House Prices: Linear Regression

The House Prices dataset contains 79 explanatory variables describing residential homes in Ames, Iowa and their effects on the independent variable: SalePrice. While exploring the dataset of 1460 records, there are null values in the dependent variables, as seen in Figure 1. This is normal as these data are input by sellers and agents and could miss some information, or some variables like “PoolQC” can be null if there is no pool for the given house. To adjust, we will later replace the null value with the median for the numeric variables. Figure 2 shows a skewed distribution for the “SalePrice” after which we remove outliers in the data.

We then performed EDA on the dependent variable in Figures 3 and 4 exploring the correlation between “SalePrice” and quantitative dependent variables (14 have a >0.5 correlation coefficient) and category plots for each categorical variable. It can be seen that some categories lead to higher sales prices, such as the “EX” category in “FireplaceQU”, meaning excellent numbers of fireplaces show a higher sales price.

To better understand how dependent variables are related to 79 features, we build a linear regression model to see which features are important. First, we split the dataset into train and test datasets, with 80% training and 20% testing. We then encode every categorical feature into multiple boolean dummy variables using Sklearn one-hot encoding. This allows us to factor in categorical variables in our regression model. We then add two additional features that could be useful: 'Nonlivingarea' - The sum of GarageArea, PoolArea, WoodDeckSF. These are non-living spaces a house has. 'QualityCondition' - The sum of OveralQual and OverallCond. A house’s condition and quality are both important and worth evaluating together. Finally, we fill all null values with their respective variable median.

We first explored how simply scaling the training data using MinMax and Standard scaling would perform using the StatsModel OLS linear model. Figures 5 and 6 show the R^2 correlation coefficients are fairly high, around 0.95 meaning there’s a strong correlation, when predicting on the training data, as expected. When we test standard scaling on the test data, the value drops slightly to 0.855 (Figure 7). To improve upon this result, we used the standard scaling model and removed any columns that had p-values > 0.05. This would theoretically train a new model on a smaller set of dependent variables with a more statistically significant effect on ‘SalesPrice’. Figure 8 shows an R^2 value around 0.92 for the training data and Figure 9 shows a slightly higher value of 0.857 for the testing set. Uploading this to Kaggle gave us a score of 0.37991 compared to ~0.48 when we uploaded our most basic linear regression model using standard scaling.

Performing feature selection using the p-values of the variables shows improvement in the linear model. When analyzing this dataset to identify important features of a residential house, one might consider further refining the feature set. Analyzing p-values is one method. Another would be combining this with the correlation heatmap shown during our EDA. Sellers and agents can then stage and show houses with these features in mind. To improve upon our models we can continue to perform this feature selection or try fitting a polynomial regression model to better fit our data. Based on our EDA and modeling we saw that overall quality, year it was built, and year the home was remodeled as some of the most important factors in final sale price.

Appendix

```
from google.colab import drive
drive.mount('/content/drive')
import pandas as pd
import matplotlib.pyplot as plt
```

```python
import seaborn as sns
import sklearn
%cd /content/drive/My Drive/

df = pd.read_csv('Housing_Price/train.csv')
df.head(5)
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold	YrSold	Sal
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0	2	2008	
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0	5	2007	
2	3	[illegible]	[illegible]	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	9	2008	
3	4	[illegible]	[illegible]	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	2	2006	
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	12	2008	

Clear output

executed by Zachary Cmiel
9:19 PM (38 minutes ago)
executed in 0.229s

5 rows × 81 columns

```python
#Null Value Columns
nullseries= df.isna().sum()
print(nullseries[nullseries > 0])
```

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

Figure 1

```python
# Histogram for SalePrice
plt.figure(figsize=(12,6))
sns.histplot(df['SalePrice'],kde=True)
plt.title('Histogram of SalePrice')
plt.xlabel('Sale Price')
plt.ylabel('Frequency')
```

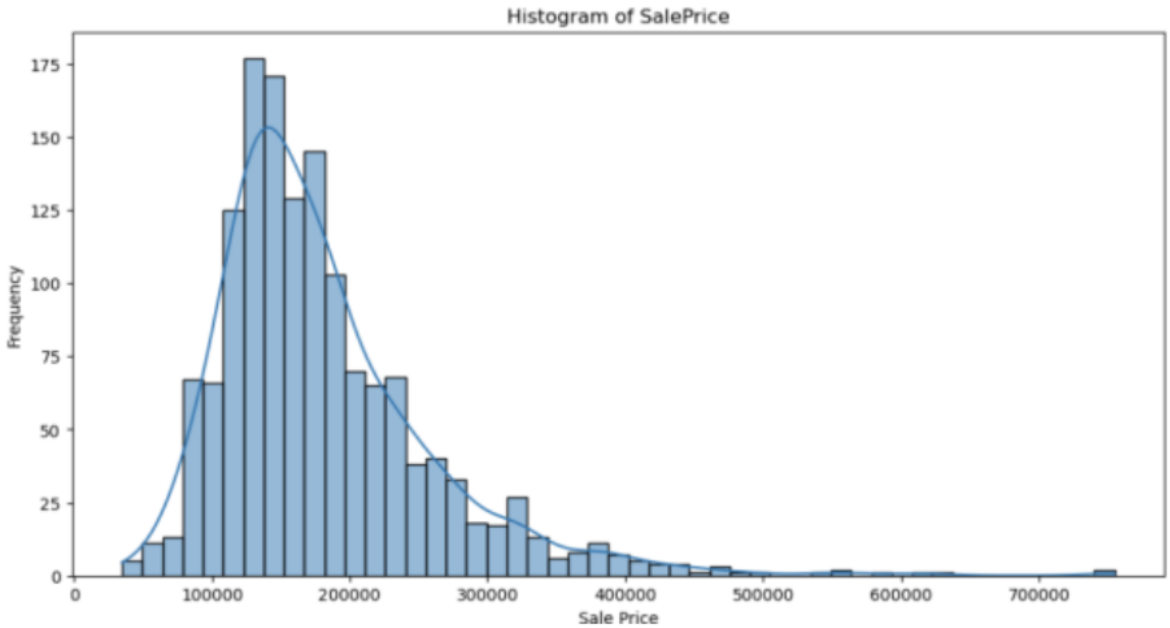
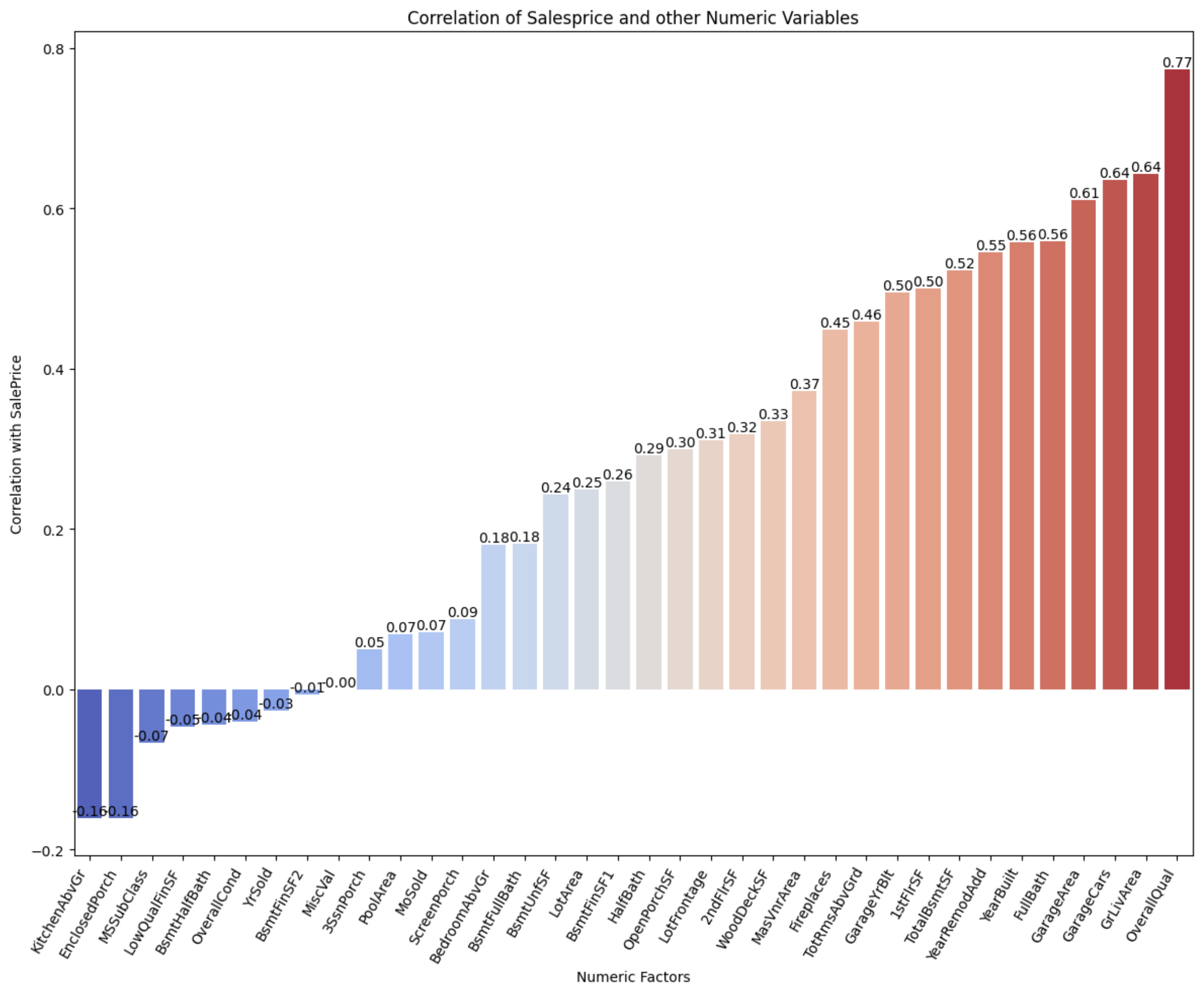


Figure 2

```
# drop outliers
Q1 = y_train.quantile(0.25)
Q3 = y_train.quantile(0.75)
IQR = Q3-Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

outliers = y_train[(y_train < lower_bound) | (y_train > upper_bound)]

# Remove outliers from the dataset
y_train_cleaned = y_train.drop(outliers.index)
x_train_cleaned = x_train.drop(outliers.index)
#Create heat map of all numeric variables
# Select only numeric variables
x_train_numeric = x_train_cleaned.select_dtypes(include=['int64',
'float64']).drop(columns=['Id'])

# Calculate the correlation matrix
train_data = pd.concat([x_train_numeric, y_train_cleaned], axis=1)
```

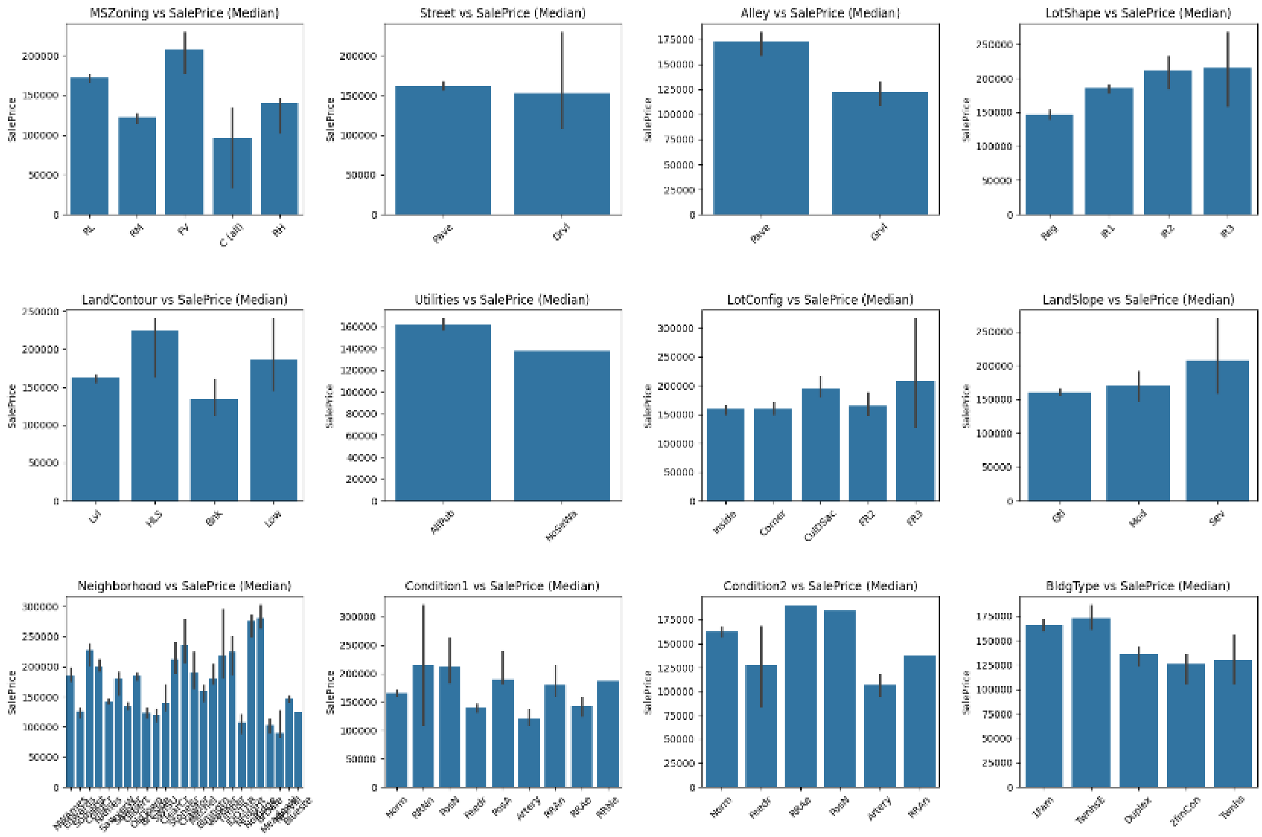
```
correlation_matrix = train_data.corr()
correlation_matrix =
correlation_matrix['SalePrice'].drop('SalePrice').sort_values()
correlation_matrix=correlation_matrix.sort_values()

# Plot barplot for correlation
plt.figure(figsize=(12, 10))
bar_plot = sns.barplot(x=correlation_matrix.index, y=correlation_matrix,
palette='coolwarm')
plt.title('Correlation of Salesprice and other Numeric Variables')
bar_plot.set_xticklabels(bar_plot.get_xticklabels(), rotation=60,
ha='right') # Rotate x-axis labels
plt.xlabel('Numeric Factors')
plt.ylabel('Correlation with SalePrice')
for index, value in enumerate(correlation_matrix):
plt.text(index, value, f'{value:.2f}', ha='center', va='bottom')
plt.tight_layout() # Adjust layout to prevent clipping of labels
plt.show()
```

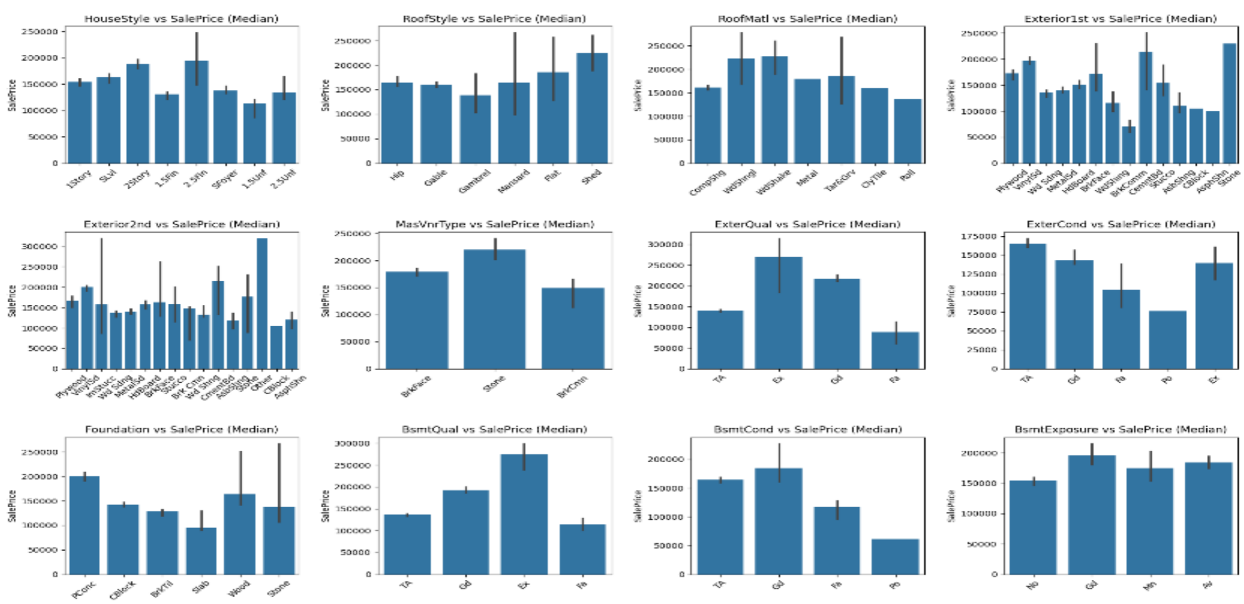



```
Figure 3

categorical_variables =
x_train_cleaned.select_dtypes(include=['object']).columns.tolist()
categorical_variables

['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']


#This is designed to run once
import numpy as np

# Create subplots
```

```
num_plots = len(categorical_variables)
cols_per_row = 4
rows = num_plots // cols_per_row + 1
fig, axes = plt.subplots(rows, cols_per_row, figsize=(18, 4*rows))

for idx, col in enumerate(categorical_variables):
row_idx = idx // cols_per_row
col_idx = idx % cols_per_row
ax = axes[row_idx, col_idx]
sns.barplot(x=x_train_cleaned[col], y=y_train_cleaned,
estimator=np.median, ax=ax)
ax.set_title(f'{col} vs SalePrice (Median)')
ax.tick_params(axis='x', rotation=45) # Rotate x-axis labels for better
readability
ax.set_xlabel('') # Remove x-axis label for better clarity
ax.set_ylabel('SalePrice')
plt.tight_layout() # Adjust layout to prevent overlapping
plt.subplots_adjust(hspace=0.5) # Add vertical spacing between subplots

# Remove empty subplots if any
if num_plots % cols_per_row != 0:
for i in range(cols_per_row - (num_plots % cols_per_row)):
fig.delaxes(axes[-1, -(i+1)])

# I can see MSZoning 'FV', Pave street, Pave Alley, IR2 lot shape, HLS
land contour, Allpub utility,
# NoRidge/NridgHr/StroneBr Neighborhood, PosN/PosA Condition2, 1Fam/TwnhsE
BldgType, 2stroy/SLvl HouseStyle,
# WdShngl RoofMatl, Exterior CemntBd/Stone/Imstucc/VinylSd, EX BsmtQual,
PConc Foundation, Gd BsmtCond, GLQ BsmtFinType1, GasA Heating, Y Central
Air
# SBrkr Electrical, Ex heatingQC, Ex KitchenQual, Ex FireplaceQu, Builtin
GarageType, Gd GarageQual, Y PavedDrive, Ex PoolQC, Tenc MiscFeature,
Con/New for SaleType
# Partial SalesCondition
```


MSZoning vs SalePrice (Median)
Street vs SalePrice (Median)
Alley vs SalePrice (Median)
LotShape vs SalePrice (Median)
LandContour vs SalePrice (Median)
Utilities vs SalePrice (Median)
LotConfig vs SalePrice (Median)
LandSlope vs SalePrice (Median)
Neighborhood vs SalePrice (Median)
Condition1 vs SalePrice (Median)
Condition2 vs SalePrice (Median)
BldgType vs SalePrice (Median)


HouseStyle vs SalePrice (Median)
RoofStyle vs SalePrice (Median)
RoofMatl vs SalePrice (Median)
Exterior1st vs SalePrice (Median)
Exterior2nd vs SalePrice (Median)
MasVnrType vs SalePrice (Median)
ExterQual vs SalePrice (Median)
ExterCond vs SalePrice (Median)
Foundation vs SalePrice (Median)
BsmtQual vs SalePrice (Median)
BsmtCond vs SalePrice (Median)
BsmtExposure vs SalePrice (Median)

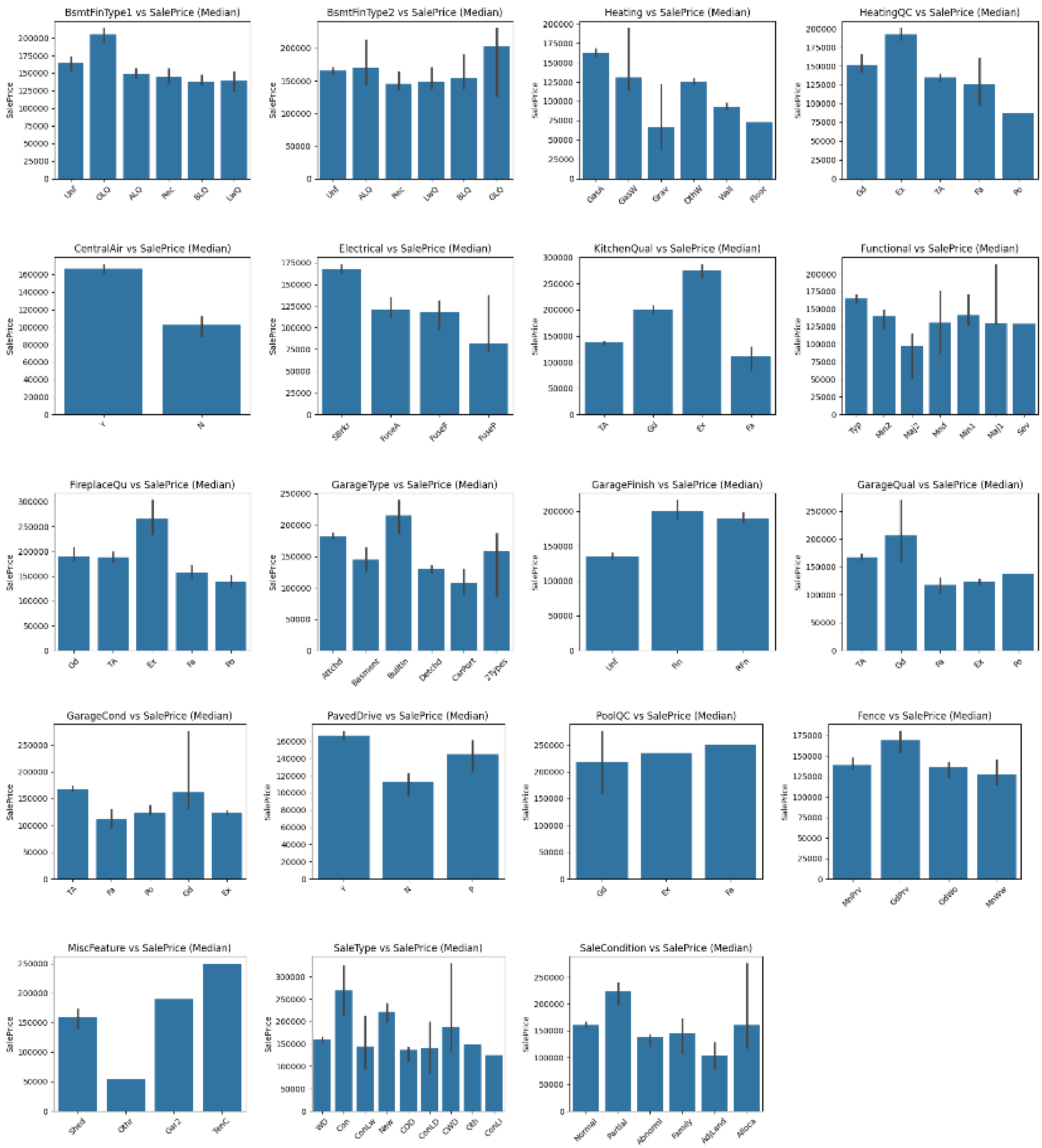


Figure 4

```
from sklearn.model_selection import train_test_split

x = df.drop(columns=['SalePrice'])
y = df['SalePrice']
```

```
# Split the dataset into 80% train and 20% test
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3,
random_state=42)

#Feature Engineering: Step 1 One Key Encoding Categorical Variable to
boolean column
x_train_cleaned_encoded = pd.get_dummies(x_train_cleaned)
x_train_cleaned_encoded.head(5)
```

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	...	SaleType_ConLw	SaleType_New	SaleType_Oth
135	136	20	80.0	10400	7	6	1970	1970	288.0	0	...	False	False	False
1452	1453	180	35.0	3675	5	5	2005	2005	80.0	547	...	False	False	False
762	763	60	72.0	8640	7	5	2009	2009	0.0	24	...	False	False	False
932	933	20	84.0	11670	9	5	2006	2006	302.0	0	...	False	False	False
435	436	60	43.0	10667	7	6	1996	1996	0.0	385	...	True	False	False

5 rows × 283 columns

```
#Feature Engineering: Step 2 Create Some Additional Variables
x_train_cleaned_encoded['Nonlivingarea']=x_train_cleaned_encoded['GarageAr
ea']+x_train_cleaned_encoded['PoolArea']+x_train_cleaned_encoded['WoodDeck
SF']
x_train_cleaned_encoded['QualityCondition']=x_train_cleaned_encoded['Overa
llQual']+x_train_cleaned_encoded['OverallCond']

#Feature Engineering: Step 3 Fill NaN with Median
x_train_cleaned_encoded =
x_train_cleaned_encoded.fillna(x_train_cleaned_encoded.median())
```

Regression Model 1 with Min Max Scaling

```
# Create Linear Model with Min/Max Scaling of Independt Variable
from sklearn.preprocessing import MinMaxScaler
import statsmodels.api as sm

scaler = MinMaxScaler()
x_train_scaled = scaler.fit_transform(x_train_cleaned_encoded) # fit it on
the training data

# Assuming X_train_cleaned_encoded is a DataFrame and the linear
regression model is already fitted
```

```
# Add a constant column to the independent variable dataset (required for
statsmodels)
x_train_scaled_with_const = sm.add_constant(x_train_scaled)

# Fit the linear regression model using statsmodels
model1 = sm.OLS(y_train_cleaned, x_train_scaled_with_const).fit()

y_pred1 = model1.predict(x_train_scaled_with_const)

#Performance Evaluation
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score


mse = mean_squared_error(y_train_cleaned, y_pred1)
print("Mean Squared Error:", mse)


# Calculate the R^2 score
r2 = r2_score(y_train_cleaned, y_pred1)
print("R^2 Score:", r2)

Mean Squared Error: 190427348.26248127 R^2 Score:
0.9453845247988569
```

Figure 5

Regression Model 2 with Standard Scaling

```
# Create Linear Model with Standard Scaling of Independent Variable
from sklearn.preprocessing import StandardScaler
import statsmodels.api as sm


scaler = StandardScaler()
x_train_scaled = scaler.fit_transform(x_train_cleaned_encoded) # fit it on
the training data
```

```python
# Assuming X_train_cleaned_encoded is a DataFrame and the linear
regression model is already fitted

# Add a constant column to the independent variable dataset (required for
statsmodels)
x_train_scaled_with_const = sm.add_constant(x_train_scaled)

# Fit the linear regression model using statsmodels
model2 = sm.OLS(y_train_cleaned, x_train_scaled_with_const).fit()

y_pred2 = model2.predict(x_train_scaled_with_const)
#Performance Evaluation
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score


mse = mean_squared_error(y_train_cleaned, y_pred2)
print("Mean Squared Error:", mse)


# Calculate the R^2 score
r2 = r2_score(y_train_cleaned, y_pred2)
print("R^2 Score:", r2)
```

```
Mean Squared Error: 190427348.26248115 R^2 Score:
0.9453845247988569
```

Figure 6

Standard Scaled Linear Regression Using Test Data

```python
# Create Linear Model with Min/Max Scaling of Independentt Variable
from sklearn.preprocessing import StandardScaler

#One Key Encoding Categorical Variable to boolean column
x_test_cleaned_encoded = pd.get_dummies(x_test)
```

```
# Create Some Additional Variables
x_test_cleaned_encoded['Nonlivingarea']=x_test_cleaned_encoded['GarageArea
']+x_test_cleaned_encoded['PoolArea']+x_test_cleaned_encoded['WoodDeckSF']
x_test_cleaned_encoded['QualityCondition']=x_test_cleaned_encoded['Overall
Qual']+x_test_cleaned_encoded['OverallCond']

# Fill NaN with Median
x_test_cleaned_encoded =
x_test_cleaned_encoded.fillna(x_test_cleaned_encoded.median())


# Make sure missing dummy variables are added to test dataset and drop
those not in trained dataset
missing_cols = set(x_test_cleaned_encoded.columns) -
set(x_train_cleaned_encoded.columns)
x_test_cleaned_encoded=x_test_cleaned_encoded.drop(columns=missing_cols)

missing_cols = set(x_train_cleaned_encoded.columns)-
set(x_test_cleaned_encoded.columns)
# Add a missing column in test set with default value equal to 0
for c in missing_cols:
x_test_cleaned_encoded[c] = False
# Ensure the order of column in the test set is in the same order than in
train set
print(len(x_test_cleaned_encoded.columns))
print(len(x_train_cleaned_encoded.columns))

# Ensure that the columns order is the same in both datasets
train_columns = x_train_cleaned_encoded.columns

x_test_cleaned_encoded = x_test_cleaned_encoded[train_columns]

scaler = StandardScaler()
x_test_scaled = scaler.fit_transform(x_test_cleaned_encoded) # fit it on
the training data

# predict using trained model
x_test_scaled = sm.add_constant(x_test_scaled)

y_pred = model2.predict(x_test_scaled)
```

```
#Performance Evaluation
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score


mse = mean_squared_error(y_test, y_pred)
print("Mean Squared Error:", mse)


# Calculate the R^2 score
r2 = r2_score(y_test, y_pred)
print("R^2 Score:", r2)

# Mean Squared Error: 3532384093.1461596
# R^2 Score: 0.49378953419641747
```

```
Mean Squared Error: 1006609493.12079 R^2 Score:
0.8557472101112479
```

Figure 7

OLS Model and Feature Selection Using P-Value

```
import numpy as np

# View the summary of the model
#print(model2.summary())

# Extract the pvalues from the first model
model2_p_values = model2.pvalues
model2_p_values = model2_p_values[1:]

# Check to see how many have large pvalues
print(len(model2_p_values))
print(len(model2_p_values[model2_p_values > 0.05]))
```

```
# Remove columns with pvalue > 0.01
column_names = x_train_cleaned_encoded.columns
print(len(column_names))
x_train_remove_cols = x_train_cleaned_encoded.copy()
x_train_remove_cols.drop([col for (index, col) in enumerate(column_names)
if model2_p_values[index] > 0.05],axis=1,inplace=True)
print(len(x_train_remove_cols.columns))

# StandardScaler
scaler = StandardScaler()
x_train_remove_cols_scaled = scaler.fit_transform(x_train_remove_cols) #
fit it on the training data

# Add a constant column to the independent variable dataset (required for
statsmodels)
x_train_remove_cols_scaled_with_const =
np.asarray(sm.add_constant(x_train_remove_cols_scaled))

# Fit the linear regression model using statsmodels
model3 = sm.OLS(y_train_cleaned,
x_train_remove_cols_scaled_with_const).fit()
y_pred3 = model3.predict(x_train_remove_cols_scaled_with_const)


#Performance Evaluation
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score


mse = mean_squared_error(y_train_cleaned, y_pred3)
print("Mean Squared Error:", mse)


# Calculate the R^2 score
r2 = r2_score(y_train_cleaned, y_pred3)
print("R^2 Score:", r2)

Mean Squared Error: 263234390.2897185 R^2 Score:
0.9245031165631754
```

Figure 8

```
# Create Linear Model with Min/Max Scaling of Independentt Variable
from sklearn.preprocessing import MinMaxScaler

#One Key Encoding Categorical Variable to boolean column
x_test_cleaned_encoded = pd.get_dummies(x_test)

# Create Some Additional Variables
x_test_cleaned_encoded['Nonlivingarea']=x_test_cleaned_encoded['GarageArea
']+x_test_cleaned_encoded['PoolArea']+x_test_cleaned_encoded['WoodDeckSF']
x_test_cleaned_encoded['QualityCondition']=x_test_cleaned_encoded['Overall
Qual']+x_test_cleaned_encoded['OverallCond']

# Fill NaN with Median
x_test_cleaned_encoded =
x_test_cleaned_encoded.fillna(x_test_cleaned_encoded.median())


# Make sure missing dummy variables are added to test dataset and drop
those not in trained dataset
missing_cols = set(x_test_cleaned_encoded.columns) -
set(x_train_cleaned_encoded.columns)
x_test_cleaned_encoded=x_test_cleaned_encoded.drop(columns=missing_cols)

missing_cols = set(x_train_cleaned_encoded.columns)-
set(x_test_cleaned_encoded.columns)
# Add a missing column in test set with default value equal to 0
for c in missing_cols:
x_test_cleaned_encoded[c] = True
# Ensure the order of column in the test set is in the same order than in
train set
print(len(x_test_cleaned_encoded.columns))
print(len(x_train_cleaned_encoded.columns))

# Remove columns with pvalue > 0.01
x_test_remove_cols = x_test_cleaned_encoded.copy()
for col in x_test_remove_cols.columns:
```

```python
if col not in x_train_remove_cols.columns:
x_test_remove_cols.drop(col, axis=1, inplace=True)

print(len(x_test_remove_cols.columns))
print(len(x_train_remove_cols.columns))

# Ensure that the columns order is the same in both datasets
train_columns = x_train_remove_cols.columns

x_test_remove_cols = x_test_remove_cols[train_columns]

scaler = StandardScaler()
x_test_standard_scaled = scaler.fit_transform(x_test_remove_cols) # fit it
on the test data

# predict using trained model
x_test_standard_scaled = sm.add_constant(x_test_standard_scaled)

y_pred = model3.predict(x_test_standard_scaled)

#Performance Evaluation
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score


mse = mean_squared_error(y_test, y_pred)
print("Mean Squared Error:", mse)


# Calculate the R^2 score
r2 = r2_score(y_test, y_pred)
print("R^2 Score:", r2)
```

```
Mean Squared Error: 994225725.938798 R^2 Score:
0.8575218734514443
```

Figure 9

```
df=pd.read_csv('Housing_Price/test.csv')

#One Key Encoding Categorical Variable to boolean column
df_encoded = pd.get_dummies(df)

# Create Some Additional Variables
df_encoded['Nonlivingarea']=df_encoded['GarageArea']+df_encoded['PoolArea'
]+df_encoded['WoodDeckSF']
df_encoded['QualityCondition']=df_encoded['OverallQual']+df_encoded['Overa
llCond']

# Fill NaN with Median
df_encoded = df_encoded.fillna(df_encoded.median())


# Make sure missing dummy variables are added to test dataset and drop
those not in trained dataset
missing_cols = set(df_encoded.columns) -
set(x_train_cleaned_encoded.columns)
df_encoded=df_encoded.drop(columns=missing_cols)

missing_cols = set(x_train_cleaned_encoded.columns)- set(df_encoded)
# Add a missing column in test set with default value equal to 0
for c in missing_cols:
df_encoded[c] = False
# Ensure the order of column in the test set is in the same order than in
train set
print(len(df_encoded.columns))
print(len(x_train_cleaned_encoded.columns))

# Remove columns with pvalue > 0.05
df_remove_cols = df_encoded.copy()
for col in df_remove_cols.columns:
if col not in x_train_remove_cols.columns:
df_remove_cols.drop(col, axis=1, inplace=True)

# Ensure that the columns order is the same in both datasets
train_columns = x_train_remove_cols.columns

df_remove_cols = df_remove_cols[train_columns]
```

```
scaler = MinMaxScaler()
df_encoded_scaled = scaler.fit_transform(df_remove_cols) # fit it on the training data

# predict using trained model
df_encoded_scaled = sm.add_constant(df_encoded_scaled)

y_pred = model3.predict(df_encoded_scaled)

df=pd.read_csv('Housing_Price/test.csv')
result=pd.concat([df['Id'],pd.DataFrame(y_pred)],axis=1)
result.rename(columns={0:'SalePrice'},inplace=True)
result.to_csv('Housing_Price/model3prediction.csv',index=False)
```

Kaggle Username - zacharycmiel

4031	**Zachary Cmiel**	0.37991	10	3m

Figure 10