### Case Study - AutoML for Robust Anomaly Detection

Simon Kluettermann

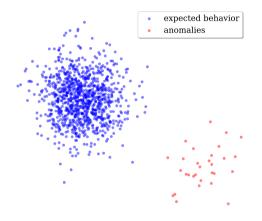
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14. September 2022

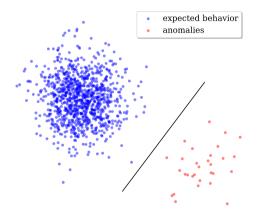
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# Anomaly Detection

- Two distributions
  - One known (=normal)
  - One unknown (=anomalies)
- Seperate them

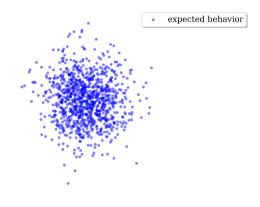


- Two distributions
  - One known (=normal)
  - One unknown (=anomalies)
- Seperate them
- Problem: few anomalies



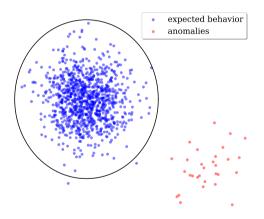
## Anomaly Detection

- Anomalies are rare, so often only a few datapoints known (e.g. Machine Failure in an Aircraft)
- In practice, anomalies might appear that are not known during testing
- $\Rightarrow$ So train the model only on normal samples
- Unsupervised Machine Learning
  - What can we say without knowing anomalies?
  - "Understand you dataset"

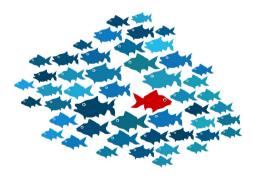


## Anomaly Detection

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- Seems easy? Now do this
  - in thousands of dimensions
  - with complicated distributions
  - and overlap between anomalies and normal points



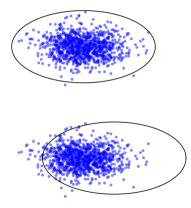
- Most machine learning requires Hyperparameter Optimisation
- (Find model parameters that result in the best results)
- ⇒AutoML: Do this automatically as fast as possible

# FLAML 1.0.12 pip install FLAML

from flaml import tune
tune.run(evaluation\_function, config={\_}, low\_cost\_partial\_config={\_}, time\_budget\_s=3600)

- So lets combine both (Auto Anomaly Detection)
- $\Rightarrow$  Problem
  - AutoMI requires Evaluation (loss, accuracy, AUC) to optimize
  - AD can only be evaluated with regards to the anomalies
  - $\Rightarrow$ no longer unsupervised
- So most Anomaly Detection is "unoptimized"

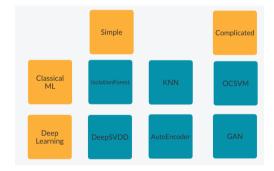
- So how to solve this?
- One option: Think of some function to evaluate only the normal points
- $\Rightarrow$  A bit hard to do in a case study



- So how to solve this?
- One option: "Just find the best solution directly"
- $\bullet \ \Rightarrow \mathsf{Zero} \ \mathsf{Shot} \ \mathsf{Auto}\mathsf{ML}$
- Find best practices for hyperparameters
- Requires optimisation for each model seperately  $\Rightarrow$  matches the case study structure quite well!

Course

- Basics of Scientific Computing
- Basics of AD
- Basics of AutoML
- Build groups for each algorithm
  - Choose a set of Hyperparameters
  - Find "best practice's" for them
  - Maybe consider more complicated Transformations (Preprocessing, Ensemble)
- Compare between groups (best algorithm for current situation)
- Evaluate on new datasets
- Write a report/Present your work



- Requirements:
  - MD Req 1 $\Rightarrow$ MD Req 8
  - Basic Python/Math Knowledge
  - Motivation to learn something new;)