Knowledge Distillation of Large Language Models

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Abstract

Knowledge Distillation (KD) is a promising technique for reducing the high computational demand of large language models (LLMs). However, previous KD methods are primarily applied to white-box classification models or training small models to imitate black-box model APIs like ChatGPT. How to effectively distill the knowledge from white-box generative LLMs is still under-explored, which becomes more and more important with the prosperity of LLMs. In this work, we propose MINILLM that distills smaller language models from generative larger language models. We first replace the forward Kullback-Leibler divergence (KLD) objective in the standard KD approaches with reverse KLD, which is more suitable for KD on generative language models, to prevent the student model from overestimating the low-probability regions of the teacher distribution. Then, we derive an effective optimization approach to learn this objective. Extensive experiments in the instruction-following setting show that the MINILLM models generate more precise responses with the higher overall quality, lower exposure bias, better calibration, and higher long-text generation performance. Our method is also scalable for different model families with 120M to 13B parameters. We will release our code and model checkpoints at https://aka.ms/MiniLLM.

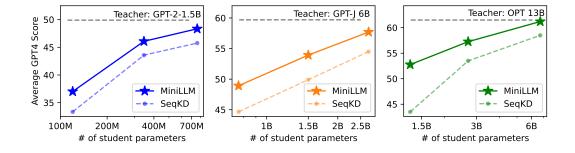


Figure 1: The comparison of MINILLM with the sequence-level KD (SeqKD) in terms of the average GPT-4 feedback score on our evaluation sets. **Left**: GPT-2-1.5B as the teacher and GPT-2 125M, 340M, 760M as the students. **Middle**: GPT-J 6B as the teacher and GPT-2 760M, 1.5B, GPT-*Neo* 2.7B as the students. **Right**: OPT 13B as the teacher and OPT 1.3B, 2.7B, 6.7B as the students.

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1 Introduction

With the rapid development of large language models (LLMs; HZD⁺21, BHA⁺21, BMR⁺20, Ope23, CND⁺22), a common technique to reduce high computational resource demand is knowledge distillation (KD; HVD15), where we train a small student model with supervision from a large teacher model. Two categories of KD are commonly applied: *black-box* KD, where only the teacher predictions are accessible, and *white-box* KD, where the teacher parameters are available to use [JBMD21]. Recently, *black-box* KD has shown promising results in fine-tuning small models on the prompt-response pairs generated by LLM APIs [TGZ⁺23, CLL⁺23, WWZ⁺23, PLH⁺23]. With the emergence of more open-source LLMs [ZRG⁺22, TLI⁺23], *white-box* KD becomes more valuable for both research communities and industry sectors because student models receive better signals from white-box teacher models, thereby potentially resulting in higher performance. However, *white-box* KD approaches are mostly studied for small (< 1B parameters) language understanding models [SDCW19, WWD⁺20], while *white-box* KD for generative LLMs is yet to be explored.

In this work, we investigate white-box KD of LLMs. We argue that the standard KD objectives [KR16, SST+20] are sub-optimal for LLMs that perform tasks in a generative manner. Given the teacher distribution p(y|x) and the student distribution $q_{\theta}(y|x)$ parameterized by θ , standard KD objectives (including several variants for sequence-level models) essentially minimize the approximated forward Kullback-Leibler divergence (KLD) between the teacher and the student distribution, termed as $\mathrm{KL}[p||q_{\theta}]$, which forces p to cover all the modes of q_{θ} . For text classification tasks, $\mathrm{KL}[p||q_{\theta}]$ works well because the output space usually consists of finite-number classes such that both p(y|x) and $q_{\theta}(y|x)$ have few modes. However, for open text generation tasks, where the output spaces are much more complex and p(y|x) can contain much more modes than what $q_{\theta}(y|x)$ can express due to the limited model capacity. Minimizing forward KLD can cause q_{θ} to assign unreasonably high probabilities to the void regions of p [MG19] and produces samples very unlikely under p during free-run generation [Hus15].

To alleviate this problem, we propose to minimize the *reverse* KLD, $\mathrm{KL}[q_{\theta}||p]$, which is widely used in computer vision [KW13] and reinforcement learning [CPO+19]. Compared to $\mathrm{KL}[p||q_{\theta}]$, minimizing $\mathrm{KL}[q_{\theta}||p]$ causes q_{θ} to seek the major modes of p, and assign low probabilities to the p's void regions [M+05], which is illustrated by a pilot experiment in Section 2.1. In language generation of LLMs, this means the student model avoids learning too many long-tail variants [HBD+20] of the teacher distribution and focuses on the correctness of the generated response, which is critical in practical scenarios that require truthfulness and reliability [JLF+23]. To optimize $\min_{\theta} \mathrm{KL}[q_{\theta}||p]$ as shown in Section 2.2, we derive the gradient of the objective with Policy Gradient [SMSM99]. Although recent works have shown success in fine-tuning PLMs with policy optimization [OWJ+22, RAB+23], we found that training the model still suffers from high variance, reward hacking, and generation length bias. Therefore, we introduce (1) single-step regularization to reduce variance, (2) teacher-mixed sampling to alleviate reward hacking, and (3) length normalization to eliminate the length bias. Finally, we introduce the algorithm of MINILLM in Section 2.3.

We apply MINILLM to various generative language models [RWC⁺19, ZRG⁺22, TLI⁺23] with parameter sizes ranging from 120M to 13B in the instruction-following setting [SWR⁺22, WBZ⁺22] that covers a large range of NLP tasks. We use five instruction-following datasets with the GPT-4 feedback and Rouge-L [Lin04] for evaluation. Our experiments show that MINILM consistently outperforms the standard KD baselines on all the datasets and scales up well from 120M to 13B models (see Figure 1). More analysis shows that MINILLM has lower exposure bias, better calibration, and performs better at generating long responses with better diversity.

2 Method

We consider conditional language generation tasks where the model produces a response $\mathbf{y} = \{y_t\}_{t=1}^T$ conditioning on a prompt \mathbf{x} sampled from the distribution $p_{\mathbf{x}}$. We formulate KD as an optimization problem to minimize the difference between a fixed teacher model distribution $p(\mathbf{y}|\mathbf{x})$ and a student model distribution $q_{\theta}(\mathbf{y}|\mathbf{x})$ parameterized by θ . The standard KD for generative models approximately² minimizes the *forward* KLD: $\mathrm{KL}[p||q_{\theta}] = \mathbb{E}_{\mathbf{x} \sim p_{\mathbf{x}}, \mathbf{y} \sim p'} \log \frac{p(\mathbf{y}|\mathbf{x})}{q_{\theta}(\mathbf{y}|\mathbf{x})}$,

 $^{^{2}}$ We say "approximately" because for word-level KD, y is sampled from the real distribution, not the teacher distribution. For a strong enough teacher model, we can consider the two distributions approximately the same.

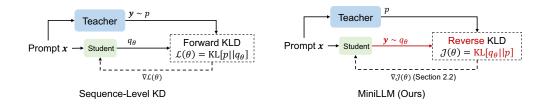


Figure 3: Comparison between sequence-level KD (left) and our MINILLM (right). Sequence-level KD forces the student to memorize all teacher-generated samples, while MINILLM allows the student model to improve its own generation with the teacher's feedback.

where p' can be real data distribution (word-level KD) or teacher distribution p (sequence-level KD). Though widely used, $\mathrm{KL}[p||q_{\theta}]$ has been shown to overestimate the void regions of p in language generation tasks when q_{θ} is insufficiently expressive to cover all the modes of p' [JKH+23]. KD for LLMs fits the case because LLMs perform various tasks in a generative manner, such that the low-capacity student models cannot perfectly imitate the complex language generation distribution of the teacher models or humans.

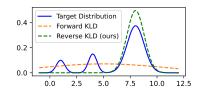


Figure 2: The toy experiment. We fit a Gaussian mixture with a Gaussian distribution using *forward* KLD and *reverse* KLD.

2.1 MiniLLM: Knowledge Distillation with Reverse KLD

In this work, we consider minimizing the *reverse* KLD between the student and teacher distributions as the learning objective of MINILLM:

$$\theta = \arg\min_{\theta} \mathcal{J}(\theta) = \arg\min_{\theta} \text{KL}[q_{\theta}||p]$$

$$= \arg\min_{\theta} \underset{\boldsymbol{x} \sim p_{\boldsymbol{x}}, \boldsymbol{y} \sim q_{\theta}}{\mathbb{E}} \log \frac{q_{\theta}(\boldsymbol{y}|\boldsymbol{x})}{p(\boldsymbol{y}|\boldsymbol{x})}.$$
(1)

[Hus15] has shown that minimizing $\mathrm{KL}[q_\theta||p]$ leads to a mode-seeking behavior, where q_θ assigns high probabilities to p's large modes, ignoring the small ones. Figure 2 illustrates the difference between the two KLDs when a Gaussian distribution tries to fit a Gaussian mixture. We can see that minimizing *forward* KLD causes q_θ to place large probability mass on the zero-probability places of p, which corresponds to the generation of low-quality texts in practice, while *reverse* KLD focuses on p's major modes, which is crucial to ensure the correctness and faithfulness of language generation.

We term our KD method for LLMs by minimizing the *reverse* KLD as **MINILLM**, which is illustrated in Figure 3. Unlike sequence-level KD, MINILLM does not force q_{θ} to fit all \boldsymbol{y} sampled from the teacher distribution p. Instead, it encourages the student to generate samples preferred by the teacher within its own capacities, which is more possible to achieve.

2.2 Optimization with Policy Gradient

Gradient Derivation We notice that the gradient of the objective function $\mathcal{J}(\theta)$ described in Equation (1) can be derived using the Policy Gradient Theorem [Wil92, HTAL17]:

$$\nabla \mathcal{J}(\theta) = - \underset{\boldsymbol{y} \sim q_{\theta}(\cdot|\boldsymbol{x})}{\mathbb{E}} \sum_{t=1}^{T} (R_{t} - 1) \nabla \log q_{\theta}(y_{t}|\boldsymbol{y}_{< t}, \boldsymbol{x}),$$
 (2)

where $T=|\pmb{y}|$ and $R_t=\sum_{t'=t}^T\log\frac{p(y_{t'}|\pmb{y}_{< t'},\pmb{x})}{q_\theta(y_{t'}|\pmb{y}_{< t'},\pmb{x})}$ is the accumulation of $r_{t'}=\log\frac{p(y_{t'}|\pmb{y}_{< t'},\pmb{x})}{q_\theta(y_{t'}|\pmb{y}_{< t'},\pmb{x})}$ that measures the quality of each step generation. Intuitively, we want the generation to have high probabilities under the teacher distribution by increasing $p(y_{t'}|\pmb{y}_{< t'},\pmb{x})$, but simultaneously stay diverse by lowering $q_\theta(y_{t'}|\pmb{y}_{< t'},\pmb{x})$. The expectation is computed by Monte-Carlo sampling. However, policy gradient suffers from high variance and reward hacking [SHKK22]. Although subsequent works proposed better solutions like PPO [SWD+17], we find that these issues still remain. Besides, we notice that R_t favors short sentences, which causes our model to output empty responses. Therefore, we propose three strategies to mitigate these problems.

Single-Step Regularization [CPO⁺19] has found that the single-step generation quality r_t is critical to the training variance because the error in the front tokens accumulates along the whole sentence. To pay more attention to r_t , we re-write $\nabla \mathcal{J}(\theta)$ to split r_t from R_t and directly compute the gradient of $\mathbb{E}_{u_t \sim q_\theta(t)}[r_t]$ as a regularization (see Appendix A.2 for the full derivation):

$$\nabla \mathcal{J}(\theta) = \underset{\boldsymbol{y} \sim q_{\theta}(\cdot|\boldsymbol{x})}{\mathbb{E}} \left[-\sum_{t=1}^{T} R_{t+1} \nabla \log q_{\theta}(y_{t}|\boldsymbol{y}_{< t}, \boldsymbol{x}) \right] + \underset{\boldsymbol{y} \sim q_{\theta}(\cdot|\boldsymbol{x})}{\mathbb{E}} \left[-\sum_{t=1}^{T} \nabla \underset{\boldsymbol{y}_{t} \sim q_{\theta}(t)}{\mathbb{E}} [r_{t}] \right]$$

$$= (\nabla \mathcal{J})_{\text{Main}} + (\nabla \mathcal{J})_{\text{Reg}},$$
(3)

where $q_{\theta}(t) = q_{\theta}(\cdot|\boldsymbol{y}_{< t}, \boldsymbol{x})$. Note that $\mathbb{E}_{y_t \sim q_{\theta}(t)}[r_t]$ can be computed directly by summing over the vocabulary instead of using Monte-Carlo sampling and is derivable with respect to θ . This regularization gives a more precise and efficient estimation of the single-step generation quality, which reduces the variance during training and accelerates convergence.

Teacher-Mixed Sampling We observe reward hacking [SHKK22] when training with Equation 2 because q_{θ} sometimes produces degenerated sentences y that receive high scores from the teacher (e.g., repeated phrases) during sampling, especially for small student models. To create a better sampling distribution, we mix the teacher and the student distribution at each time step:

$$\widetilde{p}(y_t|\boldsymbol{y}_{< t}, \boldsymbol{x}) = \alpha \cdot p(y_t|\boldsymbol{y}_{< t}, \boldsymbol{x}) + (1 - \alpha) \cdot q_{\theta}(y_t|\boldsymbol{y}_{< t}, \boldsymbol{x}), \tag{4}$$

where α controls the strength of the teacher mix-in. Sampling from \widetilde{p} suppresses low-quality generation with the teacher's help and alleviates reward hacking. We re-write $(\nabla \mathcal{J})_{\text{Main}}$ and $(\nabla \mathcal{J})_{\text{Reg}}$ with importance sampling to get to an unbiased estimator of the gradient [PSS00]:

$$(\nabla \mathcal{J})_{\text{Main}} = - \underset{\boldsymbol{y} \sim \tilde{p}(\cdot|\boldsymbol{x})}{\mathbb{E}} \sum_{t=1}^{T} w_{t} R_{t+1} \nabla \log q_{\theta}(y_{t}|\boldsymbol{y}_{< t}, \boldsymbol{x}),$$

$$(\nabla \mathcal{J})_{\text{Reg}} = - \underset{\boldsymbol{y} \sim \tilde{p}(\cdot|\boldsymbol{x})}{\mathbb{E}} \left[\sum_{t=1}^{T} w_{t} \nabla \underset{y_{t} \sim q_{\theta}(t)}{\mathbb{E}} [r_{t}] \right],$$
(5)

where $w_t = \prod_{t'=1}^t \frac{q_\theta(y_{t'}|y_{< t'},x)}{\widetilde{p}(y_{t'}|y_{< t'},x)}$ is the importance weight. However, in practice, using w_t has been found to be sensitive to hyper-parameters and converge slowly. Therefore, we approximately set $w_t \approx \frac{q_\theta(y_t|y_{< t},x)}{\widetilde{p}(y_t|y_{< t},x)}$ to reduce the variance of the estimator in Equation 5 [LKTF20].

Length Normalization We found that long sequences tend to have small R_{t+1} , which encourages the model to produce short responses. Therefore, we add length normalization to R_{t+1} in Equation 3:

$$R_{t+1}^{\text{Norm}} = \frac{1}{T - t - 1} \sum_{t'=t+1}^{T} \log \frac{p(y_{t'}|\boldsymbol{y}_{< t'}, \boldsymbol{x})}{q_{\theta}(y_{t'}|\boldsymbol{y}_{< t'}, \boldsymbol{x})}.$$
 (6)

In Summary Combining the strategies listed above, we have the final optimization gradient:

$$\nabla \mathcal{J}(\theta) = - \underset{\boldsymbol{y} \sim \tilde{p}(\cdot|\boldsymbol{x})}{\mathbb{E}} \left[\sum_{t=1}^{T} w_{t} \left[R_{t+1}^{\text{Norm}} \frac{\nabla q_{\theta}(y_{t}|\boldsymbol{y}_{< t}, \boldsymbol{x})}{q_{\theta}(y_{t}|\boldsymbol{y}_{< t}, \boldsymbol{x})} + \nabla \sum_{y' \in V} q_{\theta}(y'|\boldsymbol{y}_{< t}, \boldsymbol{x}) \log \frac{p(y'|\boldsymbol{y}_{< t}, \boldsymbol{x})}{q_{\theta}(y'|\boldsymbol{y}_{< t}, \boldsymbol{x})} \right] \right], (7)$$

where V is the vocab size of the language model.

2.3 Training Algorithm

The training algorithm of MINILLM is shown in Algorithm 2.3. We initialize the student model from a checkpoint fine-tuned on the training data with the lowest validation loss and add the PPO clipping strategy [SWD⁺17] to $(\nabla \mathcal{J})_{Main}$ to improve training stability. Note that we do not use the value network and the KL regularization in PPO to improve the training efficiency. Same as [OWJ⁺22], we add a language modeling loss \mathcal{L}_{PT} on the pre-training corpus.

Algorithm 1 MINILLM: Knowledge Distillation of LLMs

Input: Conditional generation dataset \mathcal{D} consisting of prompts and ground truth responses

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Pre-training corpus \mathcal{D}_{\text{PT}} consisting of long-document plain texts A teacher model with output distribution p An initial student model with the output distribution q_{\theta} Output: A student model with the output distribution q_{\theta} Fine-tune the student model from \theta_0 on \mathcal{D} and select the model \theta with the lowest validation loss. repeat Sample batch of prompts from \mathcal{D} and collect responses from \widetilde{p} to get \mathcal{S} = \{(\boldsymbol{x}^m, \boldsymbol{y}^m)\}_{m=1}^M Sample mini-batch \mathcal{D}'_{\text{PT}} = \{\boldsymbol{d}^m\}_{m=1}^M from \mathcal{D}_{\text{PT}} Compute (\nabla \mathcal{J})_{\text{Main}} = -\frac{1}{|M|} \sum_{\boldsymbol{x}, \boldsymbol{y} \in \mathcal{S}} \sum_{t=1}^T R_{t+1}^{\text{Norm}} \nabla \min[\rho_t(\theta), \text{clip}(\rho_t(\theta), 1 - \epsilon, 1 + \epsilon)], where \rho_t(\theta) = \frac{q_{\theta}(y_t | y_{<t}, \boldsymbol{x})}{\widetilde{p}(y_t | y_{<t}, \boldsymbol{x})} \Rightarrow Eq. 5, Eq. 6 Compute (\nabla \mathcal{J})_{\text{Reg}} = -\frac{1}{M} \sum_{\boldsymbol{x}, \boldsymbol{y} \in \mathcal{S}} \sum_{t=1}^T w_t \nabla \sum_{y_t \in V} q_{\theta}(y_t | \boldsymbol{y}_{<t}, \boldsymbol{x}) \log \frac{p(y_t | \boldsymbol{y}_{<t}, \boldsymbol{x})}{q_{\theta}(y_t | y_{<t}, \boldsymbol{x})} \Rightarrow Eq. 3 Compute the gradient of the pre-training loss \nabla \mathcal{L}_{\text{PT}} = -\frac{1}{M} \sum_{\boldsymbol{d} \in \mathcal{D}'_{\text{PT}}} \nabla \log q_{\theta}(\boldsymbol{d}) Update model parameters: \theta \leftarrow \theta - (\nabla \mathcal{J})_{\text{Main}} - (\nabla \mathcal{J})_{\text{Reg}} - \nabla \mathcal{L}_{\text{PT}} until converge and return q_{\theta}
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3 Experiments

3.1 Experimental Setup

We conduct experiments by first fine-tuning a large model on the instruction-response dataset \mathcal{D} as the teacher p. Then, we compare different KD methods to distill a smaller student model on \mathcal{D} with the teacher's guidance by evaluating the instruction-following performance of the distilled model.

Base Models We distill three kinds of models with various sizes: GPT-2 [RWC⁺19] (120M, 340M, 760M), OPT [ZRG⁺22] (1.3B, 2.7B, 6.7B), and LLaMA [TLI⁺23] (7B), using GPT-2-1.5B, OPT-13B, and LLaMA-13B as the teacher for each model type respectively. We also present the results using GPT-J [WK21] as the teacher in Appendix C.1.

Training We construct the training data from databricks-dolly-15k³ consisting of 15K human-written instruction-response pairs. We randomly split 14K samples as the training set \mathcal{D} and left 500 samples for validation and testing, respectively. For \mathcal{D}_{PT} , we use the OpenWebText [GCPT19] for the GPT-2 family and the RoBERTa training corpus [LOG+19] for other models. We set the teacher-mix-in strength $\alpha=0.2$ throughout the experiments. We use the Rouge-L [Lin04] score on the validation set to select the hyper-parameters because it aligns with human preference better than the validation loss [WMA+22]. More training details are shown in Appendix B.1.

Evaluation We evaluate the trained models on five instruction-following datasets:

- **DollyEval**: the 500-sample test set we split from the databricks-dolly-15k dataset.
- **SelfInst** [WKM⁺22]: A user-oriented instruction-following set with 252 samples.
- VicunaEval [CLL⁺23]: The 80 challenging questions used in the Vicuna evaluation.
- S-NI: The test set of SUPER-NATURALINSTRUCTIONS [WMA⁺22] consisting of 9K samples ranging from 119 tasks. Following [PLH⁺23], we split the set into 3 subsets whose ground truth response lengths lie in [0,5], [6,10], and $[11,+\infty]$. We use the $[11,+\infty]$ subset in Section 3.2 and conduct an analysis on all subsets in Section 3.3.
- UnNI: The core set of UNNATURALINSTRUCTIONS [HSLS22] containing 60K samples. Similar to S-NI, we first conduct the evaluations on the $[11, +\infty]$ subset, followed by an analysis of the performance on all subsets in Appendix C.2.

We adopt two metrics to evaluate the model-generated responses:

- **R-L**: The Rouge-L [Lin04] score to measure the precision of the model generation. [WMA⁺22] has shown that Rouge-L is suitable for large-scale instruction-following evaluation.
- **GPT4**: The GPT-4 [Ope23] feedback by asking GPT-4 to compare model-generated responses with the ground truth answers⁴ and raise 1-10 scores for both responses (see Appendix B.2 for

³https://github.com/databrickslabs/dolly/tree/master

⁴We use the ChatGPT's generation [Ope22] for VicunaEval's ground truth responses

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2.7B KD 60.5 25.9 48.6 13.8 51.3 16.7 26.3 30.2 SeqKD 57.6 27.5 40.5 13.3 44.5 16.5 25.3 32.3 MINILLM 63.2 27.4 52.7 17.2 55.9 19.1* 30.7* 35.1 SFT w/o KD 67.9 27.6 56.4 16.4 57.3 17.8 30.3 28.6 KD 68.6 28.3 58.0 17.0 57.0 17.5 30.7* 26.7 SeqKD 69.6 28.5 54.0 17.0 57.6 17.9* 30.4 28.2 MINILLM 70.8* 29.0 58.5* 17.5 60.1* 18.7* 32.5* 36.7* LLama SFT w/o KD 73.0 26.3 69.2 20.8 61.6 17.5 32.4 35.8 KD 73.7 27.4 70.5 20.2 62.7 18.4 33.7 37.9 SeqKD 73.6 27.5 71.5 20.8 62.6 18.1 33.7 37.6 Company			MiniLLM	60.7	26.7	47.0	14.8	50.6	17.9*	28.6	33.4
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LLaMA SFT w/o KD 73.0 26.3 69.2 20.8 61.6 17.5 32.4 35.8 35.			MINILLM	70.8*	29.0	58.5*	17.5	60.1*	18.7*	32.5*	36.7*
7B KD 73.7 27.4 70.5 20.2 62.7 18.4 33.7 37.9 73.6 27.5 71.5 20.8 62.6 18.1 33.7 37.6		13B	Teacher	79.0	29.7	75.5	23.4	65.1	19.4	35.8	38.5
7B KD 73.7 27.4 70.5 20.2 62.7 18.4 33.7 37.9 78.6 27.5 71.5 20.8 62.6 18.1 33.7 37.6	II oM A		SFT w/o KD	73.0	26.3	69.2	20.8	61.6	17.5	32.4	35.8
SeqKD /3.6 2/.5 /1.5 20.8 62.6 18.1 33.7 37.6	LLawiA	7D	KD								
MINILLM 76.4 29.0 73.1 23.2 64.1 20.7* 35.5 40.2*		/ B	SeqKD	73.6	27.5		20.8		18.1	33.7	37.6
			MiniLLM	76.4	29.0	73.1	23.2	64.1	20.7*	35.5	40.2*

Table 1: Evaluation results. GPT4 and R-L stand for the average GPT-4 feedback scores and Rouge-L scores across 5 random seeds. The best scores of each model size are **boldfaced**, and the scores where the student model outperforms the teacher are marked with *.

the prompt we use). We report the ratio of the total score of model responses and ground truth answers. This metric is only applied to DollyEval, SelfInst, and VicunaEval.

For all test sets, we sample the responses with the temperature = 1 and report the average scores of 5 generations for each prompt with different random seeds.

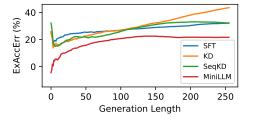
Baselines We consider three baselines in our main experiment:

- SFT w/o KD directly fine-tunes the student model on $\mathcal D$ supervised with the golden responses.
- **KD** [SDCW19] fine-tunes the student model on \mathcal{D} using the teacher distribution as the supervision at each token step, also known as word-level KD.
- SeqKD [KR16] fine-tunes the student model on the teacher-generated data.

3.2 Results

We present the evaluation results in Table 1, from which we have four observations.

First, by comparing SFT with KD and SeqKD that approximately minimize the *forward* KLD, we can see that these standard KD methods successfully distill knowledge from the teacher model in



	SS	Γ2	BoolQ			
	ECE	ECE Acc. E		Acc.		
Teacher	0.025	93.0	0.356	74.5		
KD	0.191	84.7	0.682	63.5		
SeqKD	0.243	66.5	0.681	62.8		
MINILLM	0.099	89.7	0.502	67.8		

Figure 4: The excess error caused by the training-decoding discrepancy (ExAccErr) accumulated with the generation length. Lower ExAccErr means the method introduces less exposure bias.

Table 2: The ECE and accuracy scores on SST2 and BoolQ datasets. The best scores among student models are **boldfaced**.

most cases, achieving better Rouge-L and GPT-4 feedback scores, which restates the conclusions in previous works [KR16, SDCW19, SST⁺20].

Second, by comparing the GPT-4 feedback score of MINILLM with the baselines, we observe that the model distilled by our method outperforms the baselines in almost all cases when trained with different base models and tested on various evaluation sets. This indicates that MINILLM is a general method to distill small models with high overall performance. We also find that MINILLM generally works better on datasets other than DollyEval compared with the baselines, indicating the good out-of-distribution generalization of our method.

Third, the Rouge-L scores show that the MINILLM models produce the most precise responses that have high overlaps with the ground truth. We notice that in some cases, especially on VicunaEval, S-NI, and UnNI, student models reach higher Rouge-L scores than the teacher, which matches the observation in [FLT⁺18]. We conjecture the reason is that the standard teacher-forcing fine-tuning brings the teacher training-inference discrepancy, also known as exposure bias [BVJS15]. On the contrary, MINILLM is optimized with policy optimization methods, which alleviates exposure bias [PH21]. We include further analysis on exposure bias in Section 3.3.

Fourth, comparing the results across model sizes and model families, we can see that the improvement of MINILLM is consistent when the base model sizes vary from 120M to 13B across three model families. This tendency is also illustrated in Figure 1, which demonstrates the excellent scalability and generalization of our method in the era of LLMs.

3.3 Analysis

Exposure Bias Language generation models trained to minimize *forward* KLD are known to suffer from exposure bias [BVJS15] caused by the discrepancy between teacher-forcing training and free-run generation. In MINILLM, we collect the samples from the student model during the training stage, which alleviates the minimatch between the training and evaluation [PH21]. In Figure 4, we use the ExAccErr metric [AEABC22] defined in Appendix B.3 to measure the excess accumulated error due to exposure bias in auto-regressive decoding. The experiment is based on GPT-2-125M, with GPT-2-1.5B as the teacher, using DollyEval as the test set. For each prompt, we sample 10 responses to reduce the variance. We can see that the ExAccErr of the fine-tuned model continuously grows during generation, while MiniLLM has a much lower ExAccErr, and the error stops accumulating for long text generation (> 150 tokens).

Calibration [Ope23] has shown that the RL-trained model is likely to be poorly calibrated. We test the calibration of MINILLM and the KD baselines on two widely-used text classification datasets: SST2 [SPW+13] and BoolQ [CLC+19], based on the LLaMA-7B model. We design zero-shot classification instructions (see Appendix B.2) and take the probability of the label words to compute the ECE scores [NDZ+19]. From Figure 2, we can see that the models trained with KD and SeqKD are worse calibrated than the teacher model, which potentially explains their low performance on canonical benchmarks [GWS+23]. We suspect the reason is that minimizing *forward* KLD causes the models to push high probabilities to zero-probability points of the target distribution, which leads to significant distribution difference between the student and the teacher (see the intuitive example

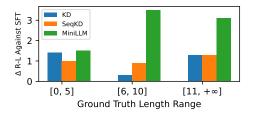


Figure 5: The Rouge-L scores of the distilled models against SFT on the different subsets of S-NI split by the golden responses' length.

	Dolly	Eval	SelfInst			
	Dist-4	Loss	Dist-4	Loss		
Teacher	99.3	3.55	99.1	4.44		
SFT	99.5	3.89	99.0	5.28		
MiniLLM	99.0	3.95	98.6	5.33		

Table 3: The distinct 4-grams (Dist-4) and language modeling loss (Loss) on the test sets based on the LLaMA family. MINILLM preserves generation diversity.

in Figure 2). In contrast, MINILLM focuses on accurately learning the major parts of the target distribution, which narrows the ECE scores gap between the student and the teacher.

Performance on Different Response Length We study the models' performance when the golden response lengths belong to different ranges. In Figure 5, we illustrate the Rouge-L scores of different KD models against the SFT models on three S-NI subsets split by the length of the ground truth responses. We can see that all methods achieve low scores on prompts that expect short responses (≤ 5 tokens), probably because most responses in our training set are long sentences, which introduces a distribution shift between training and testing [PLH $^+$ 23]. Furthermore, the output spaces of these prompts are relatively small, allowing the student model to cover most modes of the teacher, and thus *reverse* KLD and *forward* KLD have similar performance. For prompts with longer responses (≥ 6 tokens), the teacher distribution contains more modes than the students due to the complex output spaces, which shows the advantage of MINILLM against standard KD approaches. Similar results on UnNI are shown in Appendix C.2.

Generation Diversity [CCF⁺20] has found that the model optimized by minimizing *reverse* KLD is likely to lose modes, which affects the generation diversity. We follow [PH21] to discuss generation diversity from three aspects: (i) generating multiple distinct responses given a prompt. (ii) generating linguistically complex responses. (iii) the ability to generate contents that have high coverage of the real data distribution. For (i), we argue that for many NLP applications, generating one **correct** response is sufficient, especially for those scenarios demanding high truthfulness and reliability [JLF⁺23]. For (ii) and (iii), we report the responses' distinct 4-gram proportion and the language modeling loss on the test sets in Table 3, using the base models from the LLaMA family. We can see that MINILLM preserves the distinct 4-gram proportion in the generated responses and does not cause the language modeling loss on the test set to increase much.

3.4 Ablations

Effect of Optimization Strategies We conduct ablation studies on the three strategies proposed to stabilize and accelerate optimization in Section 2.2 by distilling a GPT-2-125M model from the GPT-2-1.5B model. In Table 4, we report the best Rouge-L scores on the validation set of each run and the evaluation results of the corresponding checkpoints. We also plot the *reverse* KLD between the student and the teacher during training in Figure 6, where the lines are smoothed by 32 steps. We can see that Teacher-Mixed Sampling and Length Normalization are critical to stabilizing training. Although the *reverse* KLDs also decrease without these strategies, we find that the models quickly learn to generate repeated, short, or meaningless strings that have high probabilities in the teacher distribution (see examples in Appendix D), which is known as reward hacking [SHKK22]. This also leads to the low generation performance in Table 4. From Figure 6, we also observe that the Single-Step Regularization effectively reduces the variance of the training process, which also results in higher performance on the validation and test sets.

Effect of Teacher-Mix-in Strength α In Figure 7, we plot the best Rouge-L scores on the validation set of GPT-2-125M, OPT-1.3B, and LLaMA-7B using GPT-2-1.5B, OPT-13B, and LLaMA-13B as the teachers, with different teacher-mix-in strength α in MINILLM. $\alpha = 0.0$ means we only sample from the student distribution, and when $\alpha = 1.0$, we sample entirely from the teacher distribution.

	Valid.	Dol	lyEval
	R-L	R-L	GPT-4
MINILLM	27.4	24.6	44.7
w/o Length Norm.	17.4	14.7	22.4
w/o Teacher-Mixed	22.3	20.4	36.1
w/o Single-Step Reg.	27.0	23.7	41.7

Table 4: The performance on the validation Figure 6: The forward KLD between the teacher and test set when different combinations of MINILLM optimization strategies are applied.

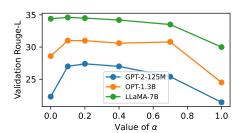
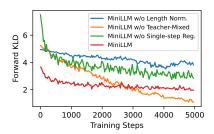


Figure 7: The effect of the α value in the teacher mix-in exploration on the validation Rouge-L score. Larger models to more robust to α .



and the students during MINILLM training when different optimization strategies are applied.

		CLS	Inst.
1.3B	MINILLM	70.2	52.8
	w/o PT Loss	65.7	53.2
7B	MINILLM	78.8	71.2
	w/o PT Loss	74.3	71.1

Table 5: The effect of adding the pre-training loss. "CLS" is the average accuracy scores on SST2 and BoolQ. "Inst." is the average Rouge-L score on DollyEval, SelfInst, and VicunaEval.

We find that $\alpha = 0.2$ is generally suitable across different model families and sizes, and larger models are more robust to the choice of α .

Effect of Adding Pre-Training Loss In Table 5, we study the effect of adding the pre-training loss in Algorithm 2.3 by comparing MINILLM with its variant where the language modeling loss on the pre-training corpus is removed (w/o PT Loss). We have a similar observation as [OWJ⁺22] that adding the pre-training loss helps to preserve the abilities on canonical NLP tasks while keeping the performance on instruction-following tasks nearly unchanged.

Related Work

Large Language Models Large language models (LLMs; BMR⁺20, Ope23, CND⁺22, ADF⁺23, TDFH⁺22) have shown their superior performance by solving various NLP tasks in a generative manner. Recent works apply instruction tuning [WBZ+22, SWR+22, CHL+22] or learning from human feedback [OWJ⁺22, BJN⁺22] to improve the alignment of LLMs with humans further and create general AI assistants [Ope22, Goo23]. There are also efforts to build open-source LLMs [TLI+23, ZRG+22, SFA+22, BSA+23, Mos23] to facilitate research and industry development. Although appealing, the broad capacities of LLMs usually only emerge with large parameter sizes [KMH⁺20, WTB⁺22] that require massive computational resources [SGM19]. Therefore, model compression is critical for the practical deployment and further research of LLMs.

Knowledge Distillation Knowledge distillation (KD; HVD15) aims at training a student model with the guidance of a teacher model and is widely used as a model compression technique in many fields of deep learning [JBMD21, SDCW19, RCG+15]. In the NLP community, many works apply KD to text classification tasks by training the student to mimic the teacher's output distribution difference [SST⁺20, ZSL⁺23], hidden states [JYS⁺20, SCGL19], or attention scores [WWD⁺20, WBH⁺21]. For text generation, the standard KD method is to approximately minimize the forward KLD between the student and the teacher generation distribution by using the teacher's output at each time step as supervision [SDCW19] or direct training on the teacher generations [KR16, TGZ⁺23, CLL⁺23, PLH⁺23]. In this paper, we propose to minimize the reverse KLD, which is more suitable for generative large language models when the teacher distribution is available.

Distribution Discrepancy Metrics in Text Generation The distribution discrepancy metrics play a significant role in learning text generation models. The *forward* Kullback-Leibler divergence (KLD) is the standard metric due to its simplicity when derived as the Maximum Likelihood Estimate (MLE) objective [ZZ19]. However, previous works show that minimizing *forward* KLD leads to zero-forcing behavior where models try to cover all modes of the target distribution and sacrifice the accuracy of major modes [Hus15]. Some works resort to using other metrics to remedy this problem, such as *reverse* KLD [JHC⁺20], Total Variation Distance [JKH⁺23], and Optimal Transport [LLW⁺20]. Our paper is the first to tackle this problem for knowledge distillation of LLMs.

5 Conclusion

In this work, we investigate the problem of distilling knowledge from larger LLMs to smaller ones. We find that the standard distillation methods that minimize the *forward* KLD is sub-optimal in language generation scenarios because the teacher's output distribution contains much more modes than the student's, and *forward* KLD forces the student distribution to over-estimate the low-probability regions of the teacher distribution. Therefore, we propose MINILLM that minimizes the *reverse* KLD between the teacher and student distribution and develop an algorithm to optimize this objective. Extensive experiments in the instruction-following setting show that MINILLM models produce more precise responses that have higher overall quality than standard KD approaches. We also find that MINILLM has lower exposure bias, better calibration, and higher performance in long-text generation with good diversity.

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A Derivations

A.1 Derivation of Equation 1

We compute the gradient of $\mathcal{J}(\theta) = \mathrm{KL}[q_{\theta}||p]$ with respect to θ using the Policy Gradient Theorem [SMSM99]:

$$\nabla \mathcal{J}(\theta) = -\nabla \underset{\boldsymbol{y} \sim q_{\theta}(\cdot|\boldsymbol{x})}{\mathbb{E}} \log \frac{p(\boldsymbol{y}|\boldsymbol{x})}{q_{\theta}(\boldsymbol{y}|\boldsymbol{x})}$$
(8)

$$= -\int \nabla \left[q_{\theta}(\boldsymbol{y}|\boldsymbol{x}) \log \frac{p(\boldsymbol{y}|\boldsymbol{x})}{q_{\theta}(\boldsymbol{y}|\boldsymbol{x})} \right] d\boldsymbol{y}$$
(9)

$$= -\int q_{\theta}(\boldsymbol{y}|\boldsymbol{x}) \nabla \log \frac{p(\boldsymbol{y}|\boldsymbol{x})}{q_{\theta}(\boldsymbol{y}|\boldsymbol{x})} d\boldsymbol{y} - \int \log \frac{p(\boldsymbol{y}|\boldsymbol{x})}{q_{\theta}(\boldsymbol{y}|\boldsymbol{x})} \nabla q_{\theta}(\boldsymbol{y}|\boldsymbol{x}) d\boldsymbol{y}$$
(10)

$$= \int q_{\theta}(\boldsymbol{y}|\boldsymbol{x}) \nabla \log q_{\theta}(\boldsymbol{y}|\boldsymbol{x}) d\boldsymbol{y} - \int q_{\theta}(\boldsymbol{y}|\boldsymbol{x}) \log \frac{p(\boldsymbol{y}|\boldsymbol{x})}{q_{\theta}(\boldsymbol{y}|\boldsymbol{x})} \nabla \log q_{\theta}(\boldsymbol{y}|\boldsymbol{x}) d\boldsymbol{y}$$
(11)

$$= - \underset{\boldsymbol{y} \sim q_{\theta}(\cdot|\boldsymbol{x})}{\mathbb{E}} \left(\log \frac{p(\boldsymbol{y}|\boldsymbol{x})}{q_{\theta}(\boldsymbol{y}|\boldsymbol{x})} - 1 \right) \nabla \log q_{\theta}(\boldsymbol{y}|\boldsymbol{x})$$
(12)

$$= - \underset{\boldsymbol{y} \sim q_{\theta}(\cdot|\boldsymbol{x})}{\mathbb{E}} \sum_{t=1}^{T} \left(\sum_{t'=1}^{T} \log \frac{p(y_{t'}|\boldsymbol{y}_{< t'}, \boldsymbol{x})}{q_{\theta}(y_{t'}|\boldsymbol{y}_{< t'}, \boldsymbol{x})} - 1 \right) \nabla \log q_{\theta}(y_{t}|\boldsymbol{y}_{< t}, \boldsymbol{x})$$
(13)

$$= - \underset{\boldsymbol{y} \sim q_{\theta}(\cdot|\boldsymbol{x})}{\mathbb{E}} \sum_{t=1}^{T} (\sum_{t'-t}^{T} \log \frac{p(y_{t'}|\boldsymbol{y}_{< t'}, \boldsymbol{x})}{q_{\theta}(y_{t'}|\boldsymbol{y}_{< t'}, \boldsymbol{x})} - 1) \nabla \log q_{\theta}(y_{t}|\boldsymbol{y}_{< t}, \boldsymbol{x}), \tag{14}$$

where Equation 14 is based on the fact that $\log q_{\theta}(y_t|\boldsymbol{y}_{< t},\boldsymbol{x})$ can only affect tokens at $\geq t$ positions in \boldsymbol{y} . By setting $R_t = \sum_{t'=t}^T \log \frac{p(y_{t'}|\boldsymbol{y}_{< t'},\boldsymbol{x})}{q_{\theta}(y_{t'}|\boldsymbol{y}_{< t'},\boldsymbol{x})}$, we obtain Equation 2.

A.2 Derivation of Equation 3

To derive Equation 3, we first denote:

$$(\nabla \mathcal{J})_{\text{Main}} = - \underset{\boldsymbol{y} \sim q_{\theta}(\cdot|\boldsymbol{x})}{\mathbb{E}} \sum_{t=1}^{T} R_{t+1} \nabla \log q_{\theta}(y_{t}|\boldsymbol{y}_{< t}, \boldsymbol{x}),$$

$$(\nabla \mathcal{J})_{\text{Reg}} = - \underset{\boldsymbol{y} \sim q_{\theta}(\cdot|\boldsymbol{x})}{\mathbb{E}} \left[\sum_{t=1}^{T} \nabla \underset{y_{t} \sim q_{\theta}(t)}{\mathbb{E}} [r_{t}] \right].$$
(15)

Then, we re-write $\nabla \mathcal{J}(\theta)$ as:

$$\nabla \mathcal{J}(\theta) = - \underset{\boldsymbol{y} \sim q_{\theta}(\cdot|\boldsymbol{x})}{\mathbb{E}} \sum_{t=1}^{T} (R_t - 1) \nabla \log q_{\theta}(y_t|\boldsymbol{y}_{< t}, \boldsymbol{x})$$
(16)

$$= - \underset{\boldsymbol{y} \sim q_{\theta}(\cdot|\boldsymbol{x})}{\mathbb{E}} \sum_{t=1}^{T} R_{t+1} \nabla \log q_{\theta}(y_{t}|\boldsymbol{y}_{< t}, \boldsymbol{x})$$
(17)

$$- \underset{\boldsymbol{y} \sim q_{\theta}(\cdot|\boldsymbol{x})}{\mathbb{E}} \sum_{t=1}^{T} \left(\log \frac{p(y_{t}|\boldsymbol{y}_{< t}, \boldsymbol{x})}{q_{\theta}(y_{t}|\boldsymbol{y}_{< t}, \boldsymbol{x})} - 1 \right) \nabla \log q_{\theta}(y_{t}|\boldsymbol{y}_{< t}, \boldsymbol{x})$$
(18)

$$= (\nabla \mathcal{J})_{\text{Main}} - \underset{\boldsymbol{y} \sim q_{\theta}(\cdot|\boldsymbol{x})}{\mathbb{E}} \sum_{t=1}^{T} \underset{y_{t} \sim q_{\theta}(\cdot|\boldsymbol{y}_{< t}, \boldsymbol{x})}{\mathbb{E}} \left(\log \frac{p(y_{t}|\boldsymbol{y}_{< t}, \boldsymbol{x})}{q_{\theta}(y_{t}|\boldsymbol{y}_{< t}, \boldsymbol{x})} - 1 \right) \nabla \log q_{\theta}(y_{t}|\boldsymbol{y}_{< t}, \boldsymbol{x})$$
(19)

$$= (\nabla \mathcal{J})_{\text{Main}} - \underset{\boldsymbol{y} \sim q_{\theta}(\cdot|\boldsymbol{x})}{\mathbb{E}} \sum_{t=1}^{T} \nabla \underset{\boldsymbol{y}_{t} \sim q_{\theta}(\cdot|\boldsymbol{y}_{< t}, \boldsymbol{x})}{\mathbb{E}} \left[-\log \frac{q_{\theta}(y_{t}|\boldsymbol{y}_{< t}, \boldsymbol{x})}{p(y_{t}|\boldsymbol{y}_{< t}, \boldsymbol{x})} \right]$$
(20)

$$= (\nabla \mathcal{J})_{\text{Main}} - \underset{\boldsymbol{y} \sim q_{\theta}(\cdot|\boldsymbol{x})}{\mathbb{E}} \left[\sum_{t=1}^{T} \nabla \underset{\boldsymbol{y}_{t} \sim q_{\theta}(t)}{\mathbb{E}} [r_{t}] \right]$$
(21)

$$= (\nabla \mathcal{J})_{\text{Main}} + (\nabla \mathcal{J})_{\text{Reg}}, \tag{22}$$

where Equation 20 uses the product rule of the gradient and $r_t = \log \frac{p(y_t | \mathbf{y}_{< t}, \mathbf{x})}{q_{\theta}(y_t | \mathbf{y}_{< t}, \mathbf{x})}$.

```
Below is an instruction that describes a task.
Write a response that appropriately completes the request.

### Instruction:
{instruction}

### Input:
{input}

### Response:
```

Figure 8: The prompt wrapper for training and evaluation.

B Experimental Details

B.1 Training Details

Baselines For models with less than 1.3B parameters, we search for the learning rates in [5e-4, 1e-4, 5e-5], the batch sizes in [32, 64], and train these models for 20 epochs. For other models, we search for the learning rate in [5e-5, 1e-5, 5e-6], the batch sizes in [32, 64], and train these models for 10 epochs. For KD, we follow [SST+20] to mix the distillation loss with the language modeling loss on the ground truth responses by a mixture rate of 0.5. The checkpoints of each baseline are selected by the Rouge-L scores on the validation set.

MINILLM As shown in Algorithm 2.3, we first fine-tune the model on the training set using the vanilla language modeling objective to get a starting point of the subsequent MINILLM training. We fine-tune the model for 3 epochs using the best learning rate and batch size of the corresponding SFT baselines. We select the checkpoint with the lowest validation loss, not the Rouge-L score. Then, we train the model as described in Algorithm 2.3 using a learning rate 5e-6, a mini-batch size 64 in all cases. Similar to PPO [SWD+17], we collect 256 sentences at once and adopt 4 inner epochs. The clipping rate ϵ is set to 0.2, and the max length of the model is 512. We use temperature = 1 when sampling from q_{θ} . We train the model for at most 5000 steps and select the final checkpoint using the Rouge-L score on the validation set. Our experiments are based on the NVIDIA V100 32G GPUs.

B.2 Evaluation Details

During the evaluation, we sample the responses from each model using temperature = 1, a max-length limit of 512, and random seeds [10, 20, 30, 40, 50]. Similar to [TGZ $^+$ 23], we adopt a prompt wrapper shown in Figure 8 to convert each instruction-response pair to a sentence. For the GPT-4 feedback, we apply the prompt in Figure 9 and set the temperature = 0.7. For the classification tasks in the calibration paragraph of Section 3.3, we prompt the model to do zero-shot text classification with the prompt in Figure 10 and 11.

B.3 Exposure Bias Analysis

Following [AEABC22], we compute the ExAccErr with the following formula:

$$\operatorname{ExAccErr}(l) = \frac{R(l) - l\epsilon(l)}{l\epsilon(l)} \times 100\%, \tag{23}$$

where R(l) is the accumulated regret of imitating the teacher distribution p at the time step l during the free-run generation:

$$R(l) = \sum_{t=1}^{T} \underset{\substack{\mathbf{y}_{t} \sim q_{\theta}(\cdot | \mathbf{x}) \\ y_{t} \sim q_{\theta}(\cdot | \mathbf{y}_{\leq t}, \mathbf{x})}}{\mathbb{E}} \log \frac{p(y_{t} | \mathbf{y}_{\leq t}, \mathbf{x})}{q_{\theta}(y_{t} | \mathbf{y}_{\leq t}, \mathbf{x})},$$
(24)

We would like to request your feedback on the performance of two AI assistants in response to the user instruction and input displayed above.

Please rate the helpfulness, relevance, accuracy, and level of detail of their responses. Each assistant receives an overall score on a scale of 1 to 10, where a higher score indicates better overall performance.

Please first output a single line containing only two values indicating the scores for Assistant 1 and 2, respectively. The two scores are separated by a space.

In the subsequent line, please provide a comprehensive explanation of your evaluation, avoiding any potential bias and ensuring that the order in which the responses were presented does not affect your judgment.

Figure 9: GPT-4 evaluation prompt.

```
Below is an instruction that describes a task.

Write a response that appropriately completes the request.

### Instruction:
Determine the sentiment of the input sentence. Please respond as positive or negative.

### Input:
{sentence}

### Response:
```

Figure 10: Zero-shot text classification prompt for SST2.

```
Below is an instruction that describes a task.

Write a response that appropriately completes the request.

### Instruction:
Read the input passage and answer the question: {question}? Your answer should be "Yes" or "No".

### Input: {passage}

### Response:
```

Figure 11: Zero-shot text classification prompt for BoolQ.

Model	Method	Dolly GPT4	Eval R-L	Selfl GPT4	Inst R-L	Vicun GPT4	aEval R-L	S-NI R-L	UnNI R-L
GPT-J-6B	Teacher	65.8	27.3	57.4	17.3	55.8	17.4	28.0	33.6
GPT-2-760M	SFT w/o KD	50.7	25.4	38.3	12.4	43.1	16.1	21.5	27.1
	KD	51.6	26.7	38.9	13.4	43.4	16.4	25.9	33.2
	SeqKD	51.4	26.0	39.2	14.0	42.0	15.3	25.5	32.5
	MINILLM	54.0	25.8	43.7	16.3	44.3	19.1 *	27.1	35.5*
GPT-2-1.5B	SFT w/o KD	58.4	27.6*	42.9	14.3	48.6	16.3	27.6	34.6*
	KD	56.5	26.6	46.0	14.5	47.2	16.5	27.6	34.9*
	SeqKD	58.5	27.0	43.2	13.6	46.6	16.9	28.0	34.2*
	MINILLM	59.6	25.9	48.5	16.6	48.9	19.4 *	28.5 *	35.9 *
GPT-Neo-2.7B	SFT w/o KD	60.7	26.8	45.4	15.8	51.5	17.0	26.5	31.6
	KD	61.5	26.7	47.0	16.0	52.1	16.9	27.2	32.7
	SeqKD	60.8	25.6	47.2	16.2	53.0	16.9	26.1	32.9
	MINILLM	63.4	28.5 *	52.5	17.1	54.1	18.6 *	29.8 *	35.4 *

Table 6: Evaluation results when GPT-J is the teacher. GPT4 and R-L stand for the average GPT-4 feedback scores and Rouge-L scores across 5 random seeds. The best scores of each model size are **boldfaced**, and the scores where the student model outperforms the teacher are marked with *.

and $\epsilon(l)$ is the average per-step error between q_{θ} and p using the oracle context sampled from p as the prefix:

$$\epsilon(l) = \frac{1}{l} \sum_{t=1}^{T} \underset{\substack{\boldsymbol{y}_{ (25)$$

Intuitively, the regret of q_{θ} during generation is made of two parts: the error to estimate p given the oracle context and the error caused by the low-quality model-generated prefix. The former is calculated by $l\epsilon(l)$, and the latter reflects the exposure bias. Therefore, ExAccErr measures the relative error caused only by exposure bias.

C Additional Results

C.1 GPT-J as the Teacher

We present the evaluation results when using GPT-J as the teacher and GPT-2-760M, GPT-2-1.5B, and GPT-*Neo*-2.7B [BLW⁺21] as the student in Table 6. MINILLM outperforms the baselines in most cases.

C.2 Performance of Response Length on U-NI

The performance on different U-NI subsets split by the length of the ground truth response is shown in Figure 12. We have the same observation as in Section 3.3 that on short responses, all KD methods perform similarly, and on long responses, MINILLM outperforms other methods.

D Cases

We provide some cases generated by the models distilled by different methods based on LLaMA in Table 7. We find that MiniLLM generates more detailed and accurate responses compared with the baselines.

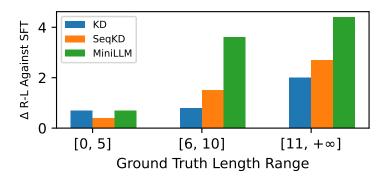


Figure 12: The Rouge-L scores of the distilled models against the SFT models on the different evaluation subsets of UnNI split by the golden responses' length.

	Case #1					
Instruction	During writing, we added an asterisk for the word that did not come to mind. You will need to provide several examples to demonstrate all the words that can be used in the sentence instead of the asterisk.					
Input	we * to know					
SFT w/o KD	We can use "know" in the sentence instead of "we * to know"					
KD	we went to know\n we will go to know\n we can go to know\n we may go to know\n we should go to know\n we must go to know					
SeqKD	$ \begin{tabular}{lllllllllllllllllllllllllllllllllll$					
MINILLM	We can use the following words in place of the asterisk:\n - want\n - have\n - do\n - used\n - ought\n - desire\n - need\n - must					
MINILLM w/o teacher-mixed	We to know					
	Case #2					
Instruction	Take the title of the product and extract its attributes. The attributes in this case refer to the characteristics of the products, such as their brand and color. Your answer must a list following the format of "attribute: value".					
Input	SAMSUNG 980 PRO SSD 2TB PCIe NVMe Gen 4 Gaming M.2 Internal Solid State Hard Drive Memory Card, Maximum Speed, Thermal Control, MZ-V8P2T0B					
SFT w/o KD	Attribute: Maximum Speed\n Value: 3500 MB/s					
KD	attribute: brand, attribute: color, attribute: memory card, attribute: maximum speed, attribute: thermal control					
SeqKD	brand: Samsung, color: black, size: 2TB, interface: PCIe NVME Gen 4, design: M.2 Internal					
MINILLM	brand: SAMSUNG\n color: 980 PRO\n capacity: 2TB\n interface: PCIe NVME Gen 4\n speed: Maximum Speed\n threshold: Thermal Control\n form factor: M.2 Internal					
MINILLM w/o teacher-mixed	SAMSUNGC 980 Pro SSD 2TB PCIe NVME Gen 4 Gaming M.II Internal Solid State Hard Drive memory Card, Max Speed, Thermal Control, AP1500K					

Table 7: Instruction-following cases from the SelfInst dataset. MINILLM better follows the instructions and provides more detailed and accurate responses. Without the teacher-mixed sampling strategy in Section 2.2, the distilled model outputs short responses (Case #1) or simply repeats the input (Cases #2).