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Classification of orbital anomalies using machine learning models

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Abstract. Orbital anomalies, such as unexpected changes in a satellite's orbit, can significantly impact satellite operations and threaten human and financial resources. Detecting these anomalies is a crucial challenge in data analysis within the spatial domain. During satellite operations, a large amount of data is generated, These data allow us to assess the satellite's state at a specific moment. This paper introduces a study aimed at developing a diagnostic algorithm using machine learning techniques to classify orbital anomalies. The proposed algorithm will be able to classify these anomalies based on their origins using various supervised learning models. The performance of the algorithms used was measured by comparing their accuracy and using the confusion matrix over five distinct classes of orbital anomalies.

Keywords. Artificial satellites, SSA awareness, Machine Learning, Anomaly Classification

1. Introduction

As the number of satellites in orbit, including satellite constellations, continues to grow, there is an increasing demand to improve trajectory models and enhance operational risk management in order to achieve a deeper understanding of the causes of orbital anomalies. This study employs machine learning models for the classification of anomalies within the orbits of artificial satellites, using their descriptions provided through Two-Line Elements(TLEs). This study will conclude by conducting a comparative analysis of the performance of these different models to analyse the advantages and limitations of the selected models. We assumed that the data provided to the classifier are true anomalies (which we have referred to as 'true positives') This work is a collaborative effort between the Oukaïmeden Observatory† and the company SpaceAble‡.

2. Experiments & methodology

SpaceAble has provided a learning database containing Two-Line Elements (TLEs) of satellites categorized as abnormal. These anomalies fall into five distinct classes: **"Deliberate"**, **"Accident"**, **"Battery"**, **"Deliberate Collision"**, **"Propulsion"**. We have chosen to use three different machine learning models for classification:

† The Oukaïmeden observatory located 50km south of Marrakech is operated by the University Cadi Ayyad and was inaugurated in 2007. https://ouca.uca.ma/an/

‡ SpaceAble is a French startup specialising in Space Situational Awareness services, founded in 2018 by Julien Cantegreil. https://spaceable.org/

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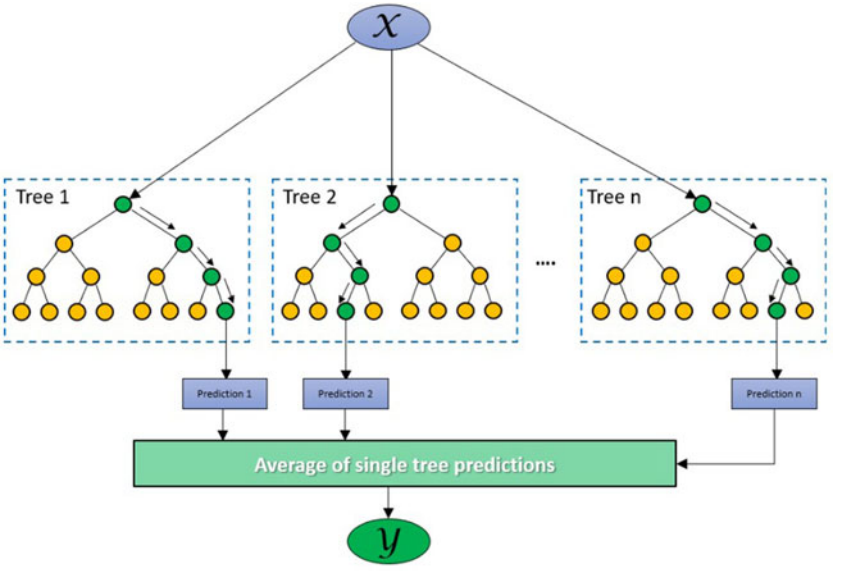


Figure 1. Random Forest Structure.
Milad, Adwan, Majeed, et al. (2021)

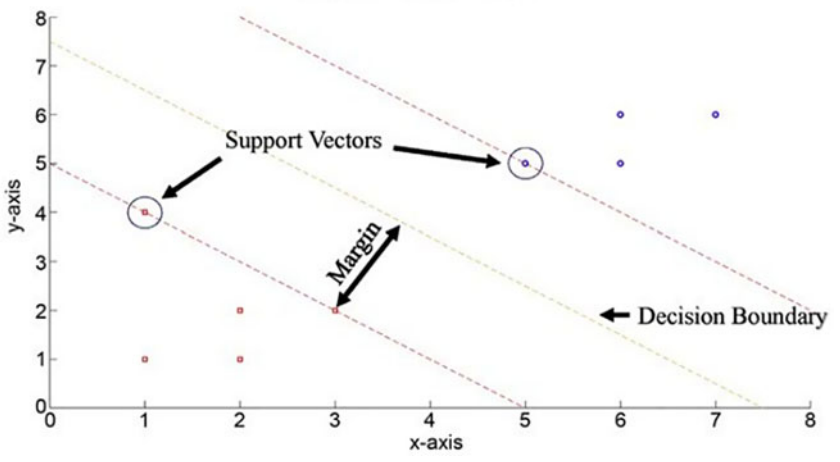


Figure 2. Support Vector Machine Example.
Forghani, Savadjiev, Chatterjee et al. (2019)

Decision Tree(DT), **The random forest(RF)** introduced by Ho (1995) and further developed by Breiman (2001) (see Figure 1) and **Support Vector Machine (SVM; see Figure 2)** a classic machine learning method that aims to find a decision boundary maximising the margin between two classes, providing robustness against noisy data by optimising between margin size and training error Lam, Ling, & Nguyen (2012).

3. Preliminary results

We used classical metrics such as the confusion matrix(Figure 3), precision, recall, and F1 score(see Table 1 and Table 2), as our preliminary results to evaluate our models.

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Table 1. The results with the Random Forest method.

	AccidentalCollision	Battery	Deliberate	DeliberateCollision	Propulsion	Average
Precision	1.00	0.00	1.00	0.00	0.69	0.54
Recall	0.50	0.00	1.00	0.00	1.00	0.50
f1-score	0.67	0.00	1.00	0.00	0.82	0.50

Table 2. The results with the SVM method.

	AccidentalCollision	Battery	Deliberate	DeliberateCollision	Propulsion	Average
Precision	0.50	0.00	0.60	0.00	0.75	0.37
Recall	1.00	0.00	1.00	0.00	0.67	0.53
f1-score	0.67	0.00	0.75	0.00	0.71	0.42

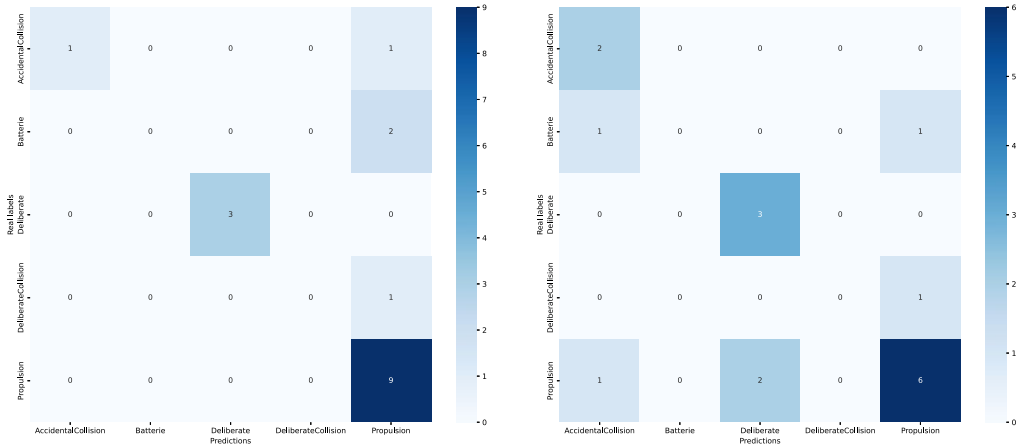


Figure 3. Left: The confusion matrix for RF method. Right: The confusion matrix for the SVM method.

4. Discussion & conclusion

The two confusion matrices (Figure 3) demonstrate that the "Propulsion" and "Deliberate" classes are easy to classify, unlike the other classes, which exhibit very poor results.

These poor performances lead to a decline in both precision and recall averages, though they remain relatively balanced (precision and recall around 0.5)(see Tables 1 and 2).

The average F1 score is generally poor.

We are still working on orbital anomaly classification using other models such as neural networks to optimise all models and compare their performance.

The classification of anomalies is possible.

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