Table 5.2 – Course specification

Study program / study programs: Advanced data analytics
Course: Advanced data analysis in pharmaceutical research and development
Teacher: Svetlana Ibrić, Ana Protić, Teodora Đikić, Biljana Otašević, Jelena Đuriš, Katarina Nikolić
Course status: Elective
ECTS points: **7**
Prerequisites: none
Course objective: Analysing complex data in pharmaceutical research and development
Learning outcomes Students will acquire new knowledge and skills in the field of data analysis in pharmaceutical research and development. Knowledge of recent and advanced computational methods of rational drug design, which include ligand based methods (QSAR, pharmacophore analysis, virtual screening of ligands databases) or structure based methods (virtual docking, molecular dynamics). Students will master advanced theoretical methods and acquire skills for use of various programs for determining bioactive conformations of ligands, formation and validation of QSAR models, virtual screening, virtual docking, and molecular dynamics. Knowledge of creating *in silico* methods and optimal procedure for rational design, evaluation, and selection of novel drug candidates with improved pharmacological, physicochemical and pharmacokinetic properties. Students will understand how to apply the concept of quality by design (QbD) in pharmaceutical research and development; by defining the target drug quality profile (QTPP), critical quality attributes and process parameters (CQA, CPP) and by defining the design space. Students will be able to compare and select appropriate methods for advanced analysis of data generated during drug formulation and manufacturing development, including machine learning methods (neural networks, decision trees, self-organizing maps, etc.) and multivariate classification and regression methods. Students will be introduced with methods which are used in quality control of finished drug products with special concern about certificate of analysis. They will gather knowledge about different separation mechanisms in selected chromatographic systems in order to apply predictive mathematical models in description of retention behaviour of analytes, as molecules with specific chemical structures. Based on that, they will be able to perform analysis of quantitative relationship between structure and retention behaviour (QSRR study), to define optimal chromatographic conditions for quality control of drugs and to evaluate the significance of selected structural characteristics and physicochemical properties on retention of molecules in chromatographic system.
Course structure and content 1. Introduction to data analysis in pharmaceutical research and development. 2. Ligands and targets databases 3. Advanced computational methods of rational drug design 4. *In silico* methods and optimal procedure for rational drug design 5. The concept of quality design (QbD) in pharmaceutical research and development 6. Critical quality attributes and process parameters (CQA, CPP). Design space. Computer methods for defining design space. 7. Advance data analysis in pharmaceutical research and development 8. Advanced data analysis in continuous process verification in the pharmaceutical industry. 9. Application of different advanced computational methods for calculation of molecular descriptors, physicochemical, quantum chemical, topological and constitutional. 10. The use of experimental design in defining the experimental region aimed for the proper recognition of patterns in retention behaviour. 11. Application of different statistical programs for building and testing of predictive QSRR models with the assistance of machine learning methods.
Literature/Readings

1. G. L. Partick ed. (2017) “An Introduction to Medicinal Chemistry“, 6th Edition, Oxford University Press UK.
2. D. J. Abraham ed. (2010) Burger’s Medicinal Chemistry and Drug Discovery, 7th Edition, Volume 1: Methods in Drug Discovery, John Wiley&Sons, Inc.
3. D. J. Abraham ed. (2010) Burger’s Medicinal Chemistry and Drug Discovery, 7th Edition, Volume 2: Discovering Lead Molecules, John Wiley&Sons, Inc.
4. Victoria PhD F. Roche PhD, S. William PhD Zito PhD, et al. (2019) Foye's Principles of Medicinal Chemistry, 8th ed. Williams DA, Lemke TL, editors. Baltimore: Lippincott Williams&Wilkins.
5. Andrew R. Leach. (2001) Molecular Modelling: Principles and Applications 2nd Edition. Glaxo Wellcome Research and Development, Pearson Education.
6. Guidelines, ICH Harmonised Tripartite. "Pharmaceutical development." *Q8 (R2) Current Step* 4 (2009); "Quality risk management." *Q9 Current Step* 5 (2006); "Pharmaceutical quality system." *Q10 Current Step* 5 (2008)
7. J. Djuris ed. (2013) Computer-Aided Applications in Pharmaceutical Technology, 1st Edition, Woodhead Publishing UK.
8. R. Kaliszan. (2017) Quantitative structure property (retention) relationships in liquid chromatography, Chapter 23 in Liquid Chromatography: Fundamentals and instrumentation, 2nd edition. Elsevier Inc.
9. L. Komsta, Y.Vander Heyden, J. Sherma. (2018) Chemometrics in Chromatography, 1st Edition, CRC Press, Taylor & Francis group, LLC.

The number of class hours per week				**Other classes:**
Lectures: 5	**Labs:**	**Workshops:** 1	**Research study:** 2	

Teaching methods
Individual and group work; lectures and labs

Evaluation/Grading (maximum 100 points)			
Pre-exam requirements	**Points**	**Final exam**	**Points**
Project (conceptual solution)	30	Project (implementation)	70

Study program / study programs: Advanced data analytics
Course: Data analysis in biological sciences
Teacher: Prof. Dr Marko Đorđević, Prof. Dr Biljana Miličić, Doc. Dr Andrej Korenić, Ass. Dr Jovana Kuzmanović Pfićer, Dr Tijana Išić Denčić
Course status: Elective
ECTS points: 7

Prerequisites: none

Course objective

Analyzing complex biological data

Learning outcomes

Students will acquire new knowledge and skills in the field of data analysis in biology. Modern computational methods used in molecular and cell biology will be presented. Students will also be able to analyse complex data obtained by processing microscopic images in histology. In addition to the image processing, this subject will also focus on aspects of signal processing in neurosciences such as resting membrane potential, action potential, local potentials, etc. Students will also be familiarized with the foundations of biostatistics, and with applying modern statistical tests in biological sciences.

Course structure and content

1. Introduction to data analysis in biology
2. Nucleic acids and protein databases
3. Basic analysis of nucleic acids and protein sequences
4. Analysis of data obtained by light and electron microscopy
5. Analysis of the resting membrane potential and action potential
6. Evaluation of local membrane potentials: application in neurosciences
7. Statistical analytical tests in biological research
8. Correlation and regression analysis in biology

Literature/Readings

- Rafael A. Irizarry. Data Analysis for the Life Sciences with R. 2017. Chapman and Hall/CRC. New York.
- S.J. Welham, S.A. Gezan, S.J. Clark, A. Mead. Statistical Methods in Biology: Design and Analysis of Experiments and Regression. 2014. Chapman and Hall/CRC. New York.
- Daniel Durstewitz. Advanced Data Analysis in Neuroscience. Springer International Publishing. 2017. London, UK
- Zvelebil, Marketa J., and Jeremy O. Baum. *Understanding bioinformatics*. Garland Science, 2007.
- Shortliffe, E.H., Cimino, J.J. Biomedical Informatics: computer applications in healthcare and biomedicine. 4th Edition, Kindle Edition. Springer-Verlag London 2014

The number of class hours per week				**Other classes:**
Lectures: 5	**Labs:**	**Workshops:** 1	**Research study:** 2	–

Teaching methods

Individual and group work; lectures and labs

Evaluation/Grading (maximum 100 points)			
Pre-exam requirements	**Points**	**Final exam**	**Points**
Project (conceptual solution)	30	Project (implementation)	70

Study program / study programs: Advanced data analytics
Course: Data analysis in fundamental and clinical medicine
Teacher: Prof. Dr Biljana Miličić, Ass. Dr Jovana Kuzmanović Pfićer, Dr Tijana Išić Denčić
Course status: Elective
ECTS points: 7
Prerequisites: none
Course objective

Adopting new knowledge and skills related to data analytics in medicine.

Learning outcomes

Training students for data processing in fundamental and clinical medical disciplines. Students will master analysis of data obtained by processing signals in the field of electrocardiography, electroencephalography, microscopy and other methods used in modern medical diagnostics. Students will also be familiarized with the basics of medical statistics, with particular reference to statistical analytical tests in medical research and computer methods for statistical processing of medical data. Within this course, students will also gain basic knowledge of medical informatics.

Course structure and content

1. Introduction to data analysis in medicine.
2. Analysis of data obtained as result of the application of diagnostic tests in medicine.
3. Analysis of electrocardiograms
4. Analysis of electroencephalograms
5. Data analysis in microscopy
6. Statistical analysis in clinical medicine
7. Fundamentals of medical informatics
8. Contemporary computer programs for statistical analysis of data in medical research
9. EDC (Electronic Data Capture) systems in medicine
10. Statistical analysis in dentistry - design of repeated measurements (split-mouth design)

Literature/Readings

- Charan Singh Rayat. Statistical Methods in Medical Research. Springer, 2018, New York
- Katherine Marconi, Harold Lehmann. Big Data and Health Analytics. Auerbach Publications; 1st Edition. 2014. New York
- Nadinia A. Davis, Betsy J. Shiland. Statistics & Data Analytics for Health Data Management. Saunders; 1 edition. 2016. London, UK
- Kim JS, Dailey R. Biostatistics for Oral Healthcare. Blackwell Pub Professional, Iowa УСА: State University Press; 2007.

The number of class hours per week				**Other classes:**
Lectures: 5	**Labs:**	**Workshops:** 1	**Research study:** 2	–

Teaching methods

Individual and group work; lectures and labs

Evaluation/Grading (maximum 100 points)			
Pre-exam requirements	**Points**	**Final exam**	**Points**
Project (conceptual solution)	30	Project (implementation)	70

Study program / study programs: Advanced data analytics

Course: Practical analysis of noisy and uneven time series

Teacher: Luka Č. Popović, Anđelka Kovačević, Dragana Ilić

Course status: Elective

ECTS points: 7

Prerequisites: -

Course objective

Most of the phenomena in nature, medicine, science, business and engineering are measured at certain time moments that are most often non-homogeneous in time. Extracting information from such series is a great challenge for analysts because standard techniques are mostly developed for evenly distributed time series without a prominent noise. Therefore, specific methods for analyzing such time series are extremely important for all mentioned data types. This course aims to explain the theoretical and practical core of the concept of time series analysis with such disadvantageous characteristics.

Learning outcomes

The student is trained for an effective analysis of noisy time series that are unevenly distributed in time, which can be encountered in the sciences, medicine, business, engineering, as well as in the analysis of the time series of social networks and those found in the sociological research.

Course structure and content

Missing data. Sample size. Stochastic and deterministic processes. The concept of stationary time series. Extrapolative and decomposition models. Methods of exponential smoothness. The concept of nonstationary time series. Non-stationary tests. Stabilization of variance, structural or regime stability.
Overview of homogeneous and non-homogeneous series. Signal and noise information in the time series. Gaussian process for time series modeling. Poisson's process for time series modeling. Random Walk model. Fourier's analysis. Wavelet analysis. Detection difficulties: (1 / f) noise in the time series, Signal detection methods in noisy and non-homogeneous series. Maximum Likelihood Estimate (MLE).

Literature/Readings

Terence Mills, *Applied Time Series Analysis*, Academic Press, 2019
Asis Kumar Chattopadhyay, Tanuka Chattopadhyay, *Statistical Methods for Astronomical Data Analysis*, Springer, 2014

The number of class hours per week 5+3				**Other classes:**
Lectures: 5	**Labs:**	**Workshops:**	**Research study:** 3	–

Teaching methods

Individual and group work; lectures and labs

Evaluation/Grading (maximum 100 points)

Pre-exam requirements	**Points**	**Final exam**	**Points**
Class activity	10	Oral exam	30
Hands on activity	60		

Study program / study programs: Advanced data analytics
Course: Big Data in space science and its analysis
Teacher: Luka Č. Popović, Andjelka Kovačević, Dragana Ilić
Course status: Elective
ECTS points: 7
Prerequisites: -
Course objective Daily large amounts of new data related to the cosmic research are being collected, using both ground-based and space-based telescopes, as well as those collected from missions that observe Earth from space (e.g. Copernicus program of satellites). Earth observation data from satellites can be used for various human activities on Earth, from sociological (migration monitoring), biological, industrial, telecommunication, to those related to the study of climate change. The goal of this course is to introduce students to what type of data can be obtained from space research, providing a broad and practical introduction to large data: data analysis techniques including databases, data mining, machine learning and visualization of data; data analysis tools, including the use of SQL and Python. Tools and techniques are practical, providing the foundation for future research and application.
Learning outcomes The student is able to handle and apply tools and techniques for processing large data in their original research areas as well as for eventual applications in the space industry.
Course structure and content Introduction: The method and technique of collecting data in astronomy using telescopes and satellites. Methods of collecting satellite data for Earth observation. The aims of these observations and their application in research and practical application. Introduction to large databases and their organization. Platforms of large databases and storage of large data. Big data in space science. Large Data Surveys and Providers in Space Science: LSST, ELT, GAIA, SDSS, etc. Database mining with the SQL and the Python, introduction to Flexible Image Transport System (FITS), FITS average and median, effective way of comparing data from different databases (cross-matching data), displaying large data from Earth's surveying satellites: visualization of large data on the map. Dimensionality Reduction: PCA, PCA kernel, PCA as noise filter in data, introduction to Scikit Learn, Hyperparameters and model validation, best model selection, categorical image characteristics, inserting inaccessible data, Bayesian classification, Regression, Classification and Clusters, Machine Learning in the Python. Data mining algorithms, Training models, Support Vector Machines with the application of recognition of parts of complex images, Decision Trees and Random forest with application, Kernel density estimation with application on recognition of parts of complex images, final project in Machine Learning in space science.
Literature/Readings 1. Aurélien Géron, *Hands-On Machine Learning with Scikit-Learn and TensorFlow Concepts, Tools, and Techniques to Build Intelligent Systems*, 2017, O'Reilly Media 2. Jake VanderPlas, *Python Data Science Handbook*, 2017, O'Reilly Media

The number of class hours per week 5+3				**Other classes:** –
Lectures: 5	**Labs:**	**Workshops:**	**Research study:** 3	

Teaching methods: Individual and group work; lectures and labs			
Evaluation/Grading (maximum 100 points)			
Pre-exam requirements	**Points**	**Final exam**	**Points**
Class activity	10	Oral exam	30
Hands on activity	60		

Study program / study programs: Advanced data analytics

Course: Introduction to time series analysis

Teacher: Marija Mitrović Dankulov, Aleksandra Alorić, Andrej Korenić

Course status: Elective

ECTS points: 10

Prerequisites: none

Course objective

Acquiring basic knowledge about theoretical and applied aspects of time series analysis.

Learning outcomes

Students will acquire knowledge about basic concepts of time series analysis and their application to data science. They will be able to analyse in detail continuous and discrete time series, to describe their characteristics, to choose a proper theoretical model and to infer the interaction matrix based on time series correlations.

Course structure and content

Main course topics:

Stationary processes, auto-correlation and autocovariance functions; Moving Average (MA) processes, Auto-Regressive (AR) processes and Auto-Regressive/Moving Average (ARMA) processes; correlogram; spectral analysis, periodogram; elements of estimation and forecasting and applications to empirical data.

Detrended fluctuation analysis. Hurst exponent. Furier transform for time series analysis and prediction.

Time series correlations and network extraction.

Literature/Readings

1. Shumway, Robert H., and David S. Stoffer (2011), Time series analysis and its applications: with R examples, Springer, ISBN: 978-1-4419-7864-6

The number of class hours per week				**Other classes:**
Lectures: 4	**Labs:**	**Workshops:**	**Research study:** 3	–

Teaching methods

Individual and group work; lectures and labs

Evaluation/Grading (maximum 100 points)			
Pre-exam requirements	**Points**	**Final exam**	**Points**
Homework	0-40	Project: application to real system	0-60

Study program / study programs: Advanced data analytics

Course: Introduction to complex networks theory

Teacher: Marija Mitrović Dankulov, Aleksandra Alorić

Course status: Elective

ECTS points: 10

Prerequisites: none

Course objective

Acquiring basic knowledge about complex networks, methods and tools for the quantitative analysis of their structure, and applications.

Learning outcomes

Students will acquire the basic concepts of theory of complex networks and be able to use various techniques of network analysis. Students will be able to map the data to various types of networks, do the statistical analysis of their structure and infer system properties based on the results of statistical analysis.

Course structure and content

Main course topics:
Network representation of systems and basic network concepts (nodes, edges, adacency matrix, temporal networks, multiplex networks, etc.)
Concepts of global, mescocopic and local network structure (degree, clustering, motifs, centrality measures, spectral properties of adjacency and laplacian matrix, community structure, etc.)
Statistical models of complex networks and their properties (Erdos-Renyi model, Barabasi-Alber model, Stochastic block model, Exponential random graphs)
Applications in biological systems
Application in social systems
Dynamical processes on networks
Introduction to networkx python module
Introduction to complex networks and data mining

Literature/Readings

M. E. J. Newman (2018), Networks: an introduction, Oxford University Press, ISBN: 978-0198805090

A. L. Barabasi (2015), Network Science, Cambridge University Press, ISBN: 978-1107076266. Available online: http://networksciencebook.com/

The number of class hours per week				**Other classes:** –
Lectures: 4	**Labs:**	**Workshops:**	**Research study:** 3	

Teaching methods

Individual and group work; lectures and labs

Evaluation/Grading (maximum 100 points)

Pre-exam requirements	Points	Final exam	Points
Homework	0-40	Project: application to real system	0-60

Study program / study programs: Advanced data analytics

Course: Analytics and optimization

Teachers: Milan Stanojević, Dragana Makajić-Nikolić, Gordana Savić, Marija Kuzmanović

Course status: Elective

ECTS points: 10

Course objective

Introduction to analytics and optimization with aim of optimal decision making using quantitative models and methods.

Learning outcomes

- Students will be able to identify and analyze real world problems and data collected in the process,
- Students will be able to formulate real world problem as an optimization problem,
- Students will be able to use optimization methods and techniques (especially methods and techniques for solving linear and integer programming models)
- Students will be able to analyze and visualize results.

Course structure and content

Basics of analytics and role of optimization in analytics. Descriptive analytics (basics of data clearing, missing data handling, summarizing, grouping, classifying, clustering, visualizing,...). Predictive analytics (basic of forecasting using trend, smoothing, regression functions...). Prescriptive analytics – mathematical modelling and optimization. Methods for solving mathematical models. Sensitivity analysis. Multicriteria analysis. Heuristics. Methods for alternative selection in the presence of uncertainly. Application of all methods using MS Excel tools, AMPL... Solving real life problems and presenting the results.

Literature/Readings

1. J.A. Lawrence, B.A. Pasternack, Applied Management Science, John Wiley & Sons Inc. 2002.
2. A. Makhorin, Modeling Language GNU MathProg Language Reference, Free Software Foundation, 2013.
3. R. Saxena, A. Srinivasan, Business Analytics: A Practitioner's Guide, Springer, 2013
4. J. R. Evans, Business Analytics: Methods, Models and Decisions, Pearson, 2013
5. R. Fourer, D.M. Gay, B.W. Kernighan, AMPL: A Modeling Language for Mathematical Programming, Duxbury Press / Brooks /Cole Publishing Company, 2002.

The number of class hours per week				Other classes:
Lectures: 4	Labs:	Workshops:	Research study: 3	

Teaching methods

Lectures are followed by the corresponding presentations; all models will be illustrated in the hypothetical example. Students will, through case studies using appropriate software, analyze the input data, define quantitative models, analyze results, and make alternative scenarios with the aim to set the basis for decision making.

Evaluation/Grading (maximum 100 points)			
Pre-exam requirements	**Points**	**Final exam**	**Points**
Participation in class	10	Written exam	30
Case study	60		

Study program / study programs: Advanced data analytics

Course: Databases

Teacher: Zoran M. Marjanović, Nenad M. Aničić, Srđa Bjeladinović, Ana Pajić Simović

Course status: Elective

ECTS points: 10

Prerequisites: none

Course objective

Acquiring basic knowledge of databases and database management systems.

Learning outcomes

Students will be able to identify data requirements and to design databases. They will get familiar with a database architecture and components and they will learn to use query languages to access and manipulate data in the databases of different types.

Course structure and content

Introduction
- Database management systems and data models

Relational databases
- Conceptual database design. Entity-relationship model
- Logical database design. Relational model.
- Normalization of relations
- Physical design of databases: Denormalization and optimization
- SQL environment: schema, catalog, clients and servers. Connections to the databases.
- SQL query language
- SQL in software environments

NoSQL databases
- The origin and concepts. CAP theorem
- BASE properties. Comparative analysis of BASE and ACID properties
- Key-value databases
- Document databases
- Column-family databases
- Graph databases
- NoSQL database design techniques
- Map reduce
- NoSQL query languages and usage

Hybrid SQL/NoSQL databases

Literature/Readings

1. Lazarević, B., Marjanović, Z., Aničić, N., & Babarogić, S. (2016). Baze podataka (7th edition, ISBN 978-86-7680-258-6). Belgrade, Serbia: FON.
2. Sadalage P., & Fowler M. (2014). NoSQL Distilled: A Brief Guide to the Emerging World of Polyglot Persistence. US:Addison-Wesley. ili Strauch C. (2011) NoSQL Databases. Available online at: https://www.christof-strauch.de/nosqldbs.pdf

The number of class hours per week				**Other classes:**
Lectures: 4	**Labs:**	**Workshops:** 3	**Research study:**	–

Teaching methods

Individual and group work; lectures and labs

Evaluation/Grading (maximum 100 points)			
Pre-exam requirements	**Points**	**Final exam**	**Points**
Project	50	Implementation	50

Study program / study programs: Advanced data analytics

Course: Models of Statistical Learning

Teacher: Bulajić Milica, Vukmirović Dragan, Radojičić Zoran, Marković Aleksandar, Jeremić Veljko, Dobrota Marina, Maričić Milica, Zornić Nikola, Mutavdžić Dragosav

Course status: Elective

ECTS points: 10

Prerequisites: none

Course objective: Acquiring the ability to employ advanced models of statistical learning, to interpret the obtained results, and the ability to recognize the model of statistical learning suitable for solving the given problem. Mastering the usage of advanced features of modern statistical and simulation software.

Learning outcomes: After the course, students will acquire the experience in understanding the concepts of advanced models of statistical learning in contemporary statistical and simulation software and the experience needed for their application in real-word business problems.

Course structure and content

The concepts and techniques of models of statistical learning are first introduced through the review and presentation of theoretical foundations, followed by practical work using contemporary statistical and simulation software.

Regression models
- Logistics regression
- Lasso regression
- Polynomial regression

Classification trees

Resampling methods
- Cross validation
- Jackknife
- Parametric and nonparametric bootstrap

Supervised learning

Unsupervised learning

Support Vector Machines (SVM)

Application of Monte Carlo simulation in advanced data analytics

Agent based-simulation – description of agent behaviour using the models of statistical learning

Implementation of the covered methods and models in contemporary statistical and simulation software

Literature/Readings

1. Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning - Data Mining, Inference, and Prediction,* Springer. Available online: https://www.springer.com/gp/book/9780387848570
2. James, G., Witten, D., Hastie, T., Tibshirani, R. (2016). *An Introduction to Statistical Learning with Applications in R,* Springer. Available online: https://www.springer.com/gp/book/9781461471370
3. Bulajić M., Jeremić, V., Radojičić, Z. (2012). *Advance in Multivariate Data Analysis – Contributions to Multivariate Data Analysis*, Faculty of Organizational Sciences
4. Wilensky, U., & Rand, W. (2015). *An introduction to agent-based modeling: modeling natural, social, and engineered complex systems with NetLogo*. MIT Press. https://mitpress.mit.edu/books/introduction-agent-based-modeling

The number of class hours per week

Lectures:	**Labs:**	**Workshops:**	**Research study:**
4		1	2

Teaching methods: Individual and group work; lectures and labs

Evaluation/Grading (maximum 100 points)

Pre-exam requirements	**Points**	**Final exam**	**Points**
Project (implementation)	60	Verbal exam	40

Study program / study programs: Advanced data analytics

Course: Neural networks and deep learning

Teacher: Zoran V. Ševarac, Dragan O. Đurić

Course status: Elective

ECTS points: 10

Prerequisites: none

<table>
<tr><td colspan="6">Course objective
To learn basic concepts and algorithms in the field of neural networks and deep learning, and methods for application of these technologies in various domains..</td></tr>
<tr><td colspan="6">Learning outcomes
Students will learn basic neural network concepts, types and application procedures, and develop skills required for their practical application.</td></tr>
<tr><td colspan="6">Course structure and content
Basic concepts: Artificial neurons, activation functions, types and architectures of neural networks, learning algorithms. Mathematical and theoretical models and analogies with biological systems.
Error functions and optimization methods.
Neural network architectures:
Multilayer perceptrons, algorithms for learning multilayer perceptrons and their application.
Convolutional neural networks and deep learning.
Problem solving problem using neural networks and deep learning, problems in the practical applications.
Methodology for different types of problems that are resolved using neural networks and deep learning: classification, clustering, prediction.
Areas of application of neural networks and deep learning: medicine, finance, production, defence, software development.</td></tr>
<tr><td colspan="6">Literature/Readings
• Neural Networks for Pattern Recognition, Christopher Bishop,Oxford University Press, 1996. ISBN-13:978-0198538646, http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.679.1104&rep=rep1&type=pdf
• Neural Networks - A Systematic Introduction, Raul Rojas, Springer-Verlag, 1996. ONLINE: http://page.mi.fu-berlin.de/rojas/neural/index.html.html
• Fundamentals of Neural Networks: Architectures, Algorithms and Applications, Laurene Fausett, PearsonEducation, 2006.
• Deep Learning, Ian Goodfellow, Yoshua Bengio, Aaron Courville, MIT Press, 2016
• Documentation and examples from Neuroph project http://neuroph.sourceforge.net/</td></tr>
<tr><td colspan="5">The number of class hours per week</td><td rowspan="2">Other classes:
–</td></tr>
<tr><td>Lectures:
4</td><td>Labs:</td><td>Workshops:</td><td colspan="2">Research study:
3</td></tr>
<tr><td colspan="6">Teaching methods
Individual and group work; lectures and labs</td></tr>
<tr><td colspan="6">Evaluation/Grading (maximum 100 points)</td></tr>
<tr><td colspan="2">Pre-exam requirements</td><td>Points</td><td colspan="2">Final exam</td><td>Points</td></tr>
<tr><td colspan="2">Practical project assignment</td><td>30</td><td colspan="2">Full implementation of practical project assignment</td><td>70</td></tr>
</table>

Study program / study programs: Advanced data analytics
Course: Programming
Teacher: Vladan B. Devedžić, Bojan B. Tomić, Zoran V. Ševarac, Dragan O. Đurić, Antun Balaž
Course status: Elective
ECTS points: 10
Prerequisites: none
Course objective Detailed introduction to current programming languages, methods and techniques in advanced data analytics.
Learning outcomes Students will master appropriate programming methods and techniques using state-of-the-art programming languages in advanced data analysis.
Course structure and content Most of the classes are focused on practical programming skills. Concepts and techniques are introduced through practical work, regardless of the programming language used in the course. It is envisaged that different programming languages will be used in classes, according to the development of the field so that it always works with state-of-the-art languages. Introduction Installation and use of appropriate programming environments Program libraries and APIs Documentation and its efficient use Data types Simple data types Arrays, strings, lists, dictionaries and other complex data types Classes and objects, constructors, inheritance Operations, expressions, loops, branching, functions, methods, exceptions Various types of operations and operands Various types of expressions Functions and methods (various types) Iterators and generators Exception handling Standard and non-standard libraries Working with libraries important in data analysis Data processing and analysis Data formats, data storage, data filtering, data display Preparation of data for analysis (various techniques) Statistical data processing and analysis using appropriate program libraries Data visualization Working with current libraries for data visualization
Literature/Readings . D. Beazley, B.K. Jones, Python Cookbook, 3rd Edition. O'Reilly Media, Inc., Boston, MA, 2013. Online. Available: https://www.oreilly.com/library/view/python-cookbook-3rd/9781449357337/ . W. Chang, Cookbook for R. 2014. Online. Available: http://www.cookbook-r.com/

The number of class hours per week				**Other classes:**
Lectures: 4	**Labs:**	**Workshops:**	**Research study:** 3	–

Teaching methods Individual and group work; lectures and labs

Evaluation/Grading (maximum 100 points)			
Pre-exam requirements	**Points**	**Final exam**	**Points**
Project (implementation)	50	Programming problem	50

Study program / study programs: Advanced data analytics

Course: Social Network Analysis

Teacher: Jelena Jovanović, Aleksandra Alorić, Marija Mitrović Dankulov

Course status: Elective

ECTS points: 10

Prerequisites: none

Course objective

To guide and assist students in:

- learning about main concepts, methods, and techniques of social network analysis (SNA)
- developing a solid understanding of i) the kinds of analytical questions and/or problems that can be dealt with using the SNA approach; ii) pros and cons of individual SNA methods and techniques, as to be able to select appropriate SNA methods / techniques for a particular problem / question
- acquiring practical skills in the analysis of network data, using publicly available SNA software tools and datasets.

Learning outcomes

Students will develop a solid understanding of main SNA concepts, methods, and techniques. They will also get an insight into the potentials and limitations of these methods and techniques, and thus be able to choose appropriate one(s) for a particular application case. Furthermore, they will acquire practical skills in using SNA software tools for doing network analysis with real-world datasets.

Course structure and content

Main course topics:

Graph-based data representation (nodes, edges, adjacency matrix, etc.)
Network features (degree distribution, connectedness, transitivity, etc.).
Centrality measures (degree centrality, betweeness centrality, eigen vector centrality, etc)
Communities in a network. Community detection.
Statistical models of network formation (e.g. ERGMs).
Diffusion of information and innovation through a network.
All course topics will be introduced through practical work with publicly available software libraries for SNA (e.g., R or Python SNA packages) and real-world network datasets. The practical work will also include network visualization, as well as data collection and preparation for network analysis.

Literature/Readings

Selected chapters from the following books:

- M. Tsvetovat and A. Kouznetsov. 2011. *Social Network Analysis for Startups: Finding connections on the social web*. O'Reilly Media Inc., Sebastopol, CA, USA.
- D. Easley and J. Kleinberg. 2010. *Networks, Crowds, and Markets: Reasoning about a Highly Connected World*. Cambridge University Press, New York, NY, USA.

The number of class hours per week				**Other classes:**
Lectures: 4	**Labs:**	**Workshops:**	**Research study:** 3	–

Teaching methods: Lectures will introduce main concepts for each course topic, and will include a lot of practical work with the topic-specific software libraries. Research study will be fully practical, based on individual and group work.

Evaluation/Grading (maximum 100 points)			
Pre-exam requirements	**Points**	**Final exam**	**Points**

Project: simple application case	0 – 40	Project: real-world application case	0 – 60

Study program / study programs: Advanced data analytics

Course: Text Mining

Teacher: Jelena Jovanović, Sonja Dimitrijević

Course status: Elective

ECTS points: 10

Prerequisites: none

Course objective

To guide and assist students in:
- developing a solid understanding of a typical text mining workflow
- learning principal text mining methods and techniques, including those used in text classification and clustering, topic modeling, key-terms extraction, and text summarization.
- developing working knowledge of text mining in R and/or Python programming language(s).

Learning outcomes

Students will be able to apply text mining methods and techniques to classify and cluster unstructured text-based content, as well as to extract key terms and main topics from such content. They will also know how to evaluate the performance of individual methods and techniques, as well as how to benchmark different methods and techniques.

Course structure and content

The course will cover the overall text mining process and examine in detail each of the key phases of a typical text mining workflow. In particular, the following will be covered:

- exploratory analysis of a given corpus (i.e. text-based dataset)
- text preprocessing
- transformation of unstructured textual content to a structured numerical format, that is, feature creation; different text representation / feature creation methods will be considered, including both traditional ones (e.g. vector space model) and more recent ones (e.g. word vectors)
- reducing typically very large feature space through feature selection techniques
- selection of a statistical, or a machine learning, or a graph-based algorithm to be used in conjunction with the created feature set to build a model for pattern mining or information extraction
- examining and evaluating the results produced by the built model.

Various methods for typical text mining tasks will be introduced, including methods for text classification and clustering, as well as those used for the detection of key-terms and topics.
Finally, the course will demonstrate the iterative (cyclic) nature of the text mining workflow, aimed at achieving better performance through alteration of individual phases of the process.
All phases of the text mining workflow will be introduced through practical work with publicly available software libraries for text mining (e.g., relevant R or Python packages) and real-world corpora (i.e. text-based datasets).

Literature/Readings

Selected chapters from the following books:

- J. Silge & D. Robinson. Text Mining with R – A Tidy Approach. O'Reilly, 2017. E-book publicly available at: http://tidytextmining.com/
- T. Kwartler. *Text Mining in Practice with R*. Wiley, 2017

The number of class hours per week				**Other classes:**
Lectures: 4	**Labs:**	**Workshops:** 1	**Research study:** 2	–

Teaching methods: Lectures will introduce main concepts for each course topic, and will include a lot of practical work with the topic-specific software libraries. Workshops and research study will be fully practical, based on individual and group work.

Evaluation/Grading (maximum 100 points)			
Pre-exam requirements	**Points**	**Final exam**	**Points**

Project: simple applic. case	0 – 40	Project: real-world application case	0 – 60

Study program / study programs: Advanced data analytics

Course: Artificial Intelligence / Machine Learning

Teacher: Vladan B. Devedžić, Bojan B. Tomić, Zoran V. Ševarac, Dragan O. Đurić, Aleksandra Alorić, Marija Mitrović Dankulov, Andrej Korenić, Sonja Dimitrijević

Course status: Elective

ECTS points: 10

Prerequisites: none

Course objective

Mastering the fundamentals, techniques and applications of artificial intelligence.

Learning outcomes

Students will learn basic concepts and techniques of artificial intelligence and gain practical skills for their application in advanced data analysis.

Course structure and content

Lectures

- Basic concepts and overview of the domain of Artificial Intelligence and Intelligent Systems.
- Basics of Machine Learning. Methods and techniques of data preparation and attribute selection. Algorithms for linear regression, classification and clustering.
- Rule-based knowledge representation. Rule-based decision making.
- Basic concepts of Neural Networks.

Labs

Practical tasks utilizing software frameworks, tools and/or services specific to each of the areas covered in this course. The software frameworks that students will work with are based on Java, Python and/or R. programming languages.

Literature/Readings

- S. Russell, P. Norvig, Artificial Intelligence - A Modern Approach, The 3rd Edition. Prentice Hall, Englewood Cliffs, NJ, 2009.
- Online materials hosted on the course website

Additional literature:

- Documentation and tutorials for software frameworks, tools and services that are used during the labs.

The number of class hours per week				**Other classes:**
Lectures: 4	**Labs:**	**Workshops:** 1	**Research study:** 2	–

Teaching methods

Lectures: slides and case studies related to the covered concepts and technologies.

Other: practical work with students on a computer covering real-world use cases, students are actively involved in the discussion.

Evaluation/Grading (maximum 100 points)

Pre-exam requirements	**Points**	**Final exam**	**Points**
Simple project	0-30	Project (implementation)	0-70

Study program / study programs: Advanced data analytics				
Course: Data Visualization				
Teacher: Dragan O. Đurić, Antun Balaž, Aleksandra Alorić, Marija Mitrović Dankulov, Andrej Korenić				
Course status: Elective				
ECTS points: 10				
Prerequisites: none				
Course objective Detailed introduction to current visualization tools, methods and techniques in advanced data analytics.				
Learning outcomes Students will master appropriate programming methods and techniques for data visualization using state-of-the-art programming languages in advanced data analysis.				
Course structure and content Most of the classes are focused on practical data visualization skills. High level concepts are introduced through practical work, regardless of the tools used in the course. Different programming languages and visualization tools will be used in classes, according to the development of the field so that it always works with state-of-the-art tools. Introduction Programming environments Data visualization libraries and tools Using the documentation Introduction to selected data visualization tools Getting started Plot components Aesthetics Geometries Toolbox Grammar of Graphics Plot Layers Scales, Axes and Legends Positioning Themes Using visualization in data analysis Data Analysis Data transformation Modeling for visualization Programming with selected data visualization tools				
Literature/Readings . Hadley Wickham, „ggplot2, Elegant Plotting for Data Analysis“, Springer; 2nd ed. 2016. . Winston Chang, „R Graphics Cookbook: Practical Recipes for Visualizing Data 2nd Edition“ O‘Reilly, 2018 . Matplotlib user's guide. Online. Avalilable: https://matplotlib.org/users/index.html				
The number of class hours per week				**Other classes:** –
Lectures: 4	**Labs:**	**Workshops:**	**Research study:** 3	
Teaching methods Individual and group work; lectures and labs				

Evaluation/Grading (maximum 100 points)			
Pre-exam requirements	**Points**	**Final exam**	**Points**
Project (implementation)	50	Data visualization problem	50

Study program / study programs: Advanced data analytics	
Course: Big Data Analytics	

Teacher: Vukmirović Dragan, Jeremić Veljko, Tomašević Nikola, Batić Marko

Course status: Elective

ECTS points: 10

Prerequisites: none

Course objective: This course will cover the basic concepts of big data analytics, methodologies for analyzing structured and unstructured data with emphasis on the relationship between the Data Scientist and the business needs.

Learning outcomes: After the course, student will be able to critically analyse existing Big Data datasets and implementations, taking practicality, and usefulness metrics into consideration. Moreover, to understand and demonstrate advanced knowledge of statistical data analytics as applied to large data sets.

Course structure and content

The concepts and techniques of Big Data analytics are first introduced through the review and presentation of theoretical foundations, followed by practical work using contemporary statistical and simulation software.

Research Methodology

Introduction to Data & Data Science

Data Analytics Lifecycle and methodology

Data Cleaning & Preparation

Data Summarization & Visualization

Building a Data Model in software environment

Data Analytics: Theory & Methods (supervised and unsupervised learning in Big Data)

Spark 2.0, Spark ML Library, R

The ethics of using (and misusing) data

Literature/Readings

- Walkowiak, S. (2016). Big Data Analytics with R: Leverage R Programming to uncover hidden patterns in your Big Data. Packt Publishing. Available online: https://www.packtpub.com/big-data-and-business-intelligence/big-data-analytics-r
- Bahga, A., & Madisetti, V. (2016). Big Data Science & Analytics: A Hands-On Approach. VPT. Available online: https://www.amazon.com/Big-Data-Science-Analytics-Hands/dp/0996025537
- Li, K. C., Jiang, H., Yang, L. T., & Cuzzocrea, A. (Eds.). (2015). Big data: Algorithms, analytics, and applications. CRC Press.. Available online: https://www.crcpress.com/Big-Data-Algorithms-Analytics-and-Applications/Li-Jiang-Yang-Cuzzocrea/p/book/9781482240559
- Erl, T., Khattak, W., & Buhler, P. (2016). Big Data Fundamentals: Concepts, Drivers & Techniques. Prentice Hall Press.. Available online: https://www.amazon.com/Big-Data-Fundamentals-Techniques-Technology/dp/0134291077
- Provost, F., & Fawcett, T. (2013). Data Science for Business: What you need to know about data mining and data-analytic thinking. O'Reilly Media. Available online: http://shop.oreilly.com/product/0636920028918.do

The number of class hours per week

Lectures:	**Labs:**	**Workshops:**	**Research study:**
4		1	2

Teaching methods: Individual and group work; lectures and labs

Evaluation/Grading (maximum 100 points)

Pre-exam requirements	**Points**	**Final exam**	**Points**
Project (implementation)	60	Verbal exam	40

Study program / study programs: Advanced data analytics

Course: Introduction to Statistical Inference

Teacher: Bulajić Milica, Vukmirović Dragan, Radojičić Zoran, Jeremić Veljko, Dobrota Marina, Maričić Milica, Alorić Aleksandra, Mutavdžić Dragosav

Course status: Elective

ECTS points: 10

Prerequisites: none

Course objective: Acquiring the ability to conduct statistical analysis, to interpret the obtained results, and to learn from the basic statistical methods and models how to study the observed phenomena as the subject of quantitative analysis. Getting acquainted with modern statistical software.

Learning outcomes: After the course, student will acquire the basics needed for understanding the concepts of advanced data analytics in contemporary statistical software.

Course structure and content

The concepts and techniques of statistical inference are first introduced through the review and presentation of theoretical foundations, followed by practical work using contemporary software.

Introduction to statistics
- Statistical set
- Statistical feature
- Sampling

Descriptive statistics
- Collection, preparation and data visualisation

Random variables and distribution models

Statistics and parameters

Estimation procedures
- Point estimates
- Confidence intervals

Hypothesis testing
- Parametric tests
- Nonparametric tests

Linear regression models
- Simple linear regression
- Multiple linear regression

Implementation of the covered methods and models in contemporary statistical software

Literature/Readings

- Vuković, N. & Bulajić, M. (2014). *Osnove statistike*. Fakultet organizacionih nauka, Beograd.
- Mann, S. P. (2016). *Uvod u statistiku*. Ekonomski fakultet, Beograd.
- Field, A., Miles, J., & Field, Z. (2012). *Discovering statistics using R*. Sage publications. https://us.sagepub.com/en-us/nam/discovering-statistics-using-r/book236067

The number of class hours per week

Lectures:	Labs:	Workshops:	Research study:
4		1	2

Teaching methods: Individual and group work; lectures and labs

Evaluation/Grading (maximum 100 points)

Pre-exam requirements	Points	Final exam	Points
Project (implementation)	60	Verbal exam	40

Study program / study programs: Advanced data analytics
Course: Big Data in Social Sciences
Teacher: Jelena Pešić, Irena Petrović, Jelisaveta Petrović, Dragan Stanojević, Oliver Tošković
Course status: Elective
ECTS points: 7
Prerequisites: /
Course objective(s) The objective of the *Big Data in Social Sciences* course is to introduce students to the social, ethical and methodological challenges that stem out from the use of big social data, as well as to familiarize them with the ways of overcoming these challenges in social sciences.
Learning outcomes - Knowledge of different types and ways of using big data in social sciences - Knowledge of methodological possibilities and restrictions on the use of big data in social sciences - Familiarization with the ways of combined use of big data and "small / micro" data sets collected by standard social research techniques (survey research, interviews, observation, etc.) - Knowledge of ethical standards in using big social data - Awareness of the legal aspects of the use of big social data - Developed ability of critical assessment of big social data
Course structure and content - Types, sources and quality of big social data - Social implications of using big data: digital inequalities and divisions, surveillance and freedom, privacy concerns, social scoring system, etc. - The use of big data in social sciences in different fields: political behaviour, consumer practices, crime, forms of communication through social networks, socio-spatial phenomena, etc. - Methodological aspects of using big data in social sciences - representativeness, bias, measurement and sampling errors, decontextualization, etc. - Combining different sets of data: "small / micro" and large in the analysis of social phenomena. - Ethical aspects of the use of big data in social sciences. - Legal frameworks for the use of big social data with a special emphasis on the European Union legislation (GDPR).
Literature/Readings . Foster, I et al. (2017) *Big Data and Social Sciences – A Practical Guide to Methods and Tools*, London: CRC Press. (selected chapters) . Hoeren, T, Kolany-Raiser (eds.) (2018) *Big Data in Context – Legal, Social and Technological Insights.* Springer Open. (selected chapters) . Petrović, J. (2018) „Veliki“ podaci – veliki izazov za sociologiju? *Sociologija* 60(3):557-582. Boyd, D., Crawford, K. (2012) Critical Questions for Big Data, *Information, Communication and Society* 15(5):662-679.

The number of class hours per week				**Other classes:**
Lectures: 5	**Labs:**	**Workshops: 1**	**Research study: 2**	

Teaching methods Individual and group work; lectures and labs.

Evaluation/Grading (maximum 100 points)			
Pre-exam requirements	**Points**	**Final exam**	**Points**
Development of the research design and Power point presentation of the research phases	0-30	Developed design of the research on selected social phenomenon using big data	0-70

Study program / study programs: Advanced data analytics
Course: Analysis of International Research Datasets
Teacher: Jelena Pešić, Irena Petrović, Jelisaveta Petrović, Dragan Stanojević, Oliver Tošković

Course status: Elective

ECTS points: 7

Prerequisites: Knowledge of basic statistical analysis techniques; skilled in SPSS

Course objective(s)

Introduction to analysis of data from international official statistics and comparative social research databases and datasets.

Learning outcomes

Getting acquainted with different international comparative databases (macro- and micro-data).
Critical evaluation of reliability, validity and comparability of international comparative data.
Mastering the application of techniques of statistical analysis on international comparative data.
Mastering analytical skills in usage of international and comparative data in solving different social problems and designing policies.

Course structure and content

Secondary data analysis. Introduction to different types of international statistical and academic databases and data. Critical evaluation of data: validity, reliability and comparability.

Overview of international comparative macro-data:

- Data on economic development (World Bank, UN - HDI, OECD, Structural Business Statistics – EUROSTAT, Global Entrepreneurship Monitor, etc.)
- Data on poverty and social exclusion (EUROSTAT, CEPAL)
- Gender Statistics (EIGE, UN Woman, etc.)

Overview of international comparative micro-data:

- European Union Statistics on Income and Living Conditions (EU SILC)
- European Union Labour Force Survey (EULFS)
- European Social Survey (ESS)
- World Value Survey (WVS)
- International Social Survey Project (ISSP)

Application of techniques of statistical analysis on comparative international micro-data. Topics:

- Individual and Social Welfare (ESS)
- General and Institutional Trust (ESS)
- Attitudes on migration (ESS)
- Attitudes on Family and Gender Roles (ISSP)
- Attitudes on Work (ISSP)
- Attitudes on Social Inequalities (WVS)
- Political Participation (WVS)

Literature/Readings

- Kiecolt & Nathan, 1990: *Secondary Data Analysis*, Sage University Papers
- MacInnes, John, 2017: *An Introduction to Secondary Data Analysis With IBM SPSS Statistics*, Sage
- Smith, Emma, 2008: *Using Secondary Data in Education and Social Research*, Mc Graw Hill Open University Press
- Jasna Soldić-Aleksić, 2015: *Primenjena analiza podataka. Rad u programima za statističku analizu i tabelarna izračunavanja*, Ekonomski fakultet, Beograd
- Republički zavod za statistiku, 2017: *Anketa o radnoj snazi*, Beograd
- EUROSTAT, 2018: Statistical cooperation – introduction (https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Statistical_cooperation_-_introduction)
- EUROSTAT, 2018: EU statistics on income and living conditions (EU-SILC) methodology (https://ec.europa.eu/eurostat/statistics-explained/index.php/EU_statistics_on_income_and_living_conditions_(EU-SILC)_methodology)

The number of class hours per week				Other classes:
Lectures: 5	**Labs:**	**Workshops:** 1	**Research study:** 2	

Teaching methods

Individual and group work; lectures and labs.

Evaluation/Grading (maximum 100 points)			
Pre-exam requirements	**Points**	**Final exam**	**Points**
Power point presentations of small research tasks	0-40	Research paper – application of statistical techniques on analysis of comparative data	0-60

Study program / study programs: Advanced data analytics

Course: Advanced data analysis in social sciences

Teacher: Jelena Pešić, Jelisaveta Petrović, Dragan Stanojević, Irena Petrović, Oliver Tošković

Course status: Elective

ECTS points: 7

Prerequisites: Knowledge of basic statistical analysis techniques

Course objective(s)

Students will have the opportunity to familiarize with the advanced statistical methods and to perform analysis and interpretation of different datasets relevant for social science. The course concentrates on the practical application of advanced statistical methods and approaches in analyzing social world using cross-sectional, comparative, longitudinal, and panel datasets.

Learning outcomes

Application of a range of advanced statistical methods on social science datasets:

- Correspondence analysis
- Linear regression
- Ordinal linear regression
- Logistic regression
- Nonlinear models
- Multilevel
- Structural equations

Use of the statistical packages SPSS, STATA and R

Interpretation of the statistical outputs

Writing reports based on advanced statistical analysis

Course structure and content

1. Introduction to practical advanced statistical modelling using social science datasets
2. Correspondence analysis
3. Linear regression
4. Ordinal regression
5. Logistic regression
6. Multinomial regression
7. Nonlinear models
8. Multilevel models – mix models
9. Structural equations modelling

Literature/Readings

- Michael Mitchell, 2012, *Interpreting and Visualizing Regression Models Using Stata,* Stata Press.
- MacInnes, John, 2017, *An Introduction to Secondary Data Analysis with IBM SPSS Statistics*, Sage.
- Jasna Soldić-Aleksić, 2015, *Primenjena analiza podataka. Rad u programima za statističku analizu i tabelarna izračunavanja*, Ekonomski fakultet, Beograd
- Andy Field, 2013, *Discovering Statistics Using IBM SPSS Statistics,* 4th Edition, SAGE Publications Ltd.

The number of class hours per week				**Other classes:**
Lectures: 5	**Labs:**	**Workshops:** 1	**Research study:** 2	

Teaching methods

Individual and group work; lectures and labs.

Evaluation/Grading (maximum 100 points)			
Pre-exam requirements	**Points**	**Final exam**	**Points**
Presentations of research project	0-30	Research paper – application of advanced statistical models on social science datasets	0-70

Study program / study programs: Advanced data analytics

Course: Discrete structures

Teacher: Vesna P. Todorčević, Nebojša T. Nikolić

Course status: Elective

ECTS points: 10

Prerequisites: none

Course objective

Mastering some standard topics of discrete mathematics as basics of mathematical logic and graph theory, relational structures, finite automata and formal languages.

Learning outcomes

The subject matter of this course is to teach the students the ways of formal deductions, to make them familiar with important applications of mathematical formalizations in the organization and the search of a large data basis as an important foundation for advanced analysis of data.

Course structure and content

Lectures

Basic notions. Propositional calculus. Rules of inference in propositional calculus. First order logic. Truth value of a first order formula. Valid sentences. Relational structures. Partially ordered set, chain and lattice. Elementary graph theory. Trees. Coding and recognition of music melodies using graph theory. Music data base. Finite machines and finite automata. Minimization of automata. Formal languages and grammars.

Labs

Properties of the logical connectives. Elimination of certain logical operations. Properties of quantifiers. Truth values of propositional formulas. Relations on finite sets. Suprema, infima, lattices. Relations on infinite sets. Representing graphs, paths in graphs. Trees. Application of trees in computability theory. Finite automata. Minimization of finite automata. Regular grammars.

Literature/Readings

Basic literature:

1. Čangalović M., Todorčević V., Baltić V. Discrete mathematical structures, textbook, FOS, 2019.
2. Todorčević V., Čangalović M., Baltić V. Book of problems from Discrete mathematical structures, FOS, 2016.

Additional literature:

1. D. Cvetković, S. Simić, Discrete Mathematics, Mathematics for computer sciences,Libra, Belgrade, 2000.
2. A.J. Anderson, Discrete Mathematics with Combinatorics, Pearson Education,2004.
3. D. Cvetković, V. Manojlović, Spectral recognition of music melodies,SYM-OP-IS 2013, 269-271.
4. D. Cvetković, T. Drobni, V. Todorčević, Recognition of music melodies in spectral graph theory, Phlogiston, 26 (2018), 165-180.

The number of class hours per week				Other classes:
Lectures: 4	**Labs:**	**Workshops:**	**Research study:** 3	–

Teaching methods

Classical teaching method using blackboards, overhead projectors and computer presentations

Evaluation/Grading (maximum 100 points)			
Pre-exam requirements	**Points**	**Final exam**	**Points**
Activity during classes	5	Written exam	20
Practical classes	5	Oral exam	40
Colloquium(s)	20		
Seminar(s)	10		

Study program / study programs: Advanced data analytics

Course: Mathematical Foundations of Data Analysis

Teacher: Tanja Stojadinović

Course status: Elective

ECTS points: 10

Prerequisites: -

Course objective(s) Acquisition of general and specific knowledge of Linear Algebra and Numerical Analysis

Learning outcomes Upon completion of the course, students have the basic knowledge of linear algebra and numerical methods. They are able to solve problems in these fields and to apply acquired concepts and techniques in other fields.

Course structure and content

-System of linear equations and Gaussian elimination
-Vectors in $\mathbf{R}^n$; linear combinations, linear spans, linear dependence; basis and dimension
-Matrices; matrix addition and scalar multiplication; transpose
-Elementary row operations; echelon matrices, rank of a matrix
-Matrix multiplication; invertible matrices
-Determinant; Properties of determinants; minors and cofactors; adjoint of a matrix
-Linear mappings; kernel and image of a linear mapping
-Matrix representation of a linear map
-Eigenvalues and eigenvectors; diagonalization
-Inner product spaces; orthogonality, orthonormal sets; orthogonal projection, applications
-Numerical methods for solving systems of linear equations; direct methods and iterative methods
-Numerical methods for computing eigenvalues and eigenvectors
-Polynomial interpolation and other methods for function approximation;
-Fourier transformation; discrete Fourier transformation; fast Fourier transformation

Literature/Readings

- 1. A. Lipkovski, Linearna algebra i analitička geometrija, 2nd edition, Zavod za udžbenike i nastavna sredstva, Beograd, 2007;
- 2. S. Lipschutz, Schaum's Outline of Theory and Problems of Linear Algebra, 2nd ed, Mc Graw-Hill, New York, 1991;
- 3. D. Radunović, Numeričke metode, Akademska misao, Beograd, 2004.
- 4. F. B. Hildebrand, Introduction to Numerical Analysis, 2nd edition, Dover Publications, INC, New York, 2013.
- 5. G.Shanker Rao, Mathematical Methods, I.K. International Publishing House, 2013.

The number of class hours per week				Other classes:
Lectures:	**Labs:**	**Workshops:**	**Research study:**	
4			3	

Teaching methods

Frontal, group, practical

Evaluation/Grading (maximum 100 points)			
Pre-exam requirements	**Points**	**Final exam**	**Points**
Exercises, Colloquia	40	Written-oral exam	60