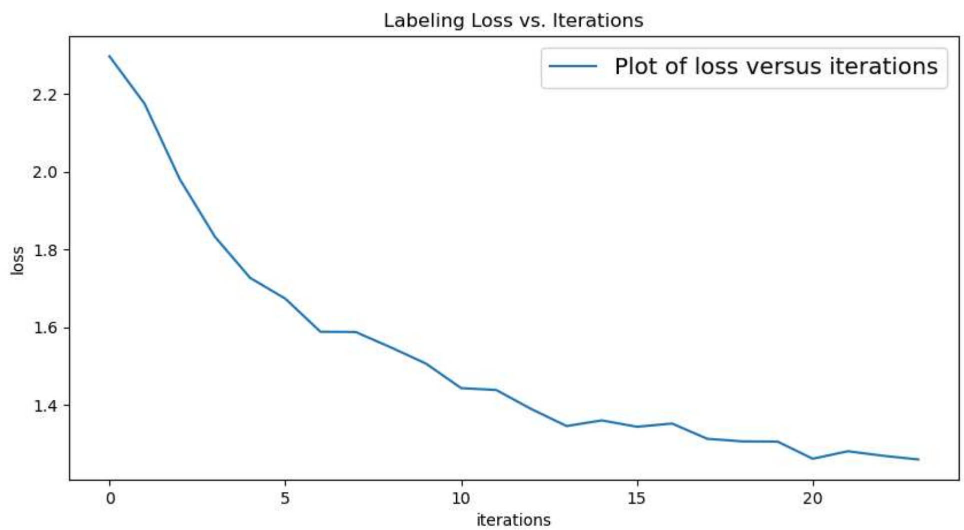
In [ ]:
```
# This is code from DLStudio-2.5.1
```

1. Net

By running playing_with_cifar10.py and switching between model = exp_cifar.Net() and model = exp_cifar.Net2(), we can obtain the training loss curve and confusion matrix for both models.

Train loss curve

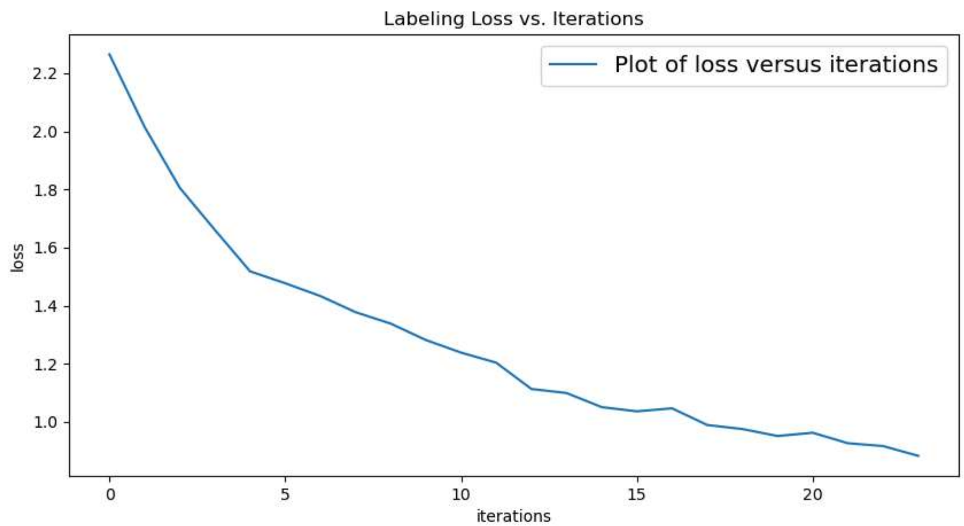


Confusion Matrix

	Plane	Car	Bird	Cat	Deer	Dog	Frog	Horse	Ship	Truck
Plane	72.60	3.00	6.00	1.40	1.30	0.20	2.10	0.40	6.40	6.60
Car	5.20	73.30	1.40	0.80	0.20	0.00	1.00	0.20	3.00	14.90
Bird	9.80	1.40	47.30	11.30	8.50	2.00	11.20	2.70	2.40	3.40
Cat	4.40	1.70	10.10	48.40	5.40	2.20	15.10	2.80	2.70	7.20
Deer	7.50	1.30	14.60	9.80	39.30	1.00	14.40	9.20	0.80	2.10
Dog	3.20	0.90	13.00	47.50	5.60	12.90	6.80	4.60	2.30	3.20
Frog	1.20	1.90	5.80	8.40	3.80	0.10	72.70	0.70	0.90	4.50
Horse	5.80	0.60	4.80	12.90	6.30	2.60	2.20	55.60	1.30	7.90
Ship	20.60	6.10	2.20	2.20	0.30	0.00	0.60	0.50	60.10	7.40
Truck	4.70	16.80	1.00	2.30	0.40	0.10	1.70	1.00	3.50	68.50

2. Net2

Train loss curve



Confusion Matrix

	Plane	**Car**	**Bird**	**Cat**	**Deer**	**Dog**	**Frog**	**Horse**	**Ship**	**Truck**
Plane	72.40	2.10	5.60	1.70	2.40	0.20	1.20	1.50	6.60	6.30
Car	0.90	78.10	0.80	0.40	0.40	0.30	0.60	0.10	1.50	16.90
Bird	6.10	0.70	53.10	4.70	12.40	6.10	8.40	3.70	2.10	2.70
Cat	1.70	0.80	6.00	46.60	8.30	15.80	8.60	4.90	2.80	4.50
Deer	1.50	0.20	5.60	3.60	67.40	2.80	8.60	7.80	2.00	0.50
Dog	1.10	0.50	5.40	16.20	6.20	58.30	2.50	5.60	1.80	2.40
Frog	0.30	0.90	3.80	4.90	2.60	1.30	82.10	0.70	0.80	2.60
Horse	0.90	0.40	2.00	3.50	6.10	6.20	0.70	77.20	0.60	2.40
Ship	5.40	4.10	0.90	0.60	0.80	0.50	0.40	0.60	83.00	3.70
Truck	1.90	5.30	0.30	0.70	0.30	0.30	0.30	1.60	3.30	86.00

3. Net3

By inheriting from DLStudio.ExperimentsWithCIFAR, we can seamlessly extend the class to introduce a new model, Net3. My deep CNN is designed with multiple convolutional layers, batch normalization, and max-pooling operations to progressively extract hierarchical features, followed by fully connected layers for final classification.

In [2]:
```
import os
import sys
current_dir = os.getcwd()
print("current_dir : %s" % current_dir)
goal = os.path.join(os.path.dirname(current_dir), "HW4/DLStudio-2.5.1")
sys.path.append(goal)
print("Navigated to:", goal)
from DLStudio import *
```

```
current_dir : d:\MS Purdue\1.5\ECE60146\HW5
Navigated to: d:\MS Purdue\1.5\ECE60146\HW4/DLStudio-2.5.1
```

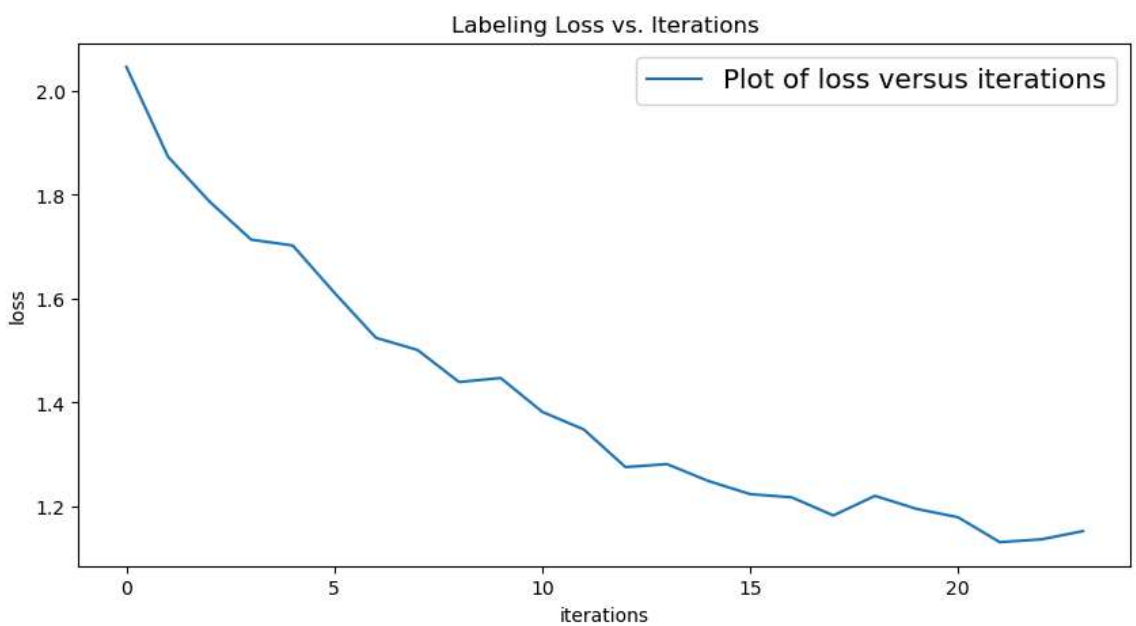
In [ ]:
```
# This code is mainly borrowed from HW5.pdf
import random
import numpy as np
import torch
import os

# Set random seed for reproducibility
seed = 0
random.seed(seed)
torch.manual_seed(seed)
torch.cuda.manual_seed(seed)
np.random.seed(seed)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmarks = False
os.environ['PYTHONHASHSEED'] = str(seed)

import torch.nn as nn
import torch.nn.functional as F

# Initialize DLStudio

dls = DLStudio(
    dataroot="./data/CIFAR-10/",
    image_size=[32, 32],
    path_saved_model="./saved_model",
    momentum=0.9,
    learning_rate=1e-3,
    epochs=2,
    batch_size=4,
    classes=('plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship',
    use_gpu=False
)

# Define Custom Experiments With CIFAR class
class CustomExperimentsWithCIFAR(DLStudio.ExperimentsWithCIFAR):
    # Define a new model Net3
    class Net3(nn.Module):
        def __init__(self):
            super(CustomExperimentsWithCIFAR.Net3, self).__init__()
            self.model = nn.Sequential(
```

```
            # First convolutional layer
            nn.Conv2d(3, 32, 3, padding=1), # Formula: ((W - K + 2P)/S) + 1. ((
            nn.BatchNorm2d(32),
            nn.ReLU(),

            # Second convolutional layer
            nn.Conv2d(32, 32, 3, padding=1), # Output: (32, 32, 32)
            nn.BatchNorm2d(32),
            nn.ReLU(),

            # Third convolutional layer
            nn.Conv2d(32, 32, 3, padding=1), # (64  -3 + 1)/1 + 1 = 32. Output:
            nn.BatchNorm2d(32),
            nn.ReLU(),
            nn.MaxPool2d(2, 2), # Output: (32, 16, 16)

            # Fourth convolutional layer
            nn.Conv2d(32, 64, 3, padding=1), # Output: (64, 16, 16)
            nn.BatchNorm2d(64),
            nn.ReLU(),

            # Fifth convolutional layer
            nn.Conv2d(64, 64, 3, padding=1), # Output: (64, 16, 16)
            nn.BatchNorm2d(64),
            nn.ReLU(),

            # Sixth convolutional layer
            nn.Conv2d(64, 64, 3, padding=1), # Output: (64, 16, 16)
            nn.BatchNorm2d(64),
            nn.ReLU(),
            nn.MaxPool2d(2, 2), # Output: (64, 16, 16)

            # Seventh convolutional layer
            nn.Conv2d(64, 128, 3, padding=1), # Output: (128, 8, 8)
            nn.BatchNorm2d(128),
            nn.ReLU(),

            # Eigth convolutional layer
            nn.Conv2d(128, 128, 3, padding=1), # Output: (128, 8, 8)
            nn.BatchNorm2d(128),
            nn.ReLU(),
            nn.MaxPool2d(2, 2), # Output: (128, 4, 4)


            # Fully connected layers
            nn.Flatten(), # Output: (128*4*4 = 2048, )
            nn.Linear(2048, 512), # Output: (512, )
            nn.BatchNorm1d(512),
            nn.ReLU(),

            nn.Linear(512, 128), # Output: (128, )
            nn.BatchNorm1d(128),
            nn.ReLU(),

            nn.Linear(128, 10) # Output: 10 classes
        )
```

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



# Use the new class
exp_cifar = CustomExperimentsWithCIFAR(dl_studio=dls)
exp_cifar.load_cifar_10_dataset()

# Instantiate the new model
# model = exp_cifar.Net()
# model = exp_cifar.Net2()
model = exp_cifar.Net3()

# Display network properties
number_of_learnable_params = sum(p.numel() for p in model.parameters() if p.require
print("\n\nThe number of learnable parameters in the model: %d" % number_of_learnab

# Run training and testing
exp_cifar.run_code_for_training(model, display_images=False)
exp_cifar.run_code_for_testing(model, display_images=False)
```

Creating CustomExperimentsCIFAR and Net3

Train loss curve



Confusion Matrix

	Plane	Car	Bird	Cat	Deer	Dog	Frog	Horse	Ship	Truck
Plane	74.80	1.80	4.50	3.10	1.30	0.80	0.80	0.40	10.90	1.60
Car	1.30	88.40	0.30	1.40	0.40	0.30	0.70	0.20	2.80	4.20

	Plane	Car	Bird	Cat	Deer	Dog	Frog	Horse	Ship	Truck
Bird	8.40	0.40	53.80	8.10	9.90	9.10	7.40	1.20	1.50	0.20
Cat	2.30	0.40	5.30	61.20	4.90	15.40	6.60	2.00	1.50	0.40
Deer	3.30	0.20	4.80	8.30	63.90	5.00	9.10	3.50	1.90	0.00
Dog	0.80	0.10	4.20	21.60	4.60	62.20	3.30	2.20	1.00	0.00
Frog	0.90	0.10	3.10	8.30	2.20	1.30	81.80	0.20	2.00	0.10
Horse	1.30	0.20	4.40	7.00	7.30	11.20	0.70	66.10	0.80	1.00
Ship	4.60	2.70	1.20	2.40	0.60	0.30	0.40	0.00	87.10	0.70
Truck	3.20	9.50	1.00	4.20	0.60	0.30	0.30	0.40	3.30	77.20

4. Overall accuracy of 3 models

	Accuracy
Net	55%
Net2	70%
Net3	71%

5. Per class accuracy of 3 models

	Net	Net2	Net3
Plane	72.60	72.40	74.80
Car	73.30	78.10	88.40
Bird	47.30	53.10	53.80
Cat	48.40	46.60	61.20
Deer	39.30	67.40	63.90
Dog	12.90	58.30	62.20
Frog	72.70	82.10	81.80
Horse	55.60	77.20	66.10
Ship	60.10	83.00	87.10
Truck	68.50	86.00	77.20

6. Observations

By observing the table of Overall accuracy of 3 models. Net, with 2 convolutional layers and 3 fully connected layers, achieves 55% accuracy. Net2, which incorporates 3 convolutional layers with max pooling after each layer and 3 fully connected layers, improves accuracy to 70%. Net3, featuring 8 convolutional layers, 3 max pooling layers, and 3 fully connected layers, only slightly outperforms Net2, reaching 71% accuracy.

Despite the significantly increased number of parameters, layers, and training time in Net3, the performance improvement remains marginal. This suggests that simply deepening the network does not necessarily enhance generalization on CIFAR-10. One possible explanation is the vanishing gradient problem, where deeper networks struggle with efficient gradient propagation during backpropagation. This can lead to slow or stalled learning in the earlier layers, preventing the model from fully leveraging its deeper feature representations.

By observing the table of Per class accuracy of 3 models, while Net3 further refines accuracy in some categories like Car, Cat, and Ship. Howerver, it performs worse than Net2 in categories on Deer, Horse, and Truck. This aligns the earlier discussion that deeper networks do not always generalize better, possibly due to vanishing gradients or overfitting to certain features.