Decision-Extraction-Generation:
A Unified Framework to Real-world Conversational Reading Comprehension

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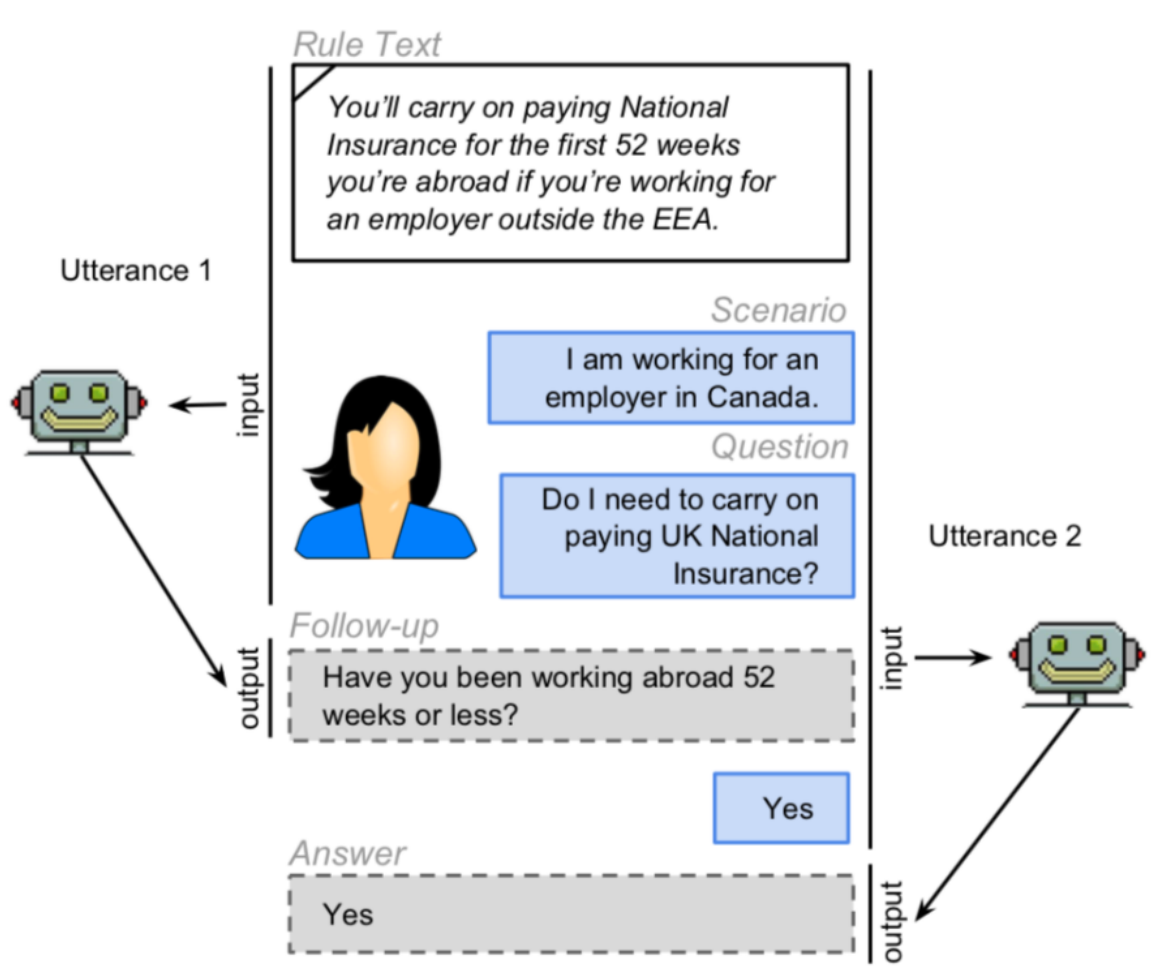
Abstract

We address the challenge of real-world conversational reading comprehension in three steps: 1) **Decision Making**: to decide if current information is enough to infer the answer; 2) **Evidence Extraction**: to extract evidence for generating follow-up question if more information is required from the end-user; 3) **Follow-up Question Generation**: to generate a follow-up question with the supporting rule text.

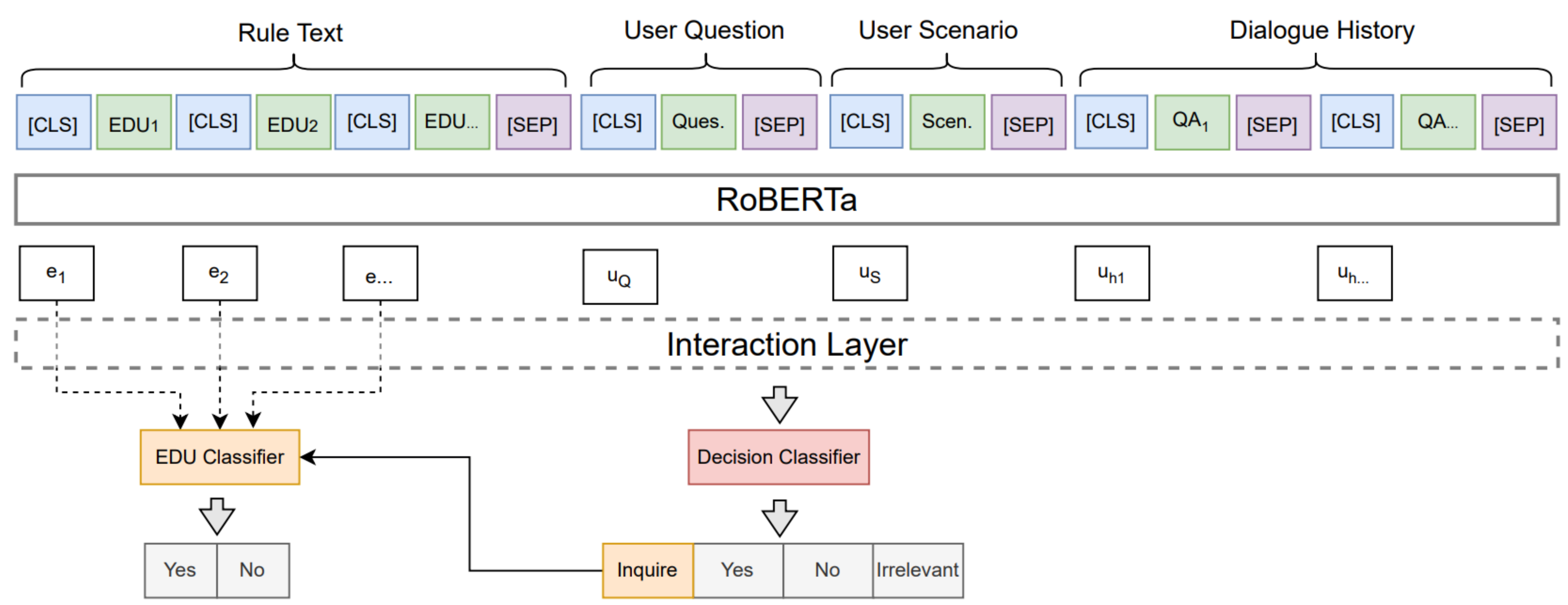
Introduction

Most work in conversational question answering focuses on question answering problems where the answer is directly expressed in the text to read. However, many real-world question answering problems require the reading of text not because it contains the literal answer, but because it contains a recipe to derive an answer together with the reader's background knowledge.

In ShARC, the goal is to answer questions by possibly asking follow-up questions first. They assume that the question is often underspecified, in the sense that the question does not provide enough information to be answered directly. It requires the model to use the supporting rule text to infer what needs to be asked in order to determine the final answer.



STEP 1 - Decision Making

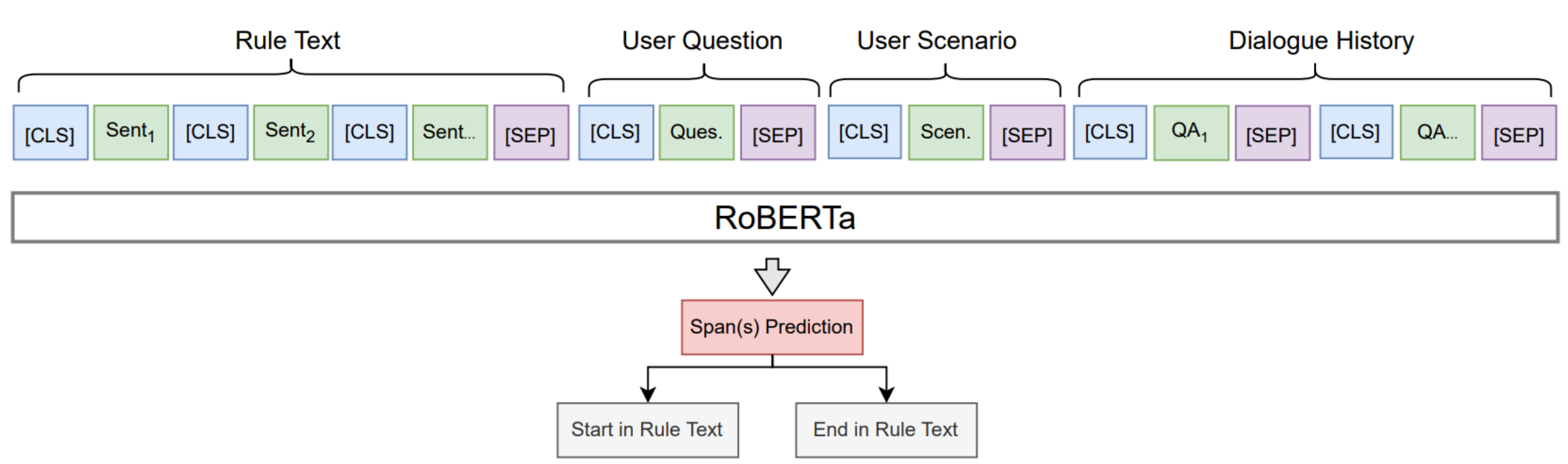


In this step, we first segment the rule text into several elementary discourse units (EDUs) as conditions using an existing technique. The goal is to understand the logical structure of the rule text and parse it into individual conditions for the ease of follow-up question generation. Ideally, each segmented unit should contain at most one condition.

Taking the segmented conditions, user question, user scenario, and dialog history as inputs, our model reasons out the decision among "Yes", "No", "Irrelevant" and "Inquire". If the decision is "Inquire", the model predicts each EDU if it needs to be clarified with the user by asking a follow-up question in Step 3 or turns to Step 2 to extract evidence for generating a follow-up question.

STEP 2 - Evidence Extraction

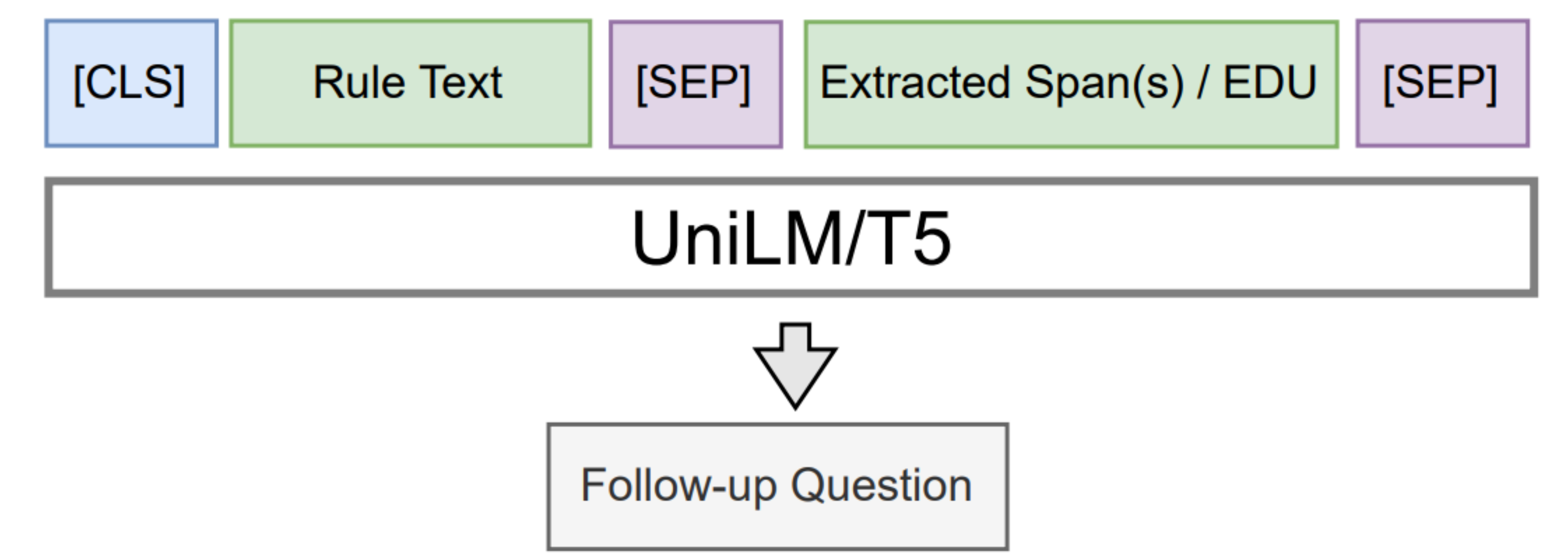
In Step 2, we have **three** methods to extract the evidence for follow-up question generation.



We split the rule text into sentences and concatenate the rule sentences and user-provided information into a sequence. Then we use RoBERTa to encode them to output the representations.
1. **EDU Selection:** We select the predicted EDU in Step 1 as the evidence for generating follow-up question;
2. **Single span extraction**: We predict the start and end position of a single span within the rule text.
3. **Multiple span extraction:** We select the top 3 predicted spans with no overlapping and connate them for next step when testing.

After extracting the evidence, the model moves forward to Step 3.

STEP 3 - Follow-up Question Generation



In Step 3, our model takes the rule text and extracted evidence i.e. span or a condition as input and rephrase it to generate a follow-up question.

Experimental Result

Model	Macro Acc	Micro Acc
RoBERTa CLS	76.0	70.0
+ 2 Transformer Layer	77.8	73.3
+ 4 Transformer Layer	75.2	68.9
+ 2 Transformer Layer & Self Attention	78.2	73.6
Discern	78.3	74.0

Table 1: Performance on the step of decision making.

Method	EM (Acc)	F1
EDU Classifier	76.3	-
Span Extraction	50.1	75.0

Table 2: Performance on the step of evidence extraction.

Evidence	Model	BLEU-1	BLEU-2	BLEU-3	BLEU-4
EDU	UniLM	-	-	-	-
	T5	-	-	-	-
Single Span	UniLM	65.7	59.4	55.4	52.4
	T5	68.7	61.3	59.2	56.3
Multiple Spans	UniLM	55.1	52.3	49.2	47.1
	T5	64.1	58.3	55.2	53.3

Table 3: Performance on the step of follow-up question generation.

Reference

Saeidi et al. Interpretation of natural language rules in conversational machine reading. EMNLP 2018.
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