Answering Ambiguous Questions through Generative Evidence Fusion and Round-Trip Prediction

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Abstract

In open-domain question answering, questions are highly likely to be ambiguous because users may not know the scope of relevant topics when formulating them. Therefore, a system needs to find possible interpretations of the question, and predict one or multiple plausible answers. When multiple plausible answers are found, the system should rewrite the question for each answer to resolve the ambiguity. In this paper, we present a model that aggregates and combines evidence from multiple passages to adaptively predict a single answer or a set of question-answer pairs for ambiguous questions. In addition, we propose a novel round-trip prediction approach to iteratively generate additional interpretations that our model fails to find in the first pass, and then verify and filter out the incorrect question-answer pairs to arrive at the final disambiguated output. Our model, named REFUEL, achieves a new state-of-the-art performance on the AMBIGQA dataset, and shows competitive performance on NQ-OPEN and Triviqa. The proposed round-trip prediction is a model-agnostic general approach for answering ambiguous open-domain questions, which improves our REFUEL as well as several baseline models. We release source code for our models and experiments at https://github.com/amzn/refuel-open-domain-qa.

1 Introduction

Open-domain Question Answering (QA) is the task of answering questions using a collection of passages with diverse topics (Chen et al., 2017; Guu et al., 2020; Karpukhin et al., 2020). Open-domain questions are highly likely to be ambiguous because people may not have the knowledge of relevant topics when formulating them. For example, in Figure 1, the prompt question “What’s the most points scored in an NBA game?” is ambiguous because the score in this question could be interpreted as the combined score in a game (Q1A1), score from a single team (Q2A2), or score from an individual player (Q3A3). Therefore, a system needs to adaptively predict a single answer, or a set of equally plausible answers when the question has multiple interpretations. When a set of multiple answers is predicted, an unambiguous rewriting of the question that leads to each answer should also be provided to clarify each interpretation.

Min et al. (2020) decompose this problem into two subtasks. Given the prompt question and Wikipedia passages, the first subtask, Answer Prediction, consists in predicting one or several plausible answers, depending on whether this question is ambiguous or not. If multiple answers are predicted, the second subtask, Question Disambiguation, requires generating a disambiguated question for each of the plausible answers. They propose SPANSEQGEN, which first retrieves and reranks

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passages using the prompt question, and then adopts a BART pre-trained sequence-to-sequence model (Lewis et al., 2020a) to generate all plausible answers, conditioned on the concatenation of the prompt question and top 8 passages. For the question disambiguation subtask, based on BART, they first pre-train a question generation model on NQ-open (Kwiatkowski et al., 2019), a large-scale open-domain QA dataset, to generate the question given the answer and top 8 passages. Then they fine-tune it as a question disambiguation model to generate the disambiguated question conditioned on the prompt question, answer, and passages.

There are three main drawbacks to SpanSeqGen. Firstly, a complete coverage of all relevant passages is essential for predicting all plausible answers of the ambiguous question. However, SpanSeqGen only takes 8 passages for answer prediction so some of the most informative passages might be excluded. Secondly, for the question disambiguation subtask, there is a mismatch between question generation pre-training on NQ-open and question disambiguation fine-tuning on AmbigQA – there is no question to disambiguate in question generation pre-training, which makes the pre-training task somewhat misaligned with fine-tuning. Thirdly, SpanSeqGen predicts a much smaller average number of answers compared to the ground truth data (1.17 vs. 2.19).

To address these issues, we propose REFUEL, Round-trip Evidence Fusion via gEneration with retrievalL, a new framework for answering ambiguous open-domain questions. To ensure a broad coverage of relevant knowledge of the question, REFUEL reads 12 times more passages (100 in our experiments) than SpanSeqGen by using Fusion-in-Decoder (Izacard and Grave, 2020) that processes each passage individually in the encoder, and then fused their encodings together in the decoder. For the question disambiguation subtask, we propose a token-deletion pre-training task to transform NQ-open into an “ambiguous” QA setting by randomly deleting an informative span for each question. Thus, pre-training and fine-tuning tasks are well aligned. Additionally, we add an insertion-based weighted loss to emphasize the newly inserted tokens in the disambiguated question, which helps the model on learning to resolve the ambiguity. Finally, we propose a round-trip prediction approach to find additional interpretations that REFUEL fails to predict in the first pass. We continuously feed the generated questions into REFUEL until there are no new answers predicted from our model. While this round-trip prediction can improve the recall of answers, we refine the quality of predicted QA pairs by filtering them with the conditional probability of the answers estimated by an answer-generation model.

Our REFUEL achieves a new state-of-the-art on the AMBIGQA dataset, outperforming the previous best model SpanSeqGen by 9.1% in answer prediction F1 and 4.4% in Edit-F1 score for question disambiguation. When directly doing inference on NQ-open and TriviaQA, REFUEL not only predicts the single answer precisely but also finds multiple interpretations if the question is ambiguous. Moreover, human evaluation shows that REFUEL can correctly generate more QA pairs on all three datasets. Finally, the proposed round-trip prediction is a model-agnostic general approach for answering ambiguous questions, which improves our REFUEL as well as several baseline models up to 3.7% for the overall performance.

The main contributions of this work, which are fundamental to significantly push the state-of-the-art in answering ambiguous questions, can be summarized as follows:

1. We present an evidence aggregation approach that can effectively use a large number of passages to uncover more candidate interpretations of the ambiguous question.
2. We propose a token-deletion pre-training task to reduce the mismatch between pre-training and fine-tuning for question disambiguation. The insertion-based weighted loss further helps to capture answer-relevant constraints.
3. We propose a round-trip prediction approach to find more interpretations missed in the first prediction pass, which we further refine using a conditional-probability-based filtering approach.

2 REFUEL

REFUEL answers questions through a three-step process illustrated in Figure 2:

1. The Passage Retrieval & Reranking module retrieves question-relevant passages from the whole Wikipedia corpus. Then the retrieved passages are further reranked (Sec. 2.1).
2. Taking the reranked passages and the prompt question as input, our single pass QA pair generation model makes the first prediction.
We use Dense Passage Retriever (DPR) (Karpukhin et al., 2020) for retrieval. First, we split all Wikipedia pages into 100-token passages, resulting in 24M passages in total. Then DPR maps all passages into $d$-dimensional vectors, computes the representation of the prompt question, and retrieves N passages whose vectors are closest to the question vector (we use N=1000).

After retrieving N passages for the prompt question, we fine-tune BERT (Devlin et al., 2019) to rerank these passages. Taking the concatenation of the prompt question and each passage as input, the reranker allows a token-level cross-attention between the prompt question and passages. The relevance score is then derived by taking the $[CLS]$ vector of the input sequence into a linear layer. After reranking, the QA pair generation model takes the top K passages as inputs (we use K=100).

2. Single Pass QA Pair Generation

The single pass QA pair generation step includes an Answer Prediction module and a Question Disambiguation module. Firstly, taking the reranked passages and the prompt question $Q^p$ as input, the Answer Prediction module generates one or multiple plausible answers $A_1, ..., A_m$. If multiple plausible answers are found, the prompt question is treated as ambiguous so that the Question Disambiguation module generates a disambiguated question $Q^{d}_i$ for each predicted answer $A_i$. Note that our general pipeline in Figure 2 does not limit the implementation of Answer Prediction module and Question Disambiguation module, and it can work for our REFUEL as well as several baselines (shown in Sec. 4.3). Our implementation is detailed in Sec. 3.

2.3 Round-Trip Prediction

During answering ambiguous questions, it might be difficult to find every possible interpretation in the first prediction pass, and existing work (Min et al., 2020) predicts 47% less answers compared with the ground truth. Therefore, we propose round-trip prediction, which includes a Round-Trip Generation step and a Language Model Verification Step.

Round-Trip Generation. Keeping the same retrieved passages, we continuously feed the generated disambiguated questions into the Answer Prediction module to check if any new answers are generated, and generate their corresponding disambiguated questions until there are no newly predicted answers. As exemplified in Figure 2, $(Q^d_1, A_1), (Q^d_2, A_2)$ are two disambiguated QA pairs of the ambiguous prompt question $Q^p$ after the first prediction pass. When feeding $Q^d_1$ to the Answer Prediction module again (1st Round-Trip Prediction), we find that besides the previously predicted answer $A_1$, a new answer candidate $A_3$ is predicted. Then we generate its corresponding question $Q^{d}_3$ accordingly. This loop continues until
there are no newly predicted answers.

**Language Model Verification.** Through the Round-Trip Generation, we generate a bunch of QA pairs from the ambiguous prompt question, but some of them are incorrect. Here we adopt a verification process to filter out these incorrect predictions. Recent works in synthetic QA pair generation (Alberti et al., 2019; Puri et al., 2020) use an “Exact Match (EM) Verification” approach to prune the QA pairs. They separately train a QA model as the verification model, and drop the predicted \((q, a)\) when the verification model’s answer \(a' \neq a\). However, this EM Verification approach is only suitable for factoid reading comprehension tasks such as SQuAD (Rajpurkar et al., 2016), in which the QA model has near-human accuracy so that it will not falsely filter out too many correct QA pairs. In open-domain QA, the current best model can only have 51.4% EM accuracy on the NQ-OPEN dataset (Izacard and Grave, 2020).

Instead of using hard filtering, we employ a “Language Model (LM) Verification” approach that is similar to the LM filtering method of Shakeri et al. (2020). LM Verification is a conditional-probability-based approach to filter out QA pairs softly. In “LM Verification”, we first train a conditional language model using the gold disambiguated QA pairs from AMBIGQA. The conditional language model is trained to estimate the likelihood of an answer given the golden disambiguated question. Once training is done, it is used to score the generated QA pair \((q, a)\) from REFUEL, which is the likelihood of the answer \(a\) given the question \(q\) and passages,

\[
\text{LM score} = \sum_{i=1}^{N_a} \log p(a^i|q, \text{passages}),
\]

where \(N_a\) is the length of the generated answer. Finally, we rerank all predicted QA pairs according to the LM score, and drop the QA pairs according to a threshold \(Th = 61\). The threshold is tuned according using the development set.

### 3. Single Pass QA Pair Generation Details

#### 3.1 Answer Prediction

SPANSEQGEN (Min et al., 2020) concatenates the prompt question and top reranked passages into a single sequence for BART encoding, which is extremely limited by the maximum input sequence length of BART (1024 subwords, equivalent to 8 passages). Consequently, SPANSEQGEN finds fewer interpretations of the prompt question compared to the ground truth (1.17 vs 2.19). To ensure a broad coverage of retrieved & reranked passages, our Answer Prediction module uses the Fusion-in-Decoder approach (Izacard and Grave, 2020), which allows us to scale the number of processed passages. As shown in Figure 3, our BART-based Answer Prediction module BART\textsubscript{AP} encodes the concatenation of the prompt question and each passage independently. Then all encoded token-level representations are concatenated into a single sequence, and the BART\textsubscript{AP} decoder performs attention over all passages to aggregate and combine evidence. Finally, the BART\textsubscript{AP} decoder generates a sequence of plausible answers token-by-token, separated by [SEP]. Since there is no cross-passage attention in the encoder, BART\textsubscript{AP} encoder reduces the computation from quadratic in the number of input passages to linear complexity. As a result, it can process 12 times larger number of input passages (up to 100 passages, 16000 subwords) than SPANSEQGEN. Given that AMBIGQA is a small dataset with only 10k training samples, we first pre-train BART\textsubscript{AP} on NQ-OPEN to predict a single answer, then fine-tune it on AMBIGQA to predict one or multiple answers.

#### 3.2 Question Disambiguation

If multiple answers are predicted, the Question Disambiguation module is activated to generate a disambiguated rewriting of the prompt question for each predicted answer. Because we do not know which input passage is the key evidence to derive the predicted answer, the Question Disambiguation Module
tion module takes the same passages in the Answer Prediction stage as inputs. Similar to the Answer Prediction module BART_{AP}, our Question Disambiguation module BART_{QD} processes the inputs under the same fashion except that BART_{QD} encoder additionally takes the predicted answer \( A_i \) from BART_{AP} in the input (shown in Figure 3).

**Token-Deletion Pre-training.** Similar to the training scheme of the Answer Prediction module, we also want to leverage the large-scale NQ-OPEN data for pre-training. One straightforward way is to train a question generation model on NQ-OPEN that generates questions given the passages and answer, and then fine-tune it for question disambiguation on AMBIGQA given the prompt question, answer, and passages. However, there is no input question to disambiguate in the question generation pre-training task, it leads to a mismatch between pre-training and fine-tuning. Ablation study shows this way of pre-training has almost no help for question disambiguation (Section 4.5).

To reduce the mismatch issue between pre-training and fine-tuning, we propose a Token-Deletion Pre-training task. The idea is to construct synthetic ambiguous questions in pre-training to reduce the mismatch. Given a question \( Q \) from NQ-OPEN, we randomly delete an informative span from it, resulting in a partial question \( Q^s \). This partial question is designed to simulate the ambiguous question \( Q^p \) in the fine-tuning stage. Then the token-deletion pre-training target is to recover the complete question \( Q \) from the partial question \( Q^s \), answer, and passages. In this way, the token-deletion pre-training aligns the fine-tuning phase.

Prompt questions are usually rewritten by adding new constraints including event/entity references, properties, answer types, etc. For example, the disambiguated question \( Q_1 \) in Figure 1 inserts “by a combined team” after the ambiguous prompt question. Therefore, we define the informative span as the span containing at least one of the following Part-of-Speech tags: ‘ADJ’, ‘NOUN’, ‘NUM’, ‘PROPN’, ‘SYM’, ‘VERB’. The length of the span is uniformly sampled in [1, 5].

**Insertion-based Weighted Loss.** Since the disambiguated question is a small modification from the ambiguous prompt question, most tokens can be directly copied from the input. Here we introduce an insertion-based weighted loss to put more emphasis on the newly added tokens of the disambiguated question, which could be the key to disambiguate the prompt question. Given the prompt question \( Q^p \), we find the newly inserted tokens from the disambiguated question \( Q^d \): \( \{q^m\} \). The final loss for fine-tuning BART_{QD} is a combination of the original negative log-likelihood loss on all question tokens augmented with a term that adds weight on the likelihood of inserted tokens:

\[
L = L_{nll} - \lambda \sum_{q_j \in \{q^m\}} \log(q_j | A, Q^p, Psg), \tag{2}
\]

where \( L_{nll} = \sum_{i=1}^n \log(q_i | A, Q^p, Psg) \), \( n \) is the number of tokens in the disambiguated question, \( \lambda = 3.5 \) is a hyperparameter tuned on the dev. set.

### 4 Experiments

#### 4.1 Experimental Setup

**Dataset.** We conduct main experiments on the AMBIGQA dataset (Min et al., 2020). AMBIGQA is constructed to address the ambiguity of questions in open-domain QA. It samples 14,042 questions from NQ-OPEN, a large-scale open-domain QA dataset in which each question has a single answer (Kwiatkowski et al., 2019), and asks annotators to search for, navigate and read multiple Wikipedia pages to find as many interpretations as possible. As a result, each question is annotated with either a single answer or multiple disambiguated QA pairs, depending on how many interpretations can be found. The train, development, and test (not public) dataset sizes are 10036, 2002, 2004, respectively \(^1\). On average, there are 2.1 distinct answers per question in AMBIGQA. To test the generalization ability of REFUEL on any possibly ambiguous questions, we additionally evaluate it on two open-domain QA datasets: NQ-OPEN and TriviaQA (Joshi et al., 2017).

**Implementation Details** are in Appendix A. We release source code for our models and experiments at [https://github.com/amzn/refuel-open-domain-qa](https://github.com/amzn/refuel-open-domain-qa).

**Evaluation Metrics.** Let \( (q_1, a_1), ..., (q_m, a_m) \) be \( m \) QA pair predictions, \( (\hat{q}_1, \hat{a}_1), ..., (\hat{q}_n, \hat{a}_n) \) be \( n \) gold QA pairs, each predicted QA pair \( (q_i, a_i) \) is evaluated in order by a correctness score towards all gold QA pairs: \( c_i = \mathbb{1}(a_i = \hat{a}_j)f(q_i, \hat{q}_j) \), where \( f(q_i, \hat{q}_j) \) is a similarity function for questions. \( (\hat{q}_j, \hat{a}_j) \) will not be further used to evaluate

\(^1\)Leaderboard: [https://nlp.cs.washington.edu/ambigqa/leaderboard.html](https://nlp.cs.washington.edu/ambigqa/leaderboard.html)
other predicted QA pairs as it is used for \((q_i, a_i)\). The overall correctness QA pairs is calculated by \(F_1\) between predictions and references,

\[
P_f = \frac{\sum_{i=1}^{m} c_i}{m}, R_f = \frac{\sum_{i=1}^{n} c_i}{n}, F_1 = \frac{2P_f R_f}{P_f + R_f}.
\]

All examples are evaluated for the answer prediction subtask, in which \(f\) function always yields 1. This metric is denoted as \(F_1\text{ans}\) (all). For the subset of examples with multiple gold QA pairs, both answer prediction subtask and question disambiguation subtask are evaluated. The answer prediction metric only computed on this subset is denoted as \(F_1\text{ans}\) (multi). To evaluate question disambiguation performance, BLEU (Papineni et al., 2002) and EDIT-F1 is used for the function \(f\), denoted as \(F_1\text{BLEU}\) and \(F_1\text{EDIT-F1}\), respectively. EDIT-F1 compute the F1 score of added and deleted unigrams from the prompt question to the predicted disambiguated question towards references.

### 4.2 Experimental Results

**Main Results.** Performance on the dev. and hidden test set of AMBIGQA is shown in Table 1. Even without having round-trip prediction, REFUEL (w/o RTP) outperforms SPANSEQGEN on both the answer prediction subtask and question disambiguation subtask by a large margin. Moreover, the round-trip prediction indeed further improves the performance by finding more and better QA pairs, going from 1.55 to 1.72 pairs per prompt question on the dev. set. A comprehensive analysis on the round-trip prediction is discussed in Sec 4.3.

**Controlled Comparison with SPANSEQGEN.** Besides round-trip prediction, REFUEL has two advantages over SPANSEQGEN in terms of input passages: (1) We retrieve top \(N=1000\) passages (instead of 100 in SPANSEQGEN) to get a higher answer recall at top 100 passages (improved from 86.2 to 89.7). (2) REFUEL takes \(K=100\) input passages whereas SPANSEQGEN takes at most 1024 subwords (\(K \approx 8\)). To establish a controlled and fair comparison, we remove the round-trip prediction part of REFUEL, and feed REFUEL (w/o RTP) with the same input passages used in SPANSEQGEN (\(N=100, K=8\)). Results are shown in Table 2. We find (1) Under the same number of passages, REFUEL (w/o RTP) (\(N=100, K=8\)) still outperforms SPANSEQGEN and generates more and better QA pairs; (2) REFUEL (w/o RTP) benefits from increasing the answer recall of retrieval stage (\(N = 100 \rightarrow 1000\)), as well as allowing more input passages (\(K = 8 \rightarrow 100\)).

**Generalization to Other Datasets.** To test how well does REFUEL answer any open-domain questions, we evaluate REFUEL on NQ-OPEN and TriviaQA as a function of the number of retrieval/reranking (\(N\)) and QA input (\(K\)) passages. \#QAs: the average number of predicted QA pairs per prompt question. *: our replicated results.

### Table 1: Results on the dev. and hidden test set of AMBIGQA. “REFUEL w/o RTP” is the single pass prediction model without using round-trip prediction. In addition to metrics introduced in Section 4.1, we also show a combined metric “Comb.” = \(F_1\text{ans}\) (all) + \(F_1\text{EDIT-F1}\) which is used to rank models on the official leaderboard.

| Model                        | \(F_1\text{ans}\) (all) | \(F_1\text{ans}\) (multi) | \(F_1\text{BLEU}\) | \(F_1\text{EDIT-F1}\) | Comb. |
|------------------------------|--------------------------|---------------------------|--------------------|------------------------|-------|
| DPR Reader (Min et al., 2020)| 28.1                     | 24.8                      | 21.9               | 18.8                   | 4.2   |
| SPANSEQGEN (Min et al., 2020)| 37.1                     | 32.3                      | 28.4               | 24.8                   | 13.4  |
| REFUEL w/o RTP (single model)| 48.4                     | 41.7                      | 37.0               | 32.7                   | 16.0  |
| SPANSEQGEN (ensemble)        | 41.2                     | 35.2                      | 29.8               | 24.5                   | 13.6  |
| REFUEL (ensemble)            | 50.4                     | 44.3                      | 38.7               | 34.8                   | 17.0  |

\(\text{Comb.} = \sum_{i=1}^{m} c_i + \sum_{i=1}^{n} c_i \), \(F_1 = \frac{2P_f R_f}{P_f + R_f}\).

### Table 2: Dev. set results of AMBIGQA as a function of the number of retrieval/reranking (\(N\)) and QA input (\(K\)) passages. \#QAs: the average number of predicted QA pairs per prompt question. *: our replicated results.

| Model                | \(N\) | \(K\) | \#QAs | \(F_1\text{ans}\) | \(F_1\text{EDIT-F1}\) |
|----------------------|-------|-------|-------|------------------|------------------------|
| SPANSEQGEN           | 100   | \(\approx 8\) | 1.17  | 39.7             | 7.2                    |
| SPANSEQGEN*          | 100   | \(\approx 8\) | 1.14  | 41.7             | 7.1                    |
| REFUEL (w/o RTP)     | 100   | 8     | 1.42  | 44.7             | 10.0                   |
| REFUEL (w/o RTP)     | 100   | 100   | 1.54  | 45.4             | 10.7                   |
| REFUEL (w/o RTP)     | 1000  | 1000  | 1.55  | 48.4             | 11.2                   |

### Table 3: Results on NQ-OPEN and TriviaQA test set. RTP: Round-Trip Prediction. NFT: No Fine-Tuning. ORQA (Lee et al., 2019), HardEM (Min et al., 2019), RAG (Lewis et al., 2020b).

| Model       | NQ-OPEN | TriviaQA |
|-------------|---------|----------|
|             | EM      | Oracle EM| EM      | Oracle EM |
| ORQA (supervised) | 33.3    | -        | 45.0    | -         |
| HardEM (supervised) | 28.1    | -        | 50.9    | -         |
| DPR (supervised)   | 41.5    | -        | 57.9    | -         |
| RAG (supervised)   | 44.5    | -        | 56.8    | -         |
| REFUEL w/o RTP (NFT) | 35.4    | 45.2     | 48.2    | 52.9      |
| REFUEL (NFT)       | 37.3    | 48.9     | 49.8    | 54.3      |
We compare our proposed Round-Trip Prediction approach (Alberti et al., 2019; Puri (1.43) is even smaller than not doing round-trip prediction (Round-Trip Generation = Round-Trip Generation & LM Verification) with “Round-Trip Generation & LM Verification” is significantly better than the same model without it under a paired bootstrap test with $10^8$ samples ($p$-value < 0.05).

Table 4: Effect of round-trip prediction to harvest more interpretations (QA pairs) on the development set of AMBIGQA. “↑” and “↓” denotes the improvement gain over the model without round-trip prediction. *: The model with ”Round-Trip Generation & LM Verification” is significantly better than the same model without it under a paired bootstrap test with $10^9$ samples ($p$-value < 0.05).

| Models                          | #QAs | $F_{1\text{ans}}$ (all) | $F_{1\text{ans}}$ (multi) | $F_{1\text{BLUE}}$ | $F_{1\text{EDIT-F1}}$ | Comb.  |
|--------------------------------|------|-------------------------|---------------------------|-------------------|------------------------|-------|
| REFUEL w/o RTP                 | 1.55 | 48.4                    | 37.0                      | 16.0              | 11.2                   | 59.6  |
| + Round-Trip Generation        | 2.06 (73.5%) | 47.6                    | 37.4                      | 16.0              | 11.4                   | 59.0  (10.9%) |
| + Round-Trip Generation & LM Verification | 1.72 (111.1%) | 48.3                    | 37.3                      | 16.2              | 11.8*                  | 60.1  (10.7%) |
| + Round-Trip Generation & EM Verification | 1.43 (7.7%) | 47.6                    | 35.4                      | 15.7              | 11.6                   | 57.2  (14.0%) |

| DPR Reader                     | 1.62 | 38.9                    | 29.9                      | 12.5              | 6.8                    | 45.7  |
| + Round-Trip Generation & EM Verification | 1.81 (111.7%) | 40.1*                   | 31.6*                     | 13.3*             | 7.3*                   | 47.4* (73.7%) |
| SPANSEQGEN                     | 1.14 | 41.7                    | 29.3                      | 12.7              | 7.1                    | 48.8  |
| + Round-Trip Generation & LM Verification | 1.28 (123.3%) | 42.4*                   | 29.9*                     | 13.0*             | 7.4*                   | 49.8* (72.1%) |

Table 5: Human evaluation results. #QAs: the average number of QA pairs per prompt question. #C-QAs & #CD-QAs: the average number of correct QA pairs, detailed in Sec. 4.4. $\kappa$: Fleiss’ kappa score.

| Models                      | Dataset | #QAs | #C-QAs | #CD-QAs | $\kappa$ |
|-----------------------------|---------|------|--------|---------|---------|
| SPANSEQGEN                  | AMBIGQA | 2.12 | 1.40    | 0.46    | 0.27    |
| REFUEL w/o RTP              | AMBIGQA | 2.80 | 1.84    | 0.98    | 0.35    |
| REFUEL                      | AMBIGQA | 3.44 | 2.40    | 1.24    | 0.34    |
| REFUEL w/o RTP              | NQ-OPEN | 2.32 | 1.30    | 0.64    | 0.20    |
| REFUEL                      | NQ-OPEN | 3.20 | 1.72    | 0.88    | 0.21    |
| REFUEL                      | TriviaQA | 2.08 | 1.02    | 0.46    | 0.34    |
| REFUEL                      | TriviaQA | 3.24 | 1.84    | 0.82    | 0.35    |

**4.3 Effect of Round-Trip Prediction**

We compare our proposed Round-Trip Prediction (Round-Trip Prediction = Round-Trip Generation + LM Verification) with several alternative approaches, as well as investigate its generalization ability to other models like SPANSEQGEN and DPR Reader. Results are shown in Table 4.

**Round-Trip Generation Only.** We investigate the necessity of the verification process by conducting only round-trip generation to REFUEL. Results show that Round-Trip Generation can generate 33.5% more QA pairs, but the lower $F_{1\text{ans}}$ (all) suggests that this strategy may over-generate QA pairs when the prompt question is not ambiguous. Hence, the verification process is necessary to prune some incorrect QAs.

**LM Verification vs. EM Verification.** As described in section 2.3, we compare the existing EM Verification approach (Alberti et al., 2019; Puri et al., 2020) with our LM Verification. Results demonstrate that EM Verification prunes too many QA pairs – the number of remaining QA pairs (1.43) is even smaller than not doing round-trip prediction (1.55). This validates our intuition in section 2.3 that EM Verification is not suitable for open-domain QA tasks because of the low performance of current open-domain QA models.

**Generalization to Other Models.** We show that round-trip prediction is a model-agnostic general approach for answering possibly ambiguous open-domain questions by using it on our replicated baseline models: DPR Reader and SPANSEQGEN. With the help of round-trip prediction, DPR Reader and SPANSEQGEN generates 11.7% and 12.3% more QA pairs, which result in a boost of 3.7% and 2.1% for the overall performance (Comb.).

**4.4 Human Evaluation**

Since the answers collected in AMBIGQA are not necessarily exhaustive, there is a possibility that a model generates correct interpretations but they are missed in AMBIGQA. Therefore, we hire 3 workers from MTurk.com to evaluate the correctness of the answer given the generated disambiguated question and retrieved passages (instructions in Appendix C). Let $(q_i, a_1), \ldots, (q_i, a_n)$ be n generated QA pairs from the same prompt question, we define two levels of correctness as follows: #C-QAs: $(q_i, a_i)$ is considered Correct if $a_i$ is a correct answer of $q_i$; #CD-QAs: $(q_i, a_i)$ is considered correct iff. (1) $a_i$ is a correct answer of $q_i$ and (2) any $a_j (j \neq i)$ is a wrong answer of $q_i$. #CD-QAs is designed to examine the Correctness of ques-
Table 6: Ablation Study of REFUEL for the question disambiguation subtask on the dev. set. QDf: Question Disambiguation Fine-tuning, QGP: Question Generation Pre-training, TDP: Token-Deletion Pre-training.

4.5 Ablations on Question Disambiguation

Table 6 compares our question disambiguation model with the prompt baseline and several ablations. The prompt baseline directly takes the prompt question as the disambiguated prediction, so its F$_1$EDIT-F1 is zero. However, F$_1$BLEU score of the prompt baseline is higher than REFUEL. This suggests that F$_1$EDIT-F1 captures the effectiveness of question disambiguation better than F$_1$BLEU.

For our ablations, we start from only using AMBIGQA dataset (None+QDf), and investigate whether it is helpful to only use answer-containing passages as inputs (None+QDf w/ filtered passages). The worse result of the latter approach suggests that we should keep all passages for question disambiguation. Second, we examine the effectiveness of pre-training. We try the question generation pre-training (QGP+QDf) and compare it with the ablation without any pre-training (None+QDf). Results show that the question generation pre-training has little help for fine-tuning. By replacing the question generation pre-training QGP with our proposed token-deletion pre-training TDP, we see the results (TDP+QDf) are better than the no pre-training ablation (None+QDf), which implies the mismatch between pre-training and fine-tuning are somewhat reduced. Finally, the insertion-based loss enables REFUEL to capture the key disambiguation phrase with less copying the prompt question, resulting in a lower BLEU but higher Edit-F1.

4.6 Case Study

Figure 4 provides example question-answer pairs generated by crowd-workers, REFUEL (w/o RTP), and REFUEL. The annotator find three interpretations from the prompt question, while our single pass model REFUEL (w/o RTP) finds in total four interpretations (QA1-4). Although QA2 predicted from our model is not included in the references, it is indeed a correct interpretation of the prompt question. In addition, the Round-Trip Prediction approach finds two correct interpretations (QA5, QA6) which the model fails to predict on the first generation pass. More cases are shown in Appendix F.

5 Related Work

Open-Domain Question Answering is answering factoid questions using a huge collection of documents such as Wikipedia pages (Voorhees, 1999;
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A Implementation Details

Evidence Corpus. We keep the version of English Wikipedia Dump consistent to the annotation timestep of NQ-OPEN and AMBIGQA, which is 2018-12-20 and 2020-01-20 respectively. Models pre-trained on NQ-OPEN use passages from dump 2018-12-20 while models fine-tuned on AMBIGQA take dump 2020-01-20. We use the AMBIGQA processed passages of these dumps, which takes the plain text and split Wikipedia pages into 100-word passages. As a result, there are 22M passages of Wikipedia Dump 2018-12-20 and 24M passages of Wikipedia Dump 2020-01-20.

Retrieval & Reranking. We use the multiset version of Dense Passage Retriever (DPR) (Karpukhin et al., 2020), which is jointly trained on five open-domain QA datasets. For the reranker, we fine-tune a bert-large-cased model with a batch size 16, learning rate 1e-5, training epoch 10 on the NQ-OPEN dataset. We sample 1 positive and 31 negative passages in training to maximize log-likelihood of the positive passage. The best reranker model is selected according to the answer recall in top 100 reranked passages. The trained reranker model is used for both NQ-OPEN and AMBIGQA dataset (we tried to finetune this model on AMBIGQA but did not receive any sensible improvement). The total training takes 10 hours and we tune the learning rate from 1e-5 to 5e-5 and select the best one.

Answer Prediction. We train a BART_{large} model on NQ-OPEN with a batch size 64, epoch 10, and learning rate 5e-5. Then we finetune the trained model on AMBIGQA with a batch size 64, epoch 30, and learning rate 3e-5. According to empirical results, we discard training samples which the gold answers do not appear in any input passages according to empirical results. The best model is selected according to $F_1^{EDIT,F1}$ for both NQ-OPEN and AMBIGQA on the development set.

LM Verification. Based on the best QA model on NQ-OPEN trained in the Answer Prediction, we finetune it using the gold disambiguated QA pairs from AMBIGQA, in which each disambiguated question is only paired with one answer. We use a batch size 64, epoch 30, and learning rate 3e-5 for finetuning, and select the best model according to the EM score on the dev. set of AMBIGQA.

All the experiments are conducted on a single machine with 8 V100 GPUs. The pre-training on NQ-OPEN takes 60 hours for models in Answer Prediction, Question Disambiguation and LM Verification, and the fine-tuning takes 10 hours on AMBIGQA.

B Error Analysis

Answer Prediction Error. In the development set of AMBIGQA, 22.9% of examples actually have multiple interpretations but REFUEL only predicts one answer. In 12.0% examples, REFUEL wrongly predicts multiple answers on the unambiguous prompt questions. In the rest 65.1% examples, REFUEL aligns with annotators in terms of the ambiguity. Since REFUEL tends to wrongly think the prompt question is unambiguous, it predicts fewer answers than ground truth (1.55 vs. 2.02 on average). In effect, the predicted answers have a relatively high precision 55.6% but low recall 48.0%. By localizing where the errors come from, we find that in 2.3% of examples, REFUEL fails to make correct predictions.

Question Disambiguation Error. We analyze the quality of disambiguated questions when the predicted answers are correct. We select 100 samples from the development data and summarize errors into five categories in Figure 5. We see that 42% of generated questions are totally wrong and 15% of them are identical to the prompt ones. Besides, there are in total 31% of generated questions (Correct but Different Constraints, Correct but Paraphrase) are actually correct but do not get credits under the current matching based evalua-
### Details of Human Evaluation

#### Instruction Details

Figure 6 shows the instruction and interface for human evaluation. We have three choices for each QA pair: “Answer is correct”, “Answer is incorrect” and “Insufficient evidence”. Since each QA pair has 100 retrieved passages, we show 5 retrieved passages (with answer highlighted) at a time. If the worker select “Insufficient evidence”, we will show the next 5 retrieved passages until this QA pair receives a “correct/incorrect” decision. If “Insufficient evidence” is still select after showing all 100 passages, then we mark this QA pair as “incorrect”.

#### Evaluation Metrics & Quality Control

Let \((q_1, a_1), \ldots, (q_n, a_n)\) be \(n\) generated QA pairs from the same prompt question, we define two levels of correctness as follows: 

- **#C-QAs**: \((q_i, a_i)\) is considered **Correct** if \(a_i\) is a correct answer of \(q_i\); 
- **#CD-QAs**: \((q_i, a_i)\) is considered **Correct** if (1) \(a_i\) is a correct answer of \(q_i\) and (2) any \(a_j (j \neq i)\) is a wrong answer of \(q_i\). 

#C-QAs is designed to examine the correctness of question disambiguation because ambiguous questions can have multiple valid answers. Moreover, it reduce the priming effect so that workers won’t have a tendency to mark all samples as correct. During annotation, workers do not know each question \(q_i\) is paired with its answer \(a_i\) or other answers \(a_j (j \neq i)\) under the same prompt question.

We only recruit workers based in the United States and pay 0.2 USD per QA pair on Mturk. For quality control, we have manually annotate 15 correct QA pairs and 15 wrong QA pairs (pair \(q_i\) with \(a_j (j \neq i)\), and randomly select 5 of them to examine the quality of annotation. The task will be approved only when 3 out of 5 hidden test QA pairs receive correct annotations.

### Discussion on Problem Formulation

**QGen-AGen.** We swap the order of answer prediction and question disambiguation in the problem formulation – firstly a QD model generates several disambiguated questions in a sequence, or predicts EoS if the question is not ambiguous; Then a QA model predicts a single answer for each predicted disambiguated question. This approach does not work in our experiments with poor performance. We think the major reason is generating multiple disambiguated question from the prompt question as the first step is much harder than the original.
formulation which only requires generating multiple plausible answers from the prompt question.

**QAGen.** Another possible approach is using a single model to predict disambiguated question-answer pairs where each answer right precedes its disambiguated question. This is certainly a possible way but it is even more challenging than QGen-AGen. We did not try this way after receiving poor performance from QGen-AGen.

### E Baselines for Round-Trip Prediction

Since the current round-trip prediction requires several iteration between the answer prediction module and the question disambiguation module, it would be better to over-generate many answers in one pass. One straightforward way to generate more QA pairs is setting a minimum length of generation for the answer prediction model, and then go through the LM Verification process to drop the low-quality predictions. We set two minimum lengths of generation (L=8/16) for our answer prediction model. As shown in Table 7, although setting a minimum length effectively increases the number of predicted QA pairs (2.10/2.88 for L=8/16), the over-generated answers are extremely noisy which in turn hurts the effectiveness of the LM Verification model, resulting in far worse performance across all metrics. Presumably, one major disadvantage of the Min-Length Generation approach is that REFUEL loses the flexibility to decide the number of possible interpretations based on the passages. Instead, it always generates multiple answers according to the minimum length.

#### F More Cases from REFUEL: Figure 7
When did the new Christopher Robin film come out in Burbank? A1: July 30, 2018

When did the new Christopher Robin film come out in California? A3: July 30, 2018

Table 7: Dev. set results on different approaches to harvest more interpretations (QA pairs) towards the ambiguous questions. "#QAs" denotes the average number of generated QA pairs per prompt question.

| Models | #QAs | F1$_{all}$ (all) | F1$_{multi}$ | F1$_{BLEU}$ | F1$_{EDIT_F1}$ | Comb. |
|--------|------|------------------|-------------|-------------|----------------|-------|
| REFUEL w/o RTP | 1.55 | 48.4 | 37.0 | 16.0 | 11.2 | 59.6 |
| + Round-Trip Generation | 2.06 | 47.6 | 37.4 | 16.0 | 11.4 | 59.0 |
| + Round-Trip Generation & LM Verification | 1.72 | 48.3 | 37.3 | 16.2 | 11.8 | 60.1 |
| + Min-Length Generation (L=8) | 2.10 | 40.8 | 36.2 | 15.5 | 11.1 | 51.9 |
| + Min-Length Generation (L=8) & LM Verification | 1.69 | 42.9 | 36.3 | 15.9 | 11.4 | 54.4 |
| + Min-Length Generation (L=16) | 2.88 | 37.2 | 34.1 | 14.6 | 10.3 | 47.5 |
| + Min-Length Generation (L=16) & LM Verification | 1.46 | 43.1 | 34.5 | 15.2 | 11.1 | 54.2 |

Figure 7: Predictions generated by REFUEL from the development data. We also manually check all the 100 retrieved and reranked passages, and list the answer-relevant passages here. However, the listed passages might be different from the passages that annotators search and read during annotation.