Language Models as Few-Shot Learner for Task-Oriented Dialogue Systems

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Abstract

Task-oriented dialogue systems use four connected modules, namely, Natural Language Understanding (NLU), a Dialogue State Tracking (DST), Dialogue Policy (DP) and Natural Language Generation (NLG). A research challenge is to learn each module with the least amount of samples (i.e., few-shots) given the high cost related to the data collection. The most common and effective technique to solve this problem is transfer learning, where large language models, either pre-trained on text or task-specific data, are fine-tuned on the few samples. These methods require fine-tuning steps and a set of parameters for each task. Differently, language models, such as GPT-2 (Radford et al., 2019) and GPT-3 (Brown et al., 2020), allow few-shot learning by priming the model with few examples. In this paper, we evaluate the priming few-shot ability of language models in the NLU, DST, DP and NLG tasks. Importantly, we highlight the current limitations of this approach, and we discuss the possible implication to future work.

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1 Introduction

Modularized task-oriented dialogues systems are the core of the current smart speaker generation (e.g., Alexa, Siri etc.). The main modules of such systems are Natural Language Understanding (NLU), Dialogue State Tracking (DST), Dialogue Policy (DP) and Natural Language Generation (NLG), each of which is trained separately using supervised and/or reinforcement learning. Thus a data collection process is required, which for some of the tasks can be laborious and expensive. For example, dialogue policy annotation has to be done by an expert, better by a professional linguist. Therefore, having a model that requires only few samples to actually perform well in the tasks is essential.

The most successful approach in few-shot learning for task-oriented dialogue systems is notably transfer learning, where a large model is firstly pre-trained on a large corpus to be then fine-tuned on specific tasks. For task-oriented dialogue systems, Wu et al. (2020) proposed TOD-BERT a large pre-trained model which can achieve better performance than BERT (Devlin et al., 2019) in few-shots NLU, DST and DP. Liu et al. (2020) proposed a two-step classification for few-shot slot-filling, a key task for the NLU module. Similarly, Peng et al. (2020b) introduced a benchmark for few-shot NLG and a pre-trained language model (SC-GPT) specialized for the task.
Further, a template rewriting schema based on T5 (Raffel et al., 2019) was developed by Kale and Rastogi (2020) for few-shot NLG in two well-known datasets. Peng et al. (2020a) proposed a pre-trained language model (LM) for end-to-end pipe-lined task-oriented dialogue systems. In their experiments, they showed promising few-shot learning performance in MWoZ (Budzianowski et al., 2018). Finally, several meta-learning approaches have been proposed for DP (Xu et al., 2020), NLG/ACT (Mi et al., 2019), pipelined end-to-end models (Qian and Yu, 2019) and personalized dialogue systems (Madotto et al., 2019).

For performing few-shot learning, existing methods require a set of task-specific parameters since the model is fine-tuned with few samples. Differently, in this paper, we perform few-shot learning by priming LMs with few-examples (Radford et al., 2019; Brown et al., 2020). In this setting, no parameters are updated, thus allowing a single model to perform multiple tasks at the same time. In this paper, we evaluate the few-shot ability of LM priming on the four task-oriented tasks previously mentioned (i.e., NLU, DST, DP, and NLG). Currently, GPT-3 (Brown et al., 2020) is not available to the public; thus we experiment on different sizes GPT-2 (Radford et al., 2019) models such as SMALL (117M), LARGE (762M), and XL (1.54B). All the experiments are run on a single NVIDIA 1080Ti GPU.

2 Basic Notation and Tasks

Let us define dialogue as the alternation of utterances between two speakers denoted by $U$ and $S$ respectively. An utterance is a sequence of words $X = x_1, \ldots, x_n$ and the concatenation of $t$ utterances denotes a dialogue with $\frac{t}{2}$ turns. In this paper, we focus on the four task-oriented dialogue system tasks, and we briefly introduce the input-output of each task.

NLU This task aims to extract slot-value pairs (SLOT-FILLING) and the intent (INTENT) from a user utterance $S$. In the literature, the most common approach for NLU is to learn a BIO tagger for the slot-value pairs, and to learn a multi-class classifier for the intent. SLOT-FILLING gets as input a user utterance $X$ and produces a dictionary $M = \{s_1 = v_1, \ldots, s_n = v_n\}$, where $s_i$ is a slot and $v_i$ is the possible value. Note that $v_i$ can also be None since some slots may not be mentioned in the utterance. The INTENT task gets a user utterance $X$ and classifies it into an intent class denoted by $Y \in \{y_1, \ldots, y_n\}$. Sometimes, the intent-classification is mixed with the domain classification.

DST This task extracts slot-value pairs for a given dialogue, which can be considered as a dialogue-level of the NLU. Given a dialogue with $t$ turns as a sequence of utterance $D = \{X_1^U, X_1^S, \ldots, X_t^U\}$ a DST model predicts a dictionary $M_t = \{s_1 = v_1, \ldots, s_n = v_n\}$ as in the NLU. Note that most of the existing DST models use the previously generated $M_{t-1}$ and just update the slots required using an NLU tagger.

ACT This task predicts the next speech-act (e.g., INFORM, REQUEST etc.) given the current dialogue state, in the form of a dialogue or dictionary of slot-value pairs. This is usually stated as a reinforcement learning task in both online and offline settings. In this paper, we simplify the tasks, and instead of learning a dialogue policy, we perform dialogue act classification. This is a multi-label classification task, since more than one speech-act can be used in an utterance. This task gets as input a user utterance $X$ and classifies it into a set of possible speech-acts in $I \in \{I_1, \ldots, I_n\}$.

NLG This task maps a dialogue-act, which is made of a speech-act plus a dictionary of slot-value pairs, into natural language. The model gets as input a speech-act concatenated with a slot-value dictionary overall denoted as $I(s_1 = v_1, \ldots, s_n = v_n)$ and it generates as output an utterance $X$.

In the few-shot setting, a small number of input-output pairs is provided to the model, expecting a high degree of generalization.

3 Priming the LM for few-shot learning

Differently from fine-tuning, few-shot learning with LMs requires designing prefixes to perform few-shot learning. In our four tasks, we use three categories of prefixes: binary, value-based and generative. In the following notation, we use $X$ to represent a generic input and $X_i$ for the $i$-th shot samples, thus implying that the prefix remains fixed during the inference and $X$ can become any input. These prefixes are provided to the LM and the generate tokens become the actual prediction, Figure 1 show an example of intent recognition.

Binary prefixes are used for classification (namely for intent-classification and speech-act de-
turn on the light → name=None
add to playlist kojak → name=kojak
add tune to my hype playlist → name=

yes, your booking is successful → booked=True
what type of food? → booked=False
i do not seem to be finding anything → booked=

Figure 2: Example of 1-shot LM priming for the SLOT-FILLING task and results in the task. CT, RZT, Coach are from (Liu et al., 2020) and they use 20-shots.

Figure 3: Example of 1-shot LM priming for the ACT task and results in the task. BERT and ToD-BERT are from (Wu et al., 2020) and they use 500-shots.

4 Experiments and Results

We use different prefix styles depending on the task and we compare the results of LM few-shot priming with those of the existing finetuning-base models. In all the experiments, we use different number of shots since different tasks may fit more or fewer samples in the 1024 max input size of GPT-2.

NLU We use the SNIPS (Coucke et al., 2018) dataset for evaluating the SLOT-FILLING and INTENT recognition tasks. For the SLOT-FILLING task, we follow the few-shot setting of Liu et al. (2020), and we use the official CoNLL F1 scorer as the evaluation metric. For the INTENT classification, we fine-tune RoBERTa (Liu et al., 2019) with 10 samples and use accuracy as the evaluation metric. We use a value-based LM prefix for the SLOT-FILLING task with a maximum of 15 shots, and binary LM prefix for the INTENT classification task with a maximum of 10 shots. An example of a prefix for the SLOT-FILLING task and the few-shot performance evaluation are shown in Figure 2. Table 1 and 2 and Figure 5 show more detailed results.

DST We use the MultiWoZ (Budzianowski et al., 2018; Eric et al., 2019; Zang et al., 2020) dataset for evaluating the DST task. Differently from other works, we use the last user utterance only as input to the model, and we update the predicted-DST through turns. For the few-shot evaluation,
From the experimental results, we observe that:

- The larger the model the better the performance in both the NLU and NLG tasks, while, instead, in the DST and ACT tasks, GPT-2 LARGE (762M) performs better than the XL (1.54B) version. This is quite counterintuitive given the results reported for GPT-3. Further investigation is required to understand whether changing the prefix can help to improve the performance of larger models;

- In the NLU, ACT and NLG, LM priming few-shot learning shows promising results, achieving similar or better performance than the weakest finetuning-based baseline, which also uses a larger number of shots. On the other hand, in DST the gap with the existing baseline is still large.

We also observe two limitations of the LM priming:

- Using binary and value-based generation requires as many forwards as the number of classes or slots. Although these forward passes are independent, achieving few-shot learning this way is not as effective as directly generating the class or the tag (e.g., NLU). In early experiments, we tried to covert all the tasks into a generative format, thus making the model directly generate the sequence of tags or the class label. Unfortunately, the results in the generative format were poor, but we are unsure if larger LMs such as GPT-3 can perform better.

- The current max-input length of GPT-2 (1024 tokens) greatly limits the number of shots that can be provided to the model. Indeed, in most of the tasks, no more than 15 shots can be provided, thus making it incomparable with existing models that use a larger number of shots.
6 Conclusion

In this paper, we demonstrate the potential of LM priming few-shot learning in the most common task-oriented dialogue system tasks (NLU, DST, ACT and NLG). Our experiments show that in most of the tasks larger LMs are better few-shot learners, confirming the hypothesis in Brown et al. (2020) and, in some cases, they can also achieve similar or better results than the weakest finetuning-based baseline. Finally, we unveil two limitations of the current LM priming few-shot learning the computational cost and the limited word context size. In future work, we plan to benchmark dialogue-specific models (e.g., DialGPT) and LM with longer context size (e.g., Transformer XL (Dai et al., 2019), LongFormer (Beltagy et al., 2020), and BigBird (Zaheer et al., 2020) etc.). We also plan to investigate adversarial triggers (Wallace et al., 2019) for improving the few-shot ability of LMs, and to benchmark end-to-end dialogue tasks.

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A Appendices
**SLOT-FILLING**

- add tune to my hype playlist → entity.name = None
- add to playlist confidence boost here comes → entity.name = here comes
- add the track bg knocc out to the rapcaviar playlist → entity.name =

**INTENT**

- listen to westbam alumb allergic on google music → playmusic = true
- rate this novel 4 points out of 6 → playmusic = false
- add sabrina salerno to the grime instrumentals playlist → playmusic =

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**Figure 5:** Example of 1-shot LM priming for the SLOT-FILLING and INTENT task and results in the task. CT, RZT, and Coach are from Liu et al. (2020) and they use 20-shots.

- i need a cab by 12:30 too → leave_at = 12:30
- i would like the taxi to pick me up from the hotel → leave_at = None
- i would like a taxi from saint john s college → leave_at =

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**Figure 6:** Example of 1-shot LM priming for the DST task and results in the task. BERT and ToD-BERT are from Wu et al. (2020) and they use 500 shots.
yes your booking is successful and your reference number is ri4vvzyc . → offerbooked=True
what type of food are you looking for ? → offerbooked=False
i do not seem to be finding anything → offerbooked=

Figure 7: Example of 1-shot LM priming for the ACT task and results in the task. BERT and ToD-BERT are from Wu et al. (2020) and they use 500 shots.

inform(name=hilton;area=chinatown)→the hilton is near chinatown
inform(name=ocean park;phone=4155667020)→the phone number for ocean park is 4155667020.
inform(name=super 8 san francisco;phone=8005369326)→

Figure 8: Example of 1-shot LM priming for the NLG task and results in the task. SC-LSTM, GPT-2, and SC-GPT-2 are from Peng et al. (2020b). BLEU the higher the better; SLOT ERROR RATE the lower the better.
Table 1: Results in terms of CoNNL F1-score for the SLOT-FILLING task.

| Model     | Shots | PlayL | Rest. | Weather | PlayM. | RateBook | SearchC. | Find. | Avg  |
|-----------|-------|-------|-------|---------|--------|----------|----------|-------|------|
| gpt2      | 1     | 31.90 | 8.03  | 16.41   | 32.81  | 43.60    | 20.49    | 24.49 | 25.39|
| gpt2      | 10    | 46.25 | 21.67 | 19.19   | 21.47  | 56.22    | 38.03    | 41.72 | 34.93|
| gpt2      | 15    | 54.74 | 26.46 | 17.73   | 28.34  | 63.84    | 41.39    | 47.05 | 39.39|
| gpt2-large| 1     | 54.75 | 39.44 | 23.52   | 20.88  | 38.36    | 26.66    | 43.06 | 35.23|
| gpt2-large| 10    | 71.66 | 39.29 | 27.73   | 48.19  | 61.45    | 44.47    | 53.84 | 49.52|
| gpt2-large| 15    | 71.65 | 45.51 | 30.79   | 46.34  | 61.79    | 37.16    | 47.05 | 33.94|
| gpt2-xl   | 1     | 53.82 | 26.21 | 23.16   | 28.76  | 43.06    | 35.23    | 67.09 | 55.19|
| gpt2-xl   | 10    | 70.47 | 40.50 | 34.71   | 40.47  | 74.39    | 52.05    | 64.41 | 53.86|
| gpt2-xl   | 15    | 67.94 | 46.98 | 30.84   | 44.46  | 77.15    | 51.87    | 67.09 | 55.19|

Table 2: Results in terms of F1-score (Micro and Macro) and Accuracy in the INTENT recognition task.

| Model     | Shots | Micro | Macro | Acc  |
|-----------|-------|-------|-------|------|
| gpt2      | 1     | 0.16  | 0.16  | 16.00|
| gpt2      | 2     | 0.17  | 0.11  | 16.71|
| gpt2      | 5     | 0.34  | 0.32  | 34.29|
| gpt2      | 10    | 0.36  | 0.37  | 36.00|
| gpt2-large| 1     | 0.13  | 0.12  | 13.43|
| gpt2-large| 2     | 0.38  | 0.39  | 37.86|
| gpt2-large| 5     | 0.33  | 0.32  | 33.00|
| gpt2-large| 10    | 0.55  | 0.58  | 55.14|
| gpt2-xl   | 1     | 0.17  | 0.14  | 17.00|
| gpt2-xl   | 2     | 0.36  | 0.32  | 35.86|
| gpt2-xl   | 5     | 0.47  | 0.44  | 46.71|
| gpt2-xl   | 10    | 0.73  | 0.75  | 73.00|

Table 3: Results in terms of F1-score (Micro and Macro) and Accuracy in the ACT detection task.

| Model     | Shots | Joint | Slot  |
|-----------|-------|-------|-------|
| gpt2      | 5     | 0.7   | 79.8  |
| gpt2      | 10    | 0.8   | 78.7  |
| gpt2      | 15    | 0.6   | 79.7  |
| gpt2-large| 5     | 2.5   | 82.7  |
| gpt2-large| 10    | 2.6   | 83.2  |
| gpt2-large| 15    | 3.5   | 83.5  |
| gpt2-xl   | 5     | 2.2   | 81.4  |
| gpt2-xl   | 10    | 2.1   | 80.4  |
| gpt2-xl   | 15    | 2.0   | 81.8  |

Table 4: Results in terms of Joint and Slot Accuracy in the DST task.
Table 5: Results in terms of BLEU score for the NLG task. SC-LSTM, GPT-2, and SC-GPT-2 are from Peng et al. (2020b).

| Model      | Shots | Shots | restaurant | laptop | hotel | tv | attraction | train | taxi | Avg   |
|------------|-------|-------|------------|--------|-------|----|------------|-------|------|-------|
| SC-LSTM    | 50    | 15.90 | 21.98      | 31.30  | 22.39 | 7.76 | 6.08       | 11.61 | 16.71|
| GPT-2      | 50    | 29.48 | 27.43      | 35.75  | 28.47 | 16.11| 13.72      | 16.27 | 23.89|
| SC-GPT     | 50    | 38.08 | 32.73      | 38.25  | 32.95 | 20.69| 17.21      | 19.70 | 28.51|
| sc-gpt     | 5     | 9.93  | 17.75      | 14.85  | 16.29 | 5.50 | 0.26       | 5.01  | 9.94 |
| gpt2       | 10    | 8.10  | 17.75      | 16.85  | 16.29 | 5.84 | 1.30       | 4.71  | 10.12|
| gpt2       | 20    | 10.68 | 17.75      | 19.15  | 16.29 | 4.89 | 3.24       | 7.28  | 11.32|
| gpt2-large | 5     | 10.60 | 24.42      | 13.92  | 24.58 | 7.38 | 0.73       | 7.86  | 12.78|
| gpt2-large | 10    | 13.10 | 24.42      | 20.68  | 24.58 | 6.68 | 3.18       | 6.25  | 14.13|
| gpt2-large | 20    | 11.47 | 24.42      | 16.13  | 24.58 | 7.97 | 5.30       | 9.36  | 14.18|
| gpt2-xl    | 5     | 13.65 | 23.39      | 14.26  | 26.61 | 6.96 | 0.74       | 6.59  | 13.17|
| gpt2-xl    | 10    | 14.51 | 23.39      | 19.42  | 26.61 | 8.21 | 4.00       | 6.40  | 14.65|
| gpt2-xl    | 20    | 17.02 | 23.39      | 21.30  | 26.61 | 6.43 | 5.68       | 9.06  | 15.64|

Table 6: Results in terms of SLOT ERROR RATE for the NLG task. SC-LSTM, GPT-2, and SC-GPT-2 are from Peng et al. (2020b).

| Model      | Shots | Shots | restaurant | laptop | hotel | tv | attraction | train | taxi | Avg   |
|------------|-------|-------|------------|--------|-------|----|------------|-------|------|-------|
| SC-LSTM    | 50    | 48.02 | 80.48      | 31.54  | 64.62 | 367.12| 189.88     | 61.45 | 120.44|
| GPT-2      | 50    | 13.47 | 11.26      | 11.54  | 9.44  | 21.10| 19.26      | 9.52  | 13.65|
| SC-GPT     | 50    | 3.89  | 3.39       | 2.75   | 3.38  | 12.72| 7.74       | 3.57  | 5.35 |
| sc-gpt     | 5     | 60.48 | 60.84      | 73.63  | 72.66 | 81.79| 60.54      | 66.67 | 68.09|
| gpt2       | 10    | 72.75 | 60.84      | 78.02  | 72.66 | 80.49| 88.75      | 59.52 | 73.29|
| gpt2       | 20    | 70.36 | 60.84      | 74.18  | 72.66 | 67.20| 68.96      | 55.95 | 67.16|
| gpt2-large | 5     | 55.39 | 36.33      | 84.62  | 44.02 | 64.31| 58.11      | 44.05 | 55.26|
| gpt2-large | 10    | 57.49 | 36.33      | 62.09  | 44.02 | 52.31| 73.27      | 25.00 | 50.07|
| gpt2-large | 20    | 48.20 | 36.33      | 85.71  | 44.02 | 56.07| 61.35      | 32.14 | 51.98|
| gpt2-xl    | 5     | 44.61 | 29.99      | 67.03  | 37.92 | 67.63| 55.82      | 44.05 | 49.58|
| gpt2-xl    | 10    | 46.41 | 29.99      | 47.80  | 37.92 | 50.87| 62.36      | 22.62 | 42.57|
| gpt2-xl    | 20    | 44.61 | 29.99      | 68.68  | 37.92 | 56.50| 52.93      | 30.95 | 45.94|