Red-Wine Analysis

In this project I will analyse Wine quality by means of kNeighborsClassification (machine learning algorithm).

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ABSTRACT:

Wine classification is a difficult task since taste is the least understood of the human senses. A good wine quality prediction can be very useful in the certification phase, since currently the sensory analysis is performed by human tasters, being clearly a subjective approach. An automatic predictive system can be integrated into a decision support system, helping the speed and quality of the performance. Furthermore, a feature selection process can help to analyze the impact of the analytical tests. If it is concluded that several input variables are highly relevant to predict the wine quality, since in the production process some variables can be controlled, this information can be used to improve the wine quality. Classification models used here is kNeighborsClassification.

KEYWORDS:

Machine Learning, Classification, kNeighbors Classification, Prediction.

Instructions:

1.Import the dataset.

2.Data quality check:

* Check if null values are present. If there are, drop those rows.

3. Exploratory Data Analysis:

- * Univariate Analysis:
 - i. Draw a minimum of 5 histograms .
 - ii. Draw boxplots for each numerical columns.
- * Bivariate analysis:
 - i. Draw a minimum of 5 scatter plots

4. Modelling:

- * Split the dataset using "train-test-split" function.
- * Apply KNN classification on "quality" column of the dataset. Select the appropriate features
- * Predict on the test set.
- * Find out the accuracy.

Step: Import Prerequisite Modules

```
In [1]: import numpy as np
   import pandas as pd
   import matplotlib.pyplot as plt
   import seaborn as sns
   from sklearn.preprocessing import StandardScaler
   from sklearn.model_selection import train_test_split
   from sklearn.neighbors import KNeighborsClassifier
   from sklearn.metrics import classification_report
   from sklearn.metrics import accuracy_score
   %matplotlib inline
   sns.set()
In []:
```

Step: Now we will load the Dataset

Dataset used here is https://www.kaggle.com/uciml/red-wine-quality-cortez-et-al-2009 (<a href="https://www.ka

```
In [2]: #Loading data
    data = pd.read_csv("./winequality-red.csv")
    #Displaying Data
    data.head()
```

Out[2]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

Step: Preliminary Checks

```
In [3]: data.describe()
```

Out[3]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	densit
count	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.00000
mean	8.319637	0.527821	0.270976	2.538806	0.087467	15.874922	46.467792	0.99674
std	1.741096	0.179060	0.194801	1.409928	0.047065	10.460157	32.895324	0.00188
min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.000000	0.99007
25%	7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.000000	0.99560
50%	7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.000000	0.99675
75%	9.200000	0.640000	0.420000	2.600000	0.090000	21.000000	62.000000	0.99783
max	15.900000	1.580000	1.000000	15.500000	0.611000	72.000000	289.000000	1.00369

Step: Data Quality Check

Check if null values are present.

```
In [4]: data.isnull().any()
Out[4]: fixed acidity
                             False
       volatile acidity
                            False
       citric acid
                            False
       residual sugar
                            False
       chlorides
                            False
       free sulfur dioxide False
       total sulfur dioxide False
       density
                            False
                             False
       рН
       sulphates
                             False
                             False
       alcohol
       quality
                             False
       dtype: bool
```

So We Don't Have Any Missing Values

Examine the features in the data-set and their data types

```
In [5]: display(data.info)
        <bound method DataFrame.info of</pre>
                                                 fixed acidity volatile acidity citric ac
        id residual sugar chlorides \
                         7.4
                                           0.700
                                                          0.00
                                                                            1.9
                                                                                     0.076
        1
                          7.8
                                           0.880
                                                          0.00
                                                                            2.6
                                                                                     0.098
         2
                         7.8
                                           0.760
                                                          0.04
                                                                            2.3
                                                                                     0.092
                         11.2
                                           0.280
                                                         0.56
                                                                            1.9
                                                                                     0.075
         4
                         7.4
                                           0.700
                                                         0.00
                                                                            1.9
                                                                                     0.076
                          . . .
                                                          . . .
                                                                            . . .
                                             . . .
        1594
                          6.2
                                           0.600
                                                         0.08
                                                                            2.0
                                                                                     0.090
        1595
                          5.9
                                           0.550
                                                         0.10
                                                                            2.2
                                                                                     0.062
                          6.3
                                                                            2.3
        1596
                                           0.510
                                                         0.13
                                                                                     0.076
        1597
                          5.9
                                           0.645
                                                          0.12
                                                                            2.0
                                                                                     0.075
        1598
                          6.0
                                           0.310
                                                          0.47
                                                                            3.6
                                                                                     0.067
               free sulfur dioxide total sulfur dioxide density
                                                                       pH sulphates
        0
                               11.0
                                                       34.0 0.99780
                                                                                  0.56
                                                                      3.51
        1
                               25.0
                                                      67.0 0.99680 3.20
                                                                                  0.68
         2
                               15.0
                                                      54.0 0.99700 3.26
                                                                                  0.65
         3
                               17.0
                                                      60.0 0.99800 3.16
                                                                                  0.58
                               11.0
                                                      34.0 0.99780 3.51
                                                                                  0.56
         . . .
                                . . .
                                                       . . .
                                                                 . . .
                                                                       . . .
                                                                                   . . .
                                                      44.0 0.99490 3.45
        1594
                               32.0
                                                                                  0.58
        1595
                               39.0
                                                      51.0 0.99512
                                                                      3.52
                                                                                  0.76
        1596
                               29.0
                                                      40.0 0.99574 3.42
                                                                                  0.75
        1597
                               32.0
                                                      44.0 0.99547
                                                                      3.57
                                                                                  0.71
        1598
                               18.0
                                                      42.0 0.99549 3.39
                                                                                  0.66
               alcohol quality
                   9.4
        0
                               5
        1
                   9.8
                   9.8
                               5
         3
                   9.8
                   9.4
                               5
                   . . .
        1594
                  10.5
                               5
        1595
                  11.2
                               6
                               6
        1596
                  11.0
                               5
        1597
                  10.2
        1598
                  11.0
```

[1599 rows x 12 columns]>

Step: Exploratory Data Analysis

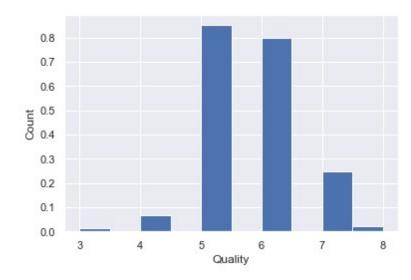
Univariate Analysis:

Quality frequency Histogram

D:\pran\anaconda3\lib\site-packages\ipykernel_launcher.py:1: MatplotlibDeprecationWarning:

The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1. Use 'density' instead.

"""Entry point for launching an IPython kernel.



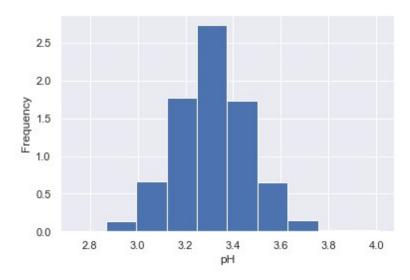
This shows quality ratings of 5,6 are high. Indicating most of the produce has been of good quality

pH Frequency Histogram

D:\pran\anaconda3\lib\site-packages\ipykernel_launcher.py:1: MatplotlibDeprecati
onWarning:

The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1. Use 'density' instead.

"""Entry point for launching an IPython kernel.



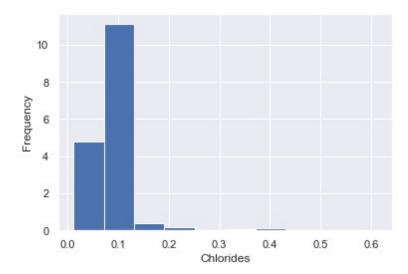
This Graph indicates pH of 3.3 was found in most test samples

Chloride Content in samples found

D:\pran\anaconda3\lib\site-packages\ipykernel_launcher.py:1: MatplotlibDeprecati
onWarning:

The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1. Use 'density' instead.

"""Entry point for launching an IPython kernel.



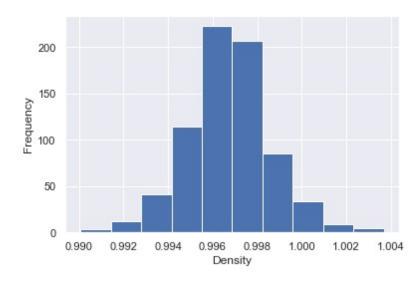
This indicates 0.1% of chlorides was found in most test Samples

Density frequency Histogram

D:\pran\anaconda3\lib\site-packages\ipykernel_launcher.py:1: MatplotlibDeprecati onWarning:

The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1. Use 'density' instead.

"""Entry point for launching an IPython kernel.



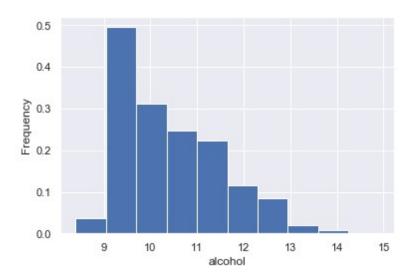
This shows 0.996-0.998 g/cm³ density was found in most wine Samples

Alcohol content histogram

D:\pran\anaconda3\lib\site-packages\ipykernel_launcher.py:1: MatplotlibDeprecati onWarning:

The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1. Use 'density' instead.

"""Entry point for launching an IPython kernel.



This graph indicates most red wine samples contained 9%-10% alcohol content

Boxplot analysis

All features

```
In [11]: plt.figure(figsize=(25,15))
data.drop(('quality'],axis = 1).boxplot()
plt.show()
```

It can percieved that there are outliers in each feature which may cause trouble in predicting outcome

Fixed Acidity boxplot

```
In [12]: sns.boxplot(y = data['fixed acidity'])
plt.show()
```

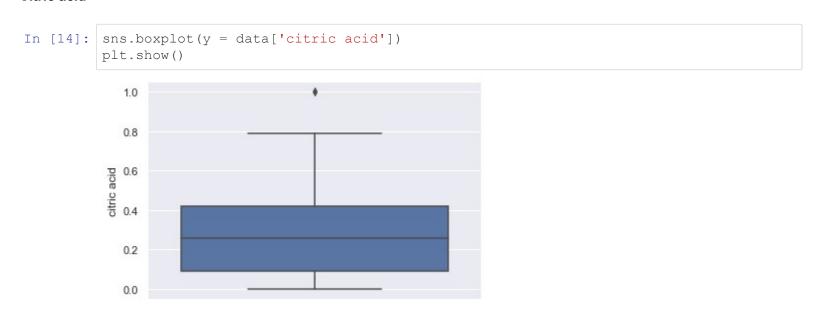
This shows there are a few outliers above the value 14.3

Volatile acidity

We have outliers above 1.6

0.2

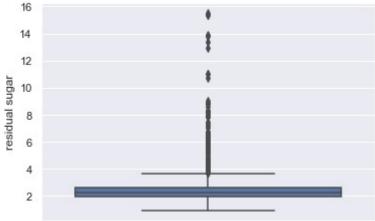
Citric acid



Outliers are negligible

Residual Sugar

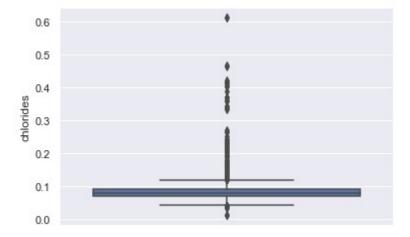
```
In [15]: sns.boxplot(y = data['residual sugar'])
  plt.show()
```



Outlier above 13

Chlorides

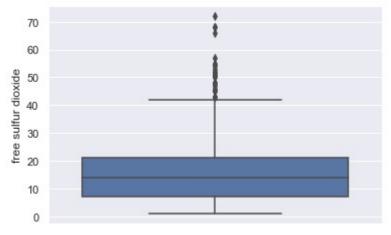
```
In [16]: sns.boxplot(y = data['chlorides'])
plt.show()
```



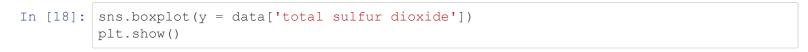
Outliers above 0.6

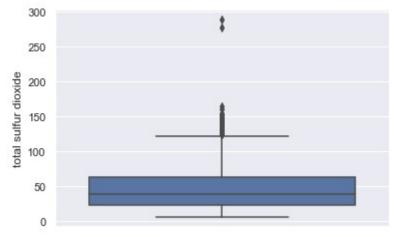
Free Sulfur Dioxides

```
In [17]: sns.boxplot(y = data['free sulfur dioxide'])
plt.show()
```



Total Sulfur Dioxide

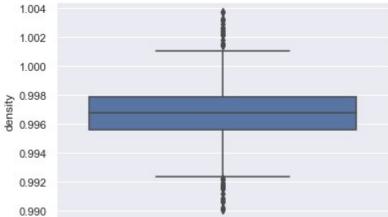




Outliers above 250

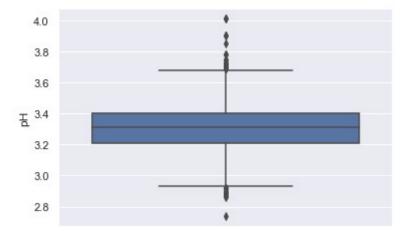
Density

```
In [19]: sns.boxplot(y = data['density'])
   plt.show()
```



рΗ

```
In [20]: sns.boxplot(y = data['pH'])
plt.show()
```



Sulphates

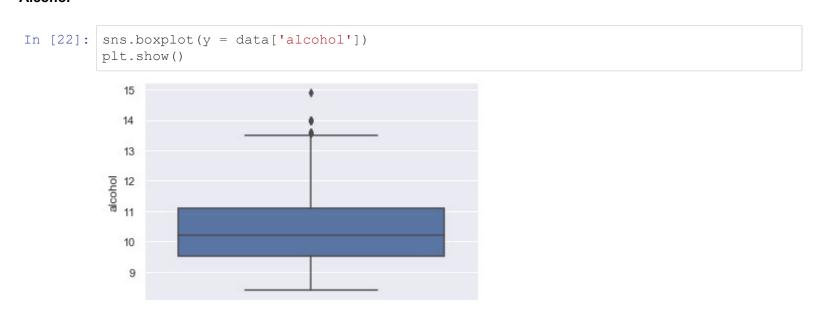
```
In [21]: sns.boxplot(y = data['sulphates'])
plt.show()

200
1.75
1.50
9 1.25
5 1.00
0.75
0.50
```

Outliers above 1.75

0.25

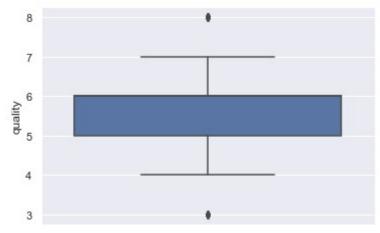
Alcohol



Outlier at 15

Brief Quality analysis via boxplot

```
In [23]: sns.boxplot(y = data['quality'])
  plt.show()
```

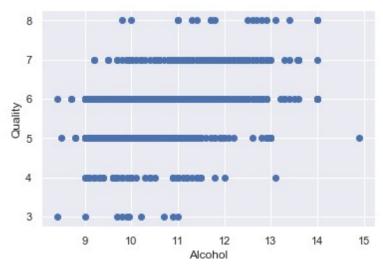


This indicates major chunk of observations had quality rating between 5-6

Bivariate Analysis

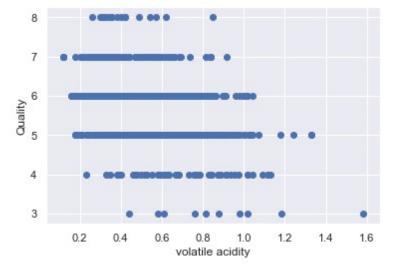
Alcohol VS quality

```
In [24]: plt.scatter(data['alcohol'], data['quality'])
    plt.xlabel('Alcohol')
    plt.ylabel('Quality')
    plt.show()
```



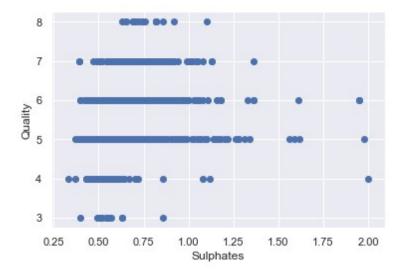
Volatile Acidity VS Quality

```
In [25]: plt.scatter(data['volatile acidity'], data['quality'])
    plt.xlabel('volatile acidity')
    plt.ylabel('Quality')
    plt.show()
```



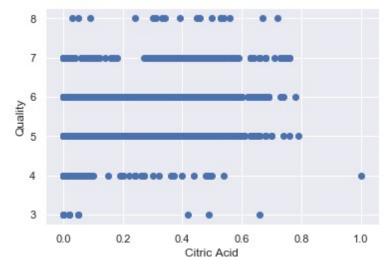
Sulphates VS Quality

```
In [26]: plt.scatter(data['sulphates'], data['quality'])
    plt.xlabel('Sulphates')
    plt.ylabel('Quality')
    plt.show()
```



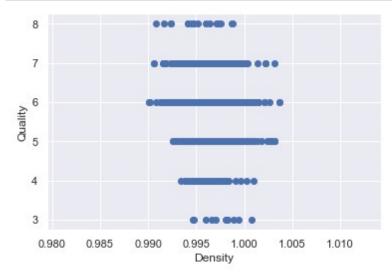
Citric Acid VS Quality

```
In [27]: plt.scatter(data['citric acid'], data['quality'])
    plt.xlabel('Citric Acid')
    plt.ylabel('Quality')
    plt.show()
```



Density VS Quality

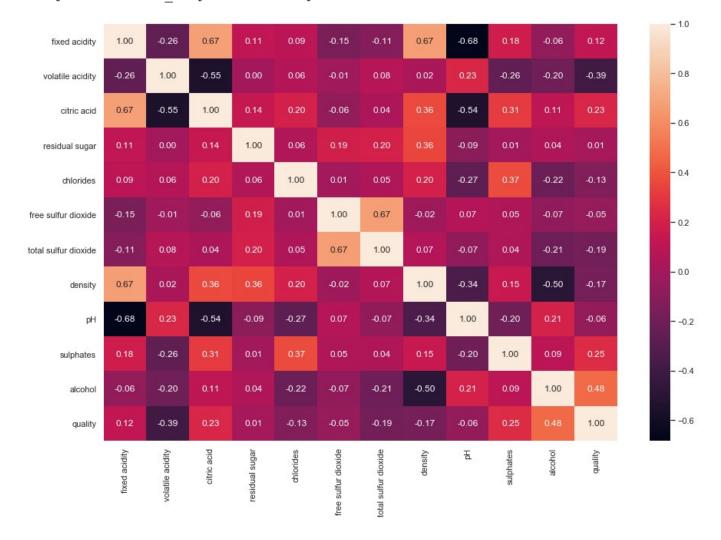
```
In [28]: plt.scatter(data['density'], data['quality'])
    plt.xlabel('Density')
    plt.ylabel('Quality')
    plt.show()
```



Correlation Heat-Map

```
In [29]: plt.figure(figsize=(15,10))
sns.heatmap(data.corr(),annot = True, fmt=".2f")
```

Out[29]: <matplotlib.axes. subplots.AxesSubplot at 0x20cf12fbe08>



This suggests Quality of Wine is more dependant on alcohol and acidity than other stuff

Feature Selection:

Inferring from the above correlation matrix we can conclude that residual sugar does not play a good role the determination of quality of red Wine.

Step: Modelling

Removing Outliers

```
In [30]: # For each feature find the data points with extreme high or low values
         for feature in data.keys():
             # TODO: Calculate Q1 (25th percentile of the data) for the given feature
             Q1 = np.percentile(data[feature], q=25)
             # TODO: Calculate Q3 (75th percentile of the data) for the given feature
             Q3 = np.percentile(data[feature], q=75)
             # TODO: Use the interquartile range to calculate an outlier step (1.5 times the
         interquartile range)
             interquartile range = Q3 - Q1
             step = 1.5 * interquartile range
             # Display the outliers
               print("Data points considered outliers for the feature '{}':".format(featur
         e))
               display(data[~((data[feature] >= Q1 - step) & (data[feature] <= Q3 + step))])</pre>
             # OPTIONAL: Select the indices for data points you wish to remove
             outliers = []
             # Remove the outliers, if any were specified
             good data = data.drop(data.index[outliers]).reset index(drop = True)
In [31]: X = good data.drop(['quality','residual sugar'], axis = 1)
```

Train-test-split

y = good data['quality']

```
In [32]: X_features = X
    X = StandardScaler().fit_transform(X)
In [33]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.21, random_state=0)
```

```
knn.fit(X train,y train)
   y pred = knn.predict(X test)
   print(y pred)
   print(classification report(y test, y pred, zero division=1))
   6 5 61
         precision
              recall f1-score
                      support
        3
               0.00
                         2
           1.00
                   0.00
        4
           1.00
               0.00
                   0.00
                        11
        5
           0.66
               0.73
                   0.69
                        144
           0.59
               0.64
                   0.61
                        146
        7
               0.28
                   0.35
                        29
           0.47
        8
           1.00
               0.00
                   0.00
                         4
                   0.62
                        336
     accuracy
    macro avg
           0.79
               0.27
                   0.28
                        336
   weighted avg
                   0.59
           0.63
               0.62
                        336
In [35]: print('Accuracy of the model is :
                   ' + str(accuracy_score(y_test, y_pred)))
```

Using Binary Quality Analysis

Here for every rating above 7 will be treated as Good Wine and rest as Bad Wine

Accuracy of the model is : 0.6160714285714286

In [34]: knn = KNeighborsClassifier(n neighbors=90)

```
In [36]: #Create Classification version of target variable
good_data['goodquality'] = [1 if x >= 7 else 0 for x in data['quality']]
# Separate feature variables and target variable
y = good_data['goodquality']
```

```
In [37]:
    X train, X test, y train, y test = train test split(X, y, test size=.21, random sta
    knn = KNeighborsClassifier(n neighbors=90)
    knn.fit(X train, y train)
    y pred = knn.predict(X test)
    print(y_pred)
    print(classification report(y test, y pred, zero division=1))
    0 0 01
          precision
                recall f1-score
                        support
         0
            0.93
                 0.99
                     0.96
                          303
         1
            0.77
                 0.30
                     0.43
                          33
                     0.92
                          336
     accuracy
            0.85
                 0.65
                     0.70
                          336
     macro avg
    weighted avg
            0.91
                 0.92
                     0.91
                          336
In [38]:
    print('Accuracy of the model is :
                     ' + str(accuracy_score(y_test, y_pred)))
```

Conclusion:

Accuracy of the model is:

Based on the box plots plotted we come to an conclusion that not all input features are essential and affect the data, for example from the bar plot against quality and residual sugar we see that as the quality increases residual sugar is moderate and does not have change drastically. So this feature is not so essential as compared to others like alcohol and citric acid, so we can drop this feature while feature selection.

0.9226190476190477

For classifying the wine quality, we have implemented algorith namely, **kNeighborsClassification** We were able to achieve maximum accuracy using of **92%** when Quality was predicted as either good or bad, while accuracy of 62% was achieved when Quality was predicted with range 0-10