

**COURSE DATA****Data Subject**

<b>Code</b>	36441
<b>Name</b>	Deep learning
<b>Cycle</b>	Grade
<b>ECTS Credits</b>	4.5
<b>Academic year</b>	2023 - 2024

**Study (s)**

<b>Degree</b>	<b>Center</b>	<b>Acad. year</b>	<b>Period</b>
1406 - Degree in Data Science	School of Engineering	4	Second term

**Subject-matter**

<b>Degree</b>	<b>Subject-matter</b>	<b>Character</b>
1406 - Degree in Data Science	18 - Deep Learning	Optional

**Coordination**

<b>Name</b>	<b>Department</b>
LAPARRA PEREZ-MUELAS, VALERO	242 - Electronic Engineering
MARTIN GUERRERO, JOSE DAVID	242 - Electronic Engineering
SORIA OLIVAS, EMILIO	242 - Electronic Engineering

**SUMMARY**

The subject “Deep Learning (DL)” deals with probably the most popular topic in machine learning. The basic idea of the DL is to build neural networks (already studied in the subject “Connectionist Models”, third year of the degree) but with the particularity that there is a large number of connections between neurons as a result of using multilayer architectures.

The idea of using this type of architecture is not new; Since the dawn of neural network research, it was logical to think that greater connectivity would lead to greater modeling capabilities. Added to the technological difficulties due to the high calculation capacity required, was the lack of effective training methods, so it was not until these problems began to be solved between 2005 and 2010, when DL began to be used in different practical problems.

The spectacular results in applications unapproachable so far, such as image segmentation or classification, automatic translation or sentiment analysis have made this discipline one of the most active at an academic level (with numerous new proposals and associated publications), technological (where



the routine use of GPUs has allowed their use in increasingly complex problems) and social (since many applications have spread systematically).

A priori, any problem that can be solved by means of a shallow neural networks can also be solved by DL, with greater modeling performance, provided that the data set is sufficiently large and diverse. However, most applications are usually related to images and prediction of temporal sequences (very commonly within the framework of natural language processing).

The main approaches to DL are the following:

- Autoencoders.
- Convolutional neural networks.
- Recurrent neural networks.
- Generative approaches.

The course will begin by introducing and reviewing the most important concepts to take into account DL, the most usual kinds of applications and the suitability of different solutions for each type of application. Once the work framework is presented, convolutional neural networks, already introduced in the subject "Connectionist Models", will be quickly reviewed, and the rest of the approaches will be described in more detail. Finally, approaches related to other types of learning will be introduced, such as Deep Reinforcement Learning.

Practical classes will reinforce the concepts introduced in theory by means of Python implementations to solve a series of practical problems: some academic problems to consolidate the theoretical notions and also practical problems to show the applicability and versatility of the AP.

The theory classes will be taught in Spanish and the practical and laboratory classes as stated in the course info available on the degree website.

## PREVIOUS KNOWLEDGE

### Relationship to other subjects of the same degree

There are no specified enrollment restrictions with other subjects of the curriculum.

### Other requirements

This is an optional course of the 4th year of the degree, when it is hence assumed that the student has already achieved the basic knowledge to develop his professional activity as a data scientist. The course can be viewed as an extension of two third grade courses (36426 - Machine Learning and especially 36428 - Connectionist Models). Therefore, it is highly recommended that students enrolled in DL have passed both subjects in order to be able to follow it correctly from the beginning. In addition, as



## OUTCOMES

### 1406 - Degree in Data Science

- (CG02) Ability to solve problems with initiative and creativity and to communicate and transmit knowledge, abilities and skills, which should include the ethical and professional responsibility of the activity of a data scientist.
- (CG03) Capability to elaborate models, calculations, reports, to plan tasks and other works analogous to the specific field of data science.
- (CT03) Ability to defend your own work with rigor and arguments and to expose it in an adequate and accurate way with the use of the necessary means.
- (CT05) Ability to evaluate the advantages and disadvantages of different methodological and / or technological alternatives in different fields of application.
- (CE03) Ability to solve classification, modelling, segmentation and prediction problems from a set of data.
- (CE07) Ability to model dependency between a response variable and several explanatory variables, in complex data sets, using machine learning techniques, interpreting the results obtained.
- (CE13) To know how to design, apply and evaluate data science algorithms for the resolution of complex problems.
- (CB3) Students must have the ability to gather and interpret relevant data (usually in their field of study) to make judgements that take relevant social, scientific or ethical issues into consideration.
- (CB4) Students must be able to communicate information, ideas, problems and solutions to both expert and lay audiences.

## LEARNING OUTCOMES

The most important learning outcomes (LO) of the course are:

- LO1: Learning the main deep neural architectures.
- LO2: Knowing the problems of deep learning problems as well as their solutions.
- LO3: Knowing the main recurrent neural network algorithms.

Each of these three outcomes allows to acquire all the competences of the course to a greater or lesser extent. In particular:

- LO1 (CG2, CB3, CB4, CT3, CE3) is essential for the student to be able to know in which situations a data-based problem can be approached with DL.
- RA2 (CG2, CG3, CB3, CB4, CT3, CT5, CE3, CE7, CE13) will enable the student to decide the most suitable DL approach to solve a problem based on data analysis, taking into account its advantages in terms of modeling, its drawbacks and possible solutions to them.
- LO3 (CG2, CG3, CB3, CB4, CT3, CT5, CE3, CE7, CE13) focuses mainly on one of the most important DL approaches, such as recurrent networks for sequence prediction.



## DESCRIPTION OF CONTENTS

### 1. Introduction

1. The deep learning framework.
  - Definitions.
  - Shallow and deep neural networks.
  - Deep networks versus kernel methods.
  - Parallelization.
2. Relevant contributions.
3. Review of convolutional neural networks.
  - Rectified linear activation functions: RELU and variants.
  - Dropout.
  - Modeling flexibility and transfer learning.
4. Featured applications.

### 2. Recurrent networks

1. Prediction of time series.
2. Deep recurrent networks for the prediction of time series with variable length.
3. Gradient control
  - Uncontrolled vanishing and exploding of the gradient.
  - The LSTM (Long Short-Term Memory) network.
  - The GRU (Gated Recurrent Unit) network.
4. Attention Models: Transformer networks.

### 3. Autoencoders

1. Justification and need of autoencoders. Main approaches.
2. Linear and non-linear autoencoders.
3. Variational autoencoders.



#### 4. Generative approaches

1. Generative versus discriminative approaches.
2. Generative Adversarial Networks: GAN.
3. Variants of GAN

#### 5. Deep Reinforcement Learning

1. Review of reinforcement learning.
2. Deep approaches.

#### 6. Laboratory practice

The laboratory practices will allow to consolidate the contents studied in theory through the model implementations and the practical resolution of academic and real problems. There will be five laboratory practices

1. Convolutional networks.
2. Recurrent networks and transfer learning.
3. Autoencoders.
4. GAN networks.
5. Deep Reinforcement Learning.

### WORKLOAD

ACTIVITY	Hours	% To be attended
Theory classes	25,00	100
Laboratory practices	15,00	100
Classroom practices	5,00	100
Attendance at events and external activities	2,00	0
Development of group work	5,00	0
Development of individual work	4,00	0
Study and independent work	28,00	0
Readings supplementary material	2,00	0
Preparation of evaluation activities	15,00	0





Preparing lectures	2,50	0
Preparation of practical classes and problem	2,50	0
Resolution of case studies	5,00	0
Resolution of online questionnaires	1,50	0
<b>TOTAL</b>	<b>112,50</b>	

## TEACHING METHODOLOGY

The teaching methodologies of this course are:

MD1 - Theoretical activities (CG3, CB4, CT3, CT5, CE3, CE7, CE13): Expository development with the participation of the students in solving specific questions. Individual evaluation questionnaires.

MD2 - Practical activities (CG2, CB3, CT5, CE3, CE7, CE13): Learning by means of problem solving, exercises and case studies that allow to acquire different competences of the course.

MD4 - Work in the laboratory and / or computer classroom (CG2, CG3, CB3, CB4, CT3, CT5, CE3, CE7, CE13): Learning by carrying out activities developed individually or in small groups and carried out in laboratories and / or computer classrooms.

## EVALUATION

The final grade for the course will be obtained as a result of the weighted average between the theory and practical parts. According to the credits assigned to each part, the theory will have a representation of 2/3 in the final grade and the practice the remaining third.

The theory grade corresponding to the first call will come out as a result of:

- SE1 (30%; CG2, CG3, CB3, CB4, CT5, CE3, CE7, CE13): Objective tests, consisting of one or more exams of theoretical questions, synthetic problems and real practical problems. To pass the course, a minimum grade of 4 (out of 10) will be required in this part.
- SE2 (60%; CG2, CG3, CB3, CB4, CT3, CT5, CE3, CE7, CE13): Papers, reports and oral presentations.
- SE3 (10%; CG2, CB4, CT3, CE3, CE7, CE13): Continuous evaluation of each student, based on the participation and degree of involvement of the student in the teaching-learning process, taking into account regular attendance at the planned face-to-face activities and the resolution of questions and problems proposed periodically.

Regarding the practice, 40% of the grade will correspond to SE2 (CG2, CG3, CB3, CB4, CT3, CT5, CE3, CE7, CE13) and 60% to SE1 (CG2, CG3, CB3, CB4, CT5, CE3, CE7, CE13). To pass the course, a minimum grade of 4 (out of 10) will be required in SE1. Of the 40% corresponding to continuous assessment, 70% will correspond to the completion of the exercises proposed in the practice session, which may be evaluated by the teacher at the end of the lab session. The remaining 30% will come from the previous preparation of the laboratory practice session and will be quickly evaluated at the beginning of each practice session. The practices can be done individually or in pairs; SE1 will be assessed in an individual basis. In addition, the teacher can choose to evaluate the regular practice sessions individually, even if they have been developed by groups of two students.



The second call will be evaluated as the first with the exception that in the theory part, SE1 will have a weight of 40% and SE3 of 0%; in the practical part, 20% will correspond to SE2 and 80% to SE1.

In any case, the evaluation system will be governed by what is established in the Evaluation and Qualification Regulation of the University of Valencia for Degrees and Masters (<https://webges.uv.es/uvTaeWeb/MuestraInformacionEdictoPublicoFrontAction.do?accion=inicio&idEdictoSeleccionado=5639>).

## REFERENCES

### Basic

- Ian Goodfellow, Yoshua Bengio and Aaron Courville (2016). Deep learning. The MIT Press.
- Valentina Emilia Balas, Sanjiban Sekhar Roy, Dharmendra Sharma, Pijush Samui (2019). Handbook of Deep Learning Applications. Springer
- Nikhil Ketkar (2017). Deep learning with Python: a hands-on introduction. Apress.
- Charu C. Aggarwal (2018). Neural Networks and Deep Learning: A Textbook. Springer.

### Additional

- Kaizhu Huang, Amir Hussain, Qiu-Feng Wang, Rui Zhang (2019). Deep Learning: Fundamentals, Theory and Applications. Springer.
- Ovidiu Calin (2020). Deep Learning Architectures: A Mathematical Approach. Springer.
- Santanu Pattanayak (2017). Pro Deep Learning with TensorFlow: A Mathematical Approach to Advanced Artificial Intelligence in Python. Apress.