Assignment 1: Classification of Iris Using MLP

In [1]:
```
"🔒"
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
"🔒"
#
# Load the iris dataset as a dataframe.
#

df = pd.read_csv('my_data/iris.csv')
```

Unit 1: constructing PyTorch datasets

In this unit, you are to implement `make_dataset`.

Hint:

- Learn how to use TensorDataset.
- You are to extract the features and target from the dataframe, and construct a TensorDataset object.
- Refer to https://pytorch.org/docs/stable/data.html

Note:

- Make sure the features are using `dtype=torch.float32`.
- Make sure the targets are using `dtype=torch.int64`.

In [3]:
```
"🔒"
import torch
from torch.utils.data import (
    DataLoader,
    TensorDataset,
    Dataset
)
```

In [4]:
```
"✍"
# @workUnit
def make_dataset(df: pd.DataFrame) -> Dataset:
    dataset = TensorDataset(torch.tensor(df.iloc[:, :-1].values, dtype=torch.float3
    return dataset
```

In [5]:
```
"🔒"
# @check
# @title: inspecting training dataset

train_dataset = make_dataset(df)
(x, y) = train_dataset[0]
print(f"First input {x}.  Its dtype must be {x.dtype}.")
print(f"First output {y}.  Its dtype must be {y.dtype}.")
```

```
First input tensor([6.1000, 2.8000, 4.7000, 1.2000]).  Its dtype must be torch.flo
at32.
First output 1.  Its dtype must be torch.int64.
```

Unit 2: constructing PyTorch dataloader

In this unit, you are to implement `make_dataloader` which converts `Dataset` to `DataLoader` with specified `batch_size` and `shuffle` flag.

Refer to https://pytorch.org/tutorials/beginner/basics/data_tutorial.html#preparing-your-data-for-training-with-dataloaders

In [6]:
```
"✍"
# @workUnit

def make_dataloader(dataset: Dataset, batch_size:int, shuffle:bool) -> DataLoader:
    dataloader = DataLoader(dataset, batch_size, shuffle)
    return dataloader
```

In [7]:
```
"🔒"
# @check
# @title: inspect training dataloader
train_dataloader = make_dataloader(train_dataset, shuffle=False, batch_size=5)
first_batch = next(iter(train_dataloader))
first_batch
```

Out[7]:
```
[tensor([[6.1000, 2.8000, 4.7000, 1.2000],
         [5.4000, 3.9000, 1.3000, 0.4000],
         [6.5000, 3.0000, 5.8000, 2.2000],
         [5.1000, 3.5000, 1.4000, 0.3000],
         [5.9000, 3.0000, 4.2000, 1.5000]]),
 tensor([1, 0, 2, 0, 1])]
```

Unit 3: Linear classifier

In this unit, you are to implement a neural network module that performs simple linear classification. Namely,

$$ y_\mathrm{pred} = xW + b $$

Hint:

- Use the built-in `nn.Linear(...)` as a layer in your module.

- You must name the attribute in the `LinearClassifier` as `linear` for you to pass the checkpoint.

In [8]:
```
"🔒"
from torch import nn
from torchsummaryX import summary
```

In [9]:
```
"✍"
# @workUnit
# initialize the `linear` attribute
# implement the forward(...) method

class LinearClassifier(nn.Module):
    def __init__(self):
        super().__init__()
        self.linear = nn.Linear(4, 3)

    def forward(self, x):
        return self.linear(x)
```

In [10]:
```
"🔒"
# @check
# @title: architecture of linear classifier

m = LinearClassifier()
summary(m, torch.zeros(32, 4));
```

```
=====================================================
         Kernel Shape Output Shape  Params  Mult-Adds
Layer
0_linear       [4, 3]      [32, 3]      15         12
-----------------------------------------------------
                      Totals
Total params              15
Trainable params          15
Non-trainable params       0
Mult-Adds                 12
=====================================================
```

Unit 4: Training loop

In this unit, you are given a function that performs the training loop.

You will use the provided training loop to train the linear classifier and inspect the accuracy.

In [11]:
```
"🔒"
from torch.optim import (Optimizer, Adam)
from torch.nn.functional import cross_entropy
from torchmetrics import Accuracy
```

In [12]:
```
"🔒"
def train(model: nn.Module, optimizer: Optimizer, dataloader: DataLoader, epochs: i
    history = []
```

```python
    accuracy = Accuracy(task='multiclass', num_classes=3)
    for epoch in range(epochs):
        for (x, target) in dataloader:
            pred = model(x)
            loss = cross_entropy(pred, target)
            loss.backward()
            optimizer.step()
            optimizer.zero_grad()
        metrics = {
            'epoch': epoch,
            'loss': loss.item(),
            'acc': accuracy(pred, target).item()
        }
        if epoch % (epochs // 10) == 0:
            print("{epoch}: loss={loss:.4f}, acc={acc:.2f}".format(**metrics))
        history.append(metrics)
    return pd.DataFrame(history)
```

In [13]:

```python
"✍"
# @workUnit

dataloader = make_dataloader(train_dataset, shuffle=False, batch_size=32)
linearclassifier = LinearClassifier()
optimizer = Adam(linearclassifier.parameters(), lr=0.01)

history_linear = train(linearclassifier, optimizer, dataloader, 100)
```

```
0: loss=1.2665, acc=0.36
10: loss=0.6259, acc=0.86
20: loss=0.4559, acc=0.86
30: loss=0.3823, acc=0.95
40: loss=0.3346, acc=0.95
50: loss=0.2990, acc=0.95
60: loss=0.2705, acc=0.95
70: loss=0.2468, acc=0.95
80: loss=0.2269, acc=0.95
90: loss=0.2099, acc=0.95
```

In [14]:

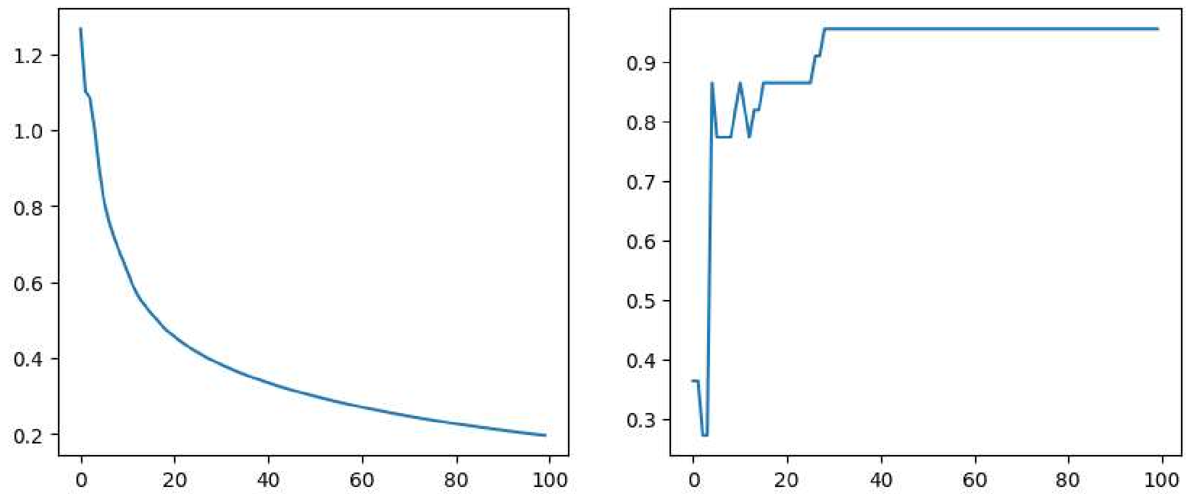
```python
"🔒"
# @check
# @title: ensure linear classifier performance

print("linear classifier acc > 50%?", history_linear.acc.iloc[-1] > 0.5)
print("linear classifier acc < 90%?", history_linear.acc.iloc[-1] < 0.9)
```

```
linear classifier acc > 50%? True
linear classifier acc < 90%? False
```

In [15]:

```python
"🔒"
#
# Plotting the loss function and accuracy
#
import matplotlib.pyplot as plt
fig, axes = plt.subplots(ncols=2, figsize=(10,4))
history_linear.loss.plot.line(ax=axes[0])
history_linear.acc.plot.line(ax=axes[1]);
```



Unit 5: MLP with hidden layer

In this section, you are to implement a multi-layer perceptron (MLP) with a single hidden layer of 100 neurons.

Note: You must name the attributes as follows.

- `linear1` : the hidden layer with 100 neurons.
- `act1` : the ReLU activation function.
- `output` : the output layer that outputs the logits over the 3 categories.

Refer to: http://db.science.uoit.ca/csci4050u/2_fitting_2d/03_mlp.html

In [16]:

```
"✍"
# @workUnit

class MLPClassifier(nn.Module):
    def __init__(self):
        super().__init__()
        self.act1 = nn.ReLU()
        self.linear1 = nn.Linear(4, 100)
        self.output = nn.Linear(100, 3)
    def forward(self, x):
        x = self.linear1(x)
        x = self.act1(x)
        x = self.output(x)
        return x
```

In [17]:

```
"🔒"
# @check
# @title: architecture of MLP classifier

m = MLPClassifier()
summary(m, torch.zeros(32, 4));
```

```
=======================================================
          Kernel Shape Output Shape Params Mult-Adds
Layer
0_linear1     [4, 100]    [32, 100]  500.0     400.0
1_act1               -    [32, 100]      -         -
2_output      [100, 3]      [32, 3]  303.0     300.0
-------------------------------------------------------
                      Totals
Total params           803.0
Trainable params       803.0
Non-trainable params     0.0
Mult-Adds              700.0
=======================================================
```

In [18]:

```
"🔒"
#
# training the MLP model
#
mlp = MLPClassifier()
optimizer = Adam(mlp.parameters())
dataloader = make_dataloader(train_dataset, shuffle=False, batch_size=32)

history_mlp = train(mlp, optimizer, dataloader, 100)
```

```
0: loss=0.9982, acc=0.77
10: loss=0.4967, acc=0.91
20: loss=0.3407, acc=0.95
30: loss=0.2651, acc=0.95
40: loss=0.2158, acc=0.95
50: loss=0.1806, acc=0.95
60: loss=0.1547, acc=0.95
70: loss=0.1351, acc=0.95
80: loss=0.1201, acc=0.95
90: loss=0.1085, acc=0.95
```

In [19]:

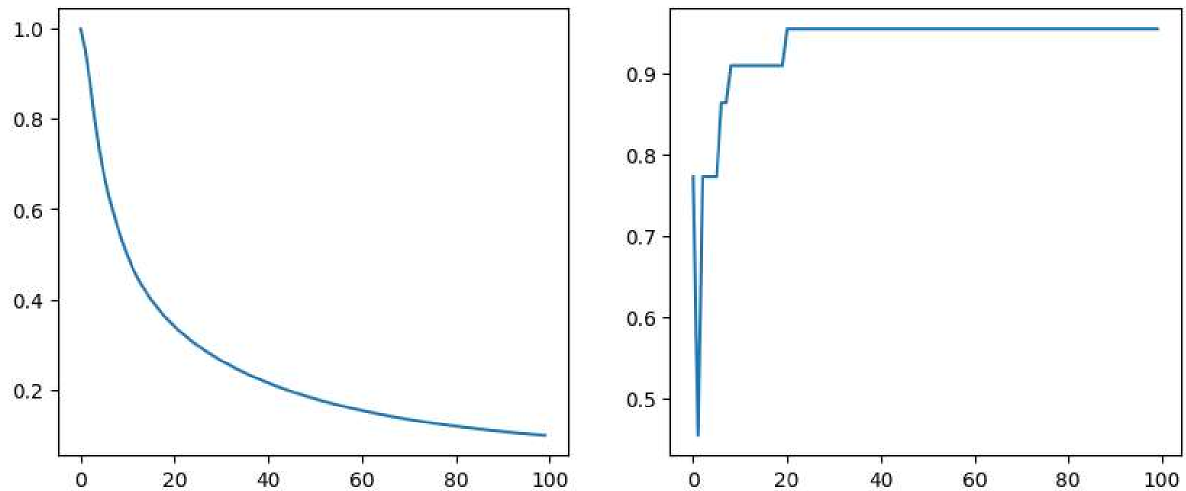
```
"🔒"
# @check
# @title: ensure MLP performance

history_mlp.acc.iloc[-1] > 0.9
```

Out[19]: True

In [20]:

```
"🔒"
#
# Plotting the loss function and accuracy
#
import matplotlib.pyplot as plt
fig, axes = plt.subplots(ncols=2, figsize=(10,4))
history_mlp.loss.plot.line(ax=axes[0])
history_mlp.acc.plot.line(ax=axes[1]);
```



Unit 6: Explaining MLP action

In this unit, we will explore ways to uncover how deep neural networks organize data by generating 2D hidden features and visualize the generated features as a scatter plot.

You must create a `MLP2DClassifier` neural network consisting of the following layers:

- `linear1` is a linear layer with 100 neurons.
- `act1` is the ReLU activation function for the `linear1` layer.
- `linear2` is a linear layer that maps the 100 dimensional hidden feature to 2 dimensional feature.
- `output` is a linear layer that maps the 2D feature to 3D logits.

It is the output of `linear2` layer provides insight into how `x2 = act1(linear1(x))` works.

Your implementation of `MLP2DClassifier` will have an additional method `hiddenFeature(x)` that will return the output of `linear2`.

In [21]:

```
"✍"
# @workUnit

class MLP2DClassifier(nn.Module):
    def __init__(self):
        super().__init__()
        self.linear1 = nn.Linear(4, 100)
        self.act1 = nn.ReLU()
        self.linear2 = nn.Linear(100, 2)
        self.output = nn.Linear(2, 3)
    def forward(self, x):
        x = self.linear1(x)
        x = self.act1(x)
        x = self.linear2(x)
        x = self.output(x)
        return x
```

```
    def hiddenFeature(self, x):
        x = self.linear1(x)
        x = self.act1(x)
        x = self.linear2(x)
        return x
```

In [22]:
```
"🔒"
# @check
# @title: MLP2DClassifier architecture

m = MLP2DClassifier()
summary(m, torch.zeros(32, 4));
```

```
======================================================
          Kernel Shape Output Shape Params Mult-Adds
Layer
0_linear1     [4, 100]    [32, 100]  500.0     400.0
1_act1               -    [32, 100]      -         -
2_linear2     [100, 2]      [32, 2]  202.0     200.0
3_output        [2, 3]      [32, 3]    9.0       6.0
------------------------------------------------------
                      Totals
Total params           711.0
Trainable params       711.0
Non-trainable params     0.0
Mult-Adds              606.0
======================================================
```

In [23]:
```
"🔒"
mlp2 = MLP2DClassifier()
optimizer = Adam(mlp2.parameters())
dataloader = make_dataloader(train_dataset, shuffle=False, batch_size=32)

history_mlp2 = train(mlp2, optimizer, dataloader, 100)
```

```
0: loss=1.2121, acc=0.41
10: loss=0.7970, acc=0.77
20: loss=0.5395, acc=0.77
30: loss=0.3972, acc=0.91
40: loss=0.3037, acc=0.95
50: loss=0.2289, acc=0.95
60: loss=0.1723, acc=0.95
70: loss=0.1327, acc=0.95
80: loss=0.1064, acc=0.95
90: loss=0.0889, acc=0.95
```

In [24]:
```
"🔒"
# @check
# @title: ensure MLP2 performance

history_mlp2.acc.iloc[-1] > 0.9
```

Out[24]: True

In [25]:
```
"🔒"
#
```

```
# compute the hidden features for the first 100 training samples
#

(x, target) = train_dataset[0:100]
with torch.no_grad():
    x2 = mlp2.hiddenFeature(x)
```

In [26]:

```
"🔒"
# @check
# @title: get the hidden layout output

x2.shape
```

Out[26]:

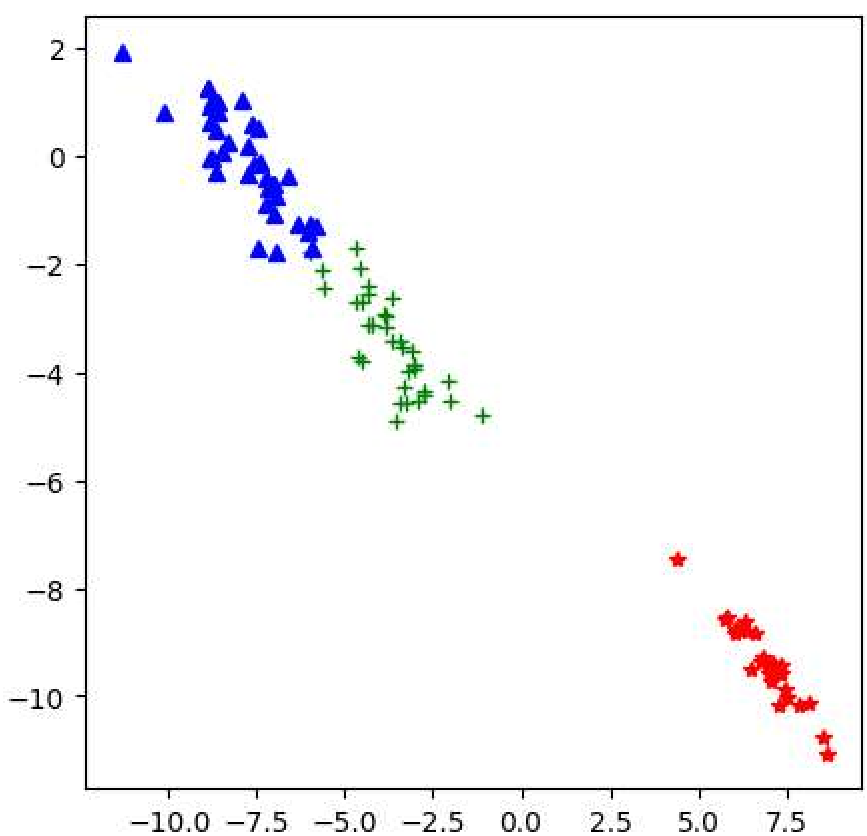
```
torch.Size([100, 2])
```

In [35]:

```
"🔒"
#
# Plot the three species using their hidden features
#

I0 = target == 0
I1 = target == 1
I2 = target == 2

plt.figure(figsize=(5,5))
plt.plot(x2[I0, 0], x2[I0, 1], '*', color='red');
plt.plot(x2[I1, 0], x2[I1, 1], '+', color='green');
plt.plot(x2[I2, 0], x2[I2, 1], '^', color='blue');
```



In [ ]:

```

```