Queen Mary School Hainan
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QHM5703 Principles of Machine Learning
Supervised learning: Classification I

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Week 10 - 12/13 Nov 2025

Recap - ML Tasks

- Target population
- Error Surface - (Empirical/True)
- Quality (True/Testing/Training)

- Test **tasks**
- Training **tasks**
- Validation **tasks**

Who should know about testing?

Flexibility, complexity and overfitting

In any machine learning project we assume that our samples follow a **pattern** and any deviation from this pattern is considered to be **noise**.

Our models need to be flexible enough to **capture the complexity of the underlying pattern**, but no too flexible, as we might end up **memorising irrelevant noise** details in our data.

A **rigorous methodology** is crucial to avoid falling into common traps, such as overfitting.

So someone has collected our dataset? Great! Let's go ahead, put our methodology to work and build a fantastic model. **Great?**

The 1936 Literary Digest Poll

Alfred Landon
Republican Party

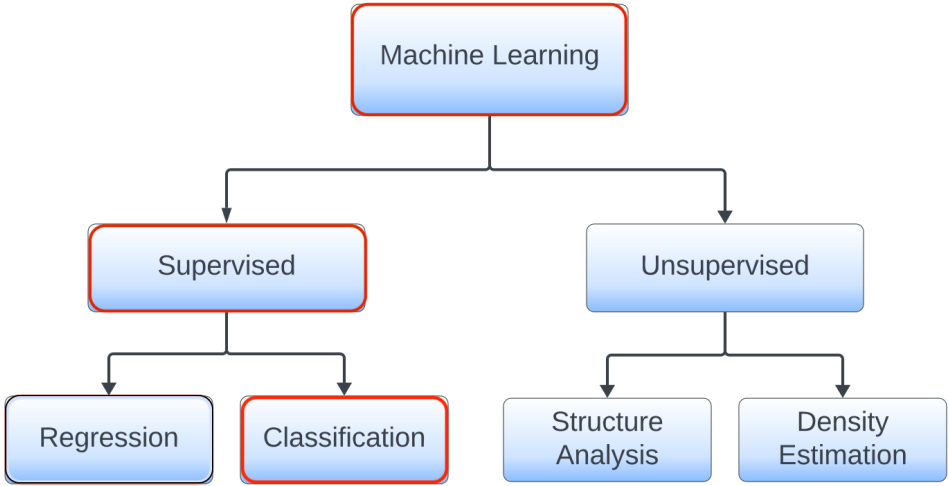
Franklin D. Roosevelt
Democratic Party

- The Literary Digest conducted one of the largest polls ever.
- Predicted Landon would get 57 % of the vote, Roosevelt 43 %. Landon ended up getting 38 % of the votes and Roosevelt 62 %.
- What happened? **Bad sampling**. Names were taken from telephone directories, club membership lists, magazine subscribers lists, etc. Samples were **not representative** of the population.

Know your data!

Agenda

Machine Learning taxonomy



Classification: Problem formulation

In **classification** (also known as **decision** or **detection**) problems:

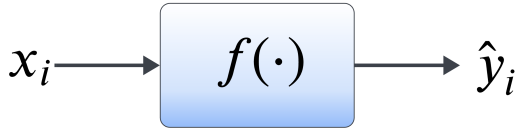
- We want to build a model that produces a **label** when shown a set of **predictors**.
- The label is **discrete** and each of its values is known as a **class**.

Question: This is not machine learning yet. Can you tell why?

Classification: Problem formulation

In a machine learning classification problem:

- We build a model $\hat{y} = f(x)$ **using a dataset** $\{(x_i, y_i) : 1 \leq i \leq N\}$.
- We have a notion of **model quality**.
- The pair (x_i, y_i) can be read as "sample i belongs to class y_i", or "the label of sample i is y_i".



A binary classification problem

Sentiment analysis seeks to identify human opinions implied by a fragment of text. Multiple opinions can be considered, but in its simplest form two are defined, namely positive and negative.

The *Large Movie Review Dataset* was created to build models that recognise polar sentiments in fragments of text:

- It contains 2500 samples for training and 2500 samples for testing
- Each instance consists of a **fragment of text** used as a **predictor** and a **binary label** (0 being negative opinion, 1 positive opinion).
- Downloadable from ai.stanford.edu/~amaas/data/sentiment/

A multiclass classification problem

Recognising digits in images containing handwritten representations is a classic multiclass classification problem. The predictor is an array of values (image) and there are 10 classes, namely $0, 1, 2, \ldots 9$.

In machine learning we use datasets of **labelled images**, i.e. pairs of **images** (predictors) and **numerical values** (label), to build such models.

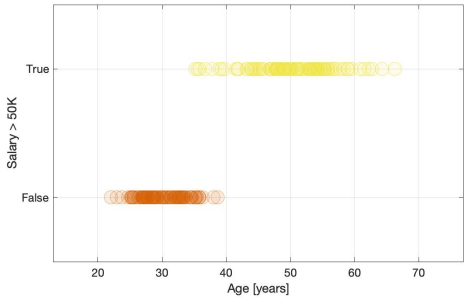
The MNIST dataset is a collection of handwritten digits:

- 60,000 images for training, 10,000 for testing
- Images are black and white, 28×28 pixels
- Downloadable from yann.lecun.com/exdb/mnist

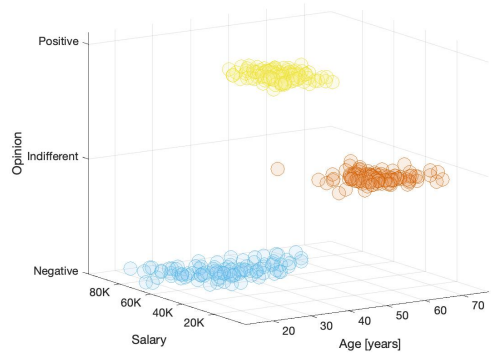
The dataset in the attribute space

Labels can be represented by numerical values on a vertical axis. Be careful: the usual notions of **ordering and distance do not apply** to categorical variables.

One predictor, two classes



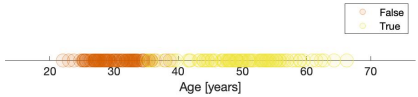
Two predictors, three classes



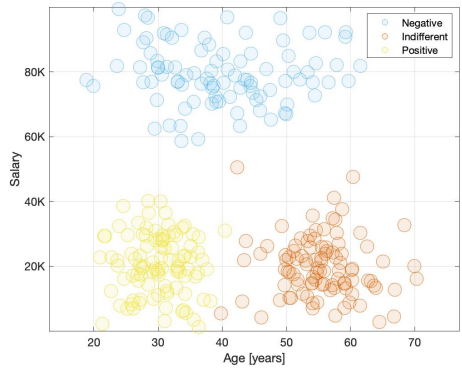
The dataset in the predictor space

A more convenient representation consists of using **different symbols for each label** in the **predictor space**.

One predictor, two classes

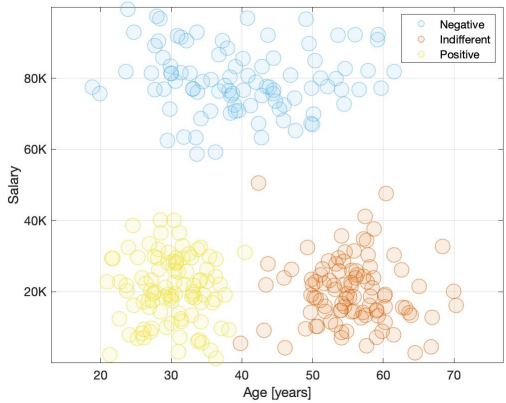


Two predictors, three classes



What does a classifier look like?

Using the training dataset below, how would you classify an individual who is 50 years old whose salary is 60K?



Go to menti.com and use code **DMT**: 3397 8416 — **ICS**: 4669 5998

What does a classifier look like?

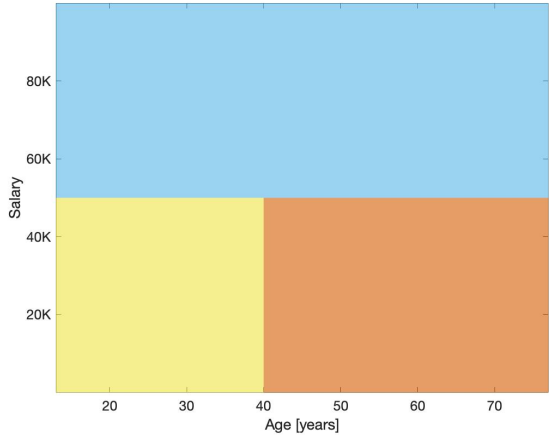
Regression models can be represented as curves/surfaces/hypersurfaces in the attribute space.

In **classification** problems we use the notion of **decision regions** in the predictor space.

- A decision region is made up of **points that are associated to the same label**.
- Regions can be defined by identifying their **boundaries**.
- A solution model in classification is a **partition of the predictor space** into decision regions separated by decision boundaries.

What does a classifier look like?

In machine learning we use data to build models: When we build classifiers, we use data to define their decision regions.



Agenda

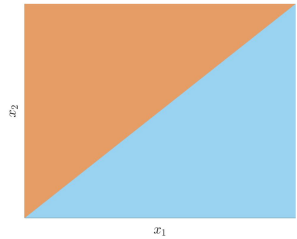
The simplest boundary

Let's consider a **binary** classification problem. The simplest boundary is:

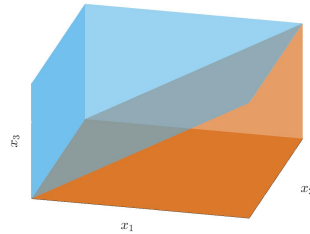
- A single point (known as **threshold**) in 1D predictor spaces.
- A straight line in 2D predictor spaces.
- A plane surface in 3D predictor spaces.

These are **linear** boundaries.

1 predictor



2 predictors



3 predictors

Definition of linear classifiers

Linear classifiers use **linear boundaries** between decision regions:

- Linear boundaries are defined by the **linear equation** $\boldsymbol{w}^T\boldsymbol{x} = 0$.
- The extended vector $\boldsymbol{x} = [1, x_1, x_2 ...]^T$ contains the predictors and $\boldsymbol{w}$ is the coefficients vector.
- To classify a sample we simply identify the **side of the boundary** where it lies.

Definition of linear classifiers

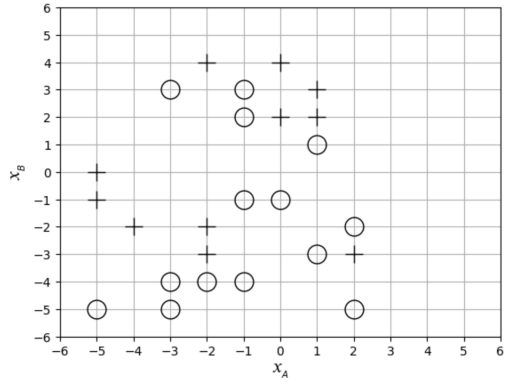
If we know the coefficients vector $\boldsymbol{w}$ of a linear boundary, classifying a sample is very simple:

- Build the extended vector $\boldsymbol{x}_i$.
- Compute $\boldsymbol{w}^T \boldsymbol{x}_i$.
- Classify using the following **facts**:
  - If $\boldsymbol{w}^T \boldsymbol{x}_i > 0$, we are on one side of the boundary.
  - If $\boldsymbol{w}^T \boldsymbol{x}_i < 0$, we are on the other!
  - If $\boldsymbol{w}^T \boldsymbol{x}_i = 0$... where are we?

Now that we know how to **use** linear classifiers during deployment, let's consider the problem of **building the best** one given a dataset. To answer this question, we need to define our **quality metric** first.

Linear classifier: Example/Question 1

Draw the boundary for the model described by $w = [0, 1, 0]$



A basic quality metric

The only operation that we can perform with categorical variables is **comparison**, i.e. we can assess whether $y_i = \hat{y}_i$ is either true or false.

By comparing predictions and true labels, we can identify in a dataset:

- The correctly classified samples (**true predictions**) in each class.
- The incorrectly classified samples (**false predictions**) in each class.

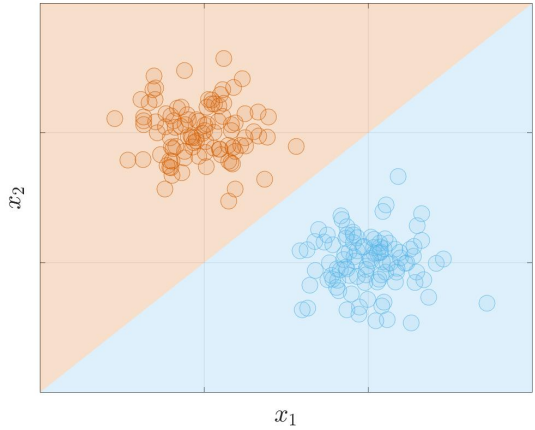
Two common and equivalent notions of quality are the **empirical accuracy** $\hat{A}$ and **error** (or misclassification) **rate** $\hat{E} = 1 - \hat{A}$, defined as:

$$\hat{A} = \frac{\#\text{true predictions}}{\#\text{samples}} \quad , \quad \hat{E} = \frac{\#\text{false predictions}}{\#\text{samples}}$$

The **true accuracy** A and **error rate** E are defined analogously on the target population.

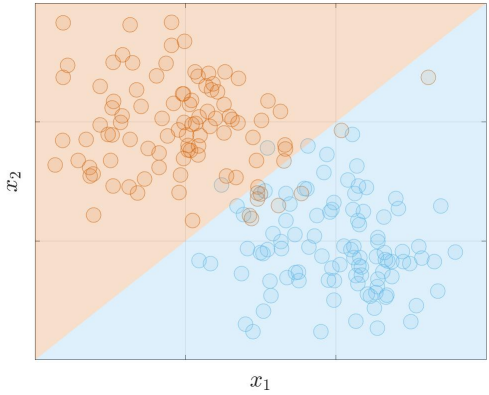
The best linear classifier: Separable case

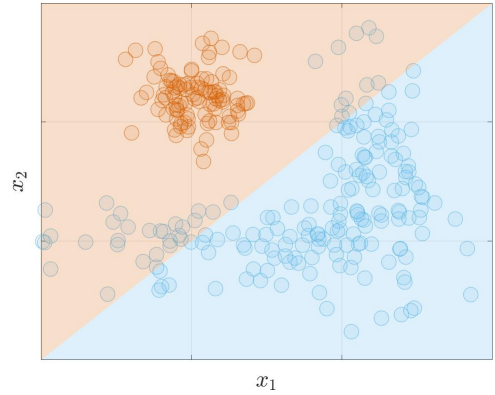
In linearly separable datasets, we can find a linear classifier that achieves the maximum accuracy ($\hat{A} = 1$, $\hat{E} = 0$).



The best linear classifier: Non separable case

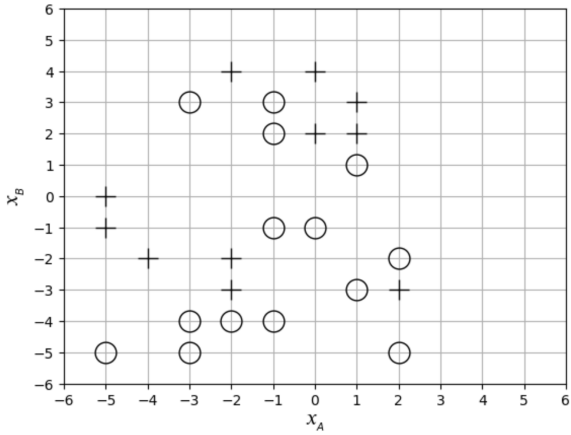
In non linearly-separable datasets, the accuracy of a linear classifier is $\hat{A} < 1$ ($\hat{E} > 0$). The best one will achieve the highest accuracy.





Linear classifier: Example/Question 2

Compute the accuracy $\hat{A}$ and the error rate $\hat{E}$ for the model described by $f_1 : w = [0.5, 1, 0]$ and the decision as if $w^T x > 0 \rightarrow \hat{y} = +$



Linear classifier: boundary

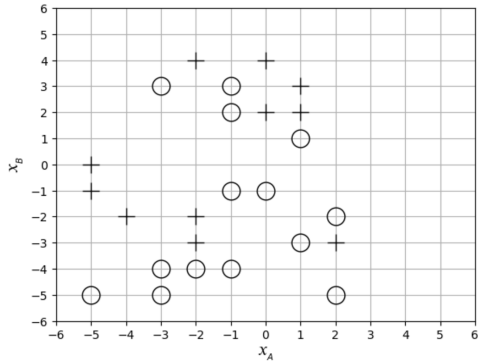
What should we do, if a sample is on the boundary?

Linear classifier: Example/Question 3

Compute the accuracy $\hat{A}$ and the error rate $\hat{E}$ for the model described as below.

- $f_1 : w = [0, 1, 0]$
- $f_2 : w = [0, 1, 1]$
- $f_3 : w = [1, 1, 1]$

Consider the decision as:
if $w^T x \geq 0 \rightarrow \hat{y} = +$



Finding the best linear classifier

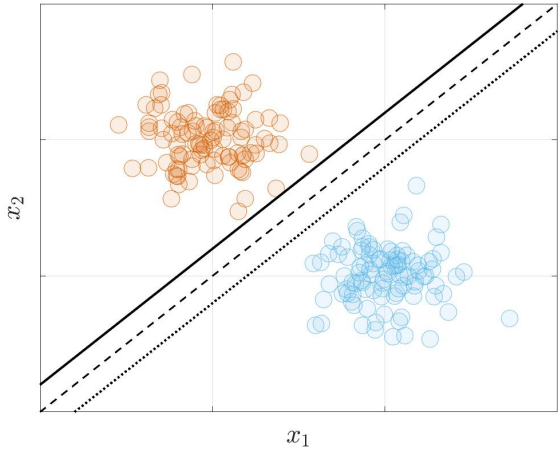
We have introduced the linear classifier and presented two quality metrics (accuracy and error rate). If we are given a linear classifier $\boldsymbol{w}$, we can use a dataset to calculate its quality.

The question we want to answer now is, how can we **use data to find** the best linear classifier?

Agenda

Best, but risky, linear solutions

Which one of the three boundaries below would you choose?



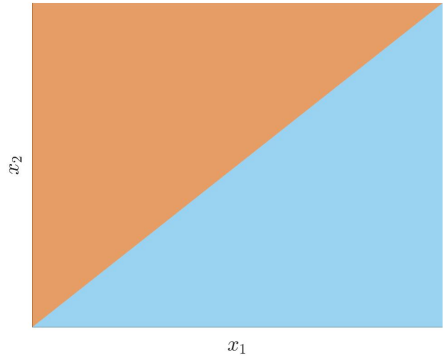
All three boundaries have same accuracy on given points.

Go to menti.com and use code 1236 2386

Keep that boundary away from me!

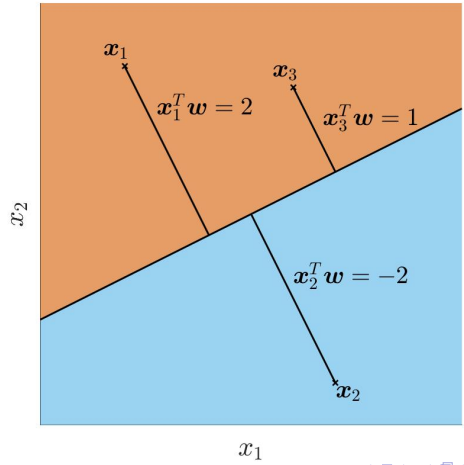
As we get closer to the decision boundary, life gets harder for a classifier: it is **noise territory** and we should beware of **jumpy samples**.

The **further** we are from the boundary, the **higher our certainty** that we are classifying samples correctly.



How far is my sample from the boundary?

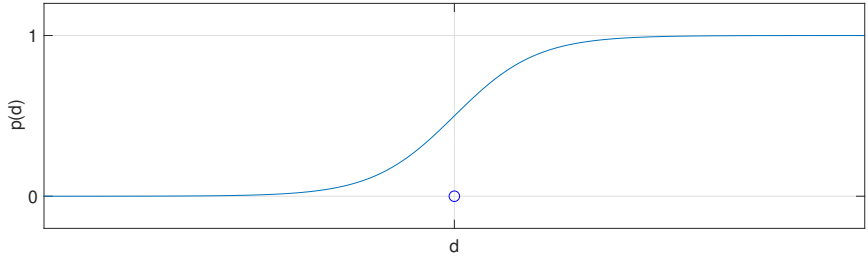
Given a linear boundary $\boldsymbol{w}$ and a sample $\boldsymbol{x}_i$, the quantity $d_i = \boldsymbol{w}^T \boldsymbol{x}_i$ can be interpreted as the **distance** from the sample to the boundary.



Quantifying our uncertainty: The logistic model

The logistic function $p(d)$ is defined as

$$p(d) = \frac{e^d}{1+e^d} = \frac{1}{1+e^{-d}}$$



Note that

- $p(0) = 0.5$.
- As $d \to \infty$, $p(d) \to 1$.
- As $d \to -\infty$, $p(d) \to 0$.

Quantifying our uncertainty: The logistic model

If we set $d = \boldsymbol{w}^T \boldsymbol{x}_i$ in the logistic function, we get:

$$p(\boldsymbol{w}^T \boldsymbol{x}_i) = \frac{e^{\boldsymbol{w}^T \boldsymbol{x}_i}}{1 + e^{\boldsymbol{w}^T \boldsymbol{x}_i}}$$

For a fixed $\boldsymbol{w}$, we will simply denote it as $p(d_i)$ to simplify the notation:

- *When* $\boldsymbol{w}^T \boldsymbol{x_i} \to \infty$, *the logistic function* $p(d_i) \to 1$
- *When* $\boldsymbol{w}^T \boldsymbol{x_i} \to -\infty$, *the logistic function* $p(d_i) \to 0$

We will use the logistic function to quantify the notion of **certainty** in classifiers. This certainty is a quantity between 0 and 1.

Quantifying our uncertainty: The logistic model

Consider a linear classifier $\boldsymbol{w}$ that labels samples such that $\boldsymbol{w}^T\boldsymbol{x}_i > 0$ as o and samples such that $\boldsymbol{w}^T\boldsymbol{x}_i < 0$ as o.

Notice that, with $d_i = \boldsymbol{w}^T\boldsymbol{x}_i$:

- If $\boldsymbol{w}^T\boldsymbol{x}_i = 0$ ($\boldsymbol{x}_i$ is on the boundary), $p(d_i) = 0.5$.
- If $\boldsymbol{w}^T\boldsymbol{x}_i > 0$ ($\boldsymbol{x}_i$ is in the o region),
  $p(d_i) \to 1$ as we move away from the boundary.
- If $\boldsymbol{w}^T\boldsymbol{x}_i < 0$ ($\boldsymbol{x}_i$ is in the o region),
  $p(d_i) \to 0$ as we move away from the boundary.

Here is the crucial point, so use **all your neurons**:

- $p(d_i)$ is the **classifier's certainty** that y_i = o true.
- $1 - p(d_i)$ is the **classifier's certainty** that y_i = o true.

The logistic classifier

We can obtain the classifier's certainty that $\boldsymbol{x}_i$ belongs to either o or o. Can we calculate the certainty for a **labelled dataset** $\{(\boldsymbol{x}_i, y_i)\}$?

The answer is yes, by **multiplying** the individual certainties:

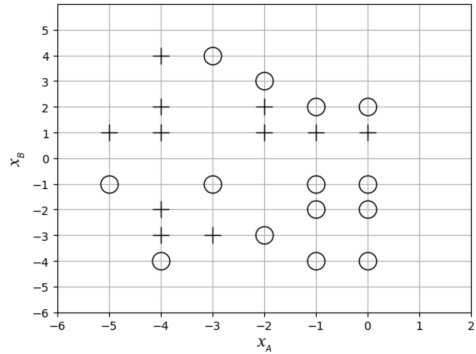
$$L = \prod_{y_i=\text{o}} (1 - p(d_i)) \prod_{y_i=\text{o}} p(d_i)$$

L is known as the **likelihood function** and defines a **quality metric**. Taking logarithms, we obtain the **log-likelihood**:

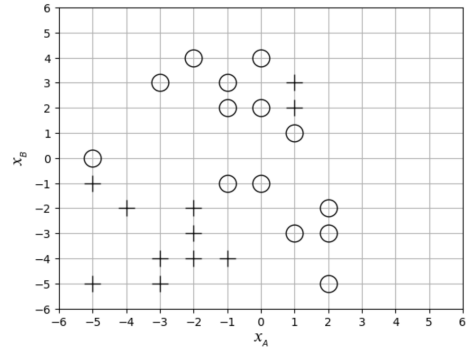
$$l = \sum_{y_i=\text{o}} \log\left[1 - p(d_i)\right] + \sum_{y_i=\text{o}} \log\left[p(d_i)\right]$$

The linear classifier that maximises L or l is known as the **Logistic Regression** classifier. It can be found using **gradient descent**.

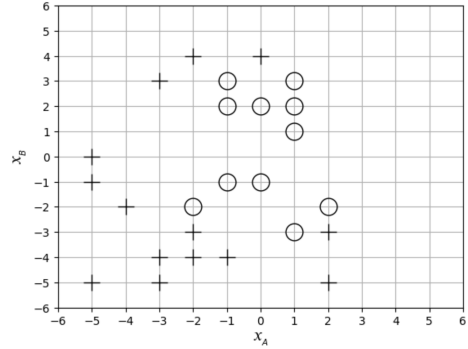
Linear classifier: Example/Question 4



Linear classifier: Example/Question 5



Linear classifier: Example/Question 6



Agenda

Parametric and non-parametric approaches

Linear classifiers belong to the family of **parametric** approaches: a shape is assumed (in this case linear) and our dataset is used to find the best boundary amongst all the boundaries with the preselected shape.

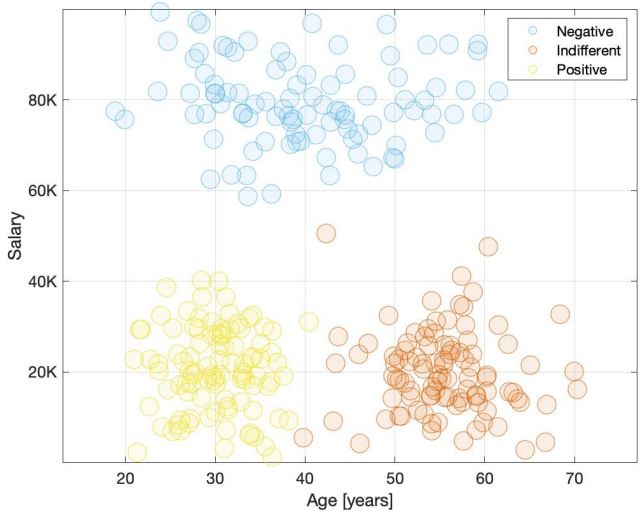
Non-parametric approaches offer a more flexible alternative, as they do not assume any type of boundary. In this section, we will study a popular non-parametric approach, namely **k Nearest Neighbours** (kNN).

Nearest Neighbours

In nearest neighbours (NN), new samples are assigned the **label of the closest (***most similar***) training sample**. Therefore:

- Boundaries are not defined explicitly (although they exist and can be obtained).
- The whole training dataset needs to be **memorised**. That's why sometimes we say NN is an **instance-based method**.

Boundaries in Nearest Neighbours classifiers



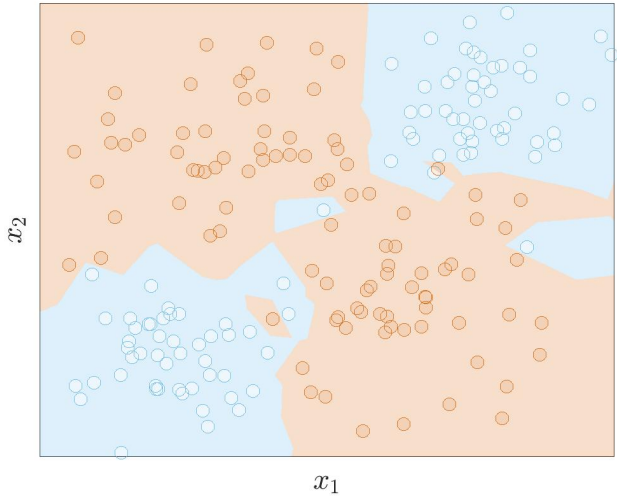
k Nearest Neighbours

Boundaries in nearest neighbours classifiers can be too complex and hard to interpret. Can we smooth them?

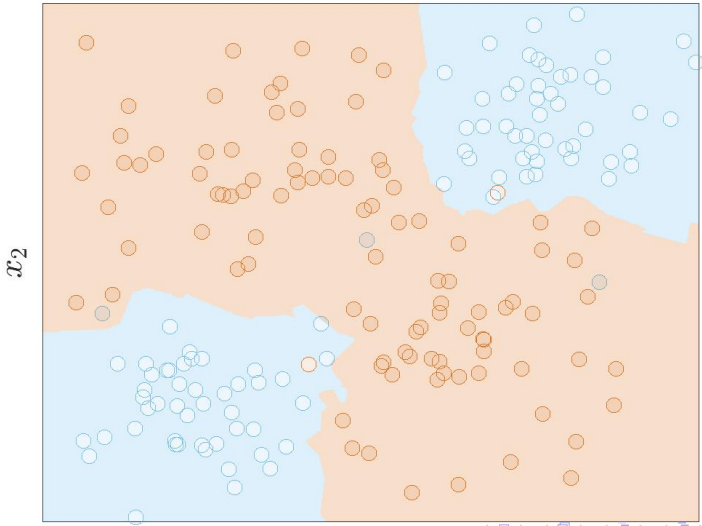
K nearest neighbours (kNN) is a simple extension of nearest neighbours that proceeds as follows. Given a new sample $\boldsymbol{x}$:

- We calculate the distance to all the training samples $\boldsymbol{x}_i$.
- Extract the K closest samples (neighbours).
- Obtain the number of neighbours that belong to each class.
- Assign the label of the most popular class among the neighbours.

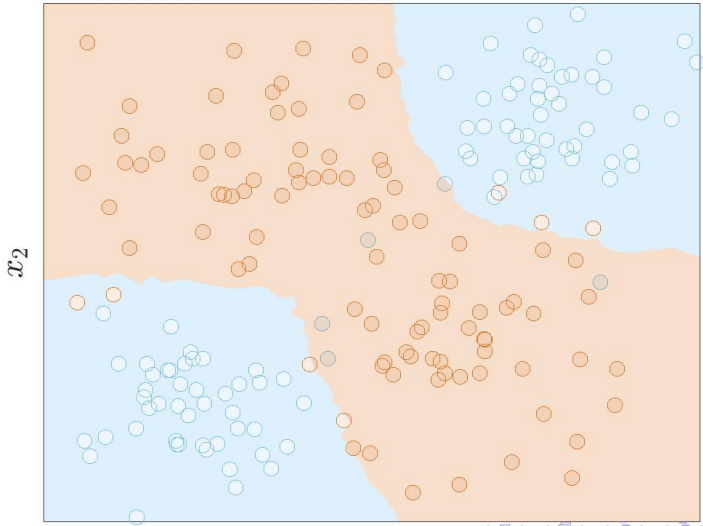
Boundaries in kNN classifiers $k = 1$



Boundaries in kNN classifiers $k = 3$



Boundaries in kNN classifiers $k = 15$



k Nearest Neighbours

Note that:

- There is always an implicit boundary, although it is not used to classify new samples.
- As K increases, the boundary becomes less complex. We move away from **overfitting** (small K) to **underfitting** (large K) classifiers.
- In binary problems, the value of K is usually an odd number. The idea is to prevent situations where half of the nearest neighbours of a sample belong to each class.
- kNN can be easily implemented in multi-class scenarios.

k Nearest Neighbours: Question

Consider a dataset with 70 samples in class A and 30 samples in class B (total 100 samples). Using k Nearest Neighbours, what would be the accuracy of the model if

- we use k=100?
- we use k=71?
- we use k=31?
- we use k=200?

Question [Think about it - HW]

- Can we solve a regression problem as classification?
- Can we solve a classification problem as regression?

Think about it, if we **can** and if we **should**.
[Homework]

Agenda

Machine learning classifiers

- Classifiers are partitions of the predictor space into **decision regions** separated by **boundaries**.
- Each decision region is associated with one label.
- In machine learning, classifiers are built using a **dataset** (otherwise it's not machine learning!).

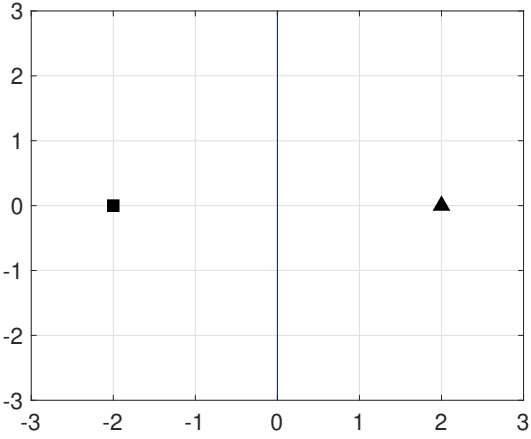
Flexibility and complexity in classifiers

- The notions of flexibility, complexity, interpretability, overfitting and underfitting also apply to classifiers.
- Linear boundaries are simple and rigid; kNN produces boundaries whose complexity depends on the value of K.
- Logistic regression is a strategy to train linear classifiers. It's called *regression* because indirectly we solve a regression problem or the classifier's certainty.
- Weirdly, kNN does not involve training as it uses all the samples each time a new sample is to be classified.

Hey, hold on a second, what's going on?

- In machine learning we use a quality metric to define what we mean by the *best* model.
- We have presented two quality metrics: **accuracy** and **error rate**.
- However, **neither** the logistic regression nor kNN classifiers **use the notion of accuracy**.
- What's going on?

Example I



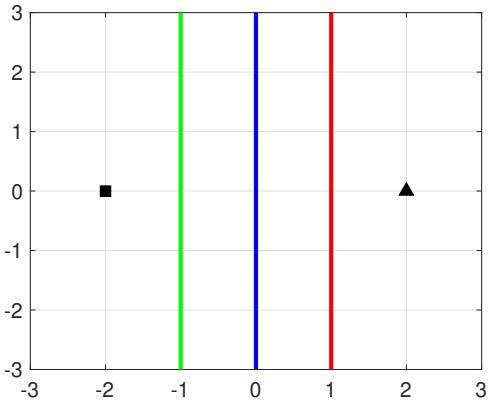
- Let's define $d_i = \boldsymbol{w}^T \boldsymbol{x}_i$
- We can rewrite the logistic function as

$$p(d_i) = \frac{e^{d_i}}{1 + e^{d_i}}$$

- For instance $p(0) = 0.5$, $p(1) \approx 0.73$, $p(2) \approx 0.88$, $p(-1) \approx 0.27$ and $p(-2) \approx 0.12$

Assume this linear classifier labels samples on the right half-plane as $\triangle$ and samples on the left half-plane as $\square$.

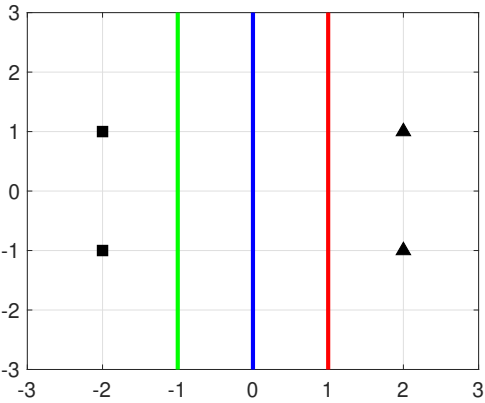
Example II



The global certainty of each classifier (i.e. boundary) is:

- $L = p(\triangle)\,(1 - p(\square)) \approx 0.70$
- $L = p(\triangle)\,(1 - p(\square)) \approx 0.77$
- $L = p(\triangle)\,(1 - p(\square)) \approx 0.70$

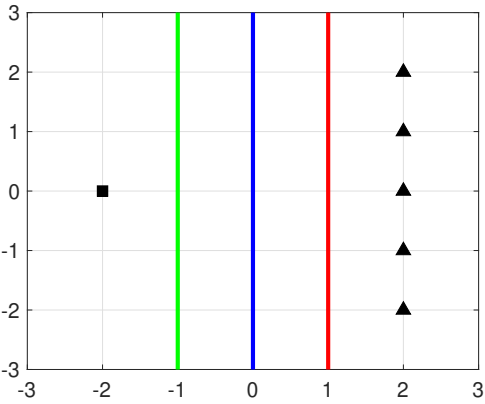
Example III



The global certainty of each classifier (i.e. boundary) is:

- $L \approx 0.49$
- $L \approx 0.60$
- $L \approx 0.49$

Example IV



The global certainty of each classifier (i.e. boundary) is:

- $L \approx 0.20$
- $L \approx 0.47$
- $L \approx 0.57$

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