

# Data-driven learning for disruption prevention and performance optimization

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Plasma Science & Fusion Center

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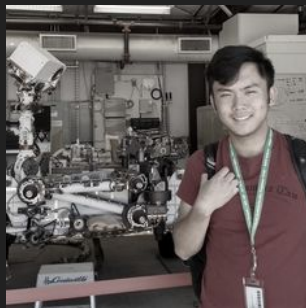
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IPAM Long Program Workshop II, UCLA IPAM, April 15th, 2026

**Special thanks to:**

**Andrew Maris, Allen Wang, & GL Trevisan, Y Wei,  
A Kumar, Z Keith,  
S Benjamin**



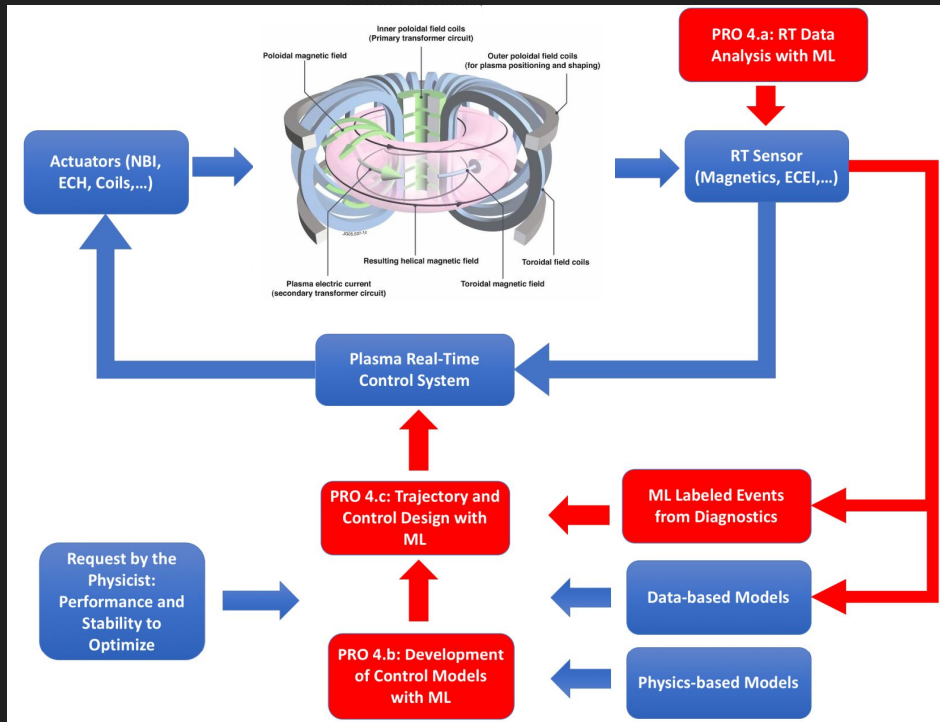
*Work partly funded by DE-FC02-04ER54698 and DE-SC0014264, DE-SC0024368, and CFS under RPP021*

# Outline

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1. Data and Machine Learning
2. Disruptions and controllability
3. Explainable and adaptive Machine Learning for disruption prevention
4. Conclusions

# Data drives fusion experiments' design, simulation, analysis, control and optimization



Adapted from D. Humphreys et al. "Advancing Fusion With Machine Learning" DOE Workshop (2020)

ML/AI tools have key role in:

- advancing science discovery
  - via database development and data analysis
- accelerating simulations via surrogates;
  - performance optimization
  - design optimization
  - ...
- predictive modeling;
  - trajectory planning and control
  - instability onset prediction
  - ...

# Large portfolio of ML/AI applications, all leverage (annotated) data availability

- Explainable and adaptive Machine Learning for disruption prevention

- Data labeling and augmentation
- DPRF + precursors' modeling
  - Density limit
  - Confinement regime identification
  - UFO disruptions
- Deep Learning modeling
  - Scenario-adaptive experiments
  - Multi-task learning
  - Transformers and CCNN
- Time-to-event frameworks
  - Survival analysis
  - Neural State Space Models + RL

- Montes, Rea et al 2021 Nuclear Fusion 61 026022
- Rath, ..., Rea et al, J. Plasma Phys. (2022), 88, 895880502
- Rea et al, Nucl. Fusion 59 (2019) 096016
- Rea et al 2021, 28th IAEA FEC, EX/P1-25
- Benjamin, Rea et al. (2024) PPCF 66 075016
- Benjamin, Rea et al. (2026) Nucl. Fusion 66 036049  
[doi:10.1088/1741-4326/ae44ad](https://doi.org/10.1088/1741-4326/ae44ad)
- Maris, Rea et al 2025 Nucl. Fusion 65 016051  
[doi:10.1088/1741-4326/ad90f0](https://doi.org/10.1088/1741-4326/ad90f0)
- J.X. Zhu, Rea et al, 2021 Nucl. Fusion 61 026007
- J.X. Zhu, Rea et al, 2021 Nucl. Fusion 114005
- J.X. Zhu, Rea et al, 2023 Nucl. Fusion 63 046009
- Spangher, Rea, Eni+MIT partnership 2025 JoFE  
<https://doi.org/10.1007/s10894-025-00495-2>
- Tinguely, Montes, Rea et al 2019 PPCF 61
- Keith, Rea et al 2024 JoFE [doi:10.1007/s10894-024-00413-y](https://doi.org/10.1007/s10894-024-00413-y)
- Boyer, Rea, Clement, Nucl. Fusion 62 (2022) 026005  
[doi:10.1088/1741-4326/ac359e](https://doi.org/10.1088/1741-4326/ac359e)
- Wang, Rea et al, 2025, Nature Comm. Physics  
<https://www.nature.com/articles/s42005-025-02146-6>
- Wang, Pau, Rea et al, 2025, Nature Comms.  
<https://doi.org/10.1038/s41467-025-63917-x>

Broader  
literature  
available

# Open source software and public datasets are crucial to develop robust ML solutions

**DisruptionPy**: an interoperable, open-source Python library for data access across different fusion devices. Enables assembly of big databases for ML applications.

<https://github.com/MIT-PSFC/disruption-py>

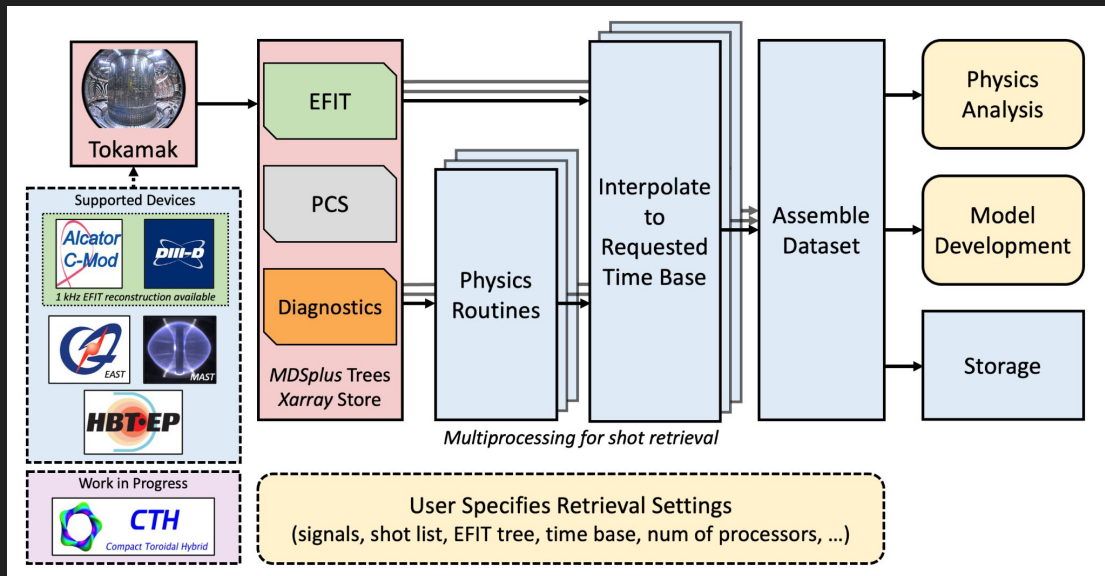
Trevisan (2026), J. Open Source Softw. 11 (119)  
[10.21105/joss.09364](https://doi.org/10.21105/joss.09364)

**C-Mod Open Density Limit Dataset**: a curated C-Mod dataset related to density limits.

[https://github.com/MIT-PSFC/open\\_density\\_limit\\_database](https://github.com/MIT-PSFC/open_density_limit_database)

**Tearing Physics Suite**: a numerically robust nonlinear tokamak tearing analysis tool for large-scale database generation.

<https://github.com/MIT-PSFC/tearing-physics-suite>



# DisruptionPy: interoperable library for data retrieval and database development across different devices

- ✓ Modular structure + version controlled
- ✓ Adopted automated unit testing, linting, and deployment workflows
- ✓ Available for **Alcator C-Mod**, **DIII-D**, **EAST**, and now supporting **MAST** open data!



★ Trevisan, Rea and the MIT Disruptions team  
<https://github.com/MIT-PSEC/disruption-py>  
- 2025 Zenodo DOI: [10.5281/zenodo.13935223](https://doi.org/10.5281/zenodo.13935223)  
- 2026 JOSS 11 (119) DOI: [10.21105/joss.09364](https://doi.org/10.21105/joss.09364)

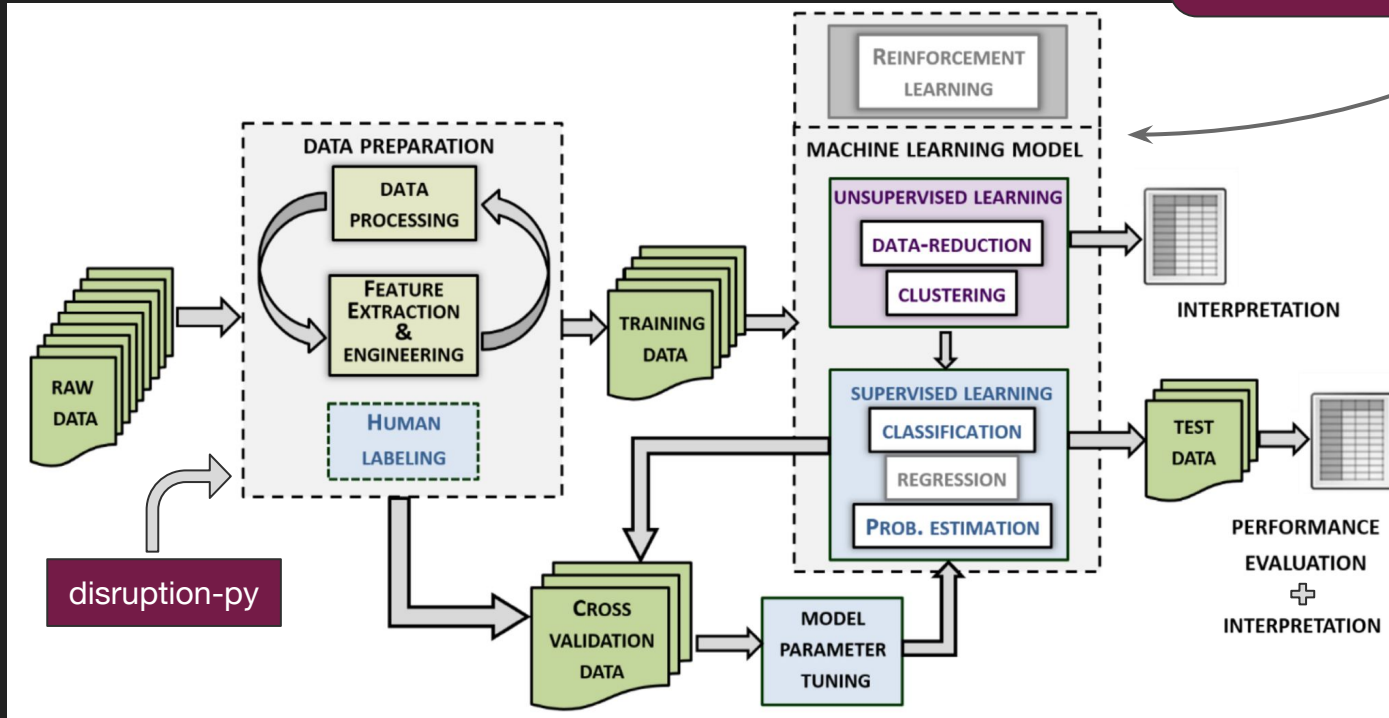
Machine	Methods	Features	Shots
C-Mod	22	62	35,000
DIII-D	20	59	75,000
EAST	31	82	40,000
HBT-EP	12	35	35,000
MAST	4	20	10,000

- ✓ Recomputed EFIT with finer time resolution of 1 kHz to support analysis of faster timescale physics
- ✓ Adopted multi-backend support to allow access to both *MDSplus* and *xarray* databases.
- Continue expanding support to new devices e.g. CTH & HBT-EP
- Integrate physics and ML-driven event labeling workflows into data pipeline, and adopt *MLOps* best practices
- **Release curated disruption prediction datasets by the end of 2026**

# Data-driven learning for disruption prevention and performance optimization

Overview of ML workflow

- Disruption Prediction (DPRF)
- Disruption Precursors' modeling
- Time-to-event frameworks



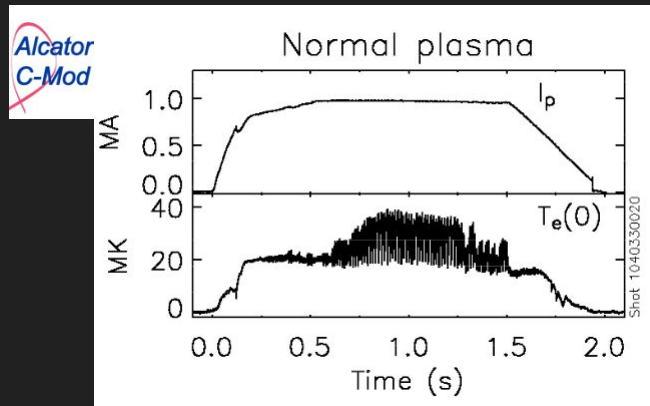
Adapted from A. Pau et al,  
Nuclear Fusion, 59(10):106017,  
2019

# Outline

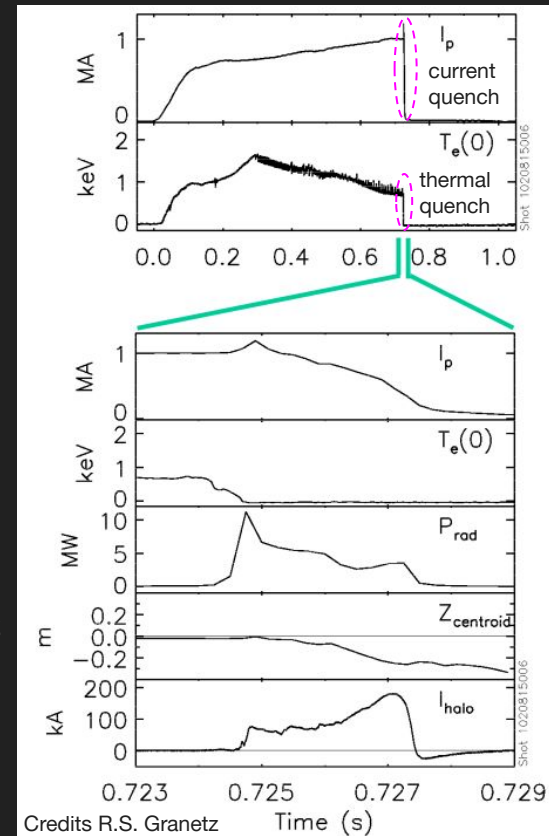
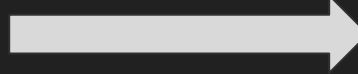
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1. Data and Machine Learning
2. Disruptions and controllability or rather, *why we don't have ROMs*
3. Explainable and adaptive Machine Learning for disruption prevention
4. Conclusions

# Plasma pushed close to operational limits → instabilities onset or control faults: disruptions



Disruptive plasma:

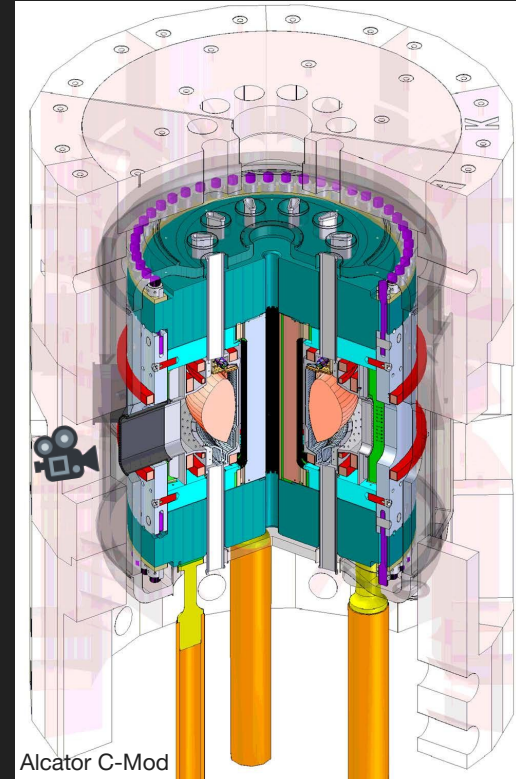


Final loss of control evolving on timescales of milliseconds:

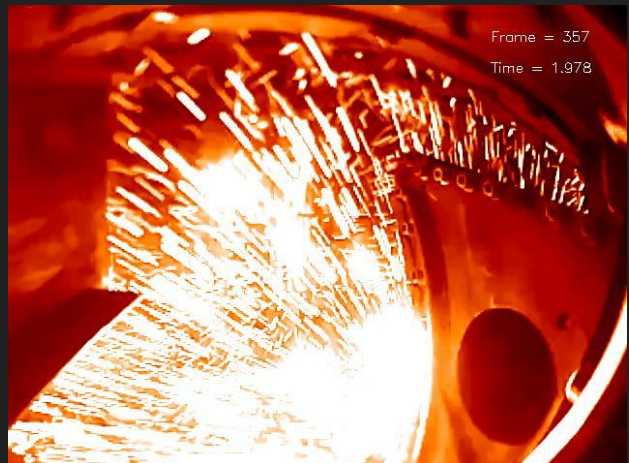
- Fast drop  $I_p$  leads to loss of confining poloidal field
- Fast  $I_p$  transient leads to large induced voltages/currents/forces
- Rapid thermal losses leads to surface damage

# What a disruption looks like:

Visible camera view of RE beam hitting Alcator C-Mod first wall. Courtesy R.A. Tinguely



# Rapid energy loss during disruptions causes strong electric field → runaway electron beam

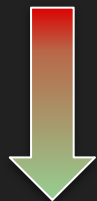


Visible camera view of RE beam hitting Alcator C-Mod first wall. Courtesy R.A. Tinguely

melting! →



JET runaway electrons damage.  
<https://www.iter.org/newsline/-/2234>



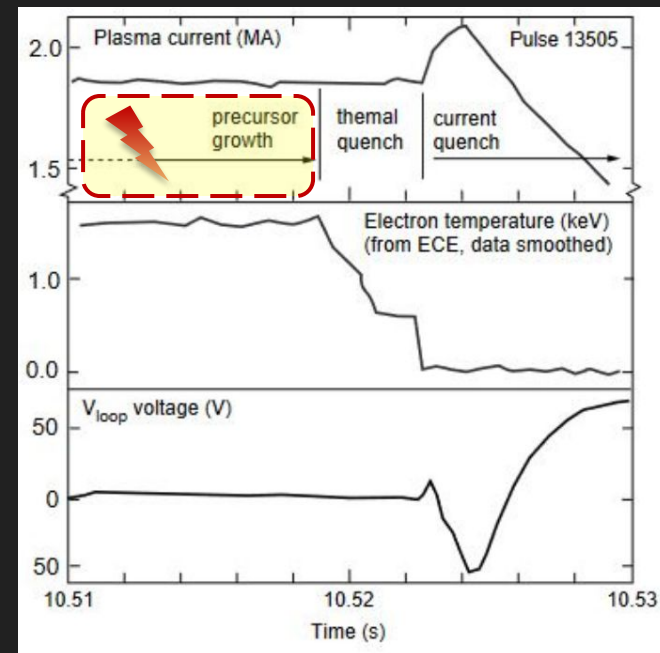
**Accept** the damage and live with it.

**Mitigate** the damage by injecting massive gas (or shattered pellets or passive coils).

**Avoid** altogether by detecting precursors & steer plasma away from disruptive boundary.

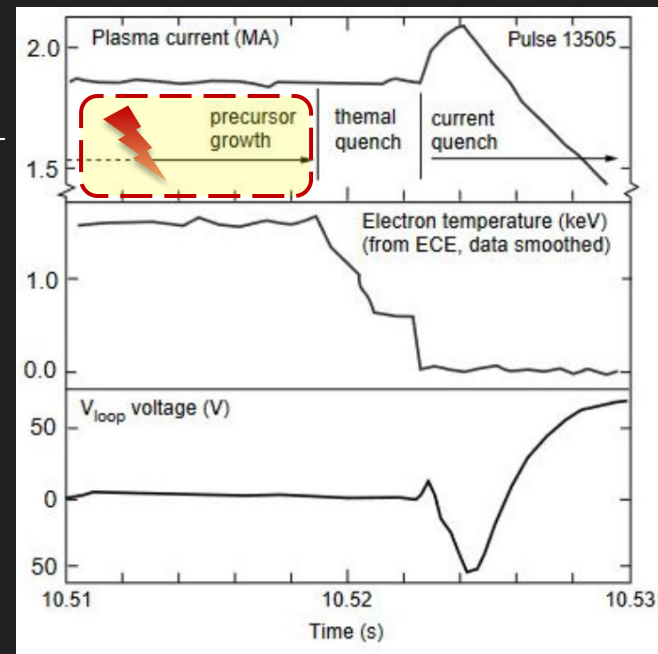
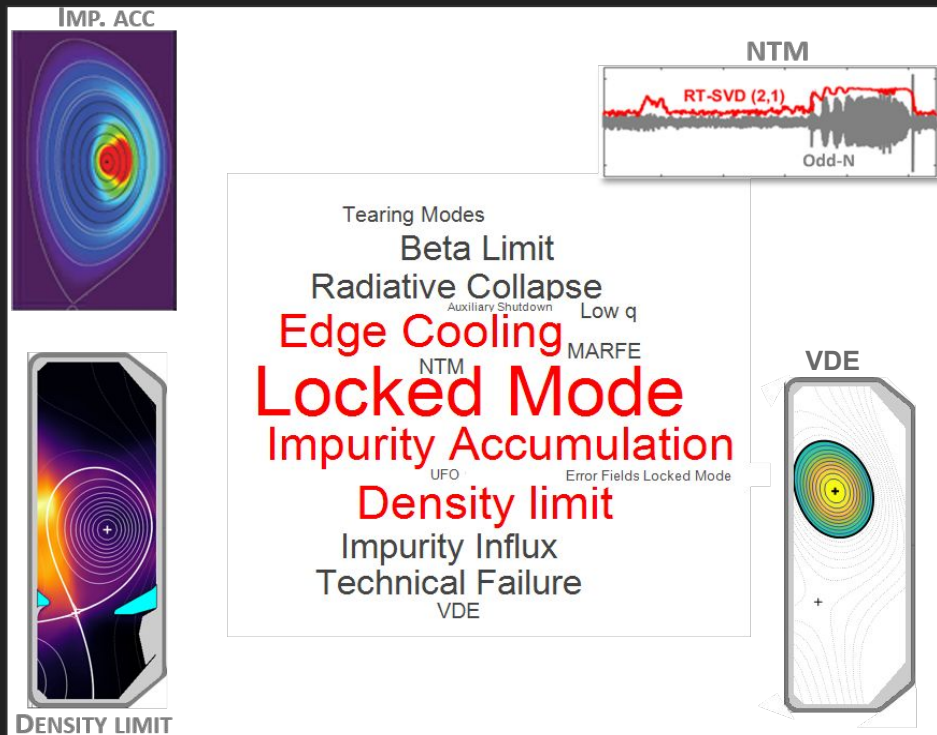
Next gen  
devices  
disruption  
rate < 1% !

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



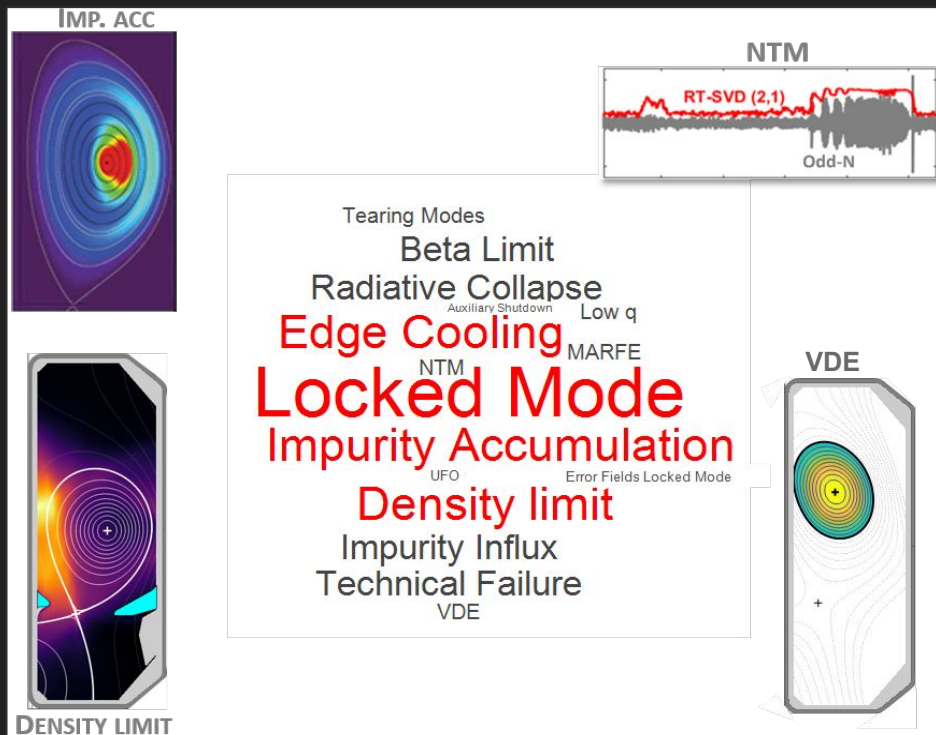
ITER Physics Expert Group on Disruptions, Plasma Control, and MHD (1999) Nucl. Fusion 39 2251

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



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

# No first-principle model to capture full pre-disruptive chain of events



- Statistical studies on disruption frequency (and type) not available across different tokamaks.
- Notable efforts on event analyses:  
KSTAR, MAST, NSTX/-U dbs → **DECAF**<sup>1</sup>  
JET, TCV → **DEFUSE**<sup>2</sup>  
  
<sup>1</sup>Sabbagh et al PoP 30 032506 (2023)  
<sup>2</sup>Pau et al 29th IAEA-FEC (2023)
- Wealth of experimental data from different tokamaks enables “**learn from data**” paradigm → ML
- The timely identification of **precursors** allows the plasma control system (PCS) to take proper **avoidance** action → extend discharge lifetime ( $\tau$ ) → make fusion!

# Outline

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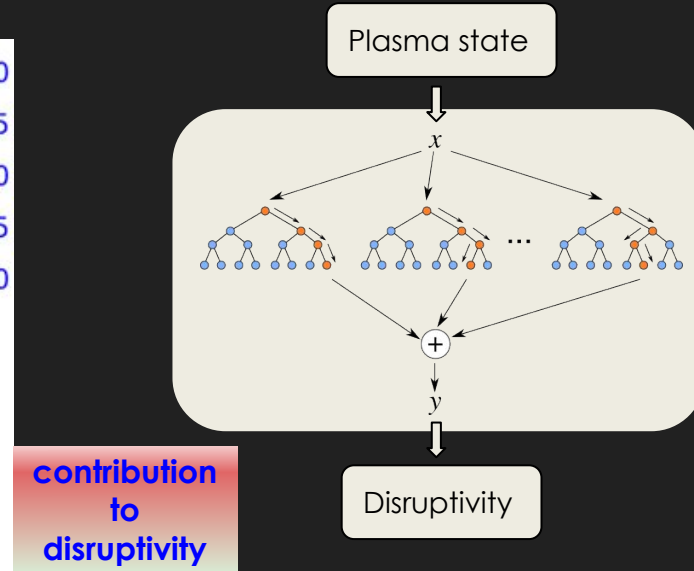
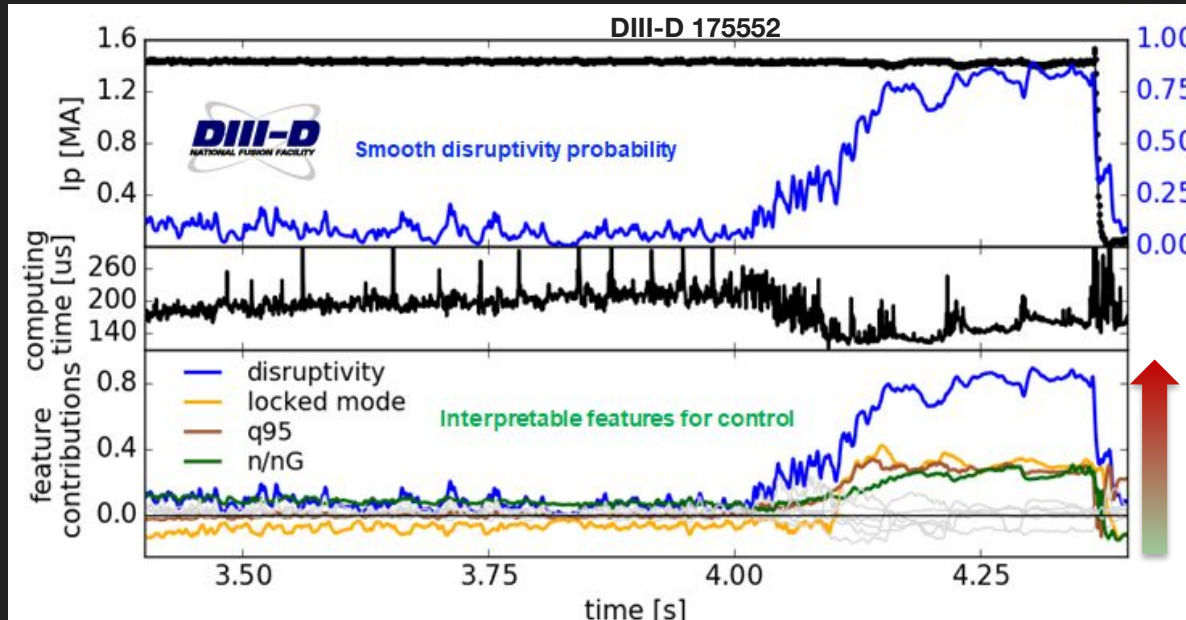
1. Data and Machine Learning
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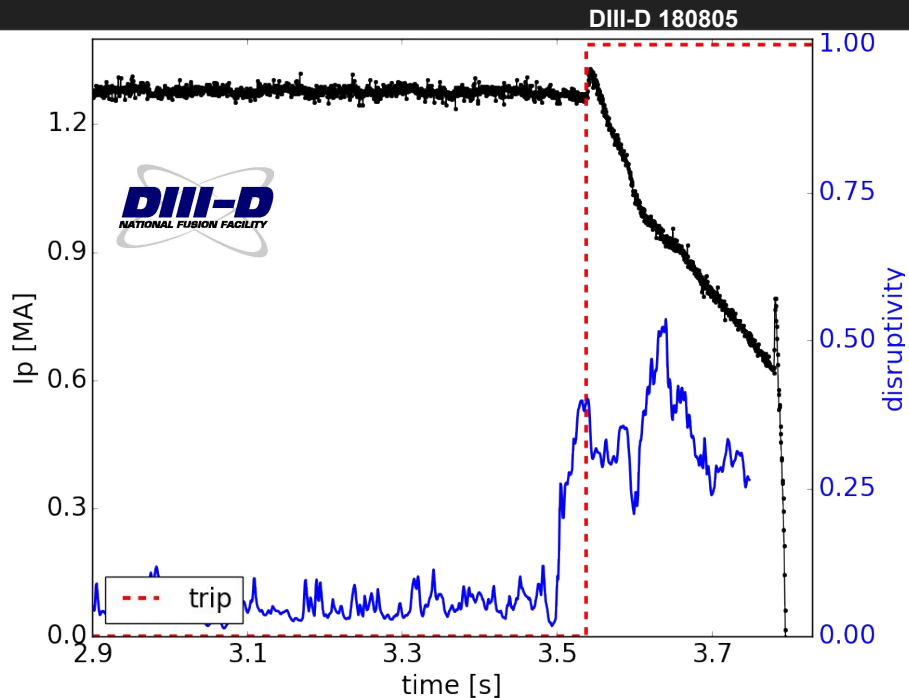
Available in real-time at DIII-D

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

- **D**isruption **P**rediction via **R**andom **F**orest (DPRF) computes probability of an impending disruption, while interpreting its drivers in real-time.
  - Available on DIII-D (and EAST).



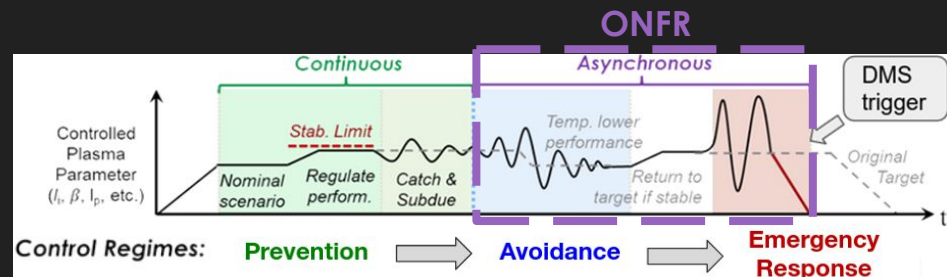
# Real-time implementation and optimization for asynchronous avoidance and emergency response



Real-time model evaluation and feature contribution computation:  $< 200 \mu\text{s}$

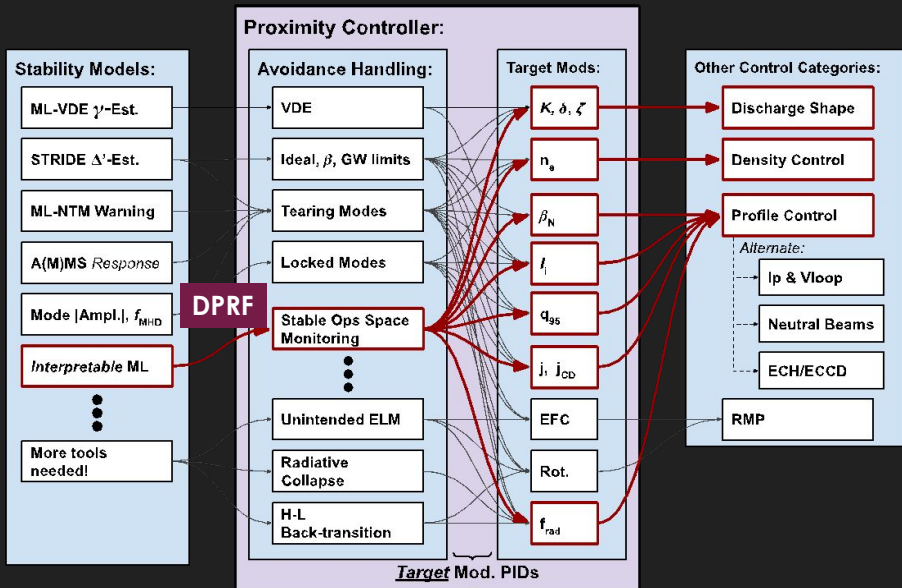
Successful ONFR integration:

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

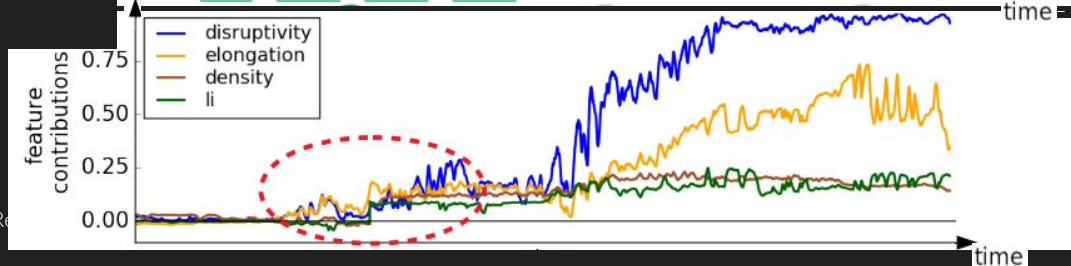
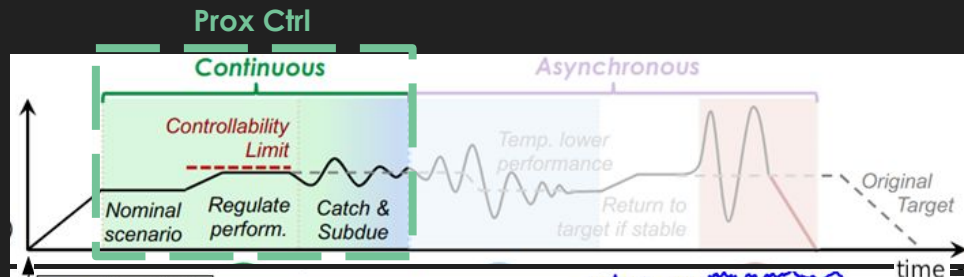


★ Rea et al, 2021 IAEA EX/P1-25

# DPRF + Proximity Controller: continuously regulate plasma stability and performance



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



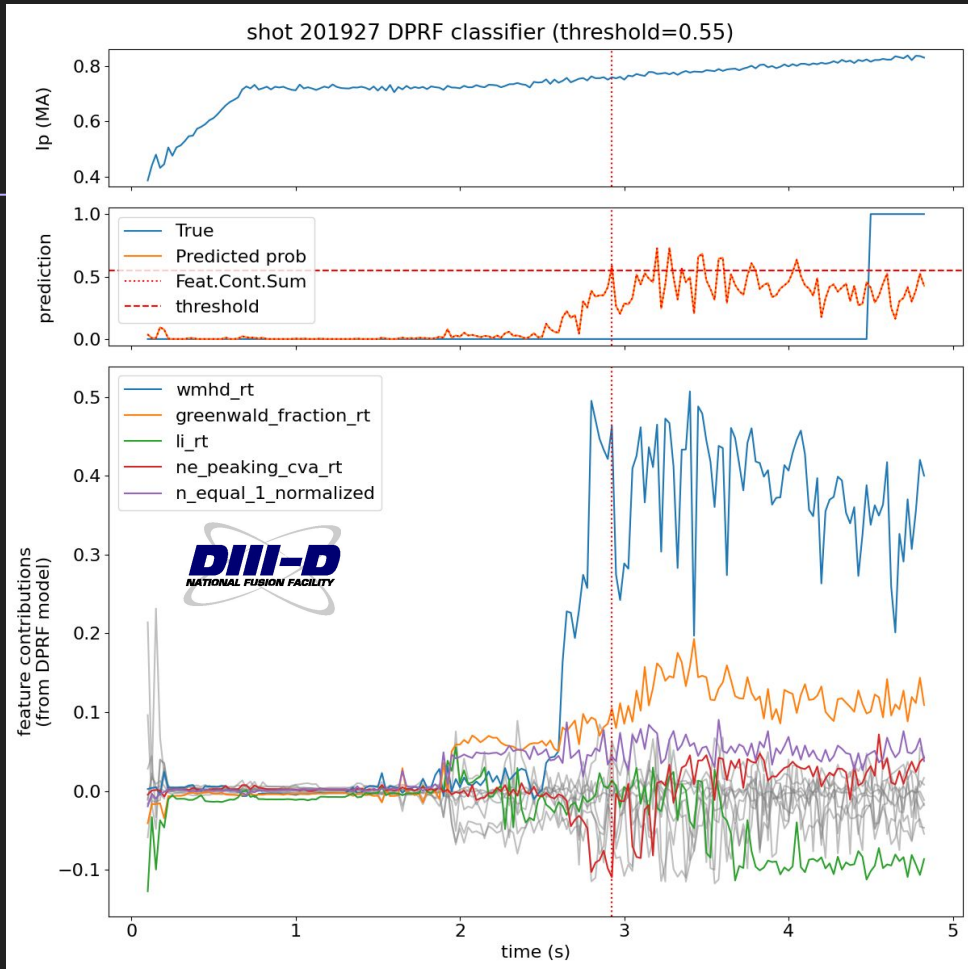
$$\Delta\kappa = PID \left[ f_{danger} * f_{\kappa,contrib} * \text{sign} \left( \frac{d\kappa}{dt} \right) \frac{\Delta\kappa_{target}}{\Delta f_{\kappa,contrib}} \right]$$

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

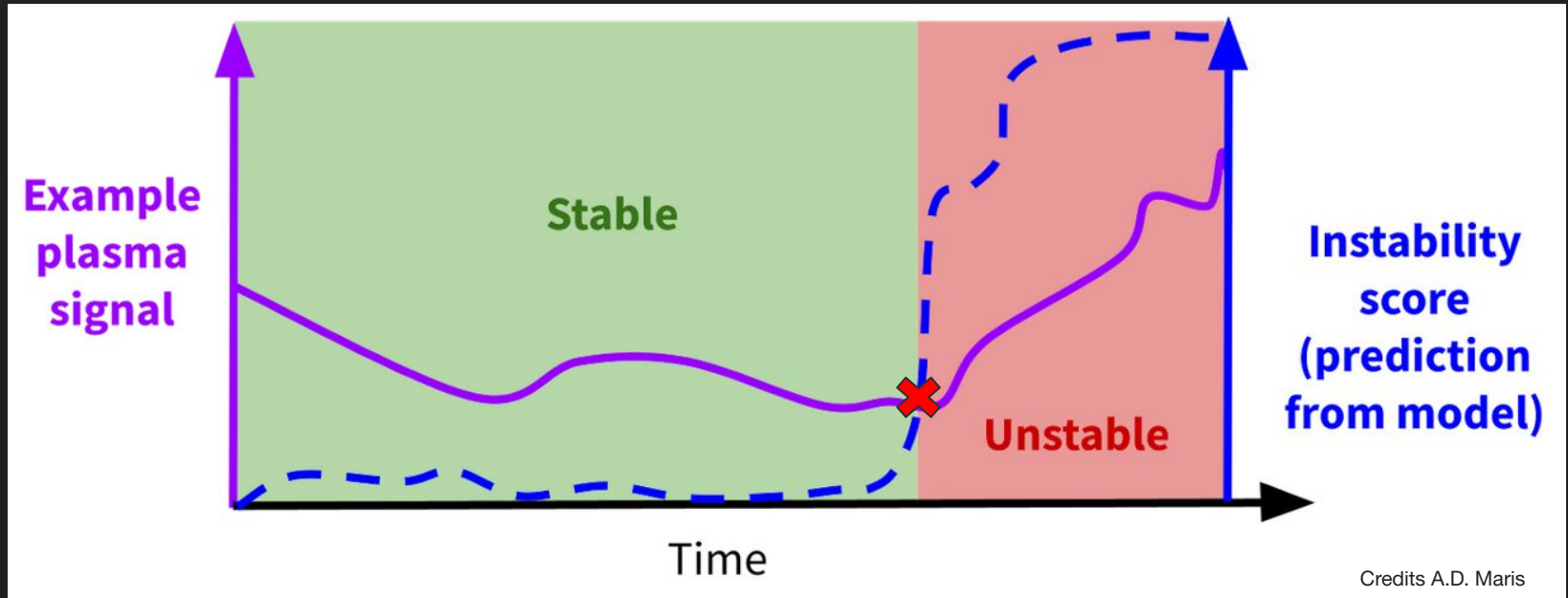
# DPRF + ProxCtrl tested in exp ~3 weeks ago

- Retrained DPRF with high betap / SVR scenario data. DisruptionPy enabled the quick retraining.
- PID control of target actuators (beams, gas) using feature contributions obtained from SHAP analysis on DPRF.
- DIII-D experiment March 24, 2026 as part of the 2025 AI Task Force. Data analysis is currently in progress.

*Experiment led by Y. Wei, A. Kumar, J. Barr  
Manuscript under preparation, 2026*



# DPRF: “gray box” + post-hoc explanation for generic disruption prediction



Shift focus on interpretable models for precursors' onset

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

density  
limit

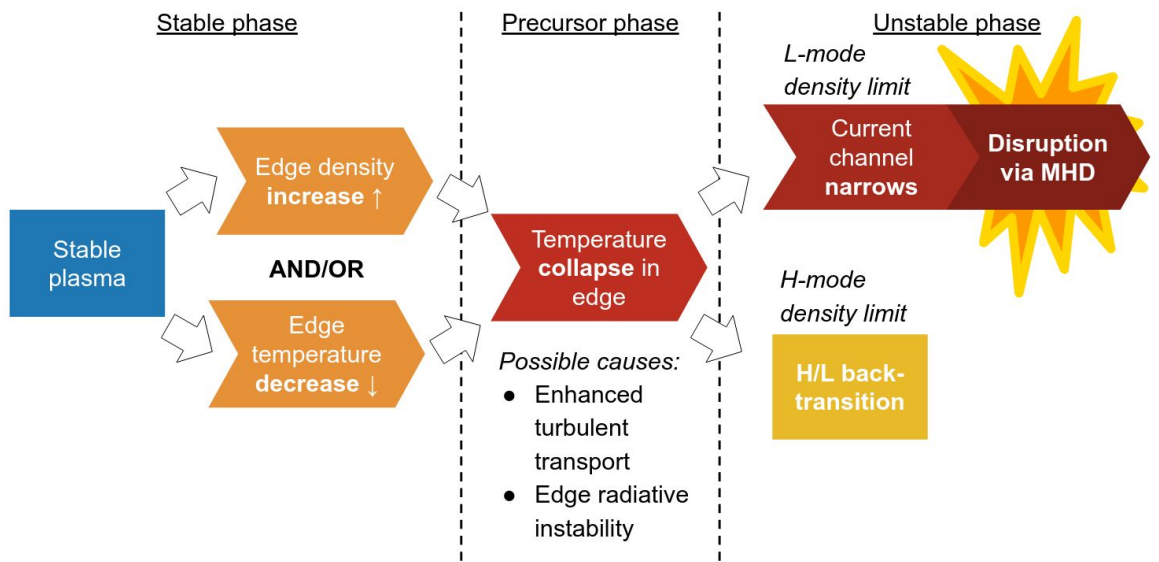
Density is critical design parameter, fusion power density  $\propto n^2$

Power plant design points usually close to empirical density limit

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

Greenwald et al., Nucl. Fusion (1988)

## Density limit phenomenology



Broad literature & multi-machine data available.

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;  
...


Interpretable tools needed to understand & avoid density limit events.

★ Maris, Rea et al 2025 Nucl. Fusion 65 016051  
[doi:10.1088/1741-4326/ad90f0](https://doi.org/10.1088/1741-4326/ad90f0)

# Recursive feature selection + ML-driven boundary id enables interpretable stability metric

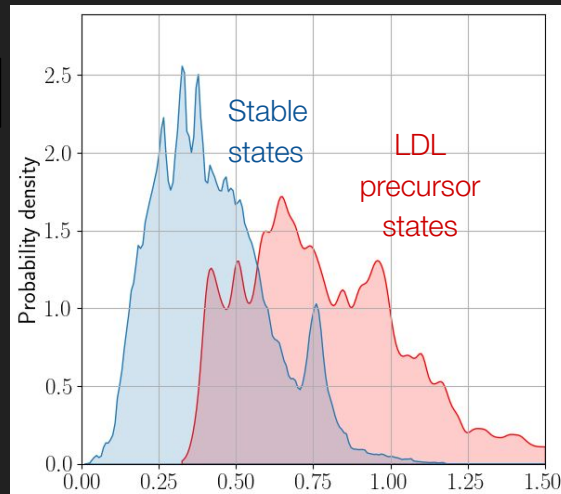
density  
limit

- L-mode density limit (LDL) database developed using: Alcator C-Mod, DIII-D, AUG, TCV
- LDL precursor risk metric:  $\nu_{*,\text{edge}}\beta_{T,\text{edge}}^{0.5}$

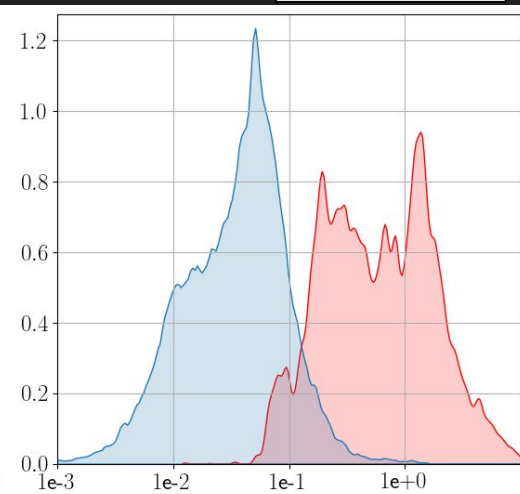
→ yields 4x fewer false positives than Greenwald 

- H-Mode analyses expanded to 5 tokamaks (348 DL events)

Greenwald fraction



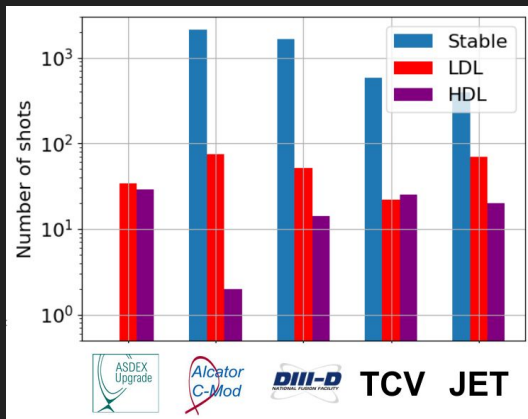
Risk metric:  $\nu_{*,\text{edge}}\beta_{T,\text{edge}}^{0.5}$



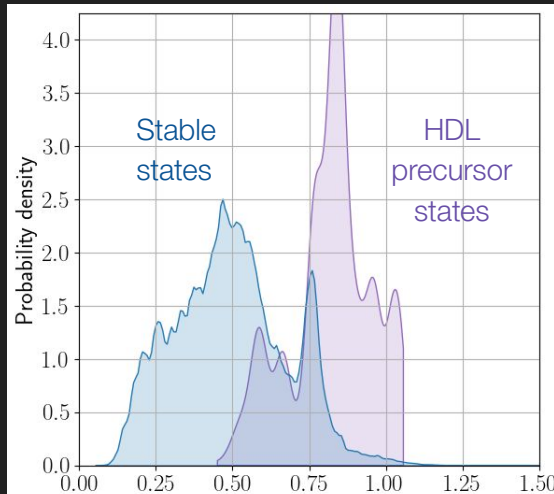
# LSVM+sequential feature selection → Risk metric integrated in real-time DIII-D PCS

density limit

# samples: ~4000 stable shots (1.5e6 timeslices), ~90 H-mode density limit events (768 HDL time slices),  
 Features: ~20  
 Size: full database is 2.5 GB

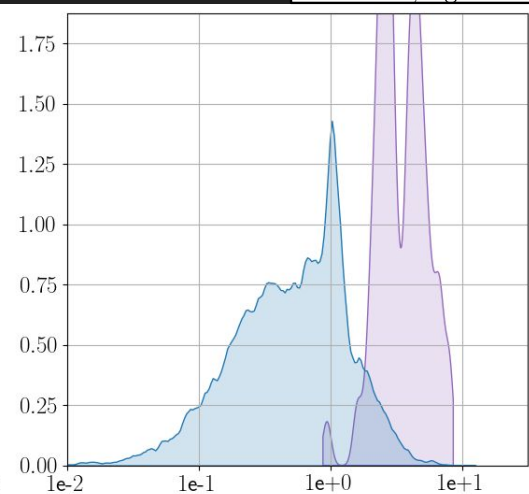


Greenwald fraction



Risk metric:

$$\frac{\nu_{*,edge} \beta_{T,edge}^{0.9} q_*^{1.1}}{\rho_{*,edge}^{0.8}}$$

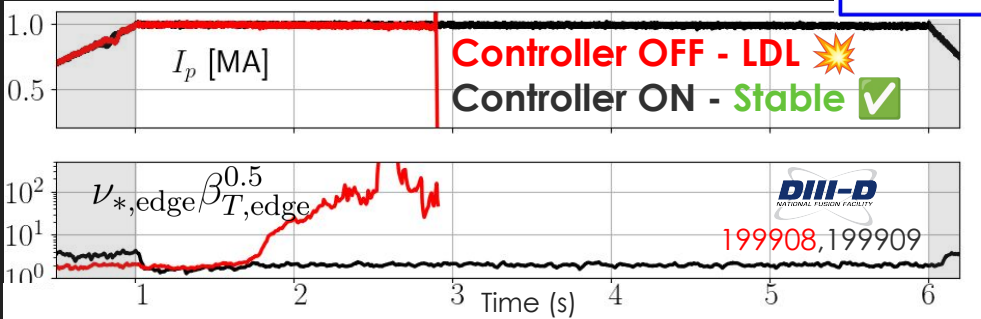
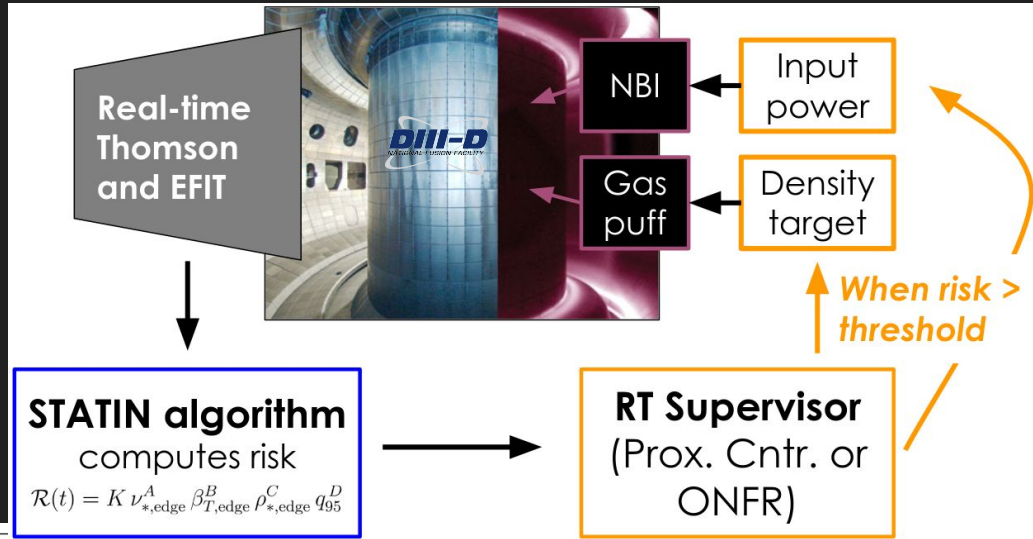
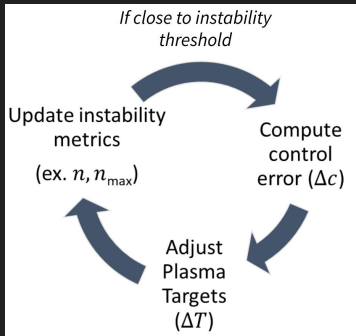


→ yields 2x fewer false positives than Greenwald ✓

★ Maris, Rea et al 2026 NF 66 056002 "Real-time avoidance of the L-mode and H-mode density limit via machine-learned stability metrics" [doi:10.1088/1741-4326/ae4efe](https://doi.org/10.1088/1741-4326/ae4efe)

# Real-time trajectory steering accomplished via Proximity Controller integration

- Goal: get as close to original targets as possible while extending discharge lifetime
- Regulation via perturbation of targets



Reproducible results, varying actuators' response

★ Maris, Rea et al 2026 NF 66 056002 doi:10.1088/1741-4326/ae4efe

# Interpretable ML leverages multi-machine database to extract new density limit (DL) scalings

## L-mode DL

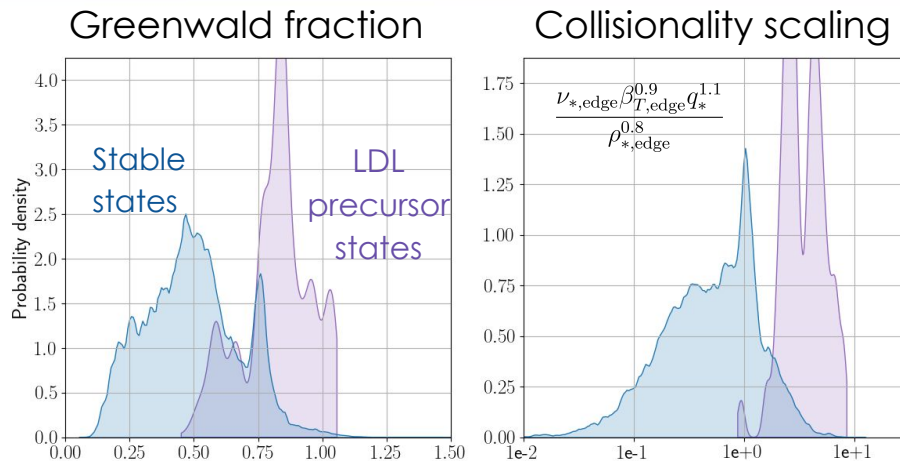
$$\nu_{*,edge} \beta_{T,edge}^{0.49}$$

## H-mode DL

$$\frac{\nu_{*,edge} \beta_{T,edge}^{0.88} q_*^{1.09}}{\rho_{*,edge}^{0.80}}$$

≥2x fewer false positives than Greenwald fraction 

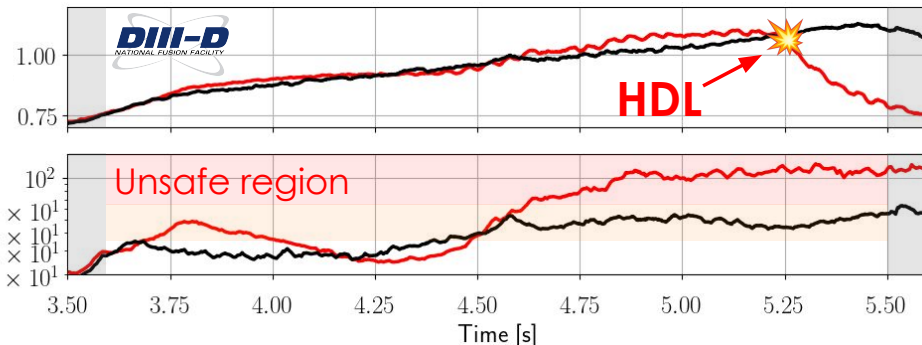
- Collisionality scalings utilized for real-time DL avoidance



$n/n_G$

Control metric:

$$\frac{\nu_{*95} \beta_T^{0.8}}{\rho_*^{0.6}}$$



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  - Disruption Precursors' modeling
  - Time-to-event frameworks or rather, *trajectory design*\*
4. Conclusions

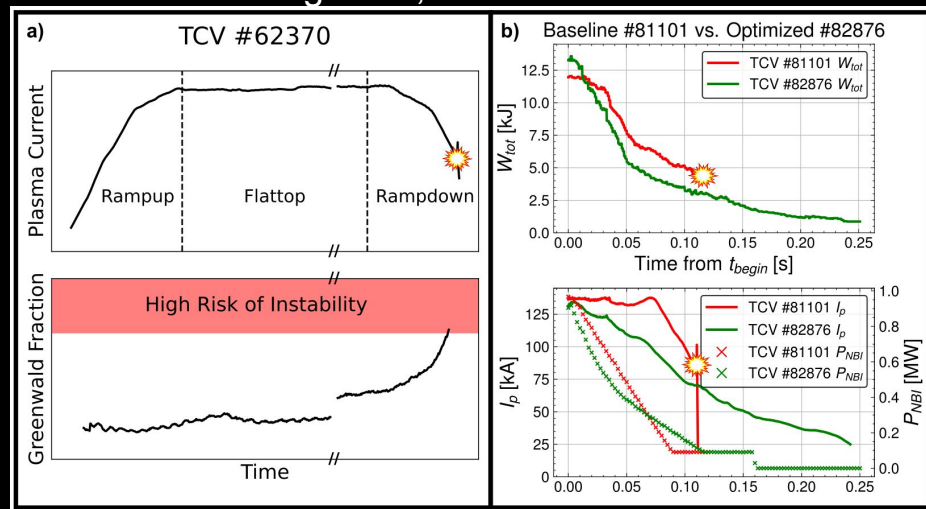
TCV experiments

*\*slides freely taken from Allen Wang's thesis defense (Jan 2026)*

# Original Motivation & Overview: Ramp-down Control + Trajectory Optimization

- **Problem:** rampdowns can push the plasma closer to instability limits
- Some limits (e.g. Greenwald fraction) are related to kinetic dynamics (temperature and density)
- Motivates simulation of plasma temperature and density evolution in response to control knobs (extremely challenging from a pure physics perspective)

Wang et al., 2025 Nature Comms.



- **SciML kinetic dynamics model** → for rampdown trajectory optimization of a high-performance scenario ( $\beta_N \sim 2$ , Greenwald Fraction  $\sim 0.8-1$ )
  - Only trained for rampdowns
  - Also predicts density dynamics and vertical instability growth rates

# Neural State-Space Models

- For control, it's important to have actions and observations in the model structure
- Classically, often done with linear state-space models
  - **Many** applications to real-world systems, including aircraft
- Modern ML frameworks allow us to program NSSMs with arbitrary combinations of physics + networks

## Linear State-Space Model

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{a}$$

$$\mathbf{o} = \mathbf{C}\mathbf{x} + \mathbf{D}\mathbf{a}$$

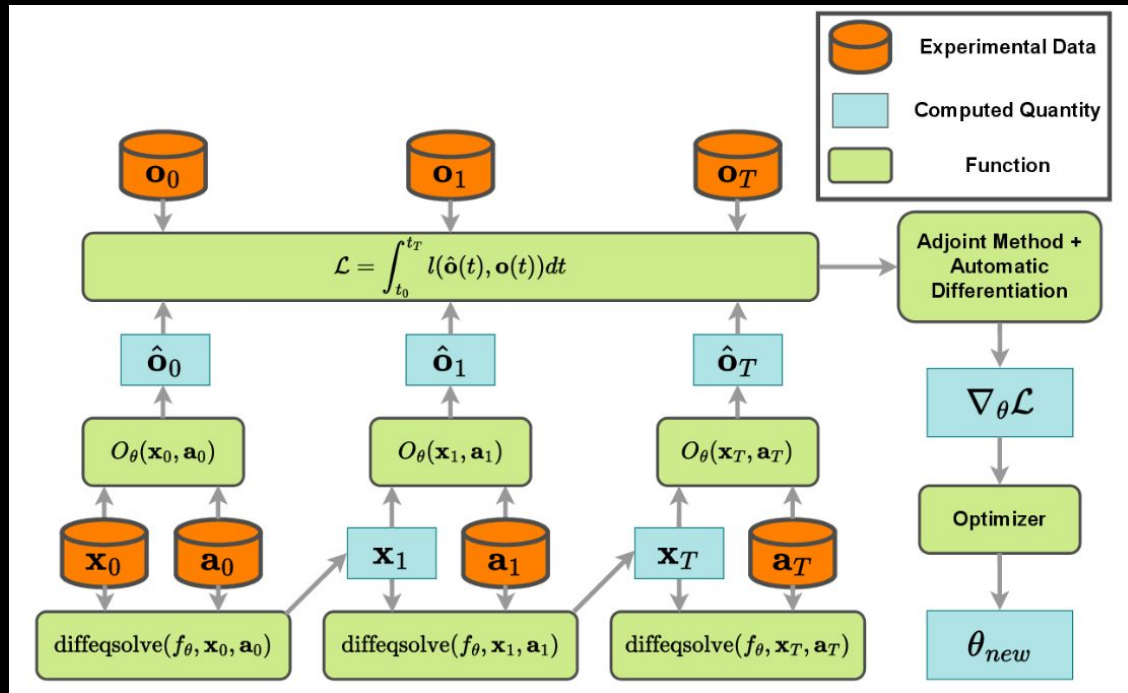
## Nonlinear State-Space Model or Neural State-Space Model (NSSM)

$$\dot{\mathbf{x}} = f_{\theta}(\mathbf{x}, \mathbf{a})$$

$$\mathbf{o} = O_{\theta}(\mathbf{x}, \mathbf{a})$$

# SciML + JAX enable time-dependent model training

- A neural network  $f(\theta)$  can be used as a system of differential equations that is integrated forward in time with a differential equations solver, and then adjoint back-propagation methods can be used in conjunction with automatic differentiation to determine the gradient of loss with respect to the network parameters  $\theta$



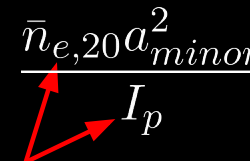
# From Observables to Actuators and Considered Constraints

$W_{tot}$	Plasma total stored energy
$\langle n_e \rangle$	Line-averaged electron density
$\langle n_{g,frac} \rangle$	Greenwald fraction
$\beta_p$	Plasma poloidal beta
$l_{95}$	Rotational transform at the 95% flux surface
$\gamma_{vgr}$	Vertical Growth Rate
$T_e(\rho)$	Electron temperature profile (not predict-first)
$n_e(\rho)$	Electron density profile (not predict-first)

$dI_p/dt$	Plasma current ramp-rate [MA/s]
$dP_{NBI}/dt$	NBI heating ramp-rate [MW/s]
$d\kappa/dt$	Elongation ramp-rate [1/s]
$da_{minor}/dt$	Minor radius ramp-rate [m/s]

## Plasma Constraints

**Greenwald Fraction**

$$f_{GW} \propto \frac{\bar{n}_{e,20} a_{minor}^2}{I_p}$$


Decreasing plasma current worsens the problem, and density dynamics are slow

**Rotational Transform**

$$l_{95} \propto \frac{I_p}{a_{minor}^2 (1 + \kappa^2)}$$

Need to avoid kink instability limits while changing shape + Ip

**Vertical Instability Growth Rate**

Need to manage as we change shapes + plasma current

**Poloidal Beta**

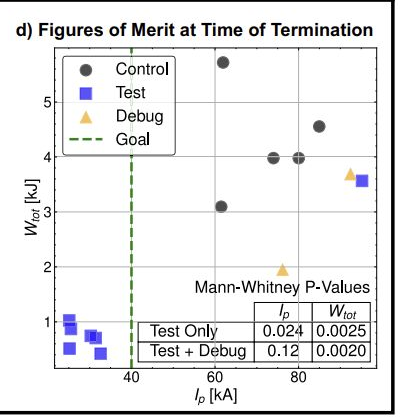
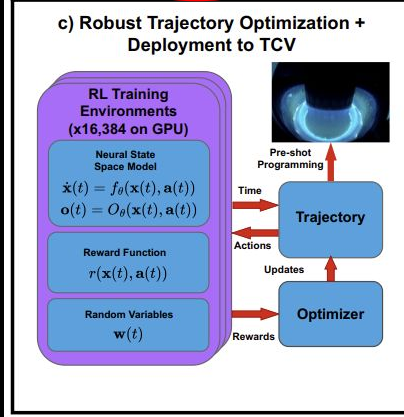
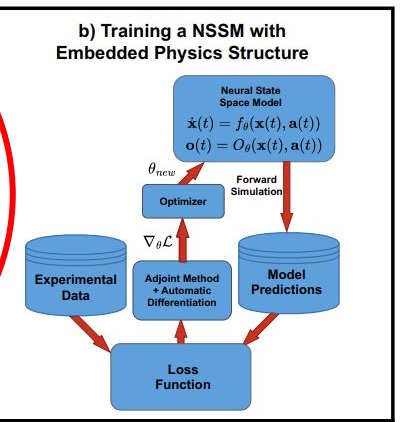
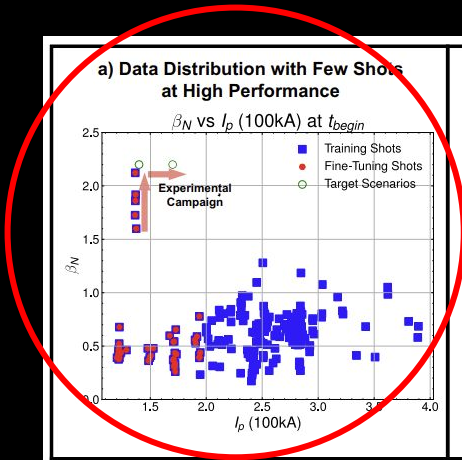
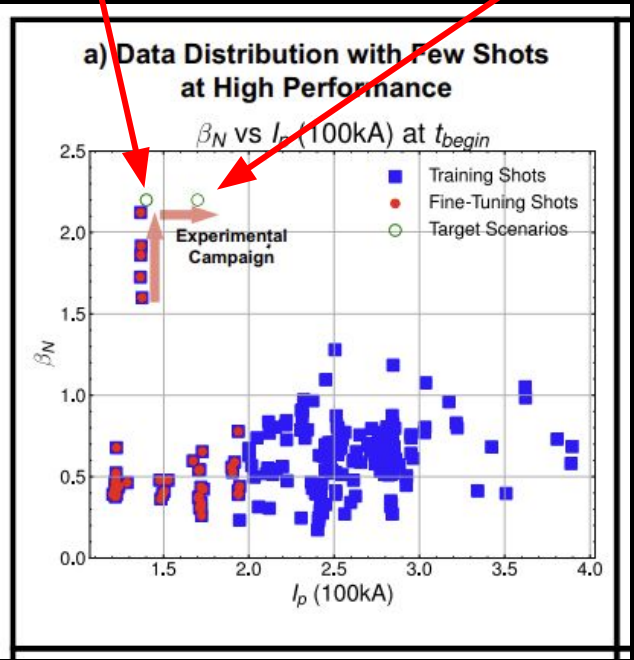
Loosely correlated with NTM drive

# The target goal:

Can we manage this scenario (140kA, baseline high performance), with minimal data?

Can the model extrapolate a bit to this scenario with zero data?

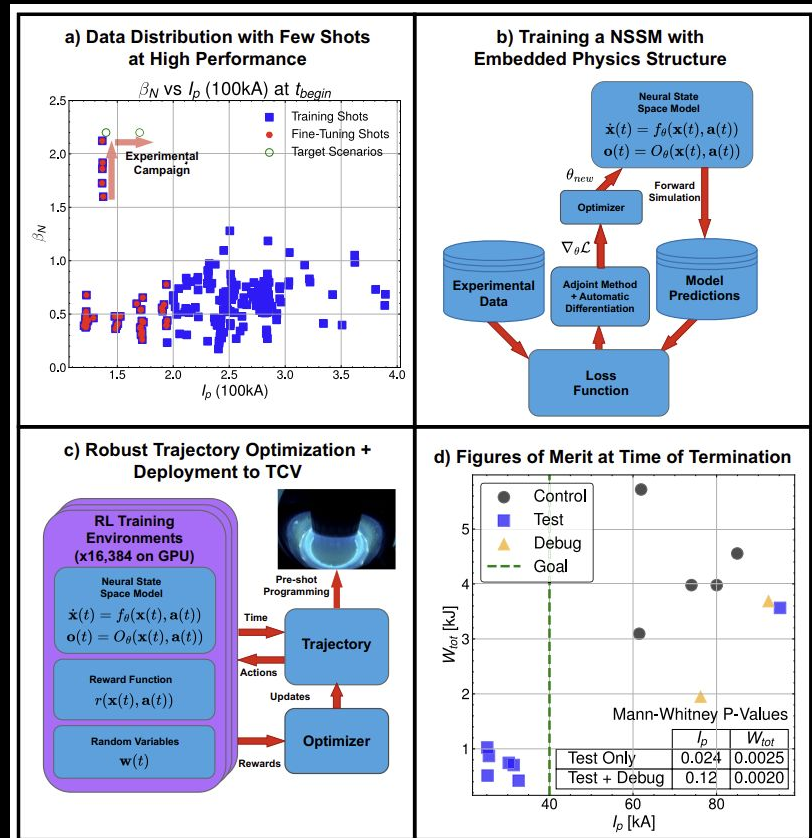
~400 shots  
~2GB



b) We train a NSSM with embedded physics structure: 0D energy and particle balance equations, which is a model that blends simple physics principles, power laws, and NNs

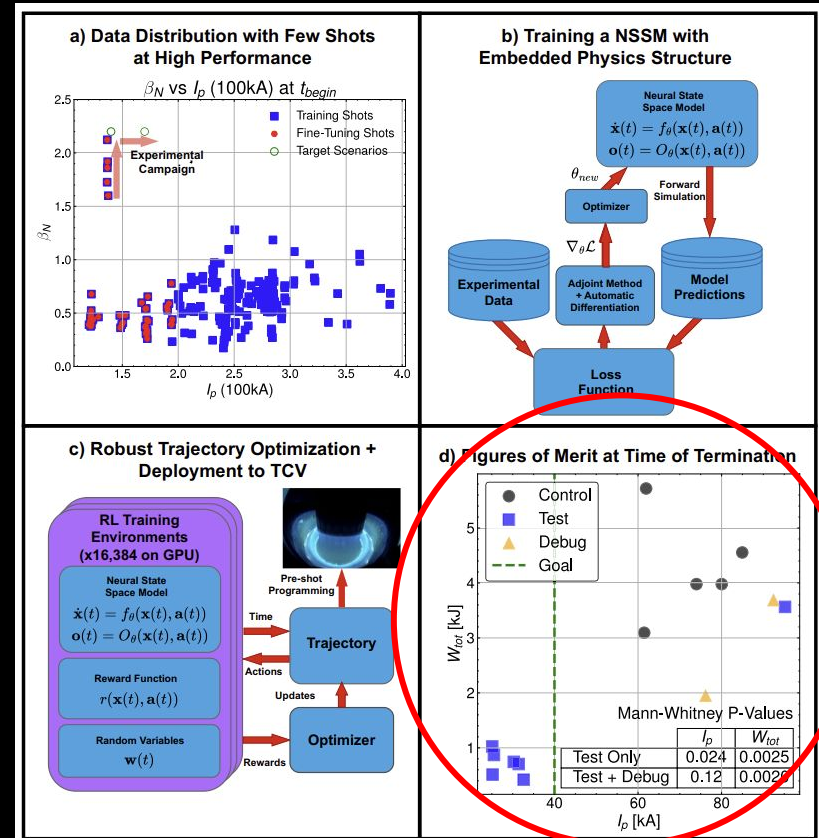
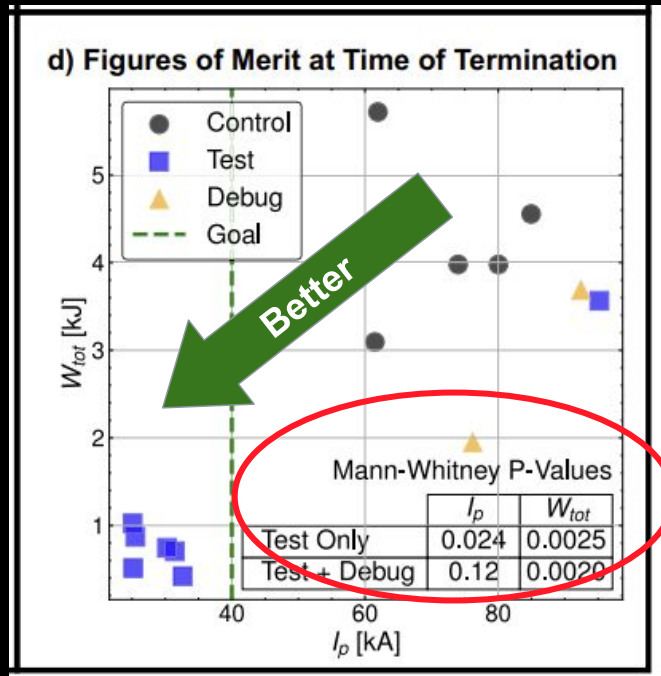
$$\frac{dW_{tot}}{dt} = - \underbrace{\frac{W_{tot}}{\tau_{E,pred}}}_{\text{Transport}} + \underbrace{I_p^2 NN_{ohm,rad,0}(\mathbf{x}, \mathbf{a})}_{\text{Ohmic Heating}} - \underbrace{\bar{n}_{e,20} V NN_{ohm,rad,1}(\mathbf{x}, \mathbf{a})}_{\text{Radiated Power}} + \underbrace{P_{NBI} + P_{ECRH}}_{\text{Aux. Heating}}$$

$$\frac{d(\bar{n}_{e,20} V)}{dt} = - \underbrace{\frac{\bar{n}_{e,20}}{\tau_{n,pred}}}_{\text{Transport}} + \underbrace{c_{NBI} P_{NBI}}_{\text{NBI Fueling}} + \underbrace{c_{gas,0} \sigma (c_{gas,1} V_{gas} + c_{gas,2})}_{\text{Gas Valve Fueling}} + \underbrace{NN_{wall}(\mathbf{x}, \mathbf{a}) \exp^{-c_{wall} g_{HFS}}}_{\text{Wall Effects}}$$



c) "RL gym" allows id of optimal trajectory ~ RL Policy that Only Observes Time

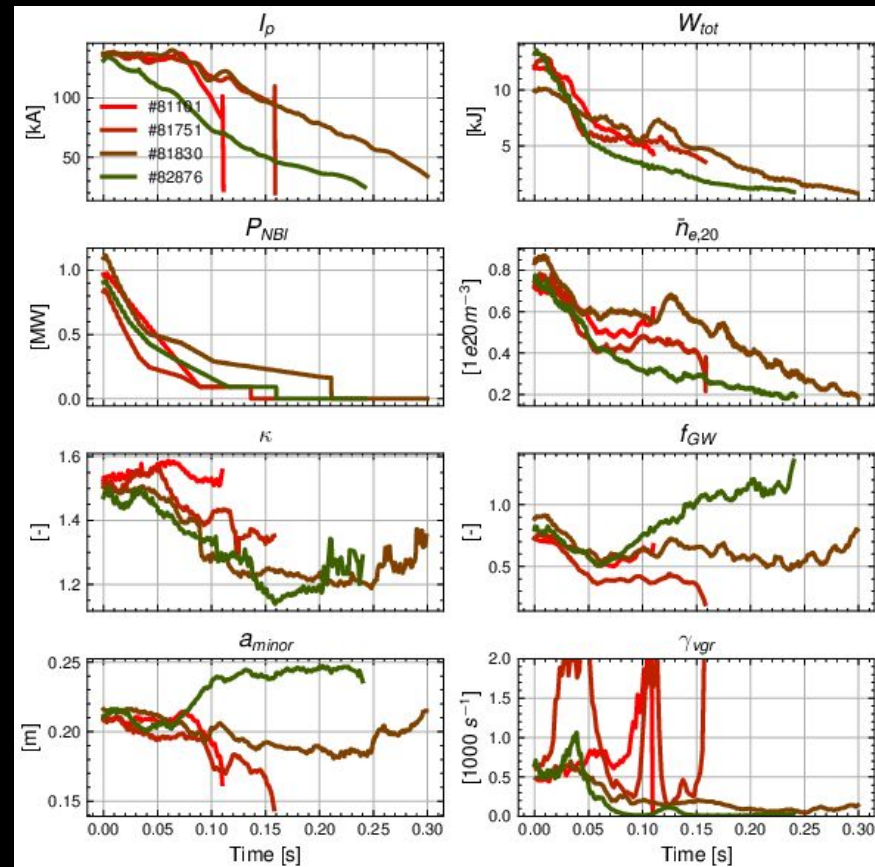
Statistical test provides degree of confidence there was improvement\*



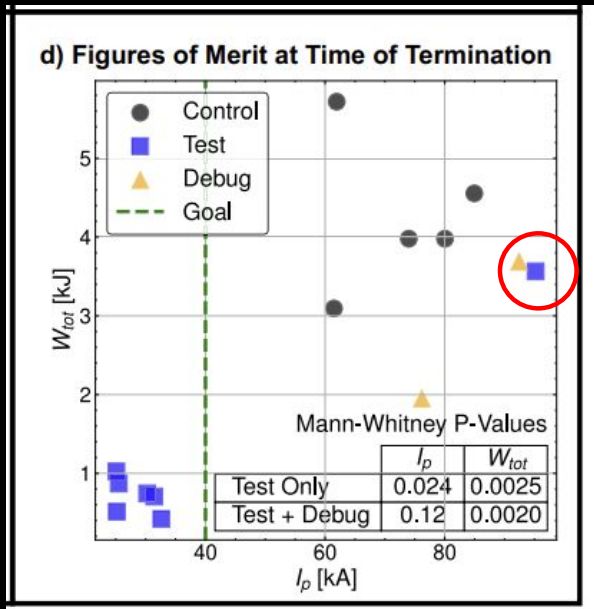
\*Tokamaks are stochastic w/ distributional drift, some skepticism is important in the absence of overwhelming statistics

# Continuous Model Validation + Updates for Incremental Improvements

- Continuously updated dynamics model + trajectories to new data
- Trajectories became faster and non-disruptive over time

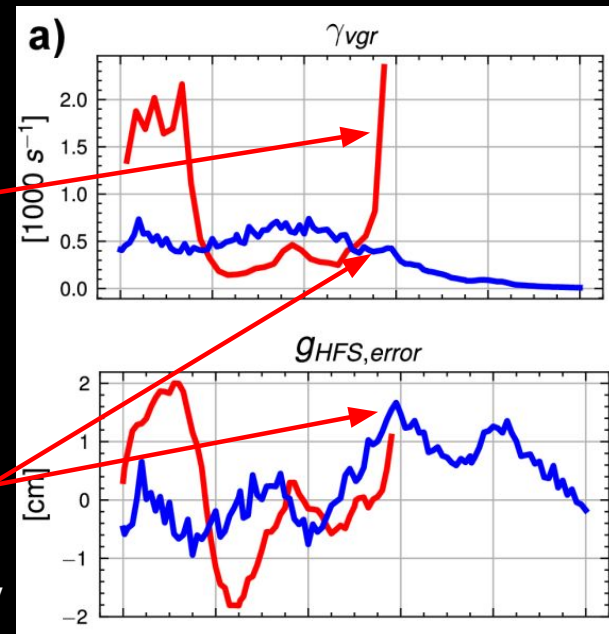


# Adding Robustness After Failure



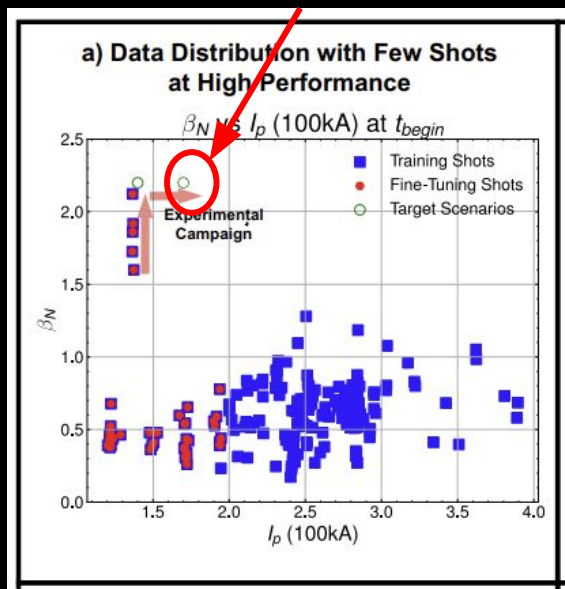
Analyzing this pulse, the designed trajectory was highly sensitive to control error

Adding a distribution to the RL environment resulted in a trajectory with similar control error, but better stability (blue)

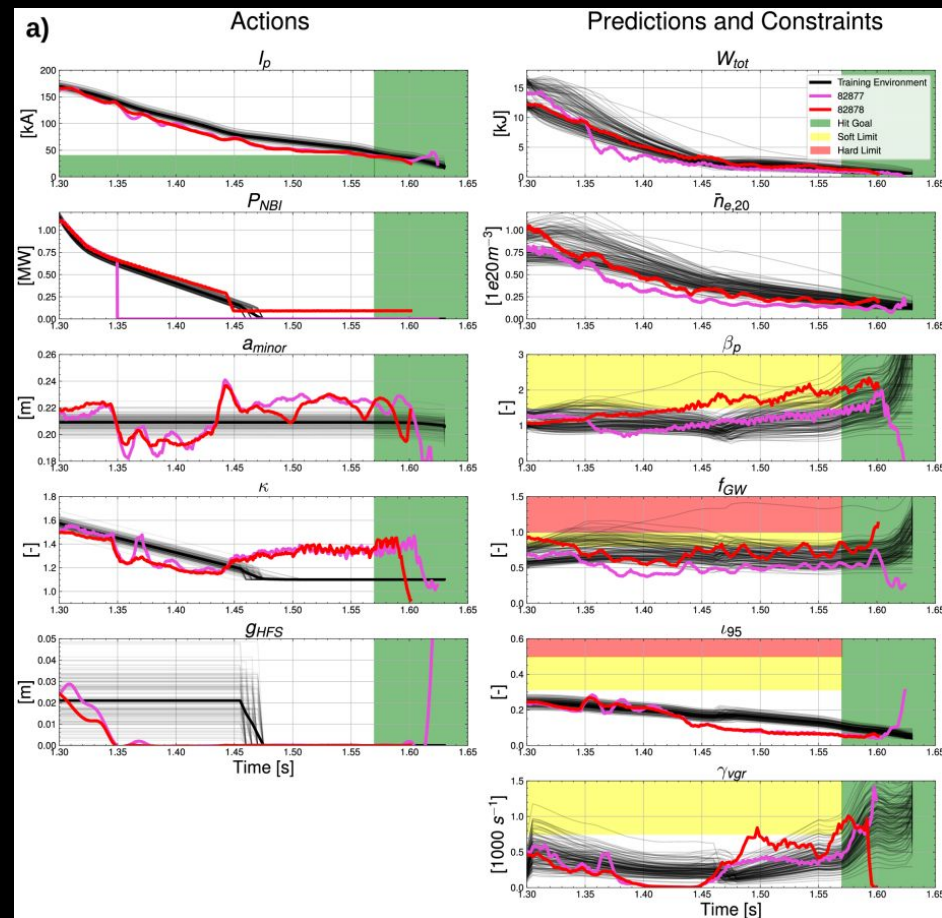


# Predict-First

Can the model design a non-disruptive trajectory and make a priori predictions slightly out-of-distribution?



Yes!



# In summary: SciML for Kinetic Dynamics (NSSM) shown useful for rampdown trajectory optimization

- Demonstrated that a RL-based approach to rampdown robust trajectory optimization can help manage disruptivity
  - Accounting for distributional uncertainty has been previously assumed to be infeasible
  - Multi-actuator trajectory optimization with success on experiment is very rare
- Biggest limitation: we did not address tungsten
  - TCV is a carbon wall machine
  - Tungsten is a major challenge for rampdowns on high performance machines
- Developed approach may be promising for full-pulse trajectory optimization
- Framework components now open-sourced!  
<https://github.com/MIT-PSFC/POPSIM-Public>

# Outline

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1. Data and Machine Learning
2. Disruptions and controllability
3. Explainable and adaptive Machine Learning for disruption prevention
  - Disruption Prediction (DPRF)
  - Disruption Precursors' modeling
  - Time-to-event frameworks
4. Conclusions

# Incomplete physics understanding of observable phenomena prompts AI/ML solutions

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- Interpretable/explainable ML = trustworthy solutions for safety-critical systems
- Continuous Model Validation + Updates are Critical
  - Even if the physics is known, models need to be continuously validated in operations and updated if necessary

# Incomplete physics understanding of observable phenomena prompts AI/ML solutions

- Interpretable/explainable ML = trustworthy solutions for safety-critical systems
- Continuous Model Validation + Updates are Critical
  - Even if the physics is known, models need to be continuously validated in operations and updated if necessary
- Multi-machine database study + interpretable ML workflow to identify boundary functional form
  - Collisionality-based scaling for density limit events in L/H-mode
  - DIII-D avoidance experiments + new risk metric
- Experimental demonstration of robust rampdown trajectory optimization at TCV
  - Improved high performance scenario, close to stability limits and with minimal data
  - Successful a priori trajectory design + prediction of a scenario slightly out of distribution

