
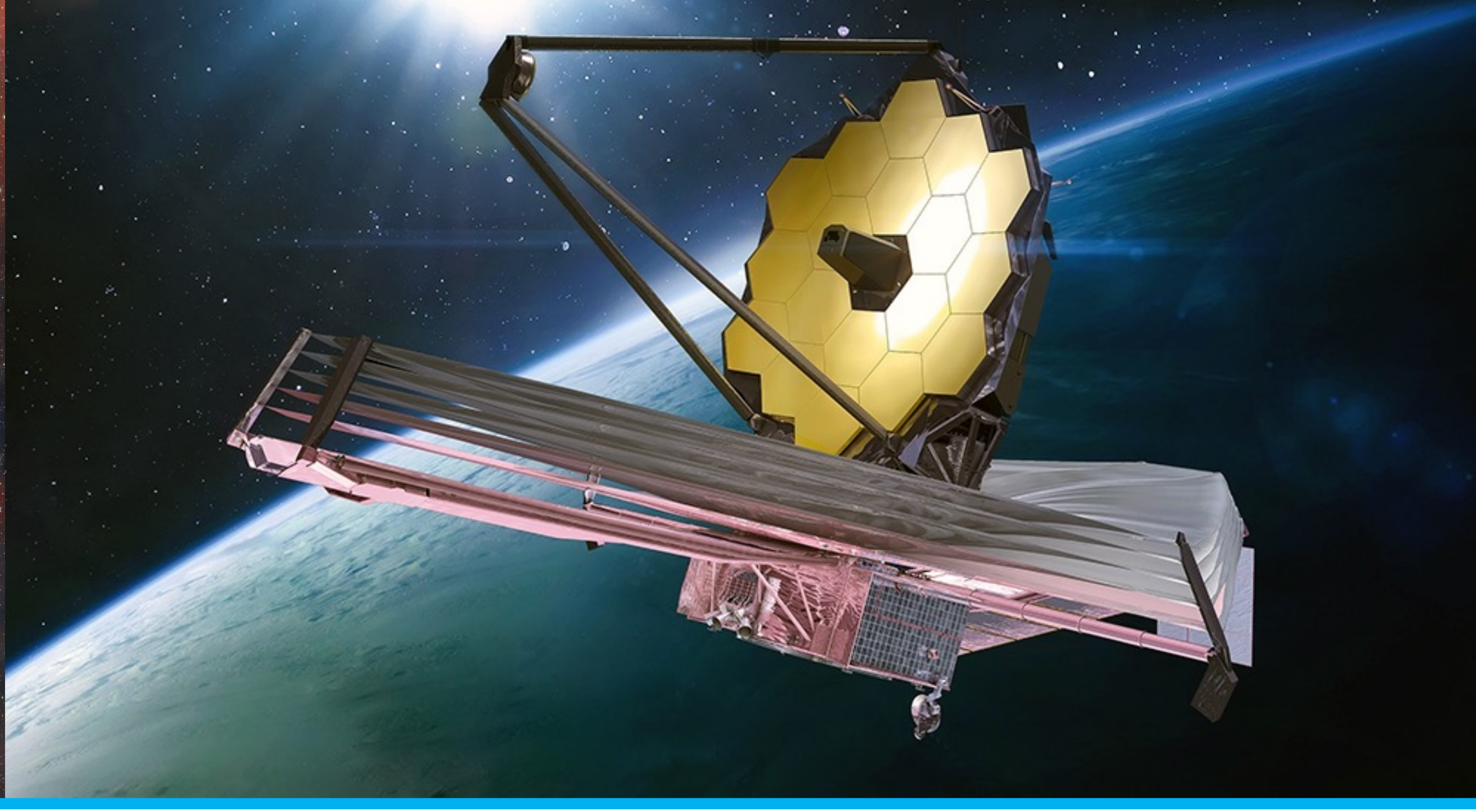

# Self-driving Telescope Schedules: A Framework for Training Reinforcement Learning Agents based on Telescope Data


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DEEP SKIES

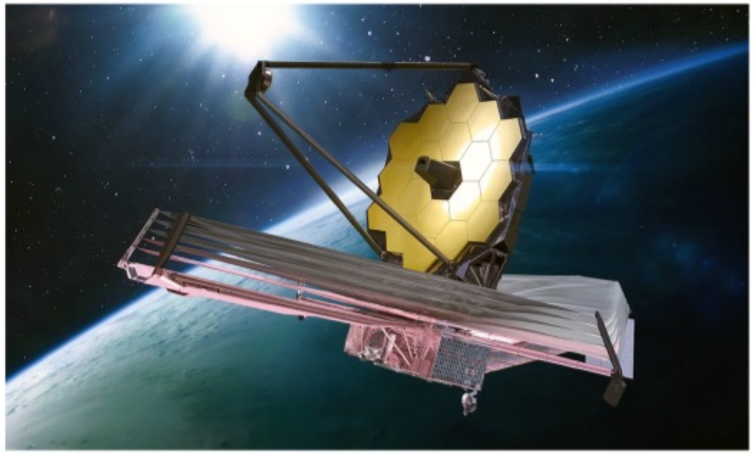
Bringing Artificial Intelligence to Astrophysics

# Self-driving telescopes could revolutionize astronomy

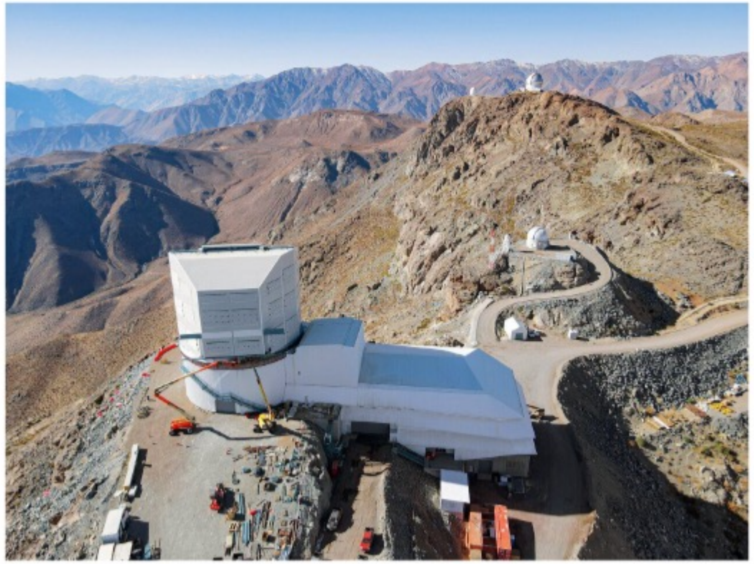
An autonomous telescope, unburdened by human biases and complications, could be able to discover solutions we've been missing this whole time.

New telescopes such as JWST and LSST have been designed and engineered in order to capture vast amounts of data. These telescopes are the possible targets of this project.

What if we could optimize the potential of telescopes as sky watchers?



(a) An image of the James Webb Space Telescope (JWST).

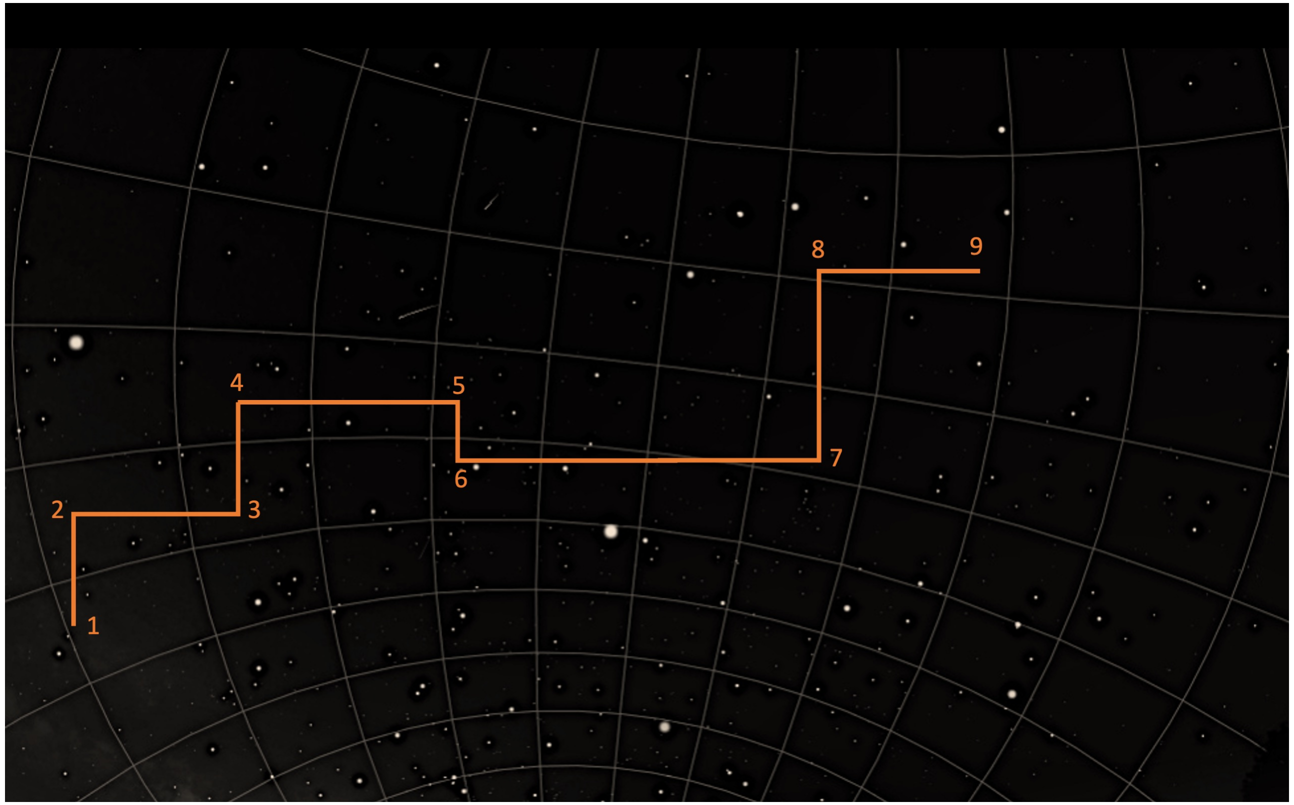


(b) An image of the Large Synoptic Survey Telescope (LSST).

# Start from the optimization of a sequential schedule

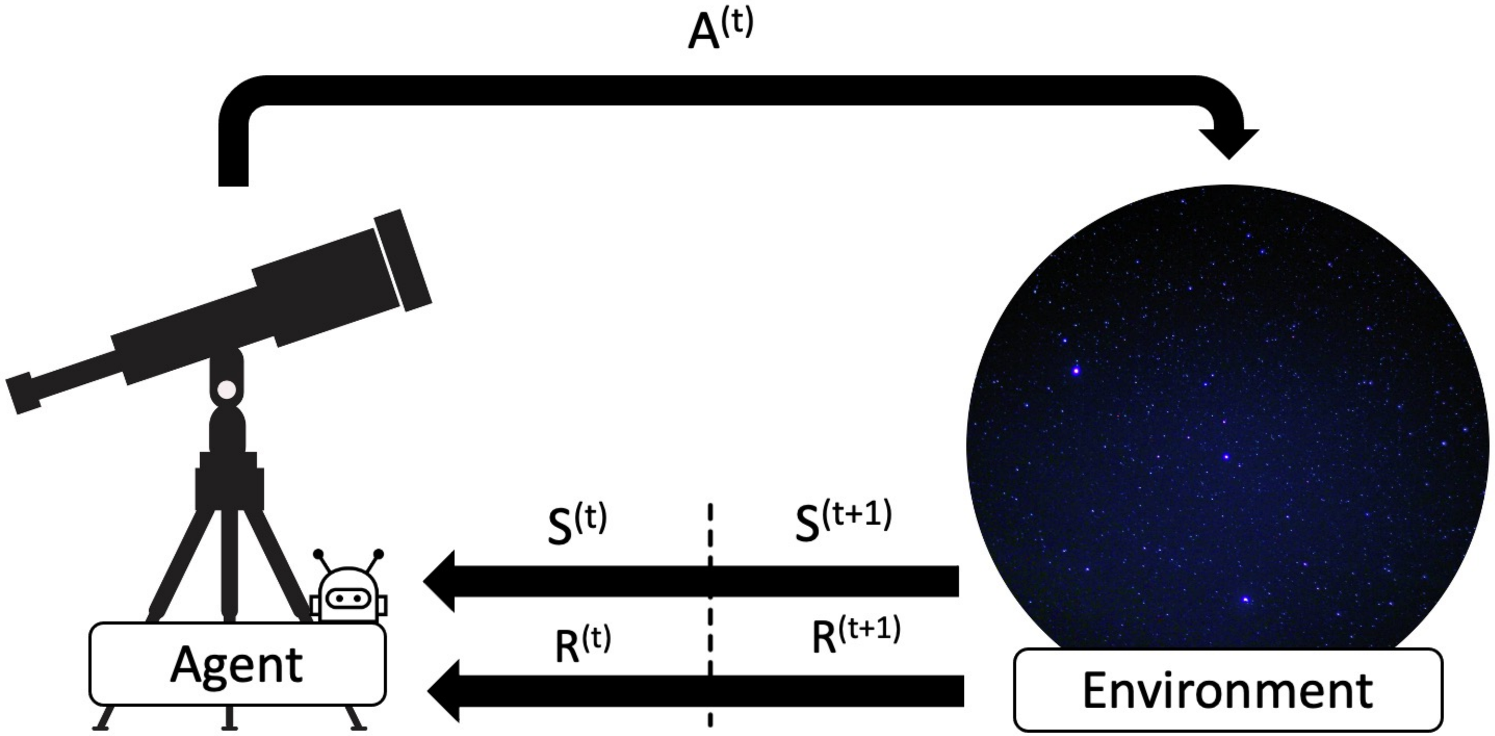
The journey toward achieving this vision begins with the crucial task of scheduling observations, a well-known NP-hard problem.

Given a potential set of sites from which to gather data, the optimization of telescope resources is crucial.

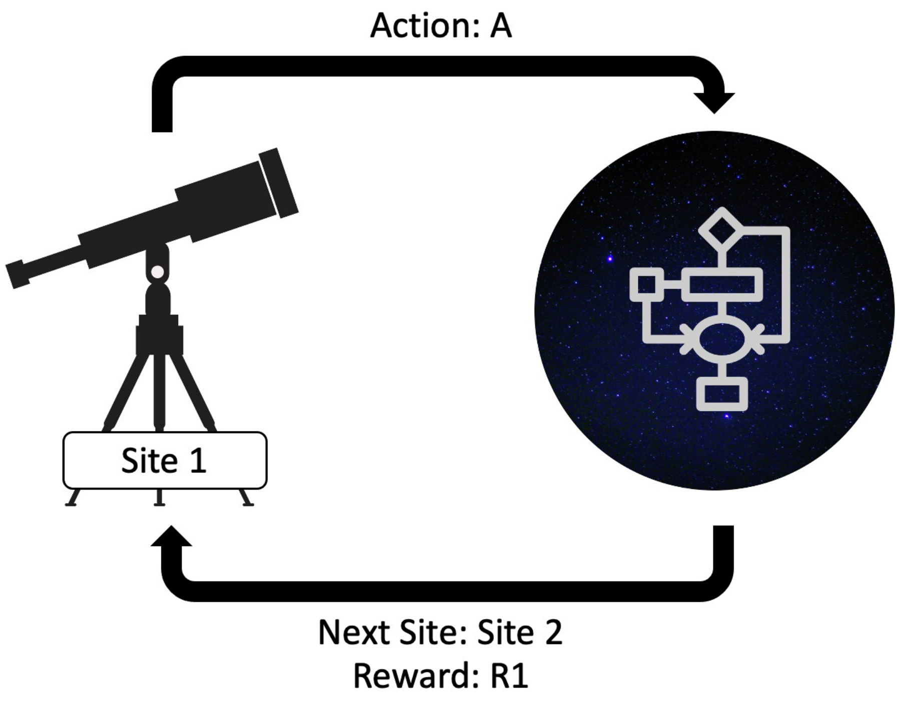


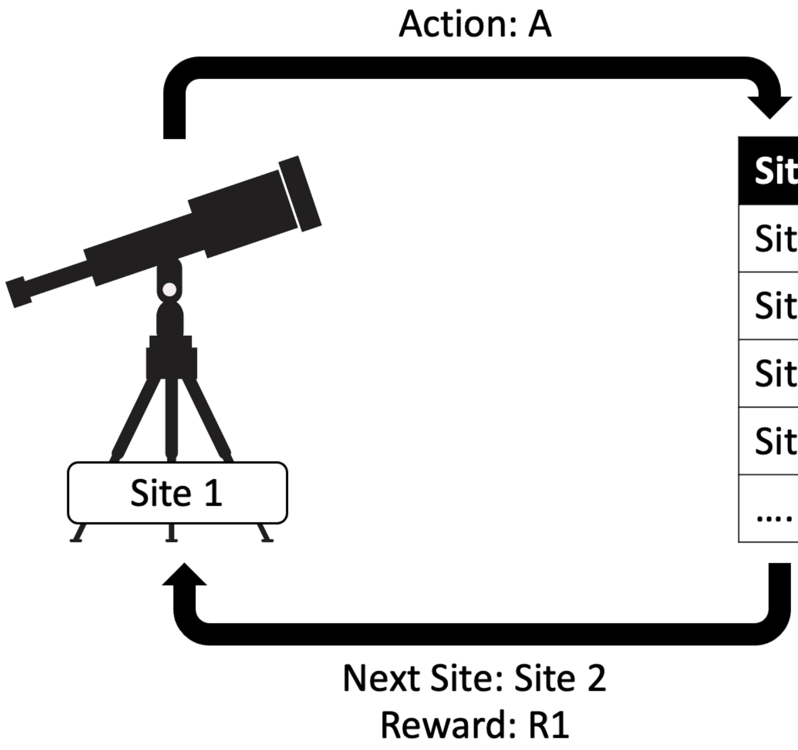
# Reinforcement Learning

Reinforcement Learning (RL) is a paradigm of Machine Learning used to train an autonomous agent able to behave optimally in a given environment.



# Reinforcement Learning: Online vs Offline




| Site | Action | Next site | Reward |
|---|---|---|---|
| Site 1 | A | Site 2 | R1 |
| Site 1 | B | Site 3 | R2 |
| Site 2 | F | Site 3 | R3 |
| Site 3 | Z | Site 4 | R4 |
| …. | …. | …. | …. |

# Environment overview

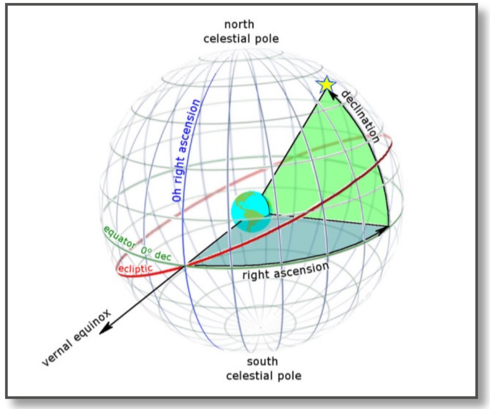
| ID | az | alt | …. | sun_ ra | sun_ decl | …. | moon_ airmass | moon _ angle | sky_ mag |
|---|---|---|---|---|---|---|---|---|---|
| ID_1 | 10.01 | 31.03 | …. | 64.77 | 21.41 | …. | 5.89 | 112.2 | 18.91 |
| ID_2 | 10.01 | 31.03 | …. | 64.77 | 21.41 | …. | 5.89 | 112.2 | 18.91 |
| …. | …. | …. | …. | …. | …. | …. | …. | …. | …. |

State space

- Metrics related to the telescope, the moon, the sky, and the sun
- Variables that can be sensed from the environment

| Right Ascension | Declination |
|---|---|
| 79.0 | 324.0 |
| 24.0 | 221.0 |
| …. | …. |

Action space




| T-Effective |
|---|
| 38 |
| 29 |
| …. |

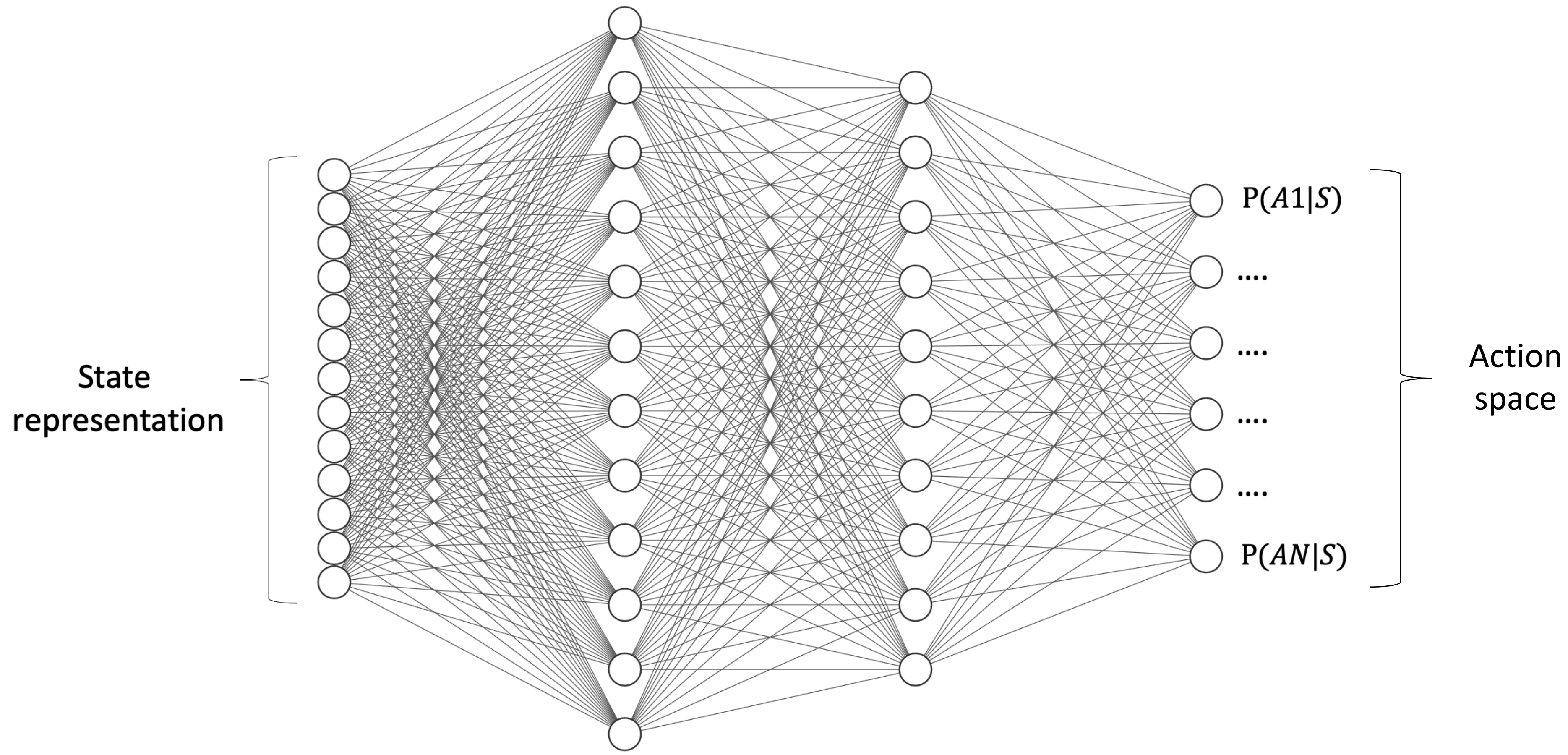
Reward

- A measure of the depth of the image
- It measures the quality of an observation

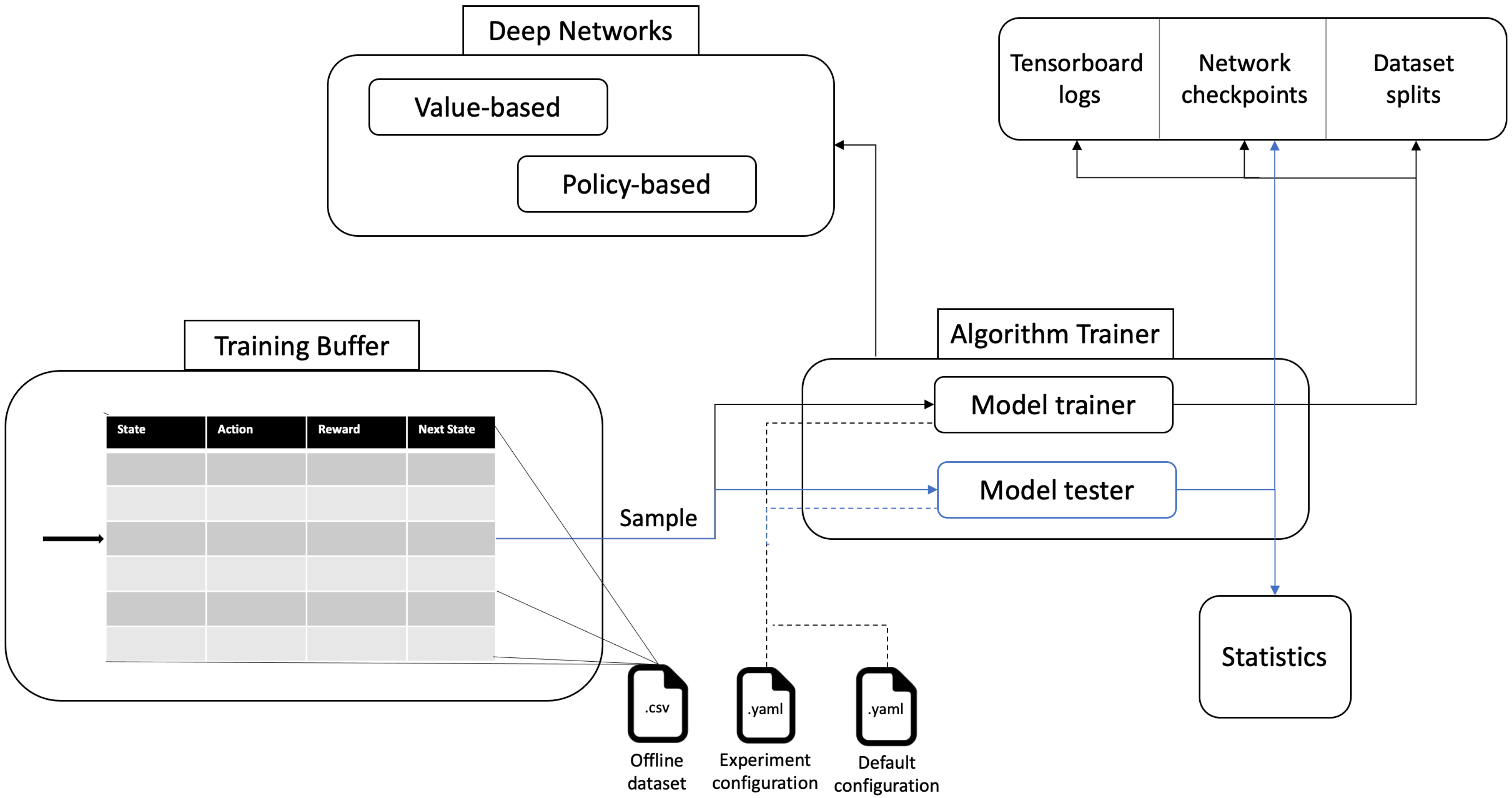
| New State |
|---|
| ID_29 |
| ID_46 |
| …. |

Next state

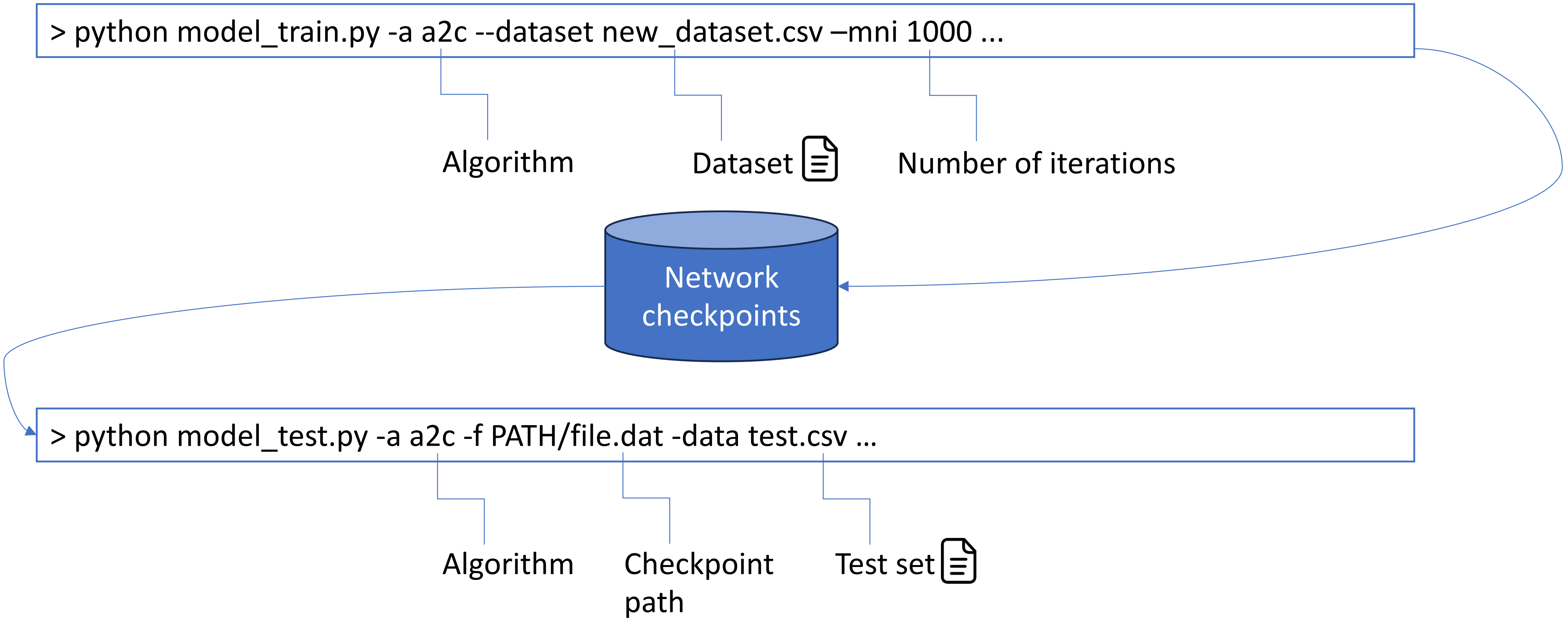
# Deep Neural Network as Function Approximator



# Framework for training/testing RL agents on any offline dataset



# Framework Command Line Interface (CLI): Examples of use



# Features & Algorithms supported

**Algorithms** available:

- Deep Q-Network (DQN) and modifications
- REINFORCE method
- Actor-Critic (A2C) method
- Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES)
- Genetic Algorithm*

*based on the paper "Deep neuroevolution: Genetic algorithms are a competitive alternative for training DNNs for RL" by F. P. Such et al.

Algorithm implementations used are based on the PyTorch AgentNet (PTAN) library!

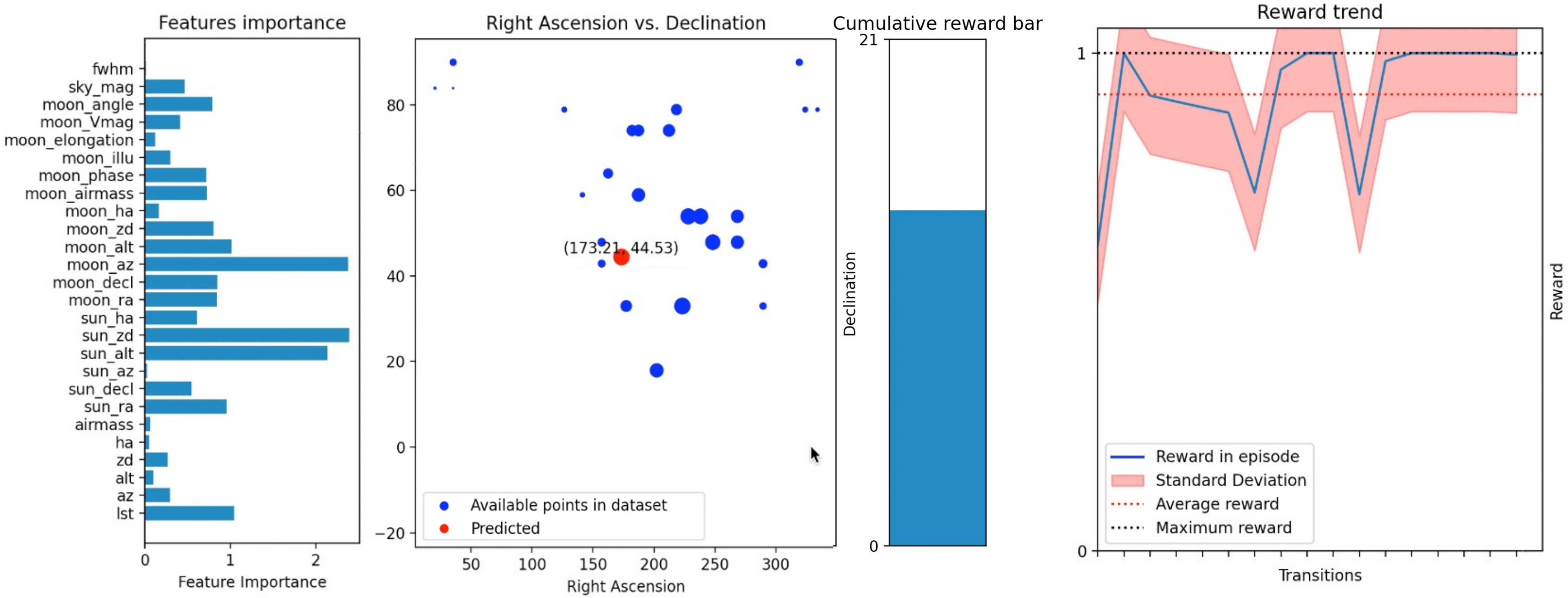
Value-based methods

Policy-based methods

**Features** supported:

- Splitting strategies by Modified Julian Date (MJD) such as the Holdout method and K-Fold Cross Validation (K-Fold CV)
- Normalization strategies
- State space reduction (Multi-collinearity reduction, PCA, etc.)
- Hyper-parameters optimization based on the Optuna library
- Reward penalization strategy to trade-off quality of observations and the variety of the data gathered
- ….

# Rendering: Visualization and Interpretability



# Conclusions & Future work

- Developed a framework for training RL agents based on any offline dataset (soon available on Github)
- Results on the SEO simulation dataset demonstrated how RL could optimize telescope scheduling observations

- An online environment could increase the amount of data available for training
- A continuous action space may push the boundaries of the problem to a higher level

Stone Edge Observatory (SEO), a privately owned observatory in California