



INTRODUCTION

Background:

- Satellites are essential for gathering and sharing data worldwide, supporting critical operations for governments, private organizations, and individuals. However, these satellites frequently experience technical challenges often triggered by space weather.
- **Space weather can be loosely** defined as events caused by the expulsion of particles from the Sun.
- **Space weather includes events** such as solar flares, coronal mass ejections, solar wind, sunspots, etc.
- Current anomaly responses are reactive.

Motivation:

- It is essential that satellites in orbit work properly in the atmosphere.
- **Disruptions to satellite systems** or damage to satellites can be very expensive.
- Preventing anomalies is crucial to the continued ability to send satellites into space.
- Space weather is difficult to accurately predict in long term.
- By using space weather conditions we can predict satellite anomalies and minimize cost.
- Therefore, satellite operators have a strong incentive to invest in building a predictive model for satellite anomalies to help minimize costs.



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Satellite Anomaly Prediction

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DATA

- Dataset used to train models to predict satellite
- anomalies was created by joining 2 datasets
- First dataset was exported from National Oceanic and **Atmospheric Administration Satellite Anomalies and had**
- specific data on the cause and type of satellite anomalies and satellite details
- Second dataset was exported from Helmholtz Centre for Geoscience and included daily weather conditions. Datasets were joined by shared dates to determine
- whether an anomaly occurred that day.
- 11,688 observations from 1963-1994 are in the dataset, with 13 variables describing space weather and satellite anomalies
- Notable variables are:
- Date
- Mean Kp value
- Mean Ap value
- SN (Daily Total Sunspot)
- AnomalyCount (total number of anomalies)
- Location of satellite was not included

RESEARCH AND RESULTS

- **Logistic Regression Model**
 - Statistical method used to predict the probability of an anomaly occurring using the day's Kp Index and transformed Total Sunspot Number.
- Yeo Johnson transformation was performed on Total Sunspot Number to normalize the data instead of removing outliers. Randomly selected 75% of the data as the training set and the remaining as the testing set.
- **Classification threshold was 50%.**
- Model's accuracy is 79.47%.
- **Classification Error Rate is 20.53%.**
- False Positive Rate is 20.53%.
- False Negative Rate is 25.00%.
- False Discovery Rate is 99.50%.
- False Omission Rate is 0.04%.



Data Mine of the Rockies Spring 2025

TSAC

FUTURE GOALS

• Identify the particular type of anomaly occurring using multi-class models Improve the accuracy of the models to be more reliable **Forecast future space weather conditions**

FUTURE DEFINITION OF SUCCESS

Ability to predict satellite anomalies reliably enough to be able to devise strategies to avoid operational disruptions and reduce economic losses