logistic_regression-for-apple detection

November 6, 2017

```
In [25]: %matplotlib inline
         import matplotlib.pyplot as plt
         import numpy as np
         import random
         import torch
         from torch.autograd import Variable
         import torch.nn
```

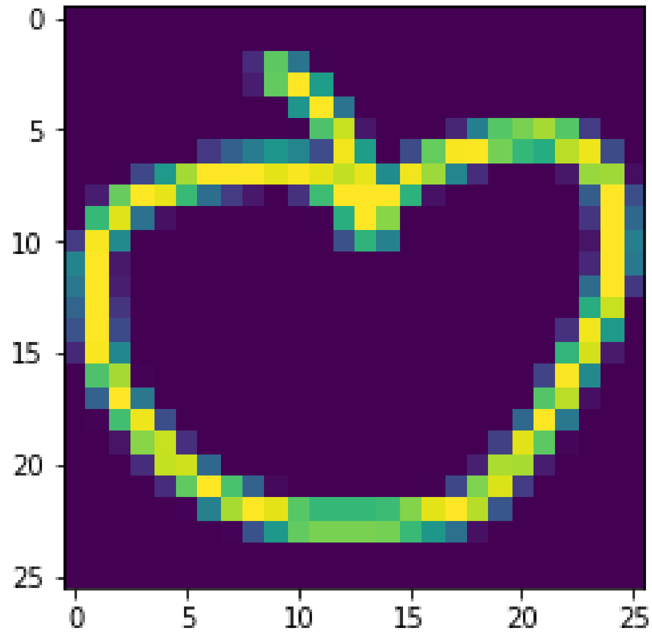
```
In [26]: images=np.load('data/images.npy')
         labels=np.load('data/labels.npy')
         labels=labels.astype(int)
         labels[labels!=0]=-1
         labels[labels==0]=1
         labels[labels==-1]=0
```

0.0.1 Number of apples in the test set = 10000

```
In [27]: apples=images[labels==1]
         print(len(apples))
         plt.imshow(apples[0])
```

```
10000
```

```
Out[27]: <matplotlib.image.AxesImage at 0x121a4eac8>
```



0.1 Flattening and normalizing the image

```
In [28]: shape_images_flat=(images.shape[0],images.shape[1]*images.shape[2])
         images_flat=np.ndarray(shape=shape_images_flat)
         for index in range(len(images)):
             images_flat[index]=images[index].flat
         images=(images_flat-images_flat.mean())/images.std()
```

```
In [29]: train_images=images[0:40000]
         train_labels=labels[0:40000]

         validation_images=images[40000:45000]
         validation_labels=labels[40000:45000]

         test_images=images[45000:50000]
         test_labels=labels[45000:50000]
```

1 Accuracy function

```
In [30]: def accuracy(y, y_hat):
             """Compute accuracy.
             Args:
             y: A 1-D int NumPy array.
             y_hat: A 1-D int NumPy array.
             Returns:
```

```
        A float, the fraction of time y[i] == y_hat[i].
        """

        a=(y==y_hat)
        return a.astype(np.float).mean()
```

2 Computes Accuracy Graph for training and validation

```
In [31]: training_accuracy_list=[]
         validation_accuracy_list=[]
         def compute_accuracy_graph(W):
             train_images_len=len(train_images)
             train_shuffler_list=list(range(0, train_images_len))
             random.shuffle(train_shuffler_list)
             shuffled_train_images=train_images[train_shuffler_list]
             shuffled_train_labels=train_labels[train_shuffler_list]

             shuffled_train_images_used=shuffled_train_images[0:1000]
             shuffled_train_labels_used=shuffled_train_labels[0:1000]

             d_train=shuffled_train_images_used.dot(W)
             d_train[d_train>0]=1
             d_train[d_train<=0]=0


             ac_train=accuracy(shuffled_train_labels_used,d_train)
             training_accuracy_list.append(ac_train)


             validation_images_len=len(validation_images)
             validation_shuffler_list=list(range(0, validation_images_len))
             random.shuffle(validation_shuffler_list)
             shuffled_validation_images=validation_images[validation_shuffler_list]
             shuffled_validation_labels=validation_labels[validation_shuffler_list]

             shuffled_validation_images_used=shuffled_validation_images[0:5000]
             shuffled_validation_labels_used=shuffled_validation_labels[0:5000]

             d_validation=shuffled_validation_images_used.dot(W)
             d_validation[d_validation>0]=1
             d_validation[d_validation<=0]=0

             ac_validation=accuracy(shuffled_validation_labels_used,d_validation)
             validation_accuracy_list.append(ac_validation)
```

3 Logistic Code

```
In [32]: I=5
         learning_rate=.0001
         reg=0.001
```

```
In [22]: X=train_images
         Y=train_labels

         W_tensor=torch.torch.DoubleTensor(X.shape[1]).zero_()
         W_tensor=Variable(W_tensor,requires_grad=True)
         number_of_images=train_images.shape[0]
         t=0
         m = np.zeros(X.shape[1], dtype=np.float)
         v = np.zeros(X.shape[1], dtype=np.float)

         M_tensor=torch.torch.DoubleTensor(X.shape[1]).zero_()
         V_tensor=torch.torch.DoubleTensor(X.shape[1]).zero_()

         M_tensor=Variable(M_tensor,requires_grad=False)
         V_tensor=Variable(V_tensor,requires_grad=False)

         for epoch in range(0,I):
             for i in range(0,number_of_images):
                 x_tensor=Variable(torch.from_numpy(X[i]),requires_grad=False)
                 w_x=torch.dot(x_tensor,W_tensor)
                 w_x=torch.sigmoid(w_x)
                 esp1, esp2 = 1e-5,1e5
                 J=(float(Y[i]))*torch.log(w_x.clamp(esp1,esp2))+(1-float(Y[i]))*torch.log((1-w
                 J.backward()
                 W_tensor.data += learning_rate * W_tensor.grad.data

                 if(i%100==0):
                     compute_accuracy_graph(W_tensor.data.numpy())

                 # Manually zero the gradients after updating weights
                 W_tensor.grad.data.zero_()

         weights_now=W_tensor.data.numpy()
```

4 Compute test accuracy

```
In [23]: X=test_images
         y=test_labels
         d=X.dot(weights_now)
         d[d>0]=1
         d[d<=0]=0
```

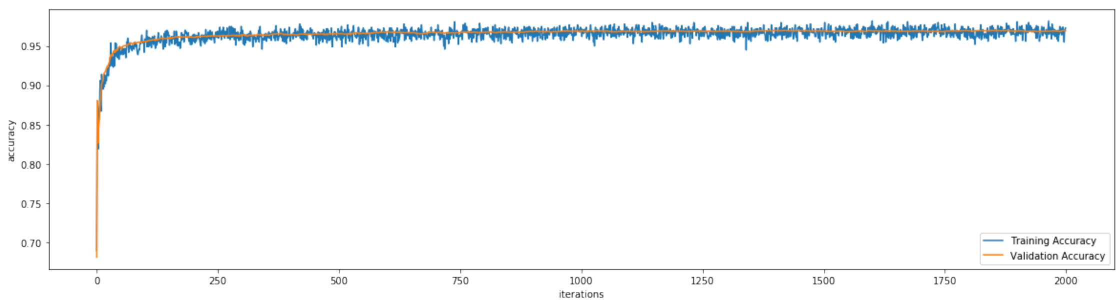
```
ac=accuracy(y,d)
print(ac)
```

```
0.9698
```

5 Plot Computation Graph for cross valiadation and training

In [24]:
```
plt.figure(figsize=(20, 5))
plt.xlabel('iterations')
plt.ylabel('accuracy')
training_accuracy_line,=plt.plot(training_accuracy_list,label='Training Accuracy')
validation_accuracy_line,=plt.plot(validation_accuracy_list,label='Validation Accuracy
plt.legend(handles=[training_accuracy_line, validation_accuracy_line])
```

Out[24]:
```
<matplotlib.legend.Legend at 0x12196ce10>
```



I am not overfitting here as there both the cross-validation and the traing accuracy follow each other quite smoothly, if i was overfitting, though my traing would shoot up but would lead to decrease in validation accuracy

Also, because this is a linear model on a non linearly seprable there is not much scope of over fitting.