



POLITÉCNICA

INTERNATIONAL
CAMPUS OF
EXCELLENCE

COORDINATION PROCESS OF
LEARNING ACTIVITIES
PR/CL/001



E.T.S. de Ingenieros de
Telecomunicacion

ANX-PR/CL/001-01

LEARNING GUIDE

SUBJECT

93001070 - Predictive And Descriptive Learning

DEGREE PROGRAMME

09AQ - Master Universitario en Ingenieria de Telecomunicacion

ACADEMIC YEAR & SEMESTER

2020/21 - Semester 1

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1. Description

1.1. Subject details

Name of the subject	93001070 - Predictive And Descriptive Learning
No of credits	6 ECTS
Type	Optional
Academic year of the programme	Second year
Semester of tuition	Semester 3
Tuition period	September-January
Tuition languages	English
Degree programme	09AQ - Master Universitario en Ingenieria de Telecomunicacion
Centre	09 - Escuela Tecnica Superior de Ingenieros de Telecomunicacion
Academic year	2020-21

2. Faculty

2.1. Faculty members with subject teaching role

Name and surname	Office/Room	Email	Tutoring hours *
Eduardo Lopez Gonzalo (Subject coordinator)	C-330	eduardo.lopez@upm.es	Sin horario. Appointment arranged by email
Luis Alfonso Hernandez Gomez	C-330	luisalfonso.hernandez@upm. es	Sin horario. Appointment arranged by email

* The tutoring schedule is indicative and subject to possible changes. Please check tutoring times with the faculty member in charge.

3. Prior knowledge recommended to take the subject

3.1. Recommended (passed) subjects

The subject - recommended (passed), are not defined.

3.2. Other recommended learning outcomes

- It is mandatory to follow this course simultaneously with the subject Machine Learning Lab
- Previous exposure to a programming language, such as MATLAB, R or Python
- Elementary course in Statistics

4. Skills and learning outcomes *

4.1. Skills to be learned

CG1 - Poseer y comprender conocimientos que aporten una base u oportunidad de ser originales en el desarrollo y/o aplicación de ideas, a menudo en un contexto de investigación.

CG2 - Que los estudiantes sepan aplicar los conocimientos adquiridos y su capacidad de resolución de problemas en entornos nuevos o poco conocidos dentro de contextos más amplios (o multidisciplinares) relacionados con su área de estudio.

CG4 - Que los estudiantes sepan comunicar sus conclusiones ?y los conocimientos y razones últimas que las sustentan? a públicos especializados y no especializados de un modo claro y sin ambigüedades.

CT1 - Capacidad para comprender los contenidos de clases magistrales, conferencias y seminarios en lengua inglesa.

CT2 - Capacidad para dinamizar y liderar equipos de trabajo multidisciplinares.

CT3 - Capacidad para adoptar soluciones creativas que satisfagan adecuadamente las diferentes necesidades planteadas.

CT4 - Capacidad para trabajar de forma efectiva como individuo, organizando y planificando su propio trabajo, de forma independiente o como miembro de un equipo.

CT5 - Capacidad para gestionar la información, identificando las fuentes necesarias, los principales tipos de documentos técnicos y científicos, de una manera adecuada y eficiente.

4.2. Learning outcomes

RA305 - Capability to design, develop and evaluate machine-learning techniques for a wide range of application areas

* The Learning Guides should reflect the Skills and Learning Outcomes in the same way as indicated in the Degree Verification Memory. For this reason, they have not been translated into English and appear in Spanish.

5. Brief description of the subject and syllabus

5.1. Brief description of the subject

This course covers the concepts and principles of a large variety of Machine Learning methods: from traditional Machine Learning models to Deep Learning. The course introduces main principles in Machine Learning: supervised, unsupervised and reinforcement learning, though main emphasis is on predictive and descriptive learning as reinforcement learning is covered in a subsequent course. Methodological issues such as model assessment and selection, and overfitting are discussed.

The course starts introducing the most relevant traditional predictive or supervised techniques: as different types of regression, generalized linear models, k-nearest neighbor classifier, classification and regression trees, ensemble methods (Bagging, Random Forests and Boosting) and kernel methods and Support Vector Machines. Then the course addresses traditional descriptive or unsupervised techniques: principal components analysis and clustering methods (k-means and hierarchical clustering). From this basic background the course presents the recent and very powerful Deep Learning models: students learn from the basics of Neural Networks to the most common architectures of Feed-Forward Networks, Convolutional Networks and Recurrent Neural Networks.

This course covers the principles and methodology for the design, evaluation and selection of a large variety of Machine Learning methods for supervised and unsupervised learning.

The students will understand the fundamentals and important topics in statistical machine learning. This outcome represents a fundamental ingredient in the training of a modern data scientist providing a solid base for its use on a wide range of applications in science and industry. In particular students will understand the ideas behind the most used and widely applicable techniques for regression, classification and clustering. Through several examples and use cases, students will also learn how important is to accurately assess the performance of a model. They will also acquire solid criteria on what could be best model for a given data and task. By the end of the course, students should be able to:

- Understand the fundamentals of the most used models and techniques for predictive and descriptive learning.
- Design a proper methodology for accurately assessing and gaining knowledge from the use of each one of the particular machine learning techniques.
- Know the strengths and weaknesses of the various approaches in order to choose the best models for a given data and application scenario.

5.2. Syllabus

1. Introduction to Machine Learning

- 1.1. What is statistical learning?
- 1.2. Types of Machine Learning
- 1.3. Assessing Model Accuracy

2. Linear Regression

- 2.1. Simple and Multiple Linear Regression
- 2.2. Linear Regression and Distributed Machine Learning Principles
- 2.3. Interpreting Regression Coefficients
- 2.4. Model Selection and Qualitative Predictors
- 2.5. Interactions and Nonlinearity
- 2.6. Comparison of Linear Regression with KNN

3. Classification

- 3.1. Logistic Regression
- 3.2. Bayes classifier and Linear Discriminant Analysis

- 3.3. Classification error analysis
- 3.4. Quadratic Discriminant Analysis
- 3.5. K-Nearest Neighbors
- 3.6. A Comparison of Classification Methods: Logistic Regression, LDA, QDA and KNN
- 4. Resampling methods
 - 4.1. Cross-validation
 - 4.2. Bootstrap
- 5. Linear Model Selection and Regularization
 - 5.1. Feature selection
 - 5.2. Optimal Model selection
 - 5.3. Regularization
 - 5.4. Dimension Reduction
 - 5.5. High-Dimensional Data
- 6. Moving Beyond Linearity
 - 6.1. Generalized Linear Models and Generalized Additive Models
- 7. Tree-Based Methods
 - 7.1. Decision trees
 - 7.2. Bagging
 - 7.3. Random Forests
 - 7.4. Boosting
- 8. Support Vector Machines
 - 8.1. Maximal Margin Classifier
 - 8.2. Support Vector Classifiers
 - 8.3. Kernels and Support Vector Machines
 - 8.4. Relationship to Logistic Regression
- 9. Descriptive Learning
 - 9.1. Supervised vs Unsupervised learning
 - 9.2. Principal Components Analysis
 - 9.3. Clustering Methods

9.4. K-means

9.5. Hierarchical Clustering

9.6. Practical Issues in Clustering

10. Introduction to Deep Learning

10.1. Simple Neural Networks models

10.2. Feed-forward Networks

10.3. Convolutional Networks

10.4. Recurrent Networks

10.5. Introduction to advanced Deep Learning models: autoencoders, Generative Adversarial Networks (GANs)

6. Schedule

6.1. Subject schedule*

Week	Face-to-face classroom activities	Face-to-face laboratory activities	Distant / On-line	Assessment activities
1	Activities Chapter 1 Duration: 02:00 Lecture Activities Chapter 2 Duration: 02:00 Lecture		Activities Chapter 1 Duration: 02:00 Lecture Activities Chapter 2 Duration: 02:00 Lecture	
2	Activities Chapter 3 Duration: 04:00 Lecture		Activities Chapter 3 Duration: 04:00 Lecture	
3	Activities Chapter 4 Duration: 02:00 Lecture Activities Chapter 5 Duration: 02:00 Lecture		Activities Chapter 4 Duration: 02:00 Lecture Activities Chapter 5 Duration: 02:00 Lecture	
4	Activities Chapter 6 Duration: 01:00 Lecture Activities Chapter 7 Duration: 03:00 Lecture		Activities Chapter 6 Duration: 01:00 Lecture Activities Chapter 7 Duration: 03:00 Lecture	
5	Activities Chapter 8 Duration: 04:00 Lecture		Activities Chapter 8 Duration: 04:00 Lecture	
6	Activities Chapter 9 Duration: 04:00 Lecture		Activities Chapter 9 Duration: 04:00 Lecture	
7	Activities Chapter 10 (10.1 , 10.2) Duration: 04:00 Lecture		Activities Chapter 10 (10.1, 10.2) Duration: 04:00 Lecture	
8	Activities Chapter 10 (10.3) Duration: 04:00 Lecture		Activities Chapter 10 (10.3) Duration: 04:00 Lecture	
9	Activities Use Case Review Duration: 02:00 Problem-solving class		Activities Use Case Review Duration: 02:00 Problem-solving class	Evaluation: Machine Learning use case Individual presentation Continuous assessment Not Presential Duration: 02:00

10	Activities Chapter 10 (10.4) Duration: 02:00 Lecture		Activities Chapter 10 (10.4) Duration: 02:00 Lecture	Evaluation: Machine Learning use case (continuation) Individual presentation Continuous assessment Not Presential Duration: 02:00
11	Activities Chapter 10 (10.4) Duration: 02:00 Lecture Activities Chapter 10 (10.5) Duration: 02:00 Lecture		Activities Chapter 10 (10.4) Duration: 02:00 Lecture Activities Chapter 10 (10.5) Duration: 02:00 Lecture	
12	Activities Chapter 10 (10.5) Duration: 04:00 Lecture		Activities Chapter 10 (10.5) Duration: 04:00 Lecture	
13	Activities Deep Learning Review Duration: 02:00 Problem-solving class Activities Final Project discussions Duration: 02:00 Problem-solving class		Activities Deep Learning Review Duration: 02:00 Problem-solving class Activities Final Project discussions Duration: 02:00 Problem-solving class	
14				
15				
16				
17				Final project evaluation Group presentation Continuous assessment Not Presential Duration: 00:15 Evaluation: Machine Learning use case Individual presentation Final examination Not Presential Duration: 02:00 Final project evaluation Group presentation Final examination Not Presential Duration: 00:15

Depending on the programme study plan, total values will be calculated according to the ECTS credit unit as 26/27 hours of student face-to-face contact and independent study time.

* The schedule is based on an a priori planning of the subject; it might be modified during the academic year, especially considering the COVID19 evolution.

7. Activities and assessment criteria

7.1. Assessment activities

7.1.1. Continuous assessment

Week	Description	Modality	Type	Duration	Weight	Minimum grade	Evaluated skills
9	Evaluation: Machine Learning use case	Individual presentation	No Presential	02:00	40%	/ 10	CG4 CT3 CT4 CT1 CT5 CG2 CG1
10	Evaluation: Machine Learning use case (continuation)	Individual presentation	No Presential	02:00	%	/ 10	
17	Final project evaluation	Group presentation	No Presential	00:15	60%	/ 10	CT2 CT3 CT4 CT1 CG4 CT5 CG2 CG1

7.1.2. Final examination

Week	Description	Modality	Type	Duration	Weight	Minimum grade	Evaluated skills
17	Evaluation: Machine Learning use case	Individual presentation	No Presential	02:00	40%	/ 10	CT4 CT1 CT5 CG2 CG4 CT3 CG1
17	Final project evaluation	Group presentation	No Presential	00:15	60%	/ 10	CG4 CT2 CT3 CT4 CT1 CT5 CG2 CG1

7.1.3. Referred (re-sit) examination

Description	Modality	Type	Duration	Weight	Minimum grade	Evaluated skills
Evaluation: Machine Learning use case	Individual presentation	Face-to-face	00:10	40%	/ 10	CT1 CG1 CT4 CG4 CT3 CG2 CT5
Final project evaluation	Group presentation	Face-to-face	00:15	60%	/ 10	CT1 CT4 CG4 CT3 CT2 CG2 CT5 CG1

7.2. Assessment criteria

Students will be qualified through continuous evaluation by default. According to the Normativa de Evaluación del Aprendizaje de la Universidad Politécnica de Madrid, students willing to renounce to continuous evaluation must complete the Moodle task entitled "Renounce to continuous evaluation" before the fourth week of the semester (deadline will be announced in Moodle).

Evaluation will assess if students have acquired all the competences of the subject. Thus, evaluation through final assessment will be carried out considering all the evaluation techniques used in continuous evaluation (EX, ET, TG, etc.), and will be celebrated in the exam period approved by Junta de Escuela for the current academic semester and year. Evaluation activities that assess learning outcomes that cannot be evaluated through a single exam can be carried out along the semester.

Extraordinary examination will be carried out exclusively by the final assessment method.

Continuous assessment will consist of:

- Individual presentations to demonstrate skills in knowing the basics of machine learning models will be made by

mid-semester

(40% of final grade).

- A final collaborative project will be developed to be evaluated by the end of the semester. Evaluation will be focused on the theoretical knowledge and criteria needed to design, select, and evaluate different machine learning models, and in particular deep learning architectures, in practical applications.

(final project assessment will represent 60% of the final grade).

Final assessment:

Those students that have renounced to continuous evaluation should address a final examination including both individual presentations to demonstrate theoretical knowledge on deep learning models (40% of final grade) and their final collaborative project (60% of the final grade).

Extraordinary examination:

Extraordinary examination consists of an individual presentations to demonstrate theoretical knowledge on machine learning models (40% of final grade) and a final collaborative project (60% of the final grade).

8. Teaching resources

8.1. Teaching resources for the subject

Name	Type	Notes
An Introduction to Statistical Learning	Bibliography	James, Gareth, Daniela Witten, Trevor Hastie, and Robert Tibshirani. An introduction to statistical learning. Vol. 112. New York: springer, 2013.
Machine learning: a probabilistic perspective	Bibliography	Kevin P. Machine learning: a probabilistic perspective. MIT press, 2012
The Elements of Statistical Learning Data Mining, Inference, and Prediction,	Bibliography	Hastie, Trevor, Tibshirani, Robert and Friedman, Jerome. The Elements of Statistical Learning Data Mining, Inference, and Prediction, Second Edition. Springer Series in Statistics, 2009
Deep learning	Bibliography	Goodfellow, I., Bengio, Y., Courville, A., & Bengio, Y. (2016). Deep learning. Cambridge: MIT press.
Neural Networks and Deep Learning	Web resource	http://neuralnetworksanddeeplearning.com/index.html
Scaling up machine learning: Parallel and distributed approaches.	Bibliography	Bekkerman, Ron, Mikhail Bilenko, and John Langford, eds. Scaling up machine learning: Parallel and distributed approaches. Cambridge University Press, 2011
Pattern recognition and machine learning (information science and statistics).	Bibliography	Christopher M. Bishop. Pattern Recognition and Machine Learning (Information Science and Statistics), 2006.

9. Other information

9.1. Other information about the subject

For on-line learning activities we will use UPM Moodle platform and tools. Moodle, GutHub and Youtube will be the environments to share specific course materials. Specific communication frameworks such as Skype for Business or Microsoft Teams could be used allowing UPM students to interact with instructors.

The increasing relevance of technological developments based on Machine Learning makes this course an educational activity directed to contribute to Goal 4.4 in Sustainable Development Goals (SDGs) 2030 United Nations Agenda, empowering our students with relevant skills, including technical and vocational skills, for employment, decent jobs and entrepreneurship.