Shri Vile Parle Kelavani Mandal's
**DWARKADAS J. SANGHVI COLLEGE OF ENGINEERING**
(Autonomous College Affiliated to the University of Mumbai)
NAAC Accredited with "A" Grade (CGPA : 3.18)

**Department of Computer Science and Engineering (Data Science)**

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# Experiment - 6

## (Model Building)

**Aim:** To build model using feature engineering.

## Theory:

Feature engineering is a critical step in the data pre-processing process in data science and machine learning. It involves creating new features or modifying existing ones in your dataset to improve the performance of machine learning models. Proper feature engineering can lead to more accurate and robust models. Here are some key aspects of feature engineering:

- Feature Extraction: Feature extraction involves transforming raw data into a format that's suitable for machine learning. For example, extracting date features (e.g., year, month, day) from a timestamp, converting text data into numerical representations (e.g., TF-IDF, word embedding), or summarizing information in image data (e.g., color histograms, edge detection).
- Feature Transformation: This involves applying mathematical or statistical transformations to your features to make them more suitable for modelling. Common techniques include scaling (e.g., standardization or normalization), log or power transformations, and encoding categorical variables (e.g., one-hot encoding or label encoding).
- Feature Creation: Sometimes, you may need to create new features based on domain knowledge or insights gained during data exploration. This could involve combining existing features, creating interaction terms, or engineering new variables to capture specific patterns or relationships.
- Handling Missing Data: Dealing with missing data is also part of feature engineering. You can choose to impute missing values using techniques like mean, median, or predictive modelling. Sometimes, you may create binary flags indicating the presence of missing data.
- Feature Selection: Feature engineering also involves selecting the most relevant features for your model. This can be done through techniques like univariate feature selection, feature importance from tree-based models, or through domain knowledge.
- Text and NLP Feature Engineering: When working with text data, you may need to perform additional feature engineering, such as tokenization, stemming, lemmatization, and sentiment analysis.
- Handling Categorical Data: Categorical variables require special attention. You can use techniques like one-hot encoding, label encoding, or target encoding to represent categorical data numerically.
- Temporal Feature Engineering: For time-series data, creating lag features or time-based aggregations can be valuable.

- Geospatial Feature Engineering: For geospatial data, you might calculate distances, create spatial clusters, or derive location-based statistics.



- Domain-Specific Feature Engineering: In some cases, domain-specific knowledge can lead to unique feature engineering approaches. This might include creating custom metrics or indicators specific to your problem.
- Feature engineering is an iterative process, and it often requires experimenting with different feature combinations and transformations to find the most informative and predictive features for your machine learning model. Effective feature engineering can significantly impact the model's performance and its ability to uncover valuable insights from the data.

**Model Evaluation / Performance Metrics**

The choice of performance metrics depends on the type of machine learning problem. Here are some common metrics for different types of problems:

- For binary classification, you can use metrics like accuracy, precision, recall, F1-score, and the receiver operating characteristic (ROC) curve.
- For multi-class classification, metrics like accuracy, precision, recall, F1-score, and confusion matrices can be useful.
- For regression problems, metrics like mean squared error (MSE), mean absolute error (MAE), and Rsquared (R2) are commonly used.

**Identify and Minimize data leakage**

•**Train-Test Split:** This is a common practice in which you divide your dataset into two subsets: one for training the model and the other for testing its performance. The split, often referred to as the training set and the test set, allows you to train your model on a portion of the data and then evaluate its performance on unseen data.

•**Cross-Validation:** Cross-validation is a more robust technique than a simple train-test split. It involves partitioning the dataset into multiple subsets (usually k subsets or "folds") and training and evaluating the model multiple times. The results are then averaged to provide a more reliable estimate of the model's performance. Common cross-validation methods include k-fold cross-validation and stratified k-fold cross-validation.

**Lab Assignment:**

- At this stage, we should be having a cleaned data. We will consider the cleaned data for feature engineering steps. Identify new features, make existing features better, remove unwanted or highly correlated features.
- We will perform train test split of the data. Train the model on the training data and evaluate the model on test data.
- Perform cross validation (changing train test split data) and then rechecking metrics to see if the model is not overfitting.

**Assignment Examples to work with**

1. House price prediction
2. Sales prediction
3. Credit card fraud detection
4. Customer segmentation
5. Diabetes prediction

In [ ]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")

from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error

from xgboost import XGBRegressor
```

In [ ]:
```
df = pd.read_csv("HousePricePrediction.csv")
```

In [ ]:
```
df.head()
```

Out[ ]:

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

5 rows × 81 columns

### Mapping Statistics of Data

In [ ]:
```
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     1452 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
```

In [ ]:
```
df.describe().T
```

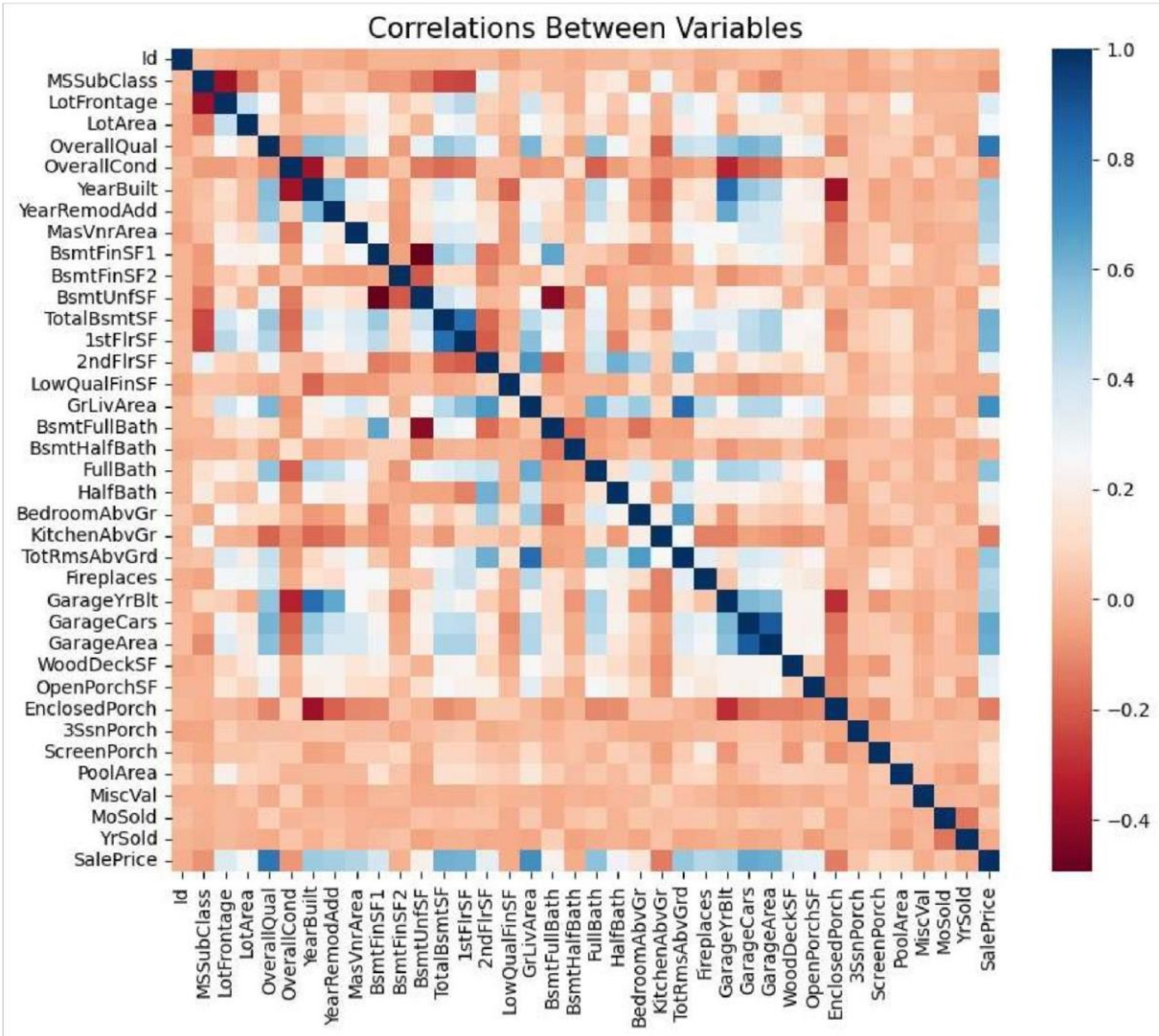
Out[ ]:

| | count | mean | std | min | 25% | 50% | 75% | |
|---|---|---|---|---|---|---|---|---|
| **Id** | 1460.0 | 730.500000 | 421.610009 | 1.0 | 365.75 | 730.5 | 1095.25 | |
| **MSSubClass** | 1460.0 | 56.897260 | 42.300571 | 20.0 | 20.00 | 50.0 | 70.00 | |
| **LotFrontage** | 1201.0 | 70.049958 | 24.284752 | 21.0 | 59.00 | 69.0 | 80.00 | |
| **LotArea** | 1460.0 | 10516.828082 | 9981.264932 | 1300.0 | 7553.50 | 9478.5 | 11601.50 | 2 |
| **OverallQual** | 1460.0 | 6.099315 | 1.382997 | 1.0 | 5.00 | 6.0 | 7.00 | |
| **OverallCond** | 1460.0 | 5.575342 | 1.112799 | 1.0 | 5.00 | 5.0 | 6.00 | |
| **YearBuilt** | 1460.0 | 1971.267808 | 30.202904 | 1872.0 | 1954.00 | 1973.0 | 2000.00 | |
| **YearRemodAdd** | 1460.0 | 1984.865753 | 20.645407 | 1950.0 | 1967.00 | 1994.0 | 2004.00 | |
| **MasVnrArea** | 1452.0 | 103.685262 | 181.066207 | 0.0 | 0.00 | 0.0 | 166.00 | |
| **BsmtFinSF1** | 1460.0 | 443.639726 | 456.098091 | 0.0 | 0.00 | 383.5 | 712.25 | |
| **BsmtFinSF2** | 1460.0 | 46.549315 | 161.319273 | 0.0 | 0.00 | 0.0 | 0.00 | |
| **BsmtUnfSF** | 1460.0 | 567.240411 | 441.866955 | 0.0 | 223.00 | 477.5 | 808.00 | |
| **TotalBsmtSF** | 1460.0 | 1057.429452 | 438.705324 | 0.0 | 795.75 | 991.5 | 1298.25 | |
| **1stFlrSF** | 1460.0 | 1162.626712 | 386.587738 | 334.0 | 882.00 | 1087.0 | 1391.25 | |
| **2ndFlrSF** | 1460.0 | 346.992466 | 436.528436 | 0.0 | 0.00 | 0.0 | 728.00 | |
| **LowQualFinSF** | 1460.0 | 5.844521 | 48.623081 | 0.0 | 0.00 | 0.0 | 0.00 | |
| **GrLivArea** | 1460.0 | 1515.463699 | 525.480383 | 334.0 | 1129.50 | 1464.0 | 1776.75 | |
| **BsmtFullBath** | 1460.0 | 0.425342 | 0.518911 | 0.0 | 0.00 | 0.0 | 1.00 | |
| **BsmtHalfBath** | 1460.0 | 0.057534 | 0.238753 | 0.0 | 0.00 | 0.0 | 0.00 | |
| **FullBath** | 1460.0 | 1.565068 | 0.550916 | 0.0 | 1.00 | 2.0 | 2.00 | |
| **HalfBath** | 1460.0 | 0.382877 | 0.502885 | 0.0 | 0.00 | 0.0 | 1.00 | |
| **BedroomAbvGr** | 1460.0 | 2.866438 | 0.815778 | 0.0 | 2.00 | 3.0 | 3.00 | |
| **KitchenAbvGr** | 1460.0 | 1.046575 | 0.220338 | 0.0 | 1.00 | 1.0 | 1.00 | |
| **TotRmsAbvGrd** | 1460.0 | 6.517808 | 1.625393 | 2.0 | 5.00 | 6.0 | 7.00 | |
| **Fireplaces** | 1460.0 | 0.613014 | 0.644666 | 0.0 | 0.00 | 1.0 | 1.00 | |
| **GarageYrBlt** | 1379.0 | 1978.506164 | 24.689725 | 1900.0 | 1961.00 | 1980.0 | 2002.00 | |
| **GarageCars** | 1460.0 | 1.767123 | 0.747315 | 0.0 | 1.00 | 2.0 | 2.00 | |
| **GarageArea** | 1460.0 | 472.980137 | 213.804841 | 0.0 | 334.50 | 480.0 | 576.00 | |
| **WoodDeckSF** | 1460.0 | 94.244521 | 125.338794 | 0.0 | 0.00 | 0.0 | 168.00 | |
| **OpenPorchSF** | 1460.0 | 46.660274 | 66.256028 | 0.0 | 0.00 | 25.0 | 68.00 | |
| **EnclosedPorch** | 1460.0 | 21.954110 | 61.119149 | 0.0 | 0.00 | 0.0 | 0.00 | |
| **3SsnPorch** | 1460.0 | 3.409589 | 29.317331 | 0.0 | 0.00 | 0.0 | 0.00 | |
| **ScreenPorch** | 1460.0 | 15.060959 | 55.757415 | 0.0 | 0.00 | 0.0 | 0.00 | |
| **PoolArea** | 1460.0 | 2.758904 | 40.177307 | 0.0 | 0.00 | 0.0 | 0.00 | |
| **MiscVal** | 1460.0 | 43.489041 | 496.123024 | 0.0 | 0.00 | 0.0 | 0.00 | |
| **MoSold** | 1460.0 | 6.321918 | 2.703626 | 1.0 | 5.00 | 6.0 | 8.00 | |

| | count | mean | std | min | 25% | 50% | 75% |
|---|---|---|---|---|---|---|---|
| **YrSold** | 1460.0 | 2007.815753 | 1.328095 | 2006.0 | 2007.00 | 2008.0 | 2009.00 |
| **SalePrice** | 1460.0 | 180921.195890 | 79442.502883 | 34900.0 | 129975.00 | 163000.0 | 214000.00 |

### Correlation Features

In [ ]:
```
plt.figure(figsize=(10,8))
sns.heatmap(df.corr(), cmap="RdBu")
plt.title("Correlations Between Variables", size=15)
plt.show()
```




### Feature Selection

```
important_num_cols = list(df.corr()["SalePrice"][(df.corr()["SalePrice"]>0.50)
| (df.corr()["SalePrice"]<-0.50)].index)
# Only those columns are selected which can be important (Subjective)
cat_cols = ["MSZoning", "Utilities","BldgType","Heating","KitchenQual","SaleCo
ndition","LandSlope"]
important_cols = important_num_cols + cat_cols
df = df[important_cols]
df
```

Out[ ]:

| | OverallQual | YearBuilt | YearRemodAdd | TotalBsmtSF | 1stFlrSF | GrLivArea | FullBath | TotRms |
|---|---|---|---|---|---|---|---|---|
| **0** | 7 | 2003 | 2003 | 856 | 856 | 1710 | 2 | |
| **1** | 6 | 1976 | 1976 | 1262 | 1262 | 1262 | 2 | |
| **2** | 7 | 2001 | 2002 | 920 | 920 | 1786 | 2 | |
| **3** | 7 | 1915 | 1970 | 756 | 961 | 1717 | 1 | |
| **4** | 8 | 2000 | 2000 | 1145 | 1145 | 2198 | 2 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **1455** | 6 | 1999 | 2000 | 953 | 953 | 1647 | 2 | |
| **1456** | 6 | 1978 | 1988 | 1542 | 2073 | 2073 | 2 | |
| **1457** | 7 | 1941 | 2006 | 1152 | 1188 | 2340 | 2 | |
| **1458** | 5 | 1950 | 1996 | 1078 | 1078 | 1078 | 1 | |
| **1459** | 5 | 1965 | 1965 | 1256 | 1256 | 1256 | 1 | |

1460 rows × 18 columns

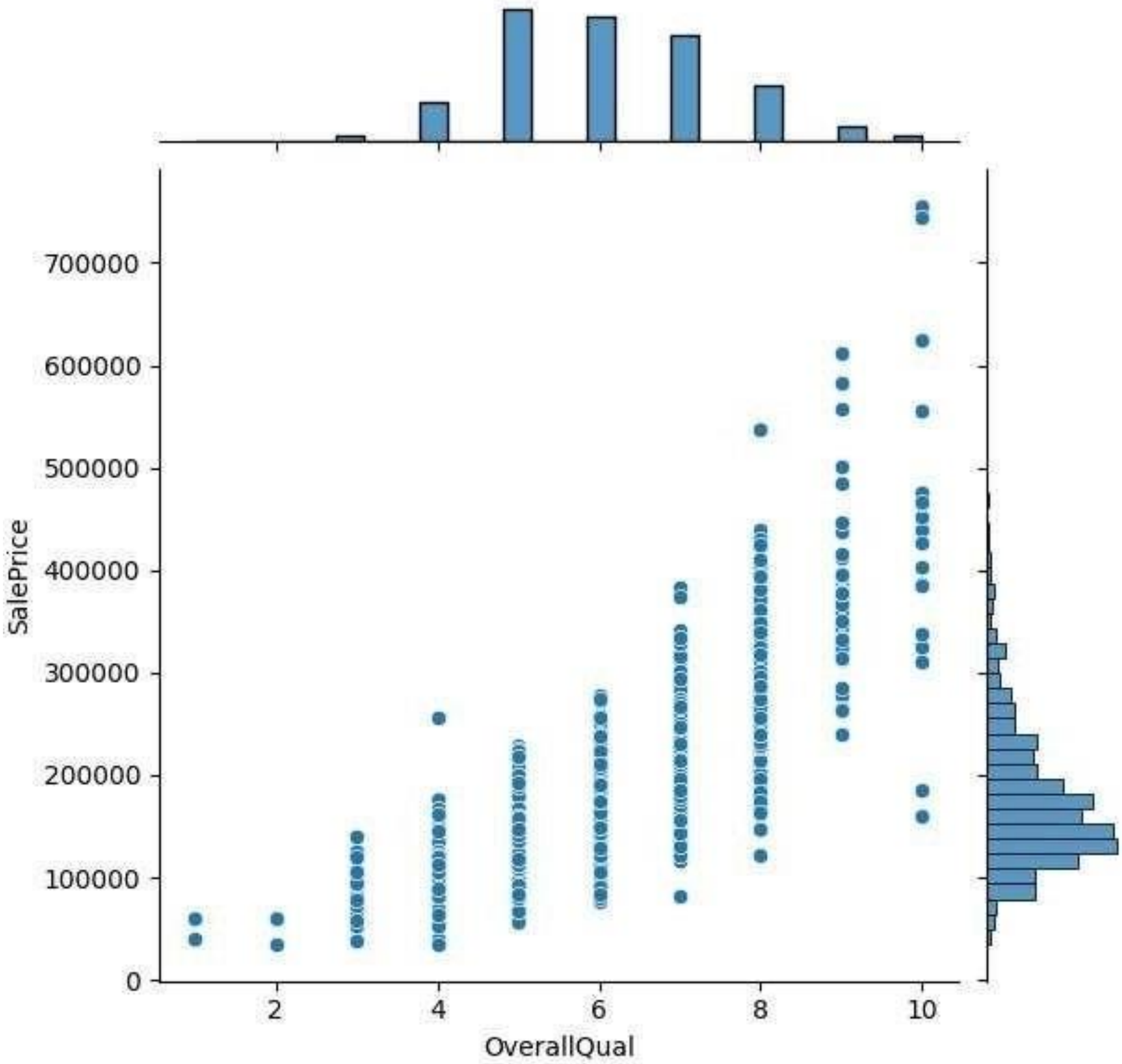
```python
print("Missing Values by Column")
print("-"*30)
print(df.isna().sum())
print("-"*30)
print("TOTAL MISSING VALUES:",df.isna().sum().sum())
```

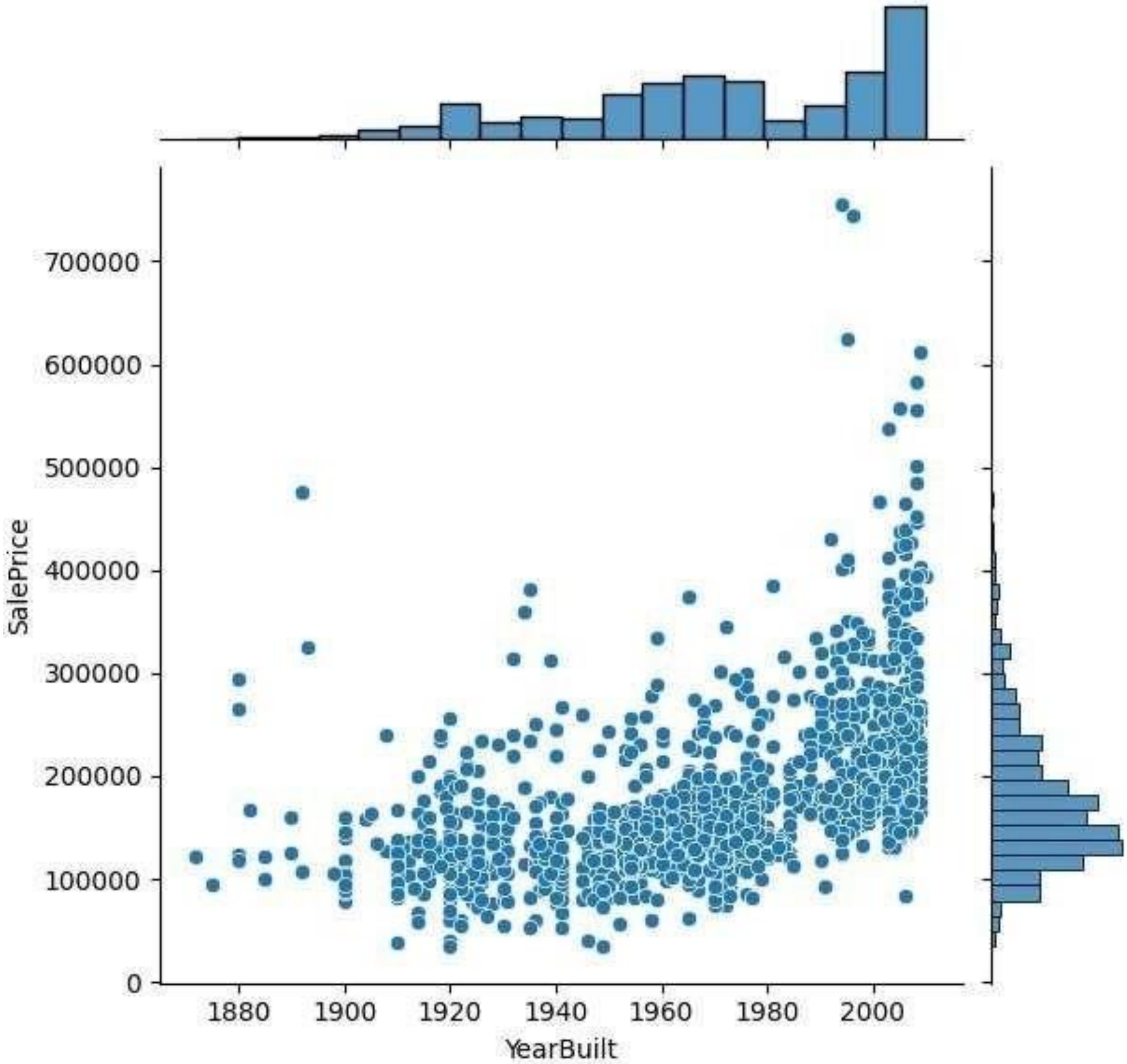
```
Missing Values by Column
------------------------------
OverallQual      0
YearBuilt        0
YearRemodAdd     0
TotalBsmtSF      0
1stFlrSF         0
GrLivArea        0
FullBath         0
TotRmsAbvGrd     0
GarageCars       0
GarageArea       0
SalePrice        0
MSZoning         0
Utilities        0
BldgType         0
Heating          0
KitchenQual      0
SaleCondition    0
LandSlope        0
dtype: int64
------------------------------
TOTAL MISSING VALUES: 0
```

### Correlation Using Joint Plots

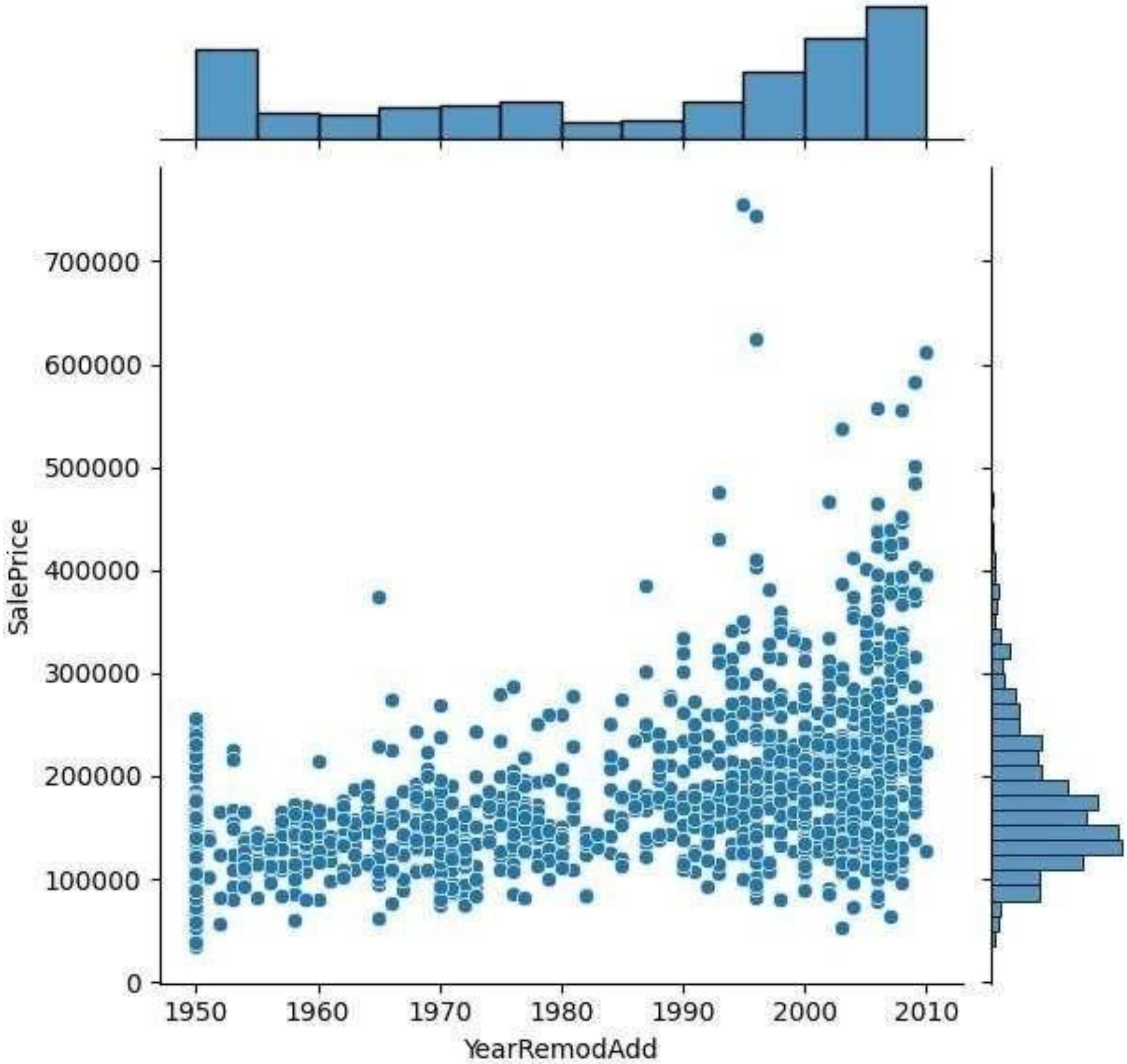
```python
plt.figure(figsize=(10,8))
for i in df.columns:
  if i not in cat_cols:
    sns.jointplot(x=df[i], y=df["SalePrice"])
    plt.show()
```

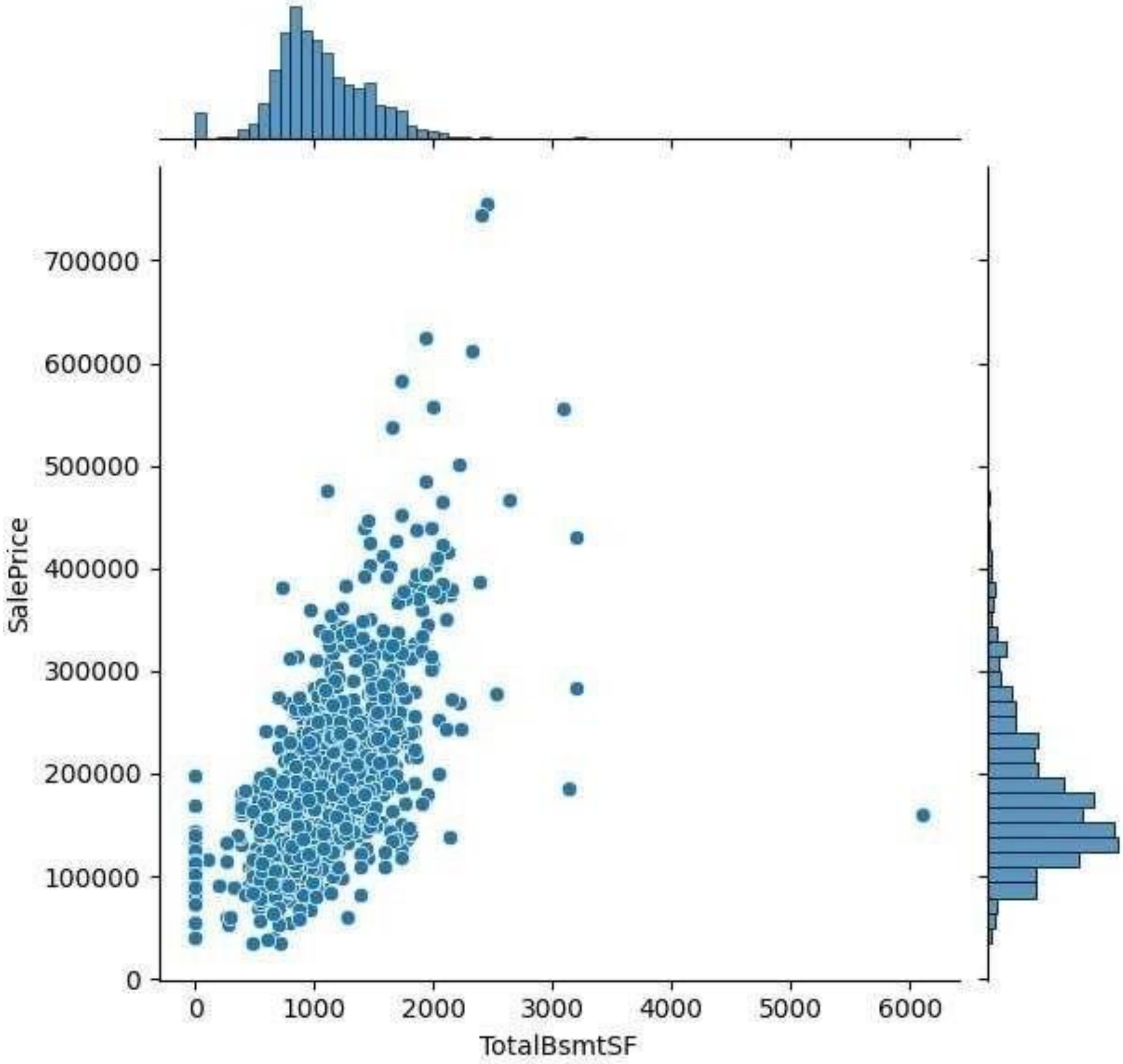
<Figure size 1000x800 with 0 Axes>

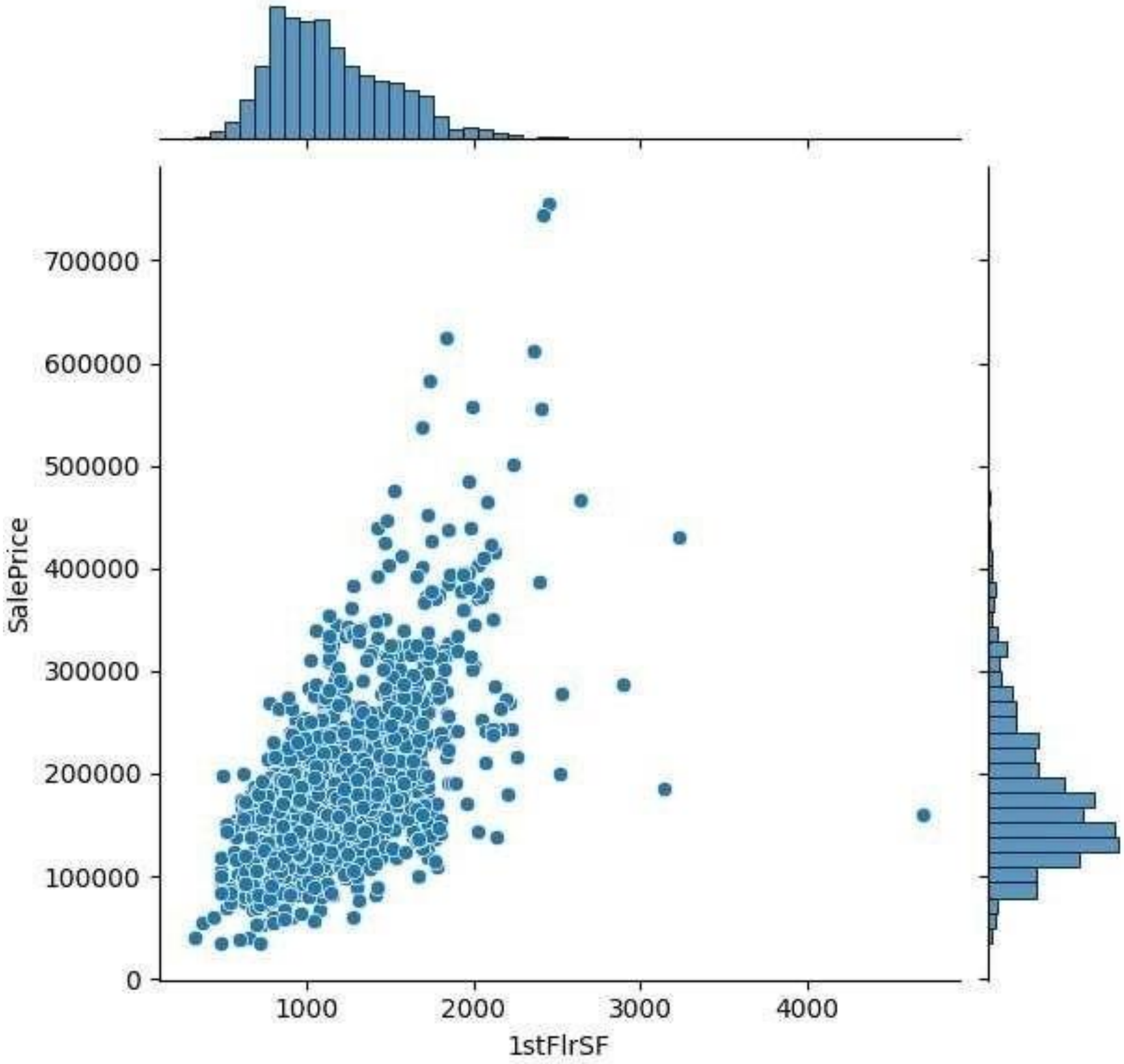




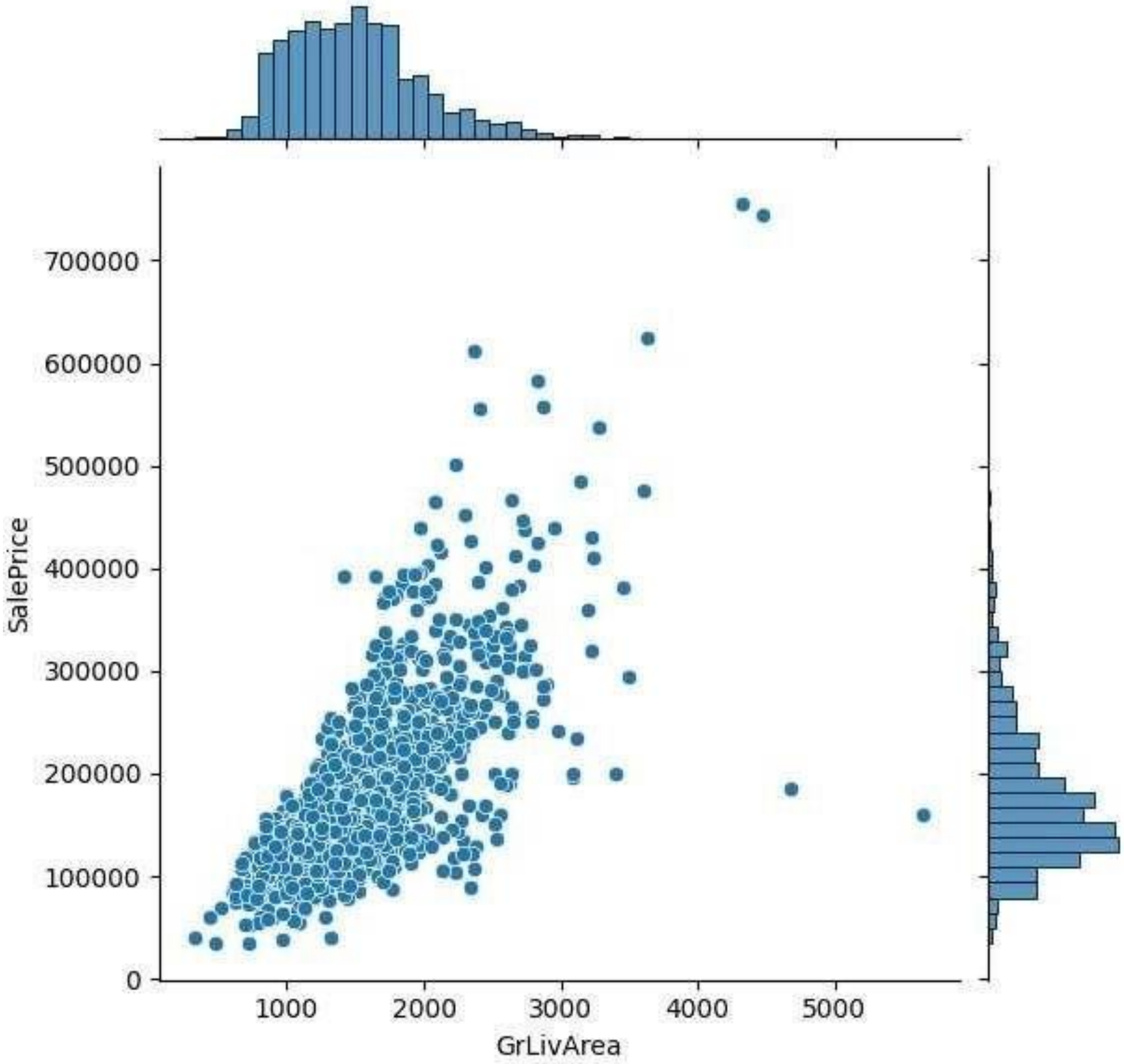
0
100000
200000
300000
400000
500000
600000
700000
SalePrice
1880
1900
1920
1940
1960
1980
2000
YearBuilt


SalePrice
YearRemodAdd
0
100000
200000
300000
400000
500000
600000
700000
1950
1960
1970
1980
1990
2000
2010

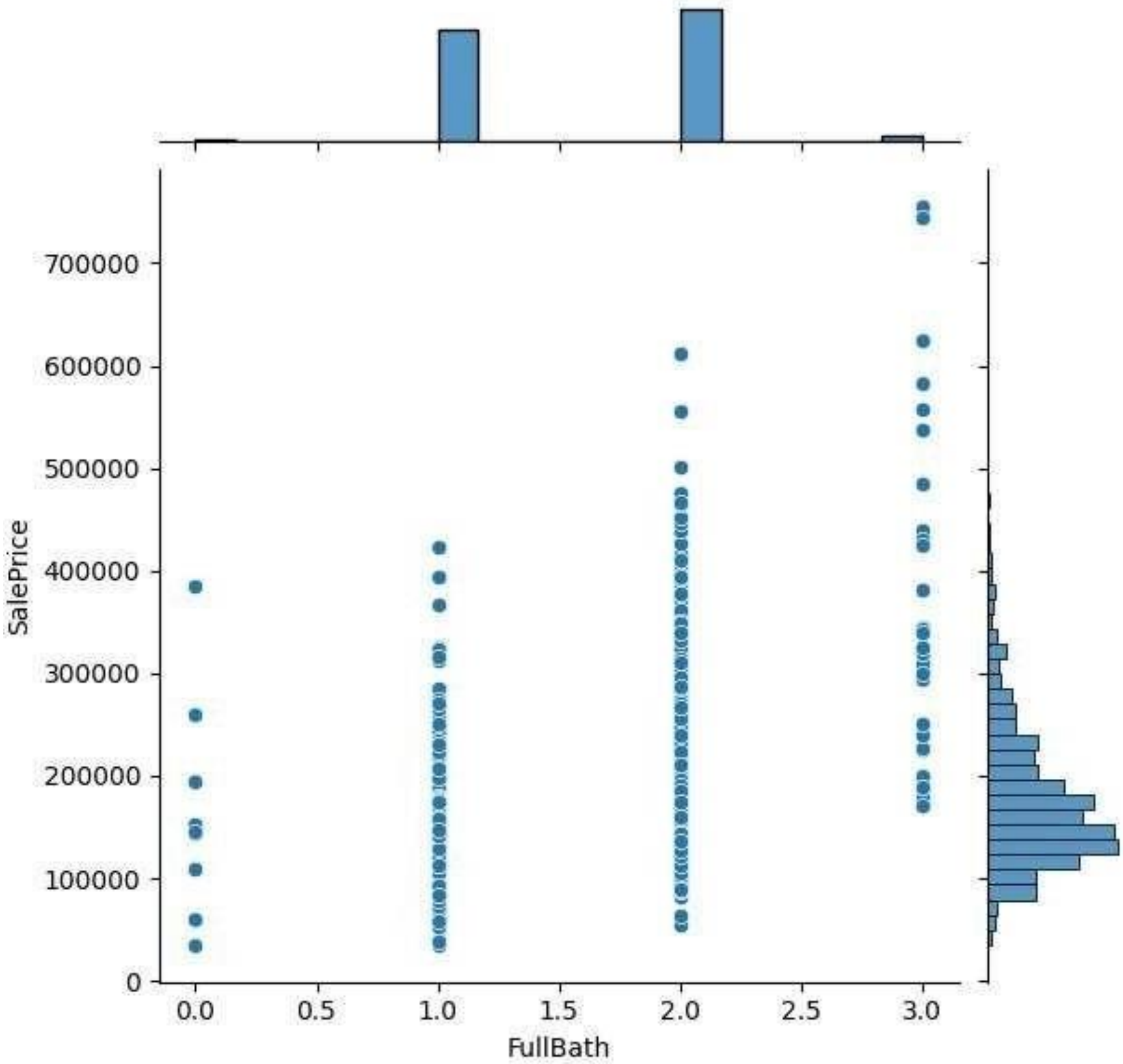

SalePrice
TotalBsmtSF
0
100000
200000
300000
400000
500000
600000
700000
0
1000
2000
3000
4000
5000
6000

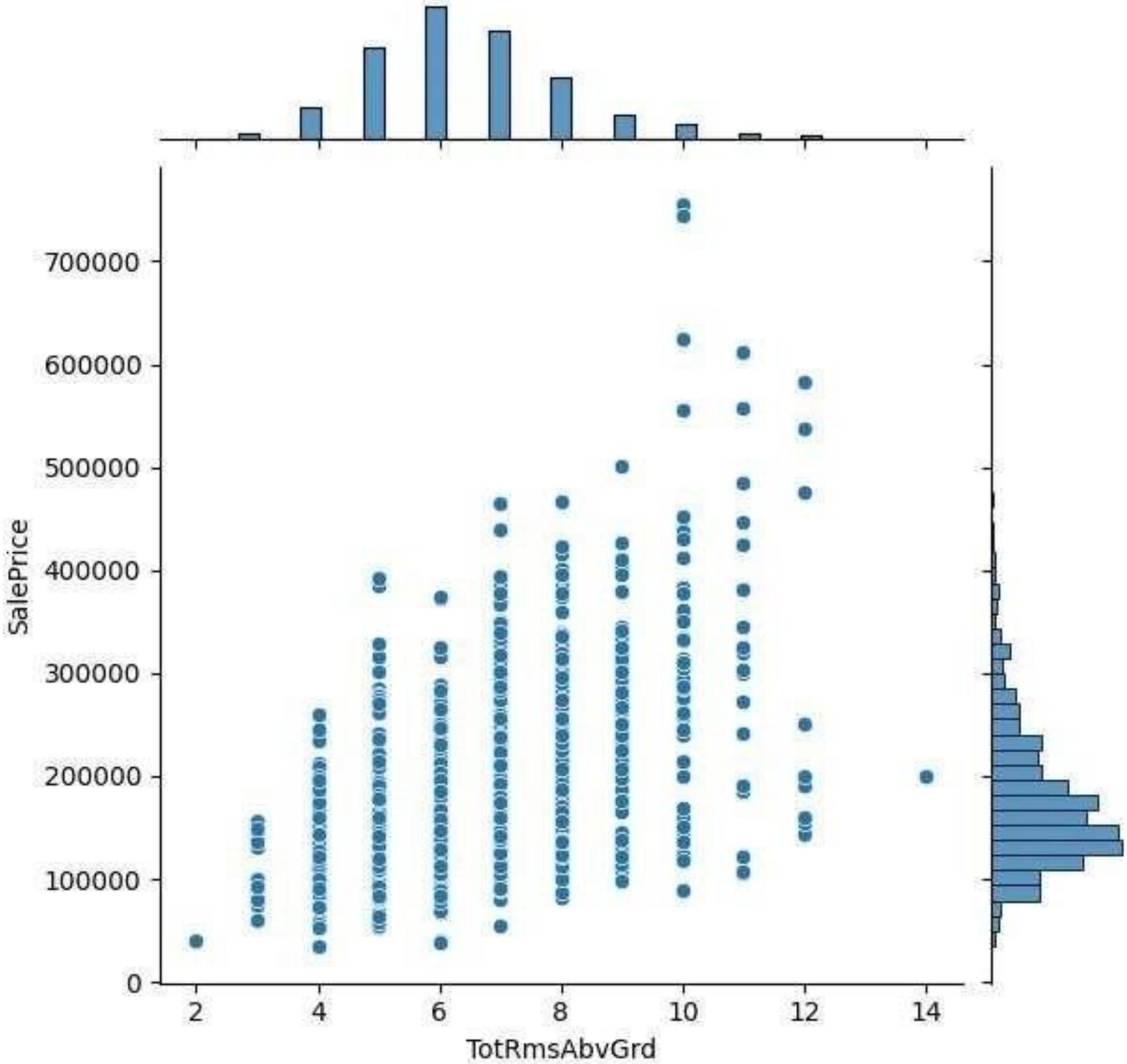


700000
600000
500000
400000
300000
200000
100000
0
SalePrice
1000
2000
3000
4000
1stFlrSF

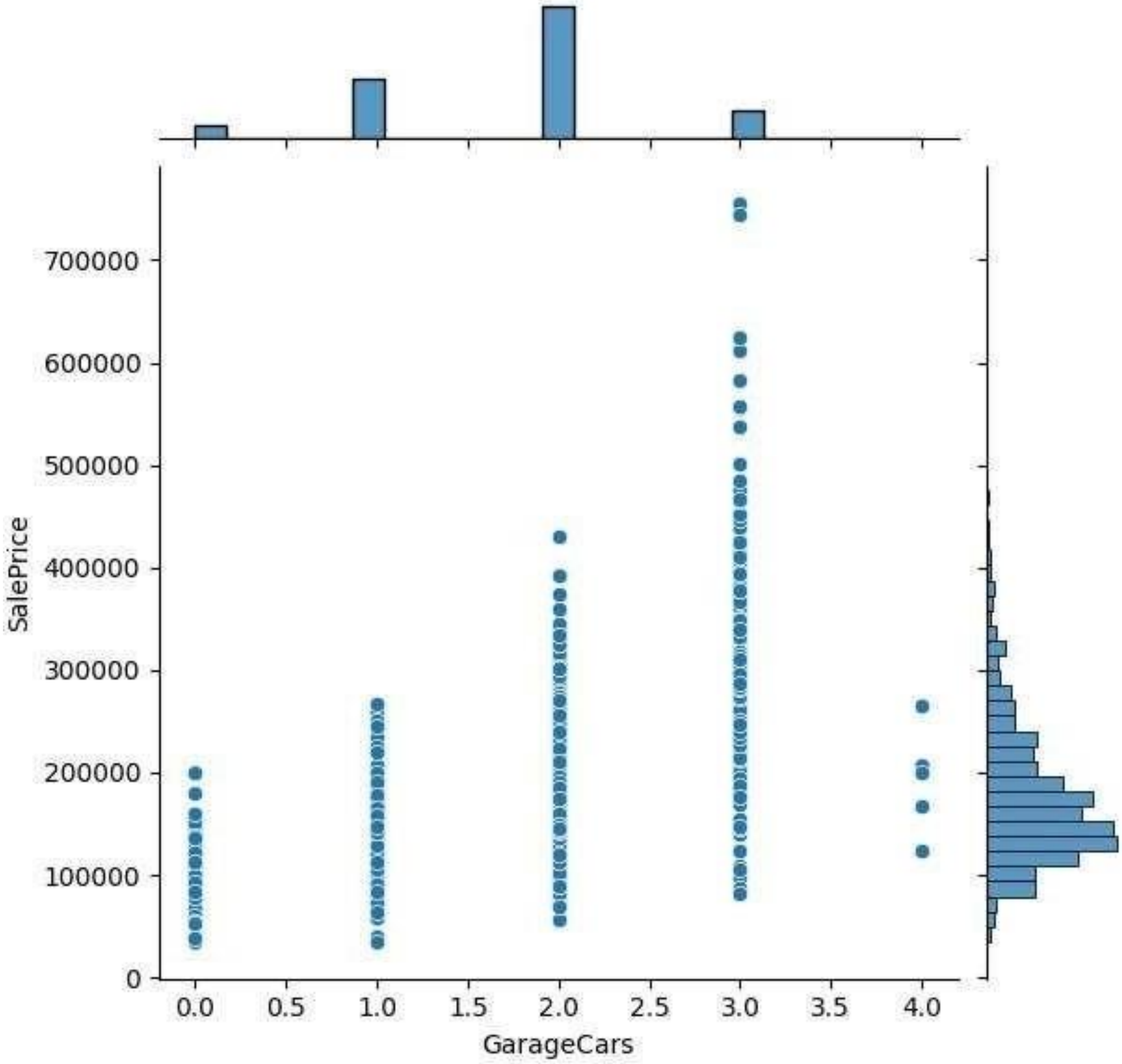


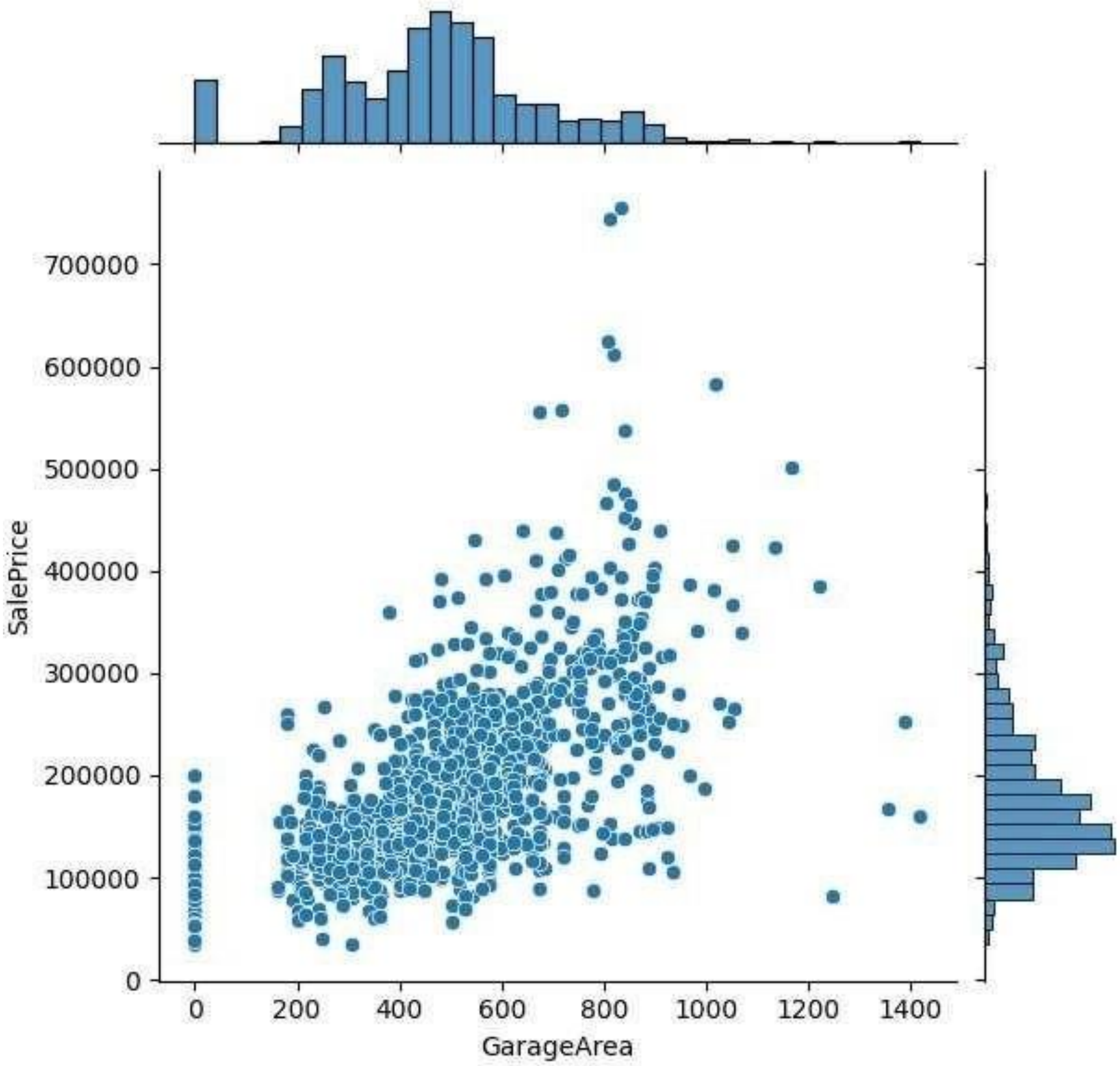
SalePrice
GrLivArea
0
100000
200000
300000
400000
500000
600000
700000
1000
2000
3000
4000
5000

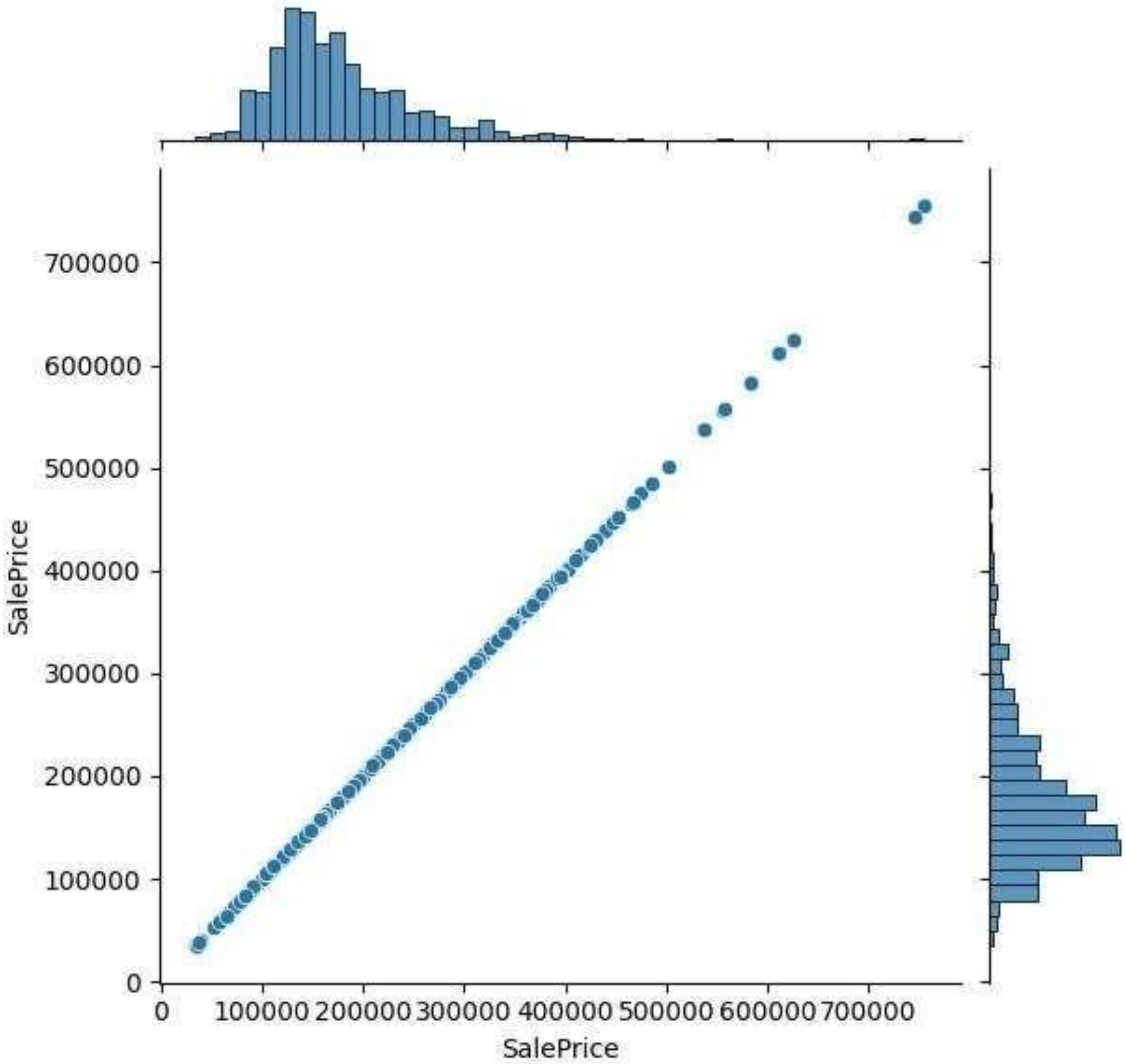

700000
600000
500000
400000
300000
200000
100000
0
SalePrice
0.0
0.5
1.0
1.5
2.0
2.5
3.0
FullBath



SalePrice
TotRmsAbvGrd
0
100000
200000
300000
400000
500000
600000
700000
2
4
6
8
10
12
14


700000
600000
500000
400000
300000
200000
100000
0
SalePrice
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
GarageCars


700000
600000
500000
400000
300000
200000
100000
0
SalePrice
0
200
400
600
800
1000
1200
1400
GarageArea




**One hot encoding**

```
df = pd.get_dummies(df, columns=cat_cols)
df
```

Out[ ]:

| | OverallQual | YearBuilt | YearRemodAdd | TotalBsmtSF | 1stFlrSF | GrLivArea | FullBath | TotRms |
|---|---|---|---|---|---|---|---|---|
| **0** | 7 | 2003 | 2003 | 856 | 856 | 1710 | 2 | |
| **1** | 6 | 1976 | 1976 | 1262 | 1262 | 1262 | 2 | |
| **2** | 7 | 2001 | 2002 | 920 | 920 | 1786 | 2 | |
| **3** | 7 | 1915 | 1970 | 756 | 961 | 1717 | 1 | |
| **4** | 8 | 2000 | 2000 | 1145 | 1145 | 2198 | 2 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **1455** | 6 | 1999 | 2000 | 953 | 953 | 1647 | 2 | |
| **1456** | 6 | 1978 | 1988 | 1542 | 2073 | 2073 | 2 | |
| **1457** | 7 | 1941 | 2006 | 1152 | 1188 | 2340 | 2 | |
| **1458** | 5 | 1950 | 1996 | 1078 | 1078 | 1078 | 1 | |
| **1459** | 5 | 1965 | 1965 | 1256 | 1256 | 1256 | 1 | |

1460 rows × 42 columns

### Scaling the numerical values

```
important_num_cols.remove("SalePrice")

scaler = StandardScaler()
df[important_num_cols] = scaler.fit_transform(df[important_num_cols])
df
```

Out[ ]:

| | OverallQual | YearBuilt | YearRemodAdd | TotalBsmtSF | 1stFlrSF | GrLivArea | FullBath | TotR |
|---|---|---|---|---|---|---|---|---|
| **0** | 0.651479 | 1.050994 | 0.878668 | -0.459303 | -0.793434 | 0.370333 | 0.789741 | |
| **1** | -0.071836 | 0.156734 | -0.429577 | 0.466465 | 0.257140 | -0.482512 | 0.789741 | |
| **2** | 0.651479 | 0.984752 | 0.830215 | -0.313369 | -0.627826 | 0.515013 | 0.789741 | |
| **3** | 0.651479 | -1.863632 | -0.720298 | -0.687324 | -0.521734 | 0.383659 | -1.026041 | |
| **4** | 1.374795 | 0.951632 | 0.733308 | 0.199680 | -0.045611 | 1.299326 | 0.789741 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **1455** | -0.071836 | 0.918511 | 0.733308 | -0.238122 | -0.542435 | 0.250402 | 0.789741 | |
| **1456** | -0.071836 | 0.222975 | 0.151865 | 1.104925 | 2.355701 | 1.061367 | 0.789741 | |
| **1457** | 0.651479 | -1.002492 | 1.024029 | 0.215641 | 0.065656 | 1.569647 | 0.789741 | |
| **1458** | -0.795151 | -0.704406 | 0.539493 | 0.046905 | -0.218982 | -0.832788 | -1.026041 | |
| **1459** | -0.795151 | -0.207594 | -0.962566 | 0.452784 | 0.241615 | -0.493934 | -1.026041 | |

1460 rows × 42 columns

### Train Test Split

In [ ]:
```
X = df.drop("SalePrice", axis=1)
y = df["SalePrice"]
```

In [ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
m_state=42)
```

### Useful Metrics Calculations

In [ ]:
```
def evaluation(y, predictions):
    mae = mean_absolute_error(y, predictions)
    mse = mean_squared_error(y, predictions)
    rmse = np.sqrt(mean_squared_error(y, predictions))
    r_squared = r2_score(y, predictions)
    return mae, mse, rmse, r_squared
```

### Modelling XG_Boost_Regressor

```
xgb = XGBRegressor(n_estimators=1000, learning_rate=0.01)
xgb.fit(X_train, y_train)
predictions = xgb.predict(X_test)

mae, mse, rmse, r_squared = evaluation(y_test, predictions)
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r_squared)
```

```
MAE: 17985.48701038099
MSE: 837038411.4275047
RMSE: 28931.616121943563
R2 Score: 0.8908731664315402
```

### Cross-Validation

In [ ]:

```
test_score = xgb.score(X_test, y_test)
test_score
```

Out[ ]:

```
0.8908731664315402
```

In [ ]:

```
k = 5
cross_val_scores = cross_val_score(xgb, X_train, y_train, cv=k)

print("Cross-Validation Scores:", cross_val_scores)
print("Mean CV Score:", np.mean(cross_val_scores))
```

```
Cross-Validation Scores: [0.82876146 0.67764145 0.86030628 0.85252966 0.86836
063]
Mean CV Score: 0.8175198945132556
```

In [ ]:

```
if np.mean(cross_val_scores) > test_score:
    print("The model may be overfitting.")
else:
    print("The model is not overfitting.")
```

```
The model is not overfitting.
```

In [ ]:

```
```