Politecnico di Milano and Università degli Studi di Milano

```
# Core libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import missingno as msno
import re

# Preprocessing and imputation
from sklearn.preprocessing import PolynomialFeatures, StandardScaler,
MinMaxScaler, OneHotEncoder
from sklearn.impute import KNNImputer
from imblearn.over_sampling import SMOTENC

# Model selection and validation tools
from sklearn.model_selection import (train_test_split, KFold,
StratifiedKFold,
                                     GridSearchCV, RandomizedSearchCV,
cross_val_score,
                                     validation_curve, ParameterGrid)

# Machine Learning Models
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import RandomForestClassifier,
GradientBoostingClassifier, BaggingClassifier
from sklearn.svm import SVC
from sklearn.metrics import precision_score, recall_score,
confusion_matrix, f1_score, accuracy_score,classification_report

# Advanced Modeling and Optimization
from scipy import stats
from scipy.stats import wasserstein_distance, randint, uniform
from bayes_opt import BayesianOptimization
from sklearn.ensemble import RandomForestClassifier,
RandomForestRegressor
from sklearn.model_selection import train_test_split


from sklearn.exceptions import ConvergenceWarning  # Import the
specific warning
import warnings

# Suppress convergence and other runtime warnings
warnings.filterwarnings("ignore", category=ConvergenceWarning)
```

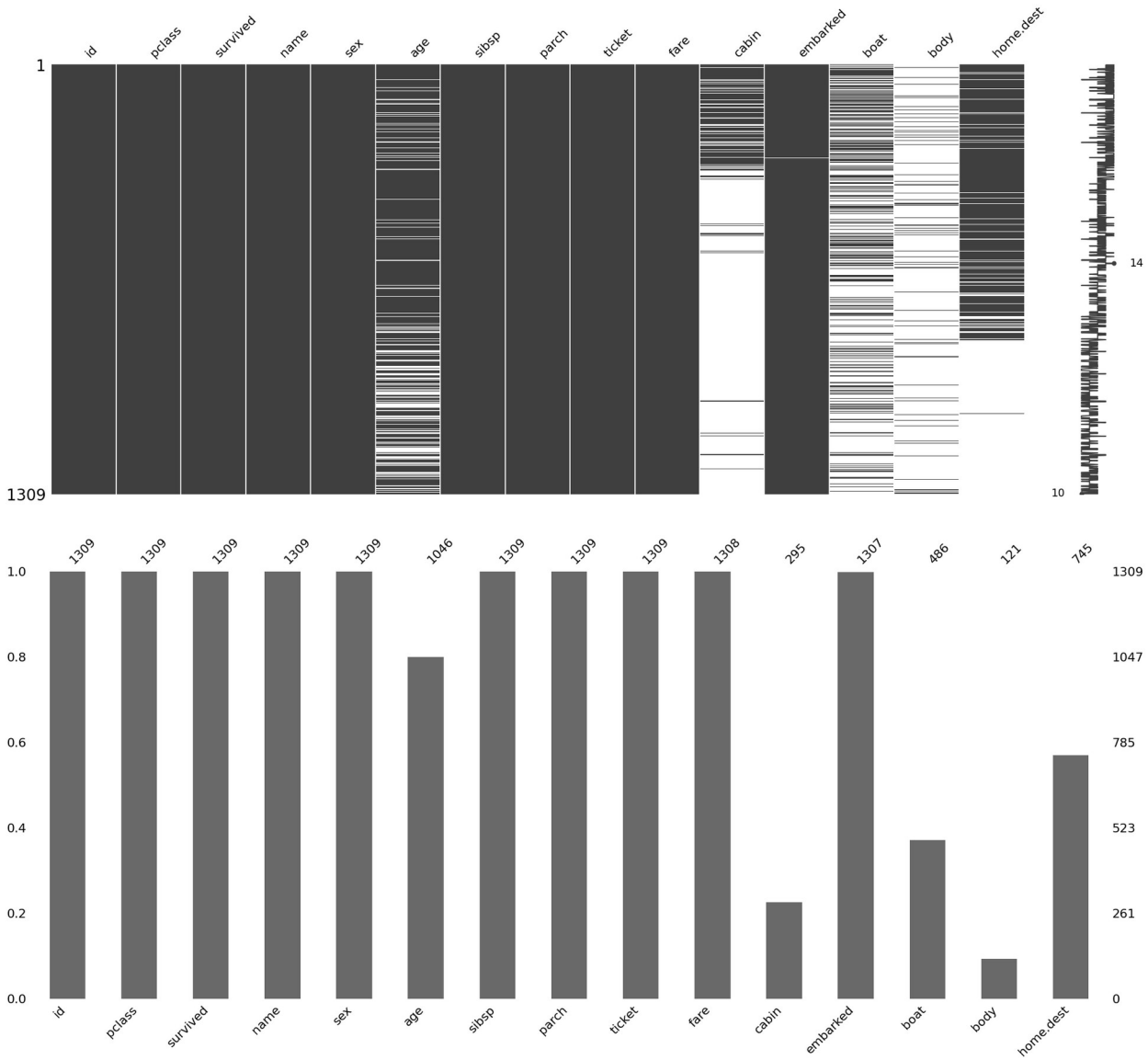
```
<frozen importlib._bootstrap>:241: RuntimeWarning:
scipy._lib.messagestream.MessageStream size changed, may indicate
binary incompatibility. Expected 56 from C header, got 64 from
PyObject
```

```
# Read the initial dataset
data = pd.read_csv('/Users/Sam/Desktop/Titanic/titanic.csv')

# Correct column names
correct_columns = ['id','pclass', 'survived', 'name', 'sex', 'age',
'sibsp', 'parch', 'ticket', 'fare', 'cabin', 'embarked', 'boat',
'body', 'home.dest']

# Load the dataset with the correct column names
data = pd.read_csv('titanic.csv', names=correct_columns, header=0)

# replace '?' with NaN
data = data.replace('?', np.nan)
data.head(100)
```

```
     id  pclass  survived
name  \
0     1       1         1                         Allen,Miss. Elisabeth
Walton
1     2       1         1                       Allison,Master. Hudson
Trevor
2     3       1         0                         Allison,Miss. Helen
Loraine
3     4       1         0                  Allison,Mr. Hudson Joshua
Creighton
4     5       1         0     Allison,Mrs. Hudson J C (Bessie Waldo
Daniels)
..  ...     ...       ...
...
95   96       1         1                Dodge,Mrs. Washington (Ruth
Vidaver)
96   97       1         0                             Douglas,Mr. Walter
Donald
97   98       1         1  Douglas,Mrs. Frederick Charles (Mary Helene
Ba...
98   99       1         1         Douglas,Mrs. Walter Donald (Mahala
Dutton)
99  100       1         1  Duff Gordon,Lady. (Lucille Christiana
Sutherla...

       sex     age  sibsp  parch    ticket      fare    cabin embarked
boat  \
0   female      29      0      0     24160  211.3375       B5        S
2
1     male  0.9167      1      2    113781    151.55  C22 C26        S
```

```
11
2   female       2      1      2    113781    151.55  C22 C26        S
NaN
3     male      30      1      2    113781    151.55  C22 C26        S
NaN
4   female      25      1      2    113781    151.55  C22 C26        S
NaN
..     ...     ...    ...    ...       ...       ...      ...      ...
...
95  female      54      1      1     33638   81.8583      A34        S
5
96    male      50      1      0  PC 17761   106.425      C86        C
NaN
97  female      27      1      1  PC 17558  247.5208  B58 B60        C
6
98  female      48      1      0  PC 17761   106.425      C86        C
2
99  female      48      1      0     11755      39.6      A16        C
1

   body                        home.dest
0   NaN                     St Louis,MO
1   NaN   Montreal,PQ / Chesterville,ON
2   NaN   Montreal,PQ / Chesterville,ON
3   135   Montreal,PQ / Chesterville,ON
4   NaN   Montreal,PQ / Chesterville,ON
..  ...                             ...
95  NaN                San Francisco,CA
96   62  Deephaven,MN / Cedar Rapids,IA
97  NaN                     Montreal,PQ
98  NaN  Deephaven,MN / Cedar Rapids,IA
99  NaN                   London / Paris

[100 rows x 15 columns]
```

```
# Visual matrix of missing values
msno.matrix(data)
plt.show()

# Bar chart of missing values
msno.bar(data)
plt.show()
```

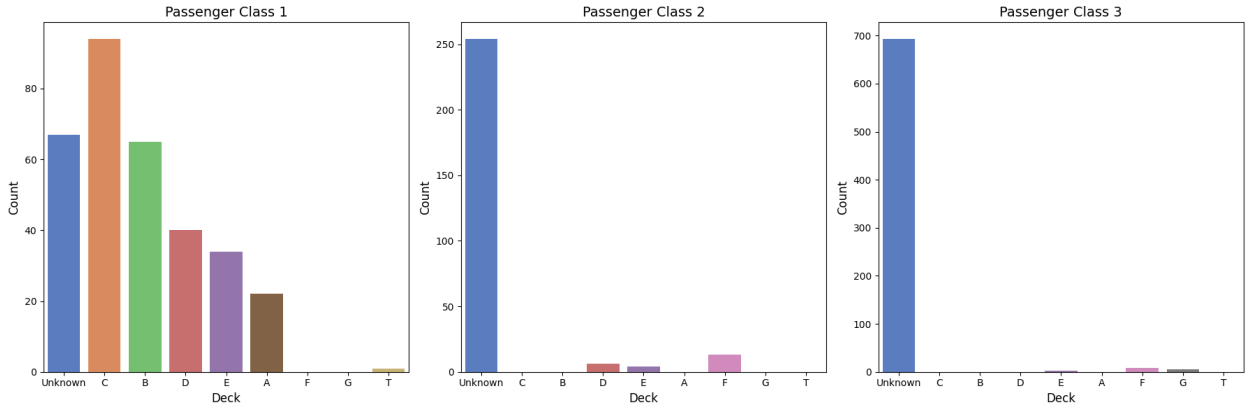


Deeling with column cabin (Finding a way to salvage the available information)

```
# Extract the first letter of the 'Cabin' column to get the deck
data['Deck'] = data['cabin'].str[0]

# Replace NaN values in 'Deck' with 'Unknown'
data['Deck'].fillna('Unknown', inplace=True)

# Create a list of passenger classes
classes = [1, 2, 3]

# Initialize the plot
plt.figure(figsize=(18, 6))

# Plot for each class
```

```
for i, passenger_class in enumerate(classes, 1):
    plt.subplot(1, 3, i)
    sns.countplot(data=data[data['pclass'] == passenger_class],
x='Deck', order=data['Deck'].value_counts().index, palette='muted')
    plt.title(f'Passenger Class {passenger_class}', fontsize=14)
    plt.xlabel('Deck', fontsize=12)
    plt.ylabel('Count', fontsize=12)

# Adjust layout
plt.tight_layout()

# Show the plot
plt.show()
```

```
/var/folders/gt/zql8qzpj6cj8n0_p_zjc053m0000gp/T/
ipykernel_1450/2965354133.py:16: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(data=data[data['pclass'] == passenger_class],
x='Deck', order=data['Deck'].value_counts().index, palette='muted')
/var/folders/gt/zql8qzpj6cj8n0_p_zjc053m0000gp/T/ipykernel_1450/296535
4133.py:16: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(data=data[data['pclass'] == passenger_class],
x='Deck', order=data['Deck'].value_counts().index, palette='muted')
/var/folders/gt/zql8qzpj6cj8n0_p_zjc053m0000gp/T/ipykernel_1450/296535
4133.py:16: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(data=data[data['pclass'] == passenger_class],
x='Deck', order=data['Deck'].value_counts().index, palette='muted')
```




```
data.head()
```

```
   id  pclass  survived
name  \
0   1       1         1                     Allen,Miss. Elisabeth
Walton
1   2       1         1                    Allison,Master. Hudson
Trevor
2   3       1         0                      Allison,Miss. Helen
Loraine
3   4       1         0             Allison,Mr. Hudson Joshua
Creighton
4   5       1         0  Allison,Mrs. Hudson J C (Bessie Waldo
Daniels)

      sex      age  sibsp  parch  ticket      fare    cabin embarked
boat body  \
0  female       29      0      0   24160  211.3375       B5        S
2  NaN
1    male   0.9167      1      2  113781    151.55  C22 C26        S
11  NaN
2  female        2      1      2  113781    151.55  C22 C26        S
NaN  NaN
3    male       30      1      2  113781    151.55  C22 C26        S
NaN  135
4  female       25      1      2  113781    151.55  C22 C26        S
NaN  NaN

                        home.dest Deck
0                     St Louis,MO    B
1  Montreal,PQ / Chesterville,ON    C
2  Montreal,PQ / Chesterville,ON    C
3  Montreal,PQ / Chesterville,ON    C
4  Montreal,PQ / Chesterville,ON    C
```

```
# drop column cabin
data.drop('cabin', axis=1, inplace=True)
```

Based on historical sources we made the hypothesis of dividing the unknown location of second class passengers on deck C D and E respectively 5%, 30% and 65%. For third class passengers the hypothesis is to divide unknown location between deck E, F and G as follows: 10% deck E, 40% deck F and 50% deck G.

Sources:

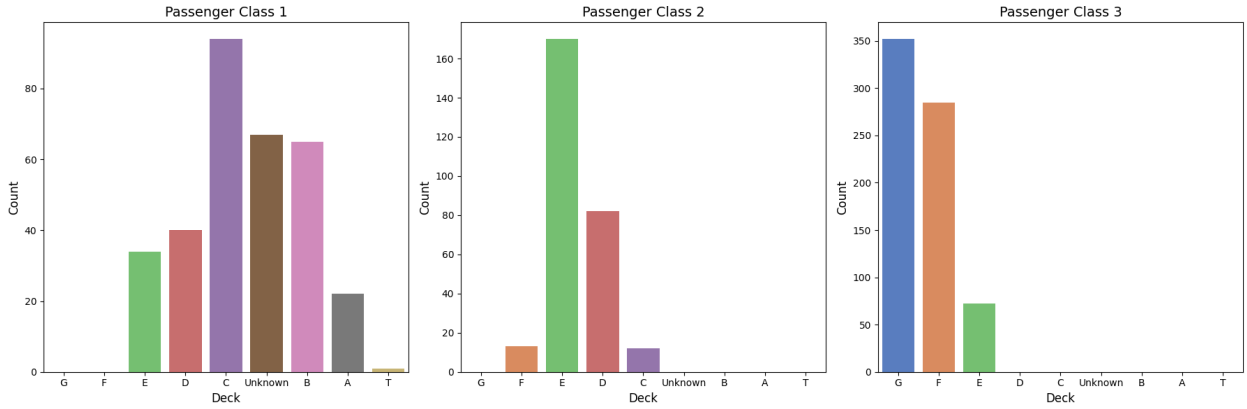
- "Titanic: The Ship Magnificent" by Bruce Beveridge and Steve Hall
- "Titanic: A Night Remembered" by Stephanie Barczewski
- "Titanic: The Official Story" by the British National Archives
- Encyclopedia Titanica

```
# Filter the dataset to only include second-class passengers
second_class_df = data[data['pclass'] == 2]

# Calculate the number of 'Unknown' values in the 'Deck' column for
second-class passengers
unknown_count = second_class_df[second_class_df['Deck'] ==
'Unknown'].shape[0]

# Calculate the allocation for each deck based on the percentage
estimates
c_deck_allocation = int(0.05 * unknown_count)
d_deck_allocation = int(0.30 * unknown_count)
e_deck_allocation = unknown_count - c_deck_allocation -
d_deck_allocation  # Remaining goes to E Deck

# Get the indices of the 'Unknown' deck values
unknown_indices = second_class_df[second_class_df['Deck'] ==
'Unknown'].index

# Assign the deck values based on the calculated allocations
data.loc[unknown_indices[:c_deck_allocation], 'Deck'] = 'C'
data.loc[unknown_indices[c_deck_allocation:c_deck_allocation +
d_deck_allocation], 'Deck'] = 'D'
data.loc[unknown_indices[c_deck_allocation + d_deck_allocation:],
'Deck'] = 'E'

# Filter the dataset to only include third-class passengers
third_class_df = data[data['pclass'] == 3]

# Calculate the number of 'Unknown' values in the 'Deck' column for
third-class passengers
unknown_count = third_class_df[third_class_df['Deck'] ==
'Unknown'].shape[0]

# Calculate the allocation for each deck based on the percentage
estimates
```

```
e_deck_allocation = int(0.10 * unknown_count)
f_deck_allocation = int(0.40 * unknown_count)
g_deck_allocation = unknown_count - e_deck_allocation -
f_deck_allocation  # Remaining goes to G Deck

# Get the indices of the 'Unknown' deck values
unknown_indices = third_class_df[third_class_df['Deck'] ==
'Unknown'].index

# Assign the deck values based on the calculated allocations
data.loc[unknown_indices[:e_deck_allocation], 'Deck'] = 'E'
data.loc[unknown_indices[e_deck_allocation:e_deck_allocation +
f_deck_allocation], 'Deck'] = 'F'
data.loc[unknown_indices[e_deck_allocation + f_deck_allocation:],
'Deck'] = 'G'

# Initialize the plot
plt.figure(figsize=(18, 6))

# Plot for each class
for i, passenger_class in enumerate(classes, 1):
    plt.subplot(1, 3, i)
    sns.countplot(data=data[data['pclass'] == passenger_class],
x='Deck', order=data['Deck'].value_counts().index, palette='muted')
    plt.title(f'Passenger Class {passenger_class}', fontsize=14)
    plt.xlabel('Deck', fontsize=12)
    plt.ylabel('Count', fontsize=12)

# Adjust layout
plt.tight_layout()

# Show the plot
plt.show()
```

```
/var/folders/gt/zql8qzpj6cj8n0_p_zjc053m0000gp/T/
ipykernel_1450/1667296542.py:7: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(data=data[data['pclass'] == passenger_class],
x='Deck', order=data['Deck'].value_counts().index, palette='muted')
/var/folders/gt/zql8qzpj6cj8n0_p_zjc053m0000gp/T/ipykernel_1450/166729
6542.py:7: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(data=data[data['pclass'] == passenger_class],
```

```
x='Deck', order=data['Deck'].value_counts().index, palette='muted')
/var/folders/gt/zql8qzpj6cj8n0_p_zjc053m0000gp/T/ipykernel_1450/166729
6542.py:7: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(data=data[data['pclass'] == passenger_class],
x='Deck', order=data['Deck'].value_counts().index, palette='muted')
```



Deeling wiht column Name: trying to extract socio-economical information from the available titles

```python
# Define a function to extract the title from the name
def extract_title(name):
    title_search = re.search(r',\s*([^.]*)\.', name)
    if title_search:
        return title_search.group(1).strip()
    return "Unknown"

# Extract titles from the "Name" column
data['Title'] = data['name'].apply(extract_title)

# Print unique titles to debug
unique_titles = data['Title'].unique()
print("Unique titles in the dataset:", unique_titles)

# Define a mapping of titles to social status
title_mapping = {
    'Mr': 'Commoner', 'Mrs': 'Commoner', 'Miss': 'Commoner', 'Master':
'Commoner',
    'Don': 'Nobility', 'Rev': 'Clergy', 'Dr': 'Professional', 'Mme':
'Commoner',
    'Ms': 'Commoner', 'Major': 'Military', 'Lady': 'Nobility', 'Sir':
'Nobility',
    'Mlle': 'Commoner', 'Col': 'Military', 'Capt': 'Military',
```

```
'Countess': 'Nobility',
    'Jonkheer': 'Nobility', 'Dona': 'Nobility'
}

# Map the titles to social status
data['SocialStatus'] = data['Title'].map(title_mapping)

# Fill NaN values with 'Unknown' for SocialStatus
data['SocialStatus'].fillna('Unknown', inplace=True)

# Display the first few rows to verify the new column
print(data[['name', 'Title', 'SocialStatus']].head(20))
```

```
Unique titles in the dataset: ['Miss' 'Master' 'Mr' 'Mrs' 'Col' 'Mme'
'Dr' 'Major' 'Capt' 'Lady' 'Sir'
 'Mlle' 'Dona' 'Jonkheer' 'the Countess' 'Don' 'Rev' 'Ms']
                                                 name   Title
SocialStatus
0                       Allen,Miss. Elisabeth Walton    Miss
Commoner
1                      Allison,Master. Hudson Trevor  Master
Commoner
2                        Allison,Miss. Helen Loraine    Miss
Commoner
3                 Allison,Mr. Hudson Joshua Creighton      Mr
Commoner
4     Allison,Mrs. Hudson J C (Bessie Waldo Daniels)     Mrs
Commoner
5                                  Anderson,Mr. Harry      Mr
Commoner
6                     Andrews,Miss. Kornelia Theodosia    Miss
Commoner
7                               Andrews,Mr. Thomas Jr      Mr
Commoner
8       Appleton,Mrs. Edward Dale (Charlotte Lamson)     Mrs
Commoner
9                             Artagaveytia,Mr. Ramon      Mr
Commoner
10                             Astor,Col. John Jacob     Col
Military
11  Astor,Mrs. John Jacob (Madeleine Talmadge Force)     Mrs
Commoner
12                       Aubart,Mme. Leontine Pauline     Mme
Commoner
13                        Barber,Miss. Ellen 'Nellie'    Miss
Commoner
14                Barkworth,Mr. Algernon Henry Wilson      Mr
Commoner
15                                 Baumann,Mr. John D      Mr
Commoner
```

```
16                              Baxter,Mr. Quigg Edmond      Mr
Commoner
17    Baxter,Mrs. James (Helene DeLaudeniere Chaput)     Mrs
Commoner
18                                 Bazzani,Miss. Albina    Miss
Commoner
19                                  Beattie,Mr. Thomson      Mr
Commoner

# drop column name
data.drop('name', axis=1, inplace=True)

data.head()

   id  pclass  survived     sex     age  sibsp  parch  ticket
fare  \
0   1       1         1  female      29      0      0   24160
211.3375
1   2       1         1    male  0.9167      1      2  113781
151.55
2   3       1         0  female       2      1      2  113781
151.55
3   4       1         0    male      30      1      2  113781
151.55
4   5       1         0  female      25      1      2  113781
151.55

  embarked boat body                        home.dest Deck   Title
SocialStatus
0        S    2  NaN                     St Louis,MO    B    Miss
Commoner
1        S   11  NaN  Montreal,PQ / Chesterville,ON    C  Master
Commoner
2        S  NaN  NaN  Montreal,PQ / Chesterville,ON    C    Miss
Commoner
3        S  NaN  135  Montreal,PQ / Chesterville,ON    C      Mr
Commoner
4        S  NaN  NaN  Montreal,PQ / Chesterville,ON    C     Mrs
Commoner
```

Dealing with body (it is a subtitute of the response, it makes no sense keeping it in)

```
# drop column body
data.drop('body', axis=1, inplace=True)
data.head()

   id  pclass  survived     sex     age  sibsp  parch  ticket
fare  \
0   1       1         1  female      29      0      0   24160
211.3375
```

```
1   2       1         1    male  0.9167      1      2  113781
151.55
2   3       1         0  female       2      1      2  113781
151.55
3   4       1         0    male      30      1      2  113781
151.55
4   5       1         0  female      25      1      2  113781
151.55

  embarked boat                      home.dest Deck   Title
SocialStatus
0        S    2                    St Louis,MO    B    Miss
Commoner
1        S   11  Montreal,PQ / Chesterville,ON    C  Master
Commoner
2        S  NaN  Montreal,PQ / Chesterville,ON    C    Miss
Commoner
3        S  NaN  Montreal,PQ / Chesterville,ON    C      Mr
Commoner
4        S  NaN  Montreal,PQ / Chesterville,ON    C     Mrs
Commoner
```

Dealing with home.dest (non relevance of the column)

```
# drop column body
data.drop('home.dest', axis=1, inplace=True)
data.head()

   id  pclass  survived     sex     age  sibsp  parch  ticket
fare  \
0   1       1         1  female      29      0      0   24160
211.3375
1   2       1         1    male  0.9167      1      2  113781
151.55
2   3       1         0  female       2      1      2  113781
151.55
3   4       1         0    male      30      1      2  113781
151.55
4   5       1         0  female      25      1      2  113781
151.55

  embarked boat Deck   Title SocialStatus
0        S    2    B    Miss     Commoner
1        S   11    C  Master     Commoner
2        S  NaN    C    Miss     Commoner
3        S  NaN    C      Mr     Commoner
4        S  NaN    C     Mrs     Commoner
```

Dealing with id (non relevant)

```
# drop column body
data.drop('id', axis=1, inplace=True)
data.head()
```

```
   pclass  survived     sex     age  sibsp  parch  ticket      fare
embarked  \
0       1         1  female      29      0      0   24160  211.3375
S
1       1         1    male  0.9167      1      2  113781    151.55
S
2       1         0  female       2      1      2  113781    151.55
S
3       1         0    male      30      1      2  113781    151.55
S
4       1         0  female      25      1      2  113781    151.55
S

  boat Deck   Title SocialStatus
0    2    B    Miss     Commoner
1   11    C  Master     Commoner
2  NaN    C    Miss     Commoner
3  NaN    C      Mr     Commoner
4  NaN    C     Mrs     Commoner
```

Dealing with boat (it is a substitute of the response, it makes no sense keeping it in)

```
# drop column body
data.drop('boat', axis=1, inplace=True)
data.head()
```

```
   pclass  survived     sex     age  sibsp  parch  ticket      fare
embarked  \
0       1         1  female      29      0      0   24160  211.3375
S
1       1         1    male  0.9167      1      2  113781    151.55
S
2       1         0  female       2      1      2  113781    151.55
S
3       1         0    male      30      1      2  113781    151.55
S
4       1         0  female      25      1      2  113781    151.55
S

  Deck   Title SocialStatus
0    B    Miss     Commoner
1    C  Master     Commoner
2    C    Miss     Commoner
3    C      Mr     Commoner
4    C     Mrs     Commoner
```

Dealing with ticket (non relevant)

```
# drop column body
data.drop('ticket', axis=1, inplace=True)
data.head()
```

```
   pclass  survived     sex     age  sibsp  parch      fare embarked
Deck  \
0       1         1  female      29      0      0  211.3375        S
B
1       1         1    male  0.9167      1      2    151.55        S
C
2       1         0  female       2      1      2    151.55        S
C
3       1         0    male      30      1      2    151.55        S
C
4       1         0  female      25      1      2    151.55        S
C

    Title SocialStatus
0    Miss     Commoner
1  Master     Commoner
2    Miss     Commoner
3      Mr     Commoner
4     Mrs     Commoner
```

Apparently deck T is an error of data gathering since there is no historical source that refers to a deck T

```
# Drop rows with Deck == 'T'
data = data[data['Deck'] != 'T']
```

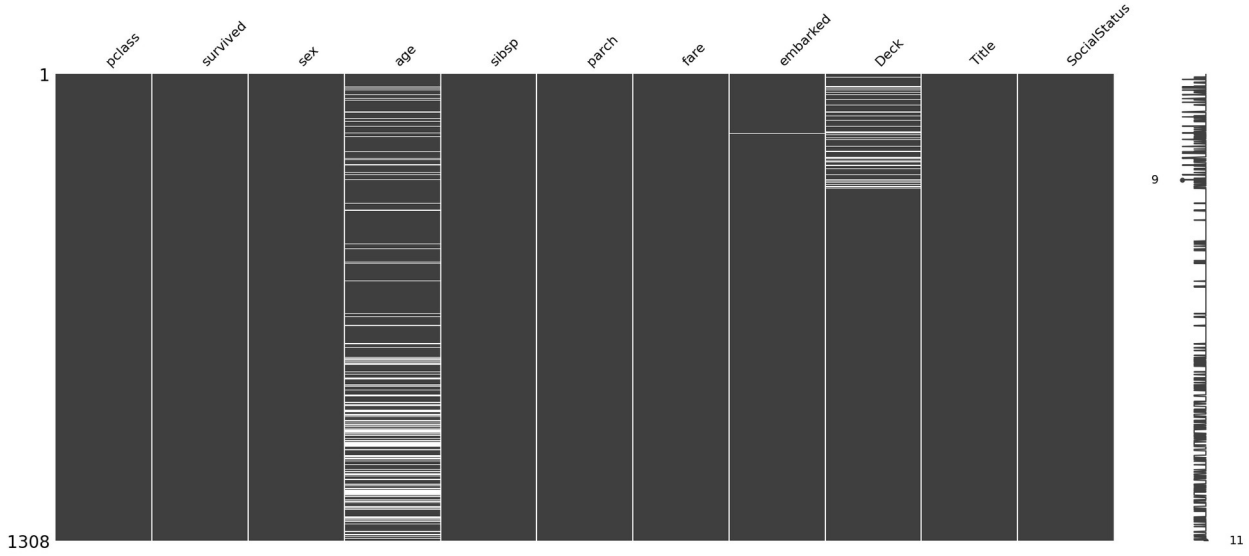
Categorization of variables

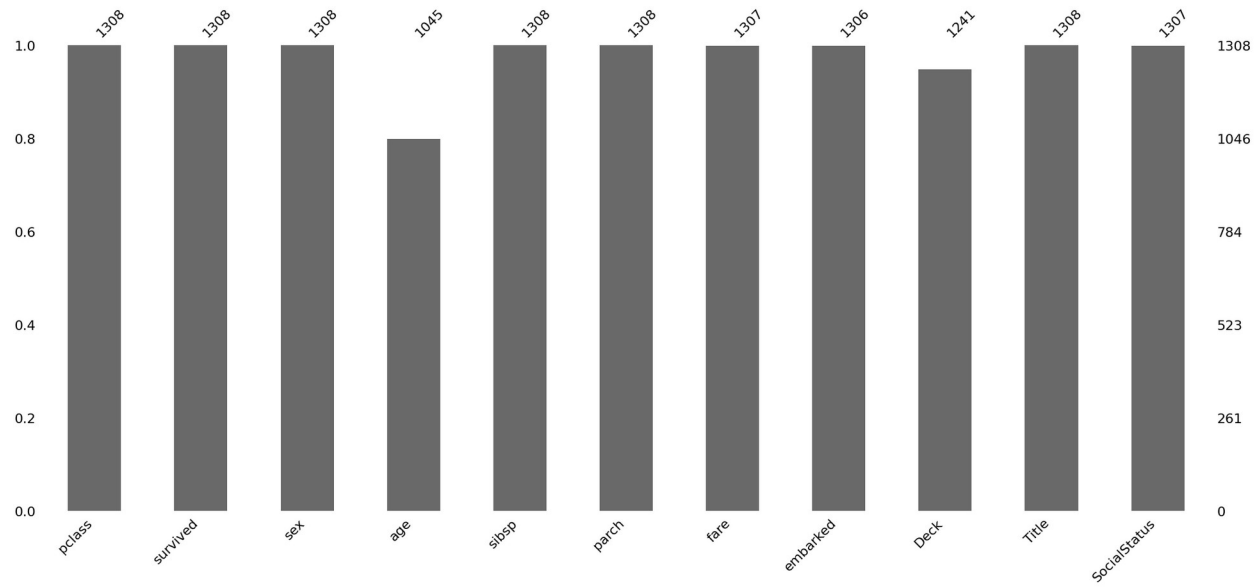
```
# Replace 'female' with 0 and 'male' with 1 in the 'sex' column
data['sex'] = data['sex'].replace({'female': 0, 'male': 1})

# Replace 'C' with 0, 'Q' with 1, and 'S' with 2 in the 'embarked'
column
data['embarked'] = data['embarked'].replace({'C': 0, 'Q': 1, 'S': 2})

# Replace 'A' with 0, 'B' with 1, 'C' with 2, 'D' with 3, 'E' with 4,
'F' with 5, 'G' with 6, 'T' with 7, and 'Unknown' with Nan
data['Deck'] = data['Deck'].replace({'A': 0, 'B': 1, 'C': 2, 'D': 3,
'E': 4, 'F': 5, 'G': 6, 'Unknown': np.nan})

# Replace Title: 'Miss' with 0, 'Mr' with 1, 'Mrs' with 2, 'Master'
with 3, 'Dr' with 4, 'Rev' with 5, 'Col' with 6, 'Mlle' with 7,
'Major' with 8, 'Capt' with 9, 'Sir' with 10, 'Jonkheer' with 11,
'Lady' with 12, 'Don' with 13, 'Mme' with 14, 'Countess' with 15, 'Ms'
```

```
with 16, 'Dona' with 17
data['Title'] = data['Title'].replace({'Miss': 0, 'Mr': 1, 'Mrs': 2,
'Master': 3, 'Dr': 4, 'Rev': 5, 'Col': 6, 'Mlle': 7, 'Major': 8,
'Capt': 9, 'Sir': 10, 'Jonkheer': 11, 'Lady': 12, 'Don': 13, 'Mme':
14, 'the Countess': 15, 'Ms': 16, 'Dona': 17})

# Replace SocialStatus: 'Commoner' with 0, 'Nobility' with 1, 'Clergy'
with 2, 'Professional' with 3, 'Military' with 4, 'Unknown' with Nan
data['SocialStatus'] = data['SocialStatus'].replace({'Commoner': 0,
'Nobility': 1, 'Clergy': 2, 'Professional': 3, 'Military': 4,
'Unknown': np.nan})
```

Check final results before imputation

```
# Visual matrix of missing values
msno.matrix(data)
plt.show()

# Bar chart of missing values
msno.bar(data)
plt.show()
```





Starting imputation process

```
# make age and fare float64
data['age'] = data['age'].astype('float64')
data['fare'] = data['fare'].astype('float64')

# Convert all variables except specified floats to nullable integers
float_vars = ['age','fare']
for column in data.columns:
    if column not in float_vars:
        data[column] = data[column].astype('Int64')  # Note the
capital 'I' which is different from 'int64'

int_columns = data.select_dtypes(include=['Int64']).columns
float_columns = data.select_dtypes(include=['float64']).columns

# Shuffle the data
data = data.sample(frac=1, random_state=42).reset_index(drop=True)
```

Random Forest Imputation

```
def impute_missing_values(df, column, model_type):
    # Split the data into sets with and without missing values
    train = df[df[column].notna()]
    test = df[df[column].isna()]

    # Define features and target
    X_train = train.drop(columns=[column])
    y_train = train[column]
    X_test = test.drop(columns=[column])

    # Initialize and train the model
```

```
    if model_type == 'classifier':
        model = RandomForestClassifier(n_estimators=100,
random_state=42)
    else:
        model = RandomForestRegressor(n_estimators=100,
random_state=42)

    model.fit(X_train, y_train)

    # Predict and impute missing values
    if len(X_test) > 0:
        df.loc[df[column].isna(), column] = model.predict(X_test)

# Applying imputation for each column
for column in int_columns:
    impute_missing_values(data, column, 'classifier')

for column in float_columns:
    impute_missing_values(data, column, 'regressor')

# Count nan
data.isna().sum()
```

```
pclass          0
survived        0
sex             0
age             0
sibsp           0
parch           0
fare            0
embarked        0
Deck            0
Title           0
SocialStatus    0
dtype: int64
```

```
data.head(10)
```

```
   pclass  survived  sex        age  sibsp  parch      fare  embarked
Deck  \
0       3         0    0  36.023099      0      0    8.0500         2
6
1       3         1    1  20.000000      1      1   15.7417         0
6
2       3         0    0  21.000000      0      0    8.6625         2
5
3       3         0    1  19.000000      0      0    8.1583         2
5
4       3         0    1  31.000000      0      0    7.7500         1
5
```

```
5         1         0    1  41.670000      0      0   50.0000         2
0
6         3         0    1  25.000000      0      0    7.9250         2
6
7         3         0    1  24.524167      0      0    7.2250         0
5
8         3         0    0  17.897667      8      2   69.5500         2
6
9         1         1    0  36.000000      0      0  262.3750         0
1
```

```
   Title  SocialStatus
0      2             0
1      1             0
2      0             0
3      1             0
4      1             0
5      1             0
6      1             0
7      1             0
8      0             0
9      0             0
```

Creation of dummies for categorical variables

```
# create a vectors for dummy variables associated to each categorical
F3_Highest_Level_of_Education
data['embarked_0'] = np.where(data['embarked']==0, 1, 0)
data['embarked_1'] = np.where(data['embarked']==1, 1, 0)
data['embarked_2'] = np.where(data['embarked']==2, 1, 0)

# create a vectors for dummy variables associated to each categorical
F3_Highest_Level_of_Education
data['pclass_0'] = np.where(data['pclass']==1, 1, 0)
data['pclass_1'] = np.where(data['pclass']==2, 1, 0)
data['pclass_2'] = np.where(data['pclass']==3, 1, 0)

# create a vectors for dummy variables associated to each categorical
F3_Highest_Level_of_Education
data['female'] = np.where(data['sex']==0, 1, 0)
data['male'] = np.where(data['sex']==1, 1, 0)

# create a vectors for dummy variables associated to each categorical
Deck
data['deck_0'] = np.where(data['Deck']==0, 1, 0)
data['deck_1'] = np.where(data['Deck']==1, 1, 0)
data['deck_2'] = np.where(data['Deck']==2, 1, 0)
data['deck_3'] = np.where(data['Deck']==3, 1, 0)
data['deck_4'] = np.where(data['Deck']==4, 1, 0)
```

```
data['deck_5'] = np.where(data['Deck']==5, 1, 0)
data['deck_6'] = np.where(data['Deck']==6, 1, 0)

# create a vectors for dummy variables associated to each categorical
Title
data['title_0'] = np.where(data['Title']==0, 1, 0)
data['title_1'] = np.where(data['Title']==1, 1, 0)
data['title_2'] = np.where(data['Title']==2, 1, 0)
data['title_3'] = np.where(data['Title']==3, 1, 0)
data['title_4'] = np.where(data['Title']==4, 1, 0)
data['title_5'] = np.where(data['Title']==5, 1, 0)
data['title_6'] = np.where(data['Title']==6, 1, 0)
data['title_7'] = np.where(data['Title']==7, 1, 0)
data['title_8'] = np.where(data['Title']==8, 1, 0)
data['title_9'] = np.where(data['Title']==9, 1, 0)
data['title_10'] = np.where(data['Title']==10, 1, 0)
data['title_11'] = np.where(data['Title']==11, 1, 0)
data['title_12'] = np.where(data['Title']==12, 1, 0)
data['title_13'] = np.where(data['Title']==13, 1, 0)
data['title_14'] = np.where(data['Title']==14, 1, 0)
data['title_15'] = np.where(data['Title']==15, 1, 0)
data['title_16'] = np.where(data['Title']==16, 1, 0)
data['title_17'] = np.where(data['Title']==17, 1, 0)

# create a vectors for dummy variables associated to each categorical
SocialStatus
data['socialstatus_0'] = np.where(data['SocialStatus']==0, 1, 0)
data['socialstatus_1'] = np.where(data['SocialStatus']==1, 1, 0)
data['socialstatus_2'] = np.where(data['SocialStatus']==2, 1, 0)
data['socialstatus_3'] = np.where(data['SocialStatus']==3, 1, 0)
data['socialstatus_4'] = np.where(data['SocialStatus']==4, 1, 0)

# Drop multiple columns
columns_to_drop = ['embarked','sex','pclass', 'Deck', 'Title',
'SocialStatus']
data.drop(columns=columns_to_drop, inplace=True)

data.head(10)
```

```
   survived        age  sibsp  parch      fare  embarked_0  embarked_1
\
0         0  36.023099      0      0    8.0500           0           0

1         1  20.000000      1      1   15.7417           1           0

2         0  21.000000      0      0    8.6625           0           0

3         0  19.000000      0      0    8.1583           0           0

4         0  31.000000      0      0    7.7500           0           1
```

```
5         0  41.670000      0      0   50.0000           0           0

6         0  25.000000      0      0    7.9250           0           0

7         0  24.524167      0      0    7.2250           1           0

8         0  17.897667      8      2   69.5500           0           0

9         1  36.000000      0      0  262.3750           1           0


   embarked_2  pclass_0  pclass_1  ...  title_13  title_14
title_15  \
0           1         0         0  ...         0         0          0

1           0         0         0  ...         0         0          0

2           1         0         0  ...         0         0          0

3           1         0         0  ...         0         0          0

4           0         0         0  ...         0         0          0

5           1         1         0  ...         0         0          0

6           1         0         0  ...         0         0          0

7           0         0         0  ...         0         0          0

8           1         0         0  ...         0         0          0

9           0         1         0  ...         0         0          0


   title_16  title_17  socialstatus_0  socialstatus_1  socialstatus_2
\
0         0         0               1               0               0

1         0         0               1               0               0

2         0         0               1               0               0

3         0         0               1               0               0

4         0         0               1               0               0

5         0         0               1               0               0

6         0         0               1               0               0

7         0         0               1               0               0
```

```
8          0          0                 1                 0                 0

9          0          0                 1                 0                 0


   socialstatus_3  socialstatus_4
0               0               0
1               0               0
2               0               0
3               0               0
4               0               0
5               0               0
6               0               0
7               0               0
8               0               0
9               0               0

[10 rows x 43 columns]

data.dtypes

survived            Int64
age               float64
sibsp               Int64
parch               Int64
fare              float64
embarked_0          int64
embarked_1          int64
embarked_2          int64
pclass_0            int64
pclass_1            int64
pclass_2            int64
female              int64
male                int64
deck_0              int64
deck_1              int64
deck_2              int64
deck_3              int64
deck_4              int64
deck_5              int64
deck_6              int64
title_0             int64
title_1             int64
title_2             int64
title_3             int64
title_4             int64
title_5             int64
title_6             int64
title_7             int64
title_8             int64
```

```
title_9              int64
title_10             int64
title_11             int64
title_12             int64
title_13             int64
title_14             int64
title_15             int64
title_16             int64
title_17             int64
socialstatus_0       int64
socialstatus_1       int64
socialstatus_2       int64
socialstatus_3       int64
socialstatus_4       int64
dtype: object
```

Standardization

```
# Standardize only float64 variables
scaler = StandardScaler()
data[data.select_dtypes(include=['float64']).columns] =
scaler.fit_transform(data.select_dtypes(include=['float64']))

data.head(10)
```

```
   survived       age  sibsp  parch      fare  embarked_0  embarked_1
\
0         0  0.453946      0      0 -0.487466           0           0

1         1 -0.727492      1      1 -0.338817           1           0

2         0 -0.653758      0      0 -0.475629           0           0

3         0 -0.801225      0      0 -0.485373           0           0

4         0  0.083576      0      0 -0.493264           0           1

5         0  0.870312      0      0  0.323255           0           0

6         0 -0.358825      0      0 -0.489882           0           0

7         0 -0.393909      0      0 -0.503410           1           0

8         0 -0.882504      8      2  0.701076           0           0

9         1  0.452243      0      0  4.427591           1           0


   embarked_2  pclass_0  pclass_1  ...  title_13  title_14
title_15  \
```

```
0           1         0         0  ...         0         0         0
1           0         0         0  ...         0         0         0
2           1         0         0  ...         0         0         0
3           1         0         0  ...         0         0         0
4           0         0         0  ...         0         0         0
5           1         1         0  ...         0         0         0
6           1         0         0  ...         0         0         0
7           0         0         0  ...         0         0         0
8           1         0         0  ...         0         0         0
9           0         1         0  ...         0         0         0

   title_16  title_17  socialstatus_0  socialstatus_1  socialstatus_2
\
0         0         0               1               0               0
1         0         0               1               0               0
2         0         0               1               0               0
3         0         0               1               0               0
4         0         0               1               0               0
5         0         0               1               0               0
6         0         0               1               0               0
7         0         0               1               0               0
8         0         0               1               0               0
9         0         0               1               0               0

   socialstatus_3  socialstatus_4
0               0               0
1               0               0
2               0               0
3               0               0
4               0               0
5               0               0
```

```
6                 0                 0
7                 0                 0
8                 0                 0
9                 0                 0

[10 rows x 43 columns]
```

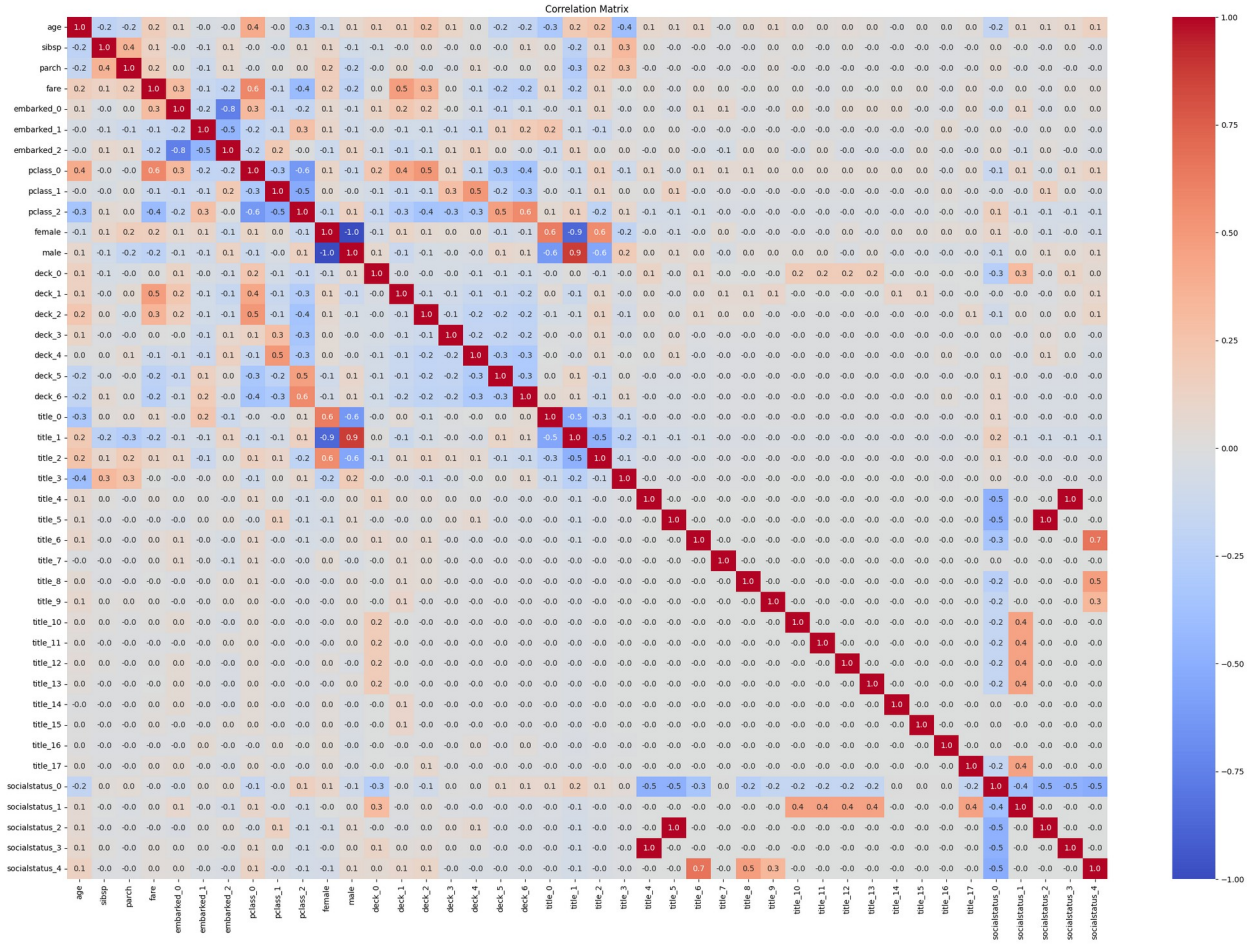
```
# Split the data into X and y
y = data['survived']
X = data.drop(columns=['survived'])
```

Oversampling

```
# Categorical_features should be a boolean mask or column indices that
specify which features are categorical
categorical_features = [True if dtype.name == 'Int64'else False for
dtype in X.dtypes]

smotenc = SMOTENC(categorical_features=categorical_features,
random_state=42)
X_resampled, y_resampled = smotenc.fit_resample(X, y)

# Step 1: Convert X_resampled to a DataFrame if it isn't one already
if not isinstance(X_resampled, pd.DataFrame):
    X_resampled = pd.DataFrame(X_resampled, columns=X.columns)

# Step 2: Add y_resampled to this DataFrame
X_resampled['target'] = y_resampled

# Unique values of y and frequency
X_resampled['target'].value_counts()
```

```
0    808
1    808
Name: target, dtype: Int64
```

```
# Split the data into X and y
y = X_resampled['target']
X = X_resampled.drop(columns=['target'])

# Create a correlation matrix
corr = pd.DataFrame(X).corr()

# Display the correlation matrix
plt.figure(figsize=(30, 20))
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt=".1f", vmin=-1,
vmax=1)
plt.title('Correlation Matrix')
plt.show()
```




```
# make X polynomial features with garde 3
poly = PolynomialFeatures(degree=3)
X = poly.fit_transform(X)

# Make X dataset
X = pd.DataFrame(X)
```

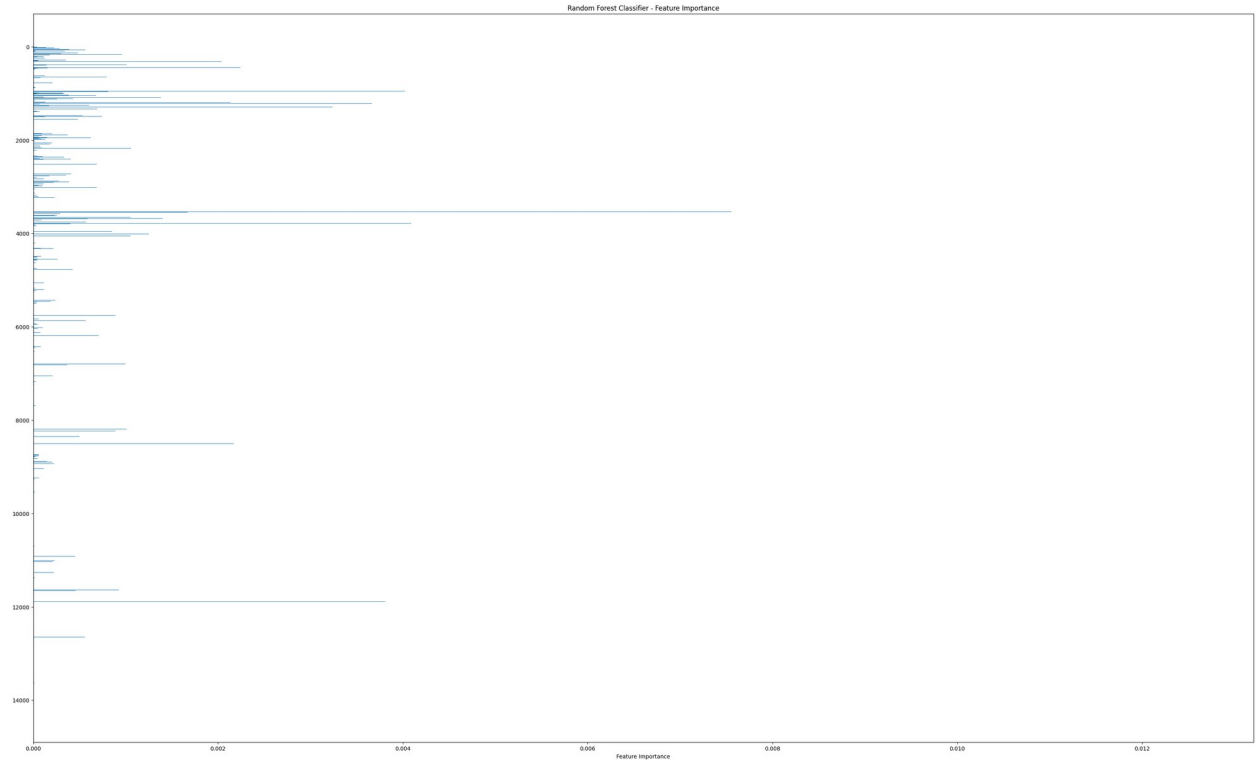
RANDOM FOREST (bayesian optimziation)

```
# Define the function to optimize
def rf_eval(n_estimators, max_depth, min_samples_split,
min_samples_leaf):

    # Ensure the parameters passed by the optimizer are integers
    n_estimators = int(n_estimators)
    max_depth = int(max_depth)
    min_samples_split = int(min_samples_split)
    min_samples_leaf = int(min_samples_leaf)

    # Train the model
    model = RandomForestClassifier(n_estimators=n_estimators,
```

```
                                    max_depth=max_depth,
min_samples_split=min_samples_split,
                                    min_samples_leaf=min_samples_leaf,
                                    random_state=42)

    # Define Stratified K-Fold cross-validator
    cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

    # Perform cross-validation
    accuracies = cross_val_score(model, X, y, cv=cv,
scoring='accuracy')
    return np.mean(accuracies)

# Hyperparameter bounds
pbounds = {
    'n_estimators': (50, 200),
    'max_depth': (1, 50),
    'min_samples_split': (2, 15),
    'min_samples_leaf': (1, 5),
}

# Bayesian Optimization
optimizer = BayesianOptimization(
    f=rf_eval,
    pbounds=pbounds,
    random_state=42,
)

optimizer.maximize(init_points=2, n_iter=10)

# Retrieve the best parameters
best_params = optimizer.max['params']
print("Best Parameters:", best_params)
```

```
|   iter    |  target   | max_depth | min_sa... | min_sa... |
n_esti... |
-------------------------------------------------------------------------
---
| 1         | 0.841     | 19.35     | 4.803     | 11.52     | 139.8
|
| 2         | 0.8267    | 8.645     | 1.624     | 2.755     | 179.9
|
| 3         | 0.8403    | 19.95     | 4.538     | 13.1      | 139.8
|
| 4         | 0.8057    | 6.661     | 4.353     | 2.928     | 120.8
|
| 5         | 0.8323    | 28.15     | 5.0       | 4.662     | 151.5
|
| 6         | 0.8187    | 8.947     | 5.0       | 14.28     | 151.3
```

```
|
| 7         | 0.841     | 29.67     | 4.421     | 7.414     | 136.1
|
| 8         | 0.8304    | 45.78     | 5.0       | 15.0      | 135.3
|
| 9         | 0.8496    | 40.96     | 1.239     | 2.421     | 119.1
|
| 10        | 0.8428    | 47.9      | 2.202     | 2.0       | 109.1
|
| 11        | 0.8441    | 37.04     | 1.0       | 13.65     | 113.0
|
| 12        | 0.8484    | 33.08     | 1.0       | 2.0       | 106.2
|
=========================================================================
===
Best Parameters: {'max_depth': 40.95594762682858, 'min_samples_leaf':
1.2394456447542637, 'min_samples_split': 2.420795694534846,
'n_estimators': 119.13732277488863}

# Train the best model using the best parameters
best_model = RandomForestClassifier(
    n_estimators=int(best_params['n_estimators']),
    max_depth=int(best_params['max_depth']),
    min_samples_split=int(best_params['min_samples_split']),
    min_samples_leaf=int(best_params['min_samples_leaf']),
    random_state=42
)
best_model.fit(X, y)

RandomForestClassifier(max_depth=40, n_estimators=119,
random_state=42)

# Extract feature importances
feature_importances = best_model.feature_importances_
feature_names = X.columns

# Create a DataFrame for feature importances
feature_importance_df = pd.DataFrame({'Feature': feature_names,
'Importance': feature_importances})
feature_importance_df =
feature_importance_df.sort_values(by='Importance', ascending=False)

# Plotting feature importance
plt.figure(figsize=(40, 24))
plt.barh(feature_importance_df['Feature'],
feature_importance_df['Importance'])
plt.xlabel('Feature Importance')
plt.title('Random Forest Classifier - Feature Importance')
plt.gca().invert_yaxis()
plt.show()
```




```
individual_tree = best_model.estimators_[0]  # Fetching the first tree

plt.figure(figsize=(12, 8))
plot_tree(individual_tree, feature_names=feature_names,
class_names=True, filled=True, rounded=True, max_depth=3)
plt.title("Visualization of an Individual Decision Tree in Random
Forest Classifier")
plt.show()
```

Visualization of an Individual Decision Tree in Random Forest Classifier