House Price Prediction Model

Import Libraries and Helpers

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

from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score


from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

Load and Inspect Dataset

Loading House Prediction Dataset

```python
df = pd.read_csv("train.csv")
df.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]
```

Inspecting Dataset

```
# checking data types
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             1460 non-null   int64  
 1   MSSubClass     1460 non-null   int64  
 2   MSZoning       1460 non-null   object 
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64  
 5   Street         1460 non-null   object 
 6   Alley          91 non-null     object 
 7   LotShape       1460 non-null   object 
 8   LandContour    1460 non-null   object 
 9   Utilities      1460 non-null   object 
 10  LotConfig      1460 non-null   object 
 11  LandSlope      1460 non-null   object 
 12  Neighborhood   1460 non-null   object 
 13  Condition1     1460 non-null   object 
 14  Condition2     1460 non-null   object 
 15  BldgType       1460 non-null   object 
 16  HouseStyle     1460 non-null   object 
 17  OverallQual    1460 non-null   int64  
 18  OverallCond    1460 non-null   int64  
 19  YearBuilt      1460 non-null   int64  
 20  YearRemodAdd   1460 non-null   int64  
 21  RoofStyle      1460 non-null   object 
 22  RoofMatl       1460 non-null   object 
 23  Exterior1st    1460 non-null   object 
 24  Exterior2nd    1460 non-null   object 
 25  MasVnrType     588 non-null    object 
 26  MasVnrArea     1452 non-null   float64
 27  ExterQual      1460 non-null   object 
 28  ExterCond      1460 non-null   object 
```

```
 29  Foundation     1460 non-null   object
 30  BsmtQual       1423 non-null   object
 31  BsmtCond       1423 non-null   object
 32  BsmtExposure   1422 non-null   object
 33  BsmtFinType1   1423 non-null   object
 34  BsmtFinSF1     1460 non-null   int64
 35  BsmtFinType2   1422 non-null   object
 36  BsmtFinSF2     1460 non-null   int64
 37  BsmtUnfSF      1460 non-null   int64
 38  TotalBsmtSF    1460 non-null   int64
 39  Heating        1460 non-null   object
 40  HeatingQC      1460 non-null   object
 41  CentralAir     1460 non-null   object
 42  Electrical     1459 non-null   object
 43  1stFlrSF       1460 non-null   int64
 44  2ndFlrSF       1460 non-null   int64
 45  LowQualFinSF   1460 non-null   int64
 46  GrLivArea      1460 non-null   int64
 47  BsmtFullBath   1460 non-null   int64
 48  BsmtHalfBath   1460 non-null   int64
 49  FullBath       1460 non-null   int64
 50  HalfBath       1460 non-null   int64
 51  BedroomAbvGr   1460 non-null   int64
 52  KitchenAbvGr   1460 non-null   int64
 53  KitchenQual    1460 non-null   object
 54  TotRmsAbvGrd   1460 non-null   int64
 55  Functional     1460 non-null   object
 56  Fireplaces     1460 non-null   int64
 57  FireplaceQu    770 non-null    object
 58  GarageType     1379 non-null   object
 59  GarageYrBlt    1379 non-null   float64
 60  GarageFinish   1379 non-null   object
 61  GarageCars     1460 non-null   int64
 62  GarageArea     1460 non-null   int64
 63  GarageQual     1379 non-null   object
 64  GarageCond     1379 non-null   object
 65  PavedDrive     1460 non-null   object
 66  WoodDeckSF     1460 non-null   int64
 67  OpenPorchSF    1460 non-null   int64
 68  EnclosedPorch  1460 non-null   int64
 69  3SsnPorch      1460 non-null   int64
 70  ScreenPorch    1460 non-null   int64
 71  PoolArea       1460 non-null   int64
 72  PoolQC         7 non-null      object
 73  Fence          281 non-null    object
 74  MiscFeature    54 non-null     object
 75  MiscVal        1460 non-null   int64
 76  MoSold         1460 non-null   int64
 77  YrSold         1460 non-null   int64
```

```
 78  SaleType       1460 non-null   object 
 79  SaleCondition  1460 non-null   object 
 80  SalePrice      1460 non-null   int64  
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

```
# summary statistics
df.describe()
```

```
                Id   MSSubClass  LotFrontage        LotArea  OverallQual  \
count  1460.000000  1460.000000  1201.000000    1460.000000  1460.000000   
mean    730.500000    56.897260    70.049958   10516.828082     6.099315   
std     421.610009    42.300571    24.284752    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    69.000000    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  1452.000000  1460.000000  ...   
mean      5.575342  1971.267808   1984.865753   103.685262   443.639726  ...   
std       1.112799    30.202904     20.645407   181.066207   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   166.000000   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]
```

```
# checking for missing values
df.isna().sum().sort_values(ascending=False)
```

```
PoolQC           1453
MiscFeature      1406
Alley            1369
Fence            1179
MasVnrType        872
                 ...
MoSold              0
YrSold              0
SaleType            0
SaleCondition       0
SalePrice           0
Length: 81, dtype: int64
```

Visual and Insights

```
# identifying numeric and categorical columns
numeric_features = df.select_dtypes(include=["int64", "float64"]).columns.tolist()
categorical_features = df.select_dtypes(include=["object"]).columns.tolist()

numeric_features, categorical_features[:10]  # preview first 10 categories
```

```
(['Id',
  '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',
```

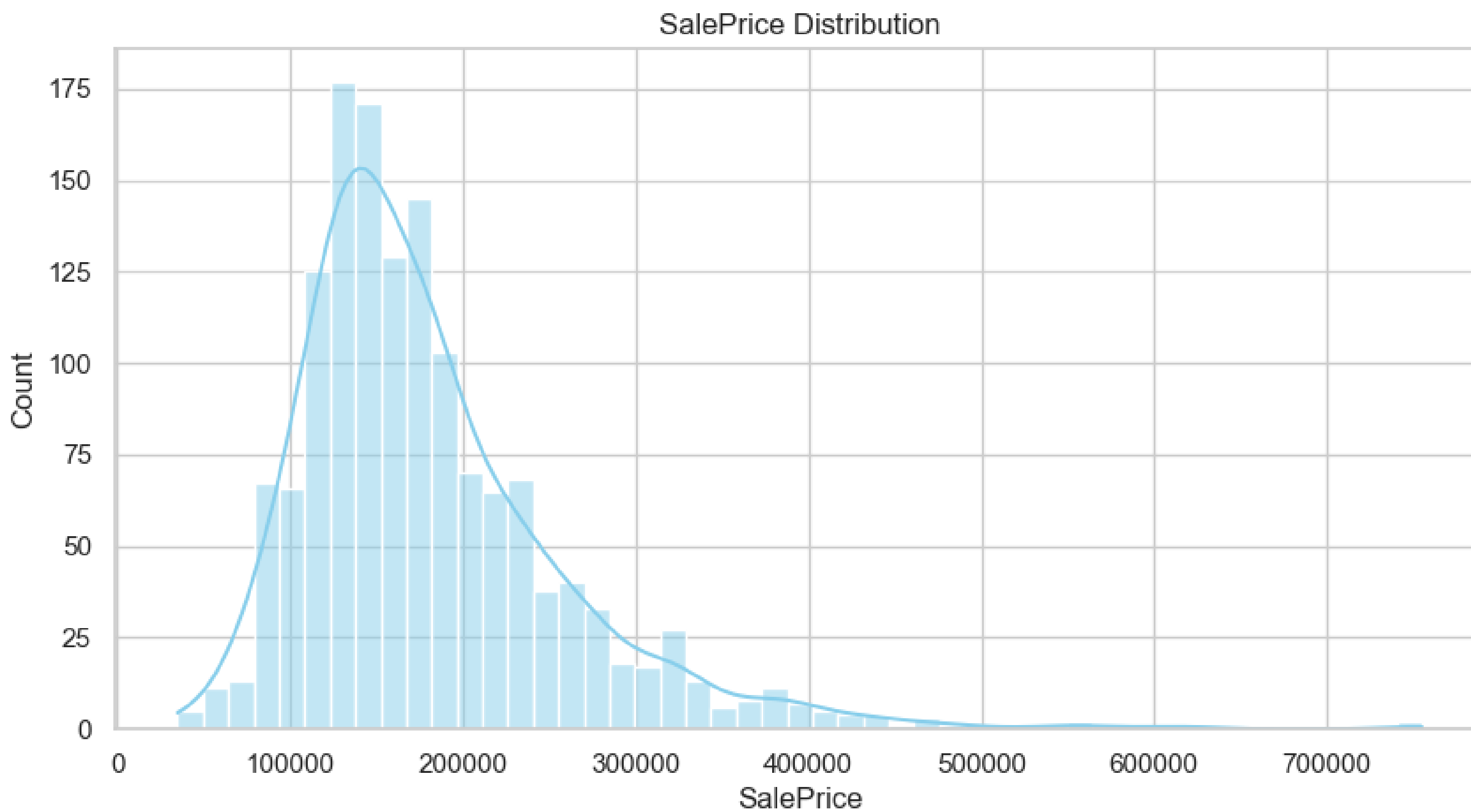
```
  'GarageCars',
  'GarageArea',
  'WoodDeckSF',
  'OpenPorchSF',
  'EnclosedPorch',
  '3SsnPorch',
  'ScreenPorch',
  'PoolArea',
  'MiscVal',
  'MoSold',
  'YrSold',
  'SalePrice'],
 ['MSZoning',
  'Street',
  'Alley',
  'LotShape',
  'LandContour',
  'Utilities',
  'LotConfig',
  'LandSlope',
  'Neighborhood',
  'Condition1'])
```

```
sns.set(style="whitegrid")
```

SalePrice Distribution - Histogram

House prices often follow a right-skewed distribution, meaning most homes are moderately priced, with fewer extremely expensive properties.

```
plt.figure(figsize=(10,5))
sns.histplot(df["SalePrice"], kde=True, color="skyblue")
plt.title("SalePrice Distribution")
plt.xlabel("SalePrice")
plt.ylabel("Count")
plt.show()
```



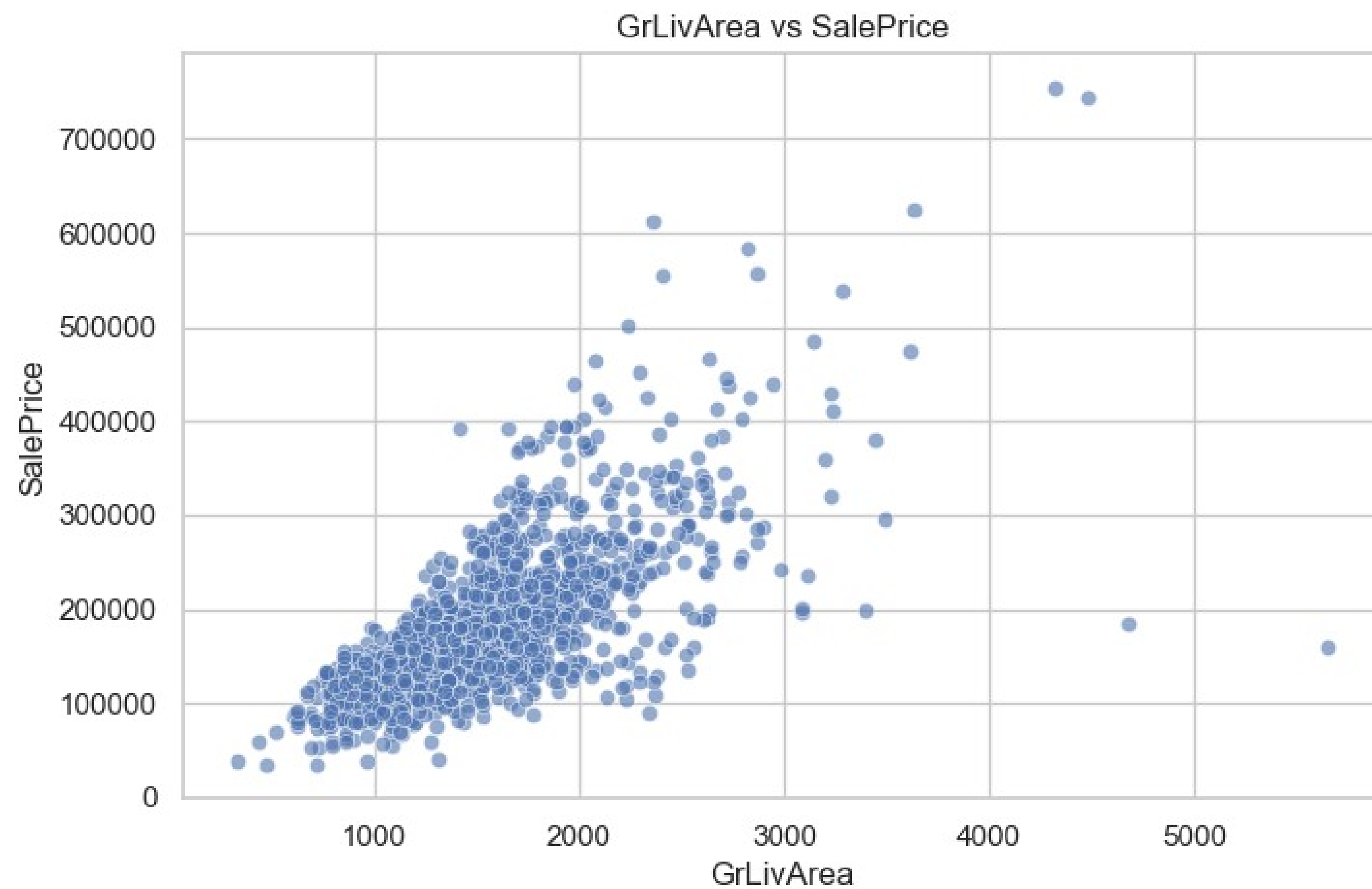
Insight:
SalePrice is strongly right-skewed. A log transformation reduces skew and stabilizes variance, which often improves regression model performance.

Numeric Features vs SalePrice

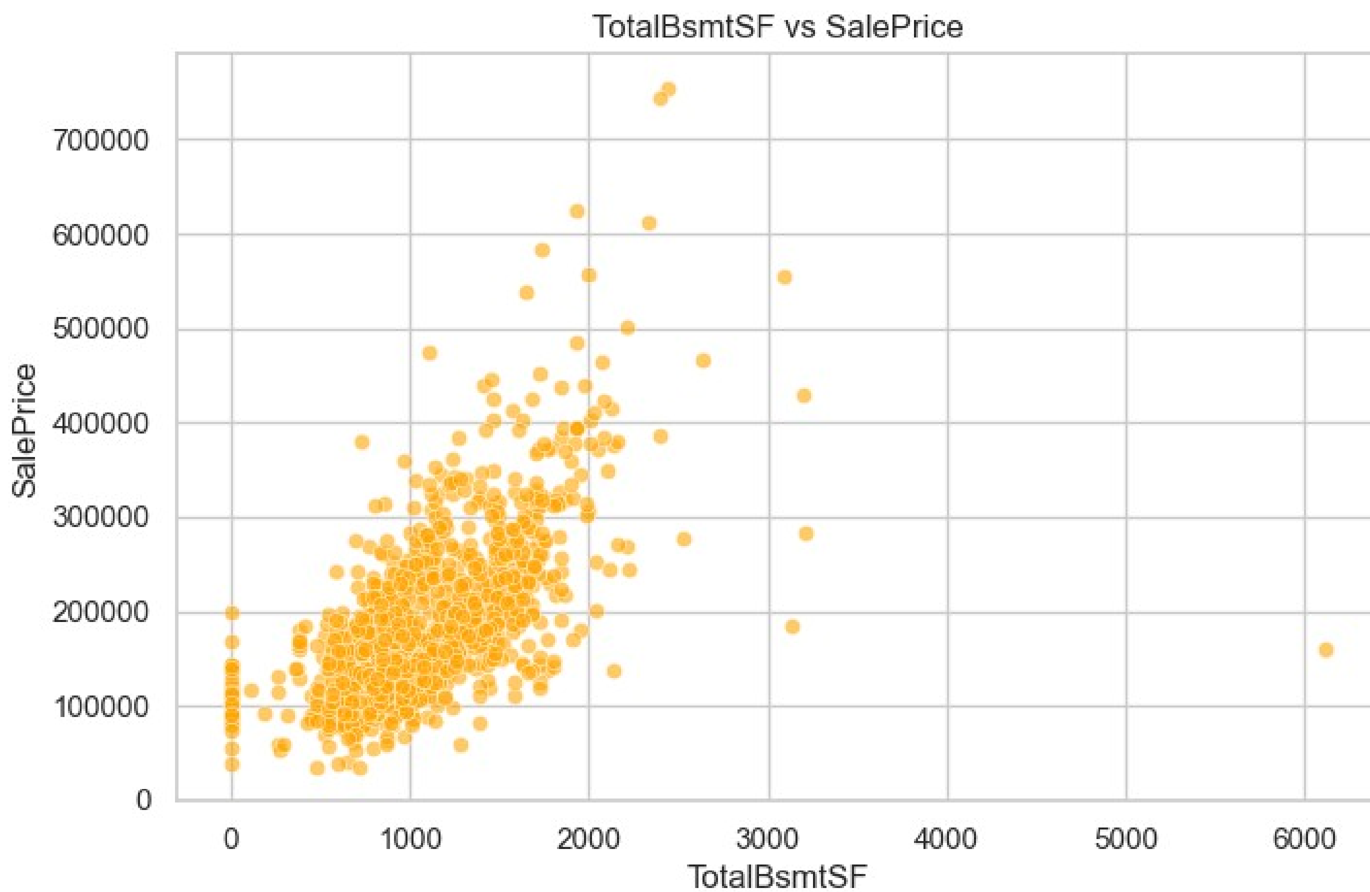
I have visualized here how major numeric predictors relate to SalePrice. I have used these 3 most important features:

- GrLivArea — Above ground living area
- TotalBsmtSF — Basement area
- OverallQual — Quality rating (1–10)

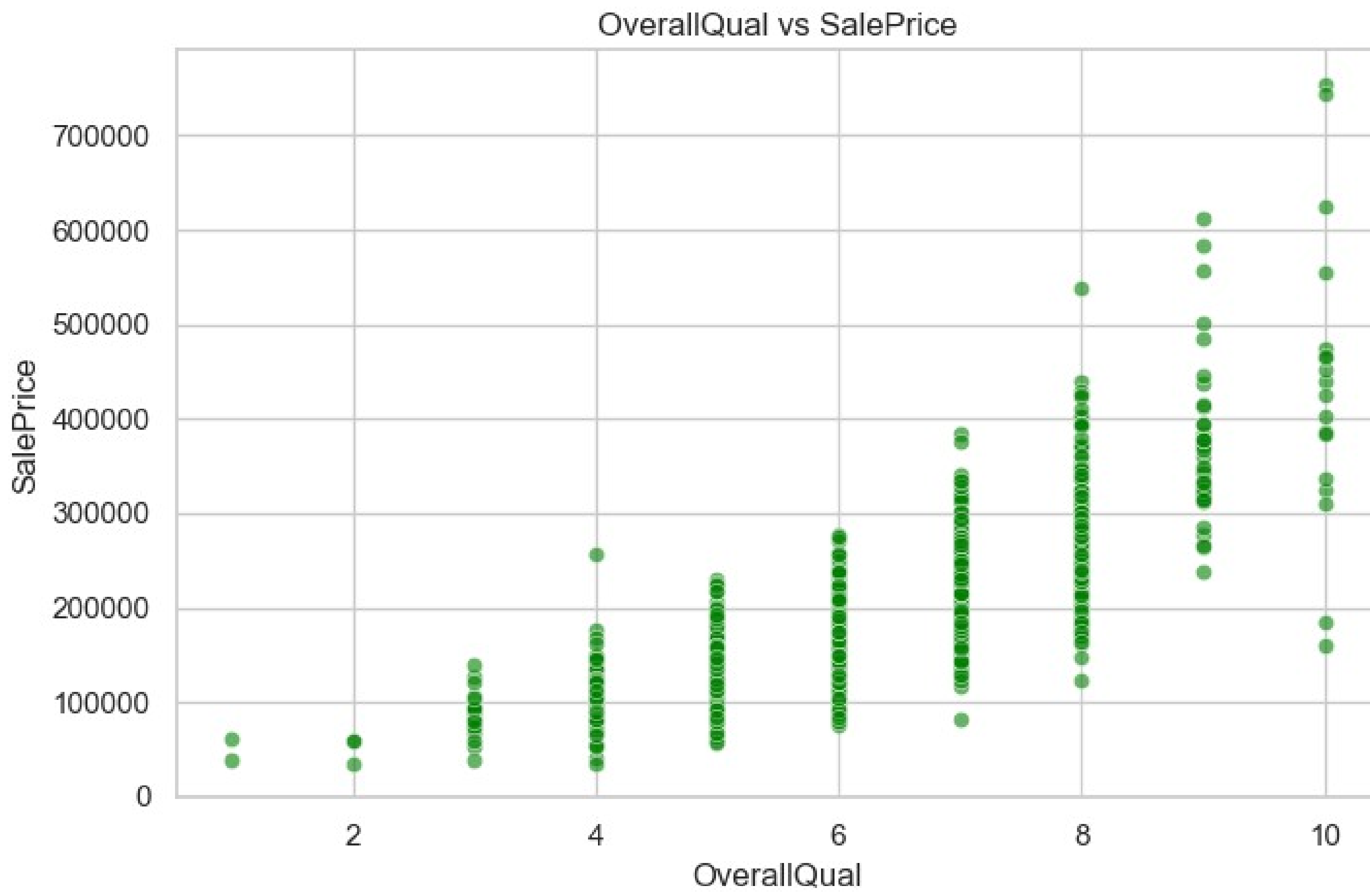
```
plt.figure(figsize=(8,5))
sns.scatterplot(data=df, x="GrLivArea", y="SalePrice", alpha=0.6)
plt.title("GrLivArea vs SalePrice")
plt.show()
```




```
plt.figure(figsize=(8,5))
sns.scatterplot(data=df, x="TotalBsmtSF", y="SalePrice", alpha=0.6, color="orange")
plt.title("TotalBsmtSF vs SalePrice")
plt.show()
```




```
plt.figure(figsize=(8,5))
sns.scatterplot(data=df, x="OverallQual", y="SalePrice", alpha=0.6, color="green")
plt.title("OverallQual vs SalePrice")
plt.show()
```



Insight:

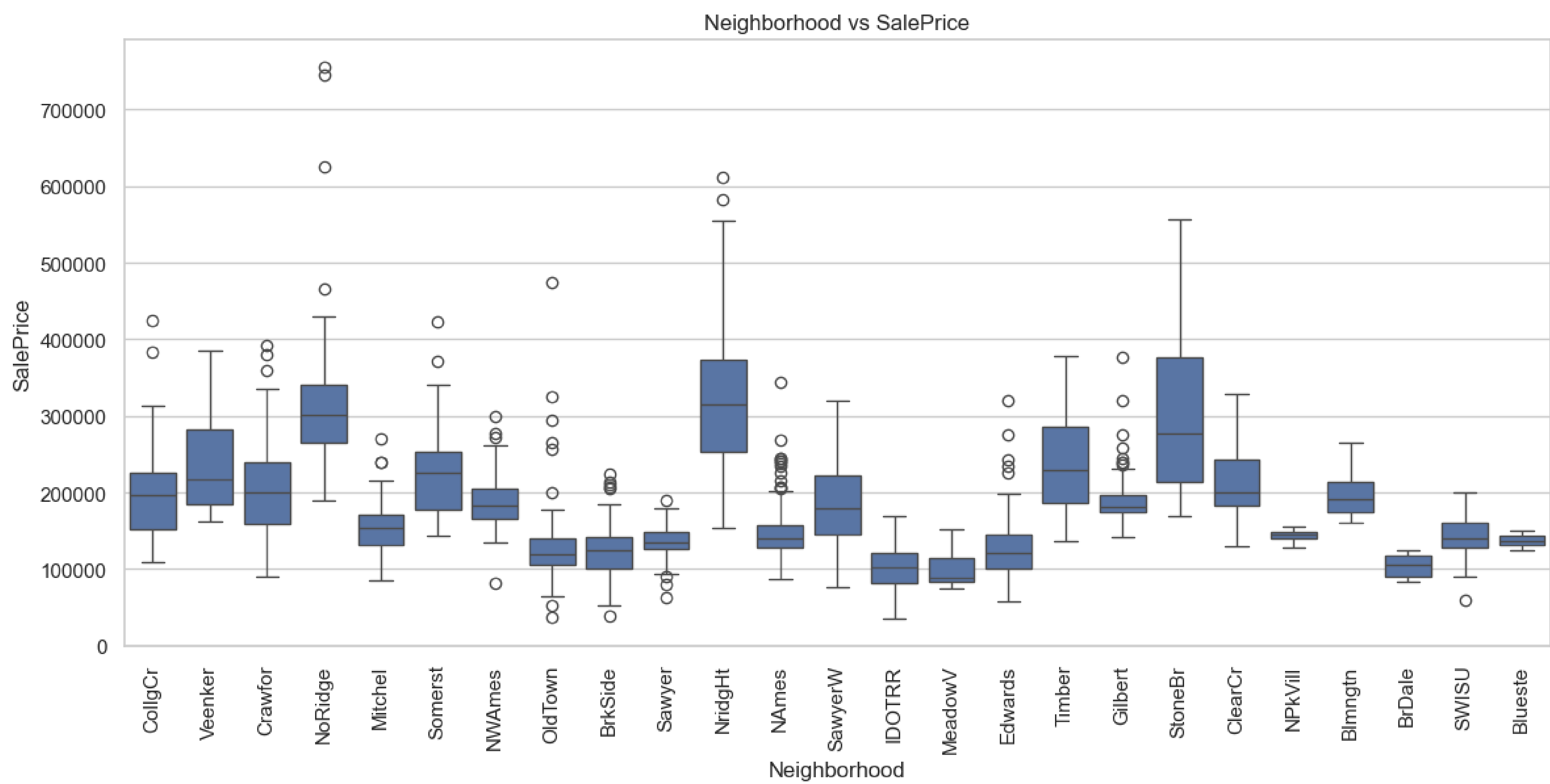
- GrLivArea and TotalBsmtSF show strong positive relationships with SalePrice — larger homes sell for more.
- OverallQual has a very strong upward trend: better quality homes command significantly higher prices.

Categorical Features vs SalePrice

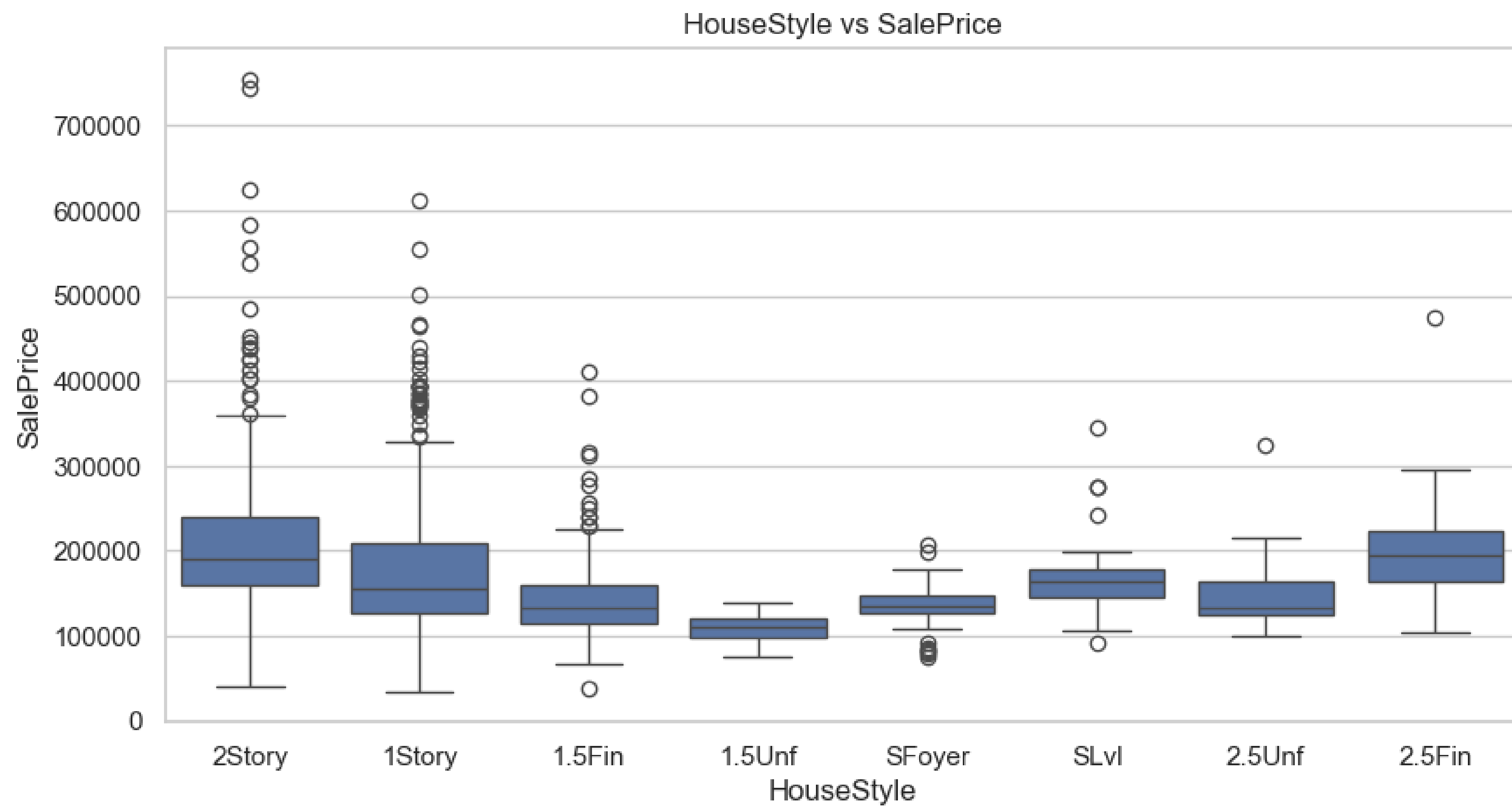
Using boxplot here to compare price ranges across categorical groups. I have used these 2 most common features:

- Neighborhood
- HouseStyle

```
# boxplot 1 - Neighborhood vs SalePrice
plt.figure(figsize=(14,6))
sns.boxplot(data=df, x="Neighborhood", y="SalePrice")
plt.xticks(rotation=90)
plt.title("Neighborhood vs SalePrice")
plt.show()
```



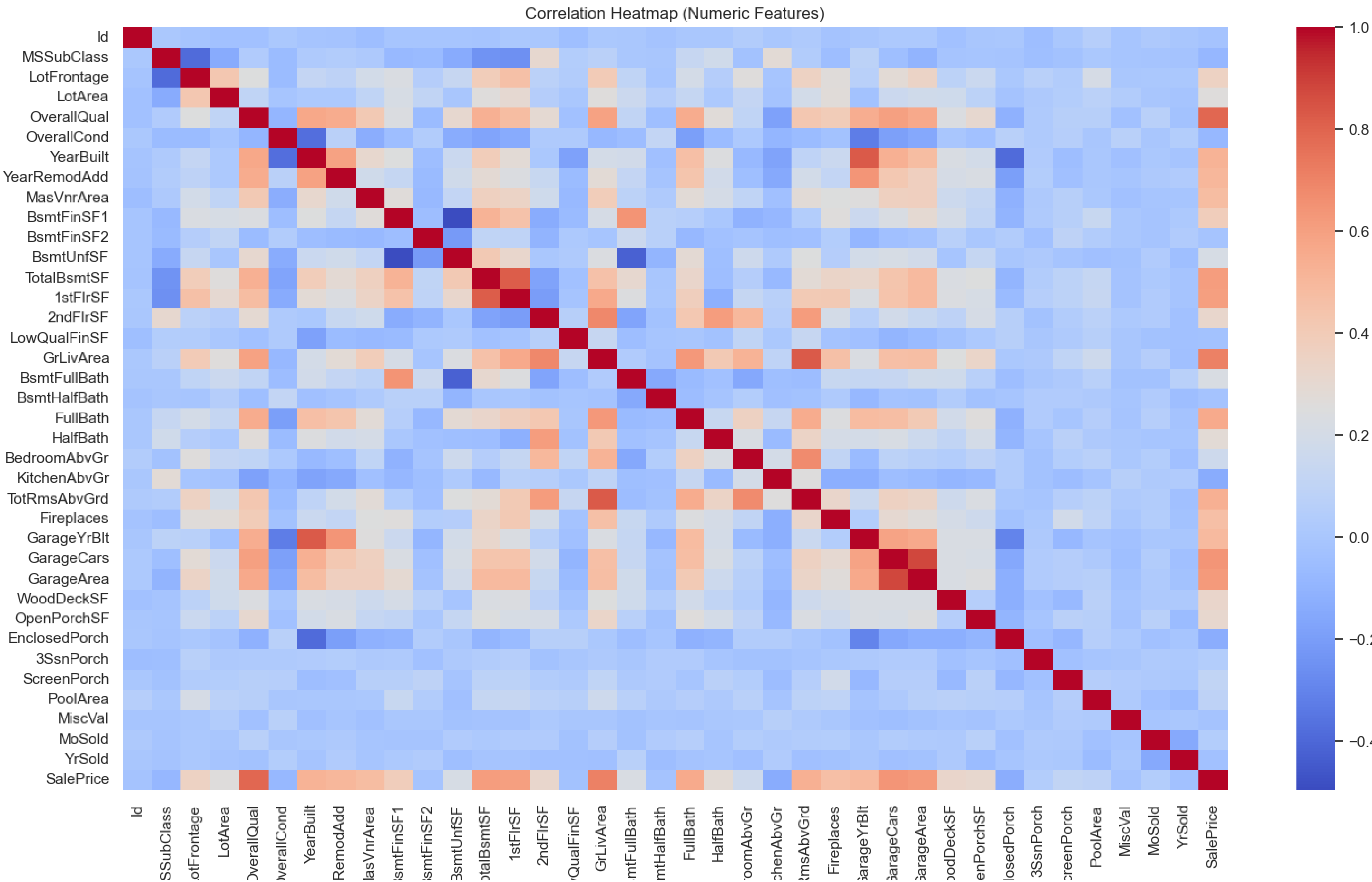

```
# boxplot 2 - HouseStyle vs SalePrice
plt.figure(figsize=(10,5))
sns.boxplot(data=df, x="HouseStyle", y="SalePrice")
plt.title("HouseStyle vs SalePrice")
plt.show()
```



Insight:
Different neighborhoods show significantly different price levels, indicating strong location effects.
House-style types also show variation, with certain styles typically commanding higher prices.

Correlation Heatmap

```
plt.figure(figsize=(18,10))
corr = df[numeric_features].corr()
sns.heatmap(corr, annot=False, cmap="coolwarm")
plt.title("Correlation Heatmap (Numeric Features)")
plt.show()
```



Correlation Heatmap (Numeric Features)
Id
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
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

Insight:
The strongest correlations with SalePrice include:

- OverallQual
- GrLivArea
- GarageCars & GarageArea
- TotalBsmtSF

These features will likely be highly important for prediction.

Preprocessing and Split Dataset

In this section:

- Remove non-informative columns
- Separate features (X) and target (y)
- Optionally apply a log transform to `SalePrice`
- Identify numeric and categorical features
- Build a preprocessing pipeline with imputation, scaling and one-hot encoding
- Split the data into training and test sets

Feature and Target Selection

```
# Drop unnecessary non-features
df = df.drop(columns=["Id"])

# Target
y = df["SalePrice"]
# Features
X = df.drop(columns=["SalePrice"])
```

House prices are very skewed; models work better on log prices.

```
# Log-transform target to reduce skew
y_log = np.log1p(y)   # log(1 + Price)

y_original = y       # keep for reference
y = y_log            # from now on use y as log-price
```

Train-Test Split Dataset

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

X_train.shape, X_test.shape
```

```
((1168, 79), (292, 79))
```

Identify numeric & categorical feature lists (on X, not df)

```
numeric_features = X.select_dtypes(include=["int64", "float64"]).columns.tolist()
categorical_features = X.select_dtypes(include=["object"]).columns.tolist()

numeric_features[:10], categorical_features[:10]  # quick preview
```

```
(['MSSubClass',
  'LotFrontage',
  'LotArea',
  'OverallQual',
  'OverallCond',
  'YearBuilt',
  'YearRemodAdd',
  'MasVnrArea',
  'BsmtFinSF1',
  'BsmtFinSF2'],
 ['MSZoning',
  'Street',
  'Alley',
  'LotShape',
  'LandContour',
  'Utilities',
  'LotConfig',
  'LandSlope',
  'Neighborhood',
  'Condition1'])
```

Building Pipelines for Feature(X) Preprocessing

Numeric pipeline: impute (median) + scale

This pipeline will fillup the missing numeric values with median and scale them.

```
numeric_transformer = Pipeline([
    ("imputer", SimpleImputer(strategy="median")),
    ("scaler", StandardScaler())
])
```

Categorical pipeline: impute (most frequent) + one-hot encode

This pipeline will fillup the missing categorical values with the most frequent ones and scale with one-hot encode

```
categorical_transformer = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="most_frequent")),
    ("onehot", OneHotEncoder(handle_unknown="ignore"))
])
```

Combining the numerical and categorical pipelines with ColumnTransformer

```
preprocessor = ColumnTransformer(
    transformers=[
        ("num", numeric_transformer, numeric_features),
        ("cat", categorical_transformer, categorical_features),
    ]
)
```

Baseline Linear Regression Model Train and Evaluation

Building the pipeline - Preprocessor + LinearRegression

```
# baseline linear regression pipeline
baseline_linreg = Pipeline([
    ("preprocessor", preprocessor),
    ("linreg", LinearRegression())
])

baseline_linreg
```

```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('num',
                                                  Pipeline(steps=[('imputer',
                                                                   SimpleImputer(strategy='median')),
                                                                  ('scaler',
                                                                   StandardScaler())]),
                                                  ['MSSubClass', 'LotFrontage',
                                                   'LotArea', 'OverallQual',
                                                   'OverallCond', 'YearBuilt',
                                                   'YearRemodAdd', 'MasVnrArea',
                                                   'BsmtFinSF1', 'BsmtFinSF2',
                                                   'BsmtUnfSF', 'TotalBsmtSF',
                                                   '1stFlrSF', '2ndFlrSF',
                                                   'LowQual...
                                                   'LandContour', 'Utilities',
                                                   'LotConfig', 'LandSlope',
                                                   'Neighborhood', 'Condition1',
                                                   'Condition2', 'BldgType',
                                                   'HouseStyle', 'RoofStyle',
                                                   'RoofMatl', 'Exterior1st',
                                                   'Exterior2nd', 'MasVnrType',
                                                   'ExterQual', 'ExterCond',
                                                   'Foundation', 'BsmtQual',
                                                   'BsmtCond', 'BsmtExposure',
                                                   'BsmtFinType1',
                                                   'BsmtFinType2', 'Heating',
                                                   'HeatingQC', 'CentralAir',
```

```
                                                    'Electrical', ...])])),
                ('linreg', LinearRegression())])
```

Fitting the model on Training Data

```
baseline_linreg.fit(X_train, y_train)
```

```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('num',
                                                  Pipeline(steps=[('imputer',
                                                                   SimpleImputer(strategy='median')),
                                                                  ('scaler',
                                                                   StandardScaler())]),
                                                  ['MSSubClass', 'LotFrontage',
                                                   'LotArea', 'OverallQual',
                                                   'OverallCond', 'YearBuilt',
                                                   'YearRemodAdd', 'MasVnrArea',
                                                   'BsmtFinSF1', 'BsmtFinSF2',
                                                   'BsmtUnfSF', 'TotalBsmtSF',
                                                   '1stFlrSF', '2ndFlrSF',
                                                   'LowQual...
                                                   'LandContour', 'Utilities',
                                                   'LotConfig', 'LandSlope',
                                                   'Neighborhood', 'Condition1',
                                                   'Condition2', 'BldgType',
                                                   'HouseStyle', 'RoofStyle',
                                                   'RoofMatl', 'Exterior1st',
                                                   'Exterior2nd', 'MasVnrType',
                                                   'ExterQual', 'ExterCond',
                                                   'Foundation', 'BsmtQual',
                                                   'BsmtCond', 'BsmtExposure',
                                                   'BsmtFinType1',
                                                   'BsmtFinType2', 'Heating',
                                                   'HeatingQC', 'CentralAir',
                                                   'Electrical', ...])])),
                ('linreg', LinearRegression())])
```

Predicting on Test Data

```
y_pred = baseline_linreg.predict(X_test)
```

Evaluating Baseline Linear Regression Model (y in log-scale)

```
# evaluating baseline linear regression
mse_log = mean_squared_error(y_test, y_pred)
rmse_log = np.sqrt(mse_log)
mae_log = mean_absolute_error(y_test, y_pred)
r2_log = r2_score(y_test, y_pred)

print(f"RMSE : {rmse_log:.4f}")
```

```
print(f"MAE  : {mae_log:.4f}")
print(f"R²   : {r2_log:.4f}")
```

```
RMSE : 0.1281
MAE  : 0.0883
R²   : 0.9121
```

Evaluating Baseline Linear Regression Model (y in original-scale)

```
# converting predictions back to original SalePrice scale
y_test_orig = np.expm1(y_test)
y_pred_orig = np.expm1(y_pred)

mse_orig = mean_squared_error(y_test_orig, y_pred_orig)
rmse_orig = np.sqrt(mse_orig)
mae_orig = mean_absolute_error(y_test_orig, y_pred_orig)
r2_orig = r2_score(y_test_orig, y_pred_orig)

print(f"RMSE (original): {rmse_orig:,.2f}$")
print(f"MAE  (original): {mae_orig:,.2f}$")
print(f"R²   (original): {r2_orig:.4f}$")
```

```
RMSE (original): 22,739.77$
MAE  (original): 14,899.28$
R²   (original): 0.9326$
```

Train and Evaluate with other Models + Comparison

Defining Other Models

```
models = {}

# 1. Linear Regressioon(untuned)
models["Linear Regression"] = Pipeline([
    ("preprocessor", preprocessor),
    ("linreg", LinearRegression())
])

# 2. Ridge Regression
models["Ridge Regression"] = Pipeline([
    ("preprocessor", preprocessor),
    ("ridgereg", Ridge())
])

# 3. Lasso Regression
models["Lasso Regression"] = Pipeline([
    ("preprocessor", preprocessor),
    ("lassoreg", Lasso())
])
```

```python
# 4. Random Forest Regressor
models["Random Forest Regressor"] = Pipeline([
    ("preprocessor", preprocessor),
    ("rfreg", RandomForestRegressor(
        n_estimators=100,
        random_state=42,
        n_jobs=-1
    ))
])

# 5. Gradient Boosting Regressor
models["Gradient Boosting Regressor"] = Pipeline([
    ("preprocessor", preprocessor),
    ("gradreg", GradientBoostingRegressor(random_state=42))
])
```

Defining Tuned Models(Random Forest and Gradient Boosting) using GridSearchCV

```python
# tuning random forest
rf_pipeline = Pipeline([
    ("preprocessor", preprocessor),
    ("rfreg", RandomForestRegressor(random_state=42, n_jobs=-1))
])

rf_param_grid = {
    "rfreg__n_estimators": [100, 200],
    "rfreg__max_depth": [None, 10, 20],
    "rfreg__max_features": ["sqrt", "log2"],
    "rfreg__min_samples_split": [2, 5]
}

rf_grid_search = GridSearchCV(
    estimator=rf_pipeline,
    param_grid=rf_param_grid,
    cv=5,
    scoring="neg_mean_squared_error",
    n_jobs=-1,
    verbose=1
)

rf_grid_search.fit(X_train, y_train)

print("Best parameters (Random Forest):")
print(rf_grid_search.best_params_)

best_rf_rmse_cv = np.sqrt(-rf_grid_search.best_score_)
print(f"Best CV RMSE (log-space): {best_rf_rmse_cv:.4f}")

best_rf_pipeline = rf_grid_search.best_estimator_
models["Random Forest Regressor (Tuned)"] = best_rf_pipeline
```

```
Fitting 5 folds for each of 24 candidates, totalling 120 fits
Best parameters (Random Forest):
{'rfreg__max_depth': None, 'rfreg__max_features': 'sqrt', 'rfreg__min_samples_split': 2, 'rfreg__n_estimators': 200}
Best CV RMSE (log-space): 0.1479
```

```
# tuning gradient boosting regressor
gb_pipeline = Pipeline([
    ("preprocessor", preprocessor),
    ("gradreg", GradientBoostingRegressor(random_state=42))
])

# hyperparameter grid for Gradient Boosting
gb_param_grid = {
    "gradreg__n_estimators": [100, 200],
    "gradreg__learning_rate": [0.05, 0.1, 0.2],
    "gradreg__max_depth": [2, 3, 4]
}

gb_grid_search = GridSearchCV(
    estimator=gb_pipeline,
    param_grid=gb_param_grid,
    cv=5,
    scoring="neg_mean_squared_error",
    n_jobs=-1,
    verbose=1
)

gb_grid_search.fit(X_train, y_train)

print("Best parameters (Gradient Boosting):")
print(gb_grid_search.best_params_)

best_gb_rmse_cv = np.sqrt(-gb_grid_search.best_score_)
print(f"Best CV RMSE (log-space): {best_gb_rmse_cv:.4f}")

best_gb_pipeline = gb_grid_search.best_estimator_
models["Gradient Boosting Regressor (Tuned)"] = best_gb_pipeline
```

```
Fitting 5 folds for each of 18 candidates, totalling 90 fits
Best parameters (Gradient Boosting):
{'gradreg__learning_rate': 0.05, 'gradreg__max_depth': 3, 'gradreg__n_estimators': 200}
Best CV RMSE (log-space): 0.1327
```

Evaluating All Models

```
# helper function to evaluate with all models
def model_evaluation(name, model, X_train, y_train, X_test, y_test):
    # train model
    model.fit(X_train, y_train)
    # predictions(in log space)
```

```python
    y_pred = model.predict(X_test)

    # convert back to original sale prices
    y_pred_orig = np.expm1(y_pred)
    y_test_orig = np.expm1(y_test)

    # metrics
    mse = mean_squared_error(y_test_orig, y_pred_orig)
    rmse = np.sqrt(mse)
    mae = mean_absolute_error(y_test_orig, y_pred_orig)
    r2 = r2_score(y_test_orig, y_pred_orig)

    print(f"{name:35s} -> RMSE : {rmse:.4f} | MAE : {mae:,.2f} | R² : {r2:.4f}")

    return rmse, mae, r2

# evaluating all models and storing results
results = []

for name, model in models.items():
    rmse, mae, r2 = model_evaluation(name, model, X_train, y_train, X_test, y_test)
    results.append({
        "Model": name,
        "RMSE": rmse,
        "MAE": mae,
        "R²": r2
    })
```

```
Linear Regression                   -> RMSE : 22739.7741 | MAE : 14,899.28 | R² : 0.9326
Ridge Regression                    -> RMSE : 23856.6945 | MAE : 15,738.72 | R² : 0.9258
Lasso Regression                    -> RMSE : 88270.8537 | MAE : 59,931.24 | R² : -0.0158
Random Forest Regressor             -> RMSE : 29963.8159 | MAE : 17,712.67 | R² : 0.8829
Gradient Boosting Regressor         -> RMSE : 30019.7658 | MAE : 16,926.73 | R² : 0.8825
Random Forest Regressor (Tuned)     -> RMSE : 34765.3740 | MAE : 18,482.06 | R² : 0.8424
Gradient Boosting Regressor (Tuned) -> RMSE : 30761.7621 | MAE : 16,742.79 | R² : 0.8766
```

```python
# comparison dataframe with all model's result
results_df = pd.DataFrame(results)
results_df = results_df.sort_values(by="RMSE", ascending=True).reset_index(drop=True)
results_df
```

	Model	RMSE	MAE	R²
0	Linear Regression	22739.774051	14899.276389	0.932585
1	Ridge Regression	23856.694526	15738.719034	0.925800
2	Random Forest Regressor	29963.815911	17712.671661	0.882948
3	Gradient Boosting Regressor	30019.765785	16926.734665	0.882510
4	Gradient Boosting Regressor (Tuned)	30761.762091	16742.794622	0.876630
5	Random Forest Regressor (Tuned)	34765.373965	18482.059355	0.842428
6	Lasso Regression	88270.853655	59931.238025	-0.015829

Final Model and Interpretation

Choosing the best model based on lowest RMSE

```python
# selecting the best model based on lowest RMSE
best_row = results_df.sort_values("RMSE").iloc[0]
best_model_name = best_row["Model"]

print("Best model based on RMSE:", best_model_name)
print(best_row)
```

```
Best model based on RMSE: Linear Regression
Model    Linear Regression
RMSE          22739.774051
MAE           14899.276389
R²                0.932585
Name: 0, dtype: object
```

```python
# retrieving the best model pipeline from the models dictionary
best_model = models[best_model_name]
best_model
```

```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('num',
                                                  Pipeline(steps=[('imputer',
                                                                   SimpleImputer(strategy='median')),
                                                                  ('scaler',
                                                                   StandardScaler())]),
                                                  ['MSSubClass', 'LotFrontage',
                                                   'LotArea', 'OverallQual',
                                                   'OverallCond', 'YearBuilt',
                                                   'YearRemodAdd', 'MasVnrArea',
                                                   'BsmtFinSF1', 'BsmtFinSF2',
                                                   'BsmtUnfSF', 'TotalBsmtSF',
                                                   '1stFlrSF', '2ndFlrSF',
                                                   'LowQual...
                                                   'LandContour', 'Utilities',
                                                   'LotConfig', 'LandSlope',
                                                   'Neighborhood', 'Condition1',
                                                   'Condition2', 'BldgType',
                                                   'HouseStyle', 'RoofStyle',
                                                   'RoofMatl', 'Exterior1st',
                                                   'Exterior2nd', 'MasVnrType',
                                                   'ExterQual', 'ExterCond',
                                                   'Foundation', 'BsmtQual',
                                                   'BsmtCond', 'BsmtExposure',
                                                   'BsmtFinType1',
                                                   'BsmtFinType2', 'Heating',
                                                   'HeatingQC', 'CentralAir',
```

```
                                                   'Electrical', ...])])),
                ('linreg', LinearRegression())])
```

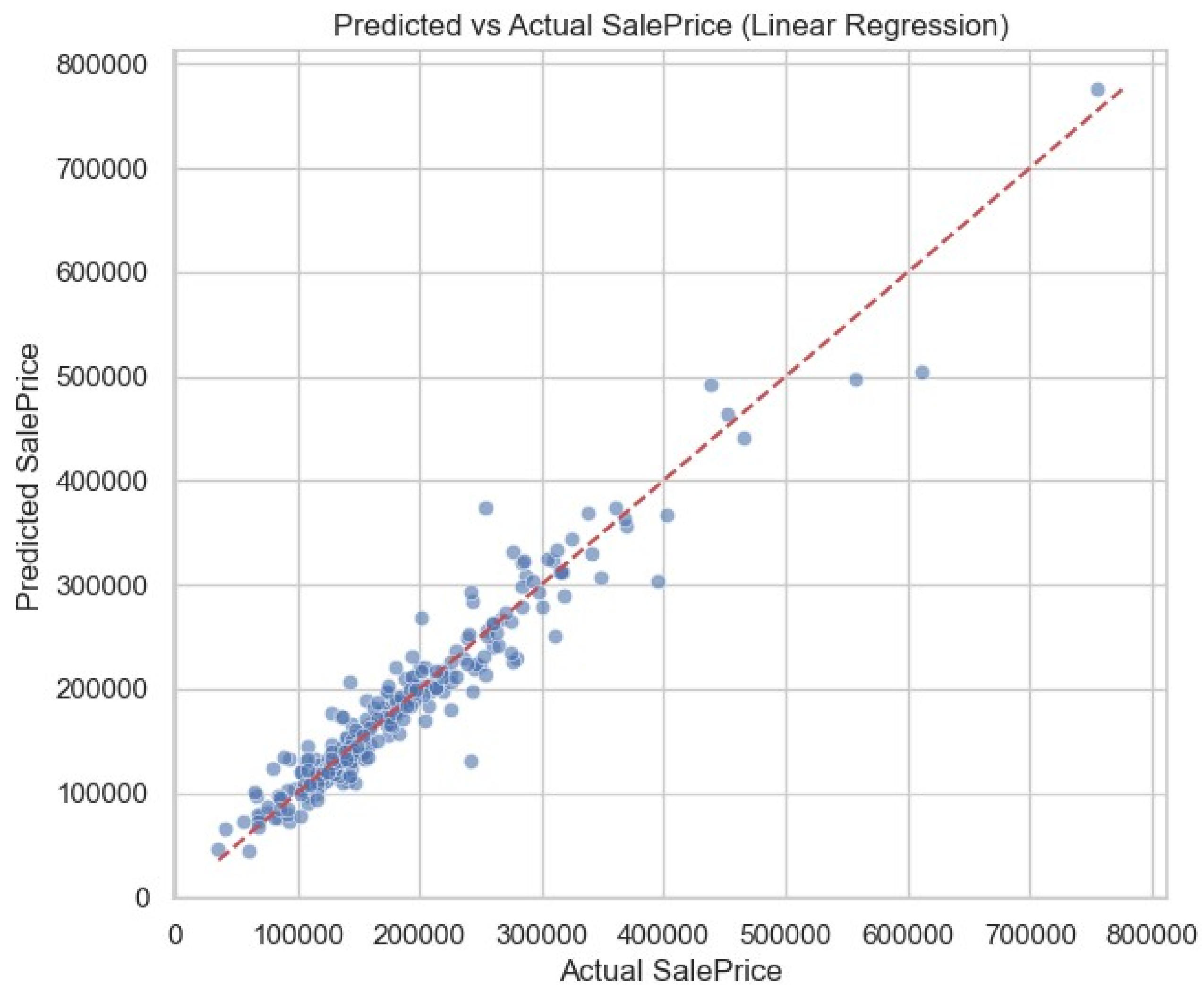
Refitting and Evaluation with Best Model

```
# training the best model on the training data
best_model.fit(X_train, y_train)

# predictions with the best model (log SalePrice)
y_pred_log = best_model.predict(X_test)

# converting back to original SalePrice scale
y_test_orig = np.expm1(y_test)
y_pred_orig = np.expm1(y_pred_log)

# final evaluation metrics
final_mse = mean_squared_error(y_test_orig, y_pred_orig)
final_rmse = np.sqrt(final_mse)
final_mae = mean_absolute_error(y_test_orig, y_pred_orig)
final_r2 = r2_score(y_test_orig, y_pred_orig)

print(f"Final Model: {best_model_name}")
print(f"RMSE (original $): {final_rmse:,.2f}")
print(f"MAE  (original $): {final_mae:,.2f}")
print(f"R²                : {final_r2:.4f}")
```

```
Final Model: Linear Regression
RMSE (original $): 22,739.77
MAE  (original $): 14,899.28
R²                : 0.9326
```

Plotting Predicted vs Actual SalePrice

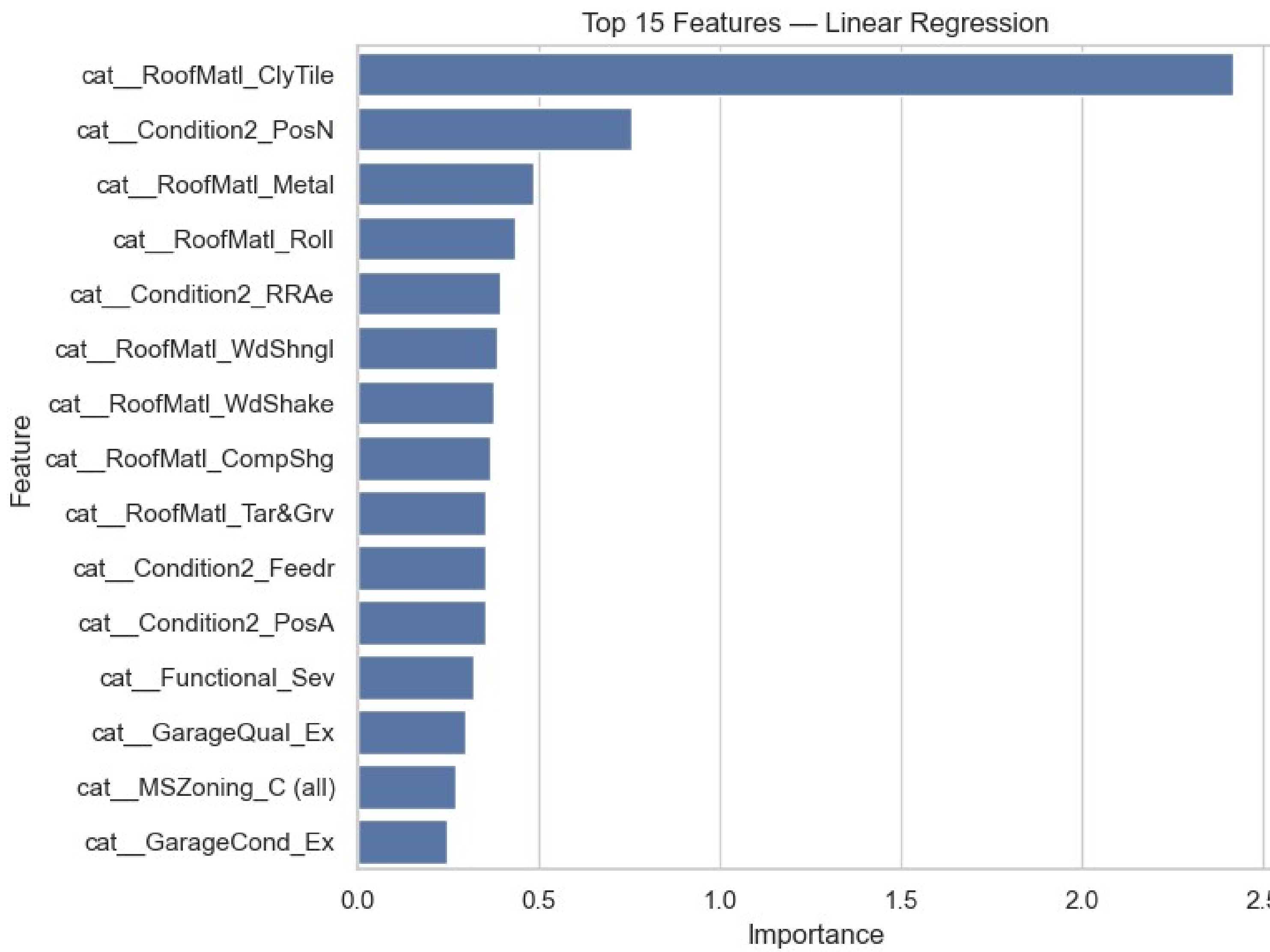
```
# predicted vs actual prices
plt.figure(figsize=(7,6))
sns.scatterplot(x=y_test_orig, y=y_pred_orig, alpha=0.6)
max_price = max(y_test_orig.max(), y_pred_orig.max())
min_price = min(y_test_orig.min(), y_pred_orig.min())

plt.plot([min_price, max_price], [min_price, max_price], "r--")  # ideal line
plt.xlabel("Actual SalePrice")
plt.ylabel("Predicted SalePrice")
plt.title(f"Predicted vs Actual SalePrice ({best_model_name})")
plt.show()
```



Feature Importance

```
# extracting feature names after preprocessing
feature_names = best_model.named_steps["preprocessor"].get_feature_names_out()

# get the final estimator inside the pipeline (last step)
final_step_name = list(best_model.named_steps.keys())[-1]
estimator = best_model.named_steps[final_step_name]

# get importance values
if hasattr(estimator, "feature_importances_"):
    importances = estimator.feature_importances_
elif hasattr(estimator, "coef_"):
    # for linear models, use absolute value of coefficients
    importances = np.abs(estimator.coef_)
else:
    importances = None
    print("This estimator does not provide feature_importances_ or coef_.")
```

```python
if importances is not None:
    # build a DataFrame of feature importances
    fi_df = pd.DataFrame({
        "Feature": feature_names,
        "Importance": importances
    }).sort_values(by="Importance", ascending=False)

    # show top 15 features
    fi_top15 = fi_df.head(15)
    fi_top15

# plotting top features
if importances is not None:
    plt.figure(figsize=(8,6))
    sns.barplot(data=fi_top15, x="Importance", y="Feature")
    plt.title(f"Top 15 Features — {best_model_name}")
    plt.tight_layout()
    plt.show()
```



Final Model Summary

The best-performing model based on lowest RMSE was **Linear Regression**. Although more complex models were tested (Ridge, Lasso, Random Forest, Gradient Boosting), Linear Regression provided the strongest generalization performance on the test set.

Performance (Original SalePrice Scale)

- RMSE: $22,739.77
- MAE: $14,899.28
- R^2: 0.9326

These results indicate that the model explains approximately 93% of the variation in house prices, with average prediction errors around $15,000. The predicted vs actual plot shows a strong linear relationship, and residuals are centered around zero, suggesting no major bias.

Interpretation

Key predictors include property quality (OverallQual), above-ground living area (GrLivArea), garage capacity, and basement size. These variables strongly influence housing prices, which aligns with common real-estate valuation factors.

Conclusion

Linear Regression, combined with proper preprocessing (imputation, scaling, encoding), provides an effective and interpretable baseline for house price prediction. The model performs well across diverse homes and can be further improved through additional feature engineering or more advanced regression techniques.