2. Data Exploration

In [2]:

```
# Importing packages
import pandas as pd
import numpy as np
from scipy.stats import norm

import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats

from sklearn.model_selection import train_test_split
from sklearn.multiclass import OneVsRestClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import Pipeline
from sklearn.cluster import KMeans
from sklearn.preprocessing import Imputer
import statsmodels.api as sm

from pandas.api.types import is_string_dtype
from pandas.api.types import is_numeric_dtype

from sklearn import model_selection
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
```

In [3]:

```
train_df = pd.read_csv('train.csv')
test_df = pd.read_csv('test.csv')
```

In [4]:

```
#test_df.describe()
```

In [5]:

```
#train_df.describe()
```

In [6]:

```
print('The number of observations is: {}'.format(train_df.shape[0]))
print('The number of independent variables is: {}'.format(train_df.shape[1] - 1)
)
```

```
The number of observations is: 1460
The number of independent variables is: 80
```

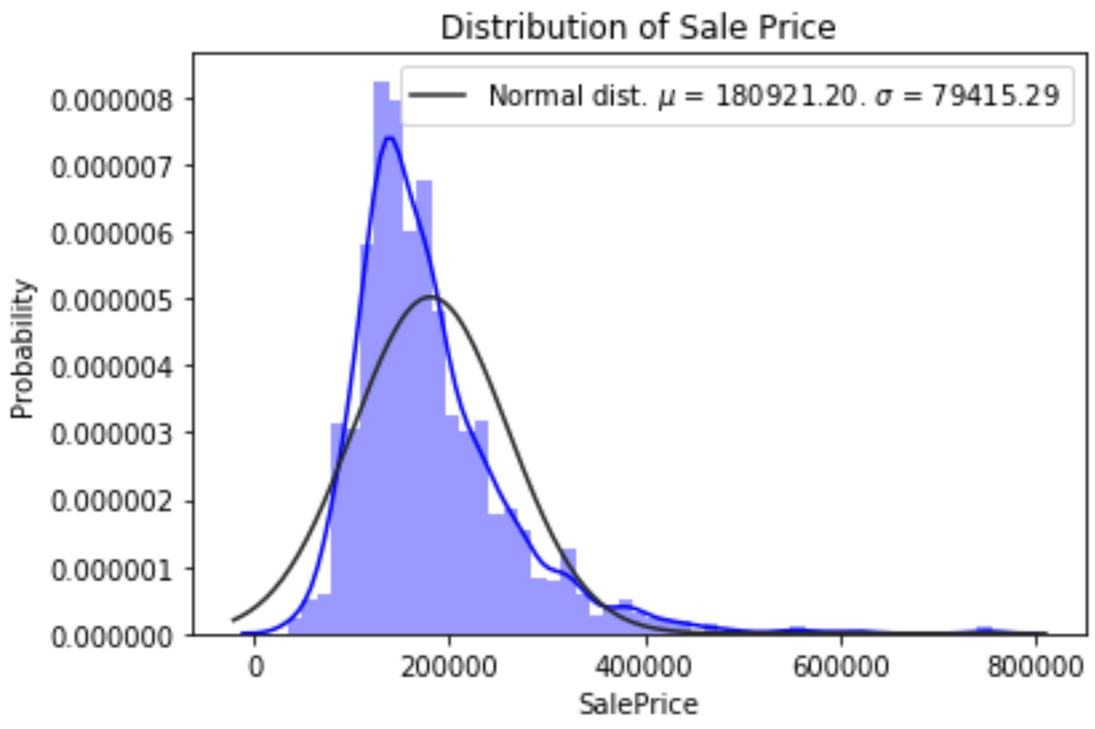
Dependent Variable:

At first, we want to explore the dependent variable which is 'SalePrice' to identify outliers and its distribution.

In [7]:

```
(mu, sigma) = norm.fit(train_df['SalePrice'])
sns.distplot(train_df['SalePrice'], fit = norm, norm_hist = True, color = 'B')
plt.legend(['Normal dist. $\mu$ = {:.2f}. $\sigma$ = {:.2f}'.format(mu, sigma)])
plt.ylabel('Probability')
plt.title('Distribution of Sale Price')
plt.show()
```

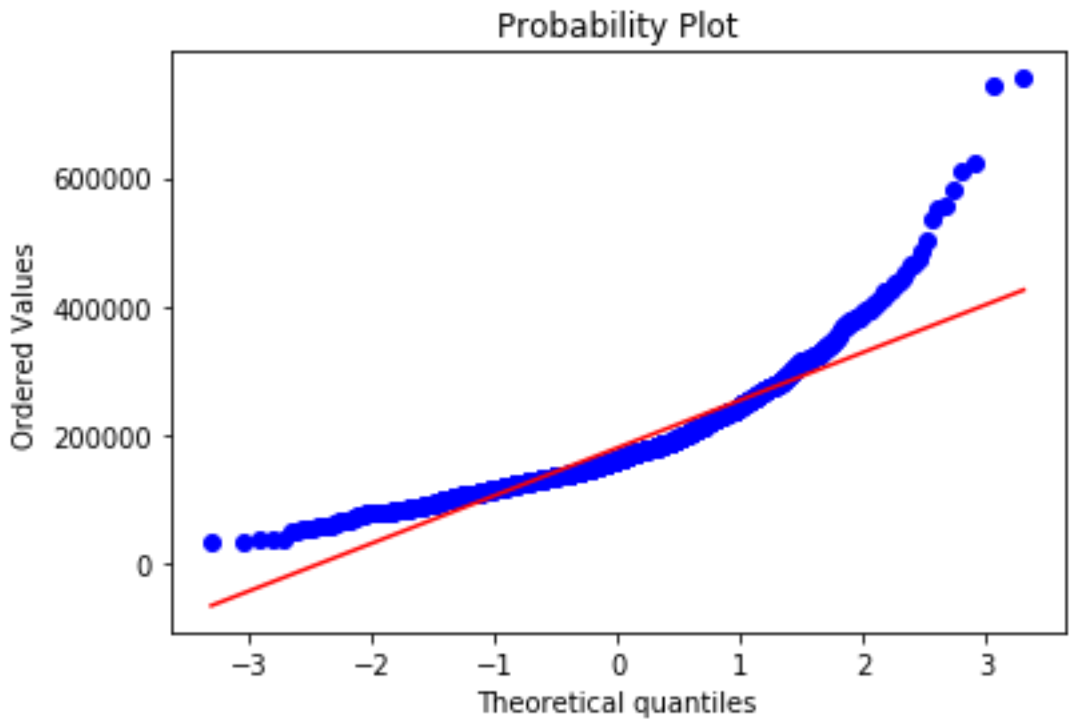
```
/Users/NhungLe/anaconda/lib/python3.6/site-packages/scipy/stats/stat
s.py:1713: FutureWarning: Using a non-tuple sequence for multidimens
ional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[
seq]`. In the future this will be interpreted as an array index, `ar
r[np.array(seq)]`, which will result either in an error or a differe
nt result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumva
l
```



As shown in the graph above, we can clearly see that the sale prices are skewed right and most sale prices range from $150, 00to$200,000. In order to double check the distribution of the sale prices, I used Q-Q (Quantile - Quantile)plot to evaluate the goodness of fit of the model fitting the best fit line for the sale prices.

In [8]:

```
# #Get also the QQ-plot of Sale Price
fig = plt.figure()
res = stats.probplot(train_df['SalePrice'], plot=plt)
plt.show()
```

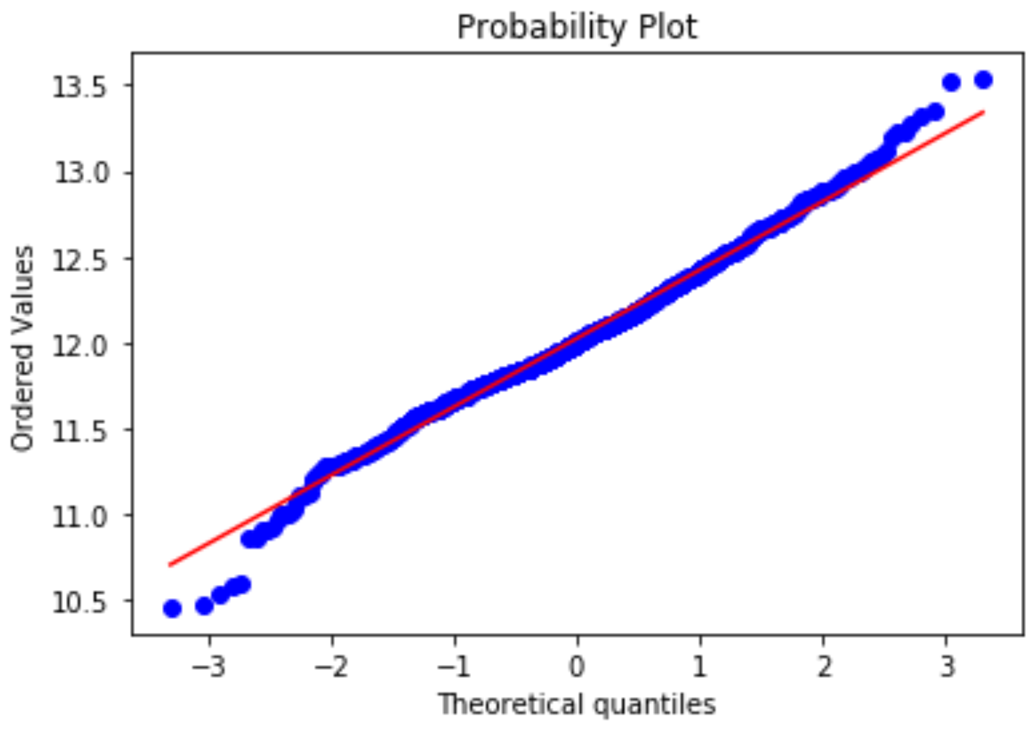


Clearly, sale prices are not normally distributed. It is because the line we see represent a normal distribution where quantiles represent standard deviation; if the sale prices are normally distributed, sale prices should follow the line.

A method to deal with skewed data is to log-transform it. Thus, I took the log of sale prices and plot the best fit line for them. Both Q-Q plot and histogram plot shown below proved that log of sale prices are normally distributed.

In [9]:

```
# #Get also the QQ-plot of Log of Sale Price
fig = plt.figure()
res = stats.probplot(np.log(train_df['SalePrice']), plot=plt)
plt.show()
```

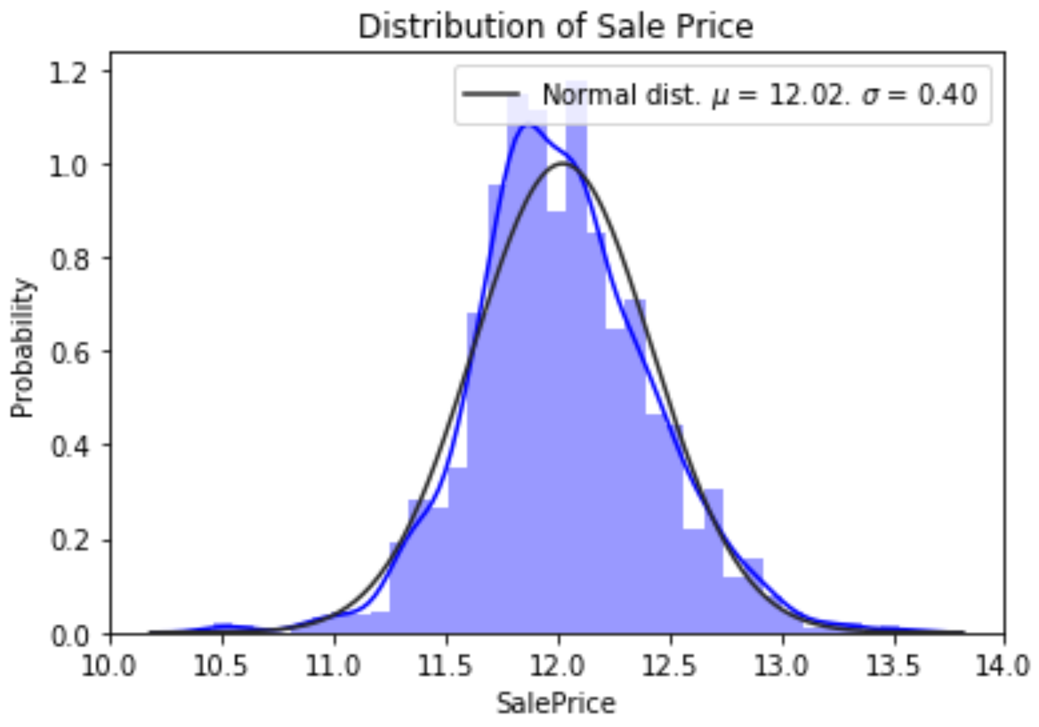


From Q-Q plot, we could see that the log of sale price seems to follow a normal distribution. We will check by plotting the log of sale price.

In [10]:

```
y = np.log(train_df['SalePrice'])
(mu, sigma) = norm.fit(y)
sns.distplot(y, fit = norm, norm_hist = True, color = 'B')
plt.legend(['Normal dist. $\mu$ = {:.2f}. $\sigma$ = {:.2f}'.format(mu, sigma)])
plt.ylabel('Probability')
plt.title('Distribution of Sale Price')
plt.show()
```

```
/Users/NhungLe/anaconda/lib/python3.6/site-packages/scipy/stats/stat
s.py:1713: FutureWarning: Using a non-tuple sequence for multidimens
ional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[
seq]`. In the future this will be interpreted as an array index, `ar
r[np.array(seq)]`, which will result either in an error or a differe
nt result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumva
l
```

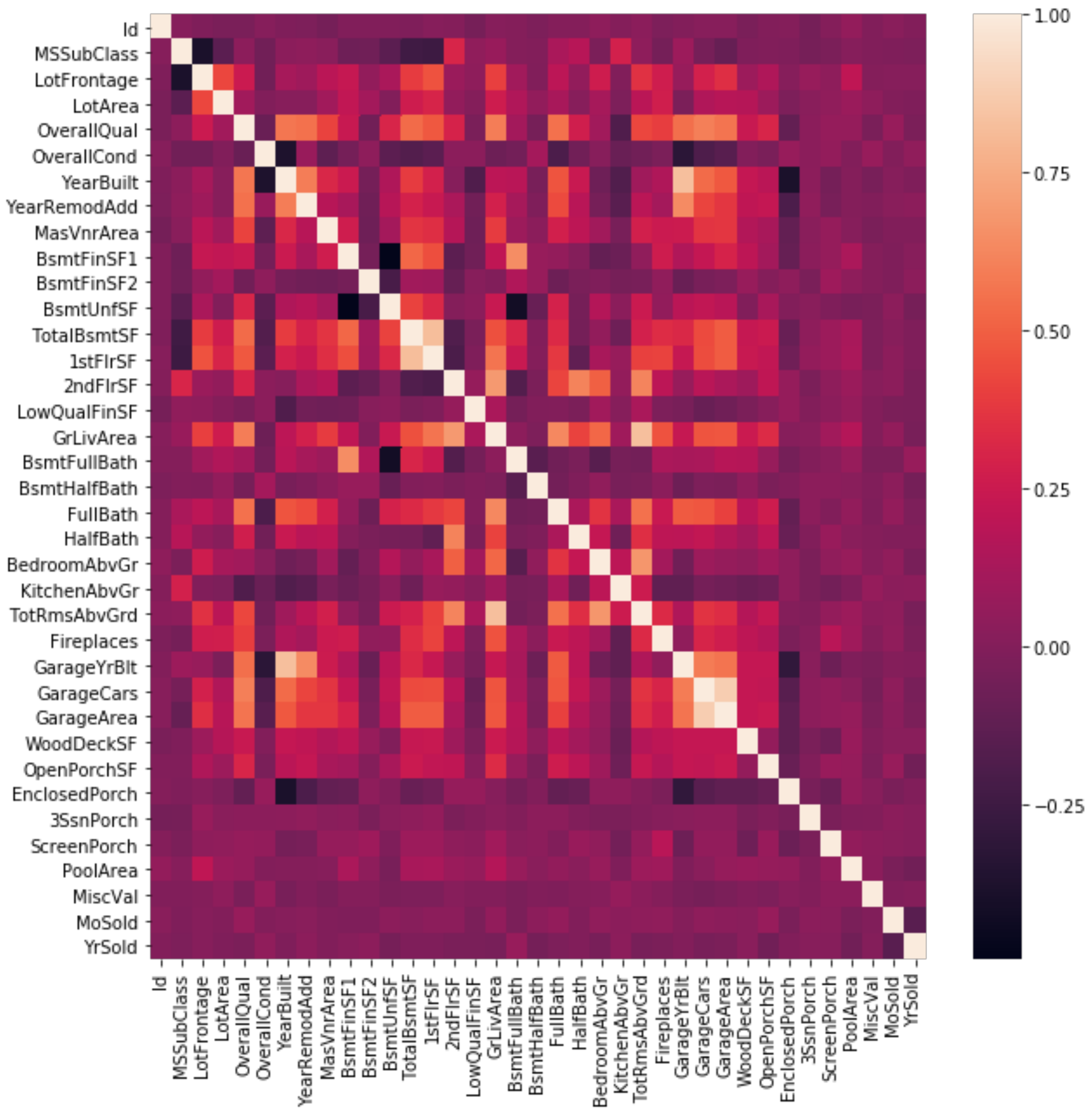


Correlation between Dependent and Independent Variables

It is necessary to understand the relationship between independent variables to identify variables that mostly impact sale prices before engineering feature and building models.

In [11]:

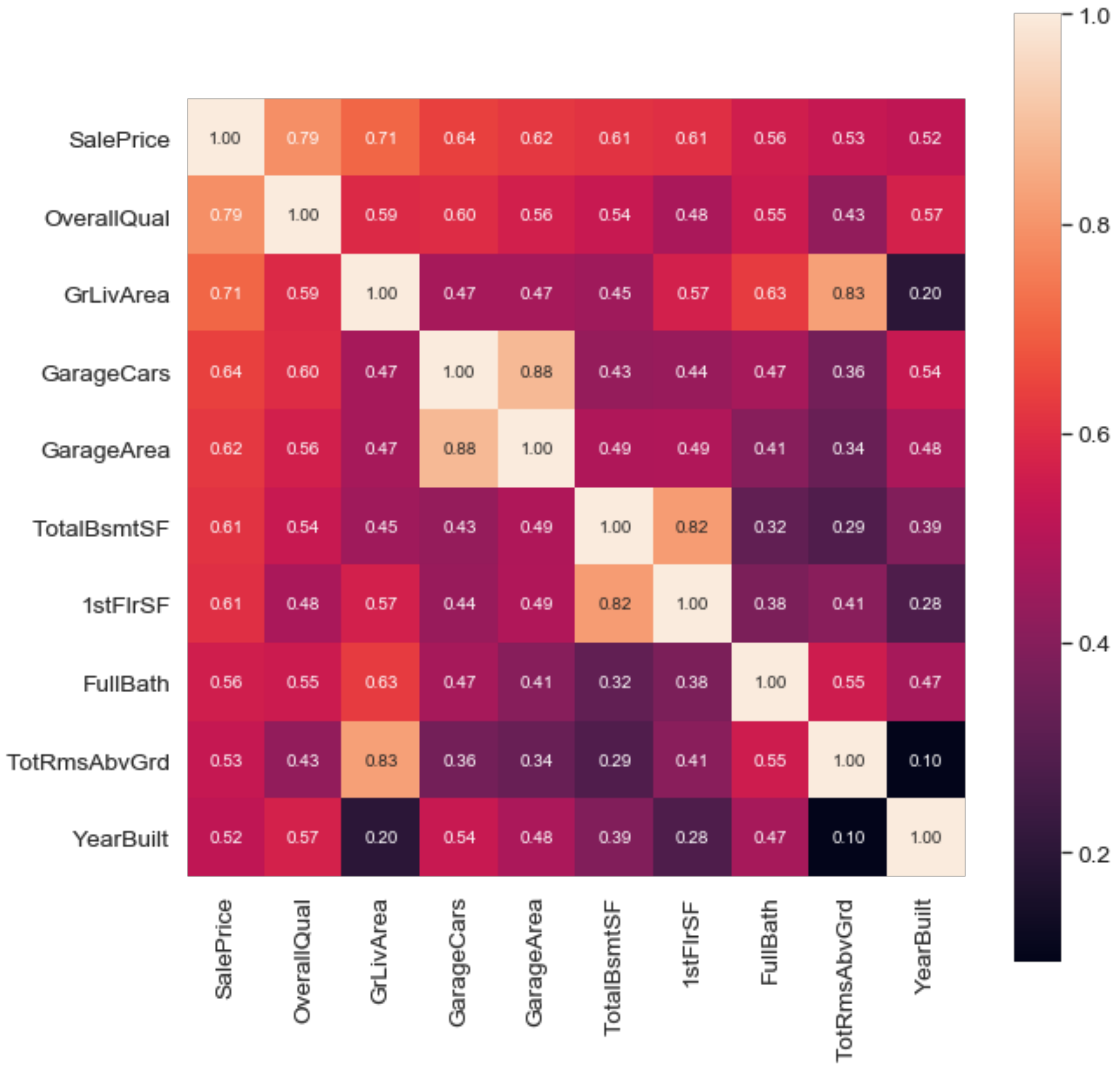
```
plt.figure(figsize = (10,10))
sns.heatmap(train_df.iloc[:, 0:80].corr())
plt.show()
```



Since it is hard to identify strongly correlated variables, it is better to have correlation value for each pair of variables.

In [12]:

```
k = 10 #number of variables for heatmap
plt.figure(figsize = (10,10))
corrmat = train_df.corr()
cols = corrmat.nlargest(k, 'SalePrice')['SalePrice'].index
cm = np.corrcoef(train_df[cols].values.T)
sns.set(font_scale=1.25)
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'
size': 10}, yticklabels=cols.values, xticklabels=cols.values)
plt.show()
```



	SalePrice	OverallQual	GrLivArea	GarageCars	GarageArea	TotalBsmtSF	1stFlrSF	FullBath	TotRmsAbvGrd	YearBuilt
SalePrice	1.00	0.79	0.71	0.64	0.62	0.61	0.61	0.56	0.53	0.52
OverallQual	0.79	1.00	0.59	0.60	0.56	0.54	0.48	0.55	0.43	0.57
GrLivArea	0.71	0.59	1.00	0.47	0.47	0.45	0.57	0.63	0.83	0.20
GarageCars	0.64	0.60	0.47	1.00	0.88	0.43	0.44	0.47	0.36	0.54
GarageArea	0.62	0.56	0.47	0.88	1.00	0.49	0.49	0.41	0.34	0.48
TotalBsmtSF	0.61	0.54	0.45	0.43	0.49	1.00	0.82	0.32	0.29	0.39
1stFlrSF	0.61	0.48	0.57	0.44	0.49	0.82	1.00	0.38	0.41	0.28
FullBath	0.56	0.55	0.63	0.47	0.41	0.32	0.38	1.00	0.55	0.47
TotRmsAbvGrd	0.53	0.43	0.83	0.36	0.34	0.29	0.41	0.55	1.00	0.10
YearBuilt	0.52	0.57	0.20	0.54	0.48	0.39	0.28	0.47	0.10	1.00

The heatmap above demonstrates some important points:

```
1. OverallQual, GrLivArea, and GarageCars are strongly correlated with Sal
ePrice.
2. OverallQual is strongly related with GarageCars, GrLivArea, and YearBui
lt. Thus, the three variables GarageCars, GrLivArea, and YearBuilt may als
o affect SalePrice.
3. GrLivArea is strongly correlated with 1stFlrST (First Floor square feet
) and TotRmsAbvGrd (Total rooms above grade (does not include bathrooms)).
These two variables also correlate with SalePrice.
4. GarageCars is highly correlated with GarageArea, suggesting that area o
f garage also influences SalePrice, knowing that GarageCars is strongly co
rrelated with SalePrice. However, given the strong corrrelationship betwee
n the two variables, we should only keep one variable, which is GarageCars
which has higher correlationship with SalePrice.
5. TotalBsmtSF and 1stFlrSF are also highly correlated so we will only kee
p one of the two as an independent variable to predict SalePrice.
6. TotRmsAbvGrd is significantly correlated with GrLivArea, so we will als
o select one of the two, which is GrLivArea whichh as higher correlation w
ith SalePrice.
```

Aggregating Data

In order to fully explore and engineer data, we would combine train and test datasets.

In [13]:

```
#train_df['Type'] = 'Train'
#test_df['Type'] = 'Test'
test_df['SalePrice'] = np.nan
```

In [14]:

```
#sorted(test_df.columns.values)
train_size = train_df.shape[0]
test_size = test_df.shape[0]
```

In [15]:

```
print('train data has: {}'.format(len(train_df.columns)))
print('test data has: {}'.format(len(test_df.columns)))
print('train data and test data has the same columns: {}'.format(sorted(train_df
.columns.values) == sorted(test_df.columns.values)))
#test_df.iloc[:, 81]
```

```
train data has: 81
test data has: 81
train data and test data has the same columns: True
```

In [16]:

```
train_df.head()
```

Out[16]:

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

5 rows × 81 columns

In [17]:

```
train_test = pd.concat([train_df, test_df])
#train_test.columns
```

In [18]:

```
train_test.drop(['Id'], axis=1, inplace=True)
```

```
In [19]:
```

```
train_test.head()
```

```
Out[19]:
```

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContou
0	60	RL	65.0	8450	Pave	NaN	Reg	Lvl
1	20	RL	80.0	9600	Pave	NaN	Reg	Lvl
2	60	RL	68.0	11250	Pave	NaN	IR1	Lvl
3	70	RL	60.0	9550	Pave	NaN	IR1	Lvl
4	60	RL	84.0	14260	Pave	NaN	IR1	Lvl

5 rows × 80 columns

Missing Data

Further investigation shows that there are 34 variables with missing data, only 11 of which has more than 5% of all data missing and worth our effort to fill in missing data. From data description, we know that:

```
- NA for PoolQC means No pool, should be filled with None
- NA for MiscFeature means no misc feature, should be filled with None
- NA for Alley means no alley access, should be filled with None
- NA for Fence means no fence, should be filled with None
- NA for FireplaceQu means no fireplace, should be filled with None
- NA for LotFrontage means missing linear feet of street connected to prop
erty value and should be filled with the LotFrontage of neighbor
- For features where NA indicates no such feature, missing values will be
filled with None. These features includ: GarageFinish, GarageQual, GarageT
ype, GarageCond, BsmtCond, BsmtExposure, BsmtQual, BsmtFinType2, BsmtFinTy
pe1
- NA for GarageYrBlt will be filled with 0
- NA for SalePrice means the SalePrice of the test set, and should not be
filled with anything
- For features with numerical values and only 1 or 2 missing values, we wi
ll fill with average value. These features include: 'BsmtFullBath', 'BsmtH
alfBath', 'GarageArea', 'GarageCars', 'BsmtUnfSF', 'BsmtFinSF2', 'BsmtFinS
F1', 'TotalBsmtSF'
- For features with categorical values, we will fill in missing data with
most popular ones. These features include 'Functional', 'Utilities', 'Exte
rior2nd', 'Electrical', 'Exterior1st', 'KitchenQual', 'SaleType', 'MasVnrT
ype', 'MSZoning'
```

In [20]:

```
nums_na = train_test.apply(lambda x: x.isnull().sum() / len(x)).sort_values(asce
nding = False).to_frame(name = 'Pct Missing')
nums_na = nums_na[nums_na['Pct Missing'] != 0]
nums_na.index
```

Out[20]:

```
Index(['PoolQC', 'MiscFeature', 'Alley', 'Fence', 'SalePrice', 'Fire
placeQu',
       'LotFrontage', 'GarageCond', 'GarageYrBlt', 'GarageQual',
       'GarageFinish', 'GarageType', 'BsmtCond', 'BsmtExposure', 'Bs
mtQual',
       'BsmtFinType2', 'BsmtFinType1', 'MasVnrType', 'MasVnrArea', '
MSZoning',
       'Utilities', 'Functional', 'BsmtFullBath', 'BsmtHalfBath', 'G
arageCars',
       'BsmtFinSF2', 'Exterior2nd', 'GarageArea', 'TotalBsmtSF', 'Bs
mtUnfSF',
       'BsmtFinSF1', 'Exterior1st', 'KitchenQual', 'SaleType', 'Elec
trical'],
      dtype='object')
```

In [21]:

```
None_replace = ['PoolQC', 'MiscFeature', 'Alley', 'Fence', 'FireplaceQu', 'LotFr
ontage',
               'GarageFinish', 'GarageQual', 'GarageType', 'GarageCond', 'BsmtCo
nd', 'BsmtExposure',
                'BsmtQual', 'BsmtFinType2', 'BsmtFinType1']
```

In [22]:

```
for col in None_replace:
    train_test[[col]] = train_test[[col]].fillna('None')
```

In [23]:

```
train_test['GarageYrBlt'] = train_test['GarageYrBlt'].fillna(0)
#train_test['GarageYrBlt'].isnull().sum()
```

In [24]:

```
num_var = ['BsmtFullBath', 'BsmtHalfBath', 'GarageArea', 'GarageCars', 'BsmtUnfS
F', 'BsmtFinSF2', 'BsmtFinSF1', 'TotalBsmtSF', 'MasVnrArea']
```

In [25]:

```
for var in num_var:
    mean_value = np.mean(train_test[var])
    train_test[var] = train_test[var].fillna(mean_value)
```

In [26]:

```
cat_var = ['Functional', 'Utilities', 'Exterior2nd', 'Electrical', 'Exterior1st'
, 'KitchenQual', 'SaleType', 'MasVnrType', 'MSZoning']
```

In [27]:

```
for var in cat_var:
    pop_value = train_test[var].value_counts().index[0]
    train_test[var] = train_test[var].fillna(pop_value)
```

Baseline model

In order to have a baseline model, we need to categorize object variables so our data is runnable. It is because Scikitlearn models (e.g., Logistic Regression, Multilinear Regression) cannot parse string values of a feature.

In [28]:

```
object_col = train_test.select_dtypes(include='object')
num_col = list(train_test.select_dtypes(include='int64').columns)
#object_col.drop('Type', axis = 1)
object_col = list(object_col.columns)
print(object_col)
#print(num_col)
```

```
['MSZoning', 'LotFrontage', 'Street', 'Alley', 'LotShape', 'LandCont
our', 'Utilities', 'LotConfig', 'LandSlope', 'Neighborhood', 'Condit
ion1', 'Condition2', 'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMat
l', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'ExterQual', 'ExterC
ond', 'Foundation', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFin
Type1', 'BsmtFinType2', 'Heating', 'HeatingQC', 'CentralAir', 'Elect
rical', 'KitchenQual', 'Functional', 'FireplaceQu', 'GarageType', 'G
arageFinish', 'GarageQual', 'GarageCond', 'PavedDrive', 'PoolQC', 'F
ence', 'MiscFeature', 'SaleType', 'SaleCondition']
```

In [29]:

```
base_train_test = train_test.copy()
```

In [30]:

```
#Use OneHotEncoder immediately, then PCA
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
from numpy import array
```

In [31]:

```
for col in object_col:
    label_encoder = LabelEncoder()
    base_train_test[col] = label_encoder.fit_transform(list(base_train_test[col]
.values))
```

In [32]:

```
base_train_clean = base_train_test[:train_size]
base_test_clean = base_train_test[train_size:]
```

In [33]:

```
#base_train_test.select_dtypes(include = 'object')
```

In [34]:

```
base_X_train = base_train_clean.drop('SalePrice', axis = 1)
base_Y_train = base_train_clean['SalePrice']
base_X_test = base_test_clean.drop('SalePrice', axis = 1)
```

In [35]:

```
import statsmodels.api as sm
model = sm.OLS(np.log(base_Y_train), base_X_train).fit() ## sm.OLS(output, input
)
predictions = model.predict(base_X_train)
# Print out the statistics
brand_model = model.summary()
```

In [36]:

```
Y_pred = np.exp(model.predict(base_X_test))
```

In [37]:

```
sub = pd.DataFrame()
sub['Id'] = test_df['Id']
sub['SalePrice'] = Y_pred
sub.to_csv('LinearReg_submission.csv',index=False)
```

In [38]:

```
#print(brand_model)
```

Feature engineering

After getting the baseline model, we can start engineering features:

```
1. Transform types of some variables from integer to string
2. Encode object variables: This parse string to number by classify object
variables.
3. OneHotCode some categorical variables.
    For some categorical variables, their classified groups entail informa
tion about the target variables and should be treated as numerical variabl
es. For example, if we believe that YearSold (i.e., the year the house was
sold) affects the house price, then the YearSold variable should be treate
d as a numerical variable.
    For other categorical variables where classified groups do not entail
information about the target variable, we should create dummy variables fo
r these groups. For example, for RoofStyle (i.e., type of roof), group 2 (
e.g., roof type = gable) does not affect the house price as twice as the g
roup 1 (e.g., roof type = flat) does, so we should have dummy variables fo
r RoofStyle.
```

In [39]:

```
#May not want to categorize 'MoSold', 'YrSold'
num_cat_var = ['MSSubClass', 'OverallCond', 'OverallQual']
for var in num_cat_var:
    train_test[var] = train_test[var].astype(str)
```

In [40]:

```
train_test['TotalSF'] = train_test['1stFlrSF'] + train_test['2ndFlrSF'] + train_
test['TotalBsmtSF']
train_test.drop(['1stFlrSF','2ndFlrSF', 'TotalBsmtSF'], axis = 1, inplace = True
)
```

In [41]:

```
#LotFrontage should be int
```

In [42]:

```
#for col in object_col:
#    print(col, train_test[col].value_counts())
```

In [43]:

```
object_col = train_test.select_dtypes(include='object').columns
object_col
```

Out[43]:

```
Index(['MSSubClass', 'MSZoning', 'LotFrontage', 'Street', 'Alley', '
LotShape',
       'LandContour', 'Utilities', 'LotConfig', 'LandSlope', 'Neighb
orhood',
       'Condition1', 'Condition2', 'BldgType', 'HouseStyle', 'Overal
lQual',
       'OverallCond', 'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exter
ior2nd',
       'MasVnrType', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQu
al',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', '
Heating',
       'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual', 'Func
tional',
       'FireplaceQu', 'GarageType', 'GarageFinish', 'GarageQual', 'G
arageCond',
       'PavedDrive', 'PoolQC', 'Fence', 'MiscFeature', 'SaleType',
       'SaleCondition'],
      dtype='object')
```

In [44]:

```
object_numerical_col = ['BldgType', 'BsmtCond', 'BsmtExposure', 'BsmtQual', 'Cen
tralAir','Condition1', 'Condition2',
 'Electrical', 'ExterCond', 'ExterQual',
       'Fence', 'FireplaceQu', 'GarageCond',
       'GarageFinish', 'GarageQual', 'HeatingQC', 'KitchenQual', 'LandContour',
'LandSlope',
       'LotFrontage', 'LotShape', 'MSSubClass', 'MSZoning', 'Neighborhood', 'Ove
rallCond', 'OverallQual',
       'PavedDrive', 'PoolQC', 'RoofMatl', 'RoofStyle', 'SaleCondition','Street'
, 'Utilities']
```

In [45]:

```
for col in object_numerical_col:
    label_encoder = LabelEncoder()
    train_test[col] = label_encoder.fit_transform(list(train_test[col].values))
```

In [46]:

```
print('Shape of the train_test data after encoding object variables: {}'.format(
train_test.shape))
```

```
Shape of the train_test data after encoding object variables: (2919,
78)
```

In [47]:

```
train_test.head()
```

Out[47]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContou
0	10	3	93	8450	1	None	3	3
1	5	3	108	9600	1	None	3	3
2	10	3	96	11250	1	None	0	3
3	11	3	88	9550	1	None	0	3
4	10	3	112	14260	1	None	0	3

5 rows × 78 columns

In [48]:

```
train_test = pd.get_dummies(train_test)
```

In [49]:

```
train_test.shape
```

Out[49]:

```
(2919, 169)
```

3. Model Selection

In [51]:

```
old_train_test = train_test[:]
```

In [52]:

```
#old_train_test.head()
```

In [53]:

```
#train_test = old_train_test
```

3.1. Normalize data

In [54]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
train_test[train_test.columns] = scaler.fit_transform(train_test)
train_test.SalePrice = old_train_test.SalePrice
```

```
/Users/NhungLe/anaconda/lib/python3.6/site-packages/sklearn/preproce
ssing/data.py:617: DataConversionWarning: Data with input dtype uint
8, int64, float64 were all converted to float64 by StandardScaler.
  return self.partial_fit(X, y)
/Users/NhungLe/anaconda/lib/python3.6/site-packages/sklearn/base.py:
462: DataConversionWarning: Data with input dtype uint8, int64, floa
t64 were all converted to float64 by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```

In [55]:

```
old_train_test.SalePrice.head()
```

Out[55]:

```
0    208500.0
1    181500.0
2    223500.0
3    140000.0
4    250000.0
Name: SalePrice, dtype: float64
```

In [56]:

```
train_clean = train_test[:train_size]
test_clean = train_test[train_size:]
```

In [57]:

```
print(train_clean.shape)
print(train_df.shape)
```

```
(1460, 169)
(1460, 81)
```

In [58]:

```
print(test_clean.shape)
print(test_df.shape)
```

```
(1459, 169)
(1459, 81)
```

In [59]:

```
X_train = train_clean.drop('SalePrice', axis = 1)
Y_train = train_clean['SalePrice']
X_test = test_clean.drop('SalePrice', axis = 1)
```

In [60]:

```
from sklearn.linear_model import ElasticNet, Lasso,  BayesianRidge, LassoLarsIC,
LinearRegression
from sklearn.ensemble import RandomForestRegressor,  GradientBoostingRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.kernel_ridge import KernelRidge
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import RobustScaler
from sklearn.base import BaseEstimator, TransformerMixin, RegressorMixin, clone
from sklearn.model_selection import KFold, cross_val_score, train_test_split
from sklearn.metrics import mean_squared_error
#import xgboost as xgb
#import lightgbm as lgb
```

3.2. RMSE (Root Mean Square Error)

This metric represents the sample standard deviation of the difference between predicted values and observed values (called residuals)

3.3. R^2 vs. Adjusted R^2

There are some problems with normal R^2 which are solved by Adjusted R^2. An adjusted R^2 will consider the marginal improvement added by an additional term in your model. So it will increase if you add the useful terms and it will decrease if you add less useful predictors. However, R^2 increases with increasing terms even though the model is not actually improving. It will be easier to understand this with an example.

In [61]:

```
def rmse(log_y_pred, log_y_true):
    n = len(log_y_pred)
    return np.sqrt((sum((log_y_pred - log_y_true)**2))/n)
```

In [62]:

```
def ValRMSE(X_train, Y_train, model, k):
    kf = KFold(n_splits = k)
    scores = []
    train_scores = []
    for cv_train, cv_validate in kf.split(X_train):
        X_cv_train = X_train.iloc[cv_train]
        X_cv_validate = X_train.iloc[cv_validate]
        Y_cv_train = Y_train.iloc[cv_train]
        log_y_cv_train = np.log(Y_cv_train)
        Y_cv_validate = Y_train.iloc[cv_validate]
        log_y_cv_validate = np.log(Y_cv_validate)
        model.fit(X_cv_train, log_y_cv_train)
        log_y_pred = model.predict(X_cv_validate)
        scores.append(rmse(log_y_pred, log_y_cv_validate))
        # toan
        log_y_train_pred = model.predict(X_cv_train)
        train_scores.append(rmse(log_y_cv_train, log_y_train_pred))
    return (np.array(scores), np.array(train_scores))
```

In [63]:

```
#Lasso Model
lasso = make_pipeline(RobustScaler(), Lasso(alpha=0.005, random_state=1))
scores, train_scores = ValRMSE(X_train, Y_train, lasso, 5)
print("\nLasso score: {:.4f} ({:.4f})\n".format(scores.mean(), scores.std()))
print("\nLasso train score: {:.4f} ({:.4f})\n".format(
    train_scores.mean(), train_scores.std()))
```

```
Lasso score: 0.1520 (0.0256)


Lasso train score: 0.1364 (0.0052)
```

In [64]:

```
#### Ridge Regression Model
KRR = KernelRidge(alpha=3, kernel='polynomial', degree=2, coef0=2.5)
scores, train_scores = ValRMSE(X_train, Y_train, KRR, 5)
print("\nKernel Ridge score: {:.4f} ({:.4f})\n".format(scores.mean(), scores.std
()))
print("\nKernel Ridge train score: {:.4f} ({:.4f})\n".format(
    train_scores.mean(), train_scores.std()))
```

```
Kernel Ridge score: 0.1411 (0.0199)


Kernel Ridge train score: 0.0901 (0.0020)
```

In [65]:

```
#Multiple Linear Regression
Multiple_linear = LinearRegression()
scores, train_scores = ValRMSE(X_train, Y_train, Multiple_linear, 5)
print("\nMultiple Linear score: {:.4f} ({:.4f})\n".format(scores.mean(), scores.
std()))
print("\nMultiple Linear train score: {:.4f} ({:.4f})\n".format(
    train_scores.mean(), train_scores.std()))
```

```
Multiple Linear score: 282784208112.7357 (469130124405.3829)


Multiple Linear train score: 0.1271 (0.0049)
```

In [66]:

```
GBoost = GradientBoostingRegressor(n_estimators=3000, learning_rate=0.05,
                                   max_depth=4, max_features='sqrt',
                                   min_samples_leaf=15, min_samples_split=10,
                                   loss='huber', random_state =5)
```

In [67]:

```
scores, train_scores = ValRMSE(X_train, Y_train, GBoost, 5)
print("\nGBoost score: {:.4f} ({:.4f})\n".format(scores.mean(), scores.std()))
print("\nGBoost train score: {:.4f} ({:.4f})\n".format(
    train_scores.mean(), train_scores.std()))
```

```
GBoost score: 0.1246 (0.0115)


GBoost train score: 0.0519 (0.0021)
```

In [68]:

```
#Decision Tree
DedTree = DecisionTreeRegressor(max_depth=5, min_samples_leaf=15, min_samples_sp
lit=10)
scores, train_scores = ValRMSE(X_train, Y_train, DedTree, 5)
print("\nDecision Tree score: {:.4f} ({:.4f})\n".format(scores.mean(), scores.st
d()))
print("\nDecision Tree train score: {:.4f} ({:.4f})\n".format(
    train_scores.mean(), train_scores.std()))
```

```
Decision Tree score: 0.1905 (0.0104)


Decision Tree train score: 0.1595 (0.0029)
```

4. Model Improvement

After running different models, we can try to tune them to improve their performance, thus selecting the best fit model.

4.1. Lasso Improvement:

The objective function of the Lasso model (or L1 regularization) is to minimize $(\|y - y^{\|})^2 + \alpha \sum_n^1 |b_i|$.

Thus, we can try different α to get the most effective Lasso model

In [69]:

```
alpha_list = [0.00001, 0.00005, 0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05]
```

In [70]:

```
cv_scores_l = []
train_scores_l = []
for alpha in alpha_list:
    lasso = make_pipeline(RobustScaler(),
                          Lasso(alpha, random_state=1,
                                max_iter=1000))
    cv_scores, train_scores = ValRMSE(X_train, Y_train, lasso, 5)
    cv_scores_l.append(cv_scores.mean())
    train_scores_l.append(train_scores.mean())
```

```
/Users/NhungLe/anaconda/lib/python3.6/site-packages/sklearn/linear_m
odel/coordinate_descent.py:491: ConvergenceWarning: Objective did no
t converge. You might want to increase the number of iterations. Fit
ting data with very small alpha may cause precision problems.
  ConvergenceWarning)
/Users/NhungLe/anaconda/lib/python3.6/site-packages/sklearn/linear_m
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  ConvergenceWarning)
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t converge. You might want to increase the number of iterations. Fit
ting data with very small alpha may cause precision problems.
  ConvergenceWarning)
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t converge. You might want to increase the number of iterations. Fit
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  ConvergenceWarning)
/Users/NhungLe/anaconda/lib/python3.6/site-packages/sklearn/linear_m
odel/coordinate_descent.py:491: ConvergenceWarning: Objective did no
t converge. You might want to increase the number of iterations. Fit
```

```
ting data with very small alpha may cause precision problems.
  ConvergenceWarning)
/Users/NhungLe/anaconda/lib/python3.6/site-packages/sklearn/linear_m
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ting data with very small alpha may cause precision problems.
  ConvergenceWarning)
/Users/NhungLe/anaconda/lib/python3.6/site-packages/sklearn/linear_m
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t converge. You might want to increase the number of iterations. Fit
ting data with very small alpha may cause precision problems.
  ConvergenceWarning)
/Users/NhungLe/anaconda/lib/python3.6/site-packages/sklearn/linear_m
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t converge. You might want to increase the number of iterations. Fit
ting data with very small alpha may cause precision problems.
  ConvergenceWarning)
/Users/NhungLe/anaconda/lib/python3.6/site-packages/sklearn/linear_m
odel/coordinate_descent.py:491: ConvergenceWarning: Objective did no
t converge. You might want to increase the number of iterations. Fit
ting data with very small alpha may cause precision problems.
  ConvergenceWarning)
/Users/NhungLe/anaconda/lib/python3.6/site-packages/sklearn/linear_m
odel/coordinate_descent.py:491: ConvergenceWarning: Objective did no
t converge. You might want to increase the number of iterations. Fit
ting data with very small alpha may cause precision problems.
  ConvergenceWarning)
```
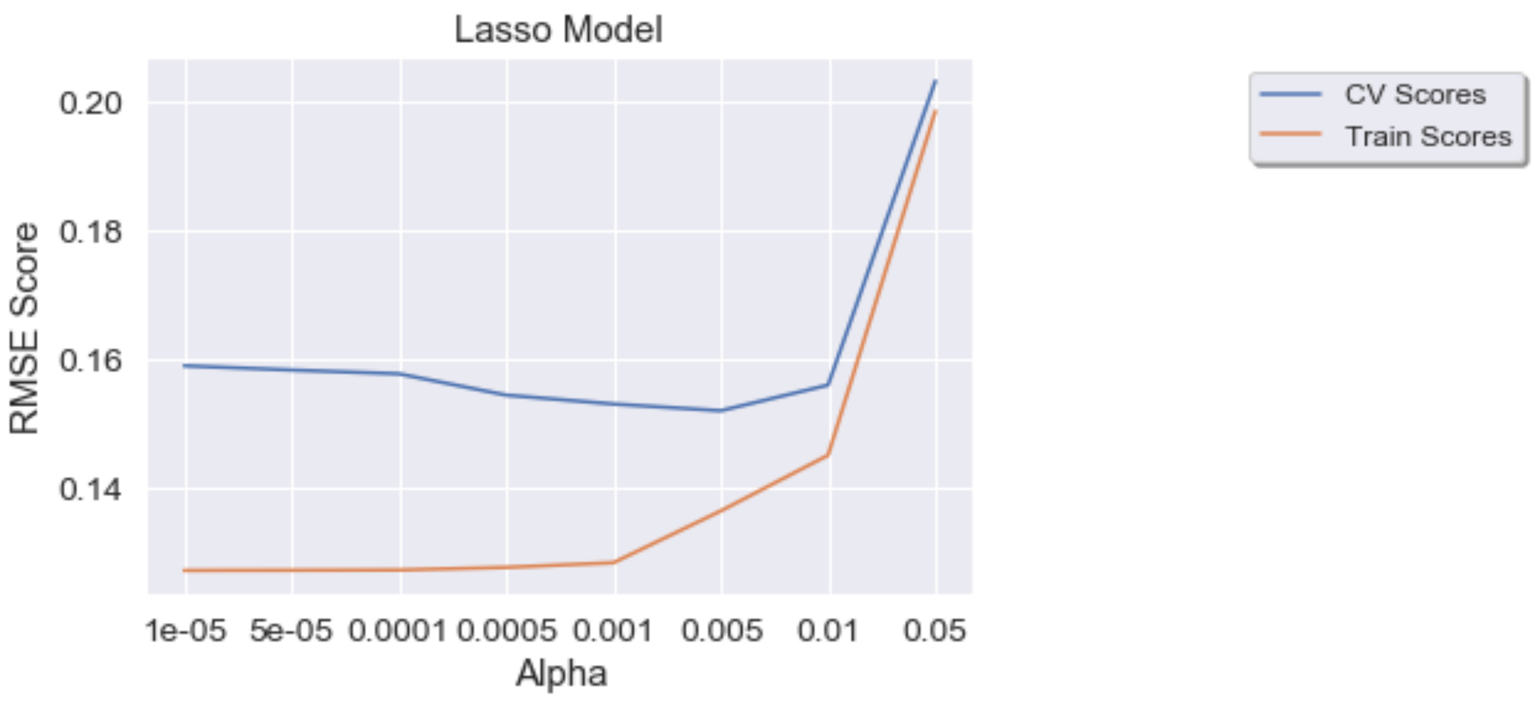

In [71]:

```
fig = plt.figure()
ax = fig.add_subplot(111)
plt.plot([str(x) for x in alpha_list], cv_scores_l, label = 'CV Scores')
plt.plot([str(x) for x in alpha_list], train_scores_l, label = 'Train Scores')
ax.legend(loc = 'upper center', bbox_to_anchor = (1.5, 1),
        fancybox = True, shadow = True, ncol = 1, prop = {'size': 12})
ax.set_xlabel('Alpha')
ax.set_ylabel('RMSE Score')
plt.title('Lasso Model')
plt.show()
```



In [ ]:

4. 2. Stacking Model

Averaging Base Model

In [72]:

```
class AveragingModels(BaseEstimator, RegressorMixin, TransformerMixin):
    def __init__(self, models):
        self.models = models

    # we define clones of the original models to fit the data in
    def fit(self, X, y):
        self.models_ = [clone(x) for x in self.models]

        # Train cloned base models
        for model in self.models_:
            model.fit(X, y)

        return self

    #Now we do the predictions for cloned models and average them
    def predict(self, X):
        predictions = np.column_stack([
            model.predict(X) for model in self.models_
        ])
        return np.mean(predictions, axis=1)
```

In [74]:

```
average_stacked_mod = AveragingModels(models = (GBoost, KRR, lasso))
scores, train_scores = ValRMSE(X_train, Y_train, average_stacked_mod, 5)
print("\nAverage Stacking score: {:.4f} ({:.4f})\n".format(scores.mean(), scores
.std()))
print("\nAverage Stacking train score: {:.4f} ({:.4f})\n".format(
    train_scores.mean(), train_scores.std()))
```

```
Average Stacking score: 0.1407 (0.0153)


Average Stacking train score: 0.0995 (0.0021)
```

5. Submission

In [591]:

```
GBoost = GradientBoostingRegressor(n_estimators=3000, learning_rate=0.05,
                                   max_depth=4, max_features='sqrt',
                                   min_samples_leaf=15, min_samples_split=10,
                                   loss='huber', random_state =5)
GBoost.fit(X_train, np.log(Y_train))
log_Y_pred = GBoost.predict(X_test)
Y_pred = np.exp(log_Y_pred)
```

In [592]:

```
log_Y_train_pred = GBoost.predict(X_train)
```

In [593]:

```
np.sqrt(np.average((log_Y_train_pred - np.log(Y_train))**2))
```

Out[593]:

```
0.05470150058862553
```

In [444]:

```
sub = pd.DataFrame()
sub['Id'] = test_df['Id']
sub['SalePrice'] = Y_pred
sub.to_csv('GBoost_submission.csv',index=False)
```

In [75]:

```
Average = AveragingModels(models = (GBoost, KRR, lasso))
Average.fit(X_train, np.log(Y_train))
log_Y_pred = GBoost.predict(X_test)
Y_pred = np.exp(log_Y_pred)
sub = pd.DataFrame()
sub['Id'] = test_df['Id']
sub['SalePrice'] = Y_pred
sub.to_csv('Average_Stacking_submission.csv',index=False)
```