Titanic_notebook

July 11, 2023

1 Final Project

Welcome to the final practical project for our course on Data Science Bootcamp. Throughout this project, you will go through the entire data science process, starting from data loading and cleaning, all the way to running a model and making predictions. This hands-on project will provide you with valuable experience and allow you to apply the concepts and techniques you've learned in the course. Get ready to dive into real-world data analysis and build your skills as a data scientist!

1.1 Important Remarks:

- The ultimate goal of this project is to conduct comprehensive data analysis and build 2 models using the provided datasets.
- Code is not the only thing graded here. Well-written and understandable documentation of your code is to be expected
- Clear reasoning behind your choices in every step of the notebook is important. Be it the choice of a data cleaning technique or selecting certain features in your analysis or the choice of your 2 models.

2 Importing packages

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
from sklearn import linear_model
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.tree import DecisionTreeRegressor, DecisionTreeClassifier
from sklearn import metrics
```

3 Load the dataset into data

[3]:
```python
data = pd.read_csv("titanic.csv")
```

4 Dataset overview and statistical summary

[4]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  1000 non-null   int64
 1   Survived     1000 non-null   int64
 2   Pclass       1000 non-null   int64
 3   Name         1000 non-null   object
 4   Sex          1000 non-null   object
 5   Age          823 non-null    float64
 6   SibSp        1000 non-null   int64
 7   Parch        1000 non-null   int64
 8   Ticket       1000 non-null   object
 9   Fare         1000 non-null   float64
 10  Cabin        299 non-null    object
 11  Embarked     998 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 93.9+ KB
```

We can see that Age, Cabin and Embarked are having some null entries

[5]:
```python
data.describe()
```

[5]:
```
       PassengerId     Survived       Pclass         Age        SibSp  \
count  1000.000000  1000.000000  1000.000000  823.000000  1000.000000
mean    500.500000     0.404000     2.274000   30.177606     0.716000
std     288.819436     0.490943     0.840018   15.138305     1.312656
min       1.000000     0.000000     1.000000    0.420000     0.000000
25%     250.750000     0.000000     1.000000   21.000000     0.000000
50%     500.500000     0.000000     3.000000   29.000000     0.000000
75%     750.250000     1.000000     3.000000   39.500000     1.000000
max    1000.000000     1.000000     3.000000   80.000000     8.000000

             Parch         Fare
count  1000.000000  1000.000000
mean      0.571000    56.732249
std       1.046926    98.014902
min       0.000000     0.000000
```

```
25%        0.000000     8.050000
50%        0.000000    17.600000
75%        1.000000    52.000000
max        6.000000   512.329200
```

It is to be noticed that Survived rate is changed from 0 to 1, in 50% to 75%

[6]:
```
data.head()
```

[6]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

5 Data cleaning

These are the description of terms in this dataset

[7]:
```
# VARIABLE DESCRIPTIONS - http://campus.lakeforest.edu/frank/FILES/MLFfiles/
↪Bio150/Titanic/TitanicMETA.pdf

# Pclass Passenger Class (1 = 1st; 2 = 2nd; 3 = 3rd)
# survival Survival (0 = No; 1 = Yes)
# name Name --
# sex Sex
# age Age
# sibsp Number of Siblings/Spouses Aboard
# parch Number of Parents/Children Aboard
# ticket Ticket Number --
# fare Passenger Fare (British pound)
# cabin Cabin
```

```
# embarked Port of Embarkation (C = Cherbourg; Q = Queenstown; S = Southampton)
```

For cleaning of data, such text values like name, ticket are not required for EDA

[8]:
```
data.isnull().sum()
```

[8]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          701
Embarked         2
dtype: int64
```

5.1 Cabin Column

- Cabin data could be usefull to get knowledge of people who survived from which cabin.
- But 299 entries are filled out of 1000. - 30%
- Predicting the rest values may result in false classifications ahead.

[9]:
```
data = data.drop(['Cabin'], axis=1)
```

Generating Median of Age for dealing with null entries

[10]:
```
data['Age'].median()
```

[10]:
```
29.0
```

[11]:
```
data['Age'] = data['Age'].fillna(data['Age'].median())
```

Applying Mode function to Embarked to cover up null entries

[12]:
```
data['Embarked'] = data['Embarked'].fillna(data['Embarked'].mode().iloc[0])
```

For Visualization purpose creating a sex_ratio column that will display plots

[13]:
```
data['Sex_Ratio'] = data['Sex'].replace(['male', 'female'], [0,1])
```

[14]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 12 columns):
```

```
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  1000 non-null   int64
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 3   Name         1000 non-null   object
 4   Sex          1000 non-null   object
 5   Age          1000 non-null   float64
 6   SibSp        1000 non-null   int64
 7   Parch        1000 non-null   int64
 8   Ticket       1000 non-null   object
 9   Fare         1000 non-null   float64
 10  Embarked     1000 non-null   object
 11  Sex_Ratio    1000 non-null   int64
dtypes: float64(2), int64(6), object(4)
memory usage: 93.9+ KB
```
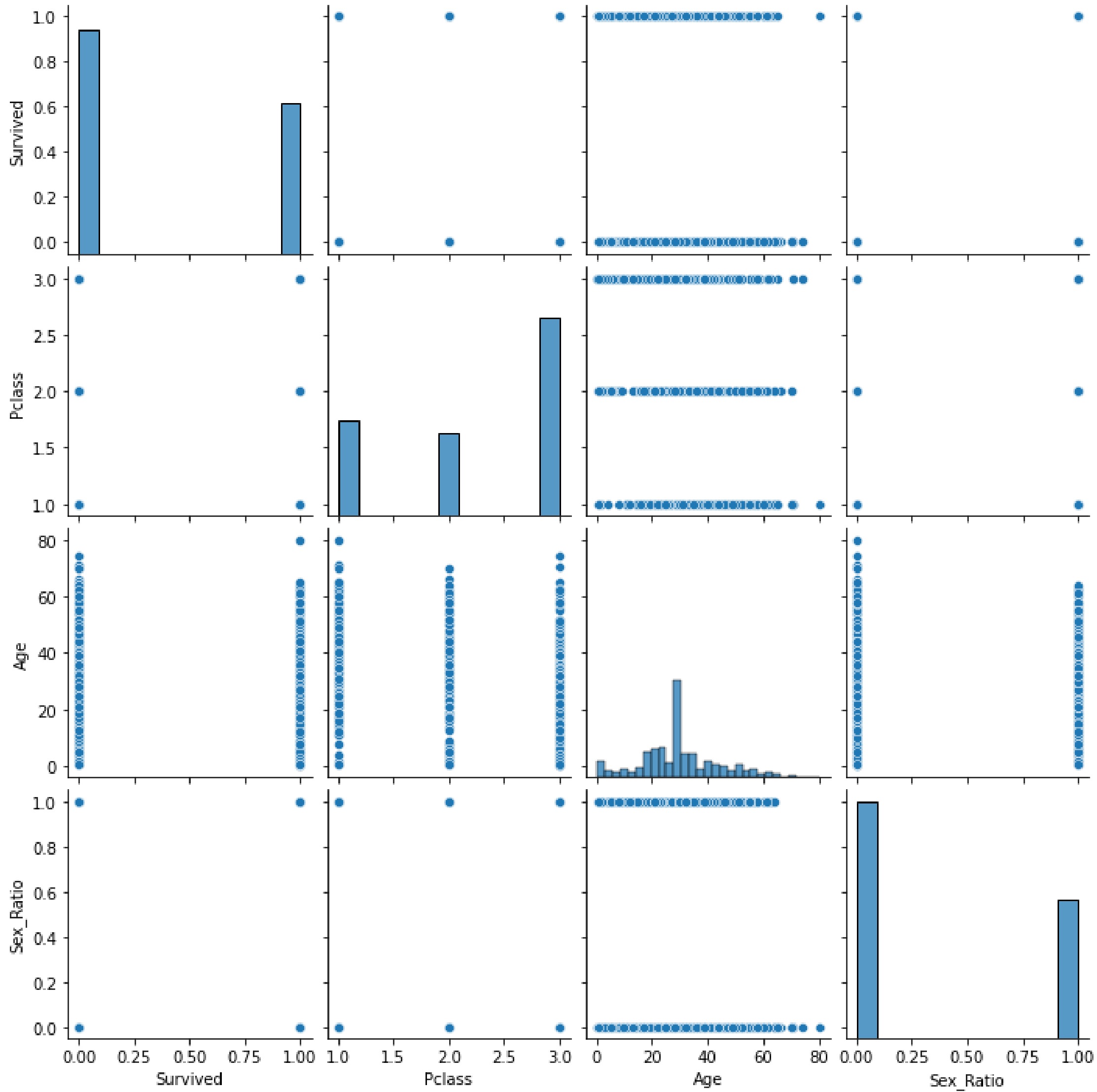

[15]:

```
sns.pairplot(data[['Survived', 'Pclass', 'Age', 'Sex_Ratio']])
```

[15]: <seaborn.axisgrid.PairGrid at 0x7f5593b4a9d0>



6 EDA

[16]:
```python
# correlations
data.corr()
```

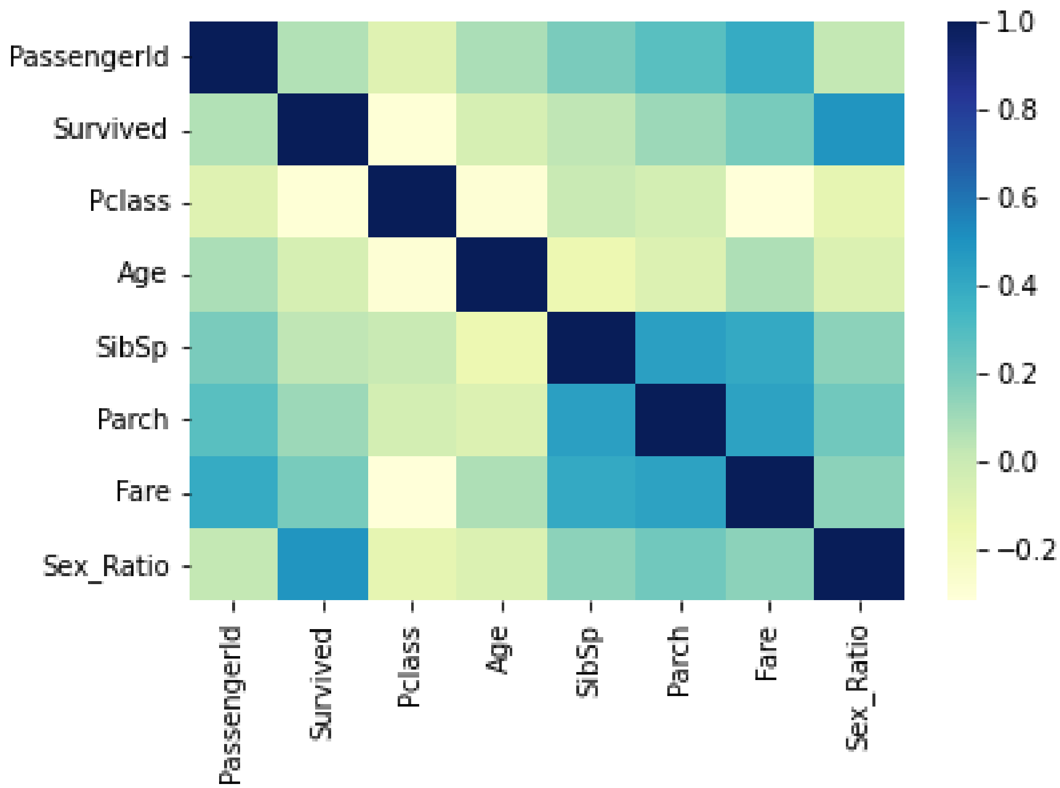
[16]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	\
PassengerId	1.000000	0.060211	-0.091191	0.074481	0.187344	0.277960	
Survived	0.060211	1.000000	-0.305096	-0.056226	0.025996	0.109678	
Pclass	-0.091191	-0.305096	1.000000	-0.297758	0.003464	-0.041493	
Age	0.074481	-0.056226	-0.297758	1.000000	-0.157325	-0.079506	
SibSp	0.187344	0.025996	0.003464	-0.157325	1.000000	0.439342	
Parch	0.277960	0.109678	-0.041493	-0.079506	0.439342	1.000000	

```
Fare            0.389904  0.192999 -0.320058  0.066701  0.397940  0.431476
Sex_Ratio       0.015860  0.487347 -0.120601 -0.077410  0.144631  0.213760

                 Fare  Sex_Ratio
PassengerId  0.389904   0.015860
Survived     0.192999   0.487347
Pclass      -0.320058  -0.120601
Age          0.066701  -0.077410
SibSp        0.397940   0.144631
Parch        0.431476   0.213760
Fare         1.000000   0.145768
Sex_Ratio    0.145768   1.000000
```

[17]:
```python
# heatmap
import matplotlib.pyplot as plt
sns.heatmap(data.corr(), cmap="YlGnBu")
```

[17]: <AxesSubplot:>



[18]:
```python
# Getting the hold of data
```

[19]:
```python
data['PassengerId'].nunique()
```

[19]: 1000

The total samples equals 1000, or 44.86%, of the 2,229 people that actually boarded the Titanic.

[20]:
```
# getting survival percent of this dataset

survived_data = data[data['Survived'] == 1]
survived = survived_data.count().values[1]
survival_percent = (survived/1000) * 100
print('The percentage of survived people in this dataset are {:.2f} %'.
 ↪format(survival_percent))
```

The percentage of survived people in this dataset are 40.40 %

[21]:
```
data['Sex'].value_counts()
```

[21]:
```
male      632
female    368
Name: Sex, dtype: int64
```

[22]:
```
# Relation between Sex and survival rate
data[['Sex', 'Survived']].groupby(['Sex'], as_index = False).mean()
```

[22]:

	Sex	Survived
0	female	0.717391
1	male	0.221519

Survival Rate based on Sex - Female: 71.73% - Male: 22.15%

[23]:
```
#Calculating the total number of passengers for each Pclass and whether they␣
 ↪survived
data[['Pclass', 'Survived']].groupby(['Pclass'], as_index = False).mean().
 ↪sort_values('Survived', ascending = False)
```

[23]:

	Pclass	Survived
0	1	0.612648
1	2	0.495455
2	3	0.265655

Survival Rate based on Pclass - 1: 61.26% - 2: 49.54% - 3: 26.56%

[24]:
```
# getting survival rate based on Pclass and sex
data[['Survived', 'Sex', 'Pclass']].groupby(['Pclass', 'Sex']).mean()
```

[24]:

Pclass	Sex	Survived
1	female	0.901786
	male	0.382979

```
2      female  0.869565
       male    0.226562
3      female  0.506098
       male    0.157025
```

[25]:
```
# actual values
data[['Survived', 'Sex', 'Pclass']].groupby(['Pclass', 'Sex']).count()
```

[25]:
```
              Survived
Pclass Sex
1      female      112
       male        141
2      female       92
       male        128
3      female      164
       male        363
```

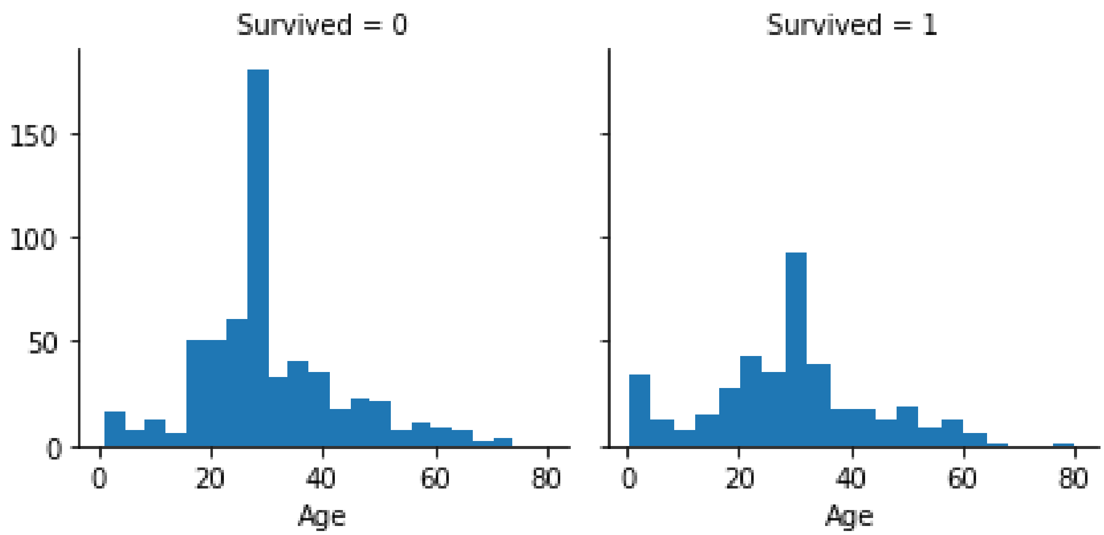
[26]:
```
# correlation values between pclass, survival, age

print('Age w/t Pclass:',data['Age'].corr(data['Pclass']))
print('Age w/t Survival:',data['Age'].corr(data['Survived']))
print('Survival w/t Pclass:',data['Survived'].corr(data['Pclass']))
```

```
Age w/t Pclass: -0.2977579877164832
Age w/t Survival: -0.05622583118618498
Survival w/t Pclass: -0.30509598788140097
```

[27]:
```
# creating a sns facegrid to display the survived vs age hist

plt.figure(figsize = (15,6))
g = sns.FacetGrid(data, col = 'Survived')
g.map(plt.hist, 'Age', bins = 20)
```

[27]:
```
<seaborn.axisgrid.FacetGrid at 0x7f558ad0c760>
```

```
<Figure size 1080x432 with 0 Axes>
```



7 Data Processing and normalization

Applying Label Encoding to the categorical data – Sex: [‘Male’,‘Female’] and Embarked: [‘C’,‘Q’,‘S’]

[28]:
```
le = LabelEncoder()
data['Sex'] = le.fit_transform(data['Sex'])
data['Embarked'] = le.fit_transform(data['Embarked'])
```

[29]:
```
X = data[['Pclass', 'Sex', 'Age','SibSp' ,'Parch' ,'Fare','Embarked']].values
y = data['Survived'].values
```

Test size can be different in scenarios - but here 0.25 is approving best predictions

[30]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
 ↪random_state=42)
```

Scaling the values, the scaling is used for making data points generalized so that the distance between them will be lower, this will help the machine.

[31]:
```
scale = StandardScaler()
```

[32]:
```
X_train_scaled = scale.fit_transform(X_train)
X_test_scaled = scale.transform(X_test)
```

8 Creating ML model 1

Using Logistic Regression

[33]:
```
lr_model = LogisticRegression(solver='liblinear', random_state=20)
```

[34]:
```
lr_model.fit(X_train_scaled, y_train)
```

[34]:
```
LogisticRegression(random_state=20, solver='liblinear')
```

8.1 Prediction on Test data

[35]:
```
y_pred_lr = lr_model.predict(X_test_scaled)
```

8.2 Model 1 Performance

[36]:
```
accuracy_score = round(lr_model.score(X_train_scaled, y_train) * 100, 2)
print("Logistic Regression Model Accuracy - Training:", accuracy_score, "%")
```

```
Logistic Regression Model Accuracy - Training: 78.13 %
```

[37]:
```
accuracy_score = round(lr_model.score(X_test_scaled, y_test) * 100, 2)
print("Logistic Regression Model Accuracy - Testing:", accuracy_score, "%")
```

```
Logistic Regression Model Accuracy - Testing: 76.4 %
```

9 Creating ML model 2

Using Decision Tree Classifier, with max_depth = 7

[38]:
```
dtc_model = DecisionTreeClassifier(max_depth=7)
```

[39]:
```
dtc_model.fit(X_train_scaled, y_train)
```

[39]:
```
DecisionTreeClassifier(max_depth=7)
```

9.1 Prediction on Test data

[40]:
```
y_pred_2 = dtc_model.predict(X_test_scaled)
```

9.2 ## Model 2 Performance

[41]:
```
accuracy_score = round(dtc_model.score(X_train_scaled, y_train) * 100, 2)
print("Decision Tree Model Accuracy - Training:", accuracy_score, "%")
```

```
Decision Tree Model Accuracy - Training: 89.07 %
```

[42]:
```
accuracy_score = round(dtc_model.score(X_test_scaled, y_test) * 100, 2)
print("Decision Tree Model Accuracy - Testing:", accuracy_score, "%")
```

```
Decision Tree Model Accuracy - Testing: 76.0 %
```

10 Report and insight from your analysis

10.1 Model and Dataset Analysis

- Logistic Regression and Decision Tree Classifier fits well with this data.
- I could get more insight of survival rate based on cabin data, but because of its huge amount of null values occurence, predicting them and moving ahead with it, will finally cause false predictions

10.2 Dataset overview and statistical summary Analysis

- The total samples equals 1000, or 44.86%, of the 2,229 people that actually were present in the Titanic.
- Survived is a categorical feature with 0 or 1 values.
- Similar goes to Sex column with Male and Female.
- According to this dataset 40.40% survived while actual survival rate was 31%.
- Highest Fare was around $512.32.

10.3 EDA Analysis

- Male: 632 and Female: 368 are present in this dataset sample of 1000.
- Survival Rate based on Sex - Female: 71.73% and Male: 22.15%
- Survival Rate based on Pclass 1: 61.26%, Pclass 2: 49.54%, Pclass 3: 26.56%
- The actual values of Survival based on Pclass and Sex are:
- [Pclass, Sex, Number] = [{1, F, 112}, {1, M, 141}, {2, F, 92}, {2, M, 128}, {3, F, 164}, {3, M, 363}]

10.4 Data Processing Analysis

- Logistic Regression Accuracy: [Training: 78.13%, Testing: 76.4%]
- Decision Tree Accuracy: [Training: 89.7%, Testing: 76.0%]