Intelligent Sytems

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Lecturer

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- Contact hours (see the webpage)
 - currently, Wednesdays, 10:00 11:00; email me for other times or video meeeting
- **Research interests**: artificial intelligence, machine learning, natural language processing, network analytics, data science, data mining, algorithms and data structures
- Teaching: courses from areas of machine learning, natural language processing, and algorithms
- Software and resources: supporting open science, author of three open source R packages from the area of
 predictive modeling and data analytics (CORElearn, semiArtificial, ExplainPrediction), many large language, and
 language resources



Assistants

- Dr Tadej Škvorc
- Aleš Žagar, PhD student
- Boshko Koloski, PhD student



 tutorials, assignments, work in Python please, prepare questions!



Syllabus

- nature inspired computing (genetic algorithms, genetic programming)
- basics of machine learning,
- bias, variance, generalization error, and overfitting
- representation learning and feature selection
- neural networks
- natural language processing
- ensemble methods
- kernel methods
- model inference and explanation
- reinforcement learning

Objectives

- students shall become acquainted with
 - nature inspired computing
 - machine learning
 - model selection and evaluation techniques
 - model comprehensibility and explanation
 - practical application of predictive modeling in R programming language and environment
 - natural language processing
 - reinforcement learning
- practical use of theoretical knowledge on (almost) real-world problems
- awareness of domain expertise and ethical issues in data science
- increase the (mental) problem-solving toolbox with
 - predictive modeling techniques
 - evolutionary optimization approaches
 - large language models
 - reinforcement learning
 - experiment design, result understanding, visualization, and explanation approaches
- for a given prediction problem students shall be able to
 - transform it to a form suitable for predictive modeling
 - select and train an appropriate predictive model
 - evaluate the model and present the results in a comprehensible form and language.

Be able to explain

- difference between different types of machine learning models
- properties of models: bias, variance, generalization, hypothesis language
- properties of the following models: kNN, decision rules, bagging, boosting, random forests, stacking, SVM, neural networks
- properties and purpose of evaluation approaches and metrics: cross-validation, bootstrapping, ROC curves, sensitivity, specificity etc.
- inference methods for predictive methods and explanation of predictions
- when and why to apply reinfocement learning
- how to prepare and process text
- when and how and to optimize a problem using evolutionary algorithms

Build and evaluate models in Python

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- visualize datasets and created models
- prepare data into a suitable form for modeling algorithms
- apply classification and regression models to solve a prediction task with a given data set
- build natural language classifier
- estimate error of models using statistically valid approaches
- select models and tune their parameters using cross-validation and bootstrapping
- visualize models and explain their predictions
- given a new dataset, select an appropriate modeling technique and evaluate the created model

Syllabus explained

Nature inspired computing

- genetic algorithms
- genetic programming
- neuro-evolution

Introduction to statistical predictive modelling

- Learning as modelling: data, evidence, background knowledge, predictive models, hypotheses, learning as optimization, learning as search, criteria of success, inductive learning, generalization.
- Classification and regression: supervised and unsupervised learning, learning discrete and numeric functions, learning relations, learning associations.
- Simple classification models: nearest neighbor, decision rules

Model selection

- Bias and variance: error decomposition, trade-off, estimating bias and variance
- Generalization performance: training and testing set error, crossvalidation, evaluation set, bootstrapping.
- Performance measures: confusion matrix, sensitivity and specificity, ROC curves, AUC, cost-based classification.
- Parameter tuning: regularization, search
- Calibration of probabilities: binning, isotonic regression.
- No free lunch theorem.

Ensemble methods

- Model averaging, why ensembles work.
- Tree based ensembles: bagging, boosting, random forests.
- MARS and AODE ensembles.
- Stacking, mixture of experts.

Kernel methods

- SVM for classification and regression: kernels, support vectors, hyperplanes.
- SVM for more than two classes: one vs. one, one vs. all.

Neural networks

- perceptron,
- backpropagation,
- RBF networks,
- setting structure of networks
- deep neural networks
- transformer architecture
- autoencoders
- GANs
- the role of embeddings in representation learning

Explaining prediction models

- Model comprehensibility, visualization and knowledge discovery.
- General methodology for explaining predictive models.
- Model level and instance level explanations, methods SHAP, LIME, EXPLAIN, and IME.

Learning with special settings

- imbalanced data,
- multi-task learning,
- multi-label learning,
- Etc.

Reinforcement learning

- basics
- Markov decision problem
- Q learning
- Deep RL

Natural language processing

- text preprocesing
- text representation
- text similarity
- text classification
- sentiment analysis
- generative models

Course organisation

Obligations

- 5 quizzes
- Two projects, 50 points
- Written exam, 50 points

Grading

Obligation	% of total	subject to
Five quizzes	0%	≥ 50% alltogether
Projects	50%	≥ 50% each
Written exam	50%	≥ 50%

Learning materials

- learning materials in eClassroom
- slides
- links to textbooks and papers
- Python notebooks with examples
- links to data sets

Readings (all freely available)

James, G., Witten, D., Hastie, T., Tibshirani, R. and Taylor, J., 2023. <u>An Introduction to</u> <u>Statistical Learning: With Applications in Python</u>. New York: Springer. (also exists for R) Further readings:

- Kevin P. Murphy: Probabilistic Machine Learning: An Introduction. MIT Press, 2022
- Friedman, J., Hastie, T., & Tibshirani, R., 2009). <u>The elements of statistical learning</u>, 2nd edition. Springer, Berlin
- Jurafsky, Daniel and James, Martin (2024): <u>Speech and Language Processing</u>, 3rd edition in progress
- Richard S. Sutton and Andrew G. Barto: <u>Reinforcement Learning, An Introduction</u>, 2nd edition, MIT Press, 2018
- Kevin P. Murphy: <u>Probabilistic Machine Learning: Advanced Topics</u>. MIT Press, 2023
- scientific papers
- many excellent machine learning and data science courses on Coursera, edX etc.



Retention of Learning

Data Science is a core of Intelligent Systems

- good job perspective
- many jobs in this area regularly occupy list of the most promising jobs
- Thomas H. Davenport, D.J. Patil: Data Scientist: The Sexiest Job of the 21st Century. *Harvard Business Review*, October 2012



MODERN DATA SCIENTIST

Data Scientist, the sexiest job of the 21th century, requires a mixture of multidisciplinary skills ranging from an intersection of mathematics, statistics, computer science, communication and business. Finding a data scientist is hard. Finding people who understand who a data scientist is, is equally hard. So here is a little cheat sheet on who the modern data scientist really is.

MATH & STATISTICS

- ☆ Machine learning
- ☆ Statistical modeling
- ✿ Experiment design
- ✿ Bayesian inference
- Supervised learning: decision trees, random forests, logistic regression
- Unsupervised learning: clustering, dimensionality reduction
- Optimization: gradient descent and variants

PROGRAMMING & DATABASE

- ☆ Computer science fundamentals
- ☆ Scripting language e.g. Python
- ✿ Statistical computing packages, e.g., R
- ✿ Databases: SQL and NoSQL
- ✿ Relational algebra
- Parallel databases and parallel query processing
- ☆ MapReduce concepts
- ☆ Hadoop and Hive/Pig
- ☆ Custom reducers
- ✿ Experience with xaaS like AWS

COMMUNICATION & VISUALIZATION

- Able to engage with senior management
- ☆ Story telling skills
- Translate data-driven insights into decisions and actions
- ☆ Visual art design
- ✿ R packages like ggplot or lattice
- Knowledge of any of visualization tools e.g. Flare, D3 js, Tableau

26

DOMAIN KNOWLEDGE & SOFT SKILLS

- ✿ Passionate about the business
- 🕁 Curious about data
- ✿ Influence without authority
- 🕁 Hacker mindset
- 🕸 Problem solver
- Strategic, proactive, creative, innovative and collaborative



Intelligent systems and media



Will robots destroy us? Will they take our jobs? Will we still need a driving licence? Will we still need doctors? How will humanoid robots evolve? What about cyborgs? What is artificial general intelligence? What is technological singularity?

New prophets of tehnological singularity

Elon Musk says humans must become cyborgs to stay relevant. Is he right?

Sophisticated artificial intelligence will make 'house cats' of humans, claims the entrepreneur, but his grand vision for mind-controlled tech may be a long way off

Some scientific opinions

- Rodney Brooks: The Seven Deadly Sins of Predicting the Future of AI. <u>https://rodneybrooks.com/the-seven-deadly-sins-of-predicting-the-future-of-ai/</u> also in MIT Technology Review
- Marko Robnik-Šikonja: Is artificial intelligence a (job) killer?. The Conversation, Jul. 2017 <u>https://theconversation.com/is-artificial-intelligence-a-job-killer-80473</u>

Short history of optimism

- starting in 1950s,
 1956 Dartmouth conference
- great expectations, enormous underestimation of problem difficculty
- Al winter (2 x)

- 1958, H. A. Simon and Allen Newell: "... within ten years a digital computer will discover and prove an important new mathematical theorem."
- 1965, H. A. Simon: "... machines will be capable, within twenty years, of doing any work a man can do."
- 1967, Marvin Minsky: "Within a generation ... the problem of creating 'artificial intelligence' will substantially be solved."
- 1970, Marvin Minsky: "In from three to eight years we will have a machine with the general intelligence of an average human being."

Hype Cycle for Emerging Technologies, 2024

Gartner

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Hype Cycle for Artificial Intelligence, 2024

Plateau will be reached: 🔘 <2 yrs. 🔍 2–5 yrs. 🌑 5–10 yrs. 🔺 >10 yrs. 😵 Obsolete before plateau

