In [ ]:

```python
import pandas as pd
import gdown
import gzip
from io import BytesIO
import copy
# Here we load the dataset into a Pandas DataFrame using Pandas
# Note for some reason I could no loger upload the file contianing the dataset so I decided to host the file on google drive.
file_id = '1g_B-ms_dmZQWzuRLOBJveFN6b7sg9AJ7'
url = f'https://drive.google.com/uc?id={file_id}'
output = 'data.csv.gz'
# The reason to us gzip is that the dataset is compressed because it is on the larger size at about 57MB
gdown.download(url, output, quiet=True)
with gzip.open(output, 'rt') as file:
# the file is a csv file
    df = pd.read_csv(file)
# We need to copy the df for our secondary cleaning and data transformation.
df_copy = copy.deepcopy(df)
```

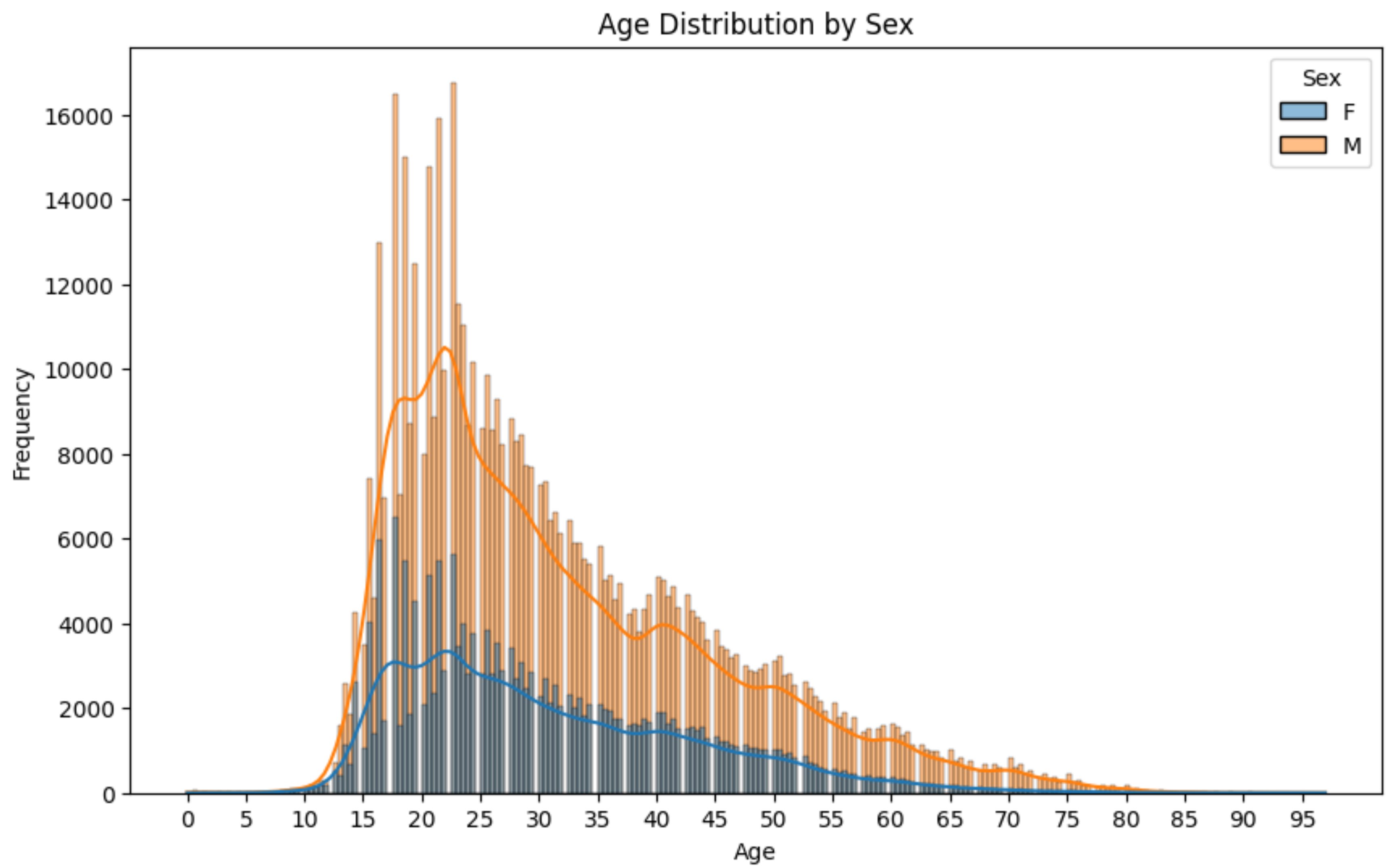
```
<ipython-input-1-183a18b708db>:15: DtypeWarning: Columns (35) have mixed types. Specify dtype option on import or set low_memory=False.
  df = pd.read_csv(file)
```

Section 1

In this section we perform a preliminary data exploration of the dataset which can be downloaded from Kaggle → Dataset

In [ ]:

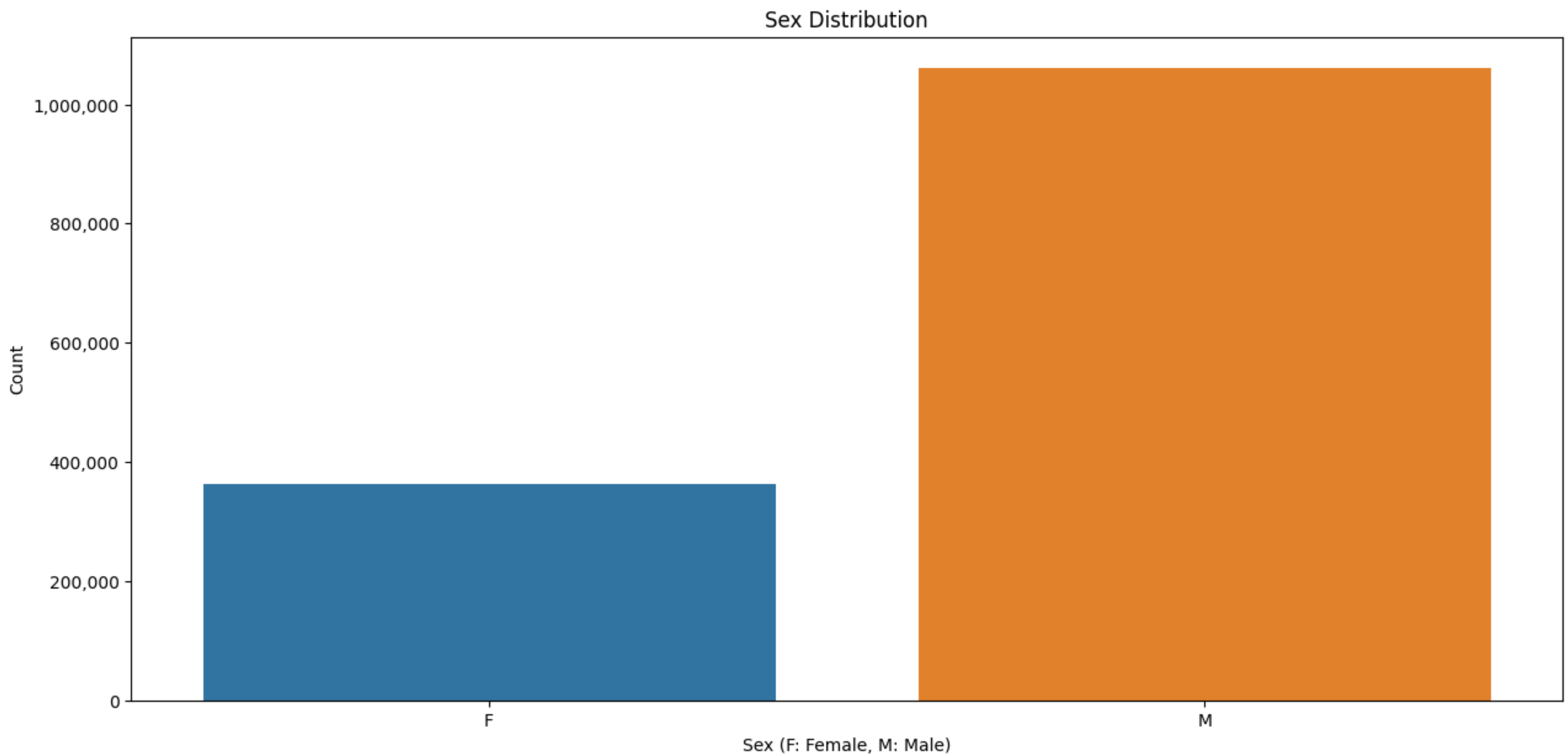
```python
import seaborn as sns
import matplotlib.pyplot as plt
# we create a temporary copy of the df to display some charts
temp = copy.deepcopy(df)
temp['Sex'] = temp['Sex'].replace({0: 'Female', 1: 'Male'})
# The folloing graph prints the distrubution of age by the sex of the lifters, this helps visualize both sexes at the same time
plt.figure(figsize=(10, 6))
sns.histplot(data=temp, x='Age', hue='Sex', kde=True)
plt.title('Age Distribution by Sex')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.xticks(range(0, 100, 5))
plt.show()
# df.head gives a an overview of what the raw data looks like we have 37 distinct columns, most of which we will find unsuable
print(df.head())
```




```
                Name Sex Event Equipment   Age AgeClass Division  BodyweightKg  \
0       Abbie Murphy   F   SBD     Wraps  29.0    24-34     F-OR          59.8
1        Abbie Tuong   F   SBD     Wraps  29.0    24-34     F-OR          58.5
2     Ainslee Hooper   F     B       Raw  40.0    40-44     F-OR          55.4
3  Amy Moldenhauer   F   SBD     Wraps  23.0    20-23     F-OR          60.0
4       Andrea Rowan   F   SBD     Wraps  45.0    45-49     F-OR         104.0

  WeightClassKg  Squat1Kg  ...  McCulloch  Glossbrenner  IPFPoints  Tested  \
0            60      80.0  ...     324.16        286.42     511.15     NaN
1            60     100.0  ...     378.07        334.16     595.65     NaN
2            56       NaN  ...      38.56         34.12     313.97     NaN
3            60    -105.0  ...     345.61        305.37     547.04     NaN
4           110     120.0  ...     338.91        274.56     550.08     NaN

   Country  Federation        Date  MeetCountry  MeetState       MeetName
0      NaN     GPC-AUS  2018-10-27    Australia        VIC  Melbourne Cup
1      NaN     GPC-AUS  2018-10-27    Australia        VIC  Melbourne Cup
2      NaN     GPC-AUS  2018-10-27    Australia        VIC  Melbourne Cup
3      NaN     GPC-AUS  2018-10-27    Australia        VIC  Melbourne Cup
4      NaN     GPC-AUS  2018-10-27    Australia        VIC  Melbourne Cup

[5 rows x 37 columns]
```

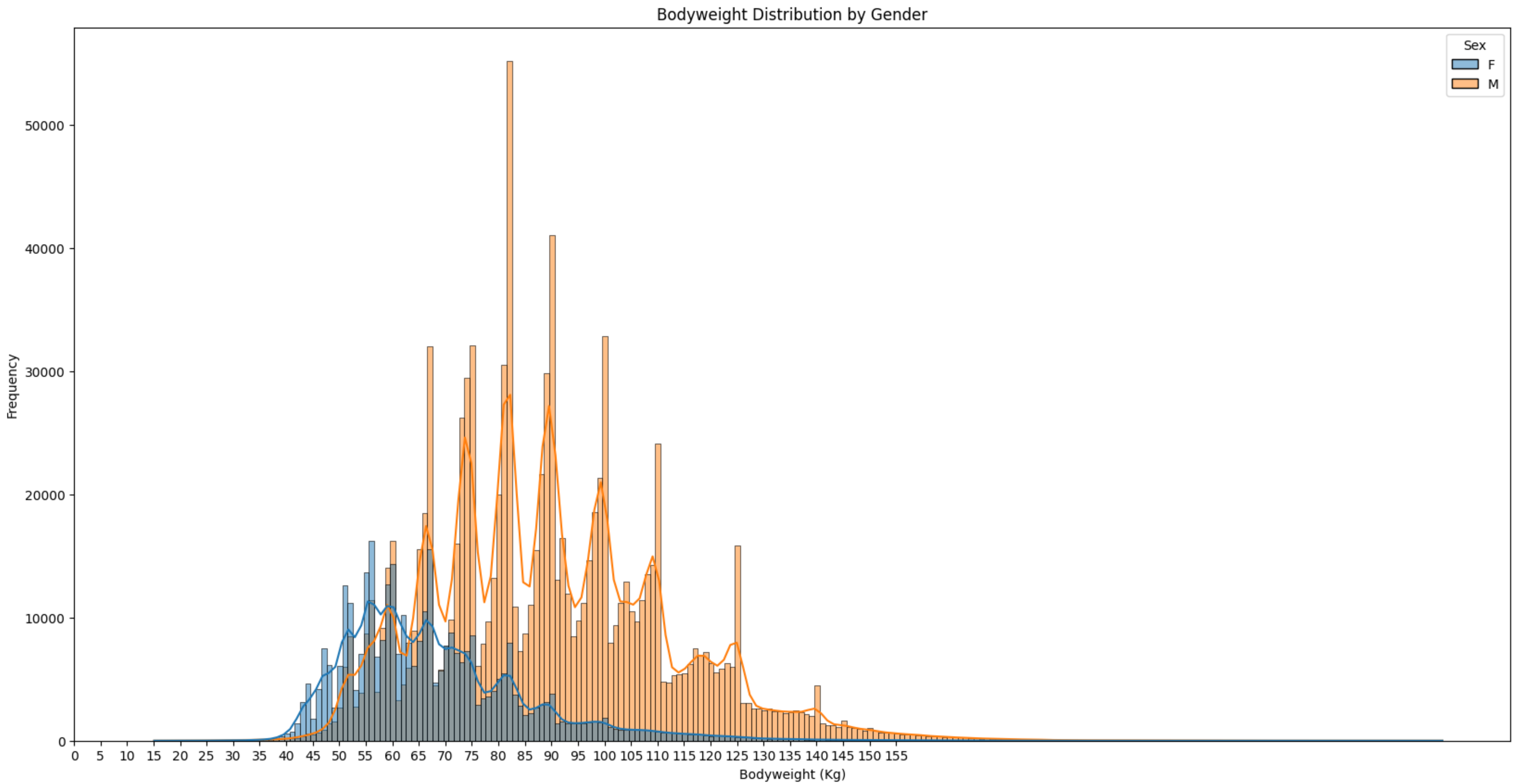
In [ ]:

```
# This graph allows us to see how many male and female competitors are in the raw data
plt.figure(figsize=(15, 7))
axis = sns.countplot(data=df, x='Sex')
plt.title('Sex Distribution')
plt.xlabel('Sex (F: Female, M: Male)')
plt.ylabel('Count')
axis.yaxis.set_major_formatter(plt.FuncFormatter(lambda x, loc: "{:,}".format(int(x))))
plt.show()
```



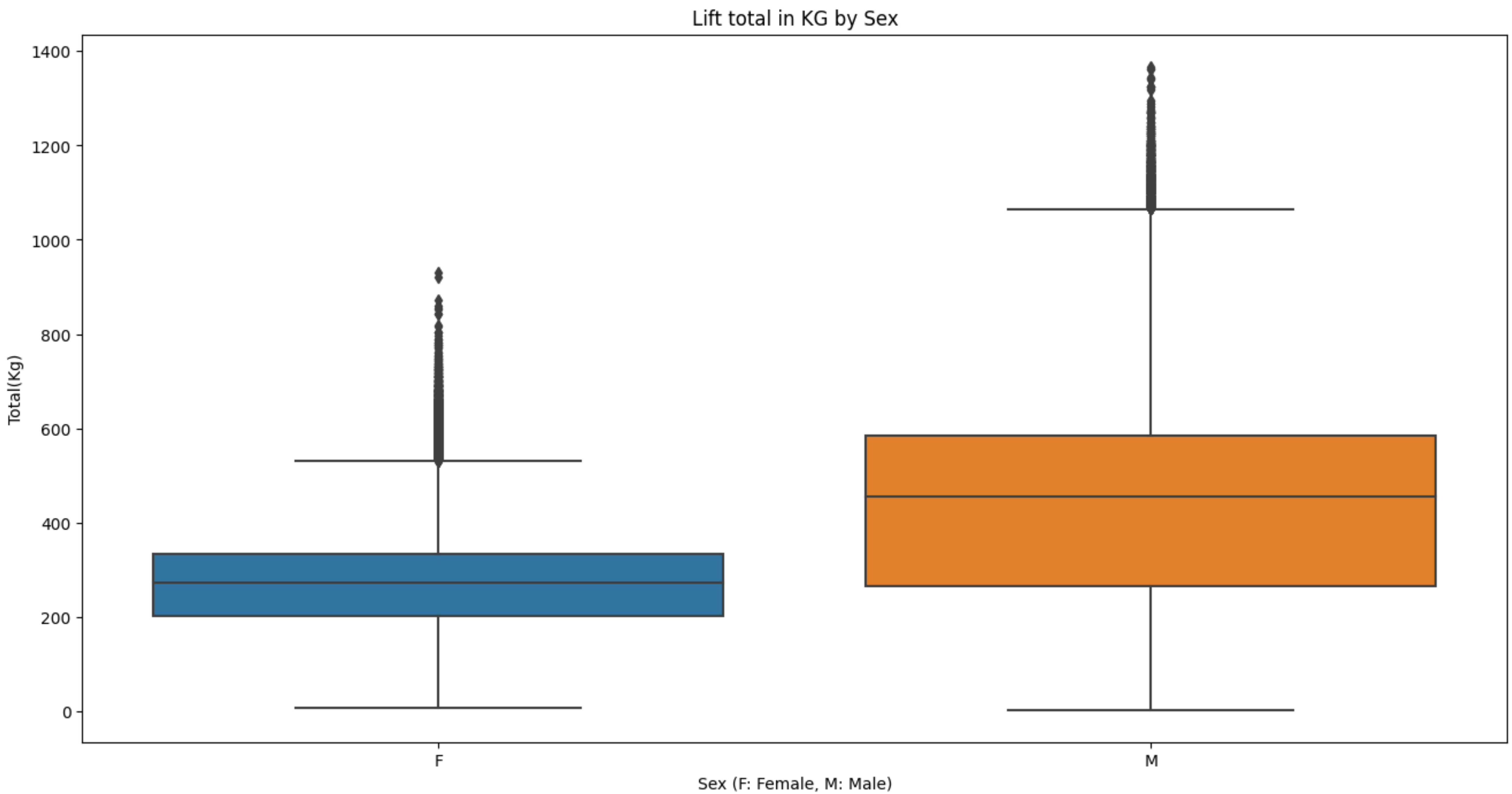
In [ ]:

```
# This graph visulises the body weight distribution of the lifters by gender
plt.figure(figsize=(20, 10))
sns.histplot(data=df, x='BodyweightKg', hue='Sex', kde=True, discrete=True)
plt.title('Bodyweight Distribution by Gender')
plt.xlabel('Bodyweight (Kg)')
plt.ylabel('Frequency')
plt.xticks(range(0, 160, 5))
plt.show()
```



In [ ]:

```
# The graph shows a the distribution of total weight lifted by competitors, most competitors are in the range 200 to 600 kgs, the outliers are due to equipped lifters which we be
# Since we care about raw powerlifting, most of the
plt.figure(figsize=(16, 8))
sns.boxplot(data=df, x='Sex', y='TotalKg')
plt.title('Lift total in KG by Sex')
plt.xlabel('Sex (F: Female, M: Male)')
plt.ylabel('Total(Kg)')
plt.show()
```



In [ ]:

```
# This section provides some statistics about the raw data, as we can see we have many duplciated data and missing values
data_description = df.describe()
print(data_description)
correlation_matrix = df.corr()
print(correlation_matrix)
missing_values = df.isnull().sum()
print("Missing values count: "+str(missing_values))
total_missing_values = df.isna().sum().sum()
print("Total NaN values: "+ str(total_missing_values))
duplicated_rows_count = df.duplicated().sum()
print("Total duplicated rows count: "+str(duplicated_rows_count))
print(df.head())
```

```
                Age  BodyweightKg       Squat1Kg       Squat2Kg  \
count  757527.000000  1.406622e+06  337580.000000  333349.000000
mean       31.501570  8.422503e+01     114.102442      92.155846
std        13.371707  2.322011e+01     147.143021     173.701524
min         0.000000  1.510000e+01    -555.000000    -580.000000
25%        21.000000  6.670000e+01      90.000000      68.000000
50%        28.000000  8.180000e+01     147.500000     145.000000
75%        40.000000  9.915000e+01     200.000000     205.000000
max        97.000000  2.580000e+02     555.000000     566.990000

            Squat3Kg     Squat4Kg  Best3SquatKg       Bench1Kg       Bench2Kg  \
count  323842.000000  3696.000000  1.031450e+06  499779.000000  493486.000000
mean       30.056842    71.356870  1.740049e+02      83.892373      55.065745
std       200.413385   194.522045  6.923931e+01     105.196350     130.302229
min      -600.500000  -550.000000 -4.775000e+02    -480.000000    -507.500000
25%      -167.500000  -107.840000  1.224700e+02      57.500000     -52.500000
50%       110.000000   135.000000  1.678300e+02     105.000000      95.000000
75%       192.500000   205.000000  2.175000e+02     145.000000     145.000000
max       560.000000   505.500000  5.750000e+02     467.500000     487.500000

            Bench3Kg  ...    Deadlift1Kg    Deadlift2Kg    Deadlift3Kg  \
count  478485.000000  ...  363544.000000  356023.000000  339947.000000
mean      -18.520481  ...     162.700840     130.228378      12.995484
std       144.225726  ...     108.681438     162.680134     215.052488
min      -575.000000  ...    -461.000000    -470.000000    -587.500000
25%      -140.000000  ...     125.000000     115.000000    -210.000000
50%       -60.000000  ...     180.000000     177.500000     117.500000
75%       117.500000  ...     226.800000     230.000000     205.000000
max       478.540000  ...     450.000000     460.400000     457.500000

       Deadlift4Kg  Best3DeadliftKg       TotalKg         Wilks     McCulloch  \
count  9246.000000     1.081808e+06  1.313184e+06  1.304407e+06  1.304254e+06
mean     78.914945     1.872585e+02  3.956148e+02  2.882247e+02  2.960682e+02
std     192.605159     6.232821e+01  2.011420e+02  1.231805e+02  1.249700e+02
min    -461.000000    -4.100000e+02  2.500000e+00  1.470000e+00  1.470000e+00
25%    -110.000000     1.383500e+02  2.325000e+02  1.979000e+02  2.048200e+02
50%     145.150000     1.850000e+02  3.787500e+02  3.052000e+02  3.120300e+02
75%     210.000000     2.300000e+02  5.400000e+02  3.745600e+02  3.837600e+02
max     418.000000     5.850000e+02  1.367500e+03  7.793800e+02  8.044000e+02

       Glossbrenner     IPFPoints
count  1.304407e+06  1.273286e+06
mean   2.718484e+02  4.854330e+02
std    1.175571e+02  1.133489e+02
min    1.410000e+00  2.160000e+00
25%    1.828100e+02  4.028600e+02
50%    2.859400e+02  4.780500e+02
75%    3.552800e+02  5.597000e+02
max    7.429600e+02  1.245930e+03

[8 rows x 22 columns]
```

```
<ipython-input-6-4ee2834543a3>:4: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only vali
d columns or specify the value of numeric_only to silence this warning.
  correlation_matrix = df.corr()
```

	Age	BodyweightKg	Squat1Kg	Squat2Kg	Squat3Kg	\
Age	1.000000	0.158509	-0.015515	-0.012730	0.014715	
BodyweightKg	0.158509	1.000000	0.161596	0.126649	0.062187	
Squat1Kg	-0.015515	0.161596	1.000000	0.148796	0.055897	
Squat2Kg	-0.012730	0.126649	0.148796	1.000000	0.128247	
Squat3Kg	0.014715	0.062187	0.055897	0.128247	1.000000	
Squat4Kg	0.054640	0.095291	0.054822	0.096211	0.065949	
Best3SquatKg	0.014667	0.604152	0.332957	0.199968	0.064689	
Bench1Kg	0.025836	0.193994	0.176815	0.127640	0.066851	
Bench2Kg	-0.003216	0.097307	0.110058	0.118657	0.101584	
Bench3Kg	-0.019552	-0.037993	0.044515	0.071562	0.099569	
Bench4Kg	0.069094	0.036419	0.071604	0.045454	0.043731	
Best3BenchKg	0.102148	0.607003	0.277993	0.160325	0.034178	
Deadlift1Kg	0.028104	0.299419	0.190362	0.137626	0.055237	
Deadlift2Kg	0.027182	0.142539	0.087328	0.115457	0.101274	
Deadlift3Kg	0.015448	-0.028371	-0.011092	0.053020	0.115213	
Deadlift4Kg	0.070567	0.018056	-0.036887	0.040110	0.100794	
Best3DeadliftKg	0.027388	0.584668	0.305305	0.190905	0.049729	
TotalKg	-0.136133	0.396248	0.330739	0.201742	0.059239	
Wilks	-0.203642	0.026734	0.269566	0.141056	0.021473	
McCulloch	-0.115789	0.020930	0.246745	0.127062	0.025073	
Glossbrenner	-0.202539	0.045800	0.287243	0.153216	0.024584	
IPFPoints	-0.020378	0.103651	0.252094	0.152462	0.038209	

	Squat4Kg	Best3SquatKg	Bench1Kg	Bench2Kg	Bench3Kg	...	\
Age	0.054640	0.014667	0.025836	-0.003216	-0.019552	...	
BodyweightKg	0.095291	0.604152	0.193994	0.097307	-0.037993	...	
Squat1Kg	0.054822	0.332957	0.176815	0.110058	0.044515	...	
Squat2Kg	0.096211	0.199968	0.127640	0.118657	0.071562	...	
Squat3Kg	0.065949	0.064689	0.066851	0.101584	0.099569	...	
Squat4Kg	1.000000	-0.014048	-0.040992	-0.000900	0.094383	...	
Best3SquatKg	-0.014048	1.000000	0.342576	0.179075	0.015449	...	
Bench1Kg	-0.040992	0.342576	1.000000	0.148200	0.028020	...	
Bench2Kg	-0.000900	0.179075	0.148200	1.000000	0.130057	...	
Bench3Kg	0.094383	0.015449	0.028020	0.130057	1.000000	...	
Bench4Kg	0.297942	0.068681	0.020147	0.072416	0.080381	...	
Best3BenchKg	0.037770	0.884485	0.374812	0.194598	-0.000068	...	
Deadlift1Kg	-0.034457	0.423891	0.230115	0.137560	0.032462	...	
Deadlift2Kg	0.068528	0.126137	0.099606	0.105658	0.073263	...	
Deadlift3Kg	0.087906	-0.151569	-0.025307	0.048406	0.087758	...	
Deadlift4Kg	0.357468	-0.082099	-0.079754	-0.013966	0.077318	...	
Best3DeadliftKg	0.051900	0.888175	0.386443	0.208905	0.021237	...	
TotalKg	0.028978	0.967193	0.194239	0.131773	0.058817	...	
Wilks	-0.028537	0.774673	0.081439	0.076524	0.071695	...	
McCulloch	-0.011682	0.740720	0.070058	0.071619	0.074931	...	
Glossbrenner	-0.026084	0.817954	0.097963	0.084838	0.070113	...	
IPFPoints	-0.053050	0.632758	0.251453	0.148762	0.022306	...	

	Deadlift1Kg	Deadlift2Kg	Deadlift3Kg	Deadlift4Kg	\
Age	0.028104	0.027182	0.015448	0.070567	
BodyweightKg	0.299419	0.142539	-0.028371	0.018056	
Squat1Kg	0.190362	0.087328	-0.011092	-0.036887	
Squat2Kg	0.137626	0.115457	0.053020	0.040110	
Squat3Kg	0.055237	0.101274	0.115213	0.100794	
Squat4Kg	-0.034457	0.068528	0.087906	0.357468	
Best3SquatKg	0.423891	0.126137	-0.151569	-0.082099	
Bench1Kg	0.230115	0.099606	-0.025307	-0.079754	
Bench2Kg	0.137560	0.105658	0.048406	-0.013966	
Bench3Kg	0.032462	0.073263	0.087758	0.077318	

Bench4Kg	-0.011695	0.015117	0.057702	0.347674
Best3BenchKg	0.413953	0.137041	-0.120944	-0.026343
Deadlift1Kg	1.000000	0.115412	-0.070460	-0.083301
Deadlift2Kg	0.115412	1.000000	0.141795	-0.037798
Deadlift3Kg	-0.070460	0.141795	1.000000	0.106620
Deadlift4Kg	-0.083301	-0.037798	0.106620	1.000000
Best3DeadliftKg	0.531479	0.221535	-0.076600	-0.090372
TotalKg	0.453955	0.162569	-0.100441	-0.064316
Wilks	0.307736	0.091039	-0.105416	-0.076961
McCulloch	0.283836	0.085846	-0.096568	-0.057145
Glossbrenner	0.338074	0.103341	-0.109219	-0.076339
IPFPoints	0.337982	0.122884	-0.090485	-0.156644

	Best3DeadliftKg	TotalKg	Wilks	McCulloch	Glossbrenner \
Age	0.027388	-0.136133	-0.203642	-0.115789	-0.202539
BodyweightKg	0.584668	0.396248	0.026734	0.020930	0.045800
Squat1Kg	0.305305	0.330739	0.269566	0.246745	0.287243
Squat2Kg	0.190905	0.201742	0.141056	0.127062	0.153216
Squat3Kg	0.049729	0.059239	0.021473	0.025073	0.024584
Squat4Kg	0.051900	0.028978	-0.028537	-0.011682	-0.026084
Best3SquatKg	0.888175	0.967193	0.774673	0.740720	0.817954
Bench1Kg	0.386443	0.194239	0.081439	0.070058	0.097963
Bench2Kg	0.208905	0.131773	0.076524	0.071619	0.084838
Bench3Kg	0.021237	0.058817	0.071695	0.074931	0.070113
Bench4Kg	0.092414	0.025473	0.005965	0.011905	0.008602
Best3BenchKg	0.866538	0.483902	0.184129	0.173727	0.227361
Deadlift1Kg	0.531479	0.453955	0.307736	0.283836	0.338074
Deadlift2Kg	0.221535	0.162569	0.091039	0.085846	0.103341
Deadlift3Kg	-0.076600	-0.100441	-0.105416	-0.096568	-0.109219
Deadlift4Kg	-0.090372	-0.064316	-0.076961	-0.057145	-0.076339
Best3DeadliftKg	1.000000	0.864799	0.607853	0.588145	0.661566
TotalKg	0.864799	1.000000	0.881385	0.867507	0.906568
Wilks	0.607853	0.881385	1.000000	0.985428	0.995393
McCulloch	0.588145	0.867507	0.985428	1.000000	0.981328
Glossbrenner	0.661566	0.906568	0.995393	0.981328	1.000000
IPFPoints	0.673613	0.267329	0.263062	0.245303	0.262000

	IPFPoints
Age	-0.020378
BodyweightKg	0.103651
Squat1Kg	0.252094
Squat2Kg	0.152462
Squat3Kg	0.038209
Squat4Kg	-0.053050
Best3SquatKg	0.632758
Bench1Kg	0.251453
Bench2Kg	0.148762
Bench3Kg	0.022306
Bench4Kg	-0.112325
Best3BenchKg	0.621578
Deadlift1Kg	0.337982
Deadlift2Kg	0.122884
Deadlift3Kg	-0.090485
Deadlift4Kg	-0.156644
Best3DeadliftKg	0.673613
TotalKg	0.267329
Wilks	0.263062
McCulloch	0.245303
Glossbrenner	0.262000

```
IPFPoints         1.000000

[22 rows x 22 columns]
Missing values count: Name                     0
Sex                    0
Event                  0
Equipment              0
Age               665827
AgeClass          636554
Division            8178
BodyweightKg       16732
WeightClassKg      13312
Squat1Kg         1085774
Squat2Kg         1090005
Squat3Kg         1099512
Squat4Kg         1419658
Best3SquatKg      391904
Bench1Kg          923575
Bench2Kg          929868
Bench3Kg          944869
Bench4Kg         1413849
Best3BenchKg      147173
Deadlift1Kg      1059810
Deadlift2Kg      1067331
Deadlift3Kg      1083407
Deadlift4Kg      1414108
Best3DeadliftKg   341546
TotalKg           110170
Place                  0
Wilks             118947
McCulloch         119100
Glossbrenner      118947
IPFPoints         150068
Tested            329462
Country          1034470
Federation             0
Date                   0
MeetCountry            0
MeetState         481809
MeetName               0
dtype: int64
Total NaN values: 18215965
Total duplicated rows count: 3084
              Name Sex Event Equipment   Age AgeClass Division  BodyweightKg  \
0     Abbie Murphy   F   SBD     Wraps  29.0    24-34     F-OR          59.8
1      Abbie Tuong   F   SBD     Wraps  29.0    24-34     F-OR          58.5
2   Ainslee Hooper   F     B       Raw  40.0    40-44     F-OR          55.4
3  Amy Moldenhauer   F   SBD     Wraps  23.0    20-23     F-OR          60.0
4     Andrea Rowan   F   SBD     Wraps  45.0    45-49     F-OR         104.0

  WeightClassKg  Squat1Kg  ...  McCulloch  Glossbrenner  IPFPoints  Tested  \
0            60      80.0  ...     324.16        286.42     511.15     NaN
1            60     100.0  ...     378.07        334.16     595.65     NaN
2            56       NaN  ...      38.56         34.12     313.97     NaN
3            60    -105.0  ...     345.61        305.37     547.04     NaN
4           110     120.0  ...     338.91        274.56     550.08     NaN

   Country  Federation        Date  MeetCountry  MeetState       MeetName
0      NaN     GPC-AUS  2018-10-27    Australia        VIC  Melbourne Cup
```

```
1      NaN     GPC-AUS  2018-10-27    Australia        VIC  Melbourne Cup
2      NaN     GPC-AUS  2018-10-27    Australia        VIC  Melbourne Cup
3      NaN     GPC-AUS  2018-10-27    Australia        VIC  Melbourne Cup
4      NaN     GPC-AUS  2018-10-27    Australia        VIC  Melbourne Cup

[5 rows x 37 columns]
```

As we can see from the graphs a large majority of lifters are male, typically powerlifting is a male dominated sport, but it has had a rise in polularity and more woman are competing. Most of the male and female lifters are also between the ages of 15 and 45, with the highest being between ages of 20 and 25, so this is more likely where we will see the strongest athletes. The majority of male lifters are between 75 and 90 kilograms. The majority of female lifters are between 50 and 60 kilograms.

Section 2a.

In this section we use our primary data cleaning technique

In [ ]:

```
from sklearn.preprocessing import LabelEncoder
# Some coloumns arent really neccasry so we drop the irrelevant columns
df = df.drop(['Squat1Kg', 'Squat2Kg', 'Squat3Kg', 'Squat4Kg',
              'Best3SquatKg', 'Bench1Kg', 'Bench2Kg', 'Bench3Kg', 'Bench4Kg',
              'Best3BenchKg', 'Deadlift1Kg', 'Deadlift2Kg', 'Deadlift3Kg', 'Deadlift4Kg',
              'Best3DeadliftKg','AgeClass','Federation','Tested','Date', 'MeetCountry',
              'MeetState', 'MeetName','Place','Country','Wilks', 'McCulloch',
              'Glossbrenner', 'IPFPoints','Event'], axis=1)
# We want to filter the dataset to include only raw and wraps equiment lifters
df_raw_wraps = copy.deepcopy(df)
df_raw_wraps = df_raw_wraps.loc[(df_raw_wraps['Equipment'] == 'Wraps') | (df_raw_wraps['Equipment'] == 'Raw')]
# There are varoius missing values as we can see so we drop them also we drop any values that are not numeric and we drop duplicates
df_raw_wraps.loc[:, 'Age'] = pd.to_numeric(df_raw_wraps['Age'], errors='coerce')
df_raw_wraps.loc[:, 'BodyweightKg'] = pd.to_numeric(df_raw_wraps['BodyweightKg'], errors='coerce')
df_raw_wraps.loc[:, 'WeightClassKg'] = pd.to_numeric(df_raw_wraps['WeightClassKg'], errors='coerce')
df_raw_wraps.loc[:, 'TotalKg'] = pd.to_numeric(df_raw_wraps['TotalKg'], errors='coerce')
df_raw_wraps = df_raw_wraps.drop_duplicates()
features = ['Sex','Age', 'WeightClassKg','BodyweightKg','Division']
df_raw_wraps = df_raw_wraps.dropna(subset=features)
df_raw_wraps.dropna(subset=['TotalKg'], inplace=True)
```

```
<ipython-input-7-ee73549aeeb8>:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_raw_wraps.loc[:, 'Age'] = pd.to_numeric(df_raw_wraps['Age'], errors='coerce')
<ipython-input-7-ee73549aeeb8>:14: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_raw_wraps.loc[:, 'BodyweightKg'] = pd.to_numeric(df_raw_wraps['BodyweightKg'], errors='coerce')
<ipython-input-7-ee73549aeeb8>:15: DeprecationWarning: In a future version, `df.iloc[:, i] = newvals` will attempt to set the values inplace instead of always setting a new array.
To retain the old behavior, use either `df[df.columns[i]] = newvals` or, if columns are non-unique, `df.isetitem(i, newvals)`
  df_raw_wraps.loc[:, 'WeightClassKg'] = pd.to_numeric(df_raw_wraps['WeightClassKg'], errors='coerce')
<ipython-input-7-ee73549aeeb8>:20: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_raw_wraps.dropna(subset=['TotalKg'], inplace=True)
```

Section 2b.

In this section we use our primary data processing technique

In [ ]:

```python
# Here we encode categorical columns to numerical values, we used this during lecture so I will use for this data cleaning
le = LabelEncoder()
df_raw_wraps['Sex'] = le.fit_transform(df_raw_wraps['Sex'])
df_raw_wraps['Equipment'] = le.fit_transform(df_raw_wraps['Equipment'])
df_raw_wraps['Division'] = le.fit_transform(df_raw_wraps['Division'])
# In this section we are normalizing the features using sklearn, and defining X and y, X refers to our feature data that we will use to predict our target variable y
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaleable_features = ['Age', 'WeightClassKg','BodyweightKg']
df_raw_wraps[scaleable_features] = scaler.fit_transform(df_raw_wraps[scaleable_features])
X = df_raw_wraps[features]
y = df_raw_wraps['TotalKg']
# We make a copy of the dataframe since we want to unscale the values as we will need to use this for data analysis
df_unscaled = df_raw_wraps.copy()
df_unscaled[scaleable_features] = scaler.inverse_transform(df_raw_wraps[scaleable_features])
```

```
<ipython-input-8-808cf907411f>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_raw_wraps['Sex'] = le.fit_transform(df_raw_wraps['Sex'])
```

Section 3a.

In this section we utilize a different data cleaning technique

In [ ]:

```
# Instead of dropping coloumns we just keep the columns of our features and totalkg which is what we are trying to predict
df_copy = df_copy[['Sex', 'Equipment', 'Age', 'WeightClassKg', 'BodyweightKg', 'TotalKg']]
df_copy = df_copy.dropna(subset=['TotalKg'])
df_copy = df_copy.drop_duplicates()
df_copy =  df_copy[df_copy['Equipment'].isin(['Raw', 'Wraps'])]
df_copy.reset_index(drop=True, inplace=True)
temp = ['Age','BodyweightKg', 'TotalKg']
for i in range(len(temp)):
  df_copy[temp[i]] = pd.to_numeric(df_copy[temp[i]], errors='coerce')
df_copy['WeightClassKg'] = df_copy['WeightClassKg'].str.replace('+', '')
df_copy['WeightClassKg'] = pd.to_numeric(df_copy['WeightClassKg'], errors='coerce')
```

```
<ipython-input-9-882e637e4d89>:10: FutureWarning: The default value of regex will change from True to False in a future version. In addition, single character regular expressions will *not* be treated as literal strings when regex=True.
  df_copy['WeightClassKg'] = df_copy['WeightClassKg'].str.replace('+', '')
```

Section 3b.

In this section we use our secondary data processing technique

In [ ]:

```
from sklearn.preprocessing import OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler
# We will utilize one-hot encoding for categorical features
OHE = OneHotEncoder(sparse=False)
Encoded_Sex = OHE.fit_transform(df_copy[['Sex']])
sex_columns = OHE.categories_[0].tolist()
df_raw_wraps_encoded = pd.DataFrame(Encoded_Sex, columns=sex_columns, index=df_copy.index)
Encoded_Equipment = OHE.fit_transform(df_copy[['Equipment']])
equipment_columns = OHE.categories_[0].tolist()
df_raw_wraps_encoded = pd.concat([df_raw_wraps_encoded, pd.DataFrame(Encoded_Equipment, columns=equipment_columns, index=df_copy.index)], axis=1)
# We have many missing values in the dataset on way to handle the missing values is to inmpute the missing values using the mean of each column
im = SimpleImputer(strategy='mean')
temp = df_copy[['Age', 'WeightClassKg', 'BodyweightKg']]
imputed_df = pd.DataFrame(im.fit_transform(temp), columns=temp.columns, index=temp.index)
df_raw_wraps_encoded  = pd.concat([df_raw_wraps_encoded, imputed_df], axis=1)

# Here we  normalize age. wight class, and body weight
MMS = MinMaxScaler()
scaled_data = MMS.fit_transform(df_raw_wraps_encoded[['Age', 'WeightClassKg', 'BodyweightKg']])
df_raw_wraps_encoded[['Age', 'WeightClassKg', 'BodyweightKg']] = scaled_data

X_prime = df_raw_wraps_encoded
y_prime = df_copy['TotalKg']
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_encoders.py:868: FutureWarning: `sparse` was renamed to `sparse_output` in version 1.2 and will be removed in 1.4. `sparse_output` is ignored unless you leave `sparse` to its default value.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_encoders.py:868: FutureWarning: `sparse` was renamed to `sparse_output` in version 1.2 and will be removed in 1.4. `sparse_output` is ignored unless you leave `sparse` to its default value.
  warnings.warn(
```

Section 4.

In this section we split the dataset into training and testing

In [ ]:

```
# In this section we are spliting the data into training and testing for both techniques used
# a common test split we discussed is 10% testing with 10% validation and 80% training the random state is set to 7
from sklearn.model_selection import train_test_split
 #Here we split the data of our initial data processing and cleaning into training, testing and validation.
X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.2, random_state=7)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=.5, random_state=7)
# Here we split the data of our alternative data processing and cleaning into training, testing and validation.
X_prime_train, X_prime_temp, y_prime_train, y_prime_temp = train_test_split(X_prime, y_prime, test_size=0.3, random_state=7)
X_prime_val, X_prime_test, y_prime_val, y_prime_test = train_test_split(X_prime_temp, y_prime_temp, test_size=0.33, random_state=7)

X_unscaled = df_unscaled[features]
y_unscaled = df_unscaled['TotalKg']
X_train_unscaled, X_test_unscaled, y_train_unscaled, y_test_unscaled = train_test_split(X_unscaled, y_unscaled, test_size=0.2, random_state=7)
```

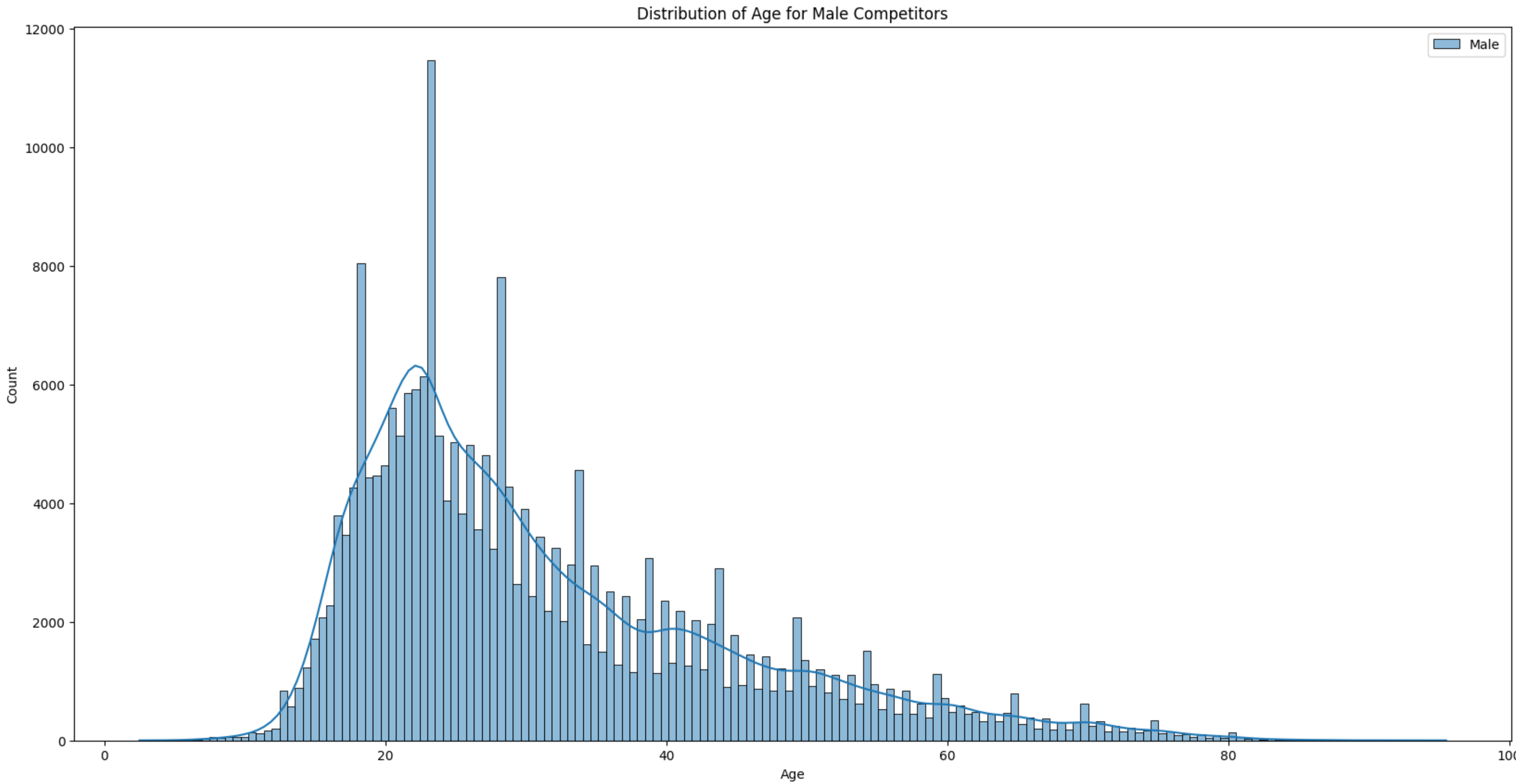
Section 5a.

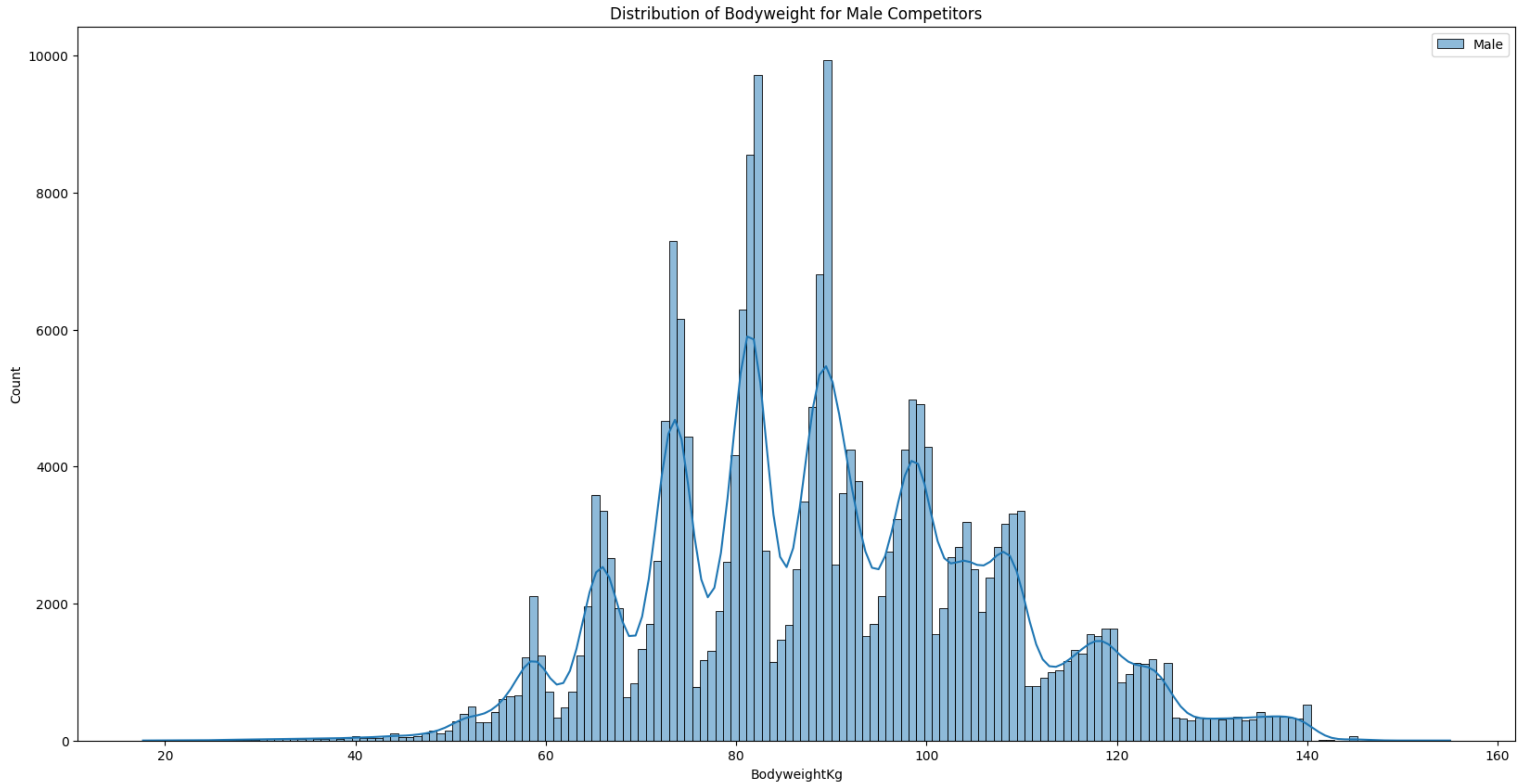
In this section we perform data analysis on the male training subset

In [ ]:

```
# In this section we look at the despritve statistics of the male competitors
male_df = X_train_unscaled[X_train_unscaled['Sex'] == 1]
print('-----------------------------------------------------')
print("Descriptive statistics of male competitors:")
print(male_df[['Age', 'BodyweightKg']].describe())
print('-----------------------------------------------------')
plt.figure(figsize=(20, 10))
sns.histplot(data=male_df, x='Age', kde=True, label='Male')
plt.legend()
plt.title('Distribution of Age for Male Competitors')
plt.show()

plt.figure(figsize=(20, 10))
sns.histplot(data=male_df, x='BodyweightKg', kde=True, label='Male')
plt.legend()
plt.title('Distribution of Bodyweight for Male Competitors')
plt.show()
```

```
----------------------------------------------------
Descriptive statistics of male competitors:
                 Age   BodyweightKg
count  231672.000000  231672.000000
mean       31.354441      89.737960
std        13.405141      18.080501
min         2.500000      17.690000
25%        21.500000      76.500000
50%        27.500000      88.900000
75%        38.500000     101.500000
max        95.500000     155.000000
----------------------------------------------------
```





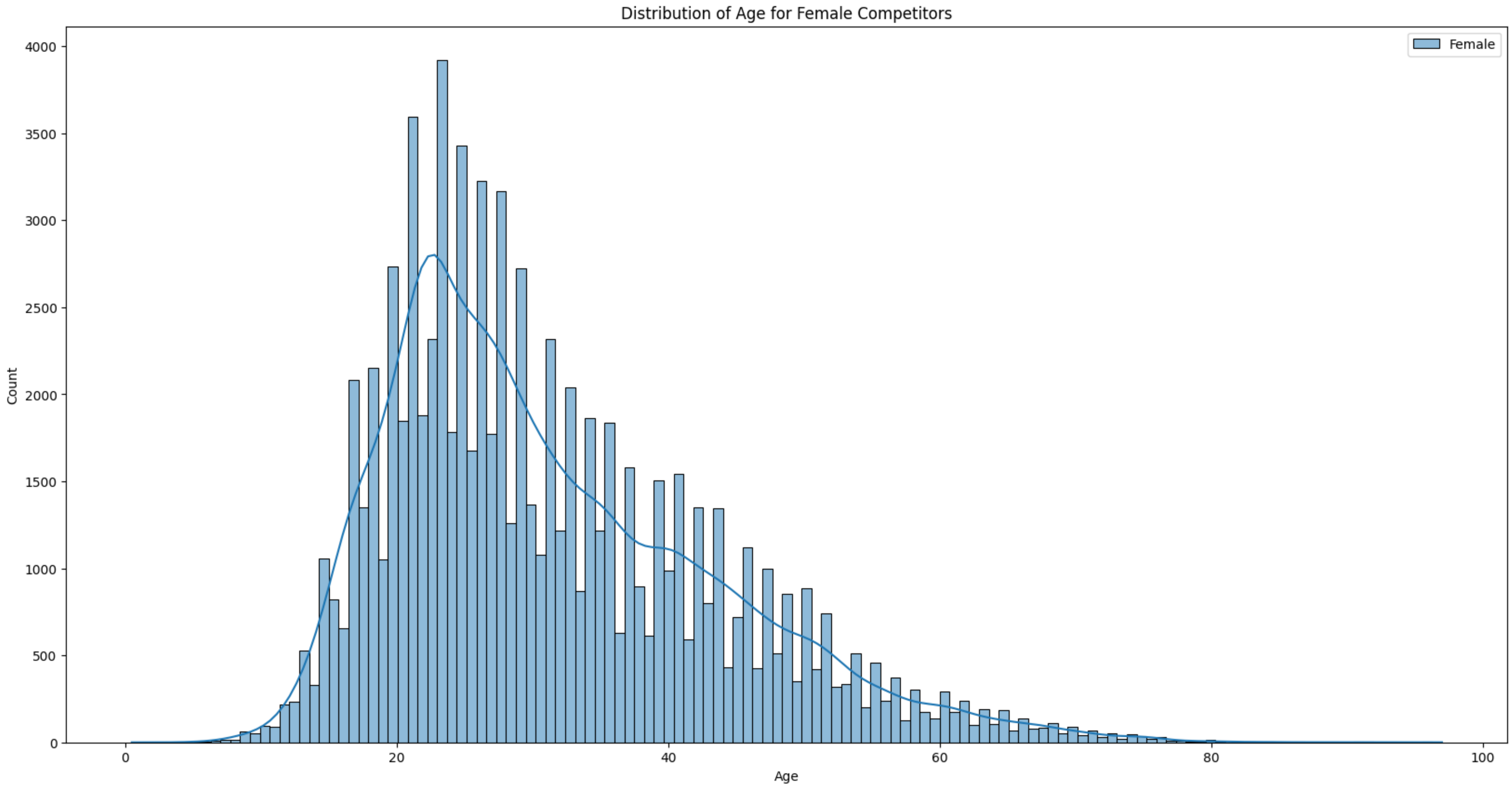
Section 5b.

In this section we perform data analysis on the female training subset

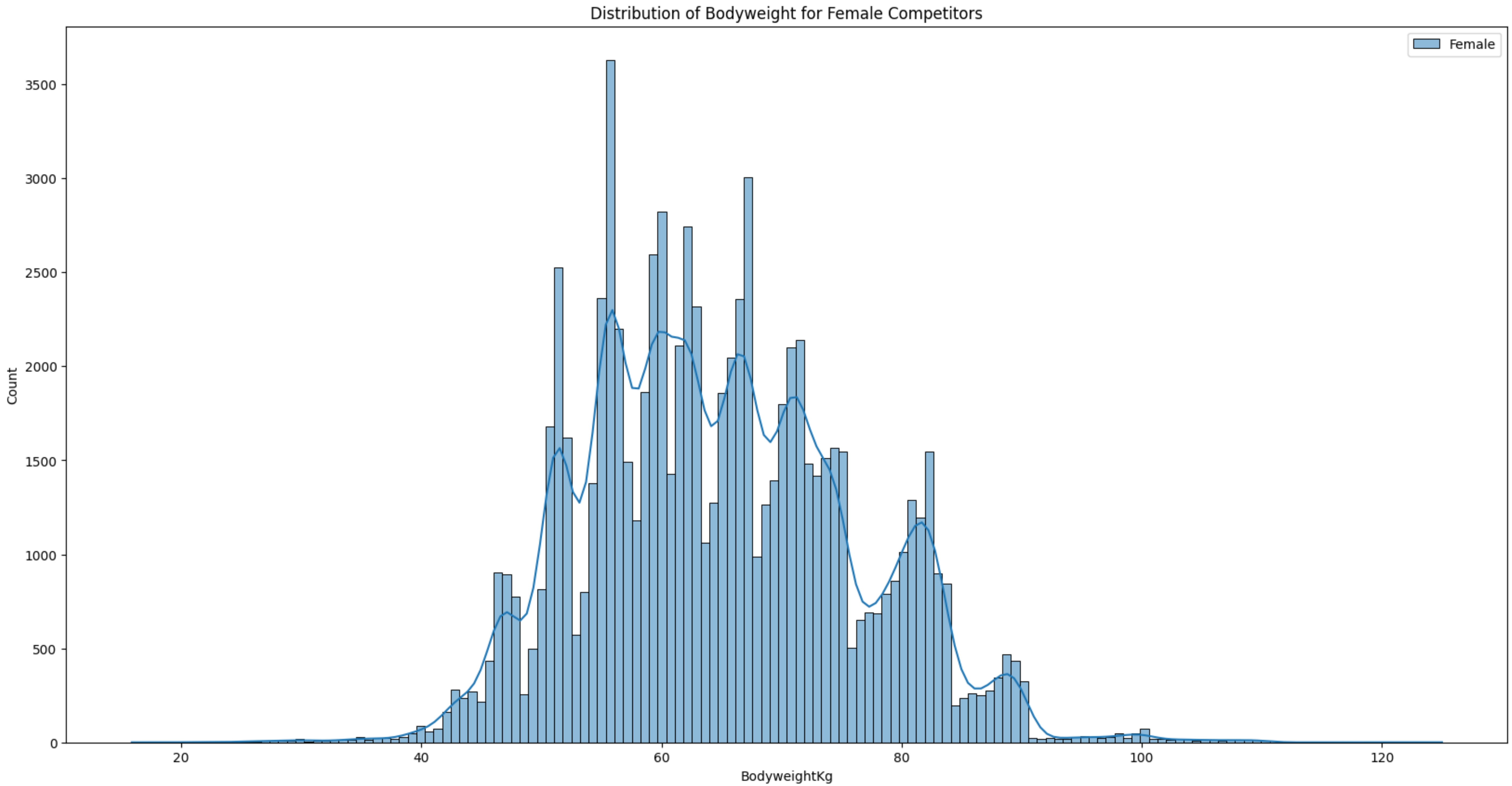
In [ ]:

```python
# In this section we look at the despritve statistics of the female competitors
female_df = X_train_unscaled[X_train_unscaled['Sex'] == 0]
print('-----------------------------------------------------')
print("Descriptive statistics of female competitors:")
print(female_df[['Age', 'BodyweightKg']].describe())
print('-----------------------------------------------------')
plt.figure(figsize=(20, 10))
sns.histplot(data=female_df, x='Age', kde=True, label='Female')
plt.legend()
plt.title('Distribution of Age for Female Competitors')
plt.show()

plt.figure(figsize=(20, 10))
sns.histplot(data=female_df, x='BodyweightKg', kde=True, label='Female')
plt.legend()
plt.title('Distribution of Bodyweight for Female Competitors')
plt.show()
```

```
-----------------------------------------------------
Descriptive statistics of female competitors:
                Age  BodyweightKg
count  84788.000000  84788.000000
mean      31.289215     64.816118
std       12.083642     11.200386
min        0.500000     15.880000
25%       22.500000     56.200000
50%       28.500000     63.800000
75%       38.500000     72.050000
max       97.000000    125.000000
-----------------------------------------------------
```



Distribution of Age for Female Competitors
Female
Count
Age
0
500
1000
1500
2000
2500
3000
3500
4000
0
20
40
60
80
100



Sections 7a-7b is used for fine tuning the models, the performance of the model is evaluated on the validation set. We define a function that allows us to evaluate model performance.

In [ ]:

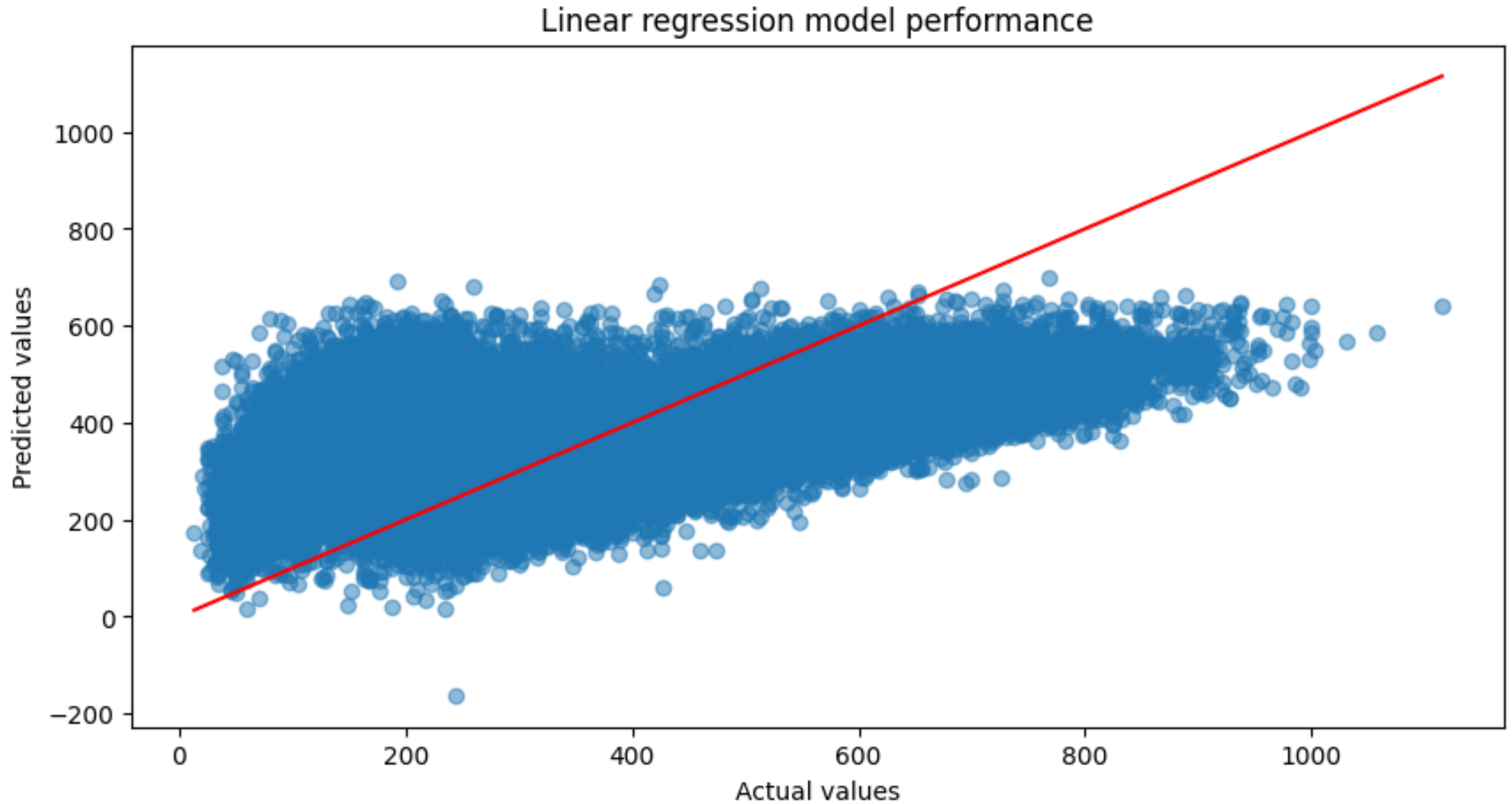
```
def evaluate_model(model, X_train, y_train, X_val, y_val, title):
    model.fit(X_train, y_train)
    y_pred_val = model.predict(X_val)

    plt.figure(figsize=(10, 5))
    plt.scatter(y_val, y_pred_val, alpha=0.5)
    plt.plot([min(y_val), max(y_val)], [min(y_val), max(y_val)], color='red')
    plt.xlabel('Actual values')
    plt.ylabel('Predicted values')
    plt.title(title)
    plt.show()

    mae = mean_absolute_error(y_val, y_pred_val)
    mse = mean_squared_error(y_val, y_pred_val)
    r2 = r2_score(y_val, y_pred_val)
    print("Mean Absolute Error: " + str(mae))
    print("Mean Squared Error: " + str(mse))
    print("R-squared: " + str(r2))
```

Section 6.

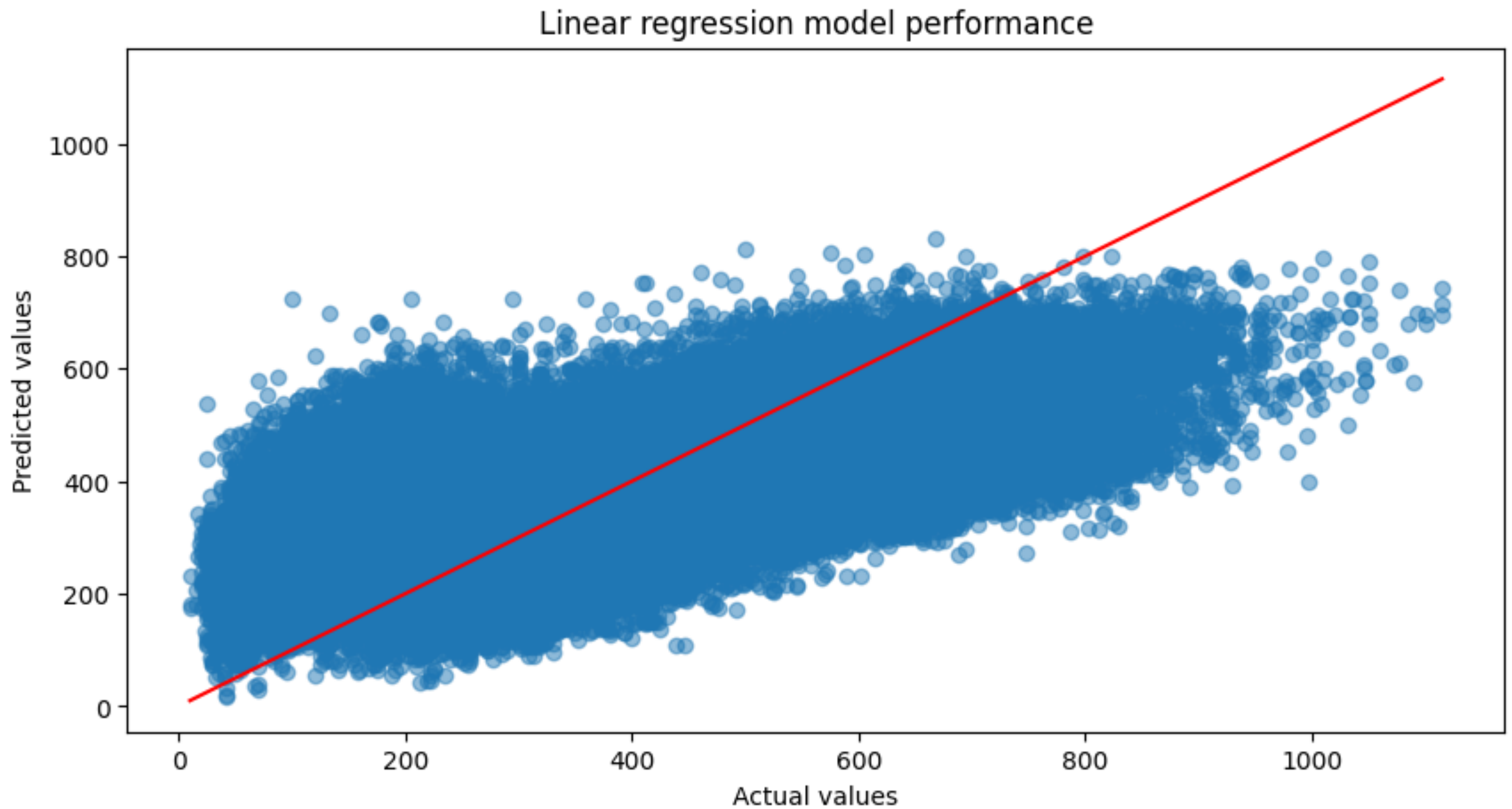
In this section we implement a base model

In [ ]:

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
# We implement linear regression and print the models performance
lr = LinearRegression()
evaluate_model(lr, X_train, y_train, X_val, y_val, 'Linear regression model performance')
evaluate_model(lr, X_prime_train, y_prime_train, X_prime_val, y_prime_val, 'Linear regression model performance')
```




```
Mean Absolute Error: 149.03692628018624
Mean Squared Error: 31114.539205523048
R-squared: 0.24317267369691398
```



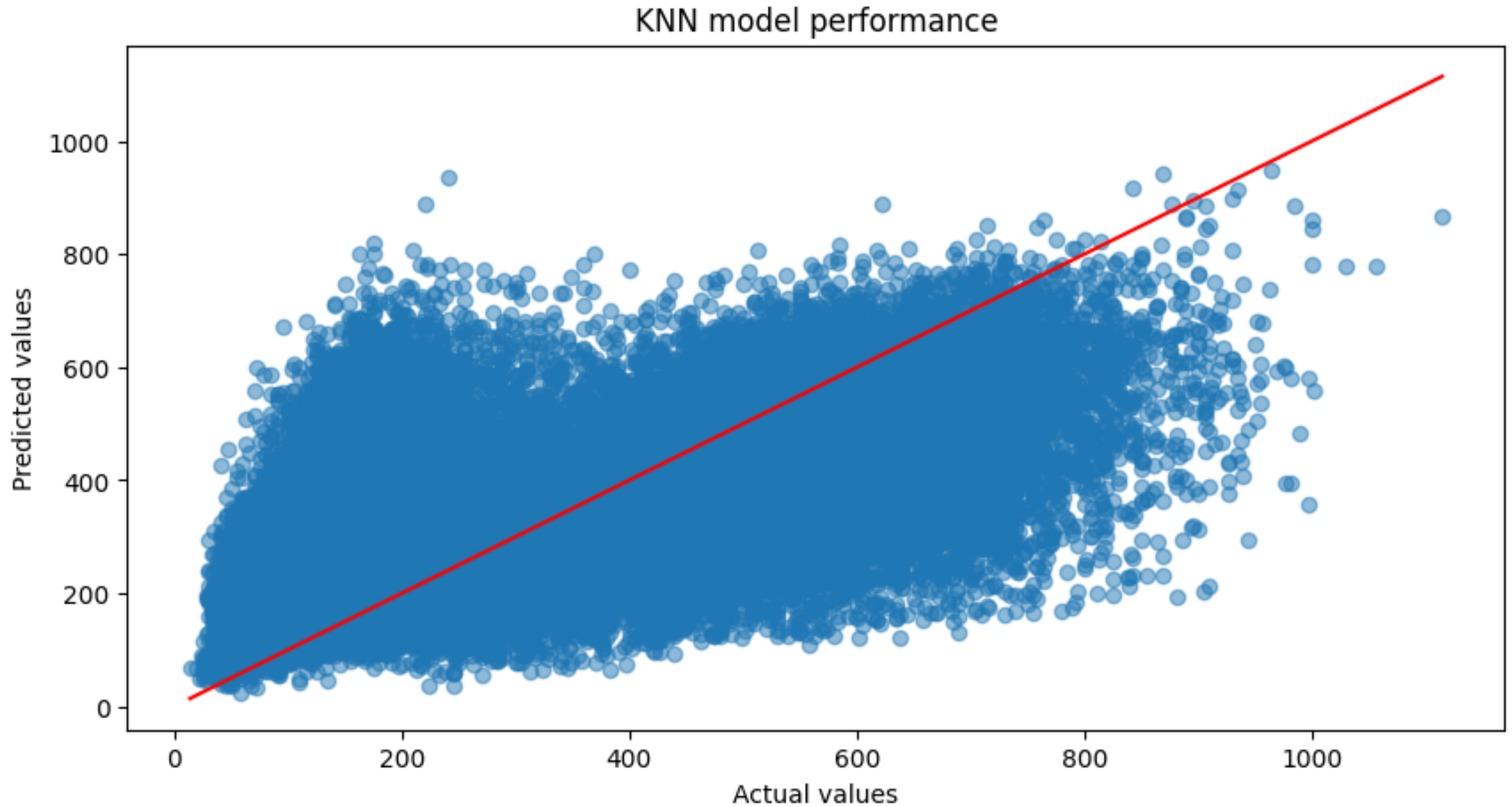

```
Mean Absolute Error: 140.8475128547402
Mean Squared Error: 27620.004192423316
R-squared: 0.33162761874234414
```

Section 7a.

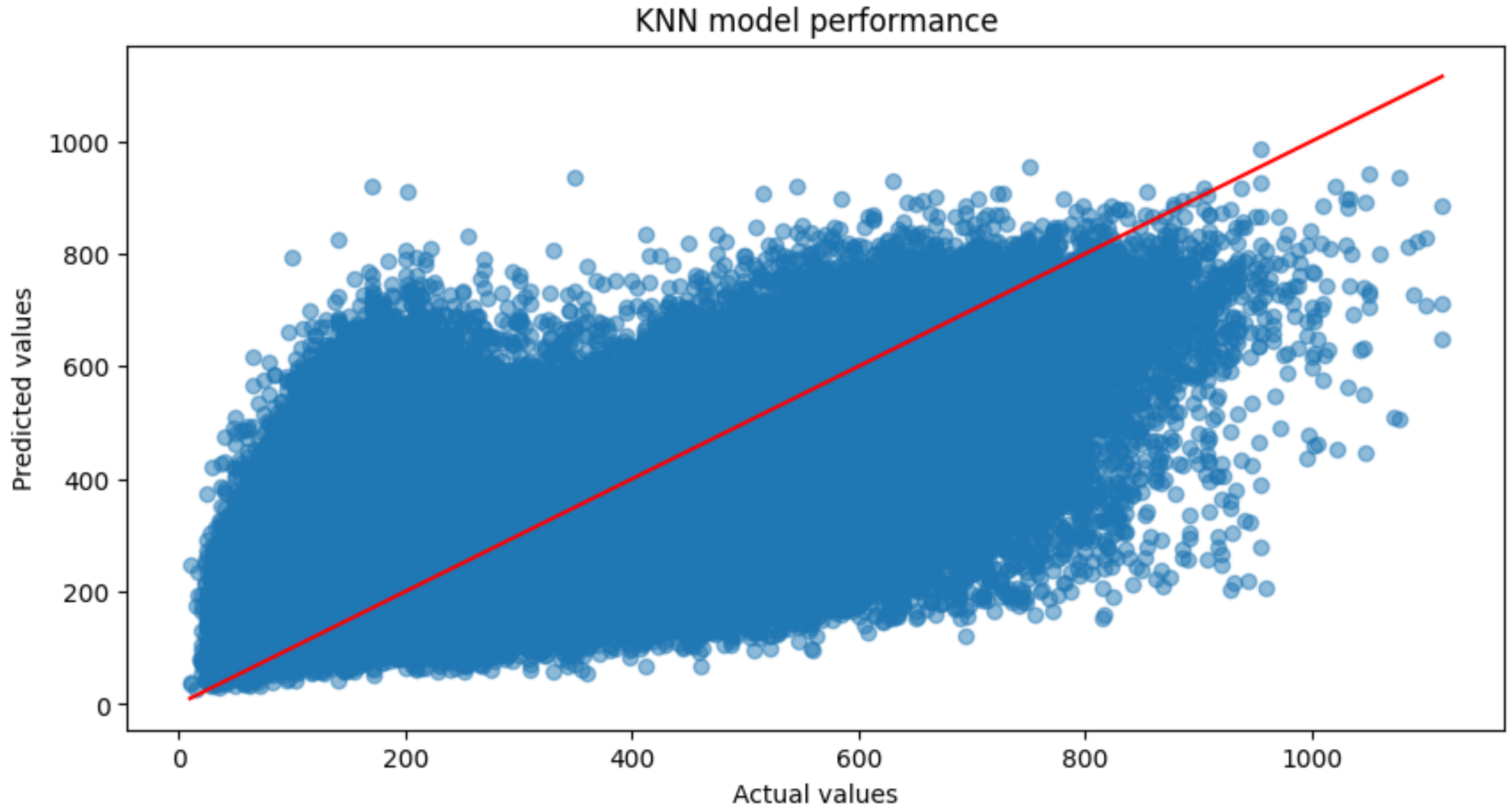
In this section we implement KNN

In [ ]:

```
from sklearn.neighbors import KNeighborsRegressor
# We implement KKN alorithm we start with k = 5
knn = KNeighborsRegressor(n_neighbors=5)
evaluate_model(knn, X_train, y_train, X_val, y_val, 'KNN model performance')
evaluate_model(knn, X_prime_train, y_prime_train, X_prime_val, y_prime_val, 'KNN model performance')
```




```
Mean Absolute Error: 129.9284232373537
Mean Squared Error: 28735.49088119251
R-squared: 0.3010404367563557
```



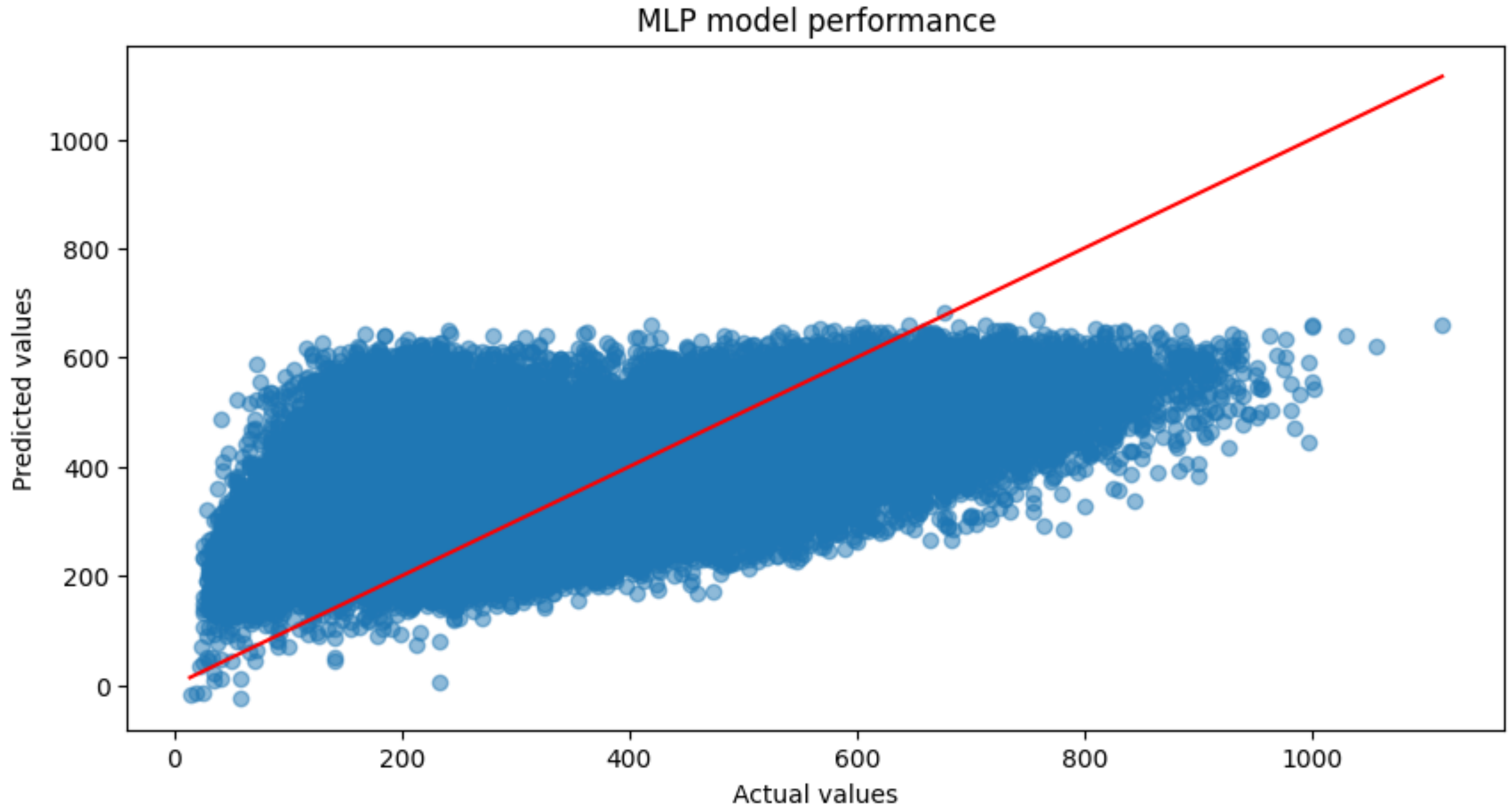

```
Mean Absolute Error: 122.56268874051409
Mean Squared Error: 25427.84724494765
R-squared: 0.3846752992881982
```

Section 7b.

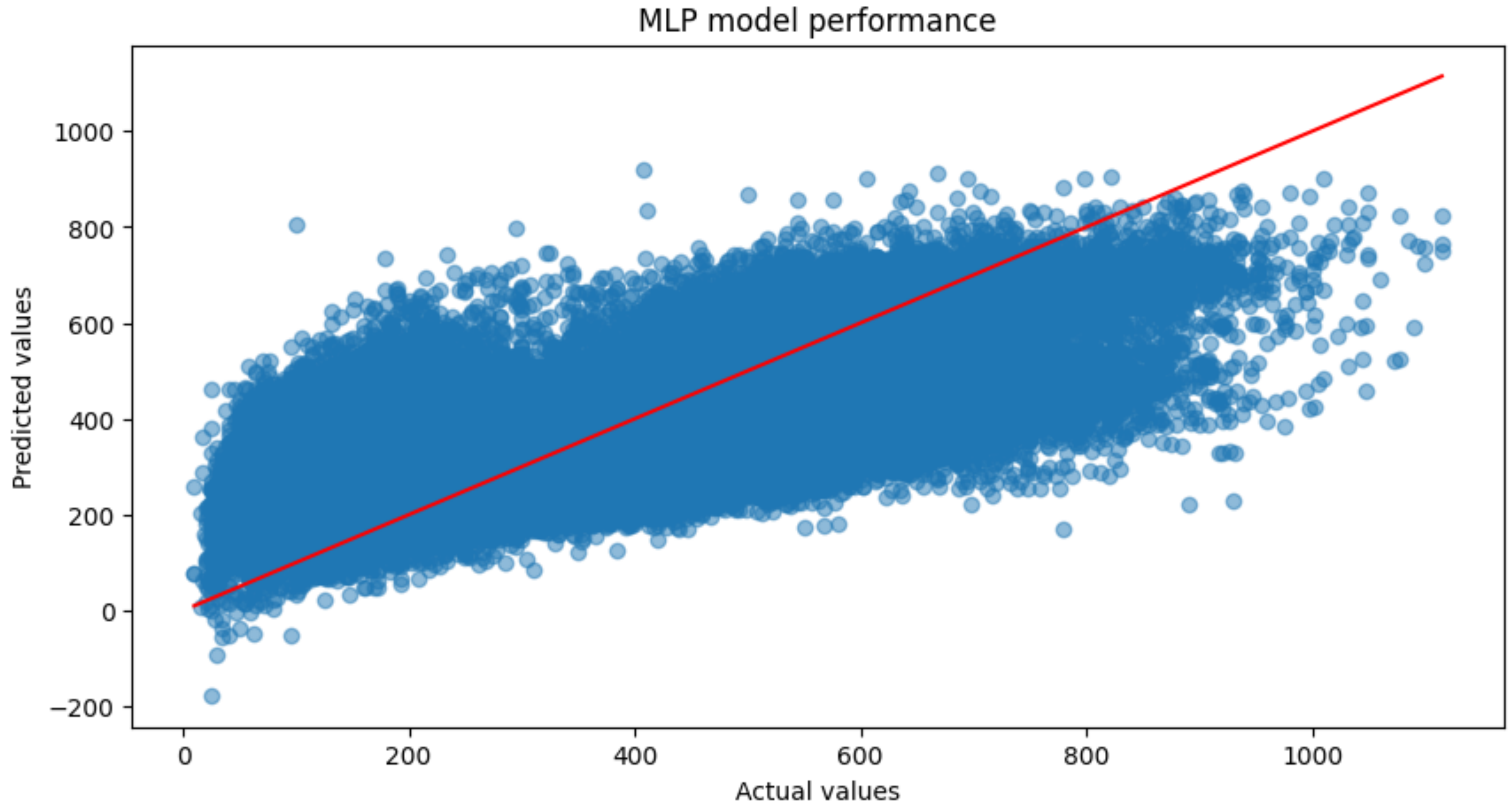
In this section we implement MLP

In [ ]:

```
from sklearn.neural_network import MLPRegressor
# We implment MLP the activation is relu, with 100 hidden layers, random state is as usual 7.
mlp = MLPRegressor(
    activation='relu',
    hidden_layer_sizes=(10, 100),
    alpha=0.001,
    random_state=7,
    early_stopping=False
)
evaluate_model(mlp, X_train, y_train, X_val, y_val, 'MLP model performance')
evaluate_model(mlp, X_prime_train, y_prime_train, X_prime_val, y_prime_val, 'MLP model performance')
```




```
Mean Absolute Error: 135.41043254080915
Mean Squared Error: 28017.956156034612
R-squared: 0.3184936885620092
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the op
timization hasn't converged yet.
  warnings.warn(
```




```
Mean Absolute Error: 129.89485201812323
Mean Squared Error: 24898.968521083167
R-squared: 0.3974735570148493
```

Section 8.

In this section we look at training performance and validation performance. We define a function model_performance, this allows us to see if the model overfit or underfit.

In [ ]:
```
def model_performance(model, X_train, y_train, X_val, y_val, model_name):
    model.fit(X_train, y_train)

    y_pred_train = model.predict(X_train)
    y_pred_val = model.predict(X_val)

    mae_train = mean_absolute_error(y_train, y_pred_train)
    mse_train = mean_squared_error(y_train, y_pred_train)
    r2_train = r2_score(y_train, y_pred_train)

    mae_val = mean_absolute_error(y_val, y_pred_val)
    mse_val = mean_squared_error(y_val, y_pred_val)
    r2_val = r2_score(y_val, y_pred_val)
    print("Model: "+ model_name)
    print("Training performance:")
    print("Mean Absolute Error: " + str(mae_train))
    print("Mean Squared Error: " + str(mse_train))
    print("R-squared: " + str(r2_train))
    print("Validation performance:")
    print("Mean Absolute Error: " + str(mae_val))
    print("Mean Squared Error: " + str(mse_val))
    print("R-squared: " + str(r2_train))
```

In [ ]:
```
lr = LinearRegression()
knn = KNeighborsRegressor(n_neighbors=5)
mlp = MLPRegressor(
    activation='relu',
    hidden_layer_sizes=(10, 100),
    alpha=0.001,
    random_state=7,
    early_stopping=False
)
model_performance(lr, X_train, y_train, X_val, y_val,"Linear regression orginal data cleaning and proccesing")
model_performance(lr, X_prime_train, y_prime_train, X_prime_val, y_prime_val,"Linear regression alternative data cleaning and proccesing")

model_performance(knn, X_train, y_train, X_val, y_val, "K Nearest Neighbor orginal data cleaning and proccesing")
model_performance(knn, X_prime_train, y_prime_train, X_prime_val, y_prime_val,"K Nearest Neighbor alternative data cleaning and proccesing")

model_performance(mlp, X_train, y_train, X_val, y_val, "Mutilayer perceptron orginal data cleaning and proccesing")
model_performance(mlp, X_prime_train, y_prime_train, X_prime_val, y_prime_val,"Mutilayer perceptron alternative data cleaning and proccesing")
```

```
Model: Linear regression orginal data cleaning and proccesing
Training performance:
Mean Absolute Error: 149.27090152337968
Mean Squared Error: 31157.59819147712
R-squared: 0.2475899161253794
Validation performance:
Mean Absolute Error: 149.03692628018624
Mean Squared Error: 31114.539205523048
R-squared: 0.2475899161253794
Model: Linear regression alternative data cleaning and proccesing
Training performance:
Mean Absolute Error: 141.2584858062405
Mean Squared Error: 27785.409727887098
R-squared: 0.32870425310137497
Validation performance:
Mean Absolute Error: 140.8475128547402
Mean Squared Error: 27620.004192423316
R-squared: 0.32870425310137497
Model: K Nearest Neighbor orginal data cleaning and proccesing
Training performance:
Mean Absolute Error: 106.12909671364473
Mean Squared Error: 19399.78974995841
R-squared: 0.531523664204997
Validation performance:
Mean Absolute Error: 129.9284232373537
Mean Squared Error: 28735.49088119251
R-squared: 0.531523664204997
Model: K Nearest Neighbor alternative data cleaning and proccesing
Training performance:
Mean Absolute Error: 103.56414726889227
Mean Squared Error: 18490.29518895408
R-squared: 0.5532743032834568
Validation performance:
Mean Absolute Error: 122.56268874051409
Mean Squared Error: 25427.84724494765
R-squared: 0.5532743032834568
Model: Mutilayer perceptron orginal data cleaning and proccesing
Training performance:
Mean Absolute Error: 135.3840051940262
Mean Squared Error: 28020.113647364185
R-squared: 0.32335554460816407
Validation performance:
Mean Absolute Error: 135.41043254080915
Mean Squared Error: 28017.956156034612
R-squared: 0.32335554460816407
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the op
timization hasn't converged yet.
  warnings.warn(
Model: Mutilayer perceptron alternative data cleaning and proccesing
Training performance:
Mean Absolute Error: 130.0991947118325
Mean Squared Error: 25014.240899441553
R-squared: 0.39565571671814004
Validation performance:
Mean Absolute Error: 129.89485201812323
Mean Squared Error: 24898.968521083167
R-squared: 0.39565571671814004
```

Section 9.

In this section we train and evaluate the performance of the model on the test set. We also time the each model and obtain the memory size of the model. We define a function train_and_evaluate, which returns total_training_time, memory_size, mae_test, mse_test, r2_test.

In [ ]:

```
import time
import sys

def train_and_evaluate(model, X_train, y_train, X_test, y_test,model_name):
  start = time.time()
  model.fit(X_train, y_train)
  end = time.time()
  total_training_time = end - start
  memory_size = sys.getsizeof(model)

  y_pred_test = model.predict(X_test)
  mae_test = mean_absolute_error(y_test, y_pred_test)
  mse_test = mean_squared_error(y_test, y_pred_test)
  r2_test = r2_score(y_test, y_pred_test)

  return  [model_name,total_training_time, memory_size, mae_test, mse_test, r2_test]

def display_results(Original, Alternative):
  print("Model:" +str(Original[0]))
  columns = ['model_name', 'Training Time', 'Memory Size', 'MAE', 'MSE', 'R^2']
  df = pd.DataFrame([Original, Alternative], columns=columns)
  for i in columns[1:]:
    print("Attribute : " +str(i))
    ax = df[i].plot(kind='bar', figsize=(6, 4), color=['blue', 'orange'])
    ax.set_ylabel('Value')
    ax.set_title(f'Comparison of {i} between original and alternative data cleaning and processing')
    ax.legend(['Original', 'Alternative'])
    plt.tight_layout()
    plt.show()

def print_results(results):
  print('---------------------------------------------')
  print("Model name: " + str(results[0]))
  print("Total training time : " + str(results[1]) + " seconds")
  print("Memory size: " + str(results[2]) + " bytes")
  print("Mean Absolute Error : " + str(results[3]))
  print("Mean Squared Error : " + str(results[4]))
  print("R-squared: " + str(results[5]))
  print('---------------------------------------------')
```

In [ ]:

```
lr = LinearRegression()
Original_lr = train_and_evaluate(lr, X_train, y_train, X_test, y_test,"linear regression")
Alternative_lr = train_and_evaluate(lr, X_prime_train, y_prime_train, X_prime_test, y_prime_test,"linear regression")
```

In [ ]:

```
knn = KNeighborsRegressor(n_neighbors=7)
Original_knn=  train_and_evaluate(knn, X_train, y_train, X_test, y_test," k-nearest-neighbor")
Alternative_knn = train_and_evaluate(knn, X_prime_train, y_prime_train, X_prime_test, y_prime_test," k-nearest-neighbor")
```

In [ ]:

```
mlp = MLPRegressor(
    activation='relu',
    hidden_layer_sizes=(10, 100),
    alpha=0.001,
    random_state=7,
    early_stopping=False
)
Original_mlp = train_and_evaluate(mlp, X_train, y_train, X_test, y_test,"multilayer perceptron")
Alternative_mlp = train_and_evaluate(mlp, X_prime_train, y_prime_train, X_prime_test, y_prime_test,"multilayer perceptron")
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the op
timization hasn't converged yet.
  warnings.warn(
```

Section 10.

In this section we print and display results, print_results shows us numercially the results, display_results shows us visually

In [ ]:

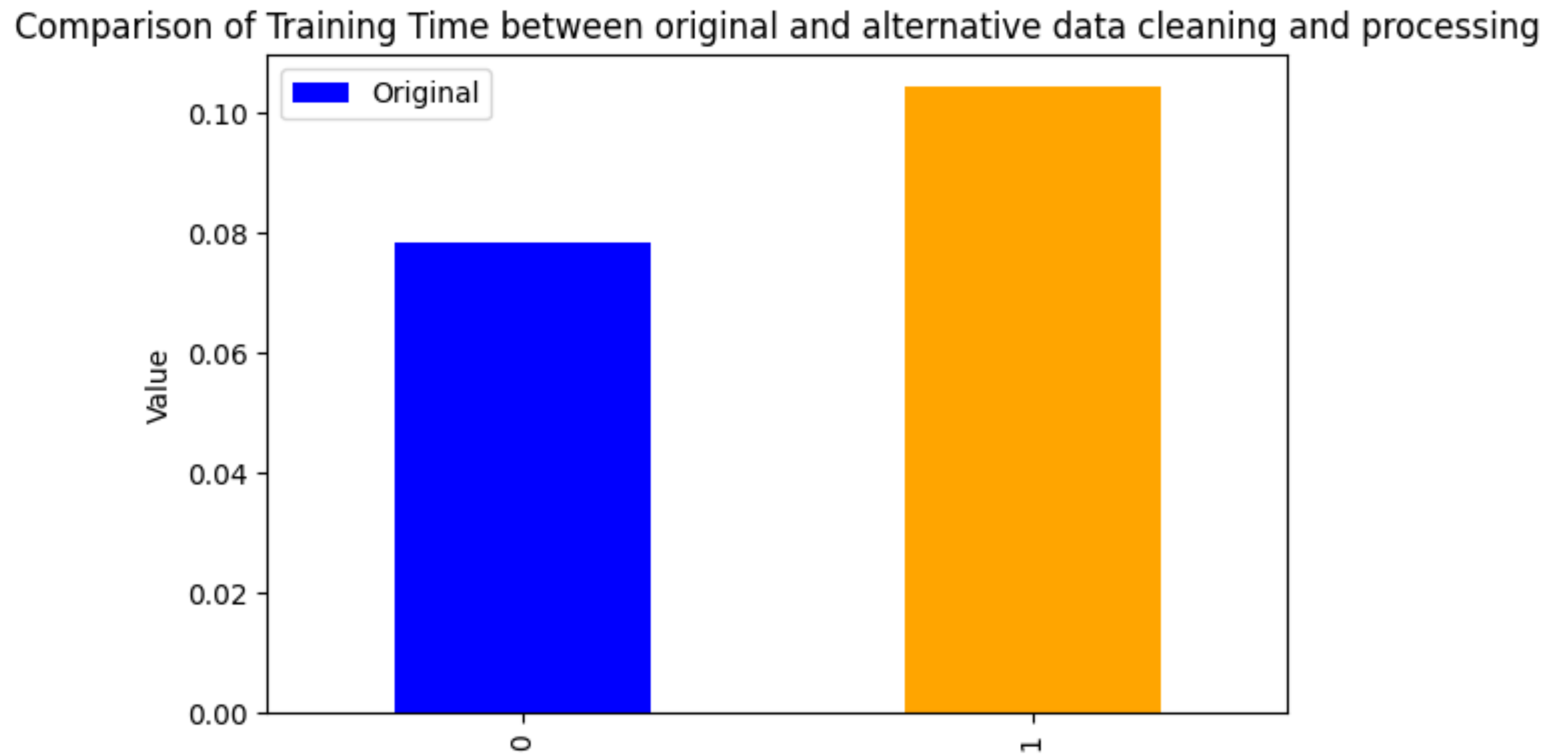
```
print_results(Original_lr)
print_results(Alternative_lr)
print_results(Original_knn)
print_results(Alternative_knn)
print_results(Original_mlp)
print_results(Alternative_mlp)
```

```
-------------------------------------------
Model name: linear regression
Total training time : 0.07825016975402832 seconds
Memory size: 48 bytes
Mean Absolute Error : 148.56010580663022
Mean Squared Error : 30980.337804732517
R-squared: 0.2505673863799529
-------------------------------------------
-------------------------------------------
Model name: linear regression
Total training time : 0.10439372062683105 seconds
Memory size: 48 bytes
Mean Absolute Error : 140.77681677226255
Mean Squared Error : 27644.238058774758
R-squared: 0.33121514168764
-------------------------------------------
-------------------------------------------
Model name:  k-nearest-neighbor
Total training time : 0.46447086334228516 seconds
Memory size: 48 bytes
Mean Absolute Error : 127.8504918275516
Mean Squared Error : 27358.322241304737
R-squared: 0.3381860756073347
-------------------------------------------
-------------------------------------------
Model name:  k-nearest-neighbor
Total training time : 0.5056524276733398 seconds
Memory size: 48 bytes
Mean Absolute Error : 119.7086877995598
Mean Squared Error : 24122.29349400316
R-squared: 0.41641999311913425
-------------------------------------------
-------------------------------------------
Model name: multilayer perceptron
Total training time : 306.41275668144226 seconds
Memory size: 48 bytes
Mean Absolute Error : 135.04628374208875
Mean Squared Error : 27910.389030681305
R-squared: 0.32483125489934017
-------------------------------------------
-------------------------------------------
Model name: multilayer perceptron
Total training time : 1124.6327872276306 seconds
Memory size: 48 bytes
Mean Absolute Error : 129.39169318843508
Mean Squared Error : 24773.67200870933
R-squared: 0.4006614800163575
-------------------------------------------
```

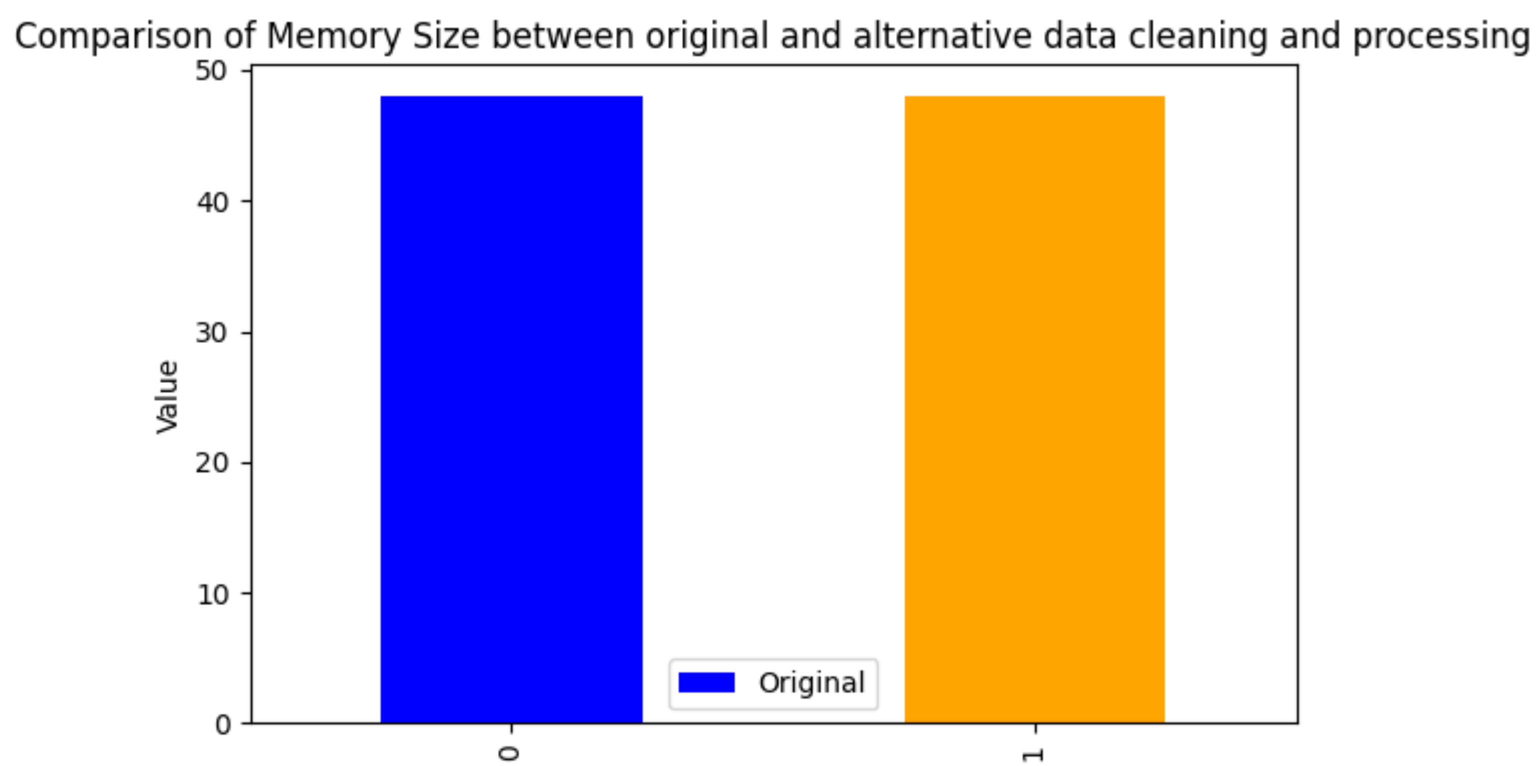
In [ ]:

```
display_results(Original_lr, Alternative_lr)
display_results(Original_knn, Alternative_knn)
display_results(Original_mlp, Alternative_mlp)
```

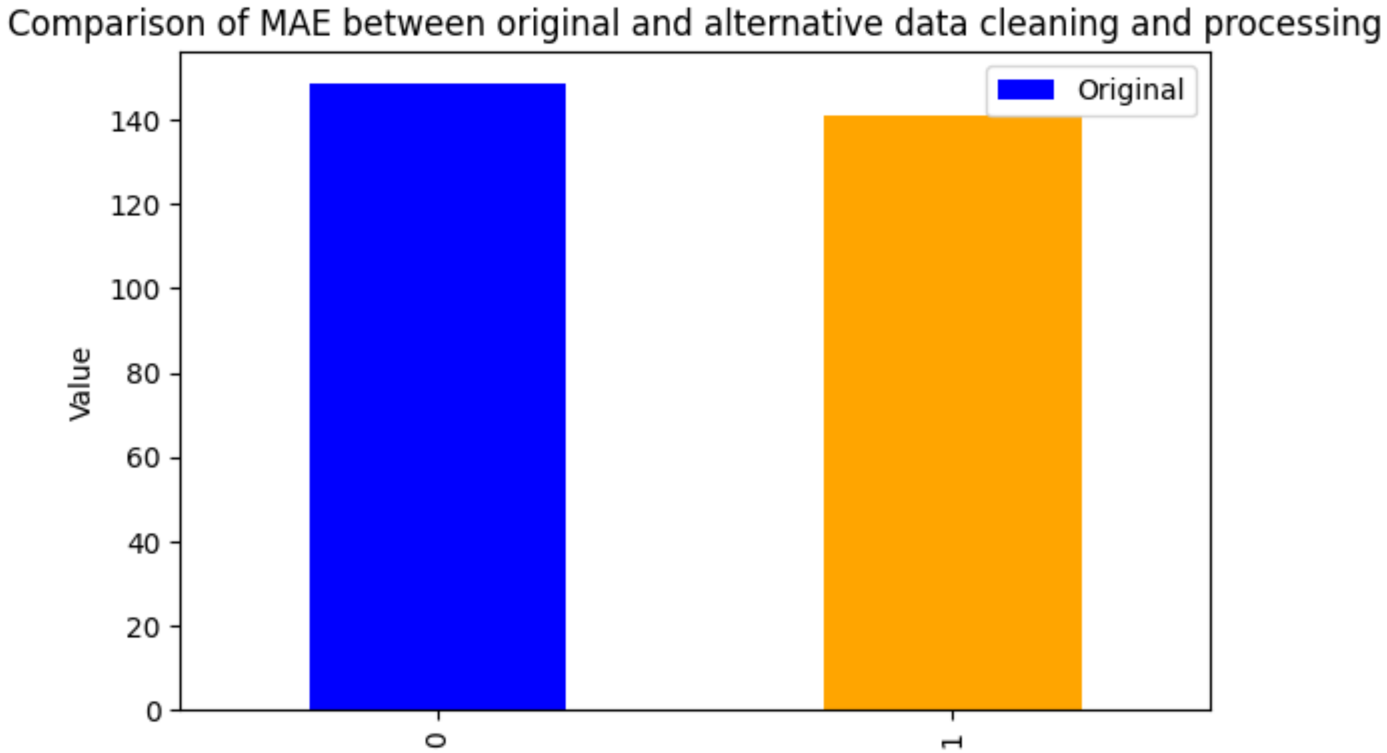
```
Model:linear regression
Attribute : Training Time
```



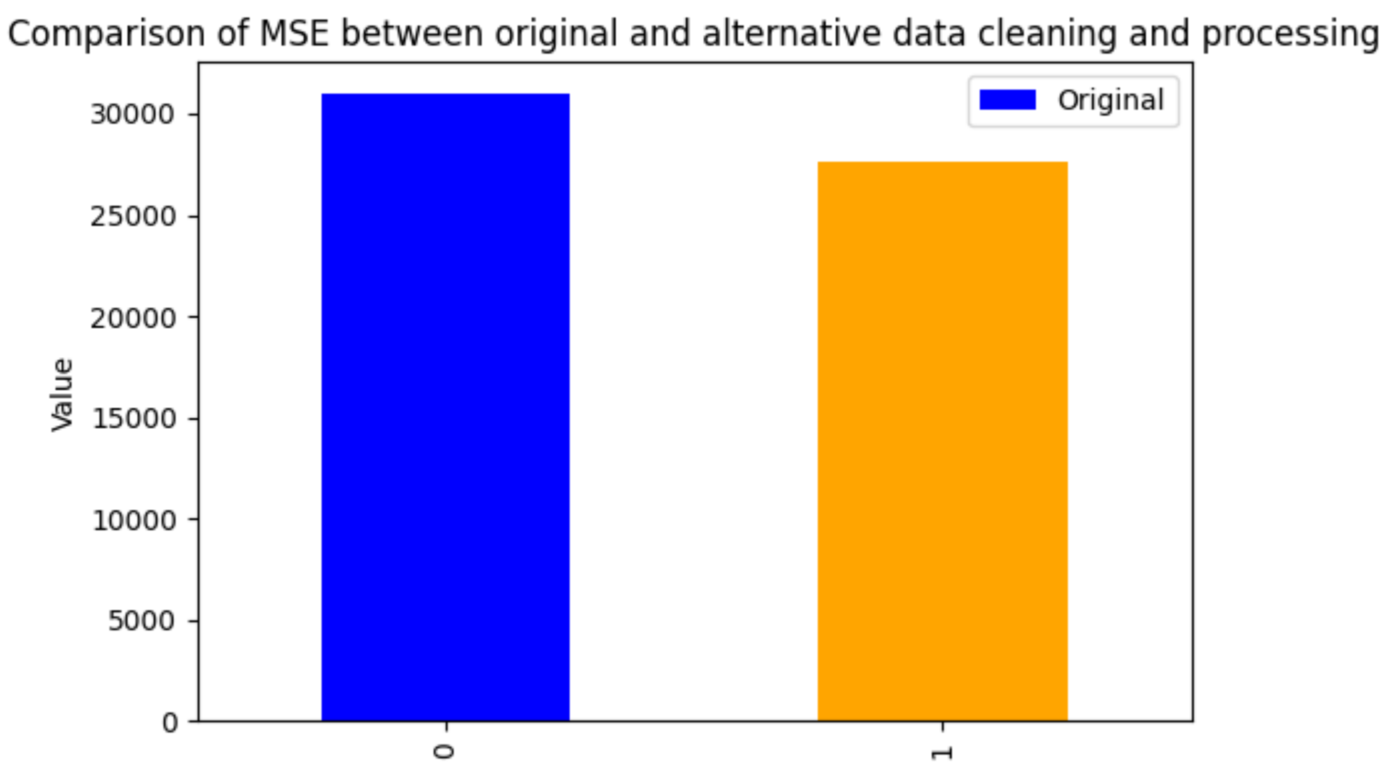
Attribute : Memory Size



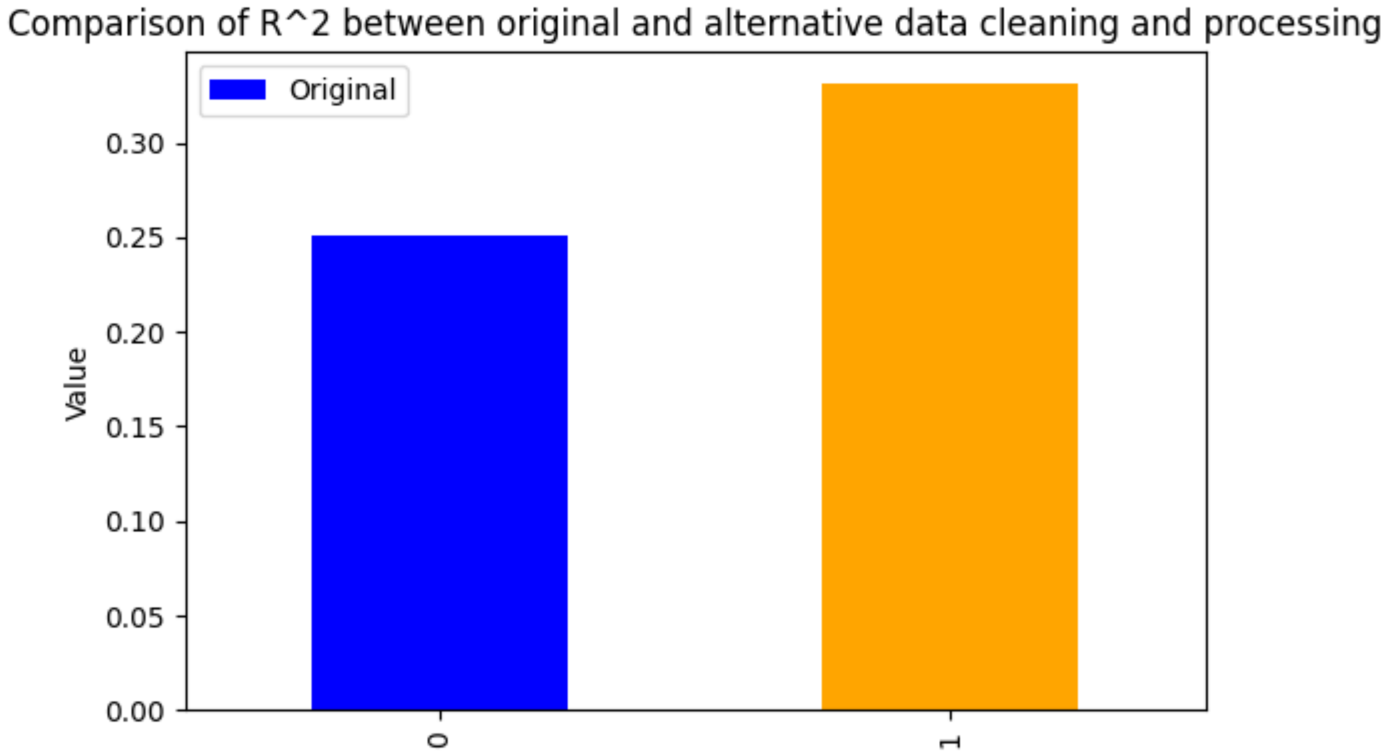
Attribute : MAE



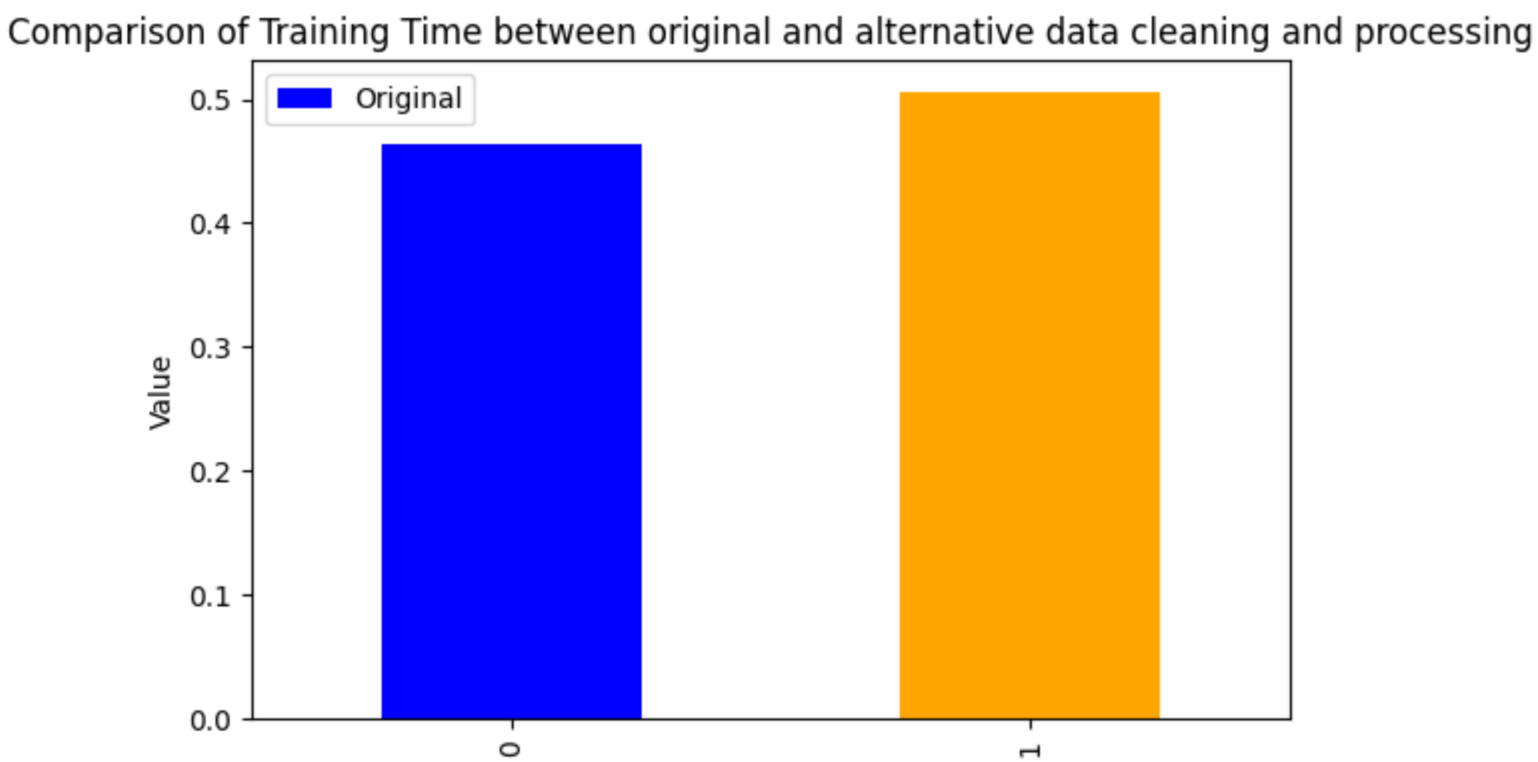
Attribute : MSE



Attribute : R^2

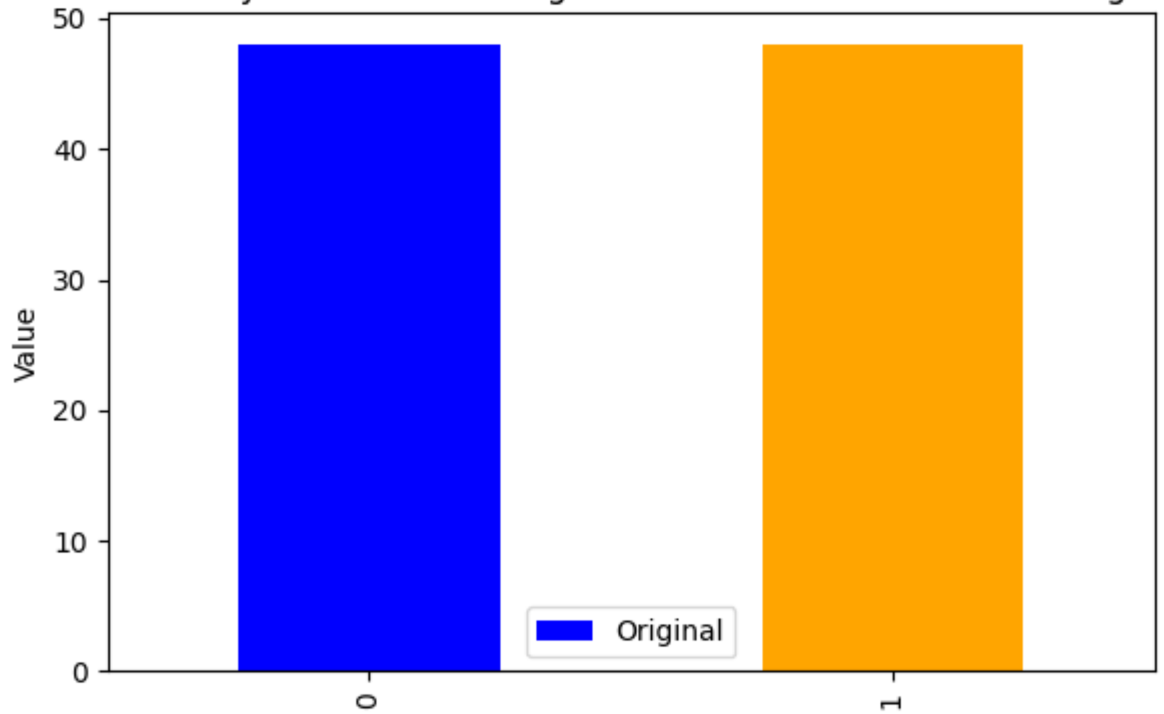



```
Model: k-nearest-neighbor
Attribute : Training Time
```



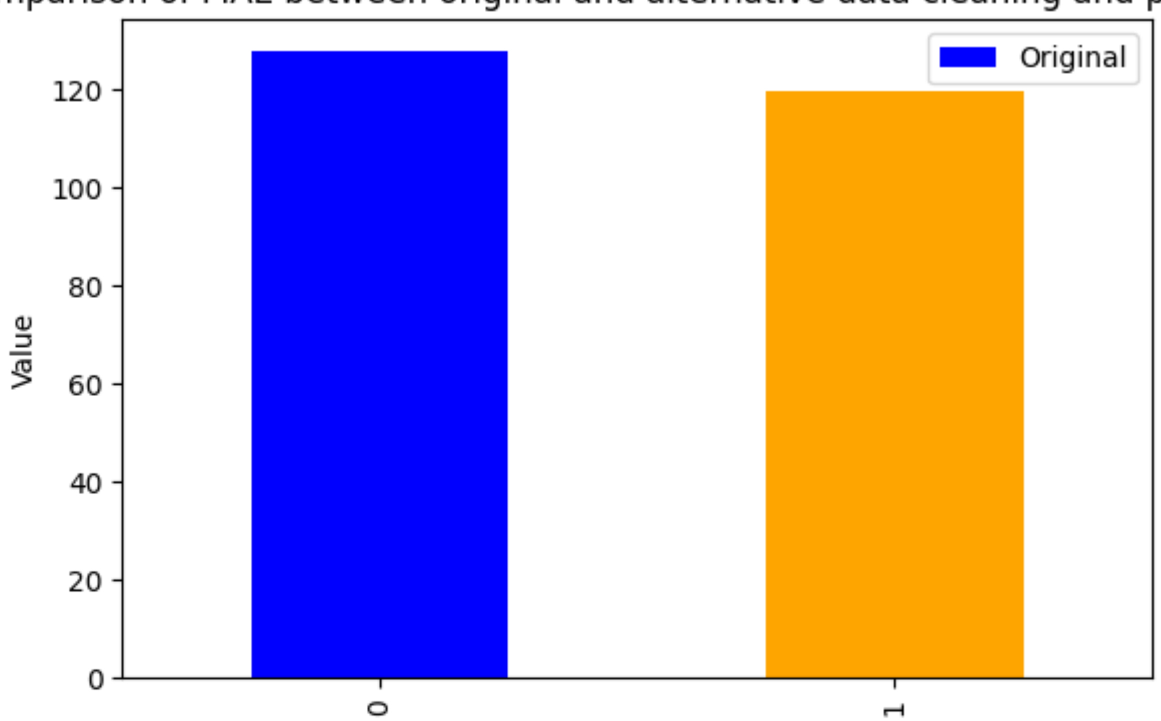

```
Attribute : Memory Size
```

Comparison of Memory Size between original and alternative data cleaning and processing

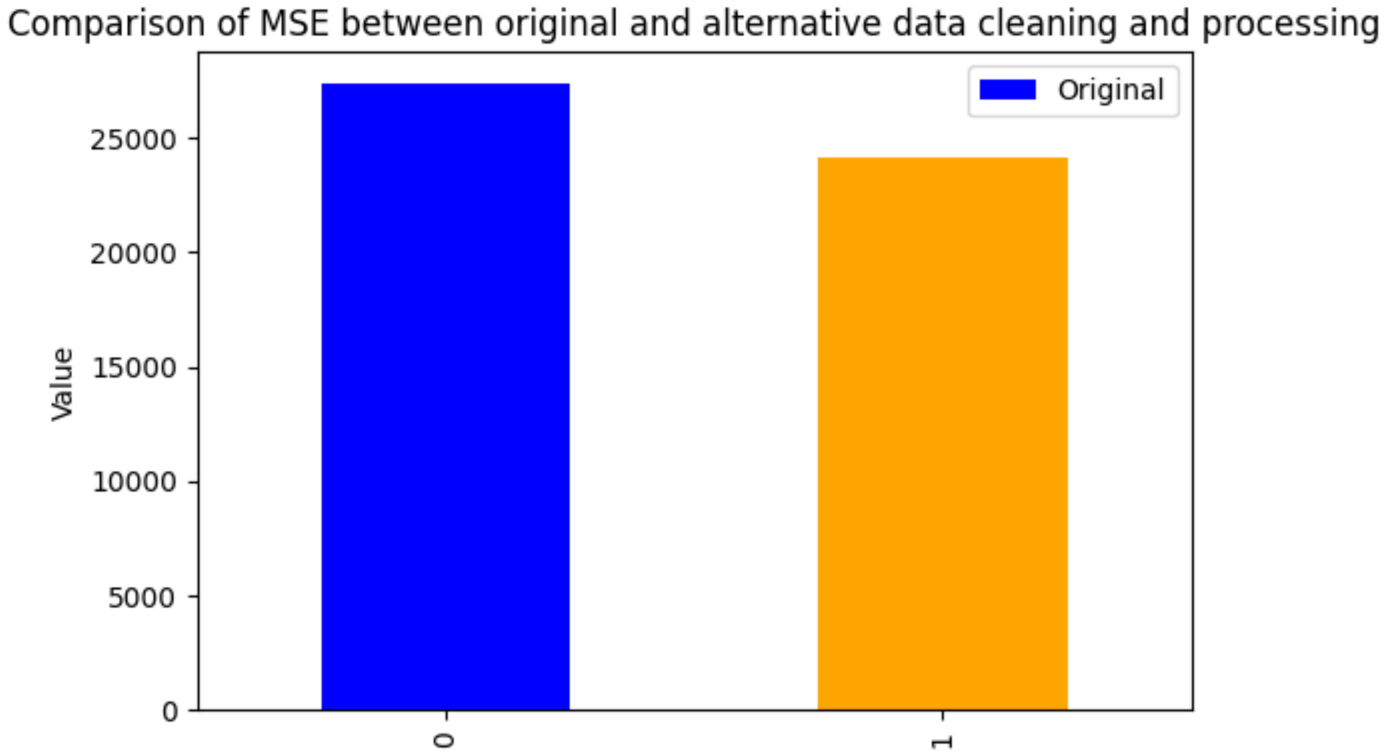


Attribute : MAE

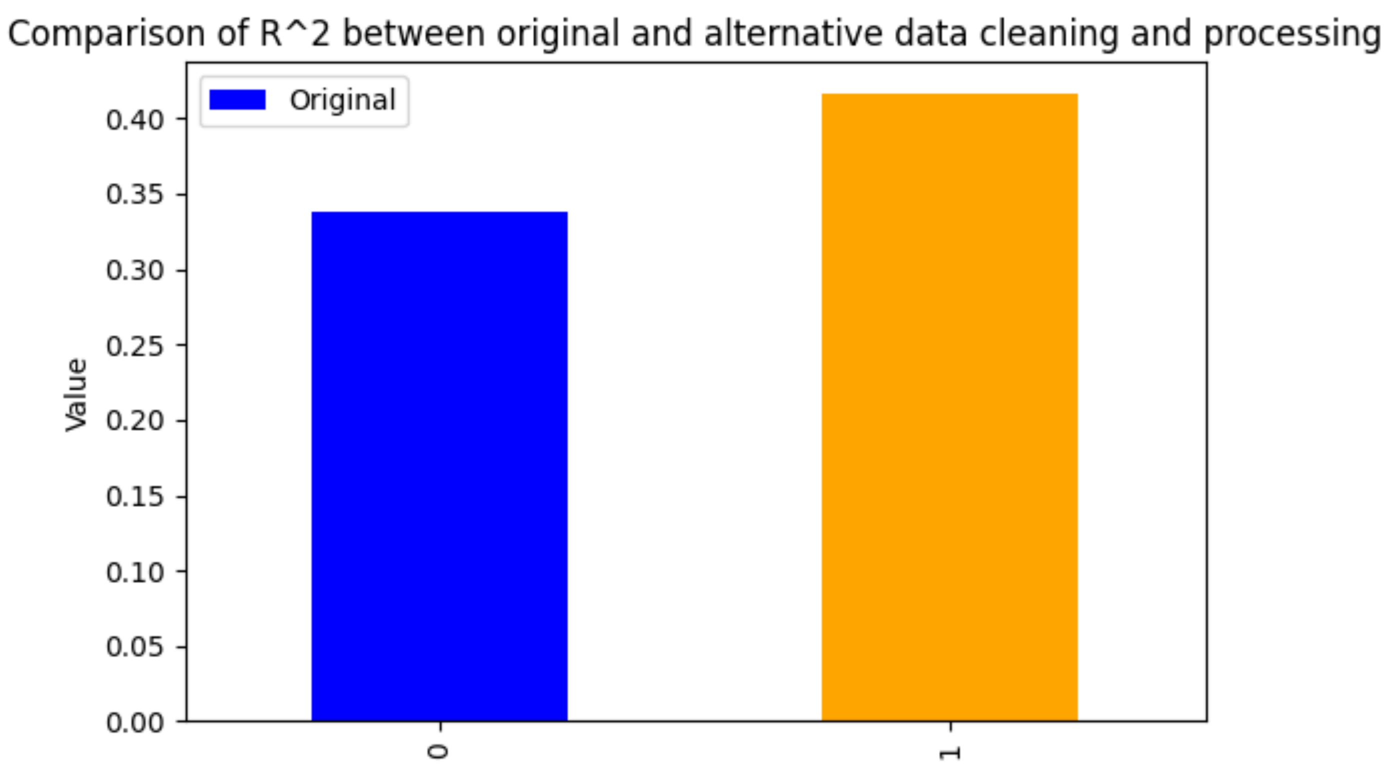
Comparison of MAE between original and alternative data cleaning and processing



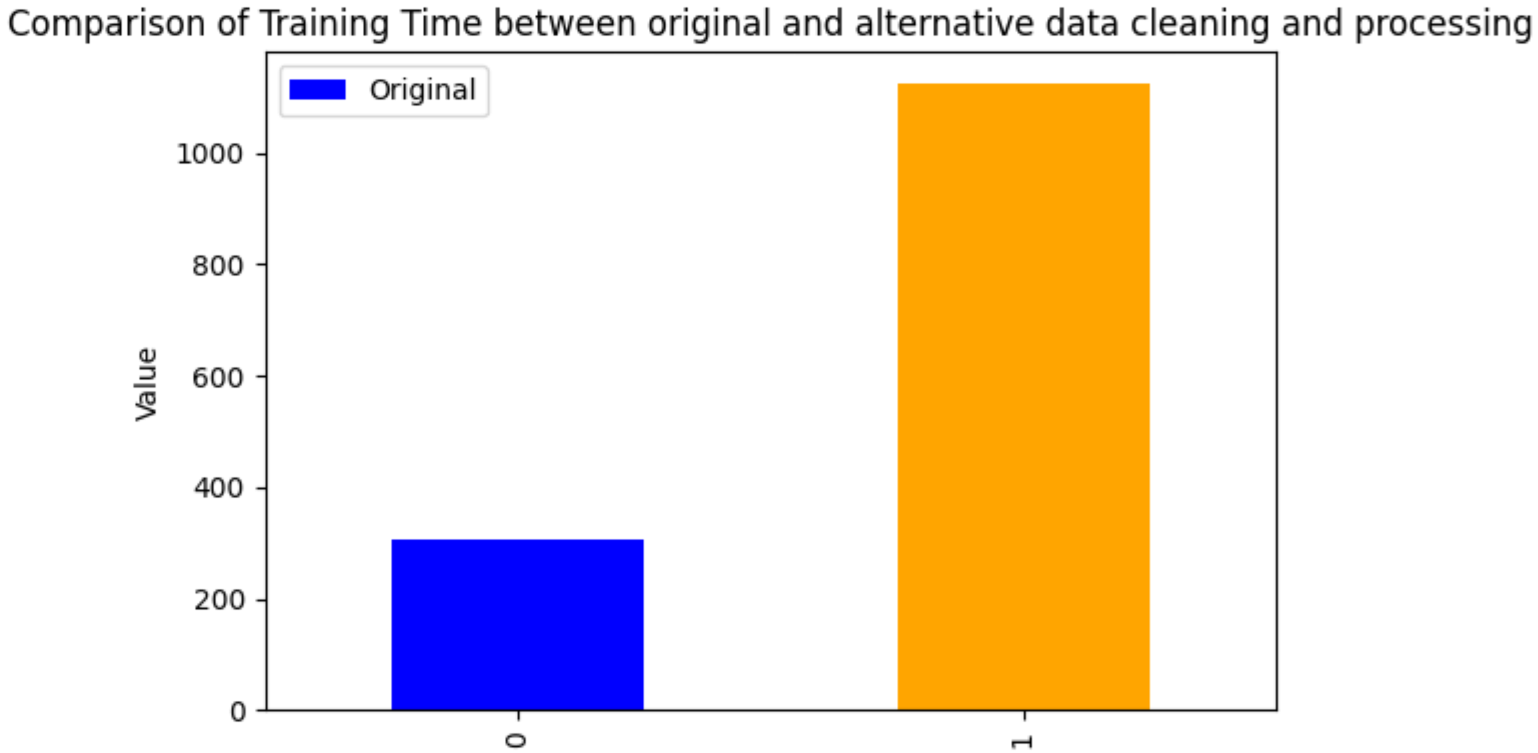
Attribute : MSE



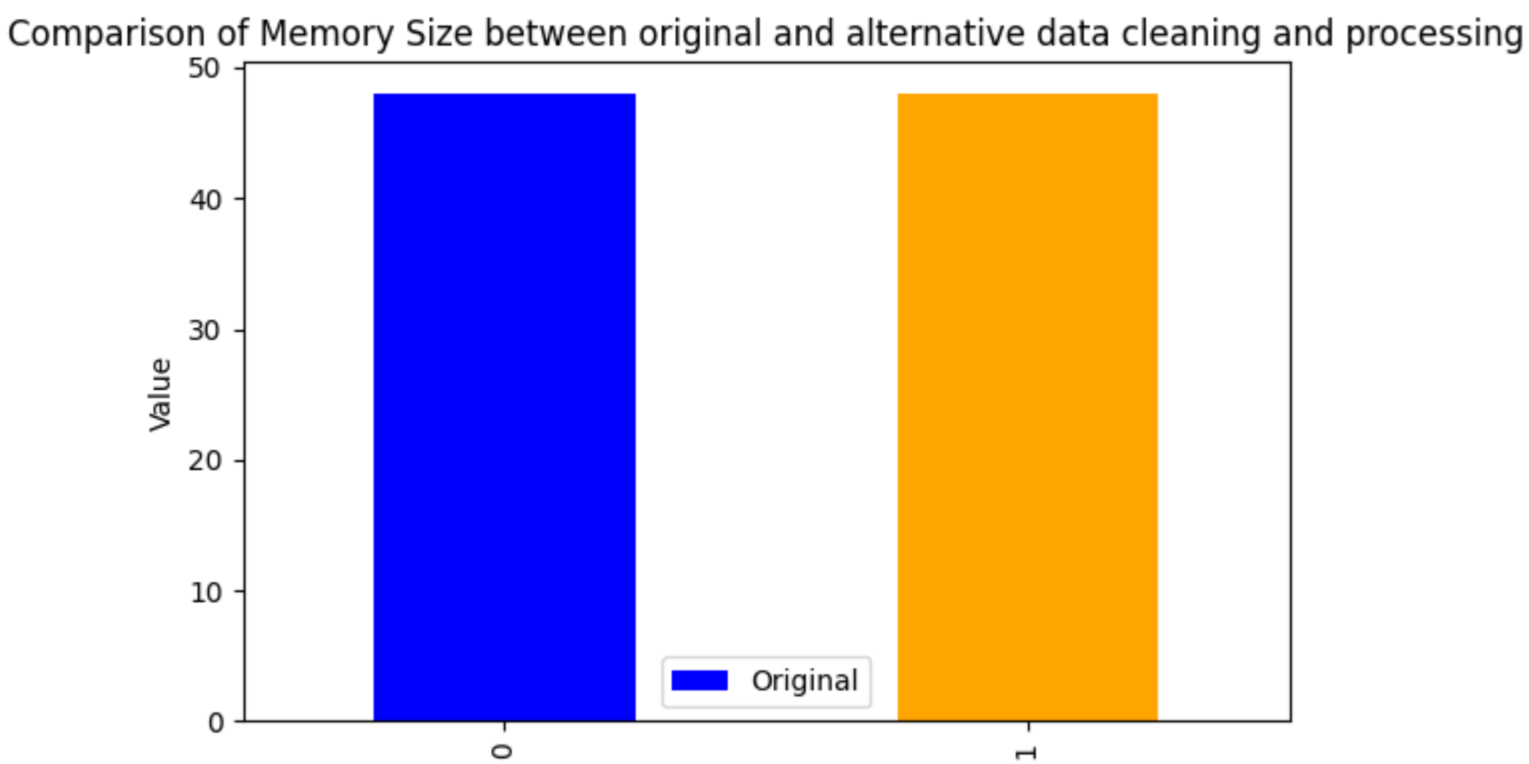

```
Attribute : R^2
```



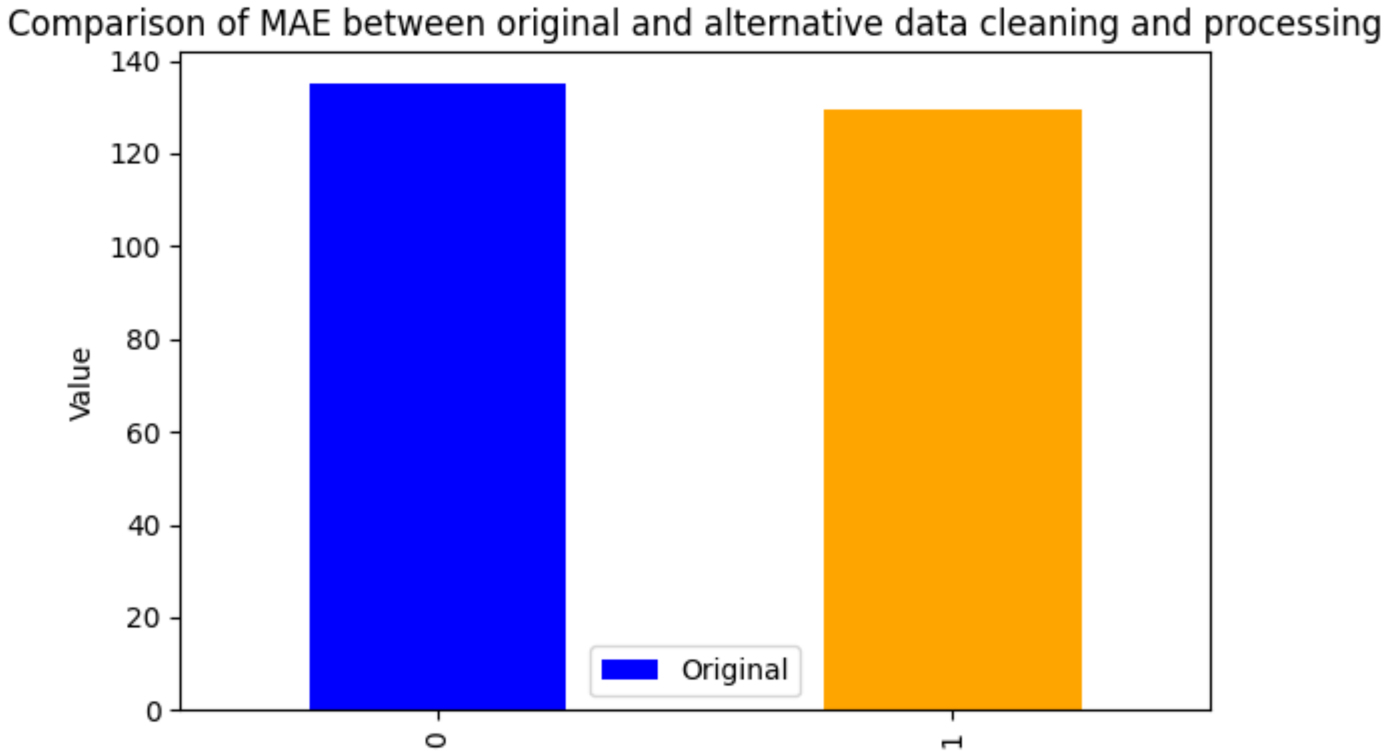

```
Model:multilayer perceptron
Attribute : Training Time
```



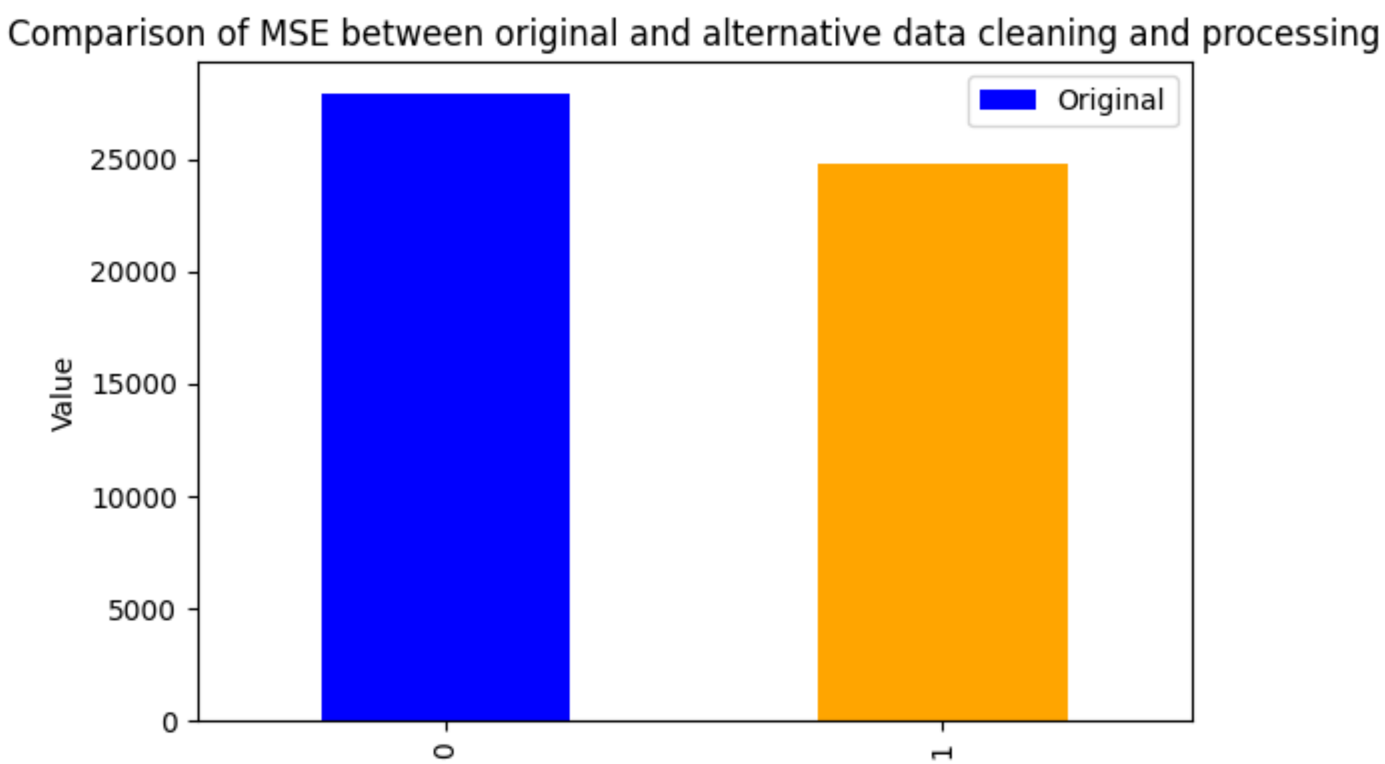
Attribute : Memory Size



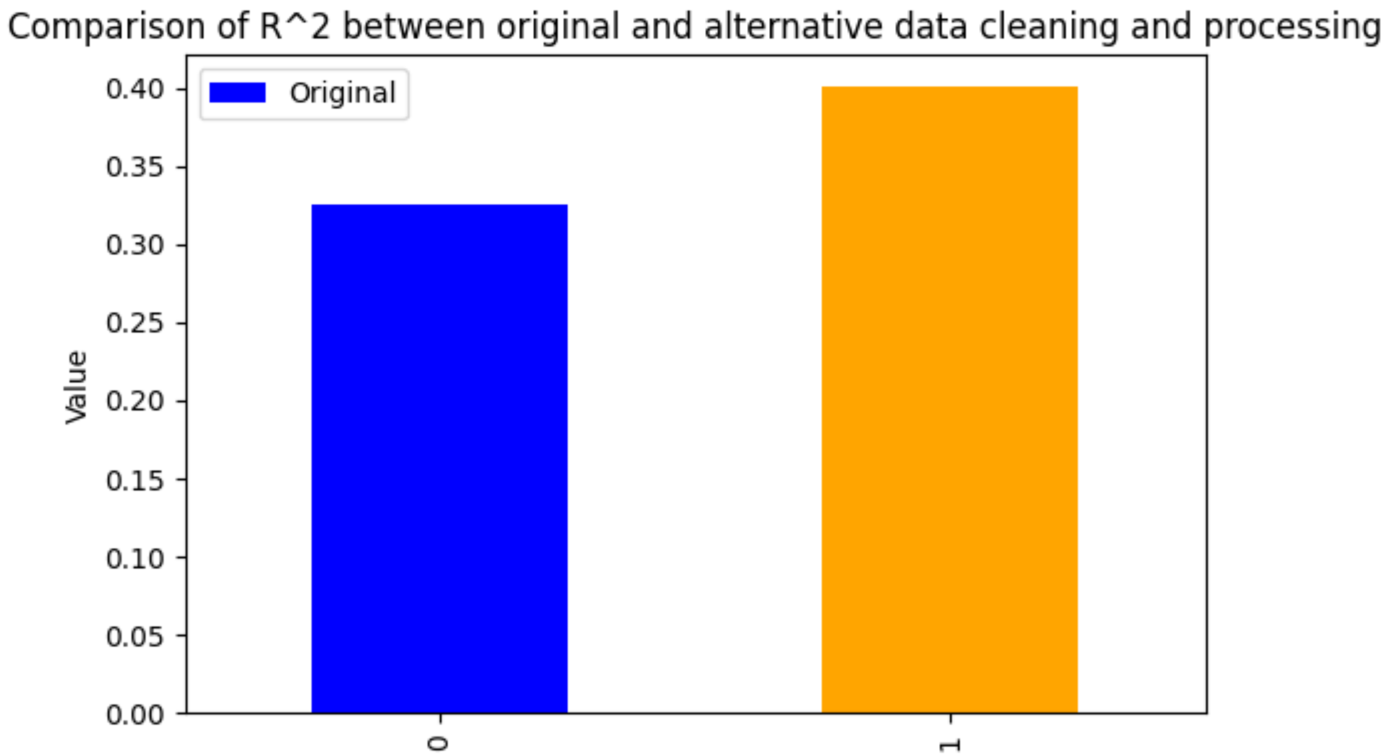
Attribute : MAE



Attribute : MSE



Attribute : R^2


Comparison of R^2 between original and alternative data cleaning and processing
Original
Value
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
0
1