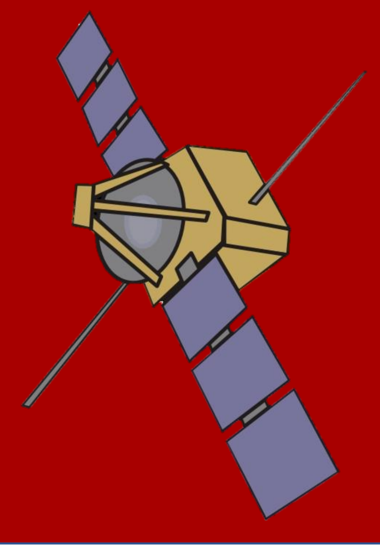
Satellite Anomaly Prediction using Survival Analysis and Machine Learning Approaches

Christopher Naughton (cwnaught@stanford.edu)
Department of Aeronautics and Astronautics, Stanford University



Introduction

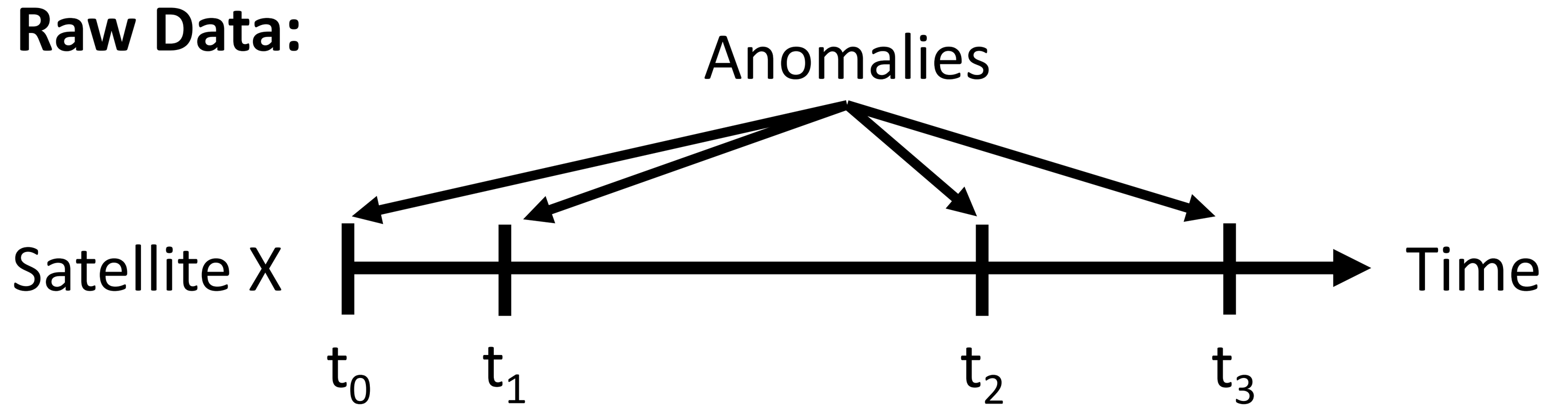
Satellites and space systems are integral to processes such as communication and navigation but are under constant threat from the space environment. As a result, agencies such as NOAA have monitored satellites and recorded hundreds of anomalous behaviors [1] [2]. Here we attempt to use this data with survival analysis and machine learning approaches to predict the time to a satellite anomaly. In the end, we found that the approaches considered did not work well with the limited and noisy data set

Data Processing

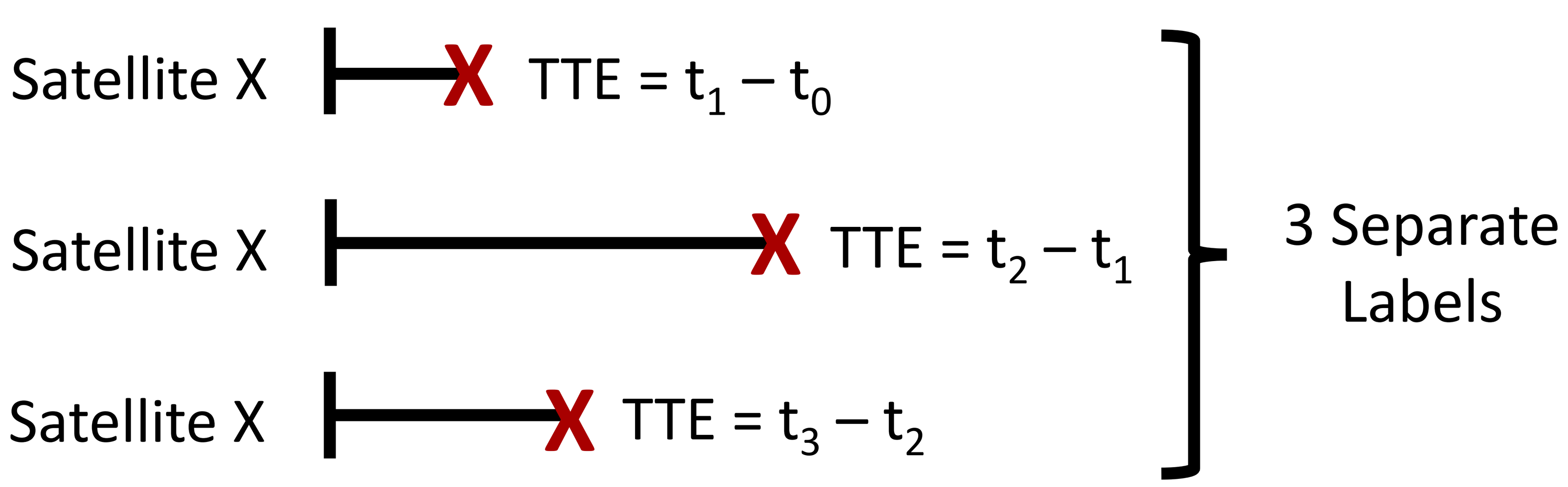
Raw data = Satellite names with anomaly timestamps

Goal: Pose problem as a "Time to Event" (TTE) prediction
- Classical treatment predicts time until patient death
- Treat each anomaly as an independent "patient"

Raw Data:



Processed Data:



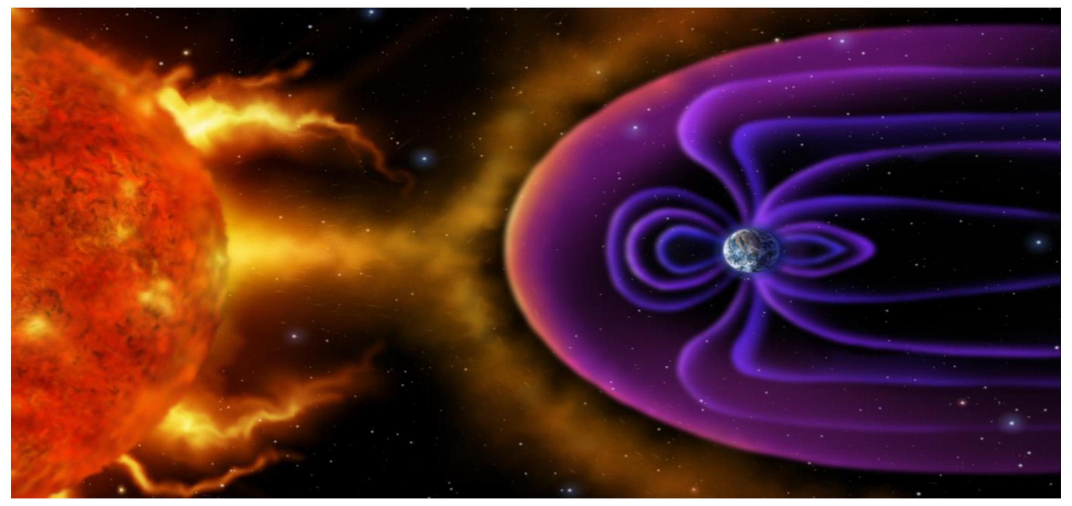
Data & Features

Processed dataset has **726 datapoints** for 10 satellites
- Anomalies recorded between 1976 and 1994

6 features:

Space Conditions:
- *Starting Month* = Position of earth around sun
- *Sun-Spot Number* = Measure of solar activity
- *X-ray Flux* = Count of high energy particles

Spacecraft attributes:
- *Mass* = Size of spacecraft
- *Perigee* = Distance from earth
- *Inclination* = Tilt of orbit



Models

Linear Regression: Initial baseline results

Support Vector Machine: Use RBF kernel to capture nonlinearities

$$\min_{W,b} \frac{1}{2}\|W\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \quad \text{constrained by} \quad \begin{array}{l} y_i - (w^T\phi(x_i) + b) \le \epsilon + \xi_i \\ (w^T\phi(x_i) + b) - y_i \le \epsilon + \xi_i^* \\ \xi_i, \xi_i^* \ \ge \ 0, \quad i = 1 \dots n \end{array}$$

Naïve Bayes: Perform classification each time step until failure

$$p(y=1|x) = \frac{\left(\prod_{j=1}^{d} p(x_j|y=1)\right) p(y=1)}{\left(\prod_{j=1}^{d} p(x_j|y=1)\right) p(y=1) + \left(\prod_{j=1}^{d} p(x_j|y=0)\right) p(y=0)}$$

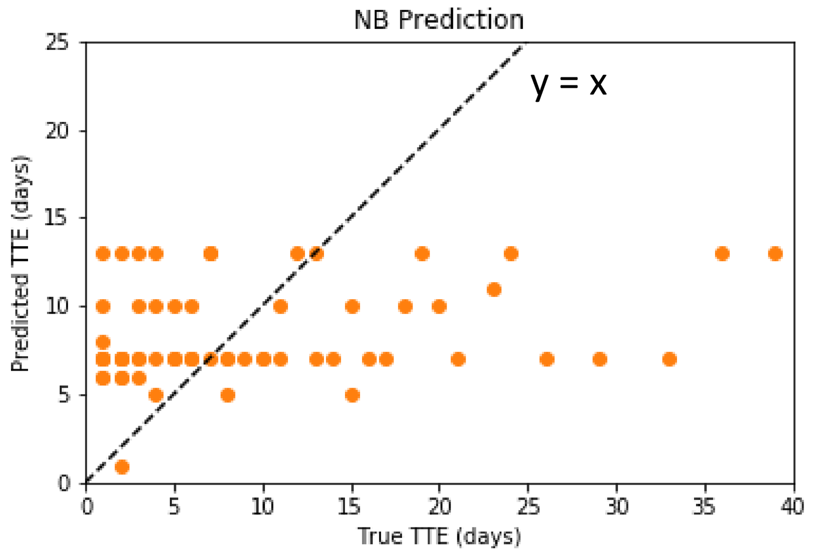
$$p(y=1) = S(t) = \prod_{i=1}^{m} 1 - \frac{1}{r_i} = Kaplan - Meier\ estimator$$

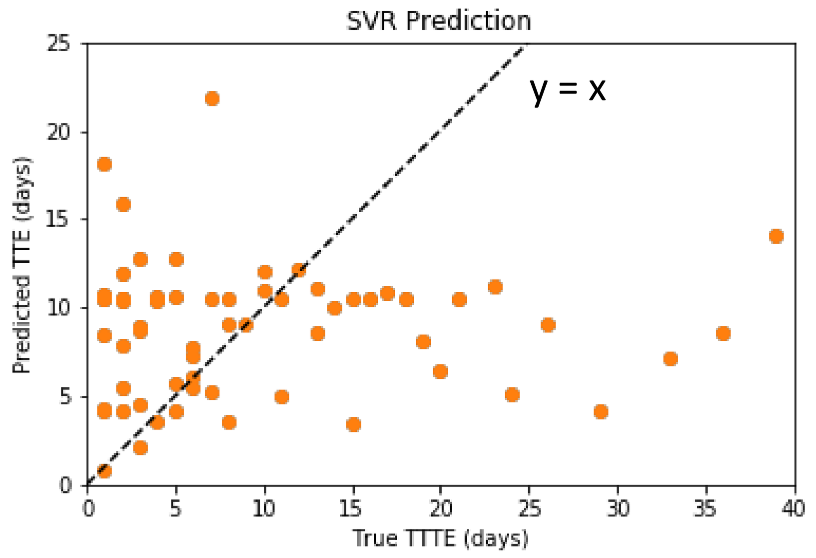
Results

Used k-fold cross validation with k=10 to evaluate

Training Set = 654 points   Test Set = 72 points

Model	Training Set Mean Error	Test Set Mean Error
Linear Regression	455%	475%
Naïve Bayes	100%	167%
Support Vector Regression	65%	190%





Discussion

- Machine Learning models did not adequately predict the satellite anomalies
- Most likely other factors were not being accounted for (e.g. space debris, geometry, etc.)
- Naïve Bayes might improve without Gaussian assumption
- Support vector regression was best on training set, but consistently overfit the training data

References

[1]: Wolfson (1993). *Satellite Anomalies*, electronic dataset, NOAA
[2]: Wilkinson et al. (1991). *TDRS-1 Single Event Upsets and the Effect of the Space Environment*. IEEE Transactions on Nuclear Science, Vol 38, No. 6
[3]: Wolfson et al. (2015). *A Naïve Bayes machine learning approach to risk prediction using censored, time-to-event data*. Stat Med