A list of core courses I took at the University of Minnesota

2018 Fall

MATH 2243 Lin Alg & Diff Equations

Text:

Edwards and Penney, DIFFERENTIAL EQUATIONS AND LINEAR ALGEBRA (4th edition).

Overview:

The course consists of two related parts, linear algebra and ODE.
Prerequisites: [1272 or 1282 or 1372 or 1572]

Covered Contents:

Linear algebra: matrices and matrix operations, Gaussian elimination, matrix inverses, determinants, vector spaces and subspaces, dependence, Wronskian, dimension, eigenvalues, eigenvectors, diagonalization. ODE: Separable and first-order linear equations with applications, 2nd order linear equations with constant coefficients, method of undetermined coefficients, simple harmonic motion, 2x2 and 3x3 systems of linear ODE's with constant coefficients, solution by eigenvalue/eigenvectors, non- homogenous linear systems; phase plane analysis of 2x2 nonlinear systems near equilibria.

MATH 2263 Multivariable Calculus

Text:

James Stewart, Calculus: Early Transcendentals, Eighth ed. vol. 2. Cengage Learning, Boston 2016.

Overview:

Multivariable calculus.
Prerequisites: [1272 or 1372 or 1572]

Covered Contents:

Curves in space, arc length and curvature, velocity and acceleration. Limits and continuity, partial differentiation, local extrema, exact differentials, chain rule, directional derivative and gradient, Lagrange multipliers, 2nd derivative test. Double integration, volume and other applications, polar coordinates, triple integration, cylindrical and spherical coordinates. Vector analysis: Vector fields, line integrals, path independence, Green's Theorem, surface integrals, Theorems of Gauss and Stokes.

PHYS 1101W Intro College Physics I

Text:

Essentials of College Physics by Serway and Vuille, Publisher Thomson.

Overview:

Physics 1101 is the first semester of a two semester introduction to physics. By the end of this semester, you should have a deeper understanding of the phenomena occurring in your surrounding physical world. You should have a clearer picture of the behavior of the universe on the largest (cosmic) scale, and on the smallest (subnuclear) scale. You should also understand a bit more about the physics of biological systems, including your own body. In addition, you should be more competent at measurement and quantitative reasoning concerning physical processes. Fundamental principles of physics in the context of everyday world. Use of kinematics/dynamics principles and quantitative/qualitative problem-solving techniques to understand natural phenomena. Lecture, recitation, lab.

Prerequisites: Linear algebra, plane geometry, trigonometry.

Covered Contents:

The main emphasis will be on the branch of physics known as mechanics. This is the study of motion and the causes of motion through the applications of fundamental principles of physics.

We begin with kinematics, the quantitative description of the motion of particles. We then build on kinematics to learn how and why motion occurs, through the application of Newton's laws of dynamics. Many examples will be considered as we explore the properties of specific forces and the details of the motion they bring about.

The next step will be to describe physical processes in terms of energy and momentum, quantities that are always "conserved." Conservation laws allow us to solve problems in mechanics that would be very difficult by other techniques and provide a powerful approach to the analysis of physical systems in general.

We then will extend our understanding of motion to the kinematics and dynamics of rotation. Finally, we will briefly study some of the physical properties of solids and fluids.

2019 Spring

CSCI 1133 Intro to Programming Concepts

Overview & Covered Contents:

Fundamental programming concepts using Python language. Problem solving skills, recursion, object-oriented programming. Algorithm development techniques. Use of abstractions/modularity. Data structures/abstract data types. Develop programs to solve real-world problems.
Prerequisites: concurrent registration is required (or allowed) in MATH 1271 or MATH 1371 or MATH 1571H or instr consent.

MATH 3283W Foundations

Text:

Lay, Analysis: With an Introduction to Proof, 5th ed., Pearson.

Overview:

Introduction to reasoning used in advanced mathematics courses. Writing-intensive component. To introduce and practice techniques of mathematical proof. To develop rigorously the analysis of sequences and series.
Prerequisites: [concurrent registration is required (or allowed) in MATH2243, MATH2263, MATH2373, or MATH2374]

Covered Contents:

Logic, mathematical induction, real number system, general/monotone/recursively defined sequences, convergence of infinite series/sequences, Taylor's series, power series with applications to differential equations, Newton's method.

MATH 4242 Applied Linear Algebra

Text:

Linear Algebra and Its Applications (4th Edition), by Gilbert Strang.

References: Peter J. Olver and Chehrzad Shakiban, Applied Linear Algebra, 2nd edition (MIT OpenCourseWare).

Overview:

This is a second, advanced course in Linear Algebra, which assumes the student has already mastered a one semester course in the subject.
Prerequisites: 2243 or 2373 or 2573.

Covered Contents:

In this course, systems of linear equations, Gaussian elimination, determinants, vector spaces, linear independence, basis and dimension, the Cramer's rule, the row, column spaces, linear transformations, inner product, orthogonality, the Gram-Schmidt algorithm, eigenvalues and eigenvectors, diagonalization, Hermitian matrices, the singular value decomposition, quadratic forms, positive definite matrices, and the Jordan canonical forms. The lectures follow the text fairly closely.

STAT 3032 Regression and Correlated Data

Text:

Applied Linear Regression (4th Ed.), by Weisberg, S.

Overview:

This is a second course in statistics with a focus on linear regression and correlated data. The intent of this course is to prepare statistics, economics and actuarial science students for statistical modeling needed in their discipline.
Prerequisites: STAT 3011 or STAT 3021.

Covered Contents:

The course covers the basic concepts of linear algebra and computing in R, linear regression, multiple linear regression, statistical inference, model diagnostics, transformations, model selection, model validation, and basics of time series and mixed models. Numerous datasets will be analyzed and interpreted using the open-source statistical software R.

2019 Fall

CSCI 2011 Discrete Structures

Text:

Rosen: Discrete Mathematics and Its Applications 7th edition. ISBN-13: 978-0073383095

Overview:

Much of the basic mathematical machinery useful in computer science will be presented, with applications. Students will actively learn the art of creating real-world proofs in these areas, preparing them for diverse regions of computer science such as architecture, algorithms, automata, programming languages, cryptography, etcetera, as well as increasing their general problem- solving abilities in all areas.
Prerequisites: [MATH 1271 or MATH 1371 or MATH 1571H], honors student.

Covered Contents:

Sets, sequences and summation, growth of functions, big-O, relations, formal logic, number theory, induction & recursion, counting, finite probability, enumeration & relations, graph, modeling computation.

MATH 5485 Numerical Methods I

Text:

Burden et al., 2016. Numerical analysis (10th), Boston, MA: Cengage Learning.

Overview:

Fall semester will cover solutions of equations and systems, numerical linear algebra and eigenvalues, interpolation and approximation, as well as numerical differentiation and integration. Prerequisites: [2243 or 2373 or 2573 or 4242], familiarity with some programming language.

Covered Contents:

Algorithm and convergence (chapter 1):
Big-O, Review of Calculus, Bisection Method.
Solutions of nonlinear equations in one variable (Chapter 2):
Bisection Method, Fixed-Point Iteration, Fixed-Point Iteration, Newton's Method, Error Analysis.
Interpolation and polynomial approximation (Chapter 3):
Interpolation, Lagrange Polynomial, Neville's Method, Divided Differences, Cubic Spline. Numerical differentiation and integration (Chapter 4):
Numerical Differentiation, Richardson's Extrapolation, Numerical Integration, Composite Numerical Integration, Romberg Integration, Adaptive Quadrature, Gaussian Quadrature, Multiple Integrals, and Improper Integrals.
Numerical solutions of initial-value problems (Chapter 5):
Elementary IVP, Euler's Method, Higher-Order Taylor Method, Runge-Kutta Methods, Error Control, Multi-step Methods, Higher-Order / System of DE, Stability.

MATH 5651 Probability-Statistics Theory

Text:

Probability and Statistics by DeGroot and Schervish, Pearson 4th Edition (University of Minnesota Edition). We will cover chapters 1- 7.3 of the text.
Reference:
Introduction to Probability, 1st ed, by D. Anderson, T. Sepp¨al¨ainen, and B. Valk´o. Introduction to Probability by C. M. Grinstead and J. L. Snell. This book can be downloaded through our school online library.

Overview:

Logical development of probability, basic issues in statistics. Probability spaces, random variables, their distributions/expected values. Law of large numbers, central limit theorem, generating functions, sampling, sufficiency, estimation.
Prerequisites: [2263 or 2374 or 2573], [2243 or 2373]; [2283 or 2574 or 3283 or 4242].

Covered Contents:

§1.4 Set Theory
§1.5 Probability
§1.6 Finite sample spaces

§1.7 Counting methods
§1.8 Combinatorial Methods
§1.9 Multinomial coefficients
§1.10 The Probability of a Union of Events
§2.1 Conditional Probability
§2.2 Independence of Events & Independent trials
§2.3 Bayes' Theorem
§2.4 Gambler's Ruin Problem
§3.1 Random Variables
§3.2 Continuous distributions
§3.3 The Cumulative distribution function
§3.4 Bivariate distributions
§3.5 Marginal Distributions
§3.6 Conditional distributions
§3.7 Multivariate distributions
§3.8 Functions of a random variable
§3.9 Functions of two or more random variables
§3.10 Markov Chains
§4.1 The Expectation of a random variable
§4.2 Properties of expectation
§4.3 Variance
§4.5 Median and Mean
§4.6 Covariance and Correlation
§4.7 Conditional expectations
§5.2 The Bernoulli and Binomial Distributions
§5.4 The Poisson Distributions
§5.6 The Normal Distribution
§5.7 The Gamma Distribution
§5.9 The Multinomial Distributions
§5.10 The Bivariate Normal Distributions
§6.2 Law of Large Numbers
§6.3 Central Limit Theorem
§6.4 The Correction for Continuity

2020 Spring

CSCI 4011 Form Lang & Autom.

Text:

Michael Sipser "Introduction to the Theory of Computation" 3rd Edition Cengage, 2013.

Overview:

Logical/mathematical foundations of computer science. Formal languages, their correspondence to machine models. Lexical analysis, string matching, parsing. Decidability, undecidability, limits of computability. Computational complexity.
Prerequisites: 2041 or instr consent, students are expected to have knowledge of computer science principles and programming.

Covered Contents:

§1: Finite automata and regular languages.
§2: Languages, grammars, pushdown automata, and Context-free.
§3: Turing machines and the formal definition of an algorithm.
§4: Decidability, and the Halting Problem.
§5: Reductions and unsolvable problems.
§6.2: Decidability of Logical Theories.
§7: Time complexity and NP-completeness.
§8: Space complexity.
§9.3: Circuit Complexity
§10.5: Parallel Computation
§10.6: Cryptography

CSCI 4041 Algs. & Data Str.

Text:

Cormen, Leiserson, Rivest, and Stein: Introduction to Algorithms 3rd edition. ISBN-13: 978- 0262033848.
References:

[1] Algorithms, 4th Edition
[2] Computer Science, An Interdisciplinary Approach, Chapter 4
[3] E. Horowitz and S. Sahni, "Fundamentals of Computer Algorithms", Computer Science Press, Rockville, MD, 1984.
[4] C.H. Papadimitriou and K. Steiglitz, "Combinatorial Optimization: Algorithms and Complexity", Dover Publications, Mineola, NY, 1998.
[5] D.E. Knuth, "The Art of Computer Programming", Addison-Wesley, Reading, MA, Volumes 1-4, Addison-Wesley, Reading, MA, 2011.
[6] U. Manber, "Introduction to Algorithms: A Creative Approach", Addison-Wesley, Reading, MA, 1989.
[7] A. Aho, J.E. Hopcroft, and J.D. Ullman, "Data Structures and Algorithms", Addison-Wesley, Reading, MA, 1983.
[8] R. Lafore, "Data Structures and Algorithms in Java", Sams Publishing, Indianapolis, IN, 2002.
[9] M. Goodrich, R. Tamassia, and M. Goldwasser, "Data Structures and Algorithms in Java", Wiley, Hoboken, NJ, 2014.
[10] R. Sedgewick and K. Wayne, "Algorithms", Addison-Wesley, Reading, MA, 2011.

Overview:

The course objective is to provide fundamental paradigms for algorithm design with the supporting data structures. Rigorous analysis of algorithms/implementation. Algorithm analysis, sorting algorithms, binary trees, heaps, priority queues, heapsort, dynamic programming, greedy algorithms, graphs, graph traversal, single source shortest path, minimum cost spanning trees, binary search trees, hash tables and hashing.
Prerequisites: [(1913 or 1933) and 2011] or instr consent.

Covered Contents:

Lecture 1: Asymptotic Runtime
Lecture 2: Big-O, Big-Theta, and Big-Omega

Lecture 3: Loop Invariants, Bubble Sort Correctness Proof
Lecture 5: Merge Sort
Lecture 6: Quicksort
Lecture 7: Heaps
Lecture 8: Priority Queues
Lecture 9: Counting Sort
Lecture 10: Radix and Bucket Sort
Lecture 11: Hash Tables
Lecture 12: Open Addressing, Binary Search Trees
Lecture 13: Binary Search Trees: Overview
Lecture 14: Binary Search Trees: Insertion/Deletion
Lecture 15: B-Trees
Lecture 16: Red-Black Trees
Lecture 17: Dynamic Programming
Lecture 18: Matrix Chain Multiplication
Lecture 19: Greedy Algorithms
Lecture 20: Huffman Coding
Lecture 21: Graphs
Lecture 22: Breadth-First Search
Lecture 23: Depth-First Search
Lecture 24: Shortest Paths and Bellman-Ford
Lecture 25: Dijkstra's Algorithm
Lecture 26: Floyd-Warshall Algorithm
Lecture 27: Minimum Spanning
Trees Lecture 28: Disjoint Sets and MSTs

CSCI 4511W Intro: Artificial Intelligence

Text:

Stuart Russell and Peter Norvig, Artificial Intelligence. A modern approach. 3rd Edition, Prentice-Hall, 2010. ISBN: 9780136042594

Overview:

The course provides a technical introduction to artificial intelligence (AI). Topics include: agents, search (search spaces and algorithms, game playing, constraint satisfaction), planning, knowledge representation, and an introduction to neural networks. The course is suitable to gain a solid technical background and as a preparation for more advanced work in AI.

Prerequisites: Students are expected to have knowledge of basic computer science principles and programming; data structures (graphs and trees); and formal logic (propositional and predicate logic).

Covered Contents:

§2: Intro, intelligent agents
§3: Problem solving and search
§4: Other search algorithms
§5: Constraint satisfaction
§6: Game playing
§7: Propositional logic

§8: First-order logic and resolution
§9: Planning
§11: Planning
§12: Neural networks and deep learning
§12: Knowledge representation

MATH 5248 Cryptology and Number Theory

Text:

Cryptology and Number Theory by Paul Garrett.
Other useful texts: A Computational Introduction to Number Theory and Algebra, by Victor Shoup.
Elementary Number Theory: Primes, Congruences, and Secrets, by William Stein.

Overview:

This is an introductory course in number theory. The primary application of the number theory we learn in this course will be cryptology, the subject of how to make ciphers and break them. Both symmetric and public key cryptosystems will be introduced. The math in this course will be heavy on “modular arithmetic,” which will be introduced and covered in depth. It also makes some use of elementary counting and probability, plus a tiny bit of linear algebra and matrices.
Prerequisites: Two semesters of sophomore level mathematics.

Covered Contents:

The Affine Cipher, The Vigenere Cipher, The Hill Cipher, Friedman Attack,
Chinese Remainder Theorem, Hensel’s Lemma,
Fermat’s little Theorem, Euler’s Criterion, Principal Square roots, Primitive Roots,
RSA,
Square root oracles, Discrete logs,
Diffie-Hellman Key Exchange, ElGamal Cipher, Superincreasing Vectors, Knapsack Ciphers,
The Legendre Symbol, Arithmetic Convolutions, Mobius inversion, Quadratic Reciprocity.

2020 Summer

CSCI 5994 Directed Research

This is an independent research advised by Prof. Maria Gini. I would like to thank my insightful advisor Prof. Maria Gini. She gives me the freedom to work on whatever I want, but also ensures that my research is always going somewhere useful. She lets me find the beauty and power of NLP and develop my interests in this field.
The primary goal of this research was to study NLP, especially sentiment analysis. After completing the necessary part, I was curious about people's perception toward COVID-19 pandemic. How does it affect the spread of COVID-19? I extended the research field to topic extraction and sequential prediction. In the end, I submitted a research paper on How Personal Perceptions of COVID-19 Have Changed Over Time in AAAI2021.

2020 Fall

CSCI 5521 Intro to Machine Learning

Text:

Introduction to Machine Learning; by Ethem Alpaydin (3rd ed) 2014.

Overview:

Neural networks, non-parametric windowing, and Bayes statistical theory are three popular methods for recognizing and classifying patterns - the process of Pattern Recognition. These are the basic machine learning algorithms applicable to high-dimensional numerical data. We introduce the fundamental concepts of these various approaches, including the classification phase and the learning phase. Part of the class will be devoted to methods for unsupervised learning and classification. We assume just some knowledge of elementary statistics, calculus, and elementary linear algebra at the upper division undergraduate level. A combination of written assignments and programming projects will be used to illustrate the concepts. Most if not all programming will be done in Matlab and/or python. For those familiar with one but not the other, side-by-side comparisons will be provided. material showing how to for those unfamiliar with it.
Prerequisites: [2031 or 2033], STAT 3021, and knowledge of partial derivatives

Covered Contents:

Intro: What is Machine Learning (Chap 1) Supervised Learning: Some basic concepts (Chap 2)
Bayes Decision Theory: Conditional Probability (Chap 3) Discriminant Functions, Normal Dist. (Chap 3)
Estimating Unknown Probability Densities, (Chap 4) Parametric Classification (Chap 4)
Multivariate Methods: estimation and classification (Chap 5) Dimensionality Reduction: feature selection PCA (Chap 6) Unsupervised Clustering: K-means EM (Chap 7)
Support Vector Machines, (Linear and Kernel) (chap 13) Linear Discriminant - the Perceptron (Chap 10)
Multilayer Perceptrons (Chap 11)
Decision trees, random forests (Chap 9)

MATH 5165 Math Logic I

Text:

A Mathematical Introduction to Logic Second Edition, Herbert B. Enderton.

Overview:

Theory of computability: notion of algorithm, Turing machines, primitive recursive functions, recursive functions, Kleene normal form, recursion theorem. Propositional logic.

Prerequisites: 2283 or 3283 or Phil 5201 or CSci course in theory of algorithms or instr consent

Covered Contents:

CHAPTER ONE Sentential Logic
- 1.1 The Language of Sentential Logic
- 1.2 Truth Assignments
- 1.3 A Parsing Algorithm
- 1.4 Induction and Recursion
- 1.5 Sentential Connectives

1.7 Compactness and Effectiveness

CHAPTER TWO First-Order Logic
- 2.1 First-Order Languages
- 2.2 Truth and Models
- 2.3 A Parsing Algorithm
- 2.4 A Deductive Calculus

2.6 Models of Theories

CHAPTER THREE Undecidability

3.0 Number Theory
- 3.2 Other Reducts of Number Theory
- 3.3 A Subtheory of Number Theory

STAT 5102 Theory of Statistics II

Text:

Introduction to Mathematical Statistics, latest edition by Hogg, McKean and Craig.

Overview:

Sampling, sufficiency, estimation, test of hypotheses, size/power. Categorical data. Contingency tables. Linear models.

Prerequisites: 5101 or Math 5651

Covered Contents:

Point estimation, confidence intervals, order statistics, first principles of hypothesis testing, convergence in probability, convergence in distributions, Central Limit Theorem, Maximum likelihood estimations, Likelihood ratio tests, Likelihood methods for multivariate parameters, Sufficiency, Hypothesis testing theory, Bayesian Statistics.

CSCI 5994 Directed Research

This is an independent research on semantic parsing and word representation advised by Prof. Maria Gini.

2021 Spring

MATH 5486 Numerical Methods II

Text:

The course will be primarily based on lecture notes (available via Moodle). References: Burden and Faires, Numerical Analysis, 10th edition.
References: Ascher, First Course In Numerical Methods.
Prerequisites: 5485

Overview:

Math 5485-6, is an introductory two-semester course about numerical methods. We will learn about basic mathematical principles for devising and analyzing numerical methods. Spring semester will cover numerical solutions of ordinary differential equations, boundary value problems, and partial differential equations, including finite elements.

CSCI 1933 Intro Algs & Data Str.

Overview & Covered Contents:

Advanced object oriented programming to implement abstract data types (stacks, queues, linked lists, hash tables, binary trees) using Java language. Inheritance. Searching/sorting algorithms. Basic algorithmic analysis. Use of software development tools. Weekly lab.
Prerequisites: 1133 or instr consent

A list of core courses I took at the University of Chicago

Fall 2022

CAAM/STAT: 31430 Applied Linear Algebra

Text:
G. Allaire and S. M. Kaber, Numerical Linear Algebra, Springer 2008 (transl. by K. Trabelsi).
Overview:
Course description: This course will provide a review and development of topics in linear algebra aimed toward preparing students for further graduate coursework in Computational and Applied Mathematics. Topics will include discussion of matrix factorizations (including diagonalization, the spectral theorem for normal matrices, the singular value decomposition, and the Schur and polar decompositions), and an overview of classical direct and iterative approaches to numerical methods for problems formulated in the language of linear algebra (including the conjugate gradient method). Additional topics will be included depending on student interests.
Prerequisites: STAT 24300 or MATH 20250 or Graduate Student in Physical Sciences Division
Covered Contents:

- Lecture 1 Download Lecture 1
    - Course overview and motivating discussion. (Note: a few misprints from the chalkboard have been corrected in these scanned notes -- thanks to everyone who pointed them out!)
- Lecture 2 Download Lecture 2
    - : We gave a perspective on the Gram-Schmidt procedure, discussed basic notions involving matrices (in particular, recalling notions of trace and determinant), and gave a brief introduction to some special classes of matrices: triangular matrices, notions of self-adjoint, unitary, and normal matrices (over C), and analogous notions of symmetric, orthogonal, and normal matrices (over R). (We'll see much more about several of these classes in the coming lectures.)
- Lecture 3 Download Lecture 3
    - : Elementary row operations (as in Gaussian Elimination) via matrix multiplication. Block matrices. A first look at the spectral theory (eigenvalues/eigenvectors) of matrices (over C). Definition of the spectral radius. Eigenspaces and generalized eigenspaces. All eigenvalues of a Hermitian matrix are real.
- Lecture 4 Download Lecture 4
    - : The minimal polynomial and the Cayley-Hamilton theorem. Spectral decomposition of C^n and connections to the Jordan canonical form. Matrices and triangular forms (part I -- every matrix can be reduced to upper triangular form).
- Lecture 5 Download Lecture 5
    - : Further comments on triangular forms; Schur factorization. Diagonalization of matrices. Spectral theorem for normal matrices. Corollaries for self-adjoint and real symmetric matrices. A first look at another view on eigenvalues: variational/min-max characterizations. The Rayleigh quotient and characterization of the smallest eigenvalue of a self-adjoint (Hermitian) matrix.
- Lecture 6 Download Lecture 6
    - : Further comments on variational characterizations of eigenvalues; Courant-Fisher min-max theorem. Singular values and existence of the SVD factorization.
- Lecture 7 Download Lecture 7
    - : Concluding remarks about SVD and a first look at applications (more applications of SVD will also be discussed later on). Moore-Penrose pseudoinverse. "Four fundamental subspaces" and the SVD. Polar decomposition. Our next topic -- toward some numerical considerations: "how to measure errors and convergence" (norms and matrix norms). Norms and inner products (a quick overview). Examples of a variety of norms on R^n, C^n;

p-norms, weighted p-norms, etc. A first look at comparing norms.

- Lecture 8 Download Lecture 8
    - : More on vector space norms (continuity of the norm, applications of Cauchy-Schwarz, all norms on R^n or C^n are equivalent). Overview of matrix norms, and subordinate matrix norms; examples and applications. Characterizations of the matrix norms subordinate to the vector norms ||.||_1, ||.||_\infty, ||.||_2.
- Lecture 9 Download Lecture 9
    - : Further comments on matrix norms and subordinate matrix norms. Connections with the spectral radius. Best approximation of matrices in M_{m,n}(C) among finite rank competitors.
- Lecture 10 Download Lecture 10
    - : Sequences and series of matrices. Matrix exponential. Our first look at algorithms for matrix computation. Matrix multiplication and Strassen's algorithm.

Spring 2022

STAT 37710 1: Machine Learning

Web:
https://sites.google.com/uchicago.edu/stat-37710-cmsc-35400-s22/
Text:
Pattern Recognition and Machine Learning; by Christopher Bishop. The textbooks will be supplemented with additional notes and readings.
Optional supplementary materials:

Probabilistic Machine Learning: An Introduction; by Kevin Patrick Murphy, MIT Press, 2021.
Understanding Machine Learning; by Shai Shalev-Shwartz and Shai Ben-David
Pattern Classification; by Duda, Hart, and Stork
Mathematics for Machine Learning; by Marc Peter Deisenroth, A Aldo Faisal, and Cheng Soon Ong. Cambridge University Press, 2020.
Prerequisites:
Appropriate for graduate students who have taken CMSC 25300/35300 (Mathematical Foundations of Machine Learning) or equivalent (e.g. Part 1 covered by Mathematics for Machine Learning).

Tentative Schedule:

- Week 1: The statistical learning framework, bias-variance trade offs
- Week 2: Point estimation (MOME, MLE, MAP)
- Week 3: Model complexity
- Week 4: Classification (logistic regression; Naive Bayes, LDA)
- Week 5: Ensemble methods (bagging, random forests, boosting)
- Week 6: Graphical models (mixtures of Gaussians, graphical models)
- Week 7: Multi-layer perceptrons and neural networks
- Week 8: Nonparametric models (Kernel ridge regression, Gaussian processes)
- Week 9: Support vector machines; active learning

CMSC 25025 / Stat 37601: Machine Learning and Large-Scale Data Analysis

Text:
The course will not follow a textbook closely. However, the following book contains some of the course material: The Elements of Statistical Learning: Data Mining, Inference, and Prediction, by T. Hastie, R. Tibshirani, and J. Friedman, Springer, 2nd edition. The book is available at:
https://web.stanford.edu/~hastie/ElemStatLearn/index.html
Overview:
This course is an introduction to machine learning and statistics. The course presents motivation, methods, implementation and some supporting theory for several types of data analysis, including classification and

regression, clustering, unsupervised feature learning, and multi-layer networks. The main objective of the course is for students to gain an understanding of and experience with some essential statistical machine learning methodology and practice. The course will also touch on social impacts of the use of machine learning.

Tentative Schedule:

- **week1** Introduction Clustering, K-means, Spectral Clustering
- **week2** PCA; Classification/Bayes classifier; Generative models for classification: Class conditional Gaussian models, different and same covariances.
- **week3** Generative models: Mixture models and EM; Quiz 1; Discriminative models for linear classifiers and optimization methods.
- **week4** Perceptrons; SVMs; From linear classifiers to Kernel based SVMs; Sparse coding/Dictionary learning.
- **week5** Multilayer perceptrons/Back propagation for SGD; Quiz 2; Convolutional neural networks.
- **week6** Recurrent Neural Networks; Language models and word embeddings; Final Project assigned.
- **week7** Transformer methods in language models.
- **week8** From EM to Variational Autoencoders; Quiz 3; Other generative models with deep networks.
- **week9** Other unsupervised methods - contrastive learning.

STAT 31240 1 Variational Methods in Image Processing

Text:

G. Aubert, P. Kornprobst. Mathematical Problems in Image Processing: Partial Differential Equations and the Calculus of Variations. (2nd edition)

Course Description:

This course discusses mathematical models arising in image processing. Topics covered will include an overview of tools from the calculus of variations and partial differential equations, applications to the design of numerical methods for image denoising, deblurring, and segmentation, and the study of convergence properties of the associated models. Students will gain an exposure to the theoretical basis for these methods as well as their practical application in numerical computations.

Prerequisites: The course will be self contained. Experience with real analysis, linear algebra and/or CAAM/Stat 31210 (Applied Functional Analysis) or CAAM/Stat 31220 (Partial Differential Equations) can be beneficial, but is not required.

Tentative Outline of Topics / Reading Assignments

- Introduction:
  – A selection of fundamental image processing problems: Denoising and Segmentation
  – An overview of some mathematical tools
  – A perspective on numerics
- Mathematical Tools: the direct method of the Calculus of Variations. (Reading: §2.1 of [AK])
  – Banach Spaces, strong and weak convergence, convexity and lower-semicontinuity.
  – Overview of Sobolev spaces. Derivation of Euler-Lagrange equations.
- "Gaussian convolution": Parabolic Smoothing (Reading: §3.3.1, pp. 95–98, §A.1, §A.3.1 of [AK])
- Denoising via Total Variation methods
  – Motivations and the Rudin-Osher-Fatemi (TV) functional
  – BV functions, existence and uniqueness of minimizers (Reading: §2.2 of [AK])
  – Strong stability results
  – "Weak stability" results
  – Further Ideas: Modified Functionals
  ∗ More general TV penalizations: existence and uniqueness of solutions for the relaxed problem. (Reading: §3.2.3 of [AK])
  ∗ Numerical approaches. (Reading: §3.2.4–3.2.5 of [AK], Boyd-Parikh-Chu-Peleato-Eckstein on ADMM methods)
  ∗ Approximate problems and the language of Gamma convergence.

    * Exact reconstruction results and L1 fidelity (Chan-Esedoglu).
    * Nonlocal modifications (if time permits).
- Return to Nonlinear PDEs
  – Total Variation Flow
  – Perona-Malik (Reading: pp. 98–107 of [AK])
  – An axiomatic approach: Alvarez-Guichard-Lions-Morel (and some material on viscosity solutions). (Reading: §2.3, §3.3.1, pp. 107–113 of [AK])
- Other topics as time permits (and according to student interests). Some possible topics may include:
  – Variational models for image segmentation – Mumford-Shah: §4.1–4.2 of [AK], [Morel-Solimini], [Vese-Le Guyadere, Chap. 6]
  – Level-set methods: §4.3 of [AK], [Osher-Fedkiw]
  – "Cartoon-Texture" decomposition : §5.2 of [AK], [Vese-Le Guyadere, Chap. 5]

Winter 2022

STAT 31020 1 Mathematical Computation IIB: Nonlinear Optimization

Text:
Numerical Optimization. Series: Springer Series in Operations Research and Financial Engineering. Nocedal, Jorge, Wright, Stephen. 2nd ed. 2006, XXII, 664 p.
https://link.springer.com/book/10.1007%2F978-0-387-40065-5
PREREQUISITES:
STAT 30900/CMSC 37810 and Analysis in R^n (e.g what is covered by Math 204 at UC undergrad)
Lecture Plan and Notes. Link to OneNote notebook. Should be viewable in real-time

https://1drv.ms/u/s!Akt_5TvE2Mwfg3qUy-d8F7v4YdUa
Links to an external site.
Lecture 1, Jan 10, 2022

Lecture notes: S310-2022-Sec1-Sec2.pdf
Download S310-2022-Sec1-Sec2.pdf
Lecture 2, Jan 12, 2022
Lecture notes:

S310-2022-Sec2.pdf
Download S310-2022-Sec2.pdf

S310-2022-Sec3.pdf
Download S310-2022-Sec3.pdf
Lecture 3, Jan 19, 2022
Lecture notes:

S310-2022-Sec3.pdf
Download S310-2022-Sec3.pdf
Lecture 4, Jan 24, 2022
Lecture notes:

S310-2022-Sec3.pdf
Download S310-2022-Sec3.pdf

S310-2022-Sec4.pdf
Download S310-2022-Sec4.pdf
Lecture 5, Jan 26, 2022

S310-2022-Sec3.pdf
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S310-2022-Sec4.pdf
Download S310-2022-Sec4.pdf
Lecture 6, Jan 31, 2022

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Download S310-2022-Sec3.pdf
S310-2022-Sec4.pdf
Download S310-2022-Sec4.pdf

Lecture 7, Feb 2, 2022

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S310-2022-Sec5.pdf
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Lecture 8, Feb 7, 2022

S310-2022-Sec5.pdf
Download S310-2022-Sec5.pdf
S310-2022-Sec6.pdf
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Lecture 9, Feb 9, 2022

S310-2022-Sec5.pdf
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S310-2022-Sec6.pdf
Download S310-2022-Sec6.pdf
S310-2022-Sec7.pdf
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Lecture 10, Feb 14, 2022

S310-2022-Sec7.pdf
Download S310-2022-Sec7.pdf
S310-2022-Sec10.pdf
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S310-2022-Sec11.pdf
Download S310-2022-Sec11.pdf

Lecture 11, Feb 21, 2022

S310-2022-Sec12.pdf
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Lecture 12, Feb 23, 2022

S310-2022-Sec12v2.pdf
Download S310-2022-Sec12v2.pdf
S310-2022-Sec13.pdf
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Lecture 13, Feb 28, 2022

S310-2022-Sec13.pdf
Download S310-2022-Sec13.pdf
S310-2022-Sec14.pdf
Download S310-2022-Sec14.pdf
S310-2022-Sec15.pdf
Download S310-2022-Sec15.pdf

Lecture 14, March 2nd, 2022

May go in order Sec 14, Sec 16, Sec 15.

S310-2022-Sec14.pdf

Download S310-2022-Sec14.pdf
S310-2022-Sec15.pdf
Download S310-2022-Sec15.pdf
S310-2022-Sec16.pdf
Download S310-2022-Sec16.pdf

Lecture 15, March 7th, 2022

S310-2022-Sec15.pdf
Download S310-2022-Sec15.pdf
S310-2022-Sec17.pdf
Download S310-2022-Sec17.pdf

Lecture 16, March 9th 2022

S310-2022-Sec18.pdf
Download S310-2022-Sec18.pdf
S310-2022-Sec19.pdf

STAT 31015 1 Mathematical Computation IIA: Convex Optimization

Course Description:

The course will cover techniques in unconstrained and constrained convex optimization and a practical introduction to convex duality. The course will focus on (1) formulating and understanding convex optimization problems and studying their properties; (2) understanding and using the dual; and (3) presenting and understanding optimization approaches, including first order methods and interior point methods. Examples will be mostly from data fitting, statistics and machine learning.

Prerequisites: Linear Algebra, Multidimensional Calculus, Undergraduate Algorithms

Specific Topics and A Tentative Timeline:

- Lecture-1: Logistics; Formalization of optimization problems; Grid Search and Bisection.
- Lecture-2: Convex sets.
- Lecture-3: Convex functions.
- Lecture-4: Standard formulations of convex optimization, including Linear, Quadratic, Conic, and Semidefinite Programming.
- Lecture-5: Local and global optima; Optimality criterion.
- Lecture-6: Unconstrained optimization methods, including Gradient Descent, Line Search, and Newton's Method; Conjugate Gradient Descent and Quasi-Newton methods.
- Lecture-7: Analysis of Newton's method; Self-concordance.
- Lecture-8: Optimal and Pareto optimal; Multi-objective optimization; Scalarization.
- Lecture-9: Constrained optimization; Lagrangian duality; Weak and strong duality.
- Lecture-10: Mid-term exam.
- Lecture-11: KKT conditions; Geometric interpretation.
- Lecture-12: Equality constrained Newton method; Infeasible start Newton method.
- Lecture-13: Inequality constrained optimization problems.
- Lecture-14: Log Barrier (Central Path) methods.
- Lecture-15: Feasibility and phase I methods.
- Lecture-16: Primal-dual method.
- Lecture-17: TBD.
- Lecture-18: Summary

Expected outcomes:

- Ability to discuss and understand optimization problems in terms of required information/access, assumptions, iteration complexity and runtime
- Ability to identify convex and non-convex optimization problems
- Ability to make informed choices about the choice of optimization algorithm

- Ability to derive the dual problem, and use the dual and KKT conditions to reason about optimal solutions
- Familiarity with unconstrained optimization methods, including Gradient Descent, Conjugate Gradient Descent, Newton's Method and Quasi-Newton Methods
- Familiarity with Interior Point methods for constrained optimization
- Familiarity with standard formulations including Linear Programming, Quadratic Programming and Semidefinite Programming
- Ability to cast abstract problems as constrained optimization problems, and in terms of standard formulations

STAT 30750 Numerical Linear Algebra

Materials (Textbook):
Linear Algebra and its Applications (Gilbert Strang, 4th edition). Recommended: Numerical Linear Algebra (Trefethen and Bau)
Objective:
This course is devoted to the basic theory of linear algebra and its significant applications in scientific computing. The objective is to provide a working knowledge and hands-on experience of the subject suitable for graduate-level work in statistics, econometrics, engineering, physics, and numerical methods in scientific computing.
Topics:
Gaussian elimination, vector spaces, linear transformations, fundamental subspaces, orthogonality and projections, eigenvectors and eigenvalues, diagonalization of real symmetric and complex Hermitian matrices, the spectral theorem, and matrix decompositions (QR, Cholesky and Singular Value Decompositions). Systematic methods applicable in high dimensions and techniques commonly used in scientific computing are emphasized.

CAAM 37830/STAT 37411 Topological Data Analysis

Web:
https://stat37411.github.io/syllabus.html
Textbook & Readings:
This is a graduate-level course on a fairly young field, so we'll draw material from a couple of different sources. There isn't a canonical textbook on the material, but we'll try to stick to a few sources/review papers.
The following book serves as the primary reference:
- Persistence Theory: From Quiver Representations to Data Analysis, by Oudot. You can find an online version through the UChicago library on the Resources page.

This book surveys the field of topological data analysis as of a few years ago, but isn't really written like a textbook (i.e. with exercises). It will serve as a good reference for most topics we'll cover. Parts of this book are more advanced than what we'll cover in this course.
There are also two optional textbooks:
- Computational Topology: An Introduction, by Edelsbrunner and Harer
- Elementary Applied Topology, by Ghrist

"Computational Topology" is a real text book, but is a little outdated (despite only being 12 years old). "Elementary Applied Topology" isn't written as a text book, but has some nice visualizations and explanations. You can find it for free on the author's website.
Course Description:
Topological data analysis seeks to understand and exploit topology when exploring and learning from data. This course surveys core ideas and recent developments in the field and will prepare students to use topology in data analysis tasks. The core of the course will include computation with topological spaces, the mapper algorithm, and persistent homology, and cover theoretical results, algorithms, and a variety of applications. Additional topics from algebraic topology, metric geometry, category theory, and quiver representation theory will be developed from applied and computational perspectives.

Prerequisites: Linear algebra, prior programming experience, exposure to graph theory/algorithms.

List of Topics:

Core constructions and algorithms

1. Topological spaces / simplicial complexes
2. The mapper algorithm
3. Homology
4. Persistent homology
5. Zigzag homology

Understanding and using topology

1. Stability of persistent homology
2. Topological features (persistence images/landscapes, algebraic functions)
3. Optimization with persistent homology

Applications

1. Reconstructing a space through samples
2. Dynamical systems
3. Drug and materials discovery

We will cover some additional topics as time permits.

Autumn 2021

STAT 30900 1 Mathematical Computation I: Matrix Computation Course

http://www.stat.uchicago.edu/~lekheng/courses/309/

Textbook:

We will not use any specific book but the following are all useful references.

References:

- D.S. Bernstein, Matrix Mathematics, 2nd Ed., Princeton, 2009.
- J. Demmel, Applied Numerical Linear Algebra, SIAM, 1997.
- G. Golub, G. Meurant, Matrices, Moments and Quadrature with Applications, Princeton, 2010.
- G. Golub, C. Van Loan, Matrix Computations, 4th Ed., John Hopkins, 2013.
- N.J. Higham, Accuracy and Stability of Numerical Algorithms, 2nd Ed., SIAM, 2002.
- M. Overton, Numerical Computing with IEEE Floating Point Arithmetic, SIAM, 2001.
- R. Thisted, Elements of Statistical Computing: Numerical Computation, CRC, 1988.
- L.N. Trefethen, D. Bau, Numerical Linear Algebra, SIAM, 1997.

Course description:

This is an introductory course on numerical linear algebra. The course will present a global overview of a number of topics, from classical to modern to state-of-the-art. The fundamental principles and techniques will be covered in depth but towards the end of the course we will also discuss some exciting recent developments.

Numerical linear algebra is quite different from linear algebra. We will be much less interested in algebraic results that follow from the axiomatic definitions of fields and vector spaces but much more interested in analytic results that hold only over the real and complex fields. The main objects of interest are real- or complex-valued matrices, which may come from differential operators, integral transforms, bilinear and quadratic forms, boundary and coboundary maps, Markov chains, graphs, metrics, correlations, hyperlink structures, cell phone signals, DNA microarray measurements, movie ratings by viewers, friendship relations in social networks, etc. Numerical linear algebra provides the mathematical and algorithmic tools for matrix problems that arise in engineering, scientific, and statistical applications.

Syllabus:

- Linear algebra over R or C: How this course differs from your undergraduate linear algebra course.
- Three basic matrix decompositions: LU, QR, SVD.
- Gaussian elimination revisited: LU and LDU decompositions.
- Backward error analysis: Guaranteeing correctness in approximate computations.
- Gram–Schmidt orthogonalization revisited: QR and complete orthogonal decompositions.
- Solving systems of linear equations in the exact and the approximate sense: Linear systems, least

squares, data least squares, total least squares.
- Low rank matrix approximations and matrix completion.
- Iterative methods: Stationary methods and Krylov subspace methods.
- Eigenvalue and singular value problems.
- Sparse linear algebra: Sparse matrices and sparse solutions.

The last two topics we would only touch upon briefly (no discussion of actual algorithms); they would be treated in greater detail in a second course.

STAT 31440 1 Applied Analysis

Textbooks:

- J. Hunter and B. Nachtergaele, Applied Analysis, https://www.math.ucdavis.edu/~hunter/book/pdfbook.html
  and
- F. C. Liu, Real Analysis Links to an external site., Oxford Univ. Press 2017

Course description:

This course provides an overview of fundamentals of mathematical analysis with an eye towards developing the toolkit of graduate students in applied mathematics. Topics covered include metric spaces and basic topological notions, aspects of mathematical analysis in several variables, and an introduction to measure and integration.

Prerequisites: The course will be self-contained. Familiarity with linear algebra at the level of STAT 243 or MATH 20250 (or equivalent) helpful

After successfully completing the course, students will be familiar with and able to reason about:

- ideas related to real analysis, metric and normed linear spaces, and topological spaces,
- the inverse and implicit function theorems, contraction mapping (and more general fixed point) methods and applications to applied mathematics, and
- foundational material related to measure theory and Lebesgue integration. Students will also develop their skills in developing and expressing their arguments in writing.

TTIC 31230: Fundamentals of Deep Learning

web:

https://mcallester.github.io/ttic-31230/

This class is intended to provide students with an understanding of the technical content of current research in deep learning. Students successfully completing the class should be able to read and understand current deep learning research papers and possess the technical knowledge necessary to both reproduce research results and to do original research in deep learning. The course covers current methods in computer vision, natural language processing and reinforcement learning for games and robotics. One of the amazing aspects of deep learning is that much of the conceptual knowledge needed for research in these areas is shared among the areas making such broad coverage possible.

Prerequisites:

This class assumes knowledge of vector calculus, basic linear algebra (Matrices, Eigenvectors, eigenvalues), and a significant familiarity with probability and statistics. Familiarity with Markov chains is advised. The course is overall quite technical and a strong technical background and mathematical maturity is advised. There are machine problems and class programming projects and previous familiarity with programming, and Python in particular, is advised.

This class is intended to provide students with an understanding of the technical content of current research in deep learning. Students successfully completing the class should be able to read and understand current deep learning research papers and possess the technical knowledge necessary to both reproduce research results and to do original research in deep learning. The course covers current methods in computer vision, natural language processing and reinforcement learning for games and robotics. One of the amazing aspects of deep learning is that much of the conceptual knowledge needed for research in these areas is shared among the areas making such broad coverage possible.

Prerequisites:

This class assumes knowledge of vector calculus, basic linear algebra (Matrices, Eigenvectors, eigenvalues),

and a significant familiarity with probability and statistics. Familiarity with Markov chains is advised. The course is overall quite technical and a strong technical background and mathematical maturity is advised. There are machine problems and class programming projects and previous familiarity with programming, and Python in particular, is advised.
In the fall of 2022 there will be three machine problem sets, three exams and a final project.

1. Introduction:
    - The History of Deep Learning and Moore's Law of AI (2020) Slides Video1 Video2
    - The Fundamental Equations of Deep Learning Slides Video
    - Some Information Theory Slides Video
2. Frameworks and Back-Propagation:
    - Deep Learning Frameworks Slides Video
    - Backpropagation for Scalar Source Code Slides Video
    - Framework Objects and Backpropagation for Tensor Source Code Slides Video
    - Mini Batching: The Batch Index Slides Video
    - The Educational Framework (EDF) Slides Video
3. Convolutional Neural Networks (CNNs):
    - Einstein Notation Slides Video
    - CNNs Slides Video
4. Trainability, Residual Connections and RNNs:
    - Trainability: Relu, Initialization, Batch Normalization and Residual Connections (ResNet) Slides Video
    - Language Modeling Slides Video
    - Recurrent Neural Networks (RNNs) Slides Video
5. Attention, Machine Translation and the Transformer:
    - Machine Translation and Attention Slides Video
    - The Transformer Part I Slides Video
    - The Transformer Part II Slides Video
    - Statistical Machine Translation (optional) Slides
6. SGD I: Convergence and Temperature.
    - The Classical Convergence Theorem Slides Video
    - The Learning Rate, the Batch Size, and Temperature Slides Video
    - Momentum and Temperature Slides Video
    - RMSProp and Adam Slides Video
7. SGD II: Continuous Time Analysis.
    - Gradient Flow Slides Video
    - Stochastic Differential Equations (SDEs) Slides Video
    - Heat Capacity: Loss (Energy) as a function of Learning Rate (Temperature). Slides Video
    - Readings: SGD as Approximate Bayesian Inference, Mandtet al. 2017
8. Generalization and Regularization I: Early Stopping and Shrinkage
    - Early Stopping and Shrinkage Slides Video
    - Early Stopping as Shrinkage, L1 regularization and Ensembles Slides Video
9. Generalization and Regularization II: PAC-Bayesian Learning Theory
    - Learning Theory I: The Occam Guarantee Slides Video
    - Learning Theory II: The PAC-Bayes Guarantee Slides Video
    - Implicit Regularization Slides Video
    - Double Descent Slides Video
10. Generative Adversarial Networks (GANs):
    - GAN Fundamentals Slides Video
    - Timeline of GAN Development Slides Video
11. Variational Autoencoders:
    - The Evidence Lower Bound (ELBO) and Variational Autoencoders (VAEs) Slides 2021 Video
    - Perils of Differential Entropy Slides 2021 Video
    - Vector Quantized VAEs Slides 2021 Video
    - Progressive VAEs Slides 2021 Video
12. Contrastive Coding:

- Contrastive Coding Slides
- Tishby, Pereira and Bialek, The Information Bottleneck Method, 2000
- McAllester, Information Theoretic Co-Training, Feb, 2018
- van den Oord et al., Contrastive Predictive Coding, July 2018
- McAllester and Stratos, Formal Limitations on the Measurement of Mutual Information, Nov. 2018
- Schneider et al., wav2vec: Unsupervised Pre-training for Speech Recognition, April 2019
- Poole et al., On Variational Bounds of Mutual Information, May 2019
- Chen et al., A Simple Framework for Contrastive Learning of Visual Representations, Feb. 2020
- Caron et al. Unsupervised Learning of Visual Features by Contrasting Cluster Assignments, Jan. 2021

13. Diffusion Models:
14. Reinforcement Learning (RL):
    - Basic Definitions, Value Iteration Slides Video
    - Q-Learning and Deep Q Networks (DQN) for Atari Slides Video
    - The REINFORCE algorithm Slides Video
    - Actor-Critic algorithms, A3C for Atari Slides Video
15. AlphaZero and AlphaStar:
    - Background Algorithms Slides Video
    - The AlphaZero Training Algorithm Slides Video
    - AlphaZero Results Slides Video
    - MuZero Slides
    - AlphaStar Slides Video
16. Energy Based Models (Deep Graphical Models) I:
17. The Quest for Artificial General Intelligence (AGI):
    - Exponential Softmax Slides Video
    - Back Propagation for Exponential Softmax: The Model Marginals Slides Video
    - Monte-Carlo Markov Chain (MCMC) Sampling Slides Video
    - Pseudo-Likelihood and Contrastive Divergence Slides Video
    - Loopy Belief Propagation (Loopy BP) Slides Video
    - Connectionist Temporal Classification (CTC) (optional) Slides
18. The Quest for Artificial General Intelligence (AGI):
    - AGI: Universality Slides Video
    - AGI: Bootstrapping Slides Video
    - AGI: Logic Slides Video
    - AGI: Natural Language Slides Video