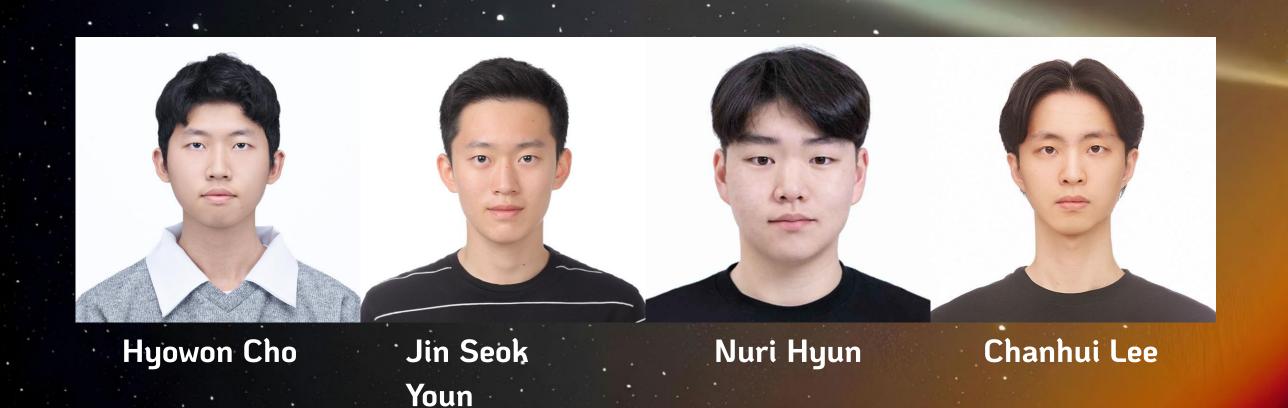
OBJECTIVES

Detecting seismic activity on Mars and the Moon is essential for understanding planetary geology and enhancing space exploration. Our goal is to develop a model to identify seismic anomalies in planetary data to identify earthquakes. We also want to determine the patterns of seismicity on the Moon and Mars that we hypothesize can be divided into foreshocks, mainshocks, and aftershocks similar to Earth.



WHAT WE DID?



First Step

For **Lunar data**, the data is relatively sufficient than Mars.

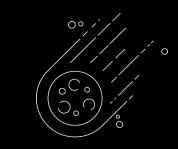
For **Mars data**, we used IQR Method to overcome the problem of insufficient data.

We trained scalar function to scale the datasets before we put them into our model.



Second Step

We used **LSTM Autoencoder** to detect anomalies in time series data.



Third Step

We visualized the detected anomalies in a graph, and highlighted the anomalies with a red marker for analysis.



Fourth Step

We outputted the **CSV files** from the data that detected anomalies on the graph.

OUR DECISIONS

LSTM Autoencoder

o This technique is particularly effective for seismic detection with anomalous datasets because they capture temporal dependencies, handle long-term relationships in the data, and are robust to noise, while providing a framework for detecting deviations from learned normal seismic patterns. This makes them ideal for detecting anomalous seismic events such as earthquakes or unusual seismic activities.

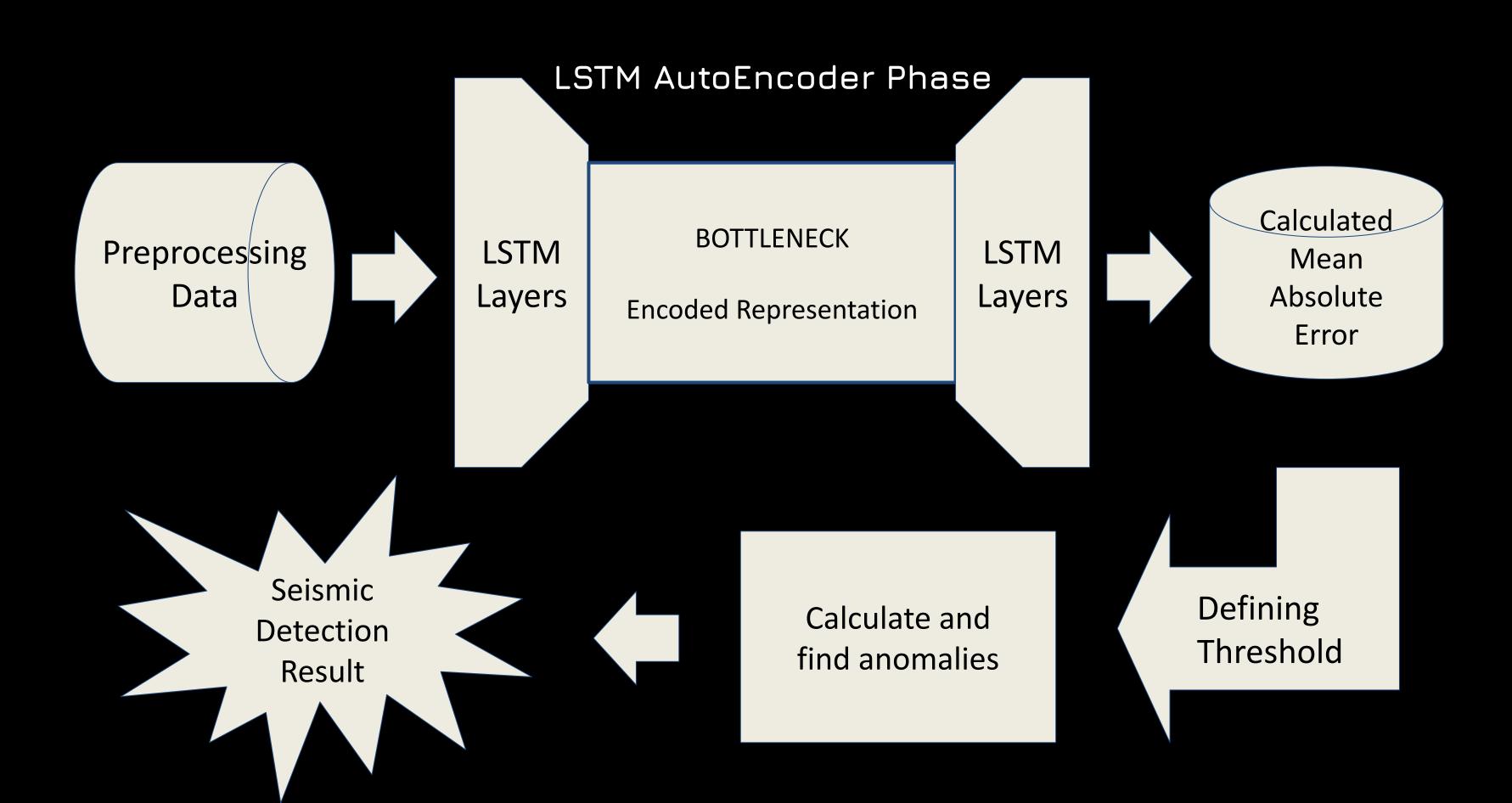
IQR

Although the Moon has sufficient data, Mars has insufficient data. Since we can distribute normal data according to the law of large numbers, we decided to filter in such cases. However, due to the insufficient data on Mars, we need to generate normal data while minimizing data contamination. To achieve this, we used the IQR (InterQuartile Range) method, defining the values outside the normal range as anomalies and training the LSTM Autoencoder using only the data within the range.

Threshold Decision

• When we plot the reconstruction MAE(Mean Absolute Error) that we calculated from the results of the LSTM autoencoder, we found that this graph is **extremely right-skewed**, which is expected as there will be extremely small portions of anomalies within training sets. With that, we have found the point where the slope of the curve decreases the most, setting that point as threshold.

Brief Algorithm Diagram

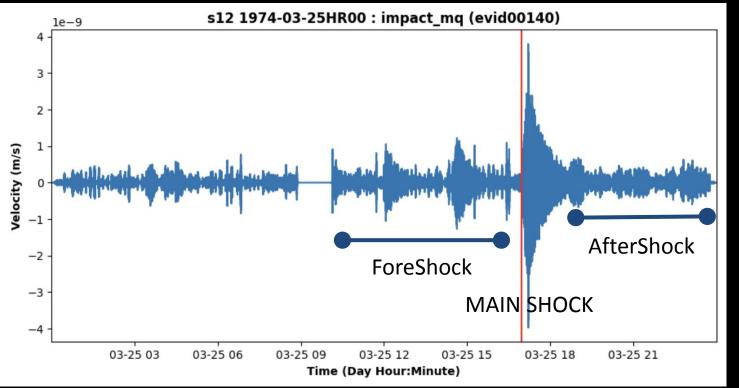


One More Thing...

OUR HYPOTHESIS

Our research extends beyond simply detecting significant seismic anomalies as shown in the dataset. We aim to uncover hidden quakes and analyze the patterns they form. Specifically, we hypothesize that seismic events, even if they differ in characteristics from those on Earth, may still exhibit patterns akin to foreshocks, mainshocks, and aftershocks, similar to how earthquakes behave on Earth.





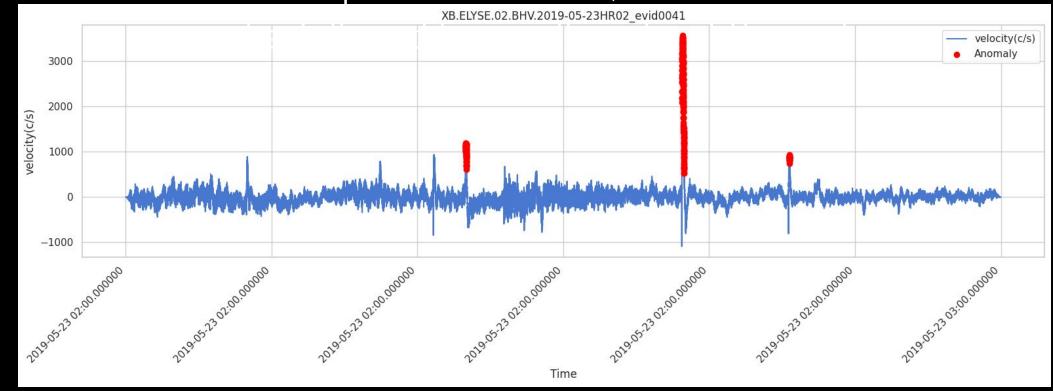
We would like to see this kind of pattern.

The CONSEQUENCES

We could not process as many test sets as we wanted to make clear evidences as we only had 24 hours on this NASA SpaceAPP Hackathon. However, some of consequence plots shows that they do have somewhat patterns that we would describe as 3 phases quake.

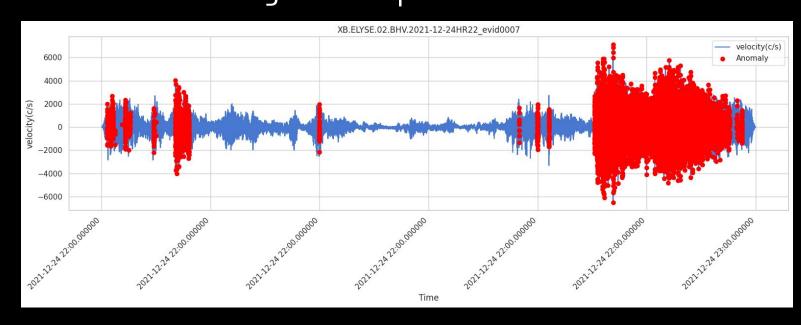
For example,

Plot 1 shows that there is one medium quake comes first, and then one hard



Plot 2 shows

3 small quake before large main quake and vibrating small quakes at the end.



CONCLUSIONS

We tried to design the best algorithm for seismic anomaly detection in a short hackathon time. Since we tried to use machine learning to detect anomalies, we were not able to train a large dataset and do the number of tests we wanted in the time available. However, we definitely developed a usable algorithm and were able to pull out meaningful test data. We also had time to analyze the patterns in the earthquakes for the assumptions we made further.