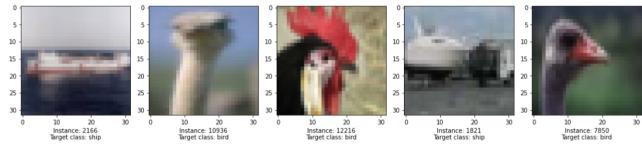
EE460J Lab 4

Lab Group Members: Tatsushi Matsumoto, Nick Taylor, Matthew Withey

```
In [1]: import matplotlib.pyplot as plt
   import numpy as np
   import pandas as pd
   import random
   from sklearn.linear_model import LogisticRegression as LR
   from sklearn.model_selection import train_test_split as TTS
   from sklearn.model_selection import cross_val_score
   from sklearn.model_selection import KFold
   from sklearn.model_selection import GridSearchCV
   from sklearn.model_selection import RandomizedSearchCV
   from sklearn.model_selection import RandomizedSearchCV
```

```
In [2]: cifar = fetch_openml('CIFAR_10_Small')
           cifar.data
Out[2]:
                              a1
                                      a2
                                             а3
                                                     а4
                                                            а5
                                                                   а6
                                                                           а7
                                                                                  а8
                                                                                          а9
                                                                                                  a3062
                                                                                                          a3063
                                                                                                                  a3064
                                                                                                                          a3065
                                                                                                                                  a3066
                                                                                                                                          a3067
                                                                                                                                                  a306
                     59.0
                             43.0
                                    50.0
                                            68.0
                                                                        145.0
                                                                               149.0
                                                                                       149.0
                                                   98.0
                                                         119.0
                                                                 139.0
                                                                                                    59.0
                                                                                                            58.0
                                                                                                                    65.0
                                                                                                                            59.0
                                                                                                                                    46.0
                                                                                                                                            57.0
                           126.0
                                   105.0
                                          102.0
                                                  125.0
                                                         155.0
                                                                 172.0
                                                                        180.0
                                                                               142.0
                                                                                       111.0
                                                                                                    22.0
                                                                                                            42.0
                                                                                                                           101.0
                                                                                                                                   122.0
                    154.0
                                                                                                                    67.0
                                                                                                                                           133.0
                                                                                                                                                   136
                    255.0
                           253.0
                                   253.0
                                          253.0
                                                  253.0
                                                         253.0
                                                                 253.0
                                                                        253.0
                                                                               253.0
                                                                                       253.0
                                                                                                    78.0
                                                                                                            83.0
                                                                                                                    0.08
                                                                                                                            69.0
                                                                                                                                    66.0
                                                                                                                                            72.0
                     28.0
                             37.0
                                    38.0
                                            42.0
                                                   44.0
                                                          40.0
                                                                  40.0
                                                                         24.0
                                                                                32.0
                                                                                        43.0
                                                                                                    53.0
                                                                                                            39.0
                                                                                                                    59.0
                                                                                                                            42.0
                                                                                                                                    44.0
                                                                                                                                            48.0
                                                                                                                                                   38
                    170.0
                           168.0
                                   177.0
                                          183.0
                                                  181.0
                                                         177.0
                                                                 181.0
                                                                        184.0
                                                                               189.0
                                                                                       189.0
                                                                                                    92.0
                                                                                                            0.88
                                                                                                                    85.0
                                                                                                                            82.0
                                                                                                                                    83.0
                                                                                                                                            79.0
                                                                                                                                                   78
                     76.0
                                                                         76.0
                                                                                                           185.0
                                                                                                                   177.0
            19995
                             76.0
                                    77.0
                                           76.0
                                                   75.0
                                                          76.0
                                                                  76.0
                                                                                76.0
                                                                                        78.0
                                                                                                   228.0
                                                                                                                          223.0
                                                                                                                                  239.0
                                                                                                                                          239.0
                                                                                                                                                  235
                                                  108.0
                                                                                0.88
                                                                                                   126.0
                                                                                                           107.0
            19996
                     81.0
                             91.0
                                    98.0
                                          106.0
                                                         110.0
                                                                  80.0
                                                                         84.0
                                                                                        90.0
                                                                                                                   143.0
                                                                                                                           155.0
                                                                                                                                   156.0
                                                                                                                                          160.0
                                                                                                                                                   173
                                                                                         9.0 ...
            19997
                     20.0
                             19 0
                                    15.0
                                            15.0
                                                   14 0
                                                          13.0
                                                                  12 0
                                                                         11 0
                                                                                 10.0
                                                                                                   114 0
                                                                                                           112.0
                                                                                                                    68.0
                                                                                                                            50.0
                                                                                                                                    52.0
                                                                                                                                            52 0
                                                                                                                                                   51
                                    23.0
                                            17.0
                                                   23.0
                                                                  74.0
                                                                                114.0
                                                                                      137.0
                                                                                                    87.0
                                                                                                            84.0
                                                                                                                    83.0
                                                                                                                            84.0
                                                                                                                                    79.0
                                                                                                                                            78.0
            19998
                     25.0
                             15.0
                                                          51.0
                                                                         91.0
                                                                                                                                                   78
            19999
                     73.0
                             98.0
                                    99.0
                                            77.0
                                                   59.0
                                                         146.0
                                                                214.0
                                                                       176.0
                                                                               125.0 218.0
                                                                                                            89.0
                                                                                                                    0.88
                                                                                                                            85.0
                                                                                                                                    93.0
                                                                                                                                            93.0
                                                                                                                                                    90
           20000 rows × 3072 columns
```

```
In [3]: # prints five random images from cifar 10 small
        def print five images():
            classes = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck']
            plt.figure(figsize=(15,10))
            for i in range(5):
                index = random.randint(0, 20000)
                im = cifar.data.loc[index,:]
                im = np.array(im).astype(int)
                im = np.reshape(im, (3, 32, 32))
                im = im.T
                im = np.fliplr(im)
                im = np.rot90(im)
                plt.subplot(1,5, i+1)
                plt.xlabel('Instance: ' + str(index) + '\nTarget class: ' + classes[int(cifar.target.loc[index])]
                plt.imshow(im)
             plt.tight_layout()
            plt.show()
        print_five_images()
```



```
In [4]: train_img, test_img, train_lbl, test_lbl = TTS(cifar.data, cifar.target, test_size=0.25, random_state=0)
    print(train_img.shape)
    print(test_img.shape)
    print(test_lbl.shape)

(15000, 3072)
    (15000,)
    (5000, 3072)
    (5000,)
```

Logistic Regression, L1

```
In [5]: def find_best_C_and_Accuracy_L1():
        C_values = [10000, 1000, 10, 10, 1, 0.1, 0.01, 0.001, 0.0001]
        grid = dict(C =C_values, multi_class=['multinomial'], solver=['saga'], tol=[0.1], penalty=['l1'], ver
        cv = KFold(n_splits=4)
        clf = LR()
        grid_search = GridSearchCV(estimator=clf, param_grid=grid, n_jobs=-1, cv=cv)
        results = grid_search.fit(train_img, train_lbl)
        print('Best for L1 penalty: accuracy of ' + str(np.round(results.best_score_, 5)) + ' using regulariz
        return results

best_L1 = find_best_C_and_Accuracy_L1()

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.

convergence after 6 epochs took 31 seconds
Best for L1 penalty: accuracy of 0.38653 using regularization coefficient 10

[Parallel(n_jobs=1)]: Done 1 out of 1 | elapsed: 30.5s finished
```

```
In [6]: L1 scores = pd.DataFrame.from dict(best L1.cv results )
         L1 scores.drop(L1_scores.columns.difference(['param_C', 'mean_test_score']), 1, inplace=True)
         L1_scores
         C:\Users\mgwit\AppData\Local\Temp/ipykernel 29888/2927872455.py:2: FutureWarning: In a future version o
         f pandas all arguments of DataFrame.drop except for the argument 'labels' will be keyword-only
           L1 scores.drop(L1 scores.columns.difference(['param C', 'mean test score']), 1, inplace=True)
Out[6]:
            param_C mean_test_score
                            0.384800
               10000
         n
                1000
                            0.384333
          1
                            0.384600
         2
                100
                            0.386533
          3
                 10
                            0.385800
                  1
                 0.1
                            0.384133
                0.01
                            0.385067
               0.001
                            0.384400
```

Logistic Regression, L2

0.324733

0.0001

```
In [7]: def find_best_C_and_Accuracy_L2():
        C_values = [10000, 1000, 100, 10, 1, 0.1, 0.01, 0.001, 0.0001]
        grid = dict(C = C_values, multi_class=['multinomial'], solver=['saga'], tol=[0.1], penalty=['l2'], ver
        cv = KFold(n_splits=4)
        clf = LR()
        grid_search = GridSearchCV(estimator=clf, param_grid=grid, n_jobs=-1, cv=cv)
        results = grid_search.fit(train_img, train_lbl)
        print('Best for L2 penalty: accuracy of ' + str(np.round(results.best_score_, 5)) + ' using regulariz
        return results

best_L2 = find_best_C_and_Accuracy_L2()

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.

convergence after 5 epochs took 9 seconds
        Best for L2 penalty: accuracy of 0.38673 using regularization coefficient 0.0001

[Parallel(n_jobs=1)]: Done 1 out of 1 | elapsed: 9.0s finished
```

```
Problems 1 and 4 - Jupyter Notebook
In [8]: L2 scores = pd.DataFrame.from dict(best L2.cv results )
         L2 scores.drop(L2 scores.columns.difference([ param C', 'mean test score']), 1, inplace=True)
         L2_scores
         C:\Users\mgwit\AppData\Local\Temp/ipykernel 29888/2948191753.py:2: FutureWarning: In a future version o
         f pandas all arguments of DataFrame.drop except for the argument 'labels' will be keyword-only
           L2 scores.drop(L2 scores.columns.difference(['param C', 'mean test score']), 1, inplace=True)
Out[8]:
            param_C mean_test_score
                            0.384867
         n
               10000
          1
                1000
                            0.382800
                            0.385200
         2
                 100
                            0.384067
          3
                 10
                            0.385533
                  1
                 0.1
                            0.382867
                0.01
                            0.384933
               0.001
                            0.384400
              0.0001
                            0.386733
In [9]: def get_loss():
             loss = np.zeros((20000, 2))
             prob_L1 = best_L1.predict_proba(cifar.data)
             prob_L2 = best_L2.predict_proba(cifar.data)
             y = cifar.target
             for i in range(20000):
                 loss[i][0] = -1*np.log2(prob_L1[i, int(y[i])])
                 loss[i][1] = -1*np.log2(prob_L2[i, int(y[i])])
             return pd.DataFrame(loss, columns=['Loss L1', 'Loss L2'])
         loss = get_loss()
         loss
Out[9]:
                 Loss L1
                         Loss L2
             0 1.256518 1.319383
             1 4.885300 4.741637
             2 0.824077 0.864509
               3.114602 3.068512
             4 3.222210 3.446920
          19995 2.386389 2.404187
          19996 2 082095 2 246407
          19997 1.900496 1.785703
          19998 3.938400 4.046385
```

20000 rows × 2 columns

19999 1.550887 1.718308

```
In [10]: def get non zeroes(w, threshold):
             count = 0
             for i in range(len(w)):
                 if w[i] > threshold :
                     count = count + 1
             return count
         def show sparsity():
             sparsity = np.zeros((10,3))
             threshold = [0,0.1,0.01,0.001,0.0001,0.00001,0.000001,0.0000001,0.00000001]
             w_L1 = best_L1.best_estimator_.coef_.ravel()
             w_L2 = best_L2.best_estimator_.coef_.ravel()
             for i in range(10):
                 w_L1_non_zeros = get_non_zeroes(w_L1, threshold[i])
                 w_L2_non_zeros = get_non_zeroes(w_L2, threshold[i])
                 sparsity[i][0] = threshold[i]
                 sparsity[i][1] = 1 - (w_L1_non_zeros/len(w_L1))
                 sparsity[i][2] = 1 - (w_L2_non_zeros/len(w_L2))
             sparsity df = pd.DataFrame(sparsity, columns=['Threshold', 'sparsity of L1', 'sparsity of L2'])
             return sparsity df
         sparsity = show_sparsity()
         sparsity
```

Out[10]: Threshold sparsity of L1 sparsity of L2 0 0.000000e+00 0.499447 0.500651 1 1.000000e-01 1.000000 1.000000 2 1.000000e-02 1.000000 1.000000

1.000000e-03

1.000000e-06

 1.000000e-04
 0.890137
 0.902474

 1.000000e-05
 0.548600
 0.554232

1.000000

0.504199

1.000000

0.506055

7 1.000000e-07 0.499870 0.501432 **8** 1.000000e-08 0.499479 0.500684

8 1.000000e-08 0.499479 0.500684 **9** 1.000000e-09 0.499447 0.500651

```
In [11]: def tune random forest cifar 10():
             grid = {
                 'n_estimators': [100, 200, 300],
                 'max_depth': [10, 20, 30],
                 'min_samples_split': [2, 5, 10],
                 'min_samples_leaf': [1, 2, 5],
                 'verbose': [1],
             }
             cv = KFold(n_splits=4)
             rf = ensemble.RandomForestClassifier()
             grid_search = RandomizedSearchCV(estimator=rf, param_distributions=grid, n_jobs=-1, cv=cv, verbose=2)
             results = grid_search.fit(train_img, train_lbl)
             print('Best accuracy of random forest is ' + str(np.round(results.best score_, 5)) + ' using paramete
             return results
         best_random_forest_cifar = tune_random_forest_cifar_10()
         Fitting 4 folds for each of 10 candidates, totalling 40 fits
         [Parallel(n jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
         Best accuracy of random forest is 0.43487 using parameters {'verbose': 1, 'n estimators': 300, 'min sam
         ples split': 10, 'min samples leaf': 2, 'max depth': 20}
         [Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed: 2.0min finished
In [12]: def tune_gb_cifar_10():
             grid = {
                 'n_estimators': [100, 200, 300],
                 'learning_rate': [0.1, 0.5, 1],
                 'max_depth': [10, 20, 30],
                 'verbose': [3],
             cv = KFold(n splits=4)
             gb = ensemble.GradientBoostingClassifier()
             grid_search = RandomizedSearchCV(estimator=gb, param_distributions=grid, n_jobs=-1, cv=cv, verbose=2)
             results = grid search.fit(train img, train lbl)
             print('Best accuracy of gradient boosting is ' + str(np.round(results.best score_, 5)) + ' using para
             return results
         #best_gb_cifar = tune_gb_cifar_10()
```

Gradient Boosting was taking hours to complete and I was not able to produce an accuracy score or best parameters

EE460J Lab 4

Lab Group Members: Tatsushi Matsumoto, Nick Taylor, Matthew Withey

```
In [15]: #Imports
    import matplotlib.pyplot as plt
    import numpy as np
    import pandas as pd
    import sklearn.datasets
    import sklearn.metrics
    from sklearn.model_selection import train_test_split
    from sklearn.model_selection import cross_val_score
    from sklearn.linear_model import LogisticRegressionCV
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.ensemble import GradientBoostingClassifier
```

Problem 1

```
In [ ]:
```

```
In [ ]: #Create train-test split of dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.60)
#Run multiclass logistic regression on split with L2 regularizer
logistic_Reg = LogisticRegressionCV(solver='saga' ,multi_class='multinomial')
logistic_Reg.fit(X_train, y_train)

result = logistic_Reg.predict(X_test)
log_reg_accuracy = logistic_Reg.score(result, y_test)

print("Split Accuracy = " + str(log_reg_accuracy))

#Run parameters on full dataset
full_result = logistic_Reg.predict(X)
full_accuracy = logistic_Reg.score(full_result, y)

print("Full Accuracy = " + str(full_accuracy))
```

```
In [ ]: #Run multiclass logistic regression on split with l1 regularizer
logistic_Reg_l1 = LogisticRegressionCV(solver='saga' ,multi_class='multinomial' ,penalty='l1')
logistic_Reg_l1.fit(X_train, y_train)

result_l1 = logistic_Reg_l1.predict(X_test)
log_reg_accuracy_l1 = logistic_Reg_l1.score(result_l1, y_test)

print("Split Accuracy for l1 = " + str(log_reg_accuracy_l1))

#Run parameters on full dataset
full_result_l1 = logistic_Reg_l1.predict(X)
full_accuracy_l1 = logistic_Reg_l1.score(full_result, y)

print("Full Accuracy for l1 = " + str(full_accuracy_l1))

#Display coefficients image
```

Problem 3

```
In [13]: #Random Forests MNIST
         random_Forest = RandomForestClassifier(n_estimators=500)
         random_Forest.fit(X, y)
         generalization_error = np.mean(cross_val_score(random_Forest, X, y, cv = 10))
         print("Generalization Error: " + str(generalization_error))
         accuracy = 1 - generalization_error
         print("Accuracy : " + str(accuracy))
         print("\nBest n_estimator parameter: 500")
         Generalization Error: 0.9705428571428574
         Accuracy: 0.029457142857142626
         Best n_estimator parameter: 500
In [ ]: #Gradient Boosting MNIST
         gradient_Boost = GradientBoostingClassifier()
         gradient_Boost.fit(X, y)
         gen_error_boost = np.mean(cross_val_score(gradient_Boost, X, y, cv = 10))
         print("Generalization Error: " + str(gen_error_boost))
         accuracy_boost = 1 - generalization_error
         print("Accuracy : " + str(accuracy_boost))
         print("\nBest n_estimator parameter: 100")
```

```
In [ ]:
```

```
In [43]: import torch
        import torchvision
        import torchvision.transforms as transforms
In [44]: transform = transforms.Compose(
            [transforms.ToTensor(),
             transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
        batch size = 4
        trainset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                             download=True, transform=transform)
        trainloader = torch.utils.data.DataLoader(trainset, batch_size=batch_size,
                                               shuffle=True, num_workers=2)
        testset = torchvision.datasets.CIFAR10(root='./data', train=False,
                                            download=True, transform=transform)
        testloader = torch.utils.data.DataLoader(testset, batch_size=batch_size,
                                              shuffle=False, num_workers=2)
```

Files already downloaded and verified Files already downloaded and verified

```
In [45]: import matplotlib.pyplot as plt
         import numpy as np
         # functions to show an image
         def imshow(img):
             img = img / 2 + 0.5
                                     # unnormalize
             npimg = img.numpy()
             plt.imshow(np.transpose(npimg, (1, 2, 0)))
             plt.show()
         # get some random training images
         dataiter = iter(trainloader)
         images, labels = dataiter.next()
         # show images
         imshow(torchvision.utils.make_grid(images))
         # print labels
         print(' '.join('%5s' % classes[labels[j]] for j in range(batch_size)))
```



frog deer deer bird

```
In [46]: import torch.nn as nn
         import torch.nn.functional as F
         class Net(nn.Module):
             def __init__(self):
                 super().__init__()
                 self.conv1 = nn.Conv2d(3, 6, 5)
                 self.pool = nn.MaxPool2d(2, 2)
                 self.conv2 = nn.Conv2d(6, 16, 5)
                 self.fc1 = nn.Linear(16 * 5 * 5, 120)
                 self.fc2 = nn.Linear(120, 84)
                 self.fc3 = nn.Linear(84, 10)
             def forward(self, x):
                 x = self.pool(F.relu(self.conv1(x)))
                 x = self.pool(F.relu(self.conv2(x)))
                 x = torch.flatten(x, 1) # flatten all dimensions except batch
                 x = F.relu(self.fc1(x))
                 x = F.relu(self.fc2(x))
                 x = self.fc3(x)
                 return x
         net = Net()
```

```
In [47]: def train(data, trainloader, optimizer):
           for epoch in range(2): # loop over the dataset multiple times
               running loss = 0.0
               for i, data in enumerate(trainloader, 0):
                   # get the inputs; data is a list of [inputs, labels]
                   inputs, labels = data
                   # zero the parameter gradients
                   optimizer.zero_grad()
                   # forward + backward + optimize
                   outputs = net(inputs)
                   loss = criterion(outputs, labels)
                   loss.backward()
                   optimizer.step()
                   # print statistics
                   running_loss += loss.item()
                   if i % 5000 == 4999: # print every 5000 mini-batches
                       print('Epoch %d loss: %.3f' %
                             (epoch + 1, running loss / 5000))
                       running_loss = 0.0
```

```
In [49]: import torch.optim as optim

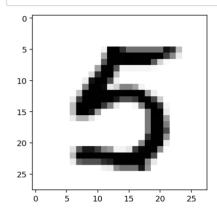
criterion = nn.CrossEntropyLoss()
rates = [0.001, 0.0001]
momentums = [0.9, 0.95]
for rate in rates:
    for momentum in momentums:
        print('Learning Rate: %.4f Momentum: %.2f' %(rate, momentum))
        optimizer = optim.SGD(net.parameters(), lr=rate, momentum=momentum)
        train(data, trainloader, optimizer)
        test(testloader)
```

```
Learning Rate: 0.0010 Momentum: 0.90
Epoch 1 loss: 1.982
Epoch 1 loss: 1.583
Epoch 2 loss: 1.394
Epoch 2 loss: 1.331
Accuracy of the network on the 10000 test images: 54 %
Learning Rate: 0.0010 Momentum: 0.95
Epoch 1 loss: 1.230
Epoch 1 loss: 1.199
Epoch 2 loss: 1.116
Epoch 2 loss: 1.124
Accuracy of the network on the 10000 test images: 58 %
Learning Rate: 0.0001 Momentum: 0.90
Epoch 1 loss: 1.038
Epoch 1 loss: 1.047
Epoch 2 loss: 0.974
Epoch 2 loss: 1.002
Accuracy of the network on the 10000 test images: 61 %
Learning Rate: 0.0001 Momentum: 0.95
Epoch 1 loss: 0.938
Epoch 1 loss: 0.953
Epoch 2 loss: 0.893
Epoch 2 loss: 0.912
Accuracy of the network on the 10000 test images: 61 %
```

```
In [50]:
         dataiter = iter(testloader)
         images, labels = dataiter.next()
         # print images
         imshow(torchvision.utils.make_grid(images))
         print('GroundTruth: ', ' '.join('%5s' % classes[labels[j]] for j in range(4)))
          10
          20
          30
                               60
                                           100
                                                  120
                                      80
         GroundTruth:
                         cat ship ship plane
In [51]: outputs = net(images)
In [52]: _, predicted = torch.max(outputs, 1)
         print('Predicted: ', ' '.join('%5s' % classes[predicted[j]]
                                       for j in range(4)))
         Predicted:
                       dog car
                                   car ship
In [53]: # prepare to count predictions for each class
         correct_pred = {classname: 0 for classname in classes}
         total_pred = {classname: 0 for classname in classes}
         # again no gradients needed
         with torch.no grad():
             for data in testloader:
                 images, labels = data
                 outputs = net(images)
                 _, predictions = torch.max(outputs, 1)
                 # collect the correct predictions for each class
                 for label, prediction in zip(labels, predictions):
                     if label == prediction:
                         correct pred[classes[label]] += 1
                     total_pred[classes[label]] += 1
         # print accuracy for each class
         for classname, correct_count in correct_pred.items():
             accuracy = 100 * float(correct_count) / total_pred[classname]
             print("Accuracy for class {:5s} is: {:.1f} %".format(classname,
         Accuracy for class plane is: 61.2 %
         Accuracy for class car is: 84.6 %
         Accuracy for class bird is: 54.1 %
         Accuracy for class cat is: 40.9 %
         Accuracy for class deer is: 51.0 %
         Accuracy for class dog is: 48.6 %
         Accuracy for class frog is: 66.6 %
         Accuracy for class horse is: 73.7 %
         Accuracy for class ship is: 75.2 %
         Accuracy for class truck is: 63.9 %
```

```
In [10]: # Import necessary packages
         %matplotlib inline
         %config InlineBackend.figure format = 'retina'
         import numpy as np
         import torch
         import torchvision
         import matplotlib.pyplot as plt
         from time import time
In [11]: import os
         from google.colab import drive
In [12]: ### Run this cell
         from torchvision import datasets, transforms
         # Define a transform to normalize the data
         transform = transforms.Compose([transforms.ToTensor(),
                                       transforms.Normalize((0.5,),(0.5,)),
                                       1)
         # Download and load the training data
         trainset = datasets.MNIST('drive/My Drive/mnist/MNIST_data/', download=True, train=True, transform=transf
         valset = datasets.MNIST('drive/My Drive/mnist/MNIST_data/', download=True, train=False, transform=transfo
         trainloader = torch.utils.data.DataLoader(trainset, batch_size=64, shuffle=True)
         valloader = torch.utils.data.DataLoader(valset, batch_size=64, shuffle=True)
         Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz (http://yann.lecun.com/exdb/mni
         st/train-images-idx3-ubyte.gz)
         Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz (http://yann.lecun.com/exdb/mni
         st/train-images-idx3-ubyte.gz) to drive/My Drive/mnist/MNIST_data/MNIST/raw/train-images-idx3-ubyte.gz
                        | 0/9912422 [00:00<?, ?it/s]
           0%1
         Extracting drive/My Drive/mnist/MNIST data/MNIST/raw/train-images-idx3-ubyte.gz to drive/My Drive/mnis
         t/MNIST_data/MNIST/raw
         Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz (http://yann.lecun.com/exdb/mni
         st/train-labels-idx1-ubyte.gz)
         Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz (http://yann.lecun.com/exdb/mni
         st/train-labels-idx1-ubyte.gz) to drive/My Drive/mnist/MNIST_data/MNIST/raw/train-labels-idx1-ubyte.gz
                        | 0/28881 [00:00<?, ?it/s]
         Extracting drive/My Drive/mnist/MNIST data/MNIST/raw/train-labels-idx1-ubyte.gz to drive/My Drive/mnis
         t/MNIST data/MNIST/raw
         Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz (http://yann.lecun.com/exdb/mnis
         t/t10k-images-idx3-ubyte.gz)
         Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz (http://yann.lecun.com/exdb/mnis
         t/t10k-images-idx3-ubyte.gz) to drive/My Drive/mnist/MNIST_data/MNIST/raw/t10k-images-idx3-ubyte.gz
                        | 0/1648877 [00:00<?, ?it/s]
         Extracting drive/My Drive/mnist/MNIST_data/MNIST/raw/t10k-images-idx3-ubyte.gz to drive/My Drive/mnist/
         MNIST_data/MNIST/raw
         Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz (http://yann.lecun.com/exdb/mnis
         t/t10k-labels-idx1-ubyte.gz)
         Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz (http://yann.lecun.com/exdb/mnis
         t/t10k-labels-idx1-ubyte.gz) to drive/My Drive/mnist/MNIST data/MNIST/raw/t10k-labels-idx1-ubyte.gz
                        | 0/4542 [00:00<?, ?it/s]
         Extracting drive/My Drive/mnist/MNIST_data/MNIST/raw/t10k-labels-idx1-ubyte.gz to drive/My Drive/mnist/
         MNIST_data/MNIST/raw
```

```
In [14]: plt.imshow(images[0].numpy().squeeze(), cmap='gray_r');
```



```
In [15]: figure = plt.figure()
    num_of_images = 60
    for index in range(1, num_of_images + 1):
        plt.subplot(6, 10, index)
        plt.axis('off')
        plt.imshow(images[index].numpy().squeeze(), cmap='gray_r')
```

```
0830551594
0690141295
721815029
9633936623
8286945101
2697633789
```

```
In [16]: from torch import nn
         # Layer details for the neural network
         input_size = 784
         hidden sizes = [128, 64]
         output_size = 10
         # Build a feed-forward network
         model = nn.Sequential(nn.Linear(input_size, hidden_sizes[0]),
                               nn.ReLU(),
                               nn.Linear(hidden_sizes[0], hidden_sizes[1]),
                               nn.ReLU(),
                               nn.Linear(hidden_sizes[1], output_size),
                               nn.LogSoftmax(dim=1))
         print(model)
         Sequential(
           (0): Linear(in_features=784, out_features=128, bias=True)
           (1): ReLU()
           (2): Linear(in_features=128, out_features=64, bias=True)
           (3): ReLU()
           (4): Linear(in_features=64, out_features=10, bias=True)
           (5): LogSoftmax(dim=1)
In [17]:
         device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
         print(device)
         model.to(device)
         cuda
Out[17]: Sequential(
           (0): Linear(in_features=784, out_features=128, bias=True)
           (1): ReLU()
           (2): Linear(in_features=128, out_features=64, bias=True)
           (3): ReLU()
           (4): Linear(in_features=64, out_features=10, bias=True)
           (5): LogSoftmax(dim=1)
In [18]: criterion = nn.NLLLoss()
         images, labels = next(iter(trainloader))
         images = images.view(images.shape[0], -1)
         logps = model(images.cuda())
         loss = criterion(logps, labels.cuda())
In [19]: print('Before backward pass: \n', model[0].weight.grad)
         loss.backward()
         print('After backward pass: \n', model[0].weight.grad)
         Before backward pass:
         After backward pass:
          tensor([[-2.2657e-03, -2.2657e-03, -2.2657e-03, ..., -2.2657e-03,
                   -2.2657e-03, -2.2657e-03],
                 \hbox{[-2.1346e-03, -2.1346e-03, -2.1346e-03, } \ldots, \hbox{-2.1346e-03,}
                  -2.1346e-03, -2.1346e-03],
                 [ 3.6523e-05, 3.6523e-05, 3.6523e-05, ..., 3.6523e-05,
                   3.6523e-05, 3.6523e-05],
                 [ 3.3214e-03, 3.3214e-03, 3.3214e-03, ..., 3.3214e-03,
                   3.3214e-03, 3.3214e-03],
                 [ 6.1648e-04, 6.1648e-04, 6.1648e-04, ..., 6.1648e-04,
                   6.1648e-04, 6.1648e-04],
                 [ 3.4574e-03, 3.4574e-03, 3.4574e-03, ..., 3.4574e-03,
                   3.4574e-03, 3.4574e-03]], device='cuda:0')
```

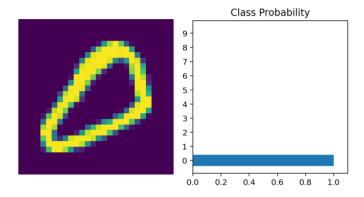
```
In [20]: # Optimizers require the parameters to optimize and a learning rate
         optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.5)
In [22]:
         print('Initial weights - ', model[0].weight)
         images, labels = next(iter(trainloader))
         images.resize (64, 784)
         # Clear the gradients, do this because gradients are accumulated
         optimizer.zero_grad()
         # Forward pass, then backward pass, then update weights
         output = model(images.cuda())
         loss = criterion(output, labels.cuda())
         loss.backward()
         print('Gradient -', model[0].weight.grad)
         Initial weights - Parameter containing:
         [-0.0089, -0.0201, 0.0191, \ldots, 0.0270, 0.0075, 0.0266],
                 [-0.0050, -0.0084, -0.0184, ..., 0.0147, 0.0211, 0.0279],
                 [-0.0343, 0.0088, -0.0013, ..., -0.0325, -0.0139, -0.0025]],
                device='cuda:0', requires grad=True)
         Gradient - tensor([[-0.0022, -0.0022, -0.0022, -0.0022, -0.0022, -0.0022],
                 [-0.0005, -0.0005, -0.0005, ..., -0.0005, -0.0005, -0.0005],
                 [0.0006, 0.0006, 0.0006, ..., 0.0006, 0.0006, 0.0006],
                 [-0.0017, -0.0017, -0.0017, ..., -0.0017, -0.0017, -0.0017],
                 [ 0.0012, 0.0012, 0.0012, ..., 0.0012, 0.0012, 0.0012], [ 0.0013, 0.0013, 0.0013, ..., 0.0013, 0.0013, 0.0013]],
                device='cuda:0')
In [23]: # Take an update step and few the new weights
         optimizer.step()
         print('Updated weights - ', model[0].weight)
         Updated weights - Parameter containing:
         tensor([[-0.0273, -0.0145, -0.0089, ..., -0.0027, -0.0260, 0.0335],
                 [0.0090, -0.0083, -0.0304, \dots, -0.0202, -0.0314, -0.0164],
                 [0.0097, 0.0004, 0.0194, \ldots, -0.0197, 0.0193, -0.0249],
                 [-0.0089, -0.0201, 0.0191, \ldots, 0.0270, 0.0075, 0.0266],
                 [-0.0050, -0.0084, -0.0184, ..., 0.0147, 0.0211, 0.0279],
[-0.0343, 0.0088, -0.0014, ..., -0.0325, -0.0139, -0.0025]],
                device='cuda:0', requires grad=True)
```

```
In [24]: optimizer = optim.SGD(model.parameters(), 1r=0.003, momentum=0.9)
         time0 = time()
         epochs = 15
         for e in range(epochs):
             running_loss = 0
             for images, labels in trainloader:
                 # Flatten MNIST images into a 784 long vector
                 images = images.view(images.shape[0], -1)
                 # Training pass
                 optimizer.zero_grad()
                 output = model(images.cuda())
                 loss = criterion(output, labels.cuda())
                 #This is where the model learns by backpropagating
                 loss.backward()
                 #And optimizes its weights here
                 optimizer.step()
                 running_loss += loss.item()
             else:
                 print("Epoch {} - Training loss: {}".format(e, running_loss/len(trainloader)))
         print("\nTraining Time (in minutes) =",(time()-time0)/60)
         Epoch 0 - Training loss: 0.6425788553793039
         Epoch 1 - Training loss: 0.282724671327928
         Epoch 2 - Training loss: 0.2230572267008552
         Epoch 3 - Training loss: 0.18020208306840932
         Epoch 4 - Training loss: 0.15242658956234517
         Epoch 5 - Training loss: 0.12949277689930663
         Epoch 6 - Training loss: 0.11337902554686168
         Epoch 7 - Training loss: 0.10130069432045415
         Epoch 8 - Training loss: 0.09172150385834134
         Epoch 9 - Training loss: 0.08139755662931784
         Epoch 10 - Training loss: 0.075294104856012
         Epoch 11 - Training loss: 0.06842541152428684
         Epoch 12 - Training loss: 0.06307056332344631
         Epoch 13 - Training loss: 0.05893389996327857
         Epoch 14 - Training loss: 0.054264334936701714
         Training Time (in minutes) = 4.007928570111592
In [25]: def view classify(img, ps):
             ''' Function for viewing an image and it's predicted classes.
             ps = ps.cpu().data.numpy().squeeze()
             fig, (ax1, ax2) = plt.subplots(figsize=(6,9), ncols=2)
             ax1.imshow(img.resize_(1, 28, 28).numpy().squeeze())
             ax1.axis('off')
             ax2.barh(np.arange(10), ps)
             ax2.set_aspect(0.1)
             ax2.set_yticks(np.arange(10))
             ax2.set_yticklabels(np.arange(10))
             ax2.set_title('Class Probability')
             ax2.set_xlim(0, 1.1)
             plt.tight_layout()
```

```
In [26]: images, labels = next(iter(valloader))
    img = images[0].view(1, 784)
    # Turn off gradients to speed up this part
    with torch.no_grad():
        logps = model(img.cuda())

# Output of the network are log-probabilities, need to take exponential for probabilities
    ps = torch.exp(logps)
    probab = list(ps.cpu().numpy()[0])
    print("Predicted Digit =", probab.index(max(probab)))
    view_classify(img.view(1, 28, 28), ps)
```

Predicted Digit = 0



```
In [27]: correct_count, all_count = 0, 0
         for images,labels in valloader:
           for i in range(len(labels)):
             img = images[i].view(1, 784)
             # Turn off gradients to speed up this part
             with torch.no_grad():
                 logps = model(img.cuda())
             # Output of the network are log-probabilities, need to take exponential for probabilities
             ps = torch.exp(logps)
             probab = list(ps.cpu().numpy()[0])
             pred_label = probab.index(max(probab))
             true_label = labels.numpy()[i]
             if(true_label == pred_label):
               correct_count += 1
             all_count += 1
         print("Number Of Images Tested =", all_count)
         print("\nModel Accuracy =", (correct_count/all_count))
```

Number Of Images Tested = 10000

Model Accuracy = 0.9708