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User-Friendly Robot Planners for Scientific Data Collection

Ian C. Rankin

Advisor: Dr. Geoff Hollinger

Ian Rankin and RDML

- 4th year PhD Student
  - Robotics Decision Making Laboratory (RDML)

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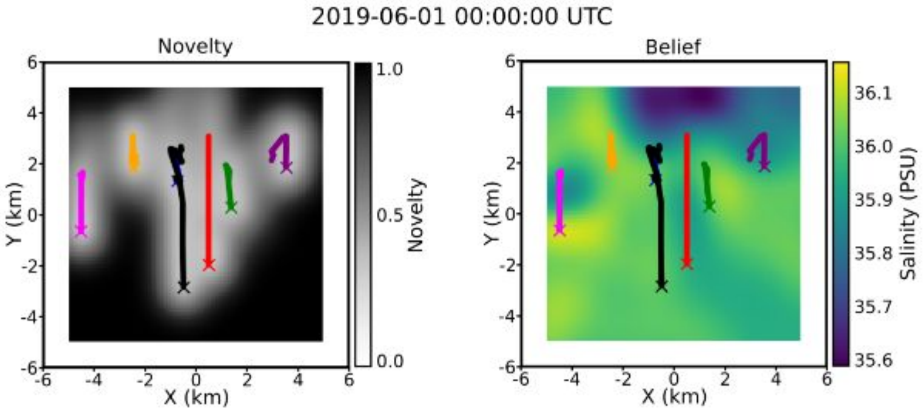
- RDML
  - Underwater manipulation
  - Underwater docking
  - Data collection with AUV's
    - Previous collaboration with Dr. Barth and Dr. Nash



McCammon, et al (2019)

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Image: Anchorage Daily News

Time-consuming

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Image: (CMU, OSU, 2019)

Hazardous

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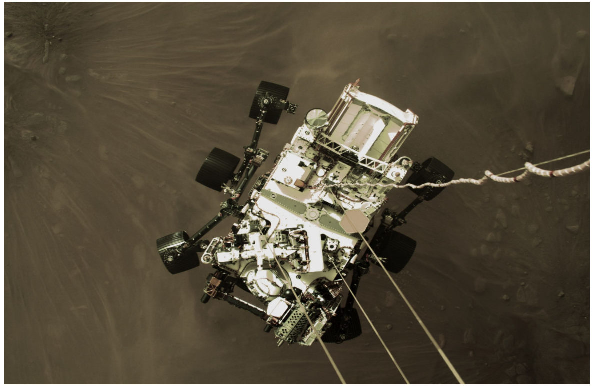

Impossible for Humans

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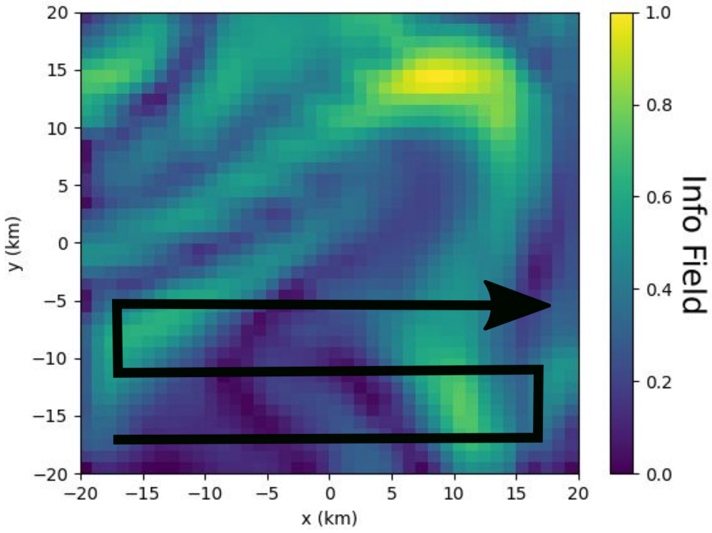
User-Friendly Robot Planning for Scientific Data Collection

➢ Robots have limited budget



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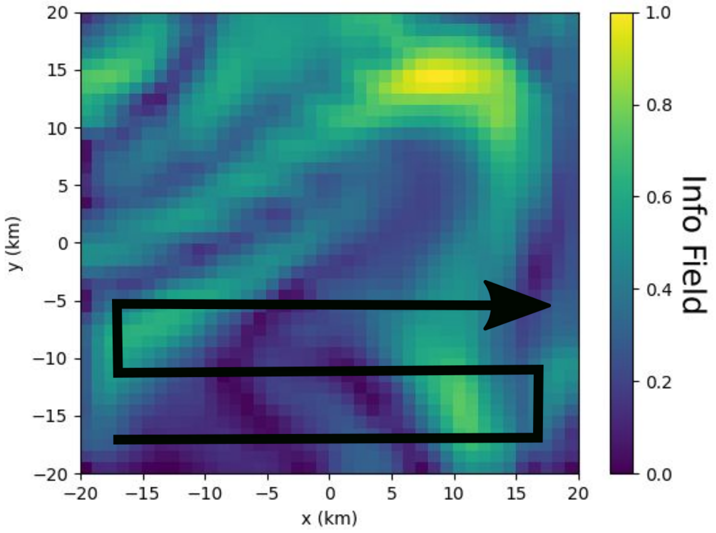
User-Friendly Robot Planning for Scientific Data Collection

- ➢ Robots have limited budget
- ➢ Exhaustive search often infeasible



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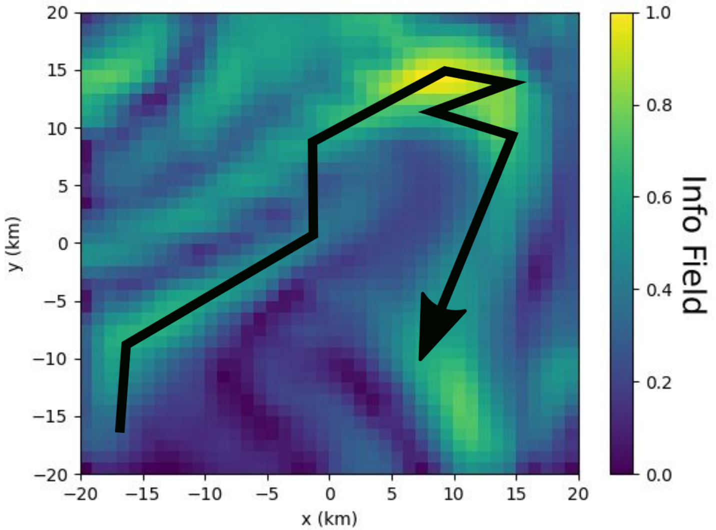
User-Friendly Robot Planning for Scientific Data Collection

- ➢ Robots have limited budget
- ➢ Exhaustive search often infeasible
- ➢ Non-uniform information distribution
    - Select path to maximize information



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User-Friendly Robot Planning for Scientific Data Collection

- Why do we care if a scientific data collection robot is user-friendly?

User-Friendly Robot Planning for Scientific Data Collection

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User-Friendly Robot Planning for Scientific Data Collection

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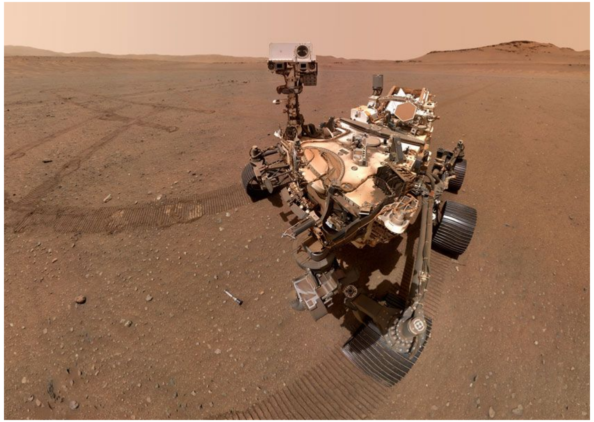

Image: NASA JPL

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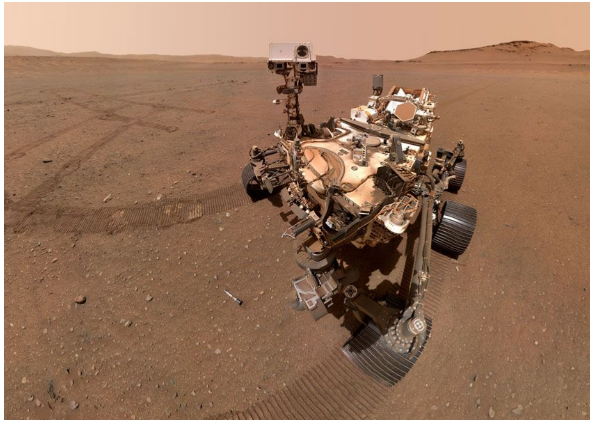
User-Friendly Robot Planning for Scientific Data Collection

- Gap between state-of-the-art and state-of-practice in autonomy



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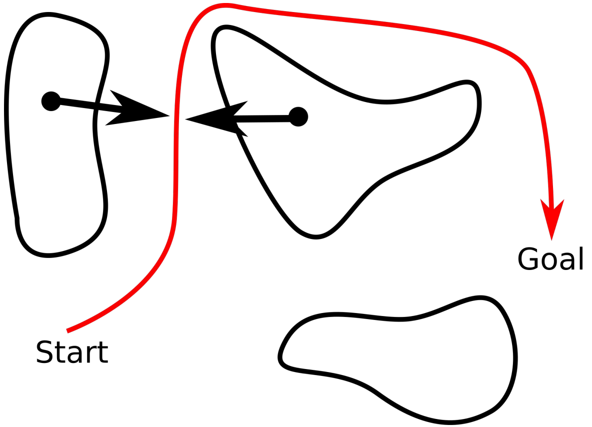
User-Friendly Robot Planning for Scientific Data Collection

- Gap between state-of-the-art and state-of-practice in autonomy
- Key gaps:
  - Constraint definition



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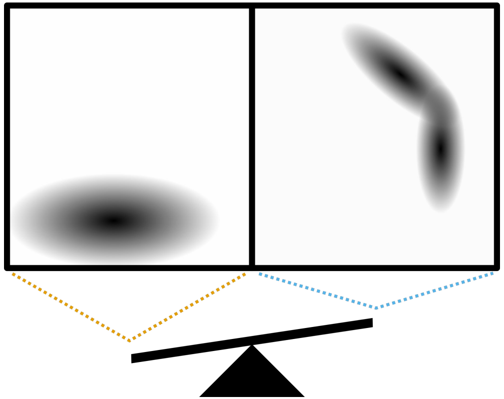

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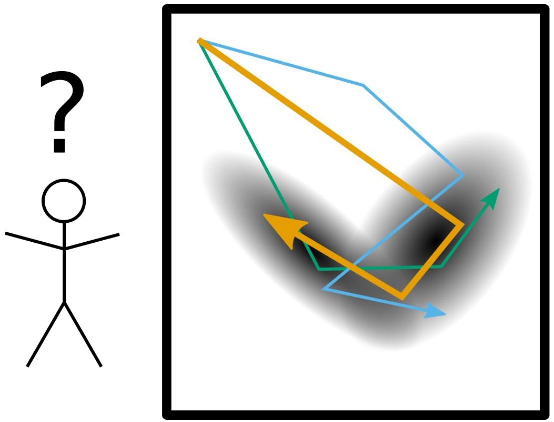
User-Friendly Robot Planning for Scientific Data Collection

- ➢ Gap between state-of-the-art and state-of-practice in autonomy
- ➢ Key gaps:
  - Constraint definition
  - Defining tradeoffs between objectives
  - Understanding robotic decisions



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Thesis Statement

Reasoning over the feedback provided to and from the user during constraint and objective definition improves the usability and transparency of robotic planning for scientific data collection.

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Contributions:

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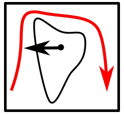

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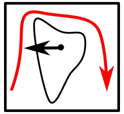

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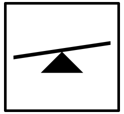

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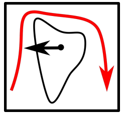

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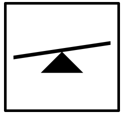
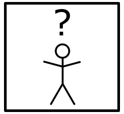


3. Robot Planner Understanding using Explainability



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User Trust

- Users need to have **Appropriate Trust** of autonomy (Lee, 2004)

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  - Under-trust: results in disuse of autonomy
  - Over-trust: results in system failure

Explainability

- eXplainable Artificial Intelligence (XAI)
  - Dates back to Expert Systems in the 80s
  - Renewed Interest
    - Deep Learning
    - DARPA push in 2017 (Gunning, 2017)

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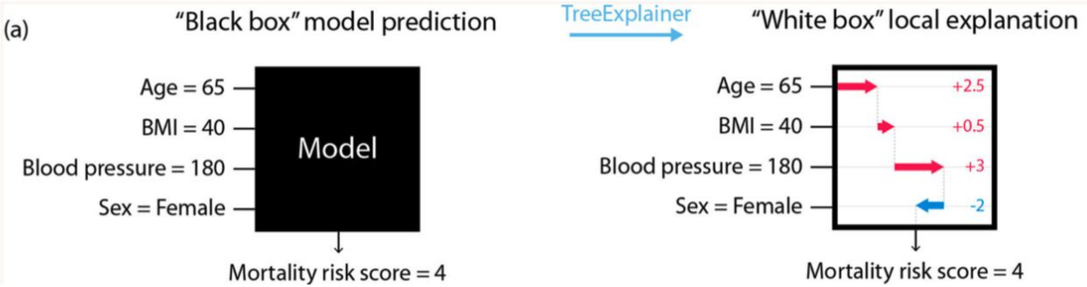
- Is explainability needed in robotics?
  - Because people expect it (Han, et al., 2021, Ambsdorf, et al., 2022)
  - Appropriately managing AI systems requires appropriate trust (Lee, 2004)

XAI approaches

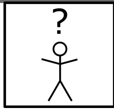
- “Saliency maps”
  - Provide explanation by showing important features
    - SHAP, LIME

(a) Original Image (b) Explaining *Electric guitar* (c) Explaining *Acoustic guitar* (d) Explaining *Labrador*

Figure 4: Explaining an image classification prediction made by Google’s Inception neural network. The top 3 classes predicted are “Electric Guitar” ($p = 0.32$), “Acoustic guitar” ($p = 0.24$) and “Labrador” ($p = 0.21$)

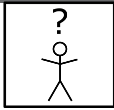


Top: Ribeiro, et al., 2016 (LIME) Bottom: Lundberg, et al., 2020 (SHAP)



Insights From Social Sciences

- XAI should be based in ideas from Social Sciences (Miller, 2018)



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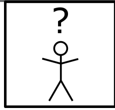

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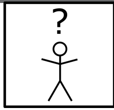
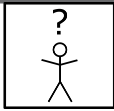


Contrastive Explanations

- Provide an illustrative contrasting example
  - Why did the robot do P?



Contrastive Explanations

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  - Instead ask why the robot did P instead of not-P
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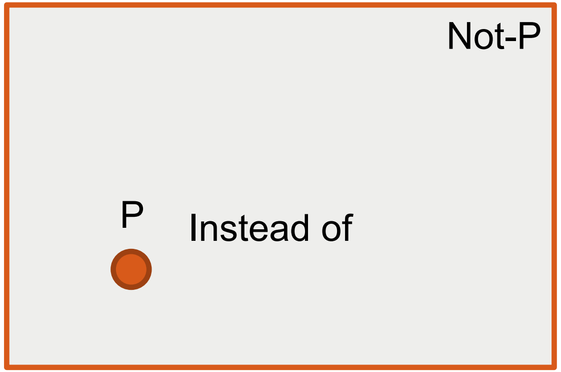

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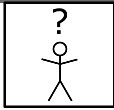

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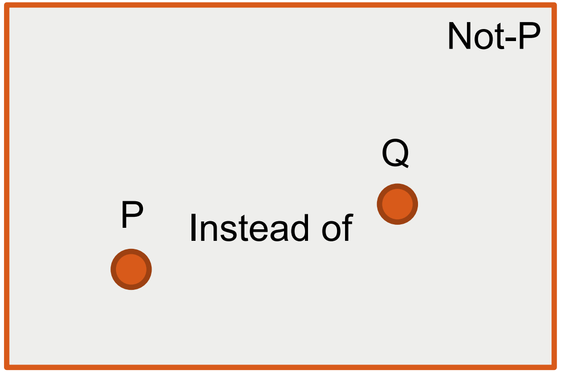

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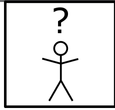

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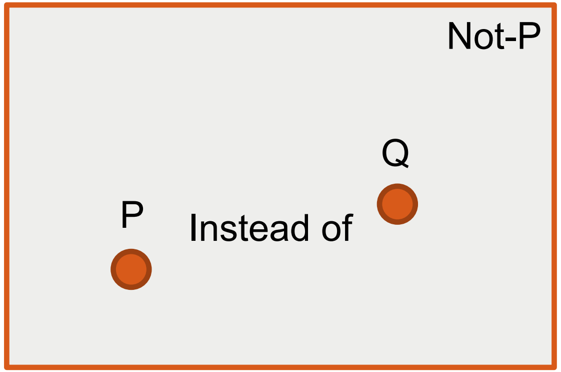
  - In explaining why a car crash happened:
    - Both cars were driving on the road at 35 MPH (on a road with a 35 limit) causing the crash. - Not helpful



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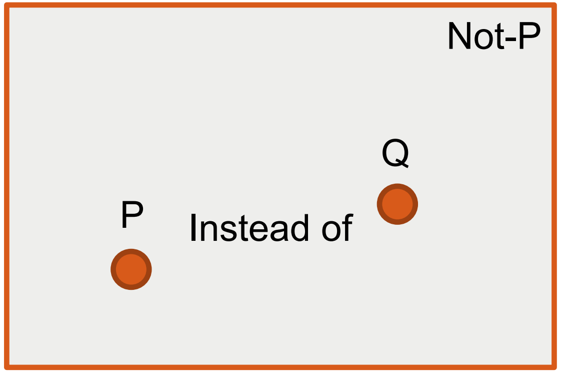

- Example:
  - In explaining why a car crash happened:
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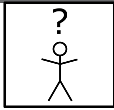
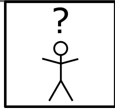
    - Car A pulled into oncoming traffic causing the crash instead of staying in its lane. - Helpful



Approaches

- We propose the Contrastive, Feature-based eXplainability (CoFeX) method



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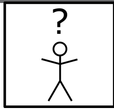
- We propose the Contrastive, Feature-based eXplainability (CoFeX) method
  - Post-hoc explanations
    - Explanation generation ran after decision making algorithm
    - Shared language of semantic features
    - Explanation framework agnostic to decision making algorithm



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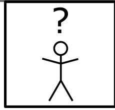

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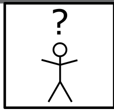
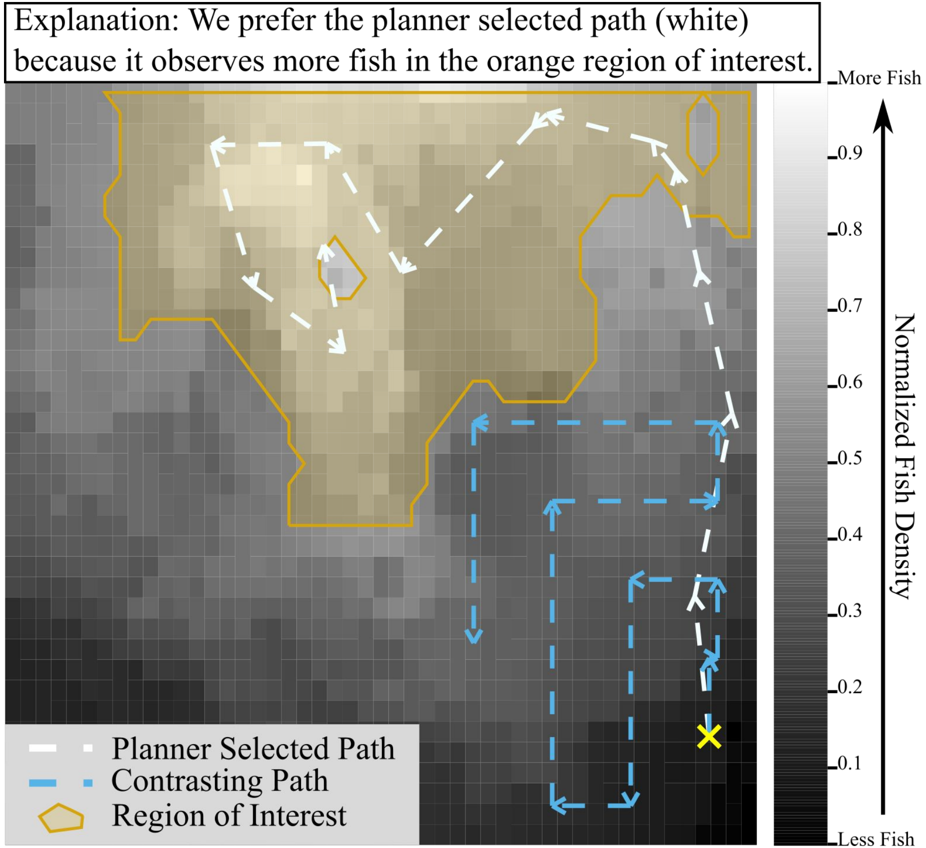
  - Contrastive Explanations
    - Select an illustrative example for the casual reason



Explanation Example



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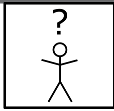
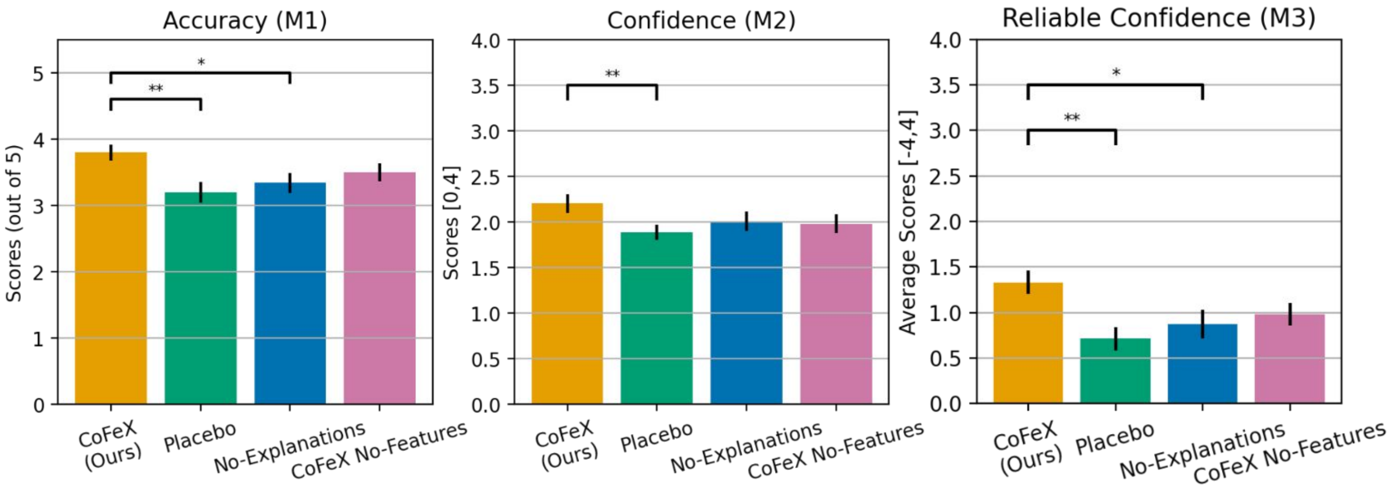


Previous User Study: Results (N=50)

* : p < 0.05, ** : p < 0.01



Results from the original study done on convenience participants (mostly roboticists). In future studies want to focus more on scientist participants since they are our target audience.

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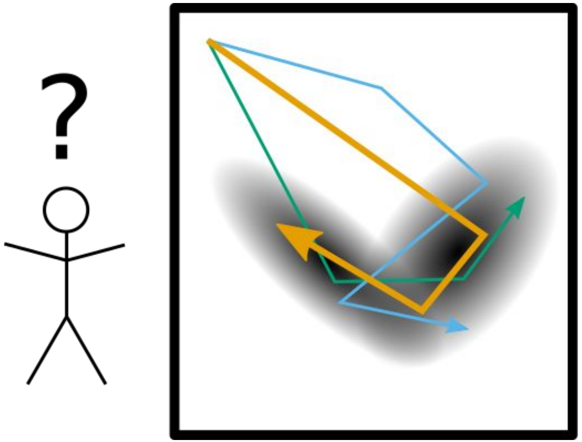
Conclusions

- A method that:
  - Uses post-hoc explanations that allows arbitrary decision making algorithms to be used.



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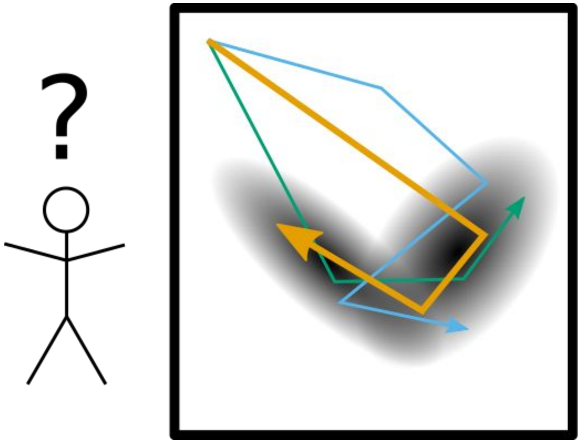

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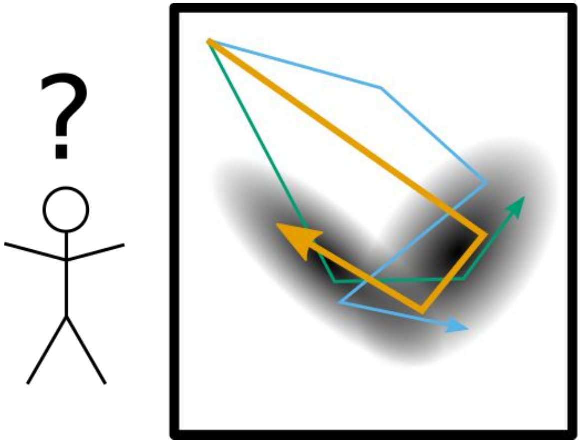
- Selects the most important reason to show to the user.
- Uses a contrasting examples to illustrate the selected reason.



Acknowledgements

- Advisor: Dr. Geoff Hollinger
- Committee
  - Dr. Julie A. Adams
  - Dr. Alan Fern
  - Dr. Maria Kavanaugh
  - Dr. Stefan Lee
- Robotic Decision Making Laboratory (RDML)
- Funding Source: National Science Foundation

How can you help?

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- Sign up: https://calendar.app.google/QaivwQEtbVAv2eKB7

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