Notable Object Detection from TLE Based on Deep Metric Learning

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ABSTRACT

Recently, there has been increased emphasis on satellites used for aspect of both our life and security. NEC operates remote sensing satellite ASNARO2, which was developed and operated in-house. On the other hand, an increase in the number of space objects (e.g. satellite constellation or debris), anti-satellite weapon (ASAT), the satellites with the purpose of rendezvous proximity operations (RPO), and such objects have led to the increasing risk of a collision and an attack when outer space is utilized. There are a considerable number of several conjunctions in operational satellites; dozen conjunctions which is received from Combined Space Operations Center (CSpOC) as a Conjunction Data Messages (CDM) have occurred in ASNARO2 over a year. The recognition of such objects is essential in dealing with a risk in terms of security and business continuity, therefore it is necessary to identify such objects from a large amount of space objects as soon as possible. Currently, NEC has managed orbits of space objects using SSA Software Suite (SSS) system developed by COMSPOC Corporation, which is based on observation data of some optical telescopes and radars. However, due to the lack of sensor and human resources associated with increased space objects, it is difficult to monitor a large amount of them. Therefore new tools and frameworks are needed to solve these operational problems to improve the capability of Space Situational Awareness (SSA) and Space Domain Awareness (SDA).

This study set out to asset the notable objects detection, which is the dynamic object differs from its normal orbit for some reason, such as a malfunction or collision, based on publicly available two line element (TLE) of Geostationary Orbit (GEO) objects, which is published in SpaceTrack.org. This study tested whether it could identify the difference between normal and notable objects from TLE. To date, there has been no detailed investigation of that feasibility. For this assessment, this study leverage the model NEC developed, which model obtains embedding of similarity between data points considering temporal information. This model is composed of the combination of time series and metric learning using Deep Neural Network (DNN). Metric Learning has been successfully used in various field, including object identification, natural language processing, speech recognition and medical diagnosis. Metric Learning learns data similarity on a distance basis and can perform similarity discriminations on unknown data. Furthermore, metric learning has achieved remarkable results in recent years when combined with DNN. This model learns mapping from TLEs to embedding in feature space, where similar TLEs are located nearby and dissimilar ones is far away, based on the unsupervised manner. To create the notable objects detection model in unsupervised manner, the model is trained on normal object TLEs that has been confirmed by expert and labeled using pseudo-labeling based on a distance. In experiments, by comparing pairwise distances between TLEs embedding of normal and notable objects, the model succeeded in detecting differences between normal and notable objects from TLEs. While this study confirms few GEO objects, it did partially substantiate the effectiveness of the model NEC developed and the feasibility of the notable objects detection based on TLE. These findings could be used to help SSA/SDA operation. Further research could also be conducted to determine the effectiveness and feasibility of Low Earth Orbit (LEO) objects.

1. INTRODUCTION

Recently, there has been increased emphasis on satellites used for aspect of both our life and security. NEC operates remote sensing satellite ASNARO2, which was developed and operated in-house. On the other hand, the number of space objects is increasing every year. Fig.1 shows the number of monthly space objects in Earth's orbit by type [13], indicating that the number of space objects have continued to increase each year since the launch of sputnik 1 in 1957. An increase in the number of space objects (e.g. satellite constellation or debris), anti-satellite weapon (ASAT), the satellites with the purpose of rendezvous proximity operations (RPO), and such objects have led to the increasing risk of a collision and an attack when outer space is utilized. There are a considerable number of several conjunctions in operational satellites; dozen conjunctions which is received from Combined Space Operations Center (CSpOC) as a Conjunction Data Messages (CDM) have occurred in ASNARO2 over a year. The recognition of such objects is essential in dealing with a risk in terms of security and business continuity, therefore it is necessary to identify such objects from a large amount of space objects as soon as possible. Currently, NEC has managed orbits of space objects using SSA Software Suite (SSS) system developed by COMSPOC Corporation, which is based on observation data of some optical telescopes and radars. However, due to the lack of sensor and human resources associated with increased space objects, it is difficult to monitor a large amount of them. Therefore new tools and frameworks are needed to solve these operational problems to improve the capability of Space Situational Awareness (SSA) and Space Domain Awareness (SDA).

To address these issues, this paper examines the feasibility of the notable object, which is the dynamic object differs from its normal orbit for some reason, such as a malfunction or collision, detection based on publicly available two line element (TLE) of Geostationary Orbit (GEO) objects with Deep Metric Learning for multivariate time series retrieval. As a preprocessing step before input to the model with Metric Learning, we employ Savitzky-Golay filtering [8] to smooth the multivariate time series data. Metric Learning has been successfully used in various fields, including object identification, natural language processing, speech recognition, and medical diagnosis. Metric Learning aims to acquire the representation of data similarity on a distance basis and can perform similarity discriminations on unknown data. Furthermore, when combined with deep learning, metric learning has achieved remarkable results in recent years. In doing Deep Metric Learning, we employ triplet loss [10], the most popular loss function in deep metric learning. Given a raw multivariate time series segment, our model performs pseudo-labeling based on a distance of time series segment to create a dataset for triplet loss, encodes temporal dynamics using Long Short-Term Memory (LSTM) [11, 12], and uses triplet loss to feature segments of raw time series learning to embed on the feature space. In this way, the temporal dynamics in the raw time series segment are learned, and the feature space embedding can be obtained. The distance of the embedding on the feature space is then computed to measure the anomaly score of segments. Based on that measurement, the anomaly of a satellite is determined. Our model is the first unsupervised learning-based approach for early anomaly detection that can acquire temporal dynamics in the raw light curve and embedding on the feature space. To demonstrate the effectiveness of our model, we used a dataset of two line element (TLE) of normal and notable object. A notable object is the dynamic objects that behave differently from their normal behavior defined by us.

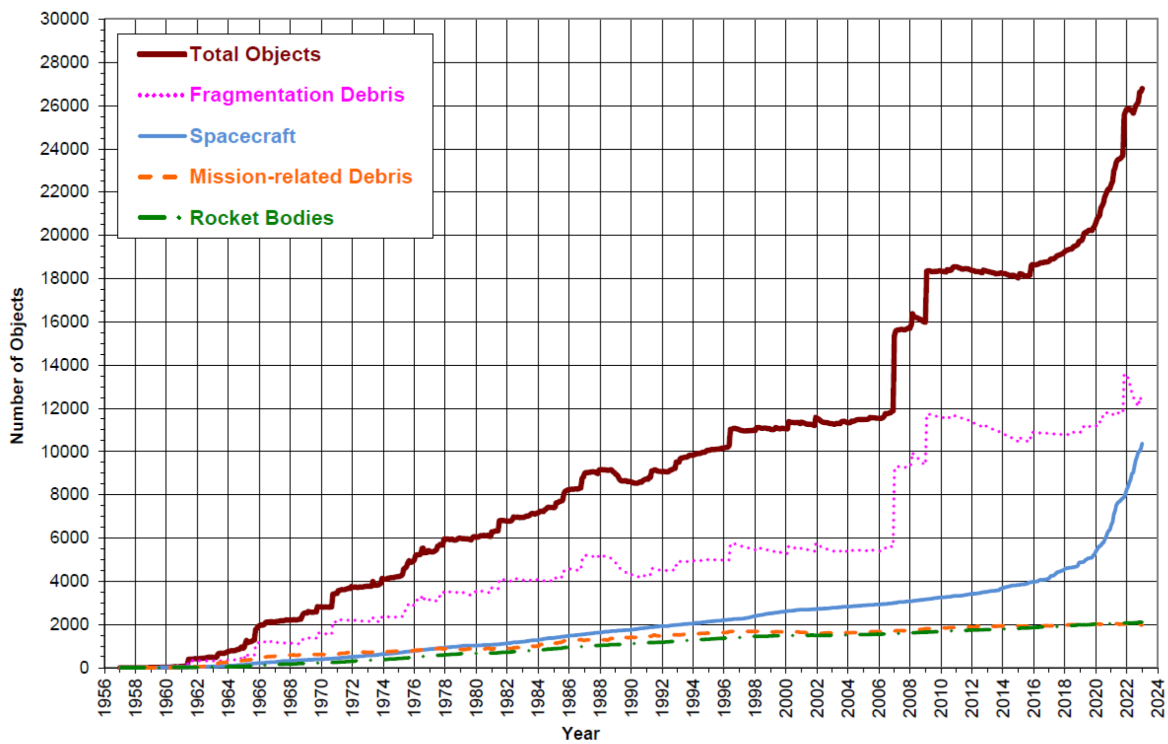

Fig.1: The number of monthly space objects in Earth's orbit by type [13]
Cowardin, Heather Mae. "Orbital Debris Quarterly News." *Orbital Debris Quarterly News* 27.1 (2023) p.12

2. RELATED WORK

This research area has not been well studied to date, and very little prior research has been done. There is much research on doing maneuver detection [2, 3] and Rendezvous Proximity Operation (RPO) [4, 5, 6, 7] for a satellite orbit analysis as a close study, maneuver detection has many techniques for analyzing or determining change of orbit, while RPO has many techniques for estimating pose of non-cooperative satellite from images and predicting the intent of Rendezvous, but they differ from our purpose. Our objective is to determine notable object from publicly available TLE. So far, we have yet to find any literature on which this has been studied.

3. DEEP METRIC LEARNING FOR NOTABLE OBJECT DETECTION

In this section, we explain our model based on deep metric learning in an unsupervised manner. Our model is influenced by the model proposed by Dongjin Song et al., (2019) [1], which paper has proposed a model that applies Metric Deep Learning to a multi-variate time series. We state the research objectives and then describe the architectural details of our model. Specifically, we explain how to acquire segment embedding using LSTM, and learn similarity based on metric learning using the features acquired by Savitzky-Golay filtering, LSTM, the triplet loss function, conduct Pseudo-Labeling to segment data, and calculate an anomaly score.

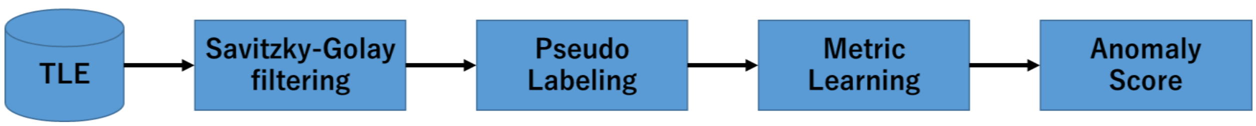

Fig. 2: Overall flow of notable object detection

3.1 Problem Statement

In this chapter, some of the key concepts are presented. The descriptions here are written concerning multivariate time series but also include the case of univariate time-series. We denote a set of a multi-variate time series, k-th segment and n input series a time t as $S = \{\boldsymbol{s}^p\}_{p=1}^N$, $\boldsymbol{s}^k = (\boldsymbol{x}_{k_1}, \boldsymbol{x}_{k_2}, \boldsymbol{x}_{k_e}, \cdots, \boldsymbol{x}_{k_T}) \in R^{n \times T}$ and $\mathbf{x}_{\mathrm{t}} = (x_t^1, \mathrm{x}_{\mathrm{t}}^2, \cdots, x_t^n) \in R^n$, where T is the length of window size, and N denotes the number of segments. Note that the interval in T do not have to be equally spaced. Given a multivariate time series segment $\boldsymbol{s}^q \in R^{n \times T}$, we aim to obtain the anomaly score of $\boldsymbol{s}^q$ as follows;

$$a^q = \sum_{m=1}^{k} \mathrm{TopK}\big(D(\boldsymbol{s}^p, \boldsymbol{s}^q)\big)_m,$$

where p denotes the index for p-th segment ($\forall p \in [1, N]$), $D(\cdot)$ represents a distance measure function, and $TopK(\cdot)$ represents the set of k elements extracted in descending order from some distance function.

3.2 Preprocessing

There are two pre-processing steps: one is notable and normal objects definition and the other is the application of Savitzky-Golay filtering. First, we performed normal and notable objects definition by expert. Then, In order to minimize the noise in the acquired TLE data, the Savitzky-Golay filtering [8] technique was employed. This method smooths the data by fitting a low-degree polynomial function to a moving window of data points, thus preserving the essential shape and patterns within the TLE dataset. The targets to be filtered are Mean Motion and Mean Motion Dot; it has been found by exploring the data that these features show the most prominent states of a space object. Therefore, Mean Motion and Mean Motion Dot are filtered, and then the data are smoothed to provide input to the model.

3.3 Metric Learning

This chapter details the approach using LSTM and Triplet Loss as models for Metric Learning and clarifies its overall structure. Metric Learning is the task of effectively evaluating the similarities and differences between data points by learning distance measures. This chapter proposes a model structure designed to function as a segment feature extractor using LSTM neural network. A Triplet Loss function is also introduced to optimize similarity during the learning process.

3.3.1 Raw Segment Representation

LSTM is a type of RNN (Recurrent Neural Network) often used in deep learning, especially for time series data and natural language processing tasks. LSTMs have three main components: input gates, forget gates, and output gates. These gates allow LSTM to capture both short-term and long-term dependencies. Specifically, the LSTM architecture is as follows.

$$\boldsymbol{f_t} = \sigma\left(\boldsymbol{W}_f[\boldsymbol{h}_{t-1}; \boldsymbol{x_t}] + \boldsymbol{b}_f\right), \tag{1}$$

$$\boldsymbol{i_t} = \sigma(\boldsymbol{W_i}[\boldsymbol{h}_{t-1}; \boldsymbol{x}_t] + \boldsymbol{b}_i), \tag{2}$$

$$\mathbf{o_t} = \sigma(\boldsymbol{W}_o[\boldsymbol{h}_{t-1}; \boldsymbol{x}_t] + \boldsymbol{b}_o), \tag{3}$$

$$\mathbf{c_t} = \boldsymbol{f_t} \cdot \boldsymbol{c}_{t-1} + \boldsymbol{i}_t \cdot \tanh(\boldsymbol{W}_c[\boldsymbol{h}_{t-1}; \boldsymbol{x}_t] + \boldsymbol{b}_c), \tag{4}$$

$$\mathbf{h_t} = \boldsymbol{o}_t \cdot \tanh(\boldsymbol{c}_t), \tag{5}$$

where $[\boldsymbol{h}_{t-1}: \boldsymbol{x}_t] \in R^{m+n}$ is a concatenation of the previous hidden state and the input at time t. $\boldsymbol{W}_f, \boldsymbol{W}_i, \boldsymbol{W_o}, \boldsymbol{W_c} \in R^{m\times(m+n)}$ and $\boldsymbol{b}_f, \boldsymbol{b}_i, \boldsymbol{b}_o, \boldsymbol{b}_c \in R^m$are learnable parameters. In the present model, a segment is used as input, and time-series-aware mapping is learned from segment to the feature space. Then, the LSTM's final output $\mathbf{h}_{\mathrm{t}}$, containing the information of all segments, is employed. These LSTM final outputs are fed into the linear layer as follows

$$\boldsymbol{s}_t = \boldsymbol{W}_s^T \boldsymbol{h_t} + \boldsymbol{b}, \tag{6}$$

The final output $\mathbf{s}_{\mathrm{t}}$ is adopted as the representation of a segment because $\mathbf{s}_{\mathrm{t}}$ considered to be an embedding of a segment that takes time information into account.

3.3.2 Triplet Loss

Triplet Loss is a loss function designed to optimize the distance function in learning feature representations. Used primarily in tasks such as face recognition, image retrieval, and clustering, Triplet Loss aims to minimize the distance between data points within the same class and maximize the distance between data points between different classes. This constructs a feature space where similar data points are placed close together, and different data points are placed farther apart. Triplet Loss is trained using pairs (triplets) of three data points. Each triplet contains the following three elements: Anchor: The data point on which the triplet is based; positive: A data point belonging to the anchor's class; negative: A data point that belongs to a different class from the anchor. Our model takes a segment as input and trains it to minimize Triplet Loss. The model learns to map similar segments closer together and dissimilar segments farther apart in feature space. We use the triplet form, representing the relative similarity of segments. (e.g., in the case of class classification, $\mathbf{s}_{\mathrm{a}}$ and $\mathbf{s}_{\mathrm{p}}$ belong to the same class, and $\mathbf{s}_{\mathrm{a}}$ and $\mathbf{s}_{\mathrm{n}}$ belong to different classes.).The Triplet Loss is described as follows:

$$L_{triplet} = \max\left(0, \left\|\boldsymbol{s}_a - \boldsymbol{s}_p\right\|_1 - \|\boldsymbol{s}_a - \boldsymbol{s}_n\|_1 + m\right), \tag{7}$$

where $\|\cdot\|_1$ is used for the representation of l_1 norm, and m is the margin. By using the above Triplet Loss, the model can map similarities closer and dissimilarities farther into the feature space in the embedding of a segment, taking time information into account.

3.4 Pseudo-Labeling

Pseudo-labeling is generally a type of semi-supervised learning. In this method, some data are unlabeled, and a supervised model is used for labeling. Pseudo-labeling aims to improve learning accuracy even when label information is limited. The pseudo-labeling we use this time is a fully unsupervised learning method applicable when not all data are labeled. Our model used pseudo-labeling based on Euclid distance, designed to learn the normal state from segments. Given two normal time series segments$\boldsymbol{s} = (\boldsymbol{x}_1, \boldsymbol{x}_2 \cdots, \boldsymbol{x}_T), \boldsymbol{s}' = (\boldsymbol{x}'_1, \boldsymbol{x}'_2, \cdots, \boldsymbol{x}'_T)$,their Euclid distance can be calculated with:

$$d(\boldsymbol{s},\boldsymbol{s}') = \sum_{t=1}^{T} \|\boldsymbol{x}_t - \boldsymbol{x}'_t\|, \boldsymbol{s},\boldsymbol{s}' \in S, \boldsymbol{s} \neq \boldsymbol{s}', \tag{8}$$

where $S = \{\boldsymbol{s}_i\}_{i=1}^{N}$ is a set of segments. We obtain the distance vector between an i-th segment and all the remaining segments by performing the above calculations. To use the advantage of the supervised method, we assign labels to the data based on the distance vectors we have just obtained. This is used to create a data set in triplet form of anchor, positive, and negative when using Triplet Loss. The distance vector of $\boldsymbol{s}^i$ is in descending order, with the kth element from the top being positive and the remaining elements being negative. Here, we denote k as the number of nearest neighbors we will extract as positive segments. Let S_{pos}^{i} denote the set of the extracted top k segments for an i-th segment, and the remaining segments S/S_{pos}^{i} are treated as negative segments. This process is performed over all segments to create a dataset of the triplet form. Using the created dataset, our model can be trained in unsupervised manner. Note that our model leverages triplet form dataset in only a training phase.

3.5 Anomaly Score

Anomaly score is a measure that quantifies the degree to which a data point is anomalous and is usually associated with a data point. The relatively higher the value, the more abnormal the data point is considered; conversely, the lower the value, the more normal the data point is considered. There are several methods for calculating an anomaly score, but the one we will use in this study is the distance-based method. This approach calculates the anomaly score by the distance between data points. Distance-based anomaly detection algorithms are well-suited for online learning. This means that the distance is easily computed as new data points are added. This allows for real-time anomaly detection in dynamic environments. Given the segment representation of a segment, the calculation of the anomaly score of an i-th segment is as follows:

$$a_i = \sum_{m=1}^{k} \underset{j}{\mathrm{TopK}}\left(\left\|\boldsymbol{s}_i - \boldsymbol{s}_j\right\|_1\right)_m, i \neq j, \forall j \in [1,n], \tag{9}$$

where n denotes the number of segments. Using the segment representation, we can calculate an anomaly score considering temporal information.

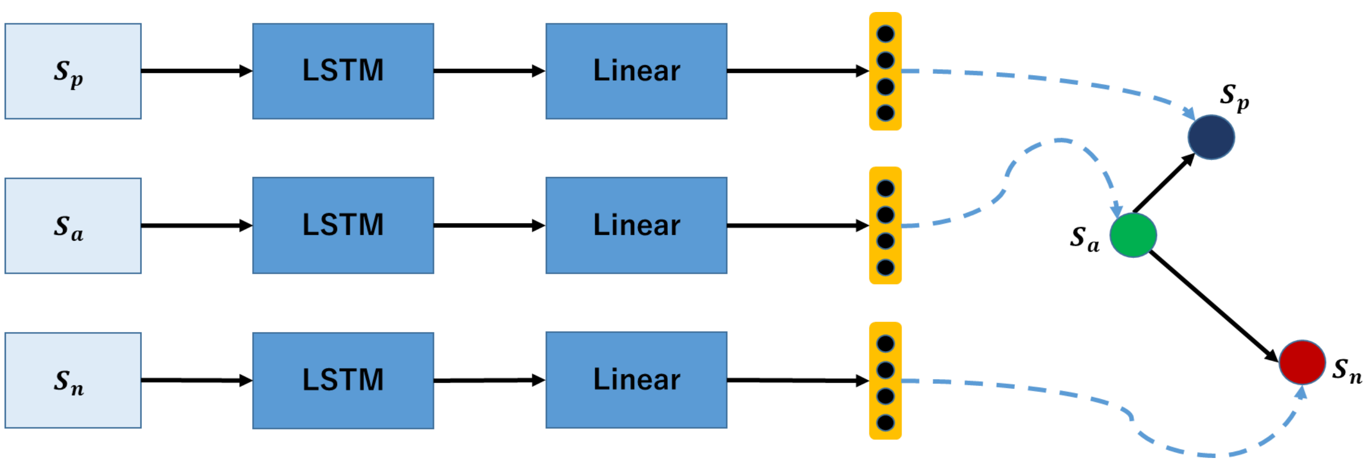

Fig. 3: Metric Deep Learning based on LSTM and triplet loss architecture.

4. EXPERIMENT

4.1 Dataset

The datasets used in this validation are several notable objects and the normal objects of TLE selected by expert. The TLE is downloaded from Space Track [9]. The TLEs of several normal objects are combined and used as one data set. This dataset is used only for training and not for inference. The TLEs of notable objects are also used only for inference. As mentioned in Section 3.2, the features used in the TLE are Mean Motion and Mean Motion Dot. Other features are not used in training and validation. The reason for using only Mean Motion and Mean Motion Dot as features is that

Mean Motion and Mean Motion Dot are well differentiated from normal and notable objects in our exploration. The target of this verification is a normal object and a notable object B, C and D as defined by expert.

4.2 Parameter Setting

Our model has 5 hyper-parameters. We experimented with the hidden size of LSTM, the size of segment embedding, and window size of a segment set to 64. For the margin in triplet loss, we set it to 1. We set the number of nearest neighbors to 1000, which means the number of positive segments at each segment. Our model is trained on a server with NVIDIA GTX 2080 graphics cards.

4.3 Evaluation

In this experiment, we trained our model on the space objects, which we defined as normal. Comparing the anomaly score of the space objects defined as normal with the anomaly score of the other space objects, which are notable objects, and the anomaly score of notable objects was higher than the normal objects. Figure 3 shows the anomaly score of normal objects and notable objects. This plot shows that the anomaly score defined as a notable object has anomaly score is higher compared to the object defined as a normal object. This suggests that the model can identify the different states of notable objects and normal objects. This result indicates that our model can capture the difference between a normal and notable object. Once trained, our model can produce an anomaly score in real time, suggesting that real-time notable object detection is possible.

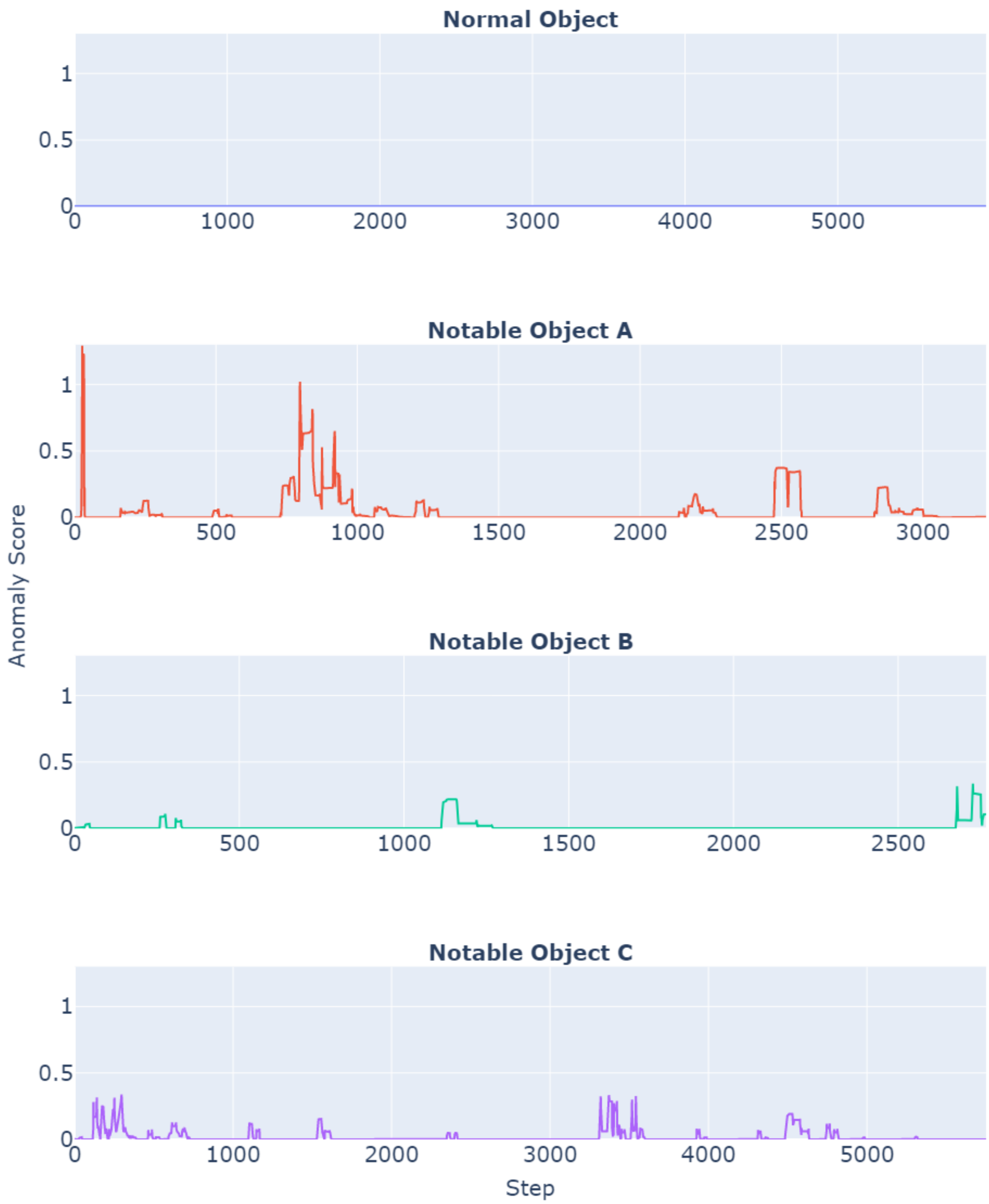

Fig. 4: The anomaly score of the normal object (top) and notable objects (2nd to 4th) are shown. The anomaly score of the normal object is very small compared to the other notable objects. This suggests that the model is able to discriminate between notable and normal objects.

5. CONCLUSIONS

We tested the feasibility of notable object detection with a model using Deep Metric Learning. First, we defined normal and notable objects and trained our model using only the TLE of the normal object. By doing so, our model can learn the behavior of normal objects. Next, we output the anomaly score of normal, and notable objects with the model learned on the normal object. This output is based on the Euclidian Distance in the feature space. Our model showed different anomaly score for normal and notable objects: the anomaly of normal objects was much lower than that of notable objects, about 1/100 of the peak value. This suggests that our model can discriminate between normal and notable objects. It also suggests that anomaly score is capable of real-time operation since it can be output in real-time. Feature plan include validation for more objects, and since this validation was only for GEO objects, we plan to extend the validation scope to Low Earth Orbit (LEO) objects.

6. REFERENCES

[1] Dongjin Song, Ning Xia, Wei Cheng, Haifeng Chen, Dacheng Tao (2018). Deep r-th Root of Rank Supervised Joint Binary Embedding for Multivariate Time Series Retrieval. KDD 2018.

[2] Roberts, Thomas G., and Richard Linares. "Geosynchronous satellite maneuver classification via supervised machine learning." Advanced Maui Optical and Space Surveillance Technologies Conference. Maui, Hawaii. 2021.

[3] Robertsa, Thomas G., and Richard Linaresa. "Satellite repositioning maneuver detection in geosynchronous orbit using two–line element (TLE) data." 71st International Astronautical Congress (IAC). 2020.

[4] Gaias, Gabriella, and Jean-Sébastien Ardaens. "Flight demonstration of autonomous noncooperative rendezvous in low earth orbit." Journal of Guidance, Control, and Dynamics 41.6 (2018): 1337-1354.

[5] He, Ying, et al. "Non-cooperative spacecraft pose tracking based on point cloud feature." Acta Astronautica 139 (2017): 213-221.

[6] Sharma, Sumant, Connor Beierle, and Simone D'Amico. "Pose estimation for non-cooperative spacecraft rendezvous using convolutional neural networks." 2018 IEEE Aerospace Conference. IEEE, 2018.

[7] Kelecy, Thomas, et al. "Predicted Intent Inferred from Real-time Rendezvous and Proximity Behavior." (2022).

[8] Savitzky, Abraham, and Marcel JE Golay. "Smoothing and differentiation of data by simplified least squares procedures." Analytical chemistry 36.8 (1964): 1627-1639.

[9] Spacetrack, [Online]. Available: https://space-track.org/documentation

[10] Schroff, Florian, Dmitry Kalenichenko, and James Philbin. "Facenet: A unified embedding for face recognition and clustering." Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.

[11] Cho, Kyunghyun, et al. "Learning phrase representations using RNN encoder-decoder for statistical machine translation." arXiv preprint arXiv:1406.1078 (2014).

[12] Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." Neural computation 9.8 (1997): 1735-1780.

[13] Cowardin, Heather Mae. "Orbital Debris Quarterly News." Orbital Debris Quarterly News 27.1 (2023).