Centre for Modeling and Simulation
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Master of Technology (M.Tech.) Programme in Modeling and Simulation

Board of Studies: Modeling & Simulation
Faculty: Science & Technology

Savitribai Phule Pune University

About This Document

The *Master of Technology (M.Tech.) Programme in Modeling and Simulation*, designed by a core group of people associated with the Centre for Modeling and Simulation, Savitribai Phule Pune University (formerly University of Pune), was approved by the University in 2007, and came into existence in the academic year 2008-09. Based on the collective and individual experience gained since then, the present document outlines a university-approved revision of this programme.

Citing This Document

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Credits and Acknowledgements

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Contributors: Listed under each individual syllabus separately.

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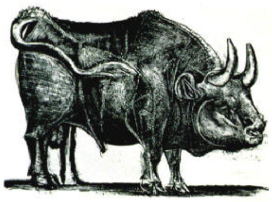
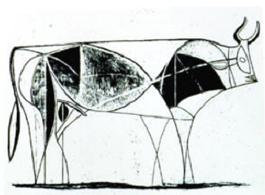
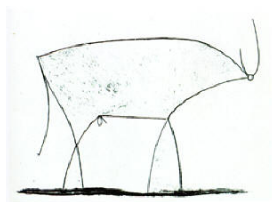
We Value Your Feedback

The utility of modeling and simulation as a methodology is extensive, and the community that uses it, academic or otherwise, is diverse. We would appreciate your feedback and suggestions on any aspect of this programme. Feedback can be sent to `office@cms.unipune.ac.in`.

About the Centre

The Centre for Modeling and Simulation, Savitribai Phule Pune University (formerly University of Pune), was established in August 2003 with a vision to promote modeling and simulation methodologies and, in keeping with world-wide trends of modern times, to encourage, facilitate, and support highly interdisciplinary approaches to basic and applied research that transcend traditional boundaries separating individual knowledge disciplines. For more information, visit `http://cms.unipune.ac.in/`.

All models are false, some are useful.
Quote attributed to George E.P. Box.

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Administrative Summary: Master of Technology (M.Tech.) Programme in Modeling and Simulation

Title of the Programme Master of Technology (M.Tech.) Programme in Modeling and Simulation.

Degree Offered Master of Technology (M.Tech.) in Modeling and Simulation.

Designed by Centre for Modeling and Simulation, Savitribai Phule Pune University.

Board of Studies Modeling and Simulation.
Faculty Faculty of Science & Technology, Savitribai Phule Pune University.

Mode of Operation Full-time, autonomous programme run by the Centre for Modeling and Simulation, Savitribai Phule Pune University in the academic flexibility/autonomy mode.

Minimum Duration 2 years.

Credits & Breakup 72 credits, with 1 credit ≡ 15 contact hours

Semester	Core	Choice	
1	18	0	**18**
2	10	8	**18**
3	8	10	**18**
4	18	0	**18**
	54	**18**	**72**

Structure and Syllabus This document, Sec. 2 onward.

Medium of Instruction English.

Number of Seats Regular Admissions: 30.
Supernumerary and other admissions (foreign, etc.): As per the prevailing Savitribai Phule Pune University policies.

Eligibility {{B.E./B.Tech. any branch} OR {M.Sc.+valid GATE score}} AND {Proficiency in Mathematics at 12+2-level science (i.e., S.Y.B.Sc.) and engineering (i.e., M1+M2+M3) programmes of Savitribai Phule Pune University}.

Admissions As per the prevailing Savitribai Phule Pune University rules and policies.

Fees As per the prevailing Savitribai Phule Pune University policies for self-supporting departments.

1 The Revised M.Tech. Programme

1.1 Overview of This Revision

1. This document details a revision of the 2018 Master of Technology (M.Tech.) Programme in Modeling and Simulation (http://cms.unipune.ac.in/reports/pd-20180701) including coursewise syllabi.

2. The basic framework for the Master of Technology (M.Tech.) Programme in Modeling and Simulation as elaborated upon in earlier programme documents including the original version of the programme (http://cms.unipune.ac.in/reports/pd-20070223) remains the same for this revision as well.

3. The revised curriculum in this document is applicable starting from Academic Year 2019-20 until superseded by the next revision.

4. The principle reasons for this revision are the following.

   (a) Recent national trend in higher education of creating leaner programmes: E.g., AICTE's model curricula[1][2] outline engineering programmes which are 68 AICTE credits in size. One AICTE credit is defined as 16 contact hours, whereas one UGC credit is 15 contact hours. Therefore, 68 AICTE credits translate to (nearly) 72 UGC credits.

   (b) Recent policy shifts at the Savitribai Phule Pune University[3][4] are also encouraging leaner programmes for a variety of reasons.

5. Therefore, while resizing the earlier 100-credit programme to 72 credits, we have actively endeavoured to keep only the most essential content of the original programme without compromising on its integrity or spirit.

6. We also envisage that, with judicious use of assistive education technologies such as course managements systems, course videos, etc., the balance of pedagogy can be shifted, at the instructor's discretion, from the conventional teaching end more towards the facilitation end.

7. All prerequisites are interpreted as indicative of the minimum background necessary to assimilate the course content meaningfully.

   Common prerequisites (CP) for all courses in this programme.

   (a) Proficiency in Mathematics at 12+2-level science (i.e., S.Y.B.Sc.) and engineering (i.e., M1+M2+M3) programmes of Savitribai Phule Pune University.

   (b) Students are assumed to have prior exposure to computer programming and to know a programming language.

   Course-specific prerequisites.

   (a) Specified in Sec. 2.1, 3.1, and 4.1, as well as on individual course pages.

   (b) Prerequisites need to be expanded recursively to get the full set of prerequisites for a course.

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[1] https://www.aicte-india.org/sites/default/files/Vol.%201_PG.pdf
[2] https://www.aicte-india.org/sites/default/files/Vol.%202_PG.pdf
[3] https://campus.unipune.ac.in/CBCS/CBCS_Regulations_for_SPPU_01.09.2018_29.09.2018.pdf
[4] Academic Section letter CBS/152 dated 21/2/2018

2 Core Credits

2.1 Structure of the Core Curriculum

Semester 1

Core credits: 18, choice-based/elective credits: 0

Code (Sec)	Name	Cr	Prerequisite/s
19.C101 (Sec. 2.2)	Real Analysis and Calculus	2	CP
19.C102 (Sec. 2.3)	Complex Analysis	2	CP
19.C103 (Sec. 2.4)	Vector Calculus	2	CP
19.C104 (Sec. 2.5)	Linear Algebra	3	CP
19.C105 (Sec. 2.6)	Probability Theory with R	3	CP
19.C106 (Sec. 2.7)	Fundamentals of Computing	3	CP
19.C107 (Sec. 2.8)	Modeling & Simulation 1	3	CP

Semester 2

Core credits: 10, choice-based/elective credits: 8

Code (Sec)	Name	Cr	Prerequisite/s
19.C201 (Sec. 2.9)	Numerical Computing 1	2	19.C101 (Sec. 2.2), 19.C104 (Sec. 2.5), 19.C106 (Sec. 2.7)
19.C202 (Sec. 2.10)	Optimization 1	2	19.C101 (Sec. 2.2), 19.C103 (Sec. 2.4), 19.C104 (Sec. 2.5), 19.C106 (Sec. 2.7)
19.C203 (Sec. 2.11)	Statistical Inference	3	19.C105 (Sec. 2.6), 19.C106 (Sec. 2.7)
19.C204 (Sec. 2.12)	Modeling & Simulation 2	3	19.C106 (Sec. 2.7), 19.C107 (Sec. 2.8)

Semester 3

Core credits: 8, choice-based/elective credits: 10

Code (Sec)	Name	Cr	Prerequisite/s
19.C301 (Sec. 2.13)	Numerical Computing 2	2	19.C201 (Sec. 2.9)
19.C302 (Sec. 2.14)	Optimization 2	3	19.C105 (Sec. 2.6), 19.C202 (Sec. 2.10)
19.C303 (Sec. 2.15)	Practical Computing	1	19.C106 (Sec. 2.7)
19.C304 (Sec. 2.16)	M&S Hands-On	2	19.C204 (Sec. 2.12)

Semester 4

Core credits: 18, choice-based/elective credits: 0

Code (Sec)	Name	Cr	Prerequisite/s
19.C401 (Sec. 2.17)	Internship	18	19.C304 (Sec. 2.16)

2.2 19.C101 Real Analysis and Calculus

Credits. 2

Prerequisites. CP

Category. Core; Theory

Rationale & Purpose, Goals & Objectives. A practical hands-on understanding of this fundamental area of mathematics is essential for dealing with the mathematical complexity of many kinds of mathematical model. This course is aimed at understanding conceptually and practically

1. real-valued sets, sequences, series;
2. functions: properties and visualization;
3. convergence, limits, continuity;
4. differentiation and (multiple) integration, their interrelation, and interpretation.

Syllabus.

1. Sets. Basics of set theory. Relations and functions. Open and closed sets. Countability.
2. Real numbers. Real numbers, real sequences, infinite series, convergence and tests of convergence.
3. Real functions. Real functions of single and several real variables, plotting graphs of such functions, limits, continuity.
4. Real functions of one real variable. Derivative, Rolle's and Lagrange mean value theorems, Taylor's theorem, order notation, extreme values and indeterminate forms.
5. Real functions of several real variables. Differentiability, Young and Schwarz theorems, partial derivatives, Taylor's theorem and extreme values, homogeneous functions and Euler's theorem, implicit functions, Jacobians.
6. Integration. Revision of integration of functions of one variable, definition, standard results and methods of integration, interpretation as area under graph, infinitesimals and Riemann sums.
7. Multiple integration. Methods of multiple integrals and their interpretation, Green's Theorem, Fubini's theorem, change of variables.

Suggested Texts/References.

1. S. C. Malik and Savita Arora, *Mathematical Analysis.* New Age Publishers, 2009.
2. Richard Courant and Fritz John, *Introduction to Calculus and Analysis, Vol 1 and Vol 2.* Springer, 1998.

Notes on Pedagogy. Depending upon the capacity of the batch of students, previous orientation and training, the teacher can adjust the depth of delivery so as to best meet the objective. The content can also be tuned accordingly. The content could even be ordered and modified according to the presentation in the prescribed text book/s.

Contributor/s.

1. Snehal Shekatkar (`http://inferred.co/`)
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2.3 19.C102 Complex Analysis

Credits. 2

Prerequisites. CP

Category. Core; Theory

Rationale & Purpose, Goals & Objectives. A practical hands-on understanding of this fundamental area of mathematics is essential for dealing with the mathematical complexity of many kinds of mathematical model. This course is intended to develop a clear, hands-on understanding of

1. complex numbers and functions;
2. analytic functions and related theory;
3. singularities, poles, zeros, residues;
4. complex integration and Cauchy residue theorem.

Syllabus.

1. Complex analytic functions. Complex Numbers. Polar form of complex numbers, triangle inequality. Curves and regions in the complex plane. Complex function, limit, continuity, derivative. Analytic function. Cauchy-Riemann equations. Laplace's equation. Rational functions, roots, exponential function, trigonometric and hyperbolic functions, logarithm, general power.
2. Complex integrals. Line integral in the complex plane. Basic properties of the complex line integral. Cauchy's integral theorem. Evaluation of line integrals by indefinite integration. Cauchy's integral formula. Derivatives of an analytic function.
3. Laurent series. Review of power series and Taylor Series. Laurent series, analyticity at infinity, zeros and singularities.
4. Complex integration by method of residues. Analytic functions and singularities. Residues, poles, and essential singularities. The residue theorem. Contours. Contour integration and Cauchy residue theorem as techniques for real integration. (Optional:) Inverse of Laplace transform using Cauchy residue theorem.

Suggested Texts/References.

1. D. G. Zill and P. D. Dhanahan, *A first course in Complex Analysis with applications*. Jones & Bartlett, 2010.
2. M. J. Ablowitz and A. S. Fokas, *Complex Variables: Introduction and Applications*. Cambridge University Press, second edition, 2003.
3. Tristan Needham, *Visual Complex Analysis*. Oxford University Press, 1999.
4. David Wunsch, *Complex Variables with Applications*. Pearson, 2009.
5. Arfken and Weber, *Mathematical Methods for Physicists*. Elsevier, 2005.

Notes on Pedagogy. On a pedagogical note, it is important to remember that students may be required to learn the evaluation of inverse integral transforms elsewhere. It would be useful if the instructor motivates the students using this as application.

Contributor/s. Bhalchandra Pujari (`http://cms.unipune.ac.in/~bspujari`)

2.4 19.C103 Vector Calculus

Credits. 2

Prerequisites. CP

Category. Core; Theory

Rationale & Purpose, Goals & Objectives. This foundational course is intended to bring the student at an acceptable level of understanding of vector analysis and calculus so that (s)he is able to assimilate related material in advanced courses later on in the programme. Specifically, this course intends to enable the student to

1. analyze vector functions;
2. find derivatives, line/surface/volume integrals, arc lengths, and curvatures;
3. understand and apply gradient, divergence, and curl operators;
4. understand and apply Gauss and Stokes theorems.

Syllabus.

1. Scalar and vector fields, surfaces and curves in space and their parametric equations.
2. Continuity and differentiability of vector and scalar fields. Partial derivatives of vector and scalar fields, the operator ∇ in Cartesian, cylindrical and spherical coordinate systems.
3. Gradient of a scalar field, level/equipotential surfaces, directional derivative and interpretation of gradient, tangent plane and normal to level surfaces.
4. Divergence and curl. Important identities relating gradient, divergence and curl.
5. Flux of a vector field through a surface, vector line/surface integrals.
6. Gauss divergence theorem. Interpretation of divergence in terms of flux.
7. Stokes' theorem. Interpretation of curl in terms of vector line integrals.

Suggested Texts/References.

1. Erwin Kreyszig, *Advanced Engineering Mathematics*. Wiley India, 2014.
2. Michael Greenberg, *Advanced Engineering Mathematics*. Pearson, 2002.
3. A. R. Vasishtha and Kiran Vasishtha, *Vector Calculus*. Krishna Prakashan Media, 2007.
4. Anil Kumar Sharma, *A Textbook of Vector Calculus*. Discovery Publishing House, 2006.
5. Shanti Narayan and P. K. Mitta, *A Textbook of Vector Calculus*. S. Chand, 1987.

Notes on Pedagogy.

Contributor/s. Bhalchandra Gore (`http://cms.unipune.ac.in/~bwgore`)

2.5 19.C104 Linear Algebra

Credits. 3

Prerequisites. CP

Category. Core; Theory

Rationale & Purpose, Goals & Objectives. This fundamental branch of mathematics has ramifications almost everywhere where mathematics is used, including mathematical modeling, statistics, and computing. This course aims at

1. familiarizing students with abstract concept of vectors, vector spaces on fields, and bases;
2. developing an understanding of linear transformations and their matrix representation on vector spaces;
3. developing the ability to invert matrices and solving system of linear equations;
4. developing the ability to diagonalize matrices and find eigenvalues and eigenvectors.

Syllabus.

1. Vector spaces. Introduction to fields. Definition of vectors and vector space over a field. Vector subspaces, linear independence, span, bases, dimension and its uniqueness, direct sums, Transformation of bases.
2. Linear operators. Definition and properties. Null space and range. Transformation of operator matrices according to basis transformations Representation of linear operators as matrices.
3. Introduction to matrices. Types of matrices, operations on and of matrices (row, column, sum, product, transpose, inverse, Hermitian adjoint) submatrices, determinants, rank, basic theorems on row and column operations on products, theorem on rank of product, elementary matrices, minors, Cofactors, and Cofactor adjoint of a matrix, relation to inverse, standard properties of matrices,symmetry and similarity transformations of matrices. Definiteness of matrices.
4. Systems of linear equations. Examples, matrix representation. Solution using inverse of matrix.
5. Eigenvalues, eigenvectors and diagonalization. Definition of eigenvectors and eigenvalues of linear operators. Diagonalization using a particular similarity transformation, application in linear equations. Optional: Linear ODEs, normal matrices and diagonalizability.
6. Inner product spaces. Definition and basic properties, examples. Norm from inner product and independent definition of norm. Angle between vectors and orthogonality. Orthogonal complement of a subset, Orthonormal vectors, their linear independence. Projection operators and Gram-Schmidt orthogonalization.

Suggested Texts/References.

1. Paul Halmos and John L. Kelley, *Finite Dimensional Vector Spaces.* Literary Licensing, LLC, 2013.
2. Kanti Bhushan Datta, *Matrix and Linear Algebra.* Prentice Hall India, 2008.
3. S.K. Mapa, *Higher Algebra: Abstract and Linear.* Levant Books, 2011.

4. Seymour Lipschutz and Marc Lipson, *Linear Algebra (Schaum Series).* McGraw-Hill India, 2005.
5. Otto Bretscher, *Linear Algebra with Applications.* Pearson, 2008.
6. Georgi Shilov, *Introduction to the Theory of Linear Spaces.* Martino Fine Books, 2013.

Notes on Pedagogy. Linear algebra is an abstract subject and students find it difficult to comprehend. Nonetheless it provides vital background for advances courses to follow. It is advisable not to trivialize the concept of vectors by restricting to 3D coordinate space.

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2.6 19.C105 Probability Theory with R

Credits. 3

Prerequisites. CP

Category. Core; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Probability is the mathematical language for quantifying uncertainty or ignorance, and is the foundation of statistical inference and all probability-based modeling. This course attempts to develop

1. a good understanding of probability theory as the basis for understanding statistical inference;
2. familiarity with basic theory and pertinent mathematical results;
3. the outlook of exploring formal concepts using simulation; and
4. some perspective on modeling using probability by way of real-life contexts and examples.

Syllabus.

1. A crisp introduction to R. Essential elements of 19.E007 (Sec. 4.8) may be used to introduce R for exploring probability concepts via computation.
2. Probability. Sample spaces and events. Probability on finite sample spaces. Independent events. Conditional probability. Bayes' theorem.
3. Random variables. Distribution functions and probability functions. Important discrete and continuous random variables. Bivariate and multivariate distributions. Independent random variables. Conditional distributions. Important multivariate distributions. Transformations on one or more random variables.
4. Expectation. Properties. Variance and covariance. Expectation and variance for important random variables. Conditional expectation. Moment generating functions.
5. Inequalities for probabilities and expectations. Markov, Chebychev, Hoeffding, Mill, etc. Inequalities for expectation: Cauchy-Schwartz, Jensen, etc.
6. Convergence and limit theorems. Notion of convergence for random variables. Types of convergence. Law of large numbers, central limit theorem, the delta method.

Suggested Texts/References.

1. Larry Wasserman, *All of Statistics*. Springer-Verlag, 2004 (Part 1 of the book).
2. Charles M. Grinstead and J. Laurie Snell, *Introduction to Probability*. American Mathematical Society, 1997. `https://math.dartmouth.edu/~prob/prob/prob.pdf`
3. Christopher R. Genovese, *Working With Random Systems: Mechanics, Meaning, and Modeling*. Unpublished, 2000. `http://www.stat.cmu.edu/~genovese/books/WWRS.ps`
4. Morris deGroot and Mark Schervish, *Probability and Statistics*. Addison-Wesley, 2002.
5. David Stirzacker, *Elementary Probability*. Cambridge University Press, 1994.

Notes on Pedagogy. R can be used liberally to illustrate (by the instructor) and explore (by the student) probability-related concepts and important results such as the central limit theorem.

Contributor/s. Mihir Arjunwadkar (`http://cms.unipune.ac.in/~mihir`)

2.7 19.C106 Fundamentals of Computing

Credits. 3

Prerequisites. CP

Category. Core; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. This course is intended to be an introduction to computing and algorithms for a non-computer-science graduate student. In principle, any programming language (`C`, `Python`, `Haskel`, `LISP`, etc.) can be used for illustrating algorithms, at the discretion of the instructor. This course is intended for

1. creating awareness about computing as a problem-solving approach;
2. developing an understanding of finite precision arithmetic;
3. developing an understanding of algorithm development and analysis; and
4. introducing basic types of algorithms used for problem solving.

Syllabus.

1. Digital computer fundamentals. Computer system organization. Number systems.
2. Algorithms. What is an algorithm, its need, Introduction to fundamental algorithms like counting, sorting; algorithms for problem solving using digital computers, flow chart and pseudocode techniques. Process of converting mathematical solution to computational solution.

   Fundamental algorithms and techniques, logic, set theory, functions, basics of number theory and enumerations and combinations (sequences-series, Sigma and PI notations for termwise summation, multiplication), mathematical reasoning–including induction.
3. Recursion. Need, advantages, disadvantages. Recurrence analysis. Introduction to recurrence equations and their solution techniques (substitution method, tree recursion method, master method). Proof of the master method for solving recurrences. Demonstration of the applicability of master theorem to a few algorithms and their analysis using recurrence equations. Example algorithms: binary search, powering a number, Strassen's matrix multiplication, etc.
4. Types of algorithms and their analysis. o and $\mathcal{O}$ notations; comparison of algorithms, notions of space and time efficiency; as an illustrative example, comparison of quick-sort algorithm with other sorting algorithms can be demonstrated.
5. Finite-precision arithmetic.

   (a) Computer representations of integers, endianness. Overflow and Underflow. Computer representations of "real" numbers: Fixed-point and floating-point; properties of floating-point numbers and representations (*e.g.*, machine epsilon, minimum and maximum representable number; *etc.*).

   (b) The rounding error. The elementary arithmetic operations on floating-point numbers, loss of precision, truncation as a result of finiteness of computer word-length. (Examples like subtraction, computing roots of a quadratic equation, etc. may be used to illustrate the concept) Analysis of the rounding error, avoiding accumulation of rounding error; *e.g.*, minimize arithmetic operations (e.g., Horner's and other methods for polynomial evaluation), re-arrange computation to avoid subtraction of nearly equal floating-point numbers (use of recurrence relations in series computation against evaluating each term, especially series like sin cos, exp, *etc.*)

(c) IEEE 754 specification. IEEE 754 representations of floating-point types and arithmetic operations. Standards for `NaN`, `Inf`, signed zero, *etc.*

Suggested Texts/References.

1. V. Rajaraman, T. Radhakrishnan, *An Introduction to Digital Computer Design.* PHI, 2007.
2. T. H. Cormen, C. E. Leiserson, R. L. Rivest, C. Stein, *Introduction to Algorithms.* PHI Learning, 2009.
3. D. E. Knuth, *The Art of Computer Programming, Vol. 1.* Addison Wesley, 2011.
4. A. V. Aho, J. E. Hopcroft, J. D. Ullman, *Design and Analysis of Algorithms.* Pearson Education, 2011.
5. E. Horowitz, S. Sahni, *Fundamentals of Computer Algorithms.* Universities Press, 2008.

Notes on Pedagogy.

1. In 1 in the syllabus, the following should be given adequate coverage: number systems; specifically, binary and hexadecimal system including conversion of numbers between them; Boolean algebra, bitwise addition and subtraction and their extension to integer multiplication and division; processor organization, memory organization (ROM-RAM), storage and display units, machine cycles, data flow, etc.
2. The syllabus above assumes that concepts and examples are illustrated using an appropriate programming language.

Contributor/s.

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2.8 19.C107 Modeling & Simulation 1

Credits. 3

Prerequisites. CP

Category. Core; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Mathematical Modeling is the ability to observe a situation around us, consider its constituent elements, describe it in words and then in symbols, such that we can bring to bear the symbolic techniques of mathematics to improve our understanding the situation. Why is mathematical modeling valuable? The answer is: given a model, we can predict real life consequences should circumstances or situations change. The changing part of our model is a parameter of the model; be it time, energy, population, force, or what you may. The model then acts as a super-calculator, enabling us to explore possible futures.

The end result of courses in mathematical modeling should be students who can clarify and simplify situations and extract the essential nugget that needs to be modeled. Specifically, they should be able answer questions such as: what aspect/s of the reality does the model capture? What aspect/s does it *not* capture? What questions can the model answer and what questions can it not answer? Why? Is the model capable of simulation? What questions need a simulation using the model to be answered? Are they different from questions that the model can answer without simulation? If so, in what way?

They then need to know how to look for, learn, and deploy the mathematical "technology" which is most suitable for their needs. While mathematical "technology" can be taught in conventional mathematics courses, the core sequence of mathematical modeling courses in this programme tries to teach the *style of thinking* that allows a modeler translate real-world scenarios to mathematics.

See also: sequels 19.C204 (Sec. 2.12) and 19.C304 (Sec. 2.16).

Syllabus. The following is not intended as a fixed course outline to be followed rigidly, but as suggestive of what should be covered in this course.

1. Mathematics in its historical context, as illustrating mathematical modeling through the works of Eratosthenes, Aryabhatta, Bhaskaracharya and Mercator for astronomy and cartography; Galileo and Newton for astronomy and mechanics, Euler and Fourier for dynamic phenomena; etc.
2. A selection of mathematical modeling examples from various problem domains, such as biology, chemistry, economics, physics, psychology, sociology, etc.
3. Modeling change. Difference equations and ordinary differential equations as models of change: examples; elementary analytical methods for solving ODE; qualitative analysis of ODE and visualization; software tools for analysis, solution, and visualization.

Suggested Texts/References.

1. John H. Holland, *Emergence: From Chaos to Order.* Helix Books, 1998.
2. Stephen Wolfram, *A New Kind of Science.* Wolfram Media, Inc, 2002.
3. Roger Penrose, *The Road to Reality: A Complete Guide to the Laws of the Universe.* Jonathan Cape, London, 2004.

Notes on Pedagogy.

1. Teaching to translate a real-world scenarios into mathematics is a difficult task. In this course, we have hoped that these translation skills would develop, to some extent at least, by studying the works of past masters of the trade.
2. Through the examples discussed, an overview of the modeling process and principles should emerge, including: Simplification, abstraction, mathematization; geometric similarity and proportionality as models; principle of parsimony AKA Occam's razor; model validation and modeling life cycle.
3. Relating to the point 1 in the syllabus: The usual sort of school courses that mention these scientists focus on their solutions, while we focus on how they reached those solutions in the context of the problems they were trying to understand or solve. The power of mathematization can be brought out through seemingly simple ideas from precalculus that get us as far as the size of the solar system, the creation of calculus to understand orbits, the use of geometry and mechanics to understand design of gear profiles, the use differential equations in biology, etc. At the end of the course, students should find that the mathematical methods they have seen in the past are now anchored to phenomena that they have experienced. Mathematics is thus seen as a tool for solving problems rather than as a set of rituals to be followed.
4. Relating to the point 3 in the syllabus: This is the only core course which includes a discussion on differential equations in this curriculum. It is, therefore, important to cover this topic in this course.

Contributor/s.

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2. Bhalchandra Pujari (`http://cms.unipune.ac.in/~bwpujari`)
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5. Mihir Arjunwadkar (`http://cms.unipune.ac.in/~mihir`)
6. Abhijat Vichare (`https://www.linkedin.com/pub/abhijat-vichare/2/822/828`)
7. Snehal Shekatkar (`http://inferred.co/`)

2.9 19.C201 Numerical Computing 1

Credits. 2

Prerequisites. 19.C101 (Sec. 2.2), 19.C104 (Sec. 2.5), 19.C106 (Sec. 2.7)

Category. Core; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Many modeling formalisms lead to situations that involve numerical computing. By *numerical computing*, we mean numerical analysis and numerical mathematics with a strong hands-on computing component. This course and its sister course 19.C301 (Sec. 2.13) are intended to cover topics of practical importance that are not covered elsewhere in the curriculum. Specific objectives of this course include the following:

1. To develop ability to understand and implement numerical algorithms.
2. To be able to make an informed choice of an appropriate numerical method to solve a given problem.
3. To be able to estimate rounding error, run time, memory and other computational requirements.

Syllabus.

1. Roots, zeros, and nonlinear equations in one variable. Are there any roots anywhere? Examples of root-finding methods. Fixed point iteration, bracketing methods such as bisection, *regula falsi*. Slope methods: Newton-Raphson, Secant. Accelerated Convergence Methods: Aitken's process, Steffensen's and Muller's method.
2. Interpolation. Concept of interpolation. Polynomial approximation. The interpolation problem and the vandermonde determinant. The Lagrange form of the interpolation polynomial. The error in polynomial interpolation. Newton's form of the interpolation polynomial. Divided differences, Newton-Gregory forward and backward differences. Piece-wise interpolation: spline interpolation and cubic splines.
3. Approximations. The Minimax approximation problem. Construction of the minimax polynomial. Least-squares and weighted least squares approximations. Solving the least-squares problem: direct and orthogonal polynomial methods.
4. Solving linear systems of equations. Gaussian elimination. Pivoting. Ill-conditioning. Gauss-Jordan method. Matrix inversion. Triangular factorization (LU). Permutation matrices. Cholesky factorization. Iterative methods for linear systems. Diagonally dominant matrices. Jacobi iteration. Gauss-Seidel iteration.

Suggested Texts/References.

1. David Goldberg, *What Every Computer Scientist Should Know About Floating-Point Numbers*. Computing Surveys, March 1991. `http://docs.sun.com/source/806-3568/ncg_goldberg.html`
2. Doron Levy, *Introduction to Numerical Analysis*. Unpublished, 2010. `http://www.math.umd.edu/~dlevy/books/na.pdf`
3. M. T. Heath, *Scientific Computing: An Introductory Survey*. McGraw-Hill, 2002. `http://heath.cs.illinois.edu/scicomp/`
4. Steven C. Chapra and Raymond P. Canale, *Numerical Methods for Engineers*. Tata McGraw-Hill, third edition, 2000.

5. H. M. Antia, *Numerical Methods for Scientists and Engineers.* Hindusthan Book Agency, second edition, 2002.
6. Kendall E. Atkinson, *An Introduction To Numerical Analysis.* Wiley India, second edition, 2008.

Notes on Pedagogy. This is not intended to be a course on formal numerical analysis per se. The hands-on computing component needs to be emphasized, a point-of-view that is consistent with the "concept-over-rigour" viewpoint that is at the heart of this programme. Exercises should involve a mix of paper-and-pencil and computing exercises using any programming language (e.g., `C` together with `GSL`) or computing environment that students are familiar with (e.g., `matlab/scilab`, `python`, `R`, etc.). Modeling contexts in which these numerical methods find their way are left to the discretion of the (expert) instructor.

Contributor/s.

1. Ankita Katre (`https://ankitamkatre.wixsite.com/my-research`)
2. Bhalchandra Gore (`http://cms.unipune.ac.in/~bwgore`)
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2.10 19.C202 Optimization 1

Credits. 2

Prerequisites. 19.C101 (Sec. 2.2), 19.C103 (Sec. 2.4), 19.C104 (Sec. 2.5), 19.C106 (Sec. 2.7)

Category. Core; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. This course is intended to build a foundation for deterministic optimization methods. The course is based on the use of key concepts in linear algebra and calculus to develop understanding of optimization methods. By completing this course, the student will be able to

1. understand the need for optimization
2. choose and implement appropriate deterministic optimization method to solve problem at hand
3. differentiate between unconstrained and constrained optimization problems

Syllabus.

1. Preliminaries. The need for optimization: A survey of problems and their modeling contexts (e.g., problems in domains like engineering/economic/agricultural industry domains, time and cost minimization, efficiency enhancement etc.); the objective function, domain of the objective function, applicable optimization methods. a minimizer, local and global minima, gradient based distinction of maxima, minima and saddle points. constrained and unconstrained optimization, convexity. Visualization: contours, surfaces, isosurfaces, normals, orthogonality; The optimization and visualization software tools available.
2. Optimization in one dimension. Numerical methods without derivatives: two-point bracketing and bisection, golden section search, parabolic interpolation and Brent's method.

   Numerical methods with derivatives: Newton's method, Davidon's method.
3. Unconstrained minimization in more than one dimension: Generalization of Newton method for multiple dimensional problems. Concepts of Jacobian and Hessian. Limitations of Newton method.

   Steepest descent method.

   conjugate direction methods.

   quasi-Newton methods: Approximating inverse Hessian, rank one correction and algorithm; rank two correction and DFP, BFGS algorithms.
4. Constrained Minimization. Equality and inequality constraints: general theory. Lagrange multipliers, Karush-Kuhn-Tucker (KKT) method.
5. Simplex method.

Suggested Texts/References.

1. E.K.P. Chong and S.H. Zak, *An Introduction To Optimization*. Wiley, India, 2016.
2. A. Ravindran, K.M. Ragsdel, and G.V. Reklaitis, *Engineering Optimization: Methods and Applications*. Wiley, India, 2006.
3. M. T. Heath, *Scientific Computing: An Introductory Survey*. McGraw-Hill, 2002.. http://heath.cs.illinois.edu/scicomp/

4. R. L. Burden and J. D. Faires, *Numerical Analysis*. Brooks Cole, 2004.

Notes on Pedagogy. Hands-on work using either `C+GSL` or through computing platforms such as `MATLAB/Scilab/Python/R` would be beneficial for the students to understand intricacies of optimization problems.

Contributor/s.

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2.11 19.C203 Statistical Inference

Credits. 3

Prerequisites. 19.C105 (Sec. 2.6), 19.C106 (Sec. 2.7)

Category. Core; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Statistical inference is a formalism for reasoning under uncertainty. It is crucial for modeling noisy data, analyzing it, and making inferences from it. In an age where almost every human endeavour is getting data-rich, knowledge of the basics of statistical inference will give an edge to the student. Objectives:

1. Good conceptual understanding of the fundamentals of statistical inference;
2. ability to apply them as appropriate;
3. ability to understand and illustrate formal concepts using simulation.

Syllabus.

1. Overview of statistical inference and learning. Parametric and nonparametric models. Fundamental concepts in inference: point estimation, confidence sets, hypothesis testing.
2. Estimating CDF and statistical functionals. The empirical distribution function, properties, confidence band, etc. Statistical functionals. Plug-in estimators for linear statistical functionals.
3. The bootstrap. Bootstrap variance estimation. Bootstrap confidence intervals.
4. Parametric inference. Parameter of interest and nuisance parameters. Method of moments (MoM), and properties of MoM estimators. Maximum likelihood (ML) estimation and properties of ML estimators. Multiparameter models. The parametric bootstrap. Role of Assumptions. (Optional:) EM algorithm.
5. Hypothesis testing. Fundamentals of hypothesis testing, type-I and type-II errors, p-values, the Neyman-Pearson lemma, etc. Commonly used tests such as: The Wald test and its connection with confidence interval, Pearson's χ^2 test for multinomial data, the permutation test, the likelihood ratio test, goodness-of-fit tests. Multiple testing problem.
6. Bayesian inference (optional). The Bayesian philosophy and method. Large sample properties of Bayes procedures. Flat, improper, and noninformative priors. Strengths and weaknesses of Bayesian inference *vis a vis* the frequentist/classical approaches.

Suggested Texts/References.

1. Larry Wasserman, *All of Statistics.* Springer-Verlag, 2004.
2. Morris deGroot and Mark Schervish, *Probability and Statistics.* Addison-Wesley, 2002.
3. John E. Freund, *Mathematical Statistics.* Prentice-Hall of India, 1998.

Notes on Pedagogy. The emphasis of the course should be on understanding concepts well rather than on mathematical rigour, on being able to interpret formal results and visualize formal constructions, and on being able to apply these concepts and methods to real problems. That said, formal reasoning and analysis should be an integral part of the course wherever it helps understand or illustrate concepts better. The course should also develop a perspective on real-life data modeling contexts where statistical inference plays a crucial role. Hands-on computational work using `R` should be used liberally as a means to illustrate (by the instructor) or understand (by the student) concepts, methods, and applications.

Contributor/s. Mihir Arjunwadkar (http://cms.unipune.ac.in/~mihir)

2.12 19.C204 Modeling & Simulation 2

Credits. 3

Prerequisites. 19.C106 (Sec. 2.7), 19.C107 (Sec. 2.8)

Category. Core; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. In this course, we consider simulation as an enhancement of mathematical modeling. Classical modeling, as illustrated in the previous M&S course 19.C107 (Sec. 2.8), has been mostly analytical; but with the emergence of computers, non-analytical, algorithmic, discretized or discrete, numerical, and computer algebra systems have come into their full power. This course thus focuses on agent-based simulation as perhaps the most general form of a computational model of a real-world phenomenon. See also: sister courses 19.C107 (Sec. 2.8) and 19.C304 (Sec. 2.16).

Syllabus. The following is not intended as a fixed course outline to be followed rigidly, but as suggestive of what should be covered in this course.

1. Introduction to the agent-based paradigm.
2. Introduction to an agent-based software platform. E.g., NetLogo.
3. Agent-based M&S hands-on. Examples such as those discussed in the Rationale section above may be worked out in the agent paradigm using the agent-based platform introduced.

Suggested Texts/References.

1. John H. Holland, *Emergence: From Chaos to Order*. Helix Books, 1998.
2. Stephen Wolfram, *A New Kind of Science*. Wolfram Media, Inc, 2002.
3. Roger Penrose, *The Road to Reality: A Complete Guide to the Laws of the Universe*. Jonathan Cape, London, 2004.

Notes on Pedagogy. Agent systems require the modeler to think of the world we see as *emergent*, arising from local interactions rather than from a global, omniscient view that usual analytical models seem to prefer. In the previous course, students have seen that calculus is in fact made of "summations of infinite small effects", but the local style of thinking used by Newton, for instance, in his justification of Kepler's laws does not quite sink in because calculus generates a global view as its end result. With agent-based modeling, this distinction now sinks in in the minds of the students. We connect the two courses by asking students to solve very similar problems, but this time with agents rather than with equations. Other forms of simulation, like discrete-event simulations, Monte Carlo methods, etc., can be explicitly discussed if time allows, or can be programmed via the randomization facilities available in agent-based modeling systems like NetLogo.

Contributor/s.

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7. Snehal Shekatkar (http://inferred.co/)

2.13 19.C301 Numerical Computing 2

Credits. 2

Prerequisites. 19.C201 (Sec. 2.9)

Category. Core; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Many modeling formalisms lead to situations that involve numerical computing. By *numerical computing*, we mean numerical analysis and numerical mathematics with a strong hands-on computing component. This course and its sister course 19.C201 (Sec. 2.9) are intended to cover topics of practical importance that are not covered elsewhere in the curriculum. Specific objectives of this course include the following:

1. To develop ability to understand and implement numerical algorithms.
2. To be able to make an informed choice of an appropriate numerical method to solve a given problem.
3. To be able to estimate rounding error, run time, memory and other computational requirements.

Syllabus.

1. Numerical differentiation. Basic concepts. Differentiation via interpolation. The method of undetermined coefficients. Numerical derivatives using forward difference, backward difference and central difference. Richardson extrapolation. Differentiation using Lagrange Polynomial, Newton Polynomial.
2. Numerical integration. Basic concepts. Integration via interpolation. Composite integration rules. Additional integration techniques. The method of undetermined coefficients. Change of an interval. General integration formulas. Simpson integration. The quadrature error. Composite Simpson rule. Gaussian quadrature. (Optional) Romberg integration. Adaptive quadrature basics.
3. Numerical solutions of ODEs. Euler method, accuracy and stability, stepsize control. Runge Kutta methods, Heun's method. Discussion about stiffness and adaptive-stepsize solvers. (Optional) Introduction to predictor-corrector method.
4. Eigenvalues and eigenvectors. Homogeneous systems, Power Method, Jacobi's method, Given's, Householder's transformation and Lanczos transformation to tridiagonal form, LR, QL/QR transformation for eigenvalues of tridiagonal matrices, determinants of tridiagonal matrices, symmetric matrices, band matrices
5. (Optional) Numerical linear algebra software. Quick working introduction to `BLAS/LAPACK`, and interfaces in `GSL`, `MATLAB/Scilab`, etc.

Suggested Texts/References.

1. H. M. Antia, *Numerical Methods for Scientists and Engineers*. Hindusthan Book Agency, second edition, 2002.
2. Doron Levy, *Introduction to Numerical Analysis*. Unpublised, 2010.. `http://www.math.umd.edu/~dlevy/books/na.pdf`
3. M. T. Heath, *Scientific Computing: An Introductory Survey*. McGraw-Hill, 2002.. `http://heath.cs.illinois.edu/scicomp/`

4. D. V. Griffiths and I. M. Smith, *Numerical Methods for Engineers.* Chapman and Hall/CRC, second edition 2011.
5. Steven C. Chapra and Raymond P. Canale, *Numerical Methods for Engineers.* Tata McGraw-Hill, second edition 2000.
6. Curtis F. Gerald and Patrick O. Wheatley, *Applied Numerical Analysis.* Addison-Wesley, fifth edition 1998.
7. Kendall E. Atkinson, *An Introduction To Numerical Analysis.* Wiley India, second edition, 2008.

Notes on Pedagogy. This is not intended to be a course on formal numerical analysis per se; the hands-on, computing component needs to be emphasized slightly more, a point-of-view that is consistent with the "concept-over-rigour" viewpoint that is at the heart of this programme. Exercises should involve a mix of paper-and-pencil and computing exercises using any programming language (e.g., `C`) or computing environment (e.g., `matlab/Scilab`, `R`, etc.) that students are familiar with. Modeling contexts in which these numerical methods find their way are left to the discretion of the (expert) instructor. Coding numerical methods oneself helps most students understand these methods better.

Contributor/s.

1. Ankita Katre (`https://ankitamkatre.wixsite.com/my-research`)
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3. Vaishali Shah (`https://www.researchgate.net/profile/Vaishali_Shah10`)

2.14 19.C302 Optimization 2

Credits. 3

Prerequisites. 19.C105 (Sec. 2.6), 19.C202 (Sec. 2.10)

Category. Core; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Stochastic optimization methods often fare better in situations involving objective functions with multiple local or global minima, when there is combinatorial complexity in the optimization problem, when the goal is to locate a global minimum, and when the measurement or computation of the objective function itself involves uncertainties. A background in these methods should be an essential part of a modeler's toolkit.

Syllabus.

1. A brief introduction to random number generators and Monte Carlo methods. Essentials from the course outline of 19.E012 (Sec. 4.13), except for detailed discussion of Markov chains.
2. Introduction to stochastic optimization. Formal problem statement. Stochastic vs. deterministic optimization. Principles of stochastic optimization. Local vs. global minimization. An overview of problems involving multiple minima, local or global.
3. Random search methods. General properties of direct random search. A few specific algorithms for random search.
4. Simulated annealing. The analogy between optimization and free-energy minimization by a physical system. The travelling salesman problem and SA.
5. Genetic algorithms. Introduction. Chromosome coding and the basic GA operations. The core genetic algorithm. Implementation aspects. Some perspective on the theory for GAs.
6. (Optional) More bio-inspired algorithms. Ant-colony and swarm optimization methods.

Suggested Texts/References.

1. James C. Spall, *Stochastic Optimization*, in J. Gentle, W. Härdle, and Y. Mori, eds., *Handbook of Computational Statistics*. Springer, 2004.
2. James C. Spall, *Introduction to Stochastic Search and Optimization: Estimation, Simulation, and Control*. Wiley, 2003.
3. M. Michell, *An Introduction to Genetic Algorithms*. MIT Press, 1996.
4. P. J. M. Van Laarhoven and E. H. L. Aarts, *Simulated Annealing: Theory and Applications*. Kluwer Academic Publishers, 1987.

Notes on Pedagogy. The syllabus outline above is partially based on the first review article above. A qualified instructor experienced in stochastic optimization methods may alter the sequence or topics without altering the overall focus of the course. A detailed exposition of more stochastic optimization methods methods may be included at the instructor's discretion.

Contributor/s.

1. VK Jayaraman (`https://scholar.google.co.in/citations?user=GRv1gLQAAAAJ&hl=en`)
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2.15 19.C303 Practical Computing

Credits. 1

Prerequisites. 19.C106 (Sec. 2.7)

Category. Core; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. When a computational problem gets complex, coding techniques and practices need to be refined to ensure readability, reusability, maintainability, and correctness. This course aims to sensitize students towards better coding practices.

Syllabus.

1. Best code development practices. Structured and modular programming. Readability, choice of names for variables, etc. Global variables. Debugging and profiling basics. Code refactoring. Documentation.
2. Managing large and/or collaborative projects. Project management (e.g., `make`). Version control (e.g., `git`).

Suggested Texts/References.

1. Robert C. Martin, *Clean Code: A Handbook of Agile Software Craftsmanship*. PHI, 2017.
2. Greg Wilson et al., *Best practices for scientific computing*. PLoS Biology, **12:1**, e1001745 (2014) DOI:10.1371/journal.pbio.1001745.

Notes on Pedagogy.

Contributor/s.

1. Bhalchandra Gore (`http://cms.unipune.ac.in/~bwgore`)
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5. Mihir Arjunwadkar (`http://cms.unipune.ac.in/~mihir`)

2.16 19.C304 M&S Hands-On

Credits. 2

Prerequisites. 19.C204 (Sec. 2.12)

Category. Core; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. This last course in the M&S stream of courses tries to brings together the ideas learn in the previous courses 19.C107 (Sec. 2.8) and 19.C204 (Sec. 2.12) by asking students to solve a single problem in depth. They may at the same time be required to learn and use new techniques (e.g., game theory) as tools in addition to ones they use. This course lets them see the tools they have learnt in action, going beyond the week-long scale problems they have seen in prior courses, and instead asking them to solve 4-month long problems with a lot of self-driven work. It also serves as preparation for the industrial internship that are required to do during their degree.

This is an individualized course where a student is to work closely with a mentor. The emphasis of this course is on developing problem-solving, self-learning/self-study, and presentation (written and oral) skills. With the help of the mentor, the student should carry out hands-on work related to the broad focus of the programme, and culminating into a written report and a presentation. With their internship 19.C401 (Sec. 2.17) on the horizon, this course is intended to prepare students to develop appropriate skills including but not limited to literature search, resourcefulness, hands-on problem-solving related to a topic not studied before, etc. See pedagogic notes below.

Syllabus.

1. Hands-on M&S miniproject and/or internship preparation. Faculty mentor to decide the best strategy to achieve aims and objectives of this course for each student separately. For students who have decided their area of internship may be given M&S hands-on work appropriate for that area.
2. An overview of the modeling process. Simplification, abstraction, mathematization. Principle of parsimony AKA Occam's razor. Distinctions: Stochastic vs deterministic, linear vs nonlinear, static vs dynamic, etc. All models are false, some are useful: Modeling as an on-going process of knowledge refinement.

Suggested Texts/References. No prescribed texts. The mentor and the student can use any individually-chosen text or reference depending on the topic of study.

Notes on Pedagogy. The role of the faculty mentor is critical for the success of this course. If a student has already decided her/his place of internship 19.C401 (Sec. 2.17), advisor, topic, etc., then the mentor should make sure, in collaboration with the organization or advisor for the internship, that (s)he spends her/his time in developing skills and background necessary for the internship. For other students, and until the details of their internship are not finalized, mentor should work on developing students' self-study, presentation (written and oral), and any other skills that may not be covered adequately elsewhere during the programme, or those in which the student may not be adequately trained. Assigning a modeling project can be one possible strategy to achieve the goals of this course. The mentor and the students need to meet on regular basis to ensure good and regular progress.

Contributor/s.

1. Snehal Shekatkar (`http://inferred.co/`)

2. Bhalchandra Pujari (http://cms.unipune.ac.in/~bwpujari)
3. Ankita Katre (https://ankitamkatre.wixsite.com/my-research)
4. Bhalchandra Gore (http://cms.unipune.ac.in/~bwgore)
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2.17 19.C401 Internship

Credits. 18

Prerequisites. 19.C304 (Sec. 2.16)

Category. Core; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Internship is the pinnacle of the Master of Technology (M.Tech.) Programme in Modeling and Simulation. The purpose of the internship is for the students to get in-depth exposure and experience in addressing challenging, real-life problems through M&S methods.

Syllabus. No fixed syllabus. Internship advisor/s and internal mentor/s at the Centre to decide the best strategy to achieve the aims and objectives of the internship for each student separately.

Suggested Texts/References. No prescribed texts.

Notes on Pedagogy. Internships are intended to be individual, and spanning a complete semester. In the best interest of the student, internships in settings external to the Centre (such as industry, research or academic institutes, NGOs, etc., depending on the interests of the student) are recommended, although possibilities of in-house internships are not ruled out. The internship topic/project may span any breadth of the M&S enterprise in any problem domain, from translating a domain-specific problem into an appropriate mathematical model, attempting to get analytical insights into the behaviour of the model, to exploring the behaviour of the model through computing/simulation. While the internship may have a substantial computing/coding component, it is not intended to be a pure software/coding project. The Centre's faculty committee is the supreme authority of all matters relating to the approval of internship topics/projects. The M&S context of the topic/project should be well-understood by the student, and should be brought out clearly in the report and presentations. The student, the external advisor/s, and the student's mentor/s at the Centre should ensure this, and have clarity as to where the internship fits into the M&S enterprise. Evaluation for this course is to be done on the basis of (a) regular reporting by the student to the external advisor/s and the internal mentor/s, (b) one or more mid-term presentations, (c) a final presentation, and (d) a final report.

Contributor/s.

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3. Bhalchandra Pujari (`http://cms.unipune.ac.in/~bspujari`)
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5. Mihir Arjunwadkar (`http://cms.unipune.ac.in/~mihir`)

3 Choice-Based Credits: In-House Elective Streams

3.1 Quick Reference to In-House Choice-Based Elective Streams

Choice-based electives listed below can be offered during any semester provided their prerequisites are satisfied. Prerequisites listed below are suggestive/indicative; they can be decided/redefined by the course instructor with approval from the Centre. Sufficient mastery over the content of the listed prerequisites, and over an appropriate programming language is assumed for all elective courses.

Code (Sec)	Name	Cr	Prerequisite/s
19.AS1 (Sec. 3.2)	Astrostatistics 1	4	19.C203 (Sec. 2.11)
19.AS2 (Sec. 3.3)	Astrostatistics 2	4	19.AS1 (Sec. 3.2)
19.CN1 (Sec. 3.4)	Complex Networks 1	4	19.C101 (Sec. 2.2), 19.C102 (Sec. 2.3), 19.C103 (Sec. 2.4), 19.C104 (Sec. 2.5), 19.C105 (Sec. 2.6), 19.C106 (Sec. 2.7)
19.CN2 (Sec. 3.5)	Complex Networks 2	4	19.CN1 (Sec. 3.4)
19.CFD1 (Sec. 3.6)	Computational Fluid Dynamics 1	4	19.C101 (Sec. 2.2), 19.C102 (Sec. 2.3), 19.C103 (Sec. 2.4), 19.C104 (Sec. 2.5), 19.E016 (Sec. 4.17)
19.CFD2 (Sec. 3.7)	Computational Fluid Dynamics 2	4	19.CFD1 (Sec. 3.6)
19.CFD3 (Sec. 3.8)	Computational Fluid Dynamics Laboratory	2	19.CFD1 (Sec. 3.6)
19.OR1 (Sec. 3.14)	Digital Signal and Image Processing 1	4	19.C101 (Sec. 2.2), 19.C102 (Sec. 2.3), 19.C103 (Sec. 2.4), 19.C104 (Sec. 2.5), 19.E017 (Sec. 4.18)
19.OR2 (Sec. 3.15)	Digital Signal and Image Processing 2	4	19.DP1 (Sec. 3.9)
19.ML1 (Sec. 3.11)	Machine Learning 1	4	19.C203 (Sec. 2.11)
19.ML2 (Sec. 3.12)	Machine Learning 2	4	19.ML1 (Sec. 3.11)
19.ML3 (Sec. 3.13)	Machine Learning Laboratory	2	19.ML1 (Sec. 3.11)
19.DP1 (Sec. 3.9)	Operations Research 1	4	19.C202 (Sec. 2.10)
19.DP2 (Sec. 3.10)	Operations Research 2	4	19.OR1 (Sec. 3.14)

3.2 19.AS1 Astrostatistics 1

Credits. 4

Prerequisites. 19.C203 (Sec. 2.11)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Outlook and rationale for this course can be summarized as follows:

> With data rates, sizes, and complexities soaring up high over the coming decades, meaningful investigation into a scientific question will require fresh ways of identifying patterns and structure in the data using sophisticated statistical and computational methodologies. (Indeed, the 21st century science has been aptly described as large datasets, complex questions science (Efron, 2011).) Technology development, which is essential for progress of science, also necessitates methodological development for its efficient and effective use. It is important to remember that it is the nature of the data and scientific questions being addressed which should dictate the method, and not vice versa (Arjunwadkar, Kashikar, and Bagchi, J. Astrophys. Astr. (2016) 37:28).

This course aims at introducing students with adequate background in statistics and computation – but not necessarily in astronomy and astrophysics (A&A) – to the field of astrostatistics. See the Notes on Pedagogy section of this syllabus document for more details.

Syllabus.

1. A crisp introduction to astronomy and astrophysics (outreach+ / undergraduate− level). Overview/survey of astronomical phenomena and their physics at a very basic level, essential terminology, and historical perspective as appropriate.
   (a) Basics of Astronomy: Observing the sky (naked eye, telescopes, and other instruments), measuring distances, distance scales, units, etc.
   (b) Basics of Astrophysics: blackbody radiation, stars, galaxies and their distribution, scaling relations.
   (c) Astronomical data: Nature of data-gathering and measurement processes together with discussion of the underlying statistical assumptions. Sources of errors in measurement and calibration.
2. Density estimation.
   (a) Histograms, bias-variance trade-off, optimal bin width, confidence bands.
   (b) Kernel Density Estimation: Univariate and multivariate, optimal bandwidth via cross-validation, confidence bands.
   (c) Adaptive smoothing: Adaptive kernel estimators, nearest-neighbour estimators.
   (d) Density estimation via normal mixtures: estimation, model selection, and bootstrap confidence intervals on parameters.
   (e) Nonparametric density estimation via orthogonal functions, and confidence sets.
3. Regression and model selection.
   (a) Generalities: Regression and regression function, quadratic prediction risk and $r(x) = \mathsf{E}(Y|X = x)$ as its minimizer, bias-variance decompositions.

(b) Simple and multiple linear regression, least squares: unweighted and weighted, maximum likelihood, confidence intervals and bands, prediction bands, hat matrix, simple tests for coefficients, diagnostics, collinearity, transformations as a way to conform to assumptions better, linearity as linearity in the coefficients.

(c) Variable/model selection: Training risk, Mallow's C_p, leave-one-out cross-validation, AIC, BIC, MDL, variable selection vs. hypothesis testing. An overview of regularization (ridge regression, LASSO and sparsity). Identifiability.

(d) Nonparametric regression: Regressogram, running mean / local average smoother, linear smoothers, smoothing (hat) matrix. Choosing the smoothing parameter: Bias-variance trade-off, predictive risk and its estimators: training risk, leave-one-out-cross-validation risk, generalized cross-validation risk, etc. Kernel regression. Nonparametric regression via orthogonal functions, and confidence sets. Local polynomials. Regularization and splines.

(e) Robust regression. Nonlinear regression. Handling (measurement) error in the covariates.

4. Clustering and classification. A crisp overview of supervised, unsupervised, and reinforcement learning, and a subset of topics in the following broad area: Generative and discriminative classifiers. Naive Bayes, Gaussian mixtures, generative adversarial classifiers, K-NN, logistic regression neural networks, decision tree and random forest classifiers. Deep neural networks. K-means, hierarchical and Gaussian mixtures for clustering. Time series classification and clustering. Hypothesis testing for classification. Attribute selection for classification.

Suggested Texts/References.

1. Fiegelson & Babu, *Modern Statistical Methods for Astronomy with R Applications.* Cambridge, 2012.
2. Wall & Jenkins, *Practical Statistics for Astronomers.* Cambridge, 2003.
3. AK Chattopadhyaya, *Statistical Methods for Astronomical Data Analysis.* Springer, 2014.
4. Starck & Murtagh, *Astronomical Image and Data Analysis.* Springer, 2006.
5. Mike Inglis, *Astrophysics is Easy! An Introduction for the Amateur Astronomer.* Springer, 2007.
6. Hastie, Tibshirani, & Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction.* Springer, 2009.
7. Efron & Hastie, *Computer Age Statistical Inference: Algorithms, Evidence, and Data Science.* Cambridge, 2016.

Notes on Pedagogy.

1. This course assumes that the audience have sufficient background in the statistics and computing, but none in A&A.
2. This course in its current form is organized around topics in statistics. Apt and appropriate applications and examples are to be chosen by the instructors from A&A.
3. Depending on the instructors' fields of expertise and the maturity level of the audience, this and/or a follow-up advanced course may also be run entirely in the problem-centric mode which weaves statistics around concrete astronomical problems and their associated datasets. In either mode, instantiations of this course should have a substantial hands-on

component (textbook as well as non-textbook) analyzing actual astronomical data sets – from exploratory data analysis all the way upto trying to answer the science questions for which the data was collected.

4. Choice of programming language, computing environment, or software is left to the discretion of the instructors.
5. The above syllabus should be taken as indicative, and not as set in stone. Topics, subtopics, and finer content may be tweaked by the instructors to suite the audience's prior training and know-how. Except for #1 and #2 in the syllabus above, other topics may be presented/discussed in the class in any order. Given the highly multidisciplinary nature of the course, it may be tweaked to match the instructors' areas of expertise in statistics, A&A, astrostatistics, etc., and new developments in these fields.
6. Given the multidisciplinary nature of the course, ideally it should be interspersed with colloquia by astronomers, astrophysicsts, statisticians, and data scientists. Such colloquia may be focused on case studies, specific applications, broad overviews – In short, anything that would help broaden the students' outlook.

Contributor/s.

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3.3 19.AS2 Astrostatistics 2

Credits. 4

Prerequisites. 19.AS1 (Sec. 3.2)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. This course is a sequel to 19.AS1 (Sec. 3.2), and introduces a few more areas of statistics which are heavily used in statistical data analysis in Astronomy & Astrophysics.

Syllabus.

1. Outliers. A crisp overview of considerations, core concepts, methods, and practice, broadly along the lines of chapters 1 and 2 of #1 in Suggested Texts/References.
2. Missing data. A crisp overview of considerations, core concepts, methods, and practice, broadly along the lines of chapters 1 and 2 of #2 in Suggested Texts/References.
3. Time-series analysis. A crisp overview of considerations, core concepts, methods, and practice, broadly along the lines of chapters 1–6 of #3 in Suggested Texts/References.
4. Spatial statistics. A crisp overview of considerations, core concepts, methods, and practice, broadly along the lines of chapters 1–3 of #6 in Suggested Texts/References.
5. Bayesian inference. Review of axioms of probability theory and Bayes Theorem for conditional probabilities. The Bayesian inferential philosophy: Classical/frequentist vs. subjective probabilities. Bayes theorem and its inferential interpretation as flow of information from prior to posterior via likelihood. Standard examples, such as Bernoulli likelihood with Beta prior, normal likelihood with normal prior; etc. Conjugate priors. Prior distributions: Proper, improper, flat, noninformative. Role of priors in making ill-defined estimation/inference problems well-behaved: E.g., Non-identifiable Gaussian mixture models with too many components (and when data is sparse), etc. Relative importance of prior and likelihood with respect to data size. Posterior distribution as the prime inferential object. Exploring the posterior through simulation. Credible intervals. Bayesian testing. Bayesian model selection. Bayesian vs. classical: Strengths and weaknesses.

Suggested Texts/References.

1. Charu C. Aggarwal, *Outlier Analysis*. Springer, 2013.
2. Little & Rubin, *Statistical Analysis with Missing Data*. Wiley, 2002.
3. Brockwell & Davis, *Introduction to Time Series and Forecasting*. Springer, 2002.
4. Gelman et al., *Bayesian Data Analysis*. CRC Press, 2013.
5. Joseph B. Kadane, *Principles of Uncertainty*. CRC Press, 2011.
6. Cressie, *Statistics for Spatial Data*. Wiley, 1993.
7. Bivand, Pebesma, & Gómez-Rubio, *Applied Spatial Data Analysis With R*. Springer, 2008.

Notes on Pedagogy. See this section for the the prequel course 19.AS1 (Sec. 3.2).

Contributor/s.

1. Mihir Arjunwadkar (`http://cms.unipune.ac.in/~mihir`)
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3.4 19.CN1 Complex Networks 1

Credits. 4

Prerequisites. 19.C101 (Sec. 2.2), 19.C102 (Sec. 2.3), 19.C103 (Sec. 2.4), 19.C104 (Sec. 2.5), 19.C105 (Sec. 2.6), 19.C106 (Sec. 2.7)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. A large number of real-world systems like Facebook, air-transport, metabolic reactions inside a living cell, and the Internet can be modelled as networks. Also several phenomena like traffic jams, rumour spreading and genetic regulations can be modelled as processes on networks making it an indispensable tool to study 'complex systems'. The theory of complex networks builds on methods borrowed from computer science, physics, statistics, social sciences and many others, and so is highly interdisciplinary. In this first part of this course stream, the student will gain understanding of

1. the abstraction called networks or graphs;
2. networks as a paradigm for certain real-world systems and their applicability;
3. quantification and analysis of network data;
4. important computer algorithms used to analyze networks;
5. insights gained about the real-world systems using the network paradigm.

Syllabus.

1. Introduction to networks. Networks as mathematical abstractions, usefulness and inappropriateness of networks while modeling the real-world systems, Empirical networks: Technological, Social, Information, Biological.
2. Mathematics of networks.
   (a) Mathematical representation, Adjacency matrix.
   (b) Weighted, directed, bipartite, multilayer, temporal/dynamic networks.
   (c) Degree, walks and paths, independent paths, cut sets, Menger's theorem
   (d) Trees, planar graphs.
   (e) Components in undirected and directed graphs
   (f) (Optional) Directed acyclic graphs
3. Network quantification.
   (a) Centrality values and distributions: degree, eigenvector, katz, pagerank, closeness, betweenness.
   (b) Cliques and k-cores, k-components
   (c) Transitivity and the global clustering coefficient, local clustering coefficient
   (d) Signed edges and structural balance
   (e) Vertex similarity: structural vs regular
   (f) Degree distributions in undirected and directed networks
   (g) Homophily and assortative mixing
4. Network algorithms.
   (a) Basics of time complexity of algorithms.

(b) Storing network data: adjacency matrix, adjacency list, edge list.
(c) Algorithms for degree distributions, clustering coefficients.
(d) Breadth-first search (BFS), Dijkstra's algorithm.
(e) Calculation of betweenness centrality using BFS

5. The structure of real-world networks.

   (a) Qualitative discussion of the types of errors and their sources in network data
   (b) Components, shortest paths and the small-world effect
   (c) Degree distributions, Scale-free networks, detection of power-laws.
   (d) Clustering coefficients, assortative mixing

Suggested Texts/References.

1. Mark Newman, *Networks: An introduction.* Oxford University Press (New York), 2018 or latest.
2. Harry Crane, *Probabilistic Foundations of Statistical Network Analysis.* Chapman and Hall/CRC, 2018.
3. Albert-László Barabasi, *Network Science.* Cambridge University Press, 2016.
4. Guido Caldarelli, *Scale-Free Networks: Complex Webs in Nature and Technology.* Oxford University Press UK, 2013.
5. S.N. Dorogovtsev and J.F.F. Mendes, *Evolution of Networks: From Biological Nets to the Internet and WWW.* Oxford University Press (Oxford), 2013.

Notes on Pedagogy. Knowledge of at least one programming language (`Python`, `R`, `C/C++`, etc.) or computational environment (`Matlab/SciLab`, `Mathematica`, etc.) is required.

Contributor/s. Snehal Shekatkar (`https://inferred.co/`)

3.5 19.CN2 Complex Networks 2

Credits. 4

Prerequisites. 19.CN1 (Sec. 3.4)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. This sequel of 19.CN1 (Sec. 3.4) deals with several intermediate- to advanced-level topics in the theory of complex networks. Mastering the material presented here will prepare the students to handle several real-world problems involving networks. The course is expected to lead the student to understand

1. the concept of random graphs, and corresponding mathematical methods;
2. possible mechanisms behind the growth of real-world networks;
3. community structure in networks, and elementary methods to detect it;
4. simple spreading processes and percolation on networks.

Syllabus.

1. Random graphs
   (a) Concept of random graphs
   (b) Erdős-Rényi (ER) graph: degree distribution, clustering coefficient
   (c) Concept of the giant component, giant component and path lengths in the ER graph
   (d) (Optional) Small components in ER graph
   (e) The configuration model, excess degree distribution and the friendship paradox, clustering coefficient
   (f) Locally-tree-like nature of the configuration model, the number of second neighbours, the giant component
   (g) The small components in the configuration model, configuration model with power-law degree distribution, diameter
   (h) Stochastic block model, the small-world model
   (i) (Optional) Generating function methods
2. Models of network formation
   (a) Preferential attachment and Price's model, Barabási-Albert model (BA model), the first mover effect
   (b) Qualitative discussion of the extensions of the preferential attachment models
   (c) Vertex copying models, network optimization model
3. Community detection
   (a) Graph partitioning and graph Laplacian, The Kernighan-Lin algorithm, spectral partitioning
   (b) Community detection, modularity maximization
   (c) Kernighan-Lin-Newman algorithm, spectral modularity maximization, division into more than two groups
   (d) Overview of the Louvain algorithm, methods based on statistical inference and the Newman-Girvan algorithm

(e) Measuring community detection algorithm performance
(f) (Optional) Resolution limit for modularity maximization, degeneracy problem

4. Spreading processes and percolation on networks.
   (a) Diffusion on networks, random walks, cascading
   (b) Introduction to the edge and vertex percolations
   (c) Computer algorithms for network percolation
   (d) Computer simulations for vertex percolation on ER and BA networks, interpretations of the results

Suggested Texts/References.

1. Mark Newman, *Networks: An introduction.* Oxford University Press (New York), 2018 or latest.
2. Albert-László Barabasi, *Network Science.* Cambridge University Press, 2016.
3. Guido Caldarelli, *Scale-Free Networks: Complex Webs in Nature and Technology.* Oxford University Press UK, 2013.
4. S.N. Dorogovtsev and J.F.F. Mendes, *Evolution of Networks: From Biological Nets to the Internet and WWW.* Oxford University Press (Oxford), 2013.
5. Alain Barrat, Marc Barthélemy and Alessandro Vespignani, *Dynamical Processes on Complex Networks.* Cambridge University Press, 2012.

Notes on Pedagogy. Knowledge of at least one programming language (`Python`, `R`, `C/C++`, etc.) or computational environment (`Matlab/SciLab`, `Mathematica`, etc.) is required.

Contributor/s. Snehal Shekatkar (`https://inferred.co/`)

3.6 19.CFD1 Computational Fluid Dynamics 1

Credits. 4

Prerequisites. 19.C101 (Sec. 2.2), 19.C102 (Sec. 2.3), 19.C103 (Sec. 2.4), 19.C104 (Sec. 2.5), 19.E016 (Sec. 4.17)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Develop intermediate-level understanding and hands-on skills in the domain of computational fluid dynamics.

Syllabus.

1. Elementary concepts. Background space, coordinate systems. Fields, scalars, vectors, tensors, transformations, distance metric. Concepts of vector calculus (flux, line integral, Gauss and Stokes theorems). Index notation and Einstein convention. Total derivative, integral curves, velocity field and co-moving derivative.
2. Balance equations. Equation of continuity. Jacobians and their rates of change. Lagrangian coordinates. Reynolds theorem. Surface forces and traction vector. Cauchy theorem and concept of stress tensor. Cauchy equation of momentum balance. Angular momentum balance equation. Heat flux density, internal energy density, energy balance equation.
3. Constitutive relations. Introduction. Thermodynamic stimulus and response, rate of response. Darcy's, Fourier's, Ohm's and Fick's laws, Hooke's law, Newton's law of viscosity. Shear, rotation and dilation of velocity field, Navier-Stokes equation, boundary conditions and their importance.
4. Examples of flow. Hagen-Poisseuille flow, Couette flow and other special cases.

Suggested Texts/References.

1. T. J. Chung, *Computational Fluid Dynamics*. Cambridge University Press, 2002.

Notes on Pedagogy.

Contributor/s. Sukratu Barve (`http://cms.unipune.ac.in/~sukratu`)

3.7 19.CFD2 Computational Fluid Dynamics 2

Credits. 4

Prerequisites. 19.CFD1 (Sec. 3.6)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Develop intermediate-level understanding and hands-on skills in the domain of computational fluid dynamics.

Syllabus.

1. FEM techniques. Finite elements. Shape functions. Finite element interpolation functions. Weighted residual approach. Assembly of element equation. Finite element formulation for advection equation.
2. Finite volume approach. Finite volume method. Finite volume discretization. Face area and cell volume. Finite volume via finite difference. Finite volume via finite element method. Comparison of finite difference, finite element, and finite volume methods.
3. Grid generation. Structured grid generation. Unstructured grid generation. Mesh adaptation. Automatic grid generation for complex geometry problems. Computing techniques.
4. Application to multiphase flows.
5. Higher-order methods for CFD.
6. Optimization through CFD. Optimization problem associated with evaluation of first derivative. Optimization problem associated with evaluation of second derivatives.
7. Advanced fluid dynamics. Intermediate structures like vortices, boundary layers, shocks, waves and caustics, stream filaments.
8. Numerical methods. Grid generation techniques for structures and unstructured grids.
9. Hands-on problem-solving through CFD. Implementation of codes for CFD. Computational environments for CFD such as `OpenFOAM, CFDExpert`. `OpenFOAM` architecture, solvers cases and utilities; writing cases and solvers. `CFDEXpert` problems.

Suggested Texts/References.

1. T. J. Chung, *Computational Fluid Dynamics*. Cambridge University Press, 2002.

Notes on Pedagogy.

Contributor/s. Sukratu Barve (`http://cms.unipune.ac.in/~sukratu`)

3.8 19.CFD3 Computational Fluid Dynamics Laboratory

Credits. 2

Prerequisites. 19.CFD1 (Sec. 3.6)

Category. CBC; Laboratory

Rationale & Purpose, Goals & Objectives. The purpose of this course is to introduce commonly used (open-source) libraries, tools, packages, and platforms for computational fluid dynamics, so as enhance the industry-preparedness of students. Such tools include, for example, `CFD Python`, `PyCFD`, etc.; meshing tools such as `Gmsh`, etc.; `SWIG`, `PyPar`, `PySPH`, and `SciPy Weave` for development of efficient parallel codes; as also `SU2` and/or `OpenFoam` at a greater depth than what is covered in 19.CFD1 (Sec. 3.6). Not all the tools mentioned above need be covered in the course. The selection of particular tool/s may change from course instance to course instance, depending on (a) the instructor's expertise and preference, (b) industry trends and developments in this field, and (c) a balance between depth and breadth.

Syllabus.

1. A broad survey of commonly used and available tools such as those mentioned above.
2. A crisp introduction to one or two such tools of instructor's choice.
3. Individual or group miniprojects. Students may survey and choose any other appropriate tools, libraries, APIs, etc., best-suited for their chosen topic, under the guidance of the instructor/s.

Suggested Texts/References. Appropriate set of internet and other resources recommended by the instructor.

Notes on Pedagogy. This course should complement the computational fluid dynamics courses 19.CFD1 (Sec. 3.6) and 19.CFD2 (Sec. 3.7). It is intended to be a hands-on course involving case studies and applications, with focus on (open-source) tools. The instructor may consider an open-laboratory, tinkering / experimentation-based approach where different students / groups may explore different (open-source) tools through individual or group mini-projects.

Contributor/s.

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3.9 19.DP1 Digital Signal and Image Processing 1

Credits. 4

Prerequisites. 19.C101 (Sec. 2.2), 19.C102 (Sec. 2.3), 19.C103 (Sec. 2.4), 19.C104 (Sec. 2.5), 19.E017 (Sec. 4.18)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. This course introduces the student to signal modeling and analysis formalisms, tools, and techniques, and their applications to solve real-life problems in various fields like electronic communication, signal detection, satellite imaging, medical diagnostic signals and images, video analysis, etc., with the view of making the student aware of (a) basic theory and mathematical, statistical and algorithmic tools (b) perspective on modeling by way of real-life contexts, examples and applications, and (c) relevant numerical methods.

Specific objectives of this course include:

1. Understanding the need for signal processing;
2. understanding the correspondence between actual devices, their operations, and their mathematical-statistical representations; learning mathematical, statistical, and algorithmic tools used to improve the quality of a signal and extract useful information from signal;
3. being able to design simple systems for signal processing (like digital filters, digital spectrum analyzer, etc.) using tools such as transforms (Fourier, Z, wavelet), difference equations, pole-zero and frequency plots, mean, median, variance, histogram, probability distributions, etc.;
4. being able to analyze given signal using appropriate tools and infer about quality, content, etc.

Syllabus.

1. Discrete time signals: sequences; representation of signals on orthogonal basis; sampling and quantization; reconstruction of signals; Nyquist's theorem; analog $\rightleftharpoons$ digital signal conversions.
2. Discrete systems: attributes, classifications, analysis of LTI systems, representation of discrete time systems using difference equations, implementation of discrete time systems; correlation of discrete time signals.
3. Z-transform, frequency analysis, discrete Fourier transform (DFT), fast Fourier transform algorithm, frequency response of a system, spectra at output of LTI system; convolution-deconvolution concepts.
4. LTI system as frequency domain filters; filter characterization, inverse systems.
5. Design of FIR and IIR filters; Gaussian, Butterworth, Chebyshev approximations; low-pass, high-pass, notch, bandpass and band-reject filters; effect of quantization on filters–round-off effects.
6. Adaptive filters; power spectrum estimation.
7. Applications of DSP to speech/music and radar/radio-telescope signal processing.

Suggested Texts/References.

1. J. G. Proakis and D. G. Manolakis, *Digital Signal Processing Principles, Algorithms, and Applications*. Pearson, 2012.
2. Oppenheim and Schafer, *Digital Signal Processing*. PHI Learning, 2008.

Notes on Pedagogy. At the discretion of the instructor, `matlab/octave/scilab` can be used for computing. This has the advantage of letting a student focus more on the domain context rather than on programming.

Contributor/s. Bhalchandra Gore (`http://cms.unipune.ac.in/~bwgore`)

3.10 19.DP2 Digital Signal and Image Processing 2

Credits. 4

Prerequisites. 19.DP1 (Sec. 3.9)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. See purpose/outlook/rationale/goals for the prequel 19.DP1 (Sec. 3.9). The focus of this follow-up course is more on digital image processing; e.g., electronic communication, satellite imaging, medical diagnostic images, video analysis, image segmentation, etc. Specific objectives of this course are:

1. Understanding the need for image processing;
2. understanding the correspondence between actual devices (camera, X-ray, tomographic devices, etc.), their operations, and their mathematical-statistical representations;
3. learning mathematical, statistical, and algorithmic tools used to improve quality of image and extract useful information from image; being able to design simple systems for image processing (like image smoothing, removal of noise, color spectrum analysis etc.) using tools like mean, median, variance, histogram, probability distribution, spatial and temporal filters, etc.;
4. being able to analyze given image using appropriate tools and infer about quality, content, etc.; learning to segment the given image to isolate different objects from it.

Syllabus.

1. What is digital image processing? Its origin, overview of fields of applications, fundamental steps in digital image processing,components of an image processing system.
2. Digital image fundamentals: Human eye and image formation; EM spectrum, image sensing and acquisition, sampling and quantization, basic relationships among pixels-neighbours, connectivity, regions, boundaries, distance measures.
3. Tools used for digital image processing: matrices and vectors, linear vs. non-linear operations, set and logical operators, image transforms, probabilistic methods.
4. Intensity transformations. Basic functions: negation, log, gamma transformation, histogram processing.
5. Spatial filtering: fundamentals, smoothing and sharpening spatial filters, unsharp masking and high boost filtering, use of gradients for non-linear image sharpening, Laplacian operator, using fuzzy techniques for spatial filtering and for intensity transformations
6. Filtering in frequency domain: Fourier series and transform, DFT, FFT, generalization for 2D image space, basic filtering in frequency domain, correspondence between spatial and frequency domain filtering, image smoothing and sharpening using frequency filters, low-pass, high-pass and band-pass filters, notch and band-reject filters, Gaussian, Butterworth, Laplacian filters.
7. Image restoration and reconstruction: Image degradation model, modeling noise, noise reduction using spatial filtering, periodic noise reduction using frequency domain filtering, estimating image degradation function using observation, experimentation and modeling; inverse filtering, statistical (Wiener's mean square error filtering, constrained least square filtering, mean filtering (arithmetic, geometric and harmonic); image restoration from projections (fundamentals of tomography).

8. Colour image processing; colour models: RGB, CMY, CMYK, HSI, relations between them; colour transformations, colour smoothing and sharpening.
9. Wavelets: Haar, Daubechies; DWT, 2D generalization, significance of wavelet coefficients, compression using wavelets.
10. Image compression techniques: spatial and temporal redundancy in images, fidelity criteria, image compression models, some image compression methods (using Huffman, Golomb, arithmetic, LZW, run-length, bit-plane and block-transform coding), relation between block-transform coding and wavelets.
11. Image segmentation fundamentals; point, line and edge detection, thresholding, region-based segmentation.
12. Overview of topics like Video analysis, morphology, watermarking, object/pattern recognition, compressed sensing, etc.

Suggested Texts/References.

1. R. C. Gonzalez and R. E. Woods, *Digital Image Processing, Third Edition.* Pearson, 2013.
2. Bose and Tamal, *Digital Signal and Image Processing.* Wiley India, 2008.

Notes on Pedagogy. At the discretion of the instructor, the computer vision library `OpenCV` can be introduced and used profusely in addition to `matlab/octave/scilab` to ease the programming effort, allowing a student to focus on the formalism and the domain context.

Contributor/s. Bhalchandra Gore (`http://cms.unipune.ac.in/~bwgore`)

3.11 19.ML1 Machine Learning 1

Credits. 4

Prerequisites. 19.C203 (Sec. 2.11)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. In the current era of data explosion, scientists and engineers are looking for methods to extract relevant information through automation. Machine learning methods enable development of algorithms to "learn" from the data and make relevant inferences and predictions. This course is designed to introduce students with the subject of machine learning via a variety of statistical tools like classification, clustering, etc. At the end of the course, students are expected to understand the basics of classification and clustering, develop necessary codes, and make correct inferences from given data.

Syllabus.

1. Introduction and background. What is machine learning? Overview and survey of applications. Problem of induction and statistical inference: Input-output functions, Boolean functions, parametric and non-parametric inference. Probability, certainty, and Bayes theorem. Introduction to typical learning tasks: regression, pattern recognition, feature selection, classification, clustering, rule induction (association). Model validation techniques: cross validation, leave-one-out, majority, etc. Measures of performance of a classifier: confusion matrix, sensitivity, specificity, ROC curves and the AUC, etc.
2. Computational environments for machine learning. Brief introduction to ML frameworks such as `Weka`, packages or modules in `R`, `python`, etc., I/O formats, basic introduction to interfaces.
3. Supervised learning. Additive models, generative models and discriminative models, logistic regression, Naïve Bayes classifier, linear discriminant analysis, neural networks and support vector machines.
4. Unsupervised learning fundamentals. Clustering: k-means, hierarchical, self-organizing map. Feature selection via principal component analysis.
5. Laboratory. Models using `Weka` or `R` on UCI benchmark data sets. Writing interfaces for a classifier as derived from a learner. Regression Models. k-means clustering, writing interface for a clusterer.

Suggested Texts/References.

1. T. Hastie, R. Tibshirani, J. H. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction.* Springer, 2013.
2. Tom Mitchell, *Machine Learning.* McGraw-Hill, 1997.
3. Peter Flach, *Machine Learning: The Art and Science of Algorithms that Make Sense of Data.* Cambridge University Press, 2012.
4. Carl Edward Rasmussen and Christopher K. I. Williams, *Gaussian Processes for Machine Learning.* MIT Press, 2005.
5. Daphne Koller and N. Friedman, *Probabilistic Graphical Models: Principles and Techniques.* MIT Press, 2009.
6. Christopher Bishop, *Pattern Recognition and Machine Learning.* Springer, 2007.

7. Kevin P. Murphy, *Machine Learning: A Probabilistic Perspective*. MIT Press, 2012.
8. Larry Wasserman, *All of Statistics: A Concise Course in Statistical Inference*. Springer, 2004.
9. David MacKay, *Information Theory, Inference and Learning Algorithms*. Cambridge University Press, 2003.
10. Y. S. Abu-Mostafa, Malik Magdon-Ismail, and Hsuan-Tien Lin, *Learning From Data*. AMLBook, 2012.
11. Mehryar Mohri, Afshin Rostamizadeh, and Ameet Talwalkar, *Foundations of Machine Learning*. MIT Press, 2012.

Notes on Pedagogy. Crowd-source platforms for data science such as http://kaggle.com/ offer challenges based on machine learning. Instructors are encouraged to involve students in such competitions.

Contributor/s. V. K. Jayaraman (https://in.linkedin.com/in/jayaraman-valadi-a7916925)

3.12 19.ML2 Machine Learning 2

Credits. 4

Prerequisites. 19.ML1 (Sec. 3.11)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Students are expected to be familiar with basic tools of machine learning by now. This course should be pitched at more advanced level than the prequel 19.ML1 (Sec. 3.11). At the end of this course, students are expected to be able to develop new hybrid algorithms for data analysis and predictions. Students may be introduced to standalone software packages that employ machine learning tools.

Syllabus.

1. Formulation of the learning problem. Learning as a statistical problem: estimation of probability measure and basic problems of statistics, learning as density estimation, risk, empirical risk and structural risk, introduction to ill-posed problems and regularization. Learning as an algebraic problem. Learning as a computational problem: learnability, PAC learning, bounds on data, algorithmic learning theory basics. Laboratory: linear models in `R`, writing basic interface for a learner.
2. Reinforcement learning.
3. Ensemble methods, boosting and bagging.
4. Intelligent agents.
5. Advanced clustering methods. Gaussian/Normal mixture models and the EM algorithm. Fuzzy clustering.
6. Feature selection. Feature selection using singular value decomposition (SVD). Various filter and wrapper methods.
7. Advanced applications, machine learning algorithms, and case studies. The machine learning approach to time series analysis. Fundamentals and application of clustering/classification to image analysis. Text analytics and natural language processing fundamentals with applications. Social media analytics. Financial analytics.
8. Laboratory. Case studies using real-life public-domain data, based on the topics covered.

Suggested Texts/References. See the **Suggested Texts/References** section for the sister course 19.ML1 (Sec. 3.11).

Notes on Pedagogy. Crowd-source platforms for data science such as `http://kaggle.com/` offer `kaggle.com` offer rich data sets and challenges for exercising machine learning skills and expertise. Instructors are encouraged to involve students in such competitions.

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3.13 19.ML3 Machine Learning Laboratory

Credits. 2

Prerequisites. 19.ML1 (Sec. 3.11)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. The purpose of this course is to introduce commonly used (open-source) libraries, tools, packages, and platforms for machine learning and artificial intelligence, so as enhance the industry-preparedness of students. Such tools include, for example, `TensorFlow`, `Scikit-learn`, `Keras`, `PyTorch`, `Theano`, `GenSim`, `Caffe`, `Chainer`, `Statsmodels`, `Neon`, `Nilearn` in the `Python` world, similar tools in the `R` world, and APIs such as `Apache Spark`, etc. Not all the tools mentioned above need be covered in the course. The selection of particular tool/s may change from course instance to course instance, depending on (a) the instructor's expertise and preference, (b) industry trends and developments in this field, and (c) a balance between depth and breadth.

Syllabus.

1. A broad survey of commonly used and available tools such as those mentioned above.
2. A crisp introduction to one or two such tools of instructor's choice.
3. Individual or group miniprojects. Students may survey and choose any other appropriate tools, libraries, APIs, etc., best-suited for their chosen topic, under the guidance of the instructor/s.

Suggested Texts/References. Appropriate set of internet and other resources recommended by the instructor.

Notes on Pedagogy. This course should complement the machine learning courses 19.ML1 (Sec. 3.11) and 19.ML2 (Sec. 3.12). It is intended to be a hands-on course involving case studies and applications, with focus on (open-source) tools. The instructor may consider an open-laboratory, tinkering / experimentation-based approach where different students / groups may explore different (open-source) tools through individual or group mini-projects.

Contributor/s.

1. V. K. Jayaraman (`https://in.linkedin.com/in/jayaraman-valadi-a7916925`)
2. Bhalchandra Pujari (`http://cms.unipune.ac.in/~bspujari`)
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4. Mihir Arjunwadkar (`http://cms.unipune.ac.in/~mihir`)

3.14 19.OR1 Operations Research 1

Credits. 4

Prerequisites. 19.C202 (Sec. 2.10)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives.

1. To make students aware of the problem domain of operations research (OR).
2. To introduce various models and simulation methods in OR.
3. Introducing software tools used in OR practices.
4. To make students aware of how the methods are used to solve real life problems.

Syllabus.

1. Linear programming. Simplex algorithm and simplex method, artificial variable methods. Degeneracy, duality in linear programming, duality theorems, dual simplex method with justification. Integer linear programming problem: pure and mixed integer programming problem, Gomory's all integer programming method. Fractional cut method, all integer and mixed integer linear programming problem, branch-and-bound method. Sensitivity analysis.
2. Transportation and assignment problems. Balance and degeneracy in transportation and trans-shipment problems. Duality theory of testing optimality of solution in transportation and trans-shipment problems. Hungarian method of assignment. Maximization, prohibition and other variations of assignment problems.
3. Dynamic programming.
4. Networking models. Graph theory concepts such as spanning trees, and algorithms for shortest path, network flow, maximum flows, etc. Transportation, trans-shipment, and assignment problems as networking problems. Network scheduling by PERT/CPM technique. Resource analysis in network scheduling.

Suggested Texts/References.

1. Kambo, N. S., *Mathematical Programming Techniques.* Affiliated East-West Press, 2002.
2. Taha, H. A., *Operations research.* Pearson, 2014 (9ed).
3. Sierksma, *Linear and Integer Programming.* CRC Press, 2002.
4. Kantiswaroop, P. K., Gupta, M. M., *Operation Research: An Introduction to Management Science.* S. Chand & Co., 2014.
5. Sharma, J. K., *Operations Research Theory and Applications.* Macmillan Publisher India, 2013 (5ed).
6. N. S. Kambo, *Mathematical Programming Techniques.* Affiliated East-West Press, 2002.
7. Ahuja, Magneti, Orline, *Network flows: Theory, Algorithm, and Applications.* Pearson, 2014.
8. T. H. Cormen, C. E. Leiserson, R. L. Rivest, C. Stein, *Introduction to Algorithms.* PHI Learning, 2009.

Notes on Pedagogy. Theory in this course should be complemented with computational exercises based on software tools such as `Lingo`, `AMPL`, `Gurobi`, `CPLEX`, and/or languages such as `Python` and `R`.

Contributor/s. Padma Pingle

3.15 19.OR2 Operations Research 2

Credits. 4

Prerequisites. 19.OR1 (Sec. 3.14)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives.

1. To make students aware of the advanced techniques in Operations Research (OR).
2. Introducing various models & theories used in OR.
3. To make students able to apply their knowledge for solving real life problems in OR.

Syllabus.

1. Advanced linear programming. Advanced techniques: Revised Simplex Method, Simplex Method versus Revised Simplex Method, Bounded variable technique, Parametric Linear Programming, Linear Fractional Programming and their applications, Karmarkar algorithm.

   (Optional) Sequential problems. Basic terms used in sequencing, n-jobs two machines sequencing problems, processing two jobs through K machines sequencing problems.
2. Queuing theory. Markovian and Non-Markovian queuing models (i.e., $(M/M/1)$, $(M/M/s)$, $(M/E_k/1)$, $(M, G, 1)$, steady-state probabilities and their characteristics, cost profit models of $(M/M/1)$ queuing systems. Simulation, event type simulation, simulation of a queuing system.
3. Applications of OR. Modeling and OR analysis of real-life problems such as inventory models, vehicle routing, job shop scheduling, production planning, facility location, etc.
4. (Optional) Game theory. Two-person Zero-sum games, Maximin-Minimax principle. Games without saddle point. Graphical solution of $2 \times n$ and $m \times 2$ games, Dominance property, Arithmetic methods for $n \times n$ games, General solution of $m \times n$ Rectangular games, Limitations and Extensions.

Suggested Texts/References.

1. Kambo, N. S., *Mathematical Programming Techniques.* Affiliated East-West Press, 2002.
2. Taha, H. A., *Operations research.* Pearson, 2014 (9ed).
3. Sierksma, *Linear and Integer Programming.* CRC Press, 2002.
4. Kantiswaroop, P. K., Gupta, M. M., *Operation Research: An Introduction to Management Science.* S. Chand & Co., 2014.
5. Sharma, J. K., *Operations Research Theory and Applications.* Macmillan Publisher India, 2013 (5ed).

Notes on Pedagogy. The focus of this course is on advanced OR techniques, applications to real-life problems, large scale optimization, and on learning new algorithms and solution methodologies.

Contributor/s. Padma Pingle

4 Choice-Based Credits: In-House Standalone Electives

4.1 Quick Reference to In-House Choice-Based Standalone Electives

Choice-based electives listed below can be offered during any semester provided their prerequisites are satisfied. Prerequisites listed below are suggestive/indicative; they can be decided/redefined by the course instructor with approval from the Centre. Sufficient mastery over the content of the listed prerequisites, and over an appropriate programming language is assumed for all elective courses.

Code (Sec)	**Name**	**Cr**	**Prerequisite/s**
19.E001 (Sec. 4.2)	Concurrent Computing	4	19.C106 (Sec. 2.7)
19.E002 (Sec. 4.3)	High-Performance Computing	4	19.C106 (Sec. 2.7)
19.E003 (Sec. 4.4)	Theory of Computation	4	19.C106 (Sec. 2.7)
19.E004 (Sec. 4.5)	Functional Programming	2	19.C106 (Sec. 2.7)
19.E005 (Sec. 4.6)	Computing with `Java`	2	19.C106 (Sec. 2.7)
19.E006 (Sec. 4.7)	Computing with `Python`	2	19.C106 (Sec. 2.7)
19.E007 (Sec. 4.8)	Computing with `R`	2	19.C106 (Sec. 2.7)
19.E008 (Sec. 4.9)	Computing with `MATLAB/Scilab`	2	19.C106 (Sec. 2.7)
19.E009 (Sec. 4.10)	Computing with `C`	2	19.C106 (Sec. 2.7)
19.E010 (Sec. 4.11)	Statistical Models and Methods	4	19.C203 (Sec. 2.11)
19.E011 (Sec. 4.12)	Advanced Data Analysis	2	19.C203 (Sec. 2.11)
19.E012 (Sec. 4.13)	Stochastic Simulation	2	19.C105 (Sec. 2.6)
19.E013 (Sec. 4.14)	Data Visualization	2	As defined by the instructor
19.E014 (Sec. 4.15)	Difference Equations	2	19.C101 (Sec. 2.2), 19.C102 (Sec. 2.3), 19.C103 (Sec. 2.4), 19.C104 (Sec. 2.5)
19.E015 (Sec. 4.16)	Ordinary Differential Equations	2	19.C101 (Sec. 2.2), 19.C102 (Sec. 2.3), 19.C103 (Sec. 2.4), 19.C104 (Sec. 2.5)
19.E016 (Sec. 4.17)	Partial Differential Equations	2	19.E015 (Sec. 4.16)
19.E017 (Sec. 4.18)	Transforms	2	19.C101 (Sec. 2.2), 19.C102 (Sec. 2.3), 19.C103 (Sec. 2.4), 19.C104 (Sec. 2.5)
19.E018 (Sec. 4.19)	A Formal Overview of M&S	2	19.C204 (Sec. 2.12)

4.2 19.E001 Concurrent Computing

Credits. 4

Prerequisites. 19.C106 (Sec. 2.7)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Concurrency is ubiquitous, and not only a part of OS courses. It can also be a program modularization technique whereby applications can be organized as a set of interacting concurrent components. The word "concurrency" not only alludes to "occurring at the same time", but also has other connotations like "agreeing on some thing", or "coming together for a task" etc. While concurrency in the first sense is often conflated with parallel computing, concurrency is broader and more pervasive. This course aims to bring out the basic issues and techniques needed to deal with concurrency.

1. Understanding of concurrency in parallel and distributed computing
2. Designing and modularising programs using concurrent tasks
3. Synchronizing and communicating between tasks in a concurrent program
4. (Optional): Formal modeling of concurrent systems

Syllabus.

1. Introduction. Introducing concurrency with simple problems like Readers-Writers, Producer-Consumer, Bounded Buffer, etc., as illustrations. Challenges in concurrency: synchronization, mutual exclusion, deadlock, livelock, starvation, non-determinism. Distinction between concurrent and distributed systems. Relation between timing and concurrency. Concurrency in algorithms and physical concurrency. Example of concurrent systems: operating systems, database systems, web servers.
2. Types of concurrency. (a) Program level – Introduction to the variety of control flows: sequential, coroutines etc. Program execution approaches: single tasking, multitasking, multiprocessing, multicomputing and distributed. (b) Data level – data structures and their concurrency, parallel computing.
3. Inter-process communication. Communication between components in a concurrent program: shared memory, message passing. Communication/Data exchange/Interaction between processes on: time shared systems, client-server systems, distributed systems. Components of a concurrent program versus interaction between processes; similarities and differences.

   Techniques of handling concurrency. Locking, Time stamp ordering, Semaphores, Monitors. Goals: Correctness or fault tolerance.
4. Distributed systems. timing and clock synchronization, time stamps, Chandy-Lamport time ordering. Global snapshot on distributed systems. Examples: from distributed snapshots, Synchronous and asynchronous systems.
5. (Sample: See note 1). Introduction to Android as a programming platform. The basic "Hello World" application on Android. Implement algorithms on Android – three sort algorithms as independent programs. IPC on Android – A pair of sort algorithms on shared data set (Scenarios: e.g., (a) One works in place, and the other on a copy – both run concurrently, (b) Both work in place and concurrently, etc. Choose a scenario).

6. (Optional: See note 2). Abstract representation of concurrent (esp. distributed) systems: Introduction to a Process Algebra, e.g., CCS. The Calculus of Communicating Systems: Syntax of the CCS, Operational semantics of the CCS (non-determinism etc.). Worked examples for the CCS.

Suggested Texts/References.

1. Clay Breshears, *The Art of Concurrency: A Thread Monkey's Guide to Writing Parallel Applications*. O'Reilly, 2009.
2. Robin Milner, *Communicating and Mobile Systems: The π Calculus*. Cambridge University Press, 1999.
3. Michel Raynal, *Concurrent Programming: Algorithms, Principles, and Foundations*. Springer, 2013.
4. A. Roscoe, *Theory and Practice of Concurrency*. Prentice Hall, 1997.
5. G. Blake Meike, *Programming Android*. Shroff, 2012.
6. Reto Meier, *Professional Android 4 Application Development (Wrox)*. Wiley, 2012.

Notes on Pedagogy.

1. This course requires programming exercises. This syllabus illustrates the concepts discussed using Android. However, any suitable system could be used based on the familiarity of the students and the instructor. For example, a Unix/Linux based system would bring out shared memory (`shm*`) system calls, message passing (`msg*`) system calls, and possibly simple socket based IPC programming. Yet another possibility is to use MPI based programming assignments with similar detailing. This component is therefore labeled as "Sample" to suggest that the *means* used to bring out concurrency may be decided by the instructor depending on the circumstances.
2. The formal aspects are truly optional and at the discretion of the instructor. The main goal of including this treatment should be to illustrate the *mathematical modeling* component of the course. The suggested syllabus uses CCS – Calculus of Communicating Systems – by Robin Milner. However, any other useful system – e.g., Petri Nets, CSP (Communicating Sequential Processes – C.A.R. Hoare) etc. – can be used.

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4.3 19.E002 High-Performance Computing

Credits. 4

Prerequisites. 19.C106 (Sec. 2.7)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives.

Syllabus.

1. HPC programming platforms. Implicit parallelism: trends in microprocessor architectures, memory system performance limitations, control structure of HPC platforms, communication model, physical organization, architecture of parallel computer, interconnection networks, network topologies, static, dynamic interconnection networks, cache coherence in multiprocessor systems, communication costs, message passing costs.
2. Programming using message-passing. Principles of message passing programming, send and receive operations, blocking and non-blocking message passing, message passing interface, introduction to MPI routines, data types, concept of communicators, communication domain, communicator groups, creating topologies using MPI, overlapping communication with computation, MPI syntax for frequently used communication calls related to send, receive, barrier, broadcast, reduction, prefix, gather, scatter, all-to-all communication. programs with MPI for addition/multiplication of list of random numbers, matrix-matrix multiplication, bubble sort, shell sort, quick sort, bucket sort, sample sort etc.
3. Parallel algorithm design. Decomposition, tasks, dependency graphs, granularity, concurrency, task interaction, processes and mapping, decomposition techniques: recursive, data, speculative, hybrid, characteristics of tasks and inter-task interactions, mapping techniques for load balancing, static mapping, dynamic mapping, methods for containing interaction overheads, parallel algorithm models: data parallel, task-graph, work pool, master-slave, producer-consumer or pipeline model.
4. Basic communication operations. Personalized Communication, Collective Communication, Collective communication operation algorithms on ring, mesh, hypercube topologies and their cost analysis, improving speed of communication operations.
5. Parallel algorithms for linear algebra. Matrix-vector multiplication with 1-D, 2-D partitioning, matrix-matrix multiplication: simple algorithm (1-D partitioning), Cannon's algorithm (2-D partitioning), DNS algorithm (3-D partitioning), solving system of linear equations with simple Gaussian elimination algorithm (1-D partitioning), 1-D partitioning with pipelined communication and computation, 2-D partitioning with pipelined communication and computation, Gaussian elimination with partial pivoting, solving a triangular system with back substitution, parallel algorithm for Jacobi's iterative method and Gauss-Seidel iterative method for solving system of linear equations.
6. (Optional) Analytical modeling of parallel programs. Overheads in parallel programs, performance metrics such as execution time, total parallel overhead, speedup, efficiency, cost, effect of granularity on performance, scalability, scaling characteristics, isoefficiency metric of scalability, cost-optimality, isoefficiency function, degree of concurrency and isoefficiency function, minimum execution time, minimum cost-optimal execution time, asymptotic analysis of parallel programs, other scalability metrics Cost analysis of parallel programs developed in the course work.

Suggested Texts/References.

1. Ananth Grama, Anshul Gupta, George Karypis and Vipin Kumar, *Introduction to Parallel Computing*. Pearson Education, 2004.
2. V. Rajaraman and C. Siva Ram Murthy, *Parallel Computers: Architecture and Programming*. Prentice-Hall India, 2000.
3. Ian Foster, *Designing and Building Parallel Algorithms*. Addison-Wesley, 1995.
4. V. Rajaraman, *Elements of Parallel Computing*. Prentice Hall, 1990.
5. Barry Wilkinson and Michael Allen, *Parallel Programming: Techniques and Applications Using Networked Workstations and Parallel Computers*. Pearson India, .
6. Michael T. Heath, *Scientific Computing*. Tata McGraw-Hill, .
7. Michael Quinn, *Parallel Programming in C with MPI and OpenMP*. Tata McGraw-Hill, .

Notes on Pedagogy.

Contributor/s. Vaishali Shah (`https://www.researchgate.net/profile/Vaishali_Shah10`)

4.4 19.E003 Theory of Computation

Credits. 4

Prerequisites. 19.C106 (Sec. 2.7)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. This is an introduction to the formal theory of computation and its modeling applications.

Syllabus.

1. Introduction to languages. Symbols, strings, words and languages. Symbolic dynamics, dynamics as language. Examples of languages. Finite representation of languages. String induction principles.
2. Finite automata. Functions as tables: introduction to theory of automata. Regular expressions and languages. Equivalence and simplification of regular expressions. Finite automata and labeled paths. Isomorphism of finite automata. Algorithms for checking acceptance and finding accepting paths. Simplification of finite automata. Proving the correctness of finite automata. Empty-string finite automata. Nondeterministic finite automata. Deterministic finite automata. Closure properties of regular languages. Transfer matrices and finite automata. Solving real-life problems with finite automata.
3. Context-free grammars. Examples of languages which are not regular. State minimization. The pumping lemma for regular languages. Context-free grammars, parse trees, stacks and queues. Dynamical systems generating context-free languages. Functions with "internal memory" and push-down automata. Isomorphism of grammars. Derivations, Converting between parse trees and derivations. Simplification and ambiguity of grammars. Determinism and parsing. Pumping lemma for context free grammars. Chomsky normal form. A parsing algorithm.
4. Turing machines. Examples which are not context free. Chomsky hierarchy. Another look at symbolic dynamics and coding theory for examples of dynamical systems in various levels of Chomsky hierarchy. Computing with dynamical systems. Functions with "external memory" and Turing machines. Computing with Turing machines. Extensions of Turing machines. Random access Turing machine. Non-deterministic Turing machines. Chaotic systems as Turing machines.
5. Universal Turing machines, complexity, computability. Universal Turing machines. Church-Turing thesis. Halting problem. Undecidable problems. Tiling problem and the Potts model. Computability and complexity theory. Classes P and NP. Cook's theorem and P-NP completeness theorems.
6. (Optional) Formal computation as a modeling paradigm. A judicious selection of topics such as: symbolic dynamics of dynamical systems, biological sequences and stochastic grammars, computational musicology, computational linguistics, natural language processing, L-systems, automata in game theory, etc.

Suggested Texts/References.

1. H. Lewis and C. Papadimitrion, *Elements of Theory of Computation*. Prentice-Hall, 1998.
2. V. E. Krishnamurthy, *Introductory Theory of Computer Science*. Springer-Verlag, 1985.

Notes on Pedagogy. Formal development should be coupled with adequate emphasis on modeling applications, and preferably some hands-on work in any form such class projects, etc.

Contributor/s.

1. Ashutosh Ashutosh (https://www.linkedin.com/profile/view?id=198572337)
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4.5 19.E004 Functional Programming

Credits. 2

Prerequisites. 19.C106 (Sec. 2.7)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Upon successful completion of this course, the student will be able to

1. Understand basics of functional programming.
2. Design an algorithm to solve problems of various kinds in modeling and simulation and implement using functional language.
3. Debug the code to spot logical errors, exceptions etc.
4. Write reasonably complex code for solving various problems in modeling and simulation.

Syllabus.

1. Introduction to theoretical framework for describing functions and their evaluation, variable binding and substitution, effective computability, Turing machine and Lambda calculus.
2. Dynamically and Statically Typed Functional Languages.
3. Other domain specific programming languages based on/implementing functional programming concepts; e.g, `R`, `SQL`, etc.
4. How does the chosen programming language (LISP/Haskell) implement the above concepts?
5. First-class and higher-order functions, pure functions, recursion.
6. Comparison with other programming paradigms.
7. Declarative *vs.* imperative, using pipelines, Computation by expression evaluation.
8. Reliability.
9. Syntax, coding style and other aspects of programming in the chosen functional language.

Suggested Texts/References. As recommended by the course instructor.

Notes on Pedagogy. Any functional programming language like such as `LISP`, `Scheme`, or `Haskell` can be chosen for this course. The concepts of functional programming, how they are used in the chosen language and programming in that language for M&S problem-solving should be clearly brought out by the instructor.

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Charulata Patil (`charulata@cms.unipune.ac.in`)

4.6 19.E005 Computing with `Java`

Credits. 2

Prerequisites. 19.C106 (Sec. 2.7)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Upon successful completion of this course, the student will

1. Understand basics of object-oriented programming (OOP), syntax, semantics of `Java`.
2. Design an algorithm to solve problems of various kinds in modeling and simulation and implement using `Java` programming language.
3. Debug the code to spot logical errors, exceptions etc.
4. Write reasonably complex `Java` code/applets for various problems in modeling and simulation.

Syllabus.

1. Overview of `Java` programming. Compiling and Running a `Java` program. Coding Standards. Introduction to `Java` programming language. Data types, operators and control structures. Primitive data classes.
2. OOAD. Class, object, inheritance, Class Design and Implementation, class responsibilities, data encapsulation, Polymorphism.
3. Exception handling. Exception handling in `Java`.
4. `Java` generics. generic programming, ready made classes and generic data structures. Generic Algorithms. Enumerations, autoboxing, and annotations. The Collections Framework
5. Threads. Thread handling in `Java`.
6. GUI. AWT library. Window, Controls, events, callback, event handlers, frames, graphics, image handling.
7. Applets. Application development and animations.

Suggested Texts/References.

1. Herb Schildt, *Java: The Complete Reference*. McGraw Hill Education (India) Private Limited, 2013.
2. Various web resources; especially, http://docs.oracle.com/javase/7/docs/api/.

Notes on Pedagogy.

Contributor/s. Bhalchandra Gore (http://cms.unipune.ac.in/~bwgore)

4.7 19.E006 Computing with `Python`

Credits. 2

Prerequisites. 19.C106 (Sec. 2.7)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. `Python` offers a powerful means for M&S via its intuitive object-oriented framework and in-built libraries. The goal of this course is not the introduction to `Python` but demonstration of how `Python` can be used in mathematical modeling. At the end of the course students are expected to develop `Python` programs to implement intermediate level of mathematical models.

Syllabus.

1. Introduction. 'Hello world' program, Understanding `Python` shell and environment. Running the codes.
2. Data and control structures. Data types and objects. Introduction to conditionals (`if`) and loops (`for` and `while`). Loading packages.
3. Functions. Defining and using functions. Using built-in functions. Recursion.
4. Advanced mathematics. Examples of using `numpy, scipy`. Simple 2D and 3D plotting.
5. User input. Reading and writing the data from/to terminal and files. Formatting output. Converting data types. `try-except` construct.
6. Strings and lists. Operations on stings. List, list-comprehensions, list of lists.
7. Classes. User defined classes, objects, methods, and functions.

Suggested Texts/References.

1. David Beazley, Brian K. Jones, *Python Cookbook*. O'Reilly Media, 2013.
2. Mark Lutz, *Programming Python*. O'Reilly Media, 2010.
3. The Official Python Documentation (`https://docs.python.org/`).

Notes on Pedagogy. Since the focus of the course is using `Python` for modeling, the syntax could be introduced as a necessity to solve the given problem. Ideally the aim of the course could be to have one `Python` project at the the end of the term, and necessary syntax and other tools are taught as the requirement along the development.

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4.8 19.E007 Computing with R

Credits. 2

Prerequisites. 19.C106 (Sec. 2.7)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. The R (http://cran.r-project.org/) statistical computing environment, built around the S programming language, is rich in computational statistics primitives. It is open-source and supported by an ever-growing community of users and contributors. It allows a variety of programming styles from quick-and-dirty explorations to elaborate imperative, procedural, object-oriented, and functional coding. It is ideally suited for statistical modeling and data analysis, graphics and visualization, as well as a platform for teaching/learning probability and statistics through hands-on exploration. As such, R is a must for any broad-based M&S curriculum with a statistical modeling/data analysis component. Goals: proficiency in computational problem-solving using R; specifically, decent algorithmic, coding, and scripting skills.

Syllabus.

1. Overview of R and S. History of R. Why use R? When not to use R? GUIs for R. Invoking and exiting the R interpreter environment. Getting help and finding information. `demo()`. The six atomic types. Assignment operators. Standard arithmetic and logical operators. Comments. Conditionals and loops. Parenthesis and braces. Expressions. Every expression has a value. Common composite data types: `vector`, `list`, `matrix`, and `data.frame`. The elementwise operations rule for `vector` and related container types. `functions`. Writing and executing R scripts: `source()` and `Rscript`.
2. Case studies illustrating R capabilities, in-built functions, and common packages. Overview of R graphics. Probability distributions and random number generators. Creating numerical and graphical data summaries, and exploratory data analysis. Complex numbers, numerical methods, etc. Character strings. Set operations. Interface to the operating system shell. Data input and output.
3. Installing R and R packages locally into a linux user account. Installing R from source: `configure` – `make` – `make install` sequence. Installing packages: `install.packages()` and the `R CMD INSTALL` mechanism.
4. Migrating from C to R. Automatic type identification in an assignment vs. explicit declaration of data type. `;` and `\n` as expression terminators. Explicit loops vs. vectorization.
5. Getting performance from R codes. Coding style guidelines. Explicit loops vs. vectorization. The `compiler` package. Debugging and profiling tools. Interfacing with `C, C++, fortran`.
6. Hands-on explorations using R. Any reasonable set of hands-on problems designed to enhance computational problem-solving and algorithmic abilities. Such problems may be related to M&S in general, or specifically to topics from other courses (e.g., probability theory, statistical inference) in the programme or the instructor's field of expertise.

Suggested Texts/References.

1. W. N. Venables, D. M. Smith, and the R Development Core Team, *An Introduction to R*. The R Project, latest available edition. http://cran.r-project.org/doc/manuals/R-intro.html

2. John Verzani, *Using R for Introductory Statistics*. Chapman & Hall/CRC, 2005.
3. Daniel Navarro, *Learning Statistics with R: A Tutorial for Psychology Students and Other Beginners*. Self-published, 2013. http://learningstatisticswithr.com/
4. Paul Murrell, *R Graphics*. Chapman & Hall/CRC, 2011.
5. Patrick Burns, *The R Inferno*. http://www.lulu.com/, 2012. Available at http://www.burns-stat.com/documents/books/the-r-inferno/.
6. W. N. Venebles and B. D. Ripley, *Modern Applied Statistics with S-Plus*. Springer, 2002.
7. R. G. Dromey, *How to Solve It By Computer*. Prentice-Hall, 1982.

Notes on Pedagogy. This syllabus is based on an outline for a longer course that was refined over several course deliveries by the course contributor. Depending on the background and capabilities of the students, this outline may need to be diluted or intensified – without compromising upon the essentials and goals for the course. Apart from familiarizing a student with R, a major emphasis of this course is on tinkering and exploration, on computational problem-solving, and on translating a problem into a computational framework leading to a solution and/or a better understanding of the problem, and on how R can be used as a M&S tool, and for exploring/visualizing probability and statistics concepts. Assignments often consist of problems that are exploratory in nature (e.g., illustrating formal results that may be difficult to grasp, such as the central limit theorem; see 19.C105 (Sec. 2.6)), or require a student to understand an algorithm from its plain-English or pseudocode description (e.g., generating permutations in the lexicographic order). Examinations may consist of problems not necessarily discussed in the class: Here, adequate information about the method of solution or algorithm is provided.

Contributor/s. Mihir Arjunwadkar (http://cms.unipune.ac.in/~mihir)

4.9 19.E008 Computing with MATLAB/Scilab

Credits. 2

Prerequisites. 19.C106 (Sec. 2.7)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. MATLAB and its open-source parallel Scilab are popular, powerful, and flexible platforms for numerical and symbolic computation, visualization and graphics, etc., and are rich in computational primitives for diverse fields from digital signal processing to statistics. This course aims at developing an intermediate skill level in writing scripts, performing calculations, using the command line, importing data from files, plotting data, and integrating with other programming languages such as C.

Syllabus.

1. Introduction. Environment. Workspaces. General syntax.
2. Numerics. Creating matrices. Matrix operations. Sub-matrices. Statistical operations. Polynomials, differential equations.
3. Plots. Plotting graphs for 2D, 3D functions. Various types of plots.
4. Programming. Functions, Scilab/MATLAB programming language, Script files and function files.
5. I/O. Reading, writing data in various formats.
6. Interfacing with programming languages such as C.

Suggested Texts/References.

1. Amos Gilat, *MATLAB: An Introduction with Applications*. Wiley, 2008.
2. Mathews and Fink, *Numerical Methods Using MATLAB*. Pearson, 2004.
3. J. C. Polking and D. Arnold, *Ordinary Differential Equations using MATLAB*. Pearson, 2003.
4. An extensive comparison of MATLAB and Scilab: http://www.professores.uff.br/controledeprocessos-eq/images/stories/Comparative-Study-of-Matlab-and-Scilab.pdf

Notes on Pedagogy. Case studies and problems used for introducing MATLAB/Scilab can be derived from other courses running concurrently.

Contributor/s. Bhalchandra Pujari (http://cms.unipune.ac.in/~bspujari)

4.10 19.E009 Computing with C

Credits. 2

Prerequisites. 19.C106 (Sec. 2.7)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Upon successful completion of this course, the student is expected to be able to

1. Understand basics of procedural/functional programming, syntax, semantics of C.
2. Design an algorithm to solve problems of various kinds in modeling and simulation and implement using C programming language.
3. Debug the code to spot logical errors, exceptions etc.
4. Write reasonably complex C code for solving various problems in modeling and simulation.

Syllabus.

1. ANSI C. Syntax, data types, concept of void, variables, operators, expressions and statements, character input and output, console input and output, inclusion of standard header files, pre-processor directives.
2. Control flows. If-else, for, while, do-while, switch-case, break and continue, code blocks and nesting of blocks.
3. Functions. Basics of functions, return statement, recursion, function blocks, static variables
4. Memory management. Dynamic versus static memory allocation, freeing memory, arrays, memory layout of multidimensional arrays.
5. Pointers. Concept of pointers, pointer arithmetic, pointers versus arrays, array of pointers.
6. Program compilation and debugging techniques. Introduction to tools like `gdb` together with `ddd`, `GNU make` and profiler `gprof`. Code organization across files. Version/revision control using `svn` or `git`.
7. Structures and Unions. Structures and unions, bit fields, typedef, self referential structures, their use in link-list, queue, stack *etc.*
8. Input and output in `C`. Files, file operations.

Suggested Texts/References.

1. Kernighan and Ritchie, *The C Programming Language.* PHI, 1990.
2. R. L. Kruse, B. P. Leung, C. L. Tondo, *Data Structures And Program Design In C.* Pearson Education, 2007.

Notes on Pedagogy. Although finite-precision arithmetic is covered at length in the course 19.C201 (Sec. 2.9), the student may be exposed here to the bare-basics of finite-precision representations and arithmetic if time permits, and at the discretion of the instructor.

Contributor/s. Bhalchandra Gore (`http://cms.unipune.ac.in/~bwgore`)

4.11 19.E010 Statistical Models and Methods

Credits. 4

Prerequisites. 19.C203 (Sec. 2.11)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Listed below in the syllabus section is a representative selection of topics for this course rated at 1 credit each. With approval from the Centre, a qualified instructor may introduce additional 1-credit topics. Any selection of topics adding up to the requisite number of credits may be offered.

Syllabus.

1. Linear and logistic regression. Simple Linear Regression. Least Squares and Maximum Likelihood. Properties of the Least Squares Estimators. Prediction. Multiple Regression. Model Selection. Logistic Regression.
2. Multivariate models. Random vectors. Estimating the correlation. Multivariate normal. Multinomial.
3. Inference about independence. Two binary variables. Two discrete variables. Two continuous variables. One continuous variable and one discrete variables.
4. Causal inference. The counterfactual model. Beyond binary treatments. Observational studies and confounding. Simpson's paradox.
5. Directed graphs and conditional independence. Conditional independence. Directed graphs. Probability and directed graphs. More independence relations. Estimation for directed graphs.
6. Undirected graphs. Undirected graphs. Probability and graphs. Cliques and potentials. Fitting graphs to data.
7. Log-linear models. The log-linear model. Graphical log-linear models. Hierarchical log-linear models. Model generators. Fitting log-linear models to data.
8. Nonparametric curve estimation. The bias-variance trade-off. Histograms. Kernel density estimation. Nonparametric regression.
9. Smoothing using orthogonal functions. Orthogonal functions and L_2 spaces. Density estimation. Regression. Wavelets.
10. Classification. Error rates and the Bayes classifier. Gaussian and linear classifiers. Linear regression and logistic regression. Relationship between logistic regression and linear discrimination analysis. Density estimation and naive Bayes. Trees. Assessing error rates and choosing a good classifier. Support vector machines. Kernelization. Other classifiers.
11. Time series analysis. Overview of the Box-Jenkins and Bayesian approaches. Principles of nonlinear and chaotic time series analysis.

Suggested Texts/References.

1. Larry Wasserman, *All of Statistics*. Springer-Verlag, 2004.
2. Larry Wasserman, *All of Nonparametric Statistics*. Springer-Verlag, 2006.

Notes on Pedagogy. The suggested syllabus is primarily the content of Part III of the first recommended reference book. Appropriate balance of theory and practice is recommended.

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4.12 19.E011 Advanced Data Analysis

Credits. 2

Prerequisites. 19.C203 (Sec. 2.11)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Given the basic background in statistical modeling developed in prior courses, this course intends to expose the student to data analysis in a hands-on and problem-centric manner, so as to develop a feel for the challenges involved. At the end of this course, the student is expected to develop understanding about

1. formulating the problem in the light of the (scientific) question being explored;
2. choosing a statistical method that is most appropriate for the problem;
3. adapting or developing computational tools; and
4. evaluating results of the analysis and the statistical models involved critically.

This course is inspired by similarly-spirited courses such as http://www.stat.cmu.edu/~cshalizi/uADA/12/ and http://stat.ethz.ch/education/semesters/ss2010/CompStat.

Syllabus. An assortment of data analysis problems from any selection of fields at the discretion of the instructor/s. Problems should be chosen to reflect the diversity of (scientific) questions probed as well as that of statistical models and methods, such as (but not limited to): simple and multiple linear regression; model selection; finite mixture models; nonparametric methods for regression, density estimation, and classification (kernel methods, smoothing splines, classification and regression trees, additive models, etc.); resampling, bootstrap, and cross-validation methods.

Suggested Texts/References.

1. Cosma Rohilla Shalizi, *Advanced Data Analysis from an Elementary Point of View*. Unpublished, 2014. Available as http://www.stat.cmu.edu/~cshalizi/uADA/12/lectures/ADAfaEPoV.pdf.
2. Peter Bühlmann and Martin Mächler, *Computational Statistics*. Unpublished, 2008. Available as https://stat.ethz.ch/education/semesters/ss2010/CompStat.

Notes on Pedagogy. An apt name that conveys the spirit of this course better could have been *Delving into Data Dungeons*. This is intended to be a highly hands-on, interactive course involving an appropriate number of individual and group projects by the students. Apart from the projects, additional case studies may be presented by the instructor or guest speakers so as to develop perspective on the challenges involved in real-life data analysis situations.

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4.13 19.E012 Stochastic Simulation

Credits. 2

Prerequisites. 19.C105 (Sec. 2.6)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. To familiarize the student with simulation methods (together with their modeling contexts) involving the use of randomness, including methods for sampling from probability distributions, Monte Carlo integration, Markov chain Monte Carlo methods, etc.

Syllabus.

1. Randomness. Randomness in natural processes: decaying nuclei, chaotic oscillators, leaky faucets, cosmic ray showers, etc. Randomness as complexity, non-compressibility of information, unpredictability, ignorance, statistical independence. Randomness as a modeling assumption. Randomness and entropy.
2. Pseudo-random number generators. Generating deterministic sequences of numbers that appear random. Uniform pseudo-random number generators their properties. Breaking correlations via shuffling. Mersenne Twister and other state-of-the-art generators: an overview. Simple transformations from the Uniform. Other distributions as transformations from the Uniform: exponential, Cauchy, Beta, etc. $N(0,1)$ using Box-Müller and other methods. Arbitrary distributions and acceptance-rejection sampling. Testing for randomness: how random is random enough? `DIEHARD` and other test batteries.
3. (Optional) Correlated random numbers. Normal random numbers with pre-specified correlations. Nataf transformation.
4. Monte Carlo integration. Estimating π using a dartboard. Estimating one-dimensional integrals: basic MC integration. Importance sampling for better estimators and tighter errorbars. Deterministic vs. Stochastic: Behaviour of the error as function of the number of dimensions.
5. Sampling and integration in more than one dimension. Markov chains, their properties, and limit theorems. Metropolis, Metropolis-Hastings and Gibbs sampling. Master equation, detailed balance, and why Metropolis-Hastings works. Relationship between Metropolis-Hastings, Metropolis, and Gibbs. Relationship between Metropolis and rejection sampling. A survey of illustrative problems involving high-dimensional distributions, integration/expectation, and simulations. Practical considerations: the adjustable step length parameter, behaviour of Markov chain Monte Carlo methods when the distribution being sampled is multimodal, burn-in or equilibration behaviour, detecting equilibration/convergence of the Markov chain, convergence diagnostics, correlations and error bars on estimates, etc.
6. (Optional) Specialized (M&)S methods involving randomness. Reaction kinetics, epidemiology, and population dynamics: The Gillespie method. Agent-based stochastic models in epidemiology and other fields. Tutorial on stochastic differential equations. Discrete versus continuous, stochastic versus deterministic: What is more appropriate/useful for given problem?

Suggested Texts/References.

1. Charles M. Grinstead and J. Laurie Snell, *Introduction to Probability.* American Mathematical Society, 1997 or later. https://math.dartmouth.edu/~prob/prob/prob.pdf
2. Hoel, Port, and Stone, *Introduction to Stochastic Processes.* Houghton Mifflin, 1972.
3. George Casella and Edward I. George, *Explaining the Gibbs Sampler*, The American Statistician **46**(3) 167–174 (1992).
4. Brooks, Gelman, Jones, and Meng (eds.), *Handbook of Markov Chain Monte Carlo.* Chapman and Hall/CRC, 2011.
5. Liang, Liu, and Carrol, *Advanced Markov Chain Monte Carlo Methods: Learning from Past Samples.* Wiley, 2010.
6. Gilks, Richardson, and Spiegelhalter, *Markov Chain Monte Carlo Methods in Practice.* Chapman and Hall, 1996.

Notes on Pedagogy. This syllabus is based on an outline for a longer course that was refined over several course deliveries by the contributor (see below). Depending on the background and capabilities of the students, this outline may need to be somewhat diluted or intensified – without compromising upon the essential content and the goals for the course. This course needs sufficient level of hands-on activities, and students require adequate computing skills. What is not mentioned explicitly in the syllabus is the modeling contexts in which stochastic methods can be useful. Exposing the student to such modeling contexts is a must. Specific modeling contexts can be chosen by the instructor according to her/his field of specialization.

Contributor/s. Mihir Arjunwadkar (http://cms.unipune.ac.in/~mihir)

4.14 19.E013 Data Visualization

Credits. 2

Prerequisites. As defined by the instructor

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. The purpose of this course is to introduce the audience to the field of visual design so as to create awareness and literacy about visual design. The intended audience of this course is assumed to be a lay audience as far as this area is concerned. The expected outcome is awareness and improved understanding of visual display of quantitative information. The design awareness created through introductory lectures should be reinforced through hands-on visualization work using available tools, packages, APIs, libraries, etc.

Syllabus.

1. Introduction to visual design. A guided tour through the world of visual/graphic design so as to create a sense of visual design awareness and literacy. A crisp overview of Edward Tufte's framework for envisioning information.
2. Data visualization. Starting from the all-familiar scatterplots, pair plots, boxplots, histograms, wiremesh plots, contour plots, etc., introduce principles and strategies for visualizing complex / hierarchical / high-dimensional data. A pedagogic approach to data visualization (such as that in Tamara Munzner's book mentioned below) is recommended for this part.
3. Hands-on work. Group and individual (mini)projects. Students to survey and choose appropriate tools, libraries, APIs, etc., best-suited for their chosen topic, under the guidance of the instructor/s.

Suggested Texts/References.

1. Robin Williams, *The Non-Designer's Design Book.* Peachpit Press, 2014.
2. Tamara Munzner, *Visualization Analysis and Design.* CRC Press, 2014.
3. Edward Tufte, *Envisioning Information.* Graphics Press, 1990. Edward Tufte, *The Visual Display of Quantitative Information.* Graphics Press, 2001.
4. David McCandless, *Information is Beautiful.* Graphics Press, 2009.
5. Nathan Yau, *Visualize This: The FlowingData Guide to Design, Visualization, and Statistics.* Wiley, 2011.
6. Manuel Lima, *Visual Complexity: Mapping Patterns of Information.* Princeton Architectural Press, 2013.
7. Stephen Few, *Now You See It: Simple Visualization Techniques for Quantitative Analysis.* Analytics Press, 2009.
8. Chun-houh Chen, Wolfgang Härdle, and Antony Unwin, *Handbook of Data Visualization.* Springer, 2008.
9. Phil Simon, *The Visual Organization: Data Visualization, Big Data, and the Quest for Better Decisions.* Wiley, 2014.
10. Kieran Healy, *Data Visualization: A Practical Introduction.* Princeton University Press, 2018.

11. Jack Dougherty & Ilya Ilyankou, *Data Visualization for All*. https://datavizforall.org/, 2019.

Notes on Pedagogy. While this course does not assume any design literacy on part of the audience, the audience may have some prior exposure to design principles from fields such as engineering design, software design, etc. Any appropriate set of books, internet resources, and software such as `ggplot2`, `D3`, etc., may be used as per the instructor's preferences.

Contributor/s.

1. Jitendra Pawagi (https://landconcern.blogspot.com/)
2. Jayant Gadgil (http://sciencepark.unipune.ac.in/about-us.html)
3. Girish Dalvi (http://www.idc.iitb.ac.in/girish/)
4. Bhalchandra Pujari (http://cms.unipune.ac.in/~bspujari)
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4.15 19.E014 Difference Equations

Credits. 2

Prerequisites. 19.C101 (Sec. 2.2), 19.C102 (Sec. 2.3), 19.C103 (Sec. 2.4), 19.C104 (Sec. 2.5)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. This course is part of a group of courses (19.E014 (Sec. 4.15), 19.E015 (Sec. 4.16), 19.E016 (Sec. 4.17)) focused on modeling change.

Syllabus.

1. Definitions of difference equations (ordinary and partial) dependent and independent variables, order and degree, types (linear, quasilinear) elliptic, hyperbolic and parabolic difference equations. Types of side conditions for each.
2. Translation operator and algebraic methods to solve degree one homogeneous and inhomogeneous difference equations. Similarity with ODE methods. Methods using the Z transform.
3. Numerical methods of solution of ordinary difference equations. Examples of usage of data structures and creation of algorithms in this context. Difference equations that result from discretization of differential equations (two examples like Euler stepping and Runge Kutta method).
4. Translation operators for partial difference equations and algebraic methods for solving basic forms of partial difference equations analytically.
5. Numerical methods for partial difference equations, classification as sweeping and stepping methods. Examples of usage of data structures and creation of algorithms in this context. Difference equations that result from discretization of partial difference equations (examples of finite difference method only).
6. Application of difference equations in population dynamics and finance.
7. Introduction to theoretical concepts of stability, oscillation and asymptotic behaviour of difference equations and their solutions.

Suggested Texts/References.

1. Saber N. Elaydi, *Introduction to Difference Equations.* Springer, 1999.
2. Ronald E. Mickens, *Difference Equations.* CRC Press, 1991.
3. Walter C. Kelley and Allan C. Peterson, *Difference Equations: An Introduction with Applications.* Academic Press, 2001.
4. *Mathematical Modelling Through Difference Equations*, Chapter 5, in: J. N. Kapur, *Mathematical Modelling.* New Age International Publishers, 2008.
5. Sui Cun Cheng, *Partial Difference Equations.* Taylor and Francis, 2003.

Notes on Pedagogy.

Contributor/s. Sukratu Barve (http://cms.unipune.ac.in/~sukratu)

4.16 19.E015 Ordinary Differential Equations

Credits. 2

Prerequisites. 19.C101 (Sec. 2.2), 19.C102 (Sec. 2.3), 19.C103 (Sec. 2.4), 19.C104 (Sec. 2.5)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. This course is part of a group of courses (19.E014 (Sec. 4.15), 19.E015 (Sec. 4.16), 19.E016 (Sec. 4.17)) focused on modeling change.

Syllabus.

1. Definition of an ordinary differential equation, order and degree along with examples, Definition of solution. General particular and singular solutions, homogeneous functions.
2. First order ODEs having homogeneous functions. Shift of origin change of variables for converting to homogeneous form. Exact first order ODEs. Standard examples of exact ODEs. Integrating factors. Standard examples of integrating factors in various categories of first order ODEs. Linear first order ODEs and integrating factor, Bernoulli's ODE First order ODEs with higher degree and methods of solution (solvable for x, y or dy/dx) Clairaut's form of first order ODE.
3. Second order ODEs (homogeneous and non-homogeneous).
4. ODEs with constant coefficients, (optional examples of analysis of spring-mass-dashpot system) differential operator and its polynomial, complementary and particular integrals, general procedure of obtaining solution.
5. ODEs with variable coefficients, method of variation of parameters (only in case of second order ODEs)
6. Revision of sequences, series and convergence. Series of functions, Power series, ratio test, radius of convergence, series solutions of ODEs, method exemplified in particular cases (second order ODEs) Bessel, Hermite and Legendre ODEs and their series solutions. Brief outline of special functions and their properties.
7. Side conditions of ODEs and their illustration in all the above techniques.
8. Conversion of higher order ODEs into first order ODEs with several dependent variables. Linear ODEs with several dependent variables, matrix formulation, interpretation of characteristic vectors and characteristic values, stability. Applications of this in perturbation of ODEs. Discussion of examples of 6 DoF analysis, control systems stability criteria, predator-prey and chemical reaction ODEs.
9. (Optional) Existence and uniqueness of solutions of first order ODEs, normed vactor space techniques, uniform continuity, Lifshitz functions and outline of Picard's theorem. Linear ordinary differential operators and resolvants. Examples of resolvants in common linear ODEs. Relation of side conditions to resolvants. Qualitative analysis of ODEs: Limit sets, fixed points, limit cycles, basins of attractors, Poincare Bendixson theorem (without proof) Lienard's theorem (without proof).

Suggested Texts/References.

1. S. Balachandra Rao and H. R. Anuradha, *Differential Equations with Applications and Programs*. Universities Press, 1996.
2. E. Rukmangadachari, *Differential Equations*. Dorling Kindersley India, 2012.

3. A. Chakrabarti, *Elements of Ordinary Differential Equations and Special Functions.* New Age International, 1990.
4. E. A. Coddington and N. Levinson, *Theory of ordinary Differential Equations.* Tata-McGraw Hill, 1972.
5. G. F. Simmons, *Differential Equations with Applications and Historical Notes.* Tata-McGraw Hill, 1991.
6. G. F. Simmons and S. G. Krantz, *Differential Equations: Theory, Techniques and Practice.* Tata-McGraw Hill, 2007.

Notes on Pedagogy.

Contributor/s. Sukratu Barve (`http://cms.unipune.ac.in/~sukratu`)

4.17 19.E016 Partial Differential Equations

Credits. 2

Prerequisites. 19.E015 (Sec. 4.16)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. This course is part of a group of courses (19.E014 (Sec. 4.15), 19.E015 (Sec. 4.16), 19.E016 (Sec. 4.17)) focused on modeling change.

Syllabus.

1. Definition of partial differential equation. Order, dependent and independent variables, themes of classification and standard categories, first and second order PDEs; Laplace, heat and wave equations as basic examples of linear second order PDEs. Examples of higher order and non linear PDEs.
2. Cauchy Problems for First Order Hyperbolic Equations. Method of characteristics, Monge cone.
3. Classification of Partial Differential Equations. Normal forms and characteristics for second order PDEs. Principal symbol and quasilinear PDEs, classification of quasilinear PDEs, types of side conditions and principal symbols. General types of side conditions occurring in applications of hyperbolic, parabolic and elliptic PDEs.
4. Initial and Boundary Value Problems. Lagrange-Green's identity and uniqueness by energy methods.
5. (Optional) Stability theory. Energy conservation and dispersion.
6. Laplace equation. Mean value property, weak and strong maximum principle, Green's function, Poisson's formula, Dirichlet's principle, existence of solution using Perron's method (without proof).
7. Heat equation. Initial value problem, fundamental solution, weak and strong maximum principle and uniqueness results (outline of proofs and emphasis on interpretations)
8. Wave equation. Uniqueness, D'Alembert's method, method of spherical means, Duhamel's principle: outline of proofs with emphasis on interpretation.
9. Methods of separation of variables for heat, Laplace and wave equations. Various other methods of solution of PDEs and brief descriptions.
10. (Optional) Numerical methods. Finite difference method as numerical methods for PDEs. Finite Difference Operators, Finite Difference methods, FDM for 1D heat and wave equations, implicit and explicit methods of solution,method of lines,Jacobi, Gauss Seidel and Relaxation methods (for 2D Laplace and Poisson equations) von Neumann stability for difference equations and applications to 2D heat and wave equations. Stability and convergence of matrix difference methods.

Suggested Texts/References.

1. Erich Zauderer, *Partial Differential Equations of Applied Mathematics.* Wiley, 2006.
2. K. Sankara Rao, *Introduction to Partial Differential Equations.* PHI Learning, 2010.
3. Phoolan Prasad and Renuka Ravindran, *Partial Differential Equations.* New Age Publishers, 2012.

4. Lokenath Debnath, *Nonlinear Partial Differential Equations for Scientists and Engineers.* Birkhäuser, 2011.
5. Lawrence C. Evans, *Partial Differential Equations.* American Mathematical Society, 2010.

Notes on Pedagogy.

Contributor/s. Sukratu Barve (http://cms.unipune.ac.in/~sukratu)

4.18 19.E017 Transforms

Credits. 2

Prerequisites. 19.C101 (Sec. 2.2), 19.C102 (Sec. 2.3), 19.C103 (Sec. 2.4), 19.C104 (Sec. 2.5)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. Integral and discrete transforms are often useful in transforming a complex problem into a simpler one. Moreover, insights about the system can be obtained through transforms. Needless to say that integral and discrete transforms are vital tools in the modeling and simulation premises. The goal of this course is to introduce students to a few commonly used transforms with substantial emphasis on Fourier transform. A significant computing aspect is also expected. Students should be able to write codes for some of the transforms. Students are also expected to learn to analyze the results of transformed signals through computational platforms such as `matlab/scilab/R`.

Syllabus.

1. Introduction and background. Brief introduction to vector spaces, function spaces and basis sets. Special functions. Function parity. Concepts in complex analysis. Kernel of an integral transform.
2. Fourier series. Periodic functions. Fourier series in trigonometric as well as complex exponent representation. Functions with arbitrary period. Solving differential equations with Fourier series.
3. Fourier transform. Fourier integrals. Fourier sine/cosine transforms. Fourier transform. Inverse Fourier transform. Properties of Fourier transform. Convolution. Applications. Solving differential equations using Fourier transform, Power spectrum and its interpretation.
4. Discrete Fourier transform and fast Fourier transform. Discretization. Sampling. Nyquist sampling. Discrete Fourier transform. Properties. Matrix representation of Discrete Fourier transform. Fast Fourier transform. Comparison.
5. Laplace transform. Laplace transform. Properties. Inverse transform using partial fractions, convolution and complex integration. Applications. Solution of differential equations.
6. (Optional) Z-transform. Definition of Z-transform. Properties. Inverse Z-translations using complex integral methods. Difference equations.
7. (Optional) Wavelet transform. Limitations of Fourier transform. Introduction to wavelets and family of wavelets. Translations and scaling. Continuous and Discrete wavelet transform. Haar scaling and wavelet functions. Functions spaces. Decomposition using Haar bases. General wavelet system. Daubechies wavelets. Multiresolution analysis. Analysis of output of wavelet transforms.

Suggested Texts/References.

1. L. C. Andrews and B. K. Shivamoggi, *Integral Transforms for Engineers.* Prentice-Hall of India, 2003.
2. Erwin Kreyszig, *Advanced Engineering Mathematics.* Wiley India, 2014.
3. R. N. Bracewell, *The Fourier transform and its applications.* Tata McGraw-Hill, 2003.

4. L. Devnath and D. Bhatta, *Integral transforms and their applications.* Chapman and Hall/CRC, 2010.

5. K. P. Soman and K. I. Ramchandran, *Insights into wavelets - From theory to practice.* Prentice-Hall India, 2005.

6. Online coursework such as Brad Osgood (Stanford), Alan Oppenheim (MIT), etc.

Notes on Pedagogy. An instructor may choose to alter the order to introduce the transforms. However it is logical to start with Fourier series for periodic function, followed by Fourier transform for non-periodic function. The limitation of Fourier transform to resolve the function in both frequency and time domains leads to use of Wavelet and on the other hand Laplace transform can be viewed as 'generalized' Fourier transform, which takes into account the real part of frequency. Similarly Z-transform can be seen as generalized discrete Fourier transform.

A significant emphasize is expected to be on students developing their own codes for various transforms.

Contributor/s. Bhalchandra Pujari (`http://cms.unipune.ac.in/~bspujari`)

4.19 19.E018 A Formal Overview of M&S

Credits. 2

Prerequisites. 19.C204 (Sec. 2.12)

Category. CBC; Theory+Laboratory

Rationale & Purpose, Goals & Objectives. This course attempts to take a student from specific examples and topics studied elsewhere in the programme to a unified view of mathematical modeling and simulation.

Syllabus.

1. Foundations of M&S. Modeling, Simulation, M&S as a newly evolved discipline of study, The multidisciplinary nature of M&S; Basic concepts, terms and their definitions; Types of models (mathematical, numerical, statistical, physical, finite element, finite volume, finite domain time difference (FDTD), data-based, agent based, etc.); Actual system and its model: what to expect.
2. M&S characteristics and descriptors. M&S paradigms–continuous, sampled, event-based, etc.; Attributes–sensitivity, constraints, resolution/granularity, etc.; Verification, Validation and Accreditation of models.
3. Classification of models. Classifications based on nature of realization of the model–physical, mathematical, statistical, graphical, etc.; classification based on nature of equation, nature of control parameters and output parameters; contrasting pairs like continuous/discrete, linear/non-linear, deterministic/stochastic, real-time/batch, static/dynamic, time varying/steady state, etc.;
4. M&S process cycle. model phase, code phase, execution phase, analysis phase, testing, verification and validation phase; feedback mechanism for improvements, quality assurance
5. Tools required for M&S Mathematical, Statistical, Numerical, Programmatic; The need to learn all of them; their use and estimating the nature of final outcome
6. Case studies. Various M&S case studies to bring out the connections between the topics learned and their applications may be chosen. Given the diversity of the M&S enterprise, these are expected to be pedagogically most demanding and a challenge to the instructor.

Suggested Texts/References.

1. J. A. Sokolowski and C. M. Banks (Ed.), *Modeling and Simulation Fundamentals.* Wiley, 2010.
2. B. P. Zeigler, Herbert Praehofer and Tag Gon Kim, *Theory of Modeling and Simulation.* Academic Press India, 2000.
3. A. M. Law, *Simulation, Modeling & Analysis.* McGraw-Hill Education, 2014.
4. P. Saxena, *Modeling and Simulation.* Narosa, 2014.
5. J. N. Kapur, *Mathematical Modelling.* New Age International Publishers, 2015.

Notes on Pedagogy.

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