THE UNIVERSITY *of* EDINBURGH
informatics

Applied Machine Learning (AML)

Further Topics

Oisin Mac Aodha • Siddharth N.

Semi-Supervised Learning

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- However, annotating data can be time consuming and expensive.
- In practice we may have a mix of labelled (i.e. supervised) and unlabelled data (i.e. unsupervised) available to us.
- The goal of semi-supervised learning is to train models with both labelled and unlabelled data.

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- In practice $N_u >> N_l$, i.e. we have more unlabelled data than labelled data.

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Semi-Supervised Learning

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Semi-Supervised Example

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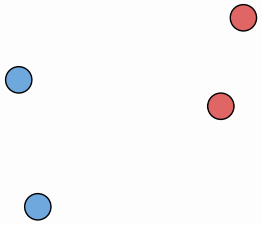

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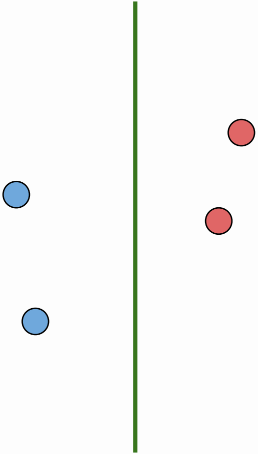
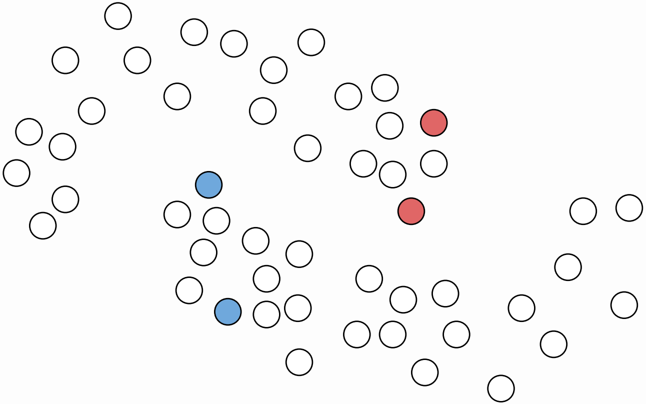


Semi-Supervised Example

- The unlabelled data indicates structure that is not captured by the previous classifier.



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- Plus many more ...

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Manifold Assumption

The data lie approximately on a manifold of much lower dimension than the input space.

Self-Training

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return $f_{\boldsymbol{\theta}}$

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- This problem is referred to as **confirmation bias**.

Entropy Minimisation

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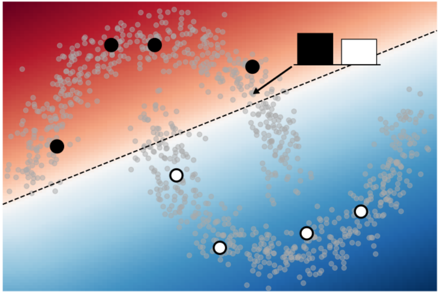

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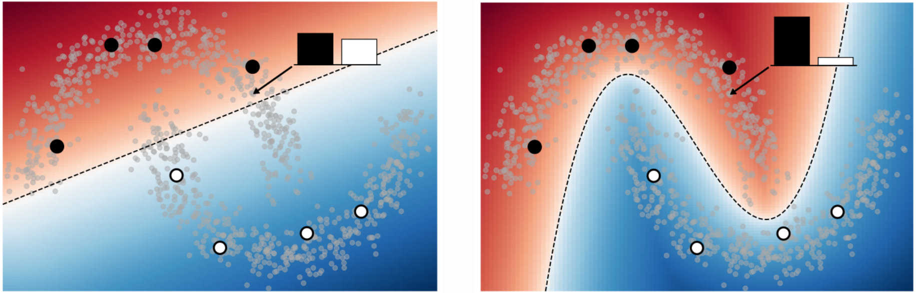

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- Known labels are ‘propagated‘ across the edges of the graph from labelled nodes to unlabelled ones.
- When complete, each unlabelled datapoint has an estimated label which can be then be used for training any supervised learning method.

Label Propagation Example

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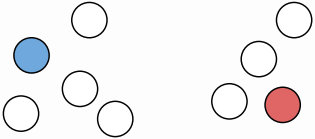

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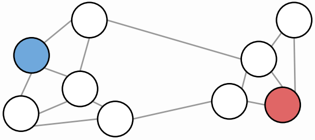

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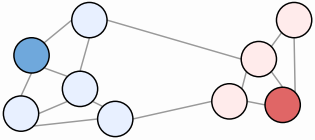

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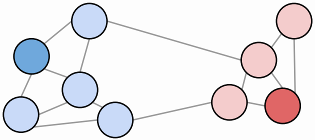

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- We have to make some assumptions about the underlying data distribution e.g. smoothness.
- There are many different techniques in the literature. Some are general purpose, others are specific to specific types of models.

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Assumption

Not all datapoints are equally informative, i.e. some are more useful than others.

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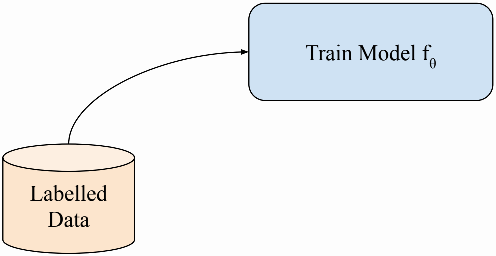

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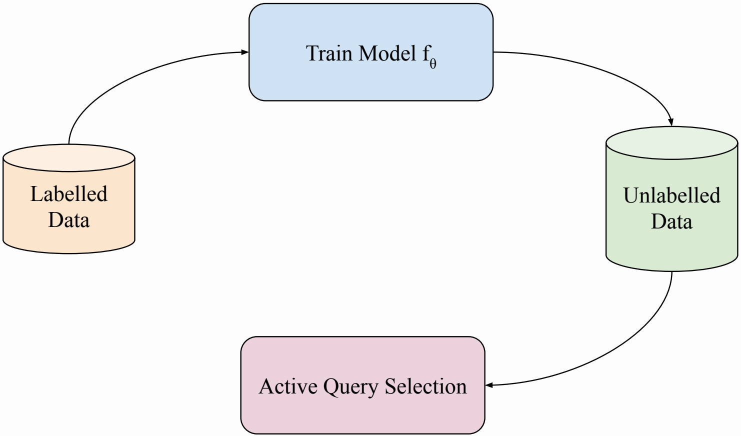

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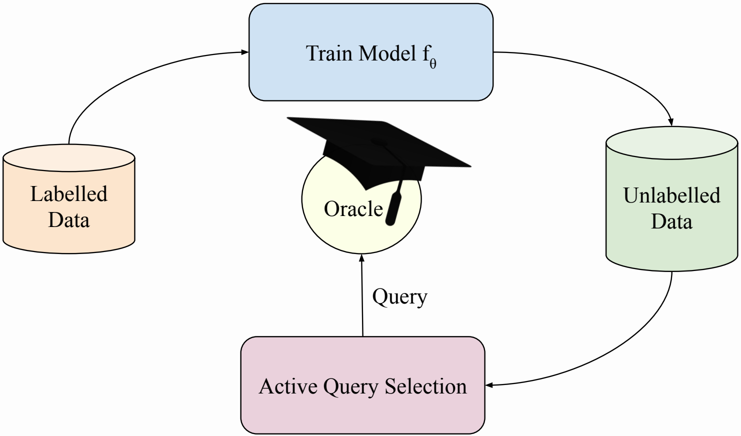

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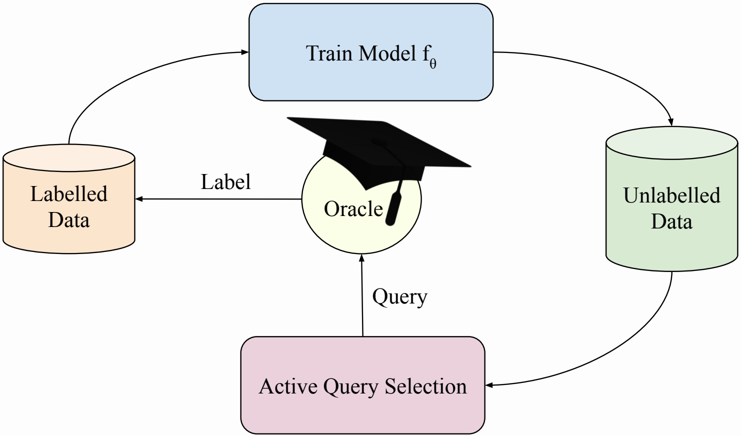

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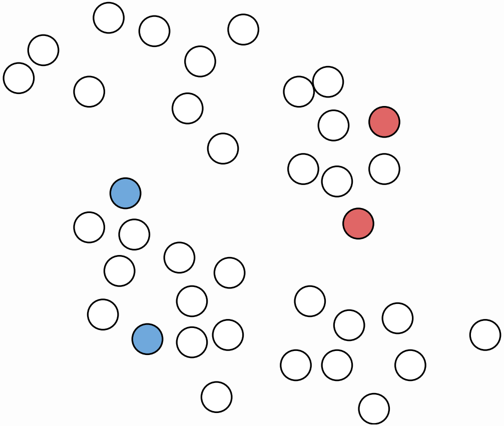
- **Expected model change**
  - Choose the query that would most change the current model if added to the training set. Expensive to compute.

Uncertainty Sampling Example

- On the right we see labelled and unlabelled data for a binary classification task.



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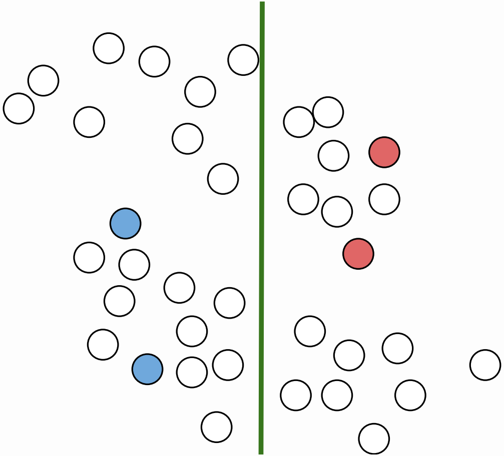

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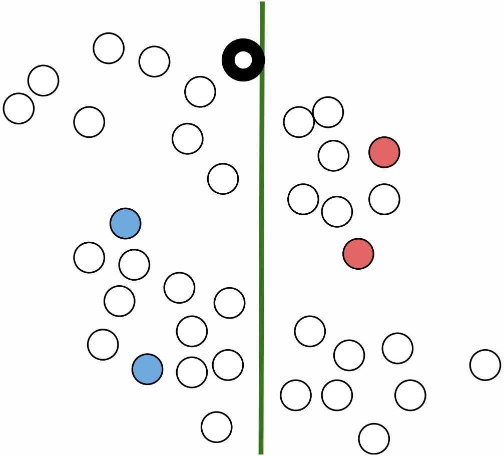
- We choose the query to be labelled that the model is most uncertain about. For a logistic regression classifier it would the datapoint closest to the decision boundary, i.e. $P(y_u|\boldsymbol{x}_u) \approx 0.5$.



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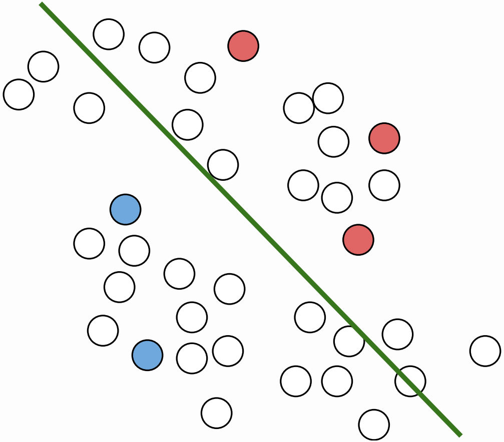

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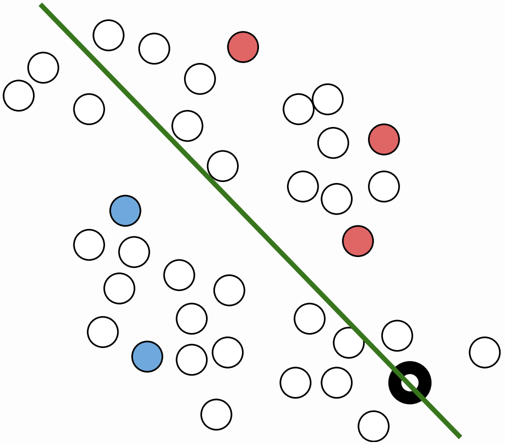
- We then repeat the process by selecting the next query to be labelled.



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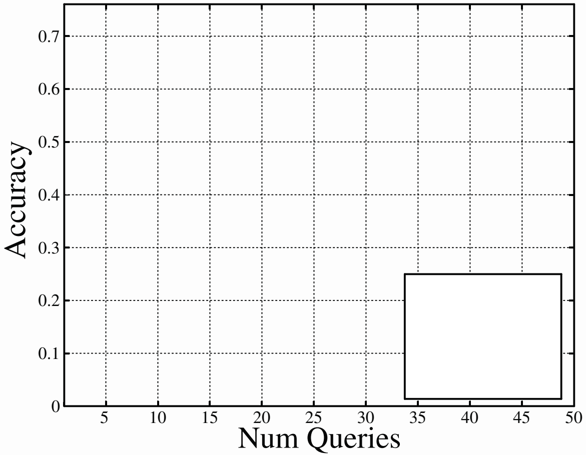
- Here we show an example of active learning applied to multiclass classification.



Figures adapted from Mac Aodha et al. CVPR 2014.

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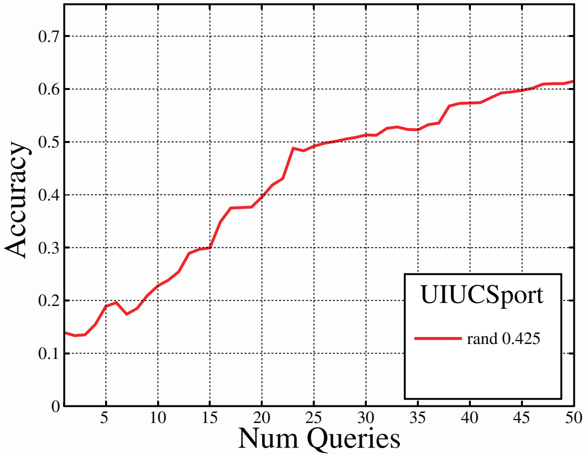

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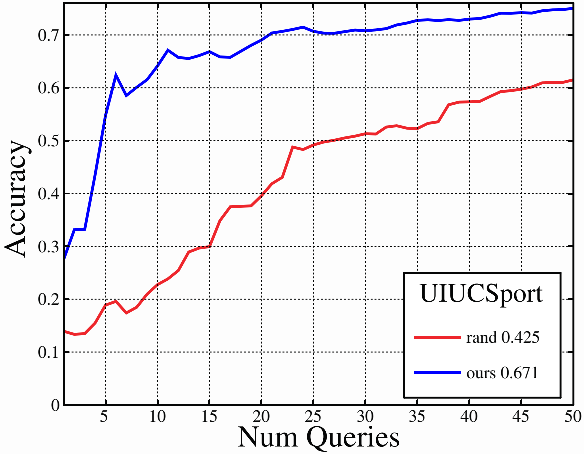

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- The aim is to obtain 'good' performance with a minimal number of training examples.
- There are several different families of query selection strategies available. The choice of which to use will depend on the specific use case.
- Active learning pipelines are often deployed in practical applications as data annotation can be expensive.