Problem Statement

A real estate agent want help to predict the house price for regions in USA.He gave us the dataset to work on to use linear regression model.Create a model that helps him to estimate of what the house would sell for

Import libraries

```
In [1]: import numpy as np
   import pandas as pd
   import matplotlib.pyplot as plt
   import seaborn as sns
```

```
In [2]: # To import dataset
df=pd.read_csv('16 Sleep csv')
df
```

Out[2]:

	Person ID	Gender	Age	Occupation	Sleep Duration	Quality of Sleep	Physical Activity Level	Stress Level	BMI Category	Blood Pressure	Heart Rate
0	1	Male	27	Software Engineer	6.1	6	42	6	Overweight	126/83	77
1	2	Male	28	Doctor	6.2	6	60	8	Normal	125/80	75
2	3	Male	28	Doctor	6.2	6	60	8	Normal	125/80	75
3	4	Male	28	Sa l es Representative	5.9	4	30	8	Obese	140/90	85
4	5	Male	28	Sa l es Representative	5.9	4	30	8	Obese	140/90	85
					•••		•••				
369	370	Female	59	Nurse	8.1	9	75	3	Overweight	140/95	68
370	371	Female	59	Nurse	8.0	9	75	3	Overweight	140/95	68
371	372	Fema l e	59	Nurse	8.1	9	75	3	Overweight	140/95	68
372	373	Female	59	Nurse	8.1	9	75	3	Overweight	140/95	68
373	374	Fema l e	59	Nurse	8.1	9	75	3	Overweight	140/95	68

374 rows × 13 columns

In [3]: # To display top 10 rows
df.head(10)

Out[3]:

	Person ID	Gender	Age	Occupation	Sleep Duration	Quality of Sleep	Physical Activity Level	Stress Level	BMI Category	Blood Pressure	Heart Rate	D S1
0	1	Male	27	Software Engineer	6.1	6	42	6	Overweight	126/83	77	4
1	2	Male	28	Doctor	6.2	6	60	8	Normal	125/80	75	10
2	3	Male	28	Doctor	6.2	6	60	8	Normal	125/80	75	10
3	4	Ma l e	28	Sales Representative	5.9	4	30	8	Obese	140/90	85	3
4	5	Male	28	Sales Representative	5.9	4	30	8	Obese	140/90	85	3
5	6	Male	28	Software Engineer	5.9	4	30	8	Obese	140/90	85	3
6	7	Male	29	Teacher	6.3	6	40	7	Obese	140/90	82	3
7	8	Male	29	Doctor	7.8	7	75	6	Normal	120/80	70	3
8	9	Male	29	Doctor	7.8	7	75	6	Normal	120/80	70	3
9	10	Male	29	Doctor	7.8	7	75	6	Normal	120/80	70	3
4												•

Data Cleaning and Pre-Processing

In [4]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 374 entries, 0 to 373
Data columns (total 13 columns):

Ducu	COTAMINA (COCAT TO COTAMINA	-,•	
#	Column	Non-Null Count	Dtype
0	Person ID	374 non-null	int64
1	Gender	374 non-null	object
2	Age	374 non-null	int64
3	Occupation	374 non-null	object
4	Sleep Duration	374 non-null	float64
5	Quality of Sleep	374 non-null	int64
6	Physical Activity Level	374 non-null	int64
7	Stress Level	374 non-null	int64
8	BMI Category	374 non-null	object
9	Blood Pressure	374 non-null	object
10	Heart Rate	374 non-null	int64
11	Daily Steps	374 non-null	int64
12	Sleep Disorder	374 non-null	object
dtype	es: float64(1), int64(7),	object(5)	

memory usage: 38.1+ KB

In [5]:

df.describe()

```
Out[5]:
                                                                     Physical
                                                        Quality of
                                               Sleep
                                                                                   Stress
                   Person ID
                                                                      Activity
                                                                                            Heart Rate
                                     Age
                                                                                                         Daily Steps
                                             Duration
                                                            Sleep
                                                                                    Level
                                                                        Level
           count 374.000000
                              374.000000
                                          374.000000
                                                      374.000000
                                                                   374.000000
                                                                               374.000000
                                                                                           374.000000
                                                                                                          374.000000
           mean 187.500000
                               42.184492
                                            7.132086
                                                         7.312834
                                                                    59.171123
                                                                                 5.385027
                                                                                            70.165775
                                                                                                         6816.844920
             std 108.108742
                                8.673133
                                            0.795657
                                                         1.196956
                                                                    20.830804
                                                                                  1.774526
                                                                                             4.135676
                                                                                                         1617.915679
                    1.000000
                               27.000000
                                             5.800000
                                                         4.000000
                                                                    30.000000
                                                                                  3.000000
                                                                                             65.000000
                                                                                                         3000.000000
             min
            25%
                   94.250000
                               35.250000
                                             6.400000
                                                         6.000000
                                                                    45.000000
                                                                                 4.000000
                                                                                             68.000000
                                                                                                         5600.000000
            50%
                  187.500000
                               43.000000
                                             7.200000
                                                         7.000000
                                                                    60.000000
                                                                                  5.000000
                                                                                            70.000000
                                                                                                         7000.000000
            75%
                  280.750000
                               50.000000
                                             7.800000
                                                         000000.8
                                                                    75.000000
                                                                                  7.000000
                                                                                            72.000000
                                                                                                         8000.000000
            max 374.000000
                               59.000000
                                             8.500000
                                                         9.000000
                                                                    90.000000
                                                                                 8.000000
                                                                                            86.000000
                                                                                                       10000.000000
In [6]: df.columns
Out[6]: Index(['Person ID', 'Gender', 'Age', 'Occupation', 'Sleep Duration',
```

```
In [7]: a = df.dropna(axis='columns')
a.columns
```

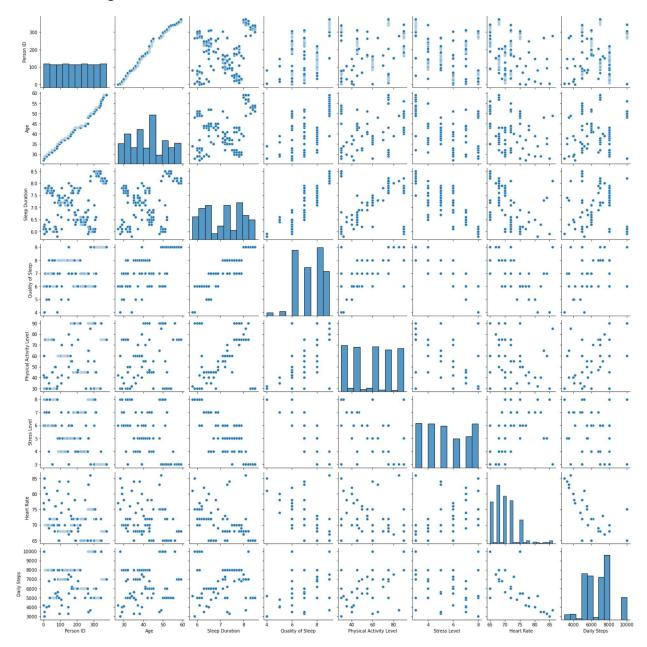
'Quality of Sleep', 'Physical Activity Level', 'Stress Level', 'BMI Category', 'Blood Pressure', 'Heart Rate', 'Daily Steps',

EDA and Visualization

'Sleep Disorder'],
dtype='object')

In [8]: sns.pairplot(a)

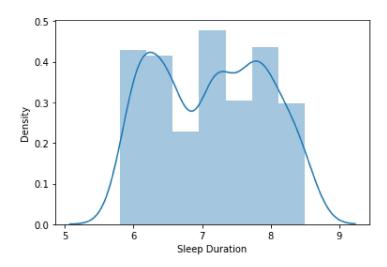
Out[8]: <seaborn.axisgrid.PairGrid at 0x27864d961f0>

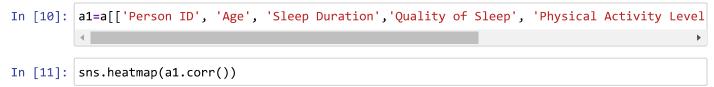


In [9]: | sns.distplot(a['Sleep Duration'])

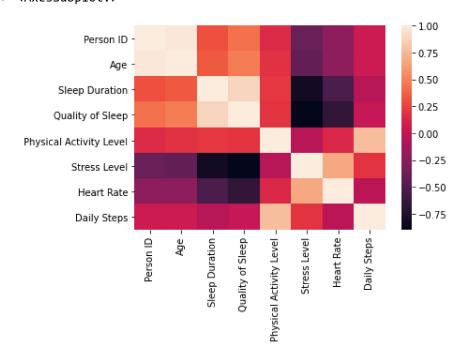
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarnin
g: `distplot` is a deprecated function and will be removed in a future version. Please
adapt your code to use either `displot` (a figure-level function with similar flexibil
ity) or `histplot` (an axes-level function for histograms).
 warnings.warn(msg, FutureWarning)

Out[9]: <AxesSubplot:xlabel='Sleep Duration', ylabel='Density'>





Out[11]: <AxesSubplot:>



To Train the Model - Model Building

We are going to train Linear Regression model; We need to split out data into two variables x and y where x

```
In [12]: x=a1[['Person ID', 'Age', 'Sleep Duration','Quality of Sleep', 'Physical Activity Level
y=a1['Sleep Duration']
```

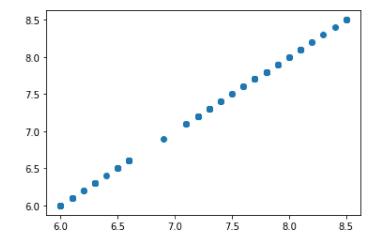
To split my dataset into training and test data

```
In [13]: from sklearn.model_selection import train_test_split
          x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.3)
In [14]: from sklearn.linear model import LinearRegression
          lr=LinearRegression()
          lr.fit(x_train,y_train)
Out[14]: LinearRegression()
In [15]: print(lr.intercept_)
          3.099742684753437e-13
          coeff=pd.DataFrame(lr.coef ,x.columns,columns=['Co-efficient'])
          coeff
Out[16]:
                                 Co-efficient
                               9.738430e-17
                     Person ID
                               1.930084e-16
                          Age
                 Sleep Duration
                               1.000000e+00
                Quality of Sleep
                              -4.931132e-16
           Physical Activity Level
                              1.385472e-17
                   Stress Level -1.777827e-17
                     Heart Rate
                               3.729460e-17
```

Daily Steps -4.912326e-17

```
In [17]: prediction=lr.predict(x_test)
    plt.scatter(y_test,prediction)
```

Out[17]: <matplotlib.collections.PathCollection at 0x2786a393550>



```
In [18]: print(lr.score(x_test,y_test))
```

1.0

ACCURACY

```
In [19]: from sklearn.linear_model import Ridge,Lasso
In [20]: rr=Ridge(alpha=10)
         rr.fit(x_train,y_train)
         rr.score(x_test,y_test)
         rr.score(x_train,y_train)
Out[20]: 0.9901000175495261
In [21]: rr.score(x_test,y_test)
Out[21]: 0.9864939832344124
In [22]: la=Lasso(alpha=10)
         la.fit(x_train,y_train)
Out[22]: Lasso(alpha=10)
In [23]: la.score(x_test,y_test)
Out[23]: 0.01650048922838787
In [24]: from sklearn.linear_model import ElasticNet
         en = ElasticNet()
         en.fit(x_train,y_train)
```

Out[24]: ElasticNet()

```
In [25]:
         print(en.coef_)
                                               0.
                                                           0.02505612 -0.
         [ 0.00096002 0.
                                   0.
          -0.08448836 -0.000312 ]
In [26]: |print(en.intercept )
         13.52071771606479
In [27]:
         print(en.predict(x_test))
         [6.93262849 7.19278867 6.70411413 7.02909079 7.82783679 6.59177357
          6.70123406 6.9047878 6.99163992 6.75802508 6.5341285 6.92974842
          7.53453571 6.91195795 6.93166846 6.61002732 7.03389091 6.28700756
          6.7036021 6.59849374 6.68299361 6.86395677 7.53841861 7.82303667
          6.65797156 6.91342801 6.6954901 7.04445117 7.20142888 6.89230749
          6.68587368 6.6090673 8.08412555 6.92251821 7.19374869 6.69835399
          5.87660498 6.93358851 6.70315411 7.56045635 7.20526898 6.99837003
          7.53457851 7.51297668 7.81535648 7.5422159 7.52881837 7.01469043
          7.00989031 7.17742829 7.01853053 6.91246799 7.52737703 6.70219409
          7.23452088 6.9301984 6.94289352 7.72991313 7.81727653 6.69739397
          8.06065641 7.53933583 7.22350943 6.91579805 7.0175705 6.68203359
          7.1860685 7.49665628 6.92878839 7.54513877 7.21198914 7.21390919
          7.53169844 6.92539828 6.90958792 7.5340972 6.88411727 7.53217715
          7.20334893 6.59081355 7.52493547 6.66187309 7.80095612 6.91054794
          6.91726811 7.03581095 6.68011354 7.51009661 7.53121713 6.8884674
          6.50963224 7.03197086 7.50049637 7.21486921 6.5888935 7.56909656
          6.70264208 6.68875375 7.5259383 7.82207664 7.45006999 7.4803007
          5.87564496 7.037731
                                7.03762141 6.8773971 6.58697345 7.82495671
          7.82687676 6.90670785 7.49329852 7.57389668 7.80863631]
In [28]: print(en.score(x_test,y_test))
         0.4428043811137372
In [29]: from sklearn import metrics
```

```
In [29]: from sklearn import metrics
    print("Mean Absolytre Error:",metrics.mean_absolute_error(y_test,prediction))
    print("Mean Squared Error:",metrics.mean_squared_error(y_test,prediction))
    print("Root Mean Squared Error:",np.sqrt(metrics.mean_squared_error(y_test,prediction))
```

Mean Absolytre Error: 6.173233016216623e-14 Mean Squared Error: 5.134549029614454e-27 Root Mean Squared Error: 7.165576759490093e-14