

Generating Self-Contained and Summary-Centric Question Answer Pairs via Differentiable Reward Imitation Learning

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Abstract

Motivated by suggested question generation in conversational news recommendation systems, we propose a model for generating question-answer pairs (QA pairs) with self-contained, summary-centric questions and length-constrained, article-summarizing answers. We begin by collecting a new dataset of news articles with questions as titles and pairing them with summaries of varying length. This dataset is used to learn a QA pair generation model producing summaries as answers that balance brevity with sufficiency jointly with their corresponding questions. We then reinforce the QA pair generation process with a differentiable reward function to mitigate exposure bias, a common problem in natural language generation. Both automatic metrics and human evaluation demonstrate these QA pairs successfully capture the central gists of the articles and achieve high answer accuracy.¹

1 Introduction

Automatic generation of question-answer pairs (QA pairs) is a widely studied problem, primarily used to improve the performance of question answering systems via data augmentation (Alberti et al., 2019; Shakeri et al., 2020). However, question generation has also recently garnered interest in the context of conversational agents, where suggested questions (SQs) (i.e., *You can also ask...*) have emerged as a promising approach to drive multi-turn dialogues by educating customers about the agent capabilities and guiding users along dialogue trajectories with more engaging content (Yin et al., 2020; Nouri et al., 2020).

As an example, consider a news chatbot engaged in a dialogue regarding COVID-19 vaccine developments producing the SQ {Q: *How effective is the Pfizer-BioNTech vaccine?*} paired with the answer

{A: *Pfizer/BioNTech vaccine is around 91% effective at preventing COVID-19, according to updated trial data. Experts fear new variants of COVID-19 from South Africa and Brazil may be resistant to existing vaccines and treatment.*} Firstly, SQs of this form mitigates the user burden regarding the necessity of both deep subject knowledge to ask good questions and awareness of the agent question answering capabilities to expect good answers. Secondly, the agent can look-ahead when selecting SQs to bias toward confidently correct answers and content expected to lead to further follow-up questions and general system engagement.

Targeting the SQ problem in news chatbot scenarios (e.g., (Laban et al., 2020)), this work examines QA pair generation corresponding to a news article summary paired with a self-contained question. Table 1 shows an example of the task. SQs based on these summary-centric QA pairs act as implicit article recommendations, complementing SQs focusing on passage-level extracted answers or factoid information. QA pairs generated for this purpose must satisfy several criteria including: (1) questions are self-contained (i.e., users need not read the corresponding articles nor require significant additional domain knowledge to unambiguously understand the questions (Yin et al., 2020)), (2) questions are summary-centric (questions capture the gists of the corresponding articles), (3) answers correctly answer the questions, and (4) answers are brief but sufficient such that users can confidently trust the results. Additionally, to support different settings (e.g., screened device, mobile device, voice-only), we explore QA pair generation for varying application-specific answer length requirements.

To satisfy these requirements, we first collect a corpus of suitable QA pairs, accomplished by curating a set of news articles with well-formed questions as their titles and for which we can confidently generate variable length summaries as an-

¹Code and Data will be made available at <https://github.com/amazon-research/SC2QA-DRIL>

Article: *President Biden’s infrastructure plan calls for an unprecedented boost in federal aid to the nation’s passenger rail system, seeking to address Amtrak’s repair backlog, extend service to more cities and modernize the network in the Northeast Corridor. The American Jobs Plan announced Wednesday calls for \$80 billion for rail – money that could be crucial in taking passenger service to cities such as Las Vegas and Nashville, and expand operations across large metropolitan areas such as Atlanta and Houston. “President Biden’s infrastructure plan is what this nation has been waiting for,” Amtrak chief executive William J. Flynn said, while echoing Biden’s push to rebuild and improve...*

Suggested Question: *What does President Biden’s infrastructure plan mean for Amtrak?*

Short Answer: *The federal funding would help Amtrak accomplish long-needed upgrades to tracks, tunnels and bridges in the Northeast.*

Long Answer: *The American Jobs Plan announced Wednesday calls for \$80 billion for rail. The federal funding would help Amtrak accomplish long-needed upgrades to tracks, tunnels and bridges in the Northeast, the nation’s busiest rail corridor. Amtrak has a \$45.2 billion backlog of projects that it says are needed to bring its assets to a state of good repair.*

Table 1: The suggested QA pair generation task. Given an article, we generate a self-contained and summary-centric question and a length-constrained answer. The question captures the gist of the article and can be understood without reading the corresponding article.

swers. Observing that the *summary generation* \rightarrow *question generation* pipeline suffers from exposure bias (Ranzato et al., 2016), we propose a novel differential reward imitation learning (DRIL) training method that samples summary answers and reconstructs questions exclusively based on the hidden states of the answer decoder. Generated summaries are capable of directly reconstructing the questions, making them more likely the answers to the questions, and generate questions more closely related to the gists of the articles. We empirically validate the model with automated and human evaluations.

In this paper, we study QA pair generation corresponding to variable length article-summarizing answers paired with self-contained and summary-centric questions. Our contributions include: (1) We collect a new QA dataset targeted for producing SQs in a news chatbot. (2) We propose a QA pair generation model where both questions and answers are well-formed, questions capture the central gists of articles, and answers are succinct while containing sufficient supporting context. (3) We propose a novel differentiable reward imita-

tion learning (DRIL) method which shows better performance over maximum likelihood estimation (MLE) and reinforcement learning (RL) for QA pair generation. (4) We perform extensive empirical evaluations to quantify DRIL-based QA pair generation improvements.

2 Related Works

Question-only Generation (QG). Both heuristic-based (Heilman and Smith, 2010) and neural models (Du et al., 2017; Zhou et al., 2017; Sun et al., 2018) have been applied to QG. Usually, neural QG models are given contexts containing answers beforehand, contrasting with our goal of jointly generating QA pairs. Tuan et al. (2020); Song et al. (2018); Zhao et al. (2018) proposed to generate questions from long text and wider contexts, which is related to our method for QG using summaries. However, these wider contexts are only used to improve QG for the specified answer spans and do not attempt to capture the central gists of articles.

Question and Answer Generation (QG+AG). QG+AG generates QA pairs jointly (Liu et al., 2020; Alberti et al., 2019; Du and Cardie, 2018, 2017; Subramanian et al., 2018; Wang et al., 2019; Krishna and Iyyer, 2019), frequently with two independent steps: identify question-worthy answer spans followed by generating answer-aware questions. Recent works train neural models to generate QA pairs (Shakeri et al., 2020; Lee et al., 2020) using QA datasets such as SQuAD (Rajpurkar et al., 2016) and Natural Questions (Kwiatkowski et al., 2019) modulo the goal of generating self-contained questions paired with succinct but sufficient article-summarizing answers.

Applications of QG and QG+AG. QG and QG+AG have been used for applications including data augmentation for QA systems (Alberti et al., 2019; Shakeri et al., 2020), information seeking in chatbots (Qi et al., 2020a; Laban et al., 2020), document understanding (Krishna and Iyyer, 2019), educational practice and assessment (Le et al., 2014), and online shopping (Yu et al., 2020).

Training Mechanism for Sequence Prediction. Sequence prediction models are commonly trained with MLE. However, MLE can lead to degeneration (Holtzman et al., 2019) caused by exposure bias (Ranzato et al., 2016). Many algorithms (Yu et al., 2017; Lamb et al., 2016; Song et al., 2020; Welleck et al., 2019) have been proposed to mitigate exposure bias. Our DRIL method not only

mitigates exposure bias, but also optimizes for a differentiable reward function that is aligned with the end goal. Please refer to Section 4.2 for comparison between DRIL and existing algorithms.

3 $(SC)^2QA$: A Self-Contained and Summary-Centric QA Dataset

While multiple QA datasets exist to train a QG or AG model, none specifically fit the goal of this paper. QA pairs in SQuAD (Rajpurkar et al., 2018), NewsQA (Trischler et al., 2017), and Natural Questions (NQ) (Kwiatkowski et al., 2019) are not designed to capture the article gists, and a significant number of questions in SQuAD and NewsQA are not self-contained.

A key observation enabling this work is that many news articles have questions as their titles (e.g. *How has the Biden administration helped student loan borrowers?*) that can be used to train a SQ generation model since these questions usually correspond to the central gists of the news articles and are designed to be understood without reading the articles. However, two challenges remain: (1) clickbait titles need to be filtered, and 2) these questions are not paired with summary-centric answers. Therefore, we developed the following data collection procedure to produce $(SC)^2QA$, our self-contained summary-centric QA dataset.

3.1 Question-Article Pairs Collection

Starting with a curated URL list of news websites, we collected all articles between September 2020 to March 2021 with a title that starts with a pre-defined list of words (e.g., *Where, What, How*) and ends with a question mark. We then define a set of rules to filter out ill-formed and clickbait titles (details in Appendix A). Finally, we remove any questions that appear in the articles to ensure we don't learn to copy the questions when present. In total, we collected 39,460 such question-article pairs.

3.2 {Question, Article, Summary, Length Constraint} 4-Tuples Collection

Given collected question-article pairs, we must pair them with suitable answers to produce QA pairs. From a preliminary study, we observed that $\sim 70\%$ of title questions can be answered by summaries of the corresponding articles. As a result, we set out to augment the question-article dataset with generated summaries as pseudo ground truth answers

using following three-step procedure:

Step 1 (Define desired answer lengths): One of our goals is to generate well-formed answers that are succinct while containing sufficient supporting context. Therefore, we generate summaries with varying brevity. Analyzing the average number of tokens for the first 1, 2 and 3 sentences of the CNN/DailyMail summaries (Hermann et al., 2015), we define three buckets of varying answer lengths: (0, 30], (30, 50] and (50, 72] BPE tokens.

Step 2 (Generate summary): For each article and desired length bucket, we use three SoTA summarization models (PEGASUS (Zhang et al., 2020), BART (Lewis et al., 2020), and CTRLSum (He et al., 2020)) fine-tuned on CNN/DailyMail to generate three candidate summaries – enforcing summary length via control of EOS token generation. Unfinished sentences are removed and the length bucket is reassigned if needed.

Step 3 (Filter-out incorrect summary answers): Not all questions can be answered by the generated summaries since: (1) even the ground truth summary may not be a correct answer to the question and (2) summaries generated by SoTA models may not be good. To identify if a candidate summary answers the question, we train a QA pair classifier using the 4 million question-snippet pairs MSMARCO dataset (Bajaj et al., 2016). For each article and length bucket, we select the candidate summary that has the highest score predicted by the trained classifier. In total, we produce 53,746 4-Tuples of {Question, Article, Summary, Length Constraint}. For additional details and dataset statistics, please refer to Appendix A.

4 Models for QA Pair Generation

In this section, we propose a family of QA pair generation models that are trained on the data collected in Section 3. Let D denote a document (news article), S denote a summary, Q denote a question, L denote a length bucket indicator (LB0, LB1 or LB2), and $\langle s \rangle$ and $\langle /s \rangle$ denote the special BOS and SEP tokens respectively.

4.1 Base $D \rightarrow S \rightarrow Q$ Model (D-S)

Our base model is shown in Figure 1, consisting of two transformer-based encoder-decoder models (Vaswani et al., 2017) where one performs answer generation (AG) and the other question generation (QG). During training, the AG model encodes a concatenation of the length bucket indicator and

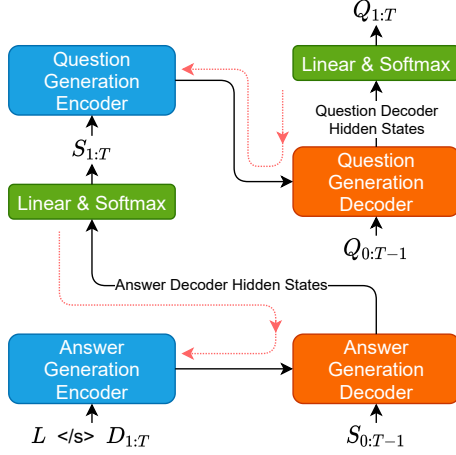


Figure 1: Training of answer generation (AG) and question generation (QG) of the **D-S** model. L, D, S, Q denotes the length bucket indicator, document, summary, and question, respectively. Red dash arrows denote gradient flow.

the document, and decodes a length-constrained summary:

$$\begin{aligned} f_{\text{enc}}^a : L + D &\rightarrow c_{\text{enc}}^a \\ f_{\text{dec}}^a : S_{0:T-1}, c_{\text{enc}}^a &\rightarrow S_{1:T} \end{aligned}$$

where θ_{enc}^a and θ_{dec}^a are the encoder and decoder parameters, c_{enc}^a is the sequence of hidden states at the last encoder layer, $S_{1:T}$ is the ground truth summary, and $S_{0:T-1}$ is the decoder input ($S_{1:T}$ offset by one timestamp and prepended by a BOS token). The AG model is trained using MLE:

$$\mathcal{L}(\theta_{\text{enc}}^a, \theta_{\text{dec}}^a) = - \sum_{n=1}^N \log p(S^{(n)} | L^{(n)} + D^{(n)})$$

where (n) represents the n -th training instance. QG is also trained via MLE, mapping an input summary to a question:

$$\begin{aligned} f_{\text{enc}}^q : S &\rightarrow c_{\text{enc}}^q \\ f_{\text{dec}}^q : Q_{0:T-1}, c_{\text{enc}}^q &\rightarrow Q_{1:T} \\ \mathcal{L}(\theta_{\text{enc}}^q, \theta_{\text{dec}}^q) &= - \sum_{n=1}^N \log p(Q^{(n)} | S^{(n)}) \end{aligned}$$

During inference, when decoding summary answers, we again control the generation of EOS to fall into the range specified by the desired length bucket. We remove any unfinished sentences at the end unless after the truncation the answer is shorter than the minimum length of the length bucket.

We use a pre-trained BART model (Lewis et al., 2020) to initialize θ_{enc}^a , θ_{dec}^a , θ_{enc}^q and θ_{dec}^q . We name

this base model **D-S** since the AG model takes the document (D) as input and the QG model takes the summary (S) as input. In Section 4.3 we will describe multiple variants of this model.

4.2 Optimizing Answer Generation by Differentiable Rewards

When using MLE to train the base model, the decoder input at timestep t is the ground truth token at timestep $t - 1$, sometimes called teacher-forcing (Williams and Zipser, 1989) and known to suffer from exposure bias (Ranzato et al., 2016) due to the mismatch between training and inference. That is, during inference the decoder input is the predicted token instead of the ground truth token of the last timestep, causing errors from each timestamp to accumulate during generation. It has been shown that neural text generation models trained with MLE lead to generic and repetitive outputs (Welleck et al., 2019; Holtzman et al., 2019). Additionally, we usually want to optimize generation metrics (e.g., ROUGE) and human feedback directly instead of optimizing training data likelihood. To mitigate these concerns, we can sample decoder output during *training* and calculate the loss of the sampled output. Several works use RL to achieve this for text generation (Stiennon et al., 2020; Ziegler et al., 2019; Yu et al., 2017) and directly optimize for preferred metrics. However, RL is not sample efficient and difficult to tune in text generation tasks due to sparse rewards. For example, Hosking and Riedel (2019) have shown that applying RL to QG do not improve human evaluation metrics.

Meanwhile, we observe that when generating a summary as the answer of a QA pair, we want to generate a summary that can better reconstruct the ground truth question without the article since: (1) a summary that can reconstruct a question is more likely to be able to answer that question and (2) a summary that better reconstructs the ground truth question leads to a generated question that is closer to the gist of the article. Moreover, the AG model is conditioned on the length bucket to control the levels of brevity, meaning that when the maximum allowed answer length is short, the question reconstruction will enforce the AG model to generate *succinct* but *informative* answers with respect to the question given the selected brevity level. We validate these assumptions in Section 5.

We now propose the differentiable reward imita-

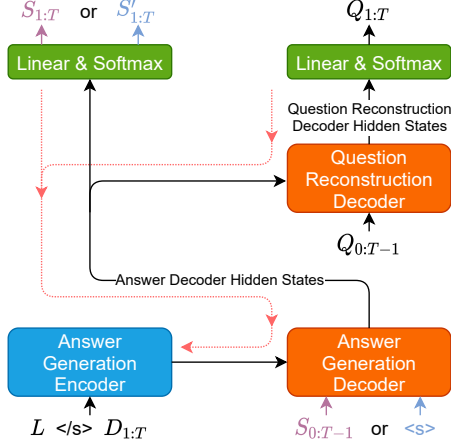


Figure 2: Training of answer generation (AG) of the **D-S-DRIL** model. The input to the AG decoder is either $S_{0:T-1}$ or $\langle s \rangle$. When the input is $S_{0:T-1}$, the AG decoder uses teacher-forcing to predict $S_{1:T}$, and the gradients back-propagate from $S_{1:T}$ to the AG decoder and AG encoder (the red dash arrow on the middle left), which is similar to the AG of the D-S model. However, when the input is $\langle s \rangle$, the AG decoder samples a summary $S'_{1:T}$, and the answer decoder hidden states are used to reconstruct the question $Q_{1:T}$. The gradients back-propagate from $Q_{1:T}$ to the AG decoder and AG encoder (the red dash arrow on the top right). This reinforces the model to generate summaries that can reconstruct the questions.

tion learning (DRIL) method for training the AG model as shown in Figure 2. During training, the AG model performs *vanilla* sampling to generate a summary:

$$\begin{aligned} f_{\theta_{\text{enc}}^a} &: L + D \rightarrow c_{\text{enc}}^a \\ f_{\theta_{\text{dec}}^a} &: \text{BOS}, c_{\text{enc}}^a \rightarrow c_{\text{dec}}^a, S' \end{aligned}$$

where c_{dec}^a is the sequence of hidden states at the last layer of the decoder, and S' is the sampled summary. This differs from teacher-forcing since summaries are sampled in training. We then use another transformer-based decoder to reconstruct the question:

$$f_{\theta_{\text{dec}}^r} : Q_{0:T-1}, c_{\text{dec}}^a \rightarrow Q_{1:T}$$

noting that this decoder only depends on the hidden states of the AG decoder (not $L + D$). This forces the model to reconstruct the question only from the summary. The gradient can back-propagate from the question to the hidden states of the AG decoder c_{dec}^a and AG encoder c_{enc}^a such that the question reconstruction loss will guide AG. To ensure generated summary fluency, we also add the MLE loss

from the base model. Overall, the AG model’s loss function is given by:

$$\begin{aligned} \mathcal{L}(\theta_{\text{enc}}^a, \theta_{\text{dec}}^a, \theta_{\text{dec}}^r) = & \\ & - \sum_{n=1}^N \lambda \log p(Q^{(n)} | S'^{(n)}, L^{(n)} + D^{(n)}) \\ & + (1 - \lambda) \log p(S^{(n)} | L^{(n)} + D^{(n)}) \end{aligned}$$

In our experiments, $\lambda = 0.3$ performs the best on the validation set. Finally, while we apply DRIL to the training of the AG model, the QG model remains the same as the base model. We do not use the question reconstruction decoder θ_{dec}^r as our QG model because its encoder input c_{dec}^a is a unidirectional representation and hence not preferred. We call this QA pair generation model **D-S-DRIL**.

Connection with RL, Unlikelihood (Welleck et al., 2019), SeqGAN (Yu et al., 2017), and Professor-forcing (Lamb et al., 2016), etc. These methods mitigate exposure bias to some degree by calculating the loss from sampled sequences during training. Unlikelihood training penalizes the likelihood of undesired sampled sequences. SeqGAN and Professor-forcing both calculate the loss using a discriminator which learns to distinguish between the generated and ground truth sequences. They don’t optimize an extrinsic reward function. Caccia et al. (2019) show that Language GANs suffer from mode collapse and do not outperform MLE on the quality and diversity evaluation. SeqGAN uses RL optimization and thus suffers from aforementioned issues. Our DRIL method, on the other hand, learns to optimize a differentiable reward function that *aligns with the end goal*, and has lower gradient variance compared with RL. We empirically compare RL with DRIL in Section 5.

Beyond this work, DRIL can be applied to other sequence prediction problems. For example, in step-by-step instruction following such as ALFRED tasks (Shridhar et al., 2020), DRIL can optimize the current step’s action trajectory such that it can reconstruct the next K instructions. The intuition is if the current step’s action trajectory is correct, then the agent should be able to follow the ground truth actions in the next steps to fulfill the tasks. From this perspective, DRIL is similar to SQIL (Reddy et al., 2020), which avoids drifting away from the demonstrations over long horizons by encouraging trajectories that return to demonstrated states when encountering unseen states. In conversational AI, Hosseini-Asl et al.

(2020) proposed to fine-tune a GPT-2 model to generate system responses turn-by-turn. DRIL can optimize response generation at each turn such that the response and dialogue context can reconstruct the next K turns’ user and system response with a similar intuition: a correct system response will increase the likelihood of the ground truth in future turns. It avoids drifting away from demonstrations and mitigates exposure bias.

4.3 Base Model Variants

In this section, we specify additional baseline QA pair generation models. Similar to the base D-S model, these models are based on transformer encoder-decoder architectures. The differences between these models are the encoder and decoder inputs during training and inference as summarized in Table 2. Models are named by the encoder input of the AG and QG models joined with a ‘-’. D-D is similar to D-S except that QG takes the document (D) rather than the summary (S) as encoder input. QD-D generates question-conditioned answers, such that the AG model becomes a question-answering model. D-SD is an extension of D-S and D-D such that the encoder of the QG model takes the concatenation of S and D. D-S-DRIL optimizes the AG model of D-S using DRIL. D-S-RL optimizes the AG model of D-S using RL, and the reward function is defined as the negative question reconstruction loss calculated by the QG model of D-S. For further details, refer to Appendix B.

5 Experiments

We conduct experiments to answer 3 research questions: (1) *How good are the QA pairs generated by each algorithm?*, (2) *Can DRIL outperform MLE and RL on QA pair generation?*, and (3) *Is our $(SC)^2QA$ dataset preferable compared with existing public QA datasets for QA pair generation?* For each generated QA pair, we are interested in evaluating the following 3 questions: (1) *Does the length-constrained summary answer the question?*, (2) *Does the question capture the article gist?*, (3) *Is the question self-contained?* We specify automated metrics and human evaluations to quantify the answers to these research questions.

5.1 Automated Metrics

ROUGE-L (R-L) and BLEU. ROUGE-L and BLEU evaluate generated summaries/questions with respect to reference summaries/questions in

the validation set.

QA Pair Classifier Scores (QACS). We need to measure how well the generated summaries answer the *generated* questions despite not having ground truth answers. Using the trained QA pair classifier from Section 3, we propose QACS, which is the average of classifier predicted scores on the generated QA pairs. The pseudo upper and lower bounds of QACS are 0.359 and 0.046 based on the average classifier predicted scores of the positive and negative QA pairs in our human evaluation.

5.2 Human Evaluation

We conduct human evaluation on Amazon Mechanical Turk. We designed 7 annotation tasks (ATs). Please refer to Appendix C for detailed human evaluation setup. Here we describe 4 ATs for which we are most concerned: **AT-1** shows a QA pair and asks *Without referring to the answer or the article, are you able to understand the question?* (Is the question self-contained?), **AT-2** follows AT-1 and asks *Does the passage in the Answer text box answers the question?*, **AT-5** shows the corresponding article and asks *Does the question in the Question text box capture the gist of the Article?* For these three tasks, annotators select either TRUE or FALSE. **AT-6** shows an article and a list of questions generated by different models and asks *Which Question shown above best captures the gist of the Article?*

5.3 Baseline

We evaluate D-S and its variants in Table 2. Beyond that, we evaluate the following baselines. **QA-Gen 2S:** This is the state-of-the-art model for QA pairs generation for improving QA systems. We train QAGen 2S on our dataset, which is similar to QD-D except that there is no length control on the answers. **CTRLSum:** We use a pre-trained CTRLSum model to generate question-dependent summaries. Questions are generated by the QG model of QD-D. **QA Transfer:** We train a question-answering model on the NewsQA dataset to answer the generated questions. Questions are generated by the QG model of QD-D. This is to verify if a pre-trained question-answering model is sufficient to answer the questions in our dataset. **D-S-NewsQA and Natural Questions (D-S-NQ):** These two models are similar to D-S, except that the QG models are trained on NewsQA and NQ, respectively. This is to verify if $(SC)^2QA$ is better than other existing QA datasets for QG tasks. Refer to Appendix B for implementation details.

	Training				Inference			
	Answer Generation		Question Generation		Answer Generation		Question Generation	
	Encoder	Decoder	Encoder	Decoder	Encoder	Decoder	Encoder	Decoder
D-S	L+D	S	S	Q	L + D	S'	S'	Q'
D-D	L + D	S	D	Q	L + D	S'	S'	Q'
D-SD	L + D	S	S + D	Q	L + D	S'	S' + D	Q'
QD-D	Q + L + D	S	D	Q	Q' + L + D	S'	D	Q'
D-S-DRIL	L + D	S/S'	S	Q	L + D	S'	S'	Q'
D-S-RL	L + D	S/S'	S	Q	L + D	S'	S'	Q'
QAGen 2S	D + Q	S	D	Q	D + Q'	S'	D	Q'

Table 2: A summary of models (D-S and its variants) we proposed for QA pair generation. Q' and S' denote the question and answer generated during inference, respectively. QAGen 2S (Shakeri et al., 2020) is a state-of-the-art baseline. A full table that includes all the baselines in our experiments is shown at Appendix Table 15.

5.4 Data

Training and Validation set. We use the data described in Section 3 for training, taking the last 5,000 out of the 53,746 examples as validation set. **Test set.** It is desirable to evaluate models on articles that do not use questions as titles. We sampled news articles between April 1 to April 7, 2021 from the following news domains: washingtonpost.com, reuters.com, foxnews.com, cnn.com, cbsnews.com, nbcnews.com, nydailynews.com. We filtered out articles that use questions as titles, and removed all questions in the articles. In total we collect 7,698 test examples. Unlike validation set, there are no ground truth questions or answers in the test set.

5.5 Quality of Generated Answers

In this section we measure the quality of answers, particularly, whether they answer the corresponding questions. In Table 3, we show the ROUGE-L score of predicted summaries on the validation set, and QACS and AT-2 accuracy on the test set, resulting in the following observation.

Models that generate questions based on answers have higher QACS and AT-2 accuracy than models that generate answers based on questions. Recall that during inference, D-S, D-D, D-S-DRIL and D-S-RL first generate summaries as answers and then generate questions based on the answers (see Table 2). These algorithms perform much better than QD-D, CTRLSum, QAGen 2S and QA Transfer which first generate questions and then generate answers to these questions. For example, D-S achieves 51.2%, 39.6%, and 23.4% higher AT-2 accuracy than QAGen 2S in each of the 3 length buckets respectively. This observation is consistent in both QACS and AT-2 accuracy. Meanwhile, QD-D achieves the best ROUGE-L scores while the QACS and AT-2 accuracy are significantly lower than D-S (e.g., AT-2 accuracy is

33.9% lower than D-S in length bucket 0). All these observations show that, to ensure the generated questions and answers match with each other, we should generate questions from answers rather than the opposite direction. This is especially true on our dataset, because the ground truth answers of our dataset are summaries, which are generated without conditioning on the questions (modulo examples generated by the CTRLSum in Section 3).

5.6 Quality of Generated Questions

5.6.1 Results on $(SC)^2QA$ Dataset

In this section, we evaluate the quality of generated questions, particularly, whether the questions capture the gists of articles. From Section 5.5 we already observed that only D-D, D-S, D-S-DRIL, and D-S-RL can generate high quality answers. Therefore, here we only focus on these four models (refer to Appendix C and Section 5.7 for results on other models). The results are shown in Table 4. We report ROUGE-L/BLEU score of predicted questions on the validation set. Questions are predicted from *predicted* summaries instead of ground truth summaries, which is consistent with inference on the test set where we also don't have ground truth summaries. We also report AT-5 accuracy on test set and make the following observations.

DRIL and RL reinforce AG with question reconstruction loss and thus better reconstruct ground truth questions on validation set and better capture gists of articles on test set. Table 4 shows that D-S-DRIL achieves higher ROUGE-L and BLEU score than D-S across all the length buckets. Note that D-S and D-S-DRIL have the same QG model so the only difference is the AG model, showing that D-S-DRIL is able to generate better summaries that can better reconstruct the ground truth questions. This aligns with our goal of designing the question reconstruction loss. Mean-

	length bucket 0			length bucket 1			length bucket 2		
	R-L	QACS	AT-2 Accuracy	R-L	QACS	AT-2 Accuracy	R-L	QACS	AT-2 Accuracy
D-S	59.993	0.219	0.623 ± 0.052	54.110	0.255	0.748 ± 0.045	52.236	0.294	0.754 ± 0.046
D-D		0.176	0.571 ± 0.053		0.224	0.683 ± 0.048		0.268	0.782 ± 0.045
D-SD		0.125	0.403 ± 0.072		0.184	0.547 ± 0.074		0.235	0.653 ± 0.071
QD-D	62.219	0.110	0.412 ± 0.072	55.200	0.167	0.508 ± 0.071	53.075	0.212	0.574 ± 0.072
D-S-DRIL	58.153	0.225	0.631 ± 0.049	53.376	0.263	0.771 ± 0.042	50.816	0.304	0.814 ± 0.038
D-S-RL	59.466	0.224	0.624 ± 0.065	53.635	0.262	0.733 ± 0.060	51.871	0.302	0.813 ± 0.053
CTRLSum	48.973	0.040	0.112 ± 0.046	52.766	0.132	0.438 ± 0.073	50.205	0.183	0.530 ± 0.075
QAGen 2S	56.881	0.112	0.412 ± 0.073	52.912	0.171	0.536 ± 0.072	51.741	0.218	0.611 ± 0.071
QA Transfer	-	0.091	0.521 ± 0.071	-	0.128	0.587 ± 0.070	-	0.156	0.687 ± 0.065

Table 3: Evaluation of Answer Quality. Underline, **bold**, and **bold** represent the best results on ROUGE-L (R-L), QACS, and human evaluation, respectively. We report a 95% binomial proportion confidence interval on human evaluation. D-S-DRIL generates higher quality answers than baselines in all three answer length bucket on test set.

while, we assume that in our dataset the ground truth questions capture the gists of articles, this means that, by optimizing question reconstruction loss, D-S-DRIL can generate questions that better capture the gists of articles. This is validated by the results on AT-5 accuracy. D-S-DRIL has about 6% and 3% higher AT-5 accuracy than D-S on length bucket 0 and 1, respectively. D-S-DRIL has lower AT-5 accuracy than D-S on length bucket 2, likely because when the maximum allowed summary length is long, there is sufficient information to reconstruct the questions even without the reconstruction loss. D-S-DRIL also shows better performance compared with D-S-RL, indicating the advantage of differentiable question reconstruction loss over the non-differentiable question reconstruction reward.

AT-6 shows one article and a list of questions generated by D-D, D-S, D-S-DRIL, and D-S-RL. Annotators select the question that best captures the gist of the displayed article. Figure 3 shows the percentage of each model selected. We can see that questions generated by D-S-DRIL are preferred in length bucket 0 and 1, which is consistent with our results in Table 4.

5.6.2 $(SC)^2QA$ v.s. Existing QA Datasets

In this section, we evaluate if $(SC)^2QA$ is better than existing publicly available QA datasets for QG. We compare with D-S-NewsQA and D-S-NQ. NewsQA and NQ datasets are designed for question-answering but not QG specifically. Similar to $(SC)^2QA$, NewsQA is in news domain but without explicitly self-contained questions. For example, the question “*what are they going to address?*” in the NewsQA dataset is incomprehensible without reading the article due to lack of pronoun resolution. The human evaluation results are

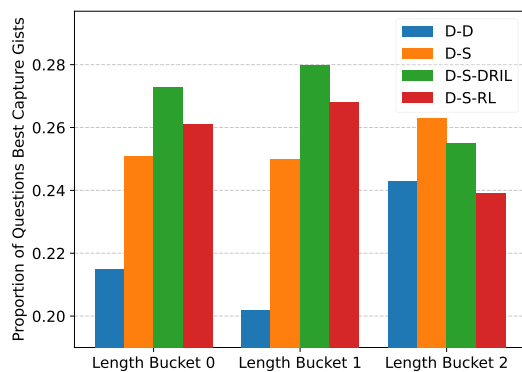


Figure 3: Proportion of most preferred AT-6 questions. (Which question best captures the gist of the article?) According to human evaluation, questions generated by D-S-DRIL best captures the gist of the article in answer length bucket 0 and 1.

shown in Figure 4, leading to the following observation.

QG models trained on NewsQA and Natural Questions cannot generate self-contained questions that capture gists of articles due to the limitations of the datasets, while QG models trained on $(SC)^2QA$ can. We can see that the QG model trained on NewsQA achieves about 50% lower AT-1 accuracy than the other two models, indicating that it cannot generate self-contained questions. Moreover, QG models trained on NewsQA and Natural Questions achieve 73.55% and 60.03% lower accuracy on AT-5 (averaged over 3 length buckets) compared with the QG model trained on $(SC)^2QA$, even though all models generate questions from summaries. We observe that D-S-NewsQA tends to ask trivial questions such as the name of a person. D-S-NQ also fails to identify the focus of a summary. For example, in the summary “*Michael Jordan has two brothers and*

	length bucket 0		length bucket 1		length bucket 2	
	R-L/BLEU	AT-5 Accuracy	R-L/BLEU	AT-5 Accuracy	R-L/BLEU	AT-5 Accuracy
D-D	37.274/9.666	0.697 ± 0.047	37.605/10.357	0.736 ± 0.045	37.643/10.688	0.782 ± 0.042
D-S	41.710/14.499	0.768 ± 0.043	41.156/13.423	0.782 ± 0.042	40.489/13.174	0.817 ± 0.040
D-S-DRIL	42.764/14.867	0.814 ± 0.040	41.445/13.668	0.806 ± 0.040	40.678/13.722	0.809 ± 0.040
D-S-RL	42.596/14.756	0.787 ± 0.042	40.335/13.100	0.779 ± 0.042	40.152/12.906	0.815 ± 0.040

Table 4: Evaluation of Question Quality. **Bold**, and **bold** represents the best results on ROUGE-L(R-L)/BLEU and AT-5 accuracy, respectively. We report a 95% binomial proportion confidence interval on human evaluation. D-S-DRIL generates significantly better questions in answer length bucket 0 and 1.

	length bucket 0	length bucket 1	length bucket 2
D-S	0.566 ± 0.036	0.670 ± 0.034	0.693 ± 0.034
D-D	0.521 ± 0.037	0.614 ± 0.035	0.681 ± 0.035
D-SD	0.398 ± 0.072	0.529 ± 0.075	0.607 ± 0.073
QD-D	0.401 ± 0.071	0.482 ± 0.071	0.563 ± 0.072
D-S-DRIL	0.576 ± 0.036	0.693 ± 0.033	0.724 ± 0.032
D-S-RL	0.566 ± 0.040	0.663 ± 0.038	0.709 ± 0.037
CTRLSum	0.112 ± 0.046	0.432 ± 0.073	0.512 ± 0.076
QAGen 2S	0.379 ± 0.071	0.514 ± 0.072	0.589 ± 0.072
QA Transfer	0.438 ± 0.140	0.447 ± 0.142	0.468 ± 0.143
D-S-NewsQA	0.184 ± 0.108	0.190 ± 0.119	0.130 ± 0.097
D-S-NQ	0.118 ± 0.108	0.171 ± 0.125	0.226 ± 0.147

Table 5: Joint accuracy on AT-1, 2 & 5. **Bold** represents our best model and underline represents best baseline. D-S-DRIL generates significantly better QA pairs than the best performing baseline in all three answer length buckets according to the joint AT-1, 2 & 5 accuracy.

two sisters. He grew up playing basketball and baseball against his older brother.”, D-S-NQ generates “Who is Michael Jordan’s brother playing against?”. However, the summary focus is *Michael Jordan* rather than *his brother*. We discuss such cases further in the qualitative analysis section.

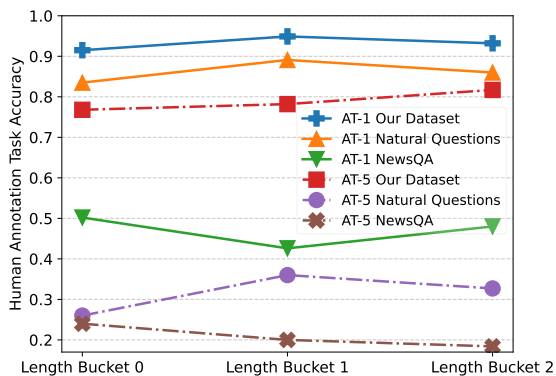


Figure 4: QG Human evaluation on different datasets. Our $(SC)^2QA$ dataset performs better than NewsQA and Natural Questions on both AT-1 and AT-5 human evaluation in all three answer length buckets.

5.7 Overall QA Pair Quality

We report the joint accuracy of {AT-1, AT-2, AT-5}, defined by the proportion of QA pairs that are

answered TRUE for all three ATs and treat it as a metric for the overall QA pair quality, reporting results in Table 5 with the following observations. **D-S-DRIL performs significantly better than the best performing baselines.** The best performing baselines are QA Transfer in length bucket 0 and QAGen 2S in length bucket 1 and 2. We observe that D-D, D-S, D-S-DRIL and D-S-RL all surpass them by a large margin. Particularly, D-S-DRIL outperforms them by 31.51%, 34.82% and 22.92% in length bucket 0, 1 and 2, respectively. **DRIL consistently outperforms RL and MLE.** We can see from Table 5 that D-S-DRIL outperforms D-S and D-S-RL by 3.22% and 2.80%, respectively (averaged over 3 length buckets). The results are consistent on human annotations (AT-2 in Table 3, AT-5 in Table 4, AT-6 in Figure 3, and joint accuracy in Table 5), and automated metrics (QACS in Table 3 and ROUGE-L/BLEU scores in Table 4). This further shows the advantage of DRIL over MLE and RL, indicating that DRIL can efficiently reinforce AG to generate better QA pairs.

5.8 Qualitative Analysis

We also conduct qualitative analyses on generated QA pairs. Please refer to Appendix D for details.

6 Conclusion

This paper proposes a model for generating QA pairs with self-contained and summary-centric questions and length-constrained article-summarizing answers. The target application is suggested questions for conversational news recommendation system. We collect a new dataset, $(SC)^2QA$, which contains news articles with questions as titles paired with summaries of varying length. We further propose differential reward imitation learning (DRIL) to efficiently mitigate exposure bias encountered with MLE. Empirically, it is shown that DRIL outperforms multiple alternative baseline neural architectures on automated and human evaluations.

7 Broader Impact

Regarding societal considerations, we consider three aspects. (1) Generating QA pairs that correspond to headlines and article summaries to power a news chatbot can provide users with a rapid glance of recent events. However, exposing users exclusively to article summaries may result in less informed users. Naturally, this can be mitigated by also developing experiences that lead to more in-depth examination of articles, but should be carefully considered. (2) Our $(SC)^2QA$ dataset collection begins with articles (and potentially news providers) that use questions as article titles. Such articles may have stylistic elements that align with certain forms of journalism (e.g., tabloids) or audience manipulation (e.g., alarmism). Accordingly, the corresponding models may learn to generate similarly biased QA pairs which is certainly undesirable. Future work in this direction may include data cleaning to remove biased QA pairs and/or design de-biased models. (3) Factuality is also a potential issue. A news article itself may be fake news. Meanwhile, the AG model may generate a summary that is factually inconsistent with the corresponding news article. Future work may incorporate recent work in optimizing the factual correctness and considering multiple perspectives of the QA pairs.

References

- Chris Alberti, Daniel Andor, Emily Pitler, Jacob Devlin, and Michael Collins. 2019. [Synthetic QA corpora generation with roundtrip consistency](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 6168–6173, Florence, Italy. Association for Computational Linguistics.
- Payal Bajaj, Daniel Campos, Nick Craswell, Li Deng, Jianfeng Gao, Xiaodong Liu, Rangan Majumder, Andrew McNamara, Bhaskar Mitra, Tri Nguyen, et al. 2016. [Ms marco: A human generated machine reading comprehension dataset](#). *arXiv preprint arXiv:1611.09268*.
- Massimo Caccia, Lucas Caccia, William Fedus, Hugo Larochelle, Joelle Pineau, and Laurent Charlin. 2019. [Language gans falling short](#). In *International Conference on Learning Representations*.
- Xinya Du and Claire Cardie. 2017. [Identifying where to focus in reading comprehension for neural question generation](#). In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 2067–2073, Copenhagen, Denmark. Association for Computational Linguistics.
- Xinya Du and Claire Cardie. 2018. [Harvesting paragraph-level question-answer pairs from Wikipedia](#). In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1907–1917, Melbourne, Australia. Association for Computational Linguistics.
- Xinya Du, Junru Shao, and Claire Cardie. 2017. [Learning to ask: Neural question generation for reading comprehension](#). In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1342–1352, Vancouver, Canada. Association for Computational Linguistics.
- Junxian He, Wojciech Kryściński, Bryan McCann, Nazneen Rajani, and Caiming Xiong. 2020. [Ctrl-sum: Towards generic controllable text summarization](#). *arXiv preprint arXiv:2012.04281*.
- Michael Heilman and Noah A. Smith. 2010. [Good question! statistical ranking for question generation](#). In *Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics*, pages 609–617, Los Angeles, California. Association for Computational Linguistics.
- Karl Moritz Hermann, Tomas Kocisky, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. 2015. [Teaching machines to read and comprehend](#). In *Advances in Neural Information Processing Systems*, volume 28. Curran Associates, Inc.
- Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. 2019. [The curious case of neural text de-generation](#). In *International Conference on Learning Representations*.
- Tom Hosking and Sebastian Riedel. 2019. [Evaluating rewards for question generation models](#). In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 2278–2283, Minneapolis, Minnesota. Association for Computational Linguistics.
- Ehsan Hosseini-Asl, Bryan McCann, Chien-Sheng Wu, Semih Yavuz, and Richard Socher. 2020. [A simple language model for task-oriented dialogue](#). In *Advances in Neural Information Processing Systems*, volume 33, pages 20179–20191. Curran Associates, Inc.
- Kalpesh Krishna and Mohit Iyyer. 2019. [Generating question-answer hierarchies](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 2321–2334, Florence, Italy. Association for Computational Linguistics.
- Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion Jones,

- Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. [Natural questions: A benchmark for question answering research](#). *Transactions of the Association for Computational Linguistics*, 7:452–466.
- Philippe Laban, John Canny, and Marti A. Hearst. 2020. [What’s the latest? a question-driven news chatbot](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, pages 380–387, Online. Association for Computational Linguistics.
- Alex M Lamb, Anirudh Goyal ALIAS PARTH GOYAL, Ying Zhang, Saizheng Zhang, Aaron C Courville, and Yoshua Bengio. 2016. [Professor forcing: A new algorithm for training recurrent networks](#). In *Advances in Neural Information Processing Systems*, volume 29. Curran Associates, Inc.
- Nguyen-Thinh Le, Tomoko Kojiri, and Niels Pinkwart. 2014. [Automatic question generation for educational applications—the state of art](#). In *Advanced computational methods for knowledge engineering*, pages 325–338. Springer.
- Dong Bok Lee, Seanie Lee, Woo Tae Jeong, Donghwan Kim, and Sung Ju Hwang. 2020. [Generating diverse and consistent QA pairs from contexts with information-maximizing hierarchical conditional VAEs](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 208–224, Online. Association for Computational Linguistics.
- 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.
- Bang Liu, Haojie Wei, Di Niu, Haolan Chen, and Yancheng He. 2020. [Asking questions the human way: Scalable question-answer generation from text corpus](#). In *Proceedings of The Web Conference 2020*, pages 2032–2043.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. [Roberta: A robustly optimized bert pretraining approach](#). *arXiv preprint arXiv:1907.11692*.
- Elnaz Nouri, Robert Sim, Adam Fourney, and Ryen W. White. 2020. [Proactive suggestion generation: Data and methods for stepwise task assistance](#). page 1585–1588.
- Peng Qi, Yuhao Zhang, and Christopher D. Manning. 2020a. [Stay hungry, stay focused: Generating informative and specific questions in information-seeking conversations](#). In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 25–40, Online. Association for Computational Linguistics.
- Weizhen Qi, Yu Yan, Yeyun Gong, Dayiheng Liu, Nan Duan, Jiusheng Chen, Ruofei Zhang, and Ming Zhou. 2020b. [ProphetNet: Predicting future n-gram for sequence-to-SequencePre-training](#). In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 2401–2410, Online. Association for Computational Linguistics.
- Pranav Rajpurkar, Robin Jia, and Percy Liang. 2018. [Know what you don’t know: Unanswerable questions for SQuAD](#). In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 784–789, Melbourne, Australia. Association for Computational Linguistics.
- Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. [SQuAD: 100,000+ questions for machine comprehension of text](#). In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 2383–2392, Austin, Texas. Association for Computational Linguistics.
- Marc’Aurelio Ranzato, Sumit Chopra, Michael Auli, and Wojciech Zaremba. 2016. [Sequence level training with recurrent neural networks](#). *International Conference on Learning Representations*.
- Siddharth Reddy, Anca D Dragan, and Sergey Levine. 2020. [Sql: Imitation learning via reinforcement learning with sparse rewards](#). In *8th International Conference on Learning Representations*.
- Steven J Rennie, Etienne Marcheret, Youssef Mroueh, Jerret Ross, and Vaibhava Goel. 2017. [Self-critical sequence training for image captioning](#). In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 7008–7024.
- Siamak Shakeri, Cicero Nogueira dos Santos, Henghui Zhu, Patrick Ng, Feng Nan, Zhiguo Wang, Ramesh Nallapati, and Bing Xiang. 2020. [End-to-end synthetic data generation for domain adaptation of question answering systems](#). In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 5445–5460, Online. Association for Computational Linguistics.
- Mohit Shridhar, Jesse Thomason, Daniel Gordon, Yonatan Bisk, Winson Han, Roozbeh Mottaghi, Luke Zettlemoyer, and Dieter Fox. 2020. [Alfred: A benchmark for interpreting grounded instructions for everyday tasks](#). In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 10740–10749.
- Linfeng Song, Zhiguo Wang, Wael Hamza, Yue Zhang, and Daniel Gildea. 2018. [Leveraging context information for natural question generation](#). In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational*

- Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, pages 569–574, New Orleans, Louisiana. Association for Computational Linguistics.
- Yuxuan Song, Ning Miao, Hao Zhou, Lantao Yu, Mingxuan Wang, and Lei Li. 2020. [Improving maximum likelihood training for text generation with density ratio estimation](#). In *International Conference on Artificial Intelligence and Statistics*, pages 122–132. PMLR.
- Nisan Stiennon, Long Ouyang, Jeff Wu, Daniel M Ziegler, Ryan Lowe, Chelsea Voss, Alec Radford, Dario Amodei, and Paul Christiano. 2020. [Learning to summarize from human feedback](#). *arXiv preprint arXiv:2009.01325*.
- Sandeep Subramanian, Tong Wang, Xingdi Yuan, Saizheng Zhang, Adam Trischler, and Yoshua Bengio. 2018. [Neural models for key phrase extraction and question generation](#). In *Proceedings of the Workshop on Machine Reading for Question Answering*, pages 78–88, Melbourne, Australia. Association for Computational Linguistics.
- Xingwu Sun, Jing Liu, Yajuan Lyu, Wei He, Yanjun Ma, and Shi Wang. 2018. [Answer-focused and position-aware neural question generation](#). In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 3930–3939, Brussels, Belgium. Association for Computational Linguistics.
- Adam Trischler, Tong Wang, Xingdi Yuan, Justin Harris, Alessandro Sordani, Philip Bachman, and Kaheer Suleman. 2017. [NewsQA: A machine comprehension dataset](#). In *Proceedings of the 2nd Workshop on Representation Learning for NLP*, pages 191–200, Vancouver, Canada. Association for Computational Linguistics.
- Luu Anh Tuan, Darsh Shah, and Regina Barzilay. 2020. [Capturing greater context for question generation](#). In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 9065–9072.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. [Attention is all you need](#). In *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc.
- Siyuan Wang, Zhongyu Wei, Zhihao Fan, Yang Liu, and Xuanjing Huang. 2019. [A multi-agent communication framework for question-worthy phrase extraction and question generation](#). In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 7168–7175.
- Sean Welleck, Ilya Kulikov, Stephen Roller, Emily Dinan, Kyunghyun Cho, and Jason Weston. 2019. [Neural text generation with unlikelihood training](#). In *International Conference on Learning Representations*.
- Ronald J Williams and David Zipser. 1989. A learning algorithm for continually running fully recurrent neural networks. *Neural Computation*, 1(2):270–280.
- Xusen Yin, Jonathan May, Li Zhou, and Kevin Small. 2020. [Question generation for supporting informational query intents](#). *arXiv preprint arXiv:2010.09692*.
- Lantao Yu, Weinan Zhang, Jun Wang, and Yong Yu. 2017. [Seqgan: Sequence generative adversarial nets with policy gradient](#). In *Proceedings of the AAAI conference on artificial intelligence*, volume 31.
- Qian Yu, Lidong Bing, Qiong Zhang, Wai Lam, and Luo Si. 2020. [Review-based question generation with adaptive instance transfer and augmentation](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 280–290, Online. Association for Computational Linguistics.
- Jingqing Zhang, Yao Zhao, Mohammad Saleh, and Peter Liu. 2020. [Pegasus: Pre-training with extracted gap-sentences for abstractive summarization](#). In *International Conference on Machine Learning*, pages 11328–11339. PMLR.
- Yao Zhao, Xiaochuan Ni, Yuanyuan Ding, and Qifa Ke. 2018. [Paragraph-level neural question generation with maxout pointer and gated self-attention networks](#). In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 3901–3910, Brussels, Belgium. Association for Computational Linguistics.
- Qingyu Zhou, Nan Yang, Furu Wei, Chuanqi Tan, Hangbo Bao, and Ming Zhou. 2017. [Neural question generation from text: A preliminary study](#). In *National CCF Conference on Natural Language Processing and Chinese Computing*, pages 662–671. Springer.
- Daniel M Ziegler, Nisan Stiennon, Jeffrey Wu, Tom B Brown, Alec Radford, Dario Amodei, Paul Christiano, and Geoffrey Irving. 2019. [Fine-tuning language models from human preferences](#). *arXiv preprint arXiv:1909.08593*.

Appendix

In Appendix A, we describe our data collection procedures. In Appendix B, we describe the training details of each algorithm. In Appendix C, we describe the human evaluation setup on Amazon Mechanical Turk. In Appendix D, we provide qualitative analysis of the generated QA pairs of each model.

A $(SC)^2QA$: A Self-Contained and Summary-Centric QA Dataset

In this paper, we propose $(SC)^2QA$, a self-contained and summary-centric QA dataset. The data construction consists of two steps. First, we collect news articles for which their titles are questions, resulting a set of question-article pairs. Second, for each question in the set, we generate 3 answers that fall into 3 different length buckets. Details are as follows.

A.1 Question-Article Collection

Starting with a curated URL list of news websites, we mined all articles between September 2020 to March 2021 with the following procedure:

1. For each news article, we check if the title starts with the following words: ‘Where’, ‘What’, ‘Did’, ‘Which’, ‘When’, ‘How’, ‘Are’, ‘Is’, ‘Can’, ‘Should’, ‘Who’, ‘Will’, ‘Why’, ‘Whose’, ‘Does’, ‘Do’, ‘Would’, ‘Could’, ‘Shall’, ‘Was’, ‘Were’, ‘Has’, ‘Have’, ‘Had’. If not, filter out that article.
2. Then we check if the title ends with ‘?’ and not ‘??’. If not, filter out that article.
3. If the title matches the following rules, filter out that article: (a) the title includes the word ‘you’, ‘Stock’, etc. from an blacklist; (b) the title contain the word ‘this’ which is not followed by a word in a pre-defined allowlist; (c) the title contains stock symbols. We filter out these titles because these are likely click-bait titles. We also filter out titles that contain punctuation marks beside the question mark at the end, as we want the ground-truth questions to be non-complex sentences.
4. Remove all questions in the articles, as we don’t want the model to learn to copy questions from articles.

5. If the number of tokens in an article is less than 100, or the number of tokens in the title is less than 3, filter out that article.

In total, we collected 39,461 question-article pairs.

A.2 {Question, Article, Summary, Length Constraint} 4-Tuples Collection

Given the collected question-article pairs, we want to augment them with answers of the questions. We observe that, since the questions are titles of articles, the answers are likely the summaries of articles. From our preliminary study, about 70% of the questions can be answered by the summaries of the corresponding articles. As a result, we propose to augment the question-article pairs with summaries as pseudo ground truth answers. Unfortunately, not all questions can be answered by the generated summaries, this is because (1) even the ground truth summary may not be the correct answer to the question, (2) summaries predicted by the SoTA models are not necessarily good. Therefore, we need a way to identify if a give summary can answer the corresponding question. This is achieved by training a question-answer classifier.

A.2.1 Question Answer Classifier

The MS MARCO (Bajaj et al., 2016) dataset contains 4,082,910 labeled question-snippet pairs. A label is either 1 which means that the snippet contains the answer to the question, or 0 which means the snippet does not contain the answer. We fine-tune a classifier based on RoBERTa-large (Liu et al., 2019) on the MS MARCO dataset. To evaluate how good the trained QA classifier is, we generated around 5000 question-summary pairs, and asked MTurk workers to label whether the summaries answers the corresponding questions. Then we use the trained QA classifier to predict the label.

AUC	0.919
Best F1	0.960 (P: 0.934, R: 0.989)
F1 at Precision=0.98	0.903 (P: 0.980, R: 0.837)
F1 at Precision=0.97	0.937 (P: 0.970, R: 0.906)

Table 6: Performance of our QA pair classifier on 5, 000 human annotated QA pairs

The performance of our QA pair classifier is shown in Table 6. We can see that the F1 score of the model is 0.96 and when the precision is 0.98, the recall is 0.903. This shows that the classifier

performs sufficiently well for our purposes. Later, we will use this classifier to filter out bad QA pairs. We pick the threshold at which the precision is 0.98.

A.2.2 The Length of Answers

For each question, we want to generate three answers, each contain 1, 2 and 3 sentences. Answers with varying length can accommodate different situations such as different screen sizes of voice assistants. Table 7 shows the average number of tokens and characters of the first K sentences in the ground truth summaries of the CNN/DailyMail dataset. In

First K sentence	1	2	3	4	5	6	7
Average #BPE tokens	28	50	72	94	120	140	159
Average #chars	128	232	336	437	558	655	738

Table 7: Average number of BPE tokens and characters in the first K sentences of ground truth summaries of the CNN/DailyMail dataset.

our work, we define 3 length buckets for answers with different ranges of number of BPE tokens:

- Length bucket 0: (0, 30]
- Length bucket 1: (30, 50]
- Length bucket 2: (50, 72]

Our goal is to be able to specify the length bucket when generate QA pairs, so that we can control the level of brevity for different circumstances (e.g., different screen size of a voice assistant device).

A.2.3 Summary (Answer) Generation

The high-level idea is to generate summaries using state-of-the-art summarization models under different length constraints and then use the QA pair classifier to filter out unmatched question-summary pairs. The summary generation procedure is shown in Figure 5 and Figure 6. In total, we used four summarization models: PEGASUS (Zhang et al., 2020), BART (Lewis et al., 2020), CTRLSum (He et al., 2020), and ProphetNet (Qi et al., 2020b). All models are fine-tuned on CNNDailyMail dataset. However, we found out ProphetNet Model fine-tuned on CNN/DailyMail is uncased² so later we removed this model.

For each article, and for each length bucket, we ask each model to generate one summary and we score each question-summary pairs with our QA

²<https://huggingface.co/microsoft/prophetnet-large-uncased-cnndm>

pair classifier (Note that when generating summaries using CTRLSum, we actually use questions as prompts so that CTRLSum can generate question-conditioned summaries). To ensure that the generated summaries are in the specified length bucket, we enforce summary length via control of the end-of-the-sentence (EOS) token generation. We remove any unfinished sentences at the end, and then reassign a length bucket.

Finally, for each article and each length bucket, we only keep one summary which has the highest score. We also filter out question-summary pairs which have scores below a threshold (which was chosen so that the QA classifier achieves a precision of 0.98 as mentioned earlier in this section). In Table 8, we show the number of summaries generated by each model and accepted by our selection strategy. In the future, one could easily introduce more SoTA summarization models in the dataset generation process. Finally, we generate a dataset containing 53,746 entries. Each entry contains the following components: question, article, summary, length bucket, QA pair classifier score, model source. Length bucket is an enumerated type consisting of ‘LB0’, ‘LB1’ and ‘LB2’. Model source is also an enumerated type consisting of ‘PEGASUS’, ‘BART’ and ‘CTRLSum’. Table 9 shows the number of BPE tokens and the number of characters of the summaries in each length bucket. Each cell’s format is #BPE/#char.

Figure 7 compares the distributions of the first word of a question in $(SC)^2QA$, NewsQA, Natural Questions, and SQuAD (Rajpurkar et al., 2018) dataset. As we can see, $(SC)^2QA$ is more diverse in terms of the first words in questions.

A.3 Examples of the Data

Tables 10 - 13 show 4 examples in our dataset.

B Training Details

We use Pytorch and the Transformers package³ to implement our algorithms and baselines. The AG models of all the algorithms are initialized by a pre-trained DistilBART model that is fine-tuned on the CNN/DailyMail dataset,⁴ and the QG models of all the algorithms are initialized by a pre-trained DistilBART model that is fine-tuned on the XSum dataset.⁵ For these two pre-trained models, the

³<https://huggingface.co/transformers/>

⁴<https://huggingface.co/sshleifer/distilbart-cnn-12-6>

⁵<https://huggingface.co/sshleifer/distilbart-xsum-12-6>

	min length	max length	mean length	median length	10% percentile length	90% percentile length
length bucket 0	10/32	32/217	24.49/105.60	25/104	18/70	31/143
length bucket 1	33/88	52/339	43.56/197.29	44/197	36/153	51/242
length bucket 2	53/167	74/454	63.98/295.18	64/293	56/224	72/349

Table 9: Number of BPE tokens and number of characters of the summaries in each length bucket. Each cell’s format is #BPE/#char.

Article (truncated): In his first formal White House press conference on Thursday night, President Joe Biden spoke to reporters to outline his plans for immigration, the COVID-19 vaccination effort and foreign policy. He also briefly commented on his own plans for the future, confirming that he does intend to stand for re-election in 2024 and launching some sly digs at his predecessor and the Republican Party. American presidents are limited to two terms in office so almost all choose to stand for a second time. However as the oldest person to be sworn in, there were some doubts as to whether the 78-year-old Biden plans to stand again in 2024. He was directly asked about this at the press conference and answered: “My plan is to run for re-election, that’s my expectation,” and added that he would fully expect Vice President Kamala Harris to be his running mate again next time around. However he did say that he could not be certain about his plans for the future so soon after taking office, leaving open the possibility that he may decide against a second term. “Look, I don’t know where you guys come from, man,” he told reporters. “I’m a great respecter of fate. I’ve never been able to plan four and a half, three and a half years ahead for certain.” Biden takes aim at Trump and the GOP Biden has made very few public appearances since taking office in comparison to former President Trump...

Question: What has Biden said about running for re-election in 2024?

Summary in length bucket 0: President Joe Biden made his first formal White House press conference on Thursday night. He confirmed that he plans to stand for re-election in 2024.

Summary in length bucket 1: President Joe Biden made his first formal White House press conference on Thursday night. He confirmed that he plans to stand for re-election in 2024 but left open the possibility that he may decide against a second term.

Summary in length bucket 2: President Joe Biden held his first White House press conference on Thursday night. He was asked directly if he plans to run for re-election in 2024. Biden confirmed that he does intend to do so. However he did say that he could not be certain about his plans for the future so soon after taking office.

Table 10: Question-Article-Summary-Length Bucket example 1/5.

number of encoder layers is 12, the number of decoder layers is 6, the dimension of hidden states is 1,024, and the number of attention head is 16.

All the experiments are conducted on AWS EC2 p3dn.24xlarge GPU instances and run with 8 GPUs in parallel. We use the `Seq2SeqTrainer` from the Transformers package to control the training process. Hyper-parameters are selected based on the ROUGE-L score on validation set described previously (the last 5,000 entries of the data we generated). All the models are optimized with Adam with linear learning rate scheduling, and the number of warm up steps is 500. All the batch sizes are set to 8. The number of beams during inference is set to 4.

D-S. The QG model’s learning rate is 2×10^{-5} and the number of iterations is 5. The AG model’s learning rate is 2×10^{-5} and the number of iterations is 10.

D-D. The QG model’s learning rate is 3×10^{-5} and the number of iterations is 10. The AG model is the same as D-S’s AG model.

D-SD. The QG model’s learning rate is 3×10^{-5}

and the number of iterations is 5. The AG model is the same as D-S’s AG model.

QD-D. The QG model’s learning rate is 3×10^{-5} and the number of iterations is 10. The AG model’s learning rate is 2×10^{-5} and the number of iterations is 10.

D-S-DRIL. The QG model is the same as D-S’s QG model. The AG model’s learning rate is 3×10^{-5} and the number of iterations is 10. Moreover, as we described in the paper, for the AG model we optimize the sum of DRIL loss and cross entropy loss, and we set λ (the weight of the DRIL loss) to 0.3.

D-S-RL. The QG model is the same as D-S’s QG model. The reward model for AG is a copy of the QG model and is fixed during training. The reward model calculates the negative log-likelihood of a generated question given a generated summary. We use self-critic (Rennie et al., 2017) to train D-S-RL. The learning rate is 2×10^{-5} and the number of iterations is 10. Similar to D-S-DRIL, we optimize the sum of RL loss and cross entropy loss, and λ (the weight of the RL loss) is set to 0.1.

Article (truncated): Public health officials say it’s important to vaccinate as many people as quickly as possible to reduce the risk posed by new coronavirus variants. One strategy to stretch existing supplies albeit with huge logistical challenges would be to give just one dose of the vaccine to people who have recovered from COVID-19. About half a dozen small studies, all consistent with one another but as yet unpublished, suggest this strategy could work. Dr. Mohammad Sajadi, at the University of Maryland medical school’s Institute of Human Virology studied health care workers who were just getting their first of two vaccine shots. His research team homed in on those who had previously been diagnosed with COVID-19. “We saw a much faster response and a much higher response,” he says, based on the protective antibodies his team measured in the blood. The infection served the same priming role as an initial dose of the Moderna or Pfizer vaccine would have, so the first shot they got was in effect a booster. It amplified and solidified immunity to COVID-19. The study was published Monday in JAMA, the journal of the American Medical Association. The Johnson & Johnson vaccine authorized Saturday by the Food and Drug Administration only requires a single dose. So, he says while vaccine is scarce, it makes sense to offer just one shot to people who have already had the disease. “You can free up automatically millions of doses,” he says, increasing vaccine supply by 4 percent or 5 percent. “We think it makes sense at this time to promote such a policy.” Federal health officials are intrigued. Dr. Anthony Fauci, who serves as COVID-19 adviser to the White House, has said it’s an idea worth further study. He is dead set against another strategy, which is stretching out the time between first and second doses. But health officials are not ready to say yes...

Question: Could a single-dose of COVID-19 vaccine after illness stretch the supply?

Summary in length bucket 0: One strategy to stretch existing supplies would be to give just one dose of the vaccine to people who have recovered from COVID-19.

Summary in length bucket 1: One strategy to stretch existing supplies would be to give just one dose of the vaccine to people who have recovered from COVID-19. About half a dozen small studies suggest this strategy could work.

Summary in length bucket 2: One strategy to stretch existing supplies would be to give just one dose of the vaccine to people who have recovered from COVID-19. About half a dozen small studies suggest this strategy could work. Federal health officials are intrigued, but are not ready to say yes.

Table 11: Question-Article-Summary-Length Bucket example 2/5.

QAGen 2S. The learning rate of both the QG and AG model is 2×10^{-5} and the number of iterations is 10. See Table 15 for training and inference pipelines.

CTRLSum. The QG model is the same as QD-D’s QG model. The AG model is the officially pre-trained CTRLSum model.⁶ When generating question-conditioned summaries (answers) using the pre-trained CTRLSum model, we use the questions as prompts. See Table 15 for training and inference pipelines.

QA Transfer. The QG model is the same as QD-D’s QG model. The AG model is trained on the NewsQA dataset. Since the provided answers in NewsQA dataset are short spans of text, we treat the sentences that contain the answer spans as ground truth answers. The input of the encoder is a concatenation of a question and an article, separated by $\langle /s \rangle$, and the label of the decoder is the ground truth answer. The learning rate is 2×10^{-5} and the number of iterations is 10. See Table 15 for training and inference pipelines.

D-S-NewsQA. The QG model is trained on the NewsQA dataset. The input of the encoder is an article, and the label of the decoder is a question.

The learning rate is 2×10^{-5} and the number of iterations is 10. The AG model is the same as D-S’s AG model. During inference, questions are generated from summaries. See Table 15 for training and inference pipelines.

D-S-NQ. The QG model is trained on the Natural Questions dataset. The input of the encoder is a long answer, and the label of the decoder is a question. The learning rate is 2×10^{-5} and the number of iterations is 10. The AG model is the same as D-S’s AG model. During inference, questions are generated from summaries. See Table 15 for training and inference pipelines.

C Human Evaluation Setup

We used Amazon Mechanical Turk to conduct human evaluations. In total we completed two rounds of annotation. In round 1, we evaluated a QA pair generated by a model. The task layout for round 1 is shown in Figure 8. Each human intelligence task (HIT) has 5 tasks. First, a QA pair is shown. Task 1 (**AT-1**) asks if the question is self-contained; Task 2 (**AT-2**) asks if the answer answers the question; Task 3 (**AT-3**) asks if the answer is both succinct and sufficient; Task 4 (**AT-4**) asks the annotator to select a span of the answer that is succinct and suf-

⁶<https://github.com/salesforce/ctrl-sum>

Article (truncated): Find out in which countries and after what cases vaccination is stopped, what scientists and officials say about the relationship between AstraZeneca and thrombosis, and how the pharmaceutical company itself responded. More than a dozen countries, mostly in the European Union, have suspended the use of the AstraZeneca Covid-19 vaccine due to concerns that some patients have developed blood clots. The World Health Organization (WHO) urged countries to continue using the vaccine, but still decided to convene a meeting due to the massive halt in AstraZeneca vaccination. In total, about 17 million people have received AstraZeneca vaccinations (at least one dose) in the European Union and the UK. Among them, 40 people had blood clots after vaccination. Whether the AstraZeneca vaccine is related to thrombosis is not clear, since its use is not long enough. Vaccine advocates argue that the drug can be used, and the proportion of patients with thrombosis is consistent with the usual statistics, and the vaccine has nothing to do with it. At the same time, many governments have decided to suspend (rather than ban entirely) the vaccination of AstraZeneca pending an investigation by the EMA regulator and estimates by WHO experts. Which countries have suspended vaccination Denmark became the first country to stop using the AstraZeneca Covid-19 vaccine for two weeks after reports of blood clots in some people and even one death on 11 March. A 60-year-old woman who was vaccinated with AstraZeneca developed a blood clot and died. She was vaccinated from the same batch used in Austria. During these two weeks of suspension of vaccinations, the EMA is to investigate. Norway, Iceland, Luxembourg, Romania, and Congo followed Denmark's example. Norwegian authorities said Saturday that four people under 50 who received the AstraZeneca vaccine had unusually low platelet counts in their blood, which could lead to severe bleeding. Bulgaria on March 12 suspended the use of the drug after the death of a 57-year-old woman a few hours after vaccination...

Question: Why major European nations suspend use of AstraZeneca vaccine?

Summary in length bucket 0: -

Summary in length bucket 1: More than a dozen countries, mostly in the European Union, have suspended the use of the AstraZeneca Covid-19 vaccine due to concerns that some patients have developed blood clots.

Summary in length bucket 2: More than a dozen countries, mostly in the European Union, have suspended the use of the AstraZeneca Covid-19 vaccine due to concerns that some patients have developed blood clots. The World Health Organization urged countries to continue using the vaccine, but still decided to convene a meeting due to the massive halt.

Table 12: Question-Article-Summary-Length Bucket example 3/5.

ficient (This task enforces the annotator to read the answers carefully). Following Task 4, we show the corresponding article. Then, Task 5 (**AT-5**) asks if the question captures the gist of the article.

Each HIT has 3 assignments, that is, each HIT will be annotated by 3 different annotators. We used majority vote to aggregate annotations. We designed a qualification task which contains 5 HITs with their annotations determined by the authors of this paper. We qualified annotators who had an accuracy (using annotations from the authors of this paper as ground truth labels) greater than or equal to 80%. We observed that on average it took about 2 minutes to annotate one HIT. We paid \$0.35 per HIT with a \$0.1 bonus. We blocked annotators who spent less than 1 minutes on average on a HIT. If an annotator was blocked, then all the annotations from that annotator were thrown away.

The annotation results in length bucket 0, 1, and 2 are shown in Tables 16 - 18, respectively. In total, we have 11 algorithms. During round 1, we realized that some algorithms performed significantly worse than the others, so there is no reason to collect the equal amount of HITs for every algorithm. Therefore, the number of completed hits for each

algorithm is different, as shown in the 'completed HITs' columns of Tables 16 - 18. Meanwhile, since we filtered out annotations from blocked annotators, this also led to different numbers of completed hits between different models. During round 1, we did 7 mini-round annotations in total (each between 50 to 150 HITs), and in the last 3 mini-rounds AT-5 was excluded. When AT-5 was excluded, the annotators did not need to read the article, so the annotation process was accelerated and we were able to collect more annotations for AT-1 to AT-4.

From round 1 we observed that D-S, D-D, D-S-DRIL, and D-S-RL perform the best. Therefore, we conducted annotation round 2, which compared the questions generated by these four models in one HIT. The task layout for round 2 is shown in Figure 9. We first show an article, and then show the questions generated by each model. If two or more questions generated by different models are the same, we then merge these questions into one. Therefore, we show 2 to 4 questions in one HIT. We randomly shuffle the order of the questions in each HIT, so that the question of a model can appear in any position. Task 1 in round 2 (corresponding to **AT-5**) asks if each of the question captures the

Article (truncated): Britain's royal family is among the world's most famous organizations – and a costly one as well. These days, the royal family is known for their lavish weddings, expansive tours and notable fashion as much as they are for their contributions to their nation. According to the BBC, the royals amass their fortune, in part, through the taxpayer-funded Sovereign Grant. However, the queen and the other royals get the money in return for surrendering the profits from their slew of properties – called the Crown Estate – to the government, according to Business Insider. Each year, the queen will receive an amount from the grant equivalent to 25% of the Crown Estate's profits, the outlet reports. The grant will pay for the palace upkeep, the family's travel, royal employee payroll and more, but according to the Telegraph, the Grant doesn't cover costs for security and royal ceremonies, per BI. Money for such assets and events comes from a portfolio of land that the family has owned for generations called the Duchy of Lancaster. The Duchy is made up of residential, commercial, and agricultural properties, Insider reports, and contains \$715 million worth of net assets. In 2019, the portfolio earned \$27 million, The Wall Street Journal reports. The money is put toward 'expenses incurred by other members of the royal family,' as the royal family's website puts it...

Question: Where does the royal family get their money?

Summary in length bucket 0: Britain's royal family amass their fortune, in part, through the taxpayer-funded Sovereign Grant.

Summary in length bucket 1: Britain's royal family amass their fortune, in part, through the taxpayer-funded Sovereign Grant. The queen and the other royals get the money in return for surrendering the profits from their slew of properties.

Summary in length bucket 2: Britain's royal family amass their fortune, in part, through the taxpayer-funded Sovereign Grant. The queen and other royals get the money in return for surrendering the profits from their slew of properties to the government. Money for such assets and events comes from a portfolio of land that the family has owned for generations called the Duchy of Lancaster.

Table 13: Question-Article-Summary-Length Bucket example 4/5.

gist of the article; Task 2 in round 2 (corresponding to **AT-6**) asks which question best capture the gist of the article; Task 3 in round 2 (corresponding to **AT-7**) asks which question is preferred if suggested by a voice assistant in a news skill. The annotation results in length bucket 0, 1, and 2 are shown in Table 19 - 21. While round 1 and round 2 both have AT-5, we observe that the three algorithm (D-S, D-D, D-S-DRIL) have lower AT-5 accuracy in round 2 than in round 1. We believe that this is because the round 2 task layout better encourages a more careful reading of the articles by the annotators. However, pairwise preference of AT-5 accuracy is consistent between round 1 and round 2.

Article (truncated): NASA’s Perseverance rover and its sibling, the Ingenuity helicopter, landed on Mars on February 18, bristling with antennas and cameras. Perseverance, the third robotic visitor from Earth to arrive at the red planet, will spend the next Martian year the equivalent of two Earth years collecting rocks, scrutinizing and photographing them. But the \$2.7-billion robotic explorer has one thing in common with something closer home. The rover has the same processor as the original iMac G3 or the ‘Bondi Blue’ from 1998. The original iMac used a PowerPC G3 or the PowerPC 750 processor which mirrors the one used in Perseverance, said a report in The Verge. The processor, a single-core, 233MHz processor with just 6 million transistors, was also used in NASA’s Curiosity rover, a car-sized rover exploring the red planet which was launched in 2011. The report says that the conditions on Mars could actually be counterproductive for a more advanced processor. Compared to Earth’s atmosphere, the atmosphere on the red planet does not offer as much insulation from harmful radiation and charged particles. This could mess up a modern, more complex processor. The Perseverance rover has two computing modules, one being a backup in case of a mishap. Perseverance’s processor, a RAD750 chip, is slightly more advanced than the one used in the iMac G3 and is built keeping Mars’s radiations in mind. It operates at up to 200 megahertz speed, 10 times the speed in Mars rovers Spirit and Opportunity’s computers. Coming to memory power, Perseverance boasts 2 gigabytes of flash memory, 256 megabytes of dynamic random access memory (RAM), and 256 kilobytes of electrically erasable programmable read-only memory. The computer also contains special memory to tolerate the extreme radiation environment that exists in space and on the Martian surface, says NASA...

Question: What do NASA’s Mars rover and a 1998 iMac have in common?

Summary in length bucket 0: The rover has the same processor as the original iMac G3 or the ‘Bondi Blue’ from 1998.

Summary in length bucket 1: Perseverance rover has same processor as the original iMac G3 or the ‘Bondi Blue’ from 1998. The processor was also used in NASA’s Curiosity rover, a car-sized rover, launched in 2011.

Summary in length bucket 2: The rover has the same processor as the original iMac G3 or the ‘Bondi Blue’ from 1998. NASA’s Perseverance rover has two computing modules, one being a backup in case of a mishap. The computer also contains special memory to tolerate the extreme radiation environment that exists in space and on the Martian surface, says NASA.

Table 14: Question-Article-Summary-Length Bucket example 5/5.

	Training				Inference			
	Answer Generation		Question Generation		Answer Generation		Question Generation	
	Encoder	Decoder	Encoder	Decoder	Encoder	Decoder	Encoder	Decoder
D-S	L + D	S	S	Q	L + D	S'	S'	Q'
D-D	L + D	S	D	Q	L + D	S'	S'	Q'
D-SD	L + D	S	S + D	Q	L + D	S'	S' + D	Q'
QD-D	Q + L + D	S	D	Q	Q' + L + D	S'	D	Q'
D-S-DRIL	L + D	S/S'	S	Q	L + D	S'	S'	Q'
D-S-RL	L + D	S/S'	S	Q	L + D	S'	S'	Q'
QAGen 2S	D + Q	S	D	Q	D + Q'	S'	D	Q'
CTRLSum	Pretrained CTRLSum model		D	Q	Q' + D	S'	D	Q'
QA Transfer	Q + D in NewsQA	A in NewsQA	D	Q	Q' + D	A'	D	Q'
D-S-NewsQA	L + D	S	D in NewsQA	Q in NewsQA	L + D	S'	S'	Q'
D-S-NQ	L + D	S	LA in Natural Questions	Q in Natural Questions	L + D	S'	S'	Q'

Table 15: A summary of our models and baselines. Q, S, D, L denote the questions, summaries, documents, and length bucket tags in our dataset, respectively. Q' and S' denote the generated questions and answers, respectively. D in NewsQA, Q in NewsQA, and A in NewsQA denote the documents, questions, and answers in the NewsQA dataset. A' denotes the answers generated by the QA model in QA Transfer. Q + D in NewsQA denotes the concatenation of questions and documents in the NewsQA dataset with </s> as the separator. LA in Natural Questions and Q in Natural Questions denote the long answers and questions in the Natural Questions dataset, respectively.

Instruction

In this assignment, you will measure the quality of a question-answer pair generated for a specific article. First, you are given the question and the answer, and you need to answer four questions regarding whether the question is understandable and whether the answer sufficiently and succinctly answers the question. Then, you are given the article, and you need to identify if the question refers to the gist of the article. (Detailed Instructions are shown below)

Please read the question and the answer below to finish task 1-4 and then read the article to finish task 5.

Question:

Why Did Energy Monster's Shares Jump 18% on Their Nasdaq Debut?

Answer:

Shares of Alibaba-backed Energy Monster jumped nearly 18% in their Nasdaq debut on Thursday. The company's initial public offering (IPO) was priced below the indicated range. Energy Monster was embroiled in an ownership dispute just as the U.S. IPO was underway.

Task 1: Is the question self-contained (without referring to the answer or the article, are you able to understand the question)?

Task Instruction:

Some questions such as "Why leave town?", "What country was the foreign agent from?" and "What did scientists say?" are not self-contained, and to understand what the questions ask exactly, we have to refer to the articles. Some other questions such as "What are educator's legal rights if they go back to work during the coronavirus pandemic?" and "How Good Was NCAA Tournament Analyst Wally Szczerbiak as a Player?" are self-contained questions and can be understood without referring to the article.

True False

Task 2: Does the passage in the Answer text box answers the question?

Task Instruction:

Imagine that you ask this question to a voice assistant (e.g., Amazon Alexa, Google Assistant, Apple Siri) and the passage in the Answer text box is returned. Do you think the Answer satisfactorily answers the corresponding Question?

True False

Task 3: To confidently trust the answer, select one of the following

Task Instruction:

Again, imagine that you ask this question to a voice assistant (e.g., Amazon Alexa, Google Assistant, Apple Siri) and the passage in the Answer text box is returned.

- (a) I would need to see more of the article to trust the Answer (i.e., it is not sufficient).
- (b) There is more content in the passage in the Answer text box than necessary (i.e., it is not succinct).
- (c) The Answer is both succinct and sufficient.

Task 4: If the answer to Task 3 is (b), please copy the substring in the Answer text box that you think is succinct and sufficient.

task4 answer

Please continue by reading the (truncated) article below.

Article:

HONG KONG (Reuters) - Shares of Alibaba-backed Energy Monster, China's largest provider of mobile charging devices, jumped nearly 18% in their Nasdaq debut on Thursday after the company's initial public offering (IPO) was priced below the indicated range. The firm's shares opened at \$10 per American depositary share (ADS), higher than the IPO price of \$8.50 per ADS. The company, which filed its prospectus under the listing vehicle's name of Smart Share Global, sold 17.65 million shares at \$8.50 each to raise about \$150 million. Energy Monster's weaker pricing comes just days after Chinese question and answer website Zhihu's shares fell as much as 10.5% in their first session on Friday. The stock is off nearly 15% since its debut on the New York Stock Exchange. Reuters revealed on Monday that Energy Monster was embroiled in an ownership dispute just as the U.S. IPO was underway. Energy Monster had flagged its shares would be sold between \$10.50 and \$12.50 each. However, volatile equities markets prompted the company to downgrade the price investors would pay for the shares. There are also ongoing concerns over the future of Chinese companies listed in the United States following the Securities and Exchange Commission's decision to press ahead with laws that would see international companies that do not meet U.S. auditing standards delisted. Energy Monster had planned to sell 17.5 million shares which would have raised \$183.75 million to \$218.7 million at the indicative range. Two Shanghai-based venture capitalists are pressing a case through both U.S. and Chinese courts against Energy Monster Chief Executive Officer Guangyuan Cai, claiming he reneged on a deal to give them a joint 3% stake in the business. In its March 12 IPO application, Energy Monster said Cai was advised by his China litigation counsel that the plaintiffs' claims are baseless and frivolous, and the CEO is contesting the claims vigorously.

Task 5: Does the question in the Question text box (copied here for convenience) capture the gist of the Article?

Question:

Why Did Energy Monster's Shares Jump 18% on Their Nasdaq Debut?

Task Instruction:

Please only rely on the truncated text of the Article but not other information such as images or audio (if they exist) to finish this task.

Yes No

Submit

Figure 8: Human annotation UI for round 1.

Instruction

In this assignment, you are given an article and 1~4 questions, and you need to identify if each question capture the gist of the article. (Detailed Instructions are shown below)

Please read the (truncated) article below.

Article:

(Reuters) - Microsoft Corp said on Thursday it was investigating an issue with its Microsoft 365 services and features, including workplace messaging app Teams and Azure, after many users were unable to access them.
Outage tracking website Downtidetector showed over 8,000 incidents of people reporting issues with Teams, an app heavily relied on by people for remote work during the COVID-19 pandemic.
"We're investigating an issue in which users may be unable to access Microsoft 365 services and features. We'll provide additional information as soon as possible," said Microsoft in a tweet here.
Downtidetector only tracks outages by collating status reports from a series of sources, including user-submitted errors on its platform. The outage might be affecting a larger number of users.

Task 1: Does the question in the Question text box capture the gist of the Article?

Task Instruction: Please only rely on the truncated text of the Article but not other information such as images or audio (if they exist) to finish this task.

Question 1: Is Microsoft Teams outage affecting a larger number of users?

Yes No

Question 2: What's going on with Microsoft Teams and Azure?

Yes No

Question 3: Why isn't Teams working?

Yes No

Question 4: What's going on with Microsoft 365?

Yes No

Task 2: Which Question shown above best capture the gist of the Article?

Question 1 Question 2 Question 3 Question 4

Task 3: If these 4 questions are suggested by a news skill of a voice assistant (e.g. Amazon Alexa, Apple Siri, etc.) on the screen, which question would you be most likely to ask?

Question 1 Question 2 Question 3 Question 4

Submit

Figure 9: Human annotation UI for round 2. Here Task 1 corresponds to AT-5 (same as Task 5 in round 1), Task 2 corresponds to AT-6 and Task 3 corresponds to AT-7.

	Completed HITS	AT-1 True	AT-1 False	AT-1 Accuracy	AT-2 True	AT-2 False	AT-2 Accuracy	AT-3 (a)	AT-3 (b)	AT-3 (c)	AT-3 (c) Accuracy	AT-3 (b)+(c) Accuracy	AT-5 True	AT-5 False	AT-5 Accuracy
D-S	340	311	29	0.915	212	128	0.624	157	6	167	0.506	0.524	144	34	0.809
D-D	334	303	31	0.907	191	143	0.572	163	1	164	0.500	0.503	139	36	0.794
D-SD	176	168	8	0.954	71	105	0.403	113	1	58	0.337	0.34302	157	19	0.892
QD-D	182	168	14	0.923	75	107	0.412	119	0	58	0.328	0.328	166	16	0.912
D-S-DRIL	377	360	17	0.955	238	139	0.631	160	19	174	0.493	0.547	144	28	0.837
D-S-RL	213	203	10	0.953	133	80	0.624	99	6	97	0.480	0.510	-	-	-
CTRLSum	178	160	18	0.899	20	158	0.112	160	2	14	0.080	0.091	153	25	0.860
QAGen 2S	177	158	19	0.893	73	104	0.412	114	6	50	0.294	0.329	150	27	0.847
QA Transfer	188	177	11	0.941	98	90	0.521	105	10	63	0.354	0.410	166	22	0.883
D-S-NewsQA	241	121	120	0.502	148	93	0.614	107	22	98	0.432	0.529	12	38	0.240
D-S-NQ	103	86	17	0.835	49	54	0.476	58	3	38	0.384	0.414	13	37	0.260

Table 16: Round 1 length bucket 0 human annotation. AT-5 annotation for D-S-RL will be in Round 2.

	Completed HITS	AT-1 True	AT-1 False	AT-1 Accuracy	AT-2 True	AT-2 False	AT-2 Accuracy	AT-3 (a)	AT-3 (b)	AT-3 (c)	AT-3 (c) Accuracy	AT-3 (b)+(c) Accuracy	AT-5 True	AT-5 False	AT-5 Accuracy
D-S	353	335	18	0.949	264	89	0.748	105	87	130	0.404	0.674	161	18	0.899
D-D	366	341	25	0.932	250	116	0.683	133	63	128	0.395	0.590	159	27	0.855
D-SD	172	162	10	0.942	94	78	0.547	81	38	39	0.247	0.487	152	20	0.884
QD-D	193	171	22	0.886	98	95	0.508	102	36	36	0.207	0.414	165	28	0.855
D-S-DRIL	380	360	20	0.947	293	87	0.771	104	102	121	0.370	0.682	151	17	0.899
D-S-RL	206	193	13	0.937	151	55	0.733	64	43	73	0.406	0.644	-	-	-
CTRLSum	176	160	16	0.909	77	99	0.438	104	37	23	0.140	0.366	155	21	0.881
QAGen 2S	183	168	15	0.918	98	85	0.536	89	37	36	0.222	0.451	166	17	0.907
QA Transfer	189	174	15	0.921	111	78	0.587	86	35	50	0.292	0.497	162	27	0.857
D-S-NewsQA	235	100	135	0.426	148	87	0.630	93	105	23	0.104	0.579	10	40	0.200
D-S-NQ	110	98	12	0.891	56	54	0.509	55	21	20	0.208	0.427	18	32	0.360

Table 17: Round 1 length bucket 1 human annotation. AT-5 annotation for D-S-RL will be in Round 2.

	Completed HITS	AT-1 True	AT-1 False	AT-1 Accuracy	AT-2 True	AT-2 False	AT-2 Accuracy	AT-3 (a)	AT-3 (b)	AT-3 (c)	AT-3 (c) Accuracy	AT-3 (b)+(c) Accuracy	AT-5 True	AT-5 False	AT-5 Accuracy
D-S	337	314	23	0.932	254	83	0.754	95	125	80	0.267	0.683	153	23	0.869
D-D	330	307	23	0.930	258	72	0.782	86	123	78	0.272	0.700	139	25	0.848
D-SD	173	165	8	0.954	113	60	0.653	64	65	25	0.162	0.384	151	22	0.873
QD-D	183	163	20	0.891	105	78	0.574	82	55	27	0.165	0.500	160	23	0.874
D-S-DRIL	393	381	12	0.969	320	73	0.814	77	181	89	0.256	0.778	164	19	0.896
D-S-RL	208	202	6	0.971	169	39	0.813	41	90	63	0.288	0.777	-	-	-
CTRLSum	168	152	16	0.905	89	79	0.530	83	58	13	0.084	0.461	147	21	0.875
QAGen 2S	180	162	18	0.900	110	70	0.611	74	61	21	0.135	0.526	156	24	0.867
QA Transfer	195	182	13	0.933	134	61	0.687	70	72	40	0.220	0.615	165	30	0.846
D-S-NewsQA	246	118	128	0.480	183	63	0.744	60	159	13	0.056	0.741	9	40	0.184
D-S-NQ	100	86	14	0.860	67	33	0.670	36	42	14	0.152	0.609	16	33	0.327

Table 18: Round 1 length bucket 2 human annotation. AT-5 annotation for D-S-RL will be in Round 2.

	AT-5 True	AT-5 False	AT-5 Accuracy	AT-6 Votes	AT-6 Proportion	AT-7 Votes	AT-7 Proportion
D-D	255	111	0.697	371	0.215	386	0.224
D-S	281	85	0.768	433	0.251	424	0.246
D-S-DRIL	298	68	0.814	472	0.273	457	0.265
D-S-RL	288	78	0.787	450	0.261	456	0.265

Table 19: Round 2 length bucket 0 human annotation.

	AT-5 True	AT-5 False	AT-5 Accuracy	AT-6 Votes	AT-6 Proportion	AT-7 Votes	AT-7 Proportion
D-D	273	98	0.736	336	0.201	349	0.210
D-S	290	81	0.782	417	0.250	420	0.253
D-S-DRIL	299	72	0.806	466	0.280	466	0.281
D-S-RL	289	82	0.779	448	0.269	426	0.256

Table 20: Round 2 length bucket 1 human annotation.

	AT-5 True	AT-5 False	AT-5 Accuracy	AT-6 Votes	AT-6 Proportion	AT-7 Votes	AT-7 Proportion
D-D	287	80	0.782	383	0.243	383	0.246
D-S	300	67	0.817	413	0.263	409	0.262
D-S-DRIL	297	70	0.809	401	0.255	397	0.254
D-S-RL	299	68	0.815	376	0.239	371	0.238

Table 21: Round 2 length bucket 2 human annotation.

D Qualitative Analysis

D.1 Example 1

The QA pairs generated by each algorithm for the article in Figure 10 are as follows. D-S-DRIL generates the best QA pair in each length bucket. The questions capture the gist of the article and the answers are accurate in all length buckets. On the other hand, D-S, D-S-RL and QAGen 2S' answer in length bucket 1 do not answer the corresponding *why* question. QA Transfer and CTRLSum generates unfinished sentences (not well-formed) as it cannot control the brevity of the answers. D-S-NewsQA generates a trivial question in length bucket 0. D-S-NQ's generated questions in length bucket 0 is way off the gist of the article.

D-S-DRIL Length Bucket 0 [Question] Are college athletes' voices getting louder and clearer? [Answer] The voices of thousands of college athletes are being heard louder and clearer than they have in years.

D-S-DRIL Length Bucket 1 [Question] Why are college athletes calling for change? [Answer] The voices of thousands of college athletes are being heard louder and clearer than they have in years. From seemingly small issues of inequality in NCAA Tournament weight rooms to life-and-death issues of police brutality and endemic racism, athletes are increasingly calling for change.

D-S-DRIL Length Bucket 2 [Question] Why are college athletes calling for change? [Answer] The voices of thousands of college athletes are being heard louder and clearer than they have in years. From seemingly small issues of inequality in NCAA Tournament weight rooms to life-and-death issues of police brutality and endemic racism, athletes are increasingly calling for change. They joined the #MeToo movement against sexual harassment and abuse.

D-S Length Bucket 0 [Question] Are college athletes' voices getting louder and clearer? [Answer] The voices of thousands of college athletes are being heard louder and clearer than they have in years.

D-S Length Bucket 1 [Question] Why are college athletes so politically active? [Answer] The voices of thousands of college athletes are being heard louder and clearer than they have in years. It is the most politically and socially active generation in a half-century, since the turbulent years of the late 1960s and early 70s.

D-S Length Bucket 2 [Question] Why are college

athletes so politically active? [Answer] The voices of thousands of college athletes are being heard louder and clearer than they have in years. It is the most politically and socially active generation in a half-century, since the turbulent years of the late 1960s and early 70s. From seemingly small issues of inequality in NCAA Tournament weight rooms to life-and-death issues of police brutality and endemic racism, athletes

D-S-RL Length Bucket 0 [Question] Are college athletes ready for the future? [Answer] College athletes are increasingly calling for change, intent on molding what the future should look like for everyone.

D-S-RL Length Bucket 1 [Question] Why are college athletes so politically active? [Answer] The voices of thousands of college athletes are being heard louder and clearer than they have in years. It is the most politically and socially active generation in a half-century, since the turbulent years of the late 1960s and early 70s.

D-S-RL Length Bucket 2 [Question] Why are college athletes so politically active? [Answer] The voices of thousands of college athletes are being heard louder and clearer than they have in years. It is the most politically and socially active generation in a half-century, since the turbulent years of the late 1960s and early 70s. From seemingly small issues of inequality in NCAA Tournament weight rooms to life-and-death issues of police brutality and endemic racism, athletes are calling

D-D Length Bucket 0 [Question] What's the latest on college sports news? [Answer] The voices of thousands of college athletes are being heard louder and clearer than they have in years.

D-D Length Bucket 1 [Question] Why are college athletes helping to shape politics? [Answer] The voices of thousands of college athletes are being heard louder and clearer than they have in years. It is the most politically and socially active generation in a half-century, since the turbulent years of the late 1960s and early 70s.

D-D Length Bucket 2 [Question] Why are college athletes involved in politics? [Answer] The voices of thousands of college athletes are being heard louder and clearer than they have in years. It is the most politically and socially active generation in a half-century, since the turbulent years of the late 1960s and early 70s. From seemingly small issues of inequality in NCAA Tournament weight

Article (truncated): *The voices of thousands of college athletes are being heard louder and clearer than they have in years and it is the most politically and socially active generation in a half-century, since the turbulent years of the late 1960s and early 70s. From seemingly small issues of inequality in NCAA Tournament weight rooms to life-and-death issues of police brutality and endemic racism, athletes are increasingly calling for change, intent on molding what the future should look like for everyone. Some of the things that have occurred this past year, its encouraged a lot of us to speak out on things, social justice, and how we feel, said Loyola Chicagos Lucas Williamson, who is working on a film project involving the schools 1963 national title team that broke down racial barriers. The things weve seen, going back to last summer, its been emotional for me, Williamson said, and its given me the confidence to go out there and speak on some things I feel confident about, and some things that I feel are just causes. While the movement gained momentum last summer, when George Floyd and Breonna Taylor died at the hands of police and protests hit Americas streets, the reality is that social unrest has been bubbling out of sight for years. It took Colin Kaepernick taking a knee to bring it to the surface. The NFL quarterbacks polarizing stance against social and racial injustice in 2016 was embraced by other pro athletes, and that in turn encouraged college athletes to take a stand. They joined the #MeToo movement against sexual harassment and abuse, and began threatening to strike to walk off the field of play unless their demands were heard and met. Protests by more than two dozen Missouri football players against on-campus racism led to he ouster of the president of the university system and the chancellor of its flagship campus. And despite pushback from legislators that threatened to strip funding for scholarships, they found support from athletes on campuses across the country...*

Figure 10: Article in test set example 1.

rooms to life-and-death issues of police brutality and endemic racism, athletes

D-SD Length Bucket 0 [Question] Why are college athletes speaking out on social issues? [Answer] The voices of thousands of college athletes are being heard louder and clearer than they have in years.

D-SD Length Bucket 1 [Question] Why are college athletes speaking out on social issues? [Answer] The voices of thousands of college athletes are being heard louder and clearer than they have in years. It is the most politically and socially active generation in a half-century, since the turbulent years of the late 1960s and early 70s.

D-SD Length Bucket 2 [Question] Why are college athletes speaking out on social issues? [Answer] The voices of thousands of college athletes are being heard louder and clearer than they have in years. It is the most politically and socially active generation in a half-century, since the turbulent years of the late 1960s and early 70s. From seemingly small issues of inequality in NCAA Tournament weight rooms to life-and-death issues of police brutality and endemic racism, athletes

QD-D Length Bucket 0 [Question] Why are athletes speaking out on social issues? [Answer] The voices of thousands of college athletes are

being heard louder and clearer than they have in years.

QD-D Length Bucket 1 [Question] Why are athletes speaking out on social issues? [Answer] The voices of thousands of college athletes are being heard louder and clearer than they have in years. From seemingly small issues of inequality in NCAA Tournament weight rooms to life-and-death issues of police brutality and endemic racism, athletes are calling for change.

QD-D Length Bucket 0 [Question] Why are athletes speaking out on social issues? [Answer] The voices of thousands of college athletes are being heard louder and clearer than they have in years. From seemingly small issues of inequality in NCAA Tournament weight rooms to life-and-death issues of police brutality and endemic racism, athletes are calling for change. The movement gained momentum last summer, when George Floyd and Breonna Taylor died at the hands of

QAGen 2S Length Bucket 0 [Question] Why Are College Athletes Calling for Change? [Answer] The voices of thousands of college athletes are being heard louder and clearer than they have in years.

QAGen 2S Length Bucket 1 [Question] Why Are College Athletes Calling for Change? [Answer] The voices of thousands of college athletes are

being heard louder and clearer than they have in years. It is the most politically and socially active generation in a half-century, since the turbulent years of the late 1960s and early 70s.

QAGen 2S Length Bucket 2 [Question] Why Are College Athletes Calling for Change? [Answer]

The voices of thousands of college athletes are being heard louder and clearer than they have in years. From seemingly small issues of inequality in NCAA Tournament weight rooms to life-and-death issues of police brutality and endemic racism, athletes are calling for change, intent on molding what the future should look like for everyone.

CTRLSum Length Bucket 0 [Question] Why are athletes speaking out on social issues? [Answer]

The voices of college athletes are being heard louder and clearer than they have in years.

CTRLSum Length Bucket 1 [Question] Why are athletes speaking out on social issues? [Answer]

The voices of college athletes are being heard louder and clearer than they have in years. A new generation of athletes is more progressive on such issues as race, gender and

CTRLSum Length Bucket 2 [Question] Why are athletes speaking out on social issues? [Answer]

The voices of college athletes are being heard louder and clearer than they have in years. A new generation of athletes is more progressive on such issues as race, gender and injustice than previous cohorts at the same age, according to a professor of sociology at Skidmore College

QA Transfer Length Bucket 0 [Question] Why are athletes speaking out on social issues? [Answer]

According to Andrew M. Linder, a professor of sociology at Skidmore College, there are two main reasons for this athlete-fueled focus on change: First,

QA Transfer Length Bucket 1 [Question] Why are athletes speaking out on social issues? [Answer]

According to Andrew M. Linder, a professor of sociology at Skidmore College, there are two main reasons for this athlete-fueled focus on change: First, younger people in general are more progressive on such issues as race, gender and injustice than previous cohorts at

QA Transfer Length Bucket 2 [Question] Why are athletes speaking out on social issues? [Answer]

According to Andrew M. Linder, a professor of sociology at Skidmore College, there are two main reasons for this athlete-fueled focus on change: First, younger people in general are

more progressive on such issues as race, gender and injustice than previous cohorts at the same age, and second, they have been emboldened by their athletic heroes.

D-S-NewsQA Length Bucket 0 [Question] What is the name of the college athletes? [Answer]

The voices of thousands of college athletes are being heard louder and clearer than they have in years.

D-S-NewsQA Length Bucket 1 [Question] What is the most politically active generation in a half century? [Answer]

The voices of thousands of college athletes are being heard louder and clearer than they have in years. It is the most politically and socially active generation in a half-century, since the turbulent years of the late 1960s and early 70s.

D-S-NewsQA Length Bucket 2 [Question] What is the most politically active generation in a half century? [Answer]

The voices of thousands of college athletes are being heard louder and clearer than they have in years. It is the most politically and socially active generation in a half-century, since the turbulent years of the late 1960s and early 70s. From seemingly small issues of inequality in NCAA Tournament weight rooms to life-and-death issues of police brutality and endemic racism, athletes

D-S-NQ Length Bucket 0 [Question] Who is speaking on the college football debate? [Answer]

The voices of thousands of college athletes are being heard louder and clearer than they have in years.

D-S-NQ Length Bucket 1 [Question] What is the political movement in college football? [Answer]

The voices of thousands of college athletes are being heard louder and clearer than they have in years. It is the most politically and socially active generation in a half-century, since the turbulent years of the late 1960s and early 70s.

D-S-NQ Length Bucket 2 [Question] Why are college athletes involved in the civil rights movement? [Answer]

The voices of thousands of college athletes are being heard louder and clearer than they have in years. It is the most politically and socially active generation in a half-century, since the turbulent years of the late 1960s and early 70s. From seemingly small issues of inequality in NCAA Tournament weight rooms to life-and-death issues of police brutality and endemic racism, athletes

D.2 Example 2

The QA pairs generated by each algorithm for the article in Figure 11 are as follows. The article is regarding the impact of Biden's infrastructure plan on Amtrak. We can see that the questions generated by D-S-DRIL in length bucket 1 capture the gist of the article, but the questions generated by D-S and D-S-RL in length bucket 1 do not capture the gist of the article. This shows the advantage of the DRIL which generates better summaries.

D-S-DRIL Length Bucket 0 [Question] Is Biden's infrastructure plan the right thing to do for America? **[Answer]** President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said.

D-S-DRIL Length Bucket 1 [Question] What does President Biden's infrastructure plan mean for Amtrak? **[Answer]** President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. The federal funding would help Amtrak along-needed upgrades to tracks, tunnels and bridges in the Northeast.

D-S-DRIL Length Bucket 2 [Question] What does President Biden's infrastructure plan mean for Amtrak? **[Answer]** President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. The federal funding would help Amtrak along-needed upgrades to tracks, tunnels and bridges in the Northeast, the nation's busiest rail corridor. Amtrak has a \$45.2 billion backlog of projects that it says are needed to bring its assets to a state of good repair.

D-S Length Bucket 0 [Question] Is Biden's infrastructure plan the right thing to do for America? **[Answer]** President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said.

D-S Length Bucket 1 [Question] What is President Biden's infrastructure plan? **[Answer]** President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. Intercity rail would receive up to a 400 percent boost in funding, according to some estimates.

D-S Length Bucket 2 [Question] What does President Biden's infrastructure plan mean for Amtrak? **[Answer]** President Biden's infrastructure

plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. Intercity rail would receive up to a 400 percent boost in funding, according to some estimates. The federal funding would help Amtrak along-needed upgrades to tracks, tunnels and bridges in the Northeast.

D-S-RL Length Bucket 0 [Question] What is the infrastructure bill? **[Answer]** The \$2 trillion infrastructure package proposes about \$600 billion of transportation investments, including \$115 billion to rebuild bridges and highways.

D-S-RL Length Bucket 1 [Question] What is President Biden's infrastructure plan? **[Answer]** President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. The \$2 trillion infrastructure package proposes about \$600 billion of transportation investments.

D-S-RL Length Bucket 2 [Question] What is President Biden's \$2 trillion infrastructure plan? **[Answer]** President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. The \$2 trillion infrastructure package proposes about \$600 billion of transportation investments, including \$115 billion to rebuild bridges and highways, \$85 billion for transit, \$25 billion to repair and upgrade airports.

D-D Length Bucket 0 [Question] Is Biden's infrastructure plan the answer to America's infrastructure crisis? **[Answer]** President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said.

D-D Length Bucket 1 [Question] What would President Biden's infrastructure plan mean for Amtrak? **[Answer]** President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. Intercity rail would receive up to a 400 percent boost in funding, according to some estimates.

D-D Length Bucket 2 [Question] What would President Biden's infrastructure plan mean for Amtrak? **[Answer]** President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. Intercity rail would receive up to a 400 percent boost in funding, according to some estimates. The federal funding would help Amtrak along-needed upgrades to tracks, tunnels and bridges in the

Article (truncated): *President Biden’s infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said, while echoing Biden’s push to rebuild and improve the busy Washington-Boston rail corridor. Under the White House plan, intercity rail would receive up to a 400 percent boost in funding, according to some estimates, a transformational investment that could bring major rail expansions and millions more riders. The passenger railroad receives about \$2 billion of federal subsidies annually to cover operations in its national and Northeast networks, as well as other grants and funding for state-sponsored service. The \$2 trillion infrastructure package proposes about \$600 billion of transportation investments, including \$115 billion to rebuild bridges and highways, \$85 billion for transit, \$25 billion to repair and upgrade airports, and \$20 billion for safety initiatives to reduce traffic fatalities. The money, to be spent over eight years, also would address mobility, climate and transportation equity concerns. Amtrak on Wednesday unveiled a plan to provide new intercity rail service to 160 communities and expand service in corridors with heightened demand for rail transportation. The passenger railroad also unveiled a map that highlights 30 possible new routes. The federal funding would help Amtrak along-needed upgrades to tracks, tunnels and bridges in the Northeast, the nation’s busiest rail corridor. Amtrak has a \$45.2 billion backlog of projects that it says are needed to bring its assets to a state of good repair in the region. Among those projects is the replacement of the Civil War-era Baltimore and Potomac Tunnel in Baltimore, expected to cost \$4.5 billion. Other improvements could be achieved by replacing the North River Tunnels, a more than century-old structure that carries about 200,000 daily passenger trips beneath the Hudson River between New Jersey and New York. An \$11.3 billion plan would double the capacity of existing tunnels, which were damaged by Hurricane Sandy in 2012. Amtrak and other rail services could travel more quickly with the elimination of choke points, additional tracks and other improvements. The passenger railroad has identified about \$18 billion of available or likely to be available funding for projects in the Northeast in the next five years, including the North River Tunnels project...*

Figure 11: Article in test set example 2.

Northeast.

D-SD Length Bucket 0 [Question] How much federal help is President Biden’s infrastructure plan for Amtrak? [Answer] President Biden’s infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said.

D-SD Length Bucket 1 [Question] How much would President Biden’s infrastructure package benefit Amtrak? [Answer] President Biden’s infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. Intercity rail would receive up to a 400 percent boost in funding, according to some estimates.

D-SD Length Bucket 2 [Question] How much would President Biden’s infrastructure package benefit Amtrak? [Answer] President Biden’s infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. Intercity rail would receive up to a 400 percent boost in funding, according to some estimates. The federal funding would help Amtrak along-needed upgrades to tracks, tunnels and

bridges in the Northeast.

QD-D Length Bucket 0 [Question] How much would Amtrak get from Biden’s infrastructure package? [Answer] President Biden’s infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn says.

QD-D Length Bucket 1 [Question] How much would Amtrak get from Biden’s infrastructure package? [Answer] President Biden’s infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. Under the White House plan, intercity rail would receive up to a 400 percent boost in funding.

QD-D Length Bucket 2 [Question] How much would Amtrak get from Biden’s infrastructure package? [Answer] President Biden’s infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. Intercity rail would receive up to a 400 percent boost in funding, according to some estimates. The federal funding would help Amtrak along-needed upgrades to tracks, tunnels and bridges in the Northeast.

QAGen 2S Length Bucket 0 [Question] What

does President Biden's infrastructure plan mean for Amtrak? [Answer] President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said.

QAGen 2S Length Bucket 1 [Question] What does President Biden's infrastructure plan mean for Amtrak? [Answer] President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. The passenger railroad receives about \$2 billion of federal subsidies annually to cover operations in its national and Northeast networks.

QAGen 2S Length Bucket 2 [Question] What does President Biden's infrastructure plan mean for Amtrak? [Answer] President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. The passenger railroad receives about \$2 billion of federal subsidies annually to cover operations in its national and Northeast networks. The federal funding would help Amtrak along-needed upgrades to tracks, tunnels and bridges in the Northeast.

CTRLSum Length Bucket 0 [Question] How much would Amtrak get from Biden's infrastructure package? [Answer] President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn says.

CTRLSum Length Bucket 1 [Question] How much would Amtrak get from Biden's infrastructure package? [Answer] President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. The \$2 trillion infrastructure package proposes about \$600

CTRLSum Length Bucket 2 [Question] How much would Amtrak get from Biden's infrastructure package? [Answer] The \$2 trillion infrastructure package proposes about \$600 billion of transportation investments, including \$115 billion to rebuild bridges and highways, \$85 billion for transit, \$25 billion to repair and upgrade airports, and \$20 billion for safety initiatives. Amtrak has a \$45

QA Transfer Length Bucket 0 [Question] How much would Amtrak get from Biden's infrastructure package? [Answer] The passenger railroad receives about \$2 billion of federal subsidies annually to cover operations in its national and Northeast networks, as well as other grants and

funding for state-sponsored service.

QA Transfer Length Bucket 1 [Question] How much would Amtrak get from Biden's infrastructure package? [Answer] The passenger railroad receives about \$2 billion of federal subsidies annually to cover operations in its national and Northeast networks, as well as other grants and funding for state-sponsored service.

QA Transfer Length Bucket 2 [Question] How much would Amtrak get from Biden's infrastructure package? [Answer] Under the White House plan, intercity rail would receive up to a 400 percent boost in funding, according to some estimates, a transformational investment that could bring major rail expansions and millions more riders. The passenger railroad receives about \$2 billion of federal subsidies annually to cover operations in its national and Northeast networks, as well as other grants and funding for state-sponsored

D-S-NewsQA Length Bucket 0 [Question] What is the name of the Amtrak chief executive? [Answer] President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said.

D-S-NewsQA Length Bucket 1 [Question] What is the name of the plan? [Answer] President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. Intercity rail would receive up to a 400 percent boost in funding, according to some estimates.

D-S-NewsQA Length Bucket 2 [Question] What would help Amtrak along? [Answer] President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. Intercity rail would receive up to a 400 percent boost in funding, according to some estimates. The federal funding would help Amtrak along-needed upgrades to tracks, tunnels and bridges in the Northeast.

D-S-NQ Length Bucket 0 [Question] Who is President's plan for the US infrastructure? [Answer] President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said.

D-S-NQ Length Bucket 1 [Question] Who is the President who wants to build America? [Answer] President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. Intercity rail

would receive up to a 400 percent boost in funding, according to some estimates.

D-S-NQ Length Bucket 2 [Question] How much money would be spent on rail in the White House? [Answer] President Biden's infrastructure plan is what this nation has been waiting for, Amtrak chief executive William J. Flynn said. Intercity rail would receive up to a 400 percent boost in funding, according to some estimates. The federal funding would help Amtrak along-needed upgrades to tracks, tunnels and bridges in the Northeast.

D.3 Example 3

The QA pairs generated by each algorithm for the article in Figure 12 are as follows. The article is about how Argentina dealt with the second wave of the COVID-19 infections. We can see that the QA pairs generated by D-S-DRIL in all length buckets are good—the questions are self-contained and summary-centric while the answers are correct. Questions generated by QAGen 2S in length bucket 0 and 1 do not have accurate answers. Questions generated by QD-D, D-S-News and D-S-NQ do not capture the gist of the article.

D-S-DRIL Length Bucket 0 [Question] How is Argentina coping with a second wave of coronavirus? [Answer] Argentina facing a second wave of infections, the South American nation has adjusted its strategy to prioritize protecting its fragile economy.

D-S-DRIL Length Bucket 1 [Question] How will Argentina respond to COVID-19 pandemic? [Answer] Argentina's President Alberto Fernandez was clear when COVID-19 first hit the country early last year. Now facing a second wave of infections, the South American nation has adjusted its strategy to prioritize protecting its fragile economy.

D-S-DRIL Length Bucket 2 [Question] How is Argentina coping with the second wave of coronavirus? [Answer] Argentina has adjusted its strategy to prioritize protecting its fragile economy. It is hoping greater experience dealing with the coronavirus, a nascent vaccine program, and short, regional lockdowns can help keep the virus in check. The second wave comes at a delicate time for the center-left Peronist government.

D-S Length Bucket 0 [Question] Can regional lockdowns keep COVID out of Argentina? [Answer] Argentina facing second wave of

coronavirus infections. Short, regional lockdowns can help keep virus in check.

D-S Length Bucket 1 [Question] How is Argentina coping with a second wave of coronavirus? [Answer] Argentina facing a second wave of infections, the South American nation has adjusted its strategy to prioritize protecting its fragile economy. It is hoping greater experience dealing with the coronavirus and short, regional lockdowns can help keep the virus in check.

D-S Length Bucket 2 [Question] Can regional lockdowns stop the second wave of coronavirus? [Answer] Argentina facing second wave of coronavirus infections. Government hopes short, regional lockdowns can help keep virus in check. Second wave comes at delicate time for the center-left Peronist government. It is heading for mid-term elections in October to defend its majority in Congress.

D-S-RL Length Bucket 0 [Question] How is Argentina coping with a second wave of coronavirus? [Answer] Argentina facing second wave of coronavirus infections. South American nation has adjusted strategy to prioritize protecting economy.

D-S-RL Length Bucket 1 [Question] How is Argentina coping with a second wave of coronavirus? [Answer] Argentina facing a second wave of infections, the South American nation has adjusted its strategy to prioritize protecting its fragile economy. It is hoping greater experience dealing with the coronavirus, a nascent vaccine program, and short, regional lockdowns can help keep the virus in check.

D-S-RL Length Bucket 2 [Question] How will the second wave of COVID-19 affect Argentina's economy? [Answer] Argentina's President Alberto Fernandez was clear when COVID-19 first hit the country early last year: saving lives at all costs trumped any economic concerns. Now facing a second wave of infections, the South American nation has adjusted its strategy to prioritize protecting its fragile economy.

D-D Length Bucket 0 [Question] How can regional lockdowns help keep COVID-19 out of Argentina? [Answer] Argentina facing second wave of coronavirus infections. Short, regional lockdowns can help keep virus in check.

D-D Length Bucket 1 [Question] Can Argentina Keep Coronavirus in Check? [Answer] Argentina facing a second wave of infections, the South American nation has adjusted its strategy to

Article (truncated): *Argentinas President Alberto Fernandez was clear when COVID-19 first hit the country early last year: saving lives at all costs trumped any economic concerns. Now facing a second wave of infections, the South American nation has adjusted its strategy to prioritize protecting its fragile economy. It is hoping greater experience dealing with the coronavirus, a nascent vaccine program, and short, regional lockdowns can help keep the virus in check. The second wave comes at a delicate time for the center-left Peronist government. It is heading for mid-term elections in October to defend its majority in Congress, its popularity bruised by a strict, lengthy lockdown last year and the hard economic hit. The grains producer is also in talks with the International Monetary Fund to revamp some \$45 billion in loans it cannot pay back and needs to fire up economic growth to bring in much needed hard currency. And creditors are looking for signs of recovery after a sovereign debt restructuring last year. The Fernandez administration wants to avoid imposing a blanket lockdown, instead using data on caseloads to establish short-term localized restrictions, reinforce sanitary measures, and maintain controls over borders, a government source said. The government also wants to accelerate a vaccine roll-out delayed by shortage of supply, aiming to have all medical workers and those at high risk vaccinated before the fast-approaching southern winter. Argentinas economy contracted around 10% last year, the third straight year of recession, and Economy Minister Martin Guzman has said it could not withstand another total shutdown. Poverty levels rose to 42% in the second half of last year. The country has recorded around 2.4 million coronavirus cases and over 56,000 deaths, and a second wave is building with recent daily cases at 80% of the peak and rising, a Reuters tally of official data shows. On Tuesday, infections reached a daily record. The second wave and incidence of cases could be even worse when the variants take hold, said Toms Orduna, an infectious disease specialist who advises the government, referring to the P1 Brazilian variant and others racing through the region....*

Figure 12: Article in test set example 3.

prioritize protecting its fragile economy. It is hoping greater experience dealing with the coronavirus and short, regional lockdowns can help keep the virus in check.

D-D Length Bucket 2 [Question] How will regional lockdowns help Argentina keep COVID-19 in check? [Answer] Argentina facing second wave of coronavirus infections. Government hopes short, regional lockdowns can help keep virus in check. Second wave comes at delicate time for the center-left Peronist government. It is heading for mid-term elections in October to defend its majority in Congress.

D-SD Length Bucket 0 [Question] How will Argentina deal with COVID-19? [Answer] Argentina facing second wave of coronavirus infections. Short, regional lockdowns can help keep virus in check.

D-SD Length Bucket 1 [Question] How will Argentina deal with COVID-19? [Answer] Argentina facing a second wave of infections, the South American nation has adjusted its strategy to prioritize protecting its fragile economy. It is hoping greater experience dealing with the coronavirus and short, regional lockdowns can

help keep the virus in check.

D-SD Length Bucket 2 [Question] How will Argentina deal with COVID-19? [Answer] Argentina facing second wave of coronavirus infections. Government hopes short, regional lockdowns can help keep virus in check. Second wave comes at delicate time for the center-left Peronist government. It is heading for mid-term elections in October to defend its majority in Congress.

QD-D Length Bucket 0 [Question] How will Argentina deal with COVID-19? [Answer] Argentina facing second wave of coronavirus infections. Short, regional lockdowns can help keep virus in check.

QD-D Length Bucket 1 [Question] How will Argentina deal with COVID-19? [Answer] Argentina facing second wave of coronavirus infections. South American nation has adjusted strategy to prioritize protecting its fragile economy. It is hoping greater experience dealing with the virus, a nascent vaccine program, and short, regional lockdowns can help keep the virus in check

QD-D Length Bucket 2 [Question] How will

Argentina deal with COVID-19? [Answer] Argentina facing second wave of coronavirus infections. South American nation has adjusted strategy to prioritize protecting economy. Hopes greater experience dealing with virus, a nascent vaccine program, and short, regional lockdowns can help keep virus in check. Second wave comes at delicate time for the center-left Peronist government.

QAGen 2S Length Bucket 0 [Question] How is Argentina dealing with a second wave of coronavirus? [Answer] Argentinas President Alberto Fernandez was clear when COVID-19 first hit the country early last year: saving lives at all costs trumped any economic concerns.

QAGen 2S Length Bucket 1 [Question] How is Argentina dealing with a second wave of coronavirus? [Answer] Argentinas President Alberto Fernandez was clear when COVID-19 first hit the country early last year: saving lives at all costs trumped any economic concerns. Now facing a second wave of infections

QAGen 2S Length Bucket 2 [Question] How is Argentina dealing with a second wave of coronavirus? [Answer] Argentinas President Alberto Fernandez was clear when COVID-19 first hit the country early last year: saving lives at all costs trumped any economic concerns. Now facing a second wave of infections, the South American nation has adjusted its strategy to prioritize protecting its fragile economy.

CTRLSum Length Bucket 0 [Question] How will Argentina deal with COVID-19? [Answer] Argentina faces second wave of coronavirus infections. Second wave comes

CTRLSum Length Bucket 1 [Question] How will Argentina deal with COVID-19? [Answer] Argentina faces second wave of coronavirus infections. Second wave comes at a delicate time for the center-left Peronist government. Argentina is heading for mid-

CTRLSum Length Bucket 2 [Question] How will Argentina deal with COVID-19? [Answer] Argentina faces second wave of coronavirus infections. Second wave comes at a delicate time for the center-left Peronist government. Argentina is heading for mid-term elections in October to defend its majority in Congress, its popularity bruised by a strict, lengthy lockdown

QA Transfer Length Bucket 0 [Question] How will Argentina deal with COVID-19? [Answer]

The Fernandez administration wants to avoid imposing a blanket lockdown, instead using data on caseloads to establish short-term localized restrictions, reinforce sanitary measures, and maintain controls

QA Transfer Length Bucket 1 [Question] How will Argentina deal with COVID-19? [Answer] The Fernandez administration wants to avoid imposing a blanket lockdown, instead using data on caseloads to establish short-term localized restrictions, reinforce sanitary measures, and maintain controls over borders, a government source said.

QA Transfer Length Bucket 2 [Question] How will Argentina deal with COVID-19? [Answer] The Fernandez administration wants to avoid imposing a blanket lockdown, instead using data on caseloads to establish short-term localized restrictions, reinforce sanitary measures, and maintain controls over borders, a government source said. Now facing a second wave of infections, the South American nation has adjusted its strategy to prioritize protecting its fragile economy.

D-S-NewsQA Length Bucket 0 [Question] What is the name of the virus? [Answer] Argentina facing second wave of coronavirus infections. Short, regional lockdowns can help keep virus in check.

D-S-NewsQA Length Bucket 1 [Question] What does Argentina want to do to protect its economy? [Answer] Argentina facing a second wave of infections, the South American nation has adjusted its strategy to prioritize protecting its fragile economy. It is hoping greater experience dealing with the coronavirus and short, regional lockdowns can help keep the virus in check.

D-S-NewsQA Length Bucket 2 [Question] What is the name of the virus? [Answer] Argentina facing second wave of coronavirus infections. Government hopes short, regional lockdowns can help keep virus in check. Second wave comes at delicate time for the center-left Peronist government. It is heading for mid-term elections in October to defend its majority in Congress.

D-S-NQ Length Bucket 0 [Question] What is the cause of the Ebola virus in Argentina? [Answer] Argentina facing second wave of coronavirus infections. Short, regional lockdowns can help keep virus in check.

D-S-NQ Length Bucket 1 [Question] What country was hit by Ebola in 2014? [Answer]

Argentina facing a second wave of infections, the South American nation has adjusted its strategy to prioritize protecting its fragile economy. It is hoping greater experience dealing with the coronavirus and short, regional lockdowns can help keep the virus in check.

D-S-NQ Length Bucket 2 [Question] What is the cause of the virus in Argentina? [Answer] Argentina facing second wave of coronavirus infections. Government hopes short, regional lockdowns can help keep virus in check. Second wave comes at delicate time for the center-left Peronist government. It is heading for mid-term elections in October to defend its majority in Congress.