Hanze
University of Applied Sciences
Groningen

Institute for Life Science & Technology

Data Science for Life Sciences
Course Catalog
2018-2019

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Program overview

	Semester 1	Semester 2	Semester 3
Projects	**Omics project (quantified self)** (10 EC)	**Omics project (integrated omics)** (10 EC)	**Graduation project and thesis** (30 EC)
Courses	**Preparatory Course** (5 EC)	**Data Science II (modeling)** (5 EC)	
	Data Science I (exploration) (5 EC)	**Data Science III (prediction)** (5 EC)	
	Programming I (design) (5 EC)	**Programming II (big data)** (5 EC)	
Research & Professional skills	**Research & professional skills** (10 EC)		

Glossary

Term	Description
Tutor groups	Small group of students that come together to discuss and explain study material to each other that is assigned weekly, and to complete accompanying exercises. The lecturer is available at the onset of meetings for coordination of the students studyprogress and furthermore on request to provide additional explanation
Courses	A course is a module. There are theoretical / skills modules like the data science modules, programming modules. There are skills related modules like the professional skills and research skills modules and there are research project modules.
Preparatory course	Based on the decision of the admission committee a student has to conduct the preparatory course. The preparatory course is a module to prepare the students up to the required level for following modules.
Lectures	A lecture usually involves a member of the senior academic teaching staff presenting themes and concepts related to a course of study to students enrolled in that course. The lecturer presents information to a large class, and while questions are encouraged, there is minimal group discussion.
Computer labs	During the computer labs you work either individually or in a small group to learn and experiment with the course material in a hands-on environment.
Tutorial session	A combination of theoretical background presentation in the format of a lecture, application of those concepts by means of tutorials with encouragement of experiments to be conducted in the computer labs
Project meetings and sprint meetings.	Meetings in which the progress of the research project (Quantified Self project and the Integrated omics project) is discussed with the team and the tutor. During project meetings feedback is provided on personal development, project performance, research (research question, hypothesis, validity and results) and the validity / future use in the field. During sprint meetings external stakeholders might attend.
Workshop / Tutorial	Workshops or Tutorials usually involve a member of teaching staff presenting themes and concepts, or the development of a skill, related to the course of study. Workshops may involve more hands-on learning however also allow discussion, interaction, presentation and debate on a given topic.
Masterclass	Masterclasses are lectures about cutting-edge knowlegde direct from researchers active in the field. These classes can be organized by the teaching staff as well as the students themselves
Graduation project and thesis	The graduation project is the final research project in which the student conducts independently a research project at master level to be reported in a master thesis.
Project in omics	The English-language neologism **omics** informally refers to a field of study in biology ending in -*omics*, such as genomics, proteomics or metabolomics. The related suffix **-ome** is used to address the objects of study of such fields, such as the genome, proteome or metabolome respectively. Omics aims at the collective characterization and quantification of pools of biological molecules that translate into the structure, function, and dynamics of an organism or organisms. There are two research projects related to the omics field (excluded the graduation project). The quantified self project and the integrated omics project.
Integrated omics	Integration of current “omics” techniques and data in order to answer research questions that cannot be answered using only one type of analysis

Module Preparatory course data science 2018-2019

master DSLS	Year 1	Semester 1 – Q1

Code	BFVM18DATASC
Content	**Overview** Calculus (2w): equations, functions, derivatives and anti-derivatives (special functions: trigonometric, exp/log, polynomial), plots, ordinary differential equations Frequentist statistics (3w): probability, marginal and conditional probabilities, null-hypothesis, p- value, type-I/II errors, sampling, descriptive statistics (mean/st.dev./corr.coef./etc.), special distributions (normal, χ^2, F, binomial, student's t), statistical testing, statistical power Linear algebra (2w): vectors and matrices, special matrices, transpose, multiplication, matrix inverse, determinant and trace, linear regression **Context learning line** In this course, the student will revise basic mathematical skills and knowledge in the fields of calculus, statistics and linear algebra. This is one of the three optional modules of the Preparatory course. Its intended for students without a sound background in mathematics and statistics. The basic mathematical skills are a required level for the data sciences subjects and introduce students in simple modeling using statistics and linear algebra
Learning outcomes	The student can: • interpret mathematical notation of calculus, statistics and linear algebra • apply basic equations analytically, including linear, rational, quadratic, trigonometric, exp/log equations in one variable • execute differentiation and integration of standard functions in simple forms • understand probabilistic concepts related to the scientific method • apply descriptive statistics and execute standard statistical tests, including Welch/Student t-test, F-test, and χ^2 tests on proportions • manipulate mathematical expressions involving matrices and vectors • apply linear systems of equations, including linear regression, using matrix algebra
Teaching method	Tutor group and self study. Twice a week, students meet in small tutor groups (1.5 hrs) to discuss and explain study material to each other that is assigned weekly, and to complete accompanying exercises. The lecturer is available at the onset of meetings for coordination of the student's study progress and furthermore on request to provide additional explanation. Students submit their completed assignments.
Literature	Suggested texts: • S. K. Chung. *Understanding basic calculus* • Illowsky, B. and Dean, S.L., 2013. *introductory statistics*. OpenStax College, Rice University. • Lane, D.M., Scott, D., Hebl, M., Guerra, R., Osherson, D. and Zimmer, H., 2017. *An Introduction to statistics*. Rice University. • S. Boyd & L. Vandenberghe 2018 *Introduction to Applied Linear Algebra* Cambrigde University Press, Chapters: 1-3, 5-8, 10-13 Suggested online courses: • Calculus: https://www.edx.org/course/pre-university-calculus-delftx-calc001x-2 • Statistics: https://stepik.org/course/701/ • Linear Algebra: Khan Academy – Math – Linear Algebra https://www.khanacademy.org/math/linear-algebra
Assessment	Written exam

Mandatory	Based on the decision of the admission committee a student has to fulfill the exam. Presence is not mandatory but strongly adviced.
Credits	2.5
Contact time	14
Self study time	56
Prerequisites	Admission test
Frequence	1× per study year

Module Data Science I: Data exploration 2018-2019

master DSLS	Year 1	Semester 1 Q2

Code	BFVM18DATASC1
Content	**Overview** Bayesian statistics (2w): Bayes' rule, prior/posterior, odds ratio, maximum likelihood estimation, bootstrapping Data processing (1w):random numbers, statistical graphics, non-normality and outliers, missing data Signal analysis (4w):nterpolation, windowing, filtering, convolution, (auto)correlation, complex numbers, Fourier transformation (DFT&FFT), splines, local regression **Context learning line** The course will start with a repetition of basic descriptive statistical concepts and extend these to Bayesian theory. The student will apply statistical methods to characterise biometric time series and perform quality control (e.g. missing data, outliers). Signal analysis techniques will be used to perform data transformations and obtain relevant summary statistics, both descriptive statistics of the data samples (mean+SD, correlation, distribution, etc.) as well as dynamic characteristics of the signal (auto-correlation, frequency-content, etc.). The student will learn to calculate and update outcomes dynamically as data streams are gathered. Methods will be implemented in Python using various data analysis modules (numpy/pandas/matplotlib).
Learning outcomes	• can assess the quality of life science data and perform data clean-up; • can apply Bayesian statistics to incrementally update estimates of time series parameters; • can analyze time-series data, including visualisation, calculation of descriptive statistics, resampling and interpolation, removal of noise and baselines, and the application of various linear filters and other data transformations in the time- and frequency domains; • can discover and investigate apparent relationships between multiple time series.
Teaching method	Lectures, tutorials, computer labs. Three times a week a tutorial session (1.5h) is held, where lectures and a computer labs are combined.
Literature	Suggested texts: • A. B. Downey. 2012 Green Tea Press *Think Bayes* Green Tea Press • McKinney, W., 2012. *Python for data analysis: Data wrangling with Pandas, NumPy, and IPython*. " O'Reilly Media, Inc.". • Unpingco, J., 2016. *Python for Signal Processing*. Springer International Pu
Assessment	Computer exam
Mandatory	No
Credits	5
Contact time	56 hrs
Self study time	84 hrs
Prerequisites	Preparatory course Data science; preparatory course Programming
Frequence	1× per study year

Module Data Science II: modeling 2018-2019

master DSLS	Year 1	Semester 2 Q1

Code	BFVM18DATASC2
Content	**Overview** Graph theory (2w):graphs, trees, adjacency matrix, directed acyclic graphs, paths and cycles, tree search, shortest path, random walks, Markov chains, sorting, algorithmic complexity Multivariate data analysis (3w):multiple linear regression, partial least squares, canonical correlations, singular value decomposition, principal component analysis Numerical analysis (2w):discretization and round-off, error-propagation, numerical differentiation and integration, finding roots and extrema **Context learning line** The course introduces the student to relational models of data, in the form of graphs and multilinear models. An introduction to graph theory is presented, with a number of methods for investigation, and assessment of relational features, with applications to the life science. In addition, the course introduces multivariate linear models for describing relations within and between complex datasets, with focus on the meaning and interpretation of results. These subjects are complemented with a number topics on numerical analysis, which have implications for numerical modeling and evaluation.
Learning outcomes	• can explain whether and how a life science data set corresponds to a graph • can implement available graph-based algorithms to process data • can explain whether and how a life science data set can be described by a multiset multilinear model • can implement a specific multiset multilinear model for integrative modelling of data • can implement numerical methods for analysis of data, including differentiation, integration and finding roots and extrema • can explain how discretization, round-off and error propagation may affect the results of outcomes
Teaching method	Lectures, tutorials, computer labs. Three times a week a tutorial session (1.5h) is held, where lectures and a computer practical are combined.
Literature	Literature will comprise of I. contemporary review articles (Annual Reviews) on methods within the context of Data Science and/or Bioinformatics, II. recent research papers demonstrating the application in a particular research project, and III. background literature.
Web	Blackboard
Assessment	Computer exam
Mandatory	No
Credits	5
Contact time	56 hrs
Self study time	84 hrs
Prerequisites	Preparatory course Data science; Preparatory course Programming
Frequence	1× per study year

Module Data science III: Machine learning and prediction 2018-2019

master DSLS	Year 1	Semester 2 Q2

Code	BFVM18DATASC3
Content	**Overview** Data reduction: forward/backward elimination, multidimensional scaling, manifold learning. Machine learning: k-nearest neighbor, logistic regression, decision trees, discriminant analysis, support vector machines, neural networks, ensembles (averaging/bagging/voting/boosting), k-means, hierarchical clustering, spectral clustering, cross-validation, over-/underfitting, regularisation Image analysis: feature detection, image segmentation, deep learning, convolutional neural networks **Context learning line** This course provides an introduction to several concepts used in predictive modelling. Data reduction techniques are discussed, and several machine learning techniques for both supervised and unsupervised learning will be covered, such as decision trees, neural networks and clustering methods. The student will learn how to validate and evaluate the employed algorithms. The application of machine learning algorithms in image analysis is covered, together with additional concepts to perform image analysis, such as image enhancement, edge detection and image segmentation. The methods will be implemented in Python using data analysis modules (scikit- learn, Tensorflow).
Learning outcomes	The student can • implement methods for reducing the complexity of datasets, including multidimensional scaling and principal component analysis • explain of several frequently used machine learning strategies and algorithms how they work and when they are applicable. • implement machine learning algorithms in Python for prediction and classification • check the validity of outcomes from the methods and algorithms used • design a (pre)processing pipeline to extract features from image data • implement a convolutional neural network to perform image classification and image recognition
Teaching method	Lectures, tutorials, computer labs. Three times a week a tutorial session (1.5h) is held, where lectures and a computer practical are combined.
Literature	Suggested texts: • Géron, A., 2017. *Hands on machine learning with scikit learn and tensorflow: concepts, tools, and techniques to build intelligent systems.* " O'Reilly Media, Inc. Chapters: 1-10, 13 • Mordvintsev, A. and Abid, K., 2014. *Opencv-python tutorials documentation. Obtenido de https://media. readthedocs. org/pdf/opencv-python-tutroals/latest/opencv-python-tutroals. pdf.* Chapters: 1.3-1.5, 1.10
Assessment	Computer exam
Mandatory	No
Credits	5
Contact time	56 hrs
Self study time	84 hrs
Prerequisites	Data Science 0, Data Science 1, Data Science 2, Programming 1
Frequence	1× per study year

Module Preparatory course programming 2018-2019

master DSLS	Year 1	Semester 1 Q1

Code	BFVM18PROGR
Content	**Overview** The course will start with introducing the basic programming concepts, code organization, data types, structures and functions/standard libraries. Followed by more advanced technologies like the concepts of object oriented programming **Context learning line** In this course, the student will revise basics of programming in preparation of the programming 1 course needed for the quantified self project assignment. This is one of the three optional modules of the Preparatory course. Its intended for students without a sound background in programming.
Learning outcomes	The student • can use different datatypes • uses the Python flow control logic • can implements functions, make/use modules /write text files • implements exceptions handling • write, document, test and maintain software products • translate a given problem into a robust and flexible object-oriented software design
Teaching method	Each week one tutorial (1.5 hr) with intro concept and tutorial assignment Each week one (1.5 hr) tutor group setting with feedback and progress assignment
Literature	Barry, P., 2016. *Head First Python: A Brain-Friendly Guide*. O'Reilly Media, Inc..
Assessment	Computer exam
Mandatory	Based on the decision of the admission committee a student has to fulfill the exam. Presence is not mandatory but strongly adviced.
Credits	2.5
Contact time	21
Self study time	49
Prerequisites	Admission test
Frequence	1× per study year

Module Programming I: software development with challenging data layers 2018-2019

master DSLS	Year 1	Semester 1

Code	BFVM18PROGR1
Content	**Overview** The course start with a quick (re-) introduction of the Python language and basic Object-Oriented principles. We will mainly focus on several aspects related to the lean/agile software development process, with a quantified self (quantified us) problem as learning case. Design patterns and principles, clean code principles and testing strategies will be discussed. There will be an emphasis on different ways to tackle large and/or complex data layers. Data layers can be represented by SQL or (distributed) NoSQL (MySQL, Hadoop, MongoDB etc.) and accessed in different ways including microservices. **Context learning line** This module builds upon the basics of the preparatory course programming.
Learning outcomes	The student can • write, document, test and maintain (Python) software products • translate a given problem into a robust and flexible object-oriented software design using the Python language and applying the SOLID principles and relevant Design Patterns • carry out a software development project within a small development team according to the standards and best practices of Agile development • select and implement the best Data Layer strategy for an application in development, taking into account that the used technologies will likely change over time.
Teaching method	Design patterns and principles, clean code principles and testing strategies will be discussed during lectures. There will be an emphasis on different ways to tackle large and/or complex data layers. Given a design challenge, students will iterate through several design / implement / test / release / refactor cycles (The Software/System Development Life Cycle SDLC). Feedback of the work will be provided during tutorials.
Literature	Martin, R.C., 2009. *Clean code: a handbook of agile software craftsmanship*. Pearson Education.
Web	Blackboard
Assessment	Computer exam
Mandatory	No
Credits	5
Contact time	56 hrs
Self study time	84 hrs
Prerequisites	Preparatory course programming
Frequence	1× per study year

Module Programming II: Paralell programming 2018-2019

master DSLS	Year 1	Semester 2

Code	BFVM18PROGR2
Content	**Overview** The Programming II course aims to make students competent in designing parallel solutions for computational problems which aren't adequately solvable by a single computer. The students will work on making an existing approach to a problem parallel. Theory will be provided parallelisation approaches on both hardware level (shared memory vs clusters) as software level (e.g. Threading, OpenMPI, Hadoop, Spark). In addition, students will learn the tools necessary to design (through software engineering) and analyze (by algorithmic analysis) the problem and possible solutions. For instance, some problems are "embarrassingly parallel" and can easy be solved on a cluster, while others need to be organised according to their data structure into parallelisable units. Additionally, appropriate storage methodologies for parallel algorithms will be explained. (E.g. HDFS, Cassandra, HBase). **Context learning line** This module assumes the skills of programming and will focus on design for efficient performance to optimize big data analysis
Learning outcomes	The student can • identify parallelisable parts of a computational problem. • analyze the requirements for parallelisation of the problem and choose a suitable technology to implement a solution. • critically evaluate the performance of the solution and identify possible improvements or if improvements are at all possible.
Teaching method	Principles design and test strategies will be discussed during lectures and tutorials. Given individual assignment(s) students will iterate through several design / implement / test / refactor cycles. Feedback of the work will be provided during tutorials.
Literature	Karau, H., Konwinski, A., Wendell, P. and Zaharia, M., 2015. *Learning spark: lightning-fast big data analysis*. " O'Reilly Media, Inc.".
Assessment	individual assignments
Mandatory	No
Credits	5
Contact time	56 hrs
Self study time	84 hrs
Prerequisites	Programming I
Frequence	1× per study year

Module Preparatory course omics 2018-2019

master DSLS	Year 1	Semester 1 Q1

Code	BFVM18OMICS
Content	**Overview** The students will be introduced to basic (animal) physiology, cell biology and molecular genetics – primarily the Central Dogma. Also, the different types of biological sequences will be introduced; their properties and ways of analysing them (alignment, mapping, Blast). **Context learning line** This is one of the three optional modules of the Preparatory course. Its intended for students without a background in (molecular) life science (e.g. ICT students). The content provides a base for annotating and understanding biological data.
Learning outcomes	The student • can understand basic physiological processes • knows the core components of both prokaryotic and eukaryotic cells, knows their role in the context of cell biology • knows all the actors and components of the Central Dogma of Genetics and is able to describe what these are and what their role is • knows the types of biological sequences, their characteristics and relationships. • Can understand basic concepts of laboratory "omics" techniques • Knows about the main methods used to analyse sequences (e.g. Blast, alignment, mapping)
Teaching method	Self study & tutor studygroups. Twice a week, students meet in tutor groups (1.5 hrs) to discuss and explain study material to each other that is assigned weekly, and to complete accompanying exercises. The Lecturer is available at the onset of meetings for coordination of the students studyprogress and furthermore on request to provide additional explanation.

Literature	Biology (eleventh edition) by Campbell (Author). Chapters: C5: Biological Marcromolecules and Lipids C7: Cell Structure and Function C12: Mitosis C13: Sexual Life and Meiosis C14: Mendelian Genetics C16: Nucleic acids and Inheritance C17: Expression of Genes C18: Control of Gene Expression C19: DNA Technology C20: The Evolution of Genomes C22: Phylogenetic Reconstruction C40: The Animal Body Introduction to Genomics (3rd Edition) Arthur Lesk (Author)Quick study guides (Lam cards): - Biology - Biology 2 - Molecular Biology - Genetics - See http://www.barcharts.com/
Assessment	Written exam
Mandatory	Based on the decision of the admission committee a student has to fulfill the exam. Presence is not mandatory but strongly adviced.
Credits	2.5
Contact time	10
Self study time	60
Prerequisites	No
Frequence	1× per study year

Module Project in omics: quantified self project 2018-2019

master DSLS	Year 1	Semester 1

Code	BFVM18OMICSQS
Content	**Overview** The project is a visualisation of a person's health data in order to answer health-related questions. Students are asked to define their own health related research question and combine these questions into one design per group. In addition, data needs to be gathered by wearables, mobile devices and other available resources. Students are stimulated to use software interfaces and communication protocols to acquire data from digital data resources. The visualisation means is through web technologies: Javascript, CSS, SVG and the appropriate libraries (JQuery, D3.js and Processing). The student applies basic data transformation / munging in order to prepare the data for visualisation. The project has a cumulative design strategy where a simple prototype with a simple data structure is succeeded by more sophisticated iterations on the same theme. Feedback sessions with field experts are organized to improve the prototype towards a valuable IT solution. **Context learning line** The kick-off project of the master aims to first of all develop a student's understanding of the Data Science field and Personalised Health. A secondary aim of the project is to reinforce the concepts learned in previous programming courses. Finally, good UI design principles are taught, and the student iterates on a design to answer the defined research question. Feedback sessions in which external expert reflect on the design will enhance entrepreneurial skills.
Learning outcomes	The student can • implement an advanced web based visualisation. • design a useable interface to answer a research question. • implement appropriate data(base) technologies given data sources. • translate design into a project approach and valuable IT solution. • collaborate with team members to organise the work involved.
Teaching method	Students are confronted with a mutli diciplinary wicked problem to provide a learning environment in which they can develop to approach a project on master Level. In the project programming skills, omics knowledge and data science knowledge and skills are challenged to enforce training and knowledge development. During project meetings feedback is provided on personal development, project impetus and performance, research (research question, hypothesis, validity and results) and the product (validity and applicability in the field). Interaction between groups, within groups and with field experts is organized by means of project meetings and sprint meetings. Masterclasses on additional theoretical topics not provided in the other modules will be organized as well.
Literature	Recommended: Tufte, E. and Graves-Morris, P., 2014. The visual display of quantitative information.; 1983 Tufte, E. and Graves-Morris, P., 2014. *The visual display of quantitative information.*
Assessment	The professional product is assessed at different stages of the project (UI design, software engineering good practices, efficiency, relevance towards research question) The final product shall be presented to field experts. This presentation is part of the assessment.

Mandatory	Precense during the kick off and sprint meetings is mandatory. During the kick off meetings further agreements will be made about availability and obligations towards the research team and stakeholders
Credits	10
Contact time	40
Self study time	240
Prerequisites	Preparatory course Programming level
Frequence	1× per study year

Module Project in omics: Integrated omics 2018-2019

master DSLS	Year 1	Semester 2

Code	BFVM18OMICSINT
Content	**Overview** This course introduces the student to the integration of current “omics” techniques in order to answer research questions that cannot be answered using only one type of analysis. “Omics” techniques are both quantitative as well as high-throughput, leading to large datasets of information amenable to analysis by advanced statistics and machine learning. First, the student is introduced to state-of-the-art lab techniques in the areas of (meta)genomics, transcriptomics, metabolomics, proteomics, epigenomics, foodomics, imaging, epidemiology etc. The student will choose a research project provided by the connected research centres like UMCG, AVEBE and the innovation workplace Digital Society Hub for which datasets of multiple types are available and formulate and test a hypothesis using appropriate quantitative methods (statistics/Machine Learning). A crucial aspect is communicating the methods and the findings to peers and clients. **Context learning line** This project builds upon the technologies mastered in the first semester. Where appropriate, visualisation and web techniques from semester I are used to report and clarify the findings.
Learning outcomes	• Formulate a clear, verifiable hypothesis on the basis of a client’s research question Identify and understand possible Omics techniques necessary for answering a research question and hypothesis • Evaluate datasets for utility in answering a client’s hypothesis • Pre-process datasets in order to be able to do inter-dataset analyse • Apply and validate statistical techniques across datasets • Apply and validate machine learning techniques in pre-processing data and meta-analysis across datasets • Identify business and economics factors applicable to the research question and integrate them with the final conclusion (where applicable) • Present findings in a clear and scientific manner to the target audience (client, researchers, peers)
Teaching method	Students are confronted with a multisource, multidiciplinary wicked problem to provide a learning environment in which they can develop their competences on master level. In the project programming skills, omics knowledge and data science knowledge and skills are challenged to enforce training and knowledge development. During project meetings feedback is provided on personal development, project performance, research (research question, hypothesis, validity and results) and the validity / future use in the field. Interaction between groups, within groups and with field experts is organized by means of project meetings and sprint meetings. Masterclasses on integraded omics theory will be provided by the UMCG in the firsts month of the project.
Literature	Relevant scientific papers will be provided on blackboard.
Assessment	The professional product is assessed at different stages of the project (hypothesis formulation, experimental and statistical design, data analysis good practices, efficiency) The final product shall be presented to the client. This presentation is part of the assessment.

Mandatory	Precense during the kick off and sprint meetings is mandatory. During the kick off meetings further agreements will be made about availability and obligations towards the research team and stakeholders
Credits	10
Contact time	60 hours
Self study time	220 hours
Prerequisites	Data Science I, Omics I
Frequence	1× per study year

Module Professional and research skills I 2018-2019

master DSLS	Year 1	Semester I

Code	BFVM18RSPFS1
Content	**Overview** This course comprises several separate activities that are organised by the institute or the student(s) themselves. They all revolve around the strengthening the students' ability to function as a critical, independent and effective researcher and professional. <u>Professional skills (2EC):</u> The professional skills development activities start with a DISC assessment. By means of a personal assessment (DISC report) students gain knowledge of different and preferred communication styles. By this students can learn to communicate effectively and advice effectively. Students will be trained to translate preferred communication style toward individual qualities and acknowledge the qualities of others in order to strengthen the team's communication, collaboration and performance. Students are asked to use the DISC assessment in their professional development. Students can practise communication skills during the projects to be proven in the portfolio. Project tutors can provide feedback on request of the students. In addition, workshops will be provided to lecture students about working in a professional environment. Topics include code management, version control, business case, IP patenting and introduction to the scrum methodology. <u>Research (3EC)</u> In the creative thinking workshop students are introduced to lateral thinking. Lateral thinking is solving problems through an indirect and creative approach, using reasoning that is not immediately obvious and involving ideas that may not be obtainable by using only traditional step-by-step logic. By means of several methods students learn to broaden their perspective and choose other point of views. In addition, students are provided lectures/tutorials on Scientific reading and writing. Recent and historical scientific papers will be analysed and discussed in terms of structure, language, science, and validity. Against that background, students will then be assigned writing tasks on the different elements of a scientific paper. Students are stimulated to contribute with own work. **Context learning line** All professional and research program outcomes are particularly trained and developed by the completion of the graduation project. During the research and professional skills modules students will develop these learning outcomes during the workshops, (peer) feedback and discussion sessions and in the project modules. The emphasis of this semester is the realisation and implementation of a professional software solution in a team effort.
Learning outcomes	Professional skills (2 EC) The student can • collaborate and communicate effectively by using different communication styles. • act in the face of a challenge in a self-directed and autonomous way.

	• demonstrate a balance between autonomous behavior and being a teamplayer • formulate a simple business case for a new product or new methodology. Research skills (3 EC) The student can • evaluate works from scientific literature • evaluate the relation of own research with respect to existing work • implement validation strategies for both data analysis methods and results
Teaching method	Professionals skills will be developed by a personal assessment, (peer) feedback sessions, (Guest) Lectures, workshops and Tutor groups. Masterclasses organized can be organized by students. Research skills will be developed by lectures and tutorials
Literature	Professional skills material is based on De, B.E., 1985. Six thinking hats. *Boston: Little, Brown* De Bono, E., 2010. *Lateral thinking: a textbook of creativity*. Penguin UK Literature will be made available on blackboard
Assessment	During the whole master program, the programme outcomes are assessed by means of a digital portfolio. The assessment criteria of the programme outcomes are to be found in the student manual. For keeping track of their own development on the competences described in the programme outcomes and in order to prove they possess the right level of the competences, students make a digital portfolio. In the portfolio, they add at least one proof for every programme outcome. Assessment criteria are based on the description of each programme outcome.
Mandatory	Guest lectures are mandatory
Credits	5
Contact time	Weekly workshops (1 professional, 1 research skills): 45 hr And personal assessment feedback session 2 times (0.5 hr)
Self study time	94
Prerequisites	N/A
Frequence	1× per study year

Module Professional and research skills II 2018-2019

master DSLS	Year 1	Semester 2

Code	BFVM18RSPFS2
Content	**Overview** This course comprises several separate activities that are organised by the institute or the student(s) themselves. They all revolve around the strengthening the students' ability to function as a critical, independent and effective scientific researcher. <u>Research (3 EC)</u> In the first semester students were stimulated to think in terms of possibilities and opportunities, applying unrestricted creative thinking. In this second semester, this is followed up by critical thinking to differentiate the viable approaches from the dead ends, allowing them to focus their efforts on promising research questions and designs. This critical thinking is also applied to question the validity of choice of methods and results of own research, as well as that of others. Background theory about the Scientific Method and Experimental Design is provided in (guest) lectures, whereas Critical Thinking is developed using active forms of learning, including teacher-guided peer-to-peer discussions. As an explicit aspect of critical thinking concerns ethical, legal and societal implications (ELSI), these are included in this module and will be made the topic of a workshop. <u>Professional Skills (2 EC)</u> Project management: Students learn to work project-based in a series of lectures. Students learn to set up and structure a project plan and how to scope the project. They learn to make a realistic planning related to time and personal and financial resources. Previous knowledge about collaboration and effective communication will be integrated in the course. **Context learning line** All professional and research competencies are particularly trained and developed by the completion of the graduation project. During the research and professional skills modules students will develop these competences during the workshops, (peer) feedback and discussion sessions and in the project modules. The emphasis of this semester is conducting a research project in a team effort.
Learning outcomes	Research skills (3 EC) • Differentiates the elements of the scientific process • Critically evaluates the design and outcomes of scientific research in data sciences and/or life sciences, both from own work as well as from others • Can implement reliable and reproducible data analysis experiments • Can evaluate possible Ethical, Legal, and Societal Implications of a research project and act accordingly. Professional skills (2 EC) • Supervises the execution of a project plan to deliver projects on-time within predescribed conditions • Improves project team performance by recognizing and facilitating the qualities and personal strength of individual project team members
Teaching method	Students learn to work project-based in a series of lectures. In addition student will be provided feedback during srum and tutor sessions.

	Background theory about the Scientific Method and Experimental Design is provided in (guest) lectures, whereas the the Critical Thinking is developed using active forms of learning, including teacher-guided peer-to-peer discussions. As an explicit aspect of critical thinking concerns ethical, legal and societal implications (ELSI), these are included in this module and will be made the topic of a workshop
Literature	All required literature will be made available on blackboard in the form of readers Optional literature: Gauch Jr, H.G., 2012. Scientific method in brief. Cambridge University Press.
Assessment	During the whole master program, the programme outcomes are assessed by means of a digital portfolio. The assessment criteria of the programme outcomes are to be found in the student manual. For keeping track of their own development on the competences described in the programme outcomes and in order to prove they possess the right level of the competences, students make a digital portfolio. In the portfolio, they add at least one proof for every programme outcome. Assessment criteria are based on the description of each programme outcome. At the end of the graduation project phase, the portfolio will be assessed by means of a criterion-based interview.
Mandatory	Guest lectures are mandatory
Credits	5
Contact time	Project management workshops: 7 lectures 1.5 hour Research skills lectures and discussions sessions 15 sessions 1.5 hour
Self study time	107
Prerequisites	N/A
Frequence	1× per study year