This work is funded by Commonwealth Fusion Systems and supported by the U.S. DOE under Award(s) DE-FC02-99ER54512, DE-SC0014264, DE-SC0010720, DE-SC0010492, and DE-FC02-04ER54698.

A Review of Machine Learning Applications to Disruptions

Cristina Rea
with S. Benjamin[1], P. Kaloyannis[1,2,4], Z. Keith[1], A. Maris[1], L. Spangher[1], H. Turner[1], J.X. Zhu[1], C. Clauser[1], R.S. Granetz[1], R.A. Tinguely[1], A. Pau[2], J. Barr[3], M.D. Boyer[4], R. Sweeney[4], K. Felker[5], K.G. Erickson[6]

[1]MIT Plasma Science and Fusion Center, Cambridge, MA, USA
[2]EPFL Swiss Plasma Centre, Lausanne, Switzerland
[3]General Atomics, San Diego, CA USA
[4]Commonwealth Fusion Systems, Cambridge, MA USA
[5]Argonne National Laboratory, Lemont, IL USA
[6]Princeton Plasma Physics Laboratory, Princeton, NJ USA

Theory and Simulation of Disruptions Workshop
Princeton Plasma Physics Laboratory, July 20th, 2023

MISTI MIT Global Experiences

CFS

DIII-D NATIONAL FUSION FACILITY

EPFL Swiss Plasma Center

Argonne NATIONAL LABORATORY

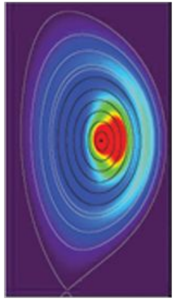
PSFC

Outline

1. Intro and motivations
2. Explainable and adaptive Machine Learning for disruption prevention
3. Conclusions

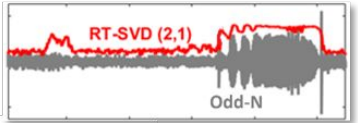
Precursor's prediction and detection crucial to avoid disruptions, but challenging task!

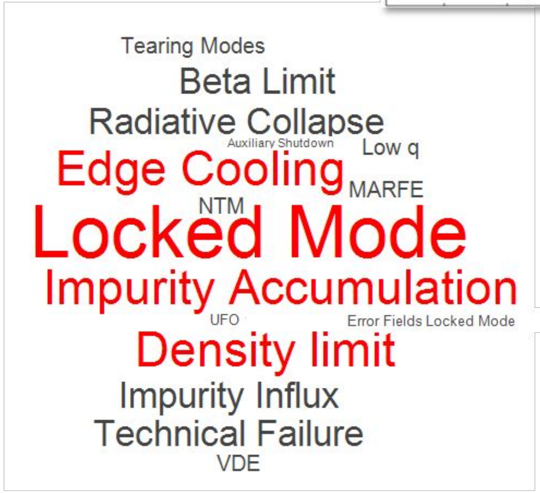
IMP. ACC



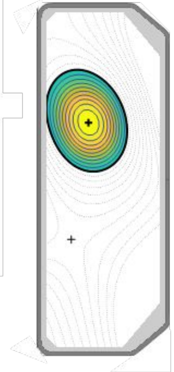
DENSITY LIMIT

NTM

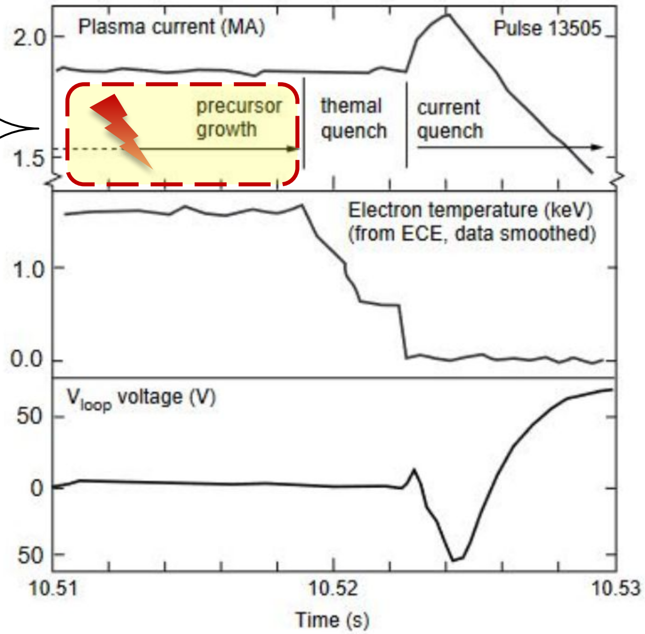




VDE



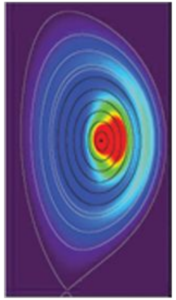
Courtesy: A. Pau, PSFC seminar, April 2023



ITER Physics Expert Group on Disruptions, Plasma Control, and MHD (1999) Nucl. Fusion 39 2251

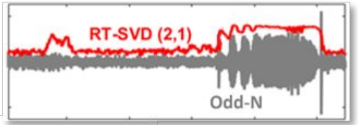
No first-principle solution to capture predisruptive chain of events

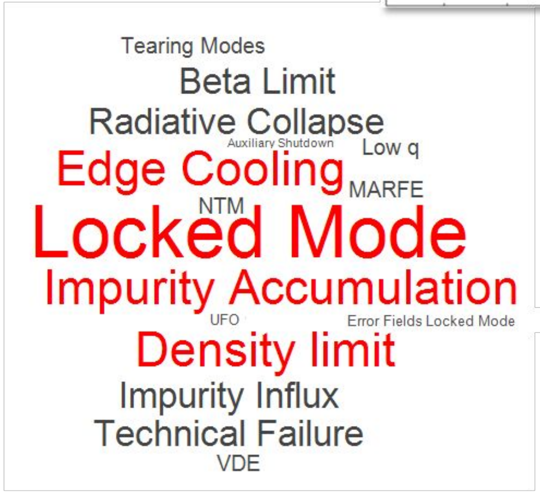
IMP. ACC



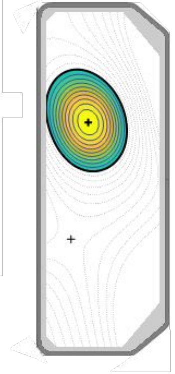
DENSITY LIMIT

NTM





VDE



Courtesy: A. Pau, PSFC seminar, April 2023

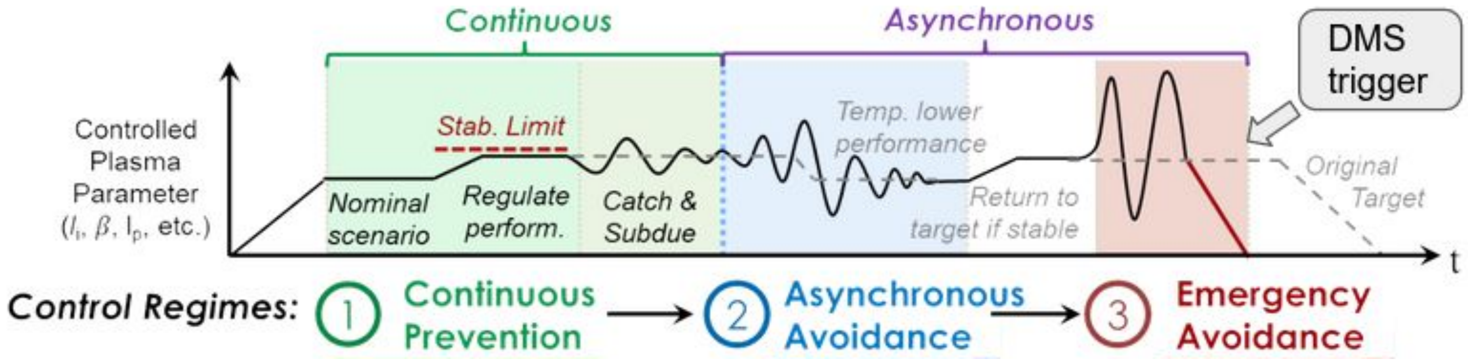
De Vries et al. NF 51 (2011) 053018 "Survey of disruption causes at JET"

- **Statistical studies on disruption frequency (and type)** not available across different tokamaks.
- Notable efforts on event analyses on KSTAR, MAST, NSTX/-U dbs → **DECAF**

  Sabbagh et al PoP 30 032506 (2023) and later talk
- **Wealth of experimental data** from different tokamaks enables Machine Learning applications.
- Need **timely identification of precursors** to allow the plasma control system (PCS) to take proper avoidance action.

Active monitoring and prediction of soft/hard limits necessary to inform transition across operational boundaries

Adapted from J. Barr IAEA TM PDM 2020 and
Sammuli et al 2021 Fusion Eng. Des. 169 112492



Performance optimization *Instability avoidance* *Disruption mitigation*

Data-driven models developed to provide

- **Explainable proximity to unstable operational space**
- **Interpretable tracking of instability onset**

Established multi-machine databases of disruption-relevant parameters foundational to ML applications

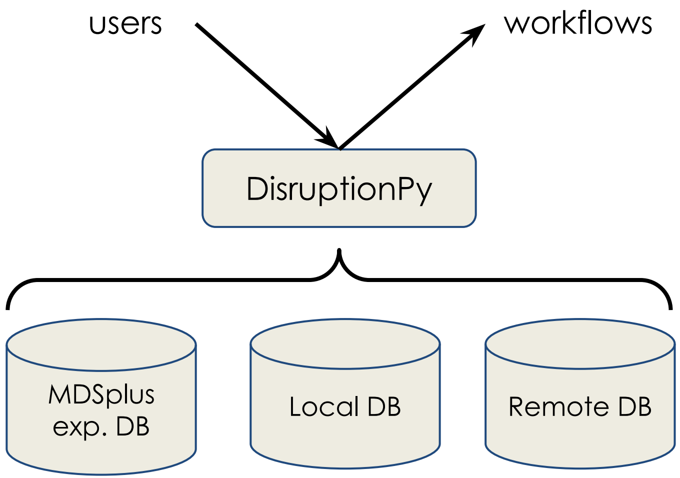
- SQL dbs of times series for > 50 plasma signals
- **Annotated events**
  - disruptive vs non-disruptive,
  - H-L back transitions,
  - radiative collapses,
  - density limit,
  - …

Rea et al, 2018 Plasma Phys Control. Fusion 60 084004
Montes, Rea et al, 2019 Nucl. Fusion 59 096015

Device	Discharges	Samples
C-Mod	5,500	500,000
DIII-D	13,000	3,000,000
EAST	19,000	1,500,000

- **DisruptionPy**: interoperable library for data retrieval and database development across different devices
  - Modular structure + version controlled
  - Available for Alcator C-Mod and DIII-D, soon EAST

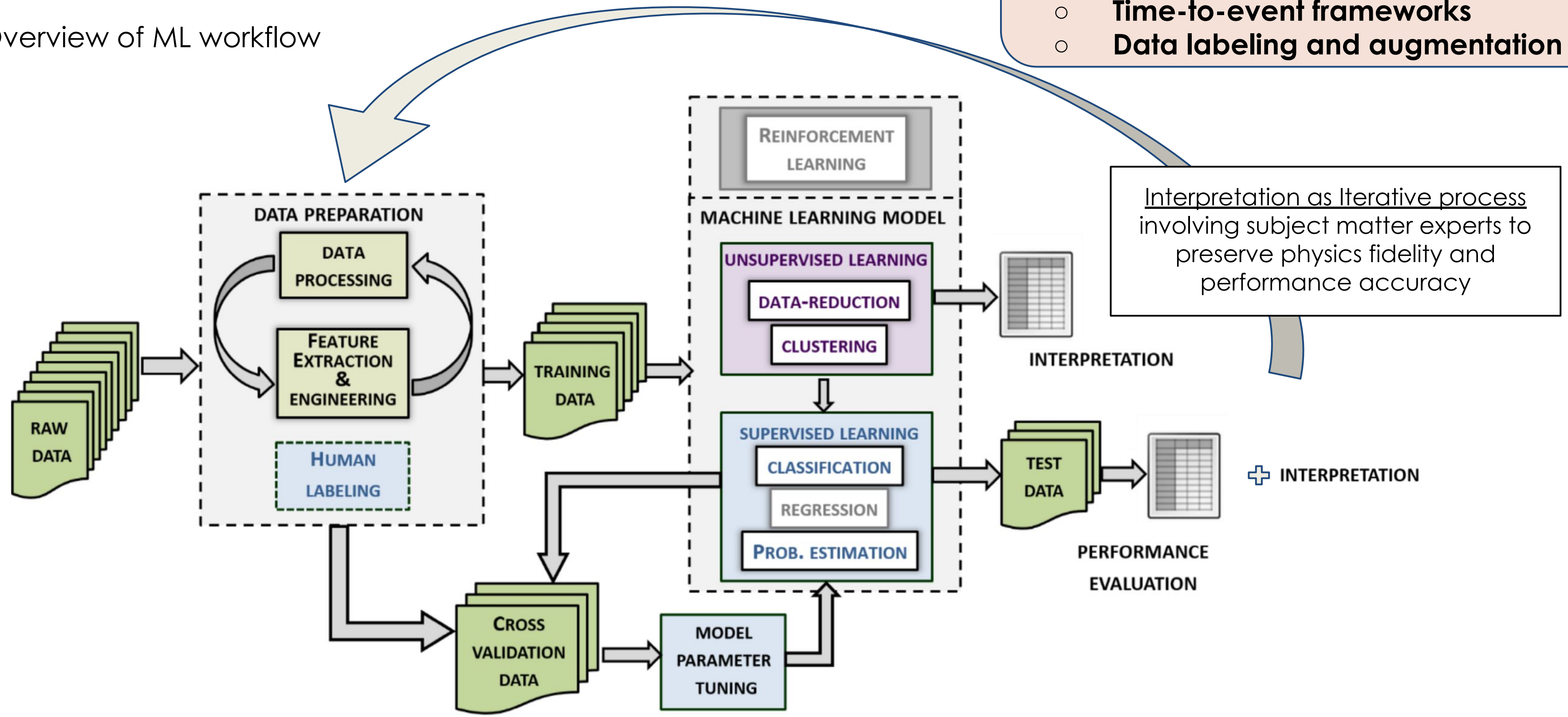
Turner, Rea (MIT)
https://github.com/MIT-PSFC/disruption-py
(currently private repo)



Advances in Disruption Prevention via Machine Learning:

- DPRF
- SORI
- Hybrid Deep Learning modeling
- Proximity-to-instability
- Time-to-event frameworks
- Data labeling and augmentation

Overview of ML workflow



Adapted from A. Pau et al, Nuclear Fusion, 59(10):106017, 2019

Outline

1. Intro and motivations

2. Explainable and adaptive Machine Learning for disruption prevention
    - DPRF
    - SORI
    - Hybrid Deep Learning modeling
    - Proximity-to-instability
    - Time-to-event frameworks
    - Data labeling and augmentation

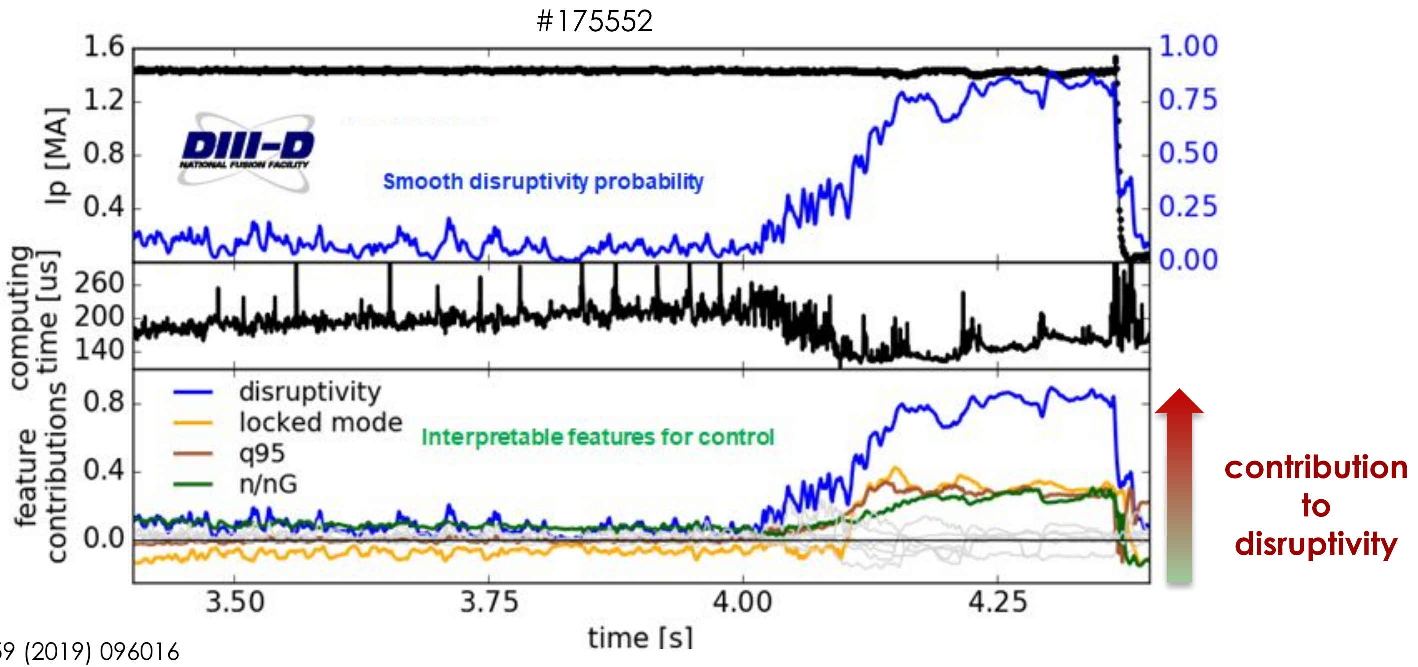
   Available in real-time at DIII-D

3. Conclusions

Explainable ML for disruption prediction and stability boundaries identification in real-time

DPRF

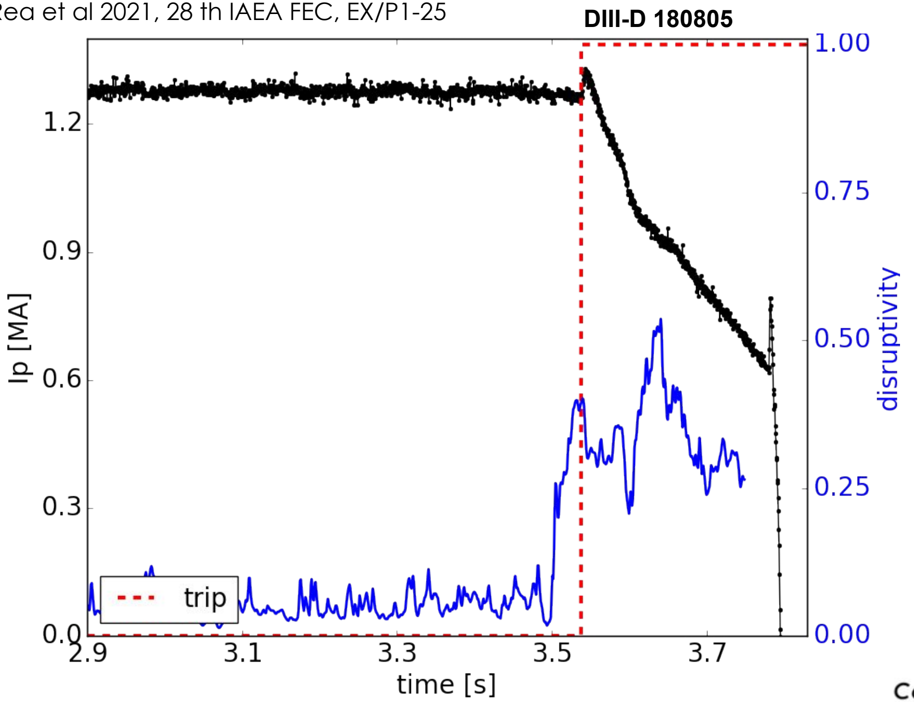
- **Disruption Prediction via Random Forest** computes **probability of an impending disruption**, while **interpreting its drivers in real-time**.
  - Available on DIII-D and EAST.



Rea et al, Nucl. Fusion 59 (2019) 096016
Rea et al, 2021 IAEA EX/P1–25,
J. Barr et al, Nucl. Fusion 61 (2021) 126019

Real-time implementation and optimization for asynchronous avoidance and emergency response

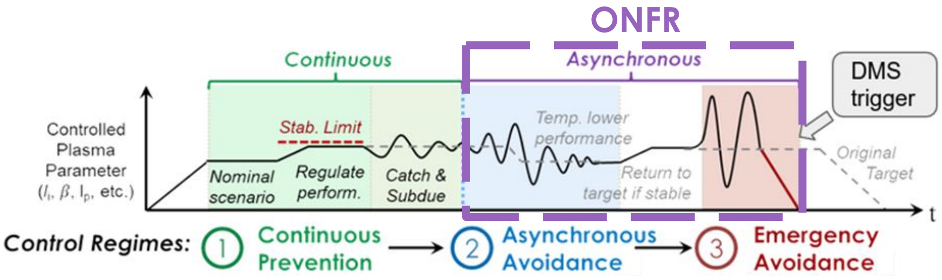
C. Rea et al 2021, 28 th IAEA FEC, EX/P1-25



Real-time model evaluation and feature contribution computation: **< 200 μs**

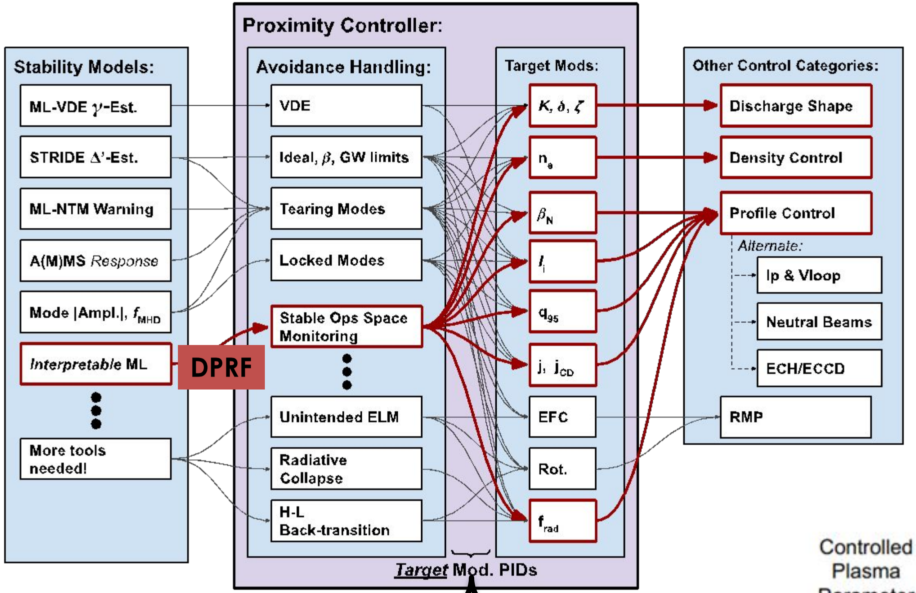
Successful ONFR integration:

- **Fast shutdown** triggered by preset disruptivity threshold.
- **MGI** response and **ECH** trigger in closed loop.



Off-Normal Fault Response → **Asynchronous and Emergency response**.
Eidietis et al., 2018 Nucl. Fusion 58 056023

Used to regulate plasma stability and performance in DIII-D Proximity Control architecture

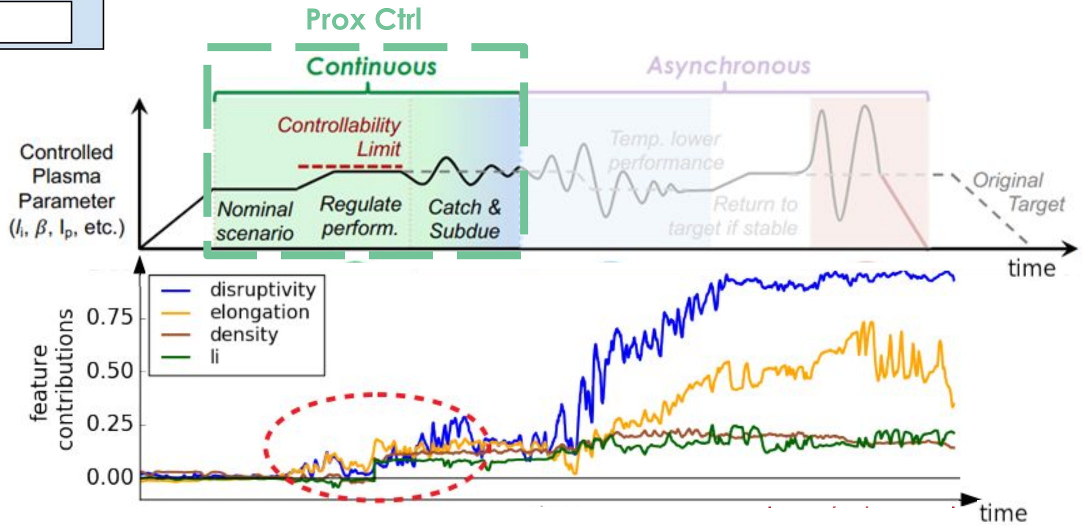


$$\Delta\kappa = PID\left[f_{danger} * f_{\kappa,contrib} * sign\left(\frac{d\kappa}{dt}\right)\frac{\Delta\kappa_{target}}{\Delta f_{\kappa,contrib}}\right]$$

Barr et al, Nucl. Fusion 61 (2021) 126019
Rea et al 2021, 28th IAEA FEC, EX/P1-25

DPRF + ProxCtrl:

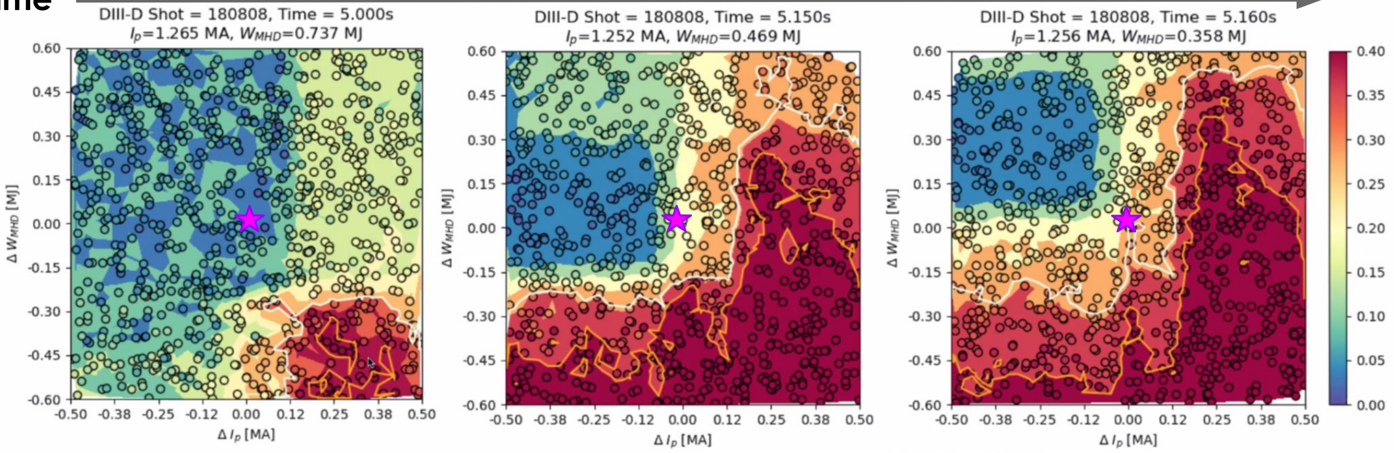
- **Disruptivity** measures **proximity to unstable operating space**
- **Feature contributions** can be mapped onto controllable plasma parameters **to regulate stability**



Safe operating regions identification (SORI) through DPRF for disruption-free trajectory planning

SORI

time



high danger

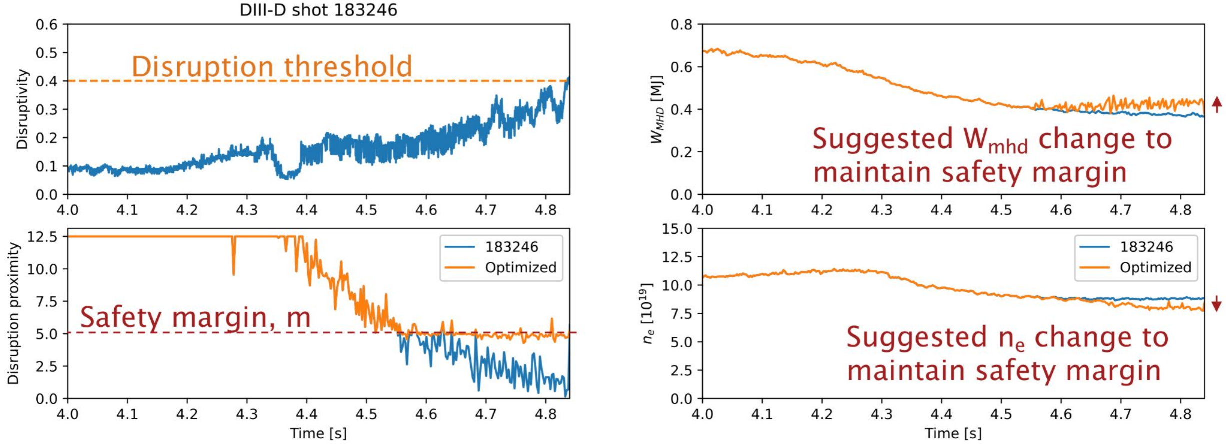
DIII-D NATIONAL FUSION FACILITY

DPRF evaluations obtained by sampling from 2D operational regime variations

safe region

ML-driven optimization (Genetic Algorithms) to identify **trajectory** across operational space and in **real-time** control systems (**DIII-D PCS**).

Best operating point found via convex set of linear constraints to calculate disruption proximity.



Boyer, Rea, Clement, Nucl. Fusion 62 (2022) 026005 and continued work by Keith, Rea (MIT), Felker (ANL), Erickson (PPPL)

Outline

1. Intro and motivations

2. Explainable and adaptive Machine Learning for disruption prevention
   - DPRF
   - SORI
   - Hybrid Deep Learning modeling
   - Proximity-to-instability
   - Time-to-event frameworks
   - Data labeling and augmentation

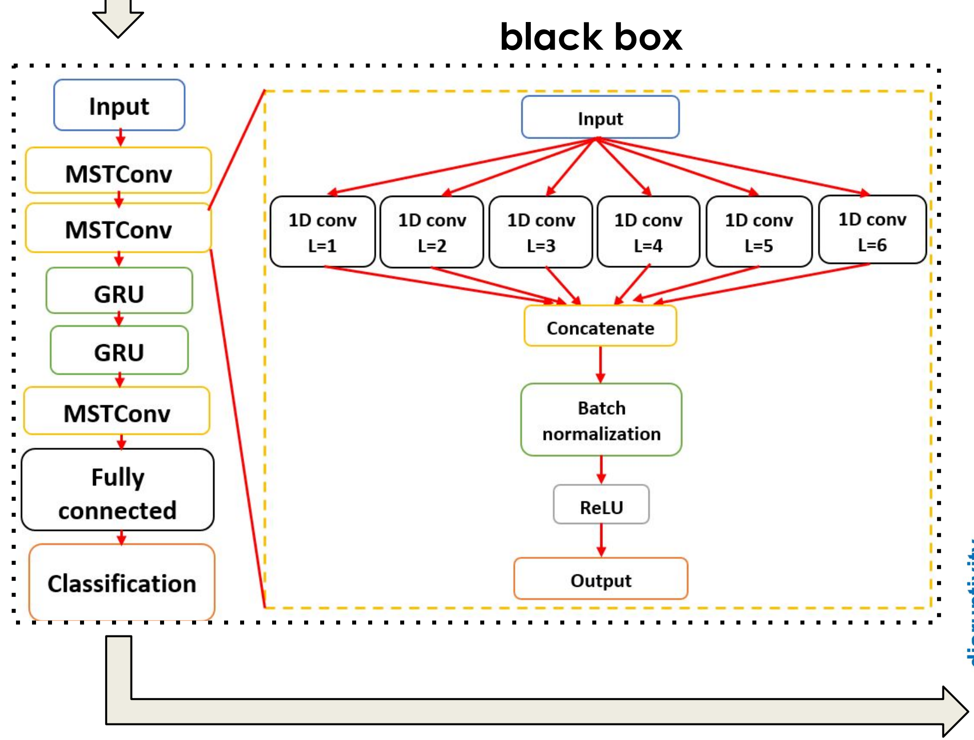
   more at APS-DPP 2023

3. Conclusions

Hybrid Deep Learning architecture for cross-machine disruption prediction using time series data

HDL

J.X. Zhu, Rea et al, 2021 Nucl. Fusion 61 026007

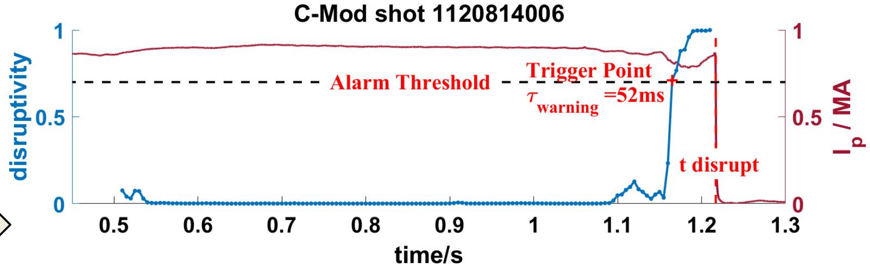


Goal: to learn general disruption dynamics from available experimental data.

Right now being benchmarked against newer / fancier architectures – i.e., **transformers**

Spangher, Rea, Eni+MIT partnership

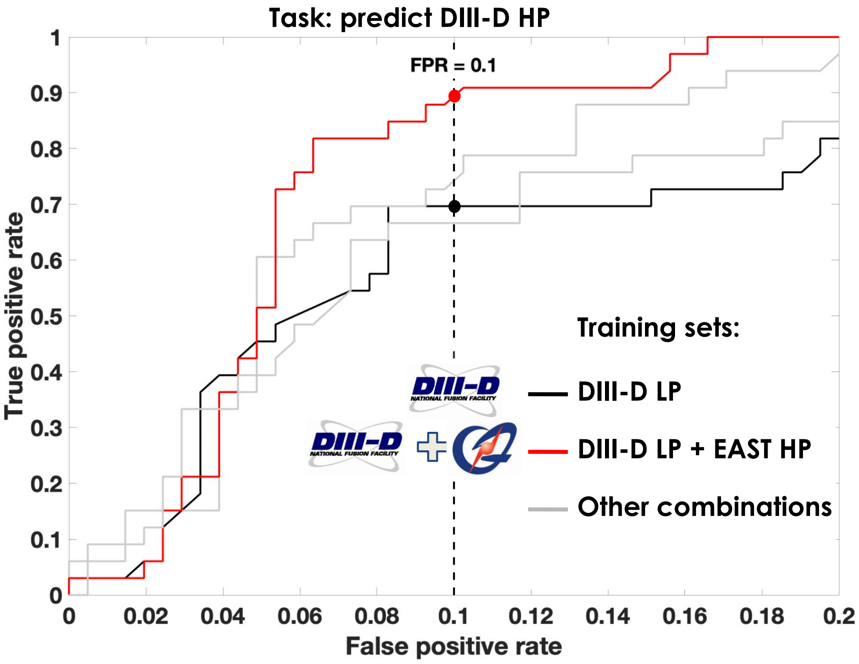
MIT | PSFC
Plasma Science and Fusion Center



Scenario-adaptive Hybrid Deep Learning predictor as DMS trigger candidate (ITER/SPARC)

- **Adapt** current state-of-the-art **ML predictors** to different operational regimes across devices (DIII-D/EAST).

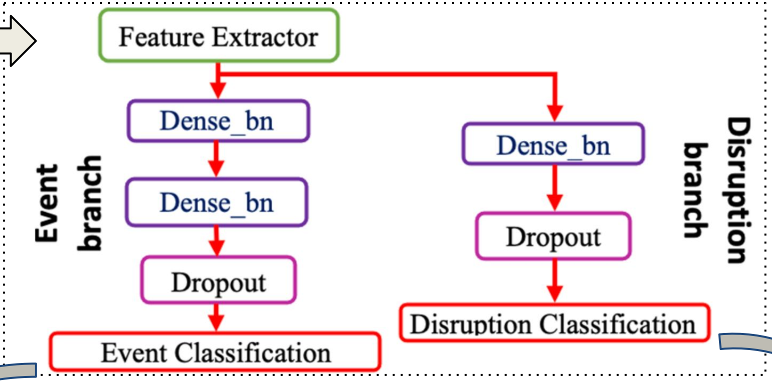
- Adaptive strategies:
  - ad-hoc design of **training sets to match target domain** by fully exploiting existing data[1],
  - **retrain predictors** after performance degradation[2].



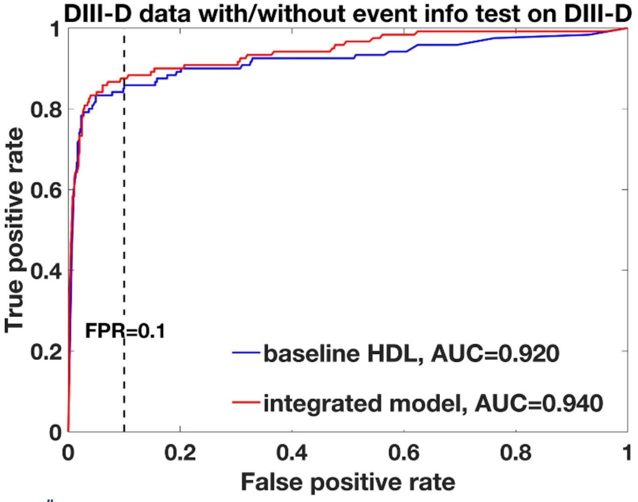
Adapted from [1]J.X. Zhu, Rea et al, Nucl. Fusion (2021) 114005
[2]J. Vega et al., *Nat. Phys.* 18, 741–750 (2022)

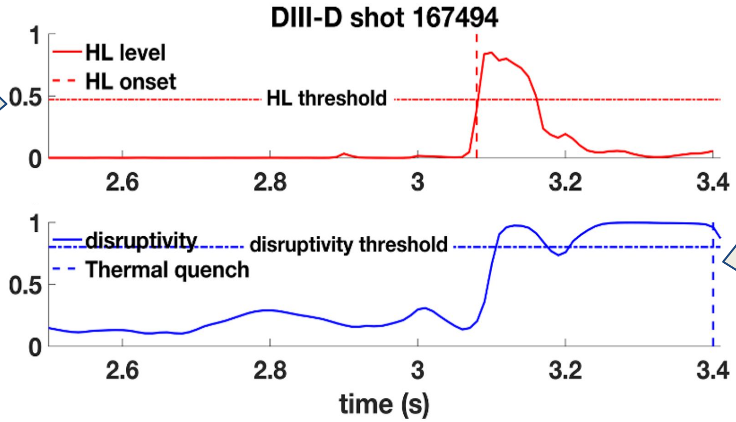
Hybrid Deep Learning architecture optimized for precursor identification via multi-task learning

Plasma state



Combined loss function for **multi-task learning** → improved accuracy





Adapted from J.X. Zhu, Rea et al, 2023
Nucl. Fusion 63 046009

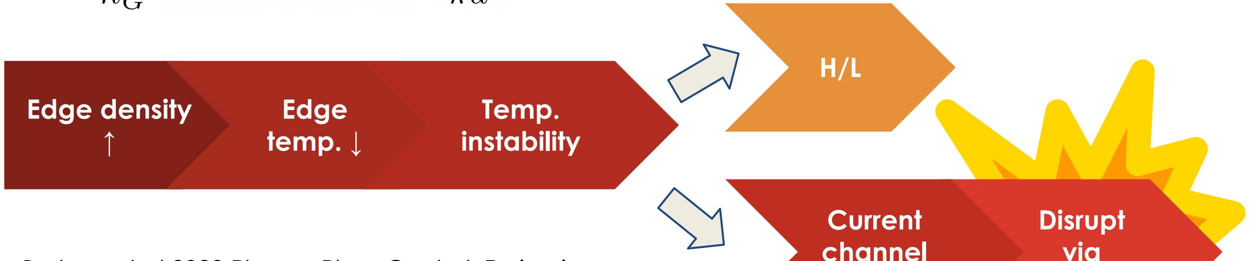
Symbolic ML for disruption-free operations in regimes close to density-limit

density limit

Density is critical design parameter:
➔ fusion power density ∝ n^2

Power plant design points usually close to the empirical density limit Greenwald et al., Nucl. Fusion (1988)

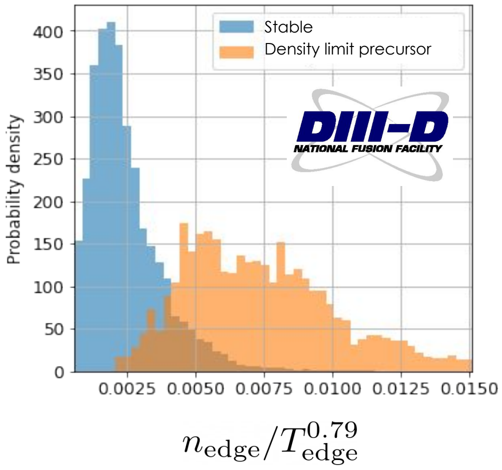
$$\frac{n}{n_G} < 1, \text{ where } n_G = \frac{I_p}{\pi a^2}$$



Berkery et al 2023 Plasma Phys. Control. Fusion in press
Manz et al 2023 Nucl. Fusion 63 076026;
Zanca et al 2019 Nucl. Fusion 59 126011;
Giacomin et al 2022 Phys. Rev. Lett. 128 185003;
Singh and Diamond 2022 Plasma Phys. Control. Fusion 64 084004;
Stroth et al 2022 Nucl. Fusion 62 076008;
Brown and Goldston 2021 Nucl. Mater. Energy 27 101002;
Bernert et al Plasma Phys. Control. Fusion 57 (2015) 014038;
Maraschek et al Plasma Phys. Control. Fusion 60 (2018) 014047; …

Better (interpretable) tools needed to understand & avoid density limit events:

- Focus on DIII-D data
- Extension to other devices (C-Mod, EAST, TCV, AUG)



Maris, Rea (MIT), Pau (EPFL), work in progress

Symbolic ML to find data-driven risk for n=1 TM onset

tearing stability

- Backward feature elimination and probabilistic model selection combined to identify the "TM risk"

- Features:

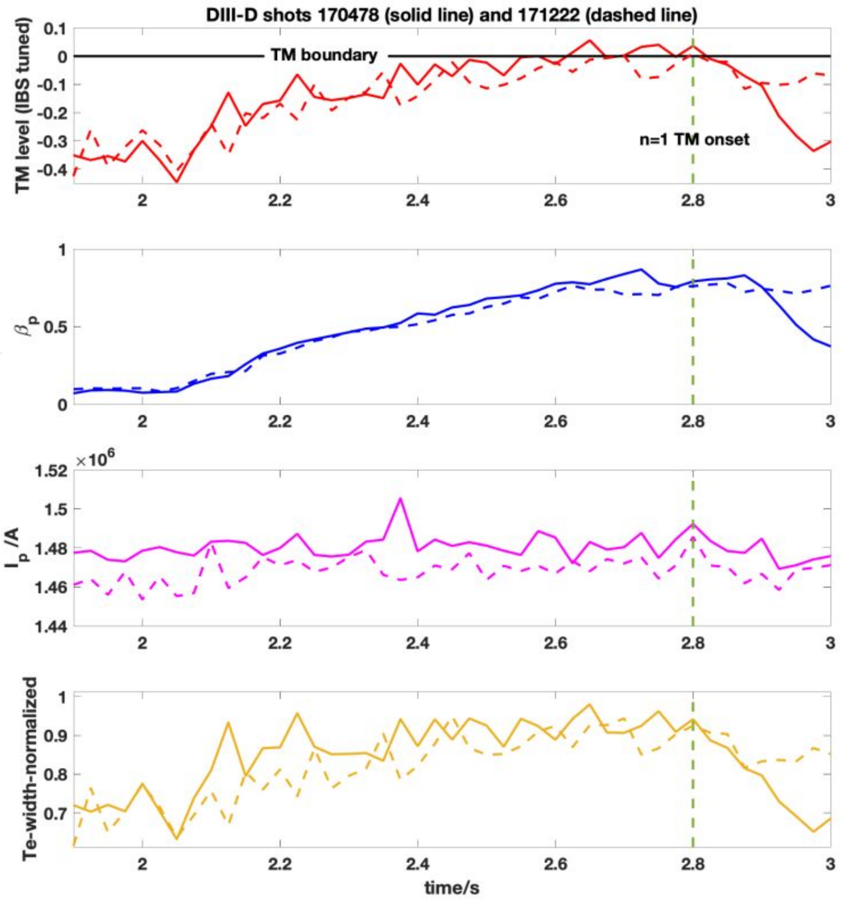
Dimensionless: β_p, q_{95}, n_G, Te_width_norm, κ, ν_*, l_i, q_0, radiated_frac, ip_error_frac

Dimensional : I_p (MA), B_{tor}, V_{loop}, n2rms (Gauss)

- Focus on ITER Baseline scenarios
  - boundary version available for scenario-agnostic runs

$$\text{TM level} = 0.20\beta_p + 0.01\nu_* + 1.81\frac{\sqrt{q_{95}T_{e_{width,norm}}}}{\kappa} + 1.69\left|\frac{I_p \times 10^{-6}}{B_{Tor}}\right| - 3.1$$

Available in real-time at DIII-D



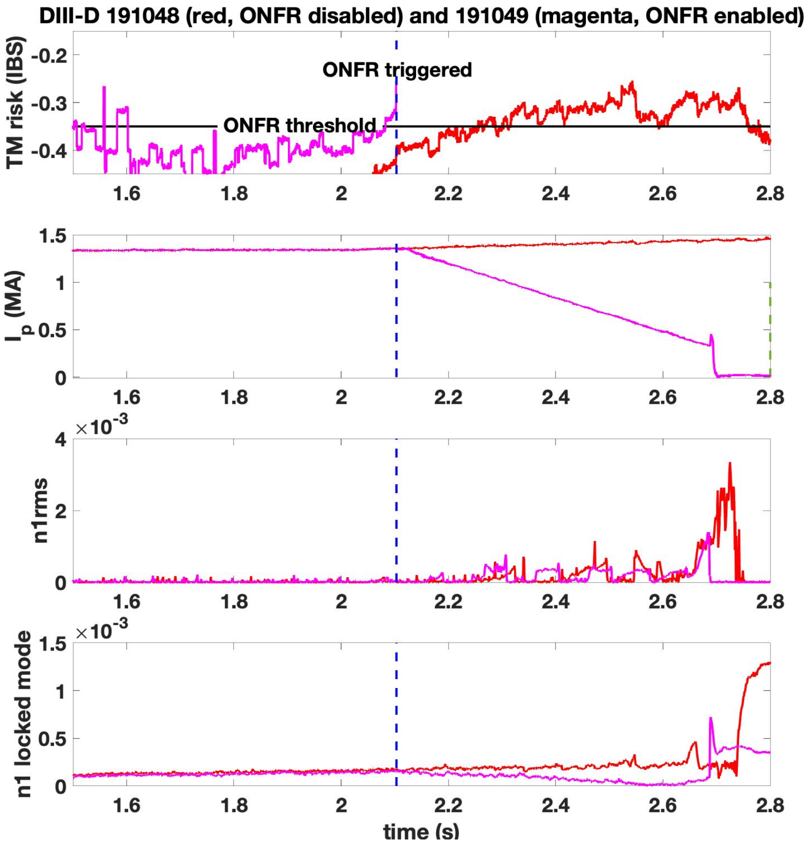
DIII-D NATIONAL FUSION FACILITY

J.X. Zhu, Rea, et al 2023 JoFE in preparation

DIII-D real-time qualification of data-driven TM risk during FY22

- LRHO DIII-D experiment (summer 2022)
- TM level integrated with ONFR (K. Erickson, J. Barr)
- Experimental plan to sweep TM level parameters (Ip, Bt, …) inter and intra shot and to scan thresholds in TM level and time delay
- Goal: trigger the ONFR for soft landing or TM avoidance.
- Successful IBS TM avoidance example: Level down Ip at 1.35MA (from 1.5MA) and trigger soft landing using ONFR and TM risk.

Available in real-time at DIII-D



J.X. Zhu, Rea, et al 2023 JoFE in preparation

Towards tearing onset prediction with physics-informed Machine Learning for scenario design

- Physics-informed ML tearing stability metric for time-independent magnetic equilibria

- Initial study with classical tearing stability, synthetic data:
  - Equilibria in cylindrical geometry generated and evolved linearly in M3D-C1
  - Predictive tool will leverage:
    - observed M3D-C1 growth rates
    - Δ' in the constant-psi approximation
    - ratios of big and small asymptotic solutions in inner resistive-MHD and outer ideal-MHD regions about the rational surface
    - growth rates from asymptotic matching

- Tearing mode database project (TMDB): a community-driven db to study ML-accelerated tearing stability
  - Collect stability terms (community-driven)
  - Focus on DIII-D data, expand to C-Mod, …
  - Provides NTM phenomena to ML predictor

- TMDB will be publicly available

Benjamin, Clauser, Rea, Sweeney, ongoing work

Outline

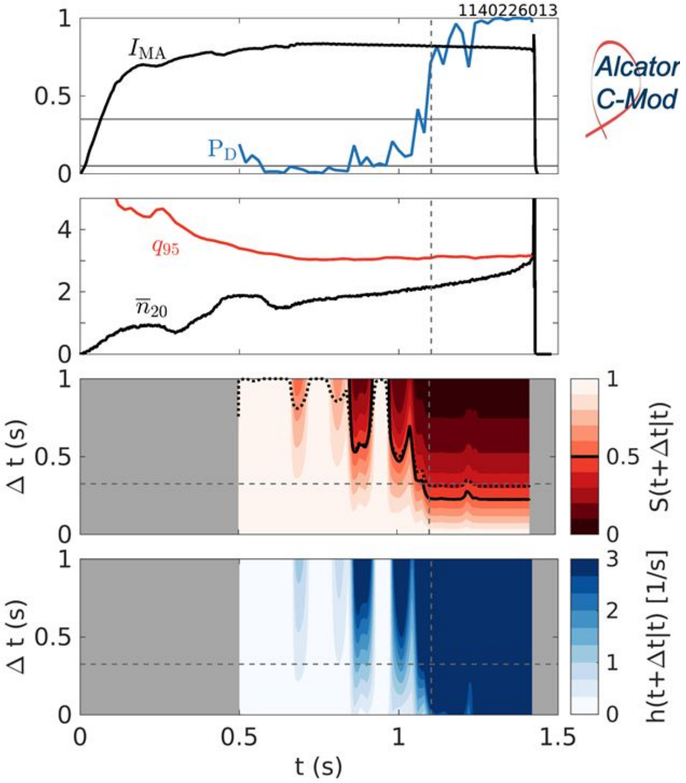
1. Intro and motivations

2. Explainable and adaptive Machine Learning for disruption prevention
   - DPRF
   - SORI
   - Hybrid Deep Learning modeling
   - Proximity-to-instability
   - Time-to-event frameworks
   - Data labeling and augmentation

3. Conclusions

Predict "time-to-disruption" risk using ML-driven classification probability

time-to-event



Any classification probability (P_D) cast between [0,1] can be used to:

- Predict the **future probability** of **plasma survival** $S(t+\Delta t\,|\,t)$
  or
- Model the **instantaneous hazard** $\hbar$=d ln$S$/dt
  to be used as probability generator.

Hazard function modeling connects dynamical systems and risk-aware control design by probability generation.

C-Mod data used as proof of concept to combine DPRF (or <u>any classifier</u>) disruptivity with survival analysis.

Tinguely, Montes, Rea et al 2019 PPCF 61
Olofsson et al 2018 PPCF 60
Olofsson et al 2018 FED 146
Continued work by Keith, Rea, Tinguely (MIT)

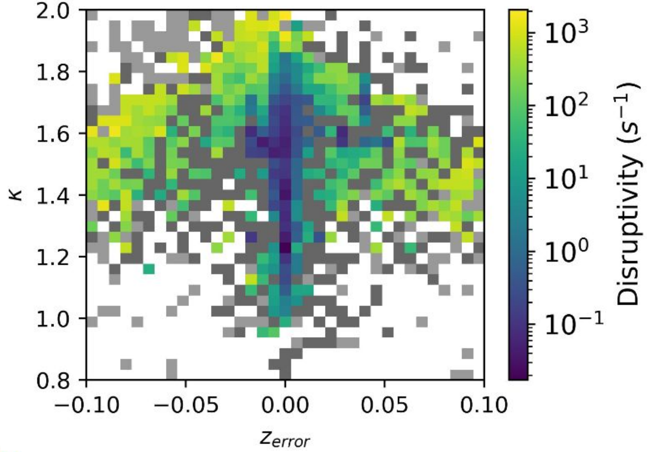
Defining data-based disruptivity in statistically robust way

- Disruptions modeled as Poisson processes with stability time inferred from database analysis:

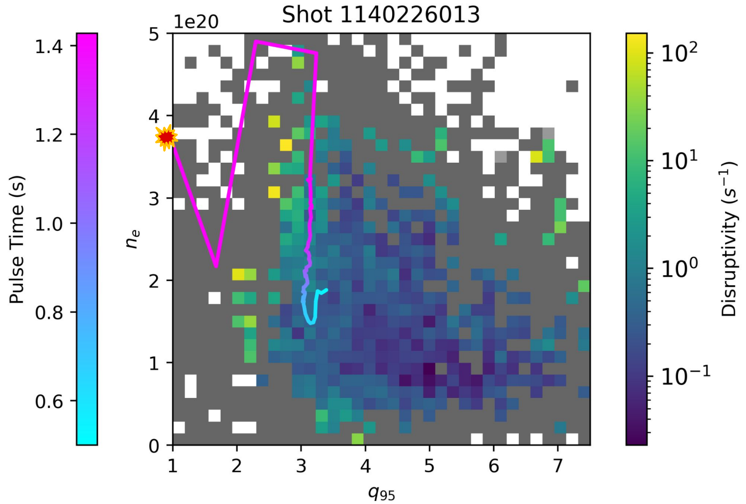
$$P(k \text{ disruptions in } \Delta t | d) = \frac{(d\Delta t)^k e^{-d\Delta t}}{k!} \Rightarrow P_D(\Delta t|d) = 1 - e^{-d\Delta t}$$

probability of disrupting in next *Δt (s)*

- Maximum likelihood estimation ensures statistical robustness, even when disruptivity (s^{-1}) very high



Pulse planning parameter space optimization



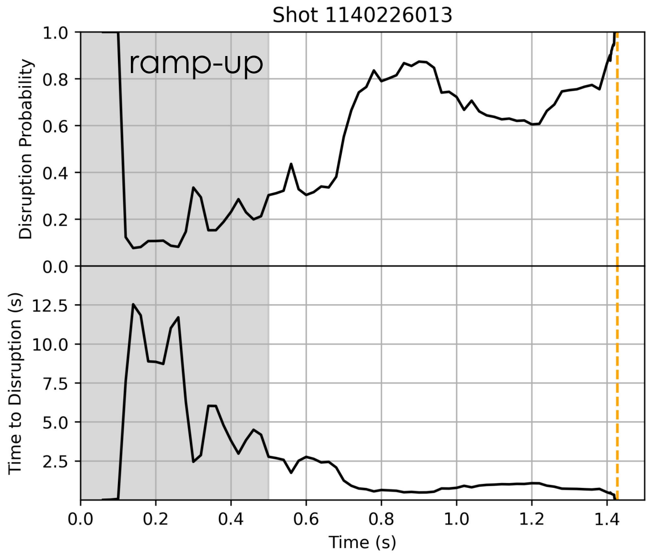
Real time nonlinear boundary avoidance

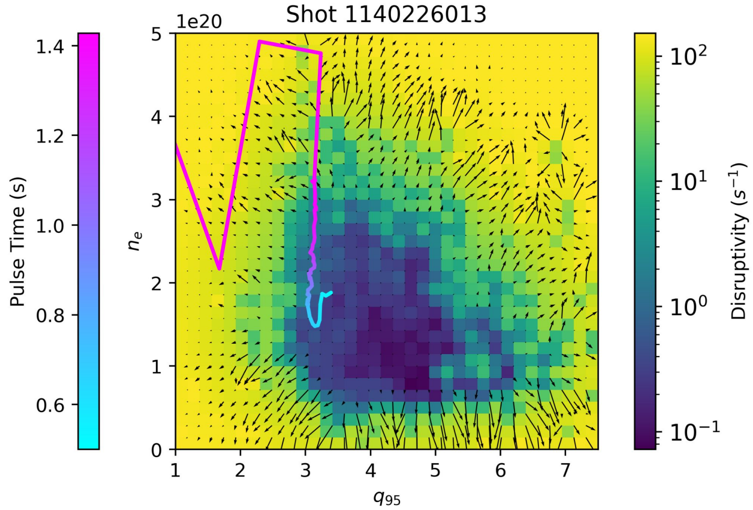
Kaloyannis (EPFL), Rea, 2023 Master's thesis

Gradient boundary avoidance from offline disruptivity maps

- From offline disruptivity, create best fit surface over plasma parameters (offline)
- Interpolate surface for the disruptivity (potentially in real-time)
- Compute the disruption probability and map's gradient
- Apply gradient descent, weighted by disruption probability

Kaloyannis (EPFL), Rea, 2023 Master's thesis





Outline

1. Intro and motivations

2. Explainable and adaptive Machine Learning for disruption prevention
   - DPRF
   - SORI
   - Hybrid Deep Learning modeling
   - Proximity-to-instability
   - Time-to-event frameworks
   - Data labeling and augmentation

3. Conclusions

Not enough time 😓

LabelProp
Montes, Rea et al 2021 Nuclear Fusion 61 026022

Student-t surrogates
Rath, Rügamer, Bischl, von Toussaint, Rea, Maris et al, 2022 J. Plasma Phys. 88

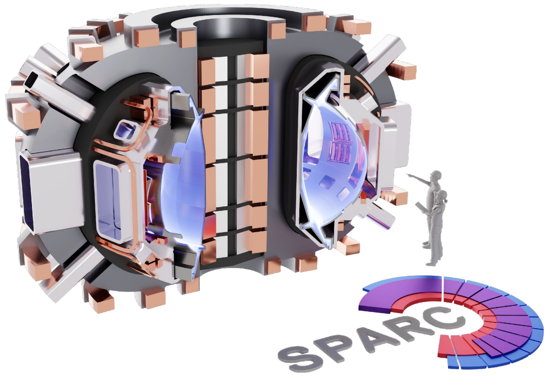
Disruption prevention solutions via ML

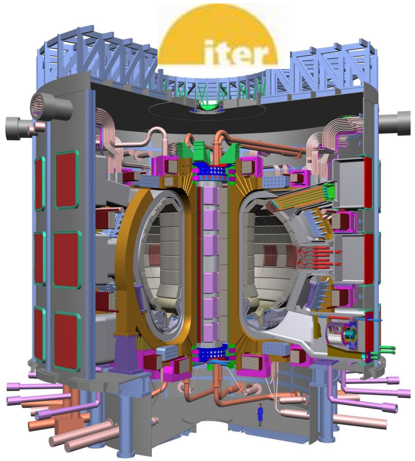
MIT | PSFC Plasma Science and Fusion Center

- Fusion energy systems need robust models featuring
    - interpretability/explainability
    - well-defined validity and extrapolability boundaries (UQ)
    - risk-awareness, conditioned on consequences/effects

- Active disruption research developing
    a. Interpretable algorithms
    b. Explainable predictions
    c. Transfer/adaptive learning
    d. Time-to-event frameworks
    e. Data augmentation and labeling
    f. …

- MIT team actively contributing to ITER disruption research and SPARC disruption strategies development.





Thank you! < crea@psfc.mit.edu >