Show, Don't Tell: Demonstrations Outperform Descriptions for Schema-Guided Task-Oriented Dialogue

Raghav Gupta[*], **Harrison Lee**[*], **Jeffrey Zhao, Abhinav Rastogi, Yuan Cao, Yonghui Wu**
Google Research
{raghavgupta, harrisonlee}@google.com

Abstract

Building universal dialogue systems that can seamlessly operate across multiple domains/APIs and generalize to new ones with minimal supervision and maintenance is a critical challenge. Recent works have leveraged natural language descriptions for schema elements to enable such systems; however, descriptions can only indirectly convey schema semantics. In this work, we propose *Show, Don't Tell*, a prompt format for seq2seq modeling which uses a short labeled example dialogue to *show* the semantics of schema elements rather than *tell* the model via descriptions. While requiring similar effort from service developers, we show that using short examples as schema representations with large language models results in stronger performance and better generalization on two popular dialogue state tracking benchmarks: the Schema-Guided Dialogue dataset and the MultiWoZ leave-one-out benchmark.

1 Introduction

Task-oriented dialogue (TOD) systems need to support an ever-increasing variety of services. Since many service developers lack the resources to collect labeled data and/or the requisite ML expertise, zero and few-shot transfer to unseen services is critical to the democratization of dialogue agents.

New approaches to TOD that can generalize to new services primarily rely on combining two techniques: large language models like BERT (Devlin et al., 2019) and T5 (Raffel et al., 2020), and schema-guided modeling i.e. using natural language descriptions of schema elements (intents and slots) as model inputs to enable inference on unseen services (Rastogi et al., 2020a,b). Models combining the two currently show state-of-the-art results on dialogue state tracking (DST) (Heck et al., 2020; Lee et al., 2021a; Zhao et al., 2022).

However, description-based schema representations have drawbacks. Writing precise natural language descriptions requires manual effort and can be tricky, and descriptions only provide indirect supervision about how to interact with a service compared to an example. Furthermore, Lee et al. (2021b) showed that state-of-the-art schema-guided DST models may not be robust to variation in schema descriptions, causing significant accuracy drops.

We propose using a single dialogue example with state annotations as an alternative to the description-based schema representation, similar to one-shot priming (Brown et al., 2020). Rather than **tell** the model about schema element semantics in natural language, we **show** the schema through a demonstration, as in Figure 1. Applying our approach, *Show, Don't Tell (SDT)*, to two SotA DST models consistently results in superior accuracy and generalization to new APIs across both the Schema-Guided Dataset (SGD) (Rastogi et al., 2020b) and MultiWoZ Leave-One-Out (Budzianowski et al., 2018; Lin et al., 2021b) benchmarks, while being more data-efficient and robust to schema variations.

2 Show, Don't Tell

Following SoTA models, we pose DST as a seq2seq task (Wu et al., 2019; Zhao et al., 2021a), where the seq2seq language model (in our case, T5) is finetuned on a DST dataset. During finetuning and evaluation, the model input consists of a *prompt* and *context*, and the *target* contains ground truth belief states. We compare against two baselines:

- **T5-ind** (Lee et al., 2021a): Model input comprises the dialogue history as context concatenated with *one slot description* as the prompt. The target is the value of that slot in the dialogue state. Inference is done per slot - i.e. values for different slots are independently decoded.

[*]Equal contribution

T5-ind	SDT-ind
P_1 = amount: The amount of money to send or request P_2 = receiver: Name of the contact or account to make the transaction with ...	P_1^{ind} = [ex] [user] I need to transfer 125 dollars [slot] amount=125 dollars P_2^{ind} = [ex] [user] Make the transfer to Victoria. [slot] receiver=Victoria ...
T5-seq	**SDT-seq**
P = 0: The amount of money to send or request 1: Name of the contact or account to make the transaction with 2: Whether the transaction is private or not a) True b) False 3: The source of money used for making the payment a) credit card b) debit card c) app balance	P^{seq} = [ex] [user] I want to make a payment to Jerry for $82 from my mastercard [system] Confirming you want to pay Jerry $82 with your credit card yes? [user] Yes that's right, make the transaction private too [slot] amount=$82 receiver=Jerry private_visibility=a of a) True b) False payment_method=a of a) credit card b) debit card c) app balance

Figure 1: Illustration of all prompt formats for a payment service for both description-based and *Show, Don't Tell* models with independent (top) and sequential (bottom) decoding of dialogue state.

- **T5-seq** (Zhao et al., 2022): Model input comprises the descriptions of *all slots* as the prompt, followed by the dialogue history as the context. The target is the sequence of slot-value pairs in the dialogue state - i.e. the dialogue state is decoded sequentially in a single pass.

We modify the prompt formats above to utilize demonstrations instead of descriptions as described below and illustrated in Figure 1.

- **SDT-ind**: A *prompt* $\mathtt{P}_i^{ind}$ comprises a single utterance labeled with a slot value pair formatted as

$$\mathtt{P}_i^{ind} = [\mathtt{ex}]; \mathtt{u}_i^{ind}; [\mathtt{slot}]; \mathtt{sv}_i$$

  where $\mathtt{u}_i^{ind}$ is a user utterance where slot $\mathtt{i}$ is active and $\mathtt{sv}_i$ is the slot value pair. $[\mathtt{ex}], [\mathtt{slot}]$ are special delimiter tokens, and ; denotes concatenation.

- **SDT-seq**: A *prompt* $\mathtt{P}^{seq}$ comprises a single labeled dialogue formatted as:

$$\mathtt{P}^{seq} = [\mathtt{ex}]; \mathtt{u}_1; ...; \mathtt{u}_n; [\mathtt{slot}]; \mathtt{sv}_1; ...; \mathtt{sv}_m$$

  where $\mathtt{u}_j$ is an utterance, and other symbols are shared with SDT-ind. In simple terms, the prompt is constructed by concatenating all utterances in the example dialogue followed by all slot-value pairs in the final dialogue state.

The *context* in both formats is a concatenation of the dialogue history for the current training example. The final model input is formed by concatenating the prompt and the context strings. The *target* string is the same as T5-*, containing only a single slot value for *-ind models and the entire turn's belief state for *-seq models.

For both T5-* (baseline) and SDT-*, we enumerate the categorical slot values in multiple-choice format in the prompt and task models with decoding the correct multiple choice letter.

More details on the prompt design and its impact on performance are provided in Appendix C.

Formulating prompt examples: It is imperative that SDT prompts contain sufficient information to infer the semantics for all slots in the schema. This is easy for SDT-ind, which uses a separate prompt for each slot. However, for SDT-seq, we only choose example dialogues where all slots in the schema are used.

3 Experimental Setup

Datasets: We conduct experiments on two DST benchmarks: Schema-guided Dialogue (SGD) (Rastogi et al., 2020b) and MultiWOZ 2.1 (Budzianowski et al., 2018; Eric et al., 2020). For MultiWOZ, we evaluate on the leave-one-out setup (Wu et al., 2019; Lin et al., 2021a), where models are trained on all domains but one and evaluated on the holdout domain. Additionally, we apply the recommended TRADE pre-processing script[1] for fair comparison with other work. For both datasets, we created concise prompt dialogues modeled after dialogues observed in the datasets.

Implementation: We train SDT models by fine-tuning pretrained T5 1.1 checkpoints. For both datasets, we select one example prompt per service schema (for SDT-seq) or slot (for SDT-ind),

[1] https://github.com/budzianowski/multiwoz#dialog-state-tracking

Model	All	Seen	Unseen
MRC+WD-DST*	86.5	92.4	84.6
T5-seq	86.4	**95.8**	83.3
T5-ind	87.7	95.3	85.2
SDT-ind	87.5±0.9	95.2±0.7	85.0±1.4
SDT-seq	**88.8±0.5**	**95.8±0.2**	**86.4±0.7**

Table 1: SGD test set JGA for SDT versus other approaches. *Data augmentation/special rules applied.

and use the same prompt for all examples for that service/slot across training and evaluation. Unless otherwise noted, all T5-based models (T5/SDT-seq/ind) are finetuned on T5-XXL (11B parameters). See appendices A and B for more details on training and baselines respectively.

4 Results

4.1 Results on SGD

Table 1 contains results on the SGD test set. Since SDT results may depend on the choice of example turn/dialogue provided in the prompt, 5 different versions of prompts are created for each service using different examples. We report the average JGA across these versions and the 95% confidence intervals. SDT-seq achieves the highest JGA, showing major gains, particularly on unseen services, over its description-based counterpart T5-seq and the next-best model T5-ind. SDT-ind is comparable to its counterpart T5-ind, and better than T5-seq. Based on these results, conveying service semantics via a single dialogue example appears more effective than using natural language descriptions.

We hypothesize that SDT-seq outperforms SDT-ind because the full dialogue prompts used in SDT-seq demonstrate more complex linguistic patterns (e.g. coreference resolution, long term dependencies) than the single utterance prompts of SDT-ind. On the other hand, T5-seq does not outperform T5-ind because no additional information is conveyed to the model through stacking descriptions. Also all-else-equal, decoding all slots in one pass is more challenging than decoding each slot independently.

We also experimented with using more than one dialogue to prompt SDT-seq, but we did not see an increase in performance.

4.2 MultiWOZ Results

Table 2 summarizes results for the MultiWOZ 2.1 leave-one-out setup. Comparing T5-seq and SDT-seq, both finetuned on T5-XXL, SDT achieves state-of-the-art results on the overall task by +2% and in 3 of the 5 domains.

Model	Attraction	Hotel	Restaurant	Taxi	Train	Avg
TRADE	20.1	14.2	12.6	59.2	22.4	25.7
SUMBT	22.6	19.8	16.5	59.5	22.5	28.2
TransferQA	31.3	22.7	26.3	61.9	36.7	35.8
T5-seq	**76.1**	28.6	69.8	**87.0**	60.4	64.4
SDT-seq	73.2	**34.2**	**71.9**	83.7	**68.4**	**66.3**

Table 2: Cross-domain (leave-one-out) JGA on MultiWOZ 2.1. Results for TRADE, SUMBT, and TransferQA from (Kumar et al., 2020), (Campagna et al., 2020), and (Lin et al., 2021a), respectively.

4.3 Impact of Model Size

T5's XXL size may be unsuitable in a number of settings; consequently, we measure SDT's performance on SGD across other model sizes in Table 3. For the base and large model sizes, both SDT variations offer higher JGA than their description-based counterparts, possibly due to smaller T5 models being less capable of inferring unseen slots with just a description. Additionally, SDT-ind outperforms SDT-seq for these sizes.

Model	Base (250M)	Large (800M)	XXL (11B)
T5-seq	72.9	80.0	86.4
T5-ind	72.6	82.2	87.7
SDT-ind	**78.2±0.6**	**83.7±0.8**	87.5±0.9
SDT-seq	76.3±1.6	83.2±0.6	**88.8±0.5**

Table 3: SGD test set JGA across T5 model sizes.

4.4 Data Efficiency

To examine the data efficiency of SDT models, we train SDT-seq in a low-resource setting with 0.16% (10-shot), 1%, and 10% of the SGD training data and evaluate on the entire test set. For 10-shot, we randomly sample 10 training dialogues from every service; for 1% and 10%, we sample uniformly across the entire dataset. SDT-seq demonstrates far higher data efficiency than T5-seq (Table 4).

Model	10-shot	1%	10%
T5-seq	51.0	79.4	83.0
SDT-seq	**70.7**	**84.5**	**87.4**

Table 4: Data efficiency experiments on SGD test set.

4.5 Robustness

Large LMs are often sensitive to the choice of prompt (Zhao et al., 2021b; Reynolds and Mc-

Example Dialogue	Error
1. T5-seq confused by similar-sounding slots I need to find tickets to **Anaheim**, CA. When would you like to travel, and where are you going to? Traveling to **Sacramento** on the 4th.	T5-seq: *to=Sacramento, from=Anaheim*
2. T5-seq misses active slots Can you please add an alarm called Grocery run.	T5-seq: *new_alarm_name=None*
3. SDT-seq misses categorical values not seen in prompt I like Broadway shows and want to see one on Tuesday next week.	SDT-seq: *event_type=music (ground truth=theater)*

Figure 2: Examples of common error patterns made by T5-seq but not SDT-seq, and vice versa.

Donell, 2021). To this end, we evaluate SDT-seq on the SGD-X (Lee et al., 2021b) benchmark, which comprises 5 variants with paraphrased slot names and descriptions per schema (see Appendix Figure 4). Table 5 shows SDT-seq achieves the highest average JGA ($JGA_{v_{1-5}}$) and lowest schema sensitivity (SS_{JGA}), indicating it is the most robust of the compared models. Even so, the JGA decline indicates SDT-seq is sensitive to how slot names are written.

Model	JGA_{Orig}	$JGA_{v_{1-5}}$	$Diff_{rel}$	SS_{JGA}
SGP-DST*	60.5	49.9	-17.5	51.9
T5-ind$_{base}$*	72.6	64.0	-11.9	40.4
T5-seq (name)★	79.7	73.0	**-8.4**	35.0
T5-seq	86.4	77.8	-10.0	27.0
SDT-seq	**88.8**	**81.2**	-8.6	**24.1**

Table 5: Robustness evaluation on the SGD-X test sets. *Results from Lee et al. (2021b). ★Result of using T5-seq with only slot names and not descriptions, from Zhao et al. (2022).

5 Discussion

5.1 Writing descriptions vs. demonstrations

We note that the information provided to SDT is not identical to what is provided to typical schema-guided models, as SDT exchanges natural language descriptions for a demonstration of identifying slots in a dialogue. However, we argue that from the developer standpoint, creating a single example is similar in effort to writing descriptions, so we consider the methods comparable. Creating the SDT-seq prompts for all 45 services in SGD took an experienced annotator ∼2 hours, compared to ∼1.5 hours for generating slot descriptions. SDT-ind prompts are even simpler to write because they relax the requirement for creating a coherent dialogue where all slots are used.

One advantage of descriptions is that they can be easier to generate than a succinct dialogue that covers all slots. However, given the performance gain, example-based prompts may be a better choice for many settings, especially for smaller model sizes where the gain is more pronounced.

5.2 Descriptions plus demonstrations

Training with descriptions has proven effective for improving DST performance (Zhao et al., 2022; Lee et al., 2021a), and our experiments show that demonstrations are even more effective. We combined both together to see if the two are complementary or overlapping, and we find that performance does not improve above using demonstrations alone (Appendix Table A1. We hypothesize that demonstrations already convey slot semantics sufficiently and descriptions become extraneous.

5.3 Prompting vs. traditional finetuning

To understand the impact of using a single demonstration as a prompt vs. traditional finetuning, we finetune T5-seq a second time on the same set of dialogues used in SDT-seq prompts; it therefore has access to both slot descriptions as well as a single demonstration for each service. In this case, T5-seq is provided strictly more information than SDT-seq. T5-seq with finetuning obtains a JGA of 87.7% on SGD, on par with T5-ind but still lower than SDT-seq, suggesting that dialogue examples are better used as prompts (Le Scao and Rush, 2021). Interestingly, finetuning on more than one dialogue example per service did not improve performance (Appendix Figure 3).

5.4 Error analysis

Figure 2 compares some common errors made by T5-seq and SDT-seq. The patterns suggest that SDT's demonstrations are helpful when multiple slots are similar to each other (#1) and when prompt dialogues closely match target dialogues

(#2). However, SDT can be limited by its prompt. For instance, in #3 it has only seen the "music" value for the *event_type* slot in the prompt, potentially resulting in under-predicting the other categorical value ("theater").

6 Related Work

Prior approaches focused on framing DST as question answering (Ruan et al., 2020; Ma et al., 2019; Zhang et al., 2021). Many MultiWoZ cross-domain models leverage slot names/descriptions (Wu et al., 2019; Lee et al., 2019; Lin et al., 2021a).

Pretrained generative LLMs (Raffel et al., 2020; Brown et al., 2020) have enabled framing NLP tasks as seq2seq problems. Some DST papers (Zhao et al., 2021a; Feng et al., 2021) look at settings with no train-test discrepancy. Many studies explore the efficacy of task-specific prompts (Jiang et al., 2020; Liu et al., 2021). Madotto et al. (2020) and prime LMs with examples for dialogue tasks, but without finetuning. Wei et al. (2021) finetunes language models to understand prompts for a different task.

7 Conclusion

We study the use of demonstrations as LM prompts to convey the semantics of APIs in lieu of natural language descriptions for TOD. While taking similar effort to construct, demonstrations outperform description-based prompts in our experiments across DST datasets (SGD and MultiWOZ), model sizes, and training data sizes, while being more robust to changes in schemata. This work provides developers of TOD systems with more options for API representations to enable transfer to unseen services. In future work, we would like to explore this representation for other TOD tasks (e.g. dialogue management and response generation).

8 Ethical Considerations

We proposed a more efficient way of building TOD systems by leveraging demonstrations in place of descriptions, leading to increased accuracy with minimal/no data preparation overhead. We conduct our experiments on publicly-available TOD datasets in English, covering domains which are popular for building conversational agents. We hope our work leads to building more accurate TOD systems with similar or less overhead, and encourages further research in the area.

References

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In *Advances in Neural Information Processing Systems*, volume 33, pages 1877–1901. Curran Associates, Inc.

Paweł Budzianowski, Tsung-Hsien Wen, Bo-Hsiang Tseng, Iñigo Casanueva, Stefan Ultes, Osman Ramadan, and Milica Gašić. 2018. MultiWOZ - a large-scale multi-domain Wizard-of-Oz dataset for task-oriented dialogue modelling. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 5016–5026, Brussels, Belgium. Association for Computational Linguistics.

Giovanni Campagna, Agata Foryciarz, Mehrad Moradshahi, and Monica Lam. 2020. Zero-shot transfer learning with synthesized data for multi-domain dialogue state tracking. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 122–132, Online. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Mihail Eric, Rahul Goel, Shachi Paul, Abhishek Sethi, Sanchit Agarwal, Shuyang Gao, Adarsh Kumar, Anuj Goyal, Peter Ku, and Dilek Hakkani-Tur. 2020. MultiWOZ 2.1: A consolidated multi-domain dialogue dataset with state corrections and state tracking baselines. In *Proceedings of the 12th Language Resources and Evaluation Conference*, pages 422–428, Marseille, France. European Language Resources Association.

Yue Feng, Yang Wang, and Hang Li. 2021. A sequence-to-sequence approach to dialogue state tracking. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 1714–1725, Online. Association for Computational Linguistics.

Michael Heck, Carel van Niekerk, Nurul Lubis, Christian Geishauser, Hsien-Chin Lin, Marco Moresi, and

Milica Gasic. 2020. TripPy: A triple copy strategy for value independent neural dialog state tracking. In *Proceedings of the 21th Annual Meeting of the Special Interest Group on Discourse and Dialogue*, pages 35–44, 1st virtual meeting. Association for Computational Linguistics.

Zhengbao Jiang, Frank F. Xu, Jun Araki, and Graham Neubig. 2020. How can we know what language models know?

Norman P. Jouppi, Cliff Young, Nishant Patil, David Patterson, Gaurav Agrawal, Raminder Bajwa, Sarah Bates, Suresh Bhatia, Nan Boden, Al Borchers, Rick Boyle, and Pierre-luc et al. Cantin. 2017. In-datacenter performance analysis of a tensor processing unit. *SIGARCH Comput. Archit. News*, 45(2):1–12.

Adarsh Kumar, Peter Ku, Anuj Goyal, Angeliki Metallinou, and Dilek Hakkani-Tur. 2020. Ma-dst: Multi-attention-based scalable dialog state tracking. *Proceedings of the AAAI Conference on Artificial Intelligence*, 34(05):8107–8114.

Teven Le Scao and Alexander Rush. 2021. How many data points is a prompt worth? In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2627–2636, Online. Association for Computational Linguistics.

Chia-Hsuan Lee, Hao Cheng, and Mari Ostendorf. 2021a. Dialogue state tracking with a language model using schema-driven prompting. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 4937–4949, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Harrison Lee, Raghav Gupta, Abhinav Rastogi, Yuan Cao, Bin Zhang, and Yonghui Wu. 2021b. Sgd-x: A benchmark for robust generalization in schema-guided dialogue systems.

Hwaran Lee, Jinsik Lee, and Tae-Yoon Kim. 2019. SUMBT: Slot-utterance matching for universal and scalable belief tracking. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 5478–5483, Florence, Italy. Association for Computational Linguistics.

Zhaojiang Lin, Bing Liu, Andrea Madotto, Seungwhan Moon, Paul Crook, Zhenpeng Zhou, Zhiguang Wang, Zhou Yu, Eunjoon Cho, Rajen Subba, and Pascale Fung. 2021a. Zero-shot dialogue state tracking via cross-task transfer.

Zhaojiang Lin, Bing Liu, Seungwhan Moon, Paul Crook, Zhenpeng Zhou, Zhiguang Wang, Zhou Yu, Andrea Madotto, Eunjoon Cho, and Rajen Subba. 2021b. Leveraging slot descriptions for zero-shot cross-domain dialogue StateTracking. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 5640–5648, Online. Association for Computational Linguistics.

Xiao Liu, Yanan Zheng, Zhengxiao Du, Ming Ding, Yujie Qian, Zhilin Yang, and Jie Tang. 2021. Gpt understands, too.

Yue Ma, Zengfeng Zeng, Dawei Zhu, Xuan Li, Yiying Yang, Xiaoyuan Yao, Kaijie Zhou, and Jianping Shen. 2019. An end-to-end dialogue state tracking system with machine reading comprehension and wide & deep classification.

Andrea Madotto, Zihan Liu, Zhaojiang Lin, and Pascale Fung. 2020. Language models as few-shot learner for task-oriented dialogue systems. *CoRR*, abs/2008.06239.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer.

Abhinav Rastogi, Xiaoxue Zang, Srinivas Sunkara, Raghav Gupta, and Pranav Khaitan. 2020a. Schema-guided dialogue state tracking task at dstc8.

Abhinav Rastogi, Xiaoxue Zang, Srinivas Sunkara, Raghav Gupta, and Pranav Khaitan. 2020b. Towards scalable multi-domain conversational agents: The schema-guided dialogue dataset. *Proceedings of the AAAI Conference on Artificial Intelligence*, 34(05):8689–8696.

Laria Reynolds and Kyle McDonell. 2021. Prompt programming for large language models: Beyond the few-shot paradigm.

Yu-Ping Ruan, Zhen-Hua Ling, Jia-Chen Gu, and Quan Liu. 2020. Fine-tuning bert for schema-guided zero-shot dialogue state tracking.

Jason Wei, Maarten Bosma, Vincent Y. Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V. Le. 2021. Finetuned language models are zero-shot learners.

Chien-Sheng Wu, Andrea Madotto, Ehsan Hosseini-Asl, Caiming Xiong, Richard Socher, and Pascale Fung. 2019. Transferable multi-domain state generator for task-oriented dialogue systems.

Yang Zhang, Vahid Noroozi, Evelina Bakhturina, and Boris Ginsburg. 2021. Sgd-qa: Fast schema-guided dialogue state tracking for unseen services.

Jeffrey Zhao, Raghav Gupta, Yuan Cao, Dian Yu, Mingqiu Wang, Harrison Lee, Abhinav Rastogi, Izhak Shafran, and Yonghui Wu. 2022. Description-driven task-oriented dialog modeling.

Jeffrey Zhao, Mahdis Mahdieh, Ye Zhang, Yuan Cao, and Yonghui Wu. 2021a. Effective sequence-to-sequence dialogue state tracking. In *Proceedings of*

the 2021 Conference on Empirical Methods in Natural Language Processing, pages 7486–7493, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Tony Z. Zhao, Eric Wallace, Shi Feng, Dan Klein, and Sameer Singh. 2021b. Calibrate before use: Improving few-shot performance of language models.

A SDT Model Details

All T5 checkpoints used are available publicly[2]. For all experiments, we use a sequence length of 2048, dropout of 10% and a batch size of 16. We used a constant learning rate of $1e-3$ or $1e-4$. All models were trained for 50k steps or until convergence, and each experiment was conducted on either 64 or 128 TPU v3 chips (Jouppi et al., 2017).

B Baseline Models

For SGD, we compare against SGP-DST (Ruan et al., 2020), MRC+WD-DST (Ma et al., 2019), T5-seq (Zhao et al., 2022) and T5-ind (Lee et al., 2021a).

For MultiWOZ, we compare against TRADE (Wu et al., 2019), SUMBT (Lee et al., 2019), TransferQA (Lin et al., 2021a), and T5-seq.

Transfer QA is based on T5-large, and T5-ind and T5-seq are based on T5-XXL in this paper unless otherwise noted.

C Prompt Design

We experimented with various formats for the SDT prompt before arriving at the final format. Below, we list alternative designs that we tried and their impact on JGA, as evaluated on the SGD test set.

C.1 Categorical value strings vs. multiple choice answers

We found that JGA dropped -2% when we tasked the model with decoding categorical values instead of multiple choice answers - e.g. `payment_method=debit card` instead of `payment_method=b` (where `b` is linked to the value `debit card` in the prompt as described in Section 2). We found that when tasking the model to decode categorical values, it would often decode related yet invalid values, which we counted as false in our evaluation. For example, instead of `debit card`, the model might decode `bank balance`.

C.2 Slot IDs vs. slot names

When we delexicalized slot names with slot IDs, JGA dropped -5%. One downside of this approach is that the model lost access to valuable semantic information conveyed by the slot name. Another downside is that the model could not distinguish two slots that had the same value in the prompt. For example, if the prompt was "I would like a pet-friendly hotel room with wifi" and the corresponding slots were `1=True` (has_wifi) and `2=True` (pets_allowed), it is ambiguous which ID refers to which slot.

The potential upside of using slot IDs was to remove dependence on the choice of slot name, but this did not succeed for the reasons above.

C.3 Decoding active slots vs. all slots

We experimented with training the model to only decode active slots rather than all slots with `none` values when they were inactive. JGA dropped -0.4%, which we hypothesized could be a result of greater dissimilarity between the slot-value string in the prompt (which contained all slots by construction) and the target, which only contained a subset of slots.

C.4 In-line annotations vs. dialogue+slots concatenated

We hypothesized that bringing the slot annotation in the prompt closer to where it was mentioned in the dialogue might help the model better understand the slot's semantic meaning. We changed the format as follows:

- Original: `[example] [user] I would like a pet-friendly hotel room with wifi [system] I found ...` **`[slot] has_wifi=True`**
- In-line: `[example] [user] I would like a pet-friendly hotel room with wifi` **`[has_wifi=True]`** `[system] I found ...`

However, this decreased JGA by more than -20%. We hypothesized that this was likely due to a mismatch between the prompt's annotations and the target string format, which remained the same.

[2] https://github.com/google-research/text-to-text-transfer-transformer/blob/main/released_checkpoints.md

Model	All	Seen	Unseen
SDT-seq + desc	88.6±0.9	95.7±0.5	86.2±1.0
SDT-seq	**88.8±0.5**	**95.8±0.2**	**86.4±0.7**

Table A1: We experiment with prompting using both descriptions and demonstrations (SDT-seq + desc) vs. demonstrations-only (SDT-seq) and find that descriptions do not improve performance.

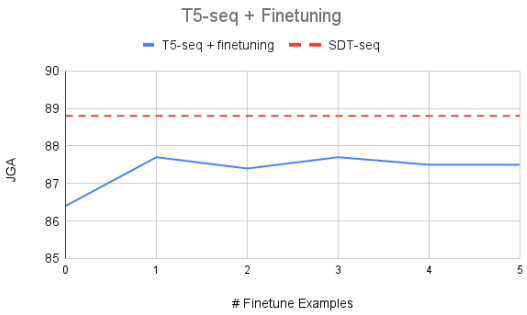

Figure 3: Results of secondarily finetuning T5-seq with dialogues, to help understand whether prompting or finetuning is more effective. The examples used for finetuning are derived from the set of dialogues used as prompts across the 5 trials of SDT-seq. From this, we observe that prompting outperforms finetuning.

Original	V1	V5
service_name: "Payment" description: "The fast, simple way to pay in apps, on the web, and in millions of stores"	service_name: "Payment" description: "Best way to pay online or in-person"	service_name: "Payment" description: "Money transfers and payment requests made easy"
name: "amount" description: "The amount of money to send or request"	name: "amt" description: "Amount sent or requested"	name: "amount_to_transfer" description: "Cash amount to transfer or ask for"
name: "receiver" description: "Name of the contact or account to make the transaction with"	name: "recipient_info" description: "Name of person to receive payment or request"	name: "contact_name_or_account_name" description: "Payment will be sent to or requested from this person/entity"
name: "private_visibility" description: "Whether the transaction is private or not"	name: "visibility" description: "Boolean flag indicating if the transaction is private or not"	name: "private_transaction_yes_or_no" description: "Hidden transaction yes/no?"
name: "payment_method" description: "The source of money used for making the payment"	name: "payment_source" description: "Source of money for transfer"	name: "money_withdrawal_source" description: "What is being used to pay, either app balance or debit/credit card"
name: "RequestPayment" description: "Request payment from someone"	name: "RequestAPayment" description: "Request money from another user"	name: "TransferRequest" description: "Ask for a money transfer from a contact"
name: "MakePayment" description: "Send money to your friends"	name: "SendPayment" description: "Send cash to friends and others"	name: "TransferMoney" description: "Make a payment to an account"

Figure 4: The original schema for a Payment service its closest (v_1) and farthest (v_5) SGD-X variants, as measured by linguistic distance functions. For the SGD-X benchmark, models are trained on the original SGD dataset and evaluated on the test set, where the original test set schemas are replaced by SGD-X variant schemas.