```
In [1]:
          import numpy as np
          from matplotlib import pyplot as plt
          import pandas as pd
In [2]:
          df=pd.read csv("Real estate.csv",index col=False)
In [3]:
          df=df.drop("No",axis=1)
          df
                       X1
                               X2
Out[3]:
                                                                                                   Y house
                                                               X4 number of
                                                                                   X5
                                        X3 distance to the
                                                                                              X6
               transaction
                            house
                                                                                                    price of
                                      nearest MRT station convenience stores
                                                                              latitude longitude
                     date
                                                                                                   unit area
                              age
            0
                 2012.917
                              32.0
                                                                            24.98298
                                                                                       121.54024
                                                                                                       37.9
                                                84.87882
                                                                          10
            1
                 2012.917
                              19.5
                                               306.59470
                                                                             24.98034 121.53951
                                                                                                       42.2
                                                                             24.98746 121.54391
            2
                                                                                                       47.3
                 2013.583
                              13.3
                                               561.98450
            3
                 2013.500
                              13.3
                                               561.98450
                                                                             24.98746
                                                                                      121.54391
                                                                                                       54.8
            4
                 2012.833
                               5.0
                                               390.56840
                                                                             24.97937 121.54245
                                                                                                       43.1
                                •••
                                                                                                         •••
          409
                 2013.000
                              13.7
                                              4082.01500
                                                                             24.94155
                                                                                      121.50381
                                                                                                       15.4
          410
                 2012.667
                               5.6
                                                90.45606
                                                                             24.97433 121.54310
                                                                                                       50.0
          411
                 2013.250
                              18.8
                                                                           7 24.97923 121.53986
                                                                                                       40.6
                                               390.96960
          412
                 2013.000
                               8.1
                                               104.81010
                                                                             24.96674 121.54067
                                                                                                       52.5
          413
                 2013.500
                               6.5
                                                90.45606
                                                                             24.97433 121.54310
                                                                                                       63.9
        414 rows × 7 columns
In [4]:
          for i in df.columns[:-1]:
               print(i)
         X1 transaction date
         X2 house age
         X3 distance to the nearest MRT station
         X4 number of convenience stores
         X5 latitude
         X6 longitude
In [5]:
          df.describe()
Out[5]:
                         X1
                                           X3 distance to
                                                           X4 number of
                                                                                                   Y house
                               X2 house
                                                                                 X5
                                                                                            X6
                  transaction
                                              the nearest
                                                            convenience
                                                                                                    price of
                                                                            latitude
                                                                                      longitude
                                    age
                                             MRT station
                                                                                                   unit area
                        date
                                                                  stores
```

414.000000

414.000000 414.000000

count

414.000000

414.000000 414.000000 414.000000

```
X4 number of
                X1
                                  X3 distance to
                                                                                              Y house
                      X2 house
                                                                          X5
                                                                                      X6
        transaction
                                                    convenience
                                                                                              price of
                                     the nearest
                                                                     latitude
                                                                               longitude
                           age
                                                          stores
              date
                                    MRT station
                                                                                             unit area
       2013.148971
                     17.712560
                                    1083.885689
                                                        4.094203
                                                                   24.969030 121.533361
                                                                                            37.980193
mean
                                    1262.109595
          0.281967
                     11.392485
                                                        2.945562
                                                                    0.012410
                                                                                0.015347
                                                                                            13.606488
  std
 min
       2012.667000
                      0.000000
                                      23.382840
                                                        0.000000
                                                                   24.932070 121.473530
                                                                                             7.600000
       2012.917000
                      9.025000
                                      289.324800
                                                        1.000000
                                                                   24.963000 121.528085
                                                                                            27.700000
 50%
       2013.167000
                     16.100000
                                     492.231300
                                                        4.000000
                                                                   24.971100 121.538630
                                                                                            38.450000
       2013.417000
                     28.150000
                                     1454.279000
                                                        6.000000
                                                                   24.977455 121.543305
                                                                                            46.600000
      2013.583000
                     43.800000
                                    6488.021000
                                                       10.000000
                                                                   25.014590 121.566270 117.500000
```

```
In [6]:
         df1=pd.read csv("Real estate.csv")
In [7]:
         class Linear Regression():
             def __init__(self,l_rate,Epochs):
                  self.l rate=l rate
                  self.Epochs=Epochs
             def fit(self, X, Y ):
                  self.m,self.n = X.shape
                 on=np.ones((self.m,1))
                  self.X=np.concatenate((on,X),axis=1)
                  self.n=self.n+1
                  self.Y=Y
                  self.W=np.zeros(self.n)
                  self.H=np.dot(self.X,self.W)
                  self.Cost=np.zeros(self.Epochs)
                 for i in range(self.Epochs):
                      self.upd weight()
                      self.Cost[i]=np.sum(np.square(self.H-self.Y))/(2*self.m)
                  return self
             def upd weight(self):
                  self.W[0]=self.W[0]-(self.l_rate/self.m)*sum(self.H-self.Y)
                 for i in range(1,self.n):
                      self.W[i]=self.W[i]-(self.l rate/self.m)*sum((self.H-self.Y)*self.X[:,i])
                  self.H=np.dot(self.X,self.W)
                 return self
             def W_C(self):
                  print(self.W[0])
                  print(self.W[1:])
             def predict(self,X):
                  return X.dot(self.W[1:])+self.W[0]
```

```
def norm(df1):
    for i in df1.columns[:]:
        df1[i]=df1[i]-df1[i].mean()
        df1[i]=df1[i]/np.sqrt(df1[i].var())
    #return np.array(df1)
    return df1
```

Part a

You will need to perform K-Fold cross-validation (K=2-5) in this exercise (implement from scratch). What is the optimal value of K? Justify it in your report along with the table for the mean accuracy of K-values and K-value.

```
In [8]:
        def K_fold_validation(k,df):
            n=len(df.index)
            fold size=n//k
            if(n%k>0):
                fold size+=1
            df = df.reindex(np.random.permutation(df.index))
            df = df.reset index(drop=True)
            df=np.array(df)
            #print(fold size)
            1=[]
            k=0
            while(k<n):</pre>
                1.append(df[k:k+fold_size,:])
               k+=fold_size
                 X_Trains=[]
            Y Trains=[]
            X_Tests=[]
            Y Tests=[]
            for i in range(len(1)):
               temp=[]
               for j in range(len(1)):
                   if(j!=i):
                       temp.append(pd.DataFrame(1[j]))
               t df=np.array(pd.concat(temp))
               X_Trains.append(t_df[:,:-1])
               Y_Trains.append(t_df[:,-1])
               X Tests.append(l[i][:,:-1])
               Y_Tests.append(l[i][:,-1])
            return X_Trains,Y_Trains,X_Tests,Y_Tests
```

In [10]:

```
for i in range(2,6):
    print("{}| {}".format(i,results_mse[i-2]))

K| MSE
2| 0.48138327722866797
3| 0.43327257038518413
4| 0.42797314694324884
5| 0.4320416914330435
```

If we look at Mse k=5 is the best

print("K| MSE ")

Part B

Plot the RMSE V/s iteration graph for all models trained with optimal value of K for K-Fold cross-validation. RMSE should be reported on the train and value set.

Choosen K = 5

```
In [11]:
          #added the RMSE list for validation as well tranning set to the model
          class Linear_Regression1():
              def __init__(self,l_rate,Epochs):
                   self.l rate=l rate
                   self.Epochs=Epochs
              def fit(self, X, Y ,X_test,Y_test):
                   self.m, self.n = X.shape
                   on=np.ones((self.m,1))
                   self.X=np.concatenate((on,X),axis=1)
                   self.n=self.n+1
                   self.Y=Y
                   self.W=np.zeros(self.n)
                   self.H=np.dot(self.X,self.W)
                   self.Cost=np.zeros(self.Epochs)
                   self.val err=[]
                   self.tr_err=[]
```

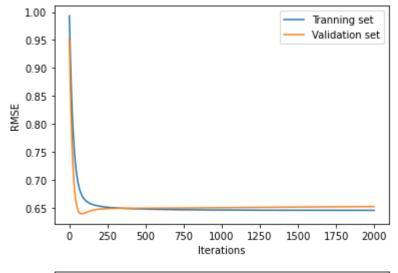
```
for i in range(self.Epochs):
        self.upd weight()
        self.val err.append(self.rmse(Y test,self.predict(X test)))
        self.tr err.append(self.rmse(Y,self.predict(X)))
        self.Cost[i]=np.sum(np.square(self.H-self.Y))/(2*self.m)
    #self.plot1()
    print("RMSE for tranning set => {}".format(self.tr_err[-1]))
    print("RMSE for validation set => {}".format(self.val_err[-1]))
    return self
def upd weight(self):
    self.W[0]=self.W[0]-(self.l rate/self.m)*sum(self.H-self.Y)
    for i in range(1,self.n):
        self.W[i]=self.W[i]-(self.l rate/self.m)*sum((self.H-self.Y)*self.X[:,i])
    self.H=np.dot(self.X,self.W)
    return self
def W C(self):
    print(self.W[0])
    print(self.W[1:])
def rmse(self,y1,y2):
    mse = (np.square(y1 - y2)).mean()
    return np.sqrt(mse)
def plot1(self):
    list1 = list(range(0, self.Epochs))
    plt.plot(list1,self.tr err,label='Tranning set')
    plt.plot(list1,self.val err,label='Validation set')
    plt.xlabel('Iterations')
    plt.ylabel('RMSE')
      plt.title("k= "+str(i)+" and model number="+str(j+1)+"th")
    plt.legend()
    plt.show()
    plt.plot(list1, self.Cost, color='g', label='cost')
      plt.title("Cost function for K = "+str(i)+" and model number="+str(j+1))
    plt.xlabel('Iterations')
    plt.ylabel('Cost')
    plt.legend()
    plt.show()
def predict(self,X):
    return X.dot(self.W[1:])+self.W[0]
```

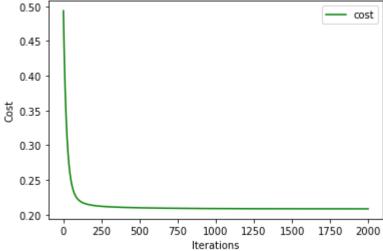
```
# the range for which one needs to run K-fold (K=5 ) so range (5,6)

for i in range(5,6):
    l=[]
    l1=[]
    X_Trains, Y_Trains, X_Tests, Y_Tests = K_fold_validation(i,norm(pd.read_csv("Real e for j in range(i):
        model=Linear_Regression1(0.01,2000)
        print("k= "+str(i)+" and model number="+str(j+1))
        model.fit(X_Trains[j],Y_Trains[j],X_Tests[j],Y_Tests[j])
    model.plot1()
```

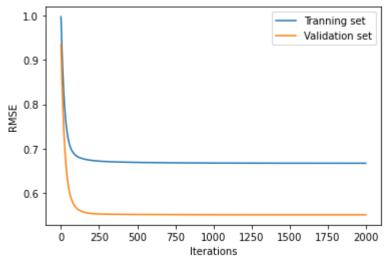
k= 5 and model number=1

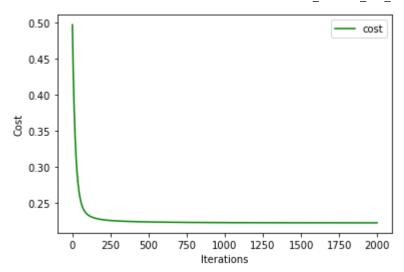
RMSE for tranning set => 0.6455807116763345 RMSE for validation set => 0.652294284531606



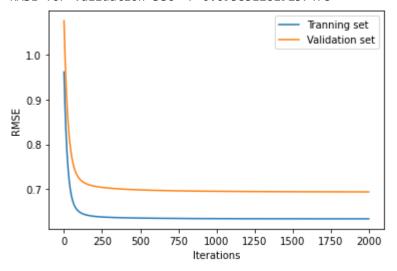


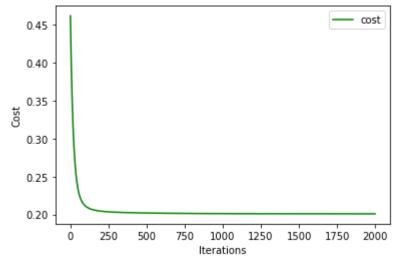
k= 5 and model number=2
RMSE for tranning set => 0.6673322954749914
RMSE for validation set => 0.5511216204356201



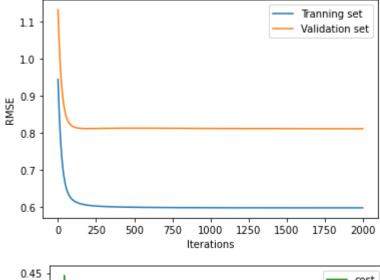


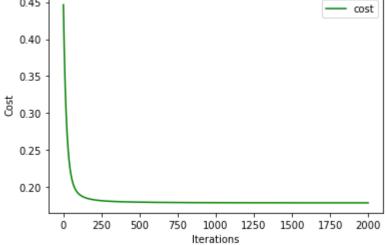
k= 5 and model number=3
RMSE for tranning set => 0.6337213018795999
RMSE for validation set => 0.6938312819257478



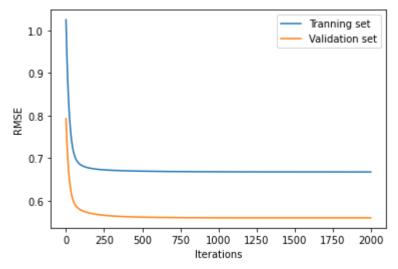


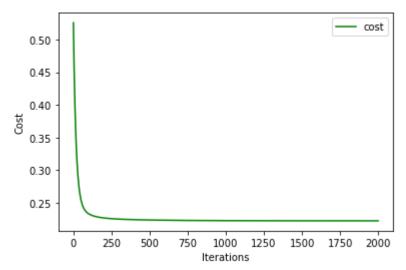
k= 5 and model number=4
RMSE for tranning set => 0.5978329170873334
RMSE for validation set => 0.8115815436018022





k= 5 and model number=5
RMSE for tranning set => 0.6673537073840736
RMSE for validation set => 0.5595258522593299





Part C

Modify your Regression implementation by including L1 (LASSO) and L2 (Ridge Regression) regularization. Implement both regularization function from scratch and train the model again. Try different values of the regularization parameter and report the best one. Plot similar RMSE V/s iteration graph as before

```
In [13]:
          class Linear Regression lasso():
              def __init__(self,l_rate,Epochs,lmd):
                   self.l rate=l rate
                   self.Epochs=Epochs
                   self.lmd=lmd
              def fit(self, X, Y ,X_test,Y_test):
                   self.m, self.n = X.shape
                   on=np.ones((self.m,1))
                   self.X=np.concatenate((on,X),axis=1)
                   self.n=self.n+1
                   self.Y=Y
                   self.W=np.zeros(self.n)
                   self.H=np.dot(self.X,self.W)
                   self.Cost=np.zeros(self.Epochs)
                   self.val err=[]
                   self.tr_err=[]
                   for i in range(self.Epochs):
                       self.upd_weight()
                       self.val_err.append(self.rmse(Y_test,self.predict(X_test)))
                       self.tr err.append(self.rmse(Y,self.predict(X)))
                       self.Cost[i]=np.sum(np.square(self.H-self.Y))/(2*self.m)
                   #self.plot1()
                   return self
              def upd weight(self):
```

```
if(self.W[0]<0):</pre>
        p=1
    elif(self.W[0]>0):
        p=-1
    self.W[0]=self.W[0]-(self.1 rate/self.m)*sum(self.H-self.Y)+(p*self.lmd)
    for i in range(1,self.n):
        p=0
        if(self.W[0]<0):</pre>
            p=1
        elif(self.W[0]>0):
            p=-1
        self.W[i]=self.W[i]-(self.1 rate/self.m)*sum((self.H-self.Y)*self.X[:,i])+(
    self.H=np.dot(self.X,self.W)
    return self
def W C(self):
    print(self.W[0])
    print(self.W[1:])
def rmse(self,y1,y2):
    mse = (np.square(y1 - y2)).mean()
    return np.sqrt(mse)
def plot1(self):
    list1 = list(range(0, self.Epochs))
    plt.plot(list1,self.tr err,label='Tranning set')
    plt.plot(list1,self.val err,label='Validation set')
      plt.title("k= "+str(i)+" and model number="+str(j+1)+"th")
    plt.legend()
    plt.xlabel('Iterations')
    plt.ylabel('RMSE')
    plt.show()
    plt.plot(list1, self.Cost, color='g', label='cost')
      plt.title("Cost function for K = "+str(i)+" and model number="+str(j+1))
    plt.legend()
    plt.xlabel('Iterations')
    plt.ylabel('Cost')
    plt.show()
def predict(self,X):
    return X.dot(self.W[1:])+self.W[0]
```

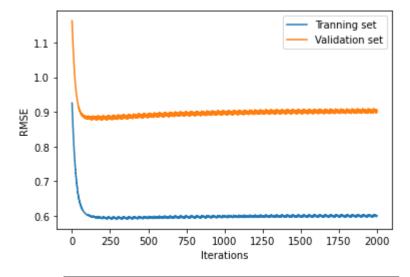
```
class Linear_Regression_ridge():
    def __init__(self,l_rate,Epochs,lmd):
        self.l_rate=l_rate
        self.Epochs=Epochs
        self.lmd=lmd

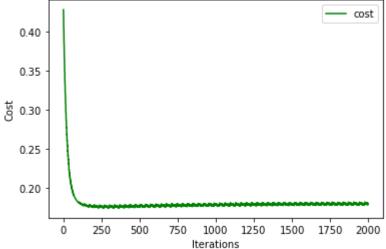
def fit(self, X, Y ,X_test,Y_test):
        self.m,self.n = X.shape
        on=np.ones((self.m,1))
        self.X=np.concatenate((on,X),axis=1)
```

```
self.n=self.n+1
          self.Y=Y
          self.W=np.zeros(self.n)
          self.H=np.dot(self.X,self.W)
          self.Cost=np.zeros(self.Epochs)
          self.val err=[]
          self.tr err=[]
          for i in range(self.Epochs):
                     self.upd weight()
                     self.val_err.append(self.rmse(Y_test,self.predict(X_test)))
                     self.tr_err.append(self.rmse(Y,self.predict(X)))
                     self.Cost[i]=np.sum(np.square(self.H-self.Y))/(2*self.m)
          #self.plot1()
          return self
def upd weight(self):
          self.W[0]=((1-2*self.l rate*self.lmd)*self.W[0])-(self.l rate/self.m)*sum(self.W[0])-(self.l rate/self.m)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(self.w)*sum(se
          for i in range(1, self.n):
                     self.W[i]=((1-2*self.1 rate*self.lmd)*self.W[i])-(self.1 rate/self.m)*sum((
          self.H=np.dot(self.X,self.W)
          return self
def W_C(self):
          print(self.W[0])
          print(self.W[1:])
def rmse(self,y1,y2):
          mse = (np.square(y1 - y2)).mean()
          return np.sqrt(mse)
def plot1(self):
          list1 = list(range(0, self.Epochs))
          plt.plot(list1,self.tr_err,label='Tranning set')
          plt.plot(list1,self.val err,label='Validation set')
               plt.title("k= "+str(i)+" and model number="+str(j+1)+"th")
          plt.legend()
          plt.xlabel('Iterations')
          plt.ylabel('RMSE')
          plt.show()
          plt.plot(list1, self.Cost, color='g', label='cost')
               plt.title("Cost function for K = "+str(i)+" and model number="+str(j+1))
          plt.legend()
          plt.xlabel('Iterations')
          plt.ylabel('Cost')
          plt.show()
def predict(self,X):
          return X.dot(self.W[1:])+self.W[0]
```

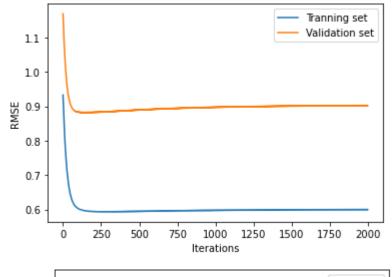
```
for i in range(5,6):
    l=[]
    l1=[]
    X_Trains, Y_Trains, X_Tests, Y_Tests = K_fold_validation(i,norm(pd.read_csv("Real e for j in range(i):
        mp=[0.01,0.001,0.000005,0.0006,0.00007]
        for m in range(5):
            model1=Linear_Regression_lasso(0.01,2000,mp[m])
            model1.fit(X_Trains[j],Y_Trains[j],X_Tests[j],Y_Tests[j])

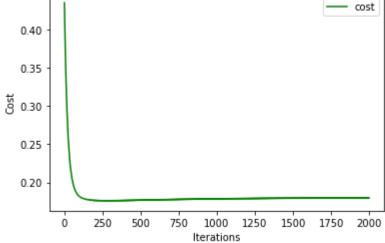
    #we got the best split at k=5 and the 1th split so only showing that one
    if(j==1):
        model1.plot1()
        print("Regularisation parameter {}".format(mp[m]))
        print("Validation Set RMSE=> {}".format(model1.val_err[-1]))
        print("Tranning Set RMSE => {}".format(model1.tr_err[-1]))
```



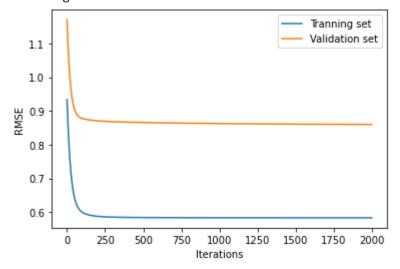


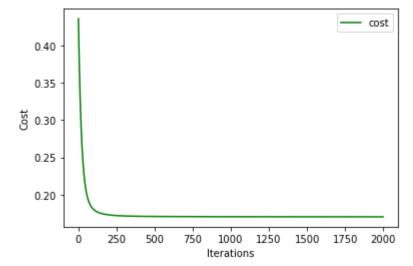
Regularisation parameter 0.01 Validation Set RMSE=> 0.9052595364454838 Tranning Set RMSE => 0.6004640526698816



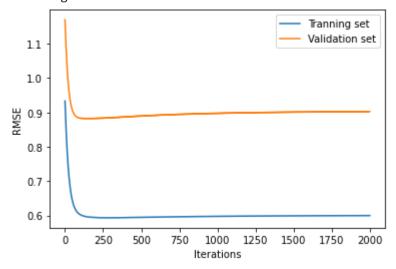


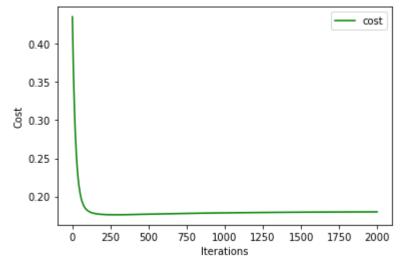
Regularisation parameter 0.001 Validation Set RMSE=> 0.9021533241674045 Tranning Set RMSE => 0.5996499679753795



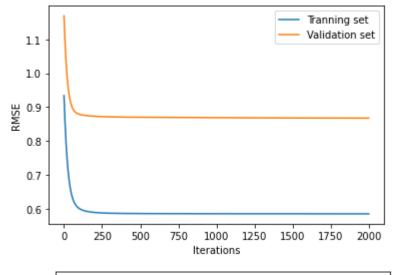


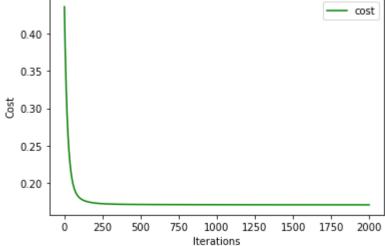
Regularisation parameter 5e-06 Validation Set RMSE=> 0.8599830377739207 Tranning Set RMSE => 0.5833127613815478





Regularisation parameter 0.0006 Validation Set RMSE=> 0.9027627515683939 Tranning Set RMSE => 0.5998633095266118



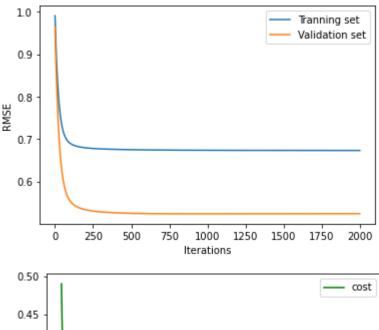


Regularisation parameter 7e-05 Validation Set RMSE=> 0.8673471706837934 Tranning Set RMSE => 0.5844403951382474

The best parameter is 0.01

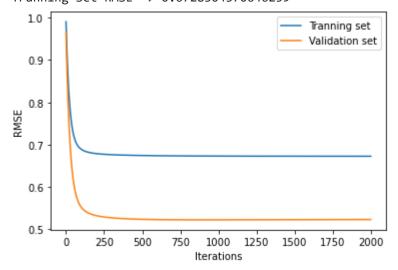
```
In [16]:
          for i in range(5,6):
              1=[]
              11=[]
              X_Trains, Y_Trains, X_Tests, Y_Tests = K_fold_validation(i,norm(pd.read_csv("Real e
              for j in range(i):
                  mp=[0.01,0.001,0.000005,0.0006,0.00007]
                  for m in range(5):
                      model1=Linear Regression ridge(0.01,2000,mp[m])
                      model1.fit(X_Trains[j],Y_Trains[j],X_Tests[j],Y_Tests[j])
                      #we got the best split at k=5 and the 1th split so only showing that one
                      if(j==1):
                           print("Regularisation parameter {}".format(mp[m]))
                          print("Validation Set RMSE=> {}".format(model1.val_err[-1]))
                          print("Tranning Set RMSE => {}".format(model1.tr_err[-1]))
                          model1.plot1()
```

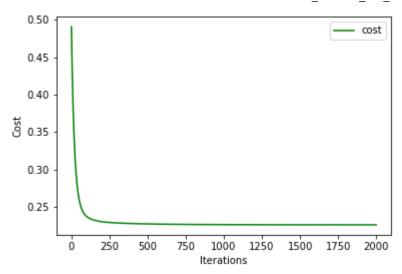
Regularisation parameter 0.01 Validation Set RMSE=> 0.5239991291862338 Tranning Set RMSE => 0.6730139364760966



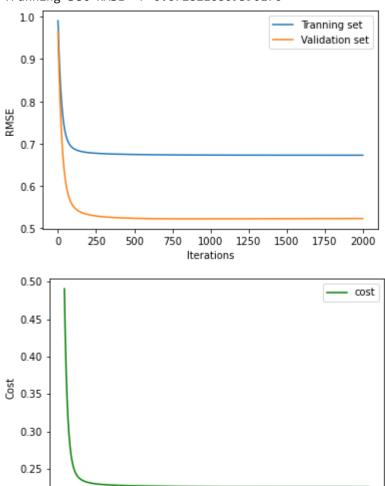
0.45 - 0.40 - 15 0.35 - 0.30 - 0.25 -

Regularisation parameter 0.001 Validation Set RMSE=> 0.5232712602950086 Tranning Set RMSE => 0.6728304370646259





Regularisation parameter 5e-06 Validation Set RMSE=> 0.523205503196435 Tranning Set RMSE => 0.6728216809390176



Regularisation parameter 0.0006 Validation Set RMSE=> 0.5232444313708448 Tranning Set RMSE => 0.672826604880376

500

750

1000

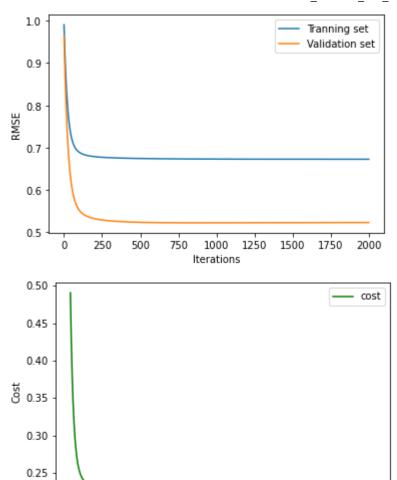
Iterations

1250

1500 1750

2000

250



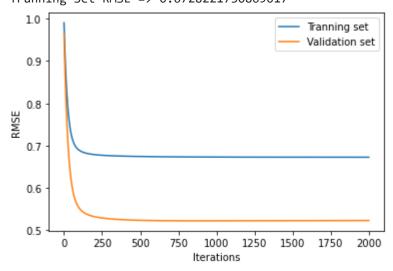
Regularisation parameter 7e-05 Validation Set RMSE=> 0.5232096981710419 Tranning Set RMSE => 0.6728221730869017

500

750

Ó

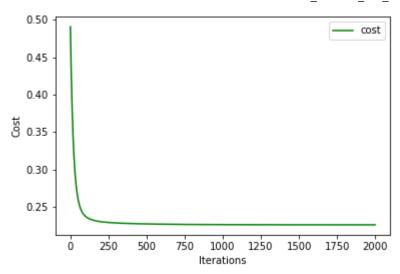
250



1250

1000 Iterations 1500 1750

2000



The best parameter is 0.005

```
In [25]:
          class LR_NORM():
              def init (self):
                   self.name=0
              def fit(self, X, Y):
                   self.m,self.n = X.shape
                  on=np.ones((self.m,1))
                   self.X=np.concatenate((on,X),axis=1)
                   self.n=self.n+1
                   self.Y=Y
                   self.normal eq()
              def normal eq(self):
                   self.W = np.linalg.inv(self.X.T.dot(self.X)).dot(self.X.T).dot(self.Y)
              def predict(self,X):
                  X=np.array(X)
                   return X.dot(self.W[1:])+self.W[0]
```

```
In [26]:
    for i in range(2,6):
        X_Trains, Y_Trains, X_Tests, Y_Tests = K_fold_validation(i,norm(pd.read_csv("Real e l_c=[]
        for j in range(i):
            model=LR_NORM()
            model.fit(X_Trains[j],Y_Trains[j])
            y_pr=model.predict(X_Tests[j])
            l_c.append(np.sqrt(np.mean(np.square(model.predict(X_Tests[j])-Y_Tests[j]))))
            print("Rmse for k={} and split ={} =>".format(i,j)+str(sum(l_c)/len(l_c)))
            print()
```

```
Rmse for k=2 and split =0 =>0.6756446887548269
Rmse for k=2 and split =1 =>0.6604265204712334
```

```
Rmse for k=3 and split =0 =>0.6541133917854346
Rmse for k=3 and split =1 =>0.6976576051546526
Rmse for k=3 and split =2 =>0.6537020357875981

Rmse for k=4 and split =0 =>0.6770590790553567
Rmse for k=4 and split =1 =>0.6281281547675499
Rmse for k=4 and split =2 =>0.6191999641902847
Rmse for k=4 and split =3 =>0.6602538105727593

Rmse for k=5 and split =0 =>0.8688665619458582
Rmse for k=5 and split =1 =>0.7588676235103131
Rmse for k=5 and split =2 =>0.7204739580173932
Rmse for k=5 and split =3 =>0.663132149920377
Rmse for k=5 and split =4 =>0.6483658795405521
```

In []: