QURIous: Question Generation Pretraining for Text Generation

Shashi Narayan  
Google Research  
shashinarayan@google.com

Gonçalo Simoes  
Google Research  
gsimoes@google.com

Ji Ma  
Google Research  
maji@google.com

Hannah Craighead  
Google  
craighead@google.com

Ryan Mcdonald  
Google Research  
ryanmcd@google.com

Abstract

Recent trends in natural language processing using pretraining have shifted focus towards pretraining and fine-tuning approaches for text generation. Often the focus has been on task-agnostic approaches that generalize the language modeling objective. We propose question generation as a pretraining method, which better aligns with the text generation objectives. Our text generation models pretrained with this method are better at understanding the essence of the input and are better language models for the target task. When evaluated on two text generation tasks, abstractive summarization and answer-focused question generation, our models result in state-of-the-art performances in terms of automatic metrics. Human evaluators also found our summaries and generated questions to be more natural, concise and informative.

1 Introduction

Unsupervised or semi-supervised pretrained encoder-decoder models are quickly becoming the standard for text generation (Khandelwal et al., 2019; Dong et al., 2019; Song et al., 2019; Rothe et al., 2019; Lewis et al., 2019), following the success of pretraining methods on popular Natural Language Understanding (NLU) benchmarks (Peters et al., 2018; Devlin et al., 2019; Radford et al., 2018, 2019; Yang et al., 2019; Liu et al., 2019). For text generation, most models focus on task-agnostic pretraining tasks that generalize the language modelling objective by (i) combining the masked language model objective with left-to-right language modelling objective (Dong et al., 2019) or (ii) reconstructing the corrupted input text using a sequence-to-sequence denoising autoencoder (Song et al., 2019; Lewis et al., 2019). These models have set new state-of-the-art results on a wide variety of text generation tasks such as summarization, sentence splitting and sentence fusion (Rothe et al., 2019; Lewis et al., 2019).

In this paper, we investigate a pretraining objective that is better tied to challenges involved in text generation, specifically understanding (i.e., identifying important content) and realization (i.e., generating the text). We propose QURIous, a QUestion geneRation pretraIning Objective which pretrains text generation models to generate questions conditioning on an answer passage or a document. Key advantages of our method are that (i) data for question generation can be easily crawled abundantly from community QA platforms such as Yahoo Answers, Quora and Stack Overflow, and more importantly, (ii) text generators trained to generate a question which can be answered from a document or a passage, will capture the salient terms or concepts expressed in the input, and will learn to aggregate and paraphrase from the input. Figure 1 shows an example answer-question pair used for our pretraining reflecting on the latter point.

In this paper, we experiment with Transformer-based sequence-to-sequence models that are compatible with publicly available pretrained BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) checkpoints, except these models were pretrained for question generation from an associated text. However, the question generation pretraining objective is model agnostic. Improved pretraining objectives have been studied before, e.g., task agnostic (Yang et al., 2019; Lan et al., 2019), multilingual (Pires et al., 2019).
or domain targeted (Lee et al., 2019). Perhaps the work closest to ours is Baldini Soares et al. (2019) who study task-specific pretraining objectives for relation extraction. Additionally, Alberti et al. (2019) use question generation to increase training data for QA. However, such task-specific objectives, and specifically question generation, have not been exploited for generation tasks.

Figure 2 demonstrates the benefit of our pretraining objective for summarization. QURIOUSZ, a zero-shot variant of QURIOUS pretrained for question generation and without any supervision for summarization, generates questions for documents centered around their reference summaries; it appears that QURIOUSZ simulates summarization experts in terms of selecting what source content is most relevant for a summary. We hypothesize that the finetuning of QURIOUSZ for summarization will guide models to focus on the salient content in the document and generate summaries that are concise and informative. We can also observe that QURIOUS generates summaries that are closer to reference summaries than those generated by RoBERTaS2S, which does not use pretraining for question generation.

The main contributions of this work are four-fold. First, we propose question-generation as a pretraining objective for text generation. Second, we demonstrate the effectiveness of our method on abstractive summarization by achieving a new state-of-the-art result on the extreme summarization task (Narayan et al., 2018). Third, we experiment with answer-focused question generation task focusing on two datasets, SQuAD (Rajpurkar et al., 2018) and Natural Questions (Kwiatkowski et al., 2019b), and demonstrate that our pretrained model generates questions that are more natural and informative, in terms of both automatic and human evaluations. Finally, we empirically demonstrate that the reciprocity of question generation as a pretraining objective to text generation tasks makes our models robust to low-resource scenarios.

## 2 Question Generation Pretraining

QURIOUS is designed for sequence-to-sequence models and aims to learn improved representations for text generation, which requires both understanding and realization, as opposed to task-agnostic pretraining objectives (Devlin et al., 2019).

**GOLD:** Former Beatle Sir Paul McCartney has topped the Sunday Times rich list of musicians with his £730m fortune.

**ROBERTaS2S:** Sir Paul McCartney has been named as Britain’s richest man in the Sunday Times rich list.

**QUrIousZ:** Who is the richest musician in the world?

**QUrIOUS:** Sir Paul McCartney has been named the richest man in the UK, with his wealth totalling £730m, according to the Sunday Times rich list.

**GOLD:** Pope Francis will go to Africa for the first time this week, visiting a refugee camp, a slum and a mosque.

**ROBERTaS2S:** Pope Francis has a big issue with the pope’s decision to visit the Central African Republic in the middle of his first trip to the continent.

**QUrIOUSZ:** What will Pope Francis talk about during his trip to Kenya?

**QUrIOUS:** Pope Francis will head to Kenya for his first visit to Africa since taking office in November.

Figure 2: Analysis of summarization models: the reference summary (GOLD), a task-agnostic pretrained Seq2Seq model (ROBERTaS2S: Liu et al.; Rothe et al., 2019) and one pretrained with a question generation objective (QUrIOUS and a zero-shot variant QUrIOUSZ).

Data for Pretraining. In this work, we collect 2 million English question-answer pairs from community question-answering resources such as StackExchange (53.8% of total, 175 subdomains), Yahoo! Answers (45.9% of total, 24 subdomains) and Zhidao Baidu (0.3%). These forums have been widely used before in community question answering (Zhang et al., 2014; Nakov et al., 2017; Nie et al., 2017). In particular, we follow Zhang et al. (2014) to mine data from community QA websites. Main differences are that Zhang et al. (2014) mine data from two community QA websites and train answer passage selection models, whereas, we (1) use a different set of websites and (2) use it for question generation pretraining. To ensure the quality of posts we only select English answer-question pairs that were positively rated by at least one user. Finally, the average lengths of questions and answers in our dataset are 11.64 tokens and 155.44 tokens, respectively.

A major advantage of QUrIOUS is that large amounts of pretraining data can be obtained for free, and annotations grow as long as people
ask/answer questions on the internet. Moreover, real information-seeking questions are typically condense and natural, thus better suited for summarization than datasets such as SQuAD (Rajpurkar et al., 2018), where questions are not naturally occurring and contain high lexical and syntactic overlap with the answer passage.

### Pretraining Text Generation Models

We apply QURIOUS to a sequence-to-sequence architecture where both encoder and decoder are composed of Transformer layers (Vaswani et al., 2017). We have experimented with base and large versions of the Transformer layer; the base model has both encoder and decoder with 12 layers, a hidden size of 768, filter size of 3072, and 12 attention heads, whereas, the large model, with 24 layers, a hidden size of 1024, filter size of 4096, and 16 attention heads. During pretraining, the input answers were truncated to 512 tokens and the length of the questions was limited to 64 tokens. We also allow our encoder and decoder to warm-start the Transformer layer using public BERT (Devlin et al., 2019) and its variant RoBERTa (Liu et al., 2019) checkpoints. Following Rothe et al. (2019), we share the parameters between encoder and decoder for all our models. We used a global batch size of 128 document-summary pairs with the standard cross entropy loss.

### Fine-tuning Text Generation Models

We fine tune our model for two text generation tasks: abstractive document summarization and answer-focused question generation. For abstractive summarization, the encoder takes a document as input and generates its summary as output. For answer-focused question generation, earlier work (Duan et al., 2017; Subramanian et al., 2018; Nema et al., 2019) has mostly focused on the factoid-based question answering dataset such as SQuAD (Rajpurkar et al., 2016). Unlike our question generation pretraining, the answer passage here can be open-ended and not necessarily a direct response to a question. We follow Nema et al. (2019) and use the target answer span together with the passage (with a separator between them) as input to generate a specific question.

## 3 Experiments and Results

### 3.1 Abstractive Document Summarization

We evaluate our model on the BBC extreme summarization (XSum; Narayan et al., 2018). Doc-

### Table 1: ROUGE F₁ scores for extreme summarization.

The models in the top block are not pretrained for question generation. See text for discussion. R1/2/L is ROUGE1/2/L.

| Models | R1 | R2 | RL |
|--------|----|----|----|
| TRANS2S (12) | 30.90 | 10.24 | 23.24 |
| BERTSUM (12) | 38.81 | 16.50 | 31.27 |
| BERTS2S (12) | 38.52 | 16.12 | 31.13 |
| BERTS2S (24) | 38.93 | 16.35 | 31.52 |
| RoBERTAS2S (12) | 39.87 | 17.50 | 32.37 |
| RoBERTAS2S (24) | 41.45 | 18.79 | 33.90 |

As can be seen in Table 1, the question generation pretraining in QURIOUS (-RoBERTa) improves over TRANS2S across all ROUGE scores (improvement of 1.42 points on average). QURI-

### Automatic Evaluation

We report on the ROUGE F₁ scores (Lin and Hovy, 2003) in Table 1. Our main baseline is a transformer-based Seq2Seq model, TRANS2S, initialized with a public BERT (Devlin et al., 2019) checkpoint (BERTS2S) as reported in Rothe et al. (2019). We also report numbers for a second BERT-based transformer model, BERTSUM (Liu and Lapata, 2019). Finally, we experimented with using a RoBERTa (Liu et al., 2019) checkpoint. This model, RoBERTAS2S, significantly improves over the state-of-the-art BERTS2S and BERTSUM.

Following the advantages of RoBERTAS2S over BERTS2S, QURIOUS initializes with the RoBERTa checkpoint and pretrains with the question generation objective, before fine tuning for extreme summarization. We also perform an ablation study where we do not initialize our model with the RoBERTa checkpoint (QURIOUS-RoBERTA). QURIOUSZ is not fine tuned for extreme summarization, it behaves as a question generation model which takes a document as input and generate a question. It assesses how close the generated questions get to the reference summary.

As can be seen in Table 1, the question generation pretraining in QURIOUS (-RoBERTa) improves over TRANS2S across all ROUGE scores (improvement of 1.42 points on average). QU-

### Table 2: Question generation scores.

The question generation scores are calculated over the test set.

| Models | Score |
|--------|-------|
| TRANS2S (12) | 30.90 |
| BERTSUM (12) | 38.81 |
| BERTS2S (12) | 38.52 |
| BERTS2S (24) | 38.93 |
| RoBERTAS2S (12) | 39.87 |
| RoBERTAS2S (24) | 41.45 |

As can be seen in Table 2, the question generation pretraining in QURIOUS (-RoBERTa) improves over TRANS2S across all ROUGE scores (improvement of 1.42 points on average). QU-

### Table 3: Validation scores.

The validation scores are calculated over the validation set.

| Models | Score |
|--------|-------|
| TRANS2S (12) | 30.90 |
| BERTSUM (12) | 38.81 |
| BERTS2S (12) | 38.52 |
| BERTS2S (24) | 38.93 |
| RoBERTAS2S (12) | 39.87 |
| RoBERTAS2S (24) | 41.45 |

As can be seen in Table 3, the question generation pretraining in QURIOUS (-RoBERTa) improves over TRANS2S across all ROUGE scores (improvement of 1.42 points on average). QU-

### Table 4: Summary scores.

The summary scores are calculated over the test set.

| Models | Score |
|--------|-------|
| TRANS2S (12) | 30.90 |
| BERTSUM (12) | 38.81 |
| BERTS2S (12) | 38.52 |
| BERTS2S (24) | 38.93 |
| RoBERTAS2S (12) | 39.87 |
| RoBERTAS2S (24) | 41.45 |
Table 2: Question generation results on SQuAD and Natural Questions (NQ) datasets. For each model, we choose its best performing variant from Table 1 for this task. B1-4 is BLEU1-4; RL is ROUGE-L.

| Models          | B1  | B2  | B3  | B4  | RL   |
|-----------------|-----|-----|-----|-----|------|
| Zhao et al.     | 45.1| 29.6| 21.6| 16.4| 44.5 |
| Nema et al.     | 46.4| 30.7| 22.4| 17.0| 45.0 |
| RoBERTaS2S      | 45.6| 29.4| 20.7| 15.1| 45.0 |
| QUIRIOUS        | 47.4| 32.0| 23.5| 17.8| 46.7 |
| NQ              |     |     |     |     |      |
| RoBERTaS2S      | 55.4| 42.8| 34.0| 27.1| 53.5 |
| QUIRIOUS        | 57.4| 45.1| 36.3| 29.3| 55.4 |

Table 2: Question generation results on SQuAD and Natural Questions (NQ) datasets. For each model, we choose its best performing variant from Table 1 for this task. B1-4 is BLEU1-4; RL is ROUGE-L.

provement is consistent for both base (12) and large (24) models. QUIRIOUS (24) achieves a new state-of-the-art on extreme summarization outperforming earlier model BERTS2S (24; Rothe et al., 2019) by 3.51 average ROUGE points. Interestingly, the question generation pretraining elevates the performance of RoBERTa initialized Seq2Seq model for summarization; our pretraining objective should also supplement recent pretraining schemes (Dong et al., 2019; Song et al., 2019; Lewis et al., 2019) for summarization.

3.2 Answer-focused Question Generation

For the Question Generation task, we evaluate our models on two factoid-based question answering datasets: SQuAD (Rajpurkar et al., 2016) and Natural Questions (NQ; Kwiatkowski et al., 2019a). For SQuAD, we use the whole paragraph as input passage and not just the sentence containing the answer as it often requires the whole paragraph as context in order to generate high quality questions. In total, this dataset is composed of 87K training examples and 10K development examples. For NQ, we use the provided long answer as input passage. We only keep those that are paragraphs and filter out list and table based long answers. We further filter Yes/No questions and also questions that are not answerable, this results in a training set of 95K examples and a development set 3.6K examples. To the best of our knowledge, we are the first to use the NQ dataset for the question generation task.1

Automatic Evaluation. We choose our best performing model from Table 1 for this task. We report on the BLEU (Papineni et al., 2002) and ROUGE-L $F_1$ (Lin and Hovy, 2003) scores, and results are listed in Table 2. Table 2 exhibits a similar pattern as that in Table 1: QUIRIOUS consistently improve model performance over RoBER-

1Alberti et al. (2019) used the NQ dataset to construct synthetic question-answer corpora to train QA models.

3.3 Human Evaluations

In addition to automatic evaluation using ROUGE and BLEU, we also evaluated system output by eliciting human judgments for both summarization and question generation. The study was conducted on the Amazon Mechanical Turk platform using Best-Worst Scaling, a less labor-intensive alternative to paired comparisons (Louviere and Woodworth, 1991; Louviere et al., 2015). For summarization, participants were presented with a document and summaries generated from two out of five systems and were asked to decide which summary was better than the other in order of informativeness (does the summary capture important information in the document?) and fluency (is the summary written in well-formed English?). For question generation, participants were presented with an answer passage, a factoid answer and questions generated from two systems and were asked to decide which question is more (i) natural (is the summary fluent and written in well-formed English?) and (ii) correct (is the question correct for the factoid answer given the passage?). In all cases, we allowed ties when both predictions were the same. Additionally, for correctness, we allowed a tie when both questions were equally correct or incorrect. We randomly selected 30 documents from the XSum test set for summarization and 30 answer-passage pairs each for question generation from SQuAD and from Natural Questions. We collected judgments from three different participants for each comparison. The order of summaries were randomized per document and the order of documents per participant. The score of a system was computed as the percentage of times it was chosen as best minus the percentage of times it was selected as worst. The scores range from -1 (worst) to 1 (best). Some of the sample predictions used in human evaluations are presented in the appendix.

QUIRIOUS outperformed RoBERTaS2S across
Table 3: Human evaluation results for summarization assessing summary ‘quality’ and answer-focused question generation assessing naturalness (nat.) and correctness (corr.) of questions.

| Models       | XSum quality | SQuAD nat. corr. | NQ nat. corr. |
|--------------|--------------|------------------|---------------|
| Nema et al.  | –            | -0.25            | -0.13         |
| ROBERTAS2S   | -0.25        | 0.01             | -0.15         |
| QURIOUS      | 0.14         | 0.12             | 0.11          |
| GOLD         | 0.11         | 0.10             | 0.08          |

Figure 3: QURIOUS predictions on the SQuAD and NQ datasets.

all tasks. Interestingly, it even performed better than human-authored summaries or questions with a single exception of the correctness assessment of questions on the NQ dataset.

We carried out pairwise comparisons between all models to assess whether system differences are statistically significant (using a one-way ANOVA with posthoc Tukey HSD tests; \( p < 0.01 \)). For summarization, ROBERTAS2S is significantly different from both QURIOUS and GOLD. For SQuAD, Nema et al. is significantly different from all other systems on naturalness and correctness, and ROBERTAS2S is significantly different from QURIOUS on correctness. For NQ, ROBERTAS2S is significantly different from QURIOUS on naturalness and from GOLD on correctness. All other differences are not statistically significant.

The difference in performance of QURIOUS on SQuAD and NQ stem from how these datasets are created. For SQuAD, human annotators started with the passage and wrote the questions, many times resorting to paraphrasing with copying involved. For NQ, the dataset creation process started with the questions, making them more natural and harder for a model to learn by copying.
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Figure 5 shows examples of BBC articles and their extreme summaries.

Figure 6 shows examples of SQuAD input passages, answer spans and questions generated from them.
**GOLD:** Former Beatle Sir Paul McCartney has topped the Sunday Times rich list of musicians with his £730m fortune.

**Document:** Sir Paul is worth an estimated £20m more than last year and enjoys a significant boost from his American heiress wife’s £150m stake in her family’s US trucking business. It puts him well ahead of his nearest rival on the list, Andrew Lloyd Webber, who is estimated to be worth £650m. The full list will be published by the newspaper on 26 April. Of the 1,000 richest people in the UK and the 250 wealthiest in Ireland, the list puts Irish band U2 at third place with £431m. Pop veteran Sir Elton John and Rolling Stones’ frontman Sir Mick Jagger follow with their fortunes, thought to be worth £270m and £225m respectively. 1. Sir Paul McCartney and Nancy Shevell £730m (Rest of the article is abbreviated ...)

**TRANS2S:** One of the richest people in the UK has topped the list of the richest people in the world.

**QURIous (-ROBERTA):** The Rolling Stones have been named the richest young band in the UK this year.

**ROBERTAS2S:** Sir Paul McCartney has been named as Britain’s richest man in the Sunday Times rich list.

**QURIous:** Sir Paul McCartney has been named the richest man in the UK, with his wealth totalling £730m, according to the Sunday Times rich list.

**GOLD:** Islanders on Skye have demanded greater availability of public toilets after complaints some visitors to the Isle are relieving themselves outside.

**Document:** There have been incidents reported at scenic spots where public conveniences are lacking or have been closed down. In Uig, where many of the complaints have been raised, the local authority-run toilets have been out of order since the beginning of the year. Highland Council said it was seeking quotes for the repair work needed. The availability of toilets on Skye has been raised previously. In 2011, Highland Council received complaints about people urinating and defecating outdoors at Staffin where public toilets were closed as part of cost cutting. **TRANS2S:** A council has asked people not to keep their toilets in a bid to save money.

**QURIous (-ROBERTA):** Highland Council is calling on public complaints about a possible route for people to urinating on Skye.

**ROBERTAS2S:** Highland Council has commissioned a review of public toilets and public toilets on Skye.

**QURIous:** Highland council is seeking information about problems with public toilets on Skye.

Figure 5: Example documents and summarization model predictions.
Passage: Under the terms of the Scotland Act 1978, an elected assembly would be set up in Edinburgh provided that the majority of the Scottish electorate voted for it in a referendum to be held on 1 March 1979 that represented at least 40% of the total electorate. The 1979 Scottish devolution referendum to establish a devolved Scottish Assembly failed. (...) 

Answer: failed

Nema et al.: What happened to the 1979 Scottish devolution referendum in 1979? 
TRANS2S: What percentage of the vote of Ireland was interpreted as a result of voting? 
ROBERTAS2S: How did the 1979 Scottish devolution referendum fail? 
QURIOUS (-ROBERTA): What did the Scottish assembly of Edinburgh vote to pass in 1979? 
QURIOUS: What was the result of the 1979 Scottish devolution referendum? 
GOLD: How did trying to establish a devolved Scottish assembly go in 1979?

Passage: Although lacking historical connections to the Middle East, Japan was the country most dependent on Arab oil. 71% of its imported oil came from the Middle East in 1970. (...) 

Answer: 71%

RefNet: What percentage of its imported oil came from Japan? 
TRANS2S: When did Japan make a national influence? 
ROBERTAS2S: How much oil did Japan’s oil from the Middle East come in in 1970? 
QURIOUS (-ROBERTA): How much of the Middle East’s oil was imported in Japan by the Middle East? 
QURIOUS: How much of Japan’s imported oil came from the Middle East? 
GOLD: How much imported oil came from the Middle East?

Figure 6: Examples produced by the answer-focused question Generation models on Squad.