浙江大学爱丁堡大学联合学院
ZJU-UoE Institute

Lecture 10 - Machine learning in image analysis

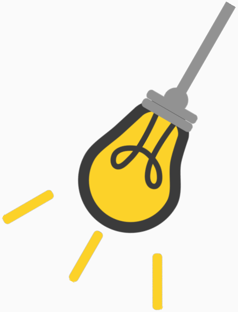
Nicola Romanò - nicola.romano@ed.ac.uk

Plan for the next weeks

- Week 8 - Traditional ML approaches in image analysis
- Week 9 - Convolutional neural networks (CNN)
- Week 10 - CNN architectures
- Week 11 - Practical aspects of using CNNs.

Learning objectives

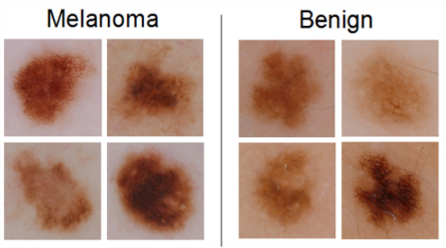
- Describe use cases for machine learning in image analysis
- Describe the different types of machine learning algorithms
- Use Python to implement supervised and unsupervised ML algorithms for image analysis



Introduction

Some example tasks that can be solved through ML

- Classification of images

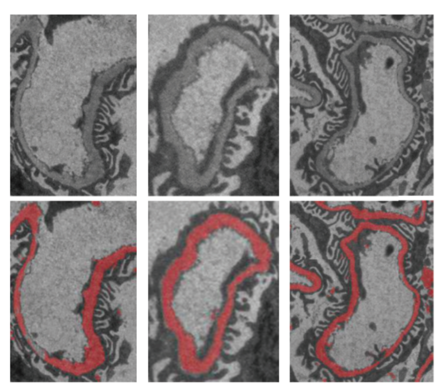


ISIC melanoma classification competition. Many different solutions, including neural networks, support vector machines, deep learning...

How can machine learning help?

Some example tasks that can be solved through ML

- Classification of images
- Classification of pixels (segmentation)

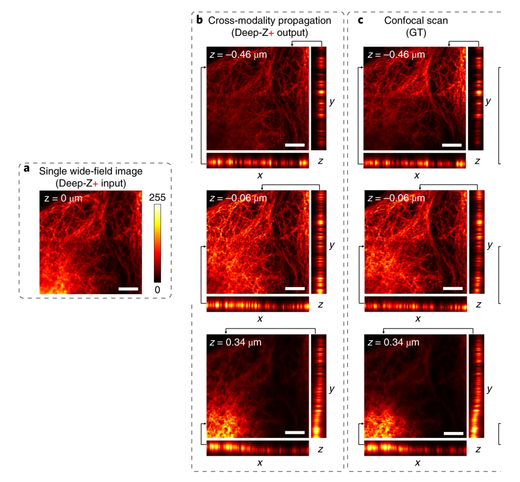


Cao et al. 2019, Classification of glomerular basament membrane using Random Forests.

How can machine learning help?

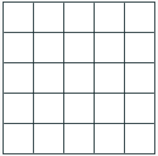
Some example tasks that can be solved through ML

- Classification of images
- Classification of pixels (segmentation)
- "Prediction" of images

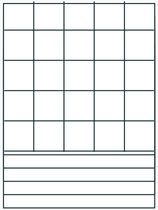


Wu et al., 2019 - Three-dimensional virtual refocusing of fluorescence microscopy images using deep learning

The general process

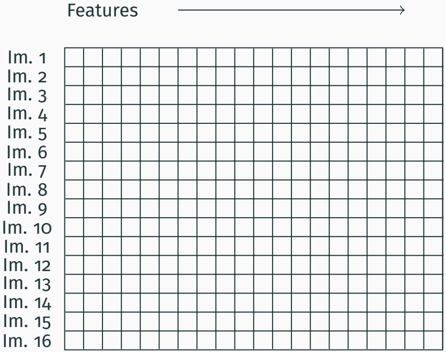


Image



Features

(Intensity, Edges, texture, ...)

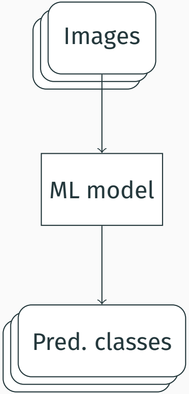


Unwrap

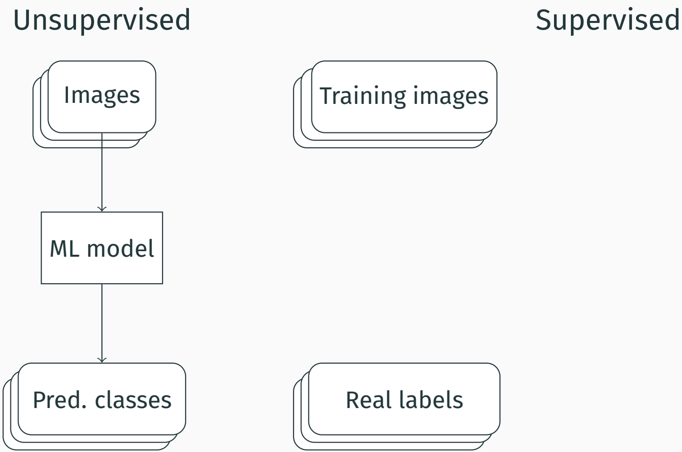
(and feed to model!)

Supervised vs unsupervised ML

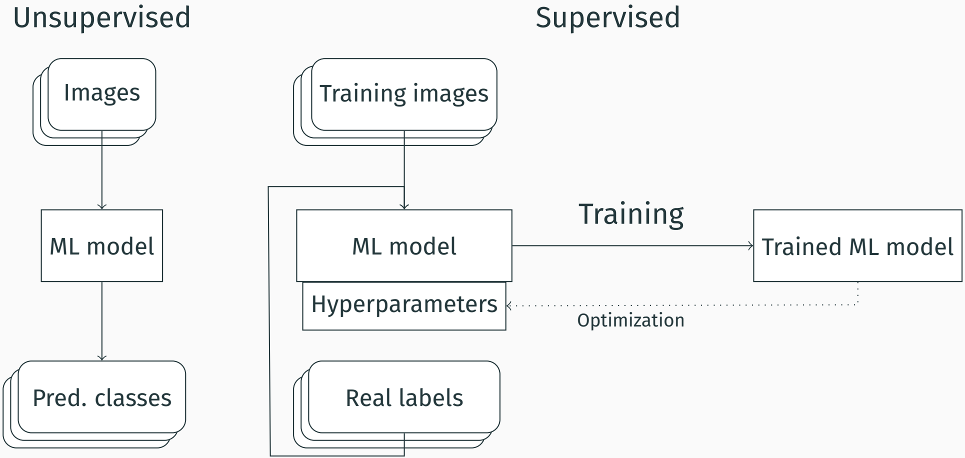
Unsupervised



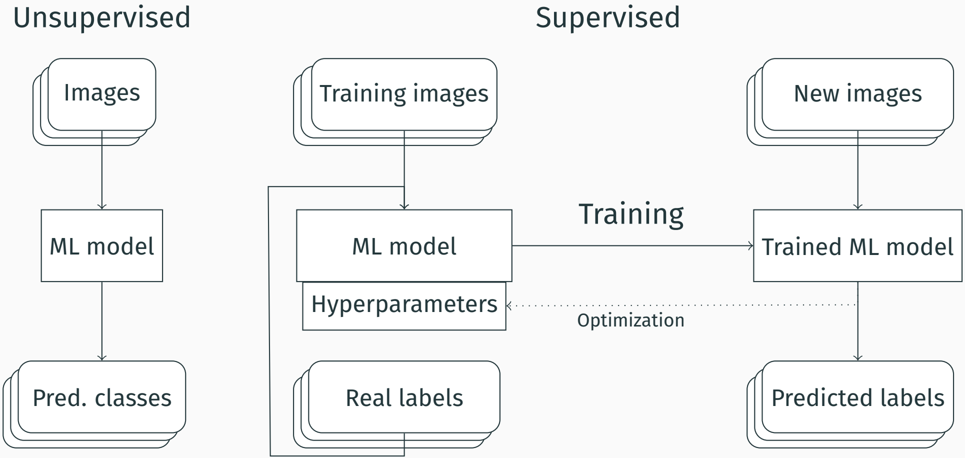
Supervised vs unsupervised ML



Supervised vs unsupervised ML



Supervised vs unsupervised ML



Unsupervised methods

Unsupervised learning

Examples of unsupervised learning include clustering methods (e.g. k-means) often combined with dimensionality reduction (PCA, UMAP).

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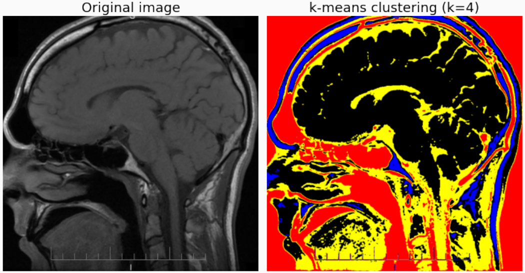
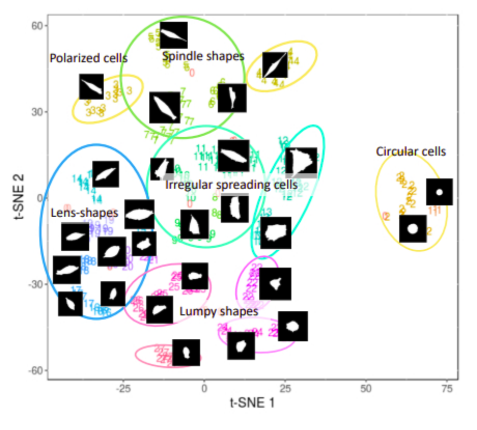
k-means for segmentation (see Lecture 7)



Examples of unsupervised learning include clustering methods (e.g. k-means) often combined with dimensionality reduction (PCA, UMAP).

t-SNE clustering of images



Bhaskar et al, 2019

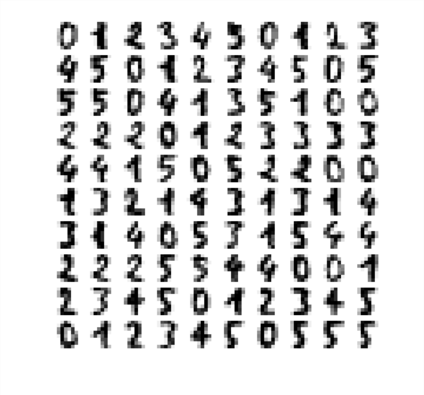
Dimensionality reduction methods map $Y = f(x_1, x_2, ..., x_n)$ to $Y = f(DR_1, ..., DR_m)$ with $m \leq n$.
They include linear transformations, such as PCA (principal component analysis), and nonlinear transformations, such as t-SNE (t-distributed stochastic neighbor embedding) or UMAP (uniform manifold approximation).

A simple example...

Let’s use t-SNE to classify handwritten digits!

We are going to use the UCI digits dataset, by E. Alpaydin and C. Kaynak, containing 1797 8x8 images of handwritten digits from 0 to 9.

It’s a simple yet large dataset useful for quick image analysis tests!



Supervised methods

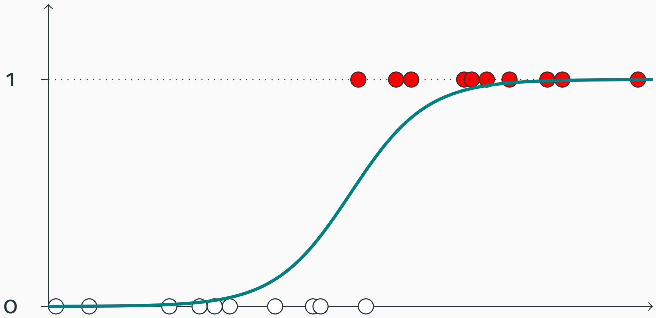
Supervised learning

Many different supervised learning algorithms have been used for image analysis.

Commonly used:

- Logistic regression
- Support vector machines (SVM)
- Random forests (RF)
- Neural networks (Lecture 11)
- Convolutional neural networks (Lectures 12 and beyond)

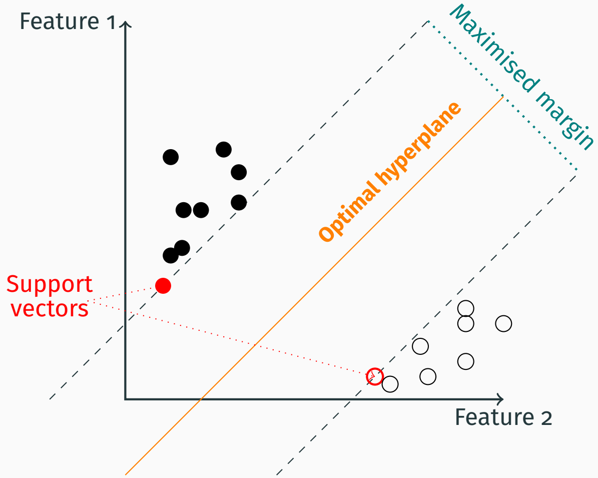
Supervised learning algorithms - Logistic regression



Logistic regression is a simple supervised learning algorithm that is used to predict the class of a given data point.

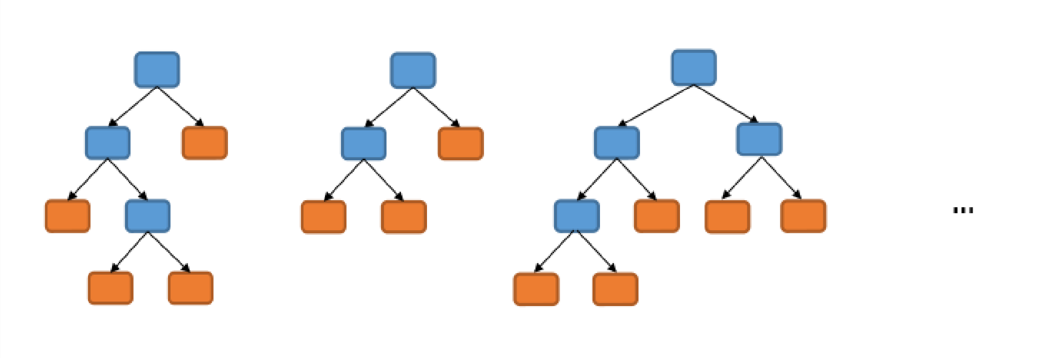
It is mostly used to predict binary outcomes but can be extended to multi-class classification (multinomial logistic regression).

Supervised learning algorithms - support vector machines



A support vector machine (SVM) uses a linear decision boundary to classify data points. It determines the optimal hyperplane that separates the data points into two classes.

Random forest

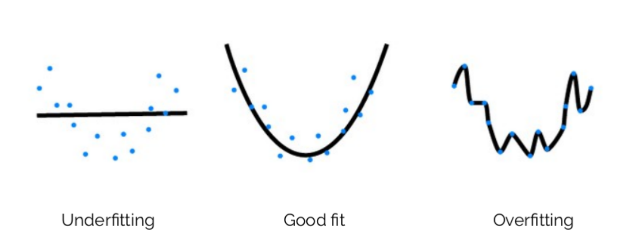


Random forest is an ensemble method for classification and regression.

It classifies samples using many binary trees, fitted on various sub-samples of the dataset. A majority votes from these trees decides the outcome. This improves prediction accuracy and controls over-fitting.

The bias-variance tradeoff

We want to train our model to perform some task. However, just like any statistical model, we don't want to **overfit**.



In ML, we often describe this in terms of **bias** and **variance** errors.

The bias-variance tradeoff

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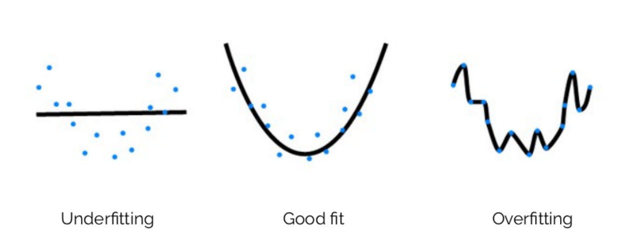

In ML, we often describe this in terms of **bias** and **variance** errors.

- **Bias** derives from erroneous assumptions in the learning algorithm. High bias can cause an algorithm to miss the relevant relations between features and target outputs (underfitting).
- **Variance** derives from sensitivity to small fluctuations in the training set. High variance may result from an algorithm modeling the random noise in the training data (overfitting).

(Adapted from Wikipedia)

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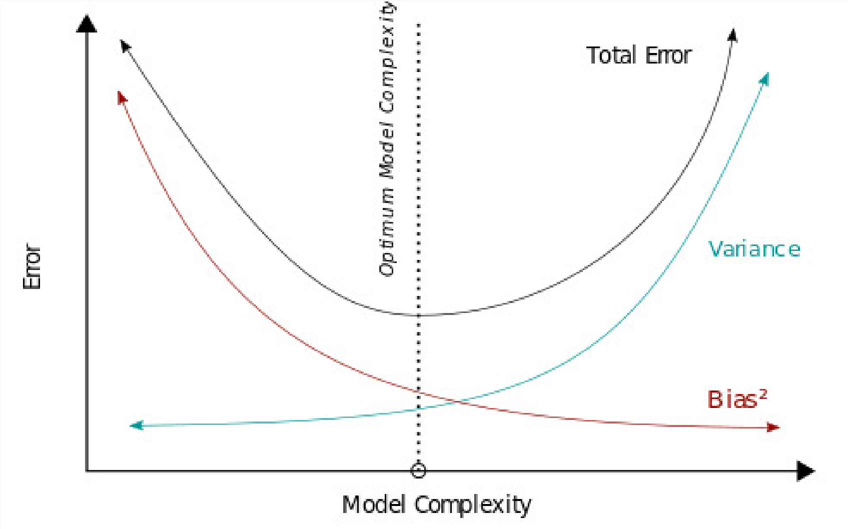
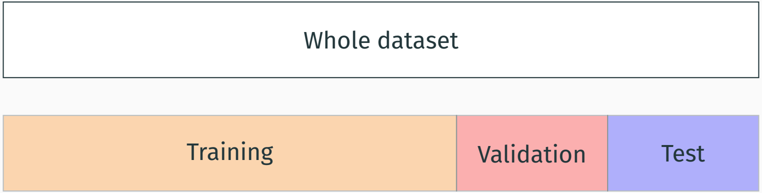


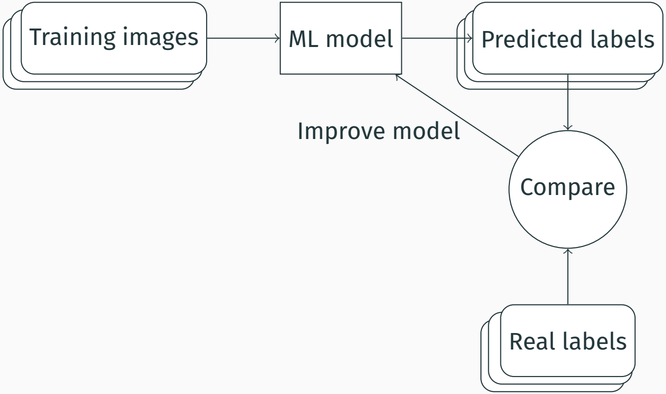
Data splitting

In order to avoid overfitting we can split our dataset in three parts:

- **Training set** - used to train the model
- **Validation set** - used to estimate model performance during training or while tuning the model hyperparameters. Especially important for neural network.
- **Test set** - used to test the trained model



The training process



We will explore this more in details in the upcoming lectures!

Supervised learning handwritten digits

We will use the handwritten digits dataset again, but this time we will train a supervised model (SVM) to predict the class of the digit.