

EXPLAINABLE ROBOTICS



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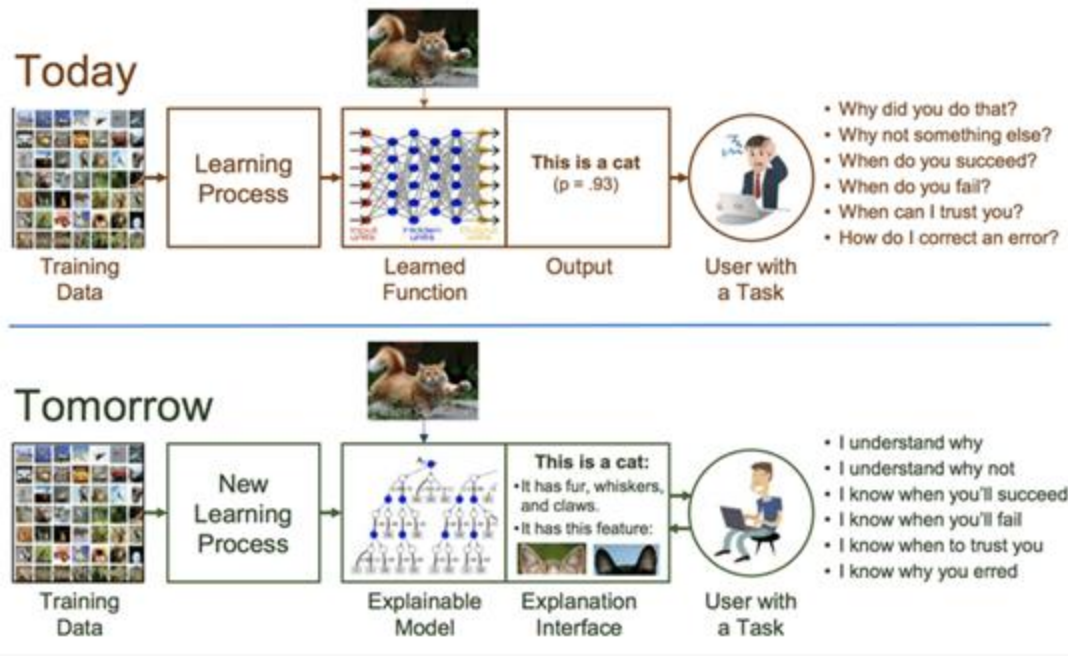
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Explainable Robot Navigation
Environment-Centered and Human-Centered Approach

Dissertation Project Presentation

Explainable AI (XAI)

- Makes AI decisions transparent and understandable
- Builds trust and supports accountability
- Applicable to different domains



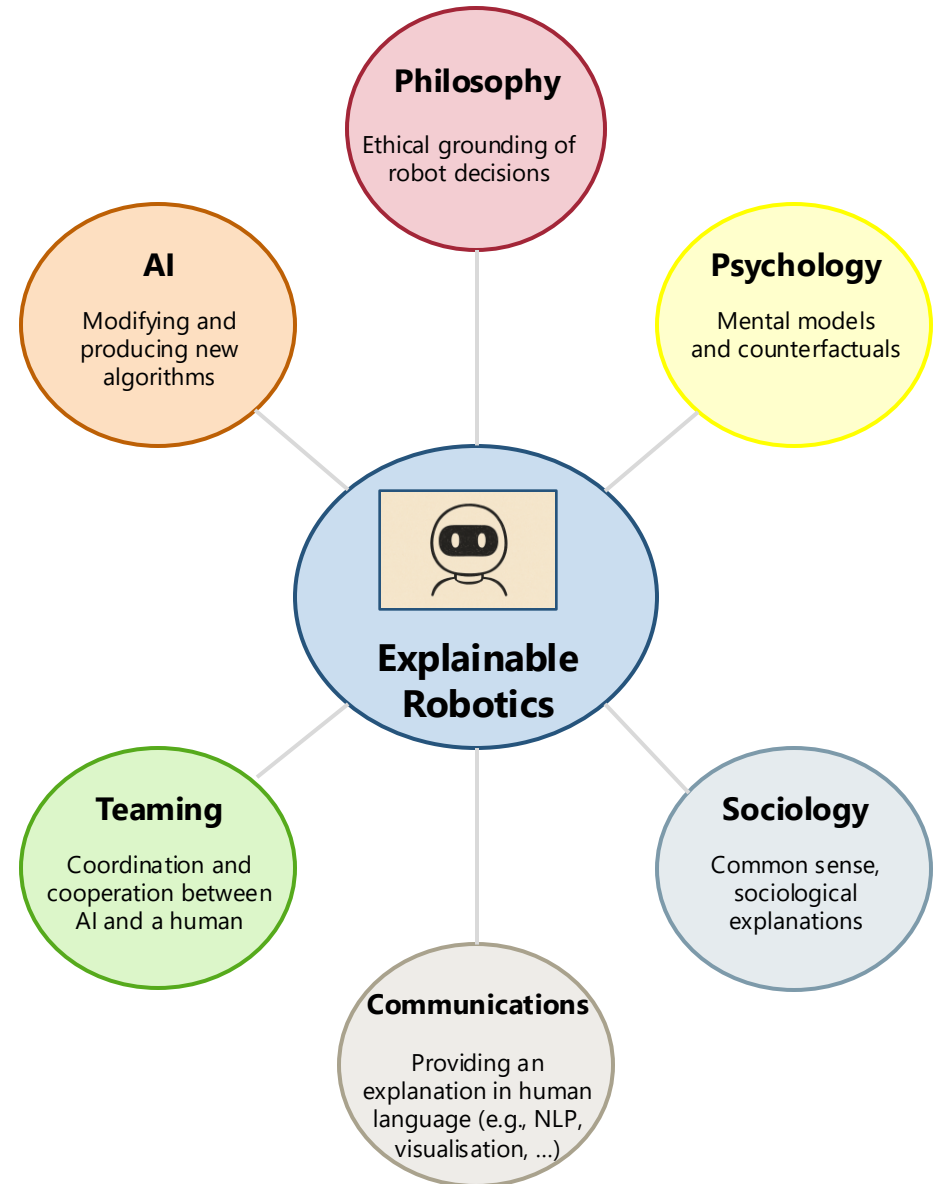
From XAI to Explainable Robotics

- Embodied, interactive, real-time agents
- Need for context-aware and multimodal explanations
- Challenges of explainability in dynamic environments

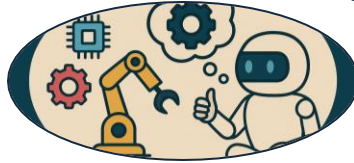


What is Explainable Robotics

- Making robotic behavior understandable to humans
- Covers task and motion planning, perception, navigation, control
- Supports trust, predictability, and team fluency

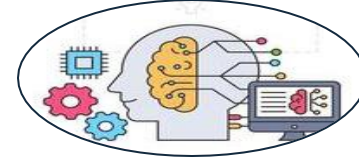
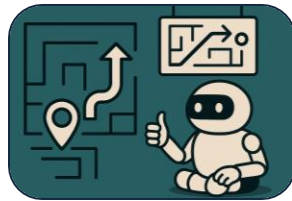


Explainable Robot Navigation



Robotics

Robot
navigation



Artificial Intelligence

Explainable
Artificial
Intelligence
(XAI)

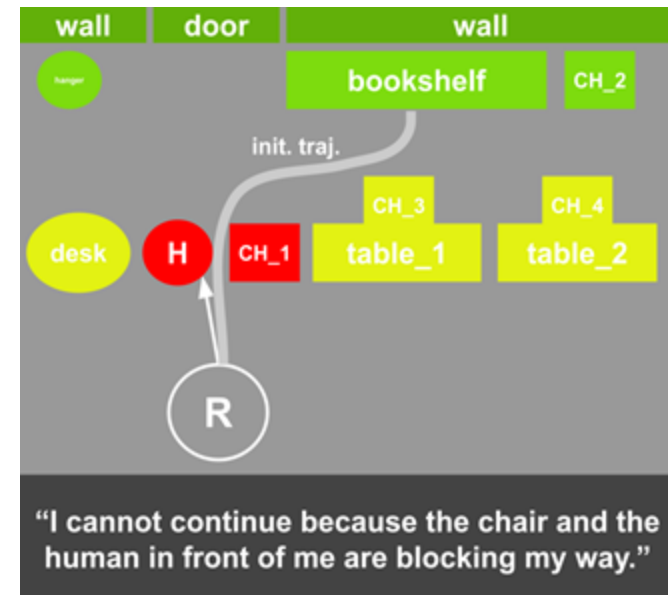


Explainable
robot
navigation



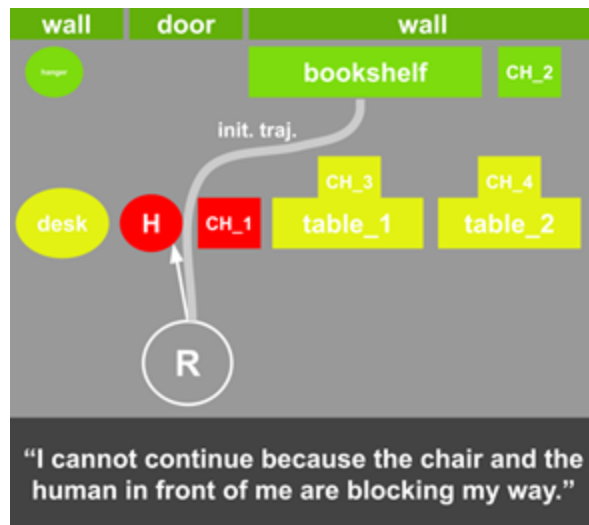
Motivational and Running Example

- Focused on service robotics
- Robot Librarian: delivers books to library visitors
- Has multimodal explanation capabilities

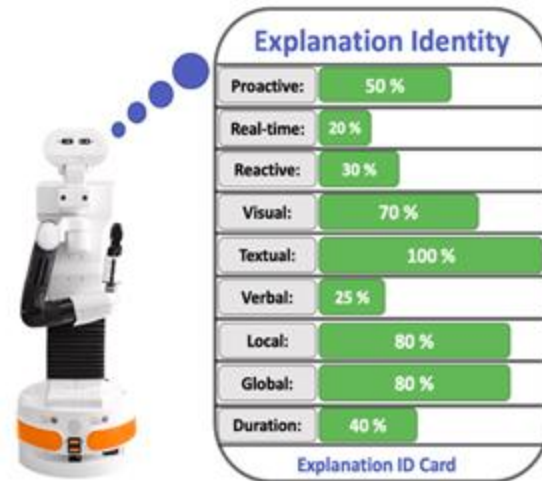


Research Challenges

Environment-centered explanation generation for robot navigation



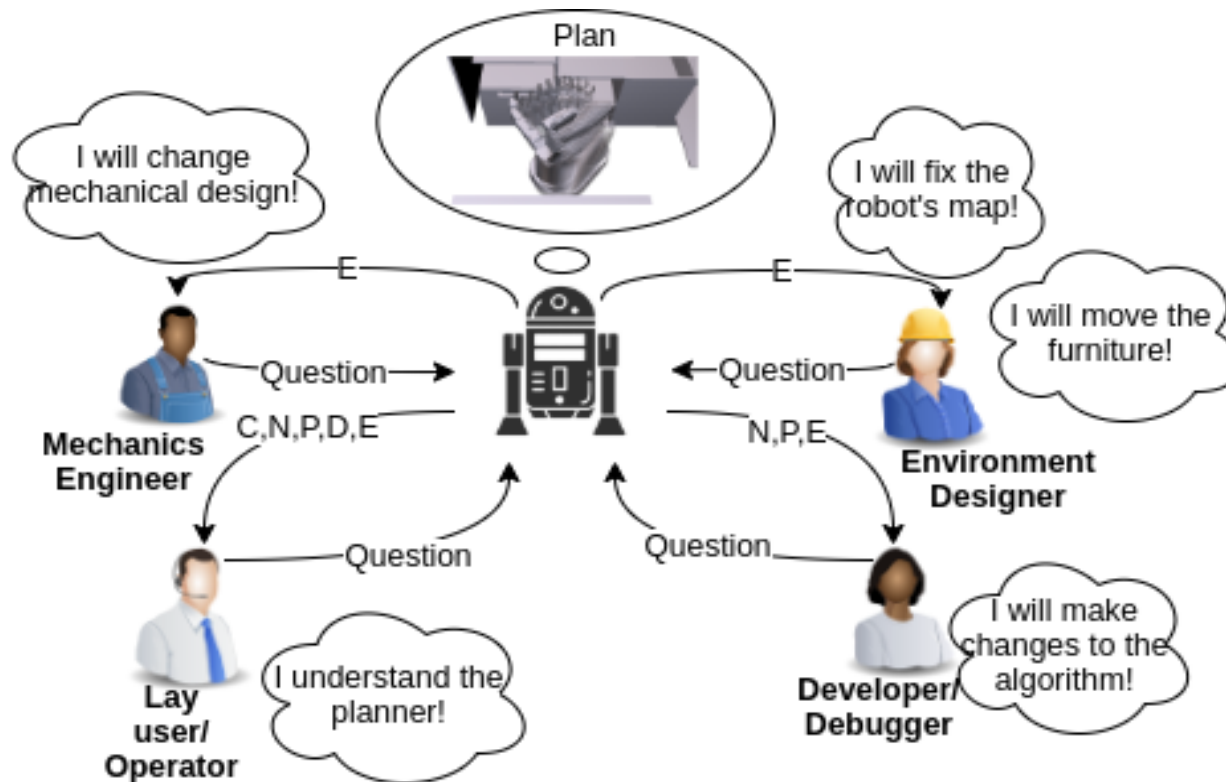
Human-centered explanation planning for robot navigation



Environment-centered explanations of robot navigation

- Focus on environment, not robot internals

Types of explanations and user needs in robot motion planning



Explanations types:

- C: Cost-based explanation
- N: Constraint-based explanation
- P: Algorithm-parameter-based explanation
- D: Design-based explanation
- E: Environment-based explanation**

Failure questions

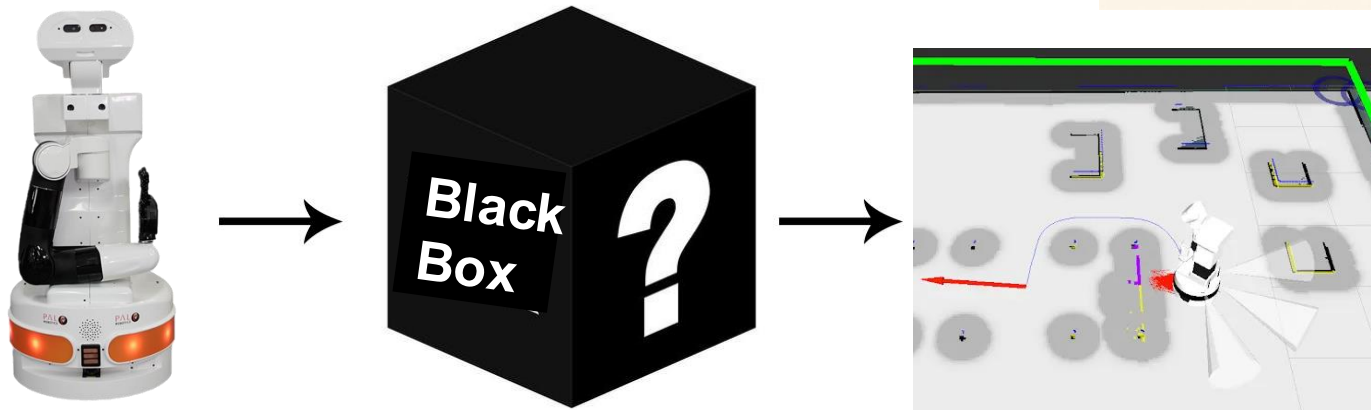
Question types:

- "Why did you fail?"
- "Why trajectory A not B?"**

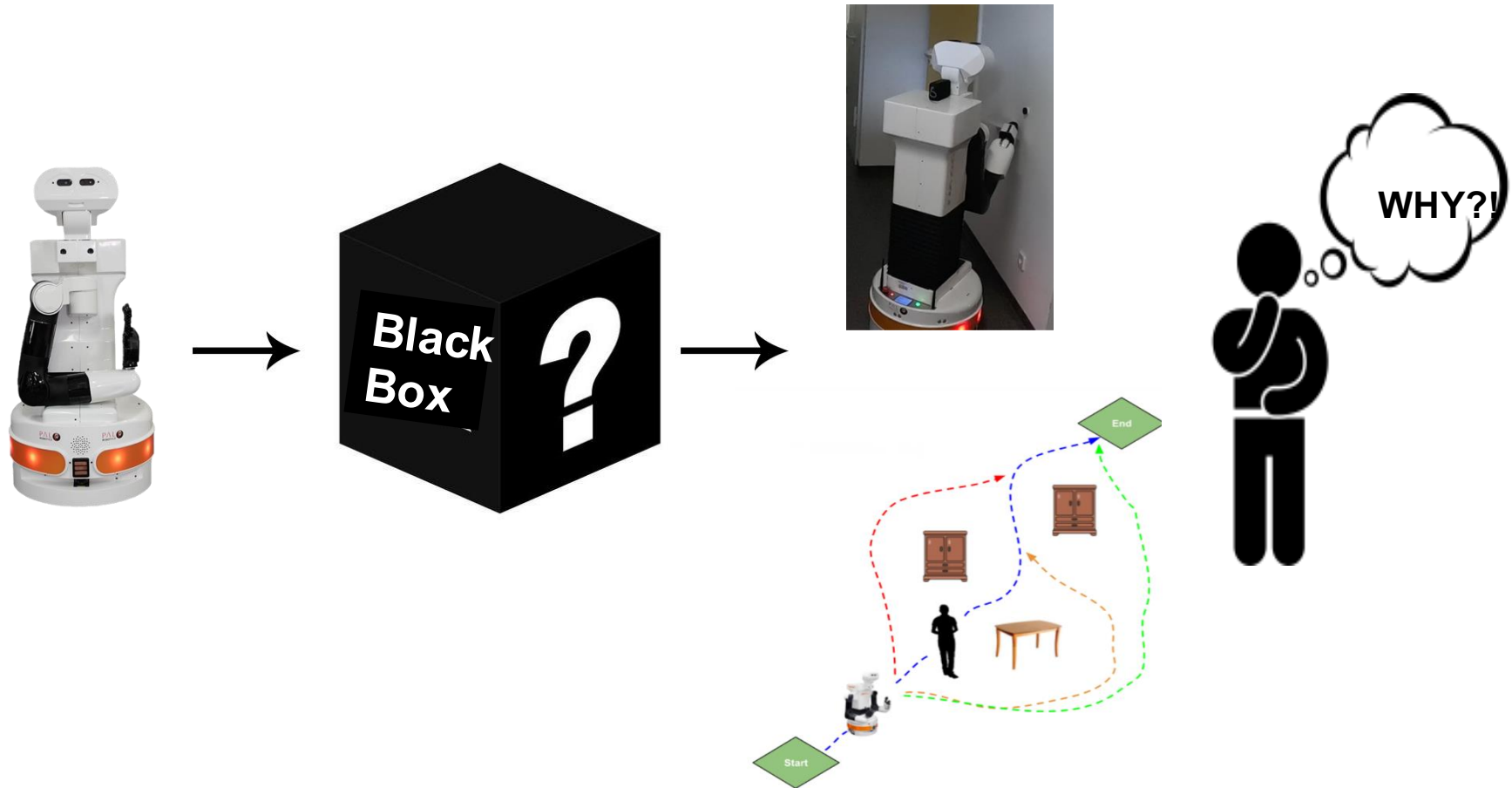
Trajectory-contrastive questions

Environment-based explanation

Motivation



Motivation



How can the robot use its environment to explain its navigational failures and decisions?

SOTA Overview

- Most of methods are constraint- or algorithm-based
- Focus on planner internals rather than environment
- Most methods explain task failures rather than planning failures
- Approaches focused on manipulation rather than navigation

A Explanation panels at a_0



Action sequence:
Approach

B Explanation panels at a_2



Action sequence:
Approach → Grasp → Push

C Explanation panels at a_8



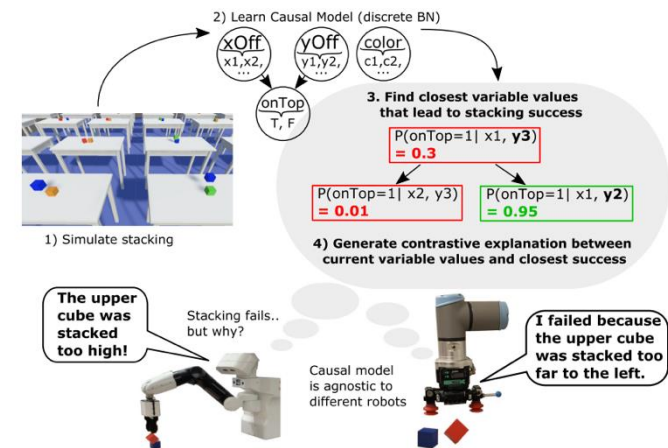
Action sequence:
Approach → Grasp → Push → Twist →
Ungrasp → Move → Grasp → Push →
Twist

D Explanation panels at a_9



Action sequence:
Approach → Grasp → Push → Twist →
Ungrasp → Move → Grasp → Push →
Twist → Pull

Edmonds, M., Gao, F., Liu, H., Xie, X., Qi, S., Rothrock, B., ... & Zhu, S. C. (2019). A tale of two explanations: Enhancing human trust by explaining robot behavior. *Science Robotics*, 4(37), eaay4663.



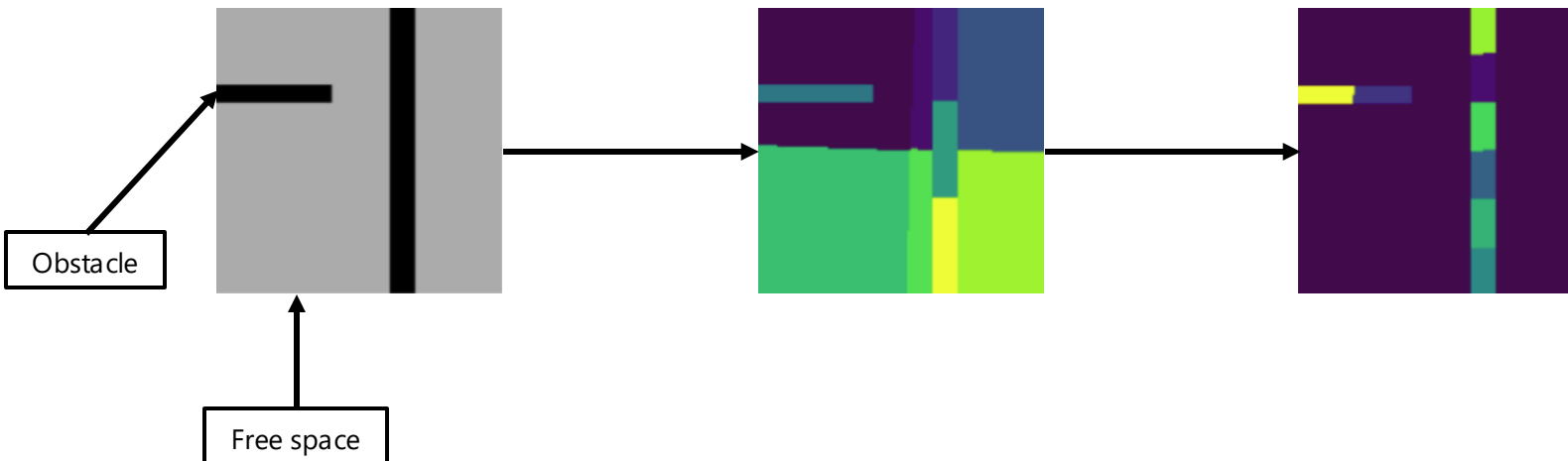
Diehl, M., & Ramirez-Amaro, K. (2022). Why did i fail? a causal-based method to find explanations for robot failures. *IEEE Robotics and Automation Letters*, 7(4), 8925-8932.

Environment-centered explanations of robot navigation

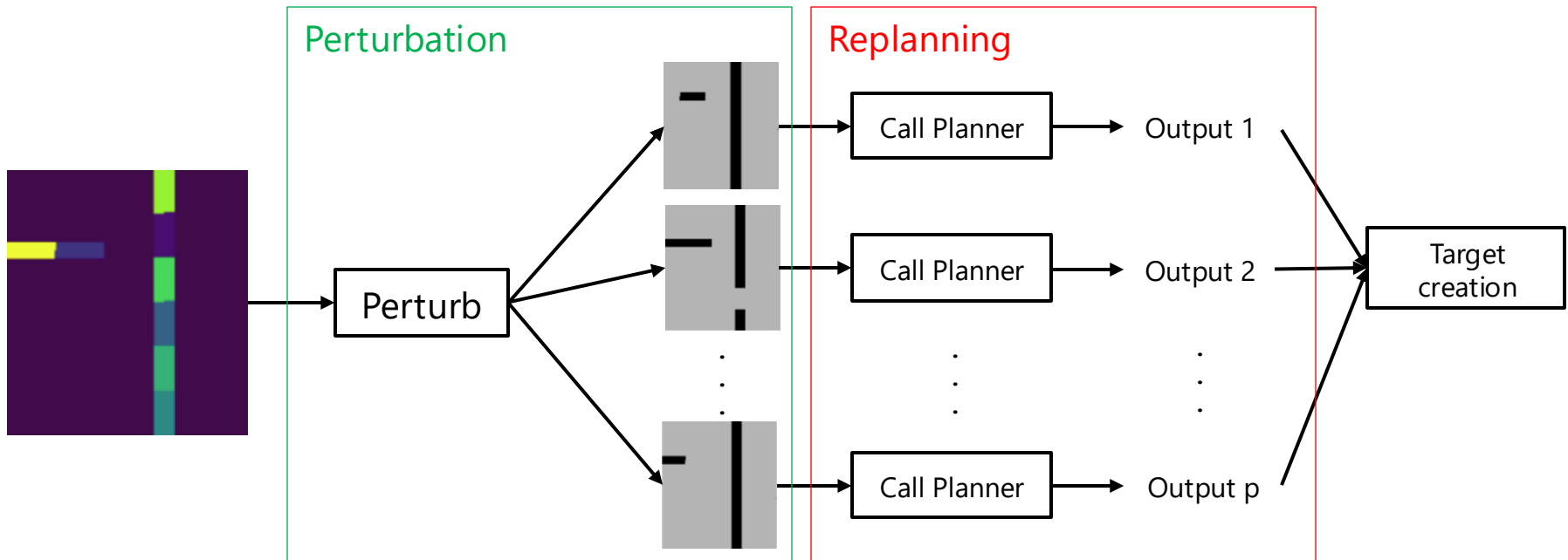
- Focus on environment, not robot internals
- Objects and their roles drive the explanation
- Replanning-based explanation generation

Environment clusterization (segmentation)

- Map (free space, obstacle) -> image representation
- Image clusterization (SLIC - Simple Linear Iterative Clustering)
- Removal of redundant information (free space clusters)
- Manual clustering to the predefined number of segments

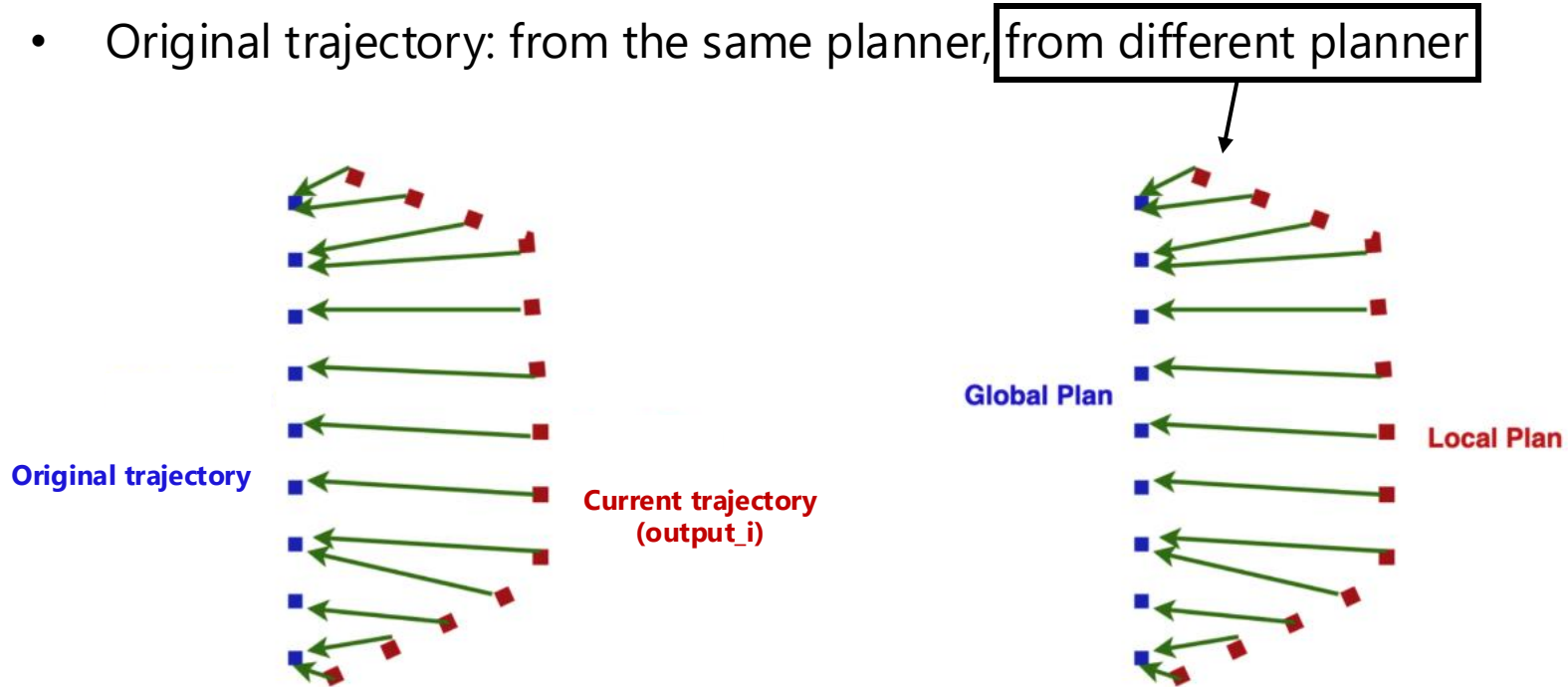


Environment perturbation and replanning

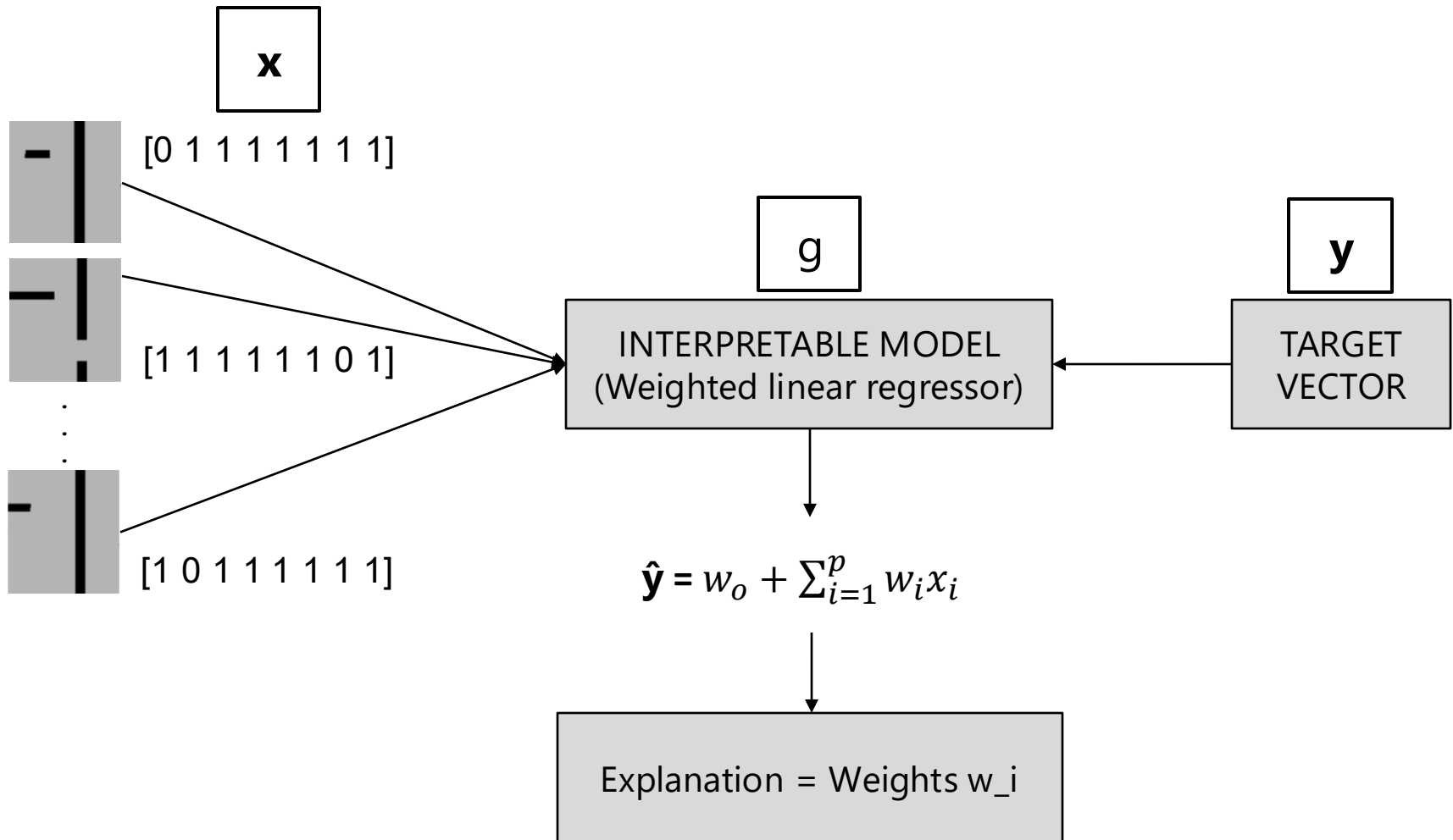


Target creation

- For each perturbation
- L2 Euclidean distance between the current trajectory (output_i) from the original trajectory
- Original trajectory: from the same planner, from different planner



Explanation generation

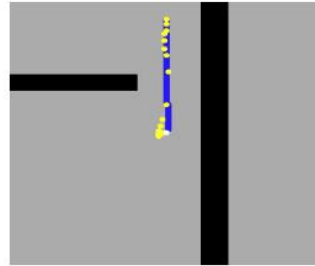


Explanation Visualization

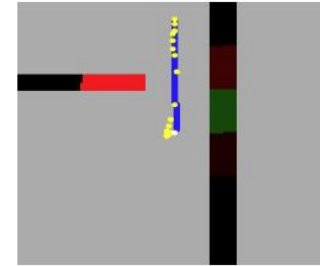
- Segment has positive weight
- Segment has negative weight



(a) C1: robot



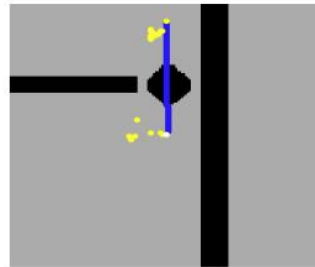
(b) C1: costmap



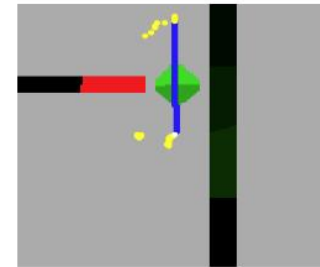
(c) C1: explanation



(d) C2: robot



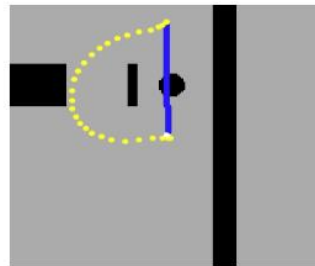
(e) C2: costmap



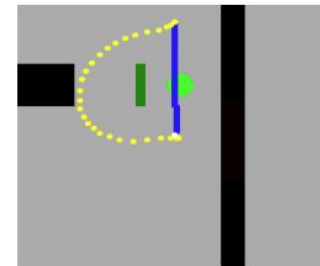
(f) C2: explanation



(g) C3: robot



(h) C3: costmap



(i) C3: explanation

Semantics were missing!

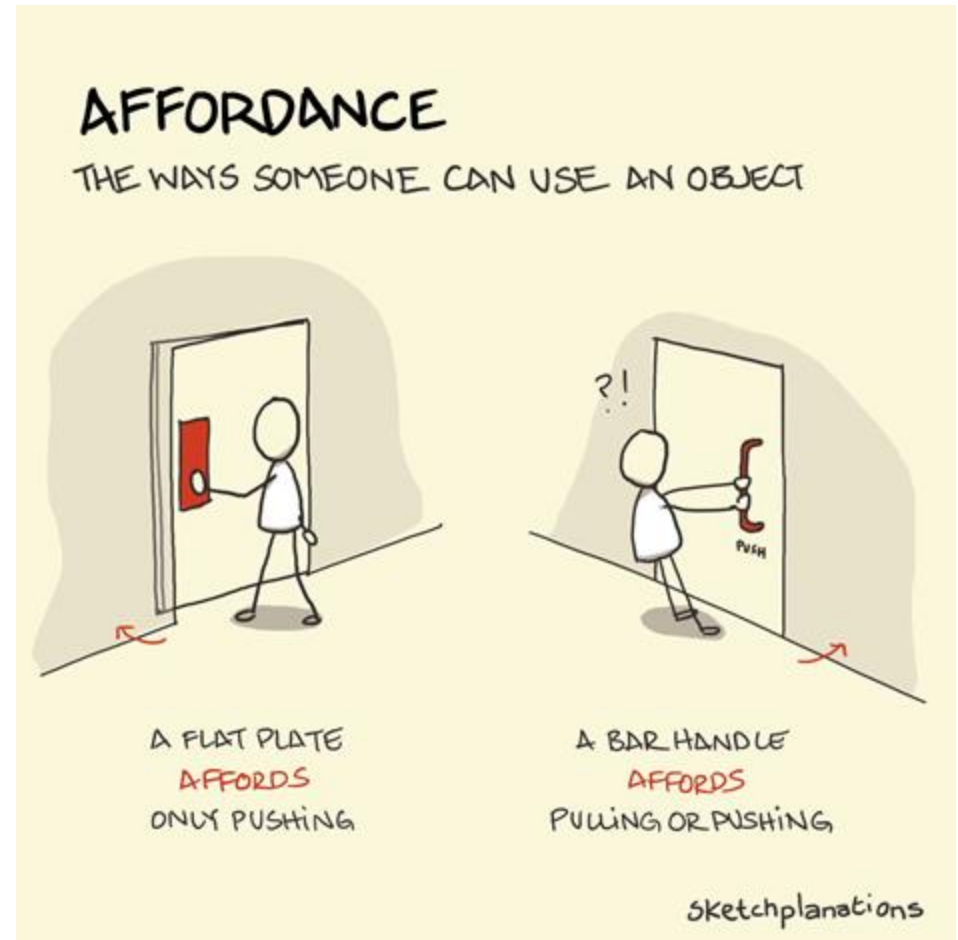
Environment-centered explanations of robot navigation

- Focus on environment, not robot internals
- Objects and their roles drive the explanation
- Perturbation-based explanation generation
- Ground explanations in human-understandable context

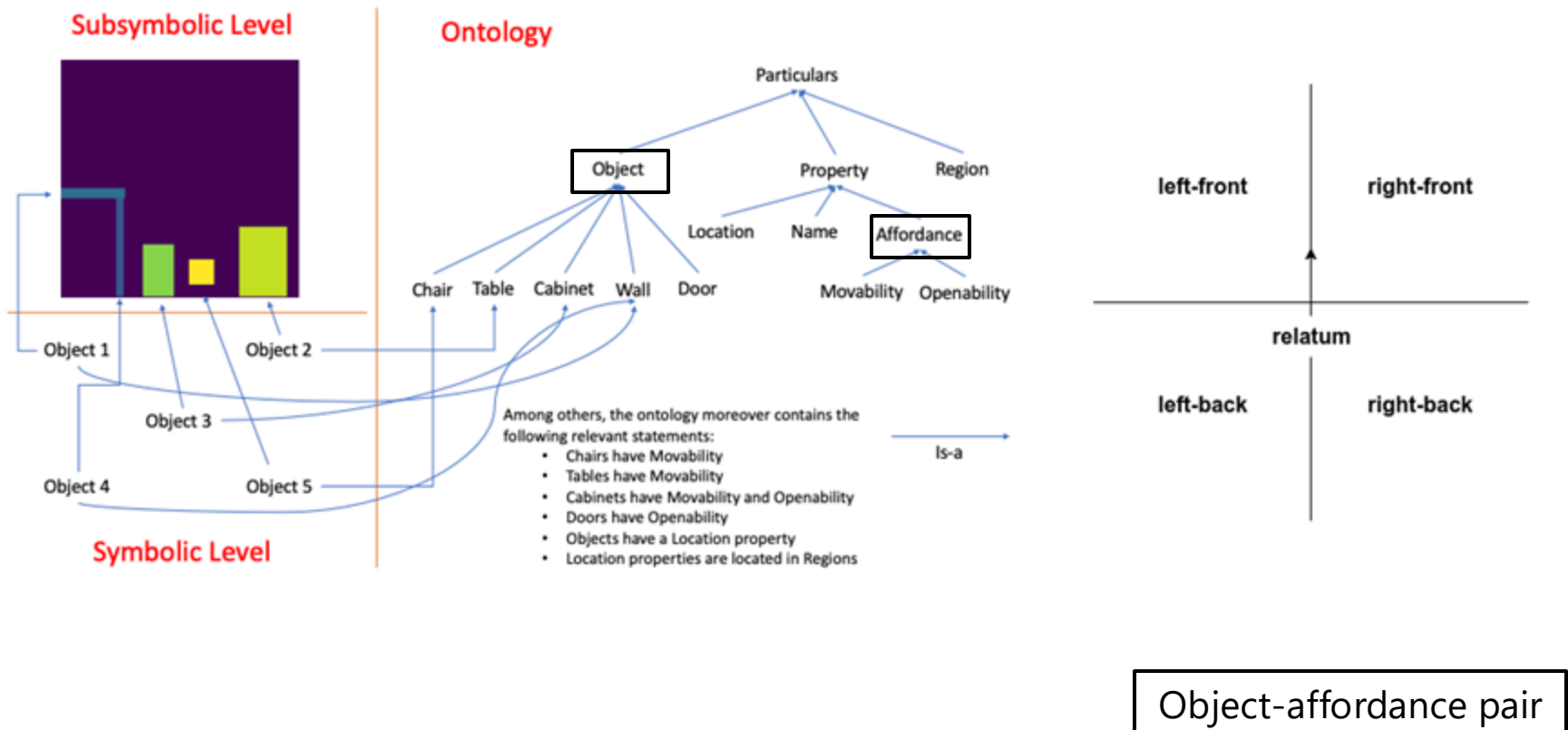
Affordances of objects



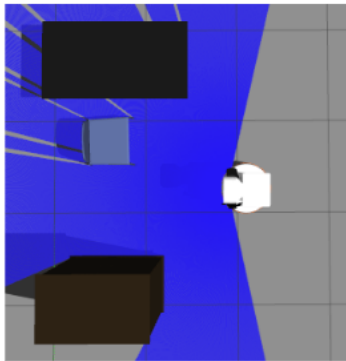
By Makito Nagawa



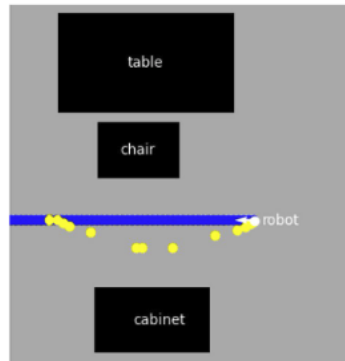
Affordance-based Ontology



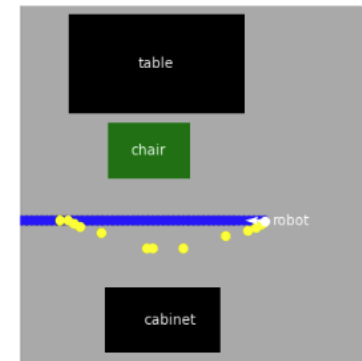
Visual-textual environment-centered explanations



Simulation scenario



Semantic map



Chair-movability explanation map
(initial state: in the robot's neighborhood)

Chair-movability textual explanation: *"Because of the chair right-front of me, I deviate from the initial plan."*

Chair-movability textual suggestion: *"Dear human, please move the chair, so I proceed more smoothly."*

Visual-textual environment-centered explanations

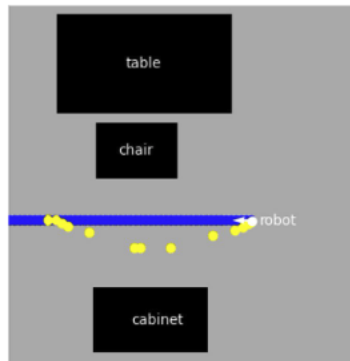
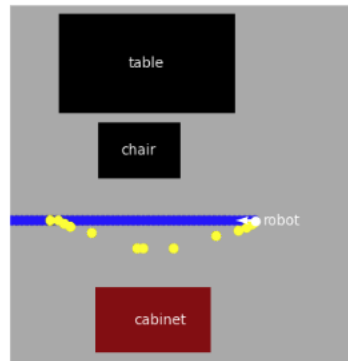
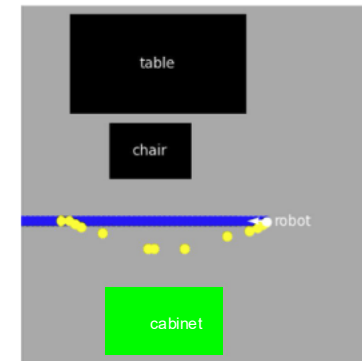


Table-movability explanation map
(initial state: in the robot's neighborhood)



Cabinet-movability explanation map
(initial state: in the robot's neighborhood)



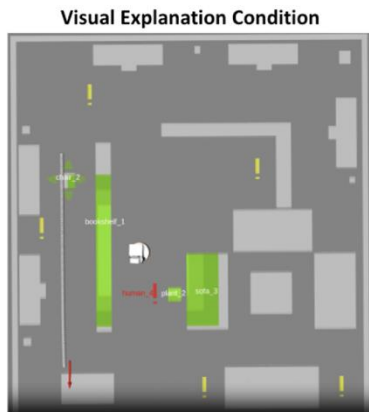
Cabinet-openability explanation map
(initial state: closed)

Cabinet-movability textual explanation: "If the cabinet left-front of me was not there, I would deviate more from the initial plan."

Cabinet-openability textual explanation: "If the cabinet left-front of me was open, I would deviate less from the initial plan."

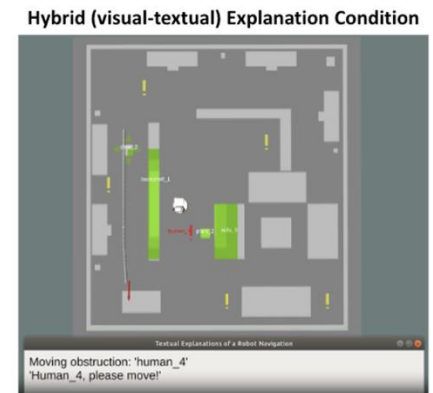
Explanation modality

- Visual and textual modalities explored
- First user study on most preferred color scheme for visual explanation
- Second user study on satisfaction with different explanation modalities (visual vs. textual vs. visual-textual)
- People are more satisfied multimodal (visual-textual) over unimodal (visual, textual) explanations



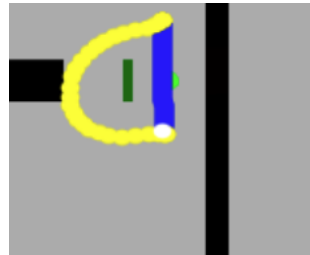
Textual Explanation Condition

Moving obstruction: 'human_4'
'Human_4, please move!'

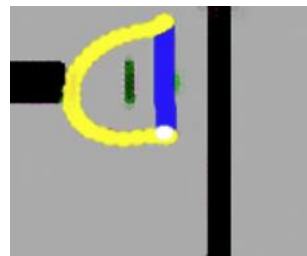


Visual explanations with generative AI

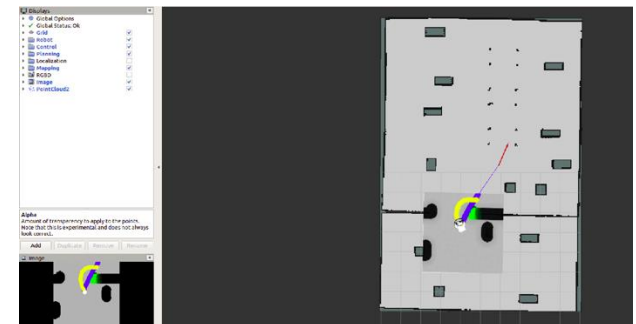
- Visual explanation generation with generative AI (GAN - Generative Adversarial Networks, image-to-image translation)
- Requires dataset created with replanning
- Faster than replanning (4 Hz), but the explanation quality is lower
- Not that scalable
- Real-time* visual explanation layer



Replanning



GAN



Visual explanation layer

Different textual explanations

- Descriptive, suggestive and counterfactual textual explanations
- Affordance-based verbalizer
- Robot librarian failure example

Descriptive explanation

"I failed to fetch a book, because the chair and the **closed** cabinet both **in front of** me blocked my path"

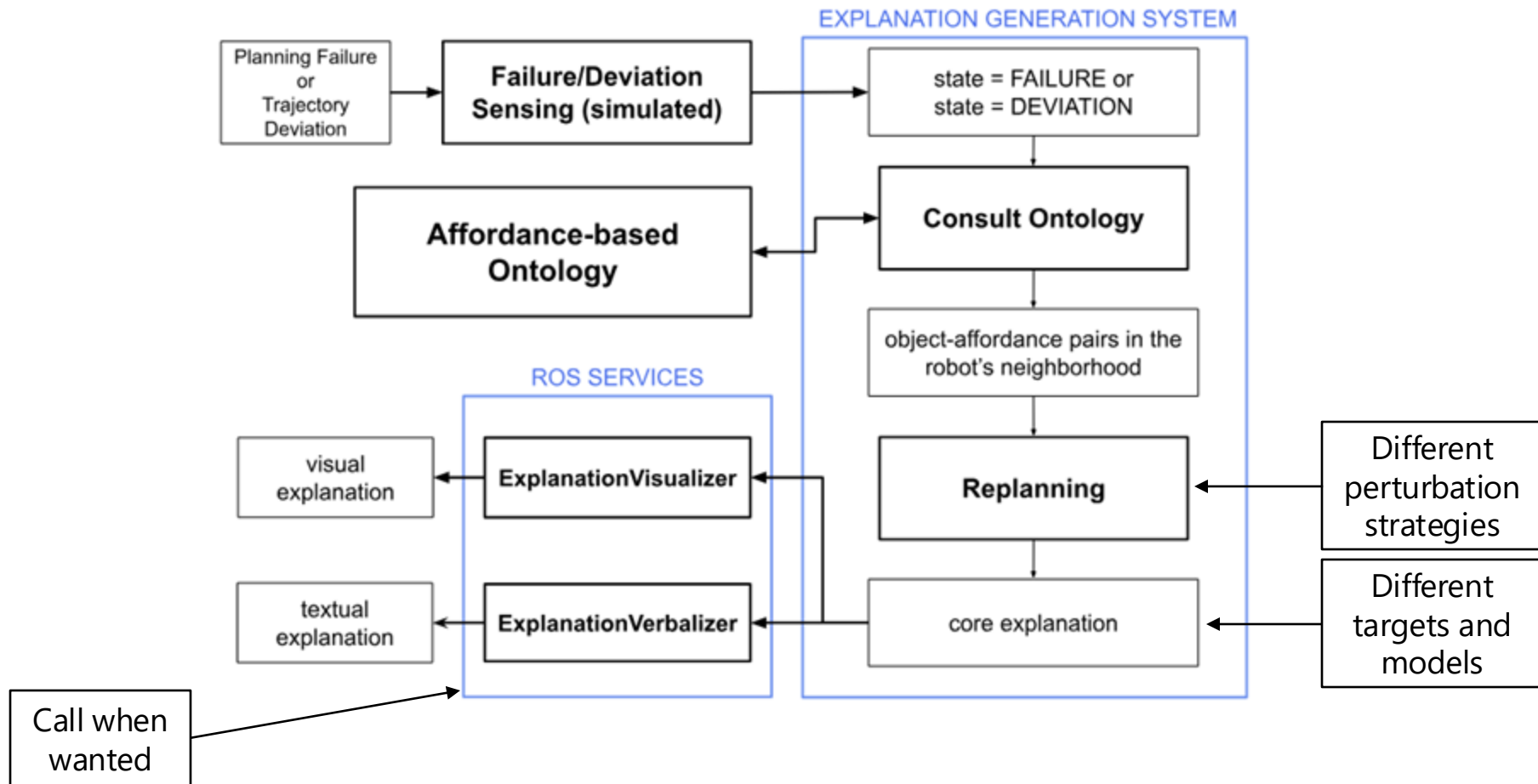
Suggestive explanation

"Dear human, please **move** the chair and **open** the cabinet, both **in front of** me, so I can fetch a book."

Counterfactual explanation

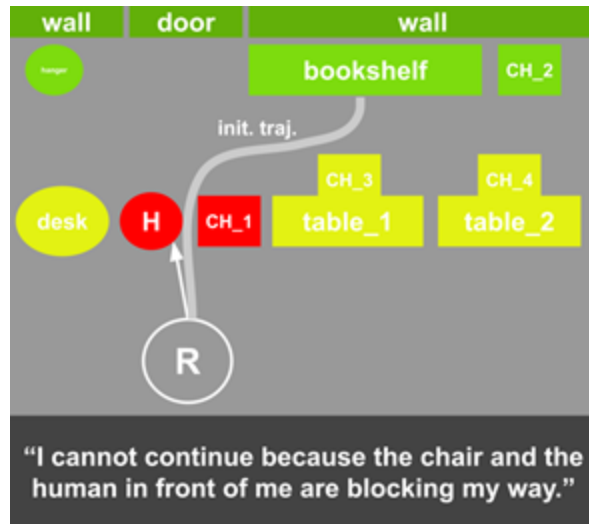
"If the chair **in front of** me was **not there** and the cabinet **in front of** me was **open**, I would not fail to fetch the book."

Explanation generation framework

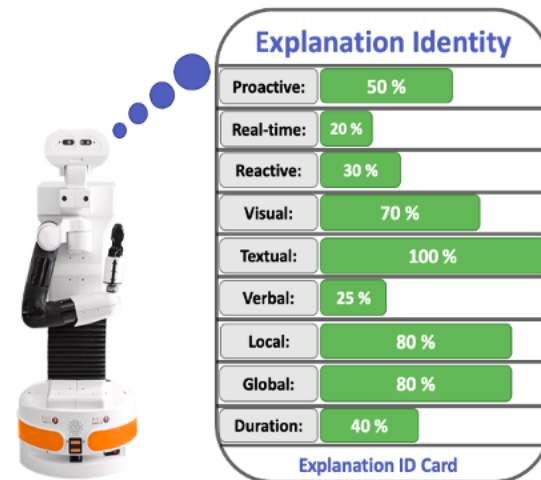


Research challenges

Environment-centered explanation generation for robot navigation

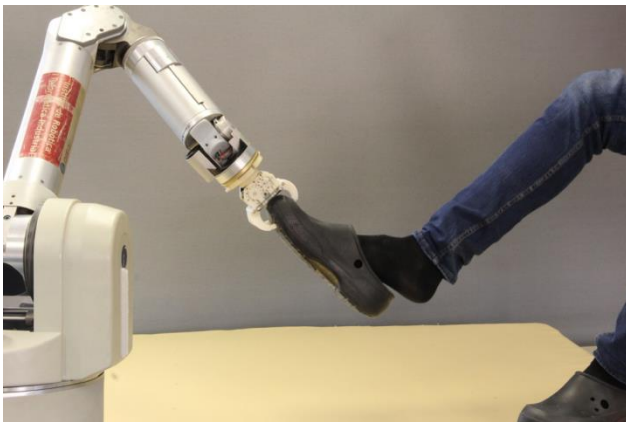


Human-centered explanation planning for robot navigation

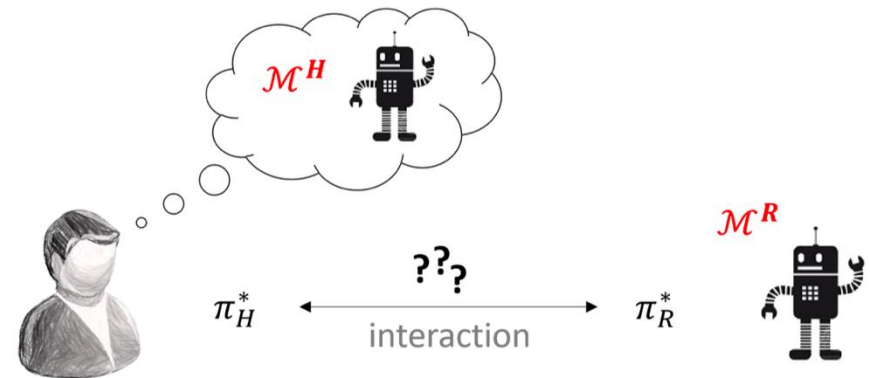


SOTA Overview

- Explainable AI Planning (XAIP) – explainable planning of robot actions, but not planning of robot explanations
- Preference-driven assistive and social robotics, but not explainable robotics
- Explanations through model reconciliation



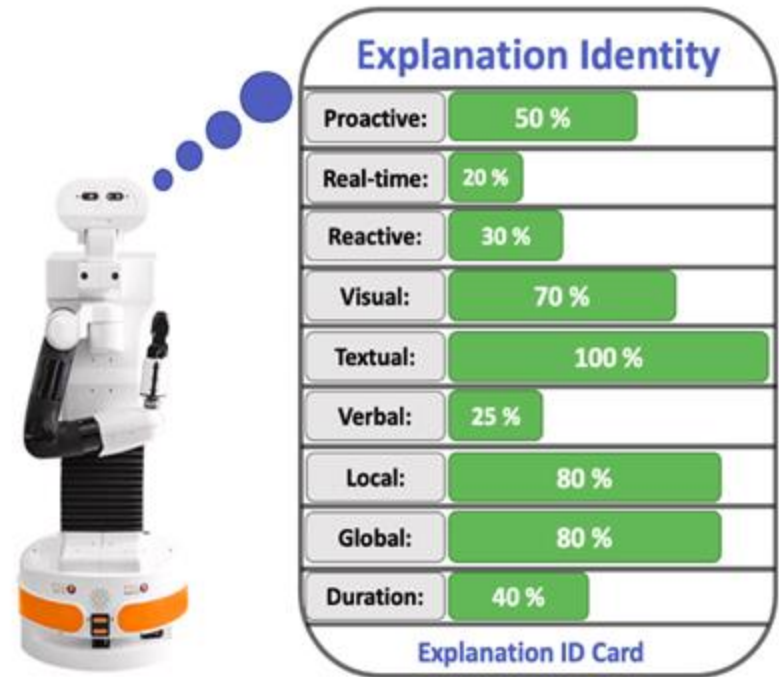
Canal, G., Alenyà, G., & Torras, C. (2019). Adapting robot task planning to user preferences: an assistive shoe dressing example. *Autonomous Robots*, 43(6), 1343-1356.



Chakraborti, T., Sreedharan, S., Zhang, Y., & Kambhampati, S. (2017). Plan explanations as model reconciliation: Moving beyond explanation as soliloquy. *arXiv preprint arXiv:1701.08317*.

Robot explanation identity

- Unique identity characteristics
- Adaptive
- Contextual
- Personalized
- Multimodal
- Probabilistic
- “Good explanations require additional knowledge represented as preferences over explanations” [1]



Halilovic & Krivic, Robot Explanation Identity, 2024.

[1] Sohrabi, S., Baier, J., & McIlraith, S. (2011, August). Preferred explanations: Theory and generation via planning. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 25, No. 1, pp. 261-267).

Key questions identified

What to explain?

- Failure
- Deviation
- Path optimality

When to explain?

- Every time step
- When human is nearby
- After a question
- Proactive, reactive, post-hoc

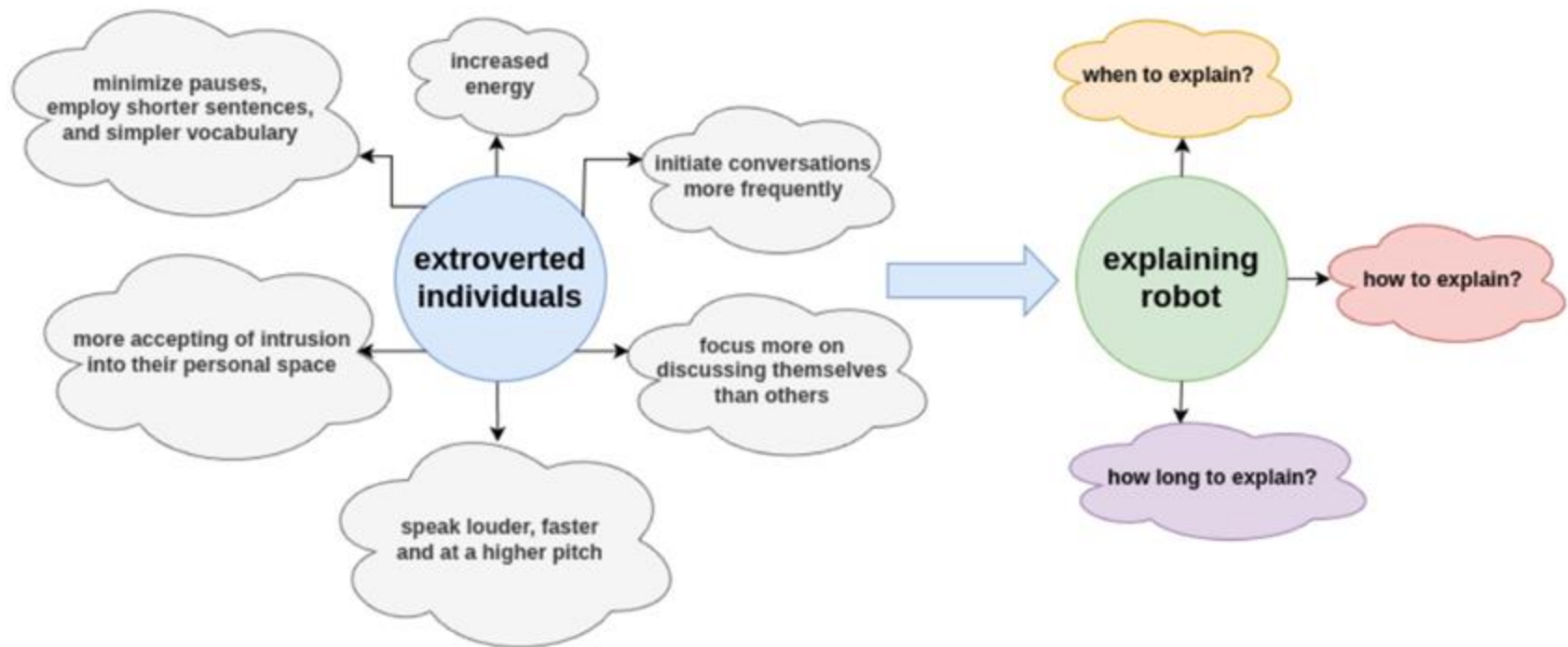
How to explain?

- Modality
- Scope

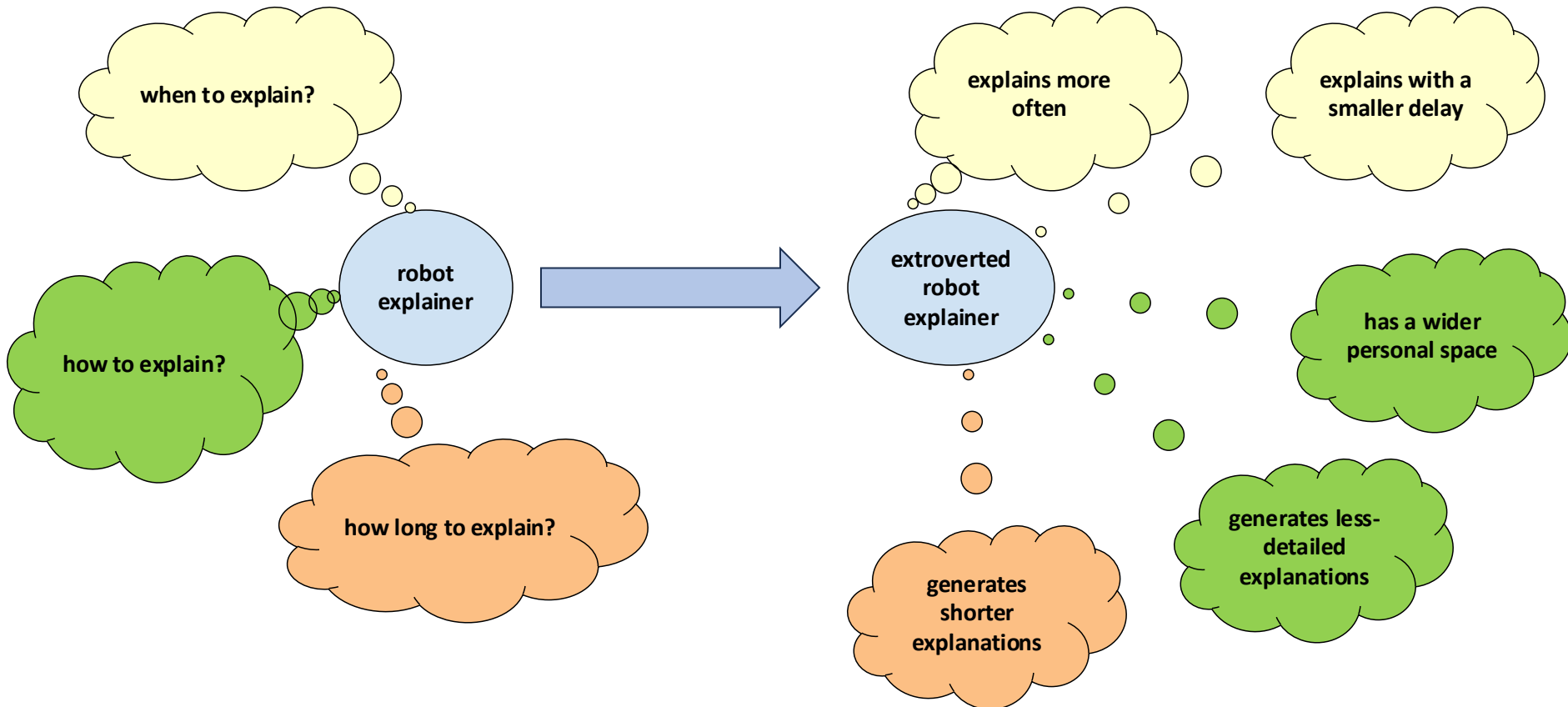
How long to explain?

- Until the action is finished
- Until human stops asking
- After a predefined interval

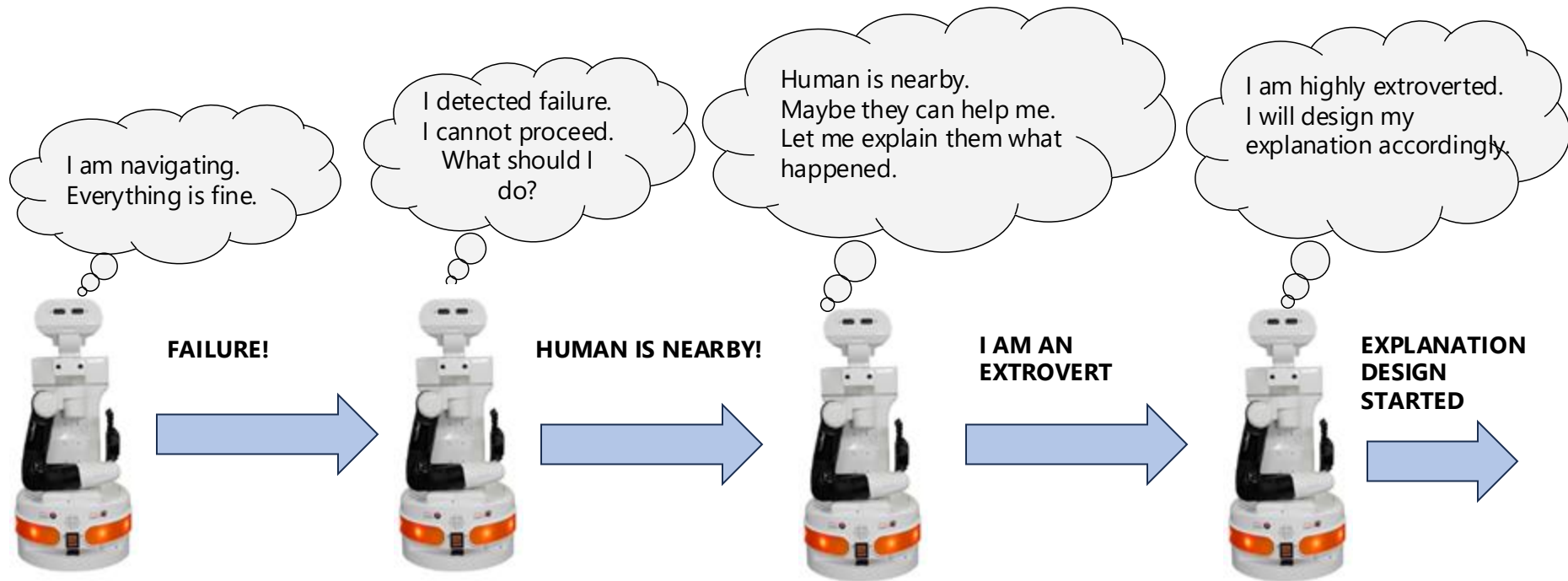
From human to robot personality



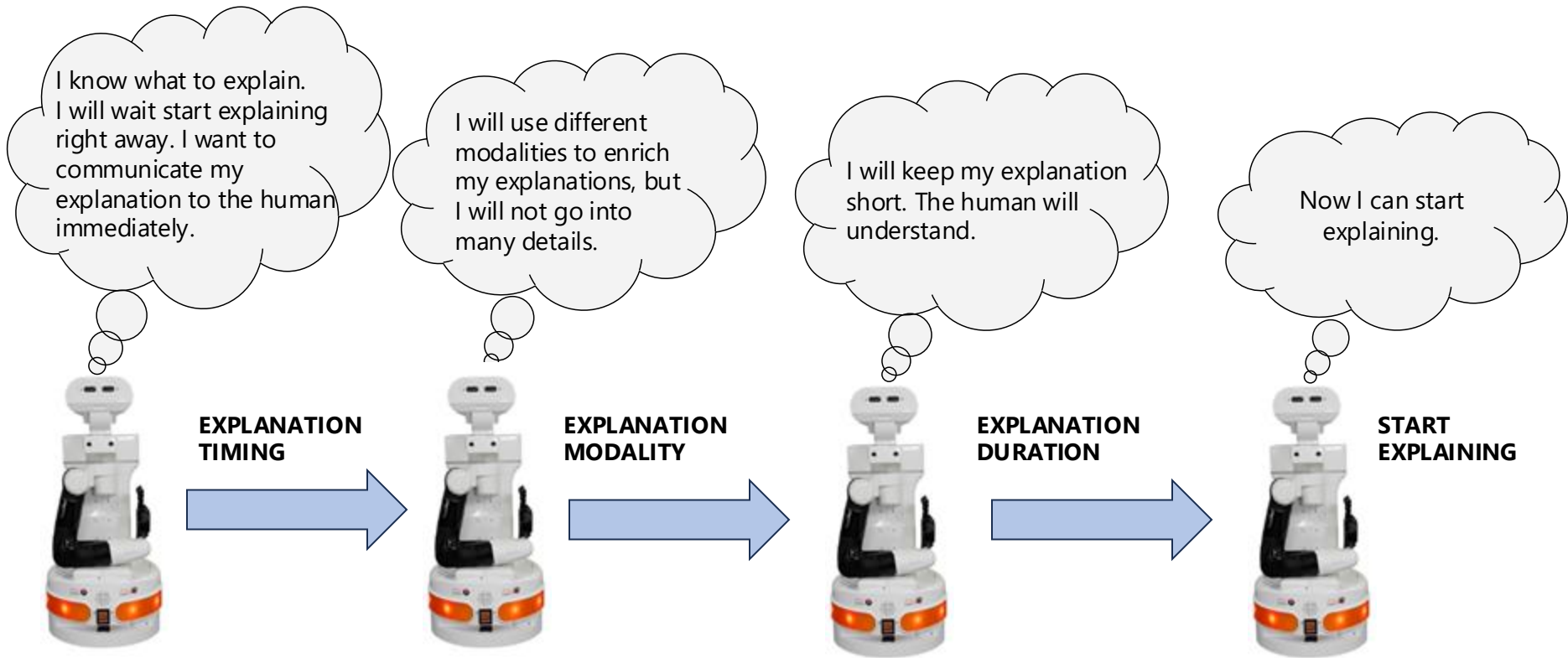
From human to robot personality



Planning of explanations

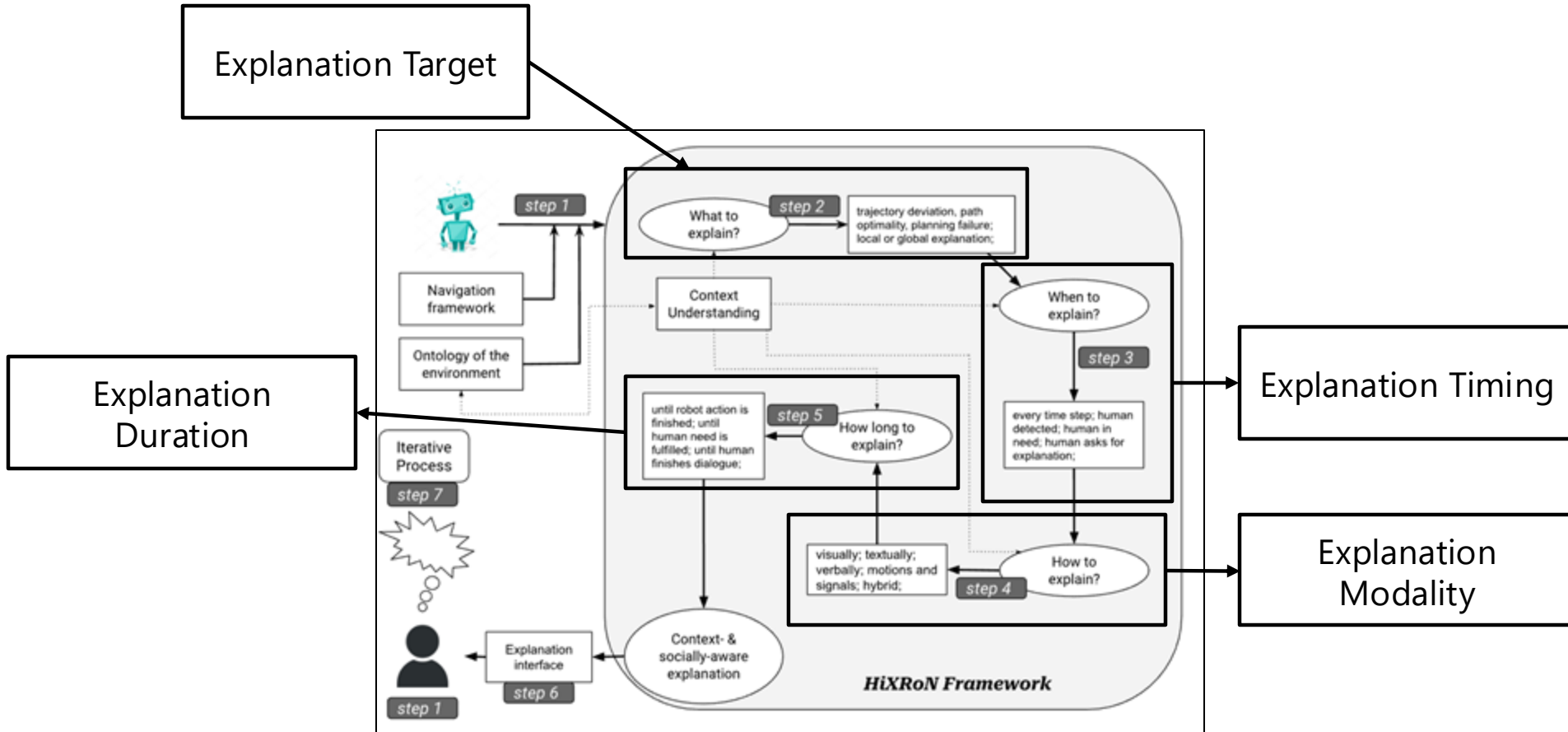


Planning of explanations



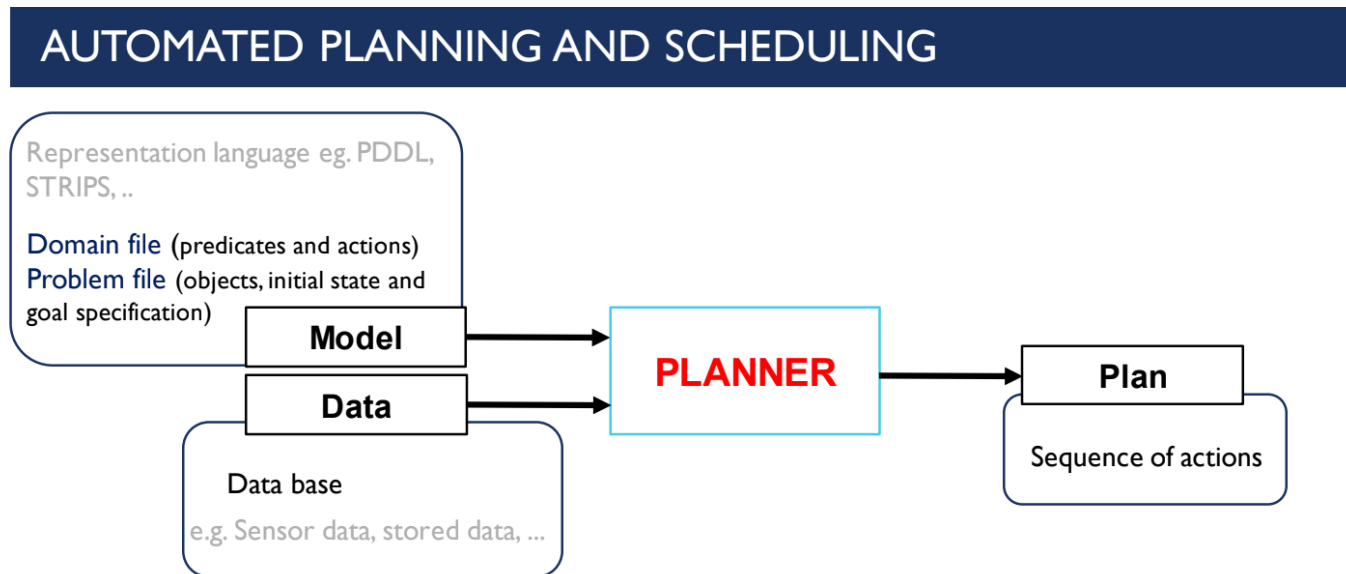
EXPLANATIONS SHOULD BE PLANNED!

Framework for explanation planning



Planning of explanations

- Planning explanations along with other robot actions.
- The explanation occurrence can vary based on parameters such as user preference or other task priorities.



Deterministic Planning

```
(:durative-action explain_failure
:parameters (?r - robot, ?h - human, ?f - failure)
:duration (= ?duration (expl_duration ?r))
:condition (and
  (at start (failure_detected ?r ?f))
  (at start (human_detected ?h))
)
:effect (and
  (at end (explained_failure ?r ?f))
)
```

Domain

```
(:init
  (is_extrovert tiago)
  (= (expl_duration tiago) 1)
  (navigating tiago)
  (at_place chair)
  (is_not_detected amar)
```

Instance

Planner

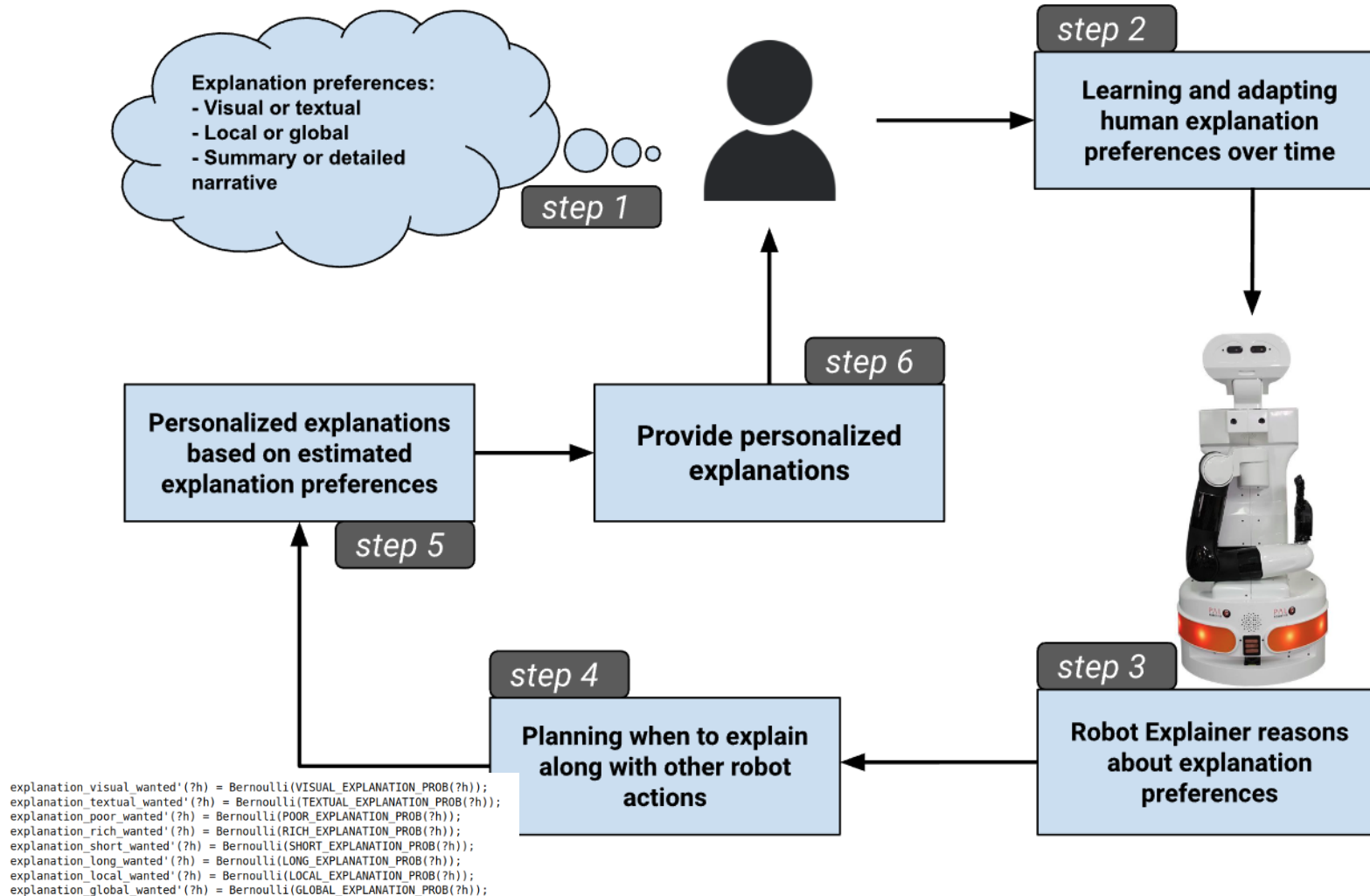
```
0.000: (detect_failure tiago) [1.000]
1.000: (detect_human tiago explainee) [1.000]
2.000: (explain_failure_start tiago explainee) [1.000]
3.000: (calculate_explanation_timing tiago) [1.000]
4.000: (pick_visual_textual_representation tiago explainee) [1.000]
5.000: (calculate_explanation_duration tiago) [1.000]
6.000: (wait tiago) [1.000]
7.000: (explain_failure tiago explainee) [1.000]
8.000: (explain_failure_ended tiago explainee) [1.000]
```

(a) Explanation plan of a totally extroverted robot

```
0.000: (detect_failure tiago) [1.000]
1.000: (detect_human tiago explainee) [1.000]
2.000: (explain_failure_start tiago explainee) [1.000]
3.000: (calculate_explanation_timing tiago) [1.000]
4.000: (pick_visual_representation tiago explainee) [1.000]
5.000: (calculate_explanation_duration tiago) [1.000]
6.000: (wait tiago) [11.000]
17.000: (explain_failure tiago explainee) [11.000]
28.000: (explain_failure_ended tiago explainee) [1.000]
```

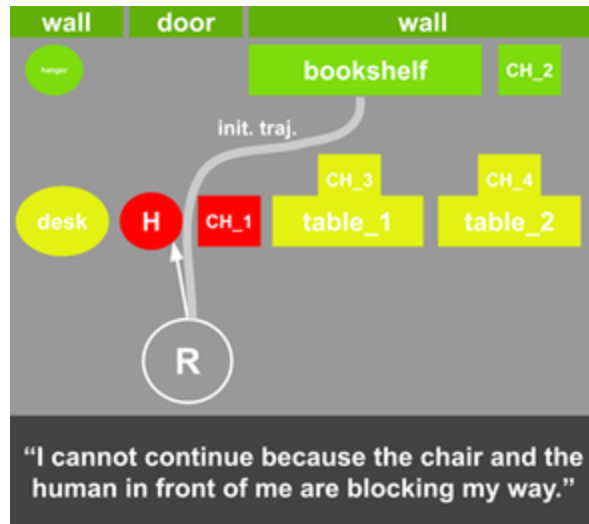
(b) Explanation plan of a totally introverted robot

Probabilistic Planning

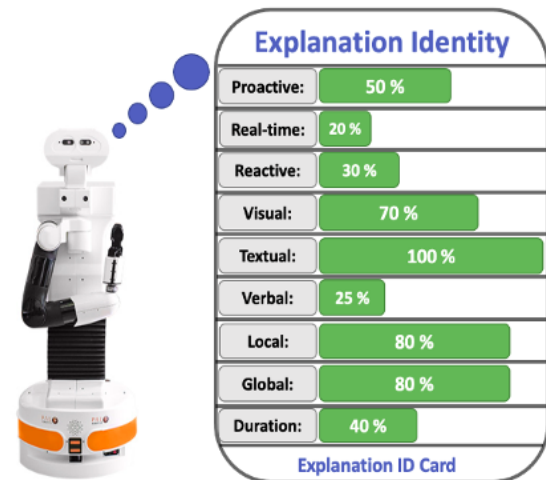


Research Contributions

Environment-centered explanation generation for robot navigation



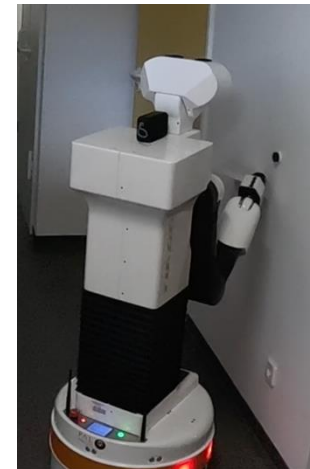
Human-centered explanation planning for robot navigation



Conclusions – Research Contributions

- Developed a framework for environment-centered explanations
- Showed that environment context (obstacles, affordances, spatial relations) and explanation representation is important for satisfiable explanations.
- Have developed a framework human-centered explanation planning
- Incorporated human explanation preferences into explanation generation to improve relevance, clarity and satisfaction.

**“When robots stumble, explanations can
help keep humans on their side.”**



Past Wins – Current Battles – Future Conquests

- Environment-centered explanations:
 - Replanning- and affordance-based framework for explanation generation
 - The impact of explanation modality and representation on user satisfaction
 - Generalizability to other domains and models (50%)
 - LLMs for explanation verbalization (20%)
 - Richer set of affordances; VLMs for scene understanding and ontology creation
- Human-centered explanations:
 - Framework for explanation planning
 - Preference-based deterministic explanation planning
 - The role of robot personality (extroversion) on explanations
 - Preference-based probabilistic explanation planning with preference learning (40%)
 - Different explanation planning timing strategies (50%)
 - Development of robot explanation identity

Conference Publications

1. **Halilovic, A.**, & Lindner, F. (2022). Explaining local path plans using LIME. In International Conference on Robotics in Alpe-Adria Danube Region (pp. 106-113). Cham: Springer International Publishing.
2. **Halilovic, A.**, & Krivic, S. (2023). The influence of a robot's personality on real-time explanations of its navigation. In International Conference on Social Robotics (pp. 133-147). Singapore: Springer Nature Singapore.
3. **Halilovic, A.**, & Krivic, S. (2024). Planning of explanations for robot navigation. In 2024 IEEE International Conference on Robotics and Automation (ICRA) (pp. 5478-5484). IEEE.
4. **Halilovic, A.**, & Krivic, S. (2025). Affordance-Based Explanations of Robot Navigation. To be published in 2025 IEEE International Conference on Robotics and Automation (ICRA). IEEE.

Other Peer-Reviewed Publications

1. **Halilovic, A.**, & Lindner, F. (2023). Visuo-textual explanations of a robot's navigational choices. In Companion of the 2023 ACM/IEEE International Conference on Human-Robot Interaction (pp. 531-535).
2. **Halilovic, A.**, & Krivic, S. (2023). Towards a Holistic Framework for Explainable Robot Navigation. In International Workshop on Human-Friendly Robotics (pp. 213-228). Cham: Springer Nature Switzerland.
3. **Halilovic, A.**, Chandrayan, V., & Krivic, S. (2024). Exploring the impact of explanation representation on user satisfaction in robot navigation. In Proceedings of the 2024 International Symposium on Technological Advances in Human-Robot Interaction (pp. 1-9).
4. **Halilovic, A.**, & Krivic, S. (2024). Robot Explanation Identity. arXiv preprint arXiv:2405.13841.
5. **Halilovic, A.**, Krivić, S., & Canal, G. (2024). Towards Probabilistic Planning of Explanations for Robot Navigation. In RSS 2024 Workshop on Unsolved Problems in Social Robot Navigation.
6. **Halilovic, A.**, & Krivic, S. (2024). Towards Fast Visual Explanations of Local Path Planning with LIME and GAN. In HI-AI@ KDD.

