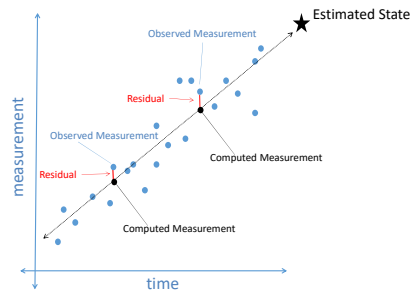


Background

We believe that there are many potential applications of Machine Learning to flight dynamics operations

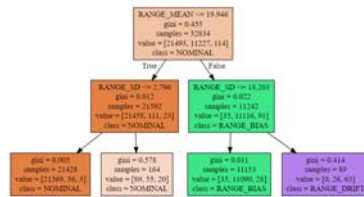
- Tracking data anomaly detection and classification
- Orbit estimation quality assurance
- Orbit estimation filter tuning
- Simultaneous localization and mapping for optical and relative navigation
- Novel methods of orbit estimation and prediction
- Space weather monitoring and prediction
- Intelligent and rapid data analysis

In this presentation we demonstrate our work so far in applying Machine Learning to tracking data evaluation



- Batch least-squares or sequential estimation is used to produce the best estimate of the satellite state based on the observations**
- The measurement residuals contain a lot of useful information, including**
 - The quality of physical models employed
 - The performance and noise characteristics of the tracking networks
- One component of the FDF's responsibilities is to evaluate the performance of a diverse set of tracking networks**
 - Simple things we look for are biases and excessive noise, but frequently tracking data anomalies are more subtle than just these

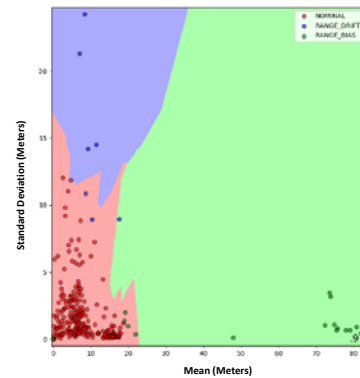
Classification/Supervised Learning



Confusion Matrix

	Nominal	Bias	Drift
Nominal	6409	9	1
Bias	78	1696	5
Drift	2	1	8

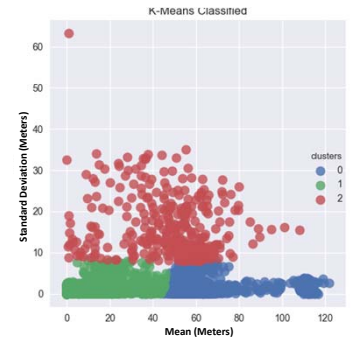
- Decision Trees, Random Forests, and Multilayer Perceptron classifiers can easily identify simple anomalies**
 - Based on simply the pass mean and standard deviation, these methods perform well at identifying the passes as NOMINAL, BIAS, or DRIFT
 - Decision Trees easily discover the criteria the analysts use for manual classification
- The data set is biased heavily toward NOMINAL instances**
 - This can be ameliorated somewhat with better training splits, but the small number of DRIFT instances is a problem



- K-Neighbors also shows promise for our application**
 - Particularly useful is the ability to obtain the confidence in the classification (**predict_proba**), as this allows us to only report on those anomalies which have high confidence
 - We need to do further work on feature selection to facilitate finer-grained anomaly identification

Clustering/Unsupervised Learning

- We want to be able to identify classes beyond simply "Nominal", "Bias", and "Drift"**
 - Conditions such as bimodal residuals, incorrect observation time tags, residual cycle slips, maneuvers, station geodetic errors
 - These currently require the attention of a trained and experienced analyst for proper identification
 - They require consideration of features beyond simply mean and standard deviation
- A problem is that our current data sets are not labeled for these classes**
 - This motivated investigation into unsupervised learning and clustering methods
 - Unsupervised learning also allows the potential of discovering new anomaly classes
- K-Means provides one method of clustering data**
 - If clear clusters emerge, the data can be "back labeled" for training classifiers
- Self Organizing Maps are also being studied**
 - Has the advantage that number of classifications could be unknown a priori
 - Maybe useful to determine "what we are missing"



Next Steps

- Investigation of other current methods of Time Series Classification**
 - Time Series Forest, 1-Nearest Neighbor with various distance metrics, Symbolic Aggregate Approximation, Convolutional Neural Networks
- The goal of this effort is a system that works alongside analysts to offer suggestions and assistance for classifying tracking data anomalies**
 - In the future, as the system becomes more competent and users gain trust in it, it can be given more responsibility for classifying tracking data, perhaps taking over as the prime analyst with task members reviewing its decisions or stepping in only when it is unable to make a confident judgement

