final_STerry

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1 Final Project: Regression Techniques with House Prices

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[1]:
```
# Import essential modules

%matplotlib inline
import numpy as np
import scipy as sp
import scipy.stats as stats
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()
import patsy
import sklearn
import statsmodels.formula.api as smf
from sklearn import linear_model
```

[16]:
```
# Read training and test data into dataframes

df_train = pd.read_csv('train.csv')
df_test = pd.read_csv('test.csv')

pd.set_option("display.max_rows", None, "display.max_columns", None)

df_train.head()
```

[16]:
```
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0   1          60       RL         65.0     8450   Pave   NaN      Reg
1   2          20       RL         80.0     9600   Pave   NaN      Reg
2   3          60       RL         68.0    11250   Pave   NaN      IR1
3   4          70       RL         60.0     9550   Pave   NaN      IR1
4   5          60       RL         84.0    14260   Pave   NaN      IR1
```

```
  LandContour Utilities LotConfig LandSlope Neighborhood Condition1  \
0         Lvl    AllPub    Inside       Gtl      CollgCr       Norm
1         Lvl    AllPub       FR2       Gtl      Veenker      Feedr
2         Lvl    AllPub    Inside       Gtl      CollgCr       Norm
3         Lvl    AllPub    Corner       Gtl      Crawfor       Norm
4         Lvl    AllPub       FR2       Gtl      NoRidge       Norm

  Condition2 BldgType HouseStyle  OverallQual  OverallCond  YearBuilt  \
0       Norm     1Fam     2Story            7            5       2003
1       Norm     1Fam     1Story            6            8       1976
2       Norm     1Fam     2Story            7            5       2001
3       Norm     1Fam     2Story            7            5       1915
4       Norm     1Fam     2Story            8            5       2000

   YearRemodAdd RoofStyle RoofMatl Exterior1st Exterior2nd MasVnrType  \
0          2003     Gable  CompShg     VinylSd     VinylSd    BrkFace
1          1976     Gable  CompShg     MetalSd     MetalSd       None
2          2002     Gable  CompShg     VinylSd     VinylSd    BrkFace
3          1970     Gable  CompShg     Wd Sdng     Wd Shng       None
4          2000     Gable  CompShg     VinylSd     VinylSd    BrkFace

   MasVnrArea ExterQual ExterCond Foundation BsmtQual BsmtCond BsmtExposure  \
0       196.0        Gd        TA      PConc       Gd       TA           No
1         0.0        TA        TA     CBlock       Gd       TA           Gd
2       162.0        Gd        TA      PConc       Gd       TA           Mn
3         0.0        TA        TA     BrkTil       TA       Gd           No
4       350.0        Gd        TA      PConc       Gd       TA           Av

  BsmtFinType1  BsmtFinSF1 BsmtFinType2  BsmtFinSF2  BsmtUnfSF  TotalBsmtSF  \
0          GLQ         706          Unf           0        150          856
1          ALQ         978          Unf           0        284         1262
2          GLQ         486          Unf           0        434          920
3          ALQ         216          Unf           0        540          756
4          GLQ         655          Unf           0        490         1145

  Heating HeatingQC CentralAir Electrical  1stFlrSF  2ndFlrSF  LowQualFinSF  \
0    GasA        Ex          Y      SBrkr       856       854             0
1    GasA        Ex          Y      SBrkr      1262         0             0
2    GasA        Ex          Y      SBrkr       920       866             0
3    GasA        Gd          Y      SBrkr       961       756             0
4    GasA        Ex          Y      SBrkr      1145      1053             0

   GrLivArea  BsmtFullBath  BsmtHalfBath  FullBath  HalfBath  BedroomAbvGr  \
0       1710             1             0         2         1             3
1       1262             0             1         2         0             3
2       1786             1             0         2         1             3
```

```
3       1717             1             0        1        0             3
4       2198             1             0        2        1             4

   KitchenAbvGr KitchenQual  TotRmsAbvGrd Functional  Fireplaces FireplaceQu  \
0             1          Gd             8        Typ           0         NaN
1             1          TA             6        Typ           1          TA
2             1          Gd             6        Typ           1          TA
3             1          Gd             7        Typ           1          Gd
4             1          Gd             9        Typ           1          TA

  GarageType  GarageYrBlt GarageFinish  GarageCars  GarageArea GarageQual  \
0     Attchd       2003.0          RFn           2         548         TA
1     Attchd       1976.0          RFn           2         460         TA
2     Attchd       2001.0          RFn           2         608         TA
3     Detchd       1998.0          Unf           3         642         TA
4     Attchd       2000.0          RFn           3         836         TA

  GarageCond PavedDrive  WoodDeckSF  OpenPorchSF  EnclosedPorch  3SsnPorch  \
0         TA          Y           0           61              0          0
1         TA          Y         298            0              0          0
2         TA          Y           0           42              0          0
3         TA          Y           0           35            272          0
4         TA          Y         192           84              0          0

   ScreenPorch  PoolArea PoolQC Fence MiscFeature  MiscVal  MoSold  YrSold  \
0            0         0    NaN   NaN         NaN        0       2    2008
1            0         0    NaN   NaN         NaN        0       5    2007
2            0         0    NaN   NaN         NaN        0       9    2008
3            0         0    NaN   NaN         NaN        0       2    2006
4            0         0    NaN   NaN         NaN        0      12    2008

  SaleType SaleCondition  SalePrice
0       WD        Normal     208500
1       WD        Normal     181500
2       WD        Normal     223500
3       WD       Abnorml     140000
4       WD        Normal     250000
```

1.1 Part 1: Data Cleaning

The first thing I did to clean this dataset was to drop the remove the extraneous 'Id' column from the two datasets, since the Pandas dataframe includes row indices automatically. I also noticed that the vast majority of 'Alley' data were NaN values, indicating that there was no alley access for that particular residence. Less than 100 residences had alley access at all, and I decided to remove this column. When I looked at the total number of NaN values for each feature in the dataset, I noticed that the majority of the data for the Pool Quality feature were null. This was because NaN values were used to encode the pool quality for those residences which did not have pools. While I thought that the presence or absence of a pool could have a significant impact on the ultimate sale price of each residence, I did not think that the quality of the pool would be as important–and anyway, I was sure that the pool quality could be reasonably predicted from some other feature, given a dataset of residences with enough pools. Since only 7 of the residences in the training data set actually had pools, I elected to drop this feature as well. I did the same for the MiscFeature (and the corresponding MiscVal) column, since few residences had a miscellaneous feature to be valued. Although several hundred data points did contain a value for the 'Fence' feature, I figured there weren't enough such residences to make this feature a useful predictor, and dropped this column as well; I did the same with the Fireplace quality feature, as there were quite a few (though not a majority of) residences without fireplaces, but since the presence/absence & number of fireplaces was encoded by the 'Fireplaces' column, I decided to keep this around. I also removed the GarageYrBlt column; although relatively few values were missing for this attribute; I thought that the quality of a garage was likely more significant than its age, and there wasn't a good way to fill in missing values for this feature.

There were a lot of NaN values for the 'LotFrontage' feature–that is, the feature encoding linear feet of street are connected to the property in question. I assumed that this meant that there was no street connected to the property, so I just filled the NaN values with 0.0 to make the type of data in this column uniform. There were a lot of features which dealt with the garages on these properties, but only the categorical features had missing values. Again, for the sake of uniformity, I filled missing values in the GarageType, GarageFinish, GarageQual & GarageCond with "None." This effectively added a new category in each of these features for residences with no garage. I did the same with the categorical attributes regarding basements, since values for these features were only NaN in the case that the property didn't have a basement and/or didn't have more than one finished area.

Finally, I looked through the full set of features and used my intuition to identify features which I thought would be less informative predictors of sale price. I probably would have saved a little bit of time if I had done this first, but I'm sure that's only the first mistake I will end up making throughout the course of this project. Nevertheless, the one feature that stood out to me was the 'Electrical' categorical feature. This feature described the type of wiring in each property. Although the description of the dataset offers some insight into the relative quality of the different wiring types, the internal workings of a property's electrical system and the quality thereof are unlikely to be salient features to most homebuyers. I removed this feature from the dataset because I thought it wouldn't be a good predictor of the sale price.

Anyway, that's how I took care of missing values. For those features with a lot of missing values, I removed the entire column. If the feature did not have very many missing values, I replaced missing values with 0 for quantitative attributes and 'None' for categorical features.

[3]:

```
# Remove columns:

df_train.drop(['Id'], axis=1, inplace=True) # Remove Id column
df_test.drop(['Id'], axis=1, inplace=True)

df_train.drop(['Alley'], axis=1, inplace=True) # Remove Alley column
df_test.drop(['Alley'], axis=1, inplace=True)

df_train.drop(['PoolQC'], axis=1, inplace=True) # Remove Pool Quality Column
```

```
df_test.drop(['PoolQC'], axis=1, inplace=True)

df_train.drop(['MiscFeature'], axis=1, inplace=True) # Remove MiscFeature/
 ↪MiscVal
df_train.drop(['MiscVal'], axis=1, inplace=True)
df_test.drop(['MiscFeature'], axis=1, inplace=True)
df_test.drop(['MiscVal'], axis=1, inplace=True)

df_train.drop(['Fence'], axis=1, inplace=True) # Remove Fence feature
df_test.drop(['Fence'], axis=1, inplace=True)

df_train.drop(['FireplaceQu'], axis=1, inplace=True) # Remove Qireplace Quality
df_test.drop(['FireplaceQu'], axis=1, inplace=True)

df_train.drop(['GarageYrBlt'], axis=1, inplace=True) # Remove GarageYrBlt
df_test.drop(['GarageYrBlt'], axis=1, inplace=True)

df_train.drop(['Electrical'], axis=1, inplace=True)
df_test.drop(['Electrical'], axis=1, inplace=True)



# Fill NaN values to make the type of each column uniform

df_train.LotFrontage.fillna(0.0, inplace=True) # Replace null values for␣
 ↪LotFrontage with 0.0
df_test.LotFrontage.fillna(0.0, inplace=True)

df_train.GarageType.fillna('None', inplace=True) # Replace null values in␣
 ↪categorical garage features with 'None'
df_test.GarageType.fillna('None', inplace=True)

df_train.GarageFinish.fillna('None', inplace=True)
df_test.GarageFinish.fillna('None', inplace=True)

df_train.GarageQual.fillna('None', inplace=True)
df_test.GarageQual.fillna('None', inplace=True)

df_train.GarageCond.fillna('None', inplace=True)
df_test.GarageCond.fillna('None', inplace=True)

df_train.BsmtQual.fillna('None', inplace=True) # Replace null values in␣
 ↪categorical basement features with 'None'
df_test.BsmtQual.fillna('None', inplace=True)

df_train.BsmtCond.fillna('None', inplace=True)
df_test.BsmtCond.fillna('None', inplace=True)
```

```python
df_train.BsmtExposure.fillna('None', inplace=True)
df_test.BsmtExposure.fillna('None', inplace=True)

df_train.BsmtFinType1.fillna('None', inplace=True)
df_test.BsmtFinType1.fillna('None', inplace=True)

df_train.BsmtFinType2.fillna('None', inplace=True)
df_test.BsmtFinType2.fillna('None', inplace=True)


df_train.isnull().sum()
```

[3]:
```
MSSubClass        0
MSZoning          0
LotFrontage       0
LotArea           0
Street            0
LotShape          0
LandContour       0
Utilities         0
LotConfig         0
LandSlope         0
Neighborhood      0
Condition1        0
Condition2        0
BldgType          0
HouseStyle        0
OverallQual       0
OverallCond       0
YearBuilt         0
YearRemodAdd      0
RoofStyle         0
RoofMatl          0
Exterior1st       0
Exterior2nd       0
MasVnrType        8
MasVnrArea        8
ExterQual         0
ExterCond         0
Foundation        0
BsmtQual          0
BsmtCond          0
BsmtExposure      0
BsmtFinType1      0
BsmtFinSF1        0
BsmtFinType2      0
```

```
BsmtFinSF2       0
BsmtUnfSF        0
TotalBsmtSF      0
Heating          0
HeatingQC        0
CentralAir       0
1stFlrSF         0
2ndFlrSF         0
LowQualFinSF     0
GrLivArea        0
BsmtFullBath     0
BsmtHalfBath     0
FullBath         0
HalfBath         0
BedroomAbvGr     0
KitchenAbvGr     0
KitchenQual      0
TotRmsAbvGrd     0
Functional       0
Fireplaces       0
GarageType       0
GarageFinish     0
GarageCars       0
GarageArea       0
GarageQual       0
GarageCond       0
PavedDrive       0
WoodDeckSF       0
OpenPorchSF      0
EnclosedPorch    0
3SsnPorch        0
ScreenPorch      0
PoolArea         0
MoSold           0
YrSold           0
SaleType         0
SaleCondition    0
SalePrice        0
dtype: int64
```

1.2 Part 2: Exploratory Data Analysis

After cleaning the dataset to remove any features with little data or of little importance, I performed an exploratory data analysis to see if I could identify any patterns which might help me develop a regression model later on. Exploratory data analysis is helpful because it allows possible features and patterns of a dataset to be identified and examined without making any concrete assumptions which could skew the accuracy of the regression model. I figured it would be best to explore the quantitative (continuous) and the categorical (discrete) data separately, so the first thing I did in my EDA was create a list of categorical features and as well as a list of quantitative features:

[4]:
```
# Divide training data into a list of categorical features & a list of␣
↪quantitative features
cat_features = []
num_features = []
for feat in df_train:
    if feat in ['YearBuilt', 'YearRemodAdd', 'MoSold', 'YrSold', 'OverallQual',␣
↪'GarageCars']: # The categories for these five features are defined by␣
↪numbers
        cat_features.append(feat)
    elif type(df_train[feat][0]) != str: # If the first feature in the␣
↪remaining columns is not a string, it is quantitative
        num_features.append(feat)
    else:
        cat_features.append(feat) # Otherwise, the features are categorical

# Print out categorical features
print("Categorical:\n")
for cat in cat_features:
    print(cat)

print('\n\n')

# Print out quantitative features
print("Quantitative:\n")
for num in num_features:
    print(num)
```

```
Categorical:

MSZoning
Street
LotShape
LandContour
Utilities
LotConfig
LandSlope
Neighborhood
Condition1
Condition2
BldgType
HouseStyle
OverallQual
YearBuilt
YearRemodAdd
RoofStyle
```

RoofMatl
Exterior1st
Exterior2nd
MasVnrType
ExterQual
ExterCond
Foundation
BsmtQual
BsmtCond
BsmtExposure
BsmtFinType1
BsmtFinType2
Heating
HeatingQC
CentralAir
KitchenQual
Functional
GarageType
GarageFinish
GarageCars
GarageQual
GarageCond
PavedDrive
MoSold
YrSold
SaleType
SaleCondition

Quantitative:

MSSubClass
LotFrontage
LotArea
OverallCond
MasVnrArea
BsmtFinSF1
BsmtFinSF2
BsmtUnfSF
TotalBsmtSF
1stFlrSF
2ndFlrSF
LowQualFinSF
GrLivArea
BsmtFullBath
BsmtHalfBath
FullBath

```
HalfBath
BedroomAbvGr
KitchenAbvGr
TotRmsAbvGrd
Fireplaces
GarageArea
WoodDeckSF
OpenPorchSF
EnclosedPorch
3SsnPorch
ScreenPorch
PoolArea
SalePrice
```

To explore the quantitative features, I decided to create a correlative matrix to highlight possible relationships which could later help build the regression model. I did so by creating this lovely little heatmap, the code for which I found here: https://www.kaggle.com/backup1123/preprocessing-pipelines-with-sklearn

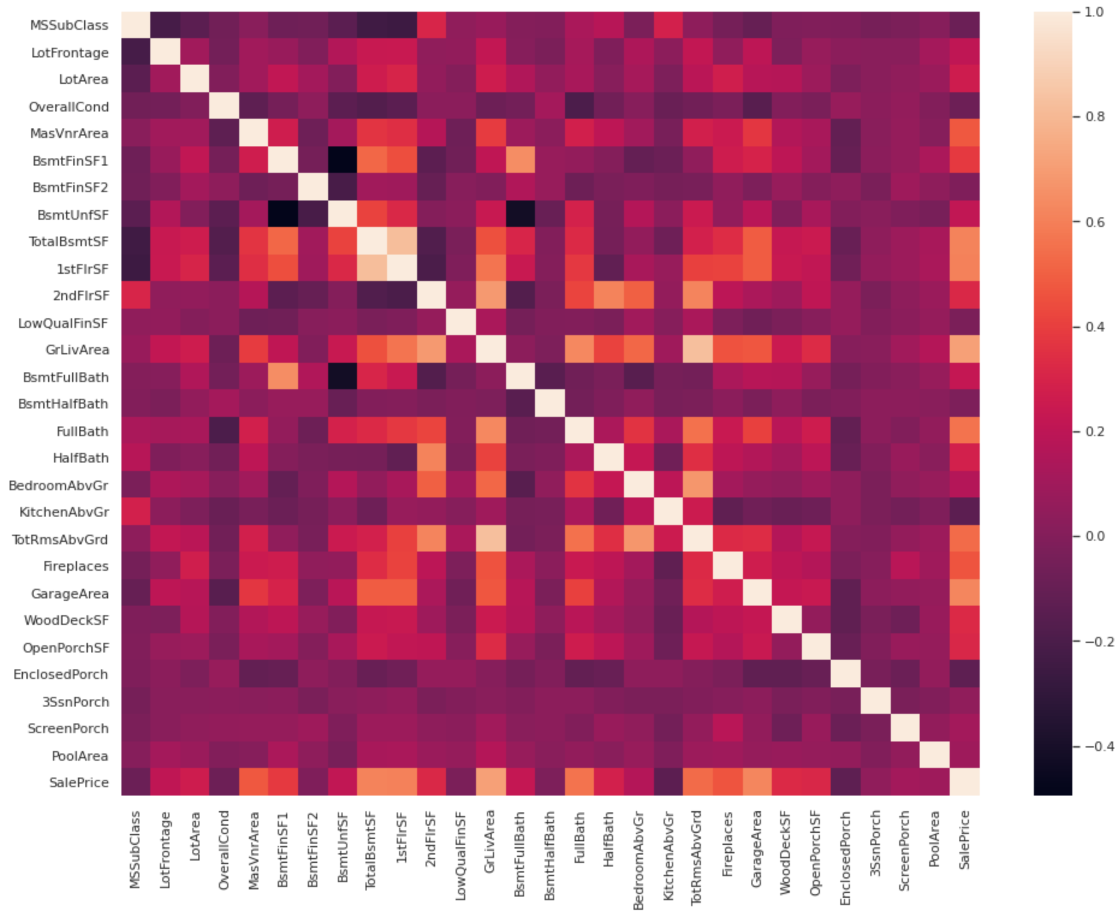
In the heatmap below, lighter colors represent a stronger correlation between the corresponding features. Of particular interest to our model is those quantitative features which correlate strongly with the rightmost column / bottom row of the heatmap, which encodes the relationship between Sale Price and other features in the dataset. Among all the quantitative features in the dataset, the five which appear to correlate most strongly with the sale price of the properties are the total square footage of the basement, the total square footage of the first floor, the square footage of the above-ground living area ('GrLivArea'), the area of the garage, and the number of cars the garage can hold.

Upon further inspection, there appears to be some multicollinearity between these features; that is, two of the features which correlate strongly with the sale price of the properties also correlate very strongly with one another–so much so, in fact, that one feature could be predicted from the other with reasonable accuracy. Namely, the square footage of the basement appears to correlate with the square footage of the first floor, while the number of cars the garage can hold appears to correlate with the square footage of the garage. These make intuitive sense; houses with larger first floors are likely to have basements of a similar size, and larger garages are able to store more cars. Consequently, it is useful for the purposes of developing a regression model to eliminate multicollinearity from the set of features we plan to consider. The strength of the correlation with sale price seems to be greater for the basement's square footage and for the number of cars stored by the garage, so we will eliminate the square footage of the first floor and the area of the garage from consideration in our model.

The exploration of the quantitative data allowed us to extract three features which are potentially predictive of the sale price of these properties: the square footage of the basement and the above-ground living area, as well as the number of cars the garage can hold.

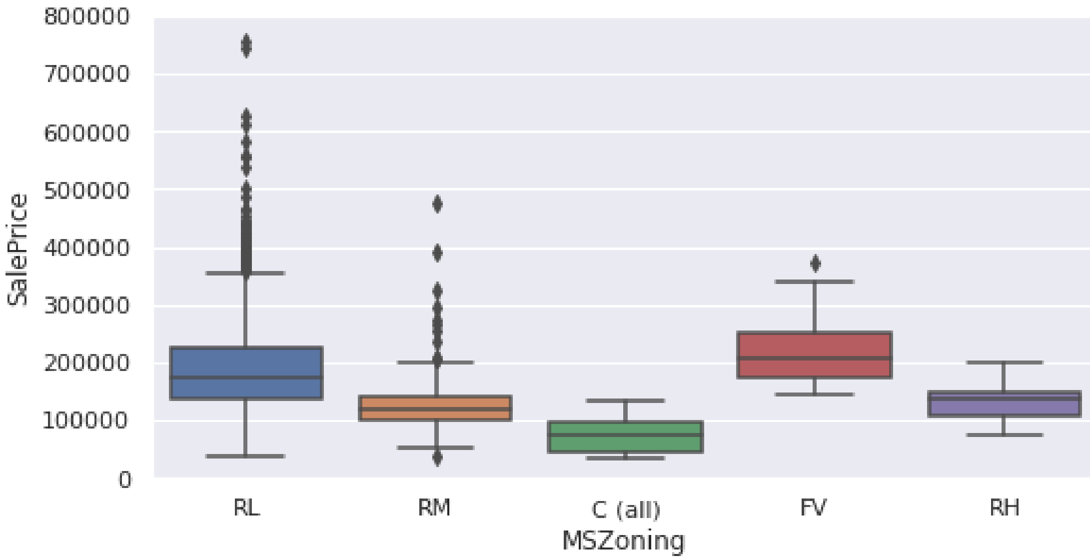
[5]:
```
corr_map = df_train[num_features].corr()
plt.figure(figsize=(16,12))
sns.heatmap(corr_map)
```

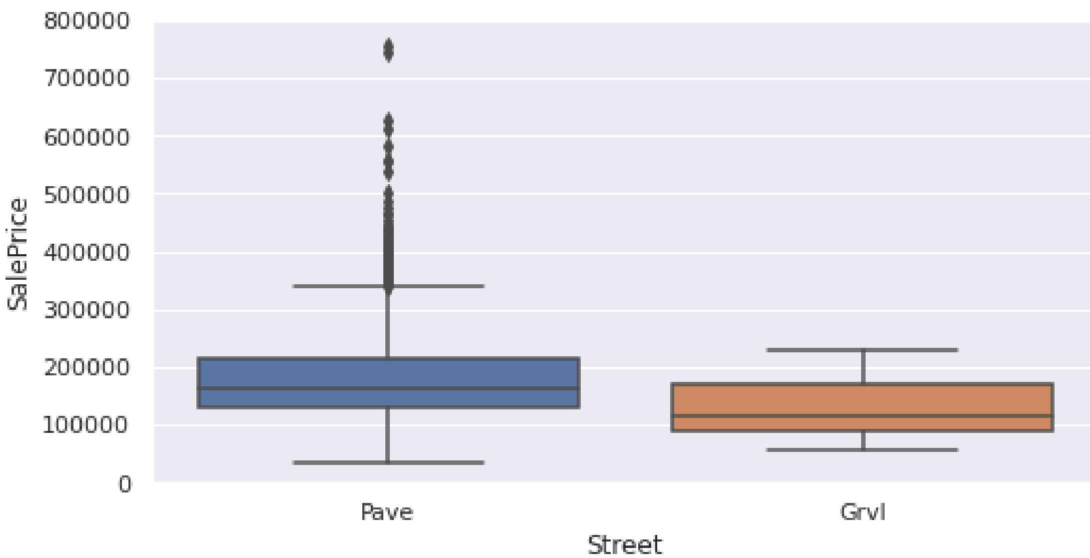
[5]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd9286001f0>
```

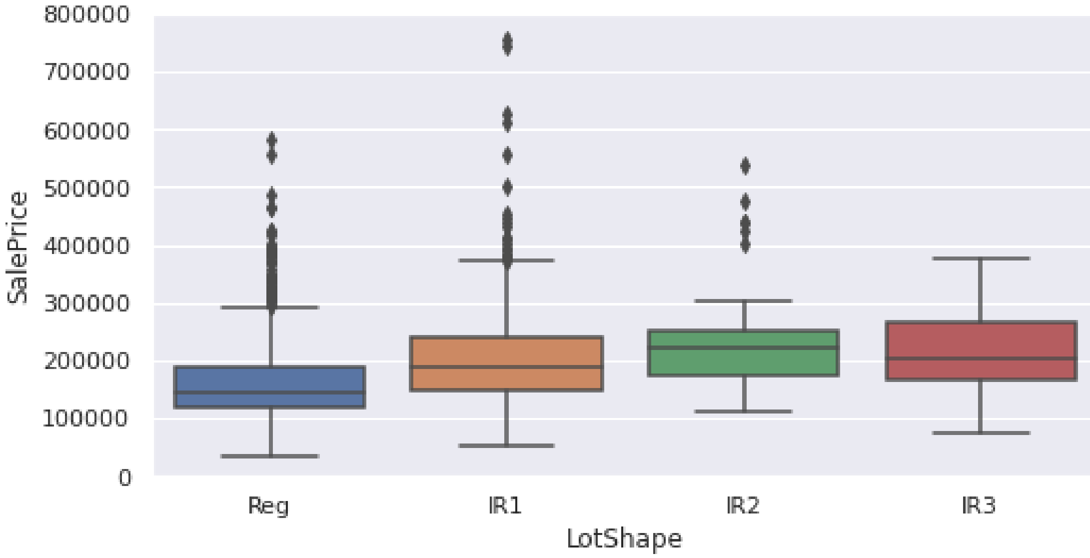


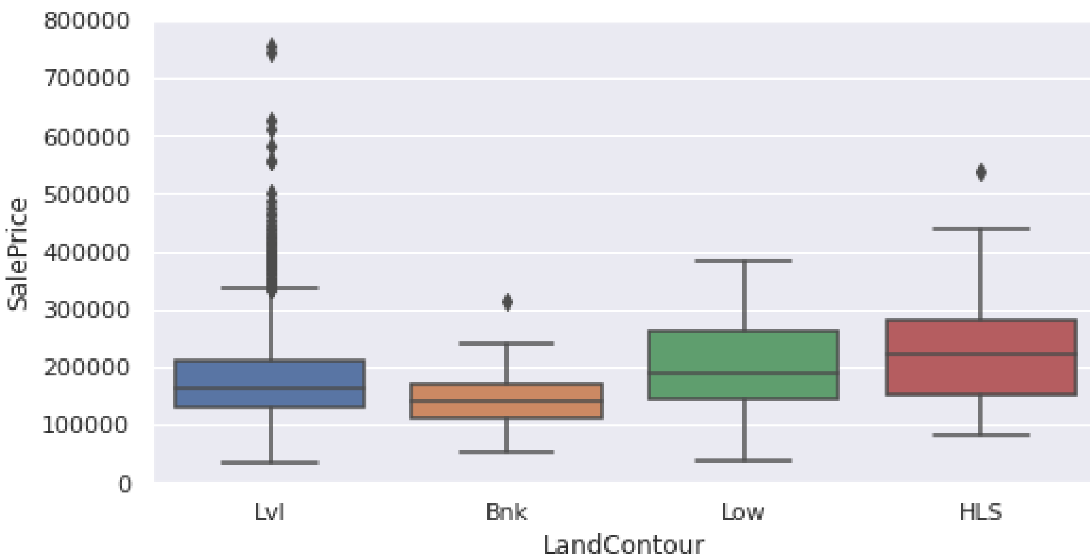
To plot the relationship between the sale price and the different categorical features, I used box plots for each feature. I found the code for plotting the categorical data from the following notebook: https://www.kaggle.com/kamakshisoni/comprehensive-data-exploration-with-python

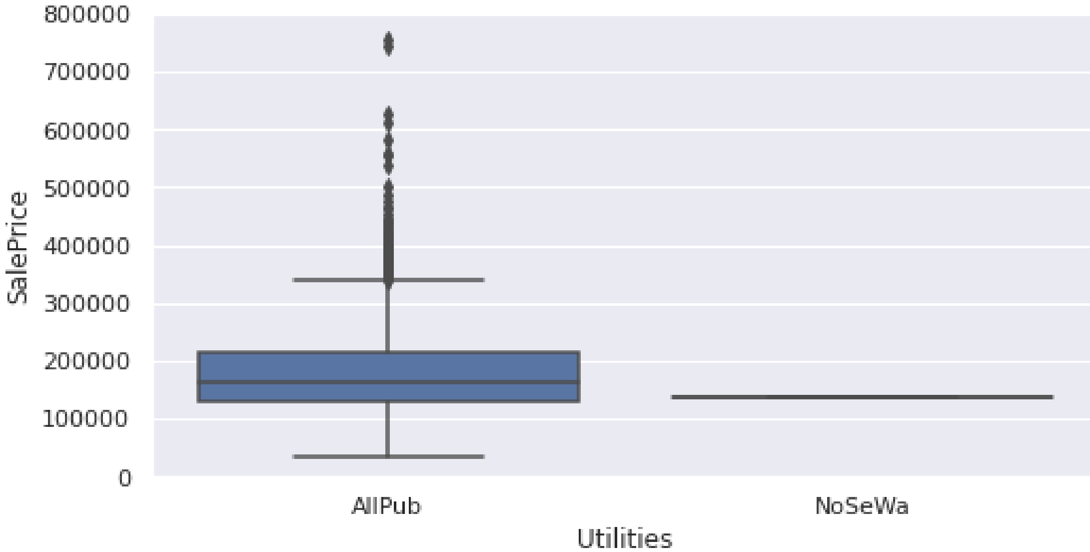
[6]:
```
for i in range(20): # Attempting to print more than 20 plots at a time will hit␣
↪a memory cap
    data = pd.concat([df_train['SalePrice'], df_train[cat_features[i]]], axis=1)
    f, ax = plt.subplots(figsize=(8, 4))
    fig = sns.boxplot(x=cat_features[i], y="SalePrice", data=data)
    fig.axis(ymin=0, ymax=800000)
```

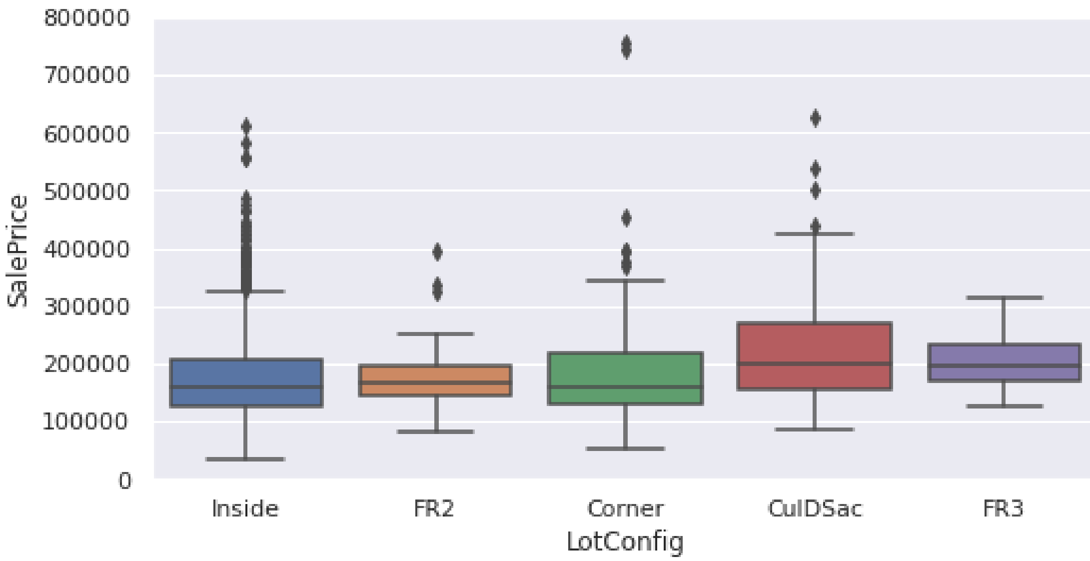

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
RL
RM
C (all)
FV
RH
MSZoning

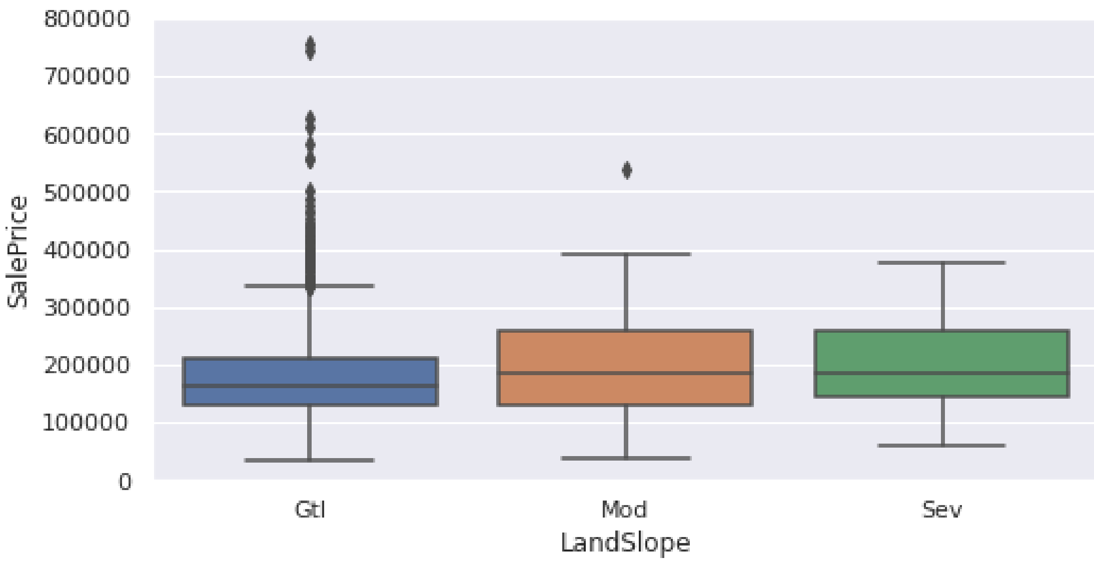

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Pave
Grvl
Street

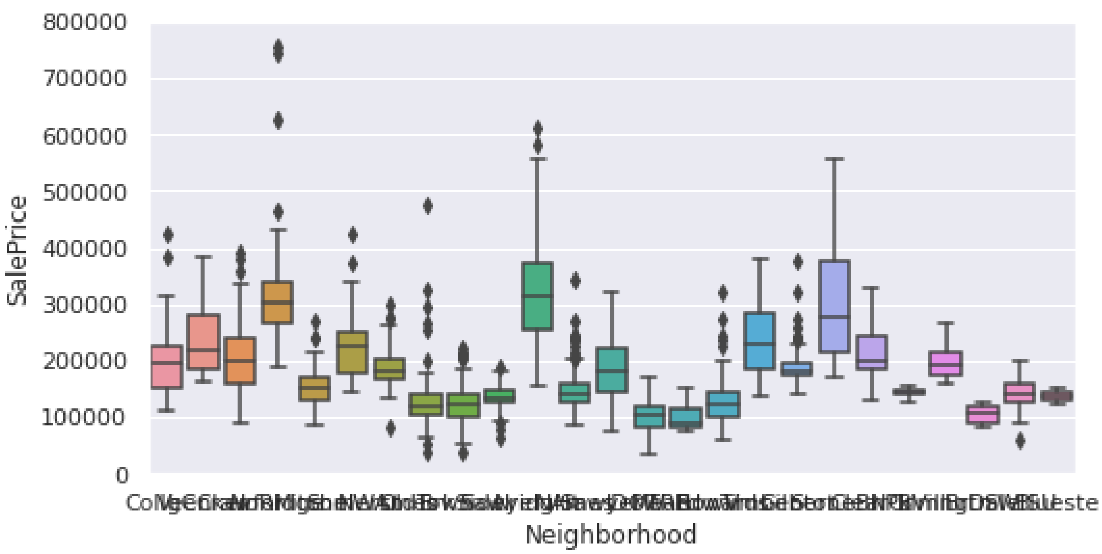

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Reg
IR1
IR2
IR3
LotShape

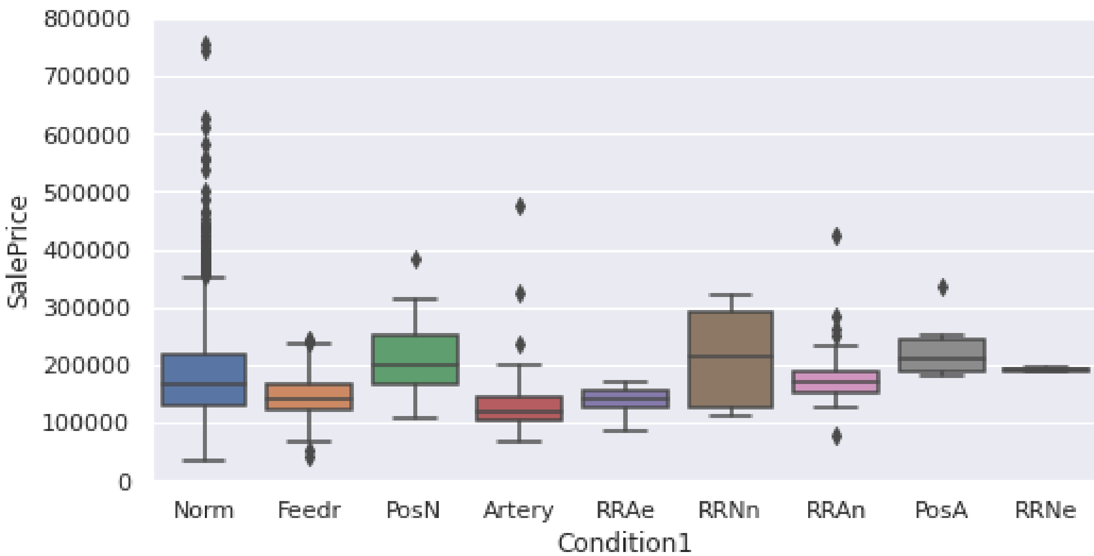

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Lvl
Bnk
Low
HLS
LandContour

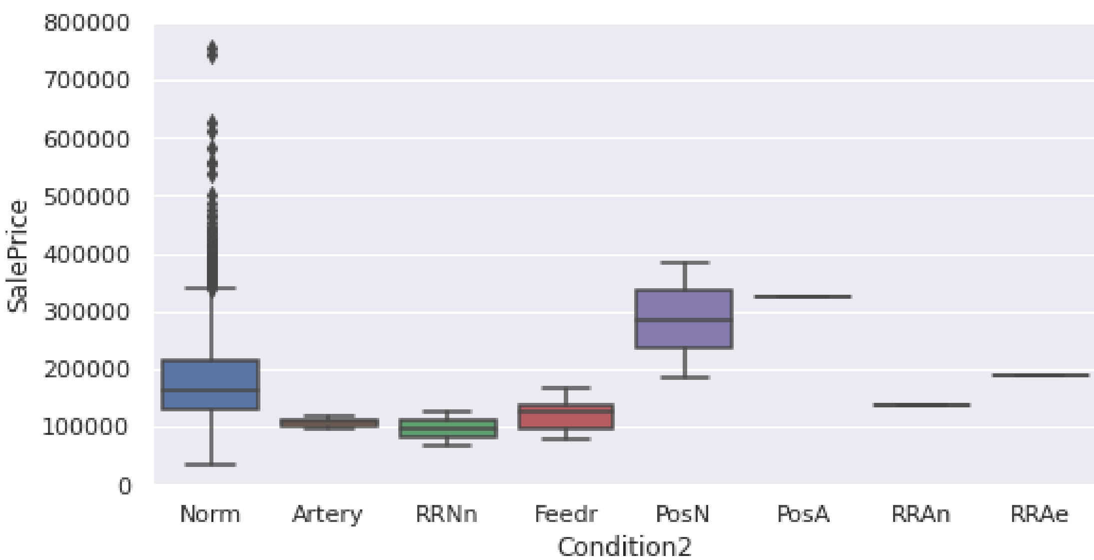

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
AllPub
NoSeWa
Utilities

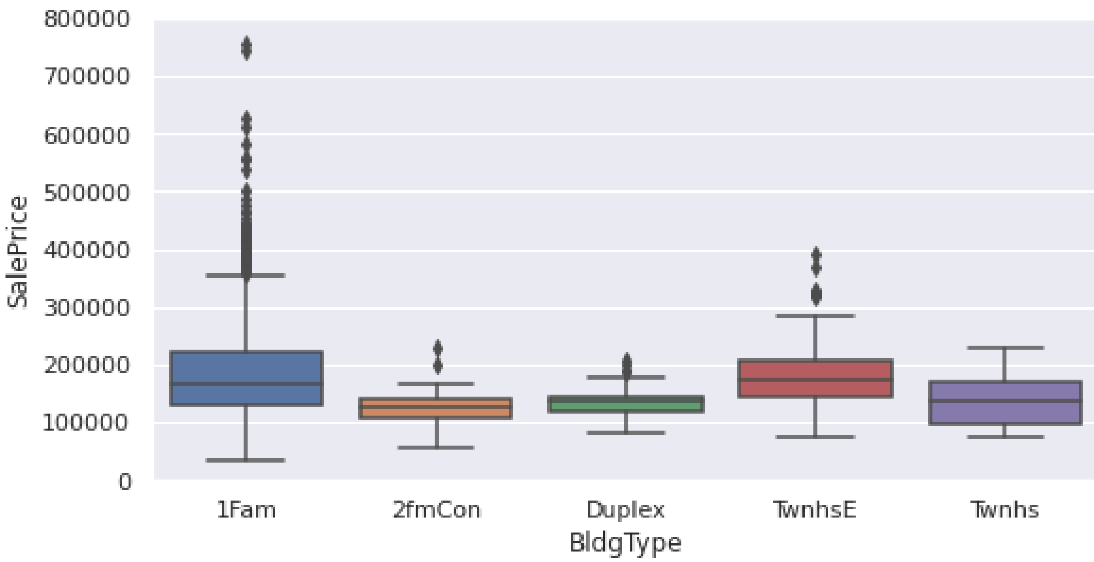

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Inside
FR2
Corner
CulDSac
FR3
LotConfig

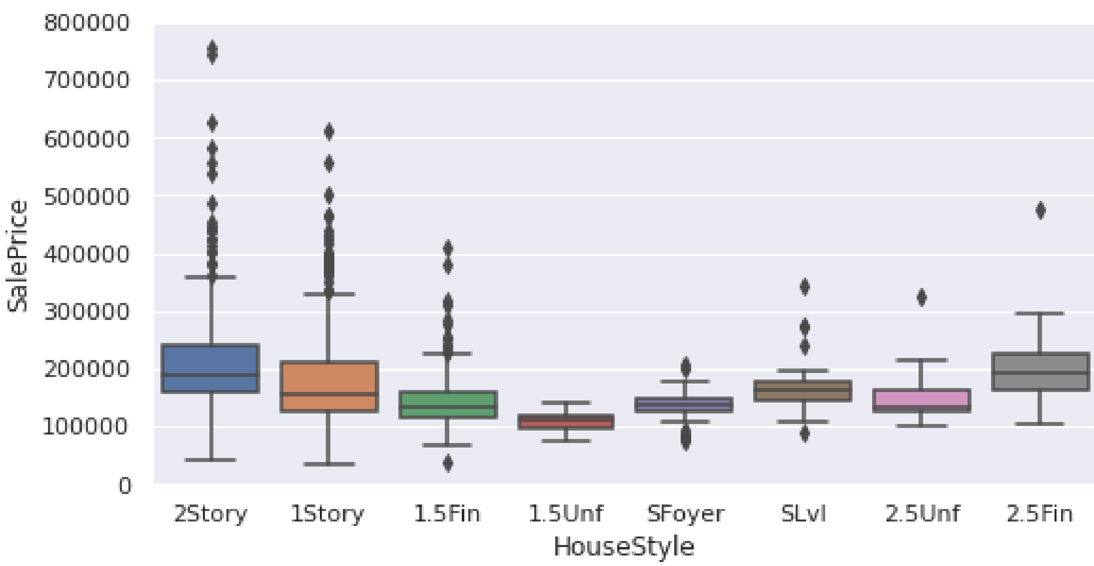

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Gtl
Mod
Sev
LandSlope

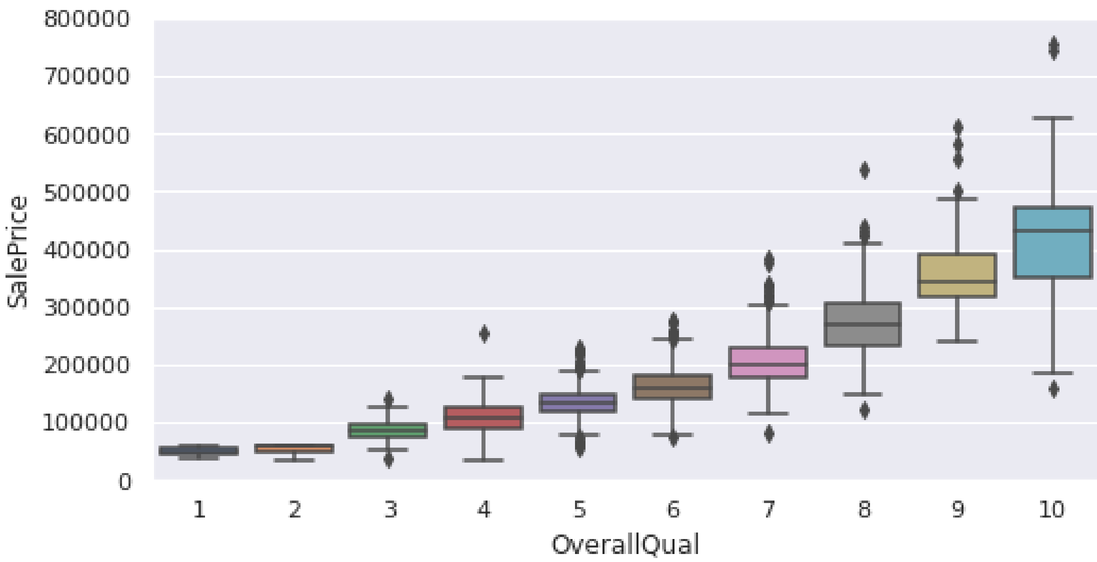

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Neighborhood

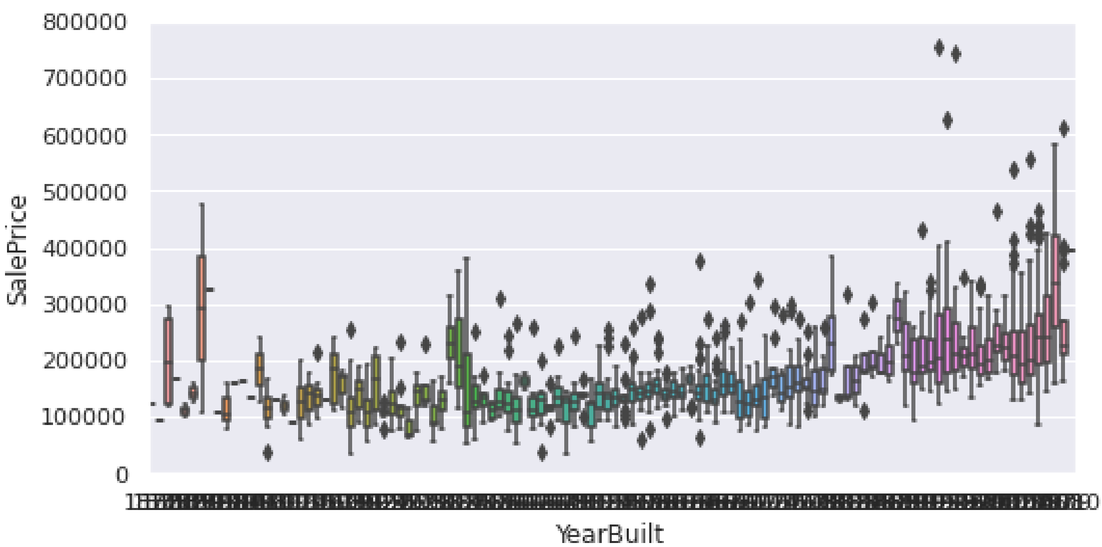

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Norm
Feedr
PosN
Artery
RRAe
RRNn
RRAn
PosA
RRNe
Condition1

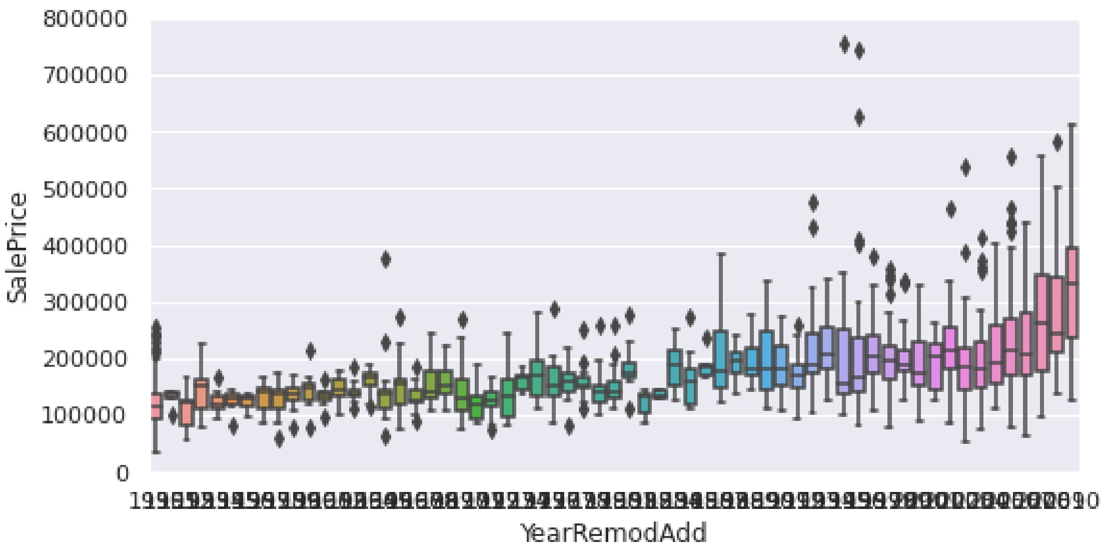

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Norm
Artery
RRNn
Feedr
PosN
PosA
RRAn
RRAe
Condition2

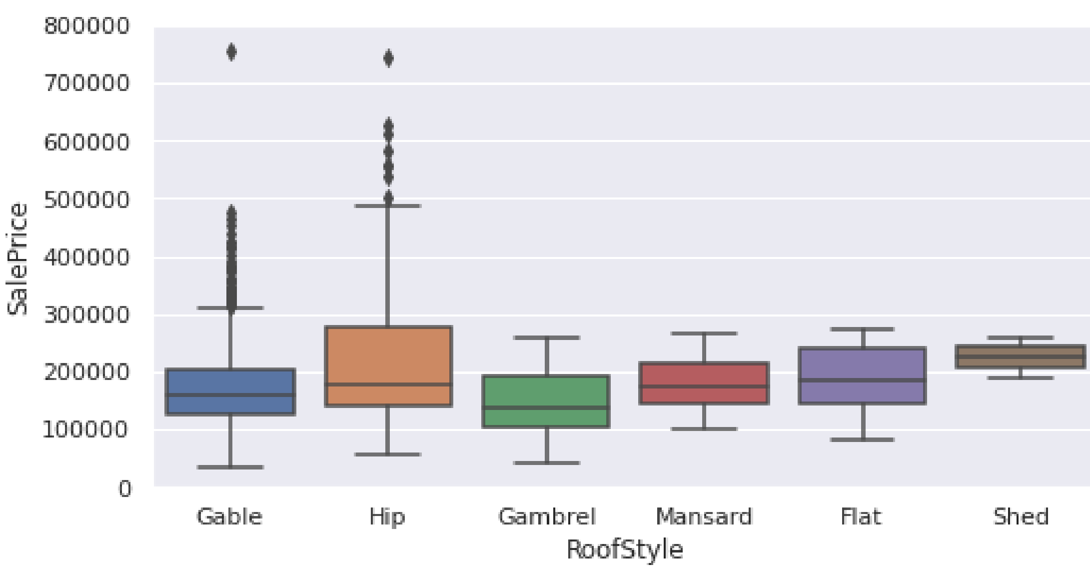

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
1Fam
2fmCon
Duplex
TwnhsE
Twnhs
BldgType

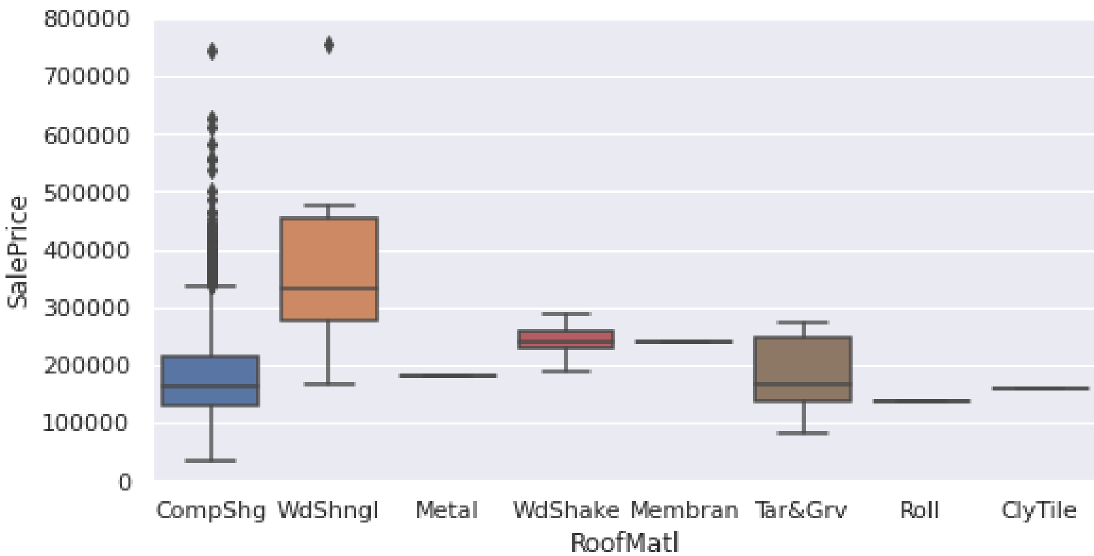

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
2Story
1Story
1.5Fin
1.5Unf
SFoyer
SLvl
2.5Unf
2.5Fin
HouseStyle

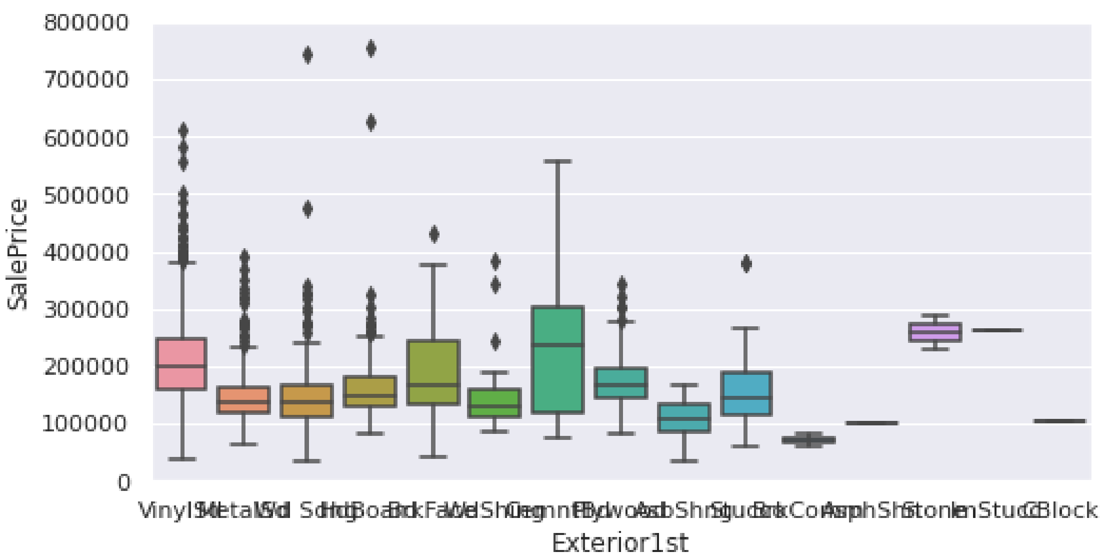

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
1
2
3
4
5
6
7
8
9
10
OverallQual

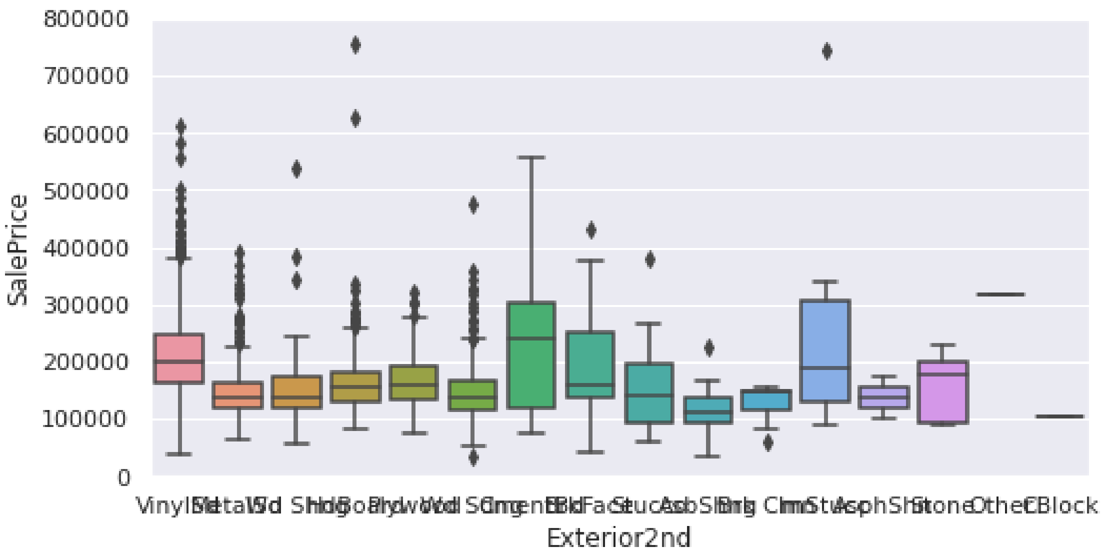

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
YearBuilt

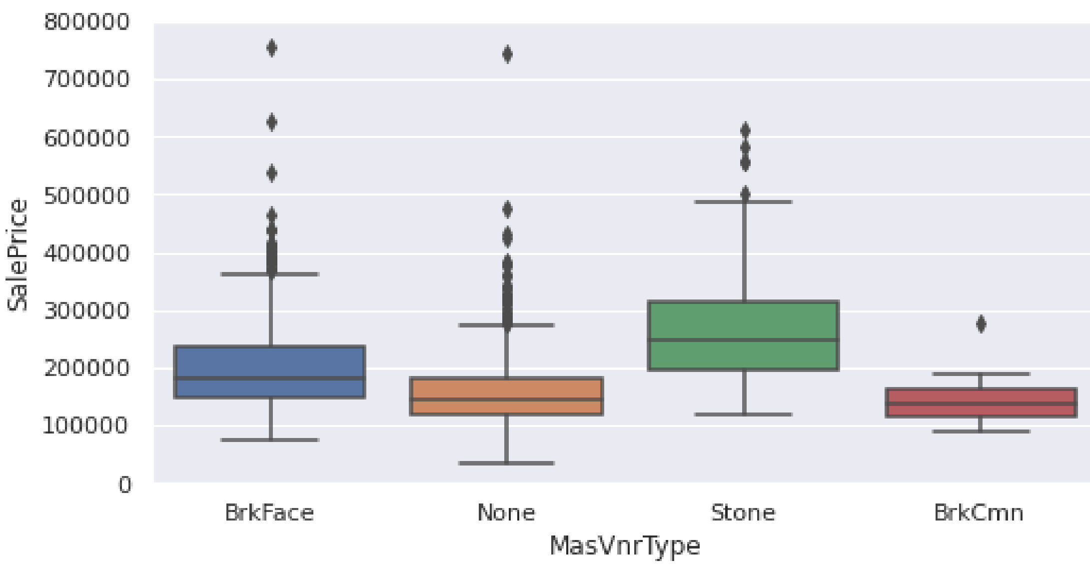

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
YearRemodAdd


800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Gable
Hip
Gambrel
Mansard
Flat
Shed
RoofStyle

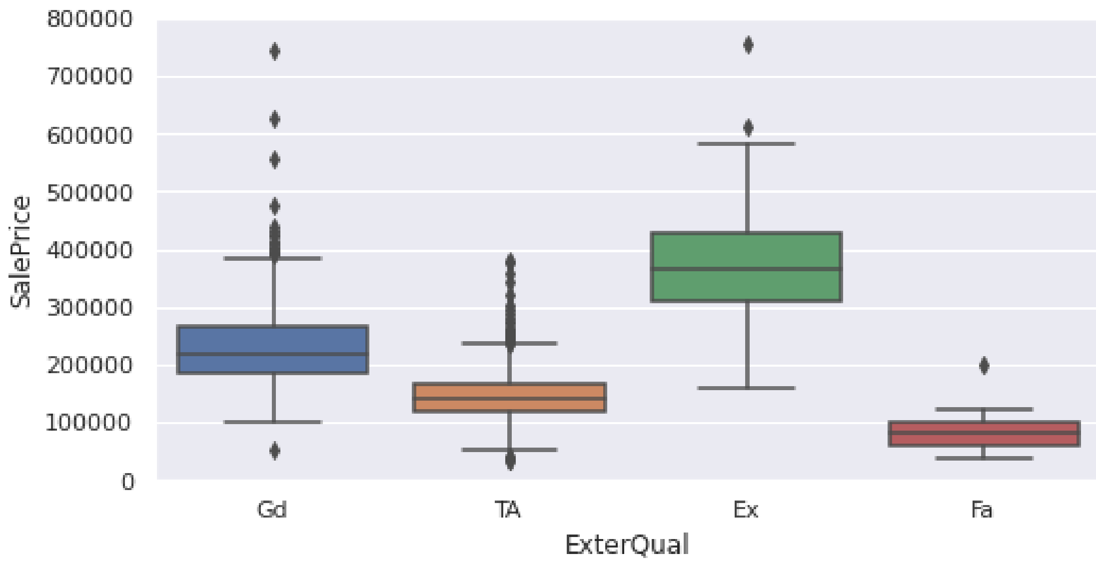

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
CompShg
WdShngl
Metal
WdShake
Membran
Tar&Grv
Roll
ClyTile
RoofMatl

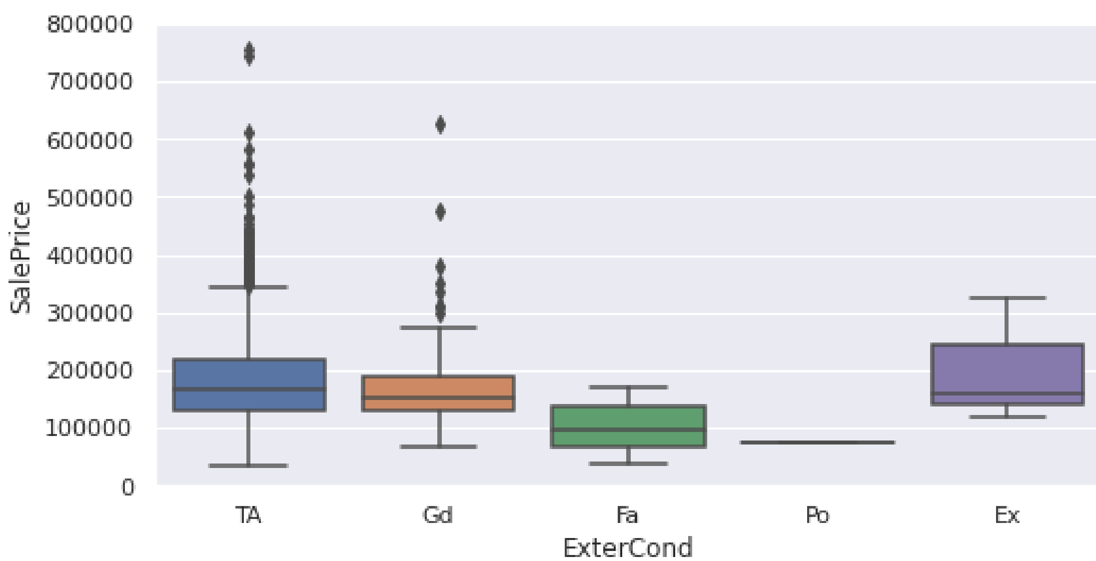

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Exterior1st

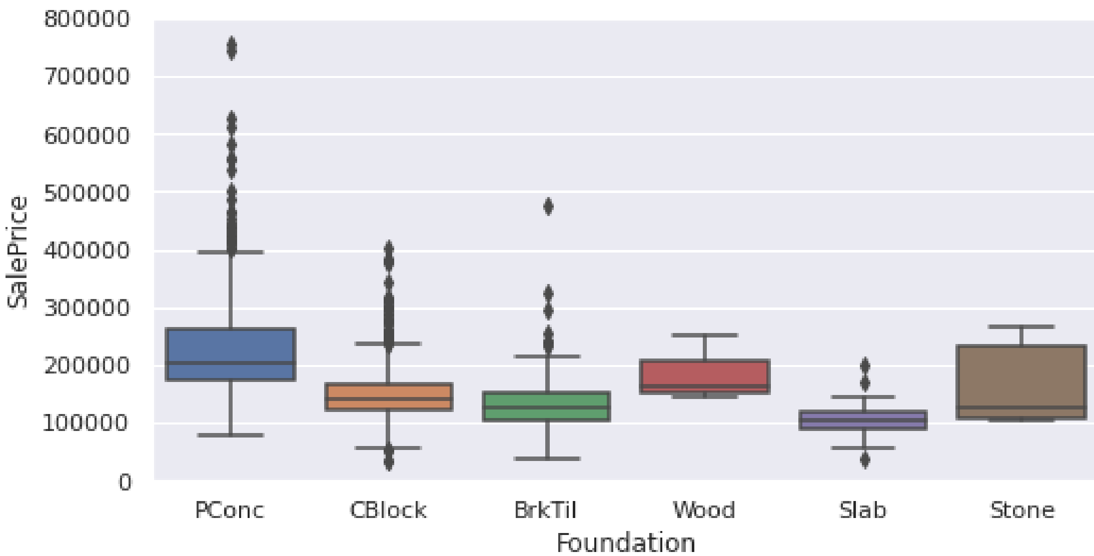




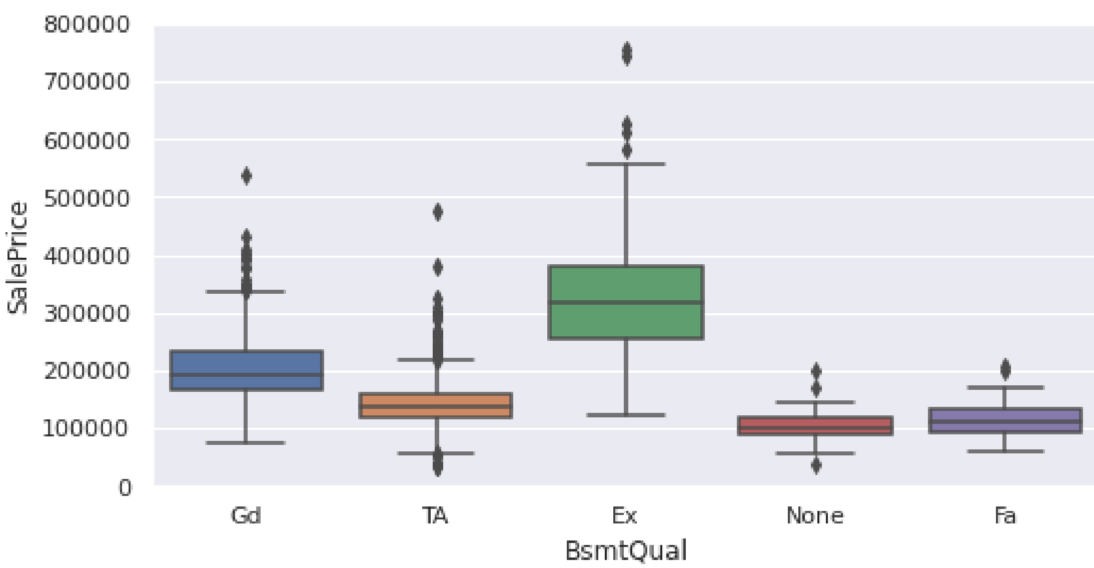
[7]:
```python
for j in range(20,40): # Plot the remaining features
    data = pd.concat([df_train['SalePrice'], df_train[cat_features[j]]], axis=1)
    f, ax = plt.subplots(figsize=(8, 4))
    fig = sns.boxplot(x=cat_features[j], y="SalePrice", data=data)
    fig.axis(ymin=0, ymax=800000)
```


800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Gd
TA
Ex
Fa
ExterQual

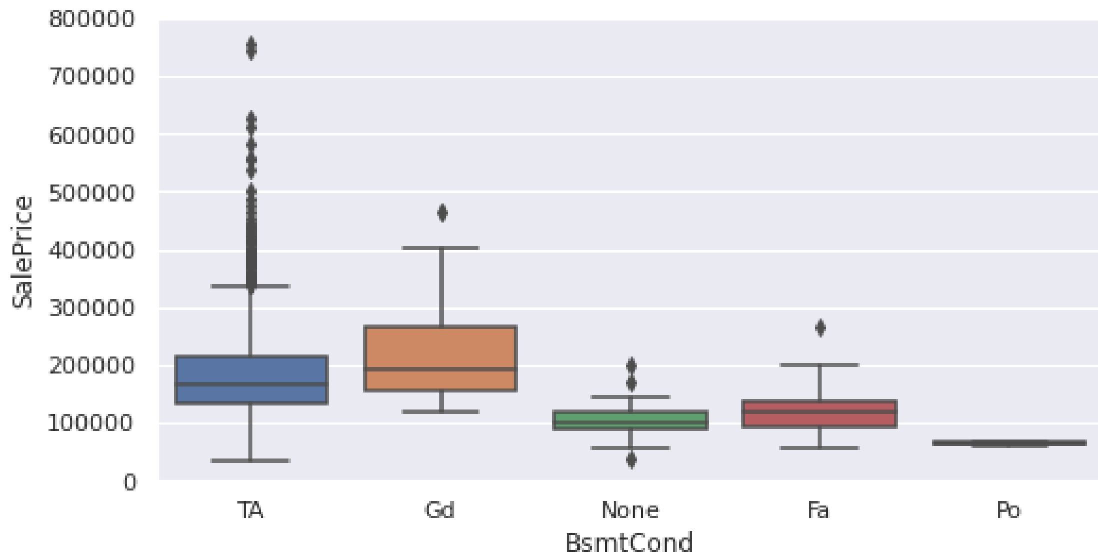

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
TA
Gd
Fa
Po
Ex
ExterCond

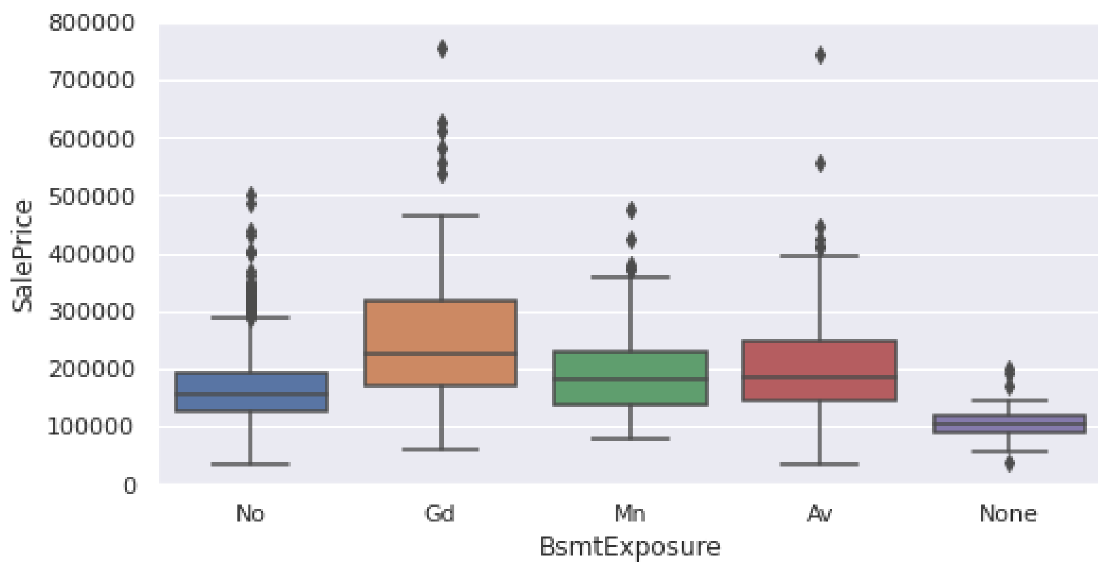


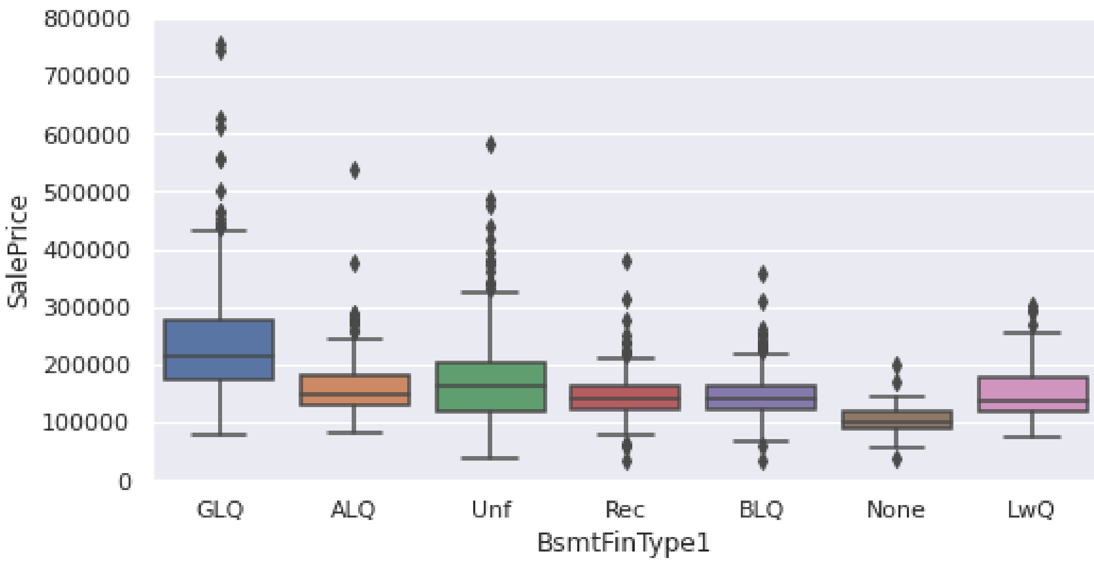
800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
PConc
CBlock
BrkTil
Wood
Slab
Stone
Foundation

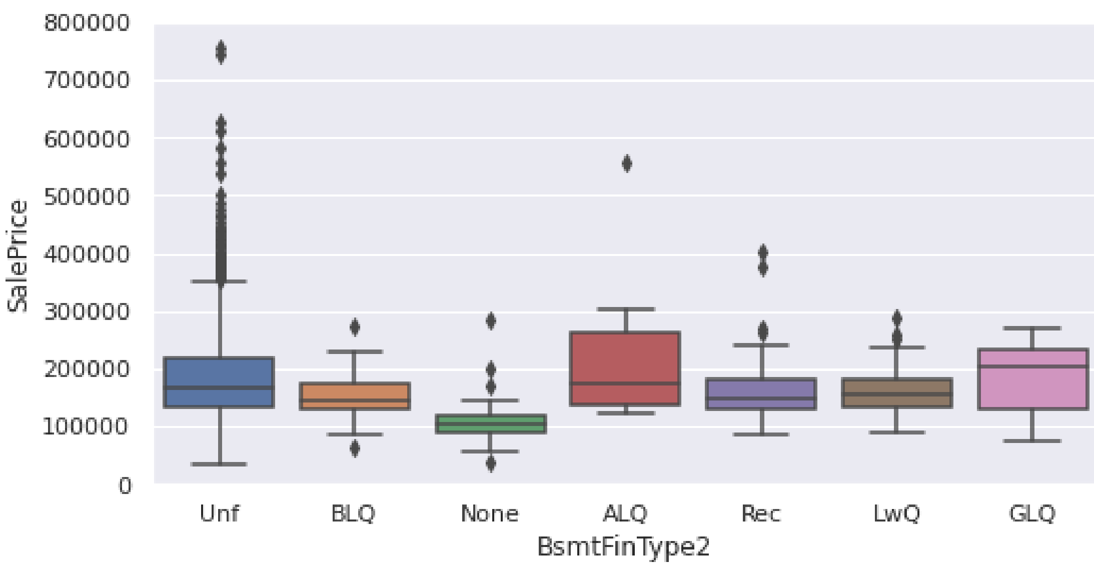


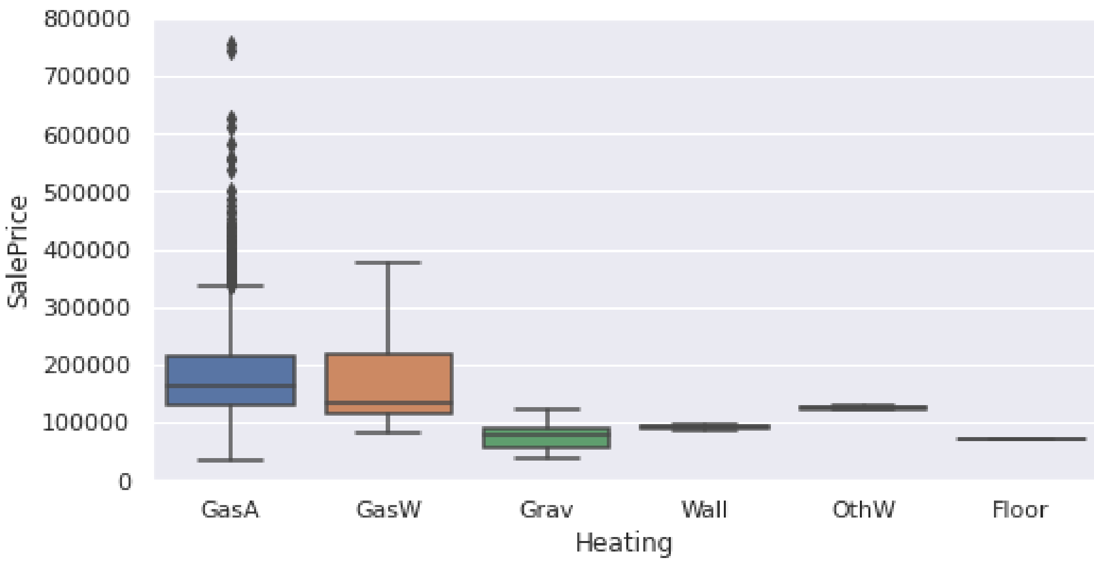
800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Gd
TA
Ex
None
Fa
BsmtQual

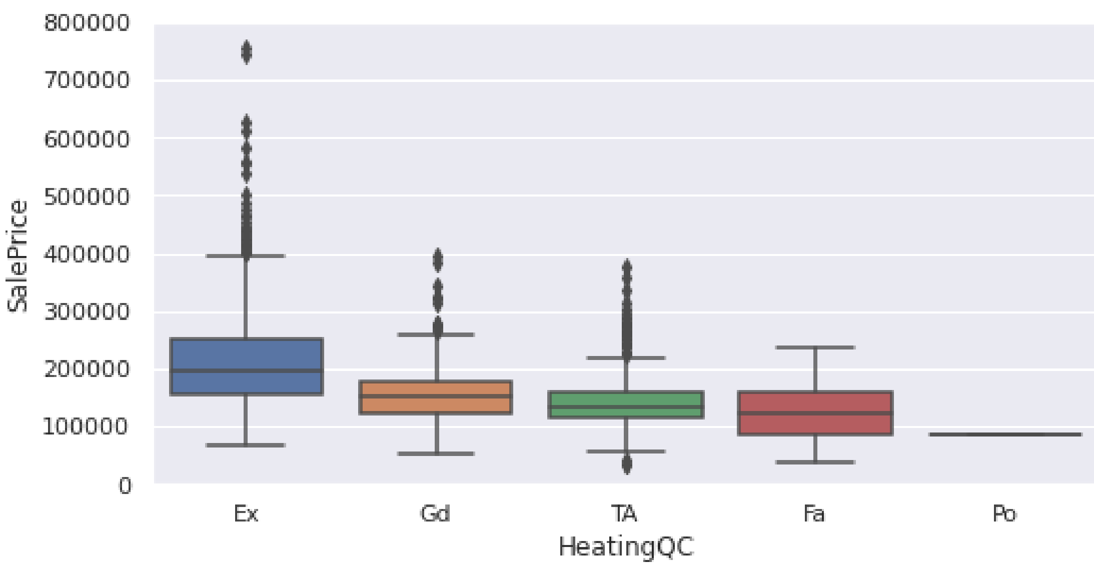

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
TA
Gd
None
Fa
Po
BsmtCond

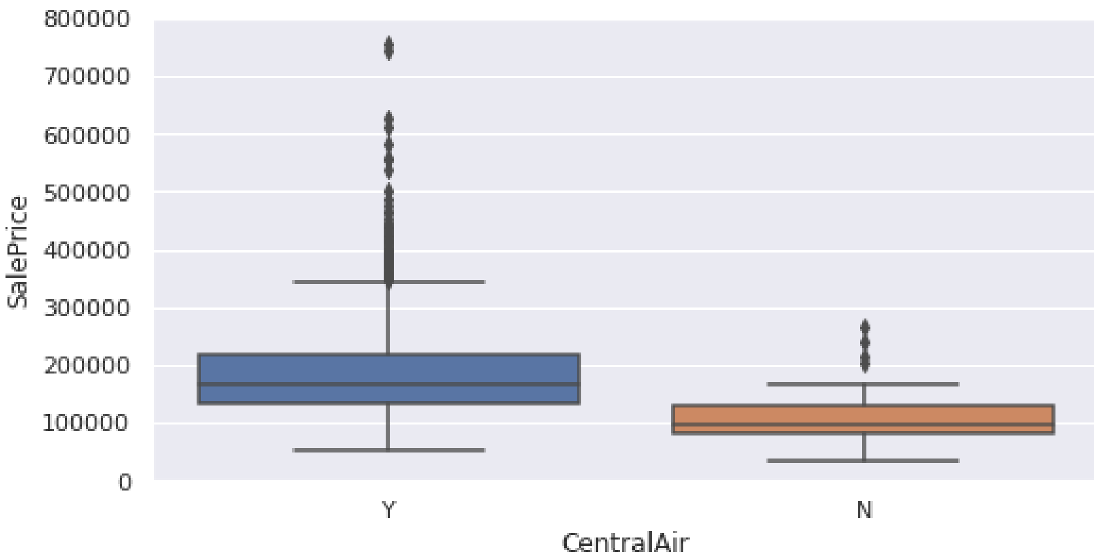

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
No
Gd
Mn
Av
None
BsmtExposure

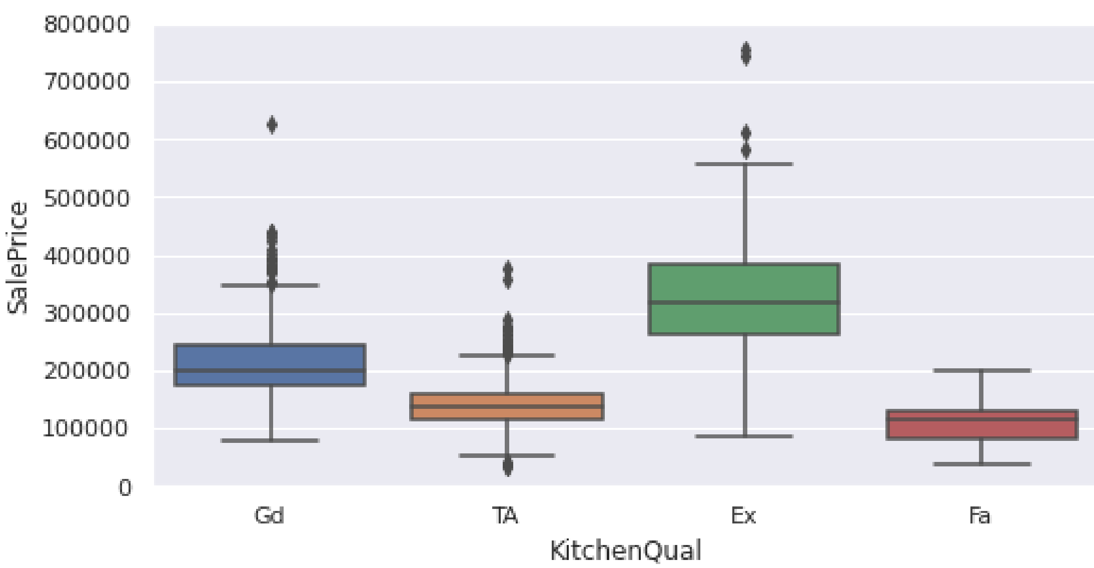

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
GLQ
ALQ
Unf
Rec
BLQ
None
LwQ
BsmtFinType1

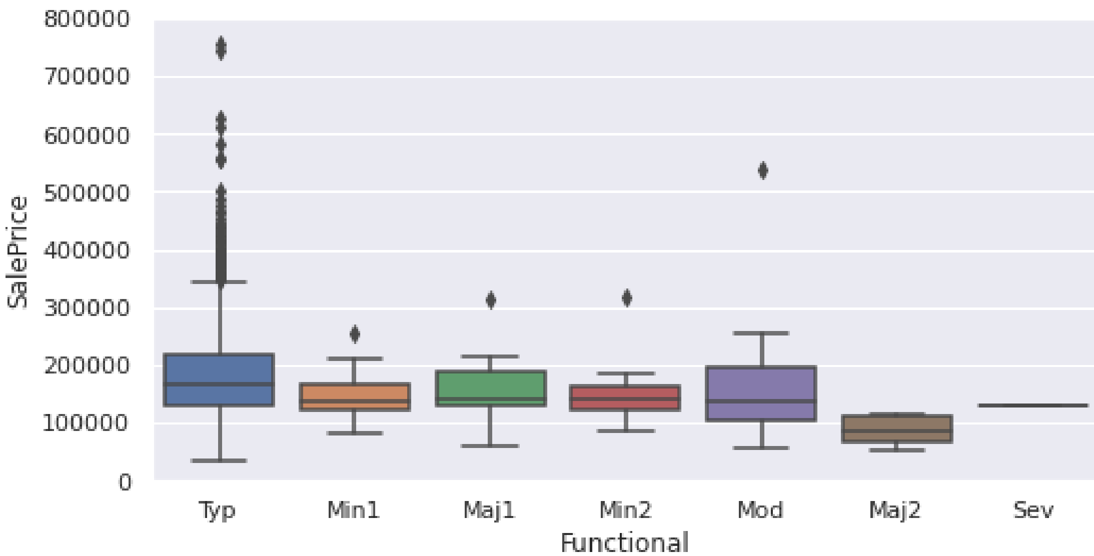

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Unf
BLQ
None
ALQ
Rec
LwQ
GLQ
BsmtFinType2

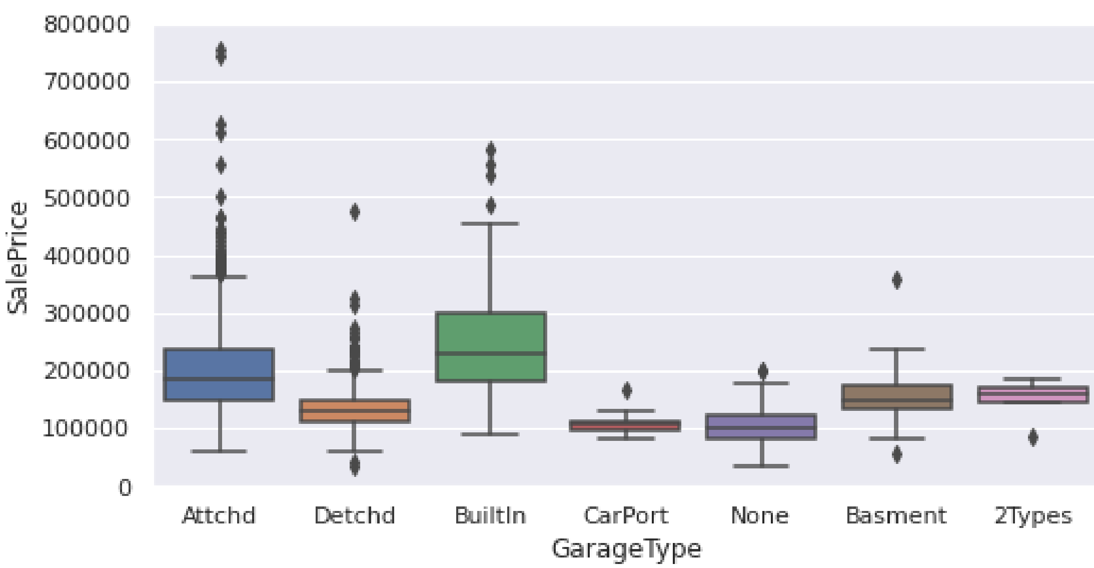

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
GasA
GasW
Grav
Wall
OthW
Floor
Heating

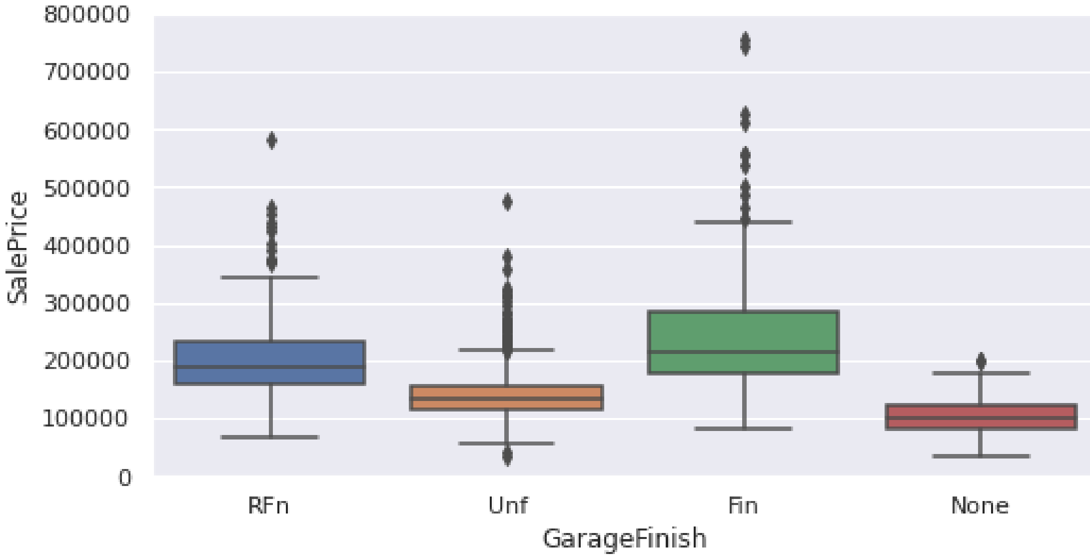

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Ex
Gd
TA
Fa
Po
HeatingQC

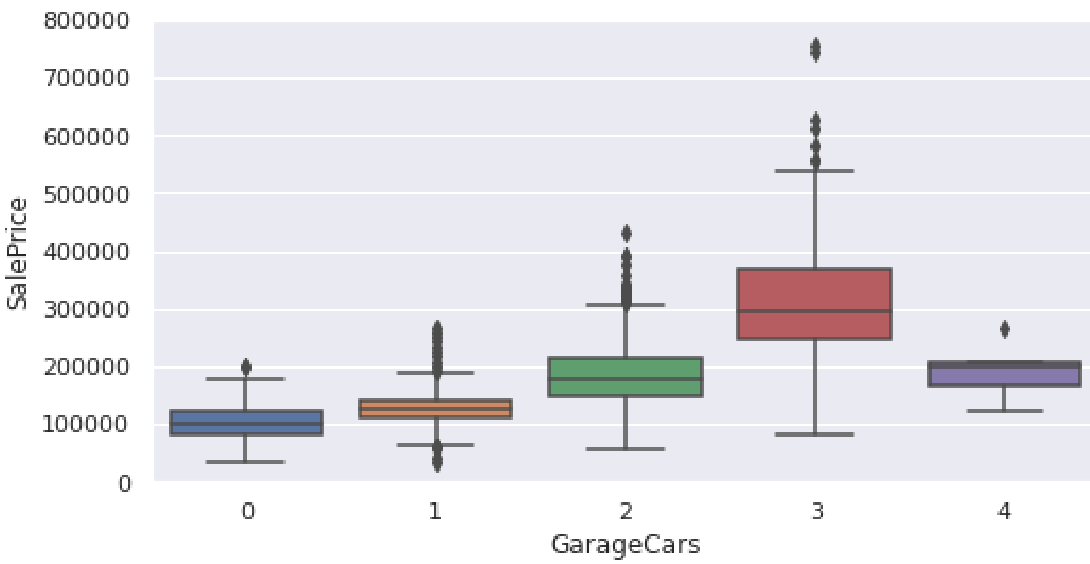

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Y
N
CentralAir

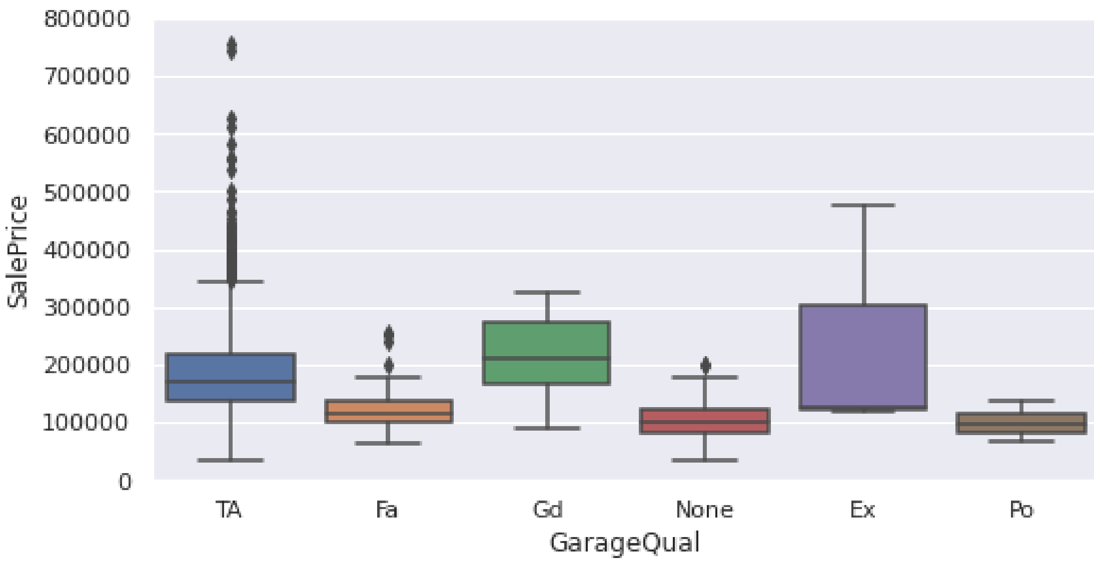

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Gd
TA
Ex
Fa
KitchenQual

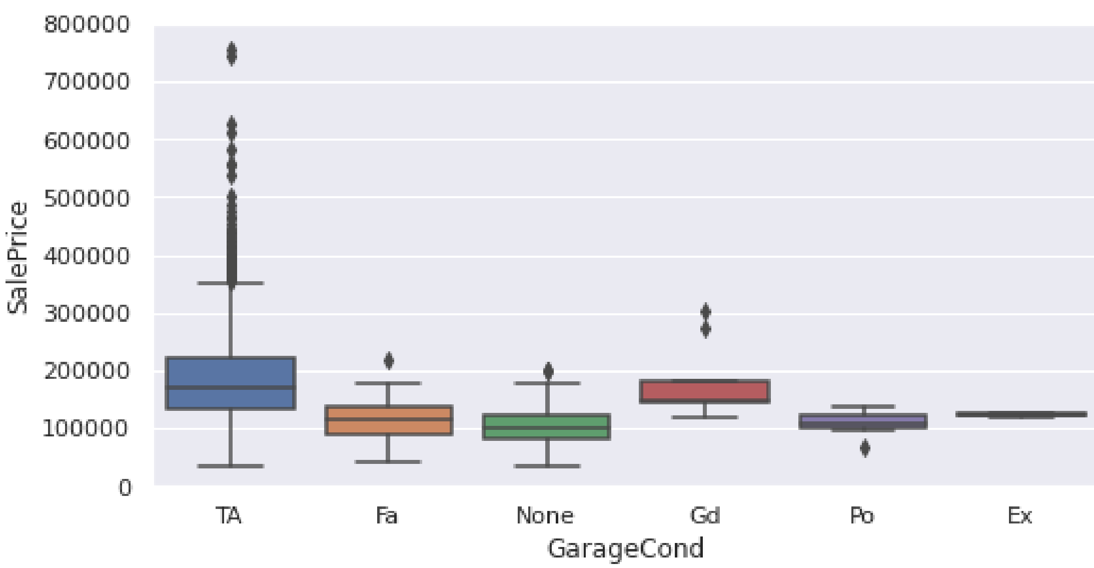

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Typ
Min1
Maj1
Min2
Mod
Maj2
Sev
Functional

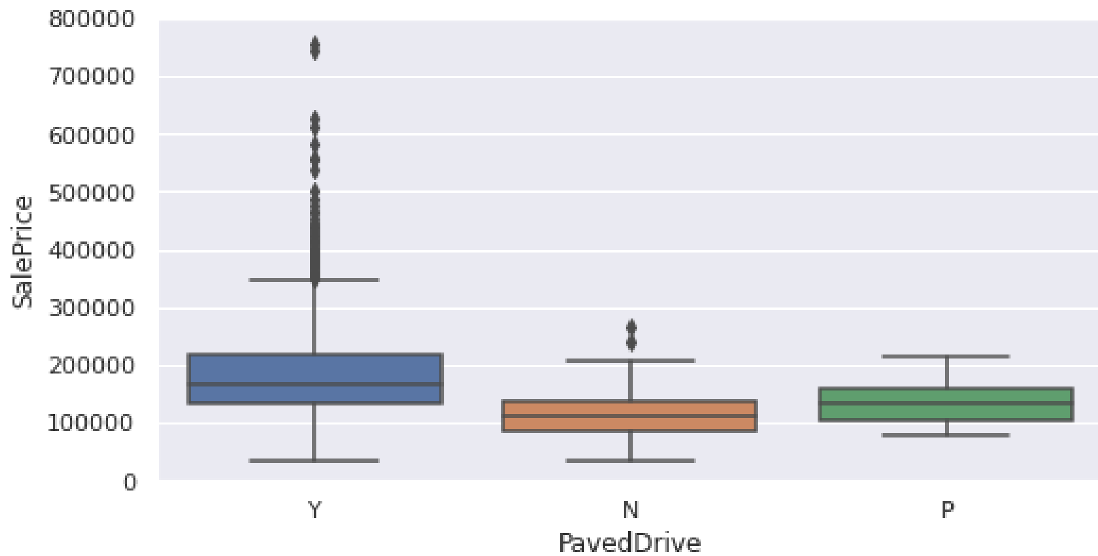

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
Attchd
Detchd
BuiltIn
CarPort
None
Basment
2Types
GarageType

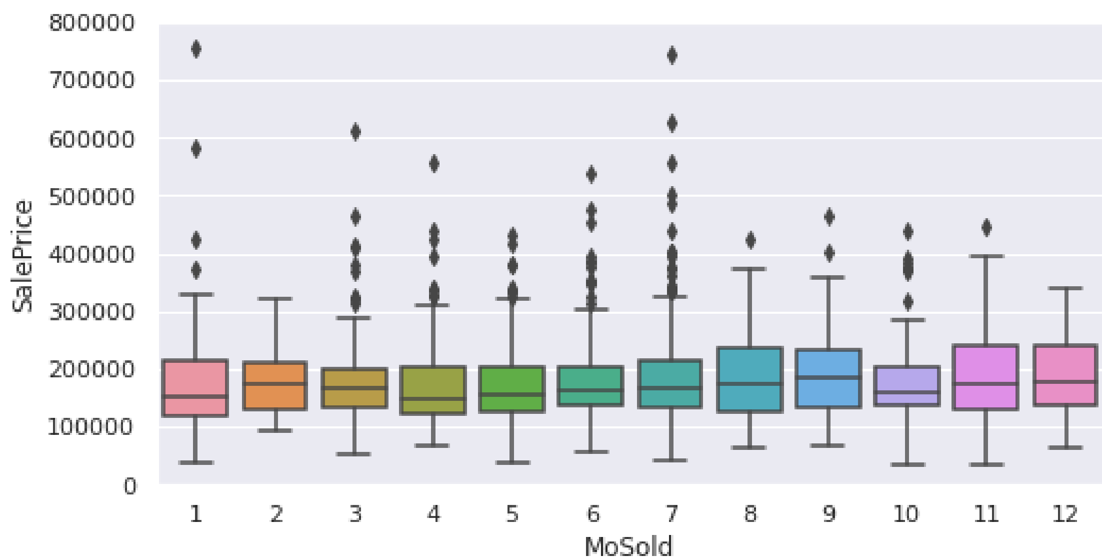

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
RFn
Unf
Fin
None
GarageFinish


800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
0
1
2
3
4
GarageCars

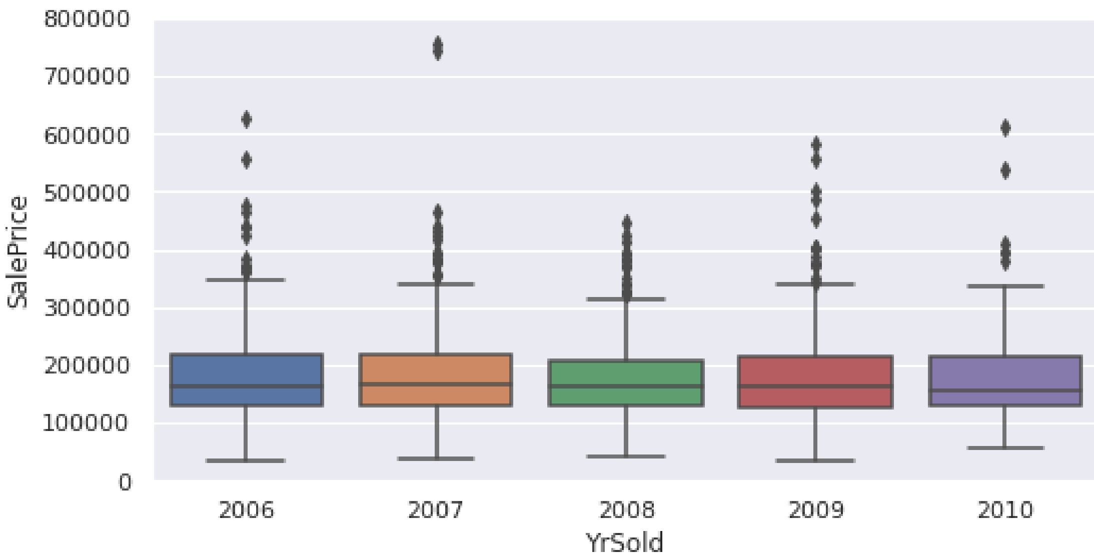

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
TA
Fa
Gd
None
Ex
Po
GarageQual

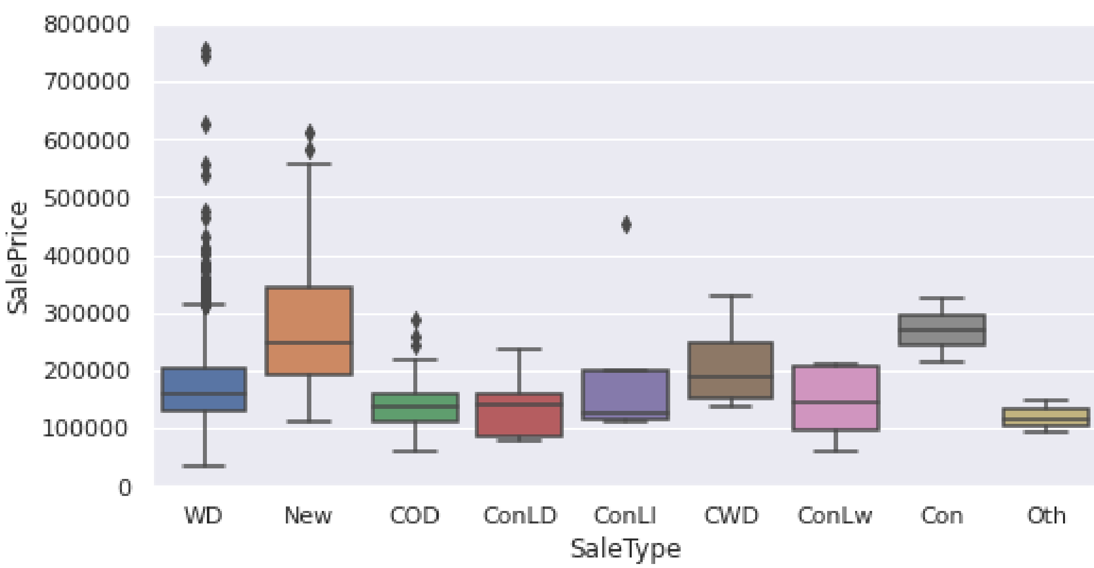

800000
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
TA
Fa
None
Gd
Po
Ex
GarageCond





[8]:
```python
for z in range(40,42): # Attempting to print more than 20 plots at a time will␣
↪hit a memory cap
    data = pd.concat([df_train['SalePrice'], df_train[cat_features[z]]], axis=1)
    f, ax = plt.subplots(figsize=(8, 4))
    fig = sns.boxplot(x=cat_features[z], y="SalePrice", data=data)
    fig.axis(ymin=0, ymax=800000)
```





Looking through the box plots of the categorical data, some features can be readily identified as having a relationship to the ultimate sale price of the property. I originally misclassified several categorical features as quantitative features, but once I corrected this, some more salient patterns in the categorical data emerged. Both the 'Year Built' and 'Year Remodelled' features correlated very strongly with the sale price of the residences; I decided to use the 'Year Built' feature for my model, because I suspect that there is some multicollinearity here (since the remodel year was the same as the build year for homes which had not been remodelled). The 'Overall Quality' feature was also correlated very strongly with the sale price, which does make intuitive sense, so I also decided to include this feature.

Besides the more obviously correlated features described above, the categorical features which stood out to me the most were that which detailed the neighborhood in which the properties are located, as well as the type of exterior covering on the first floor. While I can't say with much confidence *why* these features seemed significant to me, I would suggest, for one, that because these features both had a lot of categories, there would be more specificity in terms of the range of values associated with a particular category. These plots also appeared more structured–that is to say, there appeared to be less overlap of price ranges between the categories for each of these features than for many of the others.

While initially reluctant to rely on any categorical variables at all, as I figured I would have to use a dummy encoding for these categorical variables, I realized that I could have my regression model encode these categories automatically by using the statsmodels library to create my model with a statistical formula. In summary, I decided to start building my model of property sale price with three quantitative features (above-ground living area, number of cars storable in garage, & basement square footage) and four categorical features (year built, overall quality, first floor exterior type, and neighborhood).

1.3 Part 3: Model

To start, I decided to use the ordinary least squares method to create a multi-linear regression model involving several expanatory variables. I decided to utilize this method at first largely because its implementation seemed the most straightforward and required no additional effort to encode categorical features of the dataset. I felt far more confident about my ability to implement the OLS multi-linear regression technique than I did with any other technique, so this is the one I went with initially. Looking back on my notes, I realized there wasn't an overwhelmingly effificient way to test the predictions made by such a model; I would have to store separate coefficients for each category in the categorical features, and some such features had a *lot* of categories. So this initial model could probably better be described as a form of exploratory data analysis, inasmuch as it gave me additional insight into which features seem to serve as better predictors of residential sale price. The results below show suggest that a model based entirely on the Overall Quality rating and on the Neighborhood actually yields a reasonable adjusted r-squared value of about .750. When I included some of the other features in my regression model, I was able to raise the adjusted r-squared value as high as .830–although the condition number for this model was rather high (which, as the summary of regression results points out, could indicate strong multicollinearity or other numerical problems).

[9]:
```
# Categorical
# model_price = smf.ols(formula='SalePrice~C(Neighborhood)', data=df_train).
↪fit() # adj. r-squared = .538
# model_price = smf.ols(formula='SalePrice~C(YearBuilt)', data=df_train).fit()␣
↪# adj. r-squared = .393
# model_price = smf.ols(formula='SalePrice~C(OverallQual)', data=df_train).
↪fit() # adj. r-squared = .682
# model_price = smf.ols(formula='SalePrice~C(Exterior1st)', data=df_train).
↪fit() # adj. r-squared = .145


# Quantitative
```

```
# model_price = smf.ols(formula='SalePrice~GarageCars', data=df_train).fit() #␣
↪adj. r-squared = .410
# model_price = smf.ols(formula='SalePrice~TotalBsmtSF', data=df_train).fit() #␣
↪adj. r-squared = .376
# model_price = smf.ols(formula='SalePrice~GrLivArea', data=df_train).fit() #␣
↪adj. r-squared = .502

# Full models
model_price = smf.ols(formula='SalePrice~C(OverallQual) + C(Neighborhood)',␣
↪data=df_train).fit() # adj. r-squared = .750, cond. no. 98.1
# model_price = smf.ols(formula='SalePrice~(GarageCars * GrLivArea) +␣
↪C(YearBuilt) + C(OverallQual) + C(Neighborhood)', data=df_train).fit() # adj.
↪ r-squared = .830, cond. no. 1.57e+6



model_price.summary()
```

[9]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              SalePrice   R-squared:                       0.755
Model:                            OLS   Adj. R-squared:                  0.750
Method:                 Least Squares   F-statistic:                     133.4
Date:                Mon, 07 Dec 2020   Prob (F-statistic):               0.00
Time:                        20:51:05   Log-Likelihood:                -17516.
No. Observations:                1460   AIC:                         3.510e+04
Df Residuals:                    1426   BIC:                         3.528e+04
Df Model:                          33
Covariance Type:            nonrobust
================================================================================
==============
                                 coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
--------------
Intercept                   6.194e+04      3e+04      2.062      0.039
3020.190    1.21e+05
C(OverallQual)[T.2]         3784.7201   3.65e+04      0.104      0.917
-6.78e+04    7.54e+04
C(OverallQual)[T.3]         3.996e+04   2.96e+04      1.351      0.177
-1.81e+04     9.8e+04
C(OverallQual)[T.4]         5.458e+04   2.85e+04      1.916      0.056
-1292.990     1.1e+05
C(OverallQual)[T.5]         7.027e+04   2.84e+04      2.479      0.013
1.47e+04    1.26e+05
```

```
C(OverallQual)[T.6]         9.132e+04   2.84e+04      3.219      0.001
3.57e+04    1.47e+05
C(OverallQual)[T.7]         1.244e+05   2.85e+04      4.372      0.000
6.86e+04     1.8e+05
C(OverallQual)[T.8]         1.725e+05   2.86e+04      6.025      0.000
1.16e+05    2.29e+05
C(OverallQual)[T.9]         2.624e+05   2.92e+04      8.972      0.000
2.05e+05     3.2e+05
C(OverallQual)[T.10]        3.325e+05      3e+04     11.076      0.000
2.74e+05    3.91e+05
C(Neighborhood)[T.Blueste] -1.577e+04   2.99e+04     -0.528      0.598
-7.44e+04    4.29e+04
C(Neighborhood)[T.BrDale]  -4.219e+04   1.42e+04     -2.978      0.003
-7e+04   -1.44e+04
C(Neighborhood)[T.BrkSide] -1.102e+04   1.14e+04     -0.970      0.332
-3.33e+04    1.13e+04
C(Neighborhood)[T.ClearCr]   5.71e+04   1.24e+04      4.609      0.000
3.28e+04    8.14e+04
C(Neighborhood)[T.CollgCr]  1.733e+04   1.02e+04      1.693      0.091
-2746.983    3.74e+04
C(Neighborhood)[T.Crawfor]  4.303e+04   1.13e+04      3.813      0.000
2.09e+04    6.52e+04
C(Neighborhood)[T.Edwards] -1.257e+04   1.09e+04     -1.158      0.247
-3.39e+04    8716.055
C(Neighborhood)[T.Gilbert]  1.846e+04   1.07e+04      1.720      0.086
-2588.660    3.95e+04
C(Neighborhood)[T.IDOTRR]  -3.023e+04   1.21e+04     -2.501      0.013
-5.39e+04   -6517.765
C(Neighborhood)[T.MeadowV] -2.565e+04   1.42e+04     -1.812      0.070
-5.34e+04    2123.185
C(Neighborhood)[T.Mitchel]  8994.1275   1.15e+04      0.783      0.434
-1.35e+04    3.15e+04
C(Neighborhood)[T.NAmes]    4256.8837   1.04e+04      0.409      0.682
-1.61e+04    2.47e+04
C(Neighborhood)[T.NPkVill] -1.057e+04   1.67e+04     -0.633      0.527
-4.33e+04    2.22e+04
C(Neighborhood)[T.NWAmes]   2.296e+04   1.09e+04      2.114      0.035
1650.255    4.43e+04
C(Neighborhood)[T.NoRidge]   9.71e+04   1.17e+04      8.317      0.000
7.42e+04     1.2e+05
C(Neighborhood)[T.NridgHt]  4.928e+04   1.11e+04      4.453      0.000
2.76e+04     7.1e+04
C(Neighborhood)[T.OldTown] -1.914e+04   1.07e+04     -1.795      0.073
-4.01e+04    1776.615
C(Neighborhood)[T.SWISU]    -628.6322   1.28e+04     -0.049      0.961
-2.57e+04    2.45e+04
C(Neighborhood)[T.Sawyer]   3360.1348   1.12e+04      0.301      0.764
```

```
-1.86e+04    2.53e+04
C(Neighborhood)[T.SawyerW]  1.872e+04   1.11e+04      1.691      0.091
-2995.568    4.04e+04
C(Neighborhood)[T.Somerst]  1.818e+04   1.06e+04      1.715      0.087
-2619.560     3.9e+04
C(Neighborhood)[T.StoneBr]  5.743e+04   1.28e+04      4.480      0.000
3.23e+04    8.26e+04
C(Neighborhood)[T.Timber]   3.709e+04   1.17e+04      3.160      0.002
1.41e+04    6.01e+04
C(Neighborhood)[T.Veenker]  4.863e+04   1.55e+04      3.132      0.002
1.82e+04    7.91e+04
==============================================================================
Omnibus:                      425.945   Durbin-Watson:                   1.921
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             3619.219
Skew:                           1.111   Prob(JB):                         0.00
Kurtosis:                      10.386   Cond. No.                         98.1
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

To build an actual model, I had to encode the categorical variables. I used the LabelEncoder() method from scikit-learn to create an encoding of all the categorical features in both datasets. When I was creating tables for my test and training data, I realized that the test dataset did not contain data for the Sale Price target feature. I decided instead to split my training data up into halves, with one half actually used to train the model and the other half used to test it. I found the code for using scikit-learn's model_selection.train_test_split() method in the following thread: https://stackoverflow.com/questions/17412439/how-to-split-data-into-trainset-and-testset-randomly/39319000#39319000.

I also realized after I tried implementing my model that I was getting an enormous mean squared error result–something in the order of 10^{10}. I realized that I hadn't normalized my target data, and since the target data

[10]:
```python
from sklearn.preprocessing import LabelEncoder

# Encode categorical variables in the datasets
for column in cat_features:
    df_train[column] = LabelEncoder().fit_transform(df_train[column].
 ↪astype('str'))
    df_test[column] = LabelEncoder().fit_transform(df_test[column].
 ↪astype('str'))

# Divide training set into halves--one for training, one for testing
df_train, df_test = sklearn.model_selection.train_test_split(df_train,␣
 ↪train_size = 0.5)
```

[11]:
```
# Create tables for target data
dy_train = df_train['SalePrice']
dy_test = df_test['SalePrice']

predictors = ['GrLivArea', 'TotalBsmtSF', 'GarageCars', 'Neighborhood',␣
↪'YearBuilt', 'OverallQual', 'Exterior1st']

# Create tables of predictor data
dX_train = df_train[predictors] # These features give a MSE = 0.2734
dX_test = df_test[predictors]
```

[12]:
```
from sklearn.preprocessing import scale

# Normalize the data to bring down the mean squared error
dy_train = sklearn.preprocessing.scale(dy_train)
dy_test = sklearn.preprocessing.scale(dy_train)

# Create regression model
mod = sklearn.linear_model.LinearRegression()
skmodel_price = mod.fit(dX_train, dy_train)

# Generate predicted sale prices
pred_y = skmodel_price.predict(dX_train)

# Print out the error score for the model
print("MSE for this model:", sklearn.metrics.mean_squared_error(dy_test,␣
↪pred_y))
```

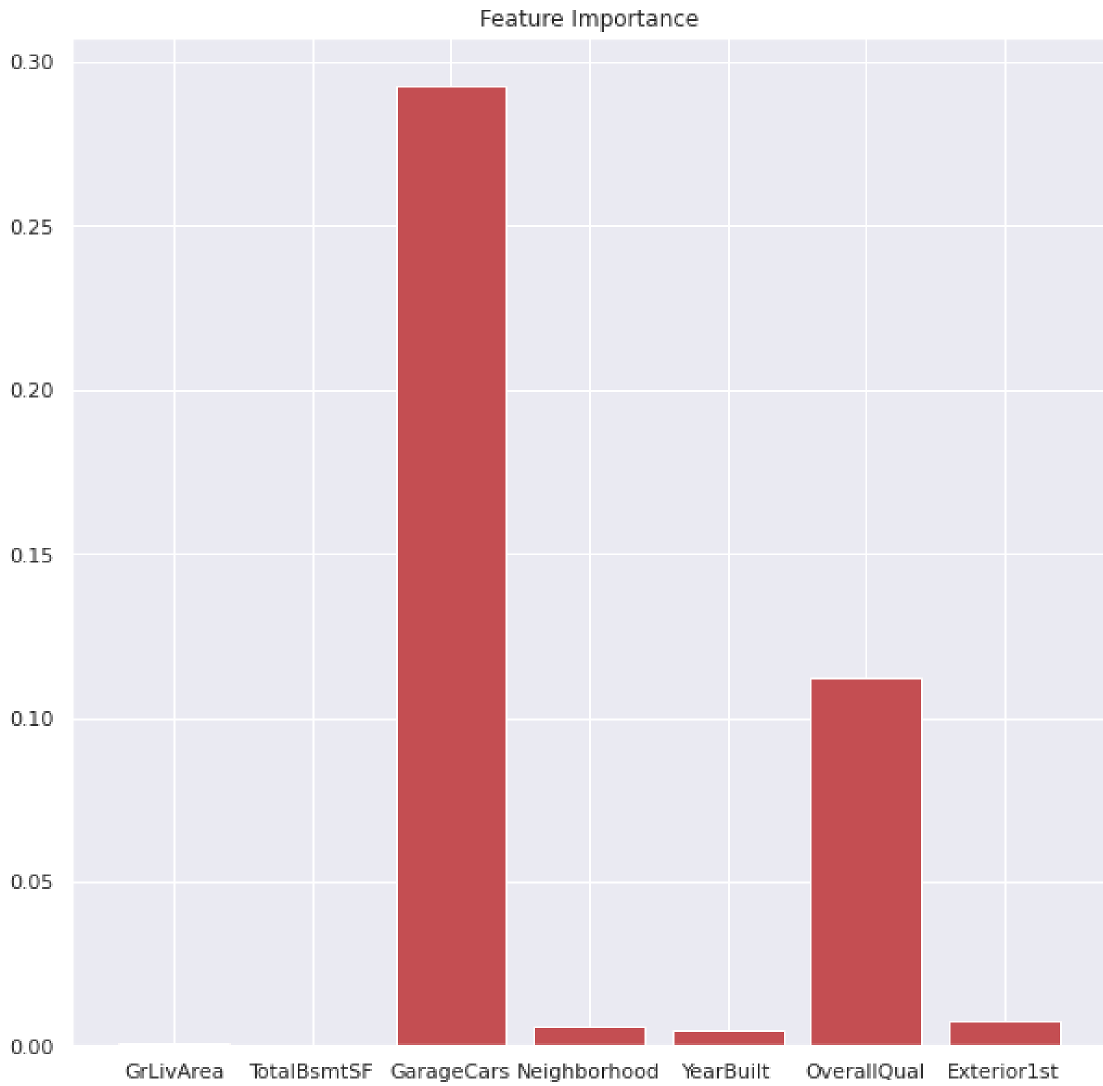
```
MSE for this model: 0.28191782505338275
```

While I wanted to see if I couldn't improve upon the score by creating the model in a different way, I was honestly just relieved I was able to get anything to work. So I decided to just take my results from this model and run. I know that better performance is possible, but frankly I'm impressed that the model scored as well as it did. I have not been confident about my knowledge of data science throughout the course of this class, and I am certainly not very confident in my ability to produce viable machine learning models, so I am more than willing to settle for mediocre results just as long as they aren't *awful*.

[13]:
```
# Use model coefficients as indices of each feature's relative importance
importance = skmodel_price.coef_

# Summarize feature importance
for i in range(len(importance)):
    report = "Feature: {0}\nImportance: {1}\n\n".format(predictors[i],␣
↪importance[i])
    print(report)

# Plot feature importance
```

```
plt.figure(figsize=(10,10))
plt.bar([feature for feature in predictors], importance, color='r')
plt.title(label="Feature Importance")
plt.show()
```

```
Feature: GrLivArea
Importance: 0.0007249594741173807


Feature: TotalBsmtSF
Importance: 0.0003985068671344045


Feature: GarageCars
Importance: 0.2928536692144019


Feature: Neighborhood
Importance: 0.005577312901057223


Feature: YearBuilt
Importance: 0.004440440677129587


Feature: OverallQual
Importance: 0.11209727173857073


Feature: Exterior1st
Importance: 0.007666772287712428
```



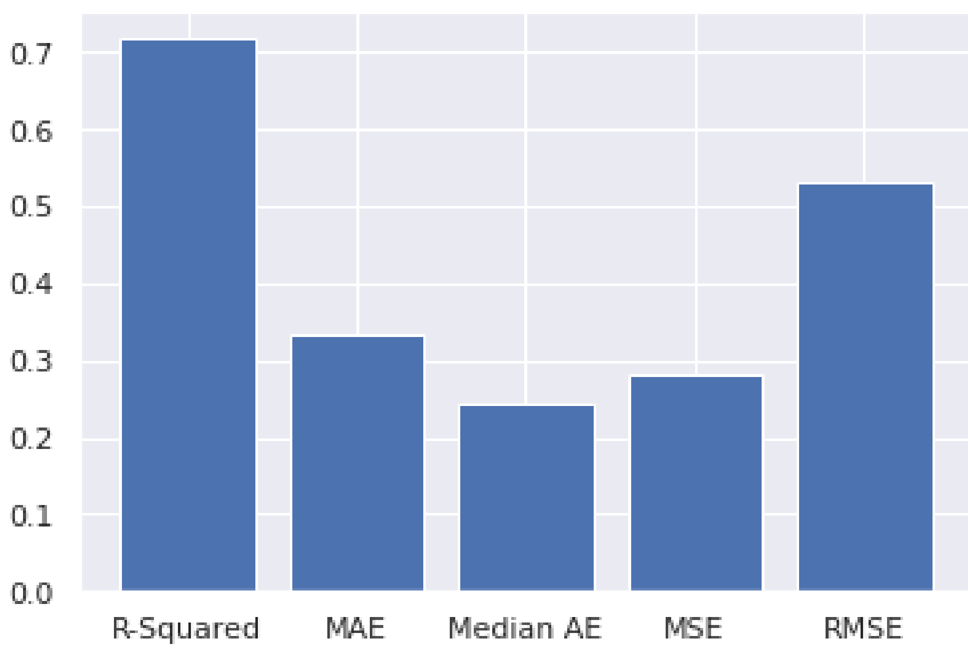
1.4 Part 4: Results & Analysis

[14]:
```
# Regression metrics
mean_absolute_error = sklearn.metrics.mean_absolute_error(dy_test, pred_y)
mse = sklearn.metrics.mean_squared_error(dy_test, pred_y)
median_absolute_error = sklearn.metrics.median_absolute_error(dy_test, pred_y)
r2 = sklearn.metrics.r2_score(dy_test, pred_y)
rmse = np.sqrt(mse)
print('R-Squared: ', round(r2,4))
print('Mean Absolute Error: ', round(mean_absolute_error,4))
print('Median Absolute Error: ', round(median_absolute_error,4))
print('Mean Squared Error: ', round(mse,4))
print('Root Mean Squared Error: ', round(rmse,4))
```

```
metric_names = ['R-Squared', 'Mean Absolute Error', 'Median Absolute Error',␣
 ↪'Mean Squared Error', 'Root Mean Squared Error']
metric_vals = [r2, mean_absolute_error, median_absolute_error, mse,␣
 ↪median_absolute_error, np.sqrt(mse)]
plt.bar(['R-Squared', 'MAE', 'Median AE', 'MSE', 'RMSE'], [r2,␣
 ↪mean_absolute_error, median_absolute_error, mse, rmse])
```

```
R-Squared:  0.7181
Mean Absolute Error:  0.3329
Median Absolute Error:  0.245
Mean Squared Error:  0.2819
Root Mean Squared Error:  0.531
```

[14]:
```
<BarContainer object of 5 artists>
```



As I constructed my multiple linear regression model, I experimented with different combinations of features from the set of possible predictors with which I began. I found, ultimately, that I got the best score when I fit my model using all seven of the features from the set.

In analyzing the results of my predictive model, I decided to just rely upon the four metrics with which I was the most familiar–that is, the R-Squared value (effectively measuring the degree to which the regression line fits the data), the Mean Absolute Error (the mean error between observations and corresponding predictions), the Mean Squared Error (the mean of the squared errors between observations & predictions), and the Root Mean Squared Error (the square root of the mean squared error).

While the calculated R-Squared value of this model was, all things considered, not terrible, it's probably worth pointing out that the value calculated here was not the *adjusted* R-squared value. As such, this model may have been overfitted at least to some degree, since the seven independent variables used to produce the model could only have increased the R-squared value. All the same, given how much more greater the coefficients were for the 'Overall Quality' and 'Garage Cars' terms than for the other features, I can't imagine that the inclusion of the other features really made that much of a difference in terms of the model's accuracy.

Of the four error metrics calculated above, I think it is probably sufficient to describe what the Mean Squared Error (MSE) means for the results of this model. It's probably worth pointing out that the mean squared error was calculated based on the normalized Sale Price values–that is, the results of transforming all the sale price values so that they fell between 0 and 1. A MSE of .2865 would be very good (probably *too good*) if the target values were the prices of the homes themselves. For the adjusted target values, this MSE is actually pretty bad–relative to the other results, at least. For reference, I believe that some of the best MSE results I saw hovered around .03. I probably should have spent more time experimenting with different techniques for creating the model, but I wasn't overwhelmingly confident in my ability to implement or even analyze those techniques.

1.5 5. Conclusion

Looking back on the work I did on this project, I think the point that I would most like to highlight is that this project should probably serve as a model for what *not* to do in creating a regressive model. As far as I can tell, everything worked, but my model was nowhere near as effective as it could have been had I taken the time to learn the tools & techniques that would have been necessary to create a better model. To take a broader view–I don't think I developed an especially sophisticated or comprehensive understanding of the main principles of data science throughout my time in this course. If I am to become confident with data science in the future (as I suspect I will eventually have to), I need to spend a lot of time reading up on the principles of statistical analysis before making any serious forays into the field of machine learning.

I only implemented one regressive model here, and while the model appeared to fit the data reasonably well (with an R-squared value of .7181), the mean standard error was fairly high, as well. There was a considerable amount of variation between the sale prices my model predicted and the actual sale prices of the properties in this dataset. What's more, the multi-linear regression technique I implemented here (the scikit-learn LinearRegression method) was a fairly basic one which we had previously covered in a homework assignment. When I looked through the notebooks of competition participants who had scored better, I didn't find any impressive results which relied upon the technique I utilized in this project.

Notwithstanding the weaknesses of my model, it would appear that I was at least able to identify two features which can serve as fairly good predictors of residential sale prices–the overall quality of the home, and the number of cars the garage can hold. This makes intuitive sense; homes which are considered "better," for one reason or another, are of course going to be in higher demand and are going to be appraised more favorably. I do think, though, that a 1 to 10 integral scale for rating the quality of a home is inherently subjective, and as such I think that features of a property which are more easily identified/calculated have better potential as predictors of the home's selling price. If the factors that go into to producing quality ratings for these properties could be seen directly, then we could probably have a better sense of what affects the home price–though then again, that much is probably obvious. There was probably strong multicollinearity between the overall quality rating and the sale price of the properties, but I did not examine the multicollinearity of categorical variables in my exploratory data analysis, so that was a possibility I didn't really consider until it was too late.

If I were to improve this project, I would probably focus on experimenting with other techniques for creating multi-linear regression models. Due to my brutal and foolhardy courseload this semester, I didn't really have the time to devote to this project that I would have needed to produce something that was actually insightful. The information I gleaned from other submissions to this Kaggle competition indicated that some techniques were particularly efficacious, but I simply wasn't confident that I would be able to figure out how to use those techniques, and I was almost certain that I would be unable to analyze my results properly when and if I had implemented said techniques. Part 3 of my project was, in my opinion, the most critical component of this project, but it was also where my performance was the weakest. I feel like I did a fairly competent job cleaning my dataset and exploring it through visualizations, but I felt like I had struggled so much with implementing the regression techniques in the homeworks that trying to work through even one unfamiliar technique would be a waste of previous time and effort.

I do think this project was useful for me, inasmuch as it allowed me to practice some of the techniques for working with important Python libraries like Pandas and matplotlib. As far as enhancing my understanding of multi-linear regression, however, I did not challenge myself enough to expand the horizons of my data science knowledge in any meaningful way. I essentially treated this project as a longer, more thorough homework assignment, and I'm sure the results of my model reflect this. I did put in a lot of work to try to make this model work well, and I can assure my evaluators that the poor performance of my model is not for lack of trying–only for lack of understanding. If ignorance is a sin, then I am Satan, but I did do my best to make this work, and in spite of the .2865 mean squared arreor value of which I am so very embarassed, I have no choice but to take pride in what I *did* manage to implement properly and was I *did* manage to learn in the course of this class.

```
[ ]:
```