The Course of STATISTICAL DATA ANALYSIS - cfu 12 Recap and Project Work for the Exam

Roberta Siciliano Stad lab

Statistics. tèchnè-loghìa, analysis of data

University of Napoli Federico II – http://www.stad.unina.it



Father of Indian Statistics: Prof. Prasanta Chandra Mahalanobis

"Statistics must have a clearly defined purpose, one aspect of which is scientific advancement and the other human welfare and national development."

https://artsandculture.google.com/story/father-of-indianstatistics-prof-prasanta-chandra-mahalanobis-indianstatistical-institute/wAURK23-669ILA?hl=en

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Calendar of the Exam Sessions and Deadlines (January, February, March)

Statistics, tèchnè-loghia, anàlysis data

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Stad Statistics.
tèchnèloghia,
anàlysis
dàto

- Statistics, techne-loghia, analysis data are key words for reading the reality as it is manifested in qualitative expressions (categories, attributes, classes, groups, labels, etc.) and quantitative ones (numbers, measurements, values, etc.) in various domain contexts or application fields.
- All starts with a real-world case study and specific questions that require statistical data analysis.

Stad – The etymological derivation

- **Statistics** from the Latin **Status** = "science dealing with data about the condition of a state or community" coined by the German political scientist Gottfried Aschenwall (1719-1772) in his "Vorbereitung zur Staatswissenschaft" (1748).
- **lèchnè-loghìa** combines two Greek words:
 - **lèchnè** = art, ability of doing, namely the human brain to 'remember', 'think', 'come to mind', 'cross the mind', 'invent something new',
 - loghia = discourse, explanation,
 - lèchnè-loghìa = "the systematic treatise on an art or how to do"
- anàlysis from the Greek = solution of a problem, "the process of breaking a complex topic into smaller parts in order to gain a better understanding of it" (Aristotele, 384-322 B.C.),
- doto from the Latin = known quantities.

Statistics, tèchnè-loghìa, anàlysis dàto

- Statistics has two fundamental missions:
 - ✓ Exploratory Data Analysis (from data to information) uses a "deducting approach" to discover significant facts, patterns, groups, anomalies, associations, correlation, similarities, typologies, clusters, and so on;
 - ✓ Confirmatory Data Analysis (from information to knowledge) uses an "inductive approach" to justify theories and hypotheses, to build up models for decision-making and prediction.
- **tèchnè-loghìa** is the rationalization process that starting from the real-world questions build up a "project" to move from theory to practice. The concrete ability pass through two attitudes:
 - ✓ Heuristic Experience through trial and error to seek solutions for a new problem,
 - ✓ **Algorithmic Experience** by applying known solutions for a problem that is very similar to others previously addressed.
- analysis of data is to find solutions from known quantities, the data.

Statistical Data Analysis: the mission

The statistician or data scientist, to understand the facts (exploration) and to confirm the theories (confirmation), makes use of reasoning and concrete skills (statistical thinking and methodology) to make the most of the available data with the related domain context information as a result of observing reality.

The final goal of **Statistical Data Analysis** is *to learn from data* and *find solutions* to a real-world problem.

All starts with real-world case study in a domain context.

The statistician or data scientist needs to transform *raw data (input)* into *useful information and knowledge (output)* (tables, plots and graphs, info-graphics, statistical indexes, models, prediction) to be correctly interpreted and analyzed such to provide answers to the real-world questions as well as some *actions and consequences (outcome) to add value* (utility, revenue, satisfaction, innovation plan, etc.) for some stakeholders.

Statistical Data Analysis Course: the Syllabus

Introduction to Statistics, <i>Technè-Loghia</i> , Analysis of Data Exploratory Data Analysis (Data Pre-processing, Descriptive Statistics, Data Visualization, Data Cross-Classification Analysis) Probability and Probability Models (Axiomatic Theory of Probability, Discrete and Continuous Models) Confirmatory Data Analysis (Classical and Bayesian Inference, Estimation and Testing Theory) Linear Regression Models (ANOVA, Linear Regression, Use of Dummy Variables in Regression, Regression Diagnostics) Non-Parametric Tests Multiple Testing Procedures Linear Models for Time Series Analysis Multidimensional Data Analysis (Principal Component Analysis, Hierarchical Clustering, K-Means Clustering) Statistical Data Analysis - Module B: Statistical Learning Statistical Learning in theory and practice Linear Models for Regression Linear Models for Supervised Classification Computational Inference Regularization and Shrinkage Methods Model Selection Methods for Non-Linearity in Regression and Classification Classification and Regression Trees Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning Survival Analysis and Censored Data	Statistical Bata Analysis Module A. Fandaments of Statistics
Probability and Probability Models (Axiomatic Theory of Probability, Discrete and Continuous Models) Confirmatory Data Analysis (Classical and Bayesian Inference, Estimation and Testing Theory) Linear Regression Models (ANOVA, Linear Regression, Use of Dummy Variables in Regression, Regression Diagnostics) Non-Parametric Tests Multiple Testing Procedures Linear Models for Time Series Analysis Multidimensional Data Analysis (Principal Component Analysis, Hierarchical Clustering, K-Means Clustering) Statistical Data Analysis - Module B: Statistical Learning Statistical Learning in theory and practice Linear Models for Regression Linear Models for Supervised Classification Computational Inference Regularization and Shrinkage Methods Model Selection Methods for Non-Linearity in Regression and Classification Classification and Regression Trees Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Introduction to Statistics, <i>Technè-Loghìa</i> , Analysis of Data
Confirmatory Data Analysis (Classical and Bayesian Inference, Estimation and Testing Theory) Linear Regression Models (ANOVA, Linear Regression, Use of Dummy Variables in Regression, Regression Diagnostics) Non-Parametric Tests Multiple Testing Procedures Linear Models for Time Series Analysis Multidimensional Data Analysis (Principal Component Analysis, Hierarchical Clustering, K-Means Clustering) Statistical Data Analysis - Module B: Statistical Learning Statistical Learning in theory and practice Linear Models for Regression Linear Models for Supervised Classification Computational Inference Regularization and Shrinkage Methods Model Selection Methods for Non-Linearity in Regression and Classification Classification and Regression Trees Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Exploratory Data Analysis (Data Pre-processing, Descriptive Statistics, Data Visualization, Data Cross-Classification Analysis)
Linear Regression Models (ANOVA, Linear Regression, Use of Dummy Variables in Regression, Regression Diagnostics) Non-Parametric Tests Multiple Testing Procedures Linear Models for Time Series Analysis Multidimensional Data Analysis (Principal Component Analysis, Hierarchical Clustering, K-Means Clustering) Statistical Data Analysis - Module B: Statistical Learning Statistical Learning in theory and practice Linear Models for Regression Linear Models for Supervised Classification Computational Inference Regularization and Shrinkage Methods Model Selection Methods for Non-Linearity in Regression and Classification Classification and Regression Trees Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Probability and Probability Models (Axiomatic Theory of Probability, Discrete and Continuous Models)
Non-Parametric Tests Multiple Testing Procedures Linear Models for Time Series Analysis Multidimensional Data Analysis (Principal Component Analysis, Hierarchical Clustering, K-Means Clustering) Statistical Data Analysis - Module B: Statistical Learning Statistical Learning in theory and practice Linear Models for Regression Linear Models for Supervised Classification Computational Inference Regularization and Shrinkage Methods Model Selection Methods for Non-Linearity in Regression and Classification Classification and Regression Trees Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Confirmatory Data Analysis (Classical and Bayesian Inference, Estimation and Testing Theory)
Multiple Testing Procedures Linear Models for Time Series Analysis Multidimensional Data Analysis (Principal Component Analysis, Hierarchical Clustering, K-Means Clustering) Statistical Data Analysis - Module B: Statistical Learning Statistical Learning in theory and practice Linear Models for Regression Linear Models for Supervised Classification Computational Inference Regularization and Shrinkage Methods Model Selection Methods for Non-Linearity in Regression and Classification Classification and Regression Trees Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Linear Regression Models (ANOVA, Linear Regression, Use of Dummy Variables in Regression, Regression Diagnostics)
Linear Models for Time Series Analysis Multidimensional Data Analysis (Principal Component Analysis, Hierarchical Clustering, K-Means Clustering) Statistical Data Analysis - Module B: Statistical Learning Statistical Learning in theory and practice Linear Models for Regression Linear Models for Supervised Classification Computational Inference Regularization and Shrinkage Methods Model Selection Methods for Non-Linearity in Regression and Classification Classification and Regression Trees Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Non-Parametric Tests
Multidimensional Data Analysis (Principal Component Analysis, Hierarchical Clustering, K-Means Clustering) Statistical Data Analysis - Module B: Statistical Learning Statistical Learning in theory and practice Linear Models for Regression Linear Models for Supervised Classification Computational Inference Regularization and Shrinkage Methods Model Selection Methods for Non-Linearity in Regression and Classification Classification and Regression Trees Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Multiple Testing Procedures
Statistical Data Analysis - Module B: Statistical Learning Statistical Learning in theory and practice Linear Models for Regression Linear Models for Supervised Classification Computational Inference Regularization and Shrinkage Methods Model Selection Methods for Non-Linearity in Regression and Classification Classification and Regression Trees Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Linear Models for Time Series Analysis
Statistical Learning in theory and practice Linear Models for Regression Linear Models for Supervised Classification Computational Inference Regularization and Shrinkage Methods Model Selection Methods for Non-Linearity in Regression and Classification Classification and Regression Trees Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Multidimensional Data Analysis (Principal Component Analysis, Hierarchical Clustering, K-Means Clustering)
Linear Models for Regression Linear Models for Supervised Classification Computational Inference Regularization and Shrinkage Methods Model Selection Methods for Non-Linearity in Regression and Classification Classification and Regression Trees Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Statistical Data Analysis - Module B: Statistical Learning
Linear Models for Supervised Classification Computational Inference Regularization and Shrinkage Methods Model Selection Methods for Non-Linearity in Regression and Classification Classification and Regression Trees Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Statistical Learning in theory and practice
Computational Inference Regularization and Shrinkage Methods Model Selection Methods for Non-Linearity in Regression and Classification Classification and Regression Trees Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Linear Models for Regression
Regularization and Shrinkage Methods Model Selection Methods for Non-Linearity in Regression and Classification Classification and Regression Trees Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Linear Models for Supervised Classification
Model Selection Methods for Non-Linearity in Regression and Classification Classification and Regression Trees Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Computational Inference
Methods for Non-Linearity in Regression and Classification Classification and Regression Trees Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Regularization and Shrinkage Methods
Classification and Regression Trees Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Model Selection
Ensemble Methods Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Methods for Non-Linearity in Regression and Classification
Support Vector Machines Projection Pursuit Regression Introduction to Deep Learning	Classification and Regression Trees
Projection Pursuit Regression Introduction to Deep Learning	Ensemble Methods
Introduction to Deep Learning	Support Vector Machines
	Projection Pursuit Regression
Survival Analysis and Censored Data	Introduction to Deep Learning
	Survival Analysis and Censored Data

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Statistical Data Analysis - Module A: Fundaments of Statistics

The Basic Practice of Statistics, (the newest is the) 9th Edition (2021), David S. Moore, William I. Notz, Michael A. Fligner, W.H. Freeman Publishers

Introduction to Statistical Learning, with applications in R. James Gareth, Daniela Witten, Trevor Hastie, Robert Tibshirani (2009).

https://hastie.su.domains/ISLR2/ISLRv2_website.pdf

Readings/Bibliography

The elements of Statistical Learning: Data Mining, Inference, and Prediction. Trevor Hastie, Robert Tibshirani, Jerome Friedman, Springer (2009).

https://web.stanford.edu/~hastie/Papers/ESLII.pdf

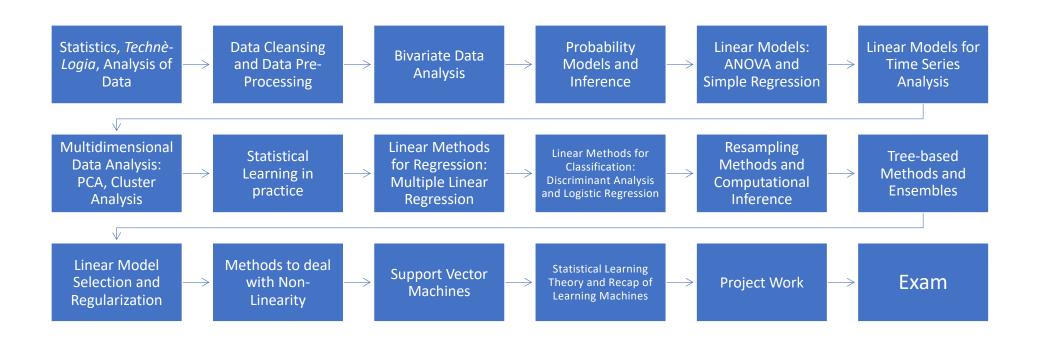
Slide and teaching material by the docent are uploaded on the Team of The Course.

Lectures Recording in the Team of The Course.

Lectures Scheduling

SDA - LN	/I DATA SCIENCE				Exploratory Data An	alysis			
Statistical Data Analysis			Module A	Fundaments of Statistics	Inference			Theory	Laboratory
			Module B	Statistical Learning	Modeling and Predic	ction		ě	000
					Project Work			_	펼
4	# Date	Day	Lecture			С	#H#	†T #	‡ L
:	04/10/22	Tuesday	Introduction	to Statistics, Technè-Loghìa, Ana	alysis of Data	Intro	3	3	
	05/10/22	Wednesday	Data Pre-Prod	cessing and Descriptive Statistic	S	EDA	2	2	
	3 06/10/22	Thursday	Bivariate Data	a Analysis and Visualization / La	boratory in R	EDA	3	2	1
4	11/10/22	Tuesday	Probability M	odels / Laboratory in R		ļ	3	2	1
!	12/10/22	Wednesday	Probability M	odels		l	2	2	
(13/10/22	Thursday	Inference / La	boratory in R		I	3	2	1
7	7 18/10/22	Tuesday	Laboratory in	R		l	3		3
8	19/10/22	Wednesday	Bayesian Infe	rence/Laboratory in R		I	2		2
9	20/10/22	Thursday	Linear Model	s for Experimental Data: ANOVA	A Modeling	M	3	3	
10	25/10/22	Tuesday	Linear Regres	sion Models / Statistical Thinkir	ng	M	3	2	1
13	-, -,	Wednesday	Laboratory in	R		M	2	2	
12	, -,	Thursday	FATER CHALL	ENGE		PW	3	2	1
13		Wednesday	Multiple Line	ar Regression		M	2	2	
14		Thursday	Regression Di	agnostics / Laboratory in R		M	3	2	1
15		Tuesday	Linear Model	s for Time Series		M	3	3	
10	6 09/11/22	Wednesday	Non-Paramet	ric Tests		l	2	2	
17	-, ,	Thursday	Non-Paramet			EDA	3	3	
18	3 15/11/22	Tuesday	Multidimensi	onal Data Analysis: PCA, Cluster		EDA	3		3
							48	34	14
19	-, ,	Wednesday		rning Theory and Machine Lear		Intro	2	2	
20		Thursday		s for Regression / Laboratory in		M	3	2	1
2:		Tuesday		s for Classification / Laboratory	in R	M	3	2	1
22	-, ,	Wednesday	Resampling N			l	2	2	
23		Thursday		nd Decision Trees / Laboratory		M	3	2	1
24		Tuesday		nd Decision Trees / Laboratory	in R	M	3	2	1
2!	, ,	Wednesday	Ensemble Me			M	2	2	
20	- , ,	Thursday	Laboratory in			M	3		3
27		Tuesday		Selection and Regularization / I	_aboratory in R	M	3	3	
28	- , ,	Wednesday	Methods for	•		M	2	2	
29	-, ,	Tuesday		Non Linearity/ Laboratory in R		M	3	2	1
30		Wednesday	Support Vector			M	2	2	
3:	-, ,	Thursday	Laboratory in			M	3		3
32	-, -, -,	Tuesday		for the Exam / Laboratory in R		PW	3	2	1
33		Wednesday	Laboratory in			PW	2		2
34	, - , -	Tuesday	Laboratory in			PW	3		3
3!	, , , .	Wednesday	Learning by d			М	2	2	
36	13/01/23	Thursday	Learning by d	oing		PW	4	2	2
							48	29	19
							96	63	33

Lectures Road Map



Examination/Evaluation Criteria

Exam

- The exam consists in developing a Project Work on a Real-World Case Study, submitting a technical report (one week earlier the exam session), presenting the quantitative story telling of the results at the exam session.
- Guidelines to develop and prepare the Technical Report are given in this presentation.
- Exam sessions will be communicated on the Team of the Course as well as on the Lecturer Web site. https://www.docenti.unina.it/.

Evaluation pattern

 The evaluation will consider the methodological knowledge, the computational aspects (code), the presentation and communication of the results (technical report and oral presentation with final discussion).

Evaluation grid

• The attribution of the vote takes place according to the criteria shown in the Table.

<18 Not sufficient	Fragmented and superficial knowledge of the contents, errors in applying the concepts, insufficient written test and insufficient exposure
18-20	Sufficient but general knowledge of the contents, simple exposition, uncertainties in the application of theoretical concepts
21-23	Appropriate but not in-depth knowledge of contents, ability to apply theoretical concepts, ability to present contents in a simple way
24-25	Appropriate and broad knowledge of contents, fair ability to apply knowledge, ability to present contents in an articulated way
26-27	Precise and complete knowledge of contents, good ability to apply knowledge, analytical skills, clear and correct presentation
28-29	Broad, complete, and in-depth knowledge of contents, good application of contents, good ability to analyze and synthesize, safe and correct exposure
30 30 et lauda	Very broad, complete, and in-depth knowledge of contents, well-established ability to apply contents, excellent ability to analyze, synthesize and interdisciplinary connections, mastery of exposure

How to pass the Exam?



Build up a Team for the Project



Select a Real-World Case Study Challenge



Develop the Project Work following the Pipeline of Statistical Data Analysis



Prepare the Technical Report using Markdown and submit it one week before the exam session



Prepare a presentation of the results and do the exam, taking into account the examination/evaluation grid

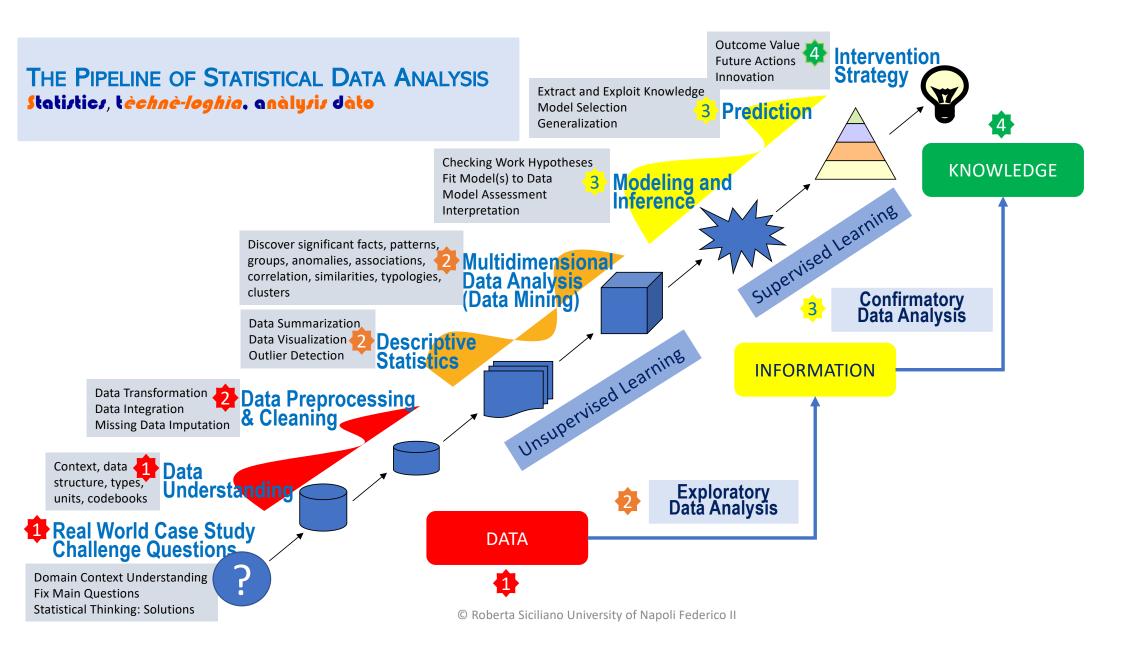
Case studies

 Kaggle Repository https://www.kaggle.com/datasets

 UCI Machine Learning Repository https://archive.ics.uci.edu/ml/index.php

 A general entry point: https://datasetsearch.research.google.com





Technical Report: sessions and contents structure





Introduce the Domain Context and the Real-World Case Study: **domain understanding** and which **challenging questions to satisfy**.

Refer to the link of the databases.

Data Understanding: describe the context, the data structure, the typology of variables, the units, time/space, etc.

Statistical thinking: convert questions into statistical problems, summarize and motivate which statistical methods to apply.





Data Pre-Processing and Cleaning: data transformation, data integration, missing data imputation.

Descriptive Statistics: data summarization, data visualization outlier detection.

Multidimensional Data Analysis (basic Data Mining strategy): dimensionality data reduction and clustering.

Statistical thinking: Summarize the relevant information derived from the Exploratory Data Analysis.



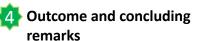


Modeling and Inference: Checking Work Hypotheses, Fit Model(s) to Data, Model Assessment, Interpretation.

Prediction: Extract and Exploit Knowledge, Model Selection and Generalization.

Statistical thinking: Summarize the knowledge extraction due to the Confirmatory Data Analysis.





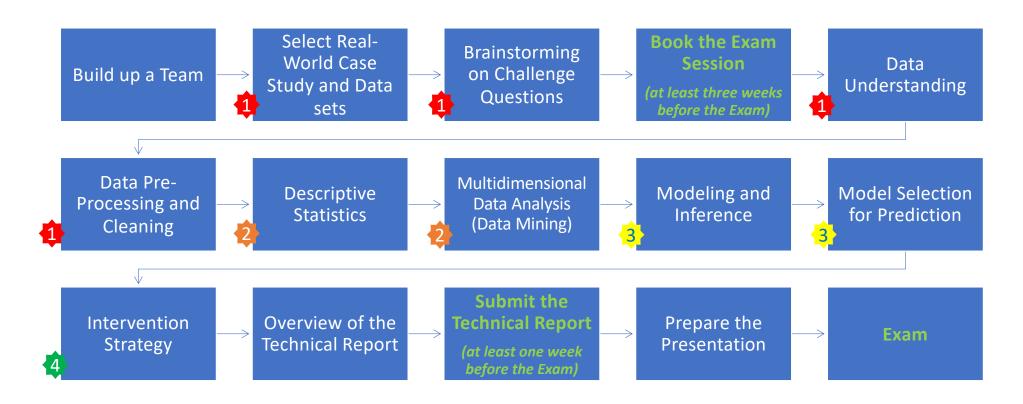
Summarize the key points of the outcome of the Statistical Data Analysis.

Intervention Strategy: Outcome Value, Future Actions, Innovation, how the beneficiary/stakeholders utilize the outcome of statistical data analysis.

How to organize the Project Work and Exam

- Build up a team of max 5 members willing to sit for the same date, possibly with different bachelor degree. You can also do the project work alone. The team does not necessarily correspond to those for the homework.
- Select the Real-World Case Study with one or more data sets from one of the Public Repositories and define a set of challenging real-world questions.
- **Team brainstorming** to discuss how to convert the real-world questions into statistical questions and methodologies to apply. You can also discuss with the Professors at the **Weekly Question Time Planned Meeting** receiving important suggestions.
- Book the Exam three weeks before the exam session using the form linked in the exam channel of the Team of the Course.
- Run your work and share the tasks in the team following the PIPELINE OF STATISTICAL DATA ANALYSIS.
- Write the Technical Report of your project using Markdown and considering the following points: introduce the case study challenge, describe well the data, justify the selected methods and R packages, comment R code, provide the correct interpretation of all output, derive the outcomes of the statistical data analysis referred to the challenge questions.
- Submit your Technical Report one week before the exam session.
- **Prepare the Quantitative-Story Telling of your project work results using the ppt presentation:** focalize the attention on how to communicate the results in interesting way for the beneficiary of the statistical data analysis.
- Present yourself at the Exam Session: be ready to answer methodological questions and to discuss about the outcome of your statistical data analysis, be convinced about the good results that you have found but also be critical toward yourself, what you could have done better, what are potential future developments.
- Mind that Your exam will be evaluated according to the published examination/evaluation criteria.

Road Map for the Project Work and Exam



Calendar of Exam Sessions and <u>Deadlines</u> (January-February-March 2023)

