Disruption Predictor Based on Neural Network and Anomaly Detection

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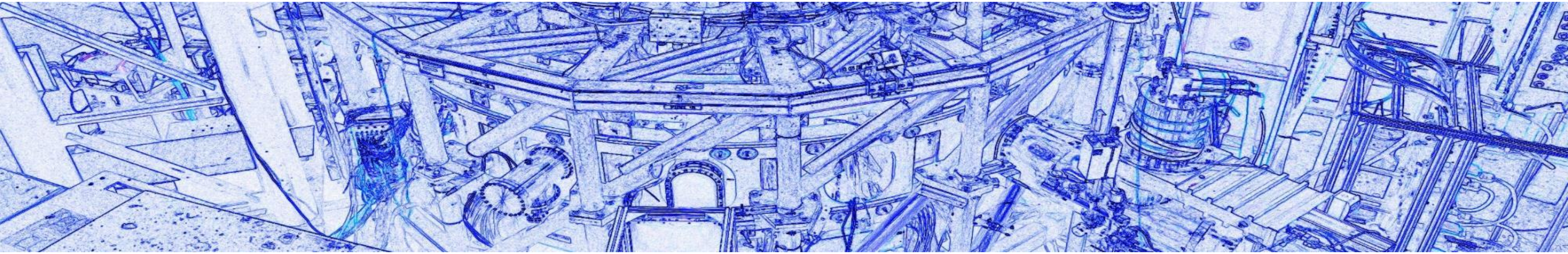
IAEA-TM CODAC 2019

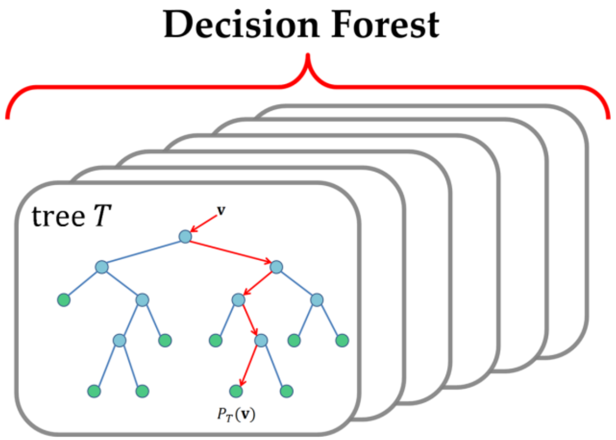


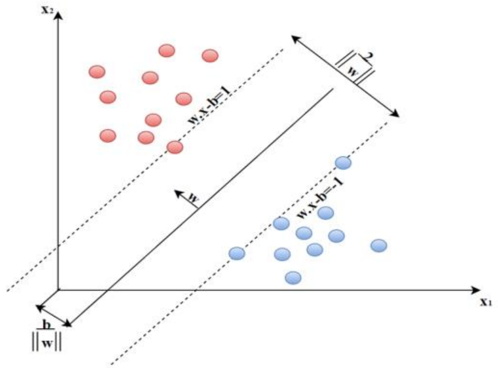
Outline

- **Current machine learning based disruption prediction and its drawbacks**
- **Anomaly detection and its application in disruption prediction**
- **Deep Neural network anomaly detection based disruption prediction and its result on J-TEXT**
- **Future work and summary**

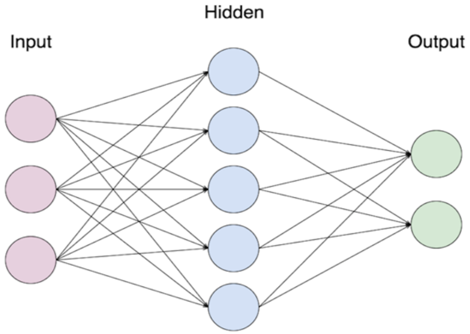
Machine learning based disruption prediction

- **As the physics behind the disruption is not clear, machine learning becomes a way to go**
- **Physics based predictors are mainly using locked-mode amplitude**
- **Performance of Machin learning predictors are great**





Support Vector Machine

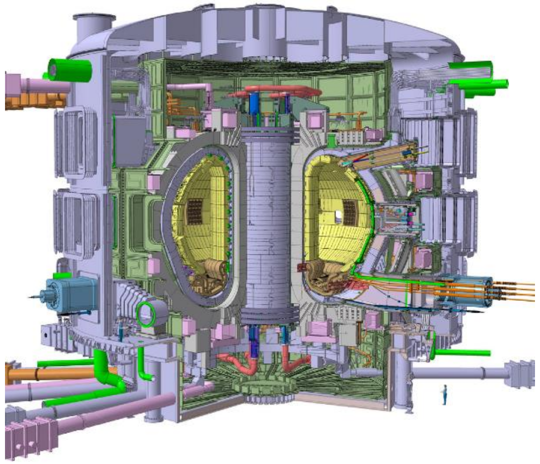


Neural Network

- **BUT, machine learning is not a silver bullet for disruption prediction**

Its drawbacks

- **It needs disruptive data.**
  - **As tokamaks get larger, disruption is getting more expensive.**



- **It's a black box.**
  - **It is almost impossible to get it work on devices other than it is trained on.**

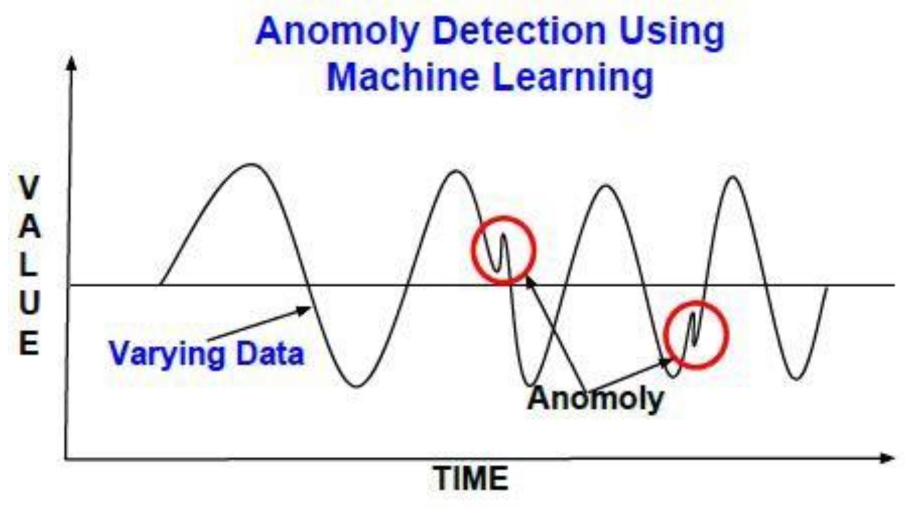
Its drawbacks

- **So it is impossible to develop a machine learning disruption predictors for a tokamak without disruptions produced by it.**

- **Or is it?**

Anomaly detection

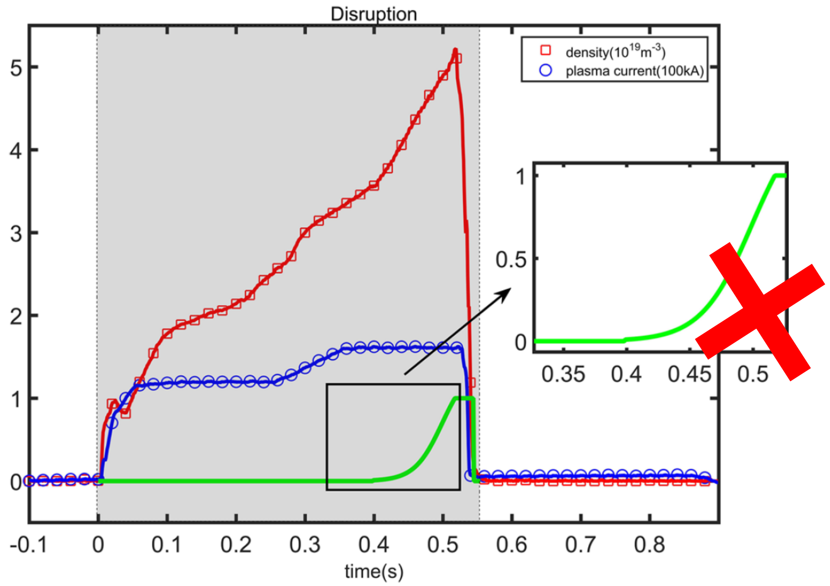
- **Anomaly detection** is the identification of rare events which raise suspicions by differing significantly from the majority of the data.



- Applicable Use Cases:
  - Very unbalanced training dataset
  - Positive samples are rare and expensive
  - Characteristics of the positive sample are unknown

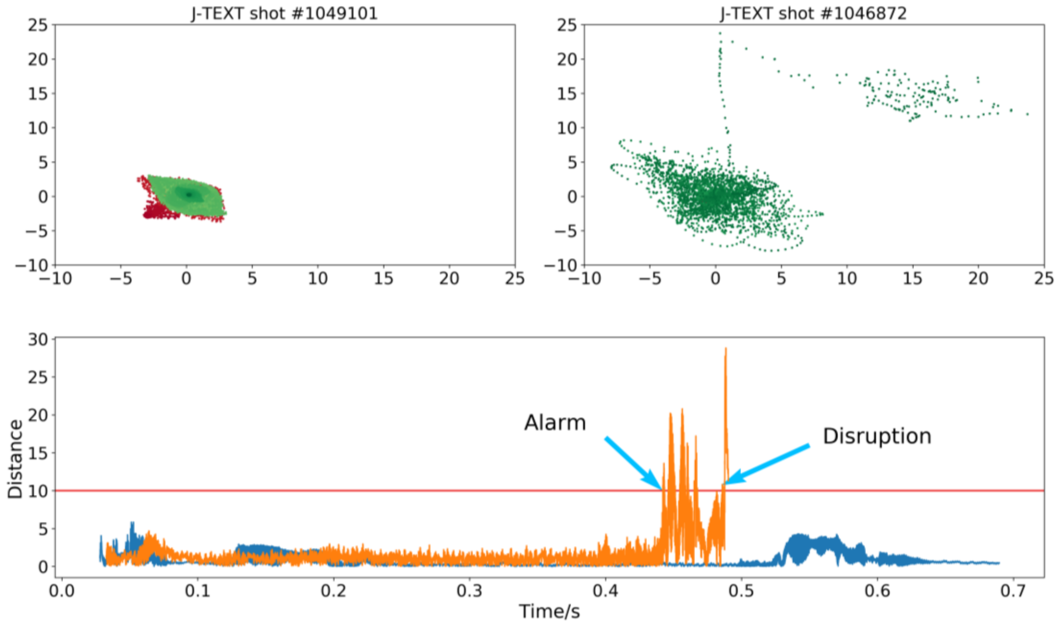
Anomaly detection

- **Non-disruptive discharges as normal scenario**
- **Disruption precursor as anomaly**
- **Benefit:**
  - No disruption needed in the training set
  - No needs to extrapolate to other devices
  - With adaptive training, can be deployed at very early stage
  - No more bias on the occurrence of disruption precursor



Anomaly detection

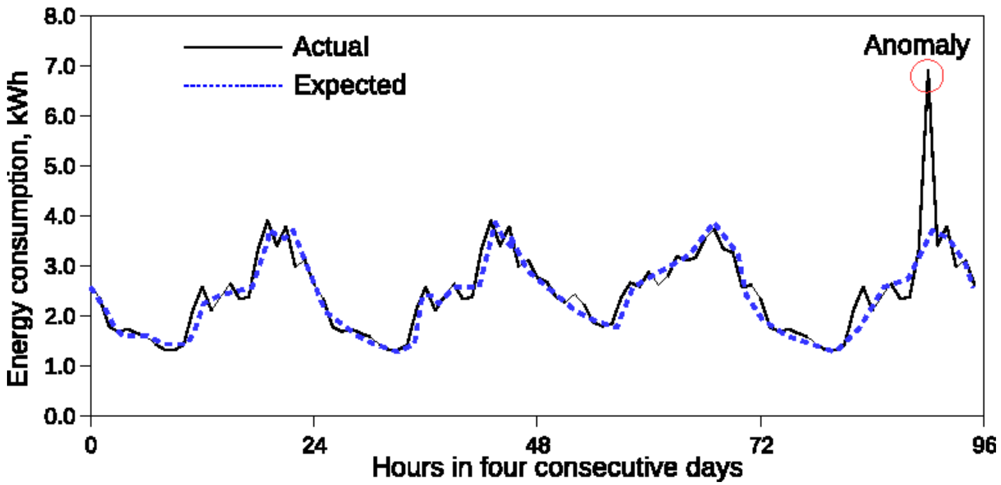
- **Preliminary experiment on J-TEXT**
  - Single signal predictor based on anomaly detection **(SPAD)** developed by JET
  - Adopted, modified and tested using J-TEXT signal
  - Using rule based feature extraction
  - Result: **High success rate** (TPR), but **very low warming time** (T_{warn}), and **very high false alarm rate** (FPR)



True Positive	False Positive	Warning Time
0.84	0.20	20ms(69%<5ms)

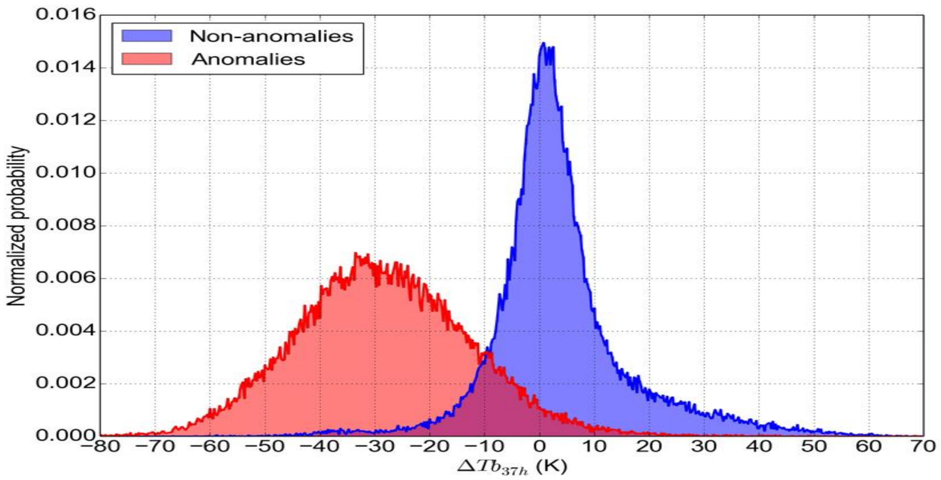
Deep learning Anomaly detection

- **(One of the) Time series anomaly detection technique**
  - Regression based Anomaly Detection
  - Using a regression model to predict the future value of some given signals,
  - If the actual signal deviate from the expected value than an anomaly is found



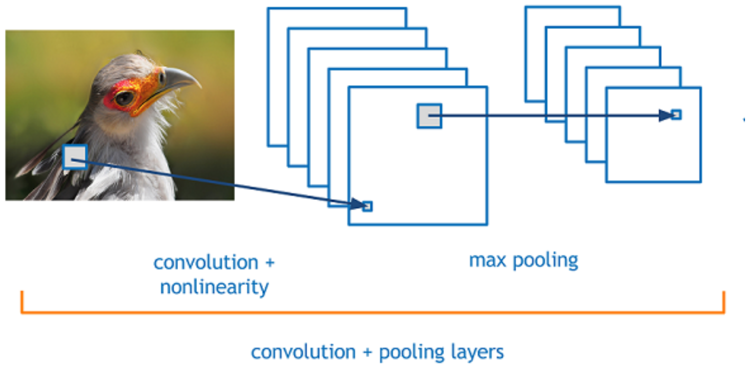
Deep learning Anomaly detection

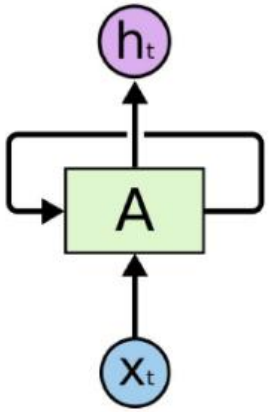
- **Theory behind the Regression based Anomaly Detection**
  - Using a regression model to extract the characteristics of the normal signals
  - Actually modeling a probability distribution of the normal signals
  - Disruption precursor is generated by a different distribution other than that generated the normal signals



Deep learning Anomaly detection

- **Deep learning time series prediction model**
  - Convolutional Neural Network + Recurrent neural network
  - CNN: extract low dimension features of the high sampling rate signal
  - RNN: remember the history of the signal





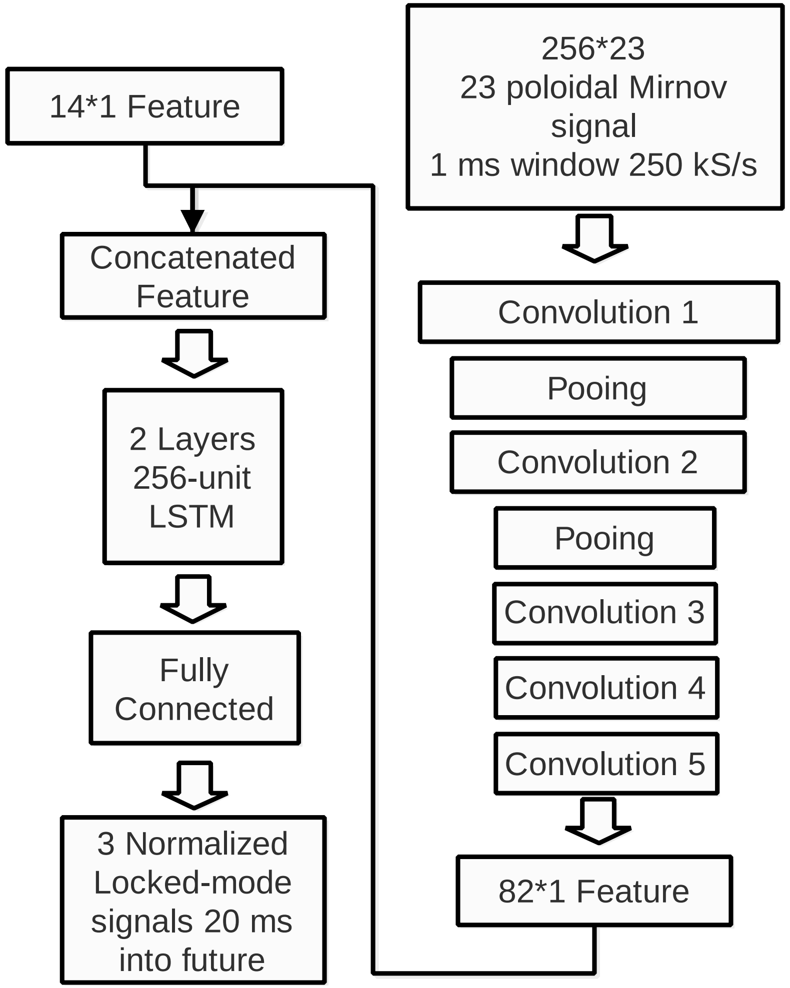
Deep learning Anomaly detection

- **Time series Deep learning prediction model**
  - The model we are using:

14 Low sampling rate signals

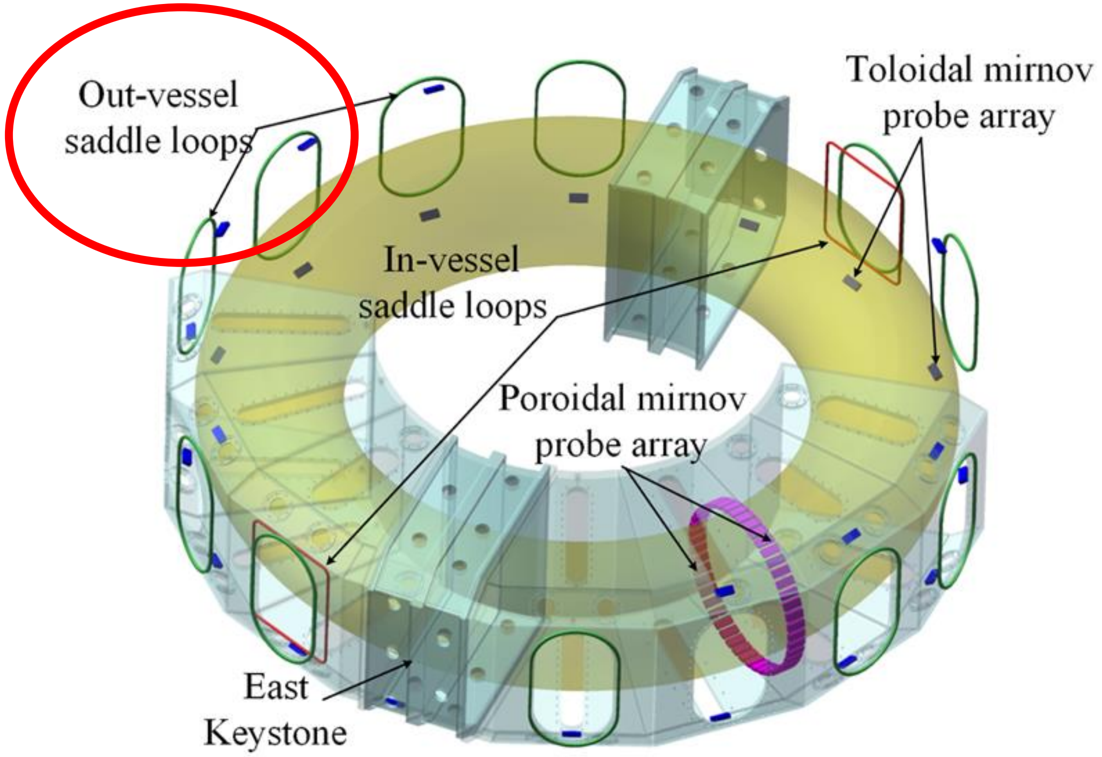
23 High sampling rate signals (23 Mirnov probes)

- **Exsad*6**
- **IP**
- **Bt**
- **AXUV**
- **Soft X-ray**
- **C_{III}**
- **ECE**
- **Ivfp**
- **Ihfp**



Deep learning Anomaly detection

- **Training target: 3 Normalized Locked-mode signals 20 ms into future**



$$\mathrm{br}_{odd\ (4-11)} = \backslash exsad2 \times 100/3.05 - \backslash exsad8 \times 100/12.71$$

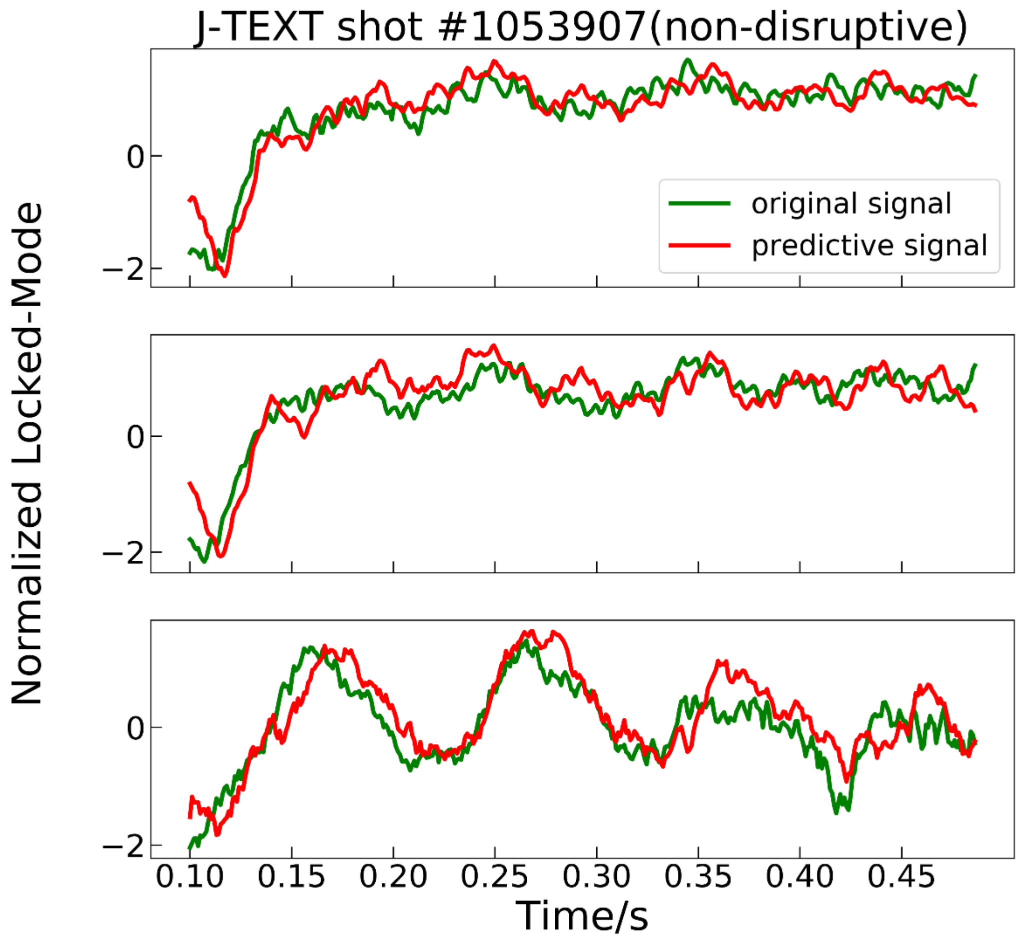
Deep learning Anomaly detection

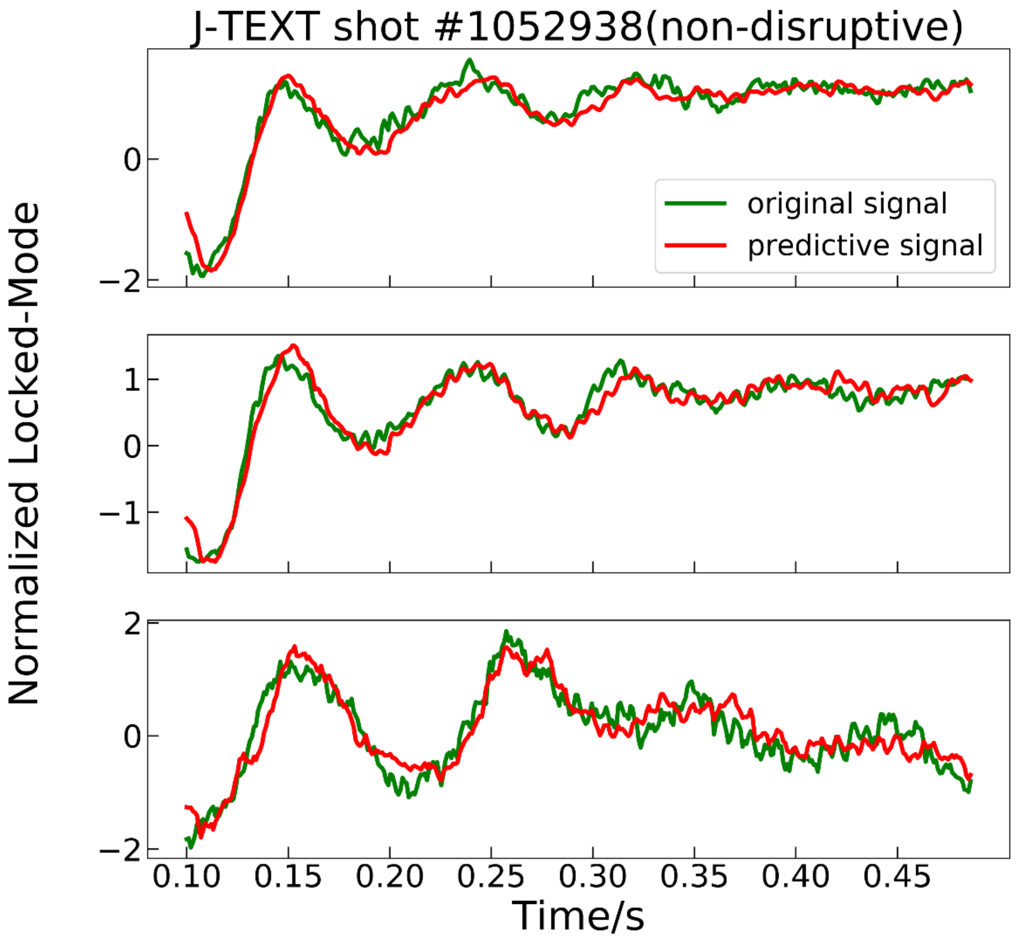
- **Data set:**
  - J-TEXT 2017 autumn experiment campaign
  - Helped by the "A Database Dedicated to the Development of Machine Learning Based Disruption Prediction"

Data set	Shot Number
Training	320 Non-disruptive only
Validation	80 Non-disruptive only
Test	170 Non-disruptive + 77 disruptions

Deep learning Anomaly detection

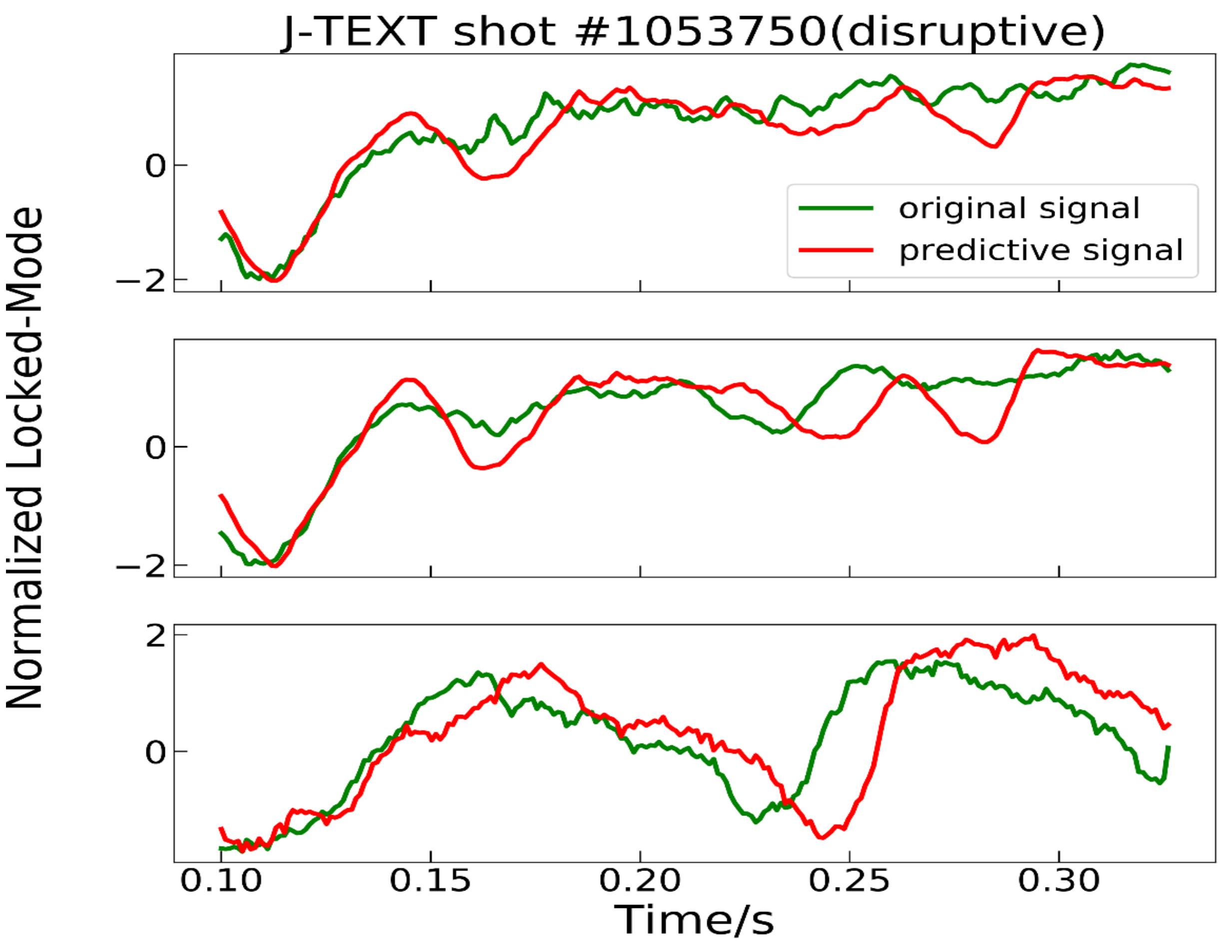
- **Prediction result –Non-disruptive**

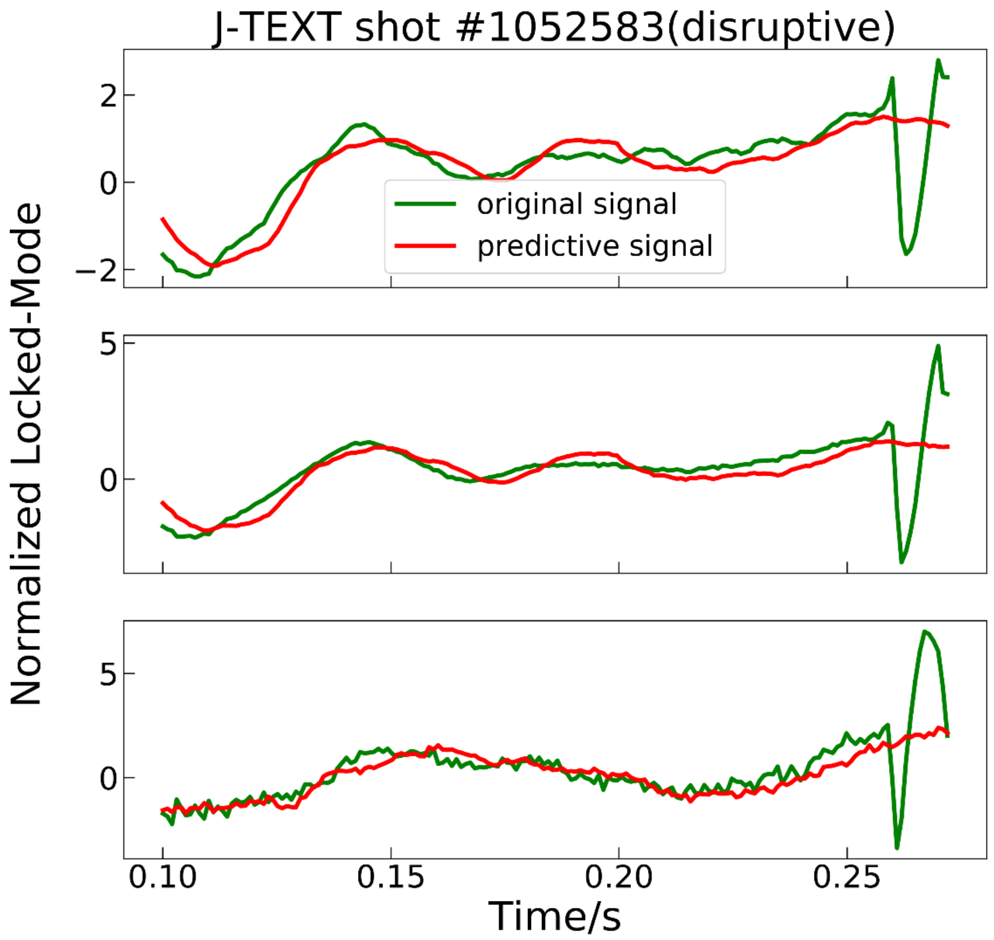




Deep learning Anomaly detection

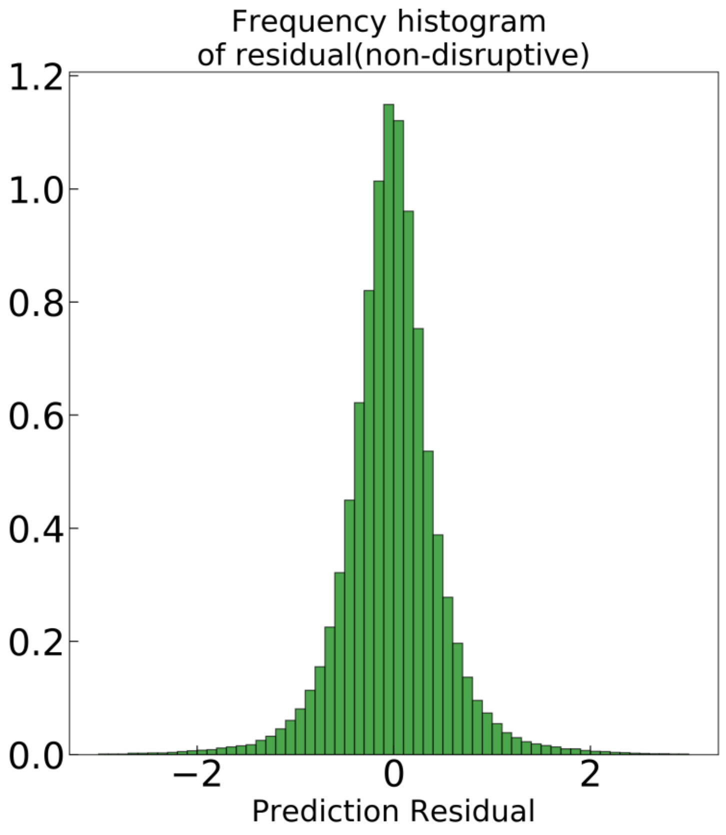
- **Prediction result -Disruptions**

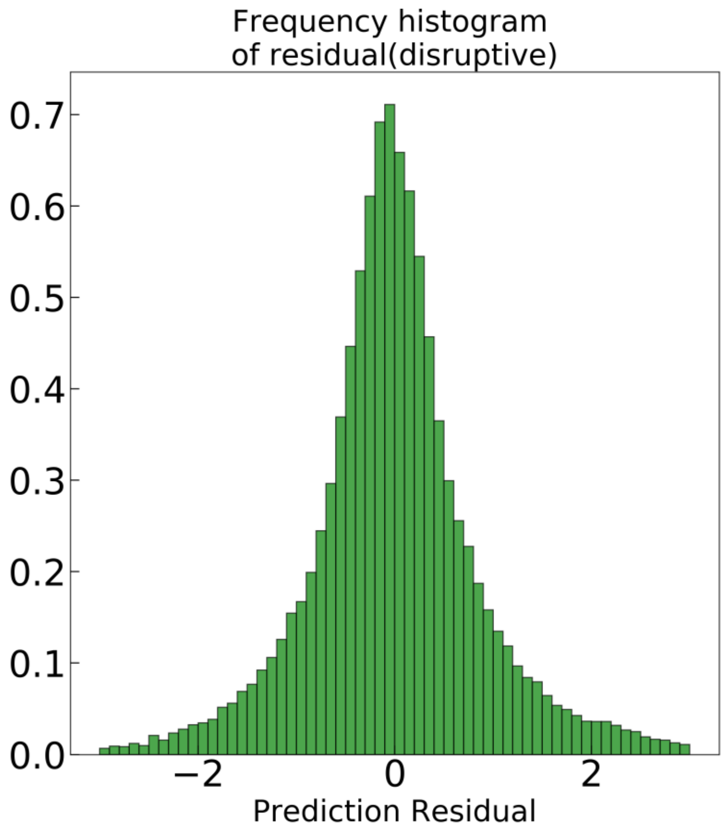




Deep learning Anomaly detection

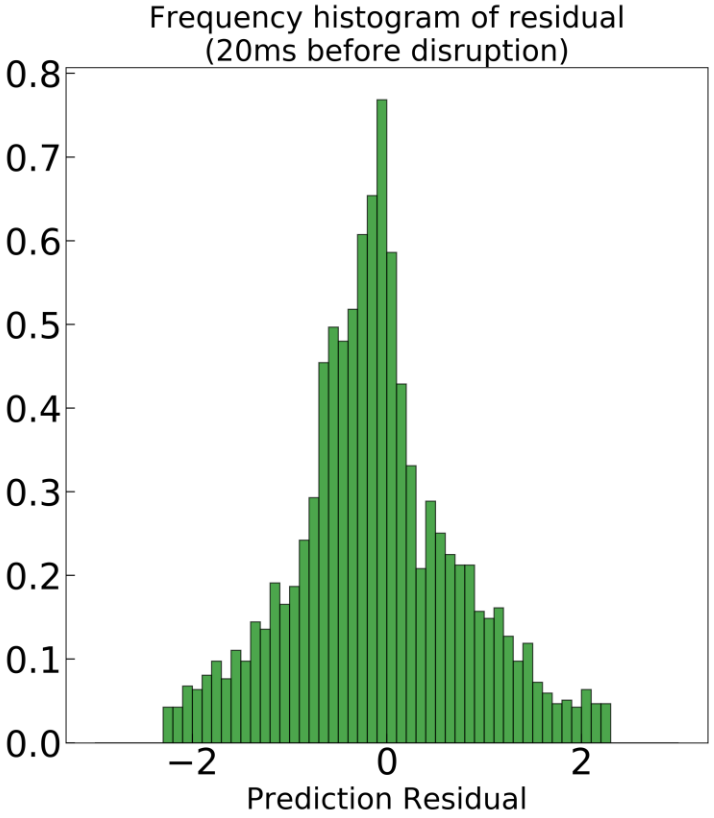
- **The distribution of prediction residual for different types of shots**



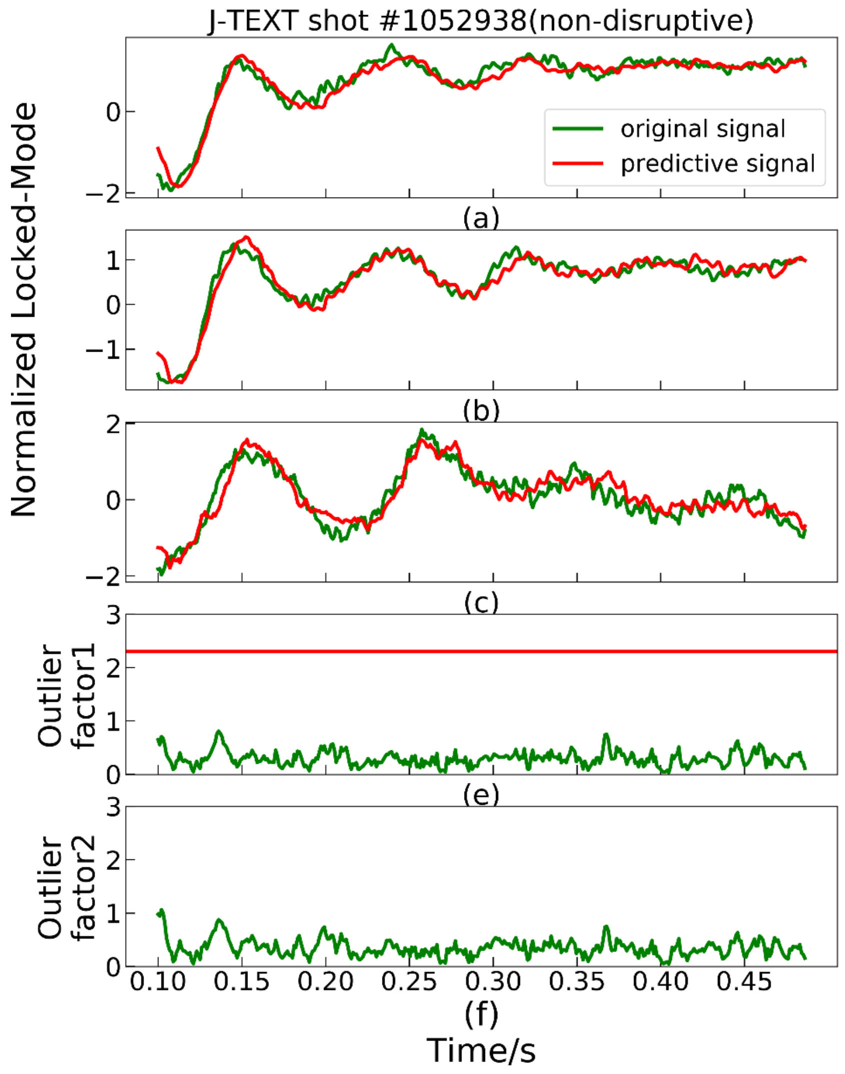


Deep learning Anomaly detection

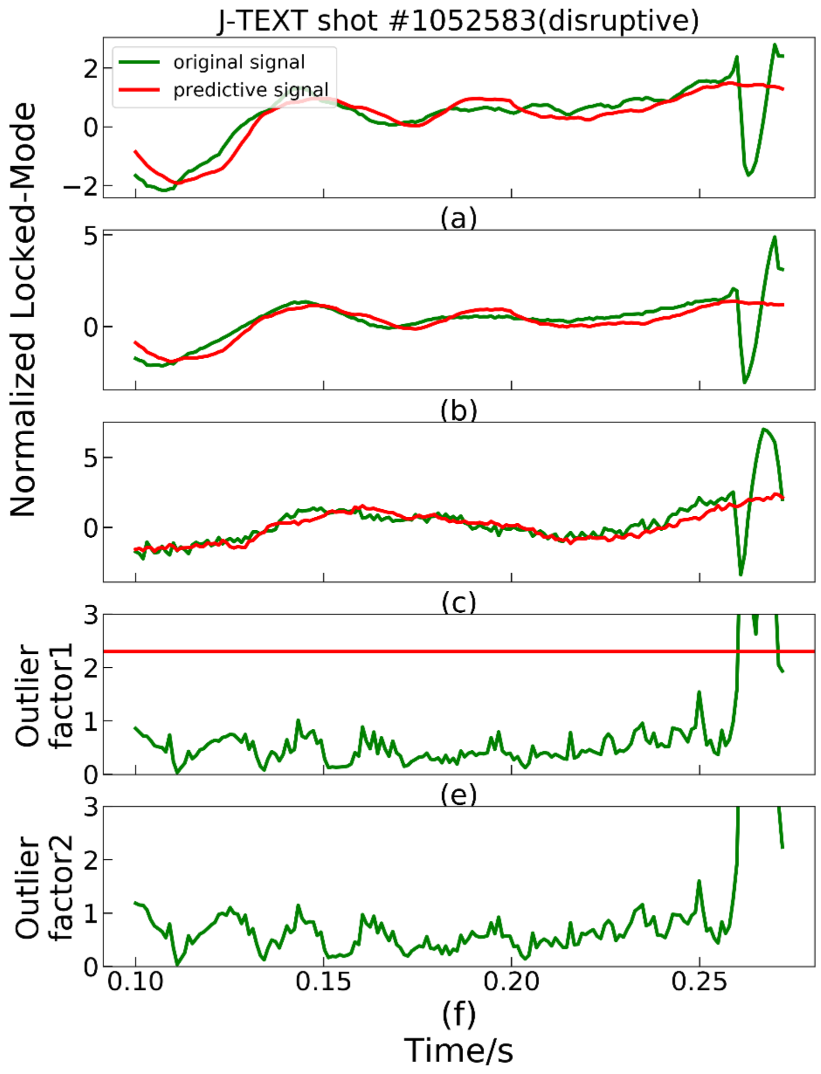
- **The evolving of the distribution of prediction residual for different types of shot**



Deep learning Anomaly detection



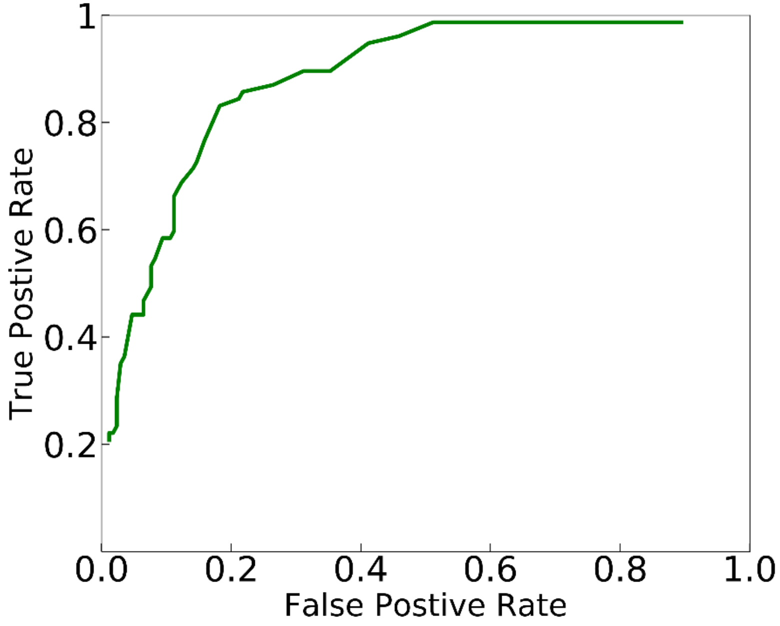
Non-disruption

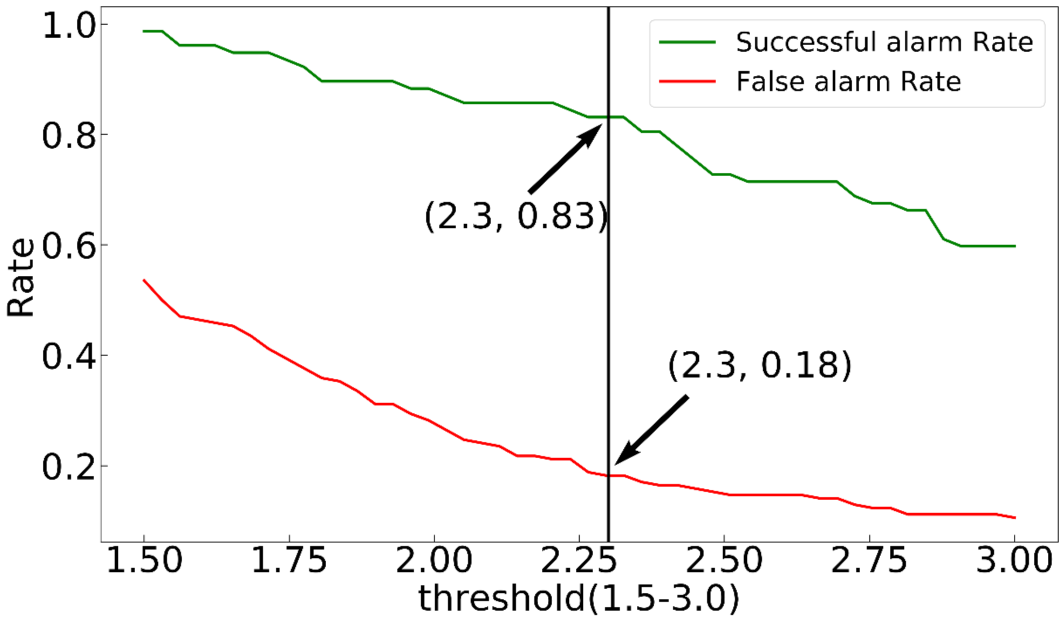


Disruption

Deep learning Anomaly detection

- **Performance evaluation**





Threshold=2.3	
True Positive:	0.83
False Positive:	0.18
Average Warning Time	36 ms

Summary

- **It is possible to build a ML disruption predictor without any disruptions in the training set.**
- **An anomaly detection and neural network based predictor is developed and tested using J-TEXT data**
- **The performance of the predictor is not as good as supervised ML disruption predictor.**
- **But there is room for improvement.**

Future work

- **More work on signal selection**
- **Further development on the disruption database and get cleaner data**
- **Hyper-parameter search**
- **Adaptive training strategies**
- **Better deep learning feature extraction method like autoencoder**

• **Thank you for your attentions**