hw4q2

```
In [231]:
             import numpy as np
                import pandas as pd
                import h5py
                import matplotlib.pyplot as plt
   [232]:
             with h5py.File('mnist_traindata.hdf5','r') as f:
                    xdata_train=np. array(f['xdata'])
                    ydata_train=np. array(f['ydata'])
                    y_train=np. zeros(len(ydata_train))
                    for i in range (len (ydata train)):
                        if np.argmax(ydata_train[i])==2:
                            y_train[i]=1
                with h5py. File ('mnist testdata. hdf5', 'r') as f:
                    xdata_test=np. array(f['xdata'])
                    ydata_test=np. array(f['ydata'])
                    y_test=np. zeros(len(ydata_test))
                    for i in range(len(ydata_test)):
                        if np.argmax(ydata_test[i])==2:
                            y \text{ test}[i]=1
                weights=[]
                bias=0
In [233]:
             def sigmoid(z):
                    return 1/(1+np. \exp(-z))
                def binary log loss (W, x, w0, y, reg type=None, lmd=0.1):
                    m=x. shape [0]
                    z=np. dot(x, W)+w0
                    p = sigmoid(z)
                    loss=-np. sum(y*np. log(p)+(1-y)*np. log(1-p))/m
                    if reg type=='11':
                        loss = (lmd/m) *np. sum(np. abs(W))
                    elif reg type=='12':
                        loss = (lmd/(2*m))*np. sum(np. square(W))
                    return loss
```

```
def plt_accuracy_loss(loss_train, loss_test, accuracy_train, accuracy_test, learni
In [234]:
                    plt.figure()
                    plt.plot(loss_train, label='loss train')
                    plt.plot(loss test, label='loss test')
                    plt.xlabel('Iteration Number')
                    plt.ylabel('Log loss')
                    plt.title(f'learning rate{learning_rate}:log loss')
                    plt.legend()
                    plt.show()
                    plt.figure()
                    plt. plot (accuracy_train, label='accuracy train')
                    plt.plot(accuracy_test, label='accuracy test')
                    plt. xlabel ('Iteration Number')
                    plt.ylabel('accuracy')
                    plt.title(f'learning rate{learning_rate}:Accuracy')
                    plt.legend()
                    plt.show()
```

```
In [235]: 
| def print_table(iter_stop, accuracy_train, loss_train, accuracy_test, loss_test, le data={
         'Learning rate':learning_rate,
         'Iter':iter_stop,
         'Accuracy train':accuracy_train,
         'Loss train':loss_train,
         'Accuracy test':accuracy_test,
         'Loss test':loss_test,
         }
         df=pd. DataFrame(data)
         print(df)
```

```
hw4q2 - Jupyter Notebook
In [236]:
             def gradient_descent(W, w0, x_train, x_test, y_train, y_test, learning_rate, max_iter
                     m=x train.shape[0]
                     loss_history_train=[]
                     loss history test=[]
                     accuracy_history_train=[]
                     accuracy history test=[]
                     threshold=1e-4
                     pre loss train=0
                     for iter in range (max_iter):
                         z_train=np. dot(x_train, W)+w0
                         p_train=sigmoid(z_train)
                         #draw initial W w0 --- loss and accuracy of test
                         if iter==0:
                             loss_train=binary_log_loss(W, x_train, w0, y_train, reg_type, lmd)
                             loss_history_train.append(loss_train)
                             loss_test=binary_log_loss(W, x_test, w0, y_test, reg_type, lmd)
                             loss history test. append (loss test)
                             z_{test} = np. dot(x_{test}, W) + w0
                             p_test=sigmoid(z_test)
                             predictions_test=np. where (p_{test}=0.5, 1, 0)
                             accuracy_test=np. mean(predictions_test==y_test)
                             accuracy_history_test.append(accuracy_test)
                         dw=np. dot(x train. T, (p train-y train))/m
                         db=np.sum(p_train-y_train)/m
                         if reg_type=='11':
                             dw = (1md/m) *np. sign(W)
                         elif reg type=='12':
                             dw = (1 \text{md/m}) *W
                         W-=learning rate*dw
                         w0-=learning_rate*db
                         loss train=binary log loss (W, x train, w0, y train, reg type, lmd)
                         loss history train.append(loss train)
                         loss_test=binary_log_loss(W, x_test, w0, y_test, reg_type, lmd)
                         loss_history_test.append(loss_test)
                         predictions_train=np. where (p_train \ge 0.5, 1, 0)
                         accuracy train=np. mean (predictions train==y train)
                         accuracy history train. append (accuracy train)
                         z \text{ test=np. dot}(x \text{ test, W})+w0
                         p_test=sigmoid(z_test)
                         predictions test=np. where (p test>=0.5, 1, 0)
                         accuracy test=np.mean(predictions test==y test)
                         accuracy history test. append (accuracy test)
                         #print(loss train-pre loss train)
                         if np.abs(loss_train-pre_loss_train) < threshold:
                             print(f"Model converged at iter {iter}")
                             break
                         pre_loss_train=loss_train
```

plt_accuracy_loss(loss_history_train, loss_history_test, accuracy_history_tr

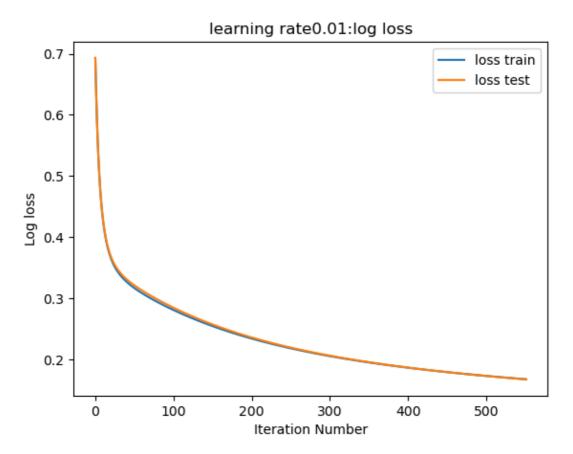
return W, w0, loss_train, loss_test, accuracy_train, accuracy_test, iter

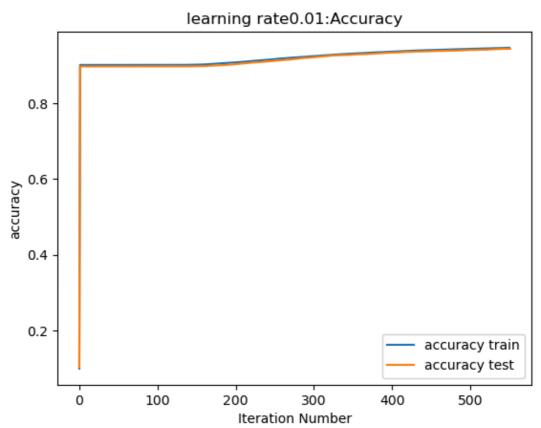
```
[237]:
            def logistic_regression(x_train, x_test, y_train, y_test, max_iter, learning_rates,
In
                    iter_stop=[]
                    final_accuracy_train=[]
                    final_loss_train=[]
                    final accuracy test=[]
                    final_loss_test=[]
                    for learning_rate in learning_rates:
                        n=x_train.shape[1]
                        W=np. zeros (n)
                        w0=0
                        W, w0, loss_train, loss_test, accuracy_train, accuracy_test, iter=gradient_d
                        iter_stop.append(iter)
                        final_accuracy_train.append(accuracy_train)
                        final_loss_train.append(loss_test)
                        final_accuracy_test.append(accuracy_test)
                        final loss test.append(loss train)
                    print_table(iter_stop, final_accuracy_train, final_loss_train, final_accuracy)
             learning_rates=[0.01, 0.1, 1, 2, 3]
```

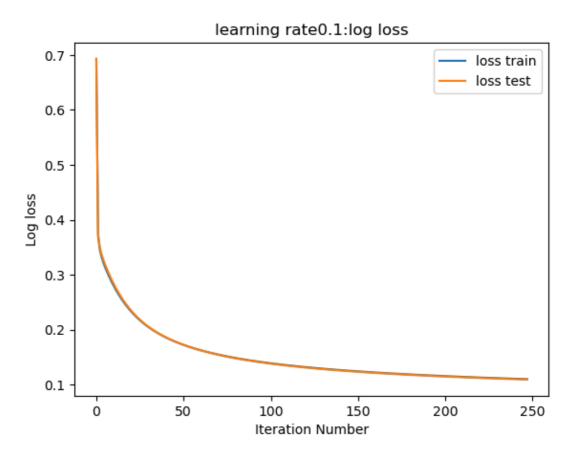
```
In [238]: | learning_rates=[0.01, 0.1, 1, 2, 3] | max_iter=1000 | 1md=0.01
```

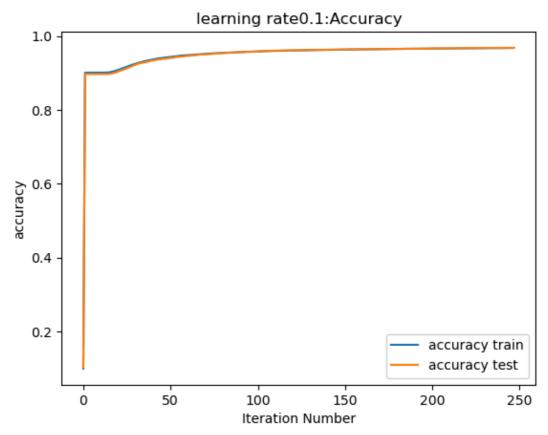
No regulariser

In [239]: Nogistic_regression(xdata_train, xdata_test, y_train, y_test, max_iter, learning_ra



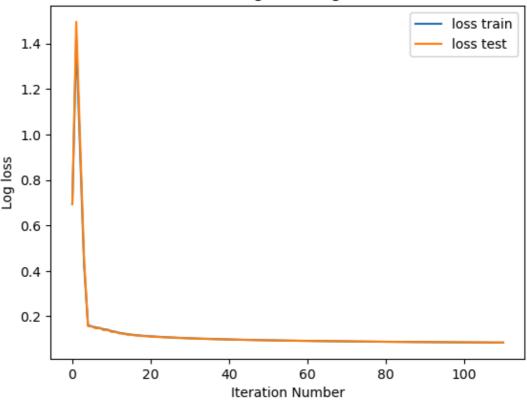




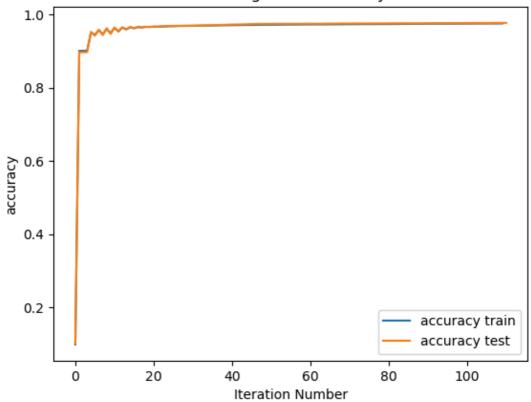


Model converged at iter 109

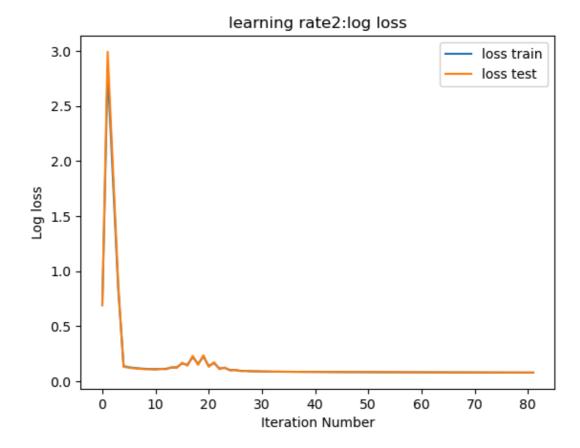
learning rate1:log loss

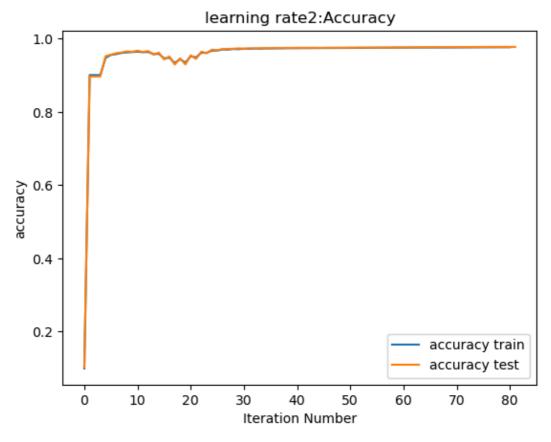


learning rate1:Accuracy



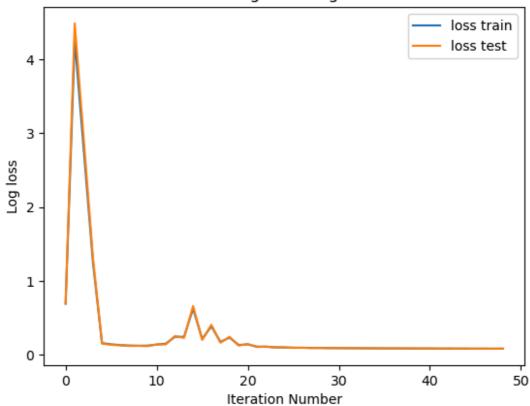
Model converged at iter 80

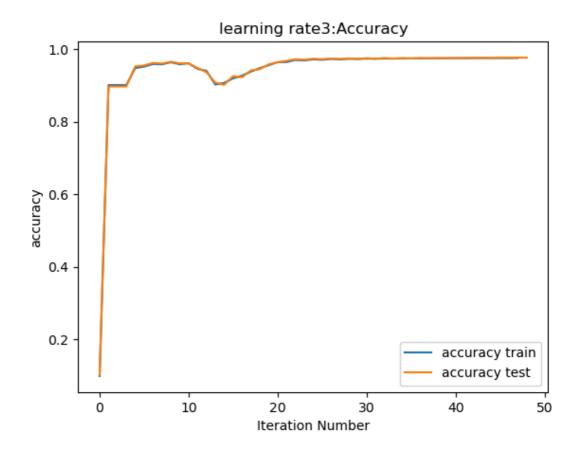




Model converged at iter 47



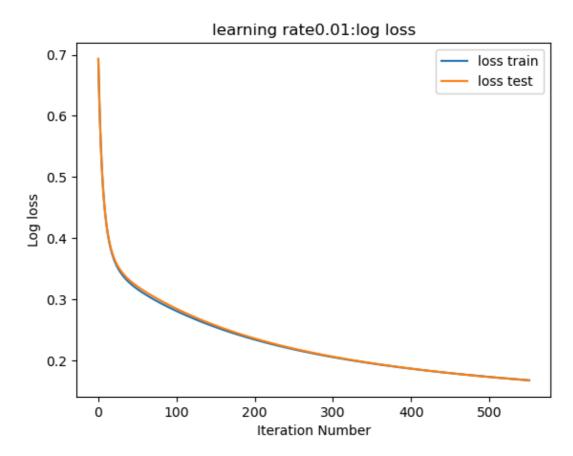


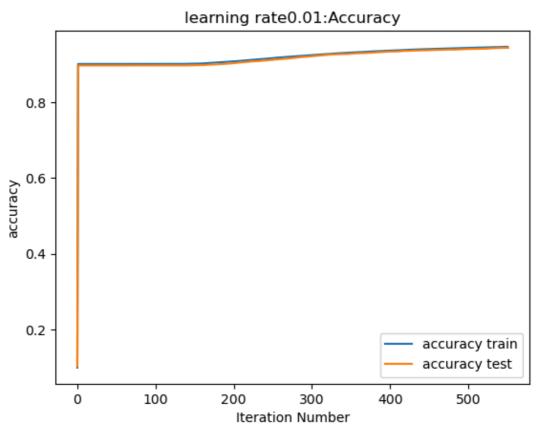


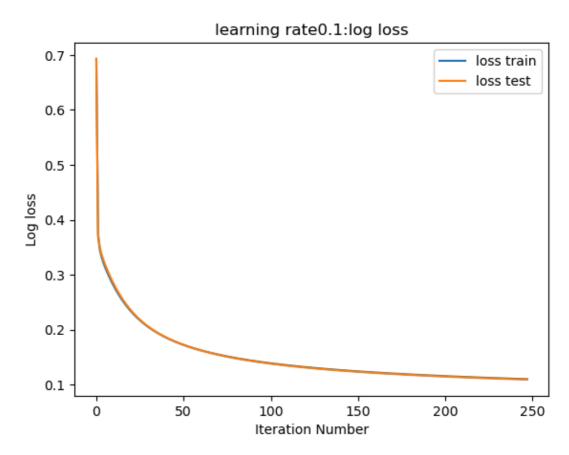
	Learning rate	Iter	Accuracy train	Loss train	Accuracy test	Loss test
0	0.01	550	0.946033	0. 167011	0.9435	0. 167308
1	0.10	246	0.967400	0.108955	0.9679	0.109749
2	1.00	109	0.975217	0.085216	0.9768	0.084703
3	2.00	80	0.976650	0.081529	0.9775	0.080554
4	3.00	47	0. 975333	0.085829	0.9761	0.083927

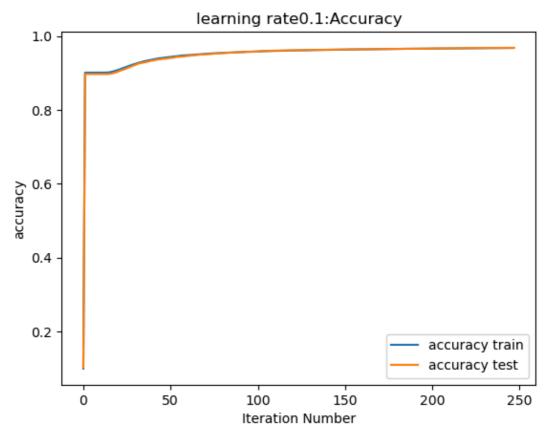
L1 regularization

In [240]: No logistic_regression(xdata_train, xdata_test, y_train, y_test, max_iter, learning_ra



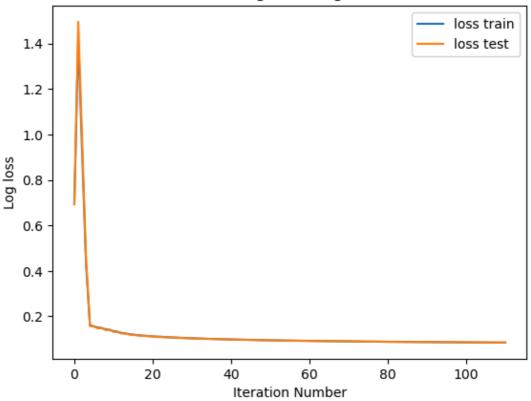




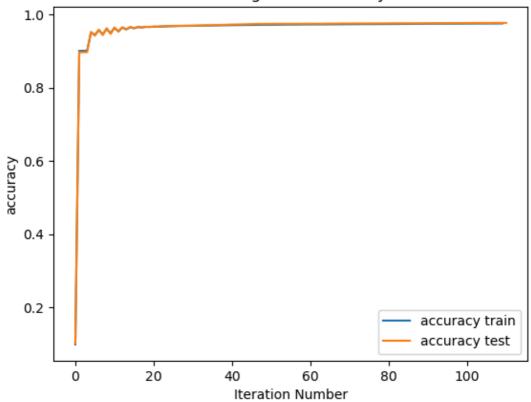


Model converged at iter 109

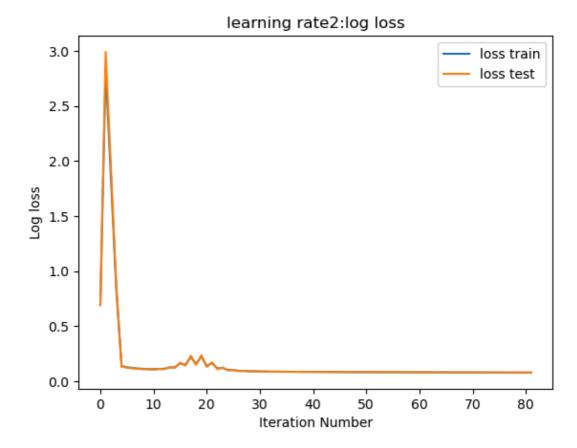
learning rate1:log loss

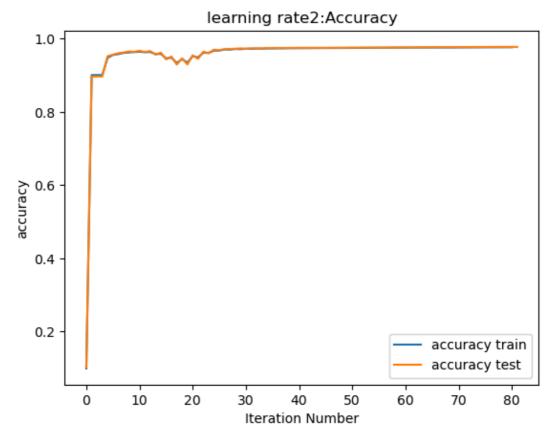


learning rate1:Accuracy



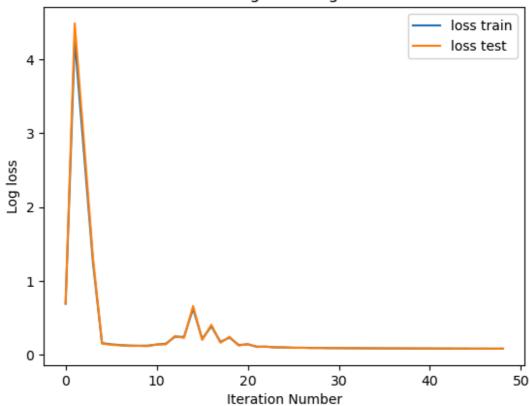
Model converged at iter 80

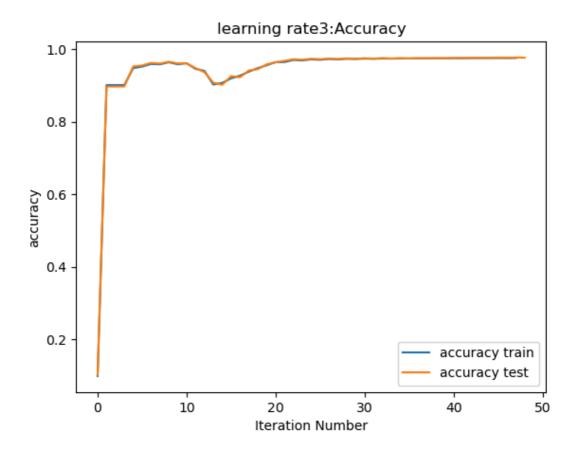




Model converged at iter 47

learning rate3:log loss

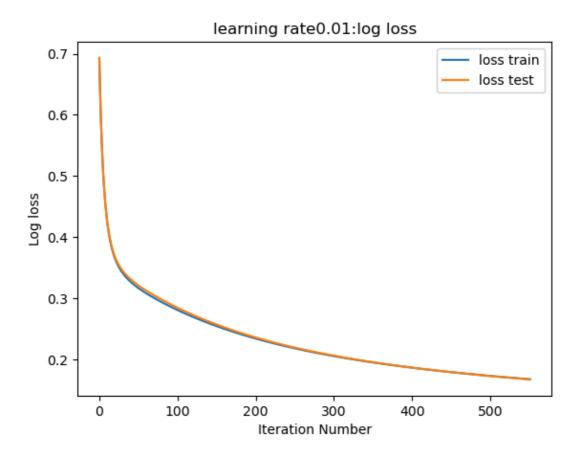


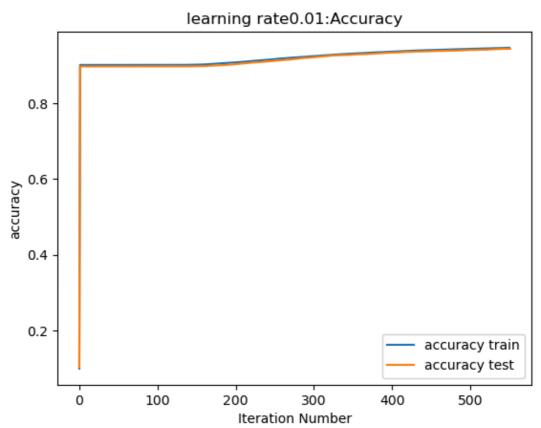


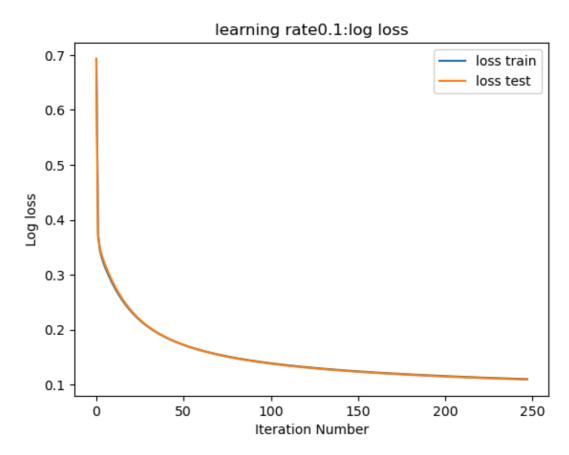
	Learning rate	Iter	Accuracy train	Loss train	Accuracy test	Loss test
0	0.01	550	0.946033	0. 167029	0.9435	0. 167312
1	0.10	246	0.967400	0.108989	0.9679	0.109755
2	1.00	109	0.975217	0.085270	0.9768	0.084714
3	2.00	80	0.976650	0.081593	0.9775	0.080565
4	3.00	47	0. 975333	0.085902	0.9761	0.083939

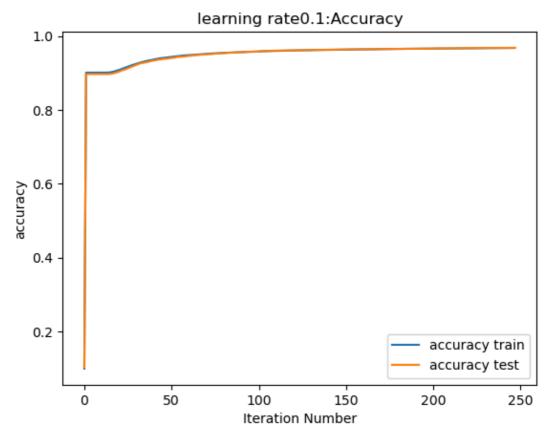
L2 regularization

In [241]: No logistic_regression(xdata_train, xdata_test, y_train, y_test, max_iter, learning_ra



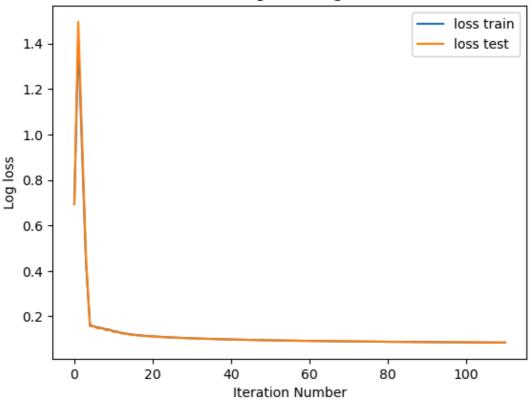




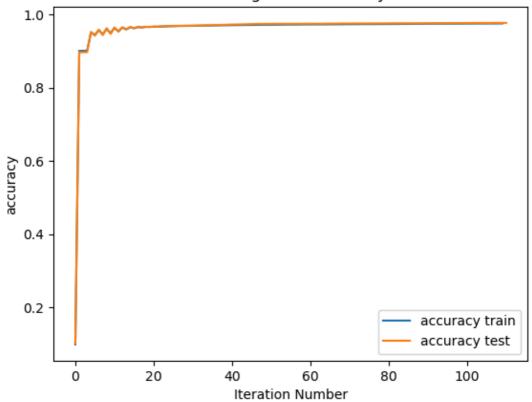


Model converged at iter 109

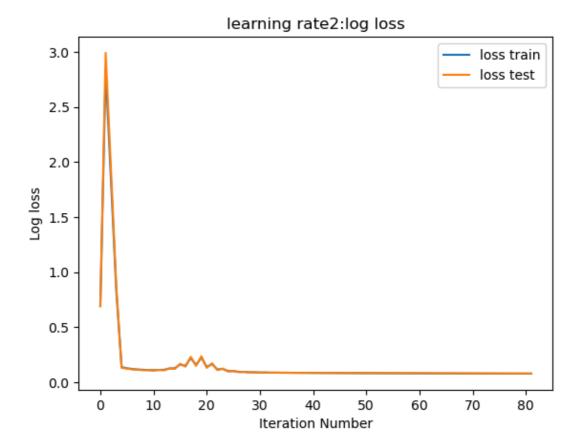
learning rate1:log loss

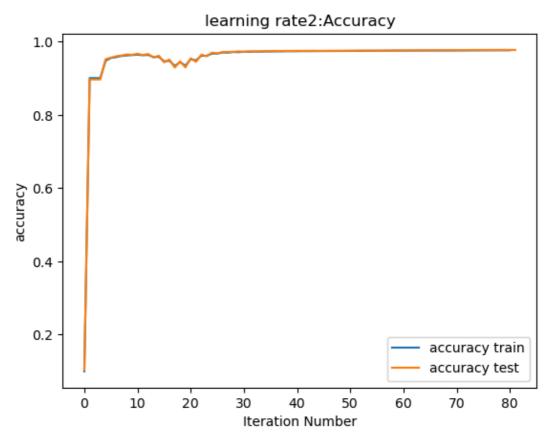


learning rate1:Accuracy



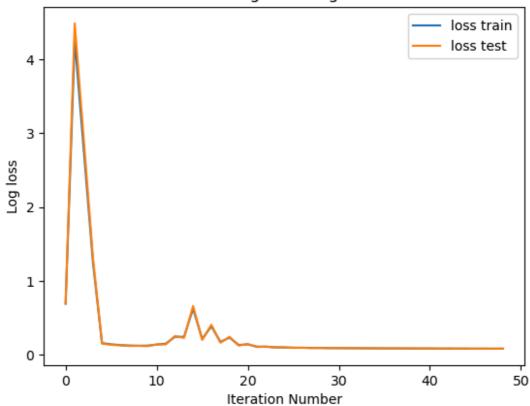
Model converged at iter 80

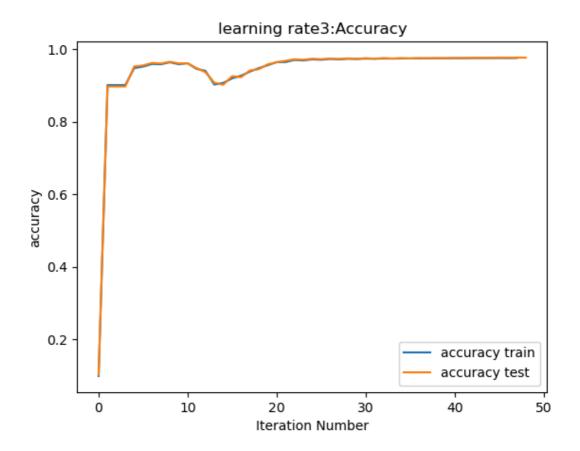




Model converged at iter 47







	Learning rate	Iter	Accuracy train	Loss train	Accuracy test	Loss test
0	0.01	550	0.946033	0. 167011	0.9435	0. 167308
1	0.10	246	0.967400	0.108957	0.9679	0.109749
2	1.00	109	0. 975217	0.085221	0.9768	0.084704
3	2.00	80	0.976650	0.081536	0.9775	0.080555
4	3.00	47	0. 975333	0.085837	0.9761	0.083927

Saving weights and bias to hdf5

```
[250]:
             M
                #pick a best result
                def gradient_descent1(W, w0, x_train, x_test, y_train, y_test, learning_rate, max_ite
                    m=x train.shape[0]
                    threshold=1e-4
                    pre loss train=0
                    for iter in range (max iter):
                        z train=np. dot(x train, W)+w0
                        p_train=sigmoid(z_train)
                         dw=np.dot(x train.T, (p train-y train))/m
                        db=np. sum(p train-y train)/m
                        W-=learning_rate*dw
                        w0-=learning rate*db
                        loss train=binary log loss (W, x train, w0, y train)
                        z test=np. dot(x test, W)+w0
                        p_test=sigmoid(z_test)
                        predictions_test=np. where (p_{test}=0.5, 1, 0)
                        accuracy_test=np. mean(predictions_test==y_test)
                         if np. abs(loss train-pre loss train) < threshold:
                             #print(f"Model converged at iter {iter}")
                        pre_loss_train=loss_train
                    return W, w0
                n=xdata train.shape[1]
                W=np. zeros (n)
                w0 = 0
                W, w0=gradient descent1 (W, w0, xdata train, xdata test, y train, y test, 2, max iter)
In [251]:
                outFile='hw4q2 wb.hd5'
             H
                weight length=784
                assert W. shape[0] == weight length, 'Error: the length is incorrect'
                with h5py. File(outFile, 'w') as hf:
                    hf. create dataset ('w', data = np. asarray (W))
                    hf.create dataset('b', data = np.asarray(w0))
                with h5py. File (outFile, 'r') as hf:
                    w copy=hf['w'][:]
                np. testing. assert array equal (W, w copy)
```

i. How did you determine a learning rate? What values did you try? What was your final value?

I set a list of learning rates (0.01,0.1,1,1.5,2), let the training model running over each of them. And then comparing the final train and test accuracies in a table to see which one performed the best

ii. Describe the method you used to establish model convergence.

I have set a max number of iterations (= 1000). And if the loss no longer change significantly (the change between two successive iterations less than thethreshold), the iteration stops.

iii. What regularizers did you try? Specifically, how did each impact your model or improve its performance?

I tried no regulariser, L1 and L2 regularisers. However, there was no significant difference in the results among the three methods, possibly because there was no over-fitting

iv. Plot log-loss (i.e., learning curve) of the training set and test set on the same figure. On a separate figure plot the accuracy against iteration number of your model on the training set and test set. Plot each as a function of the iteration number.

Plots have been given above.

v. Clasify each input to the binary output "digit is a 2" using a 0.5 threshold. Compute the final loss and final accuracy for both your training set and test set.

The data is given in the table above.