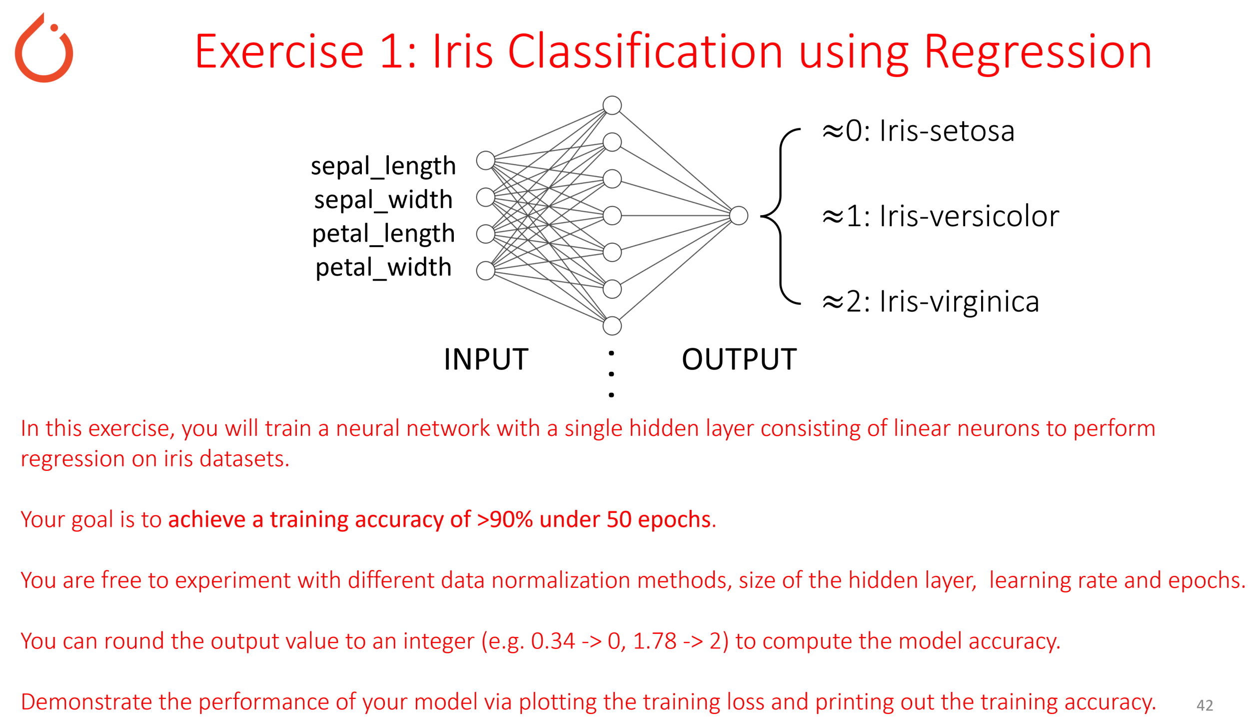
Lab 2 Report:

Iris Classification with Regression

Name:

```
# Import neccessary packages

%matplotlib inline

import numpy as np
import matplotlib.pyplot as plt
import torch


from IPython.display import Image # For displaying images in colab jupyter cell


Image('lab2_exercise1.PNG', width = 1000)
```



Prepare Data

```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
# iris dataset is available from scikit-learn package
iris = load_iris()

# Load the X (features) and y (targets) for training
X_train = iris['data']
y_train = iris['target']

# Load the name labels for features and targets
feature_names = iris['feature_names']
names = iris['target_names']

# split into train and testing data
# comment this
```

```
X_train, X_test, y_train, y_test = train_test_split(X_train, y_train, test_size=0.2, random_state=42)

# scale data
# use imported standard scaler class from scikit learn to quickly preprocess data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.fit_transform(X_test)

# convert data to tensor format, optimized for training models
# the output (y_test, y_train) needs to be long datatype to avoid compatibility issues with loss function
X_train = torch.tensor(X_train, dtype=torch.float32)
y_train = torch.tensor(y_train, dtype=torch.long)
X_test = torch.tensor(X_test, dtype=torch.float32)
y_test = torch.tensor(y_test, dtype=torch.long)

# reform dataset now that everything is transformed to tensor datatype
# small datasets for fast and lightweight training, and randomize to mitigate bias
train_dataset = torch.utils.data.TensorDataset(X_train, y_train)
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=16, shuffle=True)


# Print the first 10 training samples for both features and targets

print(X_train[:10, :], y_train[:10])
```

```
tensor([[-1.4739,  1.2037, -1.5625, -1.3126],
        [-0.1331,  2.9924, -1.2760, -1.0456],
        [ 1.0859,  0.0857,  0.3859,  0.2892],
        [-1.2301,  0.7565, -1.2187, -1.3126],
        [-1.7177,  0.3093, -1.3906, -1.3126],
        [ 0.5983, -1.2558,  0.7297,  0.9566],
        [ 0.7202,  0.3093,  0.4432,  0.4227],
        [-0.7426,  0.9801, -1.2760, -1.3126],
        [-0.9863,  1.2037, -1.3333, -1.3126],
        [-0.7426,  2.3216, -1.2760, -1.4461]]) tensor([0, 0, 1, 0, 0, 2, 1, 0, 0, 0])
```

```
# Print the dimensions of features and targets

print(X_train.shape, y_train.shape)
```

```
torch.Size([120, 4]) torch.Size([120])
```

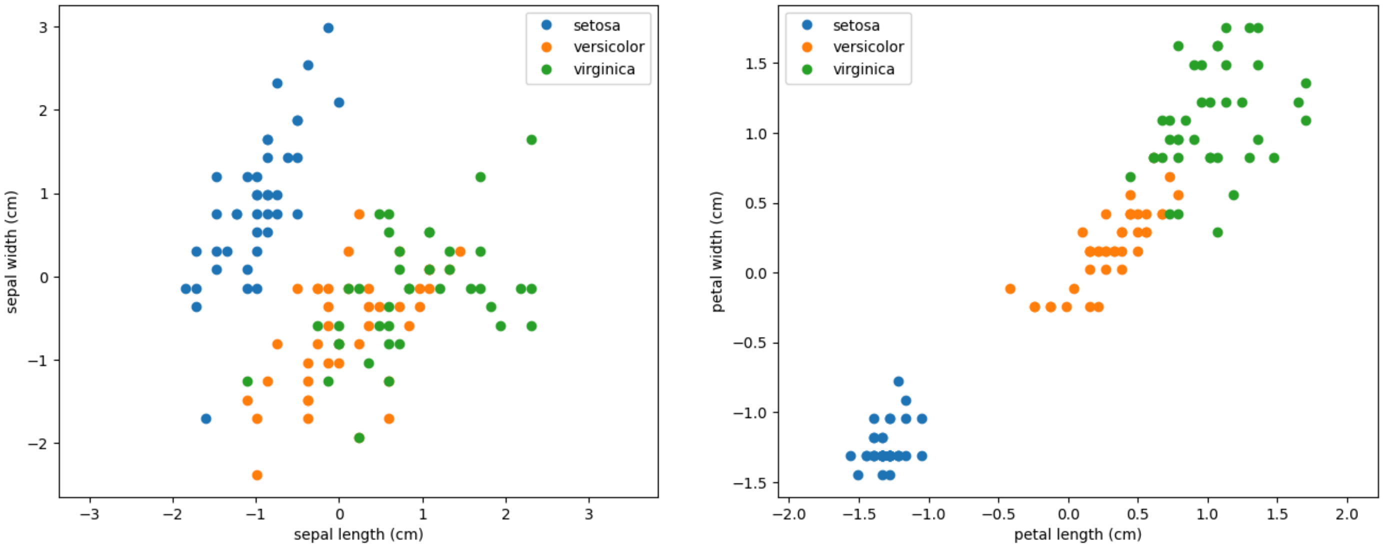
```
# feature_names contains name for each column in X_train
# For targets, 0 -> setosa, 1 -> versicolor, 2 -> virginica

print(feature_names, names)
```

```
['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)'] ['setosa' 'versicolor' 'virginica']
```

```
# We can visualize the dataset before training

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(16, 6))

# enumerate picks up both the index (0, 1, 2) and the element ('setosa', 'versicolor', 'virginica') from "names"
# loop 1: target = 0, target_name = 'setosa'
# loop 2: target = 1, target_name = 'versicolor' etc

for target, target_name in enumerate(names):

    # Subset the rows of X_train that fall into each flower category using boolean mapping
    X_plot = X_train[y_train == target]

    # Plot the sepal length versus sepal width for the flower category
    ax1.plot(X_plot[:, 0], X_plot[:, 1], linestyle='none', marker='o', label=target_name)

# Label the plot
ax1.set_xlabel(feature_names[0])
ax1.set_ylabel(feature_names[1])
ax1.axis('equal')
ax1.legend()

# Repeat the above process but with petal length versus petal width
for target, target_name in enumerate(names):

    X_plot = X_train[y_train == target]
```

```
    ax2.plot(X_plot[:, 2], X_plot[:, 3], linestyle='none', marker='o', label=target_name)

ax2.set_xlabel(feature_names[2])
ax2.set_ylabel(feature_names[3])
ax2.axis('equal')
ax2.legend()
```

<matplotlib.legend.Legend at 0x303b54740>



Define Model

```
class irisClassification(torch.nn.Module):
    # input dim auto initialized to 4 because Iris has 4 features
    # hidden dim auto is initialized to 16 neurons because the problem scope is not intensive
    # output dim auto is initialized to  3 because because there are 3 types (Setosa, Versicolor, Virginica)
    def __init__(self, input_dim=4, hidden_dim=16, output_dim=3):

        super(irisClassification, self).__init__()

        self.layer1 = torch.nn.Linear(input_dim, hidden_dim)
        self.layer2 = torch.nn.Linear(hidden_dim, output_dim)

    def forward(self, x):
        # use relu activation function for speed and efficiency
        temp = torch.nn.functional.relu(self.layer1(x))
        out = torch.nn.functional.relu(self.layer2(temp))

        return out
```

Define Hyperparameters

```
model = irisClassification()

# choose a higher learning rate to account for limited number of epochs
learning_rate = 0.15
epochs  = 40 # < 50

# We will use gradient descent for our optimizer and Cross Entropy Loss function
optimizer = torch.optim.Adam(model.parameters(), lr = learning_rate)
loss_func = torch.nn.CrossEntropyLoss()
```

Identify Tracked Values

```
# follow models performance over each epoch. Identify a metric and track it over epochs
training_loss_list = []
```

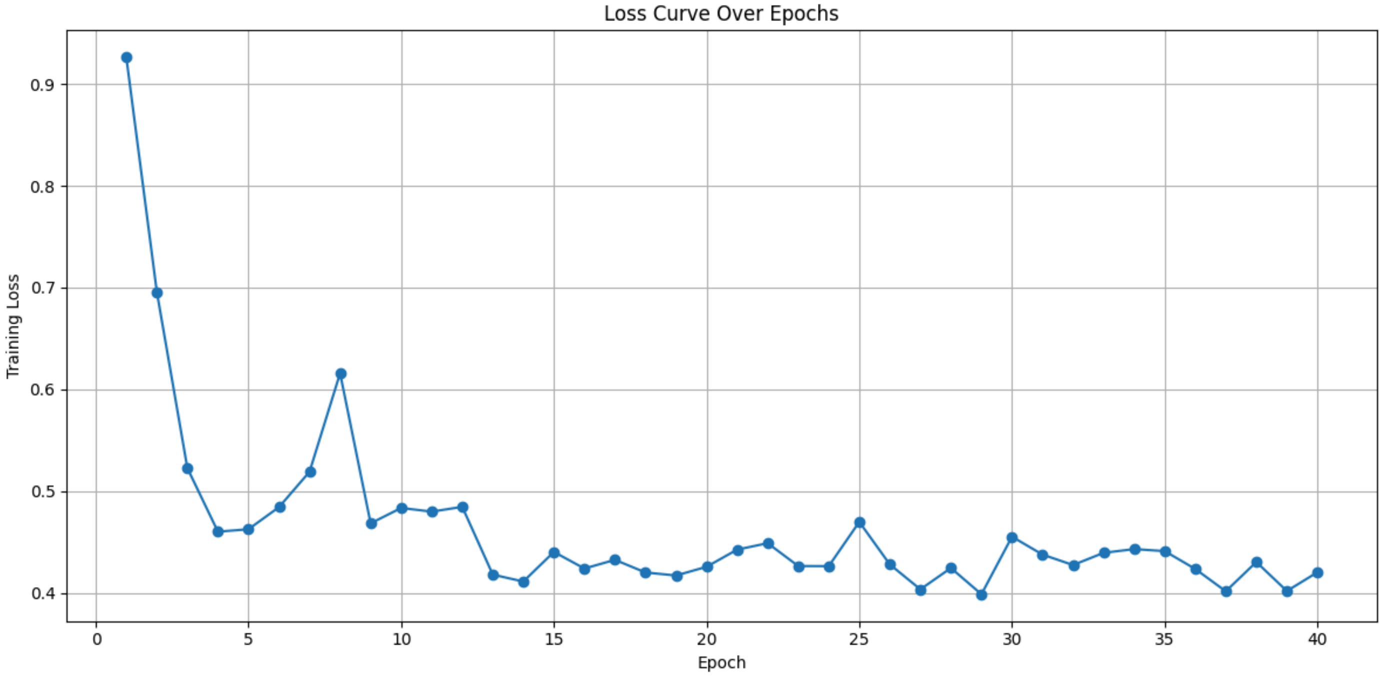
Train Model

```
# here we train the model
for epoch in range(epochs):
    epoch_loss = 0.0

    # train model in batches for computational efficiency and faster convergence
    # compute loss for each batch and update weights/biases
    for batch_X, batch_y in train_loader:
        outputs = model(batch_X)
        loss = loss_func(outputs, batch_y)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        epoch_loss += loss.item()

    # every 5th epoch, print the loss
    if epoch % 5 == 0:
        print(f"Epoch {epoch}: Loss = {loss.item():.4f}")

    # track loss per epoch
    avg_loss = epoch_loss / len(train_loader)
    training_loss_list.append(avg_loss)
```

```
Epoch 0: Loss = 0.7122
Epoch 5: Loss = 0.5579
Epoch 10: Loss = 0.2564
Epoch 15: Loss = 0.2763
Epoch 20: Loss = 0.6282
Epoch 25: Loss = 0.4147
Epoch 30: Loss = 0.4136
Epoch 35: Loss = 0.5524
```

Visualize and Evaluate Model

```
# Plot your training loss throughout the training
# Include proper x and y labels for the plot

plt.figure(figsize=(12, 6))
plt.plot(range(1, epochs + 1), training_loss_list, marker='o')
plt.xlabel('Epoch')
plt.ylabel('Training Loss')
plt.title('Loss Curve Over Epochs')
plt.grid(True)
plt.tight_layout()
plt.show()
```

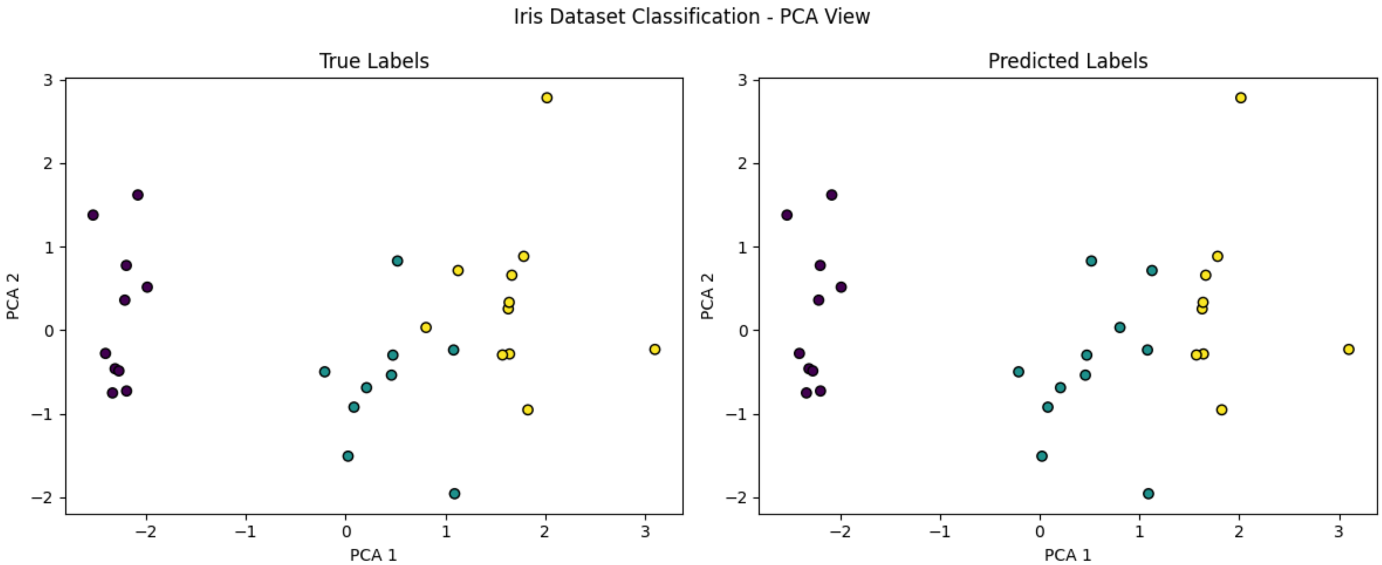



```
# Confirm that your model's training accuracy is >90%
# Training accuracy = (# of correct predictions) / (total # of training samples)
# You can round the model predictions to integer (e.g. 0.34 -> 0, 1.78 -> 2)
# use no_grad() to test model inference performance
with torch.no_grad():
    preds = model(X_test)
    predicted_classes = preds.argmax(dim=1)
    accuracy = (predicted_classes == y_test).float().mean()
    print(f"Test Accuracy: {accuracy.item():.4f}")
```

```
Test Accuracy: 0.9333
```

```
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA

# Get predictions from model
with torch.no_grad():
    logits = model(X_test)
    preds = torch.argmax(logits, dim=1)

# Perform PCA on X_test to reduce to 2D
pca = PCA(n_components=2)
X_test_2d = pca.fit_transform(X_test)

# Plot true labels vs predicted labels
fig, ax = plt.subplots(1, 2, figsize=(12, 5))

# Ground truth
ax[0].scatter(X_test_2d[:, 0], X_test_2d[:, 1], c=y_test, cmap='viridis', edgecolor='k')
ax[0].set_title('True Labels')
ax[0].set_xlabel('PCA 1')
ax[0].set_ylabel('PCA 2')

# Predicted labels
ax[1].scatter(X_test_2d[:, 0], X_test_2d[:, 1], c=preds, cmap='viridis', edgecolor='k')
ax[1].set_title('Predicted Labels')
ax[1].set_xlabel('PCA 1')
ax[1].set_ylabel('PCA 2')

plt.suptitle("Iris Dataset Classification - PCA View")
plt.tight_layout()
```

```
plt.show()
```


Iris Dataset Classification - PCA View
True Labels
Predicted Labels
PCA 1
PCA 2
3
2
1
0
−1
−2
−2
−1
0
1
2
3