Program:

```
#Importing the required libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt


#importing the dataset
df  = pd.read_csv("uber.csv")


df.head()
```

	Unnamed: 0	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
0	24238194	2015-05-07 19:52:06.0000003	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	-73.999512	40.723217	1
1	27835199	2009-07-17 20:04:56.0000002	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	-73.994710	40.750325	1
2	44984355	2009-08-24 21:45:00.00000061	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	-73.962565	40.772647	1
3	25894730	2009-06-26 08:22:21.0000001	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844	-73.965316	40.803349	3
4	17610152	2014-08-28 17:47:00.000000188	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085	-73.973082	40.761247	5

```
df.info() #To get the required information of the dataset

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 9 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Unnamed: 0         200000 non-null  int64
 1   key                200000 non-null  object
 2   fare_amount        200000 non-null  float64
 3   pickup_datetime    200000 non-null  object
 4   pickup_longitude   200000 non-null  float64
 5   pickup_latitude    200000 non-null  float64
 6   dropoff_longitude  199999 non-null  float64
 7   dropoff_latitude   199999 non-null  float64
 8   passenger_count    200000 non-null  int64
dtypes: float64(5), int64(2), object(2)
memory usage: 13.7+ MB


df.columns #TO get number of columns in the dataset
```

```
Index(['Unnamed: 0', 'key', 'fare_amount', 'pickup_datetime',
'pickup_longitude', 'pickup_latitude', 'dropoff_longitude',
'dropoff_latitude', 'passenger_count'], dtype='object')
```

```
df = df.drop(['Unnamed: 0', 'key'], axis= 1) #To drop unnamed column as it
 isn't required
```

```
df.head()
```

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
0	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	-73.999512	40.723217	1
1	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	-73.994710	40.750325	1
2	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	-73.962565	40.772647	1
3	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844	-73.965316	40.803349	3
4	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085	-73.973082	40.761247	5

```
df.shape #To get the total (Rows,Columns)
(200000, 7)
```

```
df.dtypes #To get the type of each column
fare_amount float64

pickup_datetime object

pickup_longitude float64

pickup_latitude float64

dropoff_longitude float64

dropoff_latitude float64

passenger_count int64

dtype: object
```

```
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 7 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   fare_amount        200000 non-null  float64
 1   pickup datetime    200000 non-null  object
 2   pickup_longitude   200000 non-null  float64
 3   pickup_latitude    200000 non-null  float64
 4   dropoff_longitude  199999 non-null  float64
```

```
 5   dropoff_latitude   199999 non-null  float64
 6   passenger_count    200000 non-null  int64
dtypes: float64(5), int64(1), object(1)
memory usage: 10.7+ MB
```

```
df.describe() #To get statistics of each columns
```

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
count	200000.000000	200000.000000	200000.000000	199999.000000	199999.000000	200000.000000
mean	11.359955	-72.527638	39.935885	-72.525292	39.923890	1.684535
std	9.901776	11.437787	7.720539	13.117408	6.794829	1.385997
min	-52.000000	-1340.648410	-74.015515	-3356.666300	-881.985513	0.000000
25%	6.000000	-73.992065	40.734796	-73.991407	40.733823	1.000000
50%	8.500000	-73.981823	40.752592	-73.980093	40.753042	1.000000
75%	12.500000	-73.967154	40.767158	-73.963658	40.768001	2.000000
max	499.000000	57.418457	1644.421482	1153.572603	872.697628	208.000000

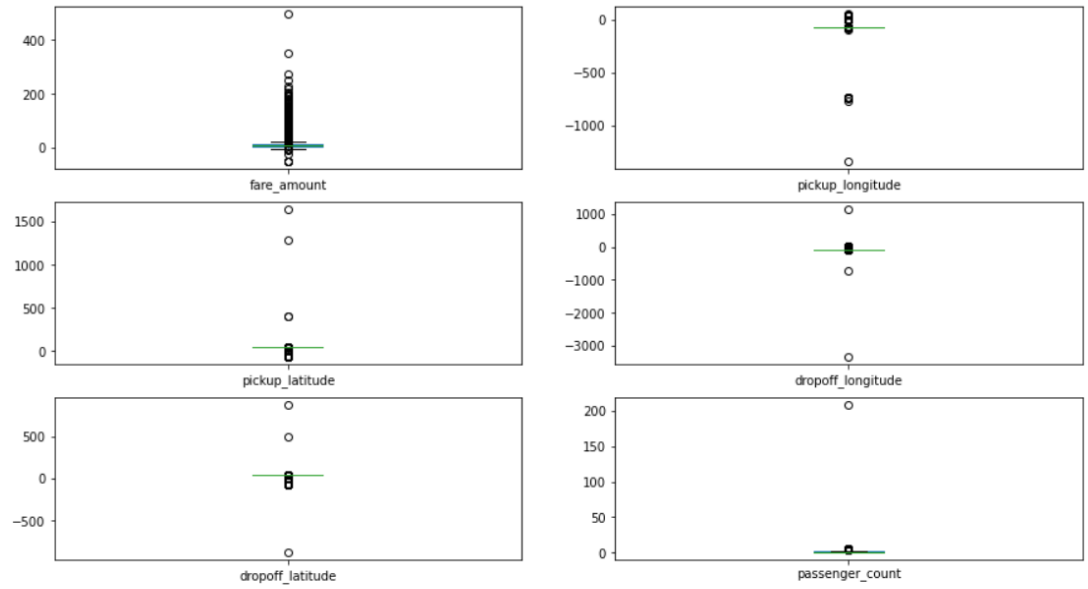
```
df.isnull().sum()
fare_amount 0

pickup_datetime 0

pickup_longitude 0

pickup_latitude 0

dropoff_longitude 1

dropoff_latitude 1

passenger_count 0

dtype: int64

df['dropoff_latitude'].fillna(value=df['dropoff_latitude'].mean(),inplace
= True)
df['dropoff_longitude'].fillna(value=df['dropoff_longitude'].median(),inpl
ace = True)
```

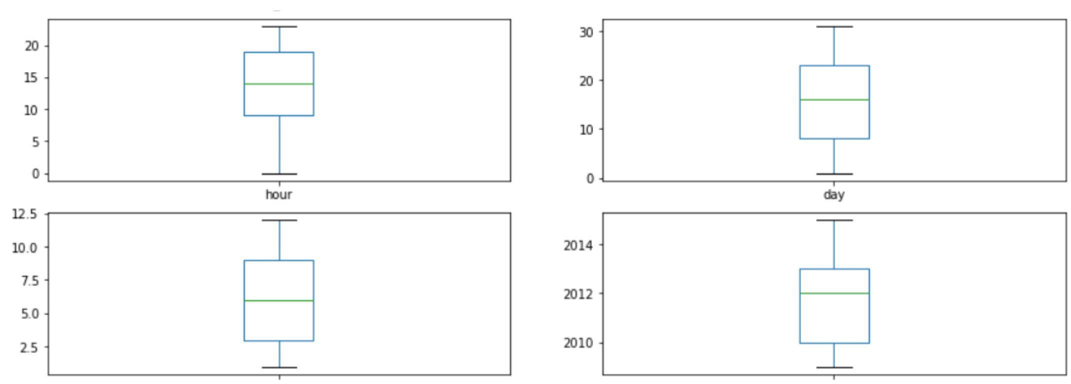
```
df.isnull().sum()
fare_amount 0

pickup_datetime 0

pickup_longitude 0

pickup_latitude 0
```

```
dropoff_longitude 0

dropoff_latitude 0

passenger_count 0

dtype: int64
```

```
df.dtypes
fare_amount float64

pickup_datetime object

pickup_longitude float64

pickup_latitude float64

dropoff_longitude float64

dropoff_latitude float64

passenger_count int64

dtype: object
```

```
df.plot(kind = "box",subplots = True,layout = (7,2),figsize=(15,20)) #Boxp
lot to check the outliers
fare_amount AxesSubplot(0.125,0.787927;0.352273x0.0920732)
pickup_longitude AxesSubplot(0.547727,0.787927;0.352273x0.0920732)
pickup_latitude AxesSubplot(0.125,0.677439;0.352273x0.0920732)
dropoff_longitude AxesSubplot(0.547727,0.677439;0.352273x0.0920732)
dropoff_latitude AxesSubplot(0.125,0.566951;0.352273x0.0920732)
passenger_count AxesSubplot(0.547727,0.566951;0.352273x0.0920732)

hour AxesSubplot(0.125,0.456463;0.352273x0.0920732)

day AxesSubplot(0.547727,0.456463;0.352273x0.0920732)

month AxesSubplot(0.125,0.345976;0.352273x0.0920732)

year AxesSubplot(0.547727,0.345976;0.352273x0.0920732)

dayofweek AxesSubplot(0.125,0.235488;0.352273x0.0920732)

dtype: object
```

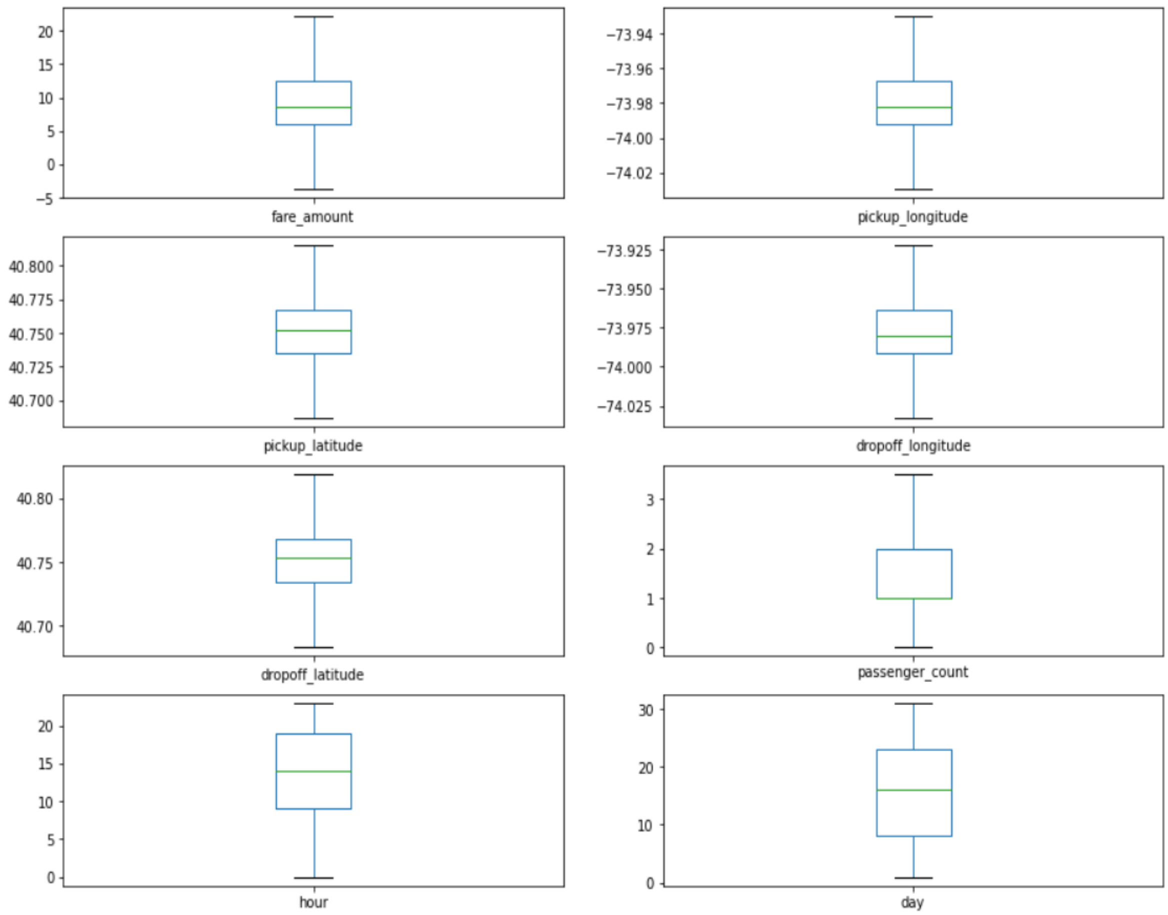


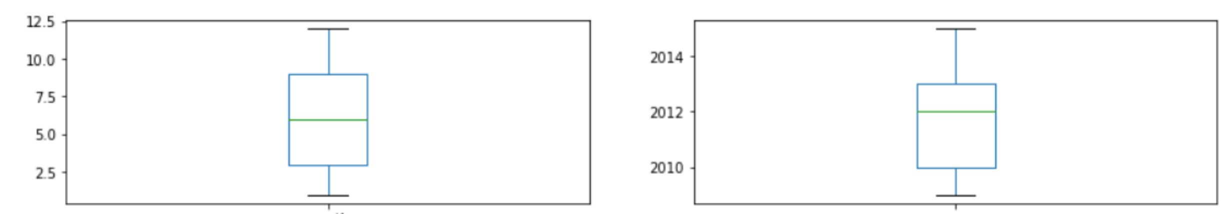



```
#Using the InterQuartile Range to fill the values
def remove_outlier(df1 , col):
    Q1 = df1[col].quantile(0.25)
    Q3 = df1[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_whisker = Q1-1.5*IQR
    upper_whisker = Q3+1.5*IQR
    df[col] = np.clip(df1[col] , lower_whisker , upper_whisker)
    return df1

def treat_outliers_all(df1 , col_list):
    for c in col_list:
        df1 = remove_outlier(df , c)
    return df1


df = treat_outliers_all(df , df.iloc[: , 0::])
```

```
df.plot(kind = "box",subplots = True,layout = (7,2),figsize=(15,20)) #Boxp
lot shows that dataset is free from outliers
```

```
fare_amount AxesSubplot(0.125,0.787927;0.352273x0.0920732)
pickup_longitude AxesSubplot(0.547727,0.787927;0.352273x0.0920732)
pickup_latitude AxesSubplot(0.125,0.677439;0.352273x0.0920732)
dropoff_longitude AxesSubplot(0.547727,0.677439;0.352273x0.0920732)
dropoff_latitude AxesSubplot(0.125,0.566951;0.352273x0.0920732)
passenger_count AxesSubplot(0.547727,0.566951;0.352273x0.0920732)
hour AxesSubplot(0.125,0.456463;0.352273x0.0920732)
day AxesSubplot(0.547727,0.456463;0.352273x0.0920732)
month AxesSubplot(0.125,0.345976;0.352273x0.0920732)
year AxesSubplot(0.547727,0.345976;0.352273x0.0920732)
dayofweek AxesSubplot(0.125,0.235488;0.352273x0.0920732)
dtype: object
```





```
#pip install haversine
import haversine as hs  #Calculate the distance using Haversine to calcula
te the distance between to points. Can't use Eucladian as it is for flat s
urface.
travel_dist = []
for pos in range(len(df['pickup_longitude'])):
        long1,lati1,long2,lati2 = [df['pickup_longitude'][pos],df['pickup_
latitude'][pos],df['dropoff_longitude'][pos],df['dropoff_latitude'][pos]]
        loc1=(lati1,long1)
        loc2=(lati2,long2)
        c = hs.haversine(loc1,loc2)
        travel_dist.append(c)
```

```
print(travel_dist)
df['dist_travel_km'] = travel_dist
df.head()
```

```
IOPub data rate exceeded.
The notebook server will temporarily stop sending output
to the client in order to avoid crashing it.
To change this limit, set the config variable
`--NotebookApp.iopub_data_rate_limit`.

Current values:
NotebookApp.iopub_data_rate_limit=1000000.0 (bytes/sec)
NotebookApp.rate_limit_window=3.0 (secs)
```

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	hour	day	month	year	dayofweek	dist_travel_km
0	7.5	-73.999817	40.738354	-73.999512	40.723217	1.0	19	7	5	2015	3	1.683325
1	7.7	-73.994355	40.728225	-73.994710	40.750325	1.0	20	17	7	2009	4	2.457593
2	12.9	-74.005043	40.740770	-73.962565	40.772647	1.0	21	24	8	2009	0	5.036384
3	5.3	-73.976124	40.790844	-73.965316	40.803349	3.0	8	26	6	2009	4	1.661686
4	16.0	-73.929786	40.744085	-73.973082	40.761247	3.5	17	28	8	2014	3	4.116088

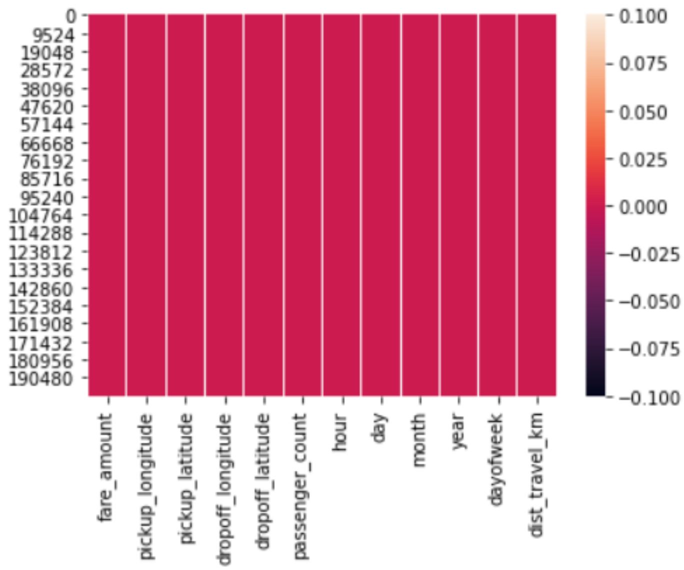
```
#Uber doesn't travel over 130 kms so minimize the distance
df= df.loc[(df.dist_travel_km >= 1) | (df.dist_travel_km <= 130)]
print("Remaining observastions in the dataset:", df.shape)
Remaining observastions in the dataset: (200000, 12)
#Finding inccorect latitude (Less than or greater than 90) and longitude (
greater than or less than 180)
incorrect_coordinates = df.loc[(df.pickup_latitude > 90) |(df.pickup_latit
ude < -90) |
                                   (df.dropoff_latitude > 90) |(df.dropoff
_latitude < -90) |
                                   (df.pickup_longitude > 180) |(df.pickup
_longitude < -180) |
                                   (df.dropoff_longitude > 90) |(df.dropof
f_longitude < -90)
                                    ]

df.drop(incorrect_coordinates, inplace = True, errors = 'ignore')

df.head()
```

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	hour	day	month	year	dayofweek	dist_travel_km
0	7.5	-73.999817	40.738354	-73.999512	40.723217	1.0	19	7	5	2015	3	1.683325
1	7.7	-73.994355	40.728225	-73.994710	40.750325	1.0	20	17	7	2009	4	2.457593
2	12.9	-74.005043	40.740770	-73.962565	40.772647	1.0	21	24	8	2009	0	5.036384
3	5.3	-73.976124	40.790844	-73.965316	40.803349	3.0	8	26	6	2009	4	1.661686
4	16.0	-73.929786	40.744085	-73.973082	40.761247	3.5	17	28	8	2014	3	4.116088

```
df.isnull().sum()
fare_amount 0

pickup_longitude 0

pickup_latitude 0

dropoff_longitude 0

dropoff_latitude 0

passenger_count 0

hour 0

day 0

month 0

year 0

dayofweek 0

dist_travel_km 0

dtype: int64
```

```
sns.heatmap(df.isnull()) #Free for null values
```

<AxesSubplot:>



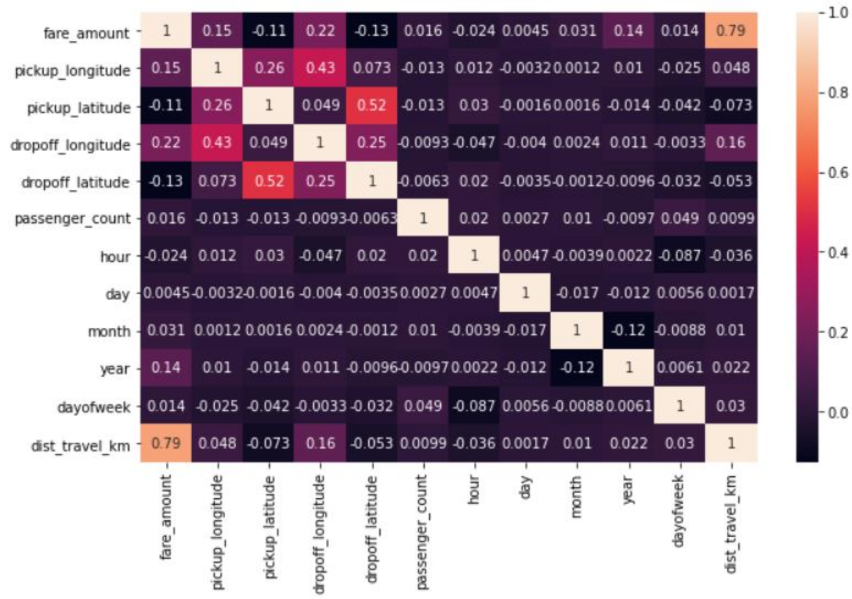

```
corr = df.corr() #Function to find the correlation
```

```
corr
```

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	hour	day	month	year	dayofweek	dist_travel_km
fare_amount	1.000000	0.154069	-0.110842	0.218675	-0.125898	0.015778	-0.023623	0.004534	0.030817	0.141277	0.013652	0.786385
pickup_longitude	0.154069	1.000000	0.259497	0.425619	0.073290	-0.013213	0.011579	-0.003204	0.001169	0.010198	-0.024652	0.048446
pickup_latitude	-0.110842	0.259497	1.000000	0.048889	0.515714	-0.012889	0.029681	-0.001553	0.001562	-0.014243	-0.042310	-0.073362
dropoff_longitude	0.218675	0.425619	0.048889	1.000000	0.245667	-0.009303	-0.046558	-0.004007	0.002391	0.011346	-0.003336	0.155191
dropoff_latitude	-0.125898	0.073290	0.515714	0.245667	1.000000	-0.006308	0.019783	-0.003479	-0.001193	-0.009603	-0.031919	-0.052701
passenger_count	0.015778	-0.013213	-0.012889	-0.009303	-0.006308	1.000000	0.020274	0.002712	0.010351	-0.009749	0.048550	0.009884
hour	-0.023623	0.011579	0.029681	-0.046558	0.019783	0.020274	1.000000	0.004677	-0.003926	0.002156	-0.086947	-0.035708
day	0.004534	-0.003204	-0.001553	-0.004007	-0.003479	0.002712	0.004677	1.000000	-0.017360	-0.012170	0.005617	0.001709
month	0.030817	0.001169	0.001562	0.002391	-0.001193	0.010351	-0.003926	-0.017360	1.000000	-0.115859	-0.008786	0.010050
year	0.141277	0.010198	-0.014243	0.011346	-0.009603	-0.009749	0.002156	-0.012170	-0.115859	1.000000	0.006113	0.022294
dayofweek	0.013652	-0.024652	-0.042310	-0.003336	-0.031919	0.048550	-0.086947	0.005617	-0.008786	0.006113	1.000000	0.030382
dist_travel_km	0.786385	0.048446	-0.073362	0.155191	-0.052701	0.009884	-0.035708	0.001709	0.010050	0.022294	0.030382	1.000000

```
fig,axis = plt.subplots(figsize = (10,6))
sns.heatmap(df.corr(),annot = True) #Correlation Heatmap (Light values mea
ns highly correlated)
```

<AxesSubplot:>



Program –

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt #Importing the libraries

df = pd.read_csv("Churn_Modelling.csv")
df.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

```
df.shape
```

(10000, 14)

```
df.describe()
```

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000	10000.000000
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239881	0.203700
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.492818	0.402769
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000	0.000000
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000	0.000000
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000	0.000000
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247500	0.000000
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.480000	1.000000

df.isnull()

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	False	False	False	False	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	False	False	False	False	False	False	False	False	False	False	False	False	False	False
9996	False	False	False	False	False	False	False	False	False	False	False	False	False	False
9997	False	False	False	False	False	False	False	False	False	False	False	False	False	False
9998	False	False	False	False	False	False	False	False	False	False	False	False	False	False
9999	False	False	False	False	False	False	False	False	False	False	False	False	False	False

10000 rows × 14 columns

df.isnull().sum()

RowNumber 0

CustomerId 0

Surname 0

CreditScore 0

Geography 0

Gender 0

Age 0

Tenure 0

Balance 0

NumOfProducts 0

HasCrCard 0

IsActiveMember 0

EstimatedSalary 0

Exited 0

dtype: int64

```
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   RowNumber        10000 non-null  int64
 1   CustomerId       10000 non-null  int64
 2   Surname          10000 non-null  object
 3   CreditScore      10000 non-null  int64
 4   Geography        10000 non-null  object
 5   Gender           10000 non-null  object
 6   Age              10000 non-null  int64
 7   Tenure           10000 non-null  int64
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64
```

```
 10  HasCrCard        10000 non-null   int64
 11  IsActiveMember   10000 non-null   int64
 12  EstimatedSalary  10000 non-null   float64
 13  Exited           10000 non-null   int64
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

```
df.dtypes
RowNumber int64
CustomerId int64
Surname object
CreditScore int64
Geography object
Gender object
Age int64
Tenure int64
Balance float64
NumOfProducts int64
HasCrCard int64
IsActiveMember int64
EstimatedSalary float64
Exited int64
dtype: object
```

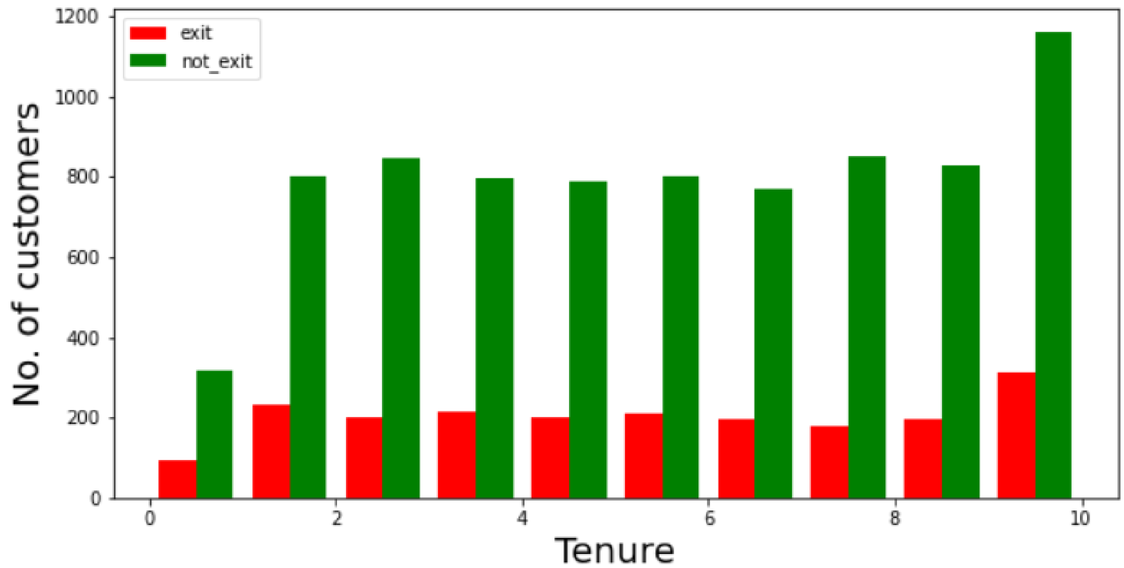
```
df.columns
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography', 'Gender', 'Age',
'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary', 'Exited'],
dtype='object')
```

```
df = df.drop(['RowNumber', 'Surname', 'CustomerId'], axis= 1) #Dropping the unnecessary colu
mns
```

```
df.head()
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

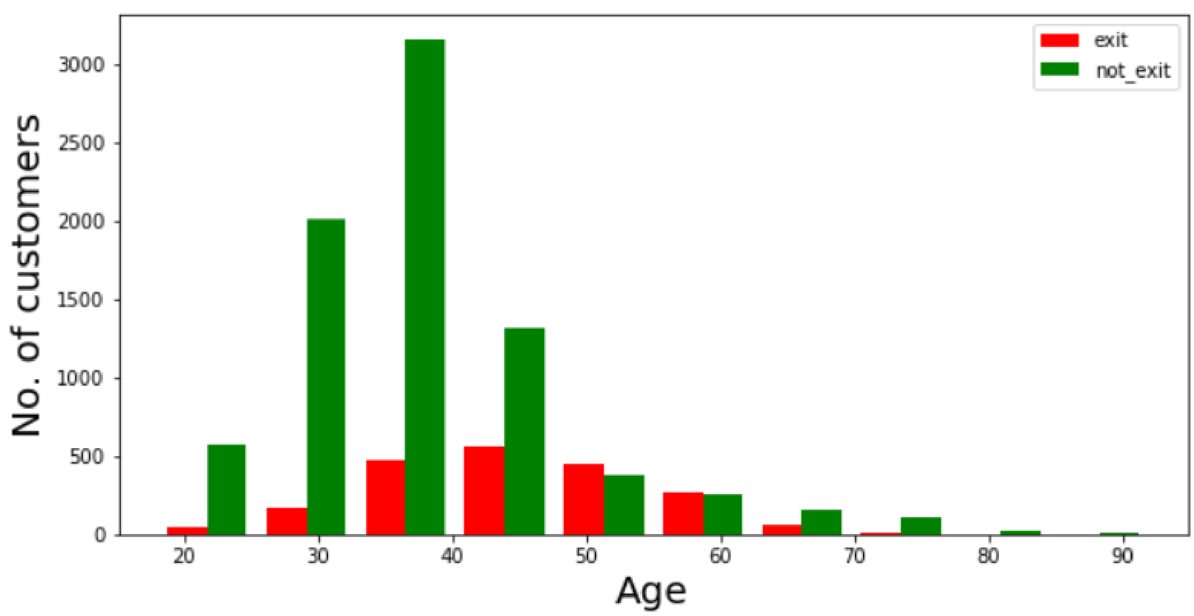
```
def visualization(x, y, xlabel):
    plt.figure(figsize=(10,5))
    plt.hist([x, y], color=['red', 'green'], label = ['exit', 'not_exit'])
    plt.xlabel(xlabel,fontsize=20)
    plt.ylabel("No. of customers", fontsize=20)
    plt.legend()


df_churn_exited  = df[df['Exited']==1]['Tenure']
df_churn_not_exited  = df[df['Exited']==0]['Tenure']


visualization(df_churn_exited,  df_churn_not_exited,  "Tenure")
```



df_churn_exited2 = df[df['Exited']==1]['Age']

df_churn_not_exited2 = df[df['Exited']==0]['Age']

visualization(df_churn_exited2, df_churn_not_exited2, "Age")



Program-

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn import metrics
df=pd.read_csv('diabetes.csv')
df.columns
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI', 'Pedigree', 'Age',
'Outcome'], dtype='object')
```

```
//Check for null values. If present remove null values from the dataset
df.isnull().sum()
Pregnancies 0

Glucose 0

BloodPressure 0

SkinThickness 0

Insulin 0

BMI 0

Pedigree 0

Age 0

Outcome 0

dtype: int64
```

Output-

//Outcome is the label/target, other columns are features.

```
X = df.drop('Outcome',axis = 1)
y = df['Outcome']
from sklearn.preprocessing import scale
X = scale(X)
# split into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 42)

print("Confusion matrix: ")
cs = metrics.confusion_matrix(y_test,y_pred)
print(cs)
```

Output-

```
Confusion matrix:
[[123  28]
 [ 37  43]]
```

```
print("Acccuracy ",metrics.accuracy_score(y_test,y_pred))
```

Output-

Acccuracy 0.7186147186147186

/*Classification error rate: proportion of instances misclassified over the whole set of instances.
Error rate is calculated as the total number of two incorrect predictions (FN + FP) divided by the total number of a dataset (examples in the dataset.
Also error_rate = 1- accuracy*/

```
total_misclassified = cs[0,1] + cs[1,0]
print(total_misclassified)
total_examples = cs[0,0]+cs[0,1]+cs[1,0]+cs[1,1]
```

```
print(total_examples)
print("Error rate",total_misclassified/total_examples)
print("Error rate ",1-metrics.accuracy_score(y_test,y_pred))
print("Precision score",metrics.precision_score(y_test,y_pred))
```

Output-

Precision score 0.6056338028169014

```
print("Recall score ",metrics.recall_score(y_test,y_pred))
```

Output-

Recall score 0.537

```
print("Classification report ",metrics.classification_report(y_test,y_pred))
```

Output-

```
Classification report               precision    recall  f1-score   support

           0       0.77      0.81      0.79       151
           1       0.61      0.54      0.57        80

    accuracy                           0.72       231
   macro avg       0.69      0.68      0.68       231
weighted avg       0.71      0.72      0.71       231
```

Program-

```
import pandas as pd
import numpy  as np
import seaborn as sns
import matplotlib.pyplot  as plt

df = pd.read_csv("sales_data_sample.csv")

df.head()
```

```
df.head()
```

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDERDATE	STATUS	QTR_ID	MONTH_ID	YEAR_ID	...	ADDRESSLINE1	ADDRESSLINE2	CITY	STATE	POSTALCODE	COUNTRY
0	10107	30	95.70	2	2871.00	2/24/2003 0:00	Shipped	1	2	2003	...	897 Long Airport Avenue	NaN	NYC	NY	10022	USA
1	10121	34	81.35	5	2765.90	5/7/2003 0:00	Shipped	2	5	2003	...	59 rue de l'Abbaye	NaN	Reims	NaN	51100	France
2	10134	41	94.74	2	3884.34	7/1/2003 0:00	Shipped	3	7	2003	...	27 rue du Colonel Pierre Avia	NaN	Paris	NaN	75508	France
3	10145	45	83.26	6	3746.70	8/25/2003 0:00	Shipped	3	8	2003	...	78934 Hillside Dr.	NaN	Pasadena	CA	90003	USA
4	10159	49	100.00	14	5205.27	10/10/2003 0:00	Shipped	4	10	2003	...	7734 Strong St.	NaN	San Francisco	CA	NaN	USA

df.dtypes

ORDERNUMBER int64

QUANTITYORDERED int64

PRICEEACH float64

ORDERLINENUMBER int64

SALES float64

ORDERDATE object

STATUS object

QTR_ID int64

MONTH_ID int64

YEAR_ID int64

PRODUCTLINE object MSRP int64

PRODUCTCODE object

CUSTOMERNAME object

PHONE object

ADDRESSLINE1 object

ADDRESSLINE2 object

CITY object

STATE object

POSTALCODE object

COUNTRY object

TERRITORY object

CONTACTLASTNAME object

CONTACTFIRSTNAME object

DEALSIZE object

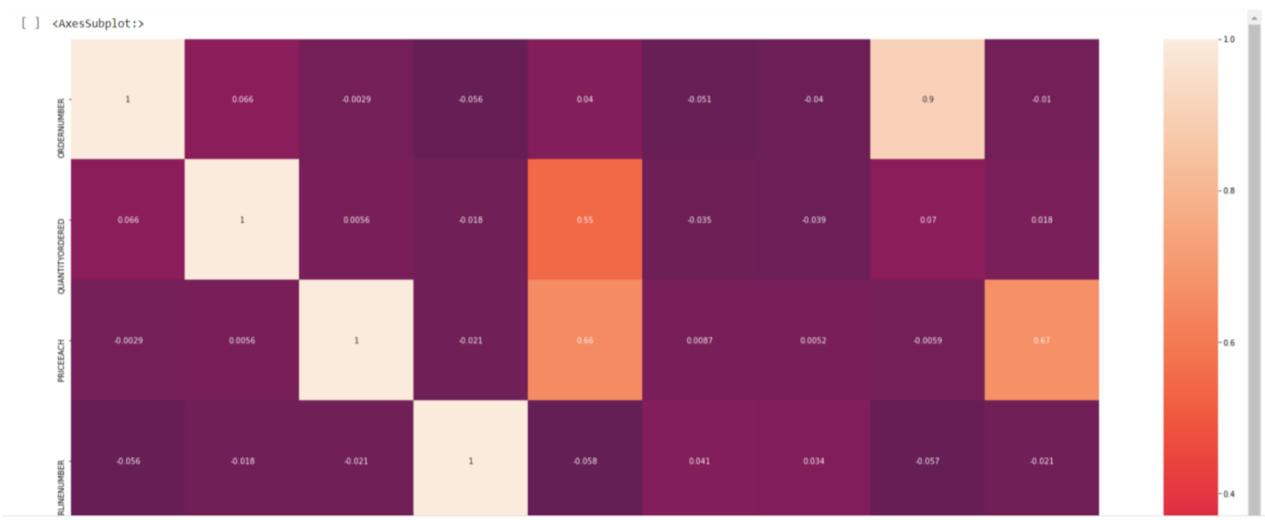
dtype: object

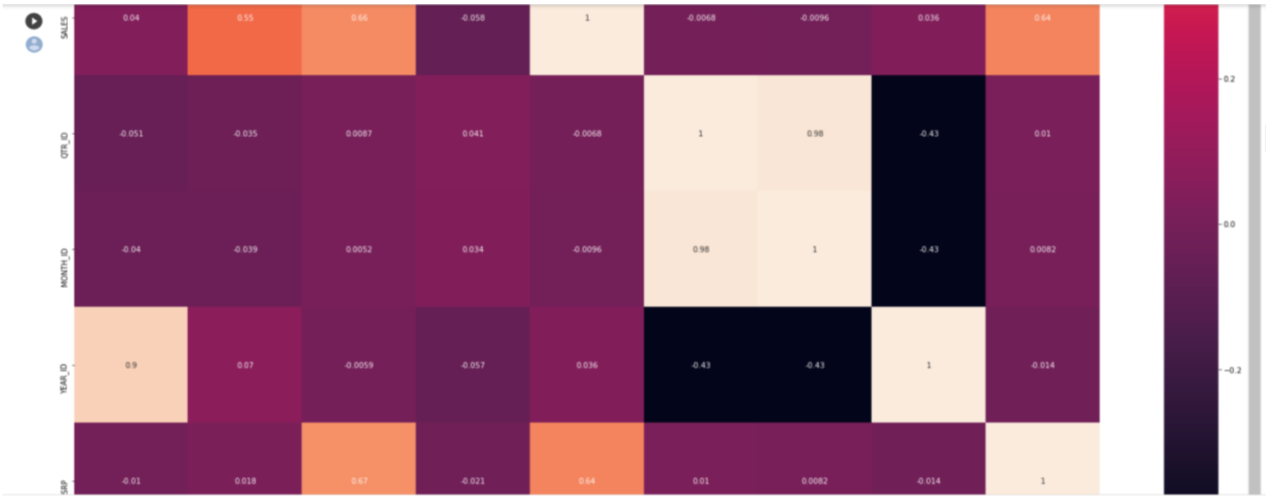
df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2823 entries, 0 to 2822
Data columns (total 25 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   ORDERNUMBER       2823 non-null   int64
 1   QUANTITYORDERED   2823 non-null   int64
 2   PRICEEACH         2823 non-null   float64
 3   ORDERLINENUMBER   2823 non-null   int64
 4   SALES             2823 non-null   float64
 5   ORDERDATE         2823 non-null   object
 6   STATUS            2823 non-null   object
 7   QTR_ID            2823 non-null   int64
 8   MONTH_ID          2823 non-null   int64
 9   YEAR_ID           2823 non-null   int64
 10  PRODUCTLINE       2823 non-null   object
 11  MSRP              2823 non-null   int64
 12  PRODUCTCODE       2823 non-null   object
 13  CUSTOMERNAME      2823 non-null   object
```

```
 14  PHONE             2823 non-null    object
 15  ADDRESSLINE1      2823 non-null    object
 16  ADDRESSLINE2      302 non-null     object
 17  CITY              2823 non-null    object
 18  STATE             1337 non-null    object
 19  POSTALCODE        2747 non-null    object
 20  COUNTRY           2823 non-null    object
 21  TERRITORY         1749 non-null    object
 22  CONTACTLASTNAME   2823 non-null    object
 23  CONTACTFIRSTNAME  2823 non-null    object
 24  DEALSIZE          2823 non-null    object
dtypes: float64(2), int64(7), object(16)
memory usage: 551.5+ KB
```

```
plt.figure(figsize = (30,26))
sns.heatmap(df.corr(),annot = True)
```





df_drop = ['ADDRESSLINE1', 'ADDRESSLINE2', 'STATUS','POSTALCODE', 'CITY', 'TERRITORY', 'PHONE', 'STATE', 'CONTACTFIRSTNAME', 'CONTACTLASTNAME', 'CUSTOMERNAME', 'ORDERNUMBER']
df = df.drop(df_drop, axis=1)

df.head()

	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDERDATE	QTR_ID	MONTH_ID	YEAR_ID	PRODUCTLINE	MSRP	PRODUCTCODE	COUNTRY	DEALSIZE
0	30	95.70	2	2871.00	2/24/2003 0:00	1	2	2003	Motorcycles	95	S10_1678	USA	Small
1	34	81.35	5	2765.90	5/7/2003 0:00	2	5	2003	Motorcycles	95	S10_1678	France	Small
2	41	94.74	2	3884.34	7/1/2003 0:00	3	7	2003	Motorcycles	95	S10_1678	France	Medium
3	45	83.26	6	3746.70	8/25/2003 0:00	3	8	2003	Motorcycles	95	S10_1678	USA	Medium
4	49	100.00	14	5205.27	10/10/2003 0:00	4	10	2003	Motorcycles	95	S10_1678	USA	Medium

df.shape
(2823, 13)

df.isnull().sum()
QUANTITYORDERED 0

PRICEEACH 0

ORDERLINENUMBER 0

SALES 0

ORDERDATE 0

QTR_ID 0

MONTH_ID 0

YEAR_ID 0

PRODUCTLINE 0

MSRP 0

PRODUCTCODE 0

COUNTRY 0

DEALSIZE 0

dtype: int64

```
df.dtypes
```

QUANTITYORDERED int64

PRICEEACH float64

ORDERLINENUMBER int64

SALES float64

ORDERDATE object

QTR_ID int64

MONTH_ID int64

YEAR_ID int64

PRODUCTLINE object

MSRP int64

PRODUCTCODE object

COUNTRY object

DEALSIZE object

dtype: object

```
country = pd.get_dummies(df['COUNTRY'])
productline = pd.get_dummies(df['PRODUCTLINE'])
Dealsize = pd.get_dummies(df['DEALSIZE'])

df = pd.concat([df,country,productline,Dealsize], axis = 1)
```

df.head()

	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDERDATE	QTR_ID	MONTH_ID	YEAR_ID	PRODUCTLINE	MSRP	...	Classic Cars	Motorcycles	Planes	Ships	Trains	Trucks and Buses	Vintage Cars	Large
0	30	95.70	2	2871.00	2/24/2003 0:00	1	2	2003	Motorcycles	95	...	0	1	0	0	0	0	0	0
1	34	81.35	5	2765.90	5/7/2003 0:00	2	5	2003	Motorcycles	95	...	0	1	0	0	0	0	0	0
2	41	94.74	2	3884.34	7/1/2003 0:00	3	7	2003	Motorcycles	95	...	0	1	0	0	0	0	0	0
3	45	83.26	6	3746.70	8/25/2003 0:00	3	8	2003	Motorcycles	95	...	0	1	0	0	0	0	0	0
4	49	100.00	14	5205.27	10/10/2003 0:00	4	10	2003	Motorcycles	95	...	0	1	0	0	0	0	0	0

```
df_drop  = ['COUNTRY','PRODUCTLINE','DEALSIZE']
df = df.drop(df_drop, axis=1)
```

df.dtypes

QUANTITYORDERED int64

PRICEEACH float64

ORDERLINENUMBER int64

SALES float64

ORDERDATE object

QTR_ID int64

MONTH_ID int64

YEAR_ID int64

MSRP int64

PRODUCTCODE object

Australia uint8

Austria uint8

Belgium uint8

Canada uint8

Denmark uint8

Finland uint8

France uint8

Germany uint8

Ireland uint8

Italy uint8

Japan uint8

Norway uint8

Philippines uint8

Singapore uint8

Spain uint8

Sweden uint8

Switzerland uint8

UK uint8

USA uint8

Classic Cars uint8

Motorcycles uint8

Planes uint8

Ships uint8

Trains uint8

Trucks and Buses uint8

Vintage Cars uint8

Large uint8 Medium uint8

Small uint8

dtype: object

df['PRODUCTCODE'] = pd.Categorical(df['PRODUCTCODE']).codes

df.dtypes
QUANTITYORDERED int64

PRICEEACH float64

ORDERLINENUMBER int64

SALES float64

ORDERDATE object

QTR_ID int64

MONTH_ID int64

YEAR_ID int64

MSRP int64

PRODUCTCODE int8

Australia uint8

Austria uint8

Belgium uint8

Canada uint8

Denmark uint8

Finland uint8

France uint8

Germany uint8

Ireland uint8

Italy uint8

Japan uint8

Norway uint8

Philippines uint8

Singapore uint8

Spain uint8

Sweden uint8

Switzerland uint8

UK uint8

USA uint8

Classic Cars uint8

Motorcycles uint8

Planes uint8

Ships uint8

Trains uint8

Trucks and Buses uint8

Vintage Cars uint8

Large uint8

Medium uint8

Small uint8

dtype: object

df.drop('ORDERDATE', axis=1, inplace=True)

df.dtypes
QUANTITYORDERED int64

PRICEEACH float64

ORDERLINENUMBER int64

SALES float64

QTR_ID int64

MONTH_ID int64

YEAR_ID int64

MSRP int64

PRODUCTCODE int8

Australia uint8

Austria uint8

Belgium uint8

Canada uint8

Denmark uint8

Finland uint8

France uint8

Germany uint8

Ireland uint8

Italy uint8

Japan uint8

Norway uint8

Philippines uint8

Singapore uint8

Spain uint8

Sweden uint8

Switzerland uint8

UK uint8

USA uint8

Classic Cars uint8

Motorcycles uint8

Planes uint8

Ships uint8

Trains uint8

Trucks and Buses uint8

Vintage Cars uint8

Large uint8

Medium uint8

Small uint8

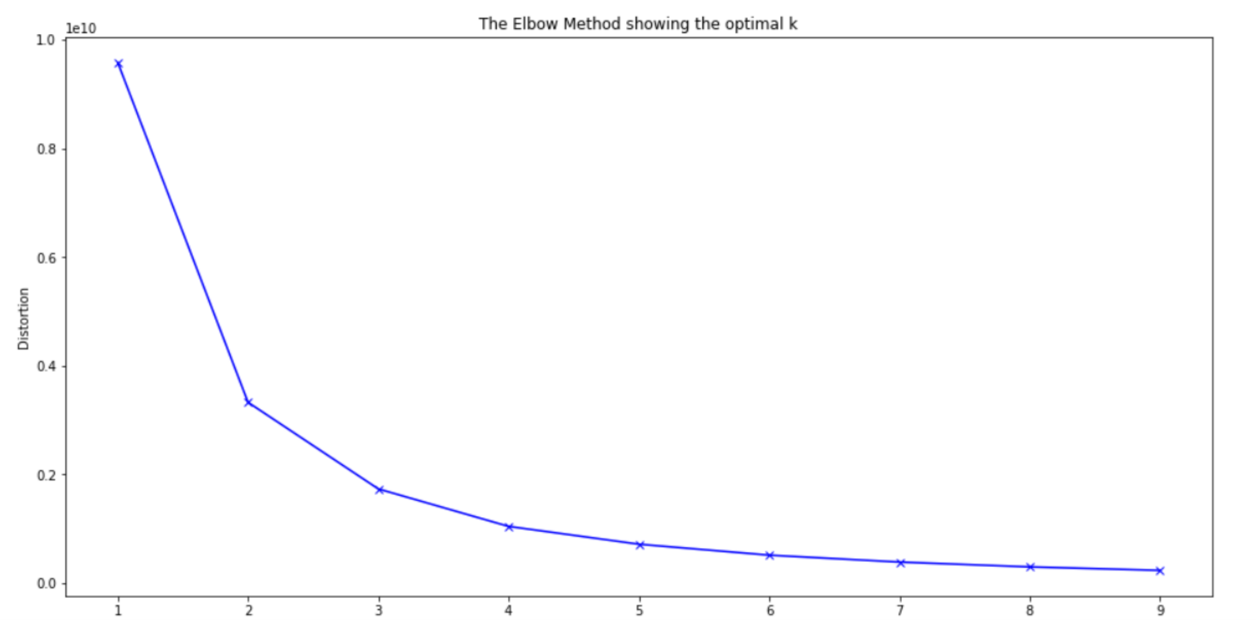
dtype: object

from sklearn.cluster import KMeans

WCSS = [] # Withhin Cluster Sum of Squares from the centroid

```
distortions = []
K = range(1,10)
for k in K:
    kmeanModel  = KMeans(n_clusters=k)
    kmeanModel.fit(df)
    distortions.append(kmeanModel.inertia_)
```

```
plt.figure(figsize=(16,8))
plt.plot(K, distortions, 'bx-')
plt.xlabel('k')
plt.ylabel('Distortion')
plt.title('The Elbow Method showing the optimal k')
plt.show()
```




```
kmeanModel  = KMeans(n_clusters=3)
y_kmeans  = kmeanModel.fit_predict
```

```
print(y_kmeans)
```

```
plt.figure(figsize  = (30,26))
sns.heatmap(df.corr(),annot  = True)
```

```
pip install yellowbrick
```

```
from yellowbrick.cluster import KElbowVisualizer
model = KMeans()
visualizer = KElbowVisualizer(model,k=(1,0),timings = False)
visualizer.fit(df)
visualizer.show()
```

```
df.head()
```

	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	QTR_ID	MONTH_ID	YEAR_ID	MSRP	PRODUCTCODE	Australia	...	Classic Cars	Motorcycles	Planes	Ships	Trains	Trucks and Buses	Vintage Cars	Large
0	30	95.70	2	2871.00	1	2	2003	95	0	0	...	0	1	0	0	0	0	0	0
1	34	81.35	5	2765.90	2	5	2003	95	0	0	...	0	1	0	0	0	0	0	0
2	41	94.74	2	3884.34	3	7	2003	95	0	0	...	0	1	0	0	0	0	0	0
3	45	83.26	6	3746.70	3	8	2003	95	0	0	...	0	1	0	0	0	0	0	0
4	49	100.00	14	5205.27	4	10	2003	95	0	0	...	0	1	0	0	0	0	0	0

5 rows × 38 columns

```
from sklearn.preprocessing import Normalizer

df_scaled = Normalizer(df)

df_x = pd.DataFrame(df_scaled,columns = df.columns )
```

Mini Project-

Build a machine learning model that predicts the type of people who survived the Titanic shipwreck using passenger data (i.e. name, age, gender, socio-economic class, etc.).

Importing the Libraries

```
# linear algebra
import numpy as np

# data processing
import pandas as pd

# data visualization
import seaborn as sns
%matplotlib inline
from matplotlib import pyplot as plt
from matplotlib import style

# Algorithms
from sklearn import linear_model
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import Perceptron
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC, LinearSVC
from sklearn.naive_bayes import GaussianNB
```

Getting the Data

```
test_df = pd.read_csv("test.csv")
train_df = pd.read_csv("train.csv")
```

Data Exploration/Analysis

```
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: 83.6+ KB
```

The training-set has 891 examples and 11 features + the target variable (survived). 2 of the features are floats, 5 are integers and 5 are objects. Below I have listed the features with a short description:

```
survival:    Survival
PassengerId: Unique Id of a passenger.
pclass:    Ticket class
sex:    Sex
Age:    Age in years
sibsp:    # of siblings / spouses aboard the Titanic
parch:    # of parents / children aboard the Titanic
ticket:    Ticket number
fare:    Passenger fare
cabin:    Cabin number
embarked:    Port of Embarkationtrain_df.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

Above we can see that **38% out of the training-set survived the Titanic**. We can also see that the passenger ages range from 0.4 to 80. On top of that we can already detect some features, that contain missing values, like the 'Age' feature.

```
train_df.head(8)
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S
5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	Q
6	7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46	S
7	8	0	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN	S
8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	NaN	S

From the table above, we can note a few things. First of all, that we **need to convert a lot of features into numeric** ones later on, so that the machine learning algorithms can process them. Furthermore, we can see that the **features have widely different ranges**, that we will need to convert into roughly the same scale. We can also spot some more features, that contain missing values (NaN = not a number), that wee need to deal with.

Let's take a more detailed look at what data is actually missing:

```
total = train_df.isnull().sum().sort_values(ascending=False)
percent_1 = train_df.isnull().sum()/train_df.isnull().count()*100
percent_2 = (round(percent_1, 1)).sort_values(ascending=False)
missing_data = pd.concat([total, percent_2], axis=1, keys=['Total', '%'])
missing_data.head(5)
```

	Total	%
Cabin	687	77.1
Age	177	19.9
Embarked	2	0.2
Fare	0	0.0
Ticket	0	0.0

The Embarked feature has only 2 missing values, which can easily be filled. It will be much more tricky, to deal with the 'Age' feature, which has 177 missing values. The 'Cabin' feature needs further investigation, but it looks like that we might want to drop it from the dataset, since 77 % of it are missing.

```
train_df.columns.values
```

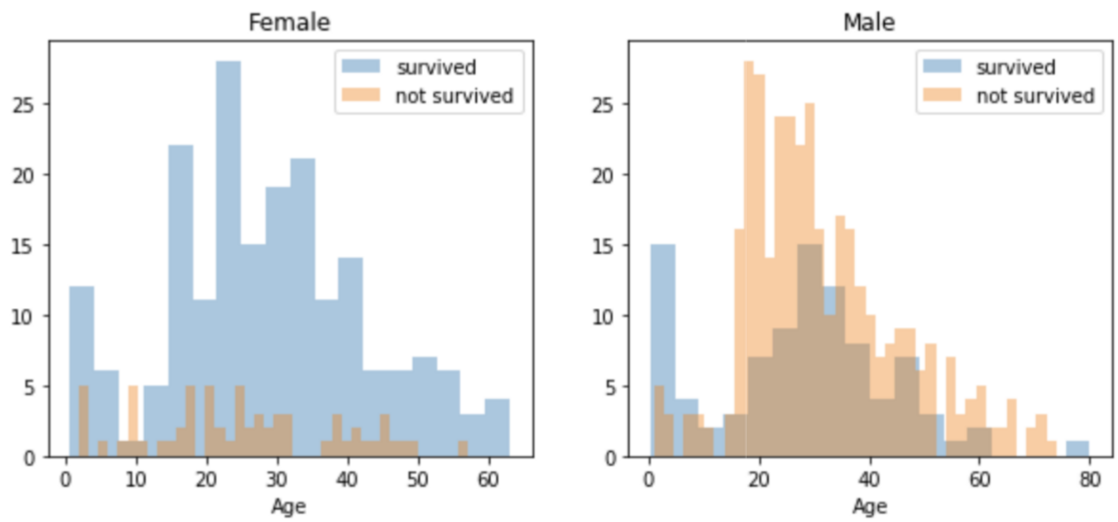
```
array(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'], dtype=object)
```

Above you can see the 11 features + the target variable (survived). **What features could contribute to a high survival rate ?**

To me it would make sense if everything except 'PassengerId', 'Ticket' and 'Name' would be correlated with a high survival rate.

1. Age and Sex:

```
survived = 'survived'
not_survived = 'not survived'
fig, axes = plt.subplots(nrows=1, ncols=2,figsize=(10, 4))
women = train_df[train_df['Sex']=='female']
men = train_df[train_df['Sex']=='male']
ax = sns.distplot(women[women['Survived']==1].Age.dropna(), bins=18, label = survived, ax = axes[0], kde =False)
ax = sns.distplot(women[women['Survived']==0].Age.dropna(), bins=40, label = not_survived, ax = axes[0], kde =False)
ax.legend()
ax.set_title('Female')
ax = sns.distplot(men[men['Survived']==1].Age.dropna(), bins=18, label = survived, ax = axes[1], kde = False)
ax = sns.distplot(men[men['Survived']==0].Age.dropna(), bins=40, label = not_survived, ax = axes[1], kde = False)
ax.legend()
_ = ax.set_title('Male')
```



You can see that men have a high probability of survival when they are between 18 and 30 years old, which is also a little bit true for women but not fully. For women the survival chances are higher between 14 and 40.

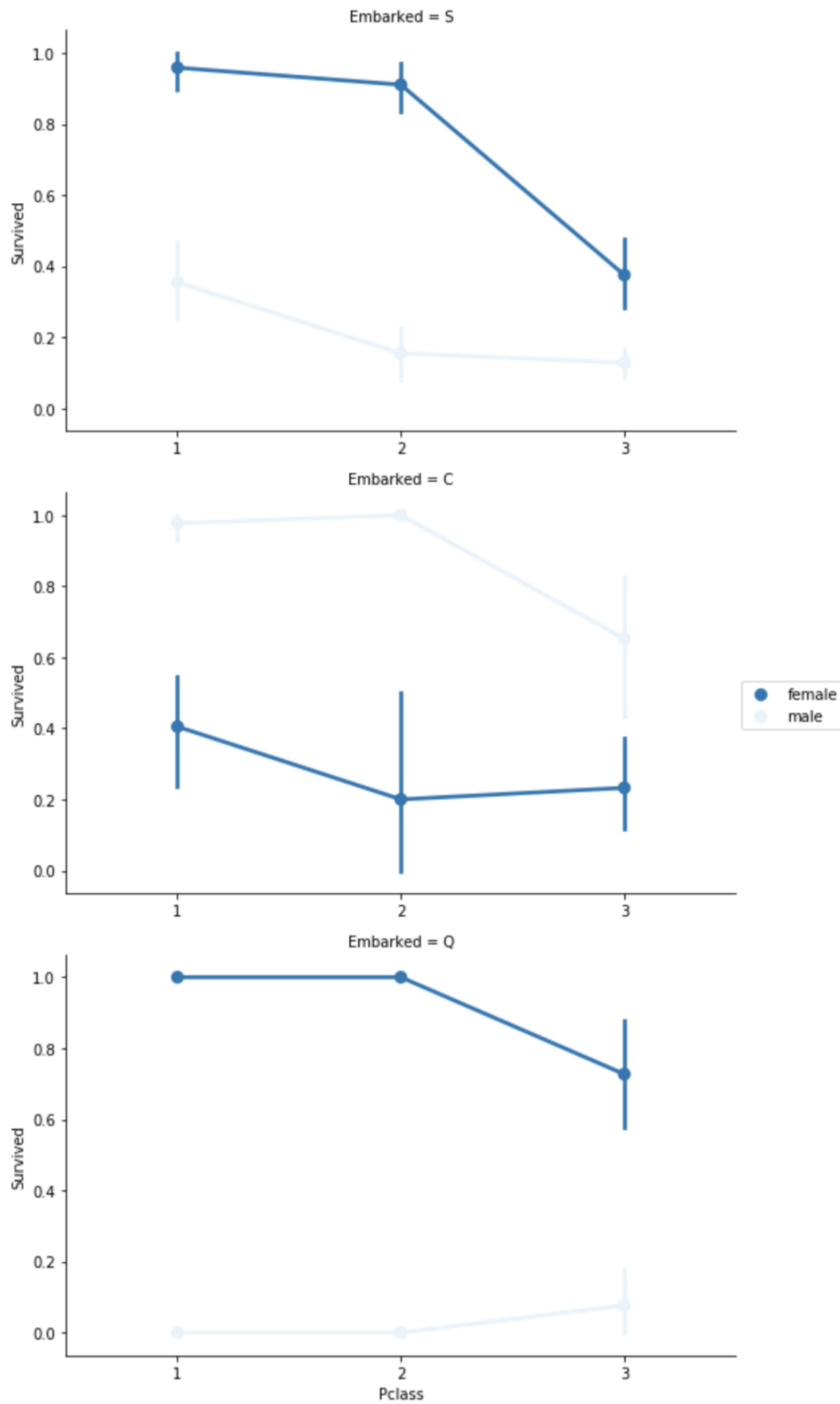
For men the probability of survival is very low between the age of 5 and 18, but that isn't true for women. Another thing to note is that infants also have a little bit higher probability of survival.

Since there seem to be **certain ages, which have increased odds of survival** and because I want every feature to be roughly on the same scale, I will create age groups later on.

3. Embarked, Pclass and Sex:

```
FacetGrid = sns.FacetGrid(train_df, row='Embarked', size=4.5, aspect=1.6)
FacetGrid.map(sns.pointplot, 'Pclass', 'Survived', 'Sex', palette=None,  order=None, hue_order=None
)
FacetGrid.add_legend()
```

`<seaborn.axisgrid.FacetGrid at 0x10ba485c0>`



Embarked seems to be correlated with survival, depending on the gender.

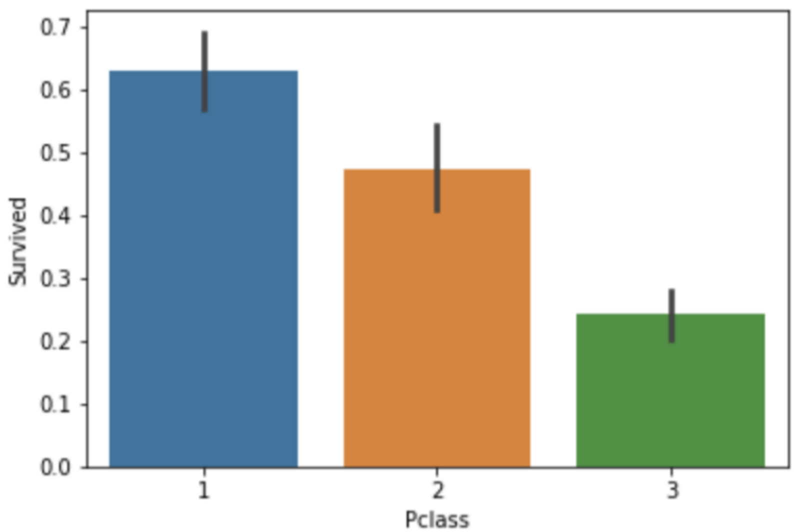
Women on port Q and on port S have a higher chance of survival. The inverse is true, if they are at port C. Men have a high survival probability if they are on port C, but a low probability if they are on port Q or S.

Pclass also seems to be correlated with survival. We will generate another plot of it below.

4. Pclass:

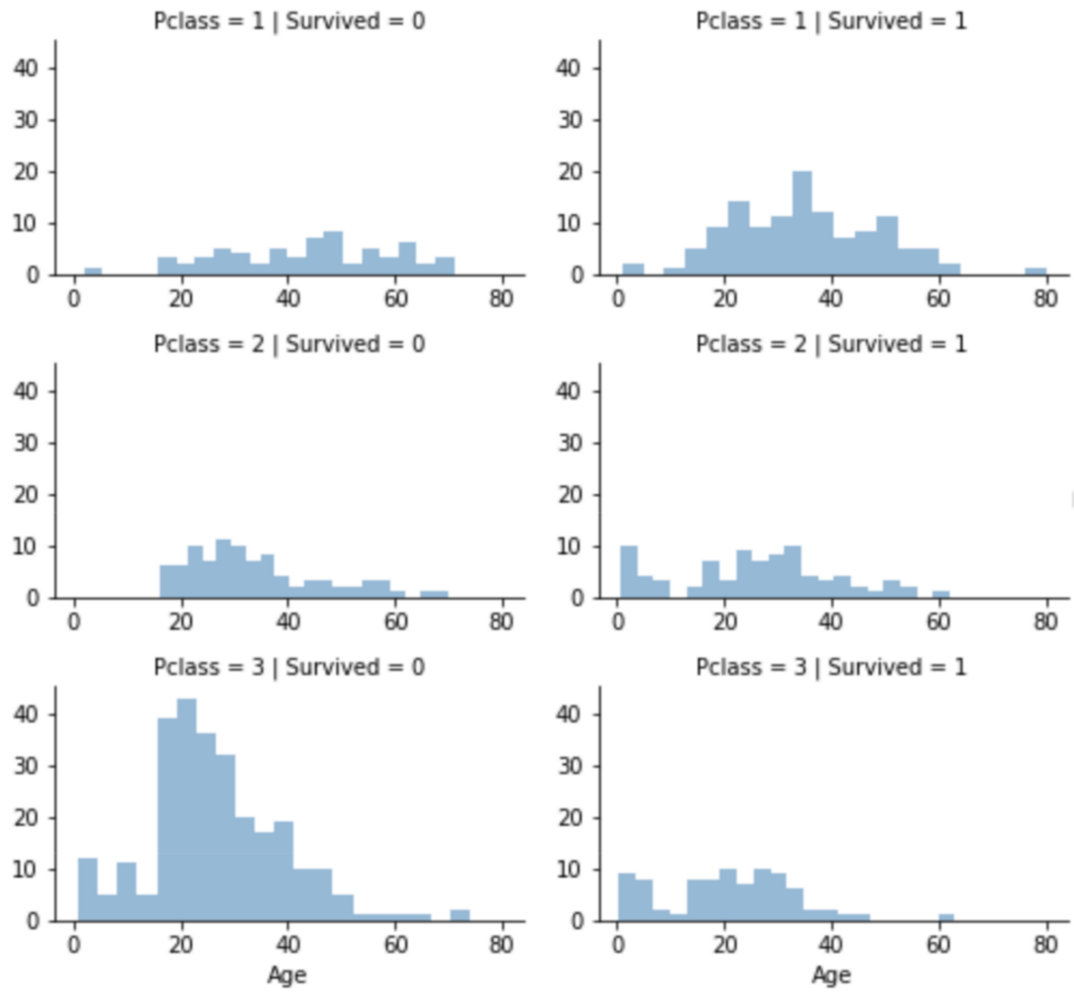
```
sns.barplot(x='Pclass', y='Survived', data=train_df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x10d1dc7b8>
```



Here we see clearly, that Pclass is contributing to a persons chance of survival, especially if this person is in class 1. We will create another pclass plot below.

```
grid = sns.FacetGrid(train_df, col='Survived', row='Pclass', size=2.2, aspect=1.6)
grid.map(plt.hist, 'Age', alpha=.5, bins=20)
grid.add_legend();
```



The plot above confirms our assumption about pclass 1, but we can also spot a high probability that a person in pclass 3 will not survive.

5. SibSp and Parch:

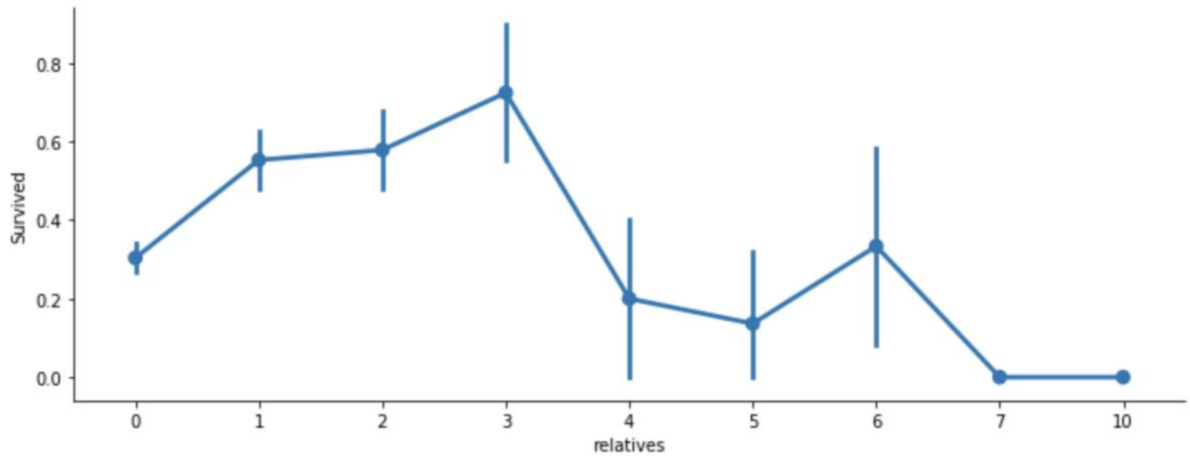
SibSp and Parch would make more sense as a combined feature, that shows the total number of relatives, a person has on the Titanic. I will create it below and also a feature that sows if someone is not alone.

```
data = [train_df, test_df]
for dataset in data:
    dataset['relatives'] = dataset['SibSp'] + dataset['Parch']
```

```
dataset.loc[dataset['relatives'] > 0, 'not_alone'] = 0
dataset.loc[dataset['relatives'] == 0, 'not_alone'] = 1
dataset['not_alone'] = dataset['not_alone'].astype(int)train_df['not_alone'].value_counts()
```

```
1     537
0     354
Name: not_alone, dtype: int64
```

```
axes = sns.factorplot('relatives','Survived',
                      data=train_df, aspect = 2.5, )
```



Here we can see that you had a high probabilty of survival with 1 to 3 realitves, but a lower one if you had less than 1 or more than 3 (except for some cases with 6 relatives).

Data Preprocessing

First, I will drop ‘PassengerId’ from the train set, because it does not contribute to a persons survival probability. I will not drop it from the test set, since it is required there for the submission.

```
train_df = train_df.drop(['PassengerId'], axis=1)
```

Missing Data:

Cabin:

As a reminder, we have to deal with Cabin (687), Embarked (2) and Age (177). First I thought, we have to delete the 'Cabin' variable but then I found something interesting. A cabin number looks like 'C123' and the **letter refers to the deck**. Therefore we're going to extract these and create a new feature, that contains a persons deck. Afterwords we will convert the feature into a numeric variable. The missing values will be converted to zero. In the picture below you can see the actual decks of the titanic, ranging from A to G.

```
import re
deck = {"A": 1, "B": 2, "C": 3, "D": 4, "E": 5, "F": 6, "G": 7, "U": 8}
data = [train_df, test_df]

for dataset in data:
    dataset['Cabin'] = dataset['Cabin'].fillna("U0")
    dataset['Deck'] = dataset['Cabin'].map(lambda x: re.compile("([a-zA-Z]+)").search(x).group())
    dataset['Deck'] = dataset['Deck'].map(deck)
    dataset['Deck'] = dataset['Deck'].fillna(0)
    dataset['Deck'] = dataset['Deck'].astype(int)# we can now drop the cabin feature
train_df = train_df.drop(['Cabin'], axis=1)
test_df = test_df.drop(['Cabin'], axis=1)
```

Age:

Now we can tackle the issue with the age features missing values. I will create an array that contains random numbers, which are computed based on the mean age value in regards to the standard deviation and is_null.

```
data = [train_df, test_df]

for dataset in data:
    mean = train_df["Age"].mean()
    std = test_df["Age"].std()
    is_null = dataset["Age"].isnull().sum()
    # compute random numbers between the mean, std and is_null
    rand_age = np.random.randint(mean - std, mean + std, size = is_null)
    # fill NaN values in Age column with random values generated
    age_slice = dataset["Age"].copy()
    age_slice[np.isnan(age_slice)] = rand_age
```

```
    dataset["Age"] = age_slice
    dataset["Age"] = train_df["Age"].astype(int)train_df["Age"].isnull().sum()
```

```
0
```

Embarked:

Since the Embarked feature has only 2 missing values, we will just fill these with the most common one.

```
train_df['Embarked'].describe()
```

```
count      889
unique       3
top          S
freq       644
Name: Embarked, dtype: object
```

```
common_value = 'S'
data = [train_df, test_df]

for dataset in data:
    dataset['Embarked'] = dataset['Embarked'].fillna(common_value)
```

Converting Features:

```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 13 columns):
Survived     891 non-null int64
Pclass       891 non-null int64
Name         891 non-null object
Sex          891 non-null object
Age          891 non-null int64
SibSp        891 non-null int64
Parch        891 non-null int64
Ticket       891 non-null object
Fare         891 non-null float64
Embarked     891 non-null object
relatives    891 non-null int64
not_alone    891 non-null int64
Deck         891 non-null int64
dtypes: float64(1), int64(8), object(4)
memory usage: 90.6+ KB
```

Above you can see that 'Fare' is a float and we have to deal with 4 categorical features: Name, Sex, Ticket and Embarked. Lets investigate and transfrom one after another.

Fare:

Converting "Fare" from float to int64, using the "astype()" function pandas provides:

```
data = [train_df, test_df]

for dataset in data:
    dataset['Fare'] = dataset['Fare'].fillna(0)
    dataset['Fare'] = dataset['Fare'].astype(int)
```

Name:

We will use the Name feature to extract the Titles from the Name, so that we can build a new feature out of that.

```
data = [train_df, test_df]
titles = {"Mr": 1, "Miss": 2, "Mrs": 3, "Master": 4, "Rare": 5}

for dataset in data:
    # extract titles
    dataset['Title'] = dataset.Name.str.extract(' ([A-Za-z]+)\.', expand=False)
    # replace titles with a more common title or as Rare
    dataset['Title'] = dataset['Title'].replace(['Lady', 'Countess','Capt', 'Col','Don', 'Dr',\
```

```
                                    'Major', 'Rev', 'Sir', 'Jonkheer', 'Dona'], 'Rare')
   dataset['Title'] = dataset['Title'].replace('Mlle', 'Miss')
   dataset['Title'] = dataset['Title'].replace('Ms', 'Miss')
   dataset['Title'] = dataset['Title'].replace('Mme', 'Mrs')
   # convert titles into numbers
   dataset['Title'] = dataset['Title'].map(titles)
   # filling NaN with 0, to get safe
   dataset['Title'] = dataset['Title'].fillna(0)train_df = train_df.drop(['Name'], axis=1)
test_df = test_df.drop(['Name'], axis=1)
```

Sex:

Convert 'Sex' feature into numeric.

```
genders = {"male": 0, "female": 1}
data = [train_df, test_df]

for dataset in data:
   dataset['Sex'] = dataset['Sex'].map(genders)
```

Ticket:

```
train_df['Ticket'].describe()
```

```
count      891
unique     681
top       1601
freq         7
Name: Ticket, dtype: object
```

Since the Ticket attribute has 681 unique tickets, it will be a bit tricky to convert them into useful categories. So we will drop it from the dataset.

```
train_df = train_df.drop(['Ticket'], axis=1)
test_df = test_df.drop(['Ticket'], axis=1)
```

Embarked:

Convert 'Embarked' feature into numeric.

```
ports = {"S": 0, "C": 1, "Q": 2}
data = [train_df, test_df]
```

```
for dataset in data:
    dataset['Embarked'] = dataset['Embarked'].map(ports)
```

Creating Categories:

We will now create categories within the following features:

Age:

Now we need to convert the 'age' feature. First we will convert it from float into integer. Then we will create the new 'AgeGroup" variable, by categorizing every age into a group. Note that it is important to place attention on how you form these groups, since you don't want for example that 80% of your data falls into group 1.

```
data = [train_df, test_df]
for dataset in data:
    dataset['Age'] = dataset['Age'].astype(int)
    dataset.loc[ dataset['Age'] <= 11, 'Age'] = 0
    dataset.loc[(dataset['Age'] > 11) & (dataset['Age'] <= 18), 'Age'] = 1
    dataset.loc[(dataset['Age'] > 18) & (dataset['Age'] <= 22), 'Age'] = 2
    dataset.loc[(dataset['Age'] > 22) & (dataset['Age'] <= 27), 'Age'] = 3
    dataset.loc[(dataset['Age'] > 27) & (dataset['Age'] <= 33), 'Age'] = 4
    dataset.loc[(dataset['Age'] > 33) & (dataset['Age'] <= 40), 'Age'] = 5
    dataset.loc[(dataset['Age'] > 40) & (dataset['Age'] <= 66), 'Age'] = 6
    dataset.loc[ dataset['Age'] > 66, 'Age'] = 6

# let's see how it's distributed train_df['Age'].value_counts()
```

```
4    165
6    158
5    147
3    129
2    124
1    100
0     68
Name: Age, dtype: int64
```

Fare:

For the 'Fare' feature, we need to do the same as with the 'Age' feature. But it isn't that easy, because if we cut the range of the fare values into a few equally big categories, 80% of the values would fall into the first category. Fortunately, we can use sklearn "qcut()" function, that we can use to see, how we can form the categories.

```
train_df.head(10)
```

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	relatives	not_alone	Deck	Title
0	0	3	0	2	1	0	7	0	1	0	8	1
1	1	1	1	5	1	0	71	1	1	0	3	3
2	1	3	1	3	0	0	7	0	0	1	8	2
3	1	1	1	5	1	0	53	0	1	0	3	3
4	0	3	0	5	0	0	8	0	0	1	8	1
5	0	3	0	4	0	0	8	2	0	1	8	1
6	0	1	0	6	0	0	51	0	0	1	5	1
7	0	3	0	0	3	1	21	0	4	0	8	4
8	1	3	1	3	0	2	11	0	2	0	8	3
9	1	2	1	1	1	0	30	1	1	0	8	3

```
data = [train_df, test_df]

for dataset in data:
    dataset.loc[ dataset['Fare'] <= 7.91, 'Fare'] = 0
    dataset.loc[(dataset['Fare'] > 7.91) & (dataset['Fare'] <= 14.454), 'Fare'] = 1
    dataset.loc[(dataset['Fare'] > 14.454) & (dataset['Fare'] <= 31), 'Fare']   = 2
    dataset.loc[(dataset['Fare'] > 31) & (dataset['Fare'] <= 99), 'Fare']   = 3
    dataset.loc[(dataset['Fare'] > 99) & (dataset['Fare'] <= 250), 'Fare']   = 4
    dataset.loc[ dataset['Fare'] > 250, 'Fare'] = 5
    dataset['Fare'] = dataset['Fare'].astype(int)
```

Creating new Features

I will add two new features to the dataset, that I compute out of other features.

1. Age times Class

```
data = [train_df, test_df]
for dataset in data:
    dataset['Age_Class']= dataset['Age']* dataset['Pclass']
```

2. Fare per Person

```
for dataset in data:
    dataset['Fare_Per_Person'] = dataset['Fare']/(dataset['relatives']+1)
    dataset['Fare_Per_Person'] = dataset['Fare_Per_Person'].astype(int)# Let's take a last look at the training set, before we start training the models.
train_df.head(10)
```

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	relatives	not_alone	Deck	Title	Age_Class	Fare_Per_Pers
0	0	3	0	2	1	0	0	0	1	0	8	1	6	0
1	1	1	1	5	1	0	3	1	1	0	3	3	5	1
2	1	3	1	3	0	0	0	0	0	1	8	2	9	0
3	1	1	1	5	1	0	3	0	1	0	3	3	5	1
4	0	3	0	5	0	0	1	0	0	1	8	1	15	1
5	0	3	0	4	0	0	1	2	0	1	8	1	12	1
6	0	1	0	6	0	0	3	0	0	1	5	1	6	3
7	0	3	0	0	3	1	2	0	4	0	8	4	0	0
8	1	3	1	3	0	2	1	0	2	0	8	3	9	0
9	1	2	1	1	1	0	2	1	1	0	8	3	2	1
10	1	3	1	0	1	1	2	0	2	0	7	2	0	0

Building Machine Learning Models

Now we will train several Machine Learning models and compare their results. Note that because the dataset does not provide labels for their testing-set, we need to use the predictions on the training set to compare the algorithms with each other. Later on, we will use cross validation.

```
X_train = train_df.drop("Survived", axis=1)
Y_train = train_df["Survived"]
X_test  = test_df.drop("PassengerId", axis=1).copy()
```

Stochastic Gradient Descent (SGD):

```
sgd = linear_model.SGDClassifier(max_iter=5, tol=None)
sgd.fit(X_train, Y_train)
```

```
Y_pred = sgd.predict(X_test)

sgd.score(X_train, Y_train)

acc_sgd = round(sgd.score(X_train, Y_train) * 100, 2)
```

Random Forest:

```
random_forest = RandomForestClassifier(n_estimators=100)
random_forest.fit(X_train, Y_train)

Y_prediction = random_forest.predict(X_test)

random_forest.score(X_train, Y_train)
acc_random_forest = round(random_forest.score(X_train, Y_train) * 100, 2)
```

Logistic Regression:

```
logreg = LogisticRegression()
logreg.fit(X_train, Y_train)

Y_pred = logreg.predict(X_test)

acc_log = round(logreg.score(X_train, Y_train) * 100, 2)
```

K Nearest Neighbor:

```
# KNN knn = KNeighborsClassifier(n_neighbors = 3) knn.fit(X_train, Y_train)  Y_pred =
knn.predict(X_test)  acc_knn = round(knn.score(X_train, Y_train) * 100, 2)
```