House Prices Prediction using Regression

In [170]:
```
# Installing libraries for analysis
%cd /Users/shimonyagrawal/Desktop
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from scipy.stats import norm
from sklearn.preprocessing import StandardScaler
from scipy import stats
import warnings
warnings.filterwarnings('ignore')
```

```
/Users/shimonyagrawal/Desktop
```

Exploratory Data Analysis

In [171]:
```
# Loading the train and test dataset
df_train = pd.read_csv('/Users/shimonyagrawal/Desktop/House Prices Predi
ction using Regression/train.csv')
# print(df_train.columns)

df_test = pd.read_csv('/Users/shimonyagrawal/Desktop/House Prices Predic
tion using Regression/test.csv')
# print(df_test.columns)
```

```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Stree
t',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgTy
pe',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRe
modAdd',
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrTy
pe',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQua
l',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heati
ng',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'Fu
llBath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'Gara
geType',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'Gara
geQual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQ
C',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleTyp
e',
       'SaleCondition', 'SalePrice'],
      dtype='object')
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Stree
t',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgTy
pe',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRe
modAdd',
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrTy
pe',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQua
l',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heati
ng',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'Fu
llBath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'Gara
geType',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'Gara
geQual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQ
C',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleTyp
e',
```

```
        'SaleCondition'],
       dtype='object')
```

In [172]:
```
# Check different columns between train and test columns
set(df_train.columns) - set(df_test.columns)
```

Out[172]:
```
{'SalePrice'}
```

In [173]:
```
# Drop column ID

df_train.drop(columns = 'Id', inplace=True)
df_test.drop(columns = 'Id', inplace=True)

print('Drop column Id completed')
```

```
Drop column Id completed
```

In [175]:
```
def plot_missing(df):
    miss_col = df.isnull().sum()[df.isnull().sum() > 0].sort_values(asce
nding = False)
    percent_miss = round((miss_col / len(df) *100), 2)
    missing = pd.DataFrame([miss_col, percent_miss]).T.rename(columns =
{0:'Feature', 1:'% missing'})
    return missing

plot_missing(df_train)
```

Out[175]:

	Feature	% missing
PoolQC	1453.0	99.52
MiscFeature	1406.0	96.30
Alley	1369.0	93.77
Fence	1179.0	80.75
FireplaceQu	690.0	47.26
LotFrontage	259.0	17.74
GarageYrBlt	81.0	5.55
GarageType	81.0	5.55
GarageFinish	81.0	5.55
GarageQual	81.0	5.55
GarageCond	81.0	5.55
BsmtFinType2	38.0	2.60
BsmtExposure	38.0	2.60
BsmtFinType1	37.0	2.53
BsmtCond	37.0	2.53
BsmtQual	37.0	2.53
MasVnrArea	8.0	0.55
MasVnrType	8.0	0.55
Electrical	1.0	0.07

In [176]:
```
plot_missing(df_test)
```

Out[176]:

	Feature	% missing
PoolQC	1456.0	99.79
MiscFeature	1408.0	96.50
Alley	1352.0	92.67
Fence	1169.0	80.12
FireplaceQu	730.0	50.03
LotFrontage	227.0	15.56
GarageYrBlt	78.0	5.35
GarageCond	78.0	5.35
GarageQual	78.0	5.35
GarageFinish	78.0	5.35
GarageType	76.0	5.21
BsmtCond	45.0	3.08
BsmtExposure	44.0	3.02
BsmtQual	44.0	3.02
BsmtFinType1	42.0	2.88
BsmtFinType2	42.0	2.88
MasVnrType	16.0	1.10
MasVnrArea	15.0	1.03
MSZoning	4.0	0.27
BsmtFullBath	2.0	0.14
BsmtHalfBath	2.0	0.14
Utilities	2.0	0.14
Functional	2.0	0.14
Exterior2nd	1.0	0.07
Exterior1st	1.0	0.07
SaleType	1.0	0.07
BsmtFinSF1	1.0	0.07
BsmtFinSF2	1.0	0.07
BsmtUnfSF	1.0	0.07
KitchenQual	1.0	0.07
GarageCars	1.0	0.07
GarageArea	1.0	0.07
TotalBsmtSF	1.0	0.07

For some feature such as PoolQC, MiscFeature and Alley there are moer than 90% of missing value but in this case NaN mean No Pool, No Miscellaneous and No alley access.We will replace NaN with 'None' and for the other features we would take into account and impute NaN to the following column.

For other features such as BsmtFinSF1, BsmtFinSF2, BsmtUnfSF, TotalBsmtSF, BsmtFullBath, BsmtHalfBath all of these are numerical features if No basement that should be replaced with 0. Likewise if No Garage GarageYrBlt, GarageArea, GarageCars should be replaced with 0 also.

In [177]:
```
none_cols = ['Alley', 'PoolQC', 'MiscFeature', 'Fence', 'FireplaceQu', 'GarageType',
             'GarageFinish', 'GarageQual', 'GarageCond', 'BsmtQual', 'BsmtCond',
             'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', 'MasVnrType']

# Impute missing value
for col in none_cols:
    df_train[col].replace(np.nan, 'None', inplace=True)
    df_test[col].replace(np.nan, 'None', inplace=True)
```

In [178]:
```
bsm = ['BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'BsmtFullBath','BsmtHalfBath','BsmtQual']
df_train[bsm].groupby('BsmtQual').sum()
```

Out[178]:

BsmtQual	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	TotalBsmtSF	BsmtFullBath	BsmtHalfBath
Ex	103495	2851	92772	199118	82	6
Fa	4575	276	20805	25656	6	2
Gd	292006	21417	385578	699001	294	27
None	0	0	0	0	0	0
TA	247638	43418	329016	620072	239	49

In [179]:
```
gar = ['GarageYrBlt', 'GarageArea', 'GarageCars','GarageQual']
df_train[gar].groupby('GarageQual').sum()
```

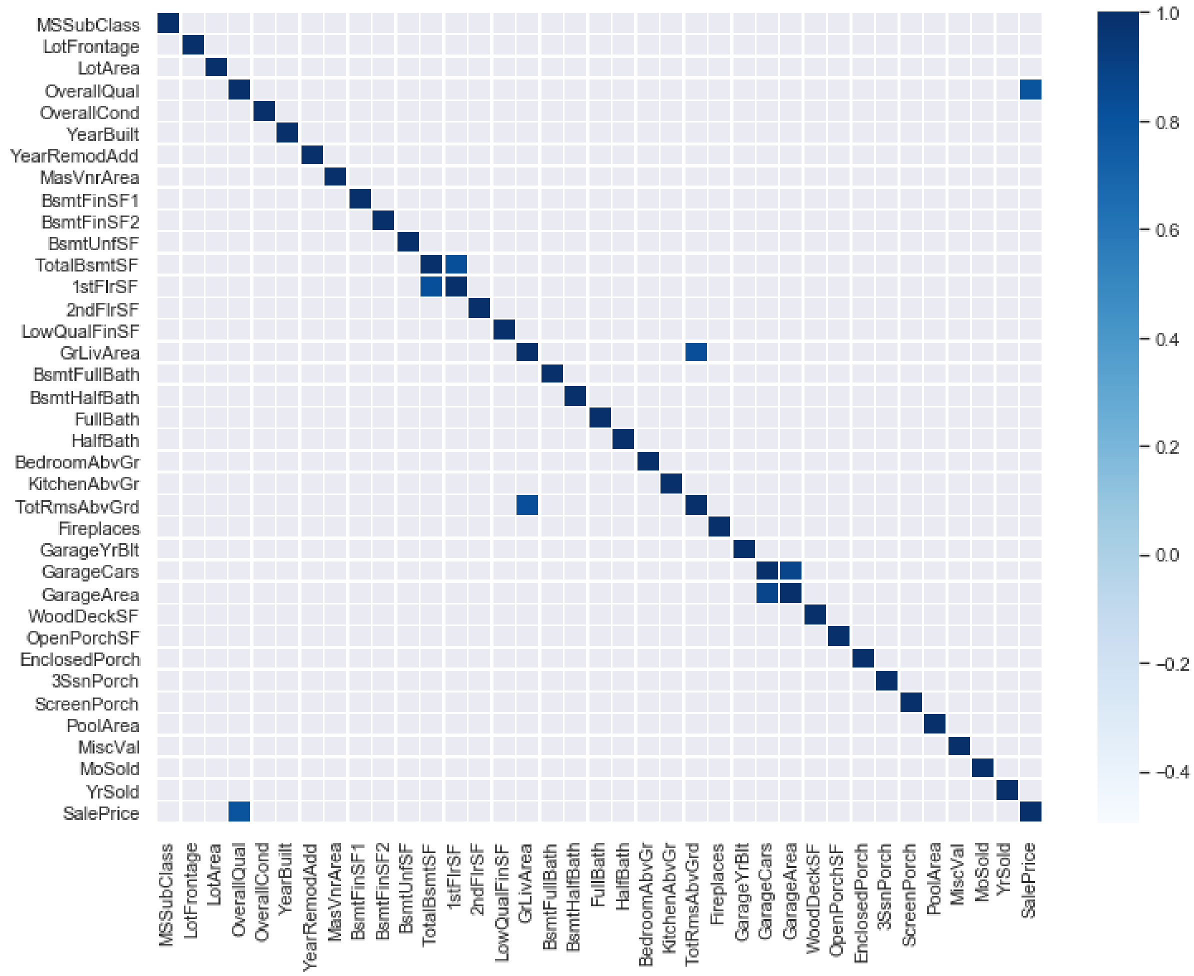
Out[179]:

GarageQual	GarageYrBlt	GarageArea	GarageCars
Ex	5967.0	2064	5
Fa	92817.0	14946	65
Gd	27733.0	7800	26
None	0.0	0	0
Po	5756.0	978	3
TA	2596087.0	664763	2481

In [180]:
```
# Replace these features by 0
zero_cols = ['BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'BsmtFullBath','BsmtHalfBath', 'GarageYrBlt', 'GarageArea', 'GarageCars', 'MasVnrArea']

for col in zero_cols:
    df_train[col].replace(np.nan, 0, inplace=True)
    df_test[col].replace(np.nan, 0, inplace=True)
```

Bivariate Analysis

In [181]:
```
plt.subplots(figsize=(12,9))

corrmat = df_train.corr()
sns.heatmap(corrmat, mask = corrmat < 0.75, linewidth = 0.5, cmap = 'Blues');
```



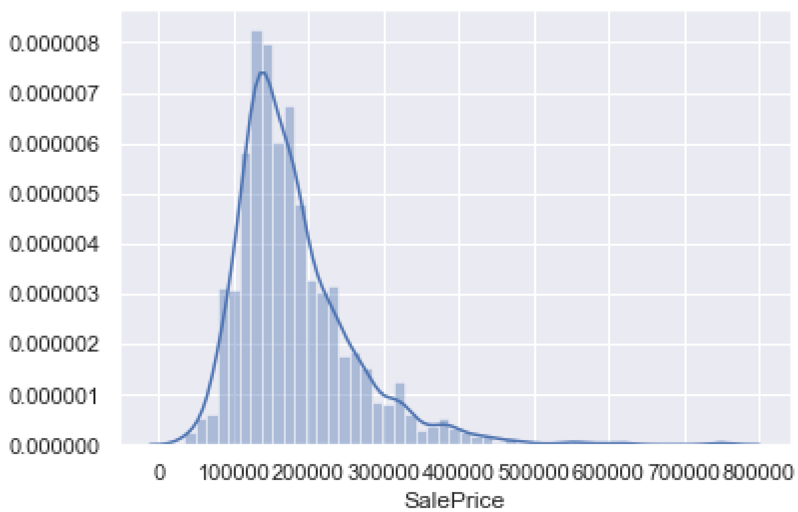
In [182]:
```
# Finding the highest correlated variables for further analysis

top_correlated = abs(corrmat.SalePrice).sort_values(ascending=False).hea
d(10)
top_correlated_col = list(top_correlated.index)
top_correlated_col.remove('SalePrice')
top_correlated
```

Out[182]:
```
SalePrice       1.000000
OverallQual     0.790982
GrLivArea       0.708624
GarageCars      0.640409
GarageArea      0.623431
TotalBsmtSF     0.613581
1stFlrSF        0.605852
FullBath        0.560664
TotRmsAbvGrd    0.533723
YearBuilt       0.522897
Name: SalePrice, dtype: float64
```

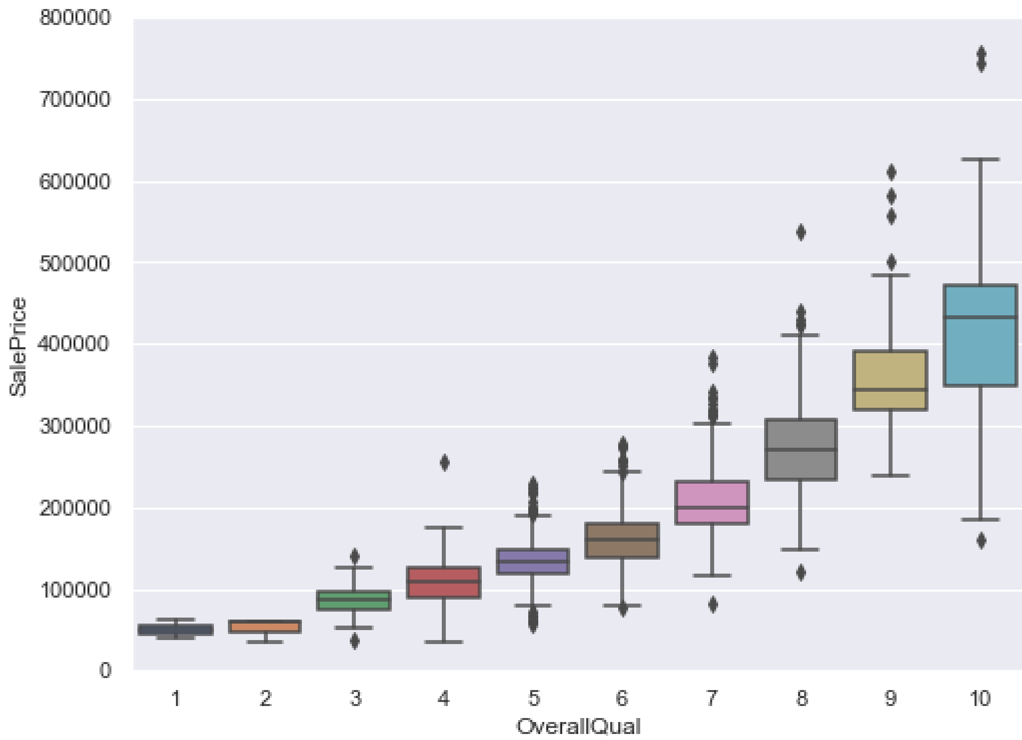
Data Preprocessing

We can visualise the data to identify outliers and remove the problematic ones that could distort further statistical analysis.

In [183]:
```
df_train['SalePrice'].describe()
sns.distplot(df_train['SalePrice']);
```



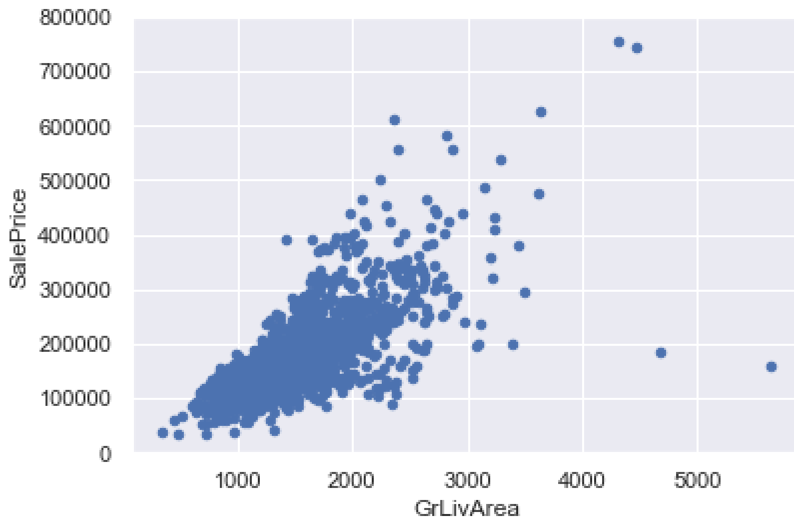
In [184]:
```
# Figure: Boxplot for overall material and finish quality and sale price
var = 'OverallQual'
data = pd.concat([df_train['SalePrice'], df_train[var]], axis=1)
f, ax = plt.subplots(figsize=(8, 6))
fig = sns.boxplot(x=var, y="SalePrice", data=data)
fig.axis(ymin=0, ymax=800000);
```



In [185]:
```
df_train = df_train.drop(df_train[(df_train['OverallQual'] < 5) & (df_tr
ain['SalePrice'] > 200000)].index)
df_train = df_train.drop(df_train[(df_train['OverallQual'] > 10) & (df_t
rain['SalePrice'] < 400000)].index)
```

In [186]:
```
# Figure: Scatter plot for above ground living area square feet and sale
price
var = 'GrLivArea'
data = pd.concat([df_train['SalePrice'], df_train[var]], axis=1)
data.plot.scatter(x=var, y='SalePrice', ylim=(0,800000));
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which sh
ould be avoided as value-mapping will have precedence in case its lengt
h matches with 'x' & 'y'.  Please use a 2-D array with a single row if
you really want to specify the same RGB or RGBA value for all points.
```



In [187]:
```
df_train = df_train.drop(df_train[(df_train['GrLivArea'] > 4000) & (df_t
rain['SalePrice'] < 400000)].index)
```

In [188]:
```
# Figure: Scatter plot for garage area and sale price
var = 'GarageArea'
data = pd.concat([df_train['SalePrice'], df_train[var]], axis=1)
data.plot.scatter(x=var, y='SalePrice', ylim=(0,800000));
```

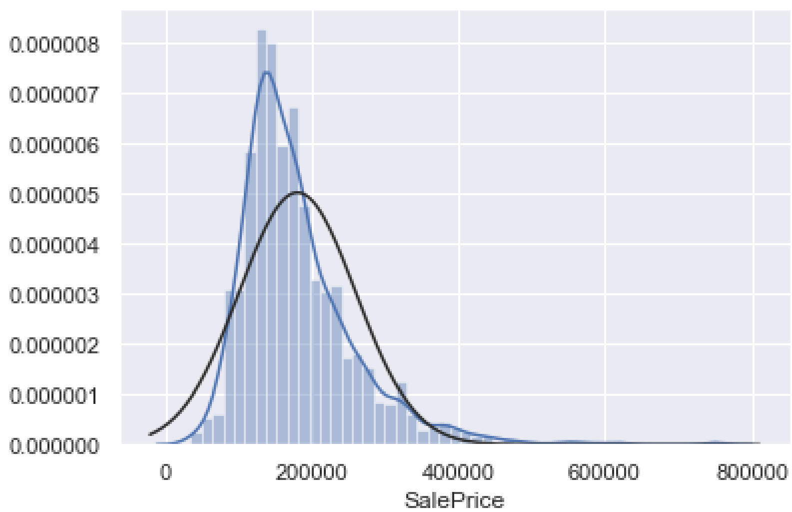
```
'c' argument looks like a single numeric RGB or RGBA sequence, which sh
ould be avoided as value-mapping will have precedence in case its lengt
h matches with 'x' & 'y'.  Please use a 2-D array with a single row if
you really want to specify the same RGB or RGBA value for all points.
```

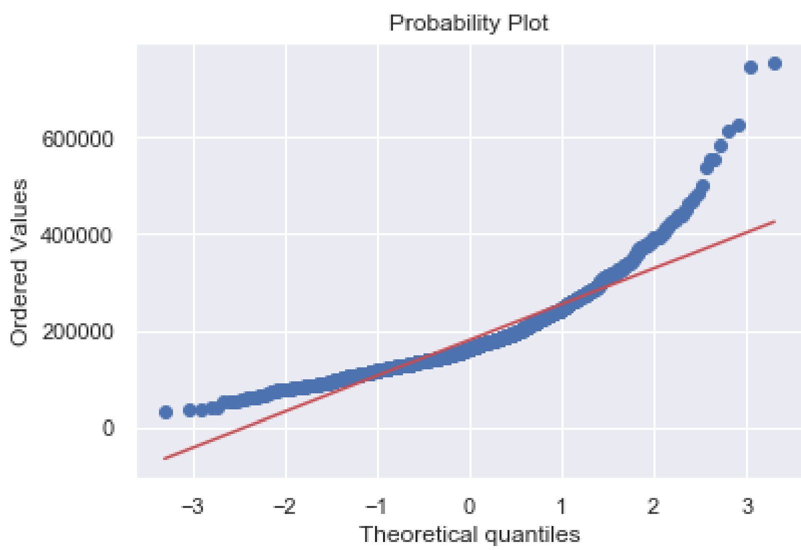
In [189]:
```
df_train = df_train.drop(df_train[(df_train['GarageArea'] > 1200) & (df_
train['SalePrice'] < 400000)].index)
```

Univariate Analysis

In [190]:
```
#histogram and normal probability plot

sns.distplot(df_train['SalePrice'], fit=norm);
fig = plt.figure()
res = stats.probplot(df_train['SalePrice'], plot=plt)

#skewness and kurtosis
# measure of lack of symmetry in data - here there is a positve skewness
print("Skewness: %f" % df_train['SalePrice'].skew())
# tailedness of frequency; actually measures the outliers in the data -
 here, it is a leptokurtic distribution
print("Kurtosis: %f" % df_train['SalePrice'].kurt())
```

```
Skewness: 1.892190
Kurtosis: 6.603841
```

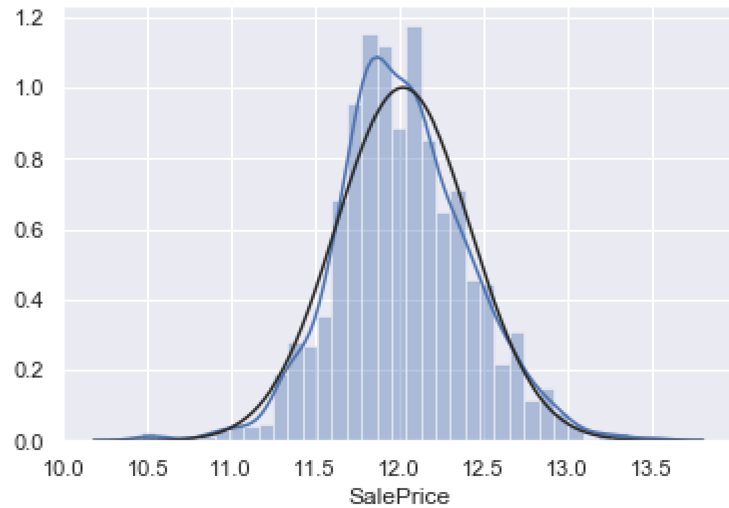


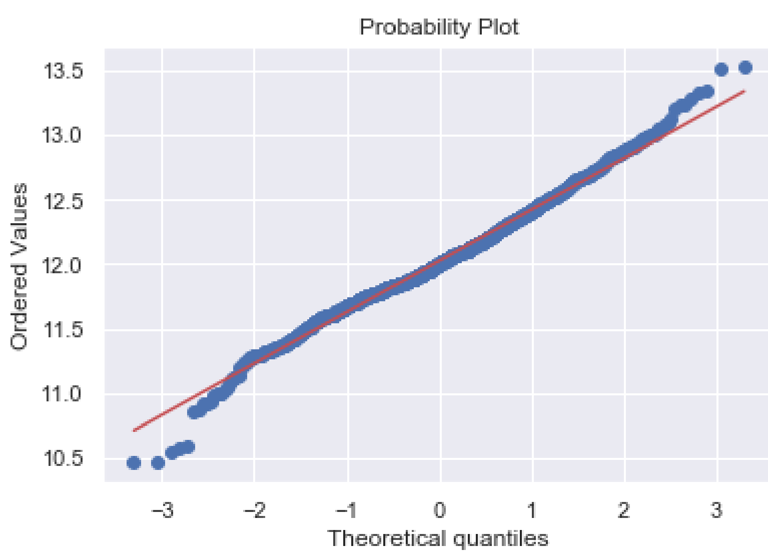


As seen from the figures above, the variable Sale Price has a positive skewness and a leptokurtic distribution which indicates high peakedness. It can be resolved by log transformation which can make the data less skewed.

In [191]:
```
# Sale Price has positive skewness, so we need to transform data by Log-
transformation of the target variable.

df_train['SalePrice'] = np.log(df_train['SalePrice'])

#transformed histogram and normal probability plot

sns.distplot(df_train['SalePrice'], fit=norm);
fig = plt.figure()
res = stats.probplot(df_train['SalePrice'], plot=plt)

#skewness and kurtosis
print("Skewness: %f" % df_train['SalePrice'].skew())
print("Kurtosis: %f" % df_train['SalePrice'].kurt())
```

```
Skewness: 0.123700
Kurtosis: 0.822109
```





Feature Engineering

In [192]:
```
# Creating a new variable Total Square Feet

df_train['TotalSF'] = df_train['BsmtFinSF1'] + df_train['BsmtFinSF2'] +
df_train['1stFlrSF'] + df_train['2ndFlrSF']

df_test['TotalSF'] = df_test['BsmtFinSF1'] + df_test['BsmtFinSF2'] + df_
test['1stFlrSF'] + df_test['2ndFlrSF']
```

In [193]:
```
# df_train.columns
```

Out[193]:
```
Index(['MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street', 'A
lley',
       'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlop
e',
       'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseSt
yle',
       'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'Roof
Style',
       'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrA
rea',
       'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond',
       'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2',
       'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating', 'HeatingQ
C',
       'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF', 'LowQualFinS
F',
       'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBa
th',
       'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual', 'TotRmsAbvGrd',
       'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType', 'Garage
YrBlt',
       'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual', 'Garag
eCond',
       'PavedDrive', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3Ss
nPorch',
       'ScreenPorch', 'PoolArea', 'PoolQC', 'Fence', 'MiscFeature', 'Mi
scVal',
       'MoSold', 'YrSold', 'SaleType', 'SaleCondition', 'SalePrice',
       'TotalSF'],
      dtype='object')
```

In [194]:
```
# df_test.columns
```

Out[194]:
```
Index(['MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street', 'A
lley',
       'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlop
e',
       'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseSt
yle',
       'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'Roof
Style',
       'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrA
rea',
       'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond',
       'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2',
       'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating', 'HeatingQ
C',
       'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF', 'LowQualFinS
F',
       'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBa
th',
       'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual', 'TotRmsAbvGrd',
       'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType', 'Garage
YrBlt',
       'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual', 'Garag
eCond',
       'PavedDrive', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3Ss
nPorch',
       'ScreenPorch', 'PoolArea', 'PoolQC', 'Fence', 'MiscFeature', 'Mi
scVal',
       'MoSold', 'YrSold', 'SaleType', 'SaleCondition', 'TotalSF'],
      dtype='object')
```

In [331]:
```
drop_col = ['MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street'
, 'Alley',
              'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandS
lope','Neighborhood',
              'Condition1', 'Condition2', 'BldgType', 'HouseStyle','Overa
llCond','YearRemodAdd',
              'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'Mas
VnrType', 'MasVnrArea',
              'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCo
nd','BsmtExposure',
              'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2','BsmtFinSF2',
'BsmtUnfSF','TotalBsmtSF',
              'Heating', 'HeatingQC','CentralAir', 'Electrical', '1stFlrS
F', '2ndFlrSF', 'LowQualFinSF',
              'BsmtFullBath', 'BsmtHalfBath','HalfBath','BedroomAbvGr',
'KitchenAbvGr',
              'KitchenQual', 'TotRmsAbvGrd','Functional', 'Fireplaces',
'FireplaceQu', 'GarageType',
              'GarageYrBlt','GarageFinish', 'GarageCars', 'GarageQual',
'GarageCond','PavedDrive',
              'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch',
'ScreenPorch', 'PoolArea', 'PoolQC',
              'Fence', 'MiscFeature', 'MiscVal','MoSold', 'YrSold']

df_train = df_train[df_train.columns.difference(drop_col)]
df_test = df_test[df_test.columns.difference(drop_col)]

print('Drop Columns Completed')
```

```
Drop Columns Completed
```

Modelling and Prediction

Splitting the dataset into training and testing data

In [236]:
```
df_train_dummies = pd.get_dummies(df_train, drop_first = True, columns =
['SaleCondition'])
df_train_dummies.columns
```

Out[236]:
```
Index(['GarageArea', 'GrLivArea', 'OverallQual', 'SalePrice', 'SaleTyp
e',
       'TotalSF', 'YearBuilt', 'SaleCondition_AdjLand', 'SaleCondition_
Alloca',
       'SaleCondition_Family', 'SaleCondition_Normal',
       'SaleCondition_Partial'],
      dtype='object')
```

In [321]:
```
# df_train_dummies.info()
```

In [241]:
```
float_col = df_train_dummies.select_dtypes(include=['float64']) # This w
ill select float columns only
# list(float_col.columns.values)

for col in float_col.columns.values:
    df_train_dummies[col] = df_train_dummies[col].astype('int64')

print(df_train_dummies.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1453 entries, 0 to 1459
Data columns (total 12 columns):
 #   Column                 Non-Null Count  Dtype 
---  ------                 --------------  ----- 
 0   GarageArea             1453 non-null   int64 
 1   GrLivArea              1453 non-null   int64 
 2   OverallQual            1453 non-null   int64 
 3   SalePrice              1453 non-null   int64 
 4   SaleType               1453 non-null   object
 5   TotalSF                1453 non-null   int64 
 6   YearBuilt              1453 non-null   int64 
 7   SaleCondition_AdjLand  1453 non-null   uint8 
 8   SaleCondition_Alloca   1453 non-null   uint8 
 9   SaleCondition_Family   1453 non-null   uint8 
 10  SaleCondition_Normal   1453 non-null   uint8 
 11  SaleCondition_Partial  1453 non-null   uint8 
dtypes: int64(6), object(1), uint8(5)
memory usage: 97.9+ KB
None
```

In [249]:
```
X = df_train_dummies[['GarageArea', 'GrLivArea', 'OverallQual', 'SaleCon
dition_AdjLand', 'SaleCondition_Alloca',
       'SaleCondition_Family', 'SaleCondition_Normal','SaleCondition_Par
tial', 'TotalSF', 'YearBuilt']]

y = df_train_dummies['SalePrice']
```

In [299]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.
3, random_state = 30)
```

In [302]:
```
# Looking at the shape of the data to test whether training features num
ber of columns match testing feature number of columns.The number of row
s to match for the respective training and testing features and the labe
ls

print('X_Train Shape:', X_train.shape)
print('Y_Train Shape:', y_train.shape)
print('X_Test Shape:', X_test.shape)
print('Y_Test Shape:', y_test.shape)
```

```
X_Train Shape: (1017, 10)
Y_Train Shape: (1017,)
X_Test Shape: (436, 10)
Y_Test Shape: (436,)
```

Simple Linear Regression

In [366]:
```
from sklearn.linear_model import LinearRegression
from sklearn import datasets, linear_model
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_
error, median_absolute_error
from sklearn import metrics

linear_model = LinearRegression()
linear_model.fit(X_train, y_train)
```

Out[366]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normaliz
e=False)
```

In [367]:
```
coefficient = pd.DataFrame(linear_model.coef_, X_train.columns, columns
= ['Coefficient'])
coefficient
```

Out[367]:

	Coefficient
GarageArea	0.000098
GrLivArea	0.000322
OverallQual	0.108783
SaleCondition_AdjLand	0.048354
SaleCondition_Alloca	-0.045575
SaleCondition_Family	-0.128103
SaleCondition_Normal	0.096601
SaleCondition_Partial	0.164352
TotalSF	0.000077
YearBuilt	0.005193

In [369]:
```
pred_train = linear_model.predict(X_train)
# pred_train
pred_test = linear_model.predict(X_test)
# pred_test

Prediction = pd.DataFrame(pred_test)
Prediction.columns = ['Predicted Value']
Prediction
```

Out[369]:

	Predicted Value
0	10.644484
1	11.840121
2	10.743492
3	11.212310
4	11.229189
...	...
431	11.359358
432	11.279523
433	12.089005
434	12.002005
435	12.277182

436 rows × 1 columns

In [370]:
```
meansqerror_train = metrics.mean_squared_error(y_train, pred_train)
print('Mean Squared Error of Training data for Linear Regression Model:
 ', meansqerror_train)
rmse_train = np.sqrt(metrics.mean_squared_error(y_train, pred_train))
print('Root Mean Squared Error of Training for data Linear Regression Mo
del: ', rmse_train)

meansqerror_test = metrics.mean_squared_error(y_test, pred_test)
print('Mean Squared Error of Testing data for Linear Regression Model: '
, meansqerror_test)
rmse_test = np.sqrt(metrics.mean_squared_error(y_test, pred_test))
print('Root Mean Squared Error of Testing data for Linear Regression Mod
el: ', rmse_test)
```

```
Mean Squared Error of Training data for Linear Regression Model:  0.102
12261882025268
Root Mean Squared Error of Training for data Linear Regression Model:
0.31956629800442454
Mean Squared Error of Testing data for Linear Regression Model:  0.1033
573633857832
Root Mean Squared Error of Testing data for Linear Regression Model:
0.3214924001991077
```

In [371]:
```
# Calculating the accuracy of our model

print("Training accuracy of Logistic Regression model:", linear_model.sc
ore(X_train, y_train))
print("Testing accuracy of Logistic Regression model:", linear_model.sco
re(X_test, y_test))
```

```
Training accuracy of Logistic Regression model: 0.6470035582377622
Testing accuracy of Logistic Regression model: 0.6275647549960413
```

Logistic Regression

In [307]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.feature_selection import RFE

logistic_model = LogisticRegression()
rfe = RFE(logistic_model, 9)
rfe = rfe.fit(X_train, y_train.values.ravel())
print(rfe.support_)  #Indicates all variables have been selected by RFE
 with a ranking of 1
print(rfe.ranking_)
```

```
[ True  True  True False  True  True  True  True  True  True]
[1 1 1 2 1 1 1 1 1 1]
```

In [316]:
```
logistic_model.fit(X_train, y_train)
```

Out[316]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=
True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbo
se=0,
                   warm_start=False)
```

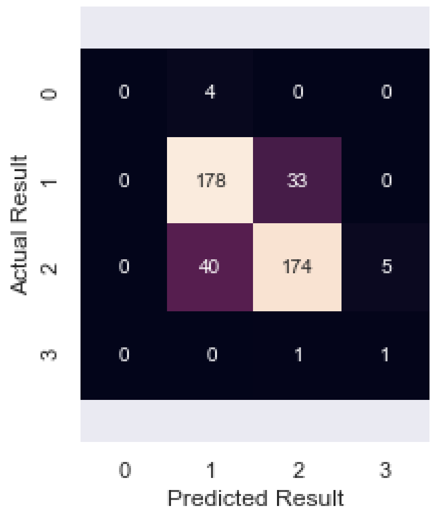
In [328]:
```
pred_train = logistic_model.predict(X_train)
# pred_train
pred_test = logistic_model.predict(X_test)
# pred_test

Prediction_logistic = pd.DataFrame(pred_test)
Prediction_logistic.columns = ['Predicted Value']
Prediction_logistic
```

Out[328]:

	Predicted Value
0	11
1	12
2	11
3	11
4	11
...	...
431	11
432	11
433	12
434	12
435	12

436 rows × 1 columns

In [327]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

mat = confusion_matrix(y_test, prediction)
sns.heatmap(mat, fmt='g', square=True, annot=True, cbar=False)
plt.xlabel("Predicted Result")
plt.ylabel("Actual Result")
a, b = plt.ylim()
a += 0.5
b -= 0.5
plt.ylim(a, b)
plt.show()
```



In [330]:
```
meansqerror_train = metrics.mean_squared_error(y_train, pred_train)
print('Mean Squared Error of Training data for Logistic Regression Mode
l: ', meansqerror_train)
rmse_train = np.sqrt(metrics.mean_squared_error(y_train, pred_train))
print('Root Mean Squared Error of Training for data Logistic Regression
 Model: ', rmse_train)

meansqerror_test = metrics.mean_squared_error(y_test, pred_test)
print('Mean Squared Error of Testing data for Logistic Regression Model:
', meansqerror_test)
rmse_test = np.sqrt(metrics.mean_squared_error(y_test, pred_test))
print('Root Mean Squared Error of Testing data for Logistic Regression M
odel: ', rmse_test)
```

```
Mean Squared Error of Training data for Logistic Regression Model:  0.1
9960668633235004
Root Mean Squared Error of Training for data Logistic Regression Model:
0.44677364104471295
Mean Squared Error of Testing data for Logistic Regression Model:  0.19
036697247706422
Root Mean Squared Error of Testing data for Logistic Regression Model:
0.43631063759329114
```

In [333]:
```
# Calculating the accuracy of our model

print("Training accuracy of Logistic Regression model:", logistic_model.score(X_train, y_train))
print("Testing accuracy of Logistic Regression model:", logistic_model.score(X_test, y_test))
```

```
Training accuracy of Logistic Regression model: 0.80039331366765
Testing accuracy of Logistic Regression model: 0.8096330275229358
```

Lasso Regression

In [352]:
```
from sklearn import linear_model

lasso_model = linear_model.Lasso(alpha = 25, max_iter = 100, tol = 0.1)
lasso_model.fit(X_train, y_train)
```

Out[352]:
```
Lasso(alpha=25, copy_X=True, fit_intercept=True, max_iter=100, normalize=False,
      positive=False, precompute=False, random_state=None, selection='cyclic',
      tol=0.1, warm_start=False)
```

In [354]:
```
pred_train = lasso_model.predict(X_train)
# pred_train
pred_test = lasso_model.predict(X_test)
# pred_test

Prediction_lasso = pd.DataFrame(pred_test)
Prediction_lasso.columns = ['Predicted Value']
Prediction_lasso
```

Out[354]:

	Predicted Value
0	10.952430
1	11.447634
2	10.981250
3	11.328890
4	11.359592
...	...
431	11.531111
432	11.311240
433	11.636441
434	11.511862
435	12.236381

436 rows × 1 columns

In [357]:
```
meansqerror_train = metrics.mean_squared_error(y_train, pred_train)
print('Mean Squared Error of Training data for Lasso Regression Model: '
, meansqerror_train)
rmse_train = np.sqrt(metrics.mean_squared_error(y_train, pred_train))
print('Root Mean Squared Error of Training for data Lasso Regression Mod
el: ', rmse_train)

meansqerror_test = metrics.mean_squared_error(y_test, pred_test)
print('Mean Squared Error of Testing data for Lasso Regression Model: ',
meansqerror_test)
rmse_test = np.sqrt(metrics.mean_squared_error(y_test, pred_test))
print('Root Mean Squared Error of Testing data for Lasso Regression Mode
l: ', rmse_test)
```

```
Mean Squared Error of Training data for Lasso Regression Model:  0.1666
6144253048681
Root Mean Squared Error of Training for data Lasso Regression Model:
0.4082418921797306
Mean Squared Error of Testing data for Lasso Regression Model:  0.15252
11273717831
Root Mean Squared Error of Testing data for Lasso Regression Model:  0.
39053953368613414
```

In [364]:
```
# Calculating the accuracy of our model

print("Training accuracy of Lasso Regression model:", lasso_model.score(
X_train, y_train))
print("Testing accuracy of Lasso Regression model:", lasso_model.score(X
_test, y_test))
```

```
Training accuracy of Lasso Regression model: 0.4239190409347754
Testing accuracy of Lasso Regression model: 0.4504093217919347
```

Ridge Regression

In [358]:
```
from sklearn.linear_model import Ridge

ridge_model = Ridge(alpha = 25, max_iter = 100, tol = 0.1)
ridge_model.fit(X_train, y_train)
```

Out[358]:
```
Ridge(alpha=25, copy_X=True, fit_intercept=True, max_iter=100, normaliz
e=False,
      random_state=None, solver='auto', tol=0.1)
```

In [362]:
```
pred_train = ridge_model.predict(X_train)
# pred_train
pred_test = ridge_model.predict(X_test)
# pred_test

Prediction_ridge = pd.DataFrame(pred_test)
Prediction_ridge.columns = ['Predicted Value']
Prediction_ridge
```

Out[362]:

	Predicted Value
0	10.668487
1	11.811649
2	10.734027
3	11.209538
4	11.226408
...	...
431	11.350600
432	11.310900
433	12.062172
434	11.974313
435	12.279308

436 rows × 1 columns

In [363]:
```
meansqerror_train = metrics.mean_squared_error(y_train, pred_train)
print('Mean Squared Error of Training data for Ridge Regression Model: '
, meansqerror_train)
rmse_train = np.sqrt(metrics.mean_squared_error(y_train, pred_train))
print('Root Mean Squared Error of Training for data Ridge Regression Mod
el: ', rmse_train)

meansqerror_test = metrics.mean_squared_error(y_test, pred_test)
print('Mean Squared Error of Testing data for Ridge Regression Model: ',
meansqerror_test)
rmse_test = np.sqrt(metrics.mean_squared_error(y_test, pred_test))
print('Root Mean Squared Error of Testing data for Ridge Regression Mode
l: ', rmse_test)
```

```
Mean Squared Error of Training data for Ridge Regression Model:  0.1024
5627327509264
Root Mean Squared Error of Training for data Ridge Regression Model:
0.32008791491571914
Mean Squared Error of Testing data for Ridge Regression Model:  0.10221
295356991246
Root Mean Squared Error of Testing data for Ridge Regression Model:  0.
31970760636855744
```

In [374]:
```
# Calculating the accuracy of our model

print("Training accuracy of Ridge Regression model:", ridge_model.score(
X_train, y_train))
print("Testing accuracy of Ridge Regression model:", ridge_model.score(X
_test, y_test))
```

```
Training accuracy of Ridge Regression model: 0.6458502502174898
Testing accuracy of Ridge Regression model: 0.6316884916723329
```

While the Logistic Regression model gave the highest accuracy, the Ridge Regression model gave the lowest mean squared error. It was interesting to note that while the accuracy ranged from 40-60%; logistic regression gave an overall higher accuracy of 80%. Based on this finding, I believe Ridge Regression would be the optimal choice with the lowest mean squared error of 10% and accuracy of 64%.