

# Asking Clarification Questions to Handle Ambiguity in Open-Domain QA



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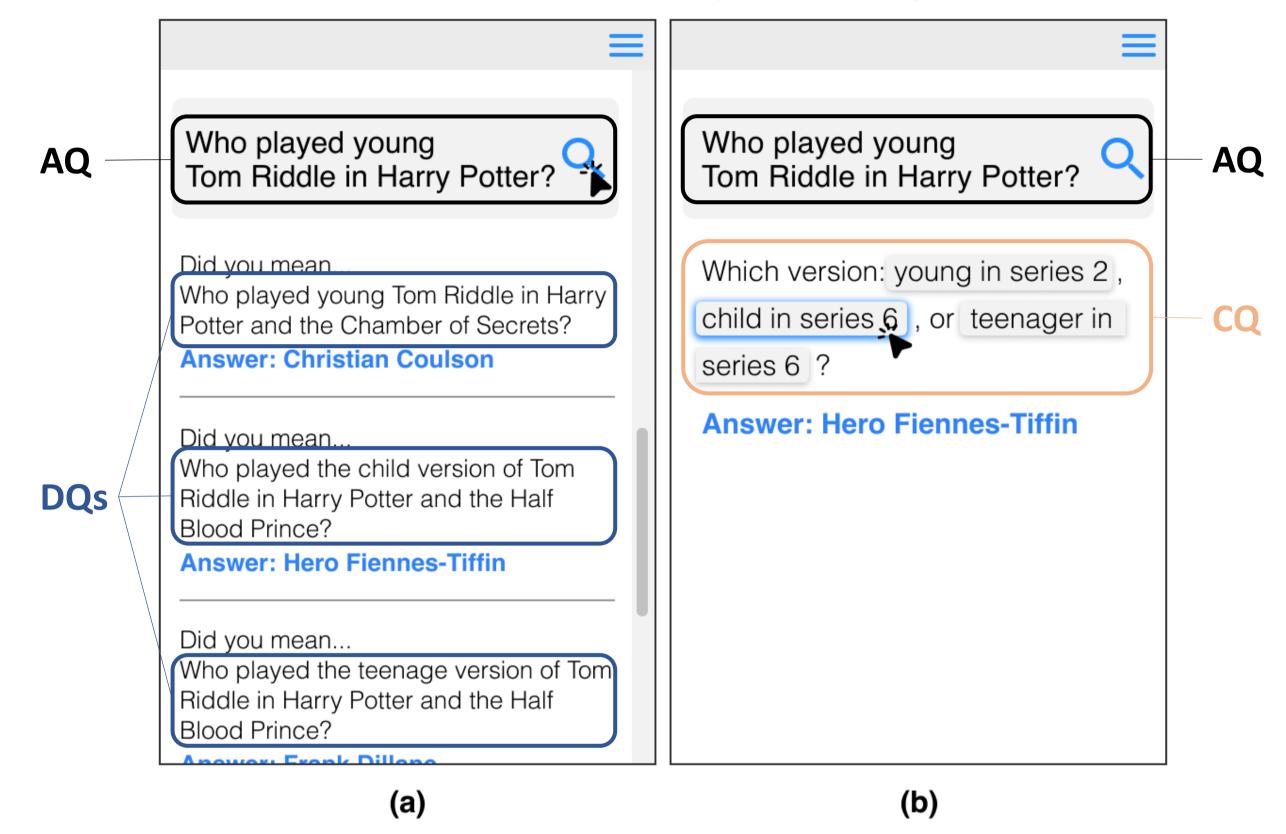


# Contributions

- We propose to use Clarification Questions (CQs) as a practical means to handle Ambiguous Questions (AQs) in Open-Domain Question Answering (ODQA).
- We **present CAMBIGNQ**, a dataset to support CQ-based handling of AQs in ODQA.
- We define a pipeline of tasks and appropriate evaluation metrics for CQ.

## **Problem**

**Ambiguity** arises in Open-Domain Question Answering (ODQA) when there exist multiple plausible answers for the given Ambiguous Question (AQ).



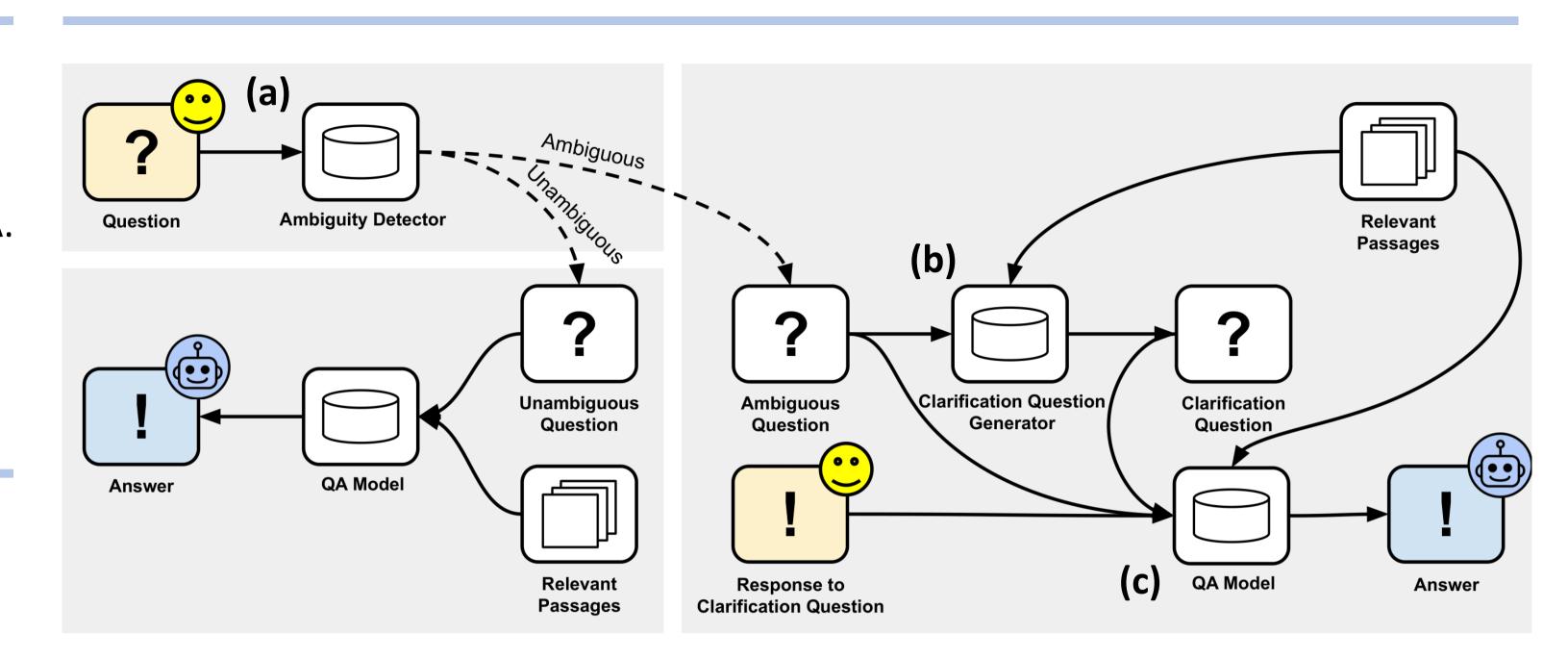
- (a) Previous works proposed Disambiguated Questions (DQs), the minimally edited modification of AQ. They enlist all DQs and corresponding answer.
- (b) Instead, we propose Clarification Questions (CQs), where the user's response will help identify the interpretation that best aligns with the user's intention.

## Dataset: CAMBIGNQ

Split	C	Q	Category	Options			
	#	Len.	Len.	Avg. #	Len.		
Train	4,699	13.6	2.8	2.9	3.3		
Validation	461	15.9	2.5	3.3	3.8		
Test	493	17.8	2.8	3.4	4.1		

We collect high-quality of CQs by leveraging power of InstructGPT and human editors: Few-shot Generation via InstructGPT and Manual Inspection and Revision.

## Method



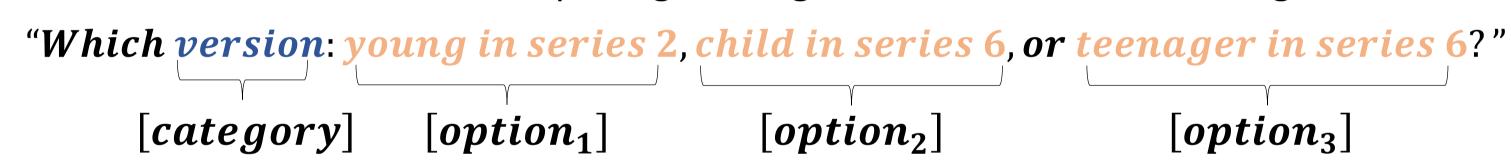
Our proposed method to handle AQs to in ODQA by asking CQs consists of three subtasks: (a) Ambiguity Detection, (b) Clarification Questions Generation, and (c) Clarification-based QA.

## (a) Ambiguity Detection

- Given a question q and relevant passages we classify whether q is ambiguous or not (binary classification)
- We test two settings: Direct Classification (BERT) and Generation-based
  Classification (BART).

## (b) Clarification Questions Generation

• Given an AQ and relevant passages, we generate a CQ with following formats:



- "version" is a [category] to which all options belong.
- each  $[option_i]$  represents single interpretation of AQ.

#### (c) Clarification-based QA

• Given an AQ, relevant passages, and a CQ, we generate a unique answer for every  $[option_i]$  by calling a QA model on AQ revised by CQ with following format:

"Who played young Tom Riddle in Harry Potter. Which version: child in series 6?

## Results

#### **Human Preference Test (CQ vs DQ)**

- Our proposed method CQ (59%) is preferred over DQ (33%).
- The prominent reasons for choice was its conciseness, ease of use, and clear guidance.

CQ	Split	DQ
0.59	0.08	0.33

## **Ambiguity Detection Evaluation**

- Direct Classification (No Answers for AQ) shows higher F1 compared to Generation based Classification (Predicted Answers for AQ)
- This is because the average # of BART-generated answer is 1.24, resulting in low recall.

Input in addition to AQ	Acc.	Pre.	Rec.	F1
No Answers for AQ	63.9	61.9	60.7	61.3
Predicted Answers for AQ	56.5	59.7	24.1	34.3

#### Clarification Questions Generation

• Evaluating generated CQs against gold CQs using automatic metrics (BLEU, BERTSCORE, EM) can not capture semantic similarity.

	CQ		Ca	ategory	Options			
Input in addition to AQ and RPs	BLEU-4	BERTSCORE	EM	BLEU-1	Pre.	Rec.	F1	Avg. #
No Answers for AQ	7.9	88.9	20.2	47.3	37.4	18.2	24.5	2.0
Predicted Answers for AQ	7.9	88.9	22.8	44.0	36.9	19.0	25.1	2.0
Ground Truth Answers for AQ	15.4	89.6	25.2	46.9	34.3	34.4	34.3	3.7

# Clarification-based QA

• The result shows **insufficient performance** across different settings. This is because the QA models, including LLMs, produce "**Same Answer**" for the **different questions**. Even though the QA model is prompted with Ground Truth CQ (Ideal case), the **model fails to capture subtle difference in the input**.

		NQ-pretrained BART				CQ-finetuned BART			
CQ used to clarify the AQ	Pre.	Rec.	F1	# Ans.	Pre.	Rec.	F1	# Ans.	
CQ generated with No Answers for AQ	47.9	25.2	33.0	1.5	54.4	31.1	39.6	1.6	
CQ generated with Predicted Answers for AQ	49.6	26.2	34.3	1.5	55.4	32.0	40.5	1.6	
CQ generated with Ground Truth Answers for AQ	39.7	37.5	38.6	2.0	47.5	49.5	48.5	2.5	
Ground Truth CQ	47.5	39.8	43.3	2.0	58.0	53.8	55.8	2.5	

Code available at: https://github.com/DongryeolLee96/AskCQ