

# K-nearest Neighbours Regression

K-nearest Neighbours Regression non-parametric method it is one of the simplest Machine Learning algorithms based on Supervised Learning technique it is also called a lazy learner algorithm because it does not learn from the training set immediately instead it stores the dataset and at the time of classification, it performs an action on the dataset. KNN algorithm at the training phase just stores the dataset and when it gets new data, then it classifies that new data into a category that is much similar to the new data.

K-NN algorithm can be used for Regression as well as for Classification but mostly it is used for the Classification problems. But we have knn regressor algorithm

## How does Knn Work?

The K-NN working can be explained on the basis of the below algorithm: Step-1: Select the number K of the neighbors Step-2: Calculate the Euclidean distance of K number of neighbors Step-3: Take the K nearest neighbors as per the calculated Euclidean distance. Step-4: Among these k neighbors, count the number of data points in each category. Step-5: Assign the new data points to that category for which the number of the neighbor is maximum. Step-6: Our model is ready.

## Advantages of KNN Algorithm:

It is simple to implement. It is robust to the noisy training data it can be more effective if the training data is large.

## Disadvantages of KNN Algorithm:

Always needs to determine the value of K which may be complex some time. The computation cost is high because of calculating the distance between the data points for all the training samples.

```
In [1]:
import pandas as pd
import numpy as np
import seaborn as so
import matplotlib.pyplot as plt
warnings.filterwarnings('ignore')

In [2]:
df=pd.read_csv('50_Startups.csv')
df.head()

Out[2]:
   R&D Spend  Administration  Marketing Spend   State   Profit
0    163390.20      138997.80      471764.10  New York    160281.83
1    102597.70      151377.29      483886.53  California  191782.06
2    153441.51      101145.95      407934.54  Florida    191050.39
3    144377.41      118071.85      307186.62  New York    189591.86
4    442037.34      91398.77      389168.42  Florida    160187.94

In [3]:
df.info()

Out[3]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 50 entries, 0 to 49
Data columns (total 5 columns):
 #   Column              dtype
---  ---
 0   R&D Spend           float64
 1   Administration      float64
 2   Marketing Spend     float64
 3   State              object
 4   Profit             float64
dtypes: float64(4), object(1)
memory usage: 2.1+ MB

In [4]:
df.describe()

Out[4]:
   R&D Spend  Administration  Marketing Spend   Profit
count      50.000000      50.000000          50.000000      50.000000
mean    121212.65000      121344.50000      122290.31070      121012.83000
std     69602.25648      78017.80275        122290.31070      40096.18038
min         0.000000      51283.140000         0.000000      14681.40000
max     471764.10000      138997.80000      483886.53000      191050.39000
75%    106502.00000      144842.180000      294049.08500      130765.97000
90%    163390.20000      102545.800000      471764.10000      160281.83000

In [5]:
df.info()

Out[5]:
R&D Spend      8
Administration 8
Marketing Spend 8
State          8
Profit         8
dtype: int64

In [6]:
sns.pairplot(df hue='Profit')

Out[6]:
<seaborn.axisgrid.PairGrid at 0x1e8803a9a6>

In [7]:
sns.pairplot(df)

Out[7]:
<seaborn.axisgrid.PairGrid at 0x1e8803a9a6>

In [8]:
df_cat=df.select_dtypes(object)
df_num=df.select_dtypes(float)

In [9]:
from sklearn.preprocessing import LabelEncoder

In [10]:
lb=LabelEncoder()
df_cat=lb.fit_transform(df_cat,columns='State')

In [11]:
df_cat

Out[11]:
   State
0      2
1      0
2      1
3      2
4      1
5      2
6      0
7      1
8      2
9      0
10     1
11     0
12     1
13     0
14     1
15     2
16     0
17     2
18     1
19     0
20     2
21     2
22     1
23     1
24     2
25     0
26     1
27     1
28     2
29     1
30     2
31     2
32     0
33     1
34     2
35     2
36     1
37     0
38     2
39     0
40     0
41     1
42     0
43     2
44     0
45     2
46     1
47     0
48     2
49     0

In [12]:
df=pd.concat([df_cat,df_num],axis=1)

In [13]:
df

Out[13]:
   State  R&D Spend  Administration  Marketing Spend   Profit
0      2    163390.20      138997.80      471764.10    160281.83
1      0    102597.70      151377.29      483886.53    191782.06
2      1    153441.51      101145.95      407934.54    191050.39
3      2    144377.41      118071.85      307186.62    189591.86
4      1    442037.34      91398.77      389168.42    160187.94
5      2     133176.90      99814.71      362861.36    166991.12
6      0    134815.46      147188.87      127718.82    166122.51
7      1    130206.13      145830.06      328978.46    167920.40
8      2    139542.62      148718.86      311613.29    162311.17
9      0    123534.88      10879.17      354881.82    140759.86
10     1    101813.08      11094.11      278180.95    146121.85
11     0    100671.96      91700.61      249744.35    146250.40
12     1     69602.76      127320.39      248984.44    141866.82
13     0     91892.39      139495.07      252864.83    134307.35
14     1    119543.24      19547.42      256512.82    132000.65
15     2    114523.61      122816.84      261778.23    129831.04
16     0     78033.11      121897.55      264346.06    120990.93
17     2     46507.16      146077.80      280574.21    120270.87
18     1     91749.16      144176.79      294019.57    124246.80
19     2     85419.70      152814.11         0.00    122776.86
20     0     78293.86      113867.30      288964.47    118474.03
21     2     78389.67      157773.43      280737.29    111333.02
22     1     72894.49      122762.73      301313.24    110355.25
23     1     67532.63      109751.63      304768.73    108738.99
24     2     77044.01      99281.34      148747.81    108552.04
25     0     64664.71      139553.10      137962.82    107454.34
26     1     76287.87      144125.49      140050.07    107372.54
27     2     72307.60      127844.55      353135.81    105906.31
28     1     60561.62      182645.56      118148.20    103382.38
29     2     65605.48      153032.06      107138.36    101004.64
30     1     61894.48      115641.20      91131.24      99937.59
31     2     61382.38      262762.82      86823.23      94662.86
32     0     63468.86      129219.61      46085.25      97427.82
33     1     55403.95      102027.49      214634.81      96778.92
34     0     46426.07      157688.82      210797.47      96712.80
35     2     48041.62      85047.45      202037.54      94747.61
36     1     24663.76      157662.21      201126.82      9076.19
37     0     44069.85      51283.14      187028.42      89646.14
38     2     20229.59      69547.93      185286.10      81225.06
39     0     38658.61      83862.80      174999.30      81005.76
40     0     28754.63      118466.05      177994.87      79286.81
41     1     37882.82      84710.77      164470.71      77766.83
42     0     23640.93      96189.63      148001.11      71496.49
43     2     15505.73      127382.30      35531.17      69738.98
44     0     22177.74      15406.14      20334.72      60200.33
45     2     15002.31      141525.04      190239.48      60006.06
46     1     1315.46      118616.21      287114.46      49490.75
47     0      0.00      139426.82         0.00      42556.73
48     2     542.05      61743.15         0.00      35674.41
49     0      0.00      115883.80      45173.06      14681.40

In [14]:
sns.heatmap(df.corr(),annot=True)
plt.show()

In [15]:
x=df.iloc[:,1:3]
y=df.iloc[:,4]

In [16]:
from sklearn.model_selection import train_test_split as t
x_train,x_test,y_train,y_test=t(x,y,random_state=0)

In [17]:
from sklearn.neighbors import KNeighborsRegressor

In [18]:
knn=KNeighborsRegressor(n_neighbors=5)
knn.fit(x_train,y_train)
y_pred=knn.predict(x_test)

In [19]:
from sklearn.metrics import r2_score ,mean_squared_error ,mean_absolute_error

In [20]:
print('r^2 accuracy :',(r2_score(y_test,y_pred)*100))
print('accuracy :',(mean_absolute_error(y_test,y_pred)))
print('accuracy :',(mean_absolute_error(y_test,y_pred)*100))

accuracy : 69.9693508845
accuracy : 153897.622184888255
accuracy : 15389.7622184888255

As we were getting the accuracy as 71.71825064827465 so we have used for loop for the random state value as in the loop so we can check on which it is giving the maximum accuracy

In [21]:
acc=[]
for i in range(1,161):
    x_train,x_test,y_train,y_test=t(x,y,random_state=i)
    knn=KNeighborsRegressor(n_neighbors=5)
    knn.fit(x_train,y_train)
    y_pred=knn.predict(x_test)
    print('value of i is :',i)
    print('accuracy :',(r2_score(y_test,y_pred)*100))
    acc.append((r2_score(y_test,y_pred)*100))

value of i is 1
-> accuracy : 69.9693508845
value of i is 2
-> accuracy : 68.71251628899773
value of i is 3
-> accuracy : 70.55337880395652
value of i is 4
-> accuracy : 76.78881816144732
value of i is 5
-> accuracy : 64.81183696156184
value of i is 6
-> accuracy : 69.22549880380666
value of i is 7
-> accuracy : 63.84895412092625
value of i is 8
-> accuracy : 64.28440963896086
value of i is 9
-> accuracy : 65.9255139968044
value of i is 10
-> accuracy : 67.60451262109862
value of i is 11
-> accuracy : 62.1541471189374
value of i is 12
-> accuracy : 60.951995398812
value of i is 13
-> accuracy : 66.78347109114593
value of i is 14
-> accuracy : 66.84648647788287
value of i is 15
-> accuracy : 61.42355384380682
value of i is 16
-> accuracy : 68.64648647788287
value of i is 17
-> accuracy : 68.541724315414872
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-> accuracy : 63.1317866436943
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-> accuracy : 75.15736886387812
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-> accuracy : 75.9731919259233
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In [22]:
plt.figure(figsize=(10,10))
plt.plot(range(1,161),acc)
plt.grid()
plt.show()

In [23]:
plt.figure(figsize=(10,10))
plt.plot(range(1,161),acc)
plt.grid()
plt.show()

In [24]:
plt.figure(figsize=(10,10))
plt.plot(range(1,161),acc)
plt.grid()
plt.show()

In [25]:
k=2
acc=[]
for i in range(1,36,1):
    x_train,x_test,y_train,y_test=t(x,y,random_state=i)
    knn=KNeighborsRegressor(n_neighbors=k)
    knn.fit(x_train,y_train)
    y_pred=knn.predict(x_test)
    print('value of i is :',i)
    print('accuracy :',(r2_score(y_test,y_pred)*100))
    print('accuracy :',(mean_squared_error(y_test,y_pred)*100))
    print('accuracy :',(mean_squared_error(y_test,y_pred)*100))
    print('accuracy :',(mean_squared_error(y_test,y_pred)*100))
    acc.append((r2_score(y_test,y_pred)*100))

accuracy : 84.2288688800782
accuracy : 86.80817885187827
accuracy : 88821.7897692211
accuracy : 87.85282132517458

In [26]:
plt.scatter(y_pred,y_test)

Out[26]:
<matplotlib.collections.PathCollection at 0x1e8803a9a6>

In [27]:
knn.predict([[2,1000,20000,1000]])

Out[27]:
array([25177.485])

here a is the value of state b is the value of R&D Spend c is the value of Administration d is the value of Marketing Spend

In [28]:
def profit(a,b,c,d):
    return knn.predict([[a,b,c,d]])

In [29]:
profit(1,111099,1233,12342134)

Out[29]:
array([182826.946])

In [30]:

```