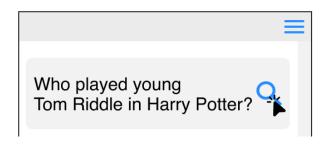
Asking Clarification Questions to Handle Ambiguity in Open-Domain QA

Dongryeol Lee*, Segwang Kim*, Minwoo Lee, Hwanhee Lee, Joonsuk Park, Sang-woo Lee, Kyomin Jun

> Machine Intelligence Lab Seoul National University

Introduction: Ambiguity in Open-Domain QA



Ambiguity

 Ambiguity arises when there exist multiple plausible answers for the given Ambiguous Question (AQ).

AQ: Who played young Tom Riddle in Harry Potter?

CQ: Which version: young in series 2, child in series 6, or teenager in series 6?

: Category summarize the options

: Option represent single interpretation of AQ.

AQ: Who played young Tom Riddle in Harry Potter?

CQ: Which version: young in series 2, child in series 6, or teenager in series 6?

DQ₁: Who played young Tom Riddle in Harry Potter and the Chamber of Secrets?

AQ: Who played young Tom Riddle in Harry Potter?

CQ: Which version: young in series 2, child in series 6, or teenager in series 6?

DQ₂: Who played child version of Tom Riddle in Harry Potter and the Half Blood Prince?

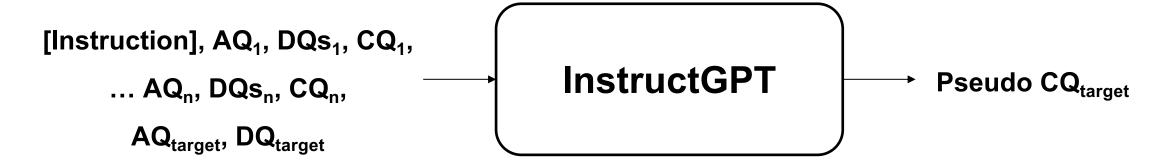
AQ: Who played young Tom Riddle in Harry Potter?

CQ: Which version: young in series 2, child in series 6, or teenager in series 6?

DQ₃: Who played the teenage version of Tom Riddle in Harry Potter and the Half Blood Prince?

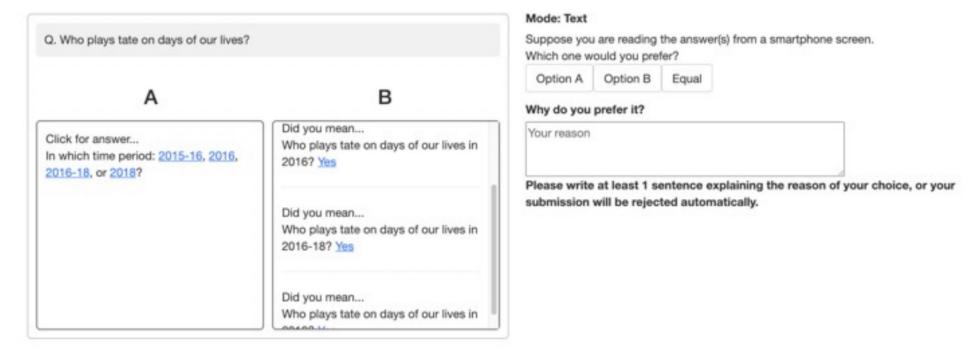
Dataset: CAMBIGNQ

Step 1: Generation via Instruct GPT



Step 2: Manual Inspection and Revision by human annotators

Human Preference Test



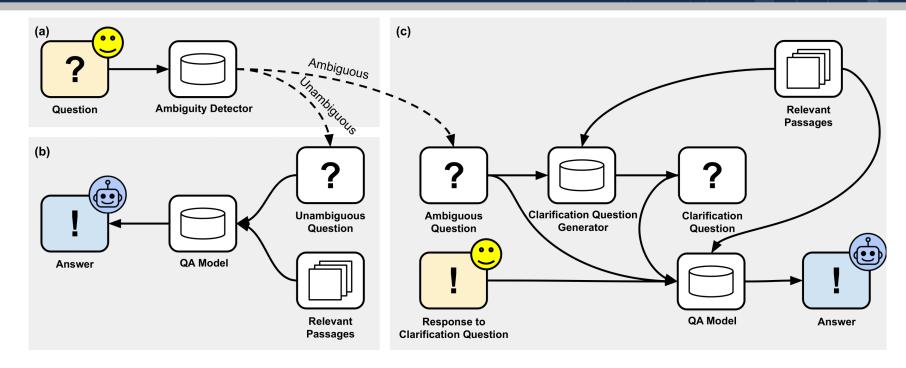
Asked 200 mturkers for preference

Human Preference Test

CQ	Split	DQ
0.59	0.08	0.33

- Our proposed method CQ (59%) is preferred over DQ (33%).
- The prominent reasons for choice was its ease of use, conciseness, interactivity, and ability to provide clear guidance.
- As the number of option becomes larger, the preference rate of CQ increased

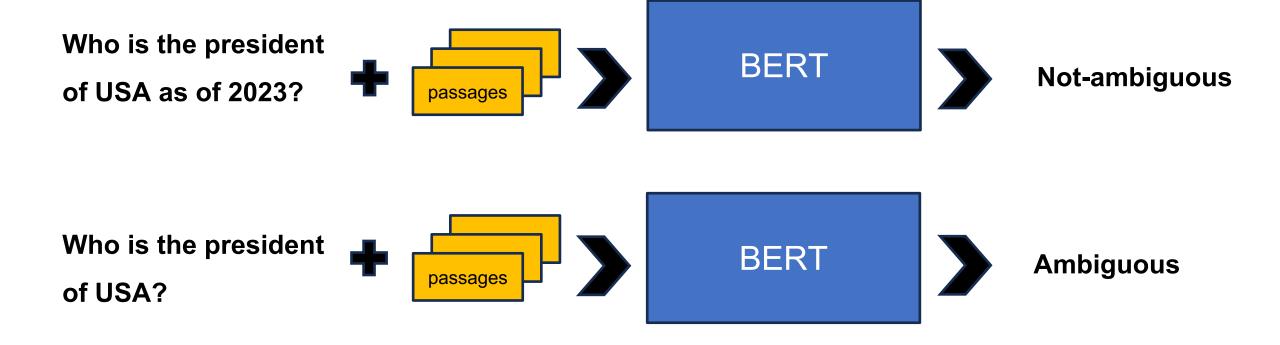
Task composition



- Ambiguity Detection: Given a question q, classify whether q is ambiguous or not (binary classification)
- Clarification Questions Generation: Given AQ and relevant passages, generate a CQ
- Clarification-based QA: Given AQ, relevant passages, and a CQ, generate a unique answer for each option

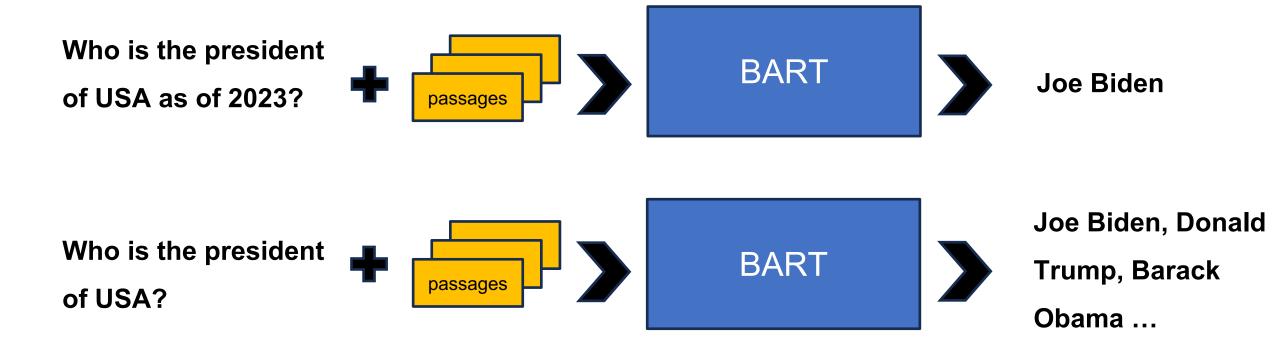
Task 1: Ambiguity Detection

Direct Classification using BERT



Task 1: Ambiguity Detection

Generation-based classification using BART



Task 1: Ambiguity Detection

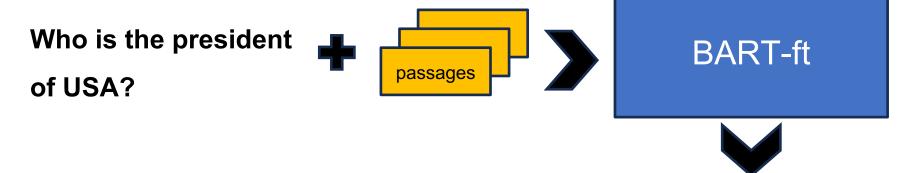
Input in addition to AQ	Acc.	Pre.	Rec.	F1
No Answers for AQ	63.9	61.9	60.7	61.3
Predicted Answers for AQ	56.5	59.7	24.1	34.3

• Ambiguity Detection: Given a question q, classify whether q is ambiguous or not (binary classification)

• Direct Classification (No Answers for AQ) shows higher F1 compared to Generation-based Classification (Predicted Answers for AQ) because average answers generated AQ is 1.24, resulting in low recall.

Task 2: Clarification Questions Generation

CQ generation by BART



Model generated CQ: In which year: 2023, 2019, 2015?

Automatic metrics (BLEU, EM, BERTSCORE ...)

Gold CQ: In which period: 2021-present, 2017-2021, 2009-2017?

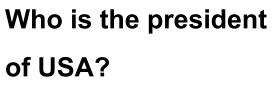
Task 2: Clarification Questions Generation

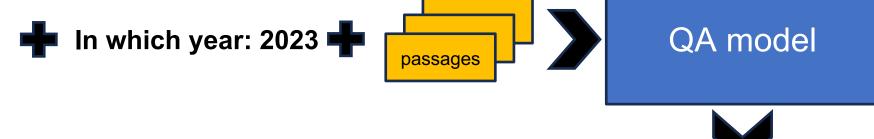
T 11111 10 100	CQ		Category		Options			
Input in addition to AQ and RPs	BLEU-4	BERTSCORE	EM	BLEU-1	Pre.	Rec.	F1	Avg. #
No Answers for AQ	7.9	88.9	20.2	47.3	37.4	18.2	24.5	2.0
Predicted Answers for AQ	7.9	88.9	22.8	44.0	36.9	19.0	25.1	2.0
Ground Truth Answers for AQ	15.4	89.6	25.2	46.9	34.3	34.4	34.3	3.7

Clarification Questions Generation: Given AQ and relevant passages, generate a CQ

 Evaluating generated CQs against gold CQs using automatic metrics can not capture semantic similarity.

Clarification-based QA







Evaluation using Precision, Recall, F1



Gold answer: Joe Biden

		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	

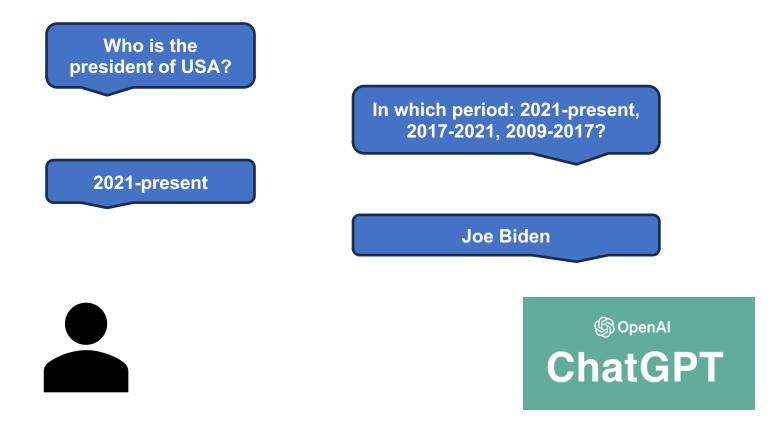
 Clarification-based QA: Given AQ, relevant passages, and a CQ, generate a unique answer for each option

 The result shows insufficient performance across different settings because the QA model produce "Same Answer" for the different questions.

Reader Model	Pre.	Rec.	F1	Acc.
CQ finetuned BART	58.0	53.8	55.8	35.8
InstructGPT	7.4	60.0	13.1	43.2

 Clarification-based QA: Given AQ, relevant passages, and a CQ, generate a unique answer for each option

Result using LLM (InstructGPT) as a reader model still shows insufficient performance



We also test the conversational setting using ChatGPT.

ChatGPT	Pre.	Rec.	F1	Accuracy
Zero-shot	8.0	64.5	14.3	50.8
Four-shot	11.3	64.0	19.2	49.9

 Clarification-based QA: Given AQ, relevant passages, and a CQ, generate a unique answer for each option

Result using ChatGPT with conversational setting, still shows insufficient performance

Contributions

Contributions

- We propose to use CQs as a practical means to handle AQs in Open-Domain QA.
- We present CAMBIGNQ, a dataset to support CQ-based handling of AQs in Open-Domain
 QA. It was built efficiently by leveraging a well-curated resource, AMBIGNQ, as well as the
 power of InstructGPT and human annotators.
- We define a pipeline of tasks and appropriate evaluation metrics for handling AQs in Open-Domain QA.

