

## Disruption Prediction for Future Tokamak Reactors from Different Perspectives and with Different Methods

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Disruption poses a great threat to tokamaks. Currently, machine learning disruption predictor is the most promising way of triggering disruption mitigation system. But it needs data from the target tokamak to be trained. However, the future tokamak reactors may not be able to provide enough data before they damage themselves. In this work, we attempt to address this issue from different perspectives.

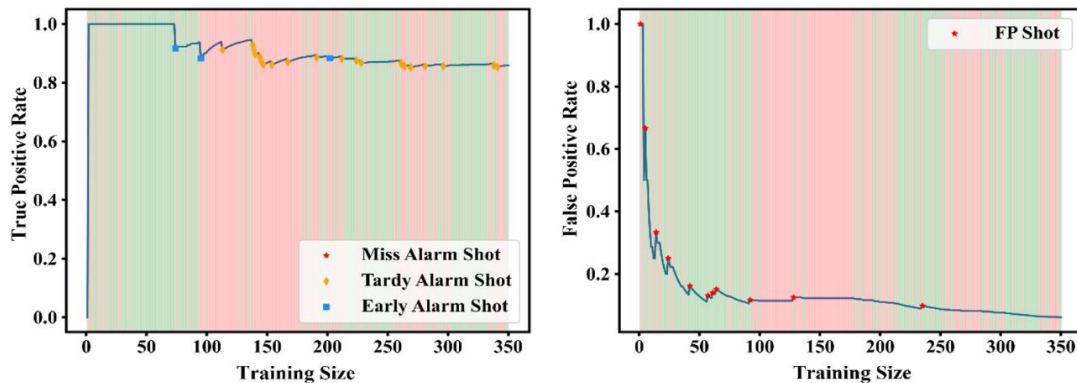
First, we try to reduce the data needed by the target tokamak by introducing known knowledge about disruption precursor to the machine learning models. This is done by extracting features that could related to disruption precursors. These features removes lots of machine specific information and with further feature alignment technique, we can transfer a model from one machine to another with litter target machine data [1-2]. Then, with deep learning we try to transfer disruption predictor trained with existing tokamaks to future reactors without any feature extraction. This allows the algorithm to exploit the data without human biases. With domain generalization, we can guide the model to learn common disruption precursor patterns from multiple existing tokamak. This will further reduce the data needed from the future tokamak [3].

The third method is using adaptive model training strategy. We pretrain an anomaly detection model on

existing tokamak. Then it will be adaptively re-trained on the new tokamak after each shot. The idea behind it is that you don't need to predict every disruption with one model, the model only need to predict the next shot accurately. This could give protection to the new tokamak from the very first shot [4]. Last we introduced the concept of disruption budget. This could guide the operation of the new tokamak so it won't damage itself before an accurate enough disruption predictor is built. The goal is to ensure the safety of the reactor though the different stages of the operation which may have different requirements on the disruption prediction. This can be a valuable reference for designing disruption predictors for future tokamak reactors.

### References

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**Figure 1.** The performance of the adaptive trained anomaly detection disruption prediction model. The left is true positive rate, the right is false positive rate. The red background indicates disruption shot. The red markers indicate missed disruption alarms or false alarms. The blue markers indicate early alarm, thus possibly lucky guesses. The yellow markers indicate tardy alarm which maybe to late for DMS to take effect.