JET 0D Variables Sensitivity Study for FRNN

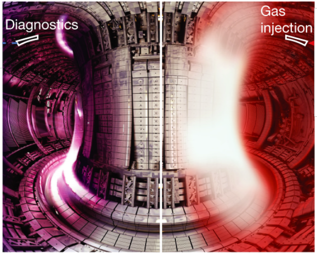
Disruption prediction for tokamaks using machine learning

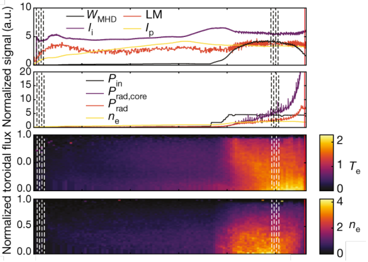
Wouter Van De Pontseele

September 6, 2019

Culham Centre for Fusion Energy

1. Introduction
2. Fusion RNN
3. JET 0D Noise and Sensitivity Studies
4. Conclusion & Outlook



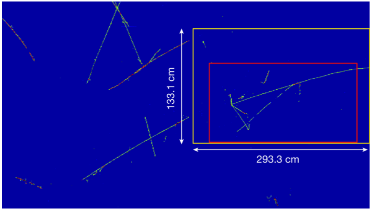


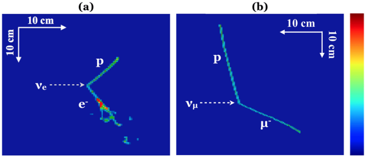
Introduction

Who Am I?

- PhD student Particle Physics
- Normal life consists of hunting for sterile neutrinos at Fermilab near Chicago with the MicroBooNE experiment
- **4 weeks internship to get a taste of CCFE and fusion research**.
- Similarities: amount of data, collaboration size, athmosprere, data-analysis tools.
- Differences: Fusion has more urgent challenges, less Monte-Carlo driven, less quantitative uncertainties.

Deep learning (CNN and Semantic segmentation) in MicroBooNE: arxiv.org/abs/1808.07269





Fusion Recurrent Neural Network (FRNN)

Framework developed by J. Kates-Harbeck and W. Tang at PPPL
Aims to predict disruptions for tokamaks.

Goals

- Generic **RNN** model independent of machines.
- As **little data processing** as possible.
- CNN structure for **1D profile signals**.
- First hopeful signs of **transfer learning** between machines.

nature.com/articles/s41586-019-1116-4
github.com/PPPLDeepLearning/plasma-python

My Project: JET 0D Sensitivity Studies

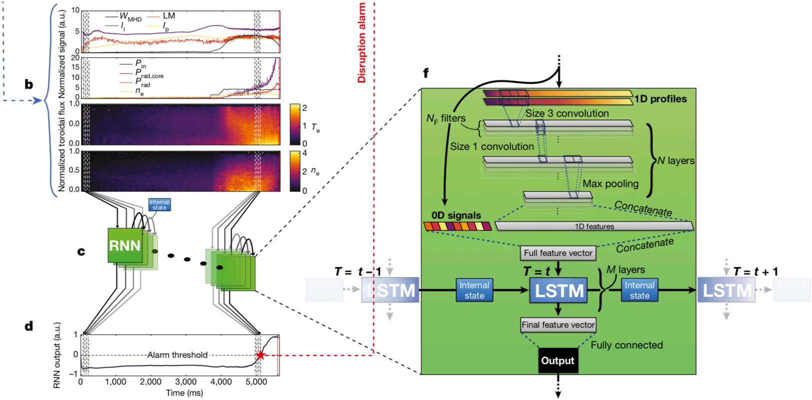
Goals

- Which input **fields** are the **most important** in the training.
- How **noisy** are the input variables?
- How does the **noise vary over time**/shots?
- How does the uncertainty on the diagnostics **influence the prediction performance**?

Strategy

- Run FRNN with different input signals to **estimate variable importance**.
- Use Fourier transformations to **estimate noise**.
- Estimate Noise **signal-by-signal and shot-by-shot**.
- Look at **noise evolution** for different shots and dirsuptive vs non-disruptive shots.
- Run FRNN with **enlarged and diminished noise contributions**.

FRNN



- 2 layers of 100 Long-Short-Term Memory cells (hyper-parameters).
- Regularisation through dropout and learning rate decay.

- All signals are sampled at 1 ms, up-sampling without violating causality.
- **Target function**: step function, 1 if $T_{Disruption} - t < T_{Warning}$ 0 otherwise. $T_{Warning} \approx 1\,\mathrm{s}$ is a hyper-parameter.
- **Loss function**: Hinge loss,

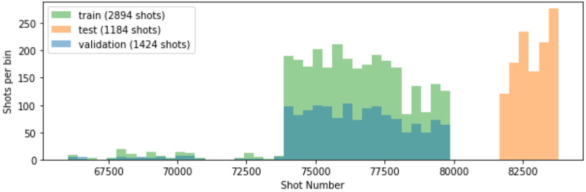
$$\ell(y) = \max(0, 1 - t \cdot y)$$

  t is the target value and y is the prediction.
- **Evaluation Metric**: Did the prediction value exceed the threshold 30 ms or more before disruption.

FRNN: Training, Validation and Test samples

1. Training: carbon wall — 2894 shots, 216 disruptive
2. Validation: carbon wall — 1424 shots, 89 disruptive
3. Testing: ITER-like wall — 1184 shots, 174 disruptive

The testing set uses a different campaign to evaluate transfer learning performance.



Disruptions: A tokamak discharge disrupts with a sudden loss of confinement, yielding a quench of the plasma current, and/or a vertical displacement event (VDE) due to the loss of vertical stability.

Training details

- Most of the training parameters are hyper-paramters.
- In practice, this **requires a hyper-parameter tuning**.
- Due to hardware and time constraints, I used a default set of hyper parameters without tuning.

$\rightarrow$ No numbers should be taken from my results and further studies are needed!

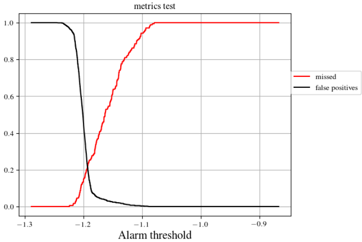
Princeton Tiger GPU cluster

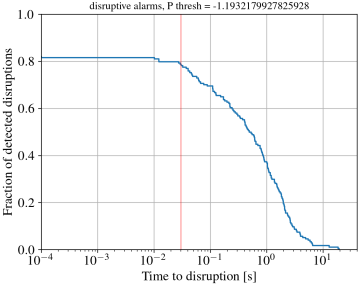
- 80 Nodes
- 28 2.4 GHz Xeon Broadwell cores/node
- 4 NVidia 1328 MHz P100 GPUs/node
- Results here obtained using:
  1 node per training,
  4 epochs, 256 shots per min-batch.

JET 0D Sensitivity Studies

Default Run with FRRN on JET 0D Signals

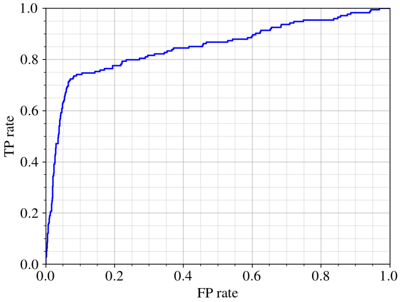
- First step is testing the importance of different input signals.
- The default signals are:
  Plasma density, Stored energy, Stored energy time derivative, Plasma current, Internal inductance, Locked mode amplitude, Input Power, Radiated Power Core, Radiated Power Edge, Radiated Power, q95 safety factor.





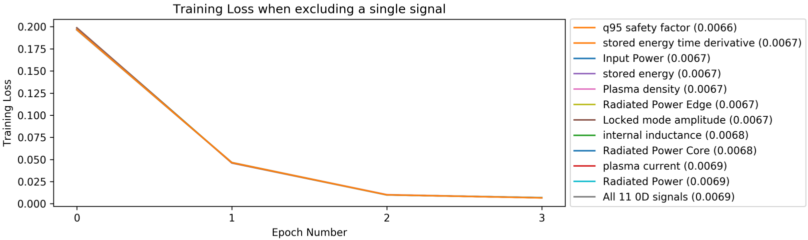
Signal Importance

- The **Area Under the ROC curve** will be used as the quality metric.
- Run the training 11 times, each time **excluding one signal**.
- The **effect of the signal exclusion** on the area under the roc curve is an **estimator** for its **importance**.



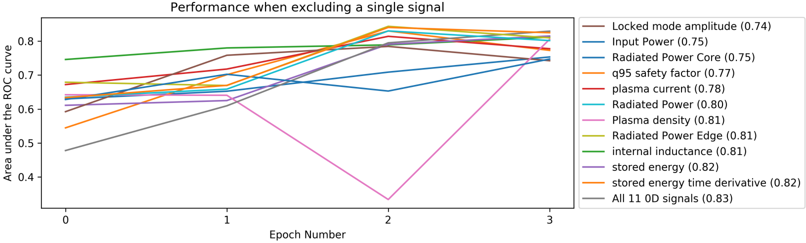
Signal Importance study

- More **hyper-parameter tuning and more epochs are clearly needed** to optimise the performance.
- The default performs the best: **FRNN is good in handling all the signals together**.
- **Locked Mode Amplitude, Input Power, Safety Factor and Radiated Power** are clearly all **important**.
- Time derivative of the energy is least important, indication **FRNN is good in extracting** this **information** directly.



Signal Importance study

- More **hyper-parameter tuning and more epochs are clearly needed** to optimise the performance.
- The default performs the best: **FRNN is good in handling all the signals together**.
- **Locked Mode Amplitude, Input Power, Safety Factor and Radiated Power** are clearly all **important**.
- Time derivative of the energy is least important, indication **FRNN is good in extracting** this **information** directly.



Sensitivity Study Approach

Goal: Noise Study for the 0D Jet Signals

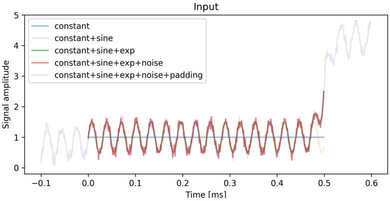
1. **Determine** reasonable **noise variations** to apply on the input.
2. Apply variations and **evaluate training performance**.

This presentation

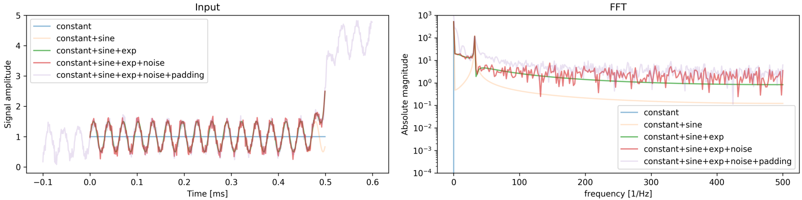
- Look at **discrete Fast Fourier Transformations** (FFT) of the signals.
- Apply **frequency band filter** on high frequencies.
- Restore high frequency part of the signals by **clipping the noise**.
- Evaluate the **dependence of the noise** on the disruptivity and shot number/length.

→ Caveat: current method violates causality.

Toy Model to Determine Noise

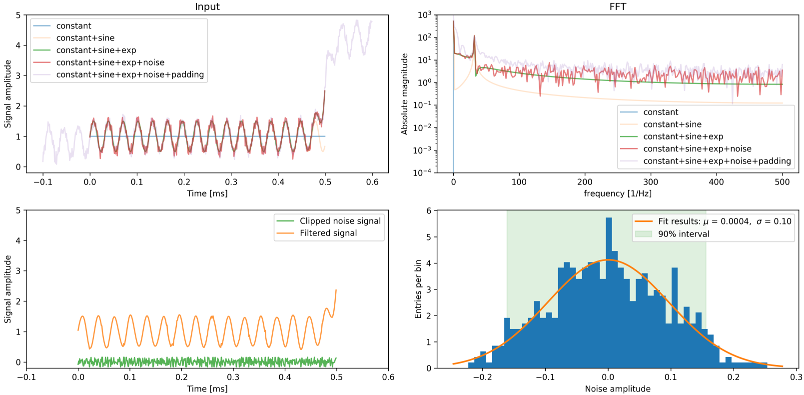


- Define a signal with disruptive end as: *constant* + *sine* + *exponential*
- Add "Additive white Gaussian noise (AWGN)" to the signal.
- Since FFT has "leakage" at the edges, pad the signal on both sides in a symmetric way to avoid sharp edges.



Calculate the discrete fast Fourier transformation.

- **Long-range** correlations are located at **low frequencies**.
- **Define the noise** as the input after filtering out the low frequency region.
- By setting the 0th bin to 0 in the frequency space, the **average of the noise in the time space** becomes **0**.
- Verify that the **noise** is indeed compatible with the **Gaussian** that was used to generate the noise in the first place.



- Clip the noise amplitude using the 90% interval.
- Define the *filtered signal* as the *input - clipped noise*.

- Applying FFT on a finite size array introduces leakage, the amount of leakage depends on the shot duration, in practice, the leakage is a lot smaller than the signal and the noise after padding.
- Defining the noise as a low-frequency-filter comes with a price:
  - The cut-off is somewhat arbitrary, for the JET shots in the following frames, 5 Hz is used, the higher the threshold is put, the less the original signal is affected. One could also define the noise as the signal FFT with the *x* highest amplitude peaks removed.
  - Especially for disruptions, high frequency signals are important, to enhance the accuracy of the filtered signal, the noise amplitude is clipped such that the signal amplitude near disruption cannot be altered more than the typical expected noise.

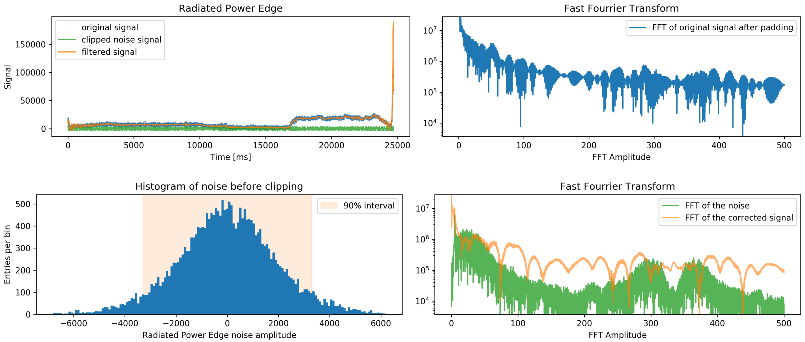
This approach enables us to vary signals on a shot-by-shot basis by subtracting/multiplying the noise contribution.

Noise Determination on 0D JET signals

This is now done shot-by-shot on all JET shots ($\approx$5500) for all 11 0D signals.

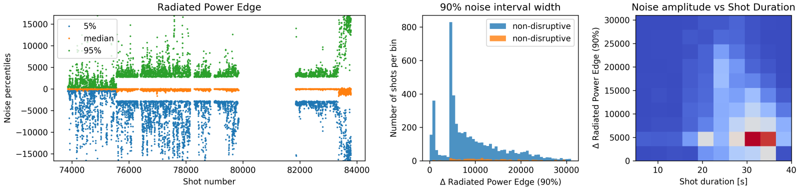
- Useful to find dependence on the shot number (experimental campaign configuration)
- The **analyses of the FFT** spectrum enables us to find **periodic effects**, for example: What is the origin of the 66 Hz peak in the power current?
- If the **noise is independent of the signal**, it is expected to be Gaussian and similar for disruptive and non-disruptive shots.

Example of Noise Determination: Single shot



- Upper left: original signal, deduced noise signal after clipping and the signal after subtracting the clipped noise.
- Upper right: FFT spectrum of the original signal.
- Lower left: the noise distribution before clipping. This is expected to be a Gaussian centred around zero. Non-Gaussian tails are corrected for by clipping values outside the 90% interval.
- Lower right: FFT spectrum of the clipped noise and filtered signal.

Example of Noise Determination: All shots



- Left: The green and the blue band correspond to the 90% interval of the noise contribution for each shot. It can clearly be seen that the noise went up around run 75800 and again around 83500.
- Middle: the width of the 90% noise interval in a histogram, split up for disruptive and non-disruptive shots. The non-Gaussian shape indicates that the experimental conditions affected the noise.
- Right: The same 90% width interval in function of the shot length.

Conclusion & Outlook

Summary

See back-up slides with the plots for all the 11 0D JET signals!

The Good

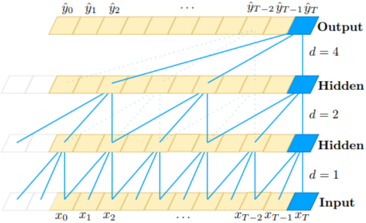
- First preliminary **signal importance evaluation on JET 0D data**.
- Signal **noise can be estimated shot-by-shot** in a computationally efficient way.
- We can train the network on input signals with **noise subtraction and noise amplification**.

Work in Progress!

- The way the FFT is calculated **violates causality**.
- The **noise distributions are not always Gaussian** and contain information about the disruptivity of the shot. (See all the slides with the 11 different signals after)
- Lots of more optimisations and interesting work to do!

Outlook

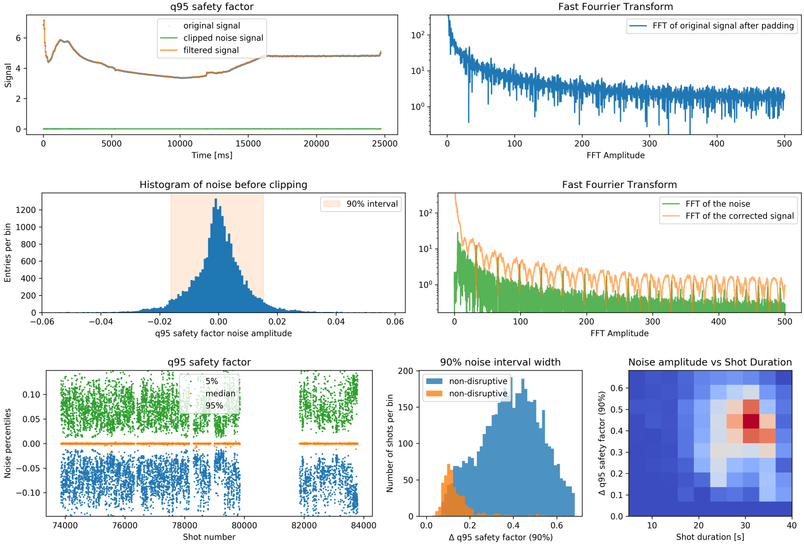
- Short term:
  - Train network using signals with **added/reduced noise**.
  - Experimenting with different, **physics-based noise models**.
- Longer term:
  - Including more ***Radiated Power* channels**.
  - **Optimise hyper-parameter scan** using Hamiltonian MC or Genetic algorithms.
  - Replacing the LSTM structure with **Temporal Convolutional structures** to improve memory length and performance for different time-scales.



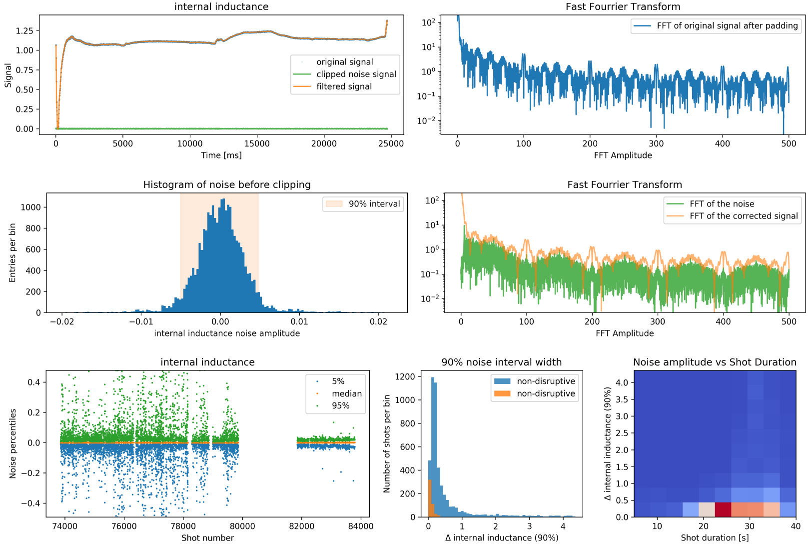
Thank you

Questions?

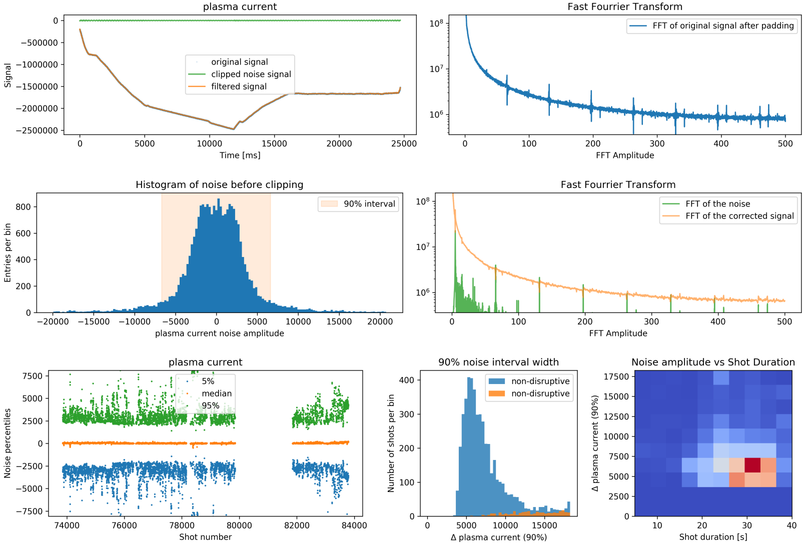
0. Q95 safety factor



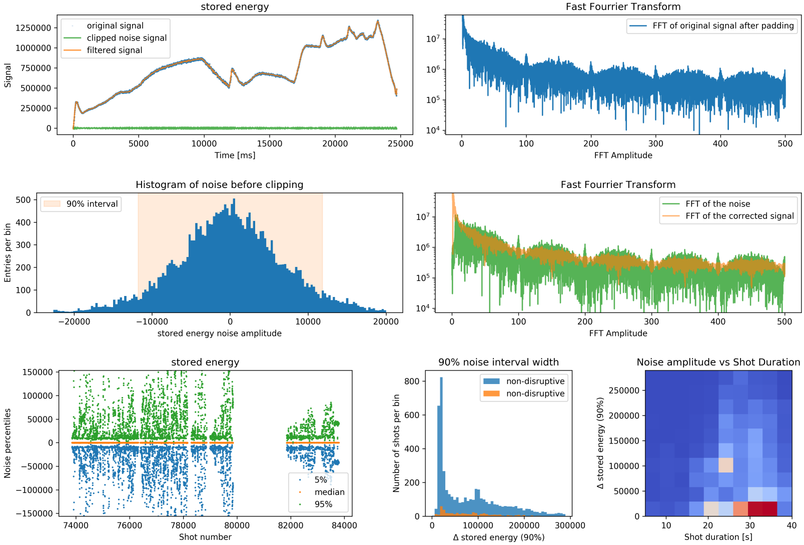
1. Internal inductance



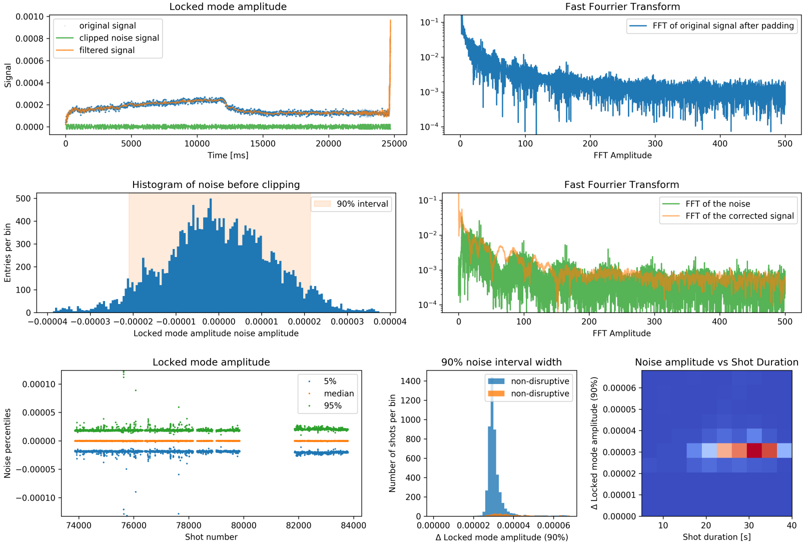
2. Plasma current



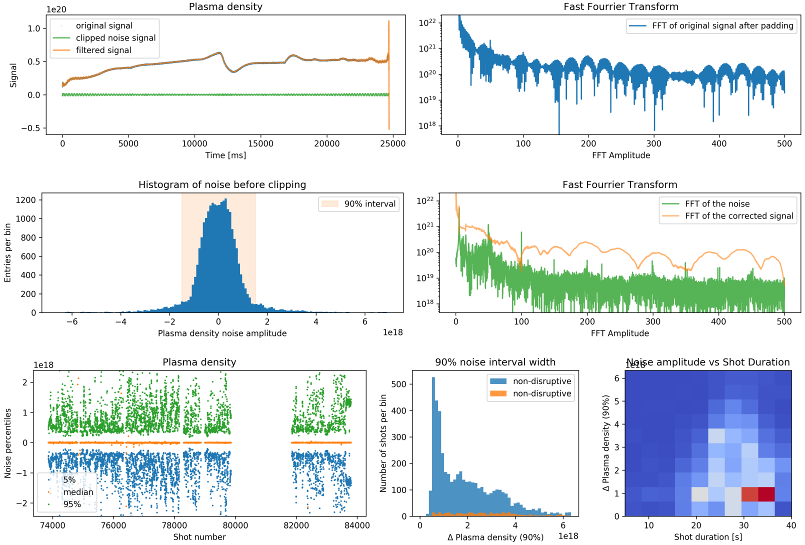
3. Stored energy



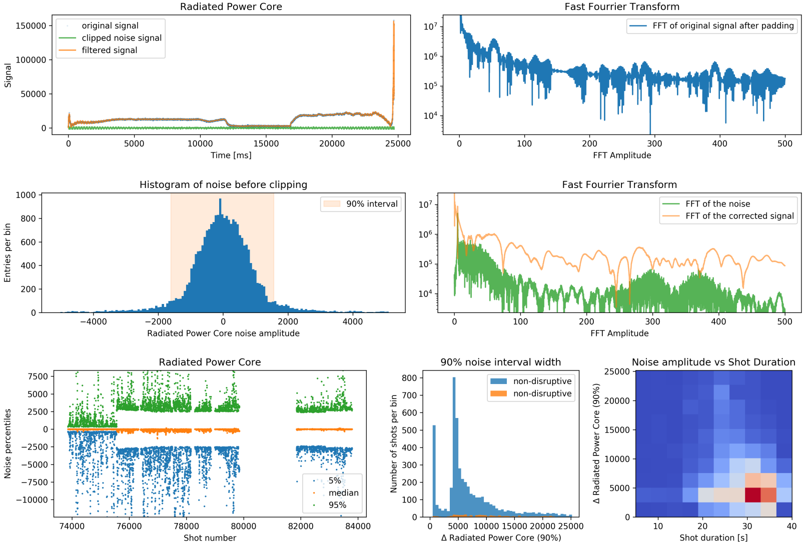
4. Locked mode amplitude



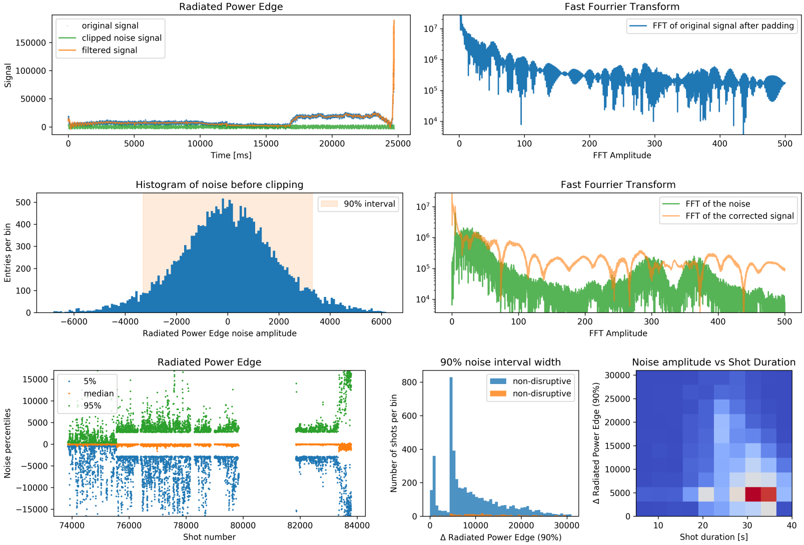
5. Plasma density



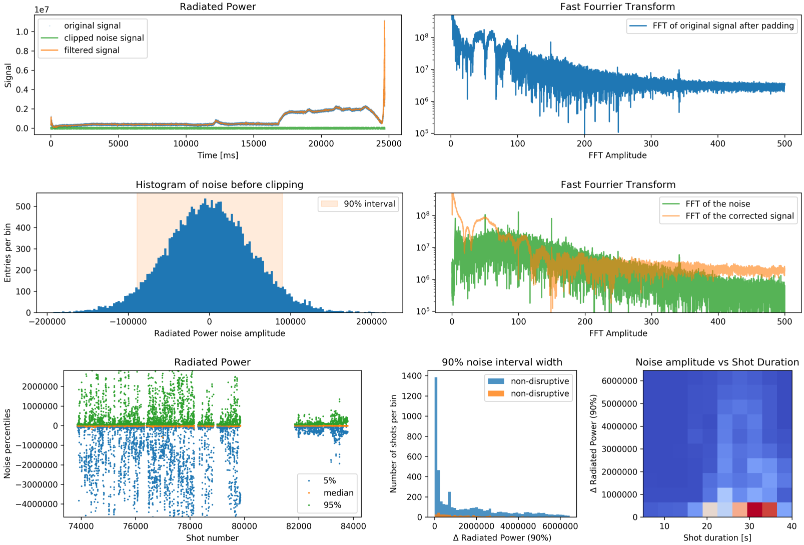
6. Radiated Power Core



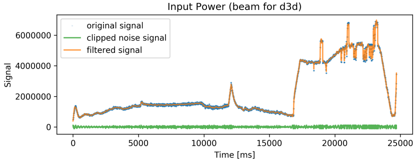
7. Radiated Power Edge

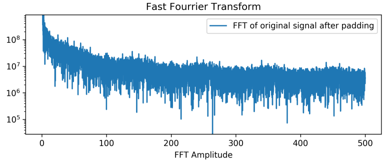


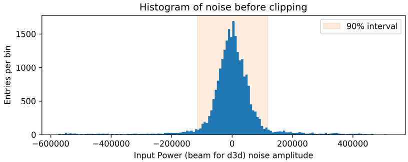
8. Radiated Power

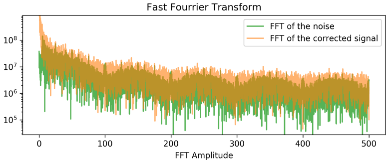


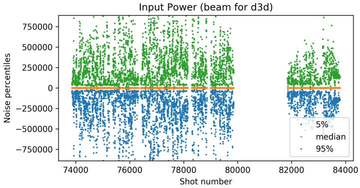
9. Input Power

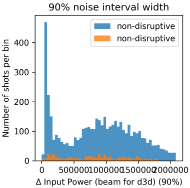


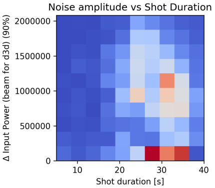












10. Stored energy time derivative