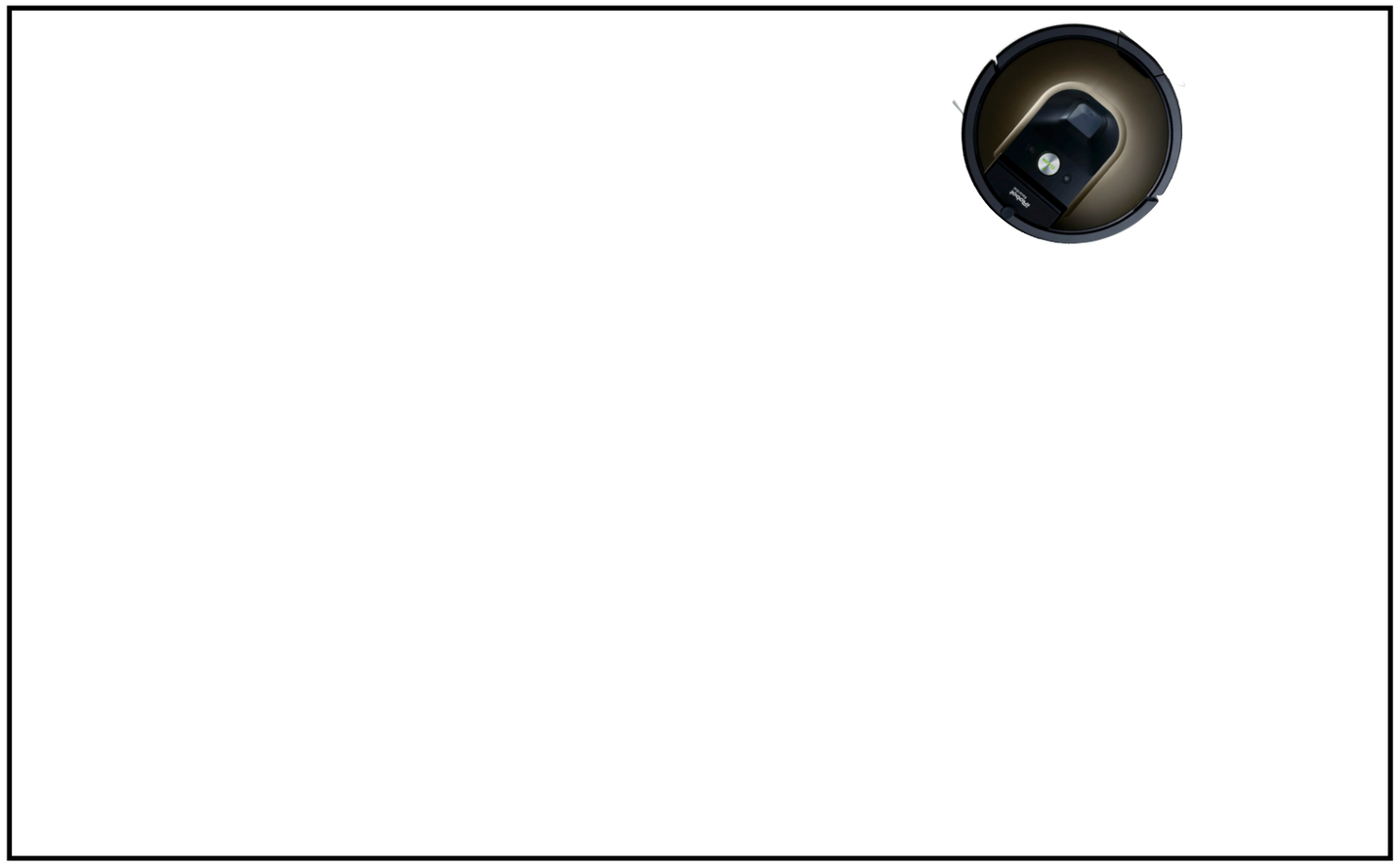
Explainable Planning and Decision Making

William Yeoh

Computer Science and Engineering
Washington University in St. Louis

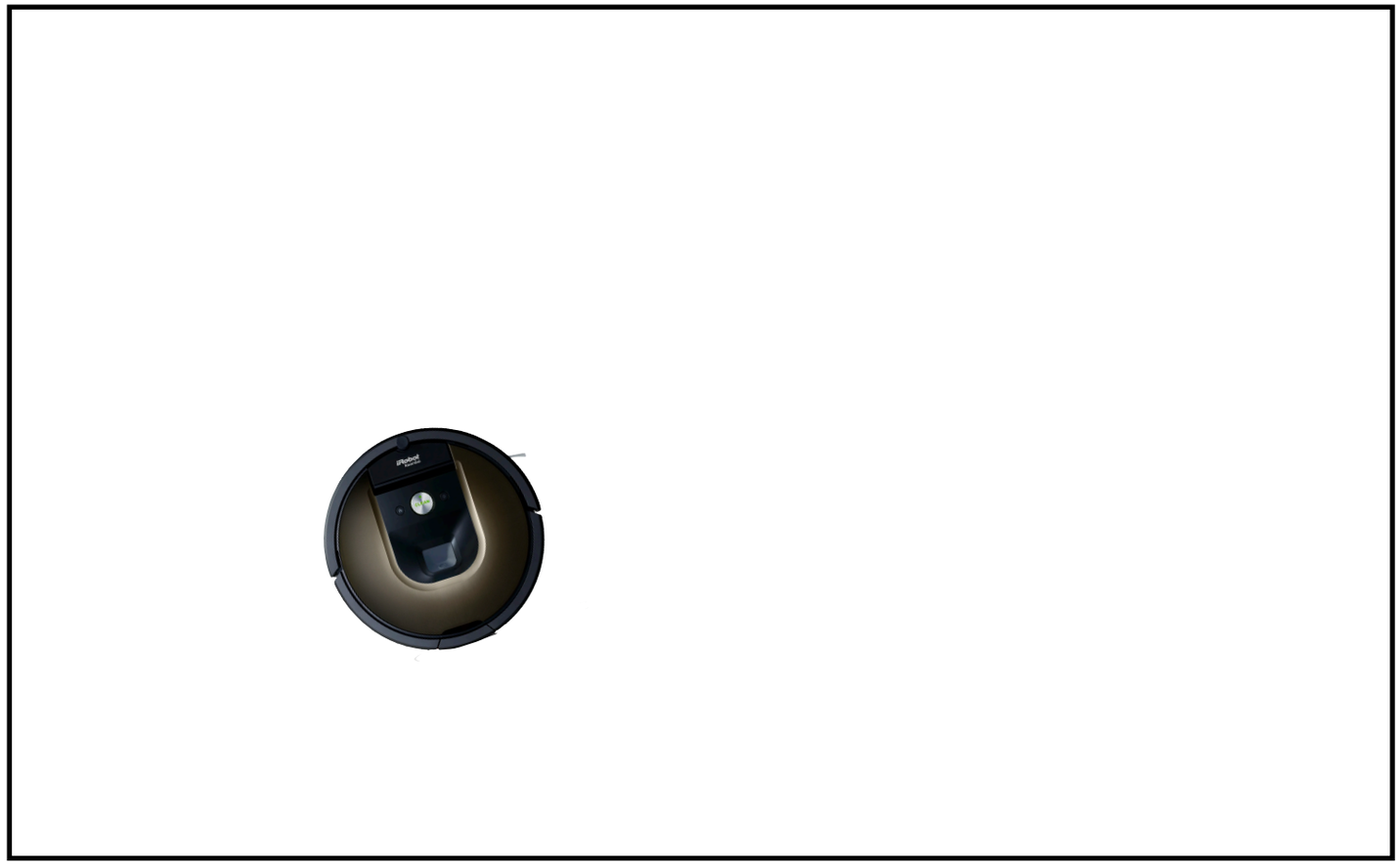
Explainable Planning



Why is the Roomba robot
behaving the way it is behaving?

- Why is it not moving parallel to the walls?
- Why is it moving back and forth?
- Why is it moving in circles?
- …

Explainable Planning



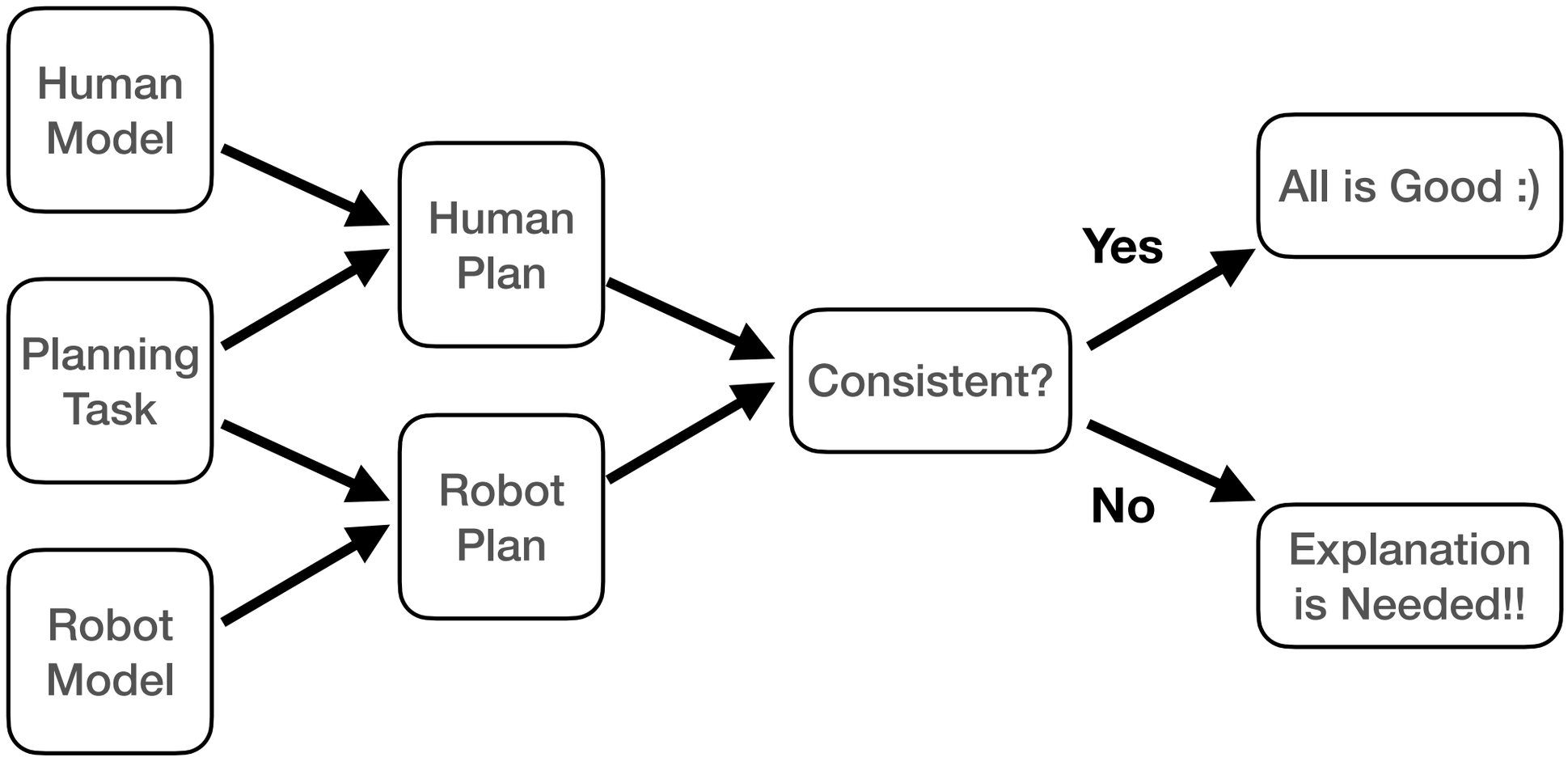
Why is the Roomba robot
behaving the way it is behaving?

- Why is it not moving parallel to the walls?
- Why is it moving back and forth?
- Why is it moving in circles?
- …

And the reason is …

- Because I have no idea how the walls are aligned
- Because I detected that this area is dirty even after I went over it
- Because my right wheel is stuck
- …

Explainable Planning



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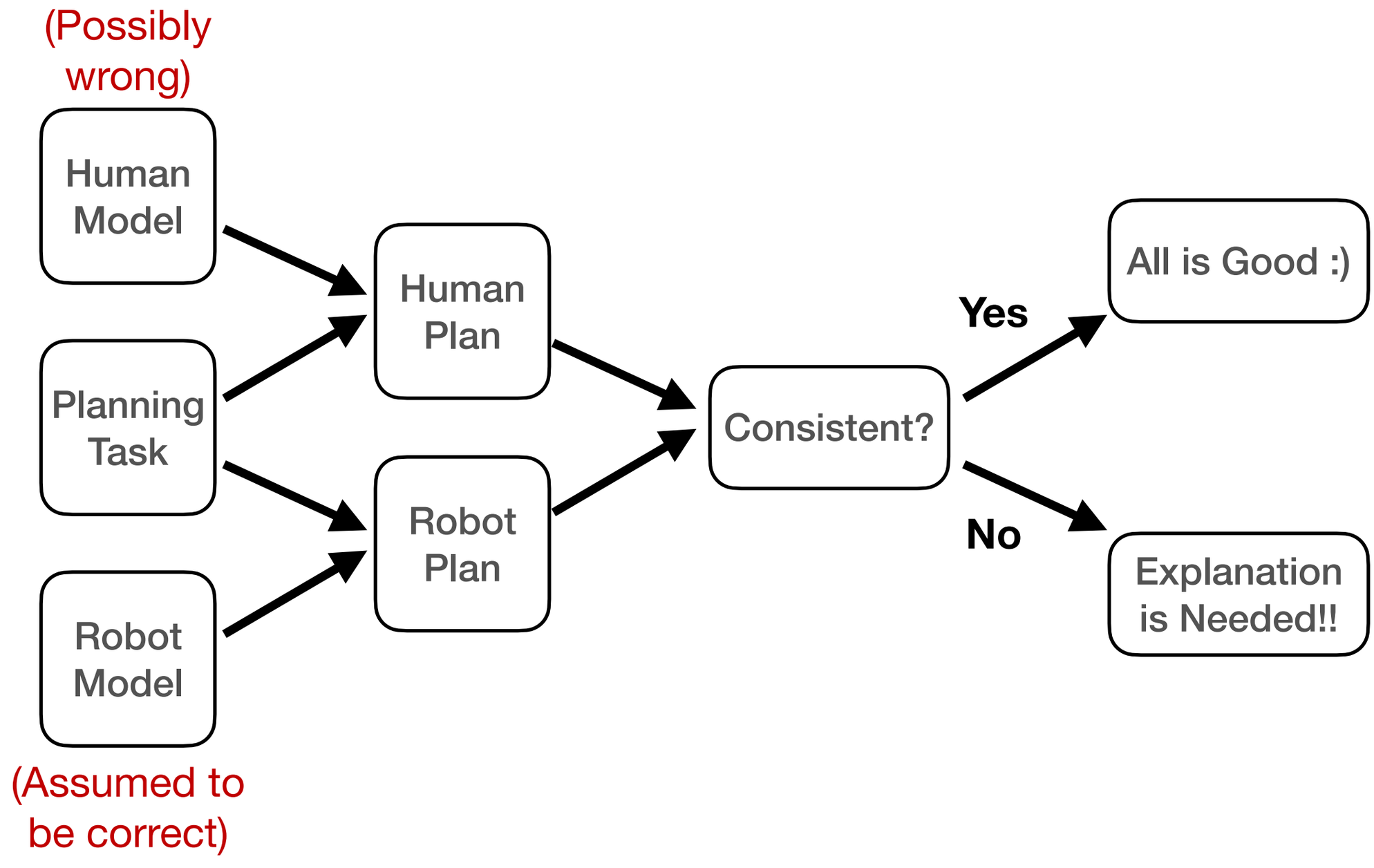

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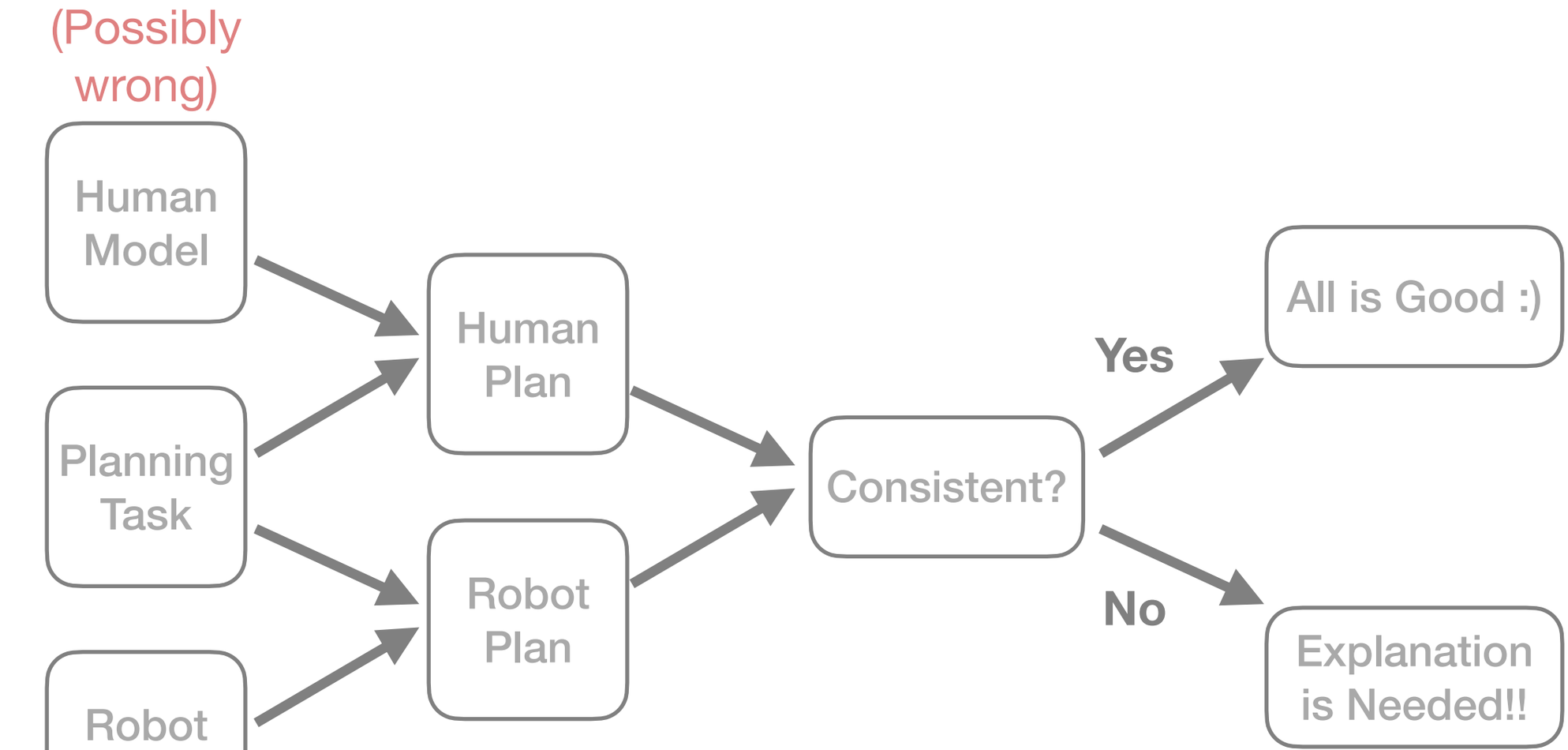

High-Level Idea: Reconcile the differences in the two models such that the human plan from the updated human model is consistent with the robot plan

YODAlab

Model Reconciliation Problem

- **Model Reconciliation Problem:**
  - Given two knowledge bases KB_a and KB_h of the agent (robot) providing an explanation and the human receiving the explanation, respectively, and a query q such that KB_a entails q, the goal is to find an explanation (ϵ^+, ϵ^-), where $\epsilon^+ \subseteq KB_a$ and $\epsilon^- \subseteq KB_h$, such that $KB_h \cup \epsilon^+ \backslash \epsilon^-$ entails q.

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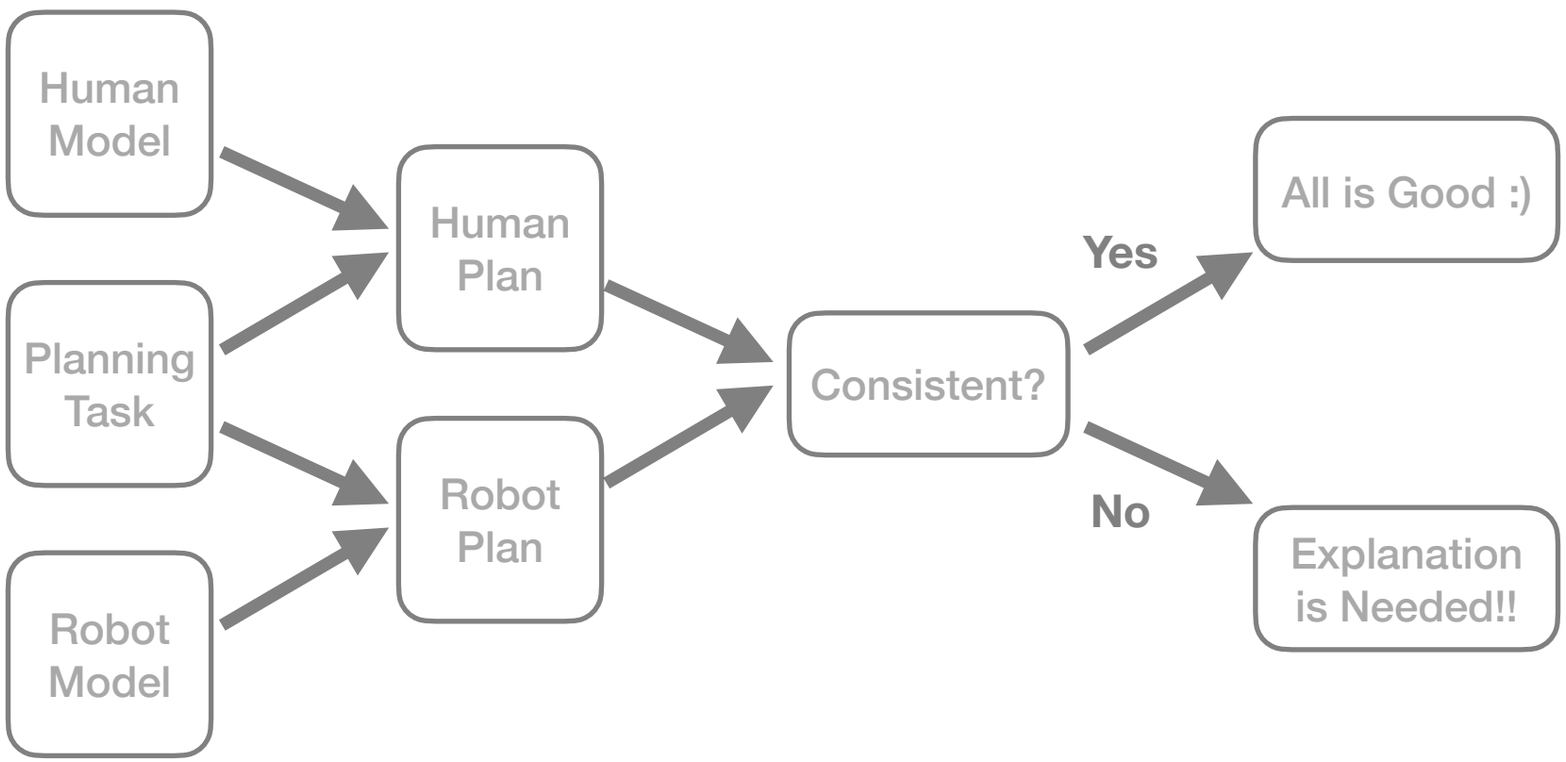

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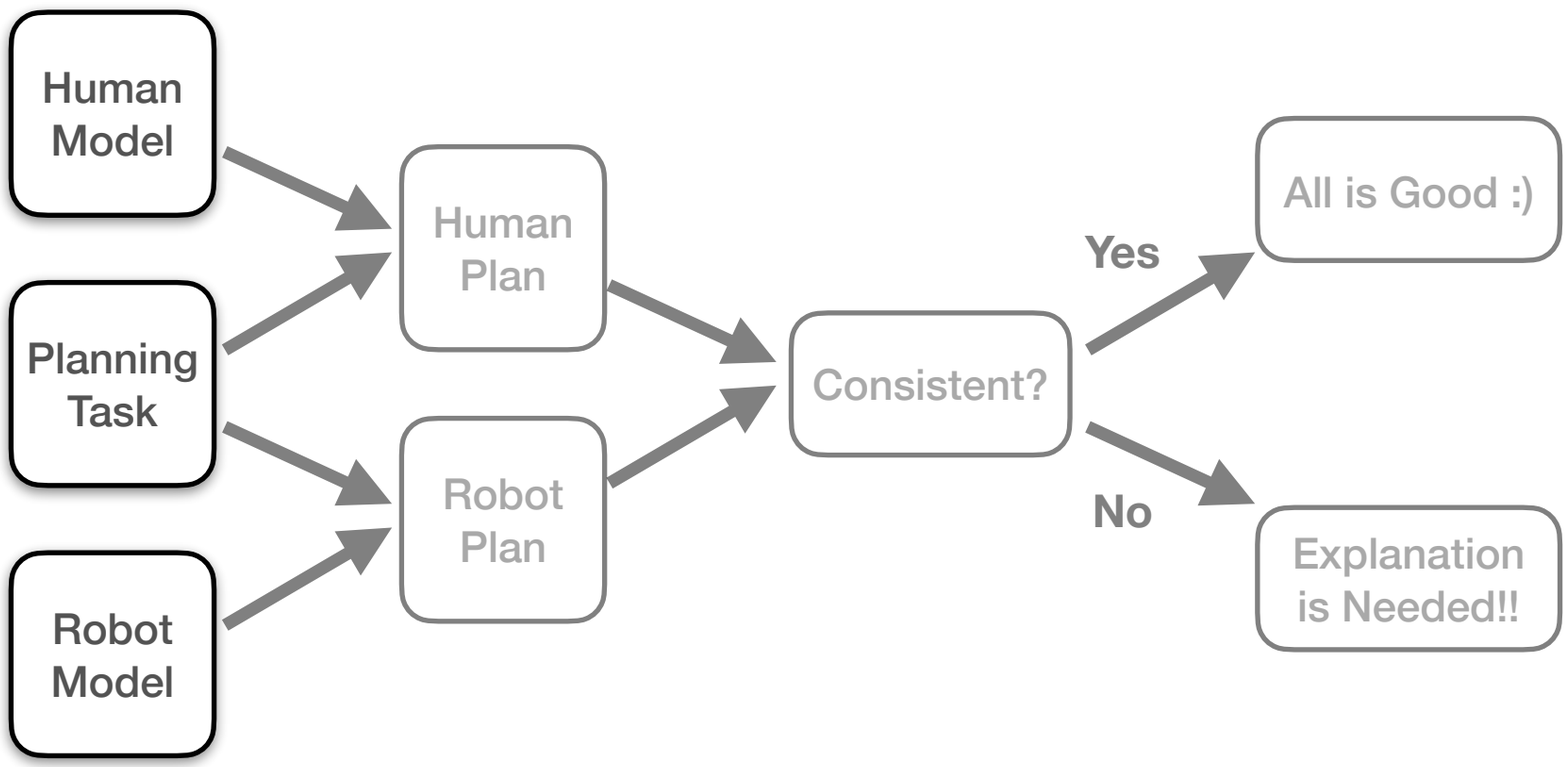

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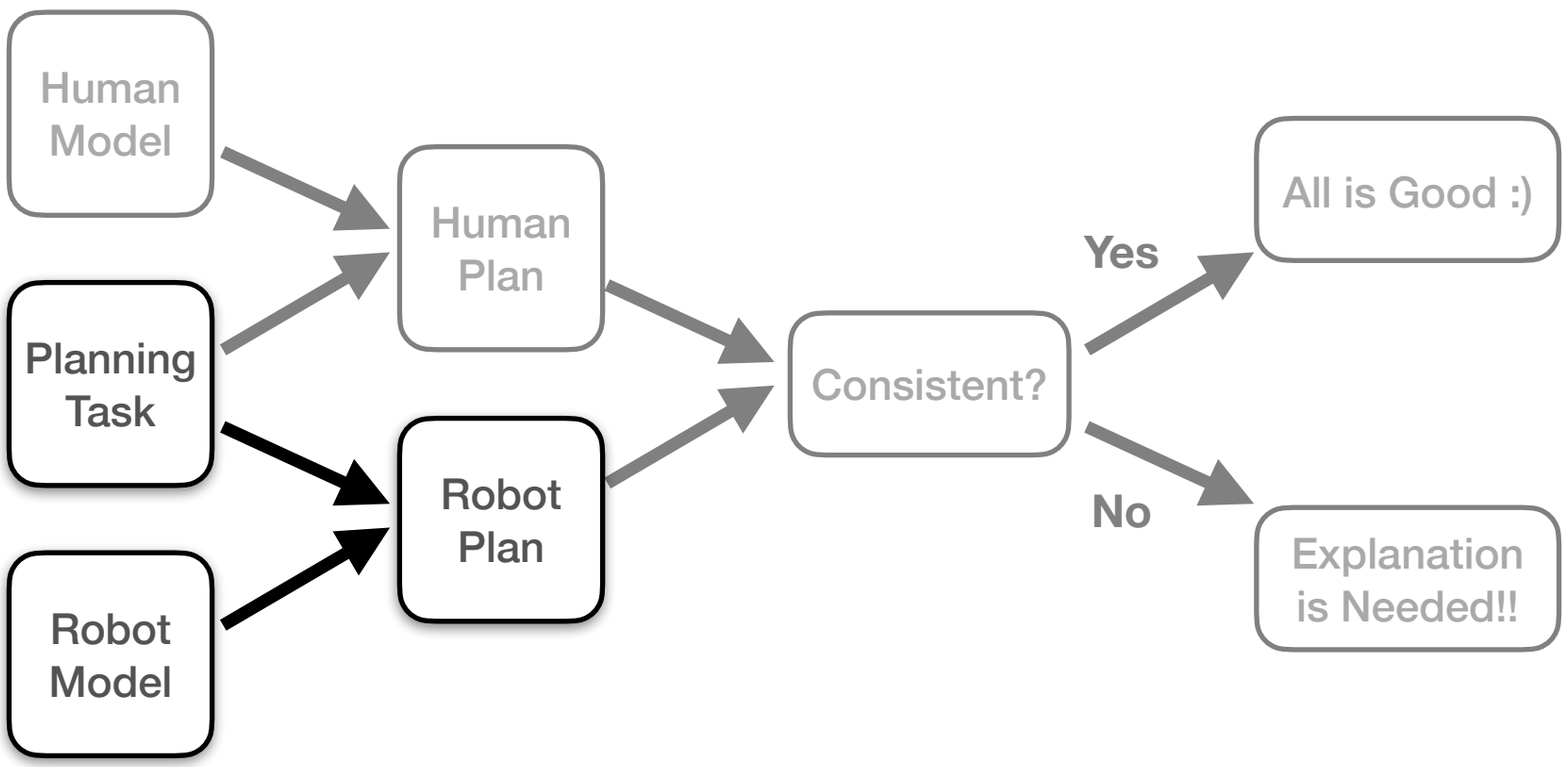

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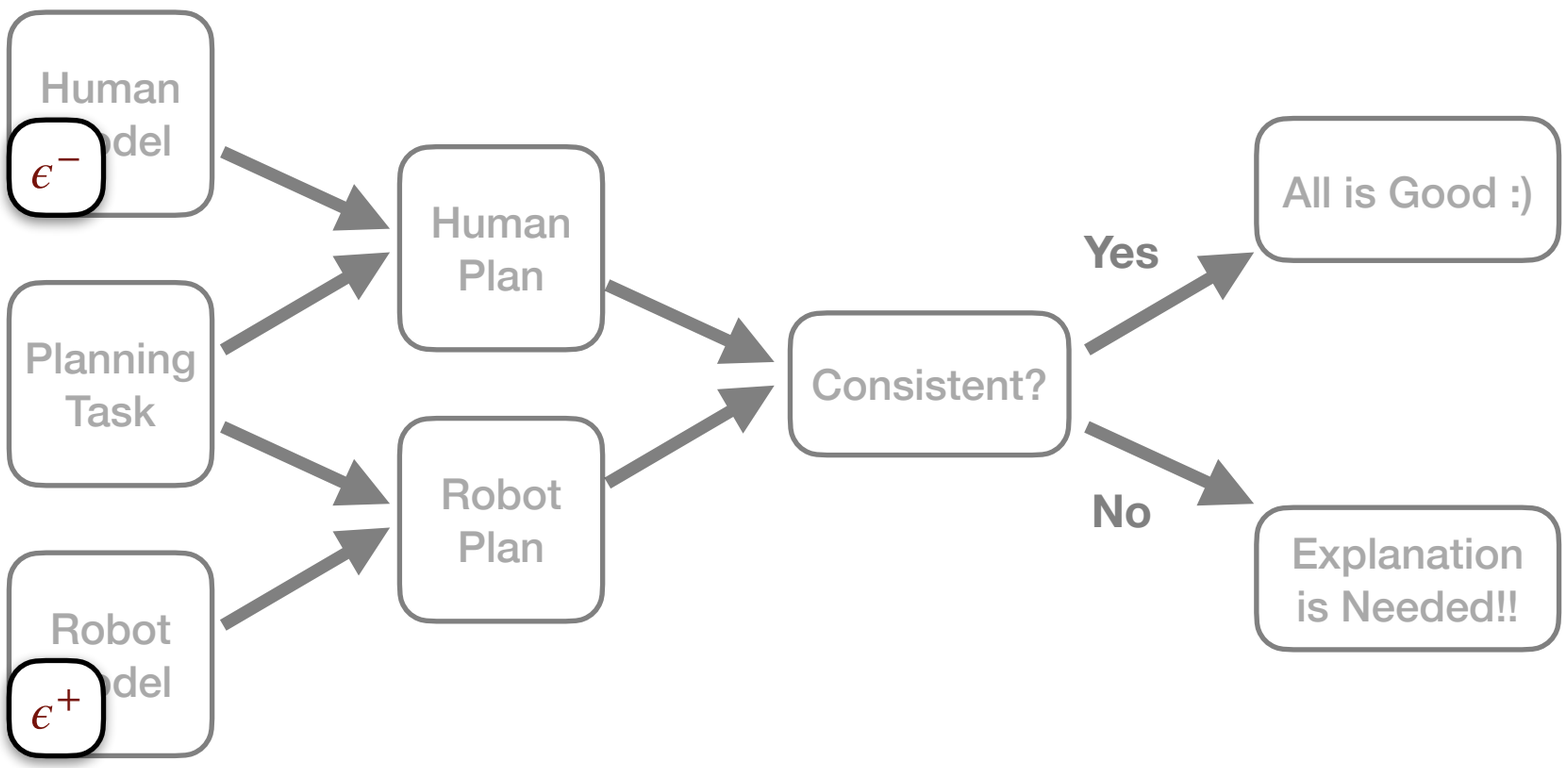

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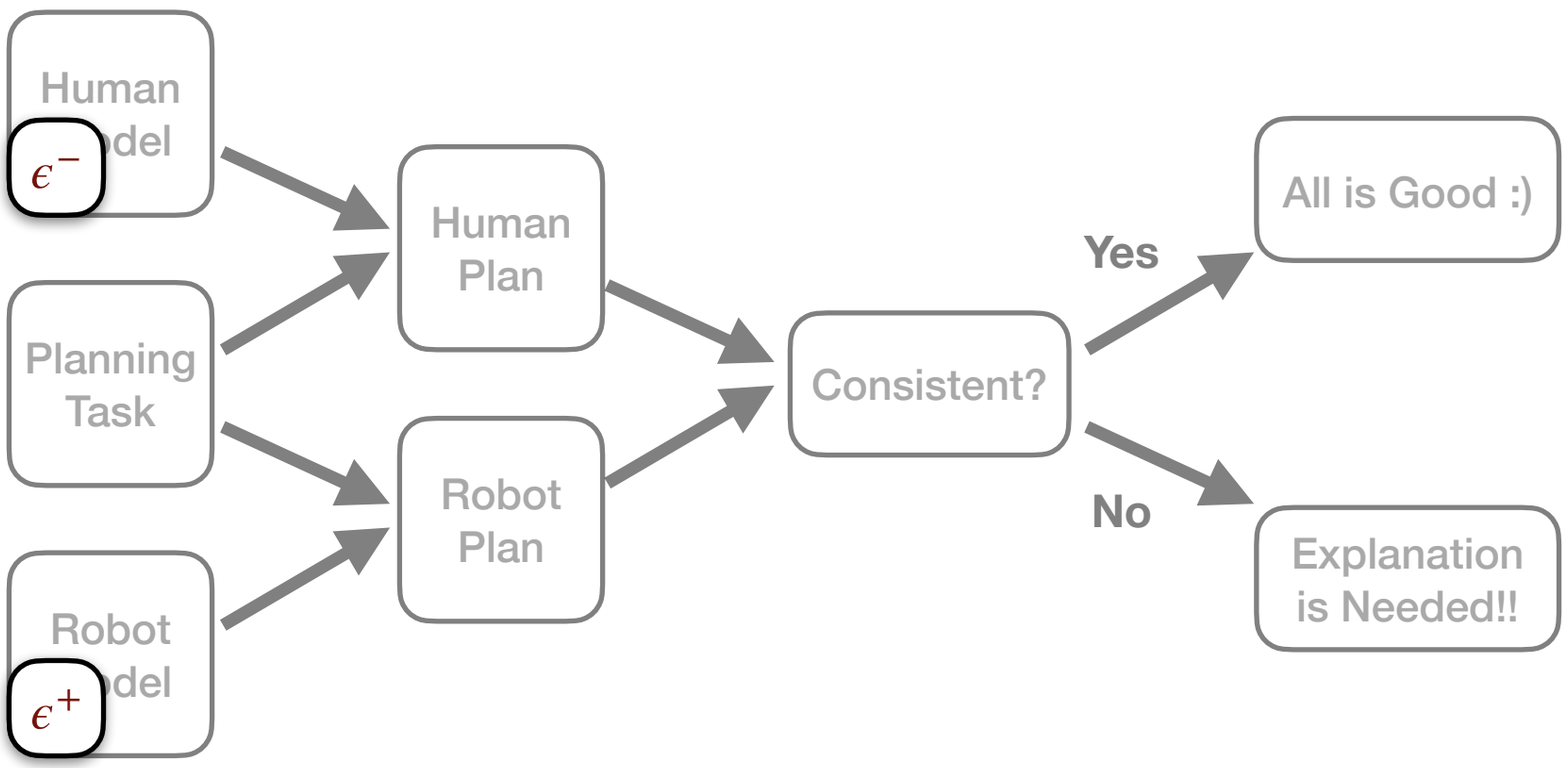

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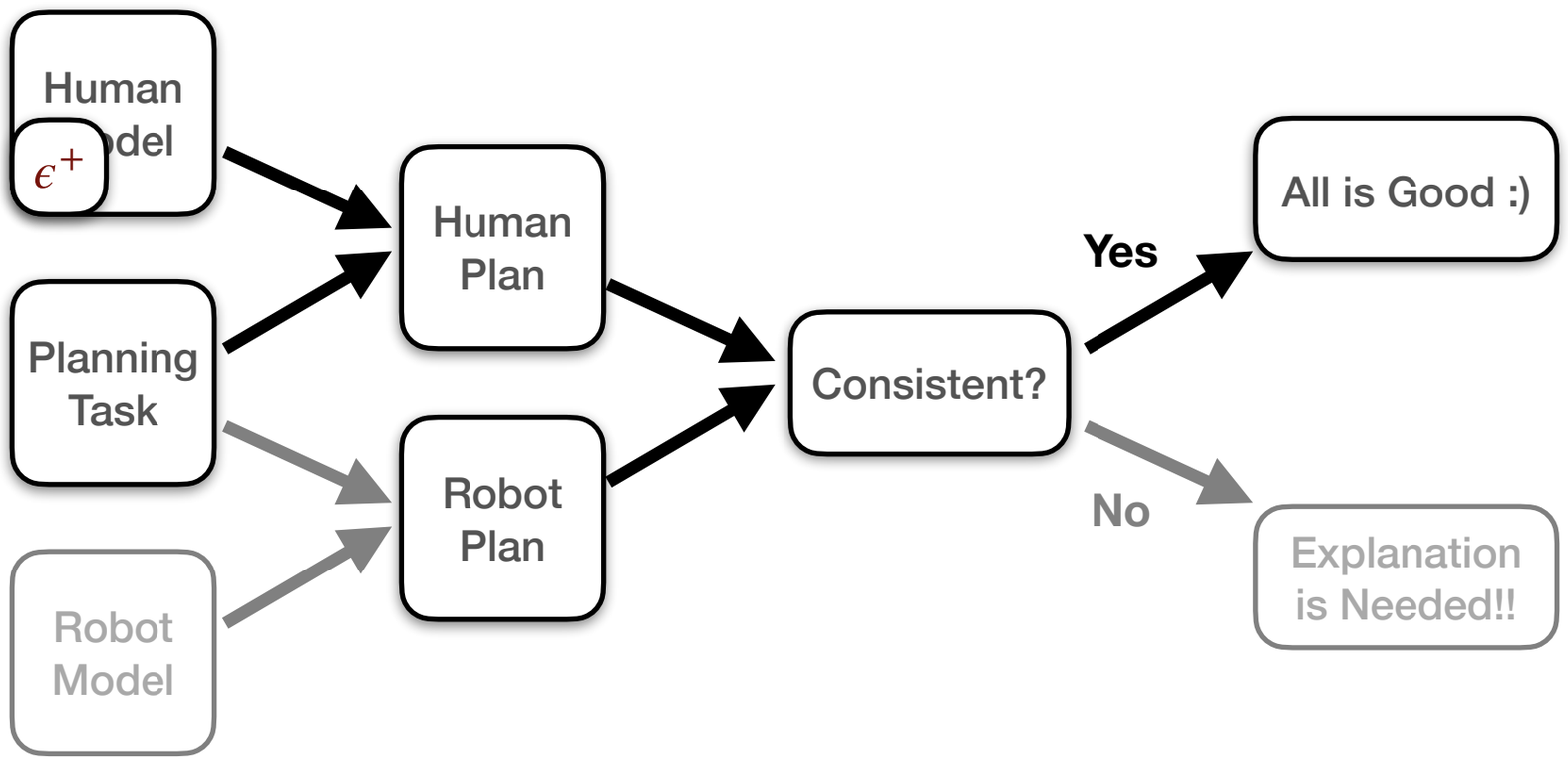

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- Research questions:
  - How to effectively find an explanation (ϵ^+, ϵ^-)?
  - How to measure the goodness of explanations?
  - How to convey explanations to the human?
  - What if we don't know the model of the human?
  - What if the model of the agent (robot) is wrong?
  - …

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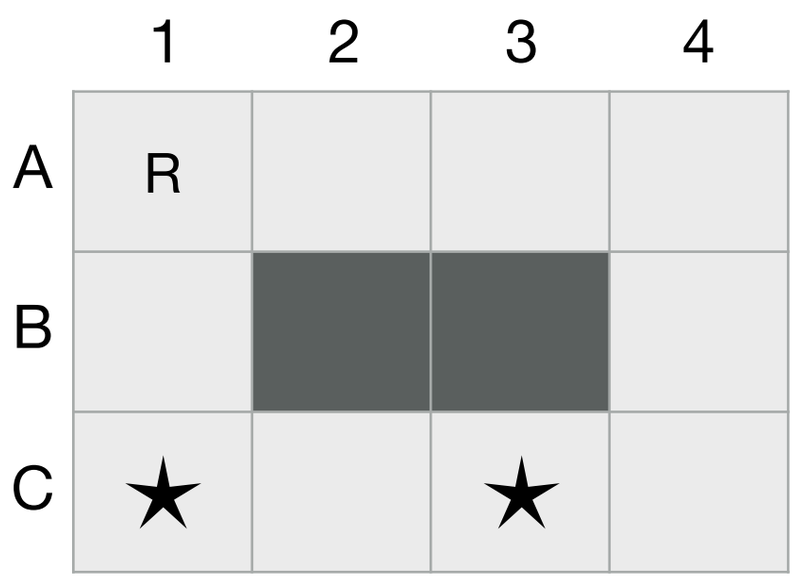
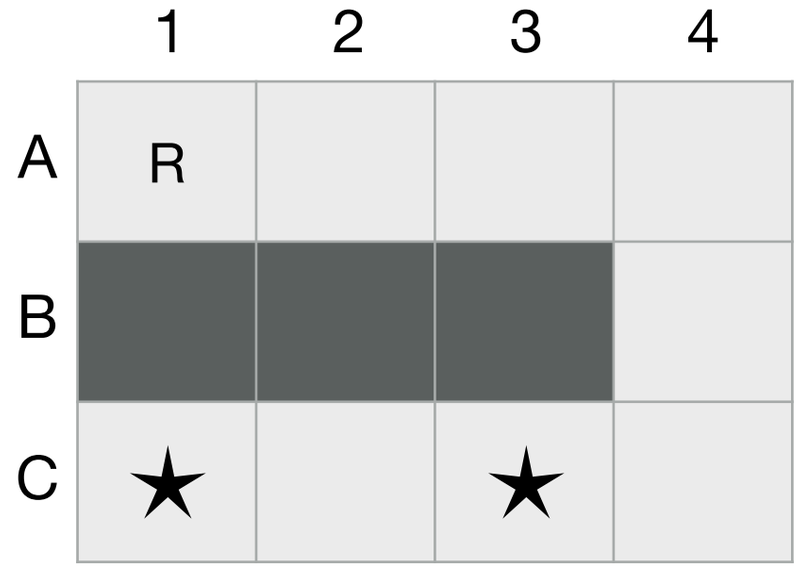
Illustrative Toy Example



Human's Model



Robot's Model

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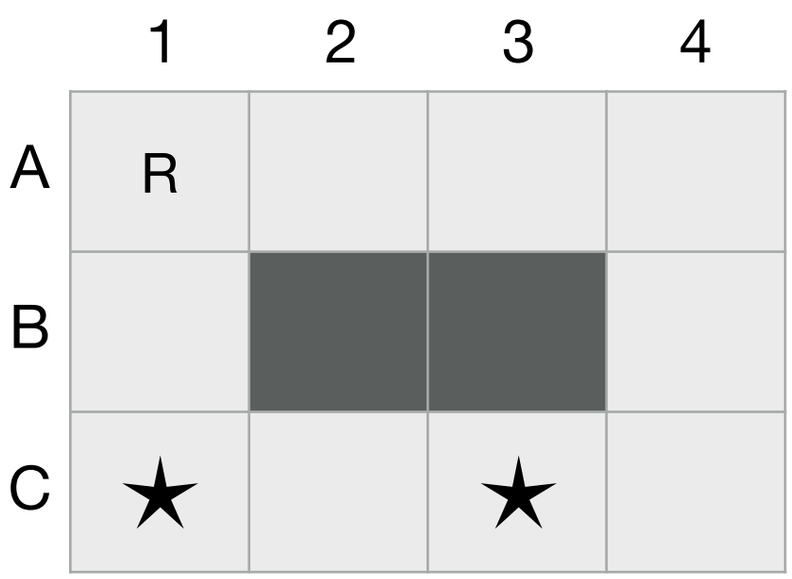

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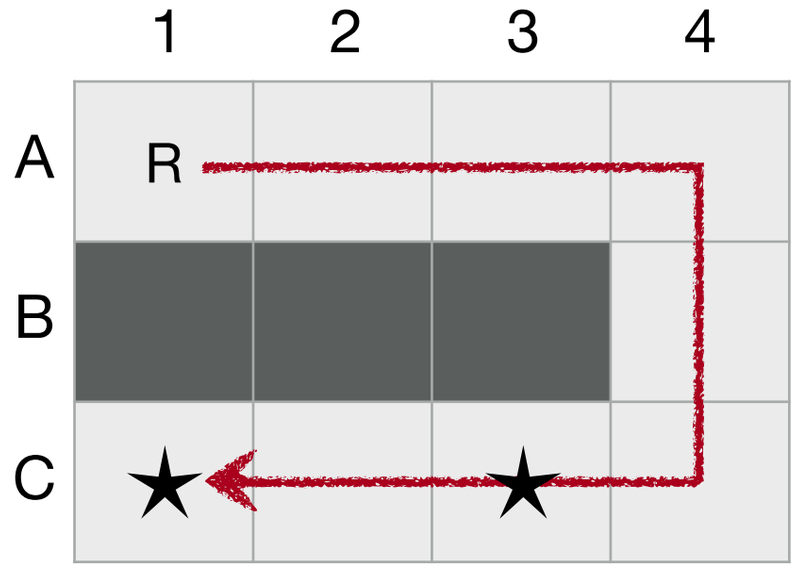
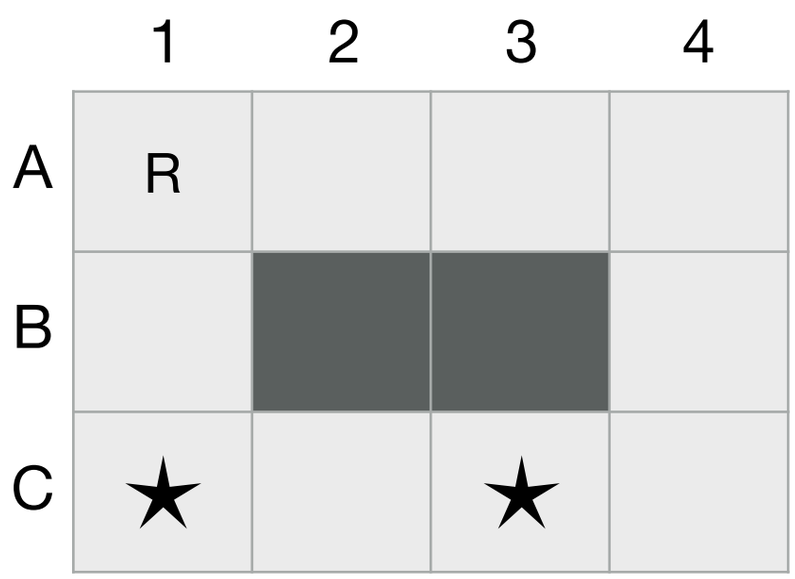


Robot's Model

Modeling Planning as SAT



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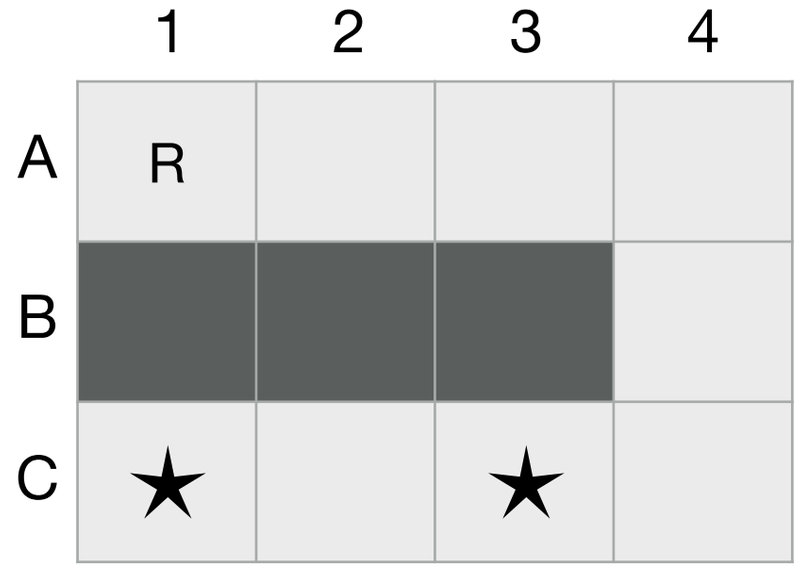
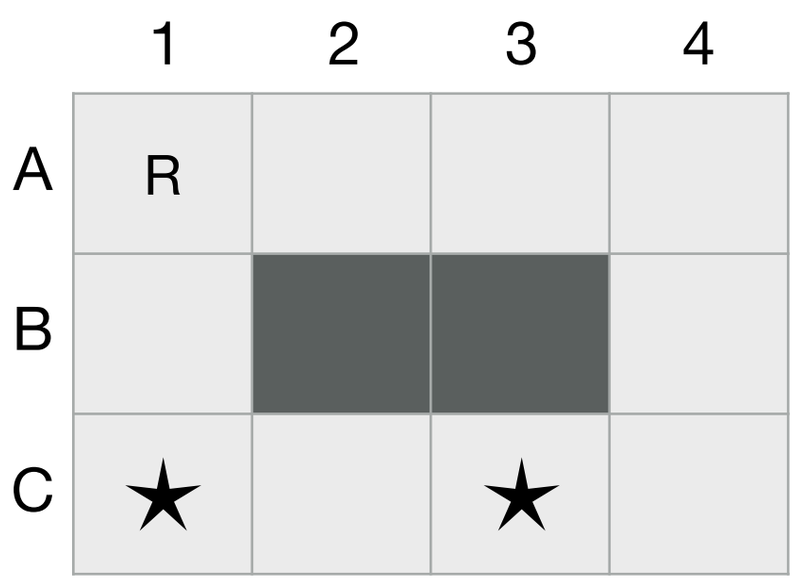


Robot's Model

- **Modeling Planning as a Boolean Satisfiability (SAT) Problem**
  - Starting robot location: $A1_0, \neg A2_0, \ldots, \neg C4_0$

Modeling Planning as SAT



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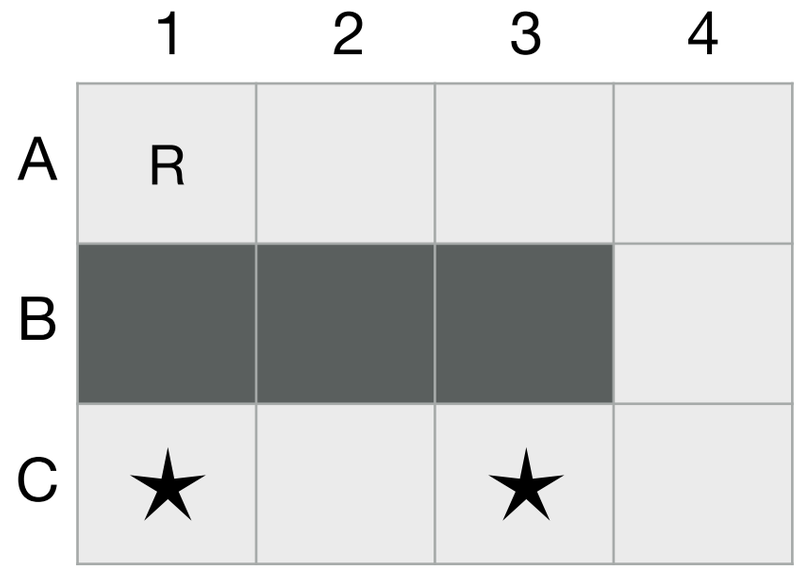

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  - Starting robot location: $A1_0, \neg A2_0, \ldots, \neg C4_0$
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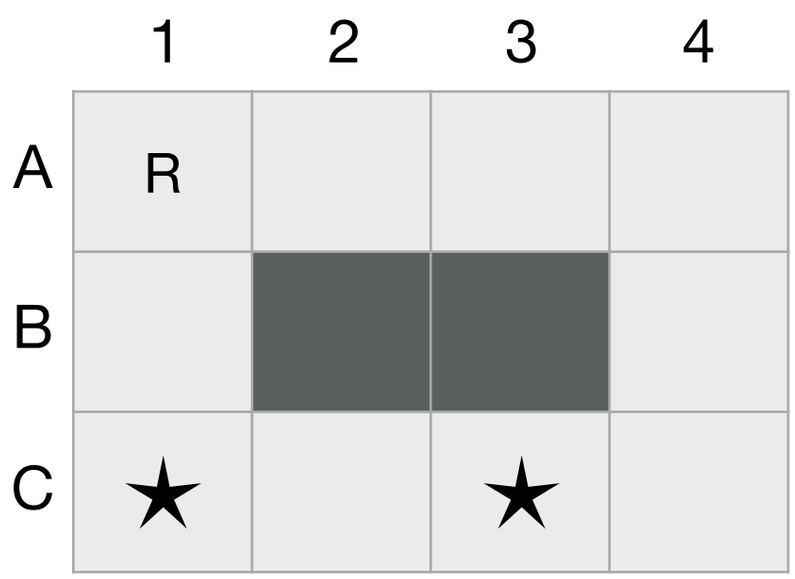

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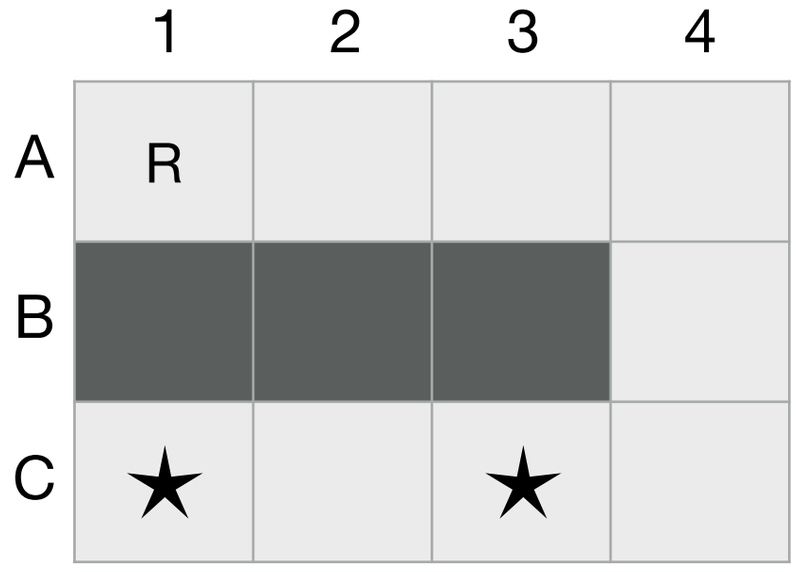

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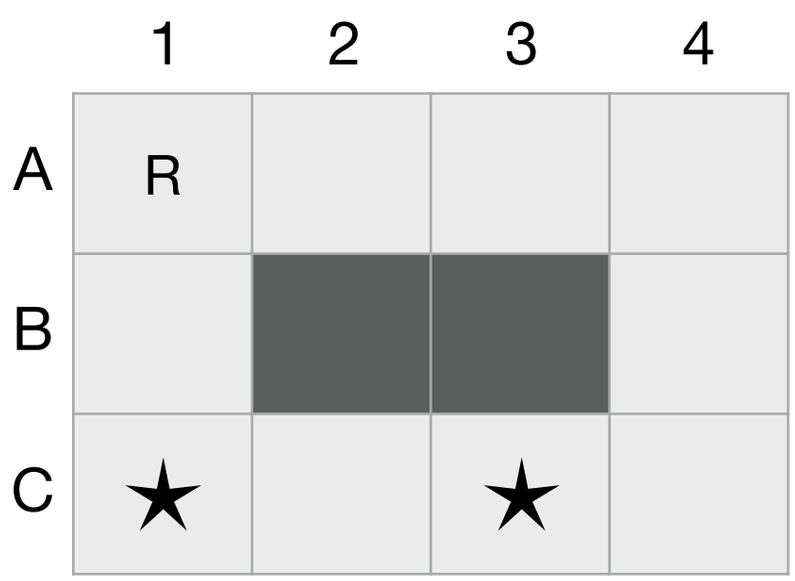

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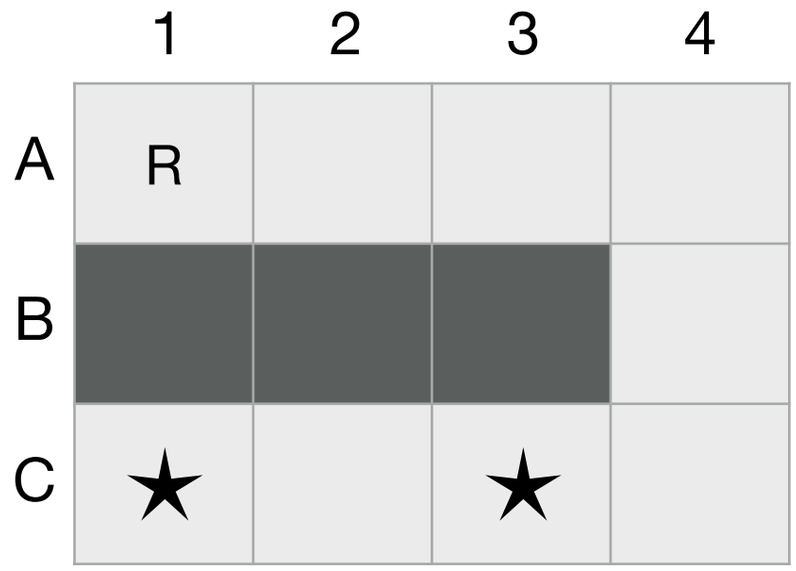

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  - Actions of robots:
    - $\downarrow_t \wedge A1_t \wedge \neg Blocked\_B1 \rightarrow B1_{t+1}$
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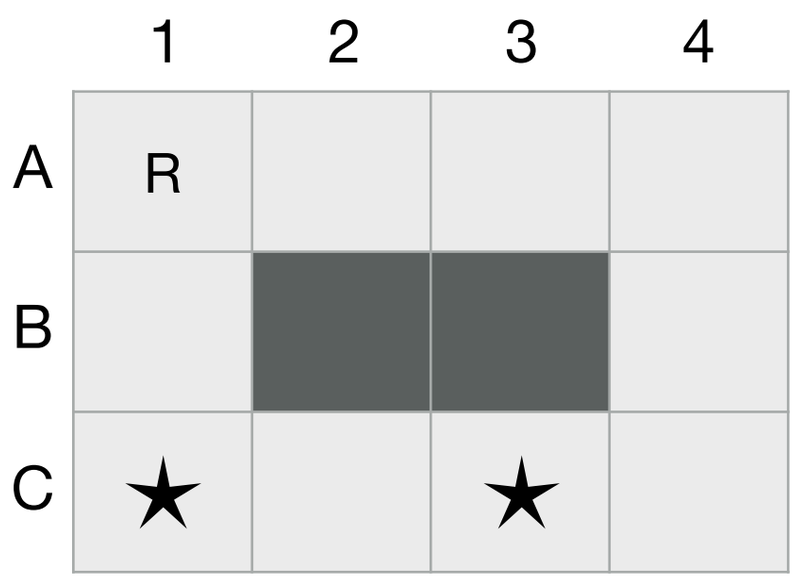
    - …

Modeling Planning as SAT



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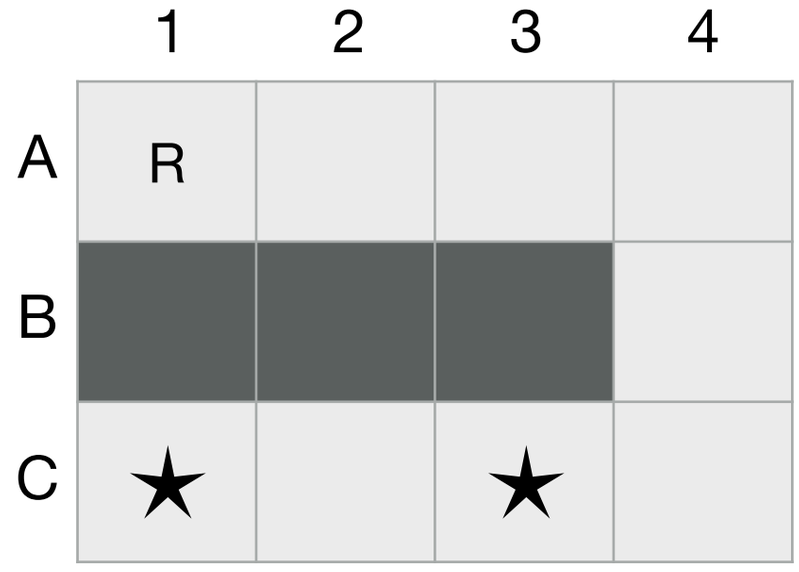

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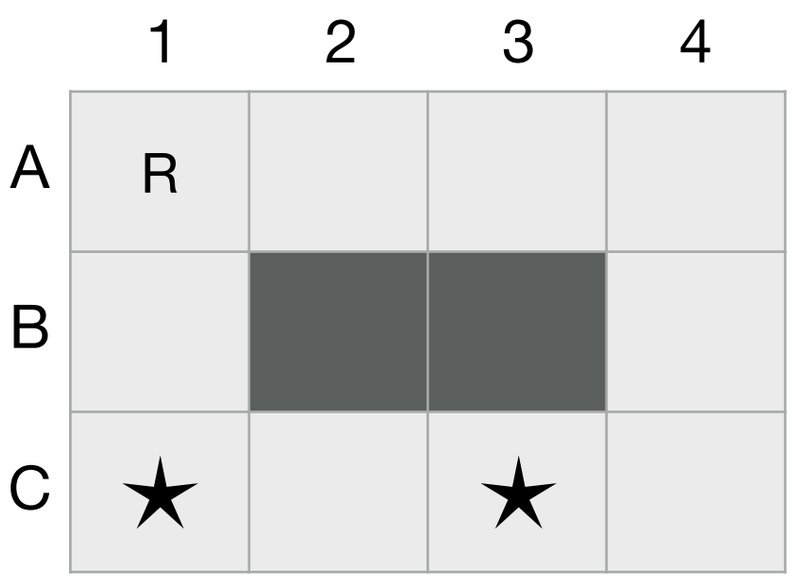
KB_h

Modeling Planning as SAT



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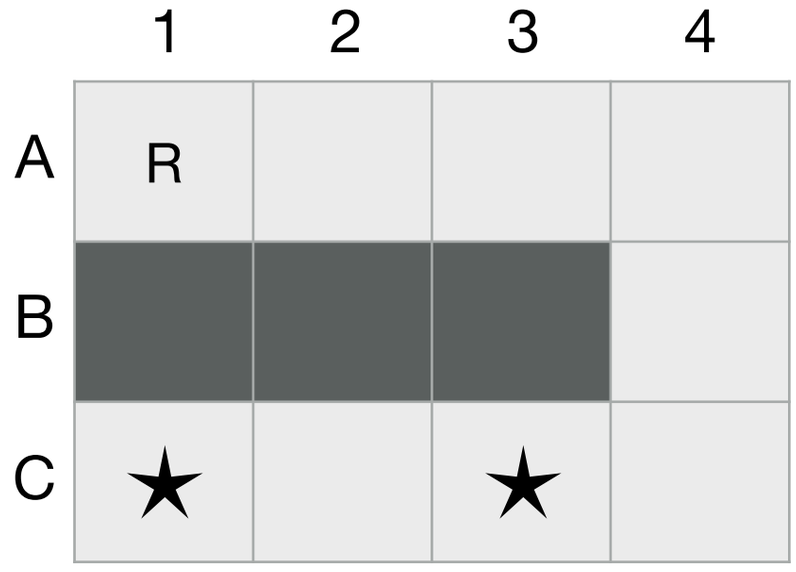

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KB_a

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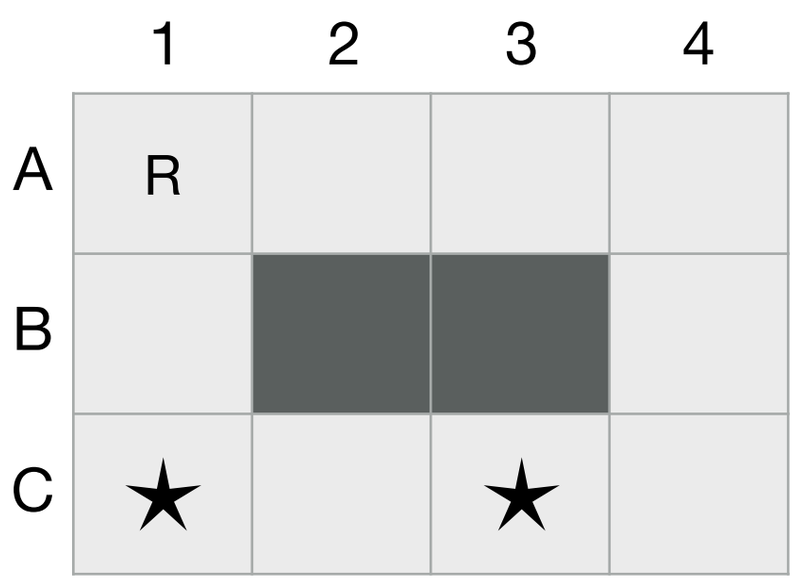

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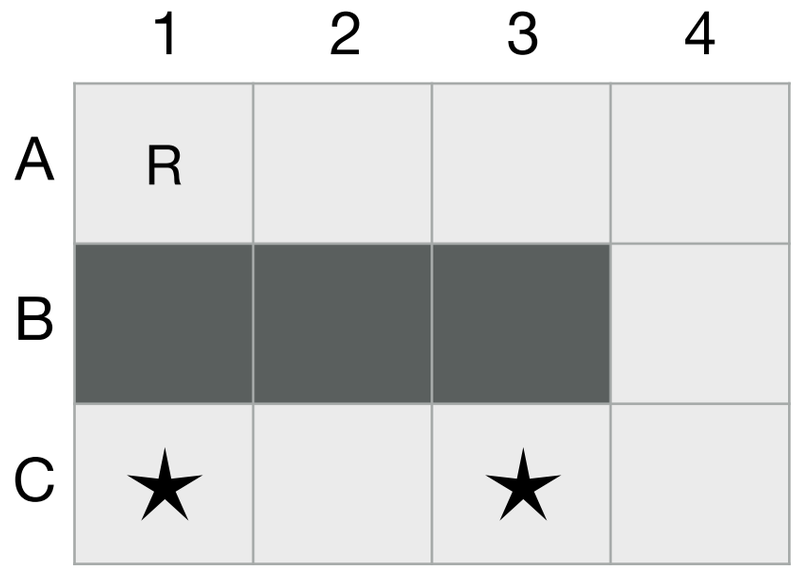
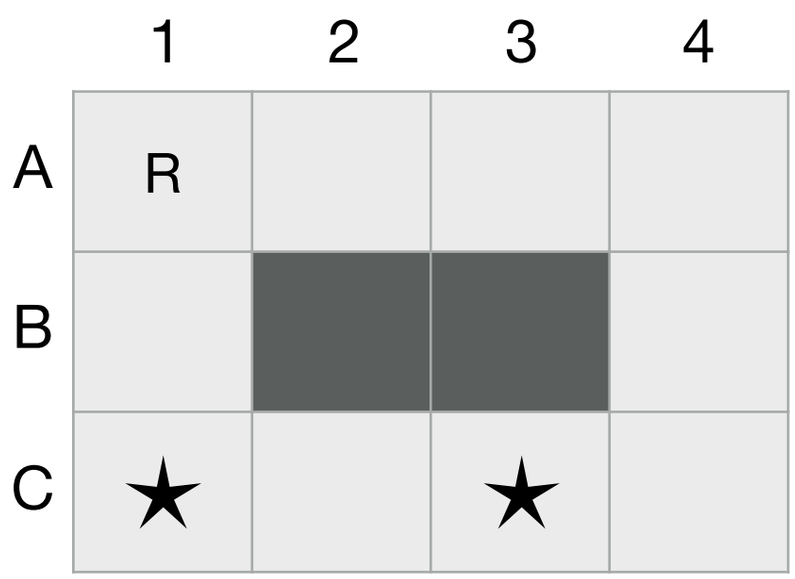


Robot's Model

- **Modeling Planning as a Boolean Satisfiability (SAT) Problem**
  - Goal: Find truth value assignments to sequence of actions such that the goal states are reached
  - A lot of efficient SAT solvers exists to solve this problem

Modeling Planning as SAT



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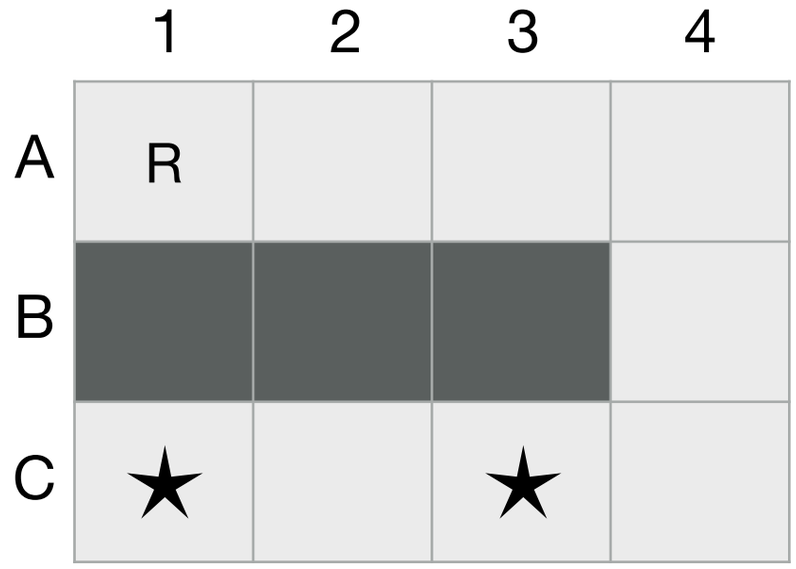

Robot's Model

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  - Goal: Find truth value assignments to sequence of actions such that the goal states are reached
    - For human: $\downarrow_0, \downarrow_1, \rightarrow_2, \rightarrow_3$ results in $C1_2, C3_4$
    - For robot: $\rightarrow_0, \rightarrow_1, \rightarrow_2, \downarrow_3, \downarrow_4, \leftarrow_5, \leftarrow_6, \leftarrow_7$ results in $C1_8, C3_6$
  - Human's question:
    - Why $\rightarrow_0, \rightarrow_1, \rightarrow_2, \downarrow_3, \downarrow_4, \leftarrow_5, \leftarrow_6, \leftarrow_7$ and not $\downarrow_0, \downarrow_1, \rightarrow_2, \rightarrow_3$?

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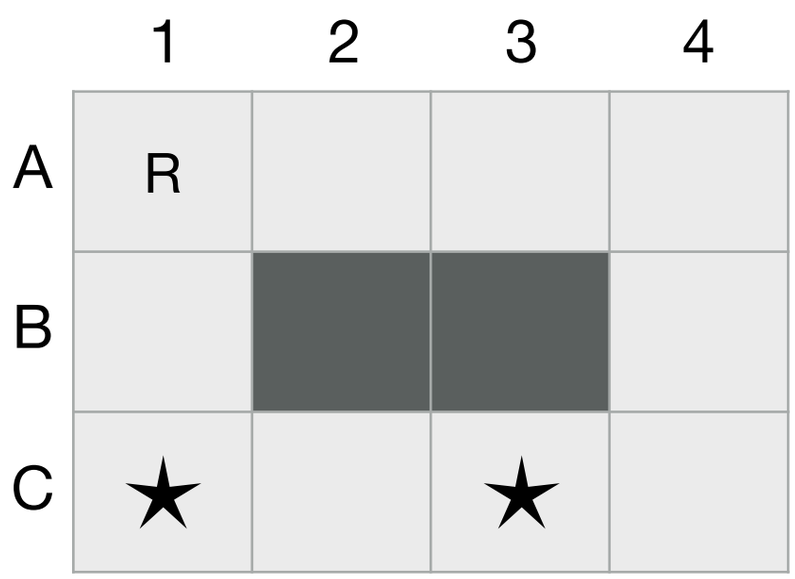

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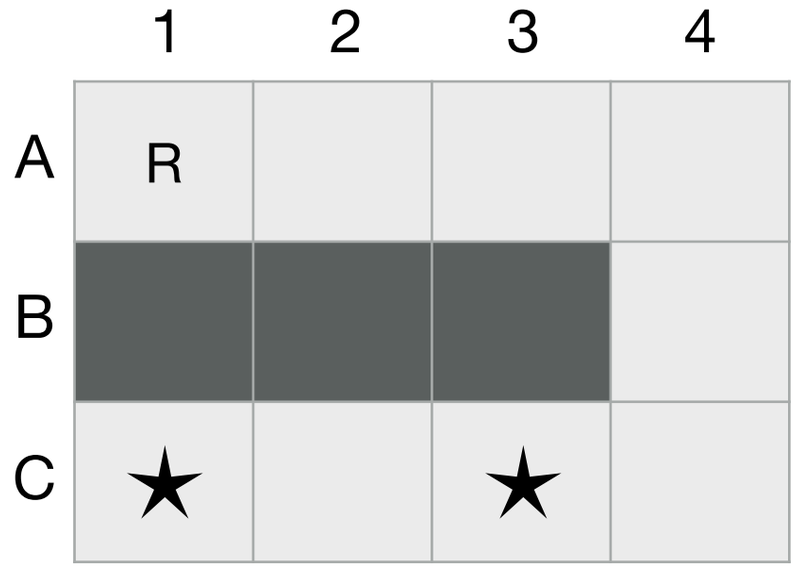

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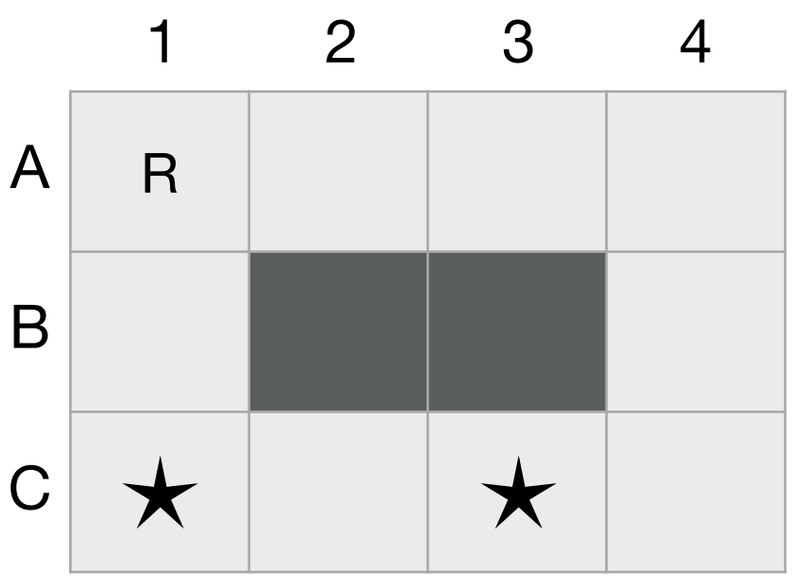
Query q

YODAlab

Model Reconciliation with SAT



Human's Model

- Blocked locations: $\neg Blocked\_A1, \neg Blocked\_B1, \ldots$
- Goal states: $C1_t \wedge C3_{t'}$ for some time steps t and t'
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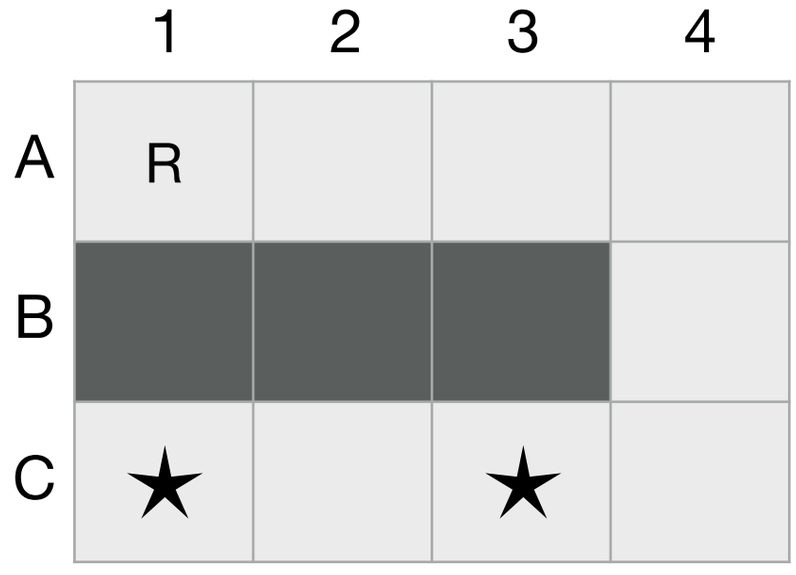

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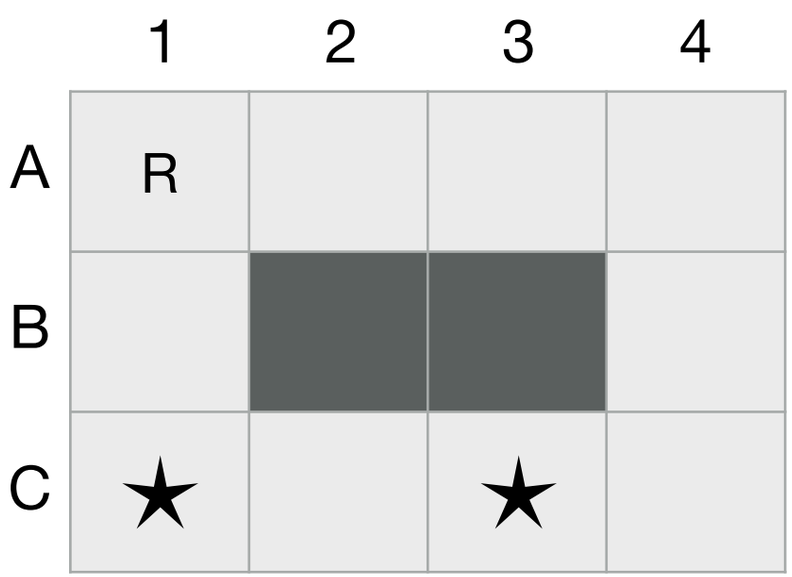
- **Model Reconciliation Problem:**
  - Find $\epsilon^- \subseteq KB_h$ to remove from human's model and $\epsilon^+ \subseteq KB_a$ from agent's model to add to human's model such that the query is entailed

Model Reconciliation with SAT



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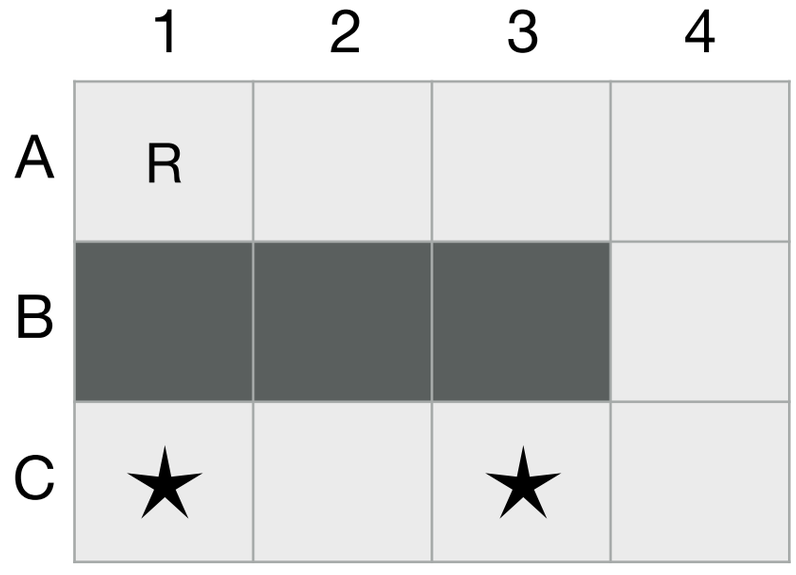

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- **Model Reconciliation Problem:**
  - Find $\epsilon^- \subseteq KB_h$ to remove from human's model and $\epsilon^+ \subseteq KB_a$ from agent's model to add to human's model such that the query is entailed
  - $\epsilon^- = \neg Blocked\_B1$ and $\epsilon^+ = Blocked\_B1$

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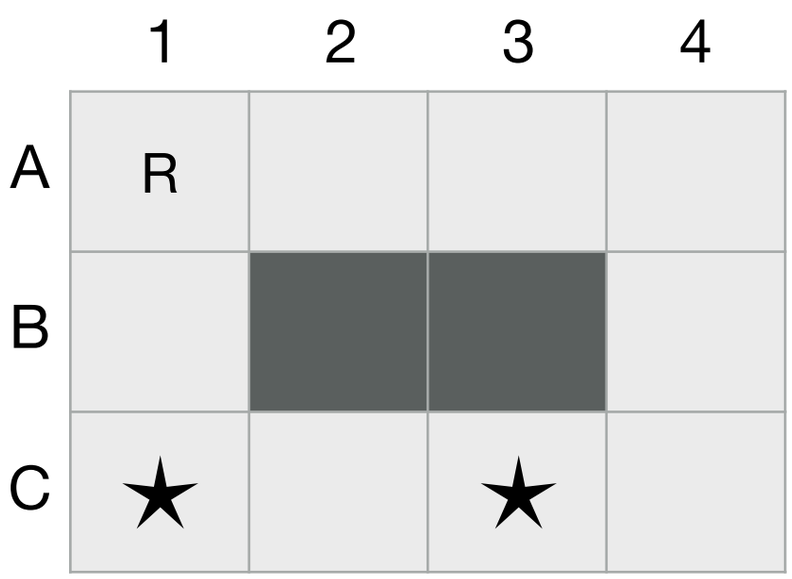
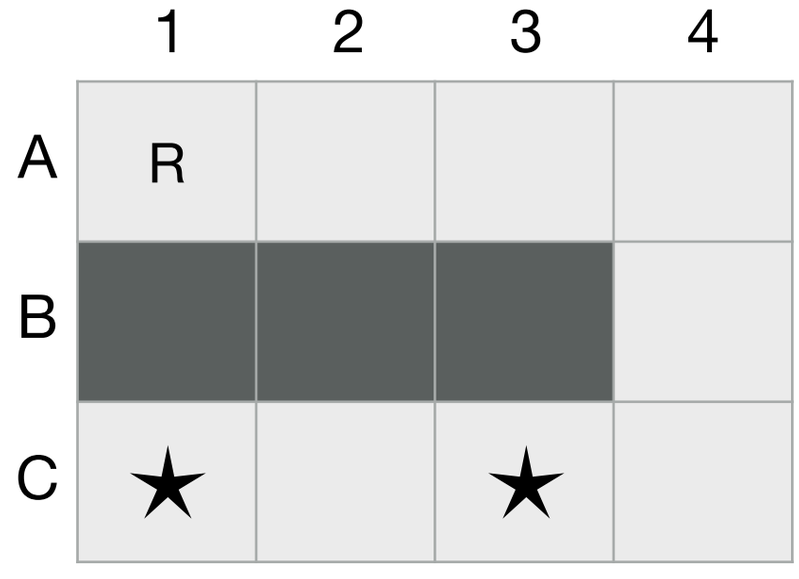
Model Reconciliation with SAT



Human's Model

- Blocked locations: $\neg Blocked\_A1, \neg Blocked\_B1, \ldots$
- Goal states: $C1_t \wedge C3_{t'}$ for some time steps t and t'
- ...



Robot's Model

- Blocked locations: $\neg Blocked\_A1, Blocked\_B1, \ldots$
- Goal states: $C1_t \wedge C3_{t'}$ for some time steps t and t'
- ...

- **Model Reconciliation Problem:**
  - Find $\epsilon^- \subseteq KB_h$ to remove from human's model and $\epsilon^+ \subseteq KB_a$ from agent's model to add to human's model such that the query is entailed
  - Solve using hitting sets [AAAI-21], logic programming [JELIA-21], etc.

Hitting Sets

- **Minimal Unsatisfiable Set (MUS):**
  - Given an inconsistent KB, a subset $U \subseteq KB$ is an MUS if U is unsatisfiable and $\forall U' \subset U$, U' is satisfiable

- **Minimal Correction Set (MCS):**
  - Given an inconsistent KB, a subset $C \subseteq KB$ is an MCS if $KB \backslash C$ is satisfiable and $\forall C' \subset C$, $KB \backslash C'$ is unsatisfiable

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- High-level ideas of our approach:
  - Utilize MUS to get ϵ^+ because MUS($KB_a \cup \neg q$) $\backslash \neg q$ is a support for query q in KB_a
  - Utilize MCS to get ϵ^- so that the updated KB_h is consistent
  - In reality: Exploits duality between MUS and MCS through hitting sets to speed up computation as well as allowing for approximations

Model Reconciliation Problem

- **Model Reconciliation Problem:**
  - Given two knowledge bases KB_a and KB_h of the agent (robot) providing an explanation and the human receiving the explanation, respectively, and a query q such that KB_a entails q, the goal is to find an explanation (ϵ^+, ϵ^-), where $\epsilon^+ \subseteq KB_a$ and $\epsilon^- \subseteq KB_h$, such that $KB_h \cup \epsilon^+ \backslash \epsilon^-$ entails q.

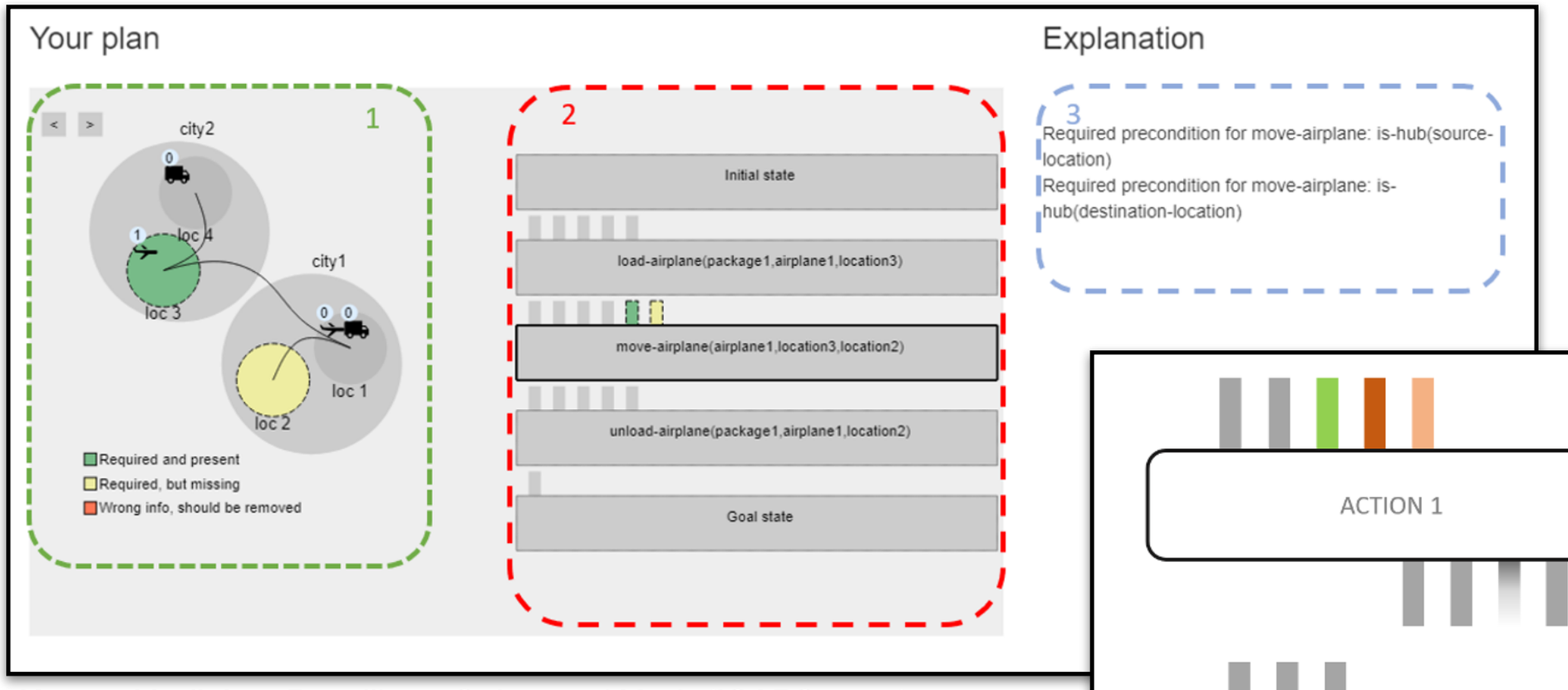
- Research questions:
  - How to effectively find an explanation (ϵ^+, ϵ^-)?
  - How to measure the goodness of explanations?
  - How to convey explanations to the human?
  - What if we don't know the model of the human?
  - What if the model of the agent (robot) is wrong?
  - …

Ongoing and Future Work

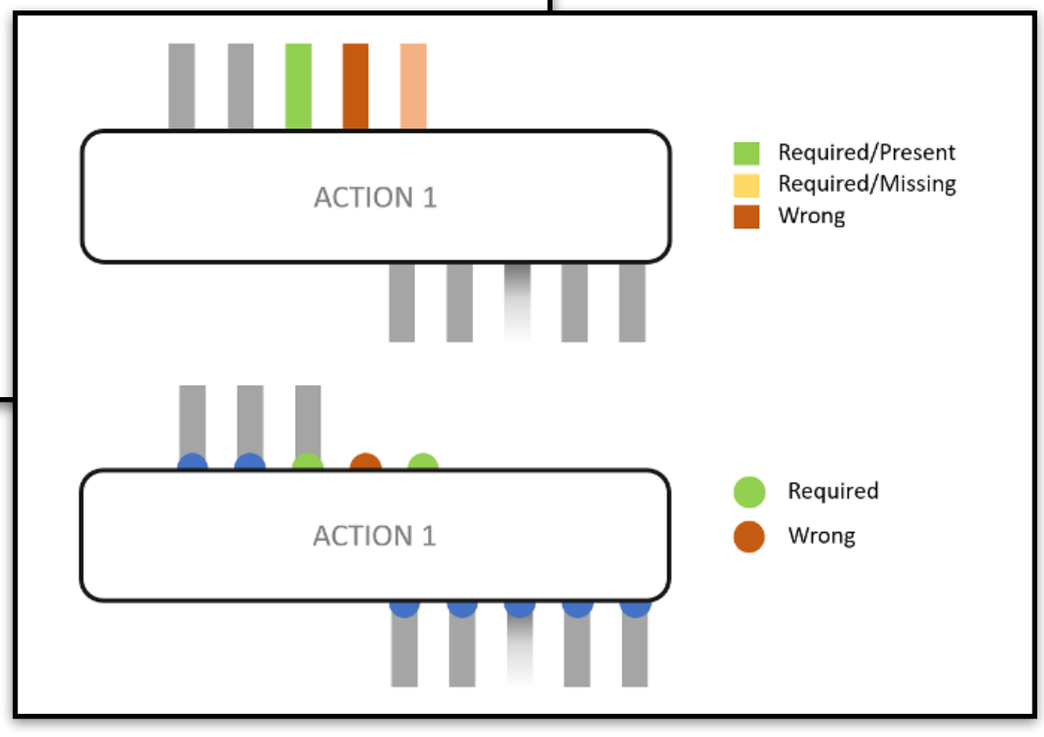
- **Measuring the goodness of an explanation:**
  - How easy it is to convey the explanation
  - How complex is the explanation (e.g., number of literals in the explanation)
  - How long is the explanation (e.g., number of rules that need to be removed/added)
  - How likely is the explanation accepted (e.g., the smaller the number of rules that we need to remove from the human's model, the better)
  - …

Ongoing and Future Work

- **Conveying explanations:** Using visualizations



Kumar, Vasileiou, Bancilhon, Ottley, and Yeoh (ICAPS 2022)



Bryce, Bonasso, Adil, Bell, and Kortenkamp (UISP 2017)

Ongoing and Future Work

- **Conveying explanations:** Argumentation-based dialogues
  - Goal: Human wants to understand why robot thinks c is true

KB_h: $e, e \rightarrow \neg c$; $i, i \rightarrow \neg f$

KB_a: $a, b, a \wedge b \rightarrow c$; $f, f \rightarrow h$; $h, h \rightarrow \neg e$

Vasileiou, Kumar, Yeoh, Son, and Toni (arXiv 2023)

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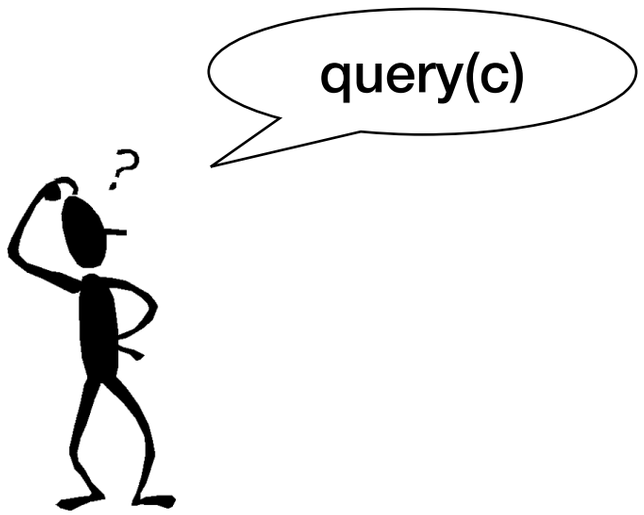

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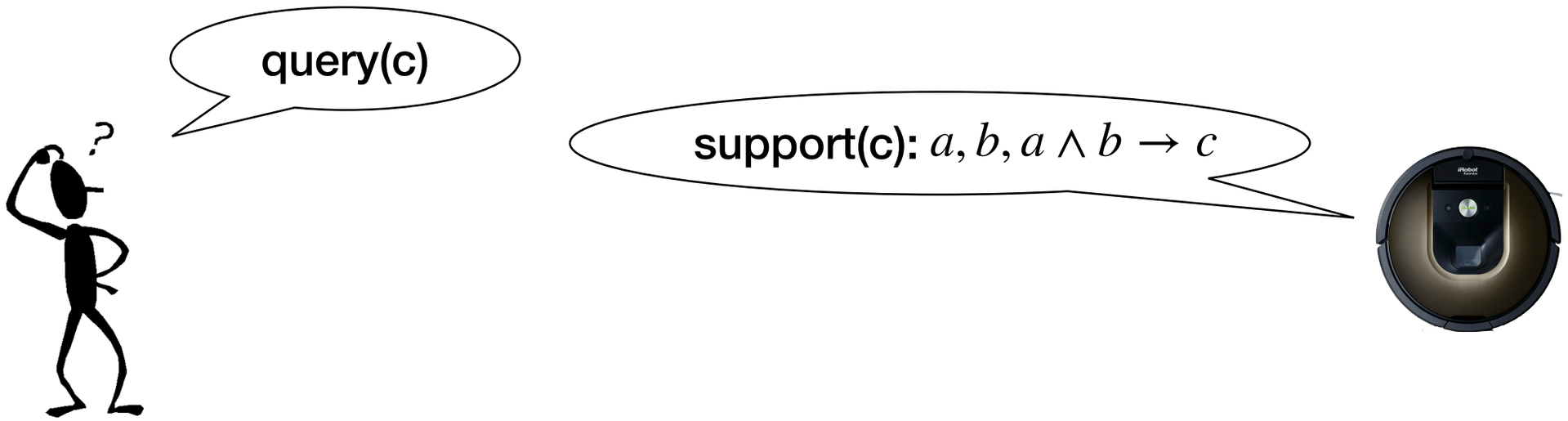

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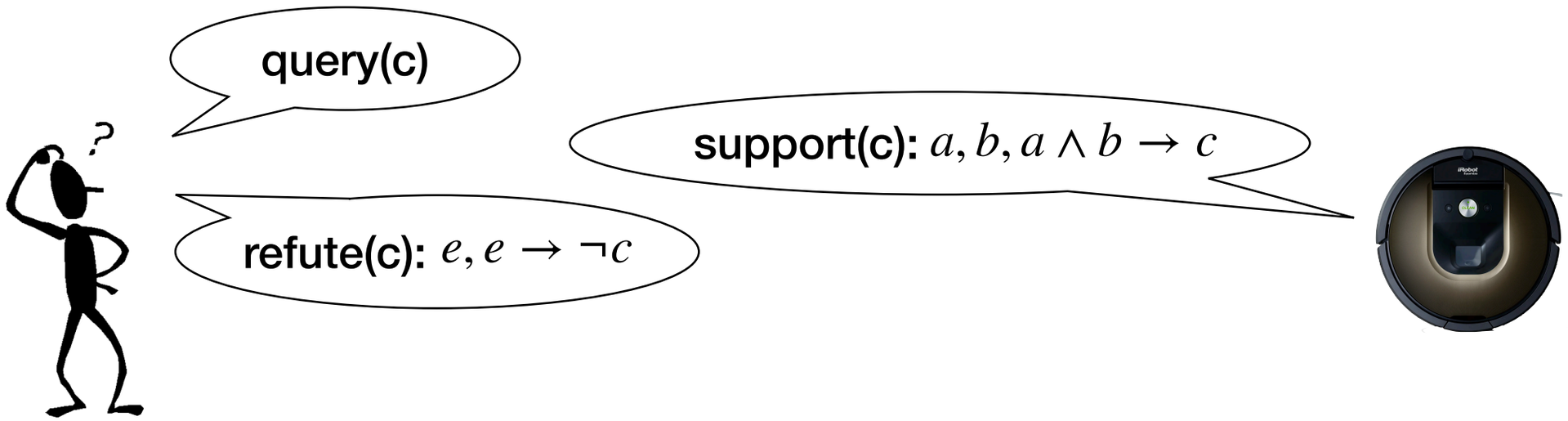

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YODAlab

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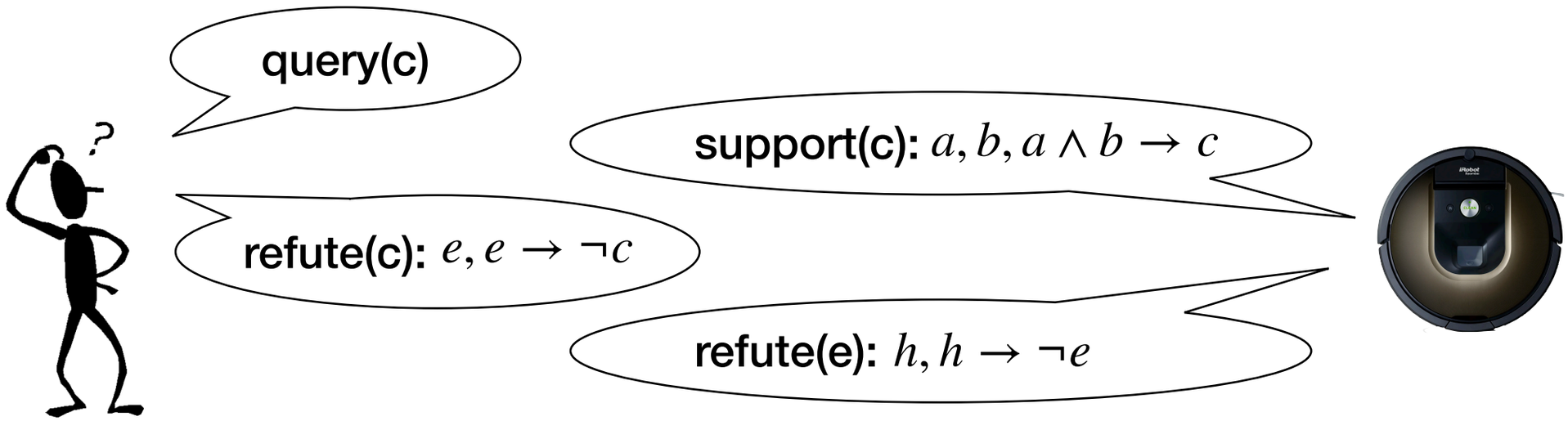

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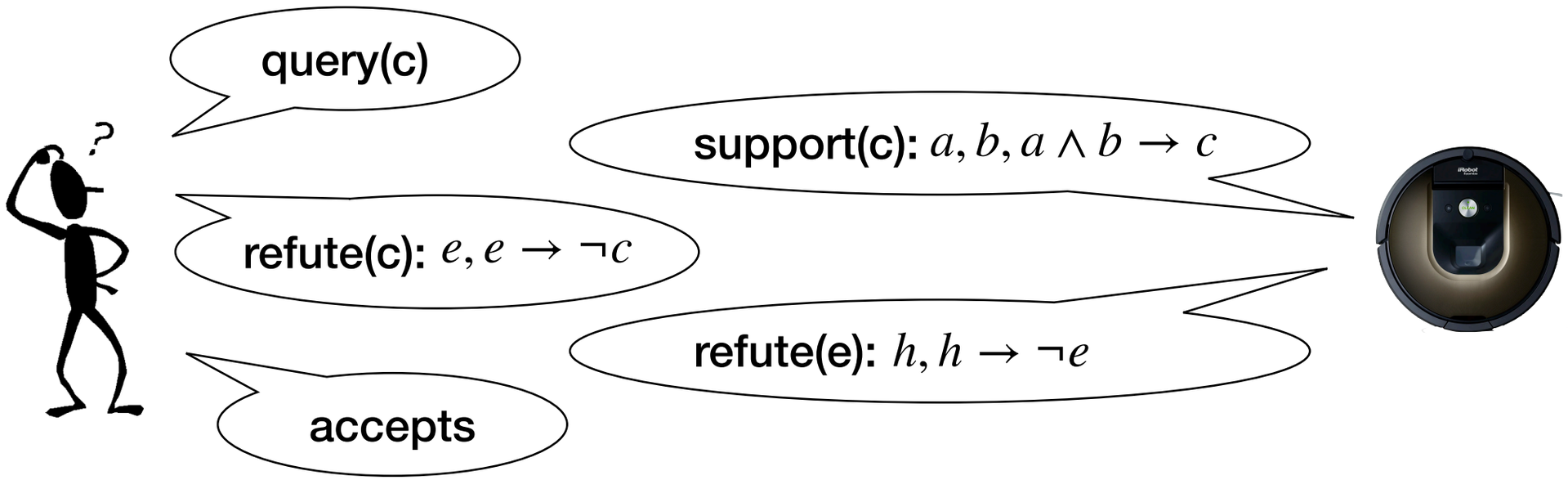

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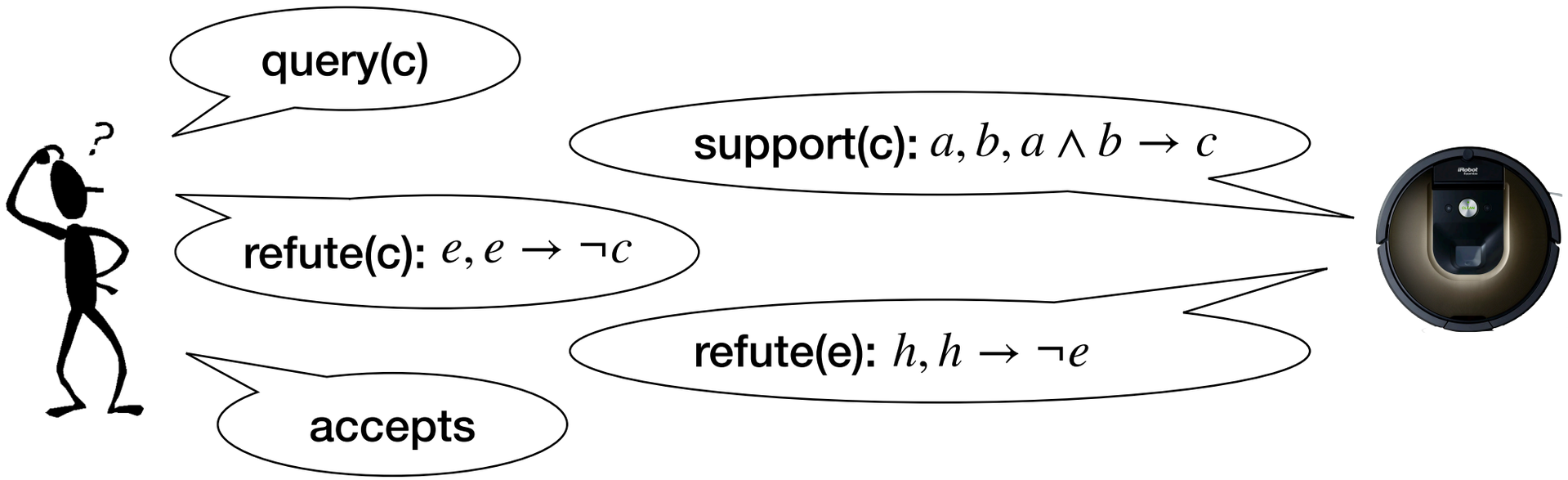

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$a, b, a \wedge b \rightarrow c$ $f, f \rightarrow h$ $h, h \rightarrow \neg e$ KB_a

- Further research questions:
  - How to learn and approximate humans' model based on interaction?
  - How to model how humans update their models? Does it depend on trust? If so, how to measure trust?
  - How to generalize to handle uncertainty and reason in the presence of uncertainty?
  - How to leverage LLMs for natural language conversations?

Ongoing and Future Work

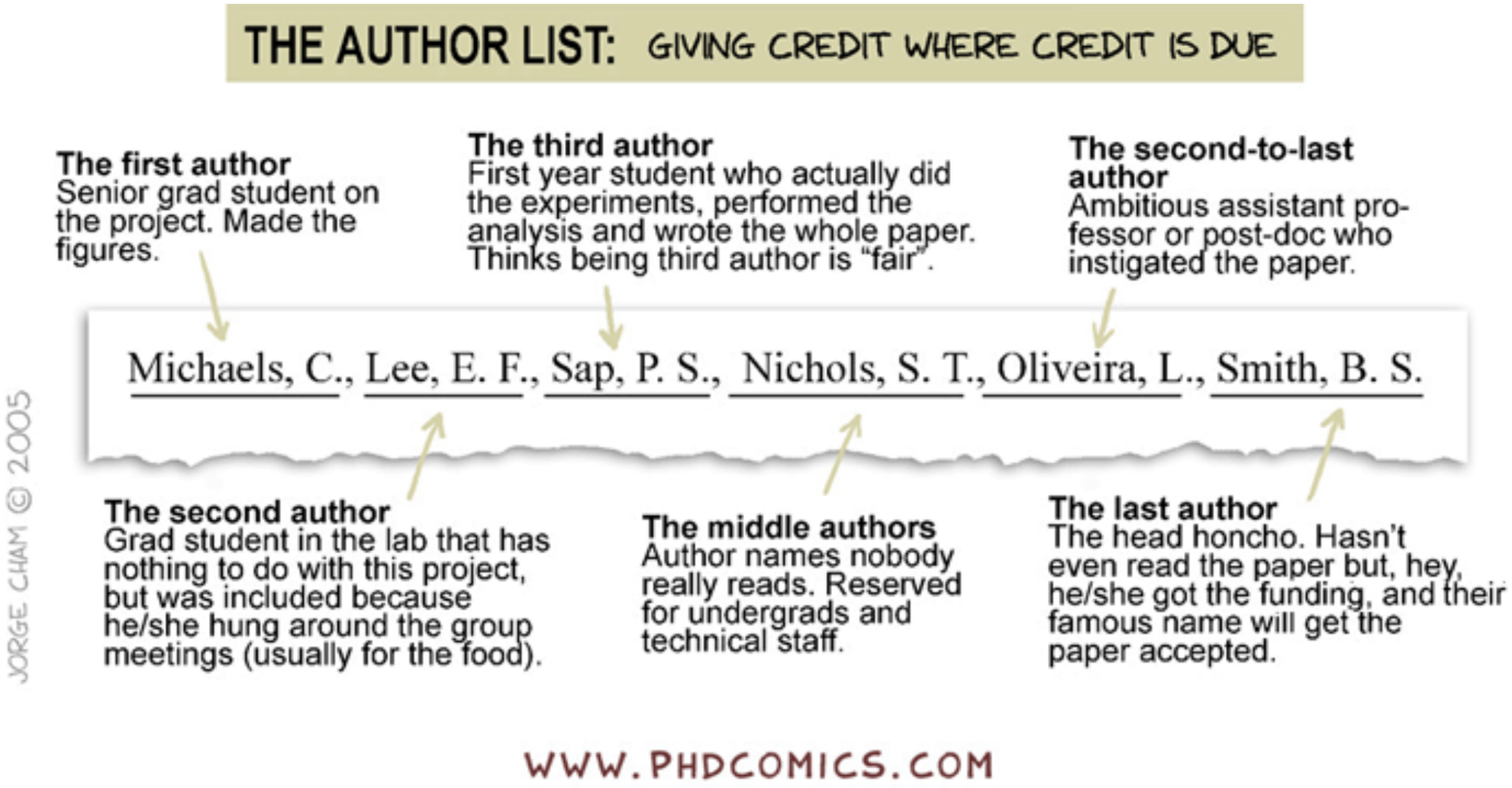
- **Conveying explanations:** Argumentation-based dialogues
  - Goal: Human wants to understand why robot thinks c is true

Medium-term Goal: LLM-like Explainable Agent
Able to provide convincing explanations that are grounded in reality in a natural conversational manner

- Further research questions:
  - [illegible]?
  - [illegible]n
  - [illegible] of uncertainty?
  - How to leverage LLMs for natural language conversations?

Ultimate Goal: Collaborative Human-Agent Teams
Enable agents to work with humans to solve problems where neither agents nor humans can solve individually!!

Acknowledgments



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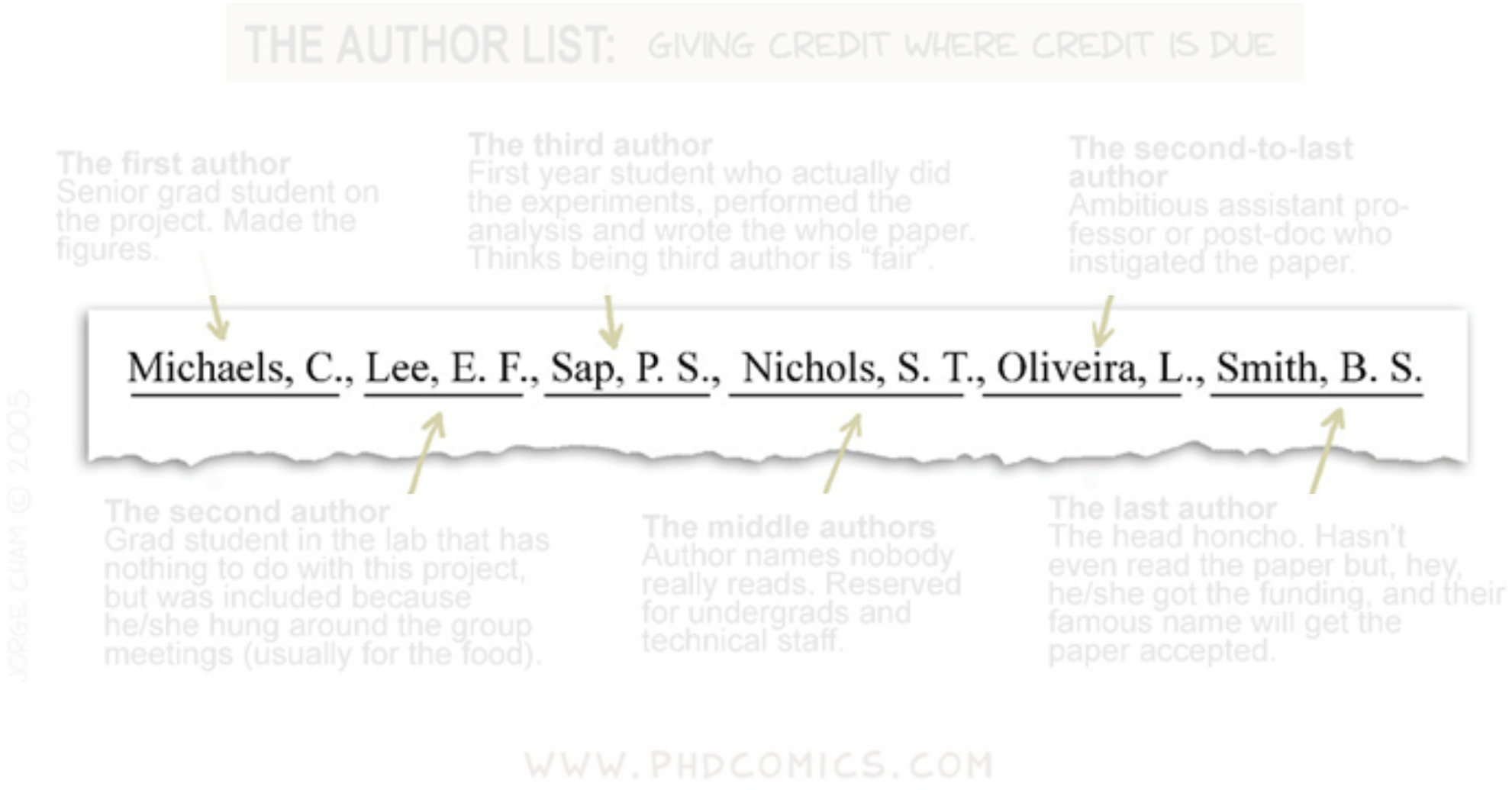
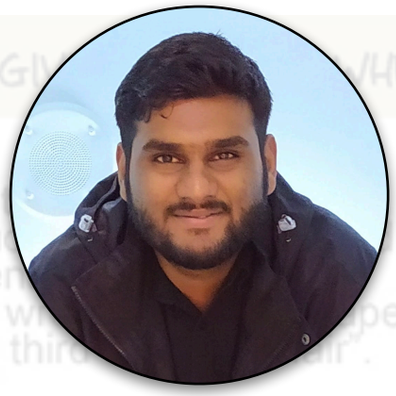


Acknowledgments

Student Collaborators



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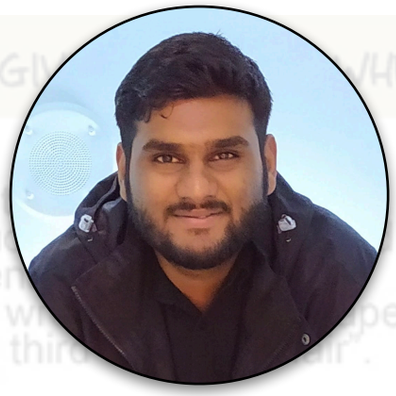


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Faculty Collaborators