Machine Learning Studies of JET Disruption

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US/EU Statistical Disruption Studies on JET [Joint European Torus]

Situation Analysis:

- – Most critical problem for MFE: *avoid/mitigate large-scale major disruptions*
- Approach: Use of big-data-driven statistical/machine-learning predictions for the occurrence of disruptions in JET
- Current Status: ~ 6 years of R&D results (led by JET) using SVM-based ML on *zero-D* time trace data executed on modern clusters yielding ~ *reported success rates ranging from 80 up to 95% for JET, BUT > 98% with false alarm rate < 2.5% actually needed for ITER (Reference – P. DeVries, et al., June 2015)*
- **PPPL Team Goals include:**

(i) improve physics fidelity via development of new *ML multi-D, time-dependent software including better classifiers;*

(ii) develop *"portable"* predictive software beyond JET to other devices and eventually ITER; and

(iii) enhance execution speed of disruption analysis for very large datasets via *deployment on HPC leadership facilities*

NOTE: → *EUROfusion JET leadership has formally agreed to provide PPPL/PU with collaborative access to its huge disruption-relevant* ***multi-dimensional data base that has yet to be analyzed.***

CLASSIFICATION

- Disruption Prediction is a "Binary Classification Problem:
  - *Disruptive or Non-Disruptive*

- Machine learning techniques for classification are ***Supervised***
  - Our approach as physics domain scientists is to combine the considerable knowledge base of observationally validated information with advanced statistical predictive methods such as Machine Learning (ML)

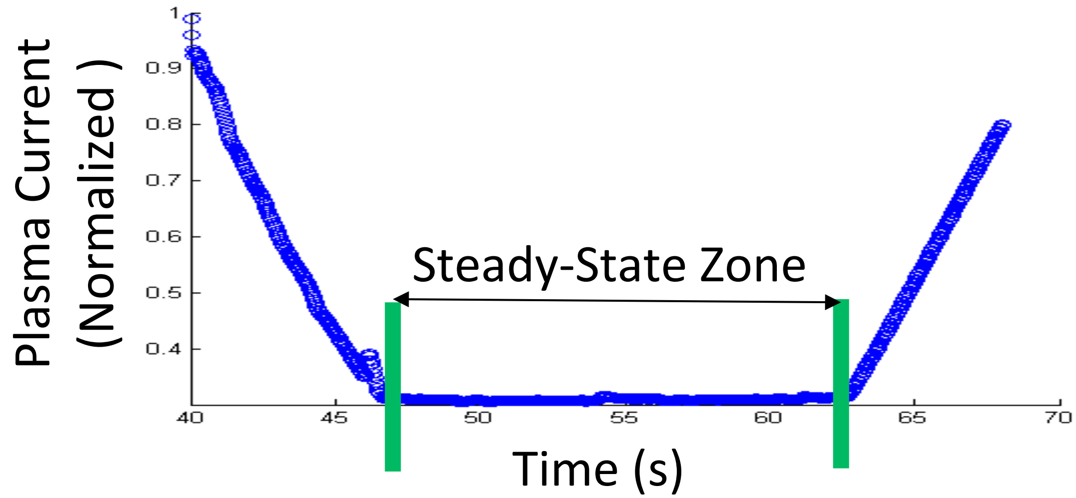
  ➔ Approach: examine relevant data base
  - Use training set to generate a model
  - Use trained model to classify new samples
  - Targeted multi-dimensional data analysis will require new signal representations other than current mean and std [*standard deviation of positive FFT spectrum (excluding first component)*]

Selecting Data From the Signals

Example*: Plasma Current

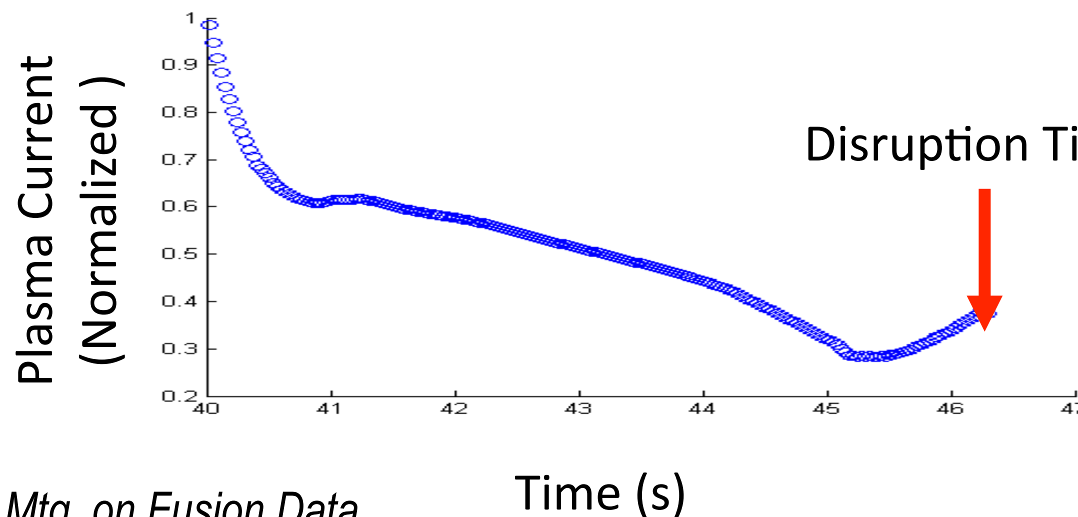
Non-Disruptive Signal:

Selecting non-disruptive points from the steady-state zone



Disruptive Signal:

Selecting disruptive points 64, 128, and 256 ms before disruption



Ref.→ S. Talabzadeh, et al. IAEA Tech. Mtg. on Fusion Data Processing, Validation, & Analysis, June 1-3, '15, Nice, France

Feature Extraction Process

- Reduce data set to form "feature vectors" $\{x_i, y_i\}$
- Consider combination of signals to describe plasma:

$$\mathbf{x} \in \Re^d$$

with

$d = 14$

7 signals* x 2 representations⁺

$$y \in \{+1, -1\}$$

{disruptive, non-disruptive state}

***Signals:**

(1) Plasma current [A]
(2) Mode lock amplitude [T]
(3) Plasma density [m^{-3}]
(4) Radiated power [W]
(5) Total input power [W]
(6) d/dt Stored Diamagnetic Energy [W]
(7) Plasma Internal Inductance

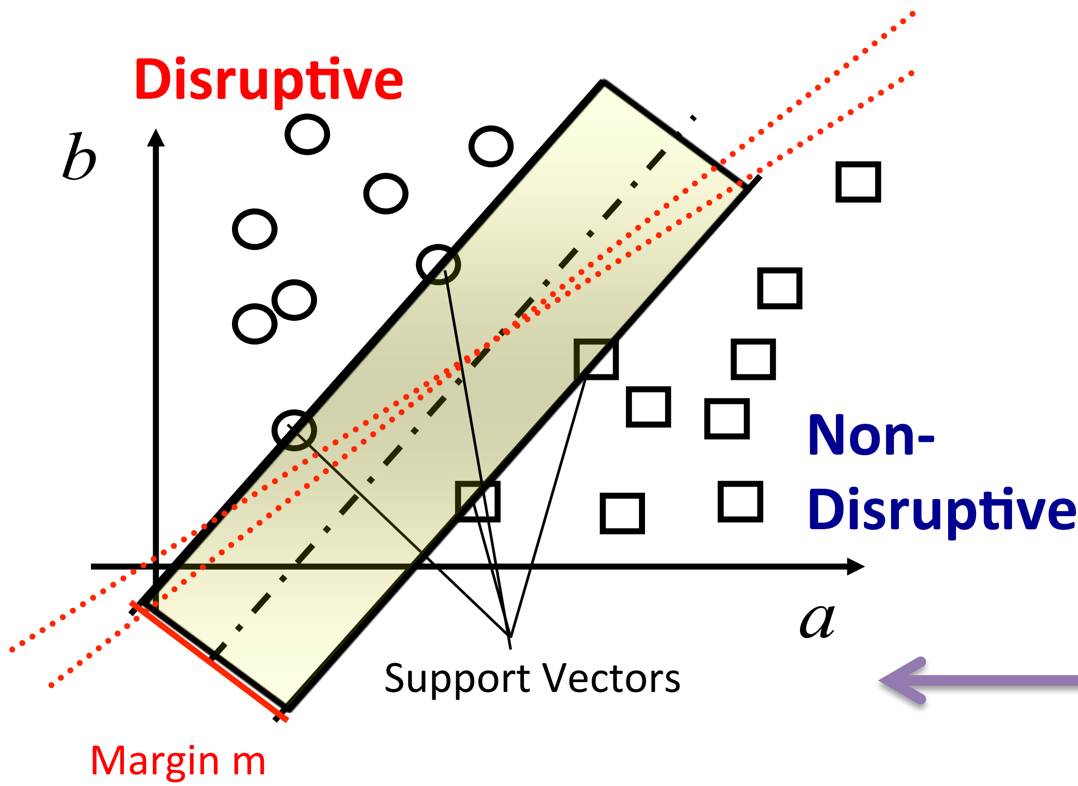
⁺Representations (set of 32 samples at 1 kHz):

(1) Mean
(2) Standard deviation of positive FFT spectrum (excluding first component)

*Each signal normalized to [0,1] over entire data set

SVM Picture

*Decision Function f(x) as hyperplane with a normal **w** and displacement b to separate disruptive & non-disruptive points in the feature space*



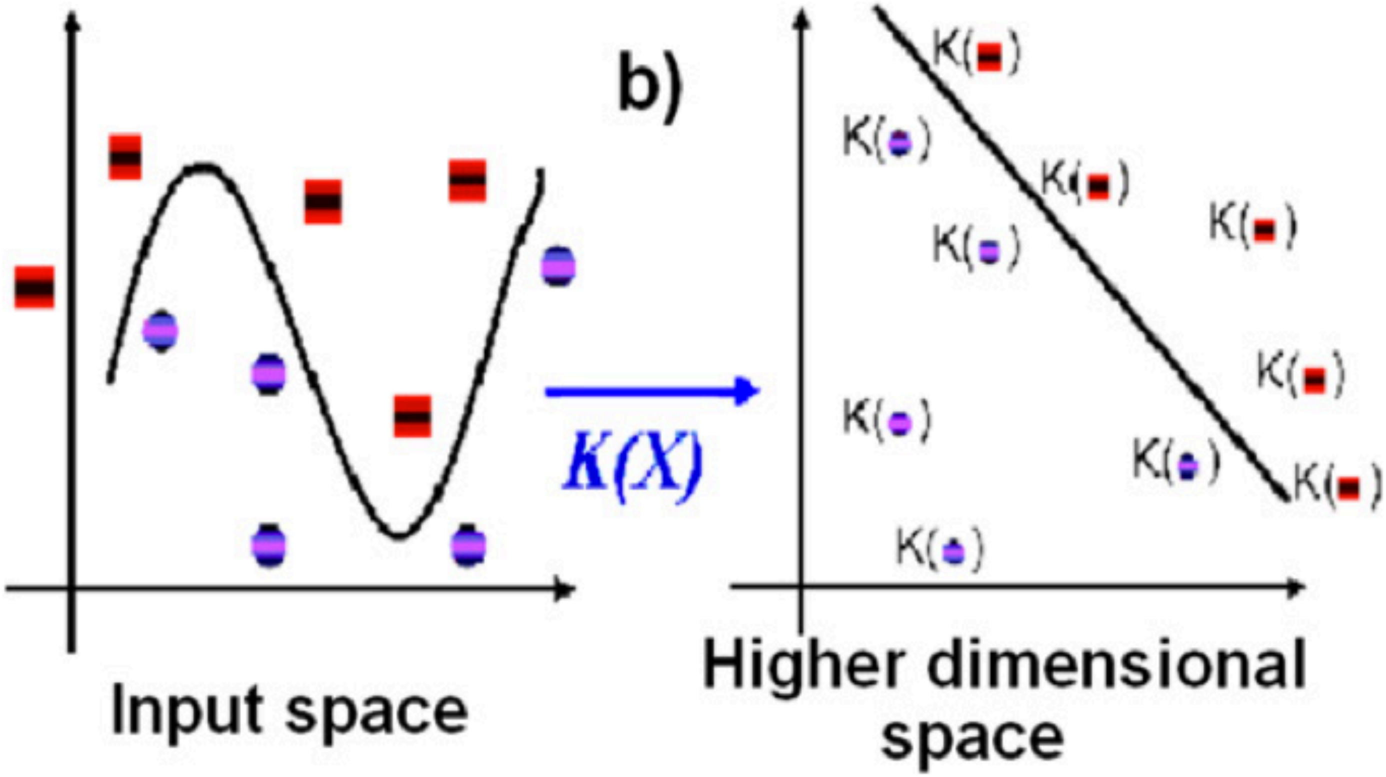
Support Vectors form boundary

TASK: *find hyperplane separating "disruptive" and "non-disruptive" states with widest possible margin*

$$f(\mathbf{x}) = \mathbf{w} \cdot \mathbf{x} + b = 0$$

BUT, real data is NOT linearly separable !

SVM Picture (continued)



➔ *K(x) represents function needed to map data to a higher dimensional space where it* <u>*can actually be separated*</u>

*Reference #2: G.A. Rattá et al. Nuclear Fusion, **50** (2010)*

$$f(\mathbf{x}) = \mathbf{w} \cdot \varphi(\mathbf{x}) + b = 0$$

SVM Decision Function

After solving the optimization problem, classify new data using:

Lagrange Multipliers

Support Vectors

$$f_D(\mathbf{x}) = \sum_i \alpha_i y_i K(\mathbf{x}_i, \mathbf{x})$$

Kernel Function
(e.g., Radial Basis Function/Gaussian)

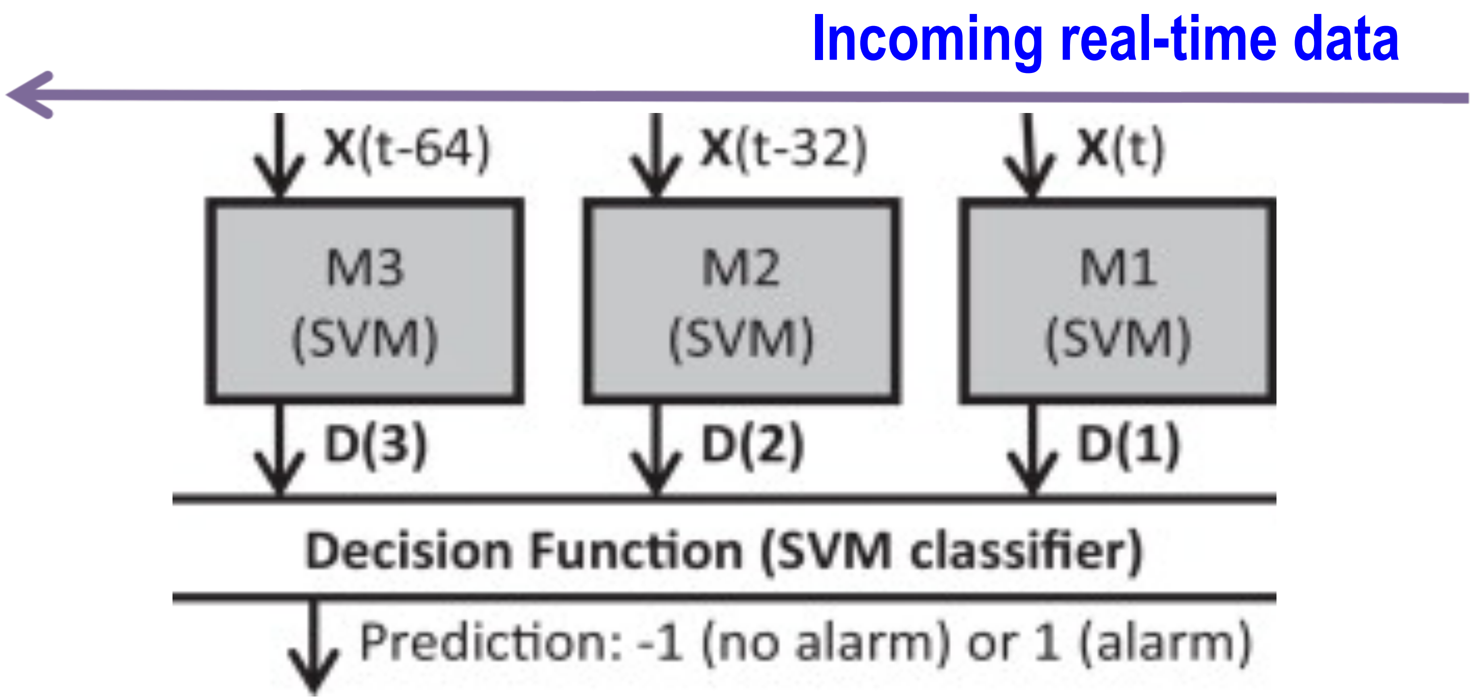
Assess accuracy in terms of:

- Correct predictions
- Missed alarms
- False alarms

Multi-tiered SVM

(separate SVM models trained for separate consecutive time intervals preceding disruption)

(applied to APODIS Code developed by J. Vega, et al.)

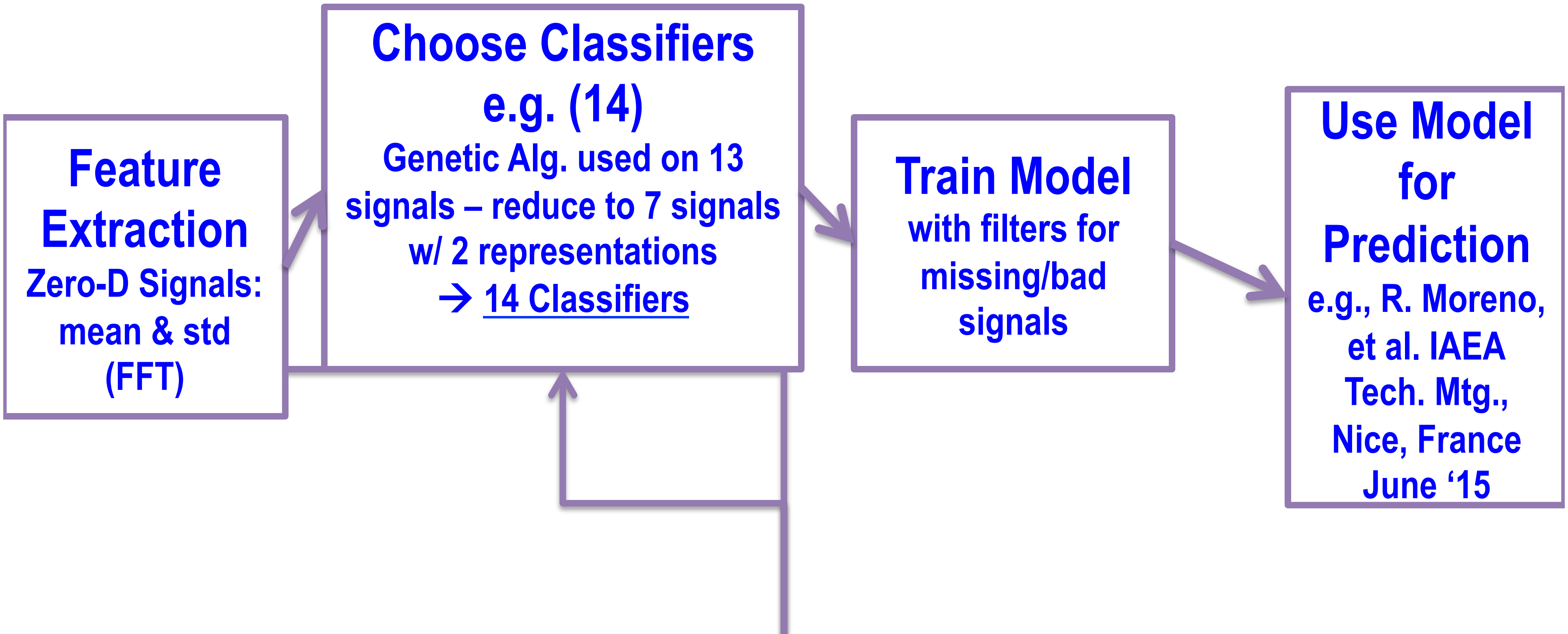


1st Tier: Three models trained separately on sequential data with RBF (Gaussian) kernel *(Note: up to 8 models were considered)*

2nd Tier: Trained with linear kernel on combined Tier 1 outputs

Reference: J. Vega *et al. Fusion Engineering and Design,* **88** (2013)
[APODIS → "Advanced Predictor of Disruptions"]

ML SVM Workflow



Moving forward, PPPL team will focus on ***multi-dimensional (instead of present zero-D time trace) signals***

e.g. radial temperature profile

Many interesting possibilities for more efficient, physics-motivated choices of classifiers

ML Predictive Challenges & Opportunities

- CHALLENGE: SVM results at JET currently delivers in range of 80% to 95% accuracy, but *need to consistently achieve > 98% for reliable ITER operation*
- PPPL FOCUS: Improve predictive performance by enhancing physics fidelity following *"Supervised ML Theme"*

➔ *Function of time + spatial dimensions, including profile/gradient information*

-- *Serve as inputs for regression-type formulation of stability thresholds for improving physics-based classifiers*

-- *Investigation of parametric scaling trends*

– Explore *multi-dimensional signals with associated introduction of much larger/more complex database*

– Explore inclusion of threshold conditions for *key disruption precursors (currently NOT included in SVM classifiers) such as Neoclassical Tearing Modes (NTM)*

ML Predictive Challenges & Opportunities

- Portability Challenge for ML Predictive Software (beyond JET):
  - First investigate applicability to NSTX/NSTX-U disruption database, and then move on to others (DIII-D, ASDEX, EAST, KSTAR, …..) → *ultimately leading to ITER*
- Alternative Methods to SVM:
  - Deterministic Annealing (collaboratively with J. Choi of ORNL)

    → Can be used in parallel with SVM or used to improve choice of classifiers as part of SVM workflow
- "Deep Learning" Algorithms

  → For feature selection approaches with broader scope than current Genetic Algorithms
- Broader Applicability of ML Methods (developed for disruption predictions)

  → e.g., apply to predictions of other important "binary" type fusion physics phenomena such as "L to H" transitions
- Deployment of more advanced ML software engaging very large dataset investigations on HPC leadership hardware

Disruption Data Subset

# Shots	Disruptive	Nondisruptive	Totals
Carbon Wall	324	4029	4353
Beryllium Wall	185	1036	1221
Totals	509	5065	5574

JET produces ~ Terabyte (TB) of data per day

Sample Signals (0-D time trace)	Data Size (GB)
Plasma Current	1.8
Mode Lock Amplitude	1.8
Plasma Density	7.8
Radiated Power	30.0
Total Input Power	3.0
d/dt Stored Diamagnetic Energy	2.9
Plasma Internal Inductance	3.0

~55 GB data collected from each JET shot

➔ ***Well over 35 TB total amount with multi-dimensional data yet to be analyzed***

JET
Disruption
Shot
#82499

~ 1 second
before
thermal
quench

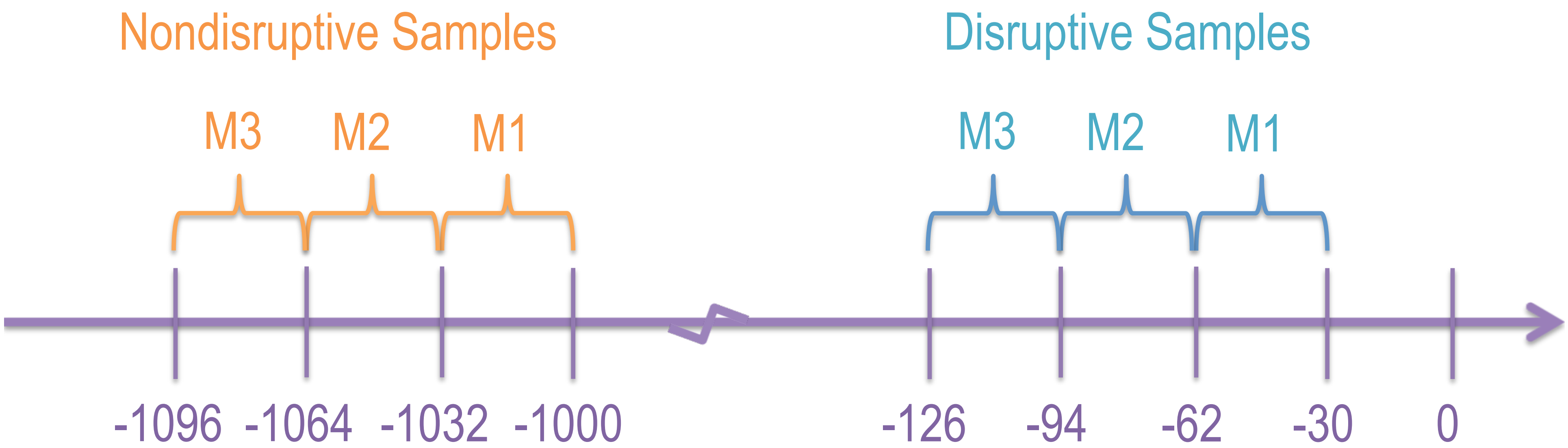
Visible light
from colder
plasma in
divertor/
wall regions

Preliminary Work at PPPL

- Gained access to JET database (MDSplus)
- Extracted signal & video
- Acquired and implemented SVM framework from APODIS
- Rewrote development framework to be self-contained within Matlab 2014, resulting in:

  -- *100x speedup over using LIBSVM by avoiding excessive I/O*
  -- Simple training / testing reduced from 85 min to < 1 min

Multi-tiered SVM Training

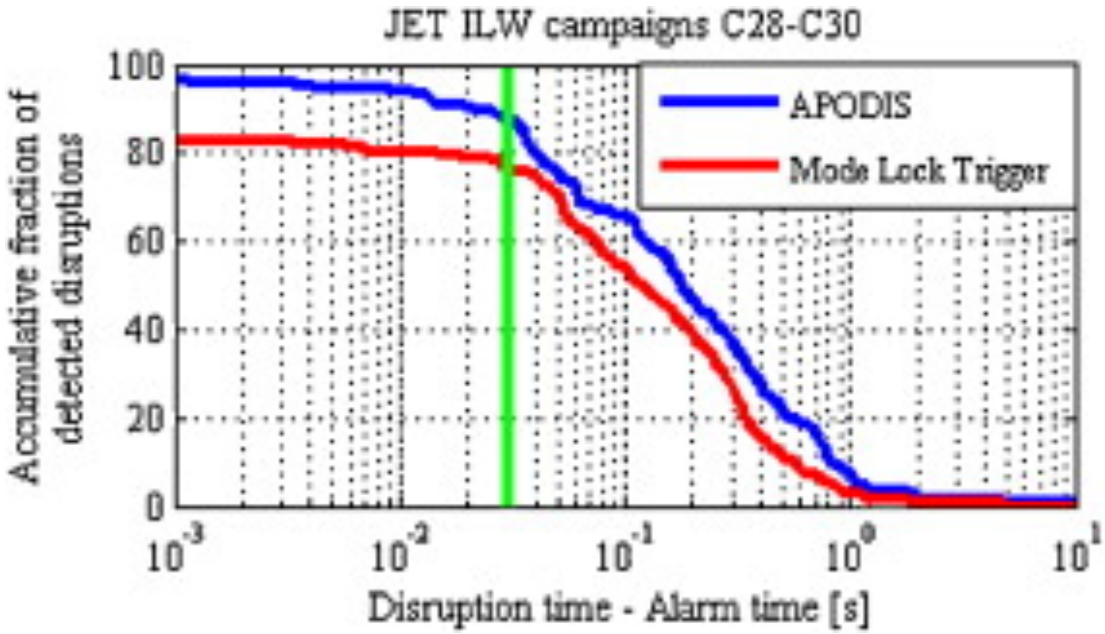


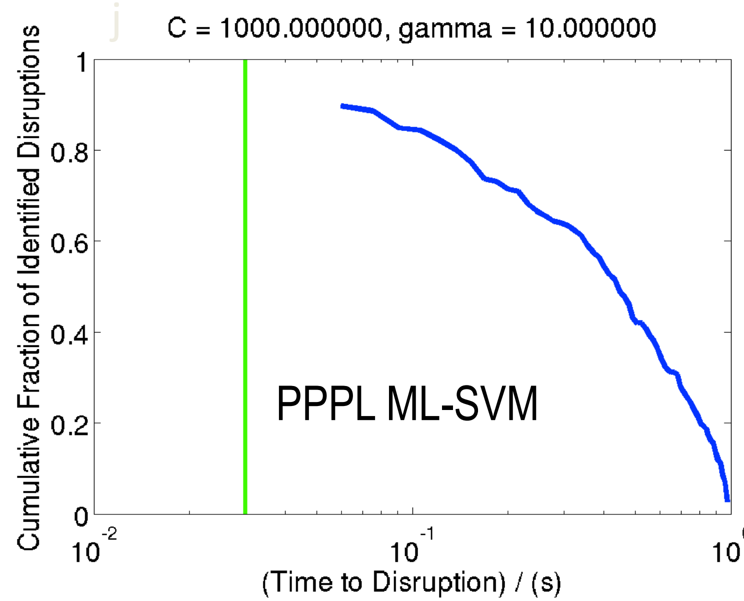
Times given as t - t_d in milliseconds

RECENT RESULTS for JET ILW Disruption Data: Comparison of Results from PPPL ML-SVM Analysis with APODIS

30 ms before disruption *(Ref.-- P. DeVries – ITER disruption prediction requirements → mitigation trigger time > 30 ms)*

APODIS predicted rate of 87.5% while PPPL ML-SVM gives 89.8%





- APODIS trained on 738 disruptive and 2,035,000 non-disruptive samples
- PPPL's version of ML-SVM trained on 975 disruptive and 975 non-disruptive samples

Projecting 14D space (7 signals x 2) into 3D space to develop SVM Classifers → movie shows separability of Disruptive from Non-Disruptive Data:

DA (Deterministic Annealing) Method

Jong Choi, ORNL

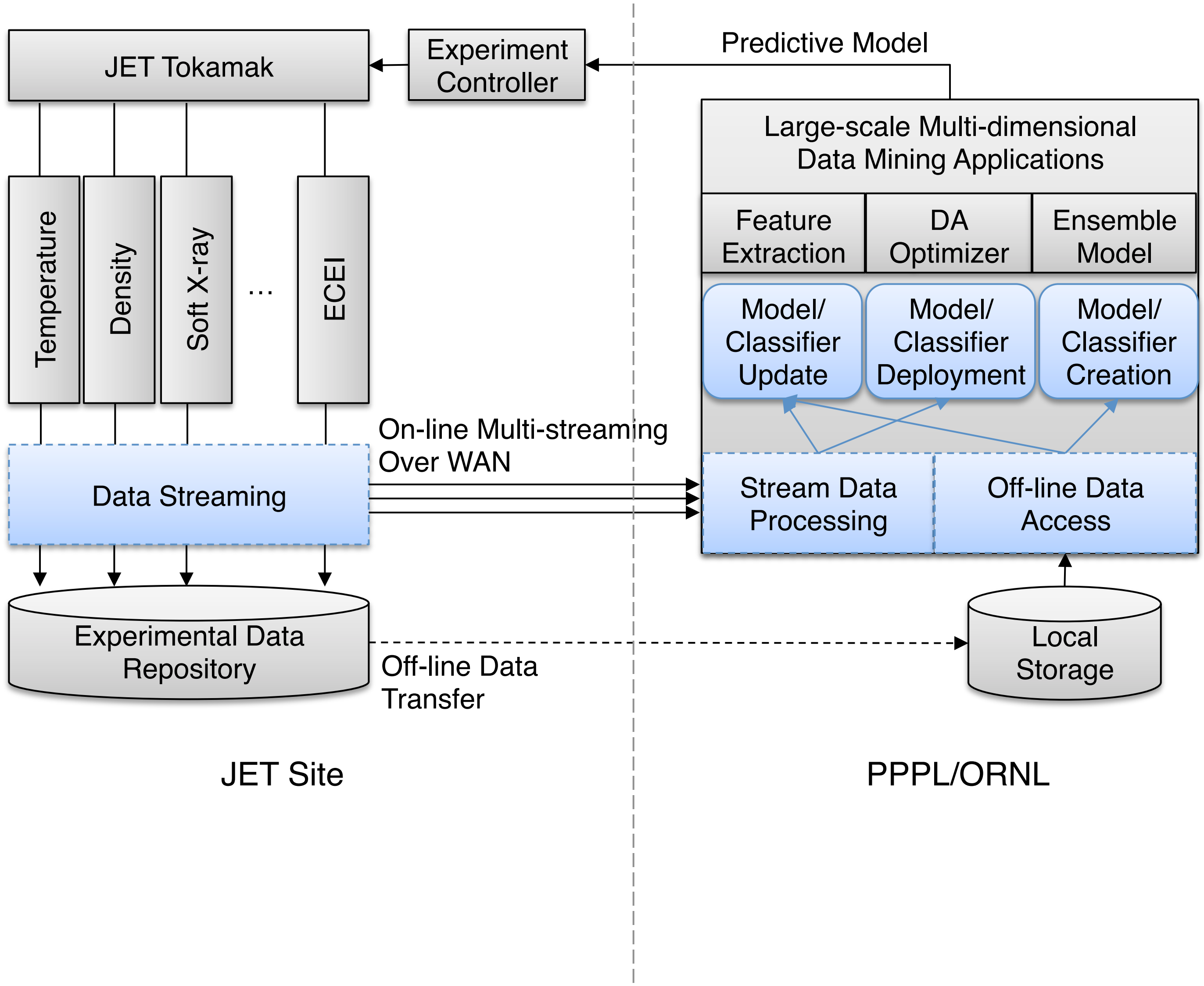
Generative Topographic Mapping (GTP) using Deterministic Annealing (DA)

References:

- J. Y. Choi, et al. Science Direct, Proc. Computer Science 00, 1-10 (2010)

- Geoffrey Fox, et al., Parallel Processing Letters, May 17, 2013.

Fusion Data Mining Diagram



Summary

• **Fusion Energy Mission Relevance**:

-- *Goal of Magnetic Fusion Energy goal is demonstrating the scientific & technical feasiblity of delivering Fusion Power*

-- *Most critical associated problem is to avoid/mitigate large-scale major disruptions*

• **Relevance to HPC:**

-- ***New focus*** *on development of large-data-driven* ***"machine-learning" statistical methods*** *as alternative/complement for conventional "hypothesis-driven/first principles" predictive methods*

• **Associated Challenge:**

→ *Significant improvements over zero-D SVM-based machine-learning capabilities to achieve >98% success rate with portability of software to ITER via enhanced physics fidelity (capturing multi-D) and execution time (moving beyond clusters to Leadership Class Facilities.*