Real-time tearing mode control on DIII-D:

Leveraging ML models for high accuracy and interpreting the ML model predictions

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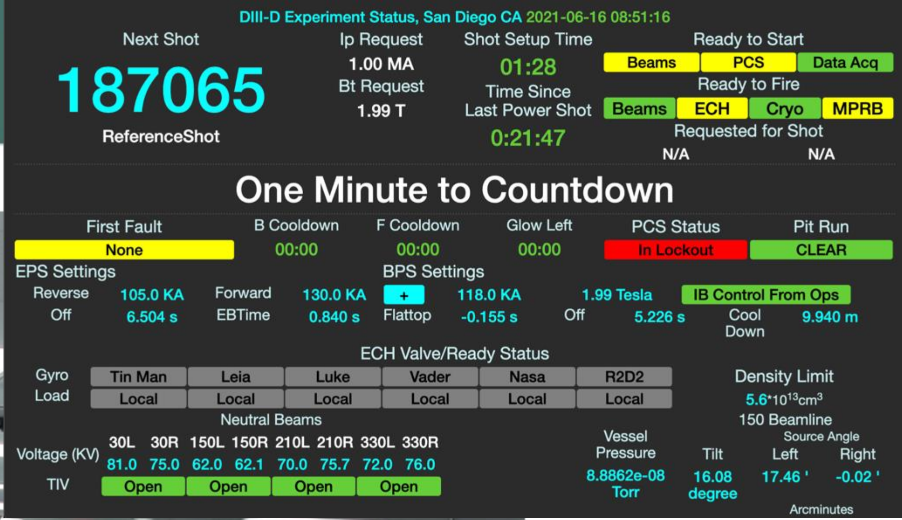


Plasma Control

Improving plasmas by trial-and-error

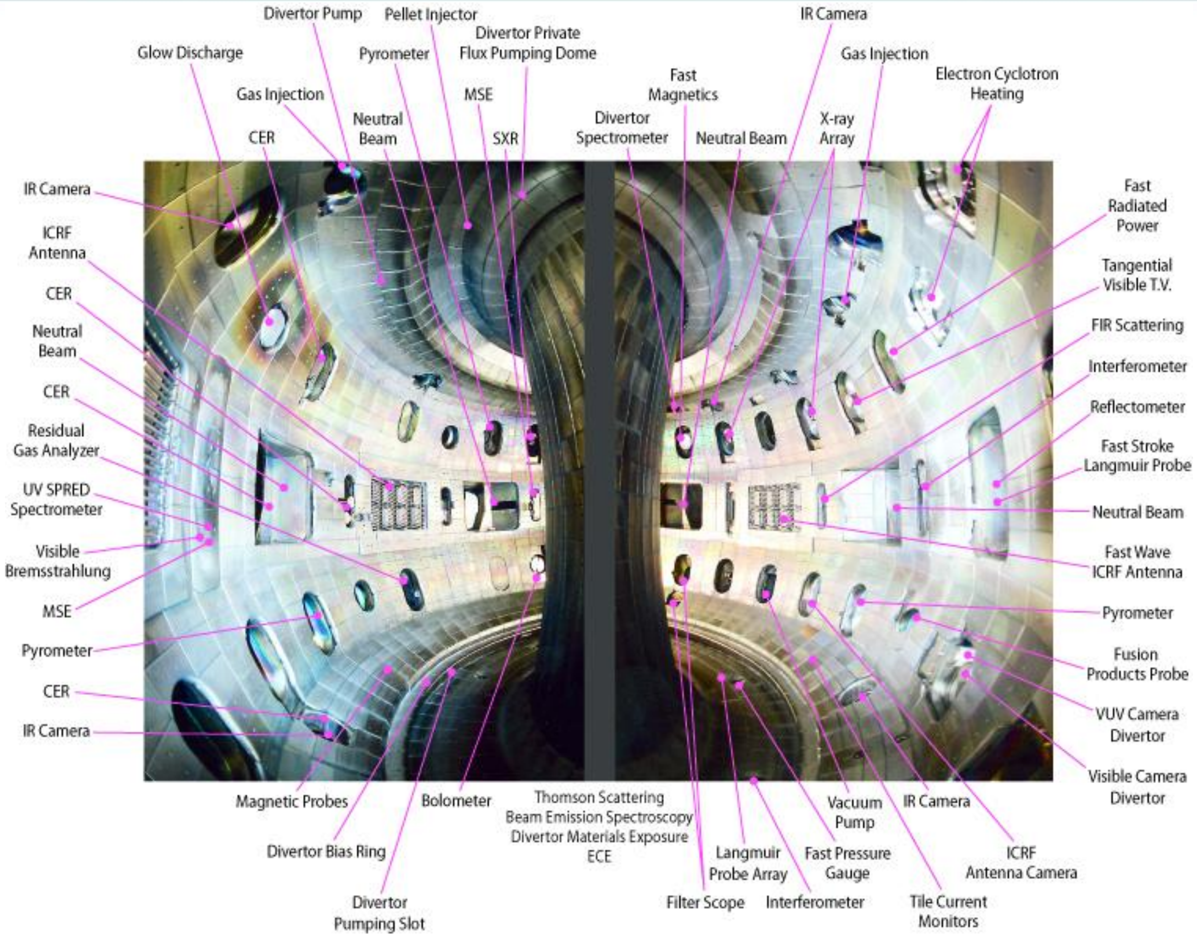
- “[after a previous full-day experiment we were] able to reproduce 133103 in 180636, 180643 and 180644.
- Many shots had MHD modes at 3 s… to try to improve that we changed **Electron Cyclotron Heating** deposition (180639-180642), and go to lower (180643-180646) and higher (180647) **plasma current**… none of which were successful.
- We also **tried lowering the voltage on the off-axis beams** (180645) to get rid of the bursty modes and **moving the BetaN ramp earlier** (180646.)”
- Ultimately, got “good reproduction of 133103, but no significant improvement”

Human operators combine simulations, heuristics, and experience to achieve desired state by trial-and-error

Outline

- **Crash course to tokamak experiments**
- Long term TM prediction and preemptive ECCD TM suppression and understanding ML predictions
- Surrogate models for real-time control

Observing the plasma state



Plasma Control

Reconstructing the plasma state

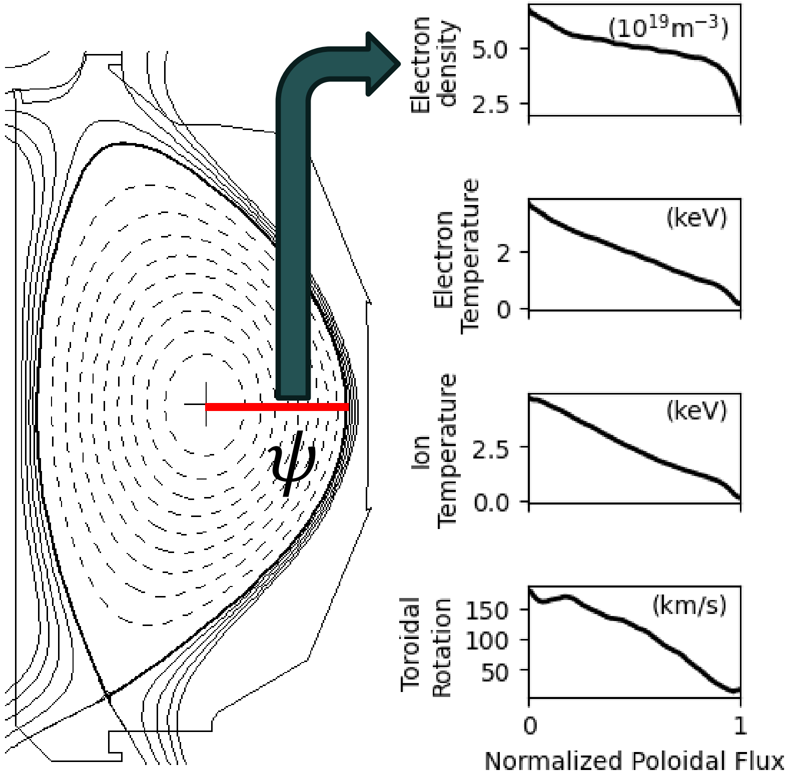
- Use diagnostic data to reconstruct plasma equilibrium

Scalar Parameters

- Plasma shape and boundary ($\kappa, \delta_{u,l}$ etc)
- Normalized pressure (β_N)
- Plasma current (I_P)
- Magnetic field (B_T)

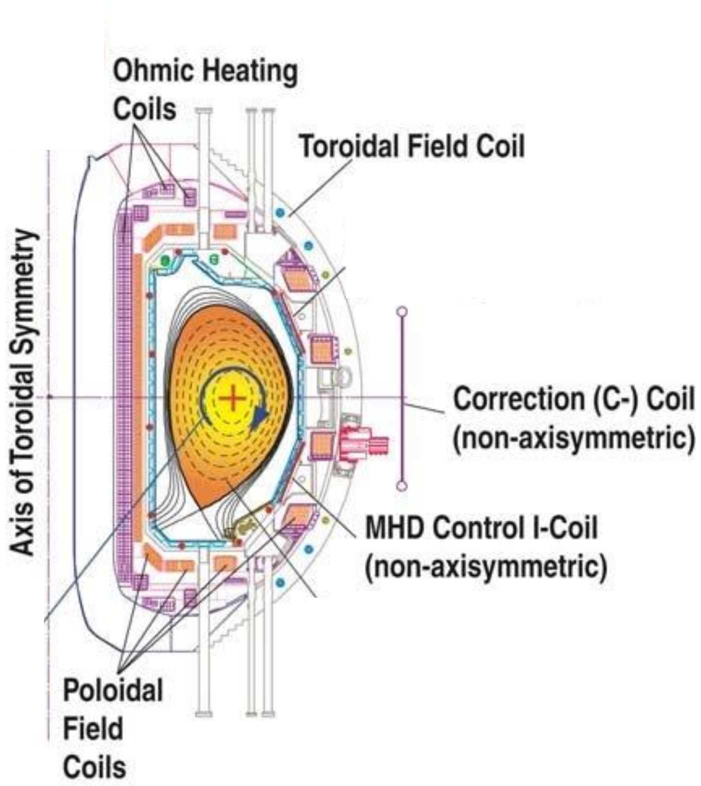
1D Profiles

- Pressure (P)
- Safety factor (q)
- Electron temperature and density (T_e, n_e)
- Ion temperature and density ($\mathrm{T_i}, \mathrm{n_i}$)
- Rotation (Ω)



Plasma Control

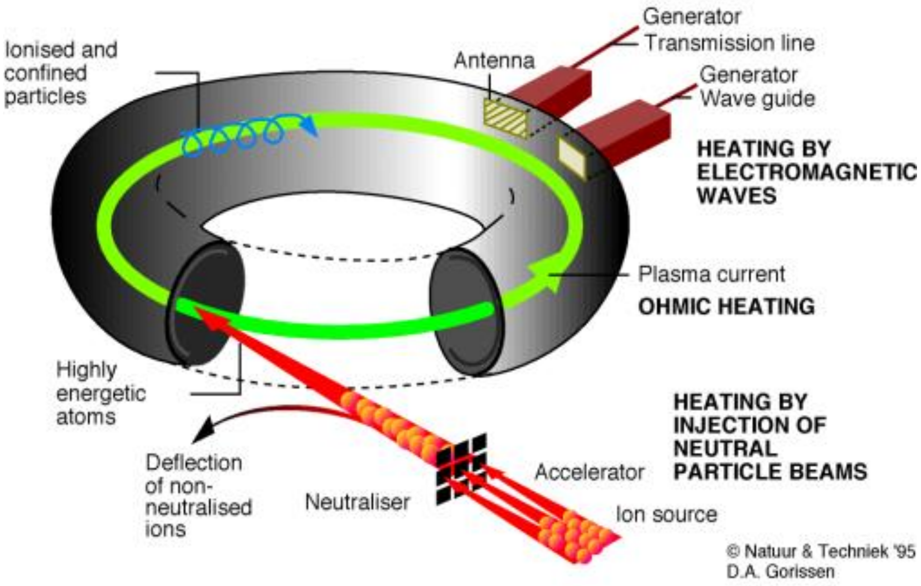
Actuators that affect plasma state



Magnetic Coils

- Central solenoid ramp rate
- Toroidal field coils
- Poloidal field coils
- 3D field coils to perturb toroidal symmetry

Actuators that affect plasma state

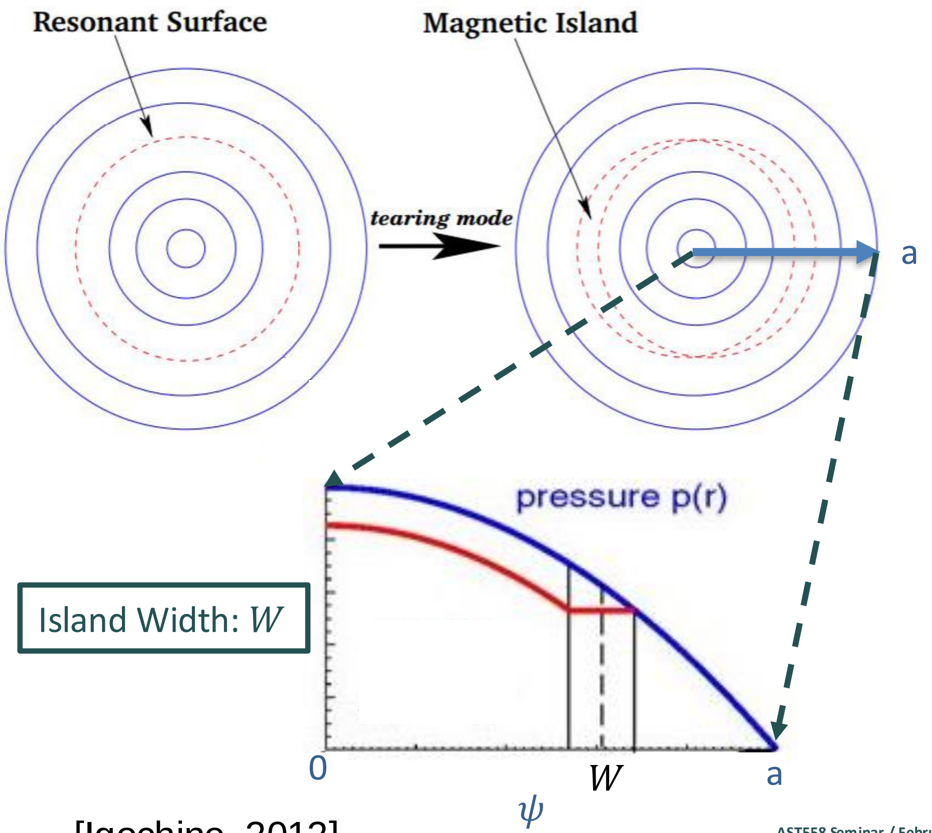


Magnetic Coils
- Central solenoid ramp rate
- Toroidal field coils
- Poloidal field coils
- 3D field coils to perturb toroidal symmetry

Heating Sources
- Neutral Beams
- Electron Cyclotron Heating
- Other RF Waves (Helicon + Lower Hybrid)

Gases
- Gas valves
- Pellet injection

What are tearing modes?



Island Width: W

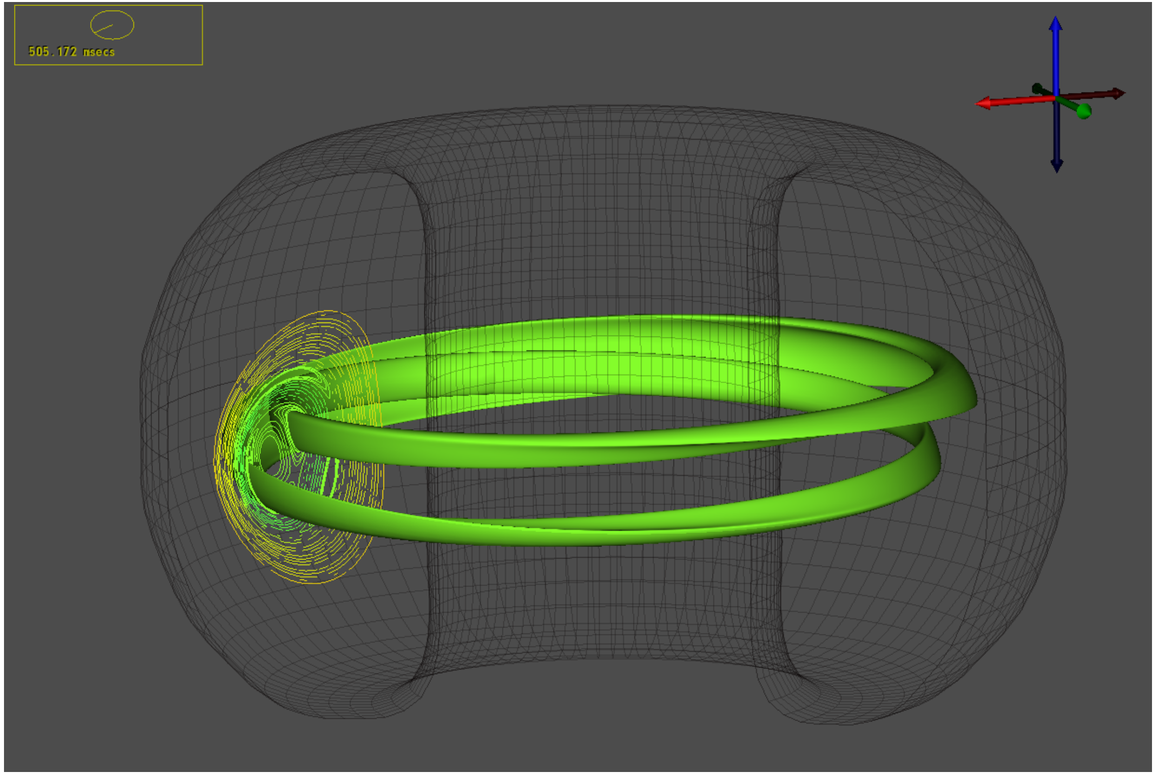
- Magnetic field reconfigures to lowest energy
- Occurs at rational surfaces
- Breaks nicely nested flux surfaces

So why do we care?

- "Short circuits" transport
- Modes can lock to wall → disrupts plasma

[Igochine, 2012]

Tearing Modes are 3D Structures

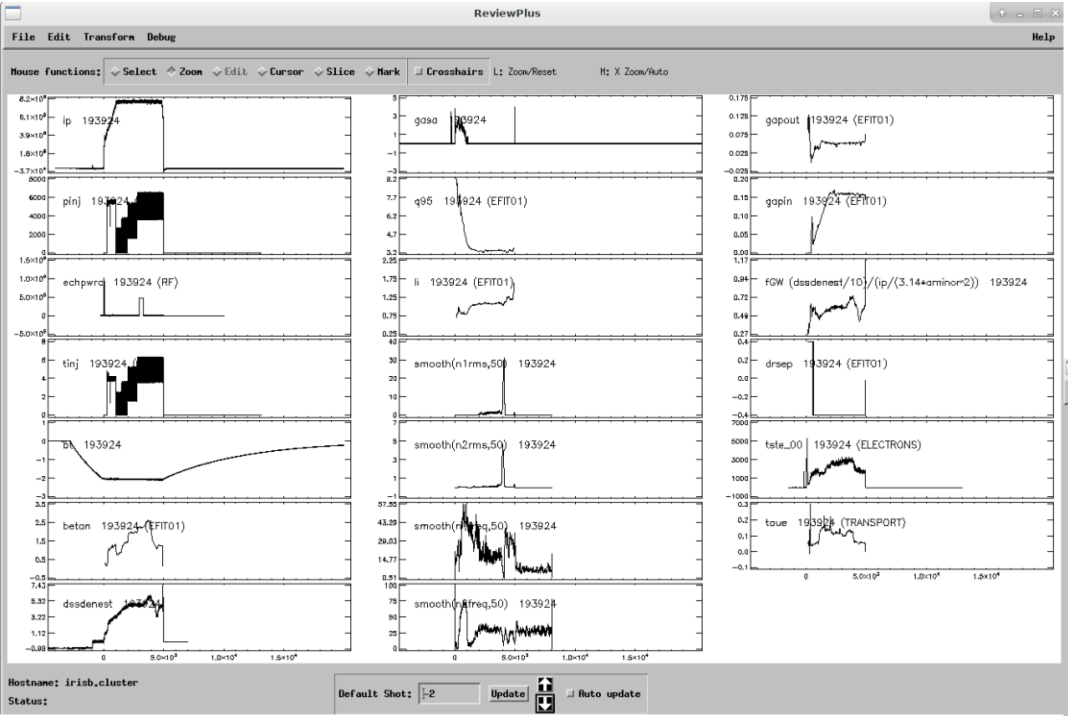


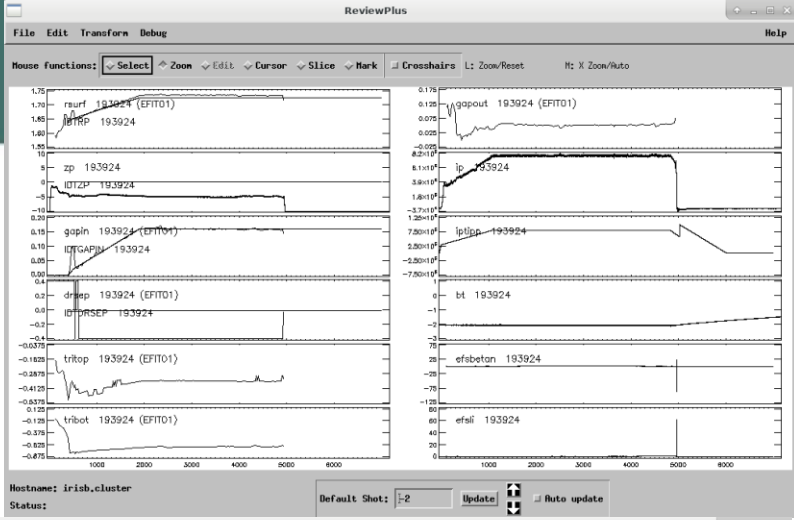
[VACET]

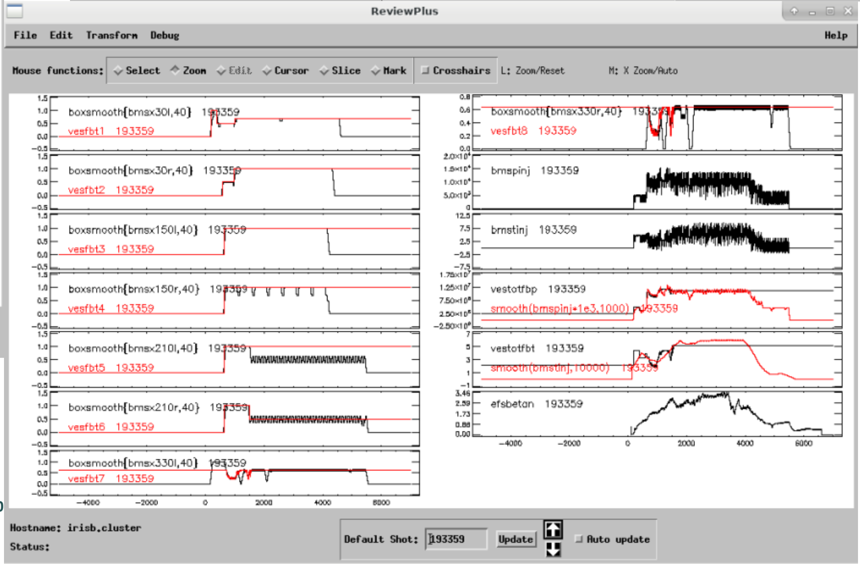
Why machine learning?

- Lots of data

Too much experimental data

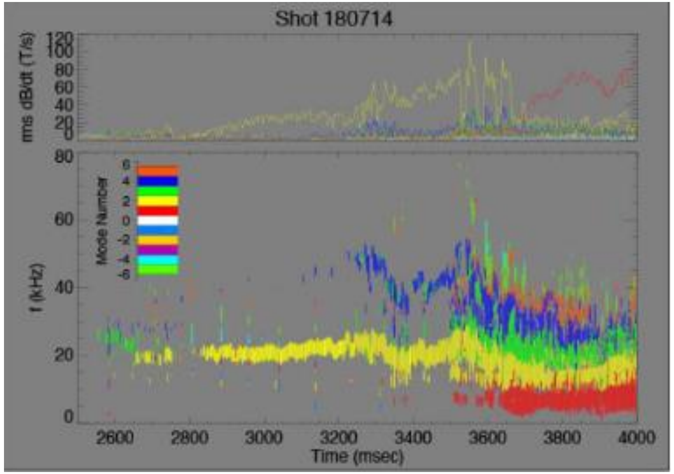


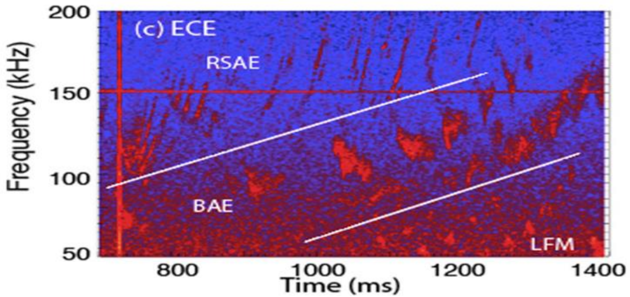




Why machine learning?

- Lots of data
- Models can be run real-time (ms time-scale)
- ML can find patterns to predict instabilities
- Can learn multi-actuator effects on the plasma





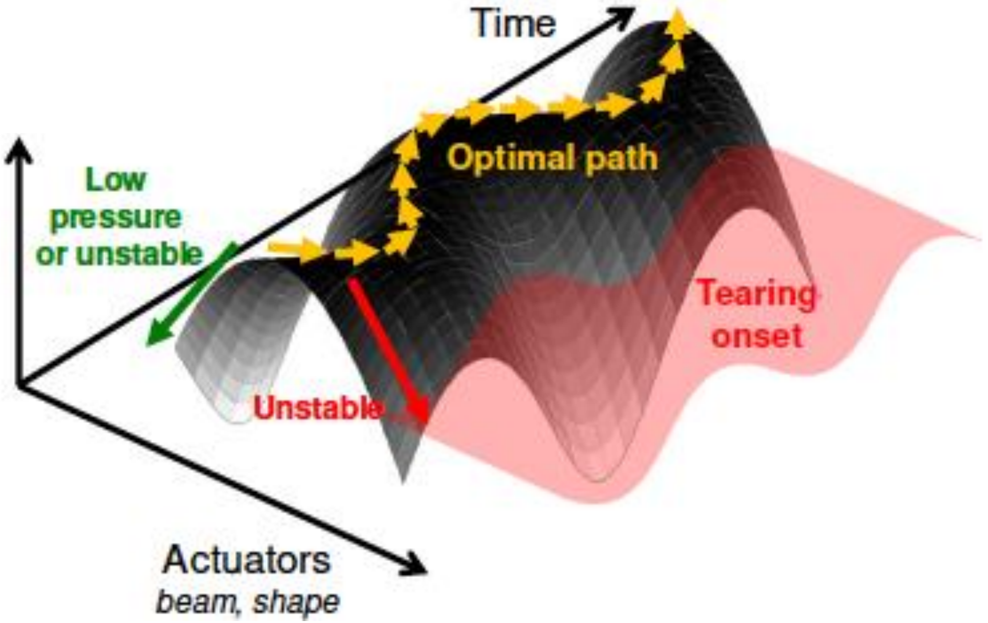
[Victor IAEA 2020]
[Heidbrink NF 2021]

Plasma Control

What should a good ML controller do?

What ML is not good for:
- Shot design - developing new scenarios
- Extrapolating to new regimes

What ML is good for:
- Maintaining stability in previously explored spaces
- Recovering from small deviations to optimized scenario



[Seo Nature 2024]

Plasma Control

Outline

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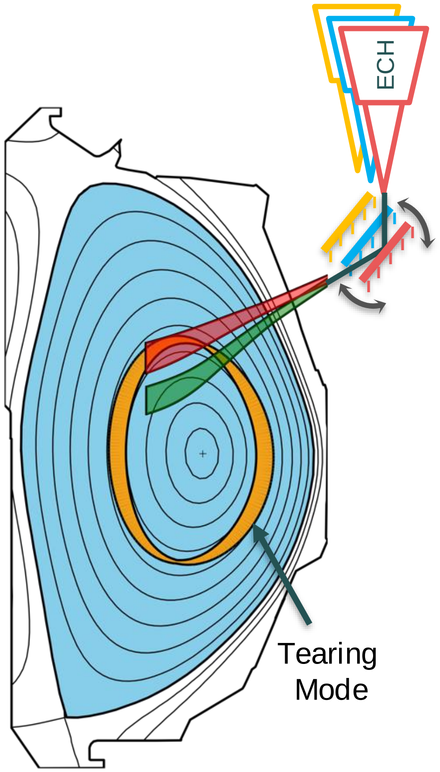
- **Long term TM prediction and preemptive ECCD TM suppression and understanding ML predictions**
- Surrogate models for real-time control

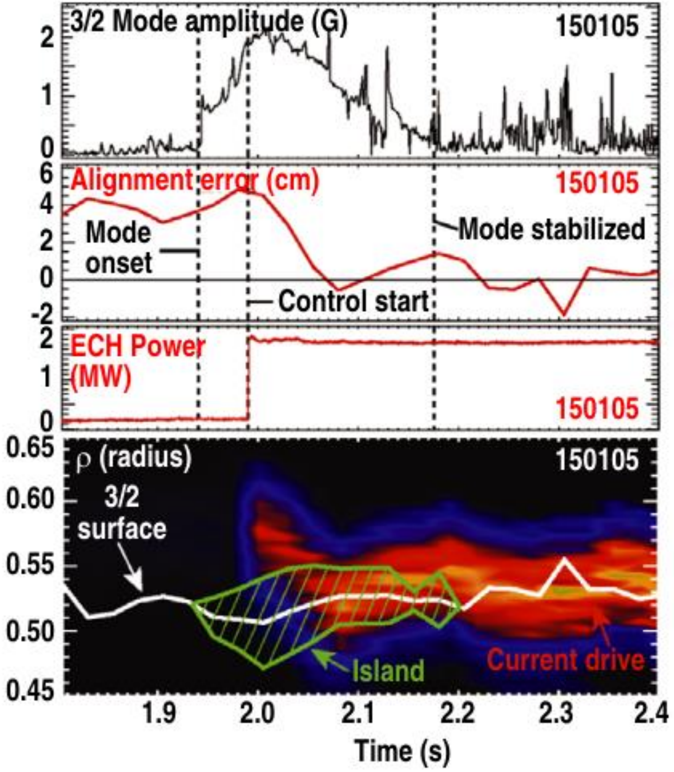
ECCD as the main actuator for TM suppression

- Electron cyclotron current drive (ECCD) has been shown to suppress TMs
  - Replaces missing bootstrap current to heal island
- Full preemption:
  - Feedforward ECH for TM control is wasteful and cannot handle dynamic scenario



A first step beyond full preemption

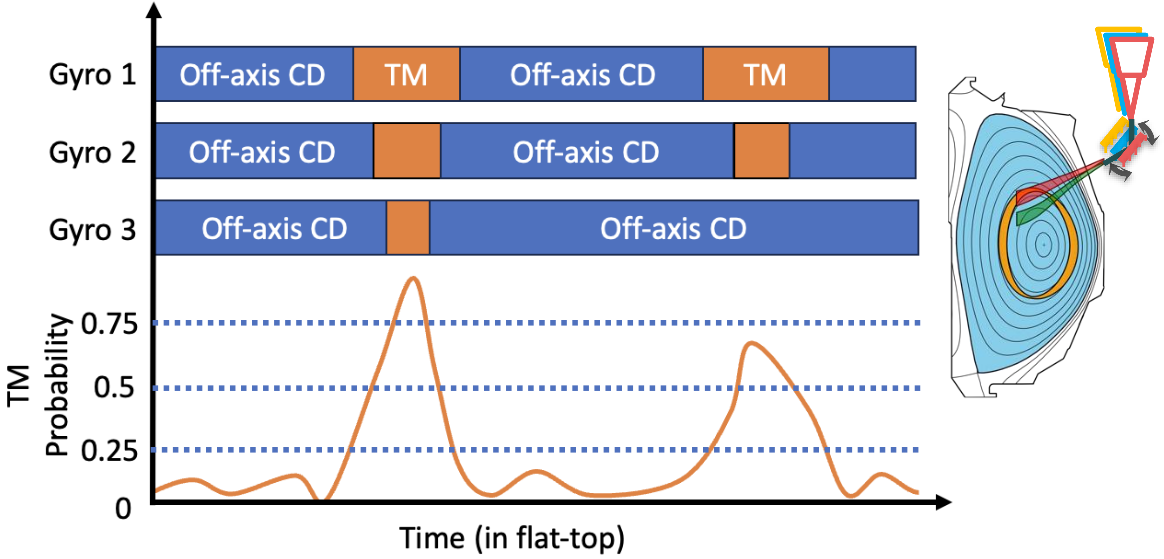
- Catch and Suppress
  - Must wait for large mode amplitude to not confuse with other magnetic activity
  - Lacks multi-tasking capabilities because all ECH mirrors must continuously follow rational surface



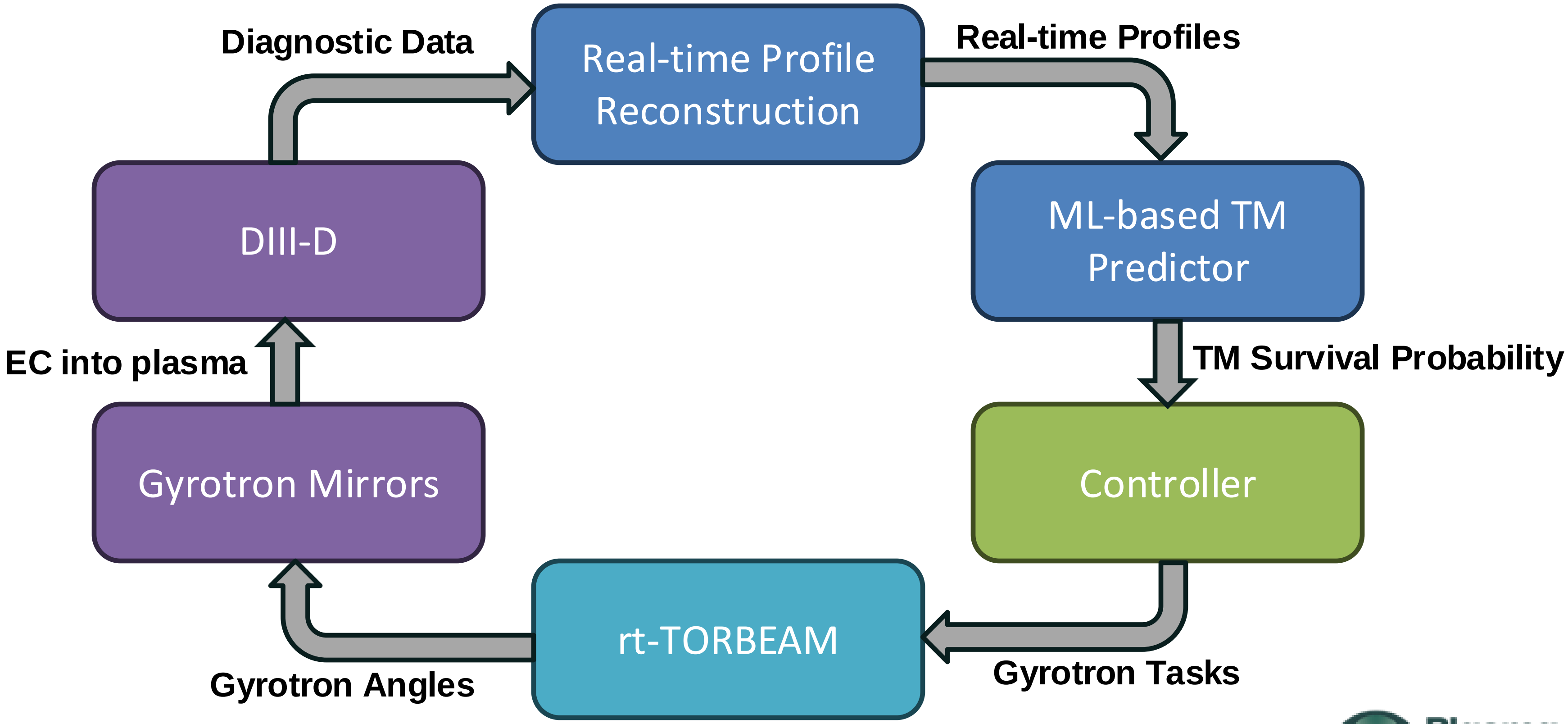
[Kolemen, NF 2014]

New control scheme capable of active TM control and EC multi-tasking

- With sufficient TM prediction time, can steer to rational surfaces when needed
- Need accurate aiming for active TM suppression task
- Allows for multi-task gyrotrons to reach other scenario goals



Closed control loop uses RTCAKENN profiles for feedback control



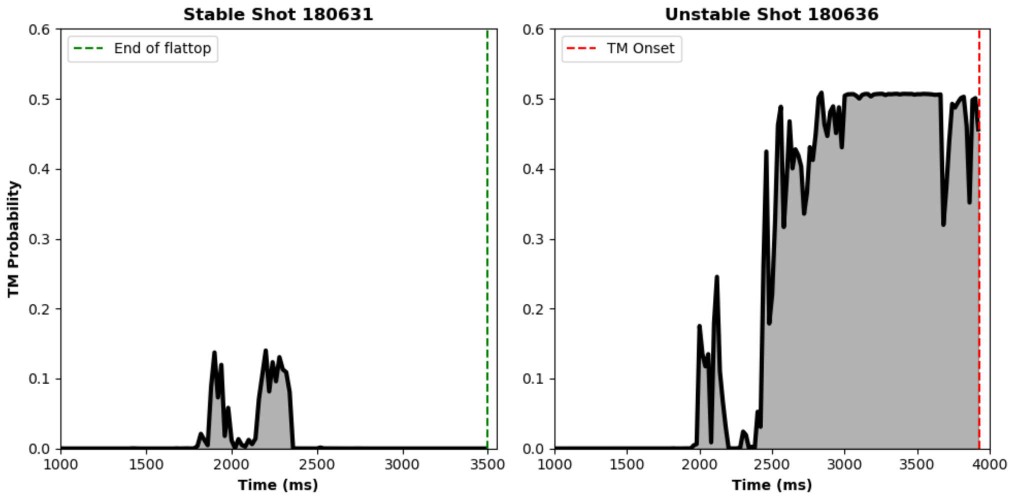
ML Model predicts TM survival probability using RTCAKENN profiles

Profile Inputs

- Electron temperature (T_e)
- Electron density (n_e)
- Ion temperature (T_i)
- Rotation (v_{tor})
- Safety Factor (q)
- Pressure (p)
- Current density (J)

Scalar Inputs

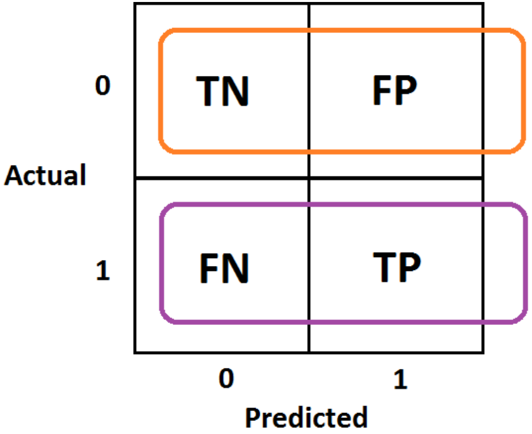
- Shape parameters: δ_{top}, δ_{bot}, κ, R_{axis}, a_{minor}
- RTEFIT scalars: q_{min}, β_N, l_i, V_{plas}
- P_{NBI}, T_{NBI}, P_{ECH}, I_P, B_T,



TM probability: probability of TM occurring over $t_{horizon}$=1000ms

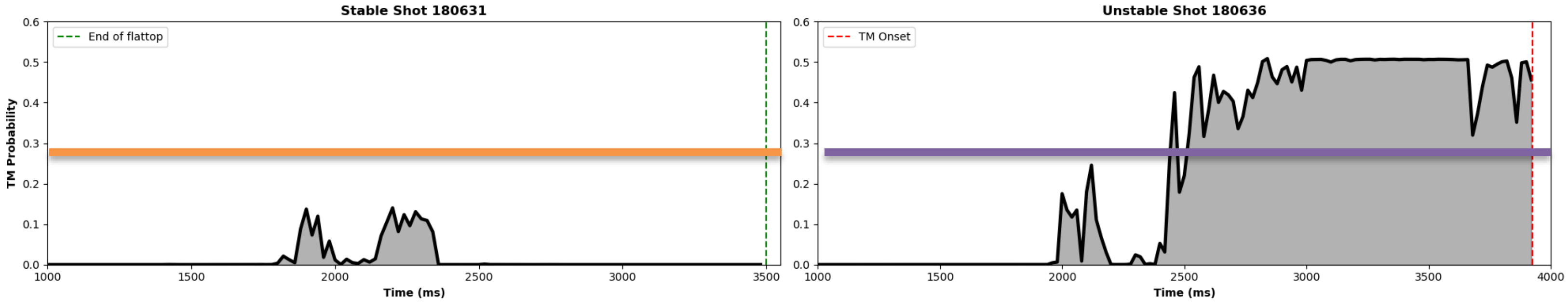
Survival models: event prediction models applied from medical fields

Assessing Event Prediction Models



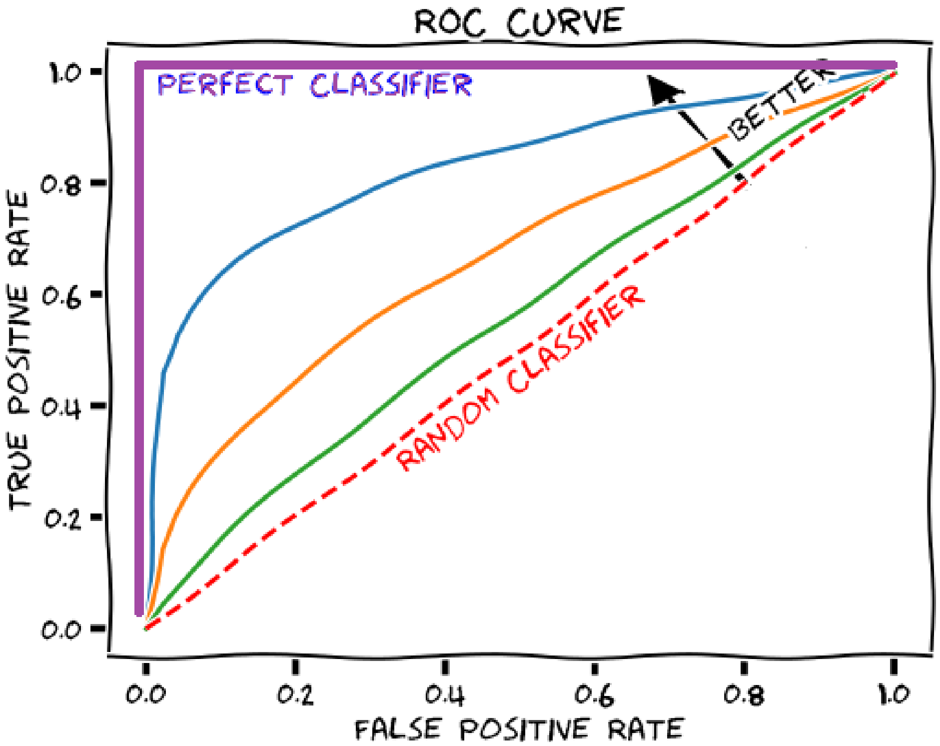
False Positive Rate (FPR) = $\dfrac{FP}{(FP + TN)}$

True Positive Rate(TPR) = $\dfrac{TP}{(TP + FN)}$



AUC Metric

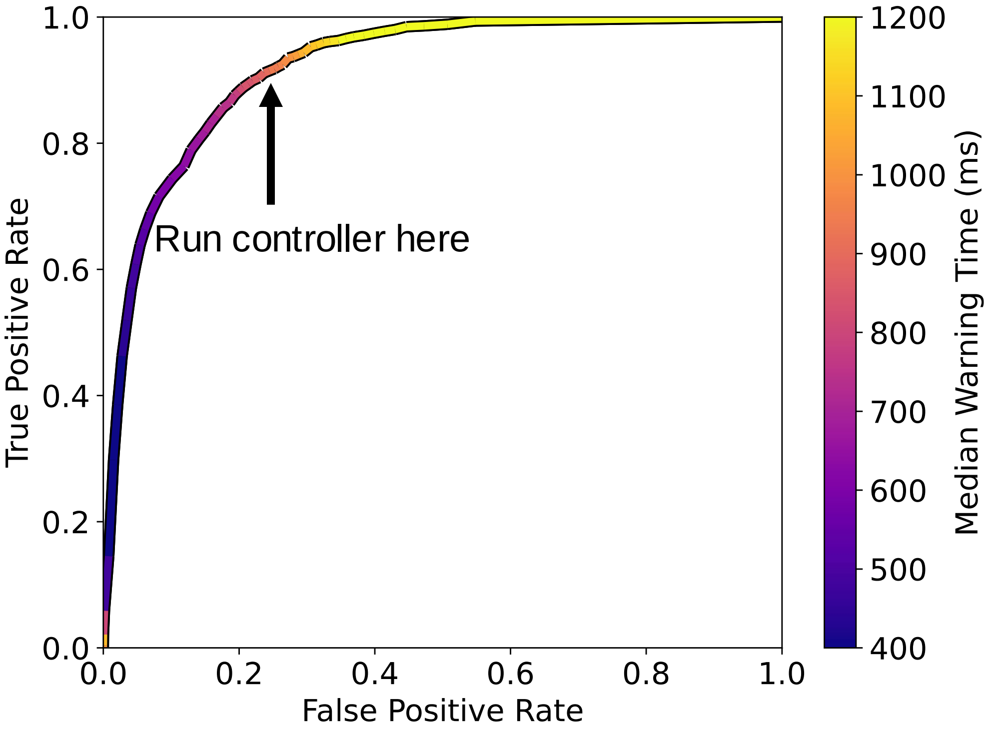
- AUC metric integrates TPR by sweeping threshold from $1 \to 0$
  - FPR sweeps from $0 \to 1$
- AUC values:
  - Perfect classifier = 1
  - Random classifier = 0.5



TM predictor performance further demonstrated with event prediction metrics

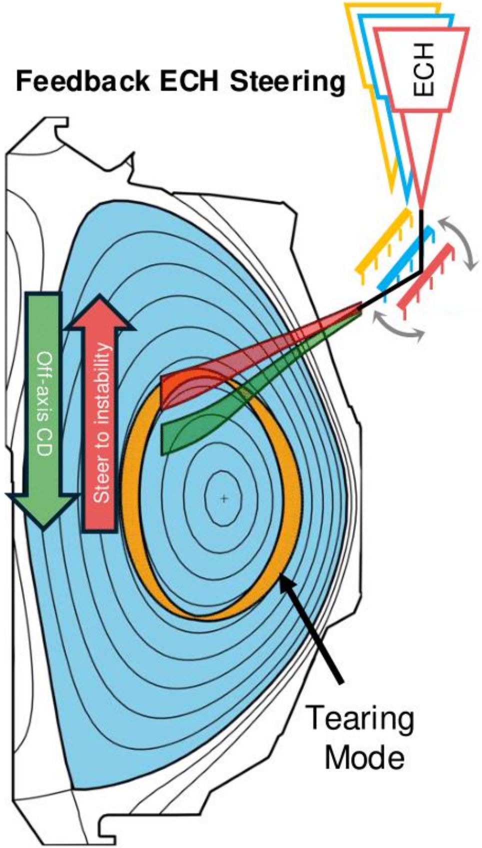
- AUROC Curve:
  - False positives are not bad because moving EC is not a costly action
  - False negatives are very costly (miss a TM) so pick high TPR
- Higher TPR and FPR also typically gives larger warning times

$$TPR = \frac{TP}{TP + FN} \qquad FPR = \frac{TN}{FP + TN}$$



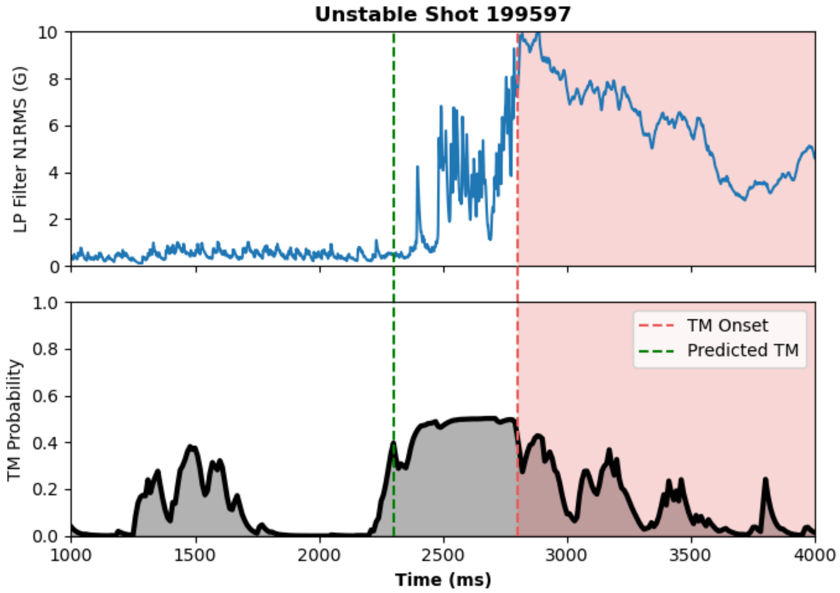
Control demonstrated on elevated q_{min} scenario which requires multi-tasking EC control

- Scenario performance requires reversed shear q-profile
  - Needs broad off-axis ECCD
- High performance generates highly unstable TMs
  - Needs feedback-controlled rational surface tracking ECCD
- EC multi-tasking is required for high performance, stable scenario operation



Unstable reference in elevated q_{min} scenario

- Reference shot with no active control, constant gyrotron location
- As expected, TM occurs in flattop phase
- Model correctly predicts with sufficient time to steer (>200ms)



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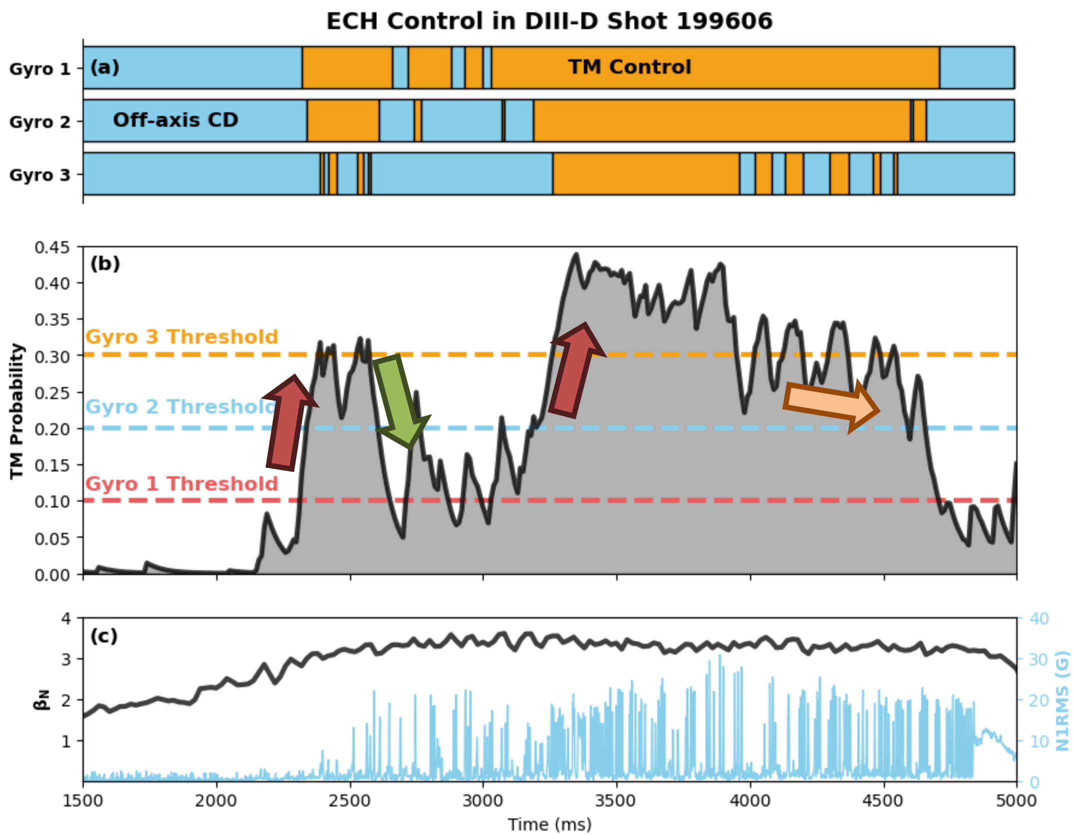
Preemptive ECCD successfully avoid TMs



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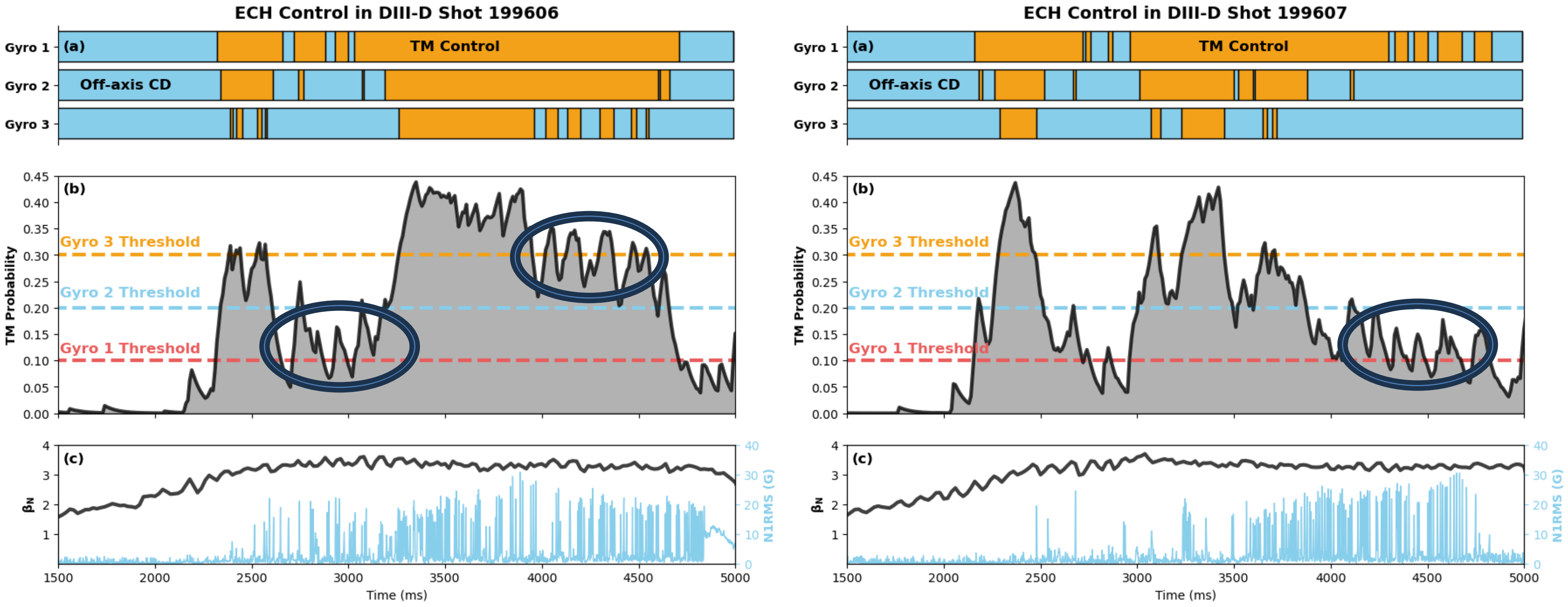
Robustness: repeated successful control



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Experimental results are promising but more analysis is needed

- Physics analysis underway to better understand profile evolution, bootstrap currents and q=2 ECCD

- Control appears to have changed scenario stability rather than suppressing seed islands when the form
  - Mode spectra show no signs of seed islands, however very noisy due to fishbone activity

- How can we understand the ML TM stability predictions?

How to understand ML predictions: Game Theory

- Example problem: Predicting football team win rates

Team	Team 1	Team 2
Cost (millions)	\$25	\$24
Age (years)	22	23
Injury count	8	5
Win rate	0.58	0.57

Team 1

Team 2

$$\text{winRate} = \frac{1}{\text{norm}}\left[2 \cdot (\text{Cost}_{\text{squad}})^2 - 10 \cdot (\text{Age}_{\text{avg}} - 24)^2 - 20 \cdot (\text{Num}_{\text{injury}})\right]$$

Plasma Control

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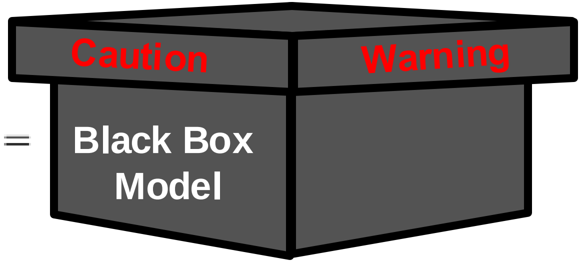

Assigning importance values to inputs: Shapley values

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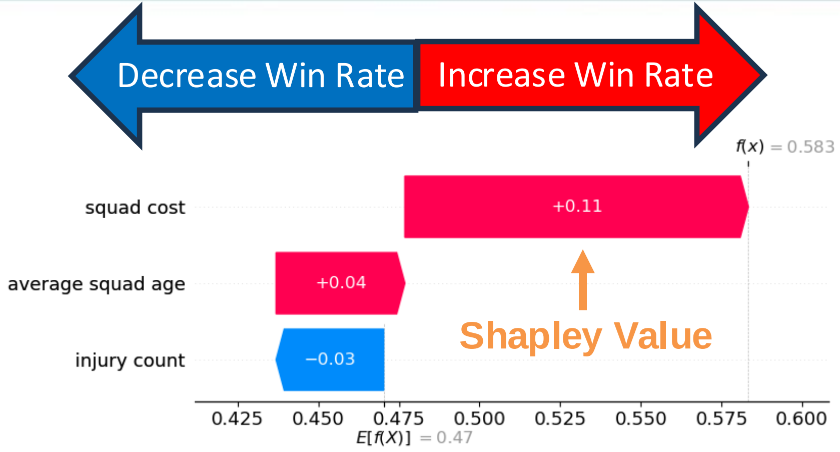
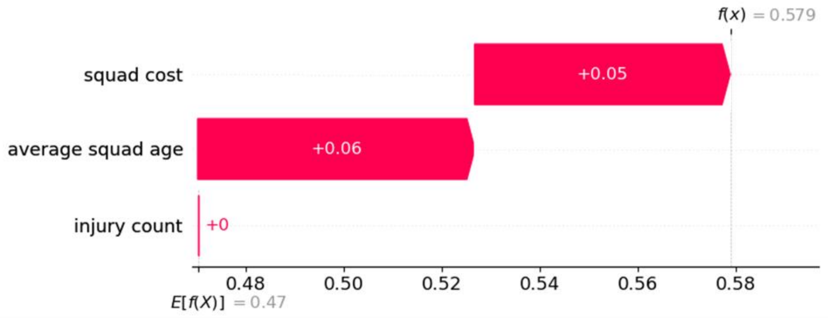




Reference distributions matter for Shapley values

- Example problem:
  - Predicting football team win rates **<u>of professionals</u>**

Team 1

VS

Team 2

Plasma Control

Reference distributions matter for Shapley values

- Example problem:
  - Predicting football team win rates **<u>of professionals</u>**
- Example problem 2:
  - Predicting football team win rates **<u>compared to amateurs</u>**

Team 1

Team 2

VS

Comparing Team 1 to different distributions changes Shapley values

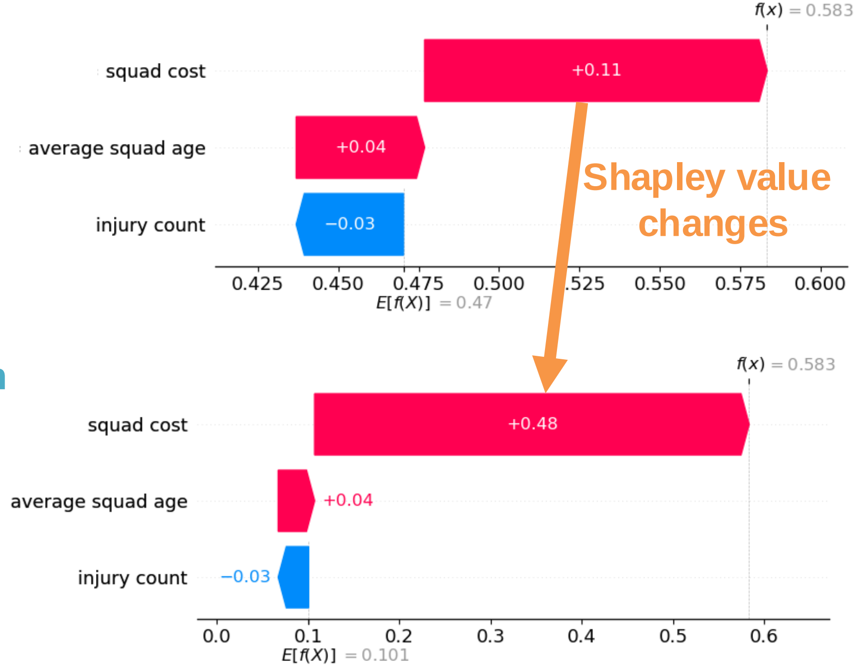
Background Distributions

League	Pro	Amateur
Cost	$15-30	$13-15
Age	20-30	20-30
Injury count	0-10	0-10

Team	Team 1
Cost	$25
Age	22
Injury count	8
Win rate	0.58

Team 1 vs Pro Team

Team 1 vs Amateur Team



Comparing Team 1 to different distributions changes Shapley values

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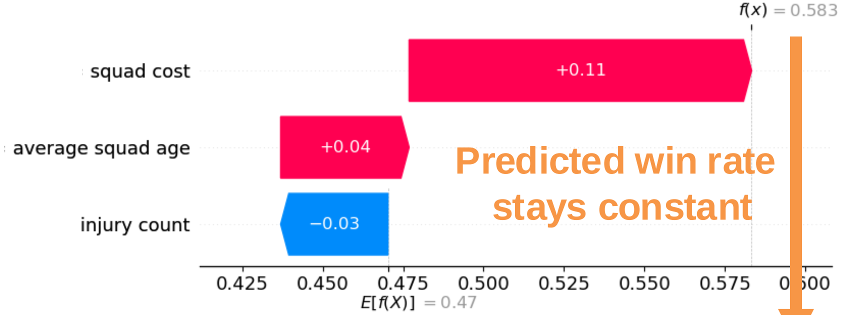
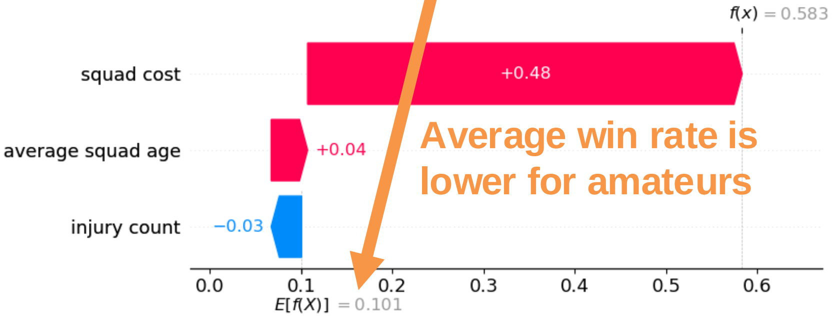


Predicted win rate stays constant

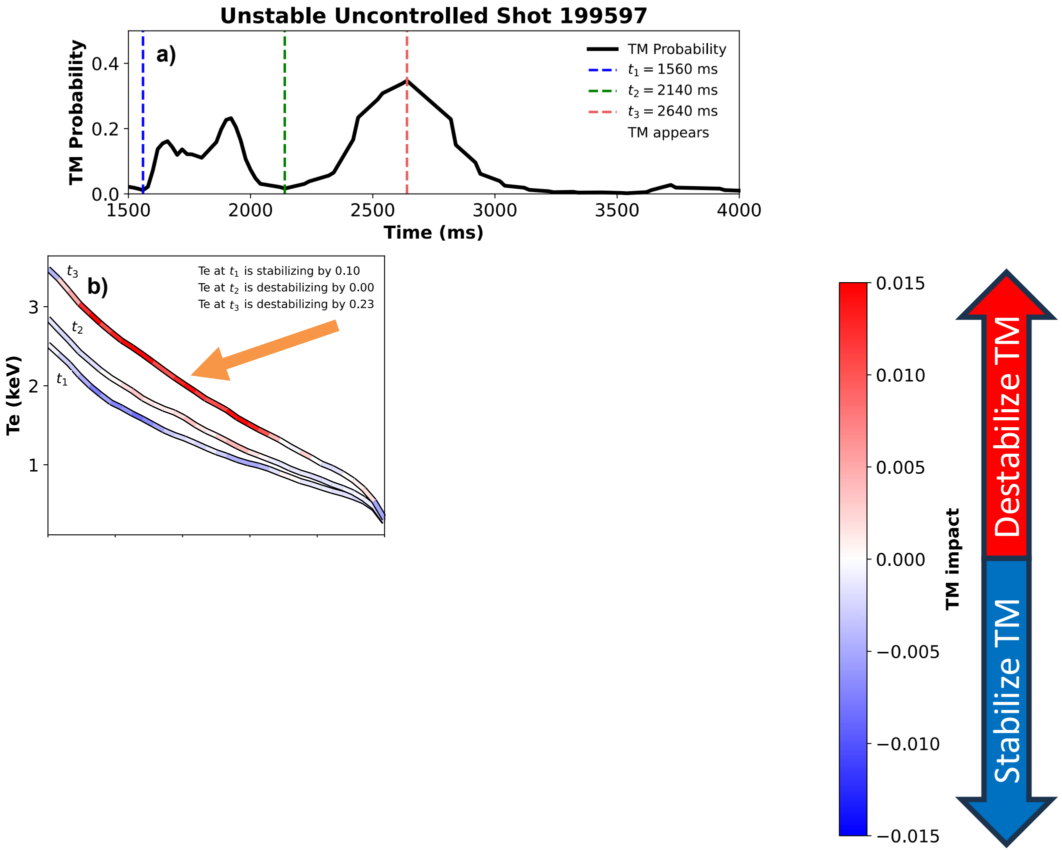
Team 1 vs Amateur Team



Average win rate is lower for amateurs

Shapley values tell us why unstable shots are unstable

- Background distribution:
  - All shots in DIII-D history
  - All advanced scenario shots
  - **All shots in single experiment**
- Higher T_e destabilizing



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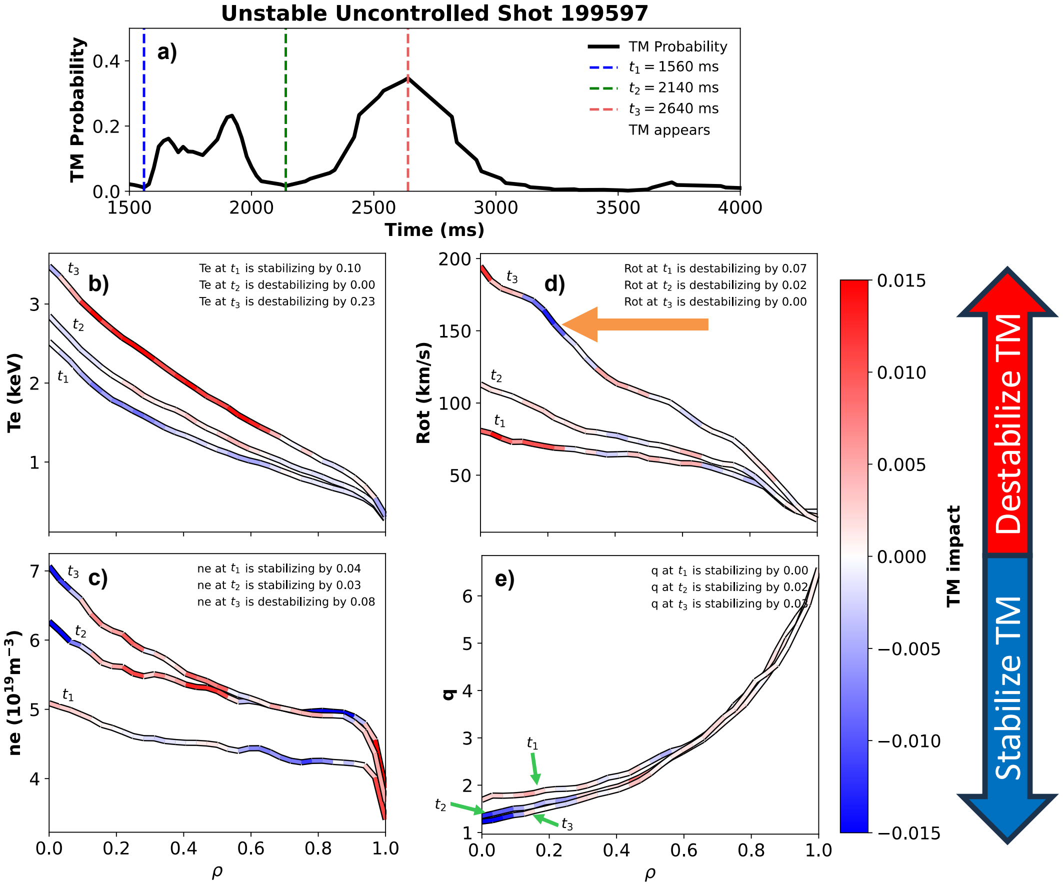
- Higher Rot (ω_{tor}) has stabilizing effect



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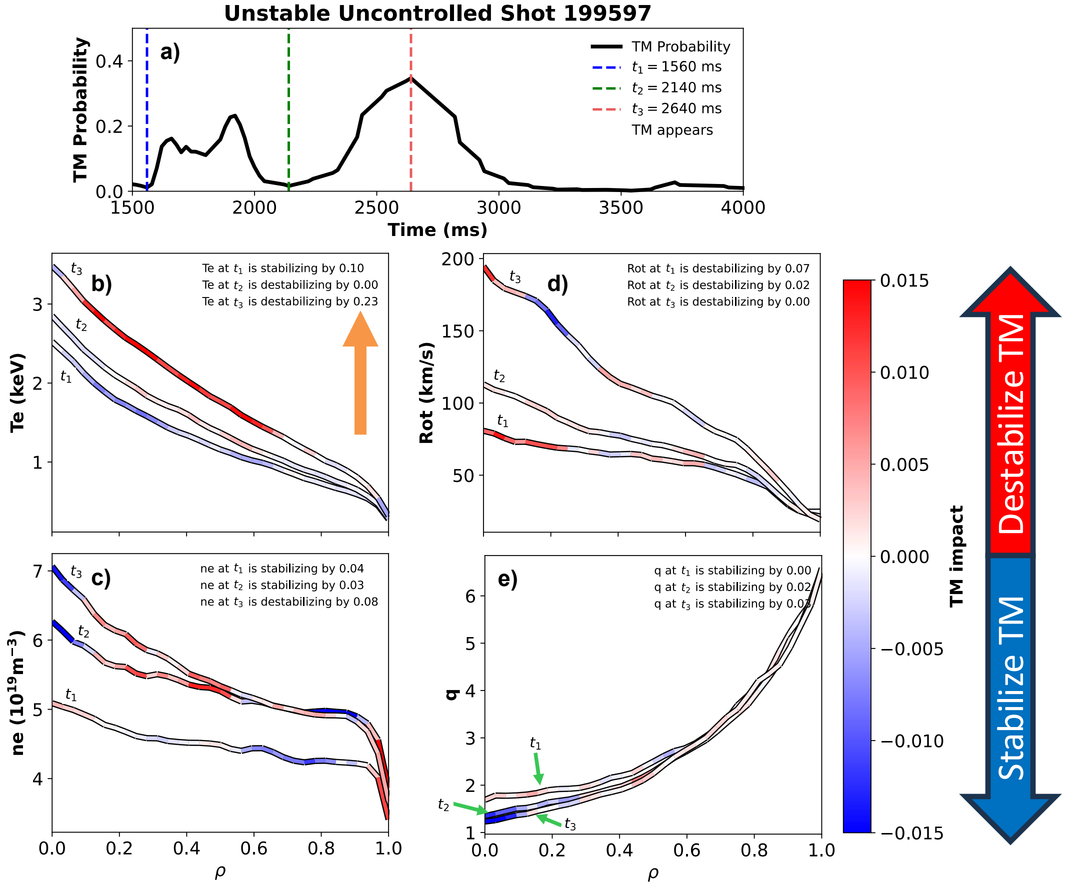
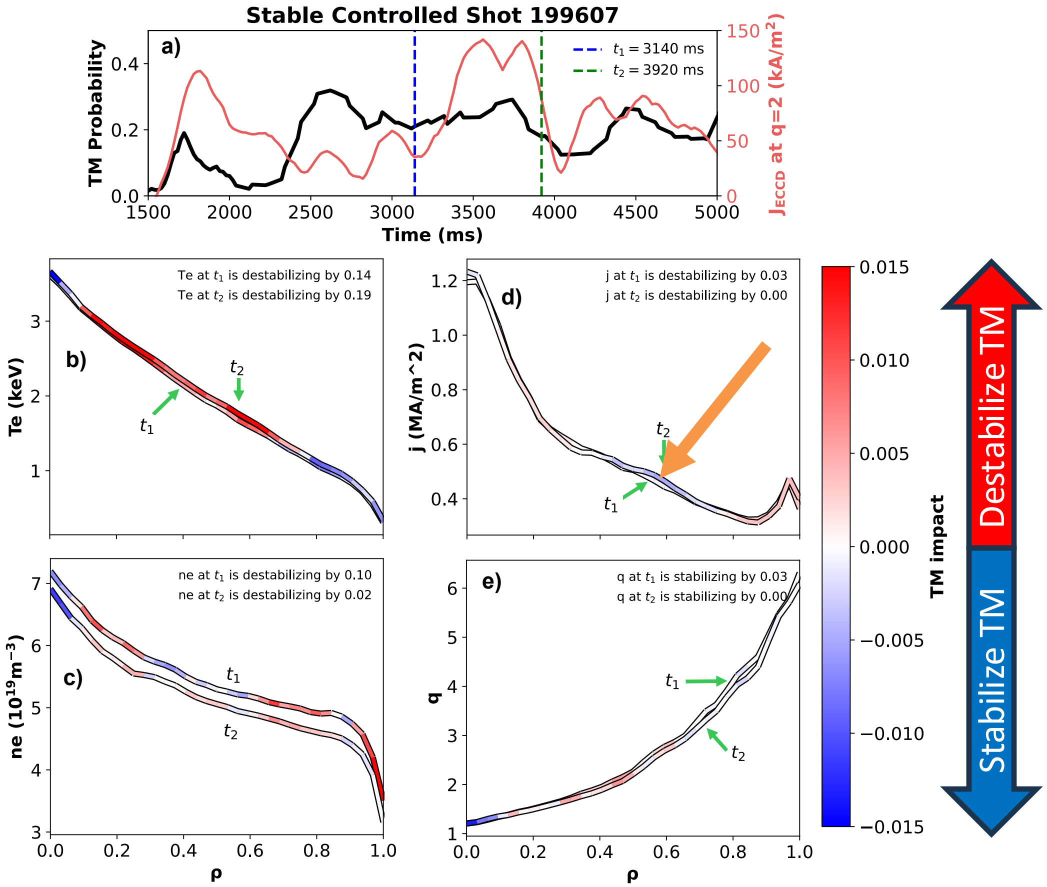
  - All shots in DIII-D history
  - All advanced scenario shots
  - **All shots in single experiment**
- Higher T_e destabilizing
- Higher Rot (ω_{tor}) has stabilizing effect
- T_e profile as whole has largest Shapley values



Shapley values show TM impact response to actuation

- Feedback control is changing localized ECH+ECCD deposition location
- Bump in current profile around $\rho \sim 0.6$ stabilizing



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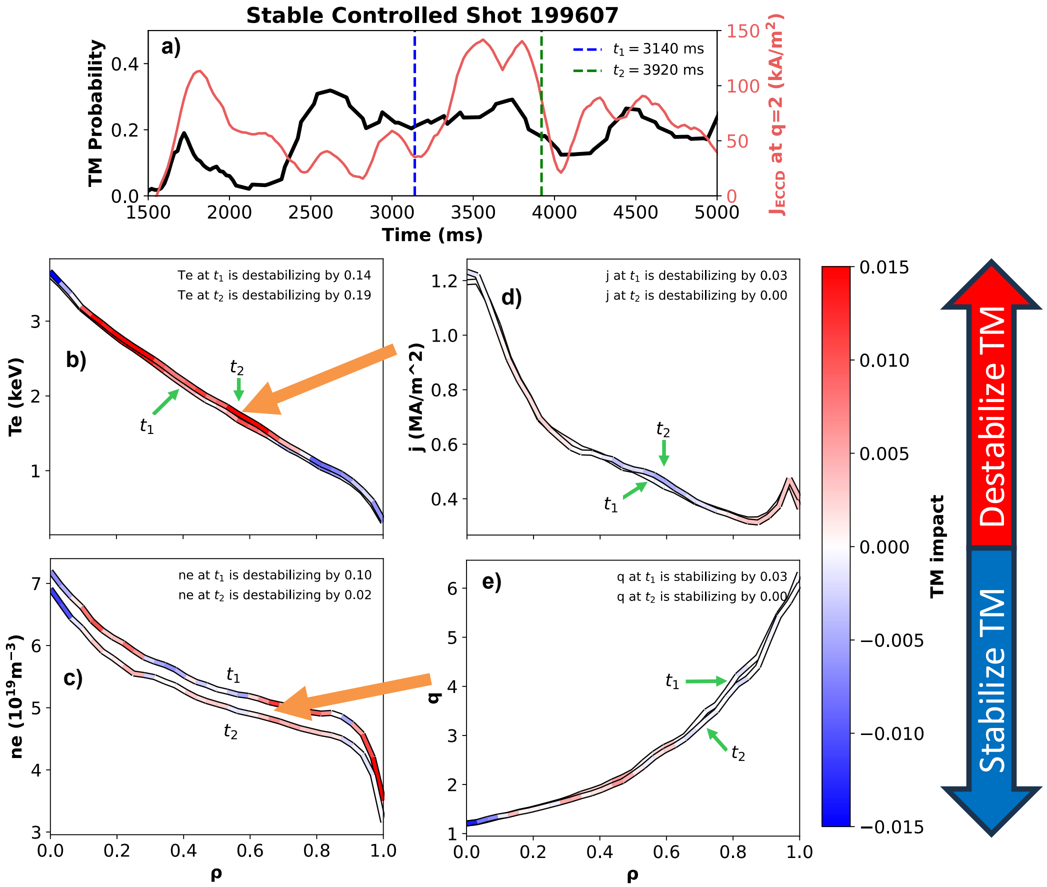
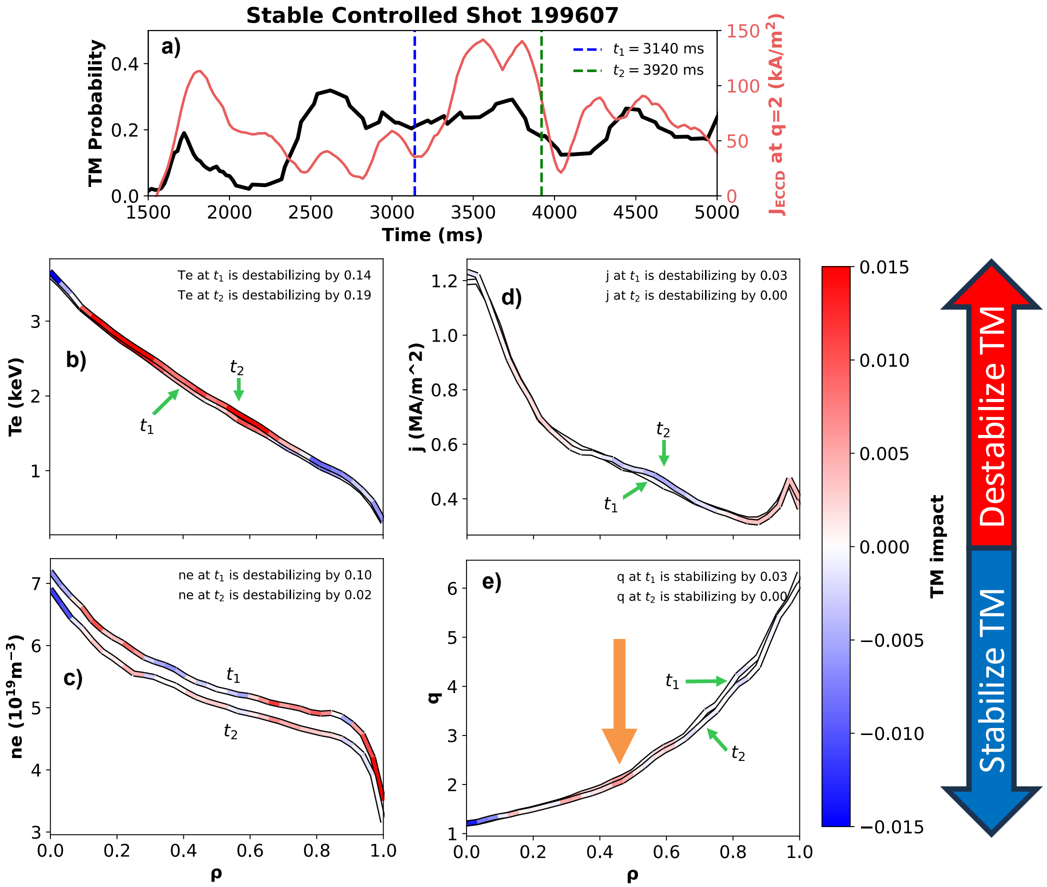


Shapley values show TM impact response to actuation

- Feedback control is changing localized ECH+ECCD deposition location
- Bump in current profile around $\rho \sim 0.6$ stabilizing
- ECH causes slight increase in T_e and density pump out effect
- Value around q=2 shows destabilizing effect



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- **Surrogate models for real-time control**

What is a surrogate model?

- We have a costly function $f(x)$
- Want to approximate as simpler function
$$\bar{f}(x) \approx f(x)$$
- For simple functions, Taylor series is an easy surrogate model
$$\bar{f}(x) \approx f(0) + f'(0)x + \cdots$$
- For more complex functions or models, need more complicated surrogates
  – Giant matrices with many basis functions (aka ML)

Outputs:
- Fitted profiles
- Transport results
- Results from physics codes

Inputs:
- Raw data
- Diagnostics

$$y = f(x)$$

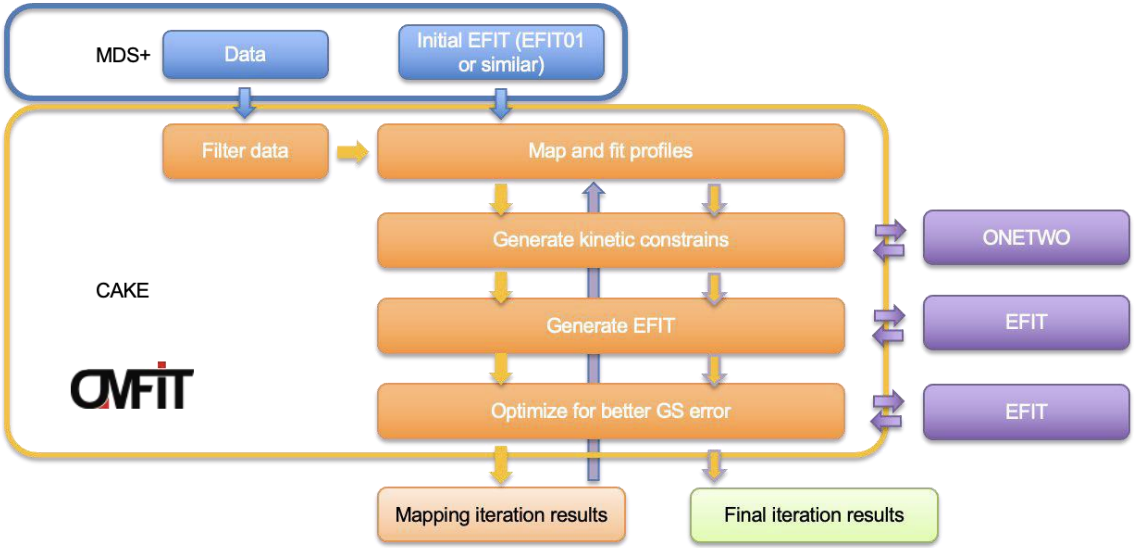
$$y \approx \bar{f}(x)$$

Surrogate model:
- Improve weights of basis functions iteratively by gradient descent
- Exact form of model "tuned" to improve accuracy

Plasma Control

Introduction to CAKE kinetic equilibria

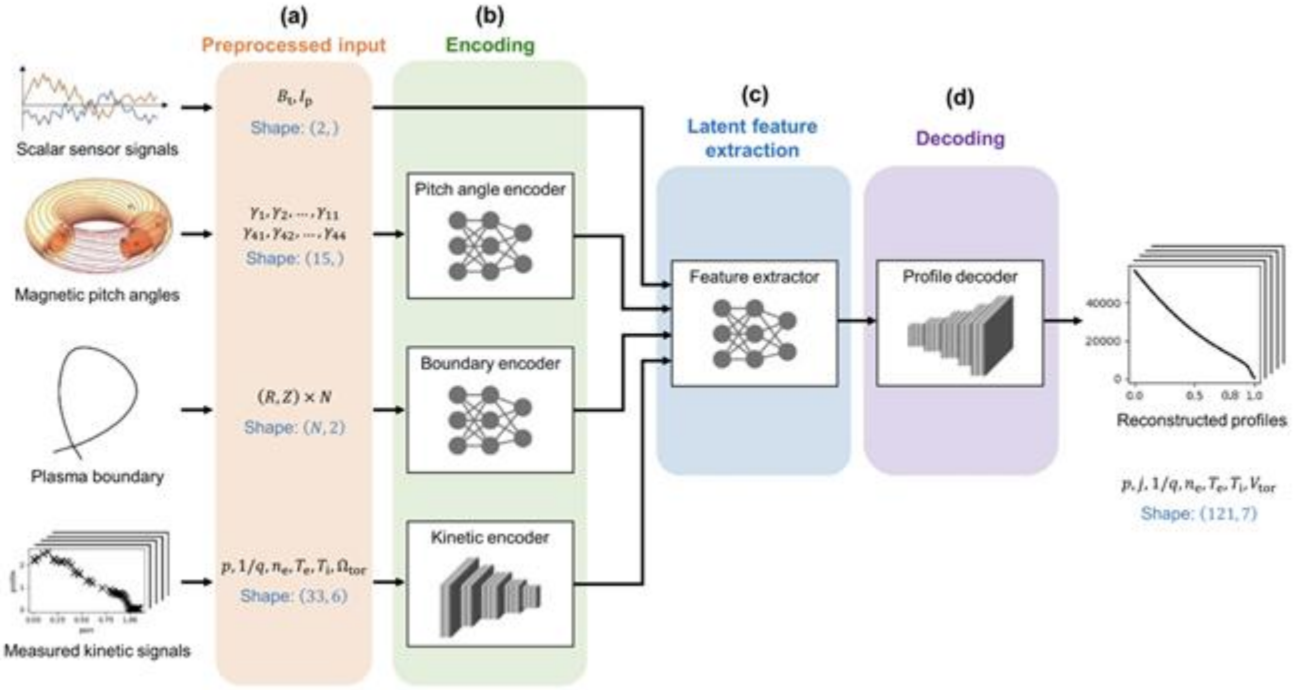
- Consistent Automatic Kinetic Equilibria (CAKE) provides automated, high-fidelity equilibria on a database scale [Xing et al. FED 2021]
- Great for database analysis (>67,000 equilibria) or generating consistent results to use with machine learning



[Courtesy of A. Xing]

RTCAKENN: CAKE-quality profiles in real-time using ML

- ML model for real-time CAKE to derive high quality rt-profiles
- Trained on 19,000 CAKE equilibria database



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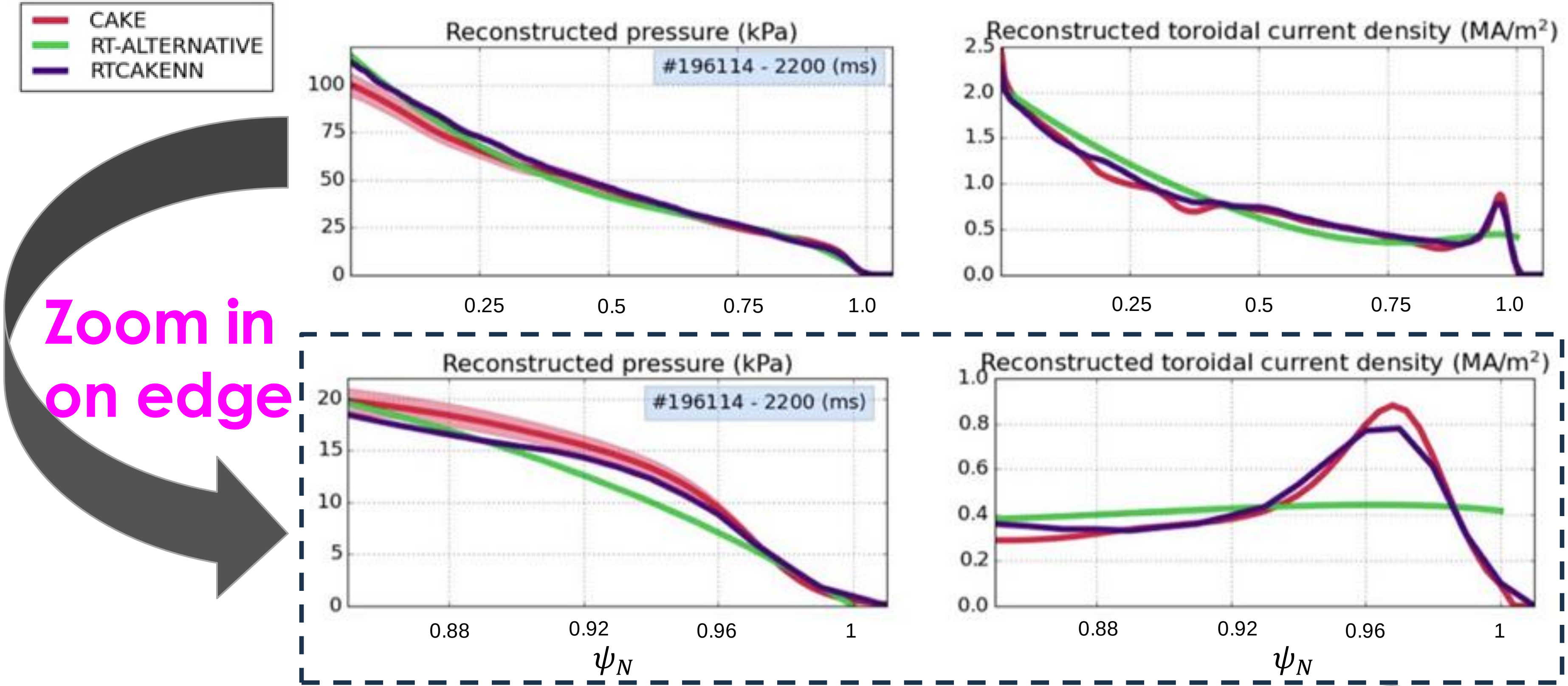
RTCAKENN gives improved real-time profiles



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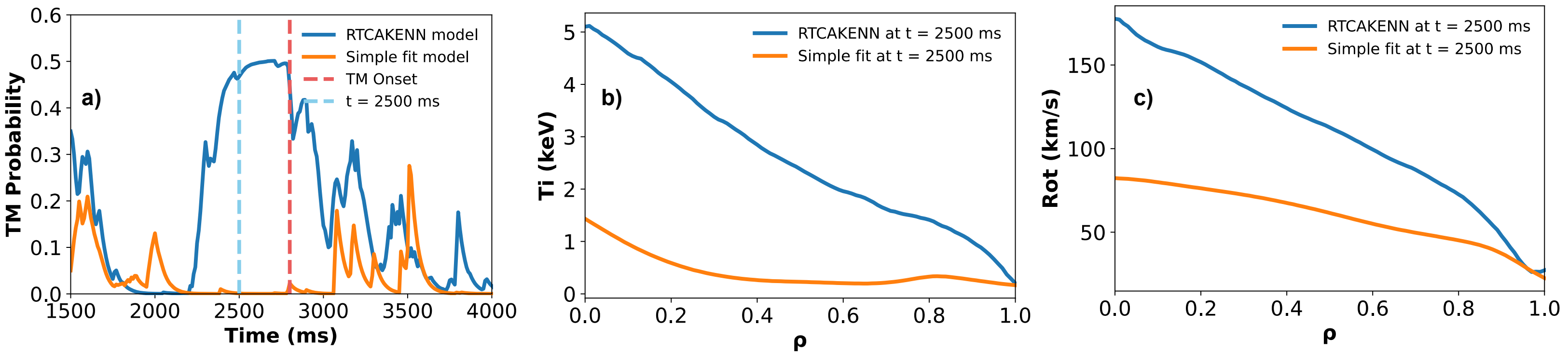
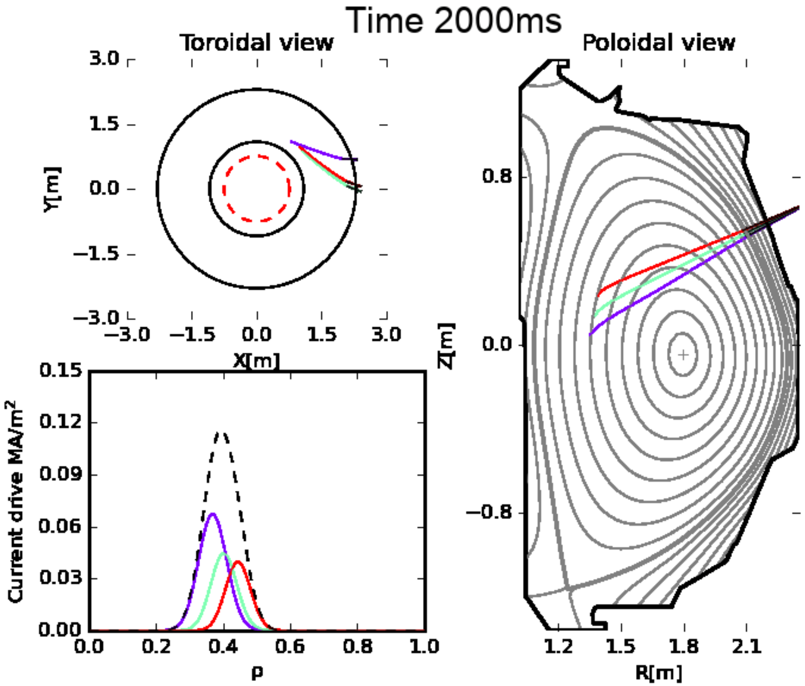
RTCAKENN models robust to diagnostic dropout

- During experiment, CER diagnostic had failure causing poor fits for T_i and Rot (ω_{tor}) profiles
- RTCAKENN shows robustness to still predict accurate profiles when classical fitting routine fails
- TM prediction using RTCAKENN remain accurate while classical fitting fails



Torbeam code provides ray tracing and ECH deposition profiles

- Torbeam calculates trajectory of electron cyclotron heating (ECH) waves
  - Also calculates absorption resonant location and heating and current drive profiles
- Real-time version runs in 10-20ms with only information about maximum deposition location
  - No deposition profiles or CD efficiency



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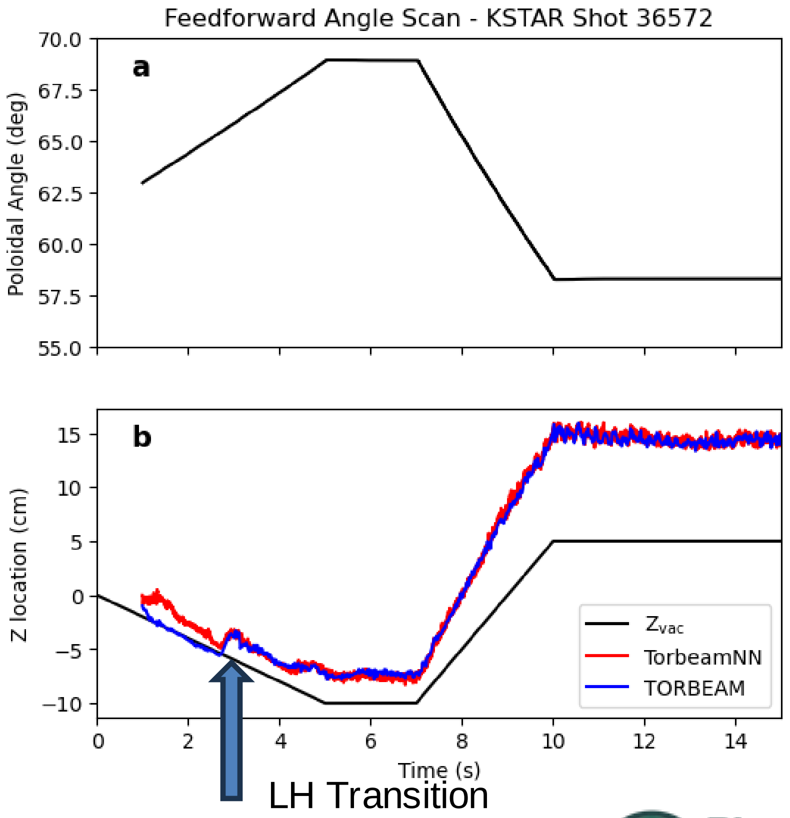
TorbeamNN: ML surrogate model speeds up ray-trace calculation

- TorbeamNN on KSTAR provides accurate information about ECH absorption location
- Coming to DIII-D soon!
  - Include full ECH deposition profiles and current drive



Plasma Control

Summary

- TM prediction models provide long warning time for TM events and enables multi-tasking gyrotrons
  - Can now better balance TM avoidance with high performance scenarios
- Shapley values provide an understanding of how ML models make their predictions
  - Framework can be used for any ML models
- High quality real-time profiles provide more accurate real-time profiles
- Dynamics models provide full shot prediction of profiles

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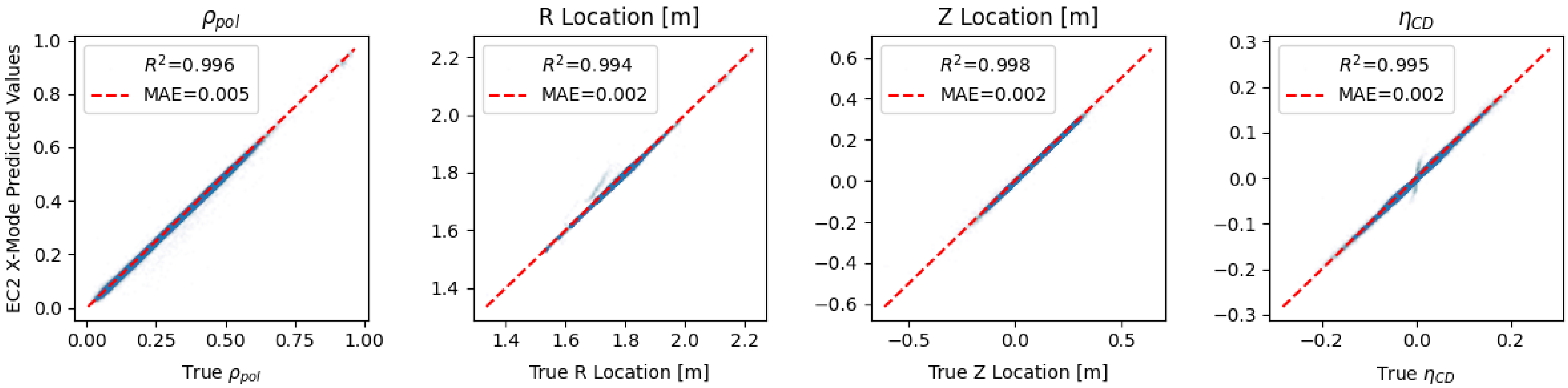
Backup Slides

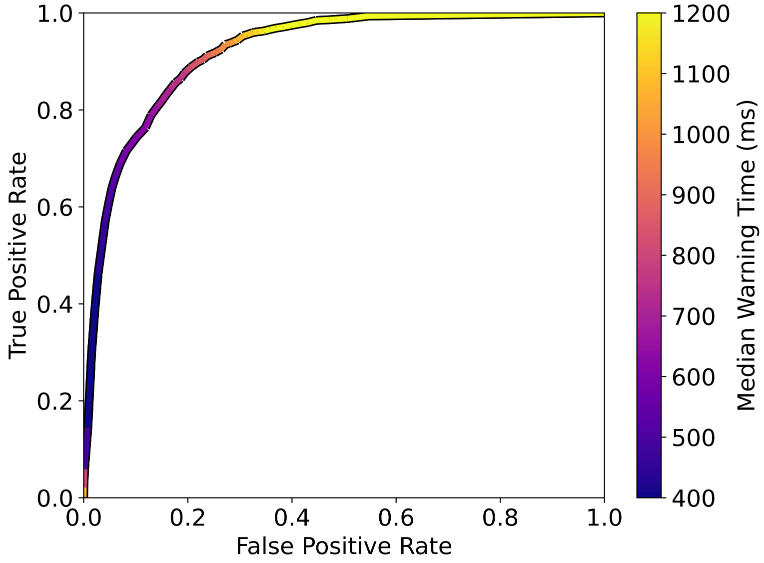
Misc Background

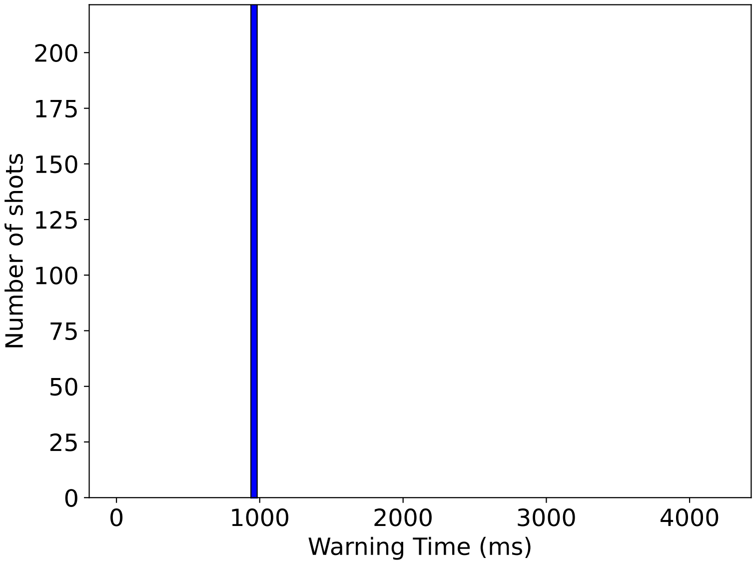
KSTAR TorbeamNN Accuracy



AUROC + Warning Times Histogram for TM predictor

- Vertical blue line is median

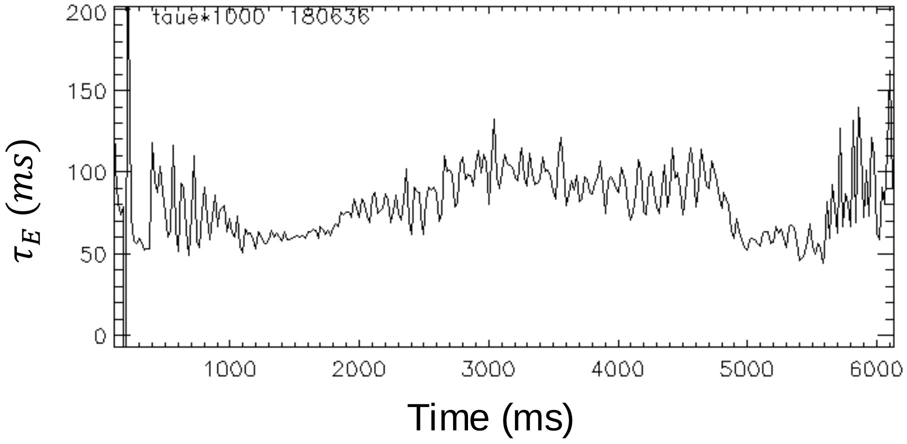




Experimental Timescales

Profile Evolution
- τ_E: 50-100ms
- τ_R: $\approx$ 1s

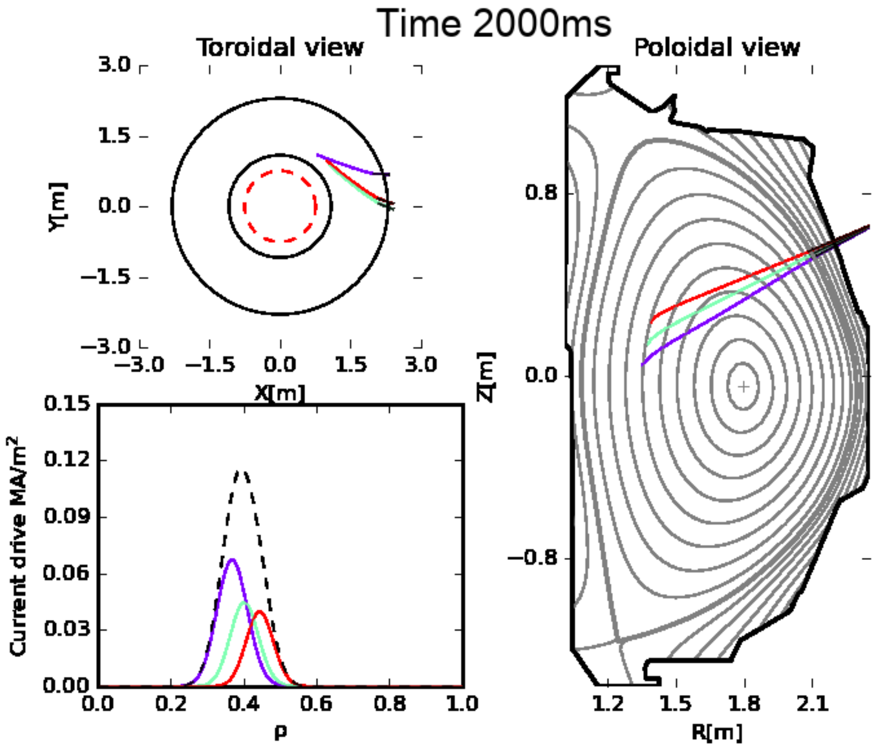
Instabilties
- Tearing Modes: 1-10ms
- VDEs: μs scale
- Disruptions: $\approx$ 1ms



Real-time control system
- Shape control: <1ms
- NBI heating: 50ms
- ECH heating: 50ms
- ML models: 1-10ms
- Magnetic diagnostics: <1ms
- Profile diagnostics: $\approx$ 20ms

Real-time TORBEAM developed and demonstrated in DIII-D

- Gyrotrons start spread out for broad, off-axis CD
- As shot progresses and becomes unstable, gyrotrons clump around q=2 location ($t = 3500ms$)
- After stabilizing, gyrotrons spread out again



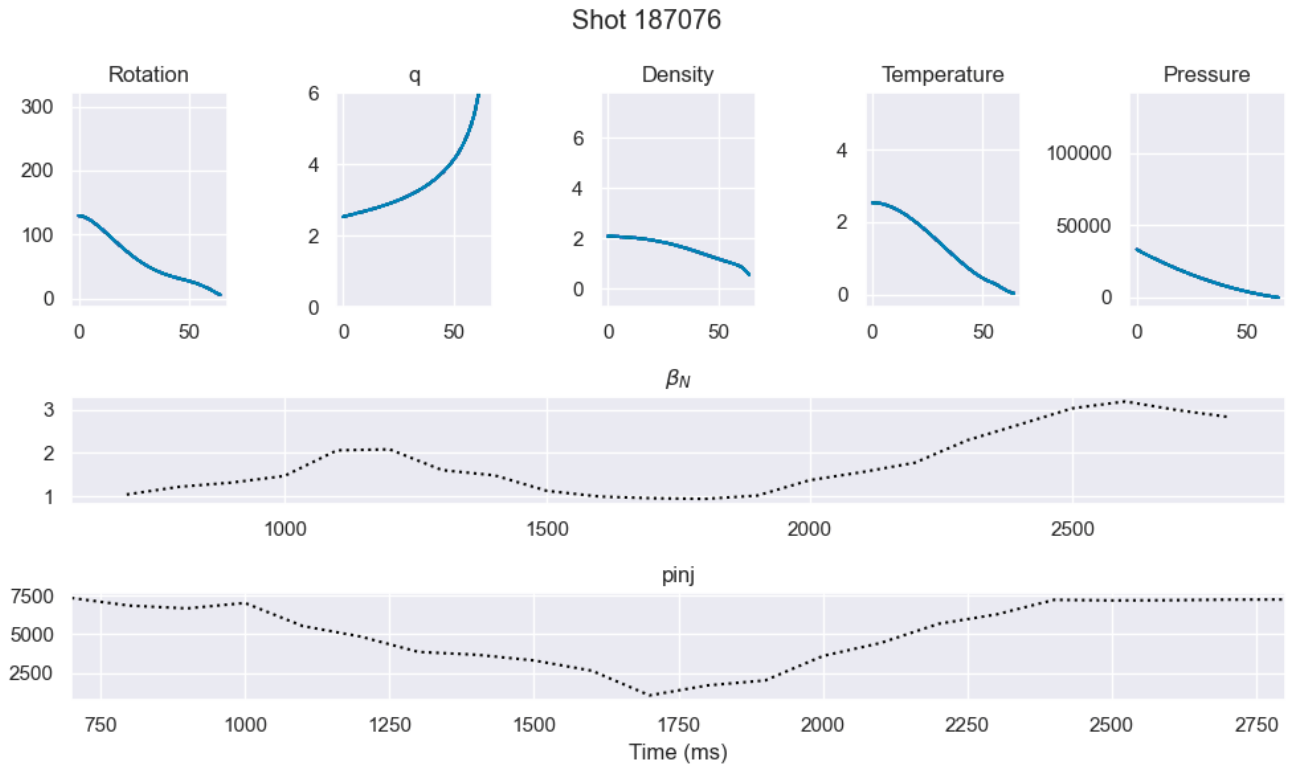
Plasma Control

Profile Prediction

Predict full shots with actuator trajectories

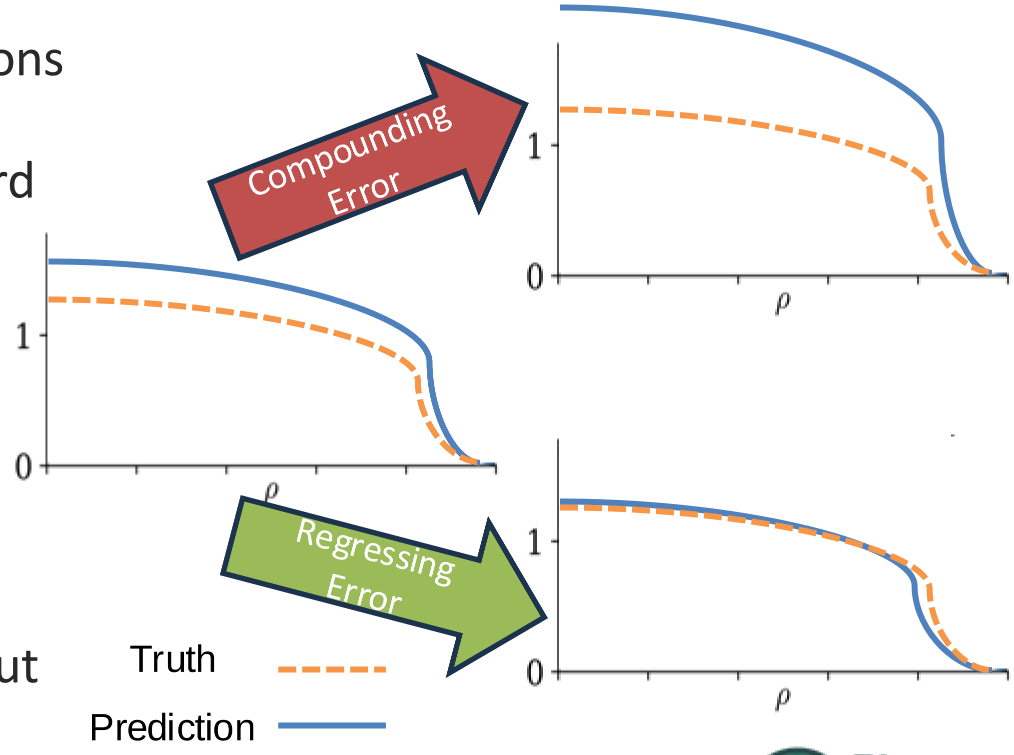
Ground Truth

Predictions



How to keep long-term predictions stable

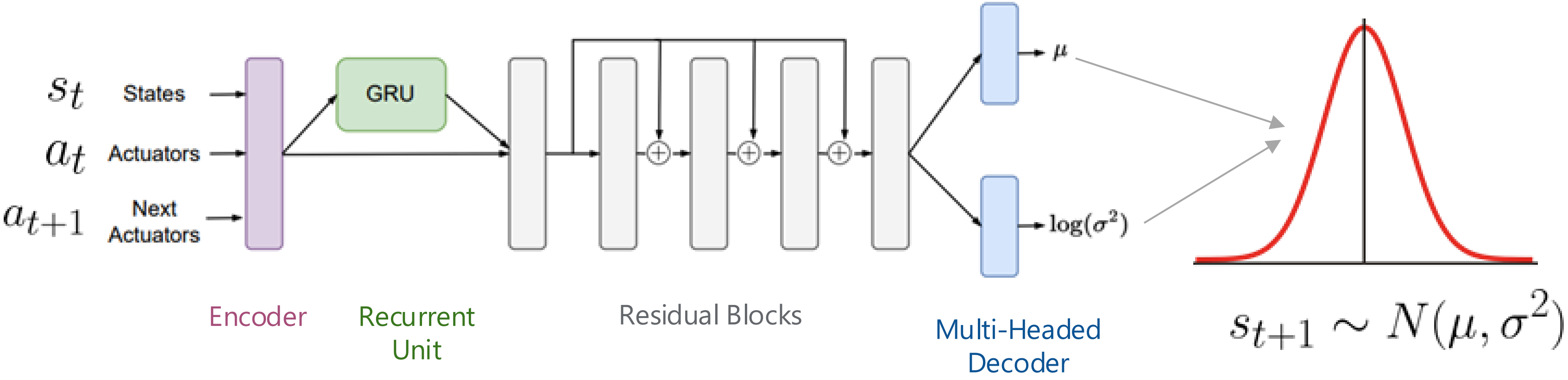
- Predicting off previous predictions causes errors to compound
- Need to have ”regression toward the mean”
- Solution 1: Uncertainty predictions
  - Predict (μ, σ)
- Solution 2: model ensembling
  - Multiple models = further averaging
- Solution 3: autoregressive rollout



Plasma Control

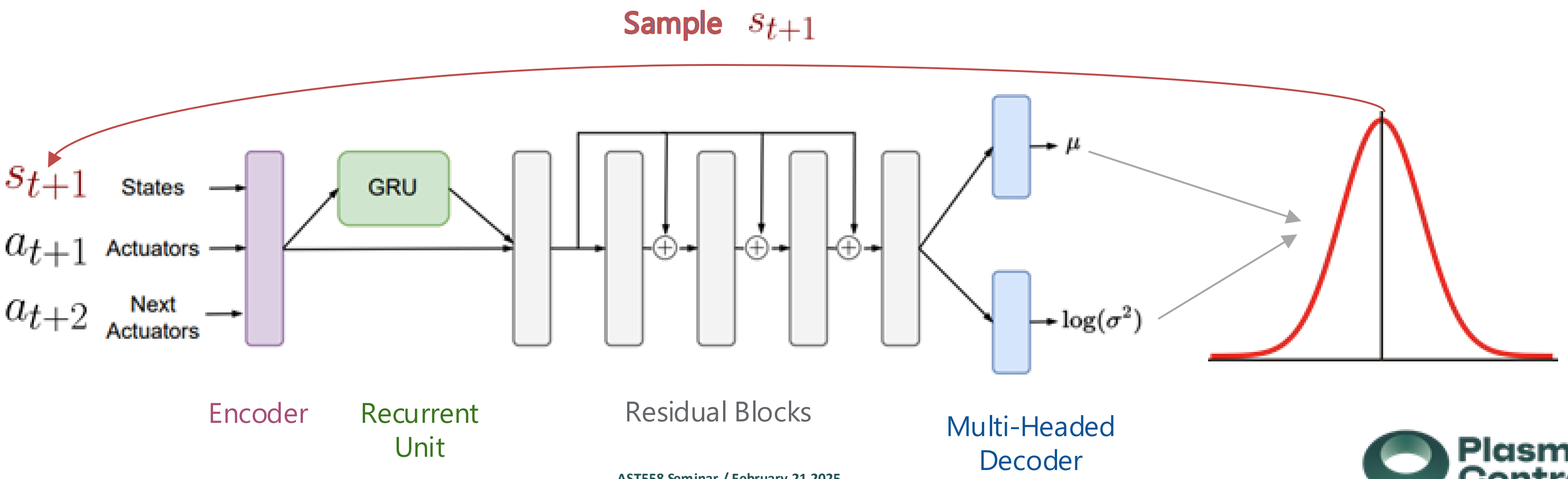
Model Architecture

- Predictions are made 25ms into future
- Model predicts a Gaussian distribution of the next state



Predicting Full Shots

- Next state sampled from Gaussian and fed back into model
- Actuators can be taken from historical data ("replaying a shot") or provided by some optimization algorithm

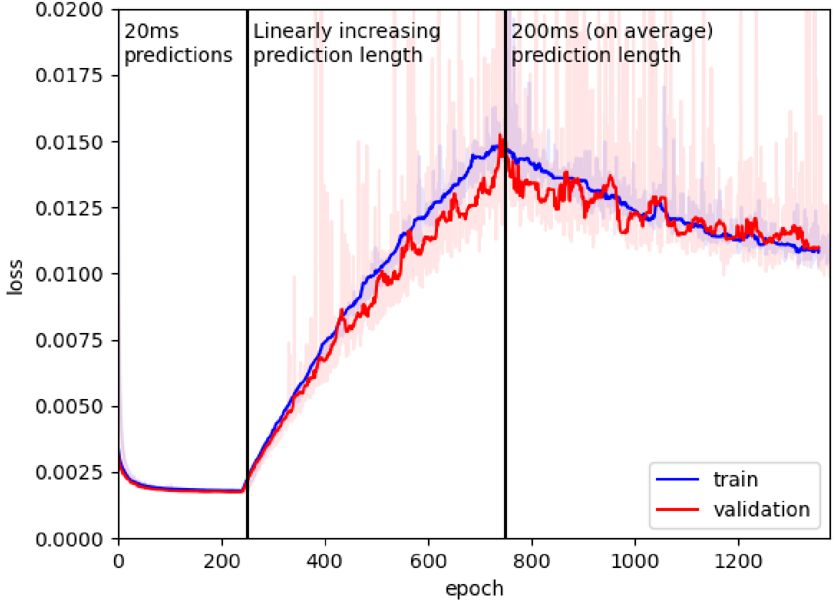


Plasma Control

Curriculum Learning stabilizes long-term predictions

- Curriculum learning (aka autoregressive rollout) is a staged approach to reach full shot profile predictions
- Start by having model predict $\mu = 1$ time steps into future
  - Use time t to predict $t + 1$
- Ramp prediction horizon from $\mu = 1$ to $\mu = 10$
- Continue training at $\mu = 10$

Training + Validation Loss



Plasma Control

MPC Control

Plasma Control

Model Predictive Control

$$x_{t+1} = Ax_t + Bu_t$$

Predicted state

Current state

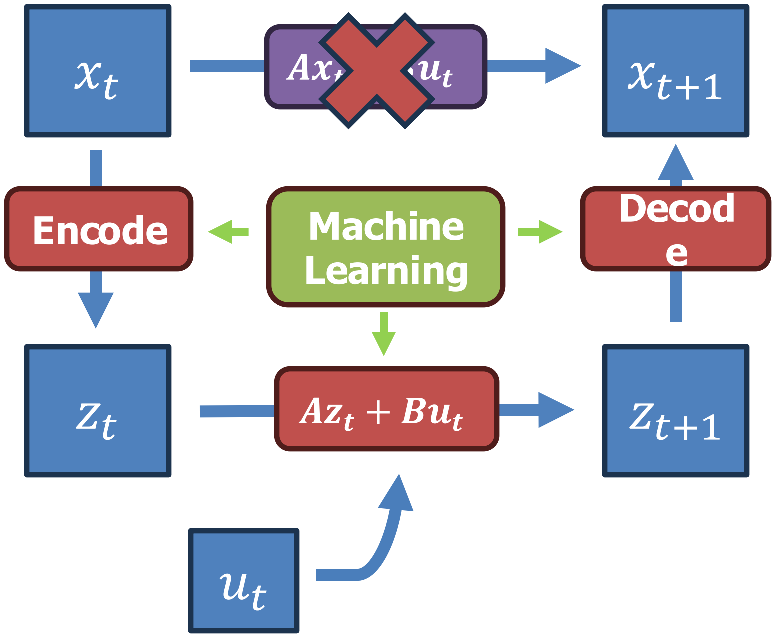
Control Actuators

$$Cost = \sum_t \overbrace{(x_{target} - x_t)^T Q (x_{target} - x_t)}^{\text{Tracking Error}} + \overbrace{u_t{}^T R u_t}^{\text{Control Effort}}$$

- MPC efficiently finds the optimal (cheapest) actuator trajectory to reach a desired state
- Requires linearized dynamics model of the plasma, but we know plasmas are strongly nonlinear!
- How can we control in real-time?

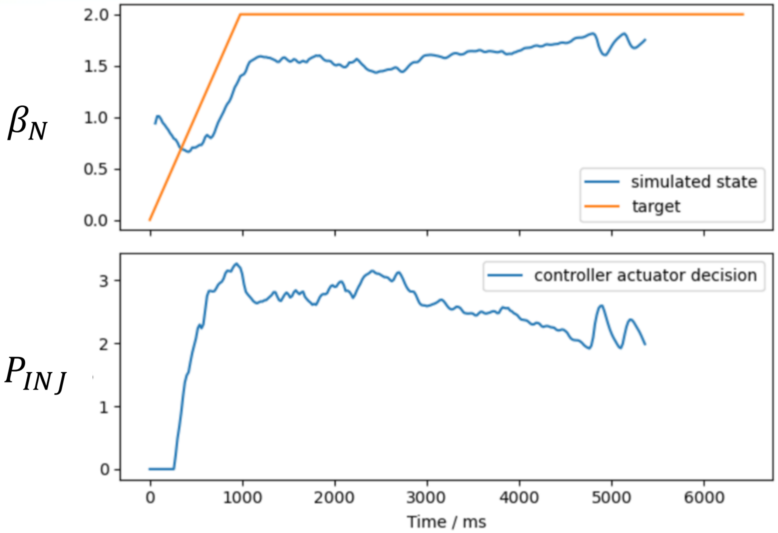
ML Linear Projection

- Nonlinear plasma behavior can be approximately mapped to a larger linear space
- The encoder, decoder, A, and B matrices are learned from DIII-D data
- MPC can be applied to this linear model to find optimal actuator trajectories



[M. Watter, 2015]

Testing out MPC Controller



Predicted result (using PP model)

β_N target

MPC Controller NBI trajectory

- Proof of concept: control β_N with NBI heating
- General behavior reasonable
  - Gets stuck with steady-state error
- Working on full profile controller given a broader set of actuators
  - NBI power and torque, ECH heating, Ip, Bt, shaping and gas injection