# A Simple Language Model for Task-Oriented Dialogue

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NeurIPS 2020



### Dialogue

There are broadly two categories of dialogue:

- Open-domain dialogue: focus on making chit-chat, open-ended conversations with humans more natural and engaging. They are usually trained end-to-end using large-scale data from social media

- Task-oriented dialogue (TOD): accomplish a goal described by a user in natural language. They often use a pipeline approach. The pipeline requires:
  - natural language understanding (NLU) for predicting domain and user intent
  - dialogue management (DM) predicting belief states and deciding which actions to take based on those beliefs
  - natural language generation (NLG) for generating responses





# **Task-Oriented Dialogue (TOD)**

Modular-based model:

- The DM module employs dialogue belief and dialogue act labels as supervision
- The NLG module accesses templatized or natural responses
- The modular dependencies of these components can lead to error propagation when information is not fully provided to subsequent modules in the pipeline

city

User

No, I am not picky as long as the prices are low.

> yes please, for 8 peoples at 18:30 on Thursday.







### **Traditional End-to-End TOD**



Seq2Seq model with attention on oracle belief state and database pointer vector (MultiWOZ baseline) [1]

[1] Budzianowski, Paweł, et al. "Multiwoz-a large-scale multi-domain wizard-of-oz dataset for task-oriented dialogue modelling." EMNLP, 2018 [2] Zhang, Yichi, et al. "Task-Oriented Dialog Systems that Consider Multiple Appropriate Responses under the Same Context." arXiv preprint arXiv:1911.10484 (2019).



- DAMD [2]: Multi-decoder Seq2Seq
- Different decoder for belief, action, response



### **SimpleTOD - Input representation**

- We propose recasting task-oriented dialogue as a simple, causal (unidirectional) language modeling task
- We show that such an approach can solve all the sub-tasks in a unified way using multi-task maximum likelihood training
- Dialogue context comprises all previous user/system responses, Ct = [U0, S0, ..., Ut]
- A single training sequence consists of the concatenation of context Ct, belief states Bt, database search results Dt, action decisions At, and system response St
- A schematic overview of each segment is shown below together with special tokens marking transition points.

Context	[context] [user] user input [system
Belief State	[belief] domain slot_name value,
DB Search	[db] #_matches, booking_status [
Action	[action] domain action_type slot_
Response	[response] system delexicalized response]

m] system response ... [user] user input [endofcontext]

*domain slot\_name value, ...* [endofbelief]

[endofdb]

\_name, domain action\_type slot\_name, ... [endofaction]

*response* [endofresponse]



# **SimpleTOD (Training)**

- A single training sequence consists of the concatenation Xt = [Ct, Bt, Dt, At, St]
- This allows us to model the joint probability p(x) over the sequence Xt
- SimpleTOD is optimized by minimizing the negative log likelihood over the joint sequence

$$p(x) = \prod_{i=1}^{n} p(x_i | x_{< i}) \qquad \qquad \mathscr{L}(D) = -\sum_{t=1}^{|D|} \sum_{i=1}^{n_t} \log p_{\theta}(x_i^t | x_{< i}^t)$$

a) training





input is a single sequence



## SimpleTOD (Inference)

### b) inference

 $B_t = SimpleTOD(C_t)$ 

### $A_t = SimpleTOD([C_t, B_t, D_t])$



 $S_t = SimpleTOD([C_t, B_t, D_t, A_t])$ 



### **Noisy Annotations**

To better understand the source of dialogue state tracking errors, we investigated MultiWOZ 2.1 annotations in depth.

We have defined four primary types of noisy-labels that could be considered mis-annotations

- 1. User provided multiple options, but context does not provide sufficient information to determine the true belief state
- Belief state is not labeled, but context provides sufficient information 2.
- Belief state is labeled, but context lacks necessary information 3.
- Belief state value is misspelled according to the context information 4.

A list of discovered noisy annotations in MultiWOZ 2.1 alongside a cleaned version of the test set are provided





### **Dialogue State Tracking (DST)**

Evaluation of Dialogue State Tracking (DST) on MultiWOZ 2.1 using joint goal accuracy metric

- **\* TRADE** proposes test label cleaning and recommended by MultiWOZ authors
- + TripPy uses label normalization and equivalent matching
- \*\* **DSTQA** uses the cleaning of TRADE model plus additional accounting for label variants
- SimpleTPDo no label-cleaning
- SimpleTOD\* uses label-cleaning
- SimpleTOD+ performs cleaning c

Model	Decoder	Context Encoder	Extra Supervision	Joint Accuracy
TRADE*	Generative + Classifier	Bidirectional		45.6
DSTQA**	Classifier	Bidirectional	knowledge graph	51.17
DST-Picklist*	Classifier	Bidirectional	-	53.3
SST*	Generative	Bidirectional	schema graph	55.23
TripPy <sup>†</sup>	Classifier	Bidirectional	action decision	55.3
SimpleTOD <sup>o</sup>	Generative	Unidirectional	-	55.72
SimpleTOD*	Generative	Unidirectional	-	55.76
SimpleTOD <sup>+</sup>	Generative	Unidirectional	1 <del></del>	57.47



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## **Understanding long, multi-domain context**

• This example also shows understanding dialogue states, where slots across domains are related.

• For example, taxi departure and taxi destination are inferred from attraction name and hotel name.

Table 9: Example of multi-domain dialogue state tracking for long context, where dialogue context spanning over 3 domains, i.e. attraction, hotel, and taxi. The belief states for taxi departure and destination (highlighted) should be inferred from hotel and attraction domains.

Context ('MUL1015', turn 10)	<li><li><li><li><li><li><li><li><li><li< th=""></li<></li></li></li></li></li></li></li></li></li>
Target	<li>delief&gt; attraction area south, attraction name the junction, attraction type theatre, hotel area centre, hotel name alexander bed and breakfast, hotel parking yes, hotel pricerange cheap, hotel type guest-house, taxi departure the junction, taxi destination alexander bed and breakfast, taxi leaveat 14:45 <li> <li>  &lt;</li></li></li>
SimpleTOD	<li>delief&gt; attraction we a south, attraction name the junction, attraction type theatre, hotel area centre, hotel name alexand r bed and breakfast, hotel parking yes, hotel pricerange cheap, hotel type guest-house, taxi departure the junction, taxi destination alexander bed and breakfast, taxi leaveat 14:45 <le>def lendof belief <le>def lendof belief</le></le></le></le></le></le></le></le></le></le></le></le></le></le></le></le></le></le></li>





### **End-to-End Evaluation**

Action and response generation uses three metrics.

inform and success rates: designed to capture how well the task was completed. **Inform rate:** measures how often the entities provided by the system are correct. **Success rate:** refers to how often the system is able to answer all the requested attributes by user. **BLUE score:** is used to measure the fluency of the generated responses. combined score: for action and response generation is computed as (BLEU + 0.5 \* (Inform + Success)).

Model	Belief State	DB Search	Action	Inform	Success	BLEU	Combined
DAMD+augmentation	generated	oracle	generated	76.3	60.4	16.6	85
SimpleTOD (ours)	generated	oracle	generated	78.1	63.4	16.91	87.66
SimpleTOD (ours)	generated	dynamic	generated	81.4	69.7	16.11	91.66
SimpleTOD (ours)	generated	-	generated	84.4	70.1	15.01	92.26

Table 2: Action and response generation on MultiWOZ 2.0 reveals that SimpleTOD, a single, causal language model, is sufficient to surpass prior work.

Model	Belief State	DB Search	Action	Inform	Success	BLEU	Combined
DAMD+augmentation	oracle	oracle	oracle	95.4	87.2	27.3	118.5
PARG	oracle	oracle	oracle	91.1	78.9	18.8	103.8
SimpleTOD (ours)	oracle	oracle	oracle	93.4	83.2	17.78	106.08
SimpleTOD (ours)	oracle	() <b>-</b> )	oracle	92.3	85.8	18.61	107.66
HDSA	oracle	oracle	generated	82.9	68.9	23.6	99.5
DAMD+augmentation	oracle	oracle	generated	89.2	77.9	18.6	102.5
ARDM	oracle	oracle	-	87.4	72.8	20.6	100.7
LaRL	oracle	oracle	generated	82.78	79.2	12.8	93.79
SimpleTOD (ours)	oracle	oracle	generated	84	72.8	16.1	94.5
SimpleTOD (ours)	oracle	() <b>=</b> )	generated	88.9	67.1	16.9	94.9

Table 7: SimpleTOD results on MultiWOZ 2.0 using oracle information.



### Interaction with human

**Description:** A human is tasked to request SimpleTOD for reserving a hotel, and then for booking a train as well

It is shown that SimpleTOD is able to

- Understand human intent
- Able to request related information for hotel and train reservation
- Able to suggest useful information about available hotel and restaurant from database



SimpleTOD

SimpleTOD is ready to chat. What would you like to ask?





### Blog: https://blog.einstein.ai/simpletod

### Code: https://github.com/salesforce/simpletod



Source code



