Towards Additive Manufacturing Process Control using Semi-Supervised Learning

Dr Ikenna A Okaro

Miss Sarini Jayasinghe

Dr Kate Black

Prof Chris Sutcliffe

Dr Paolo Paoletti

Dr Peter L Green

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People

Ikenna A Okaro
Project PDRA

Sarini Jayasinghe
PhD Student

Kate Black
Lecturer

Chris Sutcliffe
Professor and
Renishaw Contact

Paolo Paoletti
Senior Lecturer

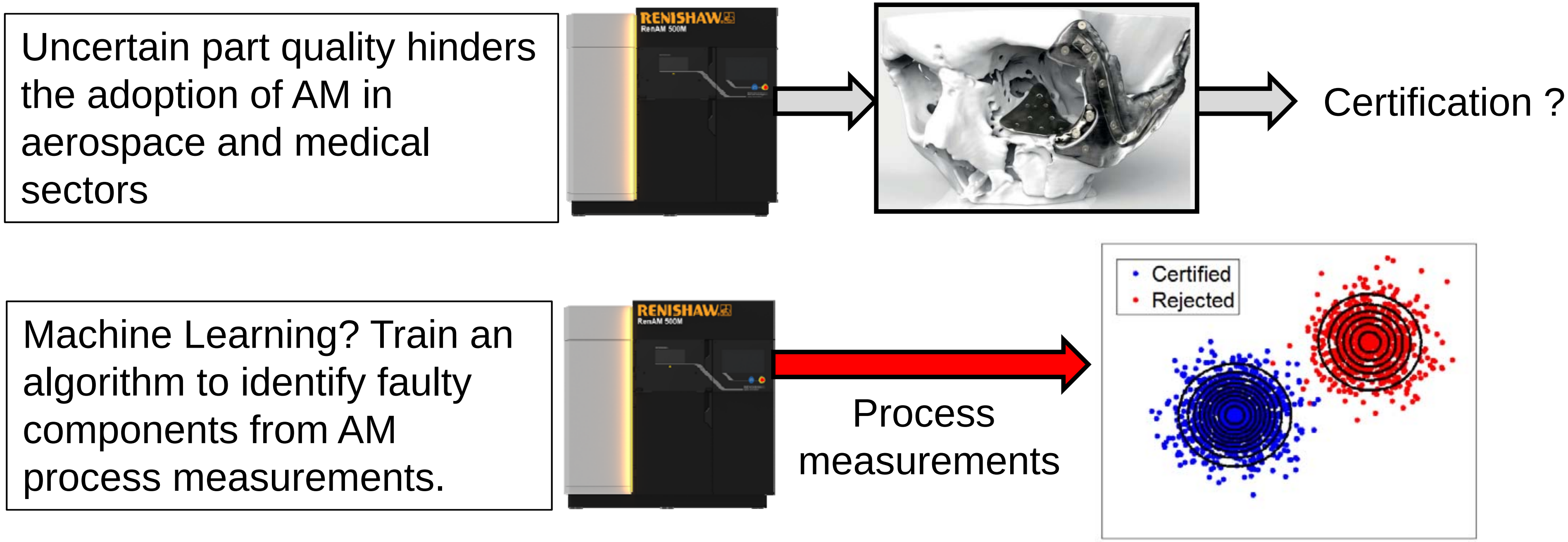
Motivation

- Additive Manufacturing is revolutionising UK industry.
- Potential in more risk-averse sectors (aerospace, healthcare etc.)
- We must de-risk AM technology to maximise its impact.
- Current issues stem from a lack of process control.

Can machine learning help us to pioneer robust process control for Additive Manufacturing ?

Uncertain part quality hinders the adoption of AM in aerospace and medical sectors

Certification ?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RENISHAW
Certification ?
Machine Learning? Train an algorithm to identify faulty components from AM process measurements.
RENISHAW
Process measurements
Certified
Rejected

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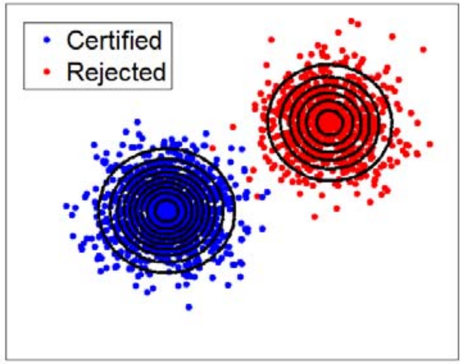
Process measurements



100s of parts need to be manually certified before the algorithm can be trained. This is far too expensive for AM.

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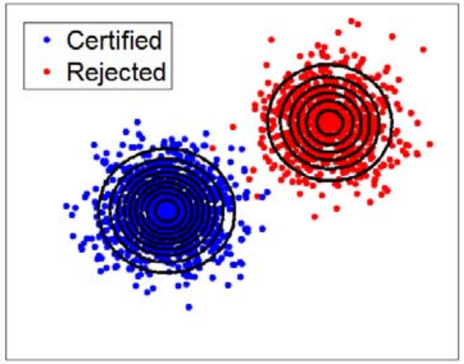

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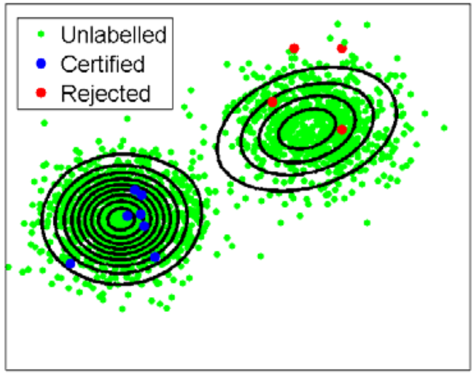
Process measurements



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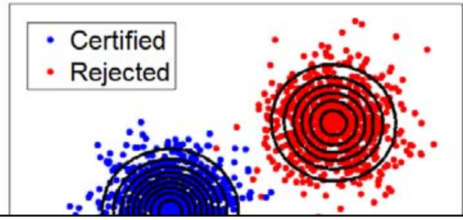

DID IT WORK?

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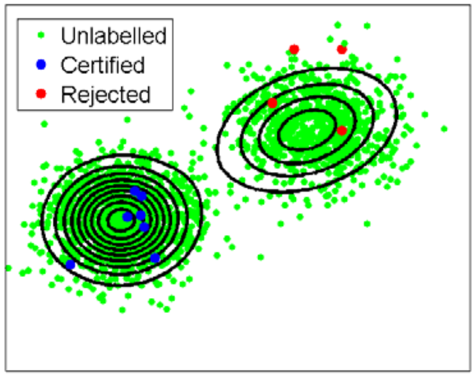

Methodology

- 2 SLM builds, each of 25 tensile test bars.

- During each build we measure:
  - Back reflected light (2 photodiodes, infrared and visible)
  - Laser position

- 400GB of data per build (!)

- Conducted tensile tests of each specimen.

Methodology

1. Label each bar as ‘good’ or ‘bad’ depending on tensile test results.

2. Extract the measurements that relate to each test bar.

3. Extract statistically significant indicators of build quality from photodiode measurements (called *features*).

4. Semi-supervised learning applied to features.
    - Can we identify faulty components?
    - Does semi-supervised learning reduce the number of certification experiments needed?

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Feature extraction - high risk part of the project!

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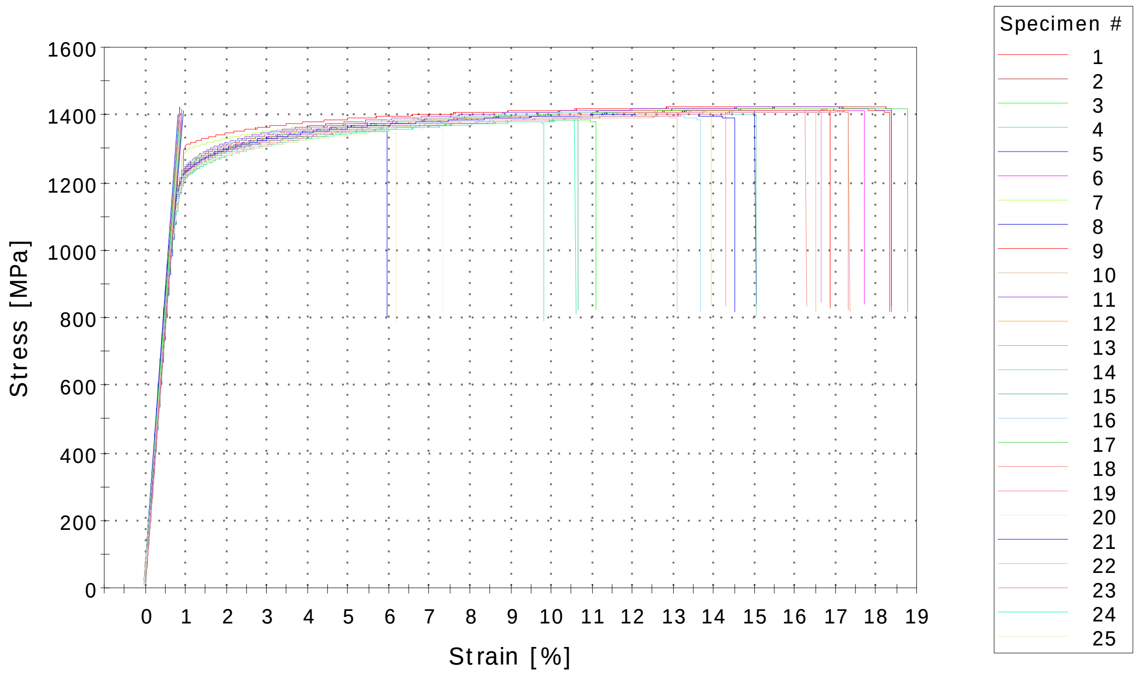
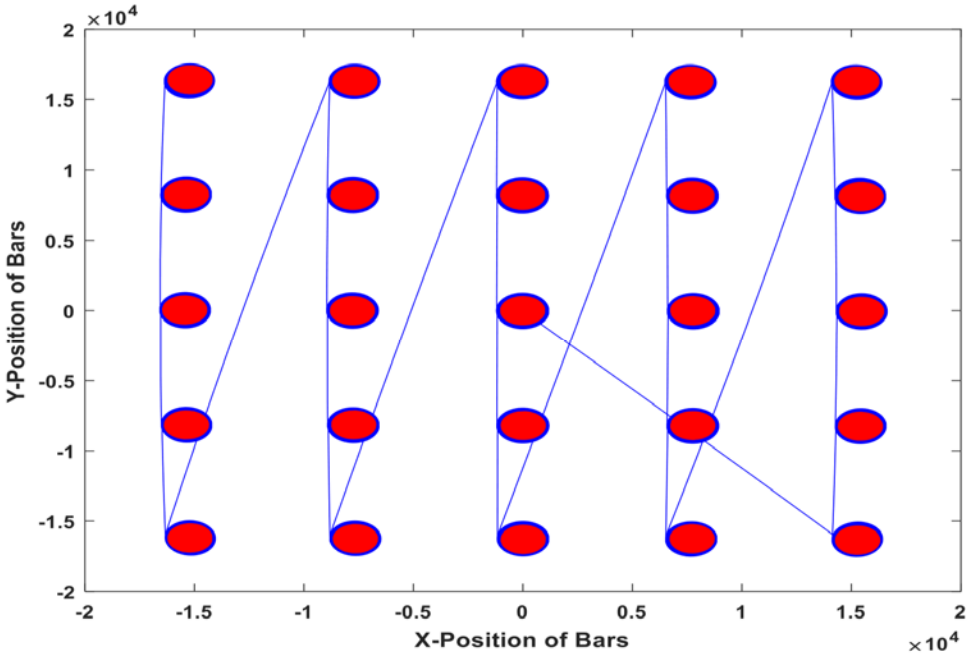
1. Labelling each specimen

- Ultimate Tensile Strength > 1400MPa labelled as ‘good’.
- A little arbitrary but sufficient for a feasibility study.
- Fatigue tests and/or CT scans will be used in the future.

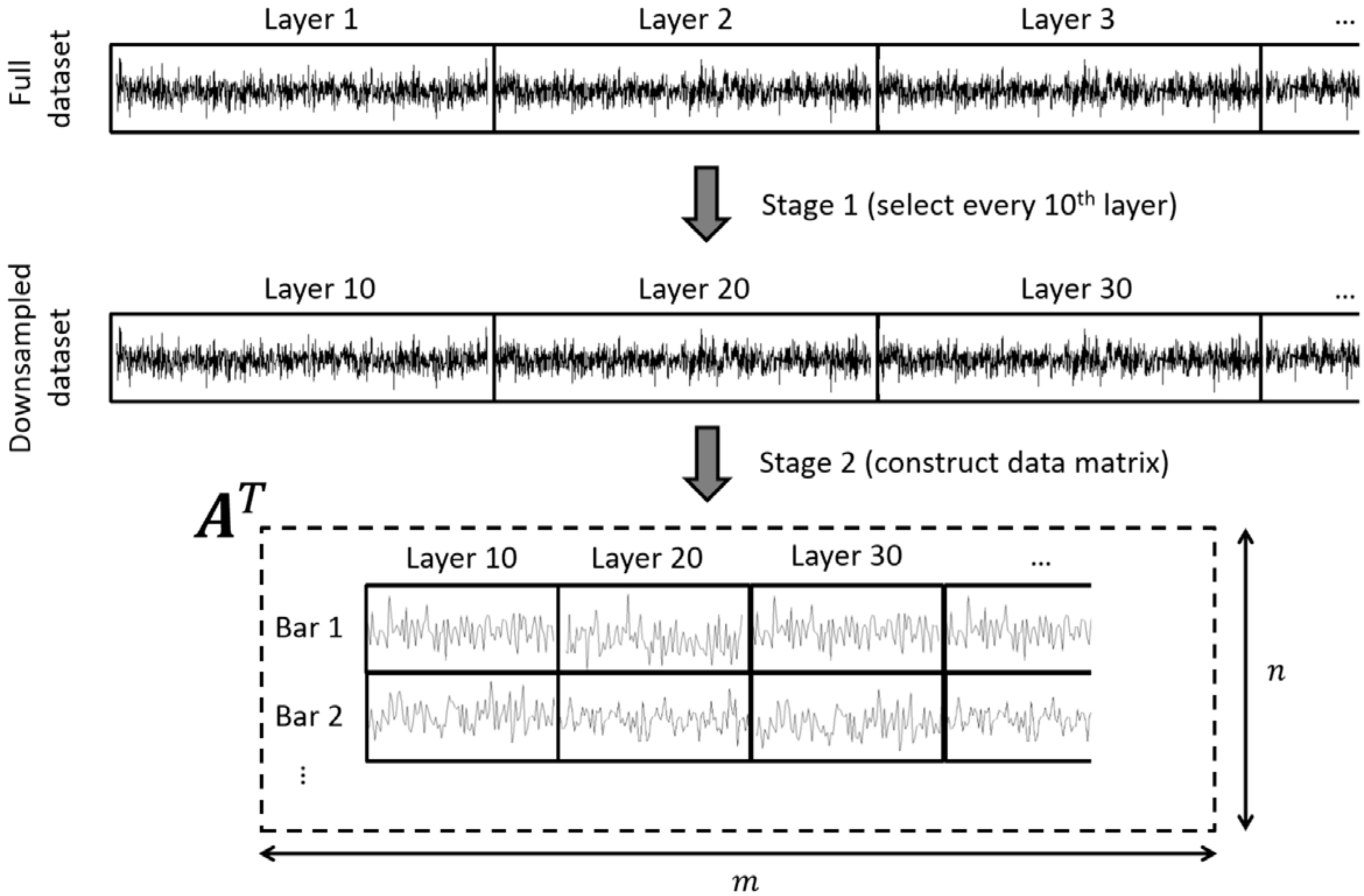


2. Extract measurements relating to each bar



- Figure shows X-Y coordinates of a single layer.
- We identify the photodiode measurements that are obtained when the laser is in a red region.
- We also omit data obtained when the laser is not running.

3. Feature Extraction (per Photodiode)



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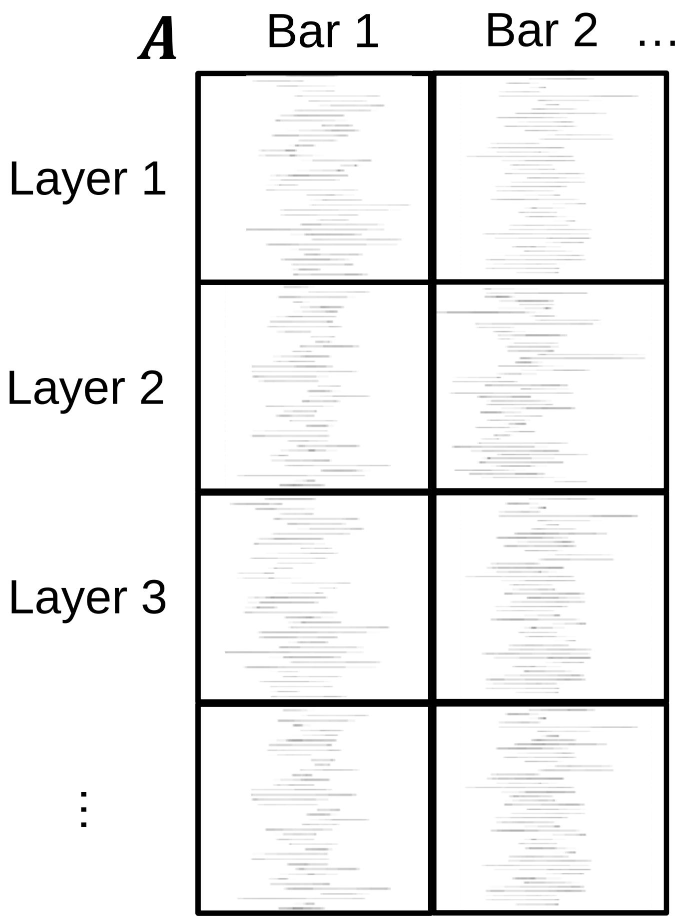

$$\boldsymbol{A} = [\boldsymbol{a_1} \quad \boldsymbol{a_2} \quad \ldots]$$

- Singular Value Decomposition (SVD)
- Each vector $\boldsymbol{a_i}$ can be written as a linear combination of basis vectors.

$$\boldsymbol{a_i} = \sum_{p=1}^{25} \boldsymbol{u_p} B_{pi}$$

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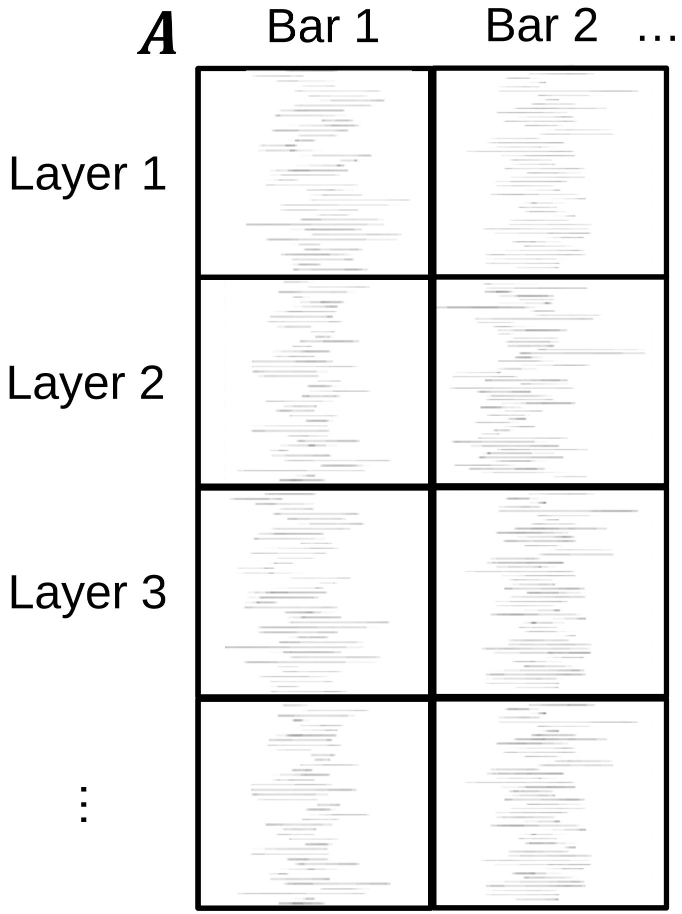

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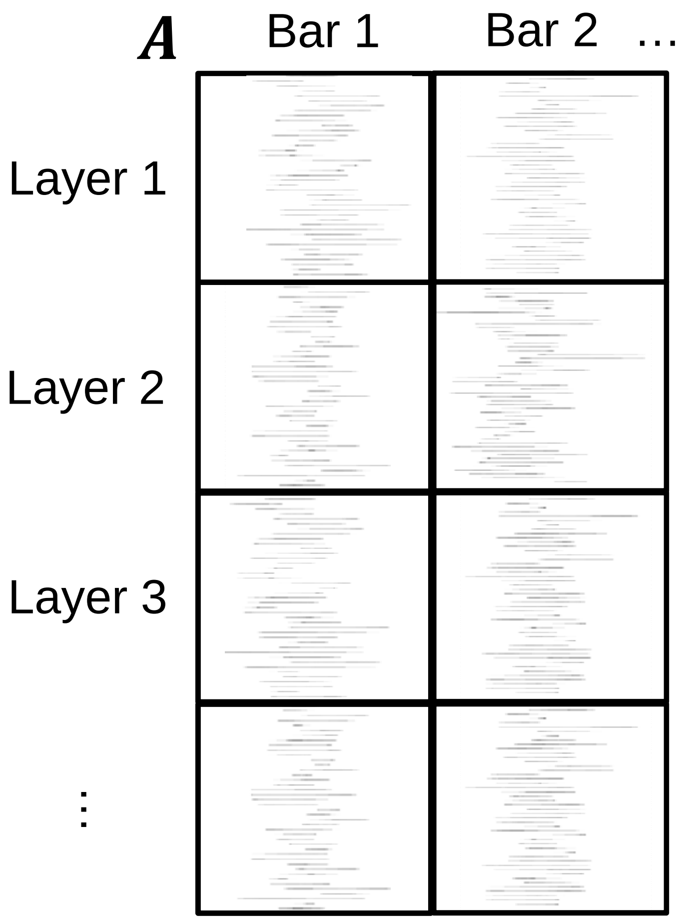
Basis vectors

Constants

3. Feature Extraction (per Photodiode)



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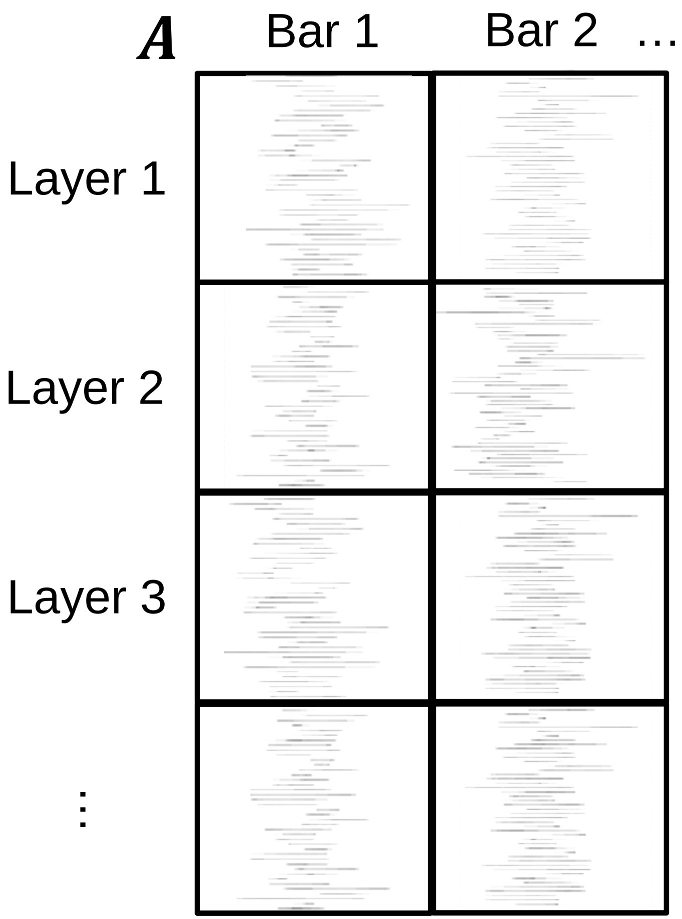

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These constants become our **<u>features</u>**

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3. Feature Extraction (per Photodiode)

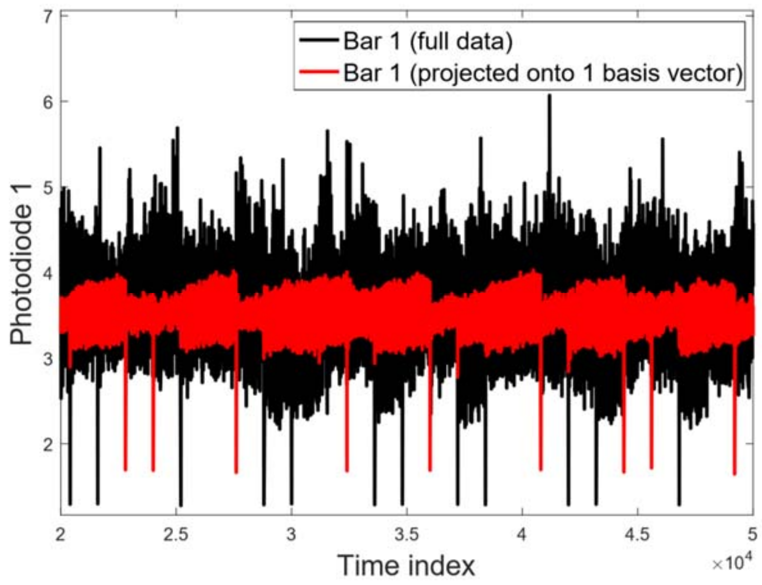
- Including both builds, we have a 50 by 3×10^6 data matrix.
- Computational cost prevents a standard SVD being applied here.
- We (Sarini!) circumvented this issue using methods form Big Data analytics:

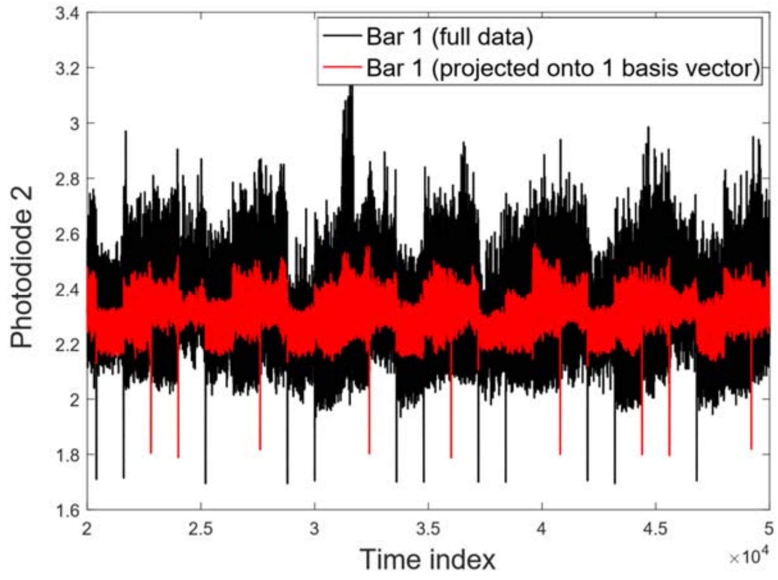
Probabilistic Singular Value Decomposition.

- For the feasibility study, we kept just 1 basis vector per photodiode.
- 2 photodiodes => 2 dimensional feature space.

3. Feature Extraction (per Photodiode)

These figures give an impression of the 'information lost' by only projecting onto 1 basis vector.

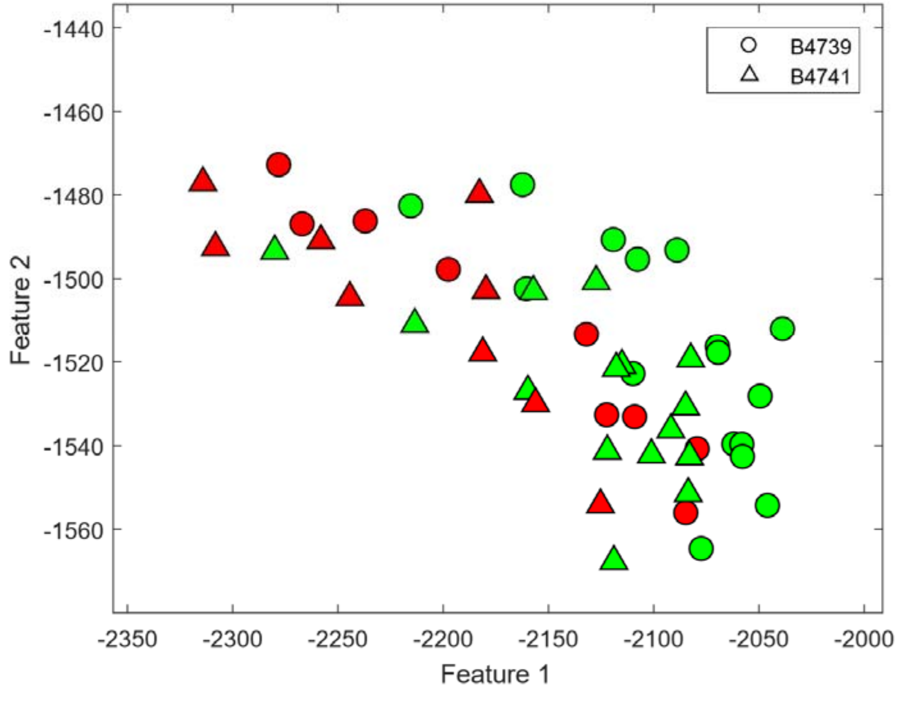




Projecting onto more basis vectors increases the dimensionality of the feature space. This trade-off can be investigated in the future.

4. Semi-Supervised Machine Learning

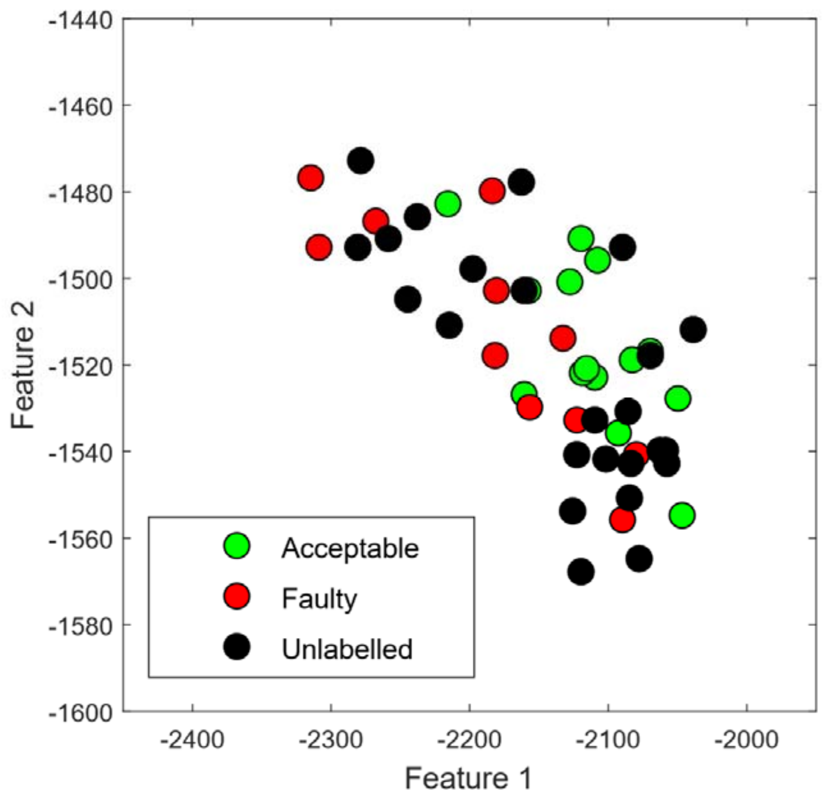
Our 2D feature space.



Green and red represent ‘good’ and ‘bad’ specimens respectively.

4. Semi-Supervised Machine Learning

To investigate the semi-supervised approach, we delete half of our labels.

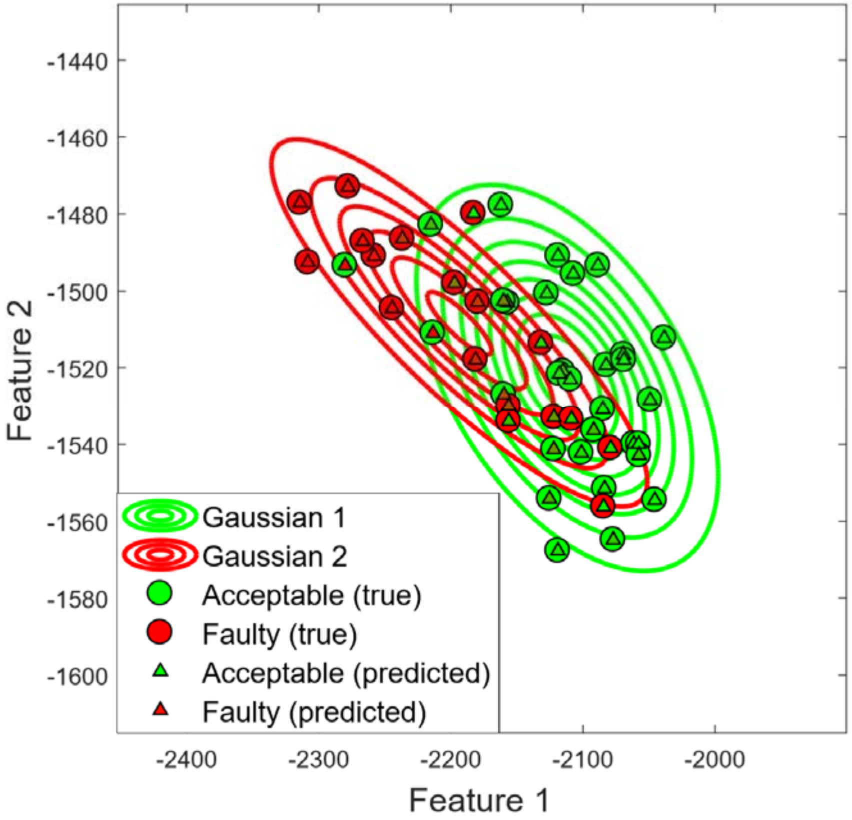


These are chosen at random.

4. Semi-Supervised Machine Learning

We fit our Gaussian Mixture Model. In this case, ‘bad’ specimens were identified with a 77% success rate.

Above 75% was a key project objective.



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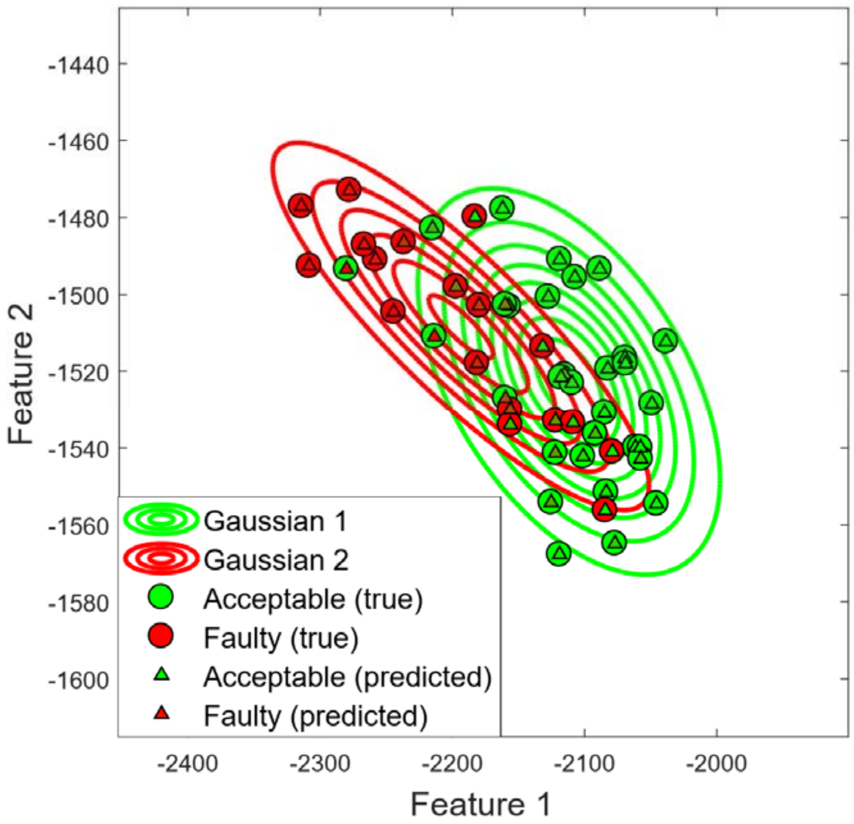

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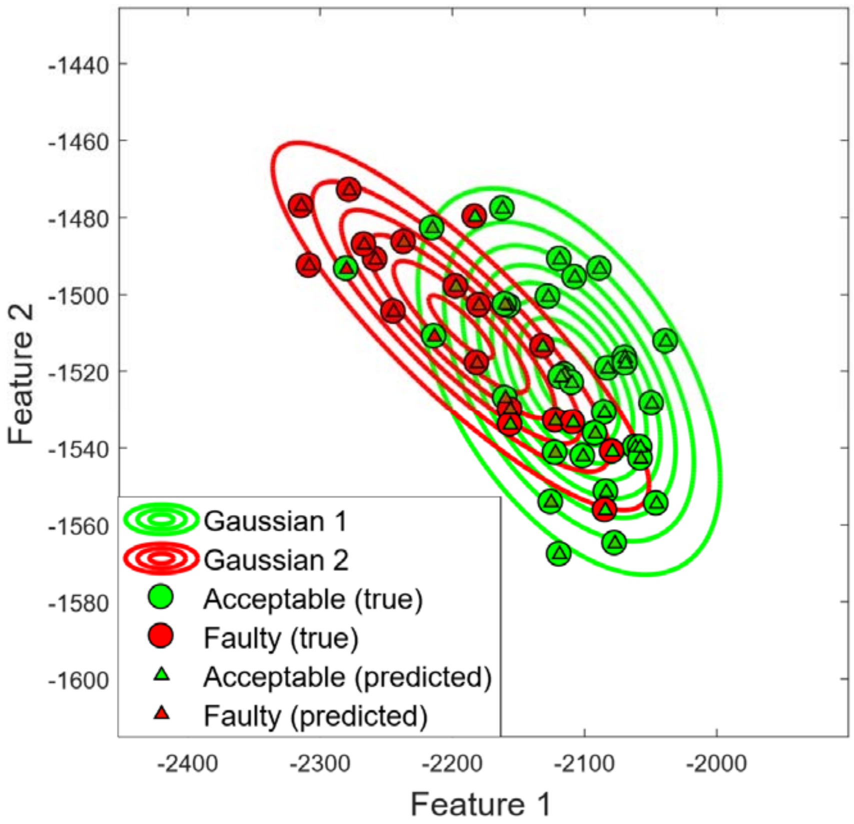
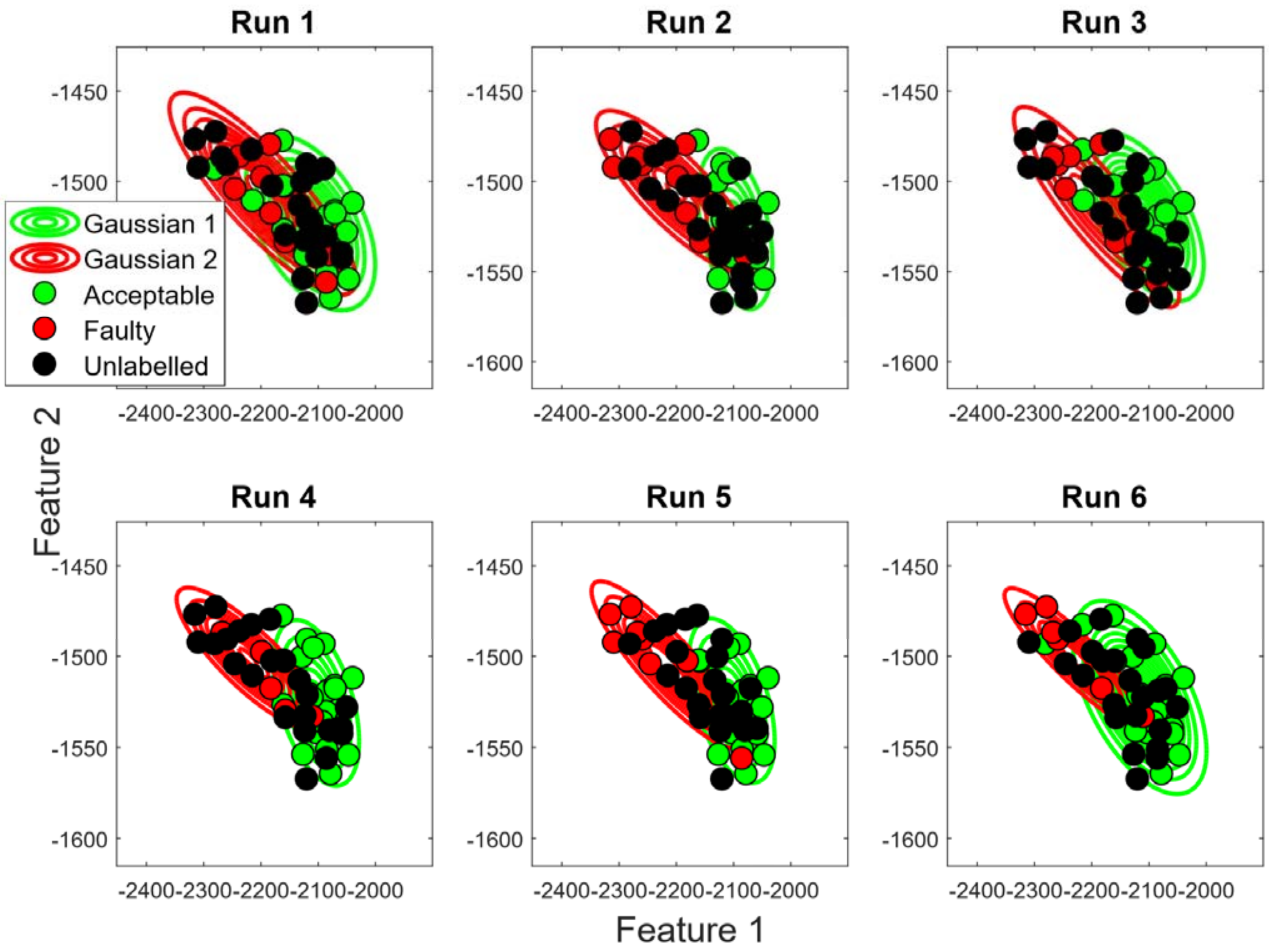


Triangles are coloured in to represent the *probability* that a component is ‘faulty’.

UQ must be included in machine learning!

4. Semi-Supervised Machine Learning

We repeat this many times, where data is randomly unlabelled in each iteration.



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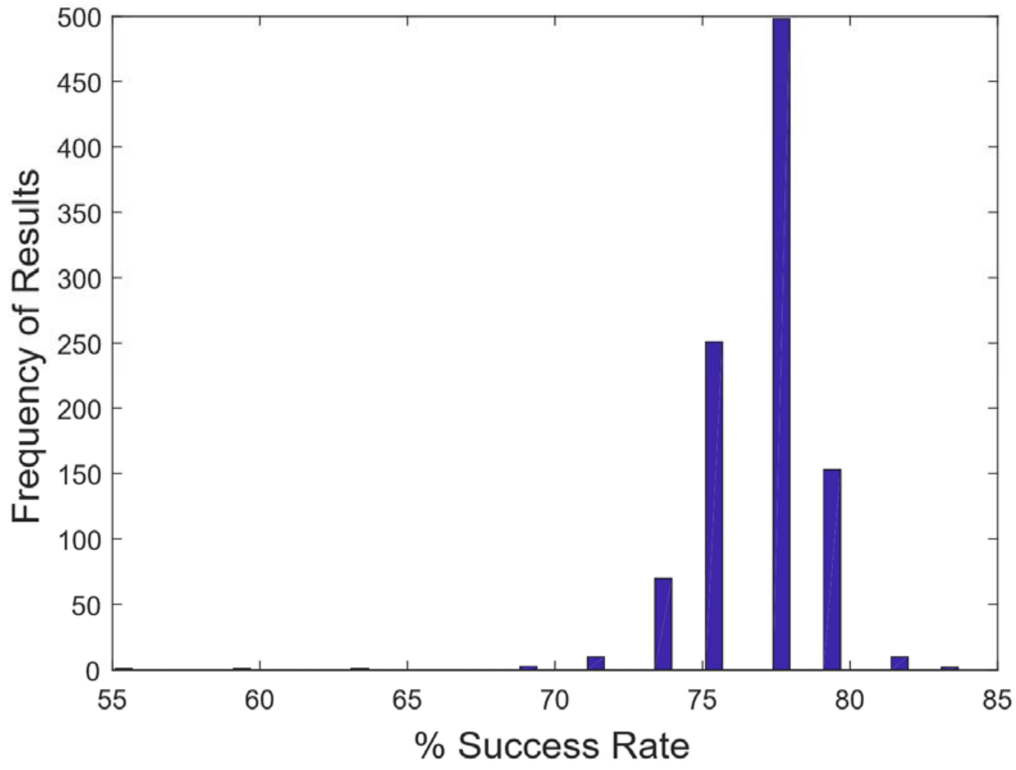
For the case where half of our specimens are unlabelled, this is the histogram of the resulting success rates:



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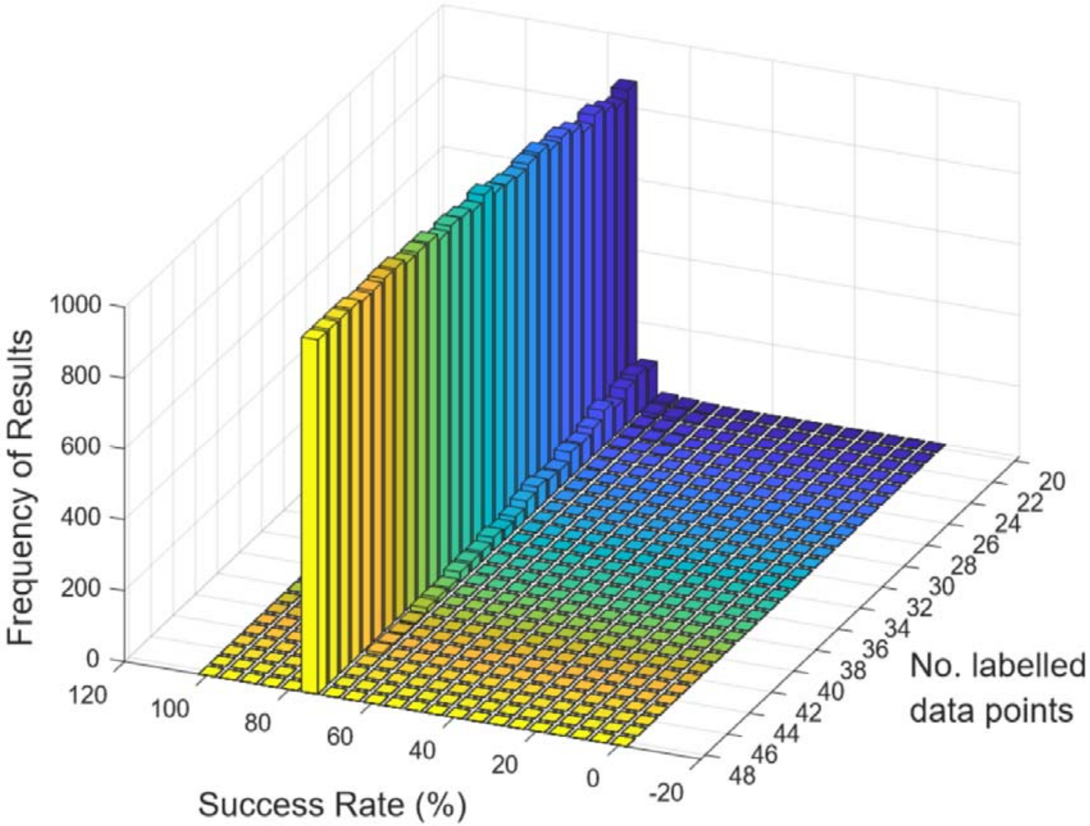
Finally, we conducted this for different numbers of labelled and unlabelled data:



It is encouraging that there is no sudden ‘drop off’ in performance.

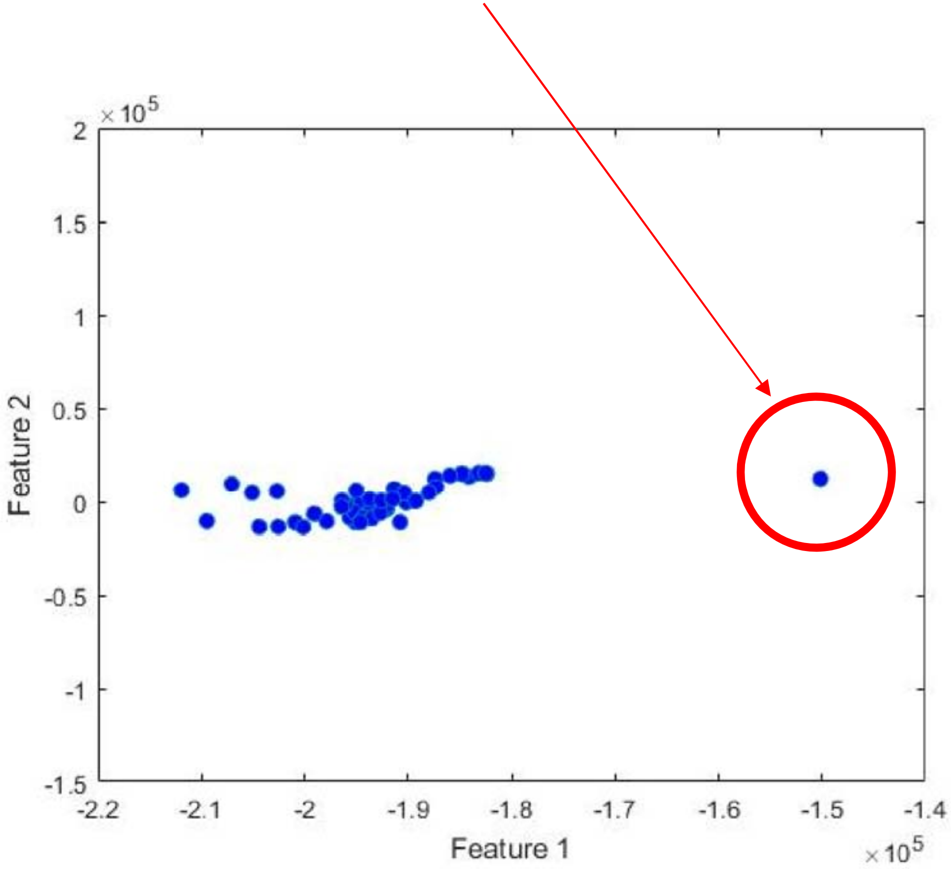
New Results

- So far we have classified specimens after the builds have finished.
- Moving towards machine-learnt control we would like to identify faults *layer-by-layer*.
- This will allow us to take *corrective actions*.
- It will also give us a much ‘richer’ dataset (more data points, essentially).
- We now have builds where faults are deliberately introduced at certain layers.
- We are trying to detect these flaws automatically using data-based techniques.

New Results

Here, each data point corresponds to a layer.

We are automatically detecting a layer where 10% less powder was deployed.



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- Has led to 3 PhD projects (including 1 Risk CDT and 1 Risk+AM CDT).

Thank you for your attention.

ANY QUESTIONS?

p.l.green@liverpool.ac.uk

liverpool.ac.uk/engineering/staff/peter-green/

Peter_Green17

@plgreen4

UNIVERSITY OF LIVERPOOL