ML Task-01

Implement a linear regression model to predict the prices of houses based on their square footage and the number of bedrooms and bathrooms.

Dataset : - https://www.kaggle.com/c/house-prices-advanced-regression-techniques/data

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

df_train = pd.read_csv('train.csv')
df_test = pd.read_csv('test.csv')

df_train.head()

   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape 
\
0   1          60       RL         65.0     8450   Pave   NaN      Reg

1   2          20       RL         80.0     9600   Pave   NaN      Reg

2   3          60       RL         68.0    11250   Pave   NaN      IR1

3   4          70       RL         60.0     9550   Pave   NaN      IR1

4   5          60       RL         84.0    14260   Pave   NaN      IR1


  LandContour Utilities  ... PoolArea PoolQC Fence MiscFeature MiscVal 
MoSold  \
0         Lvl    AllPub  ...        0    NaN   NaN         NaN       0 
2
1         Lvl    AllPub  ...        0    NaN   NaN         NaN       0 
5
2         Lvl    AllPub  ...        0    NaN   NaN         NaN       0 
9
3         Lvl    AllPub  ...        0    NaN   NaN         NaN       0 
2
4         Lvl    AllPub  ...        0    NaN   NaN         NaN       0 
12

  YrSold  SaleType  SaleCondition  SalePrice  
0   2008        WD         Normal     208500  
1   2007        WD         Normal     181500  
2   2008        WD         Normal     223500  
3   2006        WD        Abnorml     140000  
```

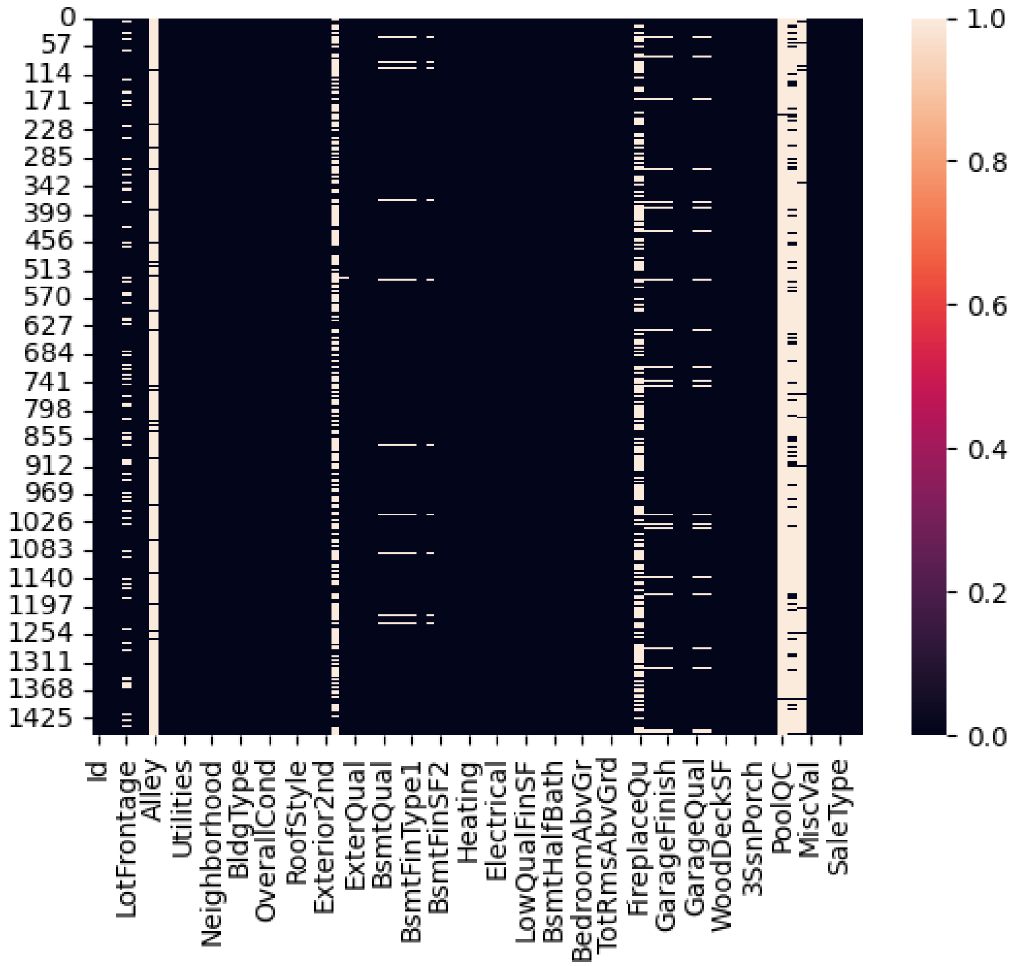
```
4   2008        WD         Normal     250000

[5 rows x 81 columns]
```

```
df_test.head()
```

```
     Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley
LotShape  \
0  1461          20       RH         80.0    11622   Pave   NaN
Reg
1  1462          20       RL         81.0    14267   Pave   NaN
IR1
2  1463          60       RL         74.0    13830   Pave   NaN
IR1
3  1464          60       RL         78.0     9978   Pave   NaN
IR1
4  1465         120       RL         43.0     5005   Pave   NaN
IR1

  LandContour Utilities  ... ScreenPorch PoolArea PoolQC  Fence
MiscFeature  \
0         Lvl    AllPub  ...         120        0    NaN  MnPrv
NaN
1         Lvl    AllPub  ...           0        0    NaN    NaN
Gar2
2         Lvl    AllPub  ...           0        0    NaN  MnPrv
NaN
3         Lvl    AllPub  ...           0        0    NaN    NaN
NaN
4         HLS    AllPub  ...         144        0    NaN    NaN
NaN

  MiscVal MoSold  YrSold  SaleType  SaleCondition
0       0      6    2010        WD         Normal
1   12500      6    2010        WD         Normal
2       0      3    2010        WD         Normal
3       0      6    2010        WD         Normal
4       0      1    2010        WD         Normal

[5 rows x 80 columns]
```

```
sns.heatmap(df_train.isnull())
```

```
<Axes: >
```




```
df_train.columns
```

```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea',
'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2',
'BldgType',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt',
'YearRemodAdd',
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd',
'MasVnrType',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation',
'BsmtQual',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF',
'Heating',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF',
'2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath',
'FullBath',
```

```
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu',
'GarageType',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea',
'GarageQual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea',
'PoolQC',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold',
'SaleType',
       'SaleCondition', 'SalePrice'],
      dtype='object')
```

```
null_columns=[]
for i in df_train.columns.tolist():
    if df_train[i].isnull().sum() >= 500:
        null_columns.append(i)
        print(i,df_train[i].isnull().sum())
```

```
Alley 1369
MasVnrType 872
FireplaceQu 690
PoolQC 1453
Fence 1179
MiscFeature 1406
```

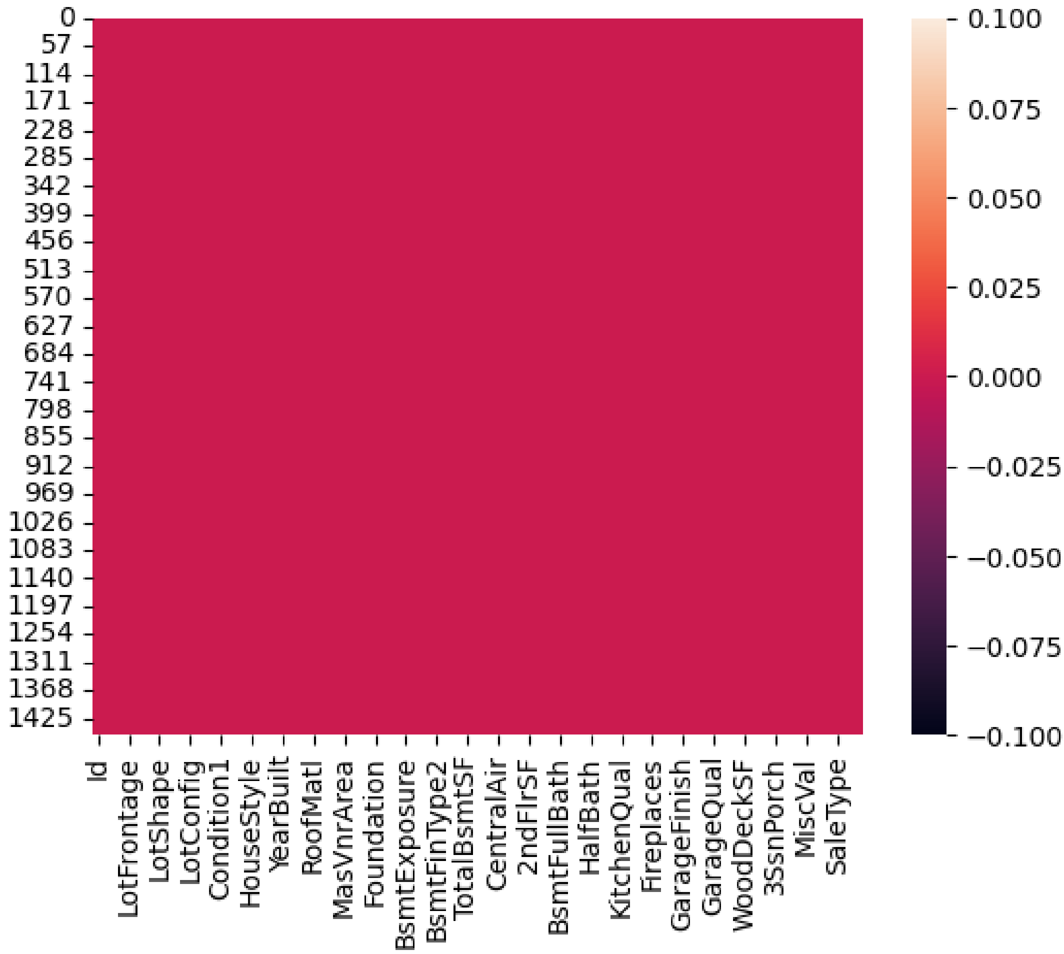
```
df_train = df_train.drop(columns=null_columns)
df_test = df_test.drop(columns=null_columns)

df_train_cleaned = df_train.ffill()
df_test_cleaned = df_test.ffill()

df_train_cleaned.head()
```

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

  Utilities LotConfig  ... EnclosedPorch 3SsnPorch ScreenPorch
PoolArea  \
0    AllPub    Inside  ...             0         0           0
0
```

```
1    AllPub       FR2  ...            0         0           0
0
2    AllPub    Inside  ...            0         0           0
0
3    AllPub    Corner  ...          272         0           0
0
4    AllPub       FR2  ...            0         0           0
0

  MiscVal MoSold  YrSold  SaleType  SaleCondition  SalePrice
0       0      2    2008        WD         Normal     208500
1       0      5    2007        WD         Normal     181500
2       0      9    2008        WD         Normal     223500
3       0      2    2006        WD        Abnorml     140000
4       0     12    2008        WD         Normal     250000

[5 rows x 75 columns]
```

```
sns.heatmap(df_train_cleaned.isnull())
```

```
<Axes: >
```

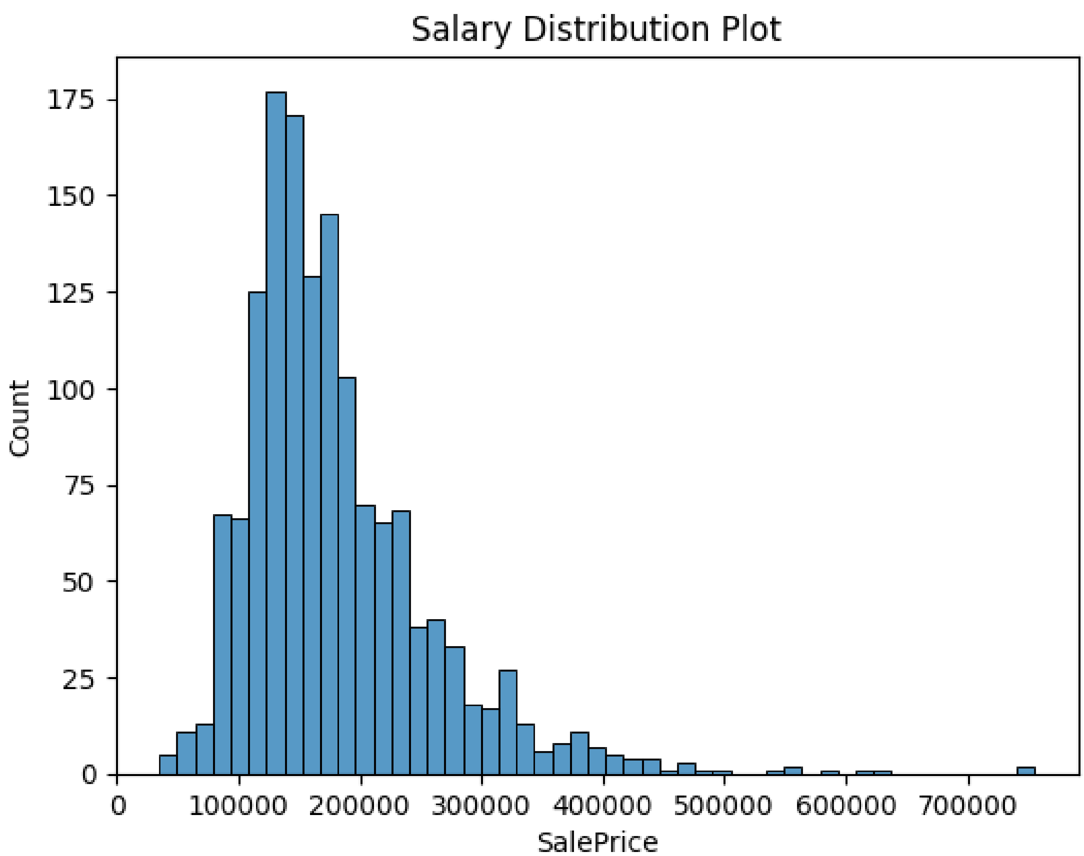



```
df_train_cleaned.describe()
```

```
                Id   MSSubClass  LotFrontage        LotArea  
OverallQual  \
count  1460.000000  1460.000000  1460.000000    1460.000000  
1460.000000
mean    730.500000    56.897260    70.104795   10516.828082  
6.099315
std     421.610009    42.300571    23.846996    9981.264932  
1.382997
min       1.000000    20.000000    21.000000    1300.000000  
1.000000
25%     365.750000    20.000000    59.000000    7553.500000  
5.000000
50%     730.500000    50.000000    70.000000    9478.500000  
6.000000
75%    1095.250000    70.000000    80.000000   11601.500000  
7.000000
max    1460.000000   190.000000   313.000000  215245.000000  
10.000000
```

```
       OverallCond    YearBuilt  YearRemodAdd   MasVnrArea
BsmtFinSF1  ...  \
count  1460.000000  1460.000000   1460.000000  1460.000000
1460.000000  ...
mean      5.575342  1971.267808   1984.865753   103.492466
443.639726  ...
std       1.112799    30.202904     20.645407   180.795612
456.098091  ...
min       1.000000  1872.000000   1950.000000     0.000000
0.000000  ...
25%       5.000000  1954.000000   1967.000000     0.000000
0.000000  ...
50%       5.000000  1973.000000   1994.000000     0.000000
383.500000  ...
75%       6.000000  2000.000000   2004.000000   165.250000
712.250000  ...
max       9.000000  2010.000000   2010.000000  1600.000000
5644.000000  ...

        WoodDeckSF  OpenPorchSF  EnclosedPorch    3SsnPorch
ScreenPorch  \
count  1460.000000  1460.000000    1460.000000  1460.000000
1460.000000
mean     94.244521    46.660274      21.954110     3.409589
15.060959
std     125.338794    66.256028      61.119149    29.317331
55.757415
min       0.000000     0.000000       0.000000     0.000000
0.000000
25%       0.000000     0.000000       0.000000     0.000000
0.000000
50%       0.000000    25.000000       0.000000     0.000000
0.000000
75%     168.000000    68.000000       0.000000     0.000000
0.000000
max     857.000000   547.000000     552.000000   508.000000
480.000000

          PoolArea      MiscVal       MoSold       YrSold
SalePrice
count  1460.000000   1460.000000  1460.000000  1460.000000
1460.000000
mean      2.758904     43.489041     6.321918  2007.815753
180921.195890
std      40.177307    496.123024     2.703626     1.328095
79442.502883
min       0.000000      0.000000     1.000000  2006.000000
34900.000000
25%       0.000000      0.000000     5.000000  2007.000000
```

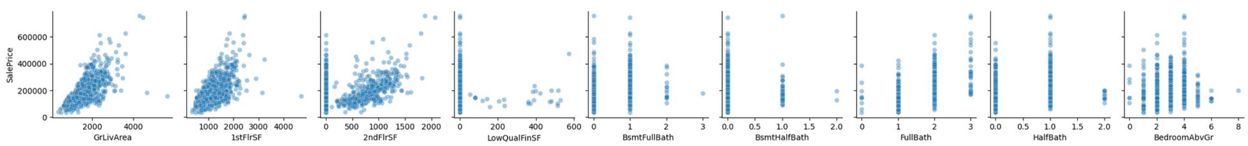
```
129975.000000
50%        0.000000      0.000000     6.000000  2008.000000
163000.000000
75%        0.000000      0.000000     8.000000  2009.000000
214000.000000
max      738.000000  15500.000000    12.000000  2010.000000
755000.000000

[8 rows x 38 columns]

plt.title('Salary Distribution Plot')
sns.histplot(df_train_cleaned['SalePrice'])
plt.show()
```



Split data

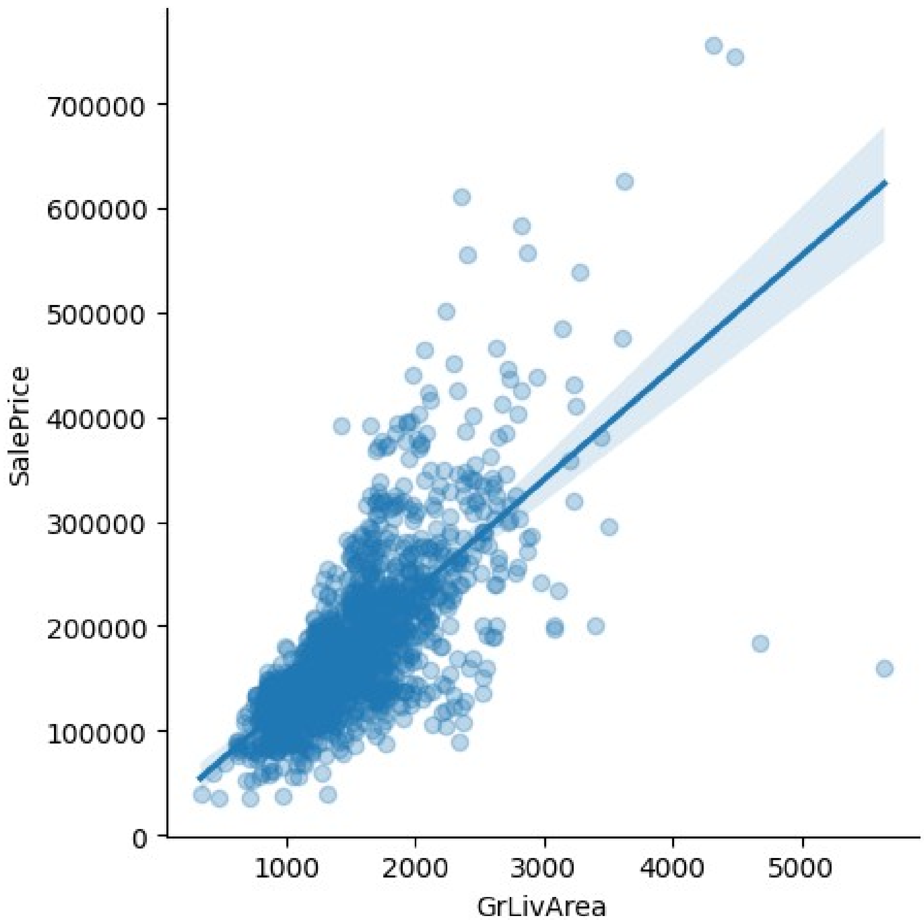
```
from sklearn.model_selection import train_test_split

features = ['GrLivArea', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
'BedroomAbvGr']
```

```
target = 'SalePrice'

X = df_train_cleaned[features]
y = df_train_cleaned[target]

df = pd.concat([X, y], axis=1)

# Plotting grid of scatter plots for each feature against the target
variable
sns.pairplot(df, x_vars=features, y_vars=[target], kind='scatter',
             plot_kws={'alpha':0.4}, diag_kws={'alpha':0.55,
'bins':40})

plt.show()
```



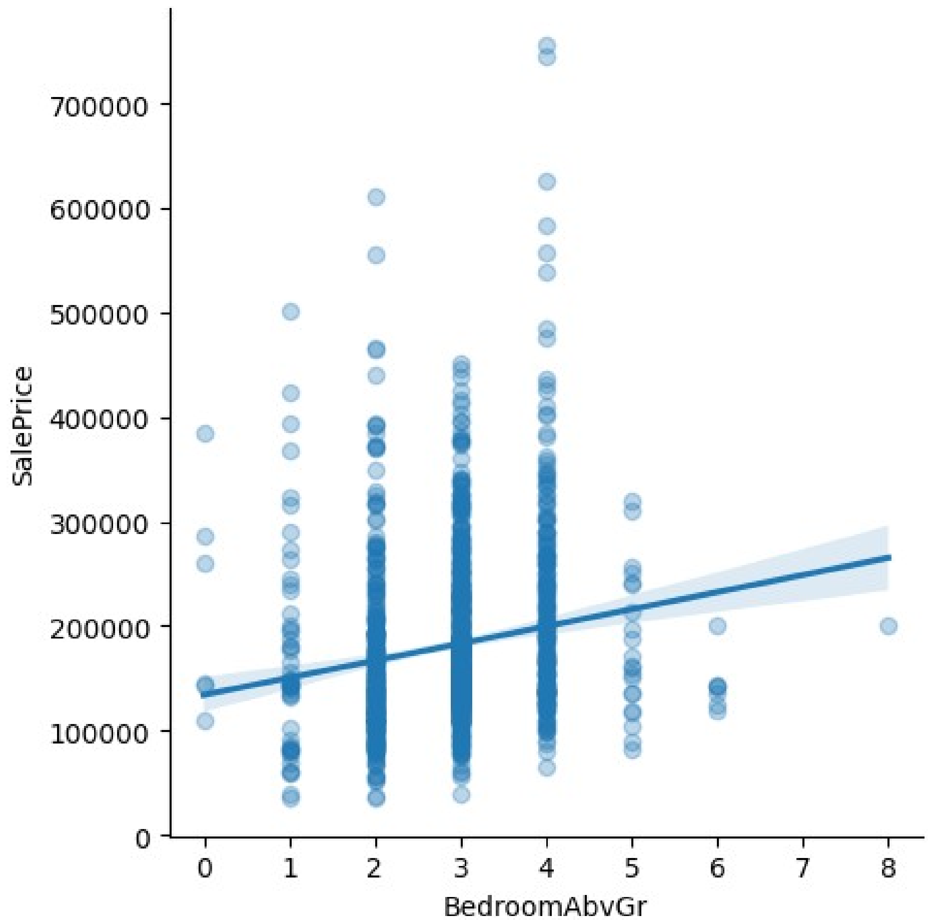

```
sns.lmplot(x='GrLivArea',
           y='SalePrice',
           data=df_train_cleaned,
           scatter_kws={'alpha':0.3})
```

```
<seaborn.axisgrid.FacetGrid at 0x17727b890>
```



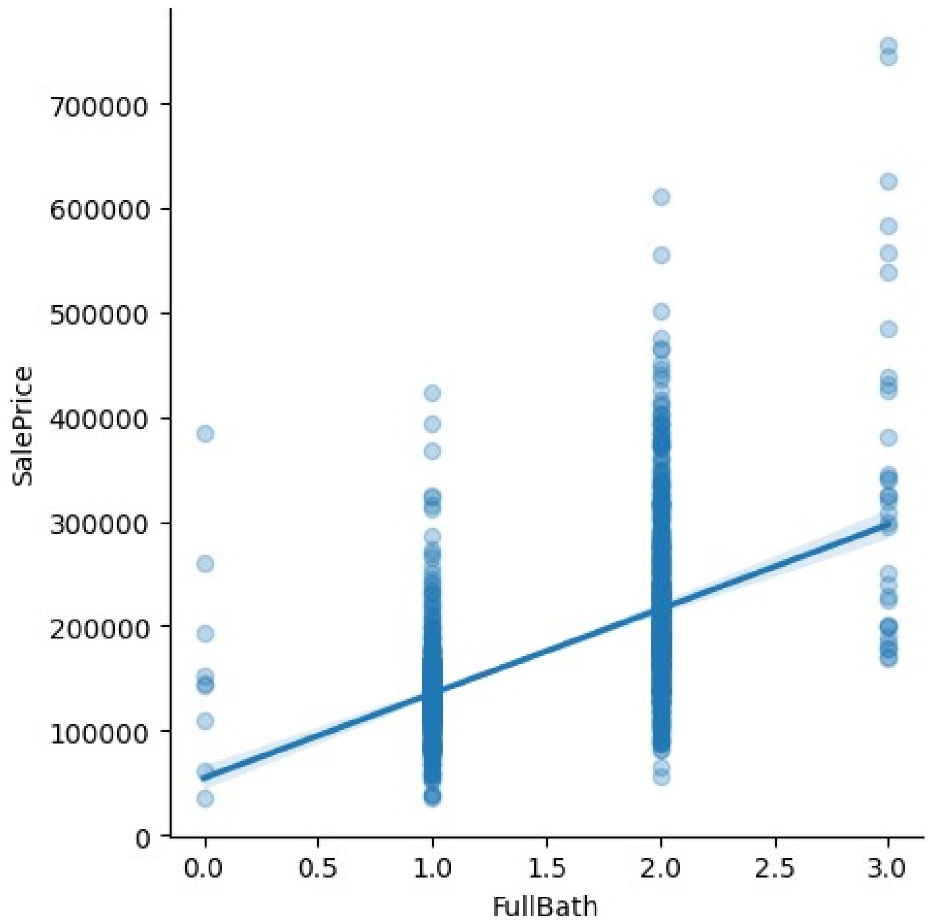

```
sns.lmplot(x='BedroomAbvGr',
           y='SalePrice',
           data=df_train_cleaned,
           scatter_kws={'alpha':0.3})
```

```
<seaborn.axisgrid.FacetGrid at 0x177079670>
```




```
sns.lmplot(x='FullBath',
           y='SalePrice',
           data=df_train_cleaned,
           scatter_kws={'alpha':0.3})
```

```
<seaborn.axisgrid.FacetGrid at 0x176f73ec0>
```




```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.2, random_state = 42)
```

Train model (Linear Regression)

```
from sklearn.linear_model import LinearRegression

model = LinearRegression()

model.fit(X_train, y_train)

LinearRegression()

coefficients = model.coef_

model.score(X, y)

0.6541686106425739
```

```
for feature, coef in zip(features, coefficients):
    print(f'{feature}: {coef}')
```

```
GrLivArea: 45.45358200866404
1stFlrSF: 70.93123244880826
2ndFlrSF: 19.004245633922277
LowQualFinSF: -44.481896073804585
BsmtFullBath: 22125.53078348177
BsmtHalfBath: 6538.890647874652
FullBath: 34869.22887902238
HalfBath: 22717.7813535538
BedroomAbvGr: -18379.60698218067
```

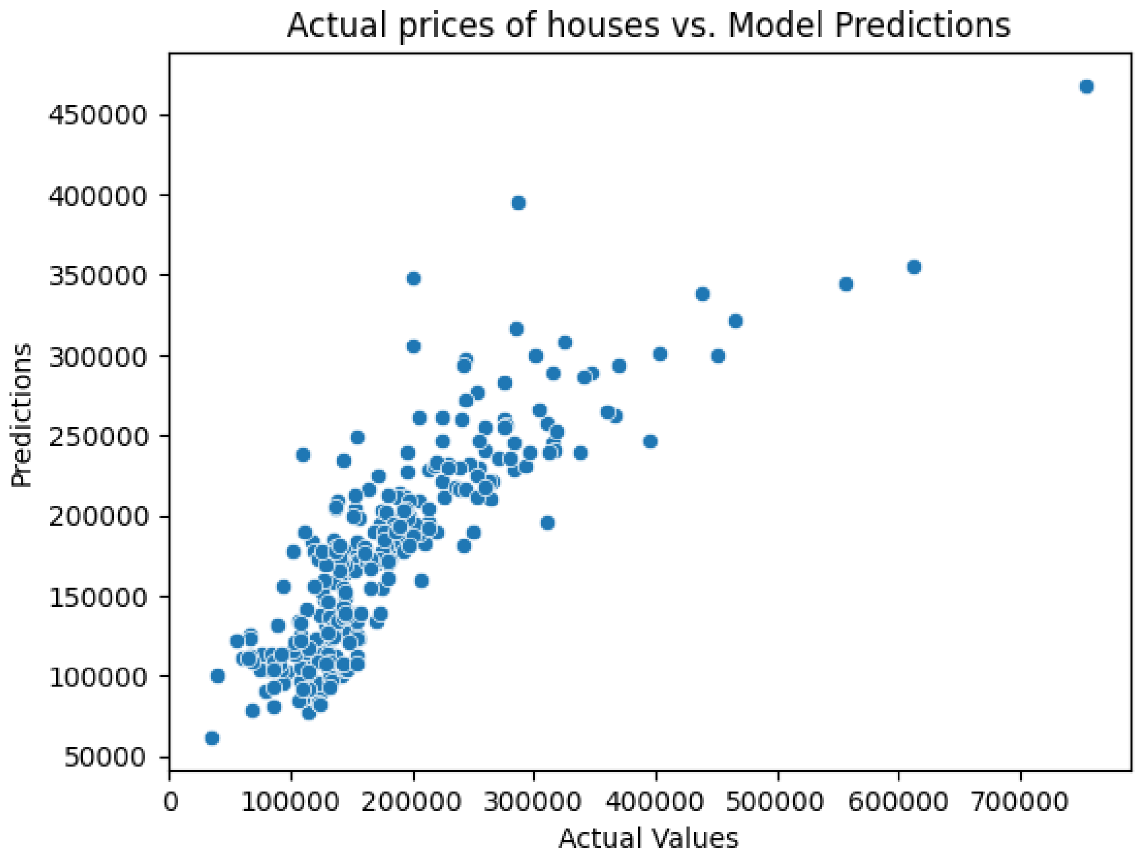
Predict results

```
predictions = model.predict(X_test)
```

```
np.set_printoptions(threshold=5)  # Print only 5 elements per array
print(predictions)
```

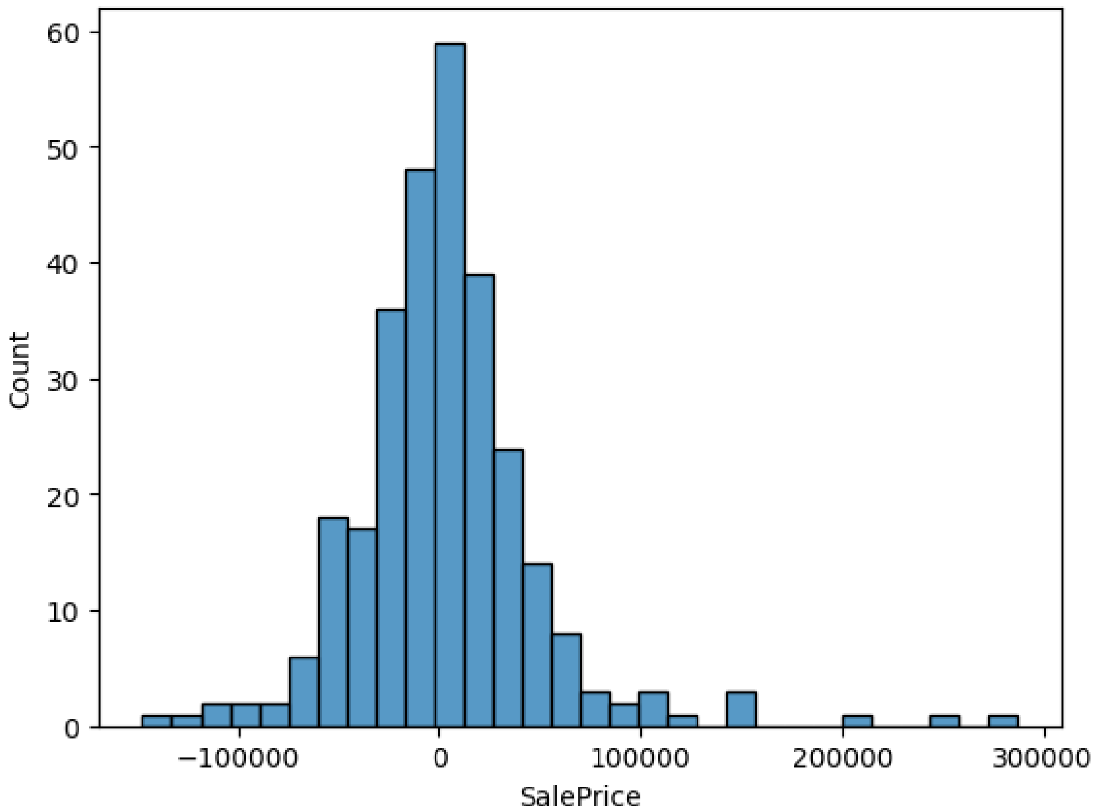
```
[112866.76155431 308640.3343831  120052.08531031 ... 193394.87353075
 122311.0076527   82585.36875711]
```

```
sns.scatterplot(x=y_test, y=predictions)
plt.xlabel('Actual Values')
plt.ylabel('Predictions')
plt.title('Actual prices of houses vs. Model Predictions')
plt.show()
```

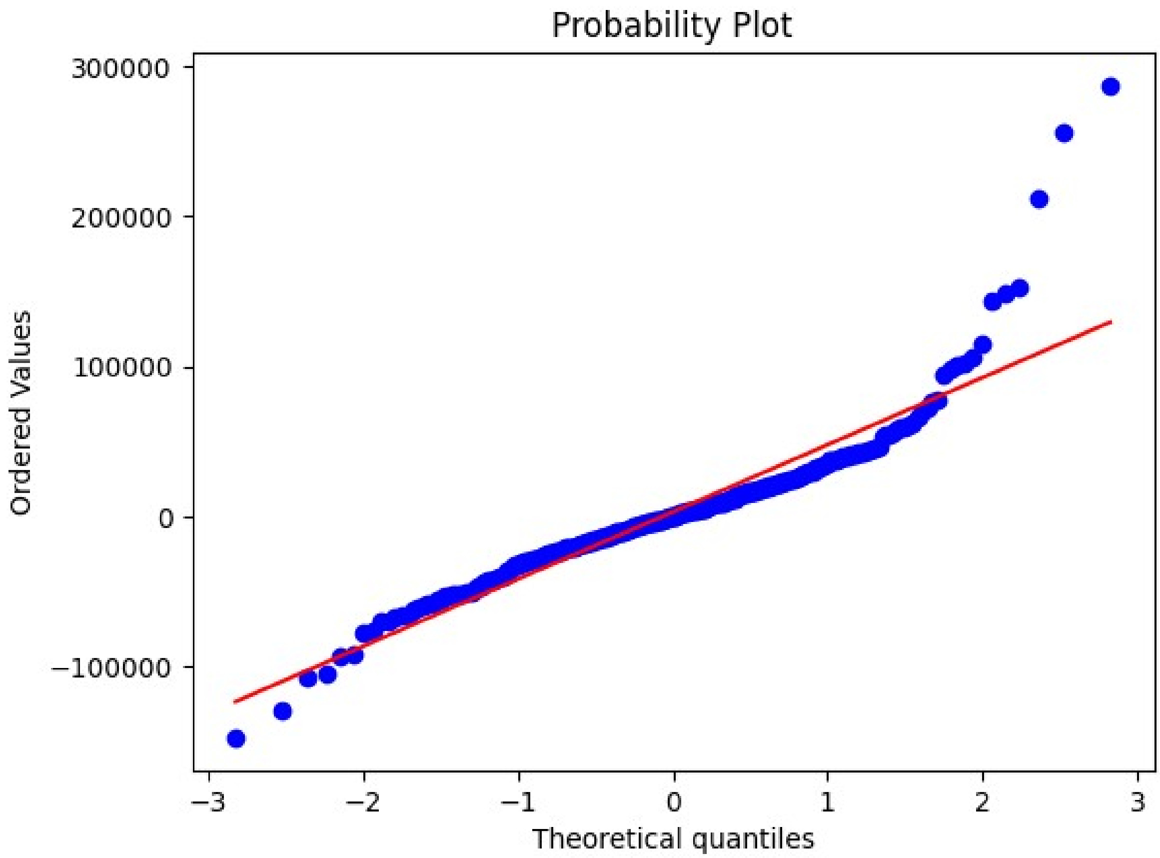


Evaluation of the model

```
from sklearn.metrics import mean_squared_error, mean_absolute_error
import math

print('Mean Absolute Error:',mean_absolute_error(y_test, predictions))
print('Mean Squared Error:',mean_squared_error(y_test, predictions))
print('Root Mean Squared Error:',math.sqrt(mean_squared_error(y_test,
predictions)))

Mean Absolute Error: 31410.205502278408
Mean Squared Error: 2269069226.157571
Root Mean Squared Error: 47634.74809587609

residuals = y_test-predictions
sns.histplot(residuals, bins=30)

<Axes: xlabel='SalePrice', ylabel='Count'>
```

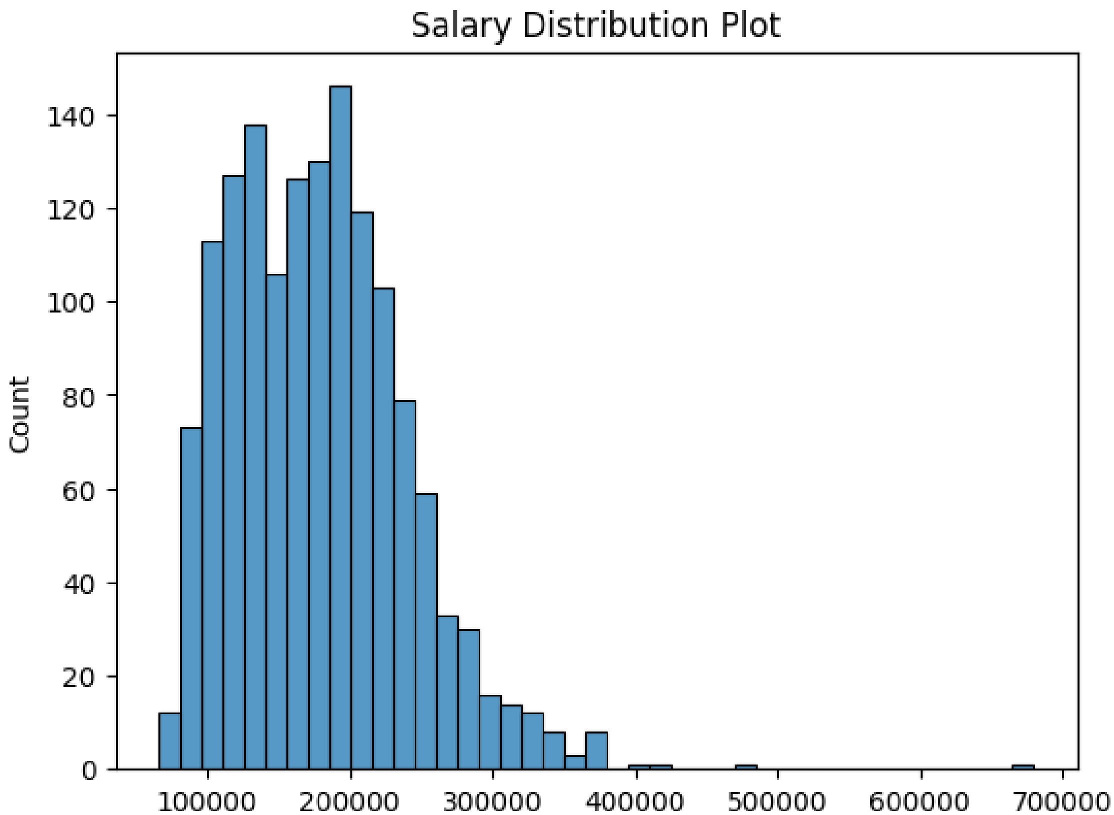



```
import pylab
import scipy.stats as stats

stats.probplot(residuals, dist="norm", plot=pylab)
pylab.show()
```



Use the trained model on our test data

```
Xt = df_test_cleaned[features]

test_predictions = model.predict(Xt)

test_predictions

array([104689.28980193, 159422.08883339, 192805.94429241, ...,
       128229.8257631 , 101461.04973747, 220250.83345123])

plt.title('Salary Distribution Plot')
sns.histplot(test_predictions)
plt.show()
```




```
submission_df = pd.DataFrame({
    'Id': df_test_cleaned['Id'],
    'SalePrice': test_predictions
})

# Save the predictions to a CSV file
submission_df.to_csv('submission.csv', index=False)
```

Conclusion

The current linear regression model provides a basic understanding of house price predictions, but the relatively high error metrics indicate room for improvement.