Exercise 4 : Linear Regression

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Importing the necessary libraries:

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sb
import matplotlib.pyplot as plt
sb.set()
```

Read the data file "train.csv" using pd.read_csv()

In [2]:

```
houseData = pd.read_csv('train.csv')
houseData.head()
```

Out[2]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Ut
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	/
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	/
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	/
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	/
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	/

5 rows × 81 columns

In [3]:

```
print("Data type : ", type(houseData))
print("Data dims : ", houseData.shape)
```

```
Data type :  <class 'pandas.core.frame.DataFrame'>
Data dims :  (1460, 81)
```

In [4]:

```
print(houseData.dtypes)
```

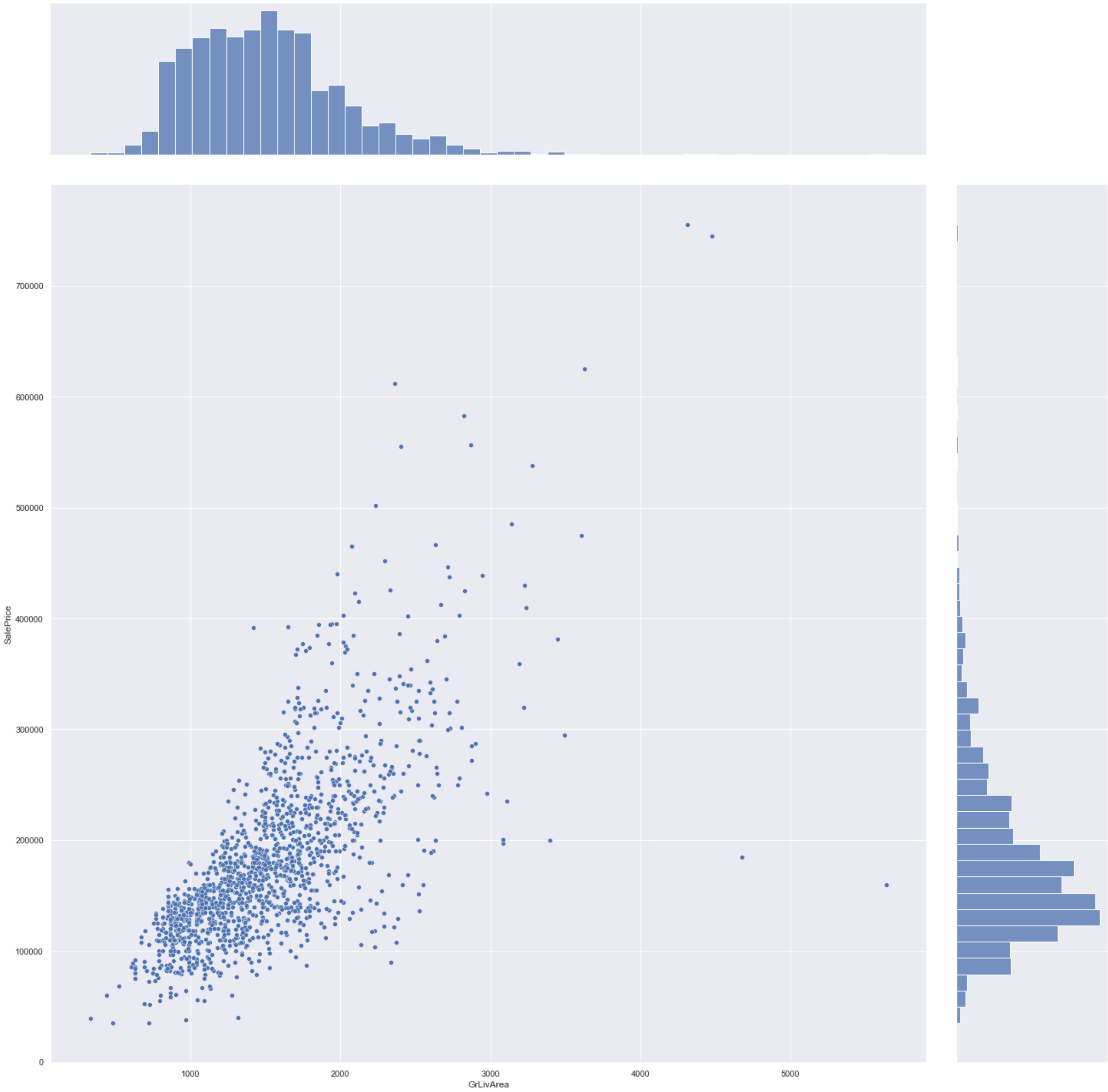
```
Id                 int64
MSSubClass         int64
MSZoning          object
LotFrontage      float64
LotArea            int64
                  ...
MoSold             int64
YrSold             int64
SaleType          object
SaleCondition     object
SalePrice          int64
Length: 81, dtype: object
```

Problem 1 : Predicting SalePrice using GrLivArea

a) Plot SalePrice against GrLivArea using any appropriate bivariate plot to note the strong linear relationship

In [5]:

```
sb.jointplot(x = "GrLivArea", y = "SalePrice", data = houseData, height = 20)
plt.show()
```



Jointplot is a good plot to see the relationship between 2 variables. Just by looking at the plot above, we can see that there is relatively strong positive linear relation between SalePrice and GrLivArea.

b) Print the correlation coefficient between these two variables to get a numerical evidence of the relationship.

In [6]:

```
tempDF = houseData[['SalePrice', 'GrLivArea']]
display(tempDF.corr())
```

	SalePrice	GrLivArea
SalePrice	1.000000	0.708624
GrLivArea	0.708624	1.000000

Correlation between SalePrice and GrLivArea is 0.71. A positive correlation. This strengthens my observation that there is a relatively strong positive correlation between SalePrice and GrLivArea.

c) Import Linear Regression model from Scikit-Learn : from sklearn.linear_model import LinearRegression

In [7]:

```
from sklearn.linear_model import LinearRegression
```

d) Partition the dataset houseData into two “random” portions : Train Data (1100 rows) and Test Data (360 rows).

In [8]:

```
train = houseData.sample(n=1100, random_state = 250)
test = houseData.drop(train.index)
```

Creating a train and test dataframes.

.sample() is used to get the "random" rows, and random_state is to ensure that whoever runs this code at any given time will get the same random data.

e) Training : Fit a Linear Regression model on the Train Dataset to predict or estimate SalePrice using GrLivArea.

In [9]:

```
SalePrice_train = pd.DataFrame(train["SalePrice"])
GrLivArea_train = pd.DataFrame(train["GrLivArea"])
linreg = LinearRegression()
linreg.fit(GrLivArea_train, SalePrice_train)
```

Out[9]:

```
LinearRegression()
```

GrLivArea_train will be used as the predictor, and SalePrice_train as the response to train the regression model.

f) Print the coefficients of the Linear Regression model you just fit, and plot the regression line on a scatterplot.

In [10]:

```
# Formula for the Regression Line
regline_x = GrLivArea_train
regline_y = linreg.intercept_ + linreg.coef_ * GrLivArea_train

# Plot the Linear Regression Line
f = plt.figure(figsize=(16, 8))
plt.scatter(GrLivArea_train, SalePrice_train)
plt.xlabel("GrLivArea Train")
plt.ylabel("SalePrice Train")
plt.plot(regline_x, regline_y, 'r-', linewidth = 3)
plt.show()

print('Intercept \t: b = ', linreg.intercept_)
print('Coefficients \t: a = ', linreg.coef_)
```


```
Intercept       : b =  [30808.2316046]
Coefficients    : a =  [[97.71713212]]
```

g) Print Explained Variance (R^2) and Mean Squared Error (MSE) on Train Data to check Goodness of Fit of model.

In [11]:

```
print("Explained Variance (R^2) \t:", linreg.score(GrLivArea_train, SalePrice_train))

def mean_sq_err(actual, predicted):
    return np.mean(np.square(np.array(actual) - np.array(predicted)))

SalePrice_pred = linreg.predict(GrLivArea_train)
mse = mean_sq_err(SalePrice_train, SalePrice_pred)
print("Mean Squared Error (MSE) \t:", mse)

R2, MSE = {}, {}
R2["GrLivArea"] = linreg.score(GrLivArea_train, SalePrice_train)
MSE["GrLivArea"] = mean_sq_err(SalePrice_train, SalePrice_pred)
```

```
Explained Variance (R^2)        : 0.47199536958556365
Mean Squared Error (MSE)        : 2993645717.7330327
```

h) Predict SalePrice in case of Test Data using the Linear Regression model and the predictor variable GrLivArea.

In [12]:

```
SalePrice_test = pd.DataFrame(test["SalePrice"])
GrLivArea_test = pd.DataFrame(test["GrLivArea"])
```

In [13]:

```
SalePrice_predtest = linreg.predict(GrLivArea_test)

print(SalePrice_predtest[0])
```

```
[198588.54745872]
```

i) Plot the predictions on a Scatterplot of GrLivArea and SalePrice in the Test Data to visualize model accuracy.

In [14]:

```
f = plt.figure(figsize=(16, 8))
plt.scatter(GrLivArea_test, SalePrice_test)
plt.xlabel("GrLivArea Test")
plt.ylabel("SalePrice Test")
plt.scatter(GrLivArea_test, SalePrice_predtest, color = "r")
plt.show()
```

j) Print the Mean Squared Error (MSE) on Test Data to check Goodness of Fit of model, compared to the Training.

In [15]:

```
print("Test Data Explained Variance (R^2) \t:", linreg.score(GrLivArea_test, SalePrice_test

mse = mean_sq_err(SalePrice_test, SalePrice_predtest)
print("Test Data Mean Squared Error (MSE) \t:", mse)
#print("Test Data Root Mean Squared Error (RMSE) \t:", np.sqrt(mse))
```

```
Test Data Explained Variance (R^2)      : 0.5481886521383491
Test Data Mean Squared Error (MSE)      : 3702369208.109554
```

Save data for later

In [16]:

```
R2_t, MSE_t = {}, {}
R2_t['GrLivArea'] = linreg.score(GrLivArea_test, SalePrice_test)
MSE_t['GrLivArea'] = mean_sq_err(SalePrice_test, SalePrice_predtest)
```

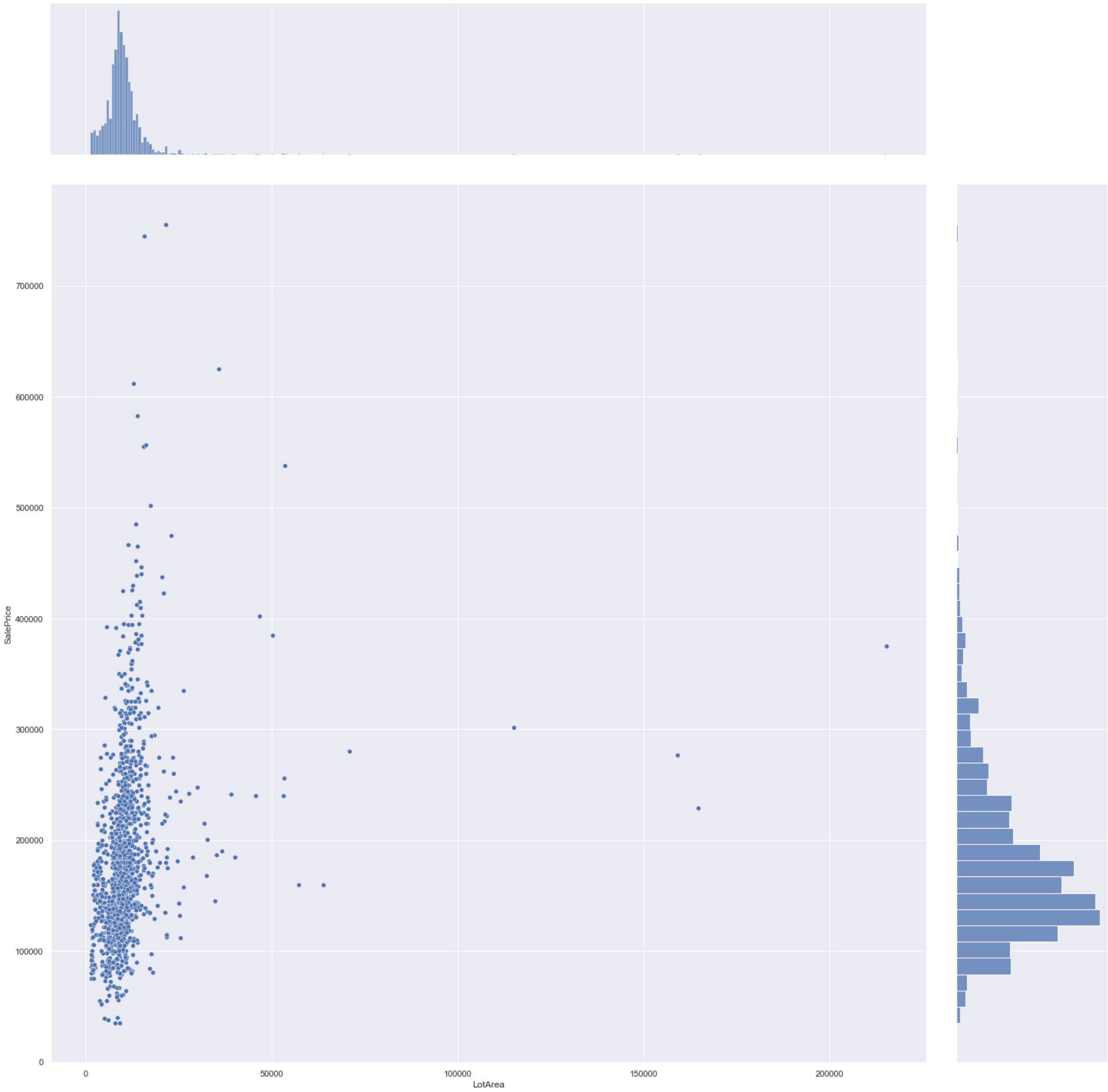
Problem 2 : Predicting SalePrice using Other Variables

Predicting SalePrice with LotArea:

a) Plot SalePrice against LotArea using any appropriate bivariate plot to note the strong linear relationship.

In [17]:

```
sb.jointplot(x = "LotArea", y = "SalePrice", data = houseData, height = 20)
plt.show()
```



We can see, from observation, that there's a relatively weak positive linear relationship between SalePrice and LotArea.

b) Print the correlation coefficient between these two variables to get a numerical evidence of the relationship.

In [18]:

```
tempDF = houseData[['SalePrice', 'LotArea']]
display(tempDF.corr())
```

	SalePrice	LotArea
SalePrice	1.000000	0.263843
LotArea	0.263843	1.000000

There is about a 0.26 correlation coefficient of SalePrice and LotArea reinforcing our initial observation for a weak positive linear relationship between these two variables.

d) Partition the dataset houseData into two “random” portions : Train Data (1100 rows) and Test Data (360 rows).

In [19]:

```
LotArea_train = pd.DataFrame(train["LotArea"])
LotArea_test = pd.DataFrame(test["LotArea"])
```

e) Training : Fit a Linear Regression model on the Train Dataset to predict or estimate SalePrice using LotArea.

In [20]:

```
SalePrice_train = pd.DataFrame(train["SalePrice"])
LotArea_train = pd.DataFrame(train["LotArea"])
linreg = LinearRegression()
linreg.fit(LotArea_train, SalePrice_train)
```

Out[20]:

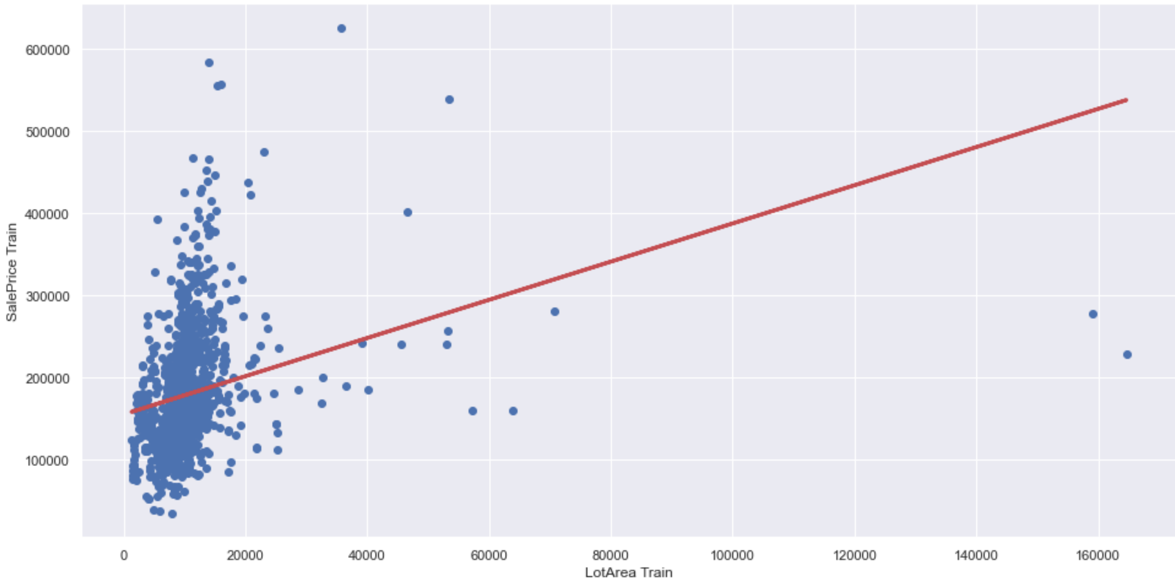
```
LinearRegression()
```

We will use LotArea_train as the predictor and SalePrice_train as the response to train our linear regression model.

f) Print the coefficients of the Linear Regression model you just fit, and plot the regression line on a scatterplot

In [21]:

```
# Formula for the Regression line
regline_x = LotArea_train
regline_y = linreg.intercept_ + linreg.coef_ * LotArea_train

# Plot the Linear Regression line
f = plt.figure(figsize=(16, 8))
plt.scatter(LotArea_train, SalePrice_train)
plt.xlabel("LotArea Train")
plt.ylabel("SalePrice Train")
plt.plot(regline_x, regline_y, 'r-', linewidth = 3)
plt.show()

print('Intercept \t: b = ', linreg.intercept_)
print('Coefficients \t: a = ', linreg.coef_)
```




```
Intercept       : b =  [154769.68878268]
Coefficients    : a =  [[2.3242535]]
```

g) Print Explained Variance (R^2) and Mean Squared Error (MSE) on Train Data to check Goodness of Fit of model.

In [22]:

```
print("Explained Variance (R^2) \t:", linreg.score(LotArea_train, SalePrice_train))

SalePrice_pred = linreg.predict(LotArea_train)
mse = mean_sq_err(SalePrice_train, SalePrice_pred)
print("Mean Squared Error (MSE) \t:", mse)

R2["LotArea"] = linreg.score(LotArea_train, SalePrice_train)
MSE["LotArea"] = mean_sq_err(SalePrice_train, SalePrice_pred)
```

```
Explained Variance (R^2)        : 0.07205342244617874
Mean Squared Error (MSE)        : 5261210107.188992
```

h) Predict SalePrice in case of Test Data using the Linear Regression model and the predictor variable LotArea.

In [23]:

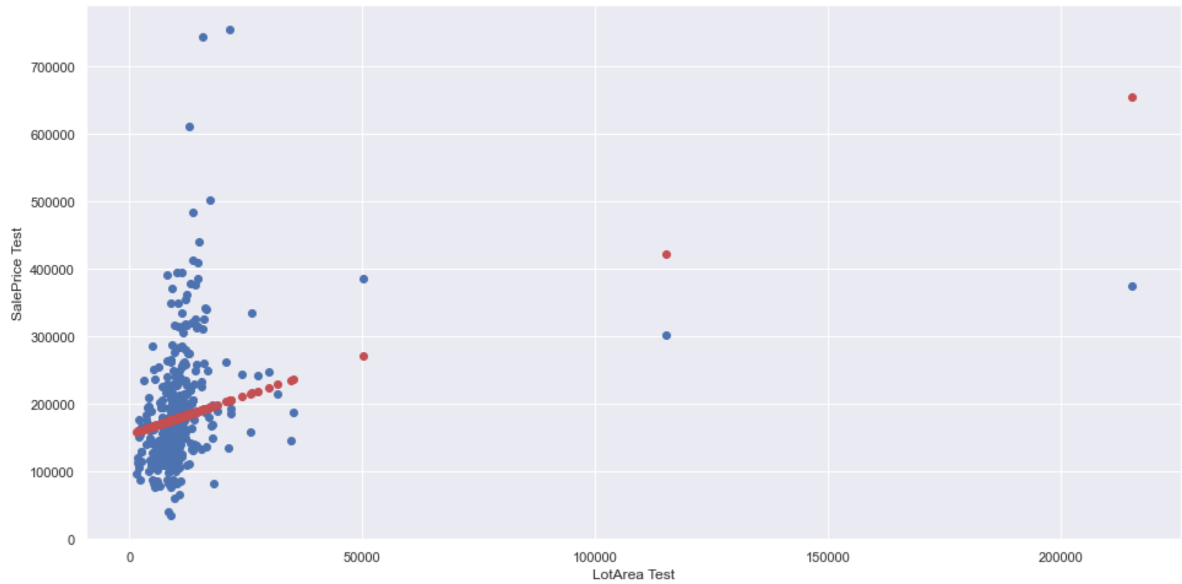
```
SalePrice_predtest = linreg.predict(LotArea_test)

print(SalePrice_predtest[0])
```

```
[176966.30969067]
```

i) Plot the predictions on a Scatterplot of LotArea and SalePrice in the Test Data to visualize model accuracy.

In [24]:

```
f = plt.figure(figsize=(16, 8))
plt.scatter(LotArea_test, SalePrice_test)
plt.xlabel("LotArea Test")
plt.ylabel("SalePrice Test")
plt.scatter(LotArea_test, SalePrice_predtest, color = "r")
plt.show()
```



j) Print the Mean Squared Error (MSE) on Test Data to check Goodness of Fit of model, compared to the Training.

In [25]:

```
print("Test Data Explained Variance (R^2) \t:", linreg.score(LotArea_test, SalePrice_test))

mse = mean_sq_err(SalePrice_test, SalePrice_predtest)
print("Test Data Mean Squared Error (MSE) \t:", mse)
#print("Test Data Root Mean Squared Error (RMSE) \t:", np.sqrt(mse))
```

```
Test Data Explained Variance (R^2)      : 0.053851964034761446
Test Data Mean Squared Error (MSE)      : 7753212422.065327
```

Save data for later.

In [26]:

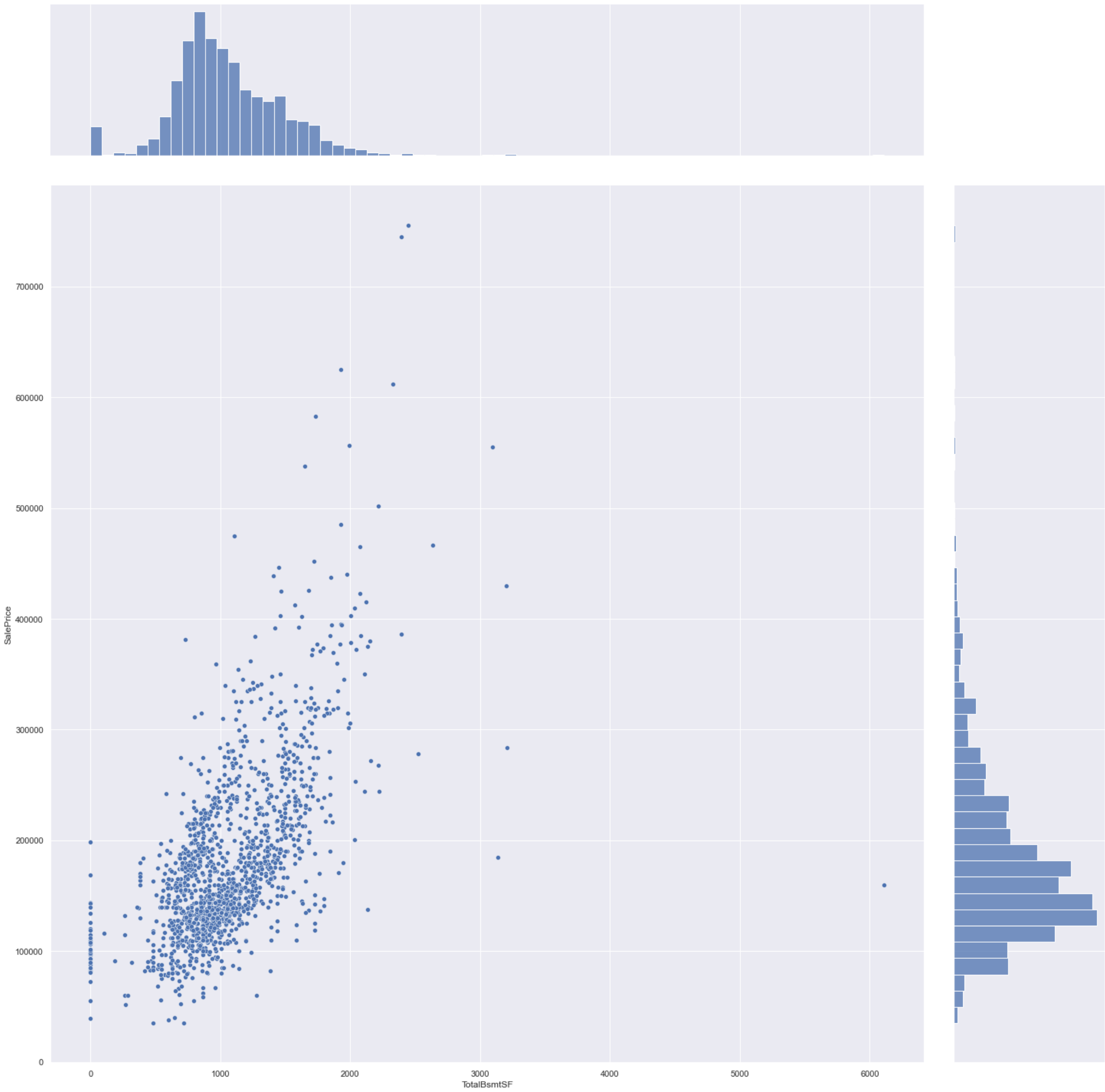
```
R2_t['LotArea'] = linreg.score(LotArea_test, SalePrice_test)
MSE_t['LotArea'] = mean_sq_err(SalePrice_test, SalePrice_predtest)
```

Predicting SalePrice with TotalBsmtSF:

a) Plot SalePrice against TotalBsmtSF using any appropriate bivariate plot to note the strong linear relationship.

In [27]:

```
sb.jointplot(x = "TotalBsmtSF", y = "SalePrice", data = houseData, height = 20)
plt.show()
```



From observation, we can see that there is a relatively strong linear relation between TotalBsmtSF and SalePrice.

b) Print the correlation coefficient between these two variables to get a numerical evidence of the relationship.

In [28]:

```
tempDF = houseData[['SalePrice', 'TotalBsmtSF']]
display(tempDF.corr())
```

	SalePrice	TotalBsmtSF
SalePrice	1.000000	0.613581
TotalBsmtSF	0.613581	1.000000

There is about a 0.61 correlation coefficient of SalePrice and LotArea reinforcing our initial observation of a strong positive linear relationship between these two variables.

d) Partition the dataset houseData into two “random” portions : Train Data (1100 rows) and Test Data (360 rows).

In [29]:

```
TotalBsmtSF_train = pd.DataFrame(train["TotalBsmtSF"])
TotalBsmtSF_test = pd.DataFrame(test["TotalBsmtSF"])
```

e) Training : Fit a Linear Regression model on the Train Dataset to predict or estimate SalePrice using TotalBsmtSF.

In [30]:

```
SalePrice_train = pd.DataFrame(train["SalePrice"])
TotalBsmtSF_train = pd.DataFrame(train["TotalBsmtSF"])
linreg = LinearRegression()
linreg.fit(TotalBsmtSF_train, SalePrice_train)
```

Out[30]:

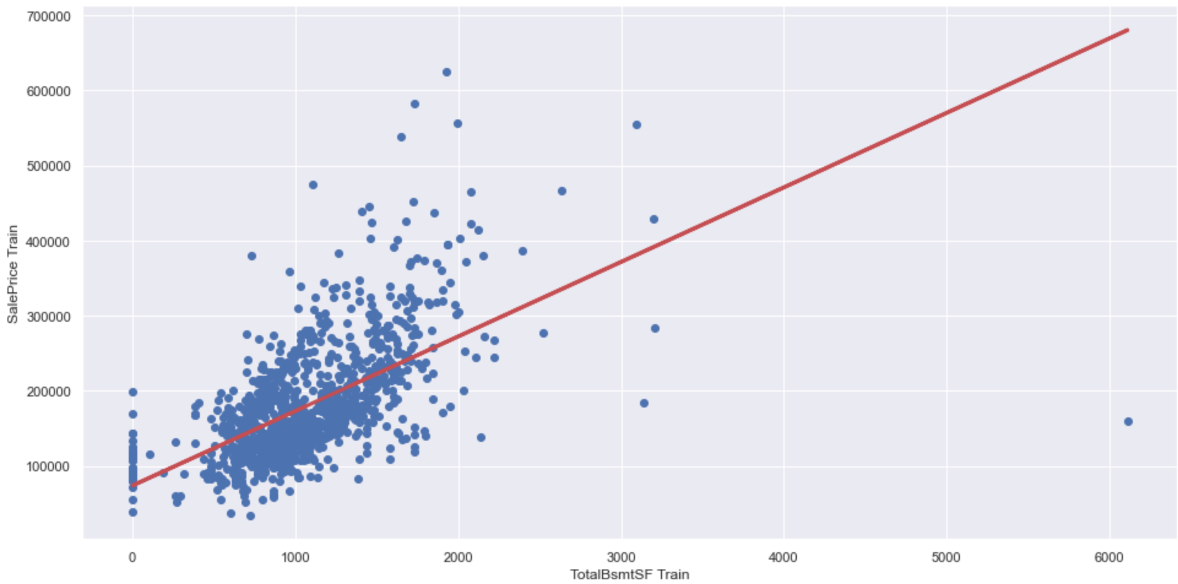
```
LinearRegression()
```

We will use TotalBsmtSF_train as the predictor and SalePrice_train as the response to train our linear regression model.

f) Print the coefficients of the Linear Regression model you just fit, and plot the regression line on a scatterplot

In [31]:

```
# Formula for the Regression Line
regline_x = TotalBsmtSF_train
regline_y = linreg.intercept_ + linreg.coef_ * TotalBsmtSF_train

# Plot the Linear Regression line
f = plt.figure(figsize=(16, 8))
plt.scatter(TotalBsmtSF_train, SalePrice_train)
plt.xlabel("TotalBsmtSF Train")
plt.ylabel("SalePrice Train")
plt.plot(regline_x, regline_y, 'r-', linewidth = 3)
plt.show()

print('Intercept \t: b = ', linreg.intercept_)
print('Coefficients \t: a = ', linreg.coef_)
```




```
Intercept       : b =  [73886.93829572]
Coefficients    : a =  [[99.25946365]]
```

g) Print Explained Variance (R^2) and Mean Squared Error (MSE) on Train Data to check Goodness of Fit of model.

In [32]:

```
print("Explained Variance (R^2) \t:", linreg.score(TotalBsmtSF_train, SalePrice_train))

SalePrice_pred = linreg.predict(TotalBsmtSF_train)
mse = mean_sq_err(SalePrice_train, SalePrice_pred)
print("Mean Squared Error (MSE) \t:", mse)

R2["TotalBsmtSF"] = linreg.score(TotalBsmtSF_train, SalePrice_train)
MSE["TotalBsmtSF"] = mean_sq_err(SalePrice_train, SalePrice_pred)
```

```
Explained Variance (R^2)        : 0.34554023089884334
Mean Squared Error (MSE)        : 3710612696.0674834
```

h) Predict SalePrice in case of Test Data using the Linear Regression model and the predictor variable TotalBsmtSF.

In [33]:

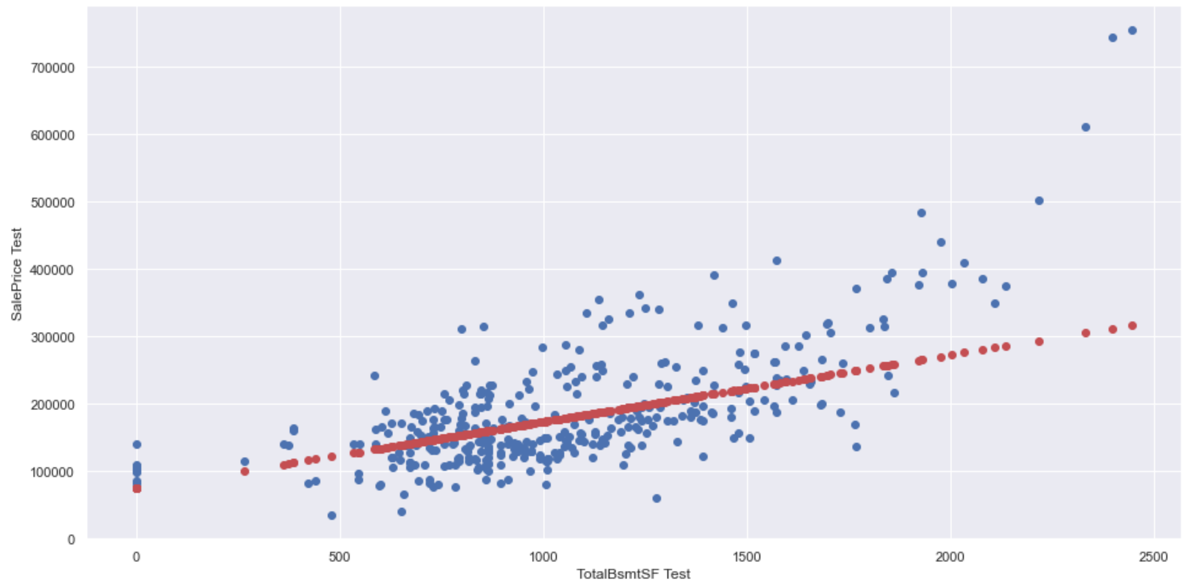
```
SalePrice_predtest = linreg.predict(TotalBsmtSF_test)

print(SalePrice_predtest[0])
```

```
[148927.09281502]
```

i) Plot the predictions on a Scatterplot of TotalBsmtSF and SalePrice in the Test Data to visualize model accuracy.

In [34]:

```
f = plt.figure(figsize=(16, 8))
plt.scatter(TotalBsmtSF_test, SalePrice_test)
plt.xlabel("TotalBsmtSF Test")
plt.ylabel("SalePrice Test")
plt.scatter(TotalBsmtSF_test, SalePrice_predtest, color = "r")
plt.show()
```



j) Print the Mean Squared Error (MSE) on Test Data to check Goodness of Fit of model, compared to the Training.

In [35]:

```
print("Test Data Explained Variance (R^2) \t:", linreg.score(TotalBsmtSF_test, SalePrice_te

mse = mean_sq_err(SalePrice_test, SalePrice_predtest)
print("Test Data Mean Squared Error (MSE) \t:", mse)

R2_t['TotalBsmtSF'] = linreg.score(TotalBsmtSF_test, SalePrice_test)
MSE_t['TotalBsmtSF'] = mean_sq_err(SalePrice_test, SalePrice_predtest)
```

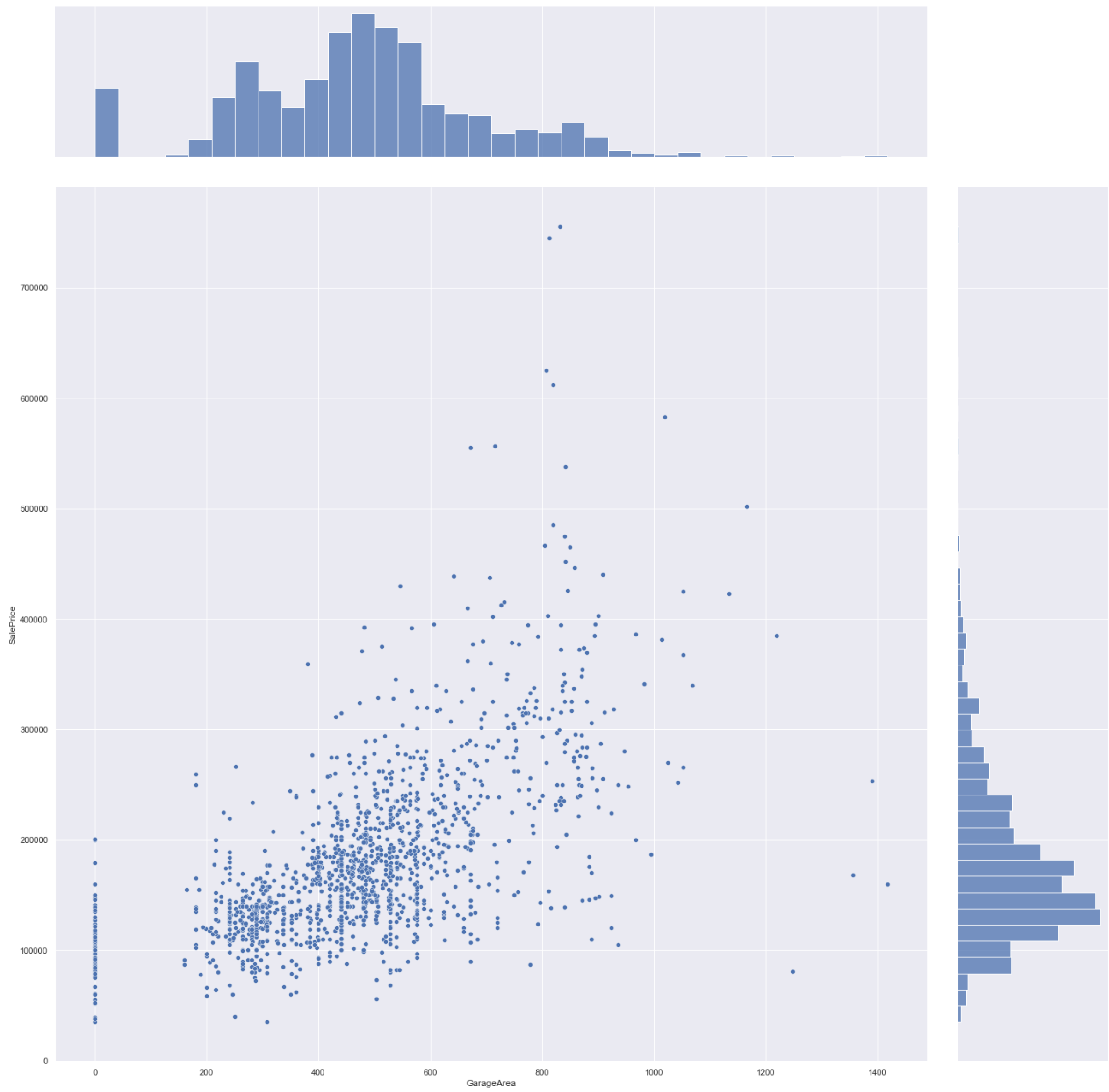
```
Test Data Explained Variance (R^2)      : 0.4219202915483147
Test Data Mean Squared Error (MSE)      : 4737075601.429644
```

Predicting SalePrice with GarageArea:

a) Plot SalePrice against GarageArea using any appropriate bivariate plot to note the strong linear relationship.

In [36]:

```
sb.jointplot(x = "GarageArea", y = "SalePrice", data = houseData, height = 20)
plt.show()
```



Based on observation, we can see that there is a relatively strong linear relationship between GarageArea and SalePrice.

b) Print the correlation coefficient between these two variables to get a numerical evidence of the relationship.

In [37]:

```
tempDF = houseData[['SalePrice', 'GarageArea']]
display(tempDF.corr())
```

	SalePrice	GarageArea
SalePrice	1.000000	0.623431
GarageArea	0.623431	1.000000

There is about a 0.62 correlation coefficient of SalePrice and LotArea reinforcing our initial observation of a strong positive linear relationship between these two variables.

d) Partition the dataset houseData into two “random” portions : Train Data (1100 rows) and Test Data (360 rows).

In [38]:

```
GarageArea_train = pd.DataFrame(train["GarageArea"])
GarageArea_test = pd.DataFrame(test["GarageArea"])
```

e) Training : Fit a Linear Regression model on the Train Dataset to predict or estimate SalePrice using GarageArea.

In [39]:

```
linreg = LinearRegression()
linreg.fit(GarageArea_train, SalePrice_train)
```

Out[39]:

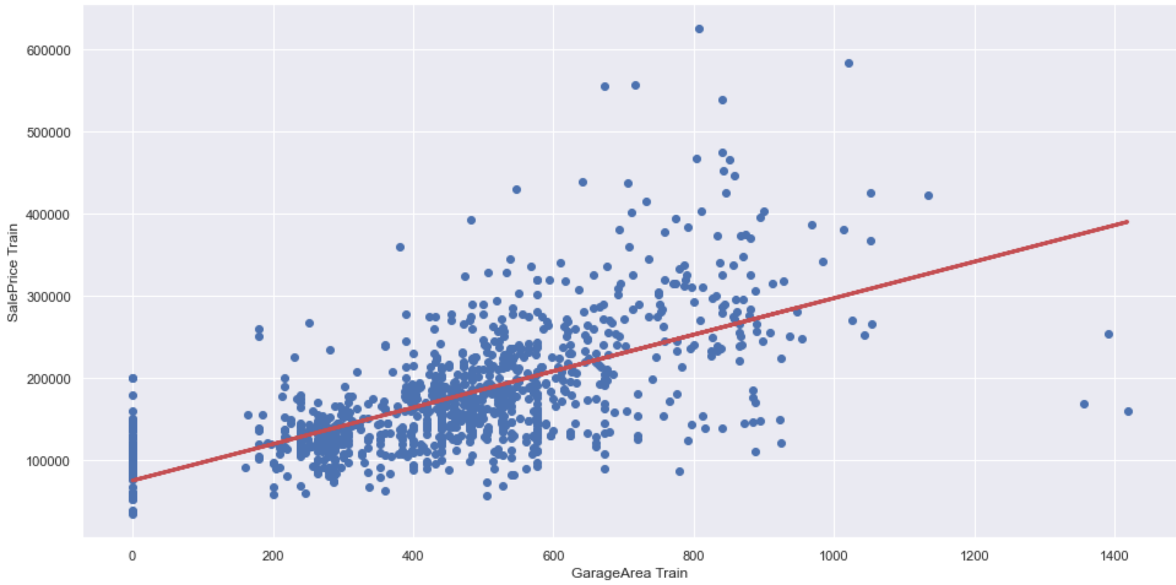
```
LinearRegression()
```

We will use GarageArea_train as the predictor and SalePrice_train as the response to train our linear regression model.

f) Print the coefficients of the Linear Regression model you just fit, and plot the regression line on a scatterplot

In [40]:

```
# Formula for the Regression Line
regline_x = GarageArea_train
regline_y = linreg.intercept_ + linreg.coef_ * GarageArea_train

# Plot the Linear Regression Line
f = plt.figure(figsize=(16, 8))
plt.scatter(GarageArea_train, SalePrice_train)
plt.xlabel("GarageArea Train")
plt.ylabel("SalePrice Train")
plt.plot(regline_x, regline_y, 'r-', linewidth = 3)
plt.show()

print('Intercept \t: b = ', linreg.intercept_)
print('Coefficients \t: a = ', linreg.coef_)
```




```
Intercept       : b =  [74834.00366279]
Coefficients    : a =  [[222.09446191]]
```

g) Print Explained Variance (R^2) and Mean Squared Error (MSE) on Train Data to check Goodness of Fit of model.

In [41]:

```
print("Explained Variance (R^2) \t:", linreg.score(GarageArea_train, SalePrice_train))

SalePrice_pred = linreg.predict(GarageArea_train)
mse = mean_sq_err(SalePrice_train, SalePrice_pred)
print("Mean Squared Error (MSE) \t:", mse)

R2["GarageArea"] = linreg.score(GarageArea_train, SalePrice_train)
MSE["GarageArea"] = mean_sq_err(SalePrice_train, SalePrice_pred)
```

```
Explained Variance (R^2)        : 0.39750984741627826
Mean Squared Error (MSE)        : 3415958802.942471
```

h) Predict SalePrice in case of Test Data using the Linear Regression model and the predictor variable GarageArea.

In [42]:

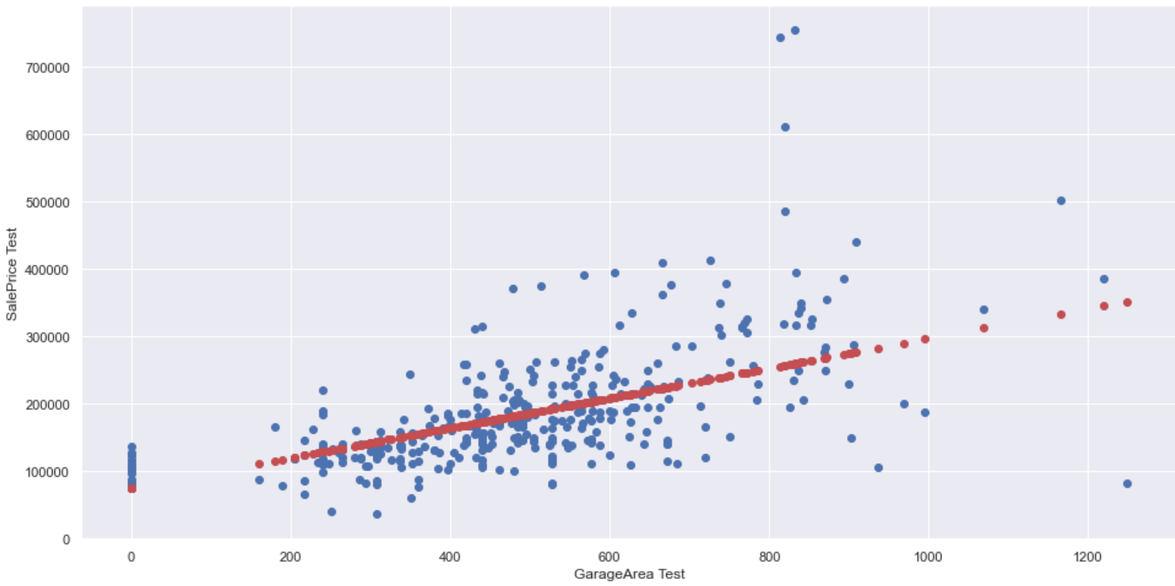
```
SalePrice_predtest = linreg.predict(GarageArea_test)

print(SalePrice_predtest[0])
```

```
[217418.6482079]
```

i) Plot the predictions on a Scatterplot of GarageArea and SalePrice in the Test Data to visualize model accuracy.

In [43]:

```
f = plt.figure(figsize=(16, 8))
plt.scatter(GarageArea_test, SalePrice_test)
plt.xlabel("GarageArea Test")
plt.ylabel("SalePrice Test")
plt.scatter(GarageArea_test, SalePrice_predtest, color = "r")
plt.show()
```



j) Print the Mean Squared Error (MSE) on Test Data to check Goodness of Fit of model, compared to the Training.

In [44]:

```
print("Test Data Explained Variance (R^2) \t:", linreg.score(GarageArea_test, SalePrice_tes

mse = mean_sq_err(SalePrice_test, SalePrice_predtest)
print("Test Data Mean Squared Error (MSE) \t:", mse)

R2_t['GarageArea'] = linreg.score(GarageArea_test, SalePrice_test)
MSE_t['GarageArea'] = mean_sq_err(SalePrice_test, SalePrice_predtest)
```

```
Test Data Explained Variance (R^2)      : 0.3629829129565094
Test Data Mean Squared Error (MSE)      : 5220038096.147267
```

Problem 3 : Best Uni-Variate Model to Predict SalePrice

We will determine the best Uni-Variate Model based on the Explained Varience (R^2) and Mean Square Error (MSE). We will use the values thay we have found from Train and Test Data for the comparison.

In [45]:

```
print("Train Data")
print("Explained Varience (R^2)")
print("GrLivArea \t:", R2["GrLivArea"])
print("LotArea \t:", R2["LotArea"])
print("TotalBsmtSF \t:", R2["TotalBsmtSF"])
print("GarageArea \t:", R2["GarageArea"])
print("")
print("Mean Squared Error (MSE)")
print("GrLivArea \t:", MSE["GrLivArea"])
print("LotArea \t:", MSE["LotArea"])
print("TotalBsmtSF \t:", MSE["TotalBsmtSF"])
print("GarageArea \t:", MSE["GarageArea"])
print("")
print("Test Data")
print("Explained Varience (R^2)")
print("GrLivArea \t:", R2_t["GrLivArea"])
print("LotArea \t:", R2_t["LotArea"])
print("TotalBsmtSF \t:", R2_t["TotalBsmtSF"])
print("GarageArea \t:", R2_t["GarageArea"])
print("")
print("Mean Squared Error (MSE)")
print("GrLivArea \t:", MSE_t["GrLivArea"])
print("LotArea \t:", MSE_t["LotArea"])
print("TotalBsmtSF \t:", MSE_t["TotalBsmtSF"])
print("GarageArea \t:", MSE_t["GarageArea"])
```

```
Train Data
Explained Varience (R^2)
GrLivArea       : 0.47199536958556365
LotArea         : 0.07205342244617874
TotalBsmtSF     : 0.34554023089884334
GarageArea      : 0.39750984741627826

Mean Squared Error (MSE)
GrLivArea       : 2993645717.7330327
LotArea         : 5261210107.188992
TotalBsmtSF     : 3710612696.0674834
GarageArea      : 3415958802.942471

Test Data
Explained Varience (R^2)
GrLivArea       : 0.5481886521383491
LotArea         : 0.053851964034761446
TotalBsmtSF     : 0.4219202915483147
GarageArea      : 0.3629829129565094

Mean Squared Error (MSE)
GrLivArea       : 3702369208.109554
LotArea         : 7753212422.065327
TotalBsmtSF     : 4737075601.429644
GarageArea      : 5220038096.147267
```

Based on the values of R^2 and MSE for each of the variables against SalePrice, I determined that the best Uni-Variate model to predict SalePrice would be GrLivArea as it has the highest R^2 value, as well as the lowest MSE value for both Train and Test data.

both Train and Test data.
Hence I conclude that, GrLivArea is the best variable in the predicition of SalePrice

In [ ]:

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