# Supervised learning

Inteligencia Artificial en los Sistemas de Control Autónomo
Máster en Ciencia y Tecnología desde el Espacio

Departamento de Automática

## Objectives

1. Extend supervised learning algorithms
2. Apply supervised learning to real-world problems

## Bibliography


- Géron, Aurélien. *Hands-On Machine Learning with Scikit-Learn, Keras & TensorFlow*. O'Reilly. 2020
- Müller, Andreas C., Guido, Sarah. *Introduction to Machine Learning with Python*. O'Reilly. 2016

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# k-Nearest Neighbors

## kNN classification (I)

Diagrama 1-NN y 3-NN.

# k-Nearest Neighbors

## kNN classification (II)

Diagrama frontera para varios valores de K

# k-Nearest Neighbors

## kNN regression

TODO

# k-Nearest Neighbors

## Summary

| Hyperparameters | Advantages | Disadvantages |
| --- | --- | --- |
| | | |

# Linear models

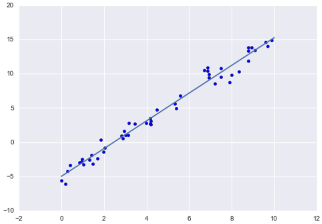
## Linear regression (I)

Lineal regression assumes a linear relationship among variables

- This limitation can be easely overcome
- Surprisingly good results in high dimensional spaces

**Lineal regression**

$$y = a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_n x_n$$



# Linear models (II)

Several methods to fit coefficients

- Ordinary Least Squares (OLS)
- Generalized Least Squares (GSL)
- Weighted Least Squares (WLS)
- Generalized Least Squares with AR Covariance Structure (GLSAR)

Regularization: Term that penalizes complexity

- L1 (Lasso regression)
- L2 (Ridge regression)
- ElasticNet: L1 and L2

**Lasso**

$\lambda \sum_j^n \beta_j^2$

**Ridge**

$\lambda \sum_j^n |\beta_j|$

**ElasticNet**

$\alpha \sum_j^n \beta_j^2 + (1-\alpha) \sum_j^n |\beta_j|$

# Linear models

## Summary

| Hyperparameters | Advantages | Disadvantages |
|---|---|---|
| | | |

# Naive Bayes Classifiers

TODO

# Naive Bayes Classifiers

## Summary

| Hyperparameters | Advantages | Disadvantages |
| --- | --- | --- |
| | | |

# Decission Trees

TODO

# Decission Trees

## Summary

| Hyperparameters | Advantages | Disadvantages |
|---|---|---|
| | | |

# Ensembles of Decision Trees

TODO

# Ensembles of Decision Trees

## Summary

| Hyperparameters | Advantages | Disadvantages |
|---|---|---|
| | | |

# Support Vector Machines

TODO

# Support Vector Machines

## Kernelized Support Vector Machines

TODO

# Support Vector Machines

## Summary

| Hyperparameters | Advantages | Disadvantages |
|---|---|---|
| | | |

# A

## B

TODO

# A

## B: Summary

| Hyperparameters | Advantages | Disadvantages |
|---|---|---|
| | | |

# Algorithms

## ARIMA (I)

AR: Autoregressive model

- Current observation depends on the last p observations
- Long term memory

MA: Moving Average model

- Current observation linearly depends on the last q innovations
- Short term memory

**AR(p)**

$$X_t = c + \sum_{i=1}^{p} \phi_i X_{t-1} + \epsilon_t$$

**MA(q)**

$$X_t = \mu + \epsilon_t + \theta_1 \epsilon_{t-1} + \ldots + \theta_q \epsilon_{t-q}$$

ARMA model = AR + MA

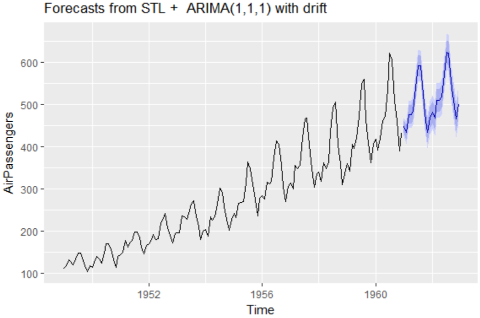
- ARMA(p, q): Two hyperparameters, p and q

# Algorithms

## ARIMA (II)

ARIMA = AR + i + MA (AR integrated MA)

- ARIMA(p, d, q)
- Three integer parameters: p, q and d (in practice, low order models)




(Source)

autoarima: search over p, q and d