Parameter-Efficient Low-Resource Dialogue State Tracking by Prompt Tuning

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Dialogue State Tracking

• Dialogue state tracking extracts structured conversation progress in a list of (slot, value) pairs from unstructured dialogue utterances

...

- Existing works formulate DST as a conditional generation task with prompt to provide information about
 - Slot name, slot description, slot type, possible values, priming examples, questions ...

[usr] while in cambridge i need a hotel that has free parking and free wifi. ... [usr] no, that s it. goodbye!

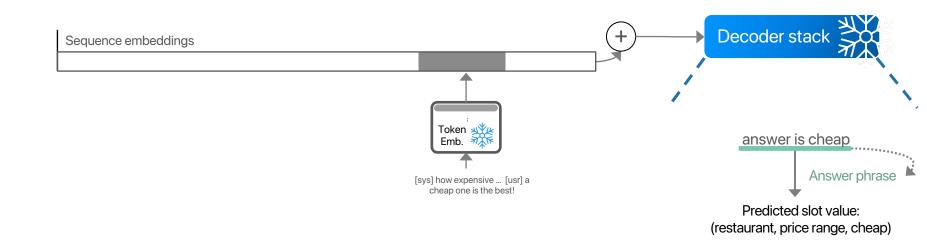
Restaurant, book time	11:30
Restaurant, name	null
Hotel, type	expensive
Hotel, internet	null

Parameter-Efficient Dialogue State Tracking

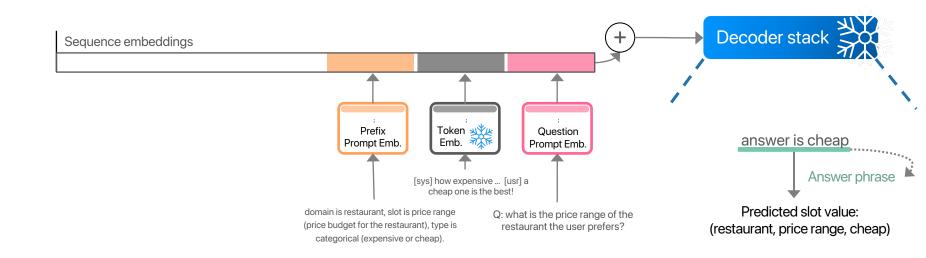
- Existing works all fine-tune the entire LM along with the prompt token embeddings
- Real-world deployment needs to train and host separate LMs for different domains and tasks
- Limited data is available for new domain or task

Parameter-efficient and **data-efficient** DST model for low-resource settings

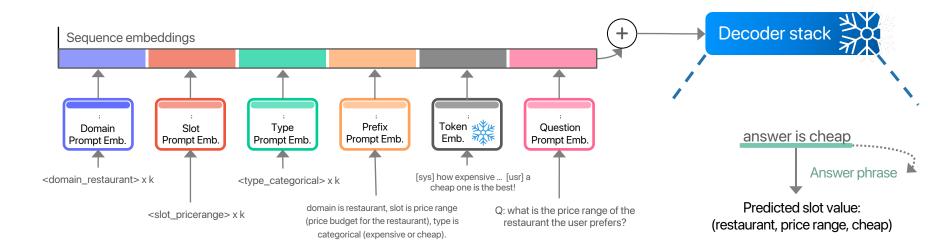
Generative seq2seq dialogue state tracking



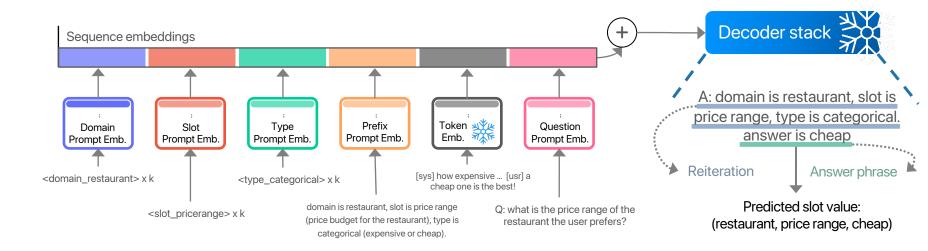
Word-mapping prompt tokens



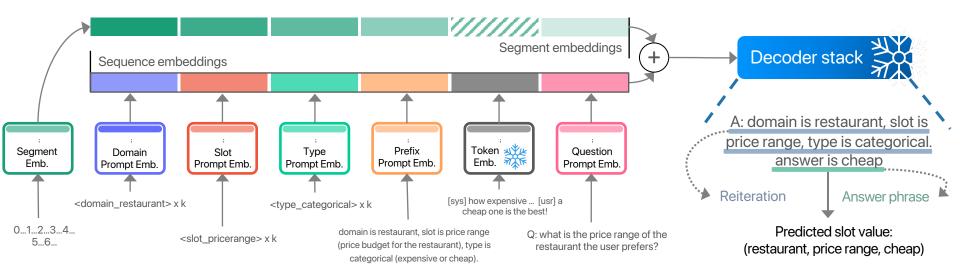
Task prompt tokens



Task metadata in objective



Distinguishing segments



N 11		5	10	20	1%	5%	10%	5	10	20	1%	5%	10%	5	10	20	1%	5%	10%
Model	Params#	ŀ	Attraction	n (3 slo	ots, 1%	= 27 co	onv.)]	Hotel (1	0 slots	, 1% =	33 con	v.)	Res	taurant	(7 slo	s, 1% :	= 38 co	onv.)
TRADE DSTQA T5DST Lee et al.	60M 60M																		
Li et al.	335M																		
Ours	271K																		
			Taxi (4	4 slots,	1% = 1	5 conv	r.)		Train (5 slots,	1% = 2	29 conv	7.)			Ave	rage		
TRADE DSTQA T5DST Lee et al. Li et al.	60M 60M 335M																		
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Dataset: MultiWOZ 2.0

Low-resource setting

N 11	D "	5	10	20	1%	5%	10%	5	10	20	1%	5%	10%	5	10	20	1%	5%	10%
Model	Params#	Attra	ction	(3 slot	s, 1% :	= 27 co	onv.)	H	Iotel (1	0 slots,	, 1% =	33 con	IV.)	Res	taurant	(7 slo	ts, 1% :	= 38 co	onv.)
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Dataset: MultiWOZ 2.0 Low-resource setting

M - 1-1	D	5	10	20	1%	5%	10%	5	10	20	1%	5%	10%	5	10	20	1%	5%	10%
Model	Params# -	Attı	raction	(3 slot	s, 1% :	= 27 co	onv.)		Hotel (1	0 slots	, 1% =	33 cor	ıv.)	Res	staurant	t (7 slo	ts, 1%	= 38 co	onv.)
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Evaluation metric: Joint Goal Accuracy

SOTA JGA using 0.5% or less parameters

M - 1-1	D#	5	10	20	1%	5%	10%	5	10	20	1%	5%	10%	5	10	20	1%	5%	10%
Model	Params#	Att	raction	(3 slot	s, 1% =	= 27 co	onv.)	H	otel (10) slots,	1% =	33 con	v.)	Res	taurant	: (7 slot	ts, 1% :	= 38 cc	onv.)
TRADE			_	_	_	52.19	58.46	—	_			31.93	41.29					47.31	53.65
DSTQA						51.58	61.77					33.08	49.69					35.33	54.27
T5DST	60M	4.77	21.93	30.57	40.68	52.12	60.13	8.19				38.76							
Lee et al.	60M	6.33	19.12	34.53	37.56	54.34	58.75	9.31	15.76	22.07	24.41	40.11	42.98	15.87	19.66	22.15	30.96	48.94	58.59
Li et al.	335M	7.90	27.09	35.63	42.18	49.13	60.85	12.49	15.15	19.44	24.04	37.88	46.47	17.27	22.30	25.68	30.70	49.75	58.50
Ours	271K	33.56	39.41	45.75	47.28	56.99	63.61	15.63	18.18	22.50	33.01	38.24	45.60	19.76	25.72	27.65	34.40	50.81	55.79
]	Гахі (4	slots, 1	l % = 1	5 conv.)	Г	rain (6	slots,	1% = 2	29 conv	<i>v</i> .)			Ave	rage		
TRADE			_	_	_	59.03	60.51		_	_	_	48.82	59.65		_	_	_	47.86	54.71
DSTQA						58.25	59.35					50.36	61.28					45.72	57.27
T5DST	60M	48.22	53.74	58.27	58.19	59.23	69.03	12.31	21.93	36.45	43.93	69.27	69.48	17.46	26.11	33.20	38.18	54.54	60.64
Lee et al.	60M	45.32	49.93	58.58	58.52	60.77	71.23	13.57	25.02	38.52	50.26	69.32	69.72	18.08	25.90	35.17	40.34	54.70	60.25
Li et al.	335M	50.99	57.47	58.49	58.26	61.68	69.23	17.56	27.42	39.27	45.32	71.69	73.45	21.24	29.89	35.70	40.10	54.03	61.70
Ours	271K	51.11	59.63	60.89	60.33	61.63	63.00	18.95	30.95	50.34	52.05	69.51	75.00	27.80	34.78	41.43	45.41	55.44	60.60

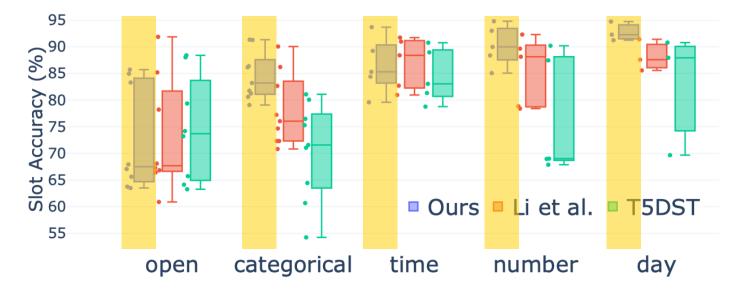
Our model achieves higher JGA than all baselines when using 1% or less training data while uses only 0.08% and 0.45% of parameters

SOTA JGA using 0.5% or less parameters

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Ours	271K	51.11	59.63	60.89	60.33	61.63	63.00	18.95	30.95	50.34	52.05	69.51	75.00	27.80	34.78	41.43	45.41	55.44	60.60

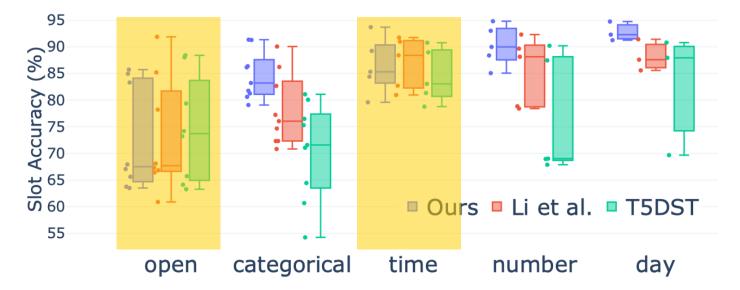
Our model achieves higher JGA than all baselines when using 1% or less training data while uses only 0.08% and 0.45% of parameters

More superior for categorical slots



Relatively worse performance on "open" slots

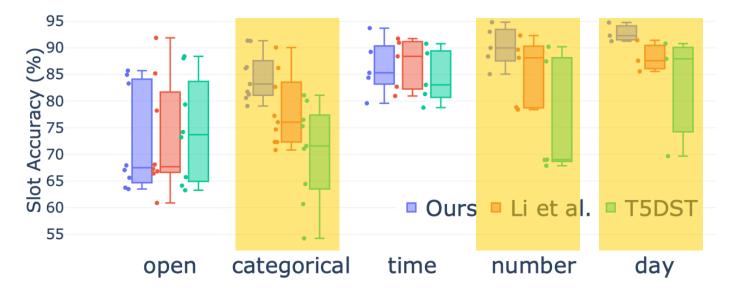
More superior for categorical slots



Compared with baselines

- Comparably on slots with larger output candidate space
- More **superior** for slots with smaller output candidate space

More superior for categorical slots



Compared with baselines

- Comparably on slots with larger output candidate space
- More **superior** for slots with smaller output candidate space

Ablation study

Model	Attr.	Hotel	Rest.	Taxi	Train	Avg
w/o segment emb.	34.35	23.18	27.33	59.69	43.30	37.57
w/o reiteration	45.08	27.57	33.48	59.89	51.08	43.42
Full model	47.28	33.01	34.40	60.33	52.05	45.41

Removing segment embedding leads to on average 7.8 points JGA drop

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w/o reiteration	45.08	27.57	33.48	59.89	51.08	43.42
Full model	47.28	33.01	34.40	60.33	52.05	45.41

Removing reiteration technique leads to an almost 2 points JGA drop

Conclusion

- We propose a parameter-efficient DST model using prompt tuning
 - It represents tasks with soft prompt tokens
 - Segment awareness
 - Reiteration
- Our model achieves state-of-the-art low-resource DST performance with less than 0.5% parameters compared with fine-tuning LM.

Thanks!