Master's Department of Engineering Sciences

Name of the unit: AI Fundamentals

Lecturer: Daniel Racoceanu (daniel.racoceanu@sorbonne-universite.fr)
Course code: UM4RBI10-FondIA
Student workload: 14h of lectures, h of tutorial sessions, 14h of lab sessions@
Credits: 3 ECTS

Specialization tracks:				
	- **E3A** :	☐ CIMES	☐ Syscom	☐ IPS
	- **AR** :	☐ ROBOT	☒ SI	☐ MeDH
	- **MECA** :	☐ MS2	☐ MF2A	☐ CompMech
		☐ ACOU	☐ EE	☐ EE APP

Semester offered: ☒ S1 ☐ S2 ☐ S3 ☐ S4
Language of instruction: ☒ French ☐ English
Targeted audience: ☒ Engineering Sciences students ☐ Other (specify):
Localization : ☒ PMC Campus ☐ Other (specify):

Course Overview

This course offers a deepening of the basic concepts used in artificial intelligence and machine learning, with a focus on fundamental paradigms/algorithms and theoretical and methodological reinforcement
Keywords: Supervised, unsupervised, self-supervised learning; Markov processes, Bayesian approaches, frequentist approaches, inverse problems, decision trees, strong randomness, ensemble learning, support vector machines, kernel trick, loss function, evaluation methodologies, bias, stochastic optimization, gluttonous approaches.

Prerequisites

Students should have previously acquired the following prerequisites to follow this course:

- Mathematics: Linear algebra, vector and matrix calculus, numerical optimization of multivariate continuous functions, probability
- Computer science: Programming (in Python: numpy, etc.), algorithms
- Machine Learning (desirable): Machine Learning Basics, Machine Learning Performance Assessment (False Positive, False Negatives, Recall, Accuracy, F1-score)

Intended Learning Outcomes

By the end of this course, students will be able to:

1. Analyze a problem: Choose an algorithm that is appropriate for the task, the data, and the resources
2. Design: Algorithmic Foundations
3. Design: Choosing the learning process
4. Implementation: Master a high-level library dedicated to learning to implement the algorithm
5. Implementation: Preparing data for training
6. Implementation: Perform the training defined in the design phase to optimize the algorithm's parameters and meta parameters
7. Implementation: Replicating learnings and experimental results
8. Assessment: Develop an adequate experimental protocol to evaluate the performance of a model

9. Assessment: Diagnose the causes of suboptimal network behavior in order to propose solutions to address it
10. Assessment: Interpreting and explaining the decisions of a model: attention map, bias checking, etc.

Indicative Teaching Sequence and Methods

Week	C/TD/TP*	Content	Preparation	Learn. outc.
S1	C1	Markov processes, dynamic programming, Bellman's equations, link with reinforcement learning	Markov property, Markov processes, dynamic programming, reinforcement learning.	AAV1,2,3
S2	TP1 (3h)	Reinforcement learning: use of Markov processes and dynamic programming in this context. Typical use cases.	Look in detail at the concepts covered in C1	AAV1-6,8
S3	C2	Bayesian vs. frequentist approaches, Bayesian networks, link with inverse problems.	Bayes' theorem, definition of inverse problems.	AAV1,2,3
S4	TP2 (3h)	Bayesian systems and Bayesian approaches vs. frequentist approaches, inverse problems	Look in detail at the concepts covered in C2	AAV1-6,8
S5	C3	Stochastic optimization in discrete space		AAV1,2,3
S6	TP3 (3h)	Stochastic optimization: discrete and continuous spaces	Look in detail at the concepts covered in courses C1 to C3	AAV1-6,8
S7	C4	Stochastic optimization in R^n discrete space, continuous space		AAV1,2,3
S8	TP4 (3h)	Stochastic optimization and reinforcement learning	Take a detailed look at the concepts covered in course C1 to C4	AAV1-6,8
S9	C5	Decision tree, random drills, set learning	Decision tree, random forests	AAV1,2,3
S10	C6	Support Vector Machines (SVMs): Fundamentally statistical nature of the approach, kernel trick;	SVM - kernel tip	AAV1,2,3
S11	C7	Methodologies for evaluation/validation and bias checking.	Evaluation, verification, bias	AAV 5,6,7,8, 10
S12	TP5 (2h)	Validation and bias verification methodologies. Use cases inspired by recent advances in the field.	Look in detail at the concepts covered in C7	AAV 5,6,7,8,10

* C/TD/TP respectively corresponds to lectures, tutorials and lab sessions.

Sequence of the unit:
The UE takes place in 3 successive sequences:
- Sequence 1: Markov processes / Bayesian approaches (C1/2 + TP1/2 + Quiz1)
- Sequence 2: stochastic optimization (C4/5 + TP3/4 + Quiz 2)
- Sequence 3: convergence / loss function + evaluation - bias (C5/6/7 + TP5) + overall ER (all courses and practical work)

The practical exercises will have a TME part (on a machine) at the beginning of the session, in order to be able to instantaneous the concepts of the course, in an easy way, before the actual start of the practical exercise.

Indicative Assessment of Intended Learning Outcomes (1st session)

Week	Individ./group	In-person/remote	Type of exam	Evaluated outcomes	Scale %
S6	Collective	In-person	Quiz	AAV1-6,8	25 %
S8	Collective	In-person	Quiz	AAV1-6,8	12 %
S10	Collective	In-person	Quiz	AAV1-6,8	12 %
S15	Collective	In-person	Written	AAV 1-10	50 %

2nde session of exam

Session	Individ./group	In-person/remote	Type of exam	Evaluated outcomes	Scale %
2	Collective	In-person	Written	AAV 1-10	50 %
1	Collective	In-person	Quiz	AAV1-8	50 %

Bibliographic references

- Stuart Russell & Peter Norvig, Artificial Intelligence : A Modern Approach, Fourth edition, 2020
- Richard S. Sutton et Andrew G. Barto, Reinforcement Learning : An Introduction, second edition

, 2018