UAB Universitat Autònoma de Barcelona

Neural Networks and Deep Learning

Code: 104362
ECTS Credits: 6

2025/2026

Degree	Type	Year
Data Engineering	OB	3

Contact

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Teaching groups languages

You can view this information at the end of this document.

Prerequisites

It is essential to have acquired a good mathematical background as well as to have a good level of programming, mainly in Python. It is essential to have taken the subject of Computational Learning in the first semester. Some of the concepts developed in this subject are the basis of the content and development of Neural Networks

Objectives and Contextualisation

Objectives and contextualization
This course aims to give a practical introduction to neural network models and deep learning.

Students will consolidate and expand their theoretical training, based on the knowledge acquired in previous subjects related to machine learning, completing their profile in this area. The aim of the course is to end up having a broad knowledge of the concepts, techniques and structures typical of neural networks, as well as being able to understand and apply the particular methodology of these techniques to real case studies, and finally develop the ability. to choose the most appropriate mechanisms and structures for each particular case of application.

Skills

Make effective use of bibliographic and electronic resources to obtain information.
Solve problems related to the analysis of large volumes of data through the design of intelligent systems and computer learning.
Students must be able to apply their knowledge to their job or vocation in a professional manner and must be able to establish arguments and problem-solving skills.
Students must be able to communicate information, ideas, problems, and solutions to both specialized and non-specialized audiences.
Using quality criteria, critically evaluate the work done.
Work cooperatively in a multidisciplinary context assuming and respecting the role of the different members of the team.

Competences

- Analyse data efficiently for the development of smart systems with the capacity for autonomous learning and/or data mining.
- Students must be capable of collecting and interpreting relevant data (usually within their area of study) in order to make statements that reflect social, scientific or ethical relevant issues.
- Work cooperatively in complex and uncertain environments and with limited resources in a multidisciplinary context, assuming and respecting the role of the different members of the group.

Learning Outcomes

1. Design and implement an integrated strategy of statistical techniques and artificial intelligence for the development of descriptive and predictive systems.
2. Students must be capable of collecting and interpreting relevant data (usually within their area of study) in order to make statements that reflect social, scientific or ethical relevant issues.
3. Work cooperatively in complex and uncertain environments and with limited resources in a multidisciplinary context, assuming and respecting the role of the different members of the group.

Content

1 Introduction and bases of neural networks

-logistic regression

-perceptron

-activation function

-gradient descent

-MLP

-backpropagation

2 Practical aspects of Neural Networks

- Overfitting

- Regularization

- Dropout

- Input normalization

- Vanishing / exploding gradients

- Initialization of weights

- Gradient check

3 Convolutional Networks

- Computer Vision

- What is convolution
- Padding, stride convolutions
- Filter algebra
- pooling layers
- softmax regression
- first networks: AlexNet, VGG

4 CNN Case Studies: Classification

- inception
- residual networks
- networ in network: 1x1 convolution

5 Practical aspects of Neural Networks II

- Adjustment of hyperparameters
- Normalization of activations, batch norm
- Data augmentation
- Transfer Learning

6 CNN: object detection

- object detection vs classification
- box prediction
- metric: intersection over union
- Non-max deletion
- Anchor boxes
- Base Networks: Yolo, FasterRCNN

7 Sequential Networks: Recurrent Neural Networks

- Model of recurrent neural networks
- Backpropagation over time

- Type of RNN

- Language model and sequence generation

- GRU & LSTM

- Word2vec

Activities and Methodology

Title	Hours	ECTS	Learning Outcomes
Type: Directed			
Theoretical content	22	0.88	1, 2
Type: Supervised			
lab practicums	16	0.64	1, 3
serminars	10	0.4	1, 2
Type: Autonomous			
Setup an ddevelopment of practical projects	52	2.08	1, 2, 3
study	28	1.12	1, 2

All course information and related documents that students may need will be available on the Virtual Campus page (http://cv.uab.cat/).

The different activities carried out in the course are organized as follows:

Theory classes
The main concepts and algorithms of each theoretical topic will be presented. These topics serve as the starting point for the course work.

Laboratory sessions
These will be classes where interaction with students is prioritized. They will be individual in nature, although the work can be developed in groups. In these sessions, practical cases will be proposed that require designing a solution using the methods covered in the theory classes. It is not possible to follow the problem-solving sessions without having followed the theoretical content. The outcome of these sessions will be the resolution of problems, which will be assessed weekly through online tests. The specific mechanism for conducting the assessments will be indicated on the course website. All laboratory sessions will be practical and will include programming a solution to the proposed problem.

Group projects
Work groups will consist of 3-4 students. These groups must remain the same throughout the course and be self-managed: role distribution, work planning, task assignment, resource management, conflict resolution, etc. Although the instructor will guide the learning process, their involvement in group management will be minimal.

Once the material has been presented to understand the challenges of various problems, the problems to be solved will be introduced, and students will define their own project. Throughout the semester, students will work in cooperative groups, analyze the chosen problem, design and implement solutions based on different machine learning algorithms covered in class, analyze the results obtained with each method, and publicly defend their project.

To develop the project, groups will work autonomously, and follow-up sessions will be used to evaluate the work done between sessions and to resolve doubts with the instructor, who will monitor the project's progress, point out errors, suggest improvements, etc. It is essential that groups attend tutorials to receive effective feedback for improving the project. In these sessions, groups must explain the work done, and the instructor will ask questions to all members to assess their contribution. Attendance at these sessions is mandatory.

In the final session of each project, groups will give a presentation explaining the developed project, the adopted solution, and the results obtained. Each group member must participate in the presentation.

Both the theory assessment and the group work will be recoverable.

Annotation: Within the schedule set by the centre or degree programme, 15 minutes of one class will be reserved for students to evaluate their lecturers and their courses or modules through questionnaires.

Assessment

Continous Assessment Activities

Title	Weighting	Hours	ECTS	Learning Outcomes
Concept tests	30%	7	0.28	1, 2
Group Project	40%	5	0.2	1, 2, 3
Problem porfolio	10	5	0.2	1, 2
Project Defence	20%	5	0.2	1, 2, 3

Activities and Assessment Tools:

This course does not offer a single-assessment option.

To evaluate the acquisition of knowledge and competencies, the assessment combines content assimilation, problem-solving skills, and, significantly, the ability to generate computational solutions to complex problems, both individually and in groups.

The assessment is divided into three parts:

– Content Evaluation

The final content grade will be calculated from several partial exams:

Content Grade = 1/N * Test_i

The number of tests may vary and will be defined at the beginning of the course. To receive a content grade, each test must be graded above 4.

These tests will be conducted during the course and will focus on conceptual understanding of the theoretical sessions.

They aim to individually assess the student's understanding and conceptualization of the techniques taught.

Recovery tests: If the content grade is insufficient, students may take the official exam to retake the failed parts.

No validation of previously passed theoretical parts is allowed.

– Evaluation of laboratory work

The goal of the problem-solving sessions is to engage students continuously with the course content through small exercises that apply theory. Weekly tests will serve as evidence of this work. After each test, students will have access to solutions for self-assessment. Combined with tutoring hours, this helps identify weaknesses.

– Group project evaluation

In the final weeks of the semester, a more extensive project will be carried out. It will be evaluated both as a group and individually. Evaluation criteria include code, report, presentation, and project follow-up during assigned sessions.

Final course grade:

Final Grade = (0.3 * Content) + (0.1 * Problem Portfolio) + (0.6 * Project)
The project will be graded on both its defense and the quality of its development.

Conditions to pass the course:

- Content grade must be ≥ 4.
- Project and its defense must be ≥ 6.

If the calculated final grade is above 5 but the minimums are not met, the final grade will be 4.5.

Honors will be awarded according to current regulations, for grades above 9. In case of ties, additional activities may be proposed.

A student will be marked as "Not Assessable" if no part of the course (theoretical or practical) has been evaluated.

Each grade release will include instructions for recovery if applicable.

Important notices:

- Continuous assessment dates and deadlines, as well as all teaching materials, will be published on the Virtual Campus (http://cv.uab.cat/) and may be subject to changes. All updates will be communicated via the Virtual Campus.
- For each assessment activity, a review date, time, and location will be provided. If the student does not attend, no further review will be allowed.
- Irregularities (copying, allowing copying, plagiarism, use of unauthorized devices, etc.) will result in a grade of 0 and cannot be recovered. If these activities are required to pass, the course will be failed. The transcript grade will be the lower of 3.0 or the weighted average.

Bibliography

Bibliography

Web links

- Subject web page: http://cv.uab.cat
- Deep Learning. MIT Press book. https://www.deeplearningbook.org

Basic Bibliography

- Deep learning with Python, François Chollet, Manning Publications, 1st Ed., 2017
- Pattern Recognition and Machine Learning, Christopher Bishop, Springer, 2011
- Neural Networks for Pattern Recognition, Christopher Bishop, Oxford University Press, 1st ed., 1996

Software

No special software other than the usual ones will be used in these studies.

Groups and Languages

Please note that this information is provisional until 30 November 2025. You can check it through this link. To consult the language you will need to enter the CODE of the subject.

Name	Group	Language	Semester	Turn
(PAUL) Classroom practices	81	Catalan	second semester	afternoon
(PAUL) Classroom practices	82	Catalan	second semester	afternoon