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# Selecting Better Samples from Pre-trained LLMs: A Case Study on Question Generation

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## Abstract

Large Language Models (LLMs) have in recent years demonstrated impressive prowess in natural language generation. A common practice to improve generation diversity is to sample multiple outputs from the model. However, there lacks a simple and robust way of selecting the best output from these stochastic samples. As a case study framed in the context of question generation, we propose two prompt-based approaches to selecting high-quality questions from a set of LLM-generated candidates. Our method works under the constraints of 1) a black-box (non-modifiable) question generation model and 2) lack of access to human-annotated references — both of which are realistic limitations for real-world deployment of LLMs. With automatic as well as human evaluations, we empirically demonstrate that our approach can effectively select questions of higher qualities than greedy generation.<sup>1</sup>

## 1 Introduction & Related Work

Large Language Models (LLMs) have recently gained tremendous popularity in the NLP community (Devlin et al., 2019; Liu et al., 2019; Bao et al., 2020; Brown et al., 2020). The ever-increasing size in both models and training data renders many traditional learning methods impractical/intractable. As a result, prompt-based learning has emerged as a new paradigm tailored specifically towards leveraging the power of LLMs (Radford et al., 2019; Petroni et al., 2019; Raffel et al., 2020; Brown et al., 2020; Schick and Sch tze, 2021b; Gao et al., 2021; Liu et al., 2021). In the zero-shot setting (such as in this study), a data sample is first “verbalized” into an input prompt and a ground-truth response — both often in natural language forms. The prompt is then issued to a pre-trained LLM to

obtain a predicted response, which can then be compared to the ground-truth for evaluation. This new technique has been successfully applied to many applications including text classification (Yin et al., 2019; Schick and Sch tze, 2021a), QA (Jiang et al., 2021), natural language generation (Li and Liang, 2021) and NLG evaluation (Yuan et al., 2021).

Despite the impressive results on popular NLP benchmarks, however, the back-end LLMs are usually pre-trained with general-domain data, leading to sub-optimal performance in new domains for prompt-based learning. There are two major challenges in successful domain adaptation. Firstly, aside from the many known issues of LLMs (Webson and Pavlick, 2021; Min et al., 2022; Zhao et al., 2021; Lampinen et al., 2022), their sheer size and/or accessibility (e.g., served via API over the internet) makes it prohibitively expensive and impractical for domain adaptation. These limitations have inspired a recent line of work known as prompt editing/tuning (Gao et al., 2021; Li and Liang, 2021; Madaan et al., 2022). The general idea is to systematically study the correlation between prompt construction and the performance on a specific task. Prompt construction comes in a wide variety of flavours ranging from adapting real-valued *prompt embeddings* to the order/wording/etc. of few-shot in-context learning examples. Meanwhile, it also introduces a second challenge: prompt-tuning often relies on the availability of ground-truth labels of the data, which imposes much uncertainty in applications where labeled data are scarce.

Given the ubiquity of the aforementioned challenges, we focus our study on alleviating the constraints on both annotation availability and access to model parameters, and consequently making LLMs more accessible to be deployed and used in real-world applications. We take a mainstream NLG task, namely question generation, as a case study (Du et al., 2017; Yuan et al., 2017; Du and

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<sup>1</sup>We open-source all code and annotated data on [github](#).

Cardie, 2018; Pan et al., 2019; Liu et al., 2020; Pyatkin et al., 2021). In this task, a model is trained to generate a natural language question conditioned on a context and an answer, such that the generated question can be answered by the provided answer using the context as supporting evidence. Question generation is the corner stone for many NLP applications including education (Kurdi et al., 2020; Abdelghani et al., 2022), automatically FAQ generation (Mass et al., 2020), information seeking (Qi et al., 2020), etc. In an educational setting, for example, a question generation system can generate demonstrations that inspire students’ curiosity and thinking (teaching), or to help assess students’ proficiency on certain knowledge or skills (examining). These use cases would benefit greatly from reduced dependency on computing resources, data availability, and the required expertise for fine-tuning an LM.

To align with these real-world scenarios, our goal is to obtain better outputs from an inference-only LLM (i.e., as a “black-box”, which is relatively more accessible, e.g., through online APIs). In particular, given the common practice of sampling multiple outputs for improved generation diversity, we propose a method that aims at selecting the best candidate based on multiple aspects of question quality in a zero-shot manner — notably without model adaptation or human annotations. Our method can be seen as a post-hoc selection process within a larger NLG pipeline, and thus is orthogonal and applicable to zero-shot and in-context learning methods (Rubin et al., 2021; Lu et al., 2022; Liu et al., 2022).

## 2 Problem Setting

**Notations** Formally, we consider a dataset of context-answer pairs  $(c, a)$  both as strings. The task of question generation is to generate a question  $q$  that can be answered by  $a$  using  $c$  as supporting evidence. We use an off-the-shelf pre-trained LLM-based question generator in a zero-shot setting (prompt construction detailed in Appendix A). To simulate the black-box generator scenario, we refrain from any form of model tuning. We do, however, assume access to a set of output sequences stochastically sampled from the question generator. We thus ground our study to this application scenario by sampling  $k$  questions  $Q = \{q_i : i = 1, \dots, k\}$ . For comparison as a baseline, we also denote  $q_g$  as the question generated

with a greedy algorithm (i.e., generating the most probable token at each time step).

Our goal is to devise an algorithm  $S$  which selects the best candidate  $q_{i^*}$  that maximizes some evaluation metric  $M : Q \mapsto \mathbb{R}$ , i.e.,  $S(Q) = i^* = \arg \max_i M(q_i)$ . We use  $M_s$ ,  $M_{\bar{s}}$ , and  $M_{\underline{s}}$  to denote the mean, min, and max of  $\{M(q) : q \in Q\}$ , resp., and  $M_g$  for the greedy output  $M(q_g)$ . Semantically,  $M_{\underline{s}} \leq M_s \leq M_{\bar{s}}$  is tautologically true, and a positive result on the design of  $S$  would translate to  $M(q_{S(Q)})$  outperforming both  $M_s$  and  $M_g$ .

**Datasets** In this work, we adopt two question generation datasets with distinctive characteristics, namely SQuAD (Rajpurkar et al., 2016) and Fairytale QA (Xu et al., 2022). SQuAD was originally proposed as an extractive question answering (QA) dataset. In the question generation literature (Du and Cardie, 2018; Yuan et al., 2017; Bao et al., 2020), it has been used as a *sentence-level* question generation task, i.e., a context  $c$  is a single sentence that contains the corresponding answer  $a$  as a substring. Fairytale QA has also been used for both question answering and question generation. It features *paragraph-level question generation* (with  $c$  being one or more paragraphs), and the answer  $a$  is not necessarily a sub-string of  $c$ . Since we do not perform any form of model/prompt tuning, we use the testing split for datasets, which consist of 11,877 data points for SQuAD and 1,007 for Fairytale QA.

**Model** We leverage a pre-trained GPT-3 model (Brown et al., 2020) for both question generation and selection (detailed in §3). In all our experiments, we prompt the GPT-3 model in a 0-shot manner. Details on all our prompts are provided in Appendix A.

**Evaluation Metrics** We use two quantitative methods to evaluate the selected question  $q' = M(q_{S(Q)})$ :

- Reference-based evaluation: Following prior works, we use BLEU-4 for SQuAD (Du and Cardie, 2018; Bao et al., 2020) and ROUGE-L for Fairytale QA (Xu et al., 2022). These metrics compare  $q'$  against the reference question  $\hat{q}$  (a.k.a. the “ground-truth” question in the existing literature).
- Human evaluation: we solicit human annotations on a subset of the data. We postulate that an over-all score given holistically to rate a question would be highly subjective and thus less likely to induce agreement among annotators. Accordingly,

[context]  
 Old Dragonbeard must have been a master swordsman standing midway between those of the first and of the second order. Molo, however, of whom this story tells, was a sword hero.  
 At that time there lived a young man named Tsui, whose father was a high official and the friend of the prince. And the father once sent his son to visit his princely friend, who was ill. The son was young, handsome and gifted. He went to carry out his father's instructions. When he entered the prince's palace, there stood three beautiful slave girls, who piled rosy peaches into a golden bowl, poured sugar over them and presented them to him. After he had eaten he took his leave, and his princely host ordered one of the slave girls, Rose-Red by name, to escort him to the gate. As they went along the young man kept looking back at her. And she smiled at him and made signs with her fingers. First she would stretch out three fingers, then she would turn her hand around three times, and finally she would point to a little mirror which she wore on her breast. When they parted she whispered to him: "Do not forget me!"  
 [question]  
 Who was Rose-Red?  
 [input1]  
 Is the [question] related to the [context]? Why?  
 [output1]  
 Yes, the question is related to the context. Rose-Red is one of the three beautiful slave girls who served the prince. The young man, Tsui, was attracted to her and she seemed to be attracted to him as well.  
 [input2]  
 Based on the above response [output1], which one of the following [options] best described [question] wrt [input1]?  
 [options]  
 1: They are not at all related; 2: They are remotely related;  
 3: They are somewhat related; 4: They are closely related.  
 [output2]  
 3: They are somewhat related.

Figure 1: Prompting GPT-3 to rate a question’s relevance. GPT-3 output is highlighted in green.

we decompose the quality of a question into seven dimensions<sup>2</sup>, and ask human annotators to rate a question on each dimension followed by an overall rating of the question. We collect three annotations from different annotators for each data points. We provide details of the human study in Appendix B.

### 3 Method

In this section we propose three question selection methods. As described in §2, each method is used to score  $k$  sampled questions in  $Q$  and the candidate with the highest score is proposed as the final output.

**$n$ -gram similarity** We use  $n$ -gram similarity between a question and its corresponding context to measure their relevance. This method reflects the intuitive assumption that favorable question be closely related to the information provided by the context. Specifically, we extract all unique  $n$ -grams<sup>3</sup>  $s^n(c)$  from a given context  $c$ ,  $s^n(q)$  from a question  $q$ . The  $n$ -gram similarity score is then defined as:

$$\text{sim}^n = \frac{|s^n(c) \cap s^n(q)|}{|s^n(q)|}, \quad (1)$$

where  $|s|$  indicates the size of set  $s$ .

**Round-trip** Intuitively, the answer to a generated question should be semantically equivalent to the answer that has been used to generated the question. Formally, a question generation model QG and a QA model (both with reasonable performance) should satisfy the following:

$$q' = \text{QG}(c, a); \quad a' = \text{QA}(c, q'); \quad a' = a. \quad (2)$$

<sup>2</sup>Namely, grammatical correctness, offensiveness, clarity, relevance, importance, specificity, and answerability.

<sup>3</sup>In all our experiments  $n$  ranges from 1 to 5.

	SQuAD (BLEU-4)	Fairytale QA (ROUGE-L)
prior works (models trained/fine-tuned on these datasets)		
(Du and Cardie, 2018)	0.152	–
(Zhang and Bansal, 2019)	0.184	–
UniLM Large (Bao et al., 2020)	0.228	–
UniLM v2 Base (Bao et al., 2020)	0.244	–
ERNIE-GEN Large (Xiao et al., 2021)	0.254	–
BART (Xu et al., 2022)	–	0.527
baselines (notations defined in §2)		
$M_g$ (greedy)	0.372	0.424
$M_s$ (sample avg)	0.359	0.399
$M_{\underline{s}}$ (lowerbound)	0.225	0.259
$M_{\overline{s}}$ (upperbound)	0.496	0.548
question selection		
bi-gram	0.382	0.403
tri-gram	0.380	0.403
round-trip	0.392	0.434
overall prompt score (OPS)	0.373	0.399
averaged prompt score (APS)	0.380	0.406
ensemble multiple methods		
APS + round-trip	0.397	<b>0.439</b>
bi-gram + round-trip	0.400	0.429
tri-gram + round-trip	0.398	0.430
bi-gram + APS	0.384	0.406
tri-gram + APS	0.383	0.409
bi-gram + APS + round-trip	<b>0.401</b>	0.431
tri-gram + APS + round-trip	<u>0.400</u>	<u>0.435</u>

Table 1: Reference-based evaluation scores. Best and second best numbers (excluding baselines) are highlighted with **boldface** and underline, respectively.

This idea is closely related to *cycle consistency* in the existing literature on image generation (Zhu et al., 2017), machine translation (Artetxe et al., 2018), and QA (Alberti et al., 2019; Shah et al., 2019)). Here, we use GPT-3 as an off-the-shelf QA model to obtain  $a'$  for each pair of  $c$  and  $q'$ , resulting in  $k$  answers  $A = \{a'_1, \dots, a'_k\}$  for the  $k$  sampled questions in  $Q$ . We then measure the similarity between each  $a'_i$  and the ground-truth answer  $a$  using  $F_1$  score for SQuAD and ROUGE-L for Fairytale QA (in accordance with the evaluation setup from the original papers for the two datasets). Finally, we select the question corresponding to the generated answer  $a'_{i^*}$  that overlaps the most with  $a$  (i.e., that can be best answered by GPT-3) Prompts used in these experiments are detailed in Appendix A.

**Prompt-based Score** We propose a two-step procedure (Figure 1) for prompting GPT-3 to answer the same set of meta-questions (i.e., questions about the quality of a given question) used for human evaluation (§2).

In step 1, given a context-question pair, GPT-3 is prompted to answer a meta-question as an open question (as opposed to choosing among a list of options) as well as to verbalize a reason for its answer. In step 2, GPT-3 is prompted to choose

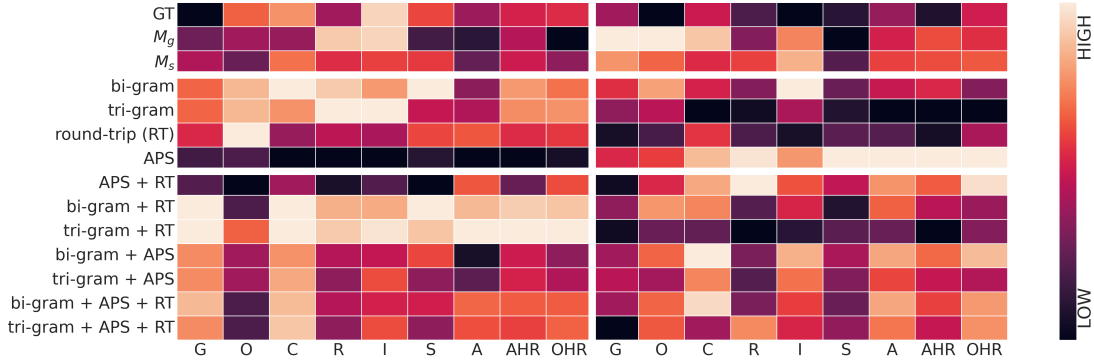


Figure 2: Human evaluation results, averaged over three annotators’ scores, normalized per column. Left: SQuAD; right: Fairytale QA. Abbreviations in x-axis denote **G**rammatical correctness, **O**ffensiveness, **C**larity, **R**elevance, **I**mportance, **S**pecificity, **A**nswerability, **A**veraged **H**uman **R**ating (over all dimensions to the left), **O**verall **H**uman **R**ating (an overall score given by annotators). Exact scores are provided in Appendix C.

from a list of options representing the rating scale of the meta-question.

We empirically observe that without the first step, GPT-3 output tends to have a low-entropy distribution, i.e., often choosing the same option for a given meta-question disregarding the different context-question pairs. In contrast, the model appears to be better primed wrt output diversity with the additional first-step, which is inline with observations made in some existing studies (Nye et al., 2021; Wei et al., 2022).

Similar to human evaluation, we also prompt GPT-3 to generate an overall score to a question. We use *overall prompt-based score (OPS)* to denote this GPT-3-labeled score, and *averaged prompt-based score (APS)* to denote the average score over all individual meta-questions.

## 4 Results and Discussion

To measure the performance of a selection method (§3), we use it to select one out of  $k$  questions stochastically sampled from GPT-3, and score the selection with the evaluation metrics outlined in §2. We set  $k = 5$  for all our experiments. Additionally, we test the ensemble performance with multiple methods. To ensure comparability, we normalize the scores obtained from each selection method into the range between 0 and 1, and use their average score to perform question selection.

### 4.1 Reference-based evaluation

Reference-based evaluation are automatic metrics that are applied to the entire test sets of SQuAD and Fairytale QA. We observe in Table 1 that on both datasets, all question selection methods outperform  $M_s$ , the average score over all five sam-

pled questions, validating the effectiveness of the proposed methods. While all individual methods outperform the greedy generation baseline  $M_g$  on SQuAD, round-trip is the best performing one, outperforming  $M_g$  on both datasets. It can be further improved via ensemble with  $n$ -gram and/or prompt-based scores (using uniform weights).

Note that prior studies require a large amount of labeled data for model training/fine-tuning, while GPT-3 performs zero-shot inference. Despite this major difference in learning paradigm, most GPT-3-based models proposed here outperform previous results by significant margins on the SQuAD dataset — even the least performant samples  $M_s$  (lowerbound) achieve competitive results. For Fairytale QA, however, only the best samples  $M_s$  (upperbound) outperform previous results (Xu et al., 2022), indicating margins for improvement on question selection strategies for future work.

### 4.2 Human Evaluation

Human evaluation consists of 16,800 annotations (collected from 87 annotators) evenly split across the two datasets (details in Appendix B). For question generation (among many language generation tasks), model outputs may exhibit linguistic diversity while maintaining semantic equivalence. It is thus highly problematic to evaluate such outputs against a single reference (i.e., “ground-truth” questions). Figure 2 empirically shows that the ground-truth (GT) questions provided in the datasets often fail to receive the highest human ratings, on many occasions scoring lower than stochastic samples from GPT-3 ( $M_s$ ). Consequently, we strongly advocate for human evaluation, which we believe is highly effective in improving generalizability of our

results to real-world applications.

Another prominent observation is that  $n$ -gram and APS perform quite differently on the two datasets. On SQuAD,  $n$ -gram similarity outperforms other individual methods, with further noticeable improvements via ensemble with round-trip. APS, on the other hand, does not work nearly as well, performing the worst for almost all meta-questions. In contrast,  $n$ -gram (particularly tri-gram) similarity shows the worst performance on Fairytale QA, while APS outperforms all other methods by a noticeable margin.

We posit that the reversed trend in comparing  $n$ -gram and APS can be explained by the distinct natures of the datasets. For SQuAD, the sentence-level contexts are relatively short and simple with strictly extractive answers (i.e., the answers being sub-strings of the corresponding contexts). As a result, paraphrasing the context can be a rather effective question generation strategy, hence the stronger correlation between question quality and the  $c$ - $q$   $n$ -gram similarity. On the other hand, with multi-paragraph contexts and abstractive, open-ended answers, questions are more likely posed about abstract ideas rather than simple context paraphrasing. Consequently,  $n$ -gram similarity, which favors local context paraphrasing, can no longer serve as a good question selection strategy.

### 4.3 Limitations and Future Work

We acknowledge that our system has some limitations that warrants further investigation. For example, one needs to be mindful of the specific downstream applications of the proposed methods, both in terms of potentially large variance in out-of-distribution performance (e.g. *divergent* question generation, [Abdelghani et al. 2022](#)) and of mitigating harmful/toxic contents in educational applications ([Bender et al., 2021](#)).

We also acknowledge the prohibitively restrictive access to the GPT-3 model at the time of writing. We do believe that this constraint will relax over time, and meanwhile, hoping that our proposal can shed light on research and applications with more accessible LLMs such as GPT-J ([Wang and Komatsuzaki, 2021](#)) and BLOOM ([BigScience, 2022](#)) for future work.

## 5 Conclusion

In this study, we investigate the practical problem

of selecting the best output from multiple samples generated by an LLM. Using question generation as a case study, we propose two prompt-based approaches that select high-quality questions according to question quality from multiple perspectives. To alleviate real-world constraints on using large LMs such as computation resources and data availability, the proposed methods do not rely on model fine-tuning nor human annotation. Extensive experiments with both automatic and human evaluations evince the effectiveness of our approach on selecting high-quality questions from stochastic samples.

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## Contents in Appendices:

- In Appendix A, we report all prompt templates we used in this work.
- In Appendix B, we provide details on the human study.
- In Appendix C, we provide the full set of our experiment results.
- In Appendix D, we report implementation details.

## A Prompt Designs

We report an example of our prompt for question generation in Figure 3.

We report an example of our prompt for QA (used in round-trip) in Figure 4.

We report an example of our prompt in obtaining prompt scores in Figure 1.

## B Human Study

We randomly sample 50 documents from each of the two datasets SQuAD and Fairytale QA. Each document correspond to one ground-truth question and six questions generated by GPT-3 (five by stochastic sampling and one by greedy search). Each question is then rated by three human annotators wrt seven meta-questions and one over-all rating, altogether constituting  $50 \times 2 \times (1 + 5 + 1) \times 3 \times (7 + 1) = 16,800$  annotations. There are in total 87 annotators involved in the annotation process, all annotators are English speakers, they are recruited from regions including Europe, the United States and United Kingdom. Each annotator on average performed 193 annotations and was paid on average \$14.1 USD per hour.

We perform a basic spam filtering process on the raw annotations. We observe a 15.4% spam rate. All human scores reported in this paper are computed after spam removal.

We report the eight meta-questions we used for human annotation in Figure 5. The eight meta-questions correspond to columns in Figure 2. We collect three annotations from different annotators for every meta-question, we report the averaged human agreement rate in Table 2.

## C Additional Results

In Table 3, we report the full experiment results for reference-based evaluation.

grammatical correctness	0.698
offensiveness	0.788
clarity	0.640
relevance	0.670
importance	0.558
specificity	0.619
answerability	0.588
overall human rating (OHR)	0.485

Table 2: Averaged human agreements among three annotators. An agreement indicates that all three annotators selected the same option for a meta-question.

	SQuAD (BLEU-4)	Fairytale QA (ROUGE-L)
prior works (models trained/fine-tuned on these datasets)		
(Du and Cardie, 2018)	0.152	–
(Zhang and Bansal, 2019)	0.184	–
UniLM Large(Bao et al., 2020)	0.228	–
UniLM v2 Base(Bao et al., 2020)	0.244	–
ERNIE-GEN Large (Xiao et al., 2021)	0.254	–
BART (Xu et al., 2022)	–	0.527
baselines (notations defined in §2)		
$M_g$ (greedy)	0.372	0.424
$M_s$ (sample avg)	0.359	0.399
$M_{\underline{s}}$ (lowerbound)	0.225	0.259
$M_{\overline{s}}$ (upperbound)	0.496	0.548
$n$ -gram-similarity		
uni-gram w/ context	0.382	0.396
bi-gram w/ context	0.382	0.403
tri-gram w/ context	0.380	0.403
4-gram w/ context	0.378	0.406
5-gram w/ context	0.375	0.404
round-trip		
round-trip	0.392	0.434
prompt scores		
grammatical correctness	0.364	0.405
offensiveness	0.374	0.403
clarity	0.373	0.406
relevance	0.372	0.396
importance	0.372	0.406
specificity	0.378	0.405
answerability	0.372	0.404
averaged prompt score (APS)	0.380	0.406
overall prompt score (OPS)	0.373	0.399
ensemble multiple methods		
APS + round-trip	0.397	<b>0.439</b>
bi-gram + round-trip	<u>0.400</u>	0.429
tri-gram + round-trip	0.398	0.430
bi-gram + APS	0.384	0.406
tri-gram + APS	0.383	0.409
bi-gram + APS + round-trip	<b>0.401</b>	0.431
tri-gram + APS + round-trip	<u>0.400</u>	<u>0.435</u>

Table 3: Reference-based evaluation scores on various question selection methods. Best and second best numbers (excluding baselines) are highlighted with **bold-face** and underline, respectively.

In Table 4, we report the full results for human evaluation on SQuAD.

In Table 5, we report the full results for human evaluation on Fairytale QA.

**Story:**

As soon as the lady had departed the fisher's son awoke, and the dark lad told him of her visit, and how he would never see her as long as he lived. At this the fisher's son felt the cold creeping up to his heart, yet he knew the fault had not been his that sleep had overtaken him.

'I will search the whole world through till I find her,' cried he, and the dark lad laughed as he heard him. But the fisher's son took no heed, and off he went, following the sun day after day, till his shoes were in holes and his feet were sore from the journey. Nought did he see but the birds that made their nests in the trees, not so much as a goat or a rabbit. On and on and on he went, till suddenly he came upon a little house, with a woman standing outside it.

**Instruction:**

Read the above story, ask a question and answer it.

**Question:**

GPT-3 FILLS IN THIS BLANK

**Answer:**

search the whole world through till he found her

Figure 3: An example of prompting GPT-3 for question generation. We use the text before `green` as prompt, and text after `green` as suffix. We refer readers to [the GPT-3 documentation](#) for more details about GPT-3's inserting completion mode.

**[Document]:**

is cheeks were red with passion, and his eyes were bright, for he could not but notice that, now that she was safe at Orphir under her true love's protection, the Lady Morna's manner had grown cold and distant again, and he was beginning to lose faith in Snorro's charm.

Angry and disappointed, he had sought his mother's room to pour out his story of vexation to her.

He stopped short, however, when he saw the wonderful waistcoat lying on the table, all gold and silver and shining colours. It was like a fairy garment, and its beauty took his breath away.

**[Question]:**

Why did Harold lose faith in Snorro's charm?

**[Answer]:**

Harold lost faith in Snorro's charm because the Lady Morna's manner had grown cold and distant again.

Figure 4: An example of prompting GPT-3 for QA. GPT-3 output is highlighted in green.

## D Implementation Details

In all experiments, we use the `text-davinci-002` (175B parameters) variant of GPT-3. It is currently the most capable GPT-3 model variant. Compared to other variants, `text-davinci-002`'s support to inserting completions can better facilitate our question generation tasks (as shown in Figure 3).

We use a temperature of 0.7 during the sampling process of question generation. In all other use

cases (e.g., QA round-trip, prompt score), we use greedy generation (temperature is set to 0).

1. Is the question grammatically correct?
  - 1) It is grammatically incorrect
  - 2) It has some grammatical issues
  - 3) It is grammatically correct
  
2. Is the question offensive to people?
  - 1) It is very offensive
  - 2) It may be offensive
  - 3) It is not at all offensive
  
3. Is the question clear?
  - 1) It is not at all clear
  - 2) It is mostly clear
  - 3) It is very clear
  
4. Is the question related to the context of the attached document?
  - 1) It is not at all related
  - 2) It is somewhat related
  - 3) It is closely related
  
5. Is the question asking about an important aspect of the context of the attached document?
  - 1) Not at all important
  - 2) It may be important
  - 3) It is very important
  
6. Is the question asking about a specific piece of information in the attached document?
  - 1) The question is very generic
  - 2) The question is somewhat generic
  - 3) The question is very specific
  
7. Can the question be answered using information in the attached document?
  - 1) No, answering the question requires completely different information
  - 2) The question can be partially answered using information from the document
  - 3) The question can be perfectly answered using information from the document
  
8. What is your overall rating of the question generated based on the attached document?
  - 1) The question is very bad
  - 2) The question is okay
  - 3) The question is very good

Figure 5: Meta-questions we designed for human evaluation.

	G	O	C	R	I	S	A	AHR	OHR
GT	0.937	0.987	0.943	0.930	0.925	0.922	0.887	0.933	0.870
$M_g$	0.950	0.983	0.927	0.953	0.925	0.905	0.870	0.930	0.833
$M_s$	0.957	0.981	0.940	0.937	0.909	0.921	0.879	0.932	0.857
bi-gram	0.968	<u>0.990</u>	<b>0.952</b>	<u>0.953</u>	0.918	<b>0.937</b>	0.885	0.943	0.880
tri-gram	0.968	<u>0.990</u>	0.943	<b>0.957</b>	<b>0.928</b>	0.917	0.890	0.942	0.885
round-trip (RT)	0.962	<b>0.992</b>	0.927	0.933	0.900	0.922	0.903	0.934	0.872
APS	0.945	0.980	0.912	0.912	0.880	0.902	0.863	0.913	0.837
APS + RT	0.947	0.977	0.928	0.915	0.890	0.898	0.903	0.923	0.875
bi-gram + RT	<b>0.983</b>	0.980	<b>0.952</b>	0.950	0.920	<b>0.937</b>	<u>0.917</u>	<u>0.948</u>	<u>0.893</u>
tri-gram + RT	<b>0.983</b>	0.987	<b>0.952</b>	<u>0.953</u>	<u>0.927</u>	<u>0.933</u>	<b>0.925</b>	<b>0.951</b>	<b>0.900</b>
bi-gram + APS	0.972	0.983	0.943	0.932	0.903	0.922	0.867	0.932	0.857
tri-gram + APS	0.972	0.983	0.945	0.928	0.910	0.912	0.878	0.933	0.862
bi-gram + APS + RT	<u>0.977</u>	0.980	0.947	0.932	0.905	0.918	0.905	0.938	0.877
tri-gram + APS + RT	<u>0.972</u>	0.980	<u>0.948</u>	0.928	0.910	0.912	0.902	0.936	0.878

Table 4: Human eval results (SQuAD). Abbreviations in the first row denote **G**rammatical correctness, **O**ffensiveness, **C**larity, **R**elevance, **I**mportance, **S**pecificity, **A**nswerability, **A**veraged **H**uman **R**ating (over all dimensions to the left), **O**verall **H**uman **R**ating (an overall score given by annotators). Best and second best numbers (excluding baselines) are highlighted with **boldface** and underline, respectively.

	G	O	C	R	I	S	A	AHR	OHR
GT	0.945	0.963	0.942	0.937	0.885	0.928	0.892	0.927	0.867
$M_g$	0.975	1.000	0.958	0.943	0.920	0.922	0.905	0.946	0.870
$M_s$	0.964	0.988	0.944	0.955	0.925	0.934	0.912	0.946	0.875
bi-gram	<b>0.953</b>	<b>0.993</b>	0.943	0.943	<b>0.932</b>	0.937	0.902	0.943	0.857
tri-gram	0.943	0.980	0.922	0.930	0.905	0.927	0.858	0.924	0.838
round-trip (RT)	0.928	0.970	0.945	0.937	0.888	0.935	0.878	0.926	0.862
APS	<u>0.952</u>	0.985	0.957	<u>0.972</u>	0.922	<b>0.977</b>	<b>0.948</b>	<b>0.959</b>	<b>0.895</b>
APS + RT	0.927	0.983	0.955	<b>0.973</b>	0.915	<u>0.948</u>	0.928	0.947	<u>0.893</u>
bi-gram + RT	0.943	<u>0.992</u>	0.952	0.938	0.910	<u>0.927</u>	0.918	0.940	<u>0.860</u>
tri-gram + RT	0.927	<u>0.973</u>	0.932	0.928	0.890	0.935	0.882	0.924	0.857
bi-gram + APS	0.945	0.988	<b>0.962</b>	0.942	<u>0.925</u>	0.945	<u>0.932</u>	<u>0.948</u>	0.888
tri-gram + APS	0.948	0.978	0.952	0.938	<u>0.918</u>	0.940	<u>0.913</u>	<u>0.941</u>	0.863
bi-gram + APS + RT	0.945	0.988	<u>0.960</u>	0.942	0.913	0.937	<u>0.932</u>	0.945	0.883
tri-gram + APS + RT	0.925	0.987	0.938	0.962	0.910	0.942	0.922	0.941	0.882

Table 5: Human eval results (Fairytale QA). Abbreviations in the first row denote **G**rammatical correctness, **O**ffensiveness, **C**larity, **R**elevance, **I**mportance, **S**pecificity, **A**nswerability, **A**veraged **H**uman **R**ating (over all dimensions to the left), **O**verall **H**uman **R**ating (an overall score given by annotators). Best and second best numbers (excluding baselines) are highlighted with **boldface** and underline, respectively.