Shaikat_303527_lab_5_Q1

November 26, 2019

1 Preprocessing Bank Marketing dataset

In [1]:
```
import pandas as pd
import sys
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
pd.options.mode.chained_assignment = None
from sklearn.model_selection import train_test_split

filename = r"E:\Documents\University of Hildesheim\Machine learning lab\lab5\bank.csv"
bank = pd.read_csv(filename,delimiter=';')
```

In [2]:
```
bank.head(5)
```

Out[2]:
```
   age          job  marital  education default  balance housing loan  \
0   30   unemployed  married    primary      no     1787      no   no
1   33     services  married  secondary      no     4789     yes  yes
2   35   management   single   tertiary      no     1350     yes   no
3   30   management  married   tertiary      no     1476     yes  yes
4   59  blue-collar  married  secondary      no        0     yes   no

    contact  day month  duration  campaign  pdays  previous poutcome   y
0  cellular   19   oct        79         1     -1         0  unknown  no
1  cellular   11   may       220         1    339         4  failure  no
2  cellular   16   apr       185         1    330         1  failure  no
3   unknown    3   jun       199         4     -1         0  unknown  no
4   unknown    5   may       226         1     -1         0  unknown  no
```

In [3]:
```
bank.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4521 entries, 0 to 4520
Data columns (total 17 columns):
age          4521 non-null int64
job          4521 non-null object
marital      4521 non-null object
education    4521 non-null object
```

```
default      4521 non-null object
balance      4521 non-null int64
housing      4521 non-null object
loan         4521 non-null object
contact      4521 non-null object
day          4521 non-null int64
month        4521 non-null object
duration     4521 non-null int64
campaign     4521 non-null int64
pdays        4521 non-null int64
previous     4521 non-null int64
poutcome     4521 non-null object
y            4521 non-null object
dtypes: int64(7), object(10)
memory usage: 600.5+ KB
```

1.0.1 Removing all NA values from the dataset

```
In [4]: bank.dropna(inplace=True)
```

1.0.2 Converting non-numeric values to numeric values using categorical encoding

```
In [5]: col=['job','marital','education','default','housing','loan','month','contact','duratio
        bank[col] = bank[col].astype('category')
```

What can be experimented with is a simple categorical encoding, wherein each unique entry is assigned it's own number. Pandas does with relative ease by assigning desired object columns to a category dtype

```
In [6]: bank.dtypes
```

```
Out[6]: age            int64
        job         category
        marital     category
        education   category
        default     category
        balance        int64
        housing     category
        loan        category
        contact     category
        day            int64
        month       category
        duration    category
        campaign       int64
        pdays          int64
        previous       int64
        poutcome    category
        y           category
        dtype: object
```

1.0.3 Encoding the category column with unique values

```
In [7]: bank_enc = bank.apply(lambda x: x.cat.codes if x.dtype.name == 'category' else x)
```

It is shown that each categorical values has its unique values

```
In [8]: bank_enc.head(3)
```

```
Out[8]:    age  job  marital  education  default  balance  housing  loan  contact  \
        0   30   10        1          0        0     1787        0     0        0
        1   33    7        1          1        0     4789        1     1        0
        2   35    4        2          2        0     1350        1     0        0

           day  month  duration  campaign  pdays  previous  poutcome  y
        0   19     10        75         1     -1         0         3  0
        1   11      8       216         1    339         4         0  0
        2   16      0       181         1    330         1         0  0
```

1.0.4 Splitting the data into train (0.8) and test (0.2) set

```
In [381]: Ydata_bank = bank_enc['y']
          Xdata_bank = bank_enc.loc[:,bank_enc.columns!='y']
          Xdata_bank = (Xdata_bank - Xdata_bank.mean())/Xdata_bank.std() #data normalized

          x_train_bank, x_test_bank, y_train_bank, y_test_bank =train_test_split(Xdata_bank,
                                                                          Ydata_bank,tra
                                                                          test_size=0.2
                                                                          random_state=(
```

```
In [383]: y_train_bank=y_train_bank.values.reshape(-1,1)
          y_test_bank=y_test_bank.values.reshape(-1,1)
          x_train_bank=x_train_bank.values
          x_test_bank=x_test_bank.values
```

2 Preprocessing wine quality-red data

```
In [221]: filename=r"E:\Documents\University of Hildesheim\Machine learning lab\lab5\winequali
          rwine_data = pd.read_csv(filename,delimiter=';')
          rwine_data.head(3)
```

```
Out[221]:    fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
          0            7.4              0.70         0.00             1.9      0.076
          1            7.8              0.88         0.00             2.6      0.098
          2            7.8              0.76         0.04             2.3      0.092

             free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
          0                 11.0                  34.0   0.9978  3.51       0.56
          1                 25.0                  67.0   0.9968  3.20       0.68
          2                 15.0                  54.0   0.9970  3.26       0.65
```

```
   alcohol  quality
0      9.4        5
1      9.8        5
2      9.8        5
```

The data has no numeric values

```
In [222]: rwine_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):
fixed acidity           1599 non-null float64
volatile acidity        1599 non-null float64
citric acid             1599 non-null float64
residual sugar          1599 non-null float64
chlorides               1599 non-null float64
free sulfur dioxide     1599 non-null float64
total sulfur dioxide    1599 non-null float64
density                 1599 non-null float64
pH                      1599 non-null float64
sulphates               1599 non-null float64
alcohol                 1599 non-null float64
quality                 1599 non-null int64
dtypes: float64(11), int64(1)
memory usage: 150.0 KB
```

```
In [255]: Xdata_rwine = rwine_data.loc[:,rwine_data.columns!='quality']
          Ydata_rwine = rwine_data[['quality']]
          Xdata_rwine = (Xdata_rwine - Xdata_rwine.mean())/Xdata_rwine.std() #data normalized
          x_train_rwine, x_test_rwine, y_train_rwine, y_test_rwine =train_test_split(Xdata_rwin
                                                                                    Ydata_rwine,t
                                                                                    test_size=0.2
                                                                                    random_state=
```

```
In [256]: y_train_rwine=y_train_rwine.values.reshape(-1,1)
          y_test_rwine=y_test_rwine.values.reshape(-1,1)
          x_train_rwine=x_train_rwine.values
          x_test_rwine=x_test_rwine.values
```

3 Preprocessing wine quality white data

```
In [257]: filename=r"E:\Documents\University of Hildesheim\Machine learning lab\lab5\winequalit
          wwine_data = pd.read_csv(filename,delimiter=';')
          wwine_data.head(3)
```

```
Out[257]:    fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
          0            7.0              0.27         0.36            20.7      0.045
          1            6.3              0.30         0.34             1.6      0.049
          2            8.1              0.28         0.40             6.9      0.050

             free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
          0                 45.0                 170.0   1.0010  3.00       0.45
          1                 14.0                 132.0   0.9940  3.30       0.49
          2                 30.0                  97.0   0.9951  3.26       0.44

             alcohol  quality
          0      8.8        6
          1      9.5        6
          2     10.1        6
```

```
In [259]: Xdata_wwine = wwine_data.loc[:,wwine_data.columns!='quality']
          Ydata_wwine = wwine_data['quality']
          Xdata_wwine = (Xdata_wwine - Xdata_wwine.mean())/Xdata_wwine.std() #data normalized

          x_train_wwine, x_test_wwine, y_train_wwine, y_test_wwine =train_test_split(Xdata_wwi
                                                                         Ydata_wwine,t
                                                                         test_size=0.2
                                                                         random_state=
```

```
In [260]: y_train_wwine=y_train_wwine.values.reshape(-1,1)
          y_test_wwine=y_test_wwine.values.reshape(-1,1)
          x_train_wwine=x_train_wwine.values
          x_test_wwine=x_test_wwine.values
```

4 Ridge Regression using mini-Batch Gradient Descent

```
In [360]: def logistic_function(X, beta):
              z = np.dot(X,beta)
              return 1 / (1 + np.exp(-z))

          def log_likelihood(x, y, beta):
              z = np.dot(x, beta)
              log = np.sum( y*z - np.log(1 + np.exp(z)) )
              return log

          betas = lambda x,y,beta,alpha,lamda : beta-alpha*(-2*np.dot(x.T,y-logistic_function(
          rmse  = lambda y,ypred: np.sqrt(np.mean((y-ypred)**2))
          cost  = lambda y,ypred: np.mean((y - ypred)**2)
```

```
In [424]: def stochastic_gradient_descent(x_train,y_train,alpha,epochs,lamda,x_test,y_test):
              m_train,n_features = np.shape(x_train)
              ini_alpha          = alpha
              beta_hat           = np.random.random(n_features).reshape(-1,1)
```

```
rmsetrain          = []
rmsetest           = []
relative_loss      = []
y_hat              = logistic_function(x_train,beta_hat)

chunk_size = 50
for i in range(epochs):
    loss_old  = cost(y_train,y_hat)
    for chunk in range(len(x_train)//chunk_size):
        x_chunk  = x_train[chunk*chunk_size:min((chunk+1)*chunk_size,len(x_train)
        y_chunk  = y_train[chunk*chunk_size:min((chunk+1)*chunk_size,len(y_train)

        beta_hat = betas(x_chunk,y_chunk,beta_hat,alpha,lamda)

    y_hat=logistic_function(x_train,beta_hat)
    loss_new  = cost(y_train,y_hat)

    rmsetest.append(rmse(y_test,logistic_function(x_test,beta_hat)))
    rmsetrain.append(rmse(y_train,logistic_function(x_train,beta_hat)))
    relative_loss.append(np.abs(loss_new-loss_old))

    if i % 10 == 0:
        print(f"epochs: {i} loss: {np.abs(loss_new-loss_old)} rmse test: {rmse(y_
    if (np.abs(loss_new-loss_old))==0:
        break

plt.plot(np.arange(len(rmsetrain)),rmsetrain,'g',label='rmse_train')
plt.plot(np.arange(len(rmsetest)),rmsetest,'r',label='rmse_test')
plt.xlabel("epochs")
plt.ylabel("RMSE")
plt.legend()
plt.show()


plt.xlabel("epochs")
plt.ylabel("RMSE")
rmsetest=[x*-1 for x in rmsetest]
plt.plot(np.arange(len(rmsetest)),rmsetest,'r',label='rmse_neg_test')
plt.plot(np.arange(len(rmsetrain)),rmsetrain,'g',label='rmse_train')
plt.legend()
plt.show()

return rmsetest,rmsetrain
```

5 Ridge Regression using mini-Batch Gradient Descent using the Bank Marketing dataset

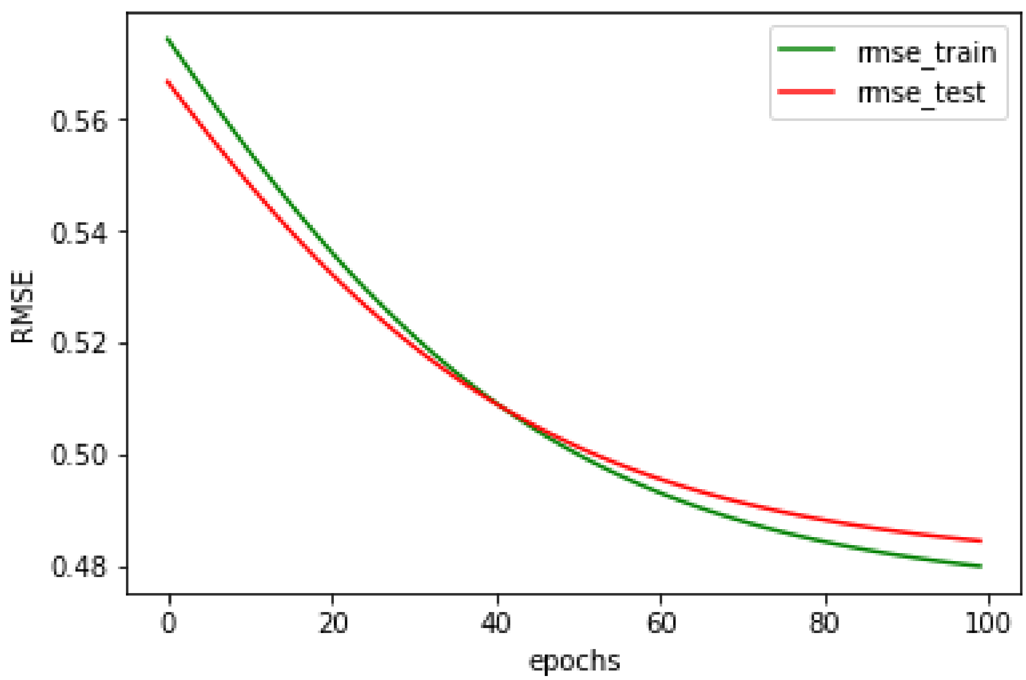
Training the bank marketing data and plotting the rmse values for three combinations of alpha and lamda values

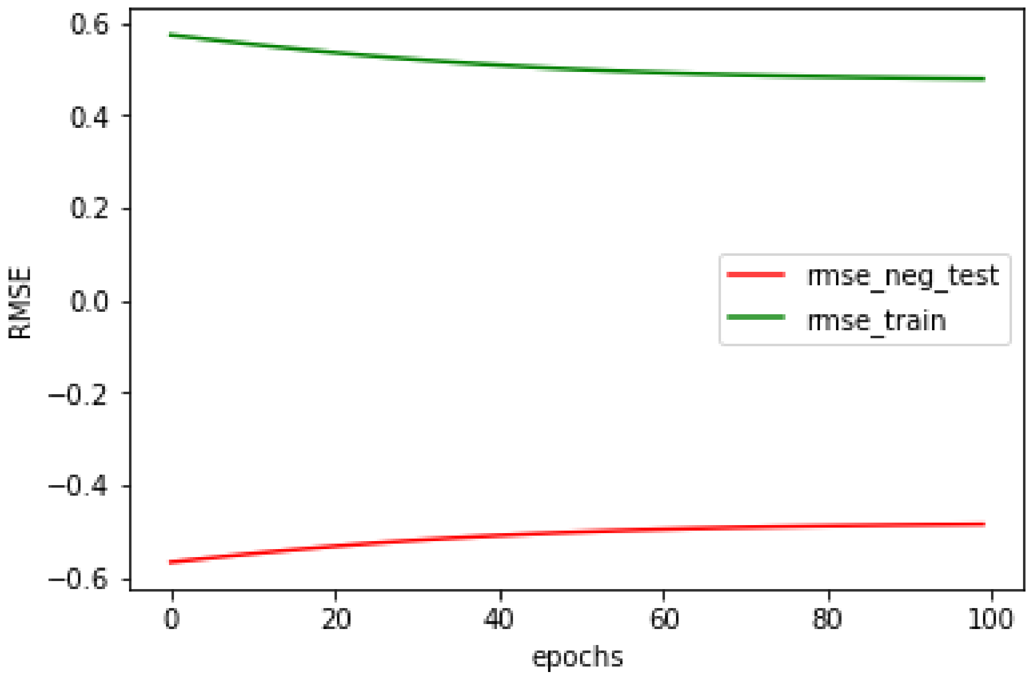
5.0.1 The first two combinations of Alpha(lr) and lamda displayed an optimal result where we can see the rmsetrain and rmsetest is almost similar

In [363]:
```
lr=0.00001
epochs=100
lamda=0.0000001

sgd=stochastic_gradient_descent(x_train_bank,y_train_bank,lr,epochs,lamda,x_test_ban
```

```
epochs: 0 loss: 0.002435144116213539 rmse test: 0.5667694855064026 rmse train: 0.5744277247782
epochs: 10 loss: 0.002153404959103O446 rmse test: 0.5482614339415794 rmse train: 0.554143593611
epochs: 20 loss: 0.0017952841283244703 rmse test: 0.5322709618257061 rmse train: 0.536167398347
epochs: 30 loss: 0.001424949376957807 rmse test: 0.5192094851284748 rmse train: 0.521126105683
epochs: 40 loss: 0.0010891781951399282 rmse test: 0.5089938579837207 rmse train: 0.509127593110
epochs: 50 loss: 0.0008103640532673151 rmse test: 0.5012424039715562 rmse train: 0.499903251908
epochs: 60 loss: 0.0005921559693751466 rmse test: 0.49547212966386023 rmse train: 0.49299900626
epochs: 70 loss: 0.00042799343608007634 rmse test: 0.4912255722423666 rmse train: 0.48792407895
epochs: 80 loss: 0.00030760787731193284 rmse test: 0.4881226915026098 rmse train: 0.48423527210
epochs: 90 loss: 0.00022071151251157328 rmse test: 0.48586591656692163 rmse train: 0.4815697098
```

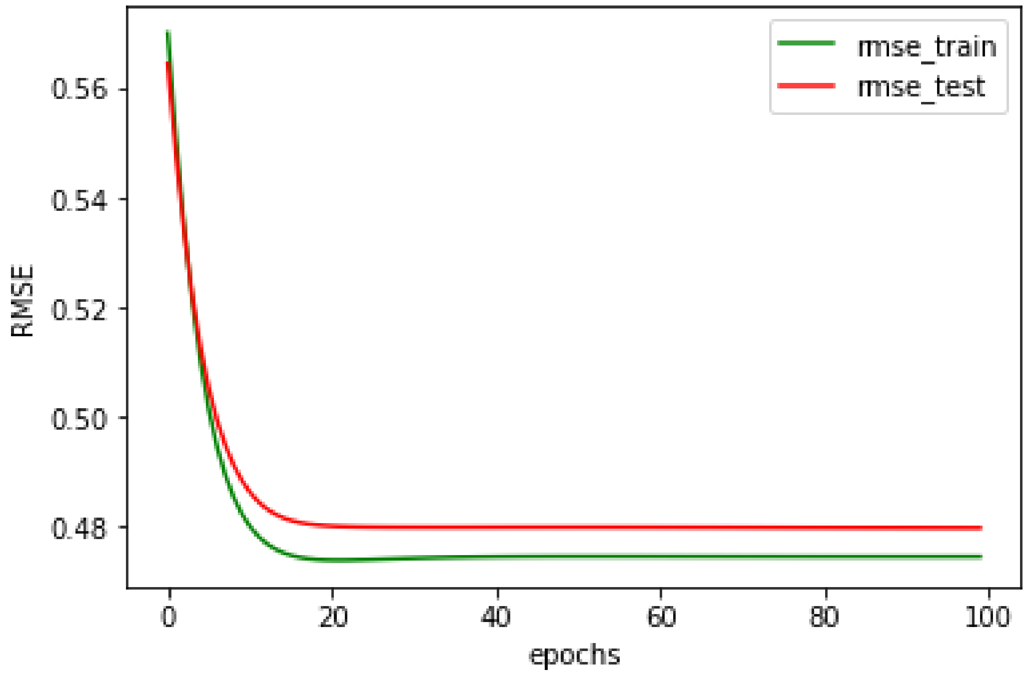


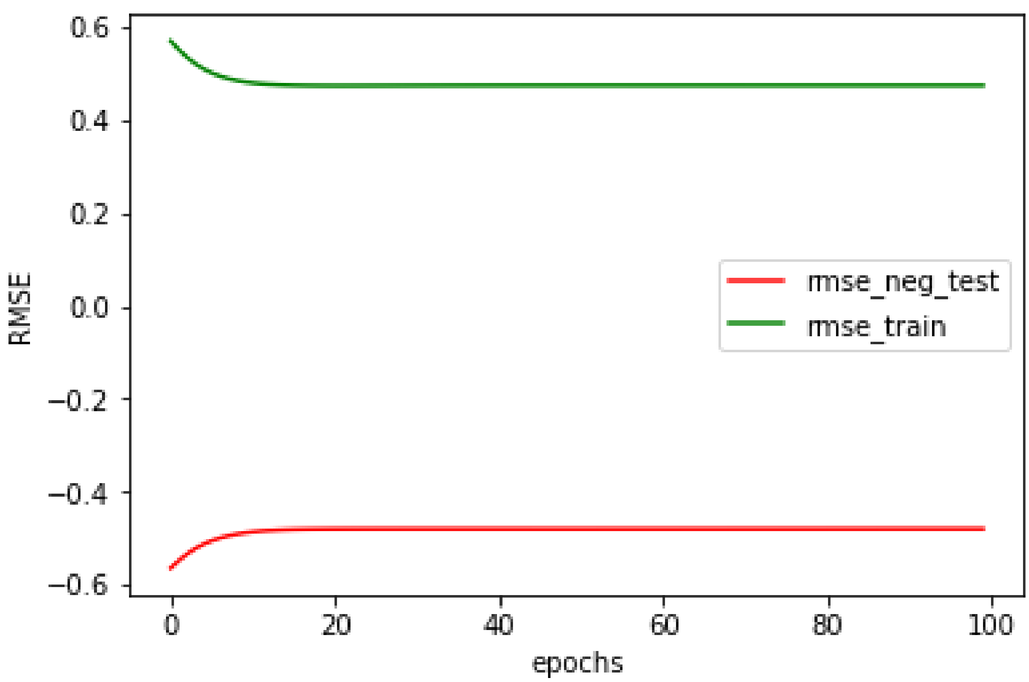



```
In [339]: lr=0.0001
          epochs=100
          lamda=0.1

          sgd=stochastic_gradient_descent(x_train_bank,y_train_bank,lr,epochs,lamda,x_test_bank
```

```
epochs: 0 loss: 0.023062767341360757 rmse test: 0.5645457503672167 rmse train: 0.5701477569122
epochs: 10 loss: 0.0022491519594182163 rmse test: 0.48635301418782906 rmse train: 0.4801129046
epochs: 20 loss: 3.964943702564061e-05 rmse test: 0.48015353694355234 rmse train: 0.473924124
epochs: 30 loss: 4.1128671128543015e-05 rmse test: 0.47993772930217266 rmse train: 0.474282562
epochs: 40 loss: 1.3254800108997156e-05 rmse test: 0.479938100019452 rmse train: 0.474545648910
epochs: 50 loss: 1.1459817071124423e-06 rmse test: 0.47994427857585537 rmse train: 0.474602461
epochs: 60 loss: 1.5320859126088937e-06 rmse test: 0.479926290377631 rmse train: 0.474594645071
epochs: 70 loss: 1.3923905377577483e-06 rmse test: 0.47989119878711056 rmse train: 0.474578275
epochs: 80 loss: 7.001488884217366e-07 rmse test: 0.47985314713173394 rmse train: 0.474567532886
epochs: 90 loss: 7.637077256705815e-08 rmse test: 0.4798202269870716 rmse train: 0.47456392609
```


rmse_train
rmse_test
RMSE
0.56
0.54
0.52
0.50
0.48
0
20
40
60
80
100
epochs

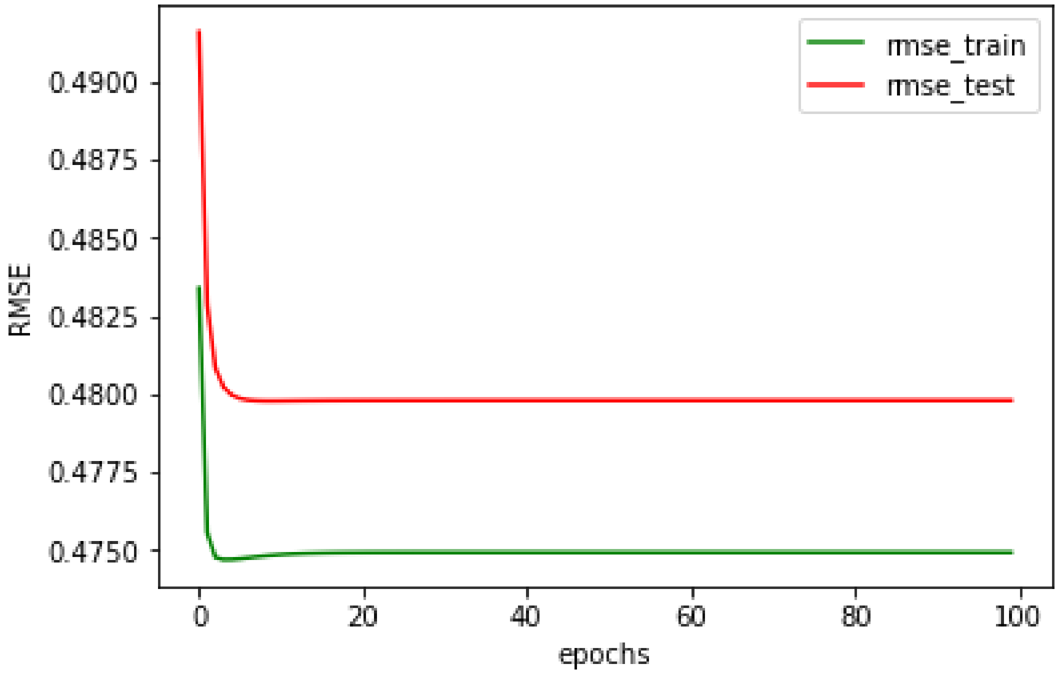

rmse_neg_test
rmse_train
RMSE
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
0
20
40
60
80
100
epochs

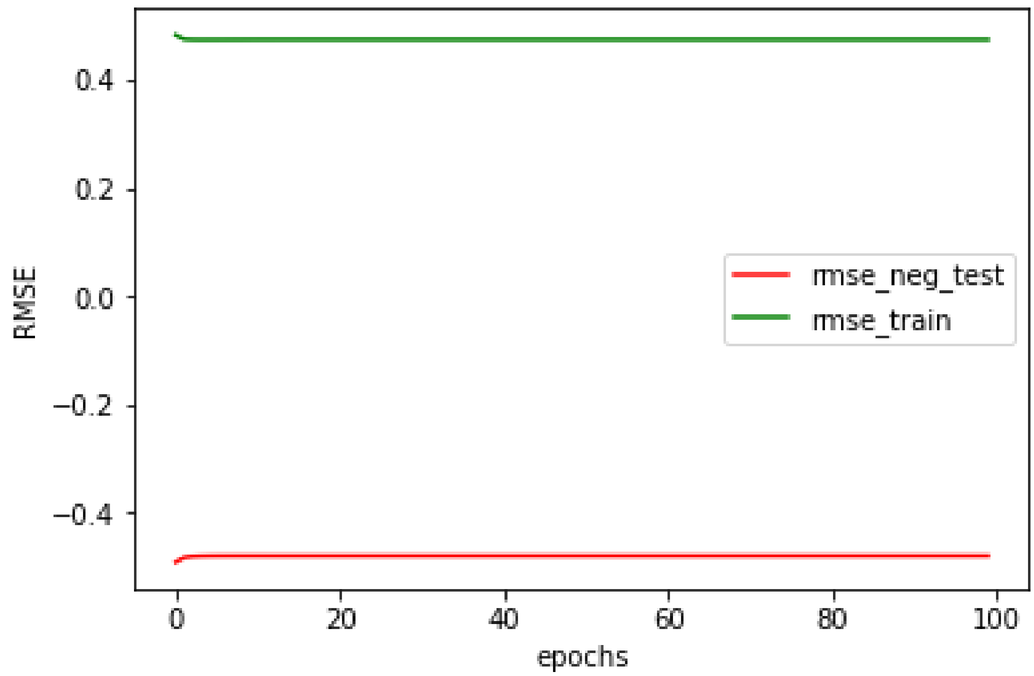
5.0.2 This combination of alpha(lr) and lamda was not optimal because the rmse of test train has a significant difference the reason behind can be the higher values of alpha(lr)

In [340]:
```
lr=0.001
epochs=100
lamda=0.5

sgd=stochastic_gradient_descent(x_train_bank,y_train_bank,lr,epochs,lamda,x_test_banl
```

```
epochs: 0 loss: 0.1012987002452139 rmse test: 0.4915859610745922 rmse train: 0.4833867419875229
epochs: 10 loss: 1.8763479428723917e-05 rmse test: 0.47977268389697897 rmse train: 0.4748526179
epochs: 20 loss: 1.2782270281952446e-06 rmse test: 0.4797878666761989 rmse train: 0.4749162403
epochs: 30 loss: 6.889696593792571e-08 rmse test: 0.47978910634522515 rmse train: 0.474920005
epochs: 40 loss: 3.670668158317625e-09 rmse test: 0.4797891735787845 rmse train: 0.474920206
epochs: 50 loss: 1.9544399432191994e-10 rmse test: 0.47978917716199065 rmse train: 0.474920217
epochs: 60 loss: 1.0406037143084745e-11 rmse test: 0.47978917735278104 rmse train: 0.47492021
epochs: 70 loss: 5.540845560148e-13 rmse test: 0.47978917736293925 rmse train: 0.4749202182658
epochs: 80 loss: 2.9531932455029164e-14 rmse test: 0.47978917736348015 rmse train: 0.47492021
epochs: 90 loss: 1.582067810090848e-15 rmse test: 0.47978917736350896 rmse train: 0.47492021
```





6 Ridge Regression using mini-Batch Gradient Descent using the Wine quality RED dataset

Training the wine quality red data and plotting the rmse values for three combinations of alpha and lamda values

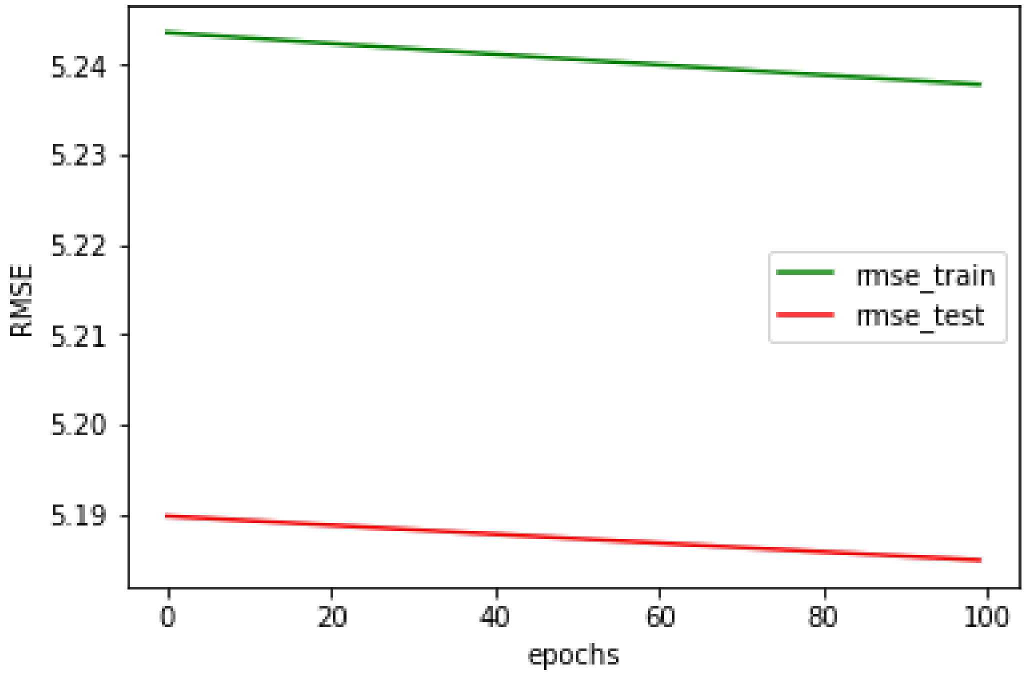
6.0.1 For this combination of parameters the rmse decreased in both case but the model is not optimal for those parameter the reason behind it can the very low value of lamda

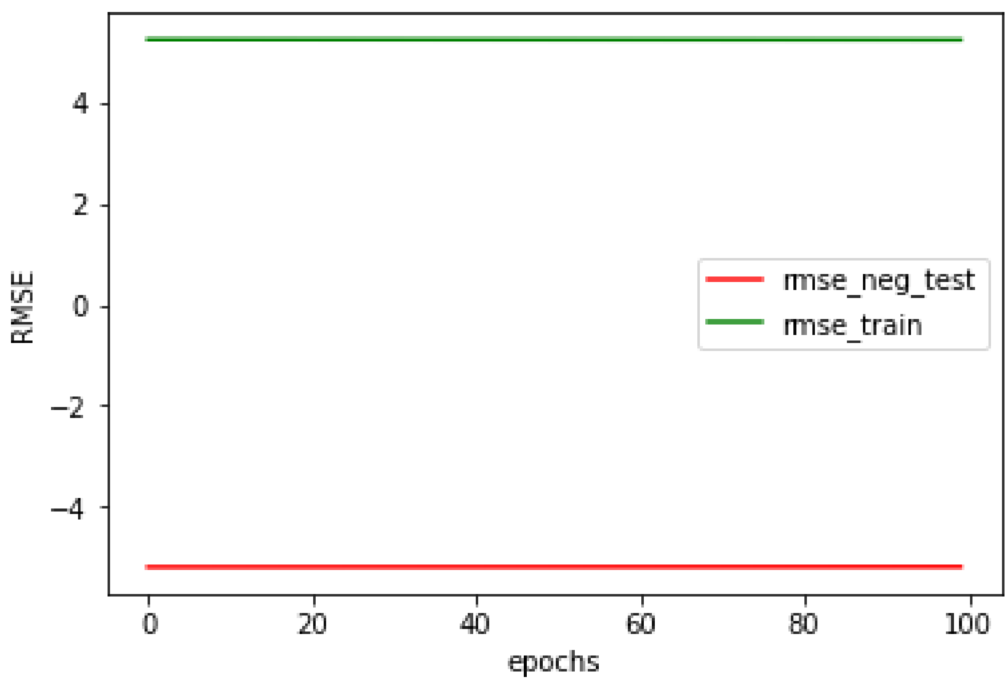
In [467]:
```
lr=0.000001
epochs=100
lamda=0.00000001

sgd=stochastic_gradient_descent(x_train_rwine,y_train_rwine,lr,epochs,lamda,x_test_rw
```

```
epochs: 0 loss: 0.0006509246559716075 rmse test: 5.189771015241054 rmse train: 5.24358264579131
epochs: 10 loss: 0.0006435340938999445 rmse test: 5.189262549077594 rmse train: 5.24296577704211
epochs: 20 loss: 0.000635878402380996 rmse test: 5.18875683651541 rmse train: 5.24235602498152
epochs: 30 loss: 0.0006279739874806012 rmse test: 5.188253941090884 rmse train: 5.24175363637 4
epochs: 40 loss: 0.0006198370758241367 rmse test: 5.187753925569301 rmse train: 5.24115884250 9
epochs: 50 loss: 0.0006114836860078299 rmse test: 5.187256852478571 rmse train: 5.24057185937 3
epochs: 60 loss: 0.0006029296030050091 rmse test: 5.186762784580742 rmse train: 5.23999288785 0
epochs: 70 loss: 0.000594190355471369 rmse test: 5.1862717852802245 rmse train: 5.23942211394 8
epochs: 80 loss: 0.0005852811955762149 rmse test: 5.185783918968442 rmse train: 5.23885970903 9
```

```
epochs: 90 loss: 0.0005762170813703449 rmse test: 5.185299251305482 rmse train: 5.2383058301247
```



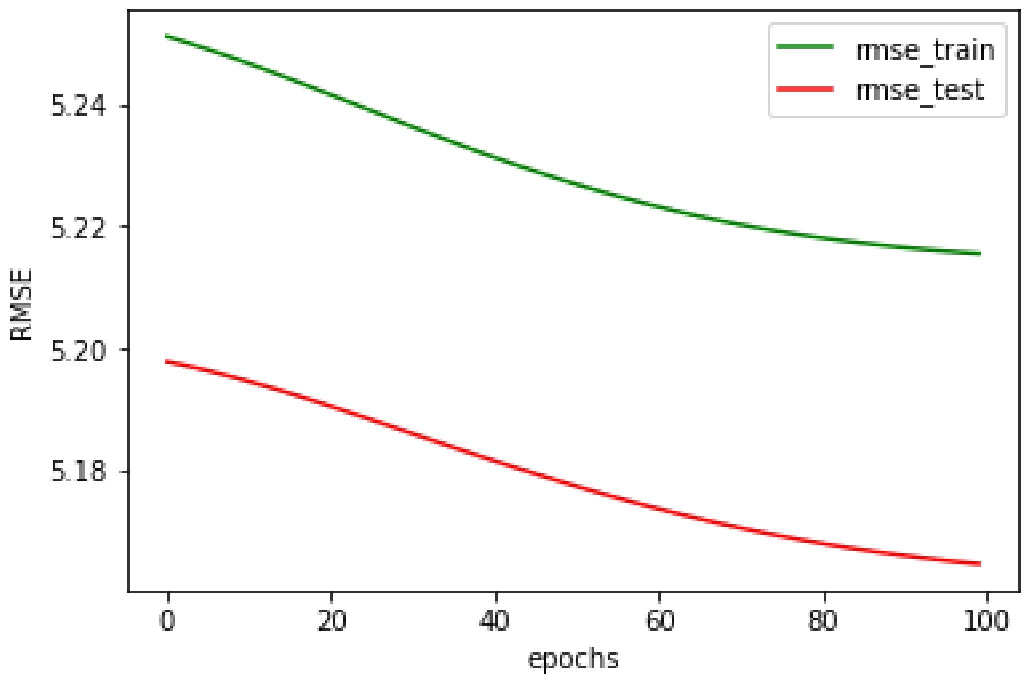


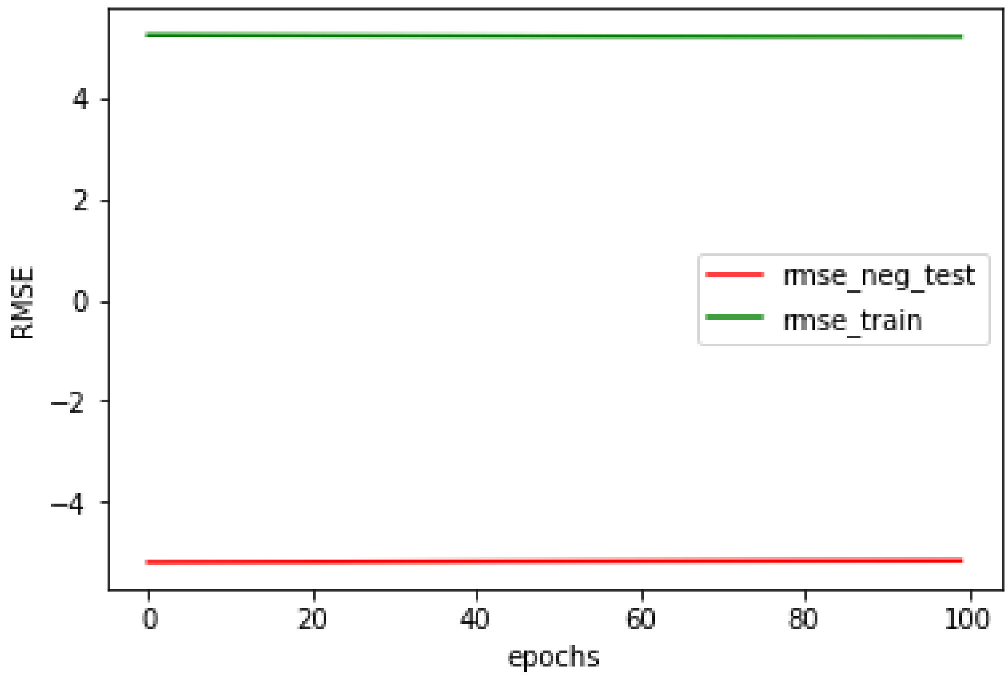
6.0.2 As the lamda values increased as well as the learning rate we can notice that the model is better than the previous one

In [342]:
```
lr=0.00001
epochs=100
lamda=0.001

sgd=stochastic_gradient_descent(x_train_rwine,y_train_rwine,lr,epochs,lamda,x_test_r
```

```
epochs: 0 loss: 0.0041321762277775065 rmse test: 5.197836846833961 rmse train: 5.2510862396012
epochs: 10 loss: 0.005069688427788321 rmse test: 5.194623807314949 rmse train: 5.24662462737955
epochs: 20 loss: 0.005516118285370908 rmse test: 5.19053899222862 rmse train: 5.24151553031185
epochs: 30 loss: 0.005458645723205535 rmse test: 5.1860538835666325 rmse train: 5.236244244282
epochs: 40 loss: 0.004998994322473749 rmse test: 5.181584353750308 rmse train: 5.2312449381150
epochs: 50 loss: 0.004290628823522269 rmse test: 5.177419404769383 rmse train: 5.2268241290340
epochs: 60 loss: 0.0034836579159964742 rmse test: 5.173729198881787 rmse train: 5.223140271391
epochs: 70 loss: 0.0026887364330399066 rmse test: 5.170596755200449 rmse train: 5.220227227788
epochs: 80 loss: 0.0019678706421792924 rmse test: 5.168047043758433 rmse train: 5.218038426663
epochs: 90 loss: 0.001344042021578673 rmse test: 5.166066146837551 rmse train: 5.2164892080708
```



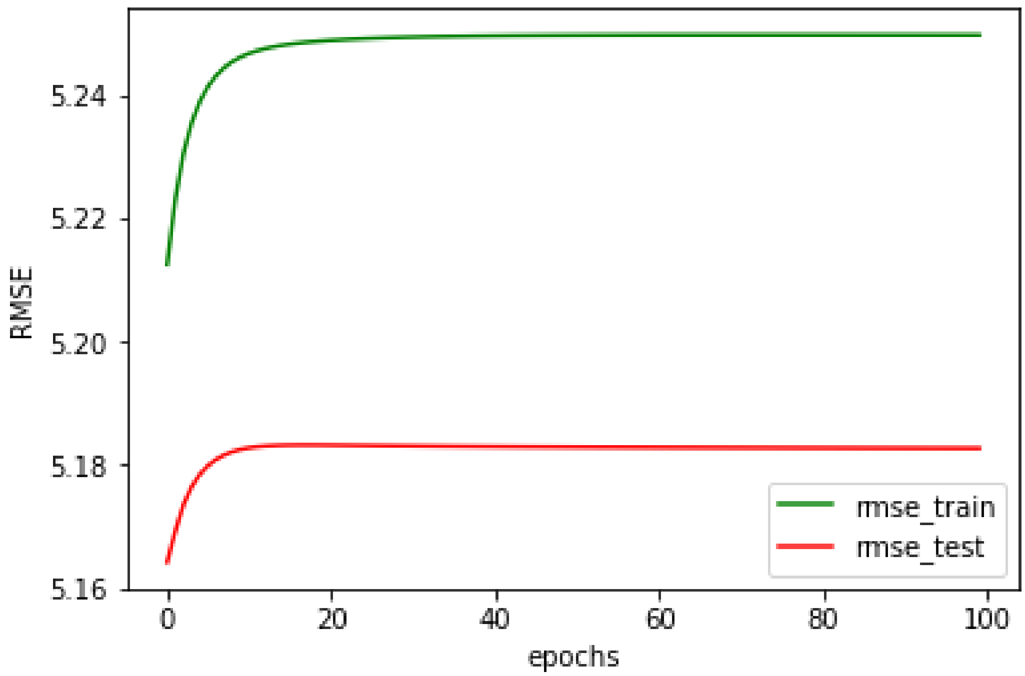


6.0.3 As the learning rate is too high that why the rmse values increased

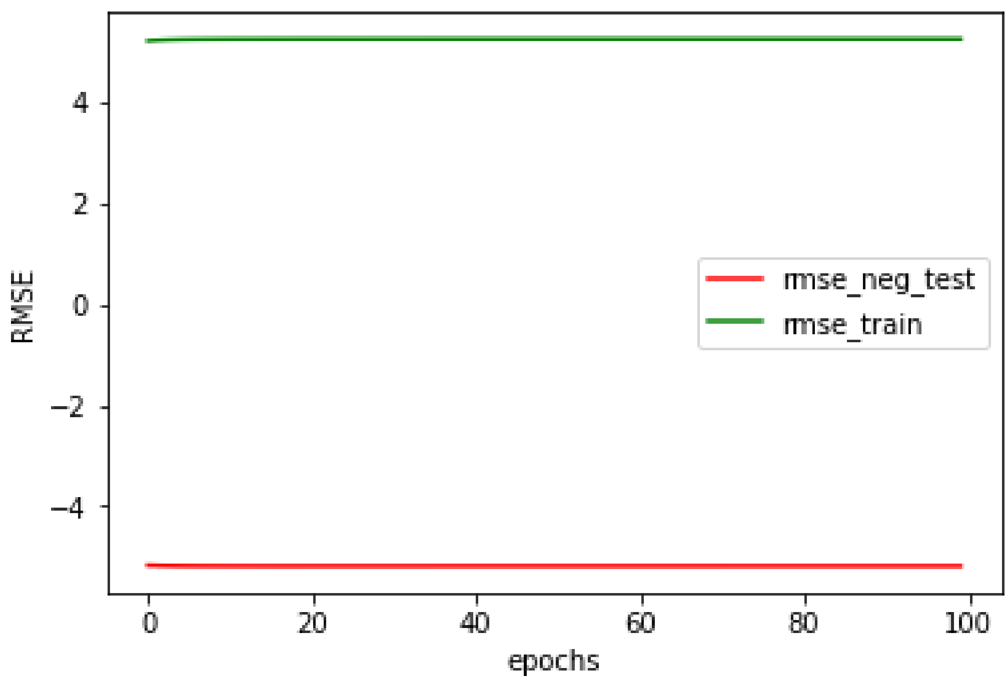
```
In [343]: lr=0.001
          epochs=100
          lamda=0.5

          sgd=stochastic_gradient_descent(x_train_rwine,y_train_rwine,lr,epochs,lamda,x_test_rw

epochs: 0 loss: 0.10771665167445477 rmse test: 5.164264008947285 rmse train: 5.212475398776306
epochs: 10 loss: 0.005909533382872922 rmse test: 5.182808901152875 rmse train: 5.24665942247505
epochs: 20 loss: 0.0009578484993255643 rmse test: 5.183234548612397 rmse train: 5.248788510066
epochs: 30 loss: 0.0003445648024111847 rmse test: 5.183103146181624 rmse train: 5.249312919481
epochs: 40 loss: 0.00014532184482973776 rmse test: 5.183001372876649 rmse train: 5.2495232348
epochs: 50 loss: 5.8955354269585314e-05 rmse test: 5.182927705884194 rmse train: 5.24961093582
epochs: 60 loss: 2.0754388341259755e-05 rmse test: 5.182872071018055 rmse train: 5.24964464413
epochs: 70 loss: 4.09833970493878e-06 rmse test: 5.182828660014807 rmse train: 5.24965459002484
epochs: 80 loss: 2.8008884029873116e-06 rmse test: 5.182794184899615 rmse train: 5.24965437999
epochs: 90 loss: 5.255175157259373e-06 rmse test: 5.182766610367428 rmse train: 5.24965019979
```



RMSE
5.24
5.22
5.20
5.18
5.16
0
20
40
60
80
100
epochs
rmse_train
rmse_test



RMSE
4
2
0
−2
−4
0
20
40
60
80
100
epochs
rmse_neg_test
rmse_train

7 Ridge Regression using mini-Batch Gradient Descent using the Wine quality WHITE dataset

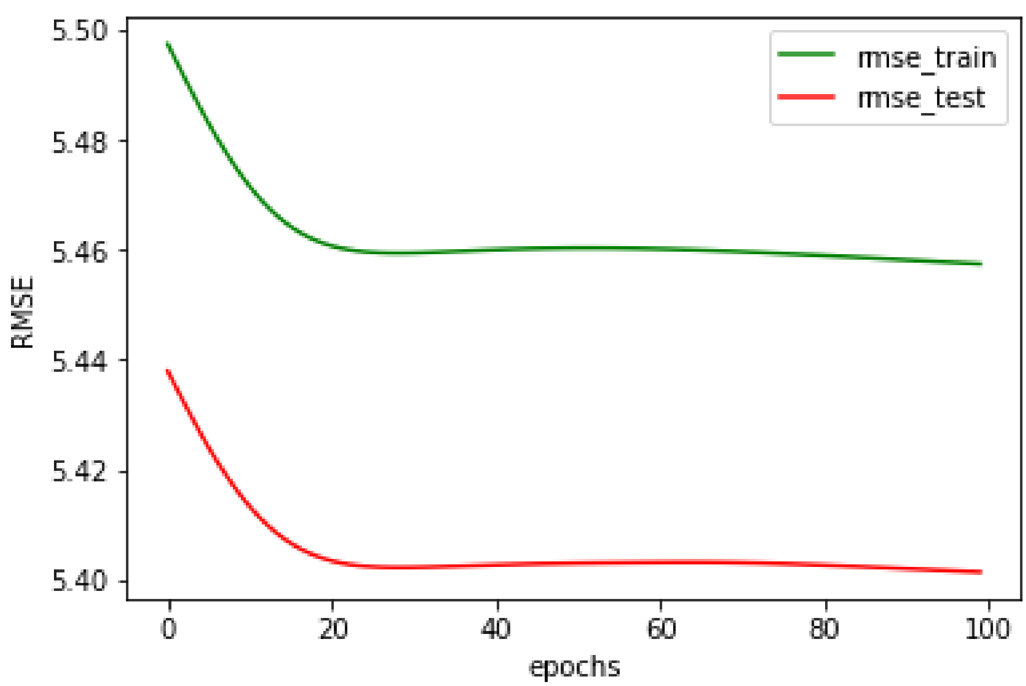
Training the wine quality white data and plotting the rmse values for three combinations of alpha and lamda values

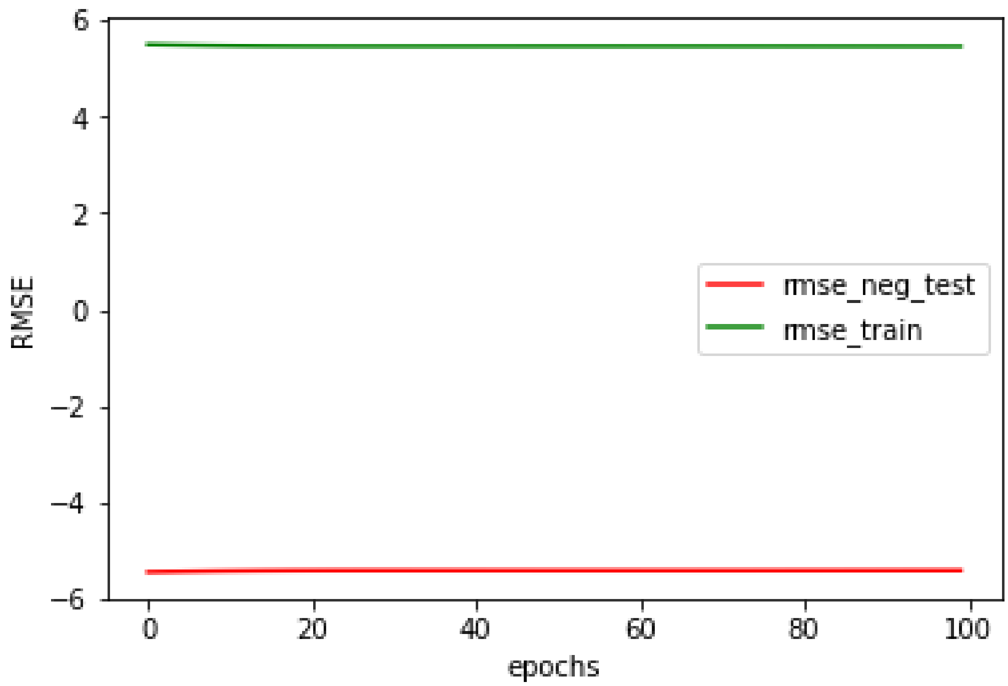
7.0.1 The first two combinations of Alpha(lr) and lamda displayed decreasing rmse but the model is not optimal as there is a gap between rmse train and rmse test

In [344]:
```
lr=0.00001
epochs=100
lamda=0.00000001

sgd=stochastic_gradient_descent(x_train_wwine,y_train_wwine,lr,epochs,lamda,x_test_ww
```

```
epochs: 0 loss: 0.03280442703835362 rmse test: 5.437965844930234 rmse train: 5.497458231222561
epochs: 10 loss: 0.021652877313009355 rmse test: 5.4133057526177035 rmse train: 5.471538162042
epochs: 20 loss: 0.005101611126974603 rmse test: 5.403431619368905 rmse train: 5.46071620338700
epochs: 30 loss: 0.0002758226316856849 rmse test: 5.402254597120471 rmse train: 5.4594488144393
epochs: 40 loss: 0.0006306304975609578 rmse test: 5.4026970433745225 rmse train: 5.460028010449
epochs: 50 loss: 9.064401385572296e-05 rmse test: 5.403020498746178 rmse train: 5.4603460765052
epochs: 60 loss: 0.0003882261440431023 rmse test: 5.403159204455013 rmse train: 5.4601730993107
epochs: 70 loss: 0.0006709203601715785 rmse test: 5.403104985917543 rmse train: 5.4596617023617
epochs: 80 loss: 0.0008078085709080085 rmse test: 5.402652109212518 rmse train: 5.4589696608835
epochs: 90 loss: 0.0008564837452702534 rmse test: 5.4020117602035045 rmse train: 5.458200285018
```

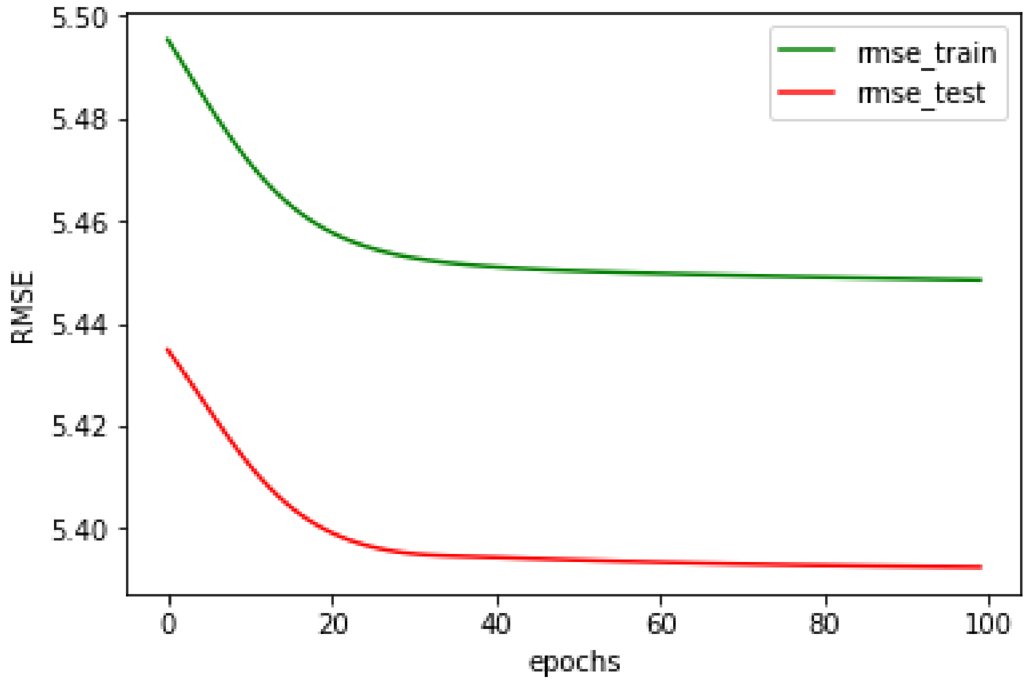


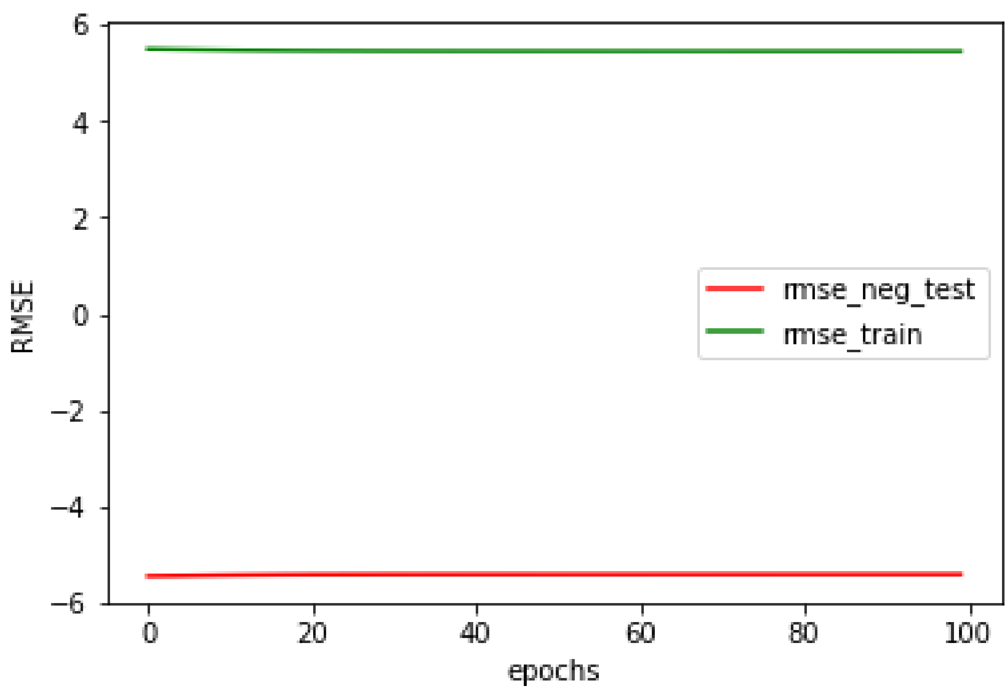



```
In [345]: lr=0.00001
          epochs=100
          lamda=0.001

          sgd=stochastic_gradient_descent(x_train_wwine,y_train_wwine,lr,epochs,lamda,x_test_ww
```

```
epochs: 0 loss: 0.02750199731630687 rmse test: 5.434855572836458 rmse train: 5.495391962871424
epochs: 10 loss: 0.022515041212358256 rmse test: 5.412345873793623 rmse train: 5.47130589243433
epochs: 20 loss: 0.009306422585112273 rmse test: 5.39918958422557 rmse train: 5.45774152470996
epochs: 30 loss: 0.003146960744768279 rmse test: 5.39508591012017 rmse train: 5.45279237417608
epochs: 40 loss: 0.0012215630958323231 rmse test: 5.394387763837499 rmse train: 5.4510573841308
epochs: 50 loss: 0.0006637598153744761 rmse test: 5.393873827178325 rmse train: 5.4502662082622
epochs: 60 loss: 0.000470282918687559 rmse test: 5.393437213897484 rmse train: 5.44976832890148
epochs: 70 loss: 0.0003865714110098395 rmse test: 5.393098538824459 rmse train: 5.44938369693277
epochs: 80 loss: 0.0003430798249439704 rmse test: 5.3928404250082425 rmse train: 5.449052792110
epochs: 90 loss: 0.00031617047243059915 rmse test: 5.39263806864584 rmse train: 5.44875233777787
```


rmse_train
rmse_test
RMSE
epochs
5.50
5.48
5.46
5.44
5.42
5.40
0
20
40
60
80
100

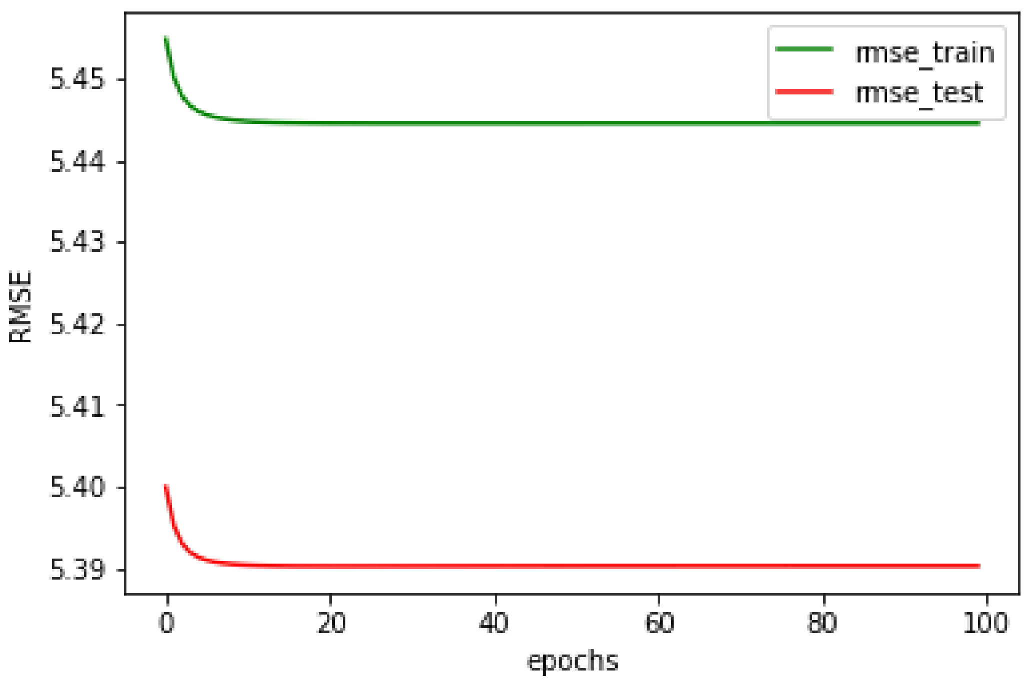

rmse_neg_test
rmse_train
RMSE
epochs
6
4
2
0
−2
−4
−6
0
20
40
60
80
100

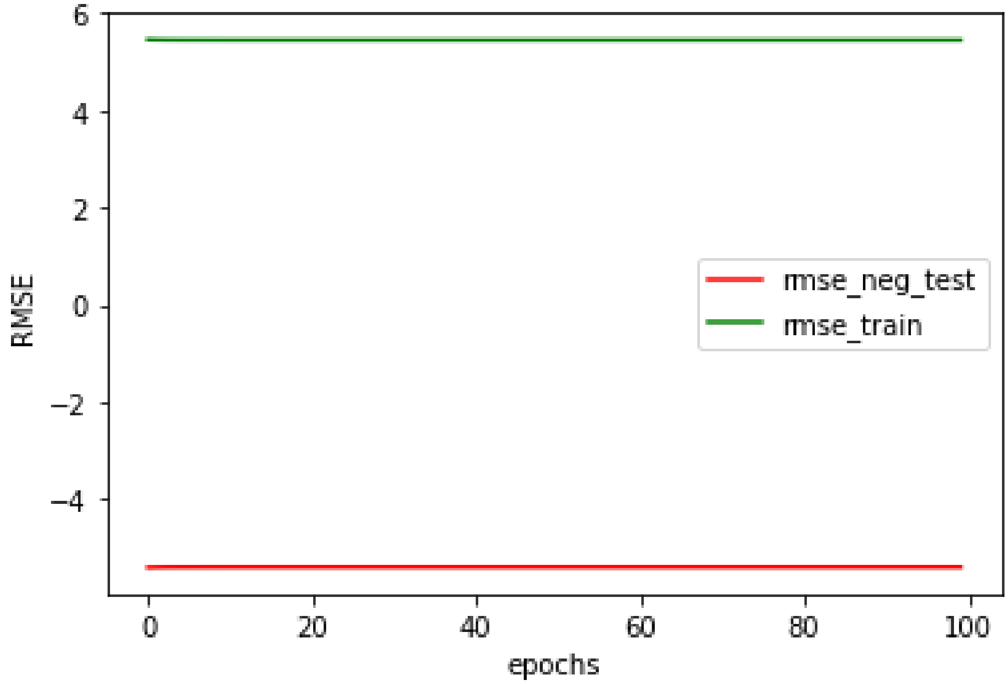
7.0.2 Due to high value of lamda the model is not optimal

In [302]:
```
lr=0.001
epochs=100
lamda=0.5

sgd=stochastic_gradient_descent(x_train_wwine,y_train_wwine,lr,epochs,lamda,x_test_ww
```

```
epochs: 0 loss: 0.3069763558754879 rmse test: 5.399939207664042 rmse train: 5.4548055310251335
epochs: 10 loss: 0.0008315851709141953 rmse test: 5.390327987293128 rmse train: 5.444733866663
epochs: 20 loss: 6.631570777670959e-05 rmse test: 5.390194768977441 rmse train: 5.444497304705
epochs: 30 loss: 2.297646947369003e-06 rmse test: 5.390203344655504 rmse train: 5.4444791710688
epochs: 40 loss: 2.429880638032955e-06 rmse test: 5.390214647830223 rmse train: 5.4444805414223
epochs: 50 loss: 1.468457579534288e-06 rmse test: 5.3902206477713674 rmse train: 5.44448233775
epochs: 60 loss: 6.483208210283919e-07 rmse test: 5.390223399707522 rmse train: 5.4444832335111
epochs: 70 loss: 2.5839322148613064e-07 rmse test: 5.390224603054633 rmse train: 5.444483607285
epochs: 80 loss: 9.78192780110021e-08 rmse test: 5.3902251195811255 rmse train: 5.4444837523446
epochs: 90 loss: 3.572495188564062e-08 rmse test: 5.3902253396752275 rmse train: 5.444483806306
```





6
4
2
0
−2
−4
RMSE
0
20
40
60
80
100
epochs
rmse_neg_test
rmse_train