



Machine Learning

Lecture 1: intro to ML

Radoslav Neychev

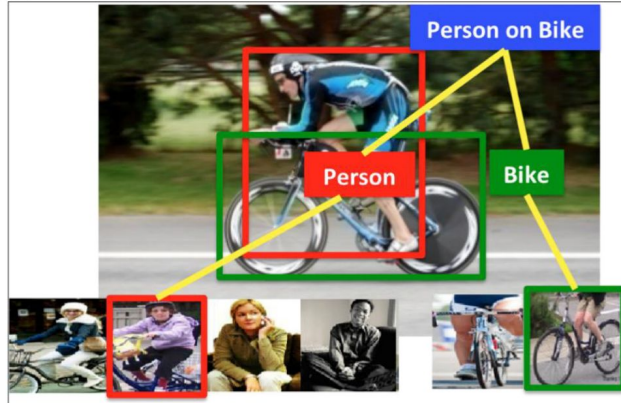
1. Introduction to Machine Learning, motivation
2. ML thesaurus and notation
3. Maximum Likelihood Estimation
4. Machine Learning problems overview (selection):
 - a. Classification
 - b. Regression
 - c. Dimensionality reduction
5. Naïve Bayes classifier
6. k Nearest Neighbours (kNN)

Motivation, historical overview and
current state of ML and AI

Machine Learning applications



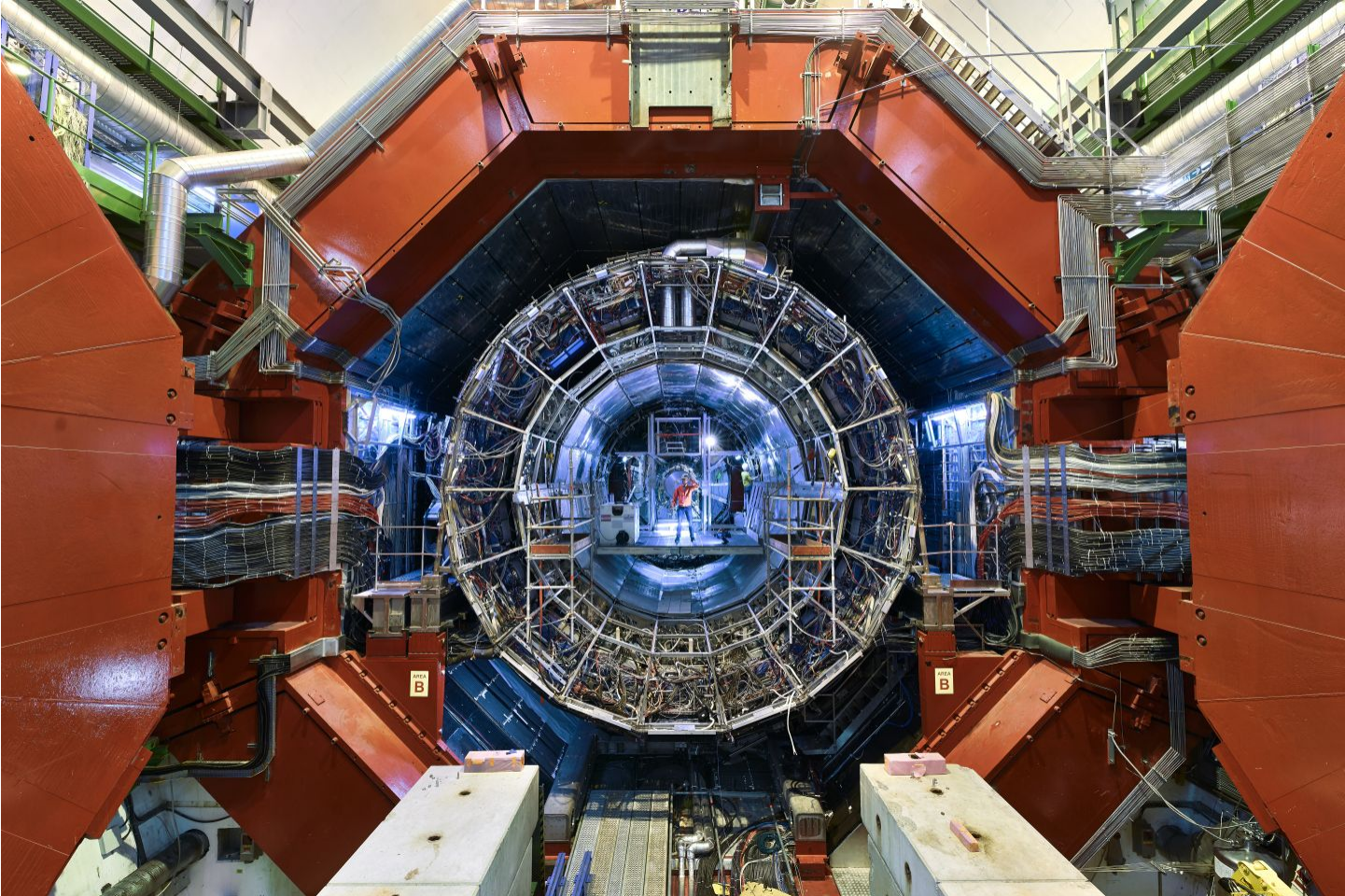
- Object detection
- Action classification
- Image captioning
- ...



Machine Learning applications

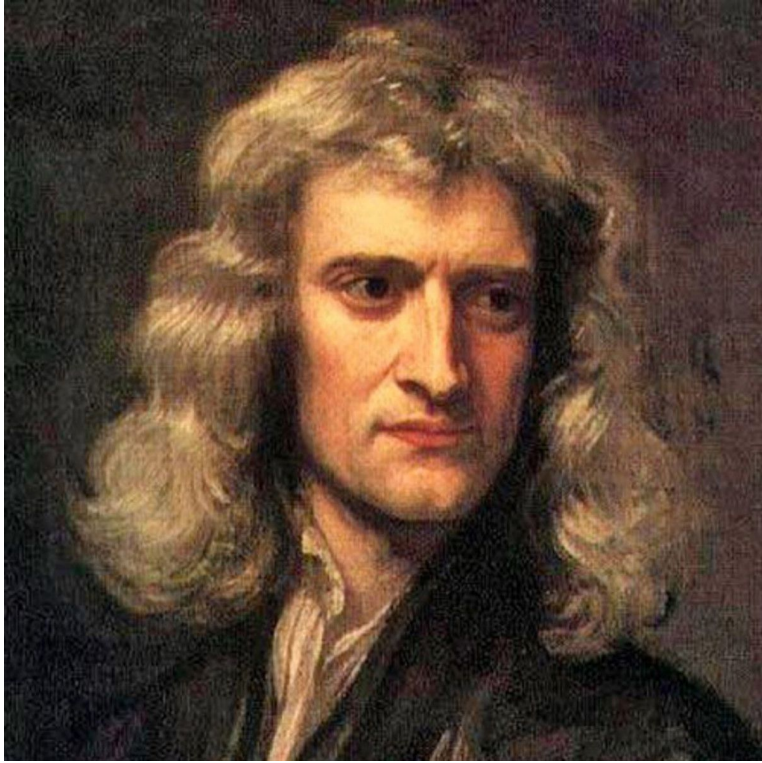


Machine Learning applications



Data → Knowledge

Long before the ML

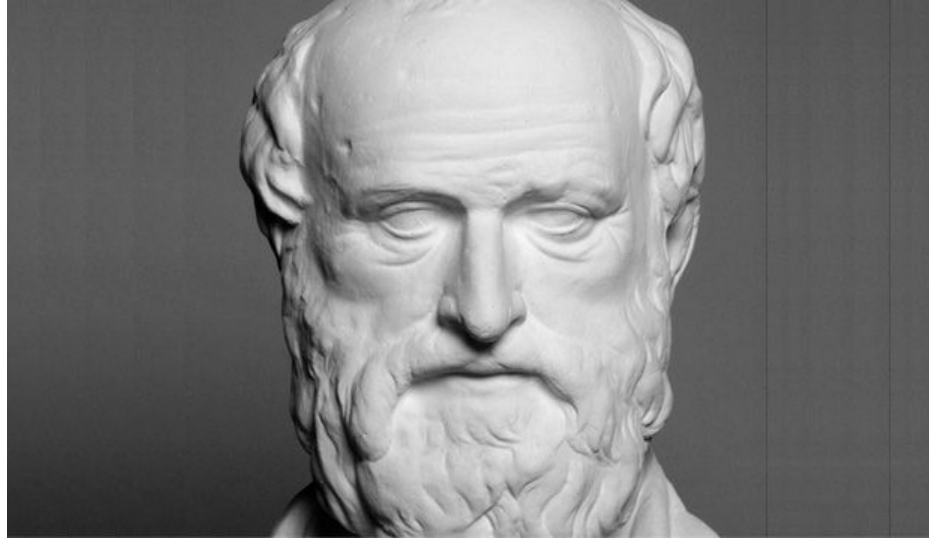


Isaac Newton



Johannes Kepler

Long before the ML



Eratosthenes

ML thesaurus

ML thesaurus

Denote the ***dataset***.

Name	Age	Statistics (mark)	Python (mark)	Eye color	Native language	Target (mark)	Target (passed)
John	22	5	4	Brown	English	5	TRUE
Aahna	17	4	5	Brown	Hindi	4	TRUE
Emily	25	5	5	Blue	Chinese	5	TRUE
Michael	27	3	4	Green	French	5	TRUE
Some student	23	3	3	NA	Esperanto	2	FALSE

Observation (or datum, or data point) is one piece of information.

Name	Age	Statistics (mark)	Python (mark)	Eye color	Native language	Target (mark)	Target (passed)
John	22	5	4	Brown	English	5	TRUE
Aahna	17	4	5	Brown	Hindi	4	TRUE
Emily	25	5	5	Blue	Chinese	5	TRUE
Michael	27	3	4	Green	French	5	TRUE
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In many cases the observations are supposed to be *i.i.d.*

- ***independent***
- ***identically distributed***

ML thesaurus

Feature (or predictor) represents some special property.



Name	Age	Statistics (mark)	Python (mark)	Eye color	Native language	Target (mark)	Target (passed)
John	22	5	4	Brown	English	5	TRUE
Aahna	17	4	5	Brown	Hindi	4	TRUE
Emily	25	5	5	Blue	Chinese	5	TRUE
Michael	27	3	4	Green	French	5	TRUE
Some student	23	3	3	NA	Esperanto	2	FALSE

ML thesaurus

These all are features



Name	Age	Statistics (mark)	Python (mark)	Eye color	Native language	Target (mark)	Target (passed)
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Michael	27	3	4	Green	French	5	TRUE
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ML thesaurus

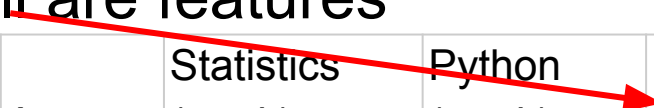
These all are features



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John	22	5	4	Brown	English	5	TRUE
Aahna	17	4	5	Brown	Hindi	4	TRUE
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Michael	27	3	4	Green	French	5	TRUE
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ML thesaurus

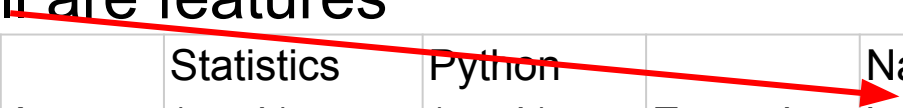
These all are features



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John	22	5	4	Brown	English	5	TRUE
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Emily	25	5	5	Blue	Chinese	5	TRUE
Michael	27	3	4	Green	French	5	TRUE
Some student	23	3	3	NA	Esperanto	2	FALSE

ML thesaurus

These all are features



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John	22	5	4	Brown	English	5	TRUE
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Emily	25	5	5	Blue	Chinese	5	TRUE
Michael	27	3	4	Green	French	5	TRUE
Some student	23	3	3	NA	Esperanto	2	FALSE

And even the name is a ***feature***



Name	Age	Statistics (mark)	Python (mark)	Eye color	Native language	Target (mark)	Target (passed)
John	22	5	4	Brown	English	5	TRUE
Aahna	17	4	5	Brown	Hindi	4	TRUE
Emily	25	5	5	Blue	Chinese	5	TRUE
Michael	27	3	4	Green	French	5	TRUE
Some student	23	3	3	NA	Esperanto	2	FALSE

(despite it might be not informative)

ML thesaurus

The ***design matrix*** contains all the features and observations.

Name	Age	Statistics (mark)	Python (mark)	Eye color	Native language	Target (mark)	Target (passed)
John	22	5	4	Brown	English	5	TRUE
Aahna	17	4	5	Brown	Hindi	4	TRUE
Emily	25	5	5	Blue	Chinese	5	TRUE
Michael	27	3	4	Green	French	5	TRUE
Some student	23	3	3	NA	Esperanto	2	FALSE

Features can even be multidimensional, we will discuss it later in this course.

ML thesaurus

Target represents the information we are interested in.

Name	Age	Statistics (mark)	Python (mark)	Eye color	Native language	Target (mark)	Target (passed)
John	22	5	4	Brown	English	5	TRUE
Aahna	17	4	5	Brown	Hindi	4	TRUE
Emily	25	5	5	Blue	Chinese	5	TRUE
Michael	27	3	4	Green	French	5	TRUE
Some student	23	3	3	NA	Esperanto	2	FALSE

*Target can be either a **number** (real, integer, etc.) – for **regression** problem*

ML thesaurus

Target represents the information we are interested in.

Name	Age	Statistics (mark)	Python (mark)	Eye color	Native language	Target (mark)	Target (passed)
John	22	5	4	Brown	English	5	TRUE
Aahna	17	4	5	Brown	Hindi	4	TRUE
Emily	25	5	5	Blue	Chinese	5	TRUE
Michael	27	3	4	Green	French	5	TRUE
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Or a ***label*** – for ***classification*** problem

ML thesaurus

Target represents the information we are interested in.

Name	Age	Statistics (mark)	Python (mark)	Eye color	Native language	Target (mark)	Target (passed)
John	22	5	4	Brown	English	5	TRUE
Aahna	17	4	5	Brown	Hindi	4	TRUE
Emily	25	5	5	Blue	Chinese	5	TRUE
Michael	27	3	4	Green	French	5	TRUE
Some student	23	3	3	NA	Esperanto	2	FALSE

Mark can be treated as a label too (due to finite number of labels: 1 to 5). We will discuss it later.

Further we will work with the numerical target (mark)

Name	Age	Statistics (mark)	Python (mark)	Eye color	Native language	Target (mark)
John	22	5	4	Brown	English	5
Aahna	17	4	5	Brown	Hindi	4
Emily	25	5	5	Blue	Chinese	5
Michael	27	3	4	Green	French	5
Some student	23	3	3	NA	Esperanto	2

ML thesaurus

The ***prediction*** contains values we predicted using some ***model***.

Name	Age	Statistics (mark)	Python (mark)	Eye color	Native language	Target (mark)	Predicted (mark)
John	22	5	4	Brown	English	5	4.5
Aahna	17	4	5	Brown	Hindi	4	4.5
Emily	25	5	5	Blue	Chinese	5	5
Michael	27	3	4	Green	French	5	3.5
Some student	23	3	3	NA	Esperanto	2	3

One could notice that prediction just averages of Statistics and Python marks. So our ***model*** can be represented as follows:

$$\text{mark}_{ML}^{\hat{}} = \frac{1}{2}\text{mark}_{Statistics} + \frac{1}{2}\text{mark}_{Python}$$

ML thesaurus

The ***prediction*** contains values we predicted using some ***model***.

Name	Age	Statistics (mark)	Python (mark)	Eye color	Native language	Target (mark)	Predicted (mark)
John	22	5	4	Brown	English	5	4.5
Aahna	17	4	5	Brown	Hindi	4	4.5
Emily	25	5	5	Blue	Chinese	5	5
Michael	27	3	4	Green	French	5	3.5
Some student	23	3	3	NA	Esperanto	2	3

Different models can provide different predictions:

$$\text{mark}_{ML}^{\hat{}} = \frac{1}{2}\text{mark}_{Statistics} + \frac{1}{2}\text{mark}_{Python}$$

ML thesaurus

The ***prediction*** contains values we predicted using some ***model***.

Name	Age	Statistics (mark)	Python (mark)	Eye color	Native language	Target (mark)	Predicted (mark)
John	22	5	4	Brown	English	5	1
Aahna	17	4	5	Brown	Hindi	4	5
Emily	25	5	5	Blue	Chinese	5	2
Michael	27	3	4	Green	French	5	4
Some student	23	3	3	NA	Esperanto	2	3

Different models can provide different predictions:

$$\text{mark}_{ML}^{\hat{}} = \text{random}(\text{integer from } [1; 5])$$

ML thesaurus

The ***prediction*** contains values we predicted using some ***model***.

Name	Age	Statistics (mark)	Python (mark)	Eye color	Native language	Target (mark)	Predicted (mark)
John	22	5	4	Brown	English	5	1
Aahna	17	4	5	Brown	Hindi	4	5
Emily	25	5	5	Blue	Chinese	5	2
Michael	27	3	4	Green	French	5	4
Some student	23	3	3	NA	Esperanto	2	3

Different models can provide different predictions.

*Usually some ***hypothesis*** lies beneath the model choice.*

Loss function measures the error rate of our model.

Square deviation	Target (mark)	Predicted (mark)
16	5	1
1	4	5
9	5	2
1	5	4
1	2	3

- ***Mean Squared Error*** (where \mathbf{y} is vector of targets):

$$MSE(\mathbf{y}, \hat{\mathbf{y}}) = \frac{1}{N} \|\mathbf{y} - \hat{\mathbf{y}}\|_2^2 = \frac{1}{N} \sum_i (y_i - \hat{y}_i)^2$$

Loss function measures the error rate of our model.

Absolute deviation	Target (mark)	Predicted (mark)
4	5	1
1	4	5
3	5	2
1	5	4
1	2	3

- ***Mean Absolute Error*** (where \mathbf{y} is vector of targets):

$$MAE(\mathbf{y}, \hat{\mathbf{y}}) = \frac{1}{N} \|\mathbf{y} - \hat{\mathbf{y}}\|_1 = \frac{1}{N} \sum_i |y_i - \hat{y}_i|$$

ML thesaurus

To learn something, our ***model*** needs some degrees of freedom:

Name	Age	Statistics (mark)	Python (mark)	Eye color	Native language	Target (mark)	Predicted (mark)
John	22	5	4	Brown	English	5	4.5
Aahna	17	4	5	Brown	Hindi	4	4.5
Emily	25	5	5	Blue	Chinese	5	5
Michael	27	3	4	Green	French	5	3.5
Some student	23	3	3	NA	Esperanto	2	3

$$\hat{\text{mark}}_{ML} = w_1 \cdot \text{mark}_{Statistics} + w_2 \cdot \text{mark}_{Python}$$

ML thesaurus

To learn something, our ***model*** needs some degrees of freedom:

Name	Age	Statistics (mark)	Python (mark)	Eye color	Native language	Target (mark)	Predicted (mark)
John	22	5	4	Brown	English	5	4.447
Aahna	17	4	5	Brown	Hindi	4	4.734
Emily	25	5	5	Blue	Chinese	5	5.101
Michael	27	3	4	Green	French	5	3.714
Some student	23	3	3	NA	Esperanto	2	3.060

$$\hat{\text{mark}}_{ML} = w_1 \cdot \text{mark}_{Statistics} + w_2 \cdot \text{mark}_{Python}$$

ML thesaurus

To learn something, our ***model*** needs some degrees of freedom:

Name	Age	Statistics (mark)	Python (mark)	Eye color	Native language	Target (mark)	Predicted (mark)
John	22	5	4	Brown	English	5	1
Aahna	17	4	5	Brown	Hindi	4	5
Emily	25	5	5	Blue	Chinese	5	2
Michael	27	3	4	Green	French	5	4
Some student	23	3	3	NA	Esperanto	2	3

$$\hat{\text{mark}}_{ML} = \text{random}(\text{integer from } [1; 5])$$

Last term we should learn for now is ***hyperparameter***.

Hyperparameter should be fixed before our model starts to work with the data.

We will discuss it later with kNN as an example.

Recap:

- Dataset
- Observation (datum)
- Feature
- Design matrix
- Target
- Prediction
- Model
- Loss function
- Parameter
- Hyperparameter

Maximum Likelihood Estimation

Denote dataset generated by distribution with parameter θ

Likelihood function:

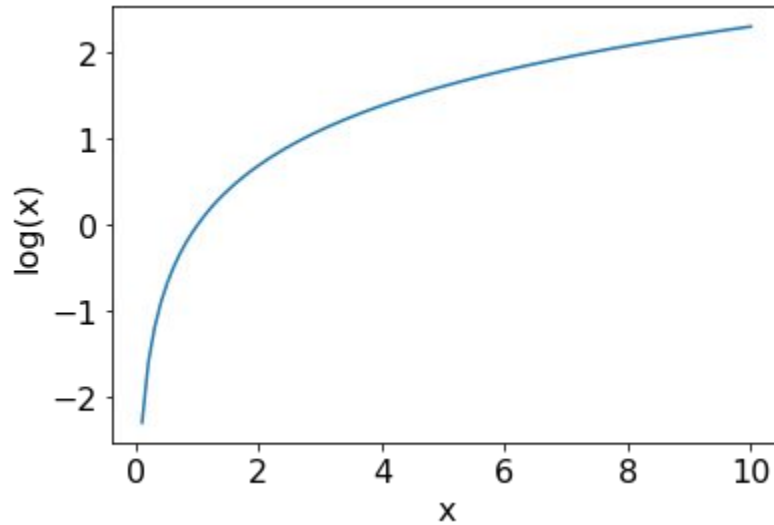
$$L(\theta|X, Y) = P(X, Y|\theta)$$

$$L(\theta|X, Y) \longrightarrow \max_{\theta}$$

**samples should
be i.i.d.**

$$L(\theta|X, Y) = P(X, Y|\theta) = \prod_i P(x_i, y_i|\theta)$$

Maximum Likelihood Estimation



Denote dataset generated by distribution with parameter θ

Likelihood function:

$$L(\theta|X, Y) = P(X, Y|\theta)$$

$$L(\theta|X, Y) \longrightarrow \max_{\theta}$$

samples should be i.i.d.

$$L(\theta|X, Y) = P(X, Y|\theta) = \prod_i P(x_i, y_i|\theta)$$

equivalent to

$$\log L(\theta|X, Y) = \sum_i \log P(x_i, y_i|\theta) \longrightarrow \max_{\theta}$$

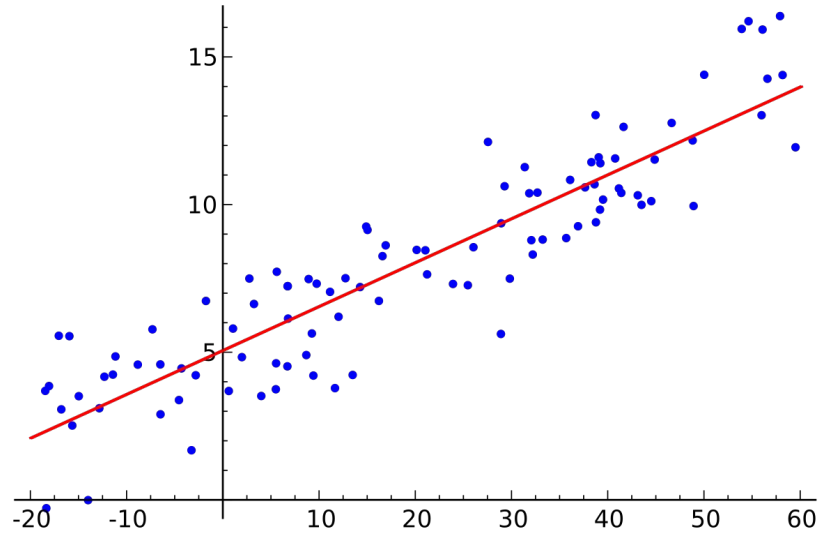
Machine Learning problems overview

Supervised learning problem statement

Let's denote:

- Training set $\mathcal{L} = \{\mathbf{x}_i, y_i\}_{i=1}^n$, where
 - $(\mathbf{x} \in \mathbb{R}^p, y \in \mathbb{R})$ for regression
 - $\mathbf{x}_i \in \mathbb{R}^p$, $y_i \in \{+1, -1\}$ for binary classification
- Model $f(\mathbf{x})$ predicts some value for every object
- Loss function $Q(\mathbf{x}, y, f)$ that should be minimized

- Regression problem



Estimated
(or predicted)
Y value for
observation i

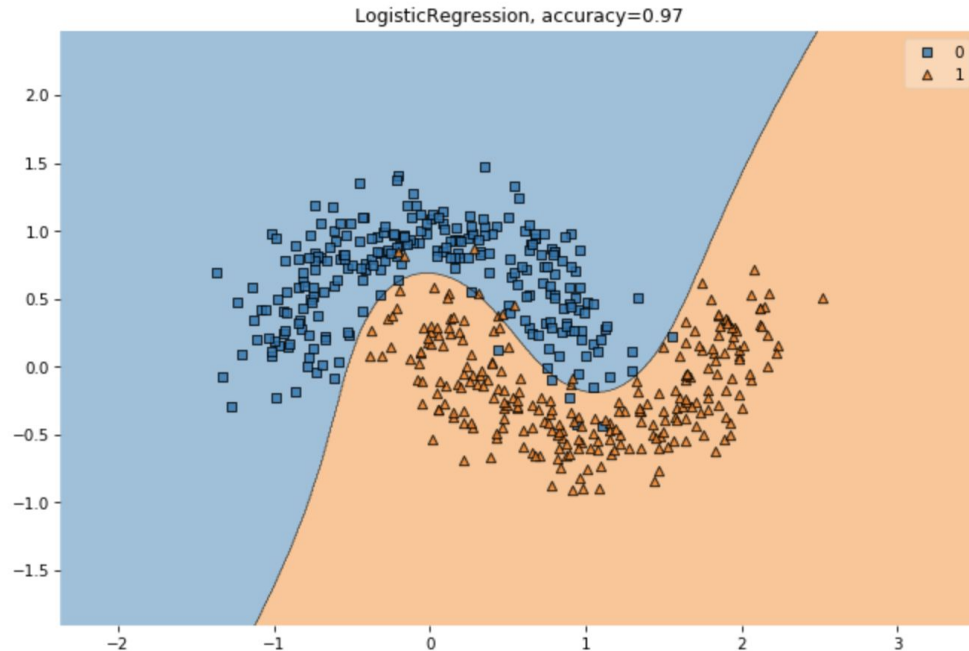
Estimate of
the regression
intercept

Estimate of the
regression slope

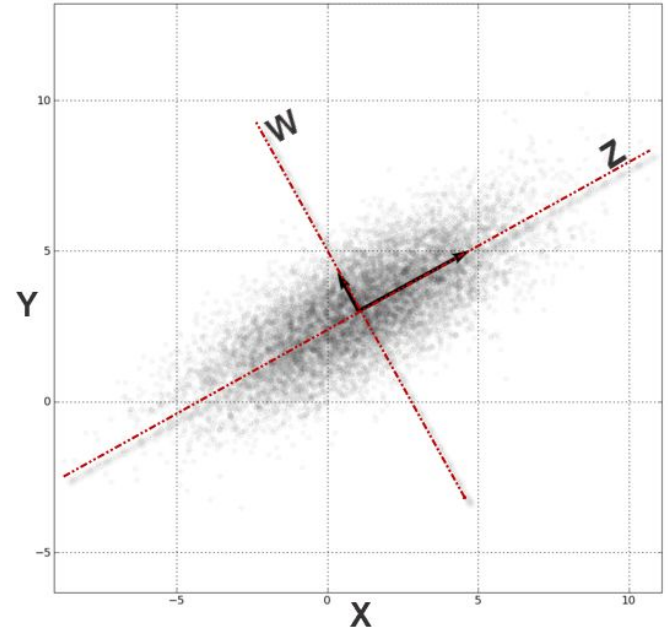
Value of X for
observation i

$$\hat{Y}_i = b_0 + b_1 X_i$$

- Regression problem
- Classification problem



- Regression problem
- Classification problem
- Dimensionality reduction



Naïve Bayes classifier

Naïve Bayes classifier

Let's denote:

- Training set $\mathcal{L} = \{\mathbf{x}_i, y_i\}_{i=1}^n$, where
 - $\mathbf{x}_i \in \mathbb{R}^p$, $y_i \in \{C_1, \dots, C_k\}$ for k-class classification

Bayes' theorem

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

or, in our case

$$P(y_i = C_k | \mathbf{x}_i) = \frac{P(\mathbf{x}_i | y_i = C_k)P(y_i = C_k)}{P(\mathbf{x}_i)}$$

Naïve Bayes classifier

Let's denote:

- Training set $\mathcal{L} = \{\mathbf{x}_i, y_i\}_{i=1}^n$, where
 - $\mathbf{x}_i \in \mathbb{R}^p$, $y_i \in \{C_1, \dots, C_K\}$ for K-class classification

$$P(y_i = C_k | \mathbf{x}_i) = \frac{P(\mathbf{x}_i | y_i = C_k) P(y_i = C_k)}{P(\mathbf{x}_i)}$$

Naïve assumption: features are **independent**

Naïve Bayes classifier

$$P(y_i = C_k | \mathbf{x}_i) = \frac{P(\mathbf{x}_i | y_i = C_k) P(y_i = C_k)}{P(\mathbf{x}_i)}$$

Naïve assumption: features are **independent**:

$$P(\mathbf{x}_i | y_i = C_k) = \prod_{l=1}^p P(x_i^l | y_i = C_k)$$

Naïve Bayes classifier

$$P(y_i = C_k | \mathbf{x}_i) = \frac{P(\mathbf{x}_i | y_i = C_k) P(y_i = C_k)}{\cancel{P(\mathbf{x}_i)}}$$

Optimal class label:

$$C^* = \arg \max_k P(y_i = C_k | \mathbf{x}_i)$$

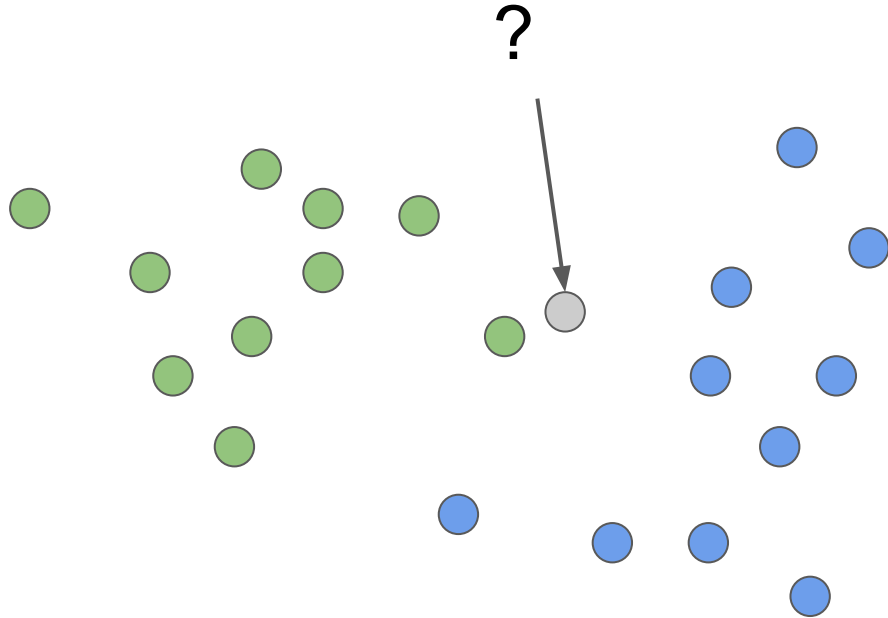
To find maximum we even do not need the denominator

But we need it to get probabilities

kNN – k Nearest Neighbors

kNN - k Nearest Neighbours

kNN - k Nearest Neighbours



k Nearest Neighbors Method

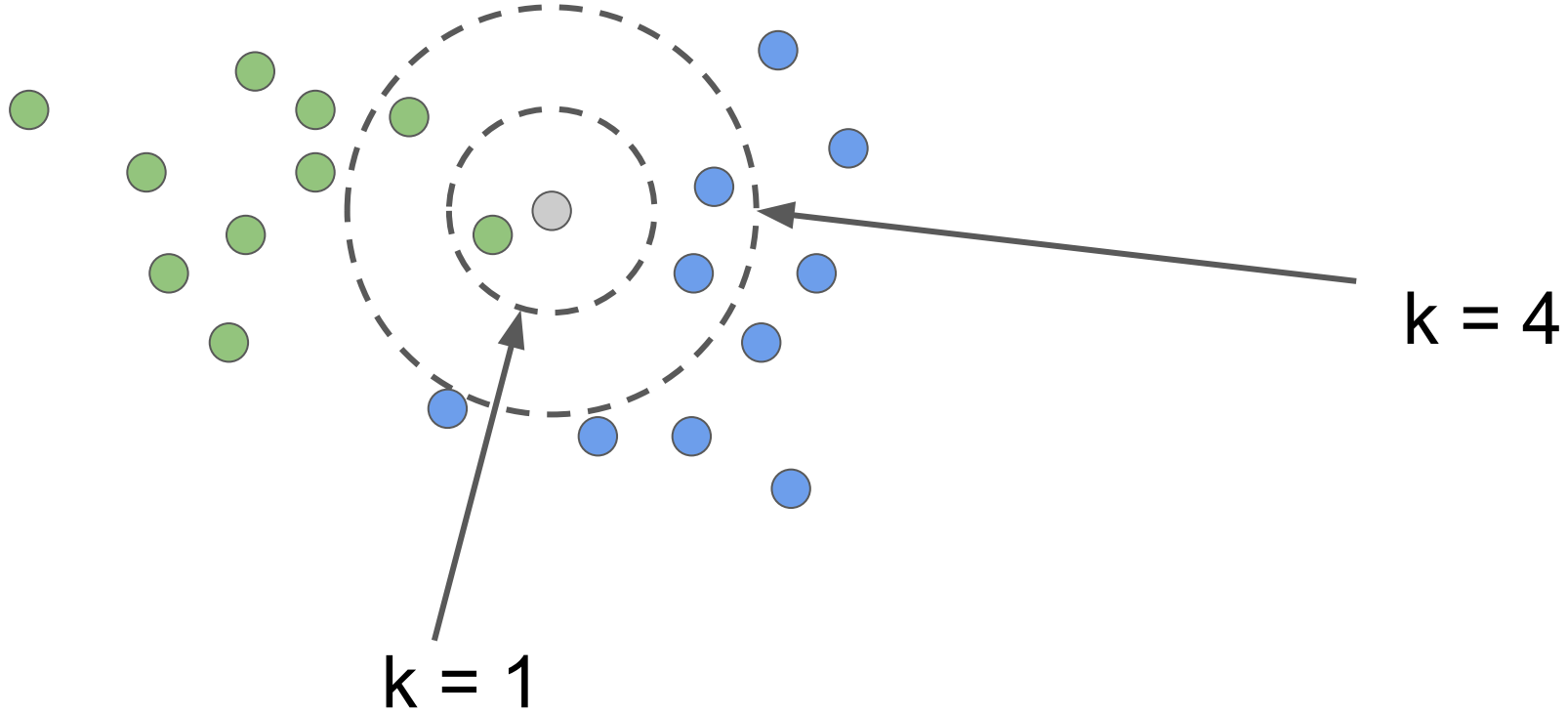
Given a *new observation*:

1. Calculate the distance to each of the samples in the dataset.
2. Select k samples from the dataset with the minimal distance to them.
3. The label of the *new observation* will be the most frequent label among those nearest neighbors.

How to make it better?

- The number of neighbors k (it is a ***hyperparameter***)

kNN - k Nearest Neighbours

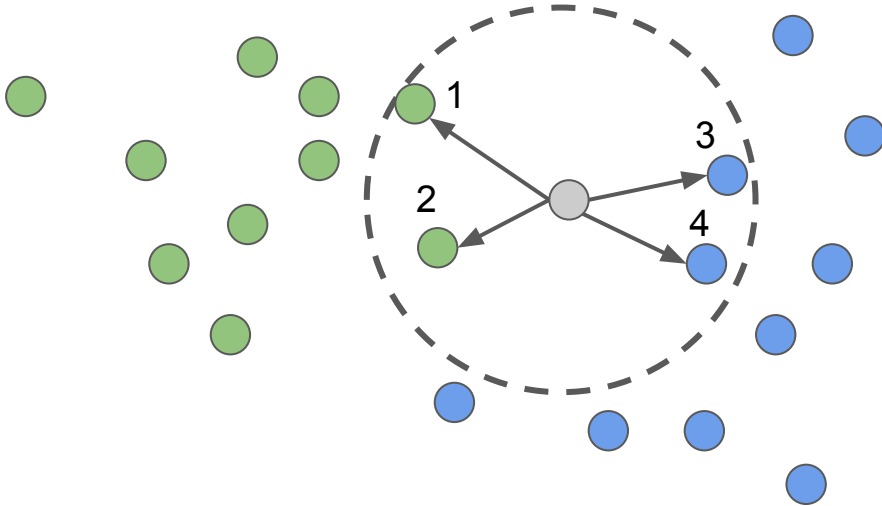


How to make it better?

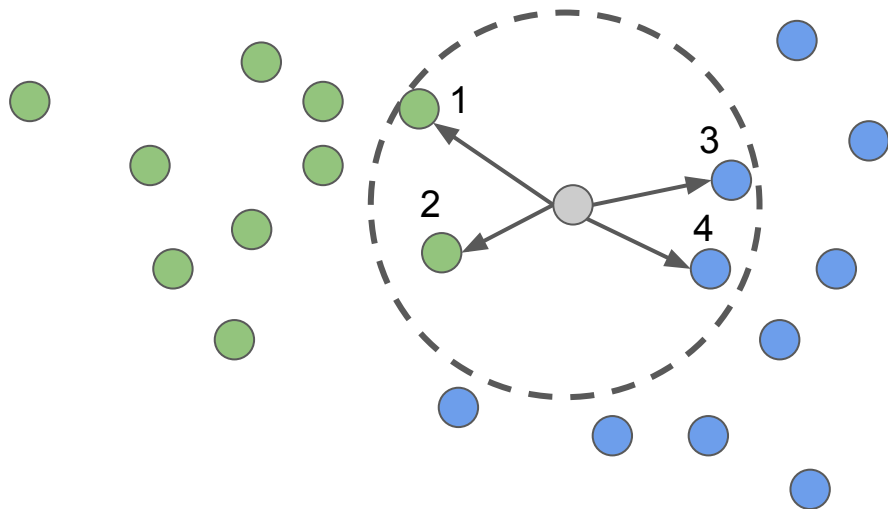
- The number of neighbors k (it is a ***hyperparameter***)
- The distance measure between samples
 - a. Hamming
 - b. Euclidean
 - c. cosine
 - d. Minkowski distances
 - e. etc.
- Weighted neighbours

$k = 4$

Weighted kNN



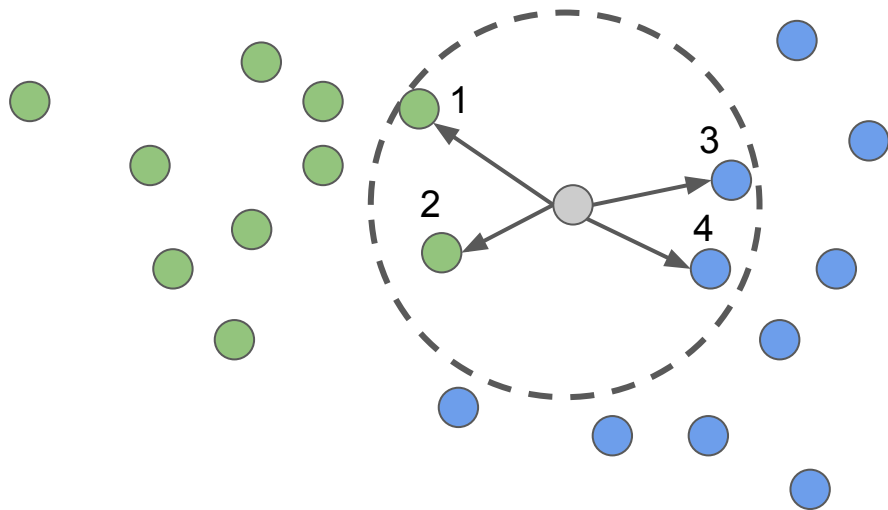
$k = 4$



Weighted kNN

- Weights can be adjusted according to the neighbors order,
 $w(\mathbf{x}_{(i)}) = w_i$

$k = 4$



Weighted kNN

- Weights can be adjusted according to the neighbors order,

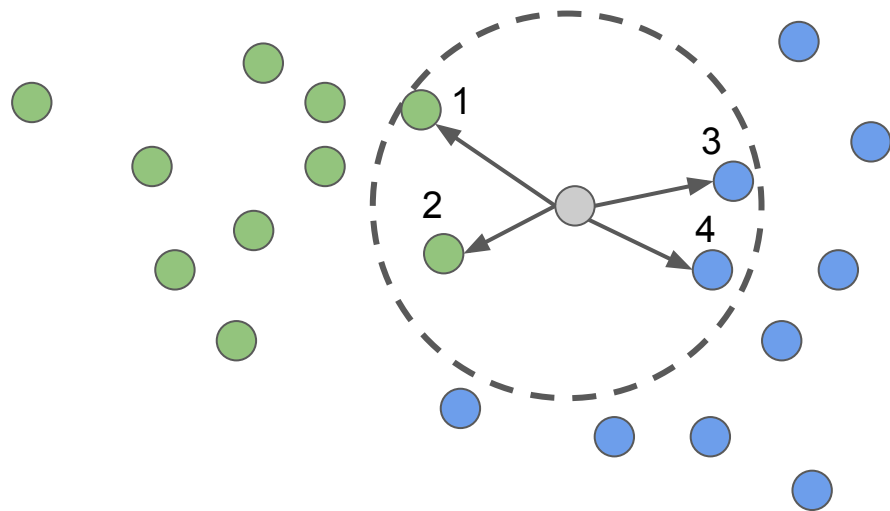
$$w(\mathbf{x}_{(i)}) = w_i$$

- or on the distance itself

$$w(\mathbf{x}_{(i)}) = w(d(\mathbf{x}, \mathbf{x}_{(i)}))$$

$k = 4$

Weighted kNN



- Weights can be adjusted according to the neighbors order,

$$w(\mathbf{x}_{(i)}) = w_i$$

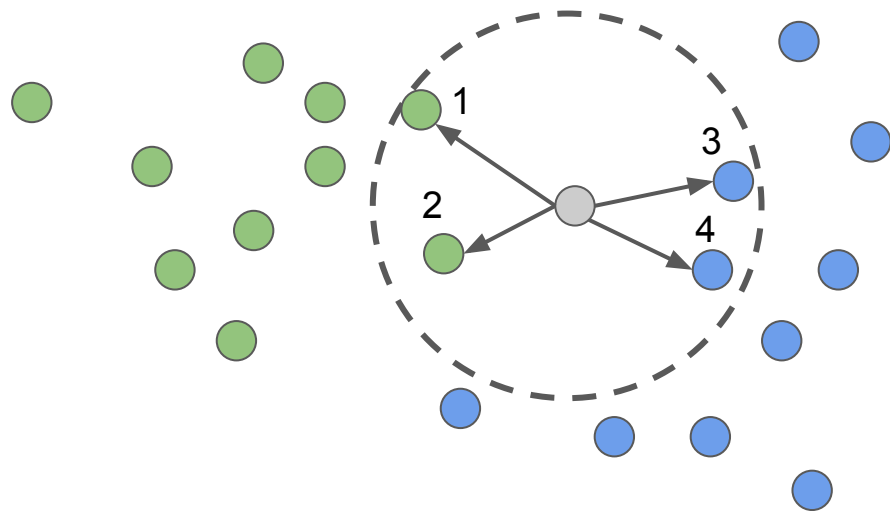
- or on the distance itself

$$w(\mathbf{x}_{(i)}) = w(d(\mathbf{x}, \mathbf{x}_{(i)}))$$

$$p_{\text{green}} = \frac{w(\mathbf{x}_1) + w(\mathbf{x}_2)}{w(\mathbf{x}_1) + w(\mathbf{x}_2) + w(\mathbf{x}_3) + w(\mathbf{x}_4)}$$

$k = 4$

Weighted kNN



- Weights can be adjusted according to the neighbors order,

$$w(\mathbf{x}_{(i)}) = w_i$$

- or on the distance itself

$$w(\mathbf{x}_{(i)}) = w(d(\mathbf{x}, \mathbf{x}_{(i)}))$$

$$p_{\text{blue}} = \frac{w(\mathbf{x}_3) + w(\mathbf{x}_4)}{w(\mathbf{x}_1) + w(\mathbf{x}_2) + w(\mathbf{x}_3) + w(\mathbf{x}_4)}$$

- Remember the **i.i.d.** property
- Usually the first dimension corresponds to the batch size, the second (and so on) to the features/time/...
- Even the naïve assumptions may be suitable in some cases
- Simple models provide great baselines

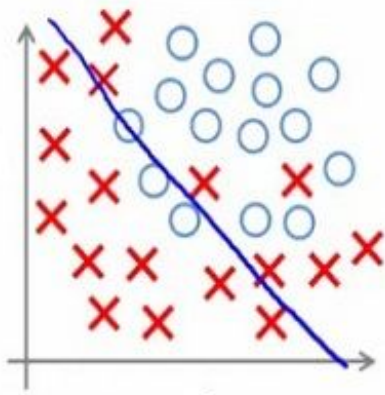
Model validation and evaluation

Supervised learning problem statement

Let's denote:

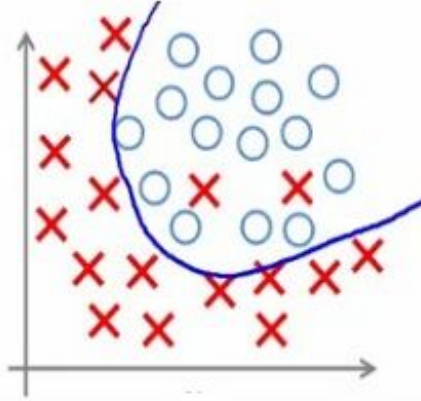
- Training set $\mathcal{L} = \{\mathbf{x}_i, y_i\}_{i=1}^n$, where
 - $(\mathbf{x} \in \mathbb{R}^p, y \in \mathbb{R})$ for regression
 - $\mathbf{x}_i \in \mathbb{R}^p$, $y_i \in \{+1, -1\}$ for binary classification
- Model $f(\mathbf{x})$ predicts some value for every object
- Loss function $Q(\mathbf{x}, y, f)$ that should be minimized

Overfitting vs. underfitting

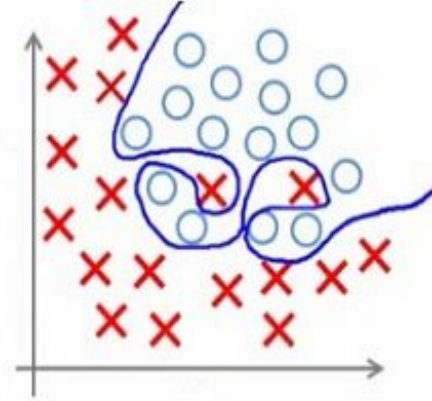


Under-fitting

(too simple to
explain the
variance)



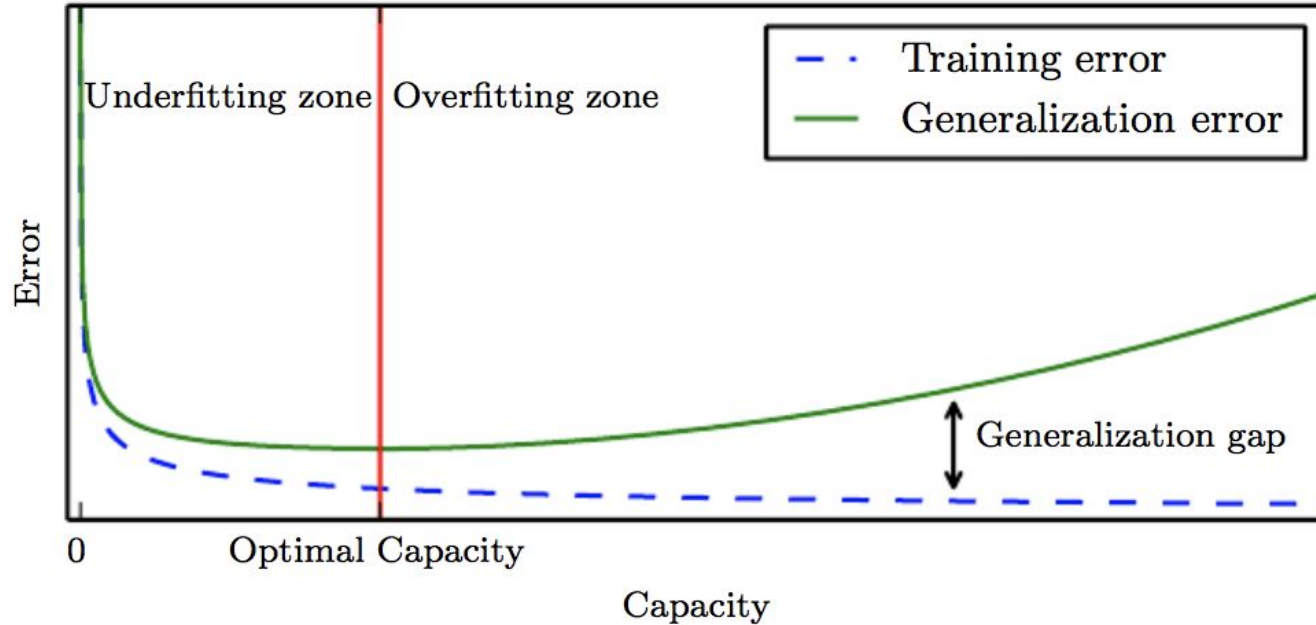
Appropriate-fitting



Over-fitting

(forcefitting -- too
good to be true)

Overfitting vs. underfitting



Overfitting vs. underfitting

- We can control overfitting / underfitting by altering model's capacity (ability to fit a wide variety of functions):
- select appropriate hypothesis space
- learning algorithm's effective capacity may be less than the representational capacity of the model family

Evaluating the quality

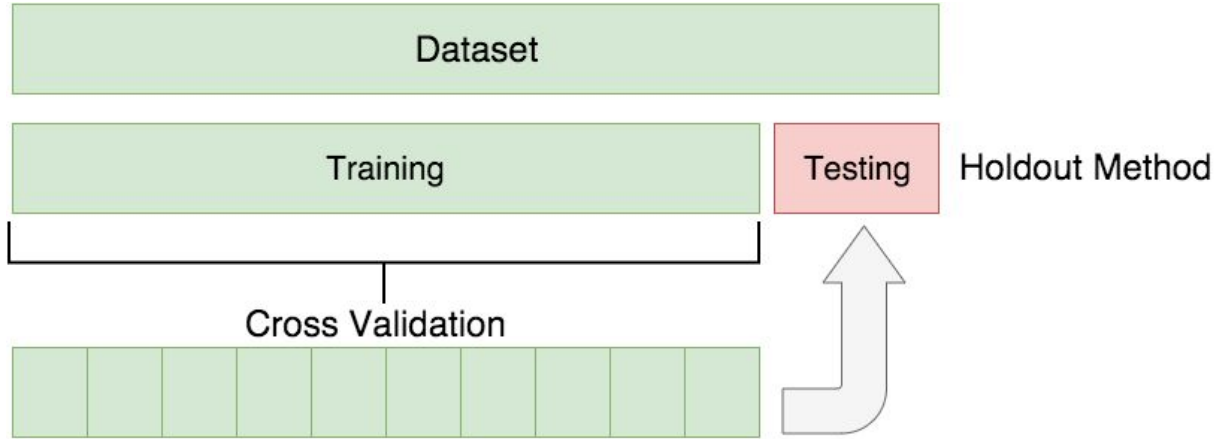


Evaluating the quality

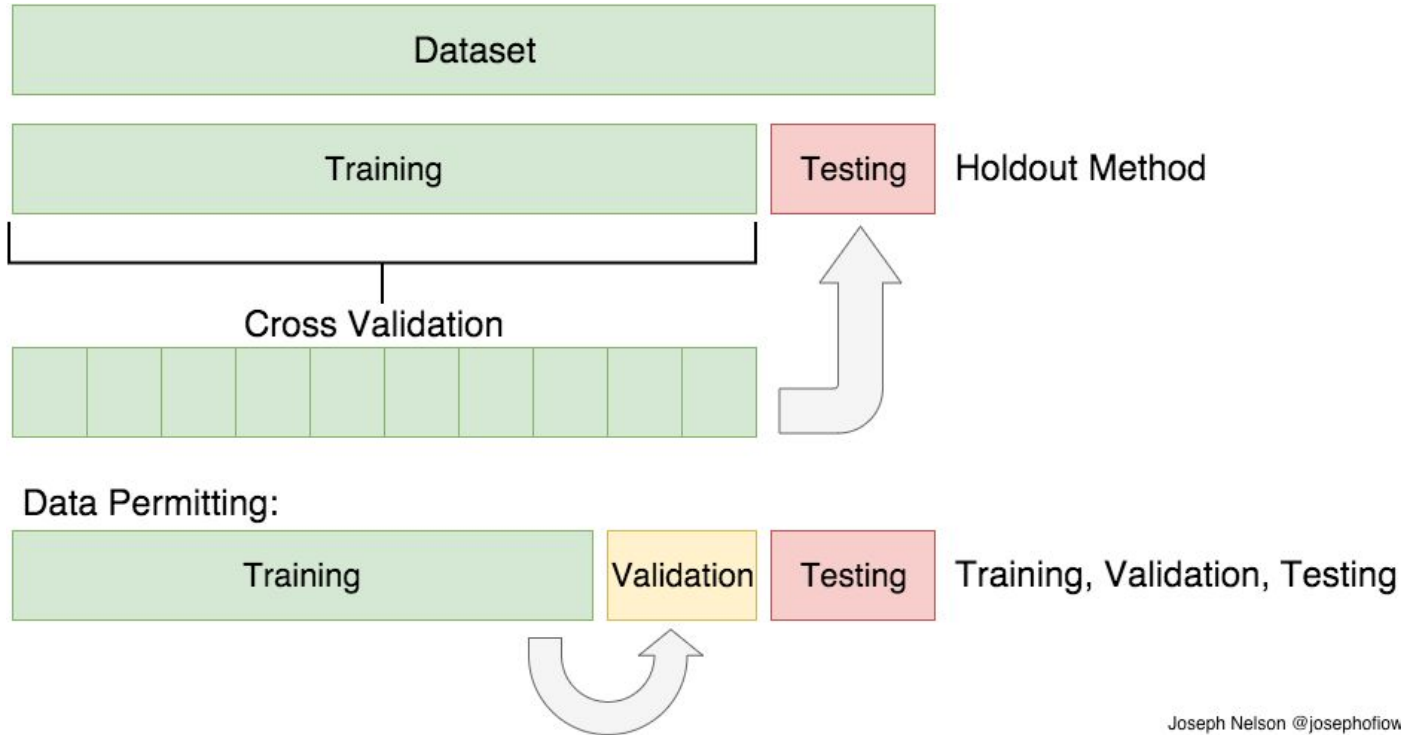


Is it good enough?

Evaluating the quality



Evaluating the quality



Joseph Nelson @josephofiowa

Cross-validation

