structured information + unstructured information of the entity
- We create a graph G(V, E) where V, the set of vertices represents all the slot values in the knowledge and an edge e ∈ E exists between two vertices if the slot-values represented by these vertices occur in at least one utterance in the dialog dataset.
- We find a maxcut of this graph so that we affect the most utterances in the dataset
- We show that training our model on this dataset leads to generalization to change in knowledge modalities at test time and that our model (JointLM) doesn't learn the source of the information (unlike other SOTA models like SeKnow [Gao et al.])

Our model (JointLM)

- We train a BART model for both entity retrieval and response generation tasks
- The model weights are shared for both the tasks and the input contains the special tokens for the two tasks



- During the entity retrieval stage, our model scores each entity in the knowledge sources based on the dialog context and we pick the best entity for response generation
- For the response generation phase, we concatenate the best entity's structured slot-values and knowledge in unstructured sources (FAQs for our dataset) to the dialog context and generate the next system response

Experiments & Results

- We train JointLM on HybridToD and SeKnow-MultiWoZ and show the performance on HybridToD, SeKnow-MultiWoZ and UnstructuredToD (where all knowledge has been moved to unstructured knowledge sources)

Entity Retrieval Performance

Train Dataset	Test Dataset	Model	success@1	success@5	Bleu-1	Bleu-4	prec.	recall	F1
HybridToD	HybridToD	JointLM	**84.50**	**86.57**	**30.59**	**8.67**	**50.56**	**45.83**	**48.08**
		SepLM	79.79	85.64	29.96	8.66	47.08	42.53	44.69
		TF-IDF	28.31	34.49	-	-	-	-	-

Response Generation Performance

					slot-values		
Train Dataset	Test Dataset	Model	Bleu-1	Bleu-4	prec.	recall	F1
HybridToD	SeKnow-MultiWOZ	JointLM	**30.63**	**8.60**	**50.48**	**45.37**	**47.79**
		SeKnow	29.20	7.83	43.16	28.65	33.14
HybridToD	HybridToD	JointLM	**30.59**	**8.67**	**50.56**	**45.83**	**48.08**
		SeKnow	29.05	7.70	44.29	29.12	35.14
HybridToD	UnstructuredToD	JointLM	**30.30**	**8.44**	**51.05**	**45.37**	**48.04**
		SeKnow	27.43	6.68	42.96	19.62	27.11

					slot-values		
Train Dataset	Test Dataset	Model	Bleu-1	Bleu-4	prec.	recall	F1
SeKnow-MultiWOZ	SeKnow-MultiWOZ	JointLM	29.07	8.06	49.74	41.31	45.13
		SeKnow	**31.00**	**9.14**	**52.17**	**44.98**	**48.31**
SeKnow-MultiWOZ	HybridToD	JointLM	**27.77**	**7.54**	**44.48**	**36.39**	**40.03**
		SeKnow	26.61	7.32	42.19	26.70	33.31
SeKnow-MultiWOZ	UnstructuredToD	JointLM	**27.03**	**7.17**	**46.29**	**34.93**	**39.82**
		SeKnow	26.19	6.42	41.96	19.48	26.53