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Orbit Determination and Propagation - SST (9)

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SPACE DOMAIN AWARENESS USING DEEP CONTINUAL LEARNING SEQUENCE PREDICTORS

Abstract

The industry standard ephemeris framework, SGP-4, cannot be used for extended forecast horizons. The single two-line element input does not allow for corrections in the model, causing the errors to accumulate over time and distort the output quickly. Due to this task's complex nature, we experimented with learning sequence predictors to forecast a satellite's motion for an arbitrary and extended horizon, with the added flexibility of learning from both state-vectors and orbital-element datasets. A hybrid SGP-4 interpolation approach was developed and deployed with corrective measures at every sample in the data to obtain a decent dataset. This interpolation algorithm allows for intelligent up-scaling of the dataset and guarantees synchronized training data. With this approach, the unsynchronized and messy publicly available datasets were up-sampled to a consistent period of one minute and fed into a deep recurrent neural network to make 10-day predictions from a 2-day history input at one sample per hour. This model is then compared to a long short-term memory network (LSTM), a gated recurrent unit network (GRU), and benchmarked against the SGP-4 standard. The quasi-universal trained model was trained with a large initial dataset of 61GiB CSV-schema data. It exhibits less than 5% mean absolute percentage error (MAPE), where the largest errors exhibit in the true anomaly predictions, which can be further enhanced by the use of proxy variables such as mean anomaly and mean motion, and greater than 0.9 correlation between actual data and 10-day prediction results across the board. These figures are a considerable improvement over that of the SGP-4 that display approx50% MAPE for the same horizon. With continual-learning enabled on the predictor model, new data can be easily incorporated to update the model, making it a sustainable and versatile replacement for SGP-4 and a platform for space domain awareness endeavours. Test runs for continual training show an average of 55.16% improvement to the accuracy of results over the entire set of variables, though the variable-effectiveness is inconsistent. Better suited variables for prediction see the most improvement to the results. With the help of the mentioned proxy variables and continual training, the expected accuracy is approx1% MAPE for the worst case and is currently being investigated. The scalability of the training procedure is addressed by using parallel computing with data-split strategies and guarantees feasibility of deployment on smaller, less powerful machines for forecasting on decentralized networks while continual training is performed on a server.