FitBit Dataset

The dataset contains the amount of calories burnt based on various parameters. The dataset contains 15 parameters, out of which Calories is Dependent variable and rest are Independent variable. The dataset has 457 rows for each variable. The analysis of Calories with different variables are done.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

In []:
df = pd.read_csv('FitBit data.csv')

In []:
df.head()
Out[]:
```

	ld	ActivityDate	TotalSteps	TotalDistance	TrackerDistance	LoggedActivitiesDistance	VeryActiveDistance	Modera
0	1503960366	3/25/2016	11004	7.11	7.11	0.0	2.57	
1	1503960366	3/26/2016	17609	11.55	11.55	0.0	6.92	
2	1503960366	3/27/2016	12736	8.53	8.53	0.0	4.66	
3	1503960366	3/28/2016	13231	8.93	8.93	0.0	3.19	
4	1503960366	3/29/2016	12041	7.85	7.85	0.0	2.16	
4				188)

```
In []:
    df.shape
Out[]:
    (457, 15)
```

Dataset description, data types and finding out any null values in the dataset

```
In []:
df.describe()
Out[]:
```

	ld	TotalSteps	TotalDistance	TrackerDistance	LoggedActivitiesDistance	VeryActiveDistance	Moderately
count	4.570000e+02	457.000000	457.000000	457.000000	457.000000	457.000000	
mean	4.628595e+09	6546.562363	4.663523	4.609847	0.179427	1.180897	
std	2.293781e+09	5398.493064	4.082072	4.068540	0.849232	2.487159	
min	1.503960e+09	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	2.347168e+09	1988.000000	1.410000	1.280000	0.000000	0.000000	
E00/	4.05740000	E006 000000	4 000000	4 000000	0 000000	0 000000	

	5U %	4.U37 193e+U9	TotalStone	4.090000 TotalDistance	4.090000 TrackerDistance	U.UUUUUU LoggedActivitiesDistance	U.UUUUUU VeryActiveDistance	Moderately
-	75%	-	10100 00000	7.160000	7.110000	0.000000	1.310000	Wioderatery
	max	8.877689e+09	28497.000000	27.530001	27.530001	6.727057	21.920000	
4					_)

The following things can be analysed by dataset description.

- 1. We see the the minimum calorie burnt is 0. Along this minimum column, we observe that expect SedentaryMinutes, all other variables /activities for burning calories are zero.
- 2. The count of all variables are 457 which implies that there are no null values.

```
In [ ]:
df.isnull().any()
Out[]:
Ιd
                           False
ActivityDate
                           False
TotalSteps
                           False
TotalDistance
                           False
TrackerDistance
                          False
LoggedActivitiesDistance
                          False
VeryActiveDistance
                          False
ModeratelyActiveDistance False
                          False
LightActiveDistance
SedentaryActiveDistance
                         False
VeryActiveMinutes
                          False
FairlyActiveMinutes
                          False
LightlyActiveMinutes
                          False
                          False
SedentaryMinutes
Calories
                           False
dtype: bool
```

We observe that the datset does not contain any null values.

```
In [ ]:
df.dtypes
Out[]:
Ιd
                            int64
ActivityDate
                           object
TotalSteps
                            int64
TotalDistance
                          float64
TrackerDistance
                          float64
LoggedActivitiesDistance float64
VeryActiveDistance
                         float64
ModeratelyActiveDistance float64
                         float64
LightActiveDistance
SedentaryActiveDistance
                        float64
VeryActiveMinutes
                           int64
FairlyActiveMinutes
                            int64
                            int64
LightlyActiveMinutes
                            int64
SedentaryMinutes
                            int64
Calories
dtype: object
```

The data types for dataset is correct. However, we shall convert the activityDate to data-time format for more analysis with respect to calories burnt.

```
In []:

df['ActivityDate'] = pd.to_datetime(df['ActivityDate'])
In []:
```

Out[]:

In []:

	ld	ActivityDate	TotalSteps	TotalDistance	TrackerDistance	LoggedActivitiesDistance	VeryActiveDistance	Modera
0	1503960366	2016-03-25	11004	7.11	7.11	0.0	2.57	
1	1503960366	2016-03-26	17609	11.55	11.55	0.0	6.92	
2	1503960366	2016-03-27	12736	8.53	8.53	0.0	4.66	
3	1503960366	2016-03-28	13231	8.93	8.93	0.0	3.19	
4	1503960366	2016-03-29	12041	7.85	7.85	0.0	2.16	
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Based on the ActiveMinutes, How are calories burnt?

```
Based on the Active minutes, now are calones built.
```

```
fig1, ax1 = plt.subplots(2, 2, figsize = (10, 10))

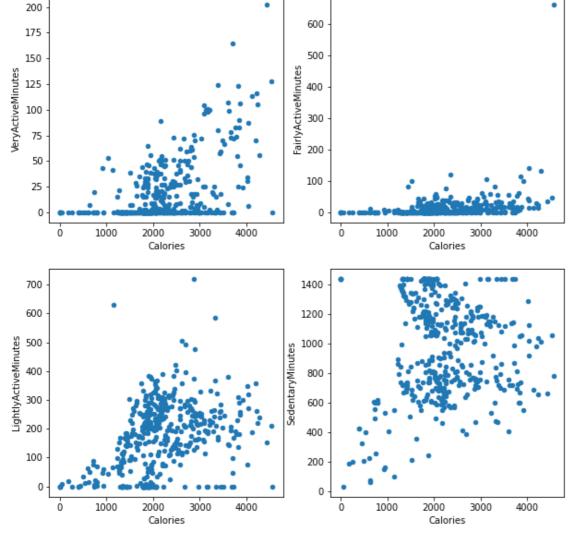
df.plot.scatter('Calories', 'VeryActiveMinutes', ax = ax1[0][0])

df.plot.scatter('Calories', 'FairlyActiveMinutes', ax = ax1[0][1])

df.plot.scatter('Calories', 'LightlyActiveMinutes', ax = ax1[1][0])

df.plot.scatter('Calories', 'SedentaryMinutes', ax = ax1[1][1])

plt.show()
```



From scatter plot analysis, we can observe following things:

- 1. More concentration of FairlyActiveMinutes is present in its low values which means that, Calories are burnt more by only few amount of FairlyActiveMinutes.
- 2. For SedentaryMinutes, the datas are scattered more in the mid and upper region. Meaning, calories are

- burnt in the range of 2000-3000 by spending the concentrated amount in SedentaryMinutes.
- 3. Also for VeryActiveMinutes and LightlyActiveMinutes, the concentration are more in the mid-region.

Based on the Distance covered, How are calories burnt?

```
In [ ]:
fig1, ax1 = plt.subplots(2, 2, figsize = (10, 10))
df.plot.scatter('Calories', 'TotalDistance', ax = ax1[0][0])
df.plot.scatter('Calories', 'TrackerDistance', ax = ax1[0][1])
df.plot.scatter('Calories', 'LoggedActivitiesDistance', ax = ax1[1][0])
df.plot.scatter('Calories', 'VeryActiveDistance', ax = ax1[1][1])
plt.show()
   25
                                                25
   20
                                                20
                                              FrackerDistance
TotalDistance
                                                15
   15
   10
                                                10
    5
             1000
                     2000
                            3000
                                    4000
                                                           1000
                                                                          3000
                                                                                  4000
                      Calories
                                                                   Calories
    7
                                                20
    6
LoggedActivitiesDistance
                                                15
                                              VeryActiveDistance
                                                10
    1
                                                           1000
             1000
                     2000
                            3000
                                    4000
                                                                  2000
                                                                                  4000
```

From the scatter plot, we can observe that TotalDistance and Tracker Distance shows a similar distribution.

Calories

Elimination of column

Calories

Since TotalDistance and TrackerDistance are same, there is no need of one of the column.

```
In [ ]:

df.drop(['TrackerDistance'], axis = 1, inplace = True)
```

Maximum calories burnt

In []:

```
#df[df['Calories'] == df['Calories'].max()]
max_calories = df.nlargest(5, ['Calories'])
max_calories.drop(['Id','SedentaryActiveDistance'], axis = 1, inplace = True)
max_calories
#SedentaryActiveDistance showed 0
```

Out[]:

	ActivityDate	TotalSteps	TotalDistance	LoggedActivitiesDistance	VeryActiveDistance	ModeratelyActiveDistance	LightAct
138	2016-04-01	0	0.000000	4.828032	0.00	0.00	
454	2016-04-10	28497	27.530001	0.000000	21.92	1.12	
304	2016-04-02	14873	11.110000	0.000000	8.19	0.60	
347	2016-04-05	9348	6.700000	0.000000	1.13	2.04	
416	2016-04-04	13935	11.050000	2.092147	4.09	0.79	
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The max_calories dataframe gives the max 5 datas grouped by calories. We can see that for a calorie burnt of 4526, total steps taken is 28497, total distance is 27.53, also veryActiveDistance is 21.92. This took place on 2016-04-10.

Calories burnt based on ActivityDate

Splitting activitydate to year, day and month.

```
In []:

df['day'] = df['ActivityDate'].dt.day
df['month'] = df['ActivityDate'].dt.month
df['year'] = df['ActivityDate'].dt.year
```

```
In [ ]:
df.head()
```

Out[]:

max calories1

	ld	ActivityDate	TotalSteps	TotalDistance	LoggedActivitiesDistance	VeryActiveDistance	ModeratelyActiveDistance
0	1503960366	2016-03-25	11004	7.11	0.0	2.57	0.4
1	1503960366	2016-03-26	17609	11.55	0.0	6.92	0.7
2	1503960366	2016-03-27	12736	8.53	0.0	4.66	0.1
3	1503960366	2016-03-28	13231	8.93	0.0	3.19	0.7
4	1503960366	2016-03-29	12041	7.85	0.0	2.16	1.0
4							<u> </u>

```
In [ ]:

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

The variable Id is not necessary. So, it can be removed.

```
In []:
df.drop('Id', axis = 1, inplace = True)

In []:
data2 = df[df['month']==3]
max calories1 = data2.nlargest(5, ['Calories'])
```

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	TotalSteps	TotalDistance	LoggedActivitiesDistance	VeryActiveDistance	ModeratelyActiveDistance	LightActiveDistance \$
181	2106	1.51	0.0	0.02	0.05	0.21
169	12483	8.99	0.0	1.45	0.57	6.90
173	10330	7.41	0.0	0.00	0.00	0.00
170	8940	6.41	0.0	0.00	0.00	0.61
178	5563	3.99	0.0	0.00	0.00	0.00
4						Þ

From this filteration, we can observe that max calories value was 4010 on 28th day of 3rd month.

```
In []:

data3 = df[df['month']==4]
max_calories2 = data3.nlargest(5, ['Calories'])
max_calories2

Out[]:
```

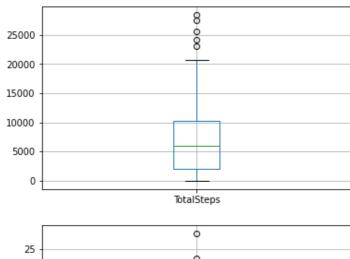
	TotalSteps	TotalDistance	LoggedActivitiesDistance	VeryActiveDistance	ModeratelyActiveDistance	LightActiveDistance
138	0	0.000000	4.828032	0.00	0.00	0.00
454	28497	27.530001	0.000000	21.92	1.12	4.46
304	14873	11.110000	0.000000	8.19	0.60	2.31
347	9348	6.700000	0.000000	1.13	2.04	3.14
416	13935	11.050000	2.092147	4.09	0.79	6.17
4)

From this filteration, we can observe that max calories value was 4562 on 28th day of 4th month.

Box plot

```
In [ ]:
```

```
fig, ax1 = plt.subplots(2, figsize = (6, 8))
df.boxplot('TotalSteps', ax = ax1[0])
df.boxplot('TotalDistance', ax = ax1[1])
plt.show()
```







The Boxpolot shows the presence of outliers in the dataFrame.

- 1. Presented here is the variable TotalSteps and TotalDistance.
- 2. We can observe that the median for TotalSteps is around 6000 and for TotalDistance is around 4.
- 3. The max for TotalSteps is around 21000 and for TotalDistance is around 16.
- 4. There are outliers present in both the dataframes which are present outside the InterQuartile range.

Correlation Matrix

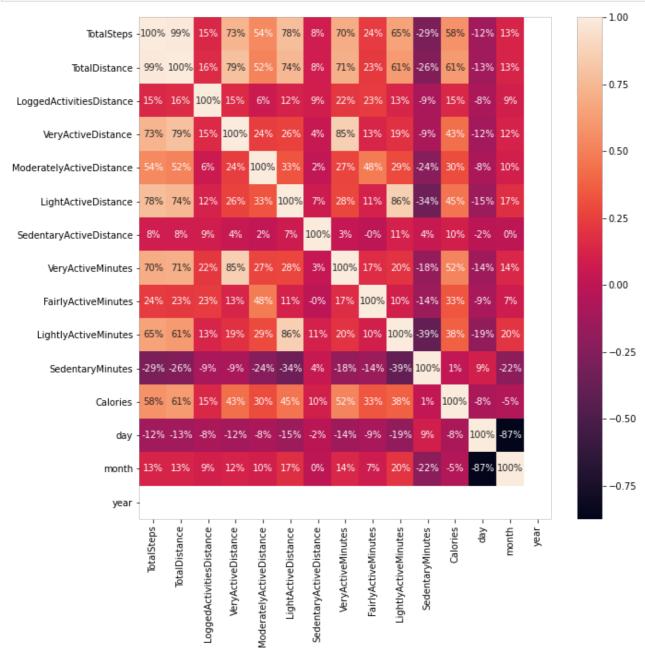
```
In [ ]:
df.corr()
Out[ ]:
```

	TotalSteps	TotalDistance	LoggedActivitiesDistance	VeryActiveDistance	ModeratelyActiveDistance
TotalSteps	1.000000	0.986789	0.146380	0.733689	0.541838
TotalDistance	0.986789	1.000000	0.164312	0.791778	0.515128
LoggedActivitiesDistance	0.146380	0.164312	1.000000	0.154754	0.060123
VeryActiveDistance	0.733689	0.791778	0.154754	1.000000	0.240440
ModeratelyActiveDistance	0.541838	0.515128	0.060123	0.240440	1.000000
LightActiveDistance	0.775562	0.744812	0.115671	0.264580	0.326959
SedentaryActiveDistance	0.081965	0.080787	0.091091	0.044666	0.016350
VeryActiveMinutes	0.699699	0.714320	0.218253	0.854292	0.272720
FairlyActiveMinutes	0.238389	0.230712	0.231675	0.129528	0.480906
LightlyActiveMinutes	0.654418	0.614152	0.133856	0.193593	0.291906
SedentaryMinutes	-0.285258	-0.260301	-0.092991	-0.087726	-0.236723
Calories	0.581380	0.613647	0.148740	0.434133	0.300781
day	-0.122238	-0.126215	-0.084718	-0.117278	-0.080761
month	0.125961	0.127902	0.092581	0.118005	0.096244
year	NaN	NaN	NaN	NaN	NaN
4					Þ

```
In [ ]:
```

```
# Co-relation matrix
plt.figure(figsize = (10, 10))
```

sns.heatmap(df.corr(), annot = True, fmt = '.0%')
plt.show()



The Correlation matrix has a lot of positive relation which means that as one variable increases, the corresponding variable increases by the respective percentage.

- 1. We can observe that Calories and TotalDistance have correlation of a percentage of 61% meaning as the TotalDistance is increased, Calories increases by 61% and so on.
- 2. There is a 86% correlation between LightActiveDistance and LightlyActiveMinutes.

Conclusion

- 1. The dataset predicts the amount of calories burnt.
- 2. The activity date has been converted to day, month and year and analysed.
- 3. Analysis based on different variables affecting the calories burnt have been done.
- 4. Correlation matrix have been analysed.
- 5. This is a regression type of problem for ML.