Detecting Anomalies in Satellite Orbit Data

# 1. Introduction

Satellites in Earth orbit play a crucial role in modern communication, navigation, weather forecasting, and defense operations. Monitoring their motion and identifying anomalous behavior—often a result of orbital maneuvers—is essential for maintaining satellite health, avoiding collisions, and ensuring accurate tracking. The 18th Space Defense Squadron regularly publishes the orbital parameters of thousands of satellites in the Two-Line Element (TLE) format. Detecting changes or anomalies in these orbital elements can provide insights into satellite maneuvers, including station-keeping, collision avoidance, and orbit changes due to mission objectives.

This project explores the problem of anomaly detection in satellite orbit data using time-series forecasting techniques. Specifically, we aim to identify anomalous behavior in the orbit of the Fengyun-2F satellite by forecasting key orbital parameters using ARIMA and SARIMAX models and analyzing the residuals to infer maneuver events. We perform a complete pipeline: data cleaning, visualization, stationarity testing, transformation, model fitting, and anomaly detection. The results are compared against known maneuver timestamps, with a view toward building robust maneuver detection tools.

# 2. Background

The TLE format encapsulates a satellite's orbital state using a compact representation of its Keplerian elements. Each update represents the satellite’s state vector at a specific epoch. Changes between successive TLEs can indicate maneuvers—intentional velocity changes made to alter the satellite's orbit.

Maneuvers may arise from:  
- Station-keeping to counteract natural drift,  
- Collision avoidance due to nearby space objects,  
- Orbit adjustments to fulfill new mission parameters.

Given that TLE data is available only once per day (on average), identifying maneuvers involves detecting significant changes in parameters like eccentricity, inclination, right ascension of ascending node (RAAN), and mean anomaly.

Time-series forecasting techniques, particularly ARIMA (AutoRegressive Integrated Moving Average) and SARIMAX (Seasonal ARIMA with exogenous variables), allow us to model and predict future values of a univariate time series. The difference between the predicted and actual values—called residuals—can be analyzed to detect outliers or anomalies. This approach assumes that forecast errors under normal conditions are small and that anomalies (e.g., maneuvers) produce unusually large residuals.

# 3. Exploratory Data Analysis

The dataset under investigation contains orbital parameters of the Fengyun-2F satellite, formatted in a time-series structure. The primary features include eccentricity, inclination, argument of perigee, right ascension, mean anomaly, and Brouwer mean motion. These features were extracted from TLE records and required preprocessing before analysis.

Initial preprocessing steps included column renaming for consistency, date parsing and indexing by timestamp, handling of missing values, and conversion of numerical columns to float format. After cleaning, the dataset comprised 2,985 data points spanning from 2012 to early 2022.

Rolling statistics (mean and standard deviation with a window size of 12 days) were plotted for all parameters to observe patterns. This revealed temporal anomalies, particularly a spike in eccentricity during 2019. This behavior aligns well with known maneuver events and was further validated using residual analysis later in the pipeline.

A key insight from the exploratory plots is that most parameters exhibit periodic or oscillatory trends. Right ascension, for instance, showed a sharp shift around 2015-2016. Inclination displayed cyclic adjustments, possibly due to regular station-keeping maneuvers.

Augmented Dickey-Fuller (ADF) tests were performed to assess stationarity. Eccentricity was found to be stationary (p < 0.05), while other features required transformation. Accordingly, we applied logarithmic transformation, first-order differencing, and Box-Cox/Yeo-Johnson transformations to ensure stationarity.

# 4. Methods

We adopt a residual-based anomaly detection strategy where the difference between predicted and actual values of orbital parameters serves as an anomaly score. The process includes model fitting, residual extraction, and threshold-based classification.

Two forecasting models were implemented:  
- ARIMA: A traditional time-series model relying on autoregressive and moving average components.  
- SARIMAX: A more flexible extension supporting seasonal components and exogenous variables.

The time-series data was split into training (60%) and testing (40%) sets. Walk-forward validation was used for prediction. After each prediction, the actual value was added to the training set to simulate real-time streaming data.

Hyperparameters for ARIMA (p=2, d=1, q=0) and SARIMAX (p=0, d=1, q=1) were selected using grid search and AIC minimization. Residuals were computed as the absolute difference between predicted and actual eccentricity. Thresholds for anomaly detection were set empirically at the 95th percentile of residuals in the training data.

# 5. Results

The performance of both ARIMA and SARIMAX models was evaluated on the test set of eccentricity values. Predictions were compared against actual values using visualizations and residual plots. Significant deviations were interpreted as indicators of maneuver events.

For the ARIMA model, the residuals showed a distinct spike around 2019, aligning closely with known maneuver dates from the Fengyun-2F ground truth data. SARIMAX exhibited even tighter predictions and lower residual variance, suggesting better generalization and improved anomaly localization.

To visualize the detection quality, residuals were plotted over time alongside a threshold curve. Anomalies were flagged at time points where residuals exceeded the threshold. These anomalies showed strong alignment with the known maneuver timestamps, validating the forecasting-based detection approach.

Quantitatively, the models were evaluated using Akaike Information Criterion (AIC) and log-likelihood. SARIMAX achieved a lower AIC (-67873.74) than ARIMA (-49135.91), indicating a better model fit. The model summaries also revealed well-behaved coefficients with significant z-values and low standard errors.

# 6. Conclusion and Discussion

This project demonstrated the effectiveness of forecasting-based anomaly detection in satellite orbital data using ARIMA and SARIMAX models. Eccentricity emerged as a particularly informative parameter for identifying maneuvers, with clear spikes during periods of known activity.

While ARIMA offered a solid baseline, SARIMAX provided more accurate predictions and smoother residuals. The residual thresholding technique successfully identified anomalous events, validating the overall methodology.

Challenges included ensuring data stationarity, managing model overfitting, and determining optimal thresholds. Future improvements may include:  
- Expanding the analysis to other orbital elements.  
- Incorporating ensemble models such as XGBoost.  
- Adding quantitative metrics such as precision, recall, and F1-score for detection evaluation.  
- Automating model tuning and anomaly scoring via machine learning pipelines.

In conclusion, the forecasting-residual framework proved effective for maneuver detection in orbital TLE data, and holds promise for large-scale automation of satellite behavior monitoring.

# 7. References

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