Problem 1. Neural Networks

Develop a Neural Network (NN) model to predict class labels for the Iris data set. Split the data into training, validation and testing set with the ratio of 0.8, 0.1 and 0.1. Train the model on the training set, select the best model based on the validation set, and test your model on the testing set. Report your training, validation and testing accuracy. You can use packages such as Tensorflow or Pytorch.

Using Pytorch to define our neural network

- Two Hidden Layers
- ReLU Activation Function

```
import torch
import torch.nn as NeuralNet

class neural_network(NeuralNet.Module):

    # There are two hidden layers in our network denoted by h1 and h2
    # ReLU is used as the activation function
    def __init__(self, numoffeatures, h1, h2,output):
        super(neural_network, self).__init__()
        self.first   = NeuralNet.Linear(numoffeatures, h1)
        self.relu1 = NeuralNet.ReLU()
        self.second   = NeuralNet.Linear(h1, h2)
        self.relu2 = NeuralNet.ReLU()
        self.third   = NeuralNet.Linear(h2, output)

    def forward(self, x):
        out = self.first(x)
        out = self.relu1(out)
        out = self.second(out)
        out = self.relu2(out)
        out = self.third(out)

        return out
```

Deciding the parameters i.e. Input Attributes, Number of nodes in the Hidden Layer and Output Classes

```
# First layer of our network
# 4 attributes as input: 'sepal lenght', 'sepal width', 'petal lenght', 'petal width'
numoffeatures = 4

# Number of nodes in 1st and 2nd hidden layers
h1 = 5
h2 = 9

# Last layer of our network
# Output Classes: 'Setosa', 'Versicolour', 'Virginica'
numofclasses = 3

# Number of iterations for backpropagation
epochs = 30
```

Implemening our Neural Network

```
lr = 0.01
m = neural_network(numoffeatures,h1,h2,numofclasses)

#choosing optimizer and desired loss function
criterion = NeuralNet.CrossEntropyLoss()
# Stochastic Optimization
optimizer = torch.optim.Adam(m.parameters(), lr=lr)
```

Loading and splitting the Iris dataset into training, validation and testing set

```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split

iris = load_iris()
x , y = iris.data, iris.target

# First splitting dataset into train and test with ratio as 0.8 and 0.2
train_x , test_x, train_y, test_y = train_test_split(x, y, test_size=0.2, random_stat

# Now splitting the test 'equally' into test and validation
```

```
# Hence our dataset is in ratio train:test:val = 0.8:0.1:0.1
test_x , val_x , test_y , val_y = train_test_split(test_x, test_y, test_size=0.5, ran
```

Getting tensors and creating loaders for training, validation and testing set

```
import torch.utils.data as utils
import torch.utils.data as td

# Training
train_x_tnsr = torch.Tensor(train_x).float()
train_y_tnsr = torch.Tensor(train_y).long()

iris_train_tnsr = utils.TensorDataset(train_x_tnsr,train_y_tnsr)

train_data_loader = td.DataLoader(iris_train_tnsr, batch_size=10, shuffle=True, num_w

# Validation
val_x_tnsr = torch.Tensor(val_x).float()
val_y_tnsr = torch.Tensor(val_y).long()
iris_val_tnsr = utils.TensorDataset(val_x_tnsr,val_y_tnsr)
val_data_loader = td.DataLoader(iris_val_tnsr, batch_size=10, shuffle=True, num_worke

# Testing
test_x_tnsr = torch.Tensor(test_x).float()
test_y_tnsr = torch.Tensor(test_y).long()

iris_test_tnsr = utils.TensorDataset(test_x_tnsr,test_y_tnsr)

test_data_loader = td.DataLoader(iris_test_tnsr, batch_size=10, shuffle=True, num_wor
```

Defining function to get training loss and validation loss

```
def train(model, loader, loader1, criterion, optimizer):

    model.train()

    t_loss = 0
    v_loss = 0

    for b, tnsr in enumerate(loader):
        curr_data, curr_target = tnsr
        # Gradients = 0
        optimizer.zero_grad()
        next = model(curr_data)
```

```
        loss = criterion(next, curr_target)
        # calculating gradients
        loss.backward()
        # Updating weights
        optimizer.step()
        t_loss = t_loss + loss.item()

    # evaluating our model
    model.eval()
    for b, tnsr in enumerate(loader1):
        curr_data, curr_target = tnsr
        next = model(curr_data)
        loss = criterion(next, curr_target)
        v_loss = v_loss + loss.item()


    # Return loss
    avg_loss_t = t_loss / len(loader.dataset)
    avg_loss_v = v_loss / len(loader1.dataset)
    return avg_loss_t, avg_loss_v
```

Defining function to get testing loss

```
def test(model, loader, criterion):

    # evaluate model
    model.eval()

    t_loss = 0
    count = 0

    with torch.no_grad():
        for b, tnsr in enumerate(loader):
            curr_data, curr_target = tnsr

            # find answer by passing data through model
            output = model(curr_data)

            # find loss
            t_loss = t_loss + criterion(output, curr_target).item()

            # find accuracy
            _, prediction = torch.max(output, 1)
            count = count + torch.sum(curr_target == prediction).item()


    avg_acc = count / len(loader.dataset)
    avg_loss = t_loss / len(loader.dataset)
```

```
    return avg_acc, avg_loss
```

Using the Neural Network

```
enums = []
tr_losses = []
val_losses = []


for epoch in range(epochs):

    # Model Training
    tr_loss, val_loss = train(m, train_data_loader, val_data_loader, criterion, optim

    enums.append(epoch)
    tr_losses.append(tr_loss)
    val_losses.append(val_loss)
    print("Epoch ",epoch+1,":")
    print("Training Loss :",tr_loss," Validation Loss :",val_loss)
```

```
Epoch  2 :
Training Loss : 0.09667361279328664  Validation Loss : 0.13526658217112222
Epoch  3 :
Training Loss : 0.07971962640682856  Validation Loss : 0.11040416161219278
Epoch  4 :
Training Loss : 0.06264254475633303  Validation Loss : 0.0895259658495585
Epoch  5 :
Training Loss : 0.046967687209447224  Validation Loss : 0.07528030077616374
Epoch  6 :
Training Loss : 0.03781860868136088  Validation Loss : 0.05907368858655294
Epoch  7 :
Training Loss : 0.03383137459556262  Validation Loss : 0.06933768192927042
Epoch  8 :
Training Loss : 0.0269201813886563  Validation Loss : 0.04795589645703634
Epoch  9 :
Training Loss : 0.022996486350893974  Validation Loss : 0.05874242385228475
Epoch  10 :
Training Loss : 0.020203165896236896  Validation Loss : 0.037839305400848386
Epoch  11 :
Training Loss : 0.017768767413993677  Validation Loss : 0.03512387077013652
Epoch  12 :
Training Loss : 0.015824378778537113  Validation Loss : 0.03647292455037435
Epoch  13 :
Training Loss : 0.013718475649754206  Validation Loss : 0.031316883365313214
Epoch  14 :
Training Loss : 0.01268013878725469  Validation Loss : 0.02904849251113484
Epoch  15 :
Training Loss : 0.011556090942273537  Validation Loss : 0.038005733489990236
```

```
Epoch  16 :
Training Loss : 0.01755756316706538  Validation Loss : 0.05909181435902913
Epoch  17 :
Training Loss : 0.012161409202963113  Validation Loss : 0.02235474487145742
Epoch  18 :
Training Loss : 0.010690142392801742  Validation Loss : 0.02431473135948181
Epoch  19 :
Training Loss : 0.00920102143039306  Validation Loss : 0.0405588428179423
Epoch  20 :
Training Loss : 0.011000736500136554  Validation Loss : 0.022339510917663574
Epoch  21 :
Training Loss : 0.009325473049345116  Validation Loss : 0.021514344215393066
Epoch  22 :
Training Loss : 0.008890969771891832  Validation Loss : 0.02685072471698125
Epoch  23 :
Training Loss : 0.01015773486190786  Validation Loss : 0.037471028168996175
Epoch  24 :
Training Loss : 0.008539251377806067  Validation Loss : 0.02310544451077779
Epoch  25 :
Training Loss : 0.011971367647250493  Validation Loss : 0.016911367078622182
Epoch  26 :
Training Loss : 0.008339773712214083  Validation Loss : 0.01804673026005427
Epoch  27 :
Training Loss : 0.008899995335377752  Validation Loss : 0.026213408509890238
Epoch  28 :
Training Loss : 0.00949114804000904  Validation Loss : 0.025344152251879373
Epoch  29 :
Training Loss : 0.009745316673070192  Validation Loss : 0.026236117879549662
Epoch  30 :
Training Loss : 0.009493014177617927  Validation Loss : 0.01516856774687767
```

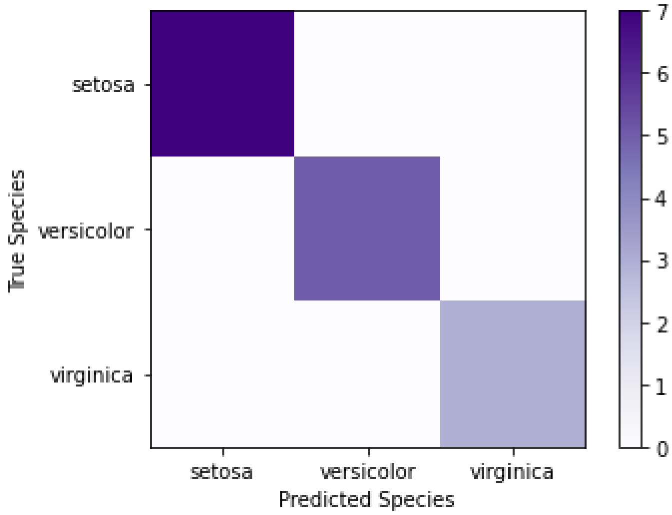
Plotting the training loss and validation loss

```
from matplotlib import pyplot as plt

plt.plot(enums, tr_losses,'b>')
plt.plot(enums, val_losses,'g')
plt.xlabel('epoch')
plt.ylabel('loss')
plt.legend(['train', 'validation'])
plt.show()
```

Confusion Matrix and Accuracy

```
from sklearn.metrics import confusion_matrix, accuracy_score
import numpy as np

accuracy, tst_loss = test(m, test_data_loader, criterion)

print("Accuracy :",accuracy * 100)
print("Test Loss: ",tst_loss)

# set model to evaluate mode
m.eval()

# get predictions
x = torch.Tensor(test_x).float()
_, predicted = torch.max(m(x).data, 1)

# Getting confusion matrix
k = accuracy_score(test_y, predicted.numpy())

cm = confusion_matrix(test_y, predicted.numpy())
plt.imshow(cm, interpolation="nearest", cmap=plt.cm.Purples)
plt.colorbar()
tick_marks = np.arange(len(iris.target_names))
plt.xticks(tick_marks, iris.target_names)
plt.yticks(tick_marks, iris.target_names)
plt.xlabel("Predicted Species")
plt.ylabel("True Species")
plt.show()
```

```
Accuracy : 100.0
Test Loss:  0.003638163829843203
```



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