session 4:

Supervised learning

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IAFIG-RMS - Bioimage Analysis With Python

Cambridge Bioinformatics Training Centre

Royal Microscopical Society

Traditional supervised learning

Traditional supervised learning still proves itself useful

It is a framework

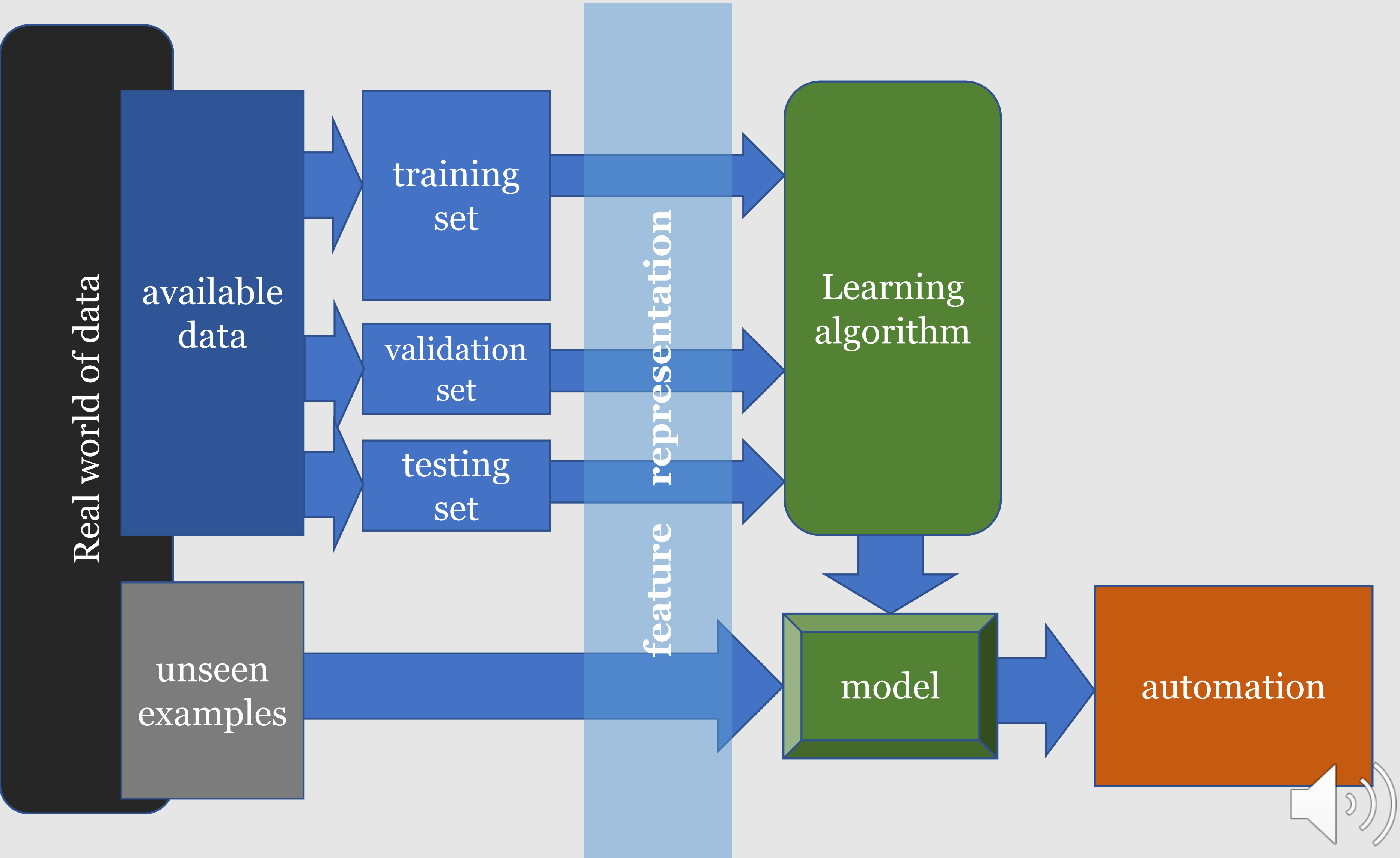
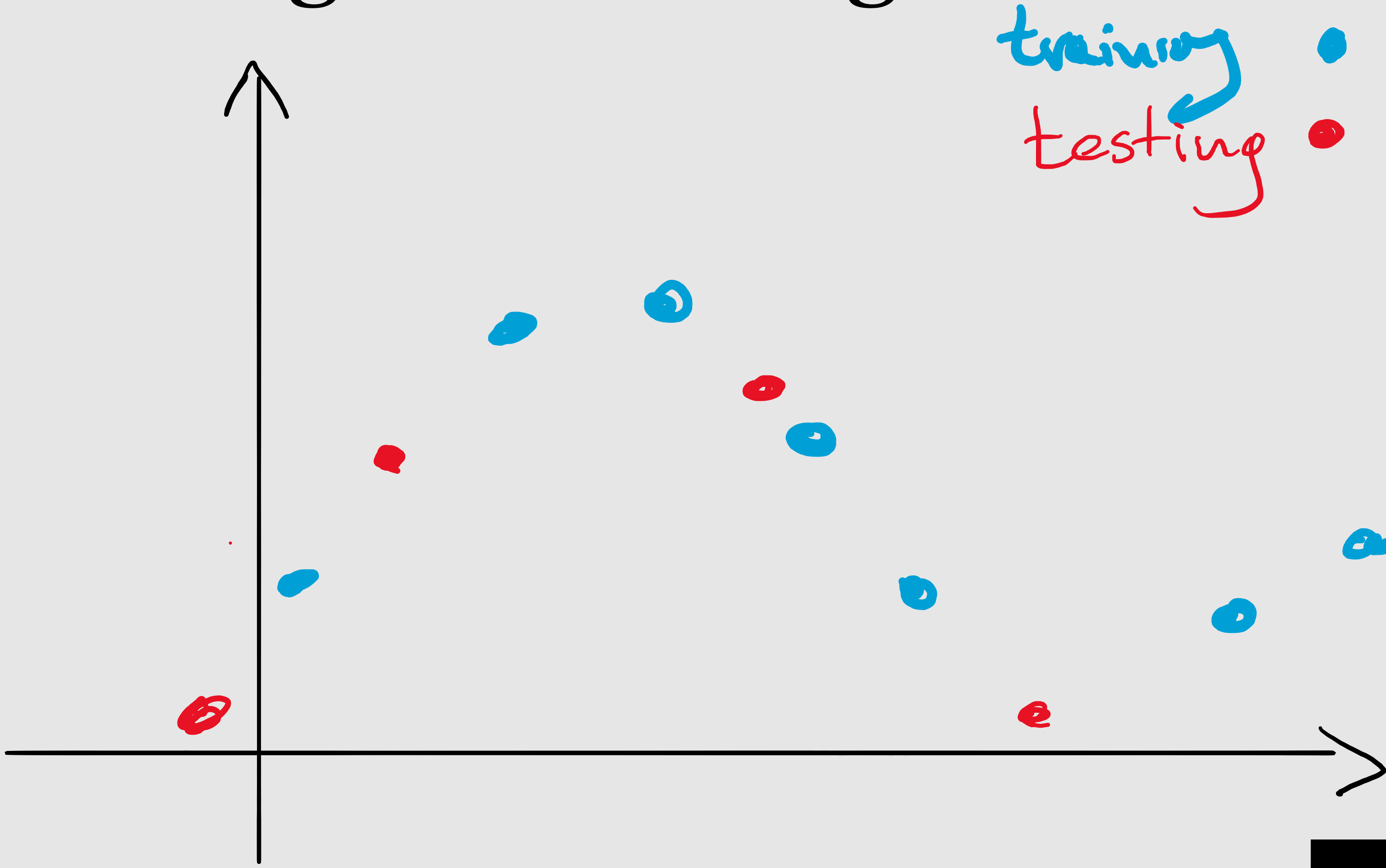


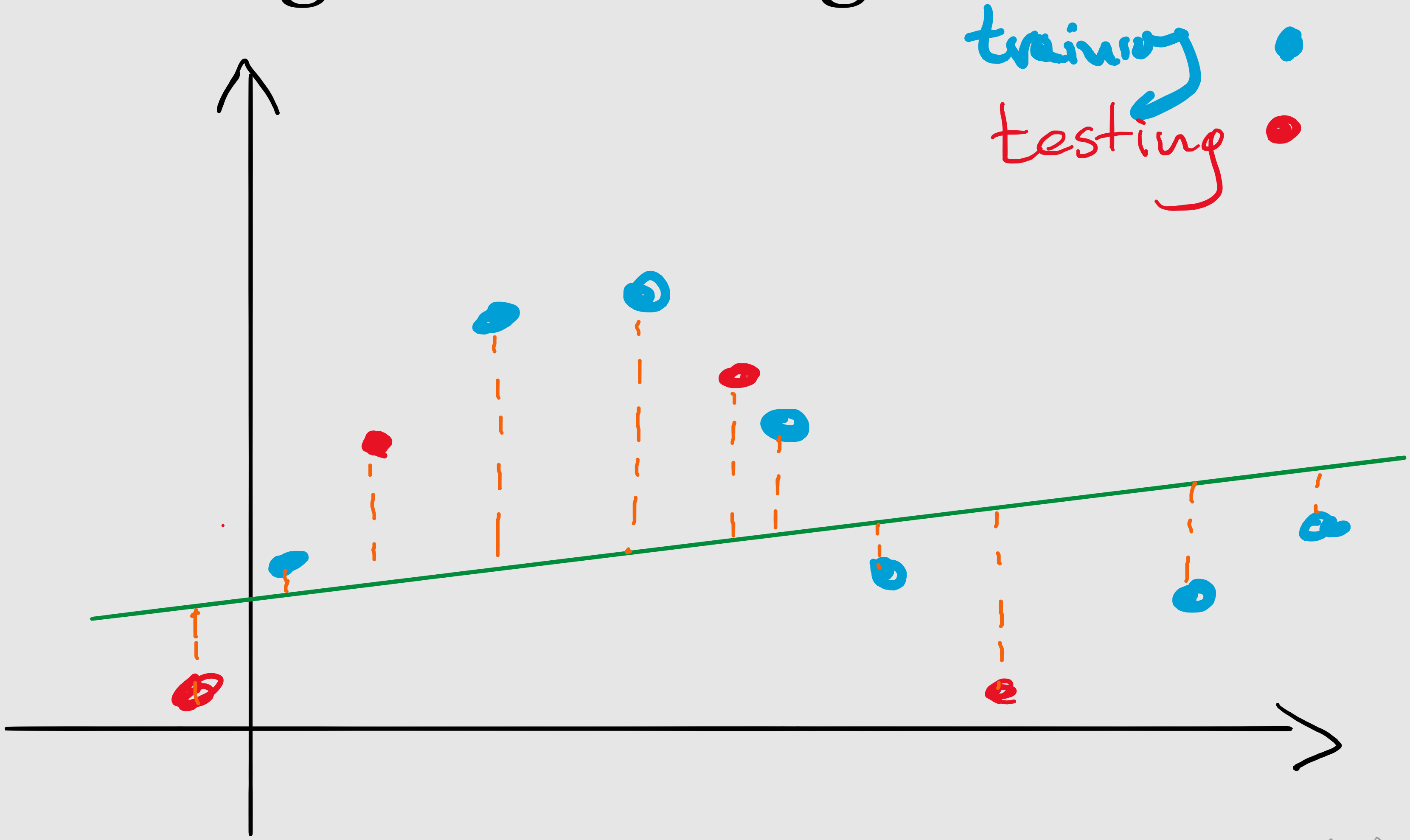
Image classification

- The most common and fundamental task
- two or more classes of objects
- object is segmented and localised => presented as an image

Training and Testing Errors



Training and Testing Errors



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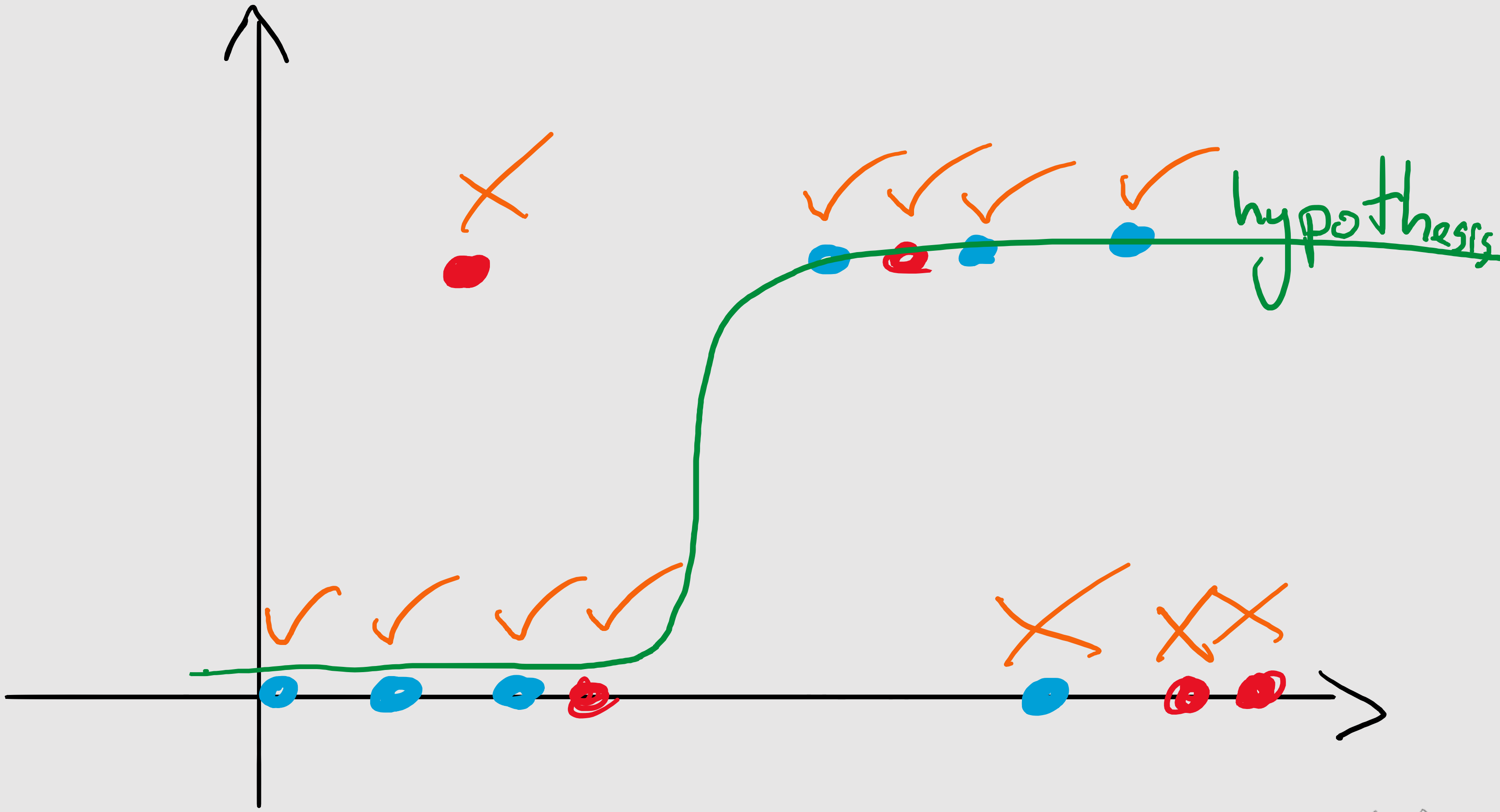
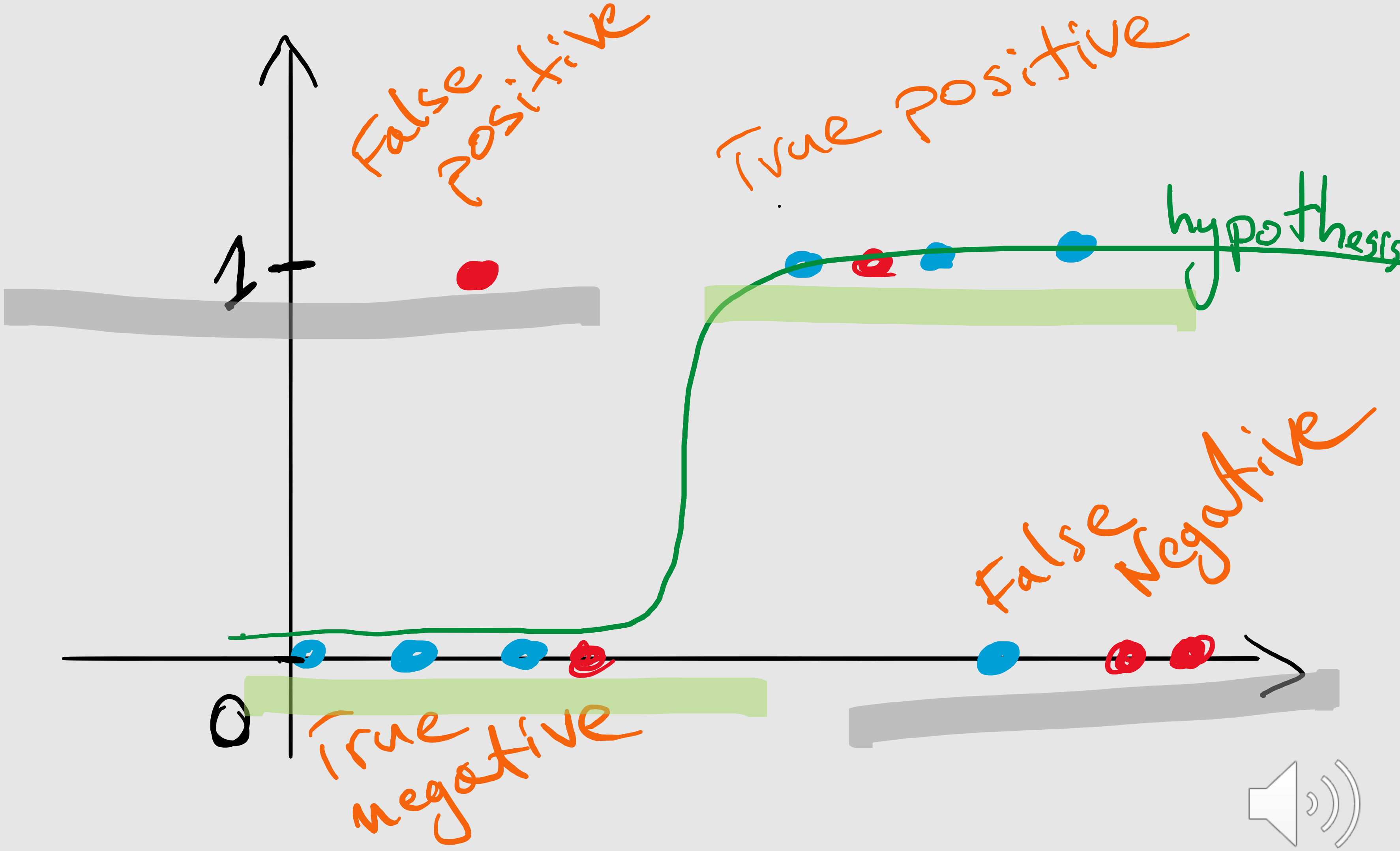


Training and Testing Errors



Performance measures

		actual	
		1	0
predicted	1	TRUE POSITIVE	FALSE POSITIVE
	0	FALSE NEGATIVE	TRUE NEGATIVE

$\text{class} \in \{1, 0\}$

Performance measures

		actual	
		1	0
predicted	1	TRUE POSITIVE	FALSE POSITIVE
	0	FALSE NEGATIVE	TRUE NEGATIVE

Precision

$$\frac{TP}{\text{Predicted Pos}} = \frac{TP}{TP + FP}$$

Recall

$$\frac{TP}{\text{Actual Pos}} = \frac{TP}{TP + FN}$$

$\text{class} \in \{1, 0\}$

F1-score

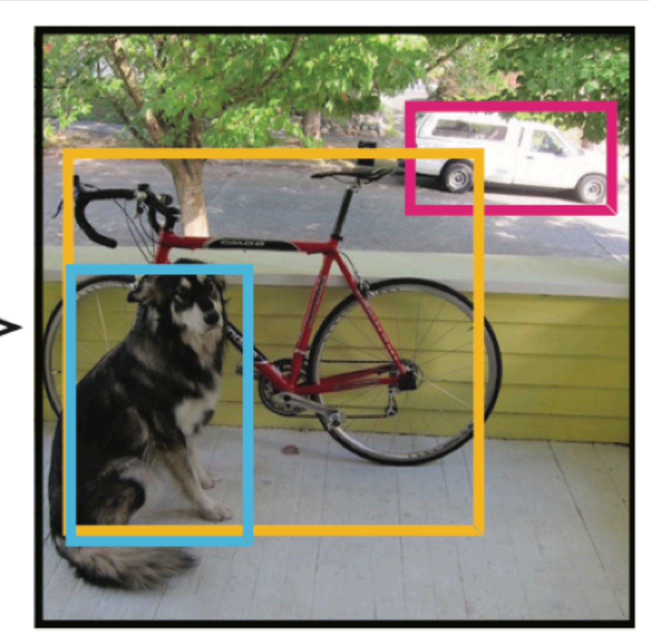
$$\frac{P+R}{2} \qquad 2\frac{PR}{P+R}$$

	Precision	Recall	Average	F1-score
Method A	0.5	0.4	0.45	0.44
Method B	0.7	0.1	0.4	0.18
Method C	0.02	1.0	0.51	0.04

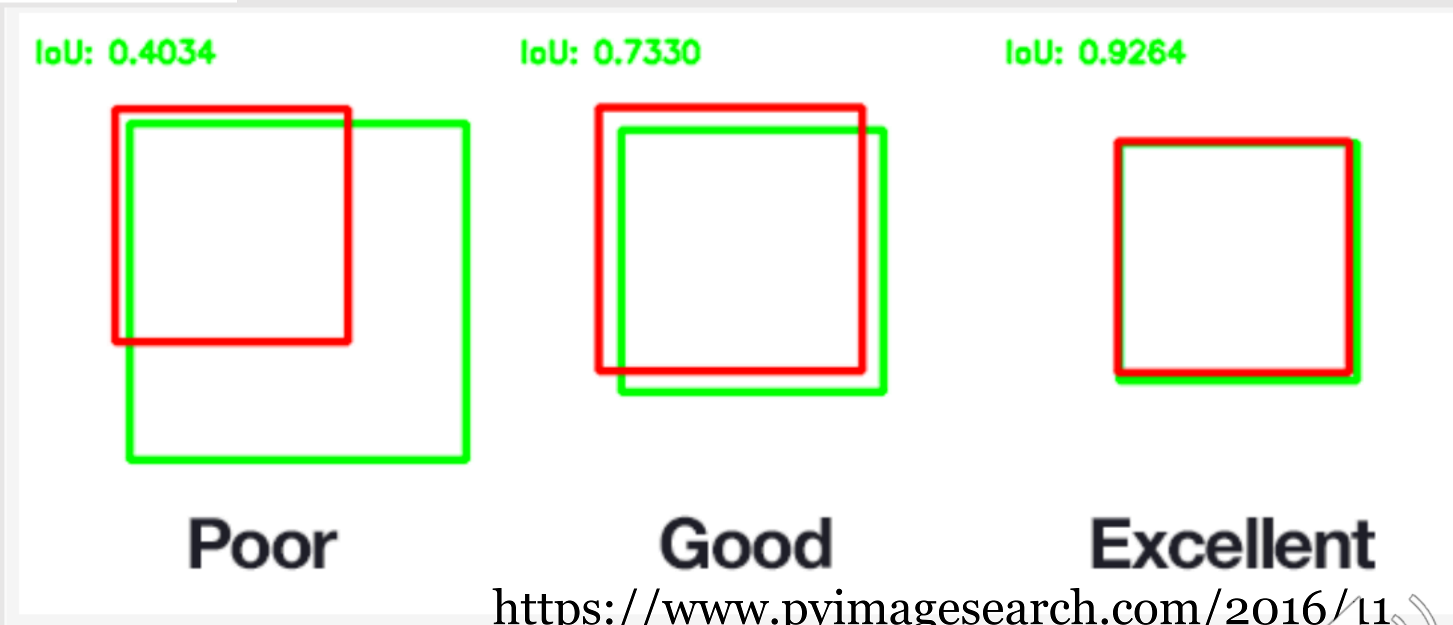
Precision == Positive Pred. Power

harmonic mean

Recall == Sensitivity

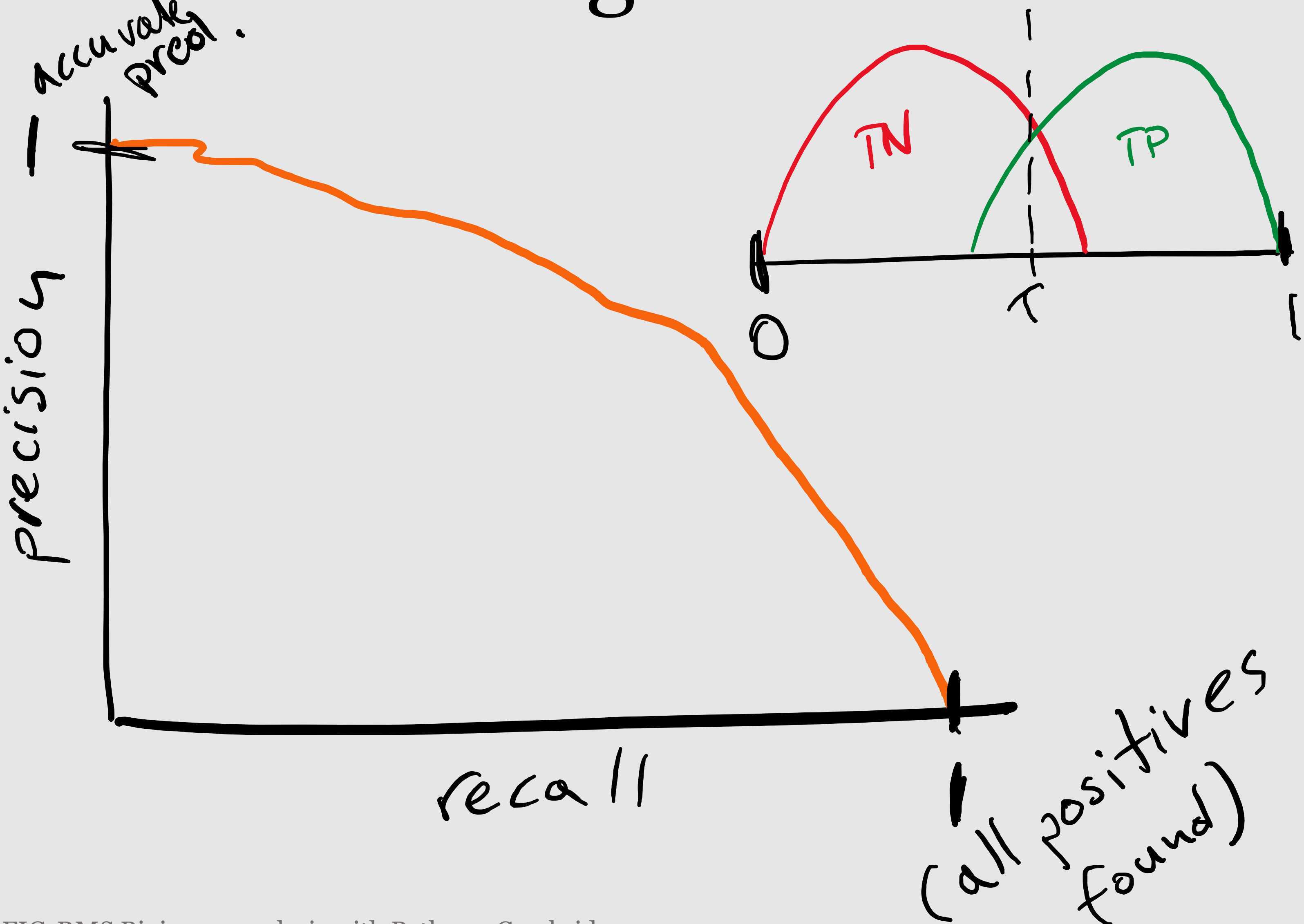


Intersection of Union



https://www.pyimagesearch.com/2016/11/07/intersection-over-union-iou-for-object-detection/

mean Average Precision



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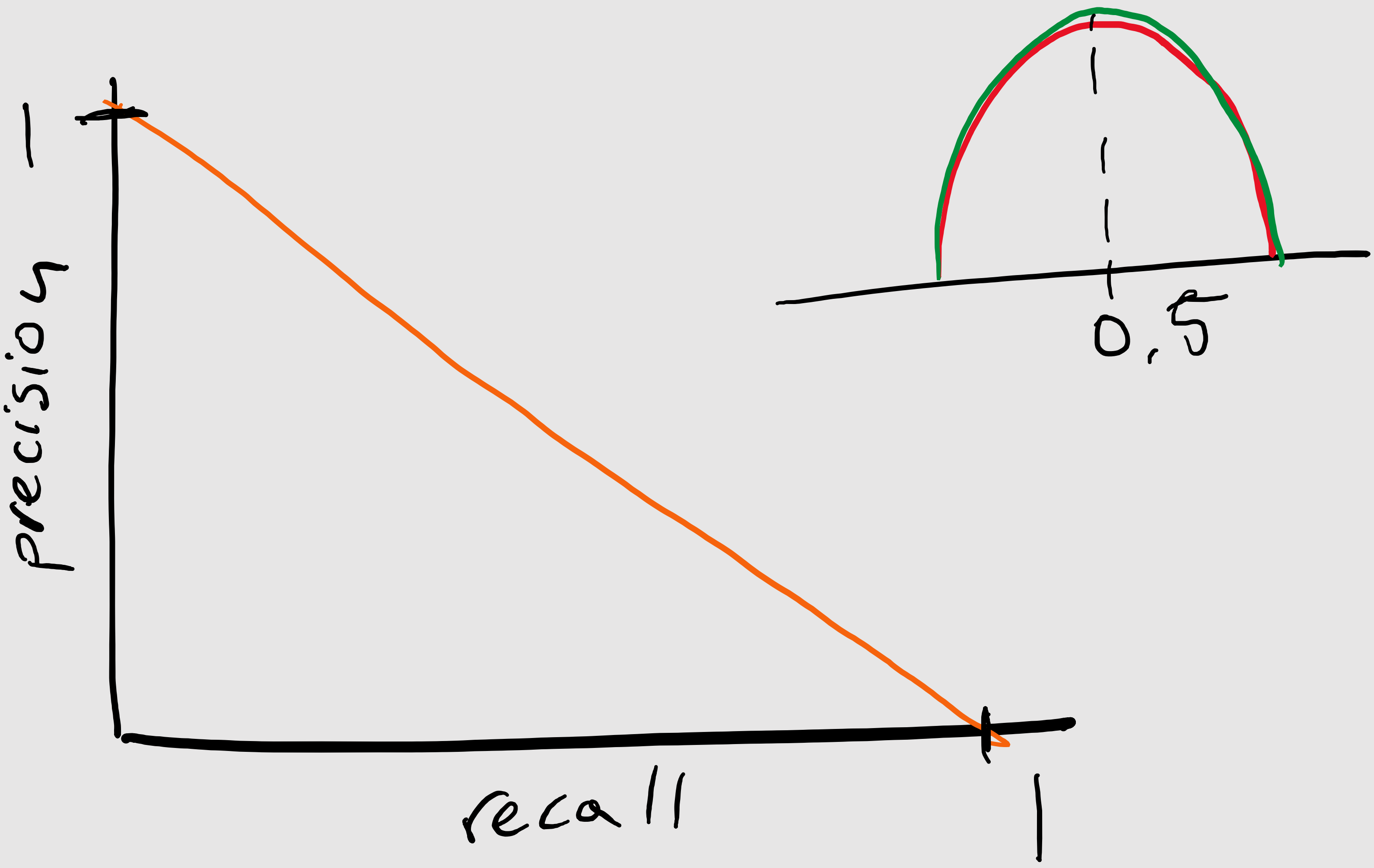

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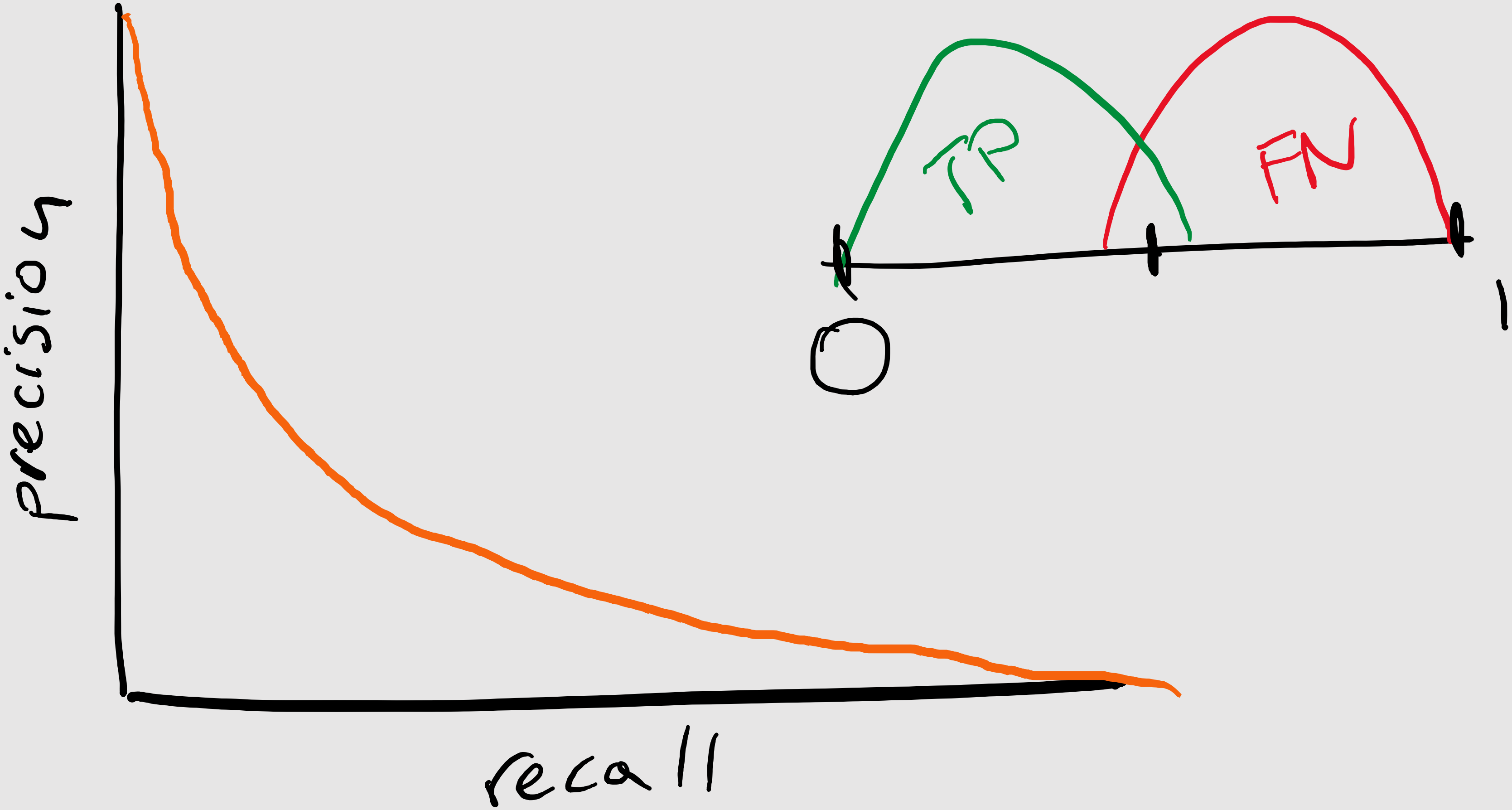

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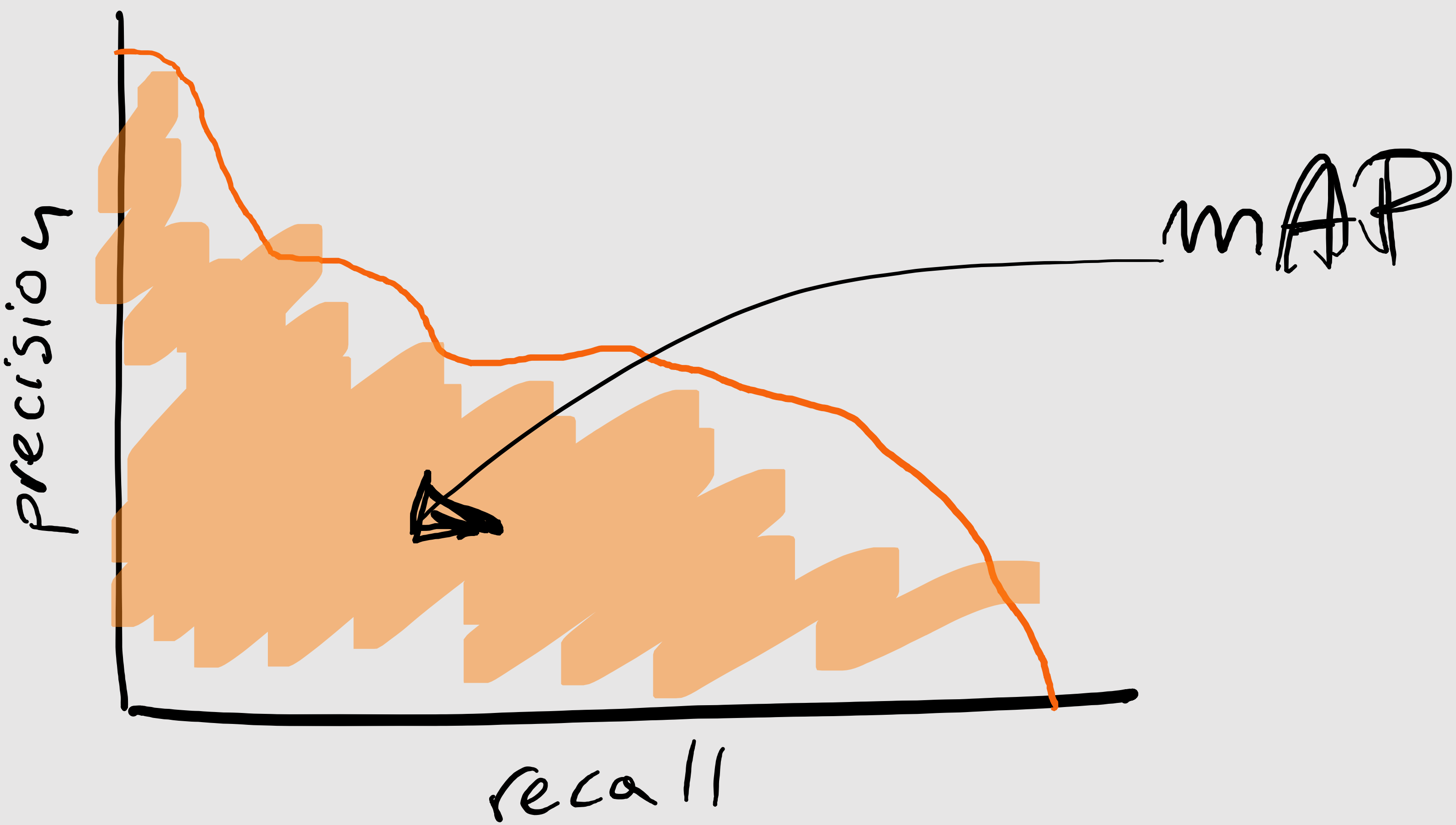
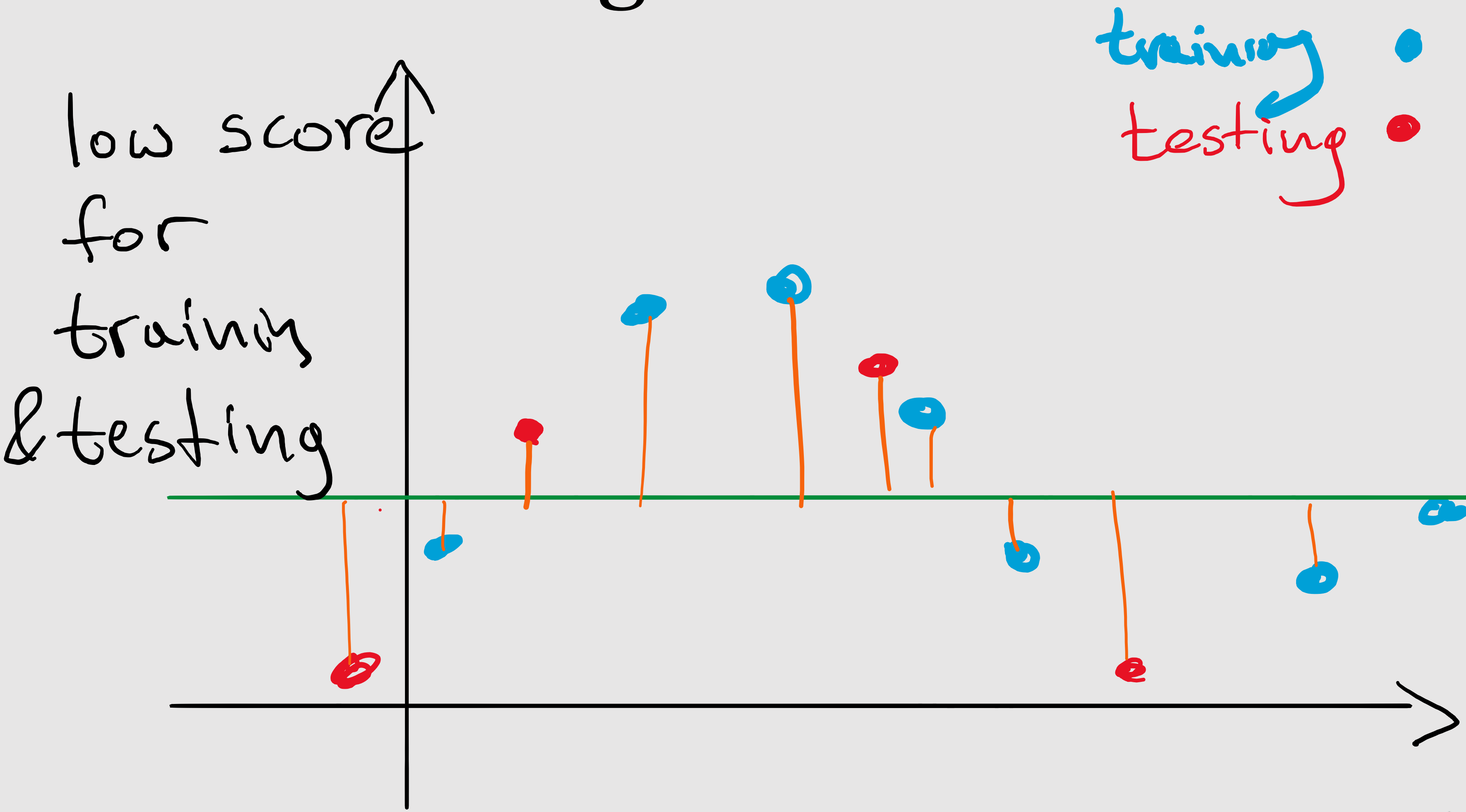
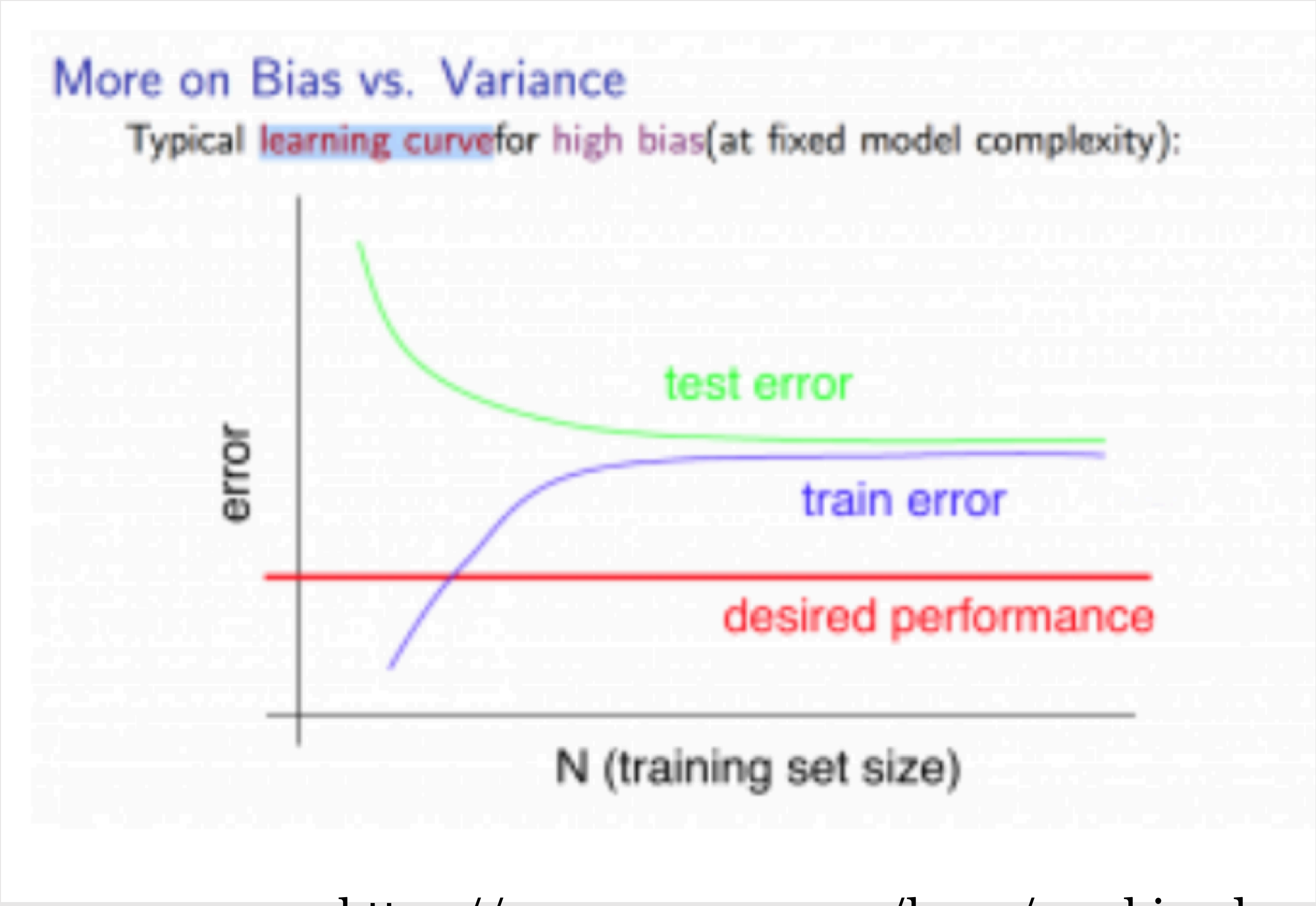


Underfitting



Underfitting – high bias



source: https://www.coursera.org/learn/machine-learning

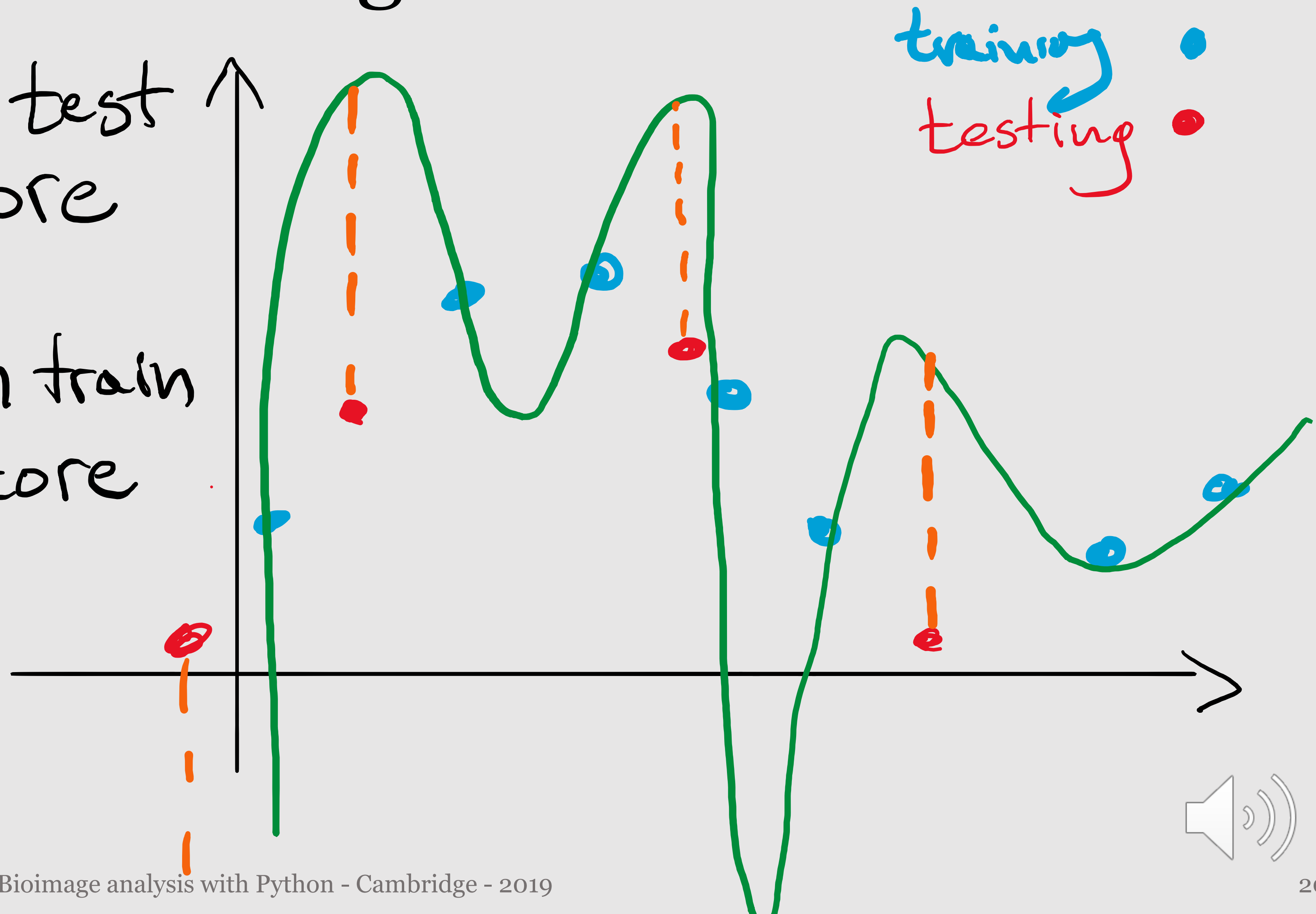
Underfitting

- more complex model
- more complex features
- more data

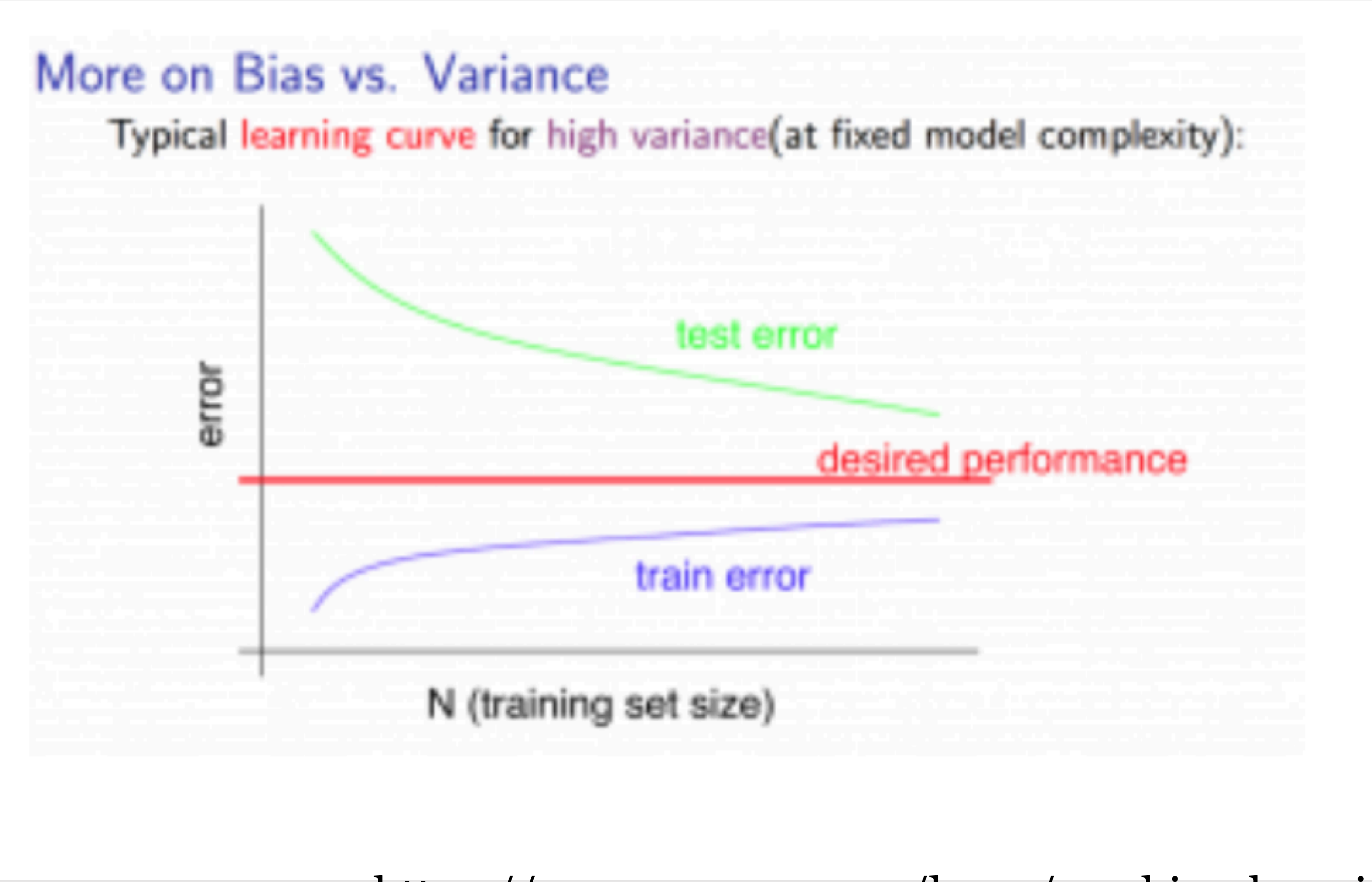
Overfitting

low test score

high train score



Overfitting – high variance



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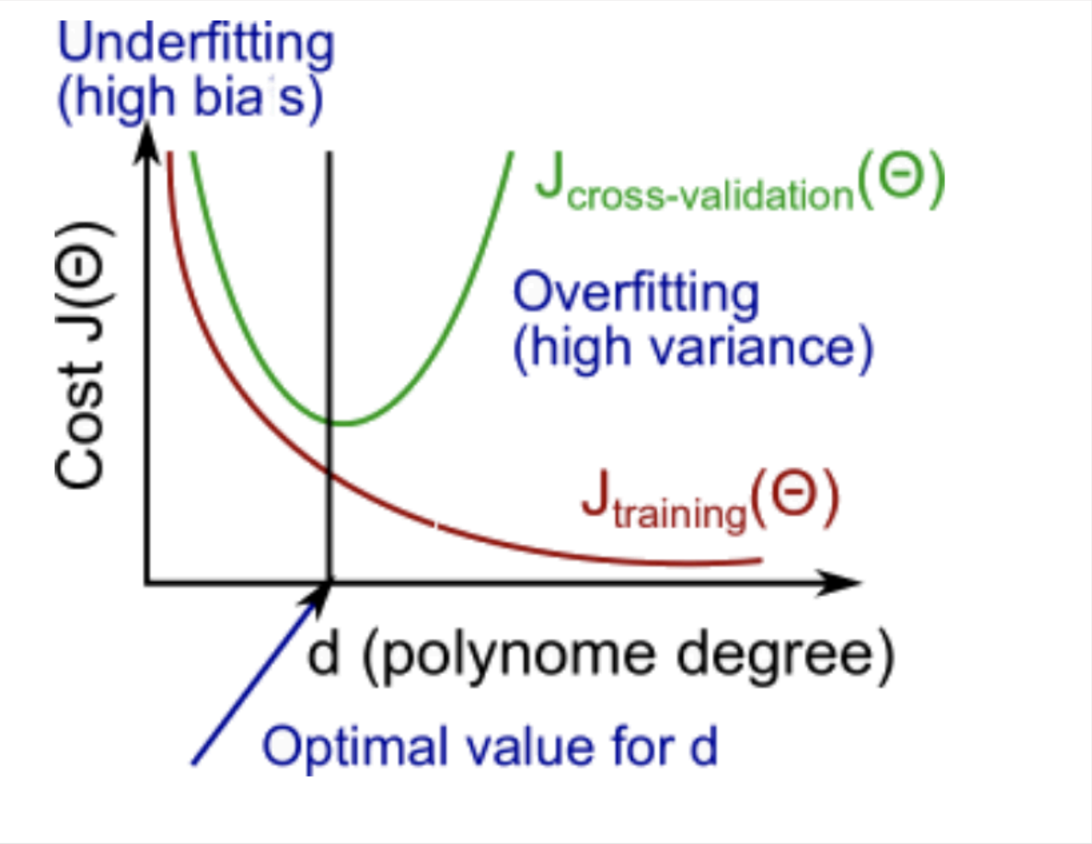
Overfitting – high variance



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Overfitting

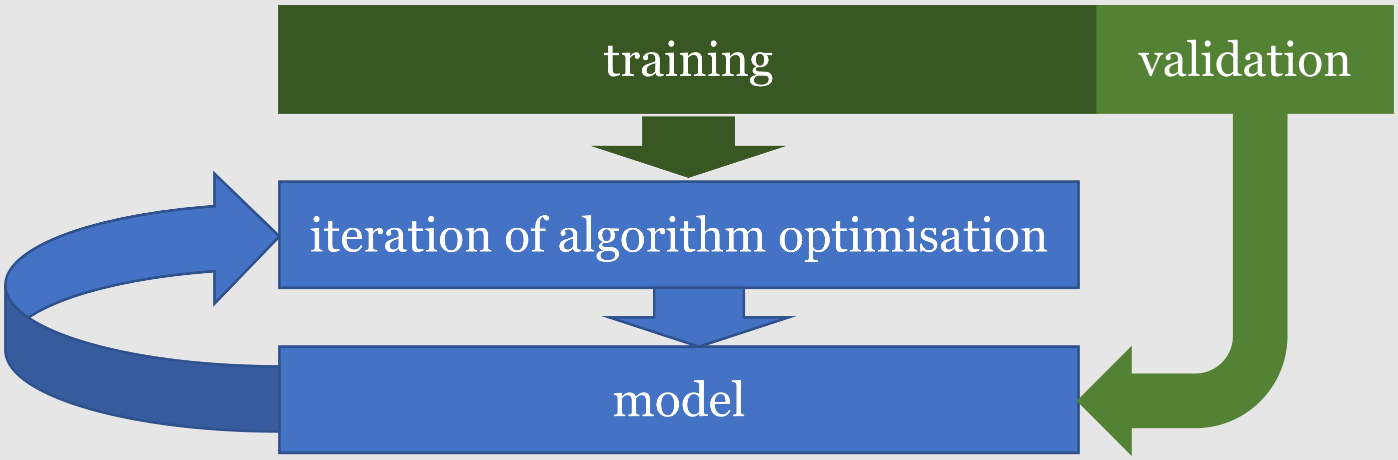
- simpler model
- regularisation
- cross-validation
- data augmentation

- Overfitting -> Underfitting? More data!

Regularisation

$$J(\theta) = \text{cost}\left(h_\theta(x), y\right) + \lambda \sum_j \theta_j^2$$

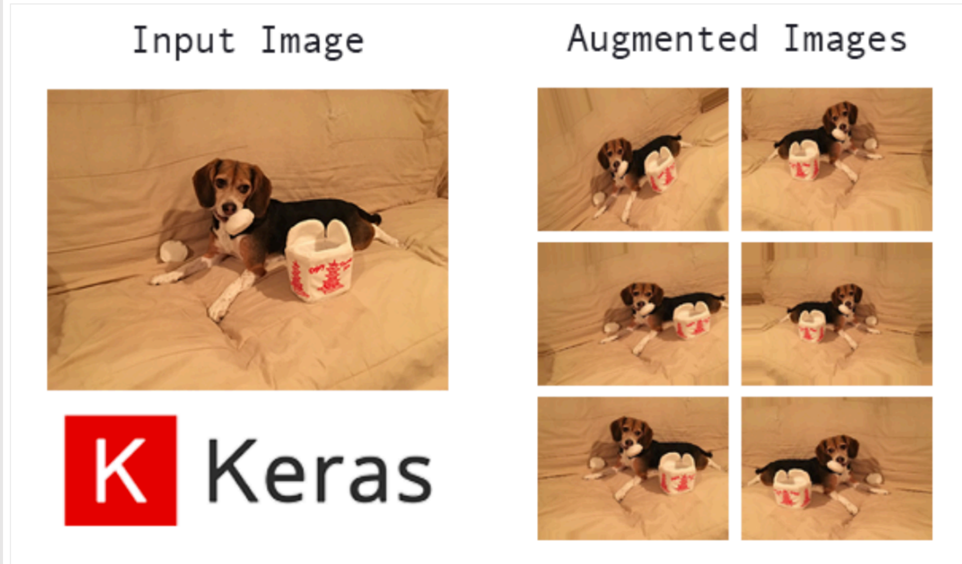
Cross-validation



k-fold CV: every iteration take different (k^{th}) part of the dataset

Data augmentation

- extending training set by artificially simulating more robust data



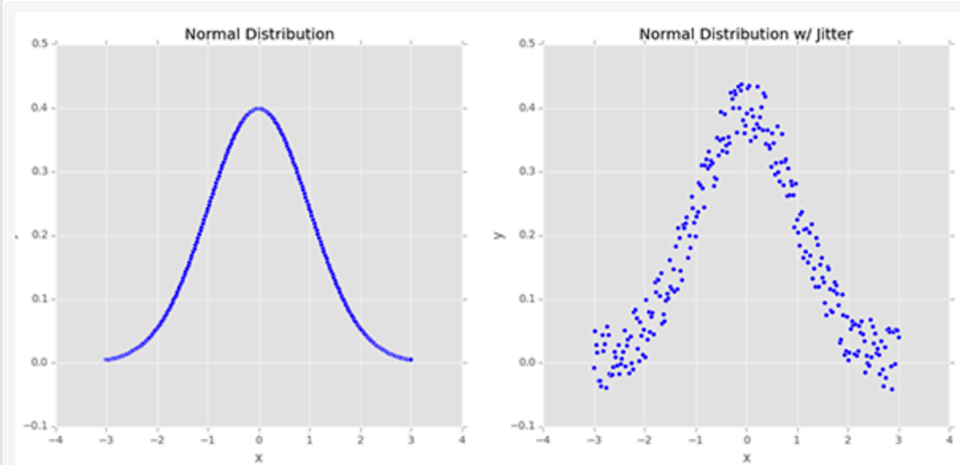
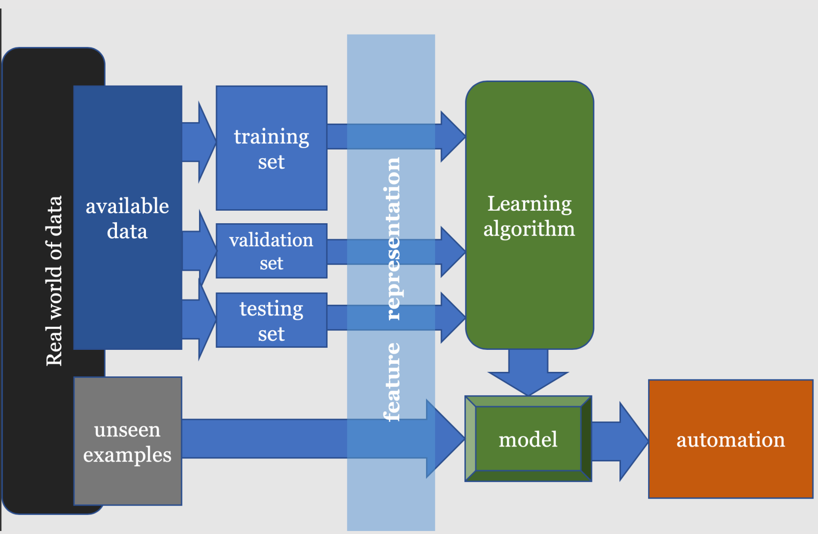


Figure 2: ***Left:*** A sample of 250 data points that follow a normal distribution exactly. ***Right:*** Adding a small mount o random “jitter” to the distribution. This type of data augmentation increases the generalizability of o ors.

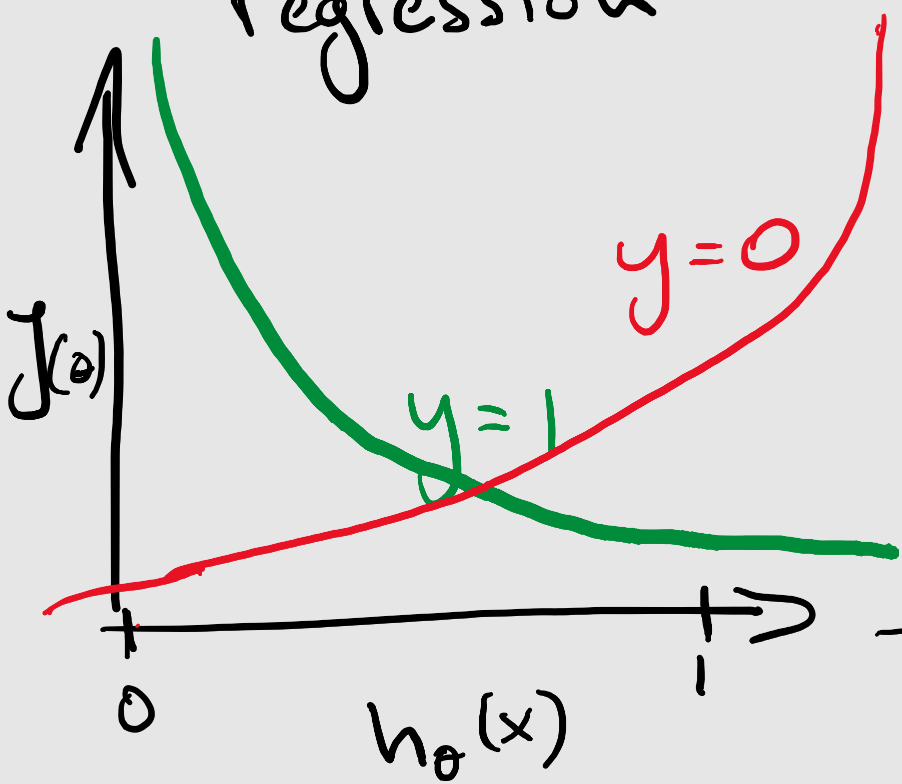
https://www.pyimagesearch.com/2019/07/08/keras-imagedatagenerator-and-data-augmentation/

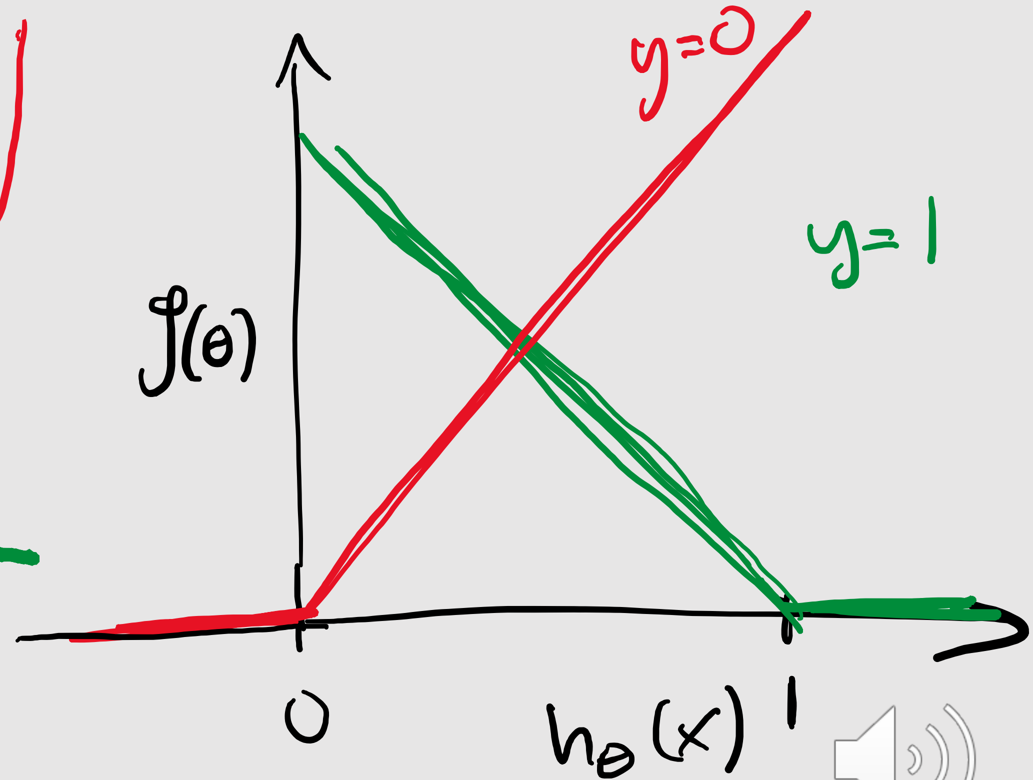


Support Vector Machine or Large Margin Classifier

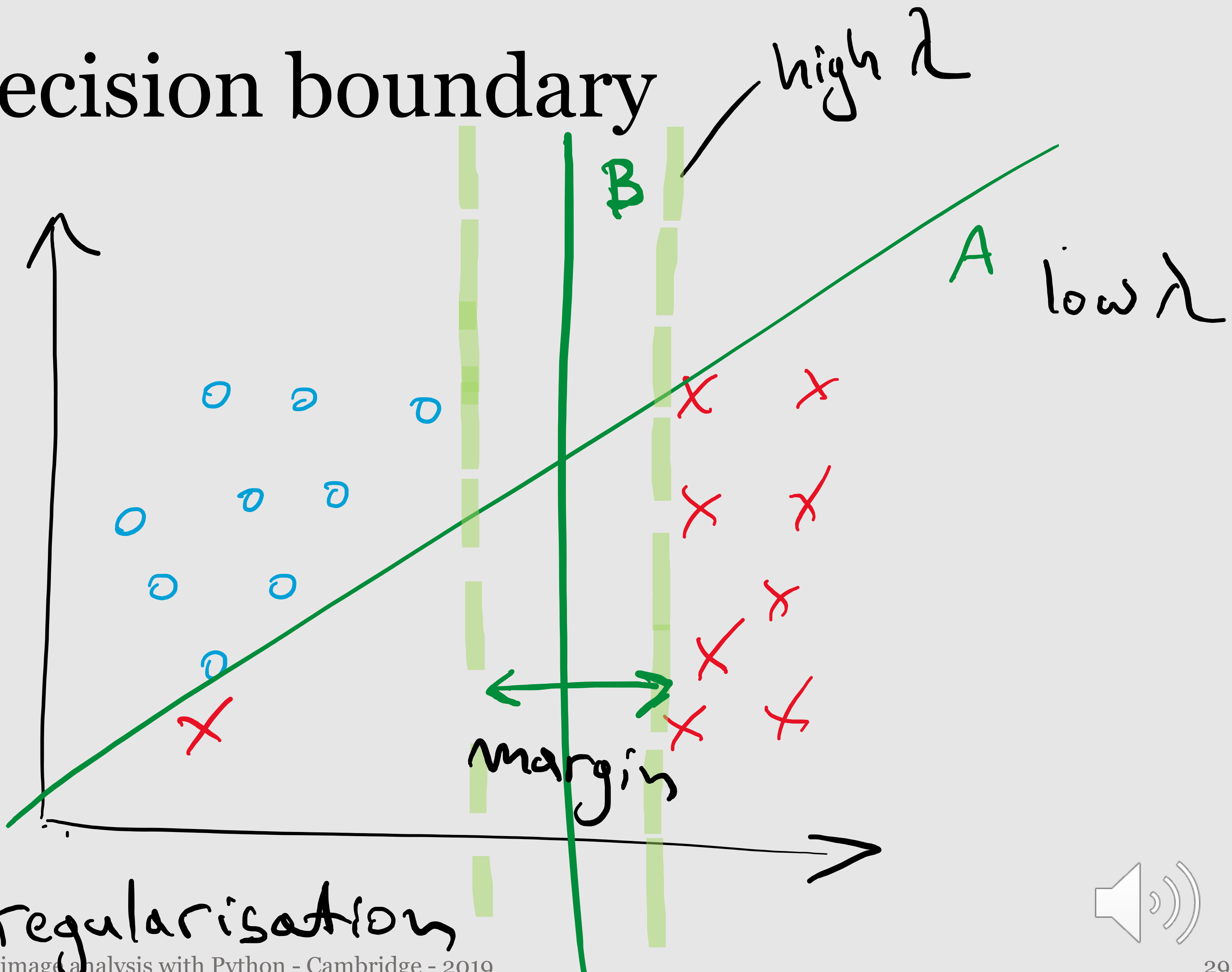
From logistic regression to kernel methods

cost in logistic regression



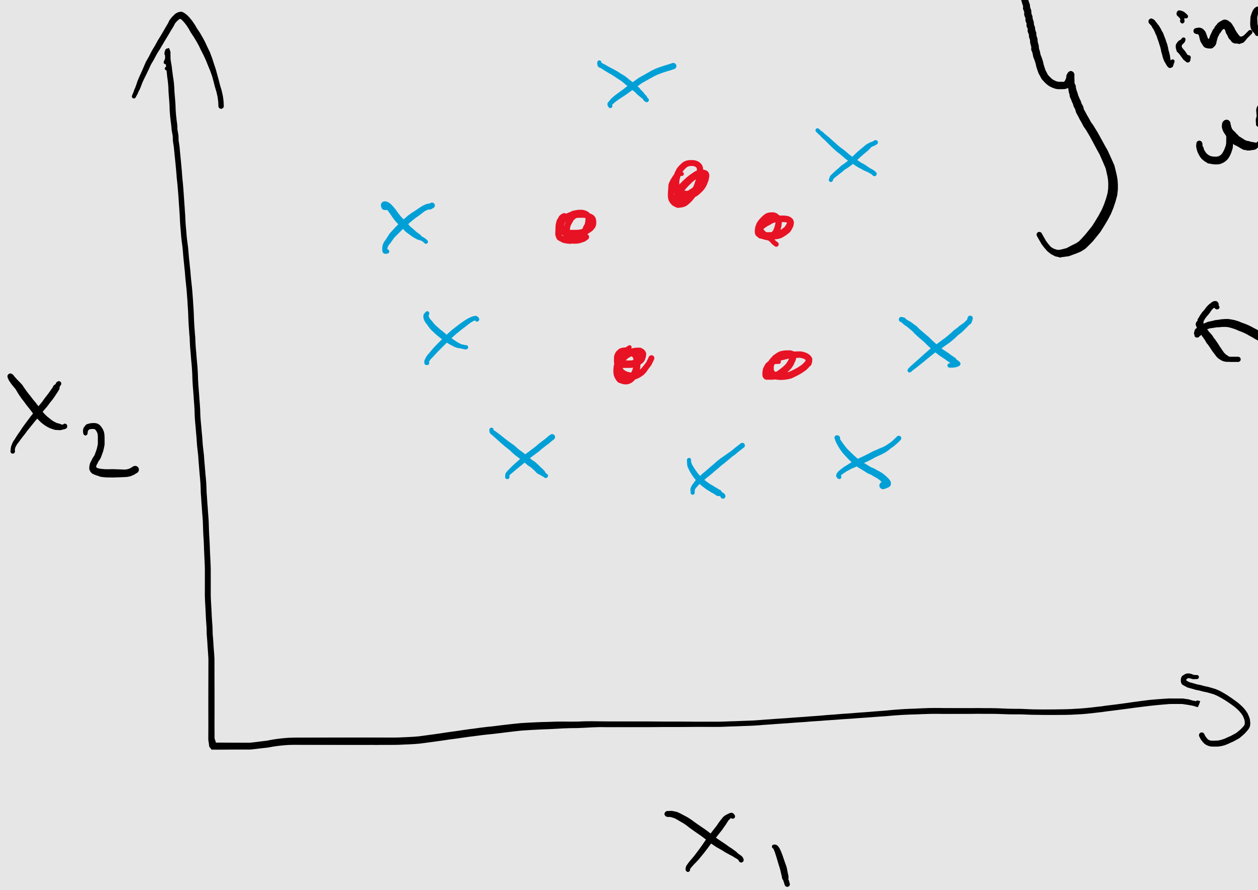


Decision boundary



λ - regularisation

Kernel "trick"

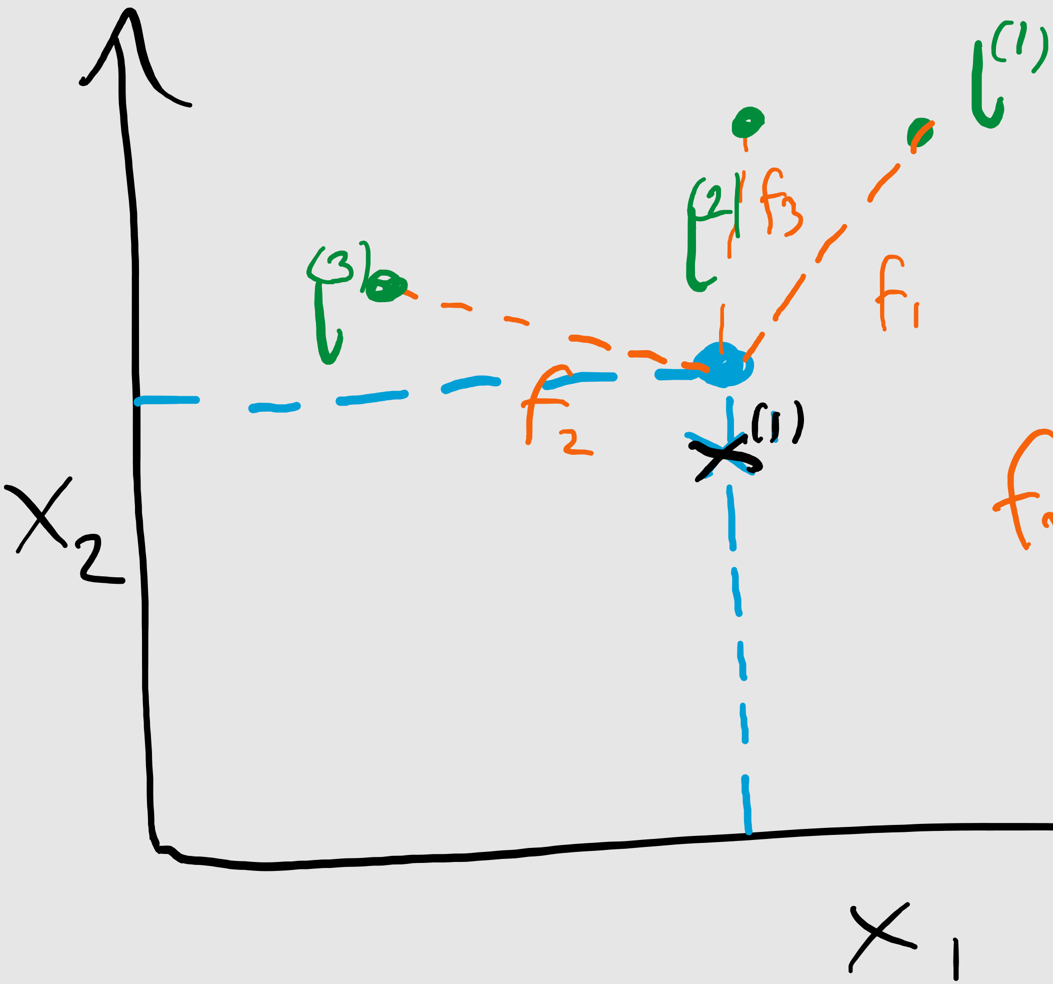


lineary unseparable

using high polynomials risks overfitting!

Kernel "trick"

$$f_n = \underbrace{\text{similarity}(x, l^{(n)})}_{\text{Kernel}}$$



$$f_n = \exp\left(-\frac{\|x - l^{(n)}\|^2}{2\sigma^2}\right)$$

$x \approx l^{(n)} \Rightarrow f_n = 1$

x far from $l^{(n)} \Rightarrow f_n = 0$

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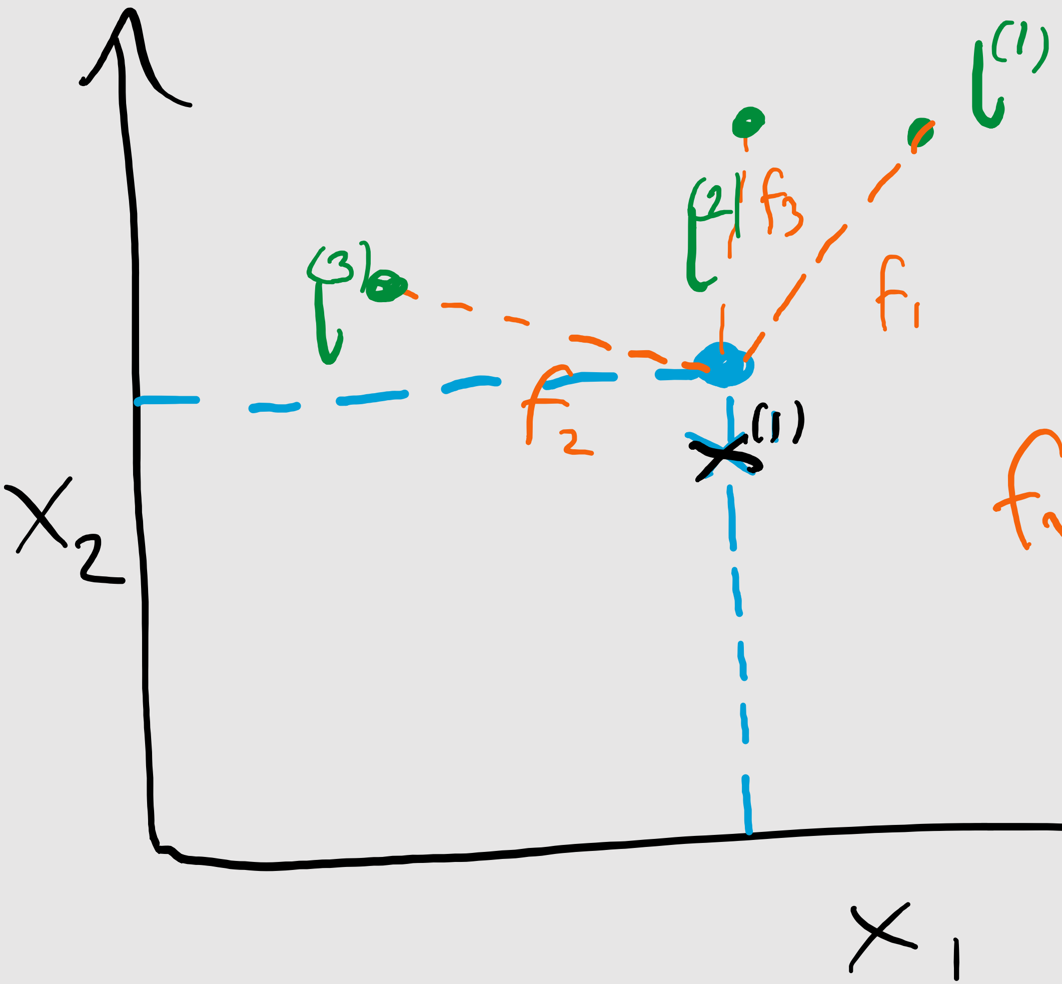

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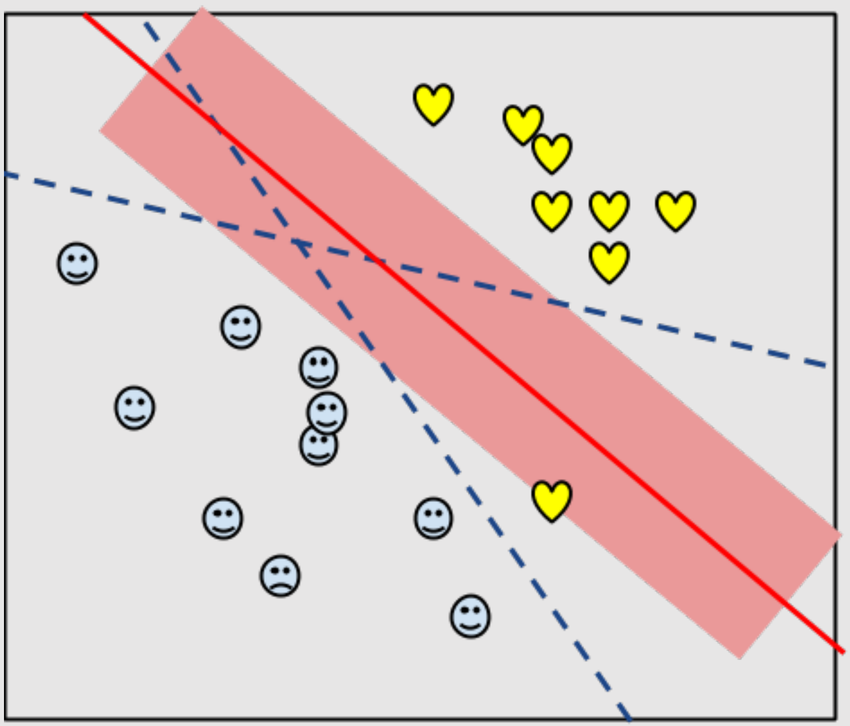
$x \approx l^{(n)} \Rightarrow f_n = 1$

x far from $l^{(n)} \Rightarrow f_n = 0$

Similarity

- If $x \approx l^{(n)} \Rightarrow f_n = 1$, x far from $l^{(n)} \Rightarrow f_n \approx 0$
- What if we have a lot of landmarks?
- What if all training examples are landmarks?
- Different kernels (Gaussian, Linear, Polynomial) depending on relationship in data

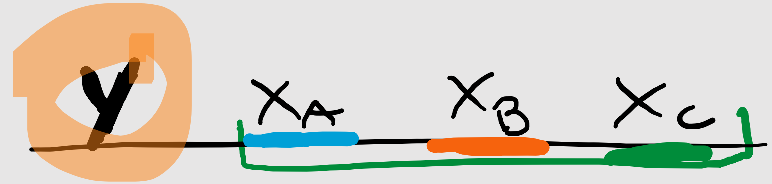
Support Vector (...machine) == Large Margin Classifier



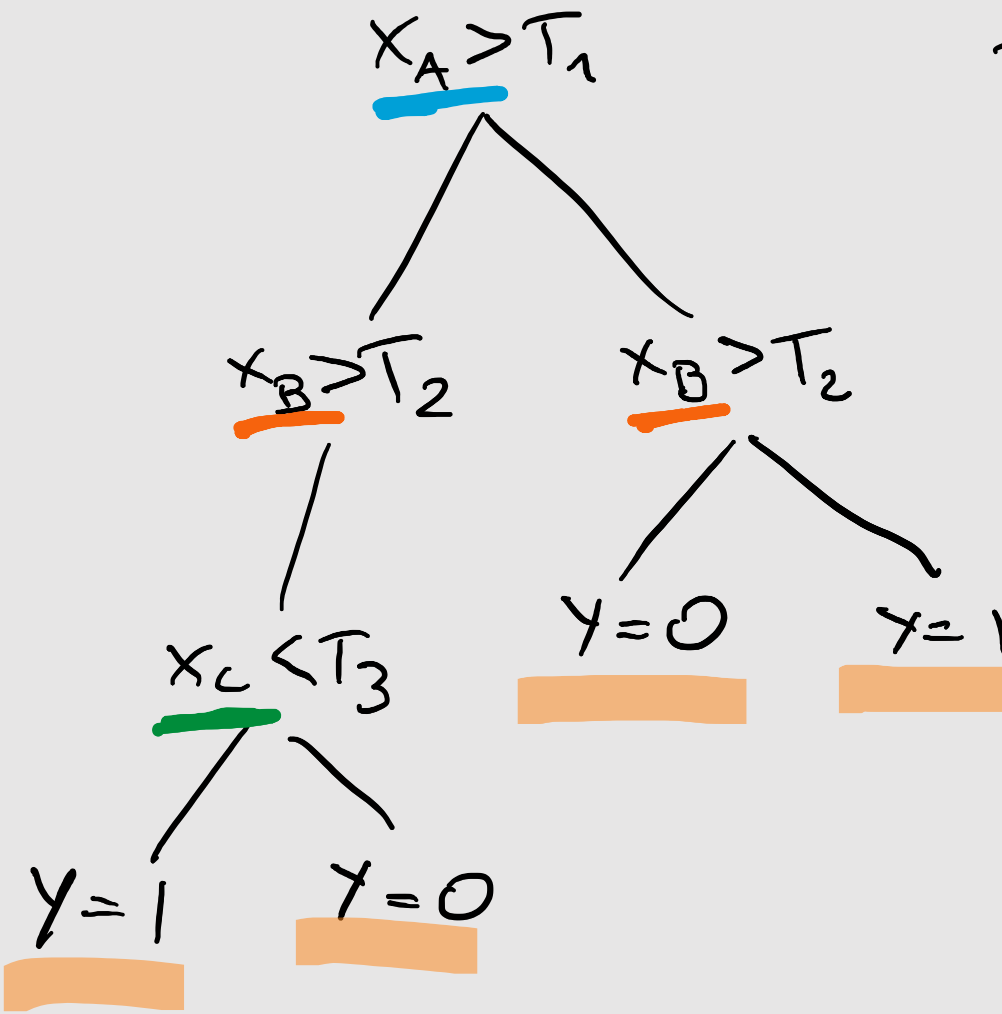
Basically, linear regression with slightly modified cost function and transformed features...

Let's make features out of data!

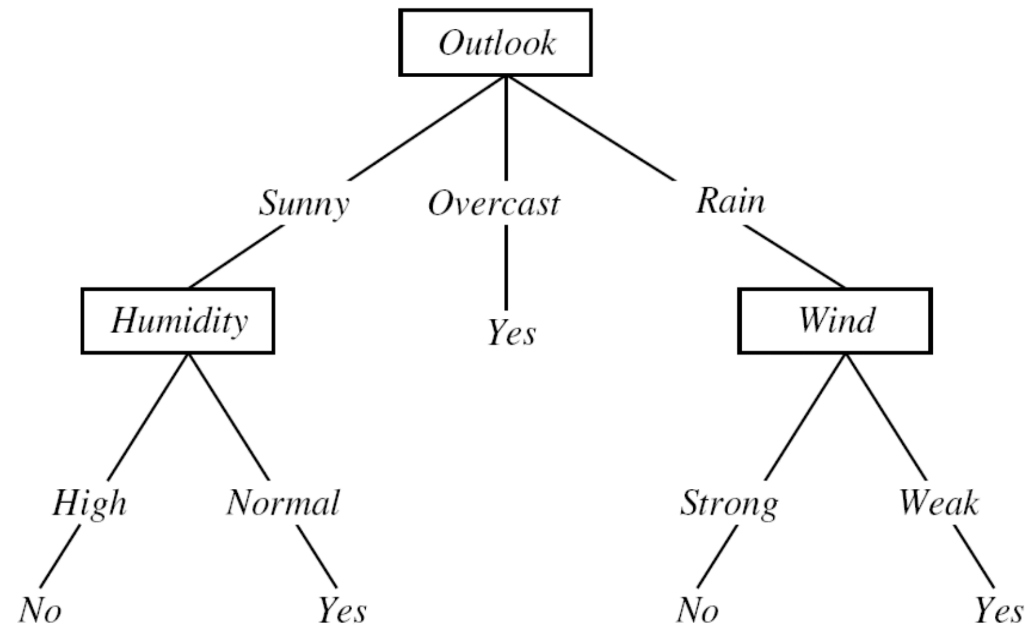
Decision tree



- optimise to minimize entropy with every division



Decision tree



Attributes

Classification

Outlook	Temperature	Humidity	Windy	Fly
Sunny	85	85	False	No
Sunny	80	90	True	No
Overcast	83	86	False	Yes
Rainy	75	80	False	Yes
…	…	…	…	…

source: http://breckon.eu/toby/teaching/mltutorial/

Random Forest

- One decision tree is a basic classifier
- Train multiple small trees (each on subset of features)
- Let them vote on the final outcome
- Principles of “many wrong”
- Small trees == regularisation, no overfitting
- Routinely used to classify vast datasets from particle physics and astronomy