Machine Learning Lab __ - Topic Name

Submitted by
Name: **Stebin George**
Register Number: **2122061**
Class: **2MSCDS**

Lab Overview

Objectives

The attached dataset has rent details of some houses in Lavasa.

Common Instructions Use Pandas to Import the Dataset Do the necessary Exploratory Data Analysis Use the train_test_split method available in SCIKIT to split the dataset into Train Dataset and Test Dataset. Show the Regression Score, Intercept and other parameters etc in the Output Use visualizations and plots wherever possible Format the outputs neatly; Do Documentation, Data Set Description, Objectives, Observations, Conclusions etc as you have done in your previous lab Questions

1. What are your observations on the Dataset?
2. What are the different Error Measures (Evaluation Metrics) in relation to Linear Regression? How much do you get in the above cases?
3. Note down the errors/losses when the train-test ratio is 50:50, 60:40, 70:30, and 80:20
4. During LinearRegression() process, what is the impact of giving TRUE/FALSE as the value for Normalize Parameter?

Cases Try to predict the rent of the below houses -

1. 1 BHK with 2 Baths in Portofino Street
2. Fully Furnished 2 BHK in School Street
3. Single Room anywhere in Lavasa

Problem Definition

- familiarising with the concept of linear regression.
- getting familiarize with the syntax of linear regression
- pre processing & exploring the data for regression.

Approach

- import all the libraries
- export the date and do some eda analysis
- Transport all categorical values into encoders.
- exporing the different options under linear regression in sklearn

Sections

1) Introduction

2) Importanting libraries

3) cleaning data

4) Questions

5) conclusion

References

- https://www.geeksforgeeks.org/linear-regression-python-implementation/
- https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html

Introduction:

Linear regression is a common method to model the relationship between a dependent variable and one or more independent variables. Linear models are developed using the parameters which are estimated from the data. Linear regression is useful in prediction and forecasting where a predictive model is fit to an observed data set of values to determine the response. Linear regression models are often fitted using the least-squares approach where the goal is to minimize the error.

Step One: Import our libraries

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn import model_selection
import seaborn as sns
import numpy as np
from sklearn import preprocessing
from sklearn import model_selection
import sklearn.metrics as metrics
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from copy import copy
```

Load the Data

In [47]:
```
x=pd.read_csv(r"C:\Users\stebi\Downloads\HousePrices - Lab3.csv")
x
```

Out[47]:

	BuildingType	Location	Size	AreaSqFt	NoOfBath	NoOfPeople	NoOfBalcony	RentPerMonth
0	Minimum Budget Rooms	Portofino H	1 BHK	400.0	1	1	1	1100.0

	BuildingType	Location	Size	AreaSqFt	NoOfBath	NoOfPeople	NoOfBalcony	RentPerMonth
1	Minimum Budget Rooms	Portofino H	1 BHK	450.0	1	1	1	1100.0
2	Minimum Budget Rooms	School Street	1 BHK	530.0	1	1	0	1166.0
3	Minimum Budget Rooms	Portofino B	1 BHK	400.0	1	1	0	1400.0
4	Minimum Budget Rooms	School Street	2 BHK	460.0	1	1	0	1500.0
...	...	...	...	...	...	...	...	...
995	Super Furnished Villa	Portofino D	4 BHK	4900.0	4	6	3	70000.0
996	Super Furnished Villa	Portofino B	4 BHK	3750.0	4	5	0	76000.0
997	Super Furnished Villa	School Street	4 BHK	5270.0	4	5	3	80000.0
998	Super Furnished Villa	Portofino B	6 BHK	5100.0	7	6	3	90000.0
999	Super Furnished Villa	Portofino B	7 BHK	6300.0	6	6	3	96000.0

1000 rows × 8 columns

Cleaning the data

In [48]:

```
x['Location'].value_counts()
```

Out[48]:

```
Clubview Road    213
Portofino B      173
School Street    138
Portofino D      105
Portofino C      103
Portofino A       95
Portofino H       62
Portofino E       54
Portofino G       26
Portofino F       22
Starter Homes      9
Name: Location, dtype: int64
```

Since portofino been splitted into various groups it has to be combined to a single location for effective data analysis.

In [50]:

```
for i in x['Location']:
```

```
    if "Portofino" in i:
        x['Location'].replace({i:'Portofino'},inplace=True)
x
```

Out[50]:

	BuildingType	Location	Size	AreaSqFt	NoOfBath	NoOfPeople	NoOfBalcony	RentPerMonth
0	Minimum Budget Rooms	Portofino	1 BHK	400.0	1	1	1	1100.0
1	Minimum Budget Rooms	Portofino	1 BHK	450.0	1	1	1	1100.0
2	Minimum Budget Rooms	School Street	1 BHK	530.0	1	1	0	1166.0
3	Minimum Budget Rooms	Portofino	1 BHK	400.0	1	1	0	1400.0
4	Minimum Budget Rooms	School Street	2 BHK	460.0	1	1	0	1500.0
...	...	...	...	...	...	...	...	...
995	Super Furnished Villa	Portofino	4 BHK	4900.0	4	6	3	70000.0
996	Super Furnished Villa	Portofino	4 BHK	3750.0	4	5	0	76000.0
997	Super Furnished Villa	School Street	4 BHK	5270.0	4	5	3	80000.0
998	Super Furnished Villa	Portofino	6 BHK	5100.0	7	6	3	90000.0
999	Super Furnished Villa	Portofino	7 BHK	6300.0	6	6	3	96000.0

1000 rows × 8 columns

In [51]:

```
x['Location'].value_counts()
```

Out[51]:

```
Portofino        640
Clubview Road    213
School Street    138
Starter Homes      9
Name: Location, dtype: int64
```

Finding if null values are present:

In [52]:

```
display(x.isna().any())
```

```
BuildingType     False
```

```
Location        False
Size            False
AreaSqFt        False
NoOfBath        False
NoOfPeople      False
NoOfBalcony     False
RentPerMonth    False
dtype: bool
```

There are no null values present in the daatset.

In [53]:

```
x.duplicated().value_counts()
```

Out[53]:

```
False    990
True      10
dtype: int64
```

In [54]:

```
duplicate = x[x.duplicated()]
duplicate
```

Out[54]:

	BuildingType	Location	Size	AreaSqFt	NoOfBath	NoOfPeople	NoOfBalcony	RentPerMonth
8	Semi Furnished Single Room	School Street	1 BHK	645.0	1	1	1	1645.0
37	Semi Furnished Single Room	School Street	2 BHK	1015.0	2	1	2	2588.0
40	Minimum Budget Rooms	Portofino	1 BHK	525.0	1	1	1	2600.0
190	Semi Furnished Single Room	Portofino	2 BHK	883.0	2	1	1	4500.0
277	Minimum Budget Rooms	Portofino	2 BHK	1200.0	2	1	2	5000.0
295	Semi Furnished Single Room	Portofino	2 BHK	1200.0	2	2	2	5200.0
296	Semi Furnished Single Room	Portofino	2 BHK	1200.0	2	2	2	5200.0
335	Semi Furnished Single Room	Portofino	2 BHK	1200.0	2	2	2	5500.0
354	Semi Furnished Single Room	Clubview Road	3 BHK	1464.0	3	2	2	5600.0
450	Semi Furnished Flat	School Street	2 BHK	1200.0	2	2	1	6500.0

The above mentioned are the 10 duplicate rows in the dataframe

Usuage of encoders to deal with categorical values:

In [55]:
```
label_encoder = preprocessing.LabelEncoder()
x['BuildingType']= label_encoder.fit_transform(data['BuildingType'])
x['Location']= label_encoder.fit_transform(data['Location'])
x['Size']= label_encoder.fit_transform(data['Size'])
x.head()
```

Out[55]:

	BuildingType	Location	Size	AreaSqFt	NoOfBath	NoOfPeople	NoOfBalcony	RentPerMonth
0	3	8	0	400.0	1	1	1	1100.0
1	3	8	0	450.0	1	1	1	1100.0
2	3	9	0	530.0	1	1	0	1166.0
3	3	2	0	400.0	1	1	0	1400.0
4	3	9	2	460.0	1	1	0	1500.0

Exploring the dataset:

1. What are your observations on the Dataset?

The attached dataset has rent details of some houses in Lavasa.

Creating a summary out of the entire dataframe

In [56]:
```
x.describe()
```

Out[56]:

	BuildingType	Location	Size	AreaSqFt	NoOfBath	NoOfPeople	NoOfBalcor
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.0000C
mean	3.834000	3.582000	2.716000	1548.270010	2.661000	2.168000	1.5440C
std	1.946852	3.167856	1.285689	1345.141175	1.247251	0.959529	0.83831
min	0.000000	0.000000	0.000000	375.000000	1.000000	1.000000	0.0000C
25%	3.000000	1.000000	2.000000	1090.000000	2.000000	2.000000	1.0000C
50%	4.000000	3.000000	3.000000	1270.000000	2.000000	2.000000	2.0000C
75%	5.000000	6.000000	3.000000	1664.250000	3.000000	2.000000	2.0000C
max	9.000000	10.000000	9.000000	35000.000000	11.000000	6.000000	3.0000C

In [57]:
```
x.columns
```

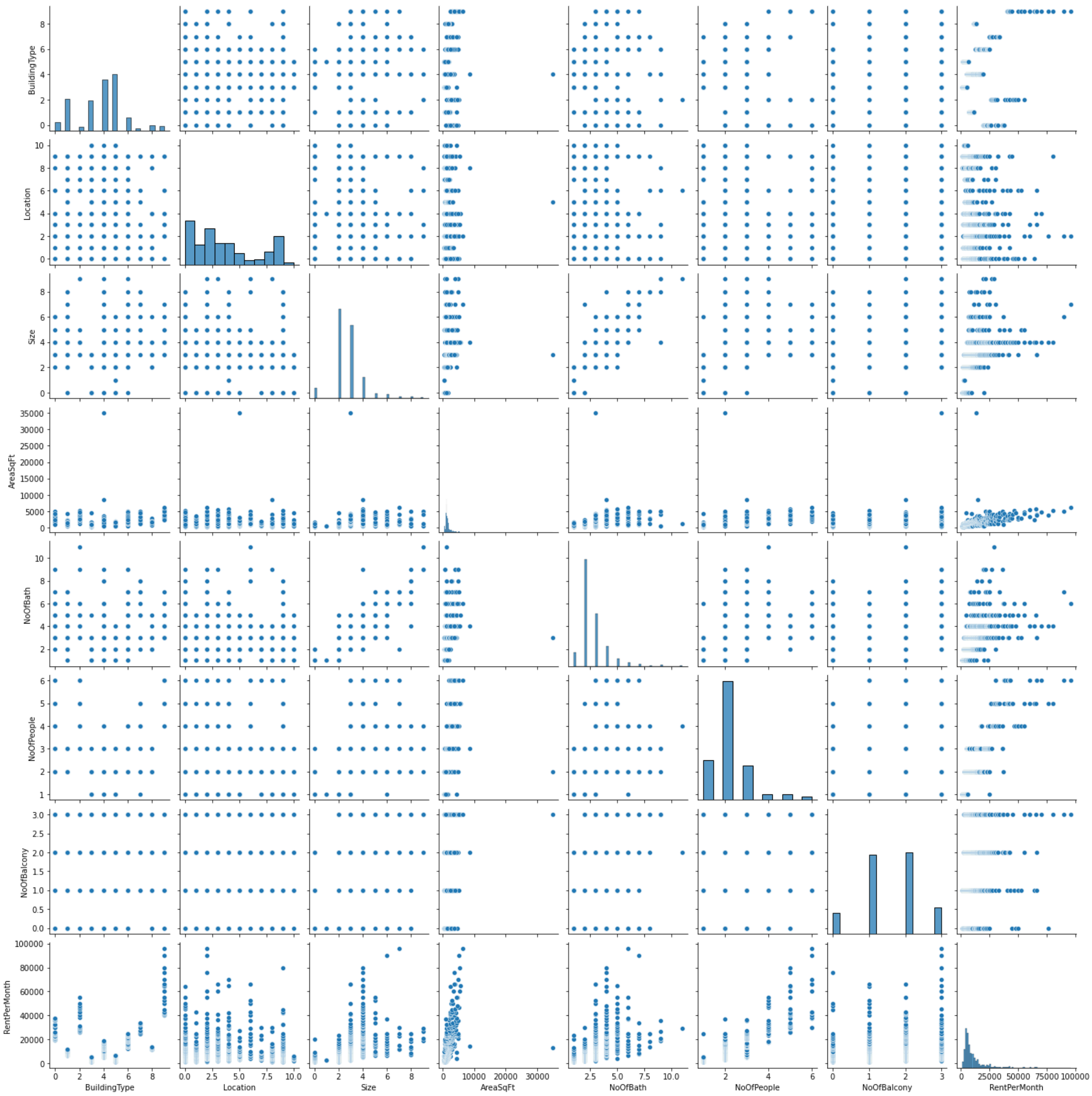
Out[57]:
```
Index(['BuildingType', 'Location', 'Size', 'AreaSqFt', 'NoOfBath',
       'NoOfPeople', 'NoOfBalcony', 'RentPerMonth'],
      dtype='object')
```

'BuildingType', 'Location', 'Size', 'AreaSqFt', 'NoOfBath','NoOfPeople', 'NoOfBalcony', 'RentPerMonth' are the different columns in the dataframe.

Plotting the various graphs:

In [58]:
```
sns.pairplot(x)
```

Out[58]: <seaborn.axisgrid.PairGrid at 0x26f3c6dc400>



Correlation relations between the features.

In [59]:
```
x.corr()
```

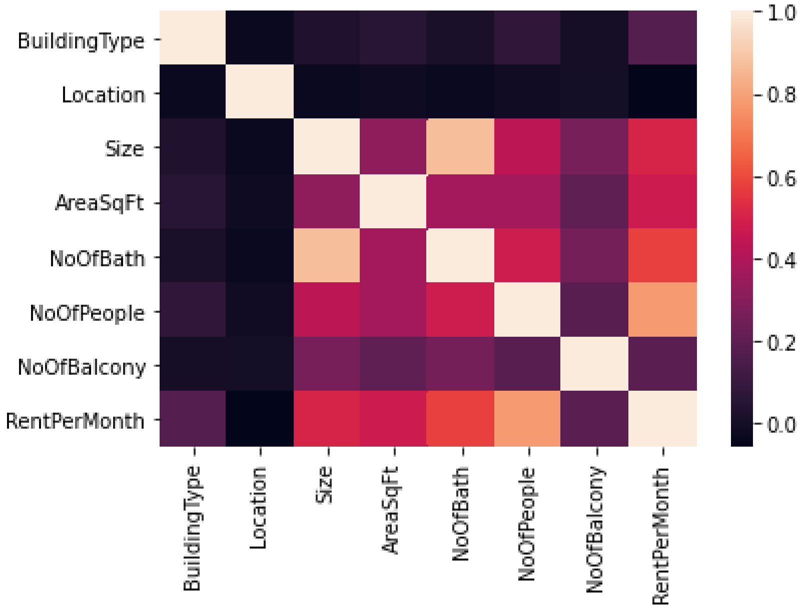
Out[59]:

	BuildingType	Location	Size	AreaSqFt	NoOfBath	NoOfPeople	NoOfBalcony
BuildingType	1.000000	-0.032037	0.031935	0.057975	0.012666	0.077638	0.003866
Location	-0.032037	1.000000	-0.026473	-0.010202	-0.030073	-0.011123	-0.033399
Size	0.031935	-0.026473	1.000000	0.325890	0.873126	0.441985	0.262365
AreaSqFt	0.057975	-0.010202	0.325890	1.000000	0.375791	0.374907	0.206123
NoOfBath	0.012666	-0.030073	0.873126	0.375791	1.000000	0.480063	0.258885
NoOfPeople	0.077638	-0.011123	0.441985	0.374907	0.480063	1.000000	0.184932
NoOfBalcony	0.003866	-0.033399	0.262365	0.206123	0.258885	0.184932	1.000000
RentPerMonth	0.174447	-0.055946	0.508411	0.473022	0.579693	0.782853	0.193619

Heatmap of the entire features:

In [15]:
```
sns.heatmap(x.corr())
```

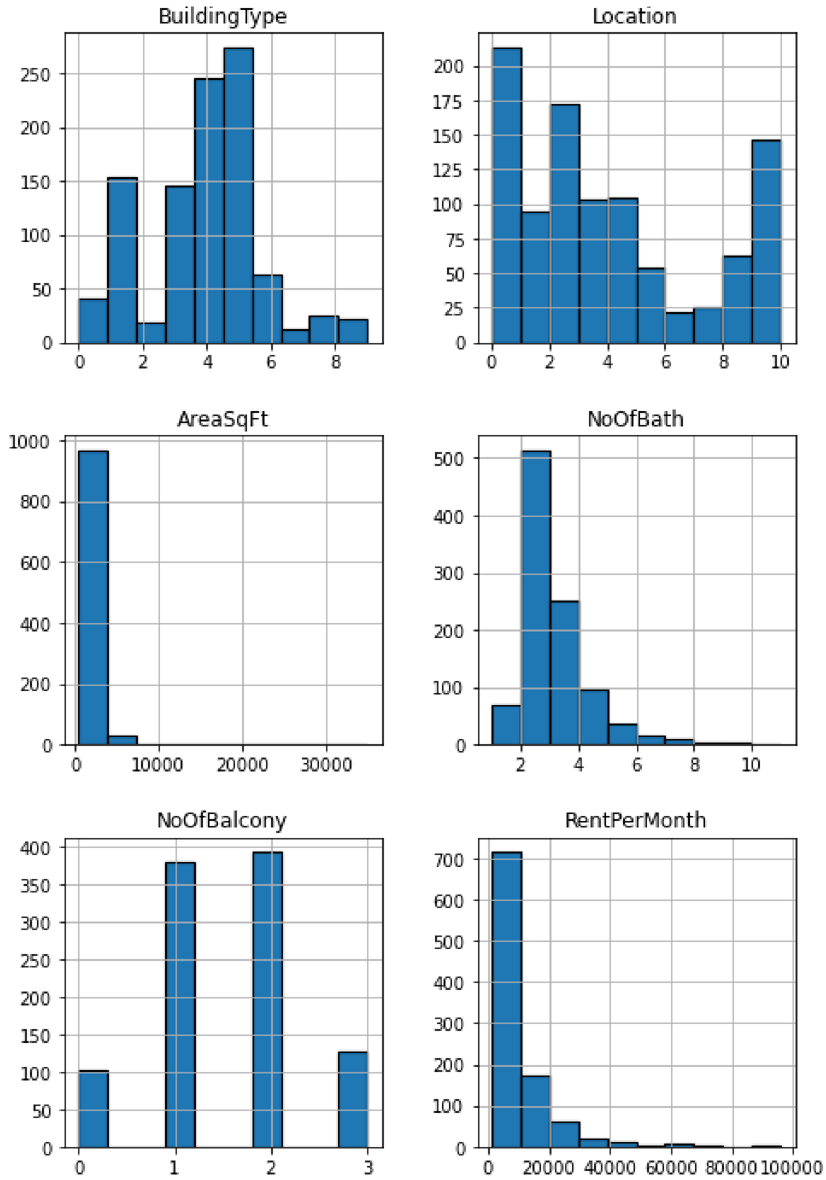
Out[15]: <AxesSubplot:>



The above graph shows that the Rentpermonth and the no.of.people are highly corelated.

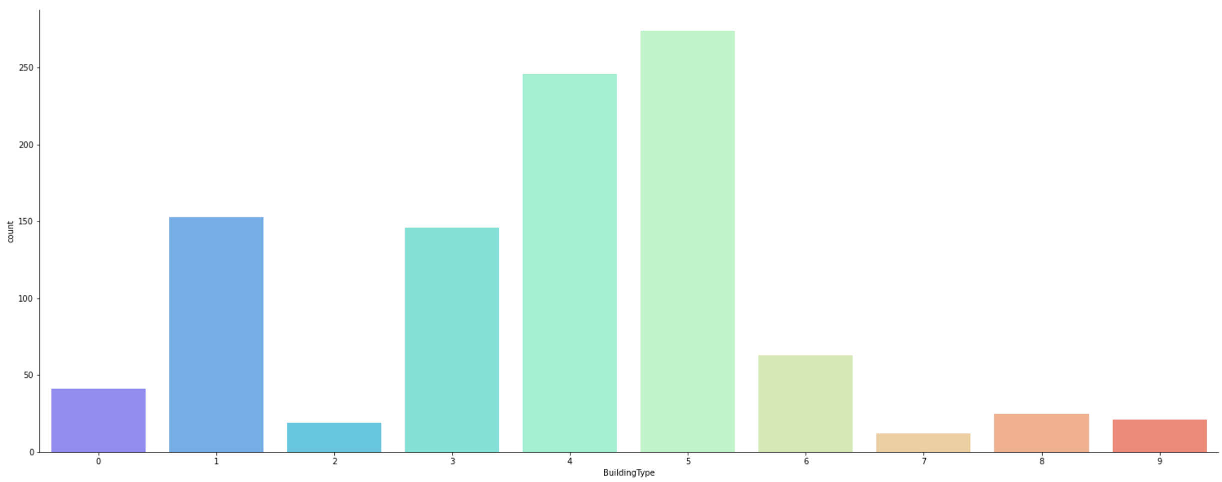
Graph shows the distribution of different features

In [60]:
```
x.hist(edgecolor='black', linewidth=1.2)
fig=plt.gcf()
fig.set_size_inches(12,12)
plt.show()
```



In [61]:

```
plt.figure(figsize = [26,10])
sns.countplot(x = 'BuildingType', palette = "rainbow", alpha = 0.7, data = x)
sns.despine()
```

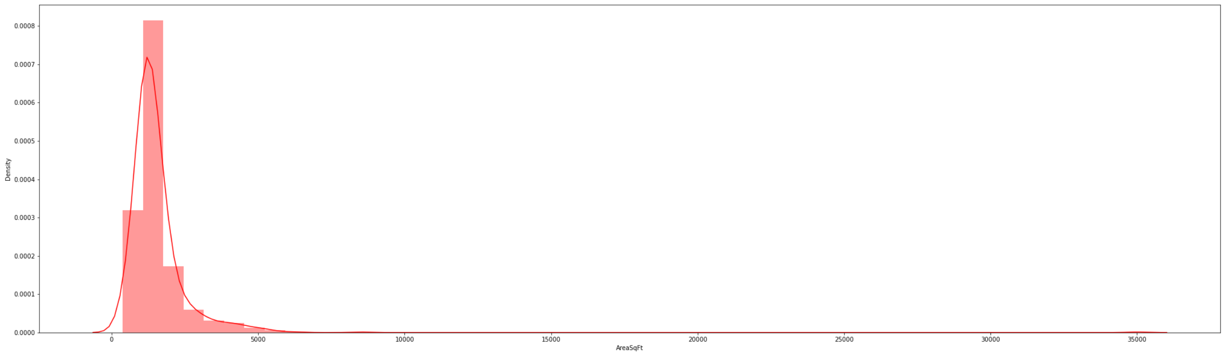


- From this countplot we can see that maximum house are Semi Furnished Single Room or Semi Furnished Flat.

In [62]:
```python
plt.figure(figsize=(35,10))
sns.distplot(x['AreaSqFt'], color = 'red')
```

```
C:\Users\stebi\anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarn
ing: `distplot` is a deprecated function and will be removed in a future version. Pl
ease adapt your code to use either `displot` (a figure-level function with similar f
lexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[62]: `<AxesSubplot:xlabel='AreaSqFt', ylabel='Density'>`

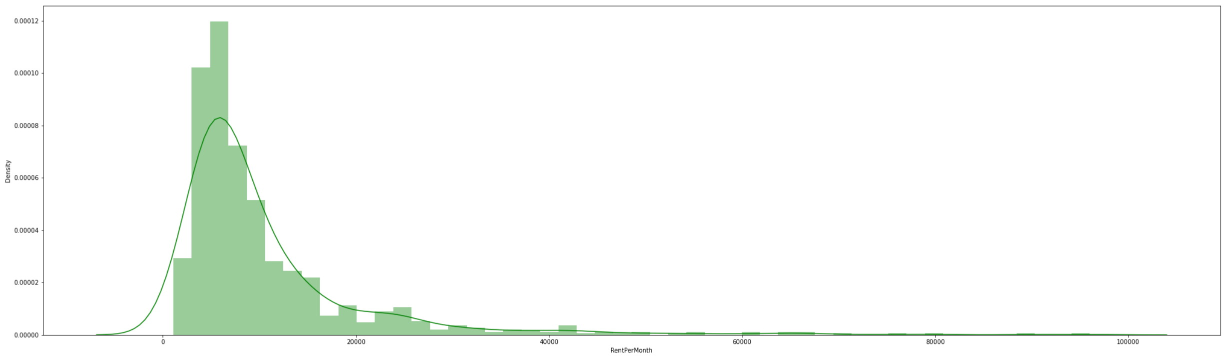


- The area square feet of major rental properties is ranging between 400 to 2500 area sq. ft.

In [26]:
```python
plt.figure(figsize=(35,10))
sns.distplot(x['RentPerMonth'], color = 'green')
```

```
C:\Users\stebi\anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarn
ing: `distplot` is a deprecated function and will be removed in a future version. Pl
ease adapt your code to use either `displot` (a figure-level function with similar f
lexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[26]: `<AxesSubplot:xlabel='RentPerMonth', ylabel='Density'>`



- The rent for major properties lie under the range of Rs 1100 to Rs 10000.

2. What are the different Error Measures (Evaluation Metrics) in relation to Linear Regression? How much do you get in the above cases?

Evaluation Metrices:

1) Mean Absolute Error (MAE): Is the mean of the absolute value of the errors. This metric gives an idea of magnitude but no idea of direction (too high or too low).

from sklearn.metrics import mean_absolute_error

print("MAE",mean_absolute_error(y_test,y_pred))

2) Mean Squared Error (MSE): Is the mean of the squared errors.MSE is more popular than MAE because MSE "punishes" more significant errors.

from sklearn.metrics import mean_squared_error print("MSE",mean_squared_error(y_test,y_pred))

3) Root Mean Squared Error (RMSE): Is the square root of the mean of the squared errors. RMSE is even more favored because it allows us to interpret the output in y-units.

print("RMSE",np.sqrt(mean_squared_error(y_test,y_pred)))

4) Root Mean Squared Log Error(RMSLE) Taking the log of the RMSE metric slows down the scale of error. The metric is very helpful when you are developing a model without calling the inputs. In that case, the output will vary on a large scale.

print("RMSE",np.log(np.sqrt(mean_squared_error(y_test,y_pred))))

5) R Squared (R2): R2 score is a metric that tells the performance of your model, not the loss in an absolute sense that how many wells did your model perform.

from sklearn.metrics import r2_score r2 = r2_score(y_test,y_pred)

3. Note down the errors/losses when the train-test ratio is 50:50, 60:40, 70:30, and 80:20

In [83]:

```
lst=[.5,.6,.7,.8]
for i in lst:
    X_train,X_test,y_train,y_test=model_selection.train_test_split(x.iloc[:,0:7],x['
    model = LinearRegression()
    model.fit(X_train,y_train)
    y_predict=model.predict(X_test)
    mse=metrics.mean_squared_error(y_test,y_predict)
    rmse = (np.sqrt(mse))
    r2 =metrics.r2_score(y_test, y_predict)
    print(f"\033[0m TRAIN SIZE\033[1m:{i*100}% ")
    print(f'\033[0mSlope\033[1m: {model.coef_}')
    print(f'\033[0mIntercept\033[1m:{model.intercept_}')
    print(f'\033[0mMSE:\033[1m: {mse}')
    print(f'\033[0mRoot mean squared error\033[1m: {rmse}')
    print(f'\033[0mR2 score:\033[1m:{r2}')
    print("\n")
```

```
 TRAIN SIZE:50.0%
Slope: [ 8.27014737e+02 -7.86842247e+01 -3.45197193e+02  8.46059724e-01
  2.35243954e+03  7.13149160e+03 -1.62561404e+02]
Intercept:-14086.416267470635
MSE:: 29671115.883120798
Root mean squared error: 5447.1199622480135
R2 score::0.6897971325198762


 TRAIN SIZE:60.0%
Slope: [ 6.39575080e+02 -1.26588387e+02 -2.14164052e+02  8.77543116e-01
  2.38334795e+03  6.81786188e+03 -1.50943174e+02]
Intercept:-13159.619546028583
MSE:: 27844585.518103708
Root mean squared error: 5276.79689945555
R2 score::0.7187844217073731
```

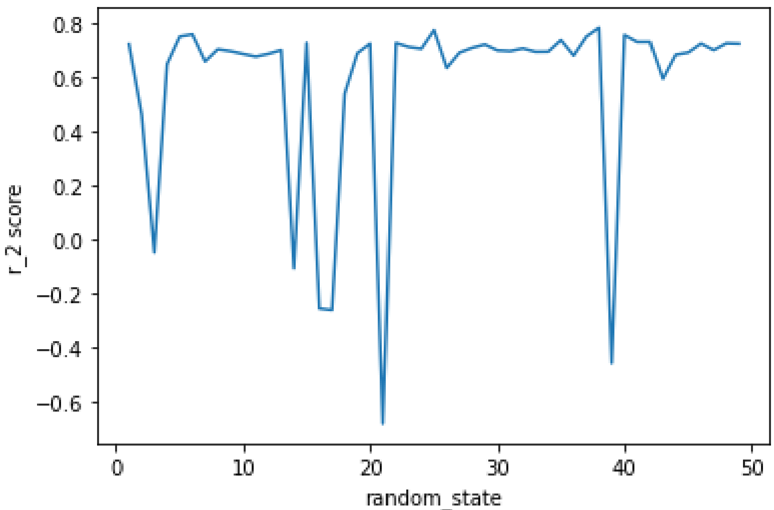
```
 TRAIN SIZE:70.0%
Slope: [ 5.54510968e+02 -1.09579548e+02 -3.25118155e+02  9.53007779e-01
  2.42496980e+03  6.73863593e+03 -1.65545237e+02]
Intercept:-12747.067880854738
MSE:: 28617931.00262994
Root mean squared error: 5349.572973857815
R2 score::0.7467658034822383


 TRAIN SIZE:80.0%
Slope: [ 5.74625788e+02 -8.50369121e+01 -5.13867060e+02  1.06021760e+00
  2.49851334e+03  6.53701164e+03 -1.11431261e+02]
Intercept:-12435.682155419774
MSE:: 30236732.210716028
Root mean squared error: 5498.793705051684
R2 score::0.7613054583028267
```

From the above block of codes it is visible that as the train size increases the better the model performs throughout

ACCURACY VS RANDOM_STATE:

In [64]:

```
import matplotlib.pyplot as plt
from importlib import reload
plt=reload(plt)
l=[]
m=[]
for i in range(1,50):
    X_train,X_test,y_train,y_test=model_selection.train_test_split(x.iloc[:,0:7],x['
    m.append(i)
    model = LinearRegression()
    model.fit(X_train,y_train)
    y_predict=model.predict(X_test)
    l.append(metrics.r2_score(y_test,y_predict))
plt.plot(m,l)
plt.xlabel("random_state")
plt.ylabel("r_2 score")
plt.show()
```



For the random state of 2 the graph has the maximum R2 value.

4. During LinearRegression() process, what is the impact of giving TRUE/FALSE as the value for Normalize Parameter?

In [84]:

```
lst=[.5,.6,.7,.8]
ls2=[False,True]
for i in lst:
    for j in ls2:
        X_train,X_test,y_train,y_test=model_selection.train_test_split(x.iloc[:,0:7]
        model = LinearRegression(normalize=j)
        model.fit(X_train,y_train)
        y_predict=model.predict(X_test)
        mse=metrics.mean_squared_error(y_test,y_predict)
        rmse = (np.sqrt(mse))
        r2 =metrics.r2_score(y_test, y_predict)
        print(f"\033[1m normalizer = {j} \033[0m")
        print(f"\033[0m TRAIN SIZE\033[1m:{i*100}% ")
        print(f'\033[0mSlope\033[1m: {model.coef_}')
        print(f'\033[0mIntercept\033[1m:{model.intercept_}')
        print(f'\033[0mMSE:\033[1m: {mse}')
        print(f'\033[0mRoot mean squared error\033[1m: {rmse}')
        print(f'\033[0mR2 score:\033[1m:{r2}')
        print("\n")
```

```
 normalizer = False
 TRAIN SIZE:50.0%
Slope: [ 8.27014737e+02 -7.86842247e+01 -3.45197193e+02  8.46059724e-01
  2.35243954e+03  7.13149160e+03 -1.62561404e+02]
Intercept:-14086.416267470635
MSE:: 29671115.883120798
Root mean squared error: 5447.1199622480135
R2 score::0.6897971325198762


 normalizer = True
 TRAIN SIZE:50.0%
Slope: [ 8.27014737e+02 -7.86842247e+01 -3.45197193e+02  8.46059724e-01
  2.35243954e+03  7.13149160e+03 -1.62561404e+02]
Intercept:-14086.416267470642
MSE:: 29671115.88312082
Root mean squared error: 5447.119962248015
R2 score::0.689797132519876


 normalizer = False
 TRAIN SIZE:60.0%
Slope: [ 6.39575080e+02 -1.26588387e+02 -2.14164052e+02  8.77543116e-01
  2.38334795e+03  6.81786188e+03 -1.50943174e+02]
Intercept:-13159.619546028583
MSE:: 27844585.518103708
Root mean squared error: 5276.79689945555
R2 score::0.7187844217073731


 normalizer = True
 TRAIN SIZE:60.0%
Slope: [ 6.39575080e+02 -1.26588387e+02 -2.14164052e+02  8.77543116e-01
  2.38334795e+03  6.81786188e+03 -1.50943174e+02]
Intercept:-13159.619546028605
MSE:: 27844585.518103715
Root mean squared error: 5276.796899455551
R2 score::0.7187844217073731


 normalizer = False
 TRAIN SIZE:70.0%
Slope: [ 5.54510968e+02 -1.09579548e+02 -3.25118155e+02  9.53007779e-01
  2.42496980e+03  6.73863593e+03 -1.65545237e+02]
Intercept:-12747.067880854738
MSE:: 28617931.00262994
```

```
Root mean squared error: 5349.572973857815
R2 score::0.7467658034822383


 normalizer = True
 TRAIN SIZE:70.0%
Slope: [ 5.54510968e+02 -1.09579548e+02 -3.25118155e+02  9.53007779e-01
  2.42496980e+03  6.73863593e+03 -1.65545237e+02]
Intercept:-12747.067880854738
MSE:: 28617931.00262996
Root mean squared error: 5349.572973857817
R2 score::0.7467658034822382


 normalizer = False
 TRAIN SIZE:80.0%
Slope: [ 5.74625788e+02 -8.50369121e+01 -5.13867060e+02  1.06021760e+00
  2.49851334e+03  6.53701164e+03 -1.11431261e+02]
Intercept:-12435.682155419774
MSE:: 30236732.210716028
Root mean squared error: 5498.793705051684
R2 score::0.7613054583028267


 normalizer = True
 TRAIN SIZE:80.0%
Slope: [ 5.74625788e+02 -8.50369121e+01 -5.13867060e+02  1.06021760e+00
  2.49851334e+03  6.53701164e+03 -1.11431261e+02]
Intercept:-12435.682155419792
MSE:: 30236732.21071601
Root mean squared error: 5498.793705051682
R2 score::0.7613054583028268
```

A linear regression has the same predictive power evenafter normalizing the data. Therefore, using normalize=True has no impact on the predictions. But there is an significant difference when a scalers are used in the model:

Using a scaler-MinMaxscaler:

In [85]:

```
scaler=MinMaxScaler()
x1=copy(x)
x1[['AreaSqFt', 'NoOfBath',
       'NoOfPeople', 'NoOfBalcony']]=scaler.fit_transform(x1[['AreaSqFt', 'NoOfBath'
       'NoOfPeople', 'NoOfBalcony']])
```

In [33]:

```
lst=[.5,.6,.7,.8]
for i in lst:
    X_train,X_test,y_train,y_test=model_selection.train_test_split(x1.iloc[:,0:7],x1
    model = LinearRegression()
    model.fit(X_train,y_train)
    y_predict=model.predict(X_test)
    mse=metrics.mean_squared_error(y_test,y_predict)
    rmse = (np.sqrt(mse))
    r2 =metrics.r2_score(y_test, y_predict)
    print(f"\033[0m TRAIN SIZE\033[1m:{i*100}% ")
    print(f'\033[0mSlope\033[1m: {model.coef_}')
    print(f'\033[0mIntercept\033[1m:{model.intercept_}')
    print(f'\033[0mMSE:\033[1m: {mse}')
    print(f'\033[0mRoot mean squared error\033[1m: {rmse}')
    print(f'\033[0mR2 score:\033[1m:{r2}')
    print("\n")
```

```
 TRAIN SIZE:50.0%
Slope: [  567.38781518  -535.3137786   -183.64862453 23809.84909379
 20151.13208052 32458.84599928  -771.5851344 ]
Intercept:-2251.631438103401
MSE:: 34088131.59190207
Root mean squared error: 5838.504225561721
R2 score::0.7197677115743534


 TRAIN SIZE:60.0%
Slope: [ 5.75240563e+02 -6.99326029e+02 -1.40250851e+02  3.00744972e+04
  2.02385704e+04  3.31670498e+04  1.62216854e+01]
Intercept:-2911.809752198409
MSE:: 28654924.316099804
Root mean squared error: 5353.029452198055
R2 score::0.7410641775156243


 TRAIN SIZE:70.0%
Slope: [  611.44489248  -685.93730196  -264.47470297 34763.48014261
 21130.27866739 33816.65180855   155.93385933]
Intercept:-3200.571917956371
MSE:: 26674765.43777921
Root mean squared error: 5164.761895555226
R2 score::0.7292451638110509


 TRAIN SIZE:80.0%
Slope: [  536.55702071  -589.23077691  -221.20341919 36625.67389338
 21422.70227394 33199.13182682  -338.28666073]
Intercept:-2918.5565077563024
MSE:: 27231758.10778498
Root mean squared error: 5218.405705556534
R2 score::0.7750443293116569
```

Cases:

Try to predict the rent of the below houses :

In [95]:

```
data3 = pd.DataFrame()
print("Please select the features from the list with their index numbers (Leave Empt
print("\n")

dict1 = {1: 'Minimum Budget Rooms',2: 'Semi Furnished Single Room',3:'Semi Furnished
                 4:'Fully Furnished Single Room',5:'Super Furnished Single Room',6:'
                 7:'Fully Furnished Flat',8: 'Super Furnished Flat',9:'Fully Furnish
print(dict1)
ip = int(input("Please select any one type of buidling type: "))

data = pd.read_csv(r"C:\Users\stebi\Downloads\HousePrices - Lab3.csv")
le = preprocessing.LabelEncoder()
le.fit(data['BuildingType'])
data3['BuildingType'] = [le.transform([dict1[ip]])[0]]




print("\n")
dict2={1:'Portofino', 2:'School Street', 3:'Clubview Road', 4:'Starter Homes'}
print(dict2)
ip = int(input("Please select any one type of location: "))
data = pd.read_csv(r"C:\Users\stebi\Downloads\HousePrices - Lab3.csv")
data["Location"] = data["Location"].replace(to_replace =["Portofino A","Portofino B"
```

```
le = preprocessing.LabelEncoder()
le.fit(data['Location'])
data3['Location'] = [le.transform([dict2[ip]])[0]]

print("\n")
dict3={1: '1 BHK', 2: '2 BHK', 3: '1 RK', 4: '3 BHK', 5: '4 BHK',6: '5 BHK', 7:'6 BH
               10:'9 BHK'}
print(dict3)
ip = int(input("Please select any one type of size: "))
data = pd.read_csv(r"C:\Users\stebi\Downloads\HousePrices - Lab3.csv")
le = preprocessing.LabelEncoder()
le.fit(data['Size'])
data3['Size'] = [le.transform([dict3[ip]])[0]]




print("\n")
ip = int(input("select square feet area available"))
data3["AreaSqFt"] = ip




print("\n")
ip = int(input("Please select number of baths you would like to have"))
data3["NoOfBath"] = ip




print("\n")
ip = int(input("How many people wish to stay in the property"))
data3["NoOfPeople"] = ip




print("\n")
ip = int(input("Please select number of balcony's you would like to have"))
data3["NoOfBalcony"] = ip

y_prediction =  model.predict(data3)
print("You selected following features with values: \n",data3.head())
print("\033[1mPredicted Rent is:\033[0m" ,y_prediction)
```

```
Please select the features from the list with their index numbers (Leave Empty For R
andom)


{1: 'Minimum Budget Rooms', 2: 'Semi Furnished Single Room', 3: 'Semi Furnished Fla
t', 4: 'Fully Furnished Single Room', 5: 'Super Furnished Single Room', 6: 'Semi Fur
nished Villa', 7: 'Fully Furnished Flat', 8: 'Super Furnished Flat', 9: 'Fully Furni
shed Villa', 10: 'Super Furnished Villa'}
Please select any one type of buidling type: 1


{1: 'Portofino', 2: 'School Street', 3: 'Clubview Road', 4: 'Starter Homes'}
Please select any one type of location: 1


{1: '1 BHK', 2: '2 BHK', 3: '1 RK', 4: '3 BHK', 5: '4 BHK', 6: '5 BHK', 7: '6 BHK',
8: '8 BHK', 9: '7 BHK', 10: '9 BHK'}
Please select any one type of size: 2
```

```
select square feet area available5000


Please select number of baths you would like to have1


How many people wish to stay in the property2


Please select number of balcony's you would like to have1
You selected following features with values:
    BuildingType  Location  Size  AreaSqFt  NoOfBath  NoOfPeople  NoOfBalcony
0             3         1     2      5000         1           2            1
Predicted Rent is: [8937.61753369]
```

The predicted rent is 8937 for the given details

Conclusion:

through this section the details about the linear regression is being studied and applied in a real world problem.

In [ ]:

```

```