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1 House Price Assignment

Summary

The objective of this assignment is predicting the Sales Price for each house based on the given data comprising of 81 explanatory variables describing (almost)every aspect of residential homes. This problem focuses on the Machine Learning Approach to the prediction, Missing data handling, Data Preprocessing, Data Cleansing, Outliers Detection and Dropping, Hyper Parameter Tuning and so on.

1.1 Approaches included but not limited to -

Loading Data and Packages, Data visualization , Finding missing data, Normalization ,Model and predictions and more.

1.2 Loading Data and Packages

In [73]:
```
import pandas as pd import numpy as
np import seaborn as sns import
matplotlib import matplotlib.pyplot
as plt import warnings import
xgboost as xgb

from sklearn.preprocessing import StandardScaler from sklearn.metrics import accuracy_score
from sklearn.metrics import mean_squared_error from sklearn.preprocessing import
LabelEncoder from scipy.stats import skew from scipy import stats from scipy.stats.stats import
pearsonr from scipy.stats import norm from collections import Counter from
sklearn.linear_model import ElasticNet, Lasso, BayesianRidge, LassoLarsIC from
sklearn.neural_network import MLPRegressor
from sklearn.metrics import mean_squared_error from sklearn.linear_model import
LinearRegression,LassoCV, Ridge, LassoLarsCV,ElasticN from sklearn.model_selection import
GridSearchCV, cross_val_score, learning_curve from sklearn.ensemble import RandomForestRegressor,
AdaBoostRegressor, ExtraTreesRegre from sklearn.preprocessing import StandardScaler, Normalizer,
RobustScaler warnings.filterwarnings('ignore')
sns.set(style='white', context='notebook', palette='deep')
```

2 Data Import

In [3]:
```
data_train = pd.read_csv('Data/train (7).csv') data_test =
pd.read_csv('Data/test (7).csv')
```

Now lets have a look at the dataframe -

2.1 Analyzing the DataFrame

In [4]: data_train.describe()

Out[4]:

	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	...

	WoodDeckSF	OpenPorchSF	EnclosedPorch	3SsnPorch	ScreenPorch	\
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	
mean	94.244521	46.660274	21.954110	3.409589	15.060959	
std	125.338794	66.256028	61.119149	29.317331	55.757415	
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	25.000000	0.000000	0.000000	0.000000	
75%	168.000000	68.000000	0.000000	0.000000	0.000000	
max	857.000000	547.000000	552.000000	508.000000	480.000000	

	PoolArea	MiscVal	MoSold	YrSold	SalePrice
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	2.758904	43.489041	6.321918	2007.815753	180921.195890
std	40.177307	496.123024	2.703626	1.328095	79442.502883
min	0.000000	0.000000	1.000000	2006.000000	34900.000000
25%	0.000000	0.000000	5.000000	2007.000000	129975.000000
50%	0.000000	0.000000	6.000000	2008.000000	163000.000000
75%	0.000000	0.000000	8.000000	2009.000000	214000.000000
max	738.000000	15500.000000	12.000000	2010.000000	755000.000000

[8 rows x 38 columns]

From the “Count” row, we can see there are a lot of missing values in this dataset. Point to be noted, they are by no means from a similar data distribution i.e normalization might be necessary. Furthermore, all of the given data might not be necessary to predict the target field “SalePrice”.
All of these will be handled further as we go on. Having a look into actual data -

In [5]: data_train.head()

Out[5]: 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 ... PoolArea PoolQC Fence MiscFeature MiscVal MoSold \

0	Lvl	AllPub ...	0	NaN	NaN	NaN	0	2
1	Lvl	AllPub ...	0	NaN	NaN	NaN	0	5
2	Lvl	AllPub ...	0	NaN	NaN	NaN	0	9
3	Lvl	AllPub ...	0	NaN	NaN	NaN	0	2
4	Lvl	AllPub ...	0	NaN	NaN	NaN	0	12

YrSold SaleType SaleCondition SalePrice

0	2008	WD	Normal	208500
1	2007	WD	Normal	181500
2	2008	WD	Normal	223500
3	2006	WD	Abnorml	140000
4	2008	WD	Normal	250000

[5 rows x 81 columns]

**Here all the data are either in categorical or in numeric value. For such, we might need to convert them into numeric data

3 Data Cleaning

In [6]:
```
train_data=data_train.copy() test_data
=data_test.copy()
#check the numbers of samples and features print("The train data size before dropping Id feature is :", data_train.shape) print("The test data size before dropping Id feature is :", data_test.shape)

#Save the 'Id' column train_ID =
data_train['Id'] test_ID =
data_test['Id']

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

```
#check again the data size after dropping the 'Id' variable print("\nThe train data size after dropping
Id feature is :", data_train.shape) print("The test data size after dropping Id feature is :",
data_test.shape)
```

The train data size before dropping Id feature is : (1460, 81)
The test data size before dropping Id feature is : (1459, 80)

The train data size after dropping Id feature is : (1460, 80)
The test data size after dropping Id feature is : (1459, 79)

3.1 Multivariable Analysis

Checking categorical data

```
In [7]: # Checking Categorical Data data_train.select_dtypes(include=['object']).columns
```

```
Out[7]: Index(['MSZoning', 'Street', 'Alley', 'LotShape', 'LandContour', 'Utilities',
       'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Condition2',
       'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st',
       'Exterior2nd', 'MasVnrType', 'ExterQual', 'ExterCond', 'Foundation',
       'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2',
       'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual',
       'Functional', 'FireplaceQu', 'GarageType', 'GarageFinish', 'GarageQual',
       'GarageCond', 'PavedDrive', 'PoolQC', 'Fence', 'MiscFeature',
       'SaleType', 'SaleCondition'], dtype='object')
```

Checking numerical data

```
In [8]: # Checking Numerical Data
        data_train.select_dtypes(include=['int64','float64']).columns
Out[8]: Index(['MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual', 'OverallCond',
       'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF',
       'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
       'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
       'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces',
       'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch',
       '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal',
       'MoSold', 'YrSold', 'SalePrice'], dtype='object')
```

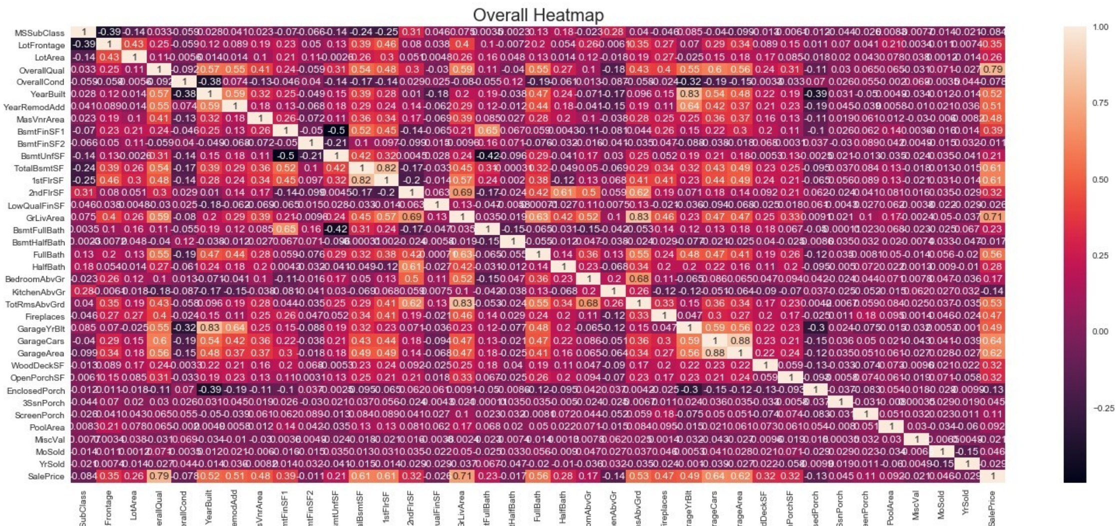
Total Features

```
In [9]: cat = len(data_train.select_dtypes(include=['object']).columns) num =
        len(data_train.select_dtypes(include=['int64','float64']).columns)
        print('Total Features: ', cat, 'categorical', '+', num, 'numerical', '=', cat+num, 'fea Total Features: 43 categorical +
```

37 numerical = 80 features

3.2 Correlation Matrix

In [10]: # *Correlation Matrix* cm = data_train.corr() plt.figure(5,
figsize=(20, 9)) sns.heatmap(cm, annot=**True**)
plt.title('Overall Heatmap', fontsize=20)
plt.tight_layout() plt.show()

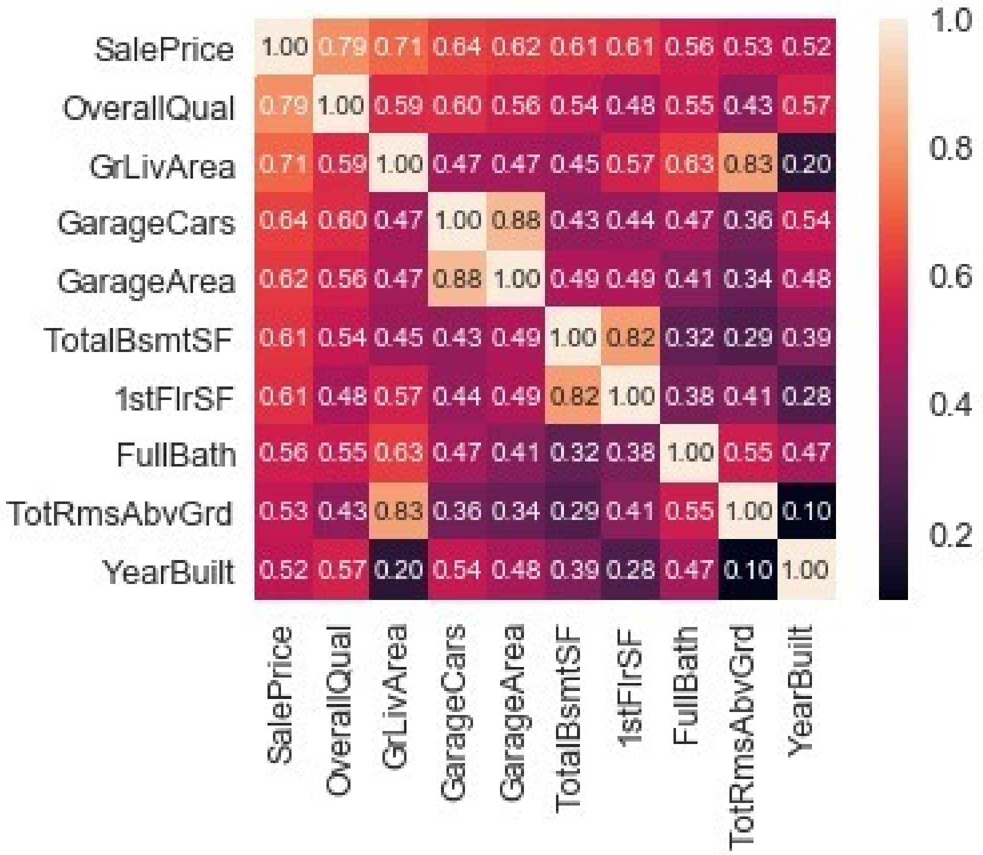


**Generally there are many data with a large range of values and proportions. So To edge up the process Lets take Yop 10 heatMap into account

Generating Top 10 Features which are most relavent to SalesPrice

In [11]: # *Top 10 Heatmap*

k = 10 *#number of variables for heatmap* cols = cm.nlargest(k, 'SalePrice')['SalePrice'].index cm = np.corrcoef(data_train[cols].values.T) sns.set(font_scale=1.25) hm = sns.heatmap(cm, cbar=**True**, annot=**True**, square=**True**, fmt='.2f', annot_kws={'size' plt.show()



In [12]:
```
most_corr = pd.DataFrame(cols) most_corr.columns = ['Most
Correlated Features'] most_corr
```

Out[12]:

	Most Correlated Features
0	SalePrice
1	OverallQual
2	GrLivArea
3	GarageCars
4	GarageArea
5	TotalBsmtSF
6	1stFlrSF
7	FullBath
8	TotRmsAbvGrd 9 YearBuilt

For obvious reasons, most correlated feature to SalePrice will be SalePrice. With the short description to other 9 , they are described below

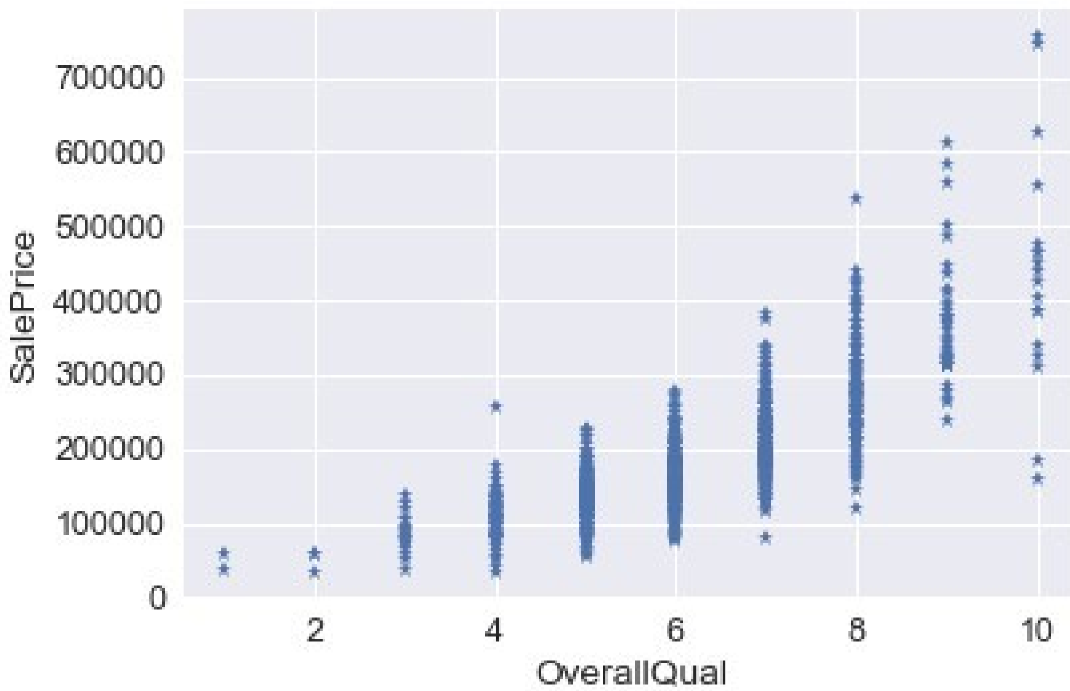
1. OverallQual: Rates the overall material and finish of the house (1 = Very Poor, 10 = Very Excellent)

2. GrLivArea: Above grade (ground) living area square feet
3. GarageCars: Size of garage in car capacity
4. GarageArea: Size of garage in square feet
5. TotalBsmtSF: Total square feet of basement area
6. 1stFlrSF: First Floor square feet
7. FullBath: Full bathrooms above grade
8. TotRmsAbvGrd: Total rooms above grade (does not include bathrooms)
9. YearBuilt: Original construction date

3.3 Manual Outliner Detection

To make the "correlated features" easy to understand, let's figure out how each can relate to SalePrice

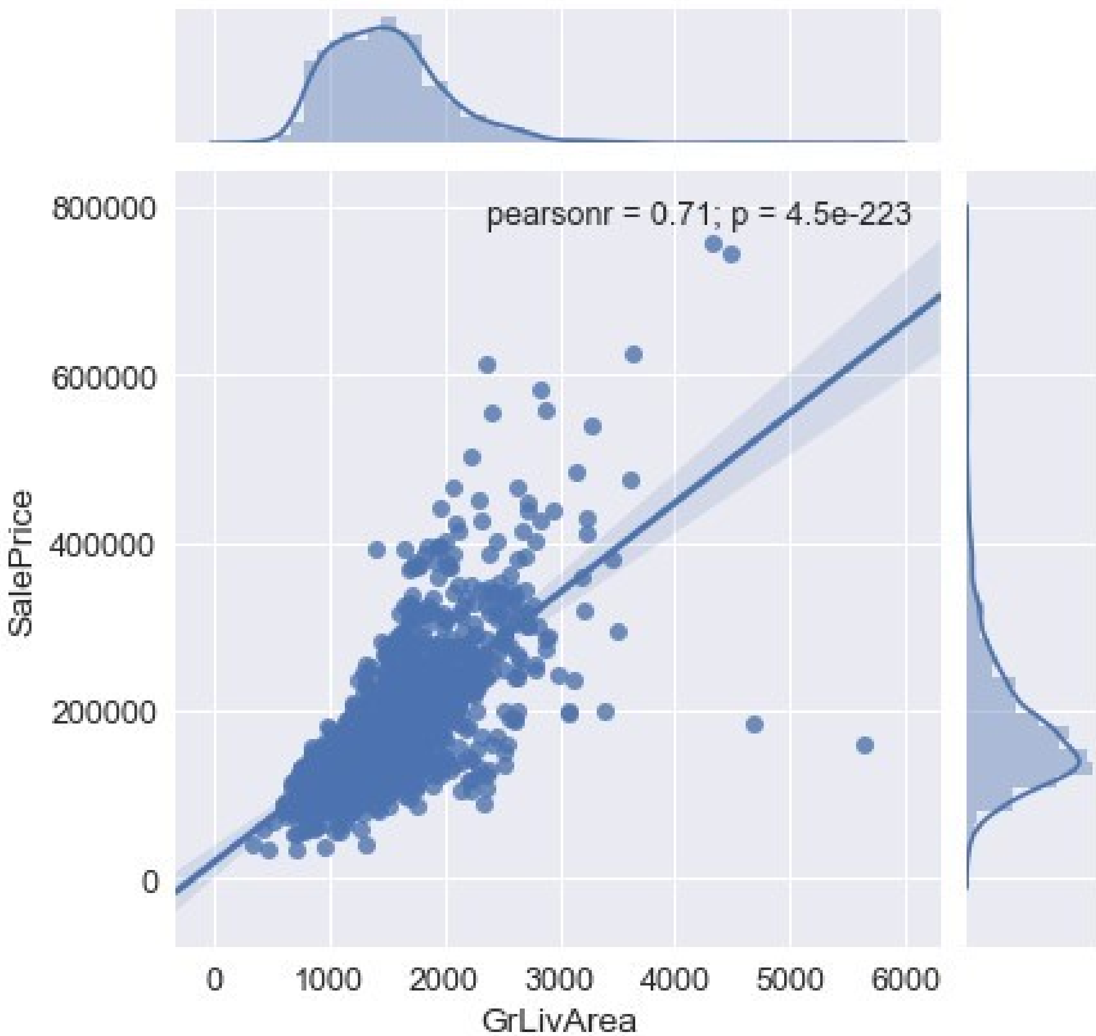
In [13]:
```
# Overall Quality vs Sale Price
plt.plot(data_train["OverallQual"],data_train["SalePrice"],"*")
plt.ylabel("SalePrice") plt.xlabel("OverallQual") plt.tight_layout() plt.show()
```



****Here People are paying more for better quality**

In [14]:
```
# Living Area vs Sale Price sns.jointplot(x=data_train['GrLivArea'], y=data_train['SalePrice'], kind='reg')
```

Out[14]: <seaborn.axisgrid.JointGrid at 0x18b5f9ee048>

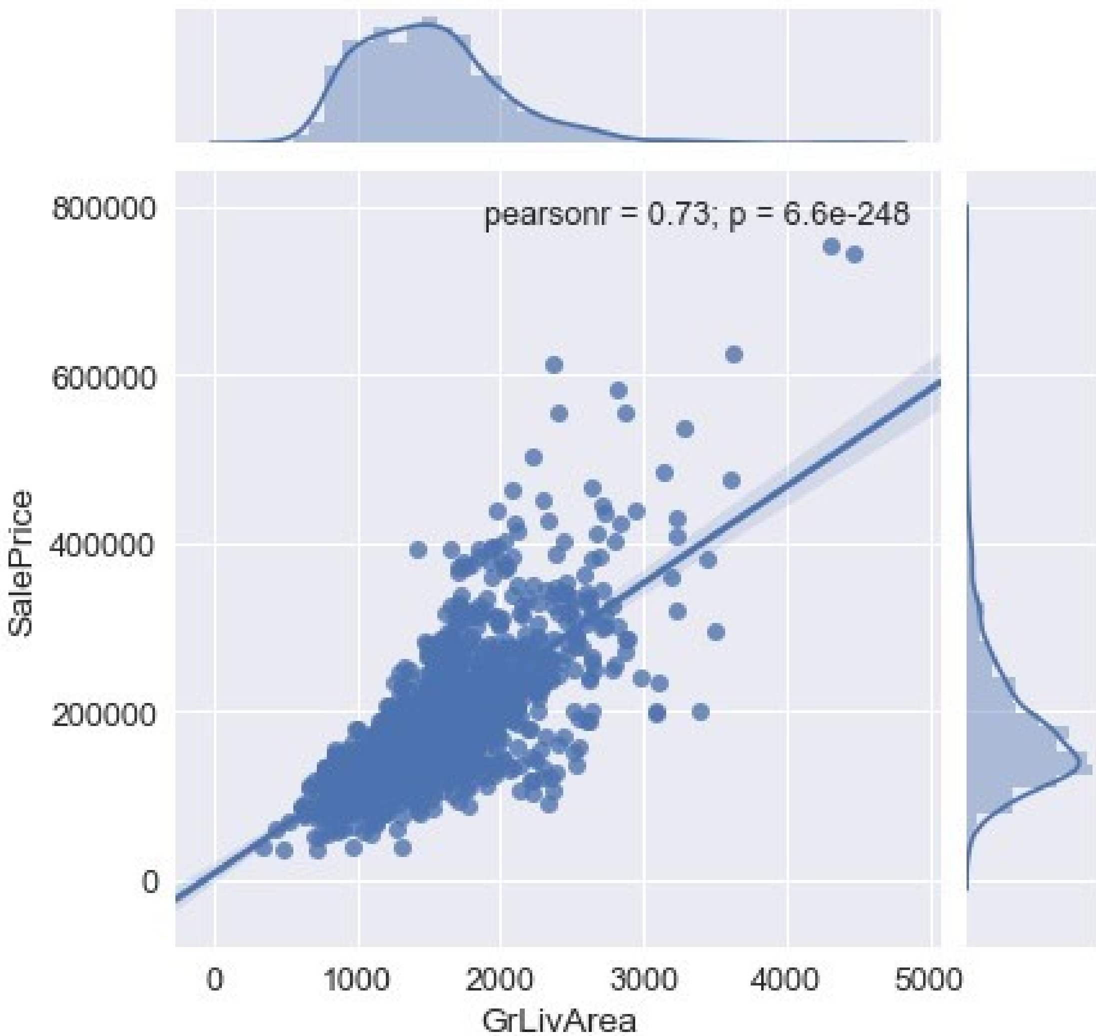


**People tend to pay more for more living area but the two datapoints at the bottom-right doesnot cut the hypothesis. considering those as outliners, these are to be removed manually

In [15]:
```
# Removing outliers manually (Two points in the bottom right) data_train =
        data_train.drop(data_train[(data_train['GrLivArea']>4000)
                                   & (data_train['SalePrice']<300000)].index).reset_index(drop=
```

In [16]:
```
# Living Area vs Sale Price sns.jointplot(x=data_train['GrLivArea'], y=data_train['SalePrice'], kind='reg')
```

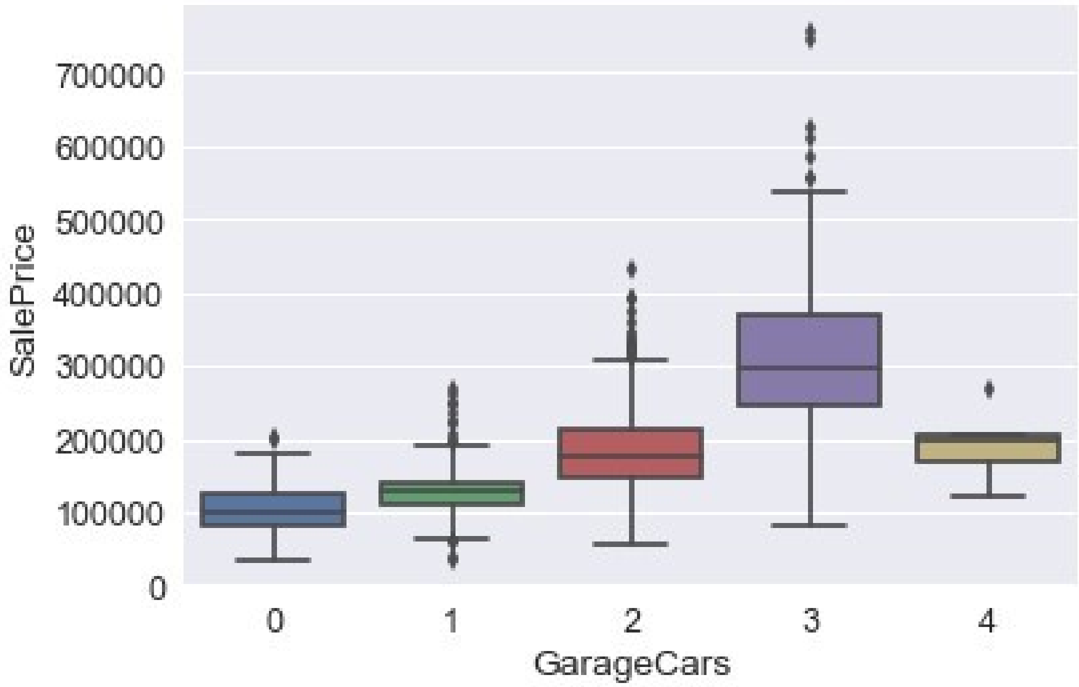
Out[16]: <seaborn.axisgrid.JointGrid at 0x18b5f9f54e0>



Without the "Outliners" The Pearson-R Score improved by .02

**Pearson's r can range from -1 to 1. An r of -1 indicates a perfect negative linear relationship between variables, an r of 0 indicates no linear relationship between variables, and an r of 1 indicates a perfect positive linear relationship between variables.

```
In [17]: # GarageCars vs Sale Price sns.boxplot(x=data_train['GarageCars'],
            y=data_train['SalePrice'])

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x18b5fa387b8>
```

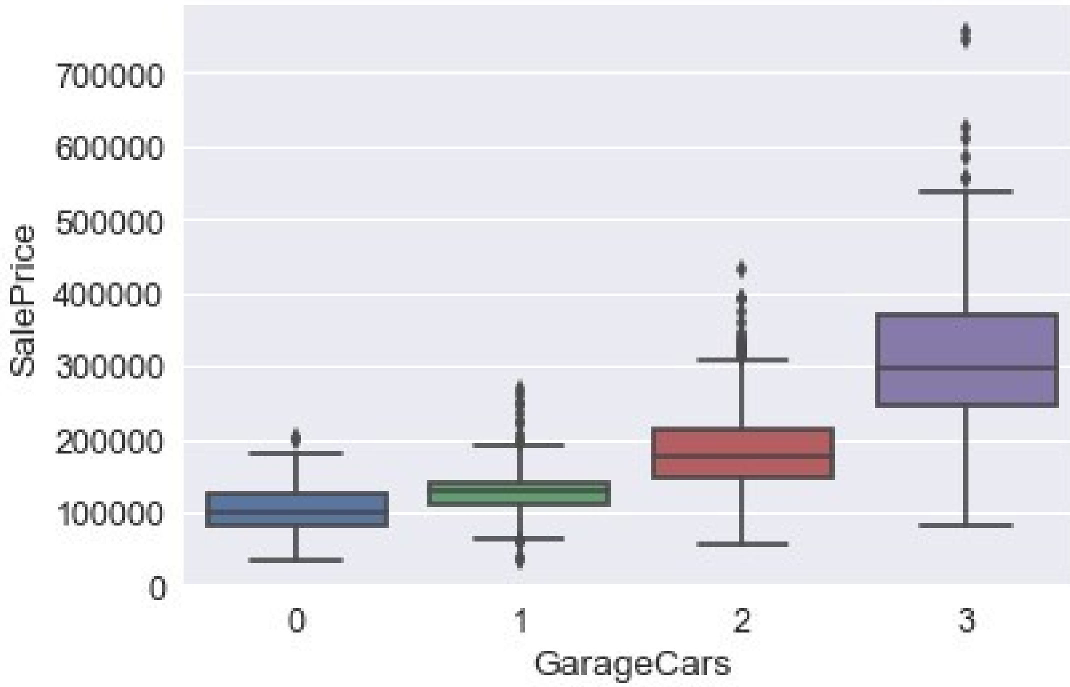


The number of Garages is also a good factor for rising the SalePrice. However, 4-car garages reseults with less price makes no sense. So, considering them as outliners, remove those from dataFrame

In [18]:
```
# Removing outliers manually (More than 4-cars, less than $300k)
data_train = data_train.drop(data_train[(data_train['GarageCars']>3) &
                                        (data_train['SalePrice']<300000)].index).rese
```

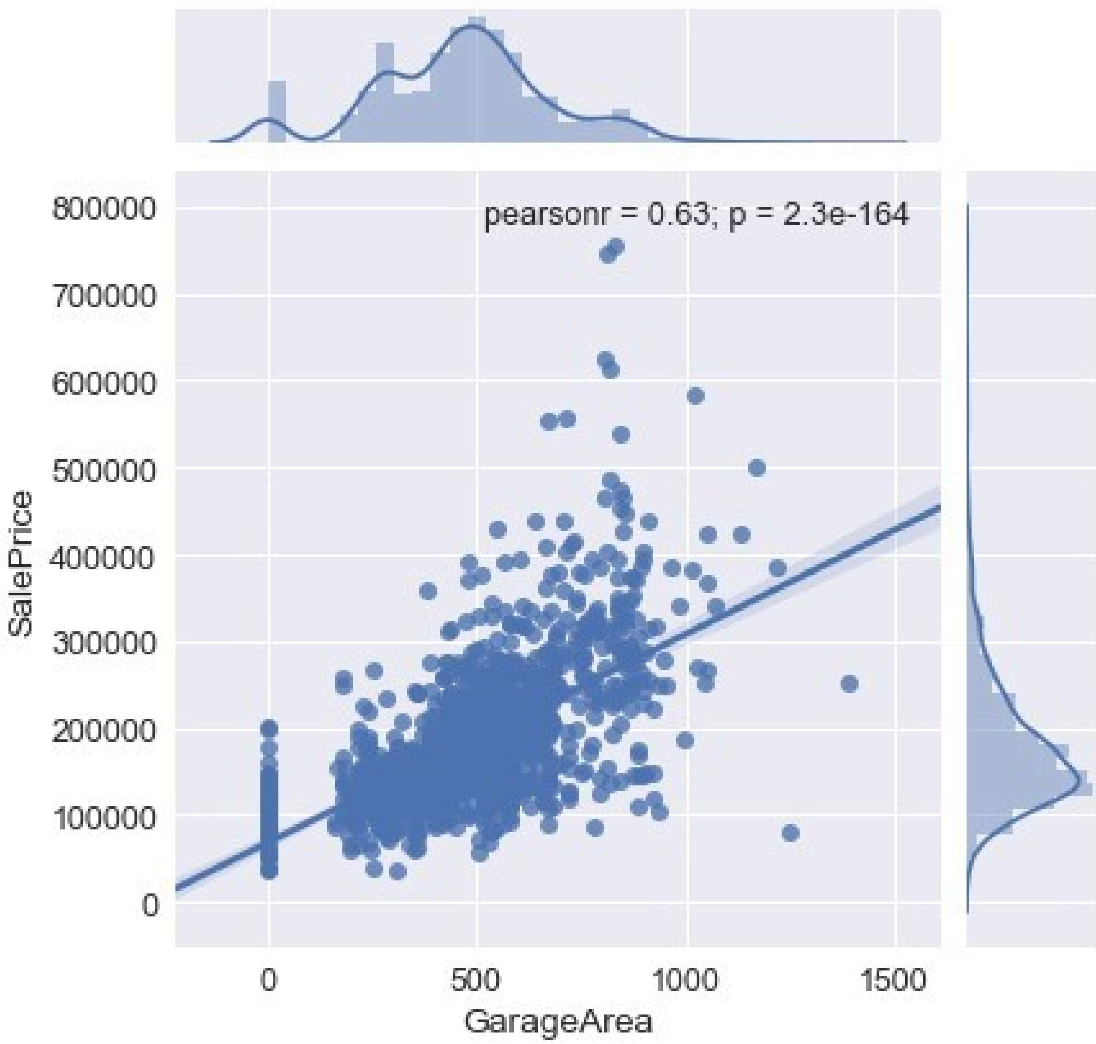
In [19]:
```
# GarageCars vs Sale Price sns.boxplot(x=data_train['GarageCars'],
y=data_train['SalePrice'])
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x18b5f866e48>



In [20]: *# Garage Area vs Sale Price* sns.jointplot(x=data_train['GarageArea'], y=data_train['SalePrice'], kind='reg')

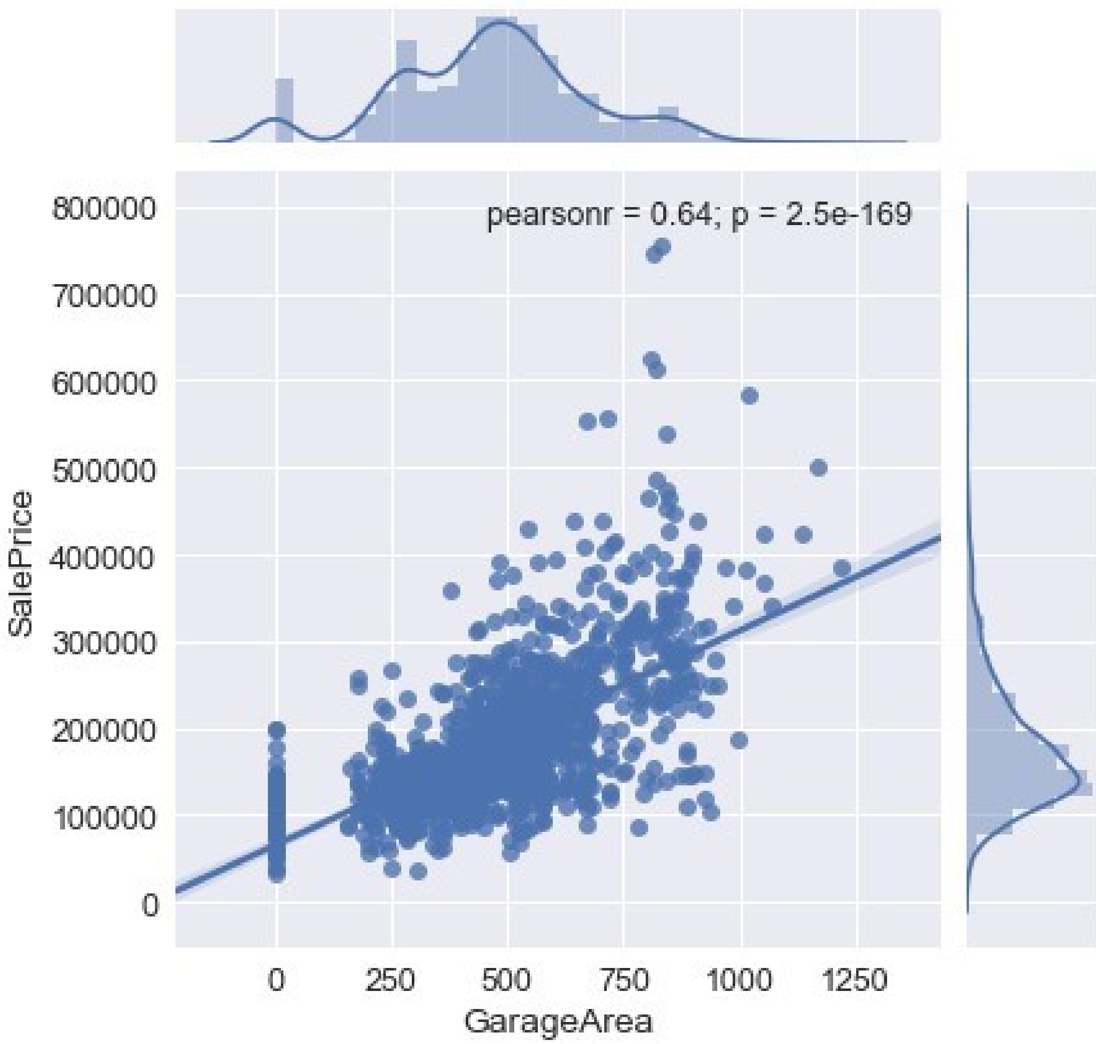
Out[20]: <seaborn.axisgrid.JointGrid at 0x18b5fcf55c0>



In [21]: # *Removing outliers manually (More than 1000 sqft, less than $300k)* data_train = data_train.drop(data_train[(data_train['GarageArea']>1000) & (data_train['SalePrice']<300000)].index).reset_index(drop=

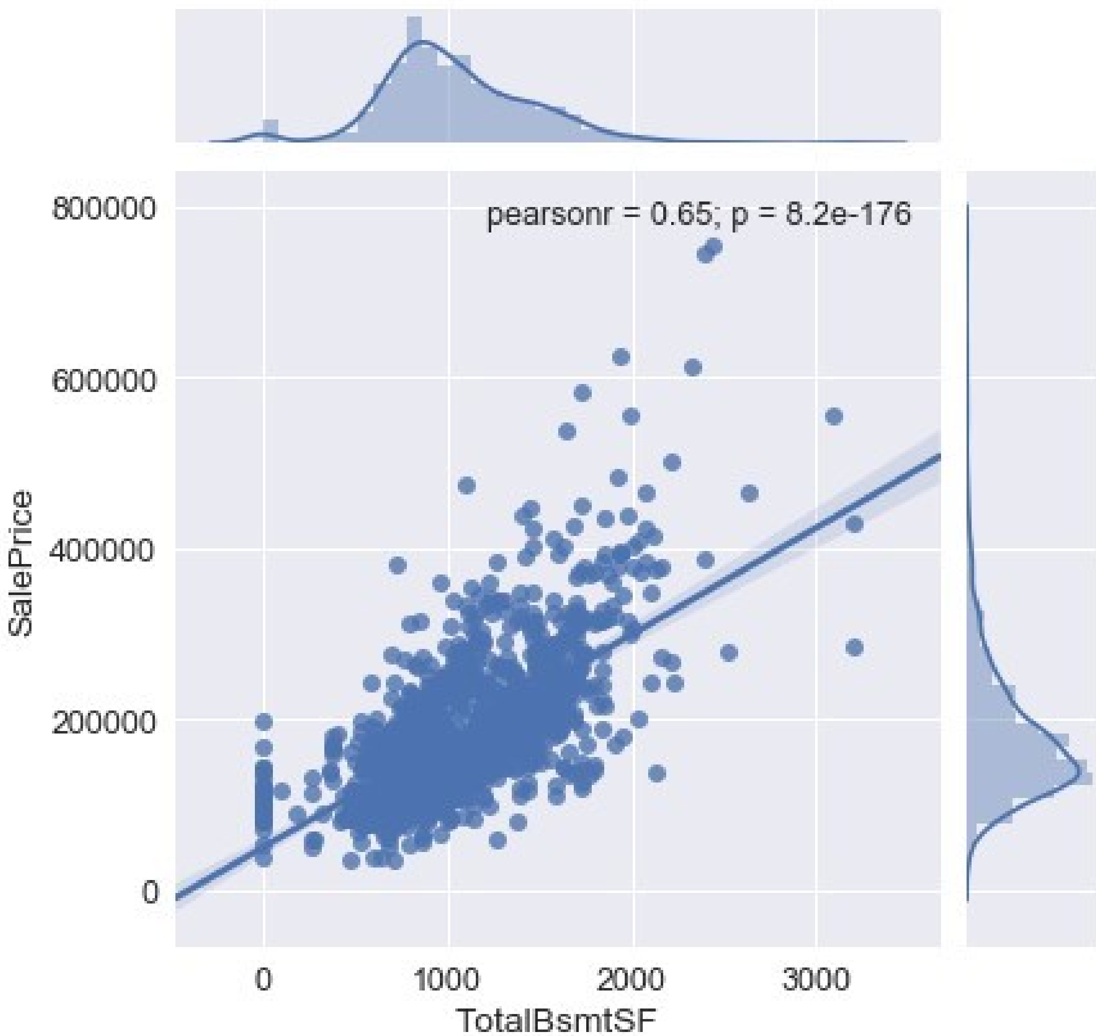
In [22]: # *Garage Area vs Sale Price* sns.jointplot(x=data_train['GarageArea'], y=data_train['SalePrice'], kind='reg')

Out[22]: <seaborn.axisgrid.JointGrid at 0x18b5f8a3a58>



In [23]: # *Basement Area vs Sale Price* sns.jointplot(x=data_train['TotalBsmtSF'], y=data_train['SalePrice'], kind='reg')

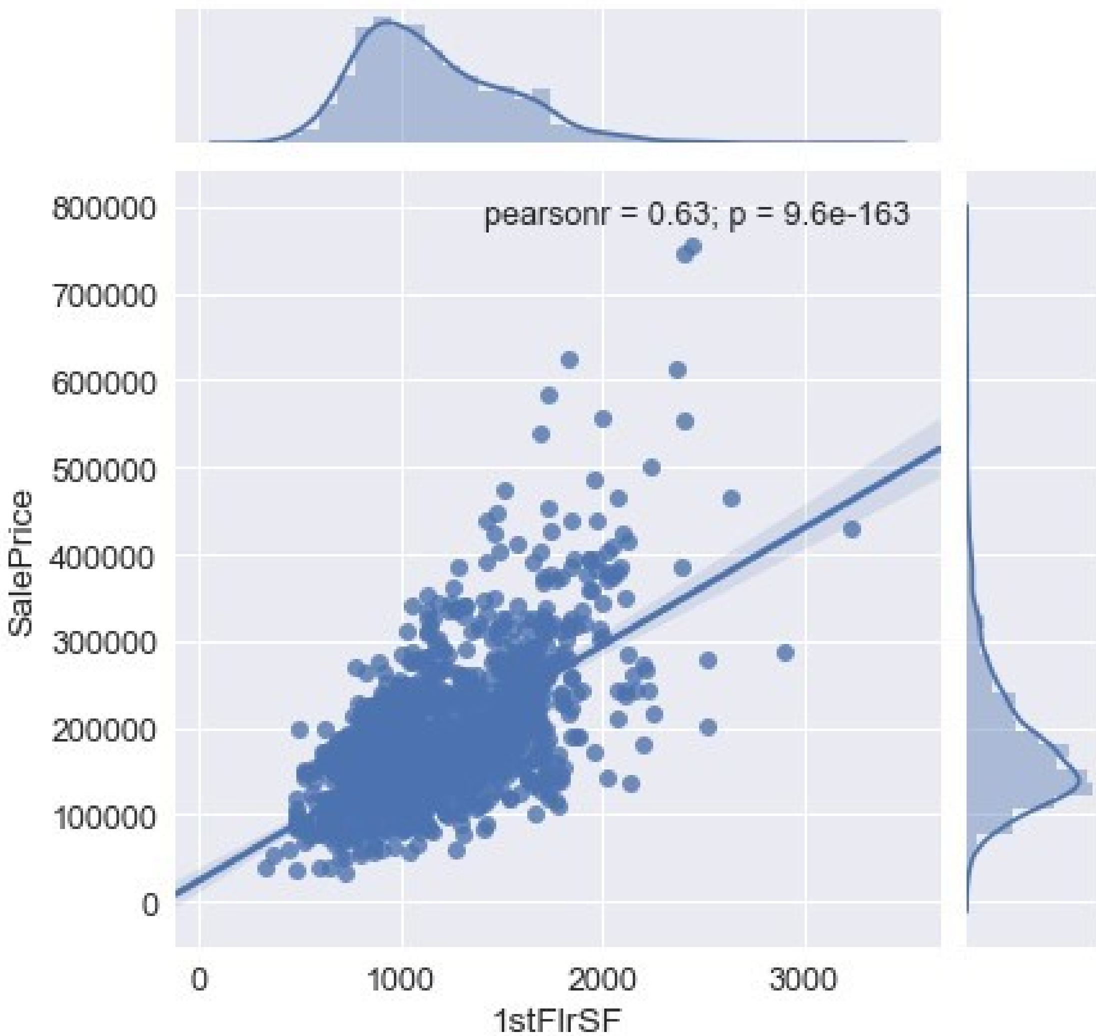
Out[23]: <seaborn.axisgrid.JointGrid at 0x18b5f8a3c50>



**Looks fine

In [24]: *# First Floor Area vs Sale Price* sns.jointplot(x=data_train['1stFlrSF'], y=data_train['SalePrice'], kind='reg')

Out[24]: <seaborn.axisgrid.JointGrid at 0x18b60201e10>

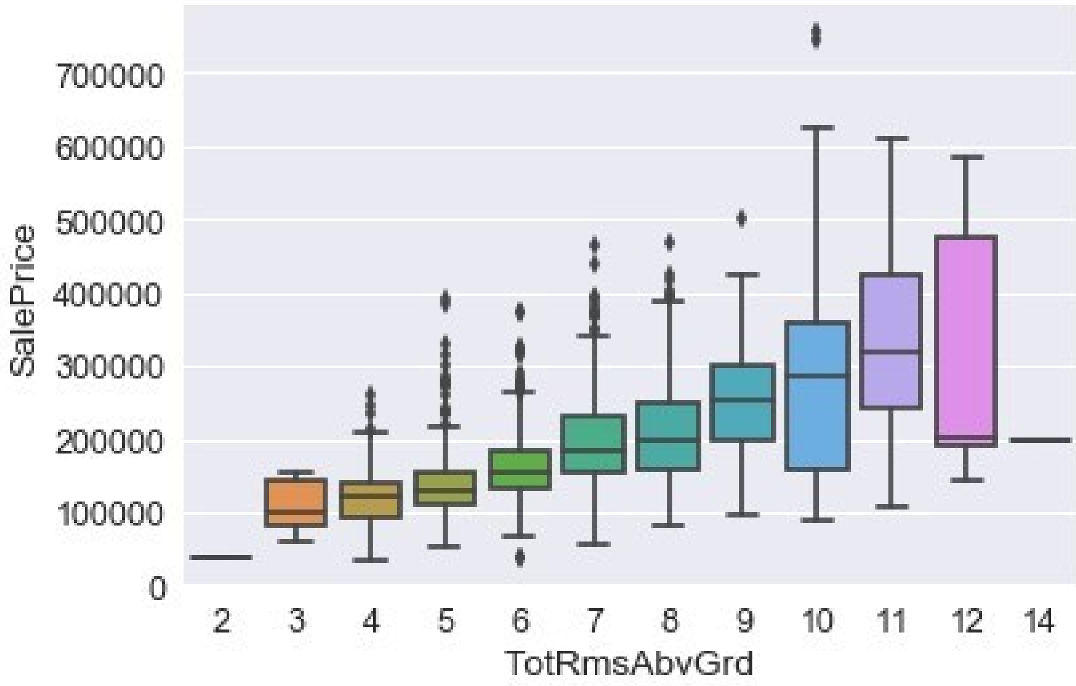


**Looks fine

In [25]: *# Total Rooms vs Sale Price*

```
sns.boxplot(x=data_train['TotRmsAbvGrd'], y=data_train['SalePrice'])
```

Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0x18b60571828>



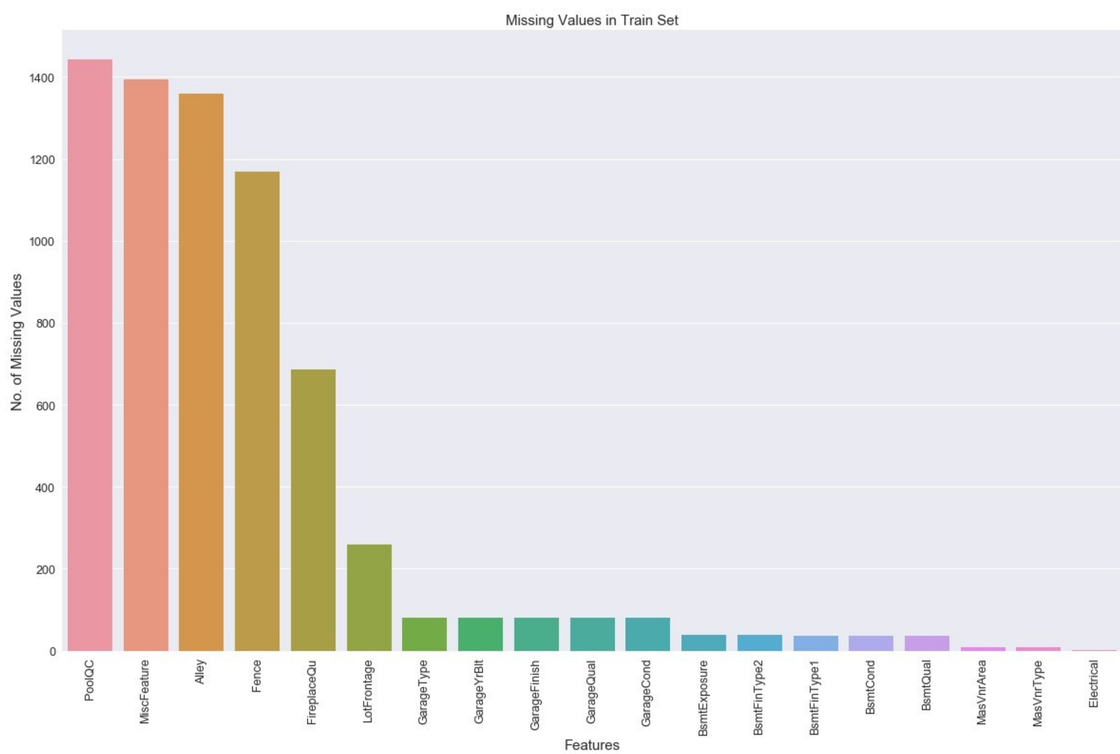
3.4 Missing Data and Clean Data

Missing data can imply a reduction in sample size. To ensure missing data handling is not biased and the process is thoeratically corrrect , Let’s look at the missing data fields that are in our datasets and combine the trainign and test dataset for further work-

In [26]:
```
#check for columns with null values and the number of null values in each of them for
cols=data_train.columns.values.tolist() mvx=[] mvy=[] cols.remove("SalePrice") for col in cols:
    if pd.isnull(data_train[col]).sum()>0: mvx = mvx + [col] mvy
        = mvy + [data_train[col].isnull().sum()] print(col,end=" :
        ") print(pd.isnull(data_train[col]).sum())

temp_df = pd.DataFrame(data={'mvx':mvx, 'mvy':mvy}) temp_df =
temp_df.sort_values(by=['mvy'], ascending=False) plt.figure(1,
figsize=(20,12)) sns.barplot(x=temp_df.mvx, y=temp_df.mvy)
plt.xticks(rotation='90') plt.title('Missing Values in Train Set', fontsize=15)
plt.xlabel('Features', fontsize=15)
plt.ylabel('No. of Missing Values', fontsize=15) plt.show()
```

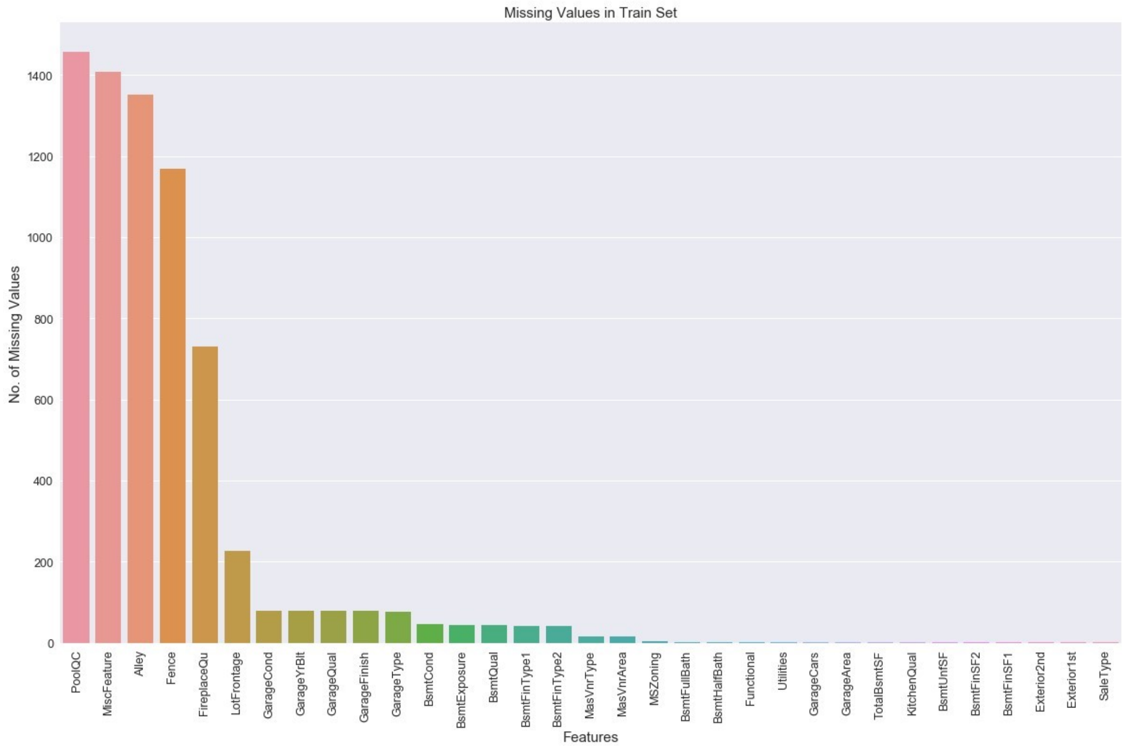
LotFrontage : 258
Alley : 1358
MasVnrType : 8
MasVnrArea : 8
BsmtQual : 37

BsmtCond : 37
BsmtExposure : 38
BsmtFinType1 : 37
BsmtFinType2 : 38
Electrical : 1
FireplaceQu : 686
GarageType : 81
GarageYrBlt : 81
GarageFinish : 81
GarageQual : 81
GarageCond : 81
PoolQC : 1442
Fence : 1168
MiscFeature : 1395



In [40]: *#check for columns with null values and the number of null values in each of them for* mvx=[] mvy=[] **for** col **in** cols:
if pd.isnull(data_test[col]).sum()>0: mvx = mvx + [col] mvy = mvy + [data_test[col].isnull().sum()] print(col,end=" : ") print(pd.isnull(data_test[col]).sum()) temp_df = pd.DataFrame(data={'mvx':mvx, 'mvy':mvy}) temp_df = temp_df.sort_values(by=['mvy'], ascending=**False**) plt.figure(1, figsize=(20,12)) sns.barplot(x=temp_df.mvx, y=temp_df.mvy) plt.xticks(rotation='90') plt.title('Missing Values in Train Set', fontsize=15) plt.xlabel('Features', fontsize=15) plt.ylabel('No. of Missing Values', fontsize=15) plt.show()

MSZoning : 4
LotFrontage : 227
Alley : 1352
Utilities : 2
Exterior1st : 1
Exterior2nd : 1
MasVnrType : 16
MasVnrArea : 15
BsmtQual : 44
BsmtCond : 45
BsmtExposure : 44
BsmtFinType1 : 42
BsmtFinSF1 : 1
BsmtFinType2 : 42
BsmtFinSF2 : 1
BsmtUnfSF : 1
TotalBsmtSF : 1
BsmtFullBath : 2
BsmtHalfBath : 2
KitchenQual : 1
Functional : 2
FireplaceQu : 730
GarageType : 76
GarageYrBlt : 78
GarageFinish : 78
GarageCars : 1
GarageArea : 1
GarageQual : 78
GarageCond : 78
PoolQC : 1456
Fence : 1169
MiscFeature : 1408
SaleType : 1



Analysis

As we can see there are a high number of missing values in the features titled PoolQC, MiscFeature, Alley and Fence. While apparently it may appear as if dropping these features would be a good idea, however, when I did drop them and tested it out without them, the results appear to worsen rather than improve. Therefore we will be keeping these features and assign a categorical value to their non-availability as well.

Garage discrepancies

There appears to be some discrepancies between the garage informations provided in the test set, namely -

1. GarageType : 76
2. GarageYrBlt : 78
3. GarageFinish : 78
4. GarageQual : 78
5. GarageCond : 78

These need some data handling. Let's see where these discrepencies are appearing at -

In [27]: temp_df = pd.DataFrame(columns=["Index","GarageType","GarageYrBlt","GarageFinish","Gar

```
new_rows = [] for index, row in
data_test.iterrows():
    if pd.notnull(row["GarageType"]) and pd.isnull(row["GarageYrBlt"]):
        new_rows.append([index,row["GarageType"],row["GarageYrBlt"],row["GarageFinish


temp_df = temp_df.append(pd.DataFrame(new_rows, columns=temp_df.columns)) print(temp_df)
```

```
   Index GarageType GarageYrBlt GarageFinish GarageQual GarageCond \
0 666       Detchd        NaN         NaN        NaN        NaN
1 1116      Detchd        NaN         NaN        NaN        NaN
    GarageCars GarageArea
0          1.0360.0
1          NaN      NaN
```

As we can see, for 666th index we have no values for GarageYr-Blt,GarageFinish,GarageQual,GarageCond. On the other hand for 1116th, we have no values given at all save for GarageType. Thus we shall fill up the former with max and median values while assume the latter has no garage

---

```
In [42]: print("GarageYrBlt : ") print(data_test["GarageYrBlt"].median())
         print("GarageFinish : ") print(data_test["GarageFinish"].mode())
         print("GarageQual : ") print(data_test["GarageQual"].mode())
         print("GarageCond : ")
         print(data_test["GarageCond"].mode())
```

```
GarageYrBlt :
1979.0
GarageFinish :
0     Unf
dtype: object
GarageQual :
0     TA
dtype: object GarageCond :
0     TA
dtype: object
```

```
In [43]: data_test.loc[666,"GarageQual"] = "TA" data_test.loc[666, "GarageCond"]
         = "TA" data_test.loc[666, "GarageFinish"] = "Unf" data_test.loc[666,
         "GarageYrBlt"] = "1979" data_test.loc[1116, "GarageType"] = np.nan
```

Data Preprocessing/ Feature Engineering

```
In [44]: # For imputing missing values: fill in missing LotFrontage values by the median LotFro

         lot_frontage_by_neighborhood = data_train["LotFrontage"].groupby(data_train["Neighborh

         print(lot_frontage_by_neighborhood.describe())
```

```
                count        mean          std min    25%   50%    75%   max
Neighborhood
Blmngtn       14.0 47.142857 4.990100 43.0 43.00 43.0     53.00  53.0 Blueste    2.0 24.000000
0.000000 24.0 24.00 24.0      24.00   24.0 BrDale    16.0 21.562500 1.209339 21.0 21.00 21.0
21.00   24.0
BrkSide            51.0 57.509804 15.528519 50.0 50.00 52.0          60.00 144.0
ClearCr            13.0 83.461538 18.875096 62.0 75.00 80.0          83.00 138.0
CollgCr           126.0 71.682540 16.359291 36.0 64.00 70.0          78.00 122.0
Crawfor            41.0 71.804878 19.436074 40.0 55.00 74.0          82.00 130.0
Edwards            90.0 64.811111 18.643850 24.0 58.25 64.5          73.75 134.0
Gilbert            49.0 79.877551 32.748176 42.0 60.00 65.0          93.00 182.0
IDOTRR             33.0 60.757576 15.435410 40.0 50.00 60.0          60.00 110.0
MeadowV            15.0 27.800000 10.107988 21.0 21.00 21.0         38.50    44.0
Mitchel            35.0 69.857143 22.380589 32.0 57.50 71.0          81.00 129.0
NAmes 184.0 76.418478 23.701327 34.0 68.75 73.0     80.00 313.0 NPkVill    7.0 32.285714
14.150551 24.0 24.00 24.0     38.50   53.0 NWAmes  45.0 81.288889 10.614360 46.0 78.00 80.0
85.00 105.0
NoRidge            33.0 91.878788 25.320147 52.0 81.00 91.0          98.00 174.0
NridgHt              75.0 81.666667 25.088672 34.0 62.50 87.0 102.00 129.0
OldTown           108.0 62.768519 18.253463 30.0 50.00 60.0          63.00 153.0
SWISU              23.0 58.913043 10.539592 50.0 52.00 60.0          60.00 102.0
Sawyer             48.0 74.437500 14.728618 40.0 65.00 71.0          80.00 115.0
SawyerW            50.0 71.500000 14.720872 50.0 63.00 66.5          80.00 116.0
Somerst            75.0 64.000000 22.741200 24.0 43.50 72.0          78.50 116.0
StoneBr            20.0 62.700000 23.445570 39.0 41.00 61.5          80.50 124.0
Timber             30.0 80.133333 23.799063 42.0 68.00 85.0          88.75 150.0
```

Veenker 7.0 59.714286 25.597619 30.0 35.00 68.0 80.00 90.0

In [45]:
```
#convert categorical features into ordinal numbers 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
```

In [46]:
```
data_train["SalePrice"].groupby(data_train["Neighborhood"]).median().sort_values()
```

Out[46]:
```
Neighborhood
MeadowV     88000
IDOTRR     104750
BrDale     106000
OldTown    118250
Edwards    119500
BrkSide    124300
Sawyer     135000
Blueste    137500
SWISU      139500
NAmes      140000
NPkVill    146000
Mitchel    150900
SawyerW    179900
Gilbert    181000
NWAmes     182900
Blmngtn    191000
CollgCr    197200
ClearCr    200250
Crawfor    200624
Veenker    218000
Somerst    222000
Timber     228475
StoneBr    278000
NoRidge    301500
NridgHt    316000
Name: SalePrice, dtype: int64
```

Saving 'SalePrice' values to var y_train

In [47]:
```
y_train = data_train.SalePrice.values
```

In [48]:
```
y_train
```

Out[48]:
```
array([208500, 181500, 223500, ..., 266500, 142125, 147500], dtype=int64)
```

Survey

As there are many neighborhoods and some having median values quite close to one another, we shall later group them further to reduce the number of categories

4 Adding test and train set

We will add test and train set just to do the preprocessing together using only the train set. It will make our work more organized as we need to do same preprocessing to both the datasets.

In [49]: data_train.head()

Out[49]:

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

	LandContour	Utilities	LotConfig	...	PoolArea	PoolQC	Fence	MiscFeature \
0	Lvl	AllPub	Inside	...	0	NaN	NaN	NaN
1	Lvl	AllPub	FR2	...	0	NaN	NaN	NaN
2	Lvl	AllPub	Inside	...	0	NaN	NaN	NaN
3	Lvl	AllPub	Corner	...	0	NaN	NaN	NaN
4	Lvl	AllPub	FR2	...	0	NaN	NaN	NaN

	MiscVal	MoSold	YrSold	SaleType	SaleCondition	SalePrice
0	0	2	2008	WD	Normal	208500
1	0	5	2007	WD	Normal	181500
2	0	9	2008	WD	Normal	223500
3	0	2	2006	WD	Abnorml	140000
4	0	12	2008	WD	Normal	250000

[5 rows x 80 columns]

In [34]:
```
# keep the length of train and test dataset saved ntrain =
data_train.shape[0] ntest = data_test.shape[0]

# https://pandas.pydata.org/pandas-docs/version/0.23.4/generated/pandas.concat.html #
https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.reset_index. all_data =
pd.concat((data_train, data_test), sort=False).reset_index(drop=True)
```

In [35]: print("all_data size is : {}".format(all_data.shape))

all_data size is : (2907, 80) In [36]:

all_data.columns Out[36]:

Index(['MSSubClass', 'MSZoning',

'LotFrontage', 'LotArea', 'Street', 'Alley',

'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope',
'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseStyle',
'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'RoofStyle',
'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea',
'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond',
'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2',
'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating', 'HeatingQC',
'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual', 'TotRmsAbvGrd',
'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType', 'GarageYrBlt',
'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual', 'GarageCond',
'PavedDrive', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch',
'ScreenPorch', 'PoolArea', 'PoolQC', 'Fence', 'MiscFeature', 'MiscVal',
'MoSold', 'YrSold', 'SaleType', 'SaleCondition', 'SalePrice'], dtype='object')

```
In [37]: all_data.SalePrice.tail()
```

```
Out[37]: 2902    NaN
         2903    NaN
         2904    NaN
         2905    NaN
         2906    NaN
         Name: SalePrice, dtype: float64
```

```
In [38]: # drop SalePrice all_data.drop(['SalePrice'], axis=1, inplace=True)
print("all_data size is : {}".format(all_data.shape)) all_data size is : (2907, 79)
```

Now **all_data** dataframe has all the features and instances in the training and test set without target feature.

We can now look for missing values for both train and test at the same time and fill them in **using the training dataset values**.

We can deal with training and test data separately but it's easy to deal with them both at the same time and it also makes sure that both train and test dataset has gone through same transformation.

5 Filling the missing or NULL values

Missing data Finding the missing data from the **all_data** dataframe

```
In [39]: # all the missing values null_val_all =
            all_data.isnull().sum().sort_values(ascending=False) null_val_all =
            null_val_all[null_val_all>0] print(null_val_all)
```

```
PoolQC          2898
MiscFeature     2803
Alley           2710
Fence           2337
FireplaceQu     1416
LotFrontage      485
GarageCond       159
GarageQual       159
GarageYrBlt      159
GarageFinish     159
GarageType       157
BsmtCond          82
BsmtExposure      82
BsmtQual          81
BsmtFinType2      80
BsmtFinType1      79
MasVnrType        24
MasVnrArea        23
MSZoning           4
BsmtHalfBath       2
Utilities          2
Functional         2
BsmtFullBath       2
BsmtFinSF2         1
BsmtFinSF1         1
Exterior2nd        1
BsmtUnfSF          1
TotalBsmtSF        1
Exterior1st        1
SaleType           1
Electrical         1
KitchenQual        1
GarageArea         1
GarageCars dtype:  1
int64
```

Here I am handling the missing values by droping coloumns. However, This is not always a good practise. Here I have checked the dataset against linear regression and It shows imputating the missing values instead of dropping them.

```
In [40]: all_data["PoolQC"] = all_data["PoolQC"].fillna("None") all_data["MiscFeature"] =
            all_data["MiscFeature"].fillna("None")

            var = ['Alley', 'Fence', 'FireplaceQu',
                   'GarageType', 'GarageFinish', 'GarageQual', 'GarageCond',
                   'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', 'MasVnr for col in var:
```

```
all_data[col] = all_data[col].fillna('None') all_data["Functional"] =

all_data["Functional"].fillna("Typ")
```

Garage Yr Blt (Discrete): Year garage was built **Garage Area** (Continuous): Size of garage in square feet **Garage Cars** (Discrete): Size of garage in car capacity
BsmtFin SF 1 (Continuous): Type 1 finished square feet
BsmtFin SF 2 (Continuous): Type 2 finished square feet
Bsmt Unf SF (Continuous): Unfinished square feet of basement area
Total Bsmt SF (Continuous): Total square feet of basement area
Bsmt Full Bath (Discrete): Basement full bathrooms
Bsmt Half Bath (Discrete): Basement half bathrooms
Mas Vnr Area (Continuous): Masonry veneer area in square feet

All of these features will null value means there is no such thing in that house. So filling up with 0 makes sense.

```
In [41]: var = ['GarageYrBlt', 'GarageArea', 'GarageCars',
                'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF','TotalBsmtSF', 'BsmtFullBath', 'BsmtHal
         'MasVnrArea'] for
    col in var:
        all_data[col] = all_data[col].fillna(0)
```

LotFrontage (Continuous): Linear feet of street connected to property

Since the area of each street connected to the house property most likely have a similar area to other houses in its neighborhood , we can fill in missing values by the mean LotFrontage of the neighborhood.

We filled in the null values by only looking into the training dataset. So the test dataset has no role to play in model building.

```
In [42]: filling_vals = all_data.groupby("Neighborhood")["LotFrontage"].mean()

    for i in range(0, len(all_data)):
        # print(all_data.loc[i, 'LotFrontage']) if np.isnan(all_data.loc[i, 'LotFrontage']): #
        print(all_data.loc[i, 'Neighborhood']) neighborhood_name = all_data.loc[i,
        'Neighborhood'] all_data.loc[i, 'LotFrontage'] = filling_vals[neighborhood_name]
            # print(all_data.loc[i, 'LotFrontage'])
```

```
In [43]: all_data.isnull().sum().sort_values(ascending=False)[:10]
```

```
Out[43]: MSZoning       4
         Utilities      2
         Exterior1st    1
         SaleType       1
         Exterior2nd    1
```

```
Electrical      1
KitchenQual     1
Foundation      0
MasVnrType      0
MasVnrArea      0
dtype: int64
```

MSZoning: Identifies the general zoning classification of the sale.

A Agriculture
C Commercial
FV Floating Village Residential
I Industrial
RH Residential High Density
RL Residential Low Density
RP Residential Low Density Park
RM Residential Medium Density

we can fill in missing values with most common value in the training dataset

```
In [44]: all_data['MSZoning'] = all_data['MSZoning'].fillna(data_train['MSZoning'].mode()[0])
```

Utilities: Type of utilities available

AllPub All public Utilities (E,G,W,& S)
NoSewr Electricity, Gas, and Water (Septic Tank)
NoSeWa Electricity and Gas Only ELO
Electricity only

Let's check the unique values in Utilities Feature and then decide what to do.

```
In [45]: print('Unique Values for Utilities')
         print(all_data['Utilities'].value_counts()) print()
         print('index of the NoSeWa type utilities:', all_data[all_data['Utilities']=='NoSeWa'
```

```
Unique Values for Utilities
AllPub     2904
NoSeWa        1
Name: Utilities, dtype: int64 index of the NoSeWa

type utilities: 938
```

Only one data shows NoSeWa for Utilities and that is in training set. So this feature is not of any use to us either way. We will just get rid of it instead of filling in those two null values.

In [46]: # *deleting the Utilities feature*

```
all_data = all_data.drop(['Utilities'], axis=1)
```

5.1 filling the rest of the missing data

In [47]:
```
all_data['Electrical'] = all_data['Electrical'].fillna(data_train['Electrical'].mode() all_data['KitchenQual'] =
all_data['KitchenQual'].fillna(data_train['KitchenQual'].mod all_data['Exterior1st'] =
all_data['Exterior1st'].fillna(data_train['Exterior1st'].mod all_data['Exterior2nd'] =
all_data['Exterior2nd'].fillna(data_train['Exterior2nd'].mod all_data['SaleType'] =
all_data['SaleType'].fillna(data_train['SaleType'].mode()[0])
```

Checking if there are any other null values

In [48]:
```
all_data.isnull().sum().max()
```

Out[48]: 0

As we read from the data desctription that, there are some categorical features with clear ordering. These are Ordinal features.

In [49]:
```
cols = ['BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', 'BsmtQual', 'Centr
```

In [50]:
```
# shape all_data.shape
```

Out[50]: (2907, 78)

These are all ordinal features because they have a sense of order amongst them. We will assign ordered numbers to them. We will just keep the distance of the ordered levels equal to keep the model less complex.

In [51]:
```
# Encode some categorical features as ordered numbers when there is information in the

all_data = all_data.replace({"BsmtCond" : {"None" : 0, "Po" : 1, "Fa" : 2, "TA" : 3,
                              "BsmtExposure" : {"None" : 0, "No" : 1, "Mn" : 2, "Av": 3, "Gd
                              "BsmtFinType1" : {"None" : 0, "Unf" : 1, "LwQ": 2, "Rec" : 3,
                                                "ALQ" : 5, "GLQ" : 6},
                              "BsmtFinType2" : {"None" : 0, "Unf" : 1, "LwQ": 2, "Rec" : 3,
                                               "ALQ" : 5, "GLQ" : 6},
                              "BsmtQual" : {"None" : 0, "Po" : 1, "Fa" : 2, "TA": 3, "Gd" :
                                  "CentralAir" : {"N" : 0, "Y" : 1},
                              "ExterCond" : {"Po" : 1, "Fa" : 2, "TA": 3, "Gd": 4, "Ex" : 5}
                              "ExterQual" : {"Po" : 1, "Fa" : 2, "TA": 3, "Gd": 4, "Ex" : 5}
                              "Fence" : {"None" : 0, "MnWw" : 1, "GdWo" : 2, "MnPrv" : 3, "Gd
                              "FireplaceQu" : {"None" : 0, "Po" : 1, "Fa" : 2, "TA" : 3, "Gd "Functional" :
                              {"Sal" : 1, "Sev" : 2, "Maj2" : 3, "Maj1" : 4,
                                           "Min2" : 6, "Min1" : 7, "Typ" : 8},
                              "GarageCond" : {"None" : 0, "Po" : 1, "Fa" : 2, "TA" : 3, "Gd"
                              "GarageFinish" : {"None" : 0, "Unf" : 1, "RFn" : 2, "Fin" : 3}
```

```
"GarageQual" : {"None" : 0, "Po" : 1, "Fa" : 2, "TA" : 3, "Gd" "HeatingQC" :
{"Po" : 1, "Fa" : 2, "TA" : 3, "Gd" : 4, "Ex" :
"KitchenQual" : {"Po" : 1, "Fa" : 2, "TA" : 3, "Gd" : 4, "Ex"
"LandSlope" : {"Sev" : 1, "Mod" : 2, "Gtl" : 3},
        "LotShape" : {"IR3" : 1, "IR2" : 2, "IR1" : 3, "Reg" : 4},
    "PavedDrive" : {"N" : 0, "P" : 1, "Y" : 2},
        "PoolQC" : {"None" : 0, "Fa" : 1, "TA" : 2, "Gd" : 3, "Ex" : 4
)
```

In [52]: all_data.shape

Out[52]: (2907, 78)

5.2 Adding new features

In [53]:
```
# split the train data and then add the target feature to it data = pd.concat([all_data[:ntrain], pd.DataFrame(y_train
    columns=['SalePrice'])], ax
```

In [55]: data.shape

Out[55]: (1448, 79)

In [56]:
```
# manipulating the correlation matrix that we made earlier

cor = data.corr()['SalePrice'].sort_values(ascending=False) print(cor[cor > 0.5])
# print(len(cor[cor > 0.5]))

# get the feature names
cor_fet = list(cor.index[1:len(cor[cor > 0.5])])
```

```
SalePrice       1.000000
OverallQual     0.821420
GrLivArea       0.724646
GarageCars      0.691649
ExterQual       0.681201
GarageArea      0.670081
KitchenQual     0.670029
TotalBsmtSF     0.648135
1stFlrSF        0.621464
BsmtQual        0.617233
GarageFinish    0.608554
FullBath        0.595782
YearBuilt       0.589709
YearRemodAdd    0.563581
FireplaceQu     0.545237
TotRmsAbvGrd    0.536930
Name: SalePrice, dtype: float64
```

Now I am creating new features using polynomials on the Top 10 features I got from Corelation Matrix

In [59]:
```
for fet in cor_fet: name_2 = fet + '_2' name_3 = fet + '_3'
        name_sq = fet + '_sq' all_data[name_2] = all_data[fet]
        ** 2 all_data[name_3] = all_data[fet] ** 3
        all_data[name_sq] = np.sqrt(all_data[fet])
```

checking the shape of **all_data** DataFrame

In [60]:
```
all_data.shape
```

Out[60]: (2907, 123)

6 Survey

Data Manipulation

Here I've manipulated the entire dataset by filling in the missing values, mapping categorical features to numeric equivalents, and sort out most of the dataset by dividing some or joining multiple features into a single feature to reduce redundencies. In short, combine all the numerical features into one big DataFrame. Some have been mapped using python dictionaries, while others have been converted based on their values and description as was given in the data description. This has been edited multiple times to see what produces the best results(for example the label encoding portion in the middle) and mostly arranged on a trial and error basis. We don't add the one-hot encoded variables here though, that will be handled later on.

As we can see our number of features have increased from 78 to 123 through this data manipulation. We shall now proceed to scale the data,however, we shall be copying the NeighborhoodBin into a temporary DataFrame because we want to use the unscaled version later on for the one-hot encoding process.

** Missing data manipultaion ends here **

6.1 Normalization

As we've previously seen the data distribution varies greatly. So, next we shall scale the data and try to minimize the variation

Reference of the skewness to make the features normal Read Here

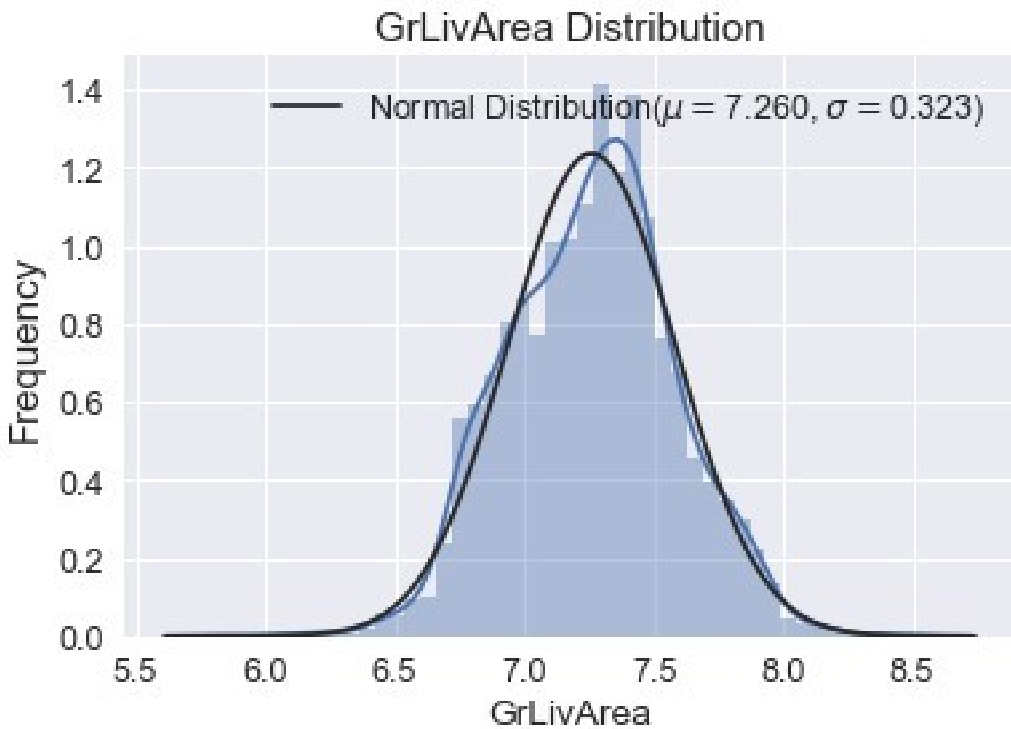
In [61]:
```
numeric_feats = all_data.dtypes[all_data.dtypes != "object"].index

    # Check the skew of all numerical features skewed_feats = all_data[numeric_feats].apply(lambda x:
    skew(x.dropna())).sort_values(a print("\nSkew in numerical features: \n") skewness =
    pd.DataFrame({'Skew' :skewed_feats}) skewness.head(10)


    skewness = skewness[abs(skewness) > 0.75]
    print("There are {} skewed numerical features to log transform".format(skewness.shape[


    # http://onlinestatbook.com/2/transformations/box-cox.html
    # https://docs.scipy.org/doc/scipy-0.19.0/reference/generated/scipy.special.boxcox1p.h
    # from scipy.special import boxcox1p
```

```
skewed_features = skewness.index
# lam = 0.15

for feat in skewed_features:
    # all_data[feat] = boxcox1p(all_data[feat], lam) all_data[feat] =
    np.log1p(all_data[feat])
```

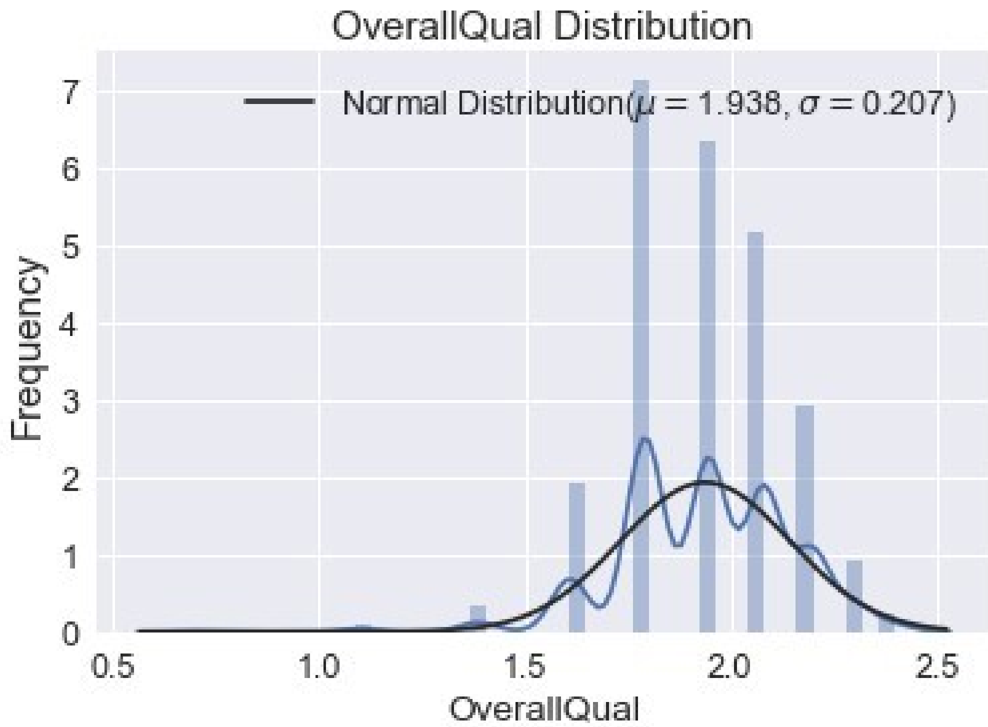
Skew in numerical features:

There are 100 skewed numerical features to log transform

In [74]:
```
import scipy.stats as scst
#For GrLivArea print()
(mu, sigma) = scst.norm.fit(all_data['GrLivArea']) mu =
round(mu,3) sigma = round(sigma,3)


plt.figure(3) sns.distplot(all_data['GrLivArea'] , fit=scst.norm) plt.title('GrLivArea Distribution',
fontsize=15) plt.ylabel('Frequency', fontsize=15) plt.legend(['Normal Distribution($\mu=$%.3f,
$\sigma=$%.3f)' % (mu,sigma)], loc='best') plt.show() print('\nmu(Mean):', mu)
print('sigma(Standard Deviation):', sigma)


#For OverallQual print()
(mu, sigma) = scst.norm.fit(all_data['OverallQual']) mu =
round(mu,3) sigma = round(sigma,3)
plt.figure(3) sns.distplot(all_data['OverallQual'] , fit=scst.norm) plt.title('OverallQual
Distribution', fontsize=15) plt.ylabel('Frequency', fontsize=15) plt.legend(['Normal
Distribution($\mu=$%.3f, $\sigma=$%.3f)' % (mu,sigma)], loc='best') plt.show()
print('\nmu(Mean):', mu) print('sigma(Standard Deviation):', sigma)
```



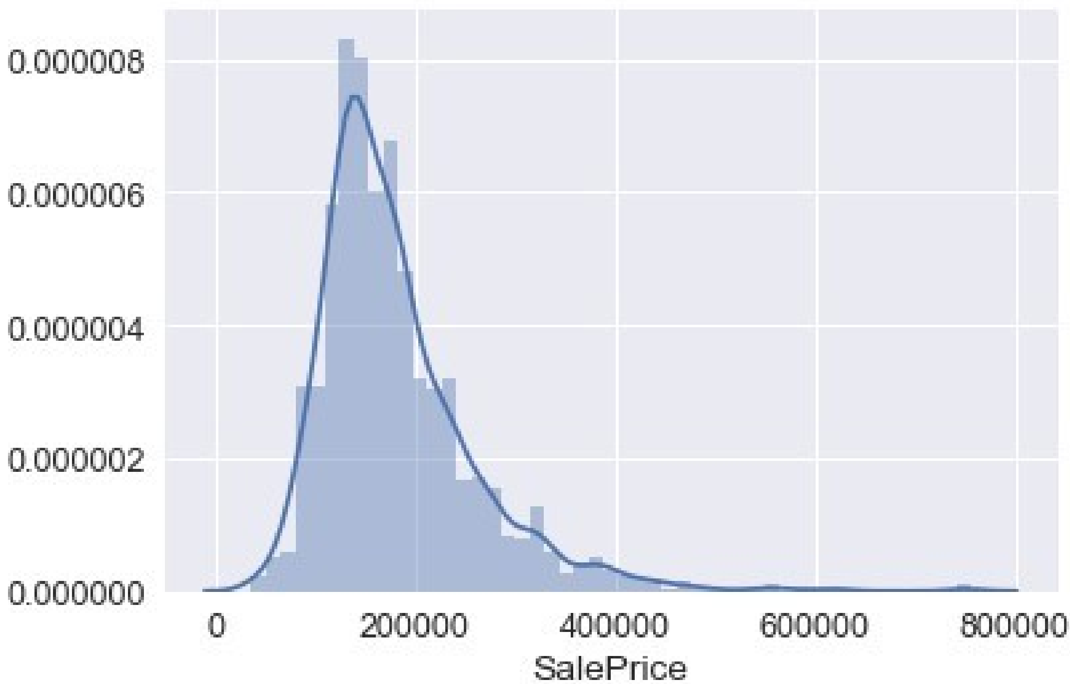
mu(Mean): 7.26 sigma(Standard Deviation): 0.323



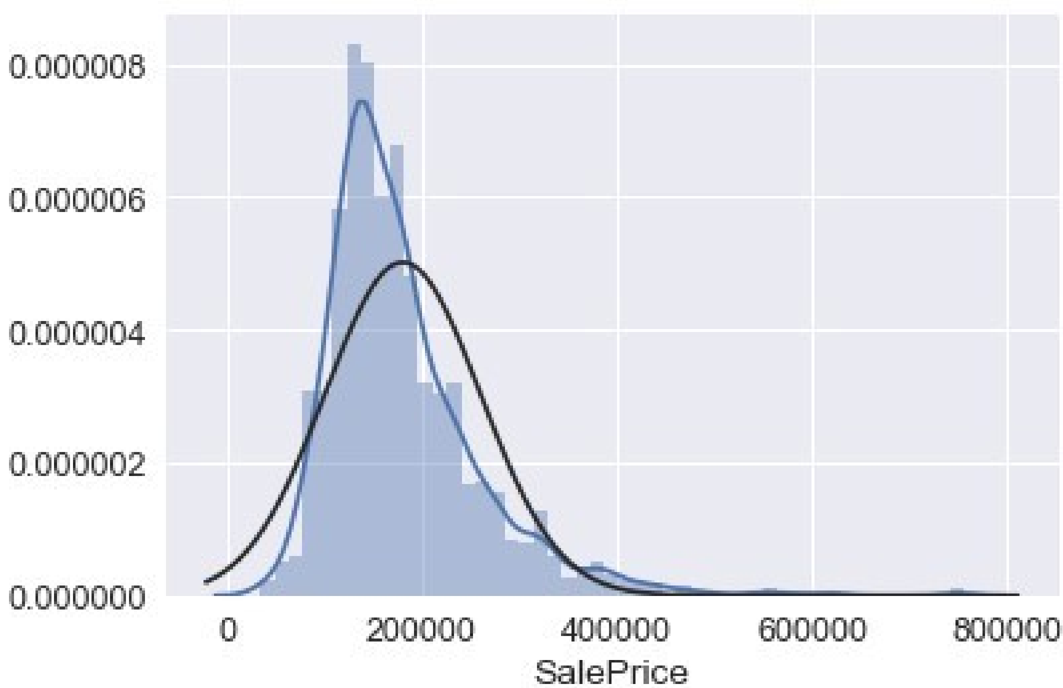
mu(Mean): 1.938
sigma(Standard Deviation): 0.207

In [28]:
```
# I used the numpy fuction log1p which applies log(1+x) to all elements of the column
# data_train["SalePrice"] = np.log1p(data_train["SalePrice"])


#histogram sns.distplot(data_train['SalePrice']);

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

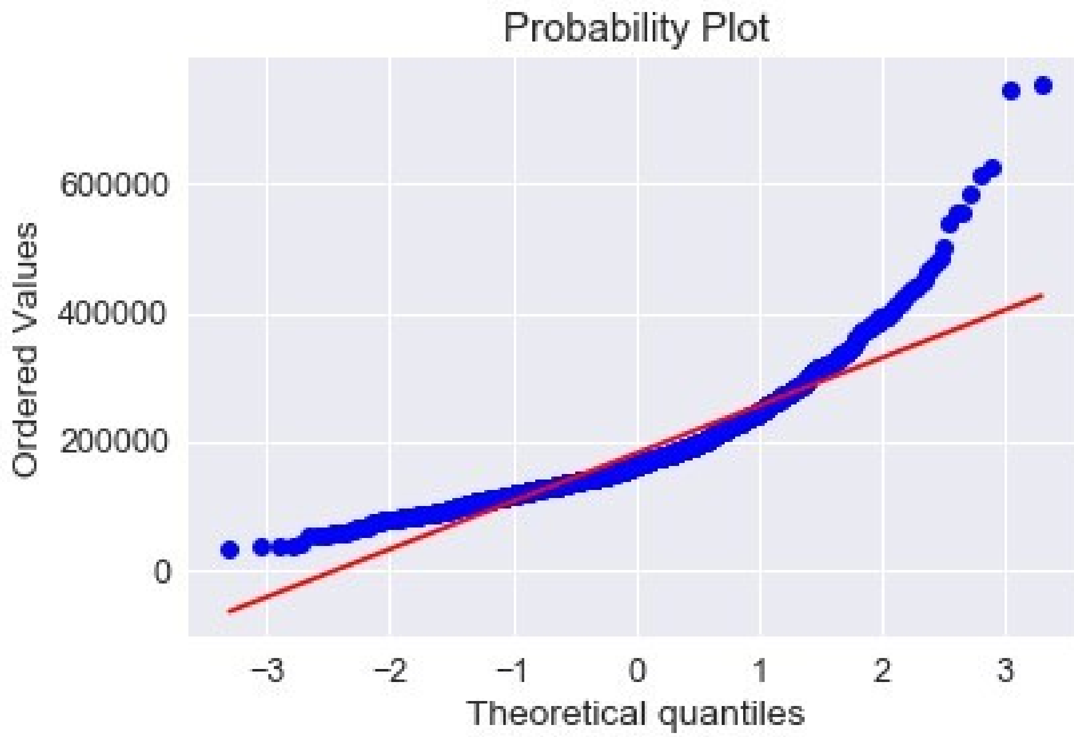
Skewness: 1.894512
Kurtosis: 6.568230



In [29]: *#histogram and normal probability plot* sns.distplot(data_train['SalePrice'], fit=norm);



In [30]: fig = plt.figure() res = stats.probplot(data_train['SalePrice'], plot=plt)

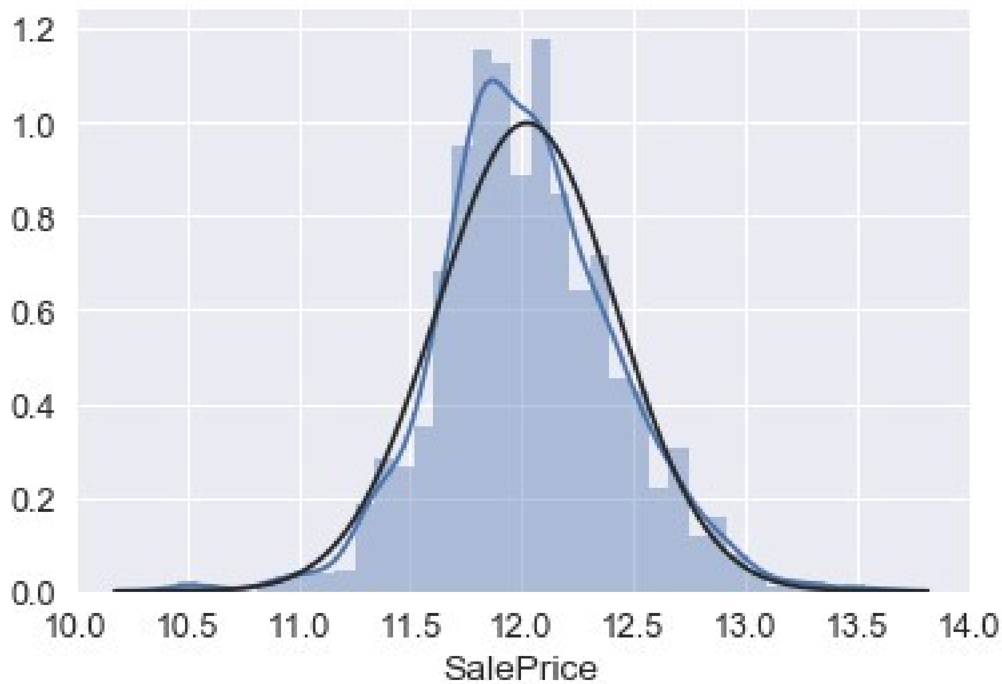


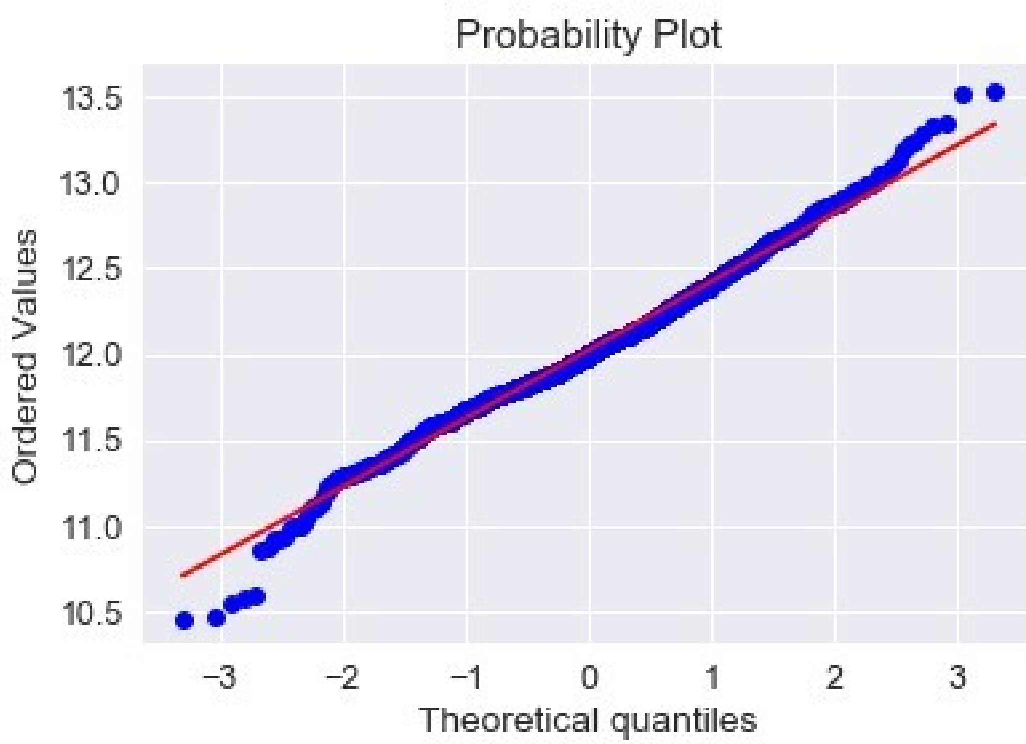
6.2 Applying log transformation

using log1p or just log? which one is better? Read more from here

```
In [31]: data_train['SalePrice'] = np.log(data_train['SalePrice'])
```

```
In [32]: #transformed histogram and normal probability plot
         sns.distplot(data_train['SalePrice'], fit=norm); fig = plt.figure() res =
         stats.probplot(data_train['SalePrice'], plot=plt)
```





In [33]: y_train = data_train.SalePrice.values y_train

Out[33]: array([12.24769432, 12.10901093, 12.31716669, ..., 12.49312952,
11.86446223, 11.90158345])

Survey
As we can see from the plot values, our data is now in a much more uniform distribution.

7 Categorical to Numerical

As we have seen in our dataframe there are not only numerical but also there are some categorical data too.
I am going to use get_dummies fuction to convert the categorical variable into numerical variable

In [62]:
```
# https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.get_dummies.html#p all_data =
pd.get_dummies(all_data) all_data.shape
```

Out[62]: (2907, 271)

7.1 Split train and test

In [63]:
```
train = all_data[:ntrain]
test = all_data[ntrain:]
```

In [64]:
```
print(test.shape) test.head()
```

(1459, 271)

Out[64]:
```
      MSSubClass LotFrontage   LotArea LotShape LandSlope OverallQual \
1448    3.044522    4.394449 9.360741 1.609438  1.386294    1.791759
1449    3.044522    4.406719 9.565775 1.386294  1.386294    1.945910
1450    4.110874    4.317488 9.534668 1.386294  1.386294    1.791759
1451    4.110874    4.369448 9.208238 1.386294  1.386294    1.945910
1452    4.795791    3.784190 8.518392 1.386294  1.386294    2.197225
      OverallCond YearBuilt YearRemodAdd MasVnrArea ... SaleType_ConLw \
1448     1.945910  7.581720     7.581720   0.000000 ...              0
1449     1.945910  7.580189     7.580189   4.691348 ...              0
1450     1.791759  7.599902     7.600402   0.000000 ...              0
1451     1.945910  7.600402     7.600402   3.044522 ...              0
1452     1.791759  7.597396     7.597396   0.000000 ...              0
      SaleType_New SaleType_Oth SaleType_WD SaleCondition_Abnorml \
1448             0            0           1                     0
1449             0            0           1                     0
1450             0            0           1                     0
1451             0            0           1                     0
1452             0            0           1                     0

      SaleCondition_AdjLand SaleCondition_Alloca SaleCondition_Family \
1448                      0                    0                    0
1449                      0                    0                    0
1450                      0                    0                    0
1451                      0                    0                    0
```

1452	0	0	0

	SaleCondition_Normal	SaleCondition_Partial
1448	1	0
1449	1	0
1450	1	0
1451	1	0
1452	1	0

[5 rows x 271 columns]

In [65]:
```
# saving to csv to use later in different algorithms
data = pd.concat([train, pd.DataFrame(y_train, columns=['SalePrice'])], axis=1)
data.to_csv('train_salePrice.csv',index=False) test.to_csv('test_salePrice.csv', index=False)
```

In [66]:
```
test_ID.shape # test_ID.head(5) ids =
pd.DataFrame(test_ID, columns=['Id'])
ids.to_csv('test_id.csv', index=False)
```

In [67]:
```
y_train.shape
```

Out[67]: (1448,)

8 Copying Available Datasets

keeping copy of Datasets that was created earlier to reuse it later on .

In [68]:
```
train_1 =train.copy() test_1 =test.copy()
df_train = data_train.copy() df_test
= data_test.copy() print ("Data copy
complete")
```

Data copy complete

In [81]:
```
y_train.shape
```

Out[81]: (1448,)

In [82]:
```
print("Train Set Shape : ",train.shape) print("Test Set
Shape :",test.shape)
```

Train Set Shape : (1448, 375)
Test Set Shape : (1459, 375)

And now we have equal number of features which is exactly what we desire. As we have taken care of the normalization, we shall now scale down the target variable SalePrice. 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 [144]: #label_df is the dataframe made solely with the target field SalePrice label_df =
          pd.DataFrame(index = train.index, columns=["SalePrice"]) label_df["SalePrice"] =
          np.log(data_train["SalePrice"]) print("label_df", label_df.shape)
```

label_df (1448, 1)

In order to check the accuracy of various models later on I've defined here a function to calculate the root mean squared error(RMSE) which shall later help to evaluate models

```
In [84]: def rmse(y_true, y_pred): return np.sqrt(mean_squared_error(y_true,
               y_pred))
```

Detect and weed out further outliers through IsolationForest

The IsolationForest is an ensemble algorithm which is used to determine anomalies/outliers.

From Scikit-Learn's documentation, which describes it well -

The IsolationForest 'isolates' observations by randomly selecting a feature and then randomly selecting a split value between the maximum and minimum values of the selected feature.

Since recursive partitioning can be represented by a tree structure, the number of splittings required to isolate a sample is equivalent to the path length from the root node to the terminating node.

This path length, averaged over a forest of such random trees, is a measure of normality and our decision function.

Random partitioning produces noticeably shorter paths for anomalies. Hence, when a forest of random trees collectively produce shorter path lengths for particular samples, they are highly likely to be anomalies.

```
In [209]: from sklearn.ensemble import IsolationForest clf = IsolationForest(n_estimators=500, max_samples=1.0,
          random_state=1001, bootstrap print('\nRunning Isolation Forest:') clf.fit(train, label_df)
          isof = clf.predict(train) label_df['isof'] = isof train['isof'] = isof #myindex =
          train['isof'] < 0 train.drop(train[train["isof"] <0].index, inplace=True)
          label_df.drop(label_df[label_df["isof"] <0].index, inplace=True) train =
          train.drop('isof', axis=1) label_df = label_df.drop('isof', axis=1) print("Train set
          shape: ", train.shape) print("Target Shape", label_df.shape)
```

Running Isolation Forest:
Train set shape: (1419, 375)
Target Shape (1419, 1)

```
In [76]: from sklearn.preprocessing import StandardScaler from
         sklearn.metrics import mean_squared_error
```

```
In [69]: # import the dataset train =
        pd.read_csv('./train_salePrice.csv') test =
        pd.read_csv('./test_salePrice.csv')

        # # target feature
        # y_tr = pd.DataFrame()
        # y_tr['SalePrice'] = train.SalePrice
```

```
In [70]: train.shape
```

```
Out[70]: (1448, 272)
```

```
In [71]: numeric_feats = list(numeric_feats) print(numeric_feats)
        # print(len(numeric_feats))
        # all the numeric features without dummy features.
```

```
['MSSubClass', 'LotFrontage', 'LotArea', 'LotShape', 'LandSlope', 'OverallQual', 'OverallCond'
```

```
In [72]: len(numeric_feats)
```

```
Out[72]: 100
```

```
In [77]: # target feature y_tr = pd.DataFrame()
        y_tr['SalePrice'] = train.SalePrice y_tr.shape
```

```
Out[77]: (1448, 1)
In [78]: train.drop("SalePrice", axis = 1, inplace = True)
```

```
In [79]: train.shape
```

```
Out[79]: (1448, 271)
```

8.1 Modelling and Predictions

For modeliing and prediction analysis analysis I have used 3 different algorithms:

1.XGBoost
2.Lasso Regression
3.Linear Regression

8.2 1. XGBoost

XGBoost provides a wrapper class to allow models to be treated like classifiers or regressors in the scikit-learn framework.

This means we can use the full scikit-learn library with XGBoost models.

The XGBoost model for classification is called XGBClassifier. We can create and and fit it to our training dataset. Models are fit using the scikit-learn API and the model.fit() function. Learn more from here

In [114]: model_xgb = xgb.XGBRegressor(colsample_bytree=0.2, gamma=0.0,
learning_rate=0.05, max_depth=6,
min_child_weight=1.5, n_estimators=7200,
reg_alpha=0.9, reg_lambda=0.6,
subsample=0.2,seed=42, silent=1, random_state =7)

model_xgb.fit(train, label_df) *#fitting the model*

#make Prediction

y_pred = model_xgb.predict(train) y_test =
label_df
print("XgBoost score on training set: ", rmse(y_test, y_pred))

XgBoost score on training set: 0.007228968106147068

Predict the result

In [212]: y_pred_xgb = model_xgb.predict(test) y_pred_xgb

Out[212]: array([0.90080935, 0.9095861 , 0.9153086 , ..., 0.91074085, 0.8963932 ,
0.9181987], dtype=float32)

8.3 Exporting Data to csv

In [213]: *#get the XGB only result* y_xgb_only=np.exp(y_pred_xgb) pred_df =
pd.DataFrame(y_xgb_only,index=test_data["Id"], columns=["SalePrice"])
pred_df.to_csv('LASSOoutput.csv', header=**True**, index_label='Id')

8.4 2. LASSO Regression

Lasso regression is a simple techniques way to reduce model complexity and prevent over-fitting which may result from simple linear regression.

Lasso regression performs L1 regularization, i.e. it adds a factor of sum of absolute value of coefficients in the optimization objective. Thus, lasso regression optimizes the following: Objective = RSS + * (sum of absolute value of coefficients) learn More here

Modelling

In [100]: best_alpha = 0.00099 *#a bit arbitrary and based on some trial and error process* print("Lasso regressor is running...") regr = Lasso(alpha=best_alpha, max_iter=50000) regr.fit(train, label_df)

y_pred = regr.predict(train)*#fitting the model* y_test = label_df

accuracy_score = rmse(y_test, y_pred)
print("Lasso score on training set: ", accuracy_score*100)

```
Lasso regressor is running...
Lasso score on training set: 0.5451509075296066
```

Predict the result

In [113]: y_pred_lasso = regr.predict(test) y_pred_lasso

```
Out[113]: array([0.90013948, 0.91105758, 0.91431241, ..., 0.90931289, 0.89626047,
       0.92361421])
```

8.5 Exporting Data to csv

In [211]: #get the LASSO only result y_lasso_only=np.exp(y_pred_lasso) pred_df = pd.DataFrame(y_lasso_only, index=test_data["Id"], columns=["SalePrice"]) pred_df.to_csv('LASSOoutput.csv', header=True, index_label='Id')

8.6 3. Linear Regression

linear regression is a linear approach to modelling the relationship between a scalar response (or dependent variable) and one or more explanatory variables (or independent variables). Linear regression attempts to model the relationship between two or more features and a response by fitting a linear equation to observed data. Learn more from here

In [214]: from sklearn.model_selection import train_test_split X_train, X_test, y1_train, y_test = train_test_split(data_train,y_train , random_state=42, test_size=

```
from sklearn import linear_model lr =
linear_model.LinearRegression() model =
lr.fit(train, label_df)

y_pred = model.predict(train) y_test =
label_df
print("Linear score on training set: ", rmse(y_test, y_pred))
```

```
Linear score on training set: 0.0028934252678305523
```

Predict the result

In [216]: y_pred_lnr = lr.predict(test) y_pred_lasso

```
Out[216]: array([[0.89971989], [0.90803969],
       [0.91487283],
       ...,
       [0.91165018],
       [0.89928341],
       [0.91816133]])
```

8.7 Exporting Data to csv

```
In [217]: y_linear_only=np.exp(y_pred_lnr) pred_df = pd.DataFrame(y_linear_only, index=test_data["Id"],
          columns=["SalePrice"]) pred_df.to_csv('Linearoutput.csv', header=True, index_label='Id')
```

9 Survey

The results of the Algorithms on their accuracy on the training sets are as follows

Algorithms	RMSE
XGBOOST	0.7228
Lasso	0.5451
Linear	0.2893

10 ANN with Tensorflow

About TensorFlow

TensorFlow is an open source software library for high performance numerical computation. Its flexible architecture allows easy deployment of computation across a variety of platforms (CPUs, GPUs, TPUs), and from desktops to clusters of servers to mobile and edge devices. Originally developed by researchers and engineers from the Google Brain team within Google's AI organization, it comes with strong support for machine learning and deep learning and the flexible numerical computation core is used across many other scientific domains.

Hyperparameters related to Network structure

Hyperparameters are the variables which determines the network structure(Eg: Number of Hidden Units) and the variables which determine how the network is trained(Eg: Learning Rate). Hyperparameters are set before training(before optimizing the weights and bias).

There are some couple of hypermetes to be tuned in NN . namely- ***number of hidden layer***, ***Dropout***, ***Activation function***, ***Learning rate***, ***number of epoches***, ***cross validation*** etc.

11 Making a simple NN or no hidden layer Model

This is the simplest NN model. In between Input to output there's no extra hidden layer.

```
In [74]: ## import Tensorflow import
         tensorflow as tf
```

```
In [83]: # specify the number of input and output n_inputs =
         train.shape[1] n_outputs = 1 print(n_inputs)
```

```
271
```

```
In [84]: y_tr.shape
```

```
Out[84]: (1448, 1)
```

11.0.1 Placeholder

The function creates the placeholders for the tensorflow session.The param input_size is scalar, input size. parameter output_size is scalar, output size.

Strategy here-

This model will try to minimize the loss of predicted values of y by tuning weights and biases. Adam Optimizer will tweak the model parameters to minimize the cost function.

We will train this model for EPOCH times and then predict the validation sets SellPrice.

Choosing EPOCH: We will let the model learn until it starts over fitting. So checking the validation loss and training loss we will select the EPOCH values.

This model has not much complexities in its architecture so it will operate like a linear regression model.

In [85]: y_train.shape

Out[85]: (965, 1)

In [86]:
```
# placeholder nodes to represent the training data and target
X = tf.placeholder(name="X", dtype=tf.float32, shape=[None, n_inputs]) y_true =
tf.placeholder(dtype=tf.float32, shape=[None, n_outputs], name = "y") print(X) print(y_true)


# weights and biases
W = tf.Variable(tf.truncated_normal([n_inputs, n_outputs], stddev=(2/np.sqrt(n_inputs) b =
tf.Variable(tf.zeros([n_outputs]), name='b')


print(W) print(b)


# Hypothesis y_pred = tf.add(tf.matmul(X, W), b,
name='output') print(y_pred)


# Mean Squared Error Cost Function
# loss = tf.losses.mean_squared_error(labels=y_true, predictions=y_pred) loss =
tf.reduce_mean(tf.square(y_pred - y_true), name='loss')


# hyperparameters of the model
learning_rate = 0.005 EPOCH = 2500


# Adam Optimizer optimizer =
tf.train.AdamOptimizer(learning_rate) train_op =
optimizer.minimize(loss)
```

```
Tensor("X_1:0", shape=(?, 271), dtype=float32)
Tensor("y_1:0", shape=(?, 1), dtype=float32)
<tf.Variable 'W_1:0' shape=(271, 1) dtype=float32_ref>
```

<tf.Variable 'b_1:0' shape=(1,) dtype=float32_ref>
Tensor("output_1:0", shape=(?, 1), dtype=float32)

12 K-fold Cross-Validation

Cross-validation is a resampling procedure used to evaluate machine learning models on a limited data sample.

Cross-validation is primarily used in applied machine learning to estimate the skill of a machine learning model on unseen data. That is, to use a limited sample in order to estimate how the model is expected to perform in general when used to make predictions on data not used during the training of the model.

The model parametes will be decided later on

In [97]: type(y_train)

Out[97]: numpy.ndarray

In [87]: Single_layer_NN_validation_score = []

```
# 3 fold cross_validation
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.KFold.html from
sklearn.model_selection import KFold
k = 3
kf = KFold(n_splits=k, shuffle=True) for train_index,

test_index in kf.split(train):

    # Partition the dataset in train + validation sets
    X_train, X_test = train.iloc[train_index], train.iloc[test_index] y_train, y_test_nn =
    y_tr.iloc[train_index], y_tr.iloc[test_index] print('------New validation set created--------')

    # scale the data stdSc =
    StandardScaler()
    X_train.loc[:, numeric_feats] = stdSc.fit_transform(X_train.loc[:, numeric_feats]) X_test.loc[:,
    numeric_feats] = stdSc.transform(X_test.loc[:, numeric_feats]) print('scaling complete!!')


    #
    ==========================================model=================
    ================


    train_loss = np.zeros(EPOCH) validation_loss =
    np.zeros(EPOCH)
```

```
# Global Variables Initializer init =
tf.global_variables_initializer()

# Starting the Tensorflow Session with
tf.Session() as sess:

    # Initializing the Variables sess.run(init)
    # Iterating through all the epochs for epoch in
    range(EPOCH):

            # Feeding data into the optimizer using Feed Dictionary
                    _, loss_value = sess.run((train_op, loss), {X:X_train, y_true:y_train.valu

        # keeping track of the loss values on train and validation set validation_loss[epoch] =
        mean_squared_error(sess.run(y_pred, {X:X_test}), train_loss[epoch] = loss_value

        # Displaying the loss after every 500 epochs if(epoch%500==0): print("epoch", str(epoch),
        'Training loss ==', round(loss_value, print('Validation loss ==', round(validation_loss[epoch],
        5))

    print("epoch", str(epoch+1), 'Training loss ==', round(loss_value, 5), end='\t print('Validation loss
    ==', round(validation_loss[epoch], 5))

    # validation set prediction y_pred_NN =
    sess.run(y_pred, {X:X_test})

            print('validation loss average: ', sum(Single_layer_NN_validation_score) / len(Single_
```

```
------New validation set created-------scaling
complete!!
epoch 0 Training loss == 164.2193          Validation loss == 162.27182
epoch 500 Training loss == 0.03555          Validation loss == 0.05466
epoch 1000 Training loss == 0.01541          Validation loss == 0.03175
epoch 1500 Training loss == 0.01057          Validation loss == 0.02497
epoch 2000 Training loss == 0.00921          Validation loss == 0.02263
epoch 2500 Training loss == 0.00871 ------New          Validation loss == 0.02205
validation set created-------scaling complete!!

epoch 0 Training loss == 156.48773          Validation loss == 153.1215
epoch 500 Training loss == 0.04514          Validation loss == 0.0662
epoch 1000 Training loss == 0.01758          Validation loss == 0.02986
epoch 1500 Training loss == 0.0114          Validation loss == 0.02215
epoch 2000 Training loss == 0.00972          Validation loss == 0.01998
epoch 2500 Training loss == 0.00911 ------New          Validation loss == 0.01905
validation set created-------scaling complete!!

epoch 0 Training loss == 158.35443          Validation loss == 153.2932
```

```
# check the rmse of validation set
Single_layer_NN_validation_score.append(mean_squared_error(y_pred_NN, y_test_n
# print(Single_layer_NN_validation_score)
```

```
epoch 500 Training loss == 0.03632            Validation loss == 0.05371
epoch 1000 Training loss == 0.0158            Validation loss == 0.02981
epoch 1500 Training loss == 0.01082            Validation loss == 0.02394
epoch 2000 Training loss == 0.00938            Validation loss == 0.02213
epoch 2500 Training loss == 0.00879            Validation loss == 0.02124
validation loss average: 0.020779885524819245
```

In [88]:
```
print('validation loss average: ', sum(Single_layer_NN_validation_score) / len(Single_
```

```
validation loss average: 0.020779885524819245
```

13 Prediction on test data

In [89]:
```
X_test_real = test.copy() X_train_full =
train.copy()

stdSc = StandardScaler()
X_train_full.loc[:, numeric_feats] = stdSc.fit_transform(X_train_full.loc[:, numeric_f X_test_real.loc[:,
numeric_feats] = stdSc.transform(X_test_real.loc[:, numeric_feats]) print('scaling complete!!')
```

```
scaling complete!!
```

In [90]:
```
# hyperparameters of the model

learning_rate = 0.001 EPOCH = 2000

train_loss = np.zeros(EPOCH)


# Global Variables Initializer init =

tf.global_variables_initializer() saver =

tf.train.Saver()

# Starting the Tensorflow Session with
tf.Session() as sess: # Initializing the
Variables sess.run(init)

    # Iterating through all the epochs for epoch in
    range(EPOCH):

        # Feeding data into the optimizer using Feed Dictionary
```

```
_, loss_value = sess.run((train_op, loss), {X:X_train_full, y_true:y_tr.values train_loss[epoch] = loss_valu
        # Displaying the loss after every 500 epochs if(epoch%500==0):
                print("epoch", str(epoch), 'Training loss ==', (loss_value))

print("epoch", str(epoch+1), 'Training loss ==', (loss_value))

# save the model path = './my_NN_model_' + '.ckpt' save_path =

saver.save(sess, path) print("Model saved in path: %s" % save_path)

y_nn = sess.run(y_pred, {X:X_test_real.values.tolist()})
```

epoch 0 Training loss == 144.8448 epoch 500
Training loss == 0.034406226 epoch 1000 Training
loss == 0.016569184 epoch 1500 Training loss ==
0.011363177 epoch 2000 Training loss ==
0.009874001 Model saved in
path: ./my_NN_model_.ckpt

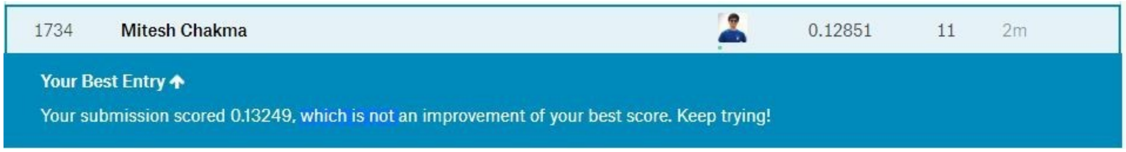
In [91]:
```
saver = tf.train.Saver()
# load the saved model to predict test set with
tf.Session() as sess: path = './my_NN_model_' +
'.ckpt' saver.restore(sess, path)
    y_nn = sess.run(y_pred, {X:X_test_real.values.tolist()})
```

INFO:tensorflow:Restoring parameters from ./my_NN_model_.ckpt

In [92]:
```
# reverse the log transformed SalePrice y_nn =
np.exp(y_nn) y_nn = y_nn.round()

# save the result to csv sub =
pd.read_csv('./test_id.csv') sub['SalePrice']
= y_nn


path = 'ANN_SUBMISSION_09' + '.csv' sub.to_csv(path,

index=False) print('predictions saved as: ', path) predictions

saved as: ANN_SUBMISSION_09.csv
```

In [93]:
```
from IPython.display import Image
Image('./ANN_submission__09.JPG')
```

Out[93]:



14 Making the DNN Model

I am going to divide the task into three phase-

- The first step is the construction phase, building the TensorFlow graph.
- The second step is the execution phase, where we actually run the graph to train the model.
- After that we can use the trained model to make prediction.

14.0.1 Number of Neurons

The number of neurons in the input and output layers is determined by the type of input and output our task requires. So we can only tune the hidden layers neurons. A common practice is to size them to form a funnel, with fewer and fewer neurons at each layer.

With the help of cross-validation different combinations of neurons for both hidden layers are tested and got better results on validation set on average with 1 and 1 neurons for first and second hidden layer.

Read More from here & Here

In [95]:
```
# number of inputs, hidden neurons and outputs n_inputs =
train.shape[1] n_hidden1 = 1 n_hidden2 = 1 n_outputs = 1
```

15 Placeholder

In [96]:
```
# placeholder nodes to represent the training data and target X = tf.placeholder(tf.float32, shape=[None,
n_inputs], name='X') y = tf.placeholder(tf.float32, shape=[None, 1], name='y') #The shape of y is (None, 1)
```

There are a lot of different activation functions to choose from to use in this model. Some of them are sigmoid, Relu, leaky relu, exponential linear unit(Elu).

- Sigmoid activation functions saturates for positive values so it is not wise to use it in DNN models.
- Relu performs well in these DNN models but it suffers from dying relu problem.
- There are other alternatives like leaky relu and exponential linear unit (ELU). These are known to perform well but these makes the models slow.

With cross-validation all the activation functions(relu, leaky-relu and elu) are compared and leaky-relu worked better of this model.

Relu has it's disadvantages as it sometimes fails because of dying relu problem. Elu function works well but it's slow. So I choose leaky-relu as activation function because it's fast at converging all the time, gives better model accuracy from the other variants of relu.

Instead of writing variables and activation for each layer every time, we will make a function to handle these for a single layer.

In [97]:
```
# def neural_network_model(x,y):
#        #hidden layer 1
#            # Calculating for the first layer
#                layer_1 = tf.add(tf.matmul(x, weights['h1']), biases['b1'])
#                layer_1 = tf.nn.relu(layer_1)#activation function 'relu'
#          dropout=tf.nn.dropout(layer_1,y)
#        #hideen layer 2
#            # Calculating for the second layer
#                layer_2 = tf.add(tf.matmul(dropout, weights['h2']), biases['b2'])
#                layer_2 = tf.nn.relu(layer_2)#activation function 'relu'
#        #hideen layer 3
#            # Calculating for the 3rd layer
#                layer_3 = tf.add(tf.matmul(layer_2, weights['h3']), biases['b3'])
#                layer_3 = tf.nn.relu(layer_3)#activation function 'relu'

#        # output layer
#                out_layer = tf.matmul(layer_3, weights['out']) + biases['out']
#        return (out_layer)



# neuron_layer function will create one layer at a time def
neuron_layer(X, n_neurons, name, activation=None):
    with tf.name_scope(name):
        n_inputs = int(X.get_shape()[1]) stddev = 2 /
        np.sqrt(n_inputs)
        init = tf.truncated_normal((n_inputs, n_neurons), stddev=stddev) W =
        tf.Variable(init, name="weights") b = tf.Variable(tf.zeros([n_neurons]),
        name="biases") z = tf.matmul(X, W) + b
        if activation=="relu": return
            tf.nn.relu(z)
        elif activation=="elu":
            return tf.nn.elu(z)
        elif activation=="leaky_relu":
            return tf.nn.leaky_relu(z)
        else:
            return z
```

Working Principle

- The first hidden layer takes X as its input.
- The second takes the output of the first hidden layer as its input.
- And finally, the output layer takes the output of the second hidden layer as its input and returns the target values.

Choice of number of hidden layers:

For many problems, a single hidden layer will give reasonable results. Deep networks have a much higher parameter efficiency than shallow ones: they can model complex functions using exponentially fewer neurons than shallow nets, making them much faster to train.

I have taken both one, two and three hidden layers separately and checked model performance against each other. After that ended up using two hidden layers because of its accuracy. With one hidden layer this model performs almost similarly but two hidden layers of 1 neurons each gave better test accuracy. So for this reason I kept the second hidden layer.

In [99]:
```
# define the layers with
    tf.name_scope("dnn"):
        hidden1 = neuron_layer(X, n_hidden1, "hidden1", activation="leaky_relu") hidden2 =
        neuron_layer(hidden1, n_hidden2, "hidden2", activation="leaky_relu") logits = neuron_layer(hidden2,
        n_outputs, "outputs")


    # define the cost function with
    tf.name_scope("loss"):
        # loss_op = tf.sqrt(tf.reduce_mean(tf.square(logits - y)), name="loss") loss_op =
        tf.reduce_mean(tf.square(logits - y), name="loss")
```

Learning rate has been chosen arbitarily with the value 0.001,0.01,0.03,0.003 where 0.003 were performed better thats why I have chosen 0.003

In [100]:
```
learning_rate = 0.003

    with tf.name_scope("train"):
        optimizer = tf.train.AdamOptimizer(learning_rate) training_op =
        optimizer.minimize(loss_op)
```

In [ ]:
```
# Global Variables Initializer init =

    tf.global_variables_initializer() saver =

    tf.train.Saver()
```

In [108]:
```
import random
```

In [115]:
```
# 3 fold cross_validation DNN_validation_score = []
```

```
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.KFold.htm from
sklearn.model_selection import KFold k = 3
kf = KFold(n_splits=k, shuffle=True, random_state=random.randint(30,70)) for train_index,

test_index in kf.split(train):

    # Partition the dataset in train + validation sets
    X_train, X_test = train.iloc[train_index], train.iloc[test_index] y_train, y_test_DNN =
    y_tr.iloc[train_index], y_tr.iloc[test_index] print('------New validation set created--------')

    # scale data stdSc =
    StandardScaler()
    X_train.loc[:, numeric_feats] = stdSc.fit_transform(X_train.loc[:, numeric_feats] X_test.loc[:,
    numeric_feats] = stdSc.transform(X_test.loc[:, numeric_feats]) print('scaling complete!!')

    #

    ============================================model================

    ================ n_epochs = 2000

    train_loss = np.zeros(n_epochs) validation_loss =
    np.zeros(n_epochs)

    # Global Variables Initializer init =

    tf.global_variables_initializer() with tf.Session() as

    sess:

        # Initializing all the Variables init.run()

        # train the model for epoch in
        range(n_epochs):
                            _, loss_value= sess.run((training_op,loss_op),feed_dict={X:X_train, y:y_

            # keep track of the losses
            train_loss[epoch] = loss_value validation_loss[epoch] = mean_squared_error(sess.run(logits,
            {X:X_test}), if(epoch%100==0):
                print("epoch", str(epoch), 'Training loss ==', round(loss_value, 5), print('Validation loss
                ==', round(validation_loss[epoch], 5))
```

```
print("epoch", str(epoch+1), 'Training loss ==', round(loss_value, 5), end=' print('Validation loss
==', (round(validation_loss[epoch], 5)))


#                   plt.figure(figsize=(20,15))
#                     plt.plot(epoch,round(loss_value, 5),'b')
#               plt.show()
# validation set prediction y_pred_DNN =
sess.run(logits, {X:X_test})


# check the rmse of validation set
DNN_validation_score.append(mean_squared_error(y_pred_DNN, y_test_DNN))
# print(DNN_validation_score)
```

```
print('validation loss average: ', sum(DNN_validation_score) / len(DNN_validation_sc
```

```
------New validation set created-------scaling
complete!!
epoch 0 Training loss == 137.88971          Validation loss == 134.392
epoch 100 Training loss == 11.01372          Validation loss == 11.86711
epoch 200 Training loss == 2.24296          Validation loss == 2.28956
epoch 300 Training loss == 0.1229          Validation loss == 0.15866
epoch 400 Training loss == 0.05928          Validation loss == 0.08816
epoch 500 Training loss == 0.03762          Validation loss == 0.0629
epoch 600 Training loss == 0.02697          Validation loss == 0.05032
epoch 700 Training loss == 0.02071          Validation loss == 0.04301
epoch 800 Training loss == 0.01684          Validation loss == 0.03857
epoch 900 Training loss == 0.01441          Validation loss == 0.03585
epoch 1000 Training loss == 0.01284          Validation loss == 0.03416
epoch 1100 Training loss == 0.01181          Validation loss == 0.03309
epoch 1200 Training loss == 0.0111          Validation loss == 0.03241
epoch 1300 Training loss == 0.0106          Validation loss == 0.03195
epoch 1400 Training loss == 0.01022          Validation loss == 0.03163
epoch 1500 Training loss == 0.00993          Validation loss == 0.03139
epoch 1600 Training loss == 0.00969          Validation loss == 0.0312
epoch 1700 Training loss == 0.0095          Validation loss == 0.03105
epoch 1800 Training loss == 0.00933          Validation loss == 0.03092
epoch 1900 Training loss == 0.00919          Validation loss == 0.03081
epoch 2000 Training loss == 0.00906          Validation loss == 0.03071
------New validation set created--------
```

scaling complete!!

epoch 0 Training loss == 164.27165 Validation loss == 158.80943 epoch 100 Training loss == 5.89532 Validation loss == 5.48474 epoch 200 Training loss == 0.18871 Validation loss == 0.21721 epoch 300 Training loss == 0.13474 Validation loss == 0.15827 epoch 400 Training loss == 0.09592 Validation loss == 0.11801 epoch 500 Training loss == 0.06854Validation loss == 0.0898 epoch 600 Training loss == 0.04969 Validation loss == 0.07007 epoch 700 Training loss == 0.03687 Validation loss == 0.0563 epoch 800 Training loss == 0.02815 Validation loss == 0.04669 epoch 900 Training loss == 0.02221Validation loss == 0.03996 epoch 1000 Training loss == 0.01813Validation loss == 0.03521 epoch 1100 Training loss == 0.0153 Validation loss == 0.03183 epoch 1200 Training loss == 0.01333 Validation loss == 0.02939 epoch 1300 Training loss == 0.01193Validation loss == 0.0276 epoch 1400 Training loss == 0.01093 Validation loss == 0.02626 epoch 1500 Training loss == 0.0102 Validation loss == 0.02525 epoch 1600 Training loss == 0.00967 Validation loss == 0.02447 epoch 1700 Training loss == 0.00927Validation loss == 0.02387 epoch 1800 Training loss == 0.00897Validation loss == 0.0234 epoch 1900 Training loss == 0.00874 Validation loss == 0.02304 epoch 2000 Training loss == 0.00856 Validation loss == 0.02275

------New validation set created-------scaling complete!!

epoch 0 Training loss == 144.35399 Validation loss == 145.35755 epoch 100 Training loss == 114.25114 Validation loss == 112.3823 epoch 200 Training loss == 25.56312 Validation loss == 24.67376 epoch 300 Training loss == 0.04137Validation loss == 0.04414 epoch 400 Training loss == 0.02145 Validation loss == 0.02417 epoch 500 Training loss == 0.01936 Validation loss == 0.02216 epoch 600 Training loss == 0.01783 Validation loss == 0.02078 epoch 700 Training loss == 0.01657 Validation loss == 0.01965 epoch 800 Training loss == 0.01547 Validation loss == 0.01867 epoch 900 Training loss == 0.01453Validation loss == 0.01783 epoch 1000 Training loss == 0.01373Validation loss == 0.0171 epoch 1100 Training loss == 0.01305 Validation loss == 0.01649 epoch 1200 Training loss == 0.01248 Validation loss == 0.01599 epoch 1300 Training loss == 0.012 Validation loss == 0.01557 epoch 1400 Training loss == 0.0116 Validation loss == 0.01523 epoch 1500 Training loss == 0.01126 Validation loss == 0.01495 epoch 1600 Training loss == 0.01098 Validation loss == 0.01473 epoch 1700 Training loss == 0.01074Validation loss == 0.01457 epoch 1800 Training loss == 0.01054Validation loss == 0.01444 epoch 1900 Training loss == 0.01037 Validation loss == 0.01434 epoch 2000 Training loss == 0.01023 Validation loss == 0.01427

validation loss average: 0.02257902235524971

A several number of iterations and tests have been done and then chosen final model parameters are:

Specs	DNN Model
Number of Hidden Layers	2
First Hidden Layer Neurons	1
Second Hidden Layer Neurons	1
Learning Rate	0.003
Epoch	1500
Validation loss average	0.022

After roughly 1500 iterations,the the improvement on loss is very thin for all the crossvalidation sets and in one case validation loss increases a bit after 1600 epochs which gives the idea that the model is over-fitting the training set. So we will keep the epochs to 1500.

16 Finalized DNN Model

copying and scaling the data

In [116]:
```
X_test_real = test.copy()
X_train_full = train.copy()

# scale the data stdSc =
StandardScaler()
X_train_full.loc[:, numeric_feats] = stdSc.fit_transform(train.loc[:, numeric_feats]) X_test_real.loc[:,
numeric_feats] = stdSc.transform(test.loc[:, numeric_feats]) print('scaling Done!!')
```

scaling Done!!

Running the model

In [117]:
```
n_epochs = 1500 train_loss =
np.zeros(n_epochs)


# Global Variables Initializer init =

tf.global_variables_initializer() saver =

tf.train.Saver() with tf.Session() as sess:

    # Initializing all the Variables init.run()
    # train the model for epoch in
    range(n_epochs):
                _, loss_value= sess.run((training_op,loss_op),feed_dict={X:X_train_full, y:y_

        train_loss[epoch] = loss_value if(epoch%100==0):
            print("epoch", str(epoch), 'loss ==', round(loss_value, 5))

    print("epoch", str(epoch+1), 'loss ==', round(loss_value, 5))



    # save the model path = './my_DNN_model.ckpt' save_path =

    saver.save(sess, path) print("Model saved in path: %s" % save_path)

    y_dnn = sess.run(logits, {X:X_test_real.values.tolist()})
```

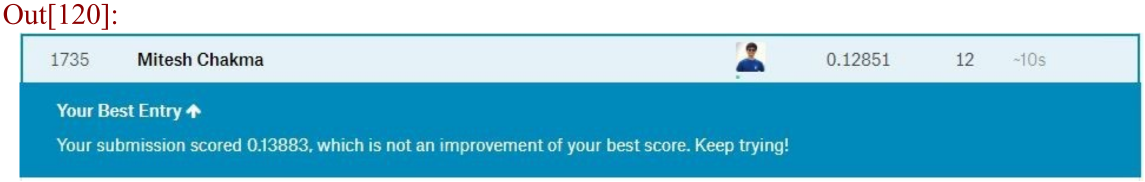
epoch 0 loss == 149.44157 epoch
100 loss == 51.70268 epoch 200 loss
== 0.63587 epoch 300 loss ==
0.0613 epoch 400 loss == 0.05103
epoch 500 loss == 0.04226 epoch
600 loss == 0.03506 epoch 700 loss
== 0.02932 epoch 800 loss ==
0.02484 epoch 900 loss == 0.02138
epoch 1000 loss == 0.01871 epoch
1100 loss == 0.01665 epoch 1200
loss == 0.01506 epoch 1300 loss ==
0.01382 epoch 1400 loss == 0.01286
epoch 1500 loss == 0.01212 epoch
1600 loss == 0.01154
Model saved in path: ./my_DNN_model.ckpt

In [118]:
```
# load the saved model to predict validation set with tf.Session()
as sess: path = './my_DNN_model.ckpt' saver.restore(sess,
path)

    # predict..
    y_dnn = sess.run(logits, {X:X_test_real})
    # reverse the log transformed SalePrice y_dnn =
np.exp(y_dnn) y_dnn = y_dnn.round() # check the
price
# print(y_dnn[0:10])


# save the result to csv sub =
pd.read_csv('./test_id.csv') sub['SalePrice'] =
y_dnn path = 'ANN_Submission_17' + '.csv'
sub.to_csv(path, index=False)
print('predictions saved as: ', path)
```

INFO:tensorflow:Restoring parameters from ./my_DNN_model.ckpt predictions saved as: ANN_Submission_17.csv

In [120]:
```
from IPython.display import Image
Image('./ANN_Submission_17.JPG')
```

Out[120]:



17 Tensorflow with Dropout

Importing TensorFlow

Importing tensorflow and converting the dataframe into array as tensorflow requires -

In [123]: y_tr.shape

Out[123]: (1448, 1)

In [124]:
```
import tensorflow as tf
x_train = train.values x_train
y_train_munged = test.values
y_train_munged.shape
y_train=y_tr.values
print(y_train.shape)
```
(1448, 1)

Here I have converted the values into “nparry” as it was suggested in the documentation and it is faster in calculations

In [126]:
```
y_train=np.reshape(np.array(y_train),(1448,1))#1448x1 being the dimension input_dim =
x_train.shape[1] print(input_dim) output_dim = 1
```

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In [127]:
```
nood_Hl_1 = 201 #layer 1
nood_Hl_2 = 100 #layer 2 nood_Hl_3 =
50 #layer 3
```

17.0.1 Placeholder

The function creates the placeholders for the tensorflow session.The param input_size is scalar, input size. parameter output_size is scalar, output size.

In [128]:
```
#tf.placeholder is used to feed actual training examples

# placeholder nodes to represent the training data and target
X = tf.placeholder(tf.float32, shape=[None, input_dim], name='X')
Y = tf.placeholder(tf.float32, shape=[None, 1], name='Y')
```

In above code we initialize placeholders for labels and features placeholders are used so that data can be fed at a later time(during training,testing,prediction) and value is set to None because any number of samples can be used as input .

Weights and biases We initialize weights biases for hidden layers

```
In [129]: weights = {
                'h1': tf.Variable(tf.contrib.layers.xavier_initializer()((input_dim, nood_Hl_1)))
                'h2': tf.Variable(tf.contrib.layers.xavier_initializer()((nood_Hl_1, nood_Hl_2)))
                'h3': tf.Variable(tf.contrib.layers.xavier_initializer()((nood_Hl_2, nood_Hl_3)))
                'out': tf.Variable(tf.contrib.layers.xavier_initializer()((nood_Hl_3, output_dim)
          } biases = {
                'b1': tf.Variable(tf.contrib.layers.xavier_initializer()([nood_Hl_1])),
                'b2': tf.Variable(tf.contrib.layers.xavier_initializer()([nood_Hl_2])),
                'b3': tf.Variable(tf.contrib.layers.xavier_initializer()([nood_Hl_3])),
                'out': tf.Variable(tf.contrib.layers.xavier_initializer()([output_dim])) }
```

We build the neural network model with each layer output being relu(W(transpose)*X +b) where relu is rectified linear unit which is used as an activation function.

The Neural Network model manually using (arbitrarily) 3 layers and using relu as our activation layers, The reason for chosing ReLu as activation function as it is non linear which means I can easily backpropagate the errors and have multiple layers of neurons being activated by the ReLU function.

```
In [130]: def neural_network_model(x,y):
                #hidden layer 1
                # Calculating for the first layer layer_1 = tf.add(tf.matmul(x, weights['h1']),
                biases['b1']) layer_1 = tf.nn.relu(layer_1)#activation function 'relu'
                dropout=tf.nn.dropout(layer_1,y)
                #hideen layer 2
                # Calculating for the second layer layer_2 = tf.add(tf.matmul(dropout,
                weights['h2']), biases['b2']) layer_2 = tf.nn.relu(layer_2)#activation function 'relu'
                #hideen layer 3
                # Calculating for the 3rd layer layer_3 = tf.add(tf.matmul(layer_2, weights['h3']),
                biases['b3']) layer_3 = tf.nn.relu(layer_3)#activation function 'relu'

                # output layer out_layer = tf.matmul(layer_3, weights['out']) + biases['out']
                return (out_layer)
```

Y_hat is the predicted output value .We define loss function as MSE and use Adam optimizer and go through data 2000 times you can always play around with the learning rate, activation functions and use different types of optimizer's.

Dropout

The term "dropout" refers to dropping out units (both hidden and visible) in a neural network. Simply put, dropout refers to ignoring units (i.e. neurons) during the training phase of certain set of neurons which is chosen at random.

More technically, At each training stage, individual nodes are either dropped out of the net with probability 1-p or kept with probability p, so that a reduced network is left; incoming and outgoing edges to a dropped-out node are also removed.

In simple words, Dropout is used to prevent over-fitting

Learn More from here

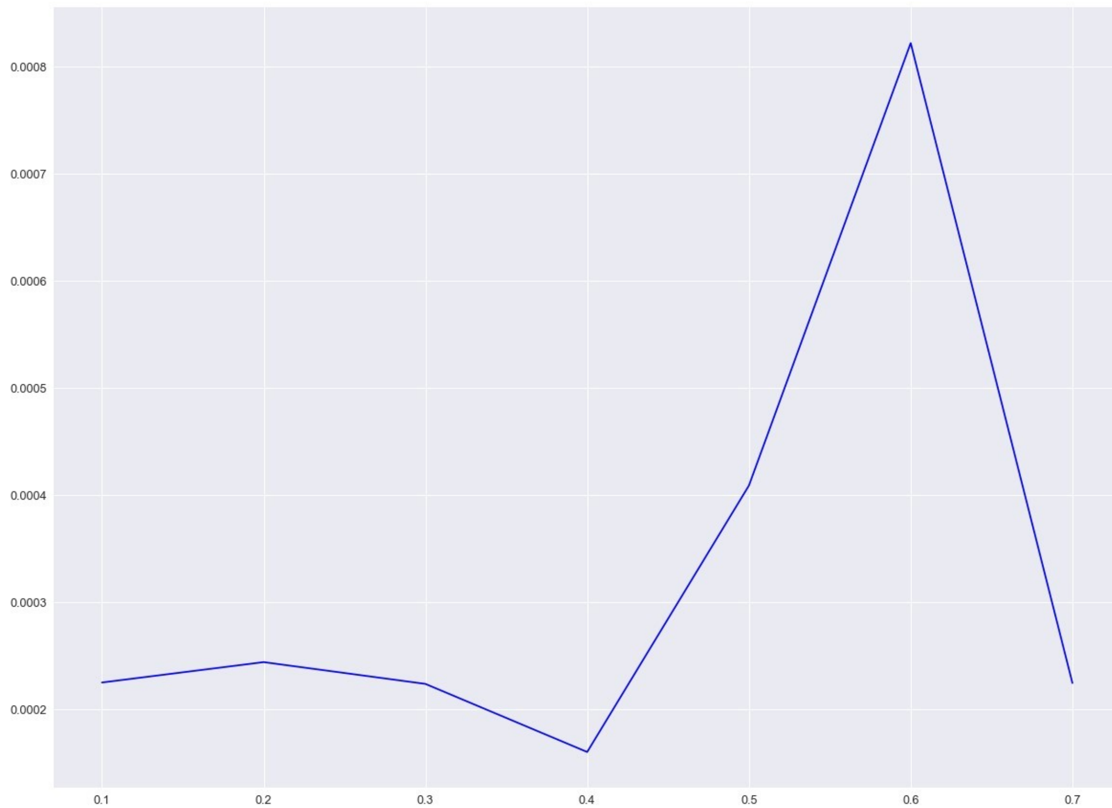
With the learning rate being 0.01, We are going to check the optimum dropout rate which we are going to use in our final model network. The optimizer here used in my caseis an Adagrad optimizer (by default)

```
In [230]: DropOuts = [float(i/10) for i in range(1,8)]
          #mse=[i for i in range(19,4,-2)]

          mseList=[] for dropout in
          DropOuts: minMSE=1000000
          Y_hat=neural_network_model
          (X,dropout)
          loss_op=tf.losses.mean_square
          d_error(Y,Y_hat)#the loss
          function optimizer =
          tf.train.AdamOptimizer(learni
          ng_rate=0.01) train_op =
          optimizer.minimize(loss_op)#
          minimize losss init =
          tf.global_variables_initializer(
          ) epoch=2000 with
          tf.Session() as sess:
          sess.run(init) for i in
          range(epoch):
                    #feed_dict is used to feed data to placeholders and pred is the actual ou
                    sess.run(train_op,feed_dict={X:x_train[0:1200],Y:y_train[0:1200]})


                    loss=sess.run(loss_op,feed_dict={X:x_train[1200:],Y:y_train[1200:]})
                    if(loss<minMSE): minMSE=loss

                    if(i%200==0): print("dropout " ,dropout,"epoch no "+str(i),(loss))
                    if(i==epoch-1):
                        mseList.append(minMSE)


          plt.figure(figsize=(20,15))
          plt.plot(DropOuts,mseList,'b') plt.show()
```

dropout 0.1 epoch no 0 1114.7267 dropout 0.1
epoch no 200 0.0044543394 dropout 0.1 epoch no
400 0.0011766134 dropout 0.1 epoch no 600
0.0012321736 dropout 0.1 epoch no 800
0.00050966506 dropout 0.1 epoch no 1000
0.0013028505 dropout 0.1 epoch no 1200
0.00049410824 dropout 0.1 epoch no 1400
0.0005572911 dropout 0.1 epoch no 1600
0.0005215744 dropout 0.1 epoch no 1800
0.0006873683 dropout 0.2 epoch no 0 1169.5883
dropout 0.2 epoch no 200 0.0069019217 dropout
0.2 epoch no 400 0.0014933583 dropout 0.2 epoch
no 600 0.00080635404 dropout 0.2 epoch no 800

0.0005502486 dropout 0.2 epoch no 1000
0.00066047825 dropout 0.2 epoch no 1200
0.0005621506 dropout 0.2 epoch no 1400
0.00050238793 dropout 0.2 epoch no 1600
0.00038006672 dropout 0.2 epoch no 1800
0.0003405274 dropout 0.3 epoch no 0 963.9143
dropout 0.3 epoch no 200 0.009833628 dropout 0.3
epoch no 400 0.0011495552 dropout 0.3 epoch no
600 0.00088906096 dropout 0.3 epoch no 800
0.00062763604 dropout 0.3 epoch no 1000
0.00051399105 dropout 0.3 epoch no 1200
0.00043655746 dropout 0.3 epoch no 1400
0.00038980765 dropout 0.3 epoch no 1600
0.00045264213 dropout 0.3 epoch no 1800
0.0003014227 dropout 0.4 epoch no 0 671.5963
dropout 0.4 epoch no 200 0.0064933533 dropout
0.4 epoch no 400 0.0023484607 dropout 0.4 epoch
no 600 0.0012341656 dropout 0.4 epoch no 800
0.000705545 dropout 0.4 epoch no 1000
0.00060656416 dropout 0.4 epoch no 1200
0.00047448563 dropout 0.4 epoch no 1400
0.00044658082 dropout 0.4 epoch no 1600
0.00024023493 dropout 0.4 epoch no 1800
0.00018851405 dropout 0.5 epoch no 0 704.40063
dropout 0.5 epoch no 200 0.03218122 dropout 0.5
epoch no 400 0.028226411 dropout 0.5 epoch no
600 0.0034439596 dropout 0.5 epoch no 800
0.0024813141 dropout 0.5 epoch no 1000
0.0018052452 dropout 0.5 epoch no 1200
0.0010653011 dropout 0.5 epoch no 1400
0.00096878404 dropout 0.5 epoch no 1600
0.00068445853 dropout 0.5 epoch no 1800
0.0004800453 dropout 0.6 epoch no 0 650.87256
dropout 0.6 epoch no 200 0.027581822 dropout 0.6
epoch no 400 0.0080908295 dropout 0.6 epoch no
600 0.008986369 dropout 0.6 epoch no 800
0.0053949296 dropout 0.6 epoch no 1000
0.0028421879 dropout 0.6 epoch no 1200
0.0024729478 dropout 0.6 epoch no 1400
0.0017332691 dropout 0.6 epoch no 1600
0.0030295984 dropout 0.6 epoch no 1800
0.002405188 dropout 0.7 epoch no 0 828.7398
dropout 0.7 epoch no 200 0.00446367 dropout 0.7
epoch no 400 0.0012879325 dropout 0.7 epoch no
600 0.0011481948 dropout 0.7 epoch no 800
0.0010898949 dropout 0.7 epoch no 1000
0.0005802291 dropout 0.7 epoch no 1200

0.0005450882 dropout 0.7 epoch no 1400
0.0017553271 dropout 0.7 epoch no 1600
0.00062697276 dropout 0.7 epoch no 1800
0.0017616211



Dropout is a regularization technique for multilayered deep learning models. We can set a value from 0 through 1.0. These are probability values. They represent the percentage of neurons whose output will be dropped out from being passed to the next layer. This effectively reduces the number of parameters and simplifies the model that is being fit. One easy thumb rule is: the noisier the dataset, higher the probability you need to set. Reference

As I got many outliers in my dataset, Dropout yeilds the best reseult with checking the learning curve. As seen from above, 0.4 yeilded the best result and I will be using it for the model reference.

```
In [138]: def neural_network(x):
              #hidden layer 1
              # Calculating for the first layer layer_1 = tf.add(tf.matmul(x, weights['h1']),
              biases['b1']) layer_1 = tf.nn.relu(layer_1)#activation function 'relu'
              dropout=tf.nn.dropout(layer_1,0.5) #hideen layer 2
              # Calculating for the second layer layer_2 = tf.add(tf.matmul(dropout,
              weights['h2']), biases['b2'] layer_2 = tf.nn.relu(layer_2)#activation function 'relu'
              #hideen layer 3
              # Calculating for the 3rd layer
```

```
layer_3 = tf.add(tf.matmul(layer_2, weights['h3']), biases['b3']) layer_3 =
tf.nn.relu(layer_3)#activation function 'relu'

# output layer out_layer = tf.matmul(layer_3, weights['out']) + biases['out']
return (out_layer)
```

In [150]:
```
minMSE=1000000
Y_hat=neural_network(X) loss_op=tf.losses.mean_squared_error(Y,Y_hat)#the loss function optimizer
= tf.train.AdamOptimizer(learning_rate=0.01) #Adam optimizer with learn train_op =
optimizer.minimize(loss_op)#minimize losss init = tf.global_variables_initializer() epoch=2000 with
tf.Session() as sess: sess.run(init) for i in range(epoch):
    sess.run(train_op,feed_dict={X:x_train,Y:y_train})
    loss=sess.run(loss_op,feed_dict={X:X_test,Y:y_test_DNN})
    if(loss<minMSE): minMSE=loss
    if(i%200==0):
        print("epoch no "+str(i),(loss)) pred=sess.run(Y_hat,feed_dict={X:test})#test=test
dataframe print(len(pred))
```

```
epoch no 0 64.61596 epoch no
200 85.97952 epoch no 400
57.80841 epoch no 600
57.47272 epoch no 800
59.5326 epoch no 1000
57.33893 epoch no 1200
59.629616 epoch no 1400
60.505074 epoch no 1600
60.780014 epoch no 1800
58.570415 1459
```

In [152]:
```
pred_mod=np.exp(pred) pred_df = pd.DataFrame(pred_mod, index=test_data["Id"],
columns=["SalePrice"]) pred_df.to_csv('TensorFlowANN_DP.csv', header=True, index_label='Id')
```

In [153]:
```
from IPython.display import Image
Image('./capture.JPG')
```

Out[153]:

18 Result

Specs	Simple NN Model	DNN Model with CV	DNN with Dropout
Number of Hidden Layers	0	2	3
First Hidden Layer Neurons	0	1	201
Second Hidden Layer Neurons	0	1	100
Third Hidden Layer Neurons	NA	NA	50
Dropout	No	No	YES
Learning Rate	0.001	0.003	0.01
Epoch	2000	1500	2000
Kaggle Result	0.13249	0.13883	0.11914

19 Ensembled result

In [ ]:
```
y_pred_lasso = regr.predict(test) y_pred_lin=lr.predict(test)
y_pred_xgb=model_xgb.predict(test)

pred_df.to_csv('ANNoutput.csv', header=True, index_label='Id')
#get the LASSO only result y_lasso_only=np.exp(y_pred_lasso) pred_df = pd.DataFrame(y_lasso_only,
index=test_data["Id"], columns=["SalePrice"]) pred_df.to_csv('LASSOoutput.csv', header=True,
index_label='Id')
#get the Linear Reg only result y_linear_only=np.exp(y_pred_lin) pred_df = pd.DataFrame(y_linear_only,
index=test_data["Id"], columns=["SalePrice"]) pred_df.to_csv('Linearoutput.csv', header=True,
index_label='Id')
#get the Xgb only result y_xgb_only=np.exp(y_pred_xgb) pred_df = pd.DataFrame(y_xgb_only,
index=test_data["Id"], columns=["SalePrice"]) pred_df.to_csv('XGBoutput.csv', header=True,
index_label='Id')
#get the Ensembled learning result y_pred = (y_pred_nn + 5*y_pred_lasso) / 6 y_pred =
np.exp(y_pred) pred_df = pd.DataFrame(y_pred, index=test_data["Id"], columns=["SalePrice"])
pred_df.to_csv('output.csv', header=True, index_label='Id')
```

20 Discussion

I tried to apply GridSearch which happens to be more time consuming considering the datasets and I think for this hyperparameter tuning is enough.

Manually updating the parameters takes too much time to yield the result.

The model can be more fine tuned by testing and implementing l2_regularization, forward_propagation technique and so on. However it will also increase the model complexity.

21 Further Improvements

With the help of keras , a lot of these fine tuning can be easily done which is less time consuming and easy to use.

22 Conclusions

For the tensoflow based ANN algorithm the best score is 0.11914. However, there are many other methods that could be applied for a better result. For further improvement of the result we need to pursue methods other than simply scikit based ANN, and in a high-end machine. It has been studied that keras/tensorflow based methods often yields better results, since this was done to get the best possible result using Scikit learn based ANN only, keras based methods have not been applied. Thus, a different approach altogether than scikit learn based ANN or a better ensemble method with other regressor algorithm might yield a far better result than thus far experienced here.

23 References

These linked helped me lot while doing this assignment specially the article "Regression in Neural Networks using TensorFlow(Low Level APIs)" was a huge help when I started doing this

- The APIs for neural networks in TensorFlow
- TENSORFLOW: LOW LEVEL API WITH IRIS DATASETS
- Regression in Neural Networks using TensorFlow(Low Level APIs)
- Dropout (neural network regularization) Data processing was a huge help for this karnels -
- Stacked Regression
- PREDICTING HOUSE PRICES ON KAGGLE: A GENTLE INTRODUCTION TO DATA SCIENCE – PART I

24 Updates in this Version –

1. Data preprocessing has been done more carefully this time as it was difficult to keep track in the earlier versions
2. DNN part has been done with new approach
    - No layer DNN with Cross validation
    - DNN with Cross validation
    - DNN with Dropout

END of SCRIPT