In [1]:
```python
# loading the packages needed for this project
import pandas as pd
import numpy as np
import zipfile
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error
```

In [2]:
```python
import os

# Define the path to the zip file and the extraction directory
desktop_path = os.path.join(os.path.expanduser('~'), 'Desktop')
zip_file_path = os.path.join(desktop_path, 'Jules', 'house-prices-advanced-regression-techniques.zip')
extraction_path = os.path.join(desktop_path, 'Jules')

# Extract the contents of the zip file
with zipfile.ZipFile(zip_file_path, 'r') as zip_ref:
    zip_ref.extractall(extraction_path)

# Load the dataset into a Pandas DataFrame
csv_file_path = os.path.join(extraction_path, 'train.csv')
train_data = pd.read_csv(csv_file_path)

# Display the first few rows of the DataFrame to ensure it loaded correctly
#print(train_data.head())
train_data
```

Out[2]:

	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

In [3]:
```python
# Inspect the dataset for missing values
missing_values = train_data.isnull().sum().sort_values(ascending=False)
missing_values
```

Out[3]:
```
PoolQC          1453
MiscFeature     1406
Alley           1369
Fence           1179
MasVnrType       872
                ...
ExterQual          0
Exterior2nd        0
Exterior1st        0
RoofMatl           0
SalePrice          0
Length: 81, dtype: int64
```

In [4]:
```python
# Separate numeric columns and non-numeric columns
numeric_cols = train_data.select_dtypes(include=['number'])
non_numeric_cols = train_data.select_dtypes(exclude=['number'])

# Fill missing values in numeric columns with the median
numeric_cols_filled = numeric_cols.fillna(numeric_cols.median())

# Combine numeric and non-numeric columns back into a single DataFrame
train_data_filled = pd.concat([numeric_cols_filled, non_numeric_cols], axis=1)

# Display the first few rows of the DataFrame to ensure it loaded correctly
print(train_data_filled.head())
```

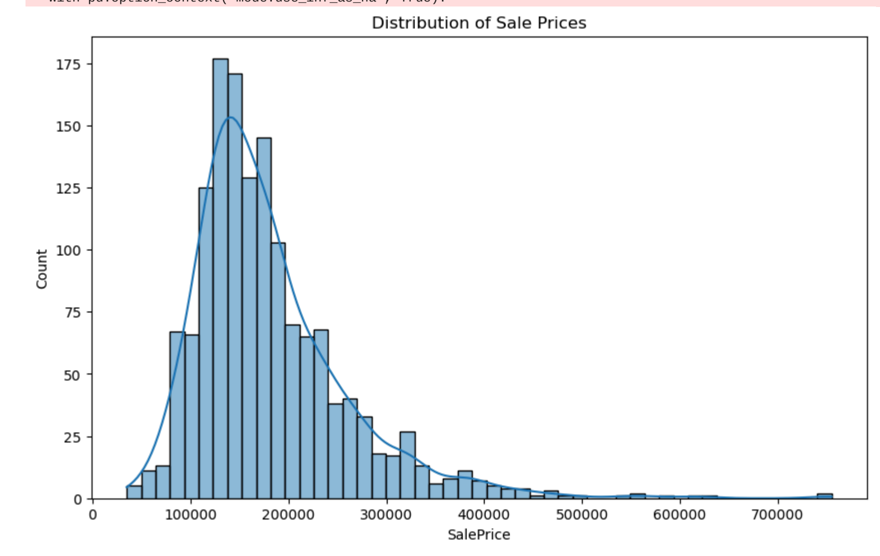
```
   Id  MSSubClass  LotFrontage  LotArea  OverallQual  OverallCond  YearBuilt  \
0   1          60         65.0     8450            7            5       2003
1   2          20         80.0     9600            6            8       1976
2   3          60         68.0    11250            7            5       2001
3   4          70         60.0     9550            7            5       1915
4   5          60         84.0    14260            8            5       2000

   YearRemodAdd  MasVnrArea  BsmtFinSF1  ...  GarageType  GarageFinish  \
0          2003       196.0         706  ...      Attchd           RFn
1          1976         0.0         978  ...      Attchd           RFn
2          2002       162.0         486  ...      Attchd           RFn
3          1970         0.0         216  ...      Detchd           Unf
4          2000       350.0         655  ...      Attchd           RFn

   GarageQual  GarageCond  PavedDrive  PoolQC  Fence  MiscFeature  SaleType  \
0          TA          TA           Y     NaN    NaN          NaN        WD
1          TA          TA           Y     NaN    NaN          NaN        WD
2          TA          TA           Y     NaN    NaN          NaN        WD
3          TA          TA           Y     NaN    NaN          NaN        WD
4          TA          TA           Y     NaN    NaN          NaN        WD

   SaleCondition
0         Normal
1         Normal
2         Normal
3        Abnorml
4         Normal

[5 rows x 81 columns]
```

In [5]:
```python
# Perform data cleaning to ensure the dataset is ready for analysis
initial_rows = train_data.shape[0]
train_data_cleaned = train_data_filled.copy()

# Display the first few rows of the cleaned data
print(train_data_cleaned.head(), initial_rows, missing_values.head(10))
```

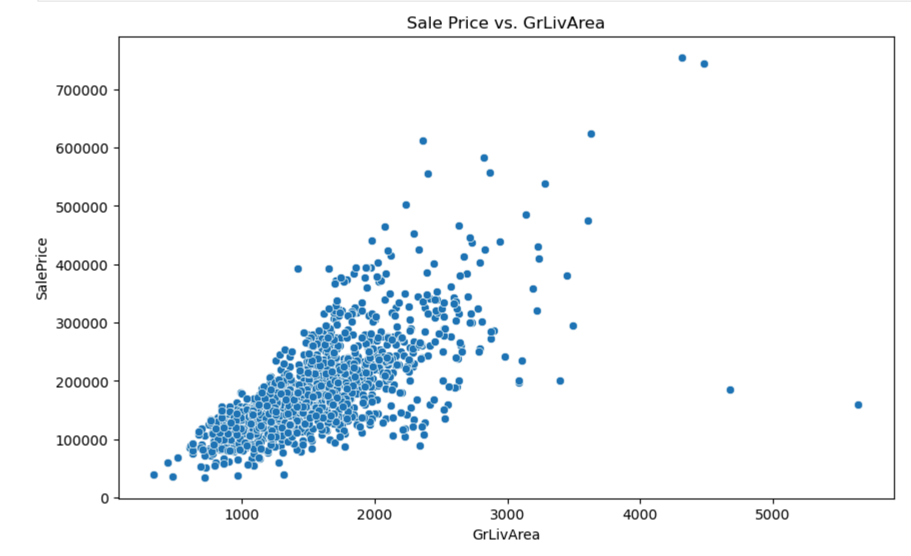
```
   Id  MSSubClass  LotFrontage  LotArea  OverallQual  OverallCond  YearBuilt  \
0   1          60         65.0     8450            7            5       2003
1   2          20         80.0     9600            6            8       1976
2   3          60         68.0    11250            7            5       2001
3   4          70         60.0     9550            7            5       1915
4   5          60         84.0    14260            8            5       2000

   YearRemodAdd  MasVnrArea  BsmtFinSF1  ...  GarageType  GarageFinish  \
0          2003       196.0         706  ...      Attchd           RFn
1          1976         0.0         978  ...      Attchd           RFn
2          2002       162.0         486  ...      Attchd           RFn
3          1970         0.0         216  ...      Detchd           Unf
4          2000       350.0         655  ...      Attchd           RFn

   GarageQual  GarageCond  PavedDrive  PoolQC  Fence  MiscFeature  SaleType  \
0          TA          TA           Y     NaN    NaN          NaN        WD
1          TA          TA           Y     NaN    NaN          NaN        WD
2          TA          TA           Y     NaN    NaN          NaN        WD
3          TA          TA           Y     NaN    NaN          NaN        WD
4          TA          TA           Y     NaN    NaN          NaN        WD

   SaleCondition
0         Normal
1         Normal
2         Normal
3        Abnorml
4         Normal

[5 rows x 81 columns] 1460 PoolQC         1453
MiscFeature    1406
Alley          1369
Fence          1179
MasVnrType      872
FireplaceQu     690
LotFrontage     259
GarageYrBlt      81
GarageCond       81
GarageType       81
dtype: int64
```

In [6]:
```python
# Phase 2: Exploratory Data Analysis (EDA)

# Distribution of target variable
plt.figure(figsize=(10, 6))
sns.histplot(train_data_cleaned['SalePrice'], kde=True)
plt.title('Distribution of Sale Prices')
plt.show()
```

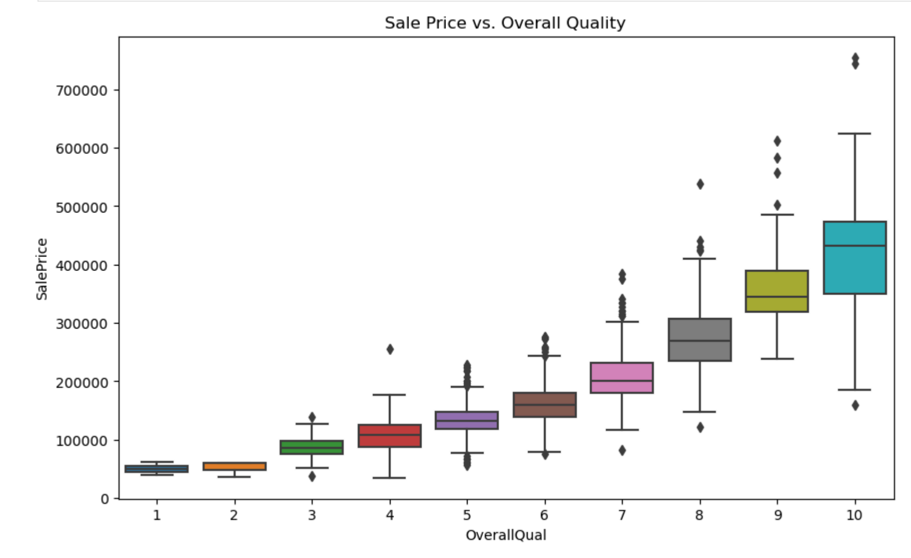
```
C:\Users\Barry J\anaconda3\envs\DS_Explore\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN be
fore operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



In [7]:
```python
# Scatter plot
plt.figure(figsize=(10, 6))
sns.scatterplot(x='GrLivArea', y='SalePrice', data=train_data_cleaned)
plt.title('Sale Price vs. GrLivArea')
plt.show()
```



In [8]:
```python
# Box plot
plt.figure(figsize=(10, 6))
sns.boxplot(x='OverallQual', y='SalePrice', data=train_data_cleaned)
plt.title('Sale Price vs. Overall Quality')
plt.show()
```



In [9]:
```python
# Identifying outliers using z-score
z_scores = stats.zscore(train_data_cleaned.select_dtypes(include=[np.number]))
abs_z_scores = np.abs(z_scores)
outliers = (abs_z_scores > 3).sum(axis=1)
outlier_rows = train_data_cleaned[outliers > 0].index
train_data_cleaned = train_data_cleaned.drop(outlier_rows)

print(train_data_cleaned.describe(), train_data_cleaned.head())
```

```
                Id   MSSubClass  LotFrontage       LotArea  OverallQual  \
count  1015.000000  1015.000000  1015.000000   1015.000000  1015.000000
mean    735.600985    53.931034    67.303448   9139.664039     6.072906
std     423.369253    40.369535    18.267801   3634.390581     1.314689
min       1.000000    20.000000    21.000000   1300.000000     2.000000
25%     377.500000    20.000000    60.000000   7200.000000     5.000000
50%     735.000000    50.000000    69.000000   9066.000000     6.000000
75%    1105.500000    60.000000    76.000000  10996.000000     7.000000
max    1457.000000   180.000000   134.000000  29959.000000    10.000000

       OverallCond    YearBuilt  YearRemodAdd   MasVnrArea   BsmtFinSF1  ...  \
count  1015.000000  1015.000000   1015.000000  1015.000000  1015.000000  ...
mean      5.521182  1975.111330   1986.039409    82.213793   413.388177  ...
std       0.984743    29.052194     20.737640   130.064354   403.773301  ...
min       3.000000  1885.000000   1950.000000     0.000000     0.000000  ...
25%       5.000000  1956.000000   1968.000000     0.000000     0.000000  ...
50%       5.000000  1977.000000   1996.000000     0.000000   386.000000  ...
75%       6.000000  2003.000000   2004.000000   143.500000   695.000000  ...
max       8.000000  2009.000000   2010.000000   640.000000  1646.000000  ...

        WoodDeckSF  OpenPorchSF  EnclosedPorch   3SsnPorch  ScreenPorch  \
count  1015.000000  1015.000000    1015.000000  1015.00000  1015.000000
mean     87.697537    42.044335      14.881773     0.02266     5.989163
std     107.115075    53.355521      43.116257     0.72193    28.824383
min       0.000000     0.000000       0.000000     0.00000     0.000000
25%       0.000000     0.000000       0.000000     0.00000     0.000000
50%       0.000000    27.000000       0.000000     0.00000     0.000000
75%     167.000000    63.000000       0.000000     0.00000     0.000000
max     468.000000   244.000000     205.000000    23.00000   182.000000

       PoolArea      MiscVal       MoSold       YrSold      SalePrice
count    1015.0  1015.000000  1015.000000  1015.000000    1015.000000
mean        0.0    14.782266     6.252217  2007.813793  172714.054187
std         0.0   101.436540     2.681560     1.343333   63514.906369
min         0.0     0.000000     1.000000  2006.000000   35311.000000
25%         0.0     0.000000     4.000000  2007.000000  128000.000000
50%         0.0     0.000000     6.000000  2008.000000  160000.000000
75%         0.0     0.000000     8.000000  2009.000000  206950.000000
max         0.0  1300.000000    12.000000  2010.000000  402861.000000

[8 rows x 38 columns]     Id  MSSubClass  LotFrontage  LotArea  OverallQual  OverallCond  YearBuilt  \
0    1          60         65.0     8450            7            5       2003
2    3          60         68.0    11250            7            5       2001
4    5          60         84.0    14260            8            5       2000
6    7          20         75.0    10084            8            5       2004
10  11          20         70.0    11200            5            5       1965

    YearRemodAdd  MasVnrArea  BsmtFinSF1  ...  GarageType  GarageFinish  \
0           2003       196.0         706  ...      Attchd           RFn
2           2002       162.0         486  ...      Attchd           RFn
4           2000       350.0         655  ...      Attchd           RFn
6           2005       186.0        1369  ...      Attchd           RFn
10          1965         0.0         906  ...      Detchd           Unf

    GarageQual  GarageCond  PavedDrive  PoolQC  Fence  MiscFeature  SaleType  \
0           TA          TA           Y     NaN    NaN          NaN        WD
2           TA          TA           Y     NaN    NaN          NaN        WD
4           TA          TA           Y     NaN    NaN          NaN        WD
6           TA          TA           Y     NaN    NaN          NaN        WD
10          TA          TA           Y     NaN    NaN          NaN        WD

    SaleCondition
0          Normal
2          Normal
4          Normal
6          Normal
10         Normal

[5 rows x 81 columns]
```

In [10]:
```python
# Phase 3: Feature Engineering

# 3.1: Create new features
train_data_cleaned['TotalSF'] = train_data_cleaned['TotalBsmtSF'] + train_data_cleaned['1stFlrSF'] + train_data_cleaned['2ndFlrSF']

# 3.2: Encode categorical variables
train_data_encoded = pd.get_dummies(train_data_cleaned)

# 3.3: Normalize or standardize numerical features
scaler = StandardScaler()
numerical_cols = train_data_encoded.select_dtypes(include=[np.number]).columns
train_data_encoded[numerical_cols] = scaler.fit_transform(train_data_encoded[numerical_cols])

# Display the first few rows of the processed data
print(train_data_encoded.head())
```

```
          Id  MSSubClass  LotFrontage   LotArea  OverallQual  OverallCond  \
0  -1.735986    0.150409    -0.126156 -0.189854     0.705529    -0.529518
2  -1.731260    0.150409     0.038149  0.580944     0.705529    -0.529518
4  -1.726533    0.150409     0.914439  1.409551     1.466540    -0.529518
6  -1.721807   -0.840925     0.421526  0.259961     1.466540    -0.529518
10 -1.712354   -0.840925     0.147685  0.567179    -0.816494    -0.529518

    YearBuilt  YearRemodAdd  MasVnrArea  BsmtFinSF1  ...  SaleType_ConLw  \
0    0.960424      0.818268    0.875277    0.725051  ...           False
2    0.891548      0.770023    0.613739    0.179922  ...           False
4    0.857110      0.673532    2.059890    0.598680  ...           False
6    0.994862      0.914759    0.798354    2.367871  ...           False
10  -0.348212     -1.015052   -0.632412    1.220622  ...           False

    SaleType_New  SaleType_Oth  SaleType_WD  SaleCondition_Abnorml  \
0          False         False         True                  False
2          False         False         True                  False
4          False         False         True                  False
6          False         False         True                  False
10         False         False         True                  False

    SaleCondition_AdjLand  SaleCondition_Alloca  SaleCondition_Family  \
0                   False                 False                 False
2                   False                 False                 False
4                   False                 False                 False
6                   False                 False                 False
10                  False                 False                 False

    SaleCondition_Normal  SaleCondition_Partial
0                   True                  False
2                   True                  False
4                   True                  False
6                   True                  False
10                  True                  False

[5 rows x 261 columns]
```

In [11]:
```python
# Phase 4: Model Training and Evaluation

# Define target and features
X = train_data_encoded.drop('SalePrice', axis=1)
y = train_data_encoded['SalePrice']

# 4.1: Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [12]:
```python
# 4.2: Choose and justify the selection of machine learning algorithms
# Linear Regression
model_lr = LinearRegression()
model_lr.fit(X_train, y_train)
y_pred_lr = model_lr.predict(X_test)
```

In [13]:
```python
# Random Forest
model_rf = RandomForestRegressor(random_state=42)
model_rf.fit(X_train, y_train)
y_pred_rf = model_rf.predict(X_test)
```

In [14]:
```python
# 4.3: Train multiple models and evaluate their performance using appropriate metrics
rmse_lr = mean_squared_error(y_test, y_pred_lr, squared=False)
rmse_rf = mean_squared_error(y_test, y_pred_rf, squared=False)
```

In [15]:
```python
# 4.4: Perform hyperparameter tuning to optimize the model's performance
param_grid = {
    'n_estimators': [50, 100],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5]
}

grid_search = GridSearchCV(RandomForestRegressor(random_state=42), param_grid, cv=3, scoring='neg_mean_squared_error')
grid_search.fit(X_train, y_train)

best_rf_model = grid_search.best_estimator_
```

In [16]:
```python
# 4.5: Select and evaluate the best-performing model on the testing set
y_pred_best = best_rf_model.predict(X_test)
rmse_best = mean_squared_error(y_test, y_pred_best, squared=False)
```

In [17]:
```python
# Summary results
rmse_results = {
    "Linear Regression RMSE": rmse_lr,
    "Random Forest RMSE": rmse_rf,
    "Best Model RMSE": rmse_best,
}
```

```
print(rmse_results, best_rf_model)
```

```
{'Linear Regression RMSE': 139260627752.467, 'Random Forest RMSE': 0.29934269764909005, 'Best Model RMSE': 0.29934269764909005} RandomForestRegressor(random_state=42)
```