TASK REPORT
HOUSE PRICE PREDICTION

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Chapter 1
Introduction

This case tries to provide insights for home developers and customers. Machine learning is expected to be able to predict house prices based on several important variables. This information can help developers and customers make good strategies. For developers, it is necessary to invest the lowest purchase price and to get the highest sales price. Developers can identify important variables that make high bids for customer. Developers can buy simple houses (at lower prices) and make them improvement (taking into account important variables) to sell it at a higher price. Instead, customers can decide the best choice in buying a home based on the variables. The buyer can estimate that the selling price is feasible or not based on its features.

Ask a home buyer to describe their dream house, and they probably won't begin with the height of the basement ceiling or the proximity to an east-west railroad. But this playground competition's dataset proves that much more influences price negotiations than the number of bedrooms or a white-picket fence. With 79 explanatory variables describing (almost) every aspect of residential homes in Ames, Iowa. This purpose is to predict the final price of each home.

Chapter 2
Progress Report

Day/Date	**Task**	**Level** (easy/medium/hard)	**Comments**
15/05/2020	Business Understanding	Medium	
15/05/2020	Data understanding and data preparation	Easy	
15/05/2020	Modeling and Evaluation	Easy	

Chapter 3
Task Report

Import Library ¶

The first step is to import the required libraries, which are Pandas, Numpy, MatplotLib, Seaborn, Scikit Learn, Scipy, etc..

In [127]:
```
import numpy as np
import pandas as pd
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
color = sns.color_palette()
sns.set_style('darkgrid')
import warnings
def ignore_warn(*args, **kwargs):
    pass
warnings.warn = ignore_warn
from scipy import stats
from scipy.stats import norm, skew
```

Load Data

Next, import the House Predict dataset using pandas. There are 2 dataset files, namely train and test dataset. Data Train will be used to build and evaluate models, while test data will be used for submission of answers in Kaggle. The data train has 1460 rows or observations and 81 columns, while the test data has 1459 rows or observations and 80 columns.

In [128]:
```
train = pd.read_csv('C:/Users/WINDOWS X/Downloads/train.csv')
test = pd.read_csv('C:/Users/WINDOWS X/Downloads/test.csv')
```

In [129]:
```
train.shape
```

Out[129]:
```
(1460, 81)
```

In [130]:
```
test.shape
```

Out[130]:
```
(1459, 80)
```

In [131]:
```
train.head()
```

Out[131]:

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

5 rows × 81 columns

Cleansing Data

The next step is cleansing the dataset. First delete the ID column, second check the data type of each variable, third check the missing value of each variable and impute the missing value, fourth check the outlier using standardized residuals regression.

Drop ID

In [132]:
```
#Save the 'Id' column
train_ID = train['Id']
test_ID = test['Id']

#Now drop the  'Id' colum since it's unnecessary for  the prediction process.
train.drop("Id", axis = 1, inplace = True)
test.drop("Id", axis = 1, inplace = True)
```

Check Data Type

The data types of all variables are suitable except for some variables that contain years. However, because the analysis used is a cross section model, the variables containing years must be numeric rather than date time.

In [133]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 80 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   MSSubClass     1460 non-null   int64  
 1   MSZoning       1460 non-null   object 
 2   LotFrontage    1201 non-null   float64
 3   LotArea        1460 non-null   int64  
 4   Street         1460 non-null   object 
 5   Alley          91 non-null     object 
 6   LotShape       1460 non-null   object 
 7   LandContour    1460 non-null   object 
 8   Utilities      1460 non-null   object 
 9   LotConfig      1460 non-null   object 
 10  LandSlope      1460 non-null   object 
 11  Neighborhood   1460 non-null   object 
 12  Condition1     1460 non-null   object 
 13  Condition2     1460 non-null   object 
 14  BldgType       1460 non-null   object 
 15  HouseStyle     1460 non-null   object 
 16  OverallQual    1460 non-null   int64  
 17  OverallCond    1460 non-null   int64  
 18  YearBuilt      1460 non-null   int64  
 19  YearRemodAdd   1460 non-null   int64  
 20  RoofStyle      1460 non-null   object 
 21  RoofMatl       1460 non-null   object 
 22  Exterior1st    1460 non-null   object 
 23  Exterior2nd    1460 non-null   object 
 24  MasVnrType     1452 non-null   object 
 25  MasVnrArea     1452 non-null   float64
 26  ExterQual      1460 non-null   object 
 27  ExterCond      1460 non-null   object 
 28  Foundation     1460 non-null   object 
 29  BsmtQual       1423 non-null   object 
 30  BsmtCond       1423 non-null   object 
 31  BsmtExposure   1422 non-null   object 
 32  BsmtFinType1   1423 non-null   object 
 33  BsmtFinSF1     1460 non-null   int64  
 34  BsmtFinType2   1422 non-null   object 
 35  BsmtFinSF2     1460 non-null   int64  
 36  BsmtUnfSF      1460 non-null   int64  
 37  TotalBsmtSF    1460 non-null   int64  
 38  Heating        1460 non-null   object 
 39  HeatingQC      1460 non-null   object 
 40  CentralAir     1460 non-null   object 
 41  Electrical     1459 non-null   object 
 42  1stFlrSF       1460 non-null   int64  
 43  2ndFlrSF       1460 non-null   int64  
 44  LowQualFinSF   1460 non-null   int64  
 45  GrLivArea      1460 non-null   int64  
 46  BsmtFullBath   1460 non-null   int64  
 47  BsmtHalfBath   1460 non-null   int64  
 48  FullBath       1460 non-null   int64  
 49  HalfBath       1460 non-null   int64  
 50  BedroomAbvGr   1460 non-null   int64  
 51  KitchenAbvGr   1460 non-null   int64  
 52  KitchenQual    1460 non-null   object 
 53  TotRmsAbvGrd   1460 non-null   int64  
```

```
 54  Functional     1460 non-null   object
 55  Fireplaces     1460 non-null   int64
 56  FireplaceQu    770 non-null    object
 57  GarageType     1379 non-null   object
 58  GarageYrBlt    1379 non-null   float64
 59  GarageFinish   1379 non-null   object
 60  GarageCars     1460 non-null   int64
 61  GarageArea     1460 non-null   int64
 62  GarageQual     1379 non-null   object
 63  GarageCond     1379 non-null   object
 64  PavedDrive     1460 non-null   object
 65  WoodDeckSF     1460 non-null   int64
 66  OpenPorchSF    1460 non-null   int64
 67  EnclosedPorch  1460 non-null   int64
 68  3SsnPorch      1460 non-null   int64
 69  ScreenPorch    1460 non-null   int64
 70  PoolArea       1460 non-null   int64
 71  PoolQC         7 non-null      object
 72  Fence          281 non-null    object
 73  MiscFeature    54 non-null     object
 74  MiscVal        1460 non-null   int64
 75  MoSold         1460 non-null   int64
 76  YrSold         1460 non-null   int64
 77  SaleType       1460 non-null   object
 78  SaleCondition  1460 non-null   object
 79  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(34), object(43)
memory usage: 912.6+ KB
```

Missing Value Check

The next step is to check the missing value of each variable. There are many variables that have missing values. Even PoolQC, MiscFeature, Alley and Fence variables have missing values above 50%.

In [134]:
```
train.isnull().sum().head(40)
```

Out[134]:
```
MSSubClass          0
MSZoning            0
LotFrontage       259
LotArea             0
Street              0
Alley            1369
LotShape            0
LandContour         0
Utilities           0
LotConfig           0
LandSlope           0
Neighborhood        0
Condition1          0
Condition2          0
BldgType            0
HouseStyle          0
OverallQual         0
OverallCond         0
YearBuilt           0
YearRemodAdd        0
RoofStyle           0
RoofMatl            0
Exterior1st         0
Exterior2nd         0
MasVnrType          8
MasVnrArea          8
ExterQual           0
ExterCond           0
Foundation          0
BsmtQual           37
BsmtCond           37
BsmtExposure       38
BsmtFinType1       37
BsmtFinSF1          0
BsmtFinType2       38
BsmtFinSF2          0
BsmtUnfSF           0
TotalBsmtSF         0
Heating             0
HeatingQC           0
dtype: int64
```

In [135]:
```
train.isnull().sum().tail(40)
```

Out[135]:
```
CentralAir          0
Electrical          1
1stFlrSF            0
2ndFlrSF            0
LowQualFinSF        0
GrLivArea           0
BsmtFullBath        0
BsmtHalfBath        0
FullBath            0
HalfBath            0
BedroomAbvGr        0
KitchenAbvGr        0
KitchenQual         0
TotRmsAbvGrd        0
Functional          0
Fireplaces          0
FireplaceQu       690
GarageType         81
GarageYrBlt        81
GarageFinish       81
GarageCars          0
GarageArea          0
GarageQual         81
GarageCond         81
PavedDrive          0
WoodDeckSF          0
OpenPorchSF         0
EnclosedPorch       0
3SsnPorch           0
ScreenPorch         0
PoolArea            0
PoolQC           1453
Fence            1179
MiscFeature      1406
MiscVal             0
MoSold              0
YrSold              0
SaleType            0
SaleCondition       0
SalePrice           0
dtype: int64
```

In [136]:
```
test.isnull().sum().head(40)
```

Out[136]:
```
MSSubClass         0
MSZoning           4
LotFrontage      227
LotArea            0
Street             0
Alley           1352
LotShape           0
LandContour        0
Utilities          2
LotConfig          0
LandSlope          0
Neighborhood       0
Condition1         0
Condition2         0
BldgType           0
HouseStyle         0
OverallQual        0
OverallCond        0
YearBuilt          0
YearRemodAdd       0
RoofStyle          0
RoofMatl           0
Exterior1st        1
Exterior2nd        1
MasVnrType        16
MasVnrArea        15
ExterQual          0
ExterCond          0
Foundation         0
BsmtQual          44
BsmtCond          45
BsmtExposure      44
BsmtFinType1      42
BsmtFinSF1         1
BsmtFinType2      42
BsmtFinSF2         1
BsmtUnfSF          1
TotalBsmtSF        1
Heating            0
HeatingQC          0
dtype: int64
```

In [137]:
```
test.isnull().sum().tail(40)
```

Out[137]:
```
HeatingQC          0
CentralAir         0
Electrical         0
1stFlrSF           0
2ndFlrSF           0
LowQualFinSF       0
GrLivArea          0
BsmtFullBath       2
BsmtHalfBath       2
FullBath           0
HalfBath           0
BedroomAbvGr       0
KitchenAbvGr       0
KitchenQual        1
TotRmsAbvGrd       0
Functional         2
Fireplaces         0
FireplaceQu      730
GarageType        76
GarageYrBlt       78
GarageFinish      78
GarageCars         1
GarageArea         1
GarageQual        78
GarageCond        78
PavedDrive         0
WoodDeckSF         0
OpenPorchSF        0
EnclosedPorch      0
3SsnPorch          0
ScreenPorch        0
PoolArea           0
PoolQC          1456
Fence           1169
MiscFeature     1408
MiscVal            0
MoSold             0
YrSold             0
SaleType           1
SaleCondition      0
dtype: int64
```

In [138]:
```
train2=train.drop(["SalePrice"],axis=1)
data_all=pd.concat([train2,test],axis=0)
data_na = (data_all.isnull().sum() / len(data_all)) * 100
data_na = data_na.drop(data_na[data_na == 0].index).sort_values(ascending=False)
missing_data = pd.DataFrame({'Missing Ratio' :data_na})
missing_data.head(20)
```

Out[138]:

	Missing Ratio
PoolQC	99.657417
MiscFeature	96.402878
Alley	93.216855
Fence	80.438506
FireplaceQu	48.646797
LotFrontage	16.649538
GarageFinish	5.447071
GarageYrBlt	5.447071
GarageQual	5.447071
GarageCond	5.447071
GarageType	5.378554
BsmtExposure	2.809181
BsmtCond	2.809181
BsmtQual	2.774923
BsmtFinType2	2.740665
BsmtFinType1	2.706406
MasVnrType	0.822199
MasVnrArea	0.787941
MSZoning	0.137033
BsmtFullBath	0.068517

Impute Missing Value

Furthermore, the variables contained in the missing value are imputed.

PoolQC : data description says NA means "No Pool". That make sense, given the huge ratio of missing value (+99%) and majority of houses have no Pool at all in general.

In [139]:
```
data_all["PoolQC"].value_counts()
```

Out[139]:
```
Gd    4
Ex    4
Fa    2
Name: PoolQC, dtype: int64
```

In [140]:
```
data_all["PoolQC"] = data_all["PoolQC"].fillna("None")
```

MiscFeature : data description says NA means "no misc feature"

In [141]:
```
train["MiscFeature"].value_counts()
```

Out[141]:
```
Shed    49
Othr     2
Gar2     2
TenC     1
Name: MiscFeature, dtype: int64
```

In [142]:
```
data_all["MiscFeature"] = data_all["MiscFeature"].fillna("None")
```

Alley : data description says NA means "no alley access"

In [143]:
```
train["Alley"].value_counts()
```

Out[143]:
```
Grvl    50
Pave    41
Name: Alley, dtype: int64
```

In [144]:
```
data_all["Alley"] = data_all["Alley"].fillna("None")
```

Fence : data description says NA means "no fence"

In [145]:
```
data_all["Fence"].value_counts()
```

Out[145]:
```
MnPrv    329
GdPrv    118
GdWo     112
MnWw      12
Name: Fence, dtype: int64
```

In [146]:
```
data_all["Fence"] = data_all["Fence"].fillna("None")
```

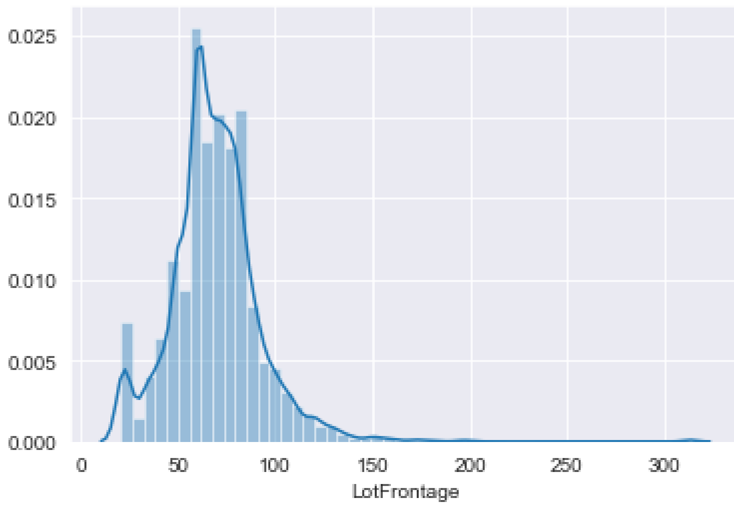
FireplaceQu : data description says NA means "no fireplace"

In [147]:
```
data_all["FireplaceQu"] =data_all["FireplaceQu"].fillna("None")
```

LotFrontage: Because the area of each road connected to the house property is likely to have an area similar to other houses in the neighborhood and this variable also has many outliers, then we can fill in the missing values by the median LotFrontage of the neighborhood.

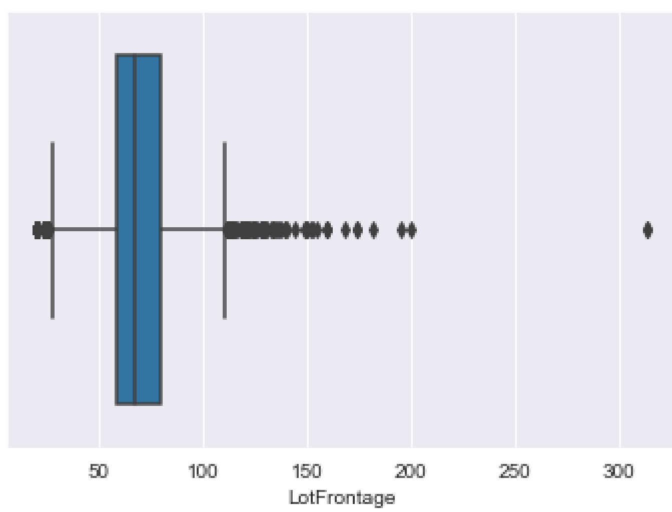
In [148]:
```
sns.distplot(data_all["LotFrontage"])
```

Out[148]: <matplotlib.axes._subplots.AxesSubplot at 0x1f6a9ca2c08>



In [149]:
```
sns.boxplot(data_all["LotFrontage"])
```

Out[149]: <matplotlib.axes._subplots.AxesSubplot at 0x1f6a9d91cc8>



In [150]:
```
#Group by neighborhood and fill in missing value by the median LotFrontage of all the ne
ighborhood
data_all["LotFrontage"] = data_all.groupby("Neighborhood")["LotFrontage"].transform(
    lambda x: x.fillna(x.median()))
```

GarageType, GarageFinish, GarageQual and GarageCond : Replacing missing data with None

In [151]:
```
for col in ('GarageType', 'GarageFinish', 'GarageQual', 'GarageCond'):
    data_all[col] = data_all[col].fillna('None')
```

GarageYrBlt, GarageArea and GarageCars : Replacing missing data with 0 (Since No garage = no cars in such garage.)

In [152]:
```
for col in ('GarageYrBlt', 'GarageArea', 'GarageCars'):
    data_all[col] = data_all[col].fillna(0)
```

BsmtFinSF1, BsmtFinSF2, BsmtUnfSF, TotalBsmtSF, BsmtFullBath and BsmtHalfBath : missing values are likely zero for having no basement

In [153]:
```
for col in ('BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF','TotalBsmtSF', 'BsmtFullBath', 'Bsmt
HalfBath'):
    data_all[col] = data_all[col].fillna(0)
```

BsmtQual, BsmtCond, BsmtExposure, BsmtFinType1 and BsmtFinType2 : For all these categorical basement-related features, NaN means that there is no basement.

In [154]:
```
for col in ('BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2'):
    data_all[col] = data_all[col].fillna('None')
```

MasVnrArea and MasVnrType : NA most likely means no masonry veneer for these houses. We can fill 0 for the area and None for the type.

In [155]:
```
data_all["MasVnrType"] = data_all["MasVnrType"].fillna("None")
data_all["MasVnrArea"] = data_all["MasVnrArea"].fillna(0)
```

MSZoning (The general zoning classification) : 'RL' is by far the most common value. So we can fill in missing values with 'RL'

In [156]:
```
data_all['MSZoning'] = data_all['MSZoning'].fillna(data_all['MSZoning'].mode()[0])
```

Utilities is imputed with their mode values.

In [157]:
```
data_all['Utilities'].value_counts()
```

Out[157]:
```
AllPub    2916
NoSeWa       1
Name: Utilities, dtype: int64
```

In [158]:
```
data_all['Utilities'] = data_all['Utilities'].fillna(data_all['Utilities'].mode()[0])
```

Functional : data description says NA means typical

In [159]:
```
data_all["Functional"] = data_all["Functional"].fillna("Typ")
```

Electrical : It has one NA value. Since this feature has mostly 'SBrkr', we can set that for the missing value.

In [160]:
```
data_all['Electrical'] = data_all['Electrical'].fillna(data_all['Electrical'].mode()[0])
```

KitchenQual: Only one NA value, and same as Electrical, we set 'TA' (which is the most frequent) for the missing value in KitchenQual.

In [161]:
```
data_all['KitchenQual'] = train['KitchenQual'].fillna(data_all['KitchenQual'].mode()[0])
```

Exterior1st and Exterior2nd : Again Both Exterior 1 & 2 have only one missing value. We will just substitute in the most common string

In [162]:
```
data_all['Exterior1st'] = data_all['Exterior1st'].fillna(data_all['Exterior1st'].mode()[
0])
data_all['Exterior2nd'] = data_all['Exterior2nd'].fillna(data_all['Exterior2nd'].mode()[
0])
```

SaleType : Fill in again with most frequent which is "WD"

In [163]:
```
data_all['SaleType'] = data_all['SaleType'].fillna(data_all['SaleType'].mode()[0])
```

MSSubClass : Na most likely means No building class. We can replace missing values with None

In [164]:
```
data_all['MSSubClass'] =data_all['MSSubClass'].fillna("None")
```

There is no missing value in the data.

In [165]:
```
data_all.isnull().sum().head(40)
```

Out[165]:
```
MSSubClass      0
MSZoning        0
LotFrontage     0
LotArea         0
Street          0
Alley           0
LotShape        0
LandContour     0
Utilities       0
LotConfig       0
LandSlope       0
Neighborhood    0
Condition1      0
Condition2      0
BldgType        0
HouseStyle      0
OverallQual     0
OverallCond     0
YearBuilt       0
YearRemodAdd    0
RoofStyle       0
RoofMatl        0
Exterior1st     0
Exterior2nd     0
MasVnrType      0
MasVnrArea      0
ExterQual       0
ExterCond       0
Foundation      0
BsmtQual        0
BsmtCond        0
BsmtExposure    0
BsmtFinType1    0
BsmtFinSF1      0
BsmtFinType2    0
BsmtFinSF2      0
BsmtUnfSF       0
TotalBsmtSF     0
Heating         0
HeatingQC       0
dtype: int64
```

In [166]:
```
data_all.isnull().sum().tail(40)
```

Out[166]:
```
HeatingQC        0
CentralAir       0
Electrical       0
1stFlrSF         0
2ndFlrSF         0
LowQualFinSF     0
GrLivArea        0
BsmtFullBath     0
BsmtHalfBath     0
FullBath         0
HalfBath         0
BedroomAbvGr     0
KitchenAbvGr     0
KitchenQual      0
TotRmsAbvGrd     0
Functional       0
Fireplaces       0
FireplaceQu      0
GarageType       0
GarageYrBlt      0
GarageFinish     0
GarageCars       0
GarageArea       0
GarageQual       0
GarageCond       0
PavedDrive       0
WoodDeckSF       0
OpenPorchSF      0
EnclosedPorch    0
3SsnPorch        0
ScreenPorch      0
PoolArea         0
PoolQC           0
Fence            0
MiscFeature      0
MiscVal          0
MoSold           0
YrSold           0
SaleType         0
SaleCondition    0
dtype: int64
```

Feature Enginer 1

Adding one more important feature

Since area related features are very important to determine house prices, we add one more feature which is the total area of basement, first and second floor areas of each house

In [167]:
```
# Adding total sqfootage feature
data_all['TotalSF'] =data_all['TotalBsmtSF'] + data_all['1stFlrSF'] + data_all['2ndFlrS
F']
```

In [168]:
```
train=pd.concat([data_all.iloc[:len(train),:],train.SalePrice],axis=1)
```

Make numerical variable for the benefit of EDA

In [169]:
```
num1=train.loc[:,train.dtypes=="int64"]
num2=train.loc[:,train.dtypes=="float64"]
num=pd.concat([num1,num2],axis=1)
```

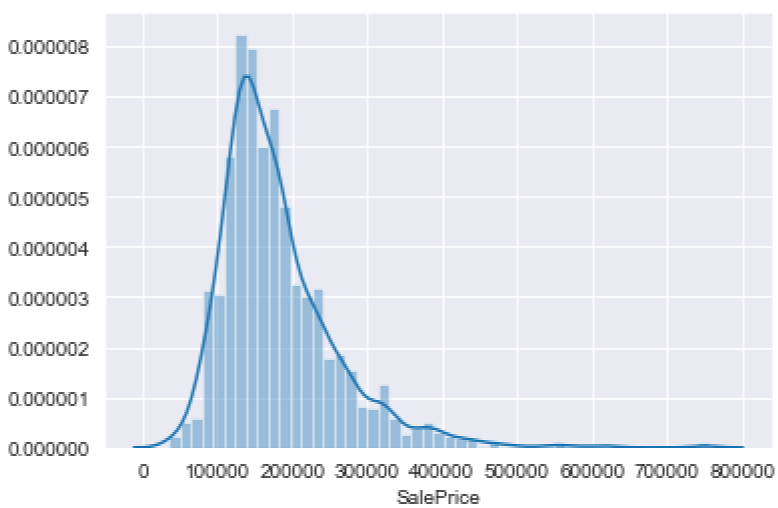
EDA

The dependent variable used is SalePrice. First we check the distribution of these variables using density plots and boxplots.

It can be seen from the density plot below that the SalePrice variable is not normally distributed and has positive skewness.

In [170]:
```
sns.distplot(train["SalePrice"])
```

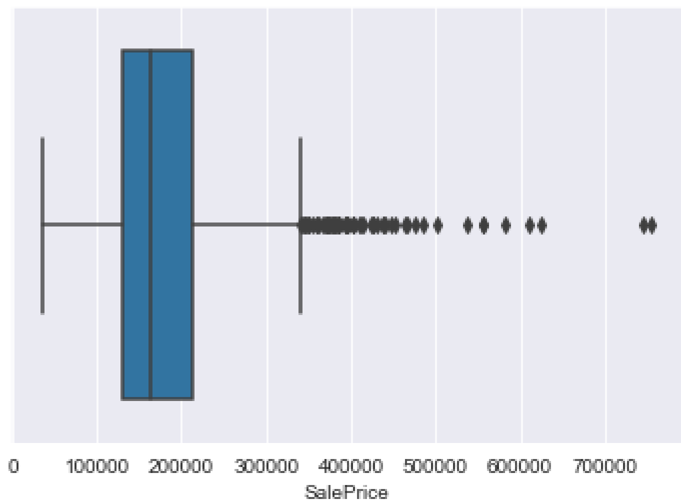
Out[170]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f69b506388>
```



In addition, based on the boxplot below it can be seen that there are quite a number of outliers on the SalePrice variable.

In [171]:
```
sns.boxplot(train["SalePrice"])
```

Out[171]: <matplotlib.axes._subplots.AxesSubplot at 0x1f6a9ea4608>

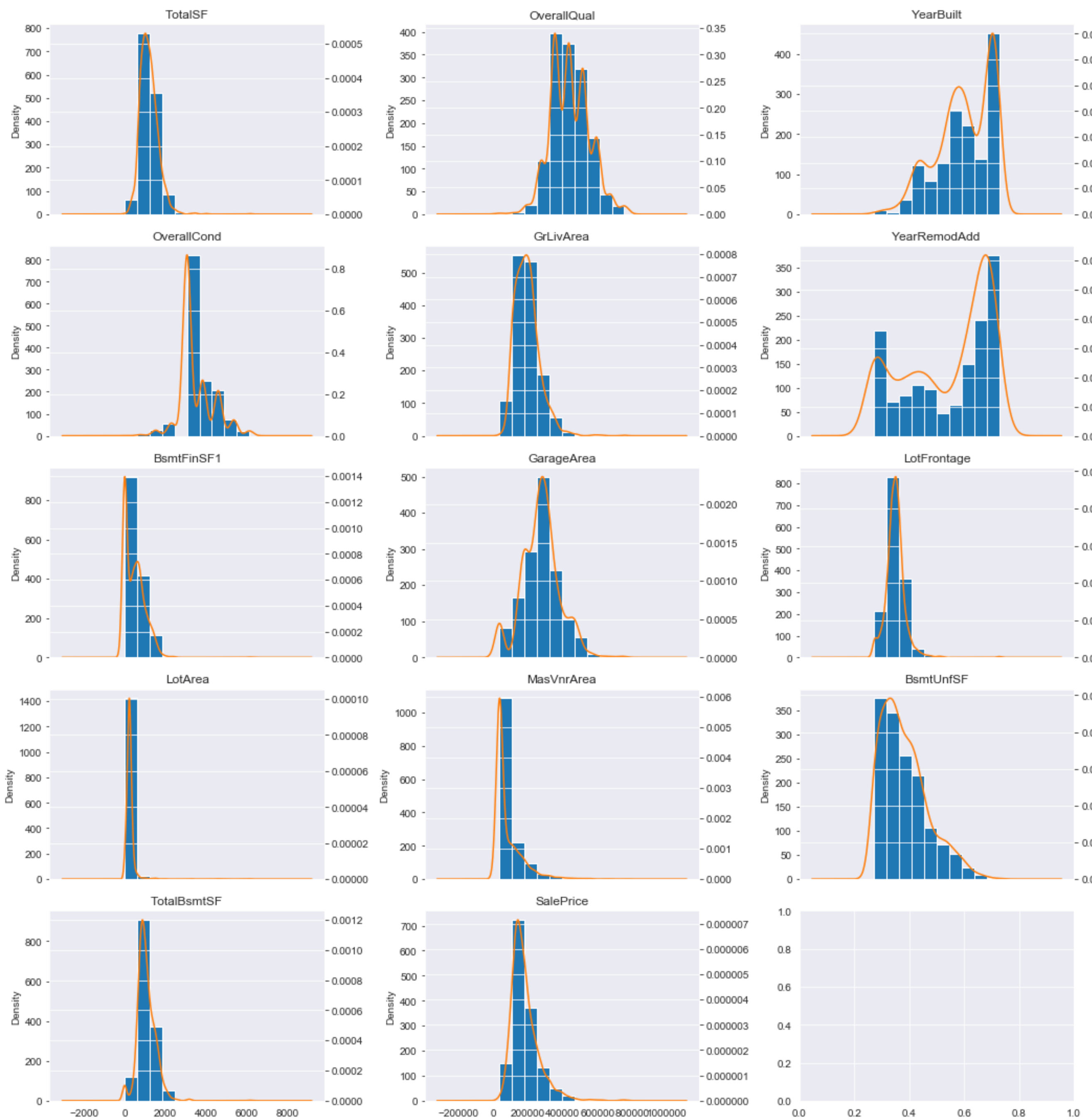


Next, we check the distribution of each independent variable with a numeric data type.

Based on the histogram and density plot below, it can be seen that none of the numerical independent variables are normally distributed.

In [172]:

```python
k = len(train[["TotalSF","OverallQual","YearBuilt","OverallCond","GrLivArea","YearRemodAdd","BsmtFinSF1","GarageArea","LotFrontage","LotArea","MasVnrArea","BsmtUnfSF","TotalBsmtSF","SalePrice"]].columns)
n = 3
m = (k - 1) // n + 1 ## Floor Division (also called Integer Division)
fig, axes = plt.subplots(m, n, figsize=(n * 5, m * 3))
for i, (name, col) in enumerate(train[["TotalSF","OverallQual","YearBuilt","OverallCond","GrLivArea","YearRemodAdd","BsmtFinSF1","GarageArea","LotFrontage","LotArea","MasVnrArea","BsmtUnfSF","TotalBsmtSF","SalePrice"]].iteritems()):
    r, c = i // n, i % n
    ax = axes[r, c]
    col.hist(ax=ax)
    ax2 = col.plot.kde(ax=ax, secondary_y=True, title=name)
    ax2.set_ylim(0)

fig.tight_layout()
```



Next, we see the relationship between numerical variables using a scater plot.

Based on the scatter plot below, it appears that there are several variables that correlate strongly enough both positively and negatively. Variables that correlate strongly with SalePrice variables are TotalSF, OverallQual, YearBuilt, GrLivArea, YearRemodAdd, and 1stFlrSF. Where these variables are positively correlated with SalePrice.

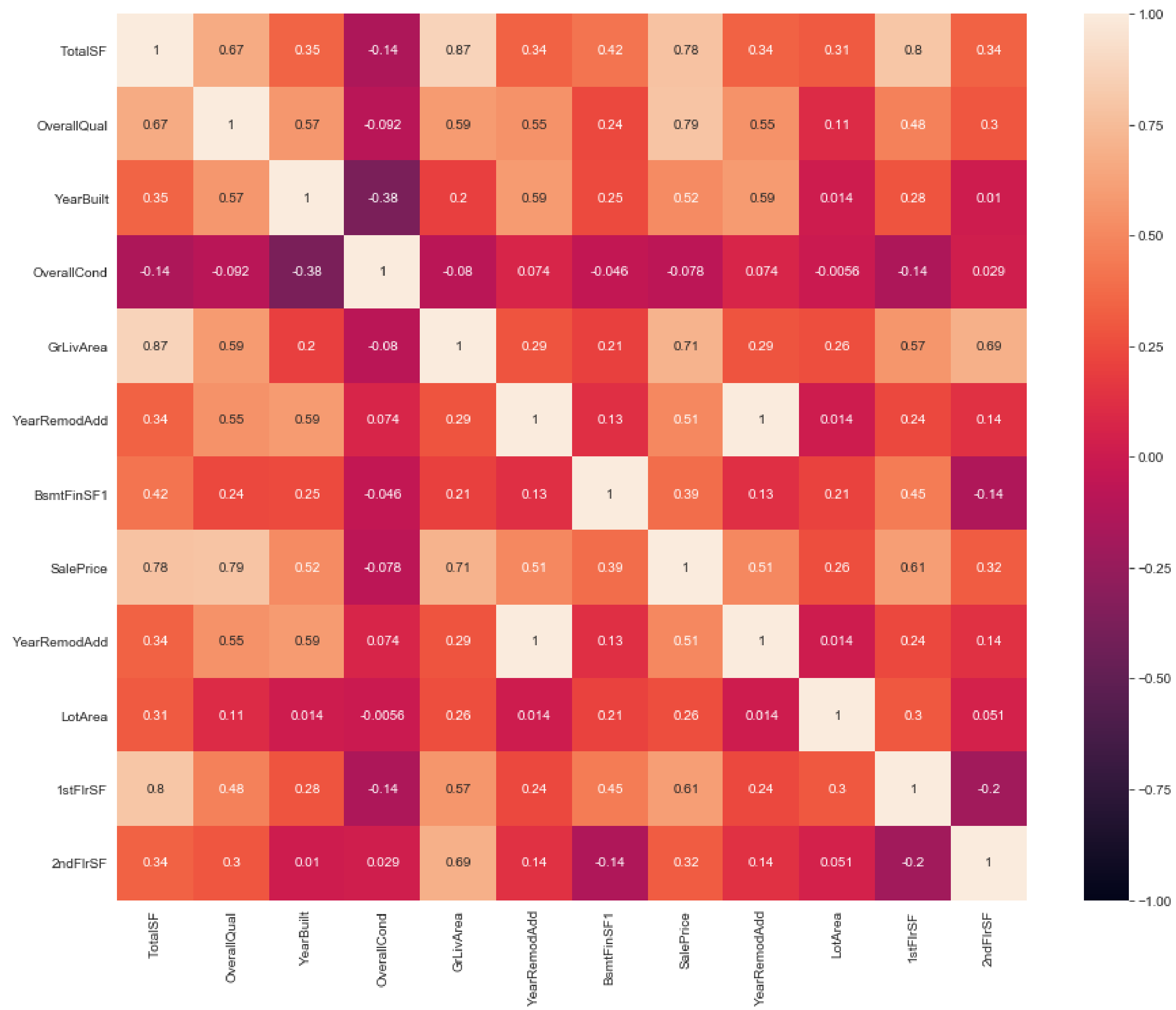
In [173]:
```
sns.pairplot(train[["TotalSF","OverallQual","YearBuilt","OverallCond","GrLivArea","YearRemodAdd","BsmtFinSF1","1stFlrSF","2ndFlrSF","SalePrice"]])
```

Out[173]: <seaborn.axisgrid.PairGrid at 0x1f69f168448>

Next, to clarify the correlation value, a heat map of the correlation between variables is created. Variables that correlate strongly with SalePrice variables are TotalSF, OverallQual, YearBuilt, GrLivArea, YearRemodAdd, and 1stFlrSF. Where these variables are positively correlated and above 0.5 with SalePrice.

In [174]:
```
cor=train[["TotalSF","OverallQual","YearBuilt","OverallCond","GrLivArea","YearRemodAdd",
"BsmtFinSF1","SalePrice","YearRemodAdd","LotArea","1stFlrSF","2ndFlrSF"]].corr()
plt.figure(figsize=(15,12))
sns.heatmap(cor,annot=True,vmin=-1,vmax=1)
```

Out[174]: <matplotlib.axes._subplots.AxesSubplot at 0x1f6adb2f948>



What is the House Style with the most expensive price?

Two and one-half story: 2nd level finished is a house style with the most expensive average sale price. Two story is a house style with the second most expensive sale price. Whereas One and one-half story: 2nd level unfinished is a house style with the lowest average sale price and even the average sale price is half of the average sale price of Two and one-half story: 2nd level finished.

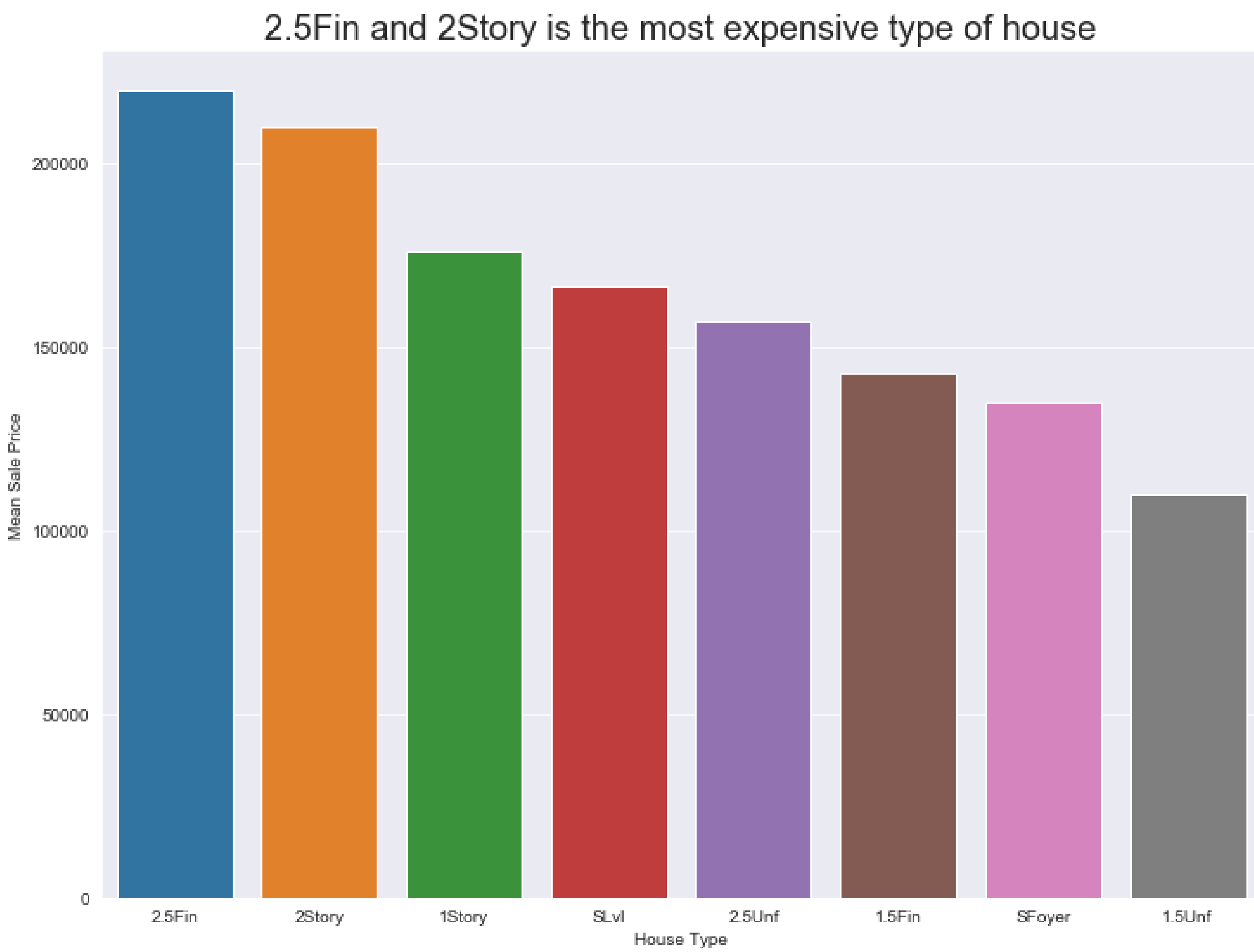
In [175]:
```
house_style_price=train.groupby(["HouseStyle"]).agg({"SalePrice":"mean"})
house_style_price=house_style_price.rename(columns={"SalePrice":"Mean Sale Price"})
house_style_price=house_style_price.reset_index().sort_values(["Mean Sale Price"],ascending=False)
house_style_price
```

Out[175]:

	HouseStyle	Mean Sale Price
3	2.5Fin	220000.000000
5	2Story	210051.764045
2	1Story	175985.477961
7	SLvl	166703.384615
4	2.5Unf	157354.545455
0	1.5Fin	143116.740260
6	SFoyer	135074.486486
1	1.5Unf	110150.000000

In [176]:
```
plt.figure(figsize=(12,9))
sns.barplot(house_style_price["HouseStyle"],house_style_price["Mean Sale Price"])
plt.title("2.5Fin and 2Story is the most expensive type of house",fontdict={'fontsize':2
0})
plt.xlabel("House Type")
plt.ylabel("Mean Sale Price")
plt.figure()
```

Out[176]: <Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>

Which year is the most expensive house with the highest value built?

In Data Train, the most recent year for home construction is 2010. Here you can see, houses built in 2010 have the highest average sale price. However, houses built in 2009 have lower average sale prices than houses built in 2008 and old houses built in 1893, 1892, 1989. Here we can conclude that there is a decrease in house prices drastically in 2009. In addition, the old houses built in 1892, 1893 and 1989 were unexpectedly having high sale prices and exceeding the sale prices of houses built in the 2000s.

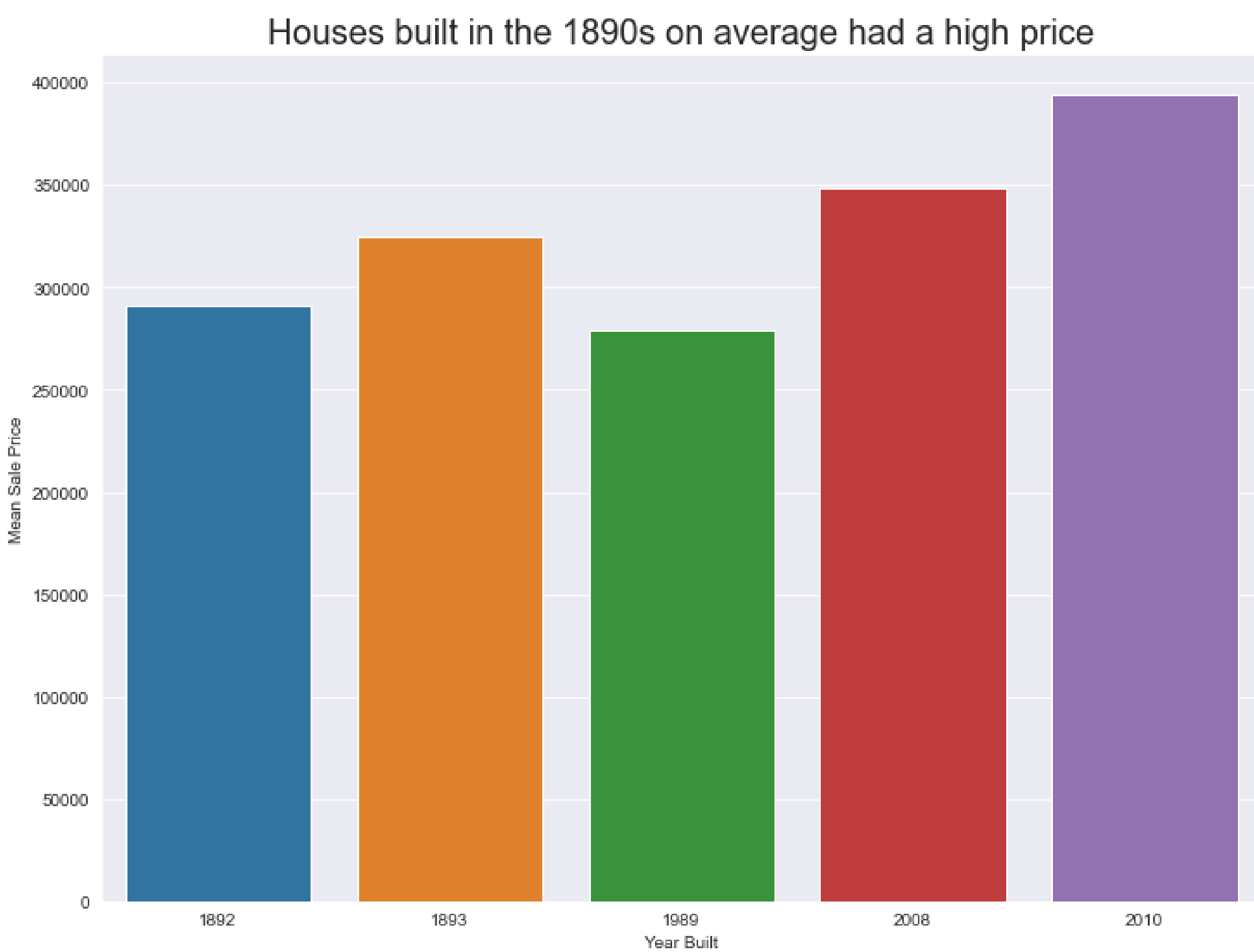
In [177]:
```
year_build_price=train.groupby(["YearBuilt"]).agg({"SalePrice":"mean"})
year_build_price=year_build_price.rename(columns={"SalePrice":"Mean Sale Price"})
year_build_price=year_build_price.reset_index()
top_5=year_build_price.sort_values(["Mean Sale Price"],ascending=False).head()
top_5
```

Out[177]:

	YearBuilt	Mean Sale Price
111	2010	394432.000000
109	2008	348849.130435
7	1893	325000.000000
6	1892	291250.000000
90	1989	279500.000000

In [178]:
```
plt.figure(figsize=(12,9))
sns.barplot(top_5["YearBuilt"].astype(str),top_5["Mean Sale Price"])
plt.title("Houses built in the 1890s on average had a high price",fontdict={'fontsize':2
0})
plt.xlabel("Year Built")
plt.ylabel("Mean Sale Price")
plt.figure()
```

Out[178]: <Figure size 432x288 with 0 Axes>



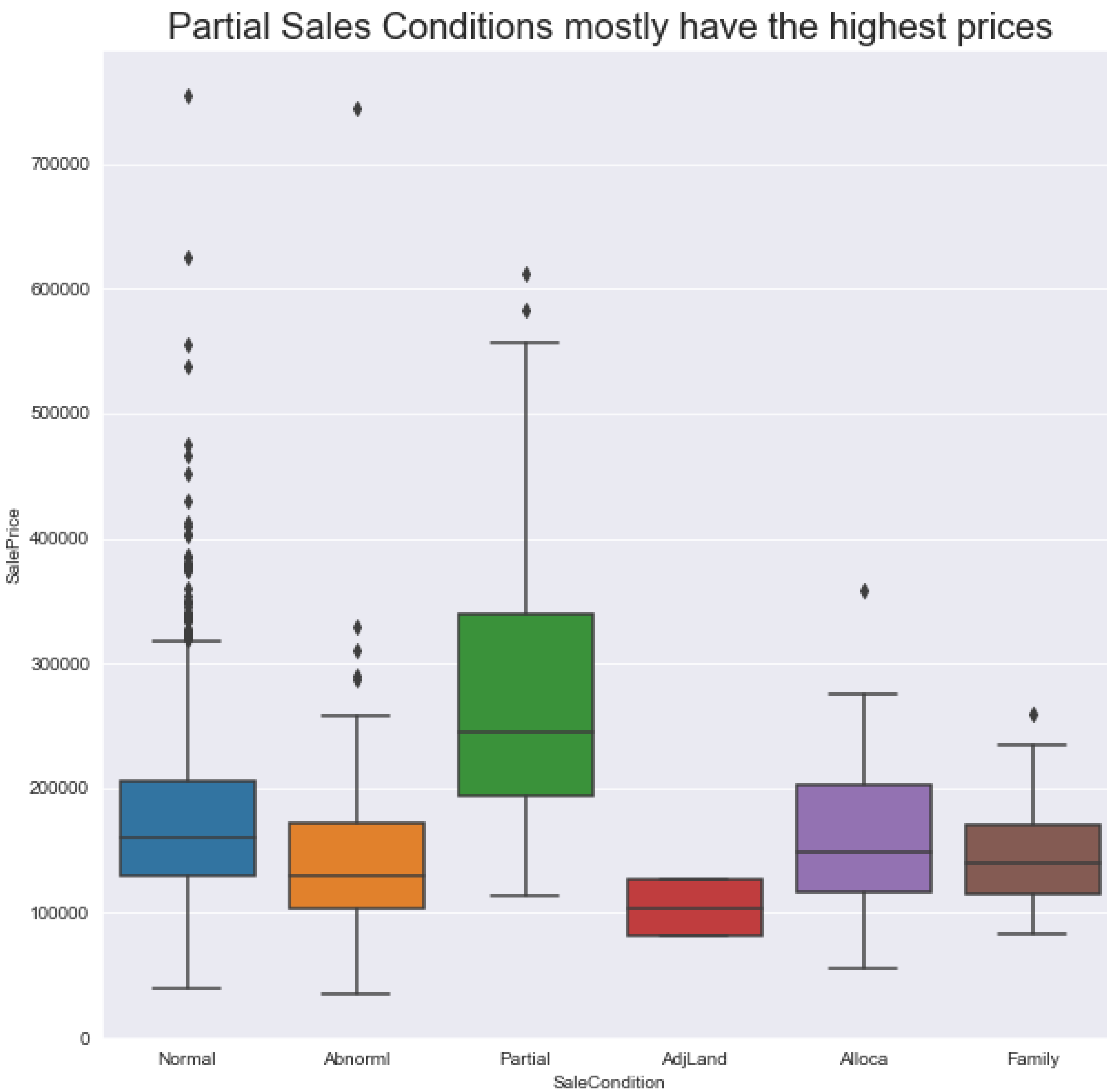
<Figure size 432x288 with 0 Axes>

Which sales conditions have the highest average sale price?

The house was not completed when it was last assessed (related to the new house) or partially had the highest average selling price. Meanwhile houses with sales conditions Adjoining Land Purchases have the lowest average selling prices.

In [179]:
```
plt.figure(figsize=(10,10))
sns.boxplot(x=train["SaleCondition"],y=train["SalePrice"])
plt.title("Partial Sales Conditions mostly have the highest prices",fontdict={'fontsize'
:20})
```

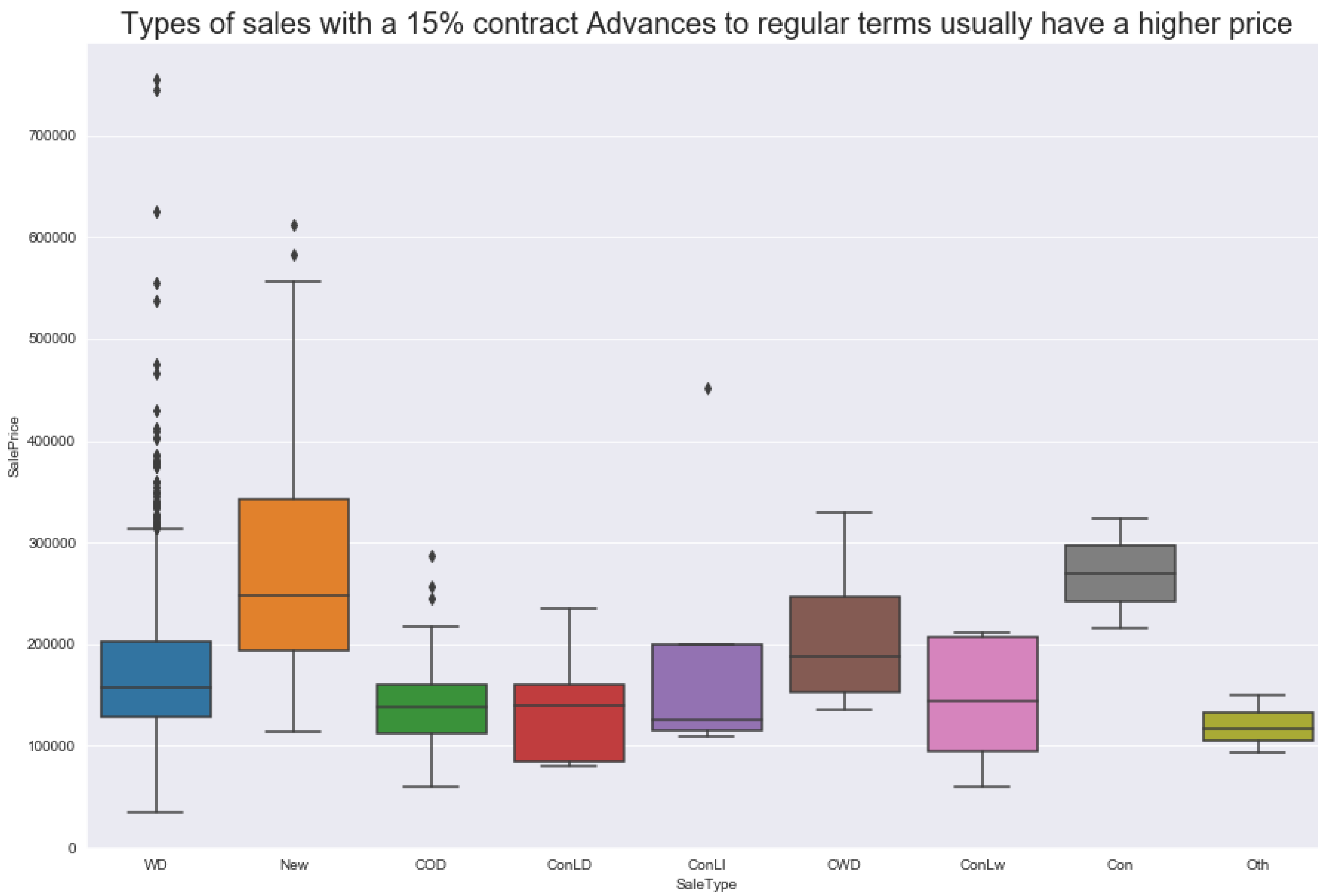
Out[179]: Text(0.5, 1.0, 'Partial Sales Conditions mostly have the highest prices')



What is the type of home sales with the highest average sale price?

In [180]:
```
plt.figure(figsize=(15,10))
sns.boxplot(x=train["SaleType"],y=train["SalePrice"])
plt.title("Types of sales with a 15% contract Advances to regular terms usually have a h
igher price",fontdict={'fontsize':20})
```

Out[180]:
```
Text(0.5, 1.0, 'Types of sales with a 15% contract Advances to regular terms usually ha
ve a higher price')
```



Does a house with Central air conditioning have a higher average price?

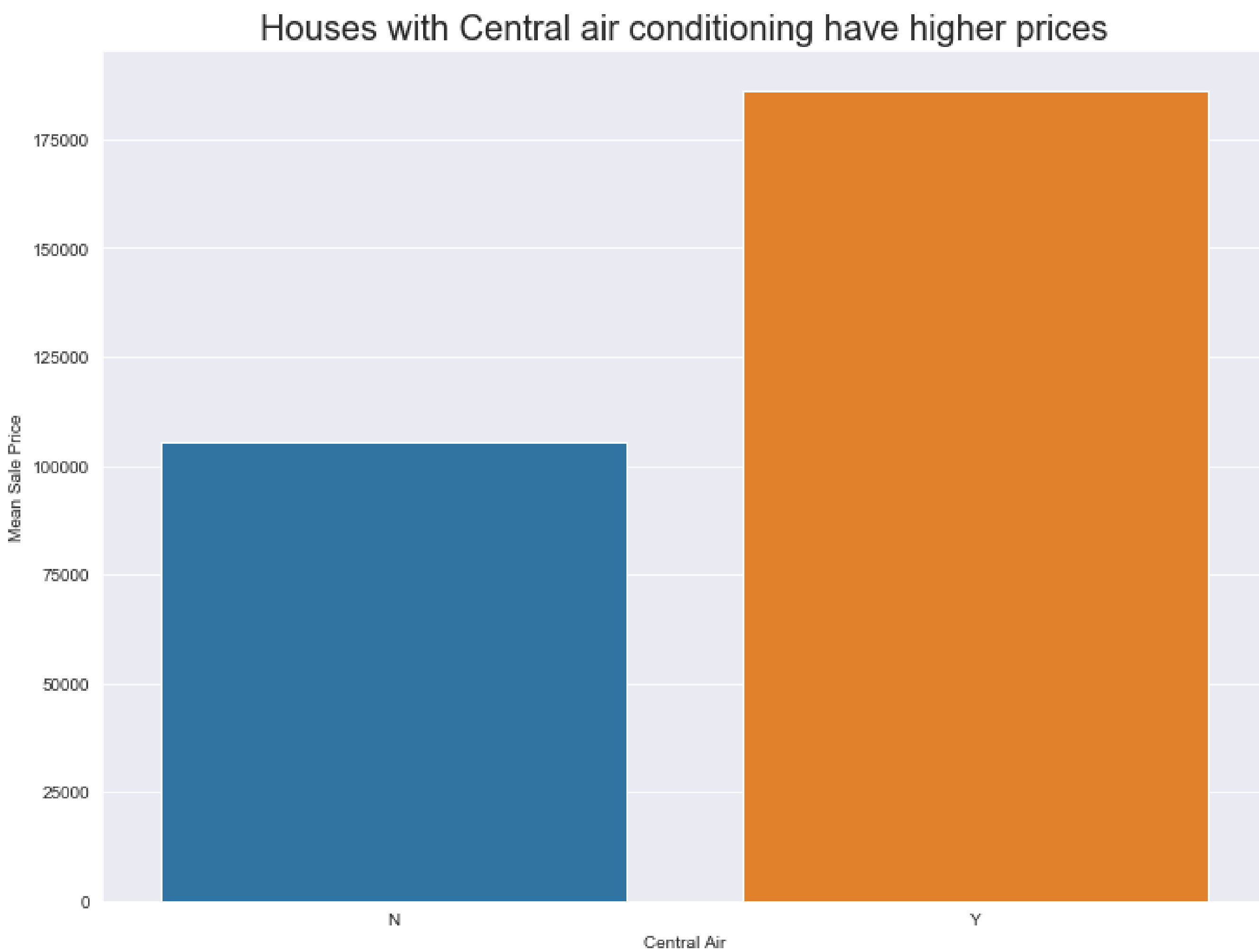
In [181]:
```
AC_price=train.groupby(["CentralAir"]).agg({"SalePrice":"mean"})
AC_price=AC_price.rename(columns={"SalePrice":"Mean Sale Price"})
AC_price=AC_price.reset_index()
AC_price
```

Out[181]:

	CentralAir	Mean Sale Price
0	N	105264.073684
1	Y	186186.709890

In [182]:
```
plt.figure(figsize=(12,9))
sns.barplot(AC_price["CentralAir"],AC_price["Mean Sale Price"])
plt.title("Houses with Central air conditioning have higher prices",fontdict={'fontsize'
:20})
plt.xlabel("Central Air")
plt.ylabel("Mean Sale Price")
plt.figure()
```

Out[182]: <Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>

Feature Engineer 2

Transform Category to Numeric

Categorical variables with nominal data types are converted to dummy variables using pandas.get_dummies. The number of dummy variables created is k-1 from k categories, So for example a variable has 3 categories, then the number of dummy variables that are bolted is 3-1 = 2 dummy variables. This must be done in a regression analysis to reduce the effects of multicollinearity on the model. The categories used as baseline values will be explained by the intercept.

In [183]:
```
from sklearn.preprocessing import LabelEncoder
cat = [x for x in data_all.columns if x not in num.columns]

data_all=pd.get_dummies(data_all,columns=cat,drop_first=True)
data_all.head()
```

Out[183]:

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

5 rows × 260 columns

Transform Numerical Variable

Standardization

Furthermore, independent variables with numerical data types have very different scales. To reduce the dominance of large-scale variables over small-scale variables, the Scaler Standard () is used to standardize these variables. After standardization, these variables will have an average value of 0 and constant variance.

In [184]:
```
from sklearn.preprocessing import StandardScaler
rs=StandardScaler()
num=num.drop(["SalePrice"],axis=1)
data_all[num.columns]=rs.fit_transform(data_all[num.columns])
data_all[num.columns].describe()
```

Out[184]:

	MSSubClass	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	1stFl
count	2.919000e+03	2.919000e+03	2.919000e+03	2.919000e+03	2.919000e+03	2.919000e+03	2.919000e
mean	6.337476e-17	1.652118e-17	2.538413e-16	3.443631e-16	-5.263195e-16	5.481702e-16	-9.829981e
std	1.000171e+00	1.000171e+00	1.000171e+00	1.000171e+00	1.000171e+00	1.000171e+00	1.000171e
min	-8.736160e-01	-1.124590e+00	-3.610024e+00	-4.101368e+00	-3.279137e+00	-1.640173e+00	-2.104493e
25%	-8.736160e-01	-3.411406e-01	-7.725525e-01	-5.072842e-01	-5.881473e-01	-9.221526e-01	-7.228790e
50%	-1.679054e-01	-9.068555e-02	-6.318454e-02	-5.072842e-01	5.570916e-02	4.181525e-01	-1.977638e
75%	3.025683e-01	1.777769e-01	6.461834e-01	3.912368e-01	9.802210e-01	9.447010e-01	5.809872e
max	3.125411e+00	2.600635e+01	2.774287e+00	3.086800e+00	1.277386e+00	1.231909e+00	1.003179e

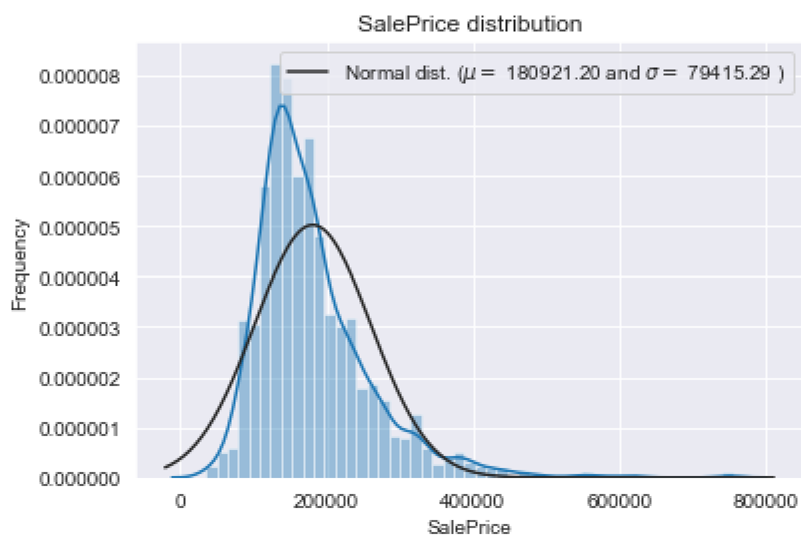
8 rows × 37 columns

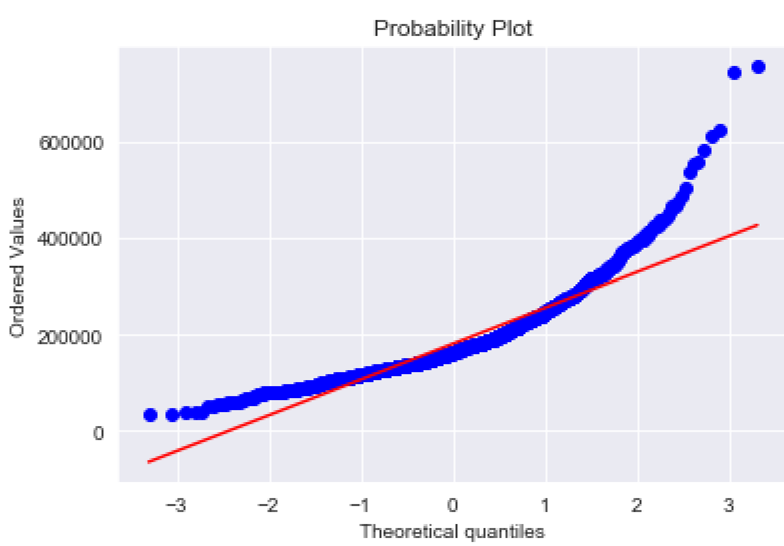
Log Transformation

In addition, the dependent variable namely SalePrice has right skewed or positive skewed. As linear models love normally distributed data , we need to transform this variable and make it more normally distributed.Therefore a log transformation is performed on SalePrice variables.

In [185]:
```
sns.distplot(train['SalePrice'] , fit=norm);

# Get the fitted parameters used by the function
(mu, sigma) = norm.fit(train['SalePrice'])
print( '\n mu = {:.2f} and sigma = {:.2f}\n'.format(mu, sigma))

#Now plot the distribution
plt.legend(['Normal dist. ($\mu=$ {:.2f} and $\sigma=$ {:.2f} )'.format(mu, sigma)],
            loc='best')
plt.ylabel('Frequency')
plt.title('SalePrice distribution')

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

```
 mu = 180921.20 and sigma = 79415.29
```

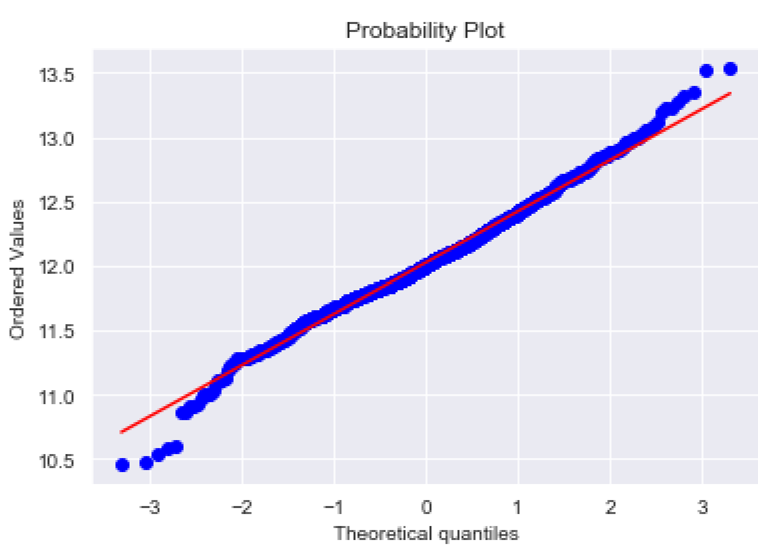




Seen after log transformation, the SalePrice variable approaches the normal distribution.

In [186]:
```python
#We use the numpy fuction log1p which  applies log(1+x) to all elements of the column
train["SalePrice"] = np.log1p(train["SalePrice"])

#Check the new distribution
sns.distplot(train['SalePrice'] , fit=norm);

# Get the fitted parameters used by the function
(mu, sigma) = norm.fit(train['SalePrice'])
print( '\n mu = {:.2f} and sigma = {:.2f}\n'.format(mu, sigma))

#Now plot the distribution
plt.legend(['Normal dist. ($\mu=$ {:.2f} and $\sigma=$ {:.2f} )'.format(mu, sigma)],
            loc='best')
plt.ylabel('Frequency')
plt.title('SalePrice distribution')

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

```
 mu = 12.02 and sigma = 0.40
```



In [187]:
```
train=pd.concat([data_all.iloc[:len(train),:],train["SalePrice"]],axis=1)
submit=data_all.iloc[len(train):,:]
```

Feature Selection using Importance Variable Random Forest

Furthermore, because there are 79 independent variables in the dataset there are 79 feature selection features to choose the variables that have a large and significant effect on the Sale Price. The featured importance of the Random Forest Regressor and variance inflation factor from multicolinearity check will be used to look for variables that have a major influence on the Sale Price.

Feature importance Random Forest Regressor

In [188]:
```
X=train.drop(["SalePrice"],axis=1)
Y=train.SalePrice
from sklearn.ensemble import RandomForestRegressor
clf = RandomForestRegressor(max_depth=5, random_state=0)
clf.fit(X, Y)
importance=clf.feature_importances_
```

In [189]:
```
importance=pd.DataFrame({"Variabel":X.columns,"Importance":importance})
```

In this case, the variables chosen are variables that have an importance value of more than 0.005. So there are 9 variables used, namely TotalSF, OverallQual, YearBuilt, OverallCond, GrLivArea, YearRemodAdd, CentralAir_Y, GarageCars, and BsmtFinSF1. These variables are also chosen based on the concept of parsimony or simplicity of the model, where if we only use 9 variables it is able to produce an R-squared adjusted value of 91.3% whereas if all variables are used it will produce an R-Squared adjusted of 92%. Of course it is a very small increase in R-Squared adjusted with the addition of a very large number of variables. Very ineffective and inefficient when using all independent variables.

In [190]:
```
importance.sort_values(by=['Importance'],ascending=False).head(15)
```

Out[190]:

	Variabel	Importance
3	OverallQual	0.514123
36	TotalSF	0.343810
196	CentralAir_Y	0.019924
25	GarageCars	0.015180
15	GrLivArea	0.010976
5	YearBuilt	0.008245
8	BsmtFinSF1	0.007786
4	OverallCond	0.007020
26	GarageArea	0.006706
6	YearRemodAdd	0.005674
12	1stFlrSF	0.004565
2	LotArea	0.003912
24	GarageYrBlt	0.003782
219	GarageType_Detchd	0.003379
13	2ndFlrSF	0.003056

In [191]:
```
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
from scipy import stats
best=["TotalSF","OverallQual","YearBuilt","OverallCond","GrLivArea","YearRemodAdd","Cent
ralAir_Y","GarageCars","BsmtFinSF1"]
X_new=X[best]
```

Variance Infaltion Factor (VIF) Multicolinearity Check

Furthermore, 9 independent variables that have been selected are checked for the value of inflation inflation factor (VIF) to check the multicollinearity of each of these variables. If the VIF value is more than 10, then there is multicollinearity on the variable so that the variable cannot be used to build the model. Meanwhile, if the VIF value is less than 10, then there is no multicollinearity on the variable so that it can be used to build the model. In this case, the 9 selected variables have a VIF value of less than 10. So that the 9 variables chosen fulfill the non-multicollinearity assumption.

In [192]:
```
vif = pd.DataFrame()
vif["VIF Factor"] = [variance_inflation_factor(X_new.values, i) for i in range(X_new.sha
pe[1])]
vif["features"] = X_new.columns
vif
```

Out[192]:

	VIF Factor	features
0	6.683489	TotalSF
1	2.768645	OverallQual
2	2.848659	YearBuilt
3	1.448884	OverallCond
4	5.179694	GrLivArea
5	2.026248	YearRemodAdd
6	1.018519	CentralAir_Y
7	1.848275	GarageCars
8	1.416609	BsmtFinSF1

Drop Outlier using Standarized Residuals

The dataset used in this case has many outliers, so the outliers' values must be handled well. In this case, outlier handling will be used using multivariate methods, namely using standardized residuals from regression analysis. observations that have an absolute value of standardized residuals of more than 2 will be considered as outliers and will be deleted from the dataset.

In [193]:
```
def outlier(sample):
    Q1=sample.quantile(0.25)
    Q3=sample.quantile(0.75)
    IQR=Q3-Q1
    lower_range = Q1 -(1.5 * IQR)
    upper_range = Q3 +(1.5 * IQR)
    number_outlier=len(sample[sample>upper_range])+len(sample[sample<lower_range])
    print("{}".format(number_outlier))
```

In [194]:

```
column=num.columns
summary_outlier=[]
for col in column :
    print(col)
    pencilan=outlier(train[col])
    summary_outlier.append(pencilan)
```

MSSubClass
103
LotArea
69
OverallQual
2
OverallCond
125
YearBuilt
7
YearRemodAdd
0
1stFlrSF
20
2ndFlrSF
2
LowQualFinSF
26
GrLivArea
31
FullBath
0
HalfBath
0
BedroomAbvGr
35
KitchenAbvGr
68
TotRmsAbvGrd
30
Fireplaces
5
WoodDeckSF
32
OpenPorchSF
77
EnclosedPorch
208
3SsnPorch
24
ScreenPorch
116
PoolArea
7
MiscVal
52
MoSold
0
YrSold
0
LotFrontage
99
MasVnrArea
98
BsmtFinSF1
7
BsmtFinSF2
167
BsmtUnfSF

```
29
TotalBsmtSF
61
BsmtFullBath
1
BsmtHalfBath
82
GarageYrBlt
81
GarageCars
5
GarageArea
21
TotalSF
25
```

In [195]:
```
X2 = sm.add_constant(X_new)
est = sm.OLS(Y, X2)
est2 = est.fit()
influence = est2.get_influence()
standardized_residuals = influence.resid_studentized_internal
standardized_residuals=pd.DataFrame({"standardized_residuals":abs(standardized_residuals
)})
delete=standardized_residuals.sort_values(['standardized_residuals'],ascending=False).he
ad(50)
```

In [196]:
```
idx=list(delete.index)
X_new=X_new.drop(idx,axis=0)
Y_new=Y.drop(idx,axis=0)
```

Modelling

The next step is to do modeling. There are 9 models to be built in this case, namely linear regression, support vector regression with linear kernel, support vector regression with kernel RBF, Lasso Regression, Kernel Ridge Regression, Elastic Net Regression, Gradient Boosting Regression, Extreme Gradient Boosting Regression and Light Gradient Boosting Machine Regression.

In [197]:
```
from sklearn.linear_model import ElasticNet, Lasso, BayesianRidge, LassoLarsIC, LinearRe
gression
from sklearn.ensemble import RandomForestRegressor,  GradientBoostingRegressor
from sklearn.kernel_ridge import KernelRidge
from sklearn.svm import SVR
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
```

The dataset will be divided into training, validation and testing data. 80% of the data is used as training data and validation using the 5-fold cross validation partition method, while the other 20% is used as testing data. Next, the evaluation metrics to be used are R-squared, MSE, MAE and MSLE.

In [198]:
```
#Validation function
x_train,x_test,y_train,y_test=train_test_split(X_new,Y_new,test_size=0.2,random_state=99
)
n_folds = 5

def model_cv(model):
    kf = KFold(n_folds, shuffle=True, random_state=42)
    r2= cross_val_score(model, x_train, y_train, cv = kf,scoring="r2").mean()
    mse= -cross_val_score(model, x_train, y_train, cv = kf,scoring="neg_mean_squared_err
or").mean()
    mae= -cross_val_score(model, x_train, y_train, cv = kf,scoring='neg_mean_absolute_er
ror').mean()
    print("R Square : {}, MSE : {}, MAE : {}.".format(r2,mse,mae))
```

The next step is to define the models that will be used. Hyperparameter values used in each model are not tuned using grid search, random search and Bayesian search because computing time is too long and the increase is not too significant.

In [199]:
```
lr=LinearRegression()
lasso =Lasso(alpha =0.0005, random_state=1)
ENet =ElasticNet(alpha=0.0005, l1_ratio=.9, random_state=3)
KRR = KernelRidge(alpha=0.6, kernel='polynomial', degree=2, coef0=2.5)
svr_linear=SVR(kernel="linear",C=1.0)
svr_rbf=SVR(kernel="rbf",gamma='scale',C=1.0)
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)
model_xgb = xgb.XGBRegressor(colsample_bytree=0.4603, gamma=0.0468,
                             learning_rate=0.05, max_depth=3,
                             min_child_weight=1.7817, n_estimators=2200,
                             reg_alpha=0.4640, reg_lambda=0.8571,
                             subsample=0.5213, silent=1,
                             random_state =7, nthread = -1)

model_lgb = lgb.LGBMRegressor(objective='regression',num_leaves=5,
                              learning_rate=0.05, n_estimators=720,
                              max_bin = 55, bagging_fraction = 0.8,
                              bagging_freq = 5, feature_fraction = 0.2319,
                              feature_fraction_seed=9, bagging_seed=9,
                              min_data_in_leaf =6, min_sum_hessian_in_leaf = 11)
```

Linear Regression

Following are the mean values of R-Squared, MSE and MAE of the 5-fold cross validation in the linear regression model.

Based on the above output, we can see that the MAE value of the model is 0.0859, the MSE is 0.01238 and the R-Squared value is 91.12%, which means as much as 91.12% of the Sale Price variability can be explained by the nine independent variables. While the remaining 8.88% is influenced by other variables outside the model.

In [200]:
```
score_lr = model_cv(lr)
```

```
R Square : 0.9111691394926137, MSE : 0.012387207209250635, MAE : 0.08599349163934192.
```

In [201]:
```
X_train2 = sm.add_constant(x_train)
est = sm.OLS(y_train, X_train2)
est2 = est.fit()
```

In [202]:
```
print(est2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              SalePrice   R-squared:                       0.914
Model:                            OLS   Adj. R-squared:                  0.913
Method:                 Least Squares   F-statistic:                     1314.
Date:                Sat, 16 May 2020   Prob (F-statistic):               0.00
Time:                        19:16:57   Log-Likelihood:                 888.03
No. Observations:                1128   AIC:                            -1756.
Df Residuals:                    1118   BIC:                            -1706.
Df Model:                           9
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const           11.9704      0.015    803.939      0.000      11.941      12.000
TotalSF          0.1194      0.009     13.616      0.000       0.102       0.137
OverallQual      0.1039      0.006     18.402      0.000       0.093       0.115
YearBuilt        0.0819      0.006     14.176      0.000       0.071       0.093
OverallCond      0.0515      0.004     12.407      0.000       0.043       0.060
GrLivArea        0.0748      0.007     10.414      0.000       0.061       0.089
YearRemodAdd     0.0205      0.005      4.336      0.000       0.011       0.030
CentralAir_Y     0.0595      0.016      3.841      0.000       0.029       0.090
GarageCars       0.0516      0.005     11.209      0.000       0.043       0.061
BsmtFinSF1       0.0435      0.004     10.800      0.000       0.036       0.051
==============================================================================
Omnibus:                       16.139   Durbin-Watson:                   1.960
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               17.443
Skew:                          -0.245   Prob(JB):                     0.000163
Kurtosis:                       3.362   Cond. No.                         12.2
==============================================================================

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

Simultaneous Test F distribution

i. Hypothesis testing

H_0: Regression coefficient has no significant effect on the model

H_1: at least one regression coefficient that has a significant effect on the model

ii. Significance level α = 5%

iii. Critical Area: is rejected if the Prob (F-statistic) <α = 0.05

iv. Test Statistics

Prob (F-statistic) = 0.00

v. Conclusion: Simultaneously there is at least one regression coefficient that has a significant effect on the model.

Partial Test t distribution

i. Hypothesis testing

H_0: The regression coefficient has no significant effect on the model

H_1: The regression coefficient has a significant effect on the model

ii. Significance level α = 5%

iii. Critical Area: is rejected if the Prob (t-statistic) <α = 0.05

iv. Test Statistics

All independent variables and constant have Prob (t-statistic) = 0.00

v. Conclusion: All regression coefficients have a significant effect on the model

Regression Equation

log(SalePrice)=11.9704 + 0.1194 *TotalSF + 0.1039* OverallQual + 0.0819 *YearBuilt + 0.0515* OverallCond + 0.0748 *GrLivArea + 0.0205* YearRemodAdd + 0.0595 *CentralAir_Yes + 0.0516* GarageCars + 0.0435 * BsmtFinSF1

Asumption Test

Normality Test (Jarque Bera Test)

i. Hypothesis testing

H_0: residuals are normally distributed

H_1: residuals are not normally distributed

ii. Significance level α = 5%

iii. Critical Area: is rejected if the Prob (JB) <α = 0.05

iv. Test Statistics

Prob (JB) = 0.000163

v. Conclusion: residuals are not normally distributed

Autocorellation Test (Durbin Watson Test)

i. Hypothesis testing
   H_0: there is no autocorrelation between residuals
   H_1: there is autocorrelation between residuals
ii. Significance level α = 5%
iii. Critical Area: is rejected if DW>1.890 or DW<1.861
iv. Test Statistics
   DW = 1.960
v. Conclusion: there is autocorrelation between residuals

Heterocesdasticity Test (White Test)

i. Hypothesis testing
   H_0: the variance of residuals is homogeneous
   H_1: the variance of residuals is heterogeneous
ii. Significance level α = 5%
iii. Critical Area: is rejected if LM test's p-value or F-test's p-value <α = 0.05
iv. Test Statistics
   LM test's p-value = 0.0000
   F-test's p-value = 0.0000
v. Conclusion: the variance of residuals is heterogeneous

In [203]:
```
from statsmodels.stats.diagnostic import het_white
from statsmodels.compat import lzip
```

In [204]:
```
keys = ['Lagrange Multiplier statistic:', 'LM test\'s p-value:', 'F-statistic:', 'F-test\'s p-value:']
hetero=het_white(est2.resid,X_train2)
lzip(keys,hetero)
```

Out[204]:
```
[('Lagrange Multiplier statistic:', 178.81823191732502),
 ("LM test's p-value:", 1.5049821884417572e-15),
 ('F-statistic:', 3.8176035031978044),
 ("F-test's p-value:", 2.886859635967055e-17)]
```

Multicolinearity Test

Furthermore, 9 independent variables that have been selected are checked for the value of inflation inflation factor (VIF) to check the multicollinearity of each of these variables. If the VIF value is more than 10, then there is multicollinearity on the variable so that the variable cannot be used to build the model. Meanwhile, if the VIF value is less than 10, then there is no multicollinearity on the variable so that it can be used to build the model. In this case, the 9 selected variables have a VIF value of less than 10. So that the 9 variables chosen fulfill the non-multicollinearity assumption.

In [205]:
```
vif = pd.DataFrame()
vif["VIF Factor"] = [variance_inflation_factor(X_new.values, i) for i in range(X_new.sha
pe[1])]
vif["features"] = X_new.columns
vif
```

Out[205]:

	VIF Factor	features
0	6.123397	TotalSF
1	2.717319	OverallQual
2	2.833293	YearBuilt
3	1.451158	OverallCond
4	4.815185	GrLivArea
5	2.017568	YearRemodAdd
6	1.018918	CentralAir_Y
7	1.864139	GarageCars
8	1.315582	BsmtFinSF1

Evaluation Metrics in Test Data

In [206]:
```
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score,mean_squared
_log_error
pred_lr=est2.predict(sm.add_constant(x_test))
```

Based on the test data, we can see that the MAE value of the model is 0.0824, the MSE is 0.0111, the MSLE is 0.000065 and the R-Squared value is 92.78%, which means as much as 92.78% of the Sale Price variability in test data can be explained by the nine independent variables. While the remaining 7.22% is influenced by other variables outside the model.

In [207]:
```
r2_score(y_test,pred_lr)
```

Out[207]: 0.9277671619651762

In [208]:
```
mean_squared_error(y_test,pred_lr)
```

Out[208]: 0.011195863356922698

In [209]:
```
mean_absolute_error(y_test,pred_lr)
```

Out[209]: 0.08240342202890907

In [210]:
```
mean_squared_log_error(y_test,pred_lr)
```

Out[210]: 6.589439570907277e-05

SVR Linear

Following are the mean values of R-Squared, MSE and MAE of the 5-fold cross validation in the SVR Linear model.

Based on the above output, we can see that the MAE value of the model is 0.0859, the MSE is 0.01247 and the R-Squared value is 91.06%, which means as much as 91.06% of the Sale Price variability can be explained by the nine independent variables. While the remaining 8.94% is influenced by other variables outside the model.

In [211]:
```
score_svrlinear=model_cv(svr_linear)
```

```
R Square : 0.9105915541830228, MSE : 0.012470963598653842, MAE : 0.08595488377890684.
```

Evaluation Metrics in Test Data

In [212]:
```
svr_linear.fit(x_train,y_train)
pred_svr_linear=svr_linear.predict(x_test)
```

Based on the test data, we can see that the MAE value of the model is 0.0829, the MSE is 0.01130, the MSLE is 0.000066 and the R-Squared value is 92.71%, which means as much as 92.71% of the Sale Price variability in test data can be explained by the nine independent variables. While the remaining 7.29% is influenced by other variables outside the model.

In [213]:
```
r2_score(y_test,pred_svr_linear)
```

Out[213]:
```
0.9270251042076901
```

In [214]:
```
mean_squared_error(y_test,pred_svr_linear)
```

Out[214]:
```
0.0113108799820725
```

In [215]:
```
mean_absolute_error(y_test,pred_svr_linear)
```

Out[215]:
```
0.08295810979308439
```

In [216]:
```
mean_squared_log_error(y_test,pred_svr_linear)
```

Out[216]:
```
6.664092171617105e-05
```

SVR RBF

Following are the mean values of R-Squared, MSE and MAE of the 5-fold cross validation in the SVR Rbf model.

Based on the above output, we can see that the MAE value of the model is 0.0915, the MSE is 0.0151 and the R-Squared value is 89.22%, which means as much as 89.22% of the Sale Price variability can be explained by the nine independent variables. While the remaining 10.78% is influenced by other variables outside the model.

In [217]:
```
score_svrrbf=model_cv(svr_rbf)
```

```
R Square : 0.8917386142227258, MSE : 0.015234619665739368, MAE : 0.09168612485611058.
```

Evaluation Metrics in Test Data

In [218]:
```
svr_rbf.fit(x_train,y_train)
pred_svr_rbf=svr_rbf.predict(x_test)
```

Based on the test data, we can see that the MAE value of the model is 0.0806, the MSE is 0.01263, the MSLE is 0.000073 and the R-Squared value is 91.85%, which means as much as 91.85% of the Sale Price variability in test data can be explained by the nine independent variables. While the remaining 8.15% is influenced by other variables outside the model.

In [219]:
```
r2_score(y_test,pred_svr_rbf)
```

Out[219]:
```
0.9183514940983266
```

In [220]:
```
mean_squared_error(y_test,pred_svr_rbf)
```

Out[220]:
```
0.012655262346625874
```

In [221]:
```
mean_absolute_error(y_test,pred_svr_rbf)
```

Out[221]:
```
0.08065159430136327
```

In [222]:
```
mean_squared_log_error(y_test,pred_svr_rbf)
```

Out[222]:
```
7.31810867271605e-05
```

Lasso Regression

Following are the mean values of R-Squared, MSE and MAE of the 5-fold cross validation in the Lasso regression model.

Based on the above output, we can see that the MAE value of the model is 0.0859, the MSE is 0.01239 and the R-Squared value is 91.11%, which means as much as 91.11% of the Sale Price variability can be explained by the nine independent variables. While the remaining 8.89% is influenced by other variables outside the model.

In [223]:
```
score_lasso = model_cv(lasso)
```

```
R Square : 0.9111398970900477, MSE : 0.012392585037443653, MAE : 0.08596181968240538.
```

Evaluation Metrics in Test Data

In [224]:
```
lasso.fit(x_train,y_train)
pred_lasso=lasso.predict(x_test)
```

Based on the test data, we can see that the MAE value of the model is 0.0824, the MSE is 0.0112, the MSLE is 0.000066 and the R-Squared value is 92.76%, which means as much as 92.76% of the Sale Price variability in test data can be explained by the nine independent variables. While the remaining 7.24% is influenced by other variables outside the model.

In [225]:
```
r2_score(y_test,pred_lasso)
```
Out[225]: 0.9275594211877974

In [226]:
```
mean_squared_error(y_test,pred_lasso)
```
Out[226]: 0.011228062525894453

In [227]:
```
mean_absolute_error(y_test,pred_lasso)
```
Out[227]: 0.08240161545415976

In [228]:
```
mean_squared_log_error(y_test,pred_lasso)
```
Out[228]: 6.611524403387667e-05

Elastic Net

Following are the mean values of R-Squared, MSE and MAE of the 5-fold cross validation in the Elastic Net regression model.

Based on the above output, we can see that the MAE value of the model is 0.0859, the MSE is 0.01239 and the R-Squared value is 91.11%, which means as much as 91.11% of the Sale Price variability can be explained by the nine independent variables. While the remaining 8.89% is influenced by other variables outside the model.

In [229]:
```
score_ElasticNet = model_cv(ENet)
```
```
R Square : 0.9111460973158929, MSE : 0.012391594448108442, MAE : 0.0859638337071965.
```

Evaluation Metrics in Test Data

In [230]:
```
ENet.fit(x_train,y_train)
pred_ENet=ENet.predict(x_test)
```

Based on the test data, we can see that the MAE value of the model is 0.0824, the MSE is 0.0112, the MSLE is 0.000066 and the R-Squared value is 92.76%, which means as much as 92.76% of the Sale Price variability in test data can be explained by the nine independent variables. While the remaining 7.24% is influenced by other variables outside the model.

In [231]:
```
r2_score(y_test,pred_ENet)
```
Out[231]: 0.9275820842625588

In [232]:
```
mean_squared_error(y_test,pred_ENet)
```
Out[232]: 0.011224549820382948

In [233]:
```
mean_absolute_error(y_test,pred_ENet)
```
Out[233]: 0.08239472844718063

In [234]:
```
mean_squared_log_error(y_test,pred_ENet)
```
Out[234]: 6.60915039248035e-05

Kernel Ridge

Following are the mean values of R-Squared, MSE and MAE of the 5-fold cross validation in the Kernel Ridge regression model.

Based on the above output, we can see that the MAE value of the model is 0.0850, the MSE is 0.0120 and the R-Squared value is 91.32%, which means as much as 91.32% of the Sale Price variability can be explained by the nine independent variables. While the remaining 8.68% is influenced by other variables outside the model.

In [235]:
```
score_KernelRidge = model_cv(KRR)
```
```
R Square : 0.9132293546977157, MSE : 0.012088389025040409, MAE : 0.08502982801722136.
```

Evaluation Metrics in Test Data

In [236]:
```
KRR.fit(x_train,y_train)
pred_KRR=KRR.predict(x_test)
```

Based on the test data, we can see that the MAE value of the model is 0.077, the MSE is 0.0098, the MSLE is 0.000058 and the R-Squared value is 93.67%, which means as much as 93.67% of the Sale Price variability in test data can be explained by the nine independent variables. While the remaining 6.33% is influenced by other variables outside the model.

In [237]:
```
r2_score(y_test,pred_KRR)
```
Out[237]: 0.9367100954191543

In [238]:
```
mean_squared_error(y_test,pred_KRR)
```
Out[238]: 0.009809736718612821

In [239]:
```
mean_absolute_error(y_test,pred_KRR)
```
Out[239]: 0.07694460273724657

In [240]:
```
mean_squared_log_error(y_test,pred_KRR)
```
Out[240]:
```
5.787993230398103e-05
```

Gradient Boosting

Following are the mean values of R-Squared, MSE and MAE of the 5-fold cross validation in the Gradient Boosting regression model.

Based on the above output, we can see that the MAE value of the model is 0.0915, the MSE is 0.0144 and the R-Squared value is 89.65%, which means as much as 89.65% of the Sale Price variability can be explained by the nine independent variables. While the remaining 10.35% is influenced by other variables outside the model.

In [241]:
```
score_Gradient_Boosting = model_cv(GBoost)
```
```
R Square : 0.8961876363584624, MSE : 0.01449638180122408, MAE : 0.09165642412226024.
```

Evaluation Metrics in Test Data

In [242]:
```
GBoost.fit(x_train,y_train)
pred_GBoost=GBoost.predict(x_test)
```

Based on the test data, we can see that the MAE value of the model is 0.0839, the MSE is 0.0122, the MSLE is 0.000072 and the R-Squared value is 92.11%, which means as much as 92.11% of the Sale Price variability in test data can be explained by the nine independent variables. While the remaining 7.89% is influenced by other variables outside the model.

In [243]:
```
r2_score(y_test,pred_GBoost)
```
Out[243]:
```
0.9213488924965952
```

In [244]:
```
mean_squared_error(y_test,pred_GBoost)
```
Out[244]:
```
0.012190674995411786
```

In [245]:
```
mean_absolute_error(y_test,pred_GBoost)
```
Out[245]:
```
0.0837550495813389
```

In [246]:
```
mean_squared_log_error(y_test,pred_GBoost)
```
Out[246]:
```
7.176168470023465e-05
```

XGBOOST

Following are the mean values of R-Squared, MSE and MAE of the 5-fold cross validation in the Extreme Gradient Boosting regression model.

Based on the above output, we can see that the MAE value of the model is 0.0847, the MSE is 0.0122 and the R-Squared value is 91.23%, which means as much as 91.23% of the Sale Price variability can be explained by the nine independent variables. While the remaining 8.77% is influenced by other variables outside the model.

In [247]:
```
score_Xgboost = model_cv(model_xgb)
```

```
R Square : 0.9123533805473591, MSE : 0.012250105602794182, MAE : 0.08482716584542857.
```

Evaluation Metrics in Test Data

In [248]:
```
model_xgb.fit(x_train,y_train)
pred_model_xgb=model_xgb.predict(x_test)
```

Based on the test data, we can see that the MAE value of the model is 0.0784, the MSE is 0.0103, the MSLE is 0.000061 and the R-Squared value is 93.34%, which means as much as 93.34% of the Sale Price variability in test data can be explained by the nine independent variables. While the remaining 6.66% is influenced by other variables outside the model.

In [249]:
```
r2_score(y_test,pred_model_xgb)
```

Out[249]:
```
0.9338582429614579
```

In [250]:
```
mean_squared_error(y_test,pred_model_xgb)
```

Out[250]:
```
0.010251764905503098
```

In [251]:
```
mean_absolute_error(y_test,pred_model_xgb)
```

Out[251]:
```
0.0783392436280902
```

In [252]:
```
mean_squared_log_error(y_test,pred_model_xgb)
```

Out[252]:
```
6.0369962442614826e-05
```

LIGHT GBM

Following are the mean values of R-Squared, MSE and MAE of the 5-fold cross validation in the light gradient boosting machine regression model.

Based on the above output, we can see that the MAE value of the model is 0.0858, the MSE is 0.0125 and the R-Squared value is 91.02%, which means as much as 91.02% of the Sale Price variability can be explained by the nine independent variables. While the remaining 8.98% is influenced by other variables outside the model.

In [253]:
```
score_LGBM = model_cv(model_lgb)
```

```
R Square : 0.9100529907032705, MSE : 0.012600179668220541, MAE : 0.08588580661013107.
```

Evaluation Metrics in Test Data

In [254]:
```
model_lgb.fit(x_train,y_train)
pred_model_lgb=model_lgb.predict(x_test)
```

Based on the test data, we can see that the MAE value of the model is 0.077, the MSE is 0.0104, the MSLE is 0.000063 and the R-Squared value is 93.32%, which means as much as 93.32% of the Sale Price variability in test data can be explained by the nine independent variables. While the remaining 6.68% is influenced by other variables outside the model.

In [255]:
```
r2_score(y_test,pred_model_lgb)
```

Out[255]:
```
0.9308673221500487
```

In [256]:
```
mean_squared_error(y_test,pred_model_lgb)
```

Out[256]:
```
0.010715348251069136
```

In [257]:
```
mean_absolute_error(y_test,pred_model_lgb)
```

Out[257]:
```
0.07780312473812004
```

In [258]:
```
mean_squared_log_error(y_test,pred_model_lgb)
```

Out[258]:
```
6.329567833339122e-05
```

The Best Model

The best Model is Kernel Ridge Regression

Submission

Submission using the best model

In [259]:
```
submit=submit[best]
submission=KRR.predict(submit)
submission=np.expm1(submission)
sub = pd.DataFrame()
sub['Id'] = test_ID
sub['SalePrice'] = submission
sub.to_csv('submission.csv',index=False)
```