Keywords Reinforcement LM: Improving End-to-End Response Generation in Task Oriented Dialog

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Abstract

In task-oriented dialogs such as MultiWoZ (Budzianowski et al., 2018), an informative and successful system response needs to include key information such as the phone number of a hotel. Therefore, we hypothesize that by asking the model to focus on generating more key quantities correctly, it can achieve better overall performance. In this paper, we propose a new training algorithm, Keywords Reinforcement Language Modeling (KRLM), that aims to use a fine-grained reward function for each token and a new per-token Reinforcement Learning procedure to help the model learn keywords generation more robustly during inference. Empirical results show that our proposed KRLM training algorithm can achieve state-of-the-art performance on the inform rate, success rate, and combined score in the MultiWoZ benchmark dataset.

1 Introduction

Task-oriented dialog (TOD) systems aim to help users complete some pre-defined tasks such as booking a 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 in metrics such as task success rate (Budzianowski et al., 2018).

Many 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 such as: a) Natural Language Understanding (NLU) module to identify user’s intent and extract task-specific information; b) Dialog State Tracking (DST) module to maintain 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 as a more holistic task of end-to-end (E2E) generation. 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. This could make dialog systems become easier to build, and work not limited to 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) objective, used especially in the E2E approach, does not directly account for TOD metrics such as task success rate, many recent work additionally introduce 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 the discounted sum of rewards, and in the context of TOD, the rewards can be defined by metrics such as task success rate. Hence, models now 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 the difficulty of using RL to maintain a natural response (e.g. a low BLEU score), and the overall training can be very time-consuming because text generation is often needed to perform exploration during RL.

In this paper, we similarly introduce techniques from RL to help improve TOD performances, but we aim to overcome the aforementioned problems by “simplifying” the text generation process.
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, need to be generated 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 tokens. Specifically, we first propose a new scoring mechanism that penalizes incorrectly generated key quantities more heavily. Then, we use this per-token reward to construct a simpler per-token RL objective (see Figure 1). Finally, we combine this per-token RL objective with the traditional LM, which directly teaches the model the correct tokens, to further shorten exploration time, and propose our algorithm Reinforced Language Modelling (RLM). As we replaced a time-consuming sequence generation task with 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 per-token RL objective accompanied by a per-token reward function, which can be used to learn key quantities in a sentence more robustly. As this objective can be computed without sequence generation, training 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 Keywords Reinforcement Language Modeling (KRLM) algorithm, which utilizes our new RL objective and symbiotically cooperates with LM to improve TOD performance.

- We evaluate KRLM on MultiWoZ, and show that using KRLM 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 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 KRLM much faster than prior RL approaches while maintaining a high BLEU score thanks to the natural language modeling objective.

3 Approach

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

$$\mathcal{L}_{LM}(\theta) = -\sum_x p(x|c) \log p_{\theta}(x|c)$$

(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 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 can be helpful to also penalize $p_{\theta}(x|c), x \neq x^{\text{gold}}$ according to “how close” it is from the gold token, and also “how important” it is. Intuitively, this could provide more signals to the model, and help it focus on learning to generate more important tokens in an utterance, rather than spending too much time on other uncritical tokens.

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

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

(2)

which becomes the simple policy gradient method (Sutton et al., 1999) in Reinforcement Learning.

3.1 Reinforcement Learning in NLP

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

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

where $x^{(i)}_t$ 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 $(\mathcal{S}, \mathcal{A}, \mathcal{R}, \mathcal{P}, \gamma)$. 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 $a^{(i)} = \{a^{(i)}_1, a^{(i)}_2, \ldots, a^{(i)}_{T-1}\}$ in an episode, where $a^{(i)}_t \in \mathcal{A}$ is the $t$-th token in the $i$-th response. The reward function $\mathcal{R}$ would represent...
the “utility” of each action contributing towards the overall performance, such as task success in TOD. Typically, this is modeled by using $R(s, a) = 0$ for non-terminal states, and $R(s_f, a)$ for terminal states which can be computed by combining scores such as task success and BLEU (Ramamurthy et al., 2022; Arora et al., 2022). The transition function $P: S \times A \rightarrow S$ would deterministically append the action $a_t$ to the current state $s_t$ so that $s_{t+1} = (c_0, \ldots, c_m, a_0, \ldots, a_t)$. 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:

$$\left\{ p(x_t^{gen}|c^{(i)}), \ldots, p(x_T^{gen}|x_{1:T-1}, c^{(i)}) \right\}$$

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 locate those key positions and penalize each generated token accordingly. Specifically, we first generate each next-token $a_t = x_t^{gen}$ by sampling from $p(X = x|x_{1:t-1}, c^{(i)})$. Then, given some reward function $R(s_t, a_t) \in [-1, 1]$ for each token (see Section 3.3 for details), we can use RL to promote the importance of learning those key tokens. Directly applying $R$ in Equation (2) we get, if $x_t^{gen} = x_t^{old}$ is generated correctly and corresponds to $R = 1$,

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

this gives the same gradient as the traditional language modeling in Equation 1.

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:

$$\mathcal{L}_{PPO} = - \min \left\{ r(\theta) \hat{A}, \text{clip}(r(\theta), 1-\epsilon, 1+\epsilon) \hat{A} \right\}$$

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 $A$ (Schulman et al., 2015b)), $\epsilon$ is the clipping parameter, and $r(\theta)$ is the ratio of the new policy to the old policy $p_\theta^{old}$:

$$x_t^{gen} \sim p_\theta(x_t|c), \quad r(\theta) = \frac{p_\theta(x_t^{gen}|c)}{p_\theta^{old}(x_t^{gen}|c)} \quad (5)$$

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 also means that such an approach can be generic to any sequence generation task beyond TOD where key tokens can be easily defined.

### 3.3 Token-Level Reward Function

To help the model improve its ability to generate key tokens, we need a reward function that potentially rewards/penalizes the model more when key tokens are generated correctly/incorrectly (i.e. importance). In Section 6.2, we empirically compared various reward functions and found that: a) providing a per-token reward measuring the semantic closeness in addition to providing a terminal reward for the entire sequence is helpful, and b) a context-aware reward can further improve performance.

To measure a per-token and context-aware score between the generated token $a_t = x_t^{gen}$ and the gold token $x_t$, we draw inspiration from BERTScore (Zhang et al., 2019a), and consider using a neural network to compute a contextual semantic score. However, different from BERTScore which in general considers an overall semantic similarity between two standalone sequences potentially of different lengths, here we want to measure a per-token score between two sequences of the same length, with one sequence generated “from” another sequence (see Figure 2). Therefore, we consider a simpler approach. First, we use a decoder network $\text{Decoder}(\phi)$ (e.g. a LM fine-tuned checkpoint) to compute the probability to generate any token $x$ at time $t$ given the context $p_\phi(X_t = x|x_{1:t-1}^{(i)}, c^{(i)})$, which can be done in a single forward pass as all contexts are gold. Then, we index into the probability to find $p_\phi(X = x_t^{gen}|x_{1:t-1}^{(i)}, c^{(i)})$ of our generated tokens, as a measure of the semantic appropriateness of
Algorithm 1 KRLM Training Algorithm

Require: generative network $p_θ$
Require: semantic scoring network $p_φ$
Require: supervised language dataset $D$
Require: empty buffer $B_L, B_S$

1: Repeat for $n$ epochs:
2: for batch $B_i$ in $D = \{B_1, \ldots, B_m\}$ 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 $\% \kappa = 0$ 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 6
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 4
16: Update generative network $p_θ$
17: Clear $B_L$ and $B_S$
18: end if
19: end for

4.3 Keyword Reinforcement LM

To further improve performance and shorten the exploration time of RL, we utilize traditional language modeling to help the model learn the correct tokens more quickly (see Appendix F). As mentioned in the previous section, LM can be seen as a special case of our token level RL when $\mu = 1$ and the model generated the correct token (if we use Equation 2). Therefore, in this view LM aims to passively instill the knowledge of correct tokens into the model, and our token-level RL aims to help the model actively practice its learned knowledge and focus on generating key quantities (see Figure 1). We thus combine LM and our token-level RL and propose our Keywords Reinforcement Language Modeling (KRLM) 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.

4.2 Evaluation Metrics

In our experiments, we primarily 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. Finally, the Combined score is calculated as $(\text{Inform} + \text{Success}) \times 0.5 + \text{BLEU}$.

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-base model pretrained on both texts and dialog datasets (but not on MultiWoZ). We implement our algorithm based on MT-TOD (Lee, 2021), which only performed minimal
Model | Backbone | Response Generation
--- | --- | ---
LABES | - | 68.5
DAMD | - | 57.9
AuGPT | GPT-2 | 76.6
MinTL | T5-small | 73.7
SOLOIST | GPT-2 | 82.3
DoTS | BERT-base | 80.4
UBAR | DistilGPT-2 | 83.4
PPTOD | T5-base | 83.1
BORT | T5-small | 85.5
MTTOD | T5-base | 85.9
GALAXY | UniLM-base | 85.4
Mars-G* | T5-small | 88.9 +KRLM GODEL-base | 86.0
Baseline (MTTOD) | GODEL-base | 86.0
+KRLM | GODEL-base | 87.3 +finetune+KRLM | 89.2

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.

network architecture modification hence easier to build upon.

For KRLM Algorithm, we use $k = 3$ and $\kappa = 0.5 \times \text{total steps per epoch}$ (see Appendix A for a full list). 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. Note that we did not additionally use a BLEU score for terminal reward, as we found the LM training in KRLM is sufficient.

4.4 Main Results

We present the results of end-to-end response generation on MultiWoZ in Table 1. Since our implementation is based on MTTOD (Lee, 2021), we retrained using its publicly released code. We use GODEL-base (Peng et al., 2022) as a backbone, and report this as "Baseline (MTTOD)" in Table 1. Since KRLM 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 result as "+KRLM". Finally, as noted by Ramamurthy et al. (2022) that in practice training with RL algorithms can be benefited by initializing with an LM finetuned checkpoint, we also trained KRLM from "Baseline" and report it as "+finetune+KRLM".

As shown in Table 1, when trained with KRLM we achieved an improvement of 1.4 in Combined Score as compared to our baseline, especially in the inform rate and success rate, with a 1.3 and 0.9 point improvement respectively. Additionally, we also observe that KRLM maintained a high BLEU score, which we believe is due to the LM objective in the algorithm. When trained from an LM finetuned checkpoint, KRLM further improves to a Combined Score of 103.8, with major improvements again in the success and inform rate. We believe this is because, as the model is already equipped with some knowledge of the correct tokens, KRLM can more easily help the model improve its ability to generate key tokens correctly, as compared to the case when trained from scratch.

5 Analysis

5.1 Keyword Learning

As KRLM aims to improve the model’s ability to generate key quantities correctly, we track the accuracy of the model in generating key quantities during training and validation in Figure 3(a) and Figure 3(b), respectively. In this experiment, we feed in the gold contexts up to the key tokens, and the model is asked to generate the next token. We then compare the generated token to the gold key token, and calculate the accuracy by measuring
how often they match. As shown in Figure 3(b), only performing LM (baseline) leads to a slow increase in keyword generation accuracy during early training, as the model focuses on learning other non-key tokens due to their abundance (also see Appendix G). On the other hand, KRLM periodically uses RL to help the model focus on learning key tokens, which leads to a higher keyword generation accuracy throughout both training and validation.

### 5.2 Error Analysis

Despite reaching a higher inform rate and success rate as more key quantities are generated correctly, we still observe cases when the model misses some key tokens. We found that in many of those cases (see Appendix E for examples) the errors originate from incorrectly generated dialog states and system acts. This is understandable as we only used KRLM to improve the following response generation. To quantify this error, we additionally asked our trained model to generate responses when a) the gold dialog state is provided and b) both the gold dialog state and the gold system action are provided. We present this result in Table 2, and found that using the gold dialog state (+DST) improved the overall score by almost 4 points, and using both the gold dialog state and the gold system action (+Both) further improved the overall score by 14.6 points, almost reaching the performance of the training dataset itself. This shows that the overall performance can further increase if techniques to improve dialog state and system act generation (e.g. Sun et al. (2022)) can be combined with KRLM, which we leave for future work.

### 6 Ablation Studies

#### 6.1 KRLM Algorithm Ablation

As KRLM combines a standard LM training with our proposed token-level RL, we train each component separately and compare the results to the full KRLM algorithm in Table 3. Specifically, LM Only refers to training the model only with the LM objective. RL Only refers to training the model only with the RL objective in Algorithm 1, and in hope of speeding up training, we additionally appended gold demonstrations/responses to the student buffer in line 13 to provide more signals to the model (Wu et al., 2021). KRLM refers to the full KRLM algorithm. As shown in Table 3, KRLM
improves upon both LM Only and RL Only. We believe that this is because during KRLM training, after LM helped the model to learn an overall fluent response, token-level RL can then more easily aid the model to focus on learning key quantities, as shown in Figure 3 (and Appendix G). For a similar reason, incorporating LM also helped KRLM to be trained much faster than RL Only (see Appendix F).

| Reward | Inform | Success | BLEU | Total |
|--------|--------|---------|------|-------|
| None   | 86.0   | 77.4    | 18.9 | 100.6 |
| Zero   | 88.3   | 77.9    | 18.9 | 102.0 |
| Error  | 88.8   | 78.5    | 18.8 | 102.5 |
| Static.| 88.7   | 78.4    | 18.8 | 102.4 |
| BERTS. | 88.5   | 78.7    | 18.9 | 102.5 |
| Prob.  | 89.2   | 80.3    | 19.0 | 103.8 |

Table 4: Performance of Training from Finetuned Weights with KRLM using Different per-token Reward. None refers to the baseline of only training with LM objective.

6.2 Token-Level Reward Function Ablation

Besides our proposed token-level reward in Section 3.3 (denote as Prob. in Table 5), we additionally experiment with 4 other approaches to show its effectiveness in our algorithm.

Specifically, we experimented with swapping out Prob. with the following alternatives: Zero, which assigns a zero score to all generated tokens, hence only using the terminal reward as a signal for the model to improve; Error, which assigns a hard penalty of $-1$ whenever the generated token is incorrect; BERTS., which uses the core mechanism in BERTScore (Zhang et al., 2019a) to measure the semantic similarity between the generated tokens and the gold tokens (see Appendix B for more details); Static., which takes the static, context-unaware token embeddings from the embedding layer of GODEL-base and compute their cosine similarity as reward. In all cases, the same hyperparameters are used to make results more comparable.

We present these results in Table 4. When trained from a finetuned checkpoint, our proposed token-level reward (Prob.) outperforms all other alternatives. Interestingly, all reward functions that specified a per-token reward (i.e. Error, BERTS., Static.) achieved improvements over Zero, which only relies on the terminal reward. This indicates that a more fine-grained per-token reward function is helpful for KRLM. Additionally, Prob. improves upon Error, BERTS., and Static., because it can additionally/correctly capture the contextual information of the generated tokens in our setting. When trained from scratch, please refer to Appendix D.

Finally, it is worth mentioning that this token-level reward function is similar in spirit to the idea of label smoothing, which also intends to provide a more fine-grained control when penalizing mistakes. However, the main difference is that RL in general aims to increase the probability of highly rewarded tokens/actions and decrease the probability of making a mistake, while label smoothing approaches generally ask the model to learn according to a specific/pre-defined prior distribution. We believe that the former is more flexible as designing a reward can be much simpler and also adaptable to different tasks (Ramamurthy et al., 2022), while the latter can require significant engineering and/or expert knowledge.

7 Conclusion and Future Work

In this work, we explored an approach to utilize Reinforcement Learning to help the model focus on generating key quantities correctly. To achieve this, we designed a reward function to specify the relative importance of each token, and proposed a per-token RL scheme to help the model focus on keyword generation. Next, we combined this new RL objective with traditional LM to shorten training/exploration time, and proposed our Keywords Reinforcement Language Modeling (KRLM) training algorithm. Finally, we evaluated KRLM on the MultiWoZ dataset and showed that it can improve the overall performance of TOD models in both the inform and success rate, reaching new state-of-the-art performance on E2E response generation.

Although KRLM is faster to train compared to traditional sequence-generation based RL approaches, it does not help the model learn high-reward sequences that might not be present in the dataset. Therefore, in this aspect KRLM trades its potential to generate responses better than the dataset with its action space reduction. It would be interesting to explore if a more fine-grained trade-off can be found between the two. Additionally, in our error analysis we found that significant improvement can be achieved when the gold dialog state and/or system act is provided. This indicates that KRLM can be potentially combined with approaches aimed at improving DST and/or system.
act generation (Sun et al., 2022), to further improve the overall performance of TOD models.

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A KRLM Hyperparameters

For KRLM in MultiWoZ, we used $k = 3$, $\kappa = 0.5 \times \text{total steps per epoch}$, sampling temperature during generation of 1.1, top-p during generation of 0.5, terminal reward scale of 5, learning rate of $5 \times 10^{-5}$, learning rate decay of $0.2 \times \text{total steps in training}$, batch size of 4, and seed 42. When trained from a finetuned checkpoint, we additionally added a regularization term using KL divergence (against the baseline model) with a weighting of 0.01 for all experiments. During testing, we used greedy decoding as (Lee, 2021) for generation.

B BERTScore for KRLM

To apply BERTScore in our setting, we first treat our sampled sequence as a standalone generated sequence, and use the cosine similarity between the embedding of each pair of token $x^\text{gen}_t, x^\text{gold}_t$ after passing through a finetuned GODEL-base as rewards. Note that we naturally have a one-to-one mapping between the generated and gold sequences, we can skip the maximal similarity matching step. However, as shown in both Table 4 and Table 5, BERTS. does not perform as well as Prob.. This is because BERTScore is designed to measure the semantic similarity between two standalone sentences, while in our setting the generated sequence is conditioned on the gold response. Therefore, in cases when many generated tokens are incorrect, viewing the sampled sequence as a standalone generated sentence will distort each token’s contextual meaning, leading to sub-optimal performance.

C Effect of $\kappa$ and $\mu$ in KRLM

We empirically tested a range of $\kappa \in [0.2, 0.5, 1.0] \times \text{steps in an epoch}$, and found that, when using a $\kappa$ that is too small, the model is updated too frequently in between RL learning periods, and when $\kappa = 1.0$, keyword learning is delayed too much hence it could be difficult to achieve the “jump” in Figure 3 during early training. We will upload a table of thorough experiments on this in the future.

D Additional Reward Function Ablation

We additionally show the effect of several per-token reward functions in our KRLM algorithm when trained from scratch. As shown in Table 5, all variants using KRLM achieved improvement from baseline. Specifically, Zero reward and Prob. reward achieved the highest and second highest, with 102.2 and 102.0 as Combined Score, respectively.

| Reward | Inform | Success | BLEU | Total |
|--------|--------|---------|------|-------|
| None   | 86.0   | 77.4    | 18.9 | 100.6 |
| Zero   | 87.7   | 78.6    | 19.0 | 102.2 |
| Error  | 86.2   | 78.6    | 19.2 | 101.6 |
| BERTS. | 87.2   | 78.1    | 19.0 | 101.7 |
| Static | 87.2   | 77.6    | 19.3 | 101.7 |
| Prob.  | 87.3   | 78.3    | 19.2 | 102.0 |

Table 5: Performance of Training from Scratch with KRLM using Different per-token Reward

E KRLM Error Examples

We present three examples in Figure 6, Figure 7, and Figure 8 when KRLM trained model does not generate the required key quantities. We observe that in most cases, error originates from incorrectly generated system action and dialog state. This hints at a direction for further improvement in lines of making dialog state and system action generation more robust (Sun et al., 2022).

F Training Speed

To demonstrate the fast learning speed of KRLM as a result of incorporating LM, we compare the validation curve of KRLM and RL only in Figure 4. As shown in Figure 4, KRLM can be trained much faster than RL only. This is because the LM objective during training directly “shows” the model the
correct tokens (see Figure 2), hence reducing the exploration time of our token-level RL.

G Additional Keyword Learning Curves

In addition to comparing the keyword generation accuracy (see Section 5.1), we also show the overall generation accuracy learning curves in Figure 5. Overall generation accuracy is measured by how often a generated token $x_{t}^{\text{gen}} | x_{1:t-1}^{\text{gold}}, c$, whether it is a key token or a non-key token, matches the ground truth $x_{t}^{\text{gold}}$.

As shown in Figure 5, KRLM can achieve higher accuracy than baseline during both training and validation. We believe this is because KRLM, especially during the early stages of training, can learn both the correct normal tokens (LM) and the correct key tokens (token-level RL) as shown in Figure 3, hence achieving also an overall higher accuracy.
Figure 5: Token Generation Accuracy during Training and Validation. **Baseline** is the standard LM training algorithm. Both baseline and KRLM are trained from scratch.

Figure 6: KRLM Generation Error Example 1. Texts in black are the input context, in blue are the generated tokens, and in yellow/gold are the ground truth. Texts highlighted in red are incorrect/missing key quantities compared to the ground truth.
Figure 7: KRLM Generation Error Example 2. Texts in black are the input context, in blue are the generated tokens, and in yellow/gold are the ground truth. Texts highlighted in red are incorrect/missing key quantities compared to the ground truth.
Figure 8: KRLM Generation Error Example 3. Texts in black are the input context, in blue are the generated tokens, and in yellow/gold are the ground truth. Texts highlighted in red are incorrect/missing key quantities compared to the ground truth.