Assignment 1

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In [1]:

```
# import all the necessary libraries here
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from numpy.linalg import inv
import matplotlib.pyplot as plt
from sklearn.metrics import r2_score
```

In [2]:

```
df = pd.read_csv('../../dataset/linear-regression.csv')
print(df.shape)
```

```
(1599, 12)
```

In [3]:

```
df.head()
```

Out[3]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	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

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         1599 non-null   float64
 1   volatile acidity      1599 non-null   float64
 2   citric acid           1599 non-null   float64
 3   residual sugar        1599 non-null   float64
 4   chlorides             1599 non-null   float64
 5   free sulfur dioxide   1599 non-null   float64
 6   total sulfur dioxide  1599 non-null   float64
 7   density               1599 non-null   float64
 8   pH                    1599 non-null   float64
 9   sulphates             1599 non-null   float64
 10  alcohol               1599 non-null   float64
 11  quality               1599 non-null   int64  
dtypes: float64(11), int64(1)
memory usage: 150.0 KB
```

In [5]:

```
df.describe()
```

Out[5]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH
count	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000
mean	8.319637	0.527821	0.270976	2.538806	0.087467	15.874922	46.467792	0.996747	3.311113
std	1.741096	0.179060	0.194801	1.409928	0.047065	10.460157	32.895324	0.001887	0.154386
min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.000000	0.990070	2.740000
25%	7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.000000	0.995600	3.210000
50%	7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.000000	0.996750	3.310000
75%	9.200000	0.640000	0.420000	2.600000	0.090000	21.000000	62.000000	0.997835	3.400000
max	15.900000	1.580000	1.000000	15.500000	0.611000	72.000000	289.000000	1.003690	4.010000

In [6]:

```
# Test train Split
X = df.iloc[:,:-1].values
Y = df.iloc[:,-1].values
X_train , X,Y_train,Y = train_test_split(X,Y,test_size=0.5,random_state=0)
X_val,X_test,Y_val,Y_test = train_test_split(X,Y,test_size = 0.4,random_state = 0)
from sklearn.preprocessing import StandardScaler
st_x= StandardScaler()
X_train= st_x.fit_transform(X_train)
X_test= st_x.transform(X_test)
# from sklearn.preprocessing import normalize
# X_train = normalize(X_train)
```

In [7]:

```
print(X_train.shape, Y_train.shape)
print(X_val.shape, Y_val.shape)
print(X_test.shape, Y_test.shape)
```

```
(799, 11) (799,)
(480, 11) (480,)
(320, 11) (320,)
```

In [8]:

```
class l2_regularization():
    def __init__(self,alpha):
        self.alpha = alpha

    def __call__(self,Weight):
        loss = np.dot(Weight.T , Weight)
        return self.alpha * 0.5 * float(loss)

    def grad(self, Weight):
        return self.alpha* Weight
```

In [9]:

```
class linear_regression():
    def __init__(self,n_epoch = 500,learning_rate = 0.0001,use_gradient = False):
        self.epoch = n_epoch
        self.learning_rate = learning_rate
        self.use_gradient = use_gradient
        self.init_weight = None
        self.final_weight = None
        self.cost = []
        self.val_cost = []
        self.l2_regularization = l2_regularization(0.01)


    def initialize_weights(self, num_features):
        threshold = np.sqrt(1/num_features)
        w = np.random.uniform(-threshold,threshold,(num_features,1))* 0.01
        b = 0
        self.init_weight = np.insert(w,0,b,axis = 0)


    def train(self,X,Y,X_val,Y_val):
        n_sample,n_feature = X.shape
        n1_sample = X_val.shape[0]
        x = np.insert(X,0,1,axis = 1)
        y = np.reshape(Y,(n_sample, 1))
        X_val = np.insert(X_val,0,1,axis = 1)
        Y_val = np.reshape(Y_val,(n1_sample, 1))
        if self.use_gradient == True:
            self.initialize_weights(n_feature)
            self.fit_gradient_descent(self.init_weight, x,y,X_val,Y_val)
        else:
            self.fit_analytic(x,y)


    def fit_analytic(self,X,Y):
        x = np.array(X)
        y = np.array(Y)

        XT_X = np.dot(x.T,x)
        XT_X_I_XT= np.dot(inv(XT_X),x.T)
        self.final_weight = np.dot(XT_X_I_XT , y)


    def fit_gradient_descent(self,weight,X,Y,X_val,Y_val):
        _weight = weight.copy()
        self.cost.append(self.MSE_cost(X,Y,_weight))
        self.val_cost.append(self.MSE_cost(X_val,Y_val,_weight))
        for iter in range(self.epoch):
            _weight = _weight - np.multiply(self.learning_rate, self.gradient_descent(_weight,X,Y))
#             print(self.gradient_descent(_weight,X,Y))
            (self.cost).append(self.MSE_cost(X,Y,_weight))
            (self.val_cost).append(self.MSE_cost(X_val,Y_val,_weight))
            if iter%100 ==0:
                print(f"The training cost for iteration ::{iter} is 
                print(f"The validation cost for iteration ::{iter} is 
        self.final_weight = _weight


    def gradient_descent(self,weight,X,Y):
        m = X.shape[0]
        inner = np.dot(X,weight) - Y
        mul = np.dot(X.T , inner) + (self.l2_regularization).grad(weight)
        return mul/(m)

    def MSE_cost(self,X,Y,weight):
        m = X.shape[0]
        diff = ((np.dot(X,weight)) - Y)
        diff_sq = np.dot(diff.T,diff)
        cost = diff_sq/(2*m) + self.l2_regularization(weight)
        return cost


    def predict(self,X):
        np.insert(X,0,1,axis = 1)
        y_pred = np.dot(X,self.final_weight)
```

```
        return y_pred


    def Analytic_RMSE_cost(self,X,Y):
        m = X.shape[0]
        X = np.insert(X,0,1,axis = 1)
        Y = np.reshape(Y,(m, 1))
#         print((np.dot(X,self.final_weight)).astype(int) - Y)
        y_pred = np.dot(X,self.final_weight)
        inner = y_pred - Y
        loss = (np.dot(inner.T,inner))/(2*m)
        loss = np.sqrt(loss)
        loss = np.squeeze(loss)
        return loss

    def Gradient_RMSE_cost(self,X,Y):
        m = X.shape[0]
        X = np.insert(X,0,1,axis = 1)
        Y = np.reshape(Y,(m,1))
        y_pred = np.dot(X,self.final_weight)
        inner = y_pred - Y
        loss = (np.dot(inner.T,inner))/(2*m)
        loss = np.sqrt(loss)
        loss = np.squeeze(loss)
        return loss

    def r2_score(self,X,Y):
        m = X.shape[0]
        X = np.insert(X,0,1,axis = 1)
        Y = np.reshape(Y,(m, 1))
        y_pred = np.dot(X,self.final_weight)
        return r2_score(Y,y_pred)

    def viswalize_plot(self):
        figure, (ax1,ax2) = plt.subplots(1,2,figsize=(10,5))

        nums = np.arange(len(self.cost))
        ax1.plot(nums, np.array(self.cost).reshape((len(self.cost,))))
        ax1.set_xlabel('Epoch')
        ax1.set_ylabel('Training cost')
        ax1.set_title('Training_cost')

        ax2.plot(nums, np.array(self.val_cost).reshape((len(self.val_cost,))))
        ax2.set_xlabel('Epoch')
        ax2.set_ylabel('validation cost')
        ax2.set_title('validation_cost')
        plt.tight_layout()
        plt.show()
```

In [10]:

```
regressor_analytic = linear_regression()
regressor_analytic.train(X_train,Y_train,X_val,Y_val)
RMSE_train = regressor_analytic.Analytic_RMSE_cost(X_train,Y_train)
R2_train = regressor_analytic.r2_score(X_train,Y_train)
RMSE_test = regressor_analytic.Analytic_RMSE_cost(X_test,Y_test)
R2_test = regressor_analytic.r2_score(X_test,Y_test)
mapping = {'RMSE':[RMSE_train,RMSE_test], 'R2':[R2_train,R2_test]}
mapit = pd.DataFrame(mapping,index=['Train', 'Test'])
```

In [11]:

```
mapit
```

Out[11]:

	RMSE	R2
Train	0.45565725096906634	0.397593
Test	0.4712886518848852	0.290613

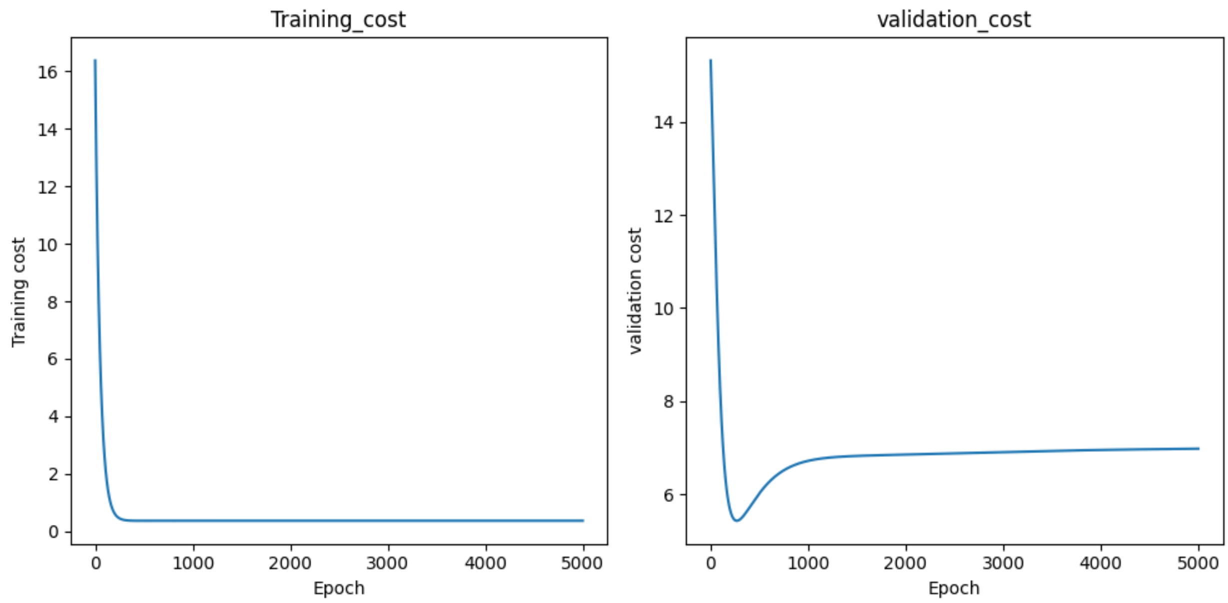
In [12]:

```
regressor_grad = linear_regression(5000,0.01,True)
regressor_grad.train(X_train,Y_train,X_val,Y_val)
```

```
The training cost for iteration ::2600 is ________________________________________________0.36886
94408546612
The validation cost for iteration ::2600 is ______________________________________________6.88484
653153662

The training cost for iteration ::2700 is ________________________________________________0.36886
936783443836
The validation cost for iteration ::2700 is ______________________________________________6.89046
7342913929

The training cost for iteration ::2800 is ________________________________________________0.36886
93144268875
The validation cost for iteration ::2800 is ______________________________________________6.89602
1862828881

The training cost for iteration ::2900 is ________________________________________________0.36886
92778891473
The validation cost for iteration ::2900 is ______________________________________________6.90148
0045360307
```

In [13]:

```
test_RMSE_cost = regressor_grad.Gradient_RMSE_cost(X_test,Y_test)
test_R2_cost = regressor_grad.r2_score(X_test,Y_test)
regressor_grad.viswalize_plot()
mapit = pd.DataFrame([[test_RMSE_cost, test_R2_cost]], columns=['RMSE','R2_Score'], index=['Test(alpha = 0.01)'])
```



In [14]:

```
mapit
```

Out[14]:

	RMSE	R2_Score
Test(alpha = 0.01)	0.47129034604097897	0.290608

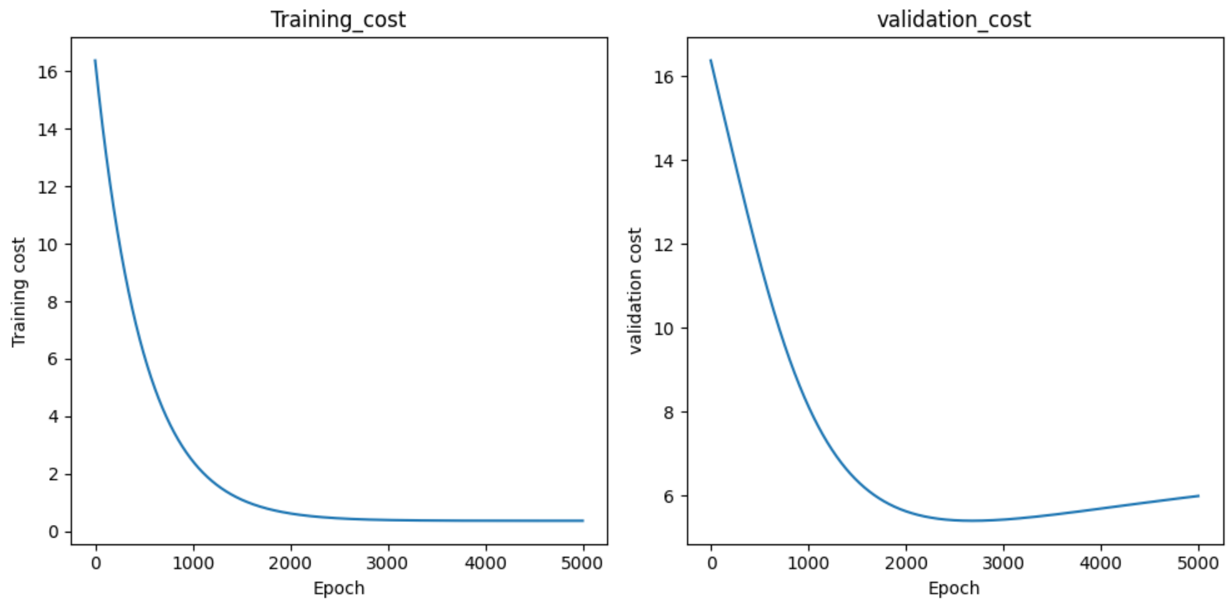
In [15]:

```
regressor_grad = linear_regression(5000,0.001,True)
regressor_grad.train(X_train,Y_train,X_val,Y_val)
```

```
The training cost for iteration ::0 is ________________________________________________16.3418101
5162137
The validation cost for iteration ::0 is ______________________________________________16.3605060
55404702

The training cost for iteration ::100 is ________________________________________________13.40303
9378735595
The validation cost for iteration ::100 is ______________________________________________15.37179
338382972

The training cost for iteration ::200 is ________________________________________________11.00475
716634392
The validation cost for iteration ::200 is ______________________________________________14.39717
823023938

The training cost for iteration ::300 is ________________________________________________9.047027
69019007
The validation cost for iteration ::300 is ______________________________________________13.43307
5788847134
```

In [16]:

```
test_RMSE_cost = regressor_grad.Gradient_RMSE_cost(X_test,Y_test)
test_R2_cost = regressor_grad.r2_score(X_test,Y_test)
regressor_grad.viswalize_plot()
mapit = pd.DataFrame([[test_RMSE_cost, test_R2_cost]], columns=['RMSE','R2_Score'], index=['Test(alpha = 0.001)'])
```



In [17]:

```
mapit
```

Out[17]:

	RMSE	R2_Score
Test(alpha = 0.001)	0.47049633842562527	0.292996

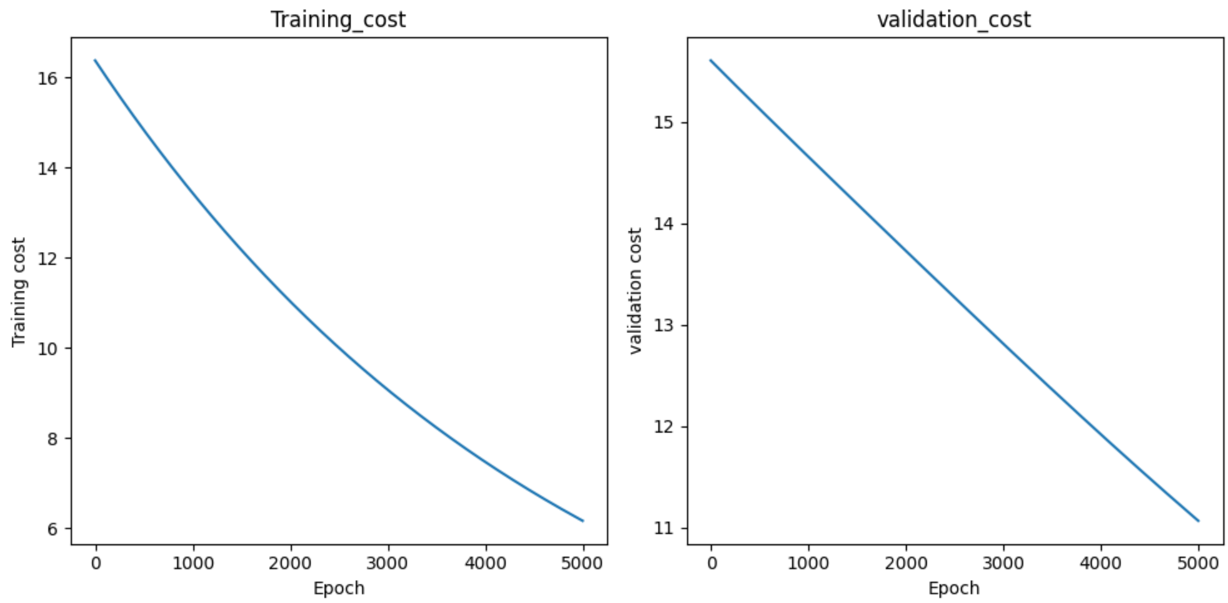
In [18]:

```
regressor_grad = linear_regression(5000,0.0001,True)
regressor_grad.train(X_train,Y_train,X_val,Y_val)
```

```
The training cost for iteration ::0 is ________________________________________________16.3705236
29949076
The validation cost for iteration ::0 is ______________________________________________15.6023747
36396838

The training cost for iteration ::100 is ________________________________________________16.04858
4970128086
The validation cost for iteration ::100 is ______________________________________________15.50575
8138447618

The training cost for iteration ::200 is ________________________________________________15.73313
0669552848
The validation cost for iteration ::200 is ______________________________________________15.40972
146010535

The training cost for iteration ::300 is ________________________________________________15.42402
8787519338
The validation cost for iteration ::300 is ______________________________________________15.31419
0776540663
```

In [19]:

```
test_RMSE_cost = regressor_grad.Gradient_RMSE_cost(X_test,Y_test)
test_R2_cost = regressor_grad.r2_score(X_test,Y_test)
regressor_grad.viswalize_plot()
mapit = pd.DataFrame([[test_RMSE_cost, test_R2_cost]], columns=['RMSE','R2_Score'], index=['Test(alpha = 0.0001)']
```



In [20]:

```
mapit
```

Out[20]:

	RMSE	R2_Score
Test(alpha = 0.0001)	2.435981623591379	-17.952101

In [ ]: