Notebook

April 5, 2018

1 Ames Housing Dataset

I have chosen Ames Housing Dataset to study. The data set contains information from the Ames Assessor's Office used in computing assessed values for individual residential properties sold in Ames, IA from 2006 to 2010. It has 82 columns which include 23 nominal, 23 ordinal, 14 discrete, and 20 continuous variables (and 2 additional observation identifiers).

This data set was constructed for the purpose of an end of semester project for an undergraduate regression course. The original data (obtained directly from the Ames Assessor's Office) is used for tax assessment purposes but lends itself directly to the prediction of home selling prices. The type of information contained in the data is similar to what a typical home buyer would want to know before making a purchase.

Some questions that can be asked are:

- What are the variables that have the most influences on the sales price ?
- How is the sales price distributed ?
- Does the variable shows multicollinearity ?
- Do Overall Quality of the house affects the sale price ?

```
In [1]: % matplotlib inline
        from sklearn.decomposition import PCA
        from sklearn.preprocessing import StandardScaler,LabelEncoder,Imputer
        from sklearn.metrics import mean_squared_error
        from sklearn.ensemble import ExtraTreesRegressor
        from sklearn.feature_selection import SelectFromModel
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        from scipy.stats import norm,skew
        from scipy import stats
```

```
In [2]: data = pd.read_csv("train.csv")
        obj_2 = data.select_dtypes(include = ['object'])
        data.head(3)
```

```
Out[2]:    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

  LandContour Utilities    ...     PoolArea PoolQC Fence MiscFeature MiscVal  \
0         Lvl    AllPub    ...            0    NaN   NaN         NaN       0
1         Lvl    AllPub    ...            0    NaN   NaN         NaN       0
2         Lvl    AllPub    ...            0    NaN   NaN         NaN       0

  MoSold YrSold  SaleType  SaleCondition  SalePrice
0      2   2008        WD         Normal     208500
1      5   2007        WD         Normal     181500
2      9   2008        WD         Normal     223500

[3 rows x 81 columns]
```

Number of Columns & shape of the dataset

```
In [3]: columns = data.columns
        print(columns)
```

```
Index(['Id', '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 [4]: data.shape
```

```
Out[4]: (1460, 81)
```

List of columns in the dataset, and we can see that there are 80 columns in this dataset which mean that we might have to find a way to reduce the number of colums to reduce computational time and resources needed

```
In [5]: categorical = ['MSSubClass','OverallQual','OverallCond']
        for category in categorical:
            data[category] = data[category].astype('str')
```

Changing the numerical to categorical

2 Data Cleaning

2.1 Check for columns with large number of missing values and drop them

```
In [6]: null = [column for column in columns if data[column].isnull().sum() > (0.5*len(data))]
        print("Columns with missing value is:\n{}".format(null))
```

```
Columns with missing value is:
['Alley', 'PoolQC', 'Fence', 'MiscFeature']
```

```
In [7]: for column in null:
            data.drop(column,axis = 1,inplace = True)
        data.drop("Id",axis = 1, inplace = True)
        columns = data.columns
```

2.2 Fixing null values in remaining columns

```
In [8]: missing = [column for column in columns if data[column].isnull().sum() > 0]
        missing
```

```
Out[8]: ['LotFrontage',
         'MasVnrType',
         'MasVnrArea',
         'BsmtQual',
         'BsmtCond',
         'BsmtExposure',
         'BsmtFinType1',
         'BsmtFinType2',
         'Electrical',
         'FireplaceQu',
         'GarageType',
         'GarageYrBlt',
         'GarageFinish',
         'GarageQual',
         'GarageCond']
```

```
In [9]: # Lot Frontage
        data["LotFrontage"] = data.groupby("Neighborhood")["LotFrontage"].transform(
            lambda x: x.fillna(x.median()))
```

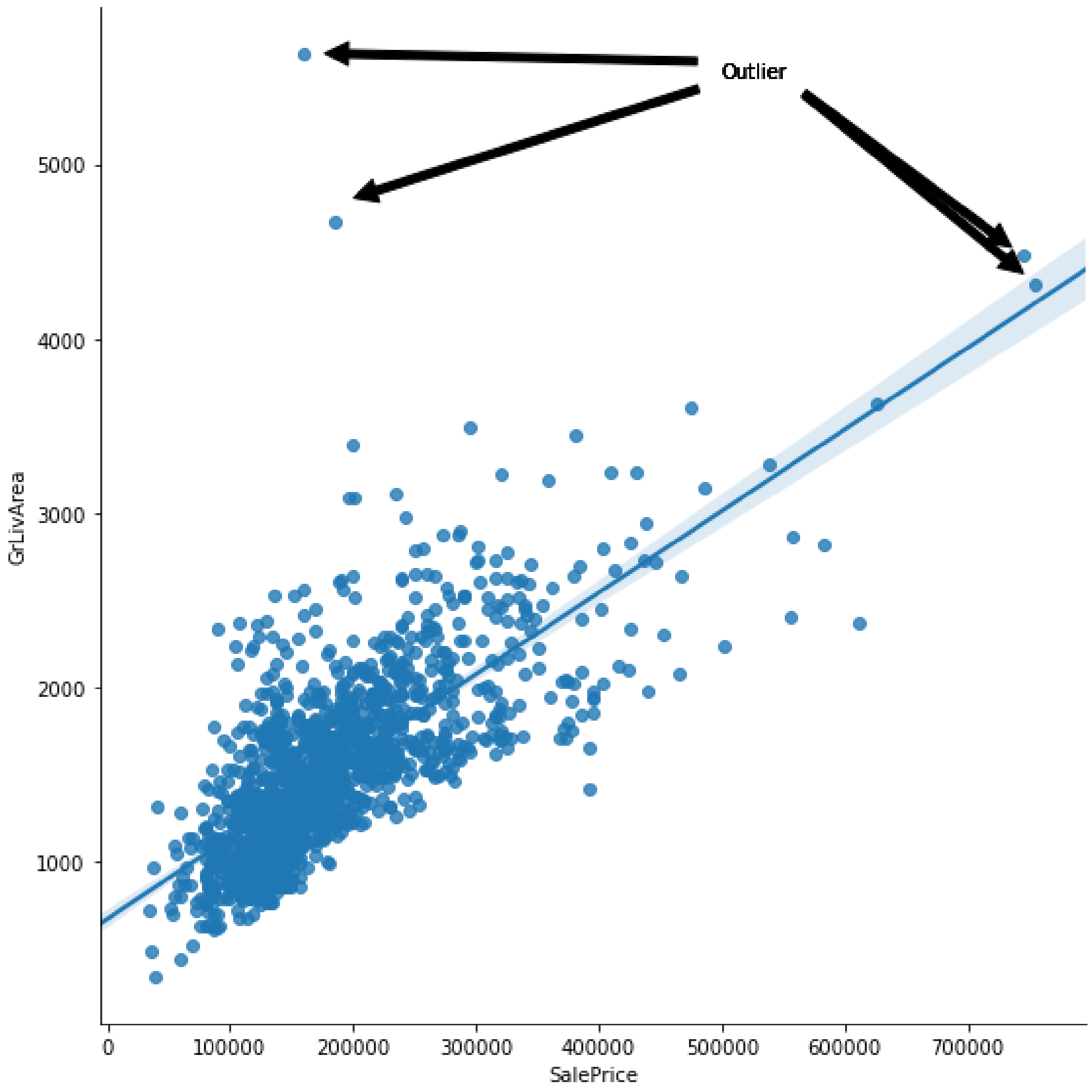
```
In [10]: # MasVnrType and Area
         data["MasVnrType"] = data["MasVnrType"].fillna("None")
         data["MasVnrArea"] = data["MasVnrArea"].fillna(0)
```

```
In [11]: for col in ('BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2'):
             data[col] = data[col].fillna('None')
```

```
In [12]: data['Electrical'] = data['Electrical'].fillna(data['Electrical'].mode()[0])
In [13]: # FireplaceQu
         data["FireplaceQu"] = data["FireplaceQu"].fillna("None")

In [14]: for col in ('GarageType', 'GarageFinish', 'GarageQual', 'GarageCond'):
             data[col] = data[col].fillna('None')

In [15]: # GarageYrBlt
         data['GarageYrBlt'] = data['GarageYrBlt'].fillna(0)
```

2.3 Treatment of outliers in GrLivArea columns due to documentation advice

```
In [16]: sns.lmplot('SalePrice','GrLivArea',size = 8,data = data)
         plt.annotate('Outlier', xy=(160000,5642), xytext=(500000, 5500),
                      arrowprops=dict(facecolor='black', shrink=0.05),
                      )
         plt.annotate('Outlier', xy=(184750,4774), xytext=(500000, 5500),
                      arrowprops=dict(facecolor='black', shrink=0.05),
                      )
         plt.annotate('Outlier', xy=(755000,4316), xytext=(500000, 5500),
                      arrowprops=dict(facecolor='black', shrink=0.05),
                      )
         plt.annotate('Outlier', xy=(745000,4476), xytext=(500000, 5500),
                      arrowprops=dict(facecolor='black', shrink=0.05),
                      )

Out[16]: <matplotlib.text.Annotation at 0x189987e0710>
```



Outliers are one of those statistical issues that everyone knows about, but most people aren't sure how to deal with. However before deciding on dropping the outlier, we need to make some considerations.

- If it is obvious that the outlier is due to incorrectly entered or measured data, we should drop the outlier.
- If the outlier does not change the results but does affect assumptions, we may drop the outlier.
- More commonly, the outlier affects both results and assumptions. In this situation, it is not legitimate to simply drop the outlier. We may run the analysis both with and without it, but we should state in at least a footnote the dropping of any such data points and how the results changed.
- If the outlier creates a significant association in the dataset(linear), we should drop the outlier and should not report any significance from the analysis.

2.4 Removing the outliers

```
In [17]: data = data[data['GrLivArea'] < 4000]
         data.head()
```

```
Out[17]:   MSSubClass MSZoning  LotFrontage  LotArea Street LotShape LandContour  \
        0          60       RL         65.0     8450   Pave      Reg         Lvl
        1          20       RL         80.0     9600   Pave      Reg         Lvl
        2          60       RL         68.0    11250   Pave      IR1         Lvl
        3          70       RL         60.0     9550   Pave      IR1         Lvl
        4          60       RL         84.0    14260   Pave      IR1         Lvl

          Utilities LotConfig LandSlope    ...     EnclosedPorch 3SsnPorch ScreenPorch  \
        0    AllPub    Inside       Gtl    ...                 0         0           0
        1    AllPub       FR2       Gtl    ...                 0         0           0
        2    AllPub    Inside       Gtl    ...                 0         0           0
        3    AllPub    Corner       Gtl    ...               272         0           0
        4    AllPub       FR2       Gtl    ...                 0         0           0

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

        [5 rows x 76 columns]
```

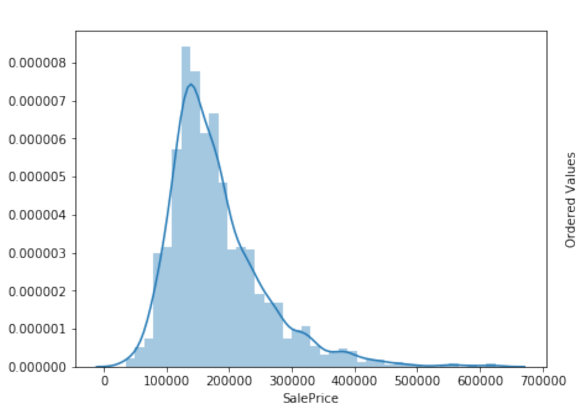
3 Data Exploration

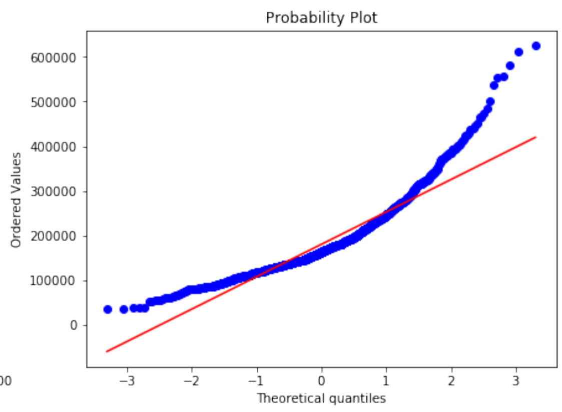
4 How is the sales price distributed

```
In [18]: data['SalePrice'].describe()
```

```
Out[18]: count      1456.000000
         mean     180151.233516
         std       76696.592530
         min       34900.000000
         25%      129900.000000
         50%      163000.000000
         75%      214000.000000
         max      625000.000000
         Name: SalePrice, dtype: float64
```

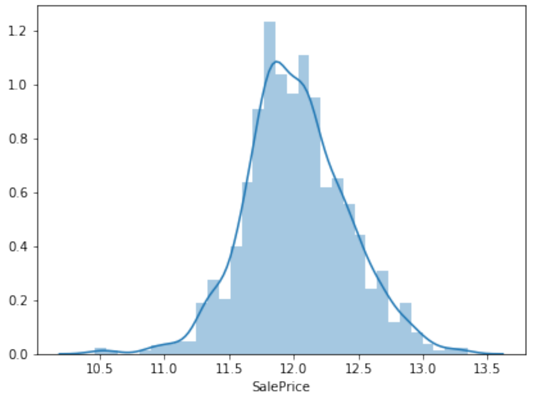
```
In [19]: fig,(ax1, ax2) = plt.subplots(1, 2,figsize=(15, 5))
         _ = sns.distplot(data['SalePrice'],ax = ax1)
         _ = stats.probplot(data['SalePrice'], plot=plt)
```

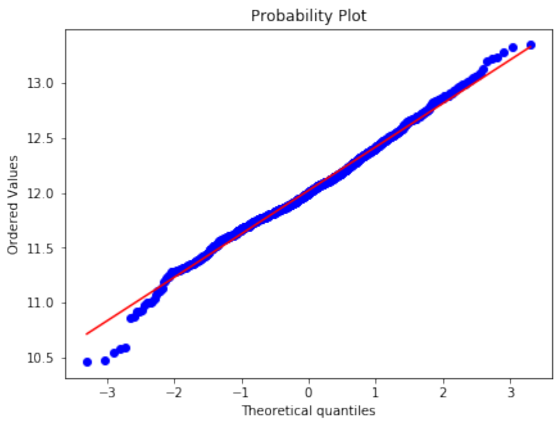




It seems that the sale price distribution differs from normal distribution, which means that we might need to normalize the value before running the data through machine learning algorithm. The distribution is also leptokurtic and has positive skewness. We will now apply log transformation to the column SalePrice.

```
In [20]: data['SalePrice'] = np.log(data['SalePrice'])
         fig,(ax1, ax2) = plt.subplots(1, 2,figsize=(15, 5))
         _ = sns.distplot(data['SalePrice'],ax = ax1)
         _ = stats.probplot(data['SalePrice'],plot=plt)
```





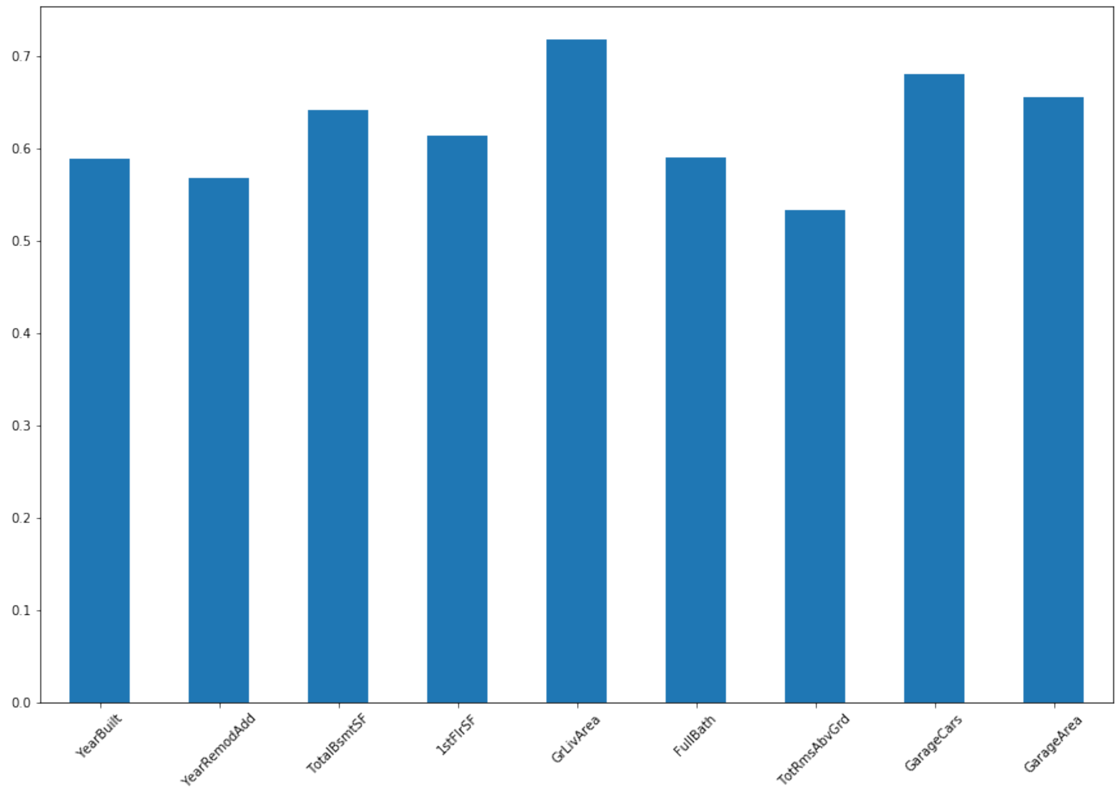
That looks much better now !

4.1 Relationship between sale price and other numerical columns

4.1.1 Which variables are highly correlated with the sales price ?

```
In [21]: num = data.select_dtypes(include = ['int64','float64'])
         corr = num.corr().loc['SalePrice']
         corr[corr >= 0.5][:-1].plot(kind = 'bar',figsize = (15,10), rot = 45)
```

```
Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x18999328208>
```



```
In [22]: num = num[['YearBuilt','YearRemodAdd','TotalBsmtSF', '1stFlrSF', 'GrLivArea',
                    'FullBath','TotRmsAbvGrd','GarageCars', 'GarageArea','SalePrice']]
         num.head()

Out[22]:    YearBuilt  YearRemodAdd  TotalBsmtSF  1stFlrSF  GrLivArea  FullBath  \
         0       2003          2003          856       856       1710         2
         1       1976          1976         1262      1262       1262         2
         2       2001          2002          920       920       1786         2
         3       1915          1970          756       961       1717         1
         4       2000          2000         1145      1145       2198         2

            TotRmsAbvGrd  GarageCars  GarageArea  SalePrice
         0             8           2         548  12.247694
         1             6           2         460  12.109011
         2             6           2         608  12.317167
         3             7           3         642  11.849398
         4             9           3         836  12.429216
```

All this columns have significant effects on the sales prices

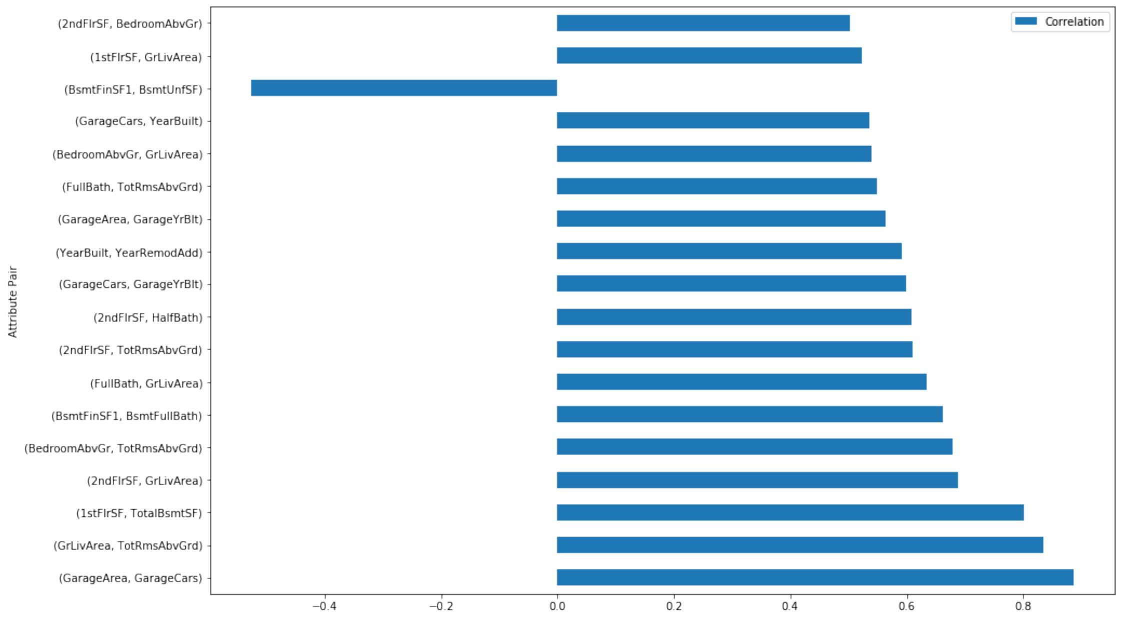
4.2 Relationship of variables with each other

4.2.1 Does the variable shows multicollinearity ?

```
In [23]: correlations=data.corr()
         attrs = correlations.iloc[:-1,:-1] # all except target

         threshold = 0.5
         important_corrs = (attrs[abs(attrs) > threshold][attrs != 1.0]) \
             .unstack().dropna().to_dict()

         unique_important_corrs = pd.DataFrame(
             list(set([(tuple(sorted(key)), important_corrs[key]) \
             for key in important_corrs])),
                 columns=['Attribute Pair', 'Correlation'])

             # sorted by absolute value
         unique_important_corrs = unique_important_corrs.loc[
             abs(unique_important_corrs['Correlation']).argsort()[::-1]]
         plt.figure(dpi = 200)
         unique_important_corrs.plot(x = 'Attribute Pair', y = 'Correlation',kind = 'barh',fig
```

```
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x1899956d908>
```

```
<matplotlib.figure.Figure at 0x189996e91d0>
```



This is an example of multicollinearity.

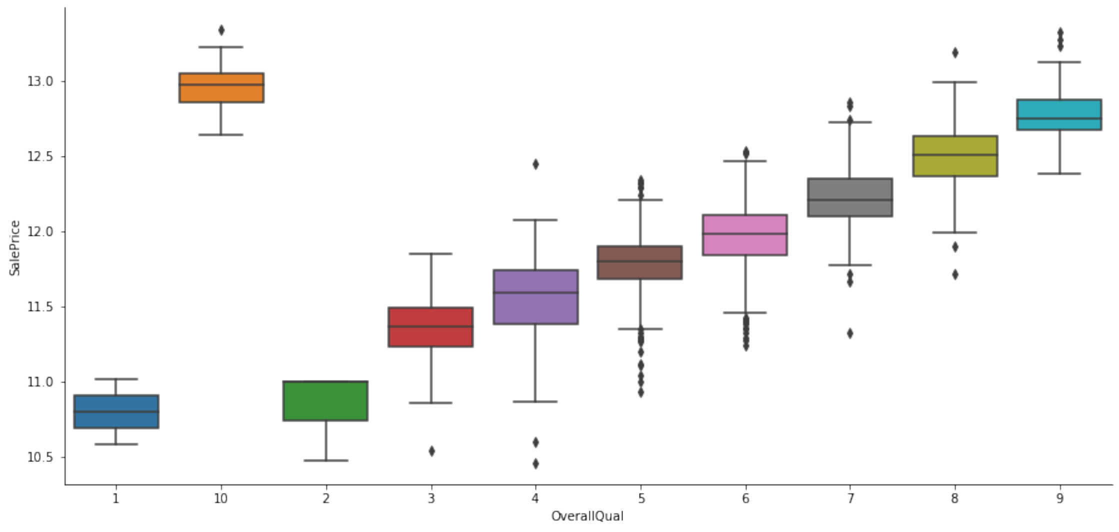
Multicollinearity generally occurs when there are high correlations between two or more predictor variables. In other words, one predictor variable can be used to predict the other. This creates redundant information, skewing the results in a regression model. Examples of correlated predictor variables (also called multicollinear predictors) are: a person's height and weight, age and sales price of a car, or years of education and annual income.

To avoid this we can do 3 things:

- Completely remove those variables
- Make new feature by adding them or by some other operation.
- Use PCA, which will reduce feature set to small number of non-collinear features.

4.3 Do Overall Quality of the house affects the sale price ?

```
In [24]: obj = data.select_dtypes(include = ['object'])
         obj_2 = data.select_dtypes(include = ['object'])
         data_object = pd.concat([num['SalePrice'],obj['OverallQual']],axis = 1)
         plt.figure(figsize = (15,7))
         sns.boxplot(x = 'OverallQual', y = 'SalePrice',data = data)
         sns.despine()
```



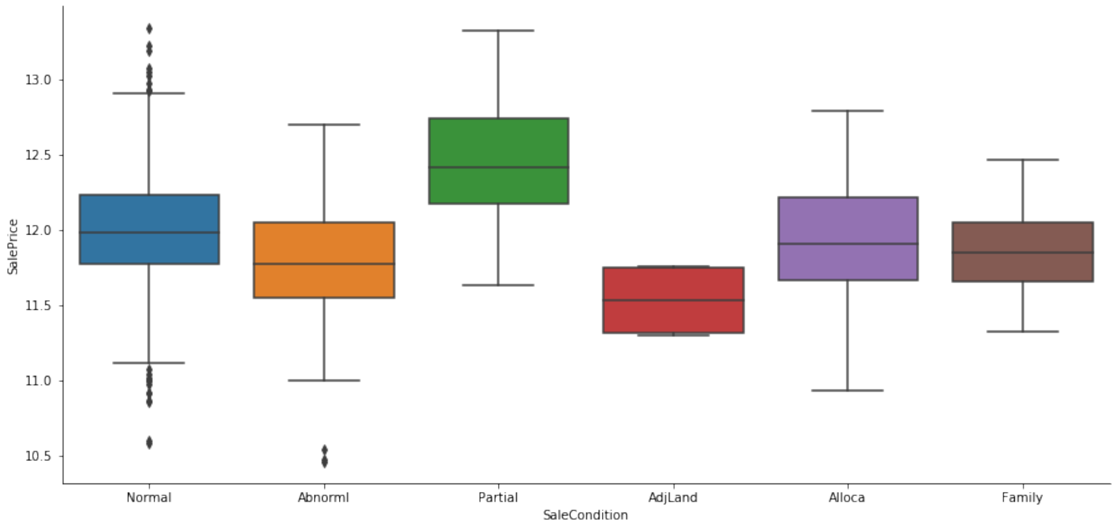
Overall Qual (Ordinal): Rates the overall material and finish of the house

```
10    Very Excellent
9     Excellent
8     Very Good
7     Good
6     Above Average
5     Average
4     Below Average
3     Fair
2     Poor
1     Very Poor
```

It is easy to see that overall quality of the house matters quite a lot in term of the final sale price

4.4 Do Sales Condition of the house affects the sale price ?

```
In [25]: data_object = pd.concat([num['SalePrice'],obj['SaleCondition']],axis = 1)
         plt.figure(figsize = (15,7))
         sns.boxplot(x = 'SaleCondition', y = 'SalePrice',data = data)
         sns.despine()
```



Sale Condition (Nominal): Condition of sale

Normal - Normal Sale

Abnorml - Abnormal Sale - trade, foreclosure, short sale

AdjLand - Adjoining Land Purchase

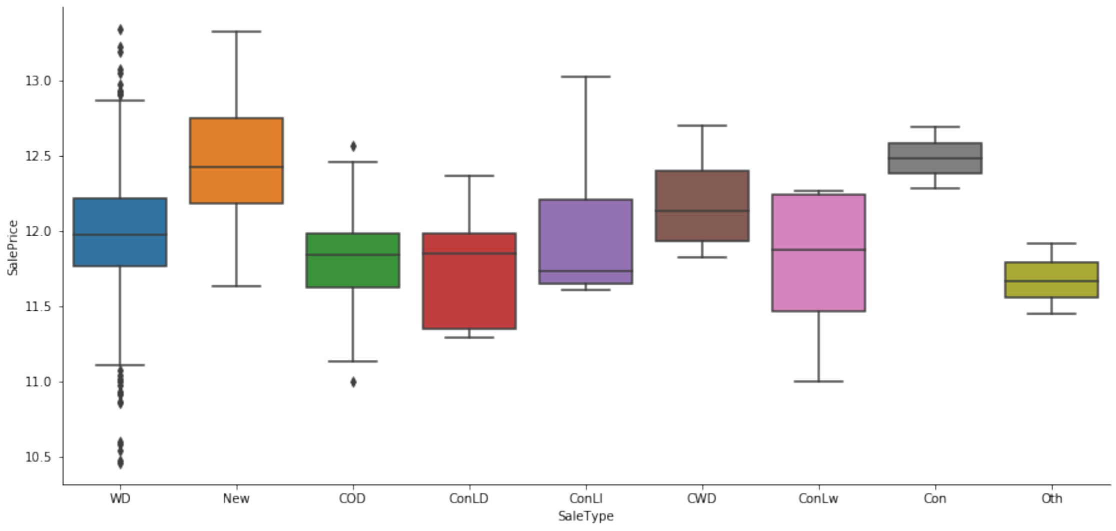
Alloca - Allocation - two linked properties with separate deeds, typically condo with a garage unit Family - Sale between family members

Partial - Home was not completed when last assessed (associated with New Homes)

From the box plot we can see that the price of normal house has more spread than any of the other type of sale condition. Sales within family on the other hand, shows a small spread which makes sense because people tend to value their family more and decide to not charge an absorbitant price. Partial home which is new house has higher mean price value than other type of sales condition. Therefore, i do think sale condition has low impact on the sales price except for new houses.

4.5 Do Sales Type of the house affects the sale price ?

```
In [26]: data_object = pd.concat([num['SalePrice'],obj['SaleType']],axis = 1)
         plt.figure(figsize = (15,7))
         sns.boxplot(x = 'SaleType', y = 'SalePrice',data = data)
         sns.despine()
```



5 Preparation before feeding data into machine learning algorithm

5.1 Check for skewness in numerical data

```
In [27]: target = data['SalePrice']
         data = data.iloc[:,:-1]

         skewness = data.select_dtypes(include = ['int64','float64']).columns
         skewed_feats = data[skewness].apply(lambda x: skew(x.dropna())).sort_values(ascending
         skewness = pd.DataFrame({'Skew' :skewed_feats})
         skewness.head(10)
```

```
Out[27]:                    Skew
         MiscVal        24.418175
         PoolArea       17.504556
         LotArea        12.574590
         3SsnPorch      10.279262
         LowQualFinSF    8.989291
         KitchenAbvGr    4.476748
         BsmtFinSF2      4.244209
         BsmtHalfBath    4.124712
         ScreenPorch     4.111400
         EnclosedPorch   3.081275
```

```
In [28]: skewness = skewness[abs(skewness) > 0.75]
         print("There are {} skewed numerical features to Box Cox transformed".format(skewness

         from scipy.special import boxcox1p
         skewed_features = skewness.index
         lam = 0.15
         for feat in skewed_features:
             #all_data[feat] += 1
             data[feat] = boxcox1p(data[feat], lam)

There are 33 skewed numerical features to Box Cox transformed
```

5.2 Getting dummy for categorical features

```
In [29]: le = LabelEncoder()
         obj = obj.apply(le.fit_transform)
         data = pd.get_dummies(data)
         data.shape

Out[29]: (1456, 315)
```

```
In [30]: from sklearn.model_selection import train_test_split
         X_train,X_test,y_train, y_test = train_test_split(data,target,random_state = 1)
```

6 Modelling

In this part of the notebook, we will run the dataset through various machine learning algorithms and evaluate the result according to Root Mean Squared Error between the true value and the predicted value. Root Mean Squared Error(RMSE) can be defined as square root of the mean square (the arithmetic mean of the squares of a set of numbers). In the modelling process we will be using vanilla version of the dataset without feature selection and try to find the best algorithm for the dataset. These three algorithm is Lasso, Elastic Net and Gradient Boosting Regressor.

6.0.1 Importing libraries

```
In [31]: from sklearn.linear_model import ElasticNet, Lasso,  BayesianRidge, LassoLarsIC
         from sklearn.ensemble import RandomForestRegressor,  GradientBoostingRegressor
         from sklearn.pipeline import make_pipeline
         from sklearn.preprocessing import RobustScaler
         from sklearn.model_selection import KFold, cross_val_score, train_test_split,GridSear
         from sklearn.metrics import mean_squared_error
```

6.0.2 Validation Function

```
In [32]: n_folds = 5

         def rmsle_cv(model):
             kf = KFold(n_folds, shuffle=True, random_state=42).get_n_splits(X_train.values)
             rmse= np.sqrt(-cross_val_score(model, X_train.values, y_train, scoring="neg_mean_
             return(rmse)
```

6.0.3 Initialize all base models

```
In [33]: lasso = make_pipeline(RobustScaler(), Lasso(random_state = 3))
         ENet = make_pipeline(RobustScaler(),ElasticNet(random_state=3))
         GBoost = GradientBoostingRegressor(random_state =3)
```

6.0.4 Results

```
In [34]: score = rmsle_cv(lasso)
         print("Lasso score: {:.4f} ({:.4f})\n".format(score.mean(), score.std()))
         score = rmsle_cv(ENet)
         print("Elastic Net score: {:.4f} ({:.4f})\n".format(score.mean(), score.std()))
         score = rmsle_cv(GBoost)
         print("Gradient Boosting score: {:.4f} ({:.4f})\n".format(score.mean(), score.std()))
```

```
Lasso score: 0.3662 (0.0108)

Elastic Net score: 0.3657 (0.0110)

Gradient Boosting score: 0.1315 (0.0126)
```

6.1 Can we improve the algorithm ?

6.1.1 Grid Search for Lasso

```
In [35]: clf = Lasso(random_state = 3)
         grid_values = {'alpha': [0.001, 0.01, 0.05, 0.1, 1, 10, 100]}

         # default metric to optimize over grid parameters: accuracy
         grid_clf_acc = GridSearchCV(clf,scoring = 'neg_mean_squared_error', cv = 5,param_grid
         grid_clf_acc.fit(X_train, y_train)

         print('Grid best parameter (Min. Mean Squared Error): ', grid_clf_acc.best_params_)
         print('Grid best score (Mean Squared Error): ', grid_clf_acc.best_score_)
```

```
Grid best parameter (Min. Mean Squared Error):  {'alpha': 0.001}
Grid best score (Mean Squared Error):  -0.0136846732482
```

6.1.2 Grid Search for Elastic Net

```
In [36]: clf = ElasticNet(random_state = 3)
         grid_values = {'alpha': [0.001, 0.01, 0.05, 0.1, 1, 10, 100],
                        'l1_ratio': [0.1,0.3,0.5,0.7,0.9]}

         # default metric to optimize over grid parameters: accuracy
         grid_clf_acc = GridSearchCV(clf,scoring = 'neg_mean_squared_error', cv = 5,param_grid
         grid_clf_acc.fit(X_train, y_train)
```

```
        print('Grid best parameter (Min. Mean Squared Error): ', grid_clf_acc.best_params_)
        print('Grid best score (Mean Squared Error): ', grid_clf_acc.best_score_)
```

```
Grid best parameter (Min. Mean Squared Error):  {'alpha': 0.001, 'l1_ratio': 0.3}
Grid best score (Mean Squared Error):  -0.0125506319811
```

6.1.3 Grid Search for Gradient Boosting

```
In [37]: clf = GradientBoostingRegressor(warm_start = True,random_state = 3)
         grid_values = {'loss': ['ls','huber'],
                        'learning_rate': [0.1,0.5],
                        'max_depth': [3,5],
                        'n_estimators': [100,300]}

         # default metric to optimize over grid parameters: accuracy
         grid_clf_acc = GridSearchCV(clf,scoring = 'neg_mean_squared_error', cv = 2,param_grid
         grid_clf_acc.fit(X_train, y_train)

         print('Grid best parameter (Min. Mean Squared Error): ', grid_clf_acc.best_params_)
         print('Grid best score (Mean Squared Error): ', grid_clf_acc.best_score_)
```

```
Grid best parameter (Min. Mean Squared Error):  {'learning_rate': 0.1, 'loss': 'huber', 'max_d
Grid best score (Mean Squared Error):  -0.0179818099182
```

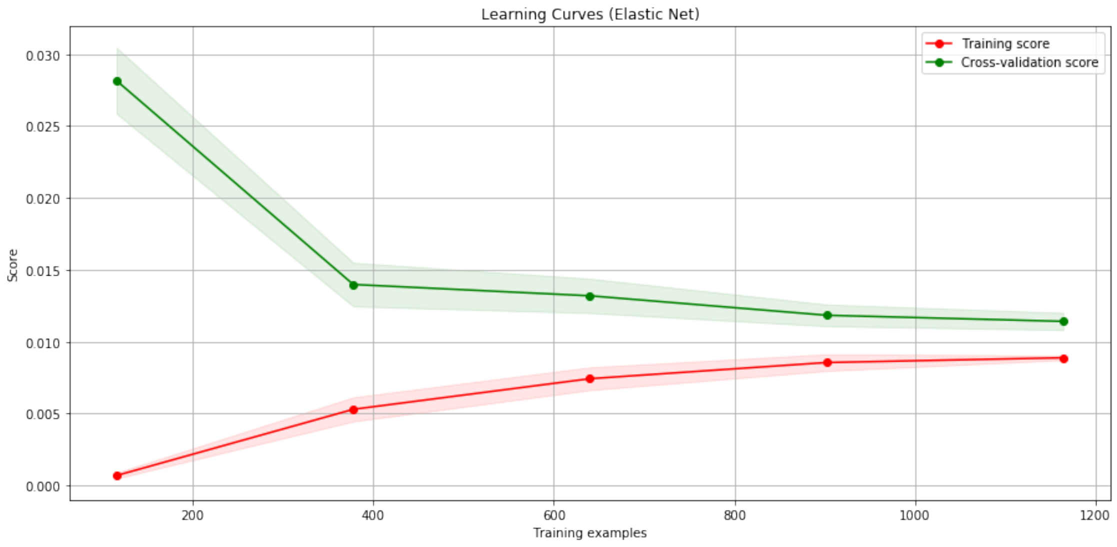
6.1.4 Initialize all tuned models

```
In [38]: lasso = make_pipeline(RobustScaler(), Lasso(alpha = 0.001,random_state = 3))
         ENet = make_pipeline(RobustScaler(),ElasticNet(alpha = 0.001, l1_ratio = 0.3,random_s
         GBoost = GradientBoostingRegressor(learning_rate = 0.1, loss = 'huber', max_depth = 3

In [39]: score = rmsle_cv(lasso)
         print("Lasso score: {:.4f} ({:.4f})\n".format(score.mean(), score.std()))
         score = rmsle_cv(ENet)
         print("Elastic Net score: {:.4f} ({:.4f})\n".format(score.mean(), score.std()))
         score = rmsle_cv(GBoost)
         print("Gradient Boosting score: {:.4f} ({:.4f})\n".format(score.mean(), score.std()))
```

```
Lasso score: 0.1127 (0.0131)

Elastic Net score: 0.1094 (0.0134)

Gradient Boosting score: 0.1221 (0.0121)
```

From this we can see that the best algorithm for the dataset is Elastic Net. Gradient has too much parameters that requires time to tune and the tradeoff between training time and performance isnt really worth it.

```
In [40]: def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None,
                                 n_jobs=1, train_sizes=np.linspace(.1, 1.0, 5)):
             plt.figure(figsize = (15,7))
             plt.title(title)
             if ylim is not None:
                 plt.ylim(*ylim)
             plt.xlabel("Training examples")
             plt.ylabel("Score")
             train_sizes,train_scores,test_scores = learning_curve(
                 estimator, X, y,scoring = 'neg_mean_squared_error',cv=cv, n_jobs=n_jobs,
                 train_sizes=train_sizes)
             train_scores_mean = abs(np.mean(train_scores, axis=1))
             train_scores_std = abs(np.std(train_scores, axis=1))
             test_scores_mean = abs(np.mean(test_scores, axis=1))
             test_scores_std = abs(np.std(test_scores, axis=1))
             plt.grid()

             plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                              train_scores_mean + train_scores_std, alpha=0.1,
                              color="r")
             plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                              test_scores_mean + test_scores_std, alpha=0.1, color="g")
             plt.plot(train_sizes, train_scores_mean, 'o-', color="r",
                      label="Training score")
             plt.plot(train_sizes, test_scores_mean, 'o-', color="g",
                      label="Cross-validation score")

             plt.legend(loc="best")
             return plt

In [41]: title = "Learning Curves (Elastic Net)"
         # Cross validation with 100 iterations to get smoother mean test and train
         # score curves, each time with 20% data randomly selected as a validation set.
         cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=0)

         estimator = ENet
         plot_learning_curve(estimator, title, data, target, cv=cv, n_jobs=4)

Out[41]: <module 'matplotlib.pyplot' from 'C:\\Users\\Parmenides\\Anaconda3\\lib\\site-package
```



From the learning curve we can see that the cross validation score increase dramatically with more training sample. However between 800 -1000, the improvement seems to falter. Which means that we might need a better model to improve the performance. However due to the constraint of processing resources, this is a good and quick model.

7 Predicting the test set

```
In [42]: ENet.fit(X_train,y_train)

Out[42]: Pipeline(memory=None,
              steps=[('robustscaler', RobustScaler(copy=True, quantile_range=(25.0, 75.0), wit
                with_scaling=True)), ('elasticnet', ElasticNet(alpha=0.001, copy_X=True, fit_i
               max_iter=1000, normalize=False, positive=False, precompute=False,
               random_state=3, selection='cyclic', tol=0.0001, warm_start=False))])

In [43]: y_pred = ENet.predict(X_test)
         mse = mean_squared_error(y_test,y_pred)
         rmse = np.sqrt(mse)
         rmse

Out[43]: 0.11810383800176444
```