Team Name: STARTORS

Team Members: Aseem Gosain, Devansh Shrestha, Lakshay Chawla, Rommel Jalasutram

Project Name: TORS (Transients Observation Recommendation System)

Problem Statement: The objective of this project is to develop a reinforcement learning-based recommendation system for astronomical observations of variable stars. The proposed system will analyze time series photometry data of variable stars and recommend the most suitable type of observation for each star.

Project Inspiration: The project is inspired by a research paper published in the Astronomical Journal (<https://iopscience.iop.org/article/10.3847/1538-3881/acb0c3>).

Data Resources: The project will utilize data from various surveys such as Gaia, Hubble, Stripe 82, skymapper, ogle, ipac, ztf, wise, tess, kepler, and glorot. These surveys release data periodically and are publicly available. Data extraction will be performed by querying sites like CasJobs.

Unique Selling Point: The uniqueness of our project lies in the following aspects:

1. We will merge data from multiple surveys instead of relying on a single source.
2. We will incorporate multiple bands in our analysis, making it a multi-band multi-survey analysis.

Methodology:

* Data Extraction: We will utilize sites like CasJobs and Gaia ADQL to cross-match data from various surveys and extract photometry data for the same star. This process may face certain challenges, such as different surveys conducting observations at different times or not all surveys being launched at the same time. However, these challenges can be mitigated by selecting suitable time periods for data extraction. This approach will provide a large amount of data for training our classification model and help create a more granular cost control system that could have real-world benefits. Additionally, by utilizing surveys that observe different bands, we can switch to a lower-cost survey telescope or a better one, depending on the observations needed.

Note: The number of classes for transient stars will depend on the data extracted and will be determined at a later stage.

* Proposed Model Architecture:
* Classification models: We plan to use RNN-based models to obtain probabilities for the reward system in the RL environment, as it makes more sense for the time-series data used in our project. This is in contrast to the random forest classification used in the research paper that inspired our project.
* RL environment: The RL environment will be designed with different states, each containing details of different band data and metadata. We will make the variables XM, XRP, XG, and XBP. The actions of the environment will be defined as the recommendation for observing the specific star from n number of surveys, and the observation can be single band, multiband (which will affect cost), or no observation at all. The reward will be set as the probability of finding the object at state (St+1) - the probability of finding the object at state (St) - cost. The cost function will depend on different bands and surveys and will be formalized after data extraction.
* RL models: The specific RL model has yet to be decided, but deep Q-learning is a technique that is likely to be used in the project.