Classification of Space Objects Using Machine Learning Methods

Mahmoud Khalil
Department of Electrical Engineering and Computer Science
Khalifa University
Abu Dhabi, United Arab Emirates
mahmoud.khalil@ku.ac.ae

Elena Fantino
Department of Aerospace Engineering
Khalifa University
Abu Dhabi, United Arab Emirates
elena.fantino@ku.ac.ae

Panos Liatsis
Department of Electrical Engineering and Computer Science
Khalifa University
Abu Dhabi, United Arab Emirates
panos.liatsis@ku.ac.ae

***Abstract*— In the last decade, the number of space objects has skyrocketed. Collecting and analyzing data about these objects is essential in maintaining security of space assets. Classifying unknown objects into satellites, rocket bodies and debris represents a significant milestone in the analysis process. In this context, we investigate the effectiveness of several machine learning methods in classifying real-world light curves of space objects. The light curves are represented with a set of features extracted using the *feets* (feATURE eXTRACTOR FOR tIME sERIES) public tool. To address the problem of class imbalance, the synthetic minority over-sampling technique (SMOTE) is applied. We also investigate the use of Principal Component Analysis (PCA) in reducing the dimensionality of the feature space, prior to classification. In the case of the original feature set, the top performing classifier is the feedforward neural network with an accuracy of 73.6%. When SMOTE is used, an improvement in accuracy of approximately 15% is observed, with the use of SVM. However, PCA-based feature transformation leads to a slight degradation in performance of around 3%, in the case of the original feature representation, and a considerable degradation of 10%-30%, when SMOTE is used.**

Keywords*— *Space Objects, Light Curves, Class Imbalance, Classification, Machine Learning

I. Introduction

Space satellites have become an established part of our digital world and are extensively used in communications, security, urban planning, environmental data analysis, etc. As assessed from the European Space Agency (ESA), the number of objects orbiting the Earth is blowing up year by year [1]. In this context, ESA has identified Space Situational Awareness (SSA), as a key area of interest for protection and secure access to space resources [2]. The objectives of SSA include the collection of data on over 22,000 space objects (SOs), 1,100 of which are active, using optical and radar sensors, to develop a detailed understanding of the SO population [3]. Understanding the behavior of the SO population is essential in discriminating between active satellites and other types of space objects. A major issue is reliable detection of space debris, i.e., fragments of collisions of satellites and space objects. This is an essential requirement for maneuvering and collision avoidance methods to ensure greater security to space satellites.

Tracking space objects can be performed by using a variety of instruments, such as cameras, and optical and radar sensors [4]. In recent years, the analysis of raw images of space objects obtained from electro-optical sensors has received considerable attention by the SSA community. However, space objects are often difficult to resolve in such images, even with the state-of-the-art sensors, due to their relatively small size, particularly in the context of deep-space regimes. Light curves (also known as photometric signatures) are a promising type of data, extracted from such non-resolved images. A light curve is the time-varying wavelength-dependent apparent magnitude of energy (e.g., photons) scattered off an object along the line-of-sight to an observer [5]. Although the amount of light collected from SOs is small, information can still be extracted from photometric data. An object's light curve is a function of several factors, including its size and shape, material composition, attitude, kinematic state, illumination geometry, stability, atmospheric effects, biases, and sensor characteristics. The solution of the inverse problem of resolving the object characteristics given a photometric signature is a challenging problem, due to its mathematical complexity, noise and the data sparsity in real light curves, which cannot be easily modelled [6].

Machine Learning (ML) techniques have been used in a variety of applications to automatically detect patterns or classify data. They build a mathematical model based on a given dataset, in order to make decisions on new data [7]. Examples of such algorithms are Decision Tree, Ensemble Classifiers, Linear Discriminant, Naïve Bayes, k-Nearest Neighbors (k-NN), Support Vector Machine (SVM) and Neural Networks (NN). In this research, machine learning techniques are applied to real light curves of space resident objects in order to classify them into three categories, namely, satellites, rocket bodies and debris. In previous work, simulated light curves have been used for this purpose, as in [3] and [8-10]. In [11], simulated and real light curves were used to classify space objects based on deep learning methods. Real light curves have also been used in [12], however, the data used is highly imbalanced, compared to the data used in this work, and a different data representation technique was used.

Our approach is based on using state-of-the-art machine learning models, which are trained on features extracted from the light curves, by using the *feets* (feATURE eXTRACTOR FOR tIME sERIES) public library [13]. A common problem encountered in light curve data is class imbalance, i.e., the number of class observations varies considerably, thus affecting the performance of classification algorithms. In this work, we consider the use of an over-sampling technique, i.e., SMOTE (Synthetic Minority Over-sampling Technique) [14], to increase the number of observations of the minority class, i.e., debris. Moreover, one of the aspects which affects the performance of machine learning systems is representation redundancy, which is sometimes manifested as feature correlations. We also explore the use of Principal Component Analysis (PCA) [15] for reduction of the feature space dimensionality, in the context of ML model generalization.

The structure of this paper is as follows: Section II explains the setup of the dataset. In Section III, feature

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extraction and over-sampling are discussed, together with the use of the PCA method to reduce feature space dimensionality. Section IV provides a brief overview of the classification methods, followed by the results and discussion in Section V. Finally, the conclusions and avenues for further research are presented in Section VI.

II. Dataset Setup

The dataset has been established by retrieving information from two sources. Firstly, from the European Space Agency – DISCOS (Database and Information System Characterising Objects in Space) [16], information of a set of identified space objects was collected, such as NORAD ID, mass, average cross sectional area, shape and class for each SO. Secondly, light curves for the collected space objects were retrieved by cross referencing the NORAD IDs with light curves from the MMT database at Kazan Federal University [17]. Some light curves consist of a small number of samples, and therefore, a minimum threshold of 200 points was considered for a valid light curve.

The dataset consists of 747 space objects, where each SO may have one or more light curve tracks. In total, there were 16194 light curves, of which 11430 are classified as satellite, 4119 are rocket body and the remaining 645 are identified as debris. Thus, the relative proportion is 70.6:25.4:4 for the satellite, rocket body and debris classes, respectively.

III. Data Preparation

A. Feature Extraction

To use the dataset for classification, light curves should be manipulated, by representing each light curve as a set of features. A popular technique for feature extraction of light curves is *FATS* (Feature Analysis for Time Series) [18]. *FATS* has been shown to provide a powerful feature extraction tool for classification of star light curves [19-21]. An improvement to *FATS* is *feets* [13]. Improvements include higher coverage rate, support for Python 3, better encapsulation of extractor and other enhancements. In this research, we apply *feets* to extract features from space object light curves.

In total, 57 features were calculated for each light curve, such as Amplitude, Skew, Lomb-Scargle, Mean Variance and Median Absolute Deviation. Interested readers are refer to [18] for further details about the features. Three of the calculated features were discarded, as they demonstrated no variance in the set of observations. Also, another feature was also discarded since most of its values were N/A and infinity. The final dataset consisted of a 53-dimensional feature set, which we will refer to as the original feature set throughout this work.

B. Over-sampling

As previously stated, the number of observations in the dataset is not balanced between the classes, which will affect the results of performance metrics. In particular, we are mostly concerned with the detection of space debris objects, which is the class with the least number of observations. To address this issue, SMOTE (Synthetic Minority Over-sampling Technique) [14] is used to generate additional observations for the minority class, thus reducing the degree of imbalance of the dataset. The basic concept of SMOTE is to calculate the k nearest neighbors for each observation in the minority class, and then create synthetic examples along the lines connecting these observations.

The distribution of samples in the over-sampled dataset following the application of SMOTE is 11430 instances in each class. We will refer to the SMOTE-processed feature set as the over-sampled feature set, to distinguish it from the original set.

C. Dimensionality Reduction

As stated in Section III.A, there are 53 features extracted from the light curves, which is quite a large number, given the size of the dataset. High dimensional data make classification problems computationally expensive, and harder for ML methods to find an appropriate model that fits the data well. To reduce the dimensionality of the feature space, we considered using the well-known method of PCA [15]. PCA essentially requires defining an orthogonal linear transformation, then the features are projected using the transformation matrix to produce a new set of uncorrelated feature vectors, called principal components. The resulting set is ordered such that the first principal component has the highest variance and thus accounts for most of the variability in the data. The second component has the second largest variance and is essentially orthogonal to the first one and hence uncorrelated to other components. The same criterion is applied to the remaining components.

Following the application of PCA on the original and the over-sampled feature sets, we found that over 99.99% of the variance is contained in the first six PCA features, extracted from both sets. Therefore, we selected the first six features after applying PCA on both, the original and the over-sampled feature sets.

In the classification experiments, we use four sets of features, i.e., the original and the over-sampled sets, both with and without PCA, and compare the performance of ML techniques.

IV. Classification Framework

MATLAB®'s Classification Learner Application and the Neural Networks toolbox were used in the experiments. Each of the four sets were split into training, validation and testing sets, consisting of 75%, 12.5% and 12.5% of the data, respectively. The machine learning models were first validated using 10-fold cross-validation. The final results were averaged so as to evaluate the performance of the individual models. Satellites, rocket bodies and debris were labelled as class 1, class 2 and class 3 respectively. The training parameters for each classifier were as follows:

a) Decision Tree: The maximum number of splits is set to 20 when training on the original feature set, and 100 when training on the over-sampled set. The split criterion is Gini's diversity index.

b) Linear Discriminant: The full covariance structure was used.

c) Naïve Bayes: The predictor conditional distribution is selected to be kernel, and the smoother density type of the kernel distribution is Gaussian.

d) SVM: The kernel function used to compute the elements of the Gram matrix is Gaussian. The kernel scale parameter was set to 7.3 when training on the original set, and 1.8 when training on the over-sampled set.

e) k-NN: The distance metric was Euclidean. The number of neighbors was chosen to be 10 when training on the original set, and 1 when training on the over-sampled set.

f) Ensemble – Bagged: The ensemble aggregation method was specified as Bag, and the learner type was Decision Tree. The number of learners was set to 30.

g) Ensemble – Subspace k-NN: The ensemble aggregation method was specified as Subspace, and the learner type was k-NN. The number of learners was set to 30. The subspace dimension was set to 27 when training on the 53 features in the original and the over-sampled sets, and 3 when training on the 6 PCA features obtained from transforming the original and the over-sampled sets.

h) Feedforward Neural Network: Levenberg-Marquardt backpropagation algorithm was selected as the training algorithm, and Mean Square Error (MSE) was the loss function. The network consisted of one hidden layer with 30 neurons when training on the original set, and two hidden layers with 100 and 30 neurons in the first and the second hidden layer respectively when training on the over-sampled set. The optimal number of hidden units for each layer was determined in the simulation trials. The activation function was set as a hyperbolic tangent sigmoid in the hidden layers and softmax in the output layer.

V. Results and Discussion

The confusion matrix was used for the evaluation of the performance of eight ML models on the test dataset. As previously mentioned, the ML classifier set consisted of Decision Tree, Linear Discriminant, Naïve Bayes, SVM, k-NN, two types of Ensemble classifiers (Bagged Trees and Subspace k-NN) and feedforward NN.

The results obtained for each of these ML were used to compare the best performance based on accuracy, generalization and feature set.

Table I shows the performance for training and testing the classifiers on the four feature sets. For the original feature set, the accuracy varied in the range of 55.0%-73.6%, with the majority of the ML classifiers performing around the 70% mark. Fig. 1 illustrates the confusion matrix of the classifier with the highest accuracy, i.e., the feedforward neural network in this case. It can be clearly seen that the classifier was unable to learn most pattern vectors from class 3, which were incorrectly classified as belonging to classes 2 and 3. Moreover, 80.2% of the patterns of class 2 were incorrectly classified as belonging to class 1. Finally, the vast majority (96.8%) of patterns belonging to class 1, which is the majority class, were correctly classified, thus biasing the evaluation of the overall performance of the classifier set.

The next round of simulation studies considered the effect of compressing the representation of information in the feature set through the application of PCA. The original 53-dimensional feature set was compressed to six dimensions, corresponding to the six transformed features with the highest eigenvalues, which accounted for over 99.99% of the information in the original feature set. This resulted in a reduction in the performance of the classifier set, as shown in Table I. The accuracy varied in the range of 66.6%-70.6%, with the top performer being SVM classifier and feedforward neural network.

The previous two rounds of experiments highlighted that classifier performance is heavily affected by class imbalance, which is clear in the low values of precision and recall of the ML classifiers. Thus, SMOTE was applied on the feature vectors of the original dataset to reduce the effect of class imbalance and subsequently, classifier bias. The performance of the classifiers for this more balanced dataset is presented in Table I. There is a marked improvement in performance for five of ML classifiers, however, performance degraded for the remaining classifiers. The accuracy varied in the range of 49.6%-88.3%, i.e., there is approximately 15% improvement in the accuracy of the top performing classifier, which in this case is SVM. Fig. 2 illustrates the confusion matrix of the classifier with the best performance, i.e., SVM. It is evident from the figure that the vast majority of patterns belonging to classes 1 and 3 are correctly classified, and 76.3% of the inputs associated with class 2 are correctly detected.

The final set of experiments aims to evaluate the combined effect of using PCA for dimensionality reduction, whilst applying SMOTE to partially address class imbalance. The performance of the classifiers on this set is shown in Table I. There is a clear decrease in the average classification performance compared to the use of SMOTE on the original feature space, with accuracy varying in the range of 42.8%-75.9%.

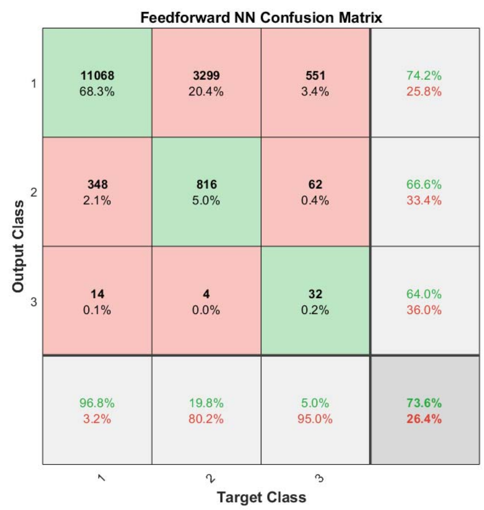

Fig. 1. Confusion matrix of feedforward neural network classifier on the original feature set.

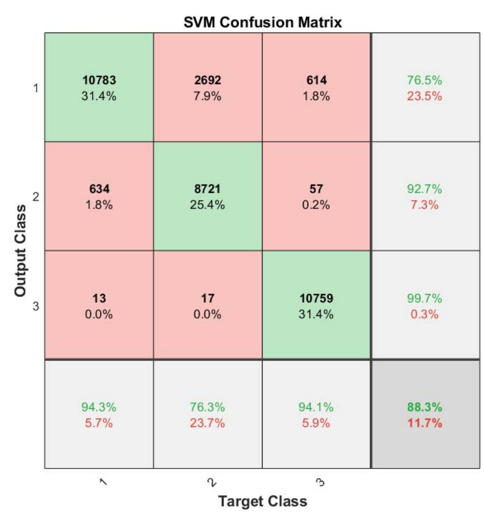

Fig. 2. Confusion matrix of SVM classifier on the over-sampled feature set.

TABLE I. PERFORMANCE COMPARISON ON THE FOUR FEATURE SETS

Classifier	Original				Original + PCA				SMOTE				SMOTE + PCA			
	Acc	*Prec*	*Rec*	*F1*	*Acc*	*Prec*	*Rec*	*F1*	*Acc*	*Prec*	*Rec*	*F1*	*Acc*	*Prec*	*Rec*	*F1*
Decision Tree	71.2	41.3	37.0	39.0	70.5	57.0	33.8	42.4	59.2	58.9	59.2	59.0	49.6	49.5	49.6	49.5
Linear Discriminant	71.0	50.4	34.9	41.2	70.5	47.5	33.4	39.2	49.6	49.3	49.6	49.4	42.8	43.0	42.8	42.9
Naïve Bayes	55.0	38.8	39.7	39.2	67.3	39.5	35.9	37.6	49.6	50.5	49.6	50.0	45.2	44.9	45.2	45.0
SVM	72.0	85.4	35.5	50.2	70.6	90.2	33.4	48.7	88.3	89.6	88.3	88.9	51.5	51.9	51.5	51.7
k-NN	69.7	60.9	37.0	46.0	68.7	51.4	35.2	41.8	80.9	83.1	80.9	82.0	70.3	70.2	70.7	70.4
Ensemble (Bagged Trees)	72.2	77.7	37.7	50.8	68.3	40.9	35.4	38.0	85.0	84.8	85.0	84.9	75.9	75.6	75.9	75.7
Ensemble (Subspace k-NN)	68.8	42.7	36.2	39.2	66.6	38.7	35.3	36.9	83.3	83.7	83.3	83.5	71.0	70.7	71.0	70.8
Feedforward NN	73.6	68.3	40.5	50.8	70.6	N/A	33.4	N/A	85.6	85.5	85.6	85.5	50.2	49.9	50.2	50.0

VI. CONCLUSION

In this paper, a number of experiments were performed to photometric data of space objects to classify them into three categories, i.e., satellite, rocket body and debris. Firstly, fifty-three features were extracted from the light curves using the *feets* library. Then, the SMOTE technique was applied to account for class imbalance. Also, feature space dimensionality was reduced by performing PCA. Finally, eight ML classifiers were utilized to classify the data. The benefits of using SMOTE and PCA were examined by comparing the classification accuracy with and without their application. Data balancing by SMOTE has improved the overall classification performance. On the other hand, despite making the resulting models more compact by reducing the feature space to six features, implementing PCA resulted in reduced performance.

As future work, we will investigate the use of pre-processing techniques on the raw data light curves. In addition, features from light curves can be extracted using different approaches. Moreover, Convolutional Neural Networks (CNNs) [22] can be used to classify the data. However, most existing CNNs are applied on 2D data, whereas light curves are 1D time series. Therefore, light curve signals need to be suitably manipulated before processing via CNNs.

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