Equipment Failure Prediction

How Machine Learning can help prevent it

- What is equipment failure?
- How can we avoid it?
- The data
- How is success measured?
- Model interpretation
- Feature importance
- Business impact

Equipment failure

When machinery doesn’t work the way they’re expected, it’s considered failure. When failure happens, it can cause multiple unwanted consequences, such as:

- human injury,
- machinery damage,
- decrease of productivity, etc

All of these consequences come at a financial cost.

How can we avoid failure?

Predictive Maintenance

Taking action to avoid failure can save money and avoid unnecessary risk to the companies and employees.

Predicting when an equipment needs maintenance before it reaches failure is the key to avoid such costs and risks, reducing downtime and increasing productivity.

Machine Learning comes in handy at this task. The models are trained on a massive amount of data produced by the machinery. That way engineers can be warned of an approaching breakdown and provide maintenance prior to the failure.

How do we know an equipment is about to fail?

Temperature

Pressure

Vibration X

Vibration Y

Vibration Z

Frequency

How do we know an equipment is about to fail?

- Temperature
- Pressure
- Vibration X
- Vibration Y
- Vibration Z
- Frequency

independent variables

How do we know an equipment is about to fail?

Temperature

Pressure

Vibration X

Vibration Y

Vibration Z

Frequency

independent variables

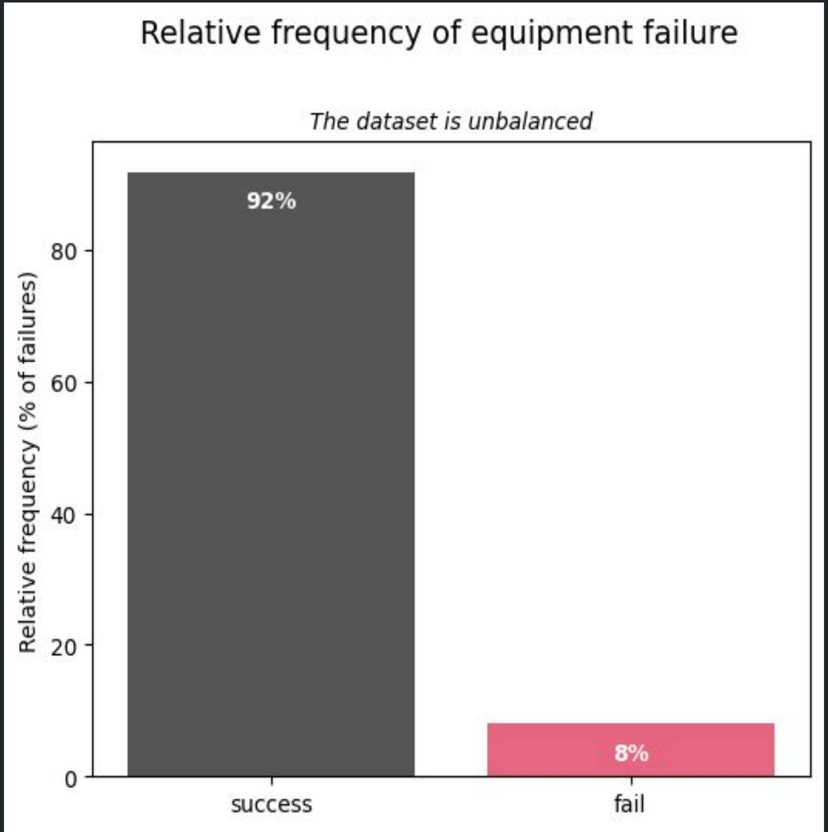
Fail

target variable

Challenge: unbalanced dataset

Most of the time, the equipment is not failing. This means we have a highly unbalanced dataset.

On the other hand, the machine learning model is sensitive to this so it is something to keep in mind (might need to be handled).



How can we measure success?

Evaluation Metric: business based

The evaluation metric should be determined before model development to make sure we have the business interest well defined from the start.

The business is what will determine how we measure success.

With this in mind, accuracy is not an appropriate metric for unbalanced classification problems as we can get a pretty great accuracy score with a simple Dummy Classifier that always predicts the larger class, that is the equipment isn't failing. That wouldn't be very helpful so we need a better metric.

Evaluation Metric: business based

	Predicted success	Predicted fail
Success	True Negative	False Positive
Fail	False Negative	True Positive

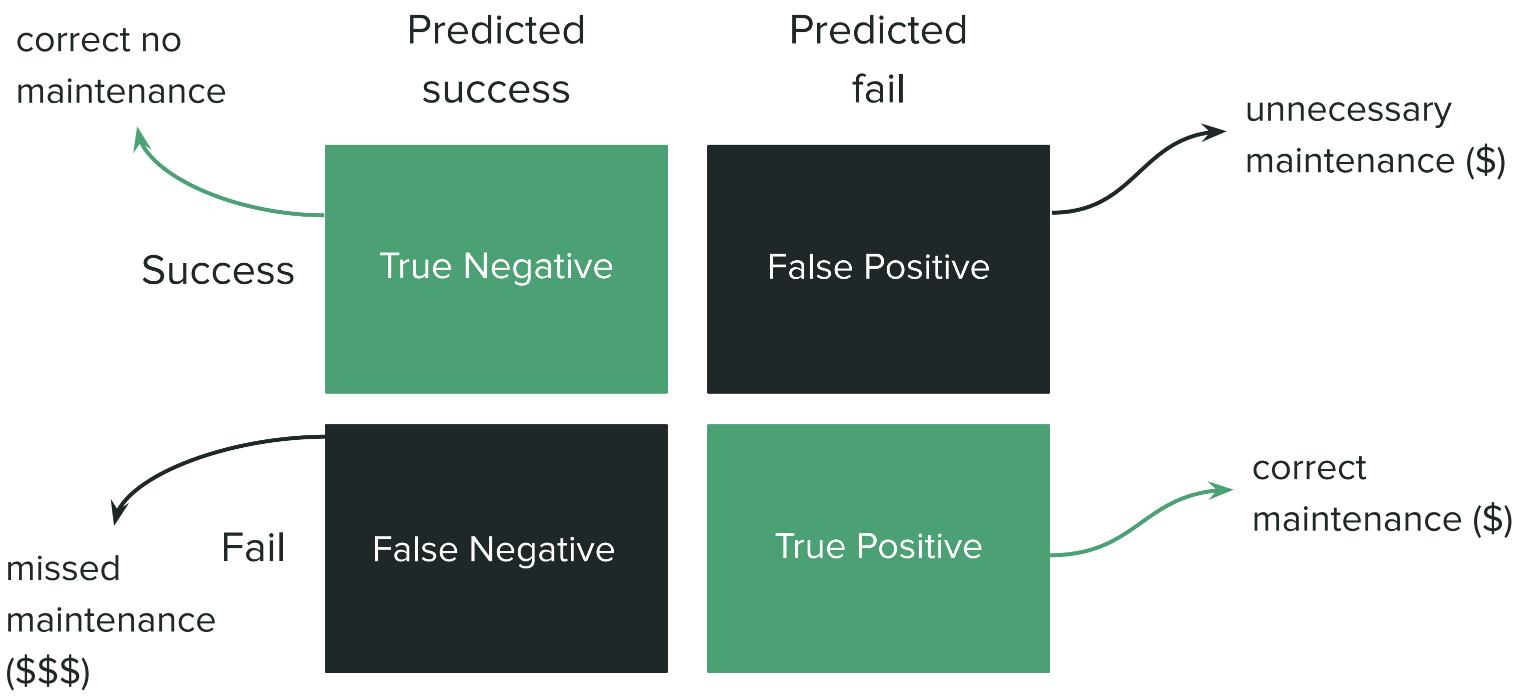
Evaluation Metric: business based

correct no maintenance

	Predicted success	Predicted fail
Success	True Negative	False Positive
Fail	False Negative	True Positive

correct maintenance ($)

Evaluation Metric: business based



Evaluation Metric: business based

Lower classification threshold → **higher recall** (more likely to correctly identify failures)

Recall: out of all the fail samples, how many did we correctly classified as failures?

It also means we can come across some **false positives**, that is, predict that the equipment is about to fail when it's actually not. This can cause some unnecessary maintenance that comes at a cost.

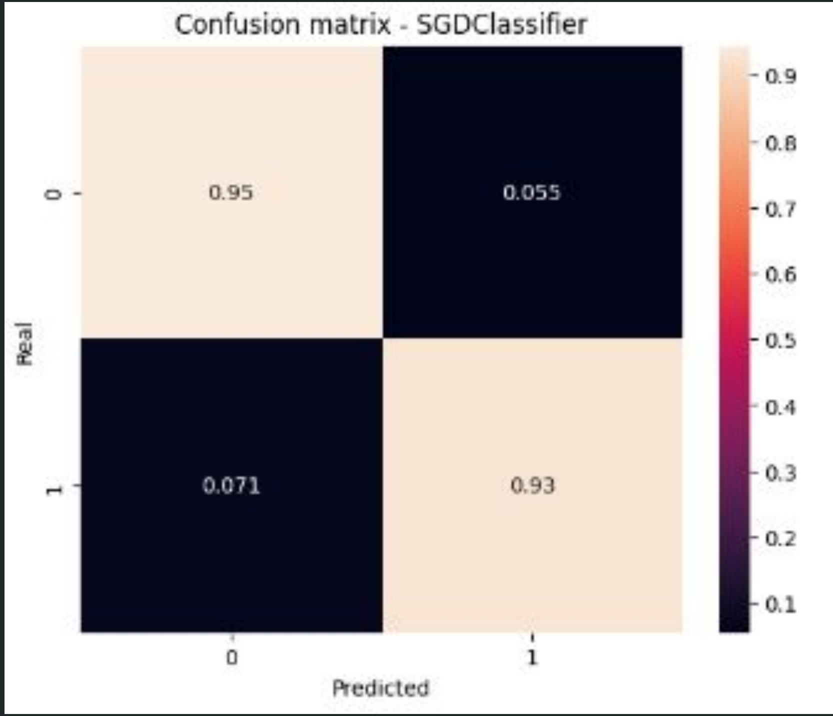
It’s also important to track **f1 score** which is basically the harmonic mean between recall and precision. This way we don't lose track of how much we're hurting precision in order to improve recall, meaning how much unnecessary maintenance we’re providing in order to not miss a single failing equipment.

The model

SGD Classifier model

False Negative
7.1% of 14 samples = ~1
Misclassified 1 data point of the fail class.

False Positive
5.5% of 146 samples = ~9
Misclassified 9 data points of the success class.



Model interpretation

When we calculate the exponential of each coefficient, we get the odds ratio.

The **odds ratio** is the probability of the equipment failing over probability of equipment not failing.

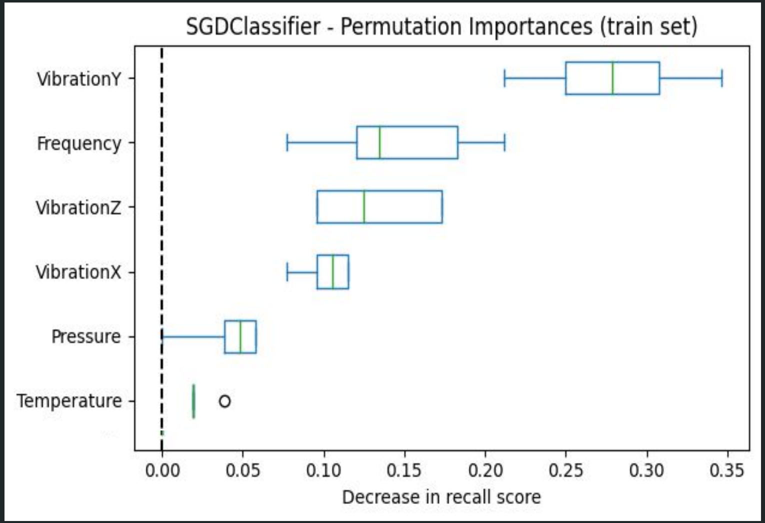
The odds ratio indicates how likely the event (fail of the equipment) is to occur when each independent feature changes.

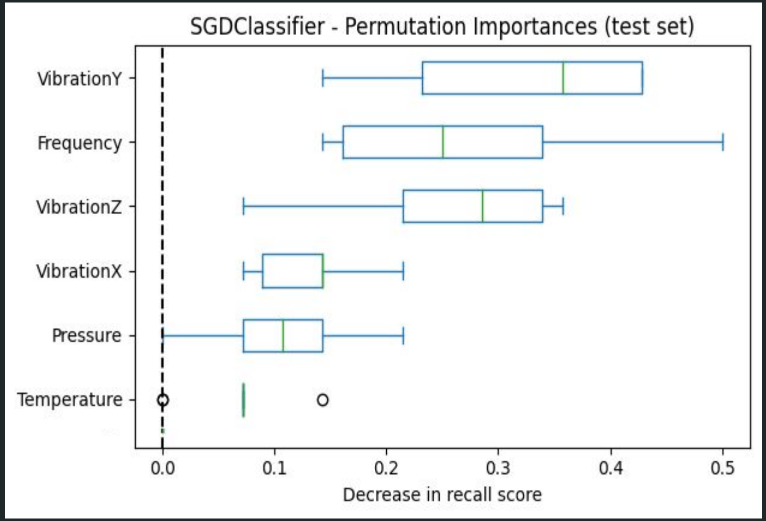
Feature	more likely to fail
Temperature	1.48 x
Pressure	1.61 x
VibrationX	1.85 x
VibrationY	2.62 x
VibrationZ	1.97 x
Frequency	2.08 x

Feature importance by permutation

Technique that shuffles a feature to see how that affects the model prediction.

The change in prediction will be correspondent to the feature importance.

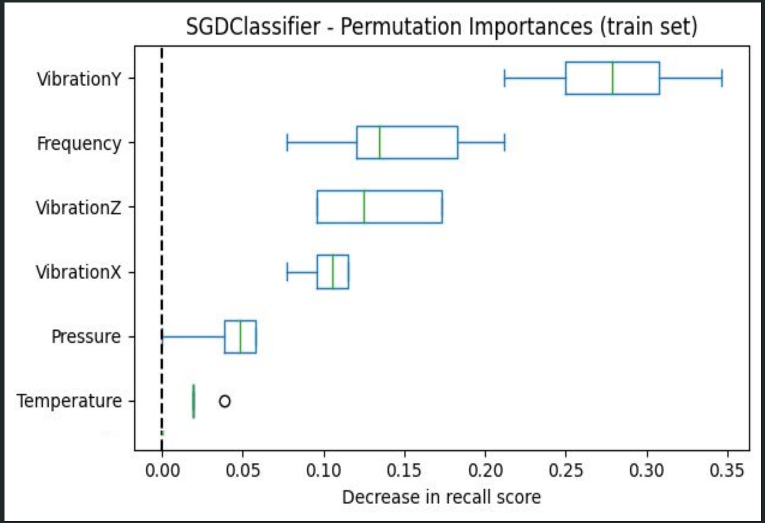


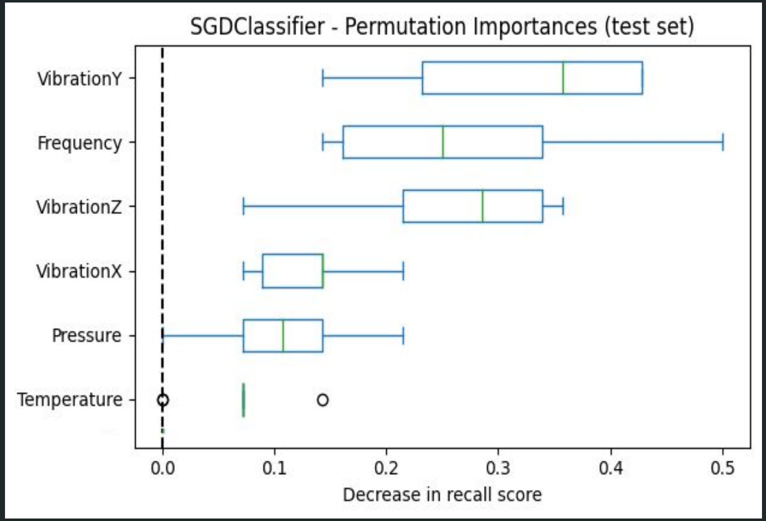


Feature importance by permutation

VibrationY is the most impactful feature for this model.

No significant sign of overfitting as the important features are the same in both sets.





What does it mean for the business?

Business impact

Hypothetically speaking, let’s assign a cost to maintenance and failure.

Maintenance cost

$ = 1

Failure cost

$$$ = 3

Business impact

No model

8% of the time the machine will fail

8% of 160 = 14 failures x $3 = $42

Total = $42 / machine

Model

13 maintenance x $1 = $13

1 FN failure x $3 = $3

9 FP maintenance x $1 = $9

Total = $25 / machine

Business impact

No model

Total = $42 / machine

Model

Total = $25 / machine

> 40% cost reduction

Thank you!

Marina Villaschi