Using Machine Learning Tools to Predict Accelerator Failure

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Overview

- Issues with accelerator reliability
- My research
- About the data
- On Machine Learning and tools
- Results
- Conclusion
- Future

This talk is a summary of two papers I've published in the area

1. M. Rescic, R. Seviour, W. Blokland, Predicting particle accelerator failures using binary classifiers, Nuclear Instruments and Methods in Physics Research Section A, Volume 955, 2020, 163240, ISSN 0168-9002, https://doi.org/10.1016/j.nima.2019.163240
2. M. Rescic, R. Seviour, W. Blokland, Improving particle accelerator pulse classification using dimensionality reduction and label threshold adjustments [SUBMITTED]

Issues with accelerator reliability

Statement: accelerators are not very reliable machines

Rephrased: they fail more often than they should by design

Unreliable means not suitable for commercial purposes

- Example application: **Industrial scale power generation**
- Requirement: **Less than 25000 trips of less than 1 second per year** [1]

[1] H. A t Abderrahim et al. Accelerator and Target Technology for Accelerator Driven Transmutation and Energy Production. 2010. DOE sponsored White Paper on Technology for Accelerator Driven Systems.

Issues with accelerator reliability, continued

Real life example from Spallation Neutron Source (SNS)

- Raw data from the Differential Beam Current Monitor (DBCM) system

  July 2020, about 3 days of data (10-13th), total: **633** trips
- **600** trips *less than 1 second*
- **23** trips *between 1 and 10 seconds*
- **9** trips *between 10 seconds and 5 minutes*
- **1** trip *longer than 5 minutes*

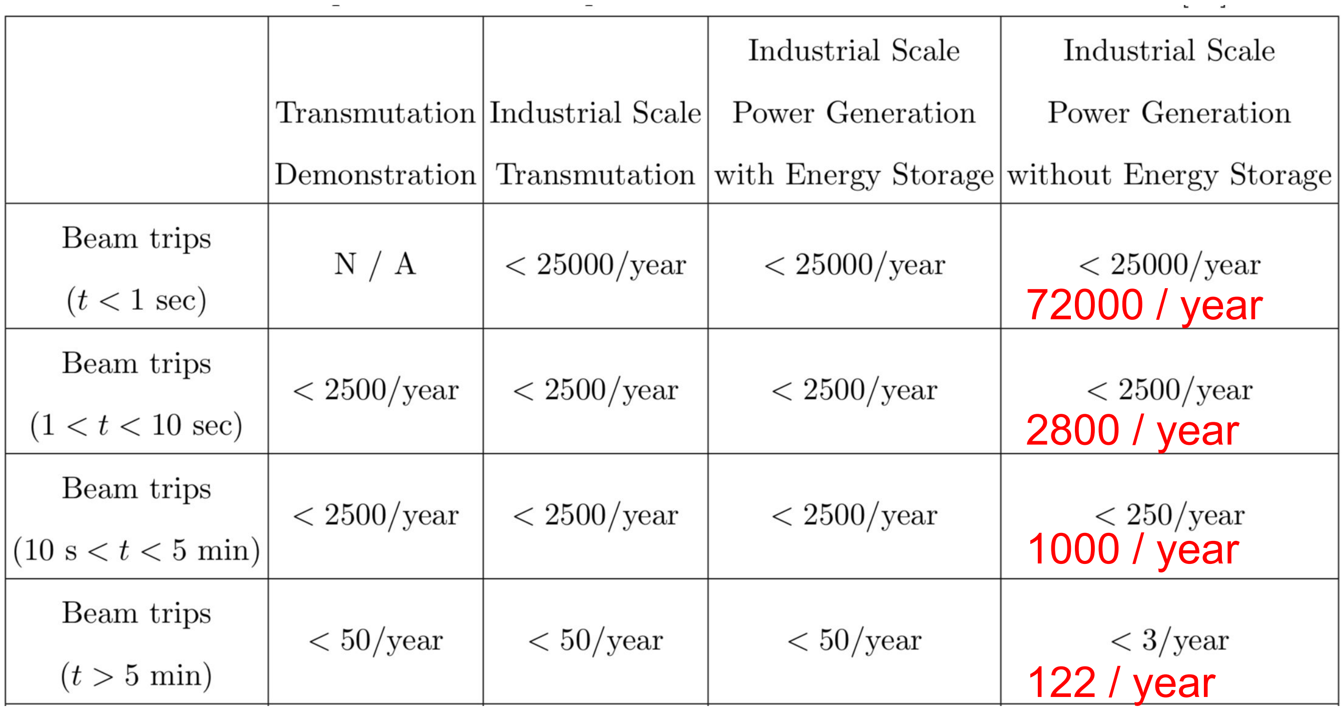
Issues with accelerator reliability, continued

Real life example from Spallation Neutron Source (SNS)

- Raw data from the Differential Beam Current Monitor (DBCM) system
  July 2020, about 3 days of data (10-13th), total: **633** trips
- **600** trips *less than 1 second* = **72000 / year**
- **23** trips *between 1 and 10 seconds* = **2800 / year**
- **9** trips *between 10 seconds and 5 minutes* = **1000 / year**
- **1** trip *longer than 5 minutes* = **122 / year**

Reliability requirements for industrial applications

Overview of all trip related requirements [1]



	Transmutation Demonstration	Industrial Scale Transmutation	Industrial Scale Power Generation with Energy Storage	Industrial Scale Power Generation without Energy Storage
Beam trips ($t < 1$ sec)	N / A	< 25000/year	< 25000/year	< 25000/year 72000 / year
Beam trips ($1 < t < 10$ sec)	< 2500/year	< 2500/year	< 2500/year	< 2500/year 2800 / year
Beam trips (10 s $< t < 5$ min)	< 2500/year	< 2500/year	< 2500/year	< 250/year 1000 / year
Beam trips ($t > 5$ min)	< 50/year	< 50/year	< 50/year	< 3/year 122 / year

Accelerator reliability (continued)

It's not only requirements, it's how accelerators are designed and build, *typically*

1. Set requirements (e.g. ACCELERATOR RELIABILITY > 97%)
2. Trickle down requirements (e.g. SYSTEM A RELIABILITY= 99.99%)
3. Analyze SYSTEM A's reliability (MTTF, RBD, FTA, FMEA...), reiterate
4. Build and install SYSTEM A
5. MAGIC
6. ACCELERATOR RELIABILITY << 97%

My research

Holistic approach to predicting accelerator failure with machine learning

- Looking at the accelerator as a whole, not individual subsystems
- Using data that is system agnostics
- Trying to identify emergent behaviour before that behaviour actually occurs
    - Looking for indicators of beam trips in data before the trips happen, not as it's happening
- Leveraging machine learning techniques
    - = reduce unknowns and assumptions

*Summary: Trying to predict failures in real time **before** they occur*

About the data

Source : Spallation Neutron Source (SNS)
Differential Beam Current Monitors

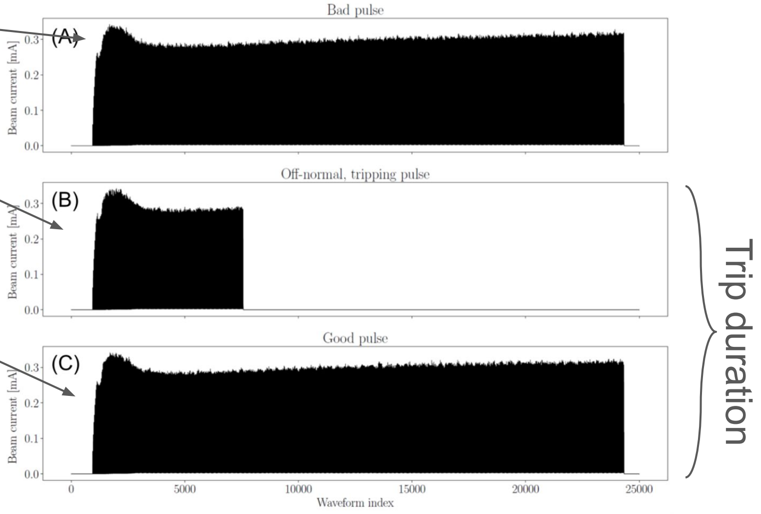
Type: 3* waveforms per trip;
before **(BAD)**, ~~during~~ (TRIP)
and after **(GOOD)** the trip

Length: 15000 waveforms (50/50 split)
25000** points per waveform

Note: we use 2015 data
(and verifying results on 2020 data)

*they collect more now (up to 25) ** they are longer now (up to 10(

Figure 1: A triplet of acquired pulses for a single MPS trip: Bad pulse (A), tripping pulse (B) and Good pulse (C).(D) zoomed in region of pulse showing bunches.



On Machine Learning

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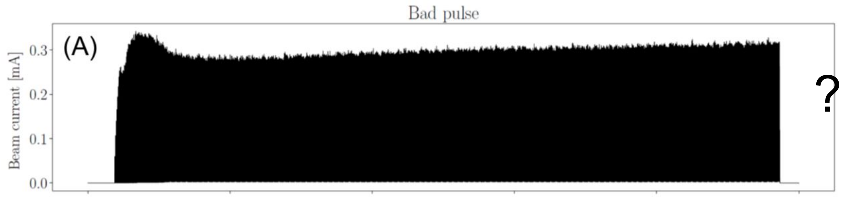
The ability of machines to *learn* and use that knowledge to classify data.
In our case to learn the difference between:

- a **GOOD pulse** - a pulse that passes through the machine and no trips follows and
- a **BAD pulse** - a pulse that passes through the machine just prior to pulse that trips the machine

This knowledge is then used to identify pulses



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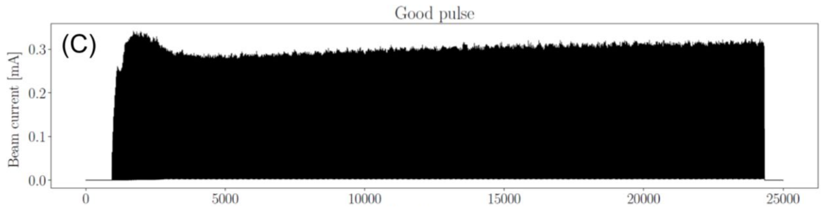
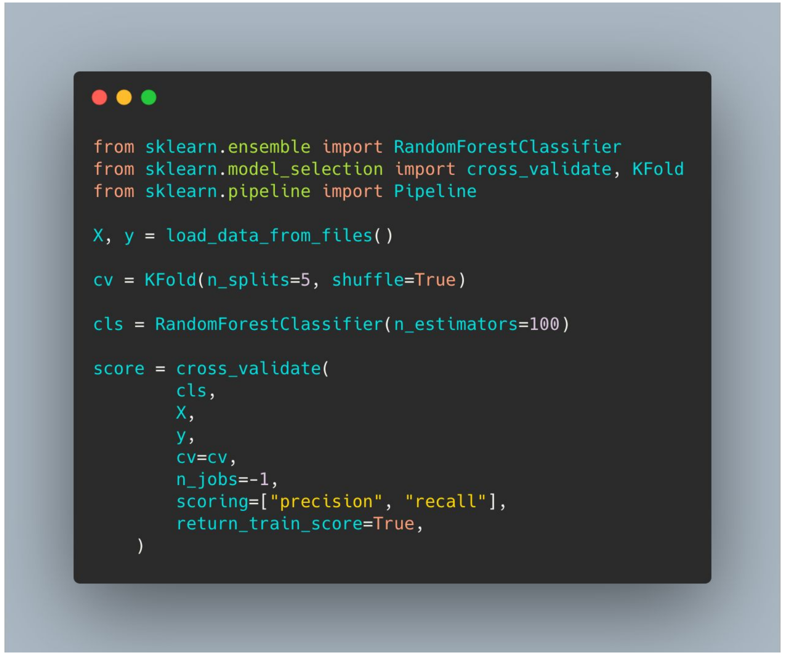


On Machine Learning, continued

Learning and identification process

1. Build model on training data
2. Use the model to identify pulses
   a. Is this pulse good or bad? With what confidence?
3. Validate model quality
   a. how many pulses were labelled correctly and how many were mislabelled



```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_validate, KFold
from sklearn.pipeline import Pipeline

X, y = load_data_from_files()

cv = KFold(n_splits=5, shuffle=True)

cls = RandomForestClassifier(n_estimators=100)

score = cross_validate(
        cls,
        X,
        y,
        cv=cv,
        n_jobs=-1,
        scoring=["precision", "recall"],
        return_train_score=True,
    )
```

Machine Learning Techniques

- **Metrics and terminology**
  - **Precision:** how many pulses correctly identified
  - **True positive** / **False negative** ratio: good pulses identified as good / bad
  - **True negative** / **False positive** ratio: bad pulses identified as bad / good
- **Data set**
  - **15000 pulses, 7500 BAD and 7500 GOOD**
  - Exhaustive 5-fold cross validation with random shuffling

Machine Learning Techniques

Classifiers: waveform in, identified pulse out (GOOD or BAD)

- **K-Nearest Neighbours (kNN)**
  - Identify pulses by analyzing their k nearest neighbours
- **Decision tree**
  - Binary tree build from data that one traverses until a label is found in a leaf
- **Random Forest (RF)**
  - Ensemble voting by a set of randomly built decision trees
- **Gradient Boosting (GB)**
  - Similar to above, but the ensemble is built by using gradient descend (optimization)

Machine Learning Techniques

Data preprocessing (dimensionality reduction): M points in, N out, N < M

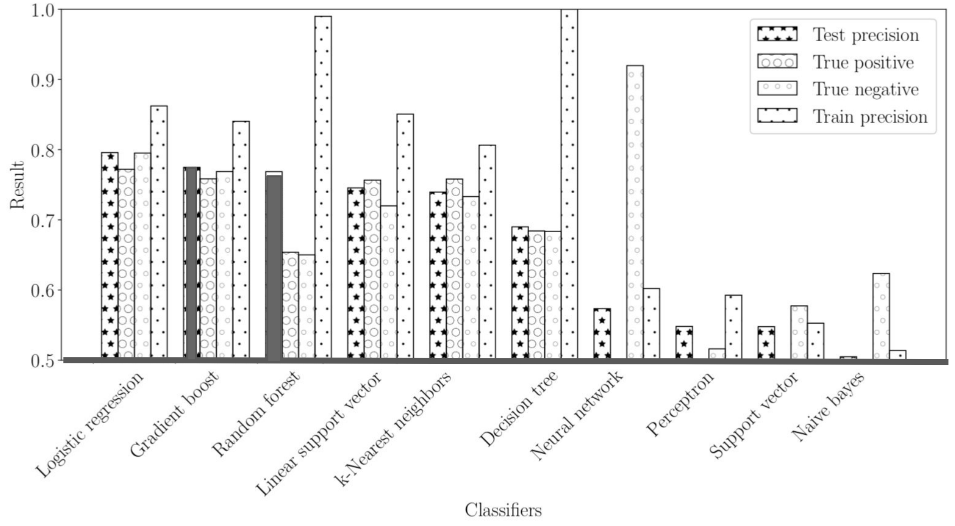
- **Principal Component Analysis (PCA)**: orthogonal components of waveform
  - The original waveform is represented as a sum of orthogonal components
- **Fast Fourier Transformation (FFT)**: from time to frequency spectrum
  - The original waveform is translated into a sum of components representing the frequency spectrum instead of time domain

Results

Precision

- Just classifiers, best precision: Random Forest and Gradient Boosting (about 80%)
- After dimensionality reduction
  PCA (88% with RF)
  FFT (92% with GB)

Figure 2: Classifier performance for the whole dataset, ranked best to worse by test accuracy

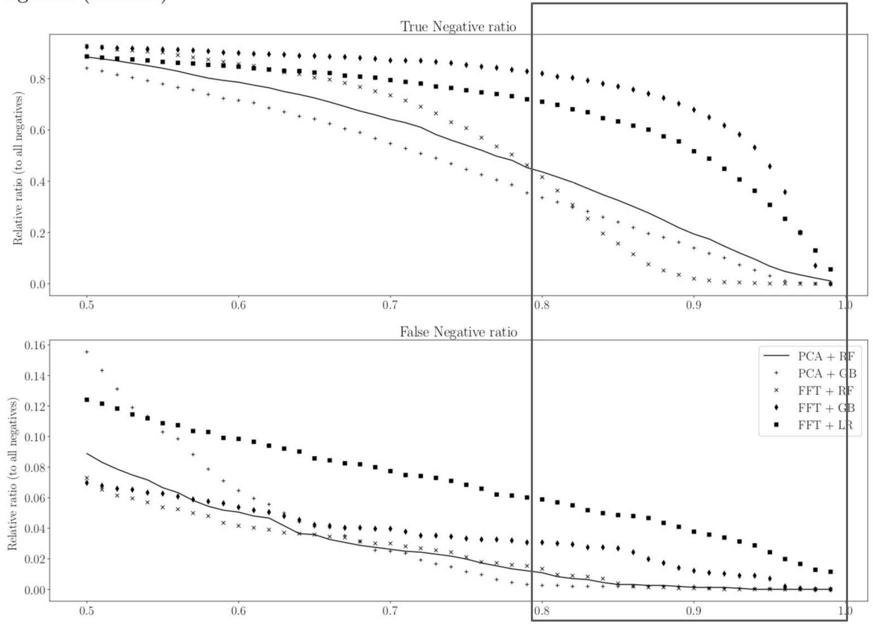


Results

Confidence

- False Negative ratio
  FFT + GB: 0.19% with confidence threshold above 0.81 while Maintaining **31% True Negative ratio**

Figure 8: Effect of label probability threshold on True Negative classification (top) and False Negative (bottom)



Conclusion

We can, with reasonable precision (**92%**), predict failures before they happen

We can drive down False Negatives (**0.2%**) while maintaining reasonable true negatives (**31%**) by adjusting label thresholds

This allows for a **16 milliseconds warning time** (on the 60Hz SNS machine)
=> Currently, SNS takes 7 micro seconds to process, identify and mitigate failure

Future

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What's next?

- Look into predicting which system is going to fail
  (as SNS records more metadata around failures, including the failing system)
- Try to predict failures sooner and with even more accuracy
  (as SNS now records up to 22 pulses prior to trip with higher resolution)

Thank you

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