

introduction to Machine Learning

What

3 lectures:

- 1: general introduction
- 2: bayesian methods and parametric gaussian models
- 3: non parametric models

Who

Ms students and last year engineers school

Credits

A. Zisserman lecture (oxford)

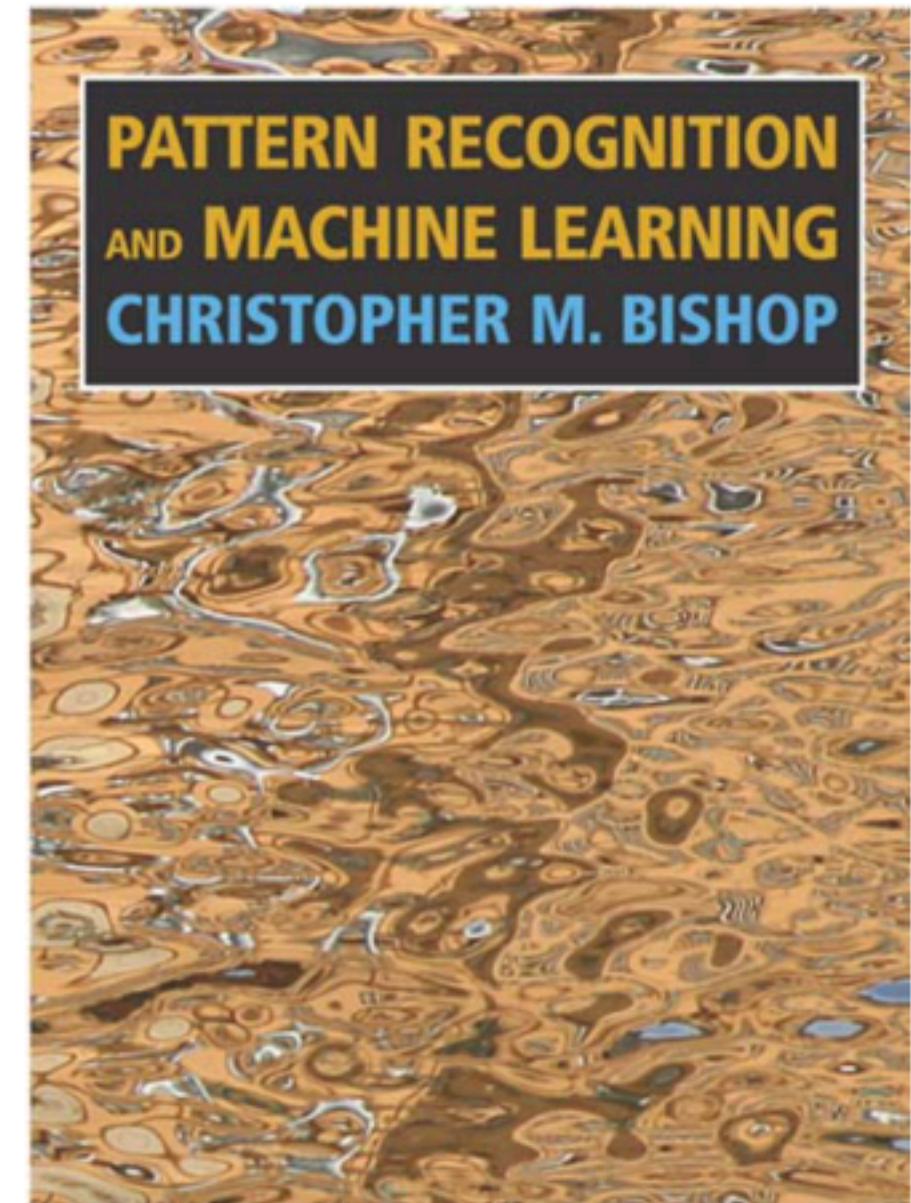
C. Wolf: LIRIS, Lyon

recommended books

- **Pattern Recognition and Machine Learning**

Christopher Bishop, Springer, 2006.

- Excellent on classification and regression



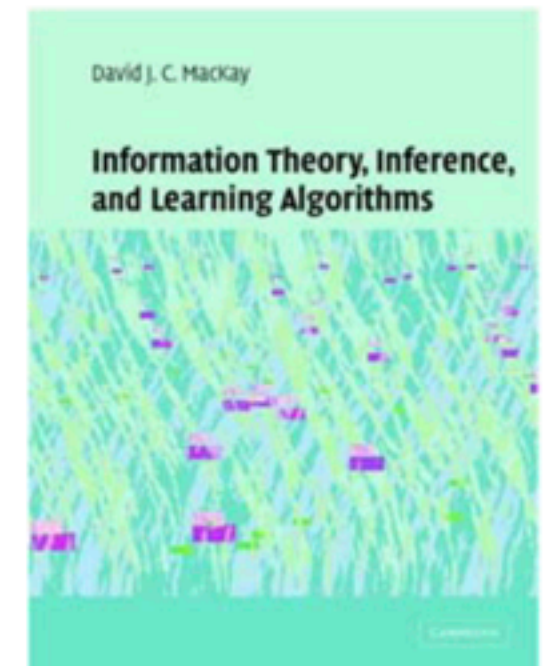
recommended books

- On line book:

Information Theory, Inference, and Learning Algorithms.

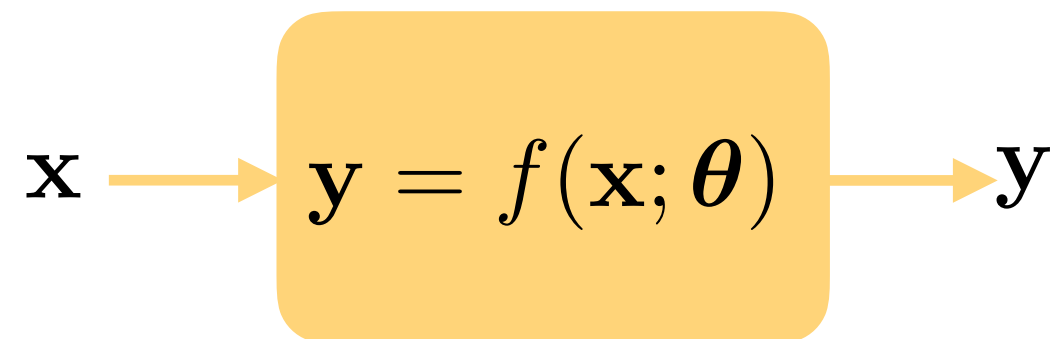
David J. C. MacKay, CUP, 2003

- Covers some of the course material though at an advanced level



What is Machine Learning?

an algorithm that can improve its performance using training data



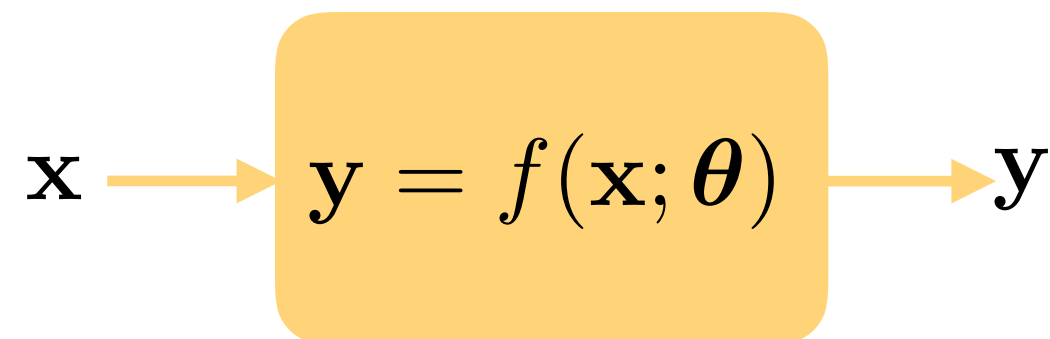
θ is a vector of parameters (large) computed from a training database

function f cannot be defined with *rules by hand*

face detection, speech recognition, stock prediction,...

What is Machine Learning?

an algorithm that can improve its performance using training data



θ is a vector of parameters (large) computed from a training database

if y is discrete: classification

if y is continuous: regression

Machine Learning

The machine learning framework

- Apply a prediction function to a feature representation of the image to get the desired output:

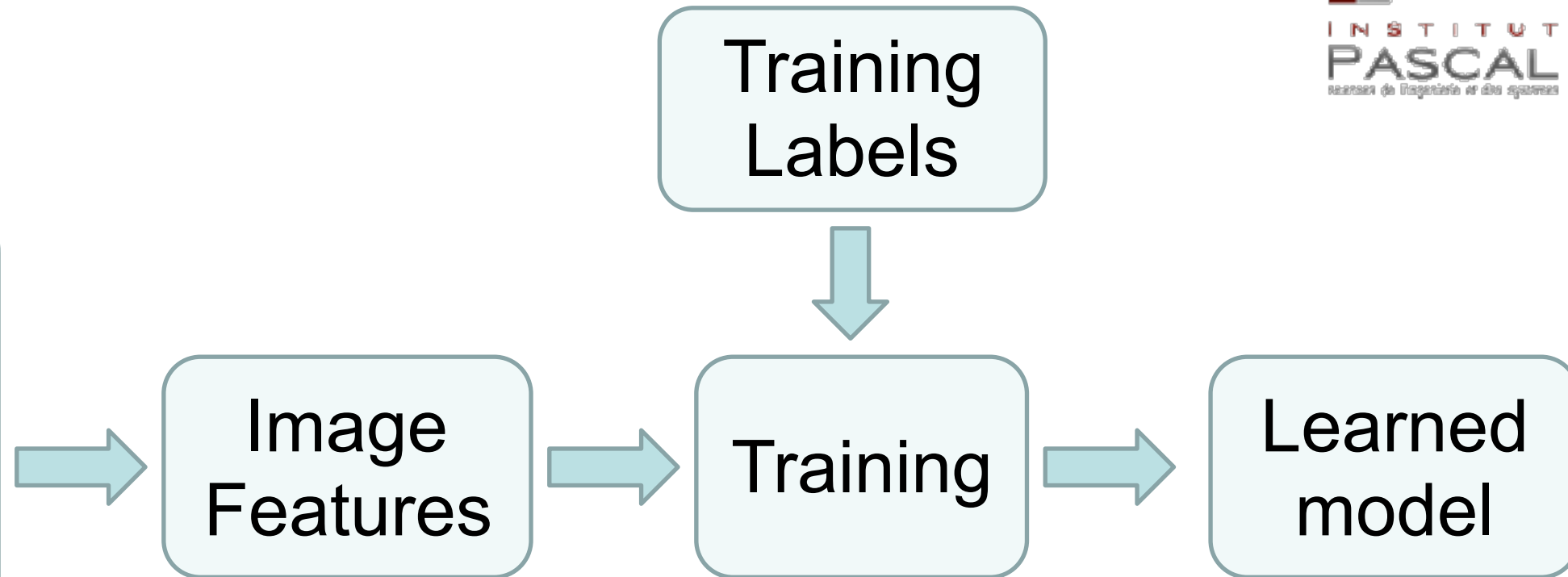
$$f(\text{apple image}) = \text{"apple"}$$

$$f(\text{tomato image}) = \text{"tomato"}$$

$$f(\text{cow image}) = \text{"cow"}$$

Traditional Machine Learning

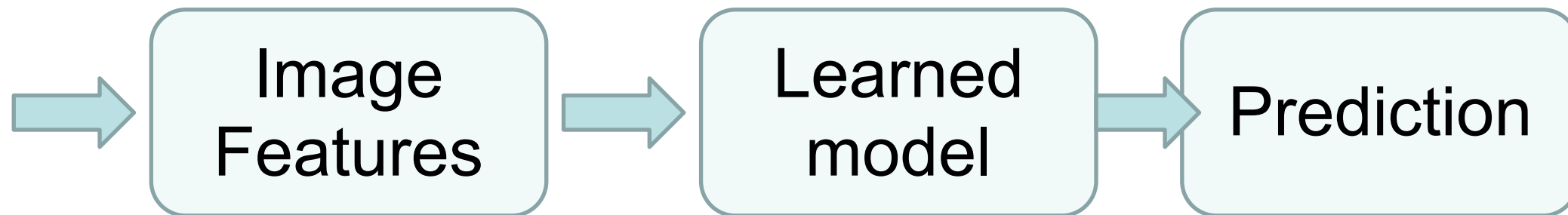
Training Training Images



Testing



Test Image



Slide credit: D. Hoiem and L. Lazebnik

Training Training Images



Training
Labels



Training

Learned
model

Testing

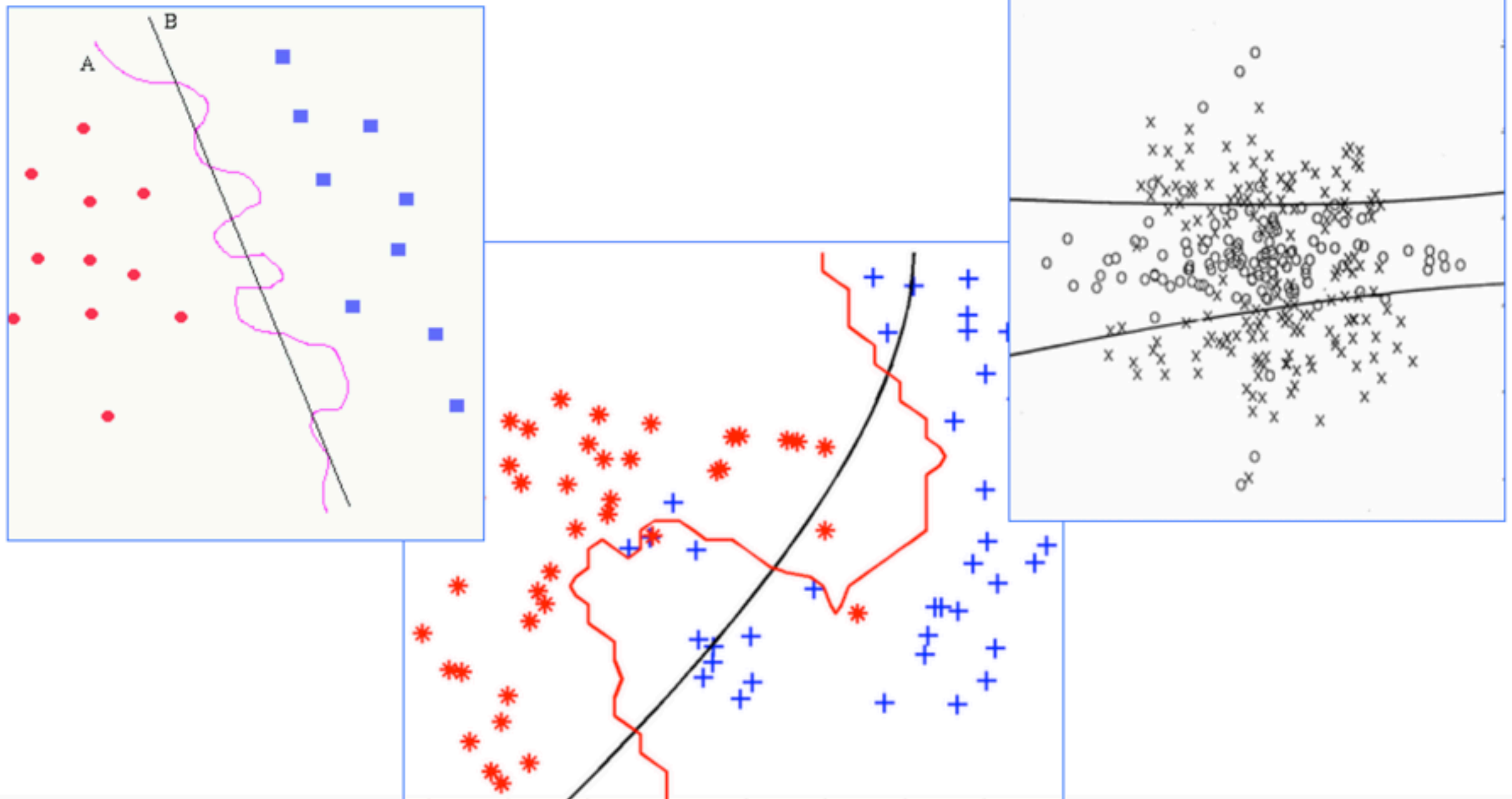


Test Image

Learned
model

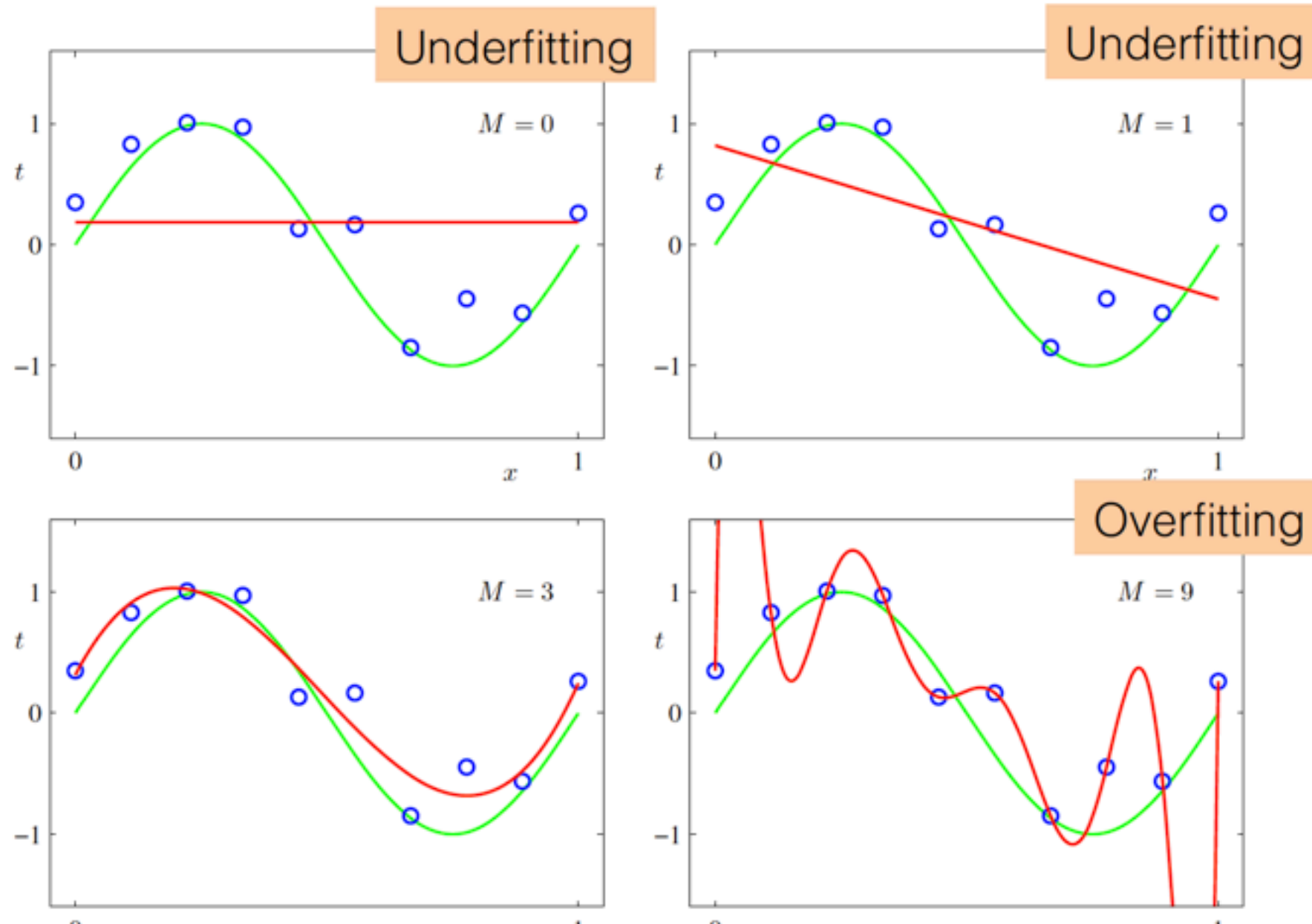
Prediction

Learn a decision function into a feature space



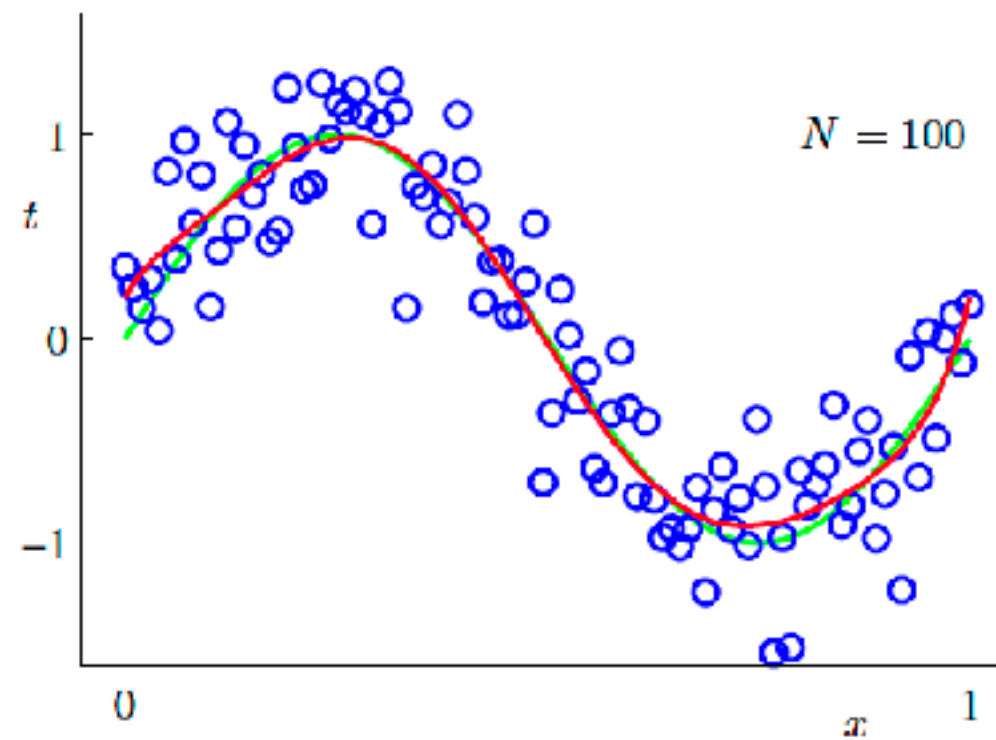
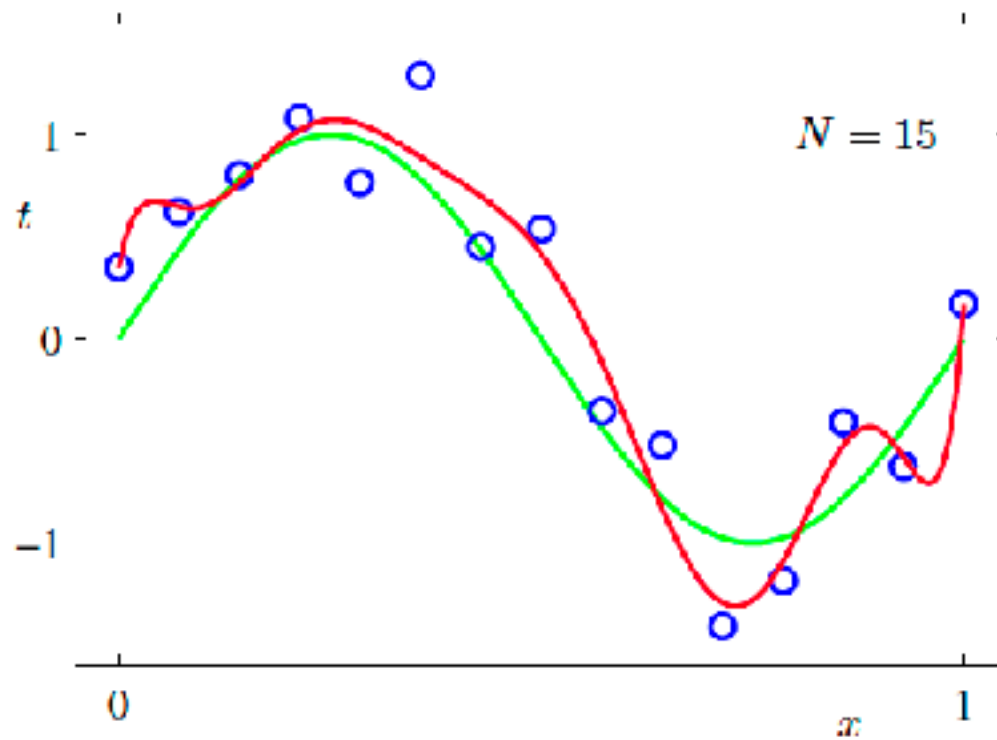
slide credits: C. Wolf

Model selection



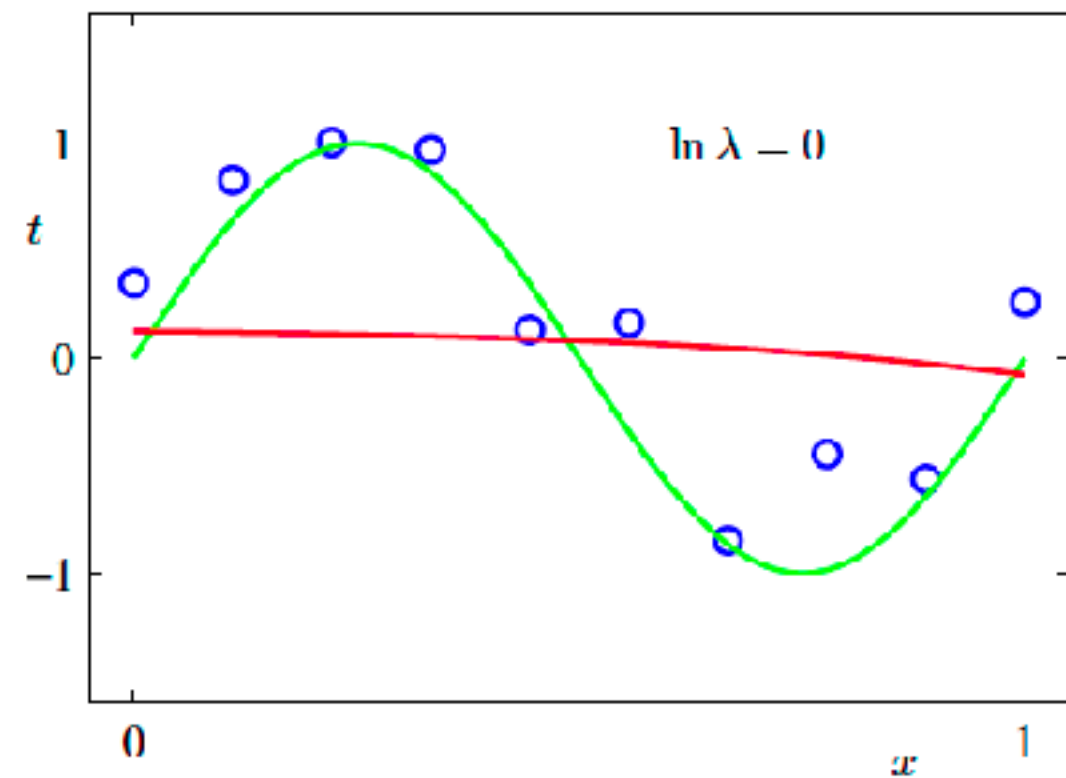
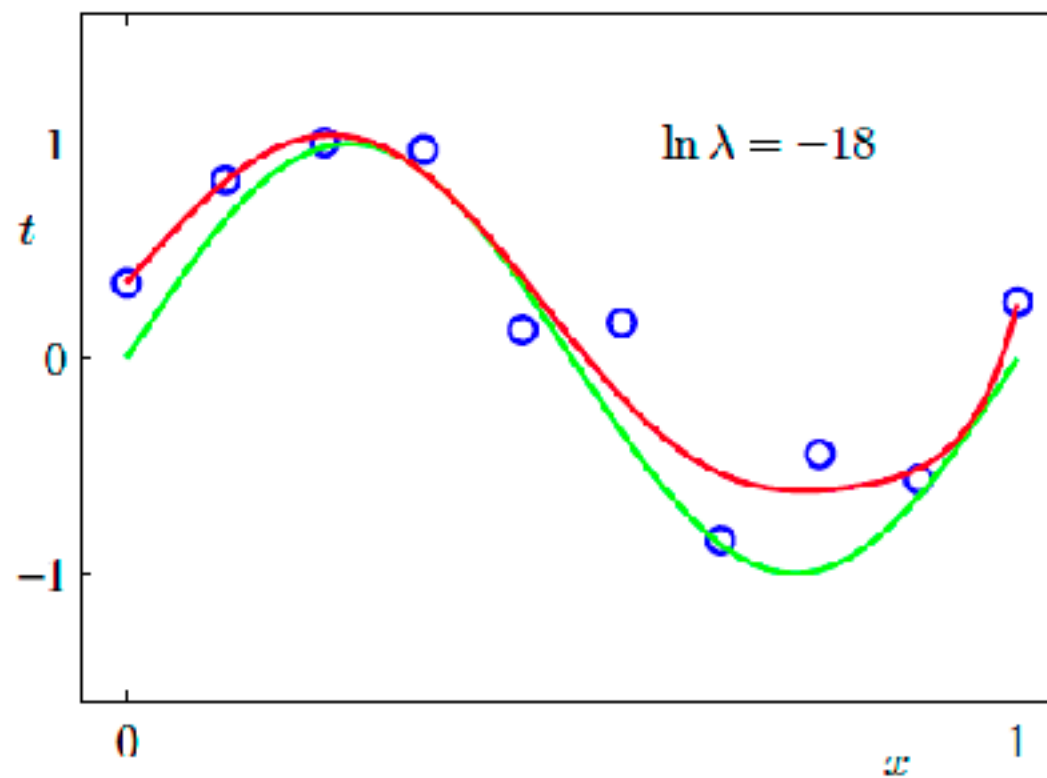
$$y(x, \mathbf{w}) = w_0 + w_1x + w_2x^2 + \dots + w_Mx^M = \sum_{j=0}^M w_jx^j$$

Overfitting can be reduced by increasing the training size



slide credits: C. Wolf

$$\tilde{E}(\mathbf{w}) = \frac{1}{2} \sum_{n=1}^N \{y(x_n, \mathbf{w}) - t_n\}^2 + \frac{\lambda}{2} \|\mathbf{w}\|^2$$



Example 1: hand written digit recognition

$$\mathbf{x} \longrightarrow \boxed{y = f(\mathbf{x}; \theta)} \longrightarrow y$$



represent input image as a vector:

$$\mathbf{x} \in \mathbb{R}^{794}$$



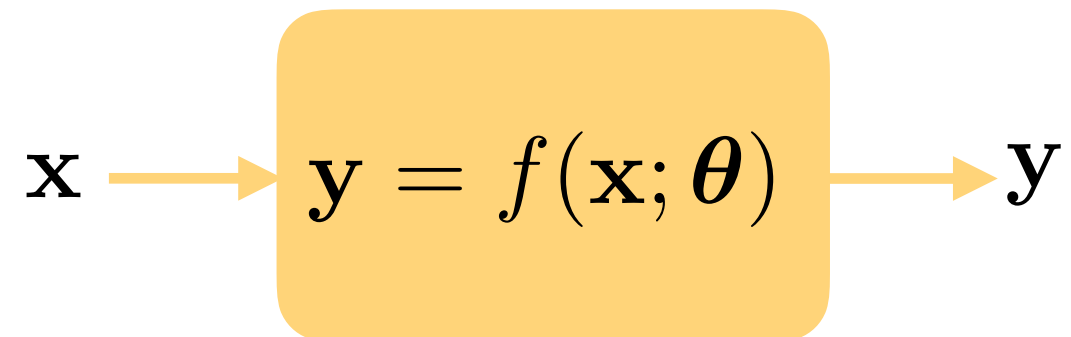
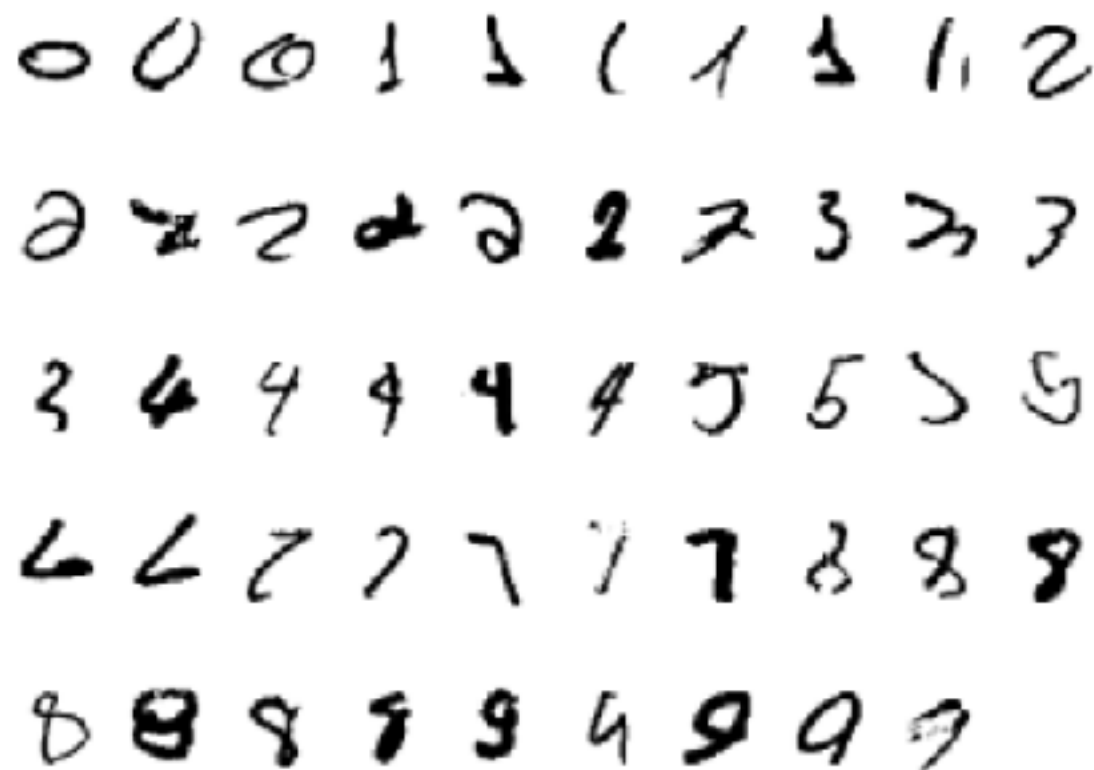
Images are 28 x 28 pixels

learn function f :

$$f : \mathbf{x} \rightarrow \{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}$$

this is a **classification** problem

Example 1: hand written digit recognition



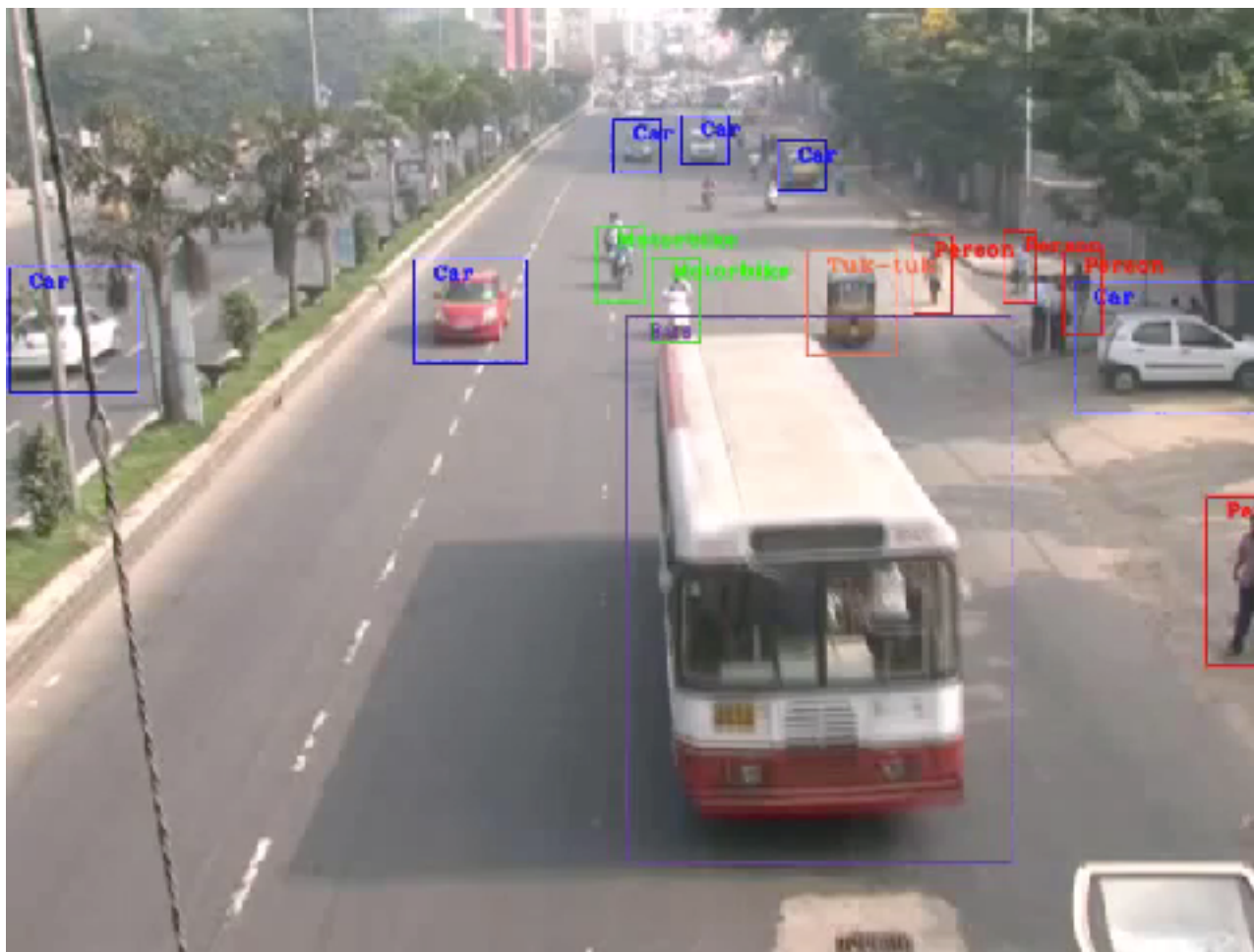
we need an annotated dataset
(supervised learning)
6000 samples to learn the
parameter vector θ

**Training based systems can
achieved a test error of 0.4%**

Example 2: vehicle detection

$$\mathbf{x} \longrightarrow y = f(\mathbf{x}; \boldsymbol{\theta}) \longrightarrow y$$

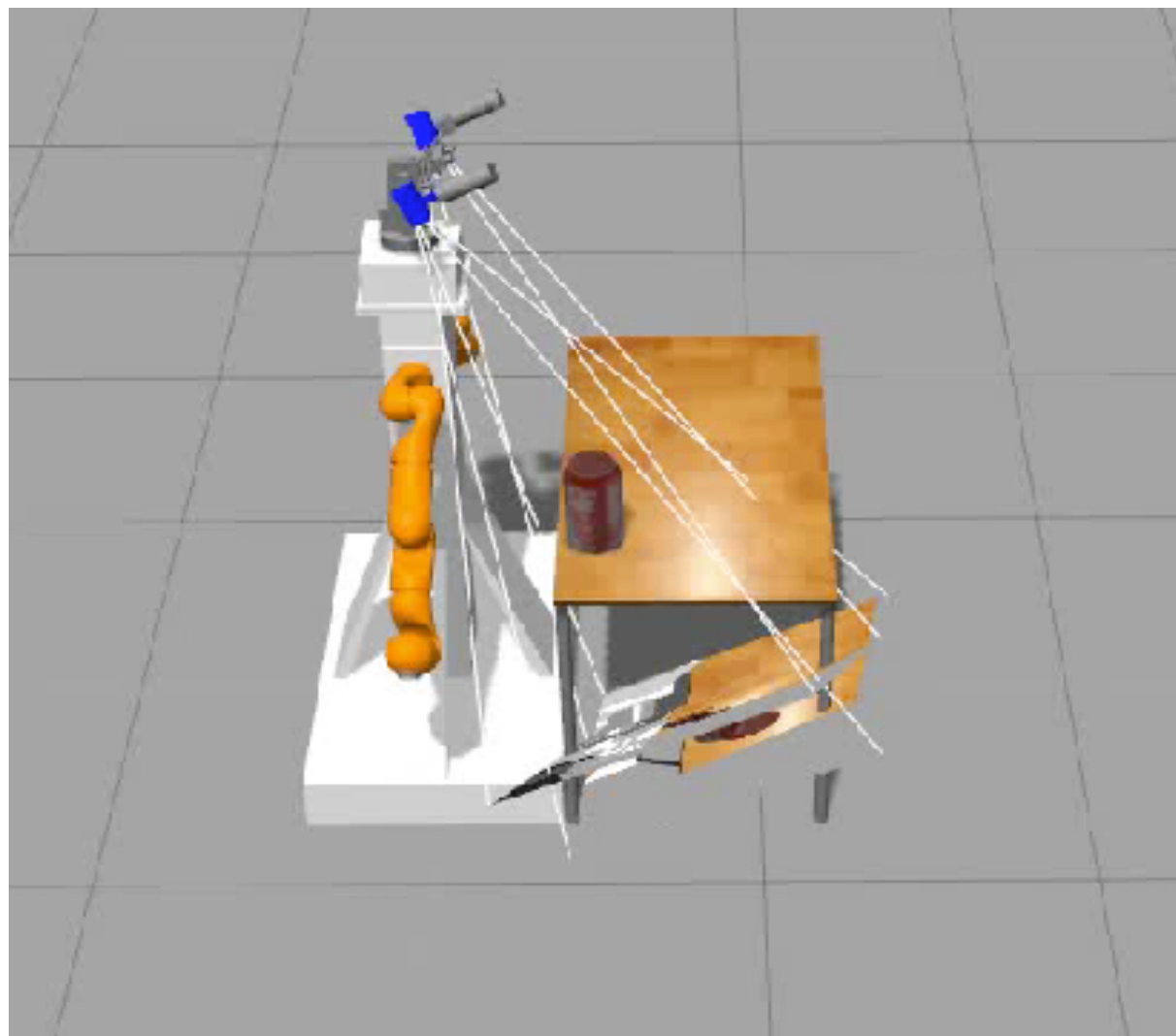
we need an annotated dataset
(supervised learning)
samples to learn the parameter
vector $\boldsymbol{\theta}$



Mhalla PhD: Pascal Institute, 2017

Example 3: sensori-motor estimation

stereo-vision focusing



François de la Bourdonnaye, PhD, 2017; IP

$$\mathbf{x} \longrightarrow \mathbf{y} = f(\mathbf{x}; \boldsymbol{\theta}) \longrightarrow \mathbf{y}$$

we need an annotated dataset
(supervised learning)
6000 samples to learn the
parameter vector $\boldsymbol{\theta}$



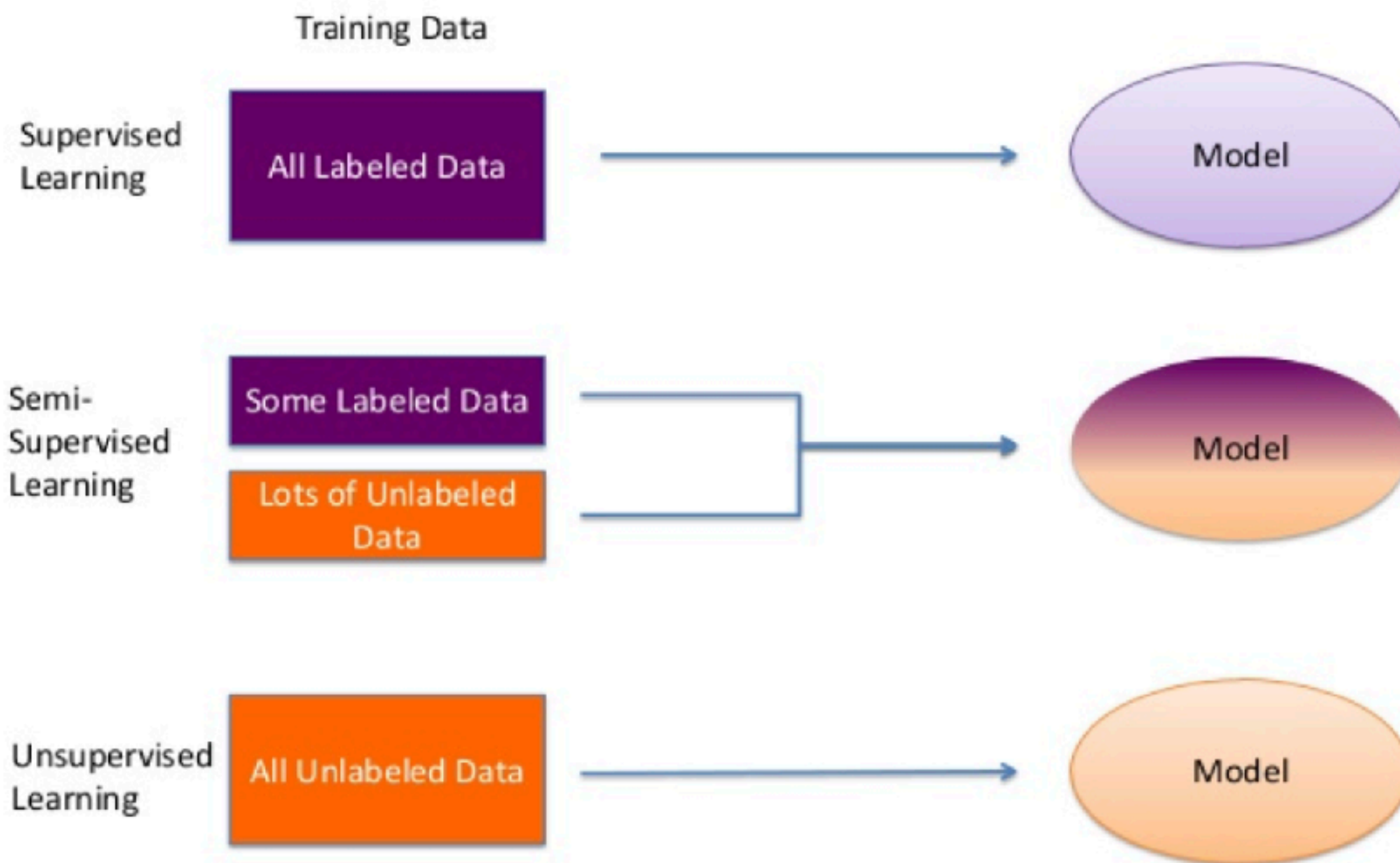
image center
object detection

Timeline of machine learning?

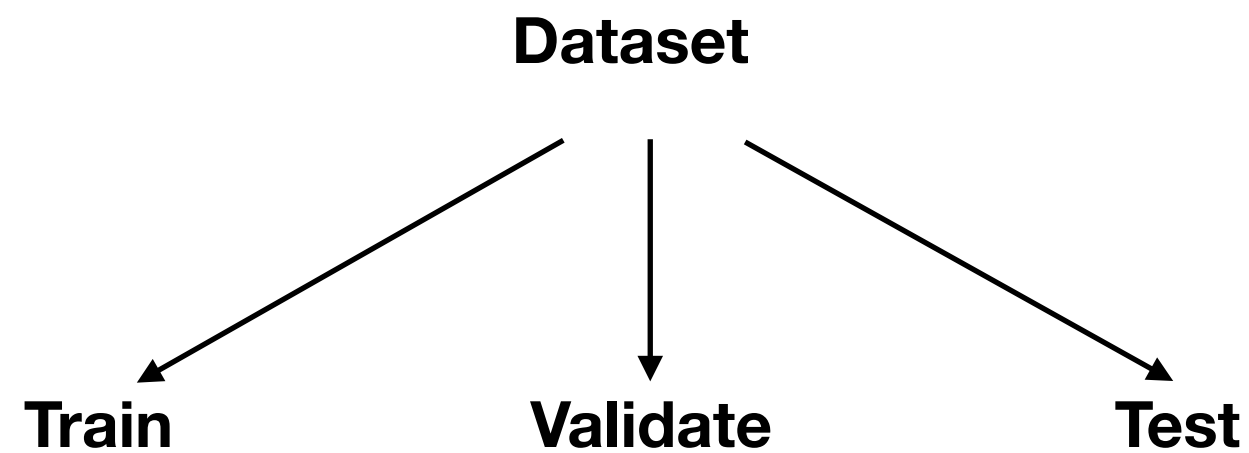
Decade	Summary
<1950s	Statistical methods are discovered and refined.
1950s	Pioneering <u>machine learning</u> research is conducted using simple algorithms.
1960s	<u>Bayesian methods</u> are introduced for <u>probabilistic inference</u> in machine learning[1].
1970s	' <u>AI Winter</u> ' caused by pessimism about machine learning effectiveness.
1980s	Rediscovery of <u>backpropagation</u> causes a resurgence in machine learning research.
1990s	Work on machine learning shifts from a knowledge-driven approach to a data-driven approach. Scientists begin creating programs for computers to analyze large amounts of data <u>Support vector machines</u> and <u>recurrent neural networks</u> become popular.
2000s	<u>Kernel methods</u> grow in popularity[3], and competitive machine learning becomes more widespread[4].
2010s	<u>Deep learning</u> becomes feasible, which leads to machine learning becoming integral to many widely used software services and applications.

https://en.wikipedia.org/wiki/Timeline_of_machine_learning

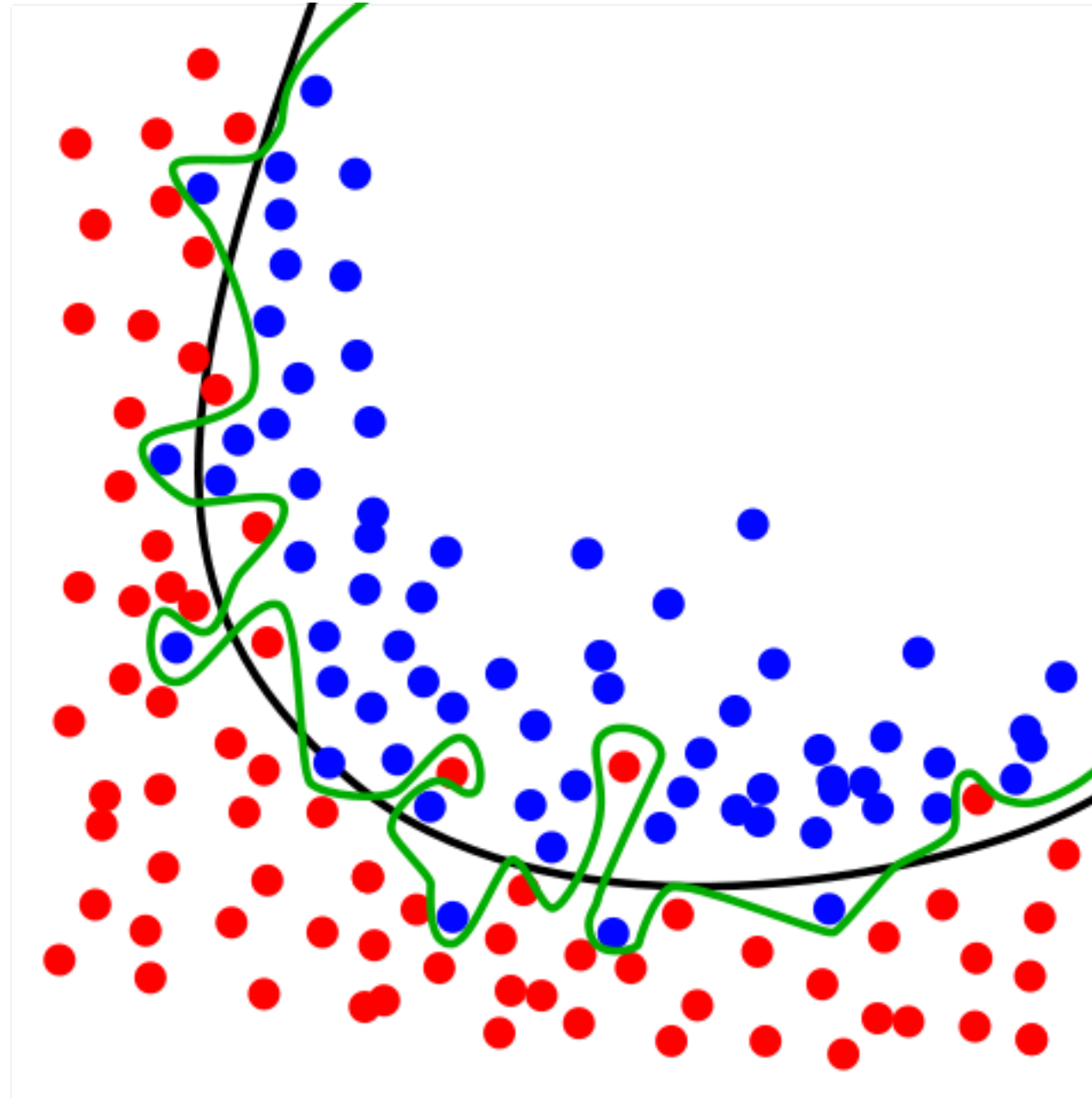
Learning based approaches



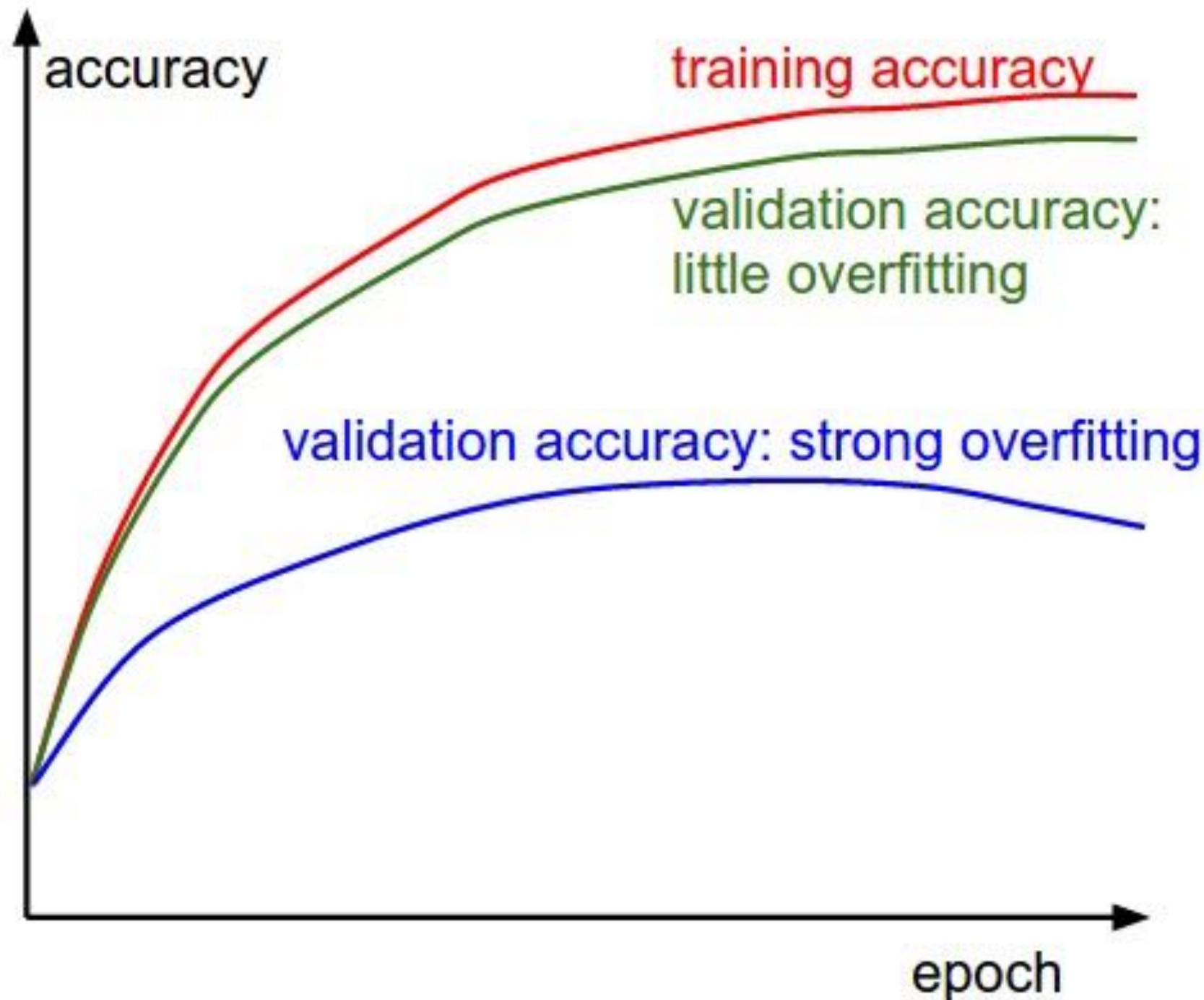
Datasets



Over-learning



Over-learning



Evaluation criteria (classification)

Accuracy on test set:

The rate of correct classification on testing set

Error Rate on test set:

the percentage of wrong predictions on test set

Confusion matrix

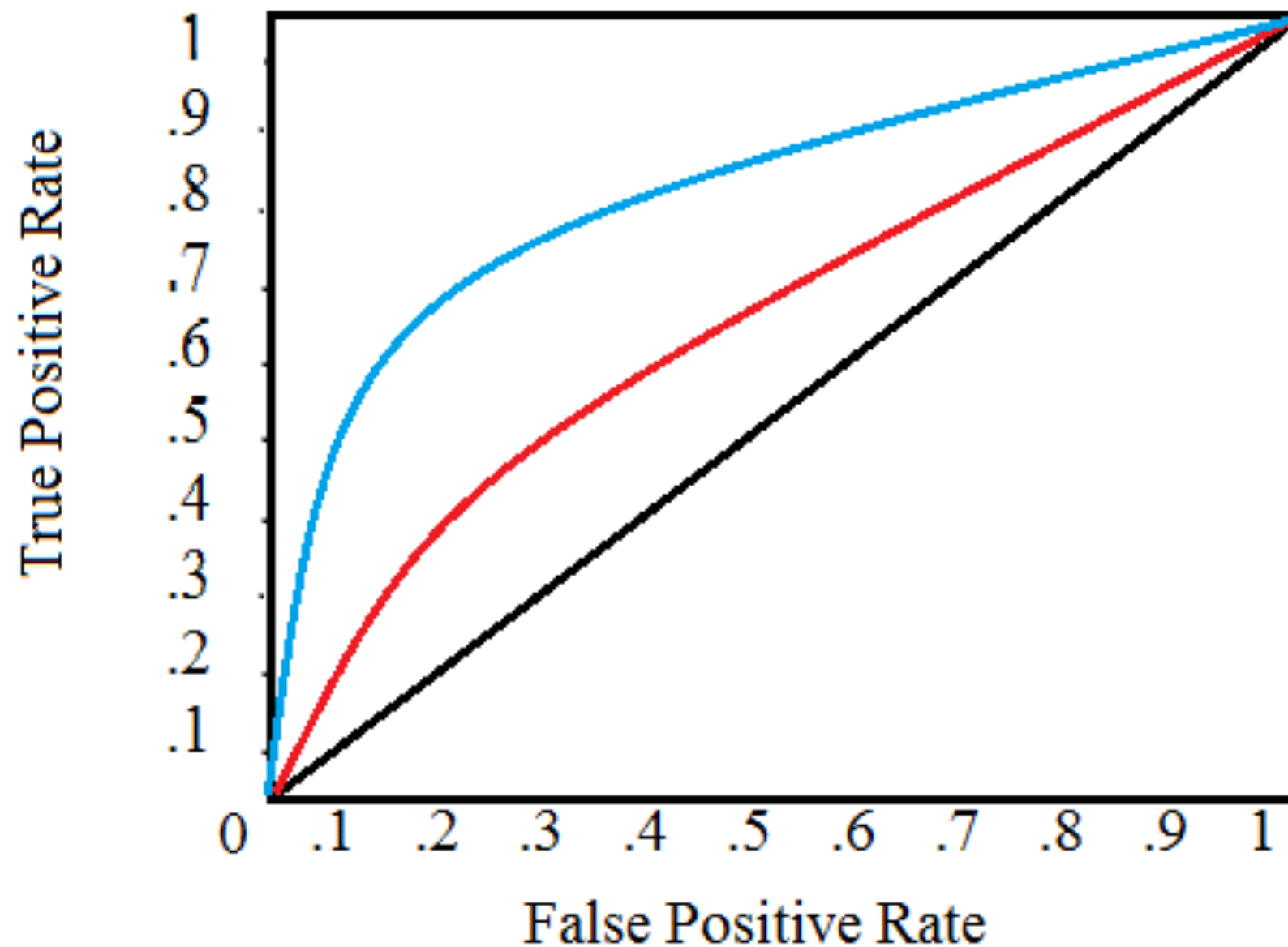
Speed and scalability:

the time to build the classifier and to classify new sample, and the scalability with respect to the data size

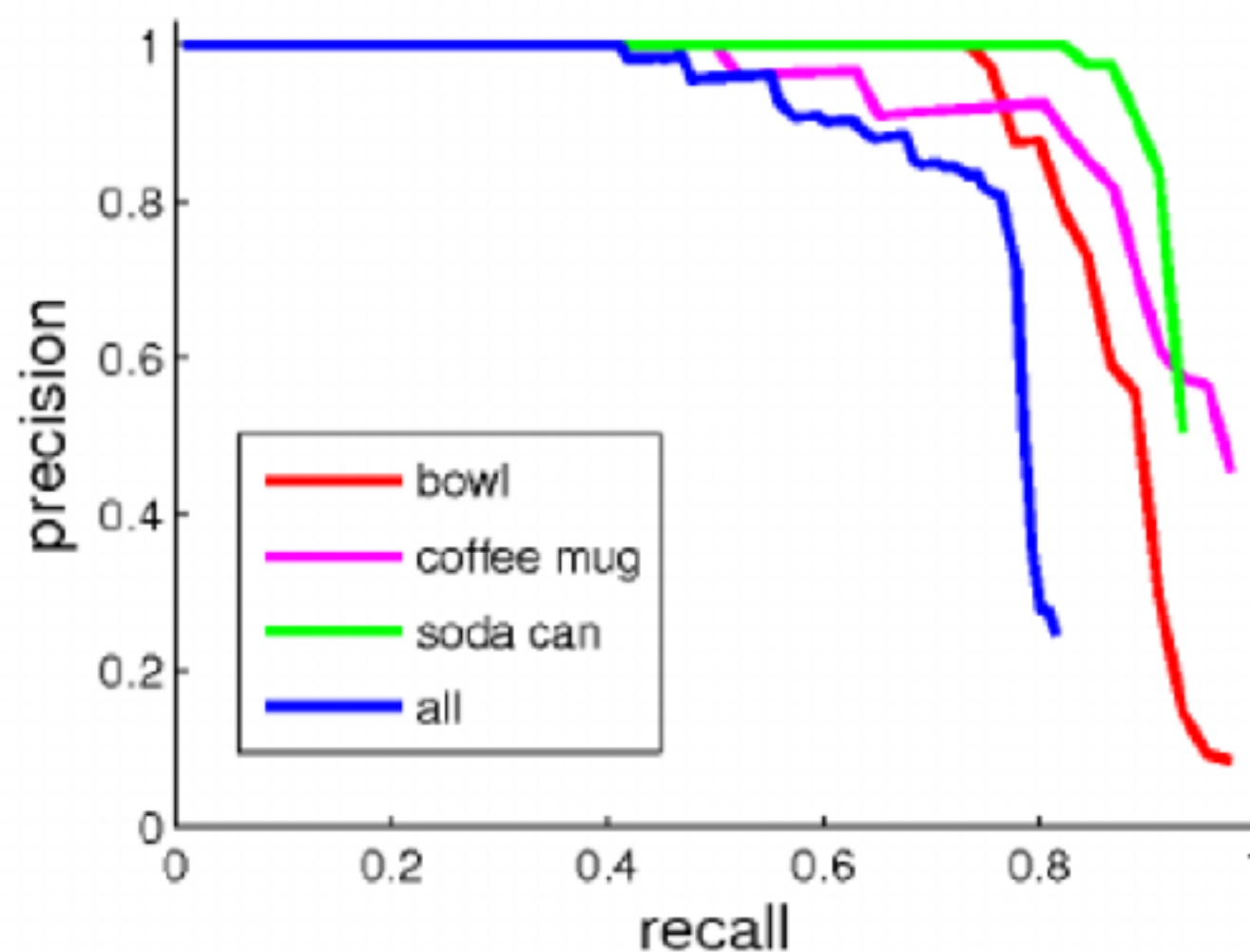
Robustness:

handling noise and missing values

Evaluation criteria (ROC curve)



Evaluation criteria (recall precision curve)



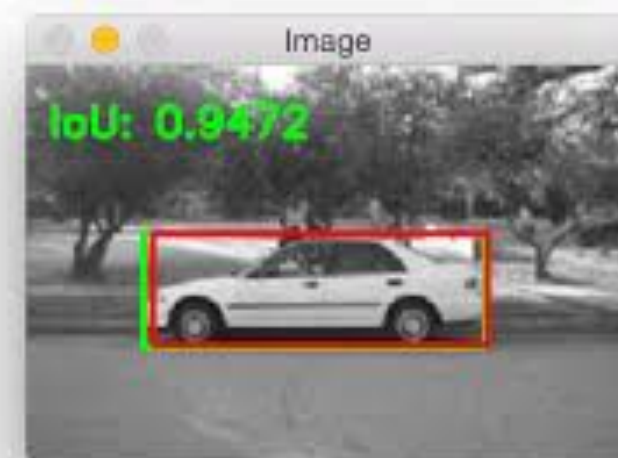
$$Precision = \frac{tp}{tp+fp} \text{ and}$$


$$Recall = \frac{tp}{tp+fn}$$

$$F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

Evaluation criteria (detection)

Intersection over Union (IoU) for object detection



$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$


Supervised classification

parametric methods

- Bayesian classifiers
- SVM
- Random forest
- Neural networks

non parametric methods

- K nearest neighbours
- Kernel density estimation

Starred algorithms

- bayes rule
- kppv
- svm
- adaboost
- ...
- neural networks