

Introduction to Machine Learning (acronym IML)

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Brief description

- This course provides an introduction on Machine Learning
- It gives an overview of many concepts, techniques and algorithms in machine learning, beginning with topics such as classification and linear regression and ending up with more recent topics such support vector machines and recommender systems



Brief description

- The course is divided into three main topics:
 - supervised learning, unsupervised learning, and machine learning theory
- Topics include:
 - (i) Supervised learning (linear decision, non linear decision)
 - (ii) Unsupervised learning (clustering, factor analysis, visualization)
 - (iii) Learning theory (bias/variance theory, empirical risk minimization)
- The course will also draw from numerous case studies and applications, so that you'll also learn how to apply learning algorithms to computer vision, medical informatics, and signal analysis



Summary

Introduction to Machine Learning

Unsupervised Learning

Supervised Learning

Decision Learning Theory

Cluster Analysis Factor Analysis

Visualization

Non Linear Decision

Linear Decision concepts of
Decision
Learning
Theory

K-Means, Fuzzy C-means EM

PCA, ICA

Self Organized Maps (SOM) , Multi-Dimensional Scaling

Lazy Learning (K-NN, IBL, CBR) Overfitting, nodel selection and feature selection

Kernel earning Learning (Trees, Adaboost

Perceptron SVM VC dimension,
Practical advice
of how to use
learning
algorithms



- 1. Introduction to Machine Learning
- 2. Introduction to unsupervised learning
- 3. Cluster analysis
 - a) Classification of clustering algorithms
 - b) K-Means, Bisecting K-Means, Fuzzy C-means
 - c) EM. Introduction to Mixture of Gaussians
- 4. Factor analysis
 - a) Principal Components Analysis (PCA)
 - b) Independent Component Analysis (ICA)



5. Visualization

- a) Self-Organized Maps (SOM)
- b) Multi-dimensional Scaling (MDS)

6. A gentle introduction to supervised learning

- a) The linear regresion model
- b) Descent optimization methods
- Application of the learning model
- d) Tour on Machine Learning terms



7. Lazy Learning

- a) Nearest Neighbour (NN) and kNN
- Instance-based Learning (IBL)
- c) Case-based Reasoning (CBR) foundations

8. Feature Selection

- a) Description of Wrappers, Filters, and embedded
- b) Feature Selection Perspectives (Search directions, Search Strategies)
- Measures for making the selection (based on information, distance, dependence, consistency, accuracy)



9. Model Selection

- a) Introduction to Model evaluation (performance metrics, confusion matrix, ROC curves, etc.)
- b) Model evaluation (hold-out, cross-validation, overfitting and underfitting, bias vs variance, regularization, etc.)

10.Kernel Learning

- a) Statistical learning theory
- b) Support Vector Machines (SVM)



11.Recommender Systems

- a) Introduction to recommendation techniques
- An overview of Collaborative Filtering
- c) An overview of Content-based Filtering
- d) Conversational Recommenders

12. Ensemble Learning

- a) Introduction to ensemble learning
- b) Additive model: Bagging
- c) Additive model: Boosting



Methodology

- The class is divided in two parts
 - Theory (2 hours): introduce the contents of the course
 - —Laboratory (1 hour) which includes:
 - Practical exercises related to work deliveries
 - Participatory class where students talk about the readings suggested to go deeper into a subject

Note: These readings will be included as theory in the final exam



Activities – work deliveries

- Work 1 (W1)
 - Clustering exercise
- Work 2 (W2)
 - Factor Analysis exercise
- Work 3 (W3)
 - Lazy Learning or kNN Recommenders
- Work 4 (W4)
 - Kernels exercise

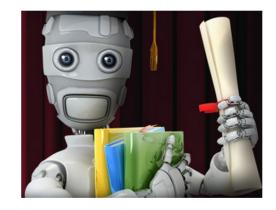


This year work is done in groups of three



Evaluation

- The course is divided into two parts:
 - Exam: an exam at the end of the term
 - Work: Work deliveries during the semester



Mark = $a \times Exam + b \times Work$ if exam >= 3,5 and Work >= 4,5

This year **a** and **b** will be established as: a = 0.4 and b = 0.6

Exam = an exam at the end of the term (14^{th} January 2020) Work = 0,3 x W1 + 0,2 x W2 + 0,3 x W3 + 0,2 x W4

 Some Works may have an exam after the delivery. The mark will be a part of the Wx.

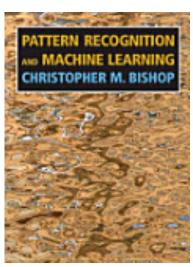


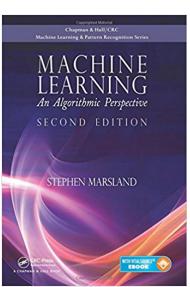
Remarks

- All the information of the course will be in Racó <u>https://raco.fib.upc.edu/</u>
- The schedule of the course is in another file, look at the notes in racó
- Work is in groups of 3 but the score is individual for each student
- Late deliveries: work or projects submitted late will mean the deduction of 1 point per day (out of 10) from the final mark
- Copy of deliveries: all the groups involved will obtain 0 points



Bibliography

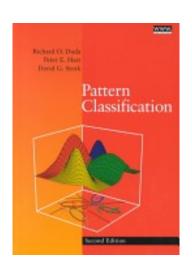




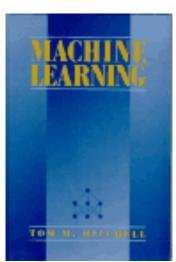
- Bishop, Christopher M., <u>Pattern</u>
 <u>Recognition and Machine Learning</u>.
 Springer. p. 738. <u>ISBN 978-0-387-31073-2</u>.
- Marsland, Stephen, <u>Machine</u>
 <u>Learning: An algorithmic</u>
 <u>Perspective</u>, 2nd ed. CRC Press,
 2015. <u>ISBN:</u> 978-1-466-58328-3



Bibliography



 Duda, Richard; Hart, Peter; and Stork, David, <u>Pattern Classification</u>, 2nd ed. John Wiley&Sons, 2001. <u>ISBN: 978-0-471-05669-0</u>



Tom Mitchell, <u>Machine Learning</u>.
 McGraw-Hill. ISBN 0-07-042807-7



Tools



Python

https://www.python.org/

http://scikit-learn.org/



Weka

http://www.cs.waikato.ac.nz/ml/weka/



PyCharm

https://www.jetbrains.com/pycharm/