Bayesian Learning for Spacecraft Collision Risk Analysis

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Abstract- As the threat of space debris grows larger, it is becoming increasingly important to develop methods to conduct spacecraft collision risk analysis, and subsequently automate spacecraft collision avoidance. To contribute towards this goal, I explored and tried to identify the most ideal method to conduct spacecraft risk analysis. In this paper, I present the result of this research, and showcase the importance of utilising Bayesian Machine Learning. A machine learning model using Bayesian Machine Learning has been trained and tested, and the results displayed.

Index Terms - Collision avoidance, space exploration, space debris, probabilistic programming, machine learning, spacecraft collision avoidance

I. Introduction

One of the biggest space challenges of the 21st century is how to tackle space debris. According to NASA, more than 27,000 pieces of orbital debris, or "space junk," are tracked by the Department of Defense's global Space Surveillance Network (SSN) sensors [1]. Much more debris -- too small to be tracked, but large enough to threaten human spaceflight and robotic missions -- exists in the near-Earth space environment. Since both the debris and spacecraft are traveling at extremely high speeds (approximately 15,700 mph in low Earth orbit), an impact of even a tiny piece of orbital debris with a spacecraft could create big problems, as shown in Figure 1 [2].

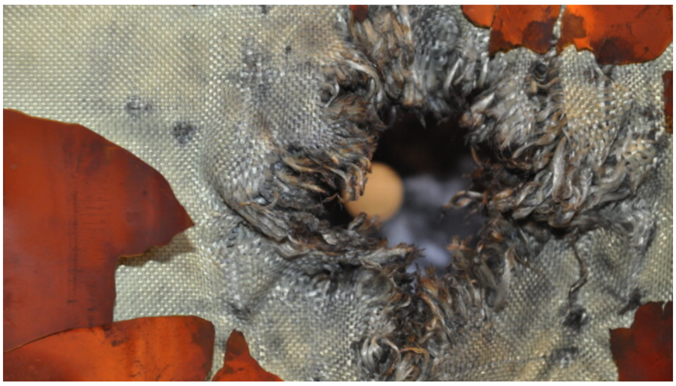

Figure 1. Damage caused by firing a 7.5-millimeter-diameter at 7 km/s into a bulletproof-vest-type fabric [2].

The anti-satellite missile test conducted on Fengyun-1C in 2007 and the collision of Iridium 33 and

Kosmos-2251 in 2009 have led to constant increase of Micrometeoroids and Orbital Debris(MMOD) in the Low Earth Orbit [3].

Figure 2. Representation of space debris with a radius greater than 1mm around Earth [4].

In 1978, the NASA scientist Donald J. Kessler proposed that a chain reaction of exploding space debris can end up making space activities and the use of satellites impossible for generations, a phenomenon we know of today as the Kessler Syndrome. Kessler Syndrome is a scenario in which when the density of space debris in Low Earth Orbit (LEO) is high enough, collisions between objects could cause a cascade in which each collision generates space debris that increases the likelihood of further collisions. Thus, the count of MMOD in LEO is expected to rise exponentially in the coming years. [5]

Therefore, it becomes extremely important to develop fully-automated satellite collision avoidance systems.

II. Current Approaches

Collision Avoidance at ESA

The ESA uses Conjunction Data Messages(CDM) distributed by the US-based Combined Space Operations Center(CSpOC) to convey information about any monitored space object, the 'primary' satellite, and the 'conjuncting' satellite. After one CDM is received, regular CDM's are received, for the next few days. [6]

The collision risk is evaluated by COllision Risk COmputation Software(CORCOS), which is a tool offered by Collision Risk Assessment and Avoidance Manoeuvre(CORAM) [3].

The collision risk threshold for any given event is mission specific (these usually fall between 10^{-5} and 10^{-4}) [3,6]. This collision risk threshold is derived by a tool called Assessment of Risk Event Statistics(ARES) [3]. If the predicted risk is close to or greater than the collision risk threshold, collision avoidance maneuvers will be conducted.

Collision avoidance at NASA

For collision avoidance, NASA uses a program called Collision Assessment and Risk Analysis(CARA). CARA is an Agency-level program required for all NASA operational assets by NPR 8715.6 [7]. The CARA Operations Team monitors and assesses potential collision threats and advises the mission team on potential avoidance maneuvers. CARA is a three-step process.

The first step consists of predictions of close approaches by assessing the trajectory of the primary spacecraft against the high Accuracy Catalog, which is a catalog of in-orbit objects maintained by the Space Surveillance Network(SSN) [7, 8]. This screening occurs twice, using different methods. The first screening is conducted by the mission owner/operator(this includes any planned maneuvers in it's calculations). The second screening is conducted based on tracking data from the SSN(this does not include any planned maneuvers in its calculations). Results of both screening runs are transferred to CARA 3x/day for LEO(Low Earth Orbit) spacecraft and 2x/day for all others [7].

The second step involves processing the data and sending updated trending information to the mission customer. The CARA team then manually analyzes any conjunctions that they consider to be high risk to determine appropriate actions to be taken [7].

Step three is Collision Avoidance, in which CARA works with the mission to assist with planning and execution of any risk mitigation strategies.

III. Related Work

Spacecraft Collision Avoidance Challenge

In October 2019, the ESA released a database of Conjunction Data Messages(CDMs) to the public as part of a challenge known as the Spacecraft Collision Avoidance Challenge. The challenge required teams to create a machine learning model which classified events as high-risk or low-risk, and predicted the risk value for any high-risk events. The teams were asked to predict future risk values, given the past CDM's in the event,

The final score for the challenge takes into account the F score for the classification, as well as the average of the sum of squared errors for high-risk problems. As a baseline, the ESA used the Latest Risk Prediction(LRP) Baseline, which put forward the last provided risk in the event as the final risk. Scores were given to every team, based on the following formula:

$$L(\hat{r}) = \frac{1}{F_2}\mathrm{MSE}_{\mathrm{HR}}(r, \hat{r}), \qquad (1)$$

where F2 is the F score given to the classification of events, and MSEHR is the average of the sum of squared errors. MSEHR is represented as:

$$\mathrm{MSE}_{\mathrm{HR}}(r, \hat{r}) = \frac{1}{N^*}\sum_{i=1}^{N} \mathbb{1}_i (r_i - \hat{r}_i)^2, \qquad (2)$$

where N is the total number of events, N* is the number of high-risk events, ri is the final risk, r̂i is the prediction and (3)

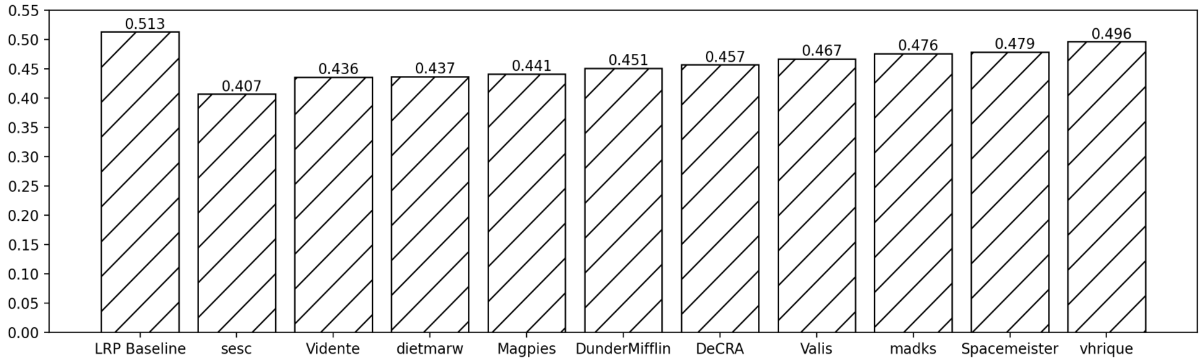

Figure 3. Bar graph showcasing the MSE_{HR} scores for the top 10 teams in the competition, as well as the LRP Baseline. Adapted from [4]

MSEHR is designed to only run through high-risk events. This metric judges the accuracy of the predicted risk, which determines whether an avoidance maneuver should be conducted.

The F score is represented as:

$$F_\beta = (1+\beta^2)\frac{p \times q}{(\beta^2 \times p) + q},$$

where p and q represent the precision and recall respectively, and β acts as a trade off between precision and recall. The ESA has set β as 2. Such an arrangement places greater importance on the recall score, penalizing false negatives. In Figure 4, we can see the lowest number of false negatives achieved was 12 in a test set of 2167. However, if artificial intelligence is to guide future space collision avoidance, this number will have to be reduced even further.

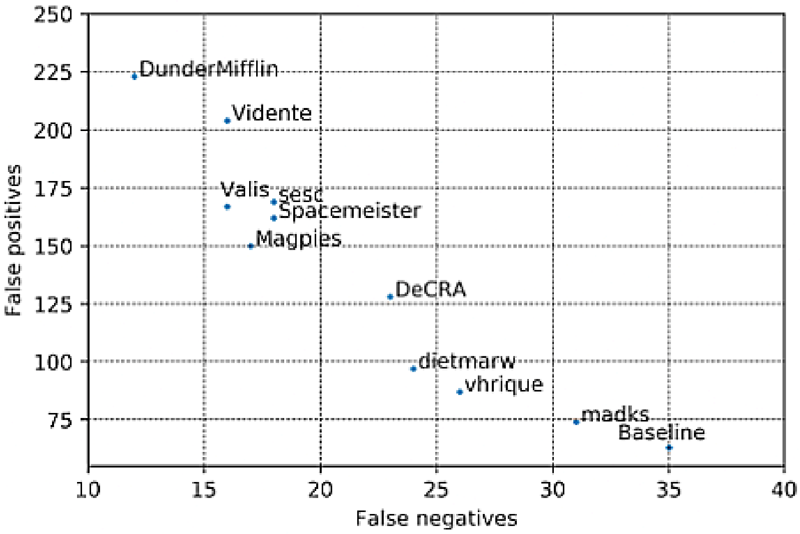

Figure 4. Scatterplot showcasing the false negatives and false positives achieved by the top teams(and the LRP Baseline) [4].

IV. Bayesian Machine Learning

Theory

A Bayesian approach for machine learning produces outputs in the form of probability distributions.

It takes in probabilities as 'priors', and then uses the observed data to create a 'posterior' probabilistic output.

A Bayesian model acts as an uncertainty measure for neural networks, to prevent overfitting and overconfidence in false answers[8].

Creation of the model

In the following test, Bayesian machine learning has been used on the dataset supplied by Kelvins for the Spacecraft Collision Avoidance Challenge[1]. The model trained is a Long-Term Short Memory(LSTM) model. This allows the model to apply time-series forecasting.

Monte Carlo dropout has been applied to this model. MC dropout serves as a way to prevent overfitting and an approximate inference for the model.[9, 10]. This makes it possible to trade off computational time, while still retaining the accuracy. Contrary to other dropout methods, during Monte Carlo dropout, dropping of the input occurs at both training and test times.

Bayesian machine learning has been conducted using an open-source Python library called Kessler[2][11]. Events from the test set were chosen, and for each event, the values of individual features were plotted for each CDM. Then, the event was given as data to the model, after manually removing the last CDM. The model was tasked with predicting the last CDM. An example of this is shown in Figure 5.

Results

The model samples events in the database as the prior, and then creates the posterior by using the CDM's in the given event. As can be seen in Figure 5, this creates an interpretable distribution for the operators which can be further analyzed for risk prediction. Most predictions in Figure 5 are accurate. However, predictions for certain other features are not accurate:

[1] https://kelvins.esa.int/collision-avoidance-challenge

[2] https://github.com/kesslerlib/kessler

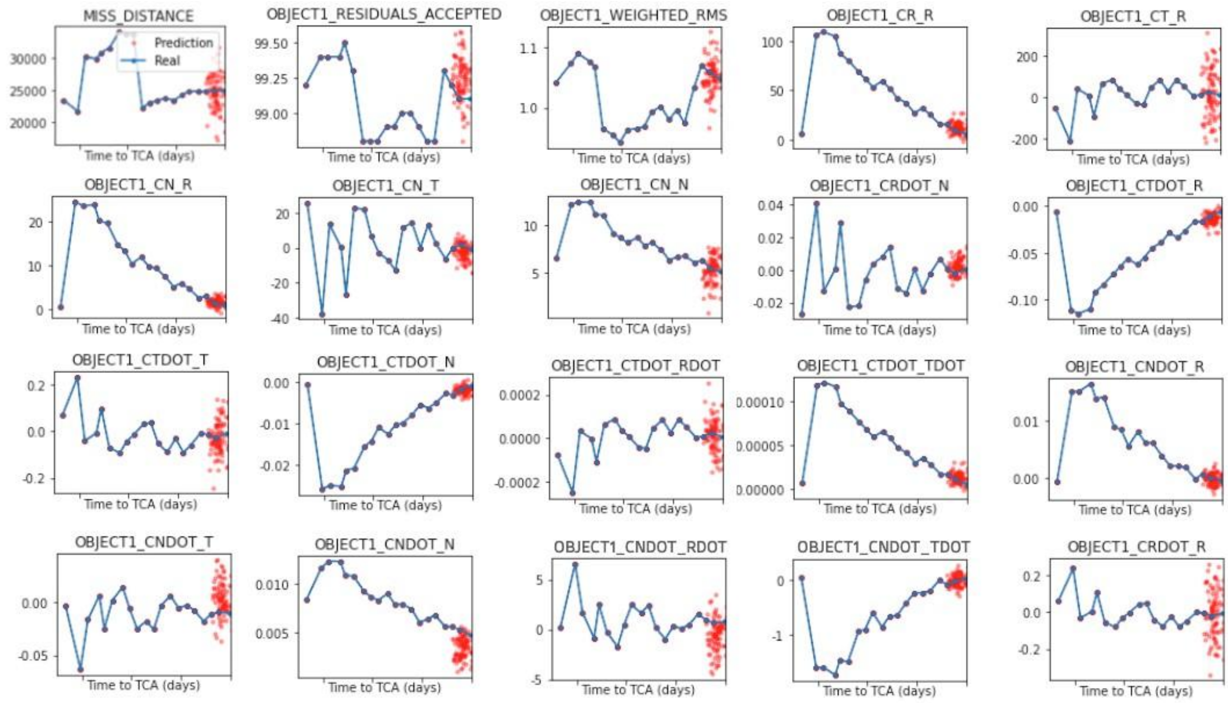

Figure 5. Predictions for each feature(in red) for a sample event given the previous CDM's in that event(in blue).

OBJECT1_CT_R, OBJECT1_CTDOT_T, OBJECT1_CN_N, OBJECT1_CTDOR_RDOT, OBJECT1_CNDOT_T, OBJECT1_CNDOT_RDOT, OBJECT1_CRDOT_R.

The value in these features is likely differing because of the varied and randomised nature of these features, the definitions of which can be found on the Kelvins website[3]. As such, the Bayesian model cannot provide a reliable prediction. For these features, as illustrated in Figure 5, the best course would be to simply return the last provided value as the prediction.

The provided Bayesian distributions can be used in multiple ways to calculate the collision risk. One of these methods could be to calculate the average predicted value for each feature. This value can then be used to calculate the risk using tools such as CORAM and CARA[3,7].

[3] https://kelvins.esa.int/challenge/data/

V. Conclusions

In this work, I analysed the usage of Bayesian Machine Learning for analysis of spacecraft collisions. The proposed method involves using Bayesian Machine Learning to predict the next CDM in an event, which can then be used to create accurate risk estimations for the near future. I also explored the shortcomings of trying to predict future collision risk without calculating the next CDM.

In conclusion, Bayesian Learning offers high-quality assistance in the field of Spacecraft Collision Avoidance. Further research into this topic is imperative, to understand how it can be used with current-day risk prediction software.

Declarations

Funding - No funding was received to assist with the preparation of this manuscript.

Interests - The authors have no relevant financial or non-financial interests to disclose.

Code - The code used in this project can be found on Github[4].

[4] Github Code

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