On Learning to Summarize with Large Language Models as References

Yixin Liu¹ Alexander R. Fabbri² Pengfei Liu³ Dragomir Radev¹ Arman Cohan^{1,4}

¹Yale University ²Salesforce AI Research ³Shanghai Jiao Tong University ⁴Allen Institute for AI {yixin.liu,arman.cohan}@yale.edu

Abstract

Recent studies have found that summaries generated by large language models (LLMs) are favored by human annotators over the original reference summaries in commonly used summarization datasets. Therefore, we investigate a new learning paradigm of text summarization models that considers the LLMs as the reference or the gold-standard oracle on commonly used summarization datasets such as the CNN/DailyMail dataset. To examine the standard practices that are aligned with the new learning setting, we propose a novel training method that is based on contrastive learning with LLMs as a summarization quality evaluator. For this reward-based training method, we investigate two different methods of utilizing LLMs for summary quality evaluation, namely GPTScore and GPTRank. Our experiments on the CNN/DailyMail dataset demonstrate that smaller summarization models trained by our proposed method can achieve performance equal to or surpass that of the reference LLMs, as evaluated by the LLMs themselves. This underscores the efficacy of our proposed paradigm in enhancing model performance over the standard maximum likelihood estimation (MLE) training method, and its efficiency since it only requires a small budget to access the LLMs. We release the training scripts, model outputs, and LLM-based evaluation results to facilitate future studies: https://github.com/yixinL7/SumLLM.

1 Introduction

Recent studies (Liu et al., 2023b; Zhang et al., 2023) have discovered that large language models (LLMs), like GPT-3.5¹ (Ouyang et al., 2022), can generate summaries that are more preferred by human annotators when compared to *reference summaries* from widely used datasets, such as CNN/DailyMail (Nallapati et al., 2016) and

XSum (Narayan et al., 2018), in a *reference-free* human evaluation setting. This quality issue of existing reference summaries effectively puts an upper bound on the performance of summarization models trained on them, which likely contributes to the performance gap between supervised summarization models and LLMs as observed by related work (Goyal et al., 2022; Liang et al., 2022; Liu et al., 2023b; Zhang et al., 2023).

Therefore, we investigate a new learning setting for text summarization models, where **LLMs are considered the reference or the gold-standard oracle for the summarization task**. Such an LLM-as-reference setting introduces interesting changes to the learning paradigm of text generation models in general with respect to both model *training* and *evaluation*, and we aim to examine the standard practices that are aligned with this paradigm shift.

Specifically, the traditional learning paradigm of summarization models usually revolves around a single reference summary – in training, the standard training algorithm, Maximum Likelihood Estimation (MLE), requires the model to predict the reference summary tokens; in evaluation, automatic evaluation metrics like ROUGE (Lin, 2004) estimate the quality of system outputs by comparing them with the reference summary. In contrast, LLMs provide a target probability distribution or quality measurement over all possible candidate summaries. As a result, LLMs can assign quality scores to arbitrary candidates, which enables training techniques beyond MLE such as contrastive learning (Liu et al., 2022b) and reinforcement learning (Paulus et al., 2018; Stiennon et al., 2020; Pang and He, 2021), and provides an oracle to assess the model output quality for model evaluation.

To align with this paradigm shift, we investigate two ways of using LLMs for summary quality evaluation: (1) GPTScore (Fu et al., 2023), which treats the LLM-predicted probability of a candidate summary as its quality score; (2) GPTRank, a

¹Documentation of GPT-3.5: https://platform.openai.com/docs/models/gpt-3-5.

new method we propose that requires an LLM to provide a quality ranking of different summaries, inspired by recent work (Liu et al., 2023a) on LLM-based evaluation. With these two evaluation methods, we adopt a contrastive learning method, BRIO (Liu et al., 2022b), for model training that requires the model to assign a higher probability to a better candidate summary as assessed by the LLM. This contrastive training method can effectively leverage the supervision signal, i.e., summary quality scores, provided by the reference LLMs, and can be used in a few-shot fine-tuning setting thanks to its offline and supervised training manner.

We conduct experiments on the CNN/DailyMail dataset, and make the following contributions:

- (1) We empirically demonstrate that a smaller summarization model, such as BART (Lewis et al., 2020), when trained with a reference LLM, can achieve performance that is on par with or superior to the reference LLM, under the evaluation from the reference LLM itself or another LLM.
- (2) Our proposed training paradigm, which leverages contrastive learning and treats LLMs as the summary quality evaluator, can effectively improve the model performance compared with the standard MLE training method, and only requires a small budget for querying the LLMs.²
- (3) We release the training scripts, model outputs, and LLM-based evaluation results,³ which can facilitate the future study along this new training paradigm we investigated in this work.

2 Summarize as Large Language Models

2.1 Preliminary

A neural abstractive text summarization model g aims to generate a text sequence S that summarizes the information of a source document D:

$$S \leftarrow g(D)$$
. (1)

When g is an *auto-regressive* generation model, it factorizes the probability of a candidate summary S given the source document D as

$$p_g(S|D) = \prod_{i=1}^{l_S} p_g(s_i|S_{< i}, D),$$
 (2)

where s_i is the *i*-th token in S and S_0 is a special begin-of-sequence (BOS) token, $S_{< i}$ is the prefix-string of S before S_i , I_S is the length of S (without

the BOS token), and p_g is a probability distribution parameterized by the summarization model g.

The standard training algorithm for g is Maximum Likelihood Estimation (MLE) with a single reference (gold standard) summary S^* . With Eq. 2, the MLE optimization on this example is equivalent to minimizing the following cross-entropy loss:

$$\mathcal{L}_{xent}(\theta) = -\log p_g(S^*|D;\theta)$$

$$= -\sum_{i=1}^{l_{S^*}} \log p_g(s_i^*|S_{< i}^*, D; \theta),$$
(3)

where θ are the learnable parameters of g. Note that Eq. 3 assumes a point-mass target distribution p^* on the reference summary S^* , i.e.,

$$p^*(S|D) = \begin{cases} 1, & S = S^*; \\ 0, & S \neq S^*. \end{cases}$$
 (4)

2.2 Large Language Models as References

Similar to Eq. 2, an auto-regressive LLM h defines a target distribution for text summarization:

$$p_h(S|D) = \prod_{i=1}^{l_S} p_h(s_i|S_{< i}, D),$$
 (5)

which is different from the point-mass distribution defined by a single reference summary (Eq. 4). Consequently, the cross-entropy loss becomes

$$\mathcal{L}_{xent}^{(h)}(\theta) = -\sum_{S \in \mathcal{S}} p_h(S|D) \log p_g(S|D;\theta), \qquad (6)$$

where S is the set of possible outputs (candidate summaries). In practice, computing Eq. 6 is intractable because S is infinite. Therefore, we investigate three types of methods to approximate the optimization process of Eq. 6.

MLE with Quasi-Reference Summary Our baseline method treats the greedy decoding results of the LLM h as the quasi-reference summaries and optimizes the summarization model g using MLE. Specifically, the loss function becomes

$$\hat{\mathcal{L}}_{xent}^{(h)}(\theta) = -\log p_g(\hat{S}|D;\theta),\tag{7}$$

where \hat{S} is the greedy decoding result of h:

$$\hat{s}_i = \arg\max_{s} p_h(s|\hat{S}_{< i}, D), \tag{8}$$

where s denotes a token in the vocabulary. Since Eq. 7 ignores all the other candidate summaries except for \hat{S} , to prevent g assigns all the probability

²The cost of OpenAI API in our experiments only ranges from \$20 to \$40 for one single experiment.

³https://github.com/yixinL7/SumLLM

mass to \hat{S} , we modify Eq. 7 with label smoothing (Szegedy et al., 2016):

$$\tilde{\mathcal{L}}_{xent}^{(h)}(\theta) = -\sum_{i=1}^{l_{\hat{S}}} \sum_{s} \tilde{p}(s|\hat{S}_{< i}, D) \log p_g(s|\hat{S}_{< i}, D; \theta).$$
(9)

 \tilde{p} is the target distribution with label smoothing:

$$\tilde{p}(s|\hat{S}_{< i}, D) = \begin{cases} 1 - \beta, & s = \hat{s}_i; \\ \frac{\beta}{N - 1}, & s \neq \hat{s}_i, \end{cases}$$
(10)

where N is the size of the vocabulary, β is the probability mass assigned to tokens not in \hat{S} .

2.3 Learning from LLM-based Evaluation

Apart from the quasi-reference summaries, the reference LLMs can provide much richer supervision signals for model training since they can be used to evaluate the quality of any candidate summary. Therefore, we adopt a sequence-level contrastive learning method, BRIO (Liu et al., 2022b), that can leverage candidate quality scores to train the summarization models. While other reward-based training methods such as reinforcement learning (Stiennon et al., 2020; Pang and He, 2021) can also be adopted, we choose BRIO because it is more stable and data-efficient thanks to its offline and supervised training manner, and it has been shown to be effective in a few-shot learning setting. With BRIO as the training method, we explore two ways of leveraging LLMs to assess the candidate summary quality – an existing method, GPTScore (Fu et al., 2023), and a new method we will introduce later, GPTRank.

Contrastive Learning To better approximate the reference LLM, we introduce a sequence-level contrastive loss (Liu et al., 2022b), which sets the following objective: given two candidate summaries S_1 , S_2 , if S_1 receives a higher quality score from the LLM-based evaluation method, the summarization model q should also assign S_1 a higher probability (Eq. 2). In more detail, this contrastive loss is defined with a set of candidate summaries S_c , which consists of those generated by g, as these are the summaries to which g assigns the highest probabilities and likely to be generated as the final output. S_c is *sorted* by the *LLM-assigned quality scores*, and the summarization model g is tasked with assigning a probability that is at least twice as large to a better candidate:

$$\frac{p_g(S_i|D)}{p_g(S_j|D)} > 2(j-i), \forall i, j, i < j,$$
(11)

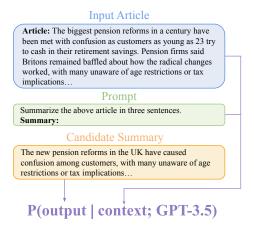


Figure 1: Illustration of GPTScore. The LLM-predicted probability of a candidate summary given the input context is interpreted as the quality score of the candidate.

which corresponds to the following margin loss:

$$\mathcal{L}_{ctr}(\theta) = \sum_{S_i, S_j \in \mathcal{S}_c, i < j} \max(0, \log p_g(S_j | D; \theta) - \log p_g(S_i | D; \theta) + \log 2(j - i)).$$
(12)

In practice, we observe that the magnitude of the log-probability in Eq. 12 is highly dependent on the length of the candidate summaries. Therefore, we introduce a modification to Eq. 12 based on the length-normalized log-probability \bar{p}_q :

$$\bar{p}_g(S|D) = \frac{\sum_{i=1}^{l_S} \log p_g(s_i|S_{< i}, D)}{l_S},$$
 (13)

and Eq. 12 is changed to

$$\hat{\mathcal{L}}_{ctr}(\theta) = \sum_{S_i, S_j \in \mathcal{S}_c, i < j} \max(0, \bar{p}_g(S_j | D; \theta) - \bar{p}_g(S_i | D; \theta) + \frac{1}{\lambda} \log 2(j - i)),$$
(14)

where λ is a scaling factor approximating the average summary length. Since Eq. 14 is defined at the sequence level, to ensure the model g can still perform auto-regressive generation, we combine the token-level label-smoothed cross-entropy loss (Eq. 9) with the contrastive loss as a multi-task loss:

$$\mathcal{L}_{mul}(\theta) = \tilde{\mathcal{L}}_{xent}^{(h)}(\theta) + \alpha \hat{\mathcal{L}}_{ctr}(\theta), \tag{15}$$

where α is the weight of the contrastive loss.

GPTScore for Summary Quality Evaluation

The contrastive learning objective (Eq. 14) requires access to ground-truth candidate summary quality scores from the reference LLM. Therefore, we first adopt GPTScore (Fu et al., 2023), an LLM-based evaluation method for the summary quality

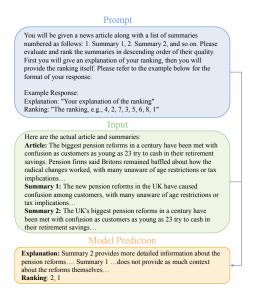


Figure 2: Illustration of GPTRank. The LLM is presented with a news article and a list of candidate summaries and is required to rank the summary quality by first providing an explanation of its ranking and then giving the actual ranking.

evaluation. Specifically, GPTScore interprets the length-normalized conditional log-probability of a candidate summary predicted by the reference LLM *h* as its quality score, i.e.,

$$\bar{p}_h(S|D) = \frac{\sum_{i=1}^{l_S} \log p_h(s_i|S_{< i}, D)}{l_S}.$$
 (16)

Consequently, the set of candidate summaries \mathcal{S}_c used in Eq. 14 is sorted based on the (normalized) target distribution (Eq. 5), such that for any $S_i, S_j \in \mathcal{S}_c, i < j, \bar{p}_h(S_i|D) > \bar{p}_h(S_j|D)$. We note that for zero-shot LLM summarization, the input D contains not only the source article but also a prompt for the summarization task, for which we provide an illustration in Fig. 1.

GPTRank for Summary Quality Evaluation

Instead of leveraging the LLM predicted probability, recent work, e.g., G-Eval (Liu et al., 2023a), has proposed LLM-based automatic evaluation methods by formulating the evaluation task as a text completion or infilling task for the LLMs. For example, given the source article and a summary, the LLM can be asked to provide a numerical quality score for the summary. However, as Liu et al. (2023a) has found that LLM predicted scores are not diverse enough and different candidate summaries are likely to receive the same score, we propose a *ranking* task to the LLM. The proposed evaluation method, **GPTRank**, requires the LLM

to provide a *ranking* to a list of different candidate summaries for the same source article. Moreover, since recent work (Liu et al., 2022a, 2023a) has found that language generation models can benefit from a self-explaining or planning stage for an evaluation task, we prompt the LLM to first generate an *explanation* before providing the actual ranking. The ranking is then used to sort the set of candidate summaries used in contrastive training (Eq. 14). We provide an example of using GPTRank in Fig. 2.

3 Learning with LLMs as References

We conduct experiments with several LLMs as the reference for the learning of smaller summarization models. We compare the standard MLE training with the contrastive, LLM-evaluation-based training we proposed, and investigate the effectiveness of two different LLM-based evaluation methods.

3.1 Experimental Setting

Data Source We conduct experiments on the CNN/DailyMail (CNNDM) dataset. We use the original validation set of CNNDM for model training and evaluation, and a subset of the test set for testing. To approximate the original data format of CNNDM, we define the summaries to be threesentence summaries and prompt the LLMs with the explicit length requirement when generating the summaries.⁴ During the LLM summary generation, the sampling temperate is set to 0 to approximate the greedy decoding process (Eq. 8).

Training Details The model training is started with a BART⁵ checkpoint that is fine-tuned on the original CNNDM dataset. We choose BART because it is widely used, with a relatively small size, and easy to fine-tune and deploy. The fine-tuning process includes three steps:

- (1) Warm-starting. We use ChatGPT⁶ to generate 10K summaries for fine-tuning and 1K summaries for validation, and fine-tuned the original BART checkpoint with MLE training (Eq. 9) to start aligning the model with the summary style of LLMs.
- (2) MLE Training. Using the fine-tuned checkpoint from Step (1), we continue find-tuning the model

⁴Further information regarding the prompts and the process of generating LLM summaries can be found in Appendix A.1.

⁵https://huggingface.co/facebook/bart-large-cnn. It contains around 350M parameters.

⁶We used the checkpoint gpt-3.5-turbo-0301 at https://platform.openai.com/docs/models/gpt-3-5.

using MLE training on the pseudo-reference summaries generated by different LLMs.

(3) Contrastive Training. Following Step (2), we keep fine-tuning the model using the multi-task, contrastive learning objective (Eq. 15) with either GPTScore or GPTRank as the evaluation method used for the contrastive loss (Eq. 14). The candidate summaries for Eq. 14 are generated from the checkpoint trained in Step (2), and diverse beam search (Vijayakumar et al., 2018) is used to generate 8 candidates for each data point.⁷

We note that for a more fair comparison, in the following sections, we compare the performance of checkpoints from Step (2) and Step (3) that are trained with similar amounts of data in terms of the budget. That is, the MLE checkpoints we report in Step (2) are trained on more data than the checkpoints that are used for the model training in Step (3). Regarding checkpoint selection, for MLE training we use the cross-entropy loss on the validation set as the criterion while for contrastive training we use the contrastive loss (Eq. 14).

Evaluation Methods Two types of automatic evaluation methods are used in the experiments. For *reference-based* evaluation, we report the ROUGE-1/2 F1 scores compared between the system outputs and the (quasi-)reference summaries generated by the reference LLM. On the other hand, for *reference-free* evaluation, we use either GPTScore (Fu et al., 2023) or GPTRank (Fig. 2) with the reference LLMs. In particular, for GPTScore we report both the un-normalized and normalized sum of log-probability.

3.2 Learning with GPTScore

We first investigate the performance of learning with GPTScore. To this end, the reference LLM we choose is OpenAI's text-davinci-003 (GPT3D3), since its API provides access to the predicted log-probability. With GPT3D3, around 2K summaries are generated for MLE training and 200 data points (100 for training and 100 for validation) are generated for contrastive learning.

We report the model performance on the test set in Tab. 1, which contains 100 CNNDM examples and reference summaries generated by GPT3D3. The following model's performance is compared: (1) GPT3D3, (2) the BART checkpoint fine-tuned on the original CNNDM dataset, (3) GPT3D2 (OpenAI's text-davinci-002), (4) a 7B Alpaca check-

Model	LP	GS	R1	R2	Len.
GPT3D3	-22.62	-0.271	100.0	100.0	85.4
BART	-59.55	-0.789	46.85	24.38	79.0
GPT3D2	-41.21	-0.547	55.40	33.72	78.7
Alpaca	-44.82	-0.567	51.53	30.18	81.8
ChatGPT	-45.12	-0.498	58.14	37.46	92.0
BART.ChatGPT	-41.08	-0.446	54.26	33.98	93.7
BART.GPT3D3	-36.13	-0.420	59.50	40.70	85.6
BRIO.GPT3D3	-26.20	-0.318	56.21	36.47	83.7

Table 1: Results on the test set regarding GPTScore. LP is the log-probability predicted by GPT3D3 (OpenAI's text-davinci-003). GS is the GPTScore based on GPT3D3, i.e., the length-normalized log-probability. R1 and R2 are the ROUGE1/2 F1 scores respectively. Len. is the average summary length (number of tokens). BART.ChatGPT is fine-tuned with MLE training and ChatGPT as the reference, BART.GPT3D3 is fine-tuned with MLE training and GPT3D3 while BRIO.GPT3D3 is fine-tuned with contrastive learning (BRIO).

point,⁸ (5) ChatGPT (gpt-3.5-turbo-0301). We make the following observations from Tab. 1: (1) Compared with the BART checkpoint trained on the original CNNDM dataset, MLE training on quasi-reference summaries from either ChatGPT or GPT3D3 can effectively improve the model performance as measured by either GPTScore or ROUGE using GPT3D3 as the reference LLM. It shows that training with better reference summaries can re-

(2) The BART checkpoint, BART.GPT3D3, finetuned with MLE training achieves better GPTScore and ROUGE scores than several LLMs including ChatGPT when using GPT3D3 as the reference.

duce the performance gap between smaller summa-

rization models and LLMs.

(3) The model that results from contrastive learning (BRIO.GPT3D3) can achieve significantly better GPTScore than the model fine-tuned with MLE training (BART.GPT3D3), demonstrating the effectiveness of contrastive learning for approximate the target distribution of the reference LLM.

(4) BRIO.GPT3D3 can already achieve a similar GPTScore as the reference LLM (GPT3D3) itself while only being trained on 100 examples with contrastive learning, showing a promising path to further close the performance gap.

3.3 Learning with GPTRank

Apart from GPTScore, we conduct experiments with GPTRank for both model training and evaluation, which requires the reference LLMs to rank

⁷Further details are in Appendix A.2.

⁸https://github.com/tatsu-lab/stanford_alpaca

Model	Win	Lose	R1	R2	Len.
ChatGPT	-	-	100.0	100.0	92.0
BART	11	88	50.54	29.31	79.0
GPT3D2	21	77	55.34	33.31	78.7
GPT3D3	34	66	58.14	37.46	85.4
Alpaca	23	76	53.41	31.48	81.8
BART.ChatGPT	36	63	62.04	43.76	94.1
BRIO.ChatGPT	51	49	61.40	40.74	93.1
BART.GPT4	43	56	62.08	43.55	91.8
BRIO.GPT4	57	42	62.79	43.65	92.8

Table 2: Results on the test set with **ChatGPT** as the reference LLM and the backbone model of GPTRank. **Win** and **Lose** is the number of times the compared model wins or loses against **ChatGPT** as evaluated by GPTRank (ties ignored). **R1** and **R2** are the ROUGE1/2 F1 scores respectively. **Len.** is the average summary length. **BART.ChatGPT** and **BART.GPT-4** are finetuned with MLE training and ChatGPT/GPT-4 as the reference, **BRIO.ChatGPT** and **BRIO.GPT-4** are finetuned with contrastive learning (BRIO).

the quality of candidate summaries in a text completion task. The reference LLMs we choose are ChatGPT and GPT-4 since they have shown state-of-the-art performance on summarization evaluation (Liu et al., 2023a). For contrastive learning with GPTRank, 500 or 1000 data points are used for model training with ChatGPT and GPT-4 as the reference LLM respectively, and 100 data points are used for validation. In addition, we fine-tuned a checkpoint from BART.ChatGPT using 1000 GPT-4 summaries with MLE training for comparison.

To enable a more accurate evaluation, we choose ChatGPT as the baseline model and use the LLMs to conduct a *pair-wise* comparison between different systems and ChatGPT. In other words, this is a special case of GPTRank where the number of candidate summaries is two. In addition, we allow the LLM to predict a tie between two summaries that have similar quality.¹⁰

The results with ChatGPT as the reference LLM are reported in Tab 2. The findings are similar to what we observed in §3.2:

- (1) Training with better references can help improve the summarization model performance.
- (2) Contrastive learning with GPTRank is more effective than the standard MLE training since the model checkpoint trained with contrastive learning (BRIO.ChatGPT) can outperform its MLE-trained

Model	Win	Lose	R1	R2	Len.
ChatGPT	-	-	63.43	44.09	92.0
BART	11	86	50.83	29.47	79.0
GPT3D2	22	77	55.17	33.23	78.7
GPT3D3	47	51	56.12	34.72	85.4
Alpaca	15	83	54.77	33.23	81.8
BART.ChatGPT	31	66	59.52	40.45	94.1
BRIO.ChatGPT	41	57	57.56	35.74	93.1
BART.GPT-4	35	62	63.22	44.70	91.8
BRIO.GPT-4	51	46	58.65	37.57	92.8

Table 3: Results on the test set with GPT-4 as the reference LLM and the backbone model of GPTRank. Win and Lose is the number of times the compared model wins or loses against ChatGPT as evaluated by GPTRank (ties ignored). R1 and R2 are the ROUGE1/2 F1 scores respectively. Len. is the average summary length. BART.ChatGPT and BART.GPT-4 are fine-tuned with MLE training and ChatGPT/GPT-4 as the reference, BRIO.ChatGPT and BRIO.GPT-4 are fine-tuned with contrastive learning (BRIO).

counterpart (BART.ChatGPT).

(3) BRIO.ChatGPT wins more than half of the comparisons against the baseline model, ChatGPT, under the evaluation of ChatGPT itself, showing that contrastive learning can efficiently optimize the summarization model with respect to a specific evaluation metric (i.e., GPTRank).

Apart from using ChatGPT as the reference LLM, we also conduct experiments with GPT-4 as the backbone model of GPTRank. We report the results in Tab. 3, and note the following:

- (1) The evaluation results of GPTRank differ when different LLMs (i.e., ChatGPT or GPT-4) are used. For example, while BRIO.ChatGPT outperforms ChatGPT under the evaluation of ChatGPT in Tab 2, GPTRank with GPT-4 still prefers ChatGPT since BRIO.ChatGPT only wins 41 times out of 100 against ChatGPT under its evaluation.
- (2) The model checkpoint (BRIO.GPT-4) trained using contrastive learning and GPT-4 as the reference LLM is able to outperform ChatGPT under GPT-4's evaluation, which also suggests that BRIO.GPT-4 can outperform BRIO.ChatGPT. It shows the importance of choosing the appropriate evaluation method used for contrastive training.
- (3) BRIO.ChatGPT can outperform BART.GPT-4 despite the fact that BRIO.ChatGPT is trained with a reference LLM that is supposedly weaker, which indicates the advantage of contrastive learning and the importance of using a better training method.

 $^{^9}We$ use the 'gpt-4-0314' version: https://platform.openai.com/docs/models/gpt-4.

¹⁰The prompt templates are shown in Appendix A.3.

4 Related Work

Training Methods of Text Generation Models The standard MLE training of text generation models has two major limitations: (1) a discrepancy between the training objective, i.e., the cross-entropy loss, and the evaluation criteria (e.g., ROUGE); (2) a discrepancy between the teacherforcing (Williams and Zipser, 1989) training manner and auto-regressive generation behavior during evaluation, which is known as the exposure bias (Bengio et al., 2015; Ranzato et al., 2016). As a result, training methods beyond MLE have been proposed to address these two limitations. Among them a family of methods is based on reinforcement learning (RL), which can optimize the text generation model toward a specific reward function and can be used in either offline or online manners (Ranzato et al., 2016; Bahdanau et al., 2016; Li et al., 2016; Paulus et al., 2018; Li et al., 2019; Stiennon et al., 2020; Pang and He, 2021). Apart from RL, training methods based on supervised learning have also been developed, such as Minimum Risk Training (Shen et al., 2016; Wieting et al., 2019), targeting a sequence-level optimization with various reward signals (Wiseman and Rush, 2016; Edunov et al., 2018). More recently, contrastive learning (Hadsell et al., 2006) has also been adopted for text generation models, which enhances the model ability by requiring the model to differentiate positive (good) and negative (bad) examples (Yang et al., 2019; Pan et al., 2021; Cao and Wang, 2021; Xu et al., 2021; Sun and Li, 2021; Liu and Liu, 2021; Xu et al., 2021; Sun and Li, 2021; Liu et al., 2022b; Zhao et al., 2022; Zhang et al., 2022). Furthermore, the latest work along this path has explored using contrastive learning to align large language models with human feedback (Yuan et al., 2023; Zhao et al., 2023), as an alternative to reinforcement learning with human feedback (Stiennon et al., 2020; Ouyang et al., 2022).

LLM-based Automatic Evaluation As LLMs have shown superior performance in various natural language processing (NLP) tasks, recent work has explored using LLMs for automatic NLP evaluation. GPTScore (Fu et al., 2023) leverages the LLM-predicted probability of text sequences as the quality score and applies the methodology to various evaluation tasks including summarization evaluation. On the other hand, a line of work (Liu et al., 2023a; Chiang and yi Lee, 2023; Gao et al.,

2023; Chen et al., 2023; Wang et al., 2023; Luo et al., 2023) proposes evaluation methods that use LLMs to perform text filling and text completion tasks, such as predicting the answer of a Likert scale evaluation or pairwise comparison. Notably, several of these studies (Fu et al., 2023; Liu et al., 2023a; Gao et al., 2023; Chen et al., 2023; Wang et al., 2023) all evaluate the LLM-based evaluation methods on SummEval (Fabbri et al., 2021), the summarization human evaluation benchmark, and found that LLM-base evaluation has a higher correlation with human judgments than previous methods such as ROUGE or BERTScore (Zhang* et al., 2020). Apart from summarization evaluation, LLM-based evaluation has also been used in text classification tasks (Gilardi et al., 2023) and for reward design for RL agents (Kwon et al., 2023).

LLM Distillation and LLM-based Data Augmentation To improve the performance of smaller NLP models using LLMs, related work has proposed methods of distilling LLMs and using LLMs for data augmentation (Wang et al., 2021; Ding et al., 2022; Kang et al., 2023). Specifically, a line of work (Shridhar et al., 2022; LI et al., 2022; Hsieh et al., 2023) uses LLMs to generate both task labels and task-related descriptions for training smaller models on reasoning tasks. As for work related to text summarization, Wang et al. (2021) introduces using GPT-3 (Brown et al., 2020) to generate reference summaries while Gekhman et al. (2023) proposes using LLMs to annotate the factual consistency (Maynez et al., 2020) of systemgenerated summaries for the training of smaller factual consistency evaluation models.

5 Conclusion

In this work, we study a new learning setting of text summarization models where the large language models are set to be the reference. For this setting, we leverage the LLM-based evaluation methods to guide the model training through contrastive learning. We empirically demonstrate the efficiency and effectiveness of our proposed training method, as we show that smaller summarization models can achieve similar performance as LLMs under LLM-based evaluation. We believe our findings shed light on the direction of applying the LLMs to the entire development loop (i.e., training-validation-evaluation) of smaller, task-specific NLP models, which has the potential of providing a balance between model performance and computational cost.

References

- Dzmitry Bahdanau, Philemon Brakel, Kelvin Xu, Anirudh Goyal, Ryan Lowe, Joelle Pineau, Aaron C. Courville, and Yoshua Bengio. 2016. An actorcritic algorithm for sequence prediction. *CoRR*, abs/1607.07086.
- Samy Bengio, Oriol Vinyals, Navdeep Jaitly, and Noam Shazeer. 2015. Scheduled sampling for sequence prediction with recurrent neural networks. In *Proceedings of the 28th International Conference on Neural Information Processing Systems Volume 1*, NIPS'15, page 1171–1179, Cambridge, MA, USA. MIT Press.
- Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual.
- Shuyang Cao and Lu Wang. 2021. CLIFF: Contrastive learning for improving faithfulness and factuality in abstractive summarization. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 6633–6649, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Yi Chen, Rui Wang, Haiyun Jiang, Shuming Shi, and Rui-Lan Xu. 2023. Exploring the use of large language models for reference-free text quality evaluation: A preliminary empirical study. *ArXiv*, abs/2304.00723.
- Cheng-Han Chiang and Hung yi Lee. 2023. Can large language models be an alternative to human evaluations? *ArXiv*, abs/2305.01937.
- Bosheng Ding, Chengwei Qin, Linlin Liu, Lidong Bing, Shafiq R. Joty, and Boyang Li. 2022. Is gpt-3 a good data annotator? *ArXiv*, abs/2212.10450.
- Sergey Edunov, Myle Ott, Michael Auli, David Grangier, and Marc'Aurelio Ranzato. 2018. Classical structured prediction losses for sequence to sequence learning. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 355–364, New Orleans, Louisiana. Association for Computational Linguistics.
- Alexander R. Fabbri, Wojciech Kryściński, Bryan Mc-Cann, Caiming Xiong, Richard Socher, and Dragomir

- Radev. 2021. SummEval: Re-evaluating summarization evaluation. *Transactions of the Association for Computational Linguistics*, 9:391–409.
- Jinlan Fu, See-Kiong Ng, Zhengbao Jiang, and Pengfei Liu. 2023. Gptscore: Evaluate as you desire. *ArXiv*, abs/2302.04166.
- Mingqi Gao, Jie Ruan, Renliang Sun, Xunjian Yin, Shiping Yang, and Xiaojun Wan. 2023. Humanlike summarization evaluation with chatgpt. *ArXiv*, abs/2304.02554.
- Zorik Gekhman, Jonathan Herzig, Roee Aharoni, Chen Elkind, and Idan Szpektor. 2023. Trueteacher: Learning factual consistency evaluation with large language models. *ArXiv*.
- Fabrizio Gilardi, Meysam Alizadeh, and Maël Kubli. 2023. Chatgpt outperforms crowd-workers for text-annotation tasks. *ArXiv*, abs/2303.15056.
- Tanya Goyal, Junyi Jessy Li, and Greg Durrett. 2022. News summarization and evaluation in the era of gpt-3. *ArXiv*, abs/2209.12356.
- Raia Hadsell, Sumit Chopra, and Yann LeCun. 2006. Dimensionality reduction by learning an invariant mapping. In *Proceedings of the 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Volume 2*, CVPR '06, page 1735–1742, USA. IEEE Computer Society.
- Cheng-Yu Hsieh, Chun-Liang Li, Chih-Kuan Yeh, Hootan Nakhost, Yasuhisa Fujii, Alexander J. Ratner, Ranjay Krishna, Chen-Yu Lee, and Tomas Pfister. 2023. Distilling step-by-step! outperforming larger language models with less training data and smaller model sizes. *ArXiv*, abs/2305.02301.
- Junmo Kang, Wei Xu, and Alan Ritter. 2023. Distill or annotate? cost-efficient fine-tuning of compact models. *ArXiv*, abs/2305.01645.
- Minae Kwon, Sang Michael Xie, Kalesha Bullard, and Dorsa Sadigh. 2023. Reward design with language models. In *The Eleventh International Conference* on Learning Representations.
- Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880, Online. Association for Computational Linguistics.
- Jiwei Li, Will Monroe, Alan Ritter, Dan Jurafsky, Michel Galley, and Jianfeng Gao. 2016. Deep reinforcement learning for dialogue generation. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1192–1202, Austin, Texas. Association for Computational Linguistics.

- SHIYANG LI, Jianshu Chen, Yelong Shen, Zhiyu Chen, Xinlu Zhang, Zekun Li, Hong Wang, Jingu Qian, Baolin Peng, Yi Mao, Wenhu Chen, and Xifeng Yan. 2022. Explanations from large language models make small reasoners better. *ArXiv*, abs/2210.06726.
- Siyao Li, Deren Lei, Pengda Qin, and William Yang Wang. 2019. Deep reinforcement learning with distributional semantic rewards for abstractive summarization. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 6038–6044, Hong Kong, China. Association for Computational Linguistics.
- Percy Liang, Rishi Bommasani, Tony Lee, Dimitris Tsipras, Dilara Soylu, Michihiro Yasunaga, Yian Zhang, Deepak Narayanan, Yuhuai Wu, Ananya Kumar, Benjamin Newman, Binhang Yuan, Bobby Yan, Ce Zhang, Christian Cosgrove, Christopher D. Manning, Christopher R'e, Diana Acosta-Navas, Drew A. Hudson, E. Zelikman, Esin Durmus, Faisal Ladhak, Frieda Rong, Hongyu Ren, Huaxiu Yao, Jue Wang, Keshav Santhanam, Laurel J. Orr, Lucia Zheng, Mert Yuksekgonul, Mirac Suzgun, Nathan S. Kim, Neel Guha, Niladri S. Chatterji, O. Khattab, Peter Henderson, Qian Huang, Ryan Chi, Sang Michael Xie, Shibani Santurkar, Surya Ganguli, Tatsunori Hashimoto, Thomas F. Icard, Tianyi Zhang, Vishrav Chaudhary, William Wang, Xuechen Li, Yifan Mai, Yuhui Zhang, and Yuta Koreeda. 2022. Holistic evaluation of language models. ArXiv, abs/2211.09110.
- Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.
- Yang Liu, Dan Iter, Yichong Xu, Shuo Wang, Ruochen Xu, and Chenguang Zhu. 2023a. G-eval: Nlg evaluation using gpt-4 with better human alignment. *ArXiv*, abs/2303.16634.
- Yixin Liu, Budhaditya Deb, Milagro Teruel, Aaron L Halfaker, Dragomir R. Radev, and Ahmed Hassan Awadallah. 2022a. On improving summarization factual consistency from natural language feedback. *ArXiv*, abs/2212.09968.
- Yixin Liu, Alexander R. Fabbri, Pengfei Liu, Yilun Zhao, Linyong Nan, Ruilin Han, Simeng Han, Shafiq R. Joty, Chien-Sheng Wu, Caiming Xiong, and Dragomir R. Radev. 2023b. Revisiting the gold standard: Grounding summarization evaluation with robust human evaluation. In *Proceedings of the 61th Annual Meeting of the Association for Computational Linguistics*.
- Yixin Liu and Pengfei Liu. 2021. SimCLS: A simple framework for contrastive learning of abstractive summarization. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short)*

- *Papers*), pages 1065–1072, Online. Association for Computational Linguistics.
- Yixin Liu, Pengfei Liu, Dragomir Radev, and Graham Neubig. 2022b. BRIO: Bringing order to abstractive summarization. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2890–2903, Dublin, Ireland. Association for Computational Linguistics.
- Zheheng Luo, Qianqian Xie, and Sophia Ananiadou. 2023. Chatgpt as a factual inconsistency evaluator for text summarization. *ArXiv*.
- Joshua Maynez, Shashi Narayan, Bernd Bohnet, and Ryan McDonald. 2020. On faithfulness and factuality in abstractive summarization. In *Proceedings* of the 58th Annual Meeting of the Association for Computational Linguistics, pages 1906–1919, Online. Association for Computational Linguistics.
- Ramesh Nallapati, Bowen Zhou, Cicero dos Santos, Caglar Gulcehre, and Bing Xiang. 2016. Abstractive text summarization using sequence-to-sequence RNNs and beyond. In *Proceedings of The 20th SIGNLL Conference on Computational Natural Language Learning*, pages 280–290, Berlin, Germany. Association for Computational Linguistics.
- Shashi Narayan, Shay B. Cohen, and Mirella Lapata. 2018. Don't give me the details, just the summary! topic-aware convolutional neural networks for extreme summarization. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1797–1807, Brussels, Belgium. Association for Computational Linguistics.
- Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke E. Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul Francis Christiano, Jan Leike, and Ryan J. Lowe. 2022. Training language models to follow instructions with human feedback. *ArXiv*, abs/2203.02155.
- Xiao Pan, Mingxuan Wang, Liwei Wu, and Lei Li. 2021. Contrastive learning for many-to-many multilingual neural machine translation. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 244–258, Online. Association for Computational Linguistics.
- Richard Yuanzhe Pang and He He. 2021. Text generation by learning from demonstrations. In *International Conference on Learning Representations*.
- Romain Paulus, Caiming Xiong, and Richard Socher. 2018. A deep reinforced model for abstractive summarization. In *International Conference on Learning Representations*.

- Marc'Aurelio Ranzato, Sumit Chopra, Michael Auli, and Wojciech Zaremba. 2016. Sequence level training with recurrent neural networks. In 4th International Conference on Learning Representations, ICLR 2016, San Juan, Puerto Rico, May 2-4, 2016, Conference Track Proceedings.
- Shiqi Shen, Yong Cheng, Zhongjun He, Wei He, Hua Wu, Maosong Sun, and Yang Liu. 2016. Minimum risk training for neural machine translation. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1683–1692, Berlin, Germany. Association for Computational Linguistics.
- Kumar Shridhar, Alessandro Stolfo, and Mrinmaya Sachan. 2022. Distilling reasoning capabilities into smaller language models. *ArXiv*.
- Nisan Stiennon, Long Ouyang, Jeffrey Wu, Daniel Ziegler, Ryan Lowe, Chelsea Voss, Alec Radford, Dario Amodei, and Paul F Christiano. 2020. Learning to summarize with human feedback. In *Advances in Neural Information Processing Systems*, volume 33, pages 3008–3021. Curran Associates, Inc.
- Shichao Sun and Wenjie Li. 2021. Alleviating exposure bias via contrastive learning for abstractive text summarization. *CoRR*, abs/2108.11846.
- C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna. 2016. Rethinking the inception architecture for computer vision. In 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 2818–2826, Los Alamitos, CA, USA. IEEE Computer Society.
- Ashwin Vijayakumar, Michael Cogswell, Ramprasaath Selvaraju, Qing Sun, Stefan Lee, David Crandall, and Dhruv Batra. 2018. Diverse beam search for improved description of complex scenes. *Proceedings of the AAAI Conference on Artificial Intelligence*, 32(1).
- Jiaan Wang, Yunlong Liang, Fandong Meng, Haoxiang Shi, Zhixu Li, Jinan Xu, Jianfeng Qu, and Jie Zhou. 2023. Is chatgpt a good nlg evaluator? a preliminary study. *ArXiv*, abs/2303.04048.
- Shuohang Wang, Yang Liu, Yichong Xu, Chenguang Zhu, and Michael Zeng. 2021. Want to reduce labeling cost? GPT-3 can help. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pages 4195–4205, Punta Cana, Dominican Republic. Association for Computational Linguistics.
- John Wieting, Taylor Berg-Kirkpatrick, Kevin Gimpel, and Graham Neubig. 2019. Beyond BLEU:training neural machine translation with semantic similarity. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4344–4355, Florence, Italy. Association for Computational Linguistics.

- Ronald J. Williams and David Zipser. 1989. A learning algorithm for continually running fully recurrent neural networks. *Neural Comput.*, 1(2):270–280.
- Sam Wiseman and Alexander M. Rush. 2016. Sequence-to-sequence learning as beam-search optimization. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1296–1306, Austin, Texas. Association for Computational Linguistics.
- Shusheng Xu, Xingxing Zhang, Yi Wu, and Furu Wei. 2021. Sequence level contrastive learning for text summarization. *CoRR*, abs/2109.03481.
- Zonghan Yang, Yong Cheng, Yang Liu, and Maosong Sun. 2019. Reducing word omission errors in neural machine translation: A contrastive learning approach. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 6191–6196, Florence, Italy. Association for Computational Linguistics.
- Zheng Yuan, Hongyi Yuan, Chuanqi Tan, Wei Wang, Songfang Huang, and Feiran Huang. 2023. Rrhf: Rank responses to align language models with human feedback without tears. *ArXiv*, abs/2304.05302.
- Tianyi Zhang*, Varsha Kishore*, Felix Wu*, Kilian Q. Weinberger, and Yoav Artzi. 2020. Bertscore: Evaluating text generation with bert. In *International Conference on Learning Representations*.
- Tianyi Zhang, Faisal Ladhak, Esin Durmus, Percy Liang, Kathleen McKeown, and Tatsunori Hashimoto. 2023. Benchmarking large language models for news summarization. *ArXiv*, abs/2301.13848.
- Xingxing Zhang, Yiran Liu, Xun Wang, Pengcheng He, Yang Yu, Si-Qing Chen, Wayne Xiong, and Furu Wei. 2022. Momentum calibration for text generation. *ArXiv*, abs/2212.04257.
- Yao Zhao, Rishabh Joshi, Tianqi Liu, Misha Khalman, Mohammad Saleh, and Peter J. Liu. 2023. Slic-hf: Sequence likelihood calibration with human feedback. *ArXiv*.
- Yao Zhao, Misha Khalman, Rishabh Joshi, Shashi Narayan, Mohammad Saleh, and Peter J. Liu. 2022. Calibrating sequence likelihood improves conditional language generation. *ArXiv*, abs/2210.00045.

A Experimental Details

A.1 LLM Summary Generation

We use the following prompt to generate the LLM summaries:

Article: {{Article}}

Summarize the above article in three sentences.

Summary:

Since text summarization is a conditional generation task that requires high accuracy, we set the sampling temperature to 0 to ensure a more accurate and deterministic behavior of the LLMs.

A.2 Candidate Generation for Contrastive Learning

The contrastive training (Eq. 14) requires a list of candidate summaries. To generate the summaries, we use the LLMs fine-tuned with MLE training and leverage diverse beam search as the sampling algorithm. For training with GPTScore (§3.2), we set 8 beam groups and 4 beams in each group, and pick the first candidate from each group as the final candidate. As for training with GPTRank (§3.3), we choose a larger search space with 32 beam groups, and pick 8 candidate outputs for the resulting 32 initial candidates by minimizing the similarity between them. This is to ensure the diverse quality of candidate summaries used with GPTRank.

A.3 Prompt Templates for GPTRank

We use the following prompt template for GP-TRank with *list-wise* comparison that is used for contrastive learning:

You will be given a news article along with a list of summaries numbered as follows: 1. Summary 1, 2. Summary 2, and so on. Please evaluate and rank the summaries in descending order of their quality. First you will give an explanation of your ranking, then you will provide the ranking itself. Please refer to the example below for the format of your response.

Example Response:

Explanation: "Your explanation of the ranking"

Ranking: "The ranking, e.g., 4, 2, 7, 3, 5, 6, 8, 1"

Here are the actual article and summaries:

Article: {{Article}}

Summaries:

- 1. {{Summary 1}}
- 2. {{Summary 2}}
- 3. {{Summary 3}}
- 4. {{Summary 4}}

For *pair-wise* comparison that is used for model evaluation, the prompt template is as follows:

You will be given a news article along with two summaries. Please compare the quality of these two summaries and pick the one that is better (there can be a tie). First you will give an explanation of your decision then you will provide your decision in the format of 1 or 2 or tie.

Response format:

Explanation: "Your explanation here".

Decision: 1 or 2 or tie.

Here's the article:

{{Article}}

Summary 1:

{{Summary 1}}

Summary 2:

{{Summary 2}}