Problem Statement

A US-based housing company named Surprise Housing has decided to enter the Australian market. The company uses data analytics to purchase houses at a price below their actual values and flip them on at a higher price. For the same purpose, the company has collected a data set from the sale of houses in Australia. The data is provided in the CSV file below.

The company is looking at prospective properties to buy to enter the market. You are required to build a regression model using regularisation in order to predict the actual value of the prospective properties and decide whether to invest in them or not.

The company wants to know:

- Which variables are significant in predicting the price of a house, and
- How well those variables describe the price of a house.

Also, determine the optimal value of lambda for ridge and lasso regression.

Business Goal

You are required to model the price of houses with the available independent variables. This model will then be used by the management to understand how exactly the prices vary with the variables. They can accordingly manipulate the strategy of the firm and concentrate on areas that will yield high returns. Further, the model will be a good way for management to understand the pricing dynamics of a new market.

In [531]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

from sklearn.preprocessing import StandardScaler

from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV

from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import LinearRegression

from sklearn.pipeline import make_pipeline
from sklearn import metrics


# Data display coustomization
pd.set_option('display.max_rows', 2000)
pd.set_option('display.max_columns', 100)

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

Data Visualization and Understanding

In [532]:
```
housing_df = pd.read_csv("train.csv")
housing_df.shape
```

Out[532]:
```
(1460, 81)
```

In [453]:
```
housing_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
Id               1460 non-null int64
MSSubClass       1460 non-null int64
MSZoning         1460 non-null object
LotFrontage      1201 non-null float64
LotArea          1460 non-null int64
Street           1460 non-null object
Alley            91 non-null object
LotShape         1460 non-null object
LandContour      1460 non-null object
Utilities        1460 non-null object
LotConfig        1460 non-null object
LandSlope        1460 non-null object
Neighborhood     1460 non-null object
Condition1       1460 non-null object
Condition2       1460 non-null object
BldgType         1460 non-null object
HouseStyle       1460 non-null object
OverallQual      1460 non-null int64
OverallCond      1460 non-null int64
YearBuilt        1460 non-null int64
YearRemodAdd     1460 non-null int64
RoofStyle        1460 non-null object
RoofMatl         1460 non-null object
Exterior1st      1460 non-null object
Exterior2nd      1460 non-null object
MasVnrType       1452 non-null object
MasVnrArea       1452 non-null float64
ExterQual        1460 non-null object
ExterCond        1460 non-null object
Foundation       1460 non-null object
BsmtQual         1423 non-null object
BsmtCond         1423 non-null object
BsmtExposure     1422 non-null object
BsmtFinType1     1423 non-null object
BsmtFinSF1       1460 non-null int64
BsmtFinType2     1422 non-null object
BsmtFinSF2       1460 non-null int64
BsmtUnfSF        1460 non-null int64
TotalBsmtSF      1460 non-null int64
Heating          1460 non-null object
HeatingQC        1460 non-null object
CentralAir       1460 non-null object
Electrical       1459 non-null object
1stFlrSF         1460 non-null int64
2ndFlrSF         1460 non-null int64
LowQualFinSF     1460 non-null int64
GrLivArea        1460 non-null int64
BsmtFullBath     1460 non-null int64
BsmtHalfBath     1460 non-null int64
FullBath         1460 non-null int64
HalfBath         1460 non-null int64
BedroomAbvGr     1460 non-null int64
KitchenAbvGr     1460 non-null int64
KitchenQual      1460 non-null object
TotRmsAbvGrd     1460 non-null int64
Functional       1460 non-null object
Fireplaces       1460 non-null int64
FireplaceQu      770 non-null object
GarageType       1379 non-null object
GarageYrBlt      1379 non-null float64
```

In [533]:
```
# Checking how many are categorial and how many numeric variable in the giv
en data-set
# to make sure this falls inline with the data-dictionary
housing_categorical=housing_df.select_dtypes(include=['object'])
housing_numeric=housing_df.select_dtypes(include=np.number)
print("categorical_vars:" + str(housing_categorical.columns))
print("numeric_vars:" +  str(housing_numeric.columns))
```

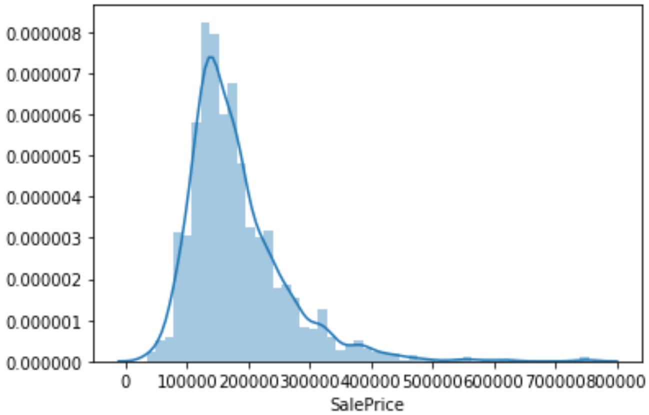
```
categorical_vars:Index(['MSZoning', 'Street', 'Alley', 'LotShape', 'LandCon
tour', 'Utilities',
       'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Condition2'
,
       'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st',
       'Exterior2nd', 'MasVnrType', 'ExterQual', 'ExterCond', 'Foundation',
       'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType
2',
       'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual',
       'Functional', 'FireplaceQu', 'GarageType', 'GarageFinish', 'GarageQu
al',
       'GarageCond', 'PavedDrive', 'PoolQC', 'Fence', 'MiscFeature',
       'SaleType', 'SaleCondition'],
      dtype='object')
numeric_vars:Index(['Id', 'MSSubClass', 'LotFrontage', 'LotArea', 'OverallQ
ual',
       'OverallCond', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF
1',
       'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBa
th',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd',
       'Fireplaces', 'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF
',
       'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolAre
a',
       'MiscVal', 'MoSold', 'YrSold', 'SalePrice'],
      dtype='object')
```

Check if the data is normally distributed against target variable `SalePrice`

In [455]:
```
housing_df['SalePrice'].describe().round(2)
```

Out[455]:
```
count      1460.0
mean     180921.2
std       79442.5
min       34900.0
25%      129975.0
50%      163000.0
75%      214000.0
max      755000.0
Name: SalePrice, dtype: float64
```

In [456]:
```
# from the dist plot it we can see price column is not normally distributed
, the Gussian curve is scewed towards left
sns.distplot(housing_df['SalePrice'])
#plt.hist(housing_df['SalePrice'])
plt.show()
```



Doing a normality test on target variable `SalePrice` using `Shapiro-Wilk` normality test from scipy module

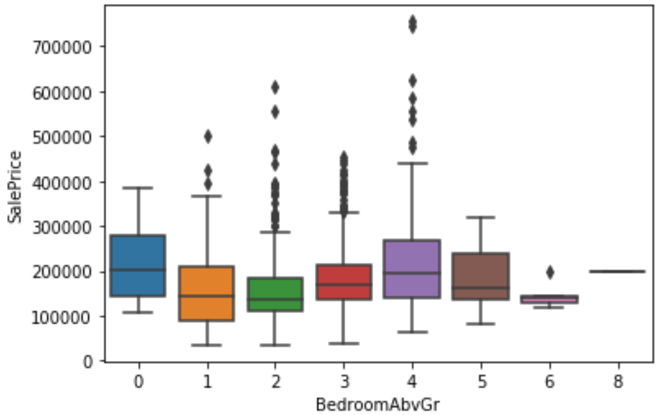
In [457]:
```
# perform normality test on target variable sale price
from scipy.stats import shapiro
def normality_test_price():
    stat,p = shapiro(housing_df['SalePrice'])
    alpha=0.05
    print('Statistics=%.3f, p=%.3f' % (stat, p))
    if p > alpha:
        print('SalePrice looks following Gaussian (fail to reject Null Hypo
thesis H0)')
    else:
        print('SalePrice does not look following Gaussian (reject Null Hypo
thesis H0)')

normality_test_price()
```

```
Statistics=0.870, p=0.000
SalePrice does not look following Gaussian (reject Null Hypothesis H0)
```

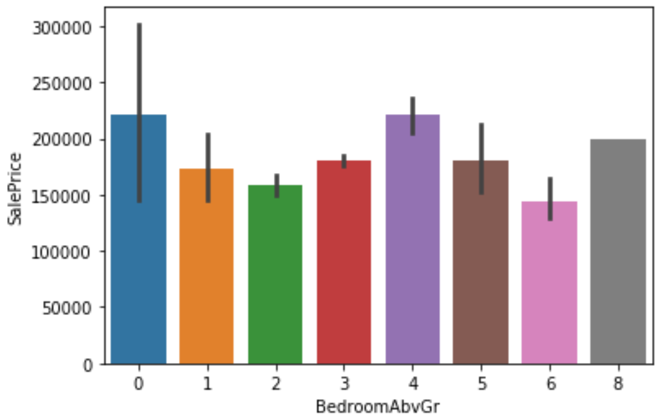
In [458]:
```
# lets see how house price varies based on number of bedroom above garage
housing_df['BedroomAbvGr'].value_counts()
```

Out[458]:
```
3    804
2    358
4    213
1     50
5     21
6      7
0      6
8      1
Name: BedroomAbvGr, dtype: int64
```

In [326]:
```
sns.boxplot(x='BedroomAbvGr',y='SalePrice', data=housing_df)
plt.show()
```



In [327]:
```
sns.barplot(x='BedroomAbvGr',y='SalePrice', data=housing_df)
plt.show()
```

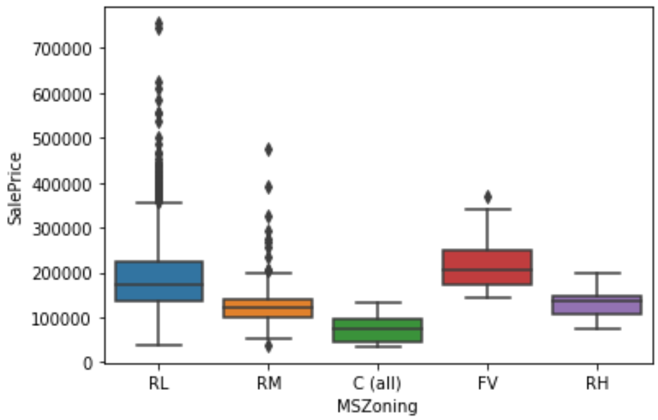


Looks like there is could be some data imbalance in the data set. Ideally house price should increase as number of bedroom increases. Here the trend is beyond 4 bedrooms the house price is not creasing. There culd be multiple reason for that. One reason could be locality/neighbourhood as well.

In [11]:
```
# MSZoning: Identifies the general zoning classification of the sale
housing_df['MSZoning'].value_counts()
```

Out[11]:
```
RL         1151
RM          218
FV           65
RH           16
C (all)      10
Name: MSZoning, dtype: int64
```

In [15]:
```
# Visualize how zoning relate to the target variable SalePrice
sns.boxplot(x=housing_df['MSZoning'],y=housing_df['SalePrice'])
plt.show()
```

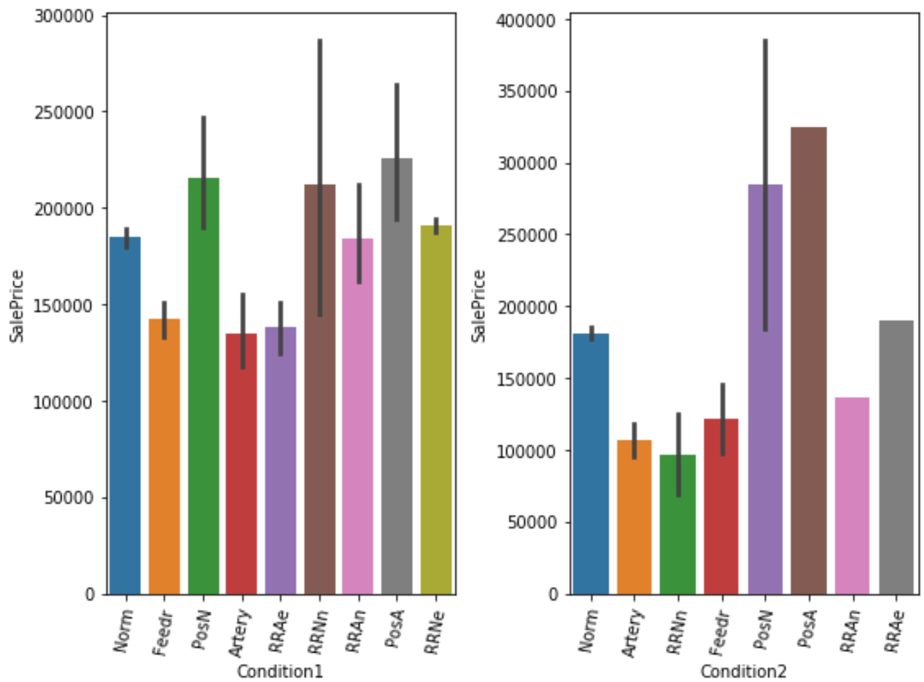


Most of the price distribution based on zoning category are lying within 400K mark. Very few residential property price is significantly high. We might need to consider those as `outliers` later.

In [19]:
```
# Utilities: Type of utilities available
housing_df['Utilities'].value_counts()
```

Out[19]:
```
AllPub    1459
NoSeWa       1
Name: Utilities, dtype: int64
```

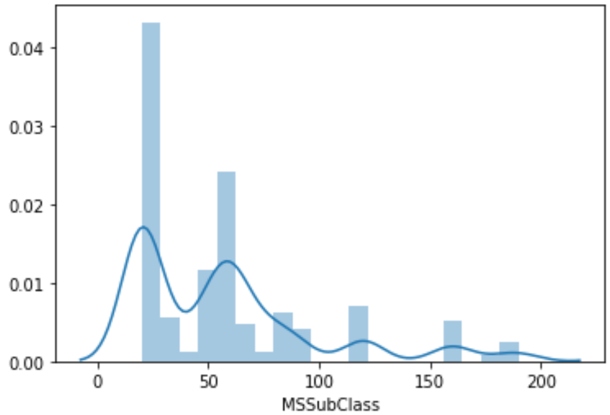
In [27]:
```
# Lets see how contision's are effecting sale price if any to understand if
this a important factor to decide upon pricing
plt.figure(figsize=(8, 6))
plt.subplot(1,2,1)
sns.barplot(y='SalePrice',x='Condition1',data=housing_df)
plt.xticks(rotation=80)

plt.subplot(1,2,2)
sns.barplot(y='SalePrice',x='Condition2',data=housing_df)
plt.xticks(rotation=80)

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



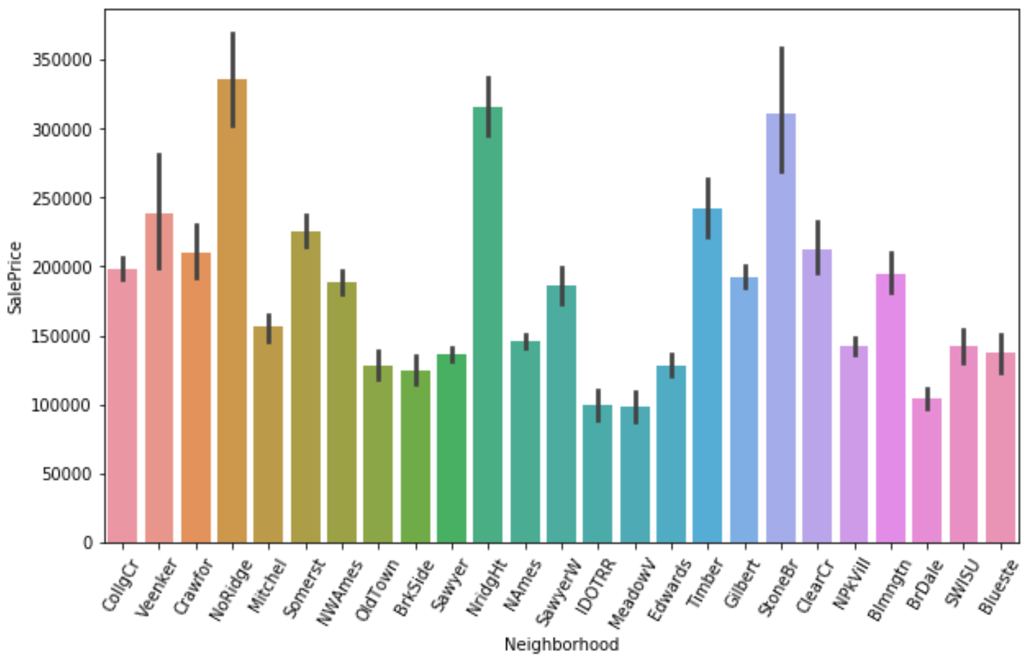
In [33]:
```
# MSSubClass: Identifies the type of dwelling involved in the sale
housing_df['MSSubClass'].value_counts()
```

Out[33]:
```
20     536
60     299
50     144
120     87
30      69
160     63
70      60
80      58
90      52
190     30
85      20
75      16
45      12
180     10
40       4
Name: MSSubClass, dtype: int64
```

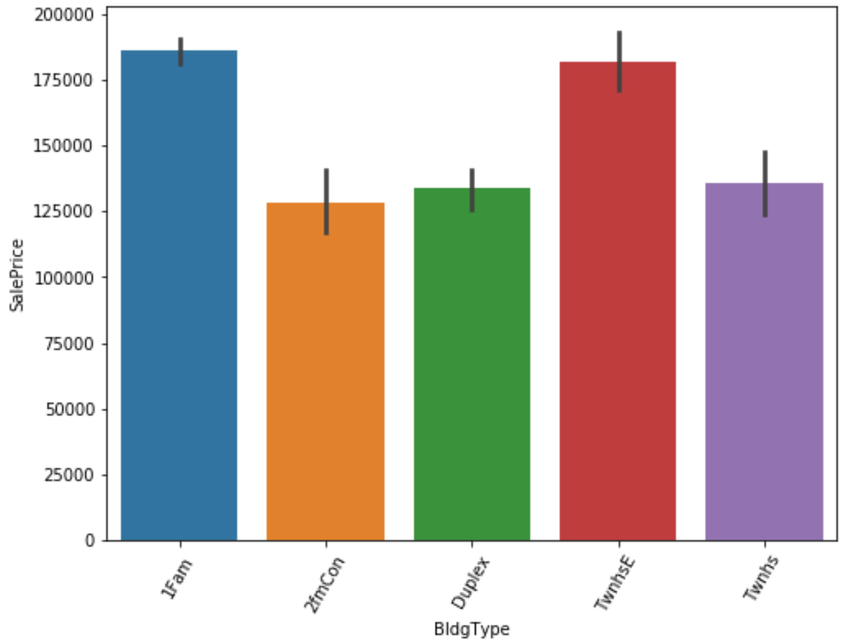
In [34]:
```
sns.distplot(housing_df['MSSubClass'])
plt.show()
```



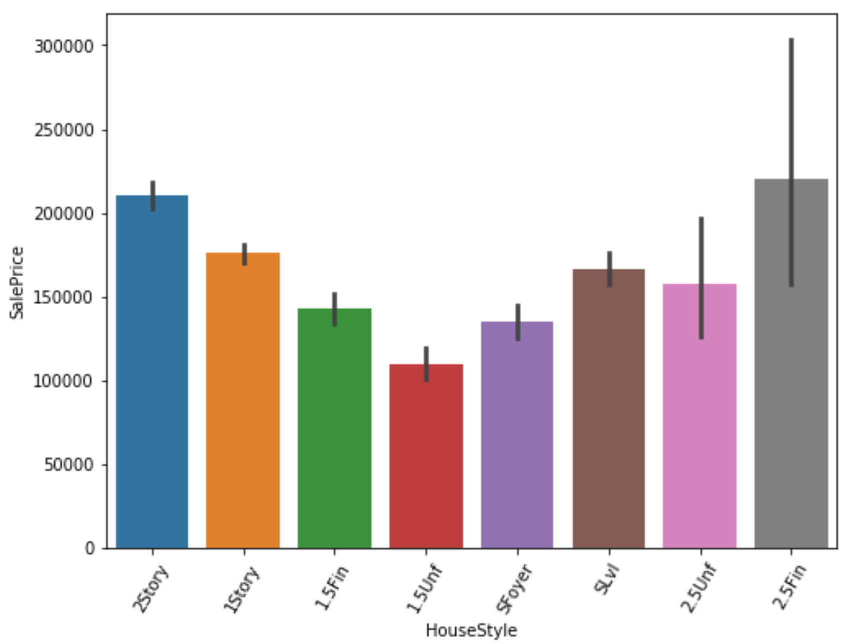
In [35]:
```
# Neighborhood: Physical locations within Ames city limits
plt.figure(figsize=(10, 6))
sns.barplot(y='SalePrice',x='Neighborhood',data=housing_df)
plt.xticks(rotation=60)
plt.show()
```



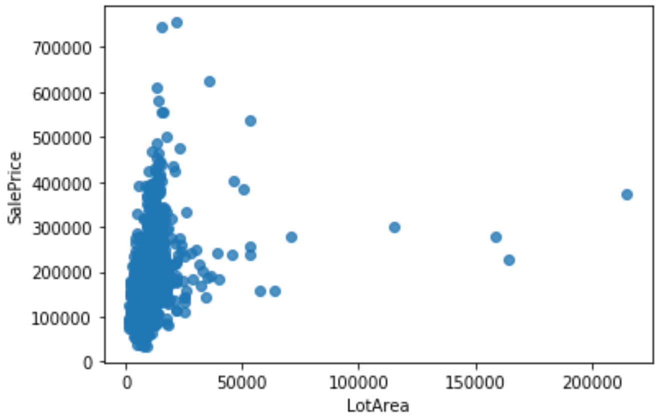
In [36]:
```
# BldgType: Type of dwelling
plt.figure(figsize=(8, 6))
sns.barplot(y='SalePrice',x='BldgType',data=housing_df)
plt.xticks(rotation=60)
plt.show()
```



In [37]:
```
# HouseStyle: Style of dwelling
plt.figure(figsize=(8, 6))
sns.barplot(y='SalePrice',x='HouseStyle',data=housing_df)
plt.xticks(rotation=60)
plt.show()
```



In [38]:
```
# LotArea: Lot size in square feet
# visualise area-price relationship
sns.regplot(x="LotArea", y="SalePrice", data=housing_df, fit_reg=False)
plt.show()
```



Data Exploration

To perform linear regression, the (numeric) target variable should be linearly related to *at least one another numeric variable*. Let's see whether that's true in this case.

We'll first subset the list of all (independent) numeric variables, and then make a **heatmap**

In [459]:
```
# all numeric (float and int) variables in the dataset
housing_numeric = housing_df.select_dtypes(include=['float64', 'int64'])
housing_numeric.head()
```

Out[459]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea
0	1	60	65.0	8450	7	5	2003	2003	196.0
1	2	20	80.0	9600	6	8	1976	1976	0.0
2	3	60	68.0	11250	7	5	2001	2002	162.0
3	4	70	60.0	9550	7	5	1915	1970	0.0
4	5	60	84.0	14260	8	5	2000	2000	350.0

In [460]:
```
housing_numeric.isnull().sum()
```

Out[460]:
```
Id                 0
MSSubClass         0
LotFrontage      259
LotArea            0
OverallQual        0
OverallCond        0
YearBuilt          0
YearRemodAdd       0
MasVnrArea         8
BsmtFinSF1         0
BsmtFinSF2         0
BsmtUnfSF          0
TotalBsmtSF        0
1stFlrSF           0
2ndFlrSF           0
LowQualFinSF       0
GrLivArea          0
BsmtFullBath       0
BsmtHalfBath       0
FullBath           0
HalfBath           0
BedroomAbvGr       0
KitchenAbvGr       0
TotRmsAbvGrd       0
Fireplaces         0
GarageYrBlt       81
GarageCars         0
GarageArea         0
WoodDeckSF         0
OpenPorchSF        0
EnclosedPorch      0
3SsnPorch          0
ScreenPorch        0
PoolArea           0
MiscVal            0
MoSold             0
YrSold             0
SalePrice          0
dtype: int64
```

We can drop `GarageYrBlt` and `LotFrontage` variables as from the data dictionary these does not sounds to impact much in our model

In [534]:
```
# dropping GarageYrBlt and LotFrontage along with ID
housing_numeric = housing_numeric.drop(['LotFrontage','Id','GarageYrBlt'],
axis=1)
```

In [493]:
```
housing_numeric['PoolArea'].value_counts()
```

Out[493]:
```
0      1453
738       1
648       1
576       1
555       1
519       1
512       1
480       1
Name: PoolArea, dtype: int64
```

In [42]:
```
housing_numeric['ScreenPorch'].value_counts()
```

Out[42]:
```
0      1344
192       6
224       5
120       5
189       4
       ... 
182       1
440       1
178       1
312       1
480       1
Name: ScreenPorch, Length: 76, dtype: int64
```

In [43]:
```
housing_numeric['3SsnPorch'].value_counts()
```

Out[43]:
```
0      1436
168       3
216       2
144       2
180       2
245       1
238       1
290       1
196       1
182       1
407       1
304       1
162       1
153       1
320       1
140       1
130       1
96        1
23        1
508       1
Name: 3SsnPorch, dtype: int64
```

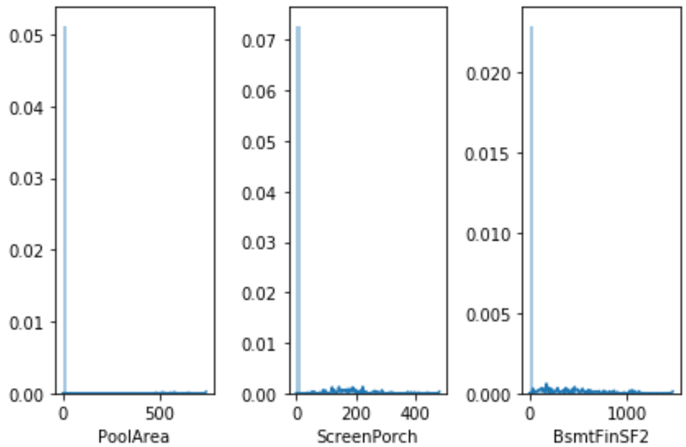
As per data dictionary definition the variables `3SsnPorch` , `ScreenPorch` , `PoolArea` should have values in feet. But for most the data points these are having 0 feet which suggests either the corresponding property does not have these facilities or it has missing value. Probably we can drop such columns where majority of the value is '0'. These variables won't be significant enough for genelizing the housing price prediction.

In [535]:
```
# replacing the value 0 with NaN to find how much percentage of such 0 valu
e variables are there
for col in housing_numeric.columns:
    #print(col)
    housing_numeric[col].replace(0,np.NaN,inplace=True)
#housing_numeric.isnull().sum()
```

In [536]:
```
nullcols=(100*(housing_numeric.isnull().sum()/len(housing_numeric.index)).r
ound(2)).sort_values(ascending=False)
nullcols[nullcols>0]
```

Out[536]:
```
PoolArea         100.0
3SsnPorch         98.0
LowQualFinSF      98.0
MiscVal           96.0
BsmtHalfBath      94.0
ScreenPorch       92.0
BsmtFinSF2        89.0
EnclosedPorch     86.0
HalfBath          63.0
MasVnrArea        60.0
BsmtFullBath      59.0
2ndFlrSF          57.0
WoodDeckSF        52.0
Fireplaces        47.0
OpenPorchSF       45.0
BsmtFinSF1        32.0
BsmtUnfSF          8.0
GarageCars         6.0
GarageArea         6.0
TotalBsmtSF        3.0
FullBath           1.0
dtype: float64
```

In [357]:
```
# for example check the distribusion of PoolArea, ScreenPorch, BsmtFinSF2 f
rom original data set
#plt.figure(figsize=(8, 6))
plt.subplot(1,3,1)
sns.distplot(housing_df['PoolArea'])

plt.subplot(1,3,2)
sns.distplot(housing_df['ScreenPorch'])

plt.subplot(1,3,3)
sns.distplot(housing_df['BsmtFinSF2'])
plt.tight_layout()
plt.show()
```



From the above analysis we can clearly drop columns where encoded NaN for corresponding 0 value is more than 89% in data set

In [407]:
```
nullcols[nullcols>88]
#
```

Out[407]:
```
PoolArea        100.0
3SsnPorch        98.0
LowQualFinSF     98.0
MiscVal          96.0
BsmtHalfBath     94.0
ScreenPorch      92.0
BsmtFinSF2       89.0
dtype: float64
```

In [537]:
```
housing_numeric.drop(columns=['PoolArea','3SsnPorch','LowQualFinSF','MiscVa
l','BsmtHalfBath','ScreenPorch','BsmtFinSF2'],
                     axis=1,inplace=True)
```

In [538]:
```
# Now check for other null/missing values
nullcols=housing_numeric.isnull().sum()
nullcols[nullcols>0]
```

Out[538]:
```
MasVnrArea        869
BsmtFinSF1        467
BsmtUnfSF         118
TotalBsmtSF        37
2ndFlrSF          829
BsmtFullBath      856
FullBath            9
HalfBath          913
BedroomAbvGr        6
KitchenAbvGr        1
Fireplaces        690
GarageCars         81
GarageArea         81
WoodDeckSF        761
OpenPorchSF       656
EnclosedPorch    1252
dtype: int64
```

In [410]:
```
#housing_numeric['EnclosedPorch'].median()
housing_numeric['BsmtFullBath'].mean()
```

Out[410]:
```
1.0281456953642385
```

In [539]:
```
# impute the null/missing values with median of the corresponding data poin
ts
for col in nullcols.index:
    housing_numeric[col].fillna(housing_numeric[col].median(), inplace=True
)
nullcols=housing_numeric.isnull().sum()
nullcols[nullcols>0]
```

Out[539]:
```
Series([], dtype: int64)
```

There are few variables which has `year` column. We need to encode the year column to include that into the model creation, otherwise year values such as 1995, 2000, 1970 etc mignt effect the overall model performance. We can get a diff of these year column from the current year 2019 and process those

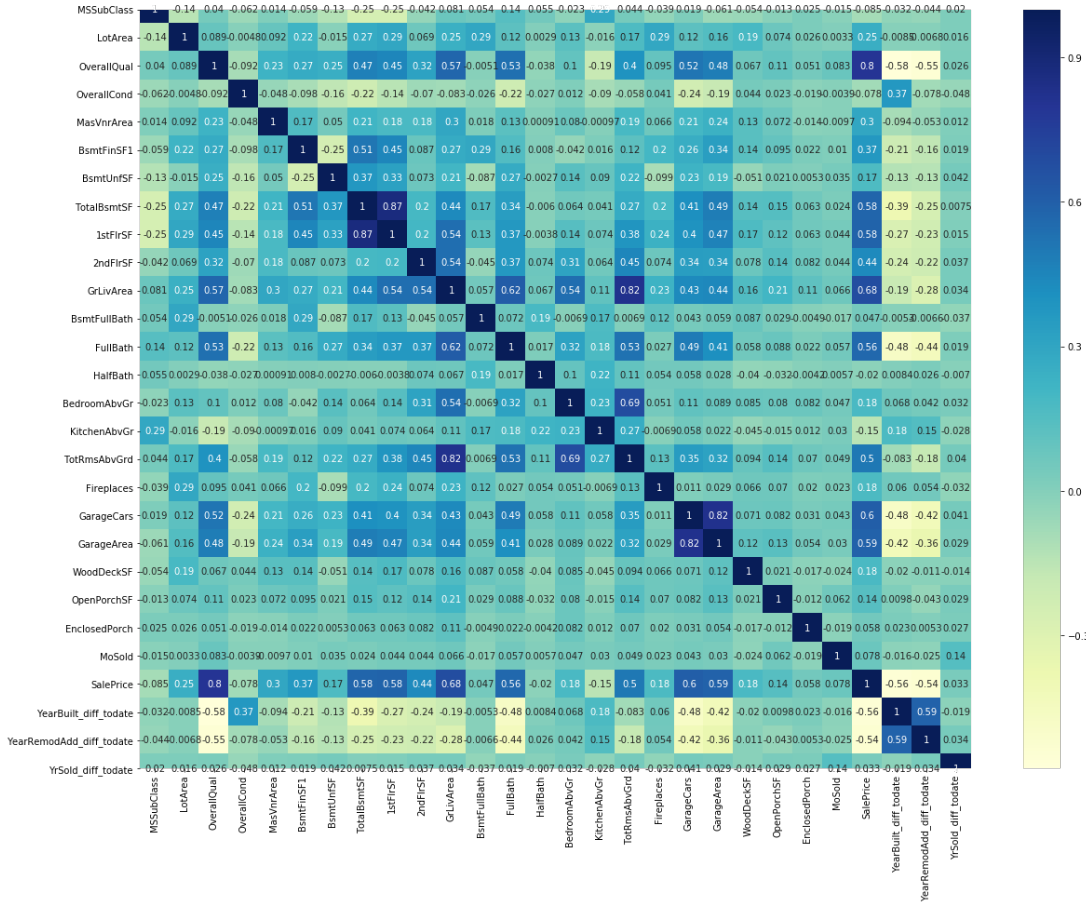
In [540]:
```
# processing year columns
for yrCol in housing_numeric.columns:
    if str(yrCol).startswith('Year') or str(yrCol).startswith('Yr'):
        #print(yrCol)
        housing_numeric[yrCol]=housing_numeric[yrCol].astype(int)
        housing_numeric[yrCol+str('_diff_todate')]=housing_numeric[yrCol].a
pply(lambda x: int(2019)-int(x))
        housing_numeric.drop(columns=[yrCol],axis=1,inplace=True)
housing_numeric.head()
```

Out[540]:

	MSSubClass	LotArea	OverallQual	OverallCond	MasVnrArea	BsmtFinSF1	BsmtUnfSF	TotalBsmtSF	1stI
0	60	8450	7	5	196.0	706.0	150.0	856.0	
1	20	9600	6	8	203.0	978.0	284.0	1262.0	
2	60	11250	7	5	162.0	486.0	434.0	920.0	
3	70	9550	7	5	203.0	216.0	540.0	756.0	
4	60	14260	8	5	350.0	655.0	490.0	1145.0	

In [421]:
```
# check the heatmap now for correlation of numeric variables
cor = housing_numeric.corr()
#cor
```

In [422]:
```
# figure size
plt.figure(figsize=(20,15))

# heatmap
sns.heatmap(cor, cmap="YlGnBu", annot=True)
plt.show()
```



We can see SalesPrice has high corelation with variables like

- GarageArea: Size of garage in square feet
- GarageCars: Size of garage in car capacity
- GrLivArea: Above grade (ground) living area square feet
- 1stFlrSF: First Floor square feet
- 2ndFlrSF: Second floor square feet

There are multicolinearity as well like GarageCars highly correlated with GarageArea which is obvious

In [541]:
```
# check the null/missing values in categorical variables
nullcols=housing_categorical.isnull().sum()
nullcols[nullcols>0]
```

Out[541]:
```
Alley           1369
MasVnrType         8
BsmtQual          37
BsmtCond          37
BsmtExposure      38
BsmtFinType1      37
BsmtFinType2      38
Electrical         1
FireplaceQu      690
GarageType        81
GarageFinish      81
GarageQual        81
GarageCond        81
PoolQC          1453
Fence           1179
MiscFeature     1406
dtype: int64
```

In [542]:
```
#drop the columns which has high count of null or missing values
housing_categorical.drop(columns=['Alley','Fence','PoolQC','MiscFeature'],
axis=1, inplace=True)
```

In [544]:
```
nullcols=housing_categorical.isnull().sum()
nullcols[nullcols>0]
```

Out[544]:
```
MasVnrType       8
BsmtQual        37
BsmtCond        37
BsmtExposure    38
BsmtFinType1    37
BsmtFinType2    38
Electrical       1
FireplaceQu    690
GarageType      81
GarageFinish    81
GarageQual      81
GarageCond      81
dtype: int64
```

Except `Electrical` all the other above variables can be imputed with no value like 'NA' or 'None'

In [545]:
```
null_col_to_impute=nullcols[nullcols>1]
for col in null_col_to_impute.index:
    if col == "MasVnrType":
        housing_categorical[col].fillna("None", inplace=True)
    else:
        housing_categorical[col].fillna("NA", inplace=True)
```

In [546]:
```
nullcols=housing_categorical.isnull().sum()
nullcols[nullcols>0]
```

Out[546]:
```
Electrical    1
dtype: int64
```

In [547]:
```
housing_categorical['Electrical'].value_counts()
```

Out[547]:
```
SBrkr    1334
FuseA      94
FuseF      27
FuseP       3
Mix         1
Name: Electrical, dtype: int64
```

In [548]:
```
# Imputing the row with Unknown for missing value for E;ectrical variable
#housing_categorical=housing_categorical[~np.isnan(housing_categorical['Ele
ctrical'])]
housing_categorical['Electrical'].fillna('Unknown', inplace=True)
```

There are rating or quality related categorical variable whose values are having abbreviation like Ex for Excellent, Gd for Good etc. Where as the similar numerical variables like `OverallQual` , `OverallCond` has integer values for such ratings. We should encode such categorical variables like `ExterQual` , `ExterCond` , `BsmtQual` , `BsmtCond` etc in numeric format like `OverallQual` , `OverallCond` .

In [430]:
```
housing_categorical['BsmtQual'].value_counts()
```

Out[430]:
```
TA    649
Gd    618
Ex    121
NA     37
Fa     35
Name: BsmtQual, dtype: int64
```

In [431]:
```
housing_categorical['FireplaceQu'].value_counts()
```

Out[431]:
```
NA    690
Gd    380
TA    313
Fa     33
Ex     24
Po     20
Name: FireplaceQu, dtype: int64
```

In [549]:
```
print(housing_categorical.shape[1])
print(housing_numeric.shape[1])
```

```
39
28
```

In [550]:
```
varlist =  ['BsmtQual', 'BsmtCond', 'ExterQual','ExterCond',
            'FireplaceQu','KitchenQual','HeatingQC']

# Defining the map function
def encode_cat_to_numeric(x):
    return x.map({'Ex': 9, "Gd": 7, "TA": 5, 'Fa': 3, 'NA': 0, 'Po': 2})

# Applying the function to the housing list
housing_numeric[varlist] = housing_categorical[varlist].apply(encode_cat_to
_numeric)
for var in varlist:
    housing_numeric[var]=housing_numeric[var].astype(int)
    housing_categorical.drop([var], axis=1, inplace=True)

print(housing_categorical.shape[1])
print(housing_numeric.shape[1])
```

```
32
35
```

Data preparation

Now its time to process the categorical variables by creating dummies

In [552]:
```
housing_dummies = pd.get_dummies(housing_categorical, drop_first=True)
housing_dummies.tail()
```

Out[552]:

	MSZoning_FV	MSZoning_RH	MSZoning_RL	MSZoning_RM	Street_Pave	LotShape_IR2	LotShape_IR3
1455	0	0	1	0	1	0	0
1456	0	0	1	0	1	0	0
1457	0	0	1	0	1	0	0
1458	0	0	1	0	1	0	0
1459	0	0	1	0	1	0	0

5 rows × 184 columns

In [553]:
```
housing_dummies.shape
```

Out[553]: (1460, 184)

In [562]:
```
# Concatenating all processed numerical and processed dummies for categoric
al
# This is the data set we will use going forward for model building
model_df = pd.concat([housing_numeric, housing_dummies], axis=1)
model_df.shape
```

Out[562]: (1460, 219)

In [561]:
```
model_df.isnull().sum()
```

Out[561]:
```
MSSubClass                 14
LotArea                    14
OverallQual                14
OverallCond                14
MasVnrArea                 14
BsmtFinSF1                 14
BsmtUnfSF                  14
TotalBsmtSF                14
1stFlrSF                   14
2ndFlrSF                   14
GrLivArea                  14
BsmtFullBath               14
FullBath                   14
HalfBath                   14
BedroomAbvGr               14
KitchenAbvGr               14
TotRmsAbvGrd               14
Fireplaces                 14
GarageCars                 14
GarageArea                 14
WoodDeckSF                 14
OpenPorchSF                14
EnclosedPorch              14
MoSold                     14
SalePrice                  14
YearBuilt_diff_todate      14
YearRemodAdd_diff_todate   14
YrSold_diff_todate         14
BsmtQual                   14
BsmtCond                   14
ExterQual                  14
ExterCond                  14
FireplaceQu                14
KitchenQual                14
HeatingQC                  14
MSZoning_FV                14
MSZoning_RH                14
MSZoning_RL                14
MSZoning_RM                14
Street_Pave                14
LotShape_IR2               14
LotShape_IR3               14
LotShape_Reg               14
LandContour_HLS            14
LandContour_Low            14
LandContour_Lvl            14
Utilities_NoSeWa           14
LotConfig_CulDSac          14
LotConfig_FR2              14
LotConfig_FR3              14
LotConfig_Inside           14
LandSlope_Mod              14
LandSlope_Sev              14
Neighborhood_Blueste       14
Neighborhood_BrDale        14
Neighborhood_BrkSide       14
Neighborhood_ClearCr       14
Neighborhood_CollgCr       14
Neighborhood_Crawfor       14
Neighborhood_Edwards       14
Neighborhood_Gilbert       14
Neighborhood_IDOTRR        14
Neighborhood_MeadowV       14
```

In [564]:
```
# because of the concat for some reason I'm getting 14 rows of NaN values i
n the merged data set model_df
# to adjust removing those rows
model_df=model_df[~np.isnan(model_df['MSSubClass'])]
#model_df.isnull().sum()
```

In [570]:
```
model_df.shape
```

Out[570]:
```
(1460, 219)
```

In [565]:
```
# split X and y
y = model_df.loc[:, 'SalePrice']
X = model_df.loc[:, model_df.columns != 'SalePrice']
```

In [566]:
```
# Scale the features using StnadardScaler
# scale
scaler = StandardScaler()
#scaler.fit(X)
scaler.fit_transform(X)
```

Out[566]:
```
array([[ 0.07337496, -0.20714171,  0.65147924, ..., -0.11785113,
         0.4676514 , -0.30599503],
       [-0.87256276, -0.09188637, -0.07183611, ..., -0.11785113,
         0.4676514 , -0.30599503],
       [ 0.07337496,  0.07347998,  0.65147924, ..., -0.11785113,
         0.4676514 , -0.30599503],
       ...,
       [ 0.30985939, -0.14781027,  0.65147924, ..., -0.11785113,
         0.4676514 , -0.30599503],
       [-0.87256276, -0.08016039, -0.79515147, ..., -0.11785113,
         0.4676514 , -0.30599503],
       [-0.87256276, -0.05811155, -0.79515147, ..., -0.11785113,
         0.4676514 , -0.30599503]])
```

In [567]:
```
# split into train and test set
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    train_size=0.7,
                                                    test_size = 0.3, random
_state=100)
```

Model Building and Evaluation

Building models usoing both Ridge and Lasso technique

Ridge Regression

In [581]:

```
def ridge_n_lasso(ml_algo):
    # list of alphas to tune
    params = {'alpha': [0.0001, 0.001, 0.01, 0.05, 0.1,
 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 2.0, 3.0,
 4.0, 5.0, 6.0, 7.0, 8.0, 9.0, 10.0, 20, 25, 40, 50]}

    # cross validation
    #folds = 5
    # creating a KFold object with 5 splits
    folds = KFold(n_splits = 5, shuffle = True, random_state = 100)

    model_ridge = GridSearchCV(estimator = ml_algo,
                        param_grid = params,
                        scoring= 'neg_mean_absolute_error',
                        cv = folds,
                        return_train_score=True,
                        verbose = 1)
    return model_ridge
```

In [582]:

```
ridge = Ridge()
model_ridge=ridge_n_lasso(ridge)
model_ridge.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 27 candidates, totalling 135 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent wor
kers.
[Parallel(n_jobs=1)]: Done 135 out of 135 | elapsed:    2.5s finished
```

Out[582]:

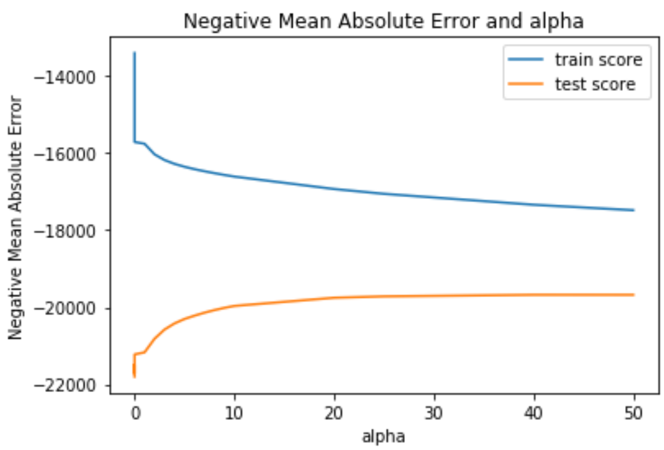
```
GridSearchCV(cv=KFold(n_splits=5, random_state=100, shuffle=True),
             error_score='raise-deprecating',
             estimator=Ridge(alpha=1.0, copy_X=True, fit_intercept=True,
                             max_iter=None, normalize=False, random_state=N
one,
                             solver='auto', tol=0.001),
             iid='warn', n_jobs=None,
             param_grid={'alpha': [0.0001, 0.001, 0.01, 0.05, 0.1, 0.2, 0.3
,
                                   0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 2.0,
3.0,
                                   4.0, 5.0, 6.0, 7.0, 8.0, 9.0, 10.0, 20,
25,
                                   40, 50]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
             scoring='neg_mean_absolute_error', verbose=1)
```

In [583]:
```
ridge_results = pd.DataFrame(model_ridge.cv_results_)
ridge_results.head()
```

Out[583]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_alpha	params	split0_test_score	sp
0	0.030818	0.015069	0.006603	0.004493	0.0001	{'alpha': 0.0001}	-22456.054552	
1	0.032220	0.019469	0.003731	0.000899	0.001	{'alpha': 0.001}	-22453.360296	
2	0.012295	0.001765	0.003154	0.000602	0.01	{'alpha': 0.01}	-22427.176359	
3	0.008849	0.000643	0.002434	0.000126	0.05	{'alpha': 0.05}	-22295.478273	
4	0.009133	0.000930	0.002668	0.000248	0.1	{'alpha': 0.1}	-22114.346561	

In [584]:
```
# plotting cv results
#ridge_results['param_alpha'] = ridge_results['param_alpha'].astype('float'
)
ridge_results['param_alpha'] = ridge_results['param_alpha'].astype('int32')

# plotting
plt.plot(ridge_results['param_alpha'], ridge_results['mean_train_score'])
plt.plot(ridge_results['param_alpha'], ridge_results['mean_test_score'])
plt.xlabel('alpha')
plt.ylabel('Negative Mean Absolute Error')
plt.title("Negative Mean Absolute Error and alpha")
plt.legend(['train score', 'test score'], loc='upper right')
plt.show()
```



We see from the plot that the test negative mean absolute error first increases and then follows a static trend. But the training negative mean absolute error keeps on decreasing as we increase the value of the hyperparameter, which is in accordance with the bias-variance trade-off.

Somewhere between alpha=8-10 test performs peak, hence the final model we would generate with alpha=9 we construct the objective function and re-run the regression algorithm on entire training data. The we can have our final model with optimal features.

In [608]:
```
alpha = 9
ridge = Ridge(alpha=alpha)

ridge.fit(X_train, y_train)
```

Out[608]:
```
Ridge(alpha=9, copy_X=True, fit_intercept=True, max_iter=None, normalize=Fa
lse,
      random_state=None, solver='auto', tol=0.001)
```

In [609]:
```
# ridge predict
y_train_pred = ridge.predict(X_train)
print("ridge train pred r2_score: " + str(metrics.r2_score(y_true=y_train,
y_pred=y_train_pred)))
y_test_pred = ridge.predict(X_test)
print("ridge test pred r2_score: " + str(metrics.r2_score(y_true=y_test, y_
pred=y_test_pred)))
```

```
ridge train pred r2_score: 0.8826345775619088
ridge test pred r2_score: 0.866495729272287
```

In [610]:
```
ridge_df=get_top_important_predictor_var(ridge)
ridge_df.head(5)
```

Out[610]:

	feature	model_coefficients
67	Neighborhood_NridgHt	27644.272840
66	Neighborhood_NoRidge	25984.035574
113	RoofMatl_WdShngl	25917.171437
151	BsmtExposure_Gd	17864.974188
57	Neighborhood_Crawfor	14469.646771

In [611]:
```
# doubling the alpha for Ridge
alpha=18
ridge=Ridge(alpha=alpha)
ridge.fit(X_train,y_train)
```

Out[611]:
```
Ridge(alpha=18, copy_X=True, fit_intercept=True, max_iter=None, normalize=F
alse,
      random_state=None, solver='auto', tol=0.001)
```

In [612]:
```
# ridge predict
y_train_pred = ridge.predict(X_train)
print("ridge train pred r2_score: " + str(metrics.r2_score(y_true=y_train,
y_pred=y_train_pred)))
y_test_pred = ridge.predict(X_test)
print("ridge test pred r2_score: " + str(metrics.r2_score(y_true=y_test, y_
pred=y_test_pred)))
```

```
ridge train pred r2_score: 0.8754148422544542
ridge test pred r2_score: 0.8658353012848261
```

In [613]:
```
ridge_df=get_top_important_predictor_var(ridge)
ridge_df.head(5)
```

Out[613]:

	feature	model_coefficients
67	Neighborhood_NridgHt	21550.333043
66	Neighborhood_NoRidge	20649.595561
151	BsmtExposure_Gd	16201.153533
113	RoofMatl_WdShngl	14563.197434
57	Neighborhood_Crawfor	11693.277195

In [575]:
```
# ridge model parameters
ridge_model_parameters=list(ridge.coef_)
len(ridge_model_parameters)
#ridge.intercept_
```

Out[575]: 218

Lasso Regression

In [614]:
```
lasso=Lasso()
model_lasso=ridge_n_lasso(lasso)
model_lasso.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 27 candidates, totalling 135 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent wor
kers.
[Parallel(n_jobs=1)]: Done 135 out of 135 | elapsed:   19.2s finished
```

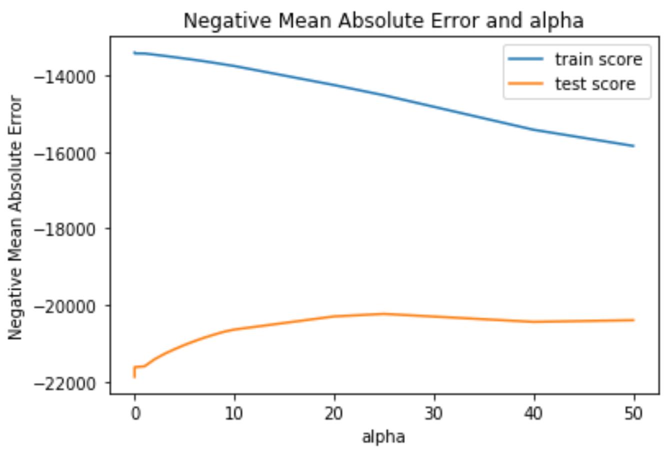
Out[614]:
```
GridSearchCV(cv=KFold(n_splits=5, random_state=100, shuffle=True),
             error_score='raise-deprecating',
             estimator=Lasso(alpha=1.0, copy_X=True, fit_intercept=True,
                             max_iter=1000, normalize=False, positive=False
,
                             precompute=False, random_state=None,
                             selection='cyclic', tol=0.0001, warm_start=Fal
se),
             iid='warn', n_jobs=None,
             param_grid={'alpha': [0.0001, 0.001, 0.01, 0.05, 0.1, 0.2, 0.3
,
                                   0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 2.0,
3.0,
                                   4.0, 5.0, 6.0, 7.0, 8.0, 9.0, 10.0, 20,
25,
                                   40, 50]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
             scoring='neg_mean_absolute_error', verbose=1)
```

In [615]:
```
lasso_results=pd.DataFrame(model_lasso.cv_results_)
lasso_results.head()
```

Out[615]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_alpha	params	split0_test_score	sp
0	0.195279	0.136348	0.002692	0.000252	0.0001	{'alpha': 0.0001}	-22368.567357	
1	0.155852	0.041877	0.005612	0.005758	0.001	{'alpha': 0.001}	-22368.640773	
2	0.130968	0.004422	0.002580	0.000090	0.01	{'alpha': 0.01}	-22369.400146	
3	0.310048	0.140838	0.003560	0.001231	0.05	{'alpha': 0.05}	-22375.592085	
4	0.303399	0.140561	0.002726	0.000201	0.1	{'alpha': 0.1}	-22370.863167	

In [589]:
```
lasso_results['param_alpha'] = lasso_results['param_alpha'].astype('int32')

# plotting
plt.plot(lasso_results['param_alpha'], lasso_results['mean_train_score'])
plt.plot(lasso_results['param_alpha'], lasso_results['mean_test_score'])
plt.xlabel('alpha')
plt.ylabel('Negative Mean Absolute Error')
plt.title("Negative Mean Absolute Error and alpha")
plt.legend(['train score', 'test score'], loc='upper right')
plt.show()
```



In [616]:
```
# select the optimal alpha as 9
alpha = 9
lasso = Lasso(alpha=alpha)
lasso.fit(X_train, y_train)
```

Out[616]:
```
Lasso(alpha=9, copy_X=True, fit_intercept=True, max_iter=1000, normalize=Fa
lse,
      positive=False, precompute=False, random_state=None, selection='cycli
c',
      tol=0.0001, warm_start=False)
```

In [617]:
```
# lasso predict
y_train_pred = lasso.predict(X_train)
print("lasso train pred r2_score: " + str(metrics.r2_score(y_true=y_train,
y_pred=y_train_pred)))
y_test_pred = lasso.predict(X_test)
print("lasso test pred r2_score: " + str(metrics.r2_score(y_true=y_test, y_
pred=y_test_pred)))
```

```
lasso train pred r2_score: 0.9343831436100587
lasso test pred r2_score: 0.8312355842656285
```

There is a significant difference between taining and test data set r2_score in `Lasso` regression. With `lambda=9` (alpha=9) `Ridge` model suggests r2_score is 86% which is much closer match the training data set r2_score. But `Lasso` model suggests r2_score is only 83% where as training data set r2_score is 93%. This shows `Lasso` model is `underfit` with `alpha=9`

In [618]:
```
# top 5 predictor vaiable for lasso when alpha=9
lasso_df=get_top_important_predictor_var(lasso)
lasso_df.head(5)
```

Out[618]:

	feature	model_coefficients
113	RoofMatl_WdShngl	613913.194110
108	RoofMatl_Membran	566075.792513
107	RoofMatl_CompShg	543666.861094
109	RoofMatl_Metal	539081.567614
111	RoofMatl_Tar&Grv	532691.993097

In [619]:
```
# adjusting the alpha to make it double
alpha = 18
lasso = Lasso(alpha=alpha)
lasso.fit(X_train, y_train)

y_train_pred = lasso.predict(X_train)
print("lasso train pred r2_score: " + str(metrics.r2_score(y_true=y_train,
y_pred=y_train_pred)))
y_test_pred = lasso.predict(X_test)
print("lasso test pred r2_score: " + str(metrics.r2_score(y_true=y_test, y_
pred=y_test_pred)))
```

```
lasso train pred r2_score: 0.9279924910225573
lasso test pred r2_score: 0.8393765560695181
```

In [620]:
```
# top 5 predictor vaiable for lasso when alpha=18
lasso_df=get_top_important_predictor_var(lasso)
lasso_df.head(5)
```

Out[620]:

	feature	model_coefficients
113	RoofMatl_WdShngl	464322.606528
107	RoofMatl_CompShg	395235.659841
108	RoofMatl_Membran	376521.872650
111	RoofMatl_Tar&Grv	370027.574375
110	RoofMatl_Roll	368979.404766

In [603]:
```
# adjusting the alpha to make it 18*2=36
alpha = 36
lasso = Lasso(alpha=alpha)
lasso.fit(X_train, y_train)

y_train_pred = lasso.predict(X_train)
print("lasso train pred r2_score: " + str(metrics.r2_score(y_true=y_train,
y_pred=y_train_pred)))
y_test_pred = lasso.predict(X_test)
print("lasso test pred r2_score: " + str(metrics.r2_score(y_true=y_test, y_
pred=y_test_pred)))
```

```
lasso train pred r2_score: 0.9079437886596565
lasso test pred r2_score: 0.8454155310419142
```

In [604]:
```
# top 5 predictor vaiable for lasso when alpha=18*2=36
lasso_df=get_top_important_predictor_var(lasso)
lasso_df.head(5)
```

Out[604]:

	feature	model_coefficients
113	RoofMatl_WdShngl	186433.733644
107	RoofMatl_CompShg	117564.346121
112	RoofMatl_WdShake	81407.903798
111	RoofMatl_Tar&Grv	75942.509302
110	RoofMatl_Roll	68375.171794

In [621]:
```
# adjusting the alpha 36*2=72
alpha = 72
lasso = Lasso(alpha=alpha)

lasso.fit(X_train, y_train)

y_train_pred = lasso.predict(X_train)
print("lasso train pred r2_score: " + str(metrics.r2_score(y_true=y_train,
y_pred=y_train_pred)))
y_test_pred = lasso.predict(X_test)
print("lasso test pred r2_score: " + str(metrics.r2_score(y_true=y_test, y_
pred=y_test_pred)))
```

```
lasso train pred r2_score: 0.8959380007832307
lasso test pred r2_score: 0.8563338291209158
```

With alpha=72 model test r2_score 85% close matches (< than 5 degree diff) the training r2_score which is close to 90%. But the training r2_score fall below 90% beyond alpha > 40

In [622]:

```
# top 5 predictor vaiable for lasso when alpha=36*2=72
lasso_df=get_top_important_predictor_var(lasso)
lasso_df.head(5)
```

Out[622]:

	feature	model_coefficients
113	RoofMatl_WdShngl	90101.229661
67	Neighborhood_NridgHt	38380.891299
66	Neighborhood_NoRidge	37301.698127
107	RoofMatl_CompShg	30448.521618
73	Neighborhood_StoneBr	23902.282064

In [260]:
```
# Check the lasso model parameters
lasso_model_parameters = list(lasso.coef_)
lasso_model_parameters.insert(0, lasso.intercept_)
lasso_model_parameters = [round(x, 3) for x in lasso_model_parameters]
cols = X.columns
cols = cols.insert(0, "constant")
list(zip(cols, lasso_model_parameters))
```

Out[260]:
```
[('constant', -93901.212),
 ('MSSubClass', -200.91),
 ('LotArea', 0.335),
 ('OverallQual', 12148.541),
 ('OverallCond', 4500.622),
 ('YearBuilt', 194.274),
 ('YearRemodAdd', 104.091),
 ('MasVnrArea', 21.75),
 ('BsmtFinSF1', -1.435),
 ('BsmtUnfSF', -10.757),
 ('TotalBsmtSF', 12.546),
 ('1stFlrSF', -6.92),
 ('2ndFlrSF', 25.388),
 ('GrLivArea', 60.894),
 ('BsmtFullBath', -3221.848),
 ('FullBath', 1736.238),
 ('HalfBath', -18005.305),
 ('BedroomAbvGr', -3723.222),
 ('KitchenAbvGr', -11719.015),
 ('TotRmsAbvGrd', 1554.766),
 ('Fireplaces', 3910.191),
 ('GarageCars', 13635.243),
 ('GarageArea', -10.996),
 ('WoodDeckSF', 15.64),
 ('OpenPorchSF', 22.918),
 ('EnclosedPorch', 6.323),
 ('MoSold', -273.451),
 ('YrSold', -313.249),
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 ('MSZoning_RL', 6961.223),
 ('MSZoning_RM', 1012.098),
 ('Street_Pave', 9713.479),
 ('LotShape_IR2', 0.0),
 ('LotShape_IR3', -29884.569),
 ('LotShape_Reg', 2369.94),
 ('LandContour_HLS', 13142.982),
 ('LandContour_Low', 5847.344),
 ('LandContour_Lvl', 9520.145),
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 ('LotConfig_CulDSac', 14187.242),
 ('LotConfig_FR2', -7093.561),
 ('LotConfig_FR3', -0.0),
 ('LotConfig_Inside', 276.884),
 ('LandSlope_Mod', 570.881),
 ('LandSlope_Sev', 10443.869),
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 ('Neighborhood_BrDale', 7654.184),
 ('Neighborhood_BrkSide', 4656.396),
 ('Neighborhood_ClearCr', 2753.336),
 ('Neighborhood_CollgCr', -992.442),
 ('Neighborhood_Crawfor', 23356.547),
 ('Neighborhood_Edwards', -9939.022),
 ('Neighborhood_Gilbert', -2051.484),
 ('Neighborhood_IDOTRR', -1533.103),
 ('Neighborhood_MeadowV', 0.0),
 ('Neighborhood_Mitchel', -9320.948),
 ('Neighborhood_NAmes', -5684.286),
 ('Neighborhood_NPkVill', 0.0),
 ('Neighborhood_NWAmes', -6586.74),
 ('Neighborhood_NoRidge', 35100.793),
 ('Neighborhood_NridgHt', 44521.819),
 ('Neighborhood_OldTown', -2328.441),
```

In [607]:
```
def get_top_important_predictor_var(regModel):
    cols = X.columns
    #cols
    model_parameters = list(regModel.coef_)
    df=pd.DataFrame(list(zip(cols, model_parameters)))

    df['feature']=df[0]
    df['model_coefficients']=df[1]
    df.drop([0,1],inplace=True,axis=1)
    df=df.sort_values(by='model_coefficients',ascending=False)
    return df
```