REGRESSION ANALYTICS

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Importing numpy, pandas and matplot modules:

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn import linear_model
```

Reading the houseprice csv file:

In [2]:
```
df=pd.read_csv("/Users/devmarwah/Downloads/House_Prices.csv")
# Printing head of our data to get a quick glance at it:
df.head()
```

Out[2]:

	LotArea	OverallQual	YearBuilt	YearRemodAdd	BsmtFinSF1	FullBath	HalfBath	BedroomAbvGr	TotRmsAbvGrd	Fireplaces	GarageArea	YrSold	SalePrice
0	8450	7	2003	2003	706	2	1	3	8	0	548	2008	208500
1	9600	6	1976	1976	978	2	0	3	6	1	460	2007	181500
2	11250	7	2001	2002	486	2	1	3	6	1	608	2008	223500
3	9550	7	1915	1970	216	1	0	3	7	1	642	2006	140000
4	14260	8	2000	2000	655	2	1	4	9	1	836	2008	250000

Reading prediction file now:

In [3]:
```
#Using read_excel command to read excel file:
df_test=pd.read_excel("/Users/devmarwah/Downloads/BA-Predict-2.xlsx")
df_test.head()
```

Out[3]:

	LotArea	OverallQual	YearBuilt	YearRemodAdd	BsmtFinSF1	FullBath	HalfBath	BedroomAbvGr	TotRmsAbvGrd	Fireplaces	GarageArea	YrSold	SalePrice
0	7340	4	1971	1971	322	1	0	2	4	0	684	2007	110000
1	8712	5	1957	2000	860	1	0	2	5	0	756	2009	153000
2	7875	7	2003	2003	0	2	1	3	8	1	393	2006	180000
3	14859	7	2006	2006	0	2	0	3	7	1	690	2006	240000
4	6173	5	1967	1967	599	1	0	3	6	0	288	2007	125500

DATA PREPRATION:

Checking number of rows and columns in our data:

In [4]:
```
df.shape
```

Out[4]:
```
(900, 13)
```

Having a look at structure of our data:

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 900 entries, 0 to 899
Data columns (total 13 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   LotArea       900 non-null    int64
 1   OverallQual   900 non-null    int64
 2   YearBuilt     900 non-null    int64
 3   YearRemodAdd  900 non-null    int64
 4   BsmtFinSF1    900 non-null    int64
 5   FullBath      900 non-null    int64
 6   HalfBath      900 non-null    int64
 7   BedroomAbvGr  900 non-null    int64
 8   TotRmsAbvGrd  900 non-null    int64
 9   Fireplaces    900 non-null    int64
 10  GarageArea    900 non-null    int64
 11  YrSold        900 non-null    int64
 12  SalePrice     900 non-null    int64
dtypes: int64(13)
memory usage: 91.5 KB
```

Having a look at basic statistics of our data:

In [6]:
```
df.describe()
```

Out[6]:

	LotArea	OverallQual	YearBuilt	YearRemodAdd	BsmtFinSF1	FullBath	HalfBath	BedroomAbvGr	TotRmsAbvGrd	Fireplaces	GarageArea	YrSold	SalePrice
count	900.000000	900.000000	900.000000	900.000000	900.000000	900.000000	900.000000	900.000000	900.000000	900.000000	900.000000	900.000000	900.000000
mean	10794.603333	6.135556	1971.445556	1985.333333	446.532222	1.564444	0.385556	2.843333	6.482222	0.627778	472.608889	2007.843333	183107.923333
std	11942.213564	1.378954	30.008422	20.336819	446.515059	0.555348	0.498287	0.817570	1.612905	0.658905	208.850262	1.321050	81908.182659
min	1491.000000	1.000000	1880.000000	1950.000000	0.000000	0.000000	0.000000	0.000000	2.000000	0.000000	0.000000	2006.000000	34900.000000
25%	7585.250000	5.000000	1954.000000	1967.750000	0.000000	1.000000	0.000000	2.000000	5.000000	0.000000	336.000000	2007.000000	130000.000000
50%	9441.500000	6.000000	1973.000000	1994.000000	384.000000	2.000000	0.000000	3.000000	6.000000	1.000000	480.000000	2008.000000	163000.000000
75%	11618.250000	7.000000	2000.000000	2004.000000	728.750000	2.000000	1.000000	3.000000	7.000000	1.000000	576.000000	2009.000000	216877.750000
max	215245.000000	10.000000	2010.000000	2010.000000	2260.000000	3.000000	2.000000	8.000000	14.000000	3.000000	1390.000000	2010.000000	755000.000000

Looking for missing values in our data:

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
LotArea         0
OverallQual     0
YearBuilt       0
YearRemodAdd    0
BsmtFinSF1      0
FullBath        0
HalfBath        0
BedroomAbvGr    0
TotRmsAbvGrd    0
Fireplaces      0
GarageArea      0
YrSold          0
SalePrice       0
dtype: int64
```

Hecnce, our data does not have any missing values. Therefore, there is no need to omit missing values.

DATA EXPLORATION

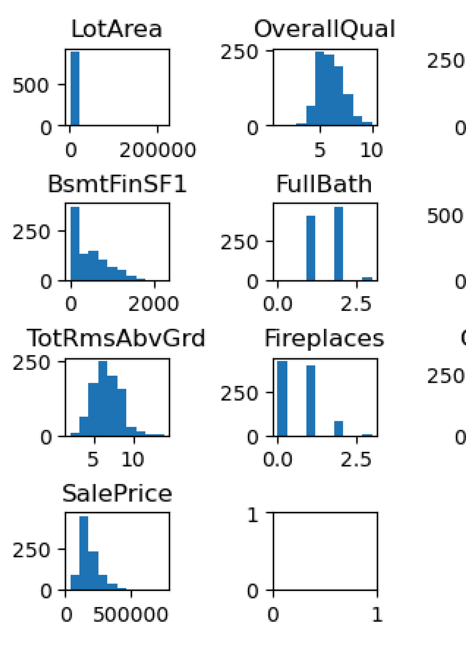
Now, we will explore our data with some plots:

In [8]:
```
df.columns
```

Out[8]:
```
Index(['LotArea', 'OverallQual', 'YearBuilt', 'YearRemodAdd', 'BsmtFinSF1',
       'FullBath', 'HalfBath', 'BedroomAbvGr', 'TotRmsAbvGrd', 'Fireplaces',
       'GarageArea', 'YrSold', 'SalePrice'],
      dtype='object')
```

PLotting histogram of all columns:

In [9]:
```
try:
    for i in range(0,15):
        plt.subplot(4,4,i+1)
        plt.hist(df.iloc[:,i])
        plt.title(df.columns[i])
except IndexError:
    pass
plt.subplots_adjust(wspace=1,hspace=1)
```



Plotting correlation plot of the data:

In [10]:
```
cor=df.corr()
cor.style.background_gradient(cmap='coolwarm')
```

Out[10]:

	LotArea	OverallQual	YearBuilt	YearRemodAdd	BsmtFinSF1	FullBath	HalfBath	BedroomAbvGr	TotRmsAbvGrd	Fireplaces	GarageArea	YrSold	SalePrice
LotArea	1.000000	0.096209	0.007639	0.012302	0.207035	0.128547	-0.002609	0.089578	0.153195	0.265592	0.152720	-0.021080	0.264372
OverallQual	0.096209	1.000000	0.569225	0.547469	0.227359	0.550709	0.304286	0.112591	0.458702	0.393486	0.598166	-0.048780	0.796213
YearBuilt	0.007639	0.569225	1.000000	0.569604	0.264598	0.462667	0.275349	-0.046072	0.128530	0.164903	0.496031	0.008918	0.526634
YearRemodAdd	0.012302	0.547469	0.569604	1.000000	0.132207	0.434997	0.205962	0.004014	0.238986	0.122247	0.379742	0.036270	0.522177
BsmtFinSF1	0.207035	0.227359	0.264598	0.132207	1.000000	0.052841	-0.003028	-0.116004	0.059287	0.292978	0.286956	-0.000784	0.404663
FullBath	0.128547	0.550709	0.462667	0.434997	0.052841	1.000000	0.129185	0.364024	0.566318	0.225219	0.410507	-0.020337	0.558013
HalfBath	-0.002609	0.304286	0.275349	0.205962	-0.003028	0.129185	1.000000	0.203046	0.331714	0.217375	0.218421	-0.023044	0.304740
BedroomAbvGr	0.089578	0.112591	-0.046072	0.004014	-0.116004	0.364024	0.203046	1.000000	0.671454	0.075402	0.081228	-0.028930	0.164427
TotRmsAbvGrd	0.153195	0.458702	0.128530	0.238986	0.059287	0.566318	0.331714	0.671454	1.000000	0.310384	0.361964	-0.068914	0.577358
Fireplaces	0.265592	0.393486	0.164903	0.122247	0.292978	0.225219	0.217375	0.075402	0.310384	1.000000	0.266260	-0.061957	0.468628
GarageArea	0.152720	0.598166	0.496031	0.379742	0.286956	0.410507	0.218421	0.081228	0.361964	0.266260	1.000000	-0.043845	0.656042
YrSold	-0.021080	-0.048780	0.008918	0.036270	-0.000784	-0.020337	-0.023044	-0.028930	-0.068914	-0.061957	-0.043845	1.000000	-0.046272
SalePrice	0.264372	0.796213	0.526634	0.522177	0.404663	0.558013	0.304740	0.164427	0.577358	0.468628	0.656042	-0.046272	1.000000

We can notice that TotRmsAbvGrd has a correlation more than 0.5 with FullBath and BedroomAbvGr. This will leaad to **Multicollinearity**. This means that our model can have unwanted errors and incorrect conclusions. Hence, we should remove TotRmsAbvGrd to avoid Multicollinearity.

In [11]:
```
#Removing TotRmsAvGrd
df=df.drop('TotRmsAbvGrd',axis=1)
df_test=df_test.drop('TotRmsAbvGrd',axis=1)
```

In [12]:
```
#Verifying that TotRmsAbvGrd was removed:
try :
    df['TotRmsAbvGrd']
except KeyError:
    print('TotRmsAbvGrd has been removed')
```

```
TotRmsAbvGrd has been removed
```

Check for data types of all columns:

In [13]:
```
df.dtypes
```

Out[13]:
```
LotArea         int64
OverallQual     int64
YearBuilt       int64
YearRemodAdd    int64
BsmtFinSF1      int64
FullBath        int64
HalfBath        int64
BedroomAbvGr    int64
Fireplaces      int64
GarageArea      int64
YrSold          int64
SalePrice       int64
dtype: object
```

Here "OverallQual","FullBath","HalfBath","BedroomAbvGr","TotRmsAbvGrd","Fireplaces" and "YrSold" are catgorical variables and shoud be defined as factors instead.

In [14]:
```
# Converting them to factors:
df[["OverallQual","FullBath","HalfBath","BedroomAbvGr","Fireplaces","YrSold"]]=df[["OverallQual","FullBath","HalfBath","BedroomAbvGr","Fireplaces","YrSold"]].astype('ca
df.dtypes
```

Out[14]:
```
LotArea            int64
OverallQual     category
YearBuilt          int64
YearRemodAdd       int64
BsmtFinSF1         int64
FullBath        category
HalfBath        category
BedroomAbvGr    category
Fireplaces      category
GarageArea         int64
YrSold          category
SalePrice          int64
dtype: object
```

It can be seen that the required variables has been converted to categorical dtype.

REGRESSION ANALYTICS:

In [15]:
```
df_test.head()
```

Out[15]:

	LotArea	OverallQual	YearBuilt	YearRemodAdd	BsmtFinSF1	FullBath	HalfBath	BedroomAbvGr	Fireplaces	GarageArea	YrSold	SalePrice
0	7340	4	1971	1971	322	1	0	2	0	684	2007	110000
1	8712	5	1957	2000	860	1	0	2	0	756	2009	153000
2	7875	7	2003	2003	0	2	1	3	1	393	2006	180000
3	14859	7	2006	2006	0	2	0	3	1	690	2006	240000
4	6173	5	1967	1967	599	1	0	3	0	288	2007	125500

Making training and testing sets

In [16]:
```
clf=linear_model.LinearRegression() #Making linear model from sklearn package
# Making training sets
x_train=df.drop('SalePrice',axis=1)
y_train=df['SalePrice']
# Making testing sets
x_test=df_test.drop('SalePrice',axis=1)
y_test=df_test['SalePrice']
```

Using Linear model on training set and predicting on testing sets:

In [17]:
```
t=clf.fit(x_train,y_train)
p=t.predict(x_test)
```

Calculating accuracy of our predictions:

In [18]:
```
s=t.score(x_test,y_test)
s
```

Out[18]:
```
0.7848875343057605
```

Hence, our model is approximately **78% accurate**

Let's check for residuals

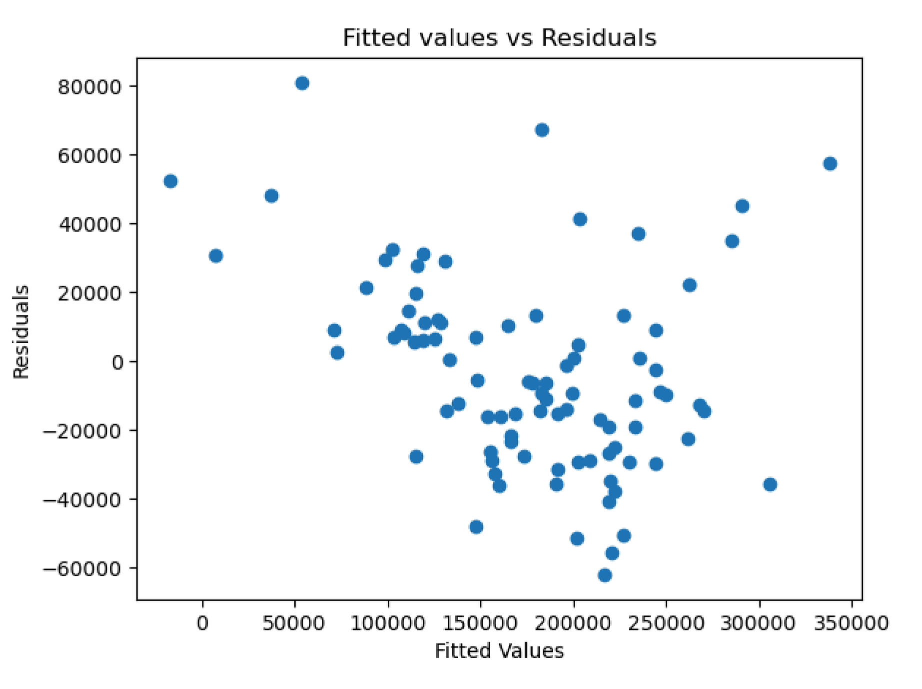
In [19]:
```
Residuals=y_test-p
Residuals.head() # Printing head() of residuals to have a look at them
```

Out[19]:
```
0     6949.683131
1   -15360.161628
2   -28898.346175
3    13084.071876
4    14481.906981
Name: SalePrice, dtype: float64
```

Plotting residuals to better analyze them.

In [20]:
```
plt.scatter(p,Residuals)
plt.title('Fitted values vs Residuals')
plt.xlabel('Fitted Values')
plt.ylabel('Residuals')
```

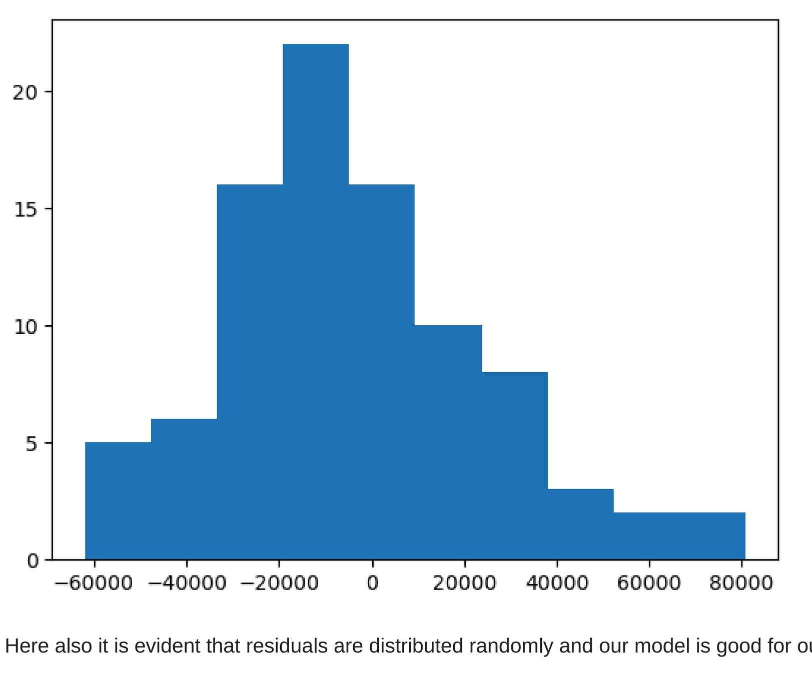
Out[20]:
```
Text(0, 0.5, 'Residuals')
```



Here, we can obsereve that graph between residuals ad fitted values is not suggesting any pattterns and seems random to us. This is exactly what we need. This goes with the assuptions of linear regression model that residuals should follow normal distribution.Hence, linear regression model is a good classifier choice for the given data.We can furthur verify the normal distribution of our residuals using a hist plot.

In [21]:
```
# Making a hist plot of residuals
plt.hist(Residuals)
```

Out[21]:
```
(array([ 5.,  6., 16., 22., 16., 10.,  8.,  3.,  2.,  2.]),
 array([-61890.72732747, -47622.12076739, -33353.51420731, -19084.90764722,
         -4816.30108714,   9452.30547294,  23720.91203302,  37989.5185931 ,
         52258.12515318,  66526.73171327,  80795.33827335]),
 <BarContainer object of 10 artists>)
```



Here also it is evident that residuals are distributed randomly and our model is good for out data.