	Block I – Data Science Bootcamp
Mathen	natics and Statistics for Data Science
Opti	imization
	Introduction to Optimality conditions
	Introduction to unconstrained local optimization methods Catabactic according to advantate Catabactic accord
	Subcristic gradient and variants
	Global optimization
	Exact global optimization methods
	Heuristic global optimization methods
	Bayesian optimization
Num	nerrari calculus and unear Algeora
	Elementi di analisi delle matrici
	Risoluzione numerica di sistemi lineari: metodi diretti
	Sistemi sovradeterminati (fattorizzazione QR e decomposizione ai valori singolari)
	Risoluzione numerica di sistemi lineari: metodi iterativi stazionari
	rreconazionatori Generalità sui Metadi di Kivlov
	GMRES
Prob	pability and stochastic processes
	Probability:
	Discrete random variables: Probability distributions, probability mass functions, cumulative distribution functions, mean and variance. Discrete models.
	Joint proceeding visit outdown, waaging o ustroutoris, conducting processing, conducting and an area and variance. Discrete moutes Continuous random variables: Probability distributions, orchability distributions (cumulative distribution functions, mean and variance. Conditional probability. Continuous models.
	Convergence theorems and normal approximation. Poisson Process and applications.
	Stochastic Processes:
	Introduction to Markov Chains and their transition matrix.
	Classification of states, invariant distributions.
	Simulated annealing and Metropolis algorithm. Bith and death chairs on failed tatls pages
Stati	bit treated teams of infine state spaces.
	Inference and linear models:
	Statistical thinking
	Frequentist (classical) inference
	Exploring associations
	Significance tests Prediction
	Generalized linear models:
	Non-normal responses
	Regression with a binary response
	Binary data The energy lighting model
	Infegence and prediction
	Generalized linear models
	Contingency tables and Poisson models
	Log-linear models
Algorith	Ine Ising model in 3 binary Variables
Algo	writhms and programming in Python and R for Data Science
	Python:
	Introduction to Python and simple Data
	Python Modules and Functions Selections and Instances
	Recurson and stratedons
	Lists and Dictionary
	Classes and Objects, Files
	Analysis of Algorithms
	Sorting and searching Pe
	Introduction to R: the R console, R packages, files. R
	Elementary objects of R: vectors, matrices, arrays, lists; different typologies of objects (numerical, characters, logical, factorial)
	Basic mathematical functions; personalization of functions
	The dataframe: definition and manipulation
	Data import and data export in K (txt files, txxel files, Stata/SAS/SPS files, IX Data files) Annoultions of hourt, 1: unique times uninter unique times unique times unique times unique times unique
	Manipulations of objects - 2: statute recooning, time variables, missing data, record umage Manipulations of objects - 2: statustical descriptione analyses (Tables, statistical escription) and the statustical description and statistical description and statistical descriptions
Intro	duction to Machine Learning
	Supervised versus unsupervised ML, essential probability theory, statistics, and distributions for ML, Bayesian versus frequentist interpretations for ML
	Linear models for supervised regression and classification
	The bias-variance decomposition, overfitting, underfitting, and model regularization
	Maximum Likelihood Estimation (MLE), the expectation-maximization (EM) algorithm, Maximum a Posteriori (MAP) versus Bayesian interence
	Commencing to a trifficial neural networks: training as a non-linear optimization problem
	Backpropagation and gradient-based methods
	Linear Support Vector Machines (SVMs)
	Non-linear SVMs and radial basis function networks
	Using the LIBSVM library
	Block II – Core Courses
Statistic	cal Learning for Data Science
Stati	istical Learning
	Introduction to statistical learning:
	Statistical point of view of machine learning
	Vaca generating protess Monte Carlo simulations
	Graphical models:
	Networks and concentration graph models
	DAG and Bayesian network
	Supervised statistical learning based on trees:
1	CART algorithm
	Pagging and Pandom forest
	Bagging and Random forest Boosted trees

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	Interpre	etable statistical learning:
	P	Predicting vs explaining
	li li	nterpretability, transparency, fairness
Geo-	-spatial a	nd network data modelling
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		ntroduction to network data
	Ν	Network representation: types of relations, graph representation, matrix representation
	H	Hints on network visualization
	C	Descriptive analysis of network data: network statistics
		Descriptive analysis of extreme data: and a tatistic
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	E	xponential Random Graph models
	S	Stochastic blockmodels
	L	.atent space models
	Geo-sp	atial data modelling:
		traduction to spatial and geographical data
		Introduction to Spatial and geographical data
	S	stochastic spatial processes and their properties
	A	Analysis of point process data
	A	Analysis of geodata random surface
	۵	Analysis of areal data (lattice data)
	3	pauar interaction data: gravity models
	li	ntroduction to Geographical Information Systems
Supervis	sed and L	Unsupervised Learning
Mac	hine lear	ning
	Introdu	tion to supervised learning and regression
	Classifi	
	Classific	cauon problems.
	Online	learning: the perceptron learning algorithm.
	Gradier	nt descent and stochastic gradient descent: analysis, MATLAB implementation, backpropagation.
	Unsupe	ervised learning, MATLAB implementation of principal component analysis and spectral clustering.
	Introdu	international department of the second departm
		Leave to substanting the UP.
	Structu	ral risk minimization and support vector machines.
	Trade-o	off between sample size and precision of supervision.
	A comp	parison of approximation error bounds for neural networks and linear approximators.
	Applica	tion of neural networks to ontimal control problems
	Applica	
	Radial d	basis function interpolating networks and their application to surrogate modeling and optimization.
	Connec	tion between supervised learning and reinforcement learning.
Deep	p learning	g, Neural Networks, and Reinforcement learning
	Sequen	ice learning and recurrent networks
	Attentio	nn merhanisms
	Casabl	
	Graphi	earning
	Explain	anie machine learning
	Explain	able deep learning
Complex	x System	S
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Block III – Elective Courses

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Data Science for Economics
Experiments and real-world evidence in economics
From theory to data (and the way back). Introduction to behavioral and experimental economics.
Learning from the data. Correlation is not causation. In search for practicable ways to go beyond correlations in social and economic phenomena.
The controlled solution: Experiments (online, in the laboratory, in the field).
The Jess controlled solution: Natural and Quasi-experiments.
Statistical analysis of experimental data. Mediator variables. modulator variables. specific statistical tests, multiple testing of hypotheses.
Case studies.
Examples of controlled experiments and their analysis (e.g., risky behaviors, addiction, strategic behaviors, moral dilemmas, marketing, persuasion, nudging).
Examples of natural experiments and their analysis (e.g., Italian clements hill and criminal hebaviors).
Examples of nucleargeniments and their analysis (e.g., numerican ending and examples in primary schools)
Dalicy evaluation and inact analysis
Introduction to a management is:
Structure Endogeneity and Identification Problems
Least-surgers Public and Load Estimators
Static agency data
Opinaling parter total The Evaluation Devaluation
Randomization and Matching Models
The Difference indifference Ferinators
Instrumental Variable
Barrassian biscontinuity Dasian
Causaity and Non-linear Models
Multinomial Models
Models for Count Data
Survival/Juration Analyses
Models with Control Functions
Data Sriance for Rusinges
Rusines analytics
Dotinization of Enancial Portfolios
Plantation of instance refutions
Portfolio choice criteria: encented of reactions and an encoded and an encoded and an encoded and an encoded an encode
Manuariane portfolio selection in action
Further tonics: dealing with high-dimensional portfolios: constraints on concentration and turnover: the Black Litterman model: constituity with inputs ("actimation rick"): mean-VaR and mean-O/AR portfolio selection
Portfolio opticationi in Matha "audorea" functiona di "portfolio" della catalita di alla della catalita di autoria di controlla catalita di autoria di controlla catalita di controlla
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Health analytics and data-driven medicine
Causal inference in healthcare with MEPS data
Predictive healthcare and patient outcome (digital records, diagnostic procedure and intervention)
Clinical trials and prescription behavior: market analysis and regulation
Epidemiology and COVID-19
Environmental and genomic data analysis
Hands-on Labs
Hands on R and STATA for Data Science:
Introduction to R and STATA
Data Modeling for policy evaluation:
Data Modeling: inference and predictive analysis
Data Modeling: causal machine learning
Hands on Python for Data Science:
Introduction to Python for data science:
Unsupervised learning
Dimensionality reduction
Neural networks and deep learning