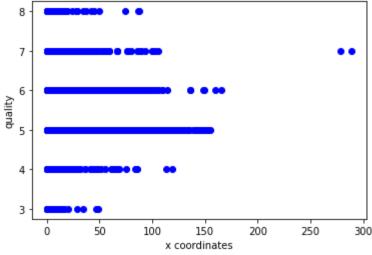
```
In [9]:
           import numpy as np
           import matplotlib.pyplot as plt
           import pandas as pd
           from sklearn.model_selection import train_test_split
           import math
           import random
           from sklearn.linear_model import LinearRegression
           from sklearn.metrics import r2_score
           from sklearn.preprocessing import StandardScaler,MinMaxScaler
In [10]:
           location="linear-regression.csv"
           df = pd.read_csv('linear-regression.csv')
           df.insert(0, 'bias', '1')
In [11]:
           df.head()
Out[11]:
                                                               free
                                                                       total
                    fixed volatile citric residual
             bias
                                                  chlorides
                                                             sulfur
                                                                      sulfur density
                                                                                      pH sulphates alcoho
                   acidity
                           acidity
                                    acid
                                           sugar
                                                            dioxide dioxide
          0
                      7.4
                                                     0.076
                                                                                                        9
                1
                              0.70
                                    0.00
                                              1.9
                                                               11.0
                                                                       34.0
                                                                             0.9978 3.51
                                                                                               0.56
           1
                1
                      7.8
                              0.88
                                    0.00
                                              2.6
                                                     0.098
                                                               25.0
                                                                       67.0
                                                                             0.9968 3.20
                                                                                               0.68
                                                                                                        9
          2
                1
                      7.8
                              0.76
                                    0.04
                                              2.3
                                                     0.092
                                                               15.0
                                                                                                        9
                                                                       54.0
                                                                             0.9970 3.26
                                                                                               0.65
          3
                                                                             0.9980 3.16
                1
                     11.2
                              0.28
                                    0.56
                                              1.9
                                                     0.075
                                                               17.0
                                                                       60.0
                                                                                               0.58
                                                                                                        9
                              0.70
                                    0.00
                                                     0.076
                                                                                                        9
                1
                      7.4
                                              1.9
                                                               11.0
                                                                       34.0
                                                                             0.9978 3.51
                                                                                               0.56
In [12]:
           data=np.array(df,dtype=np.float64)
In [13]:
           X=data[:,:12]
           Y=data[:,-1]
           print(X.shape)
           print(Y.shape)
           (1599, 12)
           (1599,)
In [14]:
           plt.xlabel('x coordinates')
           plt.ylabel('quality')
           plt.plot(X[:,1:10], Y, 'bo')
           plt.show()
```



```
300
In [15]:
          X_train, X_temp, y_train, y_temp = train_test_split(X, Y, test_size=0.5, random_state
In [16]:
          X_validation, X_test, y_validation, y_test = train_test_split(X_temp, y_temp, test_s
In [17]:
          print(len(X_train))
          print(len(X_validation))
          print(len(X_test))
         799
          480
          320
In [18]:
          def h(x,theta):
              return np.round(np.matmul(x, theta))
               '''return ans'''
In [19]:
          def cost_function(x, y, theta):
              J=((h(x,theta-y)).T*(h(x,theta-y)))/(2*len(y))
              return J
In [20]:
          def accuracy(x,y,theta):
              l=len(x)
              correct=0
              for i in range(0,1):
                   y_predicted=round(h(x[i],theta))
                   if(y_predicted==y[i]):
                       correct+=1
              percentage=correct/l
              return percentage
```

```
In [21]:
          def R_Square(x,y,theta):
              y_mean=round(np.mean(y))
              l=len(y)
              numerator=0
              denominator=0
              for i in range(1):
                  numerator = numerator + (y[i] - (h(x[i], theta)))**2
                  denominator=denominator+(y[i]-y_mean)**2
              value = numerator/denominator
              return 1-value
In [22]:
          def RMSE(x,y,theta):
              l=len(y)
              total=0
              for i in range(1):
                  y_predicted=round(h(x[i],theta))
                  total=total+(y[i]-y_predicted)**2
              total=total/1
              total=math.sqrt(total)
              return total
        Analytical Solution
In [23]:
          theta = np.linalg.inv(X_train.T.dot(X_train)).dot(X_train.T).dot(y_train)
          print(theta)
         [ 2.33689602e+01 3.05502970e-02 -1.19741412e+00 -1.87228641e-01
           1.17612142e-02 -1.81714527e+00 6.11854741e-03 -4.06437389e-03
          -1.90187880e+01 -4.42172779e-01 8.79804133e-01 2.64603431e-01]
In [24]:
          #validation set R Square
          print("R_Square score on validation set "+ str(R_Square(X_validation,y_validation,the
          #test set R_Square
          R_Square(X_test,y_test,theta)
          print("R_Square score on test set "+ str(R_Square(X_test,y_test,theta)))
         R_Square score on validation set 0.3252688172043011
         R_Square score on test set 0.4125
In [25]:
          #validation set RMSE
          print("RMSE score on validation set "+ str(RMSE(X_validation,y_validation,theta)))
          #test set RRMSE
          print("RMSE score on test set "+ str(RMSE(X_test,y_test,theta)))
         RMSE score on validation set 0.7231297716638879
```

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RMSE score on test set 0.6637959023675877

With Regularization

```
In [26]:
          Identity_matrix = np.identity(len(X_train.T.dot(X_train)), dtype = float)
          lamda=2
In [27]:
          theta_regularised = np.linalg.inv((X_train.T.dot(X_train))+(lamda*Identity_matrix)).d
In [28]:
          #validation set R square
          print("R_square score on validation set "+str(R_Square(X_validation,y_validation,the
          #test set R square
          print("R_square score on test set "+str(R_Square(X_test,y_test,theta_regularised)))
         R square score on validation set 0.31720430107526887
         R_square score on test set 0.40416666666666667
In [29]:
          #validation set RMSE
          print("RMSE score in validation set "+str(RMSE(X_validation,y_validation,theta_regular

          #test set RMSE
          print("RMSE score in test set "+str(RMSE(X_test,y_test,theta_regularised)))
         RMSE score in validation set 0.7274384280931732
         RMSE score in test set 0.6684870978560469
```

Interative Gradient Ascent

```
In [30]:
          data=np.array(df,dtype=np.float64)
          scaler=StandardScaler()
          #data=scaler.fit_transform(data)
          X=data[:,:12]
          X=scaler.fit_transform(X)
          Y=data[:,-1]
          X[:,0]+=1
          X_train, X_temp, y_train, y_temp = train_test_split(X, Y, test_size=0.5, random_state
          X_validation, X_test, y_validation, y_test = train_test_split(X_temp, y_temp, test_s)
          #scaler=StandardScaler()
          #X_train=scaler.fit_transform(X_train)
In [31]:
          def predict_y(x,theta):
              t=np.dot(x,theta)
              #t=np.round(t)
              return t
```

```
In [32]:
          def total_cost(y,x,theta):
               l=len(y)
              total=0
               for i in range(1):
                   y_p=predict_y(x[i],theta)
                   total + = ((y[i]) - y_p) **2
               return total/(2*1)
In [33]:
           def gradient_ascent(x,y,theta,learning_rate,epoch):
               l=len(x)
               cost=[]
              cost_v=[]
              y_ep=[]
               for k in range(epoch):
                   for i in range(0,1):
                       y_p=(np.dot(x[i],theta))
                       theta=theta+learning_rate*((y[i]-y_p)*x[i])
                   cost.append(total_cost(y,x,theta))
                   cost_v.append(total_cost(y_validation,X_validation,theta))
                   y_ep.append(k+1)
               plt.xlabel('Epochs')
               plt.ylabel('Cost')
               plt.plot(y_ep, cost, 'm', linewidth = "5")
               plt.plot(y_ep, cost_v, 'g', linewidth = "5")
               plt.show()
               return theta
```

learning rate 0.01

```
theta=np.ones(X_train.shape[1])
print(theta)
theta=gradient_ascent(X_train,y_train,theta,0.01,30)
#theta=gradient_ascent(X_validation,y_validation,theta,0.001,8)
print(theta)

[1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

```
In [35]: #validation set R_square
print("R_square score on validation set "+str(R_Square(X_validation,y_validation,then

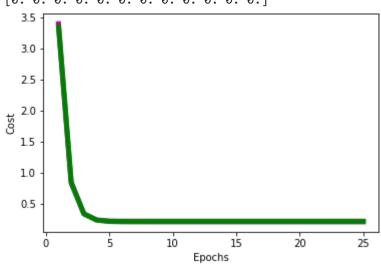
#test set R_square
print("R_square score on test set "+str(R_Square(X_test,y_test,theta)))

#validation set RMSE
print("RMSE score in validation set "+str(RMSE(X_validation,y_validation,theta)))

#test set RMSE
print("RMSE score in test set "+str(RMSE(X_test,y_test,theta)))
```

R_square score on validation set 0.303763440860215 R_square score on test set 0.3666666666666667 RMSE score in validation set 0.734563362367967 RMSE score in test set 0.689202437604511

learning rate 0.001



```
#validation set R_square
print("R_square score on validation set "+str(R_Square(X_validation,y_validation,then
#test set R_square
print("R_square score on test set "+str(R_Square(X_test,y_test,theta)))

#validation set RMSE
print("RMSE score in validation set "+str(RMSE(X_validation,y_validation,theta)))

#test set RMSE
print("RMSE score in test set "+str(RMSE(X_test,y_test,theta)))
```

R_square score on validation set 0.3360215053763441
R_square score on test set 0.408333333333333
RMSE score in validation set 0.7173446405552447
RMSE score in test set 0.6661456297237114

learning rate 0.0001

```
In [38]:
    theta=np.zeros(X_train.shape[1])
    print(theta)
    theta=gradient_ascent(X_train,y_train,theta,0.0001,100)
    #theta=gradient_ascent(X_validation,y_validation,theta,0.001,8)
    print(theta)
```

```
[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]

14
12
10
8
6
4
2
0
20
40
Epochs
```

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