e-QRAQ: A Multi-turn Reasoning Dataset and Simulator with Explanations

Clemens Rosenbaum, **Tian Gao**, Tim Klinger

Umass Amherst, IBM Research

2017 ICML Workshop on Human Interpretability in Machine Learning (WHI 2017) @ Sydney

Motivation

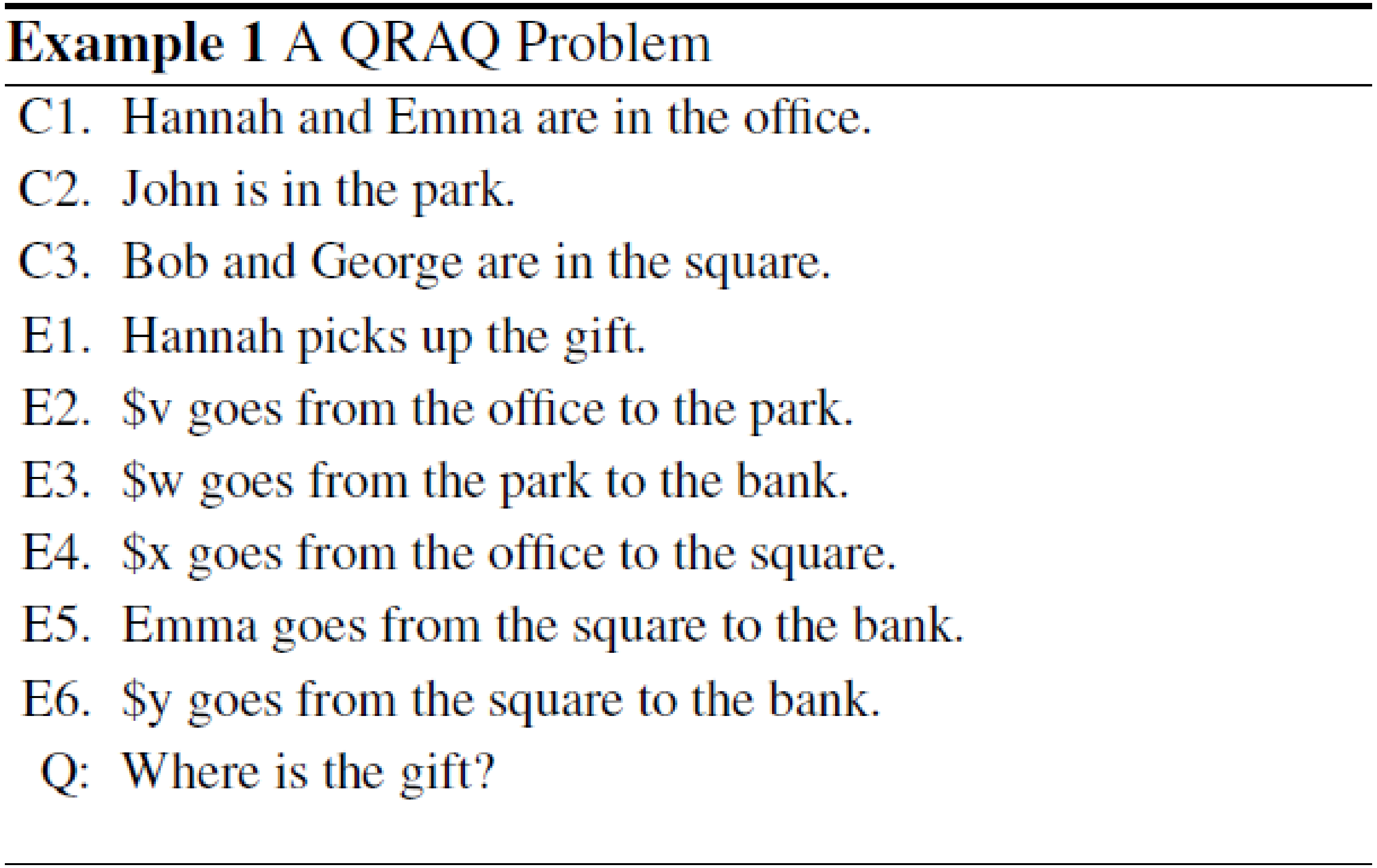
- Focus on explanation with natural language

- Lack of natural-language-based explanation
  - Vision dataset + NL explanation [Reed et al., 2016]

- Domain: Reasoning
  - No simple memorization

Query, Reason, and Answer Question (QRAQ) [Guo et al, ICLR 2017]

- A reasoning QA dataset, with ambiguity
- The interaction between the User and the Agent.
  - The User provides a short story set
  - semantically coherent but may contain hidden, sometimes ambiguous, entity references



Example 1 A QRAQ Problem

C1. Hannah and Emma are in the office.
C2. John is in the park.
C3. Bob and George are in the square.
E1. Hannah picks up the gift.
E2. $v goes from the office to the park.
E3. $w goes from the park to the bank.
E4. $x goes from the office to the square.
E5. Emma goes from the square to the bank.
E6. $y goes from the square to the bank.
Q: Where is the gift?

Overview of Main Contributions

- Extend previous QRAQ dataset to offer different explanation components ⇒ e-QRAQ
    - A simulator with natural language explanations/feedback for the QRAQ Dataset

- Some preliminary results using the explanation
    - using end-to-end memory networks (E2EMN)

e-QRAQ

- Supervised explanations require more effort to generate than labels
  - Dynamically generated detailed explanation, building on top of QRAQ
  - Using an underlying graph-based reasoner

- e-QRAQ offers three different kinds of explanation
  1. The set of relevant variables (what knowledge is required to solve the problem)
  2. The set of possible answers (what solutions are possible)
  3. Detailed explanations for provided answers in natural languages

e-QRAQ

- The context (C), events (E), and question (Q) in QRAQ

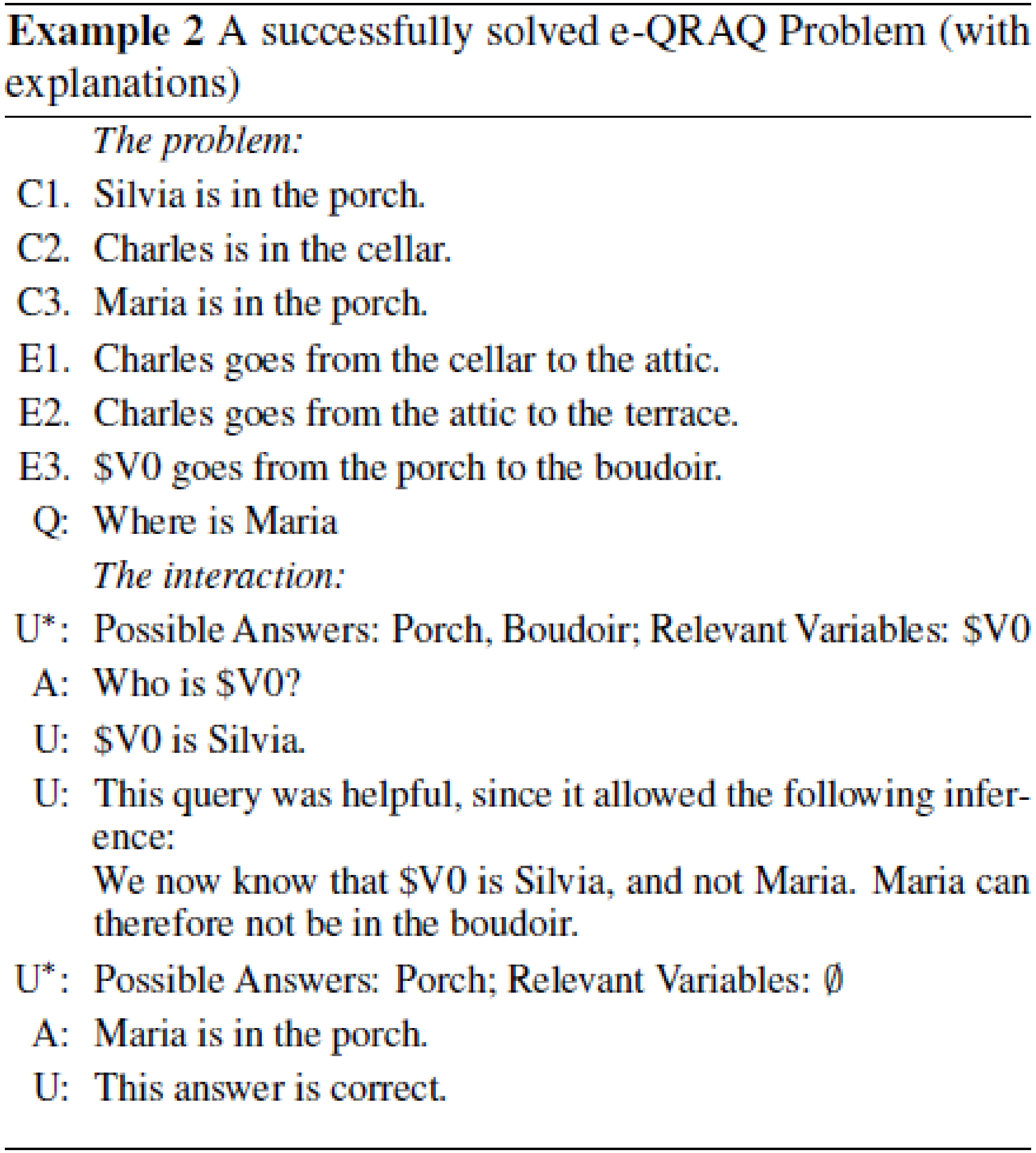
- Two New Components:
  - U indicates

    1) whether the Agent's response is correct or not

    2) a detailed description of <u>why</u>
  - U^* provides a full description of

    1) the set of relevant variables in the current state of the interaction

    2)the set of possible answers



Example 2 A successfully solved e-QRAQ Problem (with explanations)

The problem:

C1. Silvia is in the porch.

C2. Charles is in the cellar.

C3. Maria is in the porch.

E1. Charles goes from the cellar to the attic.

E2. Charles goes from the attic to the terrace.

E3. $V0 goes from the porch to the boudoir.

Q: Where is Maria

The interaction:

U*: Possible Answers: Porch, Boudoir; Relevant Variables: $V0

A: Who is $V0?

U: $V0 is Silvia.

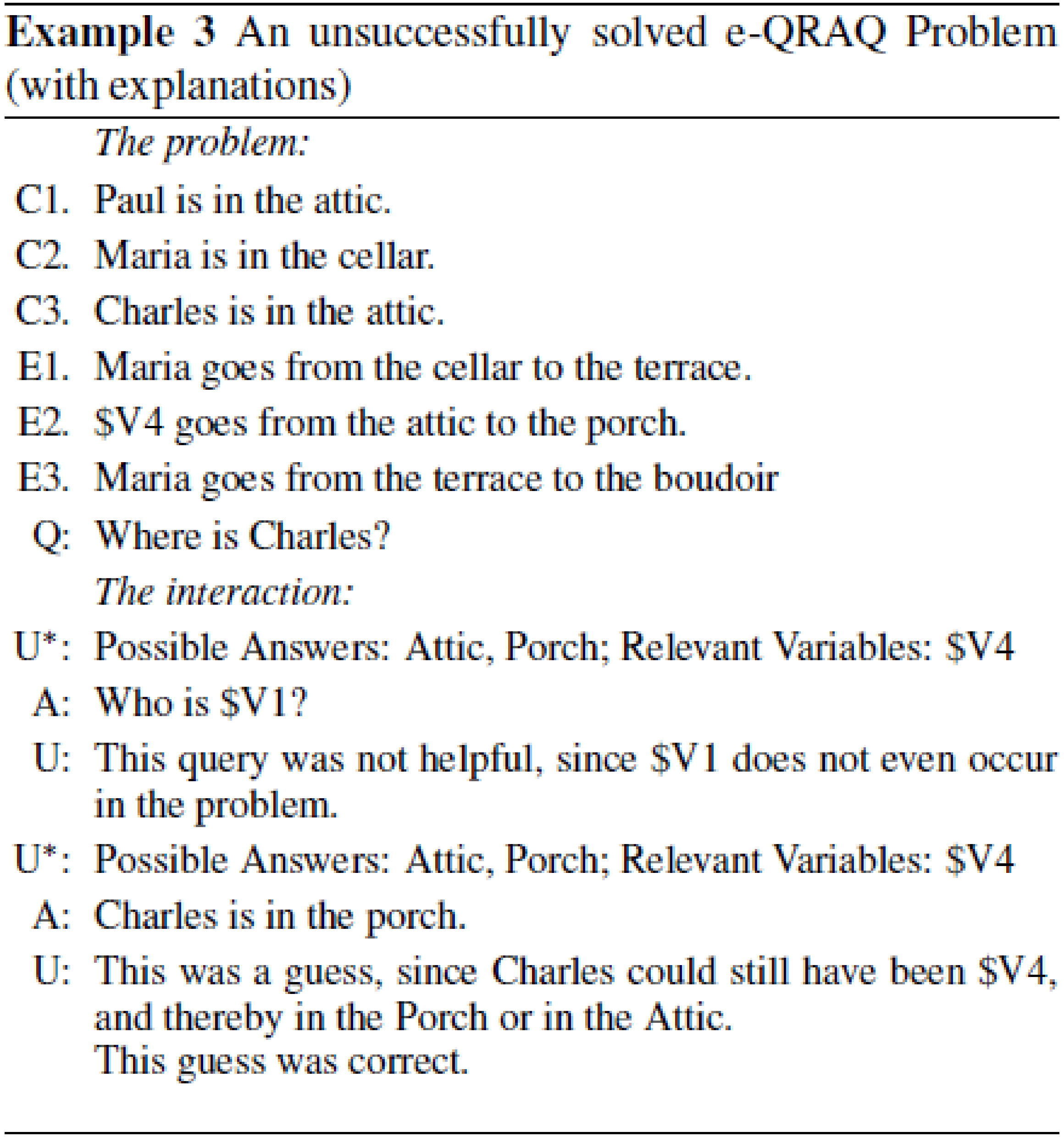
U: This query was helpful, since it allowed the following inference:
We now know that $V0 is Silvia, and not Maria. Maria can therefore not be in the boudoir.

U*: Possible Answers: Porch; Relevant Variables: ∅

A: Maria is in the porch.

U: This answer is correct.

Example



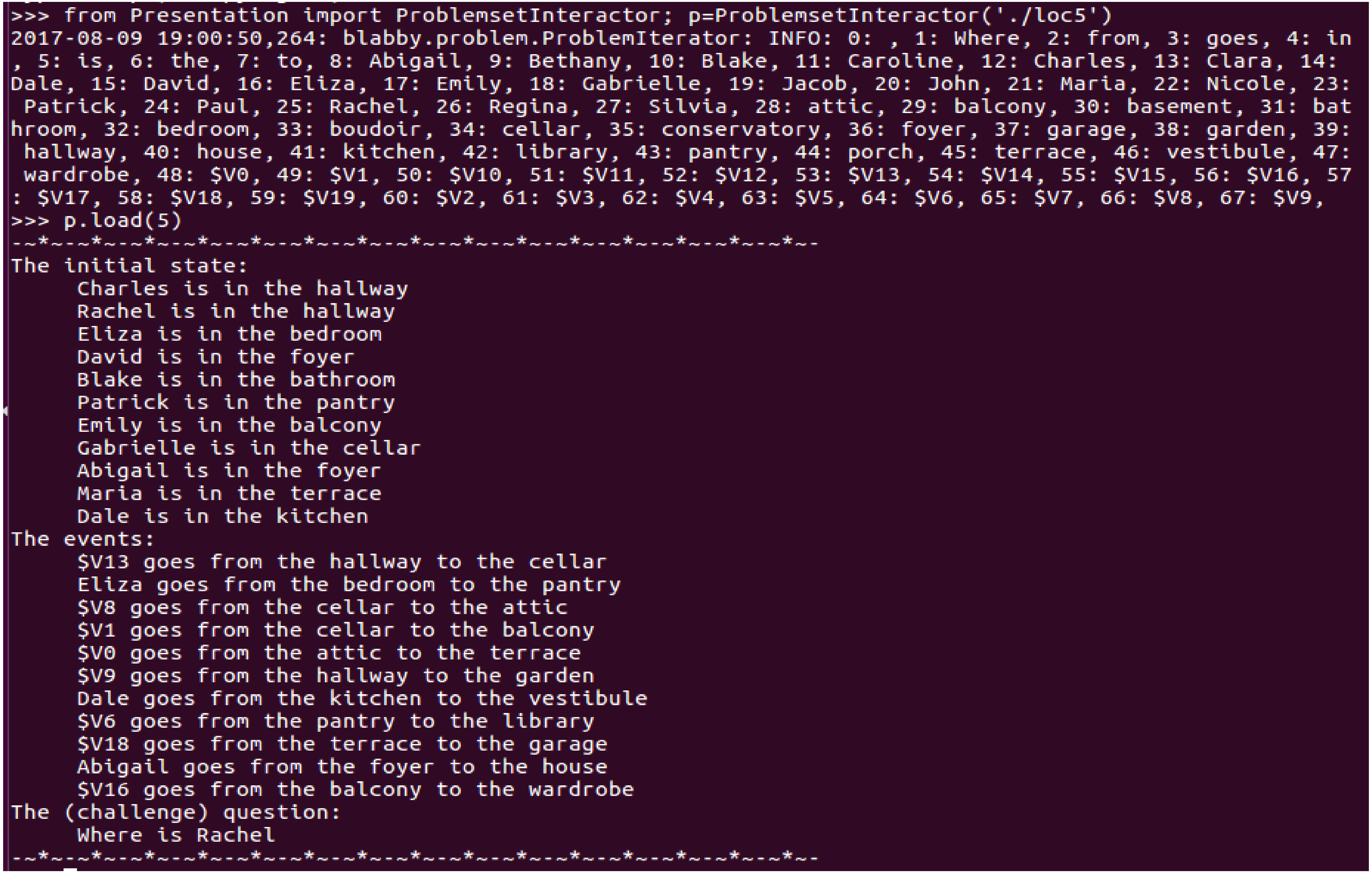
Example 3 An unsuccessfully solved e-QRAQ Problem (with explanations)

The problem:

C1. Paul is in the attic.
C2. Maria is in the cellar.
C3. Charles is in the attic.
E1. Maria goes from the cellar to the terrace.
E2. $V4 goes from the attic to the porch.
E3. Maria goes from the terrace to the boudoir
Q: Where is Charles?

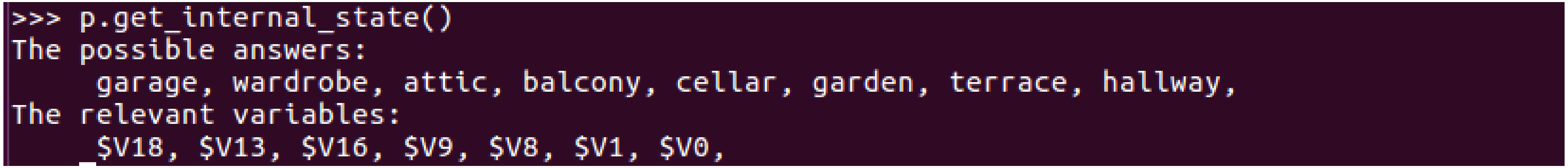
The interaction:

U*: Possible Answers: Attic, Porch; Relevant Variables: $V4
A: Who is $V1?
U: This query was not helpful, since $V1 does not even occur in the problem.
U*: Possible Answers: Attic, Porch; Relevant Variables: $V4
A: Charles is in the porch.
U: This was a guess, since Charles could still have been $V4, and thereby in the Porch or in the Attic.
This guess was correct.



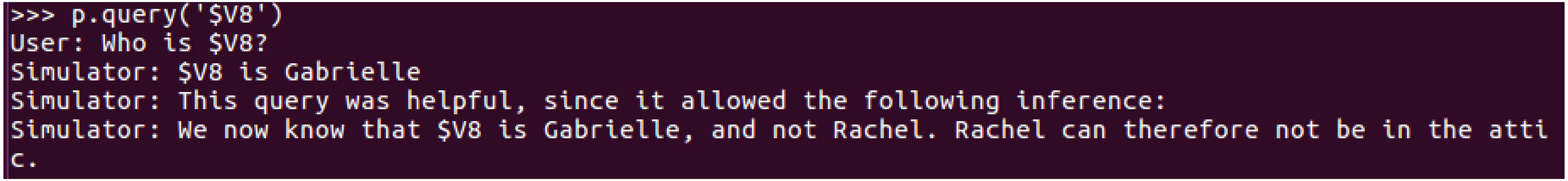
```
>>> from Presentation import ProblemsetInteractor; p=ProblemsetInteractor('./loc5')
2017-08-09 19:00:50,264: blabby.problem.ProblemIterator: INFO: 0:  , 1: Where, 2: from, 3: goes, 4: in
, 5: is, 6: the, 7: to, 8: Abigail, 9: Bethany, 10: Blake, 11: Caroline, 12: Charles, 13: Clara, 14:
Dale, 15: David, 16: Eliza, 17: Emily, 18: Gabrielle, 19: Jacob, 20: John, 21: Maria, 22: Nicole, 23:
 Patrick, 24: Paul, 25: Rachel, 26: Regina, 27: Silvia, 28: attic, 29: balcony, 30: basement, 31: bat
hroom, 32: bedroom, 33: boudoir, 34: cellar, 35: conservatory, 36: foyer, 37: garage, 38: garden, 39:
 hallway, 40: house, 41: kitchen, 42: library, 43: pantry, 44: porch, 45: terrace, 46: vestibule, 47:
 wardrobe, 48: $V0, 49: $V1, 50: $V10, 51: $V11, 52: $V12, 53: $V13, 54: $V14, 55: $V15, 56: $V16, 57
: $V17, 58: $V18, 59: $V19, 60: $V2, 61: $V3, 62: $V4, 63: $V5, 64: $V6, 65: $V7, 66: $V8, 67: $V9,
>>> p.load(5)
-~*~-~*~-~*~-~*~-~*~-~*~-~*~-~*~-~*~-~*~-~*~-~*~-~*~-~*~-~*~-
The initial state:
     Charles is in the hallway
     Rachel is in the hallway
     Eliza is in the bedroom
     David is in the foyer
     Blake is in the bathroom
     Patrick is in the pantry
     Emily is in the balcony
     Gabrielle is in the cellar
     Abigail is in the foyer
     Maria is in the terrace
     Dale is in the kitchen
The events:
     $V13 goes from the hallway to the cellar
     Eliza goes from the bedroom to the pantry
     $V8 goes from the cellar to the attic
     $V1 goes from the cellar to the balcony
     $V0 goes from the attic to the terrace
     $V9 goes from the hallway to the garden
     Dale goes from the kitchen to the vestibule
     $V6 goes from the pantry to the library
     $V18 goes from the terrace to the garage
     Abigail goes from the foyer to the house
     $V16 goes from the balcony to the wardrobe
The (challenge) question:
     Where is Rachel
-~*~-~*~-~*~-~*~-~*~-~*~-~*~-~*~-~*~-~*~-~*~-~*~-~*~-~*~-~*~-
```

U^*



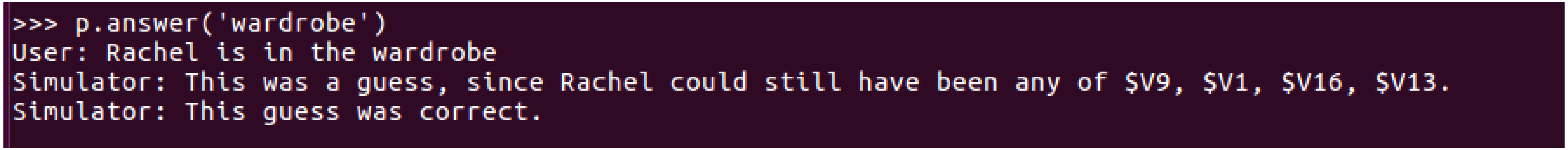
```
>>> p.get_internal_state()
The possible answers:
     garage, wardrobe, attic, balcony, cellar, garden, terrace, hallway,
The relevant variables:
     $V18, $V13, $V16, $V9, $V8, $V1, $V0,
```

U query



```
>>> p.query('$V8')
User: Who is $V8?
Simulator: $V8 is Gabrielle
Simulator: This query was helpful, since it allowed the following inference:
Simulator: We now know that $V8 is Gabrielle, and not Rachel. Rachel can therefore not be in the atti
c.
```

U answer

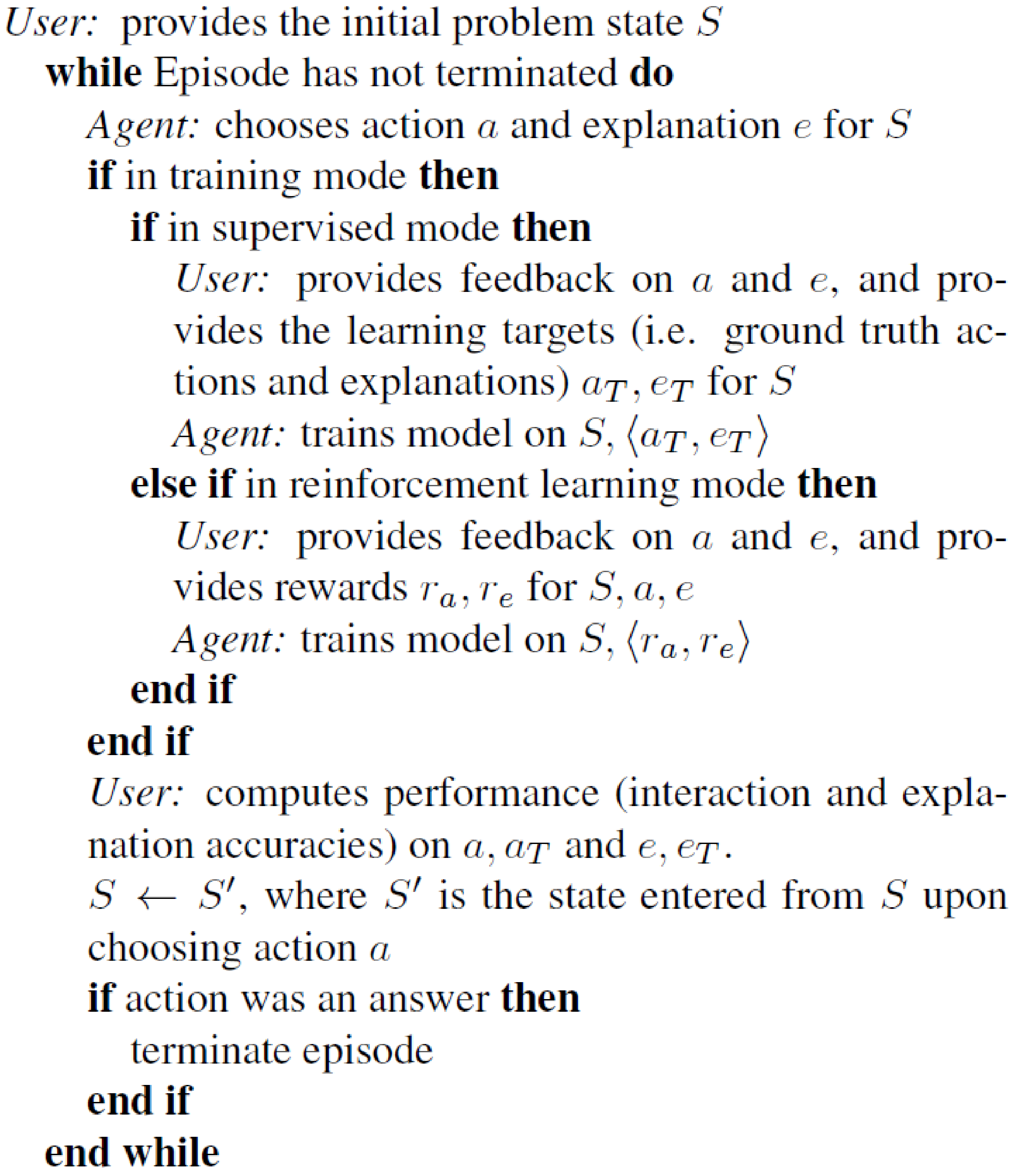


```
>>> p.answer('wardrobe')
User: Rachel is in the wardrobe
Simulator: This was a guess, since Rachel could still have been any of $V9, $V1, $V16, $V13.
Simulator: This guess was correct.
```

Interaction Flow

- For both training, testing
    - Supervised learning
    - Reinforcement learning

- Summary: The Simulator provides detailed feedback to any of the Agent’s actions



```
User: provides the initial problem state $S$
  while Episode has not terminated do
    Agent: chooses action $a$ and explanation $e$ for $S$
    if in training mode then
      if in supervised mode then
        User: provides feedback on $a$ and $e$, and provides the learning targets (i.e. ground truth actions and explanations) $a_T, e_T$ for $S$
        Agent: trains model on $S$, $\langle a_T, e_T \rangle$
      else if in reinforcement learning mode then
        User: provides feedback on $a$ and $e$, and provides rewards $r_a, r_e$ for $S, a, e$
        Agent: trains model on $S$, $\langle r_a, r_e \rangle$
      end if
    end if
    User: computes performance (interaction and explanation accuracies) on $a, a_T$ and $e, e_T$.
    $S \leftarrow S'$, where $S'$ is the state entered from $S$ upon choosing action $a$
    if action was an answer then
      terminate episode
    end if
  end while
```

Usage of e-QRAQ

- Can we learn to generate explanations?

- Can we learn to generate natural language explanations?

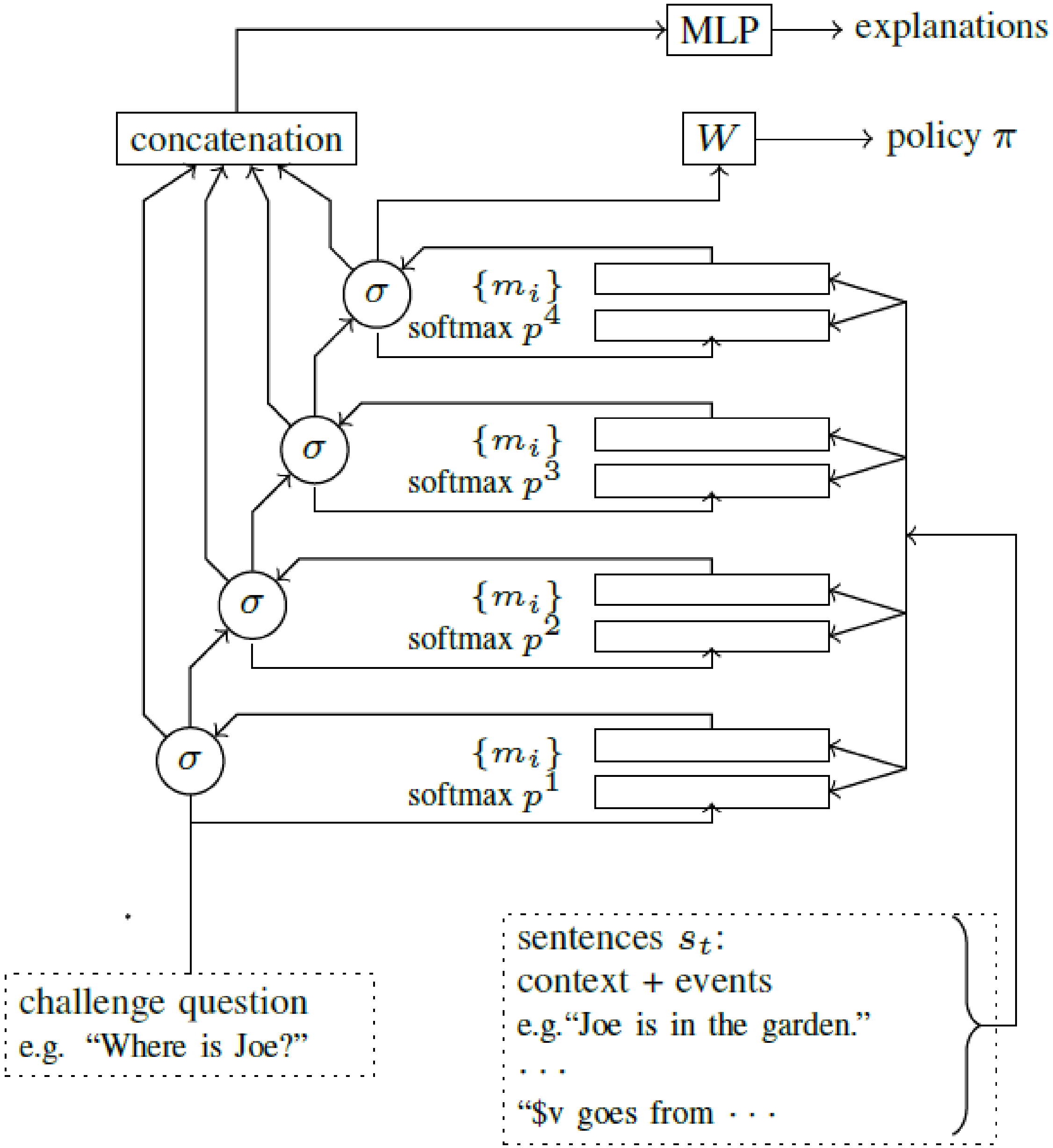
- Can explanation improve the accuracy, by acting as a regularization?

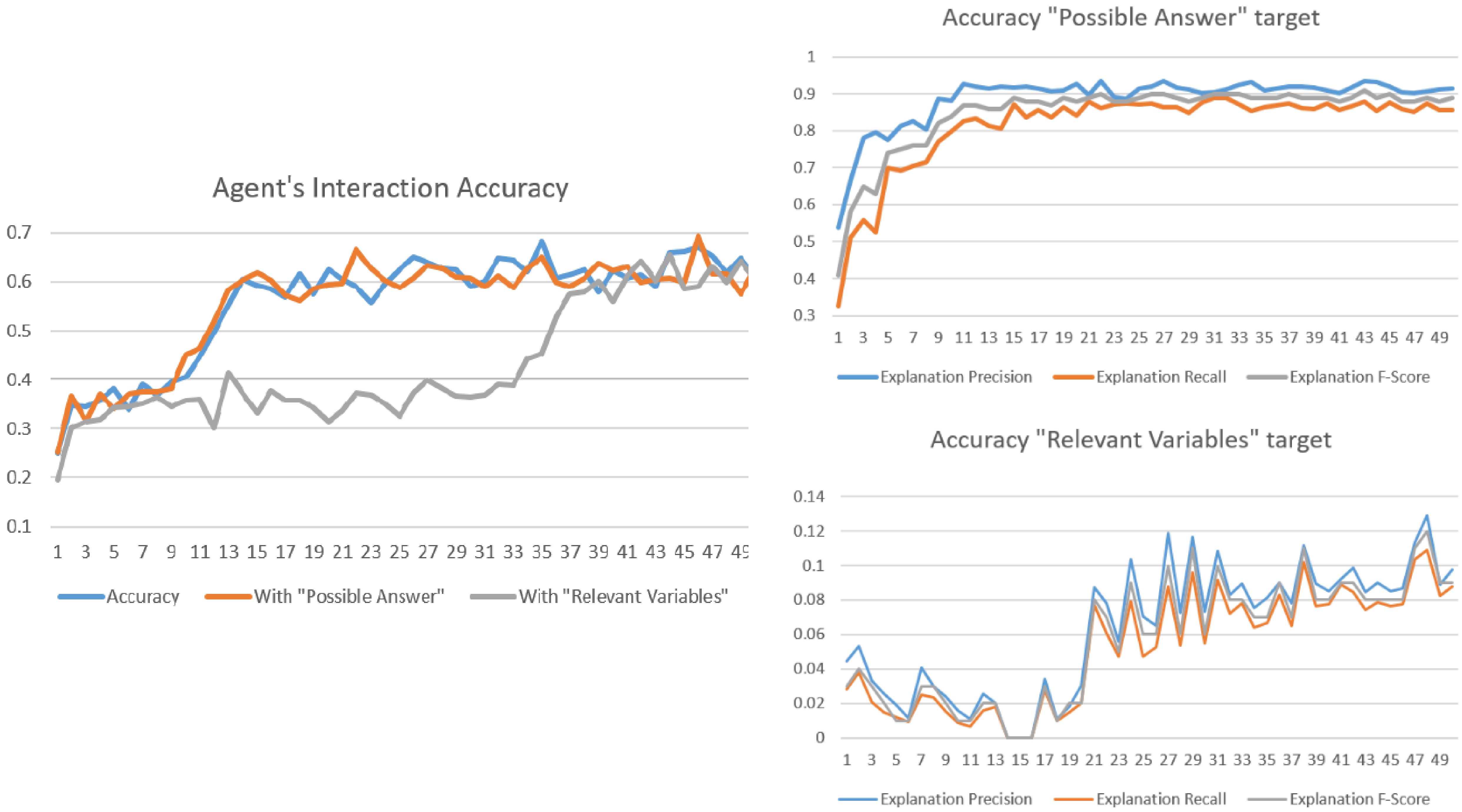
Experiment

- Joint training

$$\mathcal{L} = CE(x_i, \hat{x}_i) + ||x_e - \hat{x}_e||_2^2$$

- (i.e. on the original cross-entropy target *and* the set of possible answers/relevant variables
  - One hot encoding for explanation
  - 0.5 threshold




Agent's Interaction Accuracy
0.7
0.6
0.5
0.4
0.3
0.2
0.1
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49
Accuracy
With "Possible Answer"
With "Relevant Variables"
Accuracy "Possible Answer" target
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49
Explanation Precision
Explanation Recall
Explanation F-Score
Accuracy "Relevant Variables" target
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49
Explanation Precision
Explanation Recall
Explanation F-Score

Discussion

- Quality of the explanations strongly correlates with the quality of the predictions
- When predictions are difficult, requiring it to generate good explanation slows its learning
- Future work: NL-based explanation