Autonomous Robotic Arm Manipulation for Planetary Missions using Causal Machine Learning

Cian McDonnell
Miguel Arana-Catania
Saurabh Upadhyay
School of Aerospace, Transport and Manufacturing, Cranfield University

ASTRA Symposium, Leiden, Netherlands
17 October 2023

Overview

- Autonomy reduces need for communications in planetary missions

- Explore **causal machine learning** in policy planning of a robot manipulator, in a simulated planetary environment

- Find that the method allows manipulator to quickly learn about its surroundings

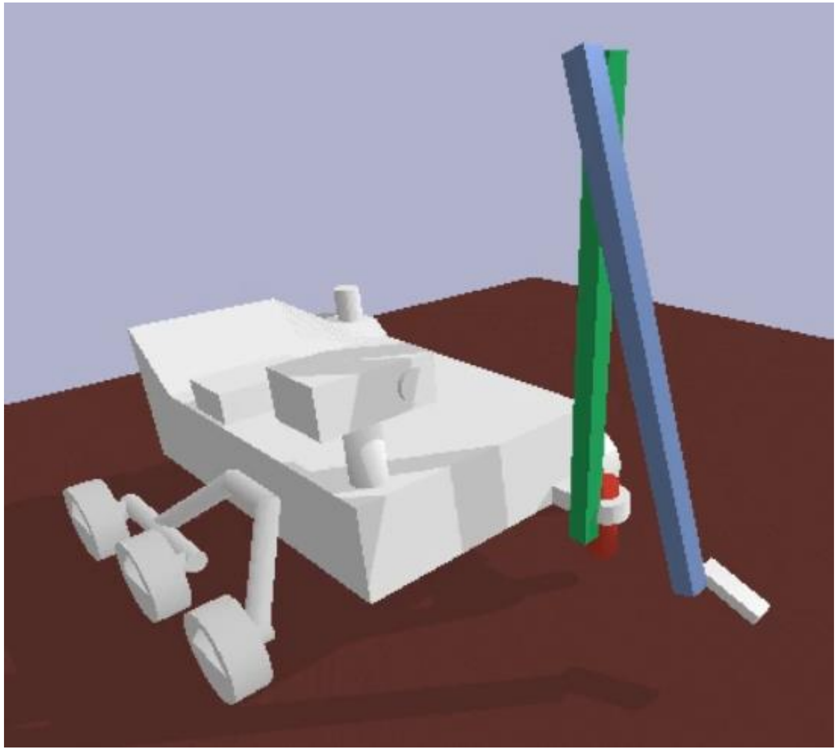


Figure 1. Manipulator used in simulations.

Current Literature

- Current literature manipulates:
    - Objects with **known** properties
    - Objects **completely unknown**
- **Known** objects: Classical control algorithms (see **[1]**, **[2]**)
- **Unknown** objects: Reinforcement learning (**[3]**, **[4]**)

- **[1]** M. Schuster et al., “The LRU Rover for Autonomous Planetary Exploration and its Success in the SpaceBotCamp Challenge,” 2016 International Conference on Autonomous Robot Systems and Competitions (ICARSC), 2016.
- **[2]** P. Lehner et al., “Mobile Manipulation for Planetary Exploration,” 2018 IEEE Aerospace Conference, 2018.
- **[3]** A. Orsula et al., “Learning to Grasp on the Moon from 3D Octree Observations with Deep Reinforcement Learning,” 2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2022.
- **[4]** D. Kalashnikov et al., “Scalable Deep Reinforcement Learning for Vision-Based Robotic Manipulation,” 2nd Conference on Robot Learning (CoRL), Zürich, Switzerland, 2021.

Knowledge Gap in State-of-the-Art

- Reinforcement learning: can be difficult to generalise to new situations

- Training data is generated on Earth, or simulated

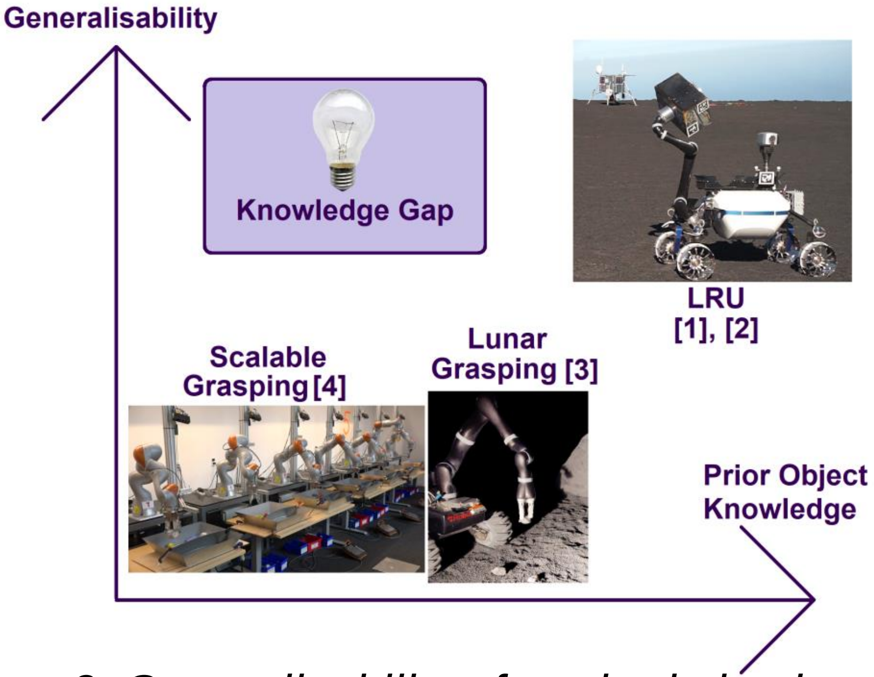


Figure 2. Generalisability of methods in planetary missions

- **[1]** M. Schuster et al., "The LRU Rover for Autonomous Planetary Exploration and its Success in the SpaceBotCamp Challenge," 2016 International Conference on Autonomous Robot Systems and Competitions (ICARSC), 2016.
- **[2]** P. Lehner et al., "Mobile Manipulation for Planetary Exploration," 2018 IEEE Aerospace Conference, 2018.
- **[3]** A. Orsula et al., "Learning to Grasp on the Moon from 3D Octree Observations with Deep Reinforcement Learning," 2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2022.
- **[4]** D. Kalashnikov et al., "Scalable Deep Reinforcement Learning for Vision-Based Robotic Manipulation," 2nd Conference on Robot Learning (CoRL), Zürich, Switzerland, 2021.

Causal Machine Learning

- Causal Curiosity (**[5]**): Uses determination of **causal factors**
- **Causal factor**: A parameter affecting outcome of actions
- Manipulator learns about objects based on changing causal factors

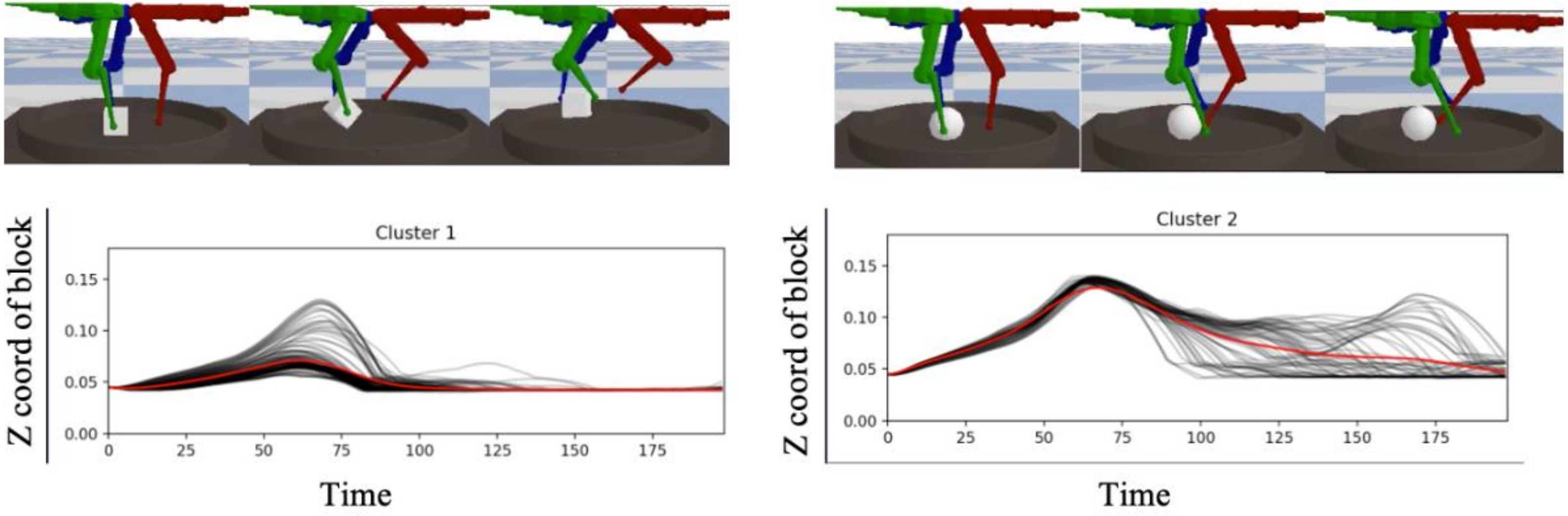


Figure 3. Difference in outcome of actions in ***[5]***

[5] S. Sontakke et al., “Causal Curiosity: RL Agents Discovering Self-supervised Experiments for Causal Representation Learning,” Proceedings of the 38th International Conference on Machine Learning, PMLR 139, 2021, 2021.

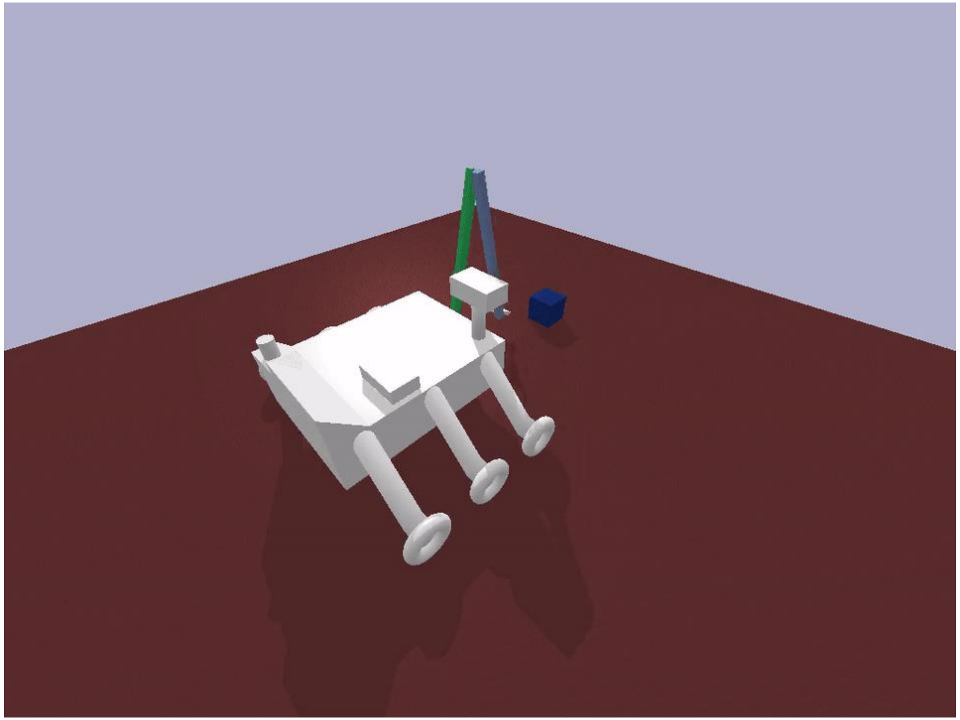
Application to Planetary Environment

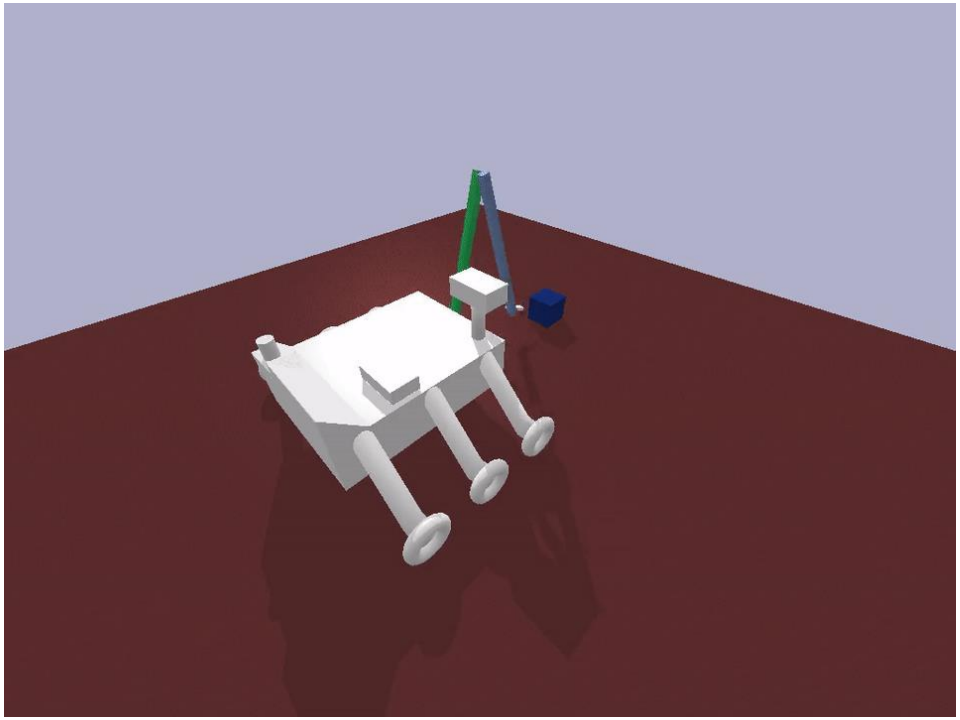
- By studying time series, should be possible to identify different clusters of objects (e.g. planetary rocks)

- Training is carried out live, **in** exploration environment

- **Goal:** Find the action that best separates objects based on causal factors

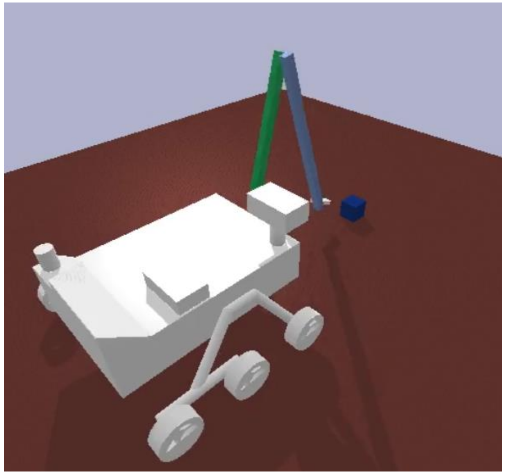
Differentiating Objects



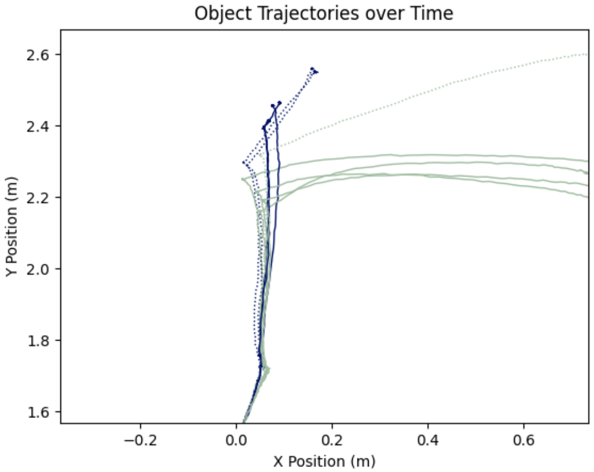


- Over time, manipulator learns actions that **can** differentiate the objects

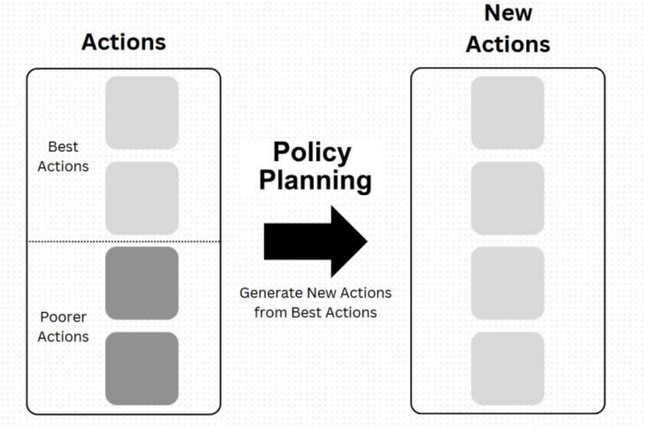
Overview of Algorithm Used



1. Simulation of Actions



2. Time series classification



3. Planning of new actions

4. Iterate

Simulation

- Simulated many environments that differ in **one** causal factor (e.g. object mass, friction, gravity)

- Manipulator uses action on planetary objects, records trajectories

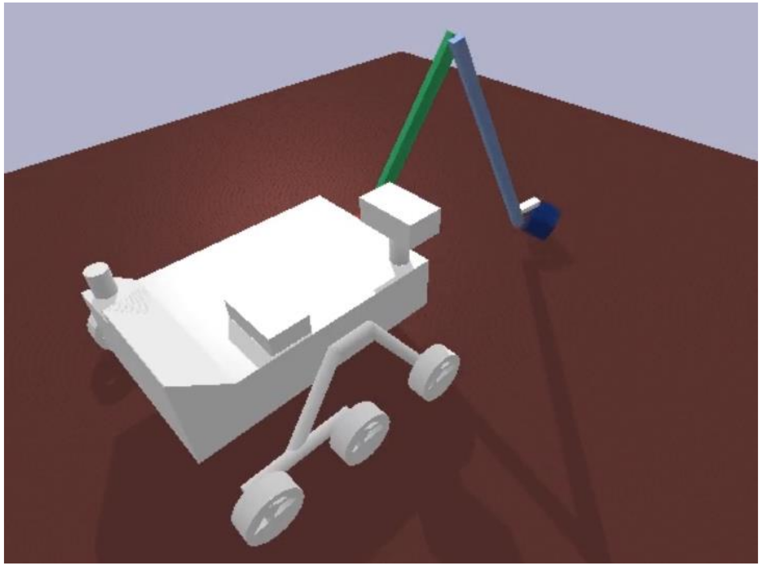


Figure 4. Manipulator pushing an object.

Trajectory Classification

- Classify using k-means clustering on time series

- Allows differentiation between e.g. light and heavy objects

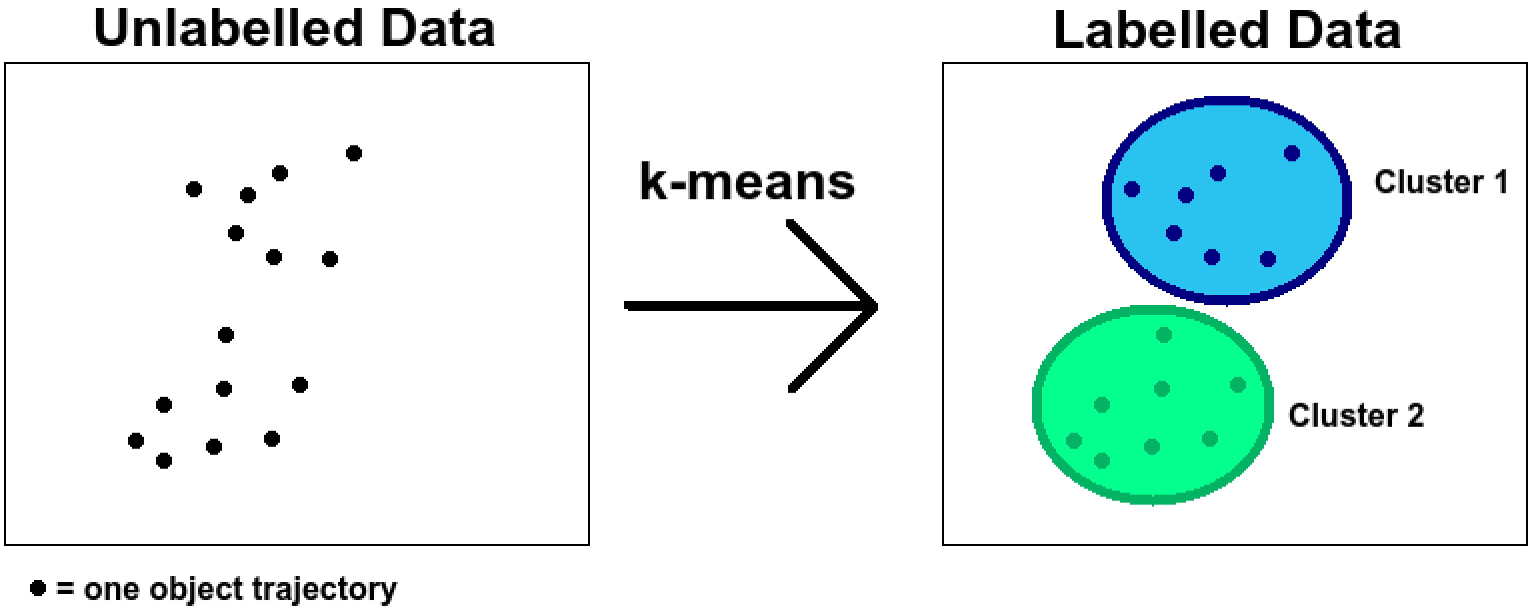


Fig 5. k-means clustering.

Classification and Scoring

- Actions scored based on how well they separate clusters
- An action that separates clusters well gives more information

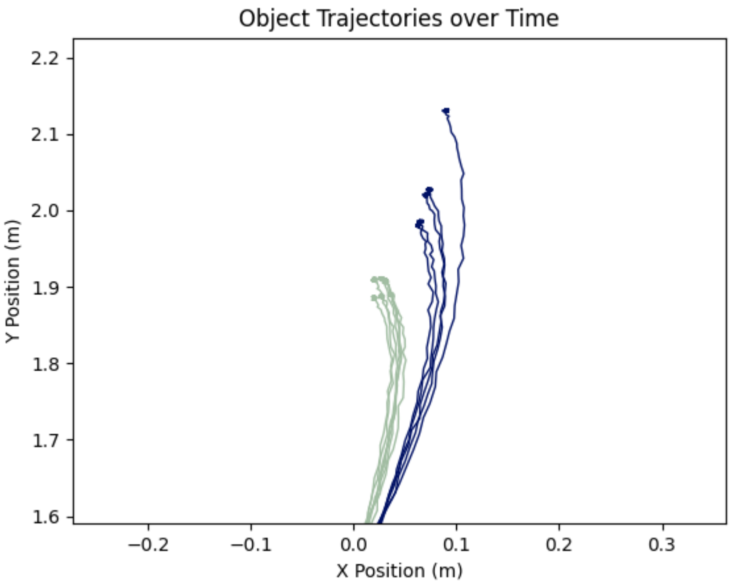


Fig 6. Example of well-separated clusters.

Policy Planning

- Using scores from Step 2, choose best actions to classify

- Generate new set of actions similar to best actions, and iterate

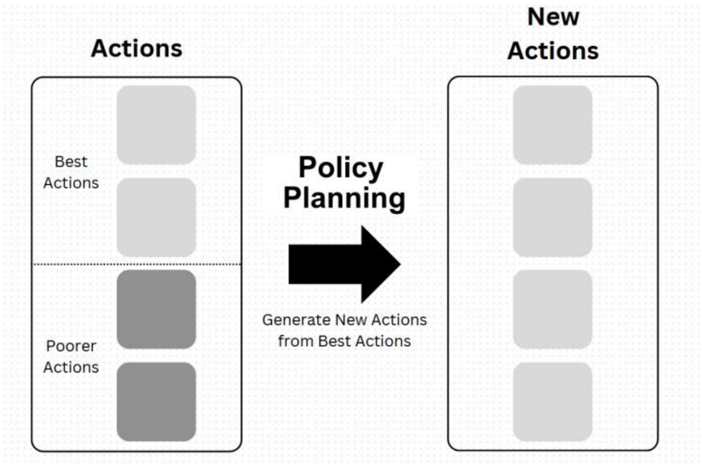


Fig 7. Diagram of policy planning.

Results – Object Mass

- Binary classification – separate the objects into **light** or **heavy** classes

- Reward function of 1 implies perfect classification

- Using more actions per iteration improves results

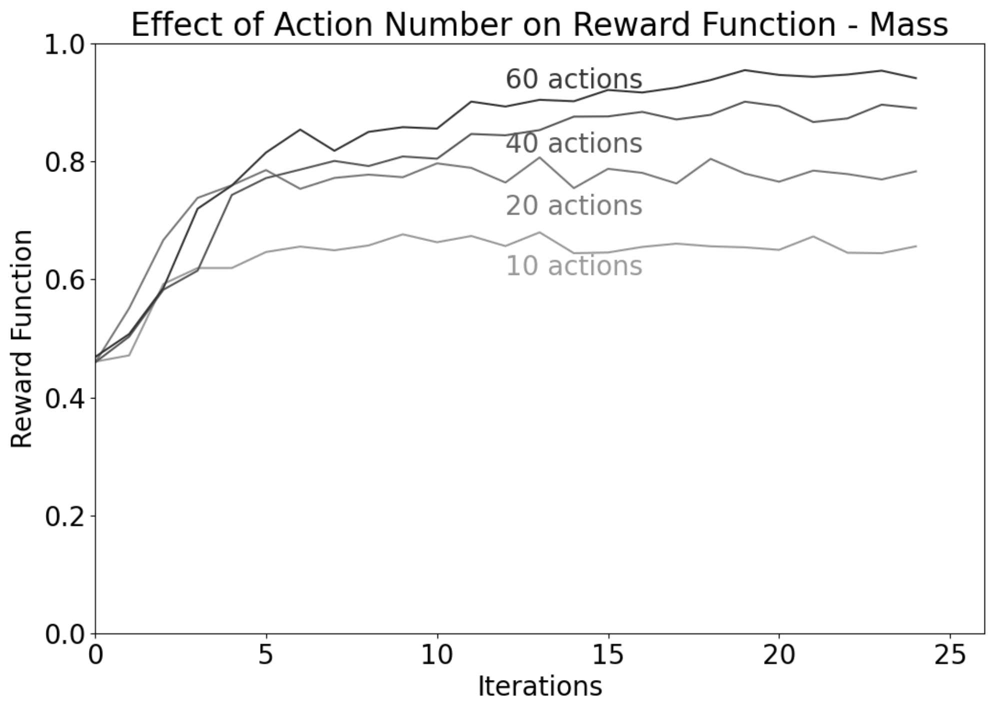


Fig 8. Effect of Number of Actions on Reward Function.

Results – Object Friction

- Separate objects based on low friction/high friction

- Similar results to case of object mass

- Manipulator tends to slide objects along ground more

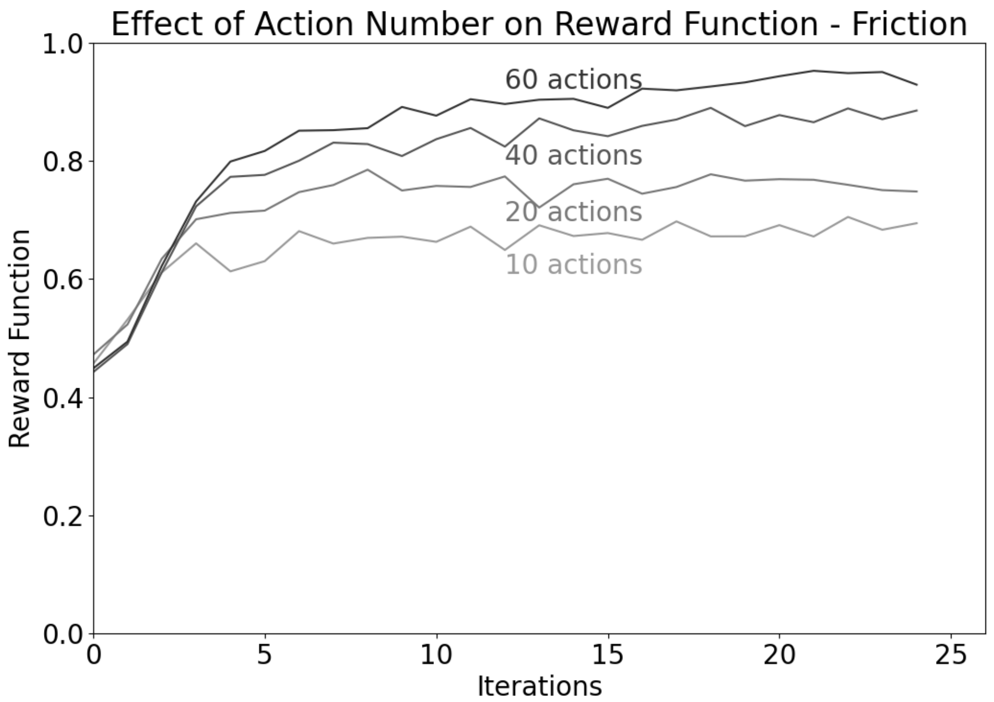


Fig 9. Effect of Number of Actions on Reward Function.

Results – Gravity

- Two clusters: Martian gravity, 3.72 m s^{-2}, and lunar gravity, 1.63 m s^{-2}

- Better overall performance as clusters are well-separated

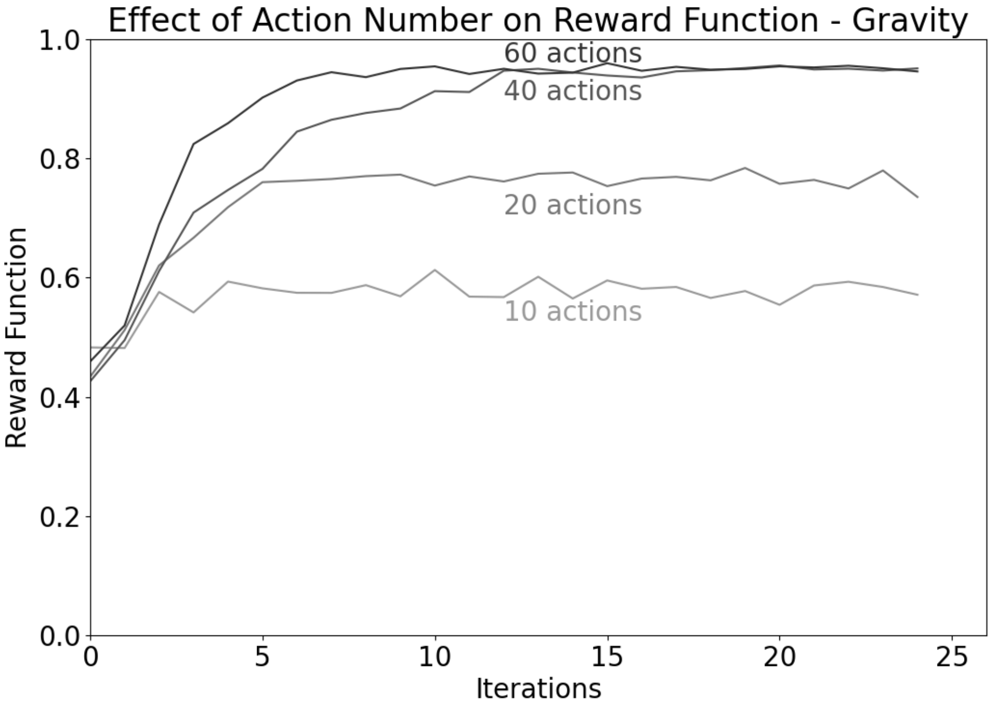


Fig 10. Effect of Number of Actions on Reward Function.

Conclusions and Motivations

- Method separates objects given wide range of causal factors

- Any causal factor affecting outcomes of actions can be studied

Motivation: Wheel Slip Prediction

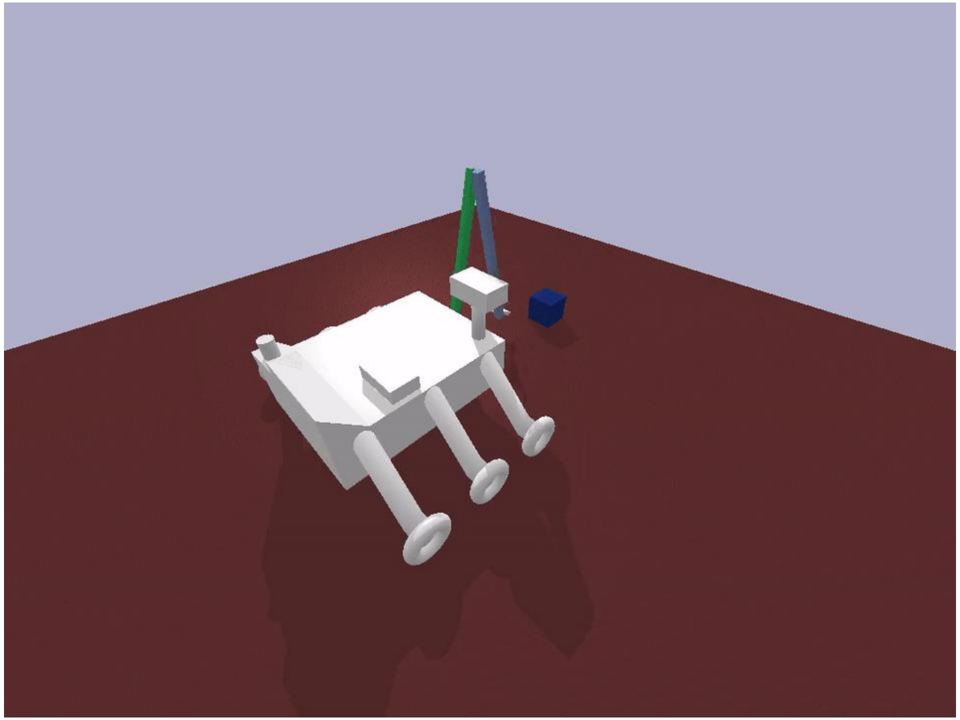
- Potential application is scouting hazardous terrain, by interacting with soil

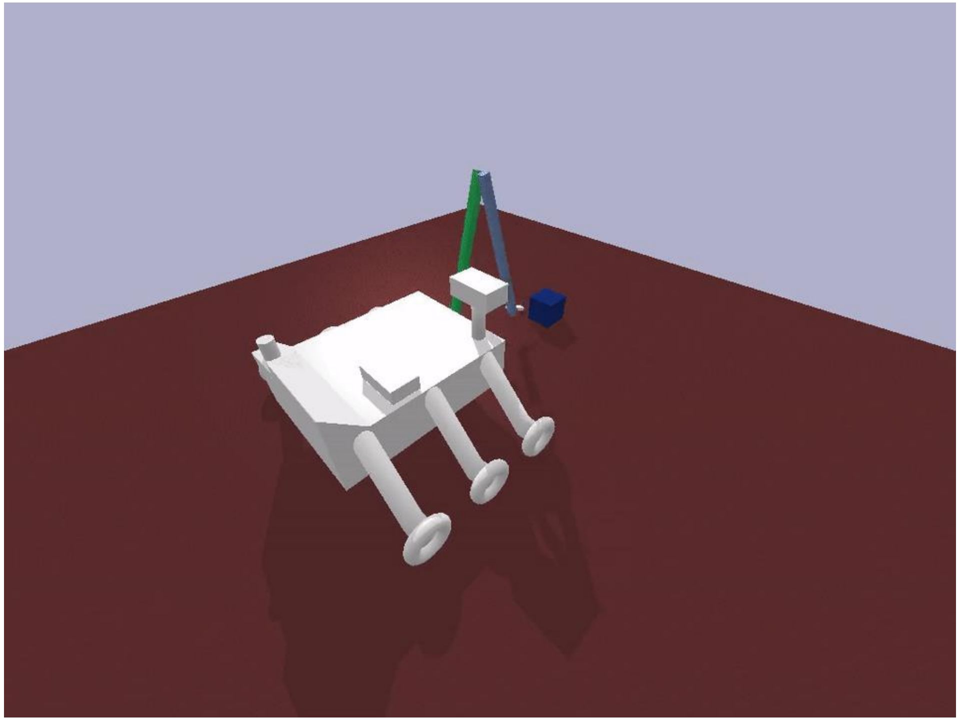
- Deeper insight than computer vision methods

Fig 10. Spirit rover caught in sand trap. Source: NASA/JPL

Questions?

Email: cian@mcdonnell.eu





References

[1] M. Schuster et al., “The LRU Rover for Autonomous Planetary Exploration and its Success in the SpaceBotCamp Challenge,” 2016 International Conference on Autonomous Robot Systems and Competitions (ICARSC), 2016.

[2] P. Lehner et al., “Mobile Manipulation for Planetary Exploration,” 2018 IEEE Aerospace Conference, 2018.

[3] A. Orsula et al., “Learning to Grasp on the Moon from 3D Octree Observations with Deep Reinforcement Learning,” 2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2022.

[4] D. Kalashnikov et al., “Scalable Deep Reinforcement Learning for Vision-Based Robotic Manipulation,” 2nd Conference on Robot Learning (CoRL), Zürich, Switzerland, 2021.

[5] S. Sontakke et al., “Causal Curiosity: RL Agents Discovering Self-supervised Experiments for Causal Representation Learning,” Proceedings of the 38th International Conference on Machine Learning, PMLR 139, 2021, 2021.