# Data-based disruption prediction: Development and comparison of machine learning algorithms for DIII-D and Applicability on ITER

**Kornee Kleijwegt**

Leonard Lupin-Jimenez, Egemen Kolemen, Nathaniel Barbour, David Eldon, Nick Eidietis

**International Energy Agency Workshop:**

**Theory and Simulation of Disruptions**

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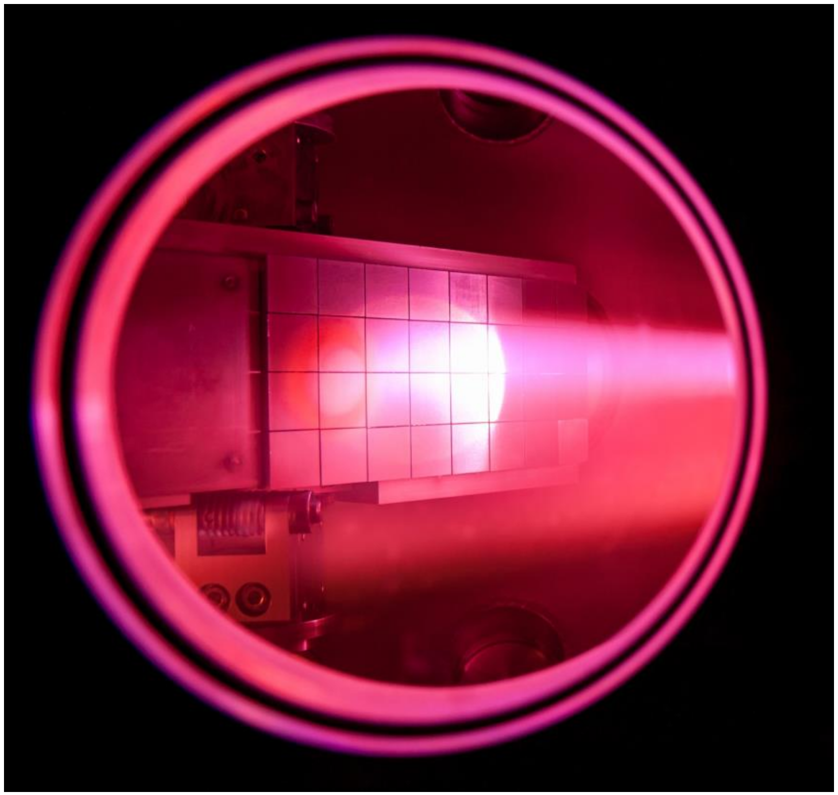
**Abstract**

Disruption predictors where developed and tested for DIII-D tokamak, using various machine learning algorithms. The results show that it is possible to identify more than 90% of the disruptions while only mis-qualifying less than 1% (false positive ratio). This performance shows that machine learning algorithms can give an adequate solution for disruption prediction on DIII-D. The data used to create these predictors consist of 630 disruptive shots and 500 non disruptive shots. Regression machine learning algorithms are used in combination with a threshold to classify and predict the disruptions. This combination gives a more versatile predictor allowing manually adaptability, which is beneficial for implementation on a physical experiment. Four algorithms are created and compared for classification of disruptions using the decision tree algorithms: Adaboost, Extremely Randomized trees, Random forest, and Bagging. The best results are obtained using Random Forest and Bagging decision tree forests, both giving the same high performance.
In future work we would like to create predictors for new experiments, such as ITER. By using relations between important plasma parameters and low plasma current shots we are working on a approach which can prevent harmful disruptions in future machines.

# Relevance and terminology



| Term | Explanation |
|---|---|
| Correct positive | Correct prediction of a disruptive shot |
| False positive | Non disruptive shot misqualified as disruptive |
| Predictor | Algorithm which predicts disruptions |
| Training data | Data used for training a predictor |
| Test data | Data used solely for analyzation purposes to validate results |

# Current research

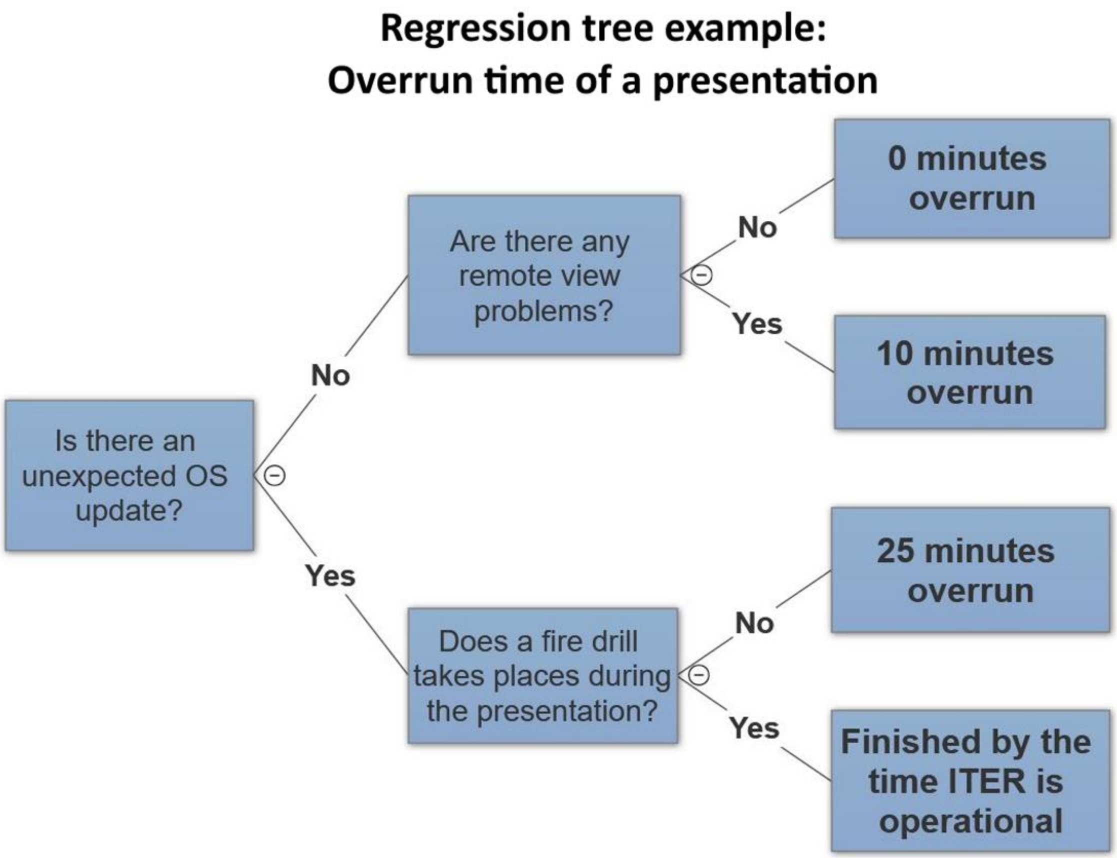
- Hard physics approach
  - Known empirical limits (Greenwald limit etc.)
  - Statistical analysis ( de Vries, Gerhardt etc)

- Machine learning prediction
  - Complicated algorithms
    Neural networks etc.

  - White box algorithms less used

# Ensemble Method – Regression algortihm

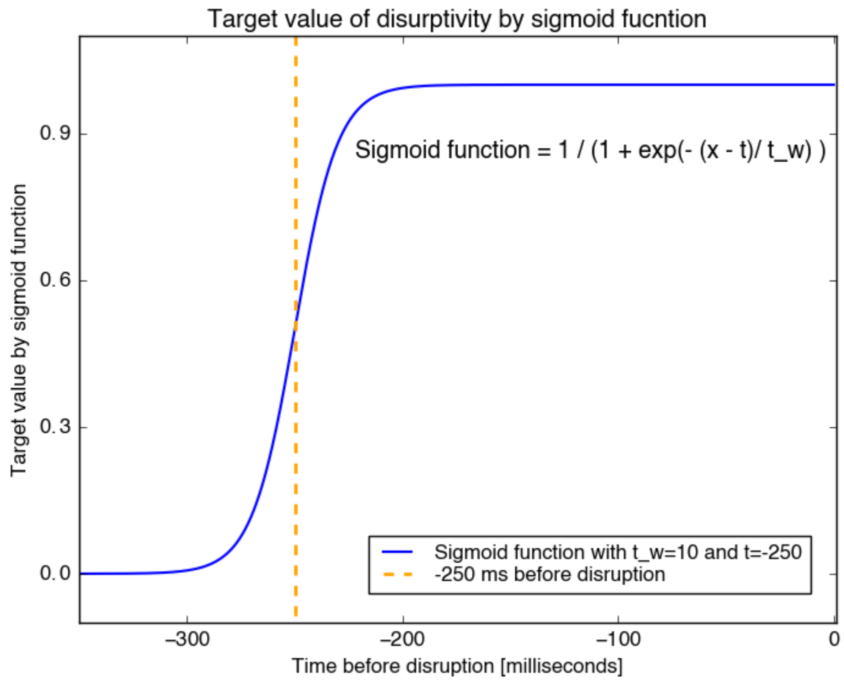
- Ensemble methods are used
- Regression tree for a classification problem

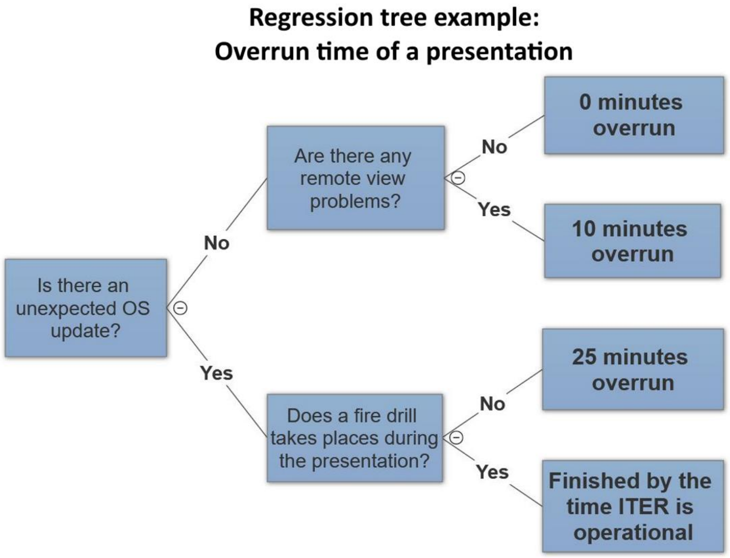


# Ensemble Method – Regression algortihm

- Ensemble methods are used
- Regression tree for a classification problem

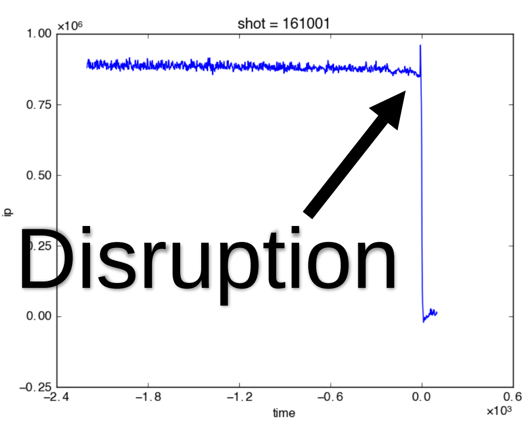
- Disruptivity created using sigmoid function (transition at 250ms before disruption)

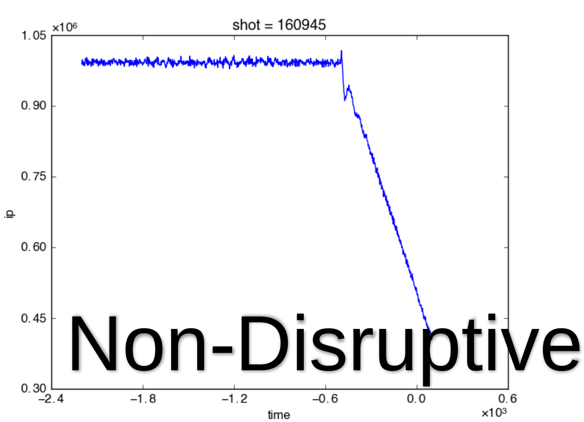


# Data used

- 1130 shots (630 disruptive)
  226000 frames are created

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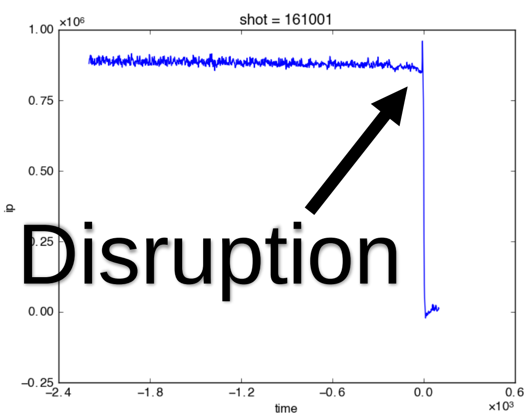
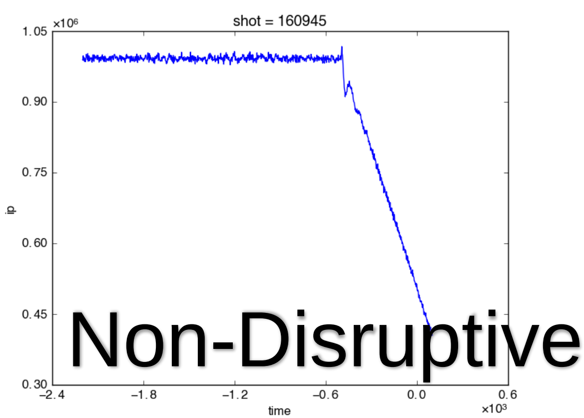
# Data used

- 1130 shots (630 disruptive)
  226000 frames are created

- 29 plasma parameters
  Of which 22 variables are derived

| Plasma parameter | Abriviation |
|---|---|
| Plasma current full simulation | $I_p$ |
| Plasma current fast simulation | $I_{p\ fast}$ |
| Plasma current direction (-1 or 1) | $\frac{I_p}{\lvert I_p \rvert}$ |
| Plasma current minus target current | $I_p - I_{p\ target}$ |
| Target plasma current | $I_{p\ target}$ |
| Real time EFIT self inductance | $li_{efit}$ |
| Real time EFIT beta normalized | $\beta_{n\ efit}$ |
| Real time EFIT total plasma energy | $W_{MHD}$ |
| ECH power input | $P_{ECH}$ |
| Interferometry line averaged plasma density | $< n_e >$ |
| Saddle loop coils n=1 radial field measurement | $B_{rot,\ saddle\ n=1}$ |
| Neutral beam power | $P_{NBI}$ |
| Neutral beam torque | $T_{NBI}$ |
| Local bolometry measurement of radiation | $P_{rad\ local}$ |
| Frequency magnetic field modes n=1 & 2 | $\tilde{B}_{n=1}$ & $\tilde{B}_{n=2}$ |
| Amplitude B field modes n=1 & 2 | $f_{B\ n=1}$ & $f_{B\ n=1}$ |
| Charge exchange recombination rotation plasma | $V_{rot}$ 0,10,20.....90 |



# Data used

- 1130 shots (630 disruptive)
  226000 frames are created
- 29 plasma parameters
  Of which 22 variables are derived
- Delay of signals by 25 ms (except Ip)

| **Plasma parameter** | **Abriviation** |
|---|---|
| Plasma current full simulation | $I_p$ |
| Plasma current fast simulation | $I_{p\ fast}$ |
| Plasma current direction (-1 or 1) | $\frac{I_p}{\lvert I_p \rvert}$ |
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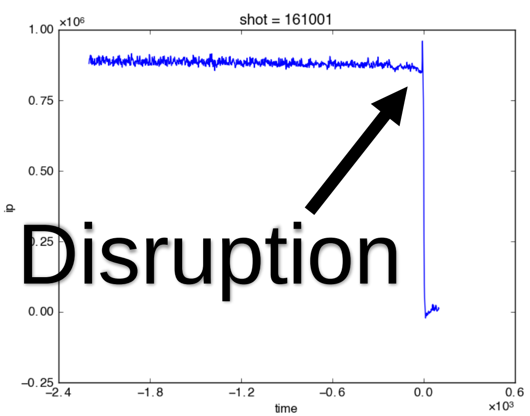


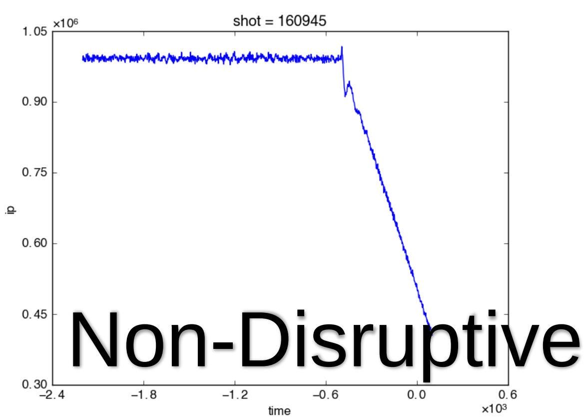

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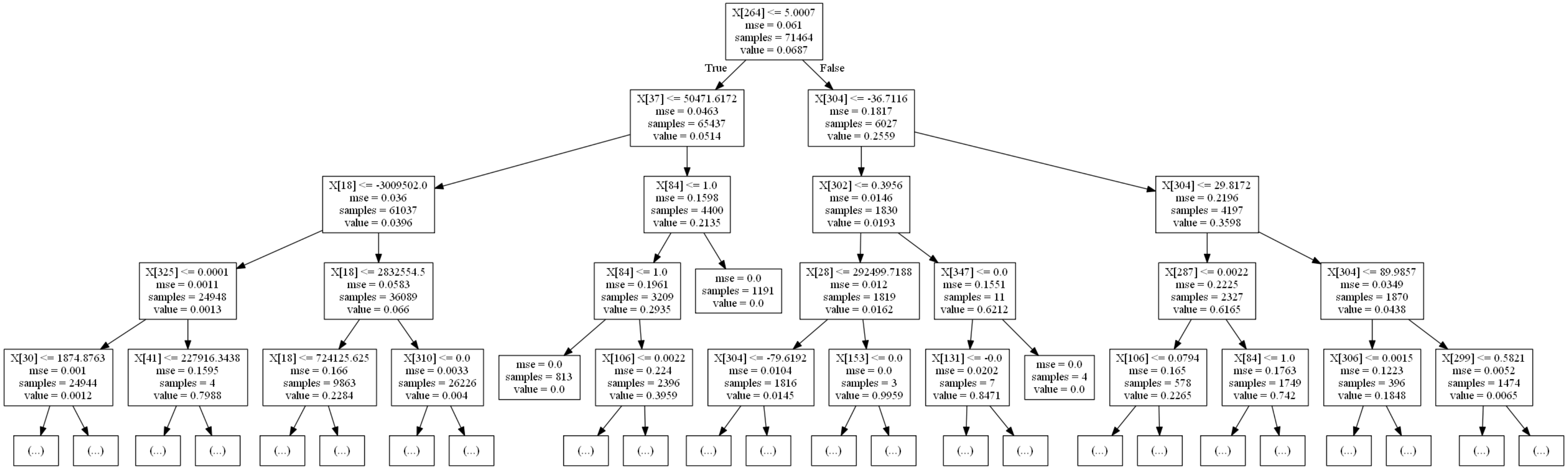
# Creation of prediction




**Decision tree forest predictor**

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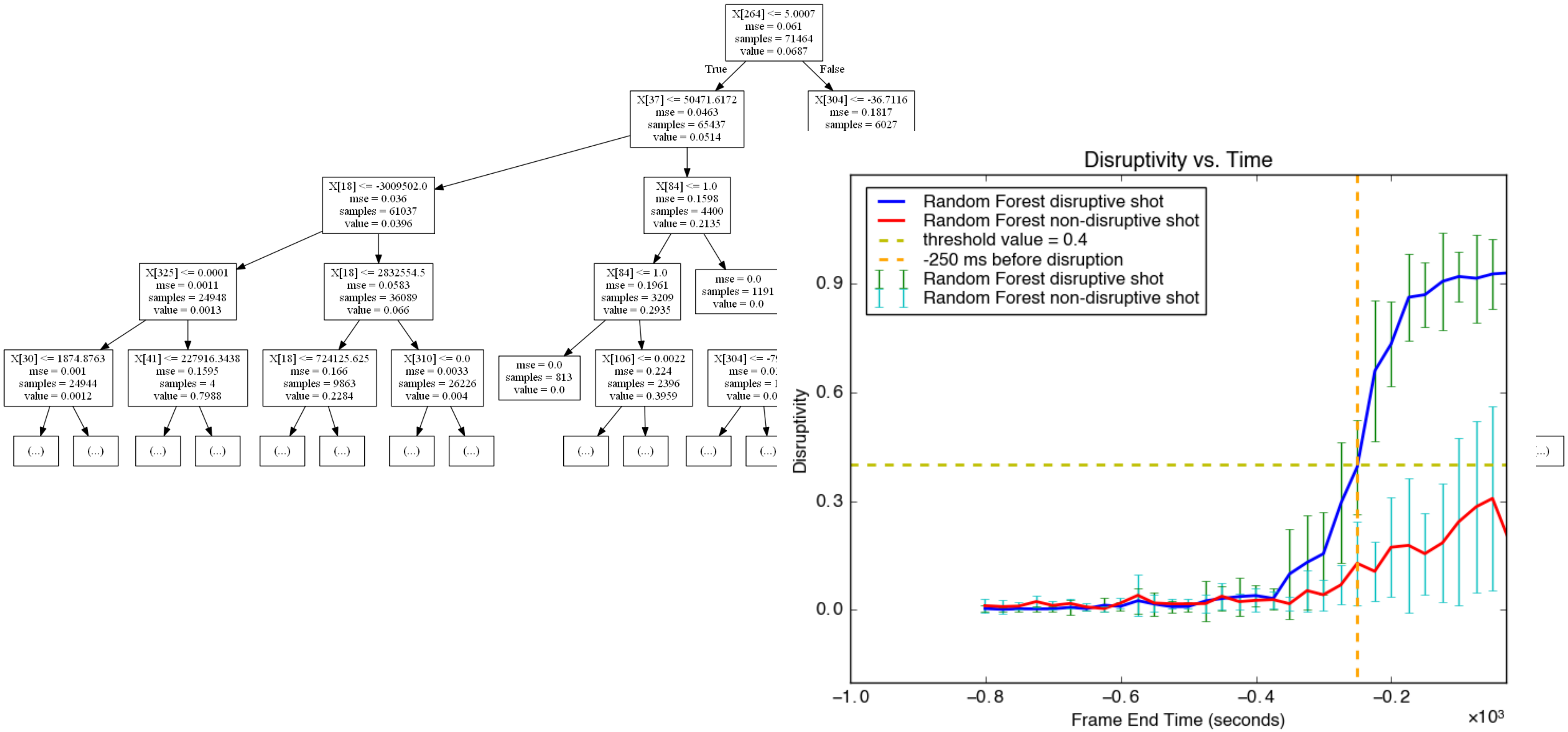
# Creation of prediction




**Decision tree forest predictor** → **Disruptivity over time**

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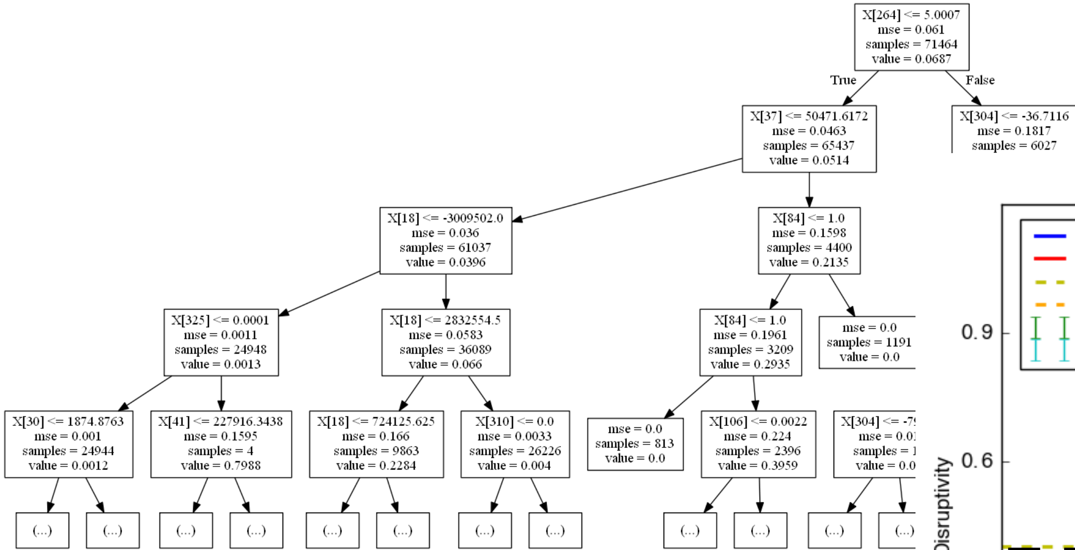
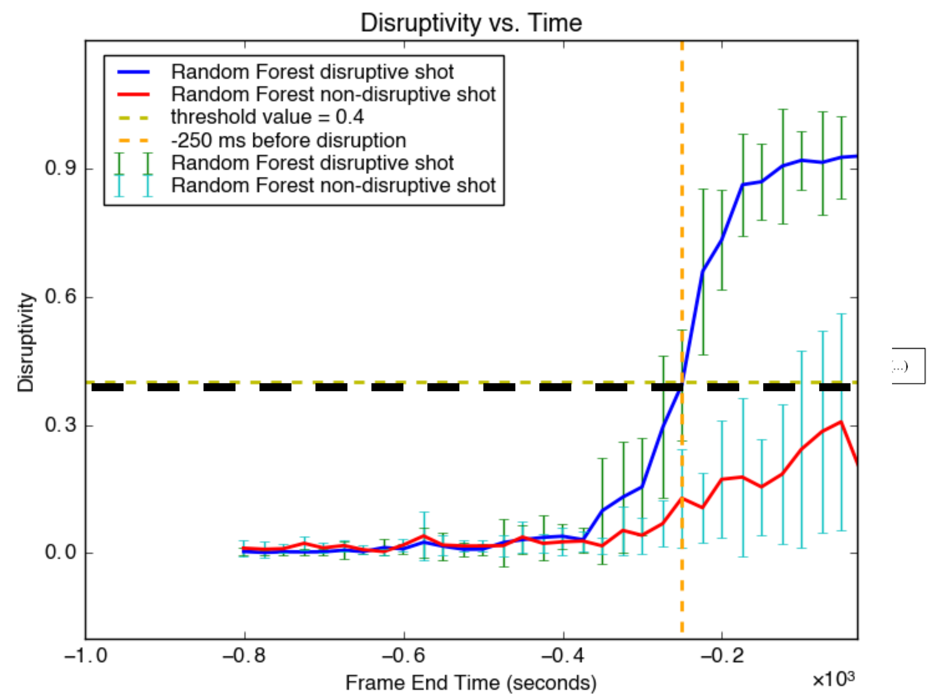
# Creation of prediction




**Decision tree forest predictor** → **Disruptivity over time** → **Prediction is made using a threshold**

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# Comparing of 4 predictor algorithms

Train each predictor on training data → Make predictions on test data → Obtain results and interpret them

**Bagging**

**Random Forest**

**Extremely Randomized Forest**

**Ada - Boost**

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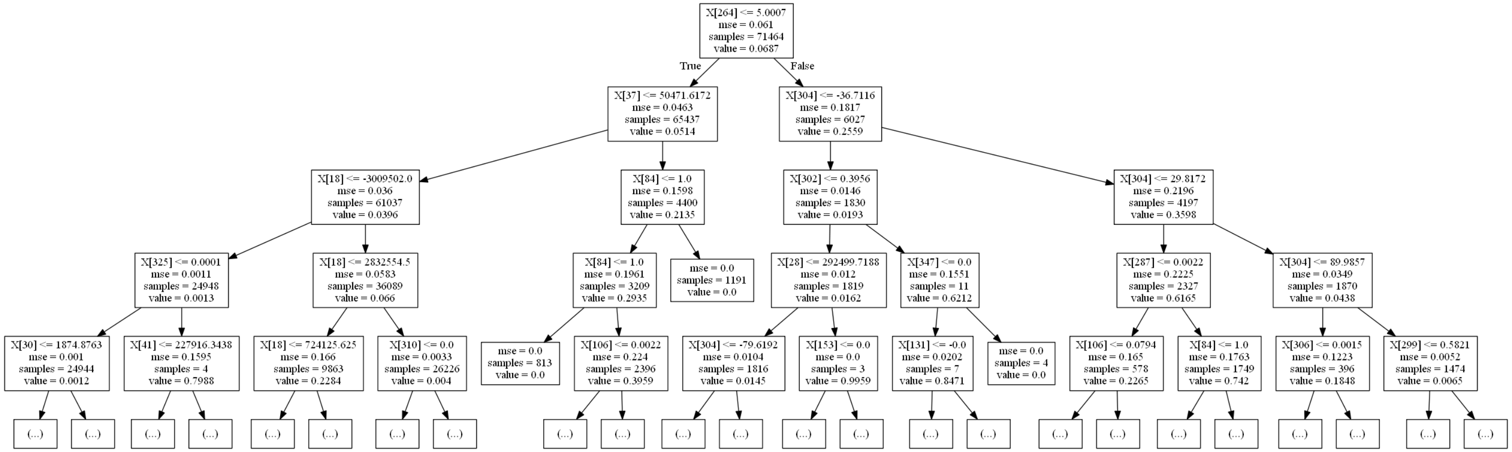
# Interpretation of results




Decision tree forest predictor → Disruptivity over time

↓

Outcome over threshold → **ROC - graph** Correct positives over false positives

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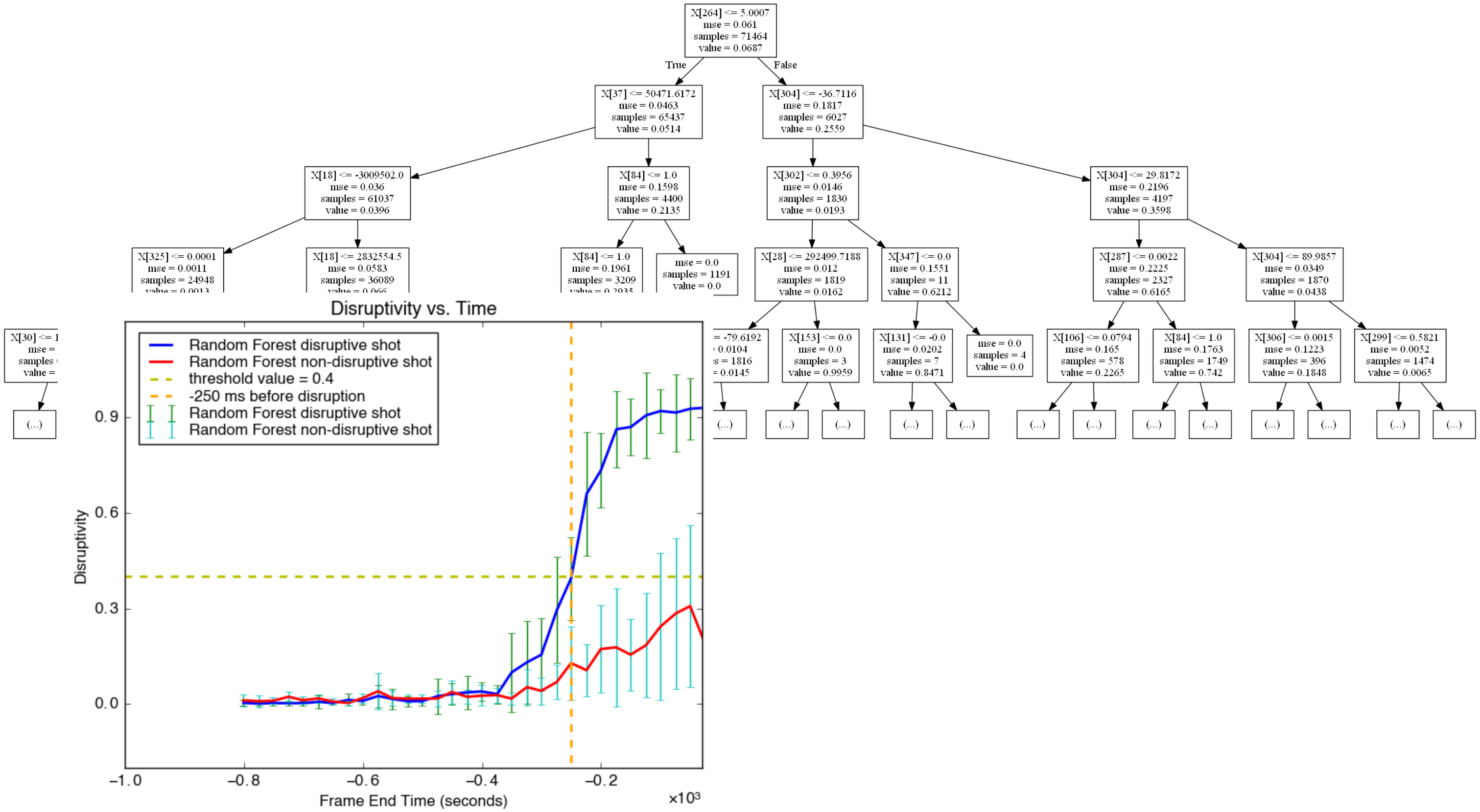
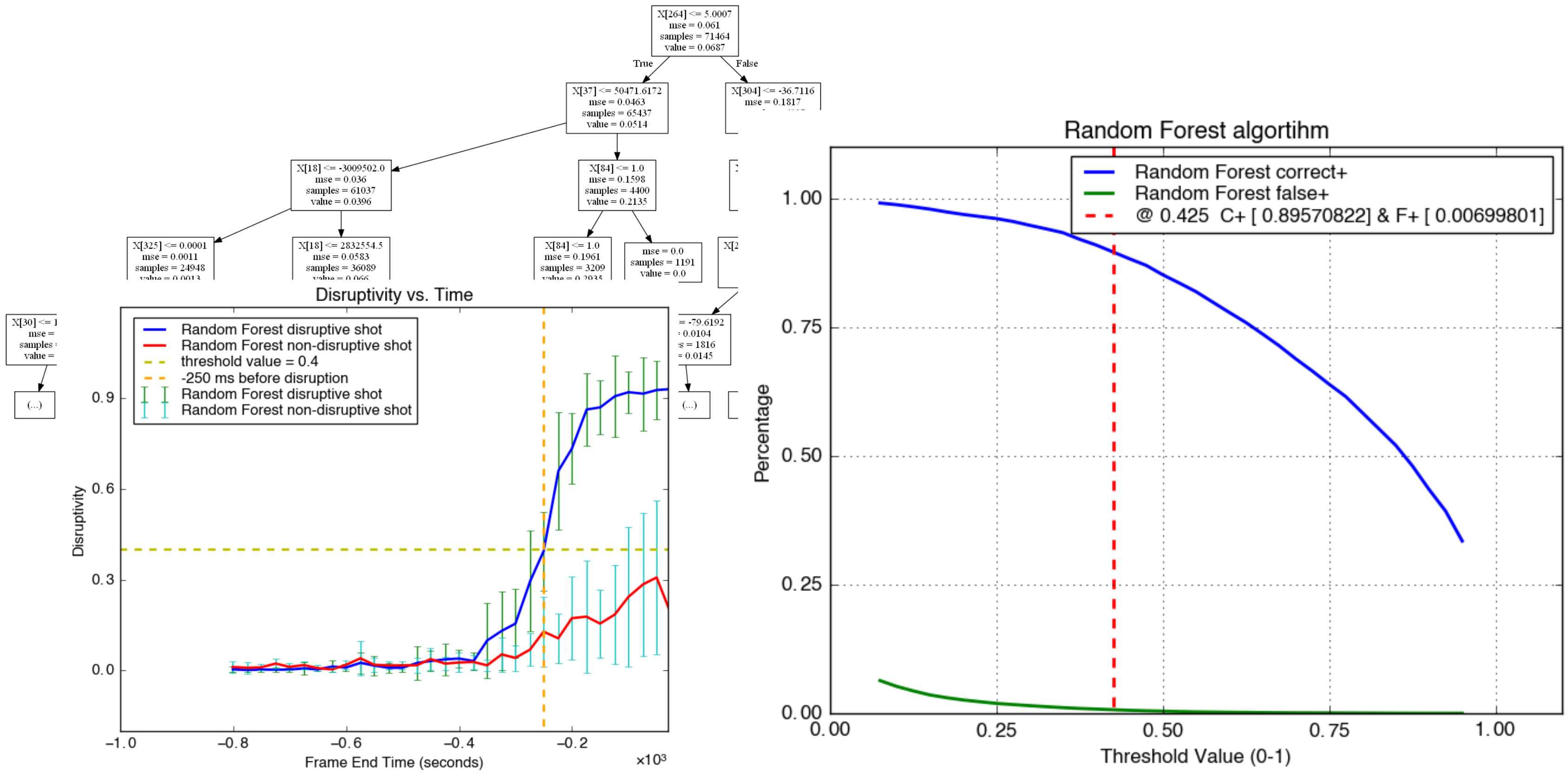
# Interpretation of results




Decision tree forest predictor → Disruptivity over time → Outcome over threshold → ROC - graph: Correct positives over false positives

# Interpretation of results




Decision tree forest predictor → Disruptivity over time → Outcome over threshold → **ROC - graph** Correct positives over false positives

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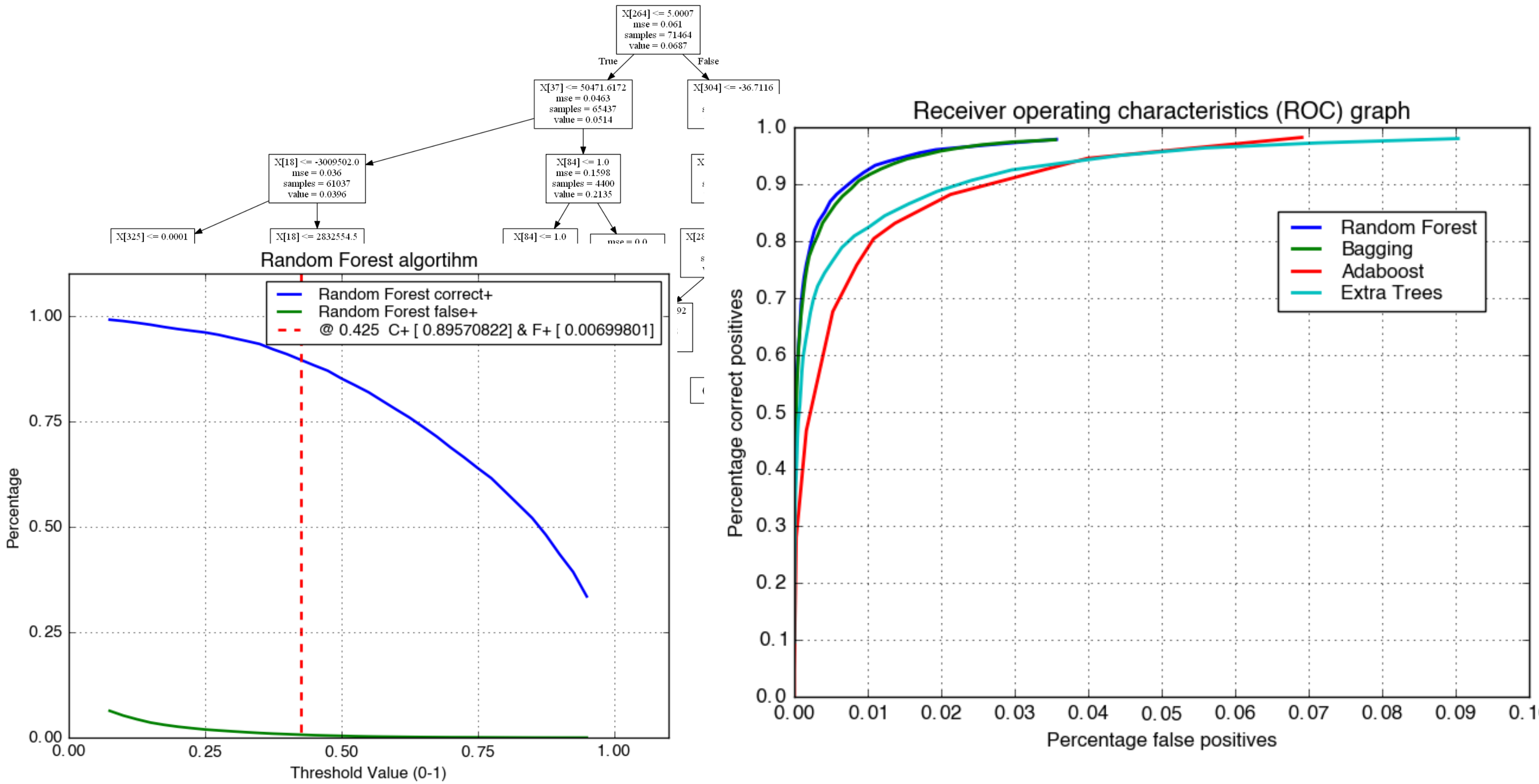
# Interpretation of results




Decision tree forest predictor → Disruptivity over time

Outcome over threshold → **ROC - graph** Correct positives over false positives

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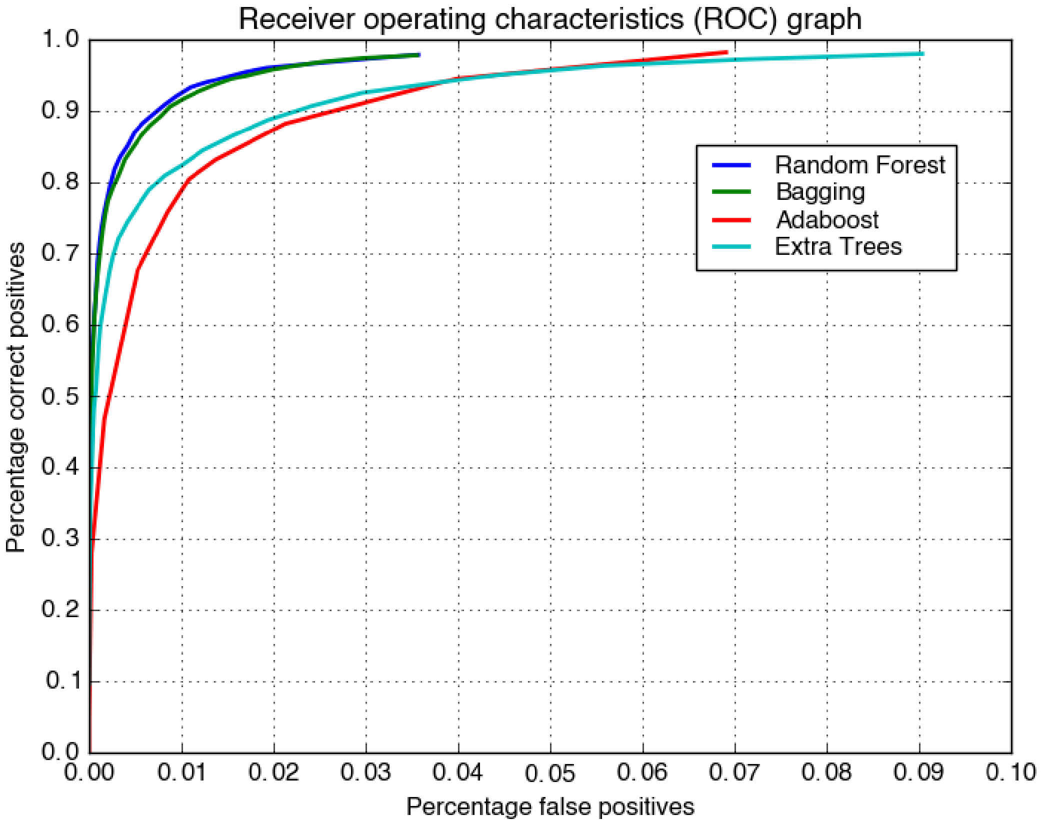
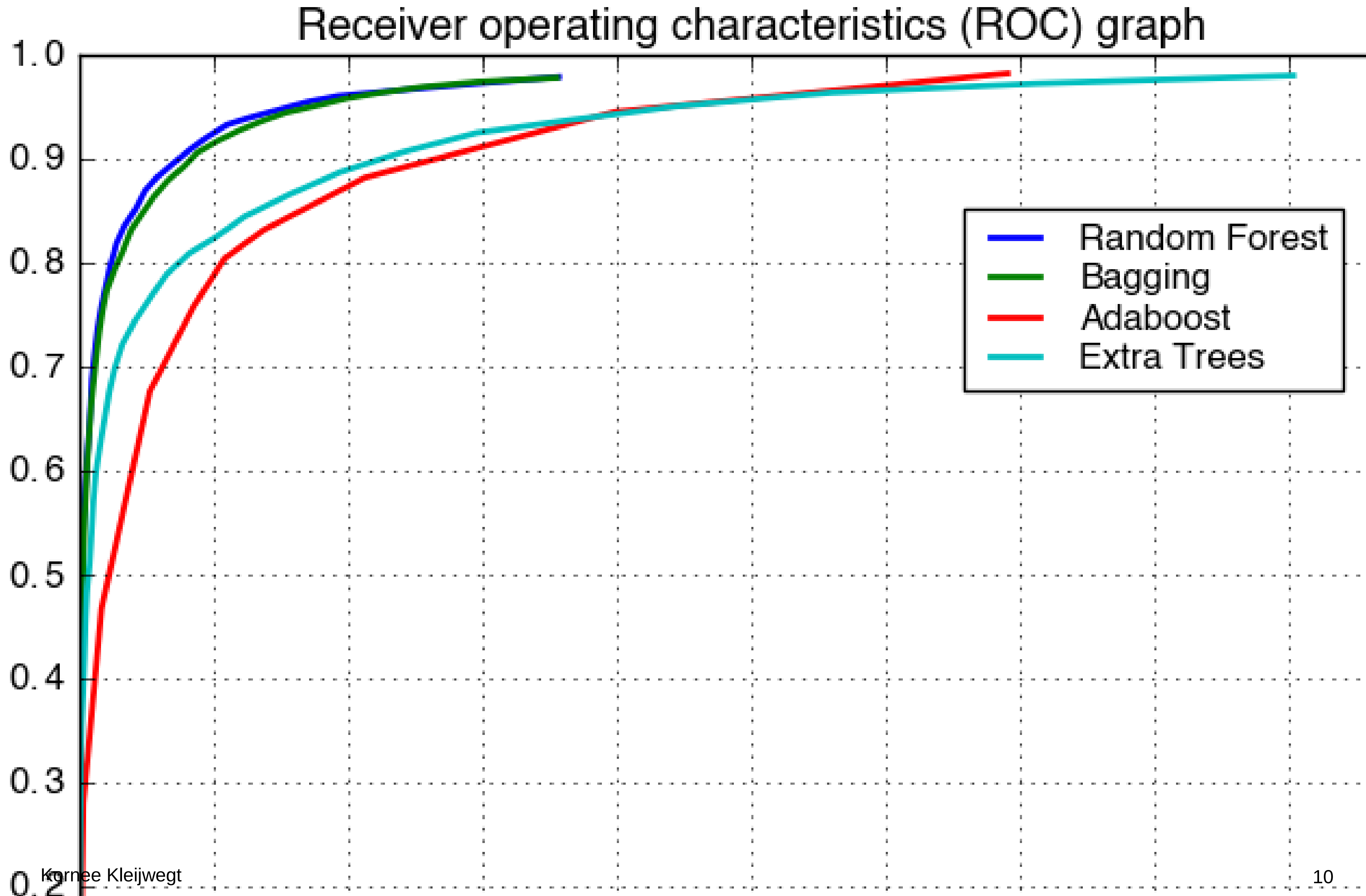
# Results



Receiver operating characteristics (ROC) graph
Percentage correct positives
Percentage false positives
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.10
Random Forest
Bagging
Adaboost
Extra Trees

# Results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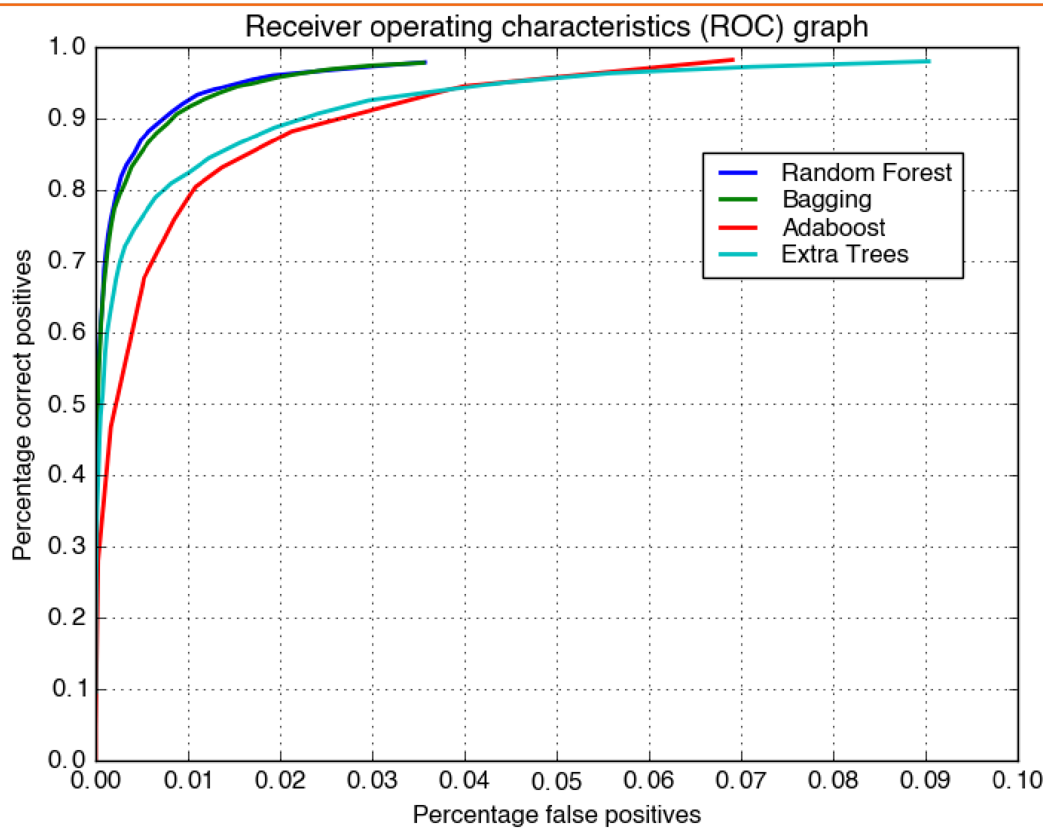



| Algorithm | Ada-Boost | Extremely Randomized Forest | Random Forest | Bagging |
|---|---|---|---|---|
| Correct positives ≈ 90% | 88% | 91% | 90% | 91% |
| False positives | 2.1% | 2.4% | 0.7% | 0.88% |

# Importance of plasma parameters

| Plasma parameter | Importance |
|---|---|
| $I_p$ | 0.19 |
| $B_{rot,\ saddle\ n=1}$ | 0.15 |
| $li_{efit}$ | 0.13 |
| $I_{p\ target}$ | 0.11 |
| $I_p - I_{p\ target}$ | 0.10 |
| $\frac{I_p}{\lvert I_p \rvert}$ | 0.08 |
| $< n_e >$ | 0.05 |

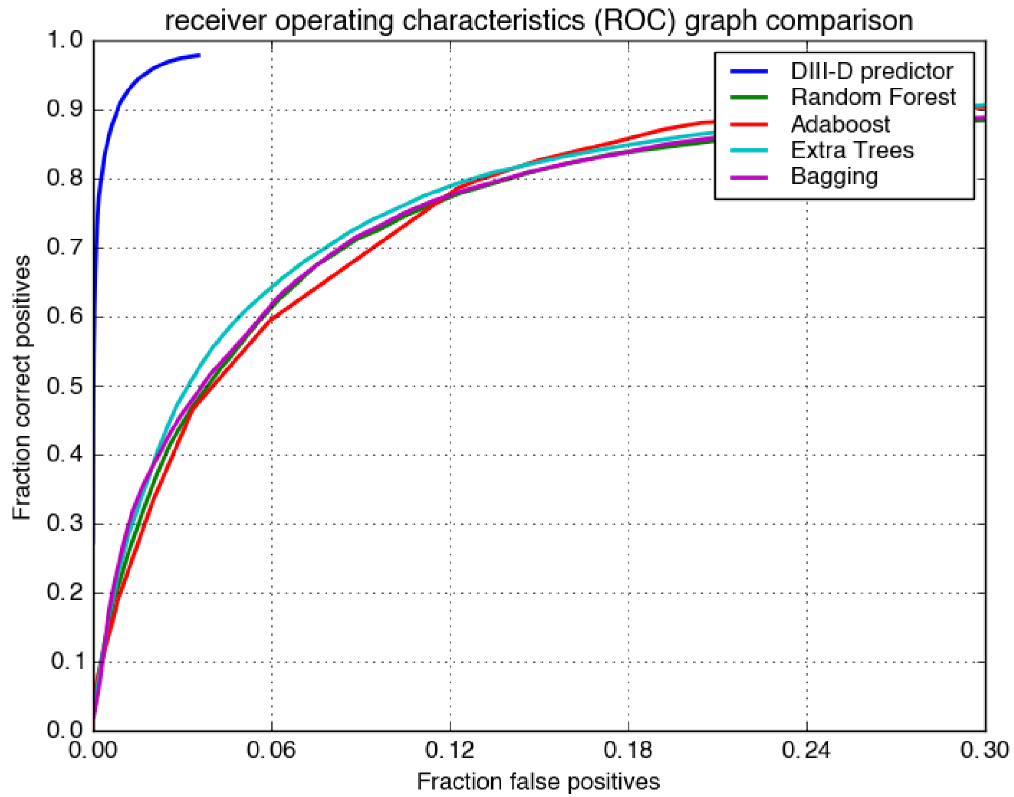
# Future work

- Disruption prediction using NSTX data
- Increasing robustness for missing data

- Disruption prediction on high Ip using low Ip training data

- Test and develop approach to create an predictor for future experiments
(such as ITER)

# **Future work:** NSTX - data

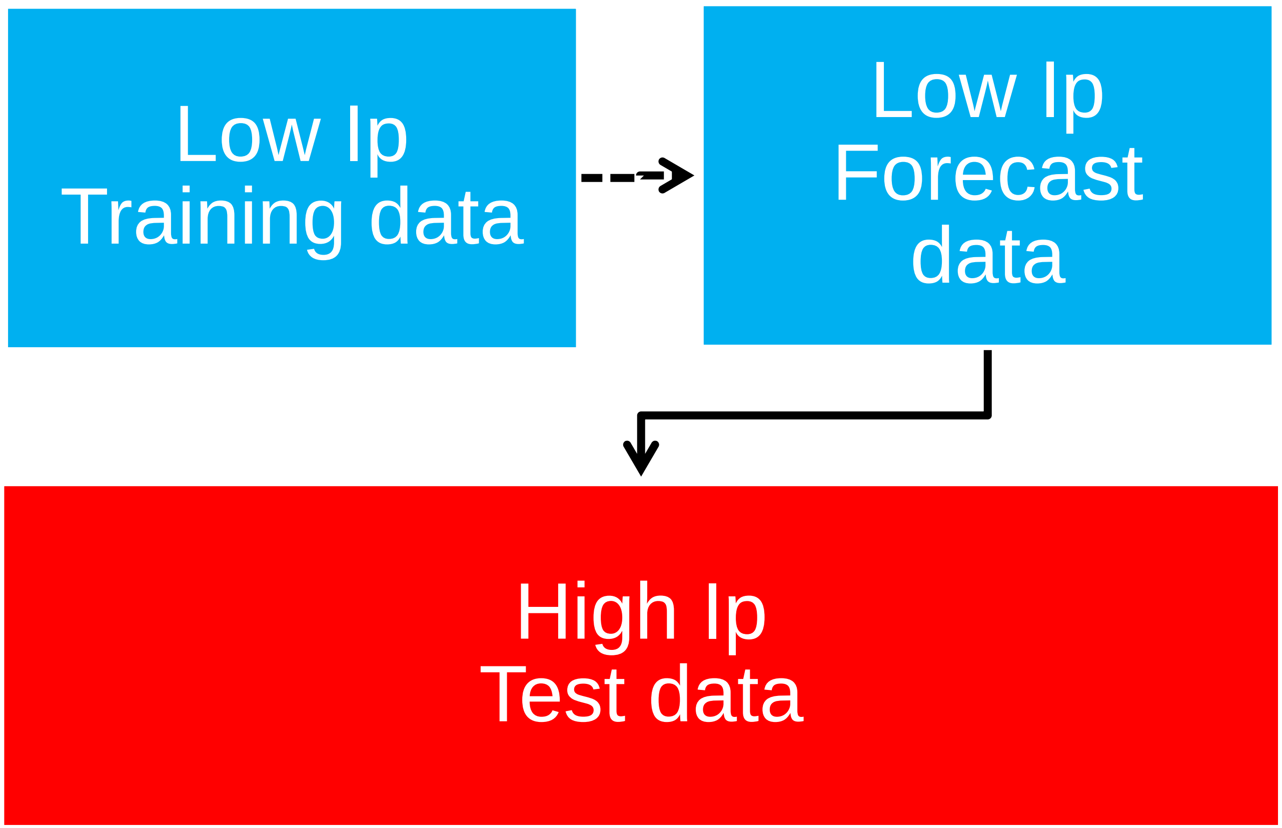



Using same plasma parameters as Gerhardt et al

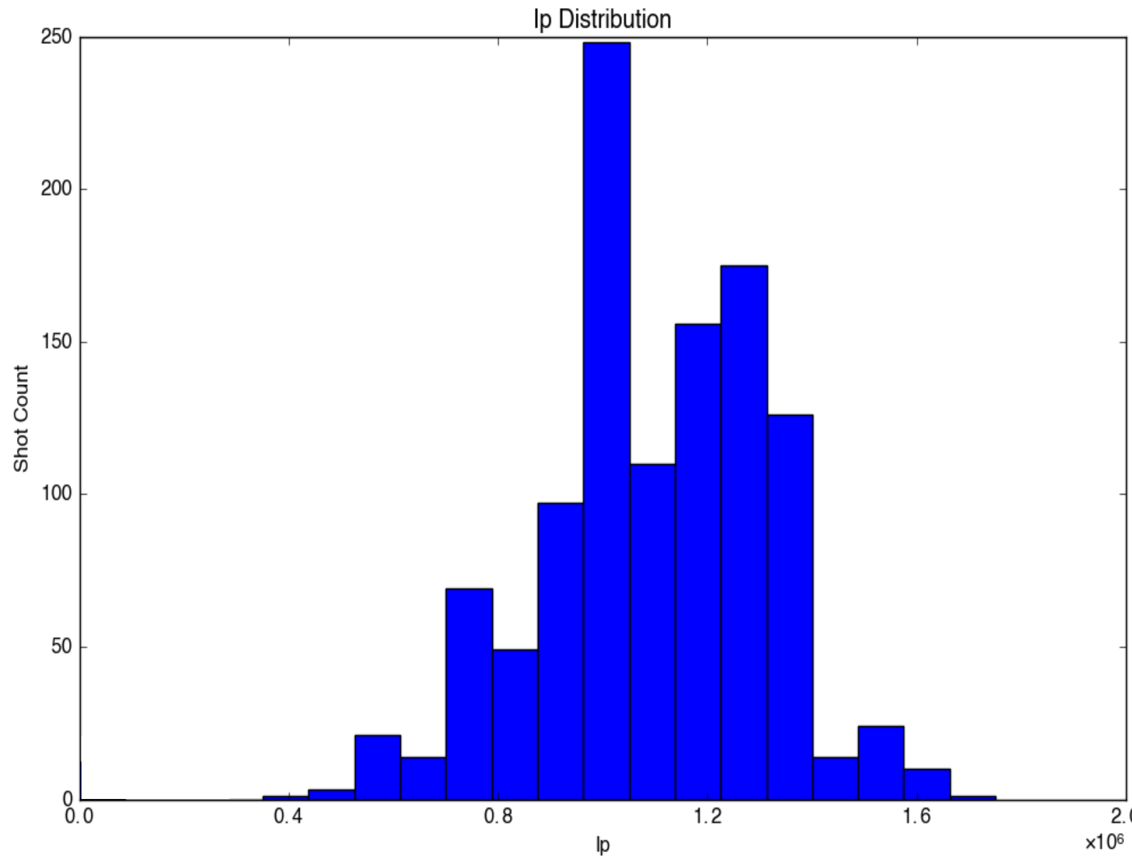
Trying to reproduce and maybe improve results

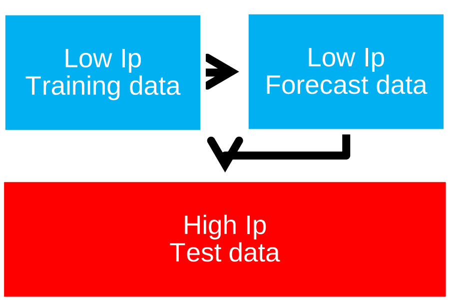
Robustness for missing signals

# **Future work:** Low Ip to High Ip

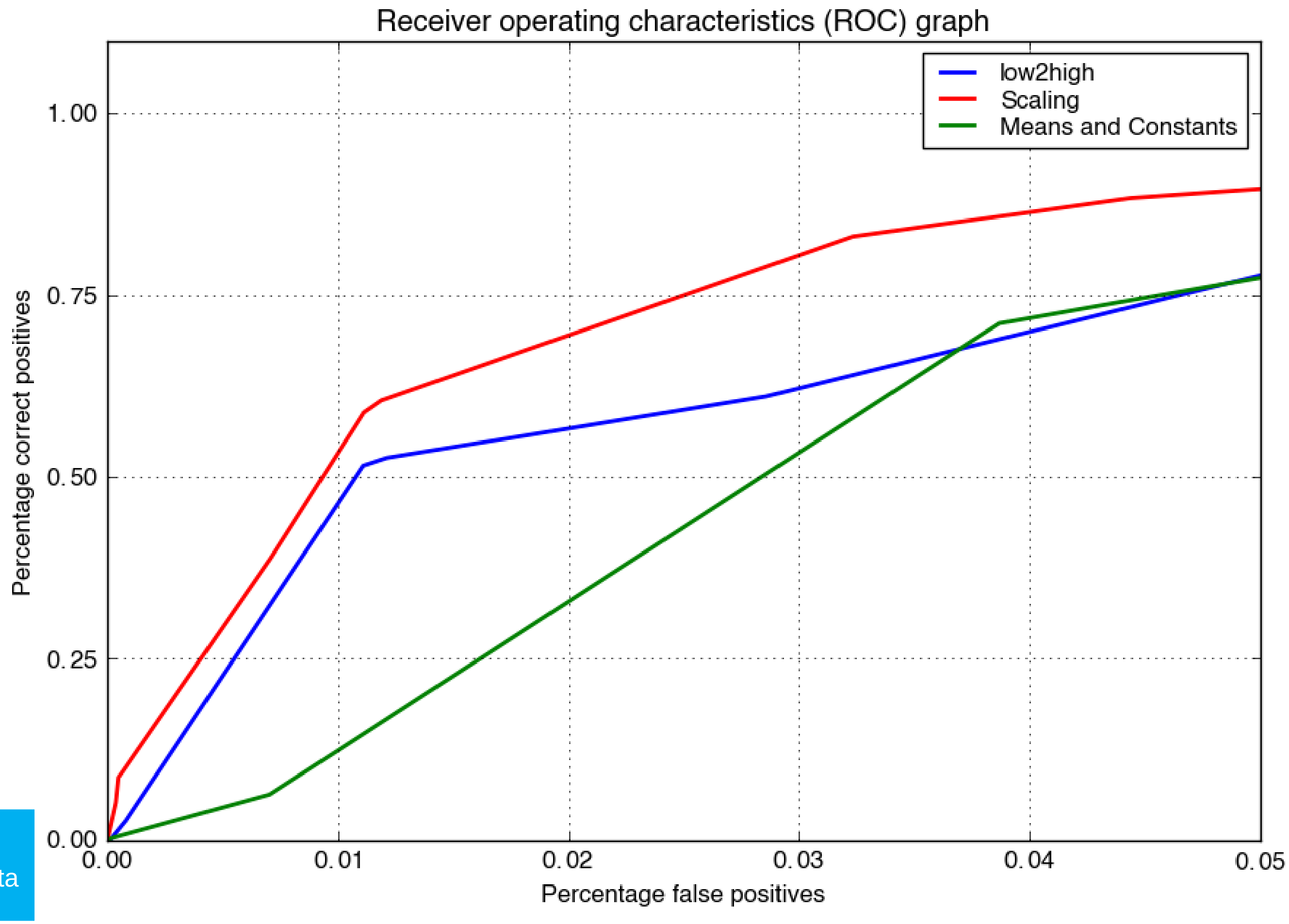


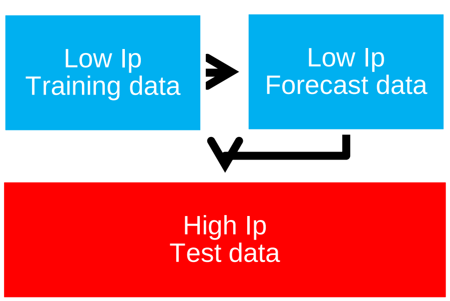
# **Future work:** Low Ip to High Ip



# **Future work:** Low Ip to High Ip

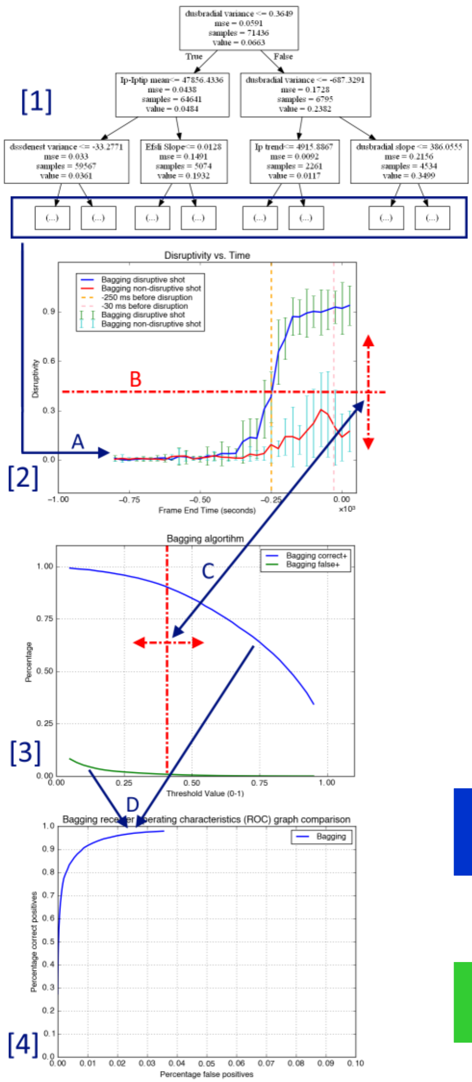


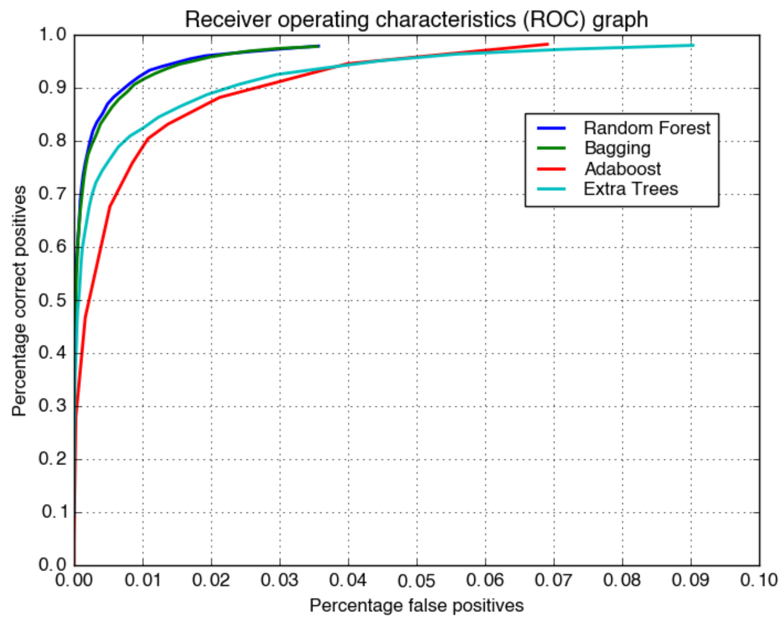



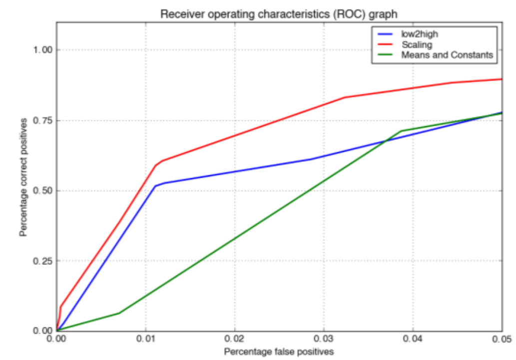
# Concluding - Summary

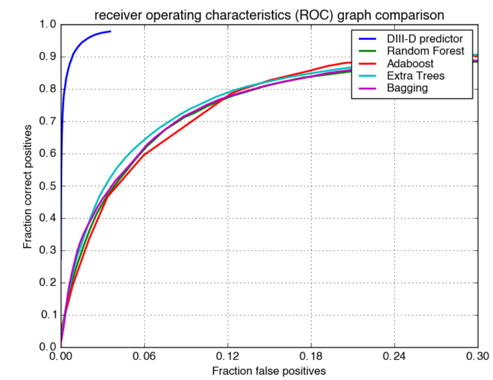
- Created a functioning disruption predictor on DIII-D after comparing and testing 4 different machine learning algorithms.
- A disruption predictor for NSTX using machine learning is under development.
- A low to high plasma current approach is developed to predict high plasma current disruptions.
- Further study should give more insight in a predictor for future reactors such as ITER. Both NSTX and DIII-D predictors help in this.

# Thanks for you attention!




Decision tree forest predictor → Disruptivity over time

Outcome over threshold → Correct positives over false positives

**ROC - graph**