



# Explicit Memory Tracker with Coarse-to-Fine Reasoning for Conversational Machine Reading

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Code & Models: [https://github.com/Yifan-Gao/explicit\\_memory\\_tracker](https://github.com/Yifan-Gao/explicit_memory_tracker)

# Machine Comprehension

SQuAD: 100,000+ Questions for Machine Comprehension of Text (Rajpurkar et al., 2016)

The current Chief Executive is **Carrie Lam**, who was selected on 26 March 2017, appointed by the Central People's Government with the State Council Decree signed by Premier Li Keqiang, on 11 April 2017 and took office on 1 July 2017.

✓ Literal Answer



Q: Who is the chief executive of Hong Kong?

A: Carrie Lam



# Conversational Question Answering

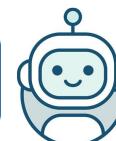
CoQA: A Conversational Question Answering Challenge (Reddy et al., 2018)

Incumbent **Democratic** President Bill Clinton was ineligible to serve a **third term** due to **term limitations** in the 22nd Amendment of the Constitution, and Vice President Gore was able to secure the Democratic nomination with relative ease.

- ✓ Literal Answer
- ✓ Dialog Understanding



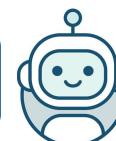
Q: What political party is Clinton a member of?



A: **Democratic**



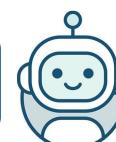
Q: What was he ineligible to serve?



A: **third term**



Q: Why?



A: **term limitations**

# However...

## Interpreting Natural Language Rules

The text to read may not contains the literal answer, but it contains a **recipe** to derive it.

You'll carry on paying National Insurance for the first 52 weeks you're abroad if you're working for an employer outside the EEA.



Q: I am working for an employer in Canada. Do I need to carry on paying UK National Insurance?

???



# Background

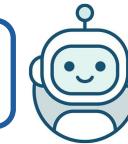
## Interpreting Natural Language Rules

You'll carry on paying National Insurance **for the first 52 weeks you're abroad** if you're working for an employer outside the EEA.



Q: I am working for an employer in Canada. Do I need to carry on paying UK National Insurance?

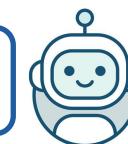
- ✓ Non-literal Answer
- ✓ Dialog Understanding
- ✓ Proactive Interaction



A: Have you been working abroad 52 weeks or less?



Yes, I have.



Yes, you need to carry on paying that.

# ShARC: Shaping Answers with Rules through Conversation

(Saeidi et al., 2018)

- ❖ A user post her scenario and asks an initial question about her final pay
- ❖ Without knowing the rule text, the initial question is usually underspecified
- ❖ A machine need to read the relevant rule text, and ask a series of clarification questions until it can conclude with a certain answer

Rule Text	## Taking more leave than the entitlement If a worker has <u>taken more leave than they're entitled to</u> , their employer must not take money from their final pay unless it's been <u>agreed beforehand</u> in writing. The rules in this situation should be outlined in the employment contract, company handbook or intranet site.
User Scenario	I have questions regarding my employer ...
Initial Question	Can my employer take money from my final pay?
Turn 1	 Decision: Yes No Irrelevant Inquire Did you take more leave than they're entitled to? 
	Yes
Turn 2	 Decision: Yes No Irrelevant Inquire Did you agree to it beforehand? 
	Yes
Turn 3	 Decision: Yes No Irrelevant Inquire Yes

# ShARC: Shaping Answers with Rules through Conversation

## Task Definition

Input  $x = (q, h, r, s)$

- ❖  $r$ : rule text
- ❖  $s$ : scenario
- ❖  $q$ : underspecified question
- ❖  $h$ : dialog history (QA1, QA2, ...)

Output (two subtasks):

- ❖ Make a decision  $y \in \{\text{Yes}, \text{No}, \text{Irrelevant}, \text{Inquire}\}$
- ❖ If Inquire, ask a follow-up question

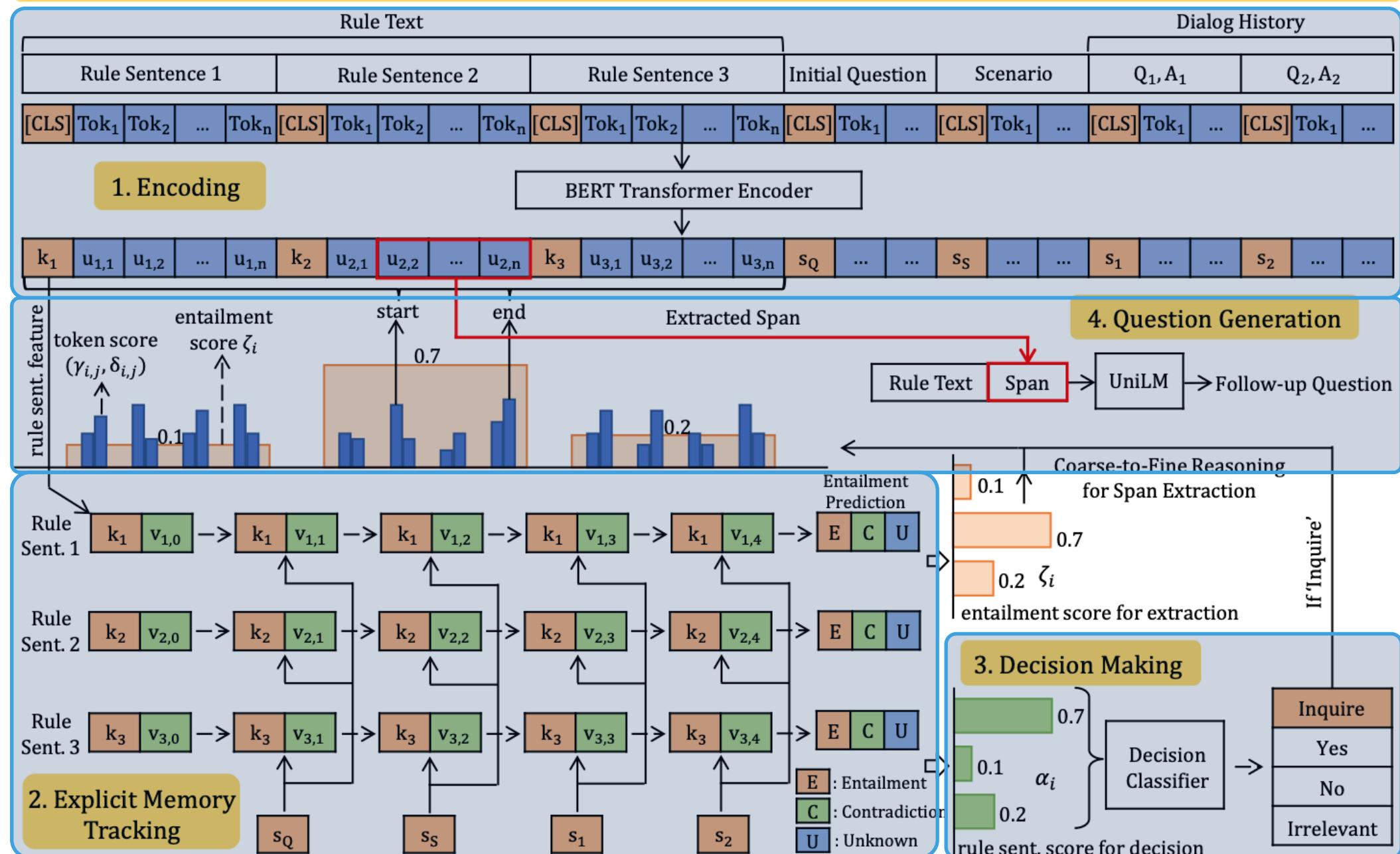
Rule Text	## Taking more leave than the entitlement If a worker has <u>taken more leave than they're entitled to</u> , their employer must not take money from their final pay unless it's been <u>agreed beforehand</u> in writing. The rules in this situation should be outlined in the employment contract, company handbook or intranet site.
User Scenario	I have questions regarding my employer ... 
Initial Question	Can my employer take money from my final pay? 
Turn 1	Decision: Yes   No   Irrelevant   Inquire  Did you take more leave than they're entitled to?  Yes
Turn 2	Decision: Yes   No   Irrelevant   Inquire  Did you agree to it beforehand?  Yes
Turn 3	Decision: Yes   No   Irrelevant   Inquire  Yes

# Proposed Solution

## Contributions

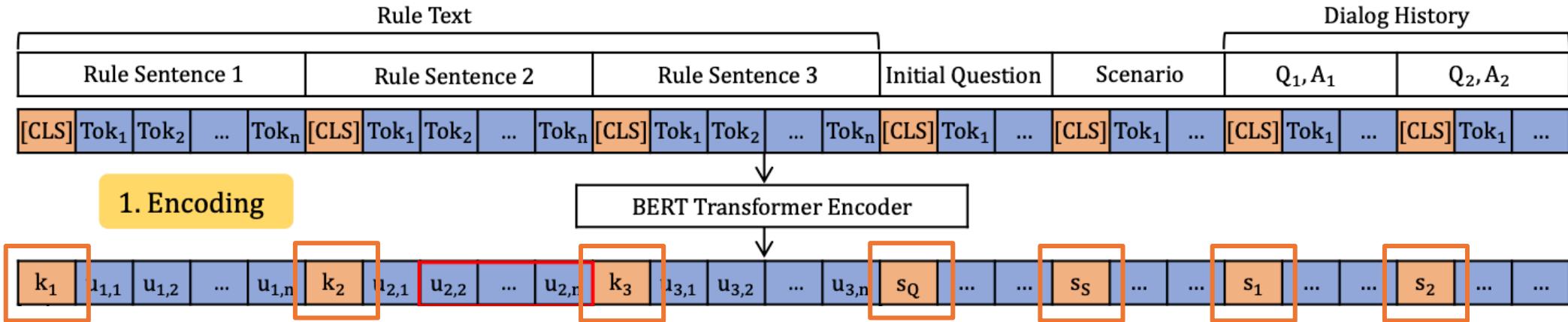
- ❖ **Explicit Memory Tracker (EMT)**
  - Explicitly track whether conditions listed in the rule text have been fulfilled or not
- ❖ **Coarse-to-fine (C2F) Reasoning**
  - A coarse-to-fine approach to reason out which part of the rule text is underspecified, and ask a question accordingly
- ❖ Our proposed solution achieves new state-of-the-art results on the ShARC benchmark

Overall Process: 1. Encoding —→ 2. Explicit Memory Tracking —→ 3. Decision Making —→ 4. Question Generation



# Proposed Solution

## Encoding



1. Parse the rule text into multiple rule sentences according to rules
2. Insert [CLS] token at the start of each rule sentence, initial question, scenario, and question-answer pairs in the dialog history
3. Concatenate all information and feed to BERT for encoding
4. [CLS] symbol is treated as the feature representation of the sentence that follows it

# Proposed Solution

## Explicit Memory Tracking

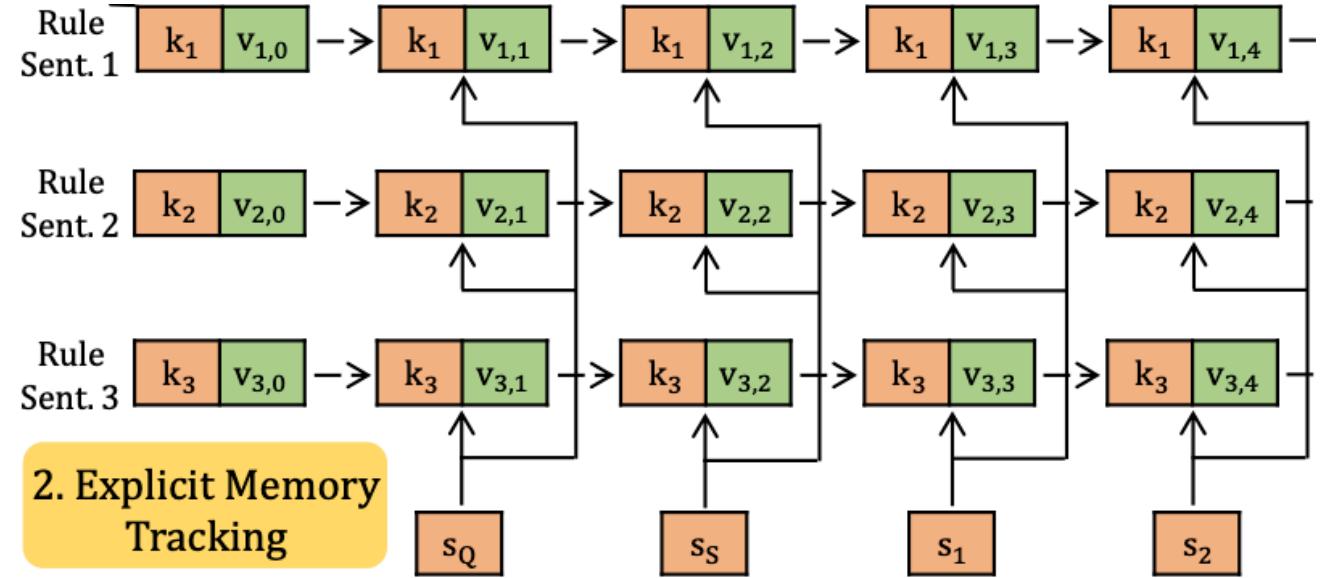
Rule sentences  $k_1, k_2, \dots, k_M$



Find Implications

User provided information:

- ❖ Initial question  $s_Q$
- ❖ Scenario  $s_S$
- ❖ Dialog history  $s_1, \dots, s_P$



- ❖ We propose Explicit Memory Tracker (EMT), a gated recurrent memory-augmented neural network
- ❖ EMT explicitly **tracks** the states of rule sentences by sequentially reading the user provided information

# Proposed Solution

## Explicit Memory Tracking

EMT assigns a state  $\mathbf{v}_i$  to each key  $\mathbf{k}_i$ , and sequentially reads user information

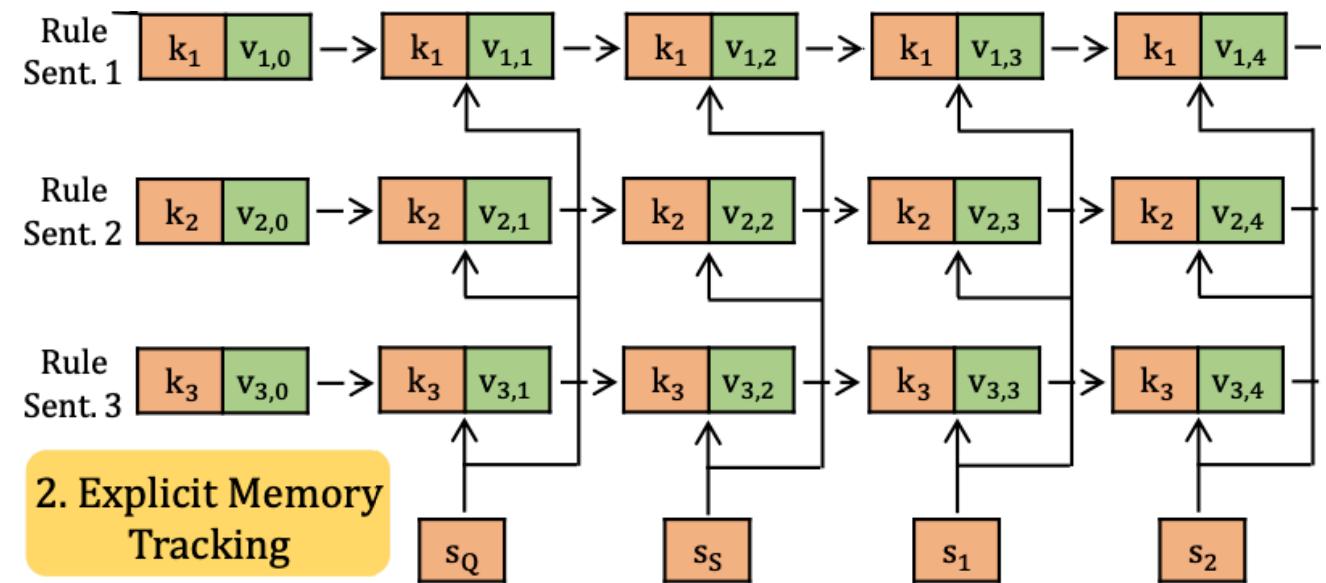
At time step  $t$ :

$$\tilde{\mathbf{v}}_{i,t} = \text{ReLU}(\mathbf{W}_k \mathbf{k}_i + \mathbf{W}_v \mathbf{v}_{i,t} + \mathbf{W}_s \mathbf{s}_t),$$

$$g_i = \sigma(\mathbf{s}_t^\top \mathbf{k}_i + \mathbf{s}_t^\top \tilde{\mathbf{v}}_{i,t}) \in [0, 1],$$

---

$$\mathbf{v}_{i,t} = \mathbf{v}_{i,t} + g_i \odot \tilde{\mathbf{v}}_{i,t} \in \mathbb{R}^d, \mathbf{v}_{i,t} = \frac{\mathbf{v}_{i,t}}{\|\mathbf{v}_{i,t}\|}$$



Keys and final states of rule sentences are denoted as  $(\mathbf{k}_1, \mathbf{v}_1), \dots, (\mathbf{k}_M, \mathbf{v}_M)$

- ❖ Decision Making Module
- ❖ Question Generation Module

# Proposed Solution

## Decision Making

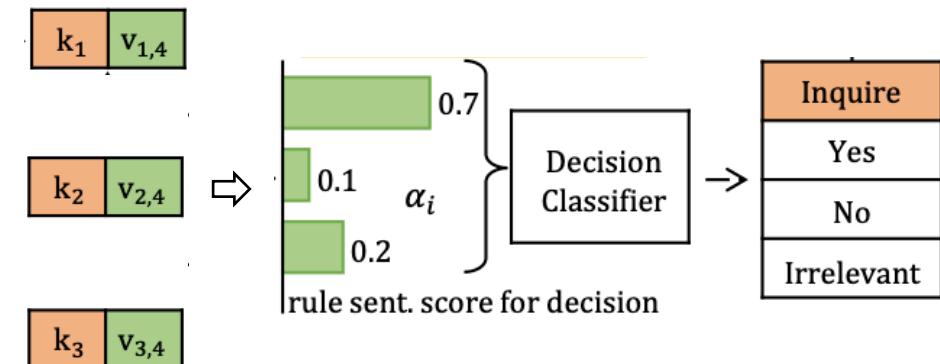
Based on the most up-to-date key-value states of rule sentences  $(\mathbf{k}_1, \mathbf{v}_1), \dots, (\mathbf{k}_M, \mathbf{v}_M)$ , EMT makes a decision among *Yes, No, Irrelevant, Inquire*

$$\alpha_i = \mathbf{w}_\alpha^\top [\mathbf{k}_i; \mathbf{v}_i] + b_\alpha \in \mathbb{R}^1$$

$$\tilde{\alpha}_i = \text{softmax}(\alpha)_i \in [0, 1]$$

$$\mathbf{c} = \sum_i \tilde{\alpha}_i [\mathbf{k}_i; \mathbf{v}_i] \in \mathbb{R}^d$$

$$\mathbf{z} = \mathbf{W}_z \mathbf{c} + \mathbf{b}_z \in \mathbb{R}^4$$



The decision making module is trained with the following cross entropy loss:

$$\mathcal{L}_{\text{dec}} = -\log \text{softmax}(\mathbf{z})_l$$

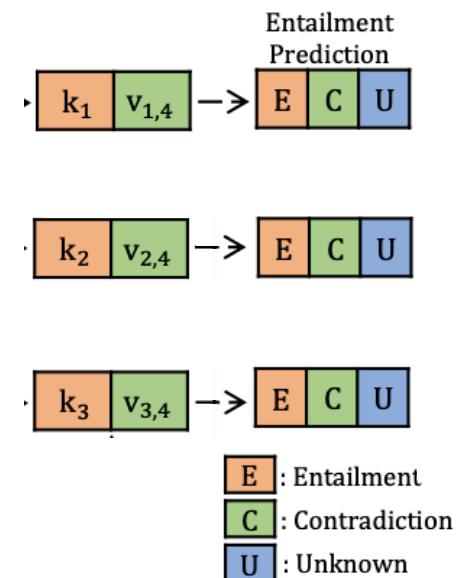
# Proposed Solution

## Subtask: Entailment State Prediction

- ❖ Explicitly track whether a condition listed in the rule has already been satisfied or not
- ❖ The possible entailment labels are:
  - **Entailment (E)**
  - **Contradiction (C)**
  - **Unknown (U)**

$$\mathbf{e}_i = \mathbf{W}_e[\mathbf{k}_i; \mathbf{v}_i] + \mathbf{b}_e \in \mathbb{R}^3$$

$$\mathcal{L}_{\text{entail}} = -\frac{1}{M} \sum_{i=1}^M \log \text{softmax}(\mathbf{e}_i)_r$$



# Proposed Solution

## Follow-up Question Generation

When the decision is ‘Inquire’, a follow-up question is required for further clarification.

We adopt a two-step approach:

1. Extract a span inside the rule text which contains the underspecified user information
2. Rephrase the extracted span into a follow-up question

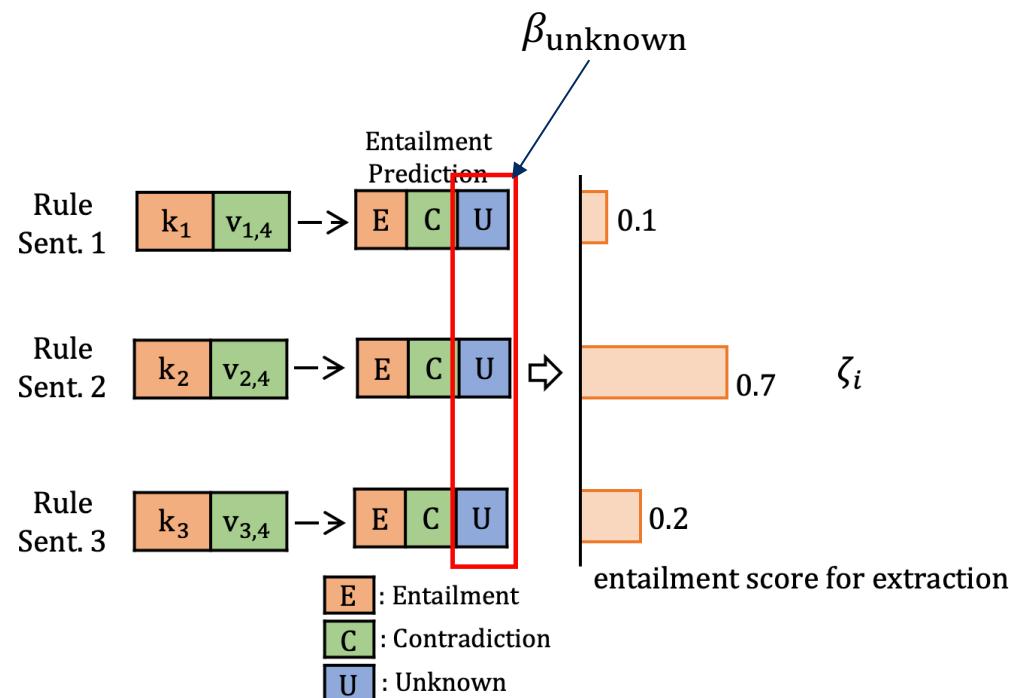
# Proposed Solution

## Follow-up Question Generation: Coarse-to-fine Underspecified Span Extraction

### 1. Coarse-to-fine Underspecified Span Extraction

- 1) Identify underspecified rule sentence  $\zeta_i$

$$\zeta_i = \text{softmax}(\beta_{\text{unknown}})_i \in [0, 1]$$

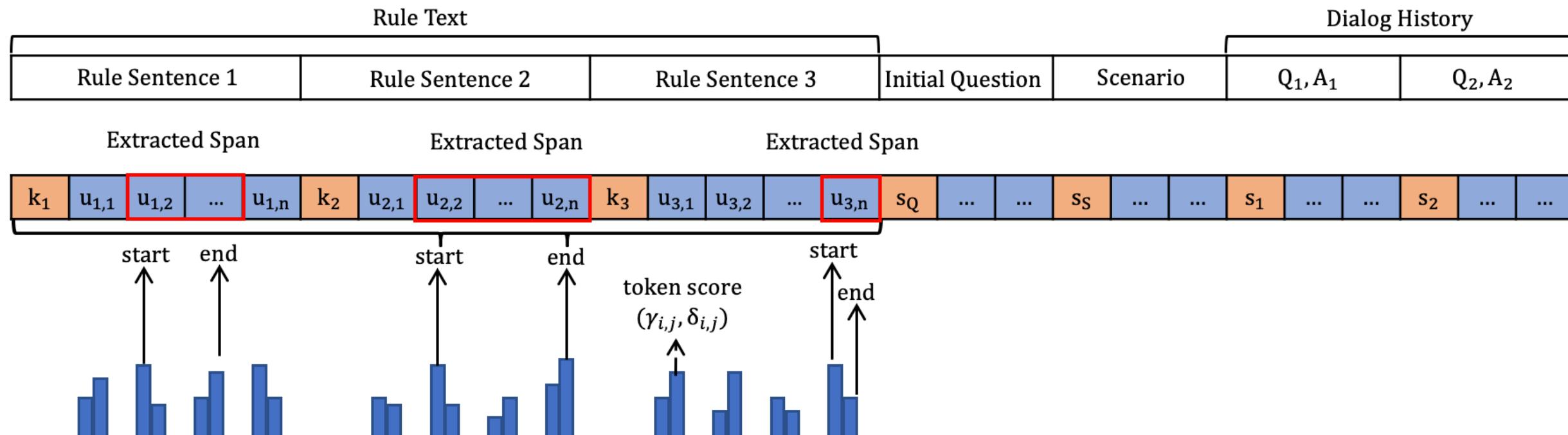


# Proposed Solution

## Follow-up Question Generation: Coarse-to-fine Underspecified Span Extraction

### 1. Coarse-to-fine Underspecified Span Extraction

- 1) Identify underspecified rule sentence  $\zeta_i$
- 2) Extract a span within each rule sentence  $(\gamma_{i,j}, \delta_{i,j})$

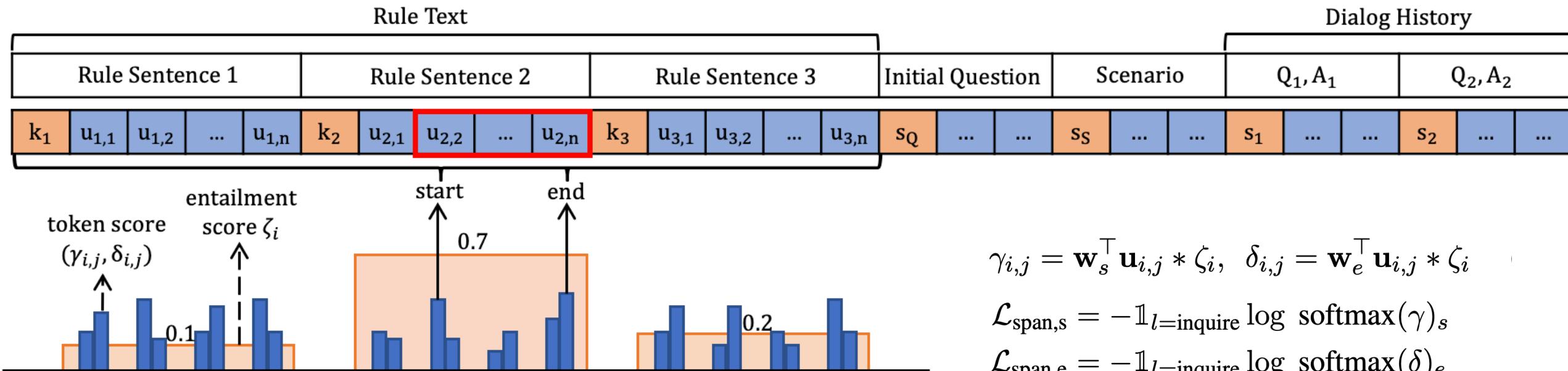


# Proposed Solution

## Follow-up Question Generation: Coarse-to-fine Underspecified Span Extraction

### 1. Coarse-to-fine Underspecified Span Extraction

- 1) Identify underspecified rule sentence  $\zeta_i$
- 2) Extract a span within each rule sentence  $(\gamma_{i,j}, \delta_{i,j})$
- 3) Select the span with the highest span score  $\zeta_i * (\gamma_{i,j}, \delta_{i,j})$

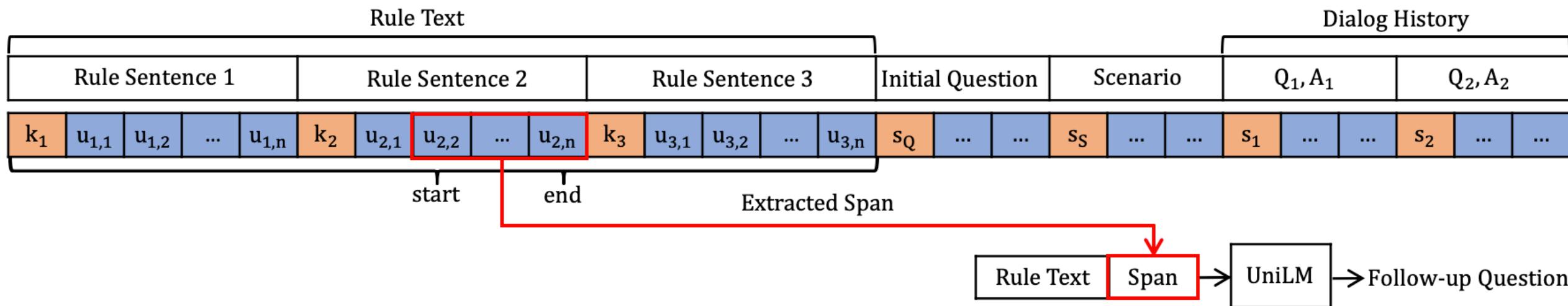


# Proposed Solution

## Follow-up Question Generation

### 2. Question Rephrasing

- 1) Finetune UniLM (Dong et al, 2019), a pretrained language model
- 2) [CLS] rule text [SEP] span [SEP]



## Proposed Solution

### Overall Loss for EMT

The overall loss is the sum of the decision loss, entailment prediction loss and span extraction loss:

$$\mathcal{L} = \mathcal{L}_{\text{dec}} + \lambda_1 \mathcal{L}_{\text{entail}} + \lambda_2 \mathcal{L}_{\text{span}}$$

# Experiments

## Experimental Setup

### ❖ Dataset:

- ShARC CMR dataset (Saeidi et al., 2020)
- Train/Dev/Test dataset sizes are 100k, 20k, 20k respectively.
- Test set is not public.
- Leaderboard: <https://sharc-dataset.s3-us-west-2.amazonaws.com/>

ShARC: End-to-end Task							
#	Model / Reference	Affiliation	Date	Micro Accuracy[%]	Macro Accuracy[%]	BLEU-1	BLEU-4
1	[Anonymous]	[Anonymous]	May 2020	73.2	78.3	64.0	49.1
2	EMT	Salesforce Research & CUHK	Nov 2019	69.4	74.8	60.9	46.0
3	EMT + entailment	Salesforce Research & CUHK	Mar 2020	69.1	74.6	63.9	49.5
4	[Anonymous]	[Anonymous]	Dec 2019	69.0	74.6	56.7	42.0
5	E3	University of Washington	Feb 2019	67.6	73.3	54.1	38.7
6	BiSon (single model)	NEC Laboratories Europe	Aug 2019	66.9	71.6	58.8	44.3

# Experiments

## Experimental Setup

### ❖ Dataset:

- ShARC CMR dataset (Saeidi et al. 2018)
- Train/Dev/Test dataset sizes are 21980/2270/8276.
- Test set is not public.
- Leaderboard: <https://sharc-data.github.io/leaderboard.html>

### ❖ Evaluation Metrics

- End-to-End Task
  - **Macro/Micro Accuracy** for the decision making task (Yes/No/Irrelevant/Inquire)
  - If both the ground truth decision and the predicted decision are *Inquire*, **BLEU** is used to evaluate the quality of the generated follow-up question  
(This evaluation metric makes the comparison unfair if two models have different *Inquire* predictions)

# Experiments

## Experimental Setup

### ❖ Dataset:

- ShARC CMR dataset (Saeidi et al. 2018)
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### ❖ Evaluation Metrics

- End-to-End Task
  - Macro/Micro Accuracy for the decision making task (Yes/No/Irrelevant/Inquire)
  - If both the ground truth decision and the predicted decision are *Inquire*, BLEU is used to evaluate the quality of the generated follow-up question
- Oracle Question Generation Task
  - We propose a new evaluation perspective.
  - We ask the models to generate follow-up questions *whenever* the ground truth decision is *Inquire*, and compute the BLEU score.

# Experiments

## Leaderboard Submission

Models	End-to-End Task (Leaderboard Performance)			
	Micro Acc.	Macro Acc.	BLEU1	BLEU4
Seq2Seq (Saeidi et al., 2018)	44.8	42.8	34.0	7.8
Pipeline (Saeidi et al., 2018)	61.9	68.9	54.4	34.4
BERTQA (Zhong and Zettlemoyer, 2019)	63.6	70.8	46.2	36.3
UrcaNet (Sharma et al., 2019)	65.1	71.2	60.5	46.1
BiSon (Lawrence et al., 2019)	66.9	71.6	58.8	44.3
E <sup>3</sup> (Zhong and Zettlemoyer, 2019)	67.6	73.3	54.1	38.7
EMT (our single model)	<b>69.1</b>	<b>74.6</b>	<b>63.9</b>	<b>49.5</b>

Table 1: Performance on the blind, held-out test set of ShARC end-to-end task.

# Experiments

## Class-wise Decision Prediction Accuracy

Models	Yes	No	Inquire	Irrelevant
BERTQA	61.2	61.0	62.6	96.4
E <sup>3</sup>	65.9	70.6	60.5	96.4
UrcaNet*	63.3	68.4	58.9	95.7
EMT	<b>70.5</b>	<b>73.2</b>	<b>70.8</b>	<b>98.6</b>

Table 2: Class-wise decision prediction accuracy on the development set (\*: reported in the paper).

# Experiments

## Oracle Question Generation Task

Models	Oracle Question Generation Task			
	Development Set		Cross Validation	
	BLEU1	BLEU4	BLEU1	BLEU4
E <sup>3</sup>	52.79±2.87	37.31±2.35	51.75	35.94
E <sup>3</sup> +UniLM	57.09±1.70	41.05±1.80	56.94	42.87
EMT	<b>62.32</b> ±1.62	<b>47.89</b> ±1.58	<b>64.48</b>	<b>52.40</b>

**Table 3:** Performance on Oracle Question Generation Task. We show both results on the development set and 10-fold cross validation. E<sup>3</sup>+UniLM replaces the editor of E<sup>3</sup> to our finetuned UniLM.

# Experiments

## Interpretability

E : Entailment

C : Contradiction

U : Unknown

$\beta_{\text{unknown}}$

Regulation Text A (parsed into six rule sentences: S1 ~ S6)		Entailment States		
		Turn 1	Turn 2	Turn 3
S1	Statutory Maternity Pay	U (99.99)	U (99.99)	U (99.99)
S2	To qualify for smp you must:	U (99.99)	U (99.99)	U (99.99)
S3	* earn on average at least £113 a week	U (99.93)	E (99.91)	E (99.67)
S4	* give the correct notice	U (99.97)	U (99.61)	C (99.81)
S5	* give proof you're pregnant	U (99.98)	U (99.75)	U (99.94)
S6	* have worked for your employer...	U (99.98)	U (99.70)	U (99.96)

Scenario: I've been old enough to get my pension. My wife just reached pension age last year. Neither of us have applied for it yet.

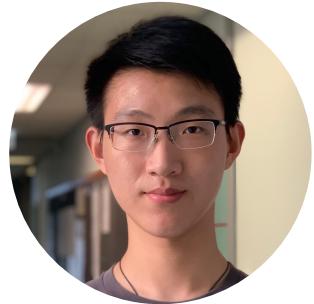
Initial Question: Do I qualify for SMP?

Decision:	Generated Question	Answer
Turn 1: Inquire	Do you earn on average at least £113 a week?	Yes
Turn 2: Inquire	Did you give the correct notice?	No
Turn 3:	No	

## Conclusion

- ❖ We propose a new approach called Explicit Memory Tracker (EMT) for conversational machine reading.
- ❖ EMT achieved a new state-of-the-art result on the ShARC CMR challenge.
- ❖ EMT also gains interpretability by showing the entailment-oriented reasoning process as the conversation flows.

# Thanks!



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**Michael R. Lyu**



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**Code & Models: [https://github.com/Yifan-Gao/explicit\\_memory\\_tracker](https://github.com/Yifan-Gao/explicit_memory_tracker)**

