Machine Learning for the Lab

Group meeting talk 08/04/2022 – Simon Geyer

Identifying Pauli spin blockade using deep learning

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(Dated: February 2, 2022)

Content

- Why Machine Learning?
- How does it work?
- What do we use it for in the Lab? Spin blockade identification

Definition

„A computer program is said to learn from experience E with respect to some class of task T and performance measure P, if its performance at tasks in T as measured by P, improves with experience E.“ –T. M. Michell

- T: recognizing hand-written letters
- E: dataset of letters
- P: the fraction of letters identified correctly

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Why Machine Learning?

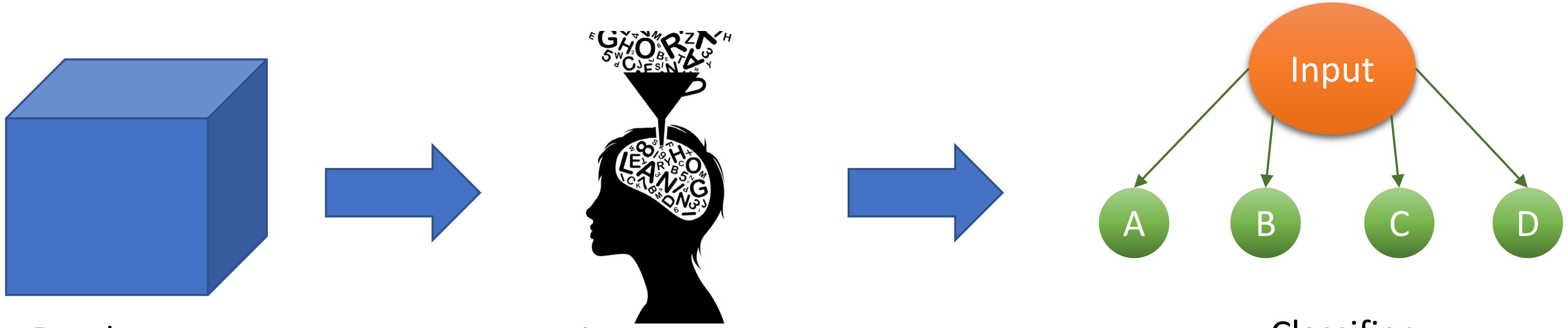
- Programs that can automatically adapt to tasks
- Can replace humans for some monotonous tasks
  that require small amount of intelligence
- Can process large amount of data
- When programs would be to complex to program them directly

Why Machine Learning?

- Personalized news
- Spam filtering
- Hand writing recognition
- …

Machine Learning

How does it work? -- Example: Spam classifier



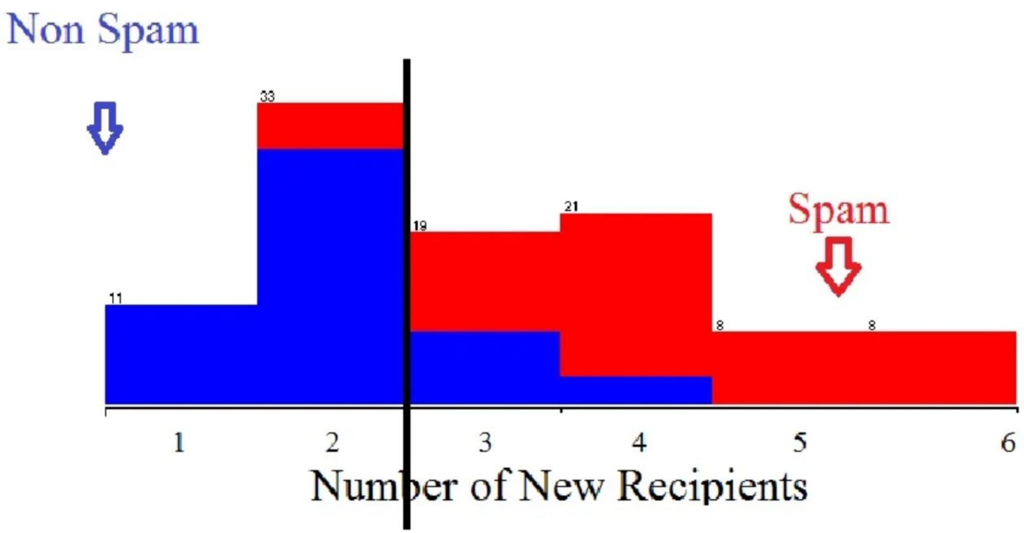
Database
Training Set

Learner
Induction Algorithm

Classifier
Classification Model

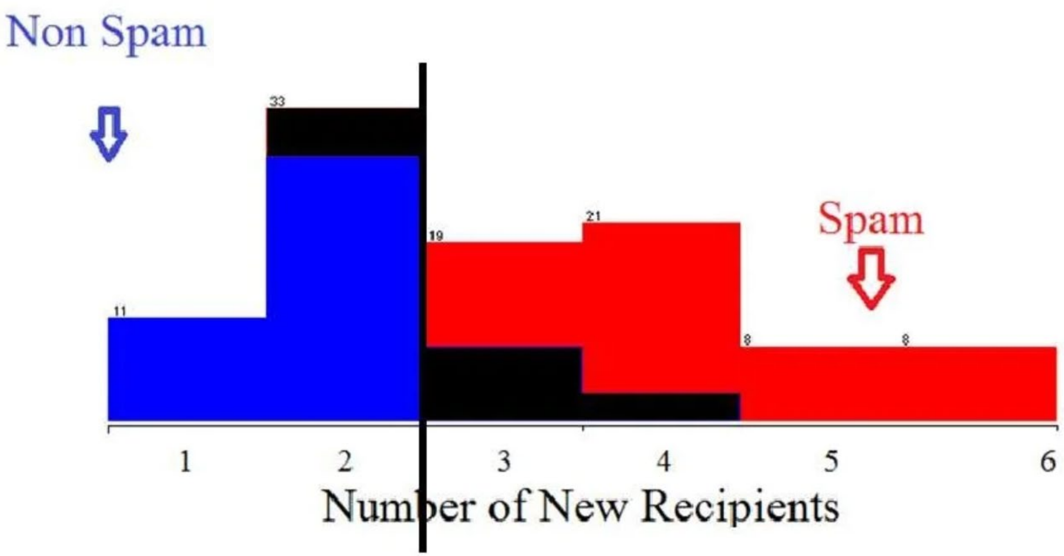
How does it work? -- Example: Spam classifier

Classification



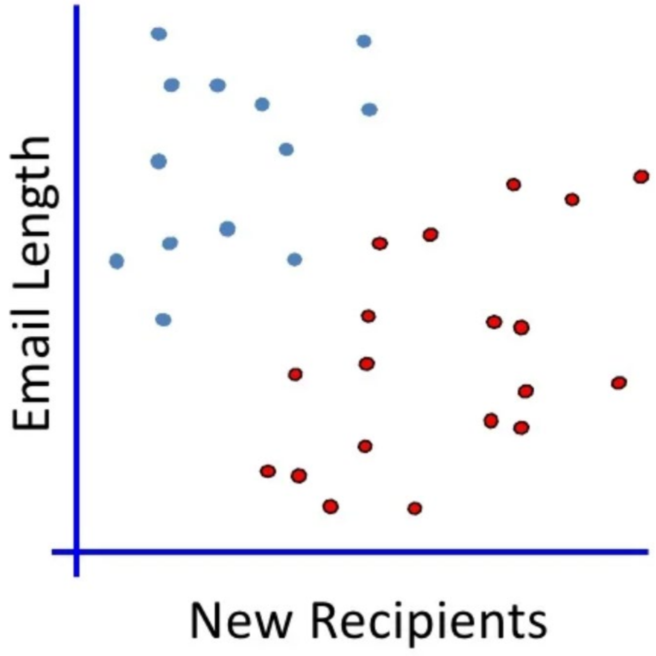
How does it work? -- Example: Spam classifier

Classification error



How does it work? -- Example: Spam classifier

Use more data for better classification



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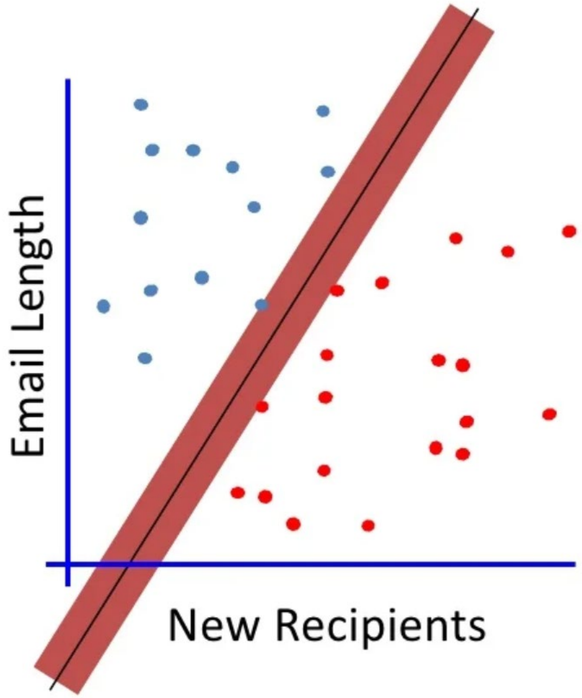
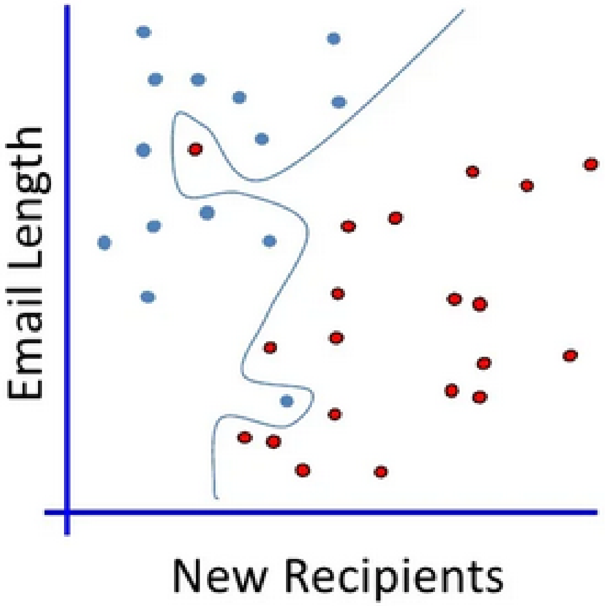
How does it work? -- Example: Spam classifier



Induction algorithm teaches machine how to classify

→ Linear classifier

How does it work? -- Example: Spam classifier



→ Non-linear classifier

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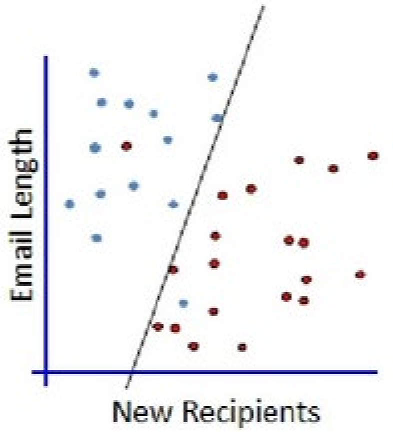
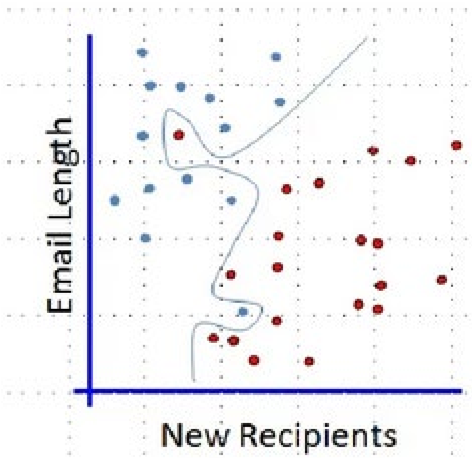
How does it work? -- Example: Spam classifier



2 Errors
Simple model



0 Errors
Complicated model

Overfitting/underfitting errors

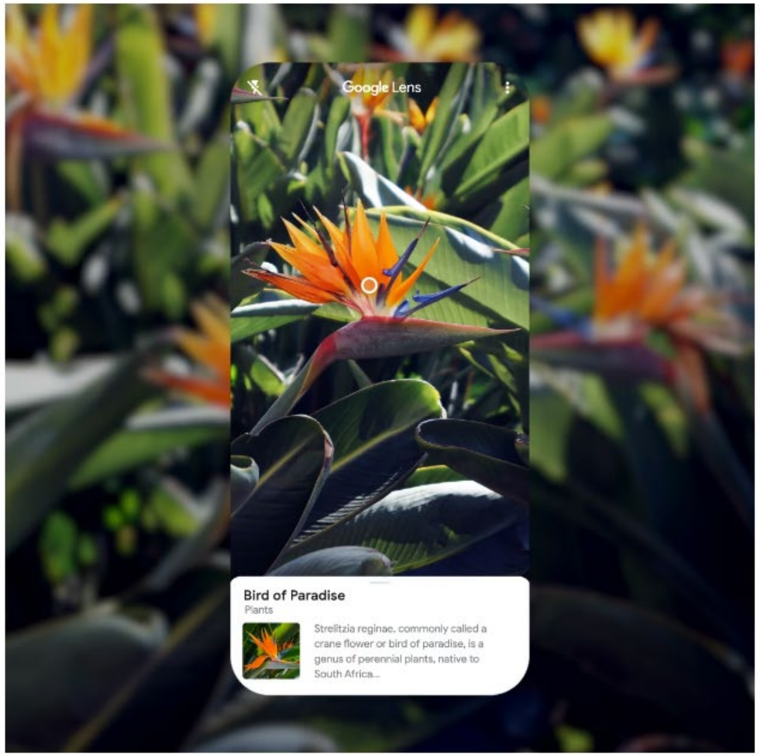
→ Non-training data needed to verify

How does it work? -- Example 2: Neuronal Network for animal identification

Google Lens

Identify plants and animals

Find out what plant is in your friend's apartment, or what kind of dog you saw in the park.



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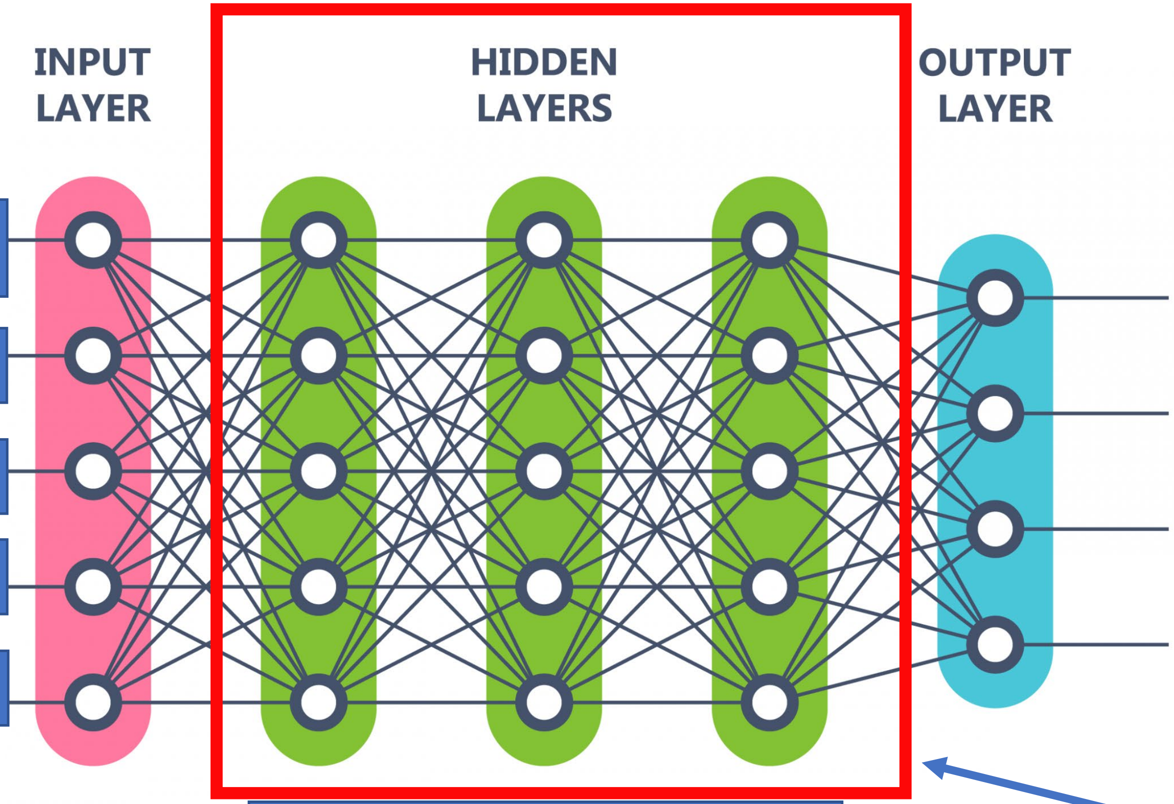
How does it work? -- Example 2: Neuronal Network

Data points

Attributes

- File name
- Time
- Pixel 1
- Pixel 2
- …



Probability of being

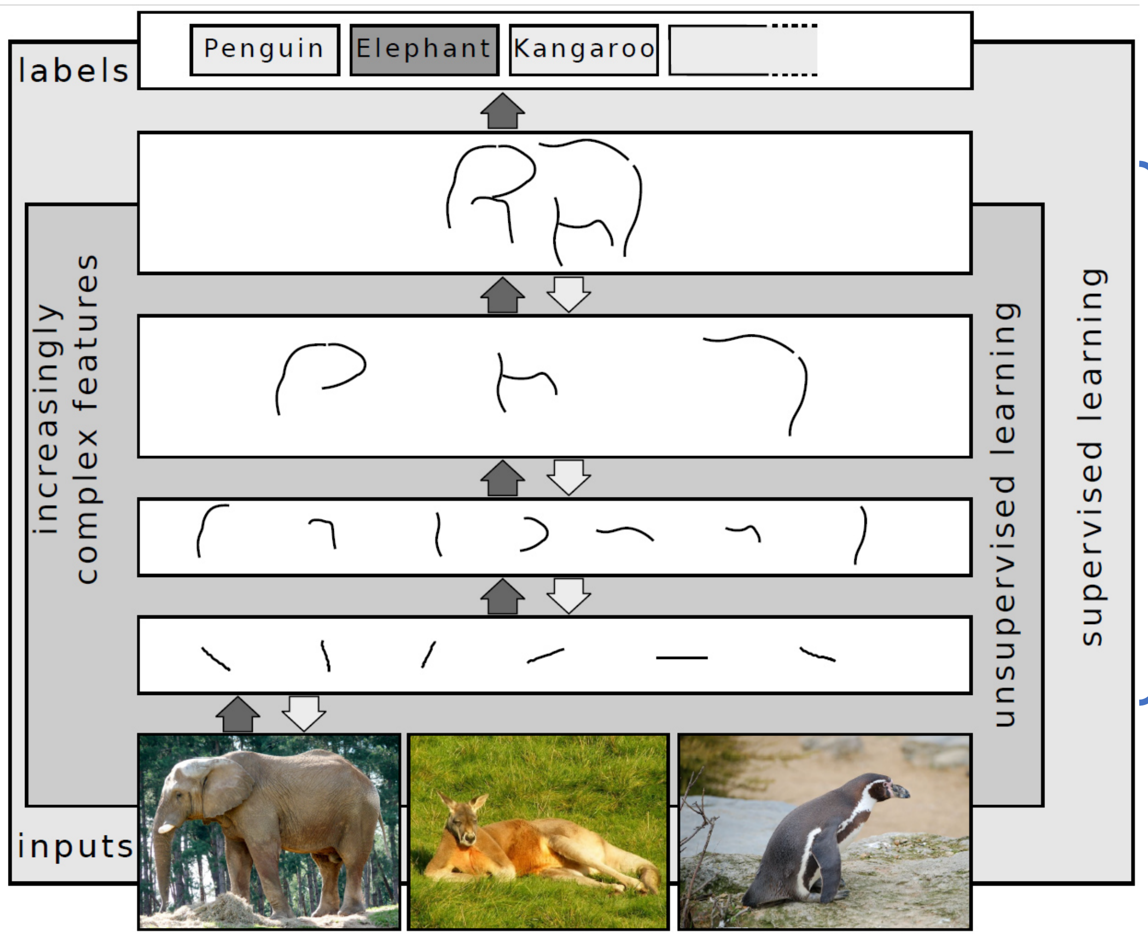
- an animal
- a plant
- a muffin
- …

Induction algorithm trains weights and features using labeled data set

many hidden layer
= deep learning

Machine Learning

How does it work? -- Example 2: Neuronal Network



hidden layers are trained to find features in the data and combine them

In general we don‘t know what happens here

How does it work? -- Example 2: Neuronal Network

What if real data is different from training data?
→ We don‘t know, Neuronal Networks are a black box

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Machine Learning in the Lab

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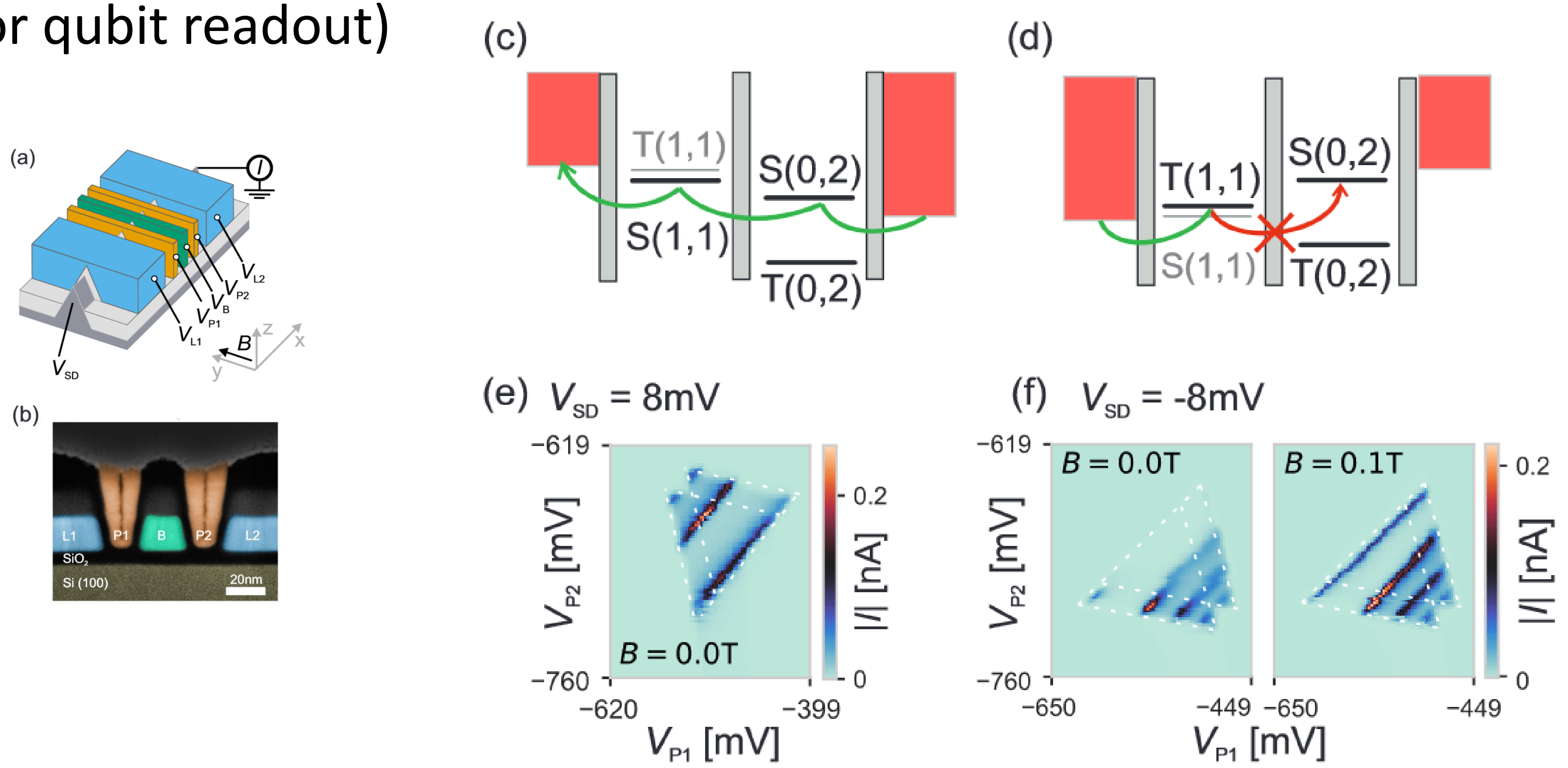
J. Schuff *et al.*, arXiv:2202.00574

Machine Learning in the Lab

Task

- Score Pauli spin blockade in a DC measurement of a DQD (useful for qubit readout)



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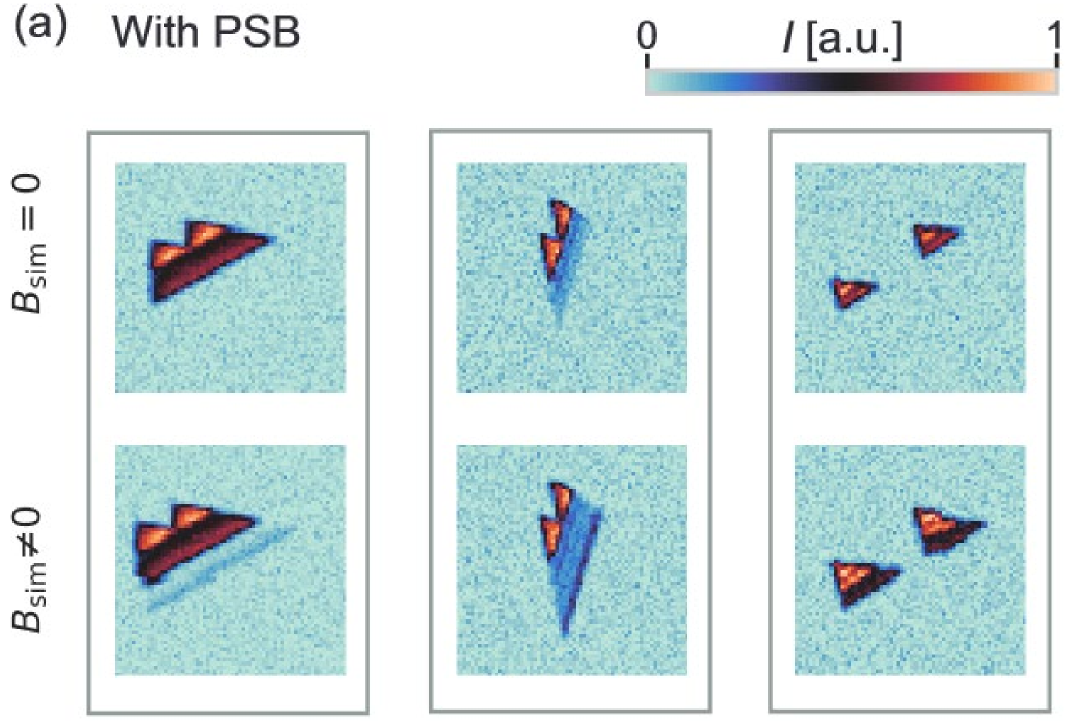
Experience

- Training data from 4 devices labeled by 4 human experts and simulations



Increase amount of data by combining real experimental data with **simulated data**

J. Schuff *et al.*, arXiv:2202.00574

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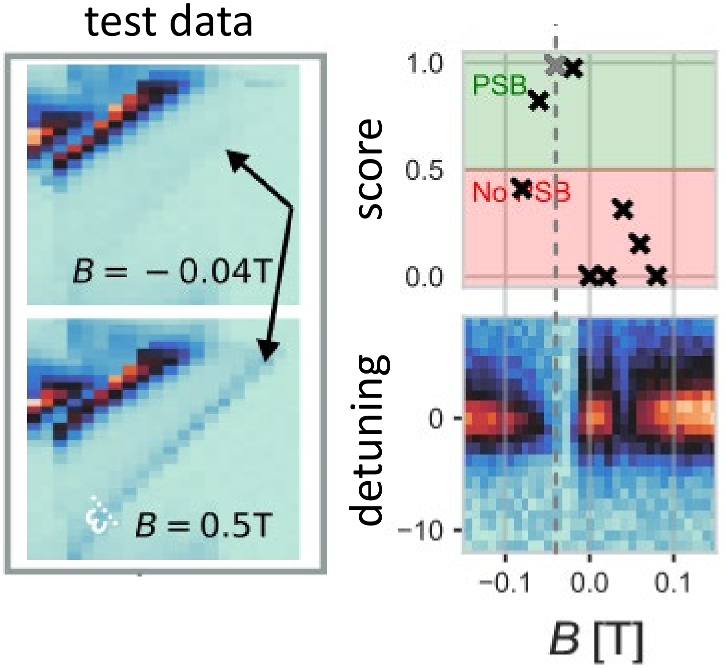
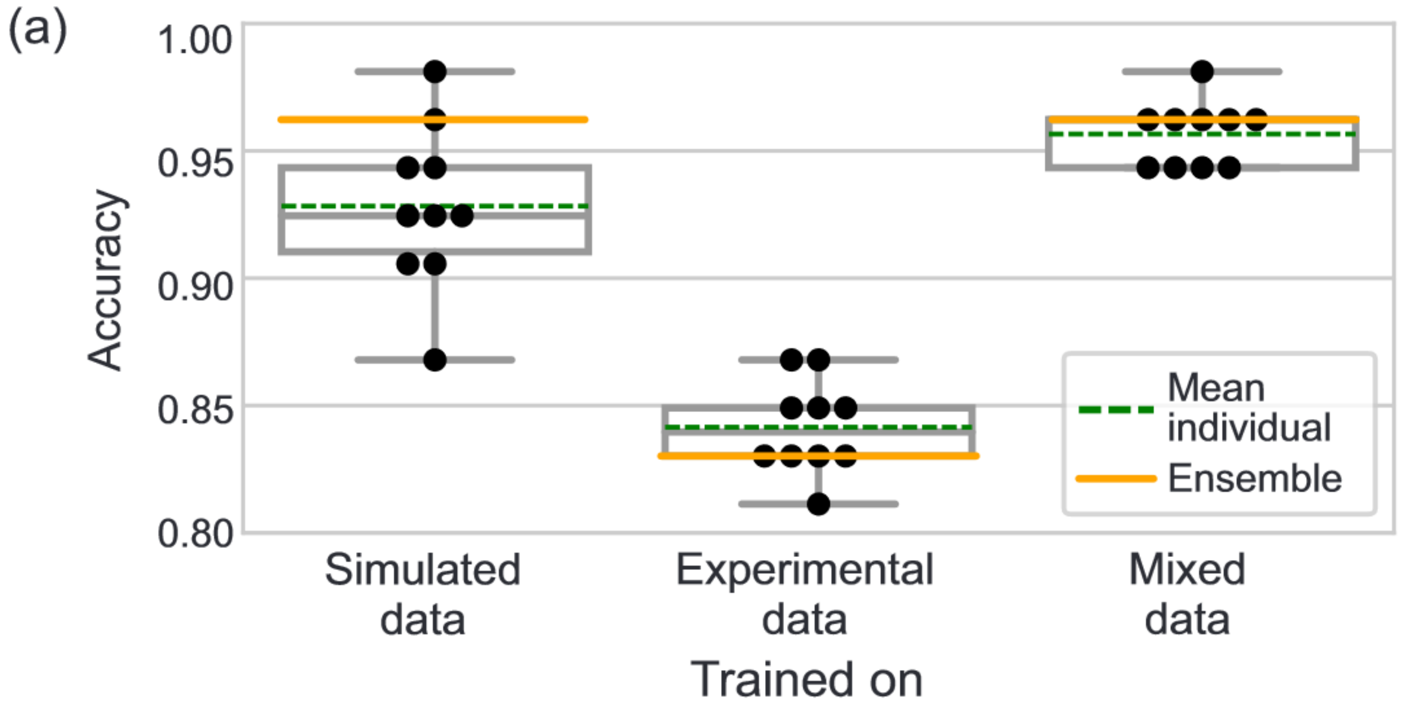
Performance

- Test on labeled data from different device and evaluate accuracy of 10 ML classifiers

test data





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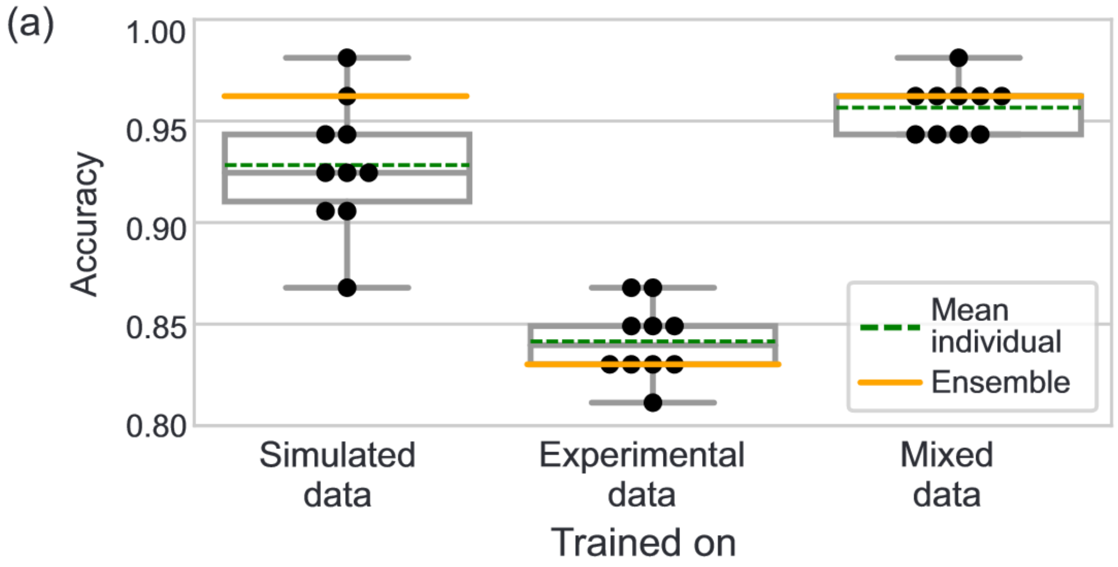
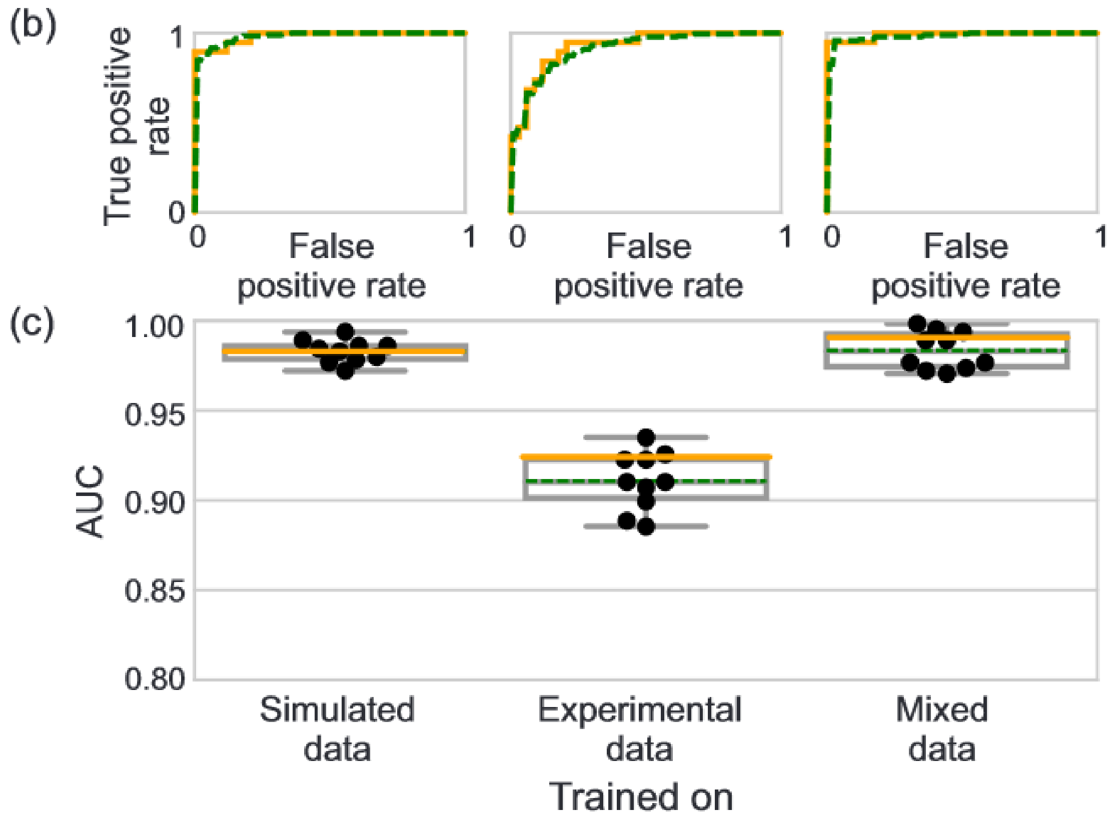
Performance

AUC is independent of score threshold:





Mean individual = average accuracy

Ensemble = average PSB score and then determine accuracy

J. Schuff *et al.*, arXiv:2202.00574

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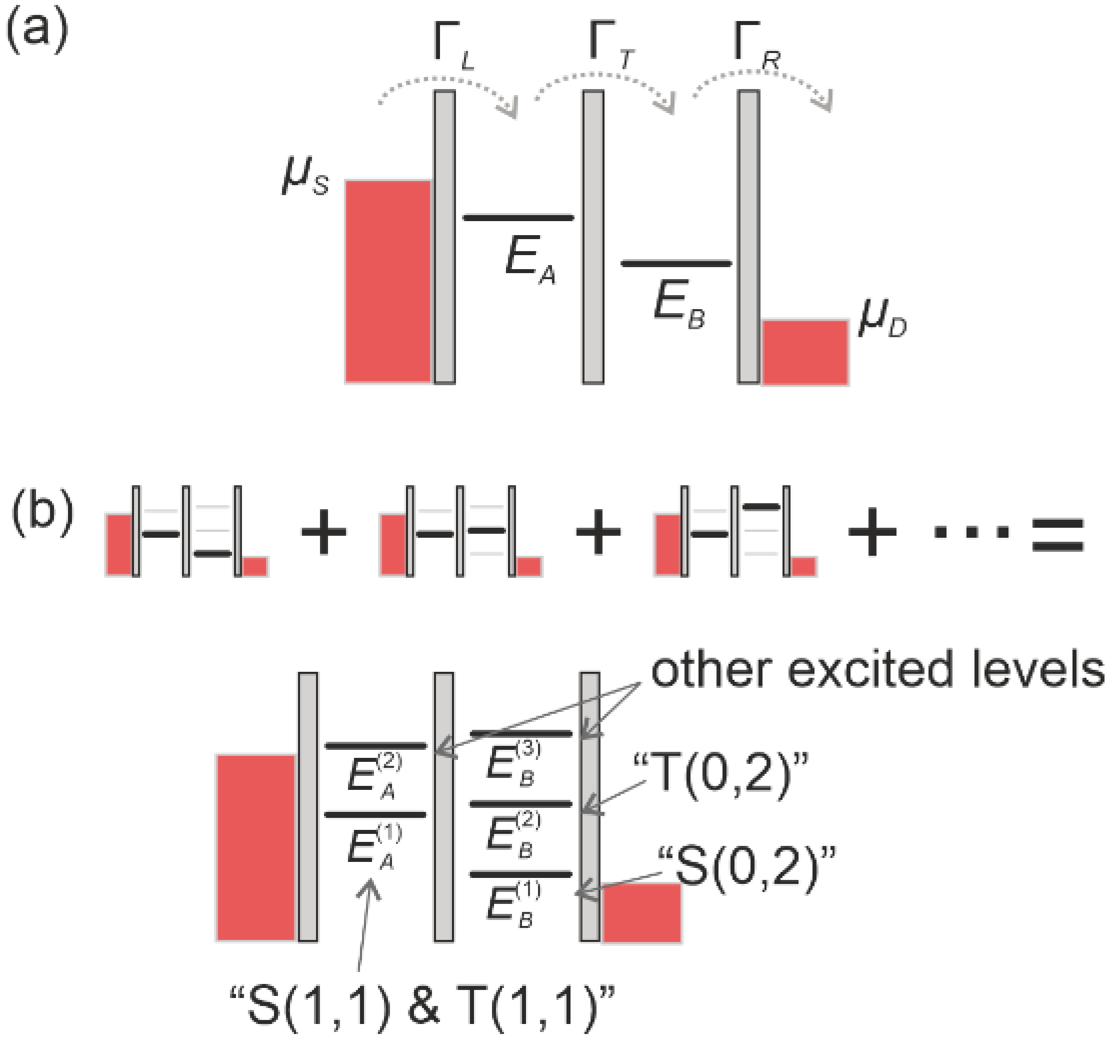
Simulator

- simulate current through randomized DQD levels w and w/o PSB and with random noise

$$I = \sum_{E_A} \sum_{E_B} I_{\text{partial}}$$

$$= \sum_{i} \sum_{k} \frac{\left(\Gamma_T^{(i,k)}\right)^2 \Gamma_R^{(k)}}{\left(\Gamma_T^{(i,k)}\right)^2 \left(2 + \Gamma_R^{(k)}/\Gamma_L^{(i)}\right) + \left(\Gamma_R^{(k)}\right)^2/4 + \epsilon_{(i,k)}^2} \tag{B2}$$

J. Schuff *et al.*, arXiv:2202.00574



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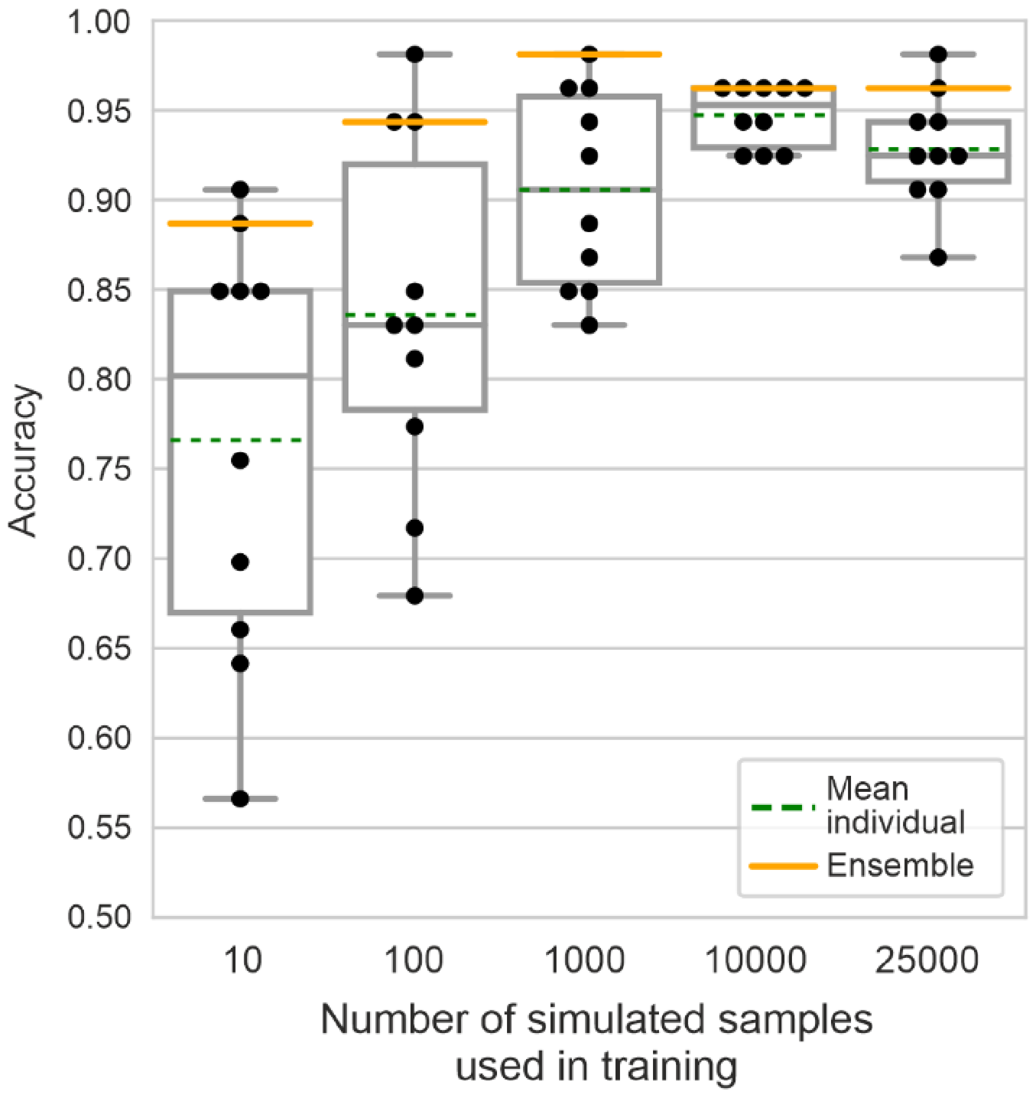
Simulator

- Machine learning relies on large data set



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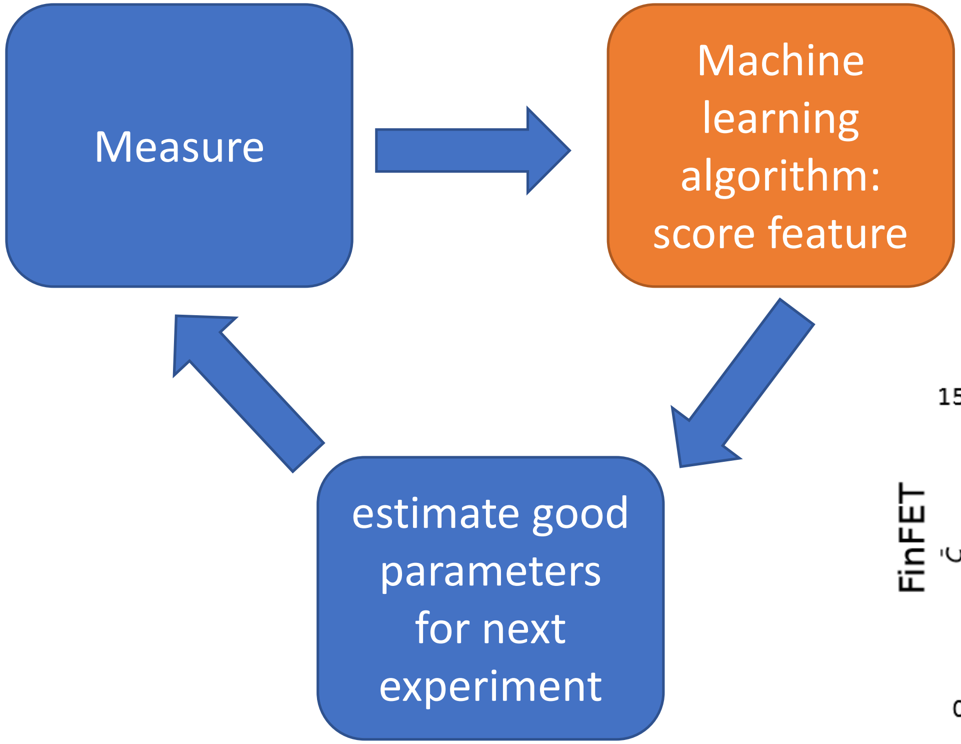
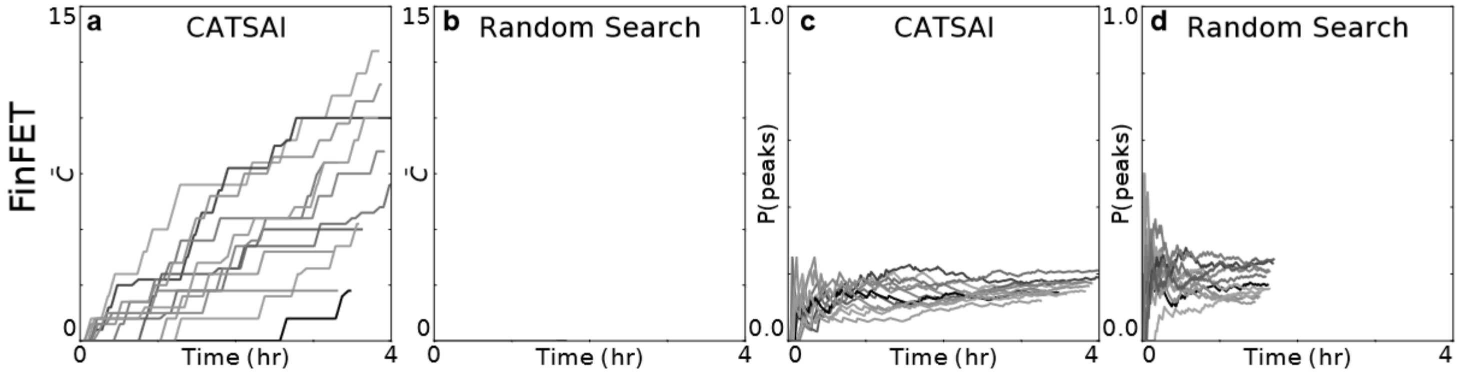
Outlook: Tune-up algorithm





B. Severin *et al.*, arXiv:2107.12975v1

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Summary

- Machine learning
  - can detect features learned from the training data
  - needs large amount of training data
  - can detect desired features in a live measurement
  - allows for automatic tune-up/optimization algorithms
- Identifying spin blockade:
  - 96.2% accuracy on a unseen device (by only looking at two bias triangles)
  - mixed dataset of experiments and simulated data makes ML feasable for rare events

Links

- https://mnassar.github.io/deeplearninghandbook/slides/05_ml.pdf
- https://de.slideshare.net/liorrokach/introduction-to-machine-learning-13809045

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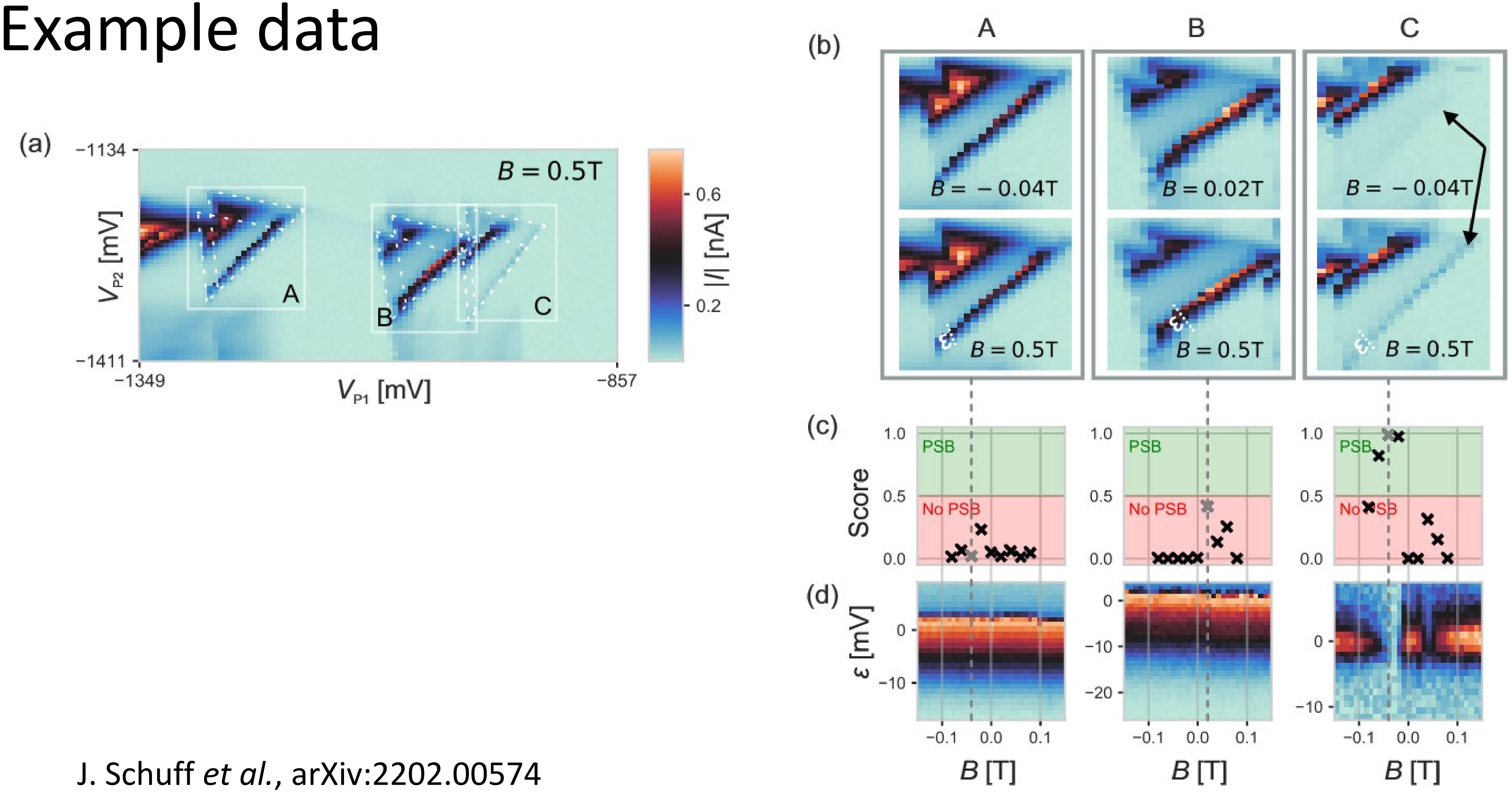
Example data



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