- 1. create a multi-layer deep learning model
- 2. load data
- 3. train and validate the model
- 4. save and load a trained model

```
1 import torch
2 import torch.nn as nn
3 import torch.nn.functional as F
```

- CREATE MODEL CLASS

```
1 #input layer features=4, hidden layer1=8 neurons, hidden layer2=9 neurons, output layer features=3
2 #fc1 --> fully connected layer 1
3 #we'll use the rectified linear unit (ReLU) function, f(x)=max(0,x)
4 #here x basically means the activation function
5 class Model(nn.Module):
    def __init__(self,in_features=4,h1=8,h2=9,out_features=3):
6
7
       super().__init__()
8
       self.fc1 = nn.Linear(in_features,h1)
                                                # input layer
9
       self.fc2 = nn.Linear(h1, h2)
                                                # hidden layer
       self.out = nn.Linear(h2, out_features) # output layer
10
   def forward(self,x):
11
12
          x = F.relu(self.fc1(x))
13
          x = F.relu(self.fc2(x))
14
          x = self.out(x)
15
          return x
1 # Instantiate the Model class using parameter defaults:
2 torch.manual_seed(32)
3 model = Model()
1 print(model)
    Model(
      (fc1): Linear(in_features=4, out_features=8, bias=True)
      (fc2): Linear(in_features=8, out_features=9, bias=True)
      (out): Linear(in_features=9, out_features=3, bias=True)
1 import pandas as pd
2 import matplotlib.pyplot as plt
3 %matplotlib inline
```

LOAD DATASET

```
1 df = pd.read_csv('/content/iris.csv') # to load iris.csv copy its path here
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
0	5.1	3.5	1.4	0.2	0.0
1	4.9	3.0	1.4	0.2	0.0
2	4.7	3.2	1.3	0.2	0.0
3	4.6	3.1	1.5	0.2	0.0
4	5.0	3.6	1.4	0.2	0.0

1 df.tail()

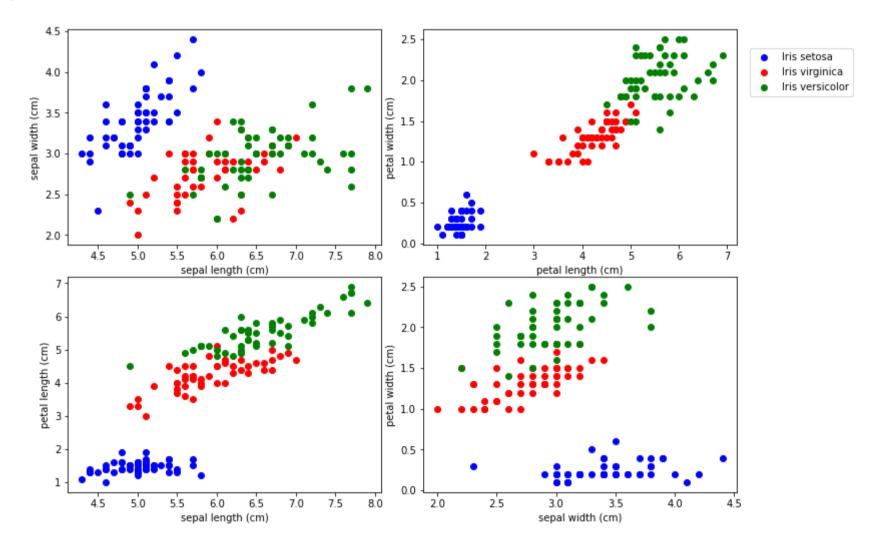
1 df.head()

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
145	6.7	3.0	5.2	2.3	2.0

146	6.3	2.5	5.0	1.9	2.0
147	6.5	3.0	5.2	2.0	2.0
148	6.2	3.4	5.4	2.3	2.0
1.40	F 0	2.0	г 4	1.0	2.0

- PLOT DATASET

```
1 #Here (0,1) sets "sepal length (cm)" as x and "sepal width (cm)" as y
2 fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(10,7))
3 fig.tight layout()
5 \text{ plots} = [(0,1),(2,3),(0,2),(1,3)]
6 colors = ['b', 'r', 'g']
7 labels = ['Iris setosa','Iris virginica','Iris versicolor']
9 for i, ax in enumerate(axes.flat):
10
      for j in range(3):
11
           x = df.columns[plots[i][0]]
12
           y = df.columns[plots[i][1]]
13
           ax.scatter(df[df['target']==j][x], df[df['target']==j][y], color=colors[j])
14
           ax.set(xlabel=x, ylabel=y)
15
16 fig.legend(labels=labels, loc=3, bbox_to_anchor=(1.0,0.85))
17 plt.show()
```



→ PERFORM TRAIN/TEST SPLIT

```
1 from sklearn.model_selection import train_test_split
```

```
1 X = df.drop('target',axis=1).values
2 y = df['target'].values
3
4 X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=33)
5
6 X_train = torch.FloatTensor(X_train)
7 X_test = torch.FloatTensor(X_test)
8
9 y_train = torch.LongTensor(y_train)
10 y_test = torch.LongTensor(y_test)
```

PREPARE DATALOADER

```
1 from torch.utils.data import Dataset, DataLoader
1 trainloader = DataLoader(X_train, batch_size=60, shuffle=True)
2 testloader = DataLoader(X_test, batch_size=60, shuffle=False)
```

- DEFINE LOSS EQUATIONS AND OPTIMIZATIONS

```
1 # for redo
2 torch.manual_seed(4)
3 model = Model()

1 # we'll use a variation of Stochastic Gradient Descent called Adam (short for Adaptive Moment Estimati
2 loss_fn = nn.CrossEntropyLoss()
3 optimizer = torch.optim.Adam(model.parameters(), lr=0.01)
```

- TRAIN MODEL

```
1 \text{ epochs} = 100
2 losses = []
4 for i in range(epochs):
5
      i+=1
 6
      y_pred = model.forward(X_train)
      loss = loss_fn(y_pred, y_train)
 7
      losses.append(loss)
8
9
10
11
      if i%10 == 0:
12
          print(f'epoch: {i} loss: {loss}')
13
14
      optimizer.zero_grad()
      loss.backward()
15
16
      optimizer.step()
    epoch: 10 loss: 0.995311975479126
    epoch: 20 loss: 0.7865303754806519
    epoch: 30 loss: 0.5158727765083313
    epoch: 40 loss: 0.3626713156700134
    epoch: 50 loss: 0.24050042033195496
    epoch: 60 loss: 0.1422368437051773
    epoch: 70 loss: 0.09449019283056259
    epoch: 80 loss: 0.07497227936983109
    epoch: 90 loss: 0.06607460975646973
    epoch: 100 loss: 0.061247698962688446
```

→ PLOT LOSS FUNC

```
1 plt.plot(range(epochs), losses)
2 plt.ylabel('Loss')
3 plt.xlabel('epoch')
```

```
U 8 -
1 #to evaluate entire test set
2 with torch.no_grad():
     y_eval = model.forward(X_test)
4
     loss = loss_fn(y_eval, y_test)
5 print(loss)
   tensor(0.0625)
                                ь'n
                                               100
1 correct = 0
2 with torch.no grad():
3
     for i,data in enumerate(X_test):
4
          y_val = model.forward(data)
5
          print(f'{i+1})
                          {str(y_val)}
                                                {y_test[i]}')
6
          if y_val.argmax().item() == y_test[i]:
7
              correct += 1
8 print(f'\n{correct} out of {len(y_test)} = \{100*correct/len(y_test):.2f\}% correct')
        tensor([-0.3360, 7.3629, 1.3780])
   1)
                                                     1
   2)
        tensor([0.2770, 8.1552, 0.4267])
   3)
        tensor([ 11.9968,
                            6.1842, -19.1980])
        tensor([-2.0192, 7.9662, 4.2445])
                                                     1
   4)
   5)
        tensor([-6.1353, 7.9516, 11.0908])
                                                     2
                             8.3102, 17.9992])
                                                        2
   6)
        tensor([-10.2640,
                            6.4316, -19.2913])
   7)
        tensor([ 12.0541,
                                                        0
   8)
        tensor([ 12.9496,
                             6.4815, -20.7530])
                                                        0
        tensor([-5.7727, 8.2435, 10.5079])
   9)
                                                     2
   10)
         tensor([-7.8872, 8.6126, 14.0726])
                                                     2
         tensor([-8.7060, 8.6074, 15.4331])
                                                      2
   11)
   12)
                              5.8164, -18.6210])
         tensor([ 11.6348,
                                                      2
   13)
         tensor([-8.1013, 8.2331, 14.3883])
   14)
         tensor([-2.0796, 7.7751, 4.3185])
                                                     1
                                                      2
         tensor([-6.0833, 8.3916, 11.0582])
   15)
         tensor([0.1354, 7.8658, 0.6407])
   16)
   17)
         tensor([-4.0880, 7.7216, 7.6638])
                                                      2
   18)
         tensor([ 13.1511,
                              6.5907, -21.0787])
   19)
         tensor([-1.5649, 8.0220, 3.4751])
                                                      1
   20)
         tensor([-6.2865, 8.9727, 11.4244])
                                                      2
         tensor([ 12.3848,
   21)
                                                         0
                              6.2568, -19.8265])
   22)
         tensor([ 13.8199,
                              7.0854, -22.1532])
                                                         0
   23)
         tensor([-8.8475, 8.3181, 15.6471])
                                                      2
   24)
         tensor([ 12.1968,
                              6.1261, -19.5250])
         tensor([-5.8089, 7.5468, 10.5336])
   25)
                                                      2
                                                      2
   26)
         tensor([-4.4530, 7.7875, 8.2861])
         tensor([-1.4289, 7.7785, 3.2325])
   27)
                                                      1
   28)
         tensor([ 0.5351, 7.5358, -0.0494])
                                                     1
         tensor([-5.8235, 8.1573, 10.5971])
   29)
                                                      2
         tensor([-5.2573, 7.7475, 9.6101])
                                                      2
   30)
   29 out of 30 = 96.67\% correct
```

- SAVE TRAINED MODEL

1 torch.save(model.state_dict(), 'IrisDatasetModel.pt')

LOAD A NEW MODEL

```
1 #weight and bias unknown to model
2 new_model = Model()
3 new_model.load_state_dict(torch.load('IrisDatasetModel.pt'))
4 new_model.eval()

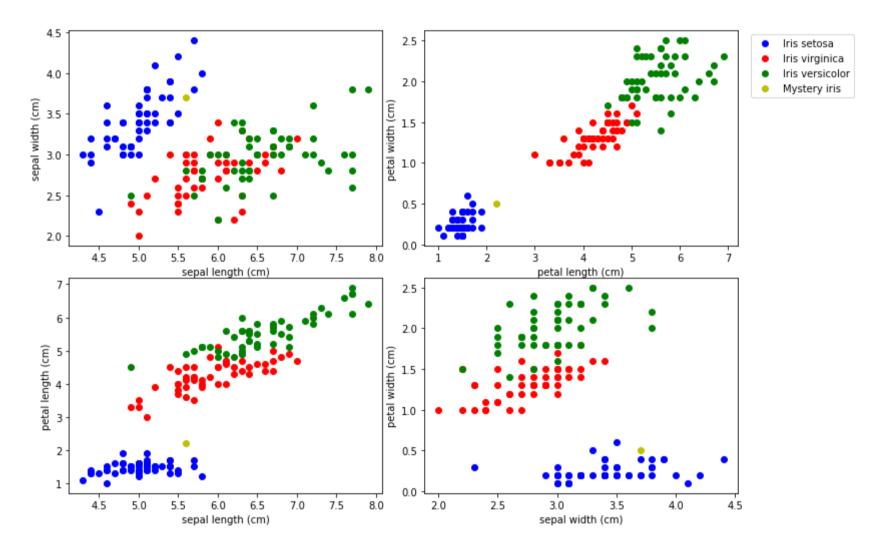
Model(
    (fc1): Linear(in_features=4, out_features=8, bias=True)
     (fc2): Linear(in_features=8, out_features=9, bias=True)
      (out): Linear(in_features=9, out_features=3, bias=True)
    )

1 with torch.no_grad():
2     y_eval = new_model.forward(X_test)
3     loss = loss_fn(y_eval, y_test)
4 print(loss)

tensor(0.0625)
```

- APPLY MODEL TO CLASSIFY NEW UNSEEN DATA

```
1 \text{ mystery\_iris} = \text{torch.tensor}([5.6,3.7,2.2,0.5])
 1 fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(10,7))
 2 fig.tight_layout()
 3
 4 plots = [(0,1),(2,3),(0,2),(1,3)]
 5 colors = ['b', 'r', 'g']
 6 labels = ['Iris setosa','Iris virginica','Iris versicolor','Mystery iris']
 8 for i, ax in enumerate(axes.flat):
       for j in range(3):
 9
           x = df.columns[plots[i][0]]
10
11
           y = df.columns[plots[i][1]]
12
           ax.scatter(df[df['target']==j][x], df[df['target']==j][y], color=colors[j])
13
           ax.set(xlabel=x, ylabel=y)
14
15
      # Add a plot for our mystery iris:
16
       ax.scatter(mystery_iris[plots[i][0]], mystery_iris[plots[i][1]], color='y')
17
18 fig.legend(labels=labels, loc=3, bbox_to_anchor=(1.0,0.85))
19 plt.show()
```



```
1 with torch.no_grad():
2    print(new_model(mystery_iris))
3    print(labels[new_model(mystery_iris).argmax()])
   tensor([ 12.2112,    7.1279, -19.5248])
   Iris setosa
```