### Introduction

- Predicting and mitigating disruptions in tokamaks is critical to the mission of sustaining a fusion plasma.
- To understand what causes disruptions, we want to answer:
  - Which parameters are correlated with the approach of a disruption? What are their threshold levels?
  - Are the thresholds reached with significant warning time?
  - Are there combinations of parameters that are useful?
- Goal: Develop a disruption warning algorithm that works in near real-time, embedded in the plasma control system.

### Disruption Warning Database

- SQL database of > 40 parameters from 1821 shots (~160k time slices) from 2015 C-Mod campaign.
- Only time slices in $i_p$ flattop included; composed of non-disruptive discharges and discharges that disrupted during the flattop.
- Ignored intentional massive gas injection (MGI) disruptions.
- Avoid processing signals with non-causal filtering; this can introduce post-disruption effects into pre-disruption data.
- Pre-processed signals in database to avoid excessive smoothing and interpolation.
- Each database record consists of all parameter values at one time slice, recorded every 20 ms; for each disruption, take additional time slices every 1 ms during the 20 ms period before disruption.
- Analyzed 7/40 dimensionless or machine-independent parameters from database using a machine learning algorithm.

### Supervised Learning for Classification

- Given input parameters $x$ and historical knowledge of disrupted shots $Y$, how can we find patterns to distinguish disruptions in our database?

- **Random forest** for classification using 3 different schemes:
  1. Binary Classification:
     - "non-disrupted" = sample from shot with no disruption
     - "disrupted" = sample from disrupted shot
     - Classification Accuracy:
       - Disrupted: 92.6%
       - Non-Disrupted: 97.0%
       - Overall: 91.2%
  2. Multi-Class Classification:
     - "non-disrupted" = sample from shot with no disruption
     - "far from disr" = sample from disrupted shot > 40 ms from disruption
     - "close to disr" = sample from disrupted shot < 40 ms from disruption
     - Classification Accuracy:
       - Disrupted: 97.4%
       - Far from Disr: 37.3%
       - Close to Disr: 53.3%
       - Overall Accuracy: 90.1%

### C-Mod and DIII-D Comparison

- Large overlap of internal inductance distributions compared to DIII-D for time slices grouped via the multi-class classification case.
- Difference in timescales on DIII-D and C-Mod evident when comparing design points and time evolution of parameters.

### Conclusions and Future Work

- Poorer predictive capability on Alcator C-Mod compared to DIII-D may be due to faster disruption-relevant timescales.
- At present data acquisition rate, difficult to predict disruptions.
- Compare performance of other ML algorithms and study dependence on new features as the database is updated.

### References