house_price

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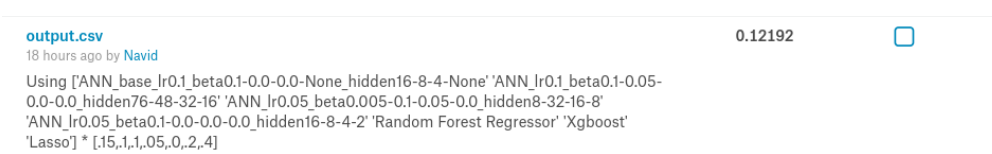
1 House Prices: Advanced Regression Techniques

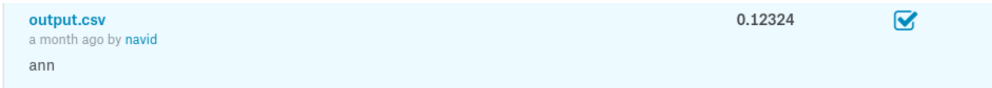
2 Abstract:

House Price prediction is a very popular dataset for data science competition. In this dataset 79 explanatory variables describing (almost) every aspect of residential homes in Ames and Iowa. This competition challenges competitor to predict the final price of each home.

In this report my main focus is how artificial neural network performs for this kind of problems and how to improve performance of the prediction using artificial neural network. So my elaboration on that section will be much more detailed.I have divided my work in four part and they are - Data processing where I have visualized, cleaned, handled missing data, carefully modified , removed and merged some features. - Testing multiple model In this part I have used gradient boosting, decision tree, random forest regression , lasso and Artificial neural network on my pre processed data. - Artificial neural network implementation In this section I have implemented ANN , performed parameter tuning, training, used grid search inside training and validate test score. - Cross Validation In this part I have used k fold cross validation on my artificial neural network model to make sure if the Data is actually independent and to fine tune few parameters on whole dataset if the cross validation score is not same as validation score. - Ensemble learning I have used bagging method for this section to improve my kaggle score.



alt text



alt text

3 Score:

3.0.1 Best Score : 0.12192 (using Ensemble Learning)

3.0.2 Best score without Ensemble : 0.12324 (ANN only)

4 Imports:

In the following section, I have imported all the necessary libraries that I will need to properly complete the assignment. - The 'Pandas' library will be used to store the 'Train' and 'Test' datasets. The particular data storing format is called a 'Dataframe'. - The 'Numpy' library is used to make mathematical calculations easier and faster to do. - 'Matplotlib' and 'Seaborn' are used to plot graphs - From the 'Scikit learn'(sklearn) library, I have imported some data processing methods, some evaluation metrics and some predictive models.

Gpu testing

In [73]:
```
import tensorflow as tf
device_name = tf.test.gpu_device_name()
if device_name != '/device:GPU:0':
  raise SystemError('GPU device not found')
print('Found GPU at: {}'.format(device_name))
```

```
Found GPU at: /device:GPU:0
```

In [74]:
```
import tensorflow as tf
import numpy as np
import pandas as pd
from sklearn.ensemble import RandomForestRegressor
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.metrics import  r2_score
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import StandardScaler
from IPython.display import Image
from sklearn.preprocessing import normalize,MinMaxScaler
import matplotlib.pyplot as plt
from sklearn.utils import shuffle
import seaborn as sns
# %matplotlib widget
%matplotlib inline
```

5 Data Pre-processing

5.0.1 Load Data

The following block of code reads the two CSV (Comma Separated Values) files and then stores the data inside them in two separate Dataframes named 'train' and 'test'.

```
In [75]: train = pd.read_csv('train.csv')#.select_dtypes(exclude=['object'])
         test = pd.read_csv('test.csv')#.select_dtypes(exclude=['object'])

         #look into datatypes of the file
         print("data types count")
         train.dtypes.groupby(train.dtypes).count()
```

```
data types count
```

```
Out[75]: int64      35
         float64     3
         object     43
         dtype: int64
```

5.0.2 Looking into data

Here I am printing the first five entries in the train dataset to look into the actual data that I will be working with. I gives me some insight about the data I am working with.

```
In [76]: print('show sample')
         pd.set_option('display.max_column', None)
         train.head()
```

```
show sample
```

```
Out[76]:    Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
         0   1          60       RL         65.0     8450   Pave   NaN      Reg
         1   2          20       RL         80.0     9600   Pave   NaN      Reg
         2   3          60       RL         68.0    11250   Pave   NaN      IR1
         3   4          70       RL         60.0     9550   Pave   NaN      IR1
         4   5          60       RL         84.0    14260   Pave   NaN      IR1

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

           Condition2 BldgType HouseStyle  OverallQual  OverallCond  YearBuilt  \
         0       Norm     1Fam     2Story            7            5       2003
```

```
1       Norm     1Fam     1Story            6            8       1976
2       Norm     1Fam     2Story            7            5       2001
3       Norm     1Fam     2Story            7            5       1915
4       Norm     1Fam     2Story            8            5       2000

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

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

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

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

   GrLivArea  BsmtFullBath  BsmtHalfBath  FullBath  HalfBath  BedroomAbvGr  \
0       1710             1             0         2         1             3
1       1262             0             1         2         0             3
2       1786             1             0         2         1             3
3       1717             1             0         1         0             3
4       2198             1             0         2         1             4

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

  GarageType  GarageYrBlt GarageFinish  GarageCars  GarageArea GarageQual  \
```

0	Attchd	2003.0	RFn	2	548	TA
1	Attchd	1976.0	RFn	2	460	TA
2	Attchd	2001.0	RFn	2	608	TA
3	Detchd	1998.0	Unf	3	642	TA
4	Attchd	2000.0	RFn	3	836	TA

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

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

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

Here I have used one of the built-in functions of pandas dataframe to display descriptive statistics that summarize the central tendency, dispersion and shape of a dataset's distribution, excluding NaN values.

In [77]:
```
print('description of data')
train.describe()
```

```
description of data
```

Out[77]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual \
count	1460.000000	1460.000000	1201.000000	1460.000000	1460.000000
mean	730.500000	56.897260	70.049958	10516.828082	6.099315
std	421.610009	42.300571	24.284752	9981.264932	1.382997
min	1.000000	20.000000	21.000000	1300.000000	1.000000
25%	365.750000	20.000000	59.000000	7553.500000	5.000000
50%	730.500000	50.000000	69.000000	9478.500000	6.000000
75%	1095.250000	70.000000	80.000000	11601.500000	7.000000
max	1460.000000	190.000000	313.000000	215245.000000	10.000000

	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1 \
count	1460.000000	1460.000000	1460.000000	1452.000000	1460.000000

mean	5.575342	1971.267808	1984.865753	103.685262	443.639726
std	1.112799	30.202904	20.645407	181.066207	456.098091
min	1.000000	1872.000000	1950.000000	0.000000	0.000000
25%	5.000000	1954.000000	1967.000000	0.000000	0.000000
50%	5.000000	1973.000000	1994.000000	0.000000	383.500000
75%	6.000000	2000.000000	2004.000000	166.000000	712.250000
max	9.000000	2010.000000	2010.000000	1600.000000	5644.000000

	BsmtFinSF2	BsmtUnfSF	TotalBsmtSF	1stFlrSF	2ndFlrSF \
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	46.549315	567.240411	1057.429452	1162.626712	346.992466
std	161.319273	441.866955	438.705324	386.587738	436.528436
min	0.000000	0.000000	0.000000	334.000000	0.000000
25%	0.000000	223.000000	795.750000	882.000000	0.000000
50%	0.000000	477.500000	991.500000	1087.000000	0.000000
75%	0.000000	808.000000	1298.250000	1391.250000	728.000000
max	1474.000000	2336.000000	6110.000000	4692.000000	2065.000000

	LowQualFinSF	GrLivArea	BsmtFullBath	BsmtHalfBath	FullBath \
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	5.844521	1515.463699	0.425342	0.057534	1.565068
std	48.623081	525.480383	0.518911	0.238753	0.550916
min	0.000000	334.000000	0.000000	0.000000	0.000000
25%	0.000000	1129.500000	0.000000	0.000000	1.000000
50%	0.000000	1464.000000	0.000000	0.000000	2.000000
75%	0.000000	1776.750000	1.000000	0.000000	2.000000
max	572.000000	5642.000000	3.000000	2.000000	3.000000

	HalfBath	BedroomAbvGr	KitchenAbvGr	TotRmsAbvGrd	Fireplaces \
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	0.382877	2.866438	1.046575	6.517808	0.613014
std	0.502885	0.815778	0.220338	1.625393	0.644666
min	0.000000	0.000000	0.000000	2.000000	0.000000
25%	0.000000	2.000000	1.000000	5.000000	0.000000
50%	0.000000	3.000000	1.000000	6.000000	1.000000
75%	1.000000	3.000000	1.000000	7.000000	1.000000
max	2.000000	8.000000	3.000000	14.000000	3.000000

	GarageYrBlt	GarageCars	GarageArea	WoodDeckSF	OpenPorchSF \
count	1379.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	1978.506164	1.767123	472.980137	94.244521	46.660274
std	24.689725	0.747315	213.804841	125.338794	66.256028
min	1900.000000	0.000000	0.000000	0.000000	0.000000
25%	1961.000000	1.000000	334.500000	0.000000	0.000000
50%	1980.000000	2.000000	480.000000	0.000000	25.000000
75%	2002.000000	2.000000	576.000000	168.000000	68.000000
max	2010.000000	4.000000	1418.000000	857.000000	547.000000

```
       EnclosedPorch     3SsnPorch  ScreenPorch     PoolArea       MiscVal  \
count    1460.000000  1460.000000  1460.000000  1460.000000   1460.000000
mean       21.954110     3.409589    15.060959     2.758904     43.489041
std        61.119149    29.317331    55.757415    40.177307    496.123024
min         0.000000     0.000000     0.000000     0.000000      0.000000
25%         0.000000     0.000000     0.000000     0.000000      0.000000
50%         0.000000     0.000000     0.000000     0.000000      0.000000
75%         0.000000     0.000000     0.000000     0.000000      0.000000
max       552.000000   508.000000   480.000000   738.000000  15500.000000

            MoSold       YrSold      SalePrice
count  1460.000000  1460.000000    1460.000000
mean      6.321918  2007.815753  180921.195890
std       2.703626     1.328095   79442.502883
min       1.000000  2006.000000   34900.000000
25%       5.000000  2007.000000  129975.000000
50%       6.000000  2008.000000  163000.000000
75%       8.000000  2009.000000  214000.000000
max      12.000000  2010.000000  755000.000000
```

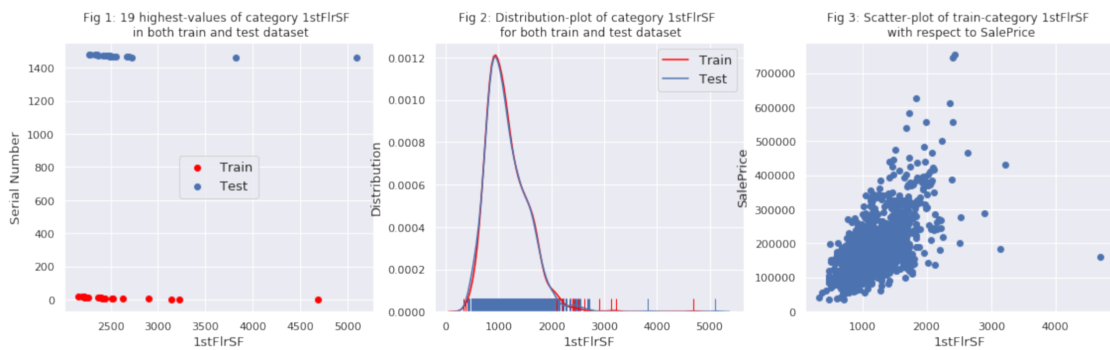
This function shows scatter-plot and distribution plot. I am going to use it to see few of the features of the dataset and observe how it changes while I process the data. I will try not to remove data so instead of removing any data point I will observe them until all my data processing is complete. If I found out after all the processing some data points are really causing problem then I will drop it.

In [78]:
```
#For showing diffrence
old_train_outlier_flag =train.copy()
old_test_outlier_flag =test.copy()
old_target_outlier_flag =train.SalePrice.copy()

# A FUNCTION THAT SHOWS SCATTER-PLOT AND DISTRIBUTION-PLOT
def outlier_check_plot(column, train_data_flag=train , test_data_flag=test , target=t
    plt.subplots(figsize=(19, 5))
    # SCATTER PLOT OF THE 19 HIGHEST-VALUES OF A COLUMN
    plt.subplot(1, 3, 1)
    plt.scatter(x = train_data_flag[column].sort_values(ascending=False)[:19], y = tra
    plt.scatter(x = test_data_flag[column].sort_values(ascending=False)[:19], y = tes
    plt.ylabel('Serial Number', fontsize=13)
    plt.xlabel(column, fontsize=13)
    plt.title('Fig 1: 19 highest-values of category {} \n in both train and test data
    plt.legend(loc='center',fontsize=13)
    # DISTRIBUTION-PLOT OF THE COLUMN
    plt.subplot(1, 3, 2)
    sns.distplot(train_data_flag[column],color='red', rug=True, hist=False, label='Tr
    sns.distplot(test_data_flag[column], rug=True, hist=False, label='Test')
    plt.ylabel('Distribution', fontsize=13)
    plt.xlabel(column, fontsize=13)
```

```
            plt.title('Fig 2: Distribution-plot of category {} \n for both train and test data
            plt.legend(fontsize=13)
            # SCATTER-PLOT OF THE COLUMN WITH RESPECT TO SALEPRICE
            plt.subplot(1, 3, 3)
            plt.scatter(x = train_data_flag[column], y = target)
            plt.ylabel('SalePrice', fontsize=13)
            plt.xlabel(column, fontsize=13)
            plt.title('Fig 3: Scatter-plot of train-category {} \n with respect to SalePrice'
            plt.show()
```

```
In [79]: print('Before outlier-removal of 1stFlrSF: ')
         outlier_check_plot('1stFlrSF')
```

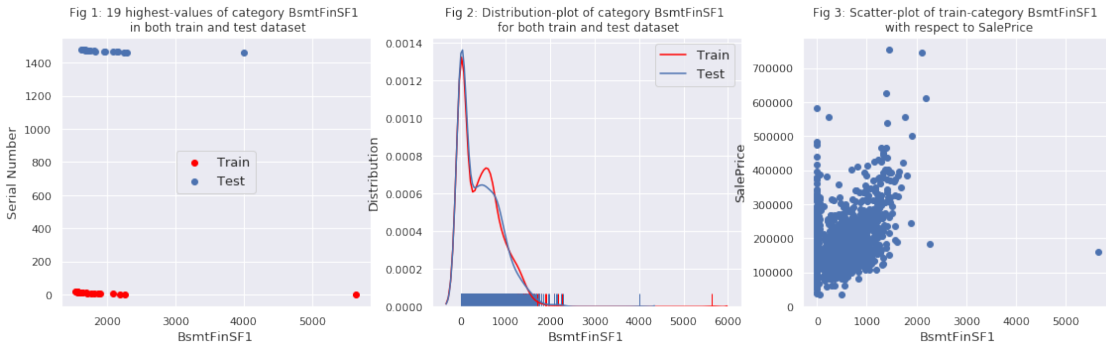
```
Before outlier-removal of 1stFlrSF:
```



We can see one value in train set that is highly contradictory with SalePrice (1stFlrSF is too high but SalePrice is too low). And there is only one such high-value point available in test dataset. So we might want to remove this outlier.

```
In [80]: print('Before outlier-removal of BsmtFinSF1: ')
         outlier_check_plot('BsmtFinSF1')
```

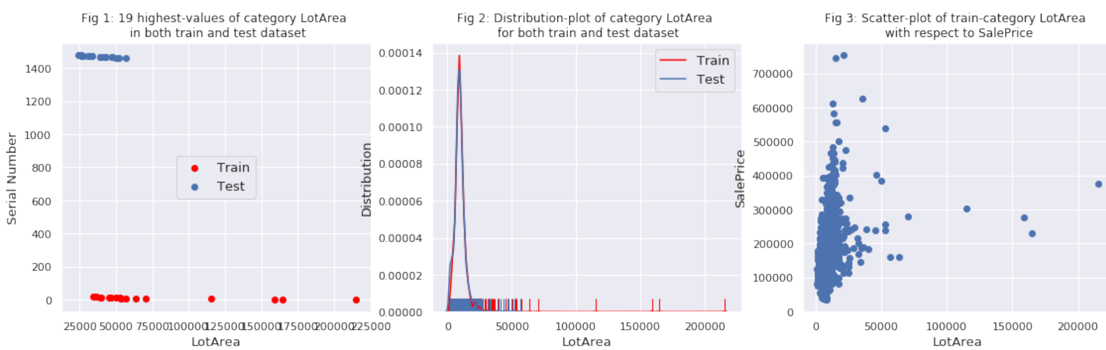
```
Before outlier-removal of BsmtFinSF1:


/home/navid/anaconda3/envs/tf/lib/python3.6/site-packages/statsmodels/nonparametric/kde.py:448
  X = X[np.logical_and(X > clip[0], X < clip[1])] # won't work for two columns.
/home/navid/anaconda3/envs/tf/lib/python3.6/site-packages/statsmodels/nonparametric/kde.py:448
  X = X[np.logical_and(X > clip[0], X < clip[1])] # won't work for two columns.
```



We can also see the same outlier here.

```
In [81]: print('Before outlier-removal of LotArea: ')
         outlier_check_plot('LotArea')
```

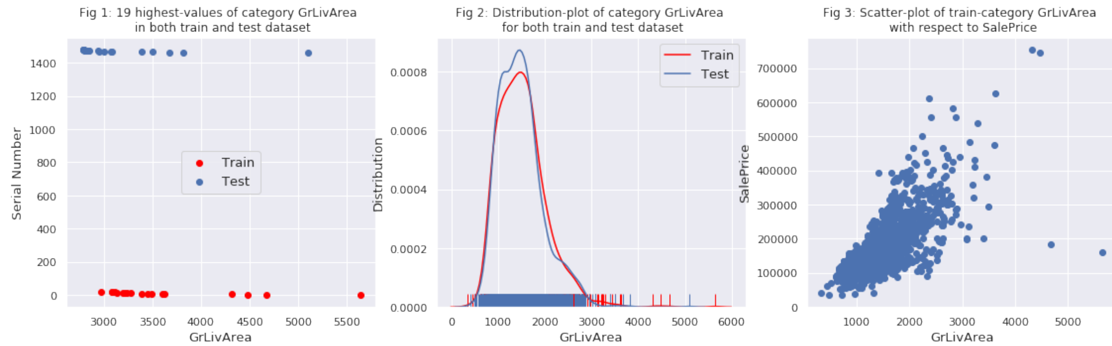
```
Before outlier-removal of LotArea:
```



We can see in Fig 3 that there are 4 LotArea train-samples above 80000 that are very high in size but comperatively very low in SalePrice. Also there are no such values present in test-data: Fig 1. So we can drop them

```
In [82]: print('Before outlier-removal of GrLivArea: ')
         outlier_check_plot('GrLivArea')
```

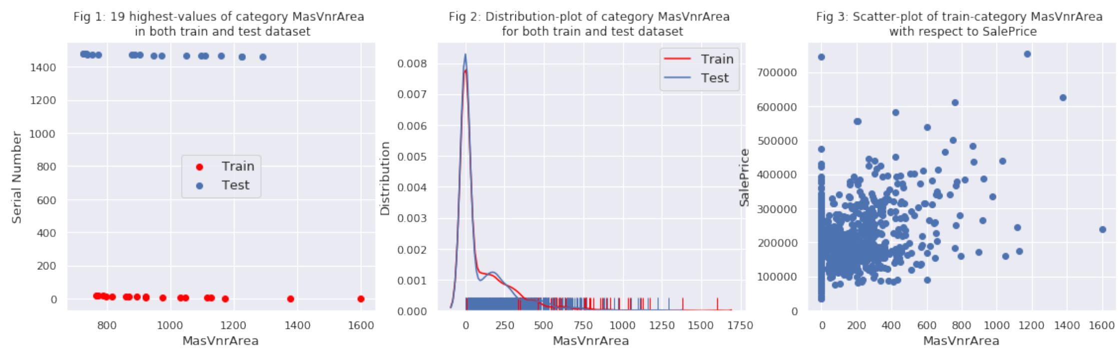
```
Before outlier-removal of GrLivArea:
```



If we compare Fig. 3 with code-cell 13 we can see that two outliers are already common in GrLivArea. These two outliers of GrLivArea train-samples were above 4000 with very low SalePrice (below 300000). We are seeing same outlier again and again.

```
In [83]: print('Before outlier-removal of MasVnrArea: ')
         outlier_check_plot('MasVnrArea')
```

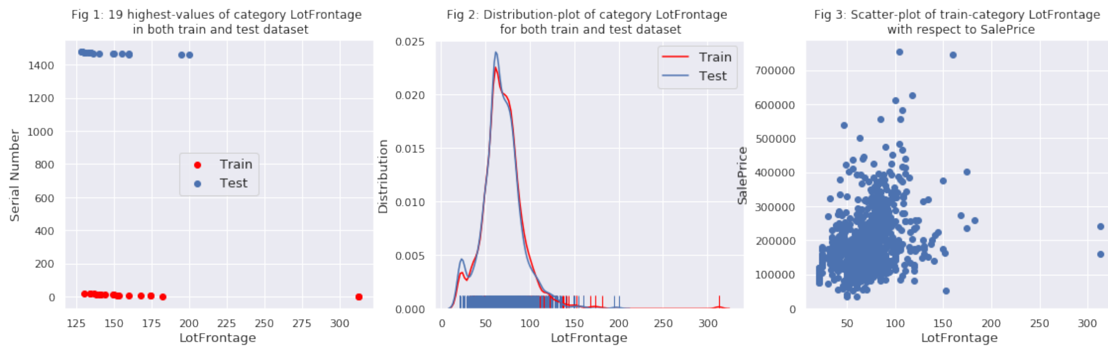
```
Before outlier-removal of MasVnrArea:
```



As we can see in Fig 3 that above 1500 there is 1 MasVnrArea train-samples that are very high in size but comperatively very low in SalePrice (below 300000) and there is no such values present in test-data: Fig 1. But this case is not so common outlier in other sections so keeping it would be safe for now.

```
In [84]: print('Before outlier-removal of LotFrontage: ')
         outlier_check_plot('LotFrontage')
```

```
Before outlier-removal of LotFrontage:
```



As we can see in Fig 3 that above 200 there is 1 LotFrontage train-samples that is very high in size but comperatively very low in SalePrice (below 300000) and there is no such value present in test-data. But one of them seems to be the common outlier which is below 20000(saleprice). We should remove the common one and observe the other.

```
In [85]: print('Before outlier-removal of TotalBsmtSF: ')
         outlier_check_plot('TotalBsmtSF')
```

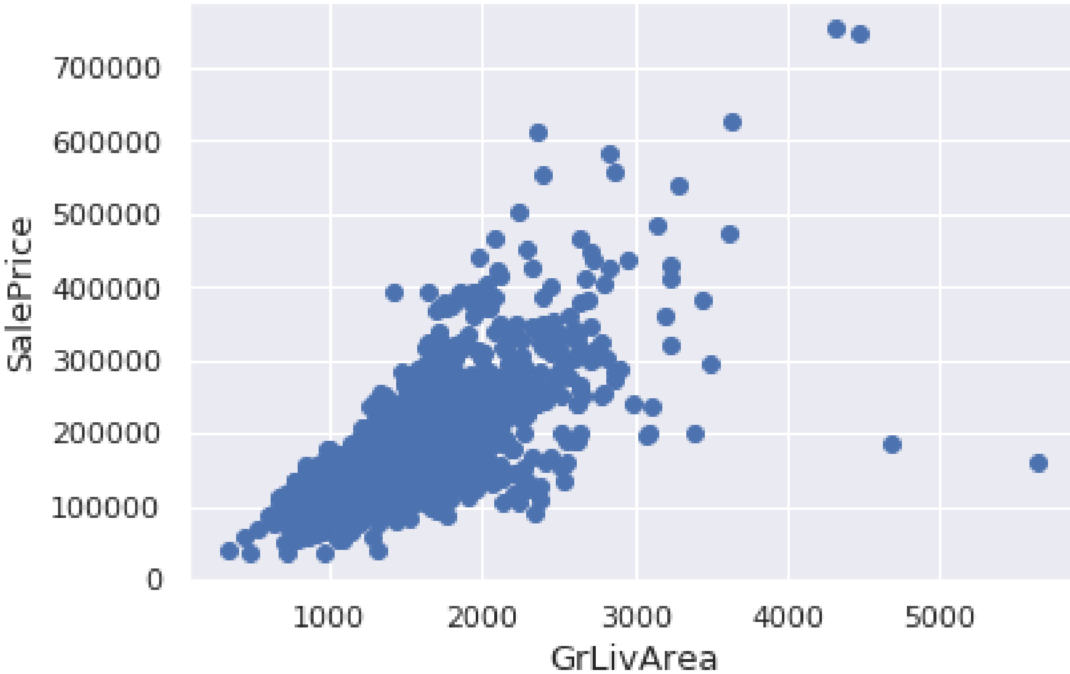
```
Before outlier-removal of TotalBsmtSF:
```

We can also see the common outlier and we would be removing the common outlier in the next section.

5.1 Common Outlier Remove

Saleprice vs GrLivArea

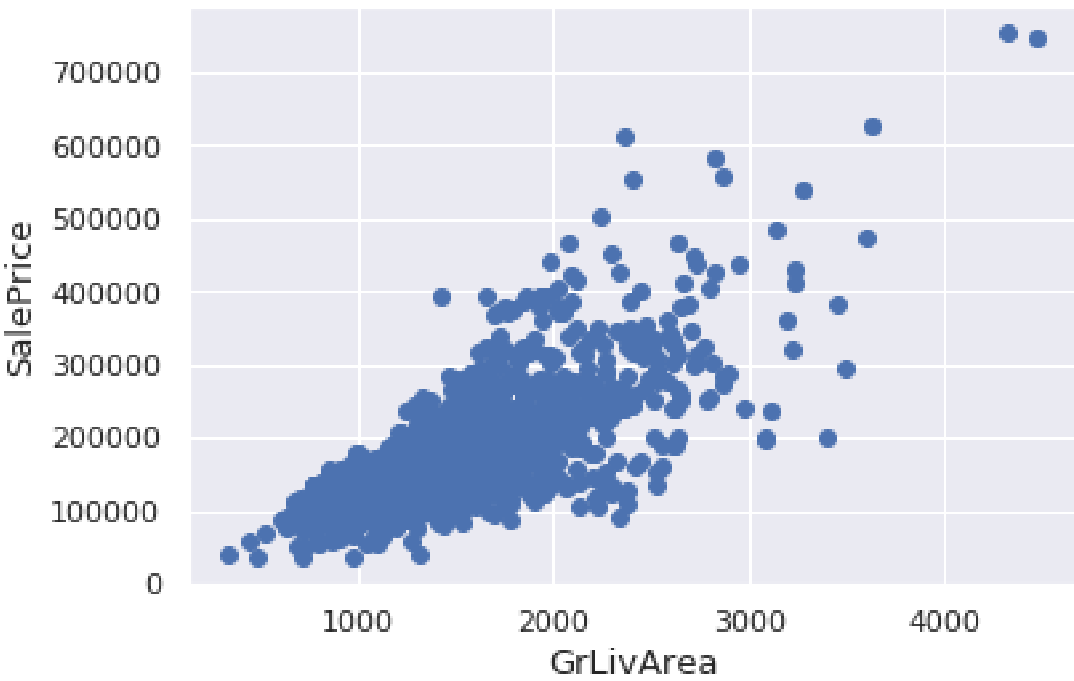
```
In [86]: fig, ax = plt.subplots()
         ax.scatter(x = train['GrLivArea'], y = train['SalePrice'])
         plt.ylabel('SalePrice', fontsize=13)
         plt.xlabel('GrLivArea', fontsize=13)
         plt.show()
```



There are a few houses with more than 4000 sq ft living area that are outliers, so we drop them from the training data.

```
In [87]: train.drop(train[ (train["GrLivArea"] > 4000) & (train['SalePrice']<400000) ].index, i
```

```
In [88]: #Check the graph again
         fig, ax = plt.subplots()
         ax.scatter(train['GrLivArea'], train['SalePrice'])
         plt.ylabel('SalePrice', fontsize=13)
         plt.xlabel('GrLivArea', fontsize=13)
         plt.show()
```

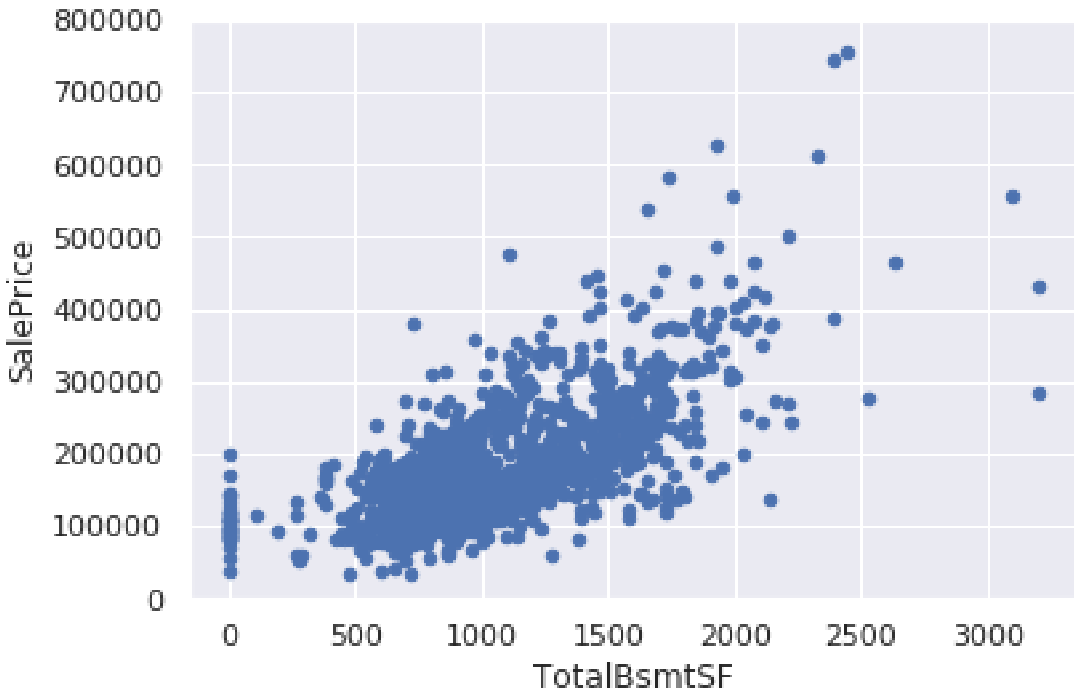


Its a linear relation so this feature is helpful to predict the price.

SalePrice vs TotalBsmSf This relationship is also linear so we can expect that it also have great impact on the price.

```
In [89]: #scatter plot totalbsmtsf/saleprice
         var = 'TotalBsmtSF'
         data = pd.concat([train['SalePrice'], train[var]], axis=1)
         data.plot.scatter(x=var, y='SalePrice', ylim=(0,800000));
```

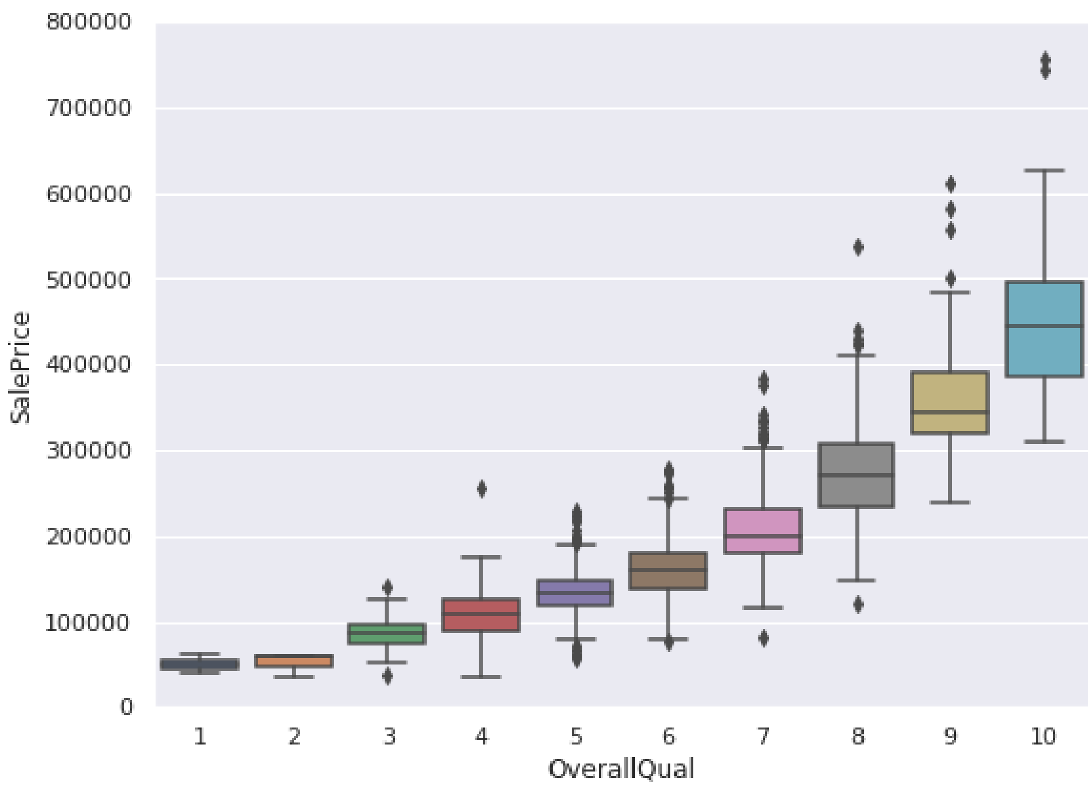
```
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as valu
```



We have removed the common outlier and now the graph seems better and we will follow up later after all the data pre processing. If any outlier remains after all processing I will remove them.

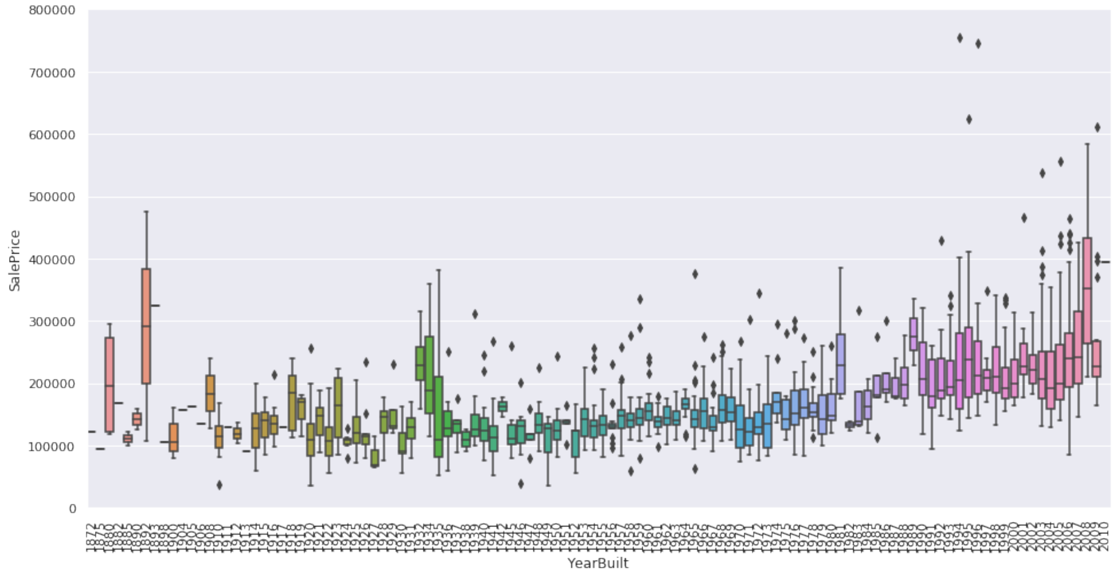
5.1.1 Relationship with categorical features

In [90]:
```
#box plot overallqual/saleprice
import seaborn as sns

var = 'OverallQual'
data = pd.concat([train['SalePrice'], 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);
```



As expected saleprice increases when overall quality increases.

```
In [91]: var = 'YearBuilt'
         data = pd.concat([train['SalePrice'], train[var]], axis=1)
         f, ax = plt.subplots(figsize=(16, 8))
         fig = sns.boxplot(x=var, y="SalePrice", data=data)
         fig.axis(ymin=0, ymax=800000);
         plt.xticks(rotation=90);
```



We can see that people tends to spend more for newly built houses. Although its does not seems really a storong feature acording to plot but its really importent if we consider other parameters too.

5.1.2 Note

- 'GrLivArea' and 'TotalBsmtSF' seem to be linearly related with 'SalePrice'. Both relationships are positive, which means that as one variable increases, the other also increases. In the case of 'TotalBsmtSF', we can see that the slope of the linear relationship is particularly high.
- 'OverallQual' and 'YearBuilt' also seem to be related with 'SalePrice'. The relationship seems to be stronger in the case of 'OverallQual', where the box plot shows how sales prices increase with the overall quality.

We have analised four variables, but there are many other that we should analyse. The trick here seems to be the choice of the right features (feature selection) and not the definition of complex relationships between them (feature engineering).

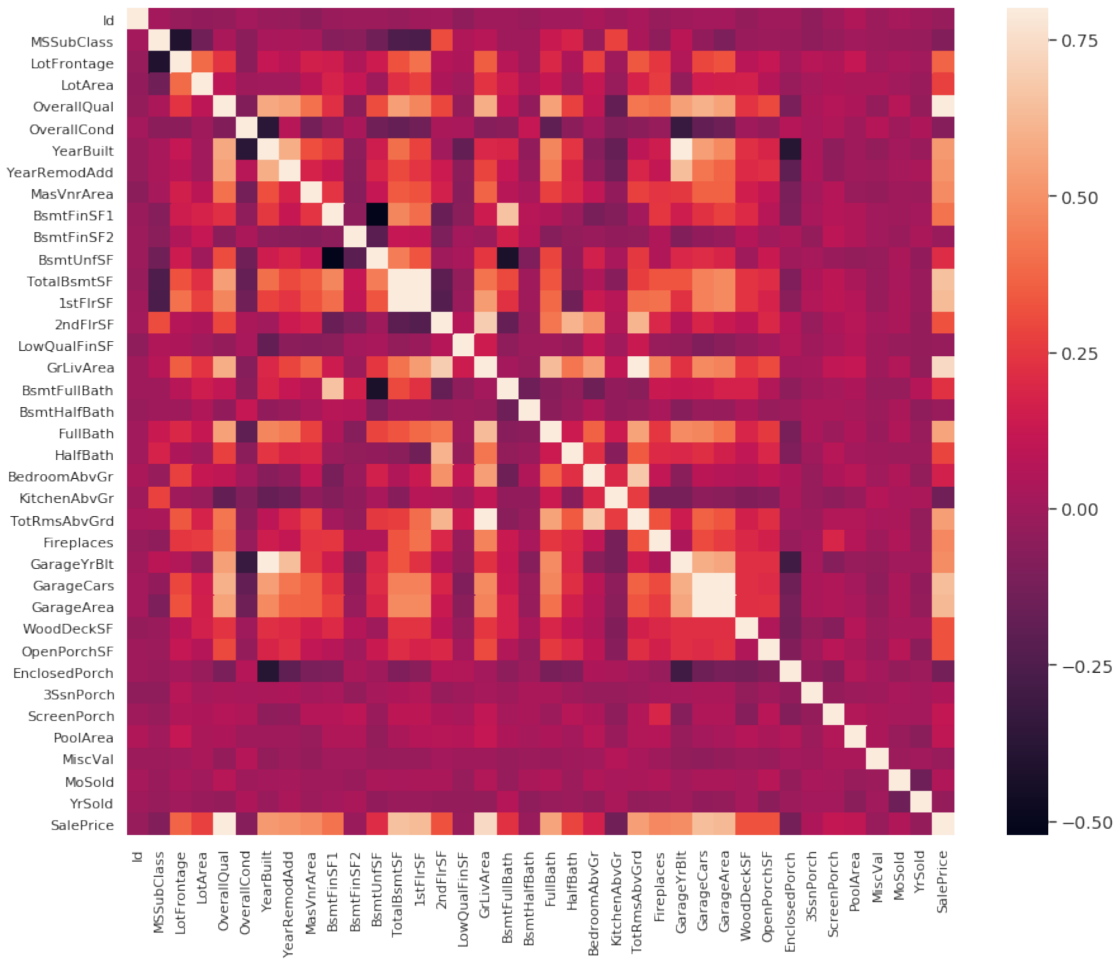
5.2 Correlation matrix (heatmap)

The correlation coefficient is a statistical calculation that is used to examine the relationship between two sets of data. The value of the correlation coefficient tells us about the strength and the nature of the relationship.

Correlation coefficient values can range between +1.00 to -1.00. If the value is exactly +1.00, it means that there is a "perfect" positive relationship between two numbers, while a value of exactly -1.00 indicates a "perfect" negative relationship.

If correlation is Positive then the values increase together and if the correlation is Negative, one value decreases as the other increases. When two sets of data are strongly linked together we say they have a High Correlation.

```python
In [92]: #correlation matrix
         corrmat = train.corr()
         f, ax = plt.subplots(figsize=(15, 12))
         sns.set(font_scale=1.25)
         sns.heatmap(corrmat, vmax=.8, square=True);
```

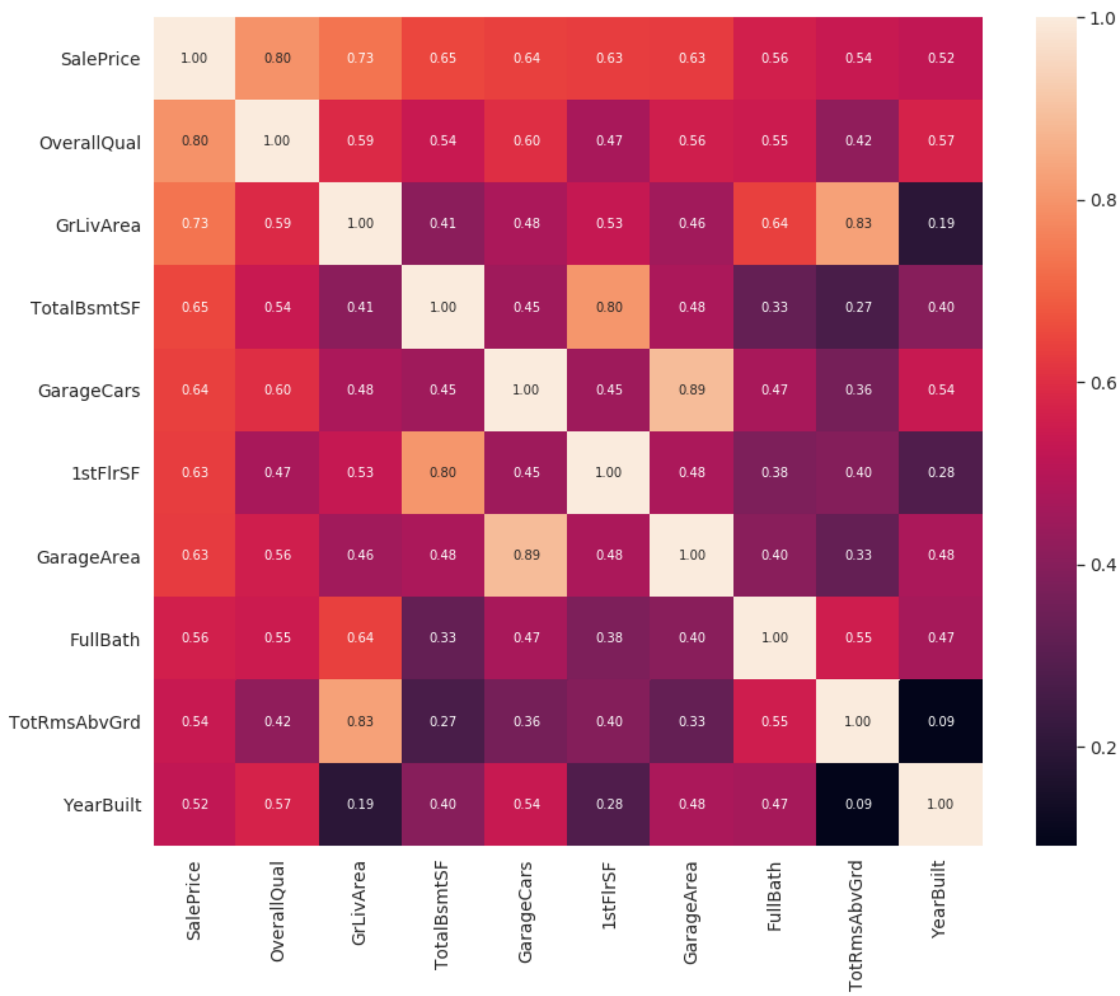


In my opinion, this heatmap is the best way to get a quick overview the relationships of a dataset.

At first sight, there are two red colored squares that get my attention. The first one refers to the 'TotalBsmtSF' and '1stFlrSF' variables, and the second one refers to the 'GarageX' variables. Both cases show how significant the correlation is between these variables. Actually, this correlation is so strong that it can indicate a situation of multicollinearity. If we think about these variables, we can conclude that they give almost the same information so multicollinearity really occurs. Heatmaps are great to detect this kind of situations and in problems dominated by feature selection, like ours, they are an essential tool.

Another thing that got my attention was the 'SalePrice' correlations. We can see our well-known 'GrLivArea', 'TotalBsmtSF', and 'OverallQual' is closely related to salePrice, but we can also see many other variables that should be taken into account. So we are zooming in.

```
In [93]: #saleprice correlation matrix
         k = 10 #number of variables for heatmap
         cols = corrmat.nlargest(k, 'SalePrice')['SalePrice'].index
         cm = np.corrcoef(train[cols].values.T)
         f, ax = plt.subplots(figsize=(15, 12))
         sns.set(font_scale=1.25)
         hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'size'
         plt.show()
```



Explanation

- 'OverallQual', 'GrLivArea' and 'TotalBsmtSF' are strongly correlated with 'SalePrice'.
- 'GarageCars' and 'GarageArea' are also some of the most strongly correlated variables.The number of cars that fit into the garage is a consequence of the garage area. 'GarageCars' and 'GarageArea' are really close.Therefore, we just need one of these variables in our analysis (we can keep 'GarageCars' since its correlation with 'SalePrice' is higher).

- 'TotalBsmtSF' and '1stFloor' also seem to be really close. We can keep 'TotalBsmtSF'
- 'FullBath' is really seems to be a important features.
- 'TotRmsAbvGrd' and 'GrLivArea' also seems very close we will decide later which to keep.
- 'YearBuilt' is slightly correlated with 'SalePrice'.

5.3 Missing Data

Important questions when thinking about missing data:

- How prevalent is the missing data?
- Is missing data random or does it have a pattern?

The answer to these questions is important for practical reasons because missing data can imply a reduction of the sample size. This can prevent us from proceeding with the analysis. Moreover, from a substantive perspective, we need to ensure that the missing data process is not biased and hiding an inconvenient truth.

```
In [94]: total = train.isnull().sum().sort_values(ascending=False)
         percent = (train.isnull().sum()/train.isnull().count()).sort_values(ascending=False)
         missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
         missing_data.head(20)
```

Out[94]:

	Total	Percent
PoolQC	1452	0.995885
MiscFeature	1404	0.962963
Alley	1367	0.937586
Fence	1177	0.807270
FireplaceQu	690	0.473251
LotFrontage	259	0.177641
GarageCond	81	0.055556
GarageType	81	0.055556
GarageYrBlt	81	0.055556
GarageFinish	81	0.055556
GarageQual	81	0.055556
BsmtExposure	38	0.026063
BsmtFinType2	38	0.026063
BsmtFinType1	37	0.025377
BsmtCond	37	0.025377
BsmtQual	37	0.025377
MasVnrArea	8	0.005487
MasVnrType	8	0.005487
Electrical	1	0.000686
Utilities	0	0.000000

6 Data processing

I have tried few approaches to data preprocessing. The current one was the best one for all the models.Below are the steps I have taken to preprocess the data.

- I have filled missing values of some data features with zero because these missing value means it does not exist in the house.
- I have label encoded the ordinal value containing features. Ordinal values are which are used something along the line of "Good","Average","Bad"
- I have label encodded object type data which are not ordinal in nature
- I have also done some feature engineering, meaning I have created some new features from already existing features.

6.0.1 Lable Encoding

Label Encoding refers to converting the labels into numeric form so as to convert it into the machine-readable form. Machine learning algorithms can then decide in a better way on how those labels must be operated.

In this dataset, there are lot of features which don't represent a quantitative value but rather is actually a label of some sort. For this particular dataset, almost all of the labeled values are in the form of 'string' or words. Only a couple of the labels are represented with numbers. For example, lets check the feature 'Alley', which denotes the type of alley access to the property using the following labels. The meaning of the labels are also given

```
Grvl    Gravel
Pave    Paved
NA  No alley access
```

In the real world, labels are in the form of words, because words are human readable. So it makes sense from that perspective. But when it comes tho machine learning models, which works with numbers, we hit a bit of a roadblock. To remedy this, there is a need to use Label Encoding. Label encoding refers to the process of transforming the word labels into numerical form. This enables the algorithms to operate on data that have textual labels

In case of the labels there are two distinct types, "nominal" and "ordinal". The terms "nominal" and "ordinal" refer to different types of categorizable data.

"Nominal" data assigns names to each data point without placing it in some sort of order. For example, the results of a test could be each classified nominally as a "pass" or "fail."

"Ordinal" data groups data according to some sort of ranking system: it orders the data. For example, this dataset has a very common ranking system which is as follows

```
Ex  Excellent
Gd  Good
TA  Average/Typical
Fa  Fair
Po  Poor
```

6.1 Imputing missing data

Two of these following part would be used in the common data processing section to impute missing data.

```
In [95]: lot_frontage_by_neighborhood = train["LotFrontage"].groupby(train["Neighborhood"])
```

Following function will be used to convert categorical features as number.

```
In [96]: from sklearn.preprocessing import LabelEncoder
         le = LabelEncoder()

         def factorize(df, factor_df, column, fill_na=None):
             factor_df[column] = df[column]
             if fill_na is not None:
                 factor_df[column].fillna(fill_na, inplace=True)
             le.fit(factor_df[column].unique())
             factor_df[column] = le.transform(factor_df[column])
             return factor_df
```

6.2 common data processing:

In this part we have label encoded some of the columns because some features are ordinal. I have replaced some null value with zero because in those case they probably meant that it may not exist . Finally I have merged some of the features to get a better feature.

Befor starting following block its important to understand which feature means what so that describing my work would be easier

- SalePrice - the property's sale price in dollars. This is the target variable that you're trying to predict.
- MSSubClass: The building class
- MSZoning: The general zoning classification
- LotFrontage: Linear feet of street connected to property
- LotArea: Lot size in square feet
- Street: Type of road access
- Alley: Type of alley access
- LotShape: General shape of property
- LandContour: Flatness of the property
- Utilities: Type of utilities available
- LotConfig: Lot configuration
- LandSlope: Slope of property
- Neighborhood: Physical locations within Ames city limits
- Condition1: Proximity to main road or railroad
- Condition2: Proximity to main road or railroad (if a second is present)
- BldgType: Type of dwelling
- HouseStyle: Style of dwelling
- OverallQual: Overall material and finish quality
- OverallCond: Overall condition rating
- YearBuilt: Original construction date

- YearRemodAdd: Remodel date
- RoofStyle: Type of roof
- RoofMatl: Roof material
- Exterior1st: Exterior covering on house
- Exterior2nd: Exterior covering on house (if more than one material)
- MasVnrType: Masonry veneer type
- MasVnrArea: Masonry veneer area in square feet
- ExterQual: Exterior material quality
- ExterCond: Present condition of the material on the exterior
- Foundation: Type of foundation
- BsmtQual: Height of the basement
- BsmtCond: General condition of the basement
- BsmtExposure: Walkout or garden level basement walls
- BsmtFinType1: Quality of basement finished area
- BsmtFinSF1: Type 1 finished square feet
- BsmtFinType2: Quality of second finished area (if present)
- BsmtFinSF2: Type 2 finished square feet
- BsmtUnfSF: Unfinished square feet of basement area
- TotalBsmtSF: Total square feet of basement area
- Heating: Type of heating
- HeatingQC: Heating quality and condition
- CentralAir: Central air conditioning
- Electrical: Electrical system
- 1stFlrSF: First Floor square feet
- 2ndFlrSF: Second floor square feet
- LowQualFinSF: Low quality finished square feet (all floors)
- GrLivArea: Above grade (ground) living area square feet
- BsmtFullBath: Basement full bathrooms
- BsmtHalfBath: Basement half bathrooms
- FullBath: Full bathrooms above grade
- HalfBath: Half baths above grade
- Bedroom: Number of bedrooms above basement level
- Kitchen: Number of kitchens
- KitchenQual: Kitchen quality
- TotRmsAbvGrd: Total rooms above grade (does not include bathrooms)
- Functional: Home functionality rating
- Fireplaces: Number of fireplaces
- FireplaceQu: Fireplace quality
- -GarageType: Garage location
- GarageYrBlt: Year garage was built
- GarageFinish: Interior finish of the garage
- GarageCars: Size of garage in car capacity
- GarageArea: Size of garage in square feet
- GarageQual: Garage quality
- GarageCond: Garage condition
- PavedDrive: Paved driveway
- WoodDeckSF: Wood deck area in square feet
- OpenPorchSF: Open porch area in square feet

- EnclosedPorch: Enclosed porch area in square feet
- 3SsnPorch: Three season porch area in square feet
- ScreenPorch: Screen porch area in square feet
- PoolArea: Pool area in square feet
- PoolQC: Pool quality
- Fence: Fence quality
- MiscFeature: Miscellaneous feature not covered in other categories
- MiscVal: $Value of miscellaneous feature
- MoSold: Month Sold
- YrSold: Year Sold
- SaleType: Type of sale
- SaleCondition: Condition of sale

In [97]:
```
def data_process(df):
    all_df = pd.DataFrame(index = df.index)

    all_df["LotFrontage"] = df["LotFrontage"]
    for key, group in lot_frontage_by_neighborhood:
        #Filling in missing LotFrontage values by the median
        idx = (df["Neighborhood"] == key) & (df["LotFrontage"].isnull())
        all_df.loc[idx, "LotFrontage"] = group.median()
        all_df["LotArea"] = df["LotArea"]

    all_df["MasVnrArea"] = df["MasVnrArea"]
    all_df["MasVnrArea"].fillna(0, inplace=True)

    all_df["BsmtFinSF1"] = df["BsmtFinSF1"]
    all_df["BsmtFinSF1"].fillna(0, inplace=True)

    all_df["BsmtFinSF2"] = df["BsmtFinSF2"]
    all_df["BsmtFinSF2"].fillna(0, inplace=True)

    all_df["BsmtUnfSF"] = df["BsmtUnfSF"]
    all_df["BsmtUnfSF"].fillna(0, inplace=True)

    all_df["TotalBsmtSF"] = df["TotalBsmtSF"]
    all_df["TotalBsmtSF"].fillna(0, inplace=True)

    all_df["1stFlrSF"] = df["1stFlrSF"]
    all_df["2ndFlrSF"] = df["2ndFlrSF"]
    all_df["GrLivArea"] = df["GrLivArea"]

    all_df["GarageArea"] = df["GarageArea"]
    all_df["GarageArea"].fillna(0, inplace=True)

    all_df["WoodDeckSF"] = df["WoodDeckSF"]
    all_df["OpenPorchSF"] = df["OpenPorchSF"]
    all_df["EnclosedPorch"] = df["EnclosedPorch"]
```

```python
all_df["3SsnPorch"] = df["3SsnPorch"]
all_df["ScreenPorch"] = df["ScreenPorch"]

all_df["BsmtFullBath"] = df["BsmtFullBath"]
all_df["BsmtFullBath"].fillna(0, inplace=True)

all_df["BsmtHalfBath"] = df["BsmtHalfBath"]
all_df["BsmtHalfBath"].fillna(0, inplace=True)

all_df["FullBath"] = df["FullBath"]
all_df["HalfBath"] = df["HalfBath"]
all_df["BedroomAbvGr"] = df["BedroomAbvGr"]
all_df["KitchenAbvGr"] = df["KitchenAbvGr"]
all_df["TotRmsAbvGrd"] = df["TotRmsAbvGrd"]
all_df["Fireplaces"] = df["Fireplaces"]

all_df["GarageCars"] = df["GarageCars"]
all_df["GarageCars"].fillna(0, inplace=True)

all_df["CentralAir"] = (df["CentralAir"] == "Y") * 1.0

all_df["OverallQual"] = df["OverallQual"]
all_df["OverallCond"] = df["OverallCond"]


"""following case are ordinal so we are performing label encoding here"""

nan = float('nan')
qual_dict = {nan: 0, "NA": 0, "Po": 1, "Fa": 2, "TA": 3, "Gd": 4, "Ex": 5}
all_df["ExterQual"] = df["ExterQual"].map(qual_dict).astype(int)
all_df["ExterCond"] = df["ExterCond"].map(qual_dict).astype(int)
all_df["BsmtQual"] = df["BsmtQual"].map(qual_dict).astype(int)
all_df["BsmtCond"] = df["BsmtCond"].map(qual_dict).astype(int)
all_df["HeatingQC"] = df["HeatingQC"].map(qual_dict).astype(int)
all_df["KitchenQual"] = df["KitchenQual"].map(qual_dict).astype(int)
all_df["FireplaceQu"] = df["FireplaceQu"].map(qual_dict).astype(int)
all_df["GarageQual"] = df["GarageQual"].map(qual_dict).astype(int)
all_df["GarageCond"] = df["GarageCond"].map(qual_dict).astype(int)

all_df["BsmtExposure"] = df["BsmtExposure"].map(
    {nan: 0, "No": 1, "Mn": 2, "Av": 3, "Gd": 4}).astype(int)

bsmt_fin_dict = {nan: 0, "Unf": 1, "LwQ": 2, "Rec": 3, "BLQ": 4, "ALQ": 5, "GLQ":
all_df["BsmtFinType1"] = df["BsmtFinType1"].map(bsmt_fin_dict).astype(int)
all_df["BsmtFinType2"] = df["BsmtFinType2"].map(bsmt_fin_dict).astype(int)

all_df["Functional"] = df["Functional"].map(
    {nan: 0, "Sal": 1, "Sev": 2, "Maj2": 3, "Maj1": 4,
```

```
     "Mod": 5, "Min2": 6, "Min1": 7, "Typ": 8}).astype(int)

all_df["GarageFinish"] = df["GarageFinish"].map(
    {nan: 0, "Unf": 1, "RFn": 2, "Fin": 3}).astype(int)

all_df["Fence"] = df["Fence"].map(
    {nan: 0, "MnWw": 1, "GdWo": 2, "MnPrv": 3, "GdPrv": 4}).astype(int)

all_df["PoolQC"] = df["PoolQC"].map(qual_dict).astype(int)

all_df["YearBuilt"] = df["YearBuilt"]
all_df["YearRemodAdd"] = df["YearRemodAdd"]

all_df["GarageYrBlt"] = df["GarageYrBlt"]
all_df["GarageYrBlt"].fillna(0.0, inplace=True)

all_df["MoSold"] = df["MoSold"]
all_df["YrSold"] = df["YrSold"]

all_df["LowQualFinSF"] = df["LowQualFinSF"]
all_df["MiscVal"] = df["MiscVal"]

all_df["PoolQC"] = df["PoolQC"].map(qual_dict).astype(int)

all_df["PoolArea"] = df["PoolArea"]
all_df["PoolArea"].fillna(0, inplace=True)

# Add categorical features as numbers too. It seems to help a bit.
all_df = factorize(df, all_df, "MSSubClass")
all_df = factorize(df, all_df, "MSZoning", "RL")
all_df = factorize(df, all_df, "LotConfig")
all_df = factorize(df, all_df, "Neighborhood")
all_df = factorize(df, all_df, "Condition1")
all_df = factorize(df, all_df, "BldgType")
all_df = factorize(df, all_df, "HouseStyle")
all_df = factorize(df, all_df, "RoofStyle")
all_df = factorize(df, all_df, "Exterior1st", "Other")
all_df = factorize(df, all_df, "Exterior2nd", "Other")
all_df = factorize(df, all_df, "MasVnrType", "None")
all_df = factorize(df, all_df, "Foundation")
all_df = factorize(df, all_df, "SaleType", "Oth")
all_df = factorize(df, all_df, "SaleCondition")

"""In following code I am converting values of those features as 0 or 1"""

# IR2 and IR3 don't appear that often, so just make a distinction
# between regular and irregular.
all_df["IsRegularLotShape"] = (df["LotShape"] == "Reg") * 1
```

```
    # Most properties are level; bin the other possibilities together
    # as "not level".
    all_df["IsLandLevel"] = (df["LandContour"] == "Lvl") * 1

    # Most land slopes are gentle; treat the others as "not gentle".
    all_df["IsLandSlopeGentle"] = (df["LandSlope"] == "Gtl") * 1

    # Most properties use standard circuit breakers.
    all_df["IsElectricalSBrkr"] = (df["Electrical"] == "SBrkr") * 1

    # About 2/3rd have an attached garage.
    all_df["IsGarageDetached"] = (df["GarageType"] == "Detchd") * 1

    # Most have a paved drive. Treat dirt/gravel and partial pavement
    # as "not paved".
    all_df["IsPavedDrive"] = (df["PavedDrive"] == "Y") * 1

    # The only interesting "misc. feature" is the presence of a shed.
    all_df["HasShed"] = (df["MiscFeature"] == "Shed") * 1.

    # If YearRemodAdd != YearBuilt, then a remodeling took place at some point.
    all_df["Remodeled"] = (all_df["YearRemodAdd"] != all_df["YearBuilt"]) * 1

    # Did a remodeling happen in the year the house was sold?
    all_df["RecentRemodel"] = (all_df["YearRemodAdd"] == all_df["YrSold"]) * 1

    # Was this house sold in the year it was built?
    all_df["VeryNewHouse"] = (all_df["YearBuilt"] == all_df["YrSold"]) * 1

    all_df["Has2ndFloor"] = (all_df["2ndFlrSF"] == 0) * 1
    all_df["HasMasVnr"] = (all_df["MasVnrArea"] == 0) * 1
    all_df["HasWoodDeck"] = (all_df["WoodDeckSF"] == 0) * 1
    all_df["HasOpenPorch"] = (all_df["OpenPorchSF"] == 0) * 1
    all_df["HasEnclosedPorch"] = (all_df["EnclosedPorch"] == 0) * 1
    all_df["Has3SsnPorch"] = (all_df["3SsnPorch"] == 0) * 1
    all_df["HasScreenPorch"] = (all_df["ScreenPorch"] == 0) * 1

    # Months with the largest number of deals may be significant.
#     mx = max(train["MoSold"].groupby(train["MoSold"]).count())
#     all_df["HighSeason"] = df["MoSold"].replace(
#         train["MoSold"].groupby(train["MoSold"]).count()/mx)

#     mx = max(train["MSSubClass"].groupby(train["MSSubClass"]).count())
#     all_df["NewerDwelling"] = df["MSSubClass"].replace(
#         train["MSSubClass"].groupby(train["MSSubClass"]).count()/mx)

    # following portion was calculated with above commented part of the code.
```

```
# Instead of the fraction value putting binary value helps for generalization
all_df["HighSeason"] = df["MoSold"].replace(
    {1: 0, 2: 0, 3: 0, 4: 1, 5: 1, 6: 1, 7: 1, 8: 0, 9: 0, 10: 0, 11: 0, 12: 0})

all_df["NewerDwelling"] = df["MSSubClass"].replace(
    {20: 1, 30: 0, 40: 0, 45: 0,50: 0, 60: 1, 70: 0, 75: 0, 80: 0, 85: 0,
     90: 0, 120: 1, 150: 0, 160: 0, 180: 0, 190: 0})


all_df.loc[df.Neighborhood == 'NridgHt', "Neighborhood_Good"] = 1
all_df.loc[df.Neighborhood == 'Crawfor', "Neighborhood_Good"] = 1
all_df.loc[df.Neighborhood == 'StoneBr', "Neighborhood_Good"] = 1
all_df.loc[df.Neighborhood == 'Somerst', "Neighborhood_Good"] = 1
all_df.loc[df.Neighborhood == 'NoRidge', "Neighborhood_Good"] = 1
all_df["Neighborhood_Good"].fillna(0, inplace=True)

# House completed before sale or not
all_df["SaleCondition_PriceDown"] = df.SaleCondition.replace(
    {'Abnorml': 1, 'Alloca': 1, 'AdjLand': 1, 'Family': 1, 'Normal': 0, 'Partial'

# House completed before sale or not
all_df["BoughtOffPlan"] = df.SaleCondition.replace(
    {"Abnorml" : 0, "Alloca" : 0, "AdjLand" : 0, "Family" : 0, "Normal" : 0, "Par

all_df["BadHeating"] = df.HeatingQC.replace(
    {'Ex': 0, 'Gd': 0, 'TA': 0, 'Fa': 1, 'Po': 1})

area_cols = ['LotFrontage', 'LotArea', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2',
             'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'GrLivArea', 'GarageArea', 'Wo
             'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'LowQualF
all_df["TotalArea"] = all_df[area_cols].sum(axis=1)

all_df["TotalArea1st2nd"] = all_df["1stFlrSF"] + all_df["2ndFlrSF"]

all_df["Age"] = 2010 - all_df["YearBuilt"]
all_df["TimeSinceSold"] = 2010 - all_df["YrSold"]

all_df["SeasonSold"] = all_df["MoSold"].map({12:0, 1:0, 2:0, 3:1, 4:1, 5:1,
                                              6:2, 7:2, 8:2, 9:3, 10:3, 11:3}).ast

all_df["YearsSinceRemodel"] = all_df["YrSold"] - all_df["YearRemodAdd"]

# Simplifications of existing features into bad/average/good.
all_df["SimplOverallQual"] = all_df.OverallQual.replace(
    {1 : 1, 2 : 1, 3 : 1, 4 : 2, 5 : 2, 6 : 2, 7 : 3, 8 : 3, 9 : 3, 10 : 3})
all_df["SimplOverallCond"] = all_df.OverallCond.replace(
    {1 : 1, 2 : 1, 3 : 1, 4 : 2, 5 : 2, 6 : 2, 7 : 3, 8 : 3, 9 : 3, 10 : 3})
all_df["SimplPoolQC"] = all_df.PoolQC.replace(
```

```
    {1 : 1, 2 : 1, 3 : 2, 4 : 2})
all_df["SimplGarageCond"] = all_df.GarageCond.replace(
    {1 : 1, 2 : 1, 3 : 1, 4 : 2, 5 : 2})
all_df["SimplGarageQual"] = all_df.GarageQual.replace(
    {1 : 1, 2 : 1, 3 : 1, 4 : 2, 5 : 2})
all_df["SimplFireplaceQu"] = all_df.FireplaceQu.replace(
    {1 : 1, 2 : 1, 3 : 1, 4 : 2, 5 : 2})
all_df["SimplFireplaceQu"] = all_df.FireplaceQu.replace(
    {1 : 1, 2 : 1, 3 : 1, 4 : 2, 5 : 2})
all_df["SimplFunctional"] = all_df.Functional.replace(
    {1 : 1, 2 : 1, 3 : 2, 4 : 2, 5 : 3, 6 : 3, 7 : 3, 8 : 4})
all_df["SimplKitchenQual"] = all_df.KitchenQual.replace(
    {1 : 1, 2 : 1, 3 : 1, 4 : 2, 5 : 2})
all_df["SimplHeatingQC"] = all_df.HeatingQC.replace(
    {1 : 1, 2 : 1, 3 : 1, 4 : 2, 5 : 2})
all_df["SimplBsmtFinType1"] = all_df.BsmtFinType1.replace(
    {1 : 1, 2 : 1, 3 : 1, 4 : 2, 5 : 2, 6 : 2})
all_df["SimplBsmtFinType2"] = all_df.BsmtFinType2.replace(
    {1 : 1, 2 : 1, 3 : 1, 4 : 2, 5 : 2, 6 : 2})
all_df["SimplBsmtCond"] = all_df.BsmtCond.replace(
    {1 : 1, 2 : 1, 3 : 1, 4 : 2, 5 : 2})
all_df["SimplBsmtQual"] = all_df.BsmtQual.replace(
    {1 : 1, 2 : 1, 3 : 1, 4 : 2, 5 : 2})
all_df["SimplExterCond"] = all_df.ExterCond.replace(
    {1 : 1, 2 : 1, 3 : 1, 4 : 2, 5 : 2})
all_df["SimplExterQual"] = all_df.ExterQual.replace(
    {1 : 1, 2 : 1, 3 : 1, 4 : 2, 5 : 2})

# Bin by neighborhood (a little arbitrarily). Values were computed by:
# train_df["SalePrice"].groupby(train_df["Neighborhood"]).median().sort_values()
neighborhood_map = {
    "MeadowV" : 0,  #  88000
    "IDOTRR" : 1,   # 103000
    "BrDale" : 1,   # 106000
    "OldTown" : 1,  # 119000
    "Edwards" : 1,  # 119500
    "BrkSide" : 1,  # 124300
    "Sawyer" : 1,   # 135000
    "Blueste" : 1,  # 137500
    "SWISU" : 2,    # 139500
    "NAmes" : 2,    # 140000
    "NPkVill" : 2,  # 146000
    "Mitchel" : 2,  # 153500
    "SawyerW" : 2,  # 179900
    "Gilbert" : 2,  # 181000
    "NWAmes" : 2,   # 182900
    "Blmngtn" : 2,  # 191000
    "CollgCr" : 2,  # 197200
```

```
        "ClearCr" : 3,   # 200250
        "Crawfor" : 3,   # 200624
        "Veenker" : 3,   # 218000
        "Somerst" : 3,   # 225500
        "Timber" : 3,    # 228475
        "StoneBr" : 4,   # 278000
        "NoRidge" : 4,   # 290000
        "NridgHt" : 4,   # 315000
    }

    all_df["NeighborhoodBin"] = df["Neighborhood"].map(neighborhood_map)
    return all_df
```

In the above block I have done following operations :

- Filled with 0 for some features like "MasVnrArea", "BsmtFinSF1" "BsmtFinSF2" "BsmtUnfSF" "TotalBsmtSF" "GarageArea" "BsmtFullBath" "BsmtHalfBath" "GarageCars" "PoolArea" "GarageYrBlt" .According to the documentation of the dataset if these features have any field empty then that means the feature is not available. So I have done this operation according to documentation of the dataset.
- CentralAir feature was given has two field only 'Y' or 'N' so I have converted that to 0 or 1
- For some ordinal features I ave performed lable encoding to map data to a numerical features. Those features are ExterQual , ExterCond, BsmtQual, BsmtCond, HeatingQC, KitchenQual etc
- I have converted some features from categorical to numerical and those features are MSSubClass, MSZoning , LotConfig, RL , LotConfig,Neighborhood, Condition1 ,BldgType, HouseStyle , HouseStyle, Exterior1st, Other, Exterior2nd, MasVnrType, Foundation, SaleType and SaleCondition
- Converted fields of some Features to 0 or 1 based on the understanding of the dataset and a little bit research. What I have done is that I have made simplified versions of existing features. For example, the Land Slope feature lets us know what type of slope the property has. Even though is has multiple labels, it all comes down to if the slope is gentle or not. Hence I have created a new feature called IsLandSlopeGentle, which is effectively tells us if the slope is gentle (==1) or is it not gentle (==0).Those features with the changing reasons are given below
  - IsRegularLotShape : Field IR2 and IR3 don't appear that often, so just make a distinction between regular and irregular.
  - IsLandLevel : Most land slopes are gentle; treat the others as "not gentle".
  - IsElectricalSBrkr : Most properties use standard circuit breakers.
  - IsGarageDetached : About 2/3rd have an attached garage.
  - IsPavedDrive : Most have a paved drive. Treat dirt/gravel and partial pavement as "not paved".
  - HasShed : The only interesting "misc. feature" is the presence of a shed.
  - Remodeled : If YearRemodAdd != YearBuilt, then a remodeling took place at some point.

  - RecentRemodel : Did a remodeling happen in the year the house was sold?
  - VeryNewHouse : Was this house sold in the year it was built?
  - sofe other features dont need to describe they are self explanatory Has2ndFloor , HasMasVnr , HasWoodDeck .HasOpenPorch ,HasEnclosedPorch ,Has3SsnPorch , HasScreenPorch

- Simplifications of existing features into bad/average/good. Features : SimplOverallQual, SimplOverallCond, SimplPoolQC ,SimplGarageCond, SimplGarageQual, SimplFireplaceQu ,SimplFunctional ,SimplKitchenQual, SimplHeatingQC ,SimplBsmtFinType1, SimplBsmtFinType2 ,SimplBsmtCond , SimplBsmtQual ,SimplExterCond ,SimplExterQual.

- mapped neighborhood based on their quality.The mapping is as followed: "MeadowV" : 0, # 88000 "IDOTRR" : 1, # 103000 "BrDale" : 1, # 106000 "OldTown" : 1, # 119000 "Edwards" : 1, # 119500 "BrkSide" : 1, # 124300 "Sawyer" : 1, # 135000 "Blueste" : 1, # 137500 "SWISU" : 2, # 139500 "NAmes" : 2, # 140000 "NPkVill" : 2, # 146000 "Mitchel" : 2, # 153500 "SawyerW" : 2, # 179900 "Gilbert" : 2, # 181000 "NWAmes" : 2, # 182900 "Blmngtn" : 2, # 191000 "CollgCr" : 2, # 197200 "ClearCr" : 3, # 200250 "Crawfor" : 3, # 200624 "Veenker" : 3, # 218000 "Somerst" : 3, # 225500 "Timber" : 3, # 228475 "StoneBr" : 4, # 278000 "NoRidge" : 4, # 290000 "NridgHt" : 4, # 315000 - the number after hash is actually median priece of that location.

In [98]:
```
train_processed = data_process(train)
test_processed = data_process(test)

print("shape of train :" , train_processed.shape)
print("shape of test :" , test_processed.shape)
```

```
shape of train : (1458, 111)
shape of test : (1459, 111)
```

Keeping NeighborhoodBin into a temporary DataFrame because we want to use the unscaled version later on (to one-hot encode it).

In [99]:
```
# Keeping NeighborhoodBin into a temporary DataFrame because we want to use the
# unscaled version later on (to one-hot encode it).
neighborhood_bin_train = pd.DataFrame(index = train.index)
neighborhood_bin_train["NeighborhoodBin"] = train_processed["NeighborhoodBin"]
neighborhood_bin_test = pd.DataFrame(index = test.index)
neighborhood_bin_test["NeighborhoodBin"] = test_processed["NeighborhoodBin"]
```

6.3 Skewness, Normalization & Standardization

According to Hair et al. (2013), four assumptions should be tested:

- **Normality** - When we talk about normality what we mean is that the data should look like a normal distribution. This is important because several statistic tests rely on this (e.g. t-statistics). In this exercise we'll just check univariate normality for 'SalePrice' (which is a limited approach). Remember that univariate normality doesn't ensure multivariate normality (which is what we would like to have), but it helps. Another detail to take into account is that in big samples (>200 observations) normality is not such an issue. However, if we solve normality, we avoid a lot of other problems (e.g. heteroscedacity) so that's the main reason why we are doing this analysis.

- **Homoscedasticity** - Homoscedasticity refers to the 'assumption that dependent variable(s) exhibit equal levels of variance across the range of predictor variable(s)' (Hair et al., 2013). Homoscedasticity is desirable because we want the error term to be the same across all values of the independent variables.

- **Linearity** - The most common way to assess linearity is to examine scatter plots and search for linear patterns. If patterns are not linear, it would be worthwhile to explore data transformations. However, we'll not get into this because most of the scatter plots we've seen appear to have linear relationships.

- **standardization** is the process of putting different variables on the same scale. This process allows you to compare scores between different types of variables. Typically, to standardize variables, you calculate the mean and standard deviation for a variable. Then, for each observed value of the variable, you subtract the mean and divide by the standard deviation.

Skewness, in basic terms, implies off-centre, so does in statistics, it means lack of symmetry. With the help of skewness, one can identify the shape of the distribution of data.

In the simplest cases, normalization of ratings means adjusting values measured on different scales to a notionally common scale, often prior to averaging.Some types of normalization involve only a rescaling, to arrive at values relative to some size variable.

We will remove skewness through normalization and then scale all the numeric features using standardization technique (Except SalePrice).

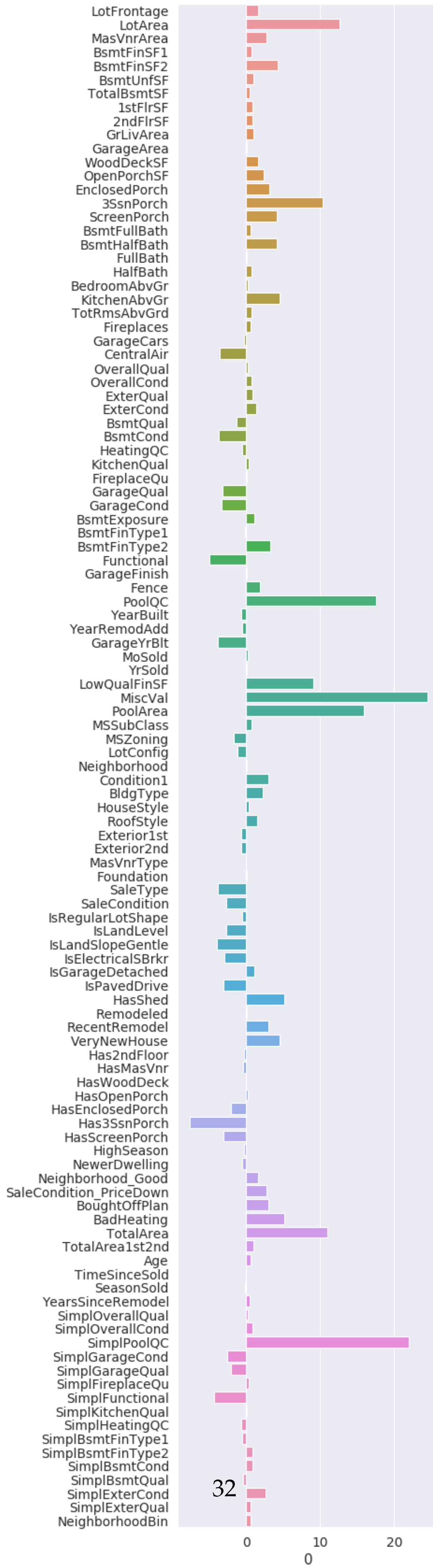
6.3.1 skewness train set

In the following part we are looking at skewness of training set and we can see that many features are highly skewed. We will be solving it with log transformation.

The log transformation is, arguably, the most popular among the different types of transformations used to transform skewed data to approximately conform to normality. If the original data follows a log-normal distribution or approximately so, then the log-transformed data follows a normal or near normal distribution.

```
In [100]: # keeping train and test data in a flag for comparison purpose
          old_train_skewness_flag = train_processed.copy()
          old_test_skewness_flag = test_processed.copy()
          old_target_skewness_flag= train["SalePrice"].copy()
          # old_target_skewness_flag
```

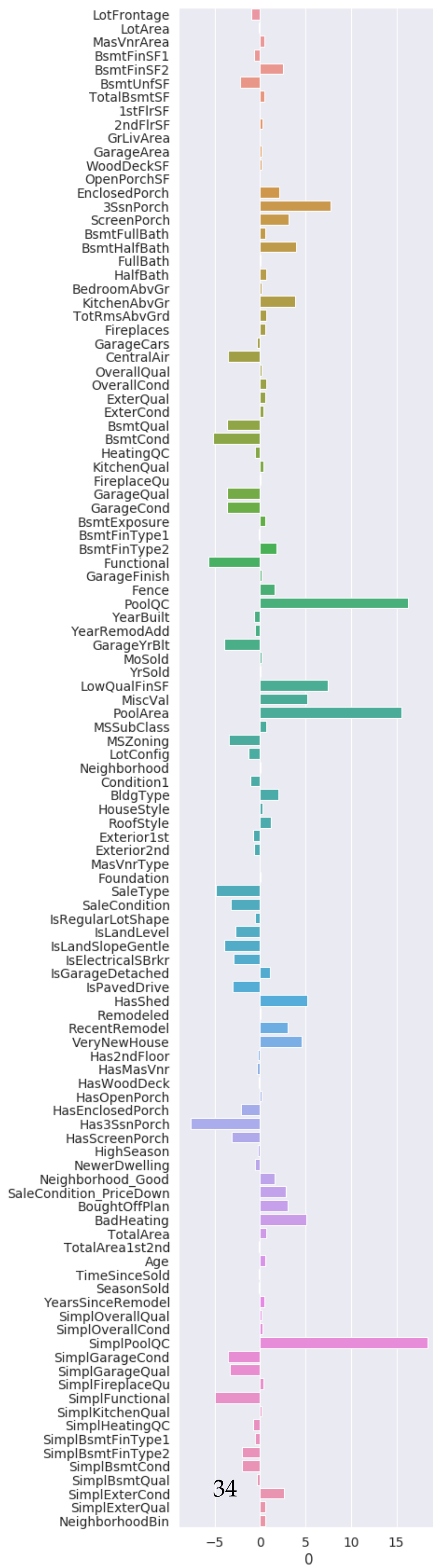
```
In [101]: from scipy.stats import skew
          numeric_features = train_processed.dtypes[train_processed.dtypes != "object"].index
          skewness = train_processed[numeric_features].skew(axis=0 , skipna =True)
          skewness = pd.DataFrame(skewness)
          plt.figure(figsize=[5,30])
          # skw = sns.load_dataset(skewness)
          ax = sns.barplot( y= skewness.index , x=skewness[0] , data = skewness)
          plt.show()
```


LotFrontage
LotArea
MasVnrArea
BsmtFinSF1
BsmtFinSF2
BsmtUnfSF
TotalBsmtSF
1stFlrSF
2ndFlrSF
GrLivArea
GarageArea
WoodDeckSF
OpenPorchSF
EnclosedPorch
3SsnPorch
ScreenPorch
BsmtFullBath
BsmtHalfBath
FullBath
HalfBath
BedroomAbvGr
KitchenAbvGr
TotRmsAbvGrd
Fireplaces
GarageCars
CentralAir
OverallQual
OverallCond
ExterQual
ExterCond
BsmtQual
BsmtCond
HeatingQC
KitchenQual
FireplaceQu
GarageQual
GarageCond
BsmtExposure
BsmtFinType1
BsmtFinType2
Functional
GarageFinish
Fence
PoolQC
YearBuilt
YearRemodAdd
GarageYrBlt
MoSold
YrSold
LowQualFinSF
MiscVal
PoolArea
MSSubClass
MSZoning
LotConfig
Neighborhood
Condition1
BldgType
HouseStyle
RoofStyle
Exterior1st
Exterior2nd
MasVnrType
Foundation
SaleType
SaleCondition
IsRegularLotShape
IsLandLevel
IsLandSlopeGentle
IsElectricalSBrkr
IsGarageDetached
IsPavedDrive
HasShed
Remodeled
RecentRemodel
VeryNewHouse
Has2ndFloor
HasMasVnr
HasWoodDeck
HasOpenPorch
HasEnclosedPorch
Has3SsnPorch
HasScreenPorch
HighSeason
NewerDwelling
Neighborhood_Good
SaleCondition_PriceDown
BoughtOffPlan
BadHeating
TotalArea
TotalArea1st2nd
Age
TimeSinceSold
SeasonSold
YearsSinceRemodel
SimplOverallQual
SimplOverallCond
SimplPoolQC
SimplGarageCond
SimplGarageQual
SimplFireplaceQu
SimplFunctional
SimplKitchenQual
SimplHeatingQC
SimplBsmtFinType1
SimplBsmtFinType2
SimplBsmtCond
SimplBsmtQual
SimplExterCond
SimplExterQual
NeighborhoodBin
0
10
20
0

Observation - A significant number of observations with value zero (houses without basement). - A big problem because the value zero doesn't allow us to do log transformations.

To apply a log transformation here, we need to add 1 and then perform log transform operation. **Note** : For real-valued input, log1p is accurate also for x so small that 1 + x == 1 in floating-point accuracy.

```
In [102]: numeric_features = train_processed.dtypes[train_processed.dtypes != "object"].index

          # Transform the skewed numeric features by taking log(feature + 1).
          # This will make the features more normal.
          from scipy.stats import skew

          skewed = train_processed[numeric_features].apply(lambda x: skew(x.dropna().astype(fl
          skewed = skewed[(skewed < -0.75) | (skewed > 0.75)]
          skewed = skewed.index

          train_processed[skewed] = np.log1p(train_processed[skewed])


          # Additional processing: scale the data.
          from sklearn.preprocessing import StandardScaler
          scaler = StandardScaler()
          scaled = scaler.fit_transform(train_processed[numeric_features])

          for i, col in enumerate(numeric_features):
              train_processed[col] = scaled[:, i]

/home/navid/anaconda3/envs/tf/lib/python3.6/site-packages/sklearn/preprocessing/data.py:645: Da
  return self.partial_fit(X, y)
/home/navid/anaconda3/envs/tf/lib/python3.6/site-packages/sklearn/base.py:464: DataConversionWa
  return self.fit(X, **fit_params).transform(X)


In [103]: from scipy.stats import skew
          numeric_features = train_processed.dtypes[train_processed.dtypes != "object"].index
          skewness = train_processed[numeric_features].skew(axis=0 , skipna =True)
          skewness = pd.DataFrame(skewness)
          plt.figure(figsize=[5,30])
          # skw = sns.load_dataset(skewness)
          ax = sns.barplot( y= skewness.index , x=skewness[0] , data = skewness)
          plt.show()
```


LotFrontage
LotArea
MasVnrArea
BsmtFinSF1
BsmtFinSF2
BsmtUnfSF
TotalBsmtSF
1stFlrSF
2ndFlrSF
GrLivArea
GarageArea
WoodDeckSF
OpenPorchSF
EnclosedPorch
3SsnPorch
ScreenPorch
BsmtFullBath
BsmtHalfBath
FullBath
HalfBath
BedroomAbvGr
KitchenAbvGr
TotRmsAbvGrd
Fireplaces
GarageCars
CentralAir
OverallQual
OverallCond
ExterQual
ExterCond
BsmtQual
BsmtCond
HeatingQC
KitchenQual
FireplaceQu
GarageQual
GarageCond
BsmtExposure
BsmtFinType1
BsmtFinType2
Functional
GarageFinish
Fence
PoolQC
YearBuilt
YearRemodAdd
GarageYrBlt
MoSold
YrSold
LowQualFinSF
MiscVal
PoolArea
MSSubClass
MSZoning
LotConfig
Neighborhood
Condition1
BldgType
HouseStyle
RoofStyle
Exterior1st
Exterior2nd
MasVnrType
Foundation
SaleType
SaleCondition
IsRegularLotShape
IsLandLevel
IsLandSlopeGentle
IsElectricalSBrkr
IsGarageDetached
IsPavedDrive
HasShed
Remodeled
RecentRemodel
VeryNewHouse
Has2ndFloor
HasMasVnr
HasWoodDeck
HasOpenPorch
HasEnclosedPorch
Has3SsnPorch
HasScreenPorch
HighSeason
NewerDwelling
Neighborhood_Good
SaleCondition_PriceDown
BoughtOffPlan
BadHeating
TotalArea
TotalArea1st2nd
Age
TimeSinceSold
SeasonSold
YearsSinceRemodel
SimplOverallQual
SimplOverallCond
SimplPoolQC
SimplGarageCond
SimplGarageQual
SimplFireplaceQu
SimplFunctional
SimplKitchenQual
SimplHeatingQC
SimplBsmtFinType1
SimplBsmtFinType2
SimplBsmtCond
SimplBsmtQual
SimplExterCond
SimplExterQual
NeighborhoodBin
−5
0
5
10
15
0

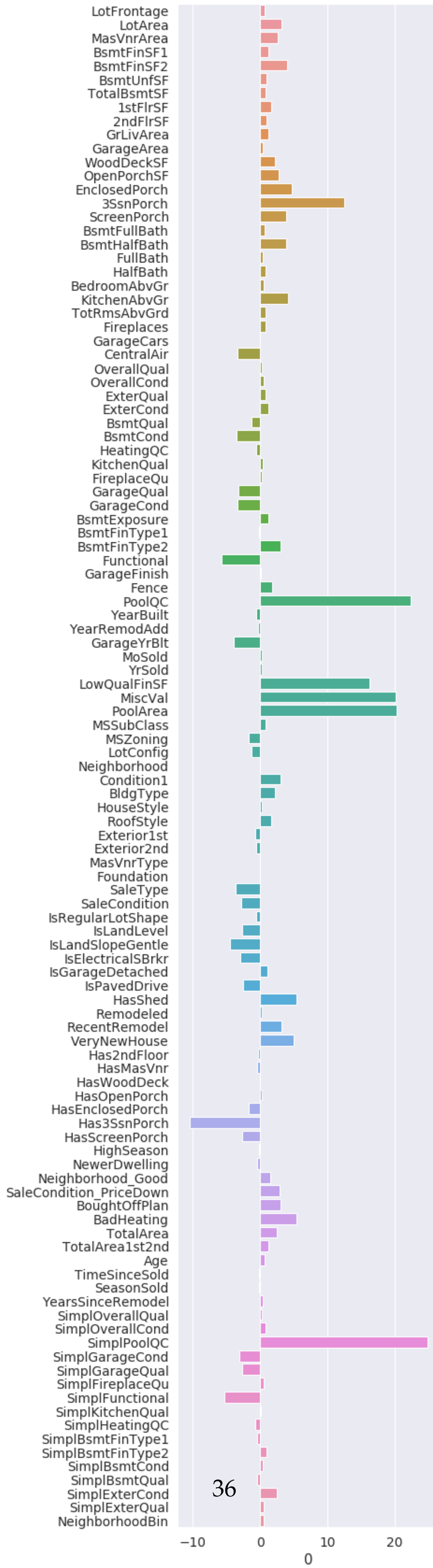
We can see that skewness of the following features decreased a lot: - LotArea - WoodDeskSf - OpenPorch - Extencond - MiscVal - TotalArea

But other numeric features also improved its skewness a little bit.

6.3.2 Test Skewness

We need to perform same operation on given test set too. Otherwise we woun't be able to predict correctly.

```
In [104]: numeric_features = test_processed.dtypes[train_processed.dtypes != "object"].index
          skewness = test_processed[numeric_features].skew(axis=0 , skipna =True)
          skewness = pd.DataFrame(skewness)

          plt.figure(figsize=[5,30])
          # skw = sns.load_dataset(skewness)
          ax = sns.barplot( y= skewness.index , x=skewness[0] , data = skewness)
          plt.show()
          # print('skew: ',test_processed[numeric_features].skew())
```


LotFrontage
LotArea
MasVnrArea
BsmtFinSF1
BsmtFinSF2
BsmtUnfSF
TotalBsmtSF
1stFlrSF
2ndFlrSF
GrLivArea
GarageArea
WoodDeckSF
OpenPorchSF
EnclosedPorch
3SsnPorch
ScreenPorch
BsmtFullBath
BsmtHalfBath
FullBath
HalfBath
BedroomAbvGr
KitchenAbvGr
TotRmsAbvGrd
Fireplaces
GarageCars
CentralAir
OverallQual
OverallCond
ExterQual
ExterCond
BsmtQual
BsmtCond
HeatingQC
KitchenQual
FireplaceQu
GarageQual
GarageCond
BsmtExposure
BsmtFinType1
BsmtFinType2
Functional
GarageFinish
Fence
PoolQC
YearBuilt
YearRemodAdd
GarageYrBlt
MoSold
YrSold
LowQualFinSF
MiscVal
PoolArea
MSSubClass
MSZoning
LotConfig
Neighborhood
Condition1
BldgType
HouseStyle
RoofStyle
Exterior1st
Exterior2nd
MasVnrType
Foundation
SaleType
SaleCondition
IsRegularLotShape
IsLandLevel
IsLandSlopeGentle
IsElectricalSBrkr
IsGarageDetached
IsPavedDrive
HasShed
Remodeled
RecentRemodel
VeryNewHouse
Has2ndFloor
HasMasVnr
HasWoodDeck
HasOpenPorch
HasEnclosedPorch
Has3SsnPorch
HasScreenPorch
HighSeason
NewerDwelling
Neighborhood_Good
SaleCondition_PriceDown
BoughtOffPlan
BadHeating
TotalArea
TotalArea1st2nd
Age
TimeSinceSold
SeasonSold
YearsSinceRemodel
SimplOverallQual
SimplOverallCond
SimplPoolQC
SimplGarageCond
SimplGarageQual
SimplFireplaceQu
SimplFunctional
SimplKitchenQual
SimplHeatingQC
SimplBsmtFinType1
SimplBsmtFinType2
SimplBsmtCond
SimplBsmtQual
SimplExterCond
SimplExterQual
NeighborhoodBin
−10
0
10
20
0

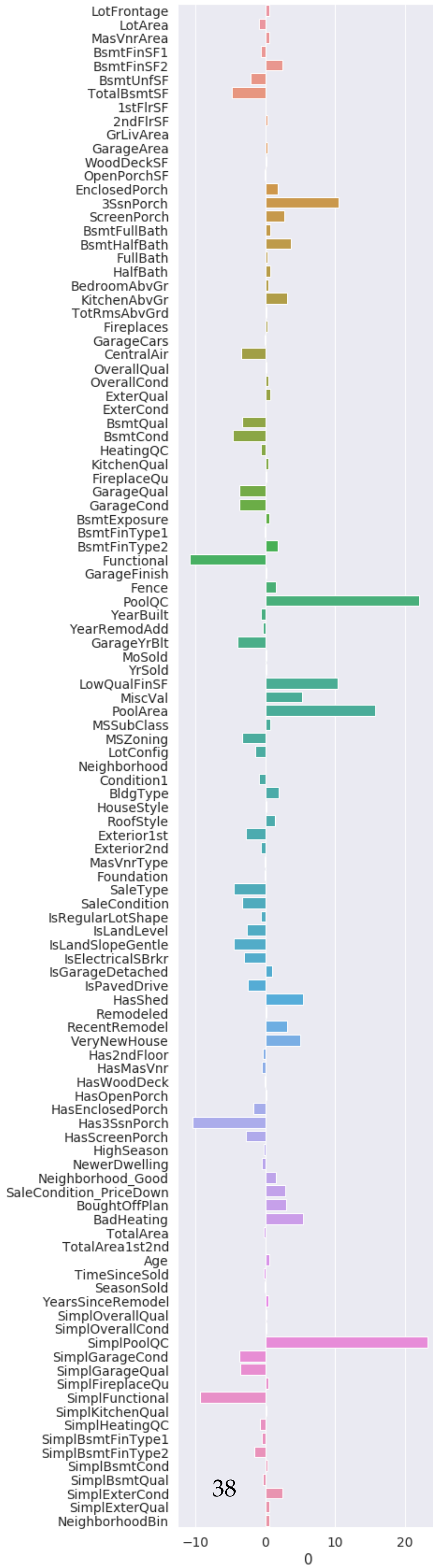
```
In [105]: numeric_features = test_processed.dtypes[train_processed.dtypes != "object"].index

          # Transform the skewed numeric features by taking log(feature + 1).
          # This will make the features more normal.
          from scipy.stats import skew

          skewed = test_processed[numeric_features].apply(lambda x: skew(x.dropna().astype(flo
          skewed = skewed[(skewed < -0.75) | (skewed > 0.75)]
          skewed = skewed.index

          test_processed[skewed] = np.log1p(test_processed[skewed])

          # Additional processing: scale the data.
          from sklearn.preprocessing import StandardScaler
          scaler = StandardScaler()

          scaled = scaler.fit_transform(test_processed[numeric_features])
          for i, col in enumerate(numeric_features):
              test_processed[col] = scaled[:, i]
```

```
/home/navid/anaconda3/envs/tf/lib/python3.6/site-packages/sklearn/preprocessing/data.py:645: Da
  return self.partial_fit(X, y)
/home/navid/anaconda3/envs/tf/lib/python3.6/site-packages/sklearn/base.py:464: DataConversionWa
  return self.fit(X, **fit_params).transform(X)
```

Observation - A significant number of observations with value zero (houses without basement). - A big problem because the value zero doesn't allow us to do log transformations.

To apply a log transformation here, we need to add 1 and then perform log transform operation. **Note** : For real-valued input, log1p is accurate also for x so small that 1 + x == 1 in floating-point accuracy.

```
In [106]: numeric_features = test_processed.dtypes[train_processed.dtypes != "object"].index
          skewness = test_processed[numeric_features].skew(axis=0 , skipna =True)
          skewness = pd.DataFrame(skewness)

          plt.figure(figsize=[5,30])
          # skw = sns.load_dataset(skewness)
          ax = sns.barplot( y= skewness.index , x=skewness[0] , data = skewness)
          plt.show()
          # print('skew: ',test_processed[numeric_features].skew())
```


LotFrontage
LotArea
MasVnrArea
BsmtFinSF1
BsmtFinSF2
BsmtUnfSF
TotalBsmtSF
1stFlrSF
2ndFlrSF
GrLivArea
GarageArea
WoodDeckSF
OpenPorchSF
EnclosedPorch
3SsnPorch
ScreenPorch
BsmtFullBath
BsmtHalfBath
FullBath
HalfBath
BedroomAbvGr
KitchenAbvGr
TotRmsAbvGrd
Fireplaces
GarageCars
CentralAir
OverallQual
OverallCond
ExterQual
ExterCond
BsmtQual
BsmtCond
HeatingQC
KitchenQual
FireplaceQu
GarageQual
GarageCond
BsmtExposure
BsmtFinType1
BsmtFinType2
Functional
GarageFinish
Fence
PoolQC
YearBuilt
YearRemodAdd
GarageYrBlt
MoSold
YrSold
LowQualFinSF
MiscVal
PoolArea
MSSubClass
MSZoning
LotConfig
Neighborhood
Condition1
BldgType
HouseStyle
RoofStyle
Exterior1st
Exterior2nd
MasVnrType
Foundation
SaleType
SaleCondition
IsRegularLotShape
IsLandLevel
IsLandSlopeGentle
IsElectricalSBrkr
IsGarageDetached
IsPavedDrive
HasShed
Remodeled
RecentRemodel
VeryNewHouse
Has2ndFloor
HasMasVnr
HasWoodDeck
HasOpenPorch
HasEnclosedPorch
Has3SsnPorch
HasScreenPorch
HighSeason
NewerDwelling
Neighborhood_Good
SaleCondition_PriceDown
BoughtOffPlan
BadHeating
TotalArea
TotalArea1st2nd
Age
TimeSinceSold
SeasonSold
YearsSinceRemodel
SimplOverallQual
SimplOverallCond
SimplPoolQC
SimplGarageCond
SimplGarageQual
SimplFireplaceQu
SimplFunctional
SimplKitchenQual
SimplHeatingQC
SimplBsmtFinType1
SimplBsmtFinType2
SimplBsmtCond
SimplBsmtQual
SimplExterCond
SimplExterQual
NeighborhoodBin
−10
0
10
20
0

We can see that skewness of the following features decreased a lot: - LotArea - WoodDeckSF - OpenPorchSF - ExterCond - MiscVal - TotalArea

But other numeric features also improved its skewness a little bit.

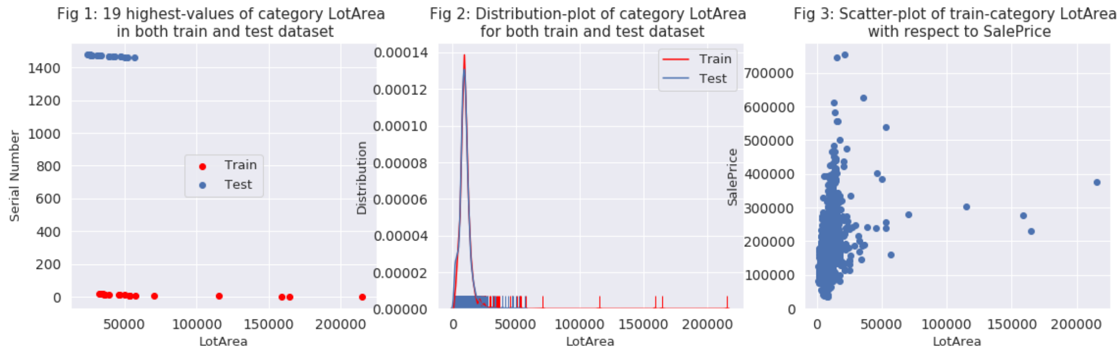
6.3.3 Observation

In this section we will observe how Distribution plot changes due to normalization and standardization of the numeric features. In the first line of plot we would be able to see the distribution before skewness section starts and every second line we will see how it changes due to skewness removal and standardization. Fig-2 is the distribution plot so we should observe it carefully. We can observe that how much skewness of the data is lost due to normalization. Fig-3 will show the relation between SalePrice and and the feature. If the relation between them is linear or close to linear then that will help us in training.

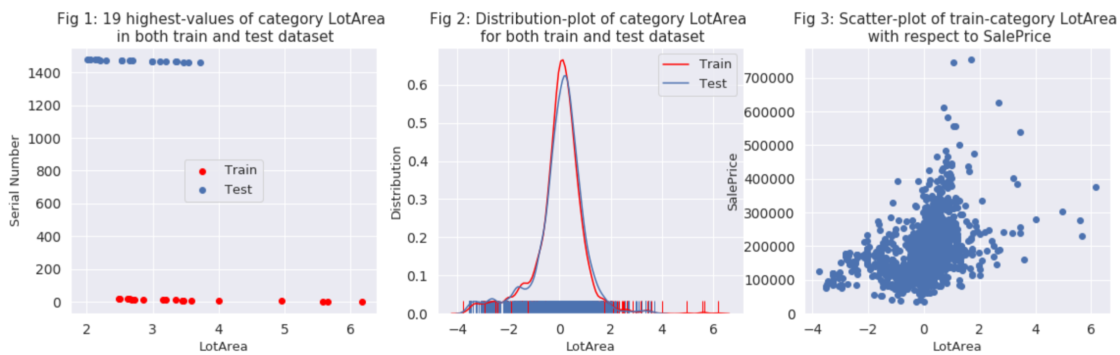
```
In [107]: from IPython.display import Markdown, display
          def printmd(string):
              display(Markdown("***"+string+"***"))

          printmd('Before skewness removal:')
          outlier_check_plot('LotArea',old_train_skewness_flag, old_test_skewness_flag, old_ta
          printmd('After skewness removal:')
          outlier_check_plot('LotArea' , train_processed, test_processed, old_target_skewness_
          
          printmd('Before skewness removal:')
          outlier_check_plot('WoodDeckSF',old_train_skewness_flag, old_test_skewness_flag, old_
          printmd('After skewness removal:')
          outlier_check_plot('WoodDeckSF', train_processed, test_processed, old_target_skewness
          
          printmd('Before skewness removal:')
          outlier_check_plot('OpenPorchSF',old_train_skewness_flag, old_test_skewness_flag, olc
          printmd('After skewness removal:')
          outlier_check_plot('OpenPorchSF', train_processed, test_processed, old_target_skewnes
          
          printmd('Before skewness removal:')
          outlier_check_plot('ExterCond',old_train_skewness_flag, old_test_skewness_flag, old_
          printmd('After skewness removal:')
          outlier_check_plot('ExterCond', train_processed, test_processed, old_target_skewness_
          
          printmd('Before skewness removal:')
          outlier_check_plot('MiscVal',old_train_skewness_flag, old_test_skewness_flag, old_ta
          printmd('After skewness removal:')
          outlier_check_plot('MiscVal', train_processed, test_processed, old_target_skewness_fl
          
          printmd('Before skewness removal:')
          outlier_check_plot('TotalArea',old_train_skewness_flag, old_test_skewness_flag, old_
          printmd('After skewness removal:')
```

```
outlier_check_plot('TotalArea', train_processed, test_processed, old_target_skewness_
```

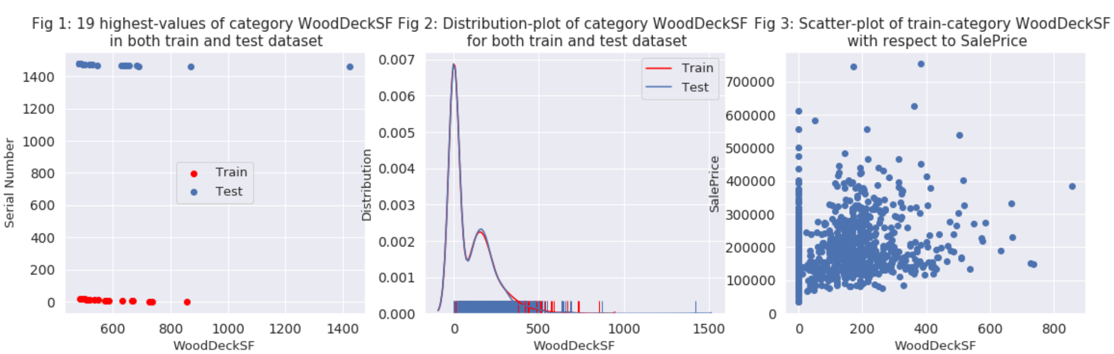
Before skewness removal:



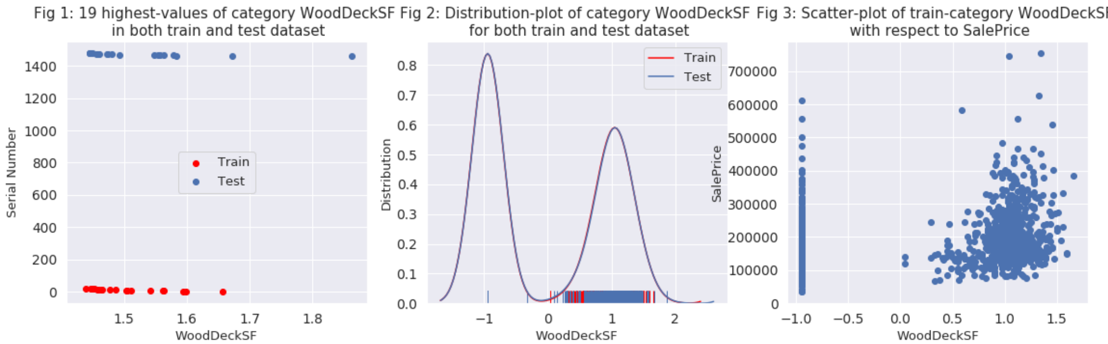
After skewness removal:



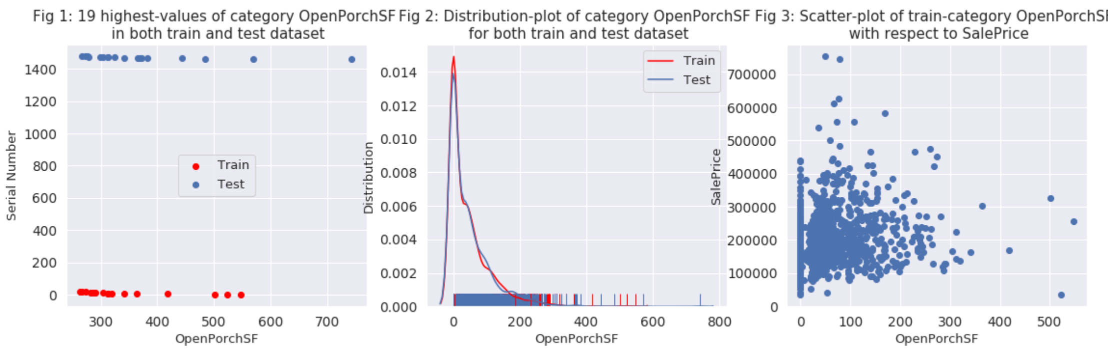
Before skewness removal:



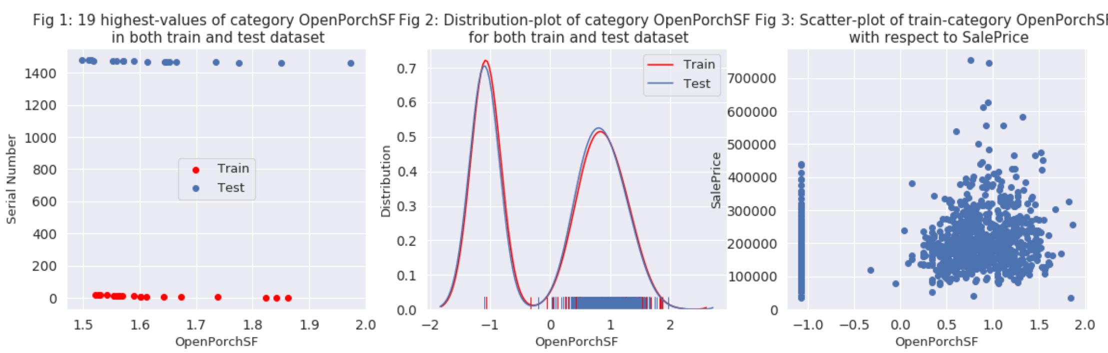
After skewness removal:



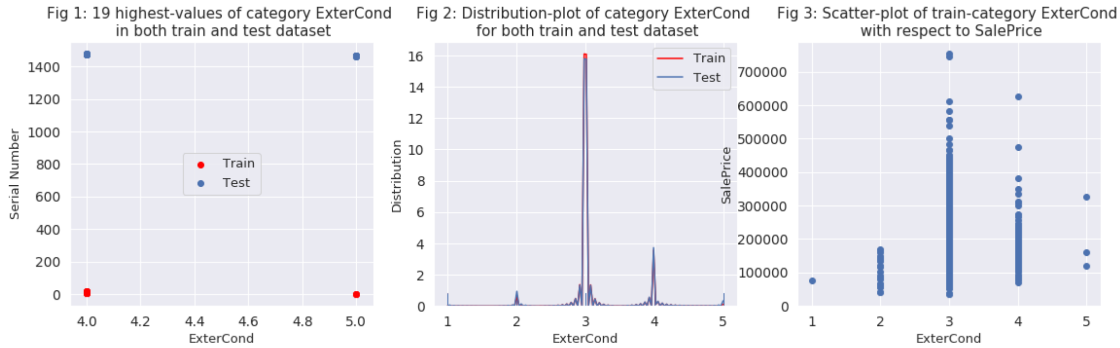
Before skewness removal:



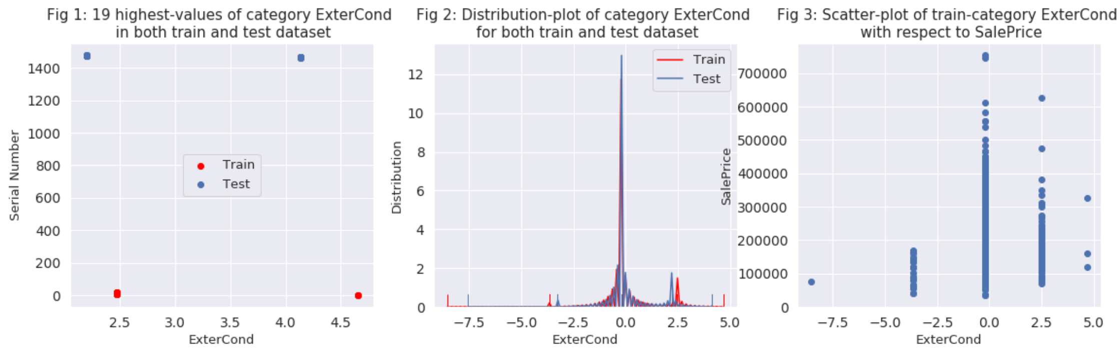
After skewness removal:



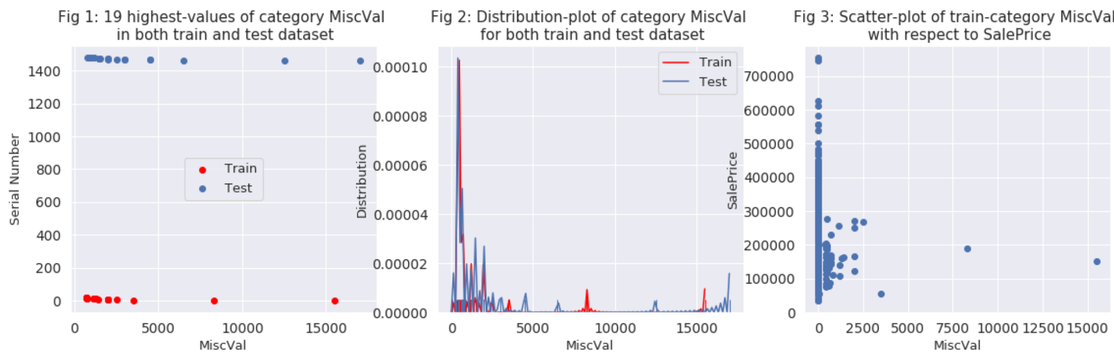
Before skewness removal:



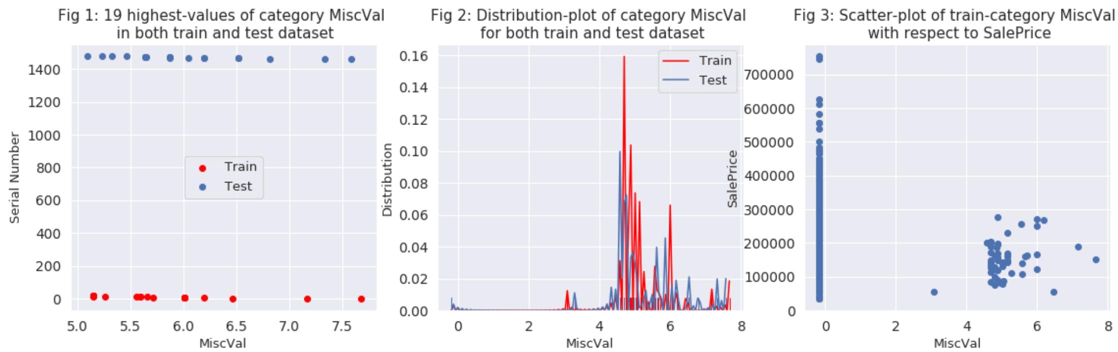
After skewness removal:



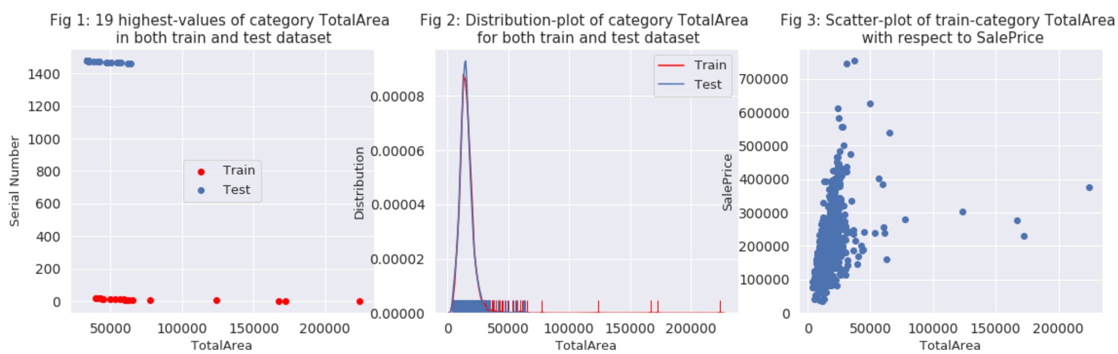
Before skewness removal:



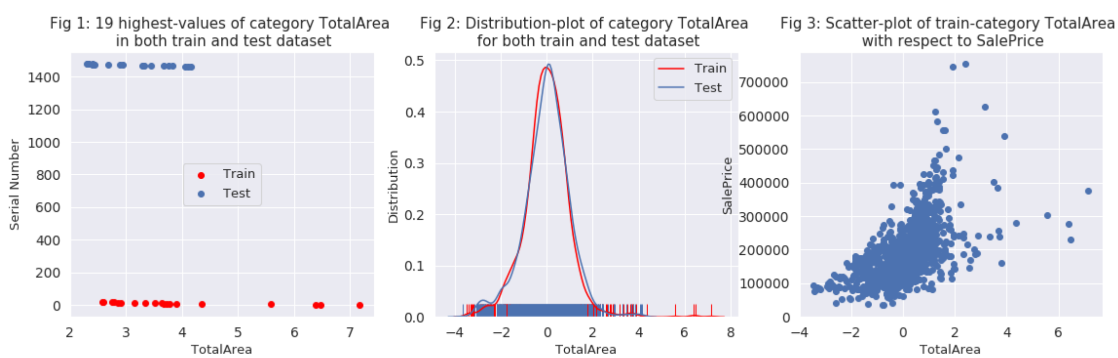
After skewness removal:



Before skewness removal:



After skewness removal:



Most of the scatterplot now seems that they have more linear relationship with saleprice and the distribution graphs are less skewed and close to normal distribution. Finally due to standarization all of the features are now in same scale this will also help us to converge. We can see that the distribution improved a little bit due to log transformation.

6.4 Additional processing to scale the data.

6.4.1 One hot encoding

To encode categorical integer features as a one-hot numeric array we are using one hot encoding. This will transform each value of catagories into a features and make those a column value of dataframe. Finally put binary values in the rows of those column.

```
In [108]: # for example:

          #
          #  CompanyName Categoricalvalue  Price
          #
          #  VW                 1            20000
          #  Acura              2            10011
          #  Honda              3            50000
          #  Honda              3            10000
          #

          # converting it to one Hot encoding:

          #
          #  VW  Acura Honda Price
          #
          #  1   0     0     20000
          #  0   1     0     10011
          #  0   0     1     50000
          #  0   0     1     10000
          #

          # refrence: https://hackernoon.com/what-is-one-hot-encoding-why-and-when-do-you-have
```

In this section at first we merge train and test data (variable name predictor_cols and predictor_cols_test). We did it because there is some features in train data which is missing in test data again same thing can happen for test data too.

```
In [109]: # Convert categorical features using one-hot encoding.
          def onehot(onehot_df, df, column_name, fill_na, drop_name):
              onehot_df[column_name] = df[column_name]
              if fill_na is not None:
                  onehot_df[column_name].fillna(fill_na, inplace=True)

              dummies = pd.get_dummies(onehot_df[column_name], prefix="_" + column_name)

              onehot_df = onehot_df.join(dummies)
              onehot_df = onehot_df.drop([column_name], axis=1)
              return onehot_df
```

performing one hot

```
In [110]: def proceed_onehot(df):
              onehot_df = pd.DataFrame(index = df.index)

              onehot_df = onehot(onehot_df, df, "MSSubClass", None, "40")
              onehot_df = onehot(onehot_df, df, "MSZoning", "RL", "RH")
              onehot_df = onehot(onehot_df, df, "LotConfig", None, "FR3")
              onehot_df = onehot(onehot_df, df, "Neighborhood", None, "OldTown")
              onehot_df = onehot(onehot_df, df, "Condition1", None, "RRNe")
              onehot_df = onehot(onehot_df, df, "BldgType", None, "2fmCon")
              onehot_df = onehot(onehot_df, df, "HouseStyle", None, "1.5Unf")
              onehot_df = onehot(onehot_df, df, "RoofStyle", None, "Shed")
              onehot_df = onehot(onehot_df, df, "Exterior1st", "VinylSd", "CBlock")
              onehot_df = onehot(onehot_df, df, "Exterior2nd", "VinylSd", "CBlock")
              onehot_df = onehot(onehot_df, df, "Foundation", None, "Wood")
              onehot_df = onehot(onehot_df, df, "SaleType", "WD", "Oth")
              onehot_df = onehot(onehot_df, df, "SaleCondition", "Normal", "AdjLand")

              # Fill in missing MasVnrType for rows that do have a MasVnrArea.
              temp_df = df[["MasVnrType", "MasVnrArea"]].copy()
              idx = (df["MasVnrArea"] != 0) & ((df["MasVnrType"] == "None") | (df["MasVnrType"]
              temp_df.loc[idx, "MasVnrType"] = "BrkFace"
              onehot_df = onehot(onehot_df, temp_df, "MasVnrType", "None", "BrkCmn")

              # Also add the booleans from calc_df as dummy variables.
              onehot_df = onehot(onehot_df, df, "LotShape", None, "IR3")
              onehot_df = onehot(onehot_df, df, "LandContour", None, "Low")
              onehot_df = onehot(onehot_df, df, "LandSlope", None, "Sev")
              onehot_df = onehot(onehot_df, df, "Electrical", "SBrkr", "FuseP")
              onehot_df = onehot(onehot_df, df, "GarageType", "None", "CarPort")
              onehot_df = onehot(onehot_df, df, "PavedDrive", None, "P")
              onehot_df = onehot(onehot_df, df, "MiscFeature", "None", "Othr")

              # Features we can probably ignore (but want to include anyway to see
              # if they make any positive difference).
              # Definitely ignoring Utilities: all records are "AllPub", except for
              # one "NoSeWa" in the train set and 2 NA in the test set.
              onehot_df = onehot(onehot_df, df, "Street", None, "Grvl")
              onehot_df = onehot(onehot_df, df, "Alley", "None", "Grvl")
              onehot_df = onehot(onehot_df, df, "Condition2", None, "PosA")
              onehot_df = onehot(onehot_df, df, "RoofMatl", None, "WdShake")
              onehot_df = onehot(onehot_df, df, "Heating", None, "Wall")

              # I have these as numerical variables too.
              onehot_df = onehot(onehot_df, df, "ExterQual", "None", "Ex")
              onehot_df = onehot(onehot_df, df, "ExterCond", "None", "Ex")
              onehot_df = onehot(onehot_df, df, "BsmtQual", "None", "Ex")
              onehot_df = onehot(onehot_df, df, "BsmtCond", "None", "Ex")
              onehot_df = onehot(onehot_df, df, "HeatingQC", "None", "Ex")
```

```
    onehot_df = onehot(onehot_df, df, "KitchenQual", "TA", "Ex")
    onehot_df = onehot(onehot_df, df, "FireplaceQu", "None", "Ex")
    onehot_df = onehot(onehot_df, df, "GarageQual", "None", "Ex")
    onehot_df = onehot(onehot_df, df, "GarageCond", "None", "Ex")
    onehot_df = onehot(onehot_df, df, "PoolQC", "None", "Ex")
    onehot_df = onehot(onehot_df, df, "BsmtExposure", "None", "Gd")
    onehot_df = onehot(onehot_df, df, "BsmtFinType1", "None", "GLQ")
    onehot_df = onehot(onehot_df, df, "BsmtFinType2", "None", "GLQ")
    onehot_df = onehot(onehot_df, df, "Functional", "Typ", "Typ")
    onehot_df = onehot(onehot_df, df, "GarageFinish", "None", "Fin")
    onehot_df = onehot(onehot_df, df, "Fence", "None", "MnPrv")
    onehot_df = onehot(onehot_df, df, "MoSold", None, None)

    # Divide up the years between 1871 and 2010 in slices of 20 years.
    year_map = pd.concat(pd.Series("YearBin" + str(i+1), index=range(1871+i*20,1891+

    yearbin_df = pd.DataFrame(index = df.index)
    yearbin_df["GarageYrBltBin"] = df.GarageYrBlt.map(year_map)
    yearbin_df["GarageYrBltBin"].fillna("NoGarage", inplace=True)

    yearbin_df["YearBuiltBin"] = df.YearBuilt.map(year_map)
    yearbin_df["YearRemodAddBin"] = df.YearRemodAdd.map(year_map)

    onehot_df = onehot(onehot_df, yearbin_df, "GarageYrBltBin", None, None)
    onehot_df = onehot(onehot_df, yearbin_df, "YearBuiltBin", None, None)
    onehot_df = onehot(onehot_df, yearbin_df, "YearRemodAddBin", None, None)

    return onehot_df

# Add the one-hot encoded categorical features.
onehot_df = proceed_onehot(train)
onehot_df = onehot(onehot_df, neighborhood_bin_train, "NeighborhoodBin", None, None)
train_processed = train_processed.join(onehot_df)
```

These onehot columns are missing in the test data, so drop them from the training data or we might overfit on them.

```
In [111]: drop_cols = [
                    "_Exterior1st_ImStucc", "_Exterior1st_Stone",
                    "_Exterior2nd_Other","_HouseStyle_2.5Fin",

                    "_RoofMatl_Membran", "_RoofMatl_Metal", "_RoofMatl_Roll",
                    "_Condition2_RRAe", "_Condition2_RRAn", "_Condition2_RRNn",
                    "_Heating_Floor", "_Heating_OthW",

                    "_Electrical_Mix",
                    "_MiscFeature_TenC",
                    "_GarageQual_Ex", "_PoolQC_Fa"
```

```
                   ]
        train_processed.drop(drop_cols, axis=1, inplace=True)
```

```
In [112]: onehot_df = proceed_onehot(test)
          onehot_df = onehot(onehot_df, neighborhood_bin_test, "NeighborhoodBin", None, None)
          test_processed = test_processed.join(onehot_df)
```

This column is missing in the training data. There is only one example with this value in the test set. So just drop it.

```
In [113]: test_processed.drop(["_MSSubClass_150"], axis=1, inplace=True)
```

6.5 Missing Value Check

```
In [114]: total = train_processed.isnull().sum().sort_values(ascending=False)
          percent = (train_processed.isnull().sum()/train_processed.isnull().count()).sort_valu
          total_test = test_processed.isnull().sum().sort_values(ascending=False)
          percent_test = (test_processed.isnull().sum()/test_processed.isnull().count()).sort_


          missing_data = pd.concat([total, percent,total_test, percent_test], axis=1,
                                   keys=['Total', 'Percent' ,'total_test ', 'percent_test'])
          missing_data.head()
```

Out[114]:

	Total	Percent	total_test	percent_test
_NeighborhoodBin_4	0	0.0	0	0.0
_Neighborhood_BrDale	0	0.0	0	0.0
_MSZoning_RH	0	0.0	0	0.0
_MSZoning_RL	0	0.0	0	0.0
_MSZoning_RM	0	0.0	0	0.0

Now there is no missing data in any of the train or test dataset so we can proceed further.

6.6 Drop Columns

Drop these columns. They are either not very helpful or they cause overfitting.

```
In [115]: drop_cols = [
              "_Condition2_PosN",    # only two are not zero
              "_MSZoning_C (all)",
              "_MSSubClass_160",
          ]
          train_processed.drop(drop_cols, axis=1, inplace=True)
          test_processed.drop(drop_cols, axis=1, inplace=True)
```

7 log transform

According to Hair et al. (2013), four assumptions should be tested:

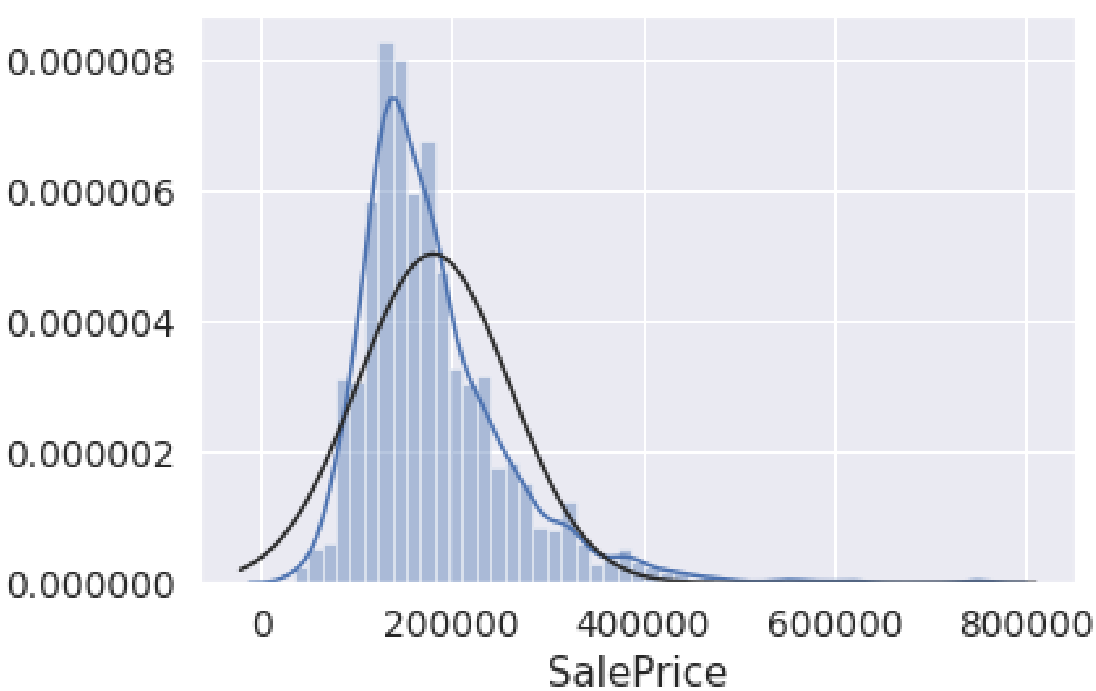
- **Normality** - When we talk about normality what we mean is that the data should look like a normal distribution. This is important because several statistic tests rely on this (e.g. t-statistics). In this exercise we'll just check univariate normality for 'SalePrice' (which is a limited approach). Remember that univariate normality doesn't ensure multivariate normality (which is what we would like to have), but it helps. Another detail to take into account is that in big samples (>200 observations) normality is not such an issue. However, if we solve normality, we avoid a lot of other problems (e.g. heteroscedacity) so that's the main reason why we are doing this analysis.

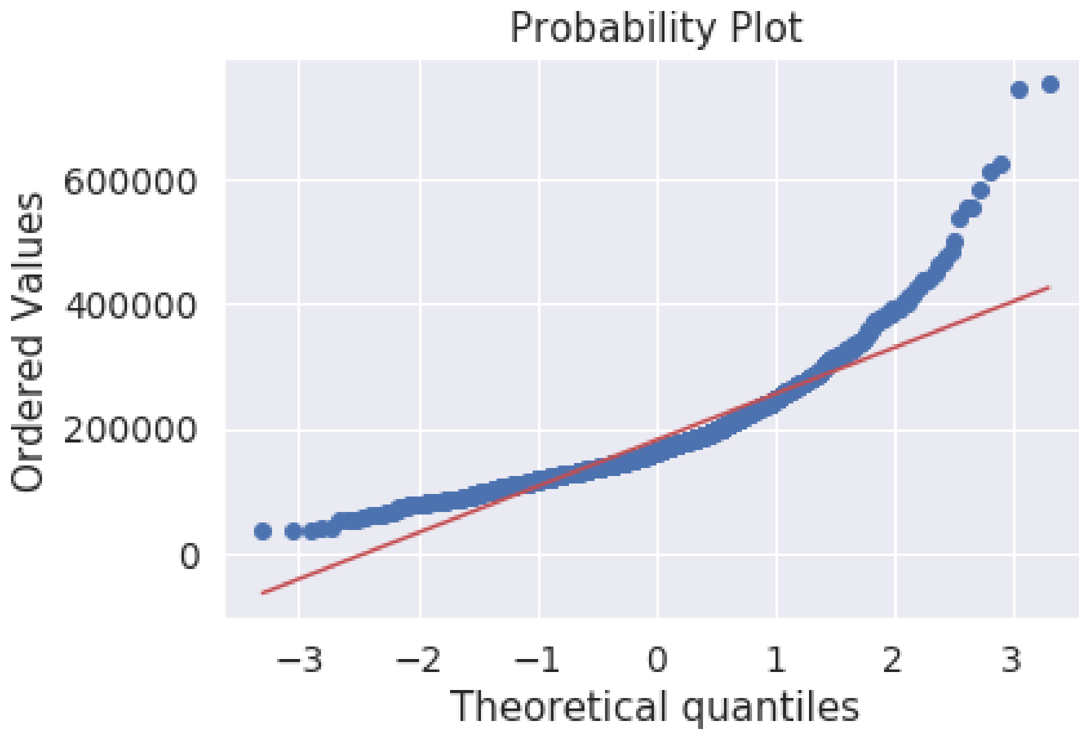
- **Homoscedasticity** - Homoscedasticity refers to the 'assumption that dependent variable(s) exhibit equal levels of variance across the range of predictor variable(s)' (Hair et al., 2013). Homoscedasticity is desirable because we want the error term to be the same across all values of the independent variables.

- **Linearity** - The most common way to assess linearity is to examine scatter plots and search for linear patterns. If patterns are not linear, it would be worthwhile to explore data transformations. However, we'll not get into this because most of the scatter plots we've seen appear to have linear relationships.

'SalePrice' is not normal. It shows 'peakedness', positive skewness and does not follow the diagonal line. But a simple data transformation can solve the problem.

```
In [116]: from scipy.stats import norm
          from scipy import stats
          #histogram and normal probability plot
          sns.distplot(train['SalePrice'], fit=norm);
          fig = plt.figure()
          res = stats.probplot(train['SalePrice'], plot=plt)
```





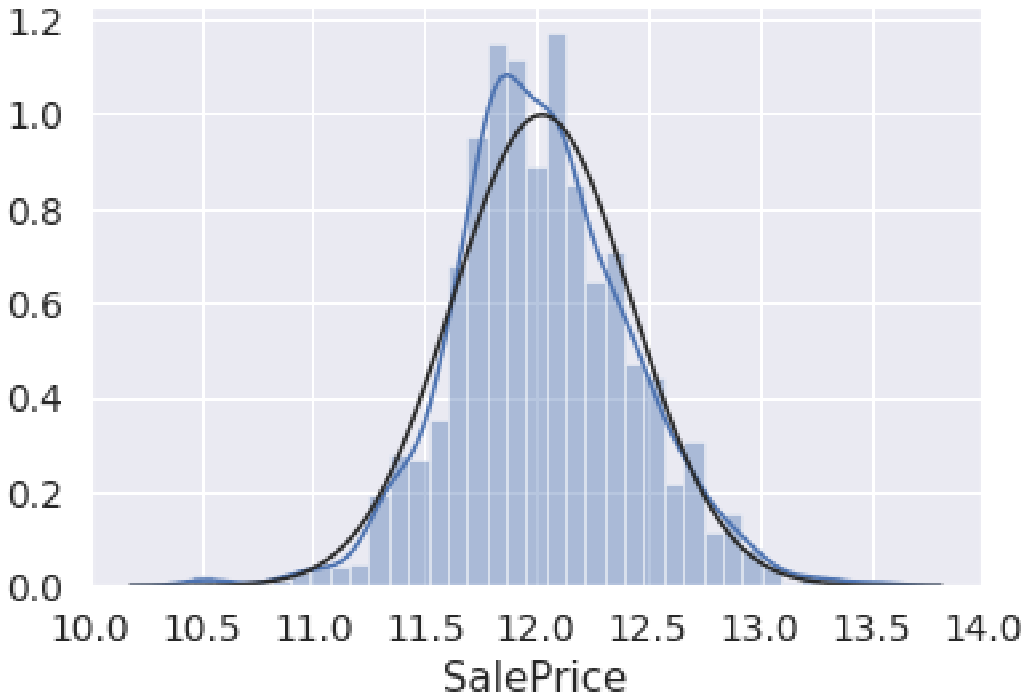
We take the log here because the error metric is between the log of the SalePrice and the log of the predicted price. That does mean we need to exp() the prediction to get an actual sale price.

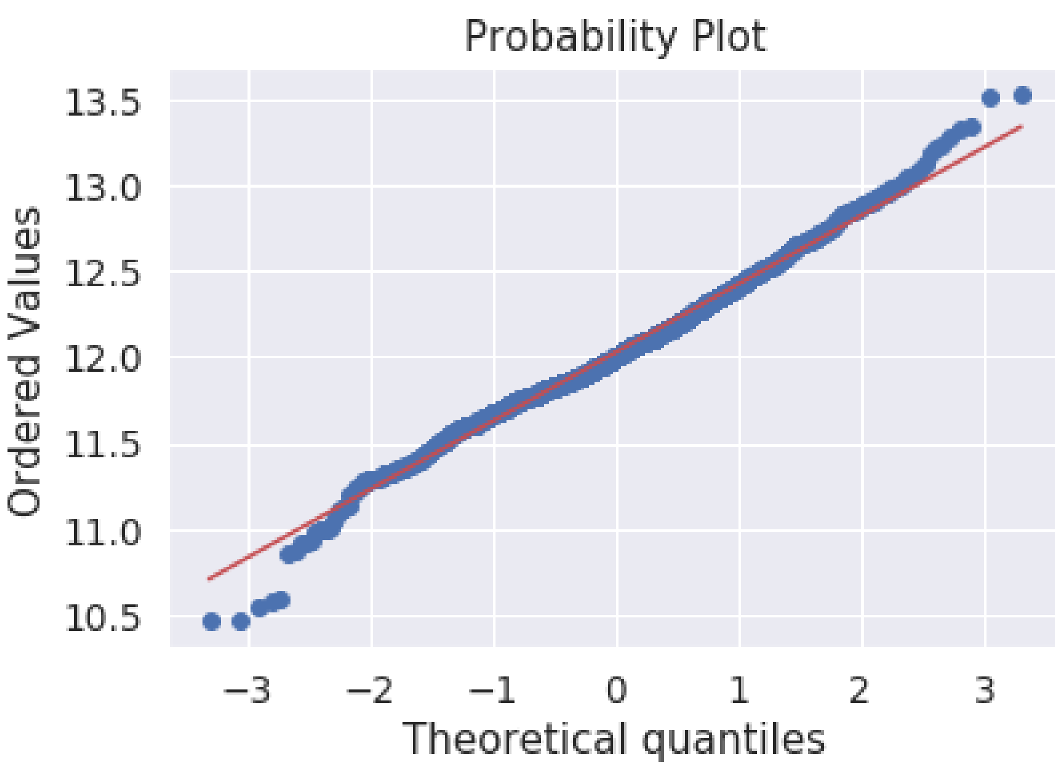
```
In [117]: target = pd.DataFrame(index = train_processed.index, columns=["SalePrice"])
          target["SalePrice"] = np.log(train["SalePrice"])
          # train_processed.drop(["SalePrice"], axis=1, inplace=True)

          print("Training set size:", train_processed.shape)
          print("Test set size:", test_processed.shape)
```

```
Training set size: (1458, 403)
Test set size: (1459, 403)
```

Now we can see the following graph is normal and the probability plot reflects linearity.

```
In [118]: from scipy.stats import norm
          from scipy import stats
          #histogram and normal probability plot
          sns.distplot(target['SalePrice'], fit=norm);
          fig = plt.figure()
          res = stats.probplot(target['SalePrice'], plot=plt)
```


1.2
1.0
0.8
0.6
0.4
0.2
0.0
10.0
10.5
11.0
11.5
12.0
12.5
13.0
13.5
14.0
SalePrice

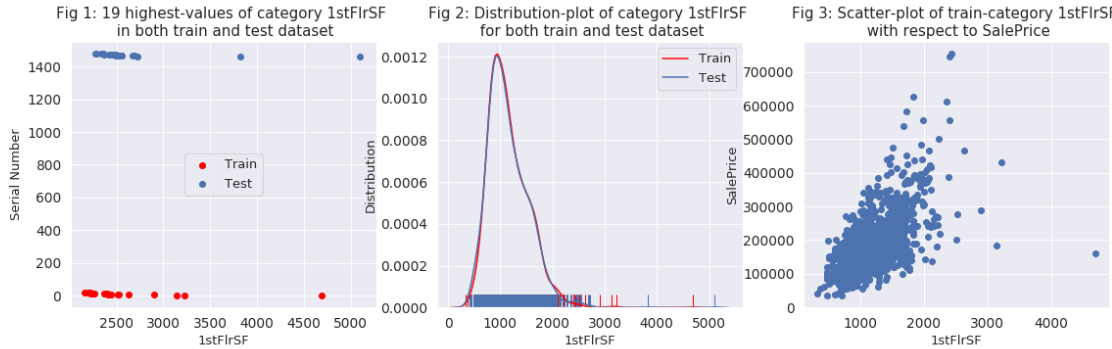

Probability Plot
13.5
13.0
12.5
12.0
11.5
11.0
10.5
Ordered Values
−3
−2
−1
0
1
2
3
Theoretical quantiles

7.0.1 Outlier Crosscheck

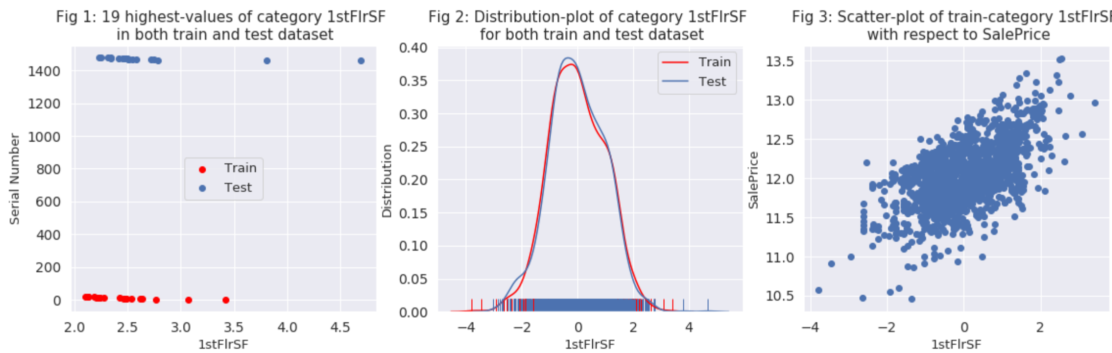
In this section we are checking again If any outlier remains after all the data processing. And the distribution plot will help us to realize the difference before and after normalization. Most of them became more close to normal distribution and less skewed after the processing. So we are not going to normalize them again.

```
In [119]: from IPython.display import Markdown, display
          def printmdmd(string):
              display(Markdown("***"+string+"***"))

          printmdmd('Before outlier-removal:')
          outlier_check_plot('1stFlrSF',old_train_outlier_flag, old_test_outlier_flag, old_tra
          printmd('After outlier-removal:')
          outlier_check_plot('1stFlrSF' , train_processed, test_processed, target)

          printmd('Before outlier-removal:')
          outlier_check_plot('BsmtFinSF1',old_train_outlier_flag, old_test_outlier_flag, old_ta
          printmd('After outlier-removal:')
          outlier_check_plot('BsmtFinSF1', train_processed, test_processed, target)

          printmd('Before outlier-removal:')
          outlier_check_plot('LotArea',old_train_outlier_flag, old_test_outlier_flag, old_targe
          printmd('After outlier-removal:')
          outlier_check_plot('LotArea', train_processed, test_processed, target)

          printmd('Before outlier-removal:')
          outlier_check_plot('GrLivArea',old_train_outlier_flag, old_test_outlier_flag, old_ta
          printmd('After outlier-removal:')
          outlier_check_plot('GrLivArea', train_processed, test_processed, target)

          printmd('Before outlier-removal:')
          outlier_check_plot('MasVnrArea',old_train_outlier_flag, old_test_outlier_flag, old_ta
          printmd('After outlier-removal:')
          outlier_check_plot('MasVnrArea', train_processed, test_processed, target)

          printmd('Before outlier-removal:')
          outlier_check_plot('TotalBsmtSF',old_train_outlier_flag, old_test_outlier_flag, old_
          printmd('After outlier-removal:')
          outlier_check_plot('TotalBsmtSF', train_processed, test_processed, target)

          printmd('Before outlier-removal:')
          outlier_check_plot('TotalBsmtSF',old_train_outlier_flag, old_test_outlier_flag, old_
          printmd('After outlier-removal:')
          outlier_check_plot('TotalBsmtSF', train_processed, test_processed, target)
```

Before outlier-removal:

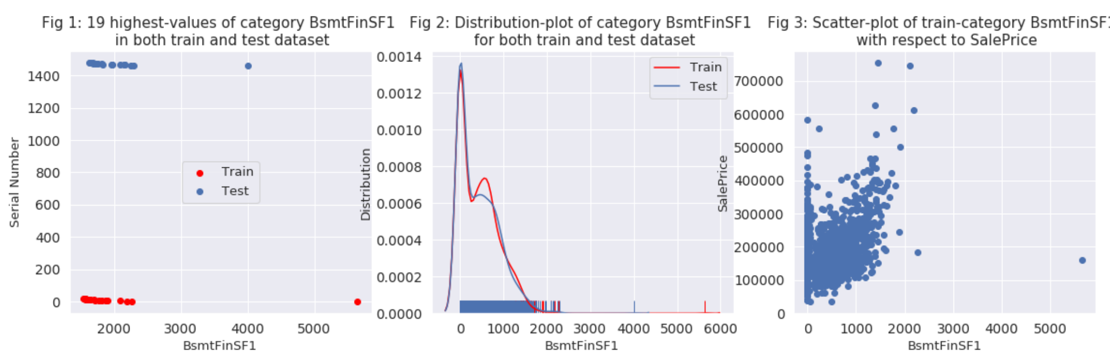


After outlier-removal:

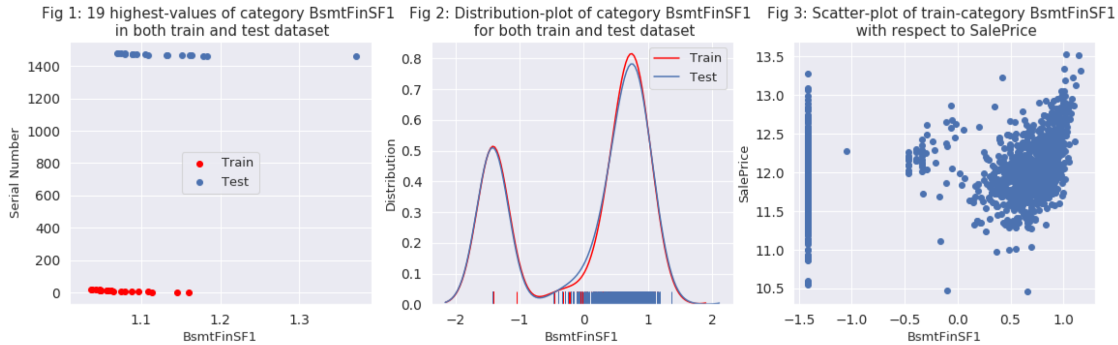


Before outlier-removal:

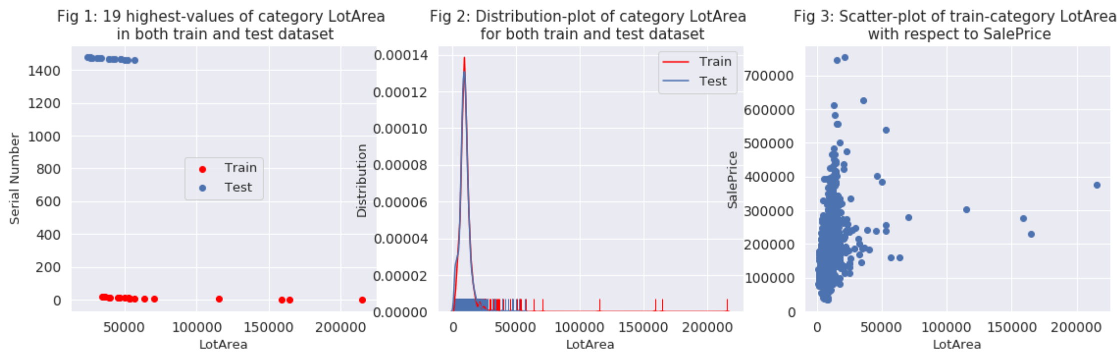
```
/home/navid/anaconda3/envs/tf/lib/python3.6/site-packages/statsmodels/nonparametric/kde.py:448
  X = X[np.logical_and(X > clip[0], X < clip[1])] # won't work for two columns.
/home/navid/anaconda3/envs/tf/lib/python3.6/site-packages/statsmodels/nonparametric/kde.py:448
  X = X[np.logical_and(X > clip[0], X < clip[1])] # won't work for two columns.
```



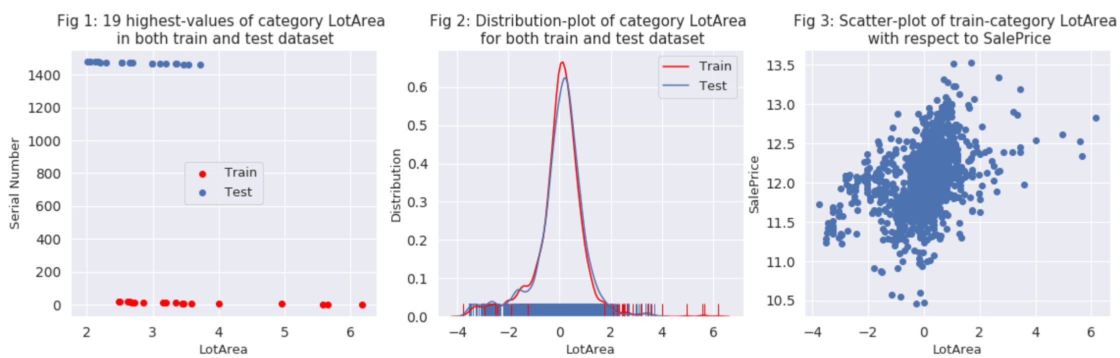
After outlier-removal:



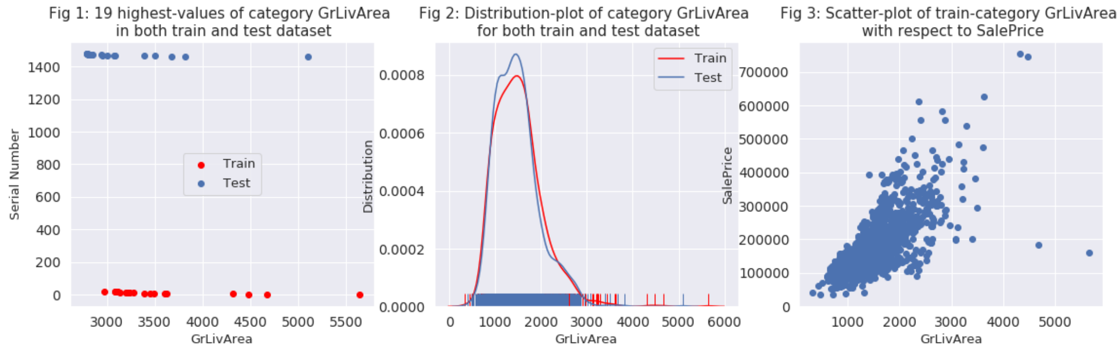
Before outlier-removal:



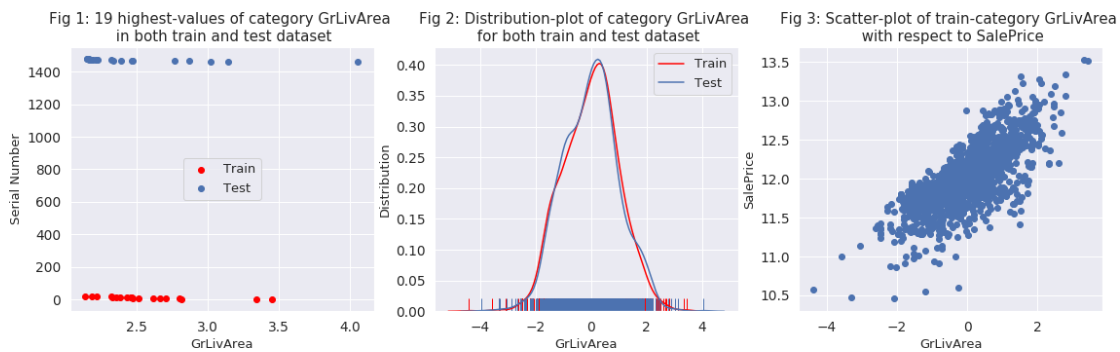
After outlier-removal:



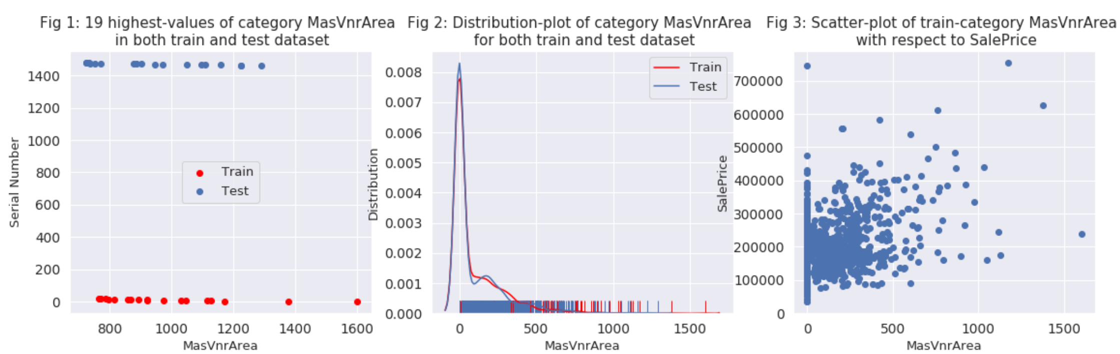
Before outlier-removal:



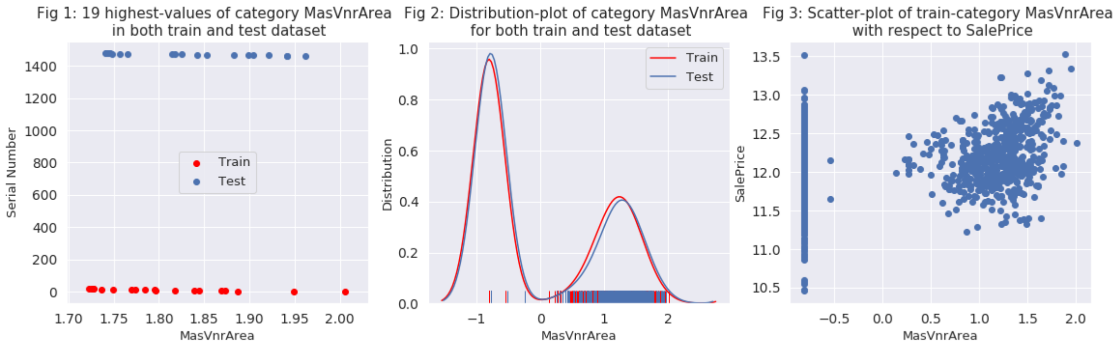
After outlier-removal:



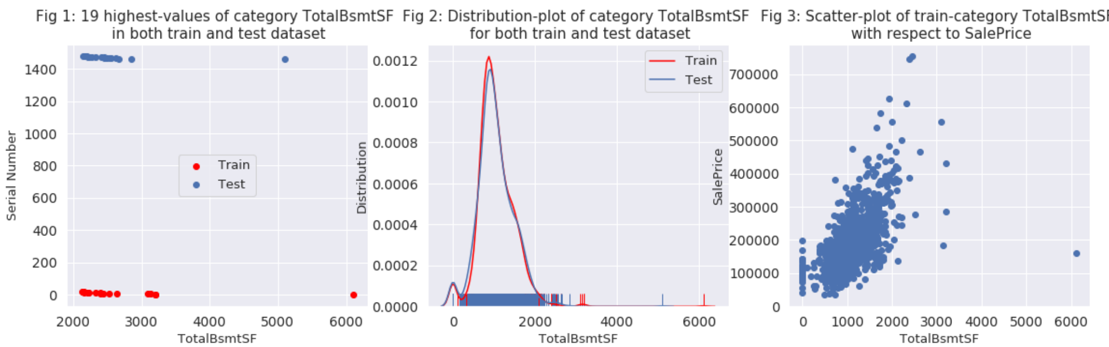
Before outlier-removal:



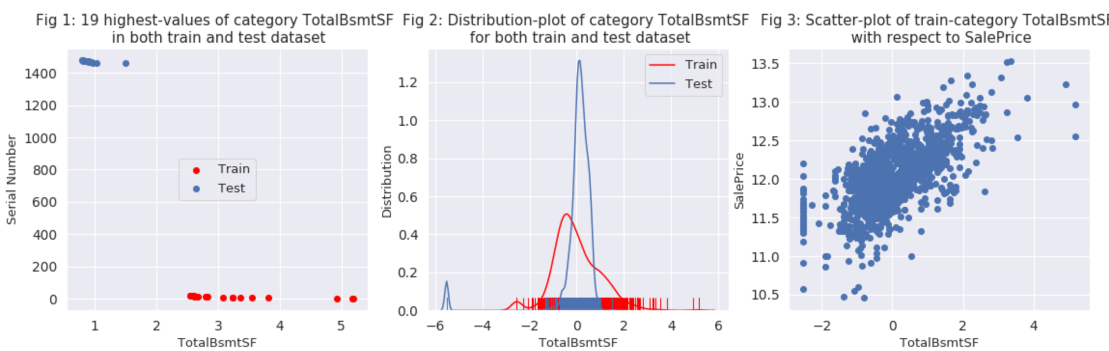
After outlier-removal:



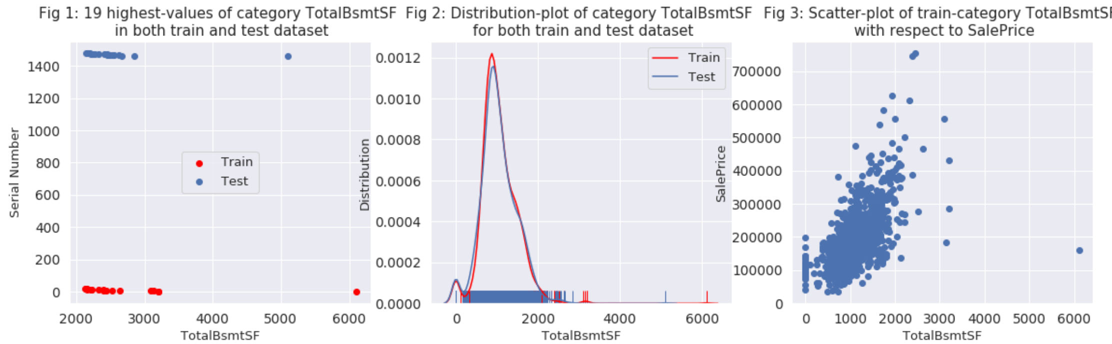
Before outlier-removal:



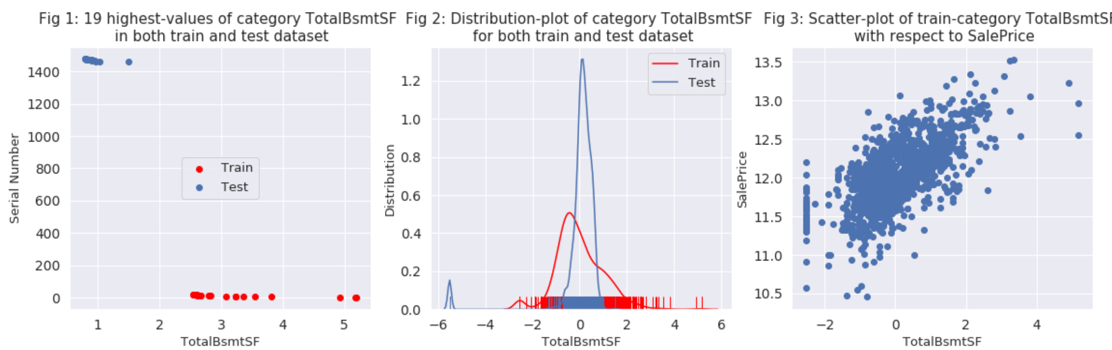
After outlier-removal:



Before outlier-removal:



After outlier-removal:



Most of the scatterplot now seems that they have linear relationship with saleprice and the distribution graphs are less skewed and close to normal distribution. Finally due to standarization all of the features are now in same scale this will also help us to converge.

This time we can see that the distribution improved a little bit due to log transformation and I was expecting that few outliers we observed earlier are no longer seems to be a outlier. Only the common outlier was the actual source of the problem. So we can now proceed to feed these data to our model.

7.1 Corelation Matrix after procesing

In [120]:
```
abc = train_processed.copy()
abc['SalePrice'] = target
abc.head()
```

Out[120]:

	LotFrontage	LotArea	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF \
0	-0.079625	-0.129624	1.207635	0.781657	-0.355617	-0.339727
1	0.558441	0.118819	-0.805570	0.890540	-0.355617	0.002819
2	0.058871	0.427643	1.135442	0.656962	-0.355617	0.230852
3	-0.325078	0.108651	-0.805570	0.386556	-0.355617	0.348451
4	0.708621	0.889295	1.427727	0.756612	-0.355617	0.296156

	TotalBsmtSF	1stFlrSF	2ndFlrSF	GrLivArea	GarageArea	WoodDeckSF	\
0	-0.473766	-0.806494	1.182829	0.539563	0.357973	-0.945331	
1	0.504925	0.428226	-0.868747	-0.380320	-0.056795	1.251286	
2	-0.319490	-0.577186	1.187064	0.671249	0.640770	-0.945331	
3	-0.714823	-0.438516	1.145834	0.551934	0.801022	-0.945331	
4	0.222888	0.118717	1.246416	1.299874	1.715398	1.082602	

	OpenPorchSF	EnclosedPorch	3SsnPorch	ScreenPorch	BsmtFullBath	\
0	0.848459	-0.404567	-0.128611	-0.292987	1.113886	
1	-1.071920	-0.404567	-0.128611	-0.292987	-0.819502	
2	0.678188	-0.404567	-0.128611	-0.292987	1.113886	
3	0.595511	2.842190	-0.128611	-0.292987	1.113886	
4	0.995271	-0.404567	-0.128611	-0.292987	1.113886	

	BsmtHalfBath	FullBath	HalfBath	BedroomAbvGr	KitchenAbvGr	TotRmsAbvGrd	\
0	-0.243100	0.793546	1.229699	0.163894	-0.207756	0.921812	
1	4.018527	0.793546	-0.760202	0.163894	-0.207756	-0.316329	
2	-0.243100	0.793546	1.229699	0.163894	-0.207756	-0.316329	
3	-0.243100	-1.025620	-0.760202	0.163894	-0.207756	0.302742	
4	-0.243100	0.793546	1.229699	1.389320	-0.207756	1.540882	

	Fireplaces	GarageCars	CentralAir	OverallQual	OverallCond	ExterQual	\
0	-0.952231	0.313159	0.264006	0.658506	-0.517649	1.094773	
1	0.605965	0.313159	0.264006	-0.068293	2.177825	-0.684302	
2	0.605965	0.313159	0.264006	0.658506	-0.517649	1.094773	
3	0.605965	1.652119	0.264006	0.658506	-0.517649	-0.684302	
4	0.605965	1.652119	0.264006	1.385305	-0.517649	1.094773	

	ExterCond	BsmtQual	BsmtCond	HeatingQC	KitchenQual	FireplaceQu	\
0	-0.206093	0.492660	0.152337	0.892277	0.741127	-1.006993	
1	-0.206093	0.492660	0.152337	0.892277	-0.770150	0.650737	
2	-0.206093	0.492660	0.152337	0.892277	0.741127	0.650737	
3	-0.206093	-0.306552	1.121847	-0.150143	0.741127	1.203313	
4	-0.206093	0.492660	0.152337	0.892277	0.741127	0.650737	

	GarageQual	GarageCond	BsmtExposure	BsmtFinType1	BsmtFinType2	\
0	0.263273	0.264156	-0.551823	1.166596	-0.23748	
1	0.263273	0.264156	1.955524	0.691883	-0.23748	
2	0.263273	0.264156	0.557696	1.166596	-0.23748	
3	0.263273	0.264156	-0.551823	0.691883	-0.23748	
4	0.263273	0.264156	1.344912	1.166596	-0.23748	

	Functional	GarageFinish	Fence	PoolQC	YearBuilt	YearRemodAdd	\
0	0.224113	0.320685	-0.48149	-0.063082	1.052959	0.880362	
1	0.224113	0.320685	-0.48149	-0.063082	0.158428	-0.428115	
2	0.224113	0.320685	-0.48149	-0.063082	0.986698	0.831900	
3	0.224113	-0.800558	-0.48149	-0.063082	-1.862551	-0.718888	
4	0.224113	0.320685	-0.48149	-0.063082	0.953567	0.734975	

```
   GarageYrBlt    MoSold    YrSold  LowQualFinSF   MiscVal  PoolArea  \
0     0.249660 -1.601578  0.138375     -0.133696 -0.190617 -0.064269
1     0.241858 -0.490155 -0.614427     -0.133696 -0.190617 -0.064269
2     0.249085  0.991743  0.138375     -0.133696 -0.190617 -0.064269
3     0.248223 -1.601578 -1.367230     -0.133696 -0.190617 -0.064269
4     0.248798  2.103167  0.138375     -0.133696 -0.190617 -0.064269

   MSSubClass  MSZoning  LotConfig  Neighborhood  Condition1  BldgType  \
0    0.200493  0.049287   0.581595     -1.207217    0.092387 -0.429604
1   -1.000488  0.049287  -0.231542      1.952788   -1.401283 -0.429604
2    0.200493  0.049287   0.581595     -1.207217    0.092387 -0.429604
3    0.440689  0.049287  -1.980323     -1.040901    0.092387 -0.429604
4    0.200493  0.049287  -0.231542      0.455943    0.092387 -0.429604

   HouseStyle  RoofStyle  Exterior1st  Exterior2nd  MasVnrType  Foundation  \
0    1.028137  -0.470424     0.742466     0.751041   -1.241299    0.836573
1   -0.542069  -0.470424    -0.508997    -0.661885    0.390634   -0.547903
2    1.028137  -0.470424     0.742466     0.751041   -1.241299    0.836573
3    1.028137  -0.470424     1.055332     1.316212    0.390634   -1.932378
4    1.028137  -0.470424     0.742466     0.751041   -1.241299    0.836573

   SaleType  SaleCondition  IsRegularLotShape  IsLandLevel  IsLandSlopeGentle  \
0  0.256484       0.252285           0.759089     0.334855           0.237743
1  0.256484       0.252285           0.759089     0.334855           0.237743
2  0.256484       0.252285          -1.317368     0.334855           0.237743
3  0.256484      -3.582285          -1.317368     0.334855           0.237743
4  0.256484       0.252285          -1.317368     0.334855           0.237743

   IsElectricalSBrkr  IsGarageDetached  IsPavedDrive   HasShed  Remodeled  \
0           0.307562         -0.601119      0.299476 -0.186484  -0.954399
1           0.307562         -0.601119      0.299476 -0.186484  -0.954399
2           0.307562         -0.601119      0.299476 -0.186484   1.047779
3           0.307562          1.663563      0.299476 -0.186484   1.047779
4           0.307562         -0.601119      0.299476 -0.186484  -0.954399

   RecentRemodel  VeryNewHouse  Has2ndFloor  HasMasVnr  HasWoodDeck  \
0      -0.303537     -0.210743    -1.148027  -1.214653     0.957027
1      -0.303537     -0.210743     0.871060   0.823280    -1.044903
2      -0.303537     -0.210743    -1.148027  -1.214653     0.957027
3      -0.303537     -0.210743    -1.148027   0.823280     0.957027
4      -0.303537     -0.210743    -1.148027  -1.214653    -1.044903

   HasOpenPorch  HasEnclosedPorch  Has3SsnPorch  HasScreenPorch  HighSeason  \
0     -0.904409          0.407922      0.129369        0.294004   -1.152854
1      1.105695          0.407922      0.129369        0.294004    0.867412
2     -0.904409          0.407922      0.129369        0.294004   -1.152854
3     -0.904409         -2.451452      0.129369        0.294004   -1.152854
```

```
4    -0.904409          0.407922      0.129369        0.294004   -1.152854

   NewerDwelling  Neighborhood_Good  SaleCondition_PriceDown  BoughtOffPlan  \
0       0.764711          -0.487536                -0.322039      -0.303537
1       0.764711          -0.487536                -0.322039      -0.303537
2       0.764711          -0.487536                -0.322039      -0.303537
3      -1.307684           2.051132                 3.105211      -0.303537
4       0.764711           2.051132                -0.322039      -0.303537

   BadHeating  TotalArea  TotalArea1st2nd       Age  TimeSinceSold  \
0   -0.188445  -0.114374         0.550552 -1.052959      -0.138375
1   -0.188445   0.068991        -0.368517 -0.158428       0.614427
2   -0.188445   0.399780         0.682121 -0.986698      -0.138375
3   -0.188445   0.072245         0.562912  1.862551       1.367230
4   -0.188445   1.059344         1.310189 -0.953567      -0.138375

   SeasonSold  YearsSinceRemodel  SimplOverallQual  SimplOverallCond  \
0   -1.829603          -0.871676          1.250917         -0.376209
1   -0.698801           0.388660         -0.695547          1.772225
2    1.562802          -0.823201          1.250917         -0.376209
3   -1.829603           0.631032          1.250917         -0.376209
4   -1.829603          -0.726252          1.250917         -0.376209

   SimplPoolQC  SimplGarageCond  SimplGarageQual  SimplFireplaceQu  \
0     -0.06008         0.217044         0.203824         -0.952387
1     -0.06008         0.217044         0.203824          0.234434
2     -0.06008         0.217044         0.203824          0.234434
3     -0.06008         0.217044         0.203824          1.421255
4     -0.06008         0.217044         0.203824          0.234434

   SimplFunctional  SimplKitchenQual  SimplHeatingQC  SimplBsmtFinType1  \
0         0.245517          1.063757        0.698395           0.889439
1         0.245517         -0.940064        0.698395           0.889439
2         0.245517          1.063757        0.698395           0.889439
3         0.245517          1.063757        0.698395           0.889439
4         0.245517          1.063757        0.698395           0.889439

   SimplBsmtFinType2  SimplBsmtCond  SimplBsmtQual  SimplExterCond  \
0          -0.002044      -0.003479       0.948618       -0.337383
1          -0.002044      -0.003479       0.948618       -0.337383
2          -0.002044      -0.003479       0.948618       -0.337383
3          -0.002044       2.898507      -0.876033       -0.337383
4          -0.002044      -0.003479       0.948618       -0.337383

   SimplExterQual  NeighborhoodBin  _MSSubClass_20  _MSSubClass_30  \
0        1.307684        -0.050394               0               0
1       -0.764711         1.030112               1               0
2        1.307684        -0.050394               0               0
```

```
3      -0.764711         1.030112                0                 0
4       1.307684         2.110619                0                 0

   _MSSubClass_40  _MSSubClass_45  _MSSubClass_50  _MSSubClass_60  \
0               0               0               0               1
1               0               0               0               0
2               0               0               0               1
3               0               0               0               0
4               0               0               0               1

   _MSSubClass_70  _MSSubClass_75  _MSSubClass_80  _MSSubClass_85  \
0               0               0               0               0
1               0               0               0               0
2               0               0               0               0
3               1               0               0               0
4               0               0               0               0

   _MSSubClass_90  _MSSubClass_120  _MSSubClass_180  _MSSubClass_190  \
0               0                0                0                0
1               0                0                0                0
2               0                0                0                0
3               0                0                0                0
4               0                0                0                0

   _MSZoning_FV  _MSZoning_RH  _MSZoning_RL  _MSZoning_RM  _LotConfig_Corner  \
0             0             0             1             0                  0
1             0             0             1             0                  0
2             0             0             1             0                  0
3             0             0             1             0                  1
4             0             0             1             0                  0

   _LotConfig_CulDSac  _LotConfig_FR2  _LotConfig_FR3  _LotConfig_Inside  \
0                   0               0               0                  1
1                   0               1               0                  0
2                   0               0               0                  1
3                   0               0               0                  0
4                   0               1               0                  0

   _Neighborhood_Blmngtn  _Neighborhood_Blueste  _Neighborhood_BrDale  \
0                      0                      0                     0
1                      0                      0                     0
2                      0                      0                     0
3                      0                      0                     0
4                      0                      0                     0

   _Neighborhood_BrkSide  _Neighborhood_ClearCr  _Neighborhood_CollgCr  \
0                      0                      0                      1
1                      0                      0                      0
```

```
2                      0                    0                    1
3                      0                    0                    0
4                      0                    0                    0

   _Neighborhood_Crawfor  _Neighborhood_Edwards  _Neighborhood_Gilbert  \
0                      0                      0                      0
1                      0                      0                      0
2                      0                      0                      0
3                      1                      0                      0
4                      0                      0                      0

   _Neighborhood_IDOTRR  _Neighborhood_MeadowV  _Neighborhood_Mitchel  \
0                     0                      0                      0
1                     0                      0                      0
2                     0                      0                      0
3                     0                      0                      0
4                     0                      0                      0

   _Neighborhood_NAmes  _Neighborhood_NPkVill  _Neighborhood_NWAmes  \
0                    0                      0                     0
1                    0                      0                     0
2                    0                      0                     0
3                    0                      0                     0
4                    0                      0                     0

   _Neighborhood_NoRidge  _Neighborhood_NridgHt  _Neighborhood_OldTown  \
0                      0                      0                      0
1                      0                      0                      0
2                      0                      0                      0
3                      0                      0                      0
4                      1                      0                      0

   _Neighborhood_SWISU  _Neighborhood_Sawyer  _Neighborhood_SawyerW  \
0                    0                     0                      0
1                    0                     0                      0
2                    0                     0                      0
3                    0                     0                      0
4                    0                     0                      0

   _Neighborhood_Somerst  _Neighborhood_StoneBr  _Neighborhood_Timber  \
0                      0                      0                     0
1                      0                      0                     0
2                      0                      0                     0
3                      0                      0                     0
4                      0                      0                     0

   _Neighborhood_Veenker  _Condition1_Artery  _Condition1_Feedr  \
0                      0                   0                  0
```

```
1                    1                  0                  1
2                    0                  0                  0
3                    0                  0                  0
4                    0                  0                  0

   _Condition1_Norm  _Condition1_PosA  _Condition1_PosN  _Condition1_RRAe  \
0                 1                 0                 0                 0
1                 0                 0                 0                 0
2                 1                 0                 0                 0
3                 1                 0                 0                 0
4                 1                 0                 0                 0

   _Condition1_RRAn  _Condition1_RRNe  _Condition1_RRNn  _BldgType_1Fam  \
0                 0                 0                 0               1
1                 0                 0                 0               1
2                 0                 0                 0               1
3                 0                 0                 0               1
4                 0                 0                 0               1

   _BldgType_2fmCon  _BldgType_Duplex  _BldgType_Twnhs  _BldgType_TwnhsE  \
0                 0                 0                0                 0
1                 0                 0                0                 0
2                 0                 0                0                 0
3                 0                 0                0                 0
4                 0                 0                0                 0

   _HouseStyle_1.5Fin  _HouseStyle_1.5Unf  _HouseStyle_1Story  \
0                   0                   0                   0
1                   0                   0                   1
2                   0                   0                   0
3                   0                   0                   0
4                   0                   0                   0

   _HouseStyle_2.5Unf  _HouseStyle_2Story  _HouseStyle_SFoyer  \
0                   0                   1                   0
1                   0                   0                   0
2                   0                   1                   0
3                   0                   1                   0
4                   0                   1                   0

   _HouseStyle_SLvl  _RoofStyle_Flat  _RoofStyle_Gable  _RoofStyle_Gambrel  \
0                 0                0                 1                   0
1                 0                0                 1                   0
2                 0                0                 1                   0
3                 0                0                 1                   0
4                 0                0                 1                   0

   _RoofStyle_Hip  _RoofStyle_Mansard  _RoofStyle_Shed  _Exterior1st_AsbShng  \
```

```
0                0                  0                0                      0
1                0                  0                0                      0
2                0                  0                0                      0
3                0                  0                0                      0
4                0                  0                0                      0

   _Exterior1st_AsphShn  _Exterior1st_BrkComm  _Exterior1st_BrkFace  \
0                     0                     0                     0
1                     0                     0                     0
2                     0                     0                     0
3                     0                     0                     0
4                     0                     0                     0

   _Exterior1st_CBlock  _Exterior1st_CemntBd  _Exterior1st_HdBoard  \
0                    0                     0                     0
1                    0                     0                     0
2                    0                     0                     0
3                    0                     0                     0
4                    0                     0                     0

   _Exterior1st_MetalSd  _Exterior1st_Plywood  _Exterior1st_Stucco  \
0                     0                     0                    0
1                     1                     0                    0
2                     0                     0                    0
3                     0                     0                    0
4                     0                     0                    0

   _Exterior1st_VinylSd  _Exterior1st_Wd Sdng  _Exterior1st_WdShing  \
0                     1                     0                     0
1                     0                     0                     0
2                     1                     0                     0
3                     0                     1                     0
4                     1                     0                     0

   _Exterior2nd_AsbShng  _Exterior2nd_AsphShn  _Exterior2nd_Brk Cmn  \
0                     0                     0                     0
1                     0                     0                     0
2                     0                     0                     0
3                     0                     0                     0
4                     0                     0                     0

   _Exterior2nd_BrkFace  _Exterior2nd_CBlock  _Exterior2nd_CmentBd  \
0                     0                    0                     0
1                     0                    0                     0
2                     0                    0                     0
3                     0                    0                     0
4                     0                    0                     0
```

```
   _Exterior2nd_HdBoard  _Exterior2nd_ImStucc  _Exterior2nd_MetalSd  \
0                     0                     0                     0   
1                     0                     0                     1   
2                     0                     0                     0   
3                     0                     0                     0   
4                     0                     0                     0   

   _Exterior2nd_Plywood  _Exterior2nd_Stone  _Exterior2nd_Stucco  \
0                     0                   0                    0   
1                     0                   0                    0   
2                     0                   0                    0   
3                     0                   0                    0   
4                     0                   0                    0   

   _Exterior2nd_VinylSd  _Exterior2nd_Wd Sdng  _Exterior2nd_Wd Shng  \
0                     1                     0                     0   
1                     0                     0                     0   
2                     1                     0                     0   
3                     0                     0                     1   
4                     1                     0                     0   

   _Foundation_BrkTil  _Foundation_CBlock  _Foundation_PConc  \
0                   0                   0                  1   
1                   0                   1                  0   
2                   0                   0                  1   
3                   1                   0                  0   
4                   0                   0                  1   

   _Foundation_Slab  _Foundation_Stone  _Foundation_Wood  _SaleType_COD  \
0                 0                  0                 0              0   
1                 0                  0                 0              0   
2                 0                  0                 0              0   
3                 0                  0                 0              0   
4                 0                  0                 0              0   

   _SaleType_CWD  _SaleType_Con  _SaleType_ConLD  _SaleType_ConLI  \
0              0              0                0                0   
1              0              0                0                0   
2              0              0                0                0   
3              0              0                0                0   
4              0              0                0                0   

   _SaleType_ConLw  _SaleType_New  _SaleType_Oth  _SaleType_WD  \
0                0              0              0             1   
1                0              0              0             1   
2                0              0              0             1   
3                0              0              0             1   
4                0              0              0             1   
```

```
   _SaleCondition_Abnorml  _SaleCondition_AdjLand  _SaleCondition_Alloca  \
0                       0                       0                      0
1                       0                       0                      0
2                       0                       0                      0
3                       1                       0                      0
4                       0                       0                      0

   _SaleCondition_Family  _SaleCondition_Normal  _SaleCondition_Partial  \
0                      0                      1                       0
1                      0                      1                       0
2                      0                      1                       0
3                      0                      0                       0
4                      0                      1                       0

   _MasVnrType_BrkCmn  _MasVnrType_BrkFace  _MasVnrType_None  \
0                   0                    1                 0
1                   0                    0                 1
2                   0                    1                 0
3                   0                    0                 1
4                   0                    1                 0

   _MasVnrType_Stone  _LotShape_IR1  _LotShape_IR2  _LotShape_IR3  \
0                  0              0              0              0
1                  0              0              0              0
2                  0              1              0              0
3                  0              1              0              0
4                  0              1              0              0

   _LotShape_Reg  _LandContour_Bnk  _LandContour_HLS  _LandContour_Low  \
0              1                 0                 0                 0
1              1                 0                 0                 0
2              0                 0                 0                 0
3              0                 0                 0                 0
4              0                 0                 0                 0

   _LandContour_Lvl  _LandSlope_Gtl  _LandSlope_Mod  _LandSlope_Sev  \
0                 1               1               0               0
1                 1               1               0               0
2                 1               1               0               0
3                 1               1               0               0
4                 1               1               0               0

   _Electrical_FuseA  _Electrical_FuseF  _Electrical_FuseP  _Electrical_SBrkr  \
0                  0                  0                  0                  1
1                  0                  0                  0                  1
2                  0                  0                  0                  1
3                  0                  0                  0                  1
```

```
4                  0                   0                   0                   1

   _GarageType_2Types  _GarageType_Attchd  _GarageType_Basment  \
0                   0                   1                    0
1                   0                   1                    0
2                   0                   1                    0
3                   0                   0                    0
4                   0                   1                    0

   _GarageType_BuiltIn  _GarageType_CarPort  _GarageType_Detchd  \
0                    0                    0                   0
1                    0                    0                   0
2                    0                    0                   0
3                    0                    0                   1
4                    0                    0                   0

   _GarageType_None  _PavedDrive_N  _PavedDrive_P  _PavedDrive_Y  \
0                 0              0              0              1
1                 0              0              0              1
2                 0              0              0              1
3                 0              0              0              1
4                 0              0              0              1

   _MiscFeature_Gar2  _MiscFeature_None  _MiscFeature_Othr  _MiscFeature_Shed  \
0                  0                  1                  0                  0
1                  0                  1                  0                  0
2                  0                  1                  0                  0
3                  0                  1                  0                  0
4                  0                  1                  0                  0

   _Street_Grvl  _Street_Pave  _Alley_Grvl  _Alley_None  _Alley_Pave  \
0             0             1            0            1            0
1             0             1            0            1            0
2             0             1            0            1            0
3             0             1            0            1            0
4             0             1            0            1            0

   _Condition2_Artery  _Condition2_Feedr  _Condition2_Norm  _Condition2_PosA  \
0                   0                  0                 1                 0
1                   0                  0                 1                 0
2                   0                  0                 1                 0
3                   0                  0                 1                 0
4                   0                  0                 1                 0

   _RoofMatl_CompShg  _RoofMatl_Tar&Grv  _RoofMatl_WdShake  _RoofMatl_WdShngl  \
0                  1                  0                  0                  0
1                  1                  0                  0                  0
2                  1                  0                  0                  0
```

```
3                  1                  0                  0                  0
4                  1                  0                  0                  0

   _Heating_GasA  _Heating_GasW  _Heating_Grav  _Heating_Wall  _ExterQual_Ex  \
0              1              0              0              0              0
1              1              0              0              0              0
2              1              0              0              0              0
3              1              0              0              0              0
4              1              0              0              0              0

   _ExterQual_Fa  _ExterQual_Gd  _ExterQual_TA  _ExterCond_Ex  _ExterCond_Fa  \
0              0              1              0              0              0
1              0              0              1              0              0
2              0              1              0              0              0
3              0              0              1              0              0
4              0              1              0              0              0

   _ExterCond_Gd  _ExterCond_Po  _ExterCond_TA  _BsmtQual_Ex  _BsmtQual_Fa  \
0              0              0              1             0             0
1              0              0              1             0             0
2              0              0              1             0             0
3              0              0              1             0             0
4              0              0              1             0             0

   _BsmtQual_Gd  _BsmtQual_None  _BsmtQual_TA  _BsmtCond_Fa  _BsmtCond_Gd  \
0             1               0             0             0             0
1             1               0             0             0             0
2             1               0             0             0             0
3             0               0             1             0             1
4             1               0             0             0             0

   _BsmtCond_None  _BsmtCond_Po  _BsmtCond_TA  _HeatingQC_Ex  _HeatingQC_Fa  \
0               0             0             1              1              0
1               0             0             1              1              0
2               0             0             1              1              0
3               0             0             0              0              0
4               0             0             1              1              0

   _HeatingQC_Gd  _HeatingQC_Po  _HeatingQC_TA  _KitchenQual_Ex  \
0              0              0              0                0
1              0              0              0                0
2              0              0              0                0
3              1              0              0                0
4              0              0              0                0

   _KitchenQual_Fa  _KitchenQual_Gd  _KitchenQual_TA  _FireplaceQu_Ex  \
0                0                1                0                0
1                0                0                1                0
```

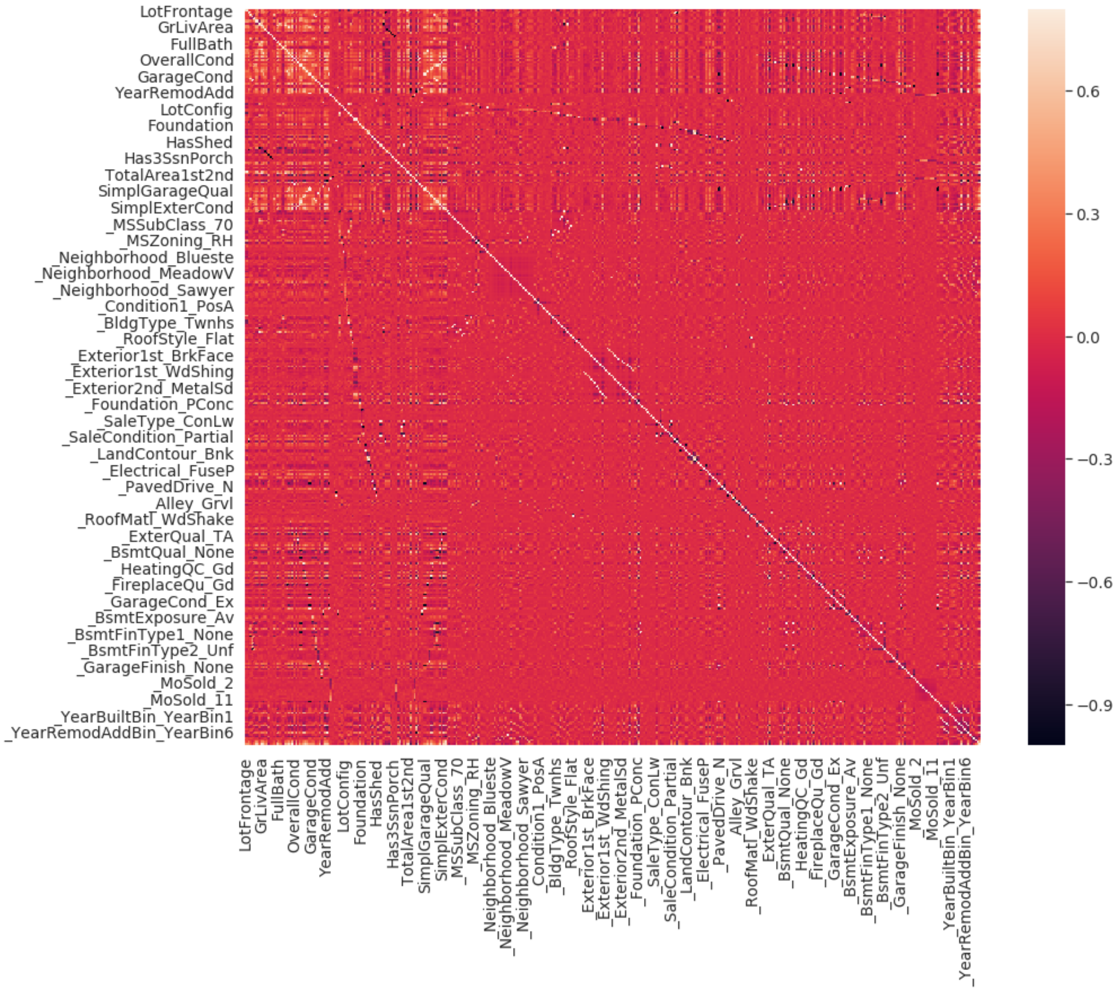
```
2                0                1                0                0
3                0                1                0                0
4                0                1                0                0

   _FireplaceQu_Fa  _FireplaceQu_Gd  _FireplaceQu_None  _FireplaceQu_Po  \
0                0                0                  1                0
1                0                0                  0                0
2                0                0                  0                0
3                0                1                  0                0
4                0                0                  0                0

   _FireplaceQu_TA  _GarageQual_Fa  _GarageQual_Gd  _GarageQual_None  \
0                0               0               0                 0
1                1               0               0                 0
2                1               0               0                 0
3                0               0               0                 0
4                1               0               0                 0

   _GarageQual_Po  _GarageQual_TA  _GarageCond_Ex  _GarageCond_Fa  \
0               0               1               0               0
1               0               1               0               0
2               0               1               0               0
3               0               1               0               0
4               0               1               0               0

   _GarageCond_Gd  _GarageCond_None  _GarageCond_Po  _GarageCond_TA  \
0               0                 0               0               1
1               0                 0               0               1
2               0                 0               0               1
3               0                 0               0               1
4               0                 0               0               1

   _PoolQC_Ex  _PoolQC_Gd  _PoolQC_None  _BsmtExposure_Av  _BsmtExposure_Gd  \
0           0           0             1                 0                 0
1           0           0             1                 0                 1
2           0           0             1                 0                 0
3           0           0             1                 0                 0
4           0           0             1                 1                 0

   _BsmtExposure_Mn  _BsmtExposure_No  _BsmtExposure_None  _BsmtFinType1_ALQ  \
0                 0                 1                   0                  0
1                 0                 0                   0                  1
2                 1                 0                   0                  0
3                 0                 1                   0                  1
4                 0                 0                   0                  0

   _BsmtFinType1_BLQ  _BsmtFinType1_GLQ  _BsmtFinType1_LwQ  \
0                  0                  1                  0
```

```
1                   0                   0                   0
2                   0                   1                   0
3                   0                   0                   0
4                   0                   1                   0

   _BsmtFinType1_None  _BsmtFinType1_Rec  _BsmtFinType1_Unf  \
0                   0                  0                  0
1                   0                  0                  0
2                   0                  0                  0
3                   0                  0                  0
4                   0                  0                  0

   _BsmtFinType2_ALQ  _BsmtFinType2_BLQ  _BsmtFinType2_GLQ  _BsmtFinType2_LwQ  \
0                  0                  0                  0                  0
1                  0                  0                  0                  0
2                  0                  0                  0                  0
3                  0                  0                  0                  0
4                  0                  0                  0                  0

   _BsmtFinType2_None  _BsmtFinType2_Rec  _BsmtFinType2_Unf  _Functional_Maj1  \
0                   0                  0                  1                 0
1                   0                  0                  1                 0
2                   0                  0                  1                 0
3                   0                  0                  1                 0
4                   0                  0                  1                 0

   _Functional_Maj2  _Functional_Min1  _Functional_Min2  _Functional_Mod  \
0                 0                 0                 0                0
1                 0                 0                 0                0
2                 0                 0                 0                0
3                 0                 0                 0                0
4                 0                 0                 0                0

   _Functional_Sev  _Functional_Typ  _GarageFinish_Fin  _GarageFinish_None  \
0                0                1                  0                   0
1                0                1                  0                   0
2                0                1                  0                   0
3                0                1                  0                   0
4                0                1                  0                   0

   _GarageFinish_RFn  _GarageFinish_Unf  _Fence_GdPrv  _Fence_GdWo  \
0                  1                  0             0            0
1                  1                  0             0            0
2                  1                  0             0            0
3                  0                  1             0            0
4                  1                  0             0            0

   _Fence_MnPrv  _Fence_MnWw  _Fence_None  _MoSold_1  _MoSold_2  _MoSold_3  \
```

```
0           0           0           1          0          1          0
1           0           0           1          0          0          0
2           0           0           1          0          0          0
3           0           0           1          0          1          0
4           0           0           1          0          0          0

   _MoSold_4  _MoSold_5  _MoSold_6  _MoSold_7  _MoSold_8  _MoSold_9  \
0          0          0          0          0          0          0
1          0          1          0          0          0          0
2          0          0          0          0          0          1
3          0          0          0          0          0          0
4          0          0          0          0          0          0

   _MoSold_10  _MoSold_11  _MoSold_12  _GarageYrBltBin_NoGarage  \
0           0           0           0                         0
1           0           0           0                         0
2           0           0           0                         0
3           0           0           0                         0
4           0           0           1                         0

   _GarageYrBltBin_YearBin2  _GarageYrBltBin_YearBin3  \
0                         0                         0
1                         0                         0
2                         0                         0
3                         0                         0
4                         0                         0

   _GarageYrBltBin_YearBin4  _GarageYrBltBin_YearBin5  \
0                         0                         0
1                         0                         0
2                         0                         0
3                         0                         0
4                         0                         0

   _GarageYrBltBin_YearBin6  _GarageYrBltBin_YearBin7  _YearBuiltBin_YearBin1  \
0                         0                         1                       0
1                         1                         0                       0
2                         0                         1                       0
3                         0                         1                       0
4                         0                         1                       0

   _YearBuiltBin_YearBin2  _YearBuiltBin_YearBin3  _YearBuiltBin_YearBin4  \
0                       0                       0                       0
1                       0                       0                       0
2                       0                       0                       0
3                       0                       1                       0
4                       0                       0                       0
```

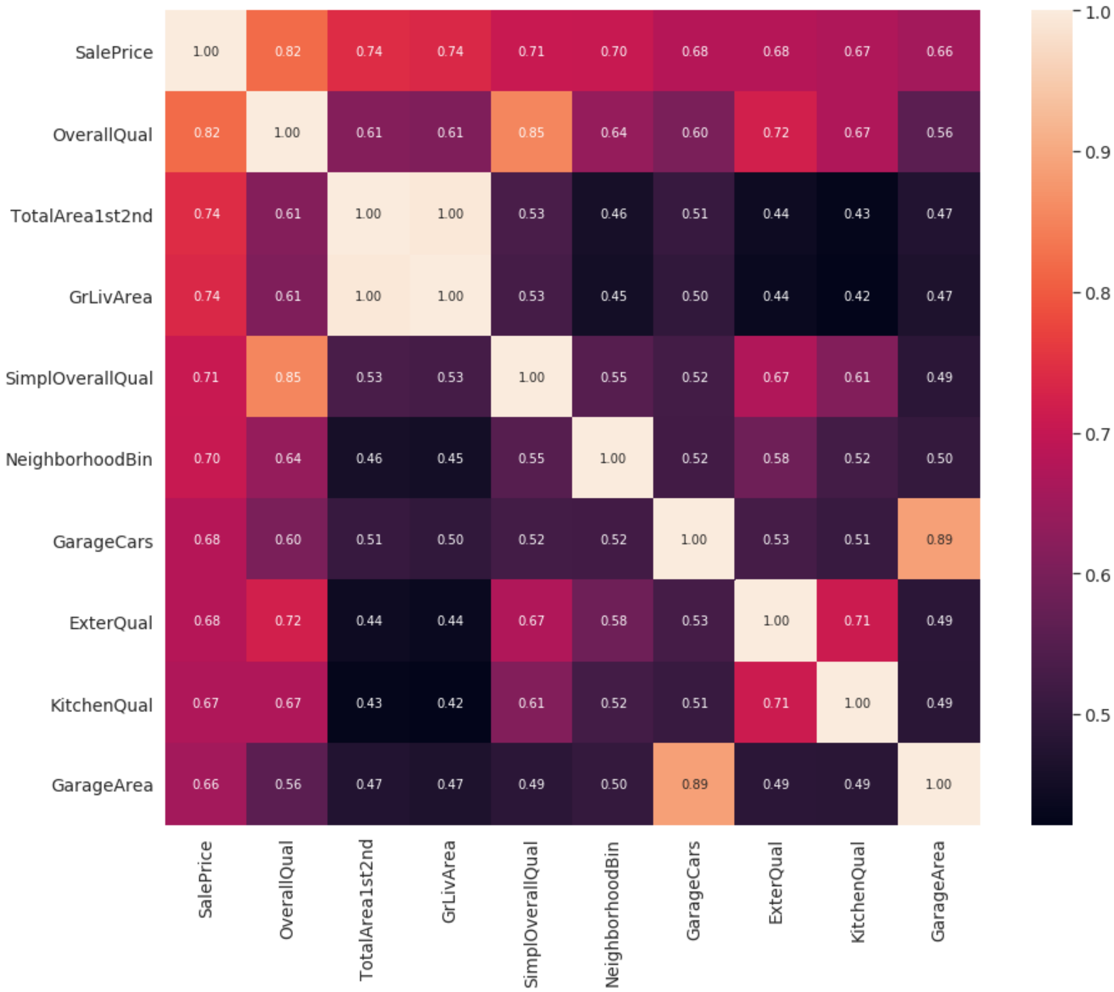
```
   _YearBuiltBin_YearBin5  _YearBuiltBin_YearBin6  _YearBuiltBin_YearBin7  \
0                       0                       0                       1   
1                       0                       1                       0   
2                       0                       0                       1   
3                       0                       0                       0   
4                       0                       0                       1   

   _YearRemodAddBin_YearBin4  _YearRemodAddBin_YearBin5  \
0                          0                          0   
1                          0                          0   
2                          0                          0   
3                          0                          1   
4                          0                          0   

   _YearRemodAddBin_YearBin6  _YearRemodAddBin_YearBin7  _NeighborhoodBin_0  \
0                          0                          1                   0   
1                          1                          0                   0   
2                          0                          1                   0   
3                          0                          0                   0   
4                          0                          1                   0   

   _NeighborhoodBin_1  _NeighborhoodBin_2  _NeighborhoodBin_3  \
0                   0                   1                   0   
1                   0                   0                   1   
2                   0                   1                   0   
3                   0                   0                   1   
4                   0                   0                   0   

   _NeighborhoodBin_4  SalePrice  
0                   0  12.247694  
1                   0  12.109011  
2                   0  12.317167  
3                   0  11.849398  
4                   1  12.429216  
```

In [121]:
```
#correlation matrix
corrmat = abc.corr()
f, ax = plt.subplots(figsize=(15, 12))
sns.set(font_scale=1.25)
sns.heatmap(corrmat, vmax=.8, square=True);
```



We can see that above graph is almost completely red that means no feature have any relation with another feature. That means all the features are now independent. So our data processing part should be good enough to get good results.

```
In [122]: #saleprice correlation matrix
          k = 10 #number of variables for heatmap
          cols = corrmat.nlargest(k, 'SalePrice')['SalePrice'].index
          cm = np.corrcoef(abc[cols].values.T)
          f, ax = plt.subplots(figsize=(15, 12))
          sns.set(font_scale=1.25)
          hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'size
          plt.show()
```

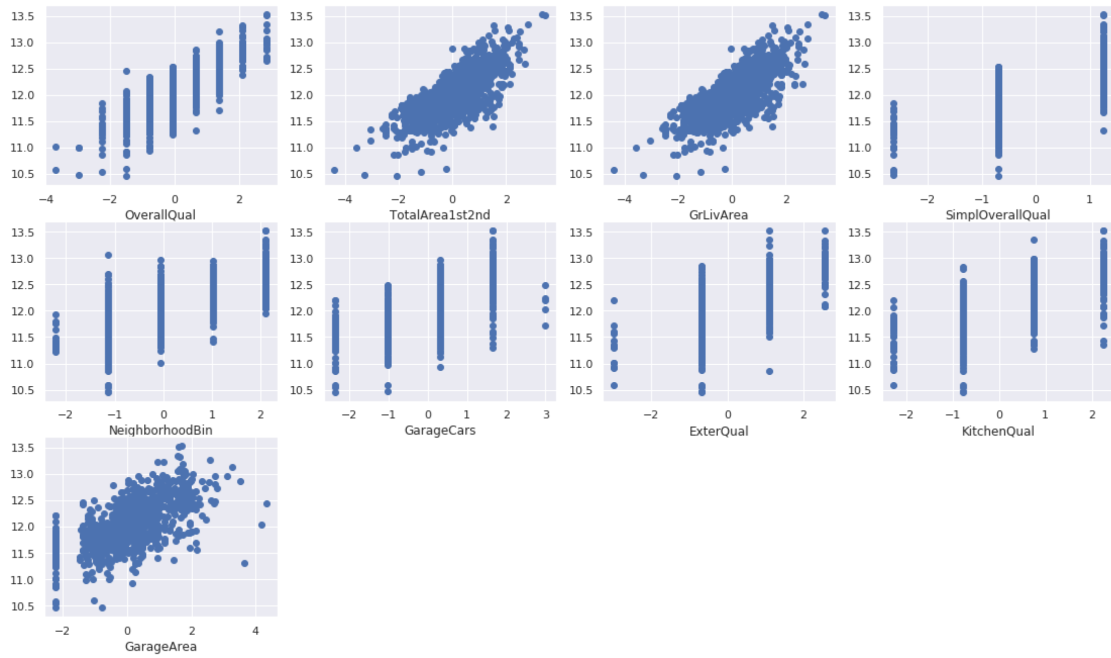


We can see that GrLivArea and TotalArea1st2nd is actually same and in the following graph we will see that the graph is also same for both of the feature. So we can remove one of them.

The following 9 features are the most important feature for determining the SalePrice and they also don't have any outlier

In [123]:
```
# A FUNCTION TO SCATTER-PLOT ALL SELECTED FEATURES AGAINST SALEPRICE
def relation_with_SalePrice(c,column):
    plt.subplot(5, 4, c)
    plt.scatter(x = train_processed[column], y = target)
    plt.xlabel(column)
c=1
sns.set(font_scale=1)
plt.subplots(figsize=(19, 19))

if 'SalePrice' in cols:
    cols = cols.drop('SalePrice')
```

```
for item in cols:
    relation_with_SalePrice(c,item)
    c=c+1
plt.show()
```



Dropping Features like GLivArea

We can safely drop features that provides Correlation coefficient value= 1. If this happens we can just keep any one of them and remove the rest of them.

In the following section we are going to observe which features have coefficient value = 1 between them.We will only remove them because they will not decrease performance.

In [124]:
```
abc = train_processed.copy()
# abc['SalePrice'] = target
abc.head()
correlation= abc.corr().unstack().sort_values(ascending=False)
# correlation=correlation.sort_values(ascending=False)
correlation[430:].head(20) #37
```

Out[124]:
```
_Neighborhood_Crawfor   _Neighborhood_Crawfor     1.00000
_Neighborhood_CollgCr   _Neighborhood_CollgCr     1.00000
_Neighborhood_ClearCr   _Neighborhood_ClearCr     1.00000
_Neighborhood_BrkSide   _Neighborhood_BrkSide     1.00000
_Neighborhood_BrDale    _Neighborhood_BrDale      1.00000
_NeighborhoodBin_1      _NeighborhoodBin_1        1.00000
_Exterior2nd_Brk Cmn    _Exterior2nd_Brk Cmn      1.00000
LotFrontage             LotFrontage               1.00000
_NeighborhoodBin_3      _NeighborhoodBin_3        1.00000
```

```
IsRegularLotShape       _LotShape_Reg           1.00000
_LotShape_Reg           IsRegularLotShape       1.00000
BoughtOffPlan           _SaleCondition_Partial  1.00000
_SaleCondition_Partial  BoughtOffPlan           1.00000
IsGarageDetached        _GarageType_Detchd      1.00000
_GarageType_Detchd      IsGarageDetached        1.00000
IsLandLevel             _LandContour_Lvl        1.00000
_LandContour_Lvl        IsLandLevel             1.00000
_PavedDrive_Y           IsPavedDrive            1.00000
IsPavedDrive            _PavedDrive_Y           1.00000
IsElectricalSBrkr       _Electrical_SBrkr       0.99565
dtype: float64
```

```
In [125]: if 'GrLivArea' in train_processed.columns and 'GrLivArea' in test_processed.columns:
              train_processed = train_processed.drop(columns='GrLivArea')
              test_processed = test_processed.drop(columns='GrLivArea')

              train_processed = train_processed.drop(
                  columns=['IsRegularLotShape','BoughtOffPlan','IsGarageDetached','IsLandLevel
              test_processed = test_processed.drop(
                  columns=['IsRegularLotShape','BoughtOffPlan','IsGarageDetached','IsLandLevel
```

Finally we have removed the following features because they coefficient value = 1 with another feature. Removed features are:

- 'IsRegularLotShape'
- 'BoughtOffPlan'
- 'IsGarageDetached'
- 'IsLandLevel'
- '_PavedDrive_Y'
- 'GrLivArea'

8 Split Data for training and testing

In this Section We have split the training dataset into two part. First one is called train and other is called val (means validation set).Training set contains X_train and y_train.Validation set also contains X_val and y_val. X means this SalePrice is excluded. Again Y means this portion only contains Saleprice. I have used 80-20 split where training contains 80% data and validation contains 20% data. I have used kaggle testing set for testing them (variable name is test_processed) and the result of the kaggle testing is also included as a screenshot after accuracy section.

```
In [126]: X_train, X_val, y_train, y_val = train_test_split(train_processed,
                                                            target,
          #                                                   train_size = 0.99,
                                                            test_size = 0.2,
                                                            random_state = 0,
                                                            shuffle = True
                                                           )
```

Following section changes the training set to 100% when we set submit=True. The reason behind it is when we train with full dataset then we use to get better accuracy. But we will set that True only when we are going to submit the prediction of the tess_proceed to kaggle.

```
In [127]: prediction_dict = dict()
          submit_prediction_dict = dict()

          submit = False
          save_score = False

          if submit :
              X_train = train_processed
              y_train = target
          else:
              X_train = X_train
              y_train = y_train
```

9 Testing different models

9.0.1 RMSE

Following function calculates root mean squire error

What is RMSE ?

The root-mean-square deviation (RMSD) or root-mean-square error (RMSE) (or sometimes root-mean-squared error) is a frequently used measure of the differences between values (sample or population values) predicted by a model or an estimator and the values observed. The RMSD represents the square root of the second sample moment of the differences between predicted values and observed values or the quadratic mean of these differences. These deviations are called residuals when the calculations are performed over the data sample that was used for estimation and are called errors (or prediction errors) when computed out-of-sample. The RMSD serves to aggregate the magnitudes of the errors in predictions for various times into a single measure of predictive power. RMSD is a measure of accuracy, to compare forecasting errors of different models for a particular dataset and not between datasets, as it is scale-dependent.[1]

```
In [128]: def rmse(y_true, y_pred):
                return np.sqrt(mean_squared_error(y_true, y_pred))
```

9.0.2 Random Forest Regressor

A random forest is a meta estimator that fits a number of classifying decision trees on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting.

```
In [129]: my_model = RandomForestRegressor(n_estimators=500,n_jobs=-1)


          my_model.fit(X_train, y_train)
          prediction = my_model.predict(X_val)
```

```
    if submit:
        submit_prediction = my_model.predict(test_processed)
        submit_prediction_dict['Random Forest Regressor'] = submit_prediction

    prediction_dict['Random Forest Regressor'] = prediction

    print('root mean absolute error: ',rmse(y_val, prediction))
    print('accuracy score: ',  r2_score(np.array(y_val),prediction) )
```

```
/home/navid/anaconda3/envs/tf/lib/python3.6/site-packages/ipykernel_launcher.py:4: DataConvers
  after removing the cwd from sys.path.
```

```
root mean absolute error:  0.12333514318294307
accuracy score:  0.9102428268390197
```

9.0.3 DecisionTree

Decision tree builds regression or classification models in the form of a tree structure. It breaks down a dataset into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed. The final result is a tree with decision nodes and leaf nodes.

```
In [130]: from sklearn.tree import DecisionTreeRegressor
          my_model = DecisionTreeRegressor()

          my_model.fit(X_train, y_train)
          prediction = my_model.predict(X_val)
          prediction_dict['DecisionTree'] = prediction
          if submit:
              submit_prediction = my_model.predict(test_processed)
              submit_prediction_dict['DecisionTree'] = submit_prediction

          print('root mean absolute error: ',rmse(y_val, prediction))
          print('accuracy score: ',  r2_score(np.array(y_val),prediction) )
```

```
root mean absolute error:  0.2070903796053185
accuracy score:  0.7469447626888546
```

9.0.4 Xgboost

XGBoost stands for eXtreme Gradient Boosting. It is an optimized distributed gradient boosting library designed to be highly efficient, flexible and portable. It implements machine learning algorithms under the Gradient Boosting framework. XGBoost provides a parallel tree boosting (also known as GBDT, GBM) that solve many data science problems in a fast and accurate way.

```
In [131]: from xgboost import XGBRegressor
          my_model = XGBRegressor(n_estimators=500, learning_rate=0.05)
```

```
my_model.fit(X_train, y_train)
prediction = my_model.predict(X_val)
prediction_dict['Xgboost'] = prediction

if submit:
    submit_prediction = my_model.predict(test_processed)
    submit_prediction_dict['Xgboost'] = submit_prediction


print('root mean absolute error: ',rmse(y_val, prediction))
print('accuracy score: ',  r2_score(np.array(y_val),prediction) )
```

```
root mean absolute error:  0.10758602616026638
accuracy score:  0.9317021213275157
```

9.1 Lasso

Lasso (least absolute shrinkage and selection operator; also Lasso or LASSO) is a regression analysis method that performs both variable selection and regularization in order to enhance the prediction accuracy and interpretability of the statistical model it produces.Lasso was originally formulated for least squares models and this simple case reveals a substantial amount about the behavior of the estimator, including its relationship to ridge regression and best subset selection and the connections between lasso coefficient estimates and so-called soft thresholding. It also reveals that (like standard linear regression) the coefficient estimates need not be unique if covariates are collinear.

```
In [132]: from sklearn.linear_model import Lasso
          my_model = Lasso(alpha=5e-3, max_iter=50000)


          my_model.fit(X_train, y_train)
          prediction = my_model.predict(X_val)
          prediction_dict['Lasso'] = prediction

          if submit:
              submit_prediction = my_model.predict(test_processed)
              submit_prediction_dict['Lasso'] = submit_prediction

          print(' root mean absolute error: ',rmse(y_val, prediction))
          print('accuracy score: ',  r2_score(np.array(y_val),prediction) )
```

```
 root mean absolute error:  0.10782602106751343
accuracy score:  0.9313970738094619
```

In the above model alpha is Constant that multiplies the L1 term. For numerical reason we cant set alpha to 0 but keeping alpha low provides good accuracy for out dataset. I have found 5e-4 provides good accuracy.

for 5e-5: root mean absolute error: 0.10973737757187135 accuracy score: 0.9289433650407954
for 1e-5: root mean absolute error: 0.11426822609093419 accuracy score: 0.9229546464396043
for 1e-3: root mean absolute error: 0.10466883446067998 accuracy score: 0.9353556969018821
for 1e-4: root mean absolute error: 0.10658498063306822 accuracy score: 0.9329671780226085
for 5e-3: root mean absolute error: 0.10794617678311977 accuracy score: 0.9312440935471524

10 ANN

10.0.1 Theory and Basics:

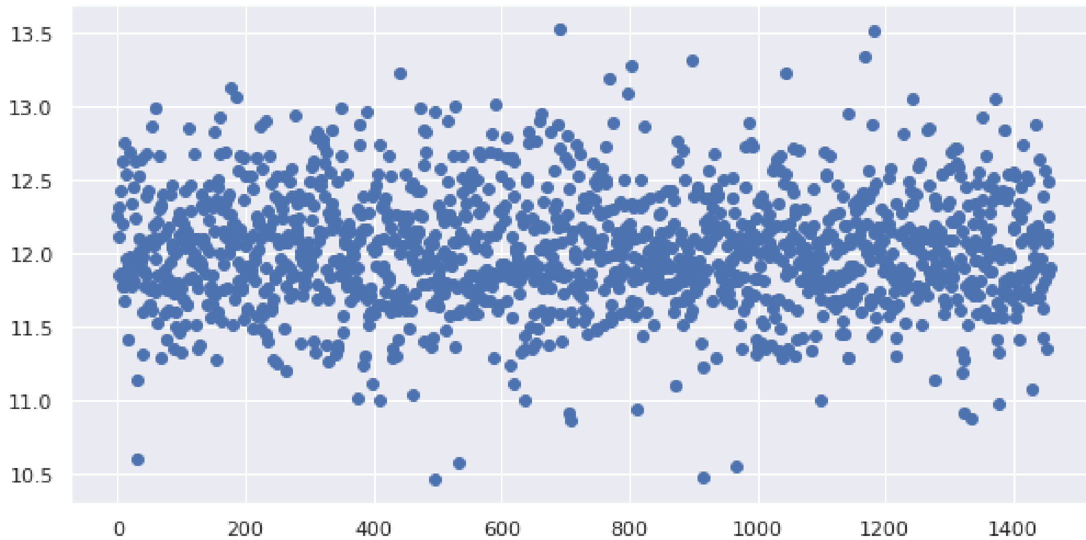
An Artificial Neurol Network (ANN) is a computational model. It is based on the structure and functions of biological neural networks. It works like the way human brain processes information. ANN includes a large number of connected processing units that work together to process information. They also generate meaningful results from it.

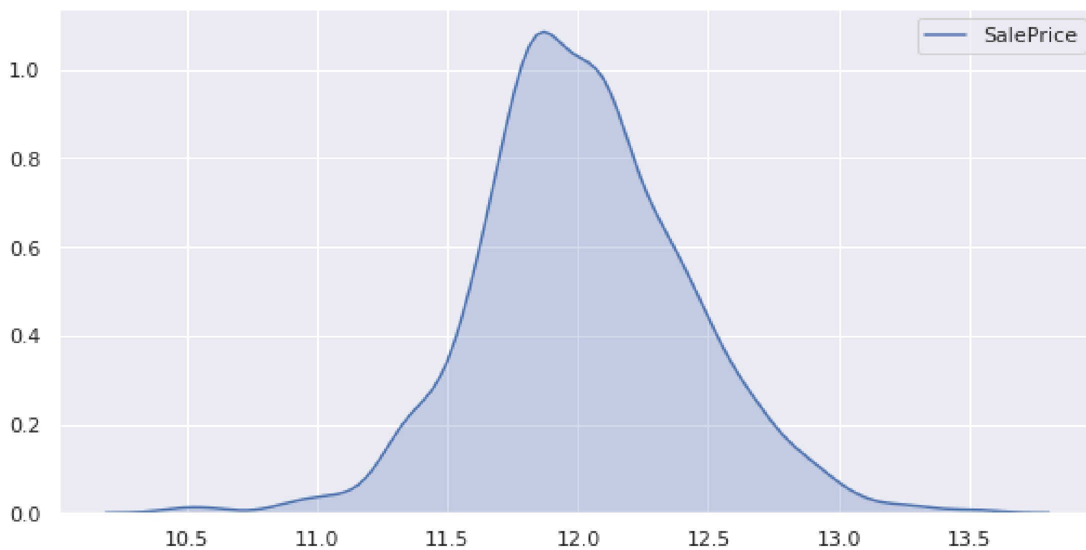
An artificial neuron is a mathematical function conceived as a model of biological neurons, a neural network. Usually each input is separately weighted, and the sum is passed through a non-linear function known as an activation function or transfer function.

The artificial Neural network is typically organized in layers. Layers are being made up of many interconnected 'nodes' which contain an 'activation function'. A neural network may contain the following 3 layers:

- Input layer The purpose of the input layer is to receive as input the values of the explanatory attributes for each observation. Usually, the number of input nodes in an input layer is equal to the number of explanatory variables. 'input layer' presents the patterns to the network, which communicates to one or more 'hidden layers'. The nodes of the input layer are passive, meaning they do not change the data. They receive a single value on their input and duplicate the value to their many outputs. From the input layer, it duplicates each value and sent to all the hidden nodes.
- Hidden Layer The Hidden layers apply given transformations to the input values inside the network. In this, incoming arcs that go from other hidden nodes or from input nodes connected to each node. It connects with outgoing arcs to output nodes or to other hidden nodes. In hidden layer, the actual processing is done via a system of weighted 'connections'. There may be one or more hidden layers. The values entering a hidden node multiplied by weights, a set of predetermined numbers stored in the program. The weighted inputs are then added to produce a single number.
- Output layer The hidden layers then link to an 'output layer'. Output layer receives connections from hidden layers or from input layer. It returns an output value that corresponds to the prediction of the response variable. In classification problems, there is usually only one output node. The active nodes of the output layer combine and change the data to produce the output values.

```
In [215]: import seaborn as sns
          import matplotlib.pyplot as plt
          plt.figure(figsize=[10,5])
          plt.scatter(range(len(train)),list(target.SalePrice.values))
          plt.show()
          plt.figure(figsize=[10,5])
          sns.kdeplot(target.SalePrice, shade= True)
          plt.show()
```





In the above graph we can see that the price range is in a normal distribution. If we provide tf.random.normal while initializing the weight it should be more helpful for training. And this initialization should provide better validation with low amount of epoches. In my kaggle score rmse 0.123 is found through random normal while uniform distribution provided rmse 0.127 score. Again Uniform distribution takes 3 times more epoches to reach rmse score 0.127. But for uniform distribution no improvement cant found after 16000 epoch and for normal distribution no improvement can't found after 6000 epoch.

Target By observing the span of the data and the data distribution we can conclude that logistic regression should perform well for this kind of problem. So we can safely say that starting with single neuron in a single hidden layer should perform well and we should look for simpler solution. Again from theoretical perspective single neurone and single layer ANN is nothing but a logistic regression and after adding layers and neurons we can regularize them so that they behave more like a logistic regression model and then we can tune parameter such a way so that it can handle little bit more complexity than a logistic regression. Finally my target is to make sure that it performs well as a logistic regression model and then improve it with more neuron/layers and proper tuning of parameters.

```
In [216]: # log_df = pd.DataFrame(columns=['learning_rate', 'num_steps', 'beta1','beta2','beta
          # log_df.to_csv("diffrent_training_results.csv", index=False)
```

10.0.2 Ann parameters

Variables A brief explanation of the variables used is given below. Some terminologies are explained in more detail when their usage comes up.

learning_rate: On a intuition level, learning rate means how fast the network will learn something new and discard the old one. On a technical level, learning rate determines how fast the **'weights'** will be updated. Learning rate should be high enough so that it won't take too long to converge, and it should be low enough so that it is able to find the minima.

epoch: The number of times the model will be trained. After each run, the **'weights'** will be updated by the means of **'optimizer'**

beta1/2/3 : These variables control how much penalty to add to the model's loss function.

hidden_1/2/3 = Determines how many neurons a layer has. The number after the **'hidden_'** part denotes the layer number. i.e. 2 means second hidden layer

input_dim: Determines the shape of the input matrix. The input size is the same as the number of features the dataset has.

output_dim: Determines the shape of the final output. As this is a regression problem the ouput is of size **one**.

X_tf/y_tf: These two are tensorflow placeholder variables. They take input during the training period.

loss for loss function I have used mean squared error.

The following ANN is build with 3 hidden layers. Output dimention is 1 because its a regration problem.

```
In [217]: tf.reset_default_graph()
          learning_rate = 0.1
          num_steps = 8000
          #for regularize weight matrix
          beta1 = 0.1
          beta2 = 0.0
          beta3 = 0.0
          beta4 = None

          hidden_1 = 16
          hidden_2 = 8
          hidden_3 = 4
          hidden_4 = None
```

```
# minimum_validation_loss is to control model saving locally
minimum_validation_loss = 0.0190000

input_dim = X_train.shape[1]  # Number of features
output_dim = 1               # Because it is a regression problem
#tf graph input
X_tf = tf.placeholder("float" )
y_tf = tf.placeholder("float" )
```

10.0.3 Weight and Bias

A weight decides how much influence the input will have on the output. A weight represent the strength of the connection between units. When a value arrives at a neuron, the value gets multiplied by a weight value.

Bias is an extra input to neurons and has it's own connection weight. But a bias node is not connected to any node in the previous layer, only connected to the next layer. This makes sure that even when all the inputs are none (all 0's) there's gonna be an activation in the neuron.

Here I have initialized the "weight" and "bias" variables as "random normal", which takes some random values from a normal distribution to use. Now there is also the option to set them all to "zero". But there is a problem to that. If all of the weights are the same, they will all have the same error and the model will not learn anything - there is no source of asymmetry between the neurons.That's why the better method is to keep the weights very close to zero but make them different by initializing them to small, non-zero numbers. With default parameters, "random normal" chooses values from a nomal distribution whose mean is 0 (zero) and has a standard deviation of 1 (one).

```
In [218]: weights = {
              'w1': tf.Variable(tf.random_normal([input_dim, hidden_1])),
              'w2': tf.Variable(tf.random_normal([hidden_1, hidden_2])),
              'w3': tf.Variable(tf.random_normal([hidden_2, hidden_3])),
              'out': tf.Variable(tf.random_normal([hidden_3, output_dim]))
          }
          biases = {
              'b1': tf.Variable(tf.random_normal([hidden_1])),
              'b2': tf.Variable(tf.random_normal([hidden_2])),
              'b3': tf.Variable(tf.random_normal([hidden_3])),
              'out': tf.Variable(tf.random_normal([output_dim]))
          }
```

10.1 Model

The following block of code is what the actual ANN model looks like. Each layer, a matrix multiplication happens and then the layer is activated by a activation function. The final output layer does not have any activation function because we are performing a regression a here.

Here, the activation function is our main concern. Currently the most popular types of Activation functions are as follows: * Sigmoid * Tanh - Hyperbolic tangent * ReLu - Rectified linear units

"Sigmoid" activation function is mathematically represented by this equation,f(x) = 1 / 1 + exp(-x) . Its output range is between 0 to 1 and it has an S-shaped curve. It is easy to understand and apply but it has "vanishing gradient" problem as well as being slow to converg. So, I have avoided using it.

"**Tanh**" activation function is mathematically represented by this equation,f(x) = 1- exp(-2x) / 1 + exp(-2x). It's output range is in between -1 to 1 i.e -1 < output < 1 . As such optimization is easier in this method but still it suffers from Vanishing gradient problem.

"**ReLu**" is a very popular currently due to its simplicity and ease of use. Mathematically, ReLu can be defined as follows-

R(x) = max(0,x) i.e if x < 0 , R(x) = 0 and if x >= 0 , R(x) = x.

From the mathamatical function it can be seen that it is very simple and efficinent. It also avoids and rectifies vanishing gradient problem . It is also relatively easier to optimize.

In the dataset Sales price are non negative number so our model is expected to return positive values so as a activation function I have used relu as it gives positive values. Again relu is easy to optimize because they are similar to linear units. The only difference is that a rectified linear unit outputs zero across half its domain. Thus derivatives through a rectified linear unit remain large whenever the unit is activate. The gradients are not only large but also consistent.

```
In [219]: def ann_model(X_input):
            # Hidden layers
              layer_1 = tf.add(tf.matmul(X_input, weights['w1']), biases['b1'])
              layer_1 = tf.nn.relu(layer_1)


              layer_2 = tf.add(tf.matmul(layer_1, weights['w2']), biases['b2'])
              layer_2 = tf.nn.relu(layer_2)

              layer_3 = tf.add(tf.matmul(layer_2, weights['w3']), biases['b3'])
              layer_3 = tf.nn.relu(layer_3)


              # Output layer
              layer_out = tf.matmul(layer_3, weights['out']) + biases['out']

              return layer_out
```

For optimization I have used Adam optimizer. Adam derives from phrase "adaptive moments". Its a varient of RMSProp. I have used adam instead of RMSProp for couple of reasons. First, in Adam, momentum is incorporated directly as an estimate of the rst-order moment (with exponential weighting) of the gradient. The most straightforward way to add momentum to RMSProp is to apply momentum to the rescaled gradients. The use of momentum in combination with rescaling does not have a clear theoretical motivation. Second, Adam includes bias corrections to the estimates of both the rst-order moments (the momentumterm) and the (uncentered) second-order moments to account for their initializationat the origin. RMSProp also incorporates an estimate of the (uncentered) second-order moment; however, it lacks the correction factor. Thus,unlike in Adam, the RMSProp second-order moment estimate may have high bias early in training. Adam is generally regarded as being fairly robust to the choice of hyperparameters, though the learning rate sometimes needs to be changed from the suggested default. Usually default rate is .001 but for our case I have used 0.1 as it gives better optimization results.

Following segment is actually initializing different parameters. From the dataset we can see that the estimation of sale price is a regression problem and neural network used here was overfitting most of the time due to higher variance. So for making it simpler I have penalized weight matrix of hidden layers with l2 regularization. Again I have found that single hidden layer with single neuron performs well and that means the prediction model don't need to be too complex. Thus I became ensured that regularization is going to improve performance.

```
In [220]: # Model Construct
          model = ann_model(X_tf)

          # Mean Squared Error function
          # loss = tf.reduce_mean(tf.square(y_tf - model))
          loss = tf.losses.mean_squared_error(y_tf , model , reduction=tf.losses.Reduction.SUM_

          # loss = tf.square(y_tf - model)
          regularizer_1 = tf.nn.l2_loss(weights['w1'])
          regularizer_2 = tf.nn.l2_loss(weights['w2'])
          regularizer_3 = tf.nn.l2_loss(weights['w3'])
          loss = tf.reduce_mean(loss + beta1*regularizer_1 + beta2*regularizer_2 + beta3*regula
          # loss = loss + beta1*regularizer_1 + beta2*regularizer_2 + beta3*regularizer_3

          # Adam optimizer will update weights and biases after each step
          optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimize(loss)


          # Initialize variables
          init = tf.global_variables_initializer()

          # Add ops to save and restore all the variables.
          saver = tf.train.Saver()
```

10.2 Training

The **training_block()** is the function where all the work finally happens. The constructed model gets the training data and the training process begins. In each epoch the code is calculating the loss function and trying to minimize that value. Training loss and validation loss of each epoch gets stored in **train_loss** and **val_loss** respectively. After each 50 epochs the current loss values are added to two lists **train_LC** and **val_LC**, which is used to plot the learning curve after the training is finished. Also after each 500 epochs, I have printed the **Training loss and validation loss.**

During the training phase, I have run a shuffle function on the input data. This is so that when the data is input into the model, there are some variation to the serial the data gets inside the model. The reason why i have done it is so that it can have the effect of training on mini batches.

```
In [221]: train_LC = []
          val_LC = []
          # session_var = None
```

Above train LC and val Lc variable keeps track of the learning rate so that learning curve can be drwan. In the following training block I have shuffled the training data in each epoch. This helps to reduce the loss difference of the validation and training. Thus it reduces the chance for over-fitting and under-fitting.

```
In [222]: def training_block(X_train,y_train, X_val,y_val):
              #reseting variables
              session_var = None
              save_path = None
              with tf.Session() as sess:

                  #running initializer
                  sess.run(init)

          #         minimum_validation_loss = 0.0190000

                  global minimum_validation_loss
                  for i in range(num_steps):
                      if submit :
                          X_train , y_train = shuffle(train_processed,target )
                      else:
                          X_train,y_train = shuffle(X_train,y_train )

                      sess.run(optimizer, feed_dict={X_tf:X_train, y_tf:y_train})
                      train_loss = sess.run(loss, feed_dict={X_tf:X_train, y_tf:y_train})
                      val_loss = sess.run(loss, feed_dict={X_tf:X_val, y_tf:y_val})
                      if submit :
                          new_minimum_validation_loss = np.min(train_loss)
                      else:
                          new_minimum_validation_loss = np.min(val_loss)

          #             if (i+1)%50 == 0:
                      train_LC.append(train_loss)
                      val_LC.append(val_loss)

                      if (i+1)%500 == 0:
                          print("epoch no : ",i+1, "  training loss: ",train_loss, "  validati

                      if new_minimum_validation_loss  < minimum_validation_loss :
                          minimum_validation_loss = new_minimum_validation_loss
          #                 global session_var
          #                 session_var = sess
          #                 Save the variables to disk.
                          save_path = saver.save(sess, "model/model.ckpt")


                  if bool(save_path):
                      sess.close()
                      print("Model saved in path: %s" % save_path)
```

```
training_block(X_train,y_train, X_val,y_val)

epoch no :  500   training loss:  56.5054   validation loss:  56.768776     minimum_validation_
epoch no :  1000   training loss:  18.997467   validation loss:  19.050062     minimum_validati
epoch no :  1500   training loss:  7.6135345   validation loss:  7.6308985     minimum_validati
epoch no :  2000   training loss:  3.145926   validation loss:  3.16356     minimum_validation_
epoch no :  2500   training loss:  1.3152529   validation loss:  1.3331934     minimum_validati
epoch no :  3000   training loss:  0.5823516   validation loss:  0.6023922     minimum_validati
epoch no :  3500   training loss:  0.29742134   validation loss:  0.31798798     minimum_valida
epoch no :  4000   training loss:  0.17566855   validation loss:  0.19880897     minimum_valida
epoch no :  4500   training loss:  0.039279543   validation loss:  0.05171471     minimum_valic
epoch no :  5000   training loss:  0.0142944455   validation loss:  0.02085596     minimum_vali
epoch no :  5500   training loss:  0.011126072   validation loss:  0.01826158     minimum_valic
epoch no :  6000   training loss:  1.2234263   validation loss:  1.2379315     minimum_validati
epoch no :  6500   training loss:  0.15917541   validation loss:  0.17402671     minimum_valida
epoch no :  7000   training loss:  0.15616769   validation loss:  0.1711704     minimum_validat
epoch no :  7500   training loss:  0.15608662   validation loss:  0.17114624     minimum_valida
epoch no :  8000   training loss:  0.15594965   validation loss:  0.17107233     minimum_valida
Model saved in path: model/model.ckpt
```

10.2.1 Grid search on epoch:

In the above block I have saved the model when validation loss is lowest. To do that I have kept another parameter called minimum_validation_loss. When validation loss reach lower I save the model, update minimum_validation_loss and continue running it. If it finds another lower validation loss it saves the model again and update minimum_validation_loss. Thus when I get the lowest validation loss my model saves again and that is the most optimum result. But when I run using all the data to predict kaggle test dataset then I use training loss to do the same.

As I mentioned earlier the epoch to reach the best validation accuracy is not fixed. Rather we can find it in 3 different range of epoch. The reason behind this is mostly because of random initializing of the weight and if we have fixed the seed value then it might change into only one single epoch range. But doing so we loose chance to improve our model further. Again if we want to ensemble different ANN model it woun't help when we use same seed and state. I have tried 1000+ parameters and combination from the start and used graph to visualize how to improve that but with grid search I might not get the exact idea why certain things provide good results or not and looking into every search result and graph is also too much so applying on the epoch seems to me more reasonable solution because the epoch for best validation result will be different in every run.

Trick I have shuffled the data in every epoch and this trick improved the validation accuracy. On the other hand I did't use batch because according to my previous experience this kind of logistic regression problem works better when its given as a whole set rather than batch or mini-batch. But if its overfitting then passing the data in a batch / mini-batch would perform better as it helps to generalize more. We can say its more like a dropout effect. And I have tried to do dropout to reduce distance of training and validation accuracy but that didn't worked well.

```
In [223]: def Prediction_block(X_val):
              with tf.Session() as sess:
                  try:
                      # Restore variables from disk.
                      saver.restore(sess, "model/model.ckpt")
                      print("Model restored.")
                  except:
                      print("------------ available checkpoint is for different model --------
                      return
                  # Check the values of the variables
                  pred =  sess.run(model, feed_dict={X_tf: X_val})
                  prediction = pred.squeeze()
                  sess.close()
                  return prediction
          #     print(np.exp(prediction))

          prediction = Prediction_block(X_val)

          pred_str = 'ANN_base_lr'+str(learning_rate)+'_beta'+str(beta1)+'-'+str(beta2)+'-'+st
          prediction_dict[pred_str] = prediction

          if submit:
              submit_prediction = Prediction_block(test_processed)
              submit_prediction_dict[pred_str] = submit_prediction
```

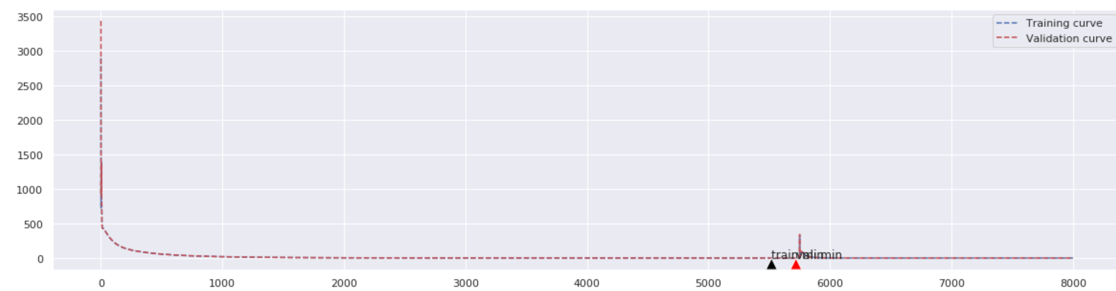
```
INFO:tensorflow:Restoring parameters from model/model.ckpt
Model restored.
```

10.3 Learning curve

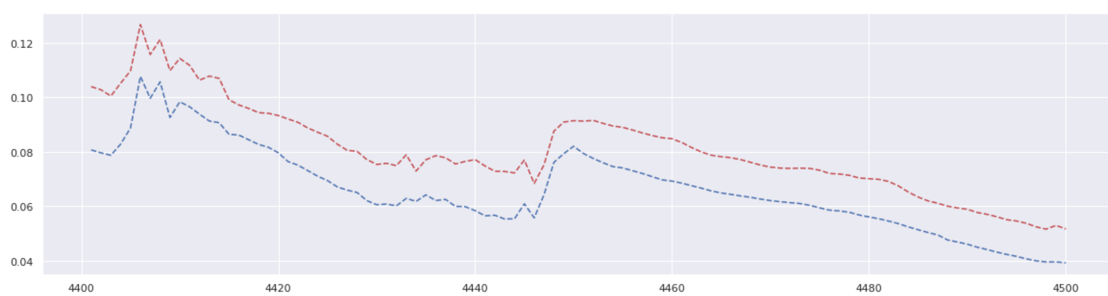
Following variables are only used to zoom into the graph - start_observation_flag = starts point to zoom in - end_observation_flag = end point to zoom in

```
In [228]: def learning_curve(start_observation_flag,end_observation_flag):
              xdata = list(range(1,len(train_LC)+1))
              minimum = min(train_LC)

              plt.figure(figsize=[20,5])
              plt.plot(xdata, train_LC, 'b--', label='Training curve')
              plt.annotate('train min', xy=(xdata[train_LC.index(minimum)], minimum),
                           arrowprops=dict(facecolor='black', shrink=0.05))

              minimum = min(val_LC)
              plt.plot(xdata, val_LC, 'r--' , label='Validation curve')
              plt.annotate('vali min', xy=(xdata[val_LC.index(minimum)], minimum),
                           arrowprops=dict(facecolor='red', shrink=0.05))
              plt.legend()
```

```
    plt.show()

    print("If we zoom into the curve we would have seen the following")

    plt.figure(figsize=[20,5])
    plt.plot(xdata[start_observation_flag:end_observation_flag], train_LC[start_obse
    plt.plot(xdata[start_observation_flag:end_observation_flag], val_LC[start_observa

    plt.show()

#Following variables are only used to zoom into the graph
start_observation_flag = 4400
end_observation_flag = 4500
learning_curve(start_observation_flag,end_observation_flag)
```




```
If we zoom into the curve we would have seen the following
```



Both of the curve actually seems to be on top of each other.The reason is: - I have applied log transformation on the SalePrice and I have also transformed all my numerical data thats why the difference between the training loss and validation loss seems to be very small and very stable. - For loss function I have used Mean Squared Error (MSE). For reducing MSE I have used SUM_BY_NONZERO_WEIGHTS which divided scalar sum by number of non-zero weights. MSE calculates squared error for all the data and then calculate the mean. Now, all my SalePrice is very small due to normalization (between 10 to 13.5). Where mean of saleprice is 12.02 . Suppose in nth epoch if - for training loss - a saleprice is 11.5 and prediction is 12 Squred error .25 - another saleprice is 13 and prediction is 12 Squred error 1 - another saleprice is 12.5 and prediction is 12 Squred error .25 - another saleprice is 11.5 and prediction is 12 Squred error .25 - another saleprice is 10.3 and prediction is 12 Squred error 1.7

```
  **MSE = (.25+1+.25+.25+1.7)/5 = .69**
- for validation loss
    - another saleprice is 12.9 and prediction is 12 Squred error .81
    - another saleprice is 13.3 and prediction is 12 Squred error 1.69
    - another saleprice is 10.8 and prediction is 12 Squred error 1.44
    - another saleprice is 11.3 and prediction is 12 Squred error .49
    - another saleprice is 11.8 and prediction is 12 Squred error .04

  **MSE = (.81+1.69+1.44+.49+.04)/5 = .894**

  **Difference between validation loss and training loss is .204**

Usually in regression problem neural network stats to predicts the average value within 5-20 ep
```

10.4 Acuracy Score

```
In [225]: def accuracy(y_val,prediction):
                test_rmse_score = rmse(y_val, prediction)
                test_r2_score =  r2_score(np.array(y_val),prediction)
                return test_rmse_score, test_r2_score

            test_rmse_score, test_r2_score = accuracy(y_val,prediction)

            print('ann root mean absolute error: ', test_rmse_score)
            print('accuracy score: ', test_r2_score  )
```

```
ann root mean absolute error:  0.11048149815328126
accuracy score:  0.9279764388154309
```

10.4.1 kaggle rmse:

In kaggle ranking the above ANN model provides the best rmse score and the score is 0.12324

10.5 Description on Learning curve and Accuracy:

We can observe where overfitting occurs. Overfitting actually occurs if the training loss goes under the validation loss even though the validation is still dropping. It is the sign that network is learning the patterns in the train set that are not applicable in the validation done. In a short note we can say::

Overfitting : training loss << validation loss
Underfitting : training loss >> validation loss
Just right : training loss ~ validation loss

According to this theory our both learning curve is exactly top of one another so in our case validation loss and training loss is almost same so we can say that our model is doing just the right thing. Again In validation score .1054 is impressive compared to other models.

10.6 Save score

```
In [144]: if save_score:
              log_df = pd.read_csv("diffrent_training_results.csv")
              log_df = log_df.append({'learning_rate' : learning_rate, 'num_steps' : num_steps
              log_df.to_csv("diffrent_training_results.csv", encoding='utf-8',index=False)
```

11 Cross validation

When we perform a random train-test split of our data, we assume that our examples are independent. That means that by knowing/seeing some instance will not help us understand other instances. However, that's not always the case. So to make sure if the Data is actually independent, to get more metrics and to use fine tuning my parameters on whole dataset I am performing cross validation.

```
In [ ]: from sklearn.model_selection import KFold
        from sklearn.model_selection import RepeatedKFold
        kf = KFold(n_splits=10, shuffle=True)

        kf_rmse_list = []
        kf_r2_list = []

        # train_processed['SalePrice'] = target.values
        for train_index, test_index in kf.split(train_processed):
            X_train, X_val = train_processed.iloc[train_index] , train_processed.iloc[test_inde
            y_train, y_val = target.iloc[train_index], target.iloc[test_index]

            training_block(X_train,y_train, X_val,y_val)
            prediction = Prediction_block(X_val)
            test_rmse_score, test_r2_score = accuracy(y_val, prediction)

            kf_rmse_list.append(test_rmse_score)
            kf_r2_list.append(test_r2_score)

            print("r2 list print", kf_r2_list)
            print('rmse list print',kf_rmse_list)

        print("r2 mean print", np.mean(kf_r2_list))
        print('rmse mean print', np.mean(kf_rmse_list))
```

11.0.1 Observation

In the cross validation section we can see that 10 fold cross validation on our best ANN model provides similar rmse to 80-20 split rmse score. So we can relay on 80-20 split on this dataset.

Thus we can say that the data in the dataset is independent.

12 Observing Few Other well performed ANN models

In this section We are observing the few other models and their learning curve. After that some of them will be used for Ensemble learning section for further improvement. In this model I have only changed the size of hidden layer, amount of neuron in each hidden layers , number of steps and learning rates. Rest of the part is same as the ANN described above.

12.1 ANN with 4 layers

12.1.1 Initialization of models

```
In [194]: tf.reset_default_graph()
          def weight_bais():
              global weights, biases
              weights = None
              biases = None

              weights = {
                  'w1': tf.Variable(tf.random_normal([input_dim, hidden_1])),
                  'w2': tf.Variable(tf.random_normal([hidden_1, hidden_2])),
                  'w3': tf.Variable(tf.random_normal([hidden_2, hidden_3])),
                  'w4': tf.Variable(tf.random_normal([hidden_3, hidden_4])),
                  'out': tf.Variable(tf.random_normal([hidden_4, output_dim]))
              }
              biases = {
                  'b1': tf.Variable(tf.random_normal([hidden_1])),
                  'b2': tf.Variable(tf.random_normal([hidden_2])),
                  'b3': tf.Variable(tf.random_normal([hidden_3])),
                  'b4': tf.Variable(tf.random_normal([hidden_4])),
                  'out': tf.Variable(tf.random_normal([output_dim]))
              }

In [195]: def ann_model(X_input):
            # Hidden layers
              layer_1 = tf.add(tf.matmul(X_input, weights['w1']), biases['b1'])
              layer_1 = tf.nn.relu(layer_1)


              layer_2 = tf.add(tf.matmul(layer_1, weights['w2']), biases['b2'])
              layer_2 = tf.nn.relu(layer_2)

              layer_3 = tf.add(tf.matmul(layer_2, weights['w3']), biases['b3'])
              layer_3 = tf.nn.relu(layer_3)

              layer_4 = tf.add(tf.matmul(layer_3, weights['w4']), biases['b4'])
              layer_4 = tf.nn.relu(layer_4)
```

```
        # Output layer
    #     layer_out = tf.add(tf.matmul(layer_4, weights['out']), biases['out'])
        layer_out = tf.matmul(layer_4, weights['out']) + biases['out']

        return layer_out

In [196]: regularizer_4 = None
    def miscellaneous_initialization():
        global model, loss , regularizer_1 , regularizer_2 ,regularizer_3, regularizer_4
        # Model Construct
        model = ann_model(X_tf)

        # Mean Squared Error loss function
        loss = tf.losses.mean_squared_error(y_tf , model , reduction=tf.losses.Reduction

        # loss = tf.square(y_tf - model)
        regularizer_1 = tf.nn.l2_loss(weights['w1'])
        regularizer_2 = tf.nn.l2_loss(weights['w2'])
        regularizer_3 = tf.nn.l2_loss(weights['w3'])
        regularizer_4 = tf.nn.l2_loss(weights['w4'])
        # loss = tf.reduce_mean(loss + beta1*regularizer_1 + beta2*regularizer_2 + beta3
        loss = tf.reduce_mean(loss + beta1*regularizer_1 + beta2*regularizer_2 + beta3*re

        # Adam optimizer will update weights and biases after each step
        optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimize(loss)


        # Initialize variables
        init = tf.global_variables_initializer()

        # Add ops to save and restore all the variables.
        saver = tf.train.Saver()
```

12.1.2 Training

ANN 1 In this section changed variables are

- learning rate = .01

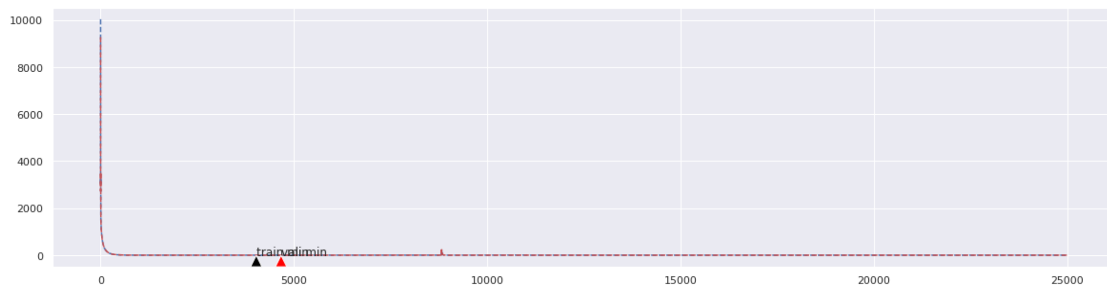
layer name	Neuron	value of beta for l2 regularization
1st hidden layer	76 Neuron	.1
2nd hidden layer	48 Neuron	.05
3rd hidden layer	32 Neuron	0
4th hidden layer	16 Neuron	0

```
In [159]: tf.reset_default_graph()
          learning_rate = 0.1
          num_steps = 25000
          #for regularize weight matrix
          beta1 = 0.1
          beta2 = 0.05
          beta3 = 0.0
          beta4 = 0.0

          hidden_1 = 76
          hidden_2 = 48
          hidden_3 = 32
          hidden_4 = 16

          minimum_validation_loss = .02101000

          input_dim = X_train.shape[1]  # Number of features
          output_dim = 1                # Because it is a regression problem

          #tf graph input
          X_tf = tf.placeholder("float" )
          y_tf = tf.placeholder("float" )

          weight_bais()
          miscellaneous_initialization()
          train_LC = []
          val_LC = []

In [160]: training_block(X_train,y_train, X_val,y_val)
          prediction = Prediction_block(X_val)
          test_rmse_score, test_r2_score = accuracy(y_val,prediction)

          print('ann root mean absolute error: ', test_rmse_score)
          print('accuracy score: ', test_r2_score  )


          pred_str = 'ANN_lr'+str(learning_rate)+'_beta'+str(beta1)+'-'+str(beta2)+'-'+str(beta
          prediction_dict[pred_str] = prediction

          if submit:
              submit_prediction = Prediction_block(test_processed)
              submit_prediction_dict[pred_str] = submit_prediction
          # Data Save
          if save_score:
              log_df = pd.read_csv("diffrent_training_results.csv")
              log_df = log_df.append({'learning_rate' : learning_rate, 'num_steps' : num_steps
              log_df.to_csv("diffrent_training_results.csv", encoding='utf-8',index=False)

epoch no :  500   training loss:  9.152113   validation loss:  9.282317    minimum_validation_
```

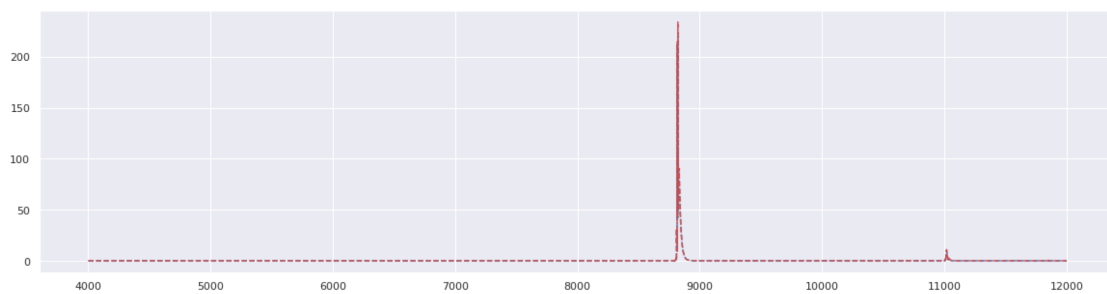
```
epoch no :  1000   training loss:  0.20901033   validation loss:  0.21484488    minimum_valida
epoch no :  1500   training loss:  0.015421187   validation loss:  0.021179948    minimum_vali
epoch no :  2000   training loss:  0.031186279   validation loss:  0.036941286    minimum_vali
epoch no :  2500   training loss:  0.036456764   validation loss:  0.040608026    minimum_vali
epoch no :  3000   training loss:  0.045841064   validation loss:  0.045596745    minimum_vali
epoch no :  3500   training loss:  0.044859868   validation loss:  0.050391782    minimum_vali
epoch no :  4000   training loss:  0.026860913   validation loss:  0.027717393    minimum_vali
epoch no :  4500   training loss:  0.030150548   validation loss:  0.033236805    minimum_vali
epoch no :  5000   training loss:  0.021404644   validation loss:  0.024278596    minimum_vali
epoch no :  5500   training loss:  0.029144902   validation loss:  0.030661756    minimum_vali
epoch no :  6000   training loss:  0.029466635   validation loss:  0.033032447    minimum_vali
epoch no :  6500   training loss:  0.019844215   validation loss:  0.02260698    minimum_valid
epoch no :  7000   training loss:  0.023882344   validation loss:  0.025650518    minimum_vali
epoch no :  7500   training loss:  0.01497797   validation loss:  0.01717949    minimum_valida
epoch no :  8000   training loss:  0.015116632   validation loss:  0.015919417    minimum_vali
epoch no :  8500   training loss:  0.046610758   validation loss:  0.04669931    minimum_valid
epoch no :  9000   training loss:  0.03208244   validation loss:  0.03291341    minimum_valida
epoch no :  9500   training loss:  0.020042604   validation loss:  0.020768417    minimum_vali
epoch no :  10000   training loss:  0.017044801   validation loss:  0.017798072    minimum_val
epoch no :  10500   training loss:  0.016078422   validation loss:  0.016857564    minimum_val
epoch no :  11000   training loss:  0.04538723   validation loss:  0.045280367    minimum_vali
epoch no :  11500   training loss:  0.015954424   validation loss:  0.01673365    minimum_vali
epoch no :  12000   training loss:  0.016400693   validation loss:  0.017110497    minimum_val
epoch no :  12500   training loss:  0.01605685   validation loss:  0.016832698    minimum_vali
epoch no :  13000   training loss:  0.015756901   validation loss:  0.016750978    minimum_val
epoch no :  13500   training loss:  0.0628026   validation loss:  0.060040284    minimum_valid
epoch no :  14000   training loss:  0.016080623   validation loss:  0.016726356    minimum_val
epoch no :  14500   training loss:  0.015788464   validation loss:  0.016408887    minimum_val
epoch no :  15000   training loss:  0.03230662   validation loss:  0.03283739    minimum_valid
epoch no :  15500   training loss:  0.016558437   validation loss:  0.017257947    minimum_val
epoch no :  16000   training loss:  0.13684726   validation loss:  0.13961771    minimum_valid
epoch no :  16500   training loss:  0.016089126   validation loss:  0.01659439    minimum_vali
epoch no :  17000   training loss:  0.023120107   validation loss:  0.02333483    minimum_vali
epoch no :  17500   training loss:  0.022086134   validation loss:  0.023336466    minimum_val
epoch no :  18000   training loss:  0.01629197   validation loss:  0.016958326    minimum_vali
epoch no :  18500   training loss:  0.038337227   validation loss:  0.037777074    minimum_val
epoch no :  19000   training loss:  0.018675286   validation loss:  0.019336913    minimum_val
epoch no :  19500   training loss:  0.032099687   validation loss:  0.032646105    minimum_val
epoch no :  20000   training loss:  0.05717164   validation loss:  0.05304123    minimum_valid
epoch no :  20500   training loss:  0.02153337   validation loss:  0.021556934    minimum_vali
epoch no :  21000   training loss:  0.019416448   validation loss:  0.019755969    minimum_val
epoch no :  21500   training loss:  0.016502503   validation loss:  0.017082477    minimum_val
epoch no :  22000   training loss:  0.016564125   validation loss:  0.017052336    minimum_val
epoch no :  22500   training loss:  0.019273043   validation loss:  0.019419659    minimum_val
epoch no :  23000   training loss:  0.06138438   validation loss:  0.06273346    minimum_valid
epoch no :  23500   training loss:  0.021176014   validation loss:  0.021865252    minimum_val
epoch no :  24000   training loss:  0.029864766   validation loss:  0.029751822    minimum_val
epoch no :  24500   training loss:  0.01791848   validation loss:  0.01821025    minimum_valid
```

```
epoch no :  25000   training loss:  0.020268222   validation loss:  0.020892637    minimum_val
Model saved in path: model/model.ckpt
INFO:tensorflow:Restoring parameters from model/model.ckpt
Model restored.
ann root mean absolute error:  0.10431903672428287
accuracy score:  0.935787050632608
```

In [161]:
```python
#Following variables are only used to zoom into the graph
start_observation_flag = 4000
end_observation_flag = 12000
learning_curve(start_observation_flag,end_observation_flag)
```



If we zoom into the curve we would have seen the following



Both of the curve actually seems to be on top of each other.The reason is: - I have applied log transformation on the SalePrice and I have also transformed all my numerical data thats why the difference between the training loss and validation loss seems to be very small and very stable. - For loss function I have used Mean Squared Error (MSE). For reducing MSE I have used SUM_BY_NONZERO_WEIGHTS which divided scalar sum by number of non-zero weights. MSE calculates squared error for all the data and then calculate the mean. Now, all my SalePrice is very small due to normalization (between 10 to 13.5). Where mean of saleprice is 12.02 . Suppose in nth epoch if - for training loss - a saleprice is 11.5 and prediction is 12 Squred error .25 - another saleprice is 13 and prediction is 12 Squred error 1 - another saleprice is 12.5 and prediction is 12 Squred error .25 - another saleprice is 11.5 and prediction is 12 Squred error .25 - another saleprice is 10.3 and prediction is 12 Squred error 1.7

```
  **MSE = (.25+1+.25+.25+1.7)/5 = .69**
- for validation loss
    - another saleprice is 12.9 and prediction is 12 Squred error .81
    - another saleprice is 13.3 and prediction is 12 Squred error 1.69
    - another saleprice is 10.8 and prediction is 12 Squred error 1.44
    - another saleprice is 11.3 and prediction is 12 Squred error .49
    - another saleprice is 11.8 and prediction is 12 Squred error .04

  **MSE = (.81+1.69+1.44+.49+.04)/5 = .894**

  **Difference between validation loss and training loss is .204**

Usually in regression problem neural network stats to predicts the average value within 5-20 ep
```

ANN 2 In this section changed variables are

- learning rate = .05

layer name	Neuron	value of beta for l2 regularization
1st hidden layer	8 Neuron	.005
2nd hidden layer	32 Neuron	.1
3rd hidden layer	16 Neuron	0.05
4th hidden layer	8 Neuron	0

In [168]:
```
tf.reset_default_graph()
learning_rate = 0.05
num_steps = 18000
#for regularize weight matrix
beta1 = 0.005
beta2 = 0.1
beta3 = 0.05
beta4 = 0.0

hidden_1 = 8
hidden_2 = 32
hidden_3 = 16
hidden_4 = 8


minimum_validation_loss = 0.02101000
#tf graph input
X_tf = tf.placeholder("float" )
y_tf = tf.placeholder("float" )

weight_bais()
miscellaneous_initialization()
```

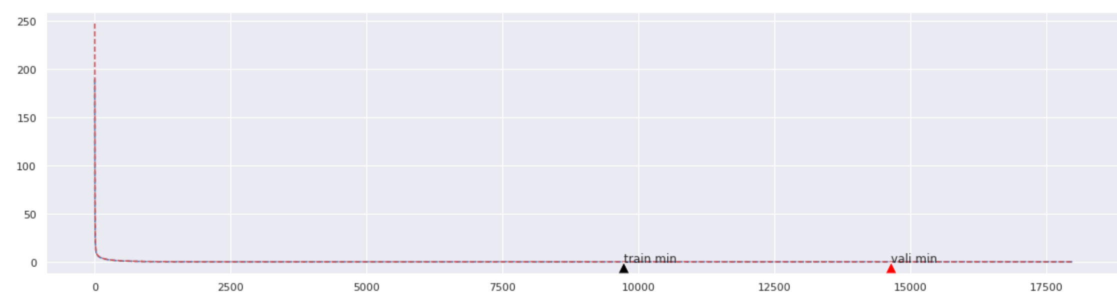
```
    train_LC = []
    val_LC = []
```

In [169]:
```
training_block(X_train,y_train, X_val,y_val)
prediction = Prediction_block(X_val)

test_rmse_score, test_r2_score = accuracy(y_val,prediction)

print('ann root mean absolute error: ', test_rmse_score)
print('accuracy score: ', test_r2_score  )
# learning_curve(start_observation_flag,end_observation_flag)



pred_str = 'ANN_lr'+str(learning_rate)+'_beta'+str(beta1)+'-'+str(beta2)+'-'+str(beta
prediction_dict[pred_str] = prediction

if submit:
    submit_prediction = Prediction_block(test_processed)
    submit_prediction_dict[pred_str] = submit_prediction
# Data Save
if save_score:
    log_df = pd.read_csv("diffrent_training_results.csv")
    log_df = log_df.append({'learning_rate' : learning_rate, 'num_steps' : num_steps
    log_df.to_csv("diffrent_training_results.csv", encoding='utf-8',index=False)
```

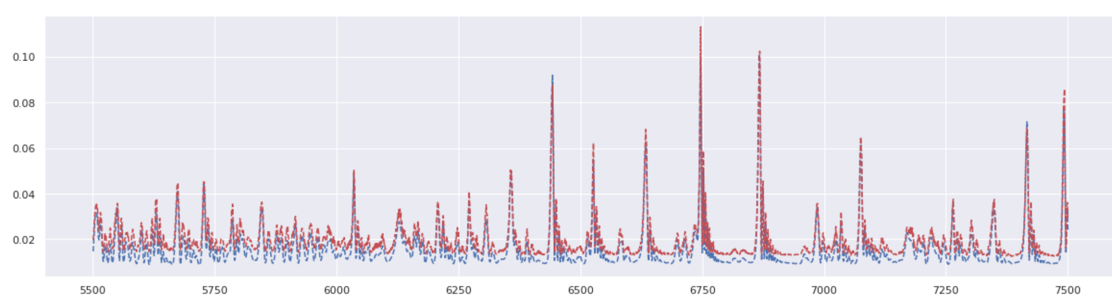
```
epoch no :  500   training loss:  0.858677   validation loss:  1.0680902     minimum_validation
epoch no :  1000   training loss:  0.19457059   validation loss:  0.27591604     minimum_valida
epoch no :  1500   training loss:  0.056262337   validation loss:  0.088357836     minimum_vali
epoch no :  2000   training loss:  0.023808574   validation loss:  0.053168852     minimum_vali
epoch no :  2500   training loss:  0.038034473   validation loss:  0.05537057     minimum_valid
epoch no :  3000   training loss:  0.012828972   validation loss:  0.026433188     minimum_vali
epoch no :  3500   training loss:  0.011956884   validation loss:  0.018907022     minimum_vali
epoch no :  4000   training loss:  0.019972812   validation loss:  0.023553263     minimum_vali
epoch no :  4500   training loss:  0.015091223   validation loss:  0.021799197     minimum_vali
epoch no :  5000   training loss:  0.0109840855   validation loss:  0.017916255     minimum_va
epoch no :  5500   training loss:  0.011670647   validation loss:  0.016786639     minimum_vali
epoch no :  6000   training loss:  0.011309172   validation loss:  0.015698181     minimum_vali
epoch no :  6500   training loss:  0.0128569   validation loss:  0.01618643     minimum_valida
epoch no :  7000   training loss:  0.016049678   validation loss:  0.020256797     minimum_vali
epoch no :  7500   training loss:  0.024060527   validation loss:  0.029733561     minimum_vali
epoch no :  8000   training loss:  0.009348931   validation loss:  0.012736999     minimum_vali
epoch no :  8500   training loss:  0.009557792   validation loss:  0.012734013     minimum_vali
epoch no :  9000   training loss:  0.009353697   validation loss:  0.012423373     minimum_vali
epoch no :  9500   training loss:  0.01617002   validation loss:  0.020691065     minimum_valid
epoch no :  10000   training loss:  0.011354242   validation loss:  0.01411328     minimum_vali
epoch no :  10500   training loss:  0.00948498   validation loss:  0.012290508     minimum_vali
epoch no :  11000   training loss:  0.009360763   validation loss:  0.012211295     minimum_va
```

```
epoch no :  11500   training loss:  0.03543232   validation loss:  0.0389947     minimum_valida
epoch no :  12000   training loss:  0.009026674   validation loss:  0.011942493     minimum_val
epoch no :  12500   training loss:  0.009235658   validation loss:  0.012067157     minimum_val
epoch no :  13000   training loss:  0.02113555   validation loss:  0.024711037     minimum_vali
epoch no :  13500   training loss:  0.009110574   validation loss:  0.011884684     minimum_val
epoch no :  14000   training loss:  0.009099278   validation loss:  0.011859325     minimum_val
epoch no :  14500   training loss:  0.009175062   validation loss:  0.011862187     minimum_val
epoch no :  15000   training loss:  0.009238499   validation loss:  0.011869497     minimum_val
epoch no :  15500   training loss:  0.009133968   validation loss:  0.011847739     minimum_val
epoch no :  16000   training loss:  0.01837526   validation loss:  0.021710504     minimum_vali
epoch no :  16500   training loss:  0.024972733   validation loss:  0.02604511     minimum_vali
epoch no :  17000   training loss:  0.009292025   validation loss:  0.011861078     minimum_val
epoch no :  17500   training loss:  0.009344881   validation loss:  0.011870008     minimum_val
epoch no :  18000   training loss:  0.009388268   validation loss:  0.011879217     minimum_val
Model saved in path: model/model.ckpt
INFO:tensorflow:Restoring parameters from model/model.ckpt
Model restored.
ann root mean absolute error:  0.10471841274035745
accuracy score:  0.9352944425199636
```

In [170]:
```
#Following variables are only used to zoom into the graph
start_observation_flag = 5500
end_observation_flag = 7500
learning_curve(start_observation_flag,end_observation_flag)
```



If we zoom into the curve we would have seen the following



ANN 3

- learning rate = .05

layer name	Neuron	value of beta for l2 regularization
1st hidden layer	16 Neuron	.1
2nd hidden layer	8 Neuron	.0
3rd hidden layer	4 Neuron	0.0
4th hidden layer	2 Neuron	0

In [171]:
```
tf.reset_default_graph()
learning_rate = 0.05
num_steps = 15000
#for regularize weight matrix
beta1 = 0.1
beta2 = 0.0
beta3 = 0.0
beta4 = 0.0

hidden_1 = 16
hidden_2 = 8
hidden_3 = 4
hidden_4 = 2

minimum_validation_loss = 0.01901000

#tf graph input
X_tf = tf.placeholder("float" )
y_tf = tf.placeholder("float" )


weight_bais()
miscellaneous_initialization()
train_LC = []
val_LC = []
```

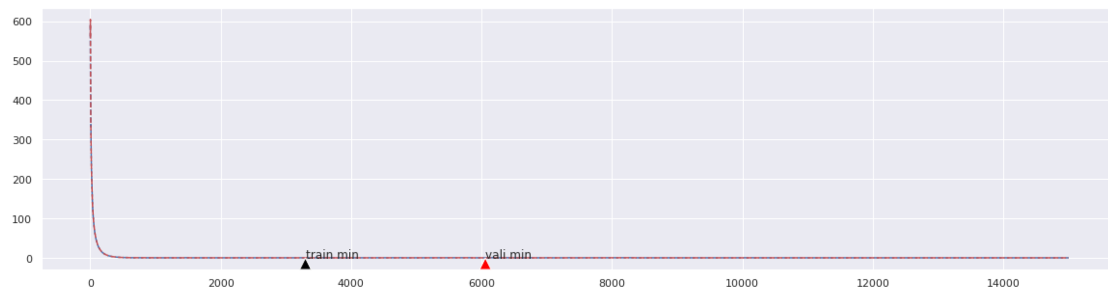
In [172]:
```
training_block(X_train,y_train, X_val,y_val)
prediction = Prediction_block(X_val)
test_rmse_score, test_r2_score = accuracy(y_val,prediction)

print('ann root mean absolute error: ', test_rmse_score)
print('accuracy score: ', test_r2_score  )
# learning_curve(start_observation_flag,end_observation_flag)
```

```python
        pred_str = 'ANN_lr'+str(learning_rate)+'_beta'+str(beta1)+'-'+str(beta2)+'-'+str(beta
        prediction_dict[pred_str] = prediction

        if submit:
            submit_prediction = Prediction_block(test_processed)
            submit_prediction_dict[pred_str] = submit_prediction
        # Data Save
        if save_score:
            log_df = pd.read_csv("diffrent_training_results.csv")
            log_df = log_df.append({'learning_rate' : learning_rate,
                                    'num_steps' : num_steps, 'beta1' : beta1,
                                    'beta2' : beta2, 'beta3' : beta3, 'beta4' : beta4,
                                    'hidden_1' : hidden_1 , 'hidden_2' : hidden_2,
                                    'hidden_3' : hidden_3, 'hidden_4' : hidden_4, 'input_dim
                                    'test_rmse_score' : test_rmse_score ,
                                    'test_r2_score' : test_r2_score}, ignore_index=True)

            log_df.to_csv("diffrent_training_results.csv", encoding='utf-8',index=False)
```

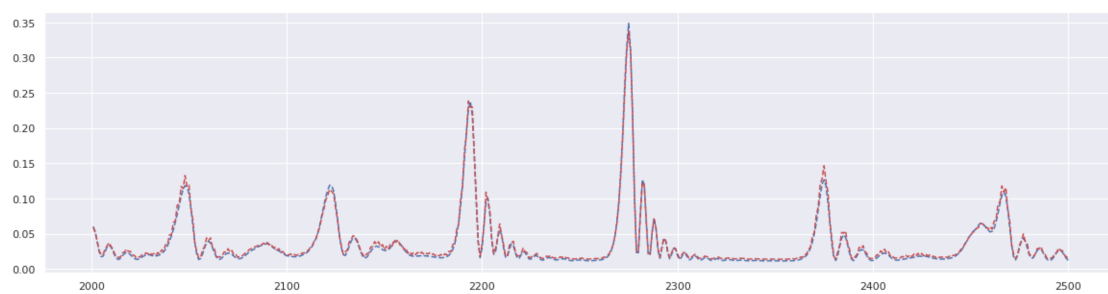
```
epoch no :  500   training loss:  0.8051993   validation loss:  0.8233882    minimum_validati
epoch no :  1000   training loss:  0.041415274   validation loss:  0.04464606    minimum_valic
epoch no :  1500   training loss:  0.01773881   validation loss:  0.02033381    minimum_valida
epoch no :  2000   training loss:  0.055215415   validation loss:  0.055317916    minimum_vali
epoch no :  2500   training loss:  0.01211351   validation loss:  0.014712055    minimum_valic
epoch no :  3000   training loss:  0.016350279   validation loss:  0.01753673    minimum_valic
epoch no :  3500   training loss:  0.052965235   validation loss:  0.05895138    minimum_valic
epoch no :  4000   training loss:  0.034773506   validation loss:  0.03464886    minimum_valic
epoch no :  4500   training loss:  0.074005865   validation loss:  0.07142498    minimum_valic
epoch no :  5000   training loss:  0.011805618   validation loss:  0.0138990125    minimum_val
epoch no :  5500   training loss:  0.026722787   validation loss:  0.0251929    minimum_valida
epoch no :  6000   training loss:  0.011427861   validation loss:  0.012761667    minimum_vali
epoch no :  6500   training loss:  0.011737584   validation loss:  0.013099316    minimum_vali
epoch no :  7000   training loss:  0.0116049135   validation loss:  0.01293156    minimum_vali
epoch no :  7500   training loss:  0.011552845   validation loss:  0.012831639    minimum_vali
epoch no :  8000   training loss:  0.011872286   validation loss:  0.0129264165    minimum_val
epoch no :  8500   training loss:  0.011618454   validation loss:  0.01287984    minimum_valic
epoch no :  9000   training loss:  0.011831014   validation loss:  0.012924822    minimum_vali
epoch no :  9500   training loss:  0.012194977   validation loss:  0.013351733    minimum_vali
epoch no :  10000   training loss:  0.0118733365   validation loss:  0.013090014    minimum_va
epoch no :  10500   training loss:  0.022951428   validation loss:  0.023219427    minimum_val
epoch no :  11000   training loss:  0.012433318   validation loss:  0.013954848    minimum_val
epoch no :  11500   training loss:  0.012077246   validation loss:  0.013398168    minimum_val
epoch no :  12000   training loss:  0.012073018   validation loss:  0.013236819    minimum_val
epoch no :  12500   training loss:  0.0147935245   validation loss:  0.017076118    minimum_va
epoch no :  13000   training loss:  0.012205046   validation loss:  0.013332042    minimum_val
epoch no :  13500   training loss:  0.012454445   validation loss:  0.013402608    minimum_val
epoch no :  14000   training loss:  0.012344656   validation loss:  0.013443576    minimum_val
epoch no :  14500   training loss:  0.012451554   validation loss:  0.013514027    minimum_val
```

```
epoch no :  15000   training loss:  0.012652044   validation loss:  0.013669206    minimum_val
Model saved in path: model/model.ckpt
INFO:tensorflow:Restoring parameters from model/model.ckpt
Model restored.
ann root mean absolute error:  0.10428013476436891
accuracy score:  0.9358349334331041
```

In [173]:
```
#Following variables are only used to zoom into the graph
start_observation_flag = 2000
end_observation_flag = 2500
learning_curve(start_observation_flag,end_observation_flag)
```




```
If we zoom into the curve we would have seen the following
```



12.1.3 Description on Learning curve and Accuracy:

We can observe where overfitting occurs. Overfitting actually occurs if the training loss goes under the validation loss even though the validation is still dropping. It is the sign that network is learning the patterns in the train set that are not applicable in the validation done. In a short note we can say::

Overfitting : training loss << validation loss
Underfitting : training loss >> validation loss

Just right : training loss ~ validation loss

According to this theory, for ANN 1,2 and 3 our both learning curve (validation loss and training loss) is exactly top of one another so in our case validation loss and training loss is almost same so we can say that our model is doing just the right thing. Again In validation score .11,.1081 and .1050 is impressive compared to other models.

Both of the curve actually seems to be on top of each other.The reason is: - I have applied log transformation on the SalePrice and I have also transformed all my numerical data thats why the difference between the training loss and validation loss seems to be very small and very stable. - For loss function I have used Mean Squared Error (MSE). For reducing MSE I have used SUM_BY_NONZERO_WEIGHTS which divided scalar sum by number of non-zero weights. MSE calculates squared error for all the data and then calculate the mean. Now, all my SalePrice is very small due to normalization (between 10 to 13.5). Where mean of saleprice is 12.02 . Suppose in nth epoch if - for training loss - a saleprice is 11.5 and prediction is 12 Squred error .25 - another saleprice is 13 and prediction is 12 Squred error 1 - another saleprice is 12.5 and prediction is 12 Squred error .25 - another saleprice is 11.5 and prediction is 12 Squred error .25 - another saleprice is 10.3 and prediction is 12 Squred error 1.7

```
  **MSE = (.25+1+.25+.25+1.7)/5 = .69**
- for validation loss
    - another saleprice is 12.9 and prediction is 12 Squred error .81
    - another saleprice is 13.3 and prediction is 12 Squred error 1.69
    - another saleprice is 10.8 and prediction is 12 Squred error 1.44
    - another saleprice is 11.3 and prediction is 12 Squred error .49
    - another saleprice is 11.8 and prediction is 12 Squred error .04

  **MSE = (.81+1.69+1.44+.49+.04)/5 = .894**

  **Difference between validation loss and training loss is .204**

Usually in regression problem neural network stats to predicts the average value within 5-20 ep
```

12.2 ANN single hidden layer

```
In [197]: tf.reset_default_graph()
          def weight_bais():
              global weights, biases
              weights = {
                  'w1': tf.Variable(tf.random_normal([input_dim, hidden_1])),
                  'out': tf.Variable(tf.random_normal([hidden_1, output_dim]))
              }
              biases = {
                  'b1': tf.Variable(tf.random_normal([hidden_1])),
                  'out': tf.Variable(tf.random_normal([output_dim]))
              }
```

```
In [198]: def ann_model(X_input):
            # Hidden layers
              layer_1 = tf.add(tf.matmul(X_input, weights['w1']), biases['b1'])
```

```
        layer_1 = tf.nn.relu(layer_1)

        # Output layer
        layer_out = tf.matmul(layer_1, weights['out'])+ biases['out']

        return layer_out
```

```
In [199]: def miscellaneous_initialization():
        global model, loss , regularizer_1 , regularizer_2 ,regularizer_3, regularizer_4
        # Model Construct
        model = ann_model(X_tf)

        # Mean Squared Error loss function
        loss = tf.losses.mean_squared_error(y_tf , model , reduction=tf.losses.Reduction

        # loss = tf.square(y_tf - model)
        regularizer_1 = tf.nn.l2_loss(weights['w1'])

        # loss = tf.reduce_mean(loss + beta1*regularizer_1 + beta2*regularizer_2 + beta3
        loss = tf.reduce_mean(loss + beta1*regularizer_1 )

        # Adam optimizer will update weights and biases after each step
        optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimize(loss)


        # Initialize variables
        init = tf.global_variables_initializer()

        # Add ops to save and restore all the variables.
        saver = tf.train.Saver()
```

ANN 4

- learning rate = .1

layer name	Neuron	value of beta for l2 regularization
1st hidden layer	16 Neuron	.1

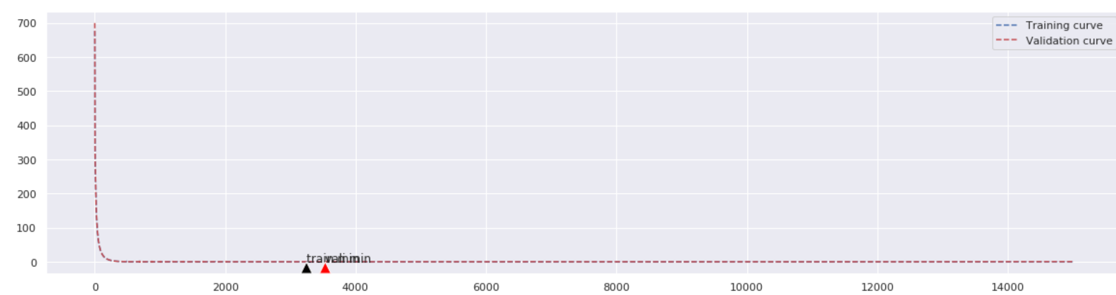
```
In [200]: tf.reset_default_graph()
        learning_rate = 0.1
        num_steps = 15000
        #for regularize weight matrix
        beta1 = 0.1
        beta2 = None
        beta3 = None
        beta4 = None
```

```
        minimum_validation_loss = 0.01901000
        hidden_1 = 16
        hidden_2 = None
        hidden_3 = None
        hidden_4 = None

        #tf graph input
        X_tf = tf.placeholder("float" )
        y_tf = tf.placeholder("float" )

        weight_bais()
        miscellaneous_initialization()
        train_LC = []
        val_LC = []
        training_block(X_train,y_train, X_val,y_val)
        prediction = Prediction_block(X_val)

        test_rmse_score, test_r2_score = accuracy(y_val,prediction)

        print('ann root mean absolute error: ', test_rmse_score)
        print('accuracy score: ', test_r2_score  )
        # learning_curve(start_observation_flag,end_observation_flag)


        pred_str = 'ANN_lr'+str(learning_rate)+'_beta'+str(beta1)+'-'+str(beta2)+'-'+str(beta
        prediction_dict[pred_str] = prediction

        if submit:
            submit_prediction = Prediction_block(test_processed)
            submit_prediction_dict[pred_str] = submit_prediction
        # Data Save
        if save_score:
            log_df = pd.read_csv("diffrent_training_results.csv")
            log_df = log_df.append({'learning_rate' : learning_rate, 'num_steps' : num_steps
            log_df.to_csv("diffrent_training_results.csv", encoding='utf-8',index=False)
```

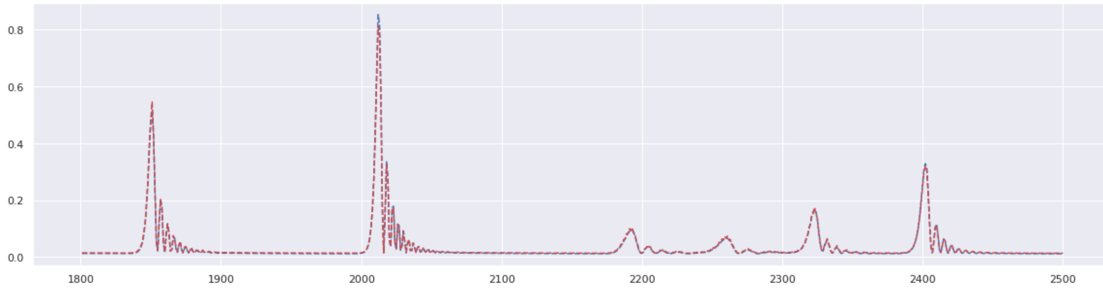
```
epoch no :  500   training loss:  0.34714127   validation loss:  0.3548761     minimum_validat
epoch no :  1000   training loss:  0.023464948   validation loss:  0.026027663     minimum_vali
epoch no :  1500   training loss:  0.01376116   validation loss:  0.015662506     minimum_valid
epoch no :  2000   training loss:  0.013004313   validation loss:  0.014583082     minimum_vali
epoch no :  2500   training loss:  0.011678733   validation loss:  0.013094134     minimum_vali
epoch no :  3000   training loss:  0.012384469   validation loss:  0.013858578     minimum_vali
epoch no :  3500   training loss:  0.01125925   validation loss:  0.012632536     minimum_valid
epoch no :  4000   training loss:  0.011583656   validation loss:  0.012851575     minimum_vali
epoch no :  4500   training loss:  0.01272952   validation loss:  0.013702571     minimum_valid
epoch no :  5000   training loss:  0.013044822   validation loss:  0.014216593     minimum_vali
epoch no :  5500   training loss:  0.012616895   validation loss:  0.0136147775     minimum_val
epoch no :  6000   training loss:  0.057354417   validation loss:  0.055700462     minimum_vali
```

```
epoch no :  6500   training loss:  0.013198766   validation loss:  0.0141413    minimum_valida
epoch no :  7000   training loss:  0.020514766   validation loss:  0.020146115    minimum_vali
epoch no :  7500   training loss:  0.0141318105   validation loss:  0.015031102    minimum_val
epoch no :  8000   training loss:  0.014284478   validation loss:  0.0151082575    minimum_val
epoch no :  8500   training loss:  0.014975703   validation loss:  0.016147537    minimum_vali
epoch no :  9000   training loss:  0.015131135   validation loss:  0.015874717    minimum_vali
epoch no :  9500   training loss:  0.015230439   validation loss:  0.015854543    minimum_vali
epoch no :  10000   training loss:  0.015886972   validation loss:  0.016589927    minimum_val
epoch no :  10500   training loss:  0.017099733   validation loss:  0.01793857    minimum_vali
epoch no :  11000   training loss:  0.015836148   validation loss:  0.016567234    minimum_val
epoch no :  11500   training loss:  0.016560555   validation loss:  0.017138269    minimum_val
epoch no :  12000   training loss:  0.01610707   validation loss:  0.016827483    minimum_vali
epoch no :  12500   training loss:  0.01644624   validation loss:  0.017276492    minimum_vali
epoch no :  13000   training loss:  0.021369023   validation loss:  0.022295065    minimum_val
epoch no :  13500   training loss:  0.020275114   validation loss:  0.02075468    minimum_vali
epoch no :  14000   training loss:  0.016651899   validation loss:  0.017373886    minimum_val
epoch no :  14500   training loss:  0.017634317   validation loss:  0.01843547    minimum_vali
epoch no :  15000   training loss:  0.45153534   validation loss:  0.43919736    minimum_valid
Model saved in path: model/model.ckpt
INFO:tensorflow:Restoring parameters from model/model.ckpt
Model restored.
ann root mean absolute error:  0.10432955692714682
accuracy score:  0.9357740986856268
```

In [201]:
```
#Following variables are only used to zoom into the graph
start_observation_flag = 1800
end_observation_flag = 2500
learning_curve(start_observation_flag,end_observation_flag)
```



If we zoom into the curve we would have seen the following



ANN 5

- learning rate = .1

layer name	Neuron	value of beta for l2 regularization
1st hidden layer	4 Neuron	.1

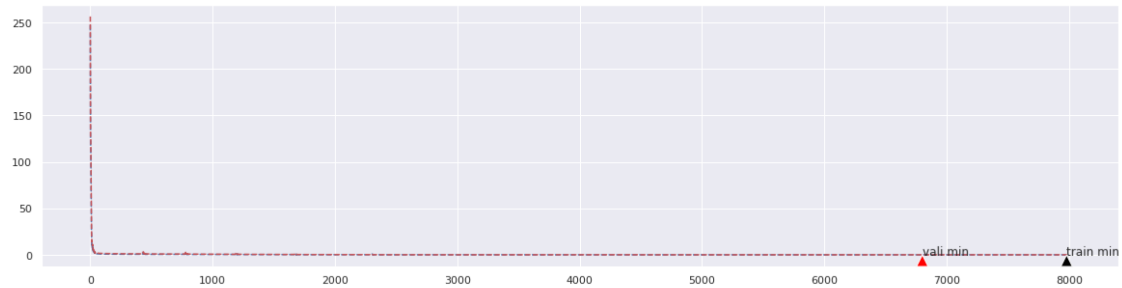
In [149]:
```
tf.reset_default_graph()
learning_rate = 0.1
num_steps = 8000
#for regularize weight matrix
beta1 = 0
beta2 = None
beta3 = None
beta4 = None

hidden_1 = 4
hidden_2 = None
hidden_3 = None
hidden_4 = None
minimum_validation_loss = 0.1701000
#tf graph input
X_tf = tf.placeholder("float" )
y_tf = tf.placeholder("float" )


weight_bais()
miscellaneous_initialization()
train_LC = []
val_LC = []
```

In [150]:
```
training_block(X_train,y_train, X_val,y_val)
prediction = Prediction_block(X_val)
```

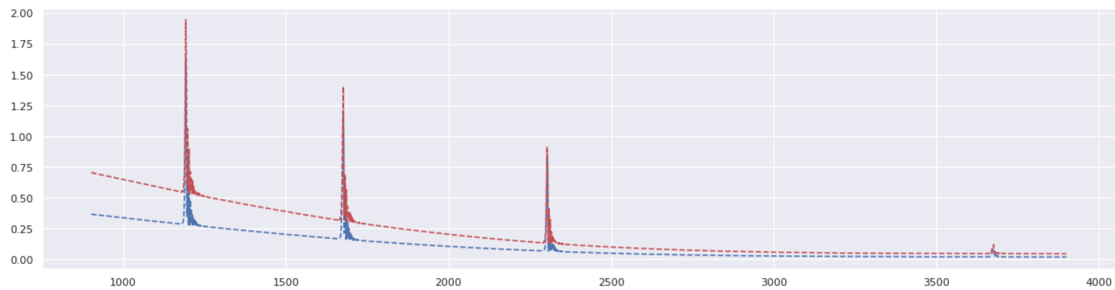
```
test_rmse_score, test_r2_score = accuracy(y_val,prediction)

print('ann root mean absolute error: ', test_rmse_score)
print('accuracy score: ', test_r2_score  )
# learning_curve(start_observation_flag,end_observation_flag)

pred_str = 'ANN_lr'+str(learning_rate)+'_beta'+str(beta1)+'-'+str(beta2)+'-'+str(beta
prediction_dict[pred_str] = prediction

if submit:
    submit_prediction = Prediction_block(test_processed)
    submit_prediction_dict[pred_str] = submit_prediction
# Data Save
if save_score:
    log_df = pd.read_csv("diffrent_training_results.csv")
    log_df = log_df.append({'learning_rate' : learning_rate, 'num_steps' : num_steps
    log_df.to_csv("diffrent_training_results.csv", encoding='utf-8',index=False)
```

```
epoch no :  500   training loss:  0.48890418   validation loss:  0.9536614     minimum_validat
epoch no :  1000   training loss:  0.33397388   validation loss:  0.64465207     minimum_valida
epoch no :  1500   training loss:  0.19940132   validation loss:  0.3847879     minimum_valida
epoch no :  2000   training loss:  0.10171368   validation loss:  0.19967784     minimum_valida
epoch no :  2500   training loss:  0.04576936   validation loss:  0.09630603     minimum_valida
epoch no :  3000   training loss:  0.023093684   validation loss:  0.05485344     minimum_valic
epoch no :  3500   training loss:  0.016941296   validation loss:  0.043713126     minimum_vali
epoch no :  4000   training loss:  0.014740163   validation loss:  0.0418022     minimum_valida
epoch no :  4500   training loss:  0.013993759   validation loss:  0.043727703     minimum_vali
epoch no :  5000   training loss:  0.012997501   validation loss:  0.043349016     minimum_vali
epoch no :  5500   training loss:  0.012286962   validation loss:  0.045035917     minimum_vali
epoch no :  6000   training loss:  0.011522833   validation loss:  0.046099808     minimum_vali
epoch no :  6500   training loss:  0.011154574   validation loss:  0.045007776     minimum_vali
epoch no :  7000   training loss:  0.010125614   validation loss:  0.04142383     minimum_valic
epoch no :  7500   training loss:  0.009870764   validation loss:  0.044705044     minimum_vali
epoch no :  8000   training loss:  0.009796628   validation loss:  0.048616253     minimum_vali
Model saved in path: model/model.ckpt
INFO:tensorflow:Restoring parameters from model/model.ckpt
Model restored.
ann root mean absolute error:  0.2001180824213444
accuracy score:  0.76369759208987
```

In [151]:
```
#Following variables are only used to zoom into the graph
start_observation_flag = 900
end_observation_flag = 3900
learning_curve(start_observation_flag,end_observation_flag)
```




```
If we zoom into the curve we would have seen the following
```



ANN 6

- learning rate = .1

layer name	Neuron	value of beta for l2 regularization
1st hidden layer	2 Neuron	.1

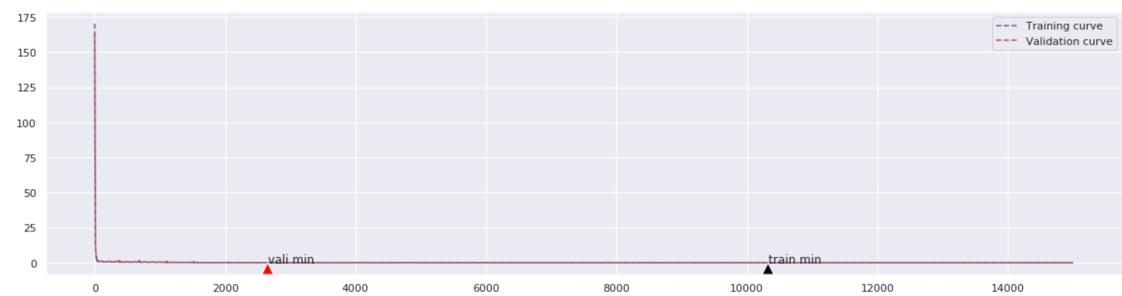
In [207]:
```
tf.reset_default_graph()
learning_rate = 0.1
num_steps = 15000
#for regularize weight matrix
beta1 = 0
beta2 = None
beta3 = None
beta4 = None

hidden_1 = 2
hidden_2 = None
hidden_3 = None
```

```
hidden_4 = None
minimum_validation_loss = 0.01901000
#tf graph input
X_tf = tf.placeholder("float" )
y_tf = tf.placeholder("float" )


weight_bais()
miscellaneous_initialization()
train_LC = []
val_LC = []
```

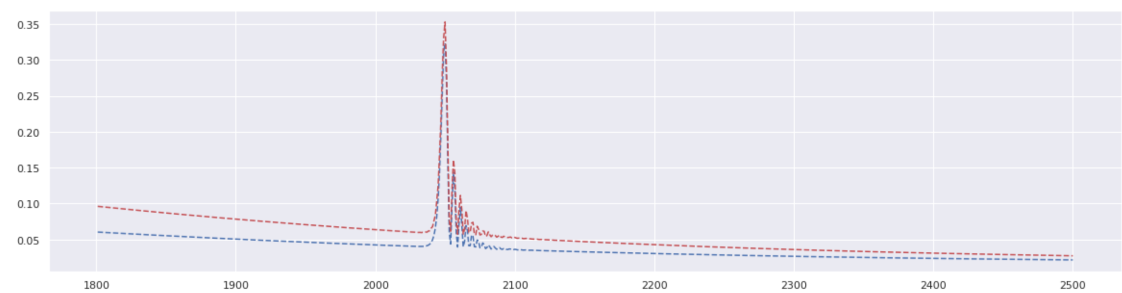
In [208]:
```
training_block(X_train,y_train, X_val,y_val)
prediction = Prediction_block(X_val)

test_rmse_score, test_r2_score = accuracy(y_val,prediction)

print('ann root mean absolute error: ', test_rmse_score)
print('accuracy score: ', test_r2_score  )
learning_curve(start_observation_flag,end_observation_flag)

pred_str = 'ANN_lr'+str(learning_rate)+'_beta'+str(beta1)+'-'+str(beta2)+'-'+str(beta
prediction_dict[pred_str] = prediction

if submit:
    submit_prediction = Prediction_block(test_processed)
    submit_prediction_dict[pred_str] = submit_prediction
# Data Save
if save_score:
    log_df = pd.read_csv("diffrent_training_results.csv")
    log_df = log_df.append({'learning_rate' : learning_rate, 'num_steps' : num_steps
    log_df.to_csv("diffrent_training_results.csv", encoding='utf-8',index=False)
```

```
epoch no :  500   training loss:  0.3733865   validation loss:  0.68490076     minimum_validat
epoch no :  1000   training loss:  0.21507877   validation loss:  0.38549396     minimum_valida
epoch no :  1500   training loss:  0.10218448   validation loss:  0.1728542     minimum_valida
epoch no :  2000   training loss:  0.042495888   validation loss:  0.063744135     minimum_val
epoch no :  2500   training loss:  0.021686587   validation loss:  0.027390916     minimum_val
epoch no :  3000   training loss:  0.008313624   validation loss:  0.012764412     minimum_val
epoch no :  3500   training loss:  0.008033975   validation loss:  0.01344995     minimum_vali
epoch no :  4000   training loss:  0.0078740325   validation loss:  0.013511795     minimum_va
epoch no :  4500   training loss:  0.0077958964   validation loss:  0.0142271     minimum_vali
epoch no :  5000   training loss:  0.0078065745   validation loss:  0.01516812     minimum_val
epoch no :  5500   training loss:  0.007635134   validation loss:  0.0144163845     minimum_va
epoch no :  6000   training loss:  0.0075642723   validation loss:  0.014529677     minimum_va
epoch no :  6500   training loss:  0.007484064   validation loss:  0.014629308     minimum_val
epoch no :  7000   training loss:  0.007393823   validation loss:  0.01463749     minimum_vali
epoch no :  7500   training loss:  0.0073258895   validation loss:  0.01472084     minimum_val
```

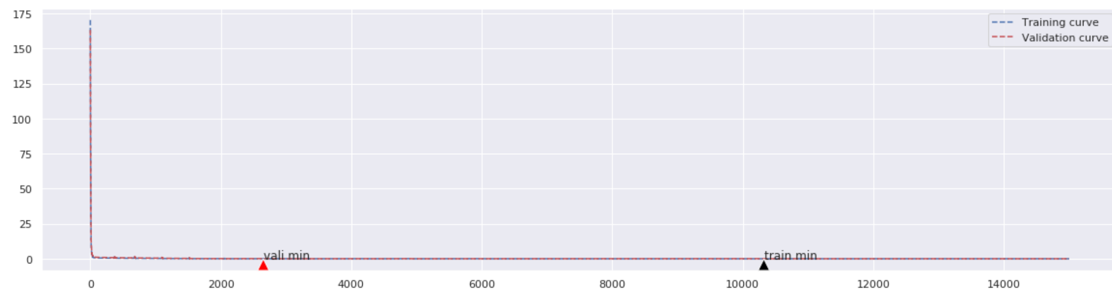
```
epoch no :  8000   training loss:  0.0073102415   validation loss:  0.014398632    minimum_val
epoch no :  8500   training loss:  0.01326747   validation loss:  0.018364793    minimum_valid
epoch no :  9000   training loss:  0.00742185   validation loss:  0.014600638    minimum_valid
epoch no :  9500   training loss:  0.0073330253   validation loss:  0.014210697    minimum_val
epoch no :  10000   training loss:  0.008513629   validation loss:  0.014270885    minimum_val
epoch no :  10500   training loss:  0.0076290607   validation loss:  0.014686921    minimum_va
epoch no :  11000   training loss:  0.0072874664   validation loss:  0.013761475    minimum_va
epoch no :  11500   training loss:  0.0073771123   validation loss:  0.014172848    minimum_va
epoch no :  12000   training loss:  0.007420873   validation loss:  0.013876043    minimum_val
epoch no :  12500   training loss:  0.0074282675   validation loss:  0.014320198    minimum_va
epoch no :  13000   training loss:  0.013997464   validation loss:  0.023341306    minimum_val
epoch no :  13500   training loss:  0.011889822   validation loss:  0.02063026    minimum_vali
epoch no :  14000   training loss:  0.007521436   validation loss:  0.014024526    minimum_val
epoch no :  14500   training loss:  0.0073499237   validation loss:  0.013574399    minimum_va
epoch no :  15000   training loss:  0.007269586   validation loss:  0.013766377    minimum_val
Model saved in path: model/model.ckpt
INFO:tensorflow:Restoring parameters from model/model.ckpt
Model restored.
ann root mean absolute error:  0.11212145456855784
accuracy score:  0.9258223742903477
```



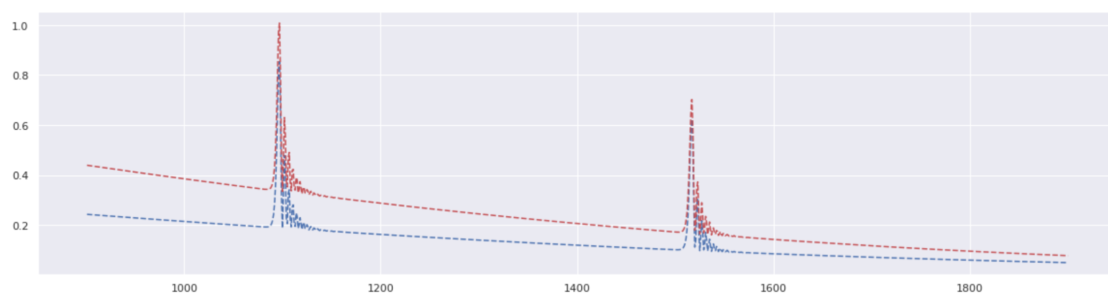
If we zoom into the curve we would have seen the following



```
In [209]: #Following variables are only used to zoom into the graph
          start_observation_flag = 900
          end_observation_flag = 1900
          learning_curve(start_observation_flag,end_observation_flag)
```




```
If we zoom into the curve we would have seen the following
```



12.2.1 Description on Learning curve and Accuracy:

We can observe where overfitting occurs. Overfitting actually occurs if the training loss goes under the validation loss even though the validation is still dropping. It is the sign that network is learning the patterns in the train set that are not applicable in the validation done. In a short note we can say::

Overfitting : training loss << validation loss

Underfitting : training loss >> validation loss

Just right : training loss ~ validation loss

According to this theory, for ANN 4 our both learning curve (validation loss and training loss) is exactly top of one another so in our case validation loss and training loss is almost same so we can say that our model is doing just the right thing. Again In validation score .1059 is impressive compared to other models.

But for ANN 5 and 6 training loss << validation loss so we can say that this two model overfit data due to lower amount of neuron but ANN 4 have just the right amount of neuron thats why with similar parameter this overfit occered.

Sometimes Both of the curve actually seems to be on top of each other.The reason is: - I have applied log transformation on the SalePrice and I have also transformed all my numerical data thats why the difference between the training loss and validation loss seems to be very small and very stable. - For loss function I have used Mean Squared Error (MSE). For reducing MSE I have used SUM_BY_NONZERO_WEIGHTS which divided scalar sum by number of non-zero weights. MSE calculates squared error for all the data and then calculate the mean. Now, all my SalePrice is very small due to normalization (between 10 to 13.5). Where mean of saleprice is 12.02 . Suppose in nth epoch if - for training loss - a saleprice is 11.5 and prediction is 12 Squred error .25 - another saleprice is 13 and prediction is 12 Squred error 1 - another saleprice is 12.5 and prediction is 12 Squred error .25 - another saleprice is 11.5 and prediction is 12 Squred error .25 - another saleprice is 10.3 and prediction is 12 Squred error 1.7

```
  **MSE = (.25+1+.25+.25+1.7)/5 = .69**
- for validation loss
    - another saleprice is 12.9 and prediction is 12 Squred error .81
    - another saleprice is 13.3 and prediction is 12 Squred error 1.69
    - another saleprice is 10.8 and prediction is 12 Squred error 1.44
    - another saleprice is 11.3 and prediction is 12 Squred error .49
    - another saleprice is 11.8 and prediction is 12 Squred error .04

  **MSE = (.81+1.69+1.44+.49+.04)/5 = .894**

  **Difference between validation loss and training loss is .204**
```

```
Usually in regression problem neural network stats to predicts the average value within 5-20 ep
```

12.2.2 Hyperparameeter tuning

Few of my hyperparameeter tuning is shown in the following block. In this data if a hidden layer value is 0 then it means that the hidden layer is turned off. For example if hidden_3 = 0 then that means hidden layer 3 is removed from the model and the model have only 2 hidden layer. And all the score is done on a validation set which is not seen by the model while training. For most of the case it was a 80-20 split. In the following results I didint kept any cross validation results but I have used diffrent seed while splitting data due to diffrent seed sometimes good hyperparameeter also provided so so accuracy.

```
In [1]: import pandas as pd
        log_df = pd.read_csv("diffrent_training_results.csv")
        # print(log_df.to_string())
        pd.set_option('display.max_rows', None)
        log_df
```

Out[1]:

	learning_rate	num_steps	beta1	beta2	beta3	hidden_1	hidden_2 \
0	0.050	7500.0	0.005	0.0050	0.005000	16.0	8.0
1	0.040	2500.0	0.005	0.0050	0.005000	16.0	8.0
2	0.050	7500.0	0.005	0.0050	0.005000	16.0	8.0
3	0.050	7500.0	0.005	0.0050	0.005000	16.0	8.0
4	0.050	7500.0	0.005	0.0050	0.005000	16.0	8.0
5	0.050	7900.0	0.005	0.0050	0.005000	16.0	8.0

6	0.050	1500.0	0.005	0.0050	0.005000	16.0	8.0
7	0.050	1500.0	0.005	0.0050	0.005000	16.0	8.0
8	0.050	7500.0	0.005	0.0050	0.005000	16.0	8.0
9	0.050	7500.0	0.005	0.0050	0.005000	16.0	8.0
10	0.100	7500.0	0.005	0.0050	0.005000	16.0	8.0
11	0.100	7500.0	0.005	0.0050	0.005000	16.0	8.0
12	0.010	7500.0	0.005	0.0050	0.005000	16.0	8.0
13	0.010	7500.0	0.005	0.0050	0.005000	16.0	8.0
14	0.010	7500.0	0.005	0.0050	0.005000	16.0	8.0
15	0.100	3500.0	0.005	0.0050	0.005000	16.0	8.0
16	0.100	2800.0	0.005	0.0050	0.005000	16.0	8.0
17	0.100	2500.0	0.005	0.0050	0.005000	16.0	8.0
18	0.100	8500.0	0.005	0.0050	0.005000	16.0	8.0
19	0.050	8500.0	0.005	0.0050	0.005000	16.0	8.0
20	0.100	2500.0	0.005	0.0050	0.005000	16.0	8.0
21	0.100	9500.0	0.005	0.0050	0.005000	16.0	8.0
22	0.001	9500.0	0.005	0.0050	0.005000	16.0	8.0
23	0.005	9500.0	0.005	0.0050	0.005000	16.0	8.0
24	0.100	7500.0	0.005	0.0050	0.005000	16.0	8.0
25	0.100	12500.0	0.005	0.0050	0.005000	16.0	8.0
26	0.100	11500.0	0.005	0.0050	0.005000	16.0	8.0
27	0.050	11500.0	0.005	0.0050	0.005000	16.0	8.0
28	0.050	11000.0	0.005	0.0050	0.005000	16.0	8.0
29	0.050	11000.0	0.005	0.0050	0.005000	16.0	8.0
30	0.050	11000.0	0.005	0.0050	0.005000	16.0	8.0
31	0.010	11000.0	0.005	0.0050	0.005000	16.0	8.0
32	0.100	11000.0	0.005	0.0050	0.005000	16.0	8.0
33	0.100	11000.0	0.005	0.0050	0.000000	16.0	8.0
34	0.050	13000.0	0.005	0.0050	0.000000	16.0	8.0
35	0.100	23000.0	0.005	0.0050	0.000000	16.0	8.0
36	0.100	23000.0	0.005	0.0050	0.005000	16.0	8.0
37	0.050	23000.0	0.005	0.0050	0.005000	16.0	8.0
38	0.050	23000.0	0.005	0.0050	0.005000	16.0	8.0
39	0.050	23000.0	0.000	0.0000	0.000000	16.0	8.0
40	0.050	23000.0	0.000	0.0000	0.000000	16.0	8.0
41	0.100	23000.0	0.000	0.0000	0.000000	16.0	8.0
42	0.100	17000.0	0.000	0.0000	0.000000	16.0	8.0
43	0.001	3000.0	0.100	0.0000	0.000000	16.0	8.0
44	0.001	3000.0	0.050	0.0000	0.000000	16.0	8.0
45	0.100	3000.0	0.100	0.0000	0.000000	16.0	8.0
46	0.100	3000.0	0.010	0.0000	0.000000	16.0	8.0
47	0.100	13000.0	0.100	0.0000	0.000000	16.0	8.0
48	0.100	2500.0	0.100	0.0000	0.000000	16.0	8.0
49	0.100	3000.0	0.100	0.1000	0.000000	16.0	8.0
50	0.100	4000.0	0.100	0.1000	0.000000	16.0	8.0
51	0.100	3500.0	0.100	0.0100	0.000000	16.0	8.0
52	0.100	3500.0	0.100	0.0010	0.000000	16.0	8.0
53	0.100	3500.0	0.100	0.0000	0.000000	16.0	8.0

54	0.100	3500.0	0.005	0.0050	0.005000	16.0	8.0
55	0.100	8500.0	0.005	0.0050	0.005000	16.0	8.0
56	0.100	7600.0	0.005	0.0050	0.005000	16.0	8.0
57	0.050	7600.0	0.005	0.0050	0.005000	16.0	8.0
58	0.100	7600.0	0.100	0.0000	0.000000	16.0	8.0
59	0.100	3500.0	0.100	0.0000	0.000000	16.0	8.0
60	0.050	8500.0	0.005	0.0050	0.005000	16.0	8.0
61	0.100	7600.0	0.005	0.0050	0.000000	16.0	8.0
62	0.100	7600.0	0.005	0.0050	0.005000	16.0	8.0
63	0.100	7600.0	0.100	0.0050	0.005000	200.0	100.0
64	0.100	9600.0	0.000	0.0000	0.000000	200.0	100.0
65	0.100	3600.0	0.100	0.0000	0.000000	200.0	100.0
66	0.100	7600.0	0.100	0.0000	0.000000	200.0	100.0
67	0.100	17600.0	0.100	0.0000	0.000000	200.0	100.0
68	0.100	15600.0	0.100	0.0000	0.000000	200.0	100.0
69	0.100	15600.0	0.100	0.0000	0.000000	32.0	16.0
70	0.100	3600.0	0.100	0.0000	0.000000	1.0	0.0
71	0.100	7500.0	0.100	0.0000	0.000000	1.0	0.0
72	0.100	7500.0	0.010	0.0000	0.000000	1.0	0.0
73	0.100	6000.0	0.010	0.0000	0.000000	1.0	0.0
74	0.100	86000.0	0.010	0.0000	0.000000	1.0	0.0
75	0.100	8600.0	0.010	0.0000	0.000000	1.0	0.0
76	0.100	8600.0	0.100	0.0000	0.000000	1.0	0.0
77	0.100	3600.0	0.100	0.0000	0.000000	4.0	0.0
78	0.100	3600.0	0.100	0.0000	0.000000	1.0	0.0
79	0.100	3600.0	0.100	0.0000	0.000000	32.0	0.0
80	0.100	3600.0	0.100	0.0000	0.000000	16.0	0.0
81	0.100	3600.0	0.100	0.0000	0.000000	16.0	0.0
82	0.100	7600.0	0.100	0.0000	0.000000	1.0	0.0
83	0.100	7600.0	0.100	0.0000	0.000000	16.0	0.0
84	0.100	3900.0	0.100	0.0000	0.000000	16.0	0.0
85	0.100	2000.0	0.100	0.0000	0.000000	16.0	8.0
86	0.100	7600.0	0.100	0.0050	0.005000	16.0	8.0
87	0.100	8600.0	0.100	0.0000	0.000000	16.0	8.0
88	0.100	8600.0	0.005	0.0050	0.005000	16.0	8.0
89	0.100	3600.0	0.100	0.0000	0.000000	16.0	8.0
90	0.100	3500.0	0.100	0.0000	0.000000	16.0	8.0
91	0.100	9600.0	0.100	0.0050	0.005000	16.0	8.0
92	0.100	9600.0	0.005	0.0050	0.005000	16.0	8.0
93	0.100	19600.0	0.005	0.0050	0.005000	16.0	8.0
94	0.100	19600.0	0.100	0.0100	0.001000	16.0	8.0
95	0.100	19600.0	0.100	0.0005	0.000005	16.0	8.0
96	0.100	19600.0	0.000	0.0000	0.000000	16.0	8.0
97	0.100	29600.0	0.100	0.0000	0.000000	16.0	8.0
98	0.100	4000.0	0.100	0.0000	0.000000	16.0	8.0
99	0.100	1750.0	0.100	0.0000	0.000000	16.0	8.0
100	0.100	3600.0	0.100	0.0000	0.000000	16.0	8.0
101	0.100	4000.0	0.100	0.0000	0.000000	16.0	8.0

102	0.100	7600.0	0.100	0.0000	0.000000	16.0	8.0
103	0.100	5500.0	0.100	0.0000	0.000000	16.0	8.0
104	0.100	7600.0	0.100	0.0000	0.000000	16.0	8.0
105	0.100	17600.0	0.100	0.0005	0.000005	16.0	8.0
106	0.100	17100.0	0.100	0.0000	0.000000	16.0	8.0
107	0.100	19500.0	0.100	0.0000	0.000000	16.0	8.0
108	0.100	29500.0	0.005	0.0050	0.005000	16.0	8.0
109	0.100	49500.0	0.100	0.0000	0.000000	16.0	8.0
110	0.100	9500.0	0.100	0.0000	0.000000	16.0	8.0
111	0.100	19500.0	0.100	0.0000	0.000000	16.0	8.0
112	0.100	19500.0	0.100	0.0000	0.000000	16.0	8.0
113	0.100	19500.0	0.100	0.0000	0.000000	16.0	8.0
114	0.100	9500.0	0.100	0.0000	0.000000	16.0	8.0
115	0.100	9500.0	0.005	0.0050	0.005000	16.0	8.0
116	0.100	19500.0	0.005	0.0050	0.005000	16.0	8.0
117	0.050	39500.0	0.005	0.0050	0.005000	16.0	8.0
118	0.100	49500.0	0.005	0.0050	0.005000	16.0	8.0
119	0.100	49500.0	0.100	0.0000	0.000000	16.0	8.0
120	0.100	9500.0	0.100	0.0000	0.000000	16.0	8.0
121	0.100	29500.0	0.100	0.0000	0.000000	16.0	8.0
122	0.100	29500.0	0.100	0.0000	0.000000	16.0	8.0
123	0.100	9500.0	0.100	0.0000	0.000000	16.0	8.0
124	0.100	9500.0	0.100	0.0000	0.000000	16.0	8.0
125	0.100	9500.0	0.100	0.0000	0.000000	16.0	8.0
126	0.100	9500.0	0.100	0.0000	0.000000	16.0	8.0
127	0.100	9500.0	0.100	0.0000	0.000000	16.0	8.0
128	0.100	26000.0	0.100	0.0000	0.000000	200.0	100.0
129	0.100	26000.0	0.100	0.0000	0.000000	200.0	100.0
130	0.100	26000.0	0.100	0.0000	0.000000	200.0	100.0
131	0.100	46000.0	0.100	0.0000	0.000000	200.0	100.0
132	0.100	26000.0	0.000	0.0000	0.000000	200.0	96.0
133	0.100	6000.0	0.000	0.0000	0.000000	200.0	96.0
134	0.100	26000.0	0.100	0.0000	0.000000	200.0	96.0
135	0.100	26000.0	0.100	0.0000	0.000000	32.0	16.0
136	0.100	46000.0	0.100	0.1000	0.000000	200.0	100.0
137	0.100	46000.0	0.100	0.1000	0.000000	200.0	100.0
138	0.100	26000.0	0.100	0.0000	0.000000	200.0	100.0
139	0.050	26000.0	0.100	0.0000	0.000000	200.0	100.0
140	0.100	15000.0	0.100	NaN	NaN	16.0	NaN
141	0.100	15000.0	0.000	NaN	NaN	1.0	NaN
142	0.100	15000.0	0.000	NaN	NaN	2.0	NaN
143	0.100	15000.0	NaN	NaN	NaN	NaN	NaN
144	0.100	35000.0	NaN	NaN	NaN	NaN	NaN
145	0.100	8000.0	0.100	0.0000	0.000000	16.0	8.0
146	0.100	20000.0	0.100	0.0500	0.000000	76.0	48.0
147	0.100	25000.0	0.100	0.0500	0.000000	128.0	64.0
148	0.100	8000.0	0.100	0.0000	0.000000	16.0	8.0
149	0.100	25000.0	0.100	0.0500	0.000000	128.0	64.0

150	0.050	35000.0	0.100	0.0000	0.000000	128.0	64.0
151	0.100	25000.0	0.100	0.0000	0.000000	256.0	128.0
152	0.050	25000.0	0.100	0.0000	0.000000	256.0	128.0
153	0.100	15000.0	0.100	0.0000	0.000000	4.0	16.0
154	0.100	35000.0	0.100	0.0000	0.000000	256.0	128.0
155	0.100	25000.0	0.100	0.1000	0.000000	256.0	128.0
156	0.050	25000.0	0.100	0.0000	0.000000	256.0	128.0
157	0.050	25000.0	0.100	0.0000	0.000000	128.0	64.0
158	0.100	35000.0	0.100	0.0000	0.000000	16.0	32.0
159	0.100	15000.0	0.100	0.0000	0.000000	16.0	8.0
160	0.050	25000.0	0.100	0.0500	0.000000	128.0	64.0
161	0.050	25000.0	0.100	0.0000	0.000000	190.0	90.0
162	0.100	8000.0	0.100	0.0000	0.000000	16.0	8.0
163	0.100	6000.0	0.100	0.0000	0.000000	16.0	8.0
164	0.100	6000.0	0.100	0.0000	0.000000	16.0	8.0
165	0.100	20000.0	0.100	0.0500	0.000000	76.0	48.0
166	0.100	6000.0	0.100	0.0000	0.000000	16.0	8.0
167	0.100	20000.0	0.100	0.0500	0.000000	76.0	48.0
168	0.100	25000.0	0.100	0.0500	0.000000	128.0	64.0
169	0.100	25000.0	0.100	0.1000	0.000000	256.0	128.0
170	0.050	25000.0	0.100	0.0500	0.000000	256.0	128.0
171	0.050	25000.0	0.100	0.0000	0.000000	190.0	90.0
172	0.100	8000.0	0.100	0.0000	0.000000	16.0	8.0
173	0.100	15000.0	0.100	NaN	NaN	16.0	NaN
174	0.100	15000.0	0.000	NaN	NaN	1.0	NaN
175	0.100	15000.0	0.000	NaN	NaN	2.0	NaN
176	0.100	35000.0	NaN	NaN	NaN	NaN	NaN
177	0.050	25000.0	0.100	0.0100	0.000000	180.0	90.0
178	0.100	20000.0	0.100	0.0500	0.000000	76.0	48.0

	hidden_3	input_dim	test_rmse_score	test_r2_score	hidden_4	beta4
0	4.0	403.0	0.128456	8.949361e-01	NaN	NaN
1	4.0	403.0	0.250470	6.005558e-01	NaN	NaN
2	4.0	403.0	0.152580	8.517686e-01	NaN	NaN
3	4.0	403.0	0.143409	8.690530e-01	NaN	NaN
4	4.0	403.0	0.127356	8.967284e-01	NaN	NaN
5	4.0	403.0	0.126758	8.976948e-01	NaN	NaN
6	4.0	403.0	0.162495	8.318785e-01	NaN	NaN
7	4.0	403.0	0.177628	7.991050e-01	NaN	NaN
8	4.0	403.0	0.139909	8.753655e-01	NaN	NaN
9	4.0	403.0	0.143775	8.683835e-01	NaN	NaN
10	4.0	403.0	0.138477	8.779036e-01	NaN	NaN
11	4.0	403.0	0.138477	8.779036e-01	NaN	NaN
12	4.0	403.0	0.154219	8.485668e-01	NaN	NaN
13	4.0	403.0	0.154219	8.485668e-01	NaN	NaN
14	4.0	403.0	0.661086	-1.782662e+00	NaN	NaN
15	4.0	403.0	0.131423	8.900259e-01	NaN	NaN
16	4.0	403.0	0.389771	-5.111744e-03	NaN	NaN

17	4.0	403.0	0.390269	-7.679426e-03	NaN	NaN
18	4.0	403.0	0.102641	9.302995e-01	NaN	NaN
19	4.0	403.0	0.135519	8.830642e-01	NaN	NaN
20	4.0	403.0	0.304550	4.094407e-01	NaN	NaN
21	4.0	403.0	0.124793	9.008422e-01	NaN	NaN
22	4.0	403.0	14.246912	-1.291369e+03	NaN	NaN
23	4.0	403.0	0.710445	-2.213707e+00	NaN	NaN
24	4.0	403.0	0.129652	8.929701e-01	NaN	NaN
25	4.0	403.0	0.142223	8.712101e-01	NaN	NaN
26	4.0	403.0	0.126000	8.989146e-01	NaN	NaN
27	4.0	403.0	0.124008	9.020864e-01	NaN	NaN
28	4.0	403.0	0.147886	8.607480e-01	NaN	NaN
29	4.0	403.0	0.105610	9.262080e-01	NaN	NaN
30	4.0	403.0	0.131099	8.905686e-01	NaN	NaN
31	4.0	403.0	2.365656	-3.463267e+01	NaN	NaN
32	4.0	403.0	0.135869	8.824604e-01	NaN	NaN
33	4.0	403.0	0.132422	8.883490e-01	NaN	NaN
34	4.0	403.0	0.126124	8.987160e-01	NaN	NaN
35	4.0	403.0	0.123945	9.021856e-01	NaN	NaN
36	4.0	403.0	0.321211	3.430598e-01	NaN	NaN
37	4.0	403.0	0.126705	8.977802e-01	NaN	NaN
38	4.0	403.0	0.126705	8.977802e-01	NaN	NaN
39	4.0	403.0	0.173484	8.083707e-01	NaN	NaN
40	4.0	403.0	0.396362	-2.986747e-04	NaN	NaN
41	4.0	403.0	0.396368	-3.297183e-04	NaN	NaN
42	4.0	403.0	0.396362	-2.981759e-04	NaN	NaN
43	4.0	403.0	2.654960	-4.388086e+01	NaN	NaN
44	4.0	403.0	7.177147	-3.269811e+02	NaN	NaN
45	4.0	403.0	0.124692	9.010024e-01	NaN	NaN
46	4.0	403.0	0.126720	8.977569e-01	NaN	NaN
47	4.0	403.0	0.396362	-2.986747e-04	NaN	NaN
48	4.0	403.0	0.136049	8.821482e-01	NaN	NaN
49	4.0	403.0	0.127360	8.967204e-01	NaN	NaN
50	4.0	403.0	0.260455	5.680732e-01	NaN	NaN
51	4.0	403.0	0.146195	8.639153e-01	NaN	NaN
52	4.0	403.0	0.396370	-3.376305e-04	NaN	NaN
53	4.0	403.0	0.113379	9.149525e-01	NaN	NaN
54	4.0	403.0	0.117934	9.079823e-01	NaN	NaN
55	4.0	403.0	0.111485	9.177711e-01	NaN	NaN
56	4.0	403.0	0.106919	9.243687e-01	NaN	NaN
57	4.0	403.0	0.119165	9.060501e-01	NaN	NaN
58	4.0	403.0	0.376772	6.081402e-02	NaN	NaN
59	4.0	403.0	0.107788	9.231341e-01	NaN	NaN
60	4.0	403.0	0.122025	9.014877e-01	NaN	NaN
61	4.0	403.0	0.389771	-5.109640e-03	NaN	NaN
62	4.0	403.0	0.109705	9.203748e-01	NaN	NaN
63	30.0	403.0	0.389676	-4.622793e-03	NaN	NaN
64	30.0	403.0	0.389825	-5.391521e-03	NaN	NaN

65	30.0	403.0	1.764792	-1.960547e+01	NaN	NaN
66	30.0	403.0	0.389774	-5.127892e-03	NaN	NaN
67	30.0	403.0	0.389772	-5.119113e-03	NaN	NaN
68	30.0	403.0	0.149463	8.522031e-01	NaN	NaN
69	8.0	403.0	0.389750	-5.006016e-03	NaN	NaN
70	0.0	403.0	0.104633	9.275680e-01	NaN	NaN
71	0.0	403.0	0.105433	9.264551e-01	NaN	NaN
72	0.0	403.0	0.104463	9.278026e-01	NaN	NaN
73	0.0	403.0	0.158149	8.345259e-01	NaN	NaN
74	0.0	403.0	0.389882	-5.682449e-03	NaN	NaN
75	0.0	403.0	0.389771	-5.109640e-03	NaN	NaN
76	0.0	403.0	0.111076	9.183720e-01	NaN	NaN
77	0.0	403.0	0.105270	9.266836e-01	NaN	NaN
78	0.0	403.0	0.104898	9.271996e-01	NaN	NaN
79	0.0	403.0	0.198056	7.404795e-01	NaN	NaN
80	0.0	403.0	0.607723	-1.443464e+00	NaN	NaN
81	0.0	403.0	0.106043	9.256030e-01	NaN	NaN
82	0.0	403.0	0.105914	9.257826e-01	NaN	NaN
83	0.0	403.0	0.107050	9.241823e-01	NaN	NaN
84	0.0	403.0	0.107679	9.232893e-01	NaN	NaN
85	4.0	403.0	0.157928	8.411961e-01	NaN	NaN
86	4.0	403.0	0.138570	8.777409e-01	NaN	NaN
87	4.0	403.0	0.133445	8.866164e-01	NaN	NaN
88	4.0	403.0	0.129291	8.935660e-01	NaN	NaN
89	4.0	403.0	0.119097	9.096871e-01	NaN	NaN
90	4.0	403.0	0.512748	-6.739936e-01	NaN	NaN
91	4.0	403.0	0.124896	9.006785e-01	NaN	NaN
92	4.0	403.0	0.205646	7.307324e-01	NaN	NaN
93	4.0	403.0	0.132143	8.888180e-01	NaN	NaN
94	4.0	403.0	0.235628	6.464929e-01	NaN	NaN
95	4.0	403.0	0.128857	8.942789e-01	NaN	NaN
96	4.0	403.0	0.396391	-4.451594e-04	NaN	NaN
97	4.0	403.0	0.148700	8.592123e-01	NaN	NaN
98	4.0	403.0	0.172257	8.110704e-01	NaN	NaN
99	4.0	403.0	0.396362	-2.980097e-04	NaN	NaN
100	4.0	403.0	0.127960	8.957456e-01	NaN	NaN
101	4.0	403.0	0.122812	9.039655e-01	NaN	NaN
102	4.0	403.0	0.127266	8.968736e-01	NaN	NaN
103	4.0	403.0	0.127831	8.959562e-01	NaN	NaN
104	4.0	403.0	399.635052	-1.016885e+06	NaN	NaN
105	4.0	403.0	0.122934	9.037754e-01	NaN	NaN
106	4.0	403.0	0.123996	9.021051e-01	NaN	NaN
107	4.0	403.0	0.122128	9.050330e-01	NaN	NaN
108	4.0	403.0	0.121803	9.055369e-01	NaN	NaN
109	4.0	403.0	0.120712	9.072223e-01	NaN	NaN
110	4.0	403.0	0.104178	9.281964e-01	NaN	NaN
111	4.0	403.0	0.089601	9.468848e-01	NaN	NaN
112	4.0	403.0	0.118142	9.076568e-01	NaN	NaN

113	4.0	403.0	0.118142	9.076568e-01	NaN	NaN
114	4.0	403.0	0.090853	9.453897e-01	NaN	NaN
115	4.0	403.0	0.090915	9.453158e-01	NaN	NaN
116	4.0	403.0	0.091638	9.444420e-01	NaN	NaN
117	4.0	403.0	0.076999	9.607748e-01	NaN	NaN
118	4.0	403.0	0.073579	9.641818e-01	NaN	NaN
119	4.0	403.0	0.087605	9.492243e-01	NaN	NaN
120	4.0	403.0	0.159089	8.325543e-01	NaN	NaN
121	4.0	403.0	0.093281	9.424324e-01	NaN	NaN
122	4.0	403.0	0.127969	8.689350e-01	NaN	NaN
123	4.0	403.0	0.117637	8.892446e-01	NaN	NaN
124	4.0	403.0	0.104068	9.283477e-01	NaN	NaN
125	4.0	403.0	0.103677	9.288849e-01	NaN	NaN
126	4.0	403.0	0.103494	9.291363e-01	NaN	NaN
127	4.0	403.0	0.103775	9.364546e-01	NaN	NaN
128	50.0	403.0	0.112221	9.256909e-01	NaN	NaN
129	50.0	403.0	0.111169	9.270777e-01	12.0	NaN
130	50.0	403.0	0.111169	9.270777e-01	12.0	NaN
131	50.0	403.0	0.411770	-4.727709e-04	12.0	NaN
132	32.0	403.0	0.411734	-2.970530e-04	4.0	NaN
133	32.0	403.0	0.412326	-3.176449e-03	4.0	0.0
134	32.0	403.0	0.411762	-4.307332e-04	4.0	0.0
135	8.0	403.0	0.411745	-3.482792e-04	4.0	0.0
136	50.0	403.0	0.411750	-3.748811e-04	25.0	0.0
137	50.0	403.0	0.411750	-3.748811e-04	25.0	0.0
138	50.0	403.0	0.411739	-3.223233e-04	12.0	0.0
139	50.0	403.0	0.412324	-3.166794e-03	12.0	0.0
140	NaN	403.0	0.115072	9.218665e-01	NaN	NaN
141	NaN	403.0	0.116185	9.203481e-01	NaN	NaN
142	NaN	403.0	0.150994	8.654721e-01	NaN	NaN
143	NaN	403.0	0.162648	8.439027e-01	NaN	NaN
144	NaN	403.0	0.147050	8.724072e-01	NaN	NaN
145	4.0	403.0	0.184813	7.984608e-01	NaN	NaN
146	32.0	403.0	0.111441	9.267196e-01	16.0	0.0
147	32.0	403.0	0.412339	-3.237055e-03	16.0	0.0
148	4.0	403.0	0.111108	9.271576e-01	NaN	NaN
149	32.0	403.0	0.150787	8.658403e-01	16.0	0.0
150	32.0	403.0	0.412324	-3.166794e-03	16.0	0.0
151	32.0	403.0	0.412324	-3.166794e-03	8.0	0.0
152	32.0	403.0	0.412324	-3.167316e-03	8.0	0.0
153	16.0	403.0	0.412324	-3.167055e-03	4.0	0.0
154	64.0	403.0	0.412325	-3.170185e-03	32.0	0.0
155	32.0	403.0	0.123334	9.102441e-01	8.0	0.0
156	64.0	403.0	0.412324	-3.167055e-03	8.0	0.0
157	16.0	403.0	0.412319	-3.141554e-03	4.0	0.0
158	48.0	403.0	0.416205	-2.213767e-02	76.0	0.0
159	4.0	403.0	0.412324	-3.166794e-03	2.0	0.0
160	16.0	403.0	0.412324	-3.167837e-03	4.0	0.0

161	30.0	403.0	0.412324	-3.165491e-03	3.0	0.0
162	4.0	403.0	0.412324	-3.166794e-03	2.0	0.0
163	4.0	403.0	0.412324	-3.165230e-03	NaN	NaN
164	4.0	403.0	0.105436	9.344041e-01	NaN	NaN
165	32.0	403.0	0.108646	9.303500e-01	16.0	0.0
166	4.0	403.0	0.103792	9.364344e-01	NaN	NaN
167	32.0	403.0	0.106511	9.330597e-01	16.0	0.0
168	32.0	403.0	0.411699	-1.253480e-04	16.0	0.0
169	32.0	403.0	0.411756	-4.026479e-04	8.0	0.0
170	16.0	403.0	0.112563	9.252368e-01	4.0	0.0
171	30.0	403.0	0.411974	-1.465819e-03	3.0	0.0
172	4.0	403.0	0.103529	9.367565e-01	2.0	0.0
173	NaN	403.0	0.106009	9.336896e-01	NaN	NaN
174	NaN	403.0	0.120667	9.140850e-01	NaN	NaN
175	NaN	403.0	0.116812	9.194859e-01	NaN	NaN
176	NaN	403.0	0.138819	8.862908e-01	NaN	NaN
177	30.0	403.0	0.411965	-1.419538e-03	6.0	0.0
178	32.0	403.0	0.110364	9.281301e-01	16.0	0.0

12.2.3 Observation and discovery :

- In the above parameter we can see that index 44 shows that for .001 learning parameter the model does not predict anything so I have changed it slowly and finally What I have found that learning parameter .1 and .05 provides the best results.
- Beta1, Beta2, Beta3, Beta4 represents the regularization parameter for hidden layer 1 ,2 ,3 and 4. Sometimes in the above table we can see that hidden layer 2,3,4 is 0 or NaN but there is some value for beta 2,3,4 that means the layer is actually off so those values actually means nothing.
- For 3 layer model when beta1, beta2, beta3 is .005, model shows significant amount of improvement while learning rate is .1 or .05 . But when learning rate is .1 and beta1=.1 , beta2=0, beta3=0 then the model performs even better most of the time and it also takes less epochs to train for the best validation accuracy
- From index 63 to 69 I have tried to use 200 , 100 , 30 neurons because the data have 403 features and its a common practice to use half amount of the neuron in the first hidden layer and this strategy does not work good enough but with my selected parameter it improved a little bit. I have used 16-8-4 combination of neuron because of this common practice. for our case 16 neuron in the first layer provided better accuracy and adding 8 and 4 in the next 2 layer improved the stability of the model and now it gives good validation accuracy after 2000 epoch and the best validation accuracy remains between the epoch range of 2000-2500 , 3300-3600 or 5000-5400 .
- From index 70 to 78 we can see that single neuron with single hidden layer performs well according to the plan stated in the target section. Then I have increased neurons and the learning curve for them is in the following block. Where y axis shows rmse and x axis shows i and i*50 represents the epoch no. Again blue curve is for training accuracy and green for validation accuracy