Module Handbook for M.Sc. Health and Medical Data Analytics

Study track at UGA

Master on Health Engineering, Study track on Data Analytics for Precision Medicine

Please note, that all modules presented are just a selection of elective courses.
For more information, please visit the website of the respective university.

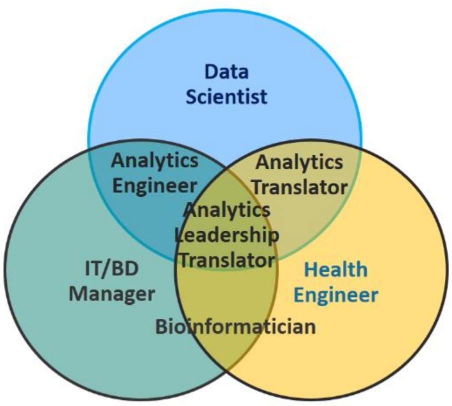
General Content

1 Proposed program

There is a great demand for data scientists in the field of medicine, health life and environmental sciences, on topics such as scientific computation, big data analysis, imaging and computer graphics. At ease in the digital domain, the data scientists have to structure large amounts of formless data and make analysis possible. They identify rich data sources, link them to other sources of potentially incomplete data, and clean up the resulting set. But in a competitive environment where challenges continue to change and data continues to circulate, the traditional backgrounds of quantitative analysts or data managers are no longer sufficient. They cannot turn unstructured data into structured data — and analyze these data.

Given the nascent state of their trade, there is little consensus on how the data scientists can add the most value, how their performance should be measured, and where their role fits in an organization. But it is becoming clear that the dominant trait among data scientists is an intense curiosity—a desire to go beneath the surface of a problem, find the questions at its heart, and distill them into a very clear set of hypotheses that can be tested. The word "scientist" fits this creative approach to closing the gap. Some of the best and brightest data scientists are PhDs in scientific fields like systems biology, ecology, physics or astrophysics.

The health sector is looking for people who can work with complex data, and has good luck recruiting among graduates with educational and work backgrounds in the fields of health engineering and medical, life or physical sciences, for designing equipment, gathering data, conducting multiple experiments, and communicating their results (cf Fig 1). But in the meantime they are searching candidates that must have strong social skills to be effective, while people without such skills might thrive in traditional data professions. Additionally, it often falls to data scientists to communicate in language that all their stakeholders understand—and to demonstrate the special skills involved in storytelling with data, whether verbally, visually, or—ideally—both.



Health Engineer	Knows the domain, defines and test the hypotheses, asks good question and break down the problems
Analytics Translator	Understands the ealth problems and translate into technical language and vice versa (Interface HM/DS)
Data Scientist	Builds the mathematical algorithms Background in Applied mathematics, Statistics, Data mining, Machine learning, Theoretical physics
Analytics Engineer	Takes the DS's algorithms and make them more efficient (Interface DS/IT/BD=
IT/BD Manager	Programmes and develops the softwares, Wrangles the data
Bioinformatician	

Fig 1. Health Data Analytics Workforce in Health Sector

The experience we have drawn from the implementation of a previous EMMC on BioHealth Computing (2011-16), teaches us the importance for students of mastering a parent discipline before switching to a wider ranging training. This disciplinary anchor should not be underestimated, especially in context of the currently uncertainty of career opportunities in cross-disciplinary research. Based on this preliminary analysis the requirements to join, this study track on Data Analytics for Precision Medicine (part of the master programme on Master on Health Engineering) are the bachelor degree (or equivalent 180 ECTS) on biotechnology or bioengineering, and life, medical, pharmaceutical, chemical, or physical sciences.

The programme is structured in four semesters: (i) semester 1 is dedicated to core courses; (ii) semesters 2 and 3 are dedicated to cross-disciplinary and advanced courses, innovation & entrepreneurship education, and mobility; and (iii) semester 4 to is dedicated to the MSc thesis. The semester 3 includes a 1st Summer School which is an integrative period, and semester 4 including 2nd Summer School which is an innovation & entrepreneurship bootcamp. While keeping the basis of the initial MSc programmes, the UGA's academic office agreed to: (i) convert some compulsory courses in elective, and (ii) increase the number of courses open to students enrolled on the different backgrounds, with a view to: (i) fostering transversal training among each track; (ii) personalizing the students' curriculum in accordance with the research topic assigned to each one.

By attending courses in several MSc programmes and joint Summer Schools, organised by the European Scientific Institute (ESI, CERN-supported), the students are better prepared to implement multidisciplinary research during the research thesis and beyond. The evaluation process for this student-centred learning will presuppose well-founded practices that express the views of the subjects involved: self-assessment and observer assessment. The main outcome of this student-centred learning will be the students' ability to work on translational and transfer programmes. The description of the courses includes a reference to the Intended Learning Outcomes of any course. A list of all ILOs of the programme is included.

2 Module List

Semester 1

I & E Fundamentals e-learning/on-site (9 ECTS)
I & E Fundamentals e-learning - 9 ECTS S1

HMDA Core (21 ECTS)
M1: Tools for Precision medicin (9 ECTS)
Molecular bases of human diseases (22h) - 3 ECTS – S1 (IS)
Molecular tools in health – (36h) - 6 ECTS S1 (IS)
Proteomics for Health Research 3 ECTS S1 (IS E-learning)
M2: Statistics and programming (9 ECTS)
Applied probability and statistics (48h) - 6 ECTS - S1 (MSIAM)
Algorithms and software tools (36h) - 3 ECTS - S1 (MSIAM)
Signal and image processing (54h) 6 ECTS- S1 (MSIAM)
M3: Research methodology (3 ECTS)
Initiation to project management (16h) - 3 ECTS - S1 (IS)
Scientific reading and writing (28h) - 3 ECTS - S1 (IS)

Semester 2

I & E for Medtech (9 ECTS)
HMDA Elective (21 ECTS)
M1: Precision medicine (6 ECTS)
High throughput in biology (70h) - 6 ECTS, S2 (BIO-PHED)
How to Become a Cancer Cell (50h) - 6 ECTS S2 (IS BIO-DCS)
Cancer disease: experimental and therapeutical approaches (40h) - 6 ECTS S2 (IS BIO-DCS)
M2: Data analytics (12 ECTS)
Data analysis, linear models and ANOVA (54h) - 6 ECTS S2 (MSIAM)
Computing science for bid data and HPC (54h) - 6 ECTS S2 (MSIAM)
Molecular and cellular imaging (microscopy) (50h) - 6 ECTS S2 (IS BIO-DD DCS)
Numerical optimization (54h) 6 ECTS S2 (MSIAM, GBX8AM02)
M3: Research methodology (6 ECTS)
Short internship - 6 ECTS S2 (IS)
Advanced biostatistics and exploitation of research work (44h) - 3 ECTS S2 (IS)

Semester 3 (autumn/winter)

I & E consolidation (9 ECTS)
Summer School on HMDA (90 h) - 6 ECTS S3 (IS)
Minor thesis Research and Development Projects – 3 ECTS S3 (IS)
Data Challenges (60h) - 3 ECTS S3 (MSIAM-LSDS)
HMDA Specialisation (21 ECTS)
M1: Precision medicine (9 ECTS)
Molecular tools for the diagnosis and treatment of genetic diseases (29h) - 3 ECTS S3 (IS)
Molecular markers for medical imaging (30h) - 3 ECTS S3 (BIOMED)
Numerical simulation and statistical data analysis (30h) - 3 ECTS S3 (BIOMED)
Modelling in systems biology (30h) - 3 ECTS S3 (BIOMED)
Biostatistics, bioinformatics and molecular modeling (39h) - 6 ECTS S3 (BIO-PHED)
Biomedicines innovative project (30h) - 6 ECTS S3 (IS)

M2: Learning algorithms (9 ECTS)
Advanced algorithms for machine learning and data mining (18h) - 3 ECTS S3 MSIAM-FDS)
Advanced learning models (18h) - 3 ECTS S3 (MSIAM-FDS)
Bayesian statistics (28h), 3 ECTS S3 (MSIAM-FDS)
Category learning and object recognition (28h) 3 ECTS. S3 (MSIAM-FDS)
Machine learning fundamentals (30h) - 3 ECTS S3 MSIAM-FDS)
Data science seminar (14h) - 3 ECTS S3 (MSIAM-LSDS)
M3: Computationnal biomedicine (6 ECTS)
Computational biology (18h) - 3 ECTS S3 (MSIAM-FDS)
High throughput in biology (70h) 6 ECTS S3 (BIO-PHED)
Fundamentals of probalistic data mining (18h) - 3 ECTS S3 (MSIAM-FDS)
Model selection for large-scale learning (60h) - 3 ECTS S3 (MSIAM-LSDS)
Information visualization (28h) - 3 ECTS S3 (MSIAM-LSDS)
Data management in large-scale distributed systems (C 18h) - 3 ECTS S3 (MSIAM-LSDS)
Data science seminar 3 ECTS, S3 Seminars (MSIAM-LSDS)
Software development tools and method (CM : 9h TP : 30h) - 3 ECTS, S3 (MSIAM-LSDS)

Semestre 4

HMDA Thesis I & E (30 ECTS)
Master thesis - 24 ECTS S4 (IS)
Summer School on Safer Nanomaterials (90 h) - 6 ECTS S4 (IS)
Summer School on Artificial Intelligence for Health (90 h) - 6 ECTS S4 (IS)

3 Module Descriptors

3.1 Semester 1

3.1.1 Molecular bases of human diseases

(22h) - 3 ECTS - S4 (IS), Arnaud Seigneurin Arnaud.Seigneurin@univ-grenoble-alpes.fr

Knowledge of the language of human pathology to facilitate dialogue between scientists and medical practitioners. Better integrate in the medical field the scientific and technical knowledge acquired in the IS Master. To show how, from the knowledge of molecular and cellular mechanisms, biotechnologies make it possible to improve the treatment or diagnosis of diseases.
Course examples:
• Pathology Basics
• Mechanisms of HIV and EBV infections
• Molecular and cellular bases of carcinogenesis
• Diabetes and its complications
• Atheroma and cardiovascular diseases
• Place of inflammation in human pathologies
• Cell bases of autoimmune diseases
• Mechanisms of host-pathogen relations: malaria

3.1.2 Molecular tools in health

(36h) - 6 ECTS S4 (IS) , Arnaud Seigneurin Arnaud.Seigneurin@univ-grenoble-alpes.fr

Presentation of the methods of preparation and transformation of macromolecules (nucleic acids, polysaccharides and analogues): in vitro and in vivo synthesis of DNA, RNA, modified DNA, principles of extraction, purification, manipulation of macromolecules by enzymes, PCR and RTPCR in real time, analytical methods and strategy in molecular biology. Knowledge of vectors: main elements constituting a vector, fast cloning methods, inducible systems, promoter activity control, genomic insertion method, mass spectrometry analysis.

The goals are to acquire:
- a knowledge of the main techniques in molecular engineering
- a knowledge of the chemical and biochemical tools used in biotechnologies using biological polymers (DNA, polysaccharides, etc.).

Examples of interventions
Synthesis of normal and modified nucleic acids
Chiral selectors applied to nucleic acids and biological polymers
NAPs and their use
Polysaccharides: Preparations, Biotechnological Changes and Sugar-Protein Interactions.
PCR and RTPCR in real time
vectors
DNA analysis: mass spectrometry, sequencing methods, capillary electrophoresis, dHPLC
Sequencing and sequencing methods for eukaryotic genomes Méthodes de séquençage et séquençage des génomes eucaryotes

3.1.3 Proteomics for Health Research

(45h) 3 ECTS (IS E-learning), S4 Sandrine Bourgoin sandrine.bourgoin@univ-grenoble-alpes.fr

Proteomics describes large-scale analysis of proteins in a biological sample. The aim of these studies is to determine the protein parts that are present in such samples and to define their concentrations, molecular states, structures, functions or connections. Today, there are different technologies being used and developed to study the different types of samples such as to find biomarker molecules that could help to diagnose diseases or even improve therapy of patients.

Course main content
The objective of the course is to present current trends for global protein analysis and to demonstrate its principles, challenges and complexity. The course will therefore provide an overview of typical proteomics applications used today, such as for biomarker discovery and validation.
The course is focused on different methods, technologies and strategies currently used within the field of proteomics in general and with an emphasis on biomarker discovery.
The lectures will cover background and recent advances for both classical proteomics methods, such as 2D-gel electrophoresis and mass spectrometry, and strategies based on high-throughput antibody generation, bioinformatics and structural approaches.
Intended learning outcomes
The aim of the course is to provide the students with an introduction to current methodologies and trends in the field of proteomics. The students should also obtain an overview and awareness of typical proteomics applications. After completed course the student should be able to describe and discuss the possibilities and advantages, and the complexity and drawbacks of various proteomics technologies compare traditional methods with emerging technologies suggest suitable approaches for specified applications and motivate the choice speculate and argue about the future of proteomics technologies participate in scientific discussions regarding proteomics technologies critically evaluate scientific results

Literature
Principles of Proteomics by R.M Twyman, Garland Science, ISBN: 9780815344728 (second edition)
Handout and articles distributed at the lectures

3.1.4 Applied probability and statistics

(CM 24h, TP 24h) 6 ECTS, S4 (MSIAM), Anatoli Iouditski anatoli.iouditski@univ-grenoble-alpes.fr Sana Louhichi sana.louhichi @ univ-grenoble-alpes.fr

Description
The aim of this course is to provide basic knowledge of applied probability and an introduction to mathematical statistics.
Contents of applied probability:

- Markov Chains: description, properties, applications.

Contents of mathematical statistics:

- Estimation (parameter)
- Sample comparison
- Statistical tests

This course includes practical sessions. Mutualized with M1 SSD Applied probability and Statistics. See the associated content from UPMF.

Grading

- 1/2 for the applied proba part
- 1/2 for the statistics part

See the contents from the associated course at UPMF.
Course content for probability
Course content for statistics

3.1.5 Algorithms and software tools

(36h) - 3 ECTS - S7 (MSIAM), Laurence Pierre laurence.pierre@univ-grenoble-alpes.fr

Description

The objective of this course is to present the computer sciences basics useful for applied mathematics.
Contents:

1. Compilation (const, inline, loops, Gnu Make …)
2. C++: genericity (template), code reuse (STL), efficient programming
3. Objects and hierarcical memory, notions of cache and locality (e.g., BLAS)
4. Basics of algorithmics
5. Complexity
6. Error propagation, floating point computing

Prerequisite

UNIX/LINUX. At least some programing langages (C, python, java).

Learning outcome

Produce code using C++, algorithms and comilation tools, taking into account complexity and errors.

Checking knowledge

Session 1 ou session unique - Contrôle de connaissances

Nature	Type	Nature d'évaluation	Durée (min)	Coeff.
UE	CC	Pratique		50/100
UE	CT	Ecrit - devoir surveillé	120	50/100

Session 2 - Contrôle de connaissances

Nature	Type	Nature d'évaluation	Durée (min)	Coeff.
UE	CC	Report de notes		50/100
UE	CT	Ecrit ou Oral		50/100

3.1.6 Signal and image processing

(CTD 36h, TP 18h) 6 ECTS, Cecile Amblard Cecile.Amblard@grenoble-inp.fr7

Description

The aim of this course is to provide the basics mathematical tools and methods of image processing and applications.

Content:

- Image definition
- Fourier transform, FFT, applications
- Image digitalisation, sampling
- Image processing: convolution, filtering. Applications
- Image decomposition, multiresolution. Application to compression

This course includes practical sessions.

Prerequisite

Geometry and analysis from L3 mathematics/applied mathematics

Learning outcomes

Tools for image processing (see objectives above)

Grading

- 1/2 practical
- 1/2 final written exam

3.1.7 Initiation to project management

(16h) - 3 ECTS - S7 (IS), Jean Breton jean.breton@univ-grenoble-alpes.fr

Content

This course provides a sketch of the traditional method of project management. The model that is discussed here forms the basis for all methods of project management. Later courses go into more depth regarding a model that is particularly appropriate for IT-related projects. Dividing a project into phases makes it possible to lead it in the best possible direction. Through this organisation into phases, the total work load of a project is divided into smaller components, thus making it easier to monitor. The following paragraphs describe a phasing model that has been useful in practice. It includes six phases:

Initiation phase
Definition phase
Design phase
Development phase
Implementation phase
Follow-up phase

Prerequisites

The plans must not necessarily have a technological characterization. They must economically be viable, but not compulsorily lucrative (partnerships, fair trade, ...).

3.1.8 Scientific reading and writing

(28h) - 3 ECTS - S7 (IS), Don Martin don.martin@univ-grenoble-alpes.fr

This course will introduce the basis to perform good oral and written presentations with several sequences of combined lecture, tutorial, workshop to allow the master students to deal with any situation of their Master 1 year or their future work.

Content

A first sequence will help the students to find an internship. A tutorial and a workshop will be organized in order to improve their CV and practice an interview.

A second teaching sequence will address the way to write a scientific report, from an internship report towards a scientific publication. This part will be followed by a lecture concerning the different modes of scientific communication, written or oral (report, meeting, lab-book, etc) within a laboratory.

A third sequence will deal with oral scientific presentation. A tutorial will explain how to prepare the presentation as well as how to present it. A workshop will give the opportunity to practice in front of an audience. It will also be the basis for an evaluation.

Another lecture will provide an opening towards electronic communication tools in order to be able to succeed in a skype interview and to be visible on the web using tools like LinkedIn or Viadeo.

A closing lecture will offer a transversal view of the different points highlighted throughout the course.

Test

Writing skills will be evaluated based on a scientific report. The report and presentation evaluation will be related to other scientific teaching units followed by the students during the first semester of the master 1 but the evaluation will not take into account scientific knowledge.

Intented learning outcomes

Students will improve their skills in written and oral presentation. The course will provide competences required for the Master 1. Students will be trained in order to be able to write their CV and internship report, achieve interviews and be able to provide convincing scientific presentation. These specific points will also be extended to other oral and written communication tools as well as electronic communication that can be needed during and after a Master 2 program.

3.2 Semester 2

3.2.1 High throughput in biology

(70h) - 6 ECTS, S2, (BIO-PHED YAX9BI38) Mickael Charrier mickael.cherrier@ibs.fr

Course outline

The lectures present the basic methodology and some advanced techniques used for high throughput *in vitro* small molecule drug discovery. The principles and statistical methods used for assay optimization and validation will also be explained.

I. Molecular biology, Biochemistry and Protein expression
II. Proteomic analysis; Mass spectrometry
III. Lab-chips and Cell-chips
IV. Structural biology: Crystallogenesis and Crystallization; RMN
V. Combinatory chemistry

Format of exams: Oral exam (at the end of December) and Research project (at the beginning of January)

Format of the course

Activities	*Hours*	*Percentage*
Lectures	*36h*	*48 %*
Tutorials and discussions		
Lab sessions		
Estimated work load at home	*40h*	*52 %*
Total	*76h*	*100 %*

Exam requirements

Nature of the exams	*Mid-term (Number of hours, % of the final grade)*	*Final (Number of hours, % of the final grade)*	*Second session*
Written exam			
Oral exam	*50 %*		*X*
Research project		*50 %*	

Prerequisite

Background in biochemistry, molecular biology and cellular biology. Knowledge in physiology, immunology and microbiology will be appreciated. Students with laboratory and/or practical skills will better understand technological benefits of the use of high throughput technologies in the lab work.

-Is the number of students limited in this course?

20 students

Targeted skills

After completion of this course, students should be able to better understand and compare different high throughput methods used, for instance, for the discovery and validation of new biomarkers.

Be able to present this knowledge in oral and written form

3.2.2 How to Become a Cancer Cell

(50h) - 6 ECTS S2 (IS BIO-DCS), Arnaud Seigneurin Arnaud.Seigneurin@univ-grenoble-alpes.fr

Description
The objective of this course is to acquire the fundamental knowledge necessary to understand key mechanisms of cancer development. This course includes a set of lectures on alterations of cellular and molecular mechanisms that are responsible for the cancer pathophysiology. These modified cellular functions include for example the cell division, apoptosis, gene expression, stem cells, angiogenesis and degradation of the extracellular matrix... The fundamental notions will be illustrated via their implications in diagnosis and therapeutics. The publication analysis will allow emphasizing the medical interest.

Learning outcomes
- Knowledge in fundamental cancer cell biology, cancer cell-host relationship, basis on corresponding targeted therapeutics
- Ability to analyze biological data from published scientific manuscripts.

3.2.3 Cancer disease: experimental and therapeutical approaches

(40h) - 6 ECTS S2 (IS BIO-DCS), Claire Rome Claire.Rome@univ-grenoble-alpes.fr

Description
To provide a comprehensive overview of cancer from basic research to clinical trials: cancer physiopathology; cancer metabolism; proteomics; circadian rhythm and cancer cell characteristics; development of new anti-cancer drugs; imaging in cancer disease

3.2.4 Biostatistics, Bioinformatics, Modeling

(39h) - 6 ECTS– S2 (IS BIO-PHED YAX9BI38) , Adeline Leclercq-Samson adeline.leclercq-samson@univ-grenoble-alpes.fr

Course outline
At the end of the course, the students should be able to analyze a "omic" dataset. More precisely, they should be able:
1- to load, explore and summarize graphically a dataset;
2- to compute confidence interval estimates for proportions, means and variances;
3- to formulate hypotheses, compute tests statistics, interpret p-values and make practical decisions for the
standard parametric and non-parametric tests;
4- to adjust simple and multiple linear models, analyses of variance (anovas), logistic regression, Cox
model;
5- to select genes that explain a response variable by applying multiple testing approaches;
6- to analyze a data set of differential gene expression.

Format of the course

Activities	Hours	Percentage
Lectures	15h	20%
Tutorials and discussions		
Lab sessions	30h	30%
Estimated work load at home	50h	50%
Total	95h	100%

Exam requirements

Nature of the exams	Mid-term (Number of hours, % of the final grade)	Final (Number of hours, % of the final grade)	Second session
Written exam			
Oral exam		30 min, 60%	20min
Research project	30 min, 20%		
Synthesis			
Practicals: report			

3.2.5 Molecular and cellular imaging (microscopy)

(50h) - 6 ECTS S2 (IS BIO-DD DCS), Arnaud Seigneurin Arnaud.Seigneurin@univ-grenoble-alpes.fr

Interactive lectures, combining theory and practice.

Lectures

Optical Microscopy:

- Basics of light microscopy, Köhler illumination, Contrast generation for transmitted light (Dark field, Polarized light, Phase contrast, DIC…)
- Fluorescence Microscopy, F-techniques, Optical Sectioning and Confocal Microscopy (Laser scanning confocal, multiphoton microscopy…)
- Processing and analysis of biological images

Electron Microscopy:

- Ultrastructural studies of the architecture of cellular components, viruses and macromolecular assemblies by electron microscopy (Transmission Electron Microscopy, Scanning, Cryo-EM…)
- Sample preparation, Image analysis

Discovering of X-Ray and near-field microscopies

Lab sessions:

Optical Microscopy: Köhler illumination, Contrasts for transmitted light, Fluorescence microscopy, Image Processing

Visits on research platforms allow the students to become familiar with modern microscopy techniques (laser scanning multiphoton, superresolution, F-techniques, imaging methods in electron microscopy ...).

Learning outcomes

- Acquisition by the students of autonomy on wide field optical microscopes,
- Thorough knowledge of the principles of electron microscopes
- Discovery of X-rays and near field microscopies.
- Practice of processing and analysis of biological images with open source software.

3.2.6 Data analysis, linear models and ANOVA

(54h) - 6 ECTS S2 (MSIAM), Jean-Baptiste Durand jean-baptiste.durand@imag.fr
Clementine Prieur clementine.prieur@grenoble-inp.fr

Description

The aim of this course is to present advanced statistics and linear modelling, variance analysis and provide practical implementation

Contents:

- Principal components analysis (PCA)
- Clissification (Linear Discr. Analysis)
- Data mining (text mining)
- Linear regression
- Estimation and test of regression parameters
- ANOVA
- ANCOVA
- Practical implementation

This is a two parts course, including practical sessions:

1. 3ECTS = Lecture 13h + Practical 5h + Lab 15h. Course mutualized with Ensimag 2A 4MMFDASM (head: Jean-Baptiste Durand)
2. 3ECTS = Lecture 14h + Lab 6h - MSIAM specific course (in-depth and practical session) (head: Clémentine Prieur)

A short description of the course content can be found here

Prerequisites

Elementary notions in probability theory (probability distribution, joint probability density function for random vectors, conditional distribution, expectation, variance, covariance, Gaussian distribution)

Elementary notions in mathematical statistics (estimator, confidence interval, statistical tests). As a bonus: simple linear regression.

Notions in linear algebra (matrix reductions). As a bonus: elementary notions in Rstudio and the R software.

3.2.7 Computing science for bid data and HPC

(54h) - 6 ECTS S2 (MSIAM), Christophe Picard christophe.picard@imag.fr

Description

The aim of this course is to give an introduction to numerical and computing problematics of large dimension problems.

Contents:

- Introduction to database
- Introduction to big data
- Introduction to high performance computing (HPC)
- Numerical solvers for HPC

Prerequisite

First semester of M1 MSIAM.

Intended learning outcome

Algorithmics of big data and HPC

Checking knowledge

Session 1 ou session unique - Contrôle de connaissances

Nature	Type	Nature d'évaluation	Durée (min)	Coeff.
UE	CC	Pratique		50/100
UE	CT	Ecrit - devoir surveillé	120	50/100

Session 2 - Contrôle de connaissances

Nature	Type	Nature d'évaluation	Durée (min)	Coeff.
UE	CC	Report de notes		50/100
UE	CT	Ecrit ou Oral		50/100

3.2.8 Numerical optimisation

(54h) 6 ECTS: S2 (MSIAM, GBX8AM02) Laurent Desbat Laurent.Desbat@univ-grenoble-alpes.fr

Description

This program combines case studies coming from real life problems or models and lectures providing the mathematical and numerical backgrounds.

Contents:

- Introduction, classification, examples.
- Theoretical results: convexity and compacity, optimality conditions, KT theorem
- Algorithmic for unconstrained optimisation (descent, line search, (quasi) Newton)
- Algorithms for non differentiable problems
- Algorithms for constrained optimisation: penalisatio, SQP methods
- Applications

Prerequisite

linear algebra, differential calculus

Intended learning outrcomes

Recognise and classify optimisation problems

Solve optimisation problems using adequate algorithms and methods

Practical implementation

Test

Session 1 ou session unique - Contrôle de connaissances

Nature	Type	Nature d'évaluation	Durée (min)	Coeff.
UE	CC			100/100
UE	CT	Ecrit - devoir surveillé	120	100/100

Session 2 - Contrôle de connaissances

Nature	Type	Nature d'évaluation	Durée (min)	Coeff.
UE	CC	Report de notes		100/100
UE	CT	Ecrit ou Oral	120	100/100

3.2.9 Advanced biostatistics and exploitation of research work

(44h) - 6 ECTS S2 (IS), Jean-luc Bosson JLBosson@chu-grenoble.fr

Parametric tests (Correlation - Regression, ANOVA, censored data analysis, PCA ...) and nonparametric tests (small sample cases) are discussed, up to complex multivariate models. The R - Rstudio software tool is used for the application examples.

There are 11 face-to-face sessions of SEPI or TD with 1 collaborative assignment (2 or 3 max) to be produced before the final MCQ-based exam. These assignments will be structured as statistical analysis protocols, preliminary stage of a scientific article and associated with a synthesis of multimedia presentation of the realized works.

3.2.10Short internship

(64h) - 6 ECTS S2 (IS)

Description

Science industrial and/or business project.

3.3 Semester 3

3.3.1 Molecular tools for the diagnosis and treatment of genetic diseases

(29h) - 3 ECTS (IS) , Jean BRETON jean.breton@univ-grenoble-alpes.fr

Course module description

This course will cover the principles of Molecular Diagnosis which is the process of identifying a disease by studying molecules, such as proteins, DNA, and RNA, in a tissue or fluid. Molecular diagnostics is a new discipline that captures genomic and proteomic expression patterns and uses the information to distinguish between two or more conditions at the molecular level. The conditions under investigation can be human genetic disease or infectious diseases. Molecular diagnostics is not confined to human diseases but can be also used in environmental monitoring, food processing ...etc.

Many of the diagnostic techniques are developed and marketed in kit format by biotechnology companies. The main source of information is web sites of companies that develop and market the molecular diagnostic kits. New methods are continuously developed. The objective of this course is learning and understanding how molecular techniques that were studied in other classes can be developed and utilized in diagnosis and sold in diagnostic kits.

Intended learning outcomes

- Knowledge and understanding of the basic principles used inmolecular diagnosis.
- Gain thinking and analysis skills to understand new diagnostic methods
- Ability to collect information to develop a new diagnostic kit.
- Knowledge and skills gained in the course should be useful in practical life in developing or using diagnostic kits

3.3.2 Molecular markers for medical imaging

(30h) 3 ECTS (BIOMED 5PMBMMI5) , Franz Bruckert franz.bruckert@grenoble-inp.fr

Goals

Series of seminars on the development and use of contrast agents and molecular markers in biomedical imaging and therapy

Content

Contrast agents and molecular markers for ultrasound, X-Ray and MRI imaging
Development and use of visible and infrared fluorophores
Application to cardiovascular diseases, cancer and neurodegenerative diseases.

Prerequisites

Molecular biology and physiology courses

Tests

The exam is given in english only
Written report based on articles proposed by the lecturers written report

3.3.3 Numerical simulation and statistical data analysis

(30h) 3 ECTS (BIOMED 5PMBNSS6) , Judith Peters Judith.Peters@grenoble-inp.fr

Content
The course will deal with the uncertainties of the experimental data, including the notions of probability, the random variable and distributions. Some hypothesis tests and confidence intervals will be presented. Simulation methods such as the Monte Carlo method will be introduced. The acquired techniques will be applied to selected examples in the field of life sciences and the environment.
Test
Writen exam (2h)

3.3.4 Modelling in systems biology

(30h) 3 ECTS (BIOMED 04PMBMSB4), Delphine ROPERS Delphine Ropers@grenoble-inp.fr
Goals
The course provides an introduction to systems biology by focusing on the behaviors emerging from interactions between genes, proteins and RNAs, taking examples from microbes to mammals. The main goal of this course is to show students that abstract computational and mathematical methods can be effectively employed for in silico modeling and analysis of living organisms. Moreover, to enhance practical skills, students will apply some of the techniques and software tools to analyze genome-scale models and models of cell metabolism and gene expression.
Content
The different steps of the model development will be presented: initial observations, hypotheses, model testing and validation. Different types of models will be described and illustrated, for instance: deterministic versus stochastic, static versus dynamic or versus non-parametric, lumped versus distributed. These notions will be illustrated by mathematical models in the biomedical field as for instance physiological models (Hodgkin-Huxley), compartment models or population models.

- Introduction to cellular networks and mathematical modelling (course: 2h)
- Mathematical modelling of cell metabolism: flux balance analysis (course: 2 hours + 2 hours computer lab exercises)
- Kinetic models of integrated networks and introduction to other modelling frameworks (4 hours + 2 hours computer lab exercises)
- Identification and inference of metabolic network models (2 hours + 2 hours computer lab exercises)

Intended Learning Outcomes
-- Understand basic knowledge about biological systems in order to model them.
-- Understand and be able to model different types of biological systems by using appropriate modeling tools.
-- Choose appropriate models and argue about these choices depending on the modeling application.
-- Make a critical analysis about the relevance and interest of mathematical models of biological systems in their capacity to predict
new experimental results and inspire original experimental protocols.

-- Use softwares and computers to implement and simulate mathematical models of biological systems.

Intended learning outcomes

-- Make a critical analysis of the scientific literature devoted to the development of original mathematical models of biological systems.

-- Make a concise and critical presentation of a scientific article related to mathematical models of biological systems.

Prerequisites:

No prerequisite

Tests:

Semester 8 - The exam is given in english only ; Continuous evaluation with homework assignment

3.3.5 Advanced algorithms for machine learning and data mining

3 ECTS 18h, Eric Gaussier Eric.Gaussier @ grenoble-inp.fr and Ahlame Douzal Ahlame.Douzal @ grenoble-inp.fr

Description

- A prior algorithms (Frequent item sets) & Page Rank
- Monte-carlo, MCMC methods: Metropolis-Hastings and Gibbs Sampling
- Matrix Factorization (Stochastic Gradient Descent, SVD)
- Generalized kmeans and its variants (Bach, Online, large scale), Kernel clustering (Support Vector Clustering), Spectral clustering
- Classification and Regression Trees, Support Vector regression
- Alignment and matching algorithms (local/global, pairwise/multiple), dynamic programming, Hungarian algorithm,…

Prerequisite

Fundamentals of probability/statistics, linear algebra and computer science (data structures and algorithms)

Bibliography

C.D. Manning, P. Raghavan and H. Schütze. *Introduction to Information Retrieval*. Cambridge University Press, USA, 2008.

A. DasGupta. *Probability for Statistics and Machine Learning*. Springer, 2011.

I. Goodfellow, Y. Bengio, A. Courville. *Deep Learning*. MIT Press, 2016.

C.M. Bishop. *Pattern Recognition and Machine Learning*. Springer Verlag, 2006.

3.3.6 Advanced learning models

3 ECTS, C. 18h, Julien Mairal Julien.Mairal @ grenoble-inp.fr and Jakob Verbeek jakob.verbeek @ inria.fr

Description :

Statistical learning is about the construction and study of systems that can automatically learn from data. With the emergence of massive datasets commonly encountered today, the need for powerful machine learning is of acute importance. Examples of successful applications include effective web search, anti-spam software, computer vision, robotics, practical speech recognition, and a deeper understanding of the human genome. This course gives an introduction to this exciting field, with a strong focus on kernels methods and neural network models as a versatile tools to represent data

This course deals with:

Topic 1: Neural networks

- Basic multi-layer networks
- Convolutional networks for image data
- Recurrent networks for sequence data
- Generative neural network models

Topic 2: Kernel methods

- Theory of RKHS and kernels
- Supervised learning with kernsl
- Unsupervised learning with kernels
- Kernels for structured data
- Kernels for generative models

It is composed of 18 hours lectures.

Evaluation :

There will be a written homework with theoretical exercises. In addition the students participate in a data challenge in which they implement a machine learning method of choice to solve a prediction problem on a given dataset. Both elements contribute equally to the final grade.

See course website.

Pré-requis

Fundamental notions in linear algebra and statistics.

Basic programming skills to implement a machine method of choice encountered in the course from scratch → http://thoth.inrialpes.fr/people/mairal/teaching/2017-2018/MSIAM

3.3.7 Bayesian statistics

18h, 3 ECTS. (MSIAM-FDS)Julyan Arbel Julyan.Arbel@univ-grenoble-alpes.fr

Objectives

The course aims at providing an overview of Bayesian parametric and nonparametric statistics. Students will learn how to model statistical and machine learning problems from a Bayesian perspective and study theoretical properties of the models.

Syllabus

This course is in two parts covering fundamentals of Bayesian parametric and nonparametric inference, respectively. It focuses on the key probabilistic concepts and stochastic modelling tools at the basis of the most recent advances in the field.

Part 1

- Foundations of Bayesian inference: exchangeability, de Finetti's representation theorem
- Conjugacy in simple models (binomial, Poisson, Gaussian)
- Some elements of posterior sampling, Markov chain Monte Carlo
- Bayesian neural networks and their Gaussian process limit

Part 2

- Clustering and Dirichlet process, random partitions
- Models beyond the Dirichlet process, random measures, Indian buffet process
- Some elements of Bayesian asymptotics

Bibliography

Hoff, P. D. (2009). A first course in Bayesian statistical methods. Springer Science & Business Media.
Neal, R. M. (2012). Bayesian learning for neural networks (Vol. 118). Springer Science & Business Media.
Hjort, N. L., Holmes, C., Müller, P., & Walker, S. G. (2010). Bayesian nonparametrics. Cambridge series in statistical and probabilistic mathematics. Cambridge: Cambridge Univ. Press.
Orbanz, P. (2012). Lecture Notes on Bayesian Nonparametrics. Available at: http://stat.columbia.edu/~porbanz/papers/porbanz_BNP_draft.pdf
Kleijn, B., van der Vaart, A., & van Zanten, H. (2012). Lectures on Nonparametric Bayesian Statistics. Available at: https://staff.fnwi.uva.nl/b.j.k.kleijn/NPBayes-LecNotes-2015.pdf
http://www.julyanarbel.com/bayesian-statistics-course

3.3.8 Category learning and object recognition

3 ECTS, C. 18h, Jakob Verbeek jakob.verbeek@inria.fr

Description :

In this course we present recent state-of-the-art methods for visual object category representation and recognition, and the techniques that underpin these methods. Methods will include so called "bag of features" approaches, Fisher vectors, and convolutional neural networks for tasks such as instance-level image retrieval, image classification, object localization, semantic segmentation, image caption generation and action recognition in videos. On the machine learning side we consider clustering methods (k-means, mixutre of Gaussians), classification techniques (SVM, logistic discriminant), and kernels to obtain non-linear classifiers, as well as the principles underlying neural networks (multi-layer perceptron, back-propagation, convolutional networks, recurrent networks).
http://www.julyanarbel.com/bayesian-statistics-course

3.3.9 Computational biology

3 ECTS, C. 18h, (MSIAM), Olivier François olivier.francois@imag.fr and Michaël Blum

Description:

This interdisciplinary MSc course is designed for applicants with a biomedical, computational or mathematical background. It provides students with the necessary skills to produce effective research in bioinformatics and computational biology. The objective of the course is to introduce mathematical biology questions, stochastic and deterministic approaches for modeling biological systems, and advanced tools for the analysis of biological data.
The topics addressed in this course include a brief introduction to stochastic processes and differential equations and their application to biological problems. The first part of the course focuses on modelling in molecular biology and evolution, and on the analysis of molecular phylogenetic or population genetic data. The second part of the course focuses on models in cellular biology and biomechanics.

Evaluation:

1st session: oral presentation E1a and written exam Practical project E1b

The final mark in session 1 is obtained as 0.5*E1a + 0.5*E1b.
2nd session: written exam E2
Prerequisites:
No specific prerequisites.

3.3.10Machine learning fundamentals

(30h) - 3 ECTS S9 (MSIAM-FDS), Massih-Reza Amini Massih-Reza.Amini @ grenoble-inp.fr
Marianne Clausel marianne.clausel @ univ-grenoble-alpes.fr

Description:

- Consistency of the Empirical Risk Minimization
- Uniform Generalization Bounds and Structural Risk Minimization
- Unconstrained Convex Optimization
- Binary Classification algorithms (Perceptron, Adaboost, Logistic Regression, SVM) and their link with the ERM and the SRM principles
- Multiclass classification
- Application and experimentations

Evaluations:
Homeworks (30%), final exam (70%)
Prerequisites :
Statistics and probability (BSc)
Learning outcomes :
Understanding of fundamental notions in Machine Learning (inference, ERM and SRM principles, generalization bounds, classical learning models, unsupervised learning, semi-supervised learning.
Bibliography :
[1] Massih-Reza Amini - Apprentissage Machine de la théorie à la pratique, Eyrolles, 2015.
[2] Christopher Bishop - Neural Networks for Pattern Recognition, Oxford University Press, 1995.
[3] Richard Duda, Peter Hart & David Strok - Pattern Classification, John Wiley & Sons, 1997.
[4] John Shawe-Taylor & Nello Cristianini - Kernel Methods for Pattern Analysis, Cambridge University Press, 2004.
[5] Colin McDiarmid - On the method of bounded differences,Surveys in Combinatorics, 141:148-188, 1989.
[6] Mehryar Mohri, Afshin Rostamzadeh & Ameet Talwalker - Foundations of Machine Learning, MIT Press, 2012.
[7] Bernhard Schölkopf & Alexander J. Smola - Learning with Kernels, MIT Press, 2002.
[8] Vladimir Kolchinskii - Rademacher penalties and structural risk minimization, IEEE Transactions on Information Theory, 47(5):1902–1914, 2001.

3.3.11 Fundamentals of probalistic data mining

(30h) – 3 ECTS S9 (MSIAM-FDS), Jean-Baptiste Durand (jean-baptiste.durand@imag.fr)

Description:

This lecture introduces fundamental concepts and associated numerical methods in model-based clustering, classification and models with latent structure. These approaches are particularly relevant to model random vectors, sequences or graphs, to account for data heterogeneity, and to present general principles in statistical modelling. The following topics are addressed:

- Principles of probabilistic data mining and generative models; models with latent variables
- Probabilistic graphical models
- Mixture models and clustering
- PCA and probabilistic PCA
- Nonparametric density estimation
- Generative models for series and graphs: hidden Markov models

Evaluation:

2-hours written exam (E1) and two reports on practicals or research work (P).The final mark in session 1 is obtained as 0.4E1+0.6P. The final mark in session 2 is obtained as E2 (a 2nd session written exam only).

Prerequisites:

Fundamental principles in probability theory (conditioning) and statistics (maximum likelihood estimator and its usual asymptotic properties).

Constrained optimization, Lagrange multipliers.

Learning outcomes:

At the end of the course, the student will be able to perform model-based clustering, analysis and segmentation of time-series with hidden Markov models, build a graphical model associated with a given distribution and represent numerical multivariate data with missing coordinates into planes.

Bibliography :

Lauritzen, S.L. Graphical Models. Clarendon Press, Oxford, United Kingdom, 1996.

Koller, D. and Friedman, N. Probabilistic graphical models: principles and techniques. MIT press, 2009.

Bishop, Christopher M. Pattern Recognition and Machine Learning. Springer Verlag, 2006.

3.3.12 Model selection for large-scale learning

(60h) - 3 ECTS S9 (MSIAM-LSDS), Emilie Devijver Emilie.Devijver@univ-grenoble-alpes.fr

Description:

When estimating parameters in a statistical model, sharp calibration is important to get optimal performances. In this course, we will focus on the selection of estimators with respect to the data. Particularly, we will consider calibration of parameters (e.g., regularization parameter for minimization of regularized empirical risk, like Lasso or Ridge

estimators) and model selection (where each estimator minimizes the empirical risk on a specified model, as mixture models with several number of clusters).
We will focus on the penalized empirical risk, where the penalty may be deterministic (as BIC or ICL) or estimated with data (as the slope heuristic).
Prerequisites :
Basic knowledges in probability and statistics
Target skills :
Learn

- When model selection is needed.
- What can be proved theoretically for existing methods.
- How those results can help in practice to choose a criterion for some specific statistical problem
- How the theory can serve to define new procedures of selection.

References:
T. Hastie, R. Tibshirani and J. Friedman, The Elements of Statistical Learning. Data Mining, Inference, and Prediction
P. Buhlmann and S. van de Geer, Statistics for High-Dimensional Data. Methods, Theory and Applications
P. Massart, Concentration Inequalities and Model Selection

3.3.13Information visualization

(C. 18h) - 3 ECTS, Renaud Blanch renaud. blanch@imag.fr

Interactive Information Visualization (InfoVis) is the study of interactive graphical representations of abstract data (e.g. graphs linking people in social networks, series of stock options values evolving over time).
Graphical representations are a powerfull way to leverage the human perceptual capabilities to allow the user to explore and make sense of abstract data, and also to expose findings and convey ideas.
But to be efficient, a visualization has to be designed using knowledge about the human visual perception, the characteristics of the data, the kind of task that will be performed on those data.
The aim of this course is to provide the keys, both theoretical and practical, to build usable and useful interactive visualizations.
Program summary:

- foundations: human visual perception, graphical variables, data types, the visualization pipeline.
- linked data: tree and graph visualization
- tabular data: time series and spatial data visualization
- dealing with large data: aggregation, multiple views, interaction
- validating visualization: visualization tasks, evaluation

3.3.14Data challenges

(60h) - 3 ECTS S9 (MSIAM-LSDS), Project, Jean-Baptiste Durand jean-baptiste.durand@imag.fr Ronald Phlypo and Olivier Michel

Description

Face up challenging real-world problems in machine learning, be involved in multidisciplinary teams of data scientists, computer scientists, mathematicians and expert students in signal processing, and contribute to leading your team to the top rank!

Different teams with M2 students issued from either MSIAM Data Science, MoSIG Data Science and SIGMA work on a same challenge on either complex, structured or big data, and maybe a combination of all three. Try and compare different approaches, take benefit from the computational power of clusters and from advice of your supervisors.

The data challenges stretch on several months, include some tutored sessions, if needed mini-courses, and of course your regular involvement over that period of time.

Evaluation

The final mark in composed as 1/3 score (ranking/performance), 1/3 report and 1/3 oral presentation.

Prerequisites :

Elementary notions in probability theory (multivariate distributions), machine learning (concepts of regression, classification and clustering) and programming (usually python, although other languages may be chosen).

Learning outcomes :

At the end of the course, the student will be able to work in teams involving various skills (machine learning, statistical modelling, programming, data bases and others). They will acquire skills in data analysis and self-training in acquiring or reinforcing skills among the four listed above.

Bibliography :

Dopplick, R. Expanding minds to big data and data sciences. *Inroads*, **6**(3) 88, 2015.

Yang, J. How we did it: Jie and Neeral on winning the first Kaggle-in-class competition at Stanford, 2010.

Organization of the data challenge in 2018-2019

Detailed description of GBX9AM20 ; MSIAM Course list ; Semester 3 (MSIAM tracks)

3.3.15Data management in large-scale distributed systems

(C 18h), 3 ECTS, S9 Thomas Ropars Thomas.Ropars@univ-grenoble-alpes.fr

Description

Target skills : Data management and knowledge extraction have become the core activities of most organizations. The increasing speed at which systems and users generate data has led to many interesting challenges, both in the industry and in the research community.

The data management infrastructure is growing fast, leading to the creation of large data centers and federations of data centers. These can no longer be handled exclusively with classic DBMS. It requires a variety of flexible data models (relational, NoSQL…), consistency semantics and algorithms issued by the database and distributed system communities. In addition, large-scale systems are more prone to failures, and should implement appropriate fault tolerance mechanisms.

The dissemination of an increasing amount of sensors and devices in our environment highly contribute to the “Big Data” and the development of ubiquitous information systems. Data is processed in continuous streams providing information related of users context, such as their movement patterns and their surroundings. This data can be used to improve the context awareness of mobile applications and directly target the needs of the users without requiring an explicit query.

Combining large amounts of data from different sources offers many opportunities in the domains of data mining and knowledge discovery. Heterogeneous data, once reconciled, can be used to produce new information to adapt to the behavior of users and their context, thus generating a richer and more diverse experience. As more data becomes available, innovative data analysis algorithms are conceived to provide new services, focusing on two key aspects: accuracy and scalability.

Program summary : In this course, we will study the fundamentals and research trends of distributed data management, including distributed query evaluation, consistency models and data integration. We will give an overview of large-scale data management systems, peer-to-peer approches, MapReduce frameworks and NoSQL systems. Ubiquitous data management and crowdsourcing will also be discussed.

Evaluation

2-hours written exam (E) and a report on practical work (P). The final mark in session 1 is obtained as 0.7E+0.3P. The final mark in session 2 is obtained as a written exam only.

Prerequisites

Fundamentals of DBMS, parallel programming (threads)

Learning outcomes

At the end of the course, the students will know how to use Big Data software tools to efficiently store and process large amounts of data, including tools that can operate in realtime.

Bibliography

Dean, Jeffrey, and Sanjay Ghemawat. “MapReduce: simplified data processing on large clusters.” Communications of the ACM 51.1 (2008): 107-113.

Zaharia, Matei, et al. “Apache spark: a unified engine for big data processing.” Communications of the ACM 59.11 (2016): 56-65.

Murray, Derek G., et al. “Naiad: a timely dataflow system.” Proceedings of the Twenty-Fourth ACM Symposium on Operating Systems Principles. ACM, 2013.

Lakshman, Avinash, and Prashant Malik. “Cassandra: a decentralized structured storage system.” ACM SIGOPS Operating Systems Review 44.2 (2010): 35-40.

Detailed description of GBX9MO08 ; MSIAM Course list ; Semester 3 (MSIAM tracks)

3.3.16Data science seminar

3 ECTS, S9 Seminars, Jean-Baptiste Durand, jean-baptiste.durand@imag.fr Ronald Phlypo and Olivier Michel

Our master programs now include a series of 6 or 7 seminars given by active researchers in the field of data processing methods and analysis.

These seminars are intended to give students some insights on modern problems and solutions developed in a data science framework, with applications in a variety of fields.

In order to make these seminars a most valuable experience for all students, a scientific paper dealing with the topic of the seminar will be selected by the speaker and dispatched to all students about 2 weeks before the seminar. Students are expected to read and study this paper, and to prepare questions, before attending the seminar. Presence at the seminars is compulsory for master students.

At the end of the seminar series, some oral exam is organized. One of the topic presented during the seminars is randomly assigned to each student a few days in advance. The oral exam consists in a 25 min summarized presentation of the scientific issues that were addressed, and a 15 min session of discussion and questions. A second different topic is chosen by the student, and he.she must write a report on that topic, based on the seminar and associated articles.

The seminars will be on Thursdays around 3:30PM (no sooner).

Follow the announcements on https://data-institute.univ-grenoble-alpes.fr/education/data-science-seminar-series/ (regularly updated)

This module is common with the M2 programmes MSIAM Data Science, MoSIG Data Science and SIGMA.

3.3.17Software development tools and method

(CM : 9h **TP :** 30h), 3 ECTS, S9 Seminars, Mourad Ismail mourad.ismail @ univ-grenoble-alpes.fr

Description

The aim of this course is to study various useful applications, libraries and methods for software engineering related to applied mathematics. For example :

- C++ project management (git and/or svn)
- Development and profiling
- Boost library
- Linear algebra (Eigen)
- Prototyping and interfacing using Python
- Post processing and visualization tools (VTK, Paraview, GMSH)

This course deals with :

Topic 1: Software Engineering

Topic 2: Programming

Evaluation

Practial sessions reports and oral presentation at the end of the course

Prerequisite

Linear algebra: fundamental notions (matrices, linear functions), Programming in C++ and python

Learning outcomes
At the end of the course, students will be able to manage and couple different libraries, to debug correctly a code (find memory leaks for example).
Bibliography

- https://git-scm.com/
- http://www.boost.org/
- http://eigen.tuxfamily.org/index.php?title=Main_Page
- http://www.vtk.org/

3.3.18Entrepreneurship and innovation

(23h Lectures; 57h Pratcticals ; 10 h Project); 6 ECTS; S 9 Daniel Bernard
daniel.bernard@univ-grenoble-alpes.fr
Objective and learning outcomes
Goal
The aim of this course is to:
- Understand the main concepts related to technology ventures management.
- Understand and apply the main tools for business model generation.
- Develop the ability to search, analyze and combine business and technology information to build a business plan.

Outcomes
During this course, students will:
- Know the concepts and tools associated with technology management
- Know and apply the tools to generate business models from the analysis of the current state of technology
- Be able to work out a business plan

At the end of the module, students should be able to achieve: ILO-B1 to ILO-B5, ILO-G1 to ILOG9, ILO-S2.
Content
1. Introduction to entrepreneurship: main concepts about technology new ventures. Main Founders' characteristics.
2. Establishing the business idea: Technology search and analysis.
3. Customer analysis: Market segmentation; End user analysis; Total Addressable Market (TAM) analysis.
4. Value proposition: Full Life Cycle; Product specification; Quantifying the value proposition.; Competitive analysis.
5. Product acquisition: understanding customers' decision process.
6. Business model generation: Business model canvas; Components' analysis; Design the business model; Lifetime Value of a customer; Cost of a Customer Acquisition.
7. Product design: defining the Minimum Viable Business Product.
8. Scaling the business & Building up the company: Technology venture financing; Negotiating deals; Company registration.

3.3.19 Entrepreneurial Process & Tools

(23h Lectures; 57h Practicals ; 10 h Tutorial), 6 ECTS, S3 Caroline Tarillon caroline.tarillon@univ-grenoble-alpes.fr

Objective and learning outcomes

Goal:

The aim of this course, is to:

- Analyse the functions developed by a biomedical engineer within an organization.
- Understand managerial concepts in a business environment.

Intended learning outcomes:

During this course, students will:

- Develop the ability to search, analyze and combine business information for decision making.
- Understand management of the main functional areas of a company: marketing, operations, finance, human resources and R&D.

At the end of the module, students should be able to achieve: ILO-B1 to ILO-B5, ILO-G1 to ILOG9, ILO-S2.

Content

1. Strategic management: Management Strategy; Business values and orientation; External analysis; Internal analysis; Corporate, Business and Functional strategies
2. Marketing: Strategic marketing; Operative marketing: Four P's
3. Operations Management: Definition & Evolution; Strategies; Supply chain; Quality management; Five P's (product, process, plan, programme and people)
4. Human Resources: Planning; Recruiting; Selection; Training; Performance appraisal; Compensation
5. Innovation management (R&D): Sources; Innovation types ; Disruptive innovation ; Managing innovation
6. Finance: General concepts on financial cycles; Main financial documents; Cost Accounting.

3.3.20 Research and Development Projects

(70h) ; 3 ECTS; S3 Jean Breton jean.breton@univ-grenoble-alpes.fr

Objective and learning outcomes

Goal

The aim of this course is to learn students how to apply the scientific method in the development of research and development projects, as well as in the dissemination of project results.:

Intended learning outcomes

During this course, students will:

- Work on bibliographical subject and make a critical discussion about the results in oral and public presentation.
- Perform an individual and a team work, developing the ability to search information sources, analyse the legislation for the collaboration of public and private entities, and apply methods for management of research projects.

• At the end of the module, students should be able to achieve: ILO-B1 to ILO-B5, ILO-G1 to ILOG9, ILO-S3, ILO-S4.

3.3.21 Biomedicines innovative project

(30h) - 6 ECTS (IS) , Jean Breton jean.breton@univ-grenoble-alpes.fr

Content

This curse takes a very practical, applied approach to the challenges of successful project management.

The essentials cover the following: structuring projects to set realistic goals and identify milestones; using effective tools for scheduling and be able to run single or parallel projects; identify project risks ; manage time, cost and quality; implement control systems to keep on top of the project.

Target

The Biomedicines innovative project has a wide range of possible applications for any initiative whose completion is fixed within specific time limits.

3.3.22 Computational Medicine Summer School

[COPD and Chronic conditions as Case Study]

35h Lectures; 50h Practicals; 30 Tutorials; 6 ECTS S3 Philippe SABATIER philippe.sabatier@univ-grenoble-alpes.fr

Objective and learning outcomes

Goal

CompMed is a Summer School, which expose participants to some of the latest biomedical advances. Students are invited to discover how engineering and computing solutions could be used to promote healthy living and active aging. The participants have the opportunity to leave a transformational experience, which will help them to develop transferable skills necessary for successful innovation. During the school, the students meet innovative scientist and high tech start-up companies, and can discuss their ideas with highly qualified professors and young entrepreneurs. They are introduced to Creative Thinking, will have a unique opportunity to promote (pitch) their ideas in front of a medical/business panel, with the opportunity for further development of promising teams, and potential links to Health Accelerator

Intended learning outcomes

By taking this course participants will:

- Know the definition of biological/pathological process; chronic disease; electronic health records; semantic data, mathematical modelling; Investigate biological/pathological process;
- Learn how design theoretical models; integrate multi-scale modelling; support interaction between deterministic model and probabilistic models; study perturbations of a biological process; explore the toolbox of biomathematics modelling.
- Study data representation and integration; explore semantic technologies and translational medicine; assess data warehouse solutions in terms of their targeted medical use case : data sharing, data interoperability and knowledge discovery.
- Discover and manage databases; Use specific and publically available datasets (BioBridge and PAC-COPD); Create semantic mapping on inference engineering; Analyse associations of co-morbidities in PAC_COPD and in the Medicare database (diseasome)

- Integrate oxygen transport models from atmosphere to cell with mitochondrial reactive oxygen species (ROS) generation and metabolic pathways.
- Provide intuitive users interfaces for clinician and bio-researchers.

  - At the end of the module, students should be able to achieve: ILO-B1 to ILO-B5, ILO-G1 to ILOG7, ILO-S1, ILO-S10, ILO-S11.

Content

CompMed learn clinicians, scientists, and engineers in computational medicine and healthcare optimization for chronic diseases (CD) focused on COPD as case study. CompMed aims to use a systems approach for the study of the underlying mechanisms of diseases' phenotypes associated with poor prognosis. To address this tricky challenge, CompMed propose a dynamic approach, based on complex problem solving. COPD is caused by unhealthy life-styles and increased life expectancy, complex gene-environment interactions, intrinsic host responses, such as local and systemic inflammation, epigenetic changes and decoupling of basic regulatory mechanisms with impact on bioenergetics, metabolome, proteome, genome, microbiome, immune responses and remodeling. Through the case study on COPD, participants are invited to work, step by step, on a better understanding of the physio-pathological mechanisms explaining co-morbidity, which seems to be crucial not only for a better diagnosis and treatment, but also to envision new formats of service delivery considering early patient stratification based on characterization of disease phenotypes. The learning process is based on the iterative loop of Systems Medicine approach: (1) Formulate and formalize a question; (2) Define, Integrate and Perturb systematically the system components; (3) Check model predictions; Collect appropriate data sets (targeted and global); Compare the observed/predicted results; (4) Refine the model so that its predictions fit better with the experimental observations; Iterate the process until an answer to the initial question is obtained. The program culminates in a capstone design-project in which students work in interdisciplinary teams co-advised by faculty members and investigators from industries and hospitals. The participants are introduced to Creative Thinking, and throughout the last day, they present (pitch) their projects in front of a business/medical panel, who will join the session and provide their valuable feedback. CompMed provides participants with a broad but high-level scientific background and important skills such as conceptual approaches, teamwork, management of complex processes, entrepreneurship and high intercultural awareness. The school combines an intensive programme of lectures, hands-on sessions (experiments, simulation and modeling) and group working. Courses are given by teachers from France, Spain, United States, Sweeden, Germany, the Netherlands, Great-Britain and Switzerland.

3.4 Semester 4

3.4.1 Master's Dissertation

280h ; 24 ECTS ; S4

Objective and learning outcomes

● The master dissertation in Biomedical Engineering is typically a research project or study, or an extended analysis of a topic of scientific or technological nature. The goal is for students to perform research and apply the knowledge acquired during their Masters while at the same time developing skills lik initiative, autonomy skills, decision and organization.

● The main learning output of this master thesis is the students' ability to work on a BME program, and to translate research into applications. This innovative approach of Healt4Lifeis based on the mobility of students, exchanging experiences in different disciplines and establishing a common high quality standard in education and training.

● At the end of the master thesis students should be able to achieve: ILO-B1 to ILO-B5, ILO-G1 to ILOG7, ILO-S1, ILO-S10, ILO-S11.

Content

The program is defined according to the supervisor orientation and to the type of theme and it is developed during one of the semesters of the last year of the MSc Course. Following the MSc procedures, the Education Committee has assessed the scientific quality and feasibility of the master thesis proposals. It is anticipated that the thesis will be relevant to the student's track and will address a question of importance in the student's field of expertise. Students are expected to design a research project, write a formal research protocol, perform the study described in it, and prepare a comprehensive scholarly scientific paper reporting the results. By October, students should hand in their definitive research proposal and start the research project. Optionally, part of the master project could be done at another institute or company outside Partner Universities, but in this case, it is always under supervision of a Partner University staff member. To achieve their research project, students are required to write a scientific paper under guidance of their research supervisors, and to give a presentation about the research performed. The scientific paper must be approved by the director and be suitable for submission to an international, scientific journal. The dissertation can take place at IST or outside IST (universities, research centers or companies, in Portugal or abroad). As mentioned above, the thesis requires an advisor from the Engineering side (usually from IST) and a co-advisor from the Medical/Biomedical side (usually from FMUL).

3.5 Summer School Artificial Intelligence for Health

35h Lectures; 50 h Practicals; 30 Tutorials; 6 ECTS; S3 Philippe SABATIER philippe.sabatier@univ-grenoble-alpes.fr

Objective and learning outcomes

● Goal: AI4Health's mission is to teach advanced topics related to Big Data computing and analytics for health and wellbeing, as well as to enhance innovation and entrepreneurial awareness amongst participants. The participants have the opportunity to leave a transformational experience, which will help them to develop transferable skills necessary for successful innovation. During the school, the students meet innovative scientist and high tech start-up companies, and can discuss their ideas with highly qualified professors and young entrepreneurs. They are introduced to Creative Thinking, will have a unique opportunity to promote (pitch) their ideas in front of a medical/business panel, with the opportunity for further development of promising teams, and potential links to Health Accelerator. IBD4Health is part of the bioHC program which educates since 2011 outstanding minds and cultivates future leaders who will explore fundamental principles underlying disease and design new biomedical technologies for health and wellbeing.

● Outcomes: By taking this course participants will:

• Know definition Big Data: (volume, velocity, variety, value), challenges. Study how and where Big Data challenges arise in a number of domains (including medicine, social media, insurance and finance). Investigate web challenges and how to engineer around them. Discover user interfaces for Big Data and their functions.

• Learn how designing theoretical models to investigate biological and pathological process of Chronic Diseases. Use the toolbox of biomathematics modelling.

• Work on data representation and integration, in particular with semantic web technologies and data sharing, data interoperability and knowledge discovery. Explore the SQL & NoSQL systems, their capabilities and pitfalls, and how the NewSQL movement addresses these issues in terms of scalability, performance, and robustness.

• Explore data representation and integration, in particular with semantic web technologies and translational medicine. Assess existing solutions in terms of their target medical use case and of data sharing, data interoperability and knowledge discovery.

• Analyze Big Data: statistical learning and evidence-based medicine.

• Propose technology transfer in healthcare, and population wellbeing. Study the ethical issues, and discover recent techniques that help building secure Big Data systems; resolving the challenges of sharing protected data and of integrating semantic-driven technologies into the clinical practice.

• Solve the obesity study case by team working; Writing and defending orally an executive summary.

● At the end of the module, students should be able to achieve: ILO-B1 to ILO-B5, ILO-G1 to ILOG7, ILO-S1, ILO-S10, ILO-S11.

Content

IBD4Health focuses on the technology, unmet needs, business, value chain, privacy and security aspects of future Health Clouds. Data collection on a large scale could provide materials for in-depth analysis of different causal and contributory factors, supporting the development of effective interventions and public health approaches to tackle obesity. IBD4Health comprises interactive morning sessions, including guest presentations, and computer practicals on case study, and afternoon sessions focused on innovation and entrepreneurship, including workshops, group assignments, etc. The programme is

organised in three sessions: 1st Session: Health, wellbeing and data challenges; 2nd Session: Data oriented design, collection, computing and analytics; 3rd Session: Innovation and entrepreneurship.
The School's program starts with an Introductive round table (session 1) and ends with a Pitching session and a Design Thinking Workshop 'session 3). Everyday sessions mix a comprehensive range of practical tools and real life experiences. Time off between the sessions allowed participants to work on individual or team projects.
Lectures & Practical Exercice on Data Design, Collection, Computing, Analytics, introduce the state-of-the-art on Big Data Technologies: from oriented design, collection, storage, computing, security and privacy and big data. Through the case study on obesity, multidisciplinary participants are invited to discover, step by step, the main sources of data and efforts to develop new tools on large-scale data processing application, which involves very complex systems and sophisticated mechanisms.
Innovation & Entrepreneurship Session is devoted to working on innovative ideas, and translating them into value creation through business model approach. At the end of the Opening Day, 5 Group Projects (GP) are selected from the Personal Projects (PP) proposed on the student's applications. Students are invited to explore the following aspects: unmet need, mobilized technology, developments to achieve, market analysis, etc. Participants are introduced to Creative Thinking as well as applied Design Thinking and Pitching. CERN BIC network proposes teaching based on the expertise of hosted SME and Spin-off. IBD4Health provides participants with a broad but high-level scientific background and important skills such as conceptual approaches, teamwork, management of complex processes, entrepreneurship and high intercultural awareness. The school combines an intensive programme of lectures, hands-on sessions (experiments, simulation and modeling) and group working. Courses are given by teachers from France, Spain, United States, Sweeden, Germany, the Netherlands, Great-Britain and Switzerland.

3.5.1 Summer School on Safer Nanomaterials

35 h Lectures; 50 h Practicals; 30 Tutorials; 6 ECTS; S4 Philippe SABATIER
philippe.sabatier@univ-grenoble-alpes.fr

Objective and learning outcomes
● Goal: SaferNano Design& Law (Safer Design for Nanomaterials) is a Summer School which focuses on advanced methods and innovative approaches to NTs' safety-by-design, in order to reduce the need of, and/or foster substitution of Critical Raw Materials (CRMs) in the main EU industrial Value Chains. The three main objectives are:
• Educate students to become highly-skilled European professionals with expertise in NT's EHS. This expertise will enable them to develop new methods for life cycle assessment and safer designing of nanomaterials.
• Enable participants to become leading practicing engineers, across all sectors of society including academia, industry and public service, with transferable skills such as innovation, ethics, intellectual property, sustainability and advanced research strategies.
• Develop a deep entrepreneurship mindset with the help and expertise of associated businesses, incubators and innovation services as well as a large panel of industries.
● Outcomes: SaferNano Design & Law provides participants with a broad but high-level scientific background in the field, of nanosafety and important skills such as teamwork, management of complex processes, conceptual approaches, entrepreneurship and high intercultural awareness. Students are trained on how to get and analyse omics data to

perform gene ontology and pathway analysis. They also become familiar with predictive toxicology via the Adverse Outcome Pathways (AOP) and Effectopedia tool. By taking this course participants will have gained :
- Broad view of the nanotechnology market and the evolving regulatory framework,
- Knowledge on theoretical and practical understanding of nanomaterial reactivity and transformation in the environment; and on the surface reactivity and on the 'nano-specific' properties useful for diverse applications.
- Knowledge on how to assess environmental impacts of nanomaterials using a life cycle assessment model, and to develop nanomaterials and nanoproducts using a safer by design approach.
- Insight on the different types of assays available to assess the impact of nanomaterial exposure at different levels (environment, organism, cell, molecule etc.
- Overview of nowadays and future nanotoxicology: the different types of assays available to assess the impact of nanomaterials exposure at the organism but also cellular and molecular levels. Finally, the students will have gained knowledge on how to assess the biological response to nanomaterial exposure.
- Mastery of the general legislation concerning eco-design at EU and national levels, as well as working knowledge of value chain issues and marketing. It also includes the capacity to analyse in specific contexts how innovative strategies may lead to improved firm performance or to new business perspectives.
● At the end of the module, students should be able to achieve: ILO-B1 to ILO-B5, ILO-G1 to ILOG7, ILO-S1, ILO-S10, ILO-S11.

Content
Nanotechnology is now bringing new opportunities to reduce the need of, and/or foster sub-stitution of Critical Raw Materials in the main EU Industrial Value Chains. SaferNano Design & Law address the tricky challenge of the Nanotechnology's transition by promoting 'safety-by-design' that minimizes the risks associated to environment and population health. By working on case studies, participants learn the main computing tools and databases for addressing the life cycle of the products. Additionally, they are introduced to Creative Thinking & 1st Session Business Creation and invited to pitch their ideas in front of a business panel. The program is organized in four sessions: 1st session: Nanomaterials and their life-cycle analysis; 2nd Session: Nanomaterials transformation in the environment; Ecosystem and Human Exposure; 3rd Session: Human toxicity; 4th Session: Innovation, Technology transfer and Business development. The school combines an intensive program of lectures, hands-on sessions (experiments, simulation and modeling) and group working. Courses are given by teachers from France, Spain, United States, Sweden, Germany, the Netherlands, Great-Britain and Switzerland.