Multiple-Choice Question Generation: Towards an Automated Assessment Framework

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Abstract

Automated question generation is an important approach to enable personalisation of English comprehension assessment. Recently, transformer-based pretrained language models have demonstrated the ability to produce appropriate questions from a context paragraph. Typically, these systems are evaluated against a reference set of manually generated questions using n-gram based metrics, or manual qualitative assessment. Here, we focus on a fully automated multiple-choice question generation (MCQG) system where both the question and possible answers must be generated from the context paragraph. Applying n-gram based approaches is challenging for this form of system as the reference set is unlikely to capture the full range of possible questions and answer options. Conversely manual assessment scales poorly and is expensive for MCQG system development. In this work, we propose a set of performance criteria that assess different aspects of the generated multiple-choice questions of interest. These qualities include: grammatical correctness, answerability, diversity and complexity. Initial systems for each of these metrics are described, and individually evaluated on standard multiple-choice reading comprehension corpora.

1 Introduction

Question generation systems have many applications such as augmenting question-answering datasets to improve machine comprehension models (Duan et al., 2017). Here, question generation is considered as a tool for education. Specifically, it is required to cater to the increased demand of people learning English (Munandar, 2015) who require high quality questions to improve their comprehension abilities. It is expensive to employ experts to generate good quality questions for comprehension passages. Therefore, it would be beneficial to develop systems that can automatically generate questions for a comprehension passage to substantially increase the resources available to students. Several bits of work has been done in literature for automatic question generation. For example, (Kriangchaivech and Wangperawong, 2019) investigates question generation as a tool to assist educators in creating quizzes and tests. They further demonstrate that a current failure mode of question generation systems, such as their BERT-based model, is that they tend to create mostly what type of questions. Other work looks at the use of a GPT-2 based model (Lopez et al., 2020) or the introduction of special highlight tokens within the passage (Chan and Fan, 2019).

Any task that requires the development of good quality systems demands an unbiased and reasonable performance metric that can be used to compare and rank various systems. It is possible to demonstrate that the susceptibility of the performance metric with respect to the number of reference samples is heavily dependent on the distribution of the true posterior distribution over all possible output sequences (see Appendix A). Greater the entropy in the true posterior distribution, the slower the growth in performance with respect to the number of reference samples. We are interested in assessing the performance of question generation systems. However, question generation is a high entropy sequence-to-sequence task as there are a large number of possible questions for a given input passage. For real question generation datasets (Chen et al., 2018; Du et al., 2017; Zhao et al., 2018), it is too expensive to provide a sufficient number of reference samples per example to account for the high entropy of the question generation task. Using a limited number of reference samples, evaluating question generation systems using generic sequence-to-sequence metrics such as BLEU (Papineni et al., 2002), ROUGE (Lin, 2004) and METEOR (Banerjee and Lavie, 2005) (see Section 4) is inappropriate as there is no reason the generated
question should match one of the reference questions provided (as there is high entropy in the true posterior distribution). In development and assessment of current state-of-the-art question generation systems, researchers attempt to bypass the challenge of a large and diverse output space in two respects: answer-aware and sentence-wise question generation (Wang et al., 2018; Bao et al., 2020; Dong et al., 2019; Varanasi et al., 2020; Li et al., 2019; Kim et al., 2019). Answer-aware question generation involves passing the answer alongside the context to generate the question. By forcing the answer beforehand, the breadth of acceptable questions is dramatically reduced and hence typical sequence generation metrics such as BLEU, METEOR and ROUGE are acceptable to compare against the small number of references. A similar purpose is achieved with sentence-wise question generation where the length of input passages is limited to consider single sentences at a time. However, the purpose of question generation systems is not to replicate the reference questions for a given input sentence from a passage. As designers of question generation systems we are interested in the quality of the questions generated. We propose the following qualities of question generation systems that we care about:

- **Grammatical fluidity**: The questions must be grammatically fluent.
- **Answerability**: The answer to the question must be present in the context.
- **Diversity**: A diverse range of questions should be possible on a given contextual passage.
- **Complexity**: Questions must be of varying complexity beyond simple answer locators.

The current approach to question generation that uses single sentences from a passage as the input seriously limits the ability to generate complex questions. In order to be able to assess question generation systems using a limited number of references, it should not be necessary to compromise the quality of questions. Therefore, we propose developing a question assessment framework where the framework should be able to give a quantitative score to each of the qualities: grammatical fluidity, answerability, diversity and complexity.

In our work, we focus on multiple-choice question generation (MCQG) for which it is necessary to be able to generate the question, the correct answer option and distractor answer options. In this set-up it becomes increasingly important to shift from n-gram based matching metrics to assessing the qualities of interest. To our knowledge, this is the first attempt to generate complete questions and answer options without explicitly extracting phrases from the context paragraph or using sentence-wise and answer-aware techniques (Ch and Saha, 2020), which necessitates sensible automated assessment approaches.

2 Related Work

Zheng et al. (2018) mention that neural text generation tasks such as machine translation (MT), summarisation and image captioning often have multiple references available for each sample because each input has multiple acceptable output sequences. Moreover, the references provided are only a tiny subset of the exponentially large space of potential references. The authors find that performance on standard evaluation datasets is improved by using multiple references at training time. They also show that performance can be further boosted by generating pseudo-references from the existing references at training time to get up to 50 references per sample; the true posterior distribution is better sub-sampled in this manner. However, the focus here is on the training process and not on handling the lack of references available in the test set.

Dreyer and Marcu (2012) suggest machine translation is a challenging task because it can be described as a one-to-n mapping, meaning there is ambiguity in the translation. The authors state that they believe that all automatic metrics (before this paper), such as BLEU or NIST, for machine translation fail in appropriateness because these metrics rely on the limited number of human references available. If there was access to all possible references for a translation, then the common automatic translation metrics would be reasonable but in reality there are very few references provided. Based on the limitations of other metrics, the paper introduces an annotation tool that efficiently creates an exponential number of correct translations for a given sentence. They then present a new evaluation metric, HYTER, that efficiently uses these large reference networks to compute the performance of the translation generated by an MT system. However, it is not clear how an equivalent annotation tool
could be used to generate a list of a large number of reference questions to assess question generation systems.

Qin and Specia (2015) propose alternative metrics to BLEU and NIST for machine translation in order to use multiple references more effectively. The main idea is that Doddington (2002) showed that bag-of-words metrics such as BLEU and NIST will not lead to the best possible results if the number of references is increased. Therefore, the alternative metrics proposed by this paper aim to make better use of the multiple references available at evaluation time. Once again, the alternative metric cannot be easily extended to the question generation task as the metrics of interest in question generation include question complexity, diversity and answerability. It is possible to have reference answerable questions but complex and diverse questions cannot be guaranteed in the labels. Therefore, the metric to be used in question generation should minimally rely on the labelled question and instead judge the quality of a generated question in its own right.

Vu and Moschitti (2021) introduce AvA as an automatic evaluation approach for question-answering (QA). They train a system that takes and predicts a set of gold standard references (for question-answering) and then return the accuracy of the system. A transformer-based model is used to encode the references and the predictions and a similarity score is essentially calculated in the encoded space. They claim their system is a lot more appropriate for QA than neural MT metrics such as BLEU. However, the challenge in automated question generation is substantially greater than question-answering because question generation as a task has a lot greater entropy in the posterior distribution and hence the few reference samples poorly capture the posterior distribution and consequently are not fair comparison points for predictions, even in the encoder space.

Dugan et al. (2022) investigate answer-agnostic (answer-unaware) question generation. They comment on the inappropriateness of n-gram based assessment as answer-unaware question generation is less restricted and hence less controlled than answer-aware question generation. Consequently, Dugan et al. (2022) assess their generated questions in terms of the qualities of relevance, interpretability and acceptability. Currently, these qualities are measured using human markers. We look to extend the assessment of our desired qualities with automated approaches.

### 3 Multiple-choice question generation

![Figure 1: Architecture for multiple-choice question generation.](image)

Here, we discuss an automated approach to generate multiple-choice questions without constraining the nature of the input context (i.e. maintain answer-unaware question generation). The MCQG task requires a system to generate a question, a correct answer option and distractor answer options when given a context paragraph. State-of-the-art systems for natural language generation predominantly rely on pre-trained language models (PLMs) (Lewis et al., 2020; Raffel et al., 2020) that are based on the transformer encoder-decoder or just the transformer decoder architecture (Radford and Narasimhan, 2018; Radford et al., 2019; Brown et al., 2020; Chowdhery et al., 2022). Figure 1 depicts the vanilla model used in this work for MCQG where the T5 (Raffel et al., 2020) PrLM is used for both the transformer encoder and decoder. The generated question and answer options are separated by special [SEP] tokens which allows the question and the answer options to be isolated from one another. The first answer option, OptionA, is treated as the correct answer option while the remaining answer options are treated as distractor answer options.

Additionally, a second baseline is considered using the GPT-3 (Brown et al., 2020) model in a zero-shot setting where it is not explicitly trained on the task of question generation. This model is based on the transformer decoder architecture. At inference time, the model takes the context as the input with the following text prepended to the input: *Multiple-choice question with 4 options.*

### 4 Assessment Framework

Typically, sequence-to-sequence models, including question generation systems, are benchmarked using the `t5-base` implementation from HuggingFace: [https://huggingface.co/t5-base](https://huggingface.co/t5-base).
on standard datasets using n-gram based performance metrics that compare the generated sequence against a reference list. However, the task of multiple-choice question generation cannot be assessed appropriately using such n-gram based approaches as the reference list is too narrow to comprehensively cover the possible questions and answer options for a context paragraph (Rajpurkar et al., 2016). Therefore, we propose an assessment framework for the assessment of multiple-choice question generation systems.

Section 3 details the method for the generation of the question and answer options as a single sequence output with each component separated by a special token. Hence, it is necessary to first ensure that four unique answer options are generated. Second, the setup assumes the first answer option generated is the correct answer option to the question. Therefore, it is necessary to ensure a good performing multiple-choice machine reading comprehension (MCMRC) system (Zeng et al., 2020) agrees the first answer option is indeed the correct answer option. Next, we describe our fundamental assessment framework based on the qualities of grammatical fluidity, answerability, diversity and complexity (introduced in Section 1). As our focus is specifically on multiple-choice question generation, we attach less importance to the criteria of diversity which is more important in other forms of question generation (Du et al., 2017) and hence we propose a more simplified approach.

### 4.1 Grammar

Grammatical fluidity assesses how well a question abides by the grammatical rules of English language. There are various automated systems available to check for grammatical mistakes in a given sentence such as ERRANT (Bryant et al., 2017). However, in the realm of pretrained transformed-based language models, grammatical fluidity is of minimal concern as the large amount of training of pretrained language models ensures these systems have an excellent grasp of the English language and consequently make very few grammatical mistakes when used for generating new sentences (including question generation). Here, we quote the grammatical error, $G$, across all the questions and answer options generated by a question generation system for reference.

### 4.2 Answerability

Answerability is essentially a binary metric that informs whether a given question is answerable based on the provided passage. If the answer to the question can be inferred from the corresponding contextual passage, the question is answerable and otherwise the question is unanswerable (Rajpurkar et al., 2018).

Unanswerability is a well-explored area in span-based machine reading comprehension (Zhang et al., 2021; Rajpurkar et al., 2018; Lan et al., 2019), while limited work has been done for multiple-choice machine reading comprehension (Raina and Gales, 2022). Raina and Gales (2022) specifically explores the situation where unanswerable examples are not present at training time and yet unanswerable questions must be identified during deployment. They suggest that ensemble-based uncertainty measures can be used for identifying unanswerable examples at test time. Therefore, in this work we consider using a set of standard ensemble multiple-choice machine reading comprehension models for measuring the unanswerability of the generated questions from our MCQG system. Specifically, we use the expected entropy, $\mathbb{E}[H]$, as our choice of uncertainty measure:

$$\mathbb{E}[H] = -\frac{1}{K} \sum_{k=1}^{K} \sum_{y} P_{M_k}(y) \log P_{M_k}(y)$$  

where $P_{M_k}$ denotes the discrete probability distribution using the $k$th machine reading comprehension model member of an ensemble of size $K$ and $y \in \{A, B, C, D\}$ (the possible answer options). We quote the unanswerability score, $A$, as a constituent of our assessment framework.

### 4.3 Diversity

There is a large amount of literature investigating different categories of question types specifically for reading comprehension (Day and Park, 2005). Here, we describe a potential diversity metric used to judge the diversity of the question types in a set of question-context pairs. For a set of questions, they can be categorised into the following question types: what, who, when, where, why, how, which, yes/no. For clarity, yes/no questions include questions that start with phrases such as is, do or does. A quantitative measure of diversity, $D$, is proposed
as the entropy over the discrete classes:

$$D = \mathcal{H}(Q) = - \sum_{q \in Q} q \log q \quad (2)$$

where $Q$ denotes the discrete probability distribution over the question types in the set of question-context pairs being considered and $Q$ is space of all question types. Note, it is fairly trivial to show that the entropy of a discrete probability distribution is a linear transformation of the KL divergence of $Q$ from a uniform distribution. Hence, the diversity metric can be interpreted as a measure of closeness to the uniform distribution over the question type classes.

In this work, the focus is on multiple-choice reading comprehension questions where the traditional categories of question types may not be the most appropriate. Hence, a simplified number of categories is considered where there are only two categories of questions. The two categories are whether a question makes sense stand-alone or not. For example, *When was King Henry born* makes sense in its own right while *What is the best title for this passage* relies on the options to be read for the question to make sense. The latter type of question can be easily identified in practice with the occurrence of the word *passage* within the question. Hence, Equation 2 is applied on the binary discrete probability distribution described with bits used as the units to give a diversity score, $D$.

### 4.4 Complexity

Complexity is a complex quality to assess. An automated metric for complexity must be able to measure the amount of reasoning that is required for a candidate to answer a question in the multiple-choice machine reading comprehension setup. The complexity measure must take the contextual passage into account too as the difficulty of a question is dictated by the choice of words in the associated passage.

Liang et al. (2019) who introduce the RACE++ dataset state that the question complexity in a comprehension exercise is directly correlated with belonging to one of the following question types where these types have been ranked from easiest to the most challenging. 1. **Word matching**: the question is an extract in the passage and the answer is straightforward. 2. **Paraphrasing**: the question paraphrases a given sentence from the passage as the answer is an extract of this sentence (SQuAD (Rajpurkar et al., 2016) style questions). 3. **Single-sentence reasoning**: the answer can be deduced from a single sentence of the passage. 4. **Multi-sentence reasoning**: the answer has to be inferred from connecting information distributed across the passage i.e. over multiple sentences. 5. **Insufficient/ambiguous**: the question has no answer or the answer is not unique.

Cheng et al. (2021) propose difficulty-controllable question generation through step-by-step rewriting. Their proposed model is able to generate questions at required difficulty levels. They motivate the need for difficulty controlled question generation to be used as a tool for curriculum-learning-based methods for QA systems as well as our motivation of designing exams of different difficulty levels for educational purposes. They discuss Gao et al. (2019) as the only other work that defines question difficulty, which in turn defines question difficulty as whether a question-answering model can correctly answer the question. However, it is clear that this definition conflates answerability and difficulty (the terminology complexity is used for difficulty in our work). Hence, the paper redefines the difficulty level of a question as: *The number of inference steps required to answer it.* This definition is based upon the number of reasoning hops required to be able to deduce the answer. In order to develop a difficulty-controlled question generation (DCQG) framework, Cheng et al. (2021) insist that it is important for the QG model to have a strong grasp over the logic and reasoning complexity of generated questions. Therefore, graph-based methods are the natural choice for such logic modelling. The approach is to convert raw text into a context (entity) graph, from which the answer is sampled as one of the entities. They then design a question generator and question rewriter that initially generates a simple question and then the question rewriter step-by-step converts it into more complex questions by feeding backwards through the reasoning chain. They train using HotpotQA (Yang et al., 2018) for which all questions require two inference steps which can be decomposed into 1-hop questions. By learning how to convert 1-hop to 2-hop questions, the question rewriter is able to extend the 2-hop questions into n-hop questions and hence generate more complex questions. The paper discusses how to generate complex (difficult) questions but it does not mention how
the question complexity can be assessed of a given question-passage pair.

In this work, we directly use the RACE++ dataset (Liang et al., 2019) to train a deep learning model to explicitly class a multiple-choice question in the complexity levels of easy, medium and hard. The RACE++ dataset is partitioned into easy, medium and hard questions (see Section 5.1) as annotated by human examiners. Therefore, a system can be trained to classify a given question as either easy, medium or hard. Typically, deep learning models output a probability distribution over the three classes such that 

\[ p_{\text{easy}} + p_{\text{medium}} + p_{\text{hard}} = 1 \]

As a part of our assessment framework for multiple-choice question generation, we report the mean \( C \) across an evaluation set.

5 Experiments

5.1 Data

Our experiments are primarily based on the multiple-choice machine reading comprehension dataset RACE++ (Liang et al., 2019) which requires a candidate to select the correct answer option from a possible choice of 4. RACE++ extends a standard benchmarking dataset, RACE (Lai et al., 2017) for MCMRC. RACE++ is comprised of English comprehension questions from middle school (RACE-M), high school (RACE-H) and college level (RACE-C). Hence, RACE-M, RACE-H and RACE-C can respectively be treated as easy, medium and hard questions. Table 1 details the number of questions in each of these subsets for the training (Trn), development (Dev) and evaluation (Evl) splits. In particular, the Trn split consists of 100,568 questions with 25.3/62.1/12.6 \% respectively for RACE-M, RACE-H and RACE-C. Similarly, Dev and Evl splits are dominated with questions from RACE-H with a total number of questions of 5,599 and 5,642 respectively.

| Dataset | Trn | Dev | Evl |
|---------|-----|-----|-----|
| RACE-M  | 25,421 | 6,409 | 25.4 |
|         | 1,436 | 368  | 1,436 |
| RACE-H  | 62,445 | 18,728 | 3,498 |
|         | 3,451 | 1,021 | 3,451 |
| RACE-C  | 12,702 | 2,437 | 708 |
|         | 712   | 136  | 712  |

Table 1: RACE++ data statistics.

5.2 Setup

This section describes the various experiments in order to be able fulfill the criteria detailed in the assessment framework of Section 4. All models have hyperparameter tuning performed on the Dev split of RACE++.

First an ensemble of 3 models is trained to perform the vanilla MCMRC task on the RACE++ dataset. The architecture of the model is based on the baseline systems from Yu et al. (2020) with the ELECTRA PrLM (Clark et al., 2020) specifically selected based on the high performance demonstrated in MCMRC tasks (Raina and Gales, 2022). The input to the transformer model is constructed as \( [\text{CLS}] \text{Context} [\text{SEP}] \text{Question} [\text{SEP}] \text{OptionA} [\text{SEP}] \text{OptionB} [\text{SEP}] \text{OptionC} [\text{SEP}] \text{OptionD} [\text{PAD}] \ldots \) where the context followed by the question concatenated with an option are separated by a special [SEP] token. The construct is repeated for each of the answer options such that the four sequences are inputted in parallel to the transformer encoder architecture (weights shared for each of the four sequences) that is followed by a classification head to return a probability distribution over the answer options. At inference, the predicted answer option is selected to be the one with the greatest probability mass associated with it. See Appendix B.1 for details about hyperparameter tuning.

Second, an ensemble of 3 models are trained to determine the question complexity of a system. These models are trained on the RACE++ splits but the classification labels used here are either easy, medium or hard corresponding to RACE-M, RACE-H and RACE-C respectively. Similar, to the MCMRC system, an ELECTRA-based model \(^2\) with a three-way classification head is used but the input to this model is of the form \( [\text{CLS}] \text{Question} [\text{SEP}] \text{Context} [\text{SEP}] \text{OptionA} [\text{SEP}] \text{OptionB} [\text{SEP}] \text{OptionC} [\text{SEP}] \text{OptionD} [\text{SEP}] [\text{PAD}] \ldots \) where the question, context and all four answer options are concatenated together with the special [SEP] tokens. See Appendix B.2 for further training details and hyperparameter tuning.

A single question generation system based on the architecture of Figure 1 from Section 3 is trained with teacher forcing (Lamb et al., 2016) based on the T5 PrLM (Raffel et al., 2020). At inference time, deterministic beam search with a beam size \(^3\) was considered but the proposed one is the simplest and best performing.
of 4 is used with a single question and set of answer options generated on each context from RACE++. Further details with regard to hyperparameter tuning are given in Appendix B.3. A second question generation model is trained using GPT-3 in the zero-shot setting.

The qualities described in the assessment framework of Section 4 are analysed on the questions generated from the T5 system. Particularly, the ELECTRA-based MCMRC system is used to derive the uncertainty scores and the ELECTRA-based question complexity (QC) system is used to derive the complexity scores. As the question generation system is uncontrolled, it is additionally important to assess what fraction of generated outputs actually have the desired number of 4 unique answer options. It is also necessary to assess the accuracy of the generated questions. From Section 3 it is expected that the first answer option generated should be the correct answer option to the generated question. Therefore, the accuracy is assessed as the fraction of generated samples where each of the three MCMRC systems in the ensemble agree at inference time that the first answer options is most likely the correct answer.

6 Results

This section presents the main results of the paper. First, the baseline performance of the vanilla systems for MCMRC and QC classification are given. Then the results of the MCQG system are given using the proposed assessment framework based on the MCMRC and QC systems.

6.1 Machine reading comprehension

| System          | M     | H     | C     | All   |
|-----------------|-------|-------|-------|-------|
| ELECTRA, single | 88.30 | 84.11 | 81.07 | 84.80 |
| ELECTRA, ensemble | 88.09 | 84.42 | 81.64 | 85.01 |

Table 2: Multiple-choice machine reading comprehension on Evl of RACE++ assessed using accuracy (%). See Appendix D.1 for standard deviations of single models.

| System                  | Accuracy | Macro F1 |
|-------------------------|----------|----------|
|                         | Dev      | Evl      | Dev    | Evl    |
| Majority-class          | 61.64    | 62.00    | 25.42  | 25.51  |
| Vocab-based             | 63.87    | 63.98    | 34.31  | 33.84  |
| ELECTRA, single         | 86.00    | 86.19    | 83.92  | 84.66  |
| ELECTRA, ensemble       | 86.66    | 86.97    | 84.65  | 85.52  |

Table 3: Question complexity results. See Appendix D.2 for standard deviations of single-seed results.

Table 2 presents the performance of the ELECTRA-based system on the RACE++ dataset for multiple-choice machine reading comprehension. It is observed that the ensembling of the ELECTRA models boosts the overall performance from an accuracy of 84.80% to 85.01% on the evaluation split. More fine-grained results are also provided on the RACE-M, RACE-H and RACE-C splits of the dataset. As expected, the systems struggle the most on the college level questions and find the middle school level questions the easiest with both the single and ensembled systems achieving approximately 7% greater accuracy on RACE-M compared to RACE-C. From these results that the overall performance of greater than 80%, it is somewhat reasonable to trust these MCMRC models as potential systems to be used as part of the MCQG assessment process in the proposed framework.

6.2 Question complexity

Table 3 presents the results of various QC systems in terms of accuracy and macro F1 (Yang and Liu, 1999) for classification between the easy (RACE-M), medium (RACE-H) and hard (RACE-C) question classes. As a baseline, the majority-class system is considered that always predicts medium as the complexity class (RACE-H is the dominant subset from Table 1). Next, a second baseline as a structured vocabulary (vocab) based system is considered. Here, standard vocabulary lists exist that have partitioned the whole vocabulary into the categories of beginner, intermediate and expert. Hence, each question, context and set of answer options has a structured complexity score calculated by determining the average vocabulary score for each example where beginner words have a score of 0.0, intermediate of 0.5 and expert of 1.0.

Various stochastic decoding approaches were considered including top-K-sampling and top-p-sampling but it was found the deterministic beam search generated the best quality questions. Latest model provided by OpenAI: text-davinci-002 in completion mode where at generation time the temperature is set to 0.4, maximum length to 1024 tokens, top P to 1 and the frequency and presence penalties to 0.

Liang et al. (2019) present baseline models on RACE++ using BERT-base but these results are omitted here for comparison due to their significantly lower performance compared to ELECTRA-large.

These lists are based on US English. Source not given to preserve anonymity.
expert of 1.0. This structured vocab-based score (with the optimal complexity thresholds between easy/medium and medium/hard determined on the Dev split) observes a performance boost compared to the majority-class by about 2% accuracy and 9% macro F1. Finally, the results of the single and ensemble versions of the ELECTRA model described in Section 5.2 are presented. Significantly better performance is observed with the ensemble system achieving an accuracy of 86.97% and macro F1 of 85.52% on the Evl split. Therefore, this QC is considered to be sufficiently well performing to use as a part of the MCQG assessment framework.

6.3 Question generation

In our results here, we present the assessment of our MCQG system (described in Section 3) using our proposed framework. In particular, we assess the grammatical fluidity (\(G\)), unanswerability (\(A\)), diversity (\(D\)) and the complexity (\(C\)) of the generated questions with the corresponding answer options. Additionally, it is necessary to assess what fraction of the questions actually have 4 unique options (4 opt) as the MCQG model does not guarantee that this will be the case. The accuracy (acc) is also reported (see Section 4) as an additional check to confirm what fraction of the generated questions and answer option sets do actually ensure the first answer option is the correct one.

Table 4 first presents the results of the assessment framework on the default human generated questions of the RACE++ dataset for the Evl split in order to provide an upperbound of performance for MCQG system (T5, all) where one question with the corresponding answer options has been generated per context. A filtered set of generated questions (T5, filt) is considered too where each of the questions has 4 unique answer options and the first answer option has been established to be the correct one. This filtered set consists of a set of 354 questions from an initial total of 1,542 (Table 1). For comparison, the results for a baseline based on GPT-3 zero-shot (GPT-3) are presented too. Note, the accuracy of the GPT-3 model is not given as it does not inform which of the answer options it generates is the correct answer. In terms of grammatical fluidity, pretrained language models have an excellent grasp of the rules of English language and hence such models generate grammatically correct questions and answer options, which leads to both the T5 and GPT-3 systems to achieve no grammatical errors (to 4 significant figures) according to the ERRANT system, reinforcing that state-of-the-art generation systems no longer need to be concerned in making mistakes with regard to grammatical structure. The unanswerability rate of the T5 generated questions is substantially higher than the human based system but is reduced by about 25% when considering the filtered set of questions. The GPT-3 system tends to naturally generate more answerable questions than the T5 model. In terms of complexity, although the MCQG system is trained using questions of mean complexity of 0.4402, the generated questions tend to be easier in nature with a slight further reduction in the complexity when
considering the filtered set. The complexity of GPT-3 appears to be comparable to the T5 system.

| System     | 4 opts Acc | \(A(\downarrow)\) | \(C(\uparrow)\) | \(D(\uparrow)\) |
|------------|------------|--------------------|-----------------|-----------------|
| Human      | 100        | 86.97              | 0.2740          | 0.4402          | 0.7750          |
| T5, all    | 77.24      | 43.77              | 0.8413          | 0.3950          | 0.6222          |
| GPT-3      | 80.93      | –                  | 0.7110          | 0.4099          | 0.5104          |
| T5, filt   | 100        | 100                | 0.6350          | 0.3839          | 0.6629          |

Table 4: Question generation assessment on Evl with unAnswerability, Complexity and Diversity.

Additionally, the quality of the T5 question generation system is further assessed by investigating its effectiveness for augmenting the training data for multiple-choice machine reading comprehension. The MCQG system is used to generate questions on the contexts from Trn. These questions are filtered as described above to remove questions that do not have 4 unique options or have any disagreement in predictions between the baseline MCMRC systems in the ensemble, leaving 5,766 questions. The set of filtered questions are used as extra augmentation data for the training of an ensembled MCMRC system. The augmented ensembled system observes a marginal performance boost on the MCMRC task for RACE++ of 0.36% on Dev and 0.12% on Evl. Future work can look at more effective filtration strategies for greater gains in the question generation augmented MCMRC task.

As a limitation of the current approach for MCQG, it is observed that some of the generated distractor options are in fact valid answer options (see Appendix C). Further work should investigate explicit methods of ensuring the distractor options do not answer the question.

7 Conclusions

This work aims to propose a sensible assessment framework for multiple choice question generation in order to encourage the question generation community to consider more appropriate methods of assessing and benchmarking developed systems to reflect the qualities of interest rather than arbitrary n-gram based approaches. Here, the first fully automated end-to-end multiple-choice question generation system is proposed for generating a question, the correct answer and distractor options for an input context without relying on explicit phrase extraction based techniques.

To assess the quality of the generated questions sensibly, an assessment framework is proposed that rates the grammatical fluidity, answerability, diversity and complexity of the questions. Standard tools are considered for assessing the rate of grammatical errors. The unanswerability of the questions is assessed by using the predictive uncertainty estimates in the predictions of an ensemble of high-performing multiple-choice reading comprehension systems. Diversity is measured as the entropy over question types. Finally, complexity assessment as a single score is captured by a directly trained supervised system to perform three-way classification between easy, medium and hard questions.

The automated assessment of high-entropy sequence-to-sequence models is critical for accelerating progress in many natural language generation tasks, and hence it is important that future work continues to consider and refine appropriate assessment frameworks to comprehensively understand the generation quality of novel systems.

8 Limitations

Here, the limitations of the current approaches are discussed. First, both measures of unanswerability and question complexity are model and corpus-specific. Hence, it is not clear about the applicability of these metrics beyond the RACE++ dataset. Specifically, the unanswerability measure runs the risk of conflating answerability with the failure of a reading comprehension question. The validity of such metrics is centred on in-domain data, which may be diminishingly effective at discriminating the performance of generative models on shifted data (e.g the nature of questions in ReClor is more logical-based and requires higher inference than questions in RACE++, which might make measures trained on RACE++ struggle at assessment on questions generated in the ReClor style). No human evaluation is performed of whether the assessment metrics correlate explicitly with human notions of answerability and complexity. Hence, further work should invest resources to comprehensively establish the validity of the proposed measures. Finally, the question complexity system is trained specifically on the meaning of complexity as described for RACE++. However, question complexity has several definitions and hence further work should establish whether this interpretation of complexity may align with other views of complexity.

Full list of generated questions can be reproduced with described training and inference process.
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Appendices

A Assessment of high-entropy sequences

In sequence-to-sequence generation tasks, one of the greatest challenges is regarding the scope of multiple possible output sequences for a given input sequence. Typically multiple reference samples will be provided for each input sequence. A model’s prediction is compared (using a performance metric such as BLEU, METEOR or ROUGE) against each of the references in turn and the performance is defined using the best performance score. However, practical limitations (e.g. expense of collecting references) means that the number of references may not fully be representative of the large number of acceptable output sequences. Consequently, a model’s prediction may achieve a low performance score by not being similar to any of the references albeit being an acceptable output sequence. Therefore, it is clear that there is expected to be some relationship between the achievable performance score with the number of reference samples available. This section aims to theoretically investigate how the number of reference samples impacts the achievable performance score.

A.1 Log-likelihood framework

A discriminative model, \( M \), defined by parameters \( \theta \), predicts the conditional representation based on its setting of \( \theta \):

\[
P_M(y_{1:T}|x_{1:K}; \theta).
\]

A theoretical measure of the performance of a model (on some test sample) is given by the log-likelihood of the output from the trained model \( (y_{1:T} \sim P_M(y_{1:T}|x_{1:K}; \theta)) \) where the log-likelihood is using the true posterior. Therefore, the performance can be defined as:

\[
\log(P(y_{1:T}|x_{1:K}))
\]

In order to get the expected performance over the output sequence, the expectation is taken with respect to the conditional distribution learnt by the discriminative model:

\[
\mathbb{E}_{P_M(y_{1:T}|x_{1:K}; \theta)} \log(P(y_{1:T}|x_{1:K})).
\]

In an ideal training scenario,

\[
P_M(y_{1:T}|x_{1:K}; \theta) \rightarrow P(y_{1:T}|x_{1:K}).
\]

Therefore,

\[
P_M(y_{1:T}|x_{1:K}; \theta) \rightarrow \mathbb{E}_{P(y_{1:T}|x_{1:K})} \log(P(y_{1:T}|x_{1:K})).
\]

\[
\mathbb{E}_{P(y_{1:T}|x_{1:K})} \log(P(y_{1:T}|x_{1:K})).
\]

\[
= - \mathbb{E}_{P(y_{1:T}|x_{1:K})}[H(Y_{1:T}|X_{1:K} = x_{1:K})]
\]

where \( H(\cdot) \) denotes the entropy of a probability distribution. So far, we have only taken expectations over the output sequence when conditioned on a particular input sequence. However, we are interested in finding the expected performance not only over the output sequence but also by considering all possible input sequences that we may be conditioned by. Thus, an expectation must be taken over the input distribution too to define the overall expected performance over the test dataset. Performance:

\[
= \mathbb{E}_{P(x_{1:K})} \left[ \mathbb{E}_{P(y_{1:T}|x_{1:K})} \log(P(y_{1:T}|x_{1:K})) \right]
\]

\[
= - \mathbb{E}_{P(x_{1:K})}[H(Y_{1:T}|X_{1:K} = x_{1:K})]
\]

A.2 Multiple draws

In practical sequence-to-sequence tasks, multiple references (labelled output sequences) are given for each input sequence in order to try and capture the number of acceptable output sequences for tasks that have high uncertainty (e.g. machine translation, summarisation, question generation). At evaluation time, typically the reference that allows the best performance to be achieved is selected. It is interesting to consider, in the theoretical sense, how
many output sequence samples are required to be drawn from the posterior (conditional) distribution in order to achieve a threshold performance.

Let us denote the number of drawn output sequences per input sequence as \( J \). Therefore, we have the pair \( (x_{1:K}, \{y_{1:T}^{(j)}\}_{j=1}^{J}) \), where \( x_{1:K} \sim P(x_{1:K}) \) and \( y_{1:T}^{(j)} \sim P(y_{1:T}|x_{1:K}) \) for \( j \in [1, J] \). We assume that each of the output sequences are drawn independently of each other from the conditional distribution. So, we are basically interested in the impact of \( J \) on the expected multi-draw performance.

The expected multi-draw performance is then given as \( E \) of:

\[
P(x_{1:K}) \prod_{j=1}^{J} P(y_{1:T}^{(j)}|x_{1:K}) = \mathbb{E}_{P(x_{1:K})} \left[ \max_{j \in [1, J]} \left\{ \log(P(y_{1:T}^{(j)}|x_{1:K})) \right\} \right] \tag{13}\]

However, it is not possible to analytically simplify the above equation. Therefore, a different mathematical framework will be considered to deduce the impact on performance of multiple draws of the reference sample from the true posterior distribution. The alternative frameworks are considered in the below sections.

### A.3 Maximum likelihood output with exact match framework

Let us define the output prediction from a trained model, \( y_{1:T}^{*} \), as the most likely output.

\[
y_{1:T}^{*} = \arg\max_{y_{1:T}} \{ P_M(y_{1:T}|x_{1:K}; \theta) \} \tag{14}\]

As before, we consider the ideal case where

\[
P_M(y_{1:T}|x_{1:K}; \theta) \rightarrow P(y_{1:T}|x_{1:K}). \tag{15}\]

Therefore \( y_{1:T}^{*} \) is the modal output from the true posterior distribution.

\[
y_{1:T}^{*} = \arg\max_{y_{1:T}} \{ P(y_{1:T}|x_{1:K}) \} \tag{16}\]

Let \( J \) reference samples be sampled from the true posterior distribution,

\[
y_{1:T}^{(j)} \sim P(y_{1:T}|x_{1:K}) \quad \text{for } j \in [1, J] \tag{17}\]

Then, let us define the performance for a given prediction as:

\[
\max_{j \in [1, J]} \left\{ F \left[ \hat{y}_{1:T}^{(j)}, y_{1:T}^{*} \right] \right\} \tag{18}\]

where \( F(\cdot) \) represents the exact match performance metric i.e. the predicted sequence has to exactly match one of the reference sequences. Thus, the expected multi-draw performance is given by:

\[
E \left[ \max_{j \in [1, J]} \left\{ F \left[ \hat{y}_{1:T}^{(j)}, y_{1:T}^{*} \right] \right\} \right] \tag{19}\]

Therefore, for the situation the mode of the posterior distribution is small (this is likely to be the case for high entropy probability distributions such as question generation), we can expect that the performance increases linearly with number of reference samples drawn from the true posterior distribution. This is an expected result as we are essentially saying that each reference sample is independently drawn of all other reference samples.

### A.4 Maximum likelihood output with fraction overlap score framework

As before, the modal output from the true posterior distribution and the \( J \) reference samples from the true distribution have the same definitions:

\[
y_{1:T}^{*} = \arg\max_{y_{1:T}} \{ P(y_{1:T}|x_{1:K}) \} \tag{27}\]

\[
\hat{y}_{1:T}^{(j)} \sim P(y_{1:T}|x_{1:K}) \quad \text{for } j \in [1, J] \tag{28}\]

Here, the precision of the overlap between the prediction and reference sample will be used (recall divides by the length of the reference sample). Multi-draw metric:

\[
\max_{j \in [1, J]} \left\{ F \left[ \hat{y}_{1:T}^{(j)}, y_{1:T}^{*} \right] \right\} \tag{29}\]

where

\[
F[a, b] = \frac{|a \cap b|}{|b|} \tag{30}\]

The focus will be on the overlap of unigrams but the argument can easily be extended for larger n-grams. Note, we are not really concerned about
different lengths of sequences (i.e. $T$ and $\tilde{T}$) because theoretically we can simply consider only sequences of all the same fixed length where an empty character can be thought of as a unigram in its own right; in this way the argument demonstrated here applies to sequences of all lengths.

Let us denote the prediction with $\alpha$ unigrams changed at some given positions across the sequence, where the specific positions being changed is given by a configuration function $c(\cdot)$ as $y^*_{1:T\setminus c(\alpha)}$. Then it will be useful to note that:

$$F\left[y^*_{1:T}\mid y^*_{1:T\setminus c(\alpha)}\right] = \frac{T - \alpha}{T}$$

Therefore, the expected multi-draw performance is given by (some steps use results directly from working in the previous section):

$$= \frac{E_{\hat{p}(\cdot|1:K)}}{E_{\hat{p}(\cdot|1:K)}} \left[ \max_{j \in [1,J]} \left\{ F\left[y^*_1, y^*_T\mid y^*_j, y^*_T\right] \right\} \right]$$

$$= \frac{E_{\hat{p}(\cdot|1:K)}}{E_{\hat{p}(\cdot|1:K)}} \left[ \sum_{x=0}^{\infty} \frac{T - \alpha}{T} \sum_{c \in C} P\left(y^*_1 = y^*_1, y^*_T|\alpha\right) \right]$$

$$\approx \frac{E_{\hat{p}(\cdot|1:K)}}{E_{\hat{p}(\cdot|1:K)}} \left[ \sum_{x=0}^{\infty} \frac{T - \alpha}{T} \sum_{c \in C} J P\left(y^*_1, y^*_T|\alpha, x_1:K\right) \right]$$

$$= J \times \text{constant}$$

The maximum likelihood output with an exact match framework and the maximum likelihood output with a fraction overlap score framework both indicated that there is a linear relationship between the performance and the number of references. Note, the theoretical arguments have assumed that there are a large number of possible output sequences and hence the probability of a prediction matching a reference sample (where both are sampled from the same true posterior distribution) is very small. $J$ references are sampled and it is assumed that each of these references is unique because we are only considering a small number of references and a large number of possible output sequences (i.e. high entropy posterior). This leads to a linear relationship between the multi-draw performance and the number of references which is only valid while the number of references is small. The behaviour for a large number of reference samples can be seen to grow non-linearly prior to the assumption being applied. Note, the linear relationship for independently drawn references is an obvious result intuitively as each independence allows the probability of matching any one reference to distinctly be added up together.

### B Training details

This section specifies the training details for all the systems trained and discussed in this work. All hyperparameter tuning was performed on the validation (development) set.

#### B.1 Multiple-choice machine reading comprehension

An ensemble of 3 models were trained using the ELECTRA-large pretrained language model. Each model in the ensemble has 340M parameters. Optimal hyperparameter values were motivated from Raina and Gales (2022) who performed a grid search to identify the best settings for performance on the RACE dataset for multiple-choice machine reading comprehension. In particular, each ensemble member was trained for 2 epochs at a learning rate of 2e-6 with a batch size of 4 and inputs truncated to 512 tokens. Cross-entropy loss was used at training time with models built using NVIDIA V100 graphical processing units with training time under 8 hours per model.

#### B.2 Question complexity

An ensemble of 3 models were trained using the ELECTRA-large pretrained language model. Each model in the ensemble has 340M parameters. The selection of hyperparameter values was achieved by performing a grid search on the learning rate $\in \{2e^{-7}, 2e^{-6}, 2e^{-5}\}$ and the batch size $\in \{2, 4\}$. In particular, each ensemble member was trained for 2 epochs at a learning rate of 2e-6 with a batch size of 4 and inputs truncated to 512 tokens. Cross-entropy loss was used at training time with models built using NVIDIA V100 graphical processing units with training time under 7 hours per model.

#### B.3 Question generation

A single question generation model was trained using the T5-base pretrained language model. The model has 220M parameters. The selection of hyperparameter values was achieved by performing a grid search on the learning rate $\in \{2e^{-7}, 2e^{-6}, 2e^{-5}\}$ and the batch size $\in \{2, 4\}$. In particular, the model was trained for 3 epochs at a learning rate of 2e-6 with a batch size of 4. The inputs were truncated to 512 tokens. Cross-entropy loss was used at training time with the model built using NVIDIA V100 graphical processing units with training time under 12 hours. At decoding time, a deterministic beam size of 4 was used with a repetition penalty.
of 2.5, a length penalty of 1.0, maximum sequence length of 80 tokens and early stopping (reaching end token) permitted.

**C  Example question generated**

Here, the example question generated demonstrates a failure mode of the proposed multiple-choice question generation approach as two of the distractor options are indeed valid answer options too.

**Context:**
When she graduates from Columbia University next year with a master’s degree in Public health, Eric Wheeler is hoping to get a job in international reproductive health. The 26-year-old post-graduate has always wanted to work in public service. But public service doesn’t pay much, and her two-year program at Columbia costs about $50,000 a year with living expenses. She has a scholarship from Columbia that covers just $4,000 a year and has taken out loans to pay for the rest. She worries that she will spend years paying back her student loans and not have money left over to put away in an IRA.

... Typically, it is projected that a borrower who performs public service under this program will repay only about one-fourth to one-half as much money as a borrower who does not, he said. He also pointed out that public service is broadly defined and includes any government and nonprofit organization job.

**Question:**
Which of the following is TRUE according to the passage?

**Options:**
1. Wheeler wants to get a job in international reproductive health.
2. Wheeler’s two-year program at Columbia costs about $50,000 a year.
3. Wheeler has taken out loans to pay for the rest.
4. Wheeler will spend years paying back her student loans.

**D  Additional results**

This section simply aims to present the standard deviations of the single seed results (insufficient space in the main text) across the 3 models in an ensemble for both the multiple-choice machine reading comprehension systems and the question complexity systems. Additionally, the results on the Dev set are given for the single seed models too for multiple-choice machine reading comprehension.

**D.1 Multiple-choice machine reading comprehension**

| System | Dev       | Evl       |
|--------|-----------|-----------|
| M      | 88.70±0.18| 88.30±0.15|
| H      | 85.59±0.18| 84.11±0.15|
| C      | 81.98±0.17| 81.07±0.46|
| All    | 85.93±0.21| 84.80±0.12|

Table 5: Single seed results for multiple-choice machine reading comprehension on Dev and Evl of RACE++ assessed using accuracy (%).

**D.2 Question complexity**

|          | Dev     | Evl     |
|----------|---------|---------|
| Accuracy | 86.00±0.36  | 86.19±0.50  |
| Macro F1 | 83.92±0.37  | 84.66±0.53  |

Table 6: Single seed results for question complexity on Dev and Evl of RACE++. 