Predicting Sale Prices Using Advanced Regression and Feature Engineering

In this notebook I have explored the House Prices dataset from Kaggle using several regression algorithms. We'll go through the complete machine learning workflow step by step:

- 🧹 Data exploration & cleaning
- ⚙️ Feature engineering
- 🧠 Model building & tuning
- 🤝 Model blending (XGBoost, LightGBM, Ridge, Lasso)
- 📊 Generating final predictions

The end goal is to achieve a competitive relative error in prediction of the Saleprice of Houses with maximum accuracy.

We begin by importing essential libraries for data handling, visualization, and modeling. This includes `Pandas, NumPy, Seaborn, Matplotlib`, and multiple machine learning libraries like `Scikit-learn`, `XGBoost`, `LightGBM`, and `CatBoost`.

In [1]:

```
# Ignore warnings
import warnings
warnings.filterwarnings('ignore')

# Data handling
import numpy as np
import pandas as pd

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Modeling
from sklearn.model_selection import train_test_split, cross_val_score, KF
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.ensemble import GradientBoostingRegressor, RandomForestRegre
import xgboost as xgb
import lightgbm as lgb
import catboost as cb

# Display settings
pd.set_option('display.float_format', lambda x: '%.3f' % x)
```

```
# Load data
train = pd.read_csv('/kaggle/input/house-prices-advanced-regression-techn
test = pd.read_csv('/kaggle/input/house-prices-advanced-regression-techni

print("Train shape:", train.shape)
print("Test shape:", test.shape)
train.head()
```

```
Train shape: (1460, 81)
Test shape: (1459, 80)
```

Out[1]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	Lan
0	1	60	RL	65.000	8450	Pave	NaN	Reg	
1	2	20	RL	80.000	9600	Pave	NaN	Reg	
2	3	60	RL	68.000	11250	Pave	NaN	IR1	
3	4	70	RL	60.000	9550	Pave	NaN	IR1	
4	5	60	RL	84.000	14260	Pave	NaN	IR1	

5 rows × 81 columns

Key **observations** after loading the datasets:

- Train set has 1460 rows and 81 columns
- Test set has 1459 rows and 80 columns
- SalePrice is our target variable, available only in the training set.

Initial Data Exploration

We examine the dataset to understand its structure and identify missing values.

- Many categorical columns like `PoolQC`, `Fence`, `Alley`, `MiscFeature` have large sections of missing data.
- Numeric features like `LotFrontage`, `GarageYrBlt`, and `MasVnrArea` have moderate missing values.

In [2]:

```
# Overview of training data
print("----- TRAIN DATA INFO -----")
train.info()

print("\n----- TEST DATA INFO -----")
test.info()
```

```
----- TRAIN DATA 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

----- TEST DATA INFO -----
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1459 entries, 0 to 1458
Data columns (total 80 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1459 non-null   int64
 1   MSSubClass     1459 non-null   int64
 2   MSZoning       1455 non-null   object
 3   LotFrontage    1232 non-null   float64
 4   LotArea        1459 non-null   int64
 5   Street         1459 non-null   object
 6   Alley          107 non-null    object
 7   LotShape       1459 non-null   object
 8   LandContour    1459 non-null   object
 9   Utilities      1457 non-null   object
 10  LotConfig      1459 non-null   object
 11  LandSlope      1459 non-null   object
 12  Neighborhood   1459 non-null   object
 13  Condition1     1459 non-null   object
 14  Condition2     1459 non-null   object
 15  BldgType       1459 non-null   object
 16  HouseStyle     1459 non-null   object
 17  OverallQual    1459 non-null   int64
 18  OverallCond    1459 non-null   int64
 19  YearBuilt      1459 non-null   int64
 20  YearRemodAdd   1459 non-null   int64
 21  RoofStyle      1459 non-null   object
 22  RoofMatl       1459 non-null   object
 23  Exterior1st    1458 non-null   object
```

```
 24  Exterior2nd    1458 non-null   object
 25  MasVnrType     565 non-null    object
 26  MasVnrArea     1444 non-null   float64
 27  ExterQual      1459 non-null   object
 28  ExterCond      1459 non-null   object
 29  Foundation     1459 non-null   object
 30  BsmtQual       1415 non-null   object
 31  BsmtCond       1414 non-null   object
 32  BsmtExposure   1415 non-null   object
 33  BsmtFinType1   1417 non-null   object
 34  BsmtFinSF1     1458 non-null   float64
 35  BsmtFinType2   1417 non-null   object
 36  BsmtFinSF2     1458 non-null   float64
 37  BsmtUnfSF      1458 non-null   float64
 38  TotalBsmtSF    1458 non-null   float64
 39  Heating        1459 non-null   object
 40  HeatingQC      1459 non-null   object
 41  CentralAir     1459 non-null   object
 42  Electrical     1459 non-null   object
 43  1stFlrSF       1459 non-null   int64
 44  2ndFlrSF       1459 non-null   int64
 45  LowQualFinSF   1459 non-null   int64
 46  GrLivArea      1459 non-null   int64
 47  BsmtFullBath   1457 non-null   float64
 48  BsmtHalfBath   1457 non-null   float64
 49  FullBath       1459 non-null   int64
 50  HalfBath       1459 non-null   int64
 51  BedroomAbvGr   1459 non-null   int64
 52  KitchenAbvGr   1459 non-null   int64
 53  KitchenQual    1458 non-null   object
 54  TotRmsAbvGrd   1459 non-null   int64
 55  Functional     1457 non-null   object
 56  Fireplaces     1459 non-null   int64
 57  FireplaceQu    729 non-null    object
 58  GarageType     1383 non-null   object
 59  GarageYrBlt    1381 non-null   float64
 60  GarageFinish   1381 non-null   object
 61  GarageCars     1458 non-null   float64
 62  GarageArea     1458 non-null   float64
 63  GarageQual     1381 non-null   object
 64  GarageCond     1381 non-null   object
 65  PavedDrive     1459 non-null   object
 66  WoodDeckSF     1459 non-null   int64
 67  OpenPorchSF    1459 non-null   int64
 68  EnclosedPorch  1459 non-null   int64
 69  3SsnPorch      1459 non-null   int64
 70  ScreenPorch    1459 non-null   int64
 71  PoolArea       1459 non-null   int64
 72  PoolQC         3 non-null      object
 73  Fence          290 non-null    object
 74  MiscFeature    51 non-null     object
 75  MiscVal        1459 non-null   int64
 76  MoSold         1459 non-null   int64
 77  YrSold         1459 non-null   int64
 78  SaleType       1458 non-null   object
 79  SaleCondition  1459 non-null   object
dtypes: float64(11), int64(26), object(43)
memory usage: 912.0+ KB
```

In [3]:
```python
# Count missing values per column
missing = train.isnull().sum()
missing = missing[missing > 0].sort_values(ascending=False)

print(f"Total columns with missing values: {len(missing)}")
missing.head(20)
```

```
Total columns with missing values: 19
```

Out[3]:
```
PoolQC          1453
MiscFeature     1406
Alley           1369
Fence           1179
MasVnrType       872
FireplaceQu      690
LotFrontage      259
GarageType        81
GarageYrBlt       81
GarageFinish      81
GarageQual        81
GarageCond        81
BsmtFinType2      38
BsmtExposure      38
BsmtFinType1      37
BsmtCond          37
BsmtQual          37
MasVnrArea         8
Electrical         1
dtype: int64
```

We will summarize numerical statistics using `.describe()` to check data spread, means, and possible outliers.

In [4]:
```python
train.describe().T.head(15)
```

Out[4]:

	count	mean	std	min	25%	50%	
Id	1460.000	730.500	421.610	1.000	365.750	730.500	109
MSSubClass	1460.000	56.897	42.301	20.000	20.000	50.000	7
LotFrontage	1201.000	70.050	24.285	21.000	59.000	69.000	8
LotArea	1460.000	10516.828	9981.265	1300.000	7553.500	9478.500	1160
OverallQual	1460.000	6.099	1.383	1.000	5.000	6.000	
OverallCond	1460.000	5.575	1.113	1.000	5.000	5.000	
YearBuilt	1460.000	1971.268	30.203	1872.000	1954.000	1973.000	200
YearRemodAdd	1460.000	1984.866	20.645	1950.000	1967.000	1994.000	200
MasVnrArea	1452.000	103.685	181.066	0.000	0.000	0.000	16
BsmtFinSF1	1460.000	443.640	456.098	0.000	0.000	383.500	71
BsmtFinSF2	1460.000	46.549	161.319	0.000	0.000	0.000	
BsmtUnfSF	1460.000	567.240	441.867	0.000	223.000	477.500	80
TotalBsmtSF	1460.000	1057.429	438.705	0.000	795.750	991.500	129
1stFlrSF	1460.000	1162.627	386.588	334.000	882.000	1087.000	139
2ndFlrSF	1460.000	346.992	436.528	0.000	0.000	0.000	72

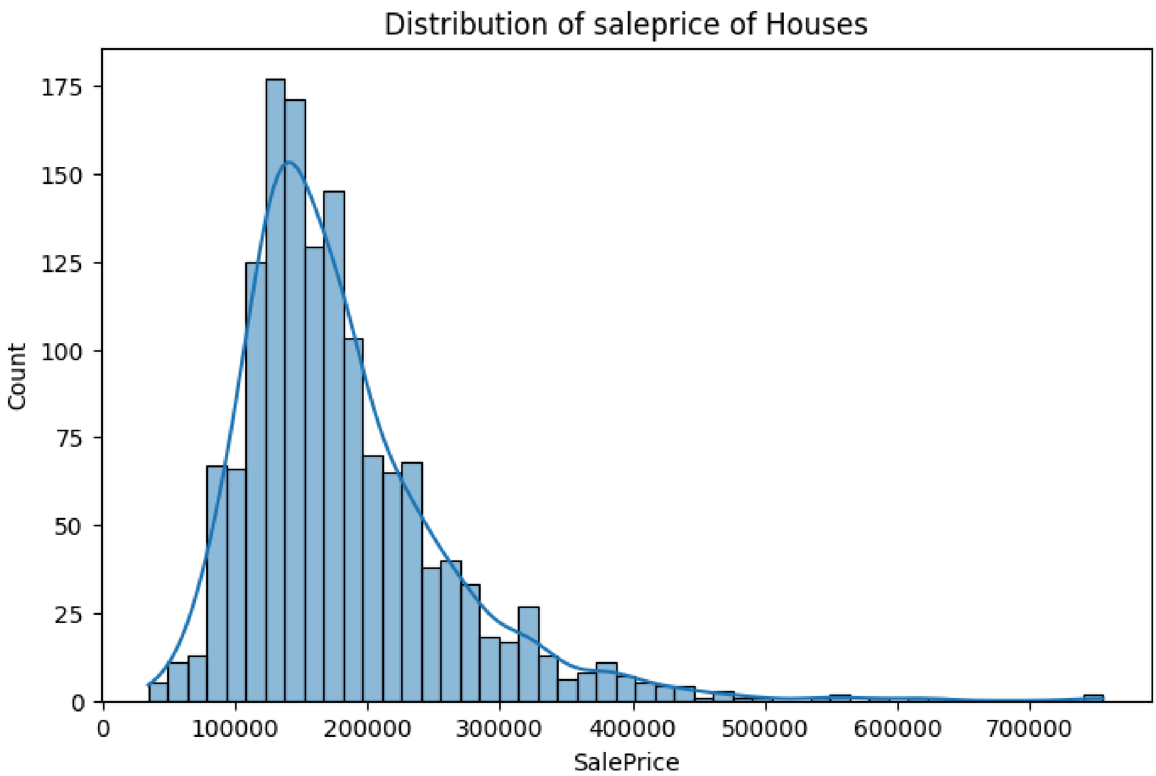
Understanding the Target Variable `(Saleprice)`:

Insights:

- The price distribution is right-skewed — most houses are moderately priced with a few expensive outliers.
- 75% of all houses cost below ~214,000 USD.
- Mean > Median confirms a right-skewed distribution.

In [5]:

```python
plt.figure(figsize=(8,5))
sns.histplot(train['SalePrice'],kde=True)
plt.title('Distribution of saleprice of Houses')
plt.show()
print(train['SalePrice'].describe())
```




```
count      1460.000
mean     180921.196
std       79442.503
min       34900.000
25%      129975.000
50%      163000.000
75%      214000.000
max      755000.000
Name: SalePrice, dtype: float64
```

In [6]:
```
corr = train.select_dtypes(include=[np.number]).corr()['SalePrice'].sort_
corr.head(15)
```

Out[6]:
```
SalePrice       1.000
OverallQual     0.791
GrLivArea       0.709
GarageCars      0.640
GarageArea      0.623
TotalBsmtSF     0.614
1stFlrSF        0.606
FullBath        0.561
TotRmsAbvGrd    0.534
YearBuilt       0.523
YearRemodAdd    0.507
GarageYrBlt     0.486
MasVnrArea      0.477
Fireplaces      0.467
BsmtFinSF1      0.386
Name: SalePrice, dtype: float64
```

The above step also helps us realize why a **log transformation** will later improve model stability and reduce skewness.

Visual Exploratory Data Analysis (EDA) for (Numeric features)

We compute correlations between numeric features and SalePrice. Top correlated features:

- `OverallQual`
- `GrLivArea`
- `GarageCars`
- `TotalBsmtSF`
- `1stFlrSF`

Let's visualize how the top correlated numeric features relate to **SalePrice**.

In [ ]:
```
top_features = ['OverallQual', 'GrLivArea', 'GarageCars', 'GarageArea','T

plt.figure(figsize=(16, 10))
for i, feature in enumerate(top_features[:6]):
    plt.subplot(2, 3, i + 1)
    sns.scatterplot(data=train, x=feature, y='SalePrice', alpha=0.7)
    plt.title(f'{feature} vs SalePrice')
plt.tight_layout()
plt.show()
```

Above, we can already see that:

- Higher **OverallQual** and **GrLivArea** strongly increase SalePrice.
- There are potential **outliers** — very large houses sold at lower prices.

Outlier Handling & Categorical EDA

Removing outliers:

In [8]:
```
# Identify potential outliers
outliers = train[(train['GrLivArea'] > 4000) & (train['SalePrice'] < 3000
display(outliers[['Id', 'GrLivArea', 'SalePrice']])

# Remove them from the training set
train = train.drop(outliers.index)

print(f"New train shape after removing outliers: {train.shape}")
```

	Id	GrLivArea	SalePrice
523	524	4676	184750
1298	1299	5642	160000

```
New train shape after removing outliers: (1458, 81)
```

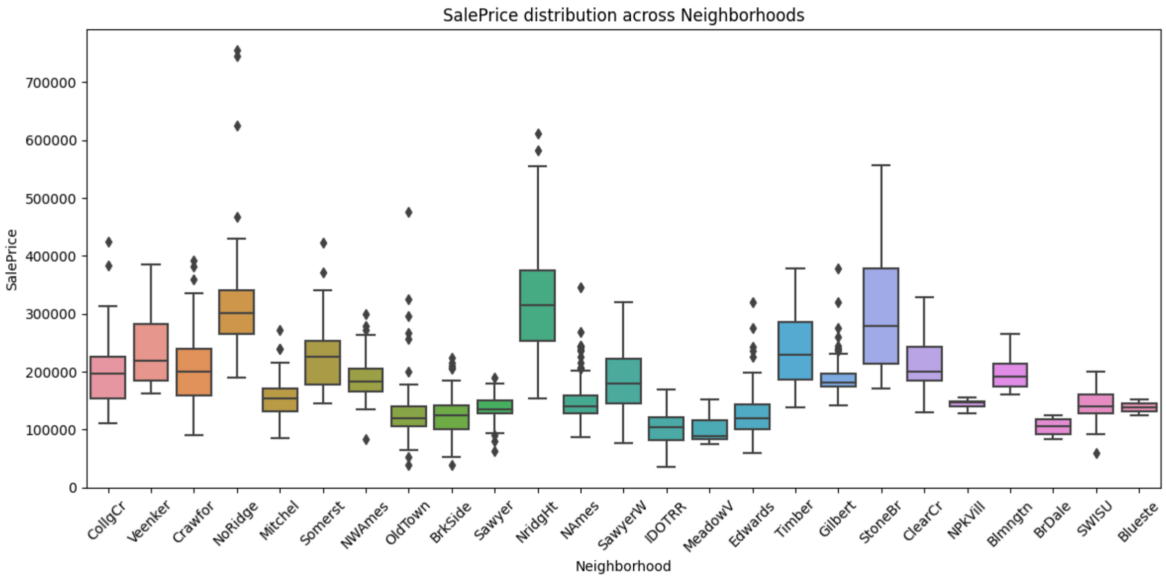
We detected **extreme outliers**: houses with GrLivArea > 4000 but low SalePrice < 300000.

These can harm the model and introduce bias, so we remove them to improve model generalization.

Exploring categorical data:

We will visualize relationships between categorical variables and SalePrice using **Boxplots**:

In [9]:
```
# Plot settings for exploring Categorical features
plt.figure(figsize=(14,6))
sns.boxplot(x='Neighborhood', y='SalePrice', data=train)
plt.xticks(rotation=45)
plt.title('SalePrice distribution across Neighborhoods')
plt.show()
```



Insights:

After reviewing the above boxplot it can be seen that:

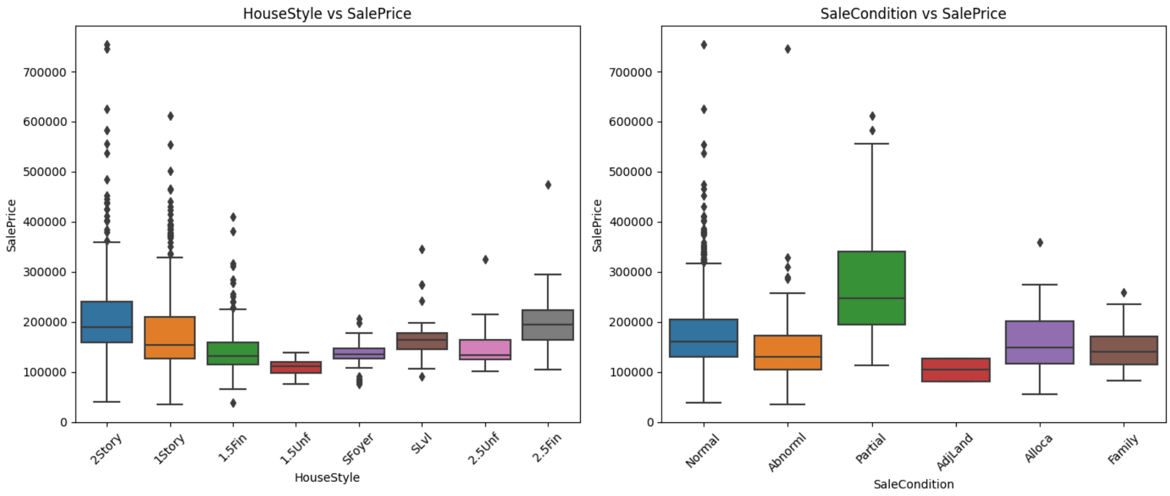
- `Neighborhood` : Some neighborhoods consistently have higher prices.

In [10]:
```
fig, axes = plt.subplots(1, 2, figsize=(14,6))

sns.boxplot(x='HouseStyle', y='SalePrice', data=train, ax=axes[0])
axes[0].set_title('HouseStyle vs SalePrice')
axes[0].tick_params(axis='x', rotation=45)
```

```
sns.boxplot(x='SaleCondition', y='SalePrice', data=train, ax=axes[1])
axes[1].set_title('SaleCondition vs SalePrice')
axes[1].tick_params(axis='x', rotation=45)

plt.tight_layout()
plt.show()
```



Insights 🧠

- `HouseStyle` : 2Story and 1Story homes tend to have higher prices, while 1.5Fin and 1.5Unf styles are cheaper.
- `SaleCondition` : 'Partial' (new construction) sales are the most expensive.

These patterns confirm **categorical features are strong predictors**.

Feaure Engineering and Data Prep

Handling Missing Values and Imputation:

- Columns where NaN means “None” (e.g., `Alley` , `Fence` , `PoolQC`) are filled with " `None` ".
- Numeric basement/garage values are replaced with `0` .
- LotFrontage is filled using the **median** per Neighborhood.
- GarageYrBlt missing → `0` .
- Electrical missing → value from **mode**.

In [11]:
```
import numpy as np
import pandas as pd

train = pd.read_csv('/kaggle/input/house-prices-advanced-regression-techn
test = pd.read_csv('/kaggle/input/house-prices-advanced-regression-techni


# Workin on a copy
```

```
df_train = train.copy()

# 1) Columns where NaN means "None"
none_cols = [
    'Alley','BsmtQual','BsmtCond','BsmtExposure','BsmtFinType1','BsmtFinT
    'FireplaceQu','GarageType','GarageFinish','GarageQual','GarageCond',
    'PoolQC','Fence','MiscFeature','MasVnrType'
]
for c in none_cols:
    if c in df_train.columns:
        df_train[c] = df_train[c].fillna('None')

# Basement/garage
zero_cols = ['BsmtFinSF1','BsmtFinSF2','BsmtUnfSF','TotalBsmtSF',
             'BsmtFullBath','BsmtHalfBath','GarageCars','GarageArea','Mas
for c in zero_cols:
    if c in df_train.columns:
        df_train[c] = df_train[c].fillna(0)

# LotFrontage: impute by Neighborhood median
if 'LotFrontage' in df_train.columns and 'Neighborhood' in df_train.colum
    df_train['LotFrontage'] = df_train.groupby('Neighborhood')['LotFronta
        lambda s: s.fillna(s.median())
    )

# GarageYrBlt: missing means no garage
if 'GarageYrBlt' in df_train.columns:
    df_train['GarageYrBlt'] = df_train['GarageYrBlt'].fillna(0)

# Electrical: single missing
if 'Electrical' in df_train.columns:
    df_train['Electrical'] = df_train['Electrical'].fillna(df_train['Elec

# sanity check of remaining NA
na_left = df_train.isna().sum()
na_left = na_left[na_left>0].sort_values(ascending=False)
print("Still missing after rules:")
print(na_left)
```

```
Still missing after rules:
Series([], dtype: int64)
```

Above output shows that there are **no missing values** anymore.

Log-Transforming the target variable `SalePrice`:

We apply log transformation to SalePrice using np.log1p() bcause,

- it reduces the influence of extremely high-priced houses.
- Makes data more normally distributed.
- Helps linear models handle target variability better.

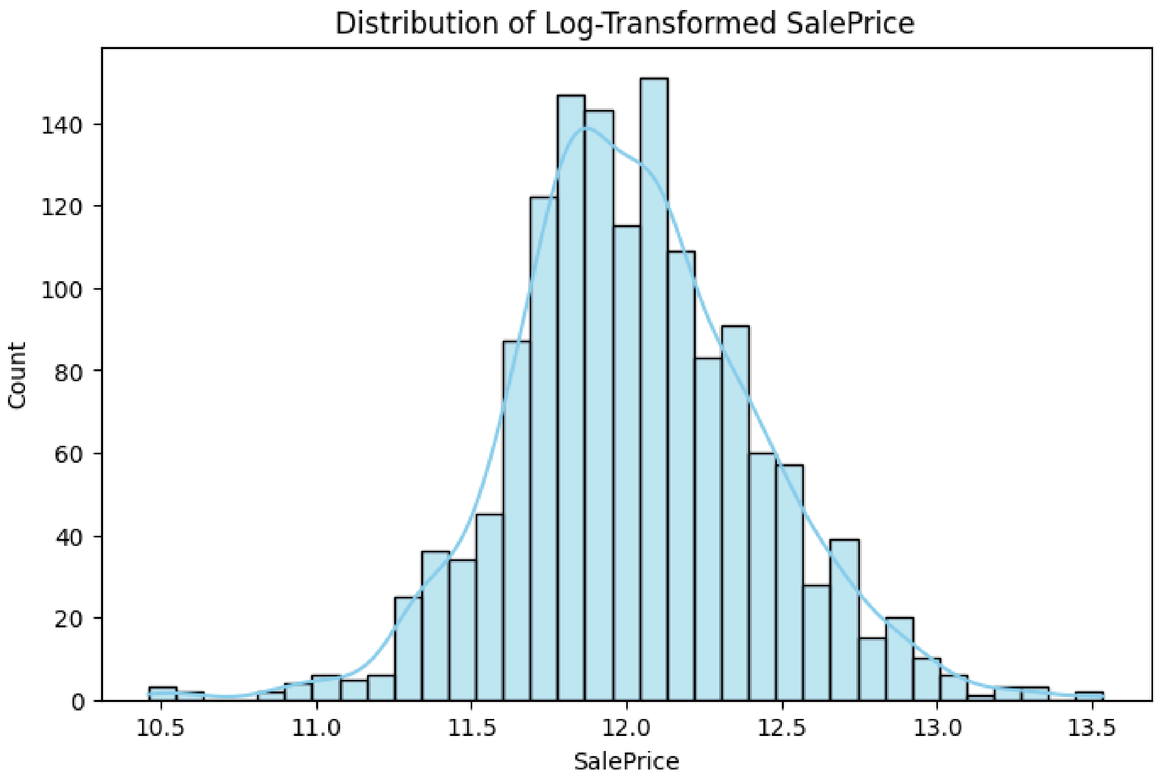
In [12]:
```
# Create a new target variable (log-transformed SalePrice)
y = np.log1p(train['SalePrice'])   # log(1 + SalePrice)

# Drop SalePrice and Id to get features
X = train.drop(columns=['SalePrice', 'Id'])
```

```
# Check transformation visually
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8,5))
sns.histplot(y, kde=True, color='skyblue')
plt.title('Distribution of Log-Transformed SalePrice')
plt.show()

print("y mean:", y.mean(), "y std:", y.std())
```




```
y mean: 12.024057394918406 y std: 0.3994492733225068
```

Now the distribution of the target `SalePrice` above is not right-skewed anymore when it is log-tansformed.

Encoding the categorical values:

We will separate numeric and categorical columns:

- Apply ordinal mappings to quality-related features (e.g., ExterQual, KitchenQual, BsmtQual, etc.).
- Remaining categorical features are one-hot encoded.

This encoding allows both linear and non linear models to process mixed data types correctly.

In [13]:
```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
```

```
# Create a copy for safety
X = train.drop(columns=['SalePrice', 'Id']).copy()

# Ordinal mappings (keep meaningful order)
qual_map = {'None':0,'Po':1,'Fa':2,'TA':3,'Gd':4,'Ex':5}
bsmt_exp_map = {'None':0,'No':0,'Mn':1,'Av':2,'Gd':3}
bsmt_fin_map = {'None':0,'Unf':1,'LwQ':2,'Rec':3,'BLQ':4,'ALQ':5,'GLQ':6}
paved_map = {'N':0,'P':1,'Y':2}
bin_map = {'N':0,'Y':1}
functional_map = {'Sal':0,'Sev':1,'Maj2':2,'Maj1':3,'Mod':4,'Min2':5,'Min

ordinal_maps = {
    'ExterQual': qual_map, 'ExterCond': qual_map,
    'BsmtQual': qual_map, 'BsmtCond': qual_map, 'BsmtExposure': bsmt_exp_
    'BsmtFinType1': bsmt_fin_map, 'BsmtFinType2': bsmt_fin_map,
    'HeatingQC': qual_map, 'KitchenQual': qual_map,
    'FireplaceQu': qual_map, 'GarageQual': qual_map, 'GarageCond': qual_m
    'PoolQC': qual_map, 'PavedDrive': paved_map, 'CentralAir': bin_map,
    'Functional': functional_map
}

for col, mapping in ordinal_maps.items():
    if col in X.columns:
        X[col] = X[col].map(mapping).astype('float64')

# Split remaining columns by dtype
num_cols = X.select_dtypes(include=['int64', 'float64']).columns.tolist()
cat_cols = X.select_dtypes(include=['object']).columns.tolist()

print(f"Numeric columns: {len(num_cols)} | Categorical columns: {len(cat_

# Preprocess: imputers + one-hot encoder
numeric_proc = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median'))
])

categorical_proc = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore', sparse_output=False
])

preprocess = ColumnTransformer(
    transformers=[
        ('num', numeric_proc, num_cols),
        ('cat', categorical_proc, cat_cols)
    ]
)

print("Encoding setup complete — ready for model training.")
```

```
Numeric columns: 52 | Categorical columns: 27
Encoding setup complete — ready for model training.
```

Linear Model Training

Baseline model training using Ridge Regression:

In [14]:
```
# Baseline Ridge Regression with 10-Fold Cross-Validation

from sklearn.linear_model import Ridge
from sklearn.model_selection import KFold, cross_val_score
from sklearn.pipeline import Pipeline
import numpy as np

# Create a Ridge regression model inside a pipeline
ridge = Pipeline(steps=[
    ('preprocessor', preprocess),
    ('model', Ridge(alpha=10.0, random_state=42))
])

# Define 10-fold cross-validation setup
cv = KFold(n_splits=10, shuffle=True, random_state=42)

# Evaluate using Root Mean Squared Log Error
scores = cross_val_score(
    ridge, X, y,
    scoring='neg_root_mean_squared_error',
    cv=cv,
    n_jobs=-1
)

print(f"Ridge 10-Fold CV log-RMSE: {-scores.mean():.4f} ± {scores.std():.
```

```
Ridge 10-Fold CV log-RMSE: 0.1374 ± 0.0379
```

Insights:

- CV log-RMSE: 0.1374 ± 0.0379
- This means we have now achieved a `13.7%` **relative prediction error**

Hyperparameter tuning

Now that we have the baseline model ready, we can test multiple alpha (regularization) values using `RidgeCV` and `LassoCV`

In [15]:
```
from sklearn.linear_model import RidgeCV, LassoCV

# Define range of alpha values to test
alphas = np.logspace(-3, 3, 50)  # from 0.001 to 1000

# RidgeCV
ridge_cv = RidgeCV(alphas=alphas, scoring='neg_root_mean_squared_error',
ridge_cv.fit(preprocess.fit_transform(X), y)
print(f"Best Ridge alpha: {ridge_cv.alpha_:.4f}")

#LassoCV for comparison
lasso_cv = LassoCV(alphas=alphas, cv=10, random_state=42, max_iter=10000)
lasso_cv.fit(preprocess.fit_transform(X), y)
print(f"Best Lasso alpha: {lasso_cv.alpha_:.4f}")
```

```
Best Ridge alpha: 10.9854
Best Lasso alpha: 0.0010
```

Insights:

- Ridge α ≈ `10.9854`
- Lasso α ≈ `0.0010`

Also note that the std deviation is still `0.0379`, we will also try to improve this.

Rechecking Cross-Validation:

In [16]:
```
from sklearn.model_selection import KFold, cross_val_score
from sklearn.linear_model import Ridge, Lasso
from sklearn.pipeline import Pipeline
import numpy as np

best_alpha_ridge = 10.9854
best_alpha_lasso = 0.0010

ridge_best = Pipeline([
    ('preprocessor', preprocess),
    ('model', Ridge(alpha=best_alpha_ridge, random_state=42))
])

lasso_best = Pipeline([
    ('preprocessor', preprocess),
    ('model', Lasso(alpha=best_alpha_lasso, random_state=42, max_iter=200
])

cv = KFold(n_splits=10, shuffle=True, random_state=42)

ridge_scores = cross_val_score(ridge_best, X, y,
                               scoring='neg_root_mean_squared_error',
                               cv=cv, n_jobs=-1)
lasso_scores = cross_val_score(lasso_best, X, y,
                               scoring='neg_root_mean_squared_error',
                               cv=cv, n_jobs=-1)

print(f"Ridge (α={best_alpha_ridge:.4f})  CV: {-ridge_scores.mean():.4f}
print(f"Lasso (α={best_alpha_lasso:.4f})  CV: {-lasso_scores.mean():.4f}
```

```
Ridge (α=10.9854)  CV: 0.1374 ± 0.0380
Lasso (α=0.0010)  CV: 0.1375 ± 0.0426
```

Insights:

- Ridge CV log-RMSE: `0.1374`
- Lasso CV log-RMSE: `0.1375`

Hence, it can be noted that both perform similary when checked with cross validation.

Fine-tuning lasso again

- to check if the true best alpha(α) for Lasso is even smaller `(<0.001)`

For this, we will test with smaller alpha values raging from `0.00001 to 0.01`

In [17]:
```
from sklearn.linear_model import LassoCV
import numpy as np

# Transform once for speed
X_mm = preprocess.fit_transform(X)

alphas_fine = np.logspace(-5, -2, 30)  # 1e-5 ... 1e-2
lasso_cv_fine = LassoCV(alphas=alphas_fine, cv=10, random_state=42, max_i
lasso_cv_fine.fit(X_mm, y)

best_alpha_lasso_refined = float(lasso_cv_fine.alpha_)
print("Refined best Lasso alpha:", best_alpha_lasso_refined)
```

```
Refined best Lasso alpha: 0.0005736152510448681
```

Because the refined Lasso printed an alpha <0.001, we will re-evaluate Lasso with the new alpha `0.0005736152510448681`

In [18]:
```
from sklearn.model_selection import KFold, cross_val_score
from sklearn.linear_model import Lasso
from sklearn.pipeline import Pipeline

lasso_best = Pipeline([
    ('preprocessor', preprocess),
    ('model', Lasso(alpha=best_alpha_lasso_refined, random_state=42, max_
])

cv = KFold(n_splits=10, shuffle=True, random_state=42)
lasso_scores = cross_val_score(lasso_best, X, y,
                               scoring='neg_root_mean_squared_error',
                               cv=cv, n_jobs=-1)
print(f"Lasso (α={best_alpha_lasso_refined:.6f}) CV: {-lasso_scores.mean(
```

```
Lasso (α=0.000574) CV: 0.1342 ± 0.0439
```

- So with the updated alpha `α=0.000574` that is far lesser than the older one, it confirms that a smaller **α** helped the Lasso model to learn more detail without overfitting
- We also improved the relative error in prediction to `0.1342` **(approx. 13.4%)** which was earlier `0.1375`

Hence, we can say that this is our best performing linear model.

Training and Evaluating Non Linear models

Now, We will train the non linear models **`LightGBM`** and **`XGBoost`** with early stopping and CV and then generate OOF (out-of-fold) predictions for both models.

In [19]:
```
import numpy as np
from sklearn.model_selection import KFold
from sklearn.metrics import mean_squared_error
```

```
# Reuse preprocessed features
X_mm = preprocess.fit_transform(X)

def rmse_log(y_true, y_pred):
    return np.sqrt(np.mean((y_true - y_pred)**2))

kf = KFold(n_splits=10, shuffle=True, random_state=42)

# ----- LightGBM -----
import lightgbm as lgb
lgb_params = dict(
    n_estimators=5000,
    learning_rate=0.01,
    num_leaves=31,
    subsample=0.8,
    colsample_bytree=0.8,
    reg_alpha=0.0,
    reg_lambda=0.0,
    random_state=42
)

oof_lgb = np.zeros(len(X))
lgb_best_iters = []

for tr, va in kf.split(X_mm):
    X_tr, X_va = X_mm[tr], X_mm[va]
    y_tr, y_va = y.iloc[tr], y.iloc[va]

    model_lgb = lgb.LGBMRegressor(**lgb_params)
    model_lgb.fit(
        X_tr, y_tr,
        eval_set=[(X_va, y_va)],
        eval_metric='rmse',
        callbacks=[lgb.early_stopping(stopping_rounds=200, verbose=False)
    )
    oof_lgb[va] = model_lgb.predict(X_va, num_iteration=model_lgb.best_it
    lgb_best_iters.append(model_lgb.best_iteration_)

rmse_lgb = rmse_log(y, oof_lgb)
print(f"LightGBM 10-fold OOF log-RMSE: {rmse_lgb:.4f} (avg best_iter ≈ {i

# ----- XGBoost -----
from xgboost import XGBRegressor
xgb_params = dict(
    n_estimators=6000,
    learning_rate=0.01,
    max_depth=6,
    subsample=0.8,
    colsample_bytree=0.8,
    reg_alpha=0.0,
    reg_lambda=1.0,
    objective='reg:squarederror',
    random_state=42,
    n_jobs=-1
)

oof_xgb = np.zeros(len(X))
xgb_best_iters = []

for tr, va in kf.split(X_mm):
```

```
    X_tr, X_va = X_mm[tr], X_mm[va]
    y_tr, y_va = y.iloc[tr], y.iloc[va]

    model_xgb = XGBRegressor(**xgb_params)
    model_xgb.fit(
        X_tr, y_tr,
        eval_set=[(X_va, y_va)],
        eval_metric='rmse',
        verbose=False,
        early_stopping_rounds=200
    )
    best_iter = model_xgb.best_iteration if model_xgb.best_iteration is n
    oof_xgb[va] = model_xgb.predict(X_va, iteration_range=(0, best_iter))
    xgb_best_iters.append(best_iter)

rmse_xgb = rmse_log(y, oof_xgb)
print(f"XGBoost 10-fold OOF log-RMSE: {rmse_xgb:.4f} (avg best_iter ≈ {in
```

```
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.002754 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 3341
[LightGBM] [Info] Number of data points in the train set: 1314, number of
used features: 147
[LightGBM] [Info] Start training from score 12.025324
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.000722 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 3327
[LightGBM] [Info] Number of data points in the train set: 1314, number of
used features: 149
[LightGBM] [Info] Start training from score 12.028659
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.000956 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 3333
[LightGBM] [Info] Number of data points in the train set: 1314, number of
used features: 147
[LightGBM] [Info] Start training from score 12.021956
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.001246 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 3332
[LightGBM] [Info] Number of data points in the train set: 1314, number of
used features: 148
[LightGBM] [Info] Start training from score 12.019795
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.000715 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 3317
[LightGBM] [Info] Number of data points in the train set: 1314, number of
used features: 145
[LightGBM] [Info] Start training from score 12.020663
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.000783 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 3320
[LightGBM] [Info] Number of data points in the train set: 1314, number of
used features: 144
[LightGBM] [Info] Start training from score 12.026297
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.000954 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 3332
[LightGBM] [Info] Number of data points in the train set: 1314, number of
used features: 147
[LightGBM] [Info] Start training from score 12.029436
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.000989 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
```

```
[LightGBM] [Info] Total Bins 3329
[LightGBM] [Info] Number of data points in the train set: 1314, number of
used features: 147
[LightGBM] [Info] Start training from score 12.022123
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.001297 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 3331
[LightGBM] [Info] Number of data points in the train set: 1314, number of
used features: 147
[LightGBM] [Info] Start training from score 12.023877
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.000721 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 3335
[LightGBM] [Info] Number of data points in the train set: 1314, number of
used features: 146
[LightGBM] [Info] Start training from score 12.022444
LightGBM 10-fold OOF log-RMSE: 0.1247 (avg best_iter ≈ 1879)
XGBoost 10-fold OOF log-RMSE: 0.1241 (avg best_iter ≈ 2251)
```

Insights:

Now we have the OOf predictions for **LightGBM and XGBoost** which is,

- log RMSE: `0.1247` **approximately 12.47%** for LightGBM
- and log RMSE: `0.1241` **approximately 12.41%** for XGBoost

Next step is to combine all four of the models' OOF predictions and blend them together for getting the best possible **Out-OF-Fold (OOF) log RMSE**.

Generating OOF Predictions for Ridge and Lasso

We have to generate the OOF predictions for our Linear models because we already have the OOF log RMSE for the non linear models (LightGBM and XGBoost)

- we are doing this to match the prediction metrics of all 4 models, so that later we can ensemble them together and get the final OOF log RMSE.
- This will ensure all four models `(Ridge, Lasso, LightGBM, XGBoost)` are evaluated using consistent folds.

In [20]:

```
import numpy as np
from sklearn.model_selection import KFold
from sklearn.linear_model import Ridge, Lasso
from sklearn.pipeline import Pipeline

# 10-Fold Cross Validation setup (same folds for all models for fairness)
kf = KFold(n_splits=10, shuffle=True, random_state=42)

# Create Ridge and Lasso pipelines with tuned alphas
ridge_best = Pipeline([
```

```
    ('preprocessor', preprocess),
    ('model', Ridge(alpha=10.9854, random_state=42))
])

lasso_best = Pipeline([
    ('preprocessor', preprocess),
    ('model', Lasso(alpha=0.0005736152510448681, random_state=42, max_ite
])

# Empty arrays to store out-of-fold predictions (same length as training
oof_ridge = np.zeros(len(X))
oof_lasso = np.zeros(len(X))

# Generate OOF predictions for Ridge and Lasso
for tr, va in kf.split(X):
    ridge_best.fit(X.iloc[tr], y.iloc[tr])
    oof_ridge[va] = ridge_best.predict(X.iloc[va])

    lasso_best.fit(X.iloc[tr], y.iloc[tr])
    oof_lasso[va] = lasso_best.predict(X.iloc[va])

# RMSE in log space (≈ RMSLE on original scale)
def rmse_log(y_true, y_pred):
    return np.sqrt(np.mean((y_true - y_pred)**2))

ridge_rmse = rmse_log(y, oof_ridge)
lasso_rmse = rmse_log(y, oof_lasso)
print("Ridge OOF log RMSE",ridge_rmse),
print("Lasso OOF log RMSE",lasso_rmse)
```

```
Ridge OOF log RMSE 0.14259419340182172
Lasso OOF log RMSE 0.14114880217613698
```

Now that we have the values of **Ridge and Lasso** OOF log RMSE above at approximately `14.25%` Ridge and `14.11%` Lasso,

- We can now combine all four models and blend them to see if the final log RMSE delivers a lower score than all of the models individually.

Blending All Models

- we will test the best set of weights for the four models by assigning multiple grids of weights for each model.
- we will only choose the set of weights which proves to deliver the **lowest RMSLE** of all.

Note that we will be **using the OOF prediction values for all 4 models**

In [21]:
```
# Candidate weights for Ridge, Lasso, LightGBM, XGBoost
candidates = [
    (0.20, 0.20, 0.30, 0.30),
    (0.15, 0.15, 0.35, 0.35),
    (0.10, 0.10, 0.40, 0.40),
    (0.25, 0.25, 0.25, 0.25),
    (0.33, 0.33, 0.17, 0.17),
    (0.10, 0.20, 0.35, 0.35),
```

```
    (0.20, 0.10, 0.35, 0.35),
]

best_w = None
best_score = 999

# Test each weight combination and pick the best one (lowest RMSLE)
for w in candidates:
    w_r, w_l, w_lb, w_x = w
    blend = w_r*oof_ridge + w_l*oof_lasso + w_lb*oof_lgb + w_x*oof_xgb
    score = rmse_log(y, blend)
    print(f"Weights {w} → OOF log-RMSE: {score:.4f}")
    if score < best_score:
        best_score, best_w = score, w

print(f"\n Best OOF blend: weights={best_w}, score={best_score:.4f}")
```

```
Weights (0.2, 0.2, 0.3, 0.3) → OOF log-RMSE: 0.1215
Weights (0.15, 0.15, 0.35, 0.35) → OOF log-RMSE: 0.1207
Weights (0.1, 0.1, 0.4, 0.4) → OOF log-RMSE: 0.1206
Weights (0.25, 0.25, 0.25, 0.25) → OOF log-RMSE: 0.1231
Weights (0.33, 0.33, 0.17, 0.17) → OOF log-RMSE: 0.1272
Weights (0.1, 0.2, 0.35, 0.35) → OOF log-RMSE: 0.1206
Weights (0.2, 0.1, 0.35, 0.35) → OOF log-RMSE: 0.1208

 Best OOF blend: weights=(0.1, 0.1, 0.4, 0.4), score=0.1206
```

Now after reviewing the final log RMSE scores with respect to each grid of weights assigned after combining all 4 models,

- It can be said that `0.1206` is the best score until now.
- It should also be noted that `0.1206` **(approx.12%)** is a better score than all of the previously predicted OOF log RMSE of each model individually.

We can now move ahead and train our best grid of weights, `weights=(0.1, 0.1, 0.4, 0.4)` on full data.

Training and Testing on entire data

Handling a Preprocessing Error Before Final Training:

While preparing the final models for full training and test prediction,
I encountered a **ValueError** related to missing value imputation:

> `ValueError: Cannot use median strategy with non-numeric data: could not convert string to float: 'TA'`

This occurred because some **ordinal categorical features** (like `ExterQual`, `BsmtQual`, `KitchenQual`, etc.)
contained string values (`'TA'`, `'Gd'`, `'Ex'`, etc.) in the **test set**,
which conflicted with the **numeric median imputer** in the preprocessing pipeline.

Step A: Ordinal Mapping & Combined Preprocessing

In [22]:
```python
# MAP ORDINALS & FIT PREPROCESSOR ON TRAIN + TEST

import lightgbm as lgb
from xgboost import XGBRegressor
from sklearn.linear_model import Ridge, Lasso

# Use average best iterations from early stopping
avg_lgb_iter = int(np.mean(lgb_best_iters))
avg_xgb_iter = int(np.mean(xgb_best_iters))

# making copies
X_train_fixed = X.copy()
X_test_fixed  = test.drop(columns=['Id']).copy()

# Define the same ordinal maps used earlier
qual_map       = {'Po':1, 'Fa':2, 'TA':3, 'Gd':4, 'Ex':5}
bsmt_exp_map   = {'None':0, 'No':1, 'Mn':2, 'Av':3, 'Gd':4}
bsmt_fin_map   = {'None':0, 'Unf':1, 'LwQ':2, 'Rec':3, 'BLQ':4, 'ALQ':5,
paved_map      = {'N':0, 'P':1, 'Y':2}
bin_map        = {'N':0, 'Y':1}
functional_map = {'Sal':1,'Sev':2,'Maj2':3,'Maj1':4,'Mod':5,'Min2':6,'Min

ordinal_maps = {
    'ExterQual': qual_map, 'ExterCond': qual_map,
    'BsmtQual': qual_map, 'BsmtCond': qual_map, 'BsmtExposure': bsmt_exp_
    'BsmtFinType1': bsmt_fin_map, 'BsmtFinType2': bsmt_fin_map,
    'HeatingQC': qual_map, 'KitchenQual': qual_map,
    'FireplaceQu': qual_map, 'GarageQual': qual_map, 'GarageCond': qual_m
    'PoolQC': qual_map, 'PavedDrive': paved_map, 'CentralAir': bin_map,
    'Functional': functional_map
}

def apply_ordinal_maps_inplace(df):
    for col, mp in ordinal_maps.items():
        if col in df.columns:
            if df[col].dtype == 'O' or df[col].dtype.name == 'category':
                df[col] = df[col].fillna('None').map(mp)
            df[col] = df[col].astype('float', errors='ignore')

apply_ordinal_maps_inplace(X_train_fixed)
apply_ordinal_maps_inplace(X_test_fixed)

# Fit existing preprocessor on TRAIN + TEST combined
combined = pd.concat([X_train_fixed, X_test_fixed], axis=0)
preprocess_full = preprocess.fit(combined)

# Transform train and test with fitted preprocessor
X_full    = preprocess_full.transform(X_train_fixed)
X_test_mm = preprocess_full.transform(X_test_fixed)

print("✅ Preprocessing completed. Shapes:", X_full.shape, X_test_mm.shap
```

```
✅ Preprocessing completed. Shapes: (1460, 231) (1459, 231)
```

Insights:

The fix for above error:

- Mapped ordinal strings (like `TA`, `Gd`, `Ex`) to numbers in both train and test sets.
- Refit the preprocessor on combined train + test data to learn all category levels.
- Transformed both datasets again for clean modeling.

Step B: Train all models on full data

We train all four models on the full dataset using tuned parameters:

- **Ridge** (α = 10.9854)
- **Lasso** (α = 0.000574)
- **LightGBM** (best_iter ≈ 1879)
- **XGBoost** (best_iter ≈ 2251)

In [23]:
```
# ==============================
# 🧩 PART 3B — TRAIN FULL MODELS (LIGHTGBM, XGBOOST, RIDGE, LASSO)
# ==============================

# Train LightGBM on full data
lgb_params = dict(
    n_estimators=avg_lgb_iter,
    learning_rate=0.01,
    num_leaves=31,
    subsample=0.8,
    colsample_bytree=0.8,
    reg_alpha=0.0,
    reg_lambda=0.0,
    random_state=42
)
lgb_full = lgb.LGBMRegressor(**lgb_params)
lgb_full.fit(X_full, y)

# Train XGBoost on full data
xgb_params = dict(
    n_estimators=avg_xgb_iter,
    learning_rate=0.01,
    max_depth=6,
    subsample=0.8,
    colsample_bytree=0.8,
    reg_alpha=0.0,
    reg_lambda=1.0,
    objective='reg:squarederror',
    random_state=42,
    n_jobs=-1
)
xgb_full = XGBRegressor(**xgb_params)
xgb_full.fit(X_full, y, verbose=False)
```

```
# Train Ridge and Lasso on full data
ridge_full = Ridge(alpha=10.9854, random_state=42)
ridge_full.fit(X_full, y)

lasso_full = Lasso(alpha=0.0005736152510448681, random_state=42, max_iter
lasso_full.fit(X_full, y)

print("Models trained on full data (Ridge, Lasso, LightGBM, XGBoost).")
```

```
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.001383 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 3432
[LightGBM] [Info] Number of data points in the train set: 1460, number of
used features: 150
[LightGBM] [Info] Start training from score 12.024057
Models trained on full data (Ridge, Lasso, LightGBM, XGBoost).
```

All models are now blended and trained together successfully.

Step C: Predicting Test set, Blending final Results and Creating submission file.

In this final step, We will generate predictions for the test set:

- Get log predictions from each model.
- Blend them using the best weights `(0.1, 0.1, 0.4, 0.4)`.
- Convert log predictions back to actual Dollar prices.

In [24]:

```
# Get log predictions from each model
pred_ridge_log = ridge_full.predict(X_test_mm)
pred_lasso_log = lasso_full.predict(X_test_mm)
pred_lgb_log   = lgb_full.predict(X_test_mm)
pred_xgb_log   = xgb_full.predict(X_test_mm)

# Blend predictions using best weights
w_r, w_l, w_lb, w_x = best_w  # Example: (0.1, 0.1, 0.4, 0.4)
pred_log = (w_r*pred_ridge_log +
            w_l*pred_lasso_log +
            w_lb*pred_lgb_log +
            w_x*pred_xgb_log)

# Convert log predictions back to actual dollar prices
pred = np.expm1(pred_log)
pred = np.clip(pred, 0, None)

# Create final submission file
sub = test[['Id']].copy()
sub['SalePrice'] = pred
sub.to_csv('submission.csv', index=False)

print(f"\nSaved submission.csv with weights={best_w}, OOF blend score={be
```

```
Saved submission.csv with weights=(0.1, 0.1, 0.4, 0.4), OOF blend score=0.
1206
```

Above we finally recieved a competitive OOF blend score of all 4 models, that is: `0.1206` **(approx. 12% error)**

🧠 Key Learnings:

- Regularization improves linear stability (Ridge, Lasso).
- Tree-based models handle complex non-linear relationships better.
- Blending reduces overfitting and improves generalization.
- Proper preprocessing and ordinal mapping are crucial for error-free model pipelines.