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study guide
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joint degree
Erasmus University Rotterdam
University of Amsterdam
Vrije Universiteit Amsterdam

Study Guide

Joint Research Master Business Data Science

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BUSINESS DATA SCIENCE: A UNIQUE PROGRAM

The English-taught Research Master Business Data Science prepares talented and motivated students to enter high quality PhD programs in Business. It is a joint initiative of the Erasmus School of Economics of the Erasmus University Rotterdam (EUR), the Faculty of Economics and Business of the University of Amsterdam (UvA), and the School of Business and Economics of the Vrije Universiteit Amsterdam (VU). Students of the Research Master Business Data Science are officially enrolled at Erasmus University Rotterdam.
The Research Master Business Data Science is a multidisciplinary research program in which course instruction is provided by top scholars from the three participating Schools with a central focus on the performance of academic research within business disciplines, such as entrepreneurship and innovation, finance, human resources and organization, marketing, and supply chains analytics.

The Business Data Science program distinguishes itself based on the following unique features:

- It is a two-year research master (120 EC) aiming to train future PhD students who will start their doctorate at one of the Schools in business and economics of the three partner universities.
- It has a strong focus on data science, presented to the students at a higher theoretical level than in a traditional master program.
- It ties the foundations of data science directly to different business fields. The availability of big data from a growing range of interconnected, interactive, and interoperable devices and the concurrent development of powerful quantitative techniques are giving rise to new perspectives and paradigms in scientific practice. This is particularly true in the field of business. As data collection has transformed from a tedious, expensive, and time-consuming practice into a continuous and, often, unobtrusive side-effect of day-to-day practices, behaviors and actions of people within and across organizations can be studied far more closely. Moreover, computing power and storage are not the limiting factors they once were. To leverage these opportunities, there is an increasing demand for highly trained specialists who can extract insights out of big data to solve business-related problems.
- It is a small-scale program, where students work in close collaboration with faculty. The class-size limit of 30 students guarantees a high level of interaction in the classroom, detailed feedback from faculty, and the support of a strong cohort. Individual field courses will generally have fewer students due to their concentration in the various tracks.
- It is embedded in the fervid research culture of three leading universities, benefitting from the expertise and research network of top-notch faculty. Not only are the rich variety of topics and methodological approaches covered in this program unique, the broad network employed/drawn on by participating faculty (with connections at MIT, NYU, LBS, and JADS, to name a few) is a valuable asset for future scholars. The Research Master Business Data Science will create and take advantage of the same excellent educational and research environment and facilities as the Tinbergen Institute Research Master program in Economics (henceforth referred to as TI), including existing practices with regard to student recruitment and placement support. The cooperation between the three Schools guarantees first-rate education provided by highly qualified scholars, embedded in an excellent infrastructure.

- In addition, the program helps students to jumpstart their PhD trajectory not only through solid training, but also with direct experience in research (provided during the seminars, research clinic, research hackathons, skill workshops, thesis, interaction with faculty, research assistantships opportunities), and teaching (e.g., teaching assistantships opportunities).

The Research Master Business Data Science is therefore highly distinctive from existing training in the field of data science: it is a Research Master's program that primarily focuses on training academic researchers who apply data science techniques in the discipline of business.

FACILITIES

Students are provided with excellent facilities. Most of the classes are organized in Amsterdam (*Zuidas*) with assigned classrooms, student work places and IT facilities for Research Master students. Classes will also be offered at the Woudestein Campus at EUR in Rotterdam with good facilities for students. Students are assisted with immigration procedures and housing. Travel costs for coursework are reimbursed. Scholarships are available for selected students.

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GRADUATE PROGRAM

CURRICULUM OVERVIEW

LEARNING OUTCOMES

Students who successfully complete the Joint Research Master Business Data Science will:

Knowledge and understanding

- **I.** have advanced knowledge and broad understanding of data science research methodology and its applications in business and management; this covers methods in statistics, econometrics, machine learning, and management science;
- **II.** have advanced knowledge and understanding of key research areas in business data science, for example in entrepreneurship, finance, human resources, marketing, and supply chain;

Application of knowledge and understanding

- **III.** be able to define research questions in business and management and answer these questions by specifying relevant theories, collecting relevant data, and applying advanced data science methods;
- **IV.** be able to apply/develop new data science approaches in order to solve relevant research questions in business and management;
- **V.** be able to design and specify models that tackle managerially-relevant research questions;
- **VI.** be able to design and implement approaches to validate model specifications and algorithms (e.g., formal proofs, analytical demonstrations, or empirical proof-of-concept in field or lab settings) in line with academic standards;

Making judgement

- **VII.** can critically evaluate research outcomes, and reflect on the ethical and social implications of the outcome of their analysis;

Communication

- **VIII.** be able to write research papers that are well structured, reflecting academic editorial standards;
- **IX.** be able to present and defend their research to an audience of academic researchers;

Learning skills

- **X.** to contribute original research to this field, under academic supervision;
- **XI.** respect and practice all current standard principles of scientific integrity, ethics, responsible data management and privacy;
- **XII.** have developed an attitude to independently keep track of the developments in one field of specialization and to embark on independent research in this field;
- **XIII.** work well in a team and reflect on own role and contribution within teams.

THE CURRICULUM, TEACHING-LEARNING ENVIRONMENT AND QUALITY OF THE TEACHING STAFF ENABLE STUDENTS TO ACHIEVE THE INTENDED LEARNING OUTCOMES.

Several factors guarantee the achievement of the intended learning outcomes for the Research Master Business Data Science:

i) the selective admission requirements ensure a high-quality, small-scale program;
ii) the intensive curriculum integrates methodological and theoretical knowledge, leveraging the small-scale of the program in interactive lectures and practical sessions;

iii) the teaching faculty has an established research and teaching track-record, further securing the achievement of the intended learning outcomes.

CURRICULUM

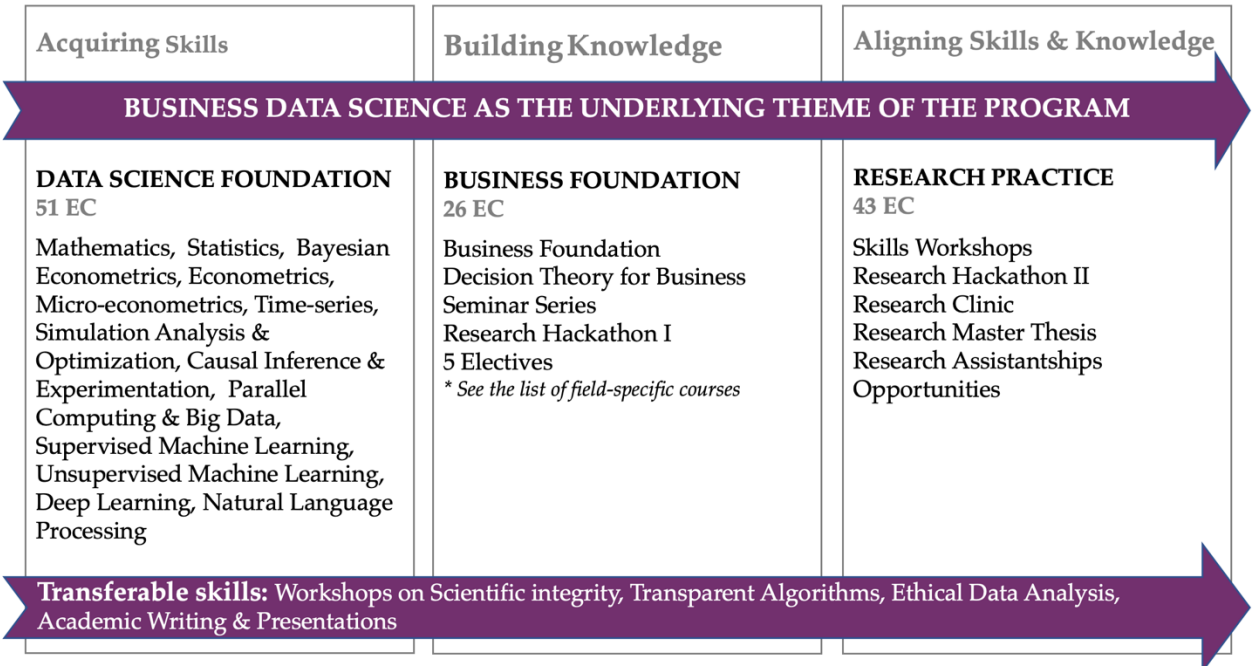
The Research Master in Business Data Science is a two-year program consisting of 120 EC. It is tailored for recent Bachelor's degree graduates, or those currently still enrolled in an undergraduate degree program, who are looking to pursue a solid course of training leading to a doctoral degree. The learning objectives of the program are achieved through a curriculum designed around a Data Science foundation, a Business foundation and Research practice.

Data Science Foundation - Acquiring skills. In year 1, the primary objective is to build a solid data science foundation and expose students to a variety of methodological approaches. These skills are applied to various business disciplines in the field courses.

Business Foundation - Building knowledge. In year 2, students focus on a given business sub-discipline, selecting from among: 1) quantitative finance, 2) management science, and 3) supply chain analytics. The courses assigned for each of these sub-disciplines have been carefully selected by a team of experts with the aim of ensuring the perfect learning trajectory that will lead to substantive contributions in the fields of each particular sub-discipline.

Research Practice - Aligning skills and knowledge. The program starts with an overview of the business problems that data science can address (in block 0), which also exposes students to fundamental components of the different business fields. This early exposure helps students to absorb and process materials presented later in courses on methodology, with respect to the various business perspectives. Students become further acquainted with the different business fields during seminars held throughout the first year, for which they will have to write a research proposal, as well as during the research hackathon. The research hackathon makes students think about how to approach the problems that arise in the various disciplines, and puts their knowledge to the test. Finally, the research clinic and the Research Master thesis represent students' final moments of integrating business and data science, and will showcase their ability to identify relevant problems and address them using cutting-edge techniques to make a substantive contribution to the field. All courses are also open to current PhD students and students in the other ARC Research Master program who fulfil the prerequisites indicated in the Study Guide and in the course manual.

To further ensure a high research mindset, the lecturers of the program are selected experts from three schools and are top researchers in their field. Since classes are in small groups, teachers can be easily addressed by students. Students are stimulated to engage in research seminars and other activities and to make contact with the various research groups and individual researchers to explore research options.
Next to taking courses, students are encouraged to select a research topic for the final thesis and to actively explore potential supervisors. The final thesis is a research project, set up by the student under experts' supervision. The matching of students and supervisors, while largely the results of individual communication between the two parties, is supported by the DGS.



TEACHING CONCEPTS AND METHODS

The teaching methods aim at activating students as much as possible. Most courses will be taught in a mixed format, combining lectures with tutorials. The course lecturer will set out the subject in plenary lectures, striving to optimize interaction with the student audience. Tutorials focus on exercises, on the application of theory discussed in lectures and on practicing skills, and therefore require active student participation. The training of methods and techniques plays an important part throughout the curriculum and mainly takes place in the tutorials. On average, these comprise 9,5 contact hours per week per block.
Students are stimulated to explore their research interests and options throughout the program. They can choose out of several electives to tailor the curriculum to their interest. Students are stimulated to be pro-active in selecting a research topic for the thesis and in soliciting potential supervisors.

COURSE CALENDAR

The courses are taught in blocks of eight weeks, with lectures during the first six (core courses) or seven weeks (field courses); the eighth week of each block typically serves as an exam week. Exception is block V which is extended by 2 weeks. First-year (core) courses have weekly one-hour tutorials, taught by a teaching assistant, in which students work on and discuss homework assignments. In core courses, no graded homework may be assigned in the week prior to the exam. Course attendance is mandatory; this applies to all core and field courses, the skills workshops, the research hackathon, the research clinic and the research seminar series. Attendance is registered via attendance sheets.

Schedule for 2020/2021:

Block 0 **Week 35**	**Block I** **Week 36-43**	**Block II** **Week 44-51**	**Block III** **Week 1-8**	**Block IV** **Week 9-16**	**Block V** **Week 18-28**
Aug 24-38	Aug31– Oct23	Oct 26 – Dec 18	Jan 4 - Feb 26	Mar 1 - Apr 23	May 3 - Jul 16

Dec 21 – Jan 3 (Week 52-53) *Christmas holidays*
April 26 – 30 (Week 17) *Spring break*

REGISTRATION FOR AND WITHDRAWAL FROM COURSES

In case of any difference between this study guide and the Academic and Examination Regulations (AER), the AER prevails.

Important note: field courses and/or tracks may be cancelled in case less than 5 students sign up for a course/track.

First-year students do not have to register for courses and the seminar series.

Students have to decide before block V of the first year on the full program of 2nd year electives (and re-sits for failed core courses). Students are allowed to register for extra field courses, which can be taken in case of course cancellations. Any other change in course selection once the registration has been closed needs an explicit motivational letter by the supervisor and the approval of the DGS. Students who would like to withdraw from one of their registered courses are requested to inform the educational office by sending an email to courses@businessdatascience.nl no later than Sunday after the first lecture.

FIRST YEAR

In the first year of the Research Master's program students have to complete 60 EC, including 12 core course blocks (48 EC), 1 field course (3 EC), Programming Basics (1 EC), Business Foundations (1 EC), Seminar series (2 EC), Integrity (1 EC) and a Research Hackathon (4 EC). Students can take the Advanced Mathematics course, instead of Mathematics, Asymptotic Theory instead of Statistics, and Advanced Econometrics instead of Econometrics.

Year 1: Building Knowledge

Year 1	Block 0	Block 1	Block 2	Block 3	Block 4	Block 5
Course	Business Foundations (EUR, UvA, VU)	Decision Theory for Business (Van den Brink & Estevez-Fernandez- VU)	Econometrics I (Schnücker - EUR)*	Econometrics II Microeconometrics (van der Klaauw & Bloemen - VU)*	Econometrics III Time-series Econometrics (Koopman -VU)*	Causal Inference & Experimentation (Roos & Chen – EUR)
ECTS	1	4	4	4	4	4
Course	Programming basics (Bos - VU)*	Mathematics (Wagener - UvA)*	Supervised Machine Learning (Groenen - EUR)	Unsupervised Machine Learning & Reinforcement Learning (Liberali & Schoonees- EUR)	Simulation analysis & Optimization (Heidergott & Ridder - VU)	Deep Learning (Raviv – EUR, UvA, VU)
ECTS	1	4	4	4	4	4
Course		Statistics (Spreij - UvA)*	Field Course 1: Parallel Computing & Big Data (De Vlaming - VU)	Research Hackathon (EUR, UvA, VU)	Research Hackathon (EUR, UvA, VU)	Research Hackathon (EUR, UvA, VU)
ECTS		4	3	3	0	1
Course					Natural Language Processing (Donkers & Morren – EUR, VU)	Skills Workshop 1: Scient. integrity, & Ethical Data Analysis (EUR)
ECTS					4	1
Course		Seminar Series	Seminar Series	Seminar Series	Seminar Series	Seminar Series
ECTS		0	0	0	0	2
Total ECTS	**2**	**12**	**11**	**11**	**12**	**12**

* courses already available at TI.

Students who select the quantitative finance track can take Asset pricing (in block III) in the first year, and postpone the start of the Research Hackathon to block IV.

All first-year students have to attend the seminar series. These seminars allow students to explore potential supervisors and fields of specialization, and vice versa, allow potential supervisors to scout talented students.
At predetermined times throughout the first year, the DGS interviews students to discuss their progress in the program. After block V of the first year, the Examination Board issues a formal advice on continuation in the program to all first-year students. In general, only students who have earned at least 48 EC of first year's credits at the end of the first year and who attended the seminar series are advised to continue in the program. In any case, students will only be admitted to second-year courses when they have earned at least 48 EC.

GRADING, CREDITS, AND RETAKES

All core courses are graded on a 1-10 scale, where 1 indicates very poor performance, 6 is the lowest passing grade, and 10 refers to outstanding performance. The final grade for a course block is round off to one decimal as .0 or .5, with the following exceptions: any grade between 5.0 and 5.5 is round off to a 5; a 5.5 is round off to 6; a 0.5 does not exist. Grades for homework or midterm examinations do not have to be rounded.

All core course blocks will be concluded by an exam. Apart from the exam, results of homework assignments form part of the examination and contribute to the final grade for a course block. The

final grade for the course block is composed of the average grade for the homework assignments and the grade for the examination as indicated in the Course Description section.
Exams are typically graded within 15 working days, and before July 15. Students can review their graded exam papers for up to four weeks after receiving their grade.

Students obtain 4 EC credits for each core course block that they have passed (grade 6 or higher), and 3 EC for field courses.
BDS does not schedule retakes. Failed exams in the first year cannot be retaken in the same academic year. Instead, students should retake failed first year course blocks in their second year in the program.
For students who have earned 48 first year ECTS or more and have completed the seminar series by August 1 of the first year, a compensation rule applies. Students may compensate at most one 5 in the core course sequence A with a 7.5 or higher obtained within the same core course sequence, and up to two courses in the core course sequence B. The compensation rule applies across years.
Core course sequences are:
Course sequence A: (Advanced) Mathematics/Statistics/Asymptotic Theory/(Advanced) Econometrics i-iii;
Course sequence B: Supervised Machine Learning/Unsupervised Machine Learning & Reinforcement Learning/Deep Learning/Natural Language Processing/Decision Theory for Business/Simulation Analysis & Optimization/Causal Inference & Experimentation.
Students cannot re-sit examinations they have already passed or for which they have earned the credits.

Students who fail an examination for a field course are allowed to replace the failed 3 credits within the same academic year at the discretion of the Director of Graduate Studies. A failed field course (grade below 6) means that the student does not qualify for a cum laude distinction.

If a student cannot take an exam due to verifiable illness or any other reason beyond that student's control, he or she may apply to the Examination Board for another opportunity to take the exam as soon as reasonably possible.

The standard program for the first-year is as follows:

Course	Block	EC
Business Foundations (EUR, UvA, VU)	0	1
Programming basics (Bos - VU)	0	1
Mathematics (Wagener - UvA)	I	4
Statistics (Spreij - UvA)	I	4
Decision Theory for Business (van den Brink & Estevez-Fernandez – VU)	I	4
Econometrics I (Schnücker - EUR)	II	4
Supervised Machine Learning (Groenen - EUR)	II	4
Field Course: Parallel Computing & Big Data (De Vlaming – VU)	II	3
Econometrics II -- Microeconometrics (van der Klaauw & Bloemen - VU)	III	4
Unsupervised Machine Learning & Reinforcement Learning (Liberali & Schoonees- EUR)	III	4
Research Hackathon (EUR, UvA, VU)	III	4

Econometrics III (Koopman – VU)	IV	4
Simulation analysis & Optimization (Heidergott & Ridder - VU)	IV	4
Natural Language Processing (Donkers - EUR, Morren - VU)	IV	4
Causal Inference & Experimentation (Roos & Chen - EUR)	V	4
Deep Learning (Raviv - APG)	V	4
Skills Workshop: Scientific integrity, Transparent Algorithms, & Ethical Data Analysis (EUR)	V	1
Seminar Series (EUR, UvA, VU)	I-V	2

Students with a sufficient background in mathematics, statics and/or econometrics can replace Mathematics, Statistics and Econometrics I, II, III with the following courses:

Course	Block	EC
Advanced Mathematics (Wagener - UvA)	I	4
Asymptotic Theory (Spreij - UvA)	I	4
Advanced Econometrics I (Bos & Fok – VU, EUR)	II	4
Advanced Econometrics II (Kleibergen & Pick– UvA, EUR)	III	4
Advanced Econometrics III (Koopman & Boswijk – VU, UvA)	IV	4

Students that are interested in Quantitative Finance can enroll in Asset Pricing in block III of year 1.

Course	Block	EC
Asset Pricing (Laeven, Vellekoop, Szymanowska (UvA, EUR)	III	3

SECOND YEAR

Students who have completed at least 48 EC from the first year courses, including via the compensation rule stipulated above, are admitted to the second year field courses. In the second year students complete at least 5 field courses (3 EC each), the course Bayesian Econometrics (3 EC), a Research Clinic (5 EC), a Skills workshop (4 EC), a Research Hackathon (3 EC) and a thesis (30 EC). 3 EC are allocated to a field course, irrespective of the amount of credits allocated to the same course elsewhere. This also applies to core course blocks taken as field course.
Students are expected to complete their thesis and at least three field courses in their track of choice (finance, management science, supply chain analytics).

The official defense of the thesis can only take place if the student has earned the credits for all other study units (core and field courses, skill workshops, seminars, research hackathon, research clinic).

Year 2: Aligning skills and knowledge

Year 2	**Block 1**	**Block 2**	**Block 3**	**Block 4**	**Block 5**
Course	Field Course 2	Bayesian Econometrics (Paap - EUR)*	Skills workshops 2, 3, 4: The Review Process, Grants Applications, & Academic Presentations	Research Hackathon (EUR, UvA, VU)	Thesis
EC	3	3	4	3	
Course	Field Course 3	Field Course 5	Field Course 6	Thesis	Thesis
EC	3	3	3		
Course	Field Course 4	Research Clinic	Thesis	Thesis	Thesis
EC	3	5			30
Total EC	**9**	**11**	**7**	**3**	**30**

*courses already existing at TI

FIELD SPECIFIC COURSES

Quantitative Finance	Lecturers
Asset Pricing	Laeven, Vellekoop (UvA), Szymanowska (EUR)
Empirical Asset Pricing	Eiling (UvA), Andonov (UvA)
Computational Finance	(UvA)
Financial Technology	(EUR)

Management Science	Lecturers
Data-driven Innovation Strategy	Bartelsman, König (VU)
Marketing Science	Pauwels (Northeastern)
Social Media Data Analytics for Business	Bos & Lindner (VU)
HR & OB Analytics	Svetlana (VU)
Prediction & Forecasting	Koopman (VU)
Supply Chain Analytics	**Lecturers**
Social Economic Networks Analysis	Heidergott & Lindner (VU)
Economics and Management of Network Businesses and Markets	Verhoef, Pels, de Graaff, König (VU)
Heuristic Optimization Methods	Gromicho & Vigo (VU), (EUR/UvA)
Integer Linear Programming	Dullaert, De Leeuw, Roberti, & Maroti (VU)
Decomposition Methods	Dabia, Roberti, & Stougie (VU), (EUR)
Other electives for all	**Lecturers**
Parallel Computing & Big Data	De Vlaming (VU)
Social Science Genetics	Koellinger & de Vlaming (VU)

FINAL EXAMINATION AND DIPLOMA

The Examination Board determines whether the student has passed all the requirements of the program and grants a diploma as proof that the student has passed his/her final examination. A GPA of 8 or higher in all examinations on the first attempt, without a compensated grade 5 and without a failed field course, within 24 months after the start of the program, entitles the student to the distinction of 'cum laude'. Degree and diploma are issued by the three participating universities as a joint degree.
Individuals who have successfully completed one or more components of the program will, on request, receive a statement stating the course(s) that have been completed together with the number of EC and the awarded grade (if applicable).

STUDENT COUNSELING

The Director of Graduate studies provides individual academic counseling for students enrolled in the program.

ADAPTATIONS FOR STUDENTS WITH A DISABILITY

A student with a disability can submit a written request to the Director of Graduate Studies to qualify for special adaptations to accommodate the student's individual disability as much as possible, but may not alter the quality or degree of difficulty of a course or an examination. In all cases, the student must fulfil the exit qualifications for the degree program. The request must be based on a recent statement from a physician or psychologist. In the case of dyslexia, a statement from a BIG, NIP or NVO accredited testing center will suffice. Where possible, the statement should include an estimation of the extent to which progress of study will be hindered. The Director of Graduate Studies decides on the adaptations concerning the teaching facilities and logistics. The Examination Board will rule on requests for adaptations with regard to examinations. A request for adaptations

will be refused if it would place a disproportionate burden on the organization or the resources of the institute.

TAKING SINGLE COURSES

EXTERNAL PARTICIPANTS

Under certain conditions and subject to approval by the Director of Graduate Studies, individuals not affiliated to one of the BDS partners (see below) are welcome to attend BDS courses. External participants pay € 2,250 for a core course (one block of 8 weeks including one exam week) and € 1,750 for a field course (one block of 8 weeks including one exam week). Special rates apply for external PhD students: € 1,500 for a core and field course.

Prospective external participants register for courses by filling out the registration form on the website. Please include your CV and a transcript of relevant earlier coursework, with grades. External applicants will only be admitted if they meet some equivalent of the BDS course entrance criteria. Capacity restrictions apply to all courses, and are particularly relevant for core courses. Deadline for registration is three weeks before the start of the block in which the course is scheduled (deadline for a block I course: August 15).

In case of withdrawal from a course: notify the educational office by sending an email to courses@businessdatascience.nl asap but no later than the Sunday after the first lecture (all BDS courses except intensive field courses). Fees will be charged in case of late withdrawal.

AFFILIATED PARTICIPANTS

PhD and research master's students affiliated to one of the partners of BDS are welcome to attend BDS courses. BDS partners are: SBE (Vrije Universiteit Amsterdam), SEB (University of Amsterdam), and ESE (Erasmus University). The DGS will check whether students meet the entrance requirements. Participation is subject to capacity constraints. Fees (€ 1,500 per course) are charged to the faculty. Course registration can be done by using the registration forms on the website. Students who would like to withdraw from courses should notify the educational office by email no later than Sunday after the first lecture (all courses except intensive field courses). Fees will be charged in case of late withdrawal.

BDS GRADUATES

Graduates from the BDS research master program working as PhD students at one of the partners of BDS (see above) are most welcome to participate in additional field courses during the later years of their studies. Please register for courses by using the registration form on the website. No fees will be charged for PhD students who have transferred from the BDS program.

BDS RESEARCH QUALIFICATION

BDS offers a special educational program for PhD students who entered the PhD track with only a one year MSc degree. BDS awards the BDS Research Qualification to PhD students who complete this special program. The requirements of the program are given below. The BDS Research Qualification is a condition for access to additional facilities provided by BDS: e.g. support on the job market in the final phase of the PhD period including an additional budget to participate in

international job market activities. Students who have completed BDS's research master program and students who have completed another, comparable high-level research master's program (to be assessed by the Director of Graduate Studies) already fulfill BDS' educational requirement and have access to the same additional facilities as students with the BDS Research Qualification.

THREE EDUCATIONAL PATHS

Three educational paths lead to the BDS Research Qualification. The objective of offering four different paths is to give individual PhD students the opportunity to participate in a limited program of PhD courses that is tailor-made to their needs and educational background, while maintaining some of the key characteristics of the full-fledged research master program:

- have an understanding of the core of business data science by taking rigorous and common training in one or more of the core subjects,
- have a sufficiently deep understanding of one business field by choosing a field in which at least 4 field courses are taken.

One of the following paths (I-III) may be chosen, depending on the student's background and interest:

Path	Core requirements	EC	Field requirements	EC	Other	EC	Total EC
I	Econometrics (or Advanced Econometrics), Unsupervised Machine Learning, Supervised Machine Learning, Natural Language Processing, Deep Learning	20	4 field courses in field of choice	12	3 other field courses or 2 additional core courses	8-9	40-41
II	Unsupervised Machine Learning, Supervised Machine Learning, Natural Language Processing, Deep Learning	16	4 field courses in field of choice	12	4 other field courses or 3 additional core courses	12	40
III	4 core courses (one course can be replaced by a field course)	16	4 field courses in field of choice	12	4 other field courses or 3 additional core courses	12	40

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ADMISSION

ADMISSION REQUIREMENTS

APPLICATION REQUIREMENTS	LANGUAGE OF THE PROGRAM	TARGET GROUP	DEGREE
Undergraduate degree GRE/GMAT* English proficiency (IELTS, TOEFL)* Strong motivation Two recommendations CV *not compulsory for Dutch degree students	English	Talented Bachelor students with strong analytical skills & interest in academic research in the field of business. The program can be seen as part of a PhD trajectory of "2+3" years (2 years for the coursework of the research master, and 3 years dedicated to research, fully paid).	MSc in Business Data Science

Specific entry requirements
Admission to the Research Master Business Data Science is achieved on a highly selective basis. No more than 30 students are admitted to the program each year. Admission is determined by an Admissions Board consisting of research fellows affiliated with the participating Schools and chaired by the Director of Graduate Studies. Criteria for admission are:

1 - Bachelor's degree
A Bachelor's degree, preferably in Econometrics, Operation Research, or Data Science. Students must complete their Bachelor's program prior to starting the Master's program.

2 - Recent GMAT and/or GRE (Graduate Record Examination)
Valid GMAT and/or GRE results from all international applicants (Students holding a Dutch Bachelor or Master degree are exempt from this requirement). Applicants with a GMAT score below 700 or a GRE Quantitative score below 160 will not be considered. Successful applicants typically rank among the top 10% of examinees on the quantitative section of the GMAT or GRE.

3 - Excellent command of English
Students whose native language is not English are required to demonstrate English proficiency in one of two ways:

a. by holding a degree from a Dutch university or an institution at which English is the language of instruction, or:
b. by scoring at least 600 on the paper-based Test of English as a Foreign Language (TOEFL), 250 on the computer-based TOEFL, 100 on the internet-based TOEFL or 7 on the International English Language Testing System (IELTS).

4 - Letter of motivation and research proposal
Students should be strongly motivated to pursue a career in (academic) research. Such motivation will be assessed based on a written letter of intent, including a research proposal (maximum two pages). The statement of purpose should be 300-500 words: it should include an explanation of the applicant's purpose for undertaking graduate study, his/her reasons for applying to the Research

Master Business Data Science in particular, his/her research interests, professional plans, and career goals. An interview with the Director of Graduate Studies and/or members of the Admission Board may be included in the selection procedure.

5 - Writing Sample (optional)
Bachelor or master thesis (in English) or a published article.

6 - Two letters of recommendation
Students must submit two letters of recommendation attesting to their capabilities and aspirations.

7 - Curriculum Vitae

APPLICATION DEADLINES

The application deadlines for enrolment in September 2020 are:

- May 15 for applicants who need to apply for a visa and residence permit
- June 30 for others
- For applications after June 30, please contact us.

All applicants are advised to submit their application early, because slots in the program and funding opportunities are limited.

Interested students should apply online through this link: https://tinbergen.embark.com/auth/login. For more detailed information on admission, fees and application procedures, please contact the BDS Admissions Officer Judith van Kronenburg, admissions@businessdatascience.nl Tel: +31 (0)10 40 88919.

TUITION FEES

For Research Master students. The tuition fees are determined annually by the Dutch government and the universities. They are due until all examinations are passed, including the completion of the research master thesis.
The annual tuition fee for the academic year 2020-2021 is:

EEA national	€ 2,143
non-EEA national	€ 15,600
students holding a Dutch MSc degree	€ 15,600

For PhD students. In the PhD phase no tuition fees are charged.

FINANCIAL SUPPORT

GRANTS AND SCHOLARSHIPS

We encourage all Business Data Science students to apply for external financial support. There are various grants and scholarships available, including:

- The Dutch Ministry of Education and Sciences offers scholarships covering costs of living expenses within the framework of cultural agreements between the Netherlands and other countries. Information is available from the Dutch embassy or consulate in your country or via Grantfinder and NUFFIC.
- In certain cases it is possible for Dutch/EU students to receive a monthly student loan or a partial refund of their tuition fees from the Dutch government. Government support is available for some groups of students:
    - Full-time students who are Dutch nationals and are under 30 years of age may be eligible for student finance in the form of a loan, a student travel product and a supplementary grant (depending on parental income).
    - The same scheme is open for selected groups of nationals of other countries.
    - Finally, EEA and Swiss nationals may be eligible for tuition fee restitution by the government.
- You can also contact the Ministry for Higher Education in your own country. There may be funds or foundations available for students planning to study abroad (e.g., the Colfuturo scholarships for students from Colombia).
- EUR, UvA, and VU scholarships:
    - Erasmus Education Fund is highly committed to recognizing excellence in academic achievement through offering financial support for talented students. Several scholarships are available per year for students who are motivated to study Bachelor's or Master's at Erasmus School of Economics. European nationals paying a statutory tuition fee have a chance to receive a one-year tuition fee compensation and non-European students can receive a € 3,000 reduction on their institution tuition fee. Also look here.
    - UvA: Amsterdam Merit Scholarship (AMS). The University of Amsterdam aims to attract the world's brightest students to its international classrooms. Outstanding students from outside the European Economic Area can apply for an (AMS), which covers your full tuition fee + a €3,500 start-up allowance. A limited number of AMS scholarships is available for non-EEA students in the Master's programs. Last year the top 8 percent of non-EEA MSc students were awarded an Amsterdam Merit Scholarship.
    - The Vrije Universiteit offers talented prospective students the unique opportunity to pursue a degree from a selection of Master's programs at Vrije Universiteit Amsterdam. Vrije Universiteit Amsterdam has committed to providing approximately 1 million euro towards attracting highly motivated, excellent students.

Business Data Science offers full or partial scholarships (covering the tuition fee, monthly installments and a contribution to health insurance costs) and tuition fee waivers (tuition fee and contribution to health insurance costs) to selected students. Scholarships and tuition waivers are granted by the Admission Board. Students who accept a BDS scholarship or tuition waiver are obliged to sign a statement in which they declare to agree with the scholarship regulations.

Scholarships are never cumulative: BDS will supplement external scholarships students may receive from an institution or governmental organization. Initially, a scholarship is granted for the program's first year (12 months) only.

Scholarships are paid to the student as long as the student actively participates in the program and as long as there is a reasonable expectation that the student will successfully complete the program according to the program's Academic and Examination Regulations. If a student is temporarily or permanently unable or unwilling to participate in the program, or if the Director of Graduate Studies asks the student to withdraw from the program because of unsatisfactory performance or misconduct, payment of the monthly installments may be discontinued. In case students withdraw from the program before the end of the academic year, students are required to cancel their registration with the university and to apply to the university for a (partial) refund of the tuition fees. Refunded fees will be repaid to TI, if a tuition waiver was part of the scholarship.

In order to maintain or be awarded a full scholarship in the second year of the program, students should fulfil the following requirements at the end of the first year of the program:

1. The student's weighted GPA for the core courses is 7.5 or higher at the end of course block IV of the first year of the program, and the student has earned sufficient credits to meet the entrance requirements for 2nd year courses;

2. Failed courses should be re-taken in the second year of the program. The scholarship will be immediately terminated in case the student fails the retake (a compensated 5 is considered as a sufficient result).

Students who do not meet these requirements may be awarded a tuition fee waiver or partial scholarship if funds are available. The scholarship is conditional on active participation in the program, fulfilling assigned TA duties, and the likelihood of completing the program according to the program's Academic and Examination Regulations.

TEACHING AND RESEARCH ASSISTANTSHIPS

The first year of the program leaves little or no time for any jobs. From the end of the first year, students can apply for teaching and research assistantships in one of the departments connected with their thesis/research interests.

TRANSITION TO THE PHD PROGRAM

Students who perform well in the program usually transfer to the three-year PhD program. Students are assisted in the transition to the PhD program and in finding one or more PhD thesis supervisors with whom they prepare a PhD thesis proposal. Ideally, but not necessarily, the thesis will be the basis of the PhD thesis proposal and the thesis supervisor will be the PhD thesis supervisor. The main PhD supervisor (the "promotor") should be a full professor in one of the departments behind BDS.
Students admitted to the PhD program are typically employed by this faculty as a PhD researcher ("promovendus"). This is a full-time position that comes with all the benefits of employment, including a good salary. Thus, such PhD students are fully funded. A gross salary starts at € 2,709 per month. In their final year, students will receive a monthly gross wage of € 2,972. More information is available here:

After completion of the BDS program, students have complied with all coursework requirements of the graduate program and typically spend most or all of their time on PhD research. Nevertheless, students are most welcome to participate in additional field courses during the later (PhD) years of their studies . PhD students can register for courses using the registration form that is available on the website. No fees will be charged for PhD students who have completed the BDS program.

LIVING EXPENSES

Students living and studying in the Netherlands for one year spend between € 800 and € 1,100 a month. More information on living expenses can be found here .

business
data science

GRADUATE PROGRAM

COURSE DESCRIPTIONS

THE MOST RECENT COURSE MANUALS ARE ALWAYS AVAILABLE ON THE INTRANET

Core courses

Statistics

Instructor: Prof. dr. P.J.C. Spreij (UvA).

Short subject description: The course starts off with the very first principles of probability and quickly passes on to essential statistical techniques. Estimation and testing theory will be reviewed, including maximum likelihood estimators, likelihood ratio test and (least squares) regression.

Course contents: In the course we treat the following topics: sample spaces, probability measures, distribution functions, random variables with discrete and continuous distributions, functions of random variables, multivariate distributions, random vectors, independent random variables, conditional distributions, functions of random vectors and their distributions, expectation and variance, covariance and correlation, the law of large numbers, central limit theorem, chi-square and t-distributions, estimation, method of moments, maximum likelihood, large sample theory, confidence intervals, Cramer-Rao bound, hypothesis testing, Neyman-Pearson paradigm, likelihood ratio tests, confidence intervals, linear regression, least squares estimation of regression parameters, testing regression hypotheses.

Course objective: After the course students will be able to apply fundamental techniques needed for statistical inference. They will also be in the position to continue study and research on a more advanced level. Information will also become available on: staff.science.uva.nl/~spreij/onderwijs/TI/statistics.html.

Literature: J. A. Rice (1995). Mathematical Statistics and Data Analysis, 2nd Edition, Duxbury Press, ISBN: 0-534-20934-3 or 3rd Edition (2007), ISBN: 0-534-39942-8.

Assessment methods, grading and criteria: written closed book exam (85%) and homework assignments (15%).

Term: Year 1, Block 1.

Credits: 4 EC.

Mathematics

Instructor: dr. F.O.O. Wagener (UvA).

Short subject description: This course reviews fundamental mathematical methods that they will need in the course of the BDS programme.

Course content:

1. matrix algebra
2. vector calculus
3. static optimisation
4. integration
5. differential equations
6. dynamic optimisation.

Course objective: The students will learn to work with mathematical results that are necessary for a fundamental understanding of economic theory.

Literature: lecture notes.

Assessment methods, grading and criteria: written closed book exam (85%) and homework assignments (15%).

Term: Year 1, Block 1.

Credits: 4 EC.

Decision Theory for Business

Instructors: dr. J.R. van den Brink (VU), dr. A. Estevez-Fernandez (VU).

Short subject description: Decision Theory models problems of individual and group decision making, trying to optimize certain objectives and/or reach desirable outcomes.

Course content: Understanding how people make decisions is essential to understand Business processes. In many decision situations in Business, agents have to make strategic decisions, trying to optimize their own objective, but taking account of the behavior of their competitors who usually have conflicting interests. This can be between firms (for example, when firms compete on markets), between firms and other agents (for example, in wage negotiations between firms and trade unions), but also within firms (for example, to decide if it is optimal to monitor employees). Strategic or non-cooperative game theory studies these strategic decision situations. Specifically, we give attention to contract theory and auctions. On the other hand, coalitional game theory is often used as a decision support system in valuation problems, for example in remuneration within firms, cost/budget allocation, or attribution problems such as its application in Google Analytics' data driven attribution model which is used in, for example, marketing conversion.
In this course, we will discuss basic methods and models of decision making, such as game theory and multi criteria analysis, and consider application to business situations. Besides the business related examples mentioned above, we discuss some decision models that are the foundation of microeconomics such as models of consumer behavior and game theoretic models of industrial organization.

Course objective: The course intends to let the students get familiar with basic models of decision making, including individual decision making, interdependent decision making (game theory) and multi criteria analysis. Moreover, the students learn how to apply these models and tools to optimize decision making in various business situations and microeconomics.

Literature: lecture notes and selected papers.

Assessment methods, grading and criteria: exam (85%) and take-home assignment (15%).

Term: Year 1, Block 1.

Credits: 4 EC.

Econometrics I

Instructor: dr. A. Schnücker (EUR).

Short subject description: This course provides knowledge on the quantitative analysis of economic data.

Course contents: In this course we provide an understanding of basic econometric methods. Knowledge of these methods allows one to understand modern empirical economic literature and to perform one's own analysis of economic and business data. The technique of regression is discussed, as well as various extensions that are needed in concrete applications to deal with, for example, heteroskedasticity, autocorrelation, endogeneity, and non-linearities. Furthermore an introduction to discrete choice modeling is given. The main emphasis of the course is on the interpretation of models and outcomes of estimation and testing procedures. The students practice this themselves by analyzing economic and business data by means of the econometric software package EViews and by interpreting and extending formulas for basic models and concepts.

Course objectives: After this course students will be able to apply econometric techniques to answer empirical questions and will be able to critically evaluate econometric models.

Literature:
C. Heij, P.M.C. de Boer, P.H. Franses, T. Kloek, and H.K. van Dijk (2004).
Econometric Methods with Applications in Business and Economics, Oxford University Press, Oxford (ISBN:0-19-926801-0)
Recommended:
M. Verbeek (2004). A Guide to Modern Econometrics (3rd edition), Wiley. J.M. Wooldridge (2000). Introductory Econometrics, a Modern Approach (4th edition), South Western College Publishing.

Assessment methods, grading and criteria: written closed book exam (85%) and homework assignments (15%).

Recommended knowledge: Statistics, Mathematics.

Term: Year 1, Block 2.

Credits: 4 EC.

Supervised Machine Learning

Instructors: prof. dr. P.J.F. Groenen (EUR), dr. P. Schoonees (EUR).

Short subject description: Statistical learning methods arising from statistics, machine learning, and data science have become more widespread available. Machine learning methods can be split in supervised learning with the aim of predicting a response variable and unsupervised learning describing the relations between all variables simultaneously. This course focusses on supervised learning and has as its goal that the student obtains a thorough technical understanding of selection of supervised machine learning techniques, can choose between them sensibly, can implement the technique in a high level language such as R, python, Julia, or Octave, and can write a report about the technique.

Course content: The book of Hastie, Tibshirani, and Friedman (2001, 1st edition) has been a milestone in connecting statistical ideas into machine learning techniques. Parts of this book will form the basis of this course. A tentative overview of techniques and ideas to be treated are a selection of linear methods for regression, linear methods for classification, basis expansion and regularization, model assessment and selection, classification and regression trees, ensemble learning (random forests, bagging, and bosting), regularized generalized canonical correlation analysis, partial least-squares, and support vector machines.

Course objective: To understanding the fundamental building blocks of several machine learning methods, being able to choose from them, being able to program these methods, and being able to apply them sensibly.

Literature: Hastie, Tibshirani, R. Tibshirani, and J. Friedman. "The elements of statistical learning New York." *NY: Springer* (2009).
Selected papers.

Assessment methods, grading and criteria: Participants of this course will do group assignments (15%) and a final exam (85%).

Recommended knowledge: business foundation, basic programming, mathematics, statistics. Required knowledge: linear algebra.

Term: Year 1, Block 2.

Credits: 4 EC.

Unsupervised Machine Learning & Reinforcement Learning

Instructors: prof. dr. G. Liberali (EUR), dr. P.C. Schoonees (EUR).

Short subject description: This course focuses on using machine learning methods to model and solve problems relevant to management science problems. The course partially focusses on unsupervised machine learning techniques that aim at finding meaningful patterns in data. Several nonparametric exploratory techniques are treated. The other main focus of this course is on

reinforcement learning. Here, it will also focus on the design, solution, and implementation of learning methods for sequential decision-making under uncertainty. Sequential decision problems involve a trade-off between exploitation (acting on the information already collected) and exploration (gathering more information). These problems arise in many important domains, ranging from online advertising, clinical trials, website optimization, marketing campaign and revenue management.

Course content:

1. principal components analysis (PCA) including PCA for big and sparse data
2. clustering techniques (k-means, hierarchical, convex clustering)
3. mixture models
4. multidimensional scaling
5. introduction to reinforcement learning and multi-armed bandits
    a. Examples, formulation and preliminary results
6. multi-armed bandit methods
    a. Optimality of index-based policies
    b. Heuristics: one-step look ahead, regret policies, Thompson sampling
7. multi-armed bandit modeling strategies and applications

Course objective: To understanding the fundamental building blocks of machine learning methods, being able to choose from them, being able to program these methods, and being able to apply them sensibly.

Literature:

Optimal Learning, by Warren B. Powell and Ilya O. Ryzhov, Wiley, 2012.
Gittins, J.C., K. Glazebrook, and R. Weber. 2011. Multi-armed bandit allocation indices. London: Wiley.
Hauser, J.R., G. Liberali, and G.L. Urban. 2014. Website morphing 2.0: Switching costs, partial exposure, random exit, and when to morph. Management Science 60 (6): 1594–1616
Schwartz, E.M., Bradlow, E.T., and Fader, P.S. 2017. Consumer acquisition via display advertising using multi-armed bandit experiments. Marketing Science, 36(4)
Scott, S.L. 2010. A modern Bayesian look at the multi-armed bandit. Applied Stochastic Models Business and Industry 26 (6): 639–658.

Assessment methods, grading and criteria: Each student will have to complete two assignments (15% of the final grade) and produce a final paper (85% of the final grade).

Recommended knowledge: business foundation, basic programming, mathematics, statistics, econometrics.
Required knowledge: Linear and logistic regression, Linear algebra, R (or Python or Matlab) skills.

Term: Year 1, Block 3.

Credits: 4 EC.

Causal Inference & Experimentation

Instructors: dr. J. M.T. Roos (EUR), dr. Xi Chen (EUR).

Short subject description: This course presents an integrated view of causal inference: the dominant theories and their connections with tools from econometrics and randomized experiments.

Course content: This course gives an integrated view of causal inference. It covers basic questions like what is causality and how is it different from correlation? It addresses conceptual issues, like how to express causal relations and prove identification. And it connects these ideas with implementations from statistics, econometrics, and experimental design. The course presents the two dominant theories of causal inference. One is Rubin's Potential Outcomes framework. The other is Pearl's graphical Structural Causal Models. The course presents Pearl's theory in depth while connecting it with Rubin's framework. Important differences between the two frameworks are also explored.
The course emphasizes techniques for exploring causality in the context of applied problems. But it also connects these tools with concepts from econometrics and randomized trials, including: instrumental variables, propensity scores, differences-in-differences, regression discontinuity, stratification, direct and indirect effects, confounding, and selection.

Course objective: Students will understand how to determine the data, assumptions, and tools needed to identify and measure causal effects.

Literature: A mix of lecture notes, online texts, and scientific articles.

Assessment methods, grading and criteria: Final exam (85%) and assignments (15%) involving a mix of analytical derivations and coding in R.

Recommended knowledge: business foundation, basic programming, mathematics, statistics, econometrics.
Required knowledge: Linear regression, Linear algebra, R (or Python or Matlab) skills.

Term: Year 1, Block 5.

Credits: 4 EC.

Econometrics II: Microeconometrics

Instructors: prof. dr. B. van der Klaauw (VU), dr. H.G. Bloemen (VU).

Short subject description: This course focuses on drawing inference from cross-sectional and panel data using techniques that are frequently used in applied econometric research.

Course content: Many empirical questions in economics require estimating causal parameters. Regression models provide correlations which only have a causal interpretation if the zero conditional mean assumption holds. This assumption is often violated, for example when there are omitted variables, non-random sampling, reversed causality or measurement errors in regressors. In this course we discuss methods dealing with these confounding factors. In particular, we consider limited dependent variable models, instrumental variables estimation, panel data models and sample weighting. In this course, we introduce the potential outcomes model, which is the most general model for defining treatment effects such as average treatment effect, average treatment

effect on the treated, quantile treatment effects and local average treatment effects. The emphasis of the course is on identification, estimation and interpretation rather than a thorough treatment of the asymptotic properties of the estimators. During the course applications of the different methods are discussed, mainly in the fields of labor economics, health economics, and the economics of education.

Course objective: The key objective of the course is applying microeconometric techniques rather than deriving econometric and statistical properties of estimators. After the course student should be able to decide about the appropriate model, apply the estimation method correctly, and they should be able to interpret the estimation results.

Literature: Cameron, A.C. and P. Trivedi (2005). Microeconometrics: Methods and Applications, Cambridge University Press.

Assessment methods, grading and criteria: written closed book exam (85%) and homework assignments (15%).

Recommended knowledge: mathematics, statistics, econometrics.
Required knowledge: Linear regression.

Term: Year 1, Block 3.

Credits: 4 EC.

Econometrics III: Time-series Econometrics

Instructor: Prof.dr S.J. Koopman (VU)

Short subject description: This course provides knowledge on the quantitative analysis of economic time series.

Course content: In this course we provide an understanding of basic econometric methods for the analysis of time series. Knowledge of these methods allows one to understand modern empirical economic literature and to perform one's own analysis of economic and business time series data. Autoregressive Moving-Average (ARMA) models are considered for stationary time series. Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are discussed for describing the time-varying volatility of time series. Models (and tests) for deterministic and stochastic trends are addressed. It is discussed how forecasts are computed and assessed. Further, multivariate time series models are considered: the Vector Autoregression (VAR) and cointegration. The main emphasis of the course is on the interpretation of models and outcomes of estimation and testing procedures. The students practice this themselves by analyzing economic and business time series by means of the econometric software package EViews and by interpreting and extending formulae for basic models and concepts.

Course objectives: After this course students will be able to apply time series models to answer empirical questions and will be able to critically evaluate such models.

Literature:
James D. Hamilton (1994), Time Series Analysis, Princeton University Press
Walter Enders (2015), Applied Econometric Time Series, Wiley, 4th Edition
M. Hashem Pesaran (2015), Time Series and Panel Data Econometrics, Oxford University Press.

Assessment methods, grading and criteria: written closed book exam (85%) and homework assignments (15%).

Recommended knowledge: mathematics, statistics, econometrics.
Required knowledge: Linear regression, Linear algebra.

Term: Year 1, Block 4.

Credits: 4 EC.

Simulation analysis & Optimization

Instructors: prof. dr. B.F. Heidergott (VU), dr. A.A.N Ridder (VU).

Short subject description: This course addresses the use of computer simulation for the analysis and optimization of stochastic dynamic models. Applications will stem from a wide range of domains from Financial Engineering and Business Processes.

Course content: This course gives a broad treatment of the important aspects of Monte Carlo simulation and its applications in areas such as inventory control, project planning, reliability, risk analysis and financial models. The emphasis is on modeling the stochastic dynamic system as a discrete event system, and analyzing and improving its performance by means of discrete event simulation. The topics covered include generating random numbers, selecting input distributions and model validation. The course also teaches the statistical output analysis and the use of simulation in optimization and learning.

Course objective: After successful completion of this course, students will be able to:
1. model real-life problems by discrete-event models,
2. conduct Monte Carlo simulation-based analysis of a problem and provide an output analysis,
3. apply simulation in optimization and learning, and to report on their findings.

Literature:
Chapters 1,2,5,6,7,8,9 of Averill Law: Simulation Modeling and Analysis, Mc Graw Hill 4-th or 5-th ed.
Chapter 11 of Cassandras and Lafortune: Introduction to Discrete Event Systems, Springer, 2nd ed, 2008.

Assessment methods, grading and criteria: sit-in written exam (3 hours; 75%, at least 5,0 required) and 2 additional take-home assignments (partly numerical computer work; 25%)

Recommended knowledge: business foundation, basic programming, mathematics, statistics, econometrics.

Term: Year 1, Block 4.

Credits: 4 EC.

Natural Language Processing

Instructor: dr. Meike Morren (VU) and prof. dr. Bas Donkers (EUR)

Short subject description: Natural language processing (NLP) comprises statistical and machine learning tools for automatically analysing text data to derive useful insights from it. Vast amounts of information are stored in this form, and hence NLP has become one of the essential technologies of the big data age. In this course, core concepts and techniques from the area will be studied, with a focus on methods that are popular in business applications. These include n-gram models, word vectors, sentiment analysis and topic modelling.

Course content:

1. Information theory, regular expressions and edit distances
2. The n-gram model and corpus processing (tokenization, stemming, lemmatization, parsing).
3. Word vectors and embeddings
4. Sentiment analysis
5. Topic and sentence modeling
6. Applications and an overview of different NLP research areas

Course objective: Understanding the fundamentals of natural language processing including different ways of representing text data for statistical analysis, being able to discuss and apply different sentiment analysis and topic modelling techniques, programming selected algorithms involved in these methods, and getting acquainted with NLP research areas.

Literature: Jurafsky, D., & Martin, J. H. (2014). *Speech and language processing* (Vol. 3). London: Pearson.
Manning, C. D., Manning, C. D., & Schütze, H. (1999). *Foundations of statistical natural language processing*. MIT press.

Selected papers, including:
Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of machine Learning research*, *3*(Jan), 993-1022.
Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems* (pp. 3111-3119).
Hu, M., & Liu, B. (2004, July). Mining opinion features in customer reviews. In *AAAI* (Vol. 4, No. 4, pp. 755-760).
Pennington, J., Socher, R., & Manning, C. (2014). Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)* (pp. 1532-1543).

Assessment methods, grading and criteria: Participants of this course will do group assignments (15%) and a final individual assignment (85%).

Recommended knowledge: business foundation, basic programming, mathematics, statistics, econometrics, machine learning.

Term: Year 1, Block 4.

Credits: 4 EC.

Bayesian Econometrics

Instructor: prof. dr. R. Paap (EUR).

Short subject description: This course provides an extensive introduction in Bayesian econometrics. It covers the Bayesian concepts and simulation techniques necessary to perform modern Bayesian analyses.

Course content: Bayesian Econometrics plays an important role in quantitative economics, marketing research and finance. This course discusses the basic tools which are needed to perform Bayesian analyses. It starts with a discussion on the difference between Bayesian and frequentist statistical approach. Next, Bayesian parameter estimation, forecasting and Bayesian testing is considered, where we deal with univariate models, multivariate models and panel data models (Hierarchical Bayes techniques). To perform a Bayesian analysis, knowledge of advanced simulation methods is necessary. Part of the course is devoted to Markov Chain Monte Carlo sampling methods including Gibbs sampling, data augmentation and Monte Carlo integration. The topics are illustrated using simple computer examples which are demonstrated during the lectures.

Course objective: After following the course, students are able to understand scientific articles in marketing, economics and finance, where Bayesian analysis is applied. Furthermore, they are able to apply and implement a Bayesian analysis in packages like Matlab or Ox and the program Winbugs.

Literature:
Lecture slides and selected papers
Greenberg, E. (2013). Introduction to Bayesian Econometrics, Cambridge University Press, 2nd edition.

Assessment methods, grading and criteria: sit-in written examination (100%).

Required knowledge: Econometrics.

Term: Year 2, Block 2.

Credits: 3 EC.

Deep Learning

Instructor: dr. E. Raviv (EUR, UvA, VU).

Short subject description: A both theoretical and practical course on deep learning, its applications, state of the art and future deep learning.

Course content:

1. Introduction to Deep Learning (theory and practice)
2. Deep Learning components (gradient descent models, loss functions, avoiding over-fitting, introducing asymmetry)
3. Feed forward neural networks
4. Transfer learning (pre-trained image classification models, pre-trained embeddings, examples of pre-trained models in images and text (GloVe embeddings, Word2Vec, VGG16, etc.) , bottleneck features and their use)
5. Convolutional neural networks
6. Embeddings
7. Recurrent neural networks
8. Long-short term memory units
9. Gated recurrent units
10. reinforcement learning.

Course objective: To understanding the fundamental building blocks of deep learning methods, being able to choose from them, being able to program these methods, and being able to apply them sensibly.

Literature: lecture notes, selected articles and book chapters.

Assessment methods, grading and criteria: assignments (15%) and exam (85%).

Recommended knowledge: business foundation, basic programming, mathematics, statistics, econometrics, machine learning.

Term: Year 1, Block 5.

Credits: 4 EC.

Advanced core courses

The most recent course manuals are always available on the Intranet.

These courses can be selected by students with a sufficient knowledge of statistics, mathematics and econometrics.

Asymptotic Theory

Instructors: Prof.dr. P.J.C. Spreij (UvA).

Short subject description: This is a crash course, highlighting the main principles of measure theory and asymptotic methods in statistics.

Course content: Part I: Sigma-algebras, measure, integration w.r.t. a measure, limit theorems, product measure and integration, change of measure, conditional expectation. Part II: Multivariate central limit theorem, quadratic forms, delta-method, moment estimators, Z-and M-estimators, consistency and asymptotic normality, maximum likelihood estimators.

Course objective: After the course students will be familiar with the mathematical fundamentals of measure theory and asymptotic methods in statistics.

Literature: lecture notes.

Assessment methods, grading and criteria: written closed book exam (85%) and homework assignments (15%).

Term: Year 1, Block 1.

Credits: 4 EC.

Advanced Mathematics

Instructor: dr. F.O.O. Wagener (UvA).

Short subject description: This course is aimed at students with a quantitative background, like econometrics, mathematics, physics etc. It reviews advanced mathematical methods that they will need in the course of the BDS programme.

Course content: After the course the students will learn to work with the main results of the following areas:
1. Real analysis, especially different notions of convergence
2. Fixed point theorems
3. Differential equations
4. Static optimisation
5. Calculus of variations and optimal control
6. Discrete time dynamic optimisation.

Course objective: The students will learn to work with mathematical results that are necessary for an advanced understanding of economic theory.

Literature: Lecture notes.

Assessment methods, grading and criteria: written closed book exam (85%) and homework assignments (15%).

Term: Year 1, Block 1.

Credits: 4 EC.

Advanced Econometrics I

Instructor: dr. C.S. Bos (VU) & Prof.dr D. Fok (EUR).

Short subject description: Advanced Econometrics I covers the background Econometric Theory and a set of Microeconometric models.

Course content: The course is built up around the book of Cameron & Trivedi, with references to the material of Hansen. The first four lectures discuss ordinary least squares and related methods, maximum likelihood, hypothesis and specification testing. They are followed by a discussion of the main micro-econometric models, including models for binary and multinomial outcomes, tobit and selection models, and finally models for duration data. Theoretical exercises are discussed throughout this course. Concepts are illustrated by means of simulations and empirical applications. In class, the Python programming environment is used, though students are free to choose their own.

Course objective: By the end of this course, students will have gained a thorough understanding of the theory behind basic least squares estimation and inference, and the extension towards estimation through a likelihood function. They are able to apply this knowledge on micro-econometric models, and understand the consequences of modelling decisions. This will have set the scene for the more general models and estimators to be covered in Advanced Econometrics II and III.

Literature: C. Cameron and P. Trivedi (2005). Microeconometrics: Methods and Applications, Cambridge
University Press. B. E. Hansen (2017). Econometrics,

Assessment methods, grading and criteria: written closed book exam (85%) and homework assignments (15%).

Term: Year 1, Block 2.

Credits: 4 EC.

Advanced Econometrics II

Instructor: prof. dr. F.R. Kleibergen (UvA) and dr. A. Pick (EUR).

Short subject description: Advanced Econometrics II develops the necessary theory for understanding core econometric techniques based on regression, GMM and likelihood methods.

Course content: The course covers Program Evaluation, Clustering, Instrumental Variables, Generalized Method of Moments and Likelihood based techniques. Modeling approaches, estimation and testing methods are developed and asymptotic techniques and finite sample properties are discussed.

Course objective: Obtaining a deep understanding of econometric theory and the practice of producing econometric inference especially with respect to the specification, estimation, and testing of models for causal inference and for linear and nonlinear relationships by least-squares, instrumental variables and GMM or likelihood based techniques.

Literature: Compulsory: Cameron A. and Trivedi, P.K. (2005). Microeconometrics: Methods and Applications,
Cambridge University Press
Recommended: Additional reading from books and papers

Assessment methods, grading and criteria: written closed book exam (85%) and homework assignments (15%).

Term: Year 1, Block 3.

Credits: 4 EC.

Advanced Econometrics III

Instructors: prof. dr. H.P. Boswijk (UvA) and prof. dr. S.J. Koopman (VU).

Short subject description: This course discusses advanced models and methods for the econometric analysis of economic and financial time series.

Course content: Several major advances in time-series econometrics and likelihood-based inference have occurred in the past years. These advances have provided a major breakthrough in the modeling of time series using advanced up-to-date econometric methodologies. The first part of the course aims to provide a thorough understanding of linear time series models, including frequency domain analysis, multivariate models and cointegration. The second part focusses on state space models and the Kalman filter, discussing signal extraction, maximum likelihood estimation and dynamic factor models. The course will also discuss ARCH and score-driven volatility models. Various empirical illustrations in economics and finance will be discussed.

Course objective: Students will receive a good training in time-series econometrics, the modeling of economic and financial time series using advanced techniques.

Literature:

Compulsory:
Durbin, J. and Koopman, S.J. (2012). Time Series Analysis by State Space Methods, Second Edition, Oxford University Press.
Van der Vaart, A.W. (2013), Time Series. Lecture notes, Universiteit Leiden. http://www.math.leidenuniv.nl/~avdvaart/timeseries/dictaat.pdf.
Recommended:
Brockwell, P.J. and Davies, R.A. (1987). Time Series: Theory and Methods, New York: Springer-Verlag
Harvey, A.C. (1989). Forecasting, Structural Time Series Models and the Kalman filter, Cambridge University Press.
Shumway, R.H. and Stoffer, D.S. (2000). Time Series Analysis and Its Applications, New York: Springer-Verlag.

Assessment methods, grading and criteria: written closed book exam (85%) and homework assignments (15%).

Term: Year 1, Block 4.

Credits: 4 EC.

Compulsory Field Courses

The most recent course manuals are always available on the Intranet.

Business Foundations (block 0 course)

Instructors: prof. dr. W.E.H. Dullaert (VU), prof. dr. W. Stam (VU), prof. dr. ir. B.G.C. Dellaert (EUR), dr. C.I.S.G. Lee (EUR), prof. dr. A. Menkveld (VU).

Short subject description: The course provides an overview of business principles, and it introduces the students to the different business disciplines they can focus on in the second year of their study program.

Course content: The course provides a synopsis of the types of decisions each business field faces, highlighting the most relevant topics and problems per field, as well as how data science can help to address these business problems. The broad objective of this course is to present the students with a business framework that will allow them to see how future courses relate to each other. It is not designed to answer all business questions, as the business world is much too complex to be "covered" in a single course. Instead, this course is designed to generate more questions than can be answered. The answers to those questions will come later as students proceed through the business data science curriculum all the way to their research master thesis.

Course objective: Upon completion of this course, students will be able to:
1. Understand the basic principles of business, including the types of decisions that each business discipline faces.
2. Explain how the various functional areas of a business (such as marketing, organization, logistic, finance) contribute to the formulation of common business decisions.

3. Identify relevant business problems per research discipline.
4. Understand how data science can be used to address these business problems.
5. Have an understanding of business that allows them to broadly read and understand the current scientific literature in business and management, and follow scientific debates across these sciences.

Literature: lectures notes and slides.

Assessment methods, grading and criteria: assignment (100%).

Term: Year 1, Block 0.

Credits: 1 EC.

Principles of Programming (block 0 course)

Instructor: dr. C.S. Bos (VU).

Short subject description: This course provides a primer to students on how to tackle in general a programming problem in Econometrics.

Course content: During four consecutive days, the basics of programming in Econometrics are explained. This course starts with a single day where we discuss the basic syntax of the programming language Python, with excursions to other languages like Matlab and/or Julia. Using Python as a workhorse, during the next three days general concepts of programming are discussed, including how to proceed from a set of equations via an algorithm to a valid program, robustness of programming, and other more practical topics related to Econometrics. Each of the topics is explained using Python code, exploring syntax and pitfalls as we go.
The course is split between a theoretical and a practical part. The theoretical part assumes a matrix-oriented programming language. It is not immediately related to a specific programming environment, though examples will be given in Python, with some Matlab and Julia for comparison. For BDS Research Master students, the practical part of the course uses Python to implement several exercises, under the guidance of assistants. Students are expected to have studied the initial exercise E0, available through the website mentioned below, before the start of the course. They are welcomed to read through the slides on the syntax, ppectr_python_syntax.pdf in advance. Background material can be found at the websites of Kevin Sheppard , or Thomas Sargent & John Stachurski.

Course objective: After the course students are able to analyze the programming problem they have at hand, to split the task into smaller subtasks and define clearly the dependencies between the tasks. They have learned how to structure their program, and how to choose wisely the data structure that is helpful in solving the problem. They are able to set up the necessary code in Python.

Literature:
Quantitative Economics, Thomas Sargent & John Stachurski,
https://lectures.quantecon.org/py/(Python)

Python for Econometrics, Kevin Sheppard,
https://www.kevinsheppard.com/Python_for_Econometrics
Slides (available through ppectr_python_syntax.pdf)

Assessment methods, grading and criteria: take home test (100%).

Term: Year 0, Block 0.

Credits: 1 EC.

Parallel Computing & Big Data

Instructor: dr. R. de Vlaming (VU).

Short subject description:
Parallel-computing techniques are increasingly important for data science in business. This course provides the underlying theory as well hands-on applications of state-of-the-art techniques for parallel computing.

Course content:
Big data is omnipresent in modern society: ranging from GPS to weather data, online shopping behaviour, biobanks holding genetic data, and so on. Moreover, big data is becoming increasingly important for data science in business. Although big data, in conjunction with machine-learning techniques, promises both new and deeper insights into, for instance, consumer behaviour, such promises cannot be fulfilled unless one is able to analyse such data efficiently. Parallel computing provides the means to make many big-data analyses feasible. This course, therefore, teaches students state-of-the-art parallel-computing techniques. The course considers both theory as well as hands-on applications.
On the theoretical side, the course considers elementary parallel algorithms, metrics to evaluate performance, the scalability of parallel algorithms, and methods for designing parallel algorithms.
On the practical side, students will get hands-on experience with parallel computing in R and Python, in particular using Apache Spark. In addition, students will get acquainted with parallel computing using dockers. Finally, students will use the Lisa system (part of the Dutch super computer facilities) to carry out parallel-programming assignments.
For this course, students are expected to have prior experience with one or more high-level programming languages, such as R, Python, C, and Matlab.

Course objectives:

1. A deep theoretical understanding of
    a. basic parallel algorithms,
    b. performance metrics in parallel computing,
    c. scalability of parallel problems, and
    d. methods for designing parallel algorithms.
2. Learn to write parallel code in R and Python.
3. Learn to handle and work with
    a. big data,
    b. the Lisa super computer system,

c. Apache Spark, and
d. dockers.

Literature: Z. J. Czech (2016). Introduction to Parallel Computing, 1st Edition, Cambridge University Press, ISBN-13: 978-1-107-17439-9.

Assessment methods: homework assignments (25%), exam (75%).

Term: Year 1, block 2.

Credits: 3 EC.

Track-Specific Field Courses: Quantitative Finance

Important note: field courses and/or tracks may be cancelled in case less than 5 students sign up for a course/track.

Asset Pricing

Instructors: prof. dr. R.J.A. Laeven (UvA), prof. dr. M.H. Vellekoop (UvA), dr. M. Szymanowska (EUR).

Short subject description: Asset Pricing is concerned with the value of uncertain future payoffs.

Course content: This course provides an introductory yet comprehensive and rigorous treatment of modern asset pricing theory. It covers the following topics:

1. Expected utility, risk aversion and single period portfolio choice;
2. Mean-variance analysis and CAPM;
3. Multifactor pricing models;
4. Stochastic discount factors and the Fundamental Theorem of Asset Pricing;
5. Dynamic programming and pricing in incomplete markets;
6. Derivatives;
7. Stochastic calculus.

Course objective: Students who successfully complete this course will have an in-depth overview of modern asset pricing theory.

Literature: Selected chapters from:
Pennacchi, G. (2008). Theory of Asset Pricing, Addison-Wesley.
Cochrane, J. (2005). Asset Pricing (revised edition), Princeton University Press (Background reading material).
Selected articles and Lecture notes and other material, to be made available via Canvas.

Assessment methods, grading and criteria: written closed book exam (85%) and homework assignments (15%).

Recommended knowledge: econometrics, machine learning.
Required knowledge: business foundation, seminar series (finance).

Term: Year 1 or 2, Block 3.

Credits: 3 EC.

Financial Technology

Instructor: tbd (EUR)

Short subject description: Financial Technology (FinTech) covers technology-enabled business model innovation in the financial services industry.

Course content: FinTech covers technology-enabled business model innovation in the financial services industry. FinTech is rapidly evolving across the globe and represents an existential challenge for major parts of the financial sector. These innovative technologies can disrupt existing industry structures and blur industry boundaries, facilitate disintermediation, radically change how firms create and deliver products and services, generate significant privacy, regulatory and law-enforcement challenges, offer new gateways for entrepreneurship, and create opportunities for inclusive growth.
In this course, we will provide an introductory overview of innovations that are central to FinTech. Specifically, these innovations include cryptocurrencies and the blockchain, mobile and digital payment systems, social trading and robo advice, marketplace lending, crowdfunding. We will also explore threats and opportunities that these technologies pose to incumbent firms and discuss the way that FinTech interacts with law enforcement and regulation issues. The approach adopted to address these themes is analytical. Furthermore, the course will feature a number of guest speakers from industry.

Course objective: At the end of this course students will be able to:

1. Demonstrate a broad understanding of what FinTech is and why it emerged.
2. Understand and explain the fundamentals of the following FinTech: blockchain/cryptocurrency, payment systems, crowdfunding, marketplace lending, social trading/robo advice.
3. Analyze the potential of these FinTech and evaluate why they may change financial services.
4. Understand and explain how technology and regulation are interacting and impacting on financial services.
5. Critically assess new technologies and FinTech business models.

Literature: Articles, to be announced. Burniske, C. and J. Tatar (2017). Cryptoassets: The Innovative Investor's Guide to Bitcoin and Beyond, McGraw-Hill (ISBN: 978-1260026672)

Assessment methods, grading and criteria: assignments (15%), and written exam (85%).

Recommended knowledge: econometrics, machine learning.
Required knowledge: business foundation, seminar series (finance), asset pricing.

Term: year 2, block 2.

Credits: 3 EC.

Empirical Asset Pricing

Instructors: dr. E. Eiling (UvA), dr. A. Andonov (UvA)

Short subject description: Empirical Asset Pricing studies the time-series and the cross-sectional behavior of asset prices. The field is highly relevant for research in financial economics. It is the basis for any study in investments and also fundamental to many financial management applications such as risk management, portfolio selection and performance evaluation.

Course content:
1. Cross-section of stock returns
2. Cross-section of stock returns (presentations)
3. Time-series return predictability
4. Mutual funds and asset management
5. The cross-section and time series of currency returns
6. Private equity and alternative assets
7. Investments and consumption-based asset pricing
8. Student presentations.

Course objective: Students who successfully complete this course will have an in-depth overview of important and broad literatures in the field. Students will become familiar with empirical methods in addressing related research topics, and they will be able to critically review existing evidence as well as replicate and extend related academic studies.

Literature: Lecture notes and selected articles.
Pennacchi, G. (2008). Theory of Asset Pricing, Addison-Wesley
Campbell, J.Y, A.W. Lo, and A.C. MacKinlay (1997). The Econometrics of Financial Markets, Princeton University Press
Cochrane, J. (2005). Asset Pricing (revised edition), Princeton University Press (Background reading material)

Assessment methods, grading and criteria: assignments (25%), term project (incl. final presentation, 75%).

Recommended knowledge: econometrics, machine learning.
Required knowledge: business foundation, seminar series (finance), asset pricing.

Term: year 1 or 2, block 5.

Credits: 3 EC.

Computational Finance

Instructor: tbd (UvA).

Short subject description: Computational finance, generally referring to the application of computational techniques to finance, has become an integral part of modeling, analysis, and decision-making in the financial industry. In this course an introduction will be given to the theory of derivative pricing.

Course content: Many models used in finance end up in formulation of highly mathematical problems. Solving these equations exactly in closed form is impossible as the experience in other fields suggests. Therefore, we have to look for efficient numerical algorithms in solving complex problems such as option pricing, risk analysis, portfolio management, etc.
Computational finance, generally referring to the application of computational techniques to finance, has become an integral part of modeling, analysis, and decision-making in the financial industry. In this course an introduction will be given to the theory of derivative pricing. Several computational approaches such as Monte Carlo methods, lattice methods, and numerical PDE (Partial Differential Equation) techniques will be covered. The application of these algorithms on distributed computing architectures will be outlined.

Course objective: Introduction into derivatives pricing models and numerical methods for solving these.

Literature: Lecture slides. Books:
Yves Hilpisch. Python for Finance: Analyze Big Financial Data. O'Reilly, 2014. ISBN 978-1-4919-4528-5 (603 pages, c. EUR 31). Code is available on.
John C. Hull. Options, Futures and Other Derivatives. 8th Edition (or later), Prentice Hall, 2012. ISBN 978-0273759072 (847 pages, c. EUR 58).
Further reading:
Yves Hilpisch. Derivatives Analytics with Python. Wiley, 2015. ISBN 978-1-119-03799-6 (374 pages, c. EUR 72). Code is available on.
Python for Data Analysis. 2nd Edition, O'Reilly, 2017. ISBN 978-1-4919-5766-0 (544 pages, c. EUR 34). Code is available on.

Assessment methods, grading and criteria: Final grade is based on a group assignment (groups of two; 25%), and exam (75%).

Recommended knowledge: programming, mathematics (calculus and probability theory), econometrics.
Required knowledge: business foundation, seminar series (finance), asset pricing.

Term: year 1, block 5.

Credits: 3 EC.

Track-Specific Field Courses: Management Science

Data-driven Innovation Strategy

Instructor: prof. dr. E. Bartelsman (VU), dr. M. König (VU).

Short subject description: This course provides an introduction to quantitative methods for innovation strategy.

Course content: Innovation is the engine of growth for firms and economies. Many competing theories have been put forward to guide decisions on scale, scope and timing of innovative investment as well as on strategies for research collaboration. In this class, we will present some of these models but also present the type of evidence that can be used to guide decisions and the methods for analyzing these data. The available data include from firm-level data on start-ups, innovative investment and growth, inventor-level data on inventor-firm linkages, patent and patent-citation data, firm-to-firm transaction data, data on adoption and diffusion of innovative products and services, and surveys on research collaborations. The course will follow the emerging literature in this area as it uses recent quantitative techniques to answer questions relevant to decision makers.

Course objective: Provide an exploration of quantitative research methods as used in recent academic literature on innovation strategy.

Literature: Selected papers from each of the topic areas.

Bartelsman, E., Hagsten, E., & Polder, M. (2018). Micro Moments Database for cross-country analysis of ICT, innovation, and economic outcomes. *Journal of Economics & Management Strategy*, *27*(3), 626–648.

Hall, B. H., Jaffe, A., & Trajtenberg, M. (2005). Market value and patent citations. *The Rand Journal of Economics; Santa Monica*, *36*(1), 16–38.

Assessment methods, grading and criteria: assignments (25%) and empirical exam (75%).

Recommended knowledge: econometrics, machine learning, natural language processing.
Required knowledge: business foundation, seminar series (entrepreneurship, innovation, marketing).

Term: Year 2, Block 2.

Credits: 3 EC.

Marketing Science

Instructors: prof. dr. K. Pauwels (VU), prof. dr. F. Sotgiu (VU), dr. U. Konus (UvA)
dr. J. Guyt (UvA)

Short subject description: This course offers an overview of the econometric, statistical and behavioral foundations in the field of marketing science. It covers several substantive topics and discusses state-of-the-art methods that academic and industry marketers can use to make sense of ubiquitous market and consumer-level data (big data), as well as several state-of-the-art techniques for primary data collection (thick data).

Course content: This course introduces students to the field of marketing science which serves all those professionals – academics or practitioners – who answer important research questions in marketing using mathematical modeling. As such, marketing science draws upon solid econometric and statistical foundations that are common to other business data sciences. For example, we will discuss state-of-the-art econometric models and predictive analytics that firms can use to better understand their customers and optimize their marketing decisions.

Marketing science goes beyond purely predictive models with the goal of understanding customer and firm behavior. Students will find that this emphasis on cause-and-effect makes the field exciting and inherently interdisciplinary. For instance, we will be discussing how to draw upon theories from different fields (e.g., marketing, economics, psychology, and sociology) to build better mathematical models capable of generating more valuable customer and market insights.

Another related distinction between marketing science and other data sciences fields is that it goes beyond big data (i.e., data with high volume, velocity and variety) and also emphasizes thick data (i.e., in-depth data about customer and firm behavior, typically gathered through experiments, surveys or even qualitative methods), as well as the combination of both. Hence, in marketing science the ability to design and interpret primary research is a must. We will be discussing how to design, gather and use primary data to complement and enrich insights garnered through secondary data. Following these topics, students will familiarize themselves with (amongst others):

1. The use of aggregate level methods to quantify the market responses to marketing mix changes
2. Introduction into individual level choice models to measure consumer responses to marketing mix changes
3. The use of machine learning in market response models
4. Individual level choice model with Bayesian model of consumer learning and knowledge generalization
5. The use customer response and choice models in multichannel setting with time-dimension and multiple touchpoints/customer contact mediums (Panel Probit and Logit)
6. Model based customer segmentation: Latent Class Clustering and Regression models
7. Modeling Conversion-Attribution: Transition Models

Course objective: After following this course students will have a deep understanding of the marketing science field, how it contributes to the generation of customer and market insights, as well as how they may possibly contribute to the field. Furthermore, students will be able to use theories from different disciplines, as well as primary data collection, to make better causal inferences and better predictions about customers and markets. Exposure to several interdisciplinary topics will also help students develop their creative skills and apply them in their own research, even if outside marketing science.

Literature: Lecture slides and selected papers. Recommended (optional): Handbook of Marketing Decision Models, Wierenga and van der Lans, 2017.

Assessment methods, grading and criteria: term paper as exam (75%) and assignments (25%).

Recommended knowledge: econometrics, machine learning, natural language processing.
Required knowledge: business foundation, seminar series (entrepreneurship, innovation, marketing, human resources, supply chain).

Term (year, semester, block, etc): year 2, Block 1.

Credits: 3 EC.

Social Media Data Analytics for Business

Instructor: dr. C.S. Bos (VU) and dr. I.D. Lindner (VU)

Short subject description: This course provides an overview on how to collect, analyze and interpret social media data for business strategies and research.

Course content: Social media data analysis is indispensable for businesses of all sizes. Social media provide a platform for customers to share reviews of products, they indicate directions in which the market develops and represent a powerful tool for marketing purposes. This course delves, hands-on, into the wealth of social media data which is readily available, and the manners in which this data can be collected, analyzed, and put to good use for business strategies and research. For this purpose, the course applies the advances in tools available, covering the use of sentiment analysis, basic machine learning and artificial intelligence for extracting the information in social media posts.

Course objective: After this course, students will be able to

1. Collect data from social media services such as Twitter and YouTube using Application Programming Interfaces (API's) and basic web scrapers.
2. Clean, visualize and analyze data from various social media services.
3. Analyze textual comments for sentiments expressed in them.
4. Understand the theory of social media communication networks.
5. Identify trends for business strategies and set up models for research and development purposes.

Literature:
Literature tbd.
We will work with a blended learning approach such that we ask students to prepare classes by watching instruction clips.
Selected papers.

Assessment methods, grading and criteria: exam (75%) and assignments (25%).

Recommended knowledge: econometrics, machine learning, natural language processing.

Term: year 2, block 2.

Credits: 3 EC.

HR and OB Analytics

Instructor: Prof. dr S.N. Khapova (VU)

Short subject description: The course HR Analytics covers the analytic approach to and statistical analysis of Human Resource (HR) and Organizational Behavior (OB) data to the benefit of employee performance and the organization's return of investment on human capital.

Course content: Most organizations today collect a wealth of data that could help improve employee performance. Still, only few succeed in using this data to improve business results. The phenomenon of Human Resource (HR) Analytics and the respective field(s) of research could potentially fill this void.
HR Analytics gained traction in recent years as a movement that could let the HR profession evolve. Contrasting with the "soft" approach that was long associated with the HR, HR Analytics seeks to add value to the organization by leveraging analytical processes, a broad range of statistical techniques, and novel data sources. In this course, we learn how to use HR data and HR Analytics to improve business outcomes and make better HR decisions. Through a sequence of readings, lectures, cases, and experiential exercises, we learn what questions to ask, how to determine which methods to use, and how to publish HR Analytic research or communicate ideas effectively within in practice. We will be studying topics such as employee engagement, turnover, performance management, compensation, and recruitment & selection. We will be discussing issues regarding data quality, privacy, rigor, and utility analysis.

Course objective: Upon completion of this course, students will have an understanding of:

1. The key HR data and metrics and the respective sources or Human Resource Information Systems (HRIS) from which they can commonly be obtained
2. How to apply different analytic techniques to address questions at the core of HR
3. The ethical and legal boundaries in HR Analytic research and practice
4. How to communicate theoretically sound and practical recommendations from HR Analytics to practitioners and scholars.

Literature: Selected seminal papers and selected chapters from, amongst others:
Pease, G. (2015). Optimize your greatest asset--your people: How to apply analytics to Big Data to improve your human capital investments. Hoboken, NJ: Wiley.
Waber, B. (2013). People analytics: How social sensing technology will transform business and what it tells us about the future of work. London: FT Press.

Assessment methods, grading and criteria: a group video presentation (20%), four pass-fail individual assignments (40%), and one individual final paper (40%).

Recommended knowledge: econometrics, machine learning, natural language processing.
Required knowledge: business foundation, seminar series (human resources).

Term: year 2, Block 1.

Credits: 3 EC.

Prediction & Forecasting

Instructor: prof. dr. S.J. Koopman (VU).

Short subject description: Every decision in finance, business and economics has an impact on the future and therefore it ultimately must depend on forecasts. This course covers all the elementary and introductory knowledge necessary for analysing, modelling, prediction and forecasting time series using basic concepts in statistics and econometrics. The course discusses the main tools for making appropriate predictions and forecasts for a variety of problems: demand for goods, market shares, financial risk, energy prices, and macroeconomic variables such as inflation. Furthermore, it discusses signal extraction and extrapolation methods for high-dimensional data sets.

Course content:

1. Introduction and basic forecasting methods
2. Decomposition of time series: trend and seasonal effects
3. Exponential smoothing methods
4. Box-Jenkins models
5. What is a good forecast?
6. Kalman filter methods
7. Score-driven models
8. Signal extraction and extrapolation for many time series.

Course objective: To provide the student with the basic methods and insights for making successful data predictions and forecasts which are based on quantitative and judgmental methods; to provide the student with the latest developments in data prediction and forecasting.

Literature: book tba and selected papers.

Assessment methods, grading and criteria: assignment (40%) and written exam (60%).

Required knowledge: econometrics.

Term: year 2, block 3.

Credits: 3 EC.

Track-Specific Field Courses: Supply Chain Analytics

Social and Economic Network Analysis

Instructors: prof. dr. B.F. Heidergott (VU), dr. I.D. Lindner (VU).

Short subject description: This course provides an overview and synthesis of models and techniques for analyzing social and economic networks.

Course content: This course discusses the complex “connectedness” of social and economic relationships which is found in numerous incarnations: the rapid growth of the world-wide-web, the ease with which communication takes place, the fast spread of news and information as well as it’s impact on opinion formation and our society.

We start with an analytical toolbox of recognizing and analyzing patterns of network data. These tools show how to simplify complexity such as (1) global patterns (degree distributions, path lengths and the small world phenomenon, decomposition of networks), (2) segregation patterns (node types and homophily), (3) local patterns (clustering, transitivity, support) as well as (4) positions in networks (neighborhoods, centrality, influence measures). Next, we will discuss research on network formation and analyze how different model assumptions leave their characteristic footprint on network data. On the one hand, there is the large class of (growing) random networks models which explains a plethora of phenomena (rich-get-richer, small world, social media communication graphs). This class also serves as an important benchmark for identifying non-random properties of networks in which links are formed strategically (business relationships, co-author models). Hybrid models lie in between these two complementary approaches and are able to explain a large class of data (islands-connections model). Finally, we will discuss dynamic implications of the network structure in the context of (1) diffusion through networks (spread of information and diseases, financial contagion) as well as (2) learning and consensus formation on networks (imitation and social influence, wisdom of crowds). Key issues for both classes of dynamics are identifying key actors and their impact on aggregate behavior and beliefs. In particular, these methods allow to analyze the value of individuals in a collectivity (value of players in football teams).

Course objective: Students will learn fundamental concepts from social network theory that allow to (1) classify network data in terms of structural properties, (2) identify the underlying incentives of network formation aggregate dynamics, and (3) derive context dependent measures and possible policy implications.

Literature:
Jackson, M.O (2010). Social and Economic Networks, Princeton University Press, Available as paperback or ebook.
Social and Economic Networks, Massive Open Online Course (MOOC), available at www.coursera.org.
Note that the MOOC at coursera.org is free of charge unless you want to earn a certificate from coursera.org (which is not necessary for our course). All you have to do is open an account at coursera.org.
Selected papers.

Assessment methods, grading and criteria: sit-in written exam (50%) and assignments (partly numerical computer work; 50%).

Recommended knowledge: econometrics, optimization, machine learning, natural language processing.
Required knowledge: business foundation, seminar series.

Term: Year 2, Block 1.

Credits: 3 EC.

Economics and Management of Network businesses and markets

Instructors: prof. dr. E.T. Verhoef, dr. A.J.H. Pels, dr. T. de Graaff, dr. M.D. König (VU)

Short subject description: This course addresses the analysis and management of network businesses and markets from the perspective of firms and society.

Course content: The course centers around the theme of networks in business and economics. We will discuss physical networks, such as those in transport, and non-physical networks, including internet-based platforms. We will address, from the business perspective as well as the societal viewpoint, phenomena such as network design, market power, congestion, economies of density, market failure, alliances, spill-overs, equilibrium versus optimum, dynamics, nodes, gravity and agglomeration. We will discuss theory and empirics, presenting methodologies to study and analyze network (behavior) from both perspectives.

Course objective: After the course students are able to apply state-of-the-art methods from business and economic sciences to analyze network businesses and markets from the theoretical and empirical perspective. This includes having acquired fundamental insights into how the specific phenomena that characterize networks, and that differentiate these from non-network businesses and markets, affect the desirability of outcomes from the private and public perspective; which policies and strategies may be employed to optimize outcomes; and which theoretical and empirical techniques to use to answer these questions.

Literature: tbd

Assessment methods, grading and criteria: sit-in written exam (3 hours; 50%, at least 5,0 required) and 2 additional take-home assignments (partly numerical computer work; 50%).

Recommended knowledge: econometrics, optimization, machine learning, natural language processing.
Required knowledge: business foundation, seminar series.

Term: tbd.

Credits: 3 EC.

Heuristic Optimization Methods

Instructors: prof. dr. D. Vigo, prof. dr. J.A. Gromicho Dos Santos (VU)

Short subject description: Heuristics are an indispensable tool for anyone working in operations management. As problems arising in practice are often too hard to be solved exactly, heuristics offer an interesting alternative. This course allows students to distinguish problems that require heuristics to be solved efficiently and on how to design and develop heuristics optimization methods

Course content: The main topics addressed in this course are classical heuristics to construct initial solutions, improvement heuristics based on structured local search and a variety of metaheuristic search strategies applied to both general optimization problems and distribution and routing problems in particular.

Course objective: A student who has met the learning objectives of the course will be able to:

1. Argue the applicability of heuristic optimization methods for different optimization problems within the Operations Management and Operations Research field
2. Distinguish heuristics in terms of efficiency, solution quality and other quantitative aspects
3. Develop and test heuristic optimization methods for a challenging practical problem under consideration.

Literature: tbd.

Assessment methods, grading and criteria: sit-in written exam (3 hours; 50%, at least 5,0 required) and 2 additional take-home assignments (partly numerical computer work; 50%).

Recommended knowledge: econometrics, optimization, machine learning.
Required knowledge: mathematics, optimization, business foundation, seminar series.

Term: tbd.

Credits: 3 EC.

Integer Linear Programming

Instructors: prof. dr. W.E.H. Dullaert, dr. R. Roberti, dr. S. de Leeuw, dr. G. Maroti (VU).

Short subject description: This course provides students with a thorough introduction to formulating and solving via integer linear programming decision-making problems arising in areas such as transportation, scheduling, and location.

Course content: The main topics addressed in this course are Integer Linear Programming, branch-and-bound, cutting planes, branch-and-cut, Lagrangian relaxation, and dynamic programming.

Course objective: A student who has met the learning objectives of the course will be able to:
1. Formulate a decision-making problem by using integer linear programming
2. Identify problems that can be formulated via dynamic programming, and develop dynamic programming recursions
3. Identify the most-common valid inequalities for MILP
4. Apply and design solution algorithms based on branch-and-bound and branch-and-cut.

Literature: tbd.

Assessment methods, grading and criteria: sit-in written exam (3 hours; 75%, at least 5,0 required) and 2 additional take-home assignments (partly numerical computer work; 25%).

Recommended knowledge: econometrics, optimization, machine learning.
Required knowledge: mathematics, optimization, business foundation, seminar series (supply chain, marketing).

Term: tbd.

Credits: 3 EC.

Decomposition Methods

Instructors: dr. S. Dabia, dr. L. Stougie, dr. R. Roberti (VU).

Short subject description: The aim of the course is to allow students to solve complex large-scale optimization problems using decomposition algorithms.

Course content: Many combinatorial optimization problems arising in a variety of real-life applications can be modeled by using Mixed Integer Linear Programming (MILP) models. In principle, these models can be cast into a general-purpose MILP solvers to find optimal or near-optimal solutions. Nevertheless, such models are not suitable to solve many large-scale instances of the magnitude of real-life applications. In this case, the MILP models can be reformulated by using the main decomposition techniques: Dantzig-Wolfe, Benders, and Lagrangean decomposition. By the end of this course students will be able to solve large-scale optimization problems using these three decomposition techniques.

Course objective: A student who has met the learning objectives of the course will be able to:

1. Analyze and formulate combinatorial optimization problems arising in different applications as Mixed Integer Linear Programming models
2. Decompose MILP models by using Dantzig-Wolfe, Benders, and Lagrangean decomposition.
3. Assess and compare alternative reformulated models.

Literature: tbd

Assessment methods, grading and criteria: sit-in written exam (3 hours; 75%, at least 5,0 required) and 2 additional take-home assignments (partly numerical computer work; 25%).

Recommended knowledge: econometrics, optimization, machine learning.
Required knowledge: mathematics, optimization, business foundation, seminar series (supply chain, marketing), integer linear programming.

Term: tbd.

Credits: 3 EC.

Other Field Courses

Social Science Genetics

Instructors: prof. dr. P.D. Koellinger, dr. R. de Vlaming (VU).

Short subject description: The course provides an overview of state-of-the-art methods that are used to study the genetic contributions to differences between people and how these genetic insights can be used in the social sciences.

Course content: After decades of scientific debate, a consensus has emerged that all human behavioral traits are partly heritable (i.e. they are affected to some degree by random genetic variation within families). Integrating genetic data into social-scientific research opens up new possibilities to (i) control for factors that are otherwise unobservable, (ii) to increase the statistical power of empirical analyses by absorbing residual variance in multiple regression analyses, (iii) to study the interactions of genetic factors and environmental exposures, (iv) to use random genetic differences among people to identify causal pathways, and (v) to better understand how social (dis)advantages are transferred across generations and how parents, peers, teachers, and policy makers can potentially alleviate or intensify such (dis)advantages.
Collecting genetic data is now feasible at high speed and high accuracy at low costs. Thus, the time is now ripe to integrate genetic data into social-scientific research, benefitting from these recent technological developments and scientific break-throughs.

Course objective: Students will become aware of the relevance of genetic factors for human behavior and socio-economic outcomes. After the course, students will be familiar with state-of-the-art statistical methods that play an important role in genetic discovery studies. This includes genome-wide association, linkage disequilibrium (LD) score regression, and genomic-relatedness-matrix restricted maximum likelihood (GREML) estimation.
Furthermore, students will learn how to construct polygenic scores, how to use them in social-scientific research, and how to interpret the findings from genetically-informed empirical studies. Finally, students will learn programming skills in PLINK and UNIX that will enable them to work with large genetic datasets.

Literature: Selected papers

Assessment methods, grading and criteria: sit-in written exam (2 hours, 75%, at least 5,0 required) and 2 additional take-home assignments (25%).

Term: tbd.

Credits: 3 EC.

Seminars, Research Clinic, Research Hackathon, Skills Workshops

Seminars

Instructor: professors of BDS affiliated research groups (EUR, UvA, VU)
Short subject description: Introduction of all research groups connected to the program and discussing relevant topics and research questions in the corresponding fields.

Course content: The seminars introduce the research groups at the three faculties to the first-year students. In the seminars, scholars relate ongoing research projects in their research groups. Attendance is mandatory and will be checked by means of attendance sheets. Signing off for fellow students is considered fraud and will disqualify the signee for the 1 EC for the seminars. After having attended all seminars in the series, students select a research topic and address a professor who is

not teaching in the first year of the program. Students write a research proposal (2-3 pages) and discuss the proposal with the researcher.

Course objective:

1. Facilitate matching process between students and prospective supervisors
2. Introduce researchers and fields not (yet) encountered in classroom
3. Stimulate independent thinking about research ideas
4. Exercise academic writing and preparing for future grant applications
5. As a beneficial side effect, the students will have a writing sample to discuss in the academic writing skills course in the beginning of the second year.

Literature: n.a.

Assessment methods, grading and criteria: Assessment: a research proposal (2-3 pages) and discuss the proposal with the researcher. Grading: pass/fail. Attendance and a pass for the research proposal required to obtain the 2 EC for the seminar series.

Term: Year 1, Block 1 to 4.

Credits: 2 EC.

Research Clinic

Instructor: (EUR, UvA, VU)
Short subject description: This course is designed to stimulate students to generate new research ideas drawing from the existing literature.

Course content: Identifying a relevant research question is not a trivial task. This course focuses on addressing a relevant problem statement. In many cases, the input for this research will be drawn from the existing literature, although it may also involve the use of computer-generated data. Its focus embraces aspects of business, and data science.

Literature: Selected papers and lecture notes.

Assessment methods, grading and criteria: assignments (100%).

Term: Year 2, Block 3-4.

Credits: 5 EC.

Research Hackathon

Instructor: tbd (EUR, UvA, VU).

Course content: Scholars and companies deal every day with large and big data. This course allows the students to put their knowledge to the test and apply it to different fields. They will analyze big

data, identify possible solutions with the help of specialized second-year research master students or PhD students.
While during the first year, they will focus on different business problems, second-year students will dedicate their attention to the assignments related to their specialization.

Course objective: After the end of this course, students will:

1. Have applied the knowledge accumulated in their first year
2. Be exposed directly to the different fields' problems
3. Fine-tune their research, programming, and data science skills
4. Work together in a multi-disciplinary team.

Literature: content of the courses provided in year 1, Block 0 to 4.

Assessment methods, grading and criteria: assignments (100%).

Term: Year 1 and 2, Block 3.

Credits: 4 EC in Year 1, 3 EC in Year.

Skills Workshops

Instructor: tbd (EUR, UvA, VU)

Short subject description: This workshop series provides students with an overview of (1) scientific integrity, transparent algorithm and ethical data management issues, (2) the review process, (3) grant application procedures, and (4) academic presentations.

Course content: The skill workshop series enables students to fine-tune skills needed for a successful academic career. The series opens by tackling important issues related to the scientific integrity, transparent algorithm and ethical data management, which are highly relevant for a business data scientist. In the second year, practical aspects related to how to handle the review process, and grant applications will be discussed. In these workshops, writing and positioning skills are emphasized. The series closes with a workshop on presentation skills for research talks and conference presentations.

Course objective: This series of workshops have the primary objectives to:

1. Provide students with a solid understanding of scientific integrity issues and ethical data management
2. Understand and practice the review process, as author and reviewer
3. Understand and practice the grant application process
4. Fine-tune their academic presentation skills.

Literature: tbd.

Assessment methods, grading and criteria: assignments (100%).

Term: Year 1, Block 2; Year 2, Block 4.

Credits: 5 EC.

Thesis

The research thesis (30 EC) is the final examination of the program and an integrative assessment demonstrating that the student has achieved the learning goals for the program: having the knowledge and the skills needed to set up and carry out scientific research projects in one area of business and management, with the use of data science techniques. The research thesis is written in cooperation with senior faculty and is potentially publishable in one of the internationally peer-reviewed journals in the field.

- At least one supervisor is assigned to each student. Supervisor(s) and student confirm with the DGS the commitment to start a thesis trajectory. The supervision capacity should cover knowledge of the research field as well as technical skills.
- The student and the supervisor discuss and agree on the definitive research question.
- The supervisor(s) are instructed to give feedback to the student's work within two weeks after submission.
- Feedback can be given orally but should always be confirmed in writing (summarized).
- The supervisor should ensure that s/he is regularly available to students. The supervisor provides the student with concrete information about his/her availability.
- During the thesis trajectory, the student can expect at least five moments of feedback.

Timeline for the research thesis

- First Year
    - During the year (Seminar Series): Display of state-of the-art research by the departments involved
    - May: Overview of possible research topics by potential supervisors
    - May-August: Students identify their field of study, interesting research area within the field and possible supervisors
    - Summer: Research assistantship opportunities
- Second Year
    - September: meeting with DGS on research topic and potential supervisor
    - December: students who did not find a supervisor, will be assisted
    - January: official start of the thesis trajectory
    - August: end of the thesis trajectory

Defense

- The thesis defense cannot be scheduled before the student has passed all other course work. Once the supervisor considers the thesis of sufficient quality, the DGS installs a thesis committee, consisting of the supervisor and 2 experts in the field. The thesis committee members are the examiners of the thesis. At least one of committee members comes from a different university than the thesis supervisor. The thesis is submitted to the committee members at least one week before the defense. The secretariat distributes the rubric for the thesis, the grade forms and the guidelines for the defense to the committee members. The paper is checked for plagiarism.
- At least 24 hrs before the defense, the committee members who are not the supervisors are required to give their opinion of the quality and level of the *paper*, including a suggestion for a grade, by submitting the assessment form for non-supervisors to the supervisor and to the secretariat. This assessment form has the same structure and criteria listed as the final grade form.

- The thesis is defended before the thesis committee in a 1-hour public seminar, announced on the website. The student presents the outcome of the research before the audience and is questioned by the examiners.

Grading

The rubric for thesis assessment describes into detail the requirements for several aspects of the thesis and the appropriate grade. Since the thesis is the final examination, the grading guidelines are a reflection of the program's learning goals. Requirements are given for:

- Research question: formulation and relevance
- Positioning in literature: assessing and reviewing previous research
- Research design: explaining considerations; appropriateness for the research question
- Description and analysis: organisation and presentation of results
- Conclusion and discussion: putting findings into context
- Oral presentation: structure and response to comments and questions
- Degree of independence: to what extent is the thesis the student's own work

The grade for the thesis is determined by the committee members who are not the supervisor(s) of the thesis. The grade is based on:

- the thesis itself;
- the process as reported by the supervisor;
- the presentation and defense of the thesis.

Feedback

Feedback is given to the student orally after the defense by the committee members, and by the supervisor in writing in a format that is provided.

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