Plasma Science & Fusion Center

A review of machine learning-driven studies of tearing modes

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[1]*MIT Plasma Science and Fusion Center*

Motivation:

Tearing modes in tokamaks reduce plasma confinement and lead to disruptions

Like fusion output, their severity generally increases with plasma pressure.

Tokamak tearing research:

- find viable tearing-free pilot plant scenarios
- predict and prevent tearing onset in real time

How has machine learning (ML) have furthered these goals?

Background

- Tearing-to-disruption
- Identifying tearing modes
- Tearing physics to motivate machine learning

Review of ML-driven tearing studies

Summary and future directions

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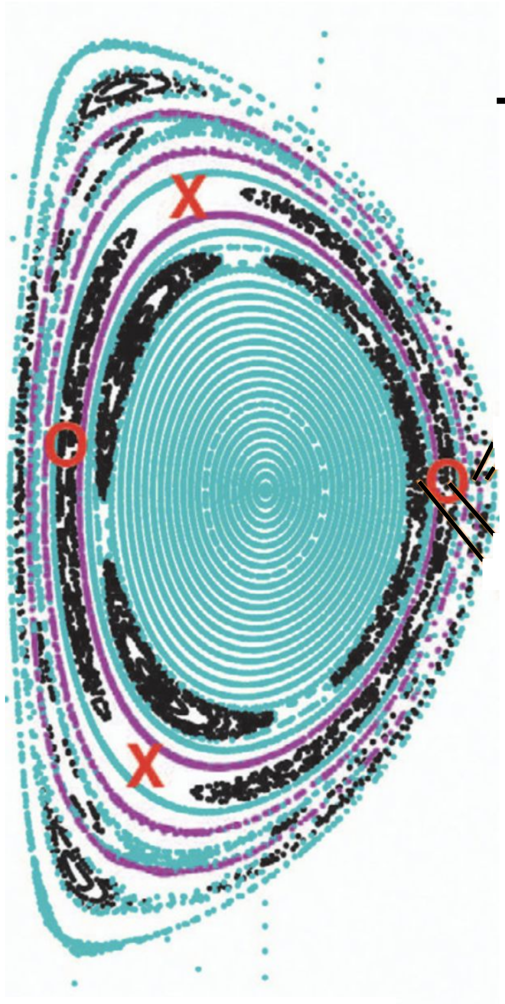
Summary and future directions

Tearing modes (TMs) in tokamaks have periodic modal structure

Simulated islands in DIII-D



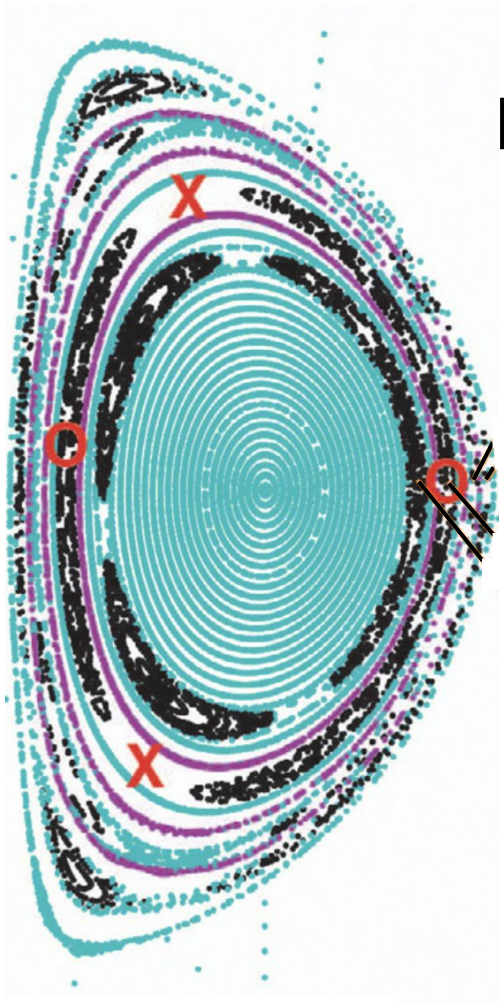
Tearing modes:

- have m,n poloidal and toroidal Fourier mode numbers
- occur on rational surfaces where field lines close on themselves with helicity $q = m/n$

Reproduced from Sweeney NF 2018

Tearing modes damage confinement

Simulated islands in DIII-D



Particles adhere to field lines:

Nested flux surfaces → particles well confined

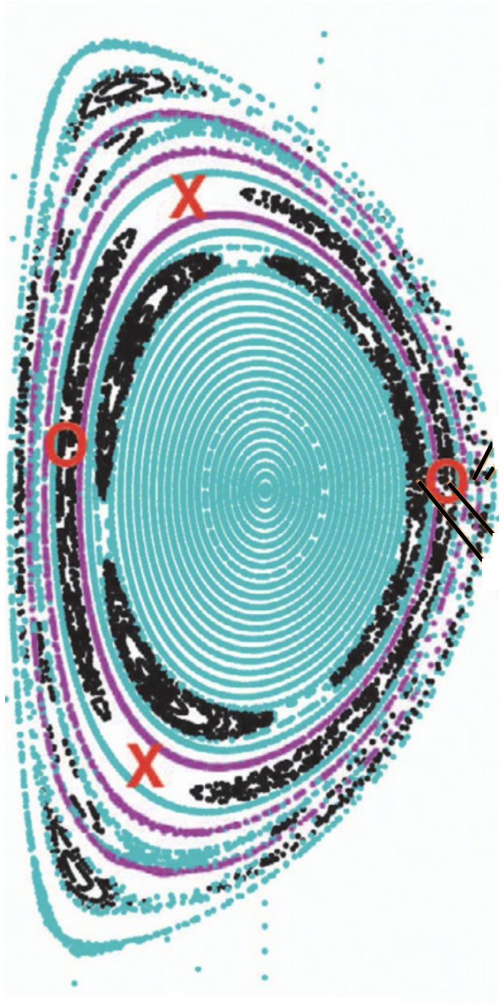
Reconnection → island fields have finite radial width

→ fast radial transport and heat loss

Reproduced from Sweeney NF 2018

Tearing-to-disruption explained

Simulated islands in DIII-D



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Rotating island:

Tearing-to-disruption explained

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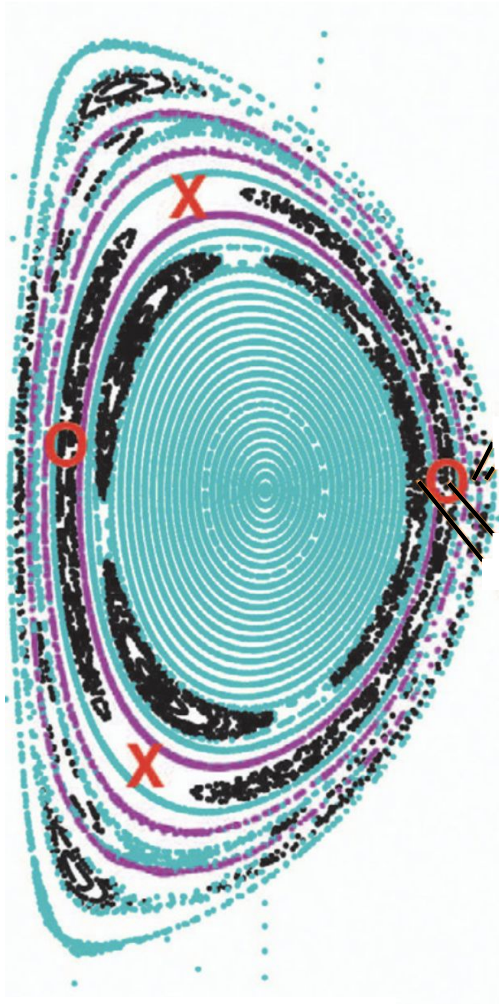

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Rotating island:

$\rightarrow$ drag via $\nabla \times \boldsymbol{E} = -\dfrac{\partial \boldsymbol{B}}{\partial t}$

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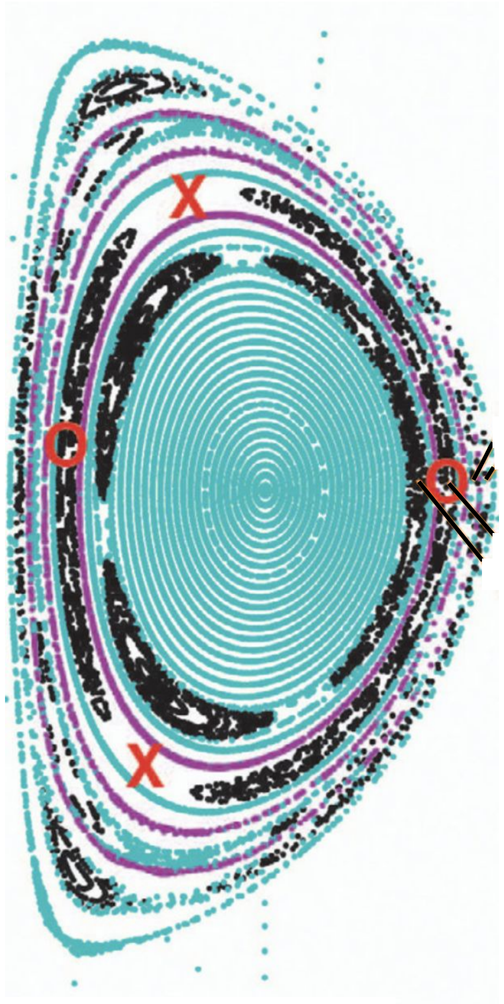

Rotating island:

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$\rightarrow$ mode locking, accelerated growth

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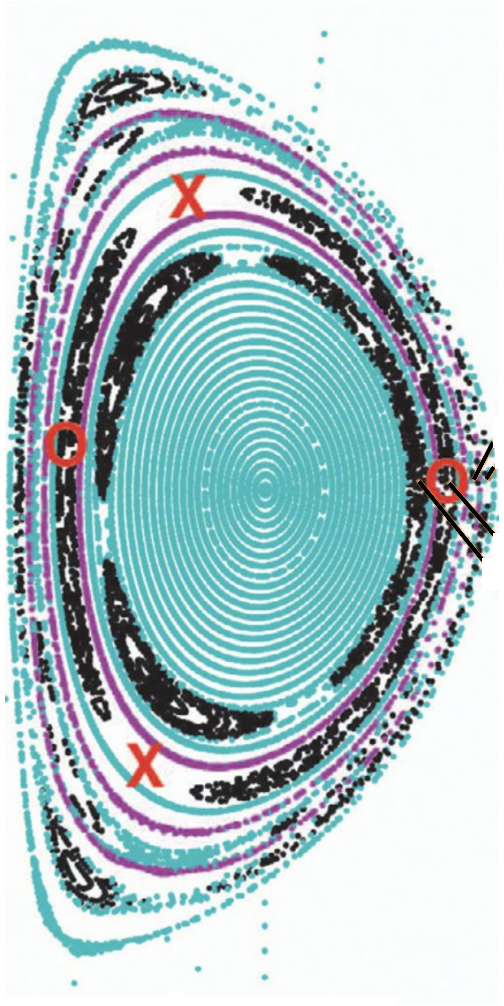

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$\rightarrow$ overlapping island chains ⇔ chaos ⇔ disruption

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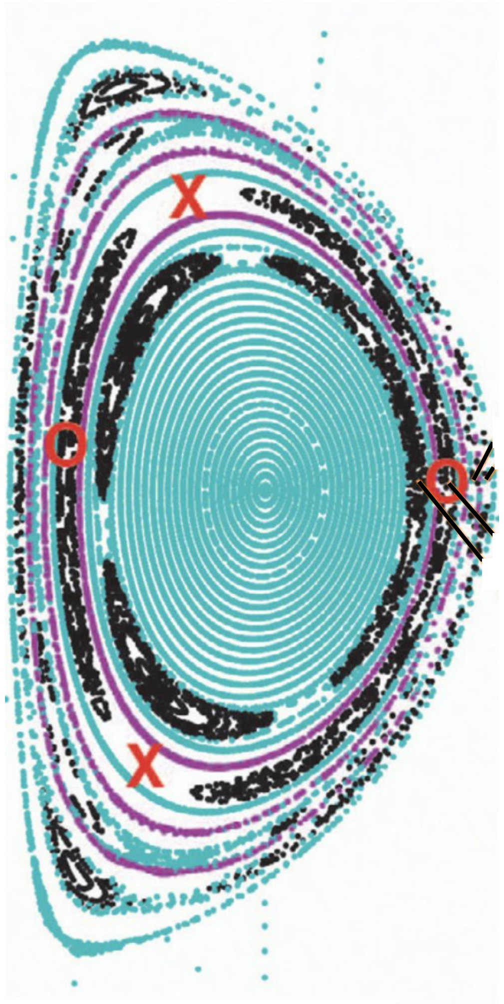

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Rotating island:

$\rightarrow$ drag via $\nabla \times \boldsymbol{E} = -\dfrac{\partial \boldsymbol{B}}{\partial t}$

$\rightarrow$ mode locking, accelerated growth

$\rightarrow$ overlapping island chains $\Leftrightarrow$ chaos $\Leftrightarrow$ disruption

Leading cause of disruptions at JET[1]

18% of disruptions at DIIID due to TMs locking[2]

[1] de Vries et al., NF (2011)
[3] Sweeney et al. NF (2016)

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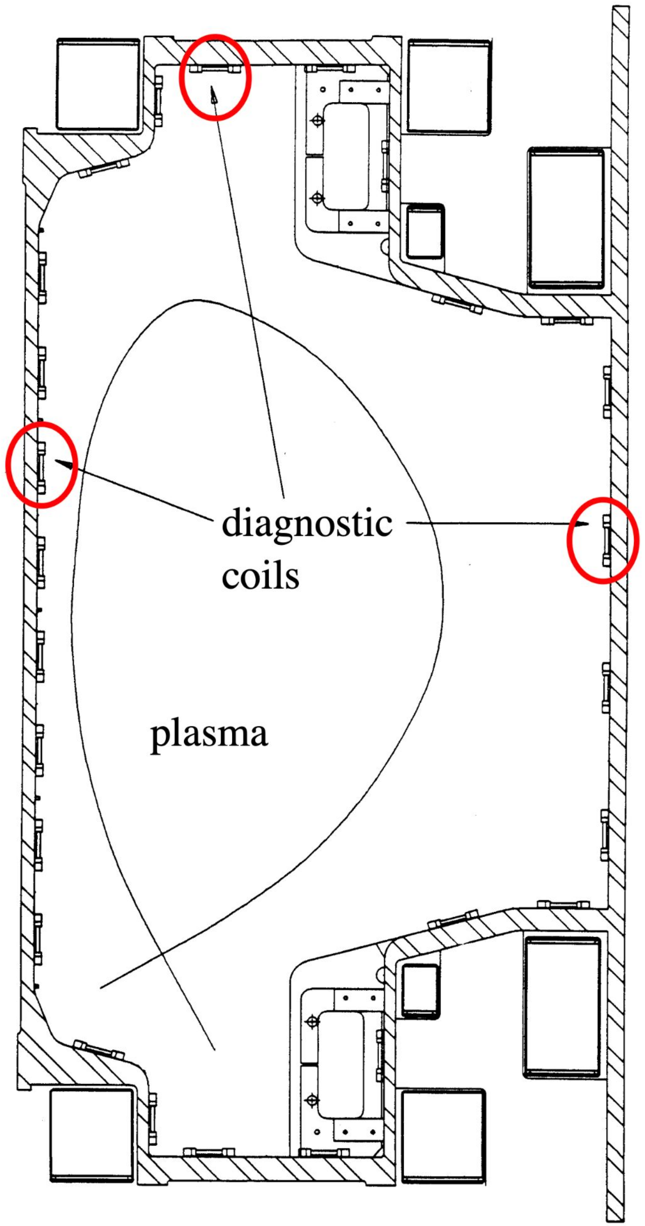
Tearing modes can identified with diagnostic coils

Rotating tearing mode

→ time varying 3D field

→ diagnostic coils experience oscillating current

MIT's Alcator C-Mod tokamak cross-section



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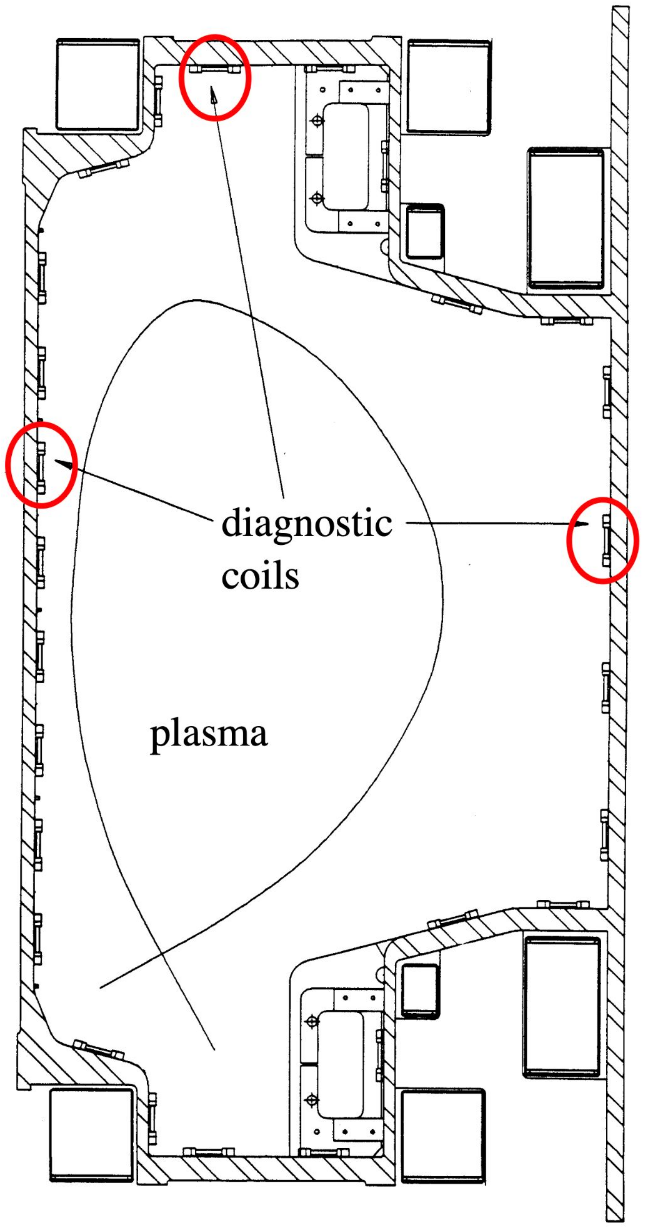
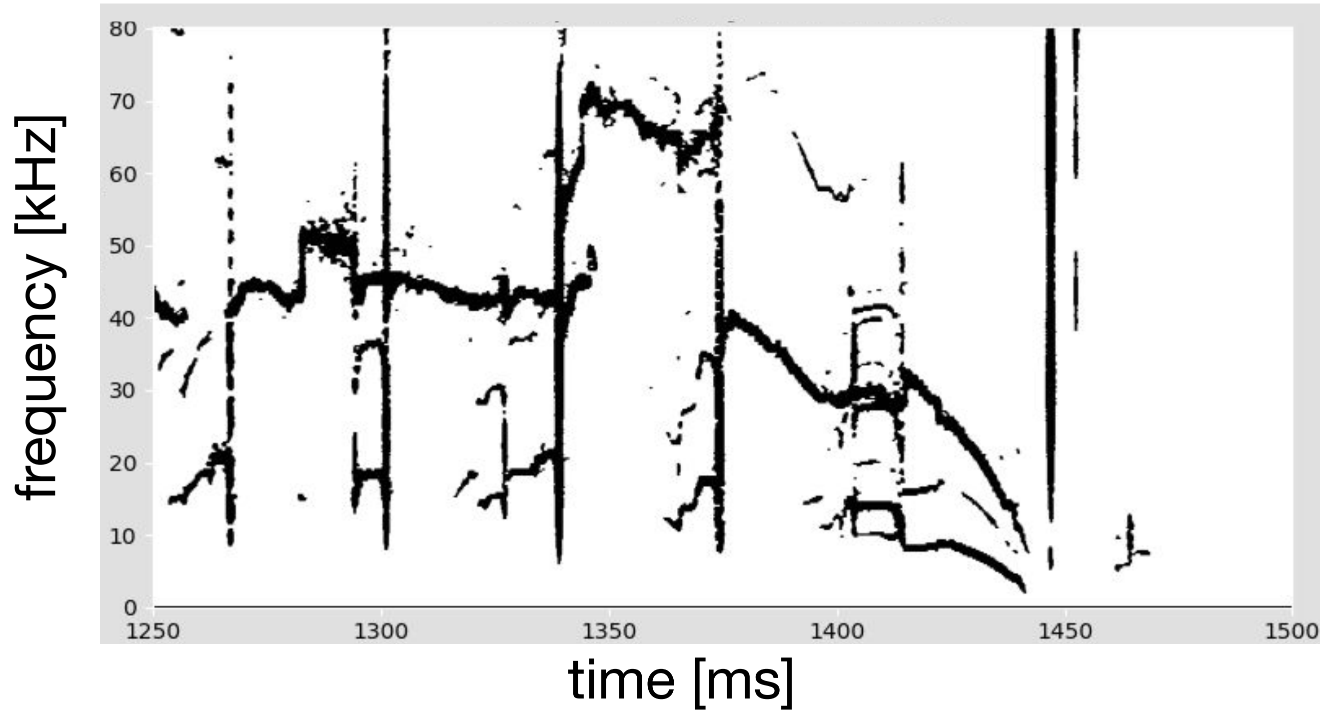


Rotating tearing mode
→ time varying 3D field
→ diagnostic coils experience oscillating current

Preprocessing step: fast fourier transform coil signals

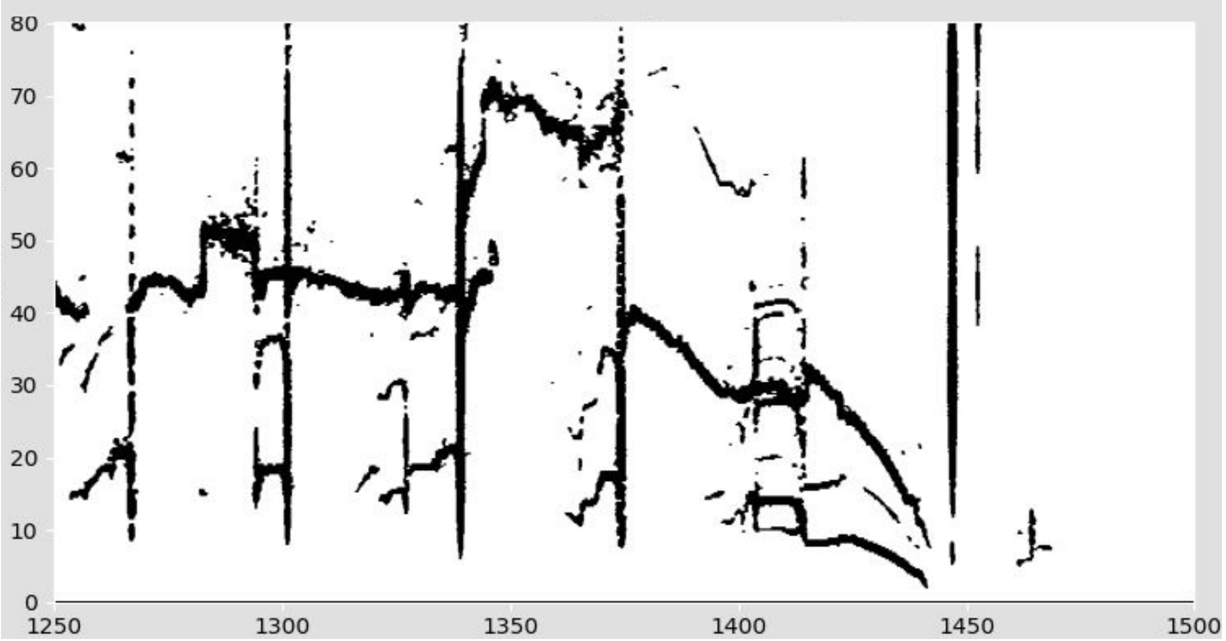


Example of tearing mode labelling on Alcator C-Mod:

Step i: Filter signal noise

Preprocessing step: fast fourier transform coil signals

frequency [kHz]



time [ms]

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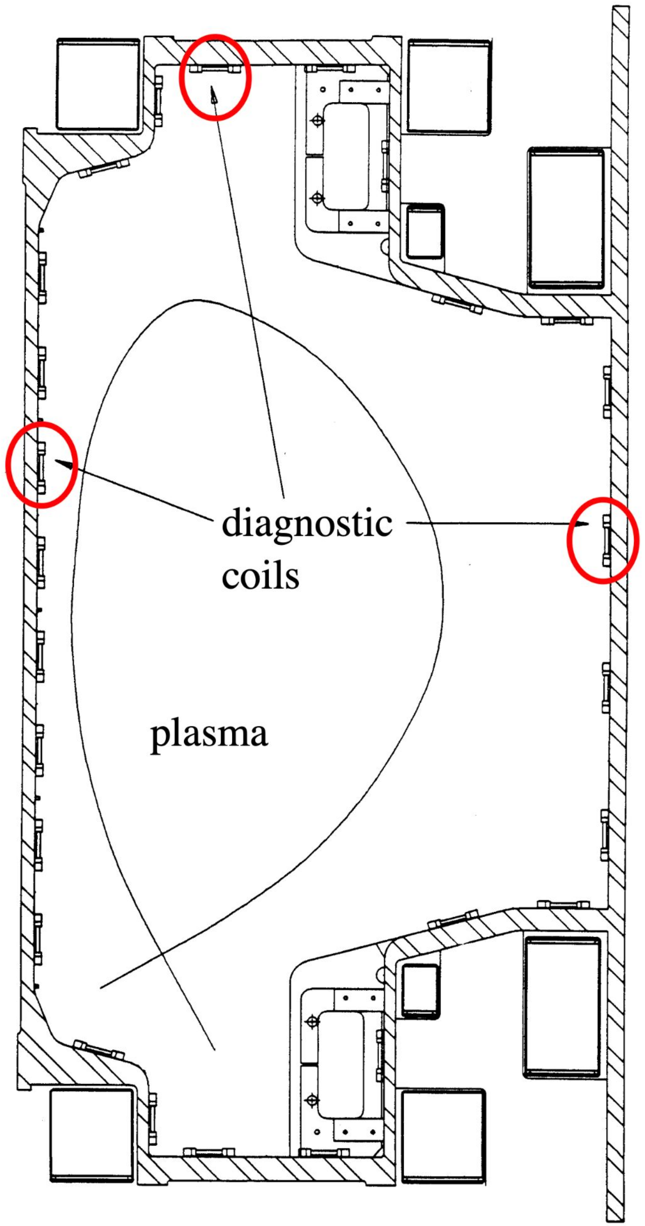

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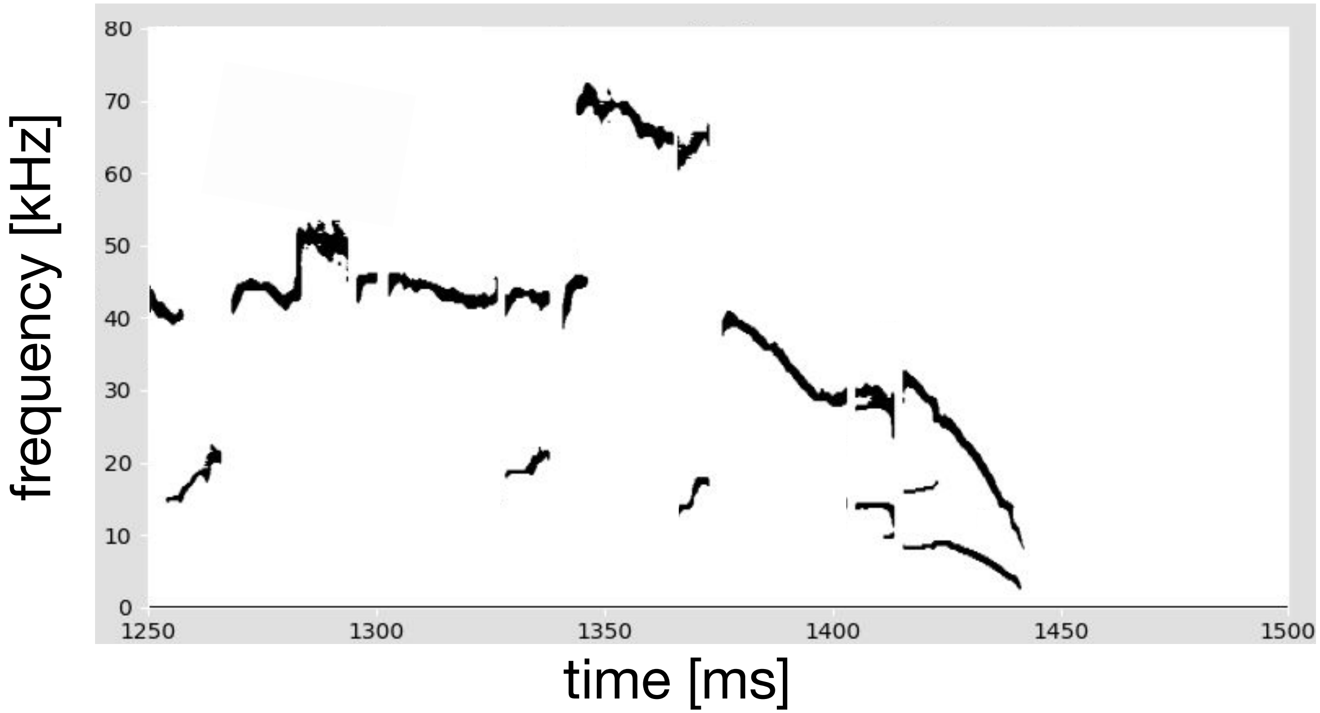

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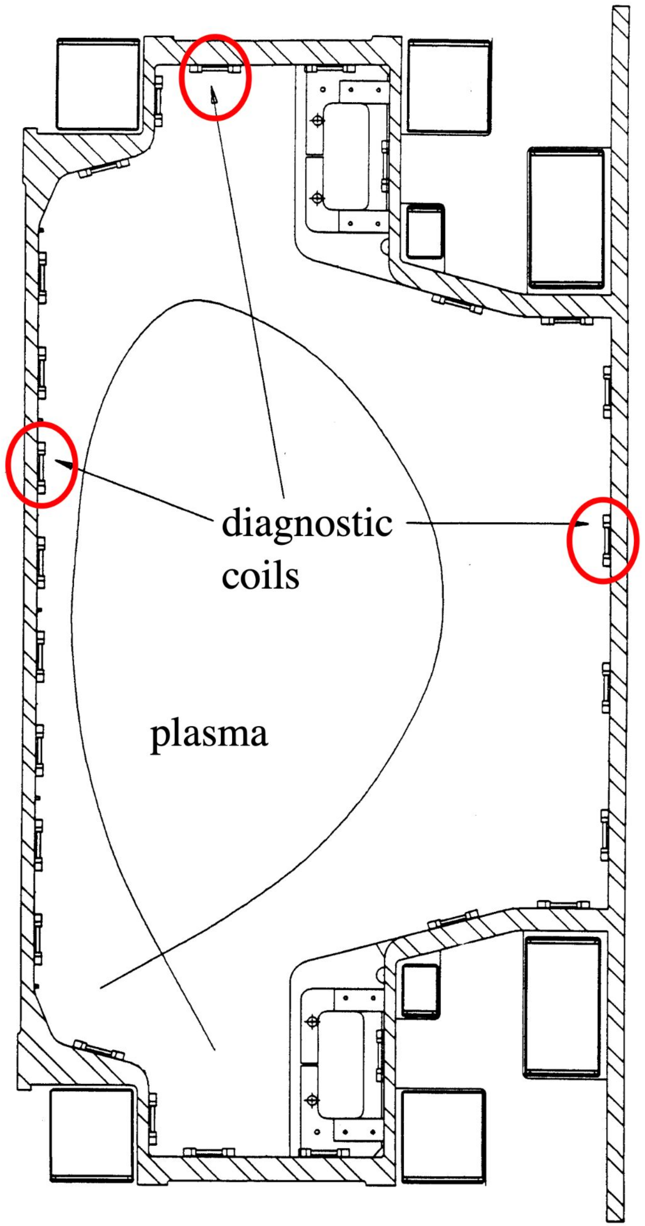

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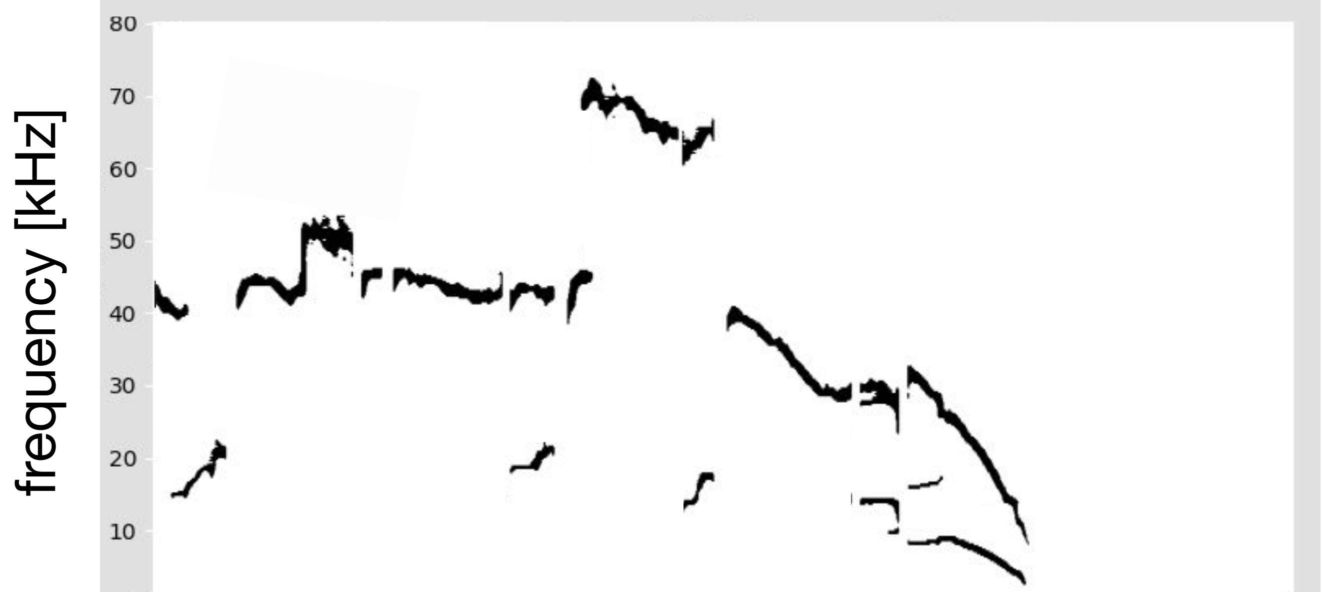
New wavelet-based tool to streamline this process: WavyStar[1,2]

Preprocessing step: fast fourier transform coil signals



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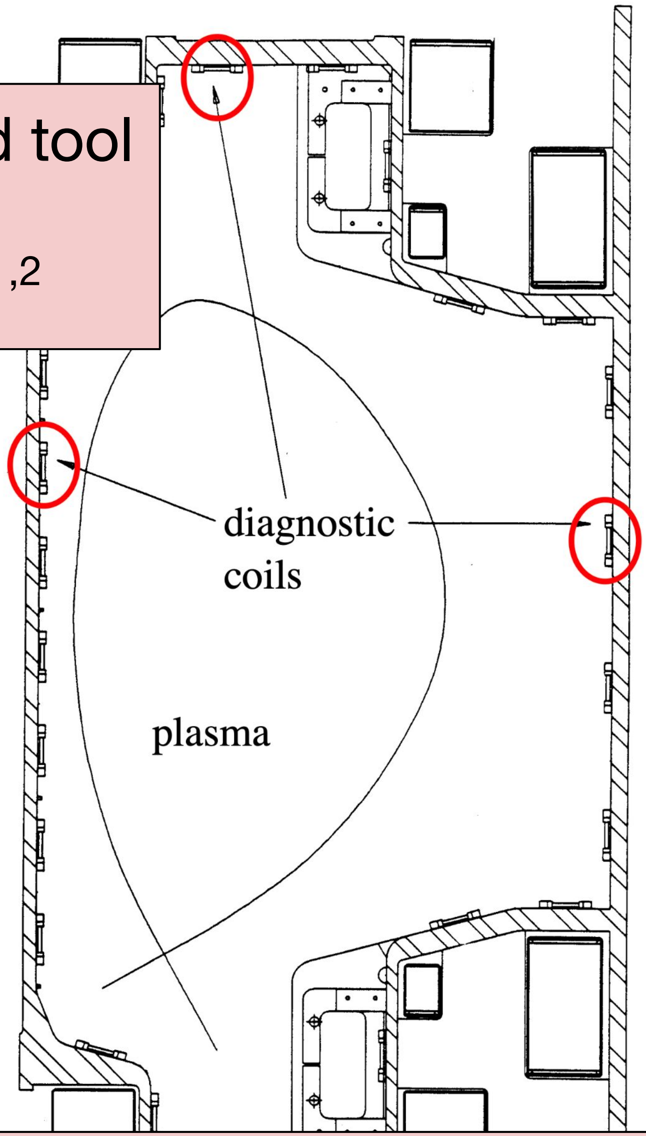

[1]E d D Zapata-Cornejo et al 2024 PPCF 66 095016
[2]E d D Zapata-Cornejo. HAL Thesis, AMU, 2024. ⟨NNT : 2024AIXM0376⟩. ⟨tel-04904999⟩, under development at MIT-PSFC

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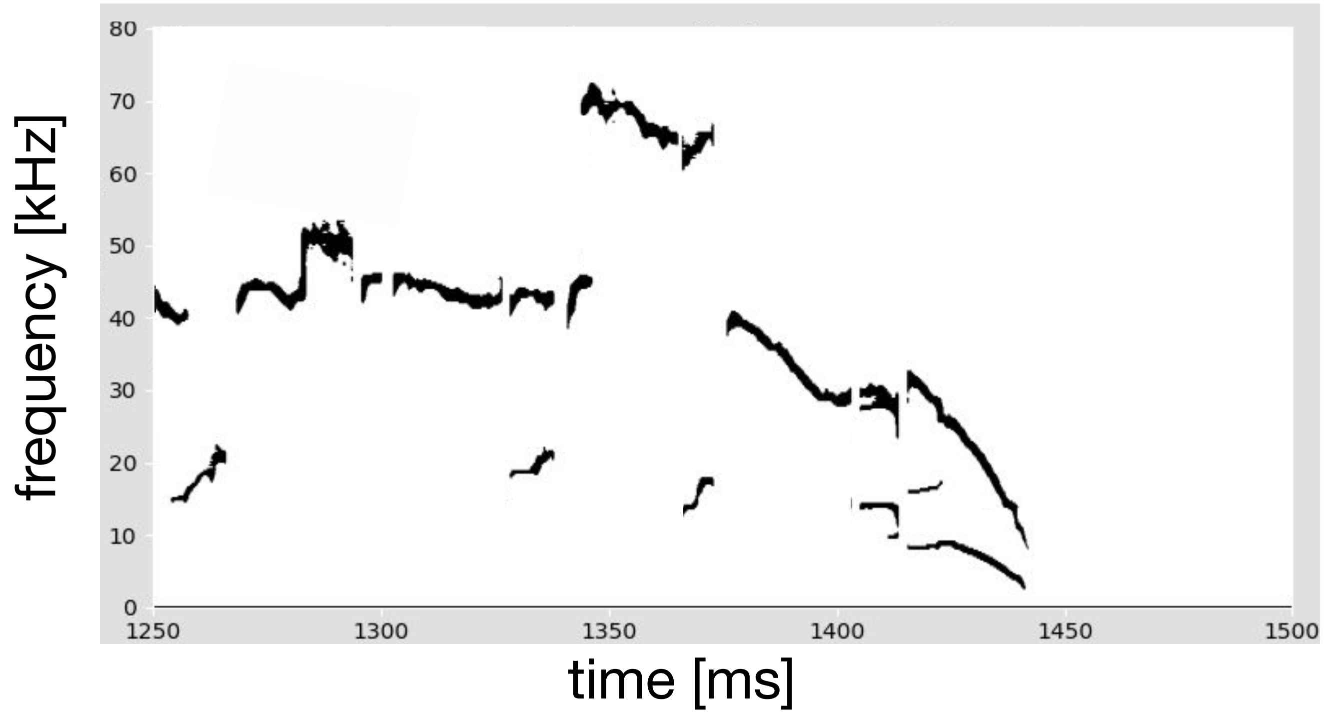

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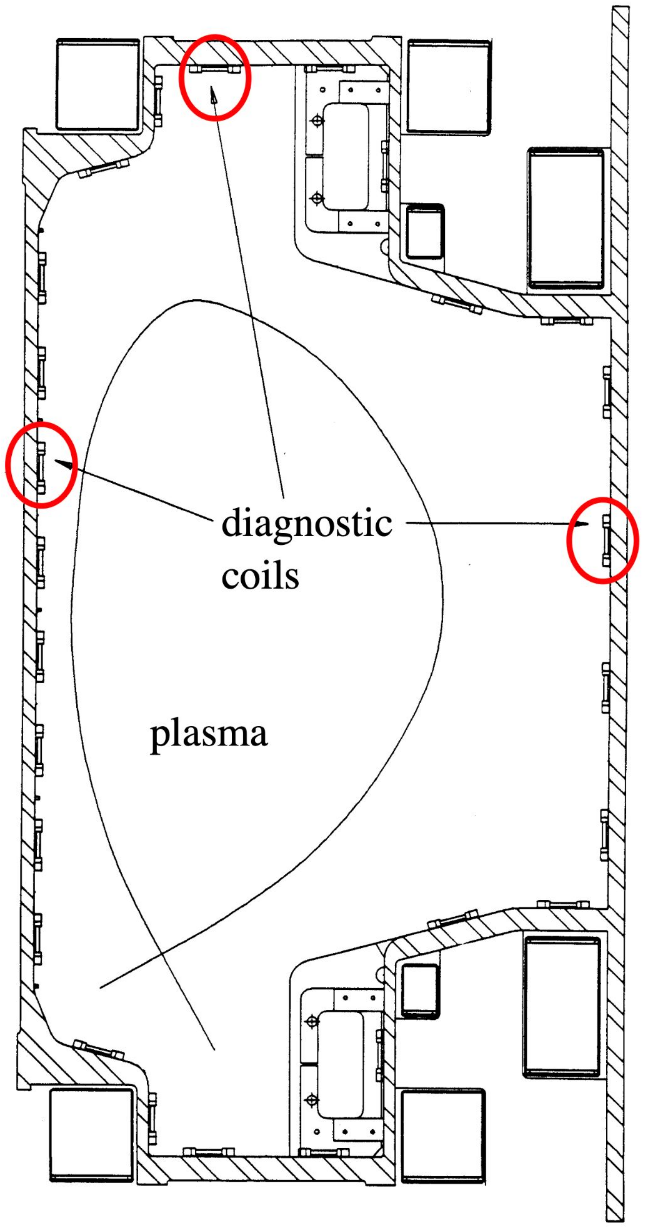

Example of tearing mode labelling on Alcator C-Mod:

Step i: Filter signal noise
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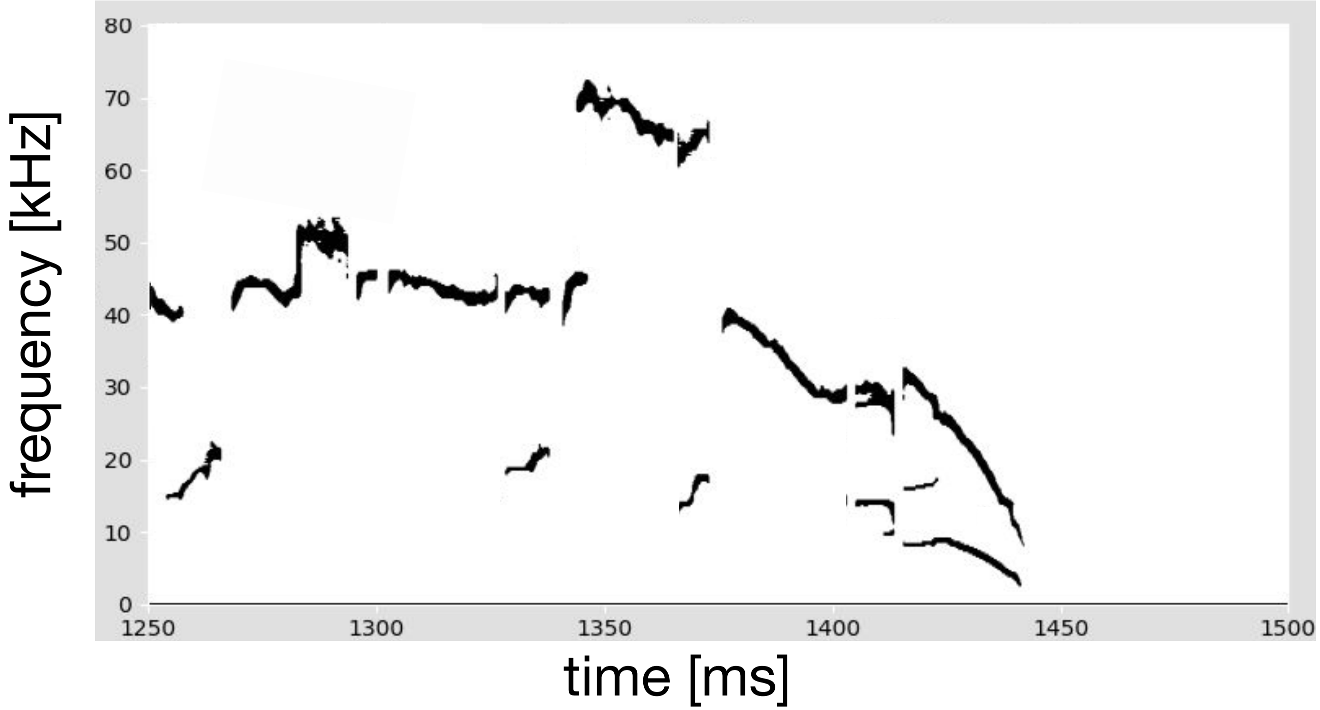
Step iii: Identify toroidal mode n using phase differences

Preprocessing step: fast fourier transform coil signals



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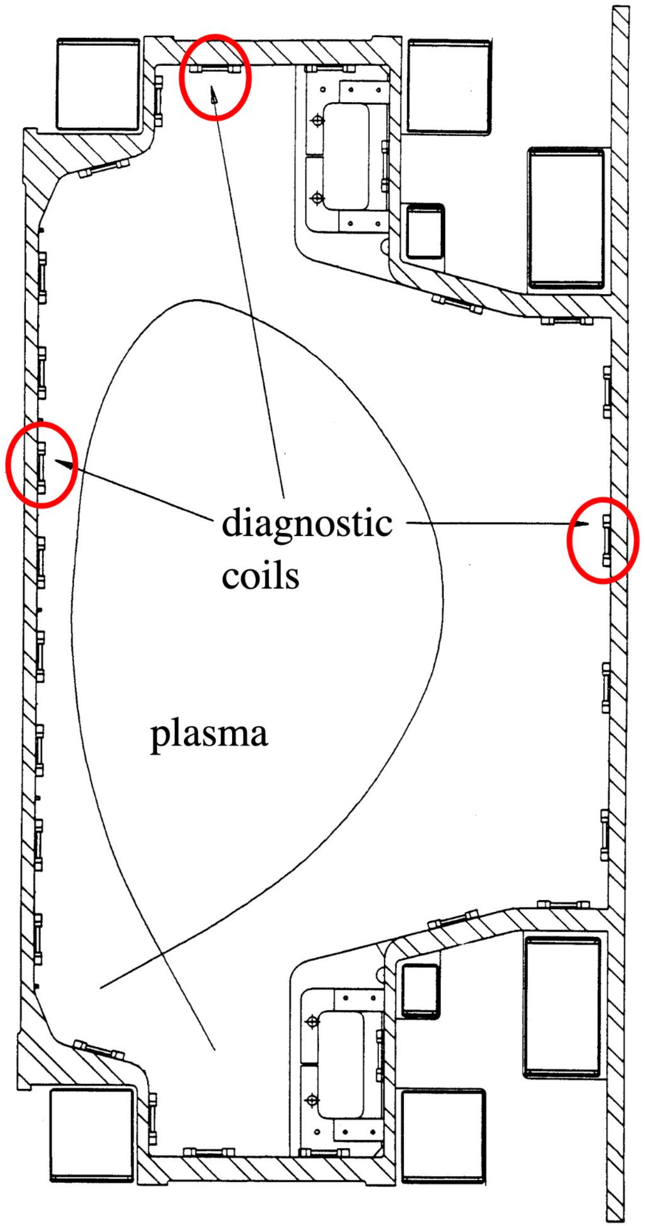

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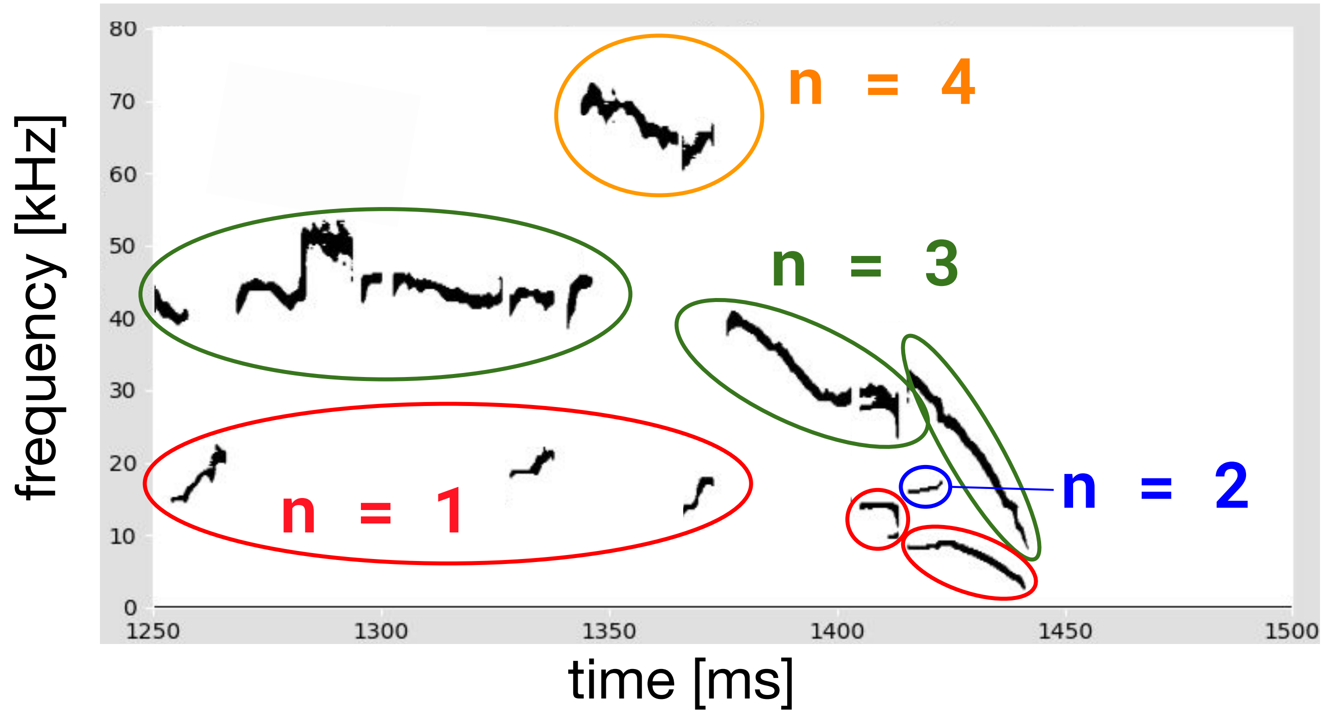

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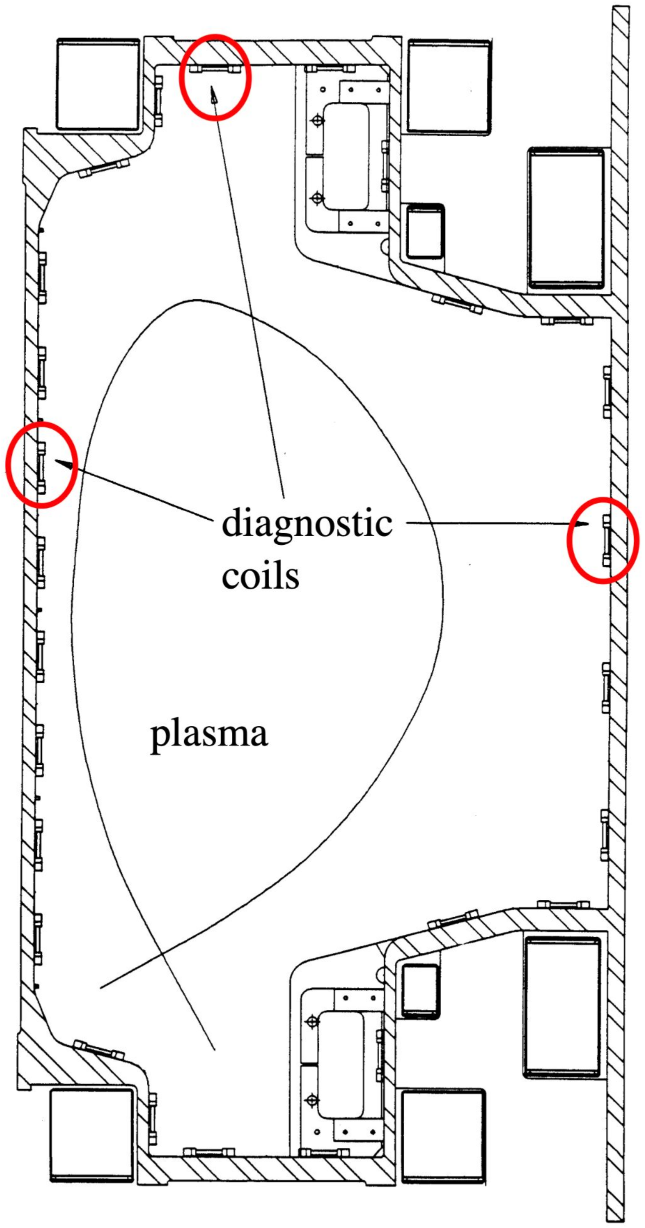

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Tokamak tearing physics can motivate and contextualise an ML approach

Predicting tearing stability is hard…

- for real time control, or scenario design

Why?

Tokamak tearing onset is moderated by multiple coupled, chaotic mechanisms

The dynamics are sensitive to gradients of equilibrium quantities

What is the simplest model that explains this, and is consistent with experiment?

A minimal description of tokamak tearing physics:

1. Nonlinear tearing dynamics:
    - modified Rutherford equation (MRE)

2. ‘Seeding’ and differential plasma rotation

3. Mode rotation as confounding variable

A minimal description of tokamak tearing physics:

1. **Nonlinear tearing dynamics:**
   - **modified Rutherford equation (MRE)**

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TMs can be modelled with MRE:

$$\frac{k_0}{\eta*}\frac{dw}{dt} = \Delta'^{*} + \Delta_{nc} + \Delta_{GGJ} + \Delta_{pol} + \ldots$$

TMs can be modelled using the modified Rutherford equation (MRE) [1][2][3][4]:

Predicts the dynamics of a single-helicity tearing mode after it has exceeded the characteristic resistive linear layer width δ_r

[1] Hegna, PoP (1999)
[2] Schlutt & Hegna, PoP (2012)
[3] La Haye, PoP (2006)
[4] La Haye et al., NF (2022)

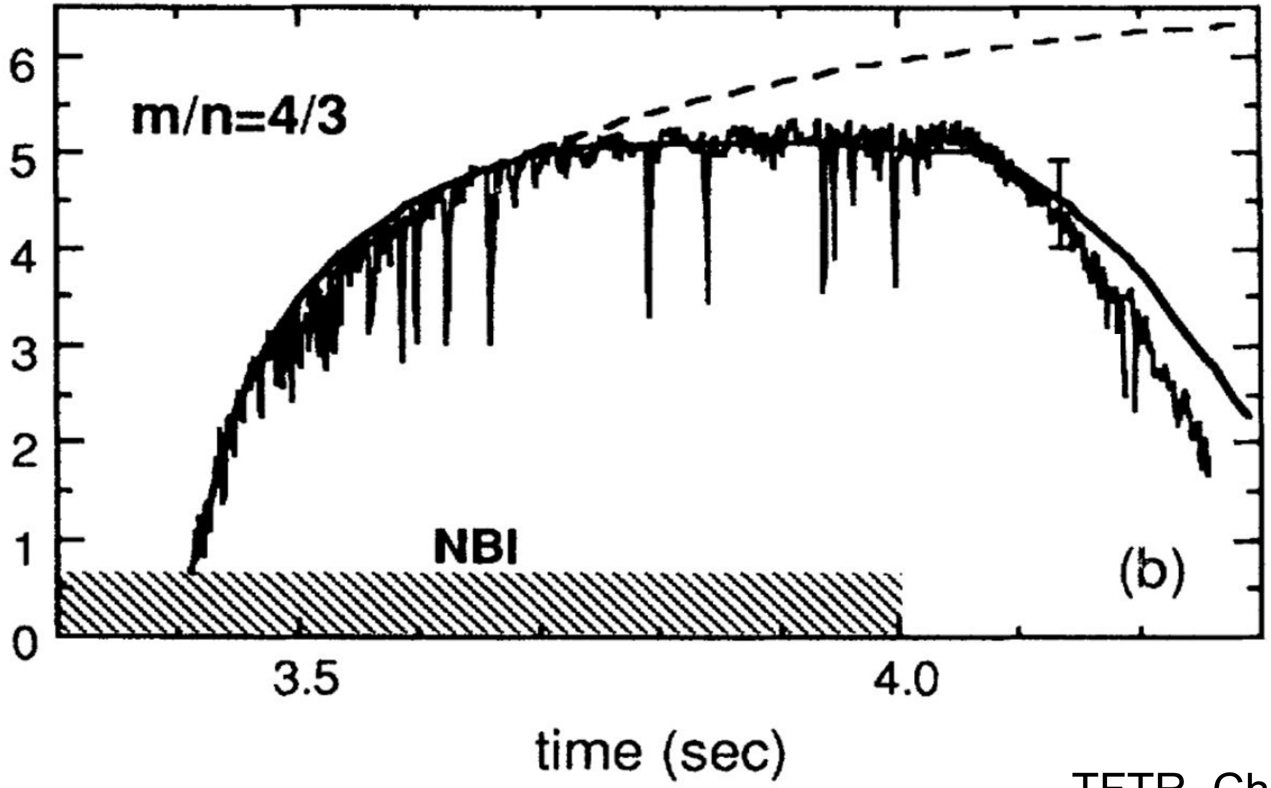
TMs can be modelled with MRE:

$$\frac{k_0}{\eta*}\frac{dw}{dt} = \Delta'^* + \Delta_{nc} + \Delta_{GGJ} + \Delta_{pol} + \ldots$$

TM

Dotted line = MRE* prediction

w (cm)
inferred from
magnetic signal



TFTR, Chang et al., PRL (1995)

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Go through term-by-term

[1] Hegna, PoP (1999)

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$$\frac{k_0}{\eta*}\frac{dw}{dt} = \Delta'^* + \Delta_{nc} + \Delta_{GGJ} + \Delta_{pol} + \dots$$

$$\Delta'^* = \Delta'|w/2|^{-\alpha_-}\sqrt{-4D_I}$$

Equilibrium ideal outer-region stability

[1] Hegna, PoP (1999)

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Equilibrium ideal outer-region stability

- Toroidal Δ'[1,2]
- Finite-pressure, general toroidal geometry[3]
- Generally stabilising

[1] Pletzer, Bondeson & Dewar, JCP (1994), [2] Glasser et al. PoP (2016), [3] Hegna, PoP (1999)

TMs can be modelled with MRE:

$$\frac{k_0}{\eta *}\frac{dw}{dt} = \Delta'^* + \Delta_{nc} + \Delta_{GGJ} + \Delta_{pol} + \dots$$

$$\Delta_{GGJ} = \frac{1}{w + k_3 w_d}\frac{k_1 D_R}{\alpha_+ - H} \qquad D_R = D_I + (H - 1/2)^2$$

Local field-line curvature term[2,3]

- Generally stabilising
- Small

[2] Hegna, PoP (1999)
[3] Schlutt & Hegna, PoP (2012)

Neoclassical term drives TM growth:

$$\frac{k_0}{\eta *}\frac{dw}{dt} = \Delta'^* + \Delta_{nc} + \Delta_{GGJ} + \Delta_{pol} + \ldots$$

$$\Delta_{nc} = \frac{w}{w^2 + 2k_1 w_d^2} k_1 D_{nc}$$

[4] La Haye, PoP (2006)

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Neoclassical drive $D_{nc} \sim \frac{J_{bs}}{J_{||}}\frac{q}{q'}$ dominates at island-widths seen during experiment: [4]

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$$w_d = \left(\frac{\chi_\perp}{\chi_\parallel}\overline{\mathcal{J}B^2}\,\overline{\mathcal{J}g^{\psi\psi}}\frac{1}{\iota'^2 m_s^2}\right)^{\frac{1}{4}}$$

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mag. island → no pressure gradient → lose local bootstrap current → drives reconnection

requires 'seed' island of width $w \sim w_d$, otherwise cross-field (turbulent) transport maintains pressure gradient across island chain [5,6]

[4] La Haye, PoP (2006)
[5] Fitzpatrick, PoP (1995)
[6] Schlutt & Hegna, PoP (2012)

A minimal description of tokamak tearing physics:

1. Nonlinear tearing dynamics:
   - modified Rutherford equation (MRE)

2. 'Seeding' and differential plasma rotation

3. Mode rotation as confounding variable

Sensitive to gradient of equilibrium quantities

eg. $$D_{nc} \sim \frac{J_{bs}}{J_{\|}} \frac{q}{q'}$$

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What is island seeding:

Fast transient perturbed field (eg. ideal m,n = 1,1 ‘sawteeth’ instability)

→ short-lived 3D fields

→ forced reconnection at core rational surfaces

^Implicit time scale separation:

tearing modes - slow reconnection

sawteeth ‘seed’ - fast reconnection

TM seeding is moderated by differential rotation:

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Relative toroidal rotation

between rational surfaces

Bardóczi et al., PoP (2023)

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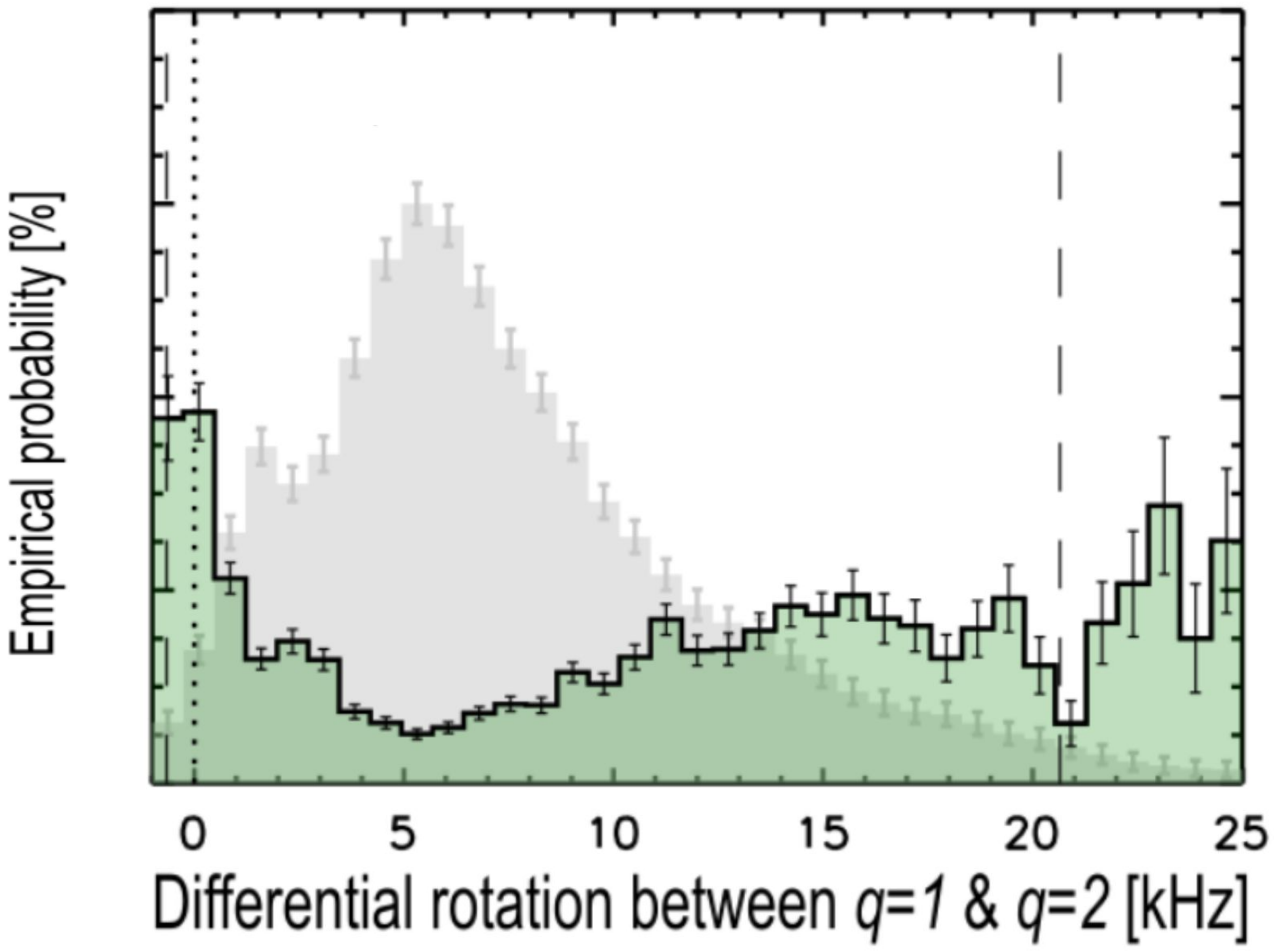
2/1 tearing onset vs differential rotation



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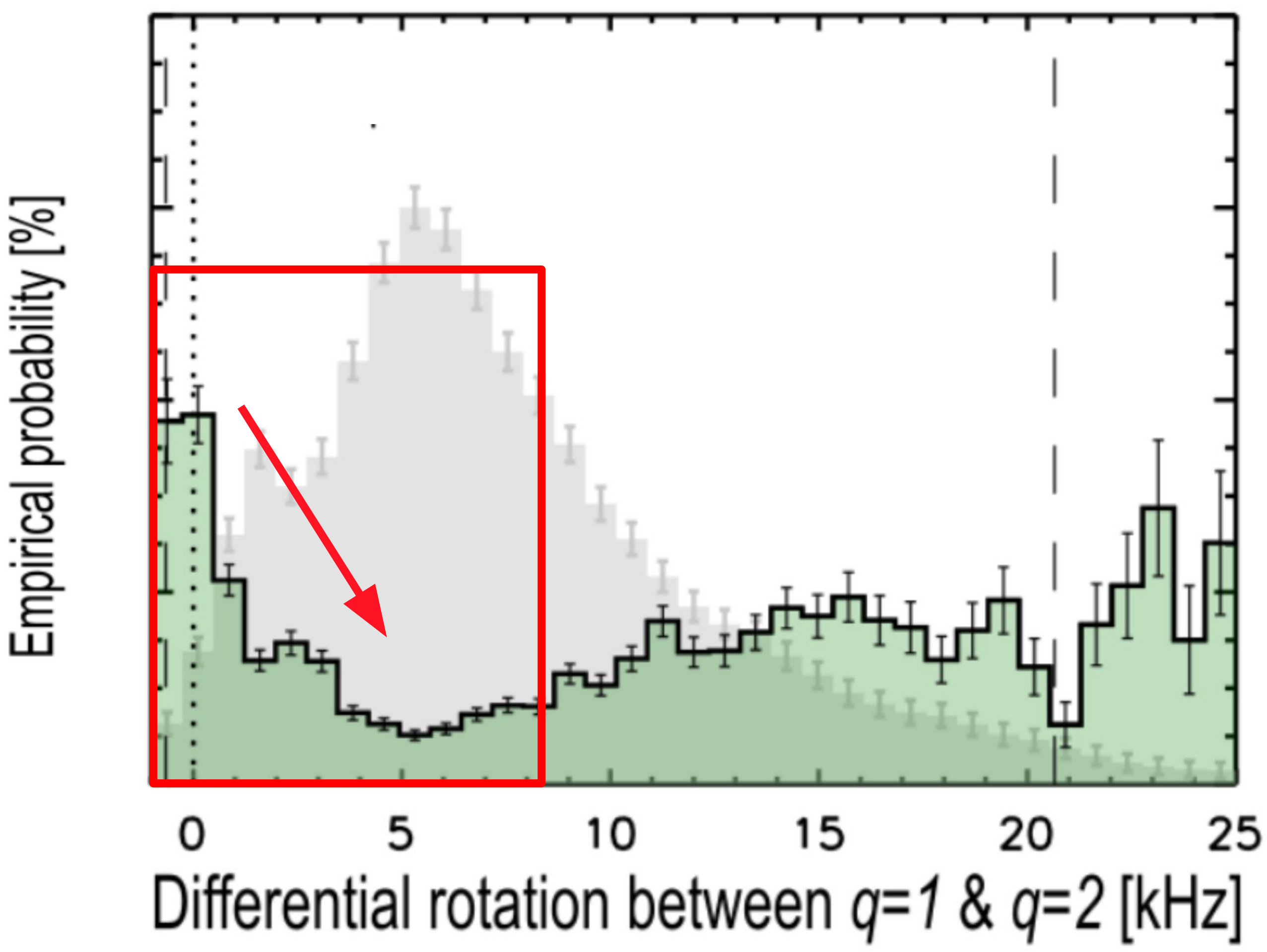

q = 1, 2 surfaces decoupled

→ no seeding from sawteeth

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3. **Mode rotation as confounding variable**

plasma rotation moderates seeding

TM stability depends on mode-rotation w.r.t plasma

$$\frac{k_0}{\eta*}\frac{dw}{dt} = \Delta'^{*} + \Delta_{nc} + \Delta_{GGJ} + \Delta_{pol} + \ldots$$

$$\Delta_{pol} \propto -\frac{w_{pol}^2}{w^3}F(\omega_m)$$

Ion polarisation current can strongly stabilise TMs at small island widths

- two-fluid effect

Relies on relative rotation between island chain and frame of zero radial field [1,2,3]

[1] Waelbroeck et al., PRL (2001)
[2] Connor et al., PoP (2001)
[3] Waelbroeck., PRL (2005)

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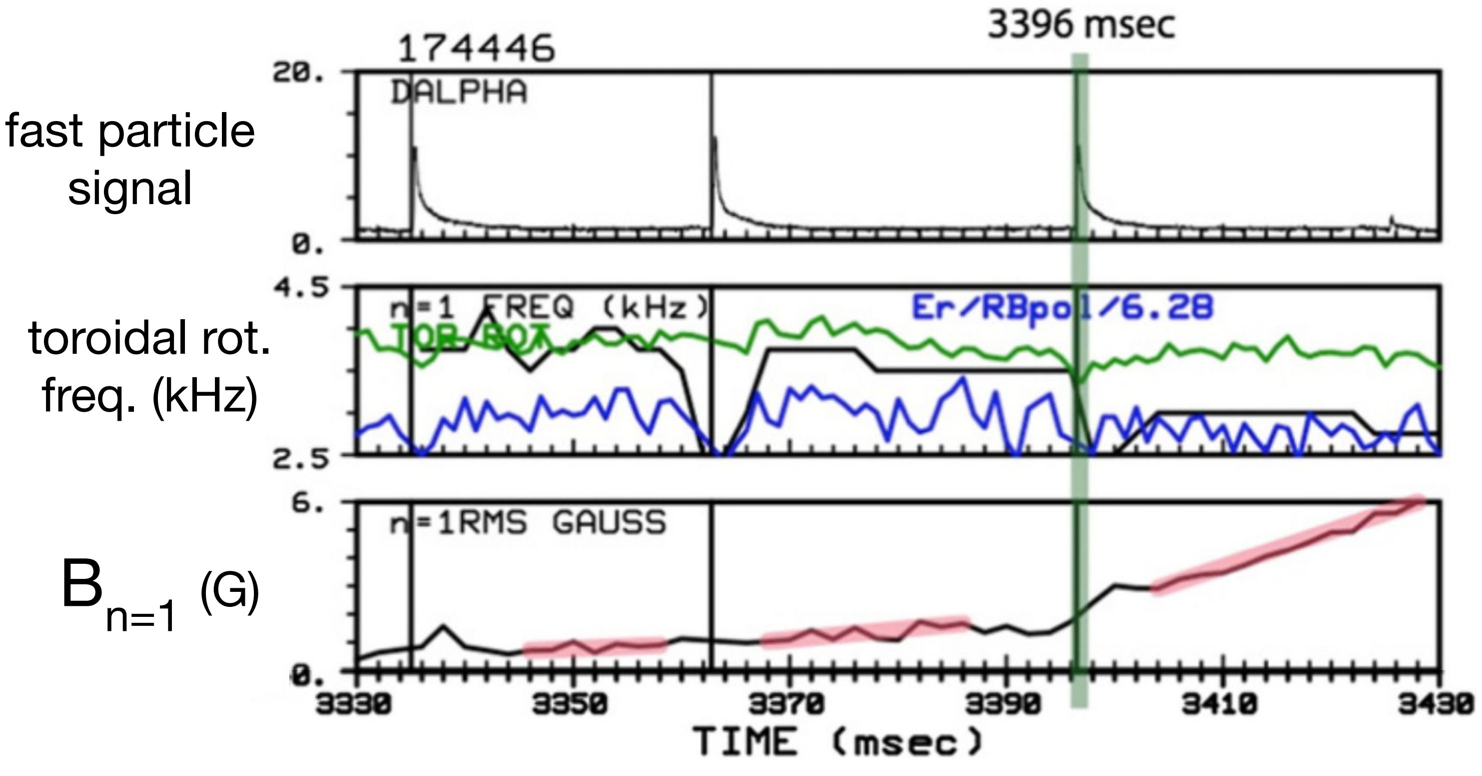

La Haye et al., NF (2022)

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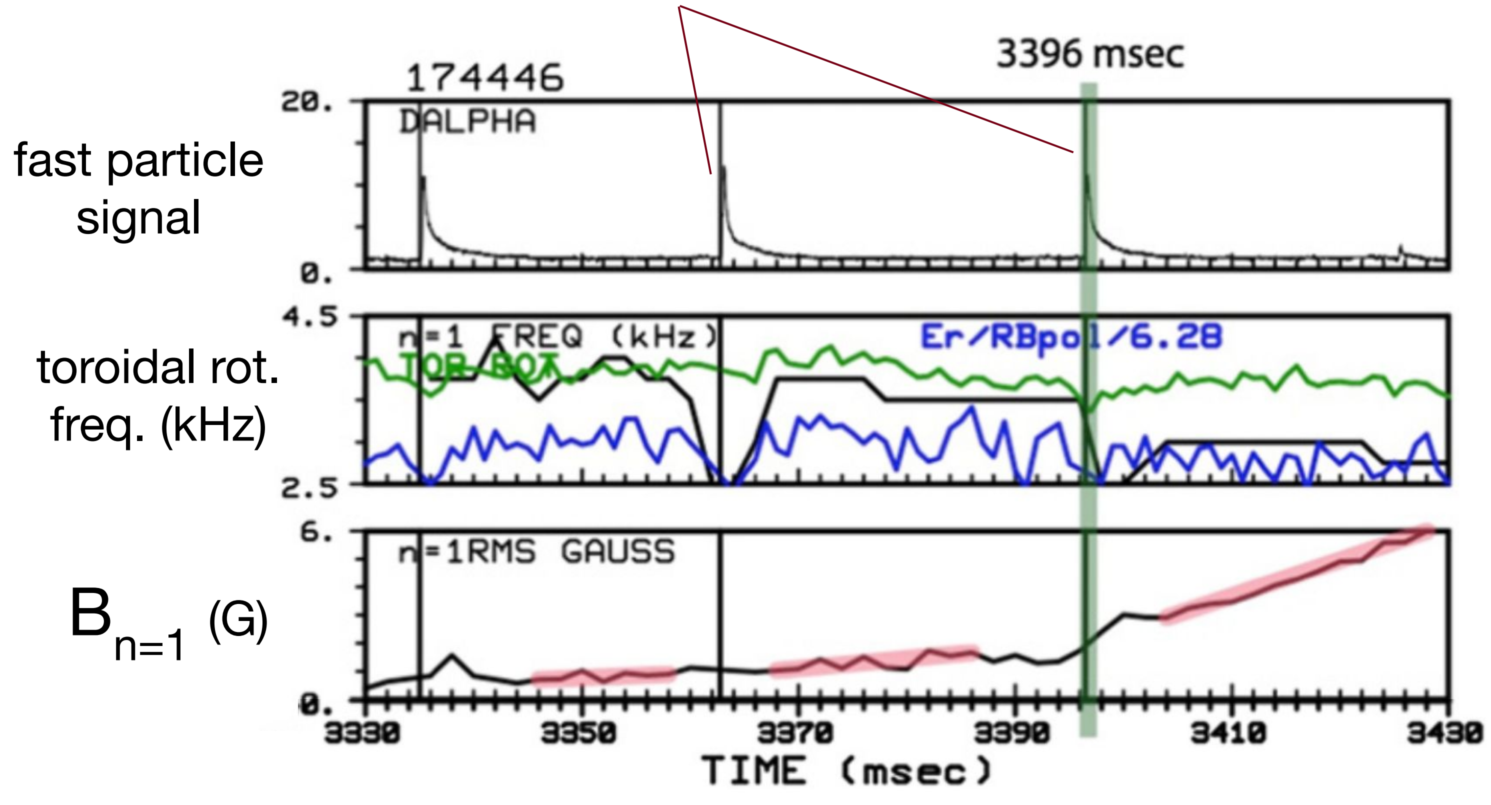

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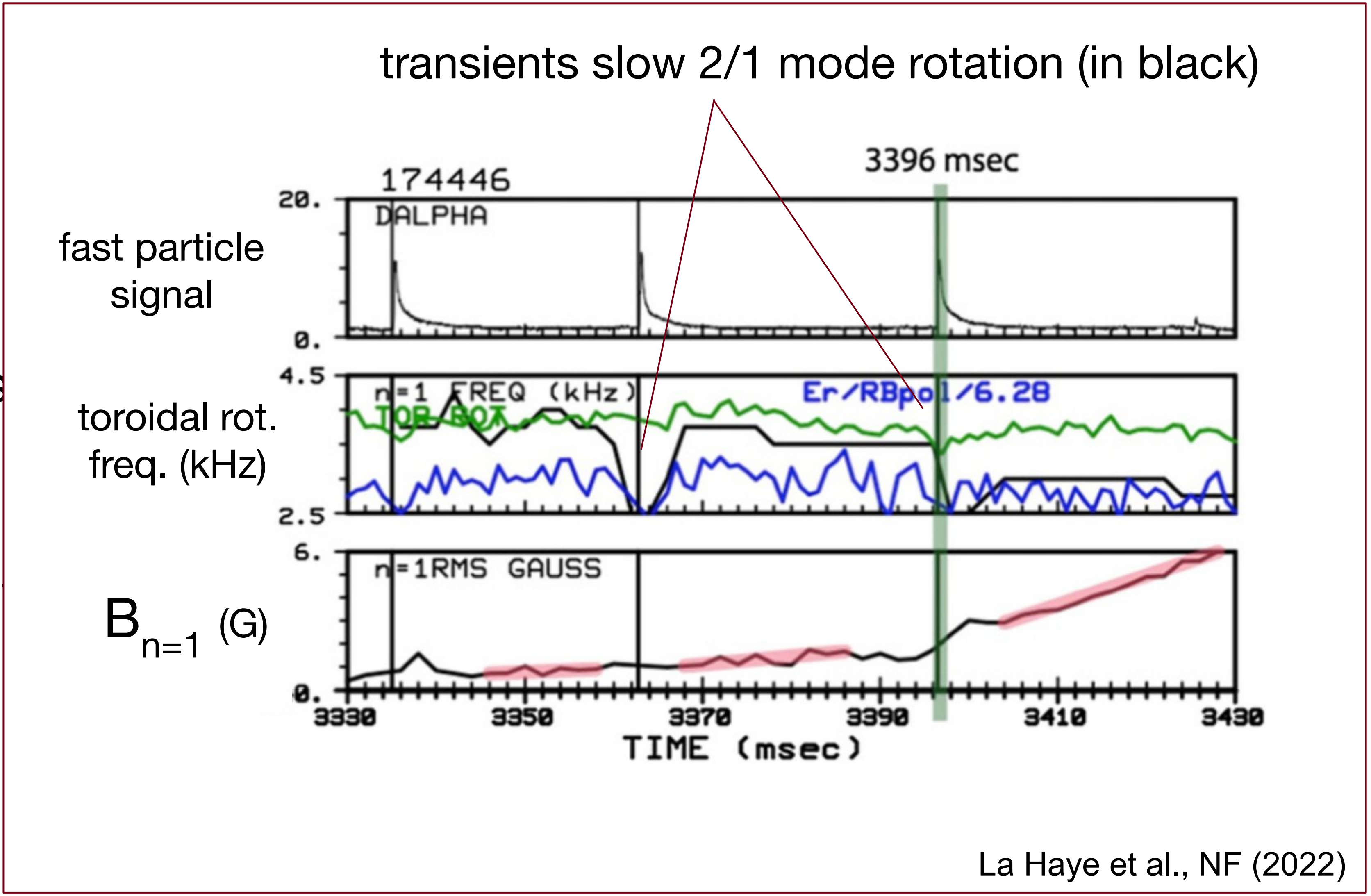

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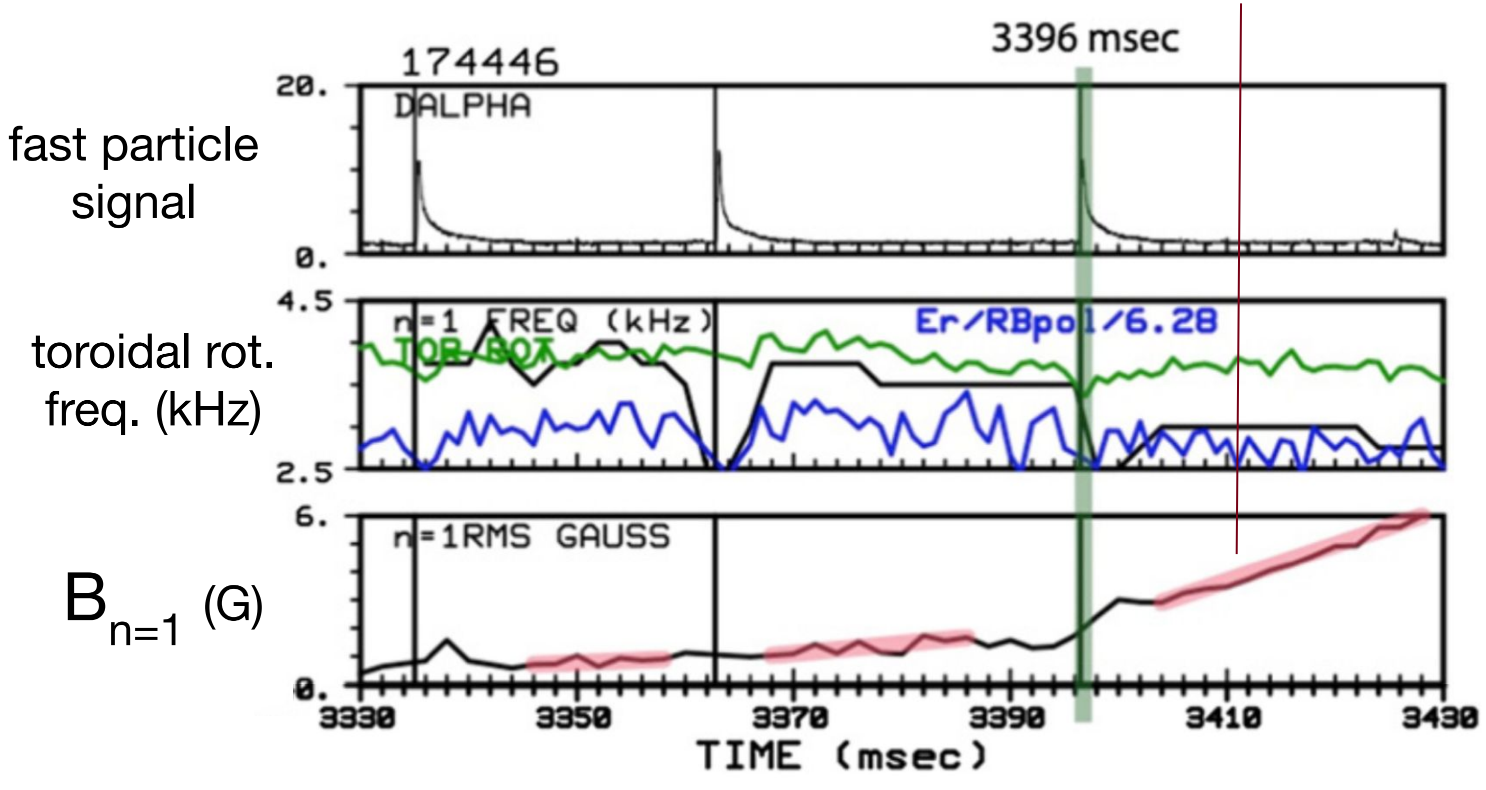
Relies on relative rotation be

no 2/1 mode rotation ⇔ robust growth



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→ experimental data captures the whole picture

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Coupled, multi-scale physics prohibits direct simulation
$\longrightarrow$ experimental data captures the whole picture

Chaotic dynamics motivates a statistical/ML approach

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- Onset prediction with ML
- TM control with ML
- Using ML to interpret tearing data

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[1] Bardóczi et al., PoP (2023)

Statistical analyses of TM onset confirm that plasma state dictates stability, despite chaotic seeding events

Bardóczi et al. 2023[1] - what plasma variables have the most influence on TM onset?

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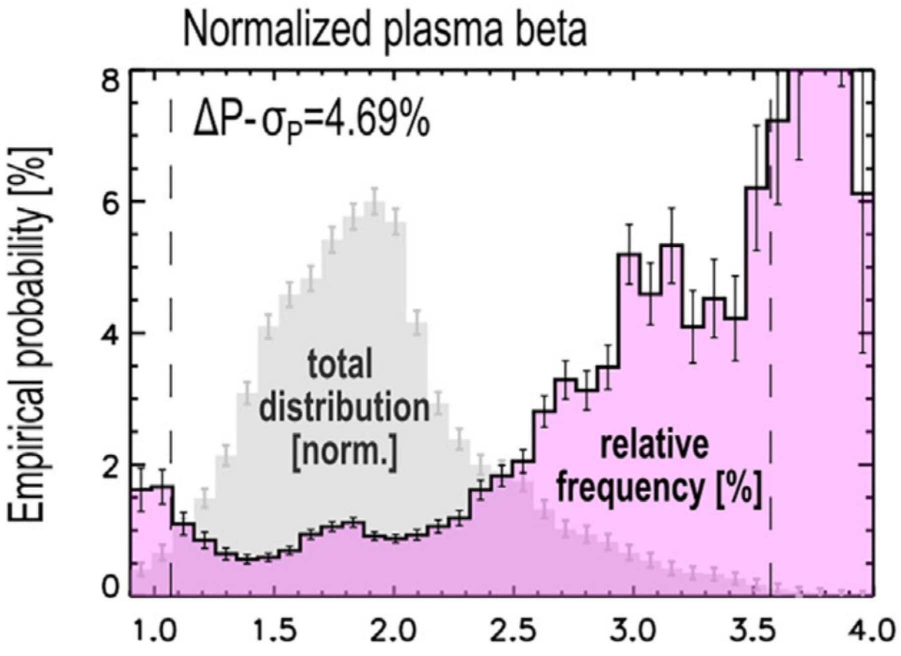

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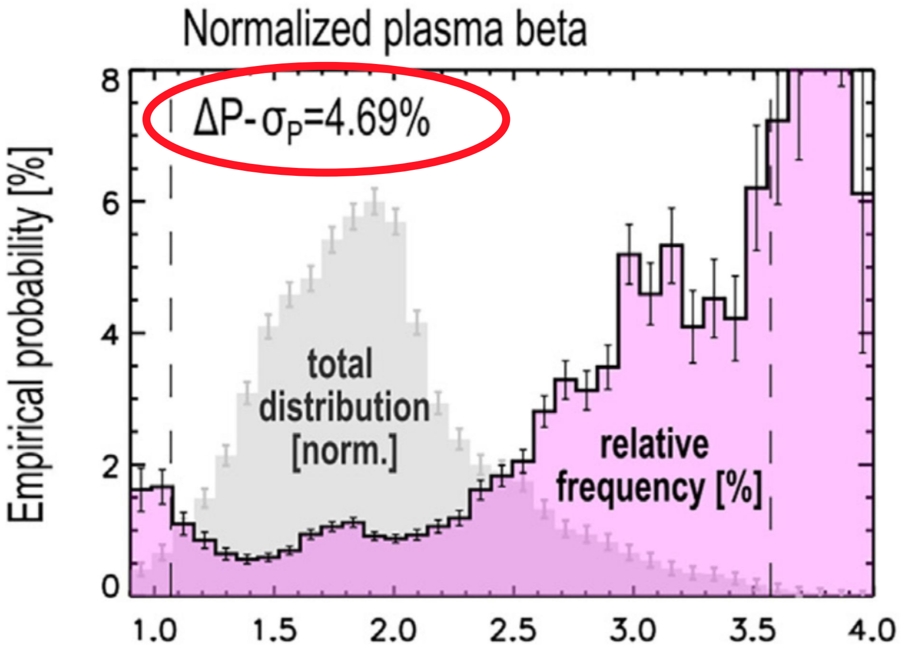

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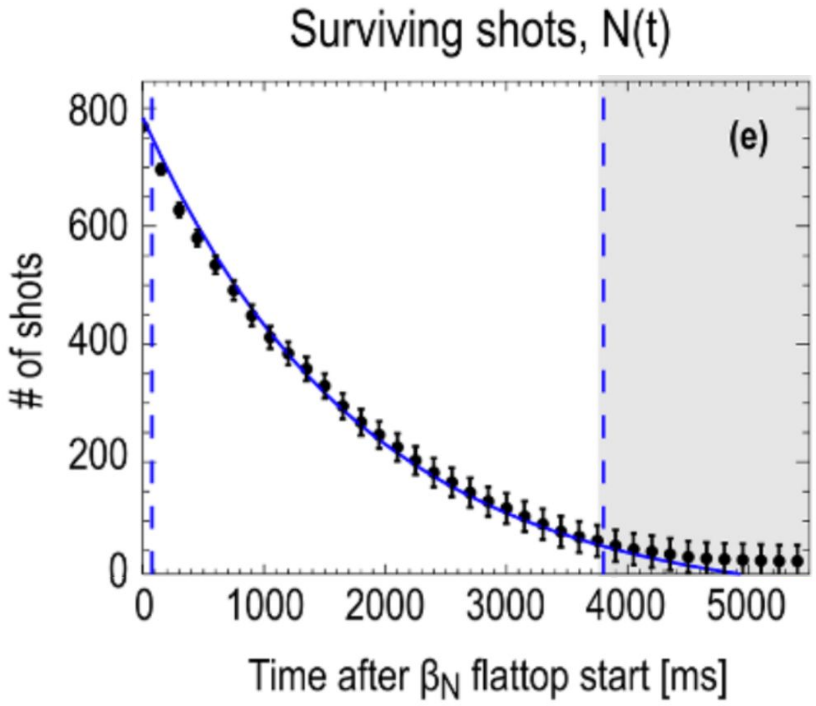

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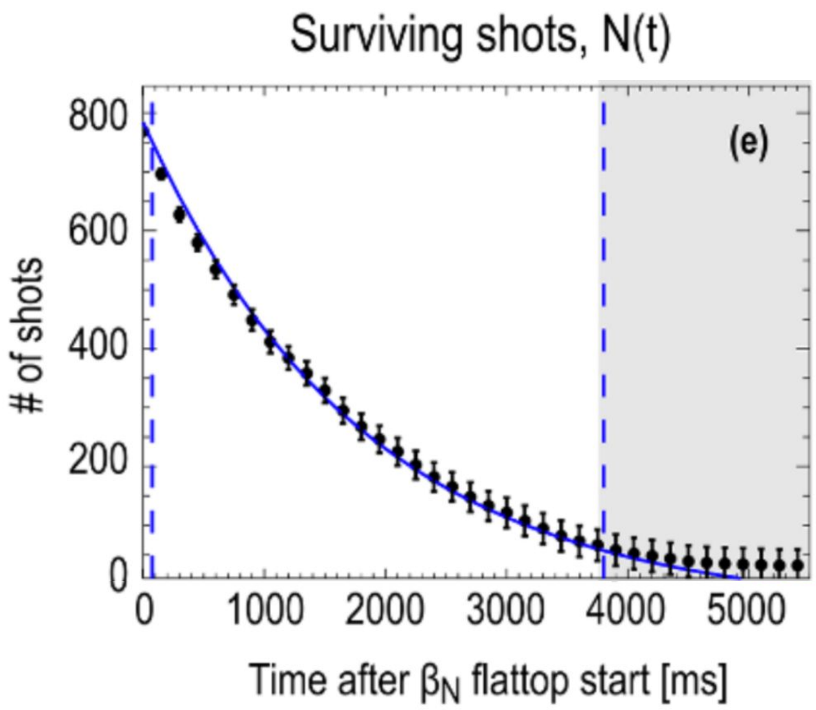

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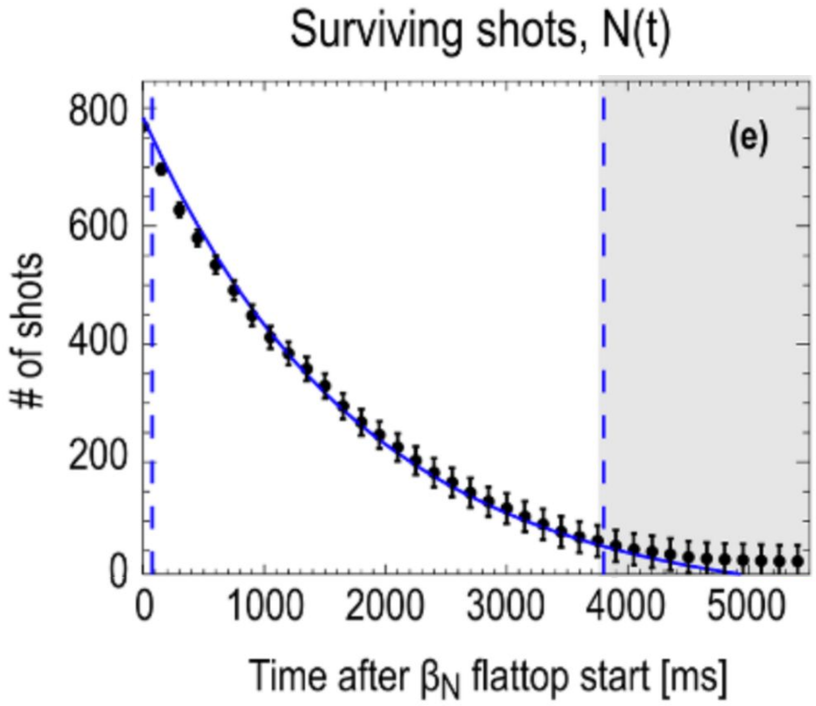

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Depends on scenario!

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Review of ML-driven tearing studies

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Machine learning can be used to warn of impending tearing modes

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List of relevant publications:

- Buttery et al. NF (2004)
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Survival analysis

- statistical framework for Pr (event | time)
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→ input:

kinetic DIII-D equilibria rapidly

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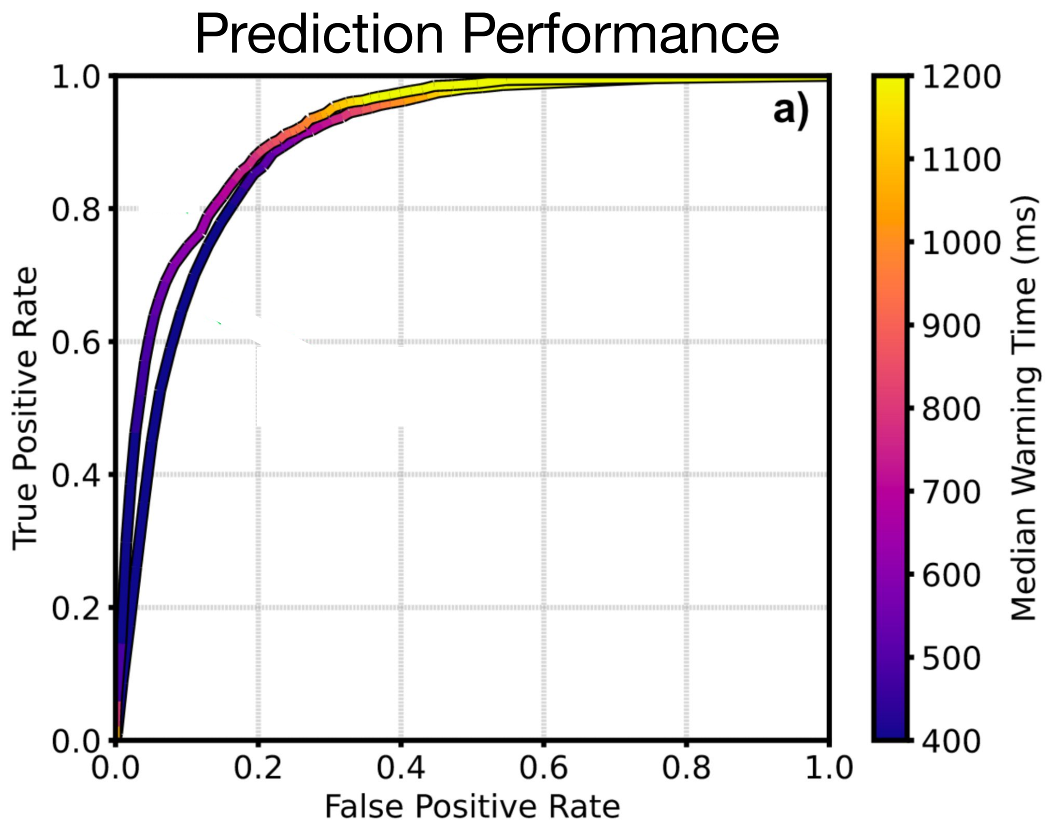

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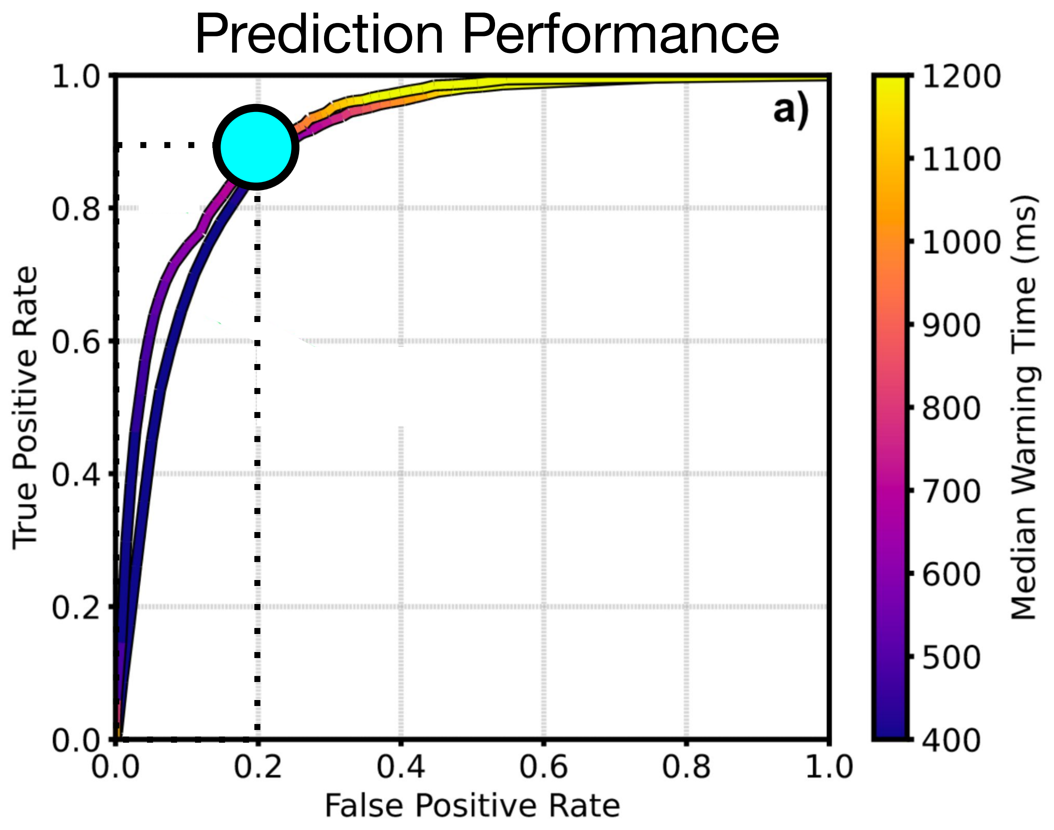
→ captured 90% of TMs with false alarm rate of 20% @ 900ms avg. warning time[4]



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Trained using 18 026 DIII-D shots

Inputs:

- Ideal MHD mag. energy distribution
- applied principal component analysis to reduce dimensionality
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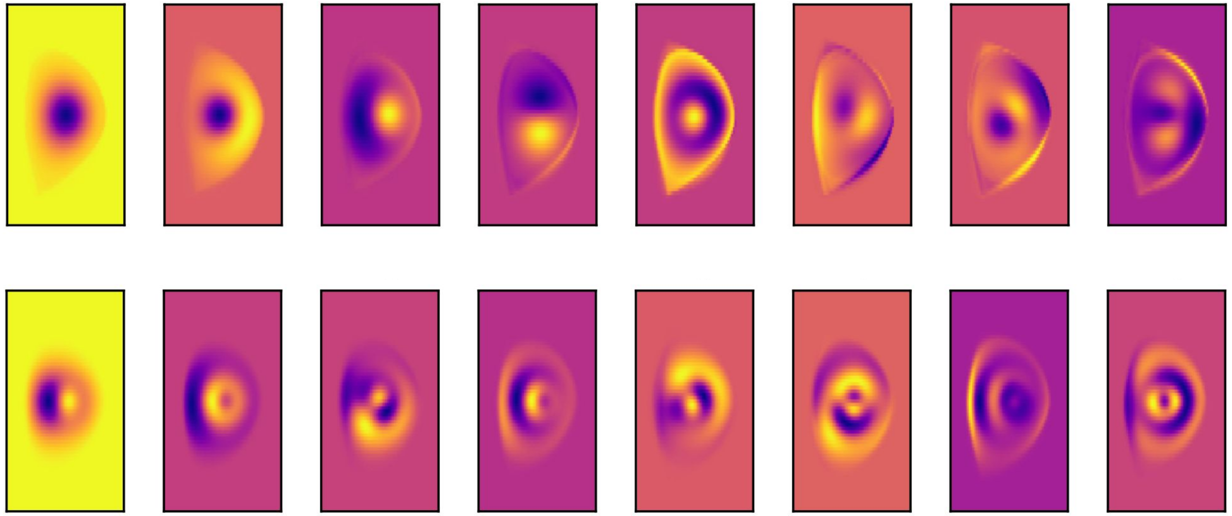
Magnetic energy principal components



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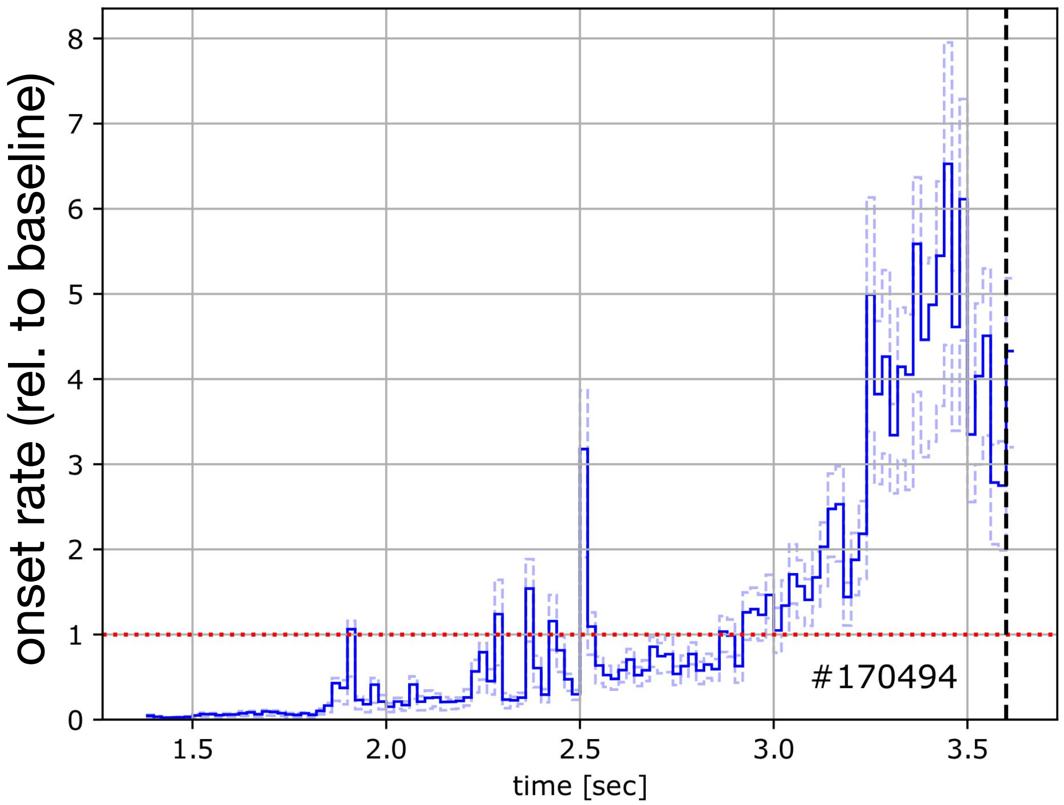
Successful TM prediction:



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Buttery et al. 2004
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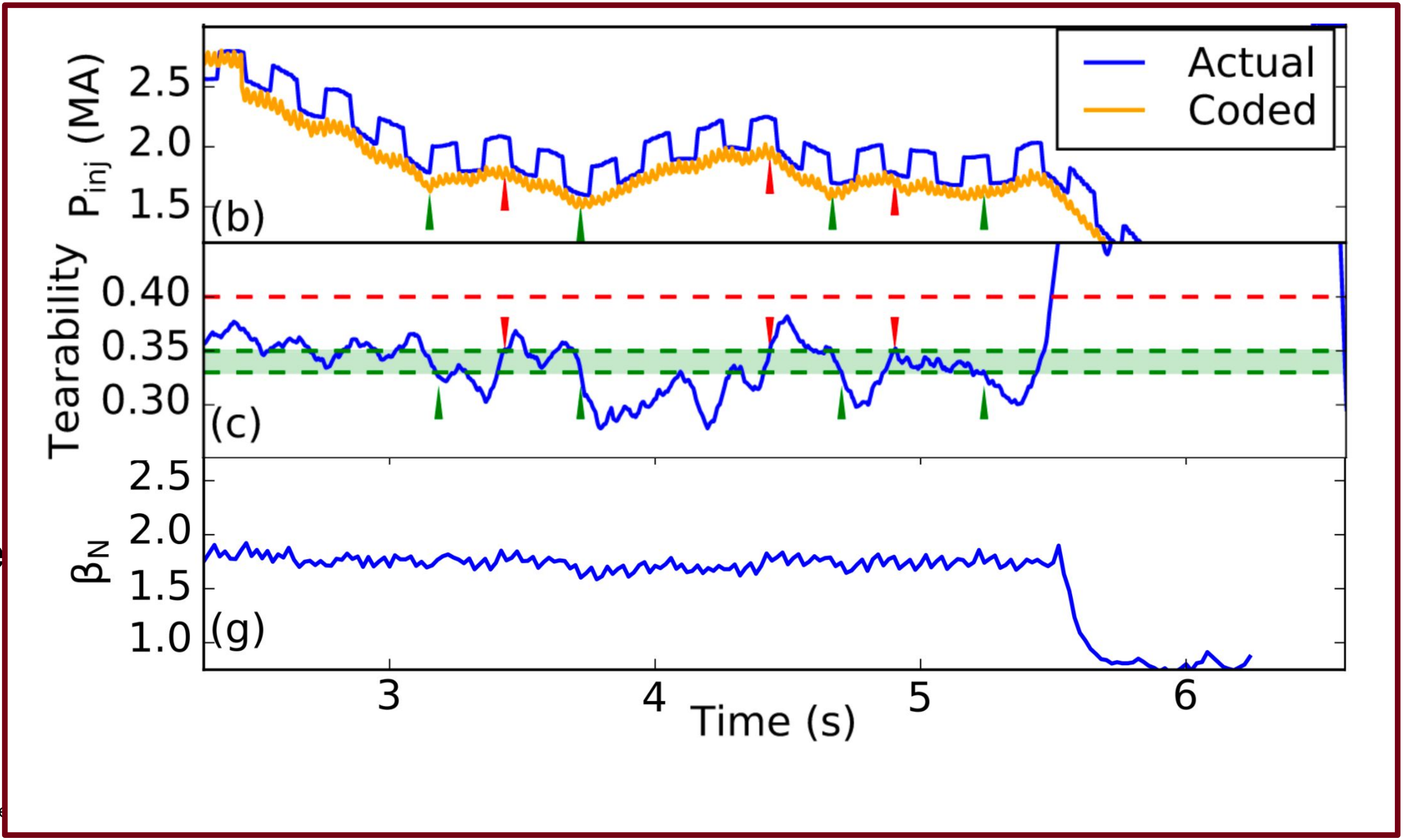

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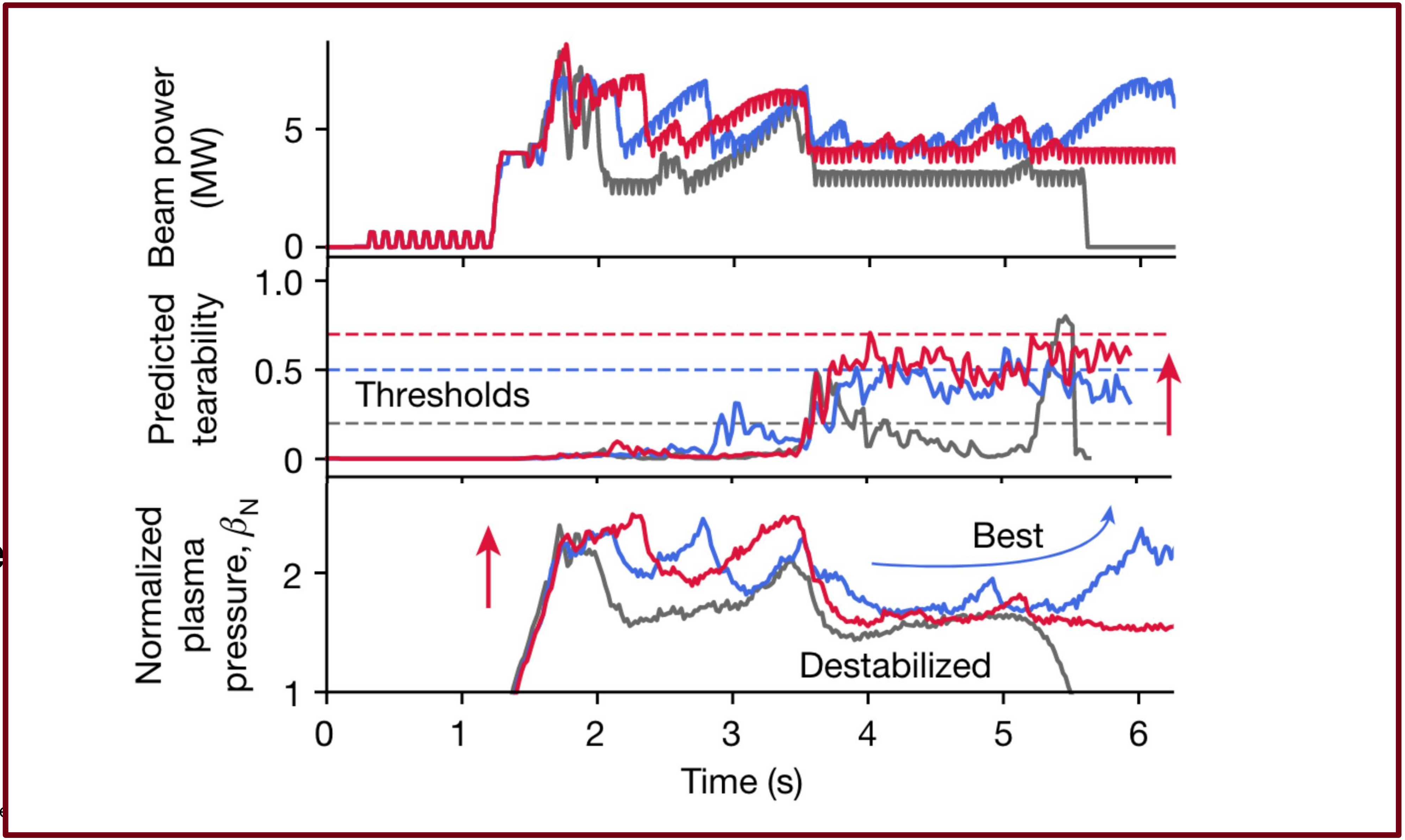

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Fu et al. 2020[1]	Tearability-actuated neutral beams for tearing avoidance
Seo et al. 2024[3]	Multi-actuator control to maximise β while avoiding TMs - uses reinforcement learning
Rothstein, Farre-Kaga et al. 2025[2]	Tearability-actuated electron cyclotron current drive response to maximise current drive efficiency while avoiding TMs

[1] Fu et al., PoP (2020) [2] Rothstein, Farre-Kaga et al., in prep (2025), [3] Seo et al., Nature (2024)

ML can be used to control the plasma to avoid TM onset

Proof of concept → completed

Fu et al. 2020
Seo et al. 2024
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Proof of concept → completed

Next step: Stress-testing ML control algorithms for pilot-plant applications

Fu et al. 2020
Seo et al. 2024
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Machine learning can identify physics correlations in multi-dimensional parameter spaces

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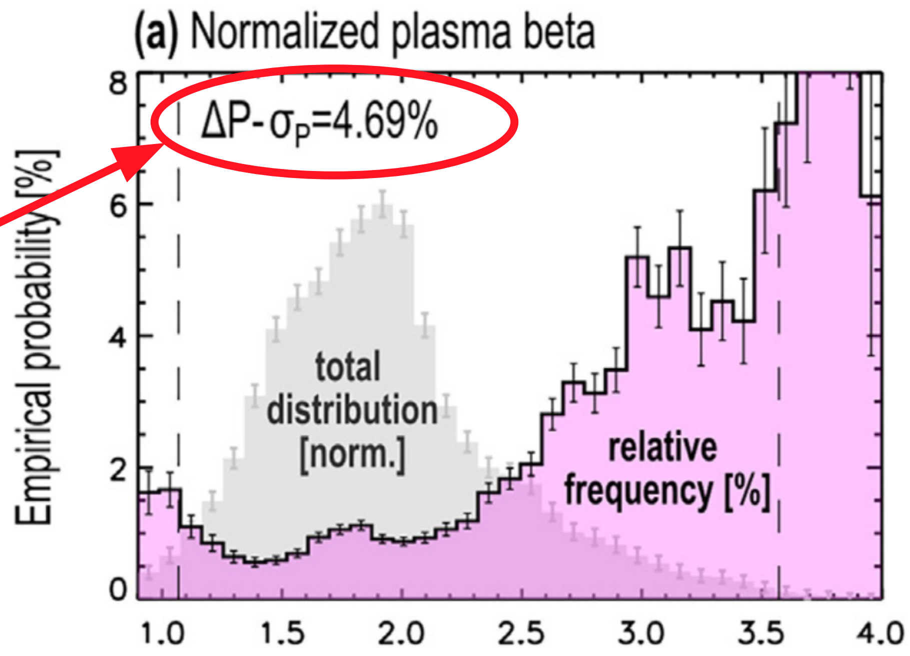

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Physics-determinants of 2/1 onset

variable	#ML impact	# ΔP-σ_{P}
Plasma beta	1	1

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Bootstrap current	2	11

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n = 2 mag. signal	3	4
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Farre-Kaga et al. 2025[2]
Olofsson et al. 2025[3]
Benjamin et al. 2025[4]

Shapley analysis:

Allows physics-based interpretation of logic encoded in ML algorithms

^see our poster

[1] Bardóczi et al., PoP (2023), [2] Farre-Kaga et al., arXiv:2502.20294v1 (2025) [3] Olofsson et al., NF (2025), [4] Manuscript in prep.

Background

- Tearing-to-disruption
- Identifying tearing modes
- Tearing physics to motivate machine learning

Review of ML-driven tearing studies

Summary and future directions

Summarising the impact of ML on tearing research in tokamaks

Tokamak tearing physics involves coupled, multi-scale dynamics, & chaos

- this motivates a data-driven approach w. statistics and ML

ML has been able to:

1. identify stability trends
2. predict tearing onset
3. control the plasma to avoid tearing modes in real time (proof of concept)

Demonstrated capabilities use diagnostics & actuators that may not be present on tokamak power plants

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sensitive to diagnostic suit[1]

rapid & effective actuators:

- neutral beams
- electron cyclotron current drive

[1] Olofsson et al., NF (2025)

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Fusion neutrons, plant economics
→ limit diagnostic suite

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High field, high density, plant economics
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SOLUTION?

We propose an increased focus on tearing-free scenarios

Let’s find the intersection* of tearing-stable scenarios and fusion pilot-plants

Method:

- Apply ML to a community-driven, multi-machine tearing mode database

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Interested in stabilising fully-inductive scenarios? Come see:

'Macroscopic trends of linear and neoclassical tearing stability in high-field H-mode tokamak pilot plants'

Work supported by Commonwealth Fusion Systems and
U.S. Department of Energy FES under Award DE-SC0014264.

BACKUP SLIDES

Shapley analysis allows physics-based interpretation of the logic encoded in ML tearing predictors

[1] Farre-Kaga et al., arXiv:2502.20294v1 (2025)

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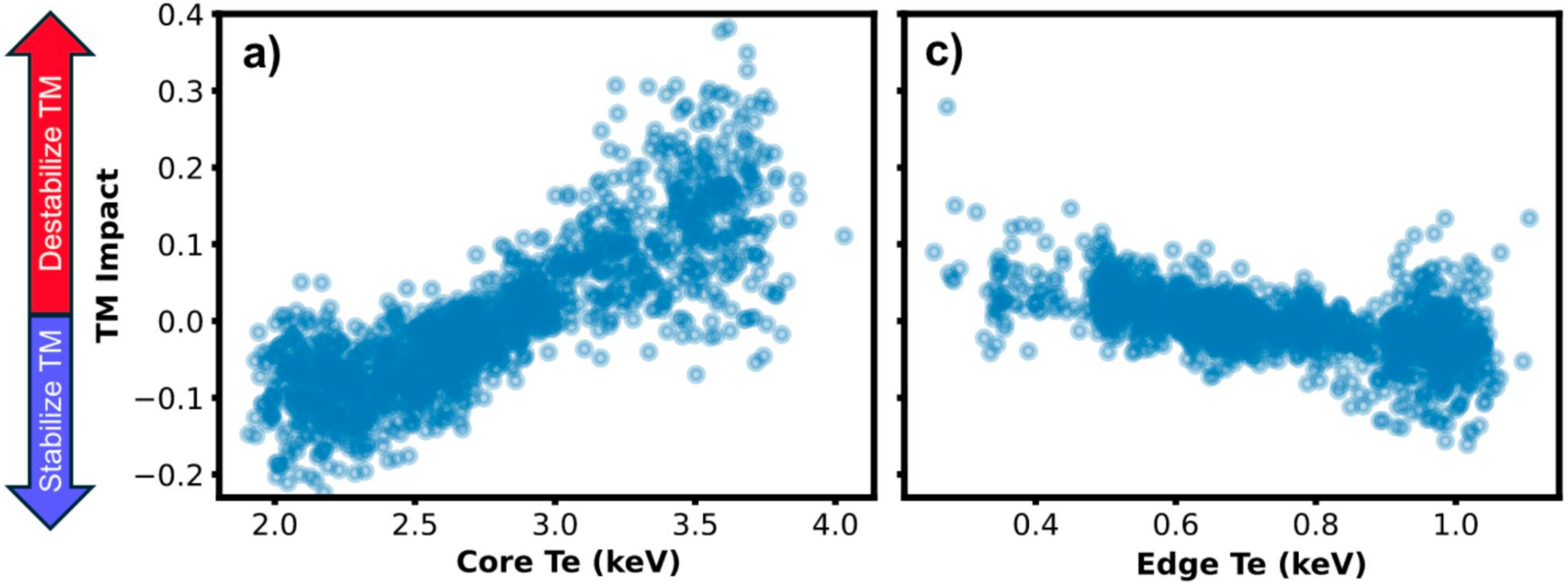

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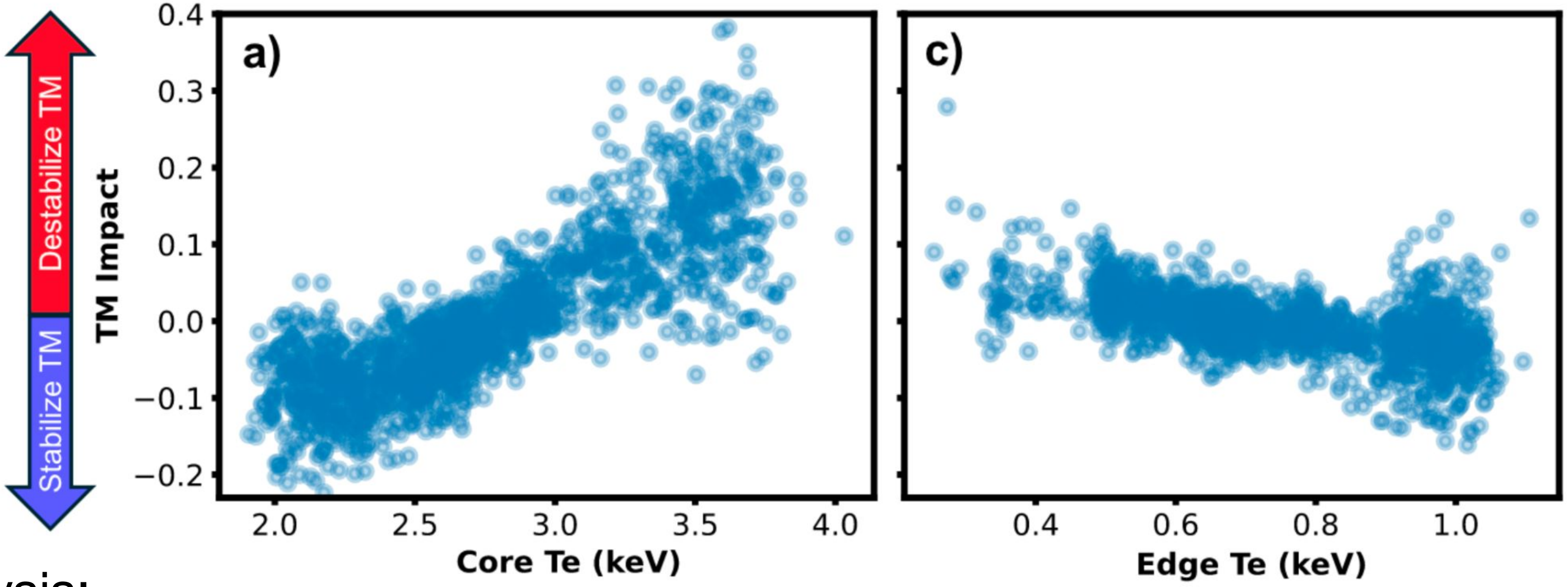

Shapley analysis:

Correlates input values to Tearability predictions, shifted by mean Tearability

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Shapley analysis allows physics-based interpretation of the logic encoded in ML tearing predictors

Farre-Kaga et al. 2025[1] - ML confirms temperature gradients destabilise TMs
Benjamin et al. 2025[2] - Δ' is well constrained by MRE curvature stabilisation term

[1] Farre-Kaga et al., arXiv:2502.20294v1 (2025) [2] Manuscript in prep.

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Monte-Carlo generated 14667 tokamak inductive pilot-plant equilibria

Calculated toroidal Δ' values using resistive DCON[3]

Trained an ML Δ' predictor using local tearing physics terms

[1] Farre-Kaga et al., arXiv:2502.20294v1 (2025) [2] Manuscript in prep. [3] Glasser et al. PoP (2016)

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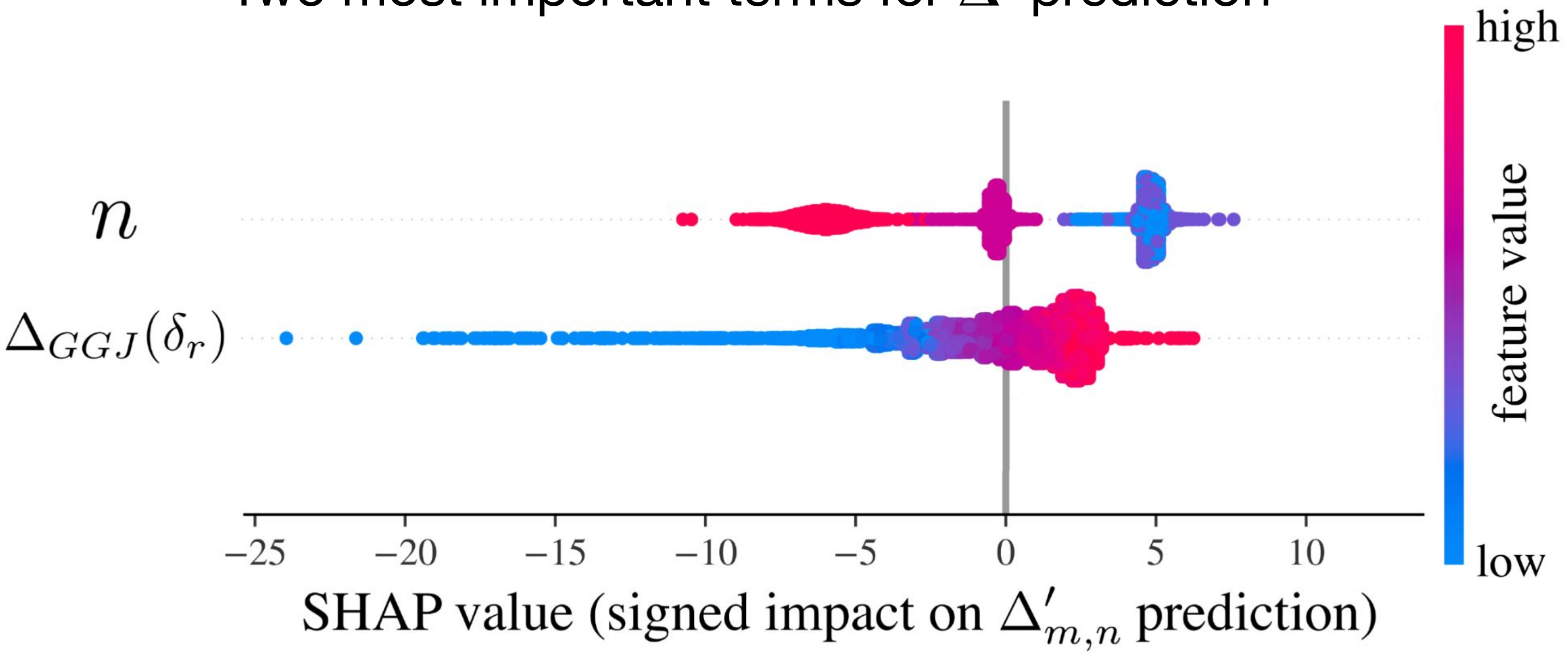
Two most important terms for Δ' prediction



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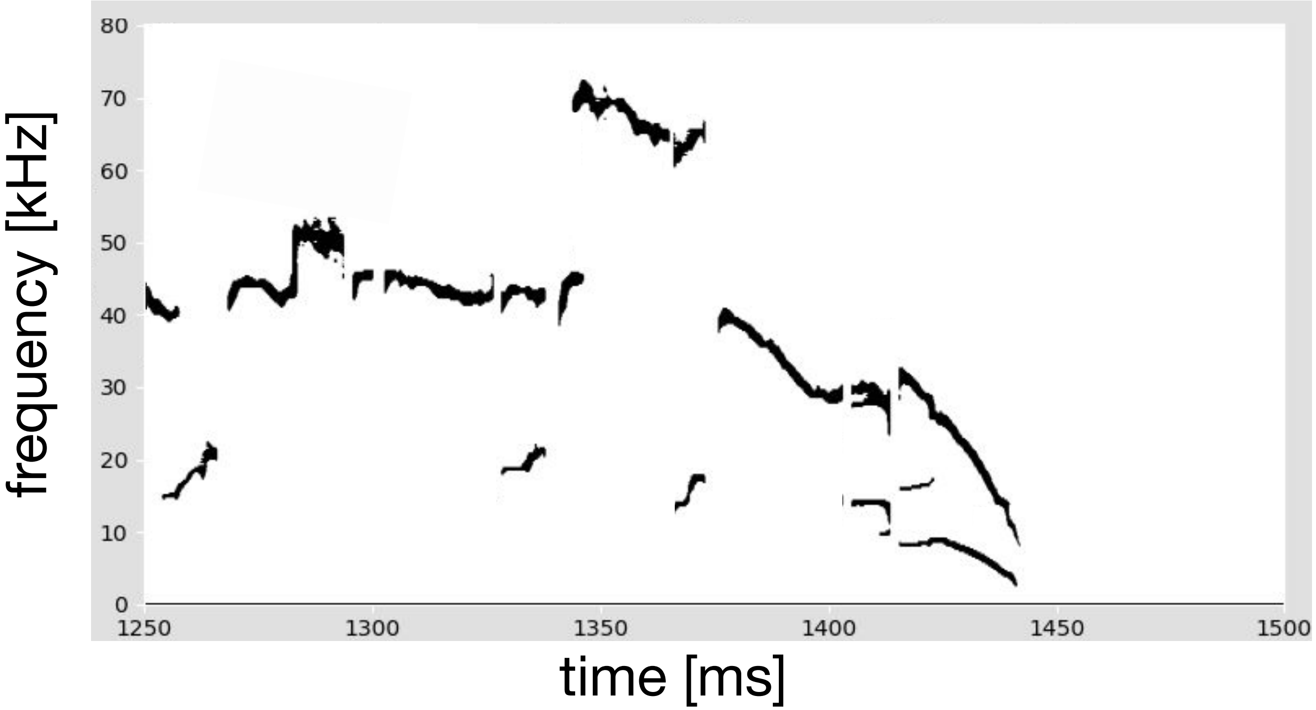
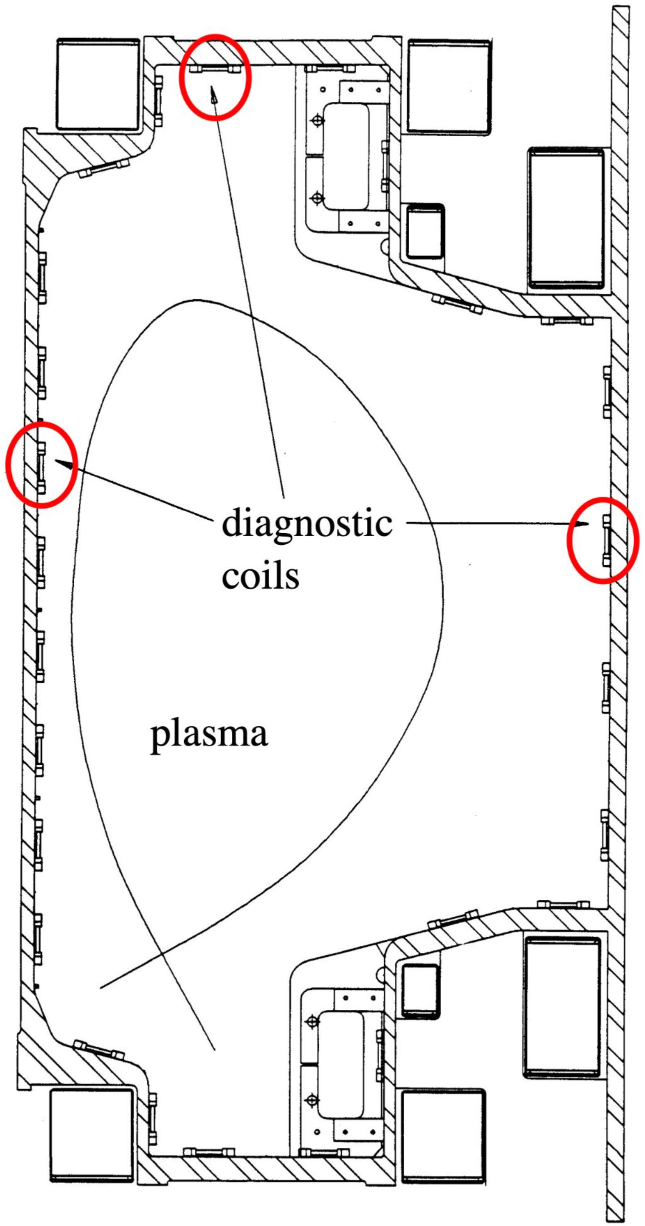
Identifying tearing poloidal and toroidal mode number - m,n

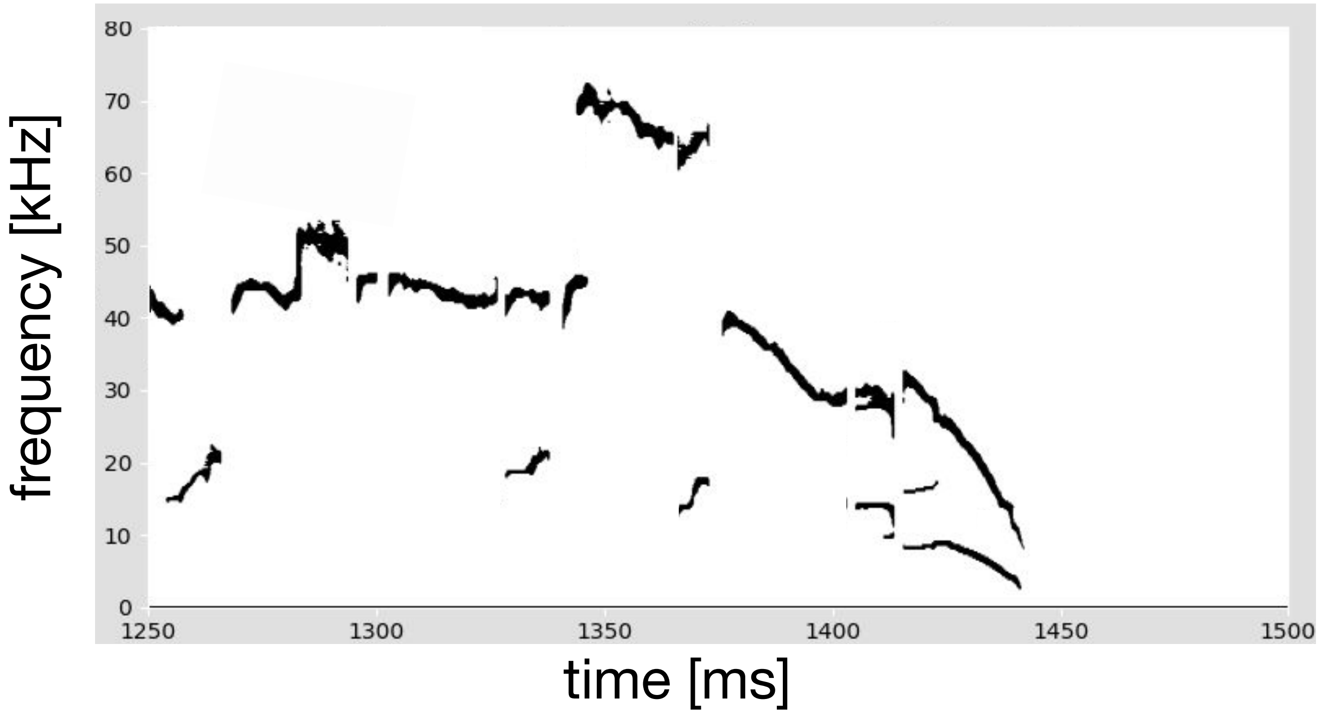


MIT's Alcator C-Mod tokamak cross-section



Identifying tearing poloidal and toroidal mode number - m,n

i. pick a point in frequency/time space



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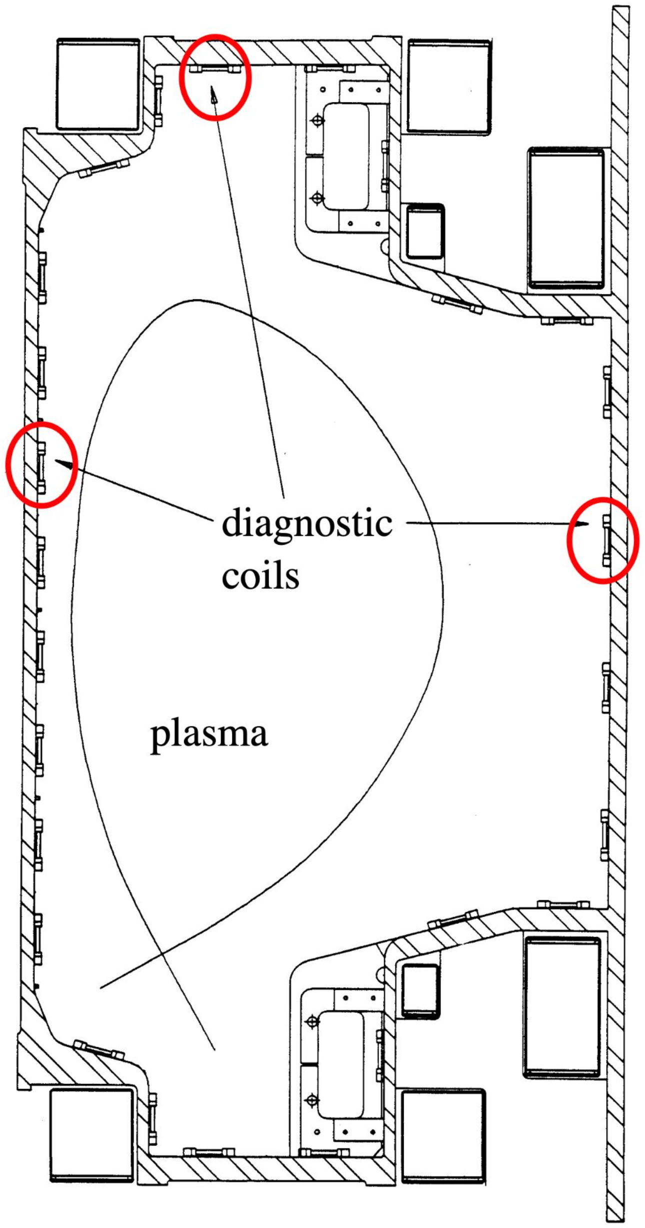

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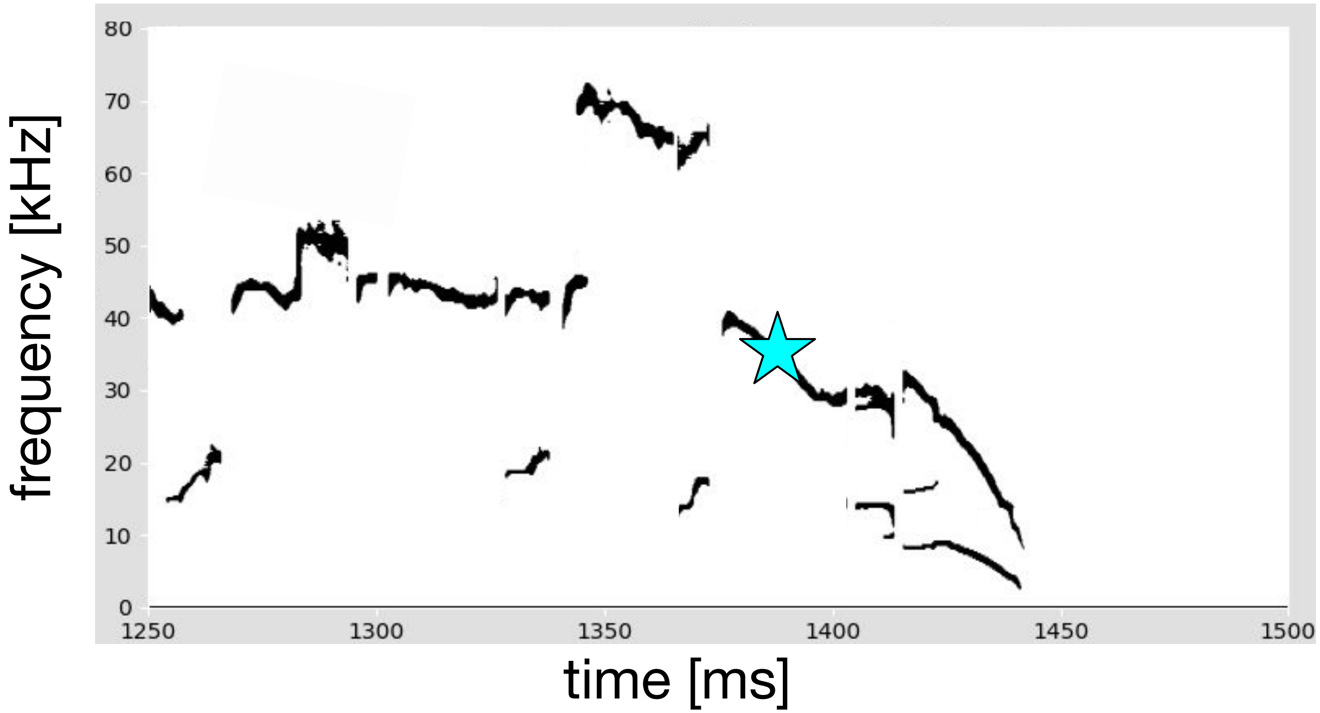

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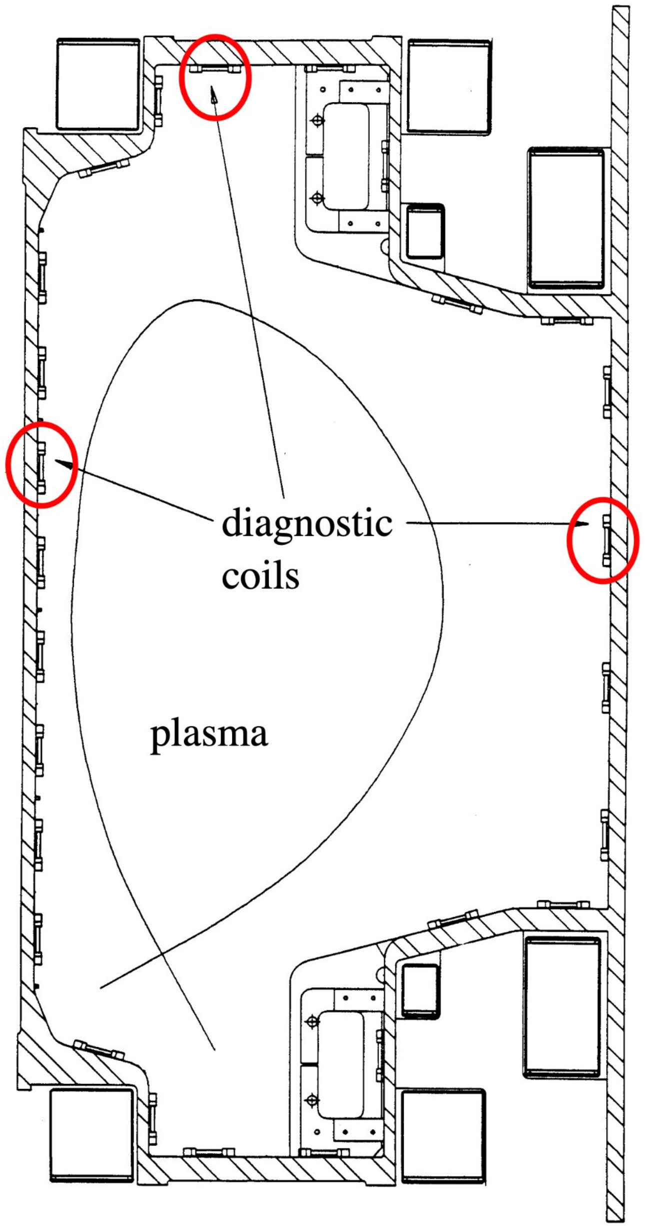
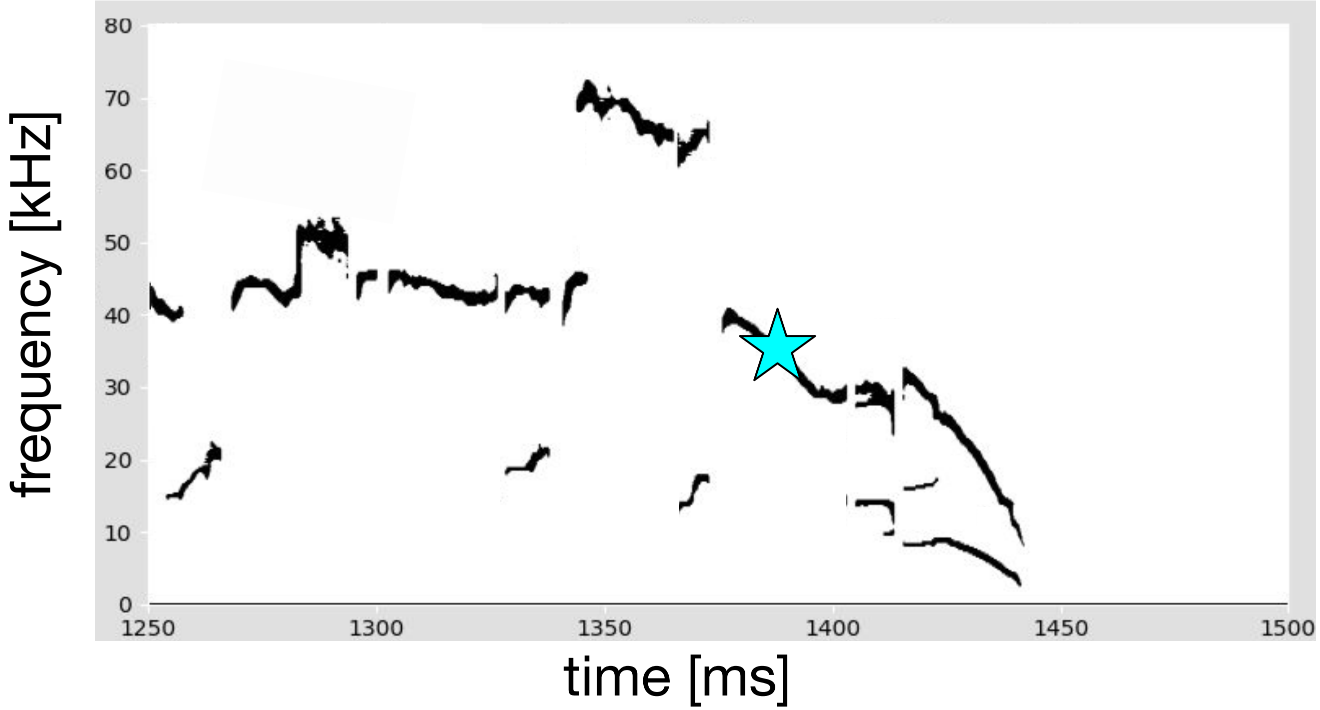


Identifying tearing poloidal and toroidal mode number - m,n

i. pick a point in frequency/time space

ii. compute phase differences across all probes



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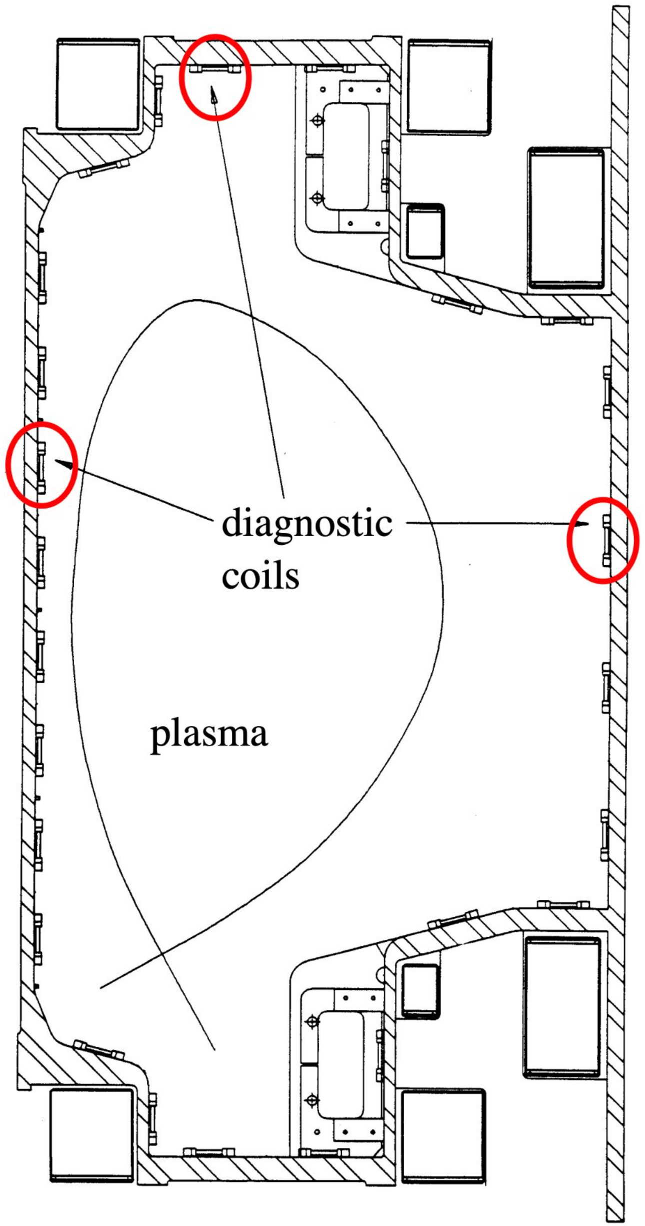
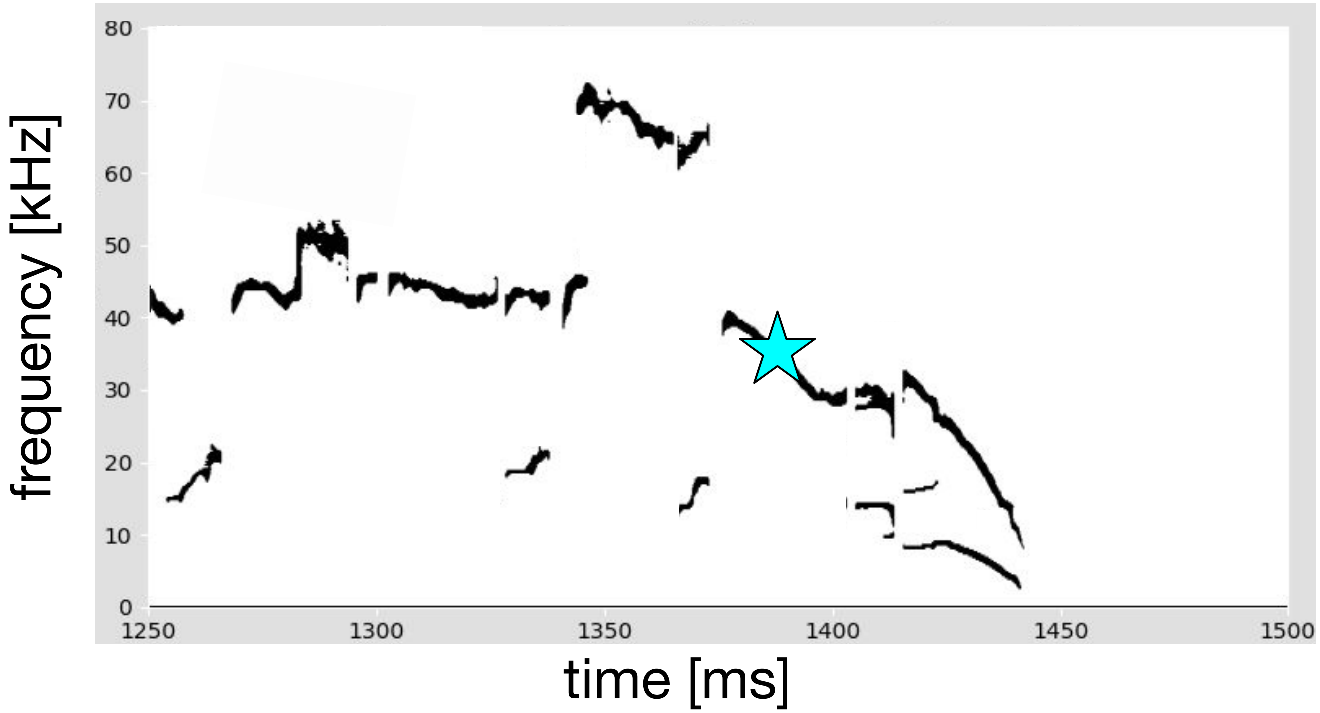


Identifying tearing poloidal and toroidal mode number - m,n

i. pick a point in frequency/time space

ii. compute phase differences across all probes

ii. compare with expected phase differences for set m, n modes



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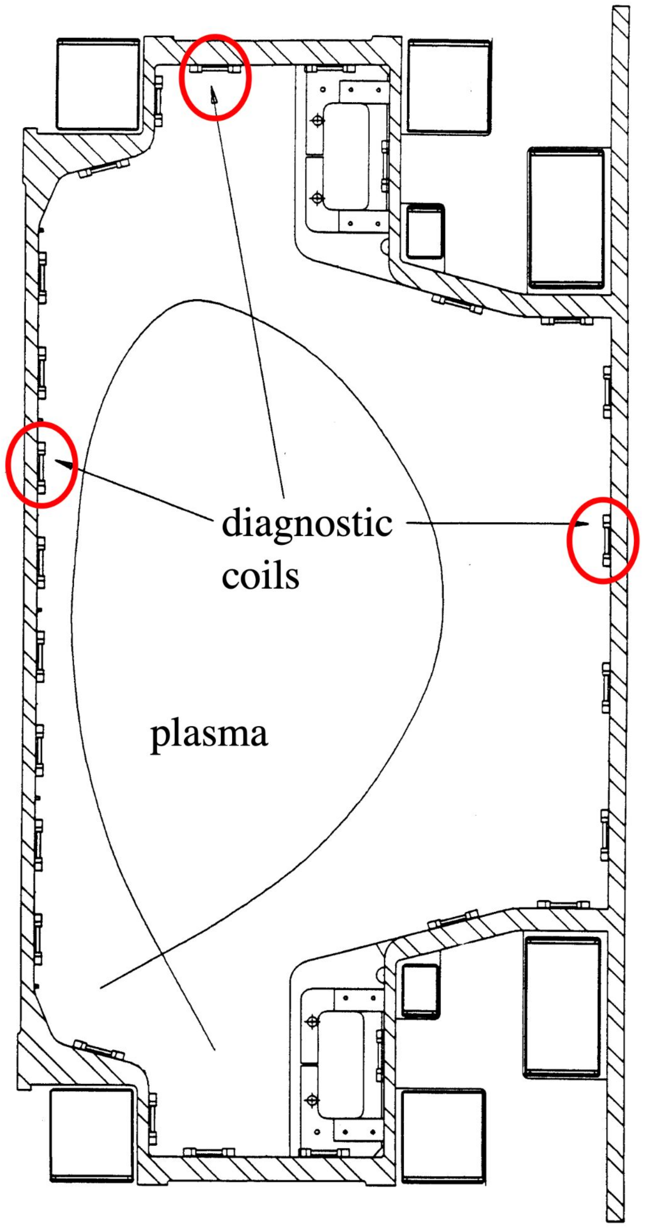

Buttery et al. 2004: Predicting time-to-disruption w. a neural network

Neural network (NN):

Layers of nonlinear activation functions that combine and transform inputs parameters into an output that minimises prediction error

Buttery et al. 2004: Predicting time-to-disruption w. a neural network

Parameters used in network
β_N, $\tau_{sawtooth}$, $\rho^*_{i\phi}$

Neural network (NN):

- Inputs are passed through `layers' of nonlinear activation functions that combine and transform them
- Produces an output that minimises prediction error

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output = time to TM onset
at set time intervals

error = Σ (predicted - actual time to onset)^2

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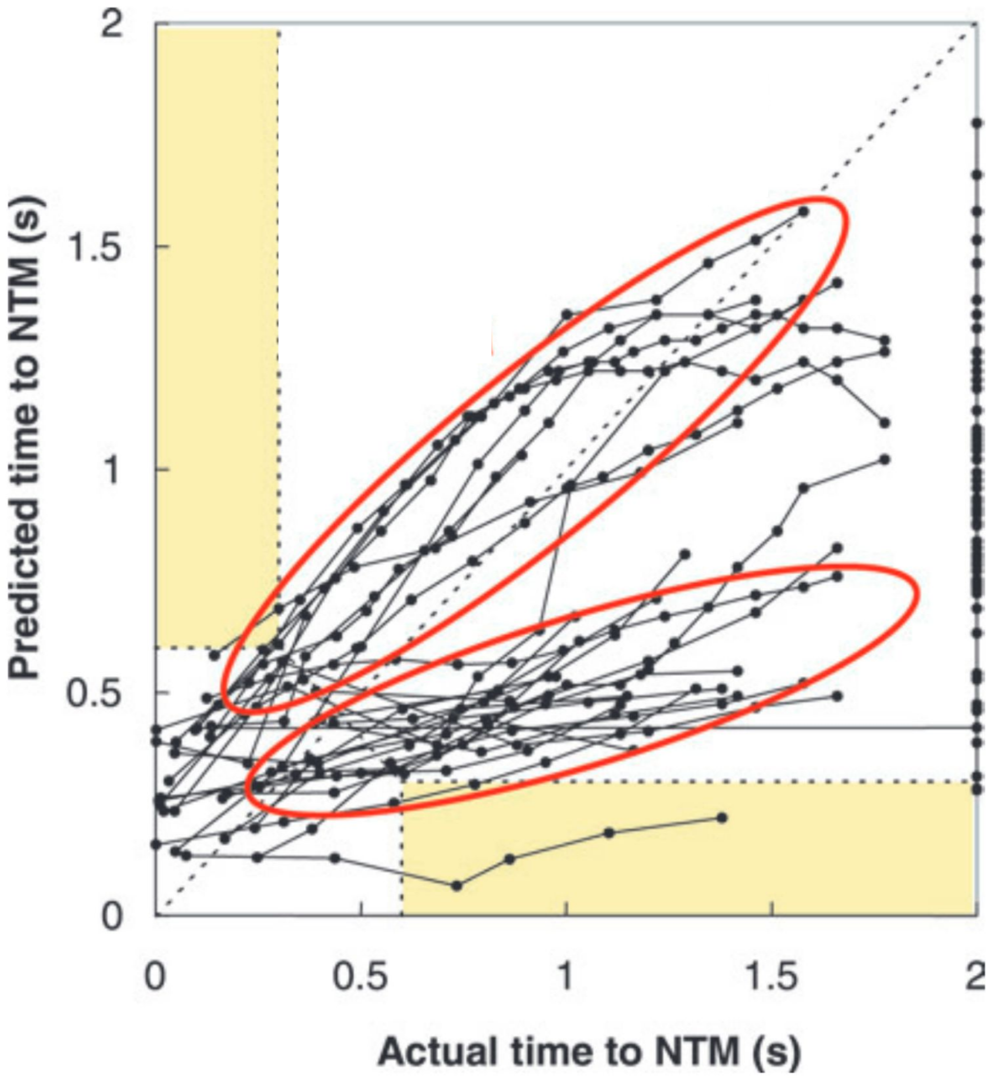

Buttery et al. 2004: Predicting time-to-disruption w. a neural network

Parameters used in network	Values of test residual	Number of errors
β_N, $\tau_{sawtooth}$, $\rho^*_{i\phi}$	34.31	6

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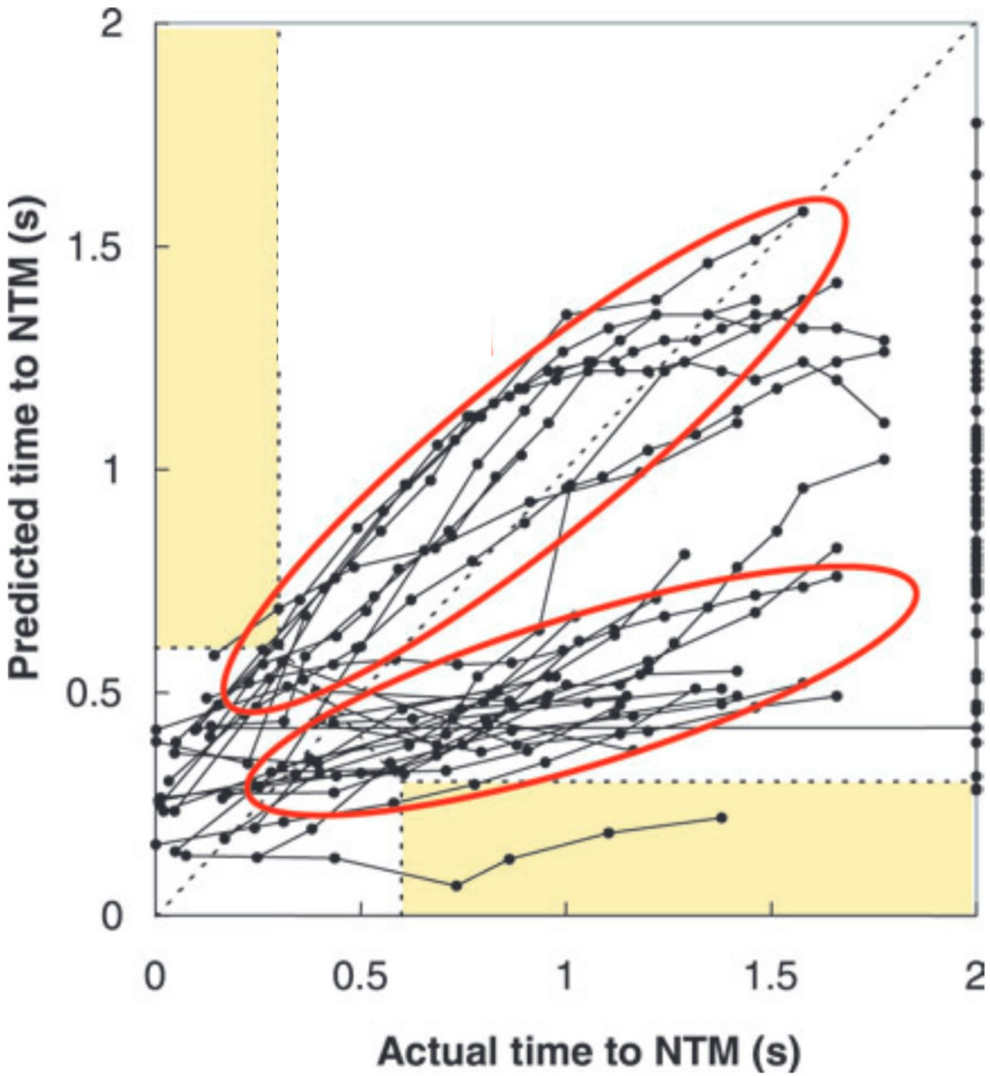
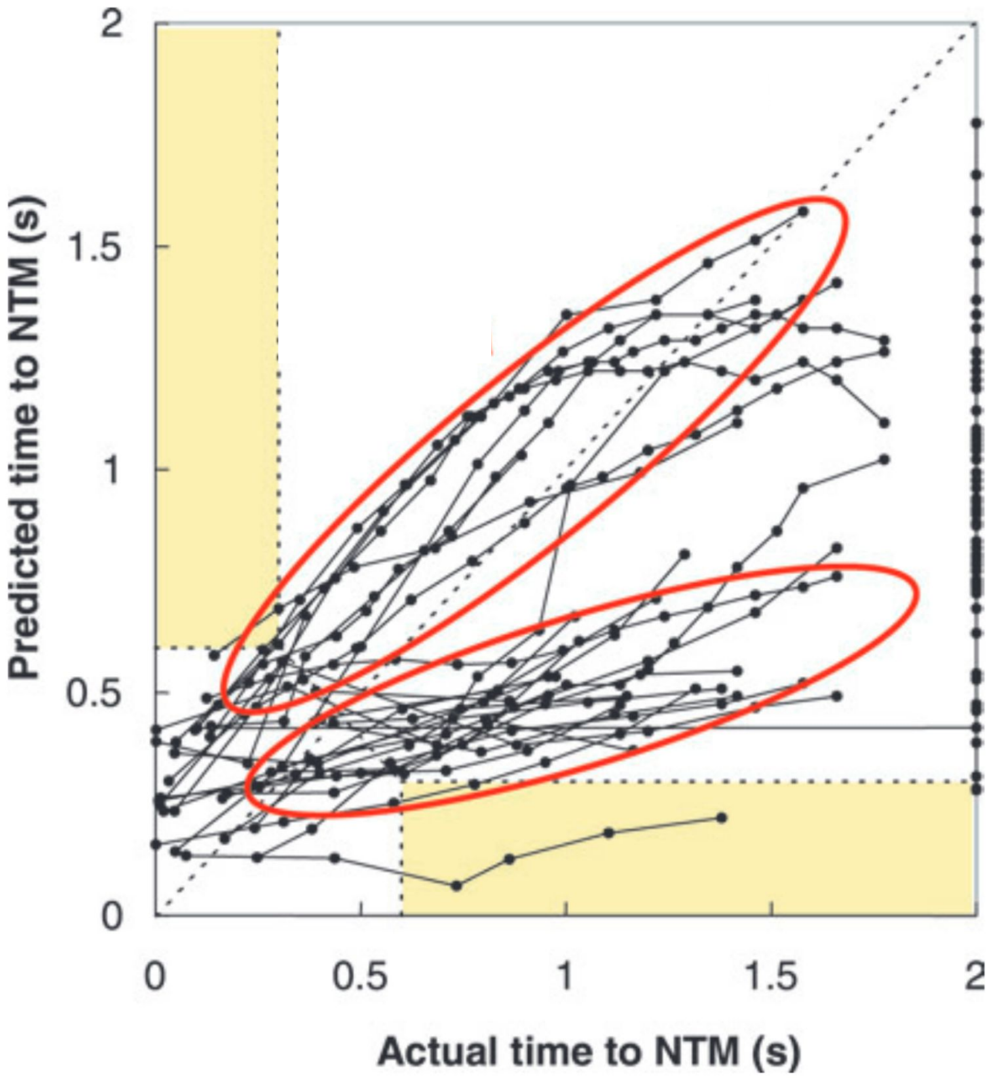


Buttery et al. 2004: Sawtooth period, β are important for prediction

Parameters used in network	Values of test residual	Number of errors
β_N, $\tau_{sawtooth}$, $\rho^*_{i\phi}$	34.31	6
β_N, $\tau_{sawtooth}$	34.41	7
β_N, $\rho^*_{i\phi}$	35.68	9
β_N	35.87	11
$\rho^*_{i\phi}$	37.45	10
$\tau_{sawtooth}$	48.85	14
$\tau_{sawtooth}$, $\rho^*_{i\phi}$	37.46	9



Buttery et al. 2004: Shorter sawtooth period → higher β limit

Parameters used in network	Values of test residual	Number of errors
β_N, τ_{sawtooth}, $\rho^*_{i\phi}$	34.31	6
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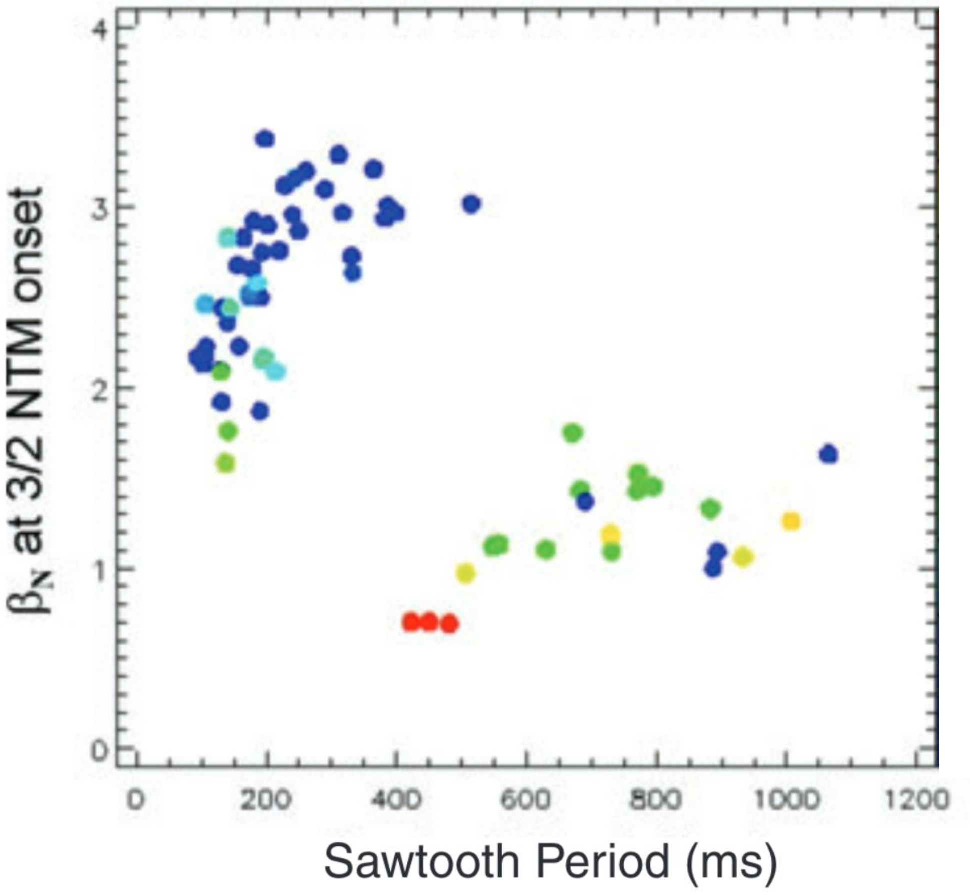

Oloffson et al. 2018: Tearing hazard function

Tearing hazard function: Average TM onset frequency as a function of plasma state

Converted into a simple optimisation problem

Trained using a boosted tree model:

Tree:
- subdivides input space into rectangular regions
- makes prediction based on average of training data in each region

Boosted tree:
Iteratively constructs trees and sums their predictions

Oloffson et al. 2018: Tearing hazard function used to understand physics behind 2/1 TM onset at DIII-D

Finding average TM onset frequency as a function of DIII-D tearing physics terms

Quantity	Text	Description
$\rho_q \Delta'$	`rdpr21`	Delta-prime proxy
$D_R^{\text{apx}} \rho_q / w_{\text{sml}}$	`merc21`	MRE Mercier term
$2\sqrt{\epsilon} L_q \rho_q / (3 L_{pe} w_{\text{sml}})$	`boot21`	MRE bootstrap term
$-(\mathrm{d}\omega/\mathrm{d}\rho) L_s \tau_A$	`nfs21`	Norm. flow shear
$\widehat{\rho}_q = \rho_q / \rho_b$	`rho21`	Norm. radial q-pos.
ℓ_i	`elli`	Internal inductance
q_{95}	`q95`	q at 95% of pol. flux
β_p	`betap`	Poloidal β
n/n_G	`grwdens`	Greenwald density
$\mu_0 I_{pl} / (\rho_b B_0)$	`iphat`	Norm. current
$\tau_{\text{crt}} P_{\text{bol}} / (W_p + W_k)$	`pradhat`	Radiated power index
$100 \times \omega \tau_A$	`alfvprc`	Norm. avrg. rotation

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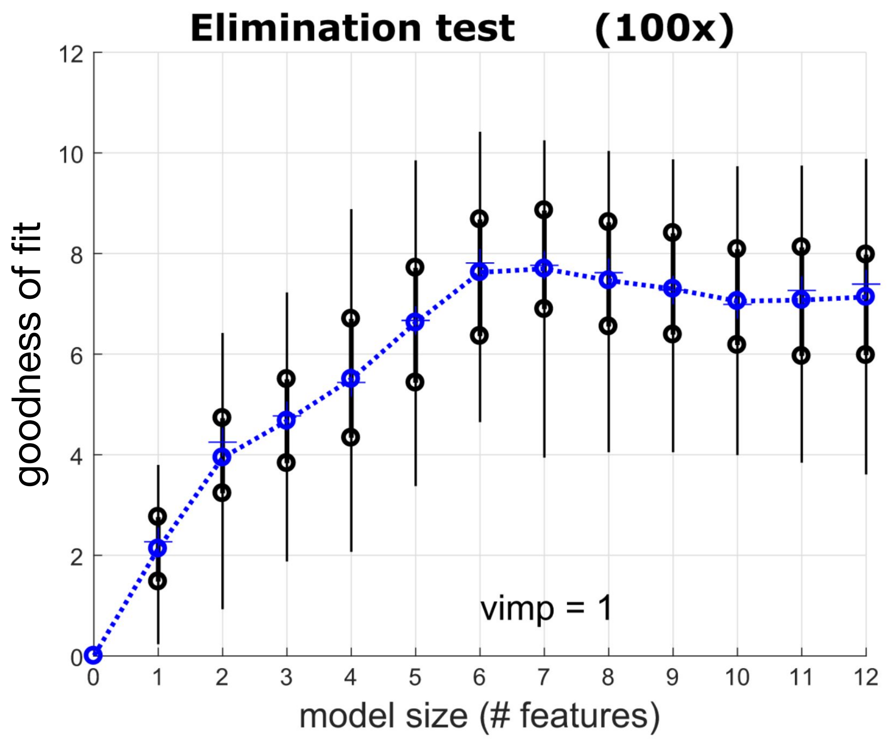
Iterative feature selection:



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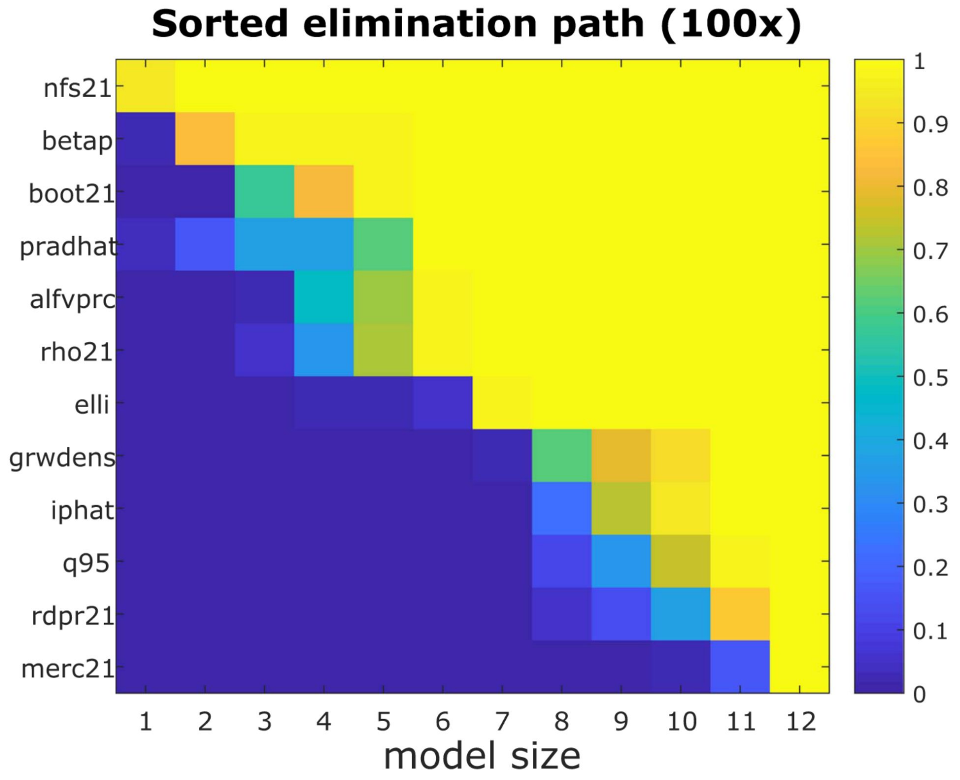

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Finding average TM onset frequency as a function of DIII-D tearing physics terms

Three most important terms:
1. flow shear
2. poloidal beta
3. MRE bootstrap current term

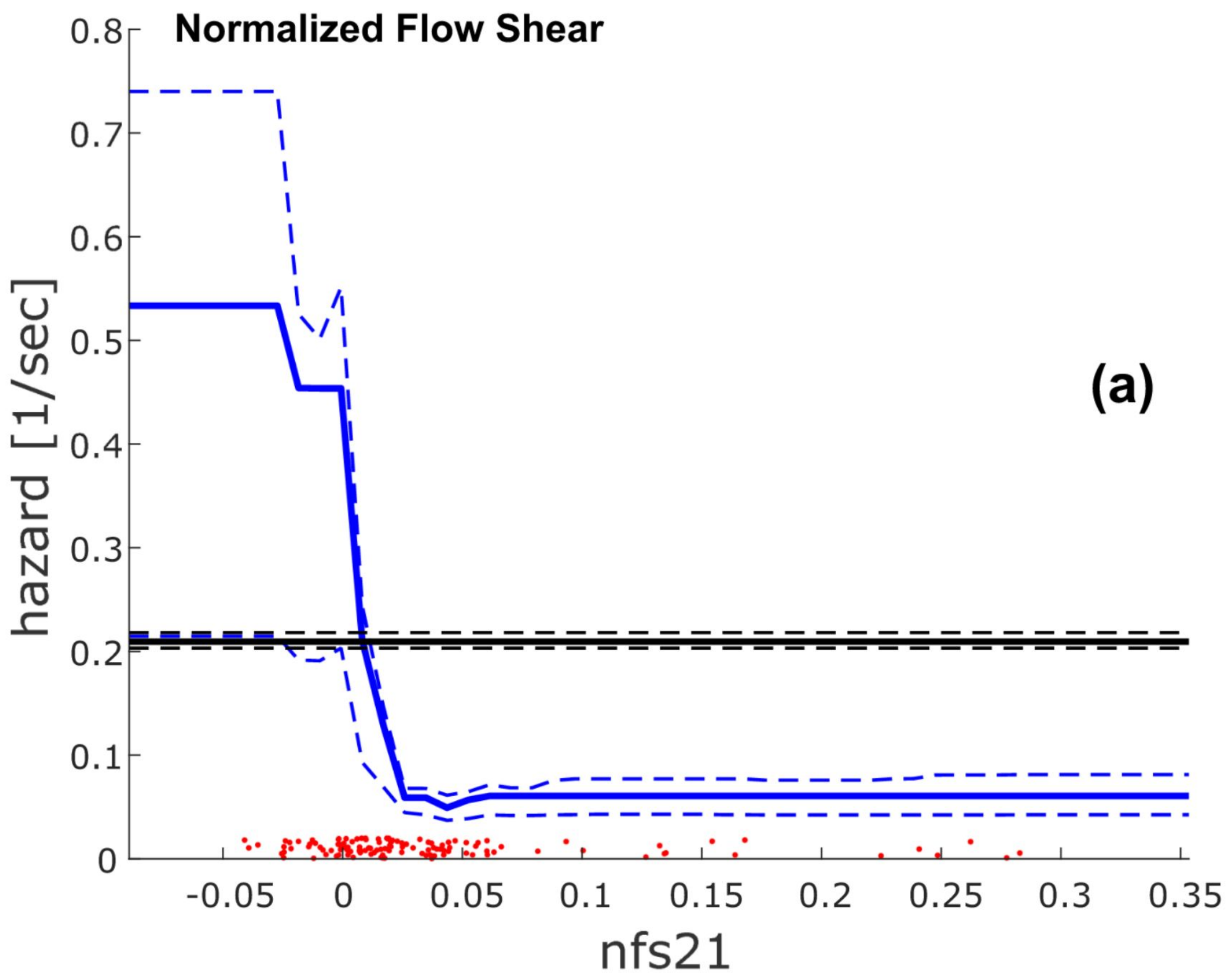
Oloffson et al. 2018: Tearing hazard function used to understand physics behind 2/1 TM onset at DIII-D

Finding average TM onset frequency as a function of DIII-D tearing physics terms

Three most important terms:
1. flow shear
2. poloidal beta
3. MRE bootstrap current term

Delta-prime proxy **not** important:
- ‘equilibrium’ value doesn’t vary significantly/not dominant term?
- high-m formulation not appropriate?
- obscured by error?

Oloffson et al. 2018: Low or reversed flow shear is extremely destabilising



Machine learning can be used to warn of impending TM onset

Fu et al. 2020 - How to construct a tearing onset predictor

Machine learning can be used to warn of impending TM onset

Fu et al. 2020 - How to construct a tearing onset predictor

Time series of training inputs
supplied to a ML fitting algorithm

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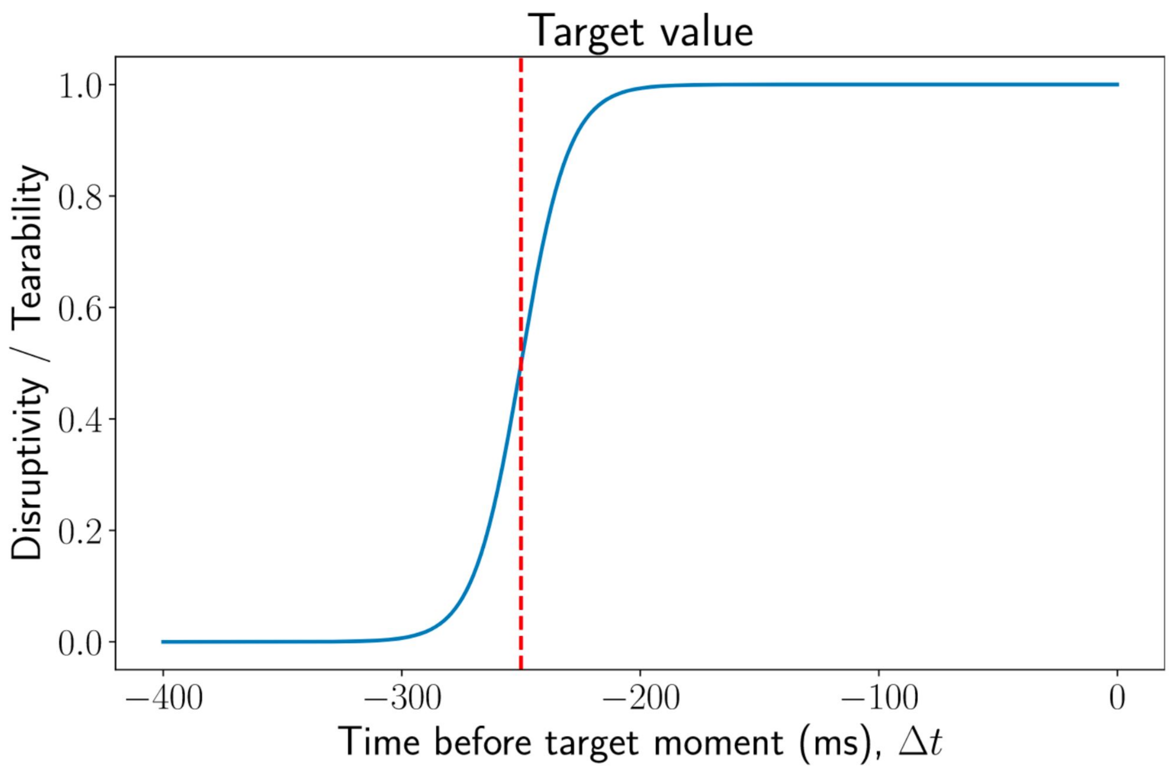
Define output ‘Tearability’ ∈ [0,1]



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Fu et al. 2020 - How to construct a tearing onset predictor

Time series of training inputs supplied to a ML fitting algorithm

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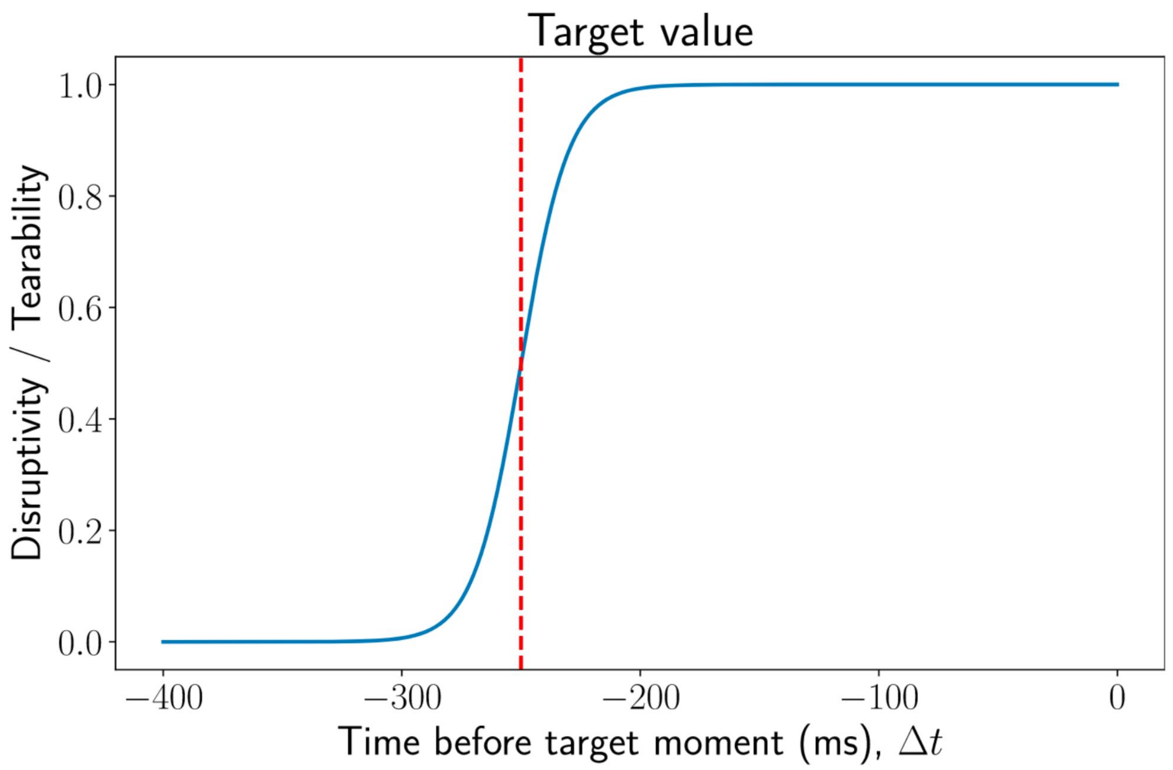
Trained on 1970 shots on DIII-D w. 0D physics quantities



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Fu et al. 2020 - How to construct a tearing onset predictor

Time series of training inputs supplied to a ML fitting algorithm

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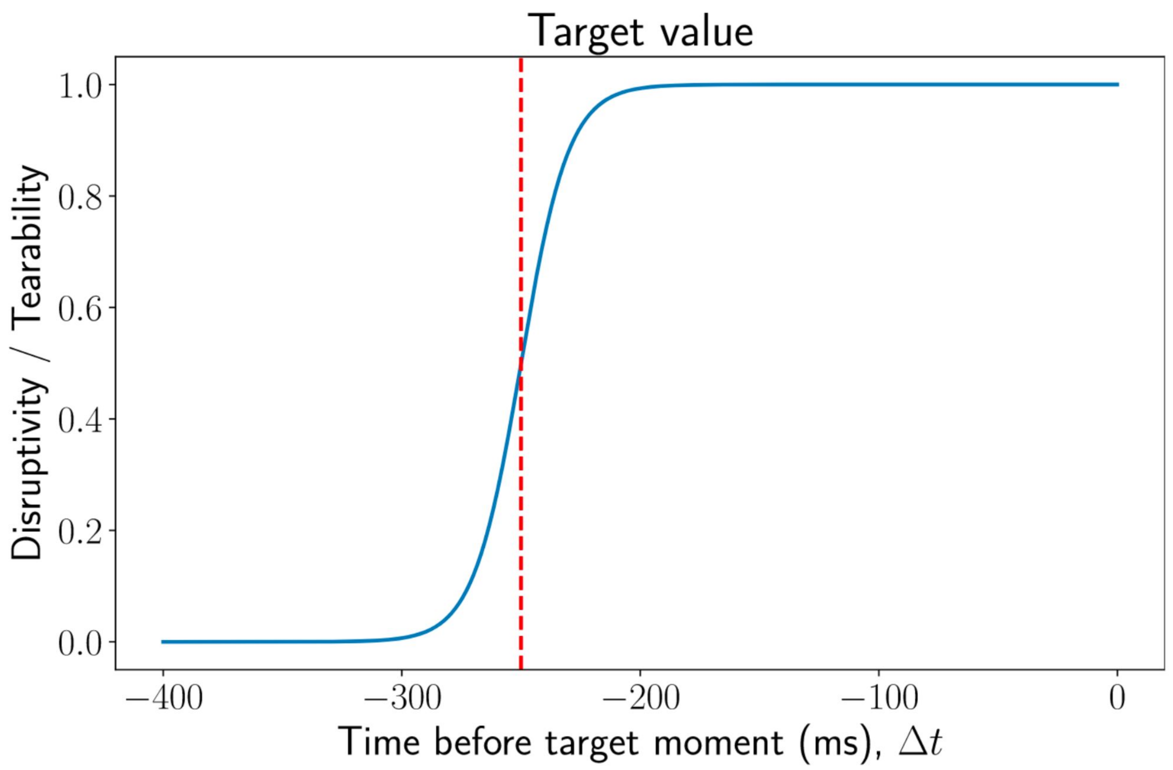
Trained on 1970 shots on DIII-D w. 0D physics quantities

Able to correctly detect 90% of TMs with a false alarm rate of 8%

> 400ms avg. warning time



Seo et al. 2024: ML can be used to actuate multiple plasma controllers to maximise plasma pressure while avoiding tearing modes

Applies deep reinforcement learning:

Neural network-based plasma controller trained to maximise reward R based on its actions:

$$R = \begin{cases} \beta_N, & \text{if } T < k \\ k - T, & \text{otherwise} \end{cases}$$

k = threshold

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Dynamical model: Seo at al., (2023)

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Dynamical model: Seo at al., (2023)

Time series data fed to neural network
Predicts Tearability ∈ [0,1] & β_N at time t + 25ms

Inputs:
- current diagnostic information
- future actuator response
- 8505 DIII-D shots, 639 555 time slices

$$R = \begin{cases} \beta_N, & \text{if } T < k \\ k - T, & \text{otherwise} \end{cases}$$

k = threshold

Seo et al. 2024: ML can be used to actuate multiple plasma controllers to maximise plasma pressure while avoiding tearing modes