Introduction to Machine Learning
Final project - Titanic

Maciej Romański

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1 Introduction

The purpose of this report is to perform an analysis of the Titanic passengers data and create a machine learning model to predict the passenger's chances of surviving the disaster.

I will train a few classifiers, which were introduced in Intel's Machine Learning Course and compare their performance.

Importing packages:

[134]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

Loading datasets to pandas DataFrames:

[135]:
```
# Importing the datasets
train_df = pd.read_csv("train.csv")
test_df = pd.read_csv("test.csv")
```

Let's display some information about the data:

[136]:
```
train_df.head()
```

[136]:

```
   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
```

[137]:

```python
train_df.describe()
```

[137]:

```
       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
```

[138]:

```python
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
```

```
Data columns (total 12 columns):
PassengerId    891 non-null int64
Survived       891 non-null int64
Pclass         891 non-null int64
Name           891 non-null object
Sex            891 non-null object
Age            714 non-null float64
SibSp          891 non-null int64
Parch          891 non-null int64
Ticket         891 non-null object
Fare           891 non-null float64
Cabin          204 non-null object
Embarked       889 non-null object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

[139]:
```
test_df.info()
```

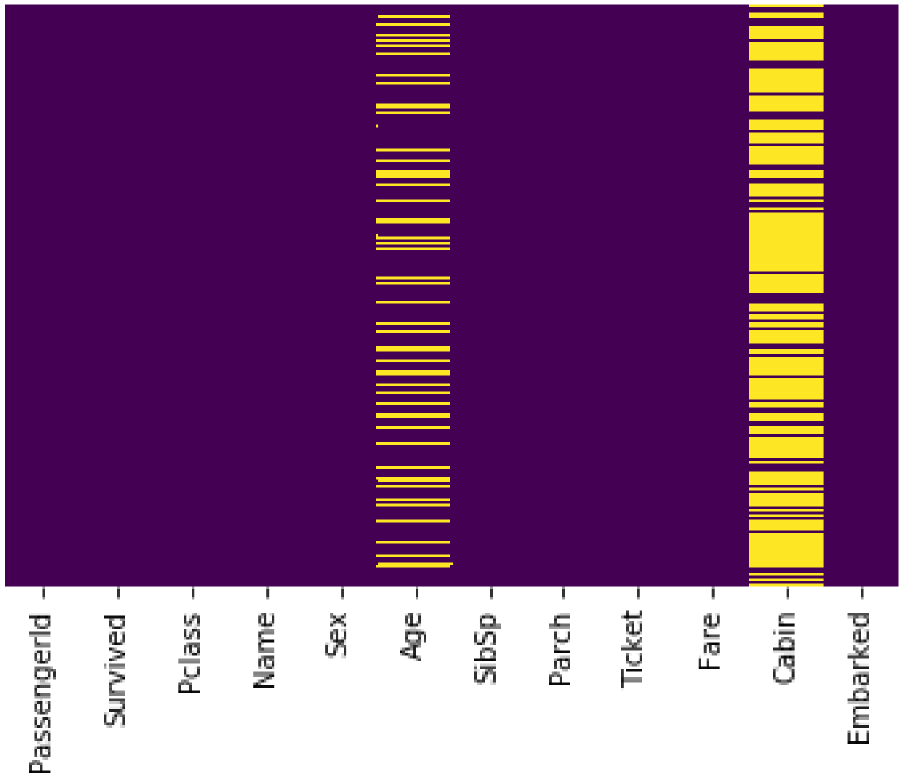
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
PassengerId    418 non-null int64
Pclass         418 non-null int64
Name           418 non-null object
Sex            418 non-null object
Age            332 non-null float64
SibSp          418 non-null int64
Parch          418 non-null int64
Ticket         418 non-null object
Fare           417 non-null float64
Cabin          91 non-null object
Embarked       418 non-null object
dtypes: float64(2), int64(4), object(5)
memory usage: 36.0+ KB
```

We should not look at the training data, so we only display the information about missing values. We will prepare the data based on training set and just make the same changes to test set, so it fits the model.

We can also visualise missing data by heatmap:

[140]:
```
sns.heatmap(train_df.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

[140]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2527120fcc8>
```



2 Data exploration and preparation

Let's take care of every feature in the dataset to make it usefull for the prediction model.

2.1 Passenger Id

We can assume, that "PassengerID" column has no correlation with surviving the disaster, so we can drop this collumn.

[141]:
```
train_df = train_df.drop("PassengerId", axis = 1)
#test_df = test_df.drop("PassengerId", axis = 1)
```

2.2 Pclass

We can see, that "Pclass" is a numerical, categorical feature with three possible values and no values are missing, so we don't have to change anything. Let's see how this feature impact surviving:

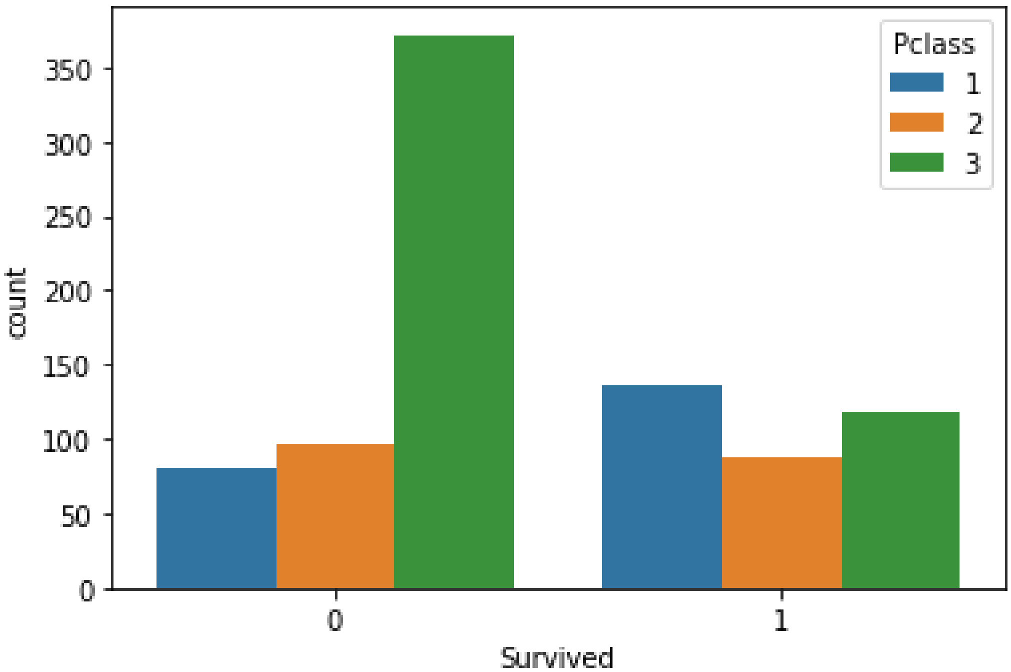
[142]:
```
train_df[['Pclass', 'Survived']].groupby(['Pclass'], as_index=False).mean()
```

[142]:
```
   Pclass  Survived
0       1  0.629630
```

```
1        2  0.472826
2        3  0.242363
```

[143]:
```
sns.countplot(x='Survived', hue='Pclass', data=train_df)
```

[143]: <matplotlib.axes._subplots.AxesSubplot at 0x2527127d408>



There is a strong correlation - third class passengers were less likely to have survived.

Now we scale these values so they are between 0 and 1:

[144]:
```
from sklearn.preprocessing import MinMaxScaler
min_max_scaler = MinMaxScaler()
train_df[["Pclass"]] = min_max_scaler.fit_transform(train_df[["Pclass"]])
test_df[["Pclass"]] = min_max_scaler.fit_transform(test_df[["Pclass"]])
```

2.3 Name

"Name" feature itself has no correlation with survivng and also the values are of different formats (some contain second names or titles). We could drop this feature but we can also try to get title from names and create the new feature from it.

[145]:
```
import re as re  # package for regular expressions

def get_title(name):
    title_search = re.search(' ([A-Za-z]+)\.', name)
```

```python
    # If the title exists, extract and return it.
    if title_search:
        return title_search.group(1)
    return ""

train_df['Title'] = train_df['Name'].apply(get_title)
test_df['Title'] = test_df['Name'].apply(get_title)

pd.crosstab(train_df['Title'], train_df['Sex'])
```

[145]:

```
Sex       female  male
Title
Capt           0     1
Col            0     2
Countess       1     0
Don            0     1
Dr             1     6
Jonkheer       0     1
Lady           1     0
Major          0     2
Master         0    40
Miss         182     0
Mlle           2     0
Mme            1     0
Mr             0   517
Mrs          125     0
Ms             1     0
Rev            0     6
Sir            0     1
```

We have a lot of values of “Title” feature, but some of them occure very rarely and some of them have similar meaning (for ex.: “Ms” and “Miss”).

[146]:

```python
train_df['Title'] = train_df['Title'].replace(['Lady', 'Countess','Capt', 'Col',
                                               'Don', 'Dr', 'Major', 'Rev',␣
 ↪'Sir', 'Jonkheer', 'Dona'], 'Rare')
train_df['Title'] = train_df['Title'].replace('Mlle', 'Miss')
train_df['Title'] = train_df['Title'].replace('Ms', 'Miss')
train_df['Title'] = train_df['Title'].replace('Mme', 'Mrs')

test_df['Title'] = test_df['Title'].replace(['Lady', 'Countess','Capt', 'Col',
                                             'Don', 'Dr', 'Major', 'Rev', 'Sir',␣
 ↪'Jonkheer', 'Dona'], 'Rare')
test_df['Title'] = test_df['Title'].replace('Mlle', 'Miss')
test_df['Title'] = test_df['Title'].replace('Ms', 'Miss')
test_df['Title'] = test_df['Title'].replace('Mme', 'Mrs')
```

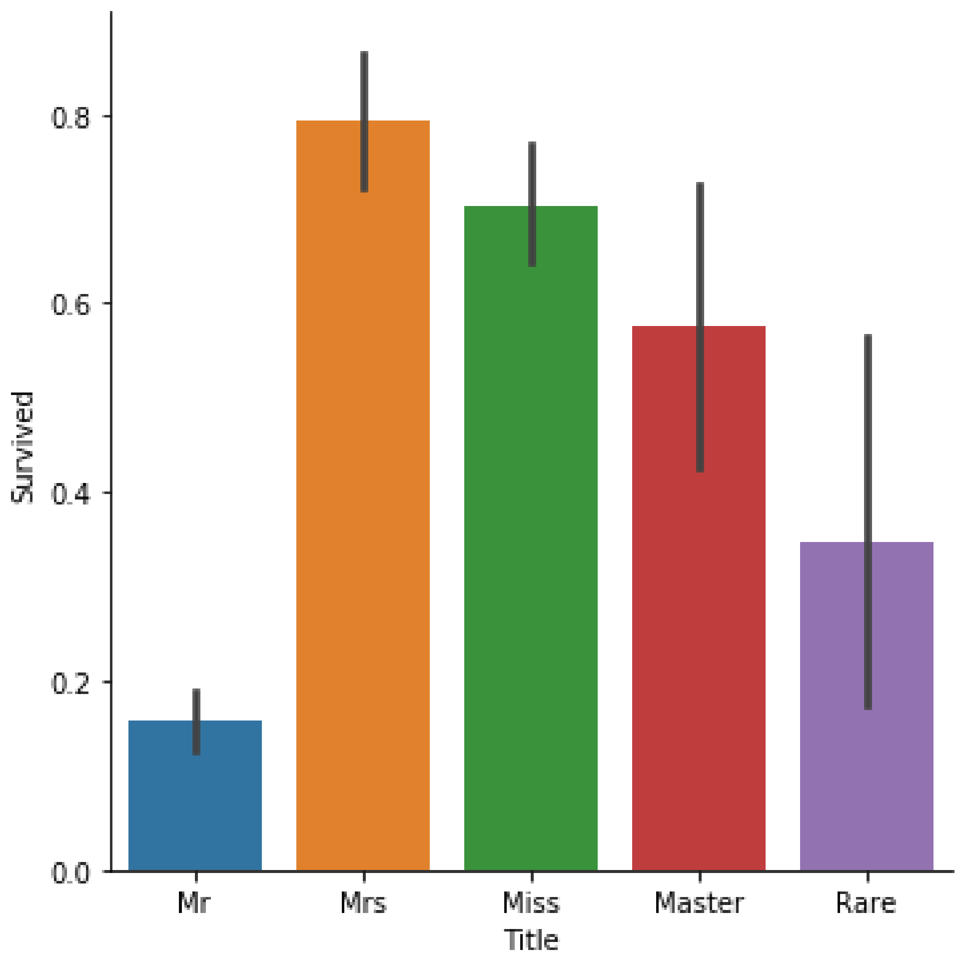
```
train_df[['Title', 'Survived']].groupby(['Title'], as_index=False).mean()
```

[146]:

	Title	Survived
0	Master	0.575000
1	Miss	0.702703
2	Mr	0.156673
3	Mrs	0.793651
4	Rare	0.347826

[147]:
```
sns.catplot(x = "Title", y = "Survived", kind = "bar", data = train_df)
```

[147]: <seaborn.axisgrid.FacetGrid at 0x252712da2c8>



Now we have to map titles into dummy numerical values. We can not just map titles into values like 1,2,3,4,5, because this may suggest graduation of titles to the predictor, which is undesirable.

```
[148]: # Trainig set:
dummy = pd.get_dummies(train_df["Title"])
train_df = pd.concat([train_df, dummy], axis = 1)

#Test set:
dummy = pd.get_dummies(test_df["Title"])
test_df = pd.concat([test_df, dummy], axis = 1)
```

Now we can drop "Name" and "Title" column:

```
[149]: train_df = train_df.drop(["Name", "Title"], axis = 1)
test_df = test_df.drop(["Name", "Title"], axis = 1)
```

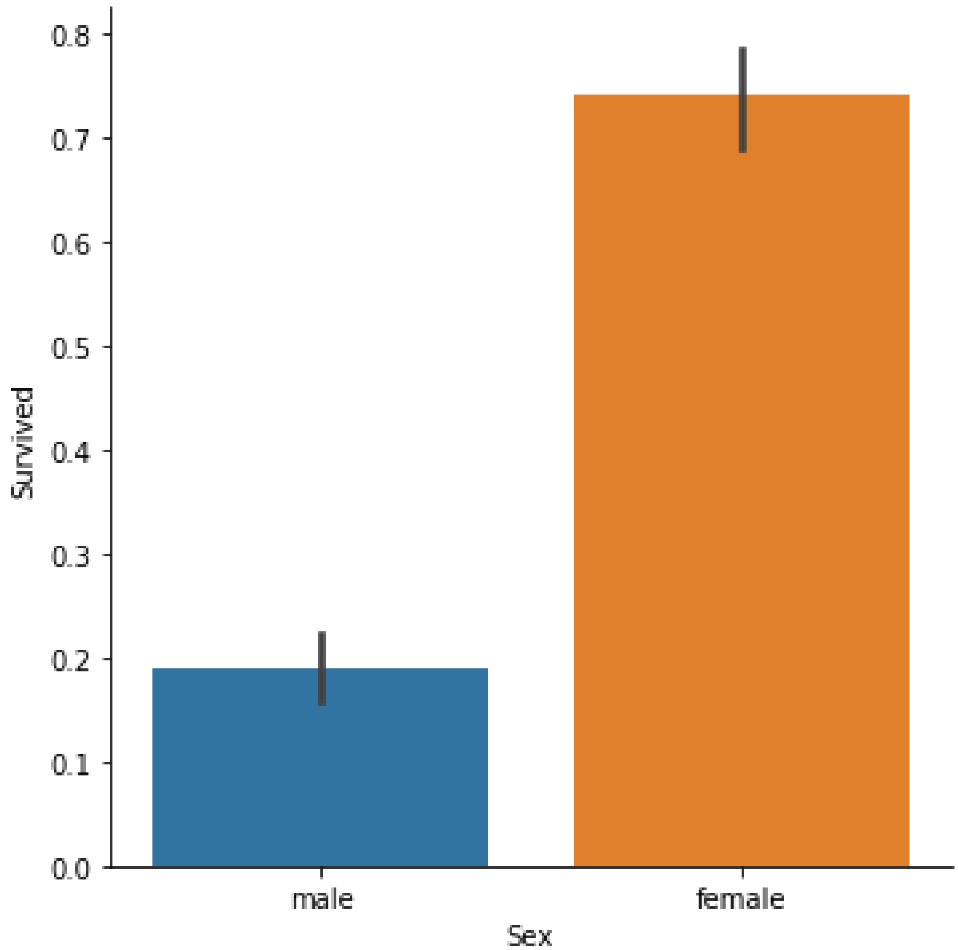
2.4 Sex

```
[150]: train_df[["Sex", "Survived"]].groupby(['Sex'], as_index=False).mean()
```

```
[150]:       Sex  Survived
       0  female  0.742038
       1    male  0.188908
```

```
[151]: sns.catplot(x = "Sex", y = "Survived", kind = "bar", data = train_df)
```

```
[151]: <seaborn.axisgrid.FacetGrid at 0x2527137dac8>
```



It is clear, that females were more likely to have survived, which was also possible to observe in "Title" feature. Values of "Sex" feature are categorical, but not numerical, so we only have to map them.

[152]:
```
train_df['Sex'] = train_df['Sex'].map( {'female': 0, 'male': 1} ).astype(int)
test_df['Sex'] = test_df['Sex'].map( {'female': 0, 'male': 1} ).astype(int)

train_df = train_df.rename(columns={'Sex': 'Male'})
test_df = test_df.rename(columns={'Sex': 'Male'})
```

The feature was rename to "Male" so 0 and 1 values are more clear to read.

2.5 Age

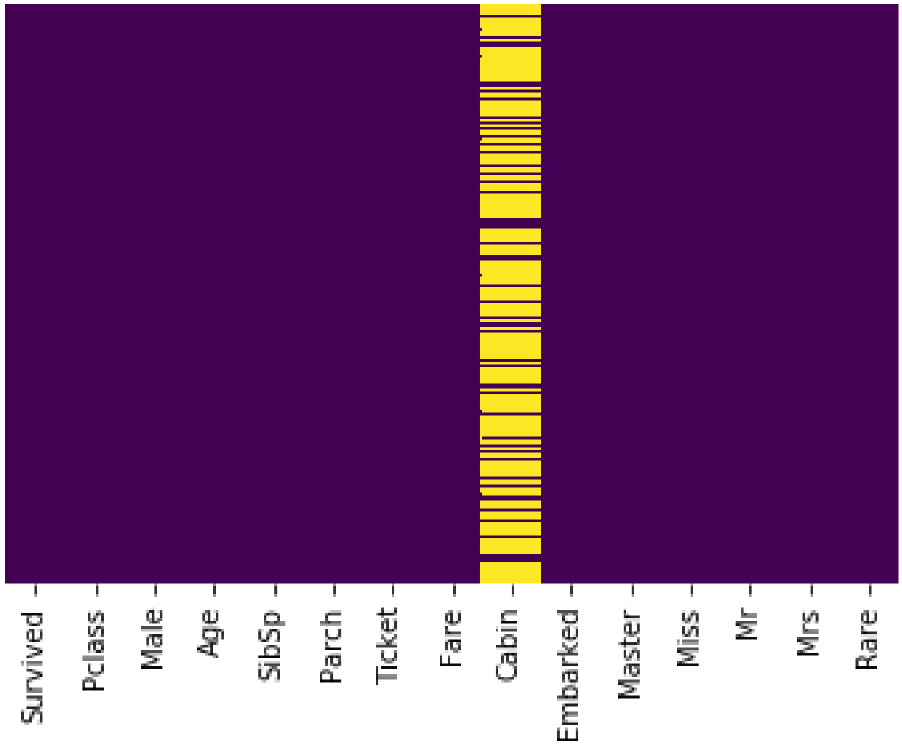
First of all, there are some missing values of this feature. The simplest method of filling them is to generate random values between (mean - std) and (mean + std). This is not the best solutions, but it shouldn't change this feature's impact on predictions, so we just use it.

[153]:
```python
# Training set:
train_age_avg = train_df['Age'].mean()
train_age_std = train_df['Age'].std()
train_age_null_count = train_df['Age'].isnull().sum()

train_age_random_list = np.random.randint(train_age_avg - train_age_std,␣
 ↪train_age_avg + train_age_std,
                                          size=train_age_null_count)
train_df['Age'][np.isnan(train_df['Age'])] = train_age_random_list
train_df['Age'] = train_df['Age'].astype(int)

# Test set:
test_age_avg = test_df['Age'].mean()
test_age_std = test_df['Age'].std()
test_age_null_count = test_df['Age'].isnull().sum()

test_age_random_list = np.random.randint(test_age_avg - test_age_std,␣
 ↪test_age_avg + test_age_std,
                                          size=test_age_null_count)
test_df['Age'][np.isnan(test_df['Age'])] = test_age_random_list
test_df['Age'] = test_df['Age'].astype(int)
```

Lets see the missing values heatmap again:

[154]:
```python
sns.heatmap(train_df.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

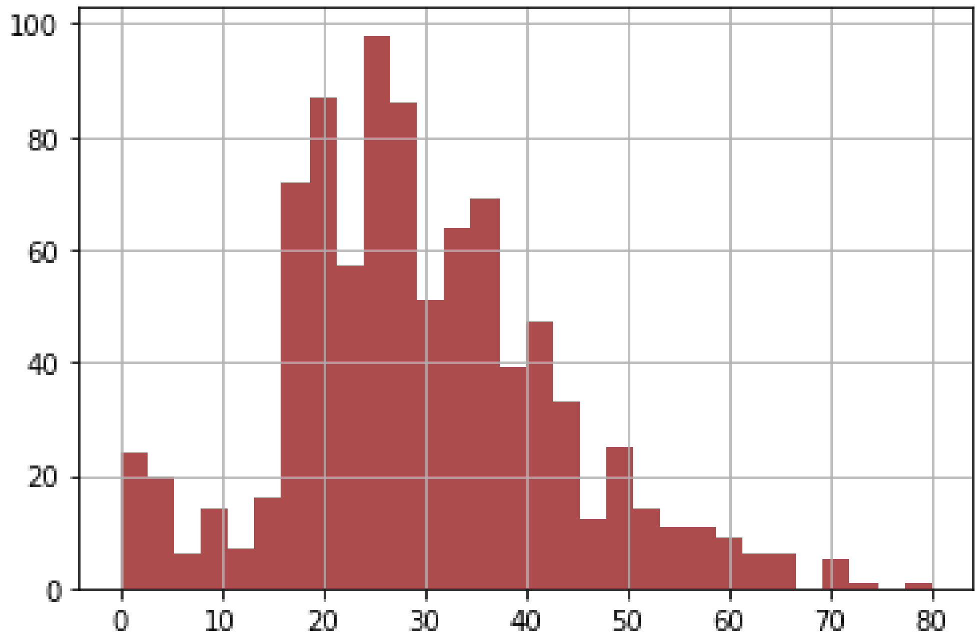
[154]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x25271621d08>
```



Lets see the distibution of “Age” feature:

[155]:
```python
train_df['Age'].hist(bins=30,color='darkred',alpha=0.7)
```

[155]: <matplotlib.axes._subplots.AxesSubplot at 0x2527168d648>



Now we categorize values of "Age" into 5 intervals to explore the correlations:

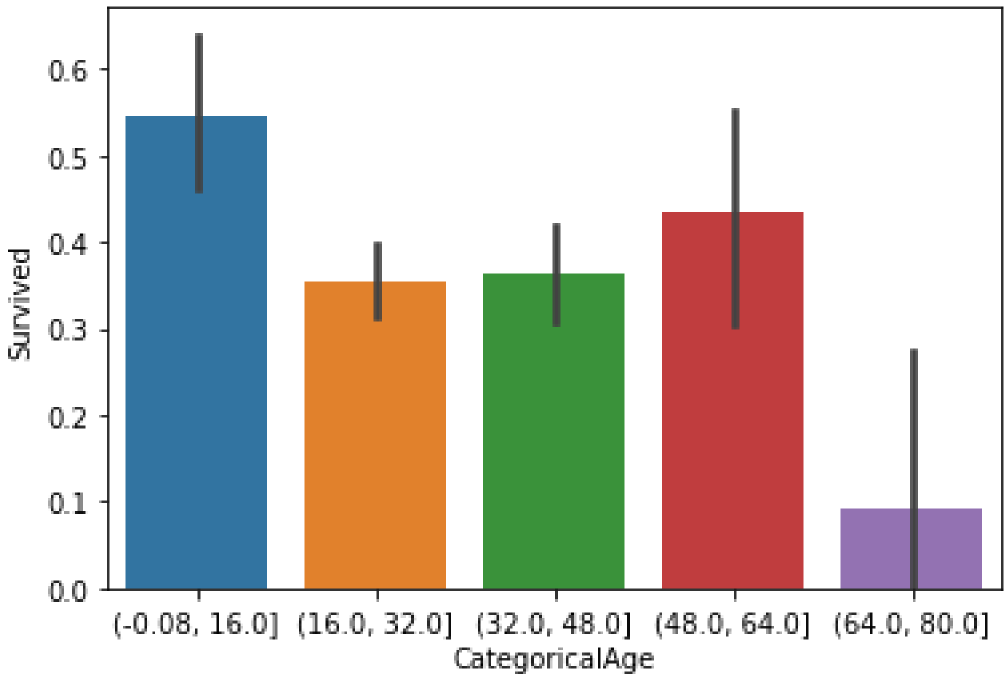
[156]:
```
train_df['CategoricalAge'] = pd.cut(train_df['Age'], 5)

train_df[['CategoricalAge', 'Survived']].groupby(['CategoricalAge'],␣
 ↪as_index=False).mean()
```

[156]:

	CategoricalAge	Survived
0	(-0.08, 16.0]	0.546296
1	(16.0, 32.0]	0.355408
2	(32.0, 48.0]	0.364000
3	(48.0, 64.0]	0.434783
4	(64.0, 80.0]	0.090909

[157]:
```
sns.barplot(x="CategoricalAge", y="Survived", data = train_df)
```

[157]: <matplotlib.axes._subplots.AxesSubplot at 0x25271770908>



We can see that the highest survival propbability was for passengers younger than 16 and the lowest for older than 64.

Combinig this information with the conclusions from "Sex" feature exploration, we can see, that women and children were rescued in the first place.

Now we drop "CategoricalAge" column.

[158]:
```
train_df = train_df.drop('CategoricalAge', axis = 1)
```

Now we scale "Age" values, so they are in range <0, 1>:

[159]:
```
train_df[["Age"]] = min_max_scaler.fit_transform(train_df[["Age"]])
test_df[["Age"]] = min_max_scaler.fit_transform(test_df[["Age"]])
```

2.6 SibSp and Parch

SibSp - number of Siblings/Spouses aboard Parch - number of Parents/Children aboard

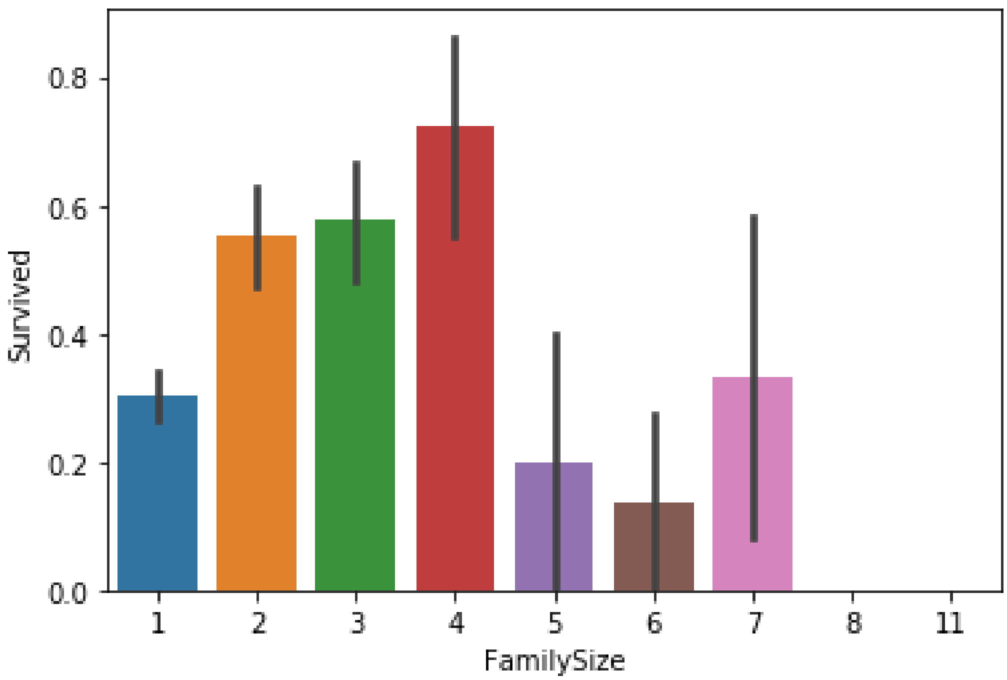
We can converse these two features into one feature discribing family size onboard:

[160]:
```
train_df['FamilySize'] = train_df['SibSp'] + train_df['Parch'] + 1
test_df['FamilySize'] = test_df['SibSp'] + test_df['Parch'] + 1

train_df[['FamilySize', 'Survived']].groupby(['FamilySize'], as_index=False).
 ↪mean()
```

[160]:
```
   FamilySize  Survived
0           1  0.303538
1           2  0.552795
2           3  0.578431
3           4  0.724138
4           5  0.200000
5           6  0.136364
6           7  0.333333
7           8  0.000000
8          11  0.000000
```

[161]:
```
sns.barplot(x="FamilySize", y="Survived", data=train_df)
```

[161]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x252717fa808>
```



There is no obvious correlation visible, so we can try to categorize passengers based on the information if they were onboard alone or with family:

[162]:
```
train_df['IsAlone'] = 0
train_df.loc[train_df['FamilySize'] == 1, 'IsAlone'] = 1

test_df['IsAlone'] = 0
test_df.loc[train_df['FamilySize'] == 1, 'IsAlone'] = 1

train_df[['IsAlone', 'Survived']].groupby(['IsAlone'], as_index=False).mean()
```

[162]:

	IsAlone	Survived
0	0	0.505650
1	1	0.303538

People with family members onboard were more likely to have survived.
Lets drop unnecessary columns:

[163]:
```
train_df = train_df.drop(["SibSp", "Parch", "FamilySize"], axis = 1)
test_df = test_df.drop(["SibSp", "Parch", "FamilySize"], axis = 1)
```

2.7 Ticket and Cabin

[164]:
```
train_df.describe(include=['O'])
```

[164]:

	Ticket	Cabin	Embarked
count	891	204	889
unique	681	147	3
top	347082	G6	S
freq	7	4	644

Majority of "Cabin" feature is missing values, so we can drop this column entirely as there is no way to complete the values reasonably.

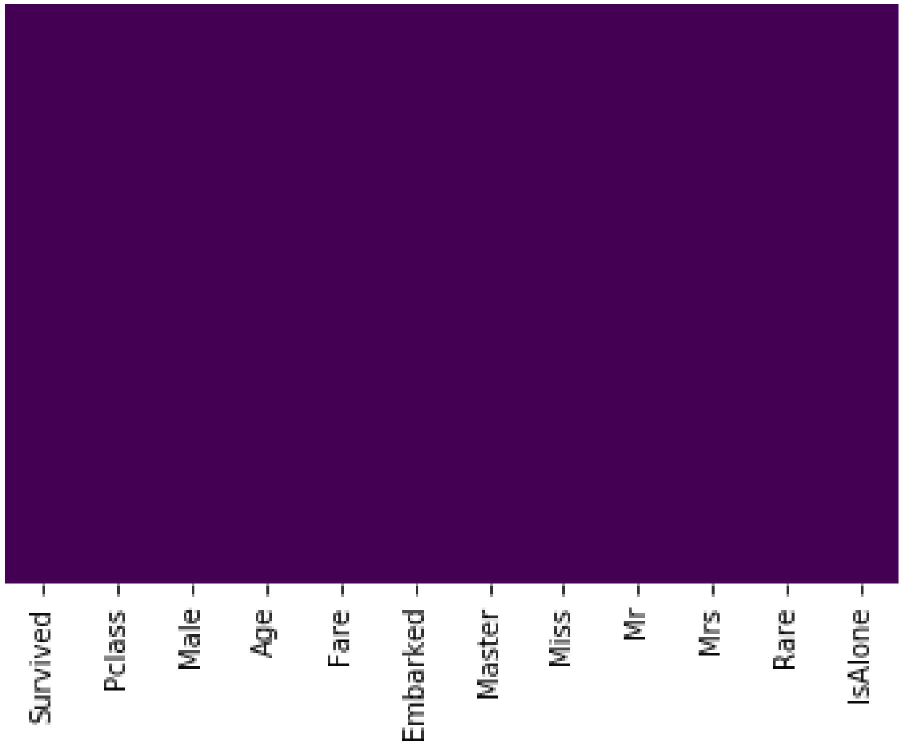
"Ticket" collumn contain 681 unique values, some of with are numerical and some are alphanumerical. These values are just random ticket numbers and have no correlation with survival, so we also drop this feature.

[165]:
```
train_df = train_df.drop(["Cabin", "Ticket"], axis = 1)
test_df = test_df.drop(["Cabin", "Ticket"], axis = 1)
```

Heatmap of missing values:

[166]:
```
sns.heatmap(train_df.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

[166]: <matplotlib.axes._subplots.AxesSubplot at 0x252711f9d48>



2.8 Fare

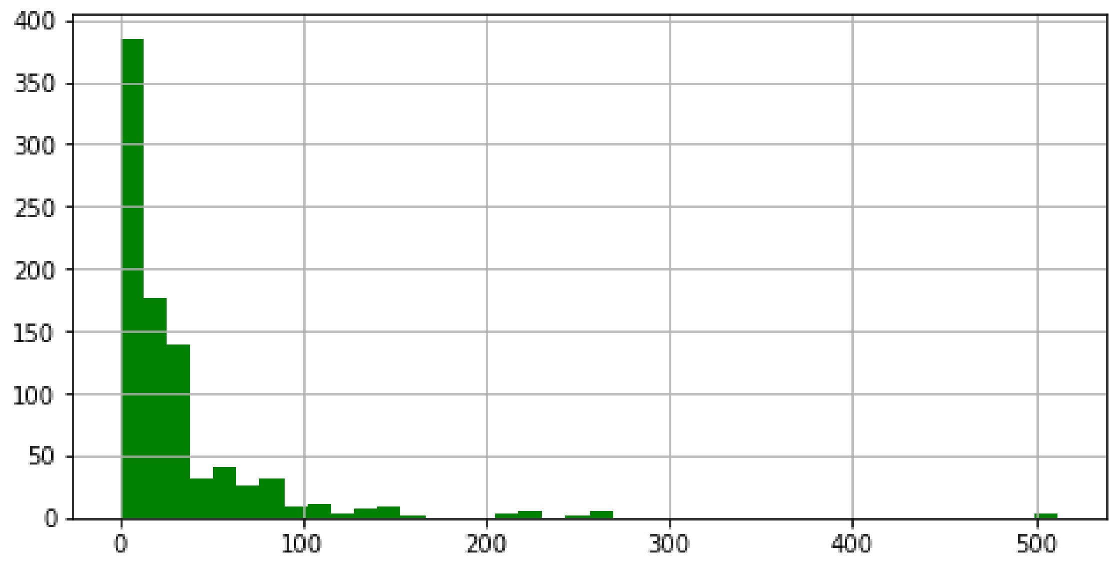
There is one missing value in test set. We will just replace it with the median:

[167]:
```
test_df['Fare'] = test_df['Fare'].fillna(train_df['Fare'].median())
```

Lets see the distribution of fare feature:

[168]:
```
train_df['Fare'].hist(color='green',bins=40,figsize=(8,4))
```

[168]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x252718dd748>
```



Now we scale values of “Fare”:

[169]:
```
train_df[["Fare"]] = min_max_scaler.fit_transform(train_df[["Fare"]])
test_df[["Fare"]] = min_max_scaler.fit_transform(test_df[["Fare"]])
```

2.9 Embarked

C = Cherbourg; Q = Queenstown; S = Southampton

[170]:
```
train_df["Embarked"].isnull().sum()
```

[170]: 2

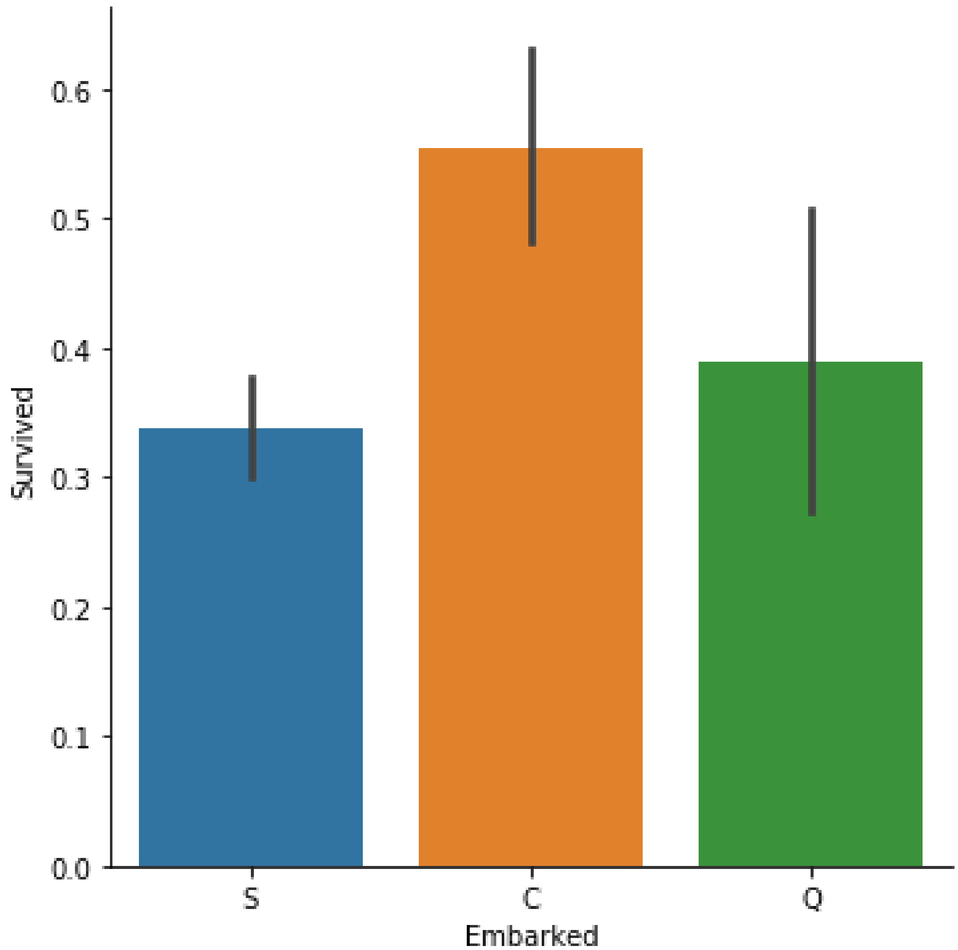
There are 2 missing values in trainig set. We will just drop these rows.

[171]:
```
train_df.dropna(inplace=True)

train_df[['Embarked', 'Survived']].groupby(['Embarked'], as_index=False).mean()
```

[171]:
```
  Embarked  Survived
0        C  0.553571
1        Q  0.389610
2        S  0.336957
```

[172]:
```
sns.catplot(x="Embarked", y="Survived", kind="bar", data=train_df)
```

[172]: <seaborn.axisgrid.FacetGrid at 0x252719be988>



We can see, that people who embarked in Cherbourg were most likely to have survived.

Now we have to create dummy values:

[173]:
```
# Trainig set:
dummy = pd.get_dummies(train_df["Embarked"])
train_df = pd.concat([train_df, dummy], axis = 1)

#Test set:
dummy = pd.get_dummies(test_df["Embarked"])
test_df = pd.concat([test_df, dummy], axis = 1)

train_df = train_df.drop("Embarked", axis = 1)
test_df = test_df.drop("Embarked", axis = 1)
```

Lets see the final dataframe:

[174]:
```
train_df
```

[174]:

```
     Survived  Pclass  Male     Age      Fare  Master  Miss  Mr  Mrs  Rare  \
0           0     1.0     1  0.2750  0.014151       0     0   1    0     0
1           1     0.0     0  0.4750  0.139136       0     0   0    1     0
2           1     1.0     0  0.3250  0.015469       0     1   0    0     0
3           1     0.0     0  0.4375  0.103644       0     0   0    1     0
4           0     1.0     1  0.4375  0.015713       0     0   1    0     0
..        ...     ...   ...     ...       ...     ...   ...  ..  ...   ...
886         0     0.5     1  0.3375  0.025374       0     0   0    0     1
887         1     0.0     0  0.2375  0.058556       0     1   0    0     0
888         0     1.0     0  0.4125  0.045771       0     1   0    0     0
889         1     0.0     1  0.3250  0.058556       0     0   1    0     0
890         0     1.0     1  0.4000  0.015127       0     0   1    0     0

     IsAlone  C  Q  S
0          0  0  0  1
1          0  1  0  0
2          1  0  0  1
3          0  0  0  1
4          1  0  0  1
..       ... .. .. ..
886        1  0  0  1
887        1  0  0  1
888        0  0  0  1
889        1  1  0  0
890        1  0  1  0

[889 rows x 14 columns]
```

[175]:

```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 889 entries, 0 to 890
Data columns (total 14 columns):
Survived    889 non-null int64
Pclass      889 non-null float64
Male        889 non-null int32
Age         889 non-null float64
Fare        889 non-null float64
Master      889 non-null uint8
Miss        889 non-null uint8
Mr          889 non-null uint8
Mrs         889 non-null uint8
Rare        889 non-null uint8
IsAlone     889 non-null int64
C           889 non-null uint8
Q           889 non-null uint8
S           889 non-null uint8
```

```
dtypes: float64(3), int32(1), int64(2), uint8(8)
memory usage: 92.1 KB
```

[176]:
```
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 14 columns):
PassengerId    418 non-null int64
Pclass         418 non-null float64
Male           418 non-null int32
Age            418 non-null float64
Fare           418 non-null float64
Master         418 non-null uint8
Miss           418 non-null uint8
Mr             418 non-null uint8
Mrs            418 non-null uint8
Rare           418 non-null uint8
IsAlone        418 non-null int64
C              418 non-null uint8
Q              418 non-null uint8
S              418 non-null uint8
dtypes: float64(3), int32(1), int64(2), uint8(8)
memory usage: 21.4 KB
```

3 Creating classifiers

Provided "test.csv" file is used for evaluating the model performance on Kaggle competition, so it does not contain "Survived" column.
The "gender_submission.csv" file is just an example of how the predictions should be submitted on Kaggle. The value of "Survived" in this file is just based on gender (male - 0, female - 1).
So to evaluate my models locally I will split train_df into train and test set.

Train and test split:

[177]:
```
y = train_df["Survived"]
X = train_df.drop("Survived", axis = 1)


from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
 ↪random_state=42, shuffle = True)
```

3.1 Logistic regression

[178]:
```python
from sklearn.linear_model import LogisticRegression
```

Creating and training the model:

[179]:
```python
logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)
```

[179]:
```
LogisticRegression()
```

Making predictions:

[180]:
```python
predictions = logmodel.predict(X_test)
```

Evaluating the model:

[181]:
```python
from sklearn.metrics import classification_report,confusion_matrix,␣
↪accuracy_score
```

[182]:
```python
accuracy_score(y_test, predictions)
```

[182]:
```
0.8089887640449438
```

[183]:
```python
print(classification_report(y_test,predictions))
```

```
              precision    recall  f1-score   support

           0       0.86      0.83      0.84       167
           1       0.73      0.78      0.75       100

    accuracy                           0.81       267
   macro avg       0.80      0.80      0.80       267
weighted avg       0.81      0.81      0.81       267
```

[184]:
```python
print(confusion_matrix(y_test,predictions))
```

```
[[138  29]
 [ 22  78]]
```

3.2 Decision tree classifier

[185]:
```python
from sklearn.tree import DecisionTreeClassifier
```

[186]:
```python
DTC = DecisionTreeClassifier()
DTC.fit(X_train, y_train)
```

[186]: DecisionTreeClassifier()

[187]:
```
predictions = DTC.predict(X_test)
```

[188]:
```
accuracy_score(y_test, predictions)
```

[188]: 0.7378277153558053

3.3 Random forest classifier

[189]:
```
from sklearn.ensemble import RandomForestClassifier
```

[190]:
```
RFC = RandomForestClassifier()
RFC.fit(X_train, y_train)
```

[190]: RandomForestClassifier()

[191]:
```
predictions = RFC.predict(X_test)
```

[192]:
```
accuracy_score(y_test, predictions)
```

[192]: 0.7715355805243446

3.4 Support vector machine classifier

[193]:
```
from sklearn.svm import SVC
```

[194]:
```
SVM = SVC()
```

[195]:
```
SVM.fit(X_train, y_train)
```

[195]: SVC()

[196]:
```
predictions = SVM.predict(X_test)
```

[197]:
```
accuracy_score(y_test, predictions)
```

[197]: 0.8052434456928839

3.5 K Neighbours classifier

[198]:
```
from sklearn.neighbors import KNeighborsClassifier
```

[199]:
```
KNC = KNeighborsClassifier()
KNC.fit(X_train, y_train)
```

[199]: KNeighborsClassifier()

[200]:
```
predictions = KNC.predict(X_test)
```

[201]:
```
accuracy_score(y_test, predictions)
```

[201]: 0.7940074906367042

3.6 Gaussian Naive Bayes classifier

[202]:
```
from sklearn.naive_bayes import GaussianNB
```

[203]:
```
NB = GaussianNB()
NB.fit(X_train, y_train)
```

[203]: GaussianNB()

[204]:
```
predictions = NB.predict(X_test)
```

[205]:
```
accuracy_score(y_test, predictions)
```

[205]: 0.7677902621722846

3.7 Gradient boosting classifier

[206]:
```
from sklearn.ensemble import GradientBoostingClassifier
```

[207]:
```
GBC = GradientBoostingClassifier()
GBC.fit(X_train, y_train)
```

[207]: GradientBoostingClassifier()

[208]:
```
predictions = GBC.predict(X_test)
```

[209]:
```
accuracy_score(y_test, predictions)
```

[209]: 0.8127340823970037

3.8 AdaBoost classifier

[210]:
```
from sklearn.ensemble import AdaBoostClassifier
```

[211]:
```
ABC = AdaBoostClassifier()
ABC.fit(X_train, y_train)
```

[211]: AdaBoostClassifier()

[212]:
```
predictions = ABC.predict(X_test)
```

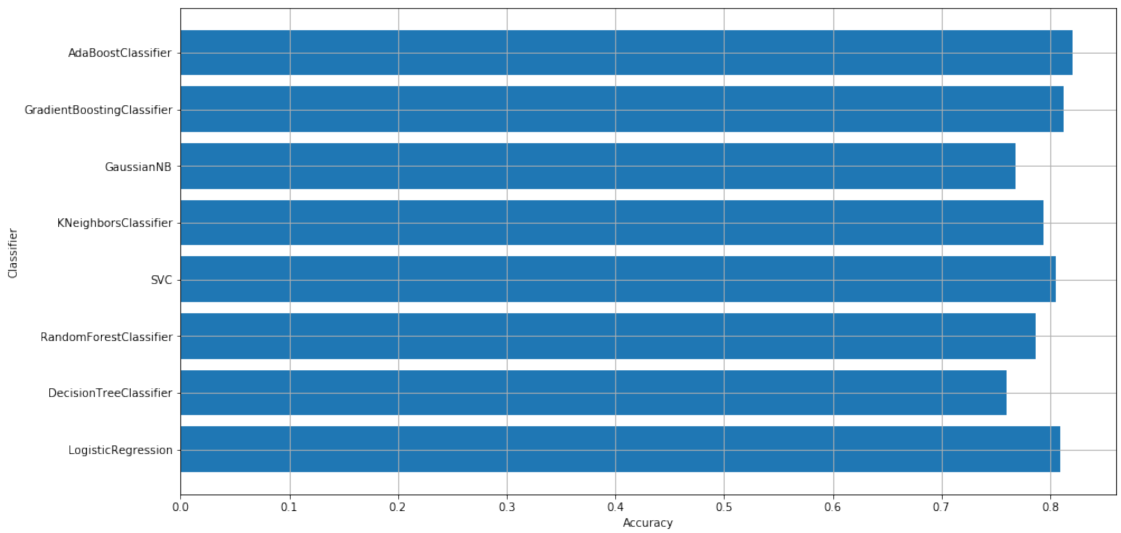
[213]:
```
accuracy_score(y_test, predictions)
```

[213]: 0.8202247191011236

4 Comparison

[214]:
```
models = [LogisticRegression(), DecisionTreeClassifier(),␣
 ↪RandomForestClassifier(), SVC(),
          KNeighborsClassifier(), GaussianNB(), GradientBoostingClassifier(),
          AdaBoostClassifier()]

evaluation = {}

for model in models:
    model.fit(X_train, y_train)
    predictions = model.predict(X_test)
    acc = accuracy_score(y_test, predictions)
    name = model.__class__.__name__
    evaluation[name] = acc

plt.figure(figsize = (15,8))
plt.barh(range(len(evaluation)), list(evaluation.values()), align='center',␣
 ↪tick_label = list(evaluation.keys()))
plt.grid()
plt.xlabel("Accuracy")
plt.ylabel("Classifier")
```

[214]: Text(0, 0.5, 'Classifier')



Creating predictions with the best classifiers for 'test.csv' data and exporting it for evaluation at Kaggle:

[215]:
```
predictions = SVM.predict(test_df.drop("PassengerId", axis = 1))
output = pd.DataFrame({'PassengerId': test_df.PassengerId, 'Survived':␣
↪predictions})
output.to_csv('SVM_submission.csv', index=False)
```

[216]:
```
predictions = ABC.predict(test_df.drop("PassengerId", axis = 1))
output = pd.DataFrame({'PassengerId': test_df.PassengerId, 'Survived':␣
↪predictions})
output.to_csv('ABC_submission.csv', index=False)
```

[217]:
```
predictions = GBC.predict(test_df.drop("PassengerId", axis = 1))
output = pd.DataFrame({'PassengerId': test_df.PassengerId, 'Survived':␣
↪predictions})
output.to_csv('GBC_submission.csv', index=False)
```

[218]:
```
predictions = logmodel.predict(test_df.drop("PassengerId", axis = 1))
output = pd.DataFrame({'PassengerId': test_df.PassengerId, 'Survived':␣
↪predictions})
output.to_csv('logmodel_submission.csv', index=False)
```

Results from Kaggle competition:

Model	Accuracy
Support Vector Classifier	0.78468
AdaBoost Classifier	0.74401
Gradient Boosting Classifier	0.77033
Logistic Regression	0.75837

5 Conclusions

Support Vector Machine Classifier seem to word the best for the Titanic dataset, but it could still be improved. First of all, the data was prepared to have been used for every classifier. All of them work differently and have different specification, so dataset could be prepared separately for each algorithm to fit its needs. What is more, every model was trained with default values of hyperparameters. The next step would be choosing one predictor and tuning hyperparameters values, for example with Grid Search Cross-Validation. This could improve performance of the model.

6 Bibliography

1. https://software.intel.com/content/www/us/en/develop/training/course-machine-learning.html
2. https://www.kaggle.com/startupsci/titanic-data-science-solutions
3. Aurélien Géron, Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, 2nd Edition