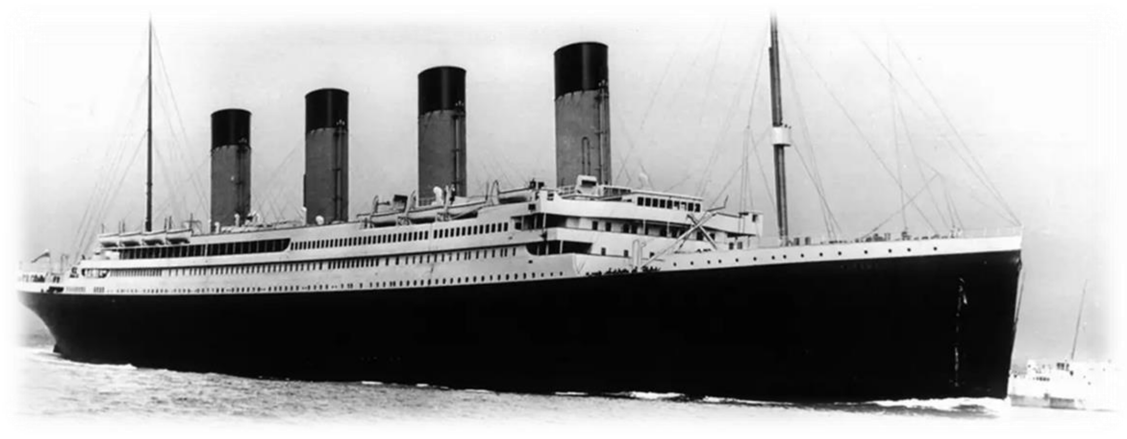
DASC591 - Non-Thesis Master Term Project

Data Science - Koç University - 2022 Fall

Titanic Dataset



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Abstract

In order to realize some of the data science applications on the selected project topic (Titanic Dataset), examinations were made. First of all, what the data looks like and what it consists of is explained and the details of the elements that make up the data are explained. Preparations were made with pre-processing on the visualized data and the influencing features were highlighted. The processed model, which was prepared for the fit and predict processes, was analyzed with various classifiers, and the results were compared within itself. The data of survivors were tried to be estimated without being included in the assessment. When models are run with existing data, prediction and actual data converge. It is ensured that people who live or die are predicted over data. This Project aims to gain practical experience over the "Titanic" dataset, which is frequently used in data science. Within the scope of the course, it is an end-to-end application in which we can see all of the various analysis applications taught during the master's degree. The script and data on which the study was carried out will be attached to this report, and each title that composes the content of this document can be viewed under "Table of Contents" - quoted on the next page.

Table of Contents

1) Introduction

The sinking of the "Titanic" is one of the most tragic tragedies in history. The tragedy took place on April 15th, 1912. The Titanic sank after colliding with an iceberg, killing 1502 out of 2224 passengers. The numbers of survivors were low due to lack of lifeboats for all passengers. Some passengers were more likely to survive than others, such as women, children, and upper-class. This project analyses what sorts of people were likely to survive this tragedy. To achieve this aim, comparisons will be made between the classifier models.

2) Related Work

A competition was held on the Kaggle platform on behalf of Titanic data, and many codes and learning models were shared in this context. The models seem to be very similar to each other, but the features, classifiers and hyperparameters of the developed models vary. In this project, "Survived" feature will be taken as the target function and classifications will be made accordingly.

(Competition Reference: https://www.kaggle.com/c/titanic)

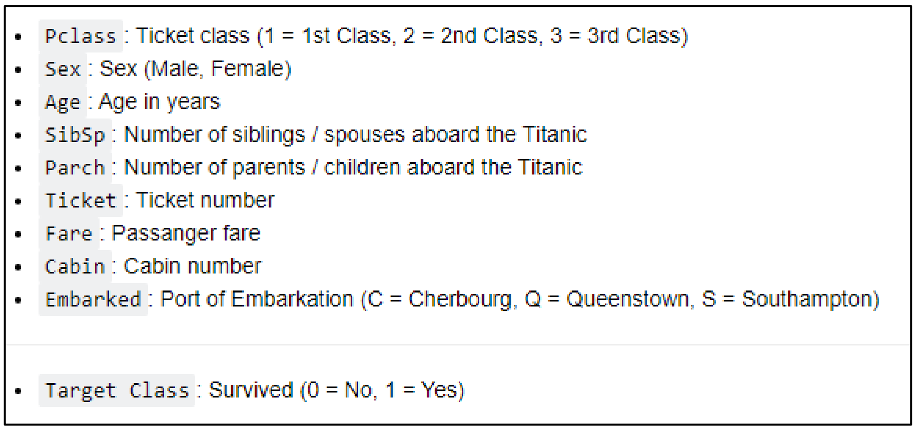
3) Approach

Approaches carried out in parallel with the "Jupyter Notebook" script will be summarized in 15 steps in the following stages.

(Reference: DASC591_NonThesisMasterTermProject_ErsinSONMEZ_Notebook.ipynb)

Step 1: Understand the Problem

In addition to the information given in the "Introduction" section, the data includes the following features, the target class is the "Survived" feature. The details are as follows:

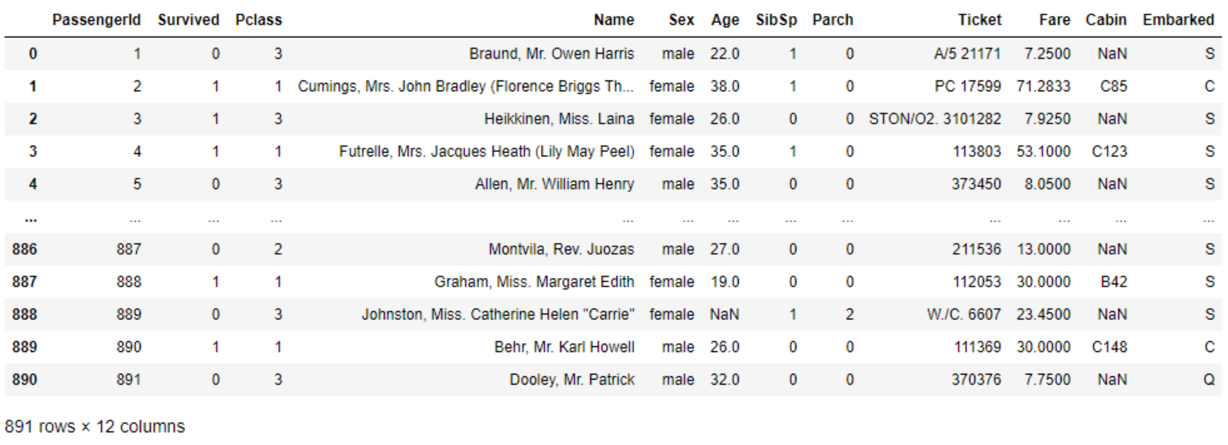


- `Pclass` : Ticket class (1 = 1st Class, 2 = 2nd Class, 3 = 3rd Class)
- `Sex` : Sex (Male, Female)
- `Age` : Age in years
- `SibSp` : Number of siblings / spouses aboard the Titanic
- `Parch` : Number of parents / children aboard the Titanic
- `Ticket` : Ticket number
- `Fare` : Passanger fare
- `Cabin` : Cabin number
- `Embarked` : Port of Embarkation (C = Cherbourg, Q = Queenstown, S = Southampton)

- `Target Class` : Survived (0 = No, 1 = Yes)

Step 2: Import Libraries and Datasets

The basic libraries "Pandas, Numpy, Matplotlib and Seaborn" were used for data manipulations and visualizations, and the "scikit-learn" library and sub-models were used for artificial learning and classification. *(It may be necessary to install with "pip install...")* The dataset is as follows:



	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S
...	...	...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	NaN	Q

891 rows × 12 columns

(With "Pandas Profiling", more detailed data analysis can be accessed, it has been commented in the code, details will not be entered in order not to overshadow the actual work. In the following sections, data will be continued to be analyzed and edited with coding Pandas functions.)

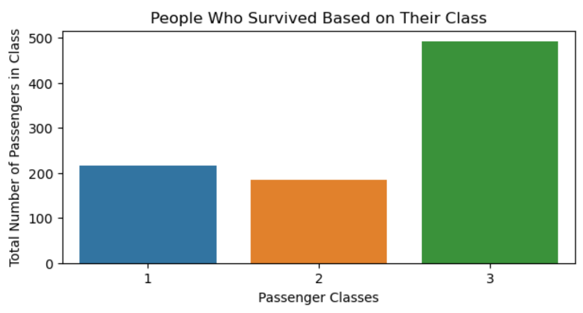
Step 3: Perform Data Visualization

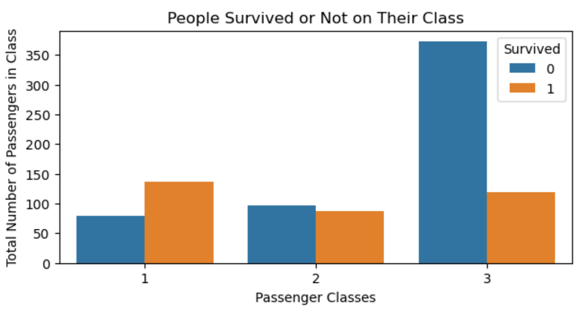
The basic statistics of passengers and the meanings extracted from the data are as follows:

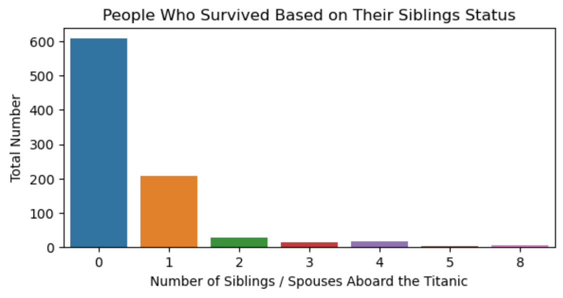
```
Total = 891
----------------------------------------
Number of passengers who survived = 342
Percentage Survived = % 38.38
----------------------------------------
Number of passengers who did not survive = 549
Percentage who did not survive = % 61.62
```

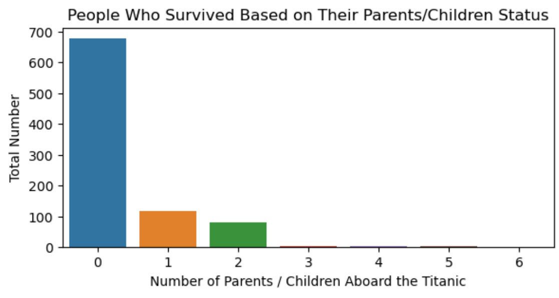
Some inferences supported by visualizations:

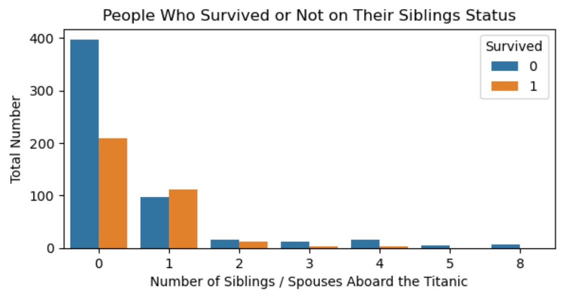
- If you are a first class, you have a higher chance of survival!
- Those who have one sibling seem to have a higher chance of survival than those without a sibling!
- If you have 1, 2, or 3 family members, you have a higher chance of survival compared to being alone!
- If you are a female, you have a higher chance of survival compared to other people!

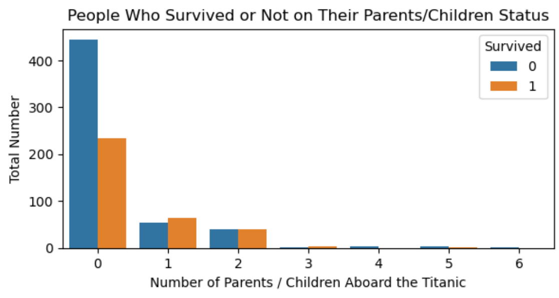


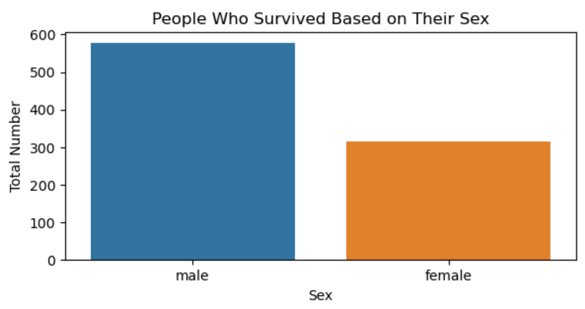


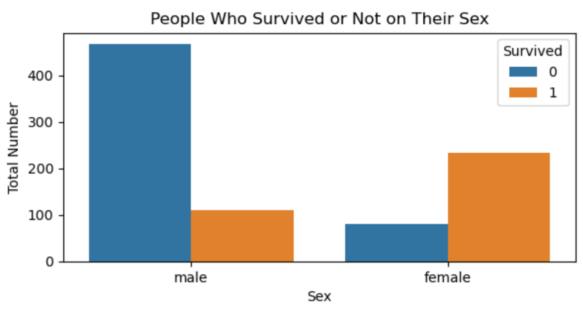




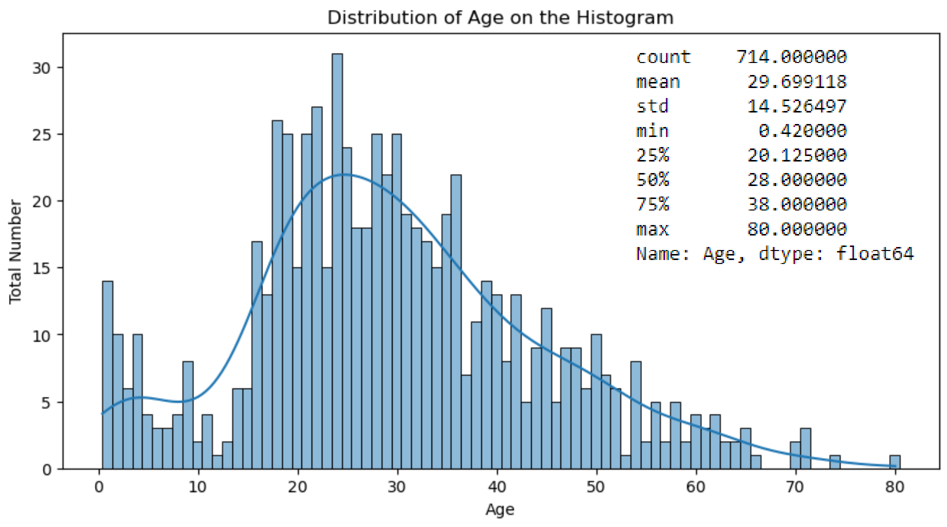






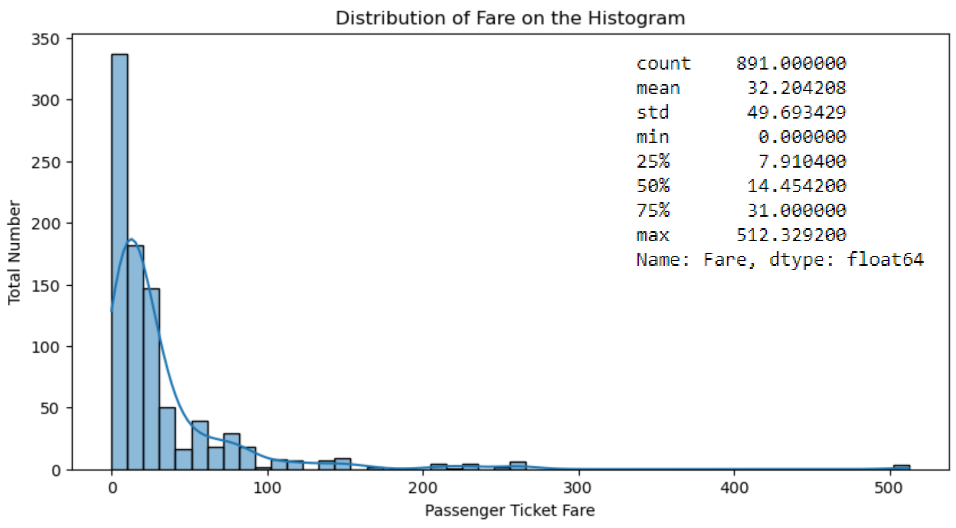


- The average age is around 30 (approx. uniformly), the majority of the passengers on board are young.



```
count    714.000000
mean      29.699118
std       14.526497
min        0.420000
25%       20.125000
50%       28.000000
75%       38.000000
max       80.000000
Name: Age, dtype: float64
```

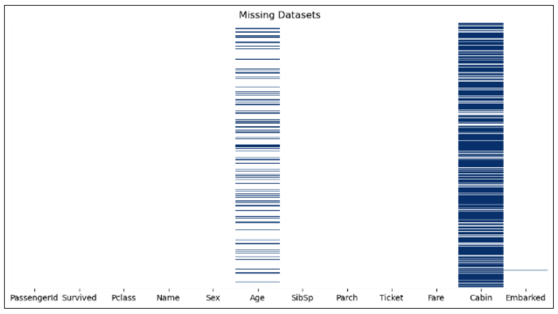
- Many passengers showed interest in affordable tickets, and very few (>500 $) bought expensive tickets. (probably 1st class passengers)



```
count    891.000000
mean      32.204208
std       49.693429
min        0.000000
25%        7.910400
50%       14.454200
75%       31.000000
max      512.329200
Name: Fare, dtype: float64
```

Step 4: Perform Data Cleaning and Feature Engineering

When the missing data was analyzed, a situation as follows was encountered. Columns "Cabin, Name, Ticket, Embarked, PassangerId" were removed from the dataframe. *(It is assumed that the effects of these data on survival are low)* Value assignment was made in the missing data of the column related to "Age". With the written function, instead of missing data, the mean age was accepted as 28 for women and 31 for men. Before this assumption, the distribution of the genders with known data on the "Box Plot" was examined, their average values were calculated and the numerical value was rounded up. After the operations, the dataset has been simplified and converted to numerical values as follows:



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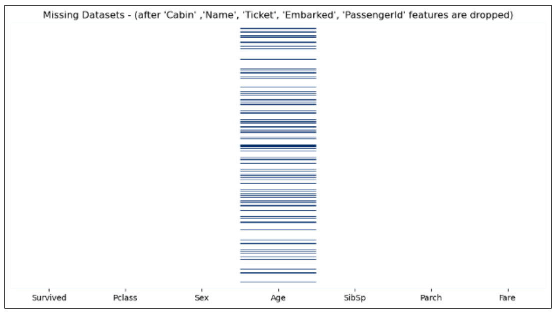
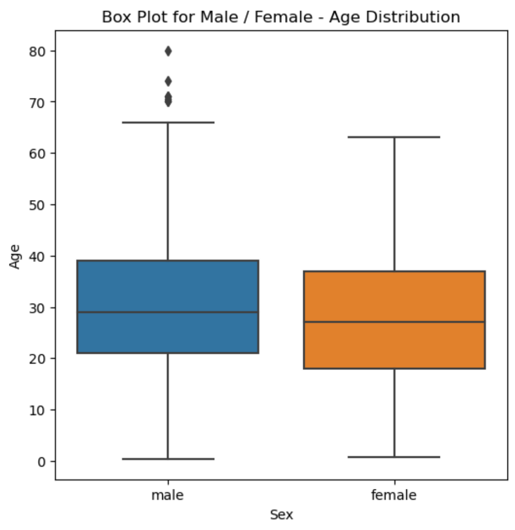
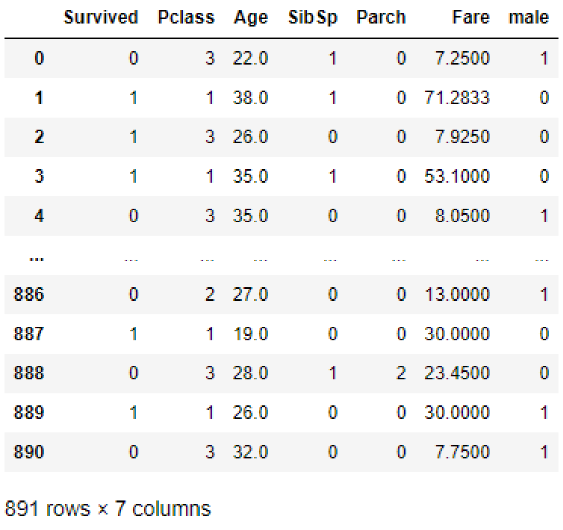






	Survived	Pclass	Age	SibSp	Parch	Fare	male
0	0	3	22.0	1	0	7.2500	1
1	1	1	38.0	1	0	71.2833	0
2	1	3	26.0	0	0	7.9250	0
3	1	1	35.0	1	0	53.1000	0
4	0	3	35.0	0	0	8.0500	1
...	...	...	...	...	...	...	...
886	0	2	27.0	0	0	13.0000	1
887	1	1	19.0	0	0	30.0000	0
888	0	3	28.0	1	2	23.4500	0
889	1	1	26.0	0	0	30.0000	1
890	0	3	32.0	0	0	7.7500	1

891 rows × 7 columns

Step 5: Drop the Target Column Before Splitting

Before the train and test splitting, the target column in the data is dropped. It will be tried to be predicted with the models to be used. (X, y)

Step 6: Train Logistic Regression Classifier Model

The data has been split into test and train so that 30 percent will be divided into tests. In the first case, it will work with the "Logistic Regression" classifier. (X_train, X_test, y_train, y_test)

Step 7: Assess Trained Model Performance for Logistic Regression

This is the part where the model is predicted, the results are transferred onto a confusion matrix. The main outputs are classification report and accuracy. Even if the classifier changes in the following steps, the process will remain the same.

Step 8: Train Naive Bayes Classifier Model

The process is the same as in "Step 6", except that the data is trained according to Naive Bayes.

Step 9: Assess Trained Model Performance for Naive Bayes

The process is the same as in "Step 7", the outputs will be compared in the following sections.

Step 10: Train Decision Tree Classifier Model

It is trained according to "Decision Trees" without changing the basic parameters.

Step 11: Assess Trained Model Performance for Decision Tree

Predictions were created without changing the basic parameters, the outputs will be compared.

Step 12: Hyperparameter Tuning for Decision Tree *(GridSearchCV)*

Since decision trees have many hyperparameters, optimizing them will increase the accuracy of the model and handle overfitting/underfitting problems. For this, the functions of the “GridSearchCV” module are used. It tries to find the optimum of the selected parameters within itself. 5-fold-cross validation is given as the input for the optimization. The best parameters obtained were used as the input of the next classifier. The main purpose is to tune hyperparameters for best results.

Step 13: Train Decision Tree Classifier Model with Optimized Hyperparameter

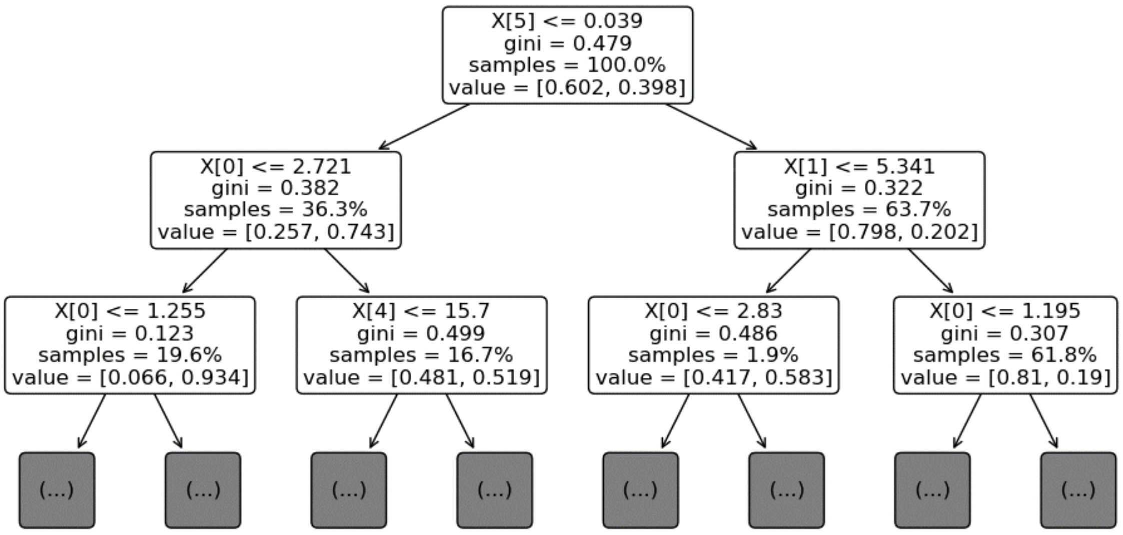
The model was fitted according to the best parameters obtained in the previous step. (Optimized)

Step 14: Optimized Trained Model Performance for Decision Tree

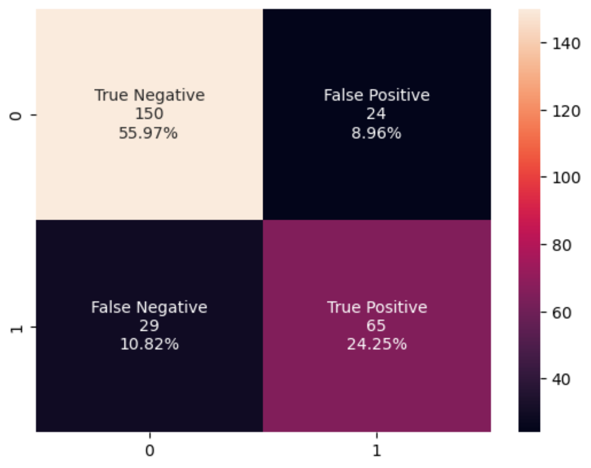
“Optimized Decision Tree” is saved to evaluate predictions and metrics, outputs will be compared.

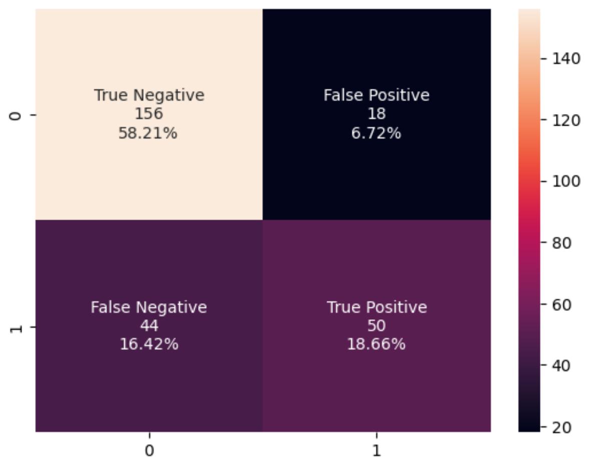
Step 15: Comparison of Classifier Models and Results

A summary visualization of the "Optimized Decision Tree" is as follows, because it branches too much, it's down to the 2nd maximum depth. The decision tree presents the idea of the classifier.

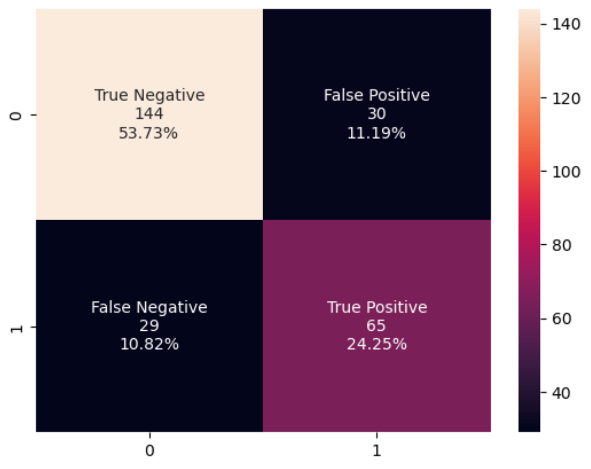


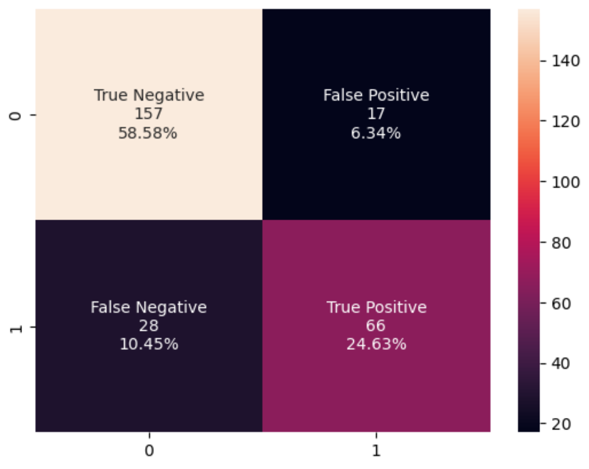
[Logistic Regression Classifier Model] vs. **[Naive Bayes Classifier Model]**





[Decision Tree Classifier Model] vs. **[Decision Tree Classifier Model (with Optimized)]**





4) Implementation Details

When it comes to data science and learning models, the first thing that comes to mind is fast applicability and access to resources. “Jupyter Notebook” is also a pretty useful IDE here. It has been preferred because it is web-based, can provide interactive outputs and is lightweight. Many libraries come preloaded with "Anaconda" in the environment settings. Most of the online training resources and repositories provide fast implementation for this notebook. For this reason, it has been preferred.

(Note: For the notebook to work properly, the "titanic.csv" dataset must be in the same directory as the script.)

5) Evaluation Details, Results and Analysis/Discussion

While comparing the scores of the models, the outputs of the classifiers were taken into account. In other words, confusion matrices are an evaluation criterion for our project. The Accuracy metric is also a score shared by each, calculated as follows: (True Positive, True Negative, False Positive, False Negative)

accuracy (ACC)

$$\mathrm{ACC} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{P}+\mathrm{N}} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}}$$

When Accuracy is calculated for all models, a summary table is obtained from the script as follows:

```
- Logistic Regression --> Accuracy Score: 0.802
- Naive Bayes --> Accuracy Score: 0.769
- Decision Tree (unoptimized) --> Accuracy Score: 0.78
- Decision Tree (optimized) --> Accuracy Score: 0.832
```

Some important outputs and notes:

- As a result of tuning the hyperparameters, the accuracy of the decision tree has increased in line with the expectations. Diagonals TN and TP in confusion matrices were able to capture more accurate predictions, thus increasing accuracy. Parameters can also be tuned for other models.
- Splitting the Test/Train sets at different rates (30% - 20%) causes minor differences.
- When the data set is considered numerically, it generally showed a uniform distribution. In parallel, the models work linearly in the spaces they are trained in.
- In this project, all of the classifiers examined give fast results, there are no bottlenecks that slow down the model. The entire script can deliver output in seconds, Resource consumption is low.
- The highest score was obtained from the "Decision Tree (Optimized)" model with 0.832 ACC.

6) Conclusion

In addition to the predictions processed in the project, when the competition examples transferred on the "Kaggle" platform are examined, it is seen that the success scores are high. I have observed that scores of 0.8 and above provide ideas with sufficient accuracy. In the future, the missing data in the model (except age) may need to be processed with different methods instead of removing them from the data set. Thus, better models can be developed through more features, categorical data can be added to the models, synthetic data can be created, and deep learning can be applied.

7) References

- Kaggle, Coursera, Lecture Notes and Applications, Python Cheat Sheets etc.