In [324]:
```
#Goal: Predict the sales price for each house.
```

In [325]:
```
#For each Id in the test set, predict the value of the SalePrice variable.
```

In [326]:
```
#Using DecisionTreeRegressor to create a model, use the model to predict on the new feature list, assign the
```

In [327]:
```
#Load the packages
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn import metrics
from sktools import GradientBoostingFeatureGenerator
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error
```

In [328]:
```
#Load data
train_df = pd.read_csv('train.csv')
test_df = pd.read_csv('test.csv')
train_df.head()
```

Out[328]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeature
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN

5 rows × 81 columns

In [329]:
```
test_df.head()
```

Out[329]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	ScreenPorch	PoolArea	PoolQC	Fen
0	1461	20	RH	80.0	11622	Pave	NaN	Reg	Lvl	AllPub	...	120	0	NaN	Mnl
1	1462	20	RL	81.0	14267	Pave	NaN	IR1	Lvl	AllPub	...	0	0	NaN	N
2	1463	60	RL	74.0	13830	Pave	NaN	IR1	Lvl	AllPub	...	0	0	NaN	Mnl
3	1464	60	RL	78.0	9978	Pave	NaN	IR1	Lvl	AllPub	...	0	0	NaN	N
4	1465	120	RL	43.0	5005	Pave	NaN	IR1	HLS	AllPub	...	144	0	NaN	N

5 rows × 80 columns

In [330]:
```
#Drop NaN Arributes
train_df=train_df.drop(['Alley','PoolQC','Fence','FireplaceQu','MiscFeature'],axis=1)
train_df.drop(['Id'],axis=1,inplace=True)
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 75 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   MSSubClass     1460 non-null   int64  
 1   MSZoning       1460 non-null   object 
 2   LotFrontage    1201 non-null   float64
 3   LotArea        1460 non-null   int64  
 4   Street         1460 non-null   object 
 5   LotShape       1460 non-null   object 
 6   LandContour    1460 non-null   object 
 7   Utilities      1460 non-null   object 
 8   LotConfig      1460 non-null   object 
 9   LandSlope      1460 non-null   object 
 10  Neighborhood   1460 non-null   object 
 11  Condition1     1460 non-null   object 
 12  Condition2     1460 non-null   object 
 13  BldgType       1460 non-null   object 
 14  HouseStyle     1460 non-null   object 
 15  OverallQual    1460 non-null   int64  
 16  OverallCond    1460 non-null   int64  
 17  YearBuilt      1460 non-null   int64  
 18  YearRemodAdd   1460 non-null   int64  
 19  RoofStyle      1460 non-null   object 
 20  RoofMatl       1460 non-null   object 
 21  Exterior1st    1460 non-null   object 
 22  Exterior2nd    1460 non-null   object 
 23  MasVnrType     1452 non-null   object 
 24  MasVnrArea     1452 non-null   float64
 25  ExterQual      1460 non-null   object 
 26  ExterCond      1460 non-null   object 
 27  Foundation     1460 non-null   object 
 28  BsmtQual       1423 non-null   object 
 29  BsmtCond       1423 non-null   object 
 30  BsmtExposure   1422 non-null   object 
 31  BsmtFinType1   1423 non-null   object 
 32  BsmtFinSF1     1460 non-null   int64  
 33  BsmtFinType2   1422 non-null   object 
 34  BsmtFinSF2     1460 non-null   int64  
 35  BsmtUnfSF      1460 non-null   int64  
 36  TotalBsmtSF    1460 non-null   int64  
 37  Heating        1460 non-null   object 
 38  HeatingQC      1460 non-null   object 
 39  CentralAir     1460 non-null   object 
 40  Electrical     1459 non-null   object 
 41  1stFlrSF       1460 non-null   int64  
 42  2ndFlrSF       1460 non-null   int64  
 43  LowQualFinSF   1460 non-null   int64  
 44  GrLivArea      1460 non-null   int64  
 45  BsmtFullBath   1460 non-null   int64  
 46  BsmtHalfBath   1460 non-null   int64  
 47  FullBath       1460 non-null   int64  
 48  HalfBath       1460 non-null   int64  
 49  BedroomAbvGr   1460 non-null   int64  
 50  KitchenAbvGr   1460 non-null   int64  
 51  KitchenQual    1460 non-null   object 
 52  TotRmsAbvGrd   1460 non-null   int64  
 53  Functional     1460 non-null   object 
 54  Fireplaces     1460 non-null   int64  
 55  GarageType     1379 non-null   object 
 56  GarageYrBlt    1379 non-null   float64
 57  GarageFinish   1379 non-null   object 
 58  GarageCars     1460 non-null   int64  
 59  GarageArea     1460 non-null   int64  
 60  GarageQual     1379 non-null   object 
 61  GarageCond     1379 non-null   object 
 62  PavedDrive     1460 non-null   object 
 63  WoodDeckSF     1460 non-null   int64  
 64  OpenPorchSF    1460 non-null   int64  
 65  EnclosedPorch  1460 non-null   int64  
 66  3SsnPorch      1460 non-null   int64  
 67  ScreenPorch    1460 non-null   int64  
 68  PoolArea       1460 non-null   int64  
 69  MiscVal        1460 non-null   int64  
 70  MoSold         1460 non-null   int64  
 71  YrSold         1460 non-null   int64  
 72  SaleType       1460 non-null   object 
 73  SaleCondition  1460 non-null   object 
 74  SalePrice      1460 non-null   int64  
dtypes: float64(3), int64(34), object(38)
memory usage: 855.6+ KB
```

In [331]:
```
test_df=test_df.drop(['Id','Alley','PoolQC','Fence','FireplaceQu','MiscFeature'],axis=1)
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1459 entries, 0 to 1458
Data columns (total 74 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   MSSubClass     1459 non-null   int64  
 1   MSZoning       1455 non-null   object 
 2   LotFrontage    1232 non-null   float64
 3   LotArea        1459 non-null   int64  
 4   Street         1459 non-null   object 
 5   LotShape       1459 non-null   object 
 6   LandContour    1459 non-null   object 
 7   Utilities      1457 non-null   object 
 8   LotConfig      1459 non-null   object 
 9   LandSlope      1459 non-null   object 
 10  Neighborhood   1459 non-null   object 
 11  Condition1     1459 non-null   object 
 12  Condition2     1459 non-null   object 
 13  BldgType       1459 non-null   object 
 14  HouseStyle     1459 non-null   object 
 15  OverallQual    1459 non-null   int64  
 16  OverallCond    1459 non-null   int64  
 17  YearBuilt      1459 non-null   int64  
 18  YearRemodAdd   1459 non-null   int64  
 19  RoofStyle      1459 non-null   object 
 20  RoofMatl       1459 non-null   object 
 21  Exterior1st    1458 non-null   object 
 22  Exterior2nd    1458 non-null   object 
 23  MasVnrType     1443 non-null   object 
 24  MasVnrArea     1444 non-null   float64
 25  ExterQual      1459 non-null   object 
 26  ExterCond      1459 non-null   object 
 27  Foundation     1459 non-null   object 
 28  BsmtQual       1415 non-null   object 
 29  BsmtCond       1414 non-null   object 
 30  BsmtExposure   1415 non-null   object 
 31  BsmtFinType1   1417 non-null   object 
 32  BsmtFinSF1     1458 non-null   float64
 33  BsmtFinType2   1417 non-null   object 
 34  BsmtFinSF2     1458 non-null   float64
 35  BsmtUnfSF      1458 non-null   float64
 36  TotalBsmtSF    1458 non-null   float64
 37  Heating        1459 non-null   object 
 38  HeatingQC      1459 non-null   object 
 39  CentralAir     1459 non-null   object 
 40  Electrical     1459 non-null   object 
 41  1stFlrSF       1459 non-null   int64  
 42  2ndFlrSF       1459 non-null   int64  
 43  LowQualFinSF   1459 non-null   int64  
 44  GrLivArea      1459 non-null   int64  
 45  BsmtFullBath   1457 non-null   float64
 46  BsmtHalfBath   1457 non-null   float64
 47  FullBath       1459 non-null   int64  
 48  HalfBath       1459 non-null   int64  
 49  BedroomAbvGr   1459 non-null   int64  
 50  KitchenAbvGr   1459 non-null   int64  
 51  KitchenQual    1458 non-null   object 
 52  TotRmsAbvGrd   1459 non-null   int64  
 53  Functional     1457 non-null   object 
 54  Fireplaces     1459 non-null   int64  
 55  GarageType     1383 non-null   object 
 56  GarageYrBlt    1381 non-null   float64
 57  GarageFinish   1381 non-null   object 
 58  GarageCars     1458 non-null   float64
 59  GarageArea     1458 non-null   float64
 60  GarageQual     1381 non-null   object 
 61  GarageCond     1381 non-null   object 
 62  PavedDrive     1459 non-null   object 
 63  WoodDeckSF     1459 non-null   int64  
 64  OpenPorchSF    1459 non-null   int64  
 65  EnclosedPorch  1459 non-null   int64  
 66  3SsnPorch      1459 non-null   int64  
 67  ScreenPorch    1459 non-null   int64  
 68  PoolArea       1459 non-null   int64  
 69  MiscVal        1459 non-null   int64  
 70  MoSold         1459 non-null   int64  
 71  YrSold         1459 non-null   int64  
 72  SaleType       1458 non-null   object 
 73  SaleCondition  1459 non-null   object 
dtypes: float64(11), int64(25), object(38)
memory usage: 843.6+ KB
```

In [332]:
```
#1. Data Preprocessing
# Handling Missing values with Mean
# training set
train_df['LotFrontage']=train_df['LotFrontage'].fillna(train_df['LotFrontage'].mean())
train_df['MasVnrArea'] = train_df['MasVnrArea'].fillna(train_df['MasVnrArea'].mean())
train_df['GarageYrBlt'] = train_df['GarageYrBlt'].fillna(train_df['GarageYrBlt'].mean())
train_df['MasVnrArea'] = train_df['MasVnrArea'].fillna(train_df['MasVnrArea'].mean())
```

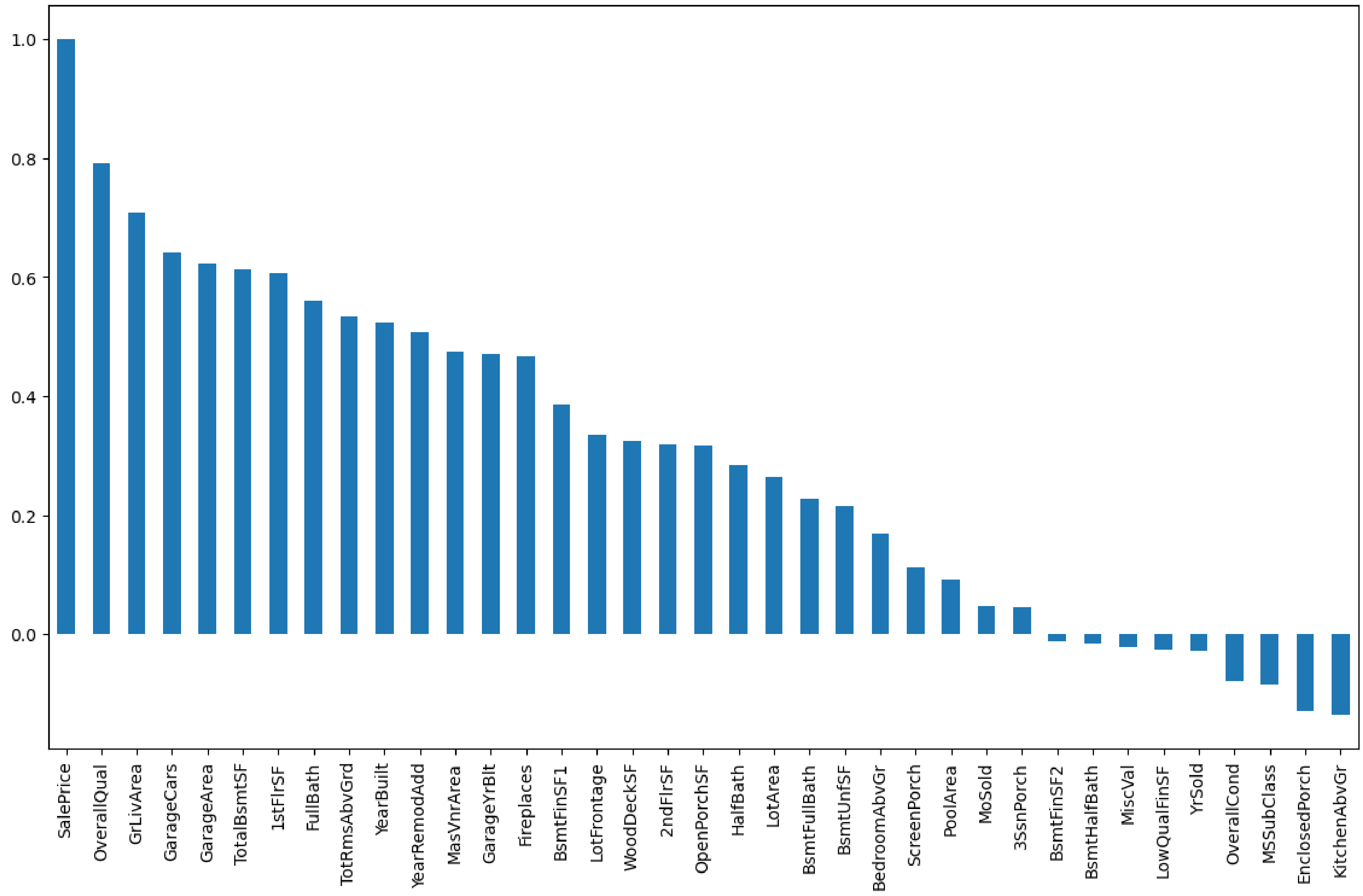
In [333]:
```
#test set
test_df['LotFrontage'] = test_df['MasVnrArea'].fillna(test_df['MasVnrArea'].mean())
test_df['MasVnrArea'] = test_df['MasVnrArea'].fillna(test_df['MasVnrArea'].mean())
test_df['BsmtFinSF1'] = test_df['BsmtFinSF1'].fillna(test_df['BsmtFinSF1'].mean())
test_df['BsmtFinSF2'] = test_df['BsmtFinSF2'].fillna(test_df['BsmtFinSF2'].mean())
test_df['BsmtUnfSF'] = test_df['BsmtUnfSF'].fillna(test_df['BsmtUnfSF'].mean())
test_df['TotalBsmtSF'] = test_df['TotalBsmtSF'].fillna(test_df['TotalBsmtSF'].mean())
test_df['BsmtFullBath'] = test_df['BsmtFullBath'].fillna(test_df['BsmtFullBath'].mean())
test_df['BsmtHalfBath'] = test_df['BsmtHalfBath'].fillna(test_df['BsmtHalfBath'].mean())
test_df['GarageCars'] = test_df['GarageCars'].fillna(test_df['GarageCars'].mean())
test_df['GarageArea'] = test_df['GarageArea'].fillna(test_df['GarageArea'].mean())
test_df['GarageYrBlt'] = test_df['GarageYrBlt'].fillna(test_df['GarageYrBlt'].mean())
```

In [334]:
```
# Filter Numerical Features
numerical_features  = train_df.select_dtypes(include=['int64','float64'])
numerical_features.columns
```

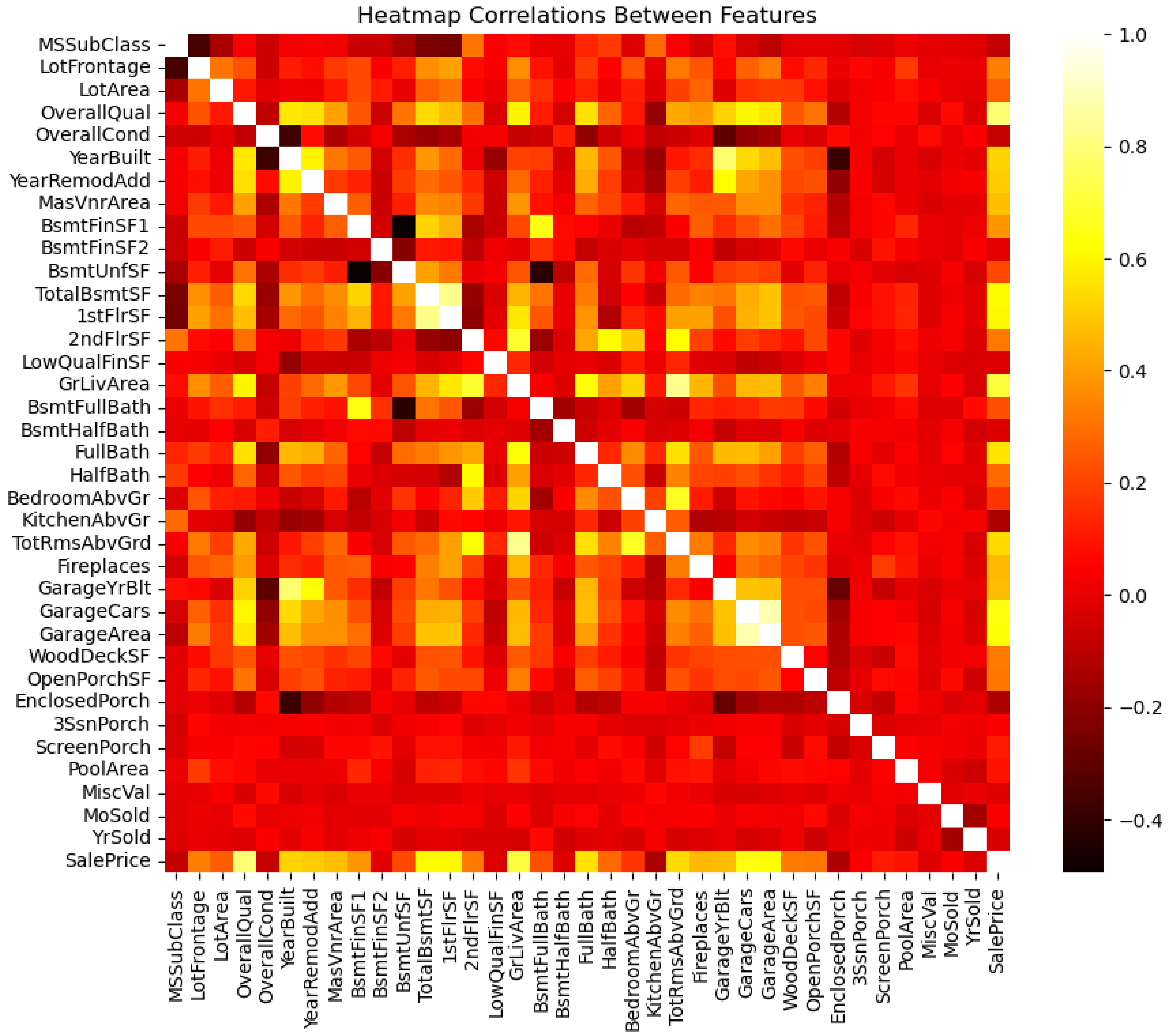
Out[334]:
```
Index(['MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual', 'OverallCond',
       'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2',
       'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
       'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
       'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces',
       'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal',
       'MoSold', 'YrSold', 'SalePrice'],
      dtype='object')
```

In [335]:
```
#2. Interactions between Features
```

In [336]:
```
#Pearson Correlation
plt.figure(figsize=(14,8))
bars=train_df.corr()['SalePrice'].sort_values(ascending=False).plot(kind='bar')
```



In [337]:
```
#Heatmap
plt.figure(figsize=(10,8))
sns.heatmap(train_df.corr(), cmap="hot")
plt.title("Heatmap Correlations Between Features")
plt.show()
```



In [338]:
```
#3. Split into test and training data
X = train_df[['MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual',
       'OverallCond', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1',
       'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd',
       'Fireplaces', 'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF',
       'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea',
       'MiscVal', 'MoSold', 'YrSold']]
y = train_df['SalePrice']
train_df.describe()
```

Out[338]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	56.897260	70.049958	10516.828082	6.099315	5.575342	1971.267808	1984.865753	103.685262	443.639726	46.549315
std	42.300571	22.024023	9981.264932	1.382997	1.112799	30.202904	20.645407	180.569112	456.098091	161.319273
min	20.000000	21.000000	1300.000000	1.000000	1.000000	1872.000000	1950.000000	0.000000	0.000000	0.000000
25%	20.000000	60.000000	7553.500000	5.000000	5.000000	1954.000000	1967.000000	0.000000	0.000000	0.000000
50%	50.000000	70.049958	9478.500000	6.000000	5.000000	1973.000000	1994.000000	0.000000	383.500000	0.000000
75%	70.000000	79.000000	11601.500000	7.000000	6.000000	2000.000000	2004.000000	164.250000	712.250000	0.000000
max	190.000000	313.000000	215245.000000	10.000000	9.000000	2010.000000	2010.000000	1600.000000	5644.000000	1474.000000

8 rows × 37 columns

In [339]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=11)
X_train.head()
```

Out[339]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	...	GarageA
449	50	50.0	6000	3	7	1948	2002	0.0	331	0	...	
409	60	85.0	10800	8	5	2007	2008	100.0	789	0	...	
398	30	60.0	8967	5	2	1920	1950	0.0	0	0	...	
932	20	84.0	11670	9	5	2006	2006	302.0	0	0	...	
499	20	70.0	7535	5	7	1958	1985	0.0	111	279	...	

5 rows × 36 columns

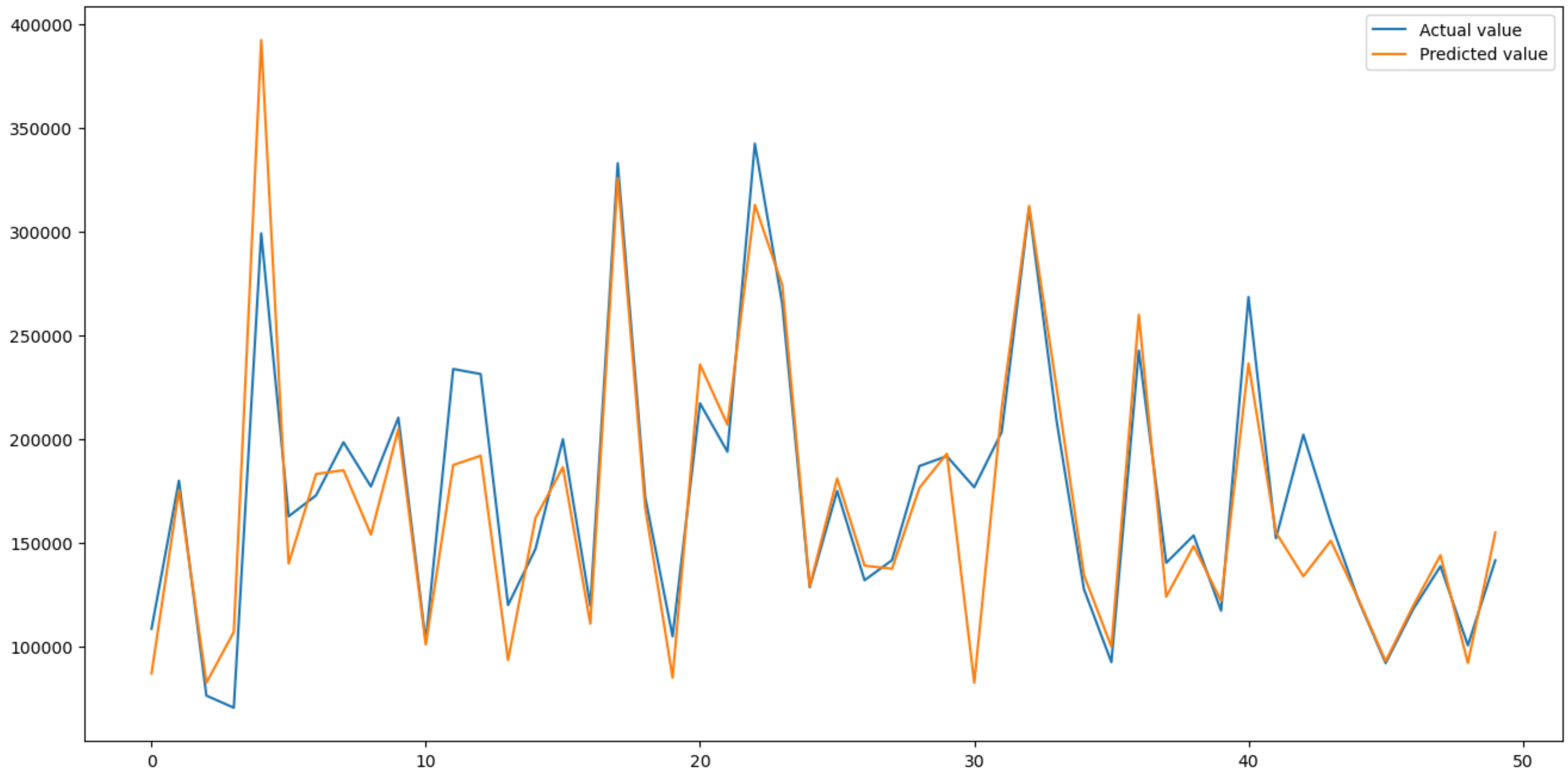
In [340]:
```
y_train.head()
```

Out[340]:
```
449    120000
409    339750
398     67000
932    320000
499    120000
Name: SalePrice, dtype: int64
```

In [341]:
```
#4. Fit a baseline model --XGBoost(XGBoostRegressor)
from xgboost import XGBRegressor
regressor=XGBRegressor()
model=regressor.fit(X_train,y_train)
y_pred=model.predict(X_test)
```

In [342]:
```
#Plot Predicted house price v.s. Actual house price(base model performance)
test=pd.DataFrame({'Predicted value':y_pred,'Actual value':y_test})
fig=plt.figure(figsize=(16,8))
test=test.reset_index()
test=test.drop(['index'],axis=1)
plt.plot(test[:50])
plt.legend(['Actual value','Predicted value'])
```

Out[342]: <matplotlib.legend.Legend at 0x7fd14909a3a0>



In [343]:
```
from sklearn.metrics import r2_score
r2_score(y_test, y_pred)
```

Out[343]: 0.8042243989969304

In [344]:
```
#Assess baseline model performance, get mean squared error..(aim to minimize)
print('Mean Absolute Error(MAE):',metrics.mean_absolute_error(y_test,y_pred))
print('Mean Squared Error(MSE):',metrics.mean_squared_error(y_test,y_pred))
print('Root Mean SquaredError(RMSE):',np.sqrt(metrics.mean_squared_error(y_test,y_pred)))
```

```
Mean Absolute Error(MAE): 19123.644067494293
Mean Squared Error(MSE): 1304569830.7689064
Root Mean SquaredError(RMSE): 36118.82931060898
```

In [345]:
```
#Using Decision Tree to generate new feature
```

In [346]:
```
#Fit a DecisionTreeRegressor, and choose max-depth at 3
from sklearn.tree import DecisionTreeRegressor

DT=DecisionTreeRegressor(max_depth=4,random_state=11)
```

In [347]:
```
DT.fit(X_train,y_train)
```

Out[347]:
```
DecisionTreeRegressor(max_depth=4, random_state=11)
```

In [348]:
```
#Extract the tree attributes
n_nodes = DT.tree_.node_count
children_left = DT.tree_.children_left
children_right = DT.tree_.children_right
feature = DT.tree_.feature
```

In [349]:
```
#Traverse the tree to get features in each branch
def extract_path_features(node, path_features):
    if children_left[node] != children_right[node]:  # check if it's an internal node
        left_path = path_features + [feature[node]]
        right_path = path_features + [feature[node]]

        left_branch = extract_path_features(children_left[node], left_path)
        right_branch = extract_path_features(children_right[node], right_path)

        return left_branch + right_branch

    return [path_features]

branch_features = extract_path_features(0, [])
```

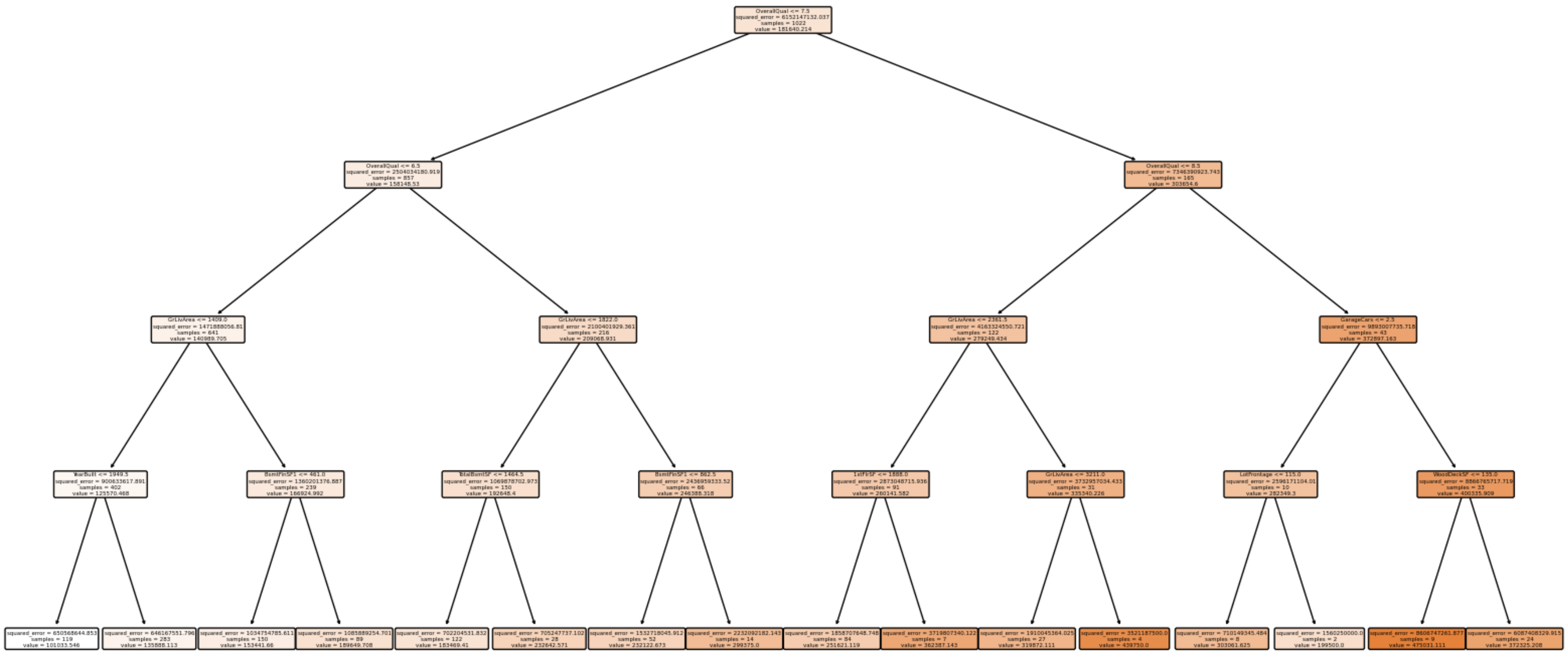
In [350]:
```
#Convert feature indices to feature names
branch_features_named = [[X.columns[f] for f in branch] for branch in branch_features]
```

In [351]:
```
#Each inner list represents a branch in the tree
branch_features_named
```

Out[351]:
```
[['OverallQual', 'OverallQual', 'GrLivArea', 'YearBuilt'],
 ['OverallQual', 'OverallQual', 'GrLivArea', 'YearBuilt'],
 ['OverallQual', 'OverallQual', 'GrLivArea', 'BsmtFinSF1'],
 ['OverallQual', 'OverallQual', 'GrLivArea', 'BsmtFinSF1'],
 ['OverallQual', 'OverallQual', 'GrLivArea', 'TotalBsmtSF'],
 ['OverallQual', 'OverallQual', 'GrLivArea', 'TotalBsmtSF'],
 ['OverallQual', 'OverallQual', 'GrLivArea', 'BsmtFinSF1'],
 ['OverallQual', 'OverallQual', 'GrLivArea', 'BsmtFinSF1'],
 ['OverallQual', 'OverallQual', 'GrLivArea', '1stFlrSF'],
 ['OverallQual', 'OverallQual', 'GrLivArea', '1stFlrSF'],
 ['OverallQual', 'OverallQual', 'GrLivArea', 'GrLivArea'],
 ['OverallQual', 'OverallQual', 'GrLivArea', 'GrLivArea'],
 ['OverallQual', 'OverallQual', 'GarageCars', 'LotFrontage'],
 ['OverallQual', 'OverallQual', 'GarageCars', 'LotFrontage'],
 ['OverallQual', 'OverallQual', 'GarageCars', 'WoodDeckSF'],
 ['OverallQual', 'OverallQual', 'GarageCars', 'WoodDeckSF']]
```

In [352]:
```
#'OverallQual': Overall material and finish quality;
#'GrLivArea':   Above grade (ground) living area square feet;
#'GarageCars':  Size of garage in car capacity
#'YearBuilt': Original construction date
#'BsmtFinSF1': Type 1 finished square feet
#'1stFlrSF': First Floor square feet
#'LotFrontage': Linear feet of street connected to property
#'WoodDeckSF': Wood deck area in square feet
```

In [353]:
```python
#Visualize this tree
from sklearn.tree import DecisionTreeRegressor, plot_tree
import matplotlib.pyplot as plt
plt.figure(figsize=(20,10))
plot_tree(DT, filled=True, feature_names=X.columns, rounded=True)
plt.show()
```



In [354]:
```python
#Find interactions by computing ratio
def create_interaction_features(data, branch_features_named):
    new_features = pd.DataFrame()
    for branch in branch_features_named:
        if len(branch) == 1:
            continue
        interaction_name = "_div_".join(branch)
        # Check if all features in branch are numerical (either int or float)
        if all(pd.api.types.is_numeric_dtype(data[col].dtype) for col in branch):
            # Compute the ratio
            denominator = data[branch[1:]].prod(axis=1)
            # Replace 0 in the denominator to avoid division by zero
            denominator = denominator.replace(0, 1)
            interaction_feature = data[branch[0]] / denominator
        else:
            # For non-numerical features, concatenate as string
            interaction_feature = data[branch].astype(str).agg("_".join, axis=1)
        new_features[interaction_name] = interaction_feature
    return new_features

new_feature_data = create_interaction_features(X, branch_features_named)
```

In [355]:
```python
#Concatenate interaction features with original features
X_extended = pd.concat([X, new_feature_data], axis=1)
X_extended
```

Out[355]:

/_OverallQual_div_GrLivArea_div_GrLivArea	OverallQual_div_OverallQual_div_GarageCars_div_LotFrontage	OverallQual_div_OverallQual_div_GarageCars_di
3.419856e-07	0.007692	
6.278867e-07	0.006250	
3.134997e-07	0.007353	
3.392028e-07	0.005556	
2.069877e-07	0.003968	
...	...	
3.686488e-07	0.008065	
2.327027e-07	0.005882	
1.826284e-07	0.015152	
8.605230e-07	0.014706	
6.339000e-07	0.013333	

In [356]:
```
#list of interaction feature names
new_feature_data_list = new_feature_data.columns.tolist()
print(new_feature_data_list)
```

```
['OverallQual_div_OverallQual_div_GrLivArea_div_YearBuilt', 'OverallQual_div_OverallQual_div_GrLivArea_div
_BsmtFinSF1', 'OverallQual_div_OverallQual_div_GrLivArea_div_TotalBsmtSF', 'OverallQual_div_OverallQual_di
v_GrLivArea_div_1stFlrSF', 'OverallQual_div_OverallQual_div_GrLivArea_div_GrLivArea', 'OverallQual_div_Ove
rallQual_div_GarageCars_div_LotFrontage', 'OverallQual_div_OverallQual_div_GarageCars_div_WoodDeckSF']
```

In [357]:
```
#Separate each element by the ',' to get new individual features
new_feature = [name.split(',') for name in new_feature_data_list]
print(new_feature)
```

```
[['OverallQual_div_OverallQual_div_GrLivArea_div_YearBuilt'], ['OverallQual_div_OverallQual_div_GrLivArea_
div_BsmtFinSF1'], ['OverallQual_div_OverallQual_div_GrLivArea_div_TotalBsmtSF'], ['OverallQual_div_Overall
Qual_div_GrLivArea_div_1stFlrSF'], ['OverallQual_div_OverallQual_div_GrLivArea_div_GrLivArea'], ['OverallQ
ual_div_OverallQual_div_GarageCars_div_LotFrontage'], ['OverallQual_div_OverallQual_div_GarageCars_div_Woo
dDeckSF']]
```

In [358]:
```
#    Remove the '_div_' part and duplicates from the feature names in the lists.
def clean_feature_names(new_feature):
    cleaned_lists = []
    for feature_list in new_feature:
        # Extracting the first element of each list and splitting it by '_div_'
        cleaned_features = feature_list[0].split('_div_')
        # Removing duplicates while preserving order
        cleaned_features = list(dict.fromkeys(cleaned_features))
        cleaned_lists.append(cleaned_features)
    return cleaned_lists

# Cleaning the feature names
cleaned_feature_lists = clean_feature_names(new_feature)
cleaned_feature_lists
```

Out[358]:
```
[['OverallQual', 'GrLivArea', 'YearBuilt'],
 ['OverallQual', 'GrLivArea', 'BsmtFinSF1'],
 ['OverallQual', 'GrLivArea', 'TotalBsmtSF'],
 ['OverallQual', 'GrLivArea', '1stFlrSF'],
 ['OverallQual', 'GrLivArea'],
 ['OverallQual', 'GarageCars', 'LotFrontage'],
 ['OverallQual', 'GarageCars', 'WoodDeckSF']]
```

In [359]:
```
total_number_of_lists = len(cleaned_feature_lists)
total_number_of_lists
```

Out[359]: 7

In [360]:
```
#Rename new features:
new_feature1=cleaned_feature_lists[0]
new_feature2=cleaned_feature_lists[1]
new_feature3=cleaned_feature_lists[2]
new_feature4=cleaned_feature_lists[3]
new_feature5=cleaned_feature_lists[4]
new_feature6=cleaned_feature_lists[5]
new_feature7=cleaned_feature_lists[6]
```

In [361]:
```
#Hyperparameter Tuning: Optimize max-depth parameters using GridSearchCV
from sklearn.tree import DecisionTreeRegressor
param_grid={
    'max_depth':[None,2,3,4]
}
DTModel=GridSearchCV(
    DecisionTreeRegressor(random_state=11),
    cv=10,
    scoring='neg_mean_squared_error',
    param_grid=param_grid
)
```

In [362]:
```
#Pass to X_train, and using fit in DecisionTree model
DTModel.fit(X_train[new_feature1],y_train)
DTModel.fit(X_train[new_feature2],y_train)
DTModel.fit(X_train[new_feature3],y_train)
DTModel.fit(X_train[new_feature4],y_train)
DTModel.fit(X_train[new_feature5],y_train)
DTModel.fit(X_train[new_feature6],y_train)
```

Out[362]:
```
GridSearchCV(cv=10, estimator=DecisionTreeRegressor(random_state=11),
             param_grid={'max_depth': [None, 2, 3, 4]},
             scoring='neg_mean_squared_error')
```

In [363]:
```
#Using Predict() to predict target variable using two new features, assign back to X_train,X_test dataset

#for feature 1
X_train=X_train.assign(OverQual_Area_Year=DTModel.predict(X_train[new_feature1]))
X_test=X_test.assign(OverQual_Area_Year=DTModel.predict(X_test[new_feature1]))
```

```
/Users/yam/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:493: FutureWarning: The feature names
should match those that were passed during fit. Starting version 1.2, an error will be raised.
Feature names unseen at fit time:
- GrLivArea
- YearBuilt
Feature names seen at fit time, yet now missing:
- GarageCars
- LotFrontage

  warnings.warn(message, FutureWarning)
/Users/yam/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:493: FutureWarning: The feature names
should match those that were passed during fit. Starting version 1.2, an error will be raised.
Feature names unseen at fit time:
- GrLivArea
- YearBuilt
Feature names seen at fit time, yet now missing:
- GarageCars
- LotFrontage

  warnings.warn(message, FutureWarning)
```

In [364]:
```
#for feature 2
X_train=X_train.assign(OverQual_Area_Bsmt=DTModel.predict(X_train[new_feature2]))
X_test=X_test.assign(OverQual_Area_Bsmt=DTModel.predict(X_test[new_feature2]))
```

```
/Users/yam/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:493: FutureWarning: The feature names
should match those that were passed during fit. Starting version 1.2, an error will be raised.
Feature names unseen at fit time:
- BsmtFinSF1
- GrLivArea
Feature names seen at fit time, yet now missing:
- GarageCars
- LotFrontage

  warnings.warn(message, FutureWarning)
/Users/yam/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:493: FutureWarning: The feature names
should match those that were passed during fit. Starting version 1.2, an error will be raised.
Feature names unseen at fit time:
- BsmtFinSF1
- GrLivArea
Feature names seen at fit time, yet now missing:
- GarageCars
- LotFrontage

  warnings.warn(message, FutureWarning)
```

In [365]:
```
#for feature 3
X_train=X_train.assign(OverQual_Area_TBsmt=DTModel.predict(X_train[new_feature3]))
X_test=X_test.assign(OverQual_Area_TBsmt=DTModel.predict(X_test[new_feature3]))
```

```
/Users/yam/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:493: FutureWarning: The feature names
should match those that were passed during fit. Starting version 1.2, an error will be raised.
Feature names unseen at fit time:
- GrLivArea
- TotalBsmtSF
Feature names seen at fit time, yet now missing:
- GarageCars
- LotFrontage

  warnings.warn(message, FutureWarning)
/Users/yam/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:493: FutureWarning: The feature names
should match those that were passed during fit. Starting version 1.2, an error will be raised.
Feature names unseen at fit time:
- GrLivArea
- TotalBsmtSF
Feature names seen at fit time, yet now missing:
- GarageCars
- LotFrontage

  warnings.warn(message, FutureWarning)
```

In [366]:
```
#for feature 4
X_train=X_train.assign(OverQual_Area_Flr=DTModel.predict(X_train[new_feature4]))
X_test=X_test.assign(OverQual_Area_Flr=DTModel.predict(X_test[new_feature4]))
```

```
/Users/yam/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:493: FutureWarning: The feature names
should match those that were passed during fit. Starting version 1.2, an error will be raised.
Feature names unseen at fit time:
- 1stFlrSF
- GrLivArea
Feature names seen at fit time, yet now missing:
- GarageCars
- LotFrontage

  warnings.warn(message, FutureWarning)
/Users/yam/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:493: FutureWarning: The feature names
should match those that were passed during fit. Starting version 1.2, an error will be raised.
Feature names unseen at fit time:
- 1stFlrSF
- GrLivArea
Feature names seen at fit time, yet now missing:
- GarageCars
- LotFrontage

  warnings.warn(message, FutureWarning)
```

In [367]:
```
#for feature 5 -- only two, but DT expecting 3 features as input
#X_train=X_train.assign(OverQual_Area=DTModel.predict(X_train[new_feature5]))
#X_test=X_test.assign(OverQual_Area=DTModel.predict(X_test[new_feature5]))
```

In [368]:
```
#for feature 6
X_train=X_train.assign(OverQual_Car_Lot=DTModel.predict(X_train[new_feature6]))
X_test=X_test.assign(OverQual_Car_Lot=DTModel.predict(X_test[new_feature6]))
```

In [369]:
```
#for feature 7
X_train=X_train.assign(OverQual_Car_Wood=DTModel.predict(X_train[new_feature7]))
X_test=X_test.assign(OverQual_Car_Wood=DTModel.predict(X_test[new_feature7]))
```

```
/Users/yam/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:493: FutureWarning: The feature names
should match those that were passed during fit. Starting version 1.2, an error will be raised.
Feature names unseen at fit time:
- WoodDeckSF
Feature names seen at fit time, yet now missing:
- LotFrontage

  warnings.warn(message, FutureWarning)
/Users/yam/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:493: FutureWarning: The feature names
should match those that were passed during fit. Starting version 1.2, an error will be raised.
Feature names unseen at fit time:
- WoodDeckSF
Feature names seen at fit time, yet now missing:
- LotFrontage

  warnings.warn(message, FutureWarning)
```

In [370]:
```
X_train.head()
```

Out[370]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	...	PoolAre
449	50	50.0	6000	3	7	1948	2002	0.0	331	0	...	
409	60	85.0	10800	8	5	2007	2008	100.0	789	0	...	
398	30	60.0	8967	5	2	1920	1950	0.0	0	0	...	
932	20	84.0	11670	9	5	2006	2006	302.0	0	0	...	
499	20	70.0	7535	5	7	1958	1985	0.0	111	279	...	

5 rows × 42 columns

In [371]:
```
X_test.head()
```

Out[371]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	...	PoolAr
127	45	55.0	4388	5	7	1930	1950	0.0	116	0	...	
455	20	80.0	9600	7	6	1973	1973	320.0	916	0	...	
1323	30	50.0	5330	4	7	1940	1950	0.0	280	0	...	
217	70	57.0	9906	4	4	1925	1950	0.0	0	0	...	
1181	120	64.0	5587	8	5	2008	2008	186.0	1480	0	...	

5 rows × 42 columns

In [372]:
```
y_train.head()
```

Out[372]:
```
449    120000
409    339750
398     67000
932    320000
499    120000
Name: SalePrice, dtype: int64
```

In [373]:
```
y_test.head()
```

Out[373]:
```
127      87000
455     175500
1323     82500
217     107000
1181    392500
Name: SalePrice, dtype: int64
```

In [374]:
```
#Re-fit baseline model using new feature to new X_train data, and predict new X_train data
regressor=XGBRegressor()
model=regressor.fit(X_train,y_train)
y_pred=model.predict(X_test)
```

In [375]:
```
#Print RMSE score to see if is reduced loss function, if yes, then have better performance due to new featur
print('Mean Absolute Error(MAE):',metrics.mean_absolute_error(y_test,y_pred))
print('Mean Squared Error(MSE):',metrics.mean_squared_error(y_test,y_pred))
print('Root Mean SquaredError(RMSE):',np.sqrt(metrics.mean_squared_error(y_test,y_pred)))
```

```
Mean Absolute Error(MAE): 18807.28407712614
Mean Squared Error(MSE): 1193076014.614751
Root Mean SquaredError(RMSE): 34540.93245143725
```

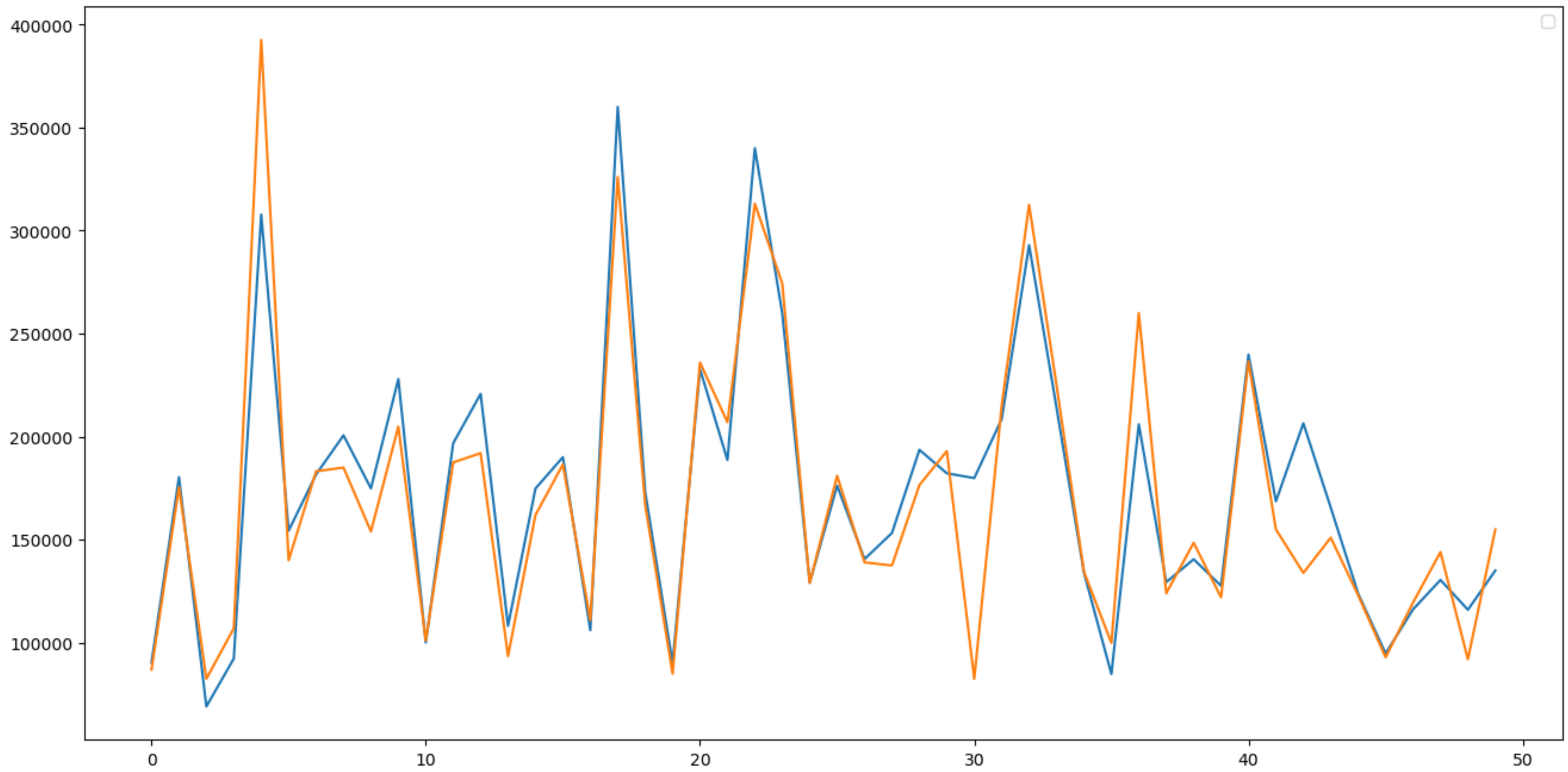
In [376]:
```
from sklearn.metrics import r2_score
r2_score(y_test, y_pred)
```

Out[376]:
```
0.8209561739858096
```

In [377]:
```
#Plot
test=pd.DataFrame({'Predicted value':y_pred,'Actual value':y_test})
fig=plt.figure(figsize=(16,8))
test=test.reset_index()
test=test.drop(['index'],axis=1)
plt.plot(test[:50])
plt.legend('Actual value','Predicted value')
```

```
/var/folders/3j/bd328j896wgfz88pgbggdm640000gn/T/ipykernel_32632/290178646.py:7: UserWarning: Legend does
not support 'A' instances.
A proxy artist may be used instead.
See: https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-adding-to-the-legend
-aka-proxy-artists (https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-addin
g-to-the-legend-aka-proxy-artists)
  plt.legend('Actual value','Predicted value')
/var/folders/3j/bd328j896wgfz88pgbggdm640000gn/T/ipykernel_32632/290178646.py:7: UserWarning: Legend does
not support 'c' instances.
A proxy artist may be used instead.
See: https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-adding-to-the-legend
-aka-proxy-artists (https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-addin
g-to-the-legend-aka-proxy-artists)
  plt.legend('Actual value','Predicted value')
/var/folders/3j/bd328j896wgfz88pgbggdm640000gn/T/ipykernel_32632/290178646.py:7: UserWarning: Legend does
not support 't' instances.
A proxy artist may be used instead.
See: https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-adding-to-the-legend
-aka-proxy-artists (https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-addin
g-to-the-legend-aka-proxy-artists)
  plt.legend('Actual value','Predicted value')
/var/folders/3j/bd328j896wgfz88pgbggdm640000gn/T/ipykernel_32632/290178646.py:7: UserWarning: Legend does
not support 'u' instances.
A proxy artist may be used instead.
See: https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-adding-to-the-legend
-aka-proxy-artists (https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-addin
g-to-the-legend-aka-proxy-artists)
  plt.legend('Actual value','Predicted value')
/var/folders/3j/bd328j896wgfz88pgbggdm640000gn/T/ipykernel_32632/290178646.py:7: UserWarning: Legend does
not support 'a' instances.
A proxy artist may be used instead.
See: https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-adding-to-the-legend
-aka-proxy-artists (https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-addin
g-to-the-legend-aka-proxy-artists)
  plt.legend('Actual value','Predicted value')
/var/folders/3j/bd328j896wgfz88pgbggdm640000gn/T/ipykernel_32632/290178646.py:7: UserWarning: Legend does
not support 'l' instances.
A proxy artist may be used instead.
See: https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-adding-to-the-legend
-aka-proxy-artists (https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-addin
g-to-the-legend-aka-proxy-artists)
  plt.legend('Actual value','Predicted value')
/var/folders/3j/bd328j896wgfz88pgbggdm640000gn/T/ipykernel_32632/290178646.py:7: UserWarning: Legend does
not support ' ' instances.
A proxy artist may be used instead.
See: https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-adding-to-the-legend
-aka-proxy-artists (https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-addin
g-to-the-legend-aka-proxy-artists)
  plt.legend('Actual value','Predicted value')
/var/folders/3j/bd328j896wgfz88pgbggdm640000gn/T/ipykernel_32632/290178646.py:7: UserWarning: Legend does
not support 'v' instances.
A proxy artist may be used instead.
See: https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-adding-to-the-legend
-aka-proxy-artists (https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-addin
g-to-the-legend-aka-proxy-artists)
  plt.legend('Actual value','Predicted value')
/var/folders/3j/bd328j896wgfz88pgbggdm640000gn/T/ipykernel_32632/290178646.py:7: UserWarning: Legend does
not support 'e' instances.
A proxy artist may be used instead.
See: https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-adding-to-the-legend
-aka-proxy-artists (https://matplotlib.org/users/legend_guide.html#creating-artists-specifically-for-addin
g-to-the-legend-aka-proxy-artists)
  plt.legend('Actual value','Predicted value')
```

Out[377]: <matplotlib.legend.Legend at 0x7fd13823e8e0>


400000
350000
300000
250000
200000
150000
100000
0
10
20
30
40
50

In [ ]: