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TOWARD AUTOMATED COLLISION AVOIDANCE: PREDICTING THE RISK OF SATELLITE COLLISIONS USING MACHINE LEARNING-POWERED TECHNIQUES

Abstract

Active collision avoidance has become an important task in space operations nowadays, and hundreds of alerts corresponding to close encounters of a satellite and other space objects are typically issued for a satellite in Low Earth Orbit every week. Such alerts are provided in the form of conjunction data messages (CDMs), and only about two actionable alerts per spacecraft and week remain to be resolved after analyzing all cases. Therefore, building fully automated techniques for predicting the collision risk can help make the process of avoiding collisions less costly, as the number of false positives could be substantially reduced. In this paper, we present both conventional machine learning- and deep learning-powered approaches for predicting the final collision risk between a satellite and a space object, which may be space debris or another satellite. Based on real-world historical CDMs released by European Space Agency (ESA) in the Collision Avoidance Challenge (103 features/CDM; each event is a varying-length series of CDMs; 13154 and 2167 unique events in the training and test sets, and the events are divided into high- and low-risk ones), we build a battery of techniques for predicting the risk in the last CDM prior to close approach. Since we witness an unprecedented success of deep learning in time-series analysis, we propose two architectures of recurrent neural networks (RNNs): (i) a standard RNN regressor (used for estimating the next risk based on the features extracted from a sequence of CDMs using both long short-term memory and gated recurrent unit-based architectures), and (ii) a sequence-to-sequence model (used for mapping an input CDM sequence to an output sequence with the predicted risk of the upcoming CDMs). In our conventional machine learning techniques, we proposed a two-step approach where the classification (high- vs. low-risk) is followed by the prediction of the actual risk of high-risk cases. For classification, we exploited multilayer perceptrons and random forests (coupled with a technique to minimize the number of false negatives and exploiting the average, weighted average and the value of the last risk in a window of n CDMs), whereas random forests have been used for regression. Our experiments showed that the two-level approach significantly outperformed RNNs and revealed that appropriate balancing of the training set using the synthetic minority oversampling were key in obtaining high-quality classification. Finally, we took the 7th place (out of 97 registered participants) in the ESA Collision Avoidance Challenge using our approach.