Week 2 Feature selection

May 23, 2019

0.1 Feature selection

In this section, we will use different techniques for feature selection such as random forest, RFECV, etc. We will try working on subset of features and also we'll try reducing the dimension of the dataaset usinn PCA and feed the results into one of the regression algorithms.

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        from sklearn.preprocessing import StandardScaler
        from sklearn.decomposition import PCA
        from sklearn.feature_selection import RFECV, mutual_info_regression
        from sklearn.linear_model import LinearRegression
        from sklearn.pipeline import make_pipeline
        from sklearn.model_selection import train_test_split
        from sklearn.ensemble import RandomForestRegressor
        from sklearn.ensemble import GradientBoostingRegressor
        from sklearn.model_selection import cross_val_score
        from sklearn.metrics import mean_absolute_error, mean_squared_error
        import seaborn as sns
        from heapq import nlargest
        %matplotlib inline
```

```
In [2]: data = pd.read_csv('../clean_data.csv', index_col=0)
        data.head()
```

```
Out[2]:    MSSubClass  LotFrontage  LotArea  OverallQual  OverallCond  YearBuilt  \
        Id
        1          60         65.0     8450            7            5       2003
        2          20         80.0     9600            6            8       1976
        3          60         68.0    11250            7            5       2001
        4          70         60.0     9550            7            5       1915
        5          60         84.0    14260            8            5       2000

            YearRemodAdd  ExterQual  ExterCond  BsmtQual          ...            \
        Id                                                        ...
        1           2003          3          2         4          ...
        2           1976          2          2         4          ...
```

```
3          2002          3          2          4          ...
4          1970          2          2          3          ...
5          2000          3          2          4          ...

    SaleType_ConLI  SaleType_ConLw  SaleType_New  SaleType_Oth  SaleType_WD  \
Id
1                0               0             0             0            1
2                0               0             0             0            1
3                0               0             0             0            1
4                0               0             0             0            1
5                0               0             0             0            1

    SaleCondition_AdjLand  SaleCondition_Alloca  SaleCondition_Family  \
Id
1                       0                     0                     0
2                       0                     0                     0
3                       0                     0                     0
4                       0                     0                     0
5                       0                     0                     0

    SaleCondition_Normal  SaleCondition_Partial
Id
1                      1                      0
2                      1                      0
3                      1                      0
4                      0                      0
5                      1                      0

[5 rows x 533 columns]
```

```
In [3]: data.shape
```

```
Out[3]: (1459, 533)
```

0.1.1 As shown in EDA, the log(sale price) makes the sale price normally distributed without any outliers.

All the models will be fit on log(Sale Price)

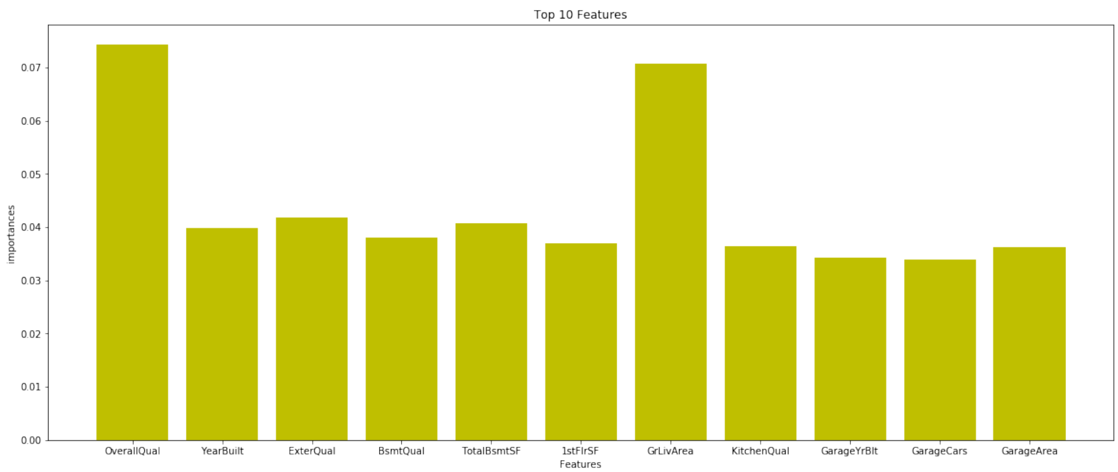
```
In [4]: y = np.log(data['SalePrice'])
        x = data.drop(labels = 'SalePrice', axis=1).astype("float64")
        x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3, random_state
```

```
In [5]: RF = RandomForestRegressor(n_estimators=1000, max_features=30, random_state=42)
        cv_score2 = cross_val_score(RF, x_train, y_train, cv=5, scoring='neg_mean_squared_erro
        print('Cross validation scores for GBR model:', np.sqrt(-cv_score2).mean())
```

```
Cross validation scores for GBR model: 0.15129308478316808
```

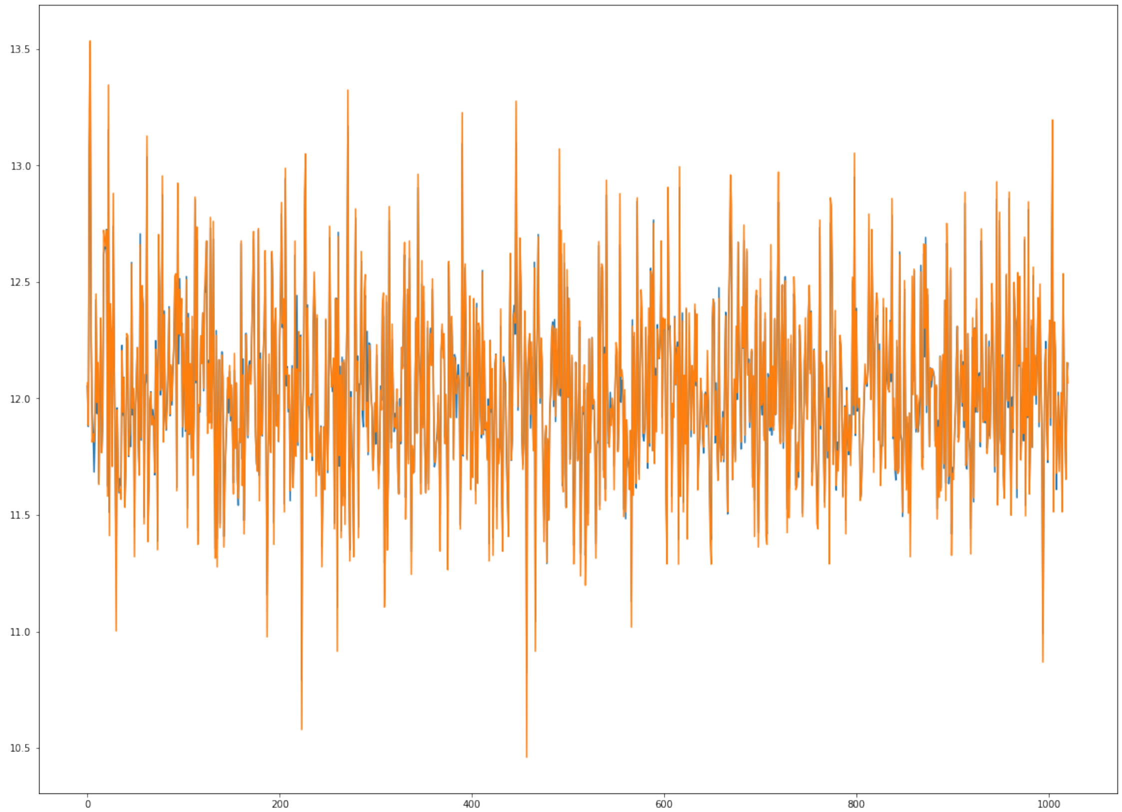
```
In [6]: RF.fit(x_train, y_train)
        y_pred_train = RF.predict(x_train)
```

```
In [7]: imp_cols = x.columns[RF.feature_importances_ > 0.0328]
        vals = RF.feature_importances_[RF.feature_importances_ > 0.0328]

        plt.figure(figsize=(20,8))
        plt.title("Top 10 Features")
        plt.bar(imp_cols,vals,
               color="y",  align="center")
        plt.xlabel('Features')
        plt.ylabel('importances')
        plt.show()
```

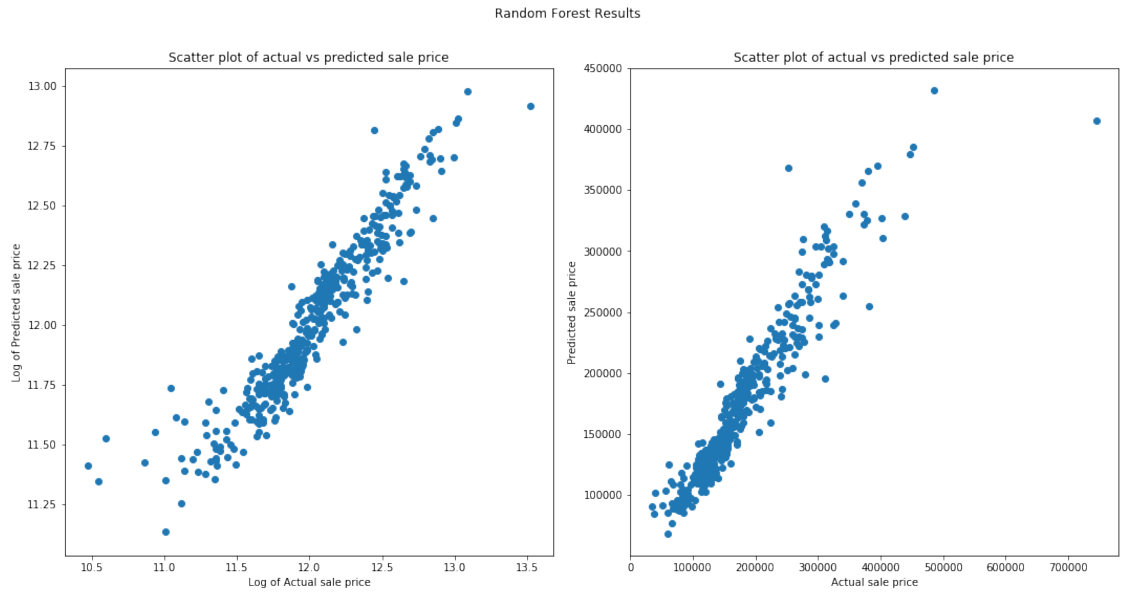



```
In [8]: plt.subplots(figsize=(20,15))
        plt.plot(y_pred_train)
        plt.plot(y_train.values)
```

```
Out[8]: [<matplotlib.lines.Line2D at 0x29236002a90>]
```



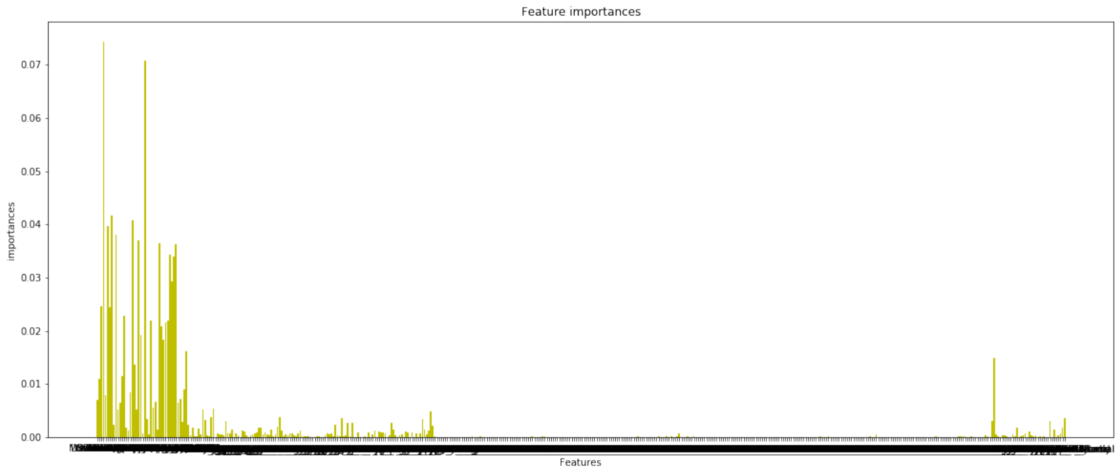

```
In [14]: y_pred = RF.predict(x_test)
         fig = plt.figure(figsize=(15,8))
         fig.suptitle('Random Forest Results')
         plt.subplot(121)
         plt.scatter(y_test, y_pred)
         plt.xlabel('Log of Actual sale price')
         plt.ylabel('Log of Predicted sale price')
         plt.title('Scatter plot of actual vs predicted sale price')
         plt.subplot(122)
         plt.scatter(np.exp(y_test.values), np.exp(y_pred))
         plt.xlabel('Actual sale price')
         plt.ylabel('Predicted sale price')
         plt.title('Scatter plot of actual vs predicted sale price')
         plt.tight_layout()
         fig.subplots_adjust(top=0.88)
```




```
In [15]: ## Calculate error with the actual values of sale price
         y_pred = RF.predict(x_test)

         MSEscore = np.sqrt(mean_squared_error(np.exp(y_pred), np.exp(y_test)))
         print('Score RMSE = {}'.format(MSEscore))

         MAEscore = np.sqrt(mean_absolute_error(np.exp(y_pred), np.exp(y_test)))
         print('Score RMAE = {}'.format(MAEscore))
```

```
Score RMSE = 29473.80466390691
Score RMAE = 130.2935307010514
```

```
In [16]: imp_cols = x.columns[RF.feature_importances_>0.0]
         vals = RF.feature_importances_[RF.feature_importances_>0.0]

         plt.figure(figsize=(20,8))
         plt.title("Feature importances")
         plt.bar(imp_cols,vals,
                color="y",  align="center")
         plt.xlabel('Features')
         plt.ylabel('importances')
         plt.show()
```



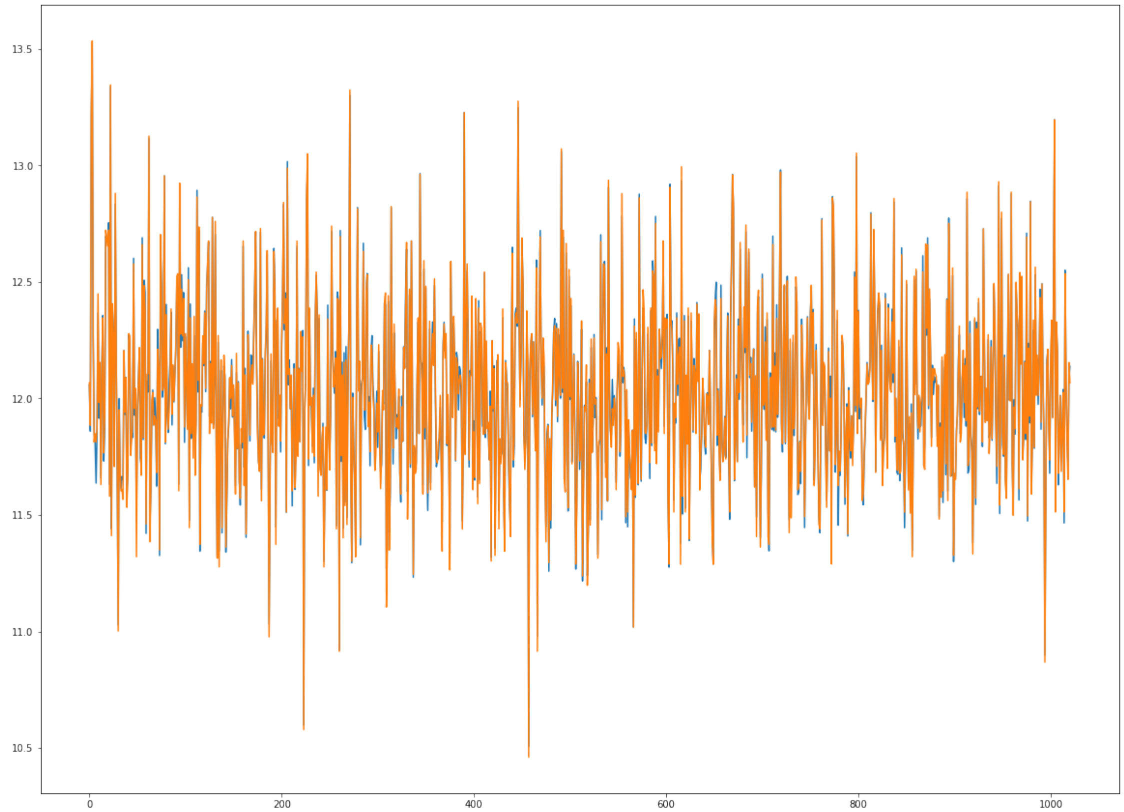
0.2 Feature Selection using GradientBoostingRegressor

```
In [17]: GBR = GradientBoostingRegressor(learning_rate= 0.1, n_estimators=1500, max_depth=2)
         cv_score = cross_val_score(GBR, x_train, y_train, cv=5, scoring='neg_mean_squared_erro
         print('Cross validation scores for GBR model:', np.sqrt(-cv_score).mean())
```

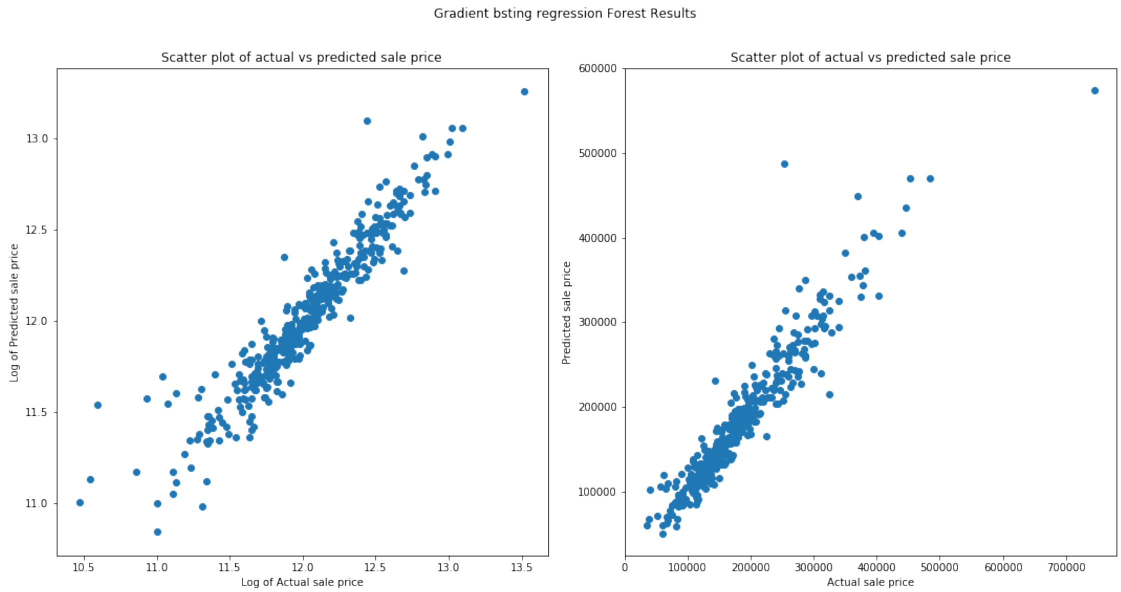
```
Cross validation scores for GBR model: 0.13754658935554992
```

```
In [18]: GBR.fit(x_train, y_train)
         y_pred_train = GBR.predict(x_train)
         plt.subplots(figsize=(20,15))
         plt.plot(y_pred_train)
         plt.plot(y_train.values)
```

```
Out[18]: [<matplotlib.lines.Line2D at 0x2923d193320>]
```

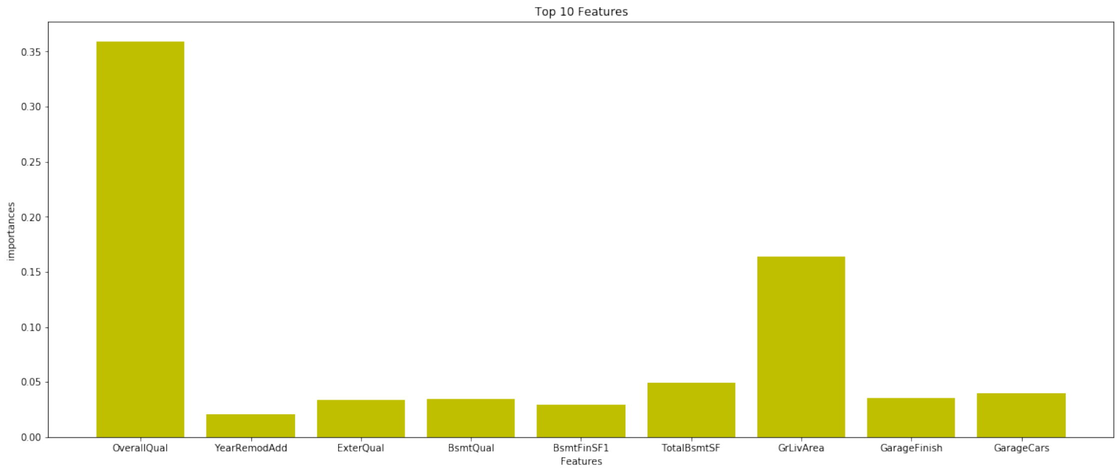



```
In [20]: y_pred = GBR.predict(x_test)
         fig = plt.figure(figsize=(15,8))
         fig.suptitle('Gradient bsting regression Forest Results')
         plt.subplot(121)
         plt.scatter(y_test, y_pred)
         plt.xlabel('Log of Actual sale price')
         plt.ylabel('Log of Predicted sale price')
         plt.title('Scatter plot of actual vs predicted sale price')
         plt.subplot(122)
         plt.scatter(np.exp(y_test.values), np.exp(y_pred))
         plt.xlabel('Actual sale price')
         plt.ylabel('Predicted sale price')
         plt.title('Scatter plot of actual vs predicted sale price')
         plt.tight_layout()
         fig.subplots_adjust(top=0.88)
```

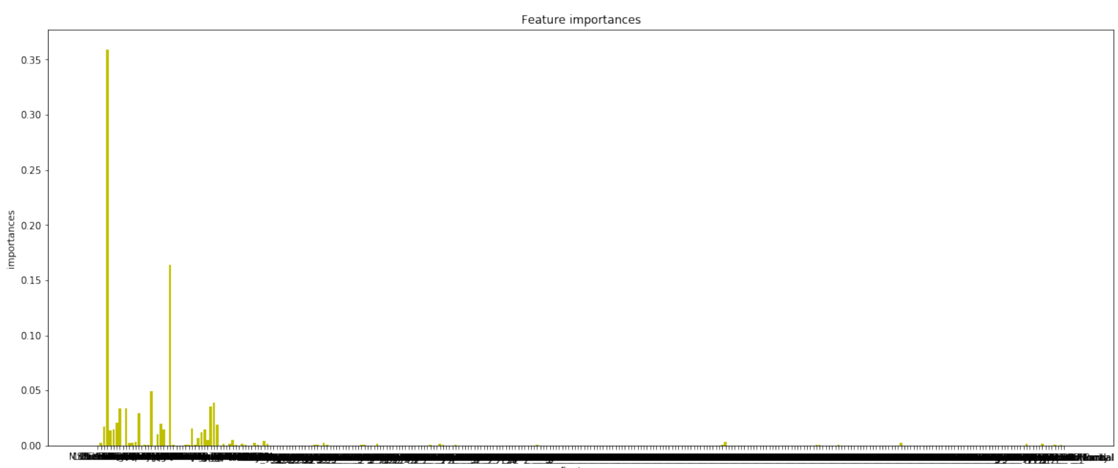



```
In [65]: ## Calculate error with the actual values of sale price
         y_pred = GBR.predict(x_test)

         MSEscore = np.sqrt(mean_squared_error(np.exp(y_pred), np.exp(y_test)))
         print('Score RMSE = {}'.format(MSEscore))

         MAEscore = np.sqrt(mean_absolute_error(np.exp(y_pred), np.exp(y_test)))
         print('Score RMAE = {}'.format(MAEscore))

Score RMSE = 24850.068530060966
Score RMAE = 123.20512665853853
```

```
In [33]: imp_cols = x.columns[GBR.feature_importances_ > 0.02]
         vals = GBR.feature_importances_[GBR.feature_importances_ > 0.02]

         plt.figure(figsize=(20,8))
         plt.title("Top 10 Features")
         plt.bar(imp_cols,vals,
                color="y",  align="center")
         plt.xlabel('Features')
         plt.ylabel('importances')
         plt.show()
```




```
In [34]: imp_cols = x.columns[GBR.feature_importances_ > 0.0]
         vals = GBR.feature_importances_[GBR.feature_importances_ > 0.0]

         plt.figure(figsize=(20,8))
         plt.title("Feature importances")
         plt.bar(imp_cols,vals,
                color="y",  align="center")
         plt.xlabel('Features')
         plt.ylabel('importances')
         plt.show()
```



Gradient boosting regressor filter out most features. Now, I will work only with a small number of features. GBR will be used to select the features.

```
In [35]: (GBR.feature_importances_>0.002).sum()
```

Out[35]: 31

```
In [36]: x.loc[:,GBR.feature_importances_>0.002].columns
```

```
Out[36]: Index(['LotFrontage', 'LotArea', 'OverallQual', 'OverallCond', 'YearBuilt',
                'YearRemodAdd', 'ExterQual', 'BsmtQual', 'BsmtCond', 'BsmtExposure',
                'BsmtFinType1', 'BsmtFinSF1', 'TotalBsmtSF', 'CentralAir', '1stFlrSF',
                '2ndFlrSF', 'GrLivArea', 'KitchenQual', 'Fireplaces', 'FireplaceQu',
                'GarageType', 'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea',
                'OpenPorchSF', 'MoSold', 'MSZoning_RL', 'Neighborhood_Crawfor',
                'MasVnrArea_209.0', 'MasVnrArea_428.0'],
               dtype='object')
```

```
In [21]: (RF.feature_importances_>0.01).sum()
```

Out[21]: 26

```
In [23]: x.loc[:,RF.feature_importances_>0.01].columns
```

```
Out[23]: Index(['LotFrontage', 'LotArea', 'OverallQual', 'YearBuilt', 'YearRemodAdd',
                'ExterQual', 'BsmtQual', 'BsmtFinType1', 'BsmtFinSF1', 'TotalBsmtSF',
                'HeatingQC', '1stFlrSF', '2ndFlrSF', 'GrLivArea', 'FullBath',
                'KitchenQual', 'TotRmsAbvGrd', 'Fireplaces', 'FireplaceQu',
                'GarageType', 'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea',
                'OpenPorchSF', 'Foundation_PConc'],
               dtype='object')
```

Most of the columns selected by GBR are the same as selected by Random forest

```
In [24]: reduced_var_data = x.loc[:,GBR.feature_importances_>0.002].copy()

         reduced_var_data['SalePrice'] = data['SalePrice']
         reduced_var_data.columns

         reduced_var_data.to_csv('reduced_var_data.csv')
```