titanic_analysis

July 31, 2021

1 Titanic Competetion

[474]:
```
import numpy as np # linear algebra
import matplotlib.pyplot as plt
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv) - R > all


import warnings ##To remove warnings
warnings.filterwarnings('ignore')
```

[475]:
```
import os
print(os.listdir("input"))
```

```
['gender_submission.csv', 'test.csv', 'train.csv']
```

[476]:
```
#importing the training and test data sets
dataset = pd.read_csv('input/train.csv')
df_train = pd.read_csv('input/train.csv')
df_test = pd.read_csv('input/test.csv')
```

[477]:
```
df_train.head()
```

[477]:
```
   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
```

[478]:
```python
df_train.shape
```

[478]:
```
(891, 12)
```

[479]:
```python
#let's summarize the dataset
#we can see the we have some missing values in the "Age" column
df_train.describe()
```

[479]:
```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

[480]:
```python
df_test.shape
```

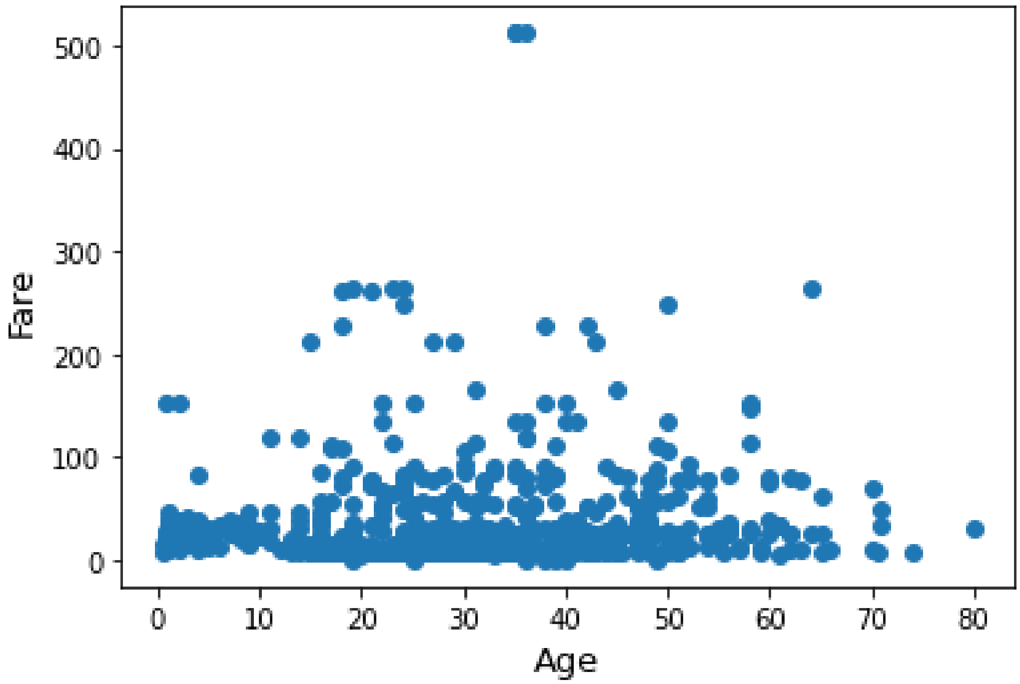
[480]:
```
(418, 11)
```

[481]:
```python
test_ID = df_test['PassengerId']
```

[482]:
```python
#delete the id column from datasets
del df_train['PassengerId']
del df_test['PassengerId']
```

[483]:
```python
#exploring outliers
#we can't find any outlier in the countinous columns
fig, ax = plt.subplots()
```

```
ax.scatter(x = df_train['Age'], y = df_train['Fare'])
plt.ylabel('Fare', fontsize=13)
plt.xlabel('Age', fontsize=13)
plt.show()
```



[484]:
```
df_train.isnull().sum()
```

[484]:
```
Survived      0
Pclass        0
Name          0
Sex           0
Age         177
SibSp         0
Parch         0
Ticket        0
Fare          0
Cabin       687
Embarked      2
dtype: int64
```

2 Handling Missing Data

[485]:
```
## https://jakevdp.github.io/PythonDataScienceHandbook/03.04-missing-values.html

## fill missing age values usiing the median
df_train["Age"] = df_train["Age"].fillna(df_train["Age"].median())
df_test["Age"] = df_test["Age"].fillna(df_train["Age"].median())

## As we've seen before, "Cabin" has too many NAs. Let's drops this col then
df_train = df_train.drop(columns="Cabin")
df_test = df_test.drop(columns="Cabin")

## At last, we drop the rows whereupon "Embarked" is NA
df_train.dropna()
```

[485]:
```
     Survived  Pclass                                               Name  \
0           0       3                            Braund, Mr. Owen Harris
1           1       1  Cumings, Mrs. John Bradley (Florence Briggs Th…
2           1       3                             Heikkinen, Miss. Laina
3           1       1       Futrelle, Mrs. Jacques Heath (Lily May Peel)
4           0       3                           Allen, Mr. William Henry
..        …       …                                                  …
886         0       2                              Montvila, Rev. Juozas
887         1       1                       Graham, Miss. Margaret Edith
888         0       3           Johnston, Miss. Catherine Helen "Carrie"
889         1       1                              Behr, Mr. Karl Howell
890         0       3                                Dooley, Mr. Patrick

        Sex   Age  SibSp  Parch            Ticket     Fare Embarked
0      male  22.0      1      0         A/5 21171   7.2500        S
1    female  38.0      1      0          PC 17599  71.2833        C
2    female  26.0      0      0  STON/O2. 3101282   7.9250        S
3    female  35.0      1      0            113803  53.1000        S
4      male  35.0      0      0            373450   8.0500        S
..      …     …    …    …               …       …      …
886    male  27.0      0      0            211536  13.0000        S
887  female  19.0      0      0            112053  30.0000        S
888  female  28.0      1      2        W./C. 6607  23.4500        S
889    male  26.0      0      0            111369  30.0000        C
890    male  32.0      0      0            370376   7.7500        Q

[889 rows x 10 columns]
```

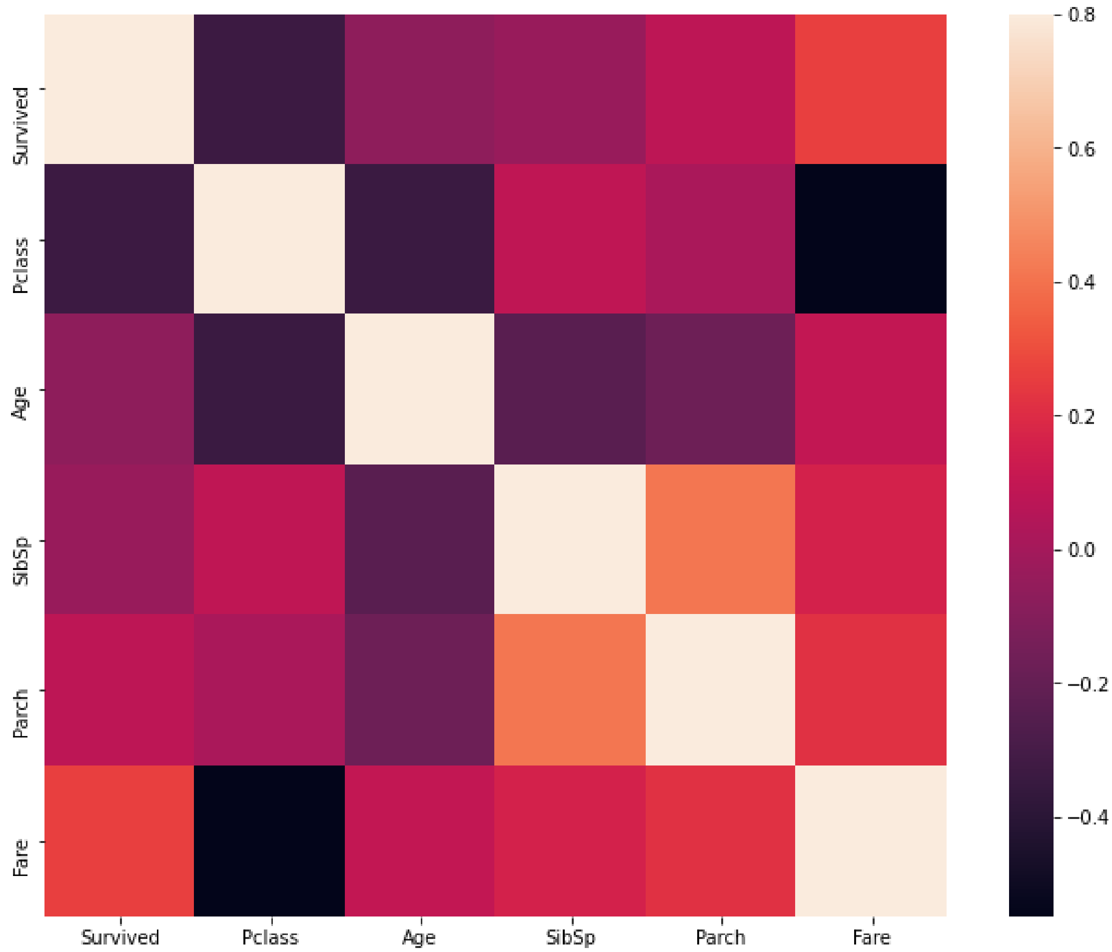
[486]:
```
# we're gonna use only the surname for this analysis
df_train["Surname"] = df_train.Name.str.split(",").str[0]
df_test["Surname"] = df_test.Name.str.split(",").str[0]
```

```
df_train = df_train.drop(columns = "Name")
df_test = df_test.drop(columns = "Name")
```

[487]:
```
df_test.shape
```

[487]: (418, 9)

[488]:
```
import seaborn as sns
#correlation matrix
# Here we can see that "Survived" and "Pclass" has a negativy correlation
corrmat = df_train.corr()
f, ax = plt.subplots(figsize=(12, 9))
sns.heatmap(corrmat, vmax=.8, square=True);
```



[489]:
```
#.sort_values(by=['surname_count'], ascending = [False])
#calcular a taxa de sobreviventes por nome de familia
```

[490]:
```
df_train.dtypes
```

[490]:
```
Survived      int64
Pclass        int64
Sex          object
Age         float64
SibSp         int64
Parch         int64
Ticket       object
Fare        float64
Embarked     object
Surname      object
dtype: object
```

[491]:
```
def ticket_type(ticket):
    if ticket.isnumeric():
        return "normal"
    else:
        return ticket.split()[0]

#df_train["Ticket"].unique()
```

[492]:
```
df_train["Ticket"] = df_train["Ticket"].map(ticket_type) ##using map because␣
 ↪it's a series
df_test["Ticket"] = df_test["Ticket"].map(ticket_type)
```

3 Analysis

[493]:
```
X = df_train.iloc[:, 1:]
y = df_train.iloc[:, 0]
```

[494]:
```
##Enconding categorical Data
categorical_cols = ["Sex", "Ticket", "Embarked", "Surname"]
X = pd.get_dummies(X, columns=categorical_cols)
```

[495]:
```
# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,␣
 ↪random_state = 1)
```

[496]:
```
X_train.loc[:, ["Age", "Fare"]]
```

[496]:
```
      Age     Fare
301  28.0  23.2500
309  30.0  56.9292
516  34.0  10.5000
```

```
120  21.0  73.5000
570  62.0  10.5000
..    …       …
715  19.0   7.6500
767  30.5   7.7500
72   21.0  73.5000
235  28.0   7.5500
37   21.0   8.0500

[712 rows x 2 columns]
```

[497]:
```
# Feature Scaling
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()

X_train.loc[:, ["Age", "Fare"]] = scaler.fit_transform(X_train.loc[:, ["Age",␣
 ↪"Fare"]])
X_test.loc[:, ["Age", "Fare"]] = scaler.transform(X_test.loc[:, ["Age",␣
 ↪"Fare"]])
```

4 Model Selection

[498]:
```
from sklearn.metrics import confusion_matrix, accuracy_score
```

[506]:
```
# Training the Random Forest Classification model on the Training set
from sklearn.ensemble import RandomForestClassifier
rf_classifier = RandomForestClassifier(n_estimators = 50, criterion =␣
 ↪'entropy', random_state = 0)
rf_classifier.fit(X_train, y_train)

# Making the Confusion Matrix
y_pred = rf_classifier.predict(X_test)
print(confusion_matrix(y_test, y_pred))
accuracy_score(y_test, y_pred)
```

```
[[102   4]
 [ 31  42]]
```

[506]: 0.8044692737430168

[507]:
```
# Training the Decision Tree Classification model on the Training set
from sklearn.tree import DecisionTreeClassifier
dt_classifier = DecisionTreeClassifier(criterion = 'entropy', random_state = 1)
dt_classifier.fit(X_train, y_train)

# Making the Confusion Matrix
```

```
y_pred = dt_classifier.predict(X_test)
print(confusion_matrix(y_test, y_pred))
accuracy_score(y_test, y_pred)
```

```
[[93 13]
 [23 50]]
```

[507]: 0.7988826815642458

[518]:
```
# Training the K-NN model on the Training set
from sklearn.neighbors import KNeighborsClassifier
knn_classifier = KNeighborsClassifier(n_neighbors = 3, metric = 'minkowski', p␣
 ↪= 2)
knn_classifier.fit(X_train, y_train)

# Making the Confusion Matrix
y_pred = knn_classifier.predict(X_test)
print(confusion_matrix(y_test, y_pred))
accuracy_score(y_test, y_pred)
```

```
[[96 10]
 [28 45]]
```

[518]: 0.7877094972067039

[519]:
```
# Training the Kernel SVM model on the Training set
from sklearn.svm import SVC
ksvm_classifier = SVC(kernel = 'rbf', random_state = 0)
ksvm_classifier.fit(X_train, y_train)

# Making the Confusion Matrix
y_pred = ksvm_classifier.predict(X_test)
print(confusion_matrix(y_test, y_pred))
accuracy_score(y_test, y_pred)
```

```
[[95 11]
 [25 48]]
```

[519]: 0.7988826815642458

[526]:
```
# Training the Logistic Regression model on the Training set
from sklearn.linear_model import LogisticRegression
lr_classifier = LogisticRegression()
lr_classifier.fit(X_train, y_train)

# Making the Confusion Matrix
y_pred = lr_classifier.predict(X_test)
print(confusion_matrix(y_test, y_pred))
```

```
accuracy_score(y_test, y_pred)
```

```
[[90 16]
 [23 50]]
```

[526]: 0.7821229050279329

[528]:
```
# Training the Naive Bayes model on the Training set
from sklearn.naive_bayes import GaussianNB
bayes_classifier = GaussianNB()
bayes_classifier.fit(X_train, y_train)

# Making the Confusion Matrix
y_pred = bayes_classifier.predict(X_test)
print(confusion_matrix(y_test, y_pred))
accuracy_score(y_test, y_pred)
```

```
[[27 79]
 [12 61]]
```

[528]: 0.49162011173184356

[529]:
```
# Training the SVM model on the Training set
from sklearn.svm import SVC
svm_classifier = SVC(kernel = 'linear', random_state = 0)
svm_classifier.fit(X_train, y_train)

# Making the Confusion Matrix
y_pred = svm_classifier.predict(X_test)
print(confusion_matrix(y_test, y_pred))
accuracy_score(y_test, y_pred)
```

```
[[91 15]
 [25 48]]
```

[529]: 0.776536312849162