Addressing Verification and Validation Challenges in Future Cyber-Physical Systems

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On Deploying Machine Learners into Embedded Systems

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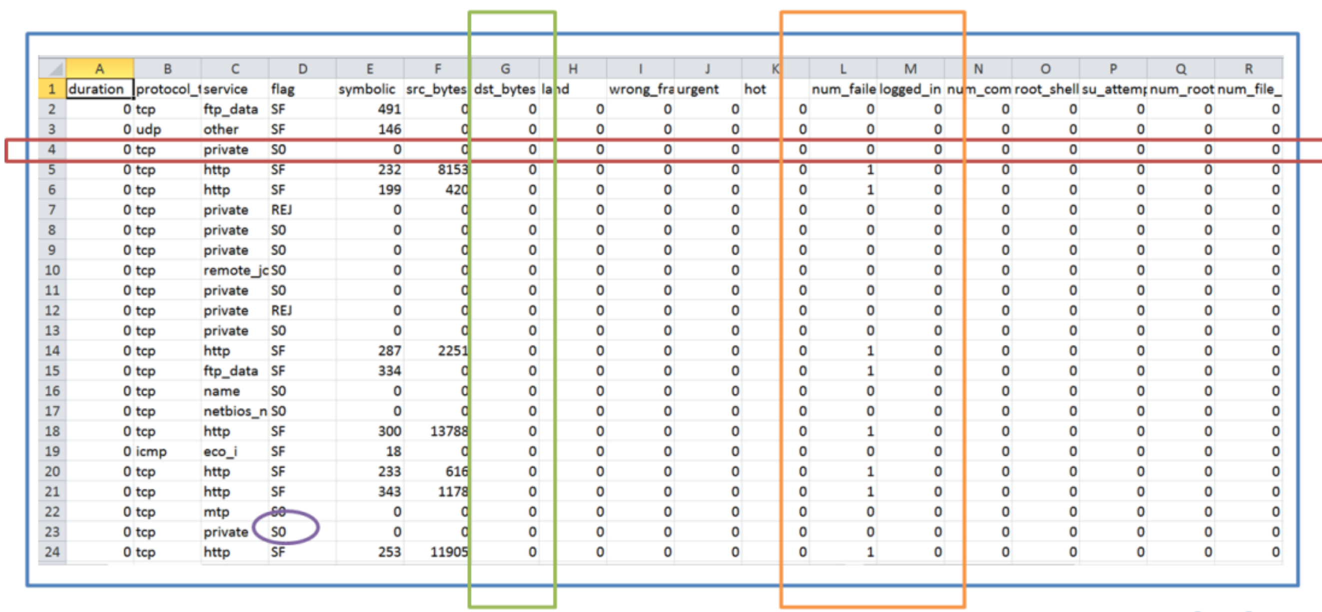
Tabular Data

- Embedded and General-Purpose systems often share the need of analysing tabular data
  - Features: system indicators (mainly networks)
  - Label: normal behavior or specific type of attack



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What Anomalies are?

Anomaly detection refers to the problem of finding patterns in data that do not conform to an expected behaviour[1]

[1] Chandola, Varun, Arindam Banerjee, and Vipin Kumar. "Anomaly detection: A survey." ACM computing surveys (CSUR) 41.3 (2009): 15.

Purpose of Anomaly Detectors

- Anomalies may have many root causes
  - Security threats
  - Misconfigurations
  - Performance Issues
  - Wrong/Slow interactions with other devices
  - Benign alterations

- Regardless of their root cause, it is always beneficial to detect them.

Embedding Anomaly Detectors

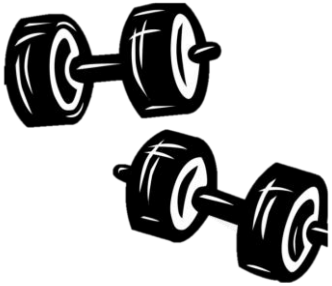
- Anomaly detectors usually rely on supervised/unsupervised ML algorithms
  - Which are usually resource and time-consuming
  - Not a huge problem for systems that do not have hardware or real-time constraints

BUT BUT BUT

- There always exists some kind of limitation to develop systems "in practise"
  - Thus, assuming "unlimited resources" is not doable

Then what?

- As a result, the best intrusion/error/anomaly detector or failure predictor for a given system must be chosen according to constraints:
  - Model size
  - Model speed
  - Detection performance
  - Availability of labelled data for training
  - …

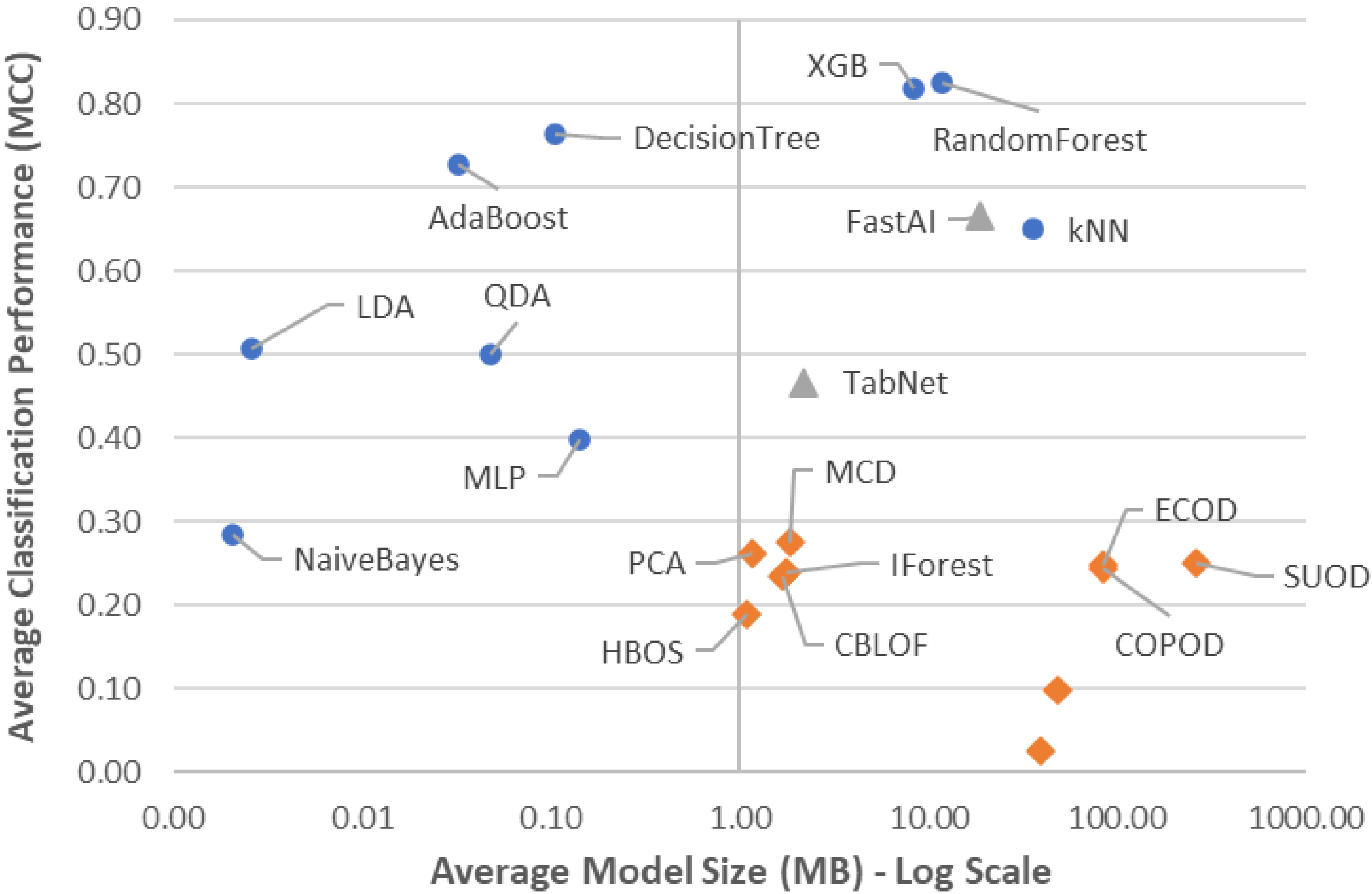


Snapshot of ML for tabular data

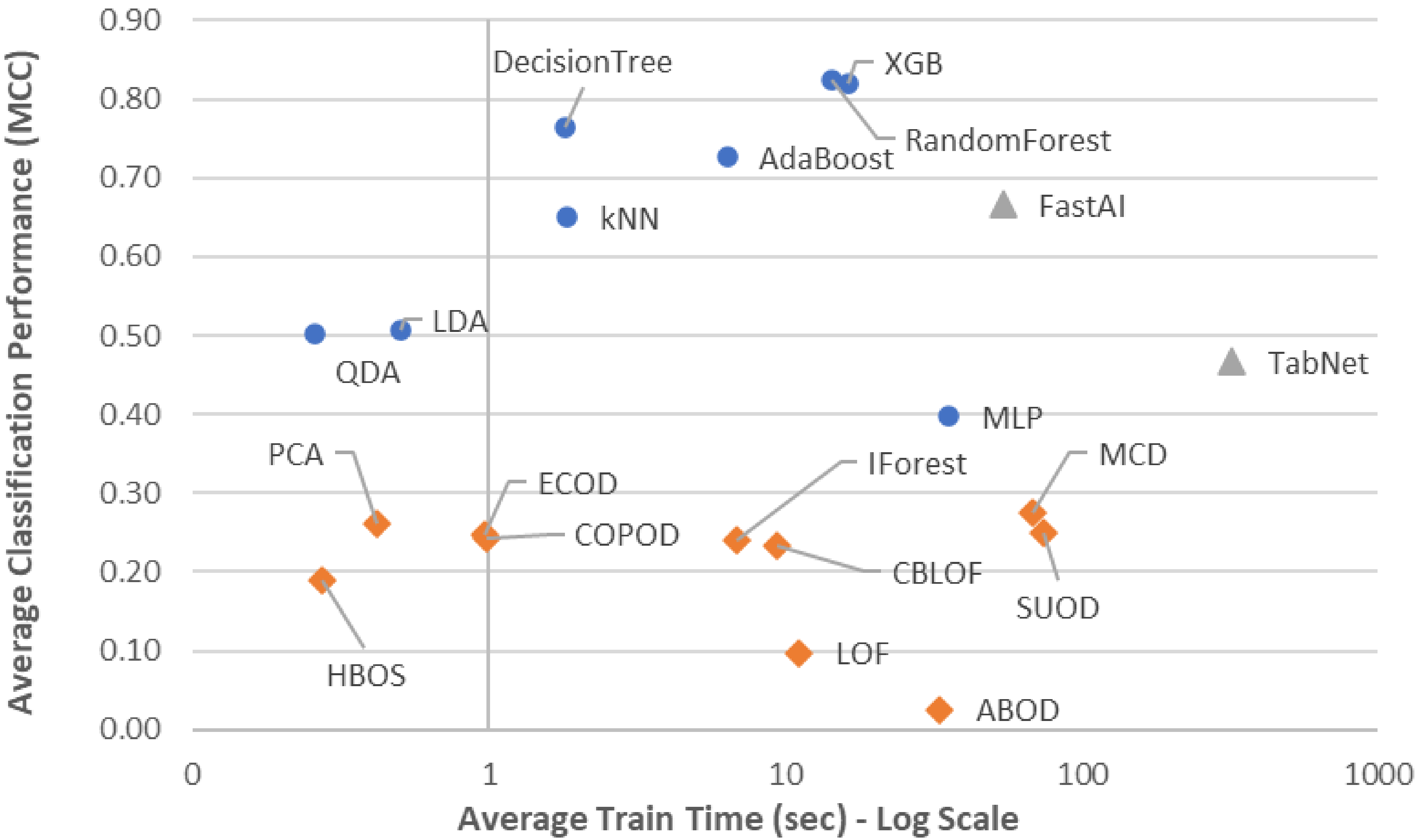
- That is why we took several SotA ML algorithms
  - Supervised: DecisionTree, RandomForest, XGB, NaiveBayes, LDA, kNN, MLP, AdaBoost, QDA
  - Unsupervised: COPOD, ABOD, HBOS, MCD, PCA, ECOD, LOF, CBLOF, Iforest, SUOD
  - Deep learning: TabNet, FastAI

- And we exercised them on a total of 33 datasets regarding critical systems to derive their average performance metrics

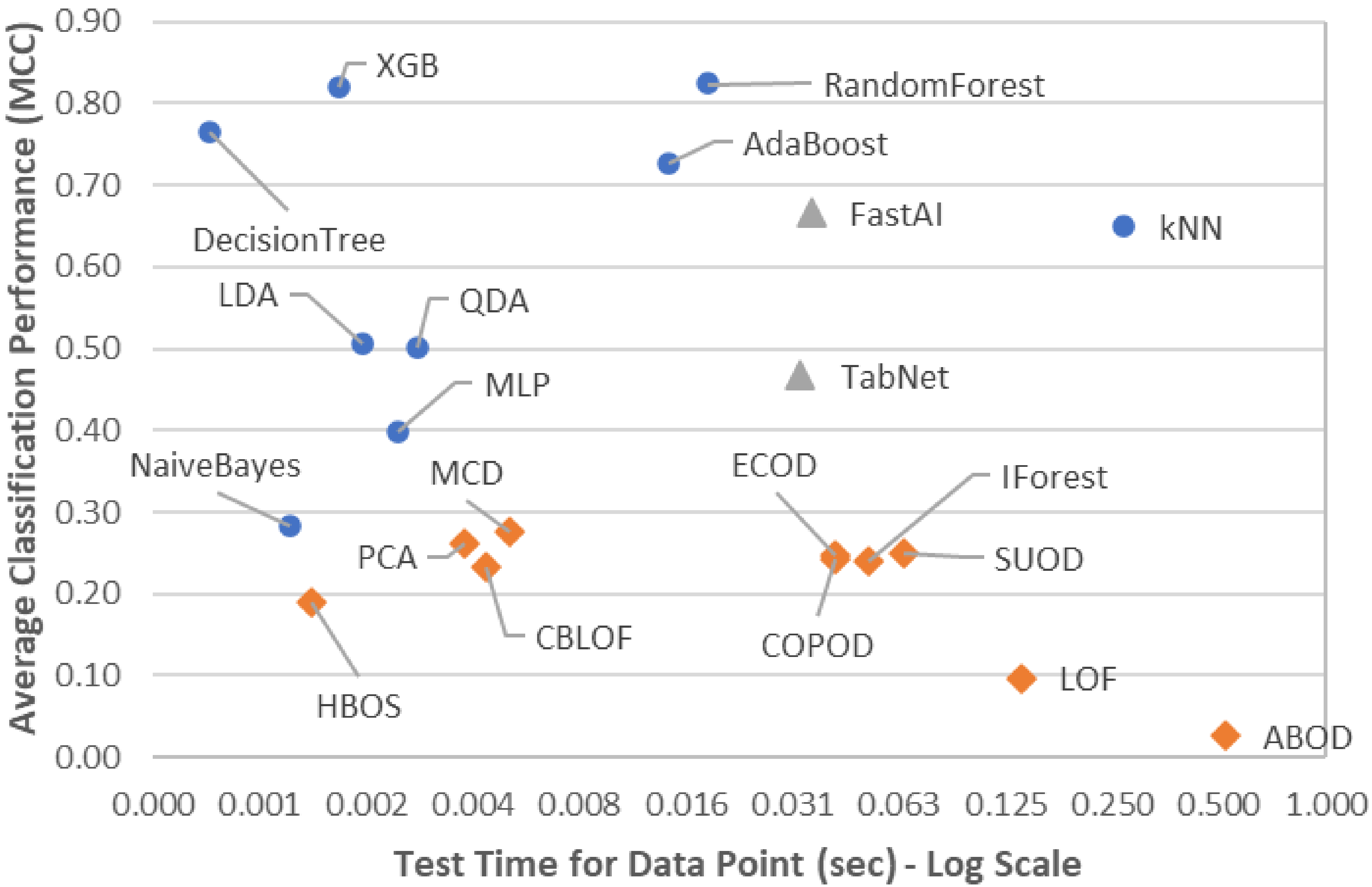
Model Size of Detectors



Model Speed of Detectors (I)

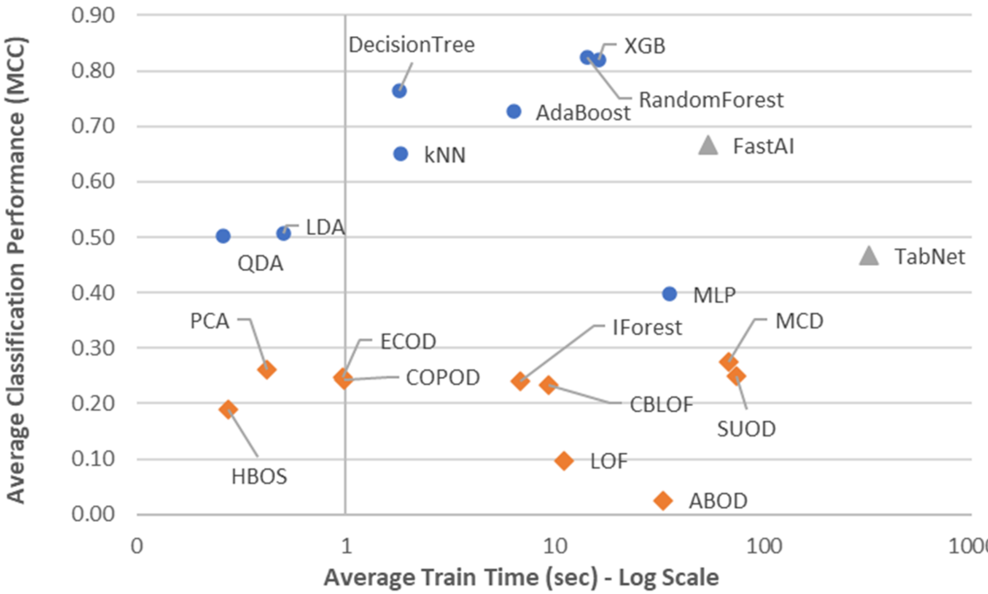


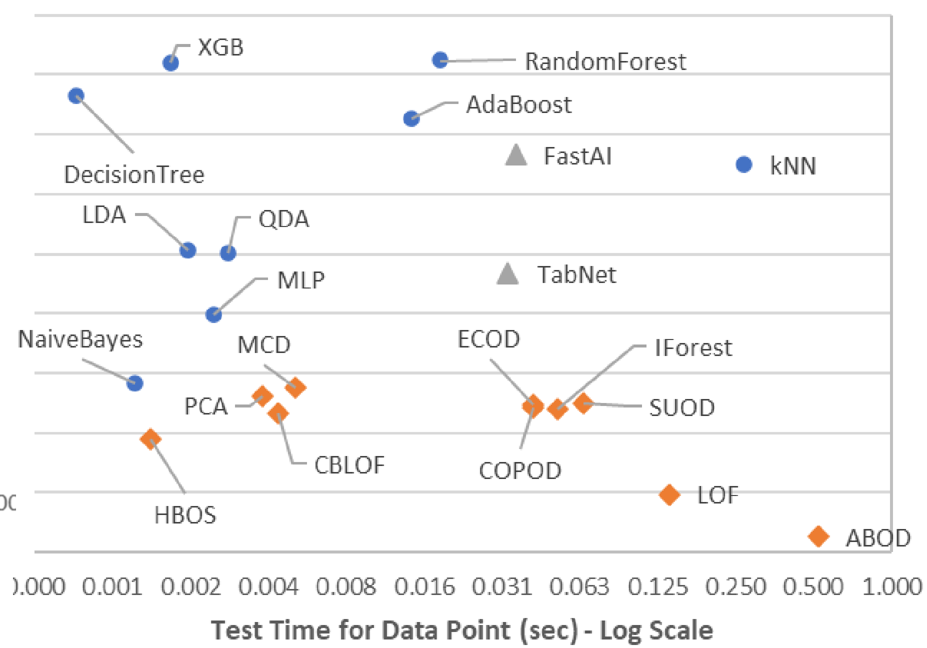
Model Speed of Detectors (II)



Model Speed of Detectors - Comments

- There are fast and slow algorithms
  - But also there are some that are fast during training and slow at runtime e.g., neighbour-based ones
  - and vice versa





Beware!

- Those numbers partially confirm the rather recent works stating that

We should not think about deep learning as the panacea for any classification task!

- For tabular data, tree-based classifiers are more interpretable, often faster and output fewer misclassifications
  - Good news for devices with limited resources!
  - See: Shwartz-Ziv, Ravid, and Amitai Armon. "**Tabular data: Deep learning is not all you need**." Information Fusion 81 (2022): 84-90 (from AI ML group at Intel Israel)

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(Finally!) Wrapping Up…

- This talk went through common constraints in deploying ML into embedded systems
  - There is no "silver bullet" algorithm to plug into a system for excellent detection capabilities and performance
  - Detectors have to be crafted for specific systems depending on their constraints
  - Availability of labels for training data is always scarce
  - This calls for unsupervised detectors, which usually have poor detection capabilities
    - There are (research) works in the direction of making unsupervised ML more accurate
    - Get in touch with us if interested!

Q&A Time


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