Guiding Large Language Models via Directional Stimulus Prompting

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Abstract

We introduce a new framework, Directional Stimulus Prompting, that uses a tuneable language model (LM) to provide guidance for the black-box frozen large language model (LLM) on downstream tasks. Unlike prior work that manually or automatically finds the optimal prompt for each task, we train a policy LM to generate discrete tokens as "directional stimulus" of each input, which is a hint/cue such as keywords of an article for summarization. The directional stimulus is then combined with the original input and fed into the LLM to guide its generation toward the desired target. The policy LM can be trained through 1) supervised learning from annotated data and 2) reinforcement learning from offline and online rewards to explore directional stimulus that better aligns LLMs with human preferences. This framework is flexibly applicable to various LMs and tasks. To verify its effectiveness, we apply our framework to summarization and dialogue response generation tasks. Experimental results demonstrate that it can significantly improve LLMs' performance with a small collection of training data: a T5 (780M) trained with 2,000 samples from the CNN/Daily Mail dataset improves Codex (175B)'s performance by 9.0% in ROUGE-Avg scores; only 80 dialogues can boost the combined score by 39.7%, achieving comparable or even better performance than some fully trained models on the MultiWOZ dataset. We have made our code publicly available. ³

1 Introduction

The past few years have witnessed the emergence of a new paradigm in natural language processing (NLP), with the Large Language Models (LLMs) (GPT-3 (Brown et al., 2020), Codex (Chen et al., 2021), PaLM (Chowdhery et al., 2022), etc) demonstrating superior performance over previously relatively small Language Models (LMs) (BERT (Kenton & Toutanova, 2019), GPT-2 (Radford et al., 2019), T5 (Raffel et al., 2020), etc) on a wide range of NLP tasks. Different from the conventional fine-tuning paradigm where the parameters of LMs can be updated for each downstream task, prompting is the de facto way of utilizing LLMs to perform diverse tasks (Brown et al., 2020; Chowdhery et al., 2022; Liu et al., 2023) by using natural language instructions in the context to steer the LLMs to produce desired outputs without parameter updates.

Although this prompting schema has enabled LLMs to achieve remarkable success on diverse tasks under the zero-shot or few-shot setting, their performance is still far from satisfactory and needs

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³https://github.com/Leezekun/Directional-Stimulus-Prompting.

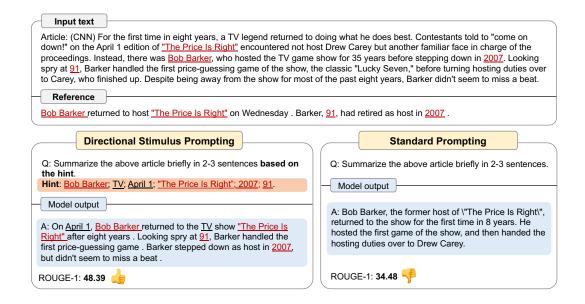


Figure 1: Comparison of our proposed Directional Stimulus Prompting with the standard prompting method to use the LLM such as GPT-3 on the summarization task. Our DSP uses a tuneable policy LM to generate the stimulus (highlighted in orange color), which is keywords in this case, to guide the LLM on generating the desired summary (highlighted in blue color) with higher rouge scores or other measures like human preference.

further improvement on some specific downstream tasks (Goyal et al., 2022; Moradi et al., 2021; Gutiérrez et al., 2022), especially when training data is available. However, directly optimizing these LLMs is not feasible for most users and researchers, as most LLMs only provide black-box inference APIs and are extremely costly to fine-tune. Therefore, how to efficiently improve LLMs' performance on specific downstream tasks, often with a few training examples, is a challenging problem that remains to be solved.

In this paper, we propose a framework *Directional Stimulus Prompting* (DSP) that uses a small tuneable LM to improve the frozen black-box LLM on downstream tasks with reinforcement learning (RL). Specifically, for each input text, a small LM (called policy LM) learns to generate a sequence of discrete tokens as *directional stimulus* (hints/cues for the question⁴), which could provide specific information or guidance on the input sample instead of a general prompt for the task. The generated stimulus is then combined with the original input and fed into the LLM to guide its generation toward the specific target, such as higher performance measure scores. To achieve that, we first perform supervised fine-tuning (SFT) with a pre-trained LM (e.g., T5) using a few collected training examples. The finetuned LM is then used to initialize the policy LM in RL and be further optimized to explore better stimulus. The training objective is to maximize the reward, which is defined as the downstream performance measure scores of the LLM's generation conditioned on stimulus generated by the policy LM. An example of the summarization task is shown in Figure 1. Keywords serve as the stimulus (hints) to guide the LLM to generate the desired summary based on the keywords. Evaluation metric scores such as ROUGE (Lin, 2004) can be used as the reward to optimize the policy LM, encouraging it to generate keywords that guide the LLM to generate better summaries.

Our proposed framework is based on the intuition that although LLMs possess great generation abilities, they often exhibit undesirable behaviors and thus require fine-grained guidance on the desired generation property and direction for specific downstream tasks. The small policy LM, although not powerful enough to generate human-like texts, is capable to generate a sequence of tokens as directional stimulus to provide the LLM sample-wise fine-grained guidance toward the desired target. RL offers a natural solution to bridge the gap between the optimized object (e.g., the small policy

⁴The inference process that LLMs generate an output/completion given the input can be seen as answering a question, where the input is the "question" while the output is LLMs' "answer". The *directional stimulus* refers to a hint/cue for the question, which is used to provide guidance for LLMs towards a specific answer. We use the terms "stimulus" and "hint" interchangeably in this paper.

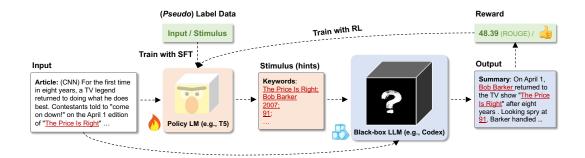


Figure 2: Overview of our proposed framework DSP, which learns a small policy LM to improve the frozen LLM's performance on specific downstream tasks. Given the input, the policy LM generates stimulus to guide the LLM's generation, which is then evaluated with downstream performance measures or human labelers. The evaluation scores are used as rewards to optimize the policy LM with RL. The parameters of LLM are frozen while the policy LM is tuneable.

LM that generates stimulus) and the optimization objective, which is defined on the generation of the LLM. Unlike prior studies that find optimal prompts via prompt engineering/optimization (Shin et al., 2020; Zhou et al., 2022; Deng et al., 2022; Prasad et al., 2022), which is trying to explain the "question" more clearly. our approach tries to provide "hints" or "cues" for each "question". It is also different from chain-of-though prompting (Wei et al., 2022) that encourages the LLM to generate intermediate reasoning steps by itself when solving reasoning tasks. Our approach uses a small tuneable model to control and guide the LLM, and is targeting on the generation tasks where there is not only one correct "answer".

We evaluate our framework on summarization and dialogue response generation tasks. We conduct experiments with the 175B Codex (Chen et al., 2021) as the LLM and use the 750M Flan-T5-large (Raffel et al., 2020; Chung et al., 2022) to initialize the policy LM. Experimental results show that Codex's performance significantly improves on downstream tasks when conditioned on the hints generated by the tuned T5. Specifically, for the summarization task, keywords that the summary should include are used as directional stimulus. T5 trained with 2,000 samples from CNN/Daily Mail dataset (Nallapati et al., 2016) can already improve Codex's performance by 9.0% in ROUGE-Avg score. As for the dialogue response generation task, we train the policy LM to generate dialog acts that define the intended meaning behind target responses on dialogues from MultiWOZ dataset (Budzianowski et al., 2018). Guided by the policy LM that was trained using only 80 dialogues, Codex's performance has improved by 39.7% in combined scores and achieves comparable or even better performance than previous methods trained with the full training dataset of 8438 dialogues.

2 Methods

We present Directional Stimulus Prompting (DSP), a framework that learns a policy LM to generate directional stimulus prompts for the black-box frozen LLM, guiding it to generate texts that better align with downstream tasks or human preferences. The policy LM is optimized with SFT and RL by minimizing the rewards defined as evaluation scores of the LLM's generation conditioned on the generated stimulus. The overview of DSP is presented in Figure 2.

2.1 Directional stimulus prompting

For a downstream task, there is an input space X, a data distribution \mathcal{D} over X, and an output space Y. It has been shown that given the input x and some demonstrations, the LLM can directly perform diverse tasks and generate the output without parameter update. We assume there exists a small piece of discrete tokens z named "stimulus" that could provide the LLM hints on generating output that better aligns with human preference or task requirements. For example, for the summarization task, the input x is an article, and the output y is the corresponding summary. Keywords that the desired summary should include could be a type of stimulus z that steers the LLM to generate better summaries. We use a policy LM $p_{\text{PLM}}(z|x)$ to generate such stimulus for each given input

 $m{x}$. Given the generated stimulus $m{z}$ and the original input $m{x}$, the LLM can generate its output $m{y}$ using its frozen generative distribution $p_{\rm LLM}(m{y}|m{x},m{z})$. Therefore, when we use the LLM with Directional Stimulus Prompting (DSP) to perform a downstream task, the output is obtained via $m{y} \sim p_{\rm LLM}(\cdot|m{x},m{z}), m{z} \sim p_{\rm PLM}(\cdot|m{x})$.

2.2 Supervised fine-tuning

To learn such a policy LM to generate stimulus for the LLM, we first perform supervised fine-tuning (SFT) on a pre-trained LM (e.g., T5, GPT-2, etc) on a small collection of annotated data. To collect the data, we could heuristically select the "pseudo-stimulus" z^* for each input x based on different downstream tasks: we use keywords in the target summary as pseudo-stimulus for the summarization task and dialog acts that indicate the intended meaning of the desired system response for the dialogue response generation task (see Section 3 for details). The obtained dataset $\mathcal{D}' = \{(x, z^*)\}$ consists of input-stimulus pairs. We then fine-tune the policy LM by maximizing the log-likelihood:

$$\mathcal{L}_{SFT} = -\mathbb{E}_{(\boldsymbol{x}, \boldsymbol{z}^*) \sim \mathcal{D}'} \log p_{\text{PLM}}(\boldsymbol{z}^* | \boldsymbol{x}). \tag{1}$$

Supervised fine-tuning can provide a good starting point for the policy LM. However, there is no guarantee that the heuristically selected pseudo-stimulus is optimal and the supervised fine-tuned policy LM could generate the stimulus that leads to the desired LLM generation. Therefore, we further fine-tune the policy model using RL to directly optimize the LLM's generation.

2.3 Reinforcement learning

Optimization objective Our goal is to improve the LLM's generation, i.e., maximizing some measures \mathcal{R} of the LLM's generation y. The measure \mathcal{R} could be downstream task performance measures (e.g., the ROUGE score for summarization), human preferences, or quality measures like diversity, fluency, naturalness, etc. Mathematically, we aim to maximize the below objective:

$$\mathbb{E}_{\boldsymbol{x} \sim \mathcal{D}, \boldsymbol{z} \sim p_{\text{PLM}}(\cdot | \boldsymbol{x}), \boldsymbol{y} \sim p_{\text{LLM}}(\cdot | \boldsymbol{x}, \boldsymbol{z})} [\mathcal{R}(\boldsymbol{x}, \boldsymbol{y})]. \tag{2}$$

Since the parameters of the LLM are frozen, we turn to tune the policy LM to generate optimal stimulus that maximizes the objective. We can cast the measure \mathcal{R} on the LLM's generation y conditioned on the generated stimulus z to another measure \mathcal{R}_{LLM} directly on z, where the LLM serves as an evaluation function. Specifically, the optimization objective in Equation 2 can be rewritten as:

$$\max_{p_{\text{PLM}}} \mathbb{E}_{\boldsymbol{x} \sim \mathcal{D}, \boldsymbol{z} \sim p_{\text{PLM}}(\cdot | \boldsymbol{x})} [\mathcal{R}_{\text{LLM}}(\boldsymbol{x}, \boldsymbol{z})], \tag{3}$$

where $\mathcal{R}_{\text{LLM}}(\boldsymbol{x}, \boldsymbol{z}) = \mathcal{R}(\boldsymbol{x}, \boldsymbol{y}), \boldsymbol{y} \sim p_{\text{LLM}}(\cdot | \boldsymbol{x}, \boldsymbol{z}).$

RL formulation However, the above optimization is intractable for the policy LM. To address the issue, we formulate the policy LM optimization as an RL problem and employ proximal policy optimization (PPO) (Schulman et al., 2017). We use the policy LM to initialize a policy network $\pi_0 = p_{\text{PLM}}$ and then update π using PPO. The process that generates a sequence of tokens as stimulus z can be seen as a Markov decision process (MDP) $\langle \mathcal{S}, \mathcal{A}, r, \mathcal{P} \rangle$ with a state space \mathcal{S} , action space \mathcal{A} , reward function r, and state-transition probability \mathcal{P} . At time step t of an episode, the agent selects an action (token) from the vocabulary \mathcal{V} according to the distribution of the current policy network $\pi(z|x,z_{< t})$. The episode ends when an end-of-sequence token is selected, and the stimulus z is generated. We can fine-tune the policy network π by optimizing the reward r:

$$\mathbb{E}_{\pi}[r] = \mathbb{E}_{\boldsymbol{x} \sim \mathcal{D}, \boldsymbol{z} \sim \pi(\cdot | \boldsymbol{x})}[r(\boldsymbol{x}, \boldsymbol{z})]. \tag{4}$$

Reward function Recall that our goal is to maximize the objective in Equation 3, which can be used as the reward r. To keep the policy network π from moving too far from the initial policy LM p_{PLM} , we also add a KL-divergence penalty reward. Therefore, the final reward is:

$$r(x, z) = \mathcal{R}_{\text{LLM}}(x, z) - \beta \log \frac{\pi(z|x)}{p_{\text{PLM}}(z|x)},$$
 (5)

$$\mathcal{R}_{\text{LLM}}(\boldsymbol{x}, \boldsymbol{z}) = \mathcal{R}(\boldsymbol{x}, \boldsymbol{y}), \boldsymbol{y} \sim p_{\text{LLM}}(\cdot | \boldsymbol{x}, \boldsymbol{z}). \tag{6}$$

Following (Ziegler et al., 2019; Ramamurthy et al., 2022), we dynamically adapt the coefficient β during training:

$$e_t = \text{clip}\left(\frac{\text{KL}(\pi_t, p_{\text{PLM}}) - \text{KL}_{\text{target}}}{\text{KL}_{\text{target}}}, -0.2, 0.2\right), \tag{7}$$

$$\beta_{t+1} = \beta_t \left(1 + K_\beta \mathbf{e}_t \right). \tag{8}$$

To explore the action space and find the optimal stimulus, we sample tokens with the policy network during training. After the training is finished, we use the beam search decoding method for inference, in order to generate deterministic stimulus.

Implementation We use the NLPO version of PPO from (Ramamurthy et al., 2022) in this work, which is specifically designed for optimizing language generators. To address the issue of large action spaces in PPO, NLPO learns to mask out less relevant tokens in the vocabulary, which is achieved via top-p sampling: restricts action space to the smallest set of tokens whose cumulative probability is greater than the given probability parameter p. We set it as 0.9 in our experiment. The policy network π and value network that estimates values for actions are both initialized from the supervised fine-tuned policy LM $p_{\rm PLM}$, except that the final layer of the value network is randomly initialized with a regression head to output a scalar value.

3 Experiments

Our proposed framework DSP can be flexibly applied to various types of LMs and generation tasks. In this paper, we evaluate DSP on the summarization and dialogue response generation tasks in the few-shot setting. We use a 780M parameter version of pre-trained Flan-T5 (Raffel et al., 2020; Chung et al., 2022)⁵ to initialize the policy LM and the 175B parameter Codex (*code-davinci-002*)⁶ as the LLM.

3.1 Summarization

Summarization is an important task in NLP. Recent work (Goyal et al., 2022) found that although LLMs such as GPT-3 are able to generate high-quality summaries in the zero- and few-shot prompting, their benchmark results fall behind fine-tuned methods, meaning that the summaries generated by GPT-3 fail to match the distribution of desired summaries very well. In this work, we use a few training data to improve Codex's performance on the benchmark dataset.

Dataset and evaluation We focus on the classic benchmark domain of news summarization and experiment on the widely-used CNN/Daily Mail dataset. We use 1,000, 2,000, and 4,000 out of the 287113 article-summary pairs from the training set as the training data, respectively. Following (Goyal et al., 2022; Suzgun et al., 2022), we use a subset of 500 pairs for validation and another 500 pairs for testing, which is proven to provide sufficient statistical power (Card et al., 2020) while keeping the cost of Codex evaluation low. We report the average score of ROUGE-1, 2, and L over 3 times of inferences with the temperature of 0.7 and top_p as 1.0. When using Codex to do inference with standard prompting and our approach DSP, the used prompts contain the same 3 demonstration examples, except that the prompts used by DSP also contain keywords for these 3 demonstrations. The used prompts are given in Figures 5 and 6 in the Appendix C.

Supervised fine-tuning details Keywords are used as the pseudo-stimulus to train the policy LM with supervised fine-tuning as discussed in Section 2.2. Specifically, we use textrank (Mihalcea & Tarau, 2004; Barrios et al., 2016)⁷ to automatically extract the keywords in the summary and only keep those that also appear in the corresponding article. Therefore, we can obtain a list of extracted keywords for each article-summary pair in the dataset. We convert them into a sentence with a split token ";" to serve as the stimulus, whose format is "[Keyword1]; [Keyword2]; ...; [KeywordN].". We use the constructed article-stimulus pairs to train the policy LM via supervised fine-tuning. The

⁵https://huggingface.co/google/flan-t5-large

⁶https://openai.com/api/

⁷https://github.com/summanlp/textrank



Figure 3: Performance comparison of Codex with standard prompting (original Codex) and our proposed DSP trained with SFT or SFT+RL, given varying numbers of training samples on the CNN/Daily Mail dataset.

input format is "Extract the keywords: [Article]", while the output is the target stimulus. The policy LM was trained for 10 epochs until the validation loss didn't decrease in consecutive 1000 steps. The learning rate is 2×10^{-5} .

RL training details As we aim to improve the benchmark performance, we use the ROUGE score as the measure of Codex's generation. Specifically, we use the ROUGE-Avg score between the reference summary and the LLM's generation as the reward with a coefficient of 0.1 for rescaling. We generate four outputs per input using the Codex with a temperature of 0.7 and use the average reward to reduce variance. In addition to the reward at the end of the episode, we also add a step-wise reward. During each episode, the policy LM generates a sequence of keywords, split by the token ";". When the current action is the split token ";", a new keyword is generated. We assign a reward of 1 if the keyword is within the target summary; otherwise, a penalty reward of -0.25. We train the policy network for 102k episodes, 5 epochs per batch with a batch size of 8 and a learning rate of 2×10^{-6} . The KL_{target} and β_0 in Equation 7 are set as 0.5 and 0.005, respectively.

Results We compare Codex's performance with standard prompting (original Codex) and our approach DSP trained with SFT or SFT+RL on varying sizes of training data. The results are presented in Figure 3. The stimulus generated by the supervised fine-tuned policy LM brings marginal improvement to the Codex's performance. Besides, with increasing training data, we didn't observe a significant upward trend in the performance gain, which suggests that the supervised fine-tuning is not enough for training policy LM to learn to generate good stimulus with the log-likelihood objective in the low-resource setting. However, after further fine-tuning the policy LM with RL, the performance improves significantly, proving that RL fine-tuning can encourage the stimulus LM to explore better

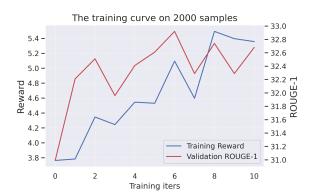


Figure 4: Training curve on 2000 samples from the CNN/Daily Mail dataset.

stimulus. Specifically, with only 4000 samples, the ROUGE-1, 2, and L scores have already improved by 6.86%, 15.18%, and 9.81%, respectively. Figure 4 presents the change of training rewards and ROUGE-1 score on the validation set during the training process on 2,000 samples. We can see that the performance is closely related to the training rewards, and the training is relatively stable using the NLPO algorithm.

We provide an example of the summaries generated by Codex with different prompting methods in Table 5 in Appendix B. It can be observed that the generated stimulus could indeed provide some hints on what the target summary should include. However, there are also a few generated keywords that are not included in the target. We attribute this to the low quality of the currently used automatically

collected dataset, which contains unimportant keywords. We believe further cleaning the dataset with human annotation could lead to better performance.

3.2 Dialog response generation

There are mainly two types of studied dialogue systems: chit-chat (open-domain) dialogue systems and task-oriented dialogue systems (TOD). The former is designed to engage with users on a wide range of topics without a specific goal or task, which LLMs are usually proficient at. The latter, on the other hand, are designed to assist users in completing specific tasks, such as making reservations, ordering food, and so on. They typically should follow a pre-defined conversation flow and respond based on information such as database query results. There has been work that utilizes the in-context learning ability of LLMs to deal with dialogue state tracking, a sub-task in task-oriented dialogue systems (Hu et al., 2022). However, it is proven that LLMs such as ChatGPT perform poorly in generating system responses that follow the conversation business flow (Bang et al., 2023). Li et al. (2022) use GPT-3 to generate the task-oriented dialogue dataset to develop small TOD models. In this work, we use a small policy model to control the LLM, guiding it to generate better system responses.

Dataset and evaluation We evaluate the dialogue response generation task on the popular taskoriented dialog dataset MultiWOZ (Budzianowski et al., 2018). We experiment on both the Multi-WOZ2.0 (the original version) and MultiWOZ2.1 version (Eric et al., 2019). The annotations of user utterances, dialog acts, and system responses for each turn of dialogues are provided. The task is to generate the system response given the dialogue context consisting of the history user utterances and system responses. The dialog act indicates the intended meanings of the corresponding system response. We thus use the dialog acts as stimulus in our experiment. There are 8,438 dialogues in the training set. We only use 1% (80 dialogs), 5% (400 dialogs), and 10% (800 dialogs) of the training data to train the policy LM and evaluate the performance on the full validation and test set, which both contain 1,000 dialogues. We use the evaluation metrics: **Inform**, which measures the rate that the appropriate entity that satisfies the user's requirements is provided; Success, which measures the rate that all the requested attributes are answered; BLEU: the corpus-level BLEU score with reference system responses; and an overall measure **Combined score** = (Inform+Success)×0.5+BLEU. Likewise, we report the average score over three inferences. We use the same three demonstration examples for Codex when using DSP or standard prompting. The prompts used by DSP also contain the stimulus (dialog acts) for these three demonstrations. We provide the used prompts of standard prompting and DSP in Figures 7 and 8 in Appendix C.

Supervised fine-tuning details To perform supervised fine-tuning, the input of each sample is formatted as "*Translate dialogue to dialogue action: [Dialog context]*". The target is the verbalized dialog acts in the same format as in (Zhang et al., 2020b; Su et al., 2021). For example, "[hotel] [inform] choice type [request] area" means that the response should inform the available choices and their types of the hotel and ask for the area that the user would like (see Table 6 for an example). We perform supervised fine-tuning with the policy LM 50 and 10 epochs on the 1% (80 dialogues) and 10% (800 dialogues) of the training dataset with the learning rate of 2×10^{-5} , respectively. The training was early stopped if the validation loss didn't decrease in consecutive 1000 steps.

RL training details The evaluation metrics Success and Inform rates are defined at the dialogue level, while the BLEU score is computed on the corpus level. However, our training and inference on conducted on the turn level. We thus use the sentence-level SacreBLEU (Post, 2018) score as the reward. Same as in the summarization experiments, we generate four outputs per input using the LLM with a temperature of 0.7. The policy network is trained 26k episodes, 5 epochs per batch with a batch size of 8 and a learning rate of 2×10^{-6} . Since the generated dialogue acts should be in the correct format so that they can be parsed and understood, the updated policy network should not deviate too far from the original policy LM. We thus set the KL_{target} and β_0 in Equation 7 are set as 0.2 and 0.01, respectively. During training, we use top-k sampling and set k as 50 to explore the action space. When doing inference, we use beam search decoding with a beam size of 5.

Results Likewise, we investigate the influence of our approach DSP on Codex. We also compare with multiple representative task-oriented dialogue models which are trained on the full training set (8438 dialogues), including DAMD (Zhang et al., 2020b), LABES-S2S (Zhang et al., 2020a), MinTL (Lin et al., 2020), Soloist (Peng et al., 2021), SimpleTOD (Hosseini-Asl et al., 2020),

Table 1: Response generation performance of different methods on the MultiWOZ 2.0&2.1 datasets, where Succ. and Comb. denote the Success and Combined Score metrics, respectively.

Method	MultiWOZ 2.0			MultiWOZ 2.1				
	Inform	Succ.	BLEU	Comb.	Inform	Succ.	BLEU	Comb.
		No tre	aining					
Codex w/ standard prompting	76.7	41.5	7.7	66.8	74.2	41.9	7.8	65.9
	1% of to	raining de	ata (80 dial	logues)				
DSP w/ SFT	74.9	66.3	11.1	81.7	72.0	66.0	11.3	80.1
DSP w/ SFT+RL	91.0	76.0	9.8	93.3	89.7	78.6	9.4	93.4
	10% of to	raining de	ıta (800 die	alogues)				
DSP w/ SFT	79.4	71.9	11.3	87.0	72.0	67.0	13.1	82.6
DSP w/ SFT+RL	96.0	86.9	10.7	102.2	94.0	86.0	9.2	99.2
	Full tra	ining date	ı (8438 dia	logues)				
DAMD (Zhang et al., 2020b)	76.3	60.4	16.6	85.0	-	-	-	-
LABES-S2S (Zhang et al., 2020a)	-	-	-	-	78.1	67.1	18.3	90.8
MinTL (Lin et al., 2020)	84.9	74.9	17.9	97.8	-		-	-
Soloist (Peng et al., 2021)	85.5	72.9	16.5	95.7	-	-	-	-
SimpleTOD (Hosseini-Asl et al., 2020)	84.4	70.1	15.0	92.3	85.0	70.5	15.2	93.0
DoTS (Jeon & Lee, 2021)	86.6	74.1	15.1	95.5	86.7	74.2	15.9	96.3
PPTOD (Su et al., 2021)	89.2	79.4	18.6	102.9	87.1	79.1	19.2	102.3
UBAR (Yang et al., 2021)	95.4	80.7	17.0	105.1	95.7	81.8	16.5	105.3
GALAXY (He et al., 2022)	94.4	85.3	20.5	110.4	95.3	86.2	20.0	110.8

DoTS (Jeon & Lee, 2021), PPTOD (Su et al., 2021), UBAR (Yang et al., 2021), and GALAXY (He et al., 2022). The overall performance comparison is shown in Table 1, from which we obtain the following observations: (1) With our proposed approach DSP, Codex's performance significantly improves on Success and Inform rate, proving that Codex can better understand the scenario and generate the response that follows the business flow. However, there is no performance gain observed on the BLEU score, which we believe is because Codex doesn't see any oracle system response and, thus responds in different speaking styles. However, it did well in helping the users and giving useful responses considering the high Success and Inform rates. (2) Training the LM with supervised fine-tuning on increasing numbers of training samples doesn't guarantee performance gain. However, using RL to further fine-tune the LM can consistently provide further improvement, which is also observed in the summarization experiments. (3) Using only 80 dialogues, our approach has already boosted Codex's performance to surpass several fully trained models, especially the Success and Inform rates. With 10% of the training data (800 dialogs), the performance is comparable to the current SOTA methods. Considering that our approach does not require a large amount of annotated data or updating LLMs, we believe it will have significant advantages in practical application. We provide an example of the generated system response and the corresponding stimulus (dialog acts) of different methods in Table 6 in Appendix B. We can see that the LLM should generate the response based on the backend information, such as the query result indicating whether there exists an entity that satisfies the user's requirement in this example.

4 Related work

Black-box large language models Recent years have witnessed the emergence of Large language models such as GPT-3 (Brown et al., 2020), Codex (Chen et al., 2021), PaLM (Chowdhery et al., 2022), and LaMDA (Thoppilan et al., 2022), which show tremendous promise in the field of NLP. These LLMs typically contain a large number of parameters (>100B) and require vast amounts of training data. Most of them are not open-sourced and can only be accessed via black-box APIs, through which the users send queries and receive responses. The internal processes and decision-making mechanisms used to arrive at the output are often not transparent or explainable. Despite the existence of open-sourced LLMs such as OPT-175B (Zhang et al., 2022) and Bloom (Scao et al., 2022), running and fine-tuning these models locally require significant computational resources, which is infeasible for most researchers and users. Although LLMs can already achieve good results on diverse tasks, they still need improvement or adjustment on some specific downstream

tasks (Goyal et al., 2022; Moradi et al., 2021; Gutiérrez et al., 2022). Shi et al. (2023) proposed to augment LLMs with relevant information retrieved from external knowledge sources to improve their performance on NLP tasks such as question-answering. Khattab et al. (2022) further proposed to bootstrap the demonstrations and search more relevant passages to insert into the prompt. However, there are still many generation tasks that do not rely on additional information and knowledge, such as summarization, data-to-text generation, and so on. In this paper, we aim to augment black-box LLMs without relying on external knowledge, which contrasts with retrieval-augmented methods. It is also different from the *Chain-of-thought Prompting* (Wei et al., 2022), which encourages LLMs to generate intermediate reasoning steps by themselves to solve complex reasoning tasks. Our proposed *Directional Stimulus Prompting* instead uses a small white-box LM to generate the intermediate text (stimulus), aiming to control the frozen black-box LLMs.

Prompt optimization Another line of work tried to improve LMs' performance by finding optimal prompts. One common approach is to tune soft prompts, which are continuous embedding vectors that can be optimized using gradient descent approaches (Li & Liang, 2021; Lester et al., 2021; Vu et al., 2021; Sun et al., 2022; An et al., 2022). However, the resulting prompts are hard for people to understand. Additionally, these methods require internal gradients for optimization, which is computationally expensive and not even available in LLMs that can only be accessed by inference APIs, such as GPT-3 and Codex. Therefore, some other work tried to find discrete prompts (i.e., a sequence of concrete tokens) via manual engineering (Petroni et al., 2019; Brown et al., 2020; Reynolds & McDonell, 2021), paraphrasing (Jiang et al., 2020), generation (Zhou et al., 2022), editing (Shin et al., 2020), optimization (Deng et al., 2022), etc. For example, Zhang et al. (2023) introduce a method that learns to construct the instance-specific discrete prompts by selecting editing strategies to update instructions, demonstration examples, and task verbalizers. Similarly, Promptist (Hao et al., 2022) utilizes a trainable model to rewrite the original user input prompt, aiming to better guide text-to-image models. These methods try to find more model-preferred instructions to help LMs better understand the task. Our approach, on the other hand, tries to provide "hints" or "cues" to LLMs for every single input.

Controllable text generation Controlling the generation of LMs has been widely studied. Prior to the emergence of extremely large-scale LMs, early approaches fine-tune the LMs on the dataset that contains the desired attributes (Gururangan et al., 2020). Keskar et al. (2019) proposed to train the class-conditioned LMs, which generate text with the prefix of pre-defined control codes. However, directly training LMs is very costly. Dathathri et al. (2019) thus proposed an approach PPLM, which trains an attribute model and passes its gradients to another LM's hidden activations to control its generation. GeDi (Krause et al., 2020) further reduces the computation complexity by training a small LM as generative discriminators, which guide generation at each step by computing probabilities for all possible next tokens via Bayesian rule by normalizing two class-conditional distributions. Similarly, DExperts (Liu et al., 2021) also use two class-conditional distributions to guide the LM's generation during decoding in a training-free manner. These methods either require further training LMs or internal gradients and logistics of the controlled LMs. In this paper, we aim to control the black-box LLMs that only take an input and return an output and all the inside is invisible, making existing work not applicable. In addition, there is no pre-defined control code provided in our case. Instead, we aim to optimize the policy LM to explore the sample-specific control code (stimulus).

Reinforcement learning for NLP Reinforcement learning has been successfully applied to various NLP tasks, such as syntactic parsing (Neu & Szepesvári, 2009; Le & Fokkens, 2017), machine translation (Wu et al., 2016; Kumar et al., 2019), summarization (Paulus et al., 2017; Stiennon et al., 2020), image caption (Rennie et al., 2017), text game (Narasimhan et al., 2015), conversational systems (Li et al., 2016), etc. Language models define probability distributions over tokens in their vocabulary, and the text generation problem can be naturally formulated as selecting an action in an RL setting. Therefore, there have been extensive research efforts on optimizing LMs with RL, usually by aligning them with human preferences (Ziegler et al., 2019; Wu et al., 2021; Lu et al., 2022; Stiennon et al., 2020). For example, the LLM InstructGPT (Ouyang et al., 2022) is optimized with RL to better follow users' instructions and intent. In contrast with these works that directly update the LLMs to align with human preferences, our work optimizes a small policy model that generate text (stimulus) to guide LLMs to generate more human-preferred output, instead of directly optimizing the LLMs, which is more efficient and feasible for most normal users and researchers. Proximal Policy Optimization (PPO) (Schulman et al., 2017) is the widely-used approach in this scenario,

which is empirically data-efficient and reliable. Natural Language Policy Optimization (Ramamurthy et al., 2022) is an extension of PPO for NLP tasks, which addresses the large action space issues by masking out the irrelevant tokens and shows better stability and performance.

5 Conclusion

In this paper, we introduce DSP, a framework that learns a policy LM to generate directional stimulus to guide the LLM on producing the generation toward the desired target. The policy LM is first trained with supervised fine-tuning and further optimized with RL by maximizing the rewards defined on the LLMs' generation. Experiment results show that our approach improves the LLM's performance with only a few training data. In addition, the generated stimulus is easier for humans to understand, which could provide valuable interpretation and insights into useful task instructions for LMs. Overall, our framework poses a new solution to using the black-box frozen LLM in a more customized and interpretable way. The main idea of our framework is using a model to generate stimulus to guide another model. Although we evaluate the idea on text generation tasks by generating verbal stimulus (text) for the LLM in this paper, we believe this framework is applicable to more extensive scenarios, such as generating visual stimulus or stimulus of other modalities for multi-modal models.

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Appendix

A Experimental Details

Table 2: Full results on the CNN/Daily Mail dataset. The performance improvement over the standard prompting are shown in brackets.

Methods	ROUGE-1	ROUGE-2	ROUGE-L	Meteor	BLEU	BertScore	
No training data							
Standard prompting	30.76	10.74	21.82	24.01	4.05	0.8748	
1000 training samples							
DSP w/ SFT	31.18 (†1.4%)	11.03 (†2.7%)	22.23 (†1.9%)	24.12 (†0.5%)	4.19 (†3.5%)	0.8758 (†0.1%)	
DSP w/ SFT+RL	32.34 (†5.1%)	12.05 (†12.2%)	23.45 (†7.5%)	24.45 (†1.8%)	4.68 (†15.6%)	0.8812 (†0.7%)	
2000 training samples							
DSP w/ SFT	31.20 (†1.4%)	11.22 (†4.5%)	22.33 (†2.3%)	24.53 (†2.2%)	4.23 (†4.4%)	0.8761 (†0.1%)	
DSP w/ SFT+RL	32.77 (†6.5%)	12.25 (†14.1%)	24.00 (†10.0%)	24.64 (†2.6%)	4.82 (†19.0%)	0.8809 (†0.7%)	
4000 training samples							
DSP w/ SFT	31.17 (†1.3%)	11.23 (†4.6%)	22.38 (†4.4%)	25.03 (†2.6%)	4.25 (†4.9%)	0.8770 (†0.3%)	
DSP w/ SFT+RL	32.87 (†6.9%)	12.37 (†15.2%)	23.96 (†9.8%)	24.96 (†4.0%)	4.82 (†19.0%)	0.8811 (†0.7%)	

A.1 CNN/Daily Mail

Table 2 presents the results of our experiments on the CNN/Daily Mail dataset using various metrics, including ROUGE-1/2/L, BLEU (Papineni et al., 2002), Meteor (Banerjee & Lavie, 2005), and BERTScore (Zhang et al., 2019). Our policy LM is trained using ROUGE-Avg as the reward, and we observe that Codex's performance improves across all metrics when guided by the stimulus generated by the policy LM. However, the improvement in BERTScore is relatively modest, which may be due to the discrepancy between the lexical-based ROUGE-Avg metric and the semantic-based BERTScore metric. Additionally, RL training further enhances the performance of our model, with improvements of 6.9%, 15.2%, and 9.8% on ROUGE-1, 2, and L scores, respectively, using only 4000 training samples.

Table 3: Full ontology for all domains in MultiWOZ2.0 Budzianowski et al. (2018) dataset. The upper script indicates which domains it belongs to. *: universal, 1: restaurant, 2: hotel, 3: attraction, 4: taxi, 5: train, 6: hospital, 7: police.

	dialog acts	inform* / request* / select ¹²³⁵ / recommend/ ¹²³ / nooffer ¹²³⁵ / offerbook ¹²⁵ /
	dialog acts	offerbooked ¹²⁵ / nobook ¹² / welcome* / greet* / bye* / reqmore*
	slots	$address^{12367}$ / $postcode^{12367}$ / $phone^{123467}$ / $name^{123}$ / $area^{123}$ / $pricerange^{12}$ /
		23 / internet 2 / parking 2 / stars 2 / departure 45 / destination 45 / leave 45 /
		arrive ⁴⁵ / people ¹²³ / reference ¹²³⁵ / id ⁵ / price ⁴⁵ / time ¹⁵ / department ⁶ /
		day^{125} / $stay^2$ / car^4 / $food^1$

A.2 MultiWOZ

We adopted the data processing method used in UBAR (Yang et al., 2021). Specifically, we used delexicalized responses by replacing specific slot values with corresponding placeholders, which can be filled based on database search results. Table 3 provides information on the dialog acts and slots that we supported. To represent dialog acts, which are originally in the form of <domain, slot, value> triplets, we converted them into text format like [domain1][inform] slot1 ... [request] slot1 ... [domain2][regmore], where domains, acts, and slot values are all bracketed.

In addition to the performance of compared models with full training data in Table 1, we also present their performance in the low-resource setting in Table 4. As the results show, these models failed to achieve acceptable performance with only 80 dialogues as training data. Even with around 800/8000 dialogues, their Inform and Success rates were worse than those of Codex guided by the policy LM with SFT and RL.

Table 4: Low-resource evaluation on the MultiWOZ 2.0 dataset, where Succ. and Comb. denote the Success and Combined Score metrics, respectively.

Method	1% of	f training (data (80 dia	alogs)	10% of training data (800 dialogs)			ialogs)
	Inform	Succ.	BLEU	Comb.	Inform	Succ.	BLEU	Comb.
DAMD (Zhang et al., 2020b)	34.4	9.1	8.1	29.9	55.3	30.3	13.0	55.8
MinTL (Lin et al., 2020)	-	-	-	-	78.1	66.9	15.5	87.9
Soloist (Peng et al., 2021)	58.4	35.3	10.6	57.4	69.9	51.9	14.6	75.5
PPTOD (Su et al., 2021)	74.4	52.4	13.0	76.4	84.4	68.4	15.6	92.0
UBAR (Yang et al., 2021)	-	-	-	-	82.5	66.6	17.7	92.3
GALAXY (He et al., 2022)	-	-	-	-	90.0	75.9	17.5	100.2
Codex w/ standard prompting	76.7	41.5	7.7	66.8	76.7	41.5	7.7	66.8
DSP w/ SFT	74.9	66.3	11.1	81.7	79.4	71.9	11.3	87.0
DSP w/ SFT+RL	91.0	76.0	9.8	93.3	96.0	86.9	10.7	102.2

B Running examples

We provide two running examples on the CNN/Daily Mail and MultiWOZ dataset in Table 5 and 6, respectively. We present the generations of Codex with standard prompting, DSP trained with SFT, and DSP trained with SFT and RL.

C Prompts

The used prompts of standard prompting and our proposed Directional Stimulus Prompting on CNN/Daily Mail and MultiWOZ datasets are given in Figures 5, 6, and Figures 7, 8, respectively. Both use 3 demonstration examples. The demonstrations used in standard prompting and DSP are the same. For the CNN/Daily Mail dataset, we add keywords as hints (stimulus) in the prompts used in DSP. For the MultiWOZ dataset, we add the dialog acts for each system turn and explanations of dialog acts.

Input article	(CNN)The FBI charged a Philadelphia woman on Thursday with trying to travel overseas				
•	to fight for ISIS. She's one of three women arrested this week on terror charges. Two				
	New York women were also taken into custody. An FBI complaint cites numerous				
	social media messages dating back to August 2013 that were sent by Keonna Thomas,				
	30, also known as "Young Lioness" and "Fatayat Al Khilafah." One Twitter message				
	said, "If we truly knew the realities we all would be rushing to join our brothers				
in the front lines pray ALLAH accept us as shuhada [martyrs]." Another said					
	you're a mujahid [violent jihadi fighter] your death becomes a wedding." The FBI said				
	Thomas purchased an electronic visa to Turkey on March 23. Turkey is known as the				
	easiest place from which to enter Syria and join ISIS. An ISIS manual advises recruits				
	to buy round-trip tickets to vacation spots such as Spain and then purchase tickets for				
	their real destination once they arrive overseas, the FBI said. On March 26, Thomas				
	purchased a ticket to Barcelona, with a March 29 departure and an April 15 return to				
	the United States, the complaint said. It's not clear when or where she was arrested.				
	She was charged with knowingly attempting to provide material support and resources				
	to a designated foreign terrorist organization. She could be sentenced to 15 years in				
	prison. On Thursday, Noelle Velentzas, 28, and her former roommate, Asia Siddiqui, 31, were arrested in New York and accused of planning to build an explosive device				
	for attacks in the United States, federal prosecutors said. In the past 18 months, the				
	Justice Department's National Security Division has prosecuted or is prosecuting more				
	than 30 cases of people attempting to travel abroad to join or provide support to terrorist				
	groups. Of those cases, 18 allegedly involve support to ISIS. "The terrorist threat is				
	more decentralized, more diffuse, more complicated," Homeland Security Secretary Jeh				
	Johnson told reporters Thursday. "It involves the potential lone wolf actor, it involves the				
	effective use of social media, the Internet.				
Reference	The <u>FBI</u> cites social media messages sent by <u>Keonna Thomas</u> , <u>30</u> . She's accused of				
summary	trying to travel overseas to join <u>ISIS</u> . Thomas is one of three women facing federal				
	terror charges this week.				
Generated	Standard prompting Keonna Thomas wanted to "join our brothers in the front lines" in Syria, send tweets				
summary	to ISIS . Keonna Thomas tried to enter Syria through Turkey and was arrested before				
(Codex)	leaving the US. Noelle Velentzas and Asia Siddiqui were arrested in New York, accused				
(Coucx)	of planning attacks in the US.				
ROUGE-1	24.10				
	Directional Stimulus Prompting (SFT)				
Generated	FBI complaint; Keonna Thomas; 30; a ticket; Barcelona; March 29; Noelle Velentzas;				
keywords (T5)	28; Asia Siddiqui; the United States. (Hit: 2/10)				
Generated	The FBI charged a Philadelphia woman, who's one of three women arrested this week				
summary	on terror charges. Keonna Thomas, 30, purchased an electronic visa to Turkey, an ISIS				
(Codex)	manual advises recruits to buy round-trip tickets to vacation spots such as Spain . Noelle				
	Velentzas, 28, and Asia Siddiqui, 31, were arrested in New York and accused of planning				
ROUGE-1	to build an explosive device for attacks in the United States . 36.54				
KOUGE-1					
Generated	Directional Stimulus Prompting (SFT+RL) FBI; Philadelphia; Keonna Thomas; 30; Turkey; ISIS; Twitter messages; March 2013.				
keywords (T5)	(Hit: 4/8)				
Generated	FBI arrested a Philadelphia woman named Keonna Thomas, 30, for trying to travel				
summary	overseas to fight for ISIS. She's one of three women arrested this week on terror charges				
(Codex)	. She tweeted to her supporters and purchased a ticket to Turkey in March 2013 .				
ROUGE-1	51.28				
Table 5: An example from the CNN/Daily Mail dataset. The policy LM (T5) generates the keyword					

Table 5: An example from the CNN/Daily Mail dataset. The policy LM (T5) generates the keywords based on which the Codex generates the summary. The "hit" keywords that appear in the reference summary are underlined and highlighted in red.

	User: please find a restaurant called nusha.				
	Assistant: i do n't seem to be finding anything called [value_name] . what type of				
	food does the restaurant serve?				
	User: i am not sure of the type of food but could you please check again and see if				
	you can find it? thank you.				
	Assistant: could you double check that you have spelled the name correctly? the				
Dialogue con-	closest i can find is [value_name] . it is not a restaurant , it is an attraction . nusha .				
text	User: oh its okay.				
text	Assistant: that is an [value_type] type located in the [value_area] at [value_address].				
	do you need their phone number ?				
	User: no, but please confirm their address again and their postcode.				
	Assistant: their address is [value_address] the postcode is [value_postcode].				
	is their anything else i can do for you?				
	User: i want indian food in the center area. [db_3]				
Oracle dialog	[restaurant] [inform] food area choice [request] price				
acts					
Oracle system	there are [value_choice] [value_food] restaurant -s in [value_area] what price range do you				
response	want?				
	Standard prompting				
Generated	[value_choice] restaurant -s come up when i search that area . would you like to narrow				
response	down your search?				
(Codex)					
SacreBLEU	18.38				
	Directional Stimulus Prompting (SFT)				
Generated di-	[restaurant] [recommend] name [offerbook]				
alog acts (T5)					
Generated	i recommend [value_name] . would you like to book a table there ?				
response					
(Codex)					
SacreBLEU	5.84				
Directional Stimulus Prompting (SFT+RL)					
Generated di-	[restaurant] [recommend] name [inform] choice area [request] price				
alog acts (T5)					
Generated	[value_name] . there are [value_choice] indian restaurants in the [value_area] . what is your				
summary	price ?				
(Codex)					
SacreBLEU	40.30				
L					

Table 6: An example from the MultiWOZ dataset. The policy LM (T5) generates the dialog acts given the dialog context. With our approach DSP, Codex generates the response conditioned on the generated dialog acts.

Standard Prompt (CNN/Daily Mail)

Given a CNN article, write a short summary of the article in 2-3 sentence

Article: Seoul (CNN) South Korea's Prime Minister Lee Wan-koo offered to resign on Monday amid a growing political scandal. Lee will stay in his official role until South Korean President Park Geun-hye accepts his resignation. He has transferred his role of chairing Cabinet meetings to the deputy prime minister for the time being, according to his office. Park heard about the resignation and called it "regrettable," according to the South Korean presidential office. Calls for Lee to resign began after South Korean tycoon Sung Woan-jong was found hanging from a tree in Seoul in an apparent suicide on April 9. Sung, who was under investigation for fraud and bribery, left a note listing names and amounts of cash given to top officials, including those who work for the President. Lee and seven other politicians with links to the South Korean President are under investigation. A special prosecutor's team has been established to investigate the case. Lee had adamantly denied the allegations as the scandal escalated: "If there are any evidence, I will give out my life. As a Prime Minister, I will accept Prosecutor Office's investigation first." Park has said that she is taking the accusations very seriously. Before departing on her trip to Central and South America, she condemned political corruption in her country. "Corruption and deep-rooted evil are issues that can lead to taking away people's lives. We take this very seriously." "We must make sure to set straight this issue as a matter of political reform. I will not forgive anyone who is responsible for corruption or wrongdoing." Park is in Peru and is expected to arrive back to South Korea on April 27, CNN's Paula Hancocks contributed to this report.

Q: Summarize the above article briefly in 2-3 sentences.

A: Calls for Lee Wan-koo to resign began after South Korean tycoon Sung Woan-jong was found hanging from a tree in Seoul . Sung, who was under investigation for fraud and bribery, left a note listing names and amounts of cash given to top officials

Article: (CNN) Two CNN Heroes are among the earthquake survivors in Kathmandu, Nepal. And they are struggling in the aftermath. Anuradha Koirala, who rescues victims of sex trafficking, has a rehabilitation center in Kathmandu that is home to 425 young women and girls. While her primary facility seems structurally unharmed, all of the children have been sleeping outdoors because of aftershocks, followed by a second earthquake on May 12. The once-vibrant campus has gone ulmanimed, all of the climiter in the climiter also has about a dozen other homes throughout the district, and all of them have been damaged. "It's really very sad for me and for my children," Koirala said. "This disaster, the noise and the way it shook, I cannot get over it. I was not afraid that I was going to be killed. I was afraid about what is going to happen next." Another CNN Hero, Pushpa Basnet, and the 45 children she cares for were also forced to evacuate their residence. They are now living on the ground in a nearby field.
"Physically, we are not hurt. But mentally, we are," said Basnet, whose Early Childhood Development Center provides a home and education to children whose parents are incarcerated. Basnet says the building's walls are all cracked, and the staff is afread with might fall down. She and the older children created a shelter using the frame of a greenhouse, taping plastic around the sides to protect themselves. "It's really cold in the middle of the night; there are lots of fox in the field," Basnet said. "We are really scared." They also don't have much water or food, Basnet says. But she is trying to stay positive. "I think for the time being, whatever we have, we should be happy, you know? Because at least we have our life," she said. "(My kids) all are safe. That's the most important thing for me." Basnet's "Butterfly Home" -- the permanent residence she was building for the children -- also suffered extensive damage in the quake. Basnet had hoped to complete construction in the next six months, with the opening ceremony set for October. Basnet purchased the land for the home with prize money she received as the 2012 Hero of the Year. "When the earthquake hit that land, all my dreams were scattered," she said. "I have to restart again." Still, Basnet is quick to point out that so many other survivors have nothing and are desperately in need of aid. To that end, several CNN Heroes have been assisting in relief efforts in Nepal. Jake Wood's disaster relief organization, Team Rubicon, has a team of experienced veterans and first responders on the ground in Kathmandu. The group deployed a medical and assessment team to aid the Nepalese people in several remote villages outside of the city. Six canine-firefipher search teams from the United States also assisted in rescue and recovery efforts. The teams were trained by Wilma Melville's National Disaster Search Dog Foundation and were deployed as part of a larger rescue force that includes structural engineers, hazmat experts and doctors. Tom Henderson's ShelterBox, which provides emergency shelter and lifesaving supplies, has so far committed to help more than 15,000 families. Dr. Laura Stachel's group, We Care Solar, sent solar suitcases to health care workers, providing them with light and power as they aid survivors. Arlene Samen's group, One Heart World-Wide, has set up tented birthing centers where pregnant women can safely deliver their babies, especially in hard-hit districts. Robin Lim, a disaster response midwife who founded Bumi Sehat, joined Samen in Kathmandu to help the mothers. Doc Hendley's one filter can provide water for up to 10 people and last for up to 10 years if maintained properly.

Q: Summarize the above article briefly in 2-3 sentences.

A: Anuradha Koirala and 425 young women and girls have been sleeping outdoors because of aftershocks. Pushpa Basnet and 45 children she cares for were forced to evacuate their residence. Seven other CNN Heroes and their organizations now assisting in relief efforts.

Article: Sao Paulo, Brazil (CNN) Brazilian police have arrested the treasurer of the ruling Workers' Party, bringing the bribery investigation at the state-run oil company Petrobras a step closer to President Dilma Rousseff. Federal police arrested Joao Vaccari Neto at his home in Sao Paulo on Wednesday morning, Vaccari faces charges of corruption and money laundering as part of the broader probe into corruption at Petrobras. Former executives who have turned state's evidence claim that construction companies paid large sums under the table to Petrobras officials and politicians in order to secure lucrative contracts with the oil giant. Vaccari has denied any wrongdoing and recently told a congressional commission that all donations to his party were legal and were reviewed by electoral authorities. Vaccari is the closest political figure to Rousseff so far implicated in the investigation. Rousseff has not been implicated, although she was the chairwoman of Petrobras when much of the alleged corruption took place. Rousseff has insisted she supports the probe and has not in any way interfered with the investigation. Sources quoted in Brazilian media have said investigators are looking at whether some of the bribes went toward Rousseff's election campaigns. Anger over what has ballooned into a multi-million dollar corruption scandal has eroded Rousseff's approval rating and prompted hundreds of thousands of Brazilians to take to the streets in protest. On Sunday, about half a million people participated in demonstrations across the country. But turnout was smaller than a month earlier, when roughly one million people marched in protest, raising questions about how long the demonstrations can last.

Q: Summarize the above article briefly in 2-3 sentences

A: A top official with President Dilma Rousseff's ruling party is arrested in bribery probe. Joao Vaccari Neto denies wrongdoing, says all donations were legal Hundreds of thousands of Brazilians have protested against Rousseff in the last few months.

Article: [[QUESTION]]

Q: Summarize the above article briefly in 2-3 sentences

Figure 5: The prompt for standard prompting on the CNN/Daily Mail dataset.

Directional Stimulus Prompt (CNN/Daily Mail)

Given a CNN article, write a short summary of the article in 2-3 sentence based on the hint.

Article: Seoul (CNN) South Korea's Prime Minister Lee Wan-koo offered to resign on Monday amid a growing political scandal. Lee will stay in his official role until South Korean President Park Geun-hye accepts his resignation. He has transferred his role of chairing Cabinet meetings to the deputy prime minister for the time being, according to his office. Park heard about the resignation and called it "regretable," according to the South Korean presidential office. Calls for Lee to resign began after South Korean tycoon Sung Woan-jong was found hanging from a tree in Seoul in an apparent suicide on April 9. Sung, who was under investigation for fraud and bribery, left a note listing names and amounts of cash given to top officials, including those who work for the President. Lee and seven other politicians with links to the South Korean President are under investigation. A special prosecutor's team has been established to investigate the case. Lee had adamantly denied the allegations as the scandal escalated: "If there are any evidence, I will give out my life. As a Prime Minister, I will accept Prosecutor Office's investigation first." Park has said that she is taking the accusations very seriously, Before departing on her trip to Central and South America, she condemned political corruption in her country. "Corruption and deep-rooted evil are issues that can lead to taking away people's lives. We take this very seriously." "We must make sure to set straight this issue as a matter of political reform. I will not forgive anyone who is responsible for corruption or wrongdoing." Park is in Peru and is expected to arrive back to South Korea on April 27. CNN's Paula Hancocks contributed to this report.

Q: Summarize the above article briefly in 2-3 sentences based on the hint.

Hint: Lee Wan-koo; resign, South Korean tycoon; Sung Woan-jong; investigation; fraud; bribery; note

A: Calls for Lee Wan-koo to resign began after South Korean tycoon Sung Woan-jong was found hanging from a tree in Seoul . Sung, who was under investigation for fraud and bribery, left a note listing names and amounts of cash given to top officials .

Article. (CNN) Two CNN Heroes are among the earthquake survivors in Kathmandu, Nepal. And they are struggling in the aftermath. Anuradha Koirala, who rescues victims of sex trafficking, has a rehabilitation center in Kathmandu that is home to 425 young women and girls. While her primary facility seems structurally unharmed, all of the children have been sleeping outdoors because of aftershocks, followed by a second earthquake on May 12. The once-vibrant campus has gone from a place of safety and healing to one of uncertainty and worry. "We are suffering with rain, strong wind. The fear is not gone from us. It is very, very hard," said Koirala, the founder of the nonprofit Maith (Papal and the 2010 CNN Hero of the Year. The public has been warned not to use the main water line due to risk of cholera. Koirala's group is relying on bottled water and is now rationing food. Still, she has offered to take in 200 other girls orphaned by the disaster. "These girls are most vulnerable, because now people will target them," Koirala said. "They could be victims of any forms of sexual abuse. Maybe rape, maybe they will be trafficked, anything. ... If I get more support I will take as many as I can." About five miles away, the wall of Koirala's HIV/AIDS hospice has crumbled. Home to 115 girls, many of whom are terminally ill, the facility is under guard. "They're not injured, but they are terrified," Koirala's squal sour adverse of the real way and the said of the many the been damaged. "It's really very sad for me and for my children," Koirala's squal pasout a dozen other homes throughout the district, and all of them have been damaged." It's really very sad for me and for my children, "Koirala's agoing to happen next." Another CNN Hero, Pushpa Basnet and the 45 children she cares for were also forced to evacuate their residence. They are now living on the ground in a nearby field. "Physically, we are not hurt. But mentally, we are," said Basnet, whose Early Childhood Development Center provides a home and deucation to chi

Hint: Anuradha Koirala; 425 young women and girls; sleeping outdoors; aftershocks; Pushpa Basnet; 45 children; evacuate their residence; CNN harrs; relief offerts

A: Anuradha Koirala and 425 young women and girls have been sleeping outdoors because of aftershocks . Pushpa Basnet and 45 children she cares for were forced to evacuate their residence . Seven other CNN Heroes and their organizations now assisting in relief efforts .

Article: Sao Paulo, Brazil (CNN) Brazilian police have arrested the treasurer of the ruling Workers' Party, bringing the bribery investigation at the state-run oil company Petrobras a step closer to President Dilma Rousseff. Federal police arrested Joao Vaccari Neto at his home in Sao Paulo on Wednesday morning. Vaccari faces charges of corruption and money laundering as part of the broader probe into corruption at Petrobras. Former executives who have turned state's evidence claim that construction companies paid large sums under the table to Petrobras officials and politicians in order to secure lucrative contracts with the oil giant. Vaccari has denied any wrongdoing and recently told a congressional commission that all donations to his party were legal and were reviewed by electoral authorities. Vaccari is the closest political figure to Roussesf of air implicated in the investigation. Rousseff has not been implicated, although she was the chairwoman of Petrobras when much of the alleged corruption took place. Rousseff has insisted she supports the probe and has not in any way interfered with the investigation. Sources quoted in Brazilian media have said investigators are looking at whether some of the bribes went toward Rousseff's election campaigns. Anger over what has ballooned into a multi-million dollar corruption scandal has eroded Rousseff's approval rating and prompted hundreds of thousands of Brazilians to take to the streets in protest. On Sunday, about half a million people participated in demonstrations across the country. But turnout was smaller than a month earlier, when roughly one million people marched in protest, raising questions about how long the demonstrations can last.

Q: Summarize the above article briefly in 2-3 sentences based on the hint.

Hint: President Dilma Rousseff; Party; bribery; Joao Vaccari Neto; wrongdoing; donations; legal; Brazilian; last few months.

A: A top official with President Dilma Rousseff's ruling party is arrested in bribery probe. Joao Vaccari Neto denies wrongdoing, says all donations were legal Hundreds of thousands of Brazilians have protested against Rousseff in the last few months.

Article: [[QUESTION]]

Q: Summarize the above article briefly in 2-3 sentences based on the hint.

Hint: [[HINT]]

A:

Figure 6: The prompt for Directional Stimulus Prompting on the CNN/Daily Mail dataset. The only difference compared with the prompts used in standard prompting shown in Figure 5 is the stimulus hints (keywords), which are highlighted in red.

```
Standard Prompt (MultiWOZ)
The following are conversations between a user and an ass
                                                                                                                                                                       king or providing information of restaurant, hotel,
attraction, taxi, train, hospital, police, and so on.
User: do you book trains for the bishops stortford?
Assistant: yes . are you departing or arriving in [value_destination]?
User: i am going there from cambridge on thursday.
Assistant: i have [value_choice] trains going to [value_destination] from [value_departure] on [value_day] . what time do you need to arrive?

User: i would like to arrive by 18:15.

Assistant: [value_id] will have you in [value_destination] by [value_arrive] .
User: i need 2 tickets
Assistant: the [value_id] will get you there by [value_arrive] . i can book you [value_people] tickets on that if you would like?
you with today ?
User: a nice place to eat that serves austrian food . in the centre of town if possible
Assistant: i am so sorry no [value_food] restaurant -s in that area , another food type perhaps ? User: okay , do you have any good restaurant -s serving british food ?
Assistant: there are [value_choice] restaurant -s in the [value_area] that serve [value_food] food , is there a price range you would like to stay in ?

User: any is fine , can i get the phone number and postcode of 1 you would recommend?

Assistant: i would recommend the [value_name] . their phone number is [value_phone] . their postcode is [value_postcode] .
User: great ! thanks . that s all i need . goodbye .
Assistant: awesome . we 're here 24 and 7 if you need us again . have a great day !
User: i ' m looking for a hotel in the moderate price range . i definitely want a hotel , not a guest house
Assistant: i'm sorry but nothing exists in [value_area] north with [value_stars] 4 star rateing in [value_price] moderate price range. Could we try another area?
User: is there 1 in the cheap range?
Oser. Is there in the cheap range. Assistant: o, there is not.

User: oh goodness. can you check once again for a hotel, star 4, in the west. cheap is fine.

Assistant: the [value_name] is located at [value_address]. do you need more information or would you like to book now?
User: yeah book for 5 people
Assistant: for how many days?
User: will this start on friday?
Assistant: yes . would you like reservations? what day will it start? how many people?
User: i would like a reservation for 5 people for 4 nights , beginning friday , at the cambridge belfry . Assistant: you are all booked and your reservation number is [value_reference]. User: thank you for the reservation . i am also looking for a lovely park in north cambridge .
Assistant: i would suggest [value_name] .
User: what is the phone number ?
Assistant: the phone number is [value_phone] .
User: i also need a taxi between the 2 place -s .
Assistant: please give me the travel time , departure location and arrival location.
User: i want to leave the hotel by 04:30. Assistant: what time do you need to leave the restaurant by ? User: i want to be pickup at at the hotel by 04:30.
Assistant: great your booking is complete . you will be picked up in a [value_car] by [value_leave] at [value_departure] and dropped off at the
[value_destination] .
User: do you have their contact number ?
Assistant: their contact number is [value_phone] . is there anything else i can help you with today? User: that will be all for today . thank you . goodbye . Assistant: thank you i ' m glad i could help . goodbye .
Conversation:
User: ivant to find place -s to go in the centre of town that are park type attractions .

Assistant: i think that you will like [value_name] . it is [value_price] , may i book it for you?

User: yes , that sounds good! please provide me with the postcode .
Assistant: i'm sorry, we are n't able to book tickets for this attraction, but their postcode [value_postcode] cb21jf, and i can provide their address and phone
if you like?
User: no . that is all i need . i would like help finding a cheap guest house though
Assistant: I have [value_choice] options for you. do you need wifi or parking? is there a part of town you prefer to stay in? User: it should include free wifi and should be in the east.
Assistant: there seems to be an opening at [value_name] . would you like me to book you a room ? User: yes , please . 5 people for 5 nights starting thursday .
Assistant: booking was successful . your reference number is : [value_reference]
User: thank you very much! State anything else i can do for you? Assistant: you are welcome. Is there anything else i can do for you? User: no thank you. I appreciate all of your help. Assistant: thank you i'm glad i could help.
Conversation:
[[DIALOG]]
```

Figure 7: The prompt for standard prompting on the MultiWOZ dataset.

Directional Stimulus Prompt (MultiWOZ) The following are conversations between a user and an assistant. Indicated by the dialog acts, the assistant can help the user with booking or providing information of [restaurant], [hotel], [attraction], [taxi], [train], [hospital], [police], and so on. [inform]: provide information for a slot; [request]: request information for a slot; [nooffer]: do not have offers that satisfy requirements; [recommend]: recor an offer; [select]: select an offer; [offerbook]: help to book a [offerbooked]: have booked an offer; [nobook]: can not book an offer; [bye]: bye; [greet]: greet; [welcome]: welcome; [reqmore]: ask if need more information or help. User: do you book trains for the bishops stortford ? Assistanti[[train] [request] departure destination); yes . are you departing or arriving in [value_destination] ? User: i am going there from cambridge on thursday . Assistant[(Irain] [inform) day choice departure destination [request] arrive): i have [value_choice] trains going to [value_destination] from [value_departure] on [value_day] . what time do you need to arrive? User: i would like to arrive by 18:15. Assistant/[train] [inform] id destination arrive): [value id] will have you in [value destination] by [value arrive] User: i need 2 tickets Assistant[[train] [inform] arrive id [offerbook] people]: the [value_id] will get you there by [value_arrive] . i can book you [value_people] tickets on that if you would like? Assistant[train] [inform] arrive in [onerbook] people): the [value_id] will get you there by [value_arrive]. I can book you [value_people] tickets on that if you woll User: 2 tickets will be fine., please. Assistant[train] [offerbooked] reference price [general] [reqmore]): tr0277 2 tickets. the total fee is [value_price] payable at the station.reference number is: Assistant[(rani) offer booked) retretice price general) required), 00217 2 tokes a tile total ree is (value_price) payable at tile station. (value_reference) a will there be anything else i can help you with today? User: a nice place to eat that serves austrian food in the centre of town if possible. Assistant[(restaurant] [nooffer] food [request] food): i am so sorry no [value_food] restaurant -s in that area, another food type perhaps? User: okay, do you have any good restaurant -s serving british food? choice food area [request] price): there are [value_choice] restaurant -s in the [value_area] that serve [value_food] food , is there a price User: any is fine, can i get the phone number and postcode of 1 you would recommend? Assistant([restaurant] [recommend] postcode phone name): i would recommend the [value_name]. their phone number is [value_phone]. their postcode is Assistant[[estatinal precommend postcode phone hame]. Notice commend the [value_name] (value_nostcode]. User: great! thanks . that s all i need . goodbye . Assistant[[general] [bye]]: awesome . we 're here 24 and 7 if you need us again . have a great day! User: i 'm looking for a hotel in the moderate price range . i definitely want a hotel , not a guest house Assistant([hotel] [inform] area choice type [request] area): of course . there are [value_choice] [value_type] in the [value_area] and [value_choice] in the [value_area] of town . do you have a preference? User: is there anything to the west, preferably with a 4 star rating? Assistant([hotel] [nooffer] area price stars [request] area): i m sorry but nothing exists in [value_area] north with [value_stars] 4 star rateing in [value_price] moderate price range. could we try another area? User is there 1 in the cheap range? Assistant([hotel] [nooffer]): no, there is not. User: objoodness. can you check once again for a hotel, star 4, in the west. cheap is fine. Assistant([hotel] [inform] name address [offerbook] [general] [reqmore]): the [value_name] is located at [value_address]. do you need more information or would you like to book now? User: yeah book for 5 people . Assistant([hotel] [request] stay): for how many days? User: will this start on friday? Assistant([hotel] [offerbook] [request] people day); yes, would you like reservations? what day will it start? how many people? Assistant[Indet] [onerbook | request people day), yes, would you me reservations a make vary with a saint and you make reservations a make vary with a saint and you will be careful tile a reservation for 5 people for 4 nights, beginning friday, at the cambridge belffy. Assistant[[hotel] [offerbooked] reference]: you are all booked and your reservation number is [value_reference]. User: thank you for the reservation, i am also looking for a lovely park in north cambridge. Assistant([attraction] [recommend] name): i would suggest [value_name] . User: what is the phone number? User: what is the pnone number / Assistant(Eartaction) [inform] phone): the phone number is [value_phone] . User: i also need a taxi between the 2 place -s . Assistant([taxi] [request] departure leave destination): please give me the travel time , departure location and arrival location . User: i want to leave the hotel by 04:30 . User: I want to leave the note by 04:30. Assistant[[taxi] [request] leave]: what time do you need to leave the restaurant by? User: I want to be pickup at at the hotel by 04:30. Assistant[[taxi] [inform] departure car leave destination): great your booking is complete. you will be picked up in a [value_car] by [value_leave] at [value_departure] and dropped off at the [value_destination] User: do you have their contact number ? Assistant/(taxil finform) phone [generall fregmore]): their contact number is [value phone], is there anything else i can help you with today? User: that will be all for today . thank you . goodbye Assistant([general] [bye]): have a great day! bye . User: i want to find place -s to go in the centre of town that are park type attractions Assistant[attraction] [inform] price name [offerbook]): i think that you will like [value_name] . it is [value_price] , may i book it for you? User: yes , that sounds good! please provide me with the postcode . Assistant([Inter] infom) choice [request] area parking internet): i have [value_choice] options for you a do you need wifi or parking? is there a part of town you prefer to stav in ? User: it should include free wifi and should be in the east Ose: It should include fee win and should be in the east. Assistant([hotel] [inform] name [offerbook]): there seems to be an opening at [value_name] . would you like me to book you a room? User: yes, please . 5 people for 5 nights starting thursday . Assistant([hotel] [offerbooked] reference): booking was successful . your reference number is : [value_reference]. Assistant[[net] point Booked | February | User: thank you very much! Assistant([general] [welcome] [reqmore]): you are welcome . is there anything else i can do for you? User: no thank you , i appreciate all of your help . ome]): thank you i ' m glad i could help Conversation: [[DIALOG]]

Figure 8: The prompt for Directional Stimulus Prompting on the MultiWOZ. Compared with the prompts used in standard prompting shown in Figure 5, we add stimulus hints (dialog acts) for each system turn, which are highlighted in red. In addition, we add explanations of dialog acts at the beginning to help the model understand their meanings.