TITANIC



Machine learning from disaster

Faculty of Engineering, Systems Engineering

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Sinking of the Titanic on April 15, 1912

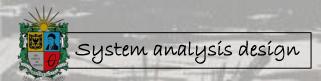


Sinking of the Titanic on April 15, 1912

The goal is to predict which passengers might survive and which might not. Different aspects need to be considered and whether this prediction is accurate.

→ BINARY SYSTEM

□ 11□



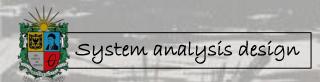
Sinking of the Titanic on April 15, 1912

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> BINARY SYSTEM

DOES NOT SURVIVE



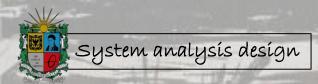


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→ BINARY SYSTEM

SURVIVE



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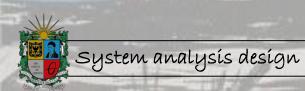
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BINARY SYSTEM

SURVIVE

Functional predictive model based on information provided

SELF-LEARNING



OPERATION

Understanding how machine learning algorithms work

IMPROVE THE ALGORITHM



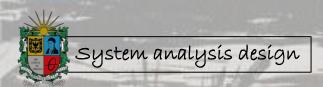
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IMPROVE THE ALGORITHM

Considering...

Factors indicated and be careful in handling information, improving the reliability of what is stated



OPERATION

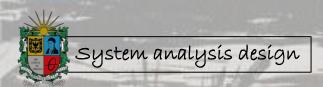
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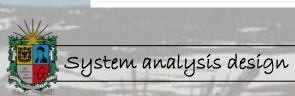
WARNING: The purpose is not only to predict who survived, it is to build a robust system that is adaptable to different contexts.



IDENTIFICATION OF THE ELEMENTS

Expected entries

	The state of the s	
Variable	Definition	Key
survival	Survival	0 = No, 1 = Yes
pclass	Ticket class	1 = 1st, 2 = 2nd, 3 = 3rd
sex	Sex	
Age	Age in years	
sibsp	# of siblings / spouses aboard the Titanic	
parch	# of parents / children aboard the Titanic	
ticket	Ticket number	
fare	Passenger fare	
cabin	Cabin number	
embarked	Port of Embarkation	C = Cherbourg, Q = Queenstown, S = Southampton



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SURVIVE

Expected departure

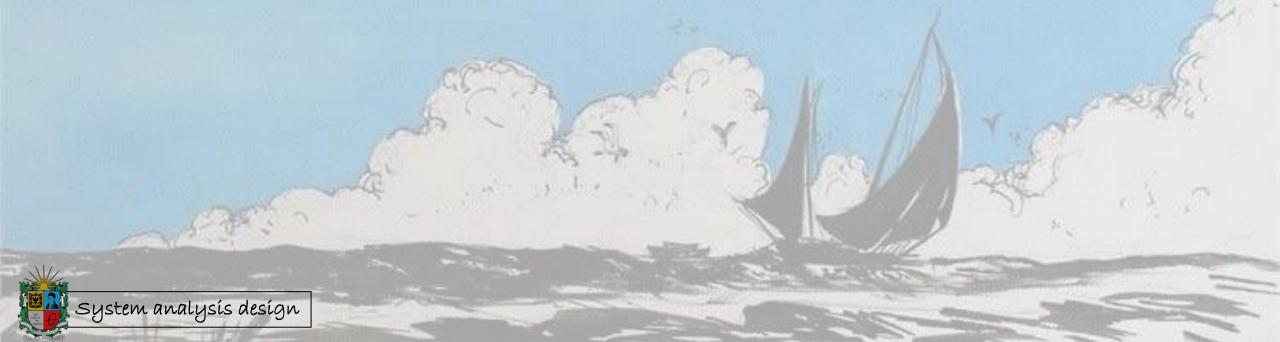
DOES NOT SURVIVE





IDENTIFICATION OF THE ELEMENTS

But it is not that simple, this brings with it a complexity and sensitivity that increases the difficulty.

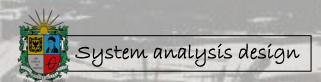


IDENTIFICATION OF THE ELEMENTS

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MISSING DATA

Passenger age



IDENTIFICATION OF THE ELEMENTS

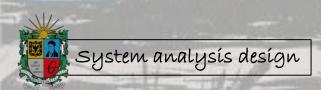
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IMBALANCE

There are more passengers who did not survive than those who did.



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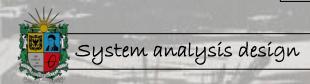
MISSING DATA

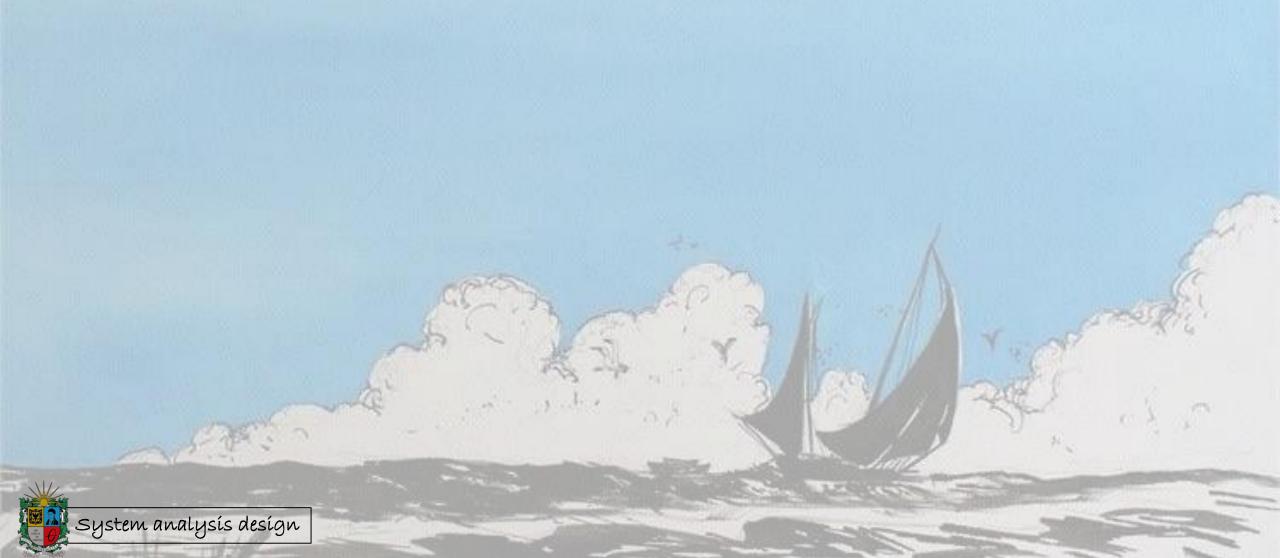
Passenger age

IMBALANCE

There are more passengers who did not survive than those who did.

A small altered input data can change the accuracy





There are unforeseen interactions between passengers

Survival depends on human factors



There are unforeseen interactions between passengers

Survival depends on human factors

All of these are factors that alter the prediction and the precision with which they intend to know the survival of the Titanic passengers.

There are unforeseen interactions between passengers

Survival depends on human factors

IMPLEMENTING A DESIGN

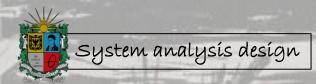
Robust

Reproducible

Intelligent

Modular

Reliable



REQUIREMENTS

ID	Requirement	Description
FR-1	Data Ingestion Mod-	Load and validate input datasets (train.csv,
	ule	test.csv, and gender_submission.csv).
FR-2	Preprocessing and	Handle missing or null values in variables such as
	Cleaning	Age, Cabin, and Embarked.
FR-3	Feature Engineering	Apply transformations (e.g., one-hot encoding for
		categorical variables).
FR-4	Model Training	Train a supervised learning model (e.g., Random
		Forest) to predict Survived.
FR-5	Evaluation and Met-	Compute model accuracy and generate submission
	rics	file.
FR-6	Submission Output	Export predictions to submission.csv following
		Kaggle's structure.

Table 1: Functional Requirements

ID	Requirement	Description
NFR-	Performance	Process datasets (1,300 records) in less than 5 sec-
1		onds.
NFR-	Scalability	Allow easy addition of features without refactor-
2		ing.
NFR-	Reproducibility	Use fixed random seeds and documented depen-
3		dencies.
NFR-	Maintainability	Modular architecture separating stages.
4		
NFR-	Usability	Provide clear workflow and outputs.
5		
NFR-	Reliability	Handle corrupted input files gracefully.
6		

Table 2: Non-Functional Requirements

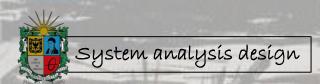
Requirements define the functions the system must perform and how it must behave to do so efficiently, reliably, and reproducibly, ensuring stable and well-structured performance.

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Table 1: Functional Requirements

Specific actions that the system must perform.

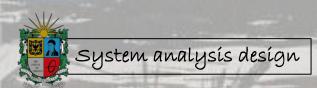


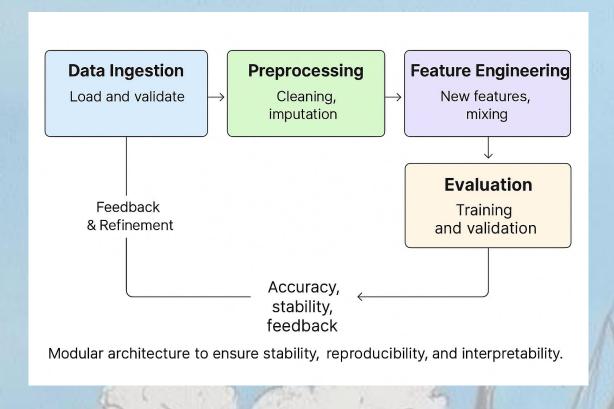
REQUIREMENTS

These requirements ensure that the system is efficient, reliable, easy to maintain and stable.

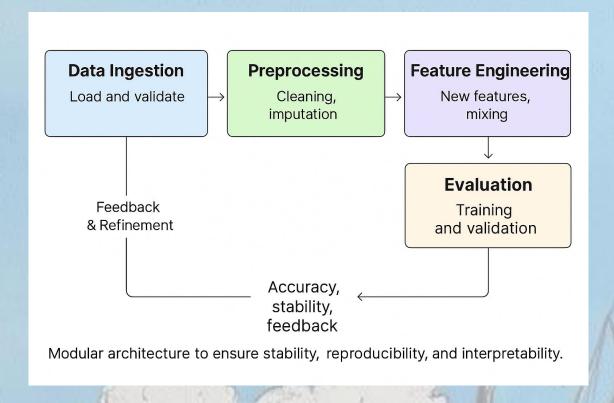
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Table 2: Non-Functional Requirements

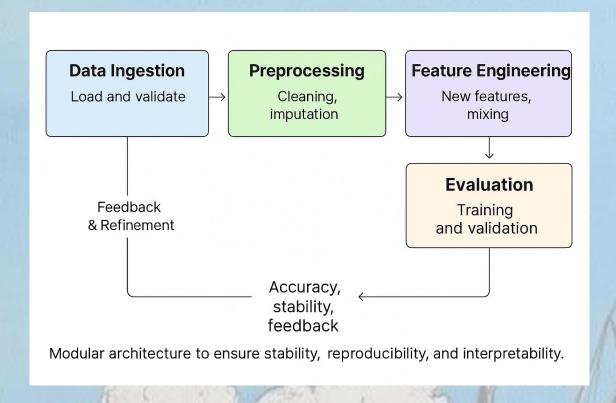




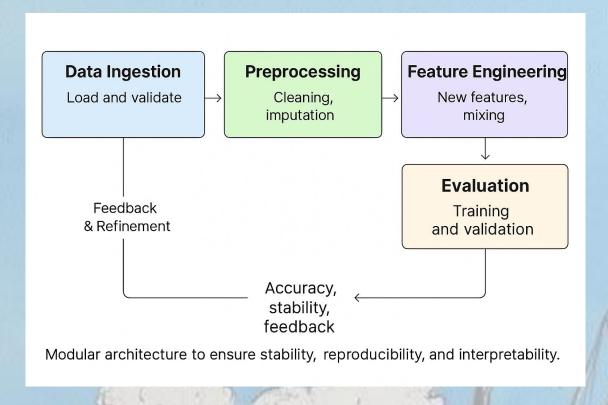
This, managing uncertainty and variability, on the Titanic



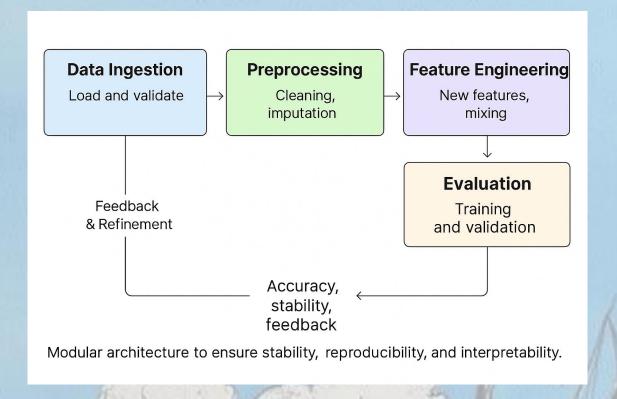
Data Ingestion, where input data is loaded and validated, Preprocessing which cleans, corrects, and transforms information



Feature Engineering, where new variables are created to improve the model's predictive capacity. Model Training, which trains and fine-tunes machine learning algorithms



and Evaluation, which measures performance and generates feedback to optimize the process, ensuring a stable and reproducible workflow.

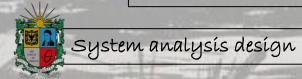


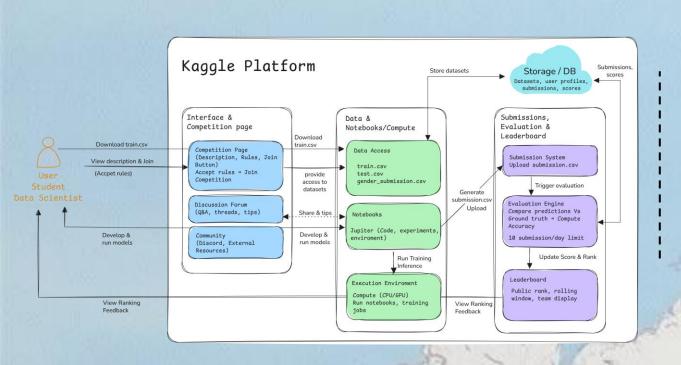
Through...

Include new variables, improving the analysis

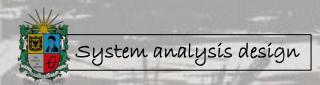
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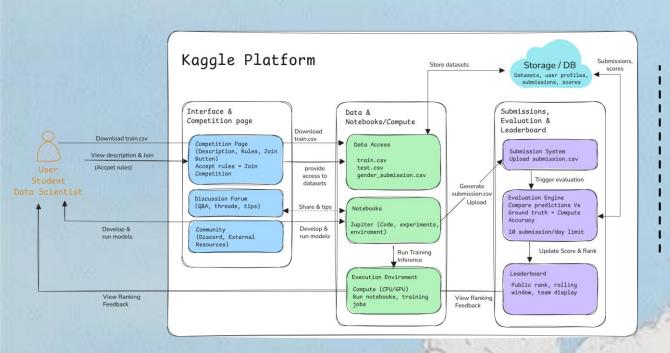
Analyze and adjust the model to unpredictable behavior





TOOLS AND TECHNIQUES

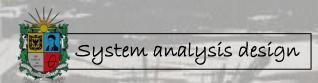


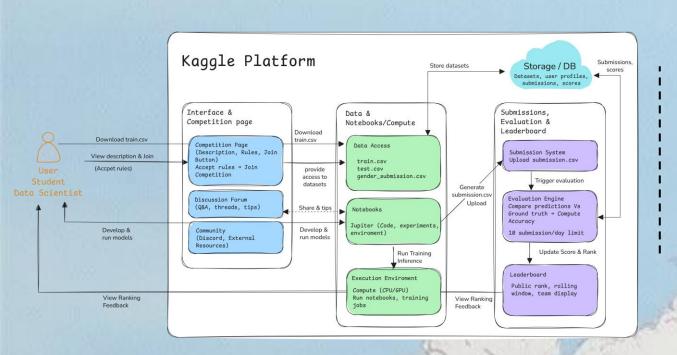


TOOLS AND TECHNIQUES

Using Python as a language

Libraries like Pandas/NumPy



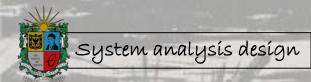


TOOLS AND TECHNIQUES

Using Python as a language

Libraries like Pandas/NumPy Pipeline structure

Works independently but connected



STILL IN PROGRESS...

BIBLIOGRAPHY

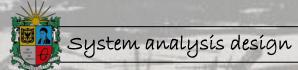
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AUN EN PROGRE

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