Machine Learning Disruption Prediction From the Very First Shot

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Disruptions remains one of the most significant issues that hinder the tokamak to become a commercially viable reactor. Reliable disruption prediction is required to trigger disruption mitigation or avoidance system. Recently machine learning disruption prediction methods are gain lots of popularity. However, for future reactors, there will be little data to train the predictors as disruptions are too dangerous for the machines. So a disruption predictor that can be deployed as early as possible is needed. In this work we present a method that can bootstrap a disruption predictor after the very first shot of that machine. The first shot does not even have to be a disruption. In this work a modified anomaly detection algorithm is used to produce a disruption prediction model after each shot with adaptive training strategy. The algorithm can learn from only negative samples which come from save shots. But when there is a missed disruption, it can also learn from positive samples from that shot. This allowed the model to be deployed after the very first shots. With adaptive learning, the model can follow the operation of the new tokamak as it expanding its operation range. To boost the performance, data from existing tokamak can also be used to bootstrap the first model. The model can achieve a more than 0.9 true positive rate throughout the whole train/test set, with a bit high false positive rate at the beginning, and falling quickly. This method can be the first guard for a new reactor before other machine learning models can be trained with acuminated data.