

Reinforced Language Modeling for End-to-End Task Oriented Dialog

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Abstract

Placeholder: Task-oriented dialog (TOD) systems aim to help users complete some pre-defined tasks such as booking an hotel and/or reserving a table in a restaurant. With the advent of numerous carefully annotated datasets, such as `MultiWoZ` (Budzianowski et al., 2018; Eric et al., 2019; Zang et al., 2020), `CamRest676` (Wen et al., 2016b,a), and `SGD` (Rastogi et al., 2020), TOD systems can now be more easily trained, evaluated, and compared against in terms of metrics such as task success rate (Budzianowski et al., 2018). Task-oriented dialog (TOD) systems aim to help users complete some pre-defined tasks such as booking an hotel and/or reserving a table in a restaurant. With the advent of numerous carefully annotated datasets, such as `MultiWoZ` (Budzianowski et al., 2018; Eric et al., 2019; Zang et al., 2020), `CamRest676` (Wen et al., 2016b,a), and `SGD` (Rastogi et al., 2020).

1 Introduction

Task-oriented dialog (TOD) systems aim to help users complete some pre-defined tasks such as booking an hotel and/or reserving a table in a restaurant. With the advent of numerous carefully annotated datasets, such as `MultiWoZ` (Budzianowski et al., 2018; Eric et al., 2019; Zang et al., 2020), `CamRest676` (Wen et al., 2016b,a), and `SGD` (Rastogi et al., 2020), TOD systems can now be more easily trained, evaluated, and compared against in terms of metrics such as task success rate (Budzianowski et al., 2018).

Many successful TOD systems have been proposed, which can be broadly classified into two approaches. Traditional TOD system is built on a modular pipeline, and typically includes components: a) Natural Language Understanding (NLU) module to identify user’s intent and extract task-specific information; b) Dialog State Tracking (DST) module to maintain a high level information of current progress based on dialog history

and user’s belief state; c) Dialog Policy Planning (DPL) module to determine the content of system’s next response and; d) Natural Language Generation (NLG) module to generate an appropriate response in natural language. However, with advances in large-scale pretrained generative models (Brown et al., 2020; Raffel et al., 2020; Zhang et al., 2020; Peng et al., 2022), many recent approaches handle TOD in an more uniformed way by treating it as an end-to-end (E2E) generation problem. In this approach, often the dialog history is used as input, and the model directly generates the responses as well as the corresponding user belief states if needed. In this setting, dialog systems become much easier to build, and works such as Yang et al. (2021); Lee (2021); He et al. (2022) have shown promising results in TOD benchmarks such as `MultiWoZ`.

However, as the standard Language Modeling (LM) does not directly account for TOD metrics such as task success rate, many recent work therefore introduces techniques from Reinforcement Learning (Zhao et al., 2019; Lubis et al., 2020; Ramamurthy et al., 2022). Reinforcement Learning (RL) aims to help a policy/model to maximize discounted sum of rewards, and in the context of TOD, the reward can be naturally defined by metrics such as task success rate. Hence, models can be trained to directly optimize for those TOD metrics, and prior approaches such as Zhao et al. (2019); Lubis et al. (2020) have shown state-of-the-art performance on task success rate and inform rate on `MultiWoZ`. However, those work also demonstrates difficulty of using RL to maintain a natural response (e.g. a low BLEU score) and to ensure a fast training speed, as time-consuming response generation is often needed to evaluate RL objectives such as policy gradient or PPO (Schulman et al., 2017).

In this paper, we similarly introduce techniques from RL to help improve TOD performances, but we aim to overcome the aforementioned problems

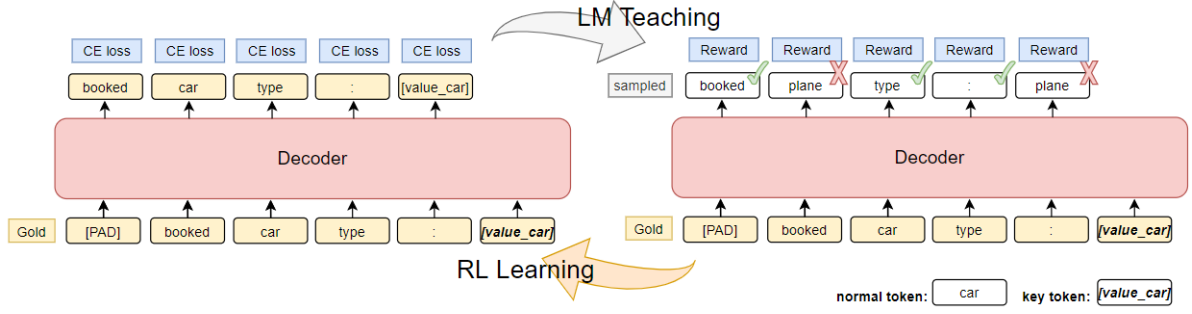


Figure 1: Reinforced Language Modelling. During LM, the model is explicitly taught the correct responses. During RL, the model is tested on the task of predicting each single next token given the gold response.

by using it in a different way. We observe that for achieving a high task success/inform rate, one needs to ensure that key quantities, such as restaurant *phone number* and *address*, needs to be produced correctly. Hence, instead of using RL algorithms to explore and find an entire response that maximizes task success/inform rate, we use RL to help the model focus its learning on those key quantities. Specifically, we first propose a new scoring mechanism that penalizes more heavily when key quantities are generated incorrectly, and use this to construct a new RL objective (see Figure 1). Next, we can shorten the exploration time of this RL objective by utilizing LM, which directly teaches the model both the correct key quantities along with the natural responses. Finally, we combine this “student generation” task from RL and “teacher teaching” task from LM, and propose our algorithm Reinforced Language Modelling (RLM). As we replaced exploration from a time-consuming sequence generation task to a faster per-token generation, we can train RLM much quicker than prior RL approaches. Additionally, the traditional LM also becomes a natural component in this algorithm, serving as a teacher to guide RL to generate the correct key quantities.

This paper makes the following contributions:

- We propose a new RL objective and an automatic per-token evaluation metric in our a token-level generation task, which aims to learn key quantities in a sentence more robustly. As this objective can be computed without response generation, computation can be done much faster.
- We show that the standard LM objective is a special case of our new RL objective when combined with the simple policy gradient, reinstating the connection between RL and LM

in our setting.

- We propose the Reinforced Language Modelling (RLM) algorithm, which utilize our new RL objective and symbiotically cooperate with LM to improve TOD performance.
- We evaluate RLM on MultiWoZ, and show that using RLM we can achieve state-of-the-art performance on E2E response generation.

2 Related Work

End-to-end dialog systems such as [Lei et al. \(2018\)](#); [Yang et al. \(2021\)](#); [Lee \(2021\)](#); [He et al. \(2022\)](#) have shown promising results in TOD benchmarks such as MultiWoZ. However, as the standard Language Modeling (LM) does not directly account for TOD metrics such as task success rate, works such as [\(Zhao et al., 2019; Lubis et al., 2020; Ramamurthy et al., 2022\)](#) further build on top of LM to incorporate RL techniques to improve TOD performance.

On one hand, approaches such as [Ramamurthy et al. \(2022\)](#) considers a “sequence-level” RL by first generating an entire sequence and then treating each word as an action $p(x^{\text{gen}}|c) = \prod_i p(x_i^{\text{gen}}|x_{1:i-1}^{\text{gen}}, c)$. This results in an astronomically large action space for the algorithm to explore, and [Ramamurthy et al. \(2022\)](#) counters this by only sampling from top- p tokens during generation. While this reduces the action space, it still requires a time-consuming generation step. Additionally, the author recommends training RL from a LM fine-tuned checkpoint, hence effectively viewing the two as a separate task.

Alternatively, [Lubis et al. \(2020\)](#) reformulates generation $p(x|c)$ to be conditioned on a latent action z , since $p(x|c) = p(x|z)p(z|c)$. By restricting the dimension of z , [Lubis et al. \(2020\)](#) can more directly use RL such as policy gradient because now

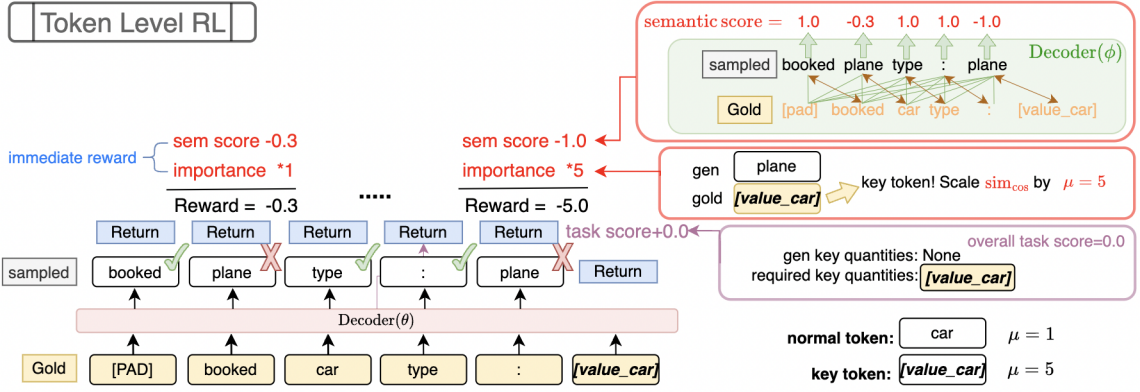


Figure 2: Token Level RL: return for each sampled token will a combination of individual immediate reward and future rewards. Immediate reward measures the semantic closeness of the generated token and the gold token, scaled by its importance μ . Future reward will help propagate final overall scores, such as task performance.

the action space is more manageable. However, the author faces challenges from interpreting the latent action z , and while reaching state-of-the-art performance on task success rate and inform rate, the generated responses are often unnatural hence having a low BLEU score on `MultiWOZ`.

In this work, we aim to utilize RL in a different way by converting the *sequence-level* generation process during exploration to a *token-level* generation task. Specifically, we employ RL on the task of generating/sampling each next token (see Figure 1), which practically reduced the action space from $|V|^T$ in a sequence-level RL of length T , to T token-level questions with action space $|V|$. This also by-passed the time-consuming generation step, and by utilizing LM as a teacher, we can train RLM much faster than prior RL approaches while maintaining a high BLEU score thanks to the natural language modelling objective.

3 Approach

Traditional language modeling aims to help the model learn the probability of generating the correct token(s) x^{gold} given some input context c . This is done by using a cross-entropy loss:

$$\begin{aligned}\mathcal{L}_{\text{LM}}(\theta) &= -\sum_x p(x|c) \log p_{\theta}(x|c) \\ &= -\log p_{\theta}(x^{\text{gold}}|c)\end{aligned}\quad (1)$$

where the probability of $p(x|c) = 0$ if $x \neq x^{\text{gold}}$ in the provided training dataset. When the training dataset is large and diverse, this objective can be effective as there would be a diverse set of x that can be generated from similar contexts c , as shown by the success of large pretrained language

models such as Raffel et al. (2020); Brown et al. (2020); Devlin et al. (2019). However, when the size of training corpus is limited, it could be helpful to also penalize $p_{\theta}(x|c)$, $x \neq x^{\text{gold}}$ according to the semantic closeness and importance of $x|c$ compared to $x^{\text{gold}}|c$. Intuitively, this could provide more signal to the model, and help it focus on generating more important tokens correctly, rather than spending too much time learning the other tokens.

Naturally, given some measure $\mathcal{R}(x|c)$ of semantic closeness and importance for each token, we can achieve this by considering a gradient that is proportional to such a measure:

$$\nabla \mathcal{L}(\theta) \propto -\mathcal{R}(x|c) \nabla \log p_{\theta}(x|c) \quad (2)$$

which becomes the simple policy gradient method in Reinforcement Learning.

3.1 Reinforcement Learning in NLP

Given a supervised dataset $\mathcal{D} = \{(c^i, x^i)\}$ where c^i is a context sequence and x^i is a response sequence, the probability of generating a response $x^{(i)}$ can be modeled as:

$$p(x^{(i)}|c^{(i)}) = \prod_{t=1}^{T-1} p(x_{t+1}^{(i)}|x_{1:t}^{(i)}, c^{(i)}),$$

where $x_t^{(i)}$ is the t -th token in the i -th response, and T is the length of the response. As mentioned in Ramamurthy et al. (2022); Lubis et al. (2020), this generation can be formulated as a MDP problem $\langle \mathcal{S}, \mathcal{A}, \mathcal{R}, \mathcal{P}, \gamma \rangle$. The input context $c^{(i)}$ would be the initial state $s_0 \in \mathcal{S}$, and the response $x^{(i)}$ would represent the sequence of actions $\mathbf{a}^{(i)} = \{a_1^{(i)}, a_2^{(i)}, \dots, a_{T-1}^{(i)}\}$ in an episode, where

$a_t^{(i)} \in \mathcal{A}$ is the t -th token in the i -th response. The reward function \mathcal{R} would represent the ‘‘utility’’ of each action towards the overall performance, such as task success in TOD. Typically, this is modeled by using $\mathcal{R}(s, a) = 0$ for non-terminal states, and for terminal states $\mathcal{R}(s_T, a)$ can be computed by combining scores such as task success and BLEU (Ramamurthy et al., 2022; Arora et al., 2022). The transition function $\mathcal{P} : \mathcal{S} \times \mathcal{A} \rightarrow \mathcal{S}$ would deterministically append the action a_t to the current state s_t so that $s_{t+1} = (c_0, \dots, c_m, a_0, \dots, a_t)$. Finally, $\gamma \in [0, 1)$ is the discount factor.

3.2 Token-Level Reinforcement Learning

In our token-level reinforcement learning, instead of the sequence generation procedure, we consider a series of token-level generation task:

$$\left\{ p(x_1^{\text{gen}} | \mathbf{c}^{(i)}), \dots, p(x_T^{\text{gen}} | x_{1:T-1}^{(i)}, \mathbf{c}^{(i)}) \right\} \quad (3)$$

where the agent is asked to generate the next token x_t^{gen} given the current context and the gold response up to $t - 1$. This is particularly suitable for our goal of training a model to focus on generating key quantities, as we can use the gold response itself as an oracle to accurately penalize each token prediction separately. First, we generate $a_t = x_t^{\text{gen}}$ by sampling from $p(X = x | x_{1:t-1}^{(i)}, \mathbf{c}^{(i)})$. Then, we can measure the semantic closeness of each generated $a_t | \bar{\mathbf{c}}$ with the gold token $x_t | \bar{\mathbf{c}}$, and produce a semantic score, $\text{semantic}(a_t, x_t, \bar{\mathbf{c}})$, for each token (see subsection 3.3), where $\bar{\mathbf{c}} = [x_{1:t-1}^{(i)}, \mathbf{c}^{(i)}]$. Finally, we scale each semantic score by its importance μ , measured by whether if the corresponding gold token is a key quantity or not (see Figure 2). This results in a reward function for every token generated:

$$\mathcal{R}(s_t, a_t) = \text{semantic}(a_t, x_t, \bar{\mathbf{c}}) \cdot \mu \quad (4)$$

where $\text{semantic}(\cdot) \in [-1, 1]$, and μ is a hyperparameter for adjusting the importance of key tokens. Note that by using $\mu = 1$ for non-key tokens in Equation 4 and placing it in policy gradient Equation 2, this gives

$$\nabla \mathcal{L}(\theta) \propto -\nabla \log p_\theta(x^{\text{gen}} | c)$$

so that if $x^{\text{gen}} = x^{\text{gold}}$ is generated correctly this reduces to language modeling (Equation 1).

Empirically, it is important to note that this token level generation can be done in a single forward

pass, followed by sampling from the output distribution. This is much faster than the generation procedure, and also allows us to use the gold response as a ‘‘self-supervised’’ metric to compute reward. Conceptually, this means that such an approach can be generic to any sequence generation task beyond TOD where key tokens can be easily defined.

Although simple policy gradient fits nicely with language modeling in this formulation, using Equation 2 directly in practice suffer from high gradient variance (Schulman et al., 2015a; Wu et al., 2021). Therefore, in this paper we use PPO (Schulman et al., 2017) which instead uses the surrogate objective:

$$\mathcal{L}_{\text{PPO}} = -\min \begin{cases} r(\theta) \hat{A}, \\ \text{clip}(r(\theta), 1 - \epsilon, 1 + \epsilon) \hat{A}, \end{cases} \quad (5)$$

where \hat{A} is the advantage function (in this work we used $\hat{A} = G_t$ the discounted sum of rewards, which is simpler while also an unbiased estimate of \hat{A} (Schulman et al., 2015b)), ϵ is the clipping parameter, and $r(\theta)$ is the ratio of the new policy to the old policy p_θ^{old} :

$$x^{\text{gen}} \sim p_\theta(x | c), \quad r(\theta) = \frac{p_\theta(x^{\text{gen}} | c)}{p_\theta^{\text{old}}(x^{\text{gen}} | c)} \quad (6)$$

3.3 Token-Level Semantic Score

To measure the semantic closeness between the generated token $a_t = x_t^{\text{gen}}$ and the gold token x_t , we experiment with the following three approaches.

In our primary approach, we draw inspiration from BERTScore (Zhang et al., 2019a), and consider using a neural network to compute the score that is context-aware. However, different from BERTScore which in general considers an overall semantic similarity between two sequence potentially of different lengths, we need to measure per-token similarity between two sequence of the same length. Therefore, as illustrated in Figure 2, we consider a simpler approach. First, we use a decoder network $\text{Decoder}(\phi)$, which preferably is a fine-tuned checkpoint of $\text{Decoder}(\theta)$, to compute $p_\phi(X_t = x | x_{1:t-1}^{(i)}, \mathbf{c}^{(i)})$, the probability to generate any token at time t given the context, which can again be done in a single forward pass. Then, we index into the probability to find $p_\phi(X = x_t^{\text{gen}} | x_{1:t-1}^{(i)}, \mathbf{c}^{(i)})$ of our generated tokens, as a measure of the semantic appropriateness of x_t^{gen} in the given context. We use this probability

as a proxy of semantic closeness instead of comparing the contextual embedding of each token in the gold and generated sequence as in BERTScore, because in our setting the generated sequence is conditioned on the gold response, which distorts its semantic meaning when viewed as standalone sentence. Next, to ensure the score correctly reflects the gold tokens as the optimal choice, we set the score to 1 if $x_t^{\text{gen}} = x_t$ for all tokens generated correctly, and in addition -1 for $x_t^{\text{gen}} \neq x_t$ for all *key* tokens. Finally, we rescale this score to $[-1, 1]$.

Alternatively, we also compare this approach with two baselines. One baseline is to still use BERTScore’s approach and compare the contextual embeddings despite the generated sequence is conditioned on the gold response. The other is to use a static token embedding that ignores the context all together. We compare our primary approach against those two methods in subsection 5.3.

Algorithm 1 Reinforced Language Modeling

Require: generative network p_θ
Require: semantic scoring network p_ϕ
Require: supervised language dataset \mathcal{D}
Require: empty buffer B_L, B_S

- 1: Repeat for n epochs:
- 2: **for** batch B_i in $\mathcal{D} = \{B_1, \dots, B_m\}$ **do**
- 3: Perform LM on B_i using Equation 1
- 4: Update generative network p_θ
- 5: Append B_i to Learned Batches B_L
- 6: **if** $i \% \kappa == 0$ **then**
- 7: **for** each batched episode B_j in B_L **do**
- 8: Collect k samples per episode
- 9: by sampling from Equation 3
- 10: Calculate per-token reward
- 11: using p_ϕ and Equation 4
- 12: Calculate per-token returns G_t
- 13: Append all to student buffer B_S
- 14: **end for**
- 15: Perform RL on B_S using Equation 5
- 16: Update generative network p_θ
- 17: Clear B_L and B_S
- 18: **end if**
- 19: **end for**

3.4 Reinforced Language Modeling

To further shorten the exploration time of RL and encourage faster training and convergence, we can utilize traditional language modeling to help learn the correct tokens more quickly (see subsection 5.2). As mentioned in the previous section,

language modeling can be seen as a special case of our token level reinforcement learning when $\mu = 1$ and the model generated the correct token (if we use Equation 2). Therefore, in this view language modeling aims to *passively* instill the knowledge of correct tokens into the model, and our token-level RL aim to help the model *actively* practice its learned knowledge and focus on generating key quantities (see Figure 1). We thus combine language modeling and our token-level RL and propose our **Reinforced Language Modeling (RLM)** algorithm in Algorithm 1.

4 Experiments

4.1 Dataset and Preprocessing

We evaluate our algorithm on the MultiWoZ dataset (Budzianowski et al., 2018). MultiWoZ is a large scale multi-domain TOD dataset consisting of 8438, 1000, and 1000 dialogs for training, validation, and test sets respectively. The dataset consists of seven domains: attraction, hotel, hospital, police, restaurant, taxi, and train. Each dialog consists of a sequence of user utterances and system responses, all annotated with the corresponding dialog state and system action.

We follow the preprocessing procedure from Zhang et al. (2019b) to delexicalize slot values for each system response, and use the standardized evaluation script released by Nekvinda and Dušek (2021), which has also been adopted by the official MultiWoZ dataset.

In the future, we also plan to test our algorithm on other TOD datasets such as Camrest676 (Wen et al., 2016b,a) and SGD (Rastogi et al., 2020) for a more comprehensive evaluation.

4.2 Evaluation Metrics

In our experiments, we primary consider the task of end-to-end response generation. In MultiWoZ, response generation performance is evaluated by a combination of three metrics: **Inform rate** measures whether the system has provided an appropriate entity; **Success rate** measures whether the system has answered all the requested attributes; **BLEU** measures the fluency as compared to the references, which are also delexicalized in the same way as our preprocessing procedure. Finally, the **Combined** score is calculated as $(\text{Inform} + \text{Success}) \times 0.5 + \text{BLEU}$.

Model	Backbone	Response Generation			
		Inform	Success	BLEU	Combined
LABES	-	68.5	58.1	18.9	82.2
DAMD	-	57.9	47.6	16.4	84.8
AuGPT	GPT-2	76.6	60.5	16.8	85.4
MinTL	T5-small	73.7	65.4	19.4	89.0
SOLOIST	GPT-2	82.3	72.4	13.6	90.9
DoTS	BERT-base	80.4	68.7	16.8	91.4
UBAR	DistilGPT-2	83.4	70.3	17.6	94.4
PPTOD	T5-base	83.1	72.7	18.2	96.1
BORT	T5-small	85.5	77.4	17.9	99.4
MTTOD	T5-base	85.9	76.5	19.0	100.2
GALAXY	UniLM-base	85.4	75.7	19.0	100.2
Mars-G*	T5-small	88.9	78.0	19.9	103.4
Baseline (MTTOD)	GODEL-base	87.2	76.7	18.6	100.6
+RLM	GODEL-base	89.7	77.7	18.3	102.0
+finetune+RLM	GODEL-base	89.0	80.1	19.0	103.6

Table 1: MultiWoZ End-to-End Response Generation Evaluation. The results of previous work are reported on the official leaderboard of MultiWOZ. * indicates concurrent work.

4.3 Model Architecture and Hyperparams

As our algorithm only requires a decoder, we can choose from both decoder-only networks such as GPT (Brown et al., 2020) and encoder-decoder networks such as T5 (Raffel et al., 2020). In this work, we use GODEL-base (Peng et al., 2022) as a backbone, which is a T5 based model pretrained on both texts and dialog datasets. We implement our algorithm based on MTTOD (Lee, 2021), which only performed minimal network architecture modification hence easier to build upon.

For RLM Algorithm, the most important hyperparameters we used are $\kappa = 0.5 \times \text{steps in epoch}$, $\gamma = 0.99$, $k = 3$, and sampling temperature of 1.1. As task success and inform rate in MultiWoZ is highly correlated with generating the key tokens correctly, we use $\mu = 5$ for key tokens such as *value_address* and $\mu = 1$ for non-key tokens. In addition, we add a terminal reward by measuring the F1-score of generated key tokens compared to the gold key tokens, as shown in Figure 2, to encourage task success and inform rate. For a full list of hyperparameters, please refer to Appendix A.

4.4 Main Results

We present the results of end-to-end response generation on MultiWoZ in Table 1. Since our implementation is based off MTTOD (Lee, 2021), we retrained using the official code but experimented with GODEL-base (Peng et al., 2022) instead of T5-

base (Raffel et al., 2020) because the former is also trained on dialog datasets (but not MultiWoZ). This results in a small improvement of 0.4, and we report this result as "Baseline (MTTOD)". Since RLM is an algorithm targeted at improving response generation, we then applied it during the response generation training in place of standard LM in MTTOD, and we report the results as "+RLM". Finally, as noted by Ramamurthy et al. (2022) that in practice training with RL algorithms can be benefited by initializing with a finetuned LM, we also trained RLM from a finetuned checkpoint (Baseline) and report it as "+finetune+RLM".

As shown in Table 1

5 Analysis

5.1 Ablation Study

As RLM is a combines a standard LM training with our proposed token-level RL, we train each component separately and compare the results to the full RLM algorithm in Table 2. Specifically, **LM Only** refers to removing the RL component in 1 and only training with LM objective. **RL Only** refers to removing the LM component and only training with RL objective. **RLM** refers to the full RLM algorithm. As shown in Table 2, the full RLM algorithm outperforms both LM Only and RL Only, which indicates that both LM and RL are important for response generation. We believe that this is because during RLM, LM helps the model to

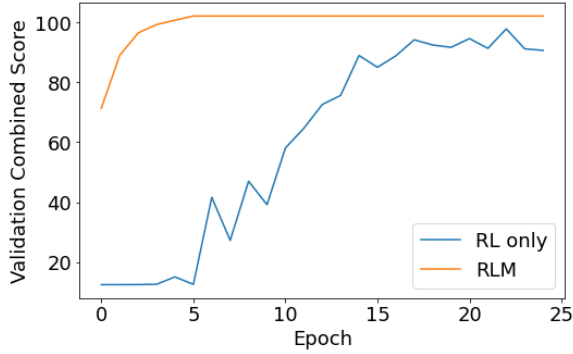


Figure 3: Performance of *RLM* and *RL Only* over Time. In *RL Only*, we remove the LM objective from *RLM*, and for each sampled episode we additionally append its corresponding gold response.

learn an overall fluent response, while token-level RL then aids the model to more finely focus on learning key quantities.

Algo	Inform	Success	BLEU	Total
LM only	87.2	76.7	18.6	100.6
PPO only	84.2	72.2	17.5	95.7
RLM	88.1	78.2	19.0	102.2

Table 2: Performance of Individual Components of the RLM Algorithm

5.2 Training Speed

To demonstrate the fast learning speed of RLM as a result of incorporating LM, we compare the validation curve of RLM and "RL only" in Figure 3. "RL only" is the same as RLM except that we remove the LM objective from RLM. Furthermore, we append the corresponding gold response to each sampled episode in "RL only" to additionally provide the model signals on the correct token to generate (Wu et al., 2021), in hope to help it speed up training.

As shown in Figure 3, RLM's fast training speed benefits from the efficient LM objective, and the RL step on top of it helps to further improve the performance (see Table 2).

5.3 Token-level Semantic Score

Besides the proposed token-level semantic score using probability of each generated token from a finetuned LM (see subsection 3.3 for more details), which we denote as **Prob.** in Table 3, we also experiment with 4 other approaches to show its effectiveness in our algorithm. Specifically,

Reward	RLM			
	Inform	Success	BLEU	Total
Zero	0.00	0.00	0.00	0.00
Error	0.00	0.00	0.00	0.00
BERTS.	0.00	0.00	0.00	0.00
Static.	0.00	0.00	0.00	0.00
Prob.	89.7	77.7	18.3	102.0

Table 3: Performance of Training from Scratch with RLM using Different per-token Reward

Reward	Finetune+RLM			
	Inform	Success	BLEU	Total
Zero	88.2	77.8	19.0	102.0
Error	87.9	78.1	19.0	102.0
BERTS.	88.2	78.1	19.0	102.2
Static.	88.3	78.0	18.9	102.1
Prob.	88.1	78.2	19.0	102.2

Table 4: Performance of Training from Finetuned Weights with RLM using Different per-token Reward

we tested the following 4 alternatives as a token-level reward. **Zero**: we assign a zero score to all generated tokens, hence only using the terminal reward as a signal for model to improve. **Error**: we assign a hard penalty of -1 if a generated token is incorrect, regardless of how semantically close that token is to the gold token. **BERTS.**: we use the core mechanism in BERTScore (Zhang et al., 2019a) to measure the semantic similarity between the generated tokens and the gold tokens. In more details, we treat our sampled sequence as a standalone generated sequence, and use the cosine similarity between the embedding of each pair of token $x_t^{\text{gen}}, x_t^{\text{gold}}$ after passing through a finetuned GODEL-base as reward. **Static.**: we take the static, context-unaware token embeddings from the embedding layer of GODEL-base and compute their cosine similarity as reward. In all cases, to make results more comparable we use the same hyperparameter for training and only swap out the respective reward function in RLM.

We present the results in Table 3 and Table 4. In Table 4 we trained RLM from a finetuned checkpoint (Baseline), whereas in Table 3 we trained RLM from scratch. When trained from a finetuned checkpoint, the proposed token-level semantic score (Prob.) has similar performance with BERTS. and Static. This is because the finetuned checkpoint already have a good token generation ability, so that the reward and return from all three

metrics have are similar, resulting in a similar performance. However, all three metrics performed better than the simple alternatives of **Zero** and **Error**. In both cases, we believe it is because by supplying a more fine-grained score for each token, the model understands better where is the error and how significant is the error, hence learn more efficiently and effectively.

However, when training from scratch, the effect of different reward should become magnified. We will update the relevant results in [Table 3](#) once we have them.

6 Conclusion and Future Work

In this work, we explored the approach to utilizing Reinforcement Learning (RL) to help model focus its learning on generating key tokens in TOD, thereby improving overall performance. We proposed a new token-level scoring mechanism for measuring the semantic closeness of each token x relative to the ground truth x_t , both conditioned on the same context c . We then formulated our token-level RL objective utilizing this semantic score as well as a terminal reward that one can define flexibly depending on the task. Next, we proposed our Reinforced Language Modeling (RLM) algorithm that combines language modeling and our token-level RL to help the model learn the correct tokens more quickly. Finally, we evaluated our algorithm on the MultiWoZ dataset and showed that our algorithm can significantly improve the overall performance of TOD models, reaching new state-of-the-art performance on E2E response generation in MultiWoZ.

Although RLM is much faster to train compared to traditional sequence-generation based RL approaches, it does not help the model learn other high-reward sequences that might not be present in the dataset. Therefore, traditional RL could potentially help the model learn to generate sequence *better than* the human-collected training dataset, while RLM aims to help the model learn key knowledges *from* the dataset more effectively. It would be interesting to explore if we can combine the two approaches, such as performing sequence-generation only for a few tokens, and then use the token-level RL, so that we can perhaps achieve more exploration without sacrificing much training speed.

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A RLM Hyperparameters

For MultiWoZ, we used TODO