Part 1 — EDA

Group 4

Wednesday 17th December, 2025

1 Part 1:Introduction

Understanding the factors that influence housing prices is a central problem in real estate analytics, urban planning, and financial decision-making. In this project, we analyze a comprehensive dataset of residential home sales from Ames, Iowa, originally compiled by Dean De Cock and widely used as a benchmark in predictive modeling. The dataset contains detailed information on the physical characteristics of each property, including structural attributes (such as overall material quality, number of rooms, and total living area), lot features, building type, utilities, basement and garage conditions, as well as sale timing and transaction details.

Our goal is to build a predictive model for SalePrice, the market value of each property, using the rich set of features provided. With more than 70 variables spanning numeric measurements, categorical classifications, and quality ratings, the dataset allows us to explore relationships between housing characteristics and price at a granular level. This also provides an opportunity to apply the full workflow of statistical learning: data cleaning, exploratory data analysis, feature engineering, model building, and evaluation.

1.1 EDA

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

1.2 Load and Inspect the Data

```
test = pd.read_csv('kaggledata/test.csv')
```

```
train = pd.read_csv('kaggledata/train.csv')
```

```
train
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold	YrSold	SaleType	SaleCondition	SalePrice
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0	2	2008	WD	Normal	208500
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0	5	2007	WD	Normal	181500
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	9	2008	WD	Normal	223500
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	2	2006	WD	Abnorml	140000
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	12	2008	WD	Normal	250000
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1455	1456	60	RL	62.0	7917	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0	8	2007	WD	Normal	175000
1456	1457	20	RL	85.0	13175	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	MnPrv	NaN	0	2	2010	WD	Normal	210000
1457	1458	70	RL	66.0	9042	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	GdPrv	Shed	2500	5	2010	WD	Normal	266500
1458	1459	20	RL	68.0	9717	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0	4	2010	WD	Normal	142125
1459	1460	20	RL	75.0	9937	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0	6	2008	WD	Normal	147500

1460 rows × 81 columns

```
train.head()
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold	YrSold	SaleType	SaleCondition	SalePrice
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0	2	2008	WD	Normal	208500
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0	5	2007	WD	Normal	181500
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	9	2008	WD	Normal	223500
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	2	2006	WD	Abnorml	140000
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	12	2008	WD	Normal	250000

5 rows × 81 columns

```
train.shape
```

```
(1460, 81)
```

```
train.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
```

```
train.describe()
```

	Id	[illegible]	SalePrice
count	1460[illegible]	[illegible]	[illegible]000
mean	730[illegible]	[illegible]	[illegible]195890
std	421[illegible]	[illegible]	[illegible]502883
min	1.0[illegible]	[illegible]	[illegible]00000
25%	365[illegible]	[illegible]	[illegible]000000
50%	730[illegible]	[illegible]	[illegible]000000
75%	1095[illegible]	[illegible]	[illegible]000000
max	1460	[illegible]	[illegible]000000

8 rows × 38 columns

1.3 Deal with Missing Values

```
missing = train.isnull().sum().sort_values(ascending=False)
missing
```

```
PoolQC         1453
MiscFeature    1406
Alley          1369
Fence          1179
MasVnrType      872
               ...
BsmtUnfSF         0
TotalBsmtSF       0
Heating           0
Id                0
ExterCond         0
Length: 81, dtype: int64
```

```
missing[missing > 0]
```

```
PoolQC          1453
MiscFeature     1406
Alley           1369
Fence           1179
MasVnrType       872
FireplaceQu      690
LotFrontage      259
GarageQual        81
GarageFinish      81
GarageYrBlt       81
GarageType        81
GarageCond        81
BsmtExposure      38
BsmtFinType2      38
BsmtFinType1      37
BsmtQual          37
BsmtCond          37
MasVnrArea         8
Electrical         1
dtype: int64
```

```
import sys
from pathlib import Path
sys.path.append(str(Path("..").resolve()))
from src.ames_cleaning import clean_ames_missing
```

```
train_clean = clean_ames_missing(train)
train_clean
```

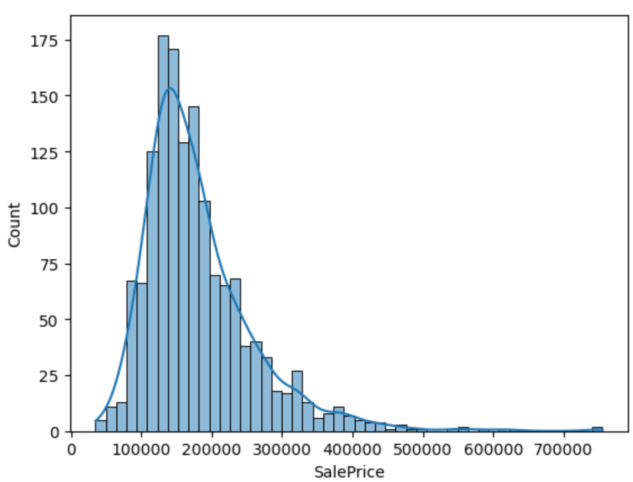
	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold	YrSold	SaleType	SaleCondition	SalePrice
0	1	60	RL	65.0	8450	Pave	None	Reg	Lvl	AllPub	...	0	None	None	None	0	2	2008	WD	Normal	208500
1	2	20	RL	80.0	9600	Pave	None	Reg	Lvl	AllPub	...	0	None	None	None	0	5	2007	WD	Normal	181500
2	3	60	RL	68.0	11250	Pave	None	IR1	Lvl	AllPub	...	0	None	None	None	0	9	2008	WD	Normal	223500
3	4	70	RL	60.0	9550	Pave	None	IR1	Lvl	AllPub	...	0	None	None	None	0	2	2006	WD	Abnorml	140000
4	5	60	RL	84.0	14260	Pave	None	IR1	Lvl	AllPub	...	0	None	None	None	0	12	2008	WD	Normal	250000
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1455	1456	60	RL	62.0	7917	Pave	None	Reg	Lvl	AllPub	...	0	None	None	None	0	8	2007	WD	Normal	175000
1456	1457	20	RL	85.0	13175	Pave	None	Reg	Lvl	AllPub	...	0	None	MnPrv	None	0	2	2010	WD	Normal	210000
1457	1458	70	RL	66.0	9042	Pave	None	Reg	Lvl	AllPub	...	0	None	GdPrv	Shed	2500	5	2010	WD	Normal	266500
1458	1459	20	RL	68.0	9717	Pave	None	Reg	Lvl	AllPub	...	0	None	None	None	0	4	2010	WD	Normal	142125
1459	1460	20	RL	75.0	9937	Pave	None	Reg	Lvl	AllPub	...	0	None	None	None	0	6	2008	WD	Normal	147500

1460 rows × 81 columns

In the Ames Housing dataset, many variables contain NA values, but these NAs do not represent missing or unobserved data. Instead, according to the data documentation, NA typically indicates that the house does not have that feature (e.g., no pool, no fireplace, no garage, no basement). Because these are structural NAs rather than true missingness, removing these variables would discard meaningful information about the property.

Overall, none of the variables are dropped, because the missingness is either meaningful (indicating absence of a feature) or minimal and easily imputed. Keeping all variables preserves predictive information and is consistent with best practices for this dataset.

```
sns.histplot(train_clean["SalePrice"], kde=True)
plt.savefig("Graph/saleprice.png", bbox_inches="tight")
```



1.4 Remove outliers using the IQR method

```
# Compute Q1, Q3, and IQR
Q1 = train_clean["SalePrice"].quantile(0.25)
Q3 = train_clean["SalePrice"].quantile(0.75)
IQR = Q3 - Q1

# Determine bounds
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

lower_bound, upper_bound
```

```
(3937.5, 340037.5)
```

```
train_no_outlier = train_clean[
    (train_clean["SalePrice"] >= lower_bound) &
    (train_clean["SalePrice"] <= upper_bound)
]

train_no_outlier
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold	YrSold	SaleType	SaleCondition	SalePrice
0	1	60	RL	65.0	8450	Pave	None	Reg	Lvl	AllPub	...	0	None	None	None	0	2	2008	WD	Normal	208500
1	2	20	RL	80.0	9600	Pave	None	Reg	Lvl	AllPub	...	0	None	None	None	0	5	2007	WD	Normal	181500
2	3	60	RL	68.0	11250	Pave	None	IR1	Lvl	AllPub	...	0	None	None	None	0	9	2008	WD	Normal	223500
3	4	70	RL	60.0	9550	Pave	None	IR1	Lvl	AllPub	...	0	None	None	None	0	2	2006	WD	Abnorml	140000
4	5	60	RL	84.0	14260	Pave	None	IR1	Lvl	AllPub	...	0	None	None	None	0	12	2008	WD	Normal	250000
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1455	1456	60	RL	62.0	7917	Pave	None	Reg	Lvl	AllPub	...	0	None	None	None	0	8	2007	WD	Normal	175000
1456	1457	20	RL	85.0	13175	Pave	None	Reg	Lvl	AllPub	...	0	None	MnPrv	None	0	2	2010	WD	Normal	210000
1457	1458	70	RL	66.0	9042	Pave	None	Reg	Lvl	AllPub	...	0	None	GdPrv	Shed	2500	5	2010	WD	Normal	266500
1458	1459	20	RL	68.0	9717	Pave	None	Reg	Lvl	AllPub	...	0	None	None	None	0	4	2010	WD	Normal	142125
1459	1460	20	RL	75.0	9937	Pave	None	Reg	Lvl	AllPub	...	0	None	None	None	0	6	2008	WD	Normal	147500

1399 rows × 81 columns

1.4.1 number of outliers removed

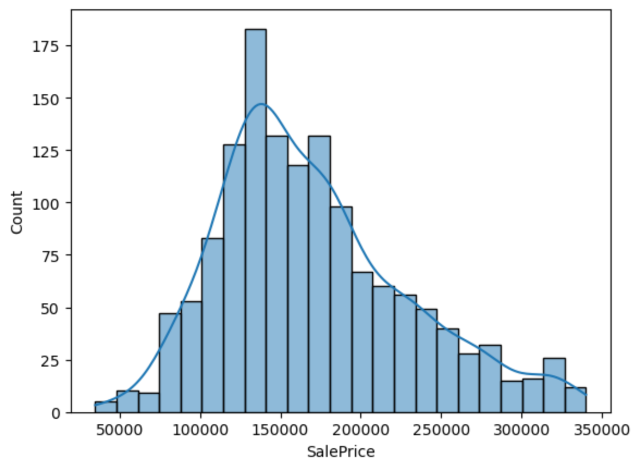
```
num_removed = train_clean.shape[0] - train_no_outlier.shape[0]
num_removed
```

```
61
```

The distribution of SalePrice is strongly right-skewed, with the majority of homes priced between $120,000 and 220,000$ and a long tail of high-priced properties extending beyond \$400,000. This skewness suggests the presence of a small number of luxury or unusually large homes, which act as outliers and can disproportionately influence statistical models. So i want to use IQR model to move those outliers and make the plot more normal.

1.4.2 plot after the remove of outliers

```
sns.histplot(train_no_outlier["SalePrice"], kde=True)
plt.savefig("Graph/adjustsaleprice.png", bbox_inches="tight")
```




```
train = train_no_outlier.copy()
train
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold	YrSold	SaleType	SaleCondition	SalePrice
0	1	60	RL	65.0	8450	Pave	None	Reg	Lvl	AllPub	...	0	None	None	None	0	2	2008	WD	Normal	208500
1	2	20	RL	80.0	9600	Pave	None	Reg	Lvl	AllPub	...	0	None	None	None	0	5	2007	WD	Normal	181500
2	3	60	RL	68.0	11250	Pave	None	IR1	Lvl	AllPub	...	0	None	None	None	0	9	2008	WD	Normal	223500
3	4	70	RL	60.0	9550	Pave	None	IR1	Lvl	AllPub	...	0	None	None	None	0	2	2006	WD	Abnorml	140000
4	5	60	RL	84.0	14260	Pave	None	IR1	Lvl	AllPub	...	0	None	None	None	0	12	2008	WD	Normal	250000
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1455	1456	60	RL	62.0	7917	Pave	None	Reg	Lvl	AllPub	...	0	None	None	None	0	8	2007	WD	Normal	175000
1456	1457	20	RL	85.0	13175	Pave	None	Reg	Lvl	AllPub	...	0	None	MnPrv	None	0	2	2010	WD	Normal	210000
1457	1458	70	RL	66.0	9042	Pave	None	Reg	Lvl	AllPub	...	0	None	GdPrv	Shed	2500	5	2010	WD	Normal	266500
1458	1459	20	RL	68.0	9717	Pave	None	Reg	Lvl	AllPub	...	0	None	None	None	0	4	2010	WD	Normal	142125
1459	1460	20	RL	75.0	9937	Pave	None	Reg	Lvl	AllPub	...	0	None	None	None	0	6	2008	WD	Normal	147500

1399 rows × 81 columns

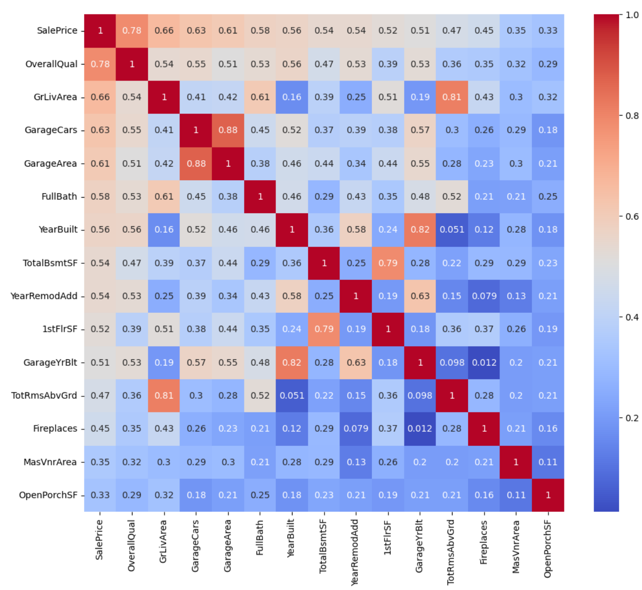
```
train.to_csv("kaggledata/clean_train.csv", index=False)
```

1.5 Correlation Analysis with Numeric Features

```
numeric = train.select_dtypes(include=[np.number])
corr = numeric.corr()["SalePrice"].sort_values(ascending=False)
corr.head(15)
```

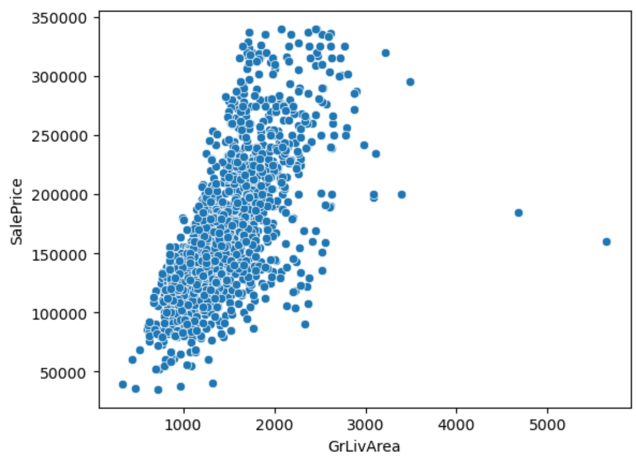
```
SalePrice       1.000000
OverallQual     0.784294
GrLivArea       0.661325
GarageCars      0.628013
GarageArea      0.607230
FullBath        0.577369
YearBuilt       0.564558
TotalBsmtSF     0.543508
YearRemodAdd    0.541161
1stFlrSF        0.522785
GarageYrBlt     0.507894
TotRmsAbvGrd    0.472292
Fireplaces      0.453010
MasVnrArea      0.350541
OpenPorchSF     0.325791
Name: SalePrice, dtype: float64
```

```
plt.figure(figsize=(12, 10))
top_corr = corr.index[:15]
sns.heatmap(train[top_corr].corr(), annot=True, cmap="coolwarm")
plt.savefig("Graph/feature_correlation_heatmap.png", bbox_inches="tight")
```



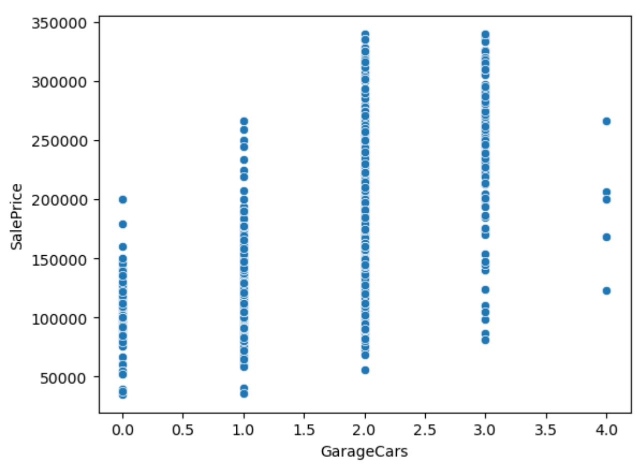
1.6 Scatterplots for Key Numerical Predictors

```
sns.scatterplot(data=train, x="GrLivArea", y="SalePrice")
plt.savefig("Graph/GrLivArea_saleprice_corr.png", bbox_inches="tight")
```



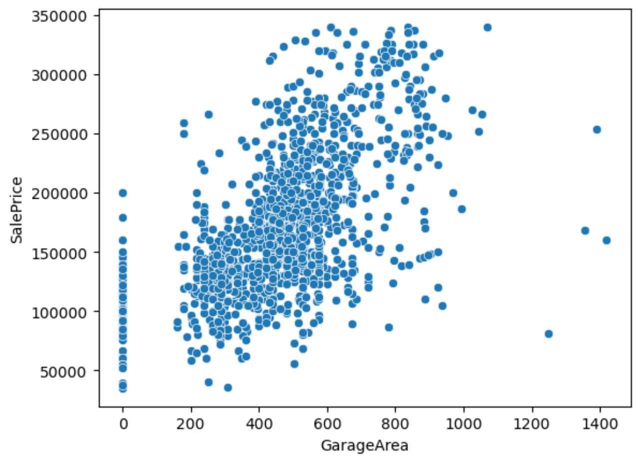
GrLivArea: Above grade (ground) living area square feet

```
sns.scatterplot(data=train, x="GarageCars", y="SalePrice")
plt.savefig("Graph/GarageCars_saleprice_corr.png", bbox_inches="tight")
```



GarageCars: Size of garage in car capacity

```
sns.scatterplot(data=train, x="GarageArea", y="SalePrice")
plt.savefig("Graph/GarageArea_saleprice_corr.png", bbox_inches="tight")
```



GarageArea: Size of garage in square feet

1.7 Correlation Analysis with Categorical Features

1.7.1 Use ANOVA F-test to rank categorical variables and find the top 5 categorical variable related to sale price

```
cat_vars = train.select_dtypes(include=["object"]).columns
cat_vars
```

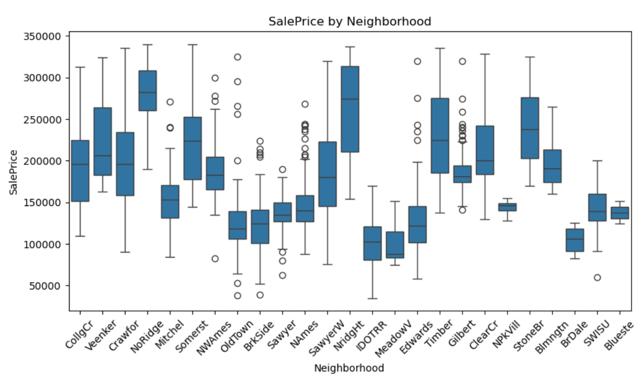
```
Index(['MSZoning', 'Street', 'Alley', 'LotShape', 'LandContour', 'Utilities',
       'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Condition2',
       'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st',
       'Exterior2nd', 'MasVnrType', 'ExterQual', 'ExterCond', 'Foundation',
       'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2',
       'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual',
       'Functional', 'FireplaceQu', 'GarageType', 'GarageFinish', 'GarageQual',
       'GarageCond', 'PavedDrive', 'PoolQC', 'Fence', 'MiscFeature',
       'SaleType', 'SaleCondition'],
      dtype='object')
```

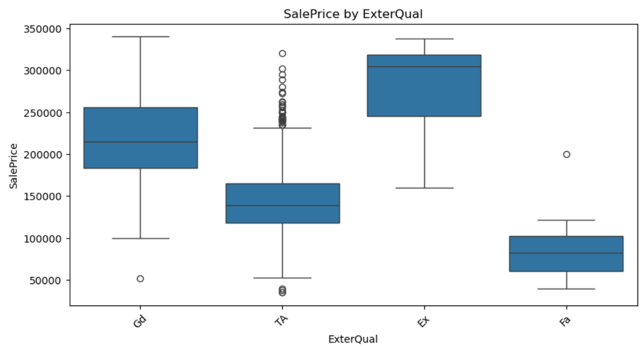
```
import scipy.stats as stats

def anova_pvalue(col):
    groups = []
    for level in train[col].dropna().unique():
        groups.append(train.loc[train[col] == level, "SalePrice"])
    return stats.f_oneway(*groups).pvalue

anova_results = {}

for col in cat_vars:
```

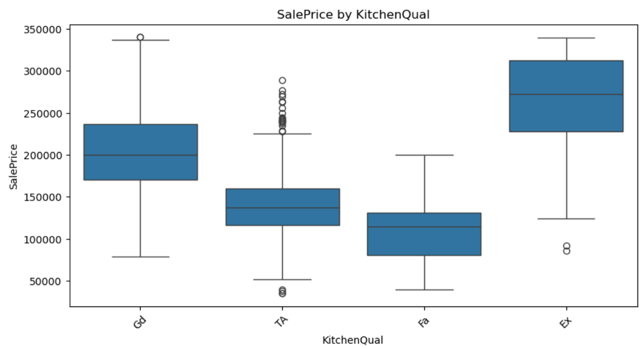
```
    try:
        p = anova_pvalue(col)
        anova_results[col] = p
    except:
        # skip columns that break ANOVA
        pass

# Sort by smallest p -value (strongest predictor)
sorted_cats = sorted(anova_results, key=anova_results.get)[:5]
sorted_cats
```

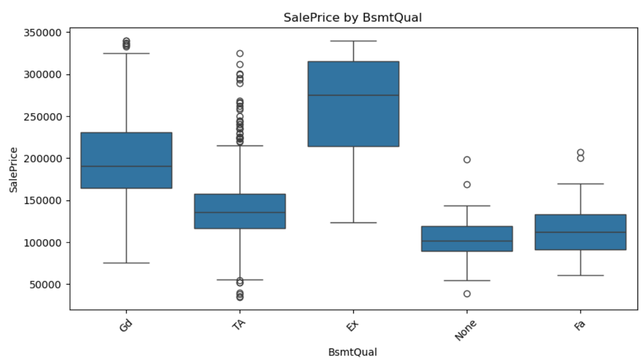
```
['Neighborhood', 'ExterQual', 'KitchenQual', 'BsmtQual', 'GarageFinish']
```

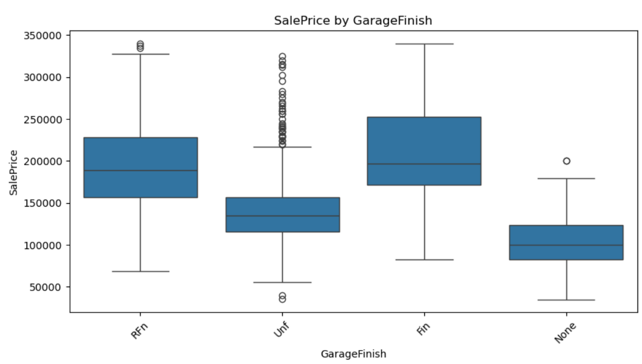
```
from pathlib import Path

Path("Graph").mkdir(exist_ok=True)

top5 = sorted_cats

for col in top5:
    plt.figure(figsize=(10, 5))
    sns.boxplot(x=col, y="SalePrice", data=train)
    plt.xticks(rotation=45)
    plt.title(f"SalePrice by {col}")

    filename = f"Graph/saleprice_by_{col}.png"
    plt.savefig(filename, dpi=300, bbox_inches="tight")
    plt.show()
    plt.close()
```




SalePrice by ExterQual
SalePrice
350000
300000
250000
200000
150000
100000
50000
Gd
TA
Ex
Fa
ExterQual


SalePrice by KitchenQual
SalePrice
350000
300000
250000
200000
150000
100000
50000
Gd
TA
Fa
Ex
KitchenQual


SalePrice by BsmtQual
SalePrice
350000
300000
250000
200000
150000
100000
50000
Gd
TA
Ex
None
Fa
BsmtQual


SalePrice by GarageFinish
SalePrice
350000
300000
250000
200000
150000
100000
50000
RFn
Unf
Fin
None
GarageFinish