First year courses

MAI Year 1 Core Courses

Data Science & Knowledge Engineering

Foundations of Agents

Full course description

Foundations of Agents introduces the student to the formal foundation of agents. An agent is a computational being, such as a software program, robot or human. Agents operate in some environment, which they can observe and in which they can realize objectives through the execution of actions. Examples of such environments are computer game environments, the internet and the physical world in case of robots and humans. This course addresses the problem of how an agent can act optimally in order to realize its objectives. It is investigated how the agent's environment, its objectives, actions and observations can be formalized to solve this problem. Initially Markov decision processes will be used to model the agent and its environment. Other models that will be investigated include logic-based models, such as epistemic logic, doxastic logic, dynamic logic, temporal logic, and BDI logics. The extension of these models towards multi-agent systems will be emphasized as often agents do no not operate alone in an environment. After completing this course the student will be familiar with the formal models of describing agents and how these models can be used to determine and agent's behaviour. The student will be able to judge which model is applicable for specific problem domains.

Prerequisites

Knowledge of Propositional and Predicate Logic, Calculus

Recommended reading

None

KEN4115

Period 1
1 Sep 2020
23 Oct 2020

Print course description
ECTS credits:
6.0
Instruction language:
English
Coordinator:
N. Roos
Teaching methods:
Project-Centered Learning

Assessment methods:
Written exam

Data Science & Knowledge Engineering

Intelligent Search & Games

Full course description

In this course the students learn how to apply advanced techniques in the framework of game-playing programs. Depending on the nature of the game these techniques can be of a more or less algorithmic nature. The following subjects will be discussed:

(1) Basic search techniques. Alpha-beta; A*.

(2) Advanced search techniques. IDA*; B*, transposition tables; retrograde analysis and endgame databases; proof-number search and variants; multi-player search methods; Expectimax and *-minimax variants.

(3) Heuristics. World representations; killer moves; history heuristic, PVS; windowing techniques; null-moves; forward-pruning techniques; selective search, GOAP.

(4) Monte Carlo methods. Monte Carlo tree search (MCTS) techniques, enhancements and applications; AlphaGo and AlphaZero approaches.

(5) Game design. Game quality metrics; self-play evaluation; procedural content generation (PCG); evolutionary game design; novelty search.

Prerequisites

Good programming skills are required.

Recommended reading

• Millington, I. and Funge, J. (2009). Artificial Intelligence for Games, 2nd Edition,
Morgan Kaufmann Publishers, ISBN: 978-0123747310.

• Russell, S.J. and Norvig, P. (2010). Artificial Intelligence: A Modern Approach, 3rd edition. Pearson Education,
New Jersey. ISBN 0-13-207148-7.

•Yannakakis, G.N. and Togelius, J. (2018) Artificial Intelligence and Games, Springer, Berlin. ISBN 978-3-319-63519-4
(eBook) 978-3-319-63518-7 (hardcover)

KEN4123

Period 1
1 Sep 2020
23 Oct 2020

Print course description

ECTS credits:
6.0
Instruction language:
English
Coordinators:
M.H.M. Winands
C.B. Browne
Teaching methods:
Project-Centered Learning
Assessment methods:
Written exam, Assignment

Data Science & Knowledge Engineering

Advanced Concepts in Machine Learning

Full course description

In Advanced Concepts in Machine Learning a selected number of recent developments in the field are presented and experimented with. Machine learning deals with the prediction of labels or real values for unseen objects, based on a set of previously encountered examples, or automatically adapting behaviour according to previous experience. In the past years, topics such as Deep Neural Networks, Recommender Systems, Relational Learning, Reinforcement Learning, Support Vector Machines and Gaussian Processes have made their appearance in the course. Besides an overview of recent Machine Learning techniques, the course also highlights the importance of representations in successful applications of machine learning. In this context, propositional representations are contrasted with multi-instance and relational representations, but also automatically generated representations through Sparse Coding, Auto encoders, Deep Belief Nets and indirect representations such as distances and kernel receive substantial attention. After completion of this course, the students are able to select most suited representations and best-fits of learning techniques for a given machine learning problem and reason about the limitations of the suggested selections.

Prerequisites

Desired Prior Knowledge: Familiarity with the basics of machine learning through a Machine Learning or Data Mining course

Recommended reading

Recommended literature: Pattern Recognition and Machine Learning - C.M.Bishop; Bayesian Reasoning and Machine Learning - D. Barber; Gaussian Processes for Machine Learning - C.E. Rasmussen & C. Williams; The Elements of Statistical Learning - T. Hastie et al.

KEN4154

Period 2
26 Oct 2020
18 Dec 2020

Print course description

ECTS credits:

6.0

Coordinator:

K. Driessens

Teaching methods:

Project-Centered Learning

Data Science & Knowledge Engineering

Multi-Agent Systems

Full course description

Multi-Agent Systems introduces the student to systems composed of multiple interacting intelligent agents. An agent is a computational being, such as a software program, robot or human. Agents operate in some environment, which they can observe and in which they can realize objectives through the execution of actions. Multi-agent systems are an enabling technology for applications that rely on distributed and parallel processing of data, information and knowledge in complex computing environments. Due to advances in inter-connectivity and interoperability of computers and software such applications are becoming standard in a variety of domains such as e-commerce, logistics, supply chain management, telecommunication, health care and manufacturing. This course covers the key conceptual, theoretical and practical foundations of multi-agent systems. The following topics, among others, will be discussed: agent-agent communication, automated negotiation and argumentation in cooperative and competitive settings, multi-agent learning and planning, automated decision making based on voting and auctioning, and development and engineering of agent-based systems. After completing this course student will be familiar with the underlying theory of agents, and multi-agent systems. The student will be able to judge whether a multi-agent approach is beneficial to use over other approaches for handling the same problem.

Prerequisites

Basic logic, basic mathematics, probability theory and Java programming.

Recommended reading

Multiagent Systems Algorithmic, Game-Theoretic, and Logical Foundations” by Yoav Shoham and Kevin Leyton-Brown. Cambridge University Press, 2009. This book is also available as ebook: http://www.masfoundations.org/.

KEN4111

Period 2

26 Oct 2020

18 Dec 2020

Print course description

ECTS credits:

6.0

Instruction language:
English
Coordinator:
G.B. Weiss
Teaching methods:
Project-Centered Learning
Assessment methods:
Written exam

Data Science & Knowledge Engineering
Research Project MAI 1

Full course description

The research project will take place in the three blocks of the first semester of the first year of the Master programme. The emphasis in the first two blocks is on exploration and modelling, and in block 3 on implementation and experimenting. The subject of the project will be closely related to the courses in the semester. The research project will be performed in small groups (3 - 5 students). During the project the student will practice team-based research and a range of scientific skills. The project will result in a project presentation, a project report, and possibly a product. At the end of each block, a project presentation will take place. Examination: Project presentation, report, and product.

Prerequisites

No Prerequisites.

Recommended reading

None.

KEN4130

Semester 1
1 Sep 2020
29 Jan 2021

Print course description
ECTS credits:
6.0
Instruction language:
English
Coordinators:
G.M. Schoenmakers
K. Driessens
Teaching methods:
Project-Centered Learning

Assessment methods:
Written exam

Data Science & Knowledge Engineering

Autonomous Robotic Systems

Full course description

Operating autonomously in unknown and dynamically changing environments is a core challenge that all robotic systems must solve to work successfully in industrial, public, and private areas. Currently popular systems that must demonstrate such capabilities include self-driving cars, autonomously operating drones, and personal robotic assistants. In this course, students obtain deep knowledge in creating autonomous robotic systems that can operate in and manipulate unknown and dynamically changing environments by autonomously planning, analysing, mapping, and modelling of such environments. Students learn to approach these challenging tasks through three main techniques: swarm intelligence, model-based probabilistic frameworks, and (mostly) model-free techniques from artificial evolution and machine learning.

Prerequisites

Discrete Mathematics, Linear Algebra, Probabilities and Statistics, Data Structures and Algorithms

Recommended reading

Some papers to be announced at Eleum.

KEN4114

Period 4
1 Feb 2021
2 Apr 2021

Print course description
ECTS credits:
6.0
Instruction language:
English
Coordinator:
R. Möckel
Teaching methods:
Project-Centered Learning
Assessment methods:
Written exam

Data Science & Knowledge Engineering

Research Project MAI 2

Full course description

The research project will take place in the three blocks of the second semester of the first year of the Master programme. The emphasis in the first two blocks is on exploration and modelling, and in block 6 on implementation and experimenting. The subject of the project will be closely related to the courses in the semester. The research project will be performed in small groups (3 - 5 students). During the project the student will practice team-based research and a range of scientific skills. The project will result in a project presentation, a project report, and possibly a product. At the end of each block, a project presentation will take place. Examination: Project presentation, report, and product.

Prerequisites

No Prerequisites.

Recommended reading

None.

KEN4131

Semester 2
1 Feb 2021
3 Jul 2021

Print course description
ECTS credits:
6.0
Instruction language:
English
Coordinators:
N. Roos
E.N. Smirnov
Teaching methods:
Project-Centered Learning

MAI Year 1 Electives

Data Science & Knowledge Engineering

Advanced Natural Language Processing

Full course description

How do I say, "Where is the next Italian restaurant" in Dutch? Can I get a summary of today's lecture?

When were artificial neural networks developed? Computers able to answer these questions are a long-time dream of humankind and currently, we see first programs to solve these problems. This course will provide the skills and knowledge to develop state-of-the-art (SOTA) solutions for these natural language processing (NLP) tasks. After a short introduction to traditional statistical approaches to NLP, the course will focus on deep learning techniques to solve these problems. In the first part of the course, we will investigate methods to model sequence labeling tasks like Named Entity recognition or Part- of-speech techniques. The second part of the lecture will focus on sequence-to-sequence models, a very powerful model to solve many NLP tasks like machine translation, summarization and question answering. In this course, major challenges when building the systems will be address: representing words in neural networks, neural network architectures to model language, methods to train complex models and algorithms to find the most probable output.

Prerequisites

None.

Recommended reading

Papers published in top international conferences and journals in machine learning field.

KEN4259

Period 4
1 Feb 2021
2 Apr 2021

Print course description
ECTS credits:
6.0
Coordinator:
J.H. Niehues
Teaching methods:
PBL

Data Science & Knowledge Engineering

Algorithms for Big Data

Full course description

The emergence of very large datasets poses new challenges for the algorithm designer. For example, the data may not fit into the main memory anymore, and caching from a hard-drive becomes a new bottleneck that needs to be addressed. Similarly, algorithms with larger than linear running time take simply too long on very large datasets. Moreover, simple sensory devices can observe large amount of data over time, but cannot store all the observed information due to insufficient storage, and an immediate decision of what to store and compute needs to be made. Classical algorithmic techniques do not address these challenges, and a new algorithmic toolkit needs to be developed. In this course, we will look at a number of algorithmic responses to these problems, such as: algorithms with (sub-)linear running times, algorithms where the data arrive as a stream, computational models where memory is organized hierarchically (with larger storage units, such as hard-drives, being slower to access than smaller, faster storage such as CPU cache memory). New programming paradigms and models such as MapReduce/Hadoop will be discussed. We will also look at a number of topics from classical algorithm design that have undiminished relevance in the era of big data such as approximation algorithms and multivariate algorithmic analysis.

Prerequisites

none

KEN4254

Period 4
1 Feb 2021
2 Apr 2021

Print course description
ECTS credits:
6.0
Coordinator:
M. Mihalak
Teaching methods:
Project-Centered Learning

Data Science & Knowledge Engineering

Computational Statistics

Full course description

Complex and high dimensional data are abundant in academia and industry. At the same time, computers are cheap and powerful. These developments enable us to fit increasingly complex statistical models using computer intensive methods. We will model and analyze both independent and dependent data from real world problems. The course is hands-on; we will use Stan (platform for statistical modelling and high-performance statistical computation) and R (statistical programming language). Key topics: Statistical modelling, uncertainty quantification, Markov chain Monte Carlo, bootstrap resampling, permutation tests, and causal inference.

KEN4258

Period 4
1 Feb 2021
2 Apr 2021

Print course description
ECTS credits:
6.0
Coordinator:
C.J. Seiler
Teaching methods:
Project-Centered Learning

Data Science & Knowledge Engineering

Dynamic Game Theory

Full course description

The course will focus on non-cooperative games and on dynamic games in the following order: matrix and bimatrix games, repeated games, Stackelberg games, differential games, specific models of stochastic games, evolutionary games. These are games in which the players are acting as strategic decision makers, who cannot make binding agreements to achieve their goals. Instead, threats may be applied to establish stable outcomes. Besides, relations with population dynamics and with “learning” will be examined. Several examples will be taken from biological settings. Knowledge and understanding Students are able to recognize and classify the main types of dynamic games, i.e. repeated games, stochastic games, Stackelberg games, differential games, and evolutionary games and formulate the main solution
concepts value, optimal strategies, Nash- and Stackelberg equilibrium.

Prerequisites

None.

Recommended reading

None.

KEN4251

Period 4
1 Feb 2021
2 Apr 2021

Print course description
ECTS credits:
6.0
Instruction language:
English
Coordinators:
F. Thuijsman
K. Stankova
Teaching methods:
Project-Centered Learning
Assessment methods:
Written exam

Data Science & Knowledge Engineering

Computer Vision

Full course description

Can we make machines look, understand and interpret the world around them? Can we make cars that can autonomously navigate in the world, robots that can recognize and grasp objects and, ultimately, recognize humans and communicate with them? How do search engines index and retrieve billions of images? This course will provide the knowledge and skills that are fundamental to core vision tasks of
one of the fastest growing fields in academia and industry: visual computing. Topics include introduction to fundamental problems of computer vision, mathematical models and computational methodologies for their solution, implementation of reallife applications and experimentation with various techniques in the field of scene analysis and understanding. In particular, after a recap of basic image analysis tools
(enhancement, restoration, color spaces, edge detection), students will learn about feature detectors and trackers, fitting, image geometric transformation and mosaicing techniques, texture analysis and classification using unsupervised techniques, object classification and face recognition, camera models, epipolar geometry and 3D reconstruction from 2D views.

Prerequisites

none

Recommended reading

Digital Image Processing", Rafael C. Gonzalez & Richard E. Woods, Addison-Wesley, 2002 / Digital Image Processing using MATLAB. 2° Edition Rafael C. Gonzalez, Richard E. Woods, Steven L. Eddins. Gatesmark Publishing

KEN4255

Period 5
5 Apr 2021
4 Jun 2021

Print course description
ECTS credits:
6.0
Coordinator:
S. Asteriadis
Teaching methods:
Lecture(s), Project-Centered Learning

Data Science & Knowledge Engineering

Deep Learning

Full course description

Conventional machine learning techniques were limited in processing data in their raw forms and a lot of domain experts were required in transforming raw data into meaningful features or representations. Deep Learning techniques have revolutionized many application domains ranging from auditory to vision signal processing. In this course we will study various concepts in deep architectures using both artificial neural networks as well as kernel based models. Several deep learning models such as convolutional neural networks, auto-encoders, generative adversarial networks and their variants among other state-of-the-art models will be covered in depth. We will further study different types of deep architectures used for domain adaptation problems where one is encountered with heterogeneous datasets as well as multi-modal datasets. The regularization and optimization methods used in deep learning framework will be discussed. Tensorflow, an open-source machine learning platform, will be introduced. In this course we will also study deep kernel based models and their connections to artificial neural network based models. This course will be equipped with a practical component, and students are expected to write their own deep learning code and test its performance on various problems. In addition they are strongly encouraged to participate in mini-projects (in a group or individual) targeting a conference paper.

Prerequisites

Advanced Concepts in Machine Learning

- Advanced Concepts in Machine Learning

Recommended reading

Papers published in top international conferences and journals in machine learning field.

KEN4257

Period 5
5 Apr 2021
4 Jun 2021

Print course description
ECTS credits:
6.0
Coordinator:
S. Mehrkanoon
Teaching methods:
Project-Centered Learning

Data Science & Knowledge Engineering

Information Retrieval and Text Mining

Full course description

Text mining refers generally to the process of extracting interesting and non-trivial information and knowledge from unstructured text. Text mining encompasses several computer science disciplines with a strong orientation towards artificial intelligence in general, including but not limited to

information retrieval (building a search engine), statistical pattern recognition, natural language processing, information extraction and different methods of machine learning, clustering
and ultimately data visualization. An important difference with standard information retrieval (search) techniques is that they require a user to know what he or she is looking for, while text mining attempts to discover information in a pattern that is not known beforehand. This is very relevant, for example, in criminal investigations, legal discovery, (business) intelligence, sentiment- & emotion mining or clinical research.

Prerequisites

None

Recommended reading

None

KEN4153

Period 5
5 Apr 2021
4 Jun 2021

[Print course description]
ECTS credits:
6.0
Instruction language:
English
Coordinator:
[J.C. Scholtes]
Teaching methods:
Project-Centered Learning

Data Science & Knowledge Engineering
Planning and Scheduling

Full course description

In many real-world processes, particularly in industrial processes and logistics, decisions need to be taken about the time of the completion of (sub)tasks, and the decision about what production machines complete the tasks. There are often constraints on the order in which tasks, or 'jobs' can be performed, and there are usually capacity constraints of the machines. This leads to natural, industrially critical
optimization problems. For example, a company might choose to buy many machines to process jobs, but then there is a risk that the machines will be underused, which is economically inefficient. On the other hand, too few machines, or an inappropriate ordering of tasks, may lead to machines spending a significant amount of time standing idle, waiting for the output of other machines, which are overcrowded with
tasks. In this course, we look at various mathematical models and techniques for optimizing planning

and scheduling problems, subject to different optimality criteria. We will discuss, among others, single-machine models, parallel-machine models, job-shop models, and algorithms for planning and scheduling (exact, approximate, heuristic) and we also touch upon the computational complexity (distinguishing
between ‘easy’ and ‘difficult’ problems) of the underlying problems. Last but not least, we will also introduce integer linear programming as a uniform and generic tool to model and solve planning and scheduling problems.

Prerequisites

Prerequisites: none Desired Prior Knowledge: Some experience with optimization (e.g. linear programming) and/or design and analysis of efficient algorithms.

KEN4253

Period 5
5 Apr 2021
4 Jun 2021

Print course description
ECTS credits:
6.0
Instruction language:
English
Coordinator:
M. Mihalak
Teaching methods:
Project-Centered Learning

Second year courses

MAI Year 2 Electives

Data Science & Knowledge Engineering

Data Mining

Full course description

Data mining is a major frontier field of computer science that studies the extraction of useful and interesting patterns from large collections of data. This course consists of a step-by-step introduction to data-mining systems. This includes a discussion of the process of acquiring raw data, as well as several pre-processing techniques. Several data-mining techniques are discussed, varying from basic models to state-of-the-art techniques. For each technique various characteristics will be highlighted which help one decide which technique to use. Several evaluation criteria will be discussed which help one decide whether the data-mining system is producing useful patterns. The lectures and labs will emphasize the practical use of the presented techniques and the problems of developing real data-mining applications. A number of real data sets will be analysed and discussed. After completing this course students will have obtained a preliminary methodological and theoretical bases for studying and applying data mining techniques to large collections of data.

Prerequisites

None.

Recommended reading

I.H. Witten and E. Frank (2005). Data Mining: Practical Machine Learning Tools and Techniques (Second Edition), Morgan Kaufmann, June 2005, ISBN 0-12-088407-0 T. Mitchell (1997). Machine Learning, McGraw-Hill, ISBN 0-07-042807-7.

KEN4113

Period 1
1 Sep 2020
23 Oct 2020

Print course description
ECTS credits:
6.0
Instruction language:
English
Coordinator:
E.N. Smirnov
Teaching methods:
Project-Centered Learning

Data Science & Knowledge Engineering

Mathematical Optimization

Full course description

Optimization (or “Optimisation”) is the subject of finding the best or optimal solution to a problem from a set of potential or feasible solutions.
Optimization problems are fundamental in all forms of decision-making, since one wishes to make the best decision in any context, and in the analysis of data, where one wishes to find the best model describing experimental data. This course treats two different areas of optimization: nonlinear optimization and combinatorial optimization. Nonlinear optimization deals with the situation that there is a
continuum of available solutions. A best solution is then usually approximated with one of several available general-purpose algorithms, such as Brent’s method for one-dimensional problems, Newton, quasi-Newton and conjugate gradient methods for unconstrained problems, and Lagrangian methods, including active-set methods, sequential quadratic programming and interior-point methods for general constrained problems. Combinatorial optimization deals with situations that a best solution from a finite number of available solutions must be chosen. A variety of techniques, such as linear programming, branch and cut, Lagrange relaxation dynamic programming and approximation algorithms are employed to tackle this type of problems. Throughout the course, we aim to provide a

coherent framework for the subject, with a focus on consideration of optimality conditions (notably the Karush-Kuhn-Tucker conditions), Lagrange multipliers and duality, relaxation and approximate problems, and on convergence rates and computational complexity.
The methods will be illustrated by in-class computer demonstrations, exercises illustrating the main concepts and algorithms, and modelling and computational work on case studies of practical interest, such as optimal control and network flow.

Prerequisites

Desired Prior Knowledge: Simplex algorithm. Calculus, Linear Algebra.

Recommended reading

1. Nonlinear Programming, Theory and Algorithms, by Bazaraa, Sherali, and Shetty (Wiley). 2. Combinatorial Optimization, Algorithm and Complexity, by Papadimitriou and Steiglitz (Dover Publications).

KEN4211

Period 1
1 Sep 2020
23 Oct 2020

Print course description
ECTS credits:
6.0
Instruction language:
English
Coordinator:
P.J. Collins
Teaching methods:
Project-Centered Learning
Assessment methods:
Written exam

Data Science & Knowledge Engineering

Signal and Image Processing

Full course description

Signal and Image processing offers the student a hands-on introduction into the area of digital signal and image processing. The course is started with the fundamental concepts and mathematical foundation of signal and image processing. This includes a brief review of Fourier analysis, z-transforms and digital filters. After this review, classical filtering from a linear systems perspective is discussed. This is followed by wavelet transforms and principal component analysis. For each of these techniques it is discussed how they relate to a variety of objectives, such as detection, noise removal, compression, prediction, reconstruction and feature extraction. The techniques in this course are explained for both signal and image processing. During the lectures several practical cases from biomedical engineering are highlighted. The course is accompanied by practical classes in which the students will apply the techniques discussed in the lectures using the software package Matlab. After completing this course the student will be familiar with the fundamental concepts of signal and image processing and their mathematical foundation. The student will be familiar with various types of filters and their properties. The student will be able to apply the various techniques discussed in the lectures to real life problems.

Prerequisites

Linear algebra, Calculus, basic knowledge of Matlab. Some familiarity with linear systems theory and transforms (such as Fourier and Laplace) is helpful.

Recommended reading

Wavelets and Filter Banks, Gilbert Strang and Truong Nguyen, Wellesley College; 2nd edition, ISBN-13: 978-0961408879 A Wavelet Tour of Signal Processing, Third Edition: The Sparse Way, Stephane Mallat, Academic Press; 3rd edition, ISBN-13: 978-0123743701 Wavelet Theory: An Elementary Approach with Applications, David K. Ruch, Patrick J. Van Fleet, Wiley, ISBN: 978-0-470-38840-2.

KEN4222

Period 1
1 Sep 2020
23 Oct 2020

Print course description
ECTS credits:
6.0
Instruction language:
English
Coordinators:
J.M.H. Karel
P. Bonizzi
Teaching methods:
Project-Centered Learning
Assessment methods:
Written exam

Data Science & Knowledge Engineering

Stochastic Decision Making

Full course description

Stochastic Decision making introduces the student to modelling dynamic processes that involve randomness. Any realistic model of a real-world phenomenon must take into account the possibility of randomness. That is, the quantities one is interested in will not be predictable in advance but instead will exhibit an inherent variation that should be taken into account by the model. This is usually accomplished by allowing the model to be probabilistic in nature. Such a model is referred to as a probability model. In this course the following topics, among others, are discussed: basic concepts of probability theory, probability distribution functions, conditional probability, expectation and probability conditioning, Markov chains, Markov decision problems, Poisson processes and continuous time Markov chains. These topics are accompanied by a discussion on their mathematical framework. After completing this course the student will have obtained knowledge of modelling dynamic processes that involve randomness. This includes knowledge about appropriate probability distributions, analysis tools and knowledge of the most relevant and applicable processes. The student will be able to model and analyse all kind of real life practical situations involving stochastic uncertainty.

Prerequisites

None.

Recommended reading

None.

KEN4221

Period 1
1 Sep 2020
23 Oct 2020

Print course description
ECTS credits:
6.0
Instruction language:
English
Coordinator:
G.M. Schoenmakers
Teaching methods:
Project-Centered Learning
Assessment methods:
Written exam

Data Science & Knowledge Engineering
Applications of Image and Video Processing

Full course description

Applications of Image Video Processing

KEN4244

Period 2

26 Oct 2020
18 Dec 2020

Print course description
ECTS credits:
6.0
Coordinator:
A. Briassouli
Teaching methods:
Project-Centered Learning

Data Science & Knowledge Engineering

Model Identification and Data Fitting

Full course description

Model Identification and Data Fitting is centred around the estimation of a mathematical model based on previous observations. This course is devoted to the various practical and theoretical aspects of such estimations (identifications) of mathematical models from several model classes. The course starts by addressing distance measures, norms, and criterion functions. After this the prediction error identification of linear regression models will be discussed. The emphasis will be on the various interpretations of these models such as deterministic, stochastic with Gaussian white noise and maximum likelihood estimation, stochastic in a Bayesian estimation context. Additionally several numerical implementation aspects such as: recursion, numerical complexity, numerical conditioning, and square root filtering will be highlighted. Next the focus will be on identification within the class of auto-regressive dynamical models, to which the Levinson algorithm applies. Other topics that will be discussed include identifiability, model reduction and model approximation. Several of the techniques that will be discussed are illustrated in Matlab. After completing this course the student will have obtained insight into the various aspects that play a key role in building a mathematical model from measurement data. The student will be able to apply the techniques learned to real world problems to construct models from observed data. The student will be able to judge and predict the quality of such models.

Prerequisites

Linear Algebra, Mathematical Modelling, Probability and Statistics.

Recommended reading

L. Ljung, System Identification: Theory for the User (2nd ed.), Prentice-Hall, 1999. T. Soderstrom and P. Stoica, System Identification, Prentice-Hall, 1989.

KEN4242

Period 2
26 Oct 2020
18 Dec 2020

Print course description

ECTS credits:

6.0

Instruction language:

English

Coordinators:

R.L.M. Peeters

P. Bonizzi

Teaching methods:

Project-Centered Learning

Assessment methods:

Written exam

Data Science & Knowledge Engineering

Advanced Natural Language Processing

Full course description

How do I say, "Where is the next Italian restaurant" in Dutch? Can I get a summary of today's lecture? When were artificial neural networks developed? Computers able to answer these questions are a long-time dream of humankind and currently, we see first programs to solve these problems. This course will provide the skills and knowledge to develop state-of-the-art (SOTA) solutions for these natural language processing (NLP) tasks. After a short introduction to traditional statistical approaches to NLP, the course will focus on deep learning techniques to solve these problems. In the first part of the course, we will investigate methods to model sequence labeling tasks like Named Entity recognition or Part- of-speech techniques. The second part of the lecture will focus on sequence-to-sequence models, a very powerful model to solve many NLP tasks like machine translation, summarization and question answering. In this course, major challenges when building the systems will be address: representing words in neural networks, neural network architectures to model language, methods to train complex models and algorithms to find the most probable output.

Prerequisites

None.

Recommended reading

Papers published in top international conferences and journals in machine learning field.

KEN4259

Period 4

1 Feb 2021

2 Apr 2021

Print course description

ECTS credits:

6.0

Coordinator:

J.H. Niehues

Teaching methods:
PBL

Data Science & Knowledge Engineering

Algorithms for Big Data

Full course description

The emergence of very large datasets poses new challenges for the algorithm designer. For example, the data may not fit into the main memory anymore, and caching from a hard-drive becomes a new bottleneck that needs to be addressed. Similarly, algorithms with larger than linear running time take simply too long on very large datasets. Moreover, simple sensory devices can observe large amount of data over time, but cannot store all the observed information due to insufficient storage, and an immediate decision of what to store and compute needs to be made. Classical algorithmic techniques do not address these challenges, and a new algorithmic toolkit needs to be developed. In this course, we will look at a number of algorithmic responses to these problems, such as: algorithms with (sub-)linear running times, algorithms where the data arrive as a stream, computational models where memory is organized hierarchically (with larger storage units, such as hard-drives, being slower to access than smaller, faster storage such as CPU cache memory). New programming paradigms and models such as MapReduce/Hadoop will be discussed. We will also look at a number of topics from classical algorithm design that have undiminished relevance in the era of big data such as approximation algorithms and multivariate algorithmic analysis.

Prerequisites

none

KEN4254

Period 4
1 Feb 2021
2 Apr 2021

Print course description
ECTS credits:
6.0
Coordinator:
M. Mihalak
Teaching methods:
Project-Centered Learning

Data Science & Knowledge Engineering

Building and Mining Knowledge Graphs

Full course description

Knowledge graphs are large-scale, machine-processable representations of entities, their attributes, and their relationships. Knowledge graphs enable both people and machines to explore, understand, and reuse information in a wide variety of applications such as answering questions, finding relevant content, understanding social structures, and making scientific discoveries. However, the sheer size and complexity of these graphs present a formidable challenge particularly when mining across different topic areas.
In this course, we will examine approaches to construct and use knowledge graphs across a diverse set of applications using cutting-edge technologies such as machine learning and deep learning, graph databases, ontologies and automated reasoning, and other relevant techniques in the area of data mining and knowledge representation.

Recommended reading

Aggarwal, C.C. and Wang, H. eds., (2010) Managing and mining graph data (Vol. 40). New York: Springer. ISBN 978-1-4419-6045-0

KEN4256

Period 4
1 Feb 2021
2 Apr 2021

Print course description
ECTS credits:
6.0
Coordinator:
M.J. Dumontier

Data Science & Knowledge Engineering
Computational Statistics

Full course description

Complex and high dimensional data are abundant in academia and industry. At the same time, computers are cheap and powerful. These developments enable us to fit increasingly complex statistical models using computer intensive methods. We will model and analyze both independent and dependent data from real world problems. The course is hands-on; we will use Stan (platform for statistical modelling and high-performance statistical computation) and R (statistical programming language). Key topics: Statistical modelling, uncertainty quantification, Markov chain Monte Carlo, bootstrap resampling, permutation tests, and causal inference.

KEN4258

Period 4
1 Feb 2021

2 Apr 2021

Print course description
ECTS credits:
6.0
Coordinator:
C.J. Seiler
Teaching methods:
Project-Centered Learning

Data Science & Knowledge Engineering

Dynamic Game Theory

Full course description

The course will focus on non-cooperative games and on dynamic games in the following order: matrix and bimatrix games, repeated games, Stackelberg games, differential games, specific models of stochastic games, evolutionary games. These are games in which the players are acting as strategic decision makers, who cannot make binding agreements to achieve their goals. Instead, threats may be applied to establish stable outcomes. Besides, relations with population dynamics and with “learning” will be examined. Several examples will be taken from biological settings. Knowledge and understanding Students are able to recognize and classify the main types of dynamic games, i.e. repeated games, stochastic games, Stackelberg games, differential games, and evolutionary games and formulate the main solution
concepts value, optimal strategies, Nash- and Stackelberg equilibrium.

Prerequisites

None.

Recommended reading

None.

KEN4251

Period 4
1 Feb 2021
2 Apr 2021

Print course description
ECTS credits:
6.0
Instruction language:
English
Coordinators:
F. Thuijsman
K. Stankova

Teaching methods:
Project-Centered Learning
Assessment methods:
Written exam

Data Science & Knowledge Engineering

Algorithms for Data Visualization

Full course description

In our modern world we are surrounded by data sets in all shapes and sizes. An essential aspect of working with data sets (whether relational, quantitative, etc.) is how they should be presented/visualized. Even for a single data set, different visualizations can be better for different tasks. Moreover, the scale of the data sets often restricts the options available when designing how it should be presented (including the choice of algorithm and the appropriateness of preprocessing/cleaning the data to a "visualizable" scale). This course will provide an overview of the basic theoretical and practical aspects of information visualization with a focus on algorithmic approaches. It includes how to visualize relational data (e.g., graphs/networks) and standard approaches for quantitative data sets such as, projecting high dimensional data to lower dimensions for visualisation (e.g,, multi-dimensional scaling and t-distributed stochastic neighbour embedding, etc.). We will also cover some aspects of augmenting visualizations with meta-data such as, labeling nodes/points, weighting relations, and information regarding grouping/clustering.

Prerequisites

None.

Recommended reading

- Tamara Munzner, Visualization Analysis and Design, 2014, ISBN 978- 1466508910 - Giuseppe Di Battista, Peter Eades, Roberto Tamassia and Ioannis G. Tollis. Graph Drawing: Algorithms for the Visualization of Graphs. Prentice Hall, 1999. - Michael Kaufmann and Dorothea Wagner (Hrsg.). Drawing Graphs: Methods and Models. Lecture Notes in Computer Science, Volume 2025. Springer-Verlag 2001.

KEN4213

Period 5
5 Apr 2021
4 Jun 2021

[Print course description]
ECTS credits:
6.0
Coordinator:
[S.A. Chaplick]
Teaching methods:
PBL

Data Science & Knowledge Engineering

Computer Vision

Full course description

Can we make machines look, understand and interpret the world around them? Can we make cars that can autonomously navigate in the world, robots that can recognize and grasp objects and, ultimately, recognize humans and communicate with them? How do search engines index and retrieve billions of images? This course will provide the knowledge and skills that are fundamental to core vision tasks of
one of the fastest growing fields in academia and industry: visual computing. Topics include introduction to fundamental problems of computer vision, mathematical models and computational methodologies for their solution, implementation of reallife applications and experimentation with various techniques in the field of scene analysis and understanding. In particular, after a recap of basic image analysis tools
(enhancement, restoration, color spaces, edge detection), students will learn about feature detectors and trackers, fitting, image geometric transformation and mosaicing techniques, texture analysis and classification using unsupervised techniques, object classification and face recognition, camera models, epipolar geometry and 3D reconstruction from 2D views.

Prerequisites

none

Recommended reading

Digital Image Processing", Rafael C. Gonzalez & Richard E. Woods, Addison-Wesley, 2002 / Digital Image Processing using MATLAB. 2° Edition Rafael C. Gonzalez, Richard E. Woods, Steven L. Eddins. Gatesmark Publishing

KEN4255

Period 5

5 Apr 2021

4 Jun 2021

Print course description

ECTS credits:

6.0

Coordinator:

S. Asteriadis

Teaching methods:

Lecture(s), Project-Centered Learning

Data Science & Knowledge Engineering

Deep Learning

Full course description

Conventional machine learning techniques were limited in processing data in their raw forms and a lot of domain experts were required in transforming raw data into meaningful features or representations. Deep Learning techniques have revolutionized many application domains ranging from auditory to vision signal processing. In this course we will study various concepts in deep architectures using both artificial neural networks as well as kernel based models. Several deep learning models such as convolutional neural networks, auto-encoders, generative adversarial networks and their variants among other state-of-the-art models will be covered in depth. We will further study different types of deep architectures used for domain adaptation problems where one is encountered with heterogeneous datasets as well as multi-modal datasets. The regularization and optimization methods used in deep learning framework will be discussed. Tensorflow, an open-source machine learning platform, will be introduced. In this course we will also study deep kernel based models and their connections to artificial neural network based models. This course will be equipped with a practical component, and students are expected to write their own deep learning code and test its performance on various problems. In addition they are strongly encouraged to participate in mini-projects (in a group or individual) targeting a conference paper.

Prerequisites

Advanced Concepts in Machine Learning

- Advanced Concepts in Machine Learning

Recommended reading

Papers published in top international conferences and journals in machine learning field.

KEN4257

Period 5
5 Apr 2021
4 Jun 2021

Print course description
ECTS credits:
6.0
Coordinator:
S. Mehrkanoon
Teaching methods:
Project-Centered Learning

Data Science & Knowledge Engineering

Information Retrieval and Text Mining

Full course description

Text mining refers generally to the process of extracting interesting and non-trivial information and knowledge from unstructured text. Text mining encompasses several computer science disciplines with a strong orientation towards artificial intelligence in general, including but not limited to information retrieval (building a search engine), statistical pattern recognition, natural language processing, information extraction and different methods of machine learning, clustering and ultimately data visualization. An important difference with standard information retrieval (search) techniques is that they require a user to know what he or she is looking for, while text mining attempts to discover information in a pattern that is not known beforehand. This is very relevant, for example, in criminal investigations, legal discovery, (business) intelligence, sentiment- & emotion mining or clinical research.

Prerequisites

None

Recommended reading

None

KEN4153

Period 5
5 Apr 2021
4 Jun 2021

Print course description
ECTS credits:
6.0
Instruction language:
English
Coordinator:
J.C. Scholtes
Teaching methods:
Project-Centered Learning

Data Science & Knowledge Engineering

Planning and Scheduling

Full course description

In many real-world processes, particularly in industrial processes and logistics, decisions need to be taken about the time of the completion of (sub)tasks, and the decision about what production machines complete the tasks. There are often constraints on the order in which tasks, or ‘jobs’ can be performed, and there are usually capacity constraints of the machines. This leads to natural, industrially critical
optimization problems. For example, a company might choose to buy many machines to process jobs,

but then there is a risk that the machines will be underused, which is economically inefficient. On the other hand, too few machines, or an inappropriate ordering of tasks, may lead to machines spending a significant amount of time standing idle, waiting for the output of other machines, which are overcrowded with
tasks. In this course, we look at various mathematical models and techniques for optimizing planning and scheduling problems, subject to different optimality criteria. We will discuss, among others, single-machine models, parallel-machine models, job-shop models, and algorithms for planning and scheduling (exact, approximate, heuristic) and we also touch upon the computational complexity (distinguishing
between 'easy' and 'difficult' problems) of the underlying problems. Last but not least, we will also introduce integer linear programming as a uniform and generic tool to model and solve planning and scheduling problems.

Prerequisites

Prerequisites: none Desired Prior Knowledge: Some experience with optimization (e.g. linear programming) and/or design and analysis of efficient algorithms.

KEN4253

Period 5
5 Apr 2021
4 Jun 2021

[Print course description]
ECTS credits:
6.0
Instruction language:
English
Coordinator:
[M. Mihalak]
Teaching methods:
Project-Centered Learning

Data Science & Knowledge Engineering

Symbolic Computation and Control

Full course description

This course consists of two interrelated parts. In the first part, we focus on basic techniques for the digital control of linear dynamical systems using feedback. We start by addressing system stability and we discuss the technique of pole placement by state feedback to solve the regulation problem. Then we introduce state observers to solve the regulation problem by output feedback. Next, we extend our scope to tracking problems. This involves the design of additional dynamics
to characterize the relevant class of reference signals, which are then integrated with the earlier set-up for output feedback. Finally, we discuss the classical topic of optimal control, which can be employed to avoid using prototype systems for pole placement, and which allows the user to design a feedback law by trading off the cost involved in
generating large inputs against the achieved tracking accuracy. In the second part, we address

computational issues, related to the field of systems and control. Classically, computers have been designed primarily to perform approximate numerical arithmetic. Modern software packages for mathematical computation, such as Maple and Mathematica, allow one to perform exact and symbolic computation too. We shall explore this new area. It is demonstrated how speed, efficiency and memory usage considerations often lead to surprising and fundamentally different algorithmic solutions in a symbolic or exact context. Applications and examples involve stability of linear systems, model approximation, and linear matrix equations with free parameters. Practical classes serve to demonstrate the techniques and to make the student familiar with exact and symbolic computation.

Prerequisites

Linear Algebra, Calculus, Mathematical Modelling.

Recommended reading

Richard J. Vaccaro, Digital Control - A State-Space Approach, McGraw- Hill International Editions, 1995. ISBN 0-07-066781-0.

KEN4252

Period 5
5 Apr 2021
4 Jun 2021

Print course description
ECTS credits:
6.0
Instruction language:
English
Coordinator:
R.L.M. Peeters
Teaching methods:
Project-Centered Learning
Assessment methods:
Written exam

Data Science & Knowledge Engineering
Master Internship

KEN4176

Year
1 Sep 2020
31 Aug 2021

Print course description

ECTS credits:
30.0
Instruction language:
English
Coordinator:
K. Driessens

Data Science & Knowledge Engineering

Master's Thesis AI

Full course description

The Master Artificial Intelligence will be completed by writing a master thesis. The thesis is produced individually and is the result of a master research project that runs during the second semester of year 2 of the master programme. In the first phase, the emphasis is on self study, subject determination, planning and some preliminary research. Then the actual research is started. The final phase is used to finalize the master thesis. The master project is completed by a presentation of the results. The master project will be supervised by one of the senior researchers. Examination: Master thesis and presentation.

KEN4160

Year
1 Sep 2020
31 Aug 2021

Print course description
ECTS credits:
30.0
Instruction language:
English
Coordinator:
M. Mihalak
Teaching methods:
Project-Centered Learning
Assessment methods:
Written exam

Data Science & Knowledge Engineering

Study Abroad

KEN3600

Semester 1

1 Sep 2020
29 Jan 2021
Semester 2
1 Feb 2021
3 Jul 2021

Print course description
ECTS credits:
30.0
Coordinator:
N. Roos

MAI Year 2

Data Science & Knowledge Engineering
Electives

KEN4170

Semester 1
1 Sep 2020
29 Jan 2021

Print course description
ECTS credits:
6.0
Coordinator:
K. Driessens

Data Science & Knowledge Engineering
Master Internship

KEN4176

Year
1 Sep 2020
31 Aug 2021

Print course description
ECTS credits:
30.0
Instruction language:

English

Coordinator:

K. Driessens

Data Science & Knowledge Engineering

Master's Thesis AI

Full course description

The Master Artificial Intelligence will be completed by writing a master thesis. The thesis is produced individually and is the result of a master research project that runs during the second semester of year 2 of the master programme. In the first phase, the emphasis is on self study, subject determination, planning and some preliminary research. Then the actual research is started. The final phase is used to finalize the master thesis. The master project is completed by a presentation of the results. The master project will be supervised by one of the senior researchers. Examination: Master thesis and presentation.

KEN4160

Year

1 Sep 2020

31 Aug 2021

Print course description

ECTS credits:

30.0

Instruction language:

English

Coordinator:

M. Mihalak

Teaching methods:

Project-Centered Learning

Assessment methods:

Written exam