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 \([\text{standard deviation of positive FFT spectrum (excluding first component)}]\)
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

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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:

  \[ \mathbf{x} \in \mathbb{R}^d \]
  with
  \[ d = 14 \]
  7 signals\(^\ast\) \times 2 \text{ representations}\(^\dagger\)

\[ y \in \{+1, -1\} \]
{disruptive, non-disruptive state}

\^\ast\text{Signals:}\n(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

\^\dagger\text{Representations (set of 32 samples at 1 kHz):}\n(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 $\mathbf{w}$ and displacement $b$ to separate disruptive & non-disruptive points in the feature space

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

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

BUT, real data is NOT linearly separable!
K(x) represents function needed to map data to a higher dimensional space where it can actually be separated.

After solving the optimization problem, classify new data using:

\[ f_D(x) = \sum_i \alpha_i y_i K(x_i, x) \]

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.)

Incoming real-time data

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

2\textsuperscript{nd} Tier: Trained with linear kernel on combined Tier 1 outputs

[APODIS \rightarrow “Advanced Predictor of Disruptions”]
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 & Totals

<table>
<thead>
<tr>
<th></th>
<th>Disruptive</th>
<th>Nondisruptive</th>
<th>Totals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carbon Wall</td>
<td>324</td>
<td>4029</td>
<td>4353</td>
</tr>
<tr>
<td>Beryllium Wall</td>
<td>185</td>
<td>1036</td>
<td>1221</td>
</tr>
<tr>
<td><strong>Totals</strong></td>
<td><strong>509</strong></td>
<td><strong>5065</strong></td>
<td><strong>5574</strong></td>
</tr>
</tbody>
</table>

### Sample Signals (0-D time trace) & Data Size (GB)

<table>
<thead>
<tr>
<th>Sample Signals</th>
<th>Data Size (GB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plasma Current</td>
<td>1.8</td>
</tr>
<tr>
<td>Mode Lock Amplitude</td>
<td>1.8</td>
</tr>
<tr>
<td>Plasma Density</td>
<td>7.8</td>
</tr>
<tr>
<td>Radiated Power</td>
<td>30.0</td>
</tr>
<tr>
<td>Total Input Power</td>
<td>3.0</td>
</tr>
<tr>
<td>d/dt Stored Diamagnetic Energy</td>
<td>2.9</td>
</tr>
<tr>
<td>Plasma Internal Inductance</td>
<td>3.0</td>
</tr>
</tbody>
</table>

JET produces ~ Terabyte (TB) of data per day

~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 Classifiers → 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:
Fusion Data Mining Diagram

- **JET Tokamak**
- **Experiment Controller**
- **Data Streaming**
- **Experimental Data Repository**
- **Local Storage**
- **PPPL/ORNL**

**JET Site**

- Temperature
- Density
- Soft X-ray
- ECEI

**PPPL/ORNL**

- **Large-scale Multi-dimensional Data Mining Applications**
  - Feature Extraction
  - DA Optimizer
  - Ensemble Model
    - Model/Classifier Update
    - Model/Classifier Deployment
    - Model/Classifier Creation
  - Stream Data Processing
  - Off-line Data Access

**On-line Multi-streaming Over WAN**

**Off-line Data Transfer**
Summary

• **Fusion Energy Mission Relevance:**
  -- *Goal of Magnetic Fusion Energy goal is demonstrating the scientific & technical feasibility 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).*