Preparation for a Statistical Study of Plasma Disruptions in JET

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PLASMA DISRUPTIONS

- Disruption is a sudden loss of plasma confinement ~ 100 ms
- Disruptions are characterized by two phases:
    - Thermal Quench – something like half of the thermal energy is lost to the walls
    - Current Quench – plasma current goes to zero
- Combination of thermal and electromagnetic loads can damage the inside of the machine
- No good models exist to predict disruptions because they result from a combination of complex phenomena
    - Locked modes
    - Vertical displacement events
    - Etc.
- For ITER, need to predict with ~98% confidence
- Need to develop machine-portable prediction software
- Machine learning provides powerful tools for data-driven science, complimentary to hypothesis-driven science

SUPPORT VECTOR MACHINES (SVM) [1]

- Classify disruptive vs. nondisruptive states [2,3]
- Plasma state described by diagnostics (e.g. density, current)
- Solve optimization problem to find hyperplane that separates disruptive/nondisruptive states in parameter space
- Use model to classify new data (e.g. live from machine)

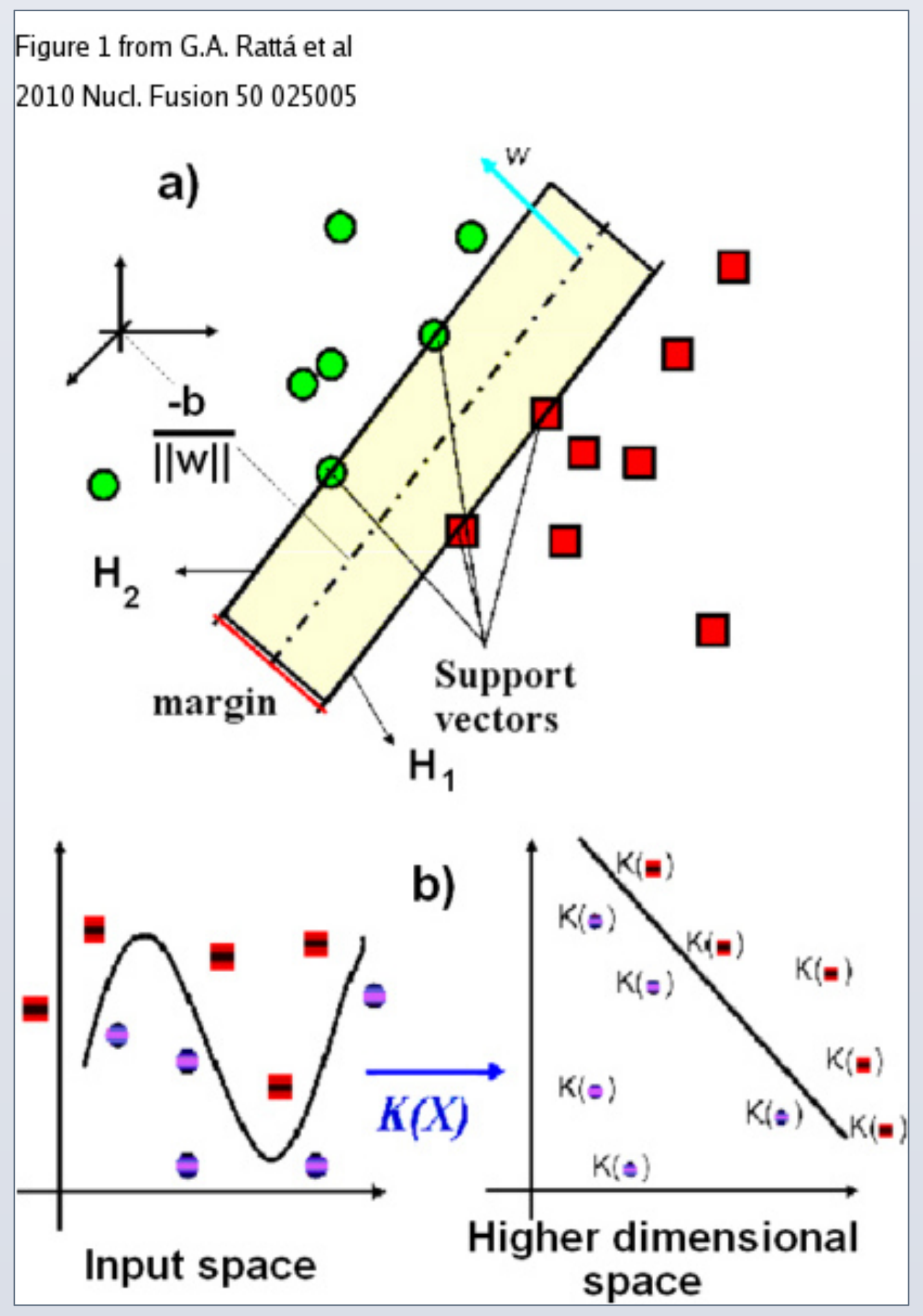
Figure 1 from G.A. Rattá et al 2010 Nucl. Fusion 50 025005

Plasma state described by *d*-dimensional vector of classifiers

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

Plasma state is either disruptive or nondisruptive

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

Lagrange Multipliers

Support Vectors

Decision Function

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

Kernel Function:
Linear, Gaussian, etc.

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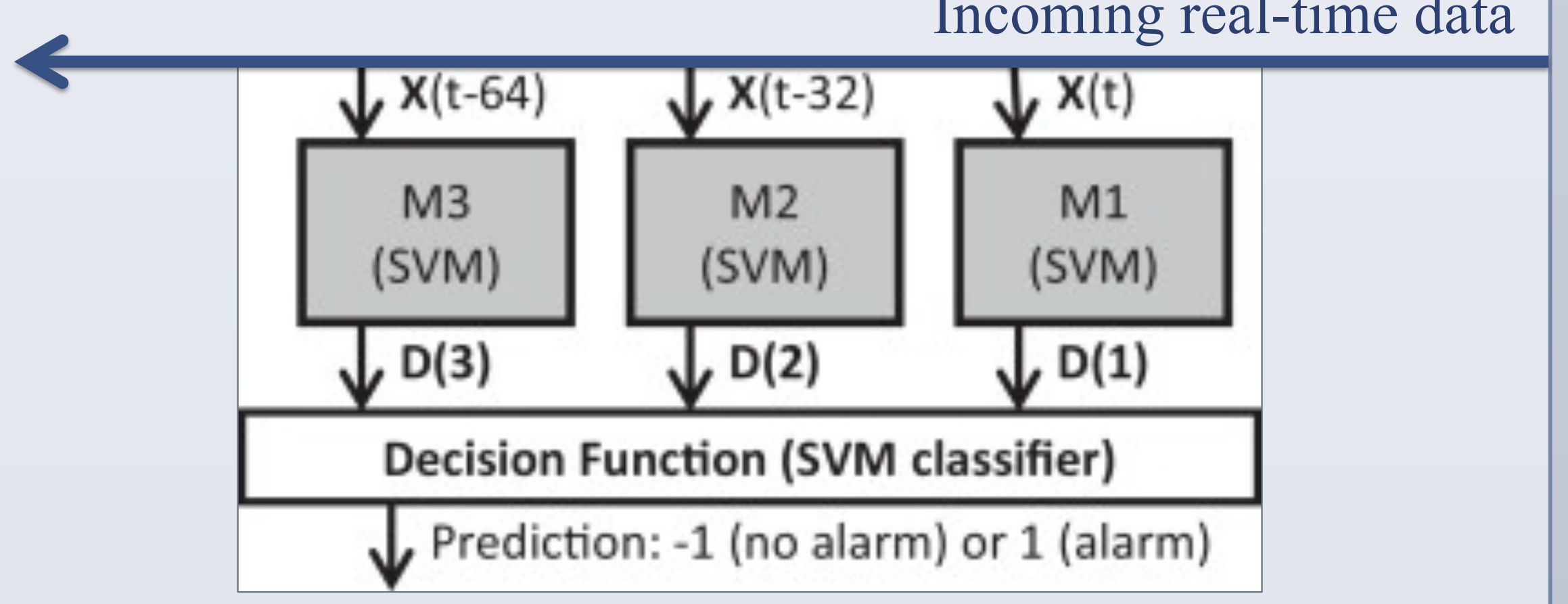
SVM CLASSIFIERS

- Classifiers are used to describe the state of the plasma
- Previous work [3] identified 14 classifiers as a baseline
    - 7 Signals
        - Plasma Current [A]
        - Mode Lock Amplitude [T]
        - Plasma Density [m^{-3}]
        - Radiated Power [W]
        - Total Input Power [W]
        - d/dt Stored Diamagnetic Energy [W]
        - Plasma Internal Inductance
    - 2 Representations, consecutive 32 ms intervals
        - mean
        - std(FFT)

MULTI-TIERED SVM [4]

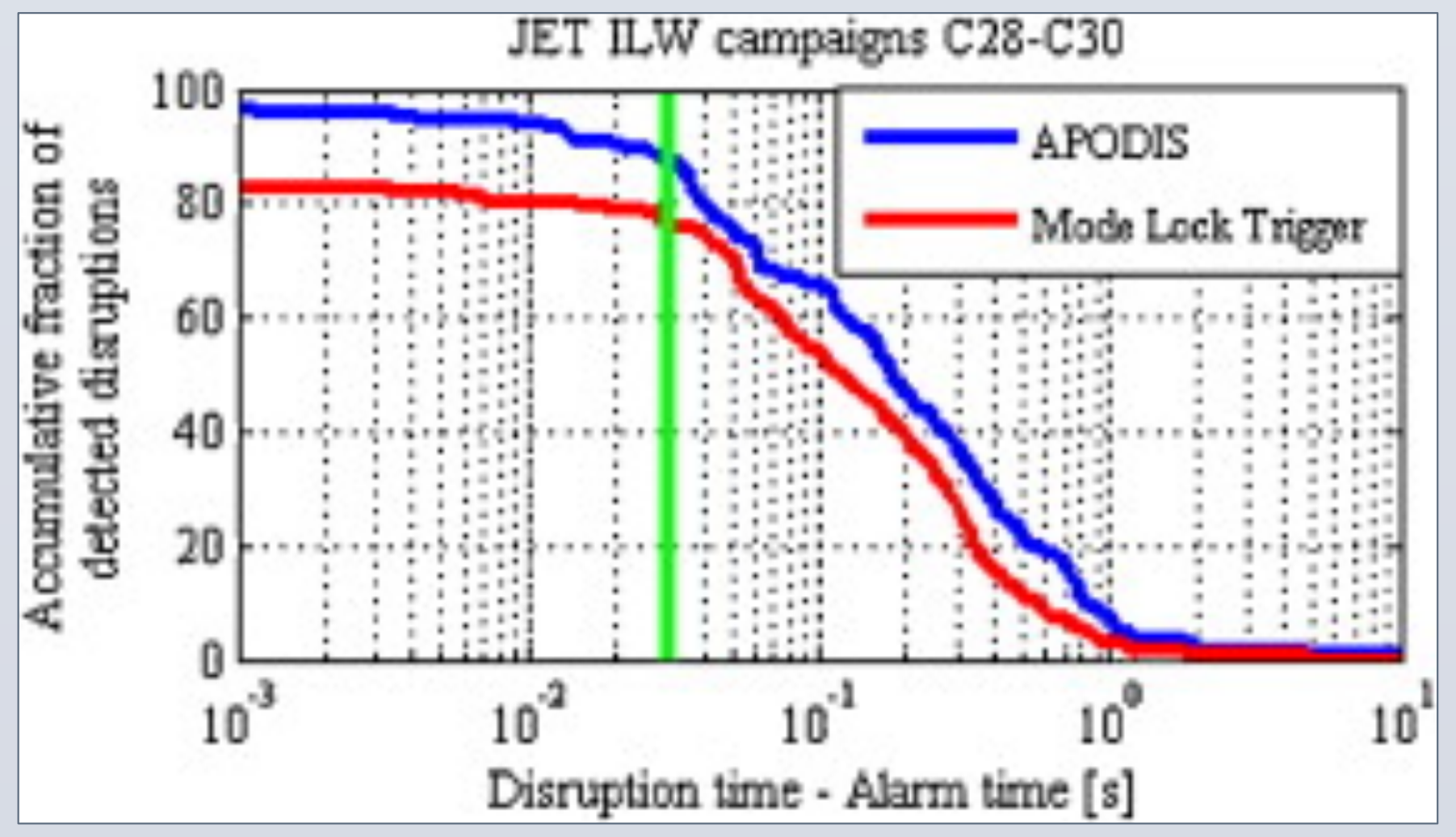
- Analyzes 3 consecutive time intervals for better accuracy
- 1st Tier – three models trained with Gaussian Kernel
- 2nd Tier – trained on combined Tier 1 output, Linear Kernel

Incoming real-time data



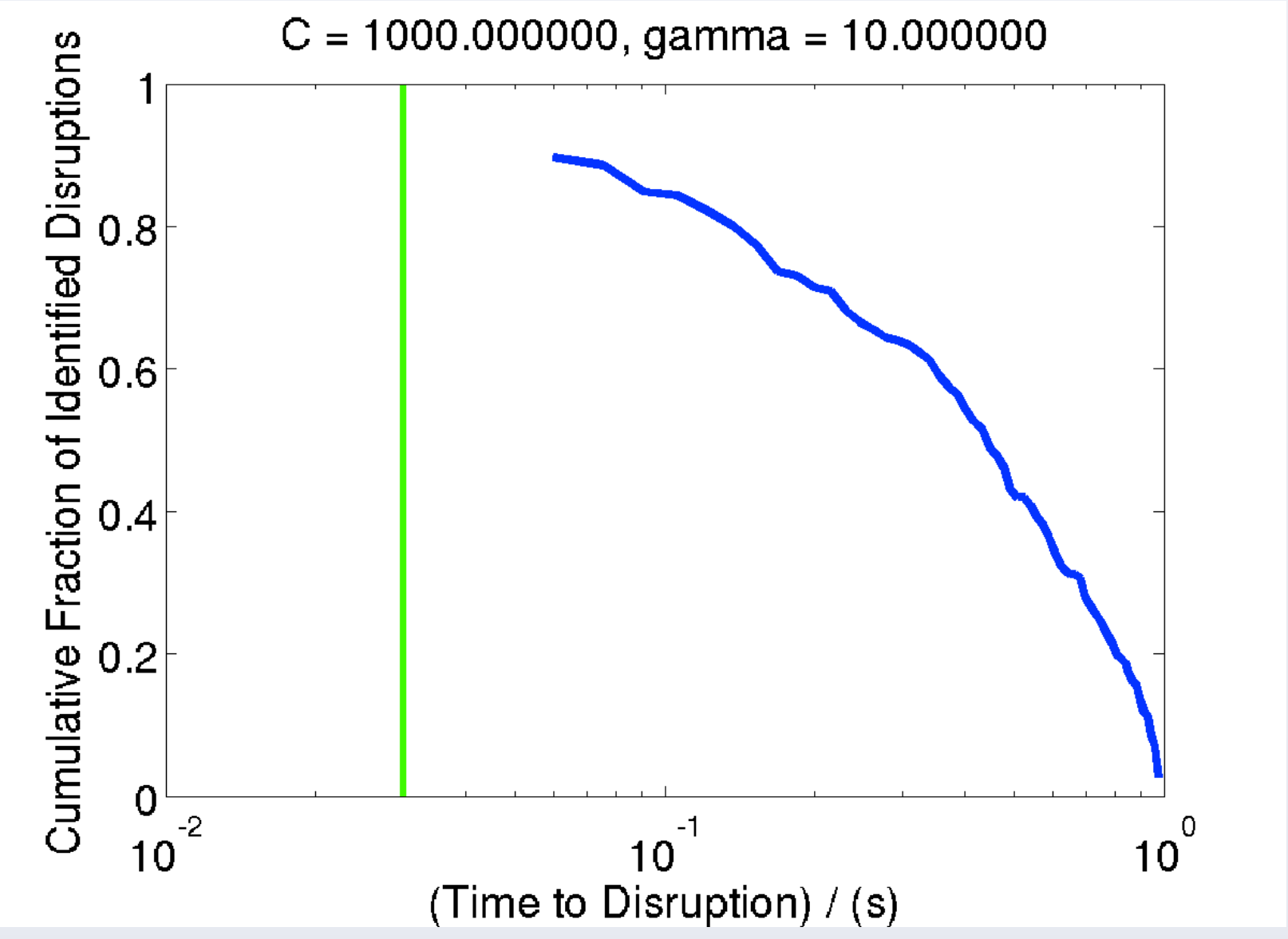
APODIS RESULTS [4]

- Trained with JET carbon-wall data
    - 738 d / 2,035,000 nd samples
- Implemented for real-time operation with ITER-like wall
- 87.5% prediction success at 30ms prior to the disruption

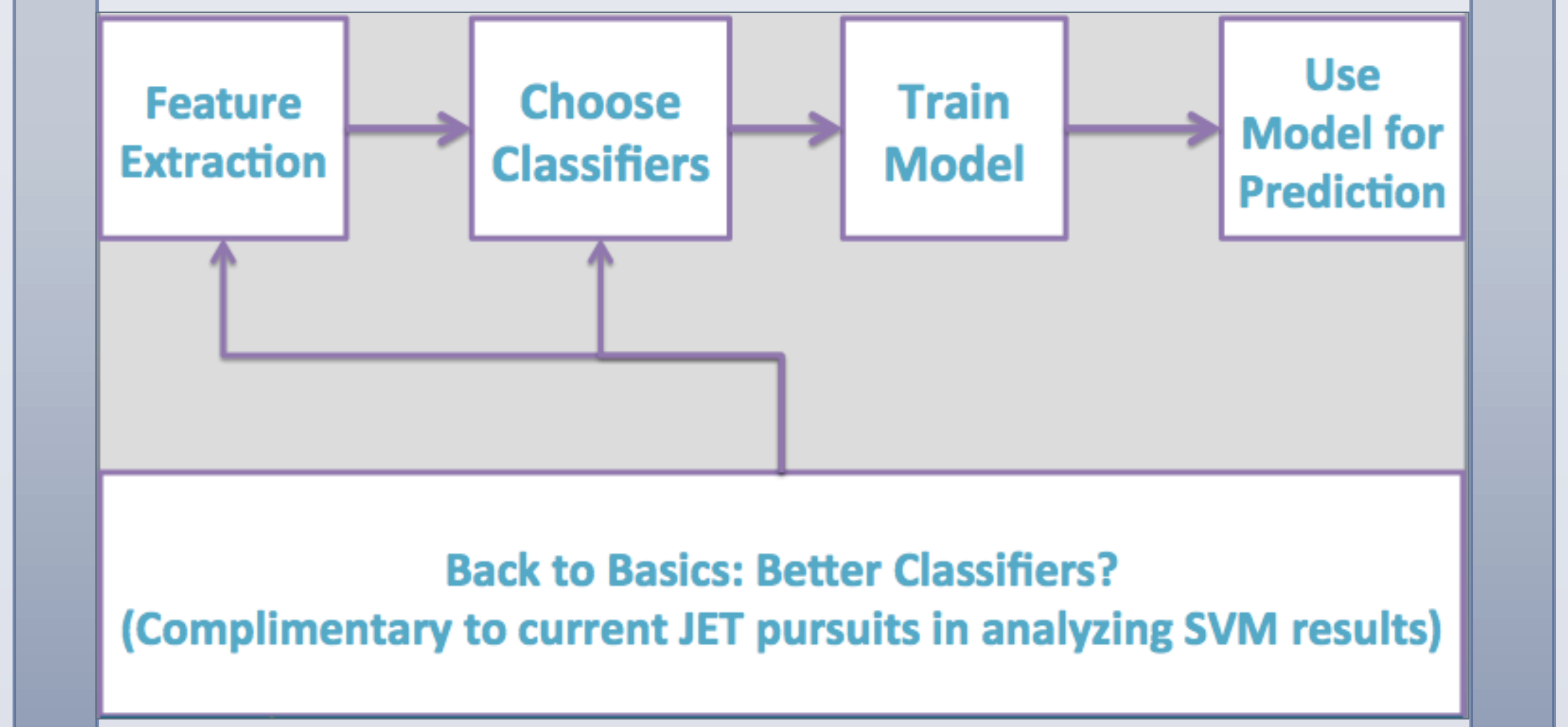


RECENT WORK AT PPPL

- Extracted 50 GB of signal data from JET MDSplus tree
- Wrote scripts for extracting features from signals
- Developed cross-validation routines for testing SVM
- Rewrote CV routines to be self-contained within Matlab
    - Achieved 100x speedup over use of C++ library
- Participated in Theory and Simulation of Disruptions Workshop to share progress and incite collaboration
- Obtained list of most recent JET disruption data
- Identified SVM model parameters to be used as a baseline
    - 975 d / 975 nd training samples
    - 89.8% success at 30ms before disruption
    - 2% of nondisruptive intervals give false alarms



NEXT STEPS


Feature Extraction

Choose Classifiers

Train Model

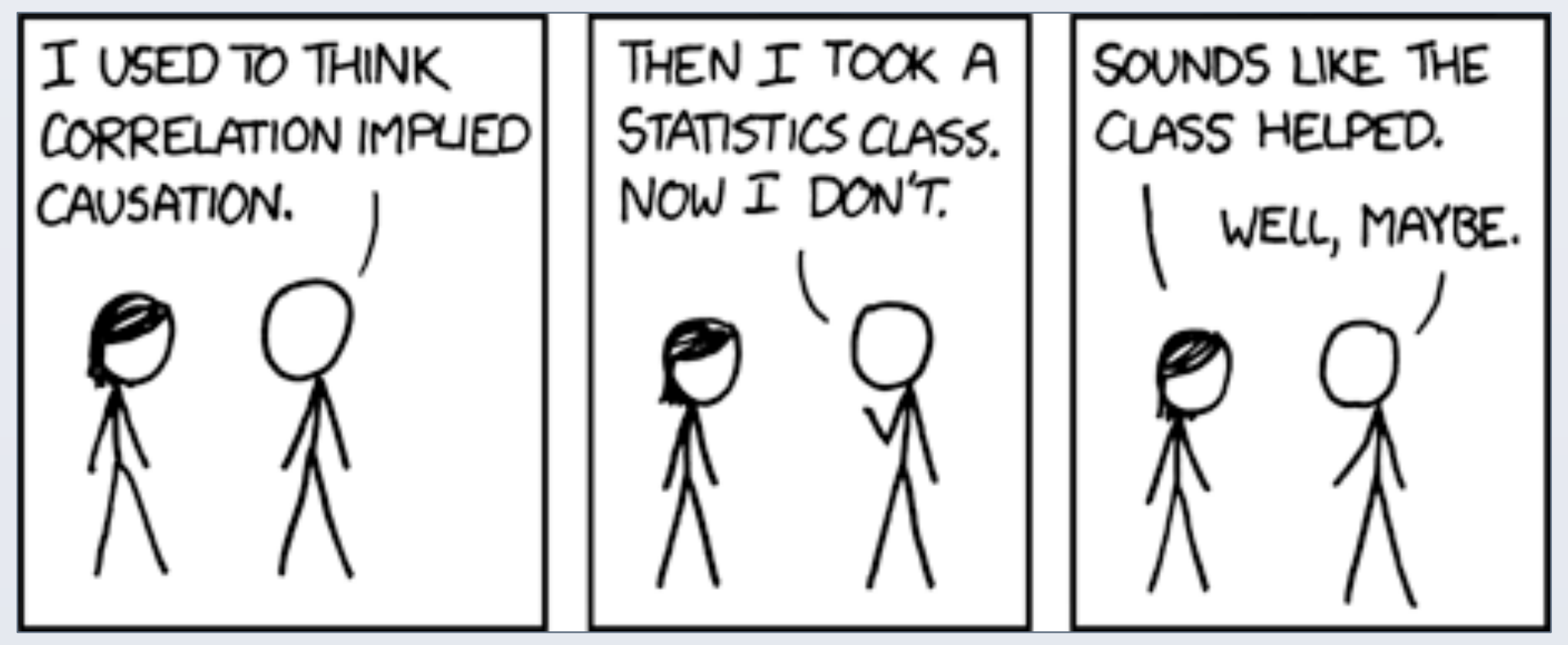
Use Model for Prediction

Back to Basics: Better Classifiers?
(Complimentary to current JET pursuits in analyzing SVM results)

- Look for better classifiers with a higher physics-fidelity
    - Go back to identifying which signals and corresponding representations are meaningful
- Start to examine signals that have a spatial dimension
    - e.g. radial profiles
- Look for ways to represent higher-dimensional signals
    - Independent channels
    - Profile peakedness
    - Principal component

OBJECTIVES FOR STUDY

- Identify physics-motivated classifiers for prediction
    - Multi-dimensional signals, better physics fidelity
    - Use as classifiers for threshold tests
- Learn about disruption dynamics
    - Similarities to other phenomena? (L-H transition?)
    - Gain ability to identify precursors (e.g. NTMs)
- Compare experiments to determine software portability
    - NSTX-U is right down the hallway!
    - Look at parameter scaling between machines
- Possibility of using SVM as backbone for prediction
    - Train SVM on outputs of multiple predictors
    - Use SVM in parallel with other predictors
    - Complexity of predictor limited by availability of computing resources for real-time analysis



Obligatory comic courtesy of Randall and xkcd.com

REFERENCES

[1] W.H. Press, *Numerical Recipes 3rd Edition* (2007)
[2] G.A. Rattá *et al. Nuclear Fusion*, **50** (2010)
[3] G. A. Rattá *et al. Nuclear Fusion*, **87** (2012)
[4] J. Vega *et al. Fusion Engineering and Design*, **88** (2013)

ACKNOWLEDGEMENTS

This project was supported in part by the U.S. Department of Energy, Office of Science, Office of Workforce Development for Teachers and Scientists (WDTS) under the Science Undergraduate Laboratory Internships Program (SULI).