

ARUNDO

Applied Machine Learning for Anomaly Detection on Equipment

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9:00 - 9:30	Welcome & Introduction to Anomaly Detection
9:30 - 10:00	Set-up environment
10:00 - 10:30	Walk through examples of AD methods in Jupyter notebooks
10:30 - 12:00	Improve models

----- LUNCH BREAK -----

13:30 - 14:00	Introduction to deployment
14:00 - 15:30	Continue to improve model & deploy to cloud
15:30 - 16:00	Make sure final model is deployed
16:00 - 16:30	Review the results and wrap-up

BUZZWORD BINGO

Digital
Transformation

Operational
Intelligence

Streaming
Analytics

IT Operations
Analytics

Industry 4.0

Blended
Analytics

Increase efficiency and productivity



Data is the
jetfuel



Decrease downtime

Unexpected downtime on a single asset can cost upwards of a million dollars per day

INTERCONNECTED AMBITIONS



Increase efficiency

Increase profits despite a decreasing price per barrel



Scalable, actionable insight

Make models which can be easily applied to the company's entire portfolio

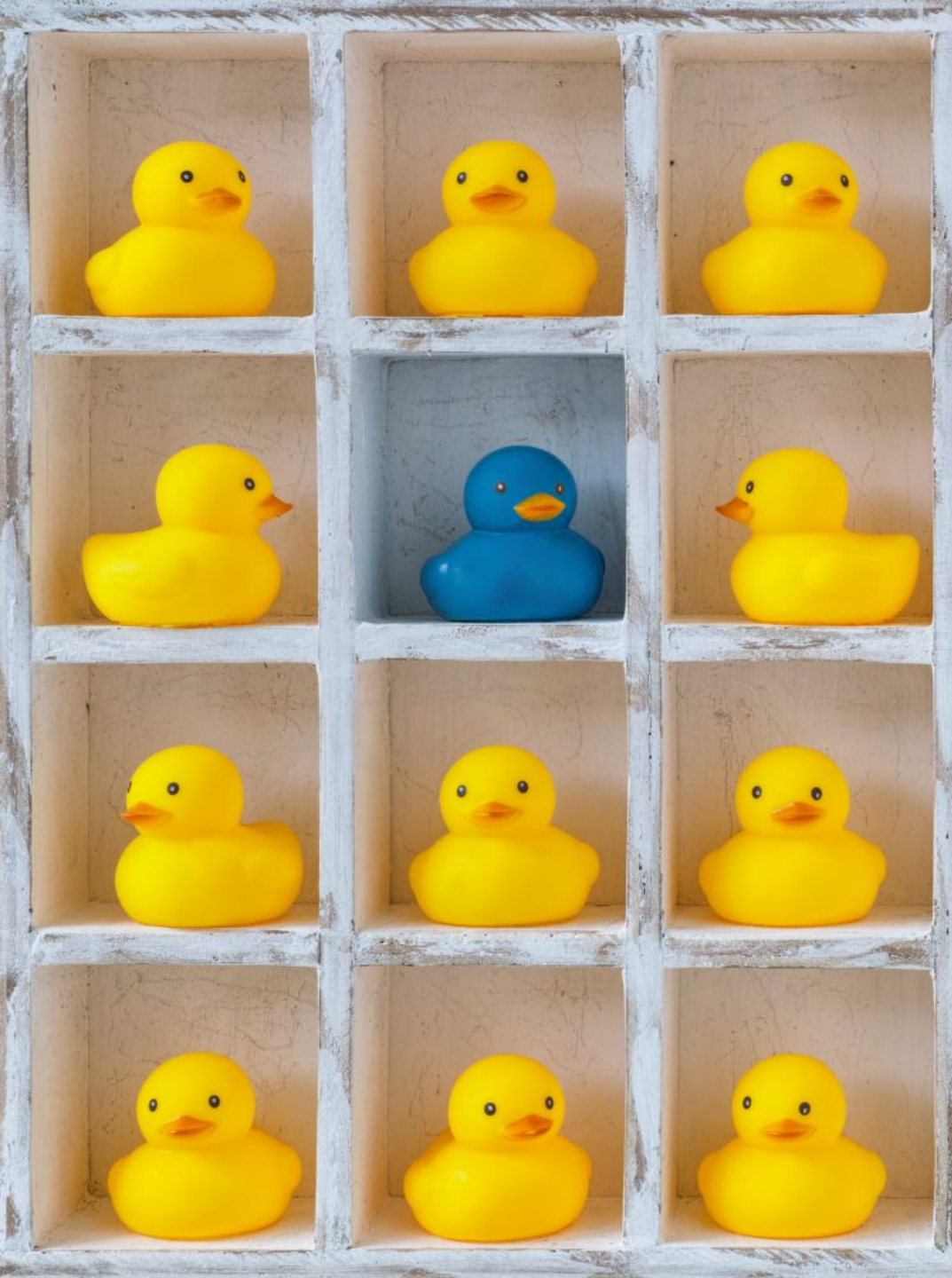
ARUNDO

provides software products to **enable**
enterprise-scale machine learning and advanced
analytics applications for **industrial companies**



A large colony of brown penguin chicks is shown, with a single adult King penguin standing out in the center. The adult penguin has a blue-grey body and a yellow-orange crest. The text "What is an anomaly?" is overlaid on the image.

What is an anomaly?



**“DATAPOINTS, ITEMS,
OBSERVATIONS OR EVENTS
THAT DO NOT CONFORM TO
THE EXPECTED PATTERN”**

Examples of anomaly detection



Health
monitoring



Video
surveillance



Equipment
monitoring



Fraud
detection

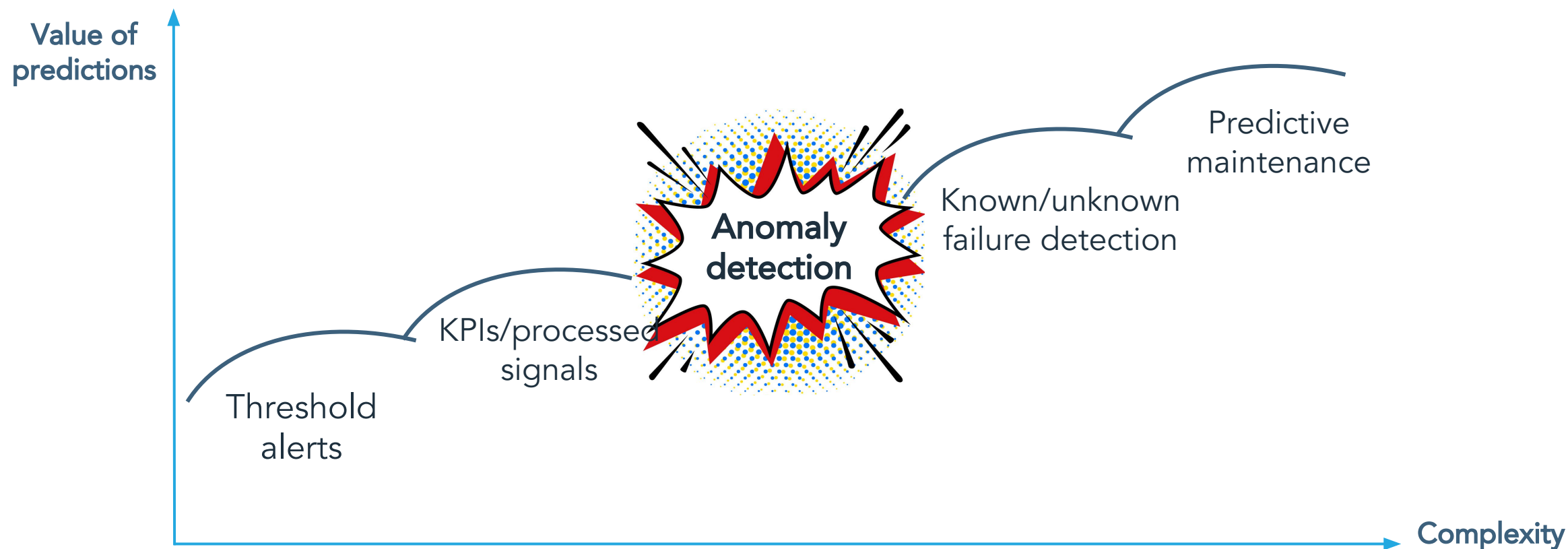


Intrusion
detection



Spam
filtering

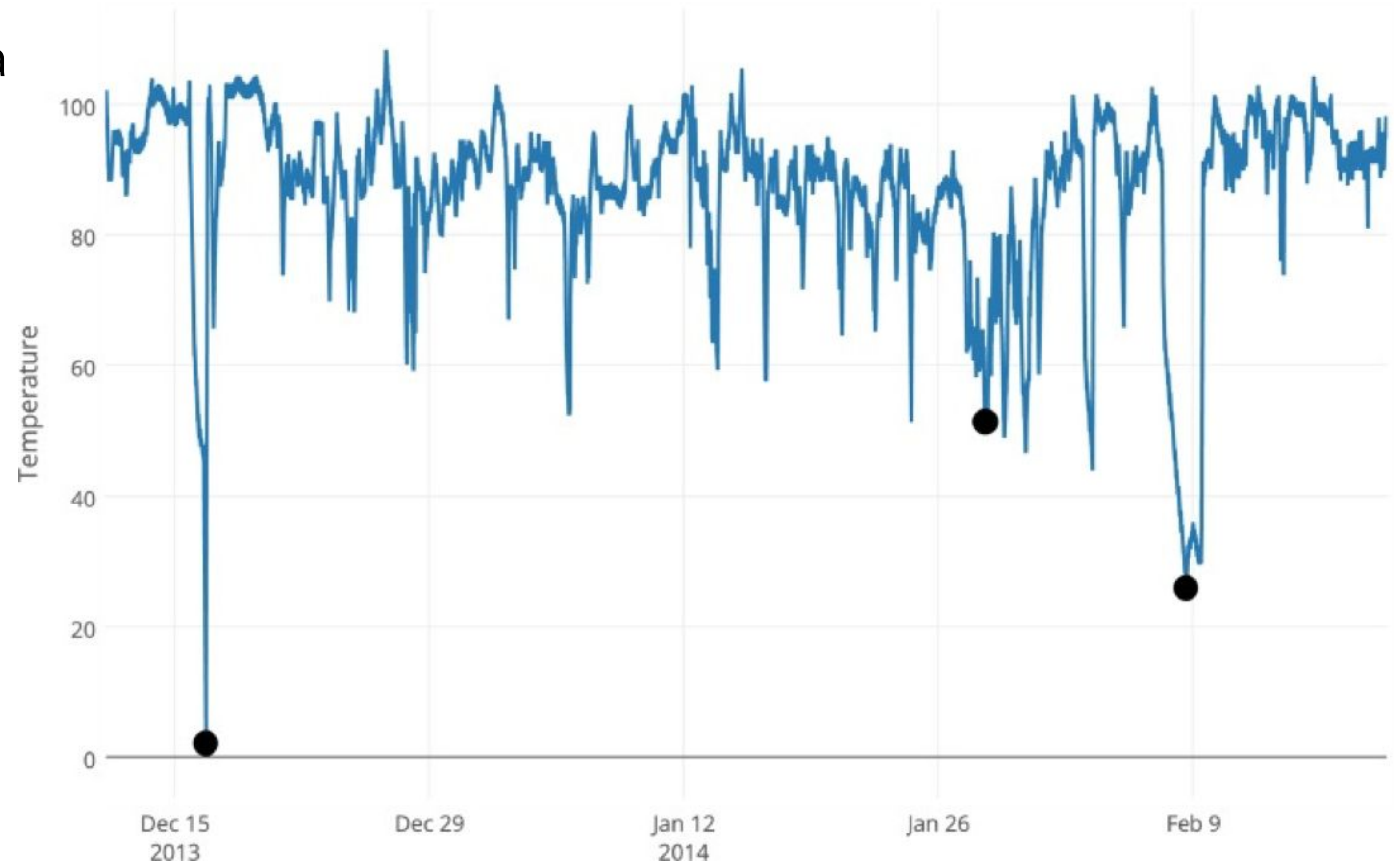
The stages of data-driven equipment monitoring



Anomaly detection in **equipment monitoring**

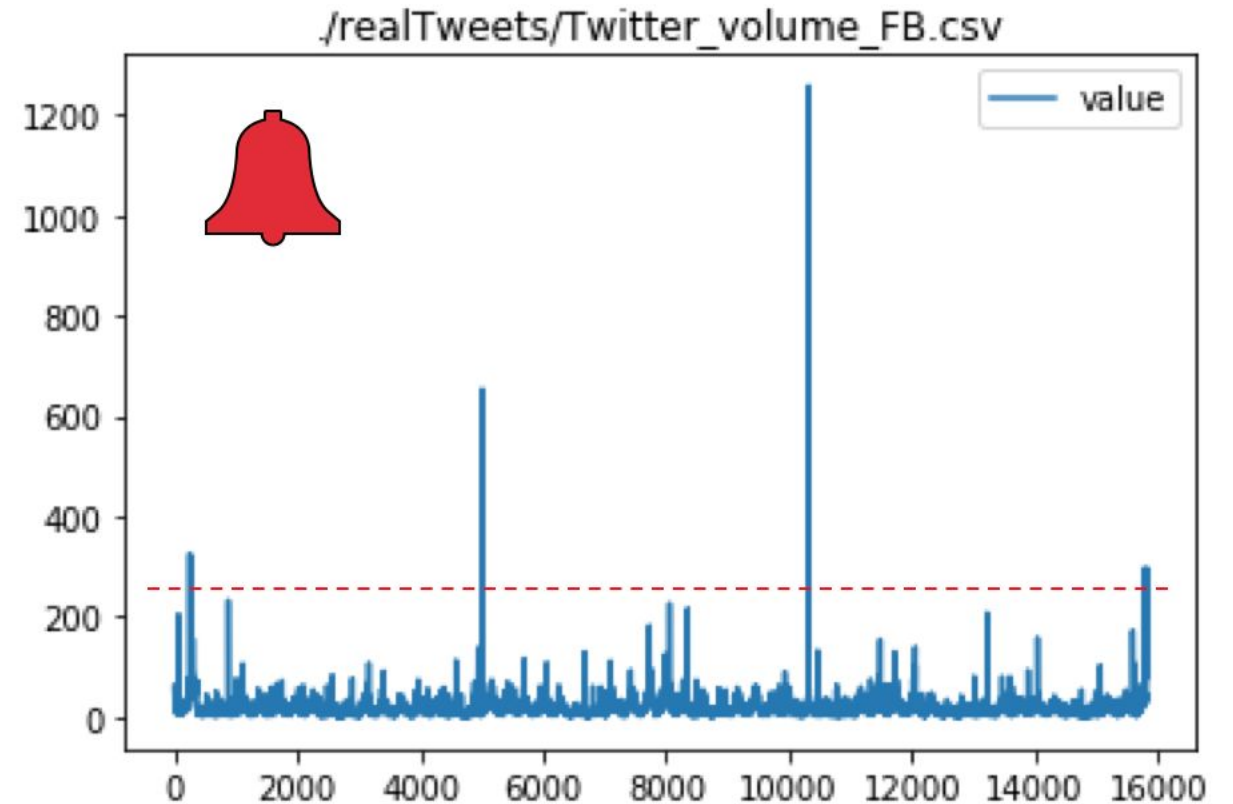
Previously unseen patterns can be a sign of:

- **misconfiguration**
- increasing mechanical **wear-out**
- **unforeseen** situations



How can you detect anomalies?

- Define a threshold for each sensor channel
- Raise a notification once a specified threshold is violated





An oil rig can have upwards of 15.000 sensors
(the newest have more than 50.000 sensors!!!)

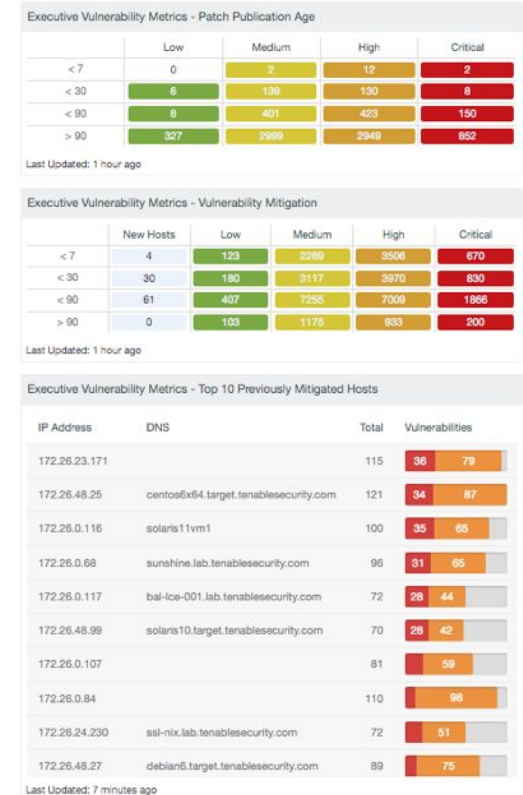
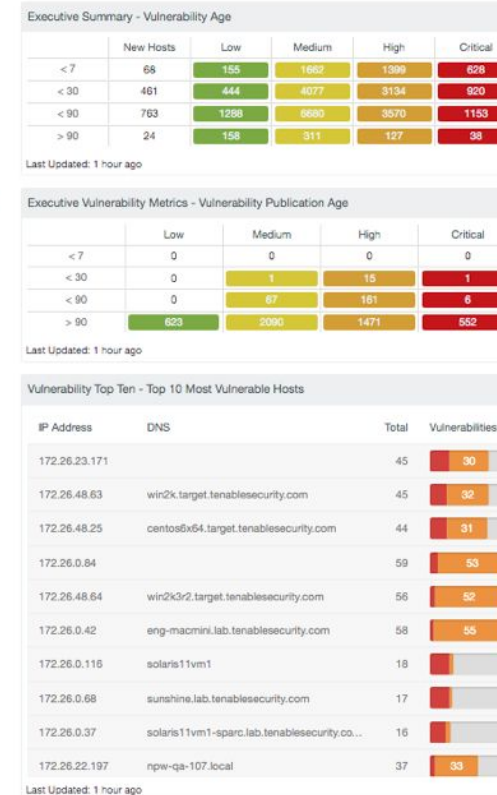
How can you detect anomalies?

- Causes many false alerts
- Does not take into account the joint characteristics of multiple channels



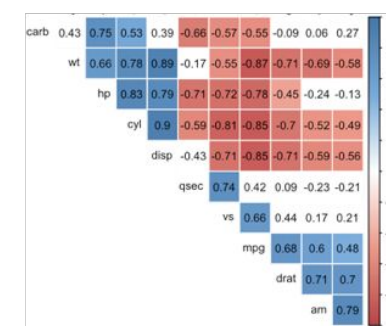
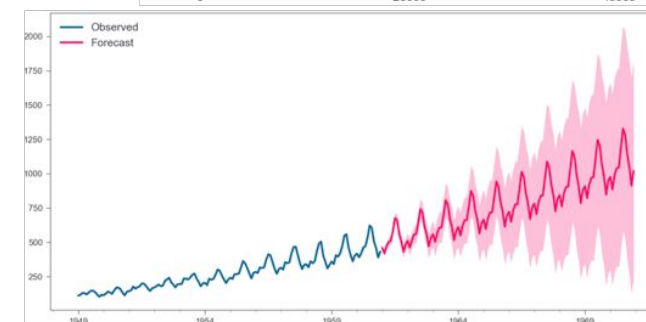
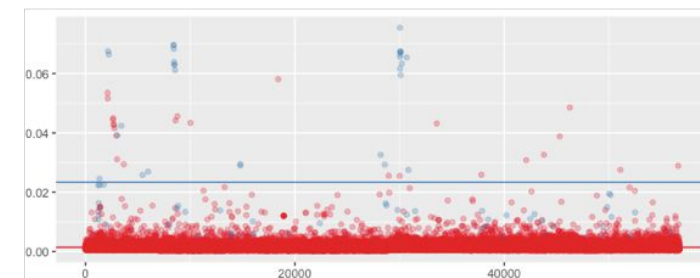
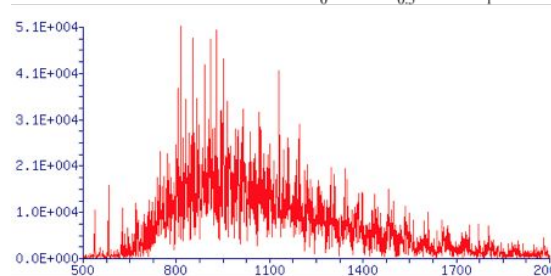
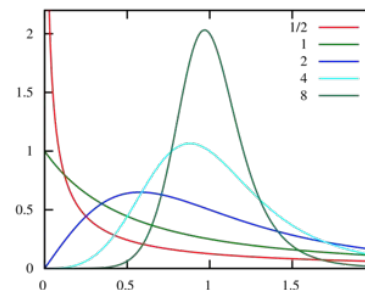
Manual analysis is immensely time-consuming and unreliable

- **Massive** amount of multi-sensor data
- **Complex** systems
- **Rare** faults



Multivariate anomaly detection

- No prior knowledge about anomalies
- No precise boundary
- Data often contain noise
- Normal behaviour keeps evolving
- Temporal dependencies
- Highly unbalanced classes
- High dimensionality and multimodal dependencies

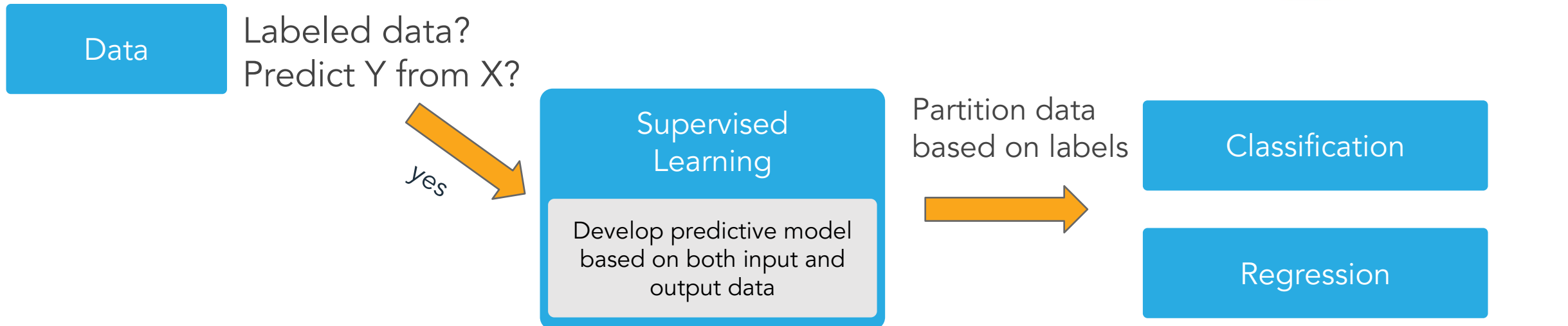


Approaches

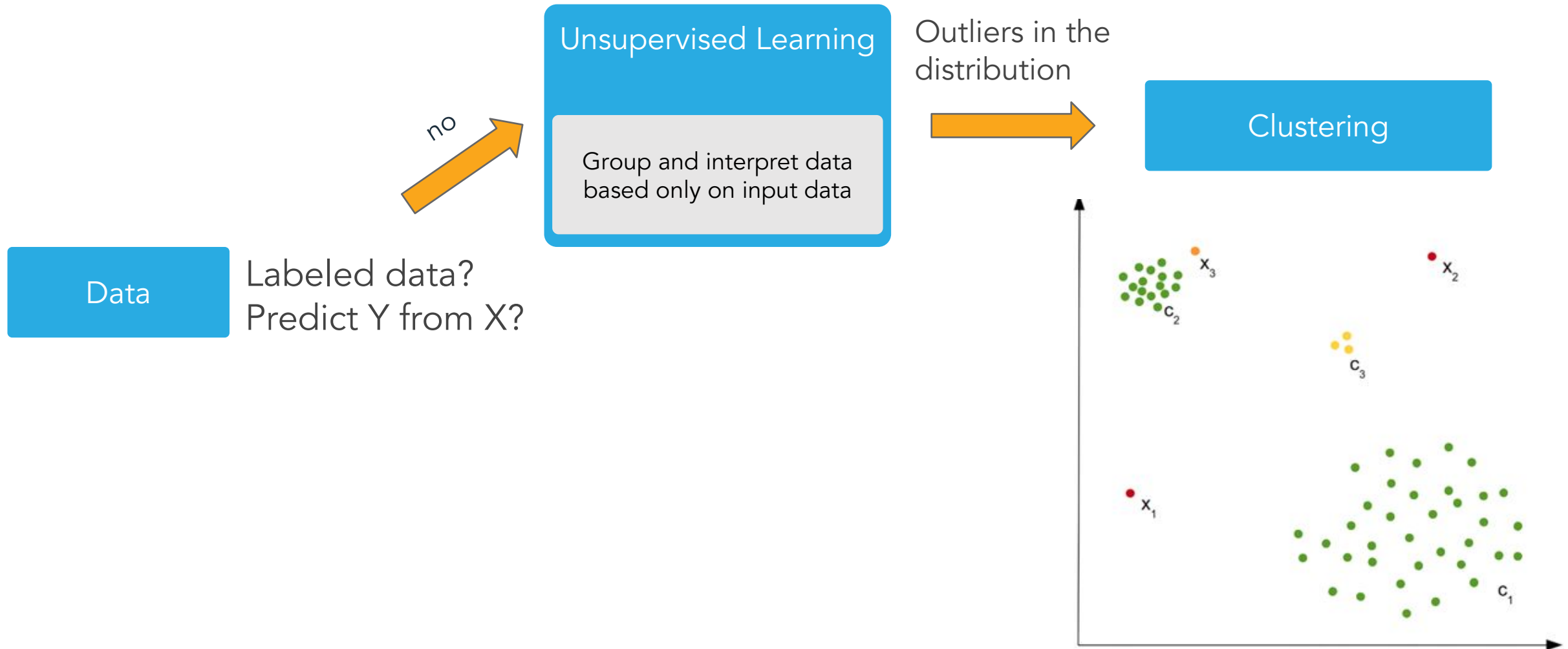
Data

Labeled data?
Predict Y from X?

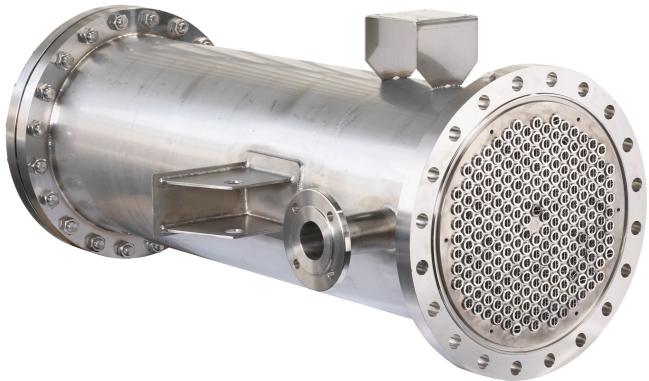
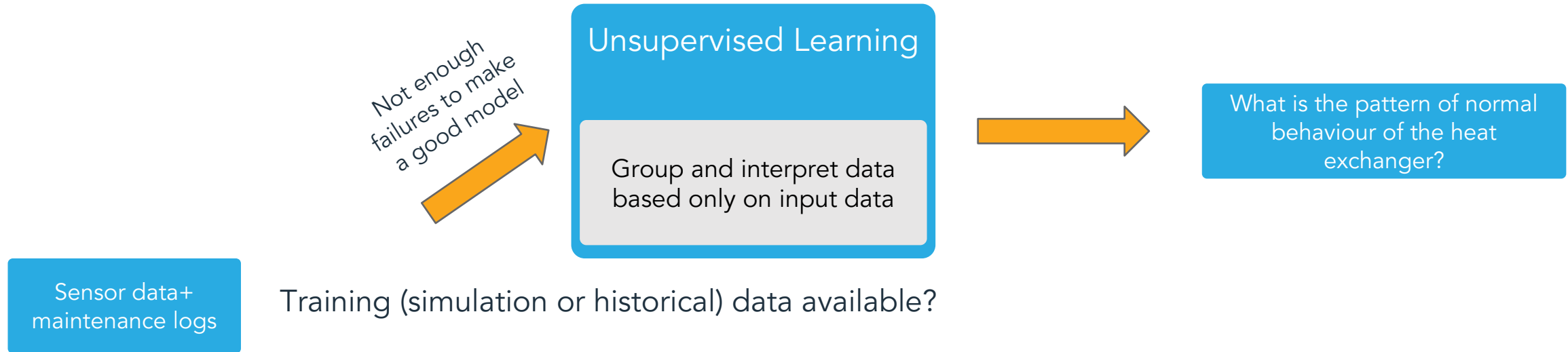
Approaches



Approaches



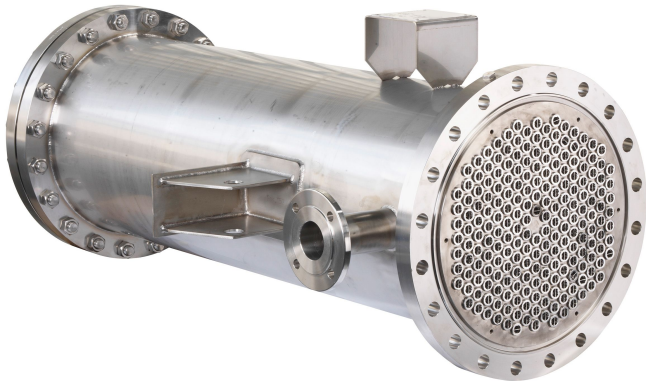
Real life example - Leakage on heat exchangers



Real life example - Leakage on heat exchangers

Sensor data+
maintenance
logs

Training (simulation or historical) data available?



Yes but not a
lot of failures

Supervised
Learning

Develop predictive model
based on both input and
output data

discrete

Has my heat exchanger sprung
a leak?

continuous

What is the predicted
performance of my heat
exchanger?

Approaches

Supervised Methods

Random Forest

Support Vector Classification

KNN Classifier

Logistic Regression

Unsupervised Methods

One Class SVM

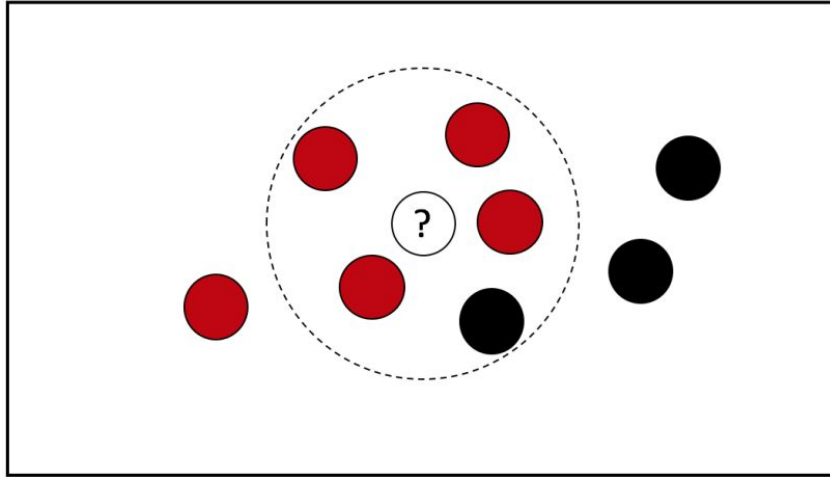
Isolation Forest

Elliptic Envelope

Local Outlier Factor

Autoencoder

k -NN Classifier



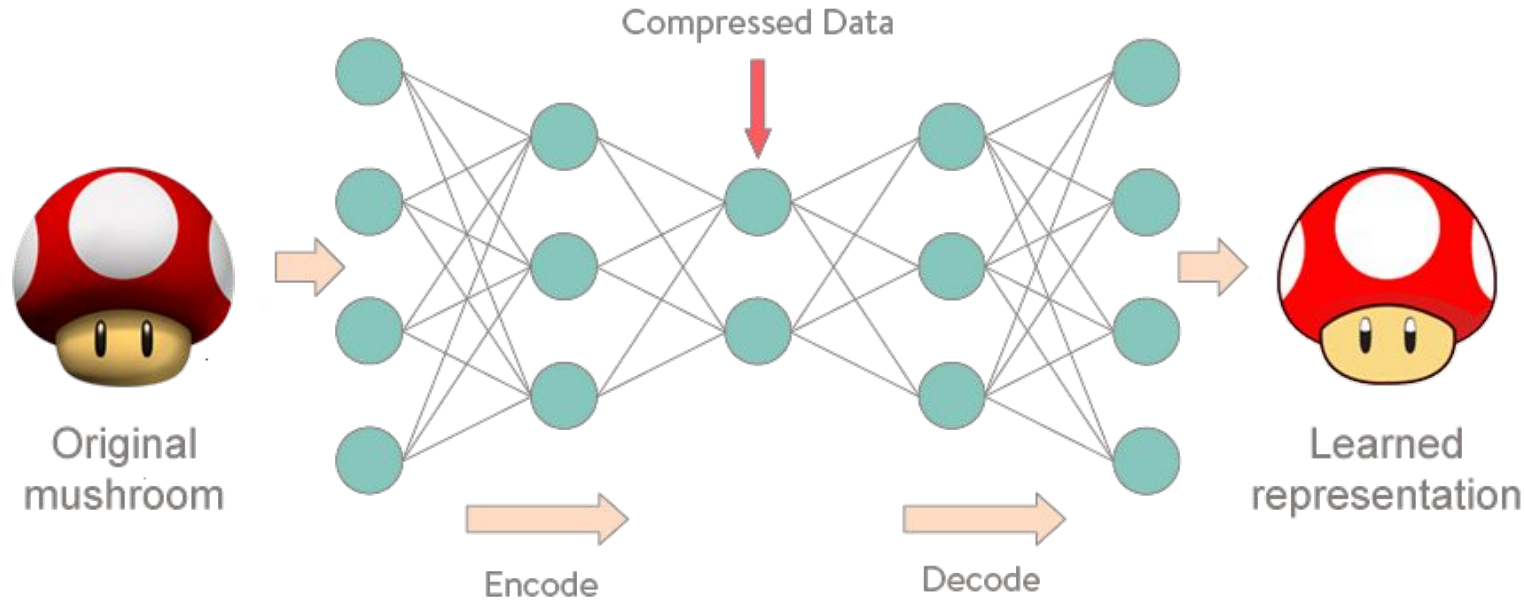
k -NN classifies a data point based on how its neighbors are classified.

If a data point is surrounded by 4 red points and 1 black point, that data point is likely a red point by majority vote.

Tune for k - the number of nearest neighbors to include in the majority voting process



Autoencoders



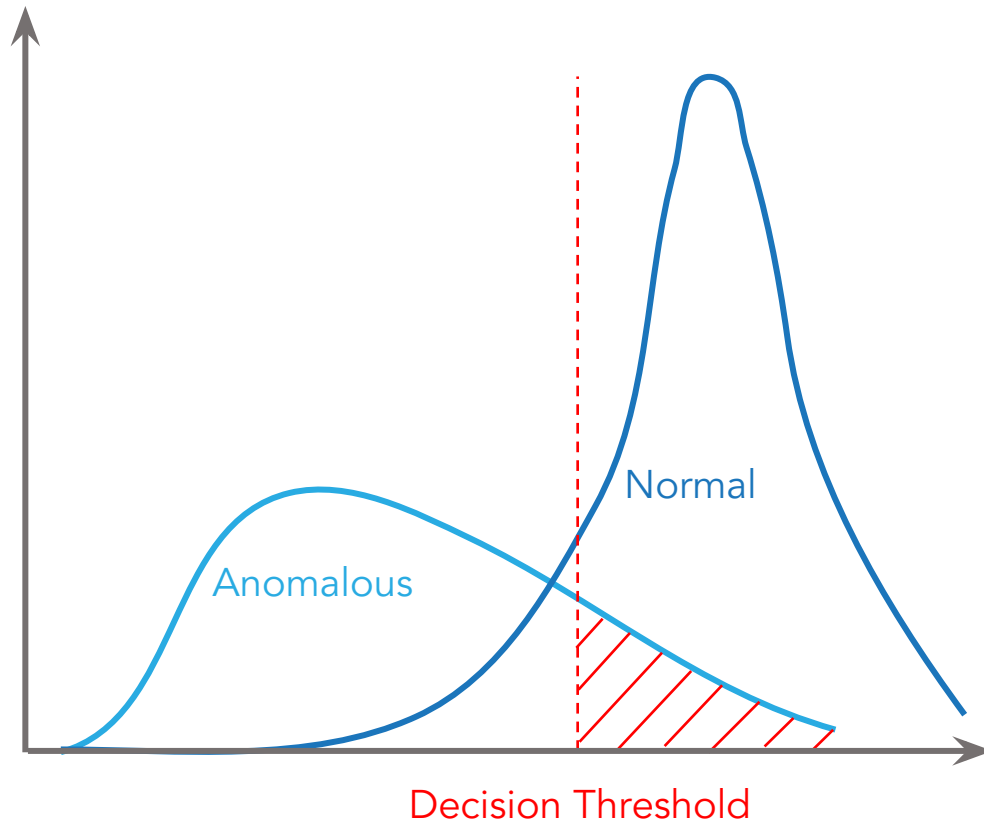
The job of those models is to predict the input, given that same input.

Learns a representation of the training data and recreates the input at the output layer.

Used for data compression and learning generative models from data.

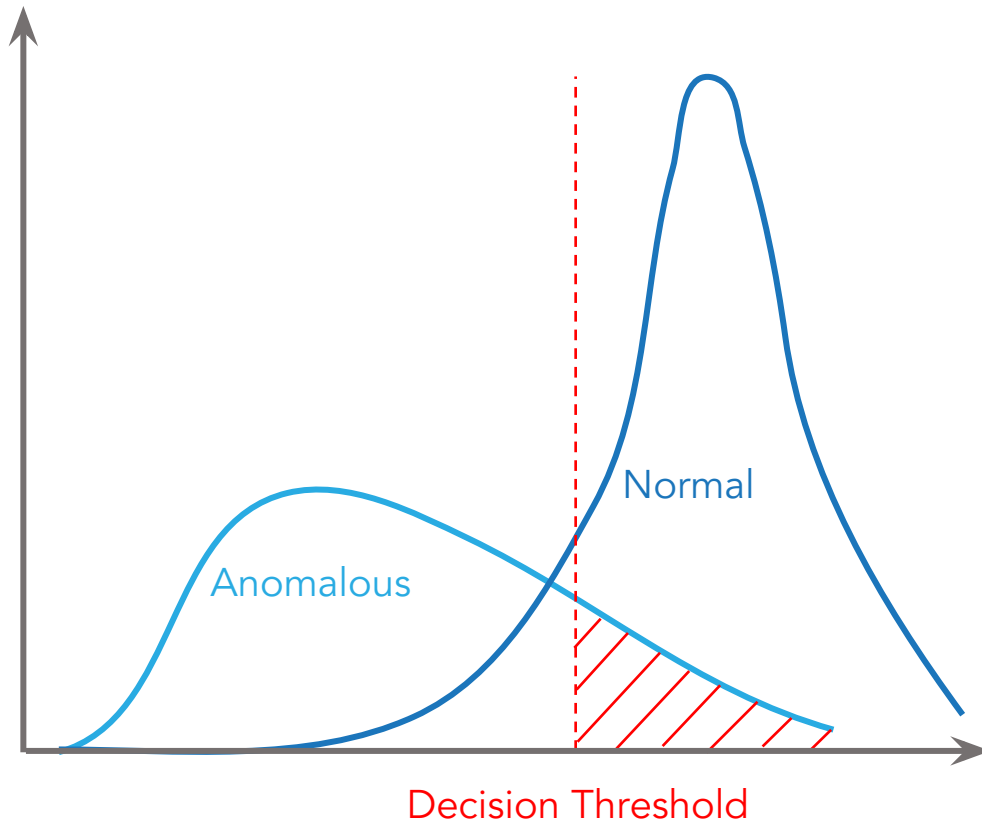
We optimize the parameters of our Autoencoder model in such way that the reconstruction error is minimized.

Machine Learning Predictions are not 100% Accurate



- False positives (ML predicts anomalous but system is normal) can and will occur
- False negatives (ML predicts normal but system is anomalous) can and will occur

Machine Learning Predictions are not 100% Accurate



- Choose trained algorithms which minimize these effects as much as possible
- Identify any additional sources of data which may further help minimize these effects
- Evaluate the expected probabilities of each scenario using independent historical data
- Retrain the system if there is evidence that probabilities change significantly with time

Workshop details

Task

- Make a model to identify anomalies based on the dataset provided
- The model will be tested on a separate test dataset
- The best model will be chosen based on f1score

Practicalities

- Share e-mail via: goo.gl/forms/HY29cLwsqxiCJAMe2
- Log on to jupyter hub using your github account
 - appliedml-lausanne-2019.arundo.com

Notebooks

- Opening and looking at the data
 - [01-Model Development](#)
- Model deployment
 - [02-Model Deployment](#)
- Please add comments to explain your code where possible