a5

May 8, 2025

1 Dados

1.1 Caminhos

[1]:
```
datasets_path     = '/home/jose-roberto/Documents/Disciplinas/INF492/assignment/
 ↪a5/datasets'
models_path       = '/home/jose-roberto/Documents/Disciplinas/INF492/assignment/
 ↪a5/models/'
tensorboard_path  = '/home/jose-roberto/Documents/Disciplinas/INF492/assignment/
 ↪a5/train_runs/'
```

1.2 Dataloader

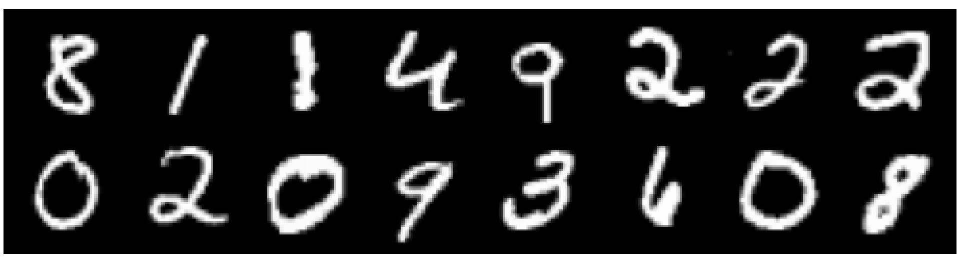
[2]:
```
from torch.utils.data import DataLoader
import torchvision

import matplotlib.pyplot as plt
import numpy as np

def my_imshow(img, dataset, numImages=10):

    if dataset == 'cifar10' :
        img = img / 2 + 0.5     # unnormalize

    img = torchvision.utils.make_grid(img[:numImages],nrow=numImages//2)

    npimg = img.numpy()
    npimg = np.transpose(npimg, (1, 2, 0))

    plt.axis('off')
    plt.imshow(npimg)
    plt.show()

def show_images(train_loader, test_loader, dataset, numImages=10) :
    print('Train samples')
    # get some random training images
    dataiter = iter(train_loader)
    images = next(dataiter)[0]
```

```
    my_imshow(images, dataset, numImages)

    print('Test samples')
    # get some random training images
    dataiter = iter(test_loader)
    images = next(dataiter)[0]
    my_imshow(images, dataset, numImages)

def get_data_cifar10 ( batch_size , show_image=False, numImages=10 ) :

    my_transform = torchvision.transforms.Compose([
                        torchvision.transforms.Resize(28),
                        torchvision.transforms.ToTensor(),
                        torchvision.transforms.Normalize(mean=[0.5],std=[0.
↪5])
                                ])

    train_dataset = torchvision.datasets.CIFAR10(
                            root=f'{datasets_path}/train/',
                            train=True,
                            transform=my_transform,
                            download=False
                            )
    test_dataset = torchvision.datasets.CIFAR10(
                            root=f'{datasets_path}/test/',
                            train=False,
                            transform=my_transform,
                            download=False
                            )
    train_loader = DataLoader(train_dataset,
                            batch_size=batch_size,
                            shuffle=True
                            )
    test_loader = DataLoader(test_dataset,
                        batch_size=batch_size,
                        shuffle=False
                        )

    if show_image :
        show_images(train_loader, test_loader, 'cifar10', numImages)

    return train_loader, test_loader, len(train_dataset)


def get_data_mnist ( batch_size , show_image=False, numImages=10 ) :

    train_dataset = torchvision.datasets.mnist.MNIST(
```

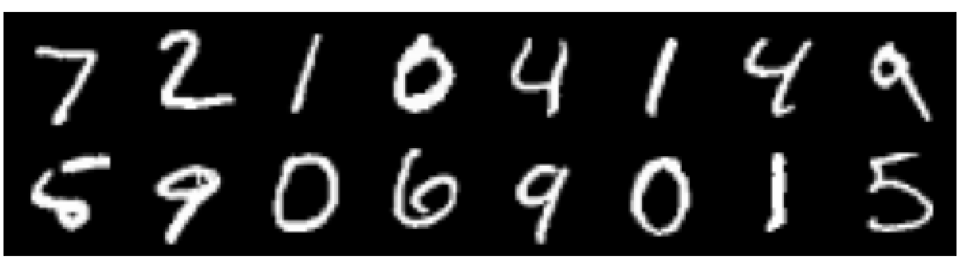
```
                            root=f'{datasets_path}/train/',
                            train=True,
                            transform=torchvision.transforms.ToTensor(),
                            download=False
                            )
    test_dataset = torchvision.datasets.mnist.MNIST(
                            root=f'{datasets_path}/test/',
                            train=False,
                            transform=torchvision.transforms.ToTensor(),
                            download=False
                            )

    train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
    test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False)

    if show_image :
        show_images(train_loader, test_loader, 'mnist', numImages)

    return train_loader, test_loader, len(train_dataset)
```

[3]:
```
get_data_mnist(batch_size=256, show_image=True, numImages=16);
```

Train samples



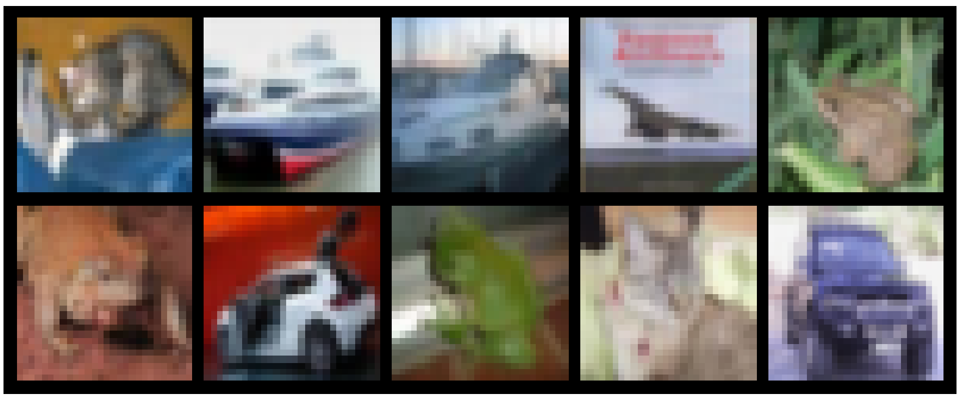
Test samples



[4]:
```
get_data_cifar10(batch_size=256, show_image=True, numImages=10);
```

```
Train samples
```

```
Test samples
```



2 Rede

2.1 Arquitetura

[24]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F

class LeNet(nn.Module) :

    def __init__(self, num_classes=10, n_channels=1, relu=False):
```

```
        super().__init__()

        self.conv1 = nn.Conv2d(in_channels=n_channels, out_channels=6,␣
↪kernel_size=5, padding=2)
        self.act1 = nn.Sigmoid() if not relu else nn.ReLU()
        self.pool1 = nn.AvgPool2d(kernel_size=2, stride=2)

        self.conv2 = nn.Conv2d(in_channels=6, out_channels=16, kernel_size=5)
        self.pool2 = nn.AvgPool2d(kernel_size=2, stride=2)

        out_channels_conv3 = 120 if n_channels == 1 else 480
        self.conv3 = nn.Conv2d(in_channels=16, out_channels=out_channels_conv3,␣
↪kernel_size=5)

        in_features_dense1 = out_channels_conv3
        self.dense1 = nn.Linear(in_features=in_features_dense1, out_features=84)
        self.act2 = nn.Tanh() if not relu else nn.ReLU()

        self.dense2 = nn.Linear(in_features=84, out_features=num_classes)

    def forward(self, x, debug=False):
        if debug : print(f'Shape de entrada: {x.shape}')
        x = self.conv1(x)
        if debug : print(f'Shape de entrada: {x.shape}')
        x = self.act1(x)
        x = self.pool1(x)
        if debug : print(f'Shape de entrada: {x.shape}')
        x = self.conv2(x)
        if debug : print(f'Shape de entrada: {x.shape}')
        x = self.act1(x)
        x = self.pool2(x)
        if debug : print(f'Shape de entrada: {x.shape}')
        x = self.conv3(x)
        if debug : print(f'Shape de entrada: {x.shape}')
        x = self.act1(x)
        x = x.view(x.size(0), -1)
        if debug : print(f'Shape de entrada: {x.shape}')
        x = self.dense1(x)
        if debug : print(f'Shape de entrada: {x.shape}')
        x = self.act2(x)
        x = self.dense2(x)
        if debug : print(f'Shape de entrada: {x.shape}')
        x = self.act2(x)

        return x
```

2.2 Informações sobre a rede

[6]:
```python
import torch

if torch.cuda.is_available():
    my_device = torch.device("cuda:0")
else:
    my_device = torch.device("cpu")

print(f"Running on {my_device.type}.")

net = LeNet(num_classes=10, n_channels=1)
net = net.to(my_device)

a = torch.rand( (1, 1, 28, 28) )

b = net( a.to(my_device), debug=True)
```

```
Running on cpu.
Shape de entrada: torch.Size([1, 1, 28, 28])
Shape de entrada: torch.Size([1, 6, 28, 28])
Shape de entrada: torch.Size([1, 6, 14, 14])
Shape de entrada: torch.Size([1, 16, 10, 10])
Shape de entrada: torch.Size([1, 16, 5, 5])
Shape de entrada: torch.Size([1, 120, 1, 1])
Shape de entrada: torch.Size([1, 120])
Shape de entrada: torch.Size([1, 84])
Shape de entrada: torch.Size([1, 10])
```

[7]:
```python
from torchsummary import summary
summary(net, input_size=(1,28,28), batch_size=256)
del net, a, b
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [256, 6, 28, 28]             156
           Sigmoid-2           [256, 6, 28, 28]               0
         AvgPool2d-3           [256, 6, 14, 14]               0
            Conv2d-4          [256, 16, 10, 10]           2,416
           Sigmoid-5          [256, 16, 10, 10]               0
         AvgPool2d-6            [256, 16, 5, 5]               0
            Conv2d-7           [256, 120, 1, 1]          48,120
           Sigmoid-8           [256, 120, 1, 1]               0
            Linear-9                  [256, 84]          10,164
           Tanh-10                  [256, 84]               0
          Linear-11                  [256, 10]             850
            Tanh-12                  [256, 10]               0
================================================================
```

```
Total params: 61,706
Trainable params: 61,706
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.77
Forward/backward pass size (MB): 28.54
Params size (MB): 0.24
Estimated Total Size (MB): 29.54
----------------------------------------------------------------
```

[25]:

```
net = LeNet(num_classes=10, n_channels=3)
net = net.to(my_device)

a = torch.rand( (1, 3, 28, 28) )

b = net( a.to(my_device), debug=True)

from torchsummary import summary
summary(net, input_size=(3,28,28), batch_size=256)
del net, a, b
```

```
Shape de entrada: torch.Size([1, 3, 28, 28])
Shape de entrada: torch.Size([1, 6, 28, 28])
Shape de entrada: torch.Size([1, 6, 14, 14])
Shape de entrada: torch.Size([1, 16, 10, 10])
Shape de entrada: torch.Size([1, 16, 5, 5])
Shape de entrada: torch.Size([1, 480, 1, 1])
Shape de entrada: torch.Size([1, 480])
Shape de entrada: torch.Size([1, 84])
Shape de entrada: torch.Size([1, 10])
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [256, 6, 28, 28]             456
           Sigmoid-2           [256, 6, 28, 28]               0
         AvgPool2d-3           [256, 6, 14, 14]               0
            Conv2d-4          [256, 16, 10, 10]           2,416
           Sigmoid-5          [256, 16, 10, 10]               0
         AvgPool2d-6            [256, 16, 5, 5]               0
            Conv2d-7           [256, 480, 1, 1]         192,480
           Sigmoid-8           [256, 480, 1, 1]               0
            Linear-9                  [256, 84]          40,404
           Tanh-10                  [256, 84]               0
          Linear-11                  [256, 10]             850
            Tanh-12                  [256, 10]               0
================================================================
Total params: 236,606
Trainable params: 236,606
```

```
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 2.30
Forward/backward pass size (MB): 29.95
Params size (MB): 0.90
Estimated Total Size (MB): 33.14
----------------------------------------------------------------
```

2.3 Treinamento

[9]:
```python
from torch.utils.tensorboard import SummaryWriter

import torch.optim

import matplotlib.pyplot as plt
import numpy as np
from tqdm import tqdm

import copy

from datetime import datetime

def train ( dataset, epochs=100, lr=1e-1, prefix='', upper_bound=99.0,␣
 ↪device='cpu',
            relu=False, save=False, debug=False, plot_histograms=False,␣
 ↪lambda_reg=0) :

    if dataset == 'mnist' :
        batch_size = 256
        train_loader, test_loader, dataset_size = get_data_mnist(batch_size,
                                                                      ␣
 ↪show_image=True
                                                                       )
        num_classes = 10
        n_channels = 1
    elif dataset == 'cifar10' :
        batch_size = 256
        train_loader, test_loader, dataset_size = get_data_cifar10(batch_size,
                                                                      ␣
 ↪show_image=True
                                                                       )
        num_classes = 10
        n_channels = 3
    else :
        print('Dataset loader not implemented.')
        return None
```

```
net = LeNet( num_classes, n_channels, relu=relu )
net.to(device)

optimizer = torch.optim.SGD(net.parameters(), lr, weight_decay=lambda_reg)
loss = nn.CrossEntropyLoss()

now = datetime.now()
suffix = now.strftime("%Y%m%d_%H%M%S")
prefix = prefix + '-' + suffix if prefix != '' else suffix

writer = SummaryWriter( log_dir=tensorboard_path+prefix )

writer.add_graph(net, next(iter(train_loader))[0].to(my_device))

accuracies = []
max_accuracy = -1.0

for epoch in tqdm( range(epochs) , desc='Training epochs...' ) :
    net.train()
    for idx, (train_x, train_label) in enumerate(train_loader):
        train_x = train_x.to(device)
        train_label = train_label.to(device)

        optimizer.zero_grad()

        predict_y = net( train_x )

        # Loss:
        error = loss( predict_y , train_label.long() )

        writer.add_scalar( 'Loss/train', error,
                        idx+( epoch*(dataset_size//batch_size) ) )

        error.backward()
        optimizer.step()

        # Accuracy:
        predict_ys = torch.max( predict_y, axis=1 )[1]
        correct    = torch.sum(predict_ys == train_label)

        writer.add_scalar( 'Accuracy/train', correct/train_x.size(0),
                        idx+( epoch*(dataset_size//batch_size) ) )

        if debug and idx % 10 == 0 :
            print(f'idx: {idx}, _error: {error}')

    if plot_histograms :
```

```python
            plot_histograms_tensorboard(writer, net, epoch)

        accuracy = validate(net, test_loader, device=device)
        accuracies.append(accuracy.cpu())
        writer.add_scalar( 'Accuracy/test', accuracy, epoch )

        if accuracy > max_accuracy:
            best_model = copy.deepcopy(net)
            max_accuracy = accuracy
            print(f'Saving Best Model with Accuracy: {max_accuracy:3.4f}')

        print( f'Epoch: {epoch+1:3d} | Accuracy : {accuracy:3.4f}%' )

        if accuracy > upper_bound :
            break

    if save :
        path = f'{models_path}{'relu-' if relu else␣
↪''}LeNet5-{dataset}-{max_accuracy:.2f}.pkl'
        torch.save(best_model.state_dict(), path)
        print('Model saved in:',path)

    plt.plot(accuracies)

    writer.flush()
    writer.close()

    return best_model
```

[10]:
```python
def plot_histograms_tensorboard ( writer, net, epoch ) :
    writer.add_histogram('Bias/conv1',   net.conv1.bias,        epoch)
    writer.add_histogram('Weight/conv1', net.conv1.weight,      epoch)
    writer.add_histogram('Grad/conv1',   net.conv1.weight.grad, epoch)

    writer.add_histogram('Bias/conv2',   net.conv2.bias,        epoch)
    writer.add_histogram('Weight/conv2', net.conv2.weight,      epoch)
    writer.add_histogram('Grad/conv2',   net.conv2.weight.grad, epoch)

    writer.add_histogram('Bias/conv3',   net.conv3.bias,        epoch)
    writer.add_histogram('Weight/conv3', net.conv3.weight,      epoch)
    writer.add_histogram('Grad/conv3',   net.conv3.weight.grad, epoch)
```

2.4 Validação

[11]:
```
def validate ( model , data , device='cpu') :
    model.eval()
    correct = 0
    sum = 0

    for idx, (test_x, test_label) in enumerate(data) :
        test_x = test_x.to(device)
        test_label = test_label.to(device)
        predict_y = model( test_x ).detach()
        predict_ys = torch.max( predict_y, axis=1 )[1]
        sum = sum + test_x.size(0)
        correct = correct + torch.sum(predict_ys == test_label)

    return correct*100./sum
```

3 Execução

3.1 Treina

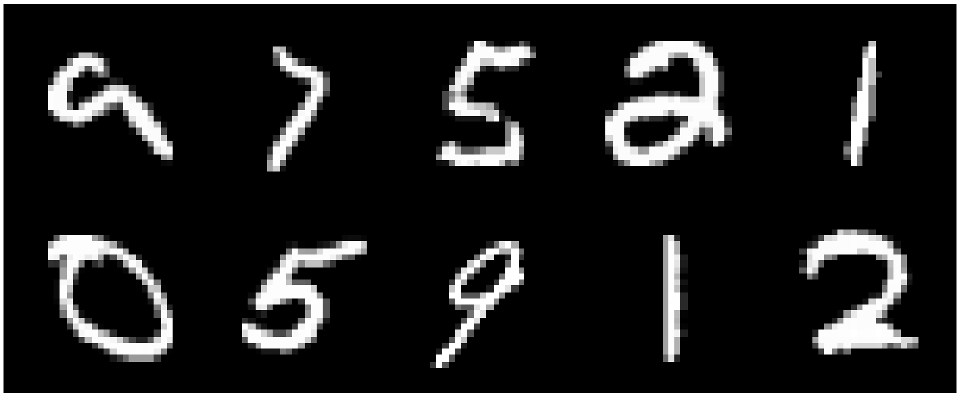
[12]:
```
if torch.cuda.is_available():
    my_device = torch.device("cuda:0")
else:
    my_device = torch.device("cpu")
print(f"Running on {my_device.type}.")
```

```
Running on cpu.
```

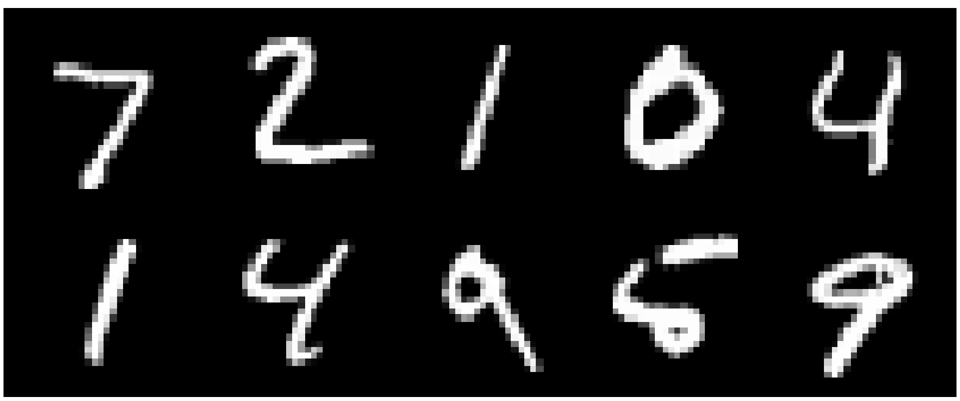
3.1.1 MNIST - Sigmoid e Tahn

[38]:
```
epochs = 30
dataset = 'mnist' # 'cifar10'
lr = 1.3e0
lambda_reg = 0

prefix = 'LeNet-{}-e-{}-lr-{}'.format(dataset, epochs, lr)

net = train( dataset=dataset, epochs=epochs, lr=lr, prefix=prefix ,␣
 ↪upper_bound=100, device=my_device,
            relu=False, save=True, debug=False, plot_histograms=True,␣
 ↪lambda_reg=lambda_reg )
```

```
Train samples
```



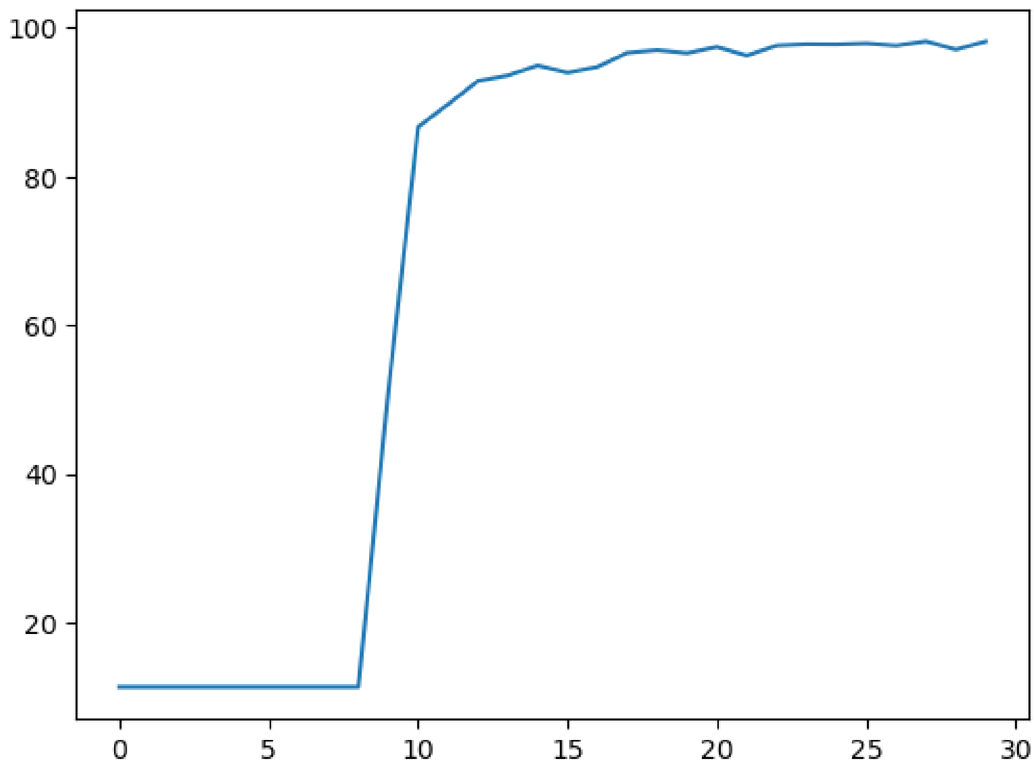
Test samples



```
Training epochs…:   3%|          | 1/30 [00:15<07:29, 15.51s/it]

Saving Best Model with Accuracy: 11.3500
Epoch:   1 | Accuracy : 11.3500%

Training epochs…:   7%|          | 2/30 [00:31<07:29, 16.07s/it]

Epoch:   2 | Accuracy : 11.3500%

Training epochs…:  10%|          | 3/30 [00:48<07:17, 16.20s/it]

Epoch:   3 | Accuracy : 11.3500%

Training epochs…:  13%|         | 4/30 [01:04<06:56, 16.03s/it]

Epoch:   4 | Accuracy : 11.3500%

Training epochs…:  17%|         | 5/30 [01:20<06:43, 16.13s/it]

Epoch:   5 | Accuracy : 11.3500%
```

```
Training epochs…:  20%|          | 6/30 [01:36<06:26, 16.09s/it]

Epoch:   6 | Accuracy : 11.3500%

Training epochs…:  23%|          | 7/30 [01:52<06:07, 15.99s/it]

Epoch:   7 | Accuracy : 11.3500%

Training epochs…:  27%|          | 8/30 [02:08<05:54, 16.11s/it]

Epoch:   8 | Accuracy : 11.3500%

Training epochs…:  30%|          | 9/30 [02:25<05:40, 16.22s/it]

Epoch:   9 | Accuracy : 11.3500%

Training epochs…:  33%|          | 10/30 [02:40<05:22, 16.11s/it]

Saving Best Model with Accuracy: 50.9600
Epoch:  10 | Accuracy : 50.9600%

Training epochs…:  37%|          | 11/30 [02:56<05:04, 16.03s/it]

Saving Best Model with Accuracy: 86.6700
Epoch:  11 | Accuracy : 86.6700%

Training epochs…:  40%|          | 12/30 [03:12<04:47, 15.95s/it]

Saving Best Model with Accuracy: 89.7200
Epoch:  12 | Accuracy : 89.7200%

Training epochs…:  43%|          | 13/30 [03:29<04:34, 16.12s/it]

Saving Best Model with Accuracy: 92.8500
Epoch:  13 | Accuracy : 92.8500%

Training epochs…:  47%|          | 14/30 [03:45<04:20, 16.26s/it]

Saving Best Model with Accuracy: 93.6000
Epoch:  14 | Accuracy : 93.6000%

Training epochs…:  50%|          | 15/30 [04:02<04:07, 16.48s/it]

Saving Best Model with Accuracy: 94.9500
Epoch:  15 | Accuracy : 94.9500%

Training epochs…:  53%|          | 16/30 [04:19<03:50, 16.50s/it]

Epoch:  16 | Accuracy : 93.9800%

Training epochs…:  57%|          | 17/30 [04:36<03:37, 16.71s/it]

Epoch:  17 | Accuracy : 94.7500%

Training epochs…:  60%|          | 18/30 [04:52<03:18, 16.53s/it]

Saving Best Model with Accuracy: 96.6400
Epoch:  18 | Accuracy : 96.6400%

Training epochs…:  63%|          | 19/30 [05:08<02:59, 16.32s/it]
```

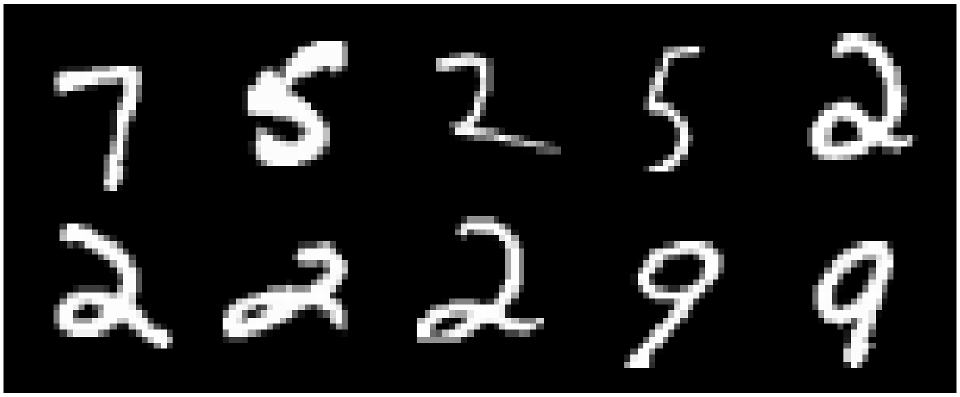
```
Saving Best Model with Accuracy: 97.0100
Epoch:  19 | Accuracy : 97.0100%

Training epochs…:  67%|       | 20/30 [05:24<02:44, 16.42s/it]

Epoch:  20 | Accuracy : 96.6000%

Training epochs…:  70%|       | 21/30 [05:40<02:26, 16.31s/it]

Saving Best Model with Accuracy: 97.4400
Epoch:  21 | Accuracy : 97.4400%

Training epochs…:  73%|      | 22/30 [05:57<02:10, 16.36s/it]

Epoch:  22 | Accuracy : 96.2700%

Training epochs…:  77%|      | 23/30 [06:14<01:55, 16.49s/it]

Saving Best Model with Accuracy: 97.6300
Epoch:  23 | Accuracy : 97.6300%

Training epochs…:  80%|      | 24/30 [06:30<01:38, 16.46s/it]

Saving Best Model with Accuracy: 97.8100
Epoch:  24 | Accuracy : 97.8100%

Training epochs…:  83%|     | 25/30 [06:47<01:22, 16.56s/it]

Epoch:  25 | Accuracy : 97.7800%

Training epochs…:  87%|     | 26/30 [07:03<01:05, 16.41s/it]

Saving Best Model with Accuracy: 97.9100
Epoch:  26 | Accuracy : 97.9100%

Training epochs…:  90%|     | 27/30 [07:19<00:49, 16.40s/it]

Epoch:  27 | Accuracy : 97.6200%

Training epochs…:  93%|    | 28/30 [07:35<00:32, 16.26s/it]

Saving Best Model with Accuracy: 98.1900
Epoch:  28 | Accuracy : 98.1900%

Training epochs…:  97%|    | 29/30 [07:51<00:16, 16.12s/it]

Epoch:  29 | Accuracy : 97.0900%

Training epochs…: 100%|    | 30/30 [08:09<00:00, 16.30s/it]

Epoch:  30 | Accuracy : 98.1800%
Model saved in: /home/jose-
roberto/Documents/Disciplinas/INF492/assignment/a5/models/LeNet5-mnist-98.19.pkl
```



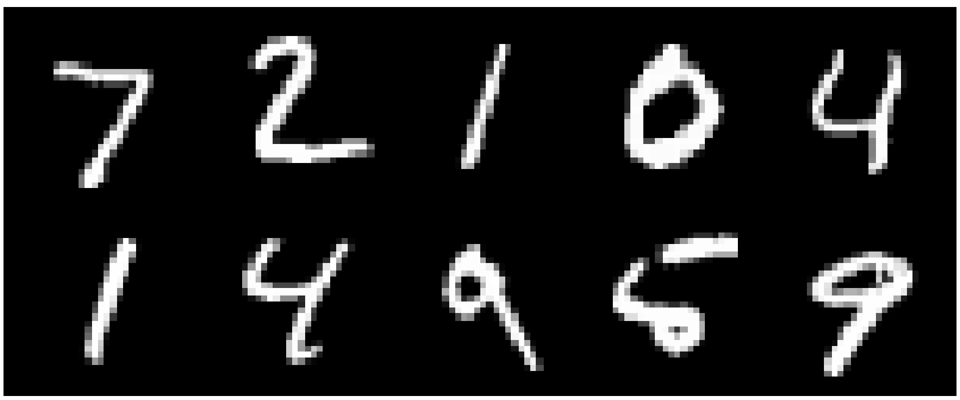
3.1.2 MNIST - ReLu

[40]:
```
epochs = 30
dataset = 'mnist' # 'cifar10'
lr = 5e-2
lambda_reg = 0

prefix = 'relu-LeNet-{}-e-{}-lr-{}'.format(dataset, epochs, lr)

net_relu = train( dataset=dataset, epochs=epochs, lr=lr, prefix=prefix ,␣
 ↪upper_bound=100, device=my_device,
             relu=True, save=True, debug=False, plot_histograms=True,␣
 ↪lambda_reg=lambda_reg )
```

```
Train samples
```



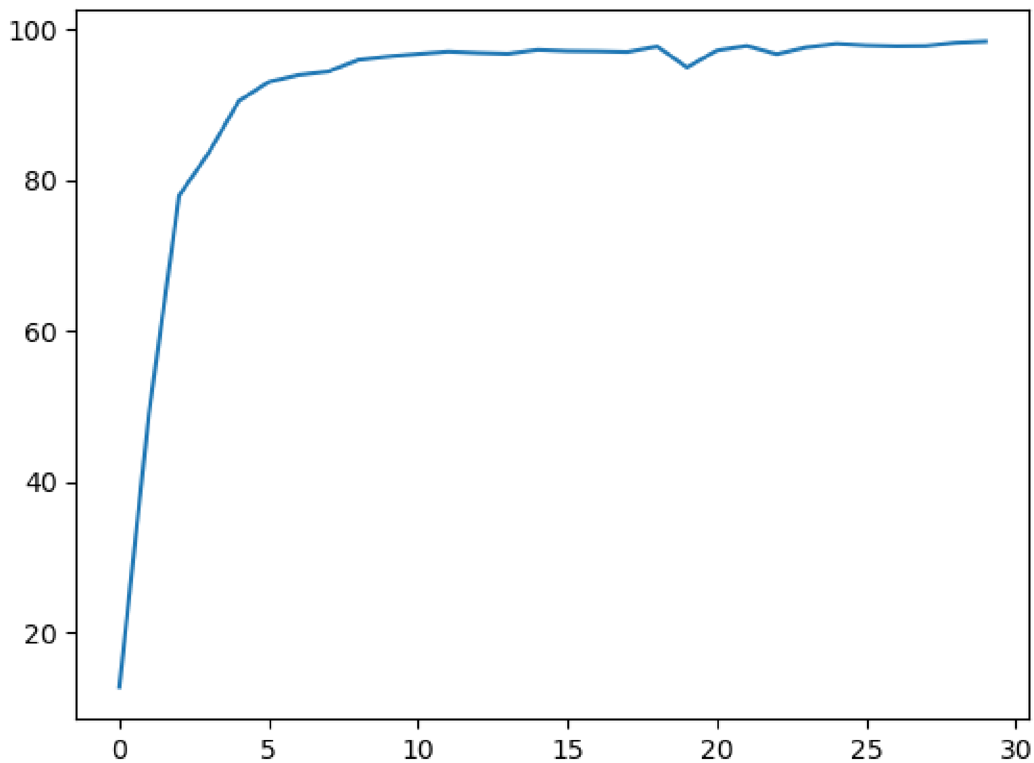
```
Test samples
```



```
Training epochs…:   3%|          | 1/30 [00:15<07:18, 15.12s/it]

Saving Best Model with Accuracy: 12.7600
Epoch:   1 | Accuracy : 12.7600%

Training epochs…:   7%|          | 2/30 [00:29<06:56, 14.86s/it]

Saving Best Model with Accuracy: 49.2600
Epoch:   2 | Accuracy : 49.2600%

Training epochs…:  10%|          | 3/30 [00:44<06:42, 14.91s/it]

Saving Best Model with Accuracy: 77.9200
Epoch:   3 | Accuracy : 77.9200%

Training epochs…:  13%|         | 4/30 [01:00<06:36, 15.27s/it]

Saving Best Model with Accuracy: 83.6800
Epoch:   4 | Accuracy : 83.6800%
```

```
Training epochs…:  17%|          | 5/30 [01:16<06:29, 15.56s/it]

Saving Best Model with Accuracy: 90.5100
Epoch:   5 | Accuracy : 90.5100%

Training epochs…:  20%|          | 6/30 [01:33<06:21, 15.89s/it]

Saving Best Model with Accuracy: 93.0100
Epoch:   6 | Accuracy : 93.0100%

Training epochs…:  23%|         | 7/30 [01:50<06:13, 16.26s/it]

Saving Best Model with Accuracy: 93.9400
Epoch:   7 | Accuracy : 93.9400%

Training epochs…:  27%|         | 8/30 [02:05<05:54, 16.11s/it]

Saving Best Model with Accuracy: 94.4200
Epoch:   8 | Accuracy : 94.4200%

Training epochs…:  30%|         | 9/30 [02:23<05:44, 16.42s/it]

Saving Best Model with Accuracy: 95.9400
Epoch:   9 | Accuracy : 95.9400%

Training epochs…:  33%|        | 10/30 [02:39<05:28, 16.43s/it]

Saving Best Model with Accuracy: 96.3800
Epoch:  10 | Accuracy : 96.3800%

Training epochs…:  37%|        | 11/30 [02:55<05:08, 16.24s/it]

Saving Best Model with Accuracy: 96.7100
Epoch:  11 | Accuracy : 96.7100%

Training epochs…:  40%|        | 12/30 [03:11<04:53, 16.30s/it]

Saving Best Model with Accuracy: 97.0300
Epoch:  12 | Accuracy : 97.0300%

Training epochs…:  43%|       | 13/30 [03:27<04:33, 16.07s/it]

Epoch:  13 | Accuracy : 96.8600%

Training epochs…:  47%|       | 14/30 [03:43<04:16, 16.02s/it]

Epoch:  14 | Accuracy : 96.7400%

Training epochs…:  50%|       | 15/30 [04:00<04:04, 16.33s/it]

Saving Best Model with Accuracy: 97.2800
Epoch:  15 | Accuracy : 97.2800%

Training epochs…:  53%|      | 16/30 [04:15<03:45, 16.13s/it]

Epoch:  16 | Accuracy : 97.1100%

Training epochs…:  57%|      | 17/30 [04:31<03:27, 15.99s/it]

Epoch:  17 | Accuracy : 97.0700%
```

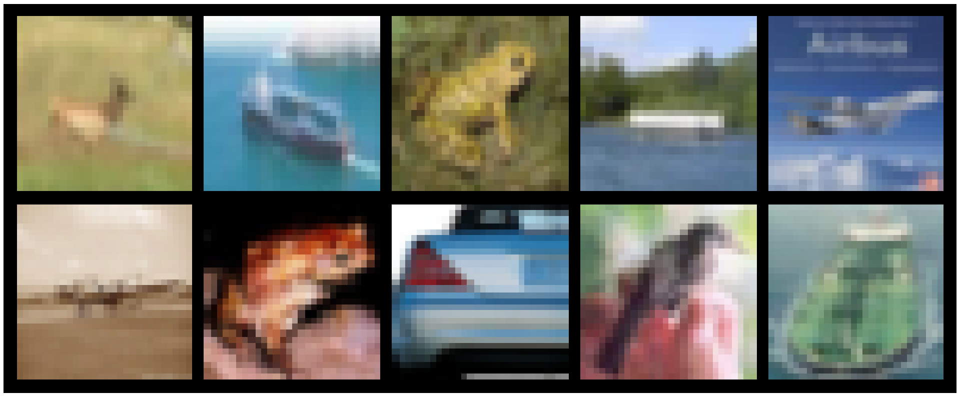
```
Training epochs…:  60%|        | 18/30 [04:47<03:11, 15.98s/it]

Epoch:  18 | Accuracy : 96.9800%

Training epochs…:  63%|       | 19/30 [05:03<02:54, 15.89s/it]

Saving Best Model with Accuracy: 97.7200
Epoch:  19 | Accuracy : 97.7200%

Training epochs…:  67%|       | 20/30 [05:18<02:38, 15.83s/it]

Epoch:  20 | Accuracy : 94.9600%

Training epochs…:  70%|       | 21/30 [05:34<02:22, 15.85s/it]

Epoch:  21 | Accuracy : 97.1800%

Training epochs…:  73%|       | 22/30 [05:51<02:08, 16.08s/it]

Saving Best Model with Accuracy: 97.8100
Epoch:  22 | Accuracy : 97.8100%

Training epochs…:  77%|       | 23/30 [06:08<01:54, 16.31s/it]

Epoch:  23 | Accuracy : 96.6900%

Training epochs…:  80%|       | 24/30 [06:24<01:38, 16.38s/it]

Epoch:  24 | Accuracy : 97.6100%

Training epochs…:  83%|      | 25/30 [06:41<01:21, 16.34s/it]

Saving Best Model with Accuracy: 98.0800
Epoch:  25 | Accuracy : 98.0800%

Training epochs…:  87%|      | 26/30 [06:57<01:05, 16.25s/it]

Epoch:  26 | Accuracy : 97.8600%

Training epochs…:  90%|      | 27/30 [07:13<00:48, 16.17s/it]

Epoch:  27 | Accuracy : 97.7700%

Training epochs…:  93%|     | 28/30 [07:29<00:32, 16.15s/it]

Epoch:  28 | Accuracy : 97.8000%

Training epochs…:  97%|     | 29/30 [07:45<00:16, 16.17s/it]

Saving Best Model with Accuracy: 98.2200
Epoch:  29 | Accuracy : 98.2200%

Training epochs…: 100%|     | 30/30 [08:01<00:00, 16.04s/it]

Saving Best Model with Accuracy: 98.4000
Epoch:  30 | Accuracy : 98.4000%
Model saved in: /home/jose-
roberto/Documents/Disciplinas/INF492/assignment/a5/models/relu-
LeNet5-mnist-98.40.pkl
```



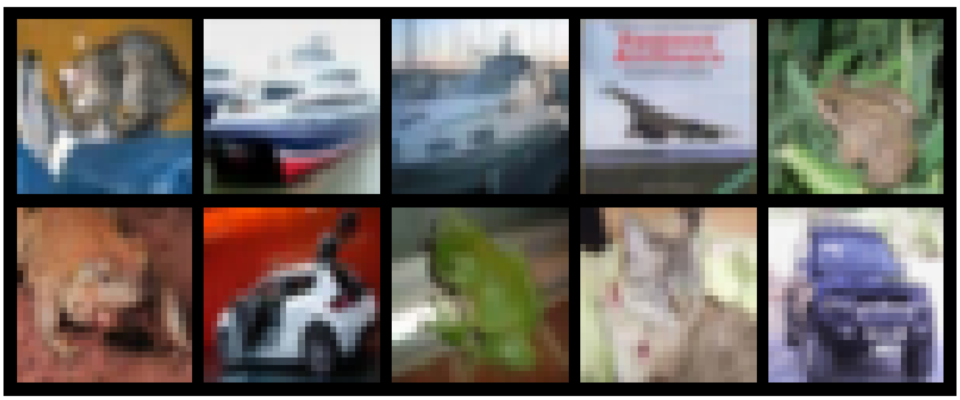
3.1.3 CIFAR10 - ReLu

[41]:
```
epochs = 30
dataset = 'cifar10' # 'mnist'
lr = 5e-2
lambda_reg = 0

prefix = 'relu-LeNet-{}-e-{}-lr-{}'.format(dataset, epochs, lr)

net_relu = train( dataset=dataset, epochs=epochs, lr=lr, prefix=prefix ,␣
 ↪upper_bound=100, device=my_device,
            relu=True, save=True, debug=False, plot_histograms=True,␣
 ↪lambda_reg=lambda_reg )
```

```
Train samples
```



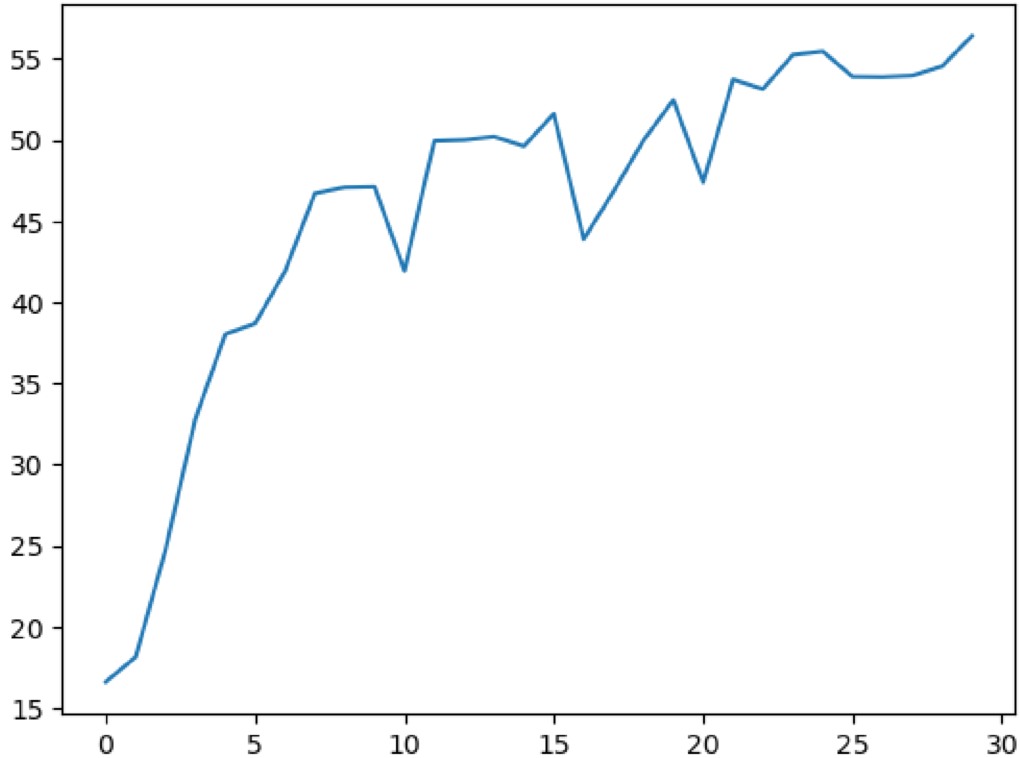
Test samples



```
Training epochs...:   3%|          | 1/30 [00:22<10:43, 22.19s/it]

Saving Best Model with Accuracy: 16.6100
Epoch:   1 | Accuracy : 16.6100%

Training epochs...:   7%|          | 2/30 [00:45<10:31, 22.56s/it]

Saving Best Model with Accuracy: 18.1400
Epoch:   2 | Accuracy : 18.1400%

Training epochs...:  10%|          | 3/30 [01:09<10:34, 23.50s/it]

Saving Best Model with Accuracy: 24.7400
Epoch:   3 | Accuracy : 24.7400%

Training epochs...:  13%|         | 4/30 [01:35<10:35, 24.46s/it]

Saving Best Model with Accuracy: 32.8100
Epoch:   4 | Accuracy : 32.8100%
```

```
Training epochs…:  17%|          | 5/30 [02:00<10:17, 24.68s/it]

Saving Best Model with Accuracy: 38.0400
Epoch:   5 | Accuracy : 38.0400%

Training epochs…:  20%|          | 6/30 [02:26<10:02, 25.12s/it]

Saving Best Model with Accuracy: 38.6900
Epoch:   6 | Accuracy : 38.6900%

Training epochs…:  23%|          | 7/30 [02:52<09:46, 25.49s/it]

Saving Best Model with Accuracy: 41.9100
Epoch:   7 | Accuracy : 41.9100%

Training epochs…:  27%|          | 8/30 [03:17<09:17, 25.34s/it]

Saving Best Model with Accuracy: 46.7100
Epoch:   8 | Accuracy : 46.7100%

Training epochs…:  30%|          | 9/30 [03:43<08:51, 25.32s/it]

Saving Best Model with Accuracy: 47.0900
Epoch:   9 | Accuracy : 47.0900%

Training epochs…:  33%|          | 10/30 [04:08<08:25, 25.27s/it]

Saving Best Model with Accuracy: 47.1300
Epoch:  10 | Accuracy : 47.1300%

Training epochs…:  37%|          | 11/30 [04:34<08:03, 25.45s/it]

Epoch:  11 | Accuracy : 41.9400%

Training epochs…:  40%|          | 12/30 [04:59<07:37, 25.43s/it]

Saving Best Model with Accuracy: 49.9500
Epoch:  12 | Accuracy : 49.9500%

Training epochs…:  43%|          | 13/30 [05:25<07:12, 25.46s/it]

Saving Best Model with Accuracy: 50.0100
Epoch:  13 | Accuracy : 50.0100%

Training epochs…:  47%|          | 14/30 [05:51<06:49, 25.61s/it]

Saving Best Model with Accuracy: 50.2100
Epoch:  14 | Accuracy : 50.2100%

Training epochs…:  50%|          | 15/30 [06:16<06:24, 25.61s/it]

Epoch:  15 | Accuracy : 49.6300%

Training epochs…:  53%|          | 16/30 [06:43<06:01, 25.84s/it]

Saving Best Model with Accuracy: 51.6200
Epoch:  16 | Accuracy : 51.6200%

Training epochs…:  57%|          | 17/30 [07:08<05:34, 25.70s/it]
```

```
Epoch:  17 | Accuracy : 43.8900%

Training epochs…:  60%|       | 18/30 [07:33<05:07, 25.65s/it]

Epoch:  18 | Accuracy : 46.8400%

Training epochs…:  63%|       | 19/30 [07:59<04:42, 25.64s/it]

Epoch:  19 | Accuracy : 49.9800%

Training epochs…:  67%|       | 20/30 [08:26<04:19, 25.94s/it]

Saving Best Model with Accuracy: 52.4700
Epoch:  20 | Accuracy : 52.4700%

Training epochs…:  70%|       | 21/30 [08:52<03:55, 26.19s/it]

Epoch:  21 | Accuracy : 47.4000%

Training epochs…:  73%|       | 22/30 [09:19<03:30, 26.33s/it]

Saving Best Model with Accuracy: 53.7300
Epoch:  22 | Accuracy : 53.7300%

Training epochs…:  77%|       | 23/30 [09:45<03:02, 26.12s/it]

Epoch:  23 | Accuracy : 53.1400%

Training epochs…:  80%|       | 24/30 [10:12<02:38, 26.36s/it]

Saving Best Model with Accuracy: 55.2500
Epoch:  24 | Accuracy : 55.2500%

Training epochs…:  83%|      | 25/30 [10:37<02:10, 26.15s/it]

Saving Best Model with Accuracy: 55.4700
Epoch:  25 | Accuracy : 55.4700%

Training epochs…:  87%|      | 26/30 [11:04<01:45, 26.40s/it]

Epoch:  26 | Accuracy : 53.9100%

Training epochs…:  90%|      | 27/30 [11:31<01:19, 26.34s/it]

Epoch:  27 | Accuracy : 53.8900%

Training epochs…:  93%|      | 28/30 [11:57<00:52, 26.37s/it]

Epoch:  28 | Accuracy : 53.9700%

Training epochs…:  97%|      | 29/30 [12:24<00:26, 26.51s/it]

Epoch:  29 | Accuracy : 54.5500%

Training epochs…: 100%|      | 30/30 [12:50<00:00, 25.68s/it]

Saving Best Model with Accuracy: 56.4200
Epoch:  30 | Accuracy : 56.4200%
Model saved in: /home/jose-
roberto/Documents/Disciplinas/INF492/assignment/a5/models/relu-
LeNet5-cifar10-56.42.pkl
```



4 Carregar Rede de arquivo

[43]:
```
path = '/home/jose-roberto/Documents/Disciplinas/INF492/assignment/a5/models/
↪LeNet5-mnist-98.19.pkl'
path_relu = '/home/jose-roberto/Documents/Disciplinas/INF492/assignment/a5/
↪models/relu-LeNet5-mnist-98.40.pkl'
path_cifar10 = '/home/jose-roberto/Documents/Disciplinas/INF492/assignment/a5/
↪models/relu-LeNet5-cifar10-56.42.pkl'

n_channels = 1

def load_LeNet ( device , path, n_channels=1, relu=False ) :
    net = LeNet(num_classes=10, n_channels=n_channels, relu=relu)
    net = net.to(device)
    net.load_state_dict(torch.load(path))
    net.eval()
    return net

net_mnist = load_LeNet(my_device, path)
```

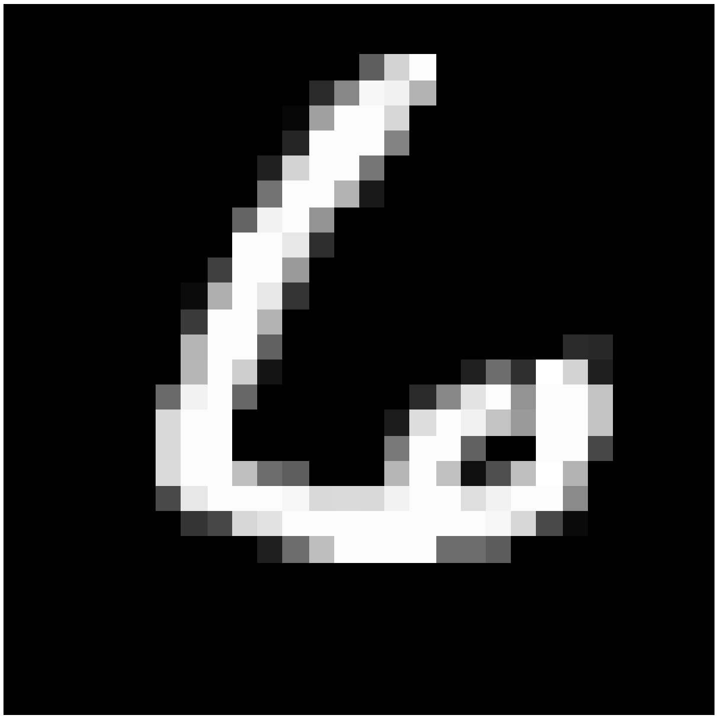
```
net_relu = load_LeNet(my_device, path_relu, relu=True)
net_cifar10 = load_LeNet(my_device, path_cifar10, n_channels=3, relu=True)
```

5 Carregar dado do MNIST e inferir

[44]:
```
import PIL
import torchvision
import numpy as np

def sample_and_predict_mnist ( net, seed=None, relu=False ) :

    if seed is not None :
        np.random.seed(seed)

    dataset = torchvision.datasets.MNIST(
                                        root=f'{datasets_path}/test/',
                                        train=False
                                        )

    i = np.random.randint(len(dataset))
    sample = dataset[i][0]

    x = torchvision.transforms.ToTensor()(sample).float()

    x = x.unsqueeze_(0)

    x = x.to(my_device)

    y = net ( x )

    if relu:
        y = torch.softmax(y, dim=1)

    confidence = torch.max(y, 1)[0]
    prediction = torch.max(y, 1)[1]

    print( 'Sample: {}'.format(i) )
    plt.axis('off')
    plt.imshow( sample , cmap='gray')

    confidence = confidence.data.cpu().numpy()[0]
    prediction = prediction.data.cpu().numpy()[0]

    return prediction, confidence, dataset[i][1]
```

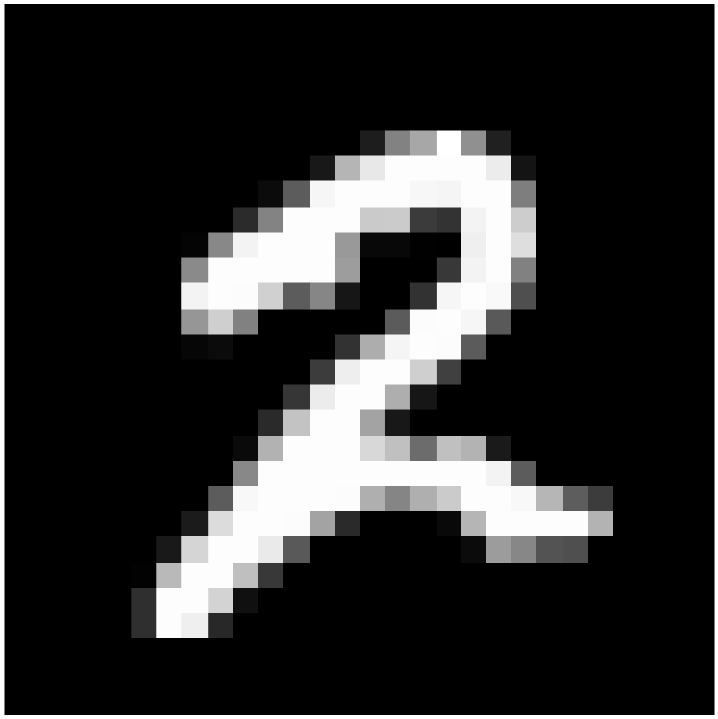
[45]:
```python
prediction, confidence, label = sample_and_predict_mnist(net_mnist)
print( f'\nPredicted clas: {prediction} \nClassifier confidence:␣
↪{confidence*100:4.2f}% \nTrue label: {label}' )
```

```
Sample: 8333

Predicted clas: 6
Classifier confidence: 99.99%
True label: 6
```



[46]:
```python
prediction, confidence, label = sample_and_predict_mnist(net_relu, relu=True)
print( f'\nPredicted clas: {prediction} \nClassifier confidence:␣
↪{confidence*100:4.2f}% \nTrue label: {label}' )
```

```
Sample: 9209

Predicted clas: 2
Classifier confidence: 99.94%
True label: 2
```



6 Carregar dado do CIFAR10 e inferir

[47]:
```
import PIL
import torchvision
import numpy as np

def sample_and_predict_cifar10 ( net, seed=None, relu=False ) :

    if seed is not None :
        np.random.seed(seed)


    my_transform = torchvision.transforms.Compose([
                        torchvision.transforms.Resize(28),
                        torchvision.transforms.ToTensor(),
                        torchvision.transforms.Normalize(mean=[0.5],std=[0.
 ↪5])
                                ])

    dataset = torchvision.datasets.CIFAR10(
                                    root=f'{datasets_path}/test/',
                                    transform=my_transform,
```

```
                                       train=False
                                       )

    i = np.random.randint(len(dataset))
    x = dataset[i][0]

    sample = np.array(x)
    sample = np.transpose(sample, (1, 2, 0))

    x = x.unsqueeze_(0)

    x = x.to(my_device)

    y = net ( x )

    if relu:
        y = torch.softmax(y, dim=1)

    confidence = torch.max(y, 1)[0]
    prediction = torch.max(y, 1)[1]

    print( 'Sample: {}'.format(i) )
    plt.axis('off')
    plt.imshow( sample )

    confidence = confidence.data.cpu().numpy()[0]
    prediction = prediction.data.cpu().numpy()[0]

    return prediction, confidence, dataset[i][1]
```

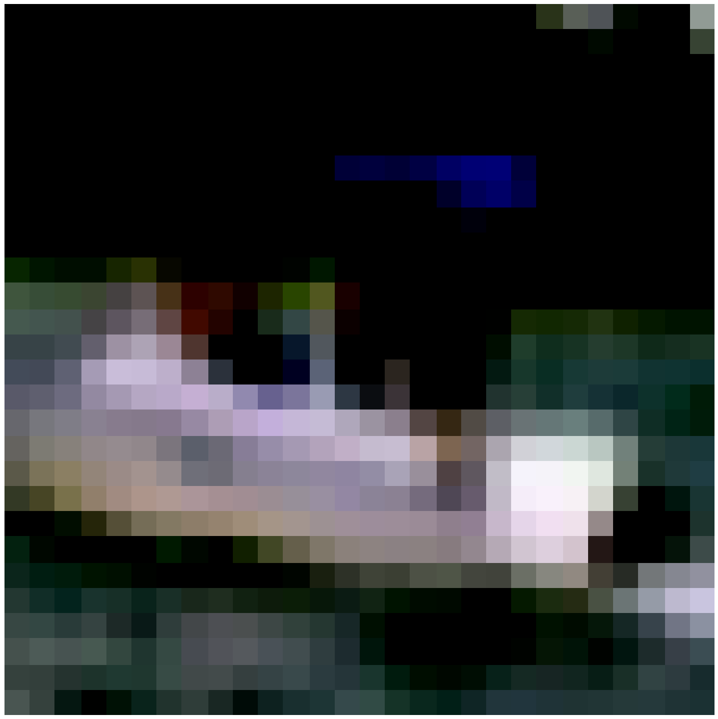
[48]:

```
prediction, confidence, label = sample_and_predict_cifar10(net_cifar10,␣
 ↪relu=True)
print( f'\nPredicted clas: {prediction} \nClassifier confidence:␣
 ↪{confidence*100:4.2f}% \nTrue label: {label}' )
```

```
/tmp/ipykernel_12544/2333663424.py:26: DeprecationWarning: __array__
implementation doesn't accept a copy keyword, so passing copy=False failed.
__array__ must implement 'dtype' and 'copy' keyword arguments. To learn more,
see the migration guide
https://numpy.org/devdocs/numpy_2_0_migration_guide.html#adapting-to-changes-in-
the-copy-keyword
  sample = np.array(x)
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers). Got range [-0.99215686..0.9843137].
```

```
Sample: 9810

Predicted clas: 5
```

```
Classifier confidence: 41.94%
True label: 8
```



7 Conclusões

Analisando os gráficos plotados no TensorBoard, temos que a Loss para Sigmoid/Tahn estabiliza-se mais rapidamente, enquanto para ReLu há um decaimento maior. Para a acurácia, vemos que com ReLu há uma convergência muito mais rápida, enquanto para Sigmoid/Tahn os valores ficam estagnados e aumentam lentamente até se estabilizarem em uma faixa superior. Acompanhando o treino, vemos que para Sigmoid/Tahn foram necessárias 28 épocas para atingir 98% de acurácia, enquanto para ReLu foram necessárias 25.

E sobre a aplicação da mesma arquitetura no dataset CIFAR10, nota-se que o resultado máximo não foi satisfatório (aprox. 56% de acurácia). Isto era esperado, pois o dado é bem mais complexo comparado com o MNIST, contendo objetos complexos do mundo real, representados em três canais (RGB) e com bastante variações entre si.

TensorBoard TIME SERIES SCALARS INACTIVE

Show data download links

Ignore outliers in chart scalin

Tooltip sorting method: default

Smoothing

0.6

Horizontal Axis

STEP RELATIVE

WALL

Runs

Write a regex to filter runs

LeNet-mnist-e-30-lr-1.3-20250508_202812

relu-LeNet-mnist-e-30-lr-0.05-20250508_204535

relu-LeNet-cifar10-e-30-lr-0.05-20250508_205420

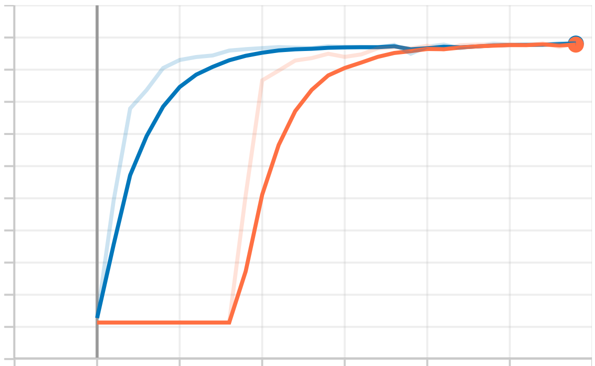
TOGGLE ALL RUNS

/home/jose-roberto/Documents/Disciplinas/INF492/assignment/a5/train_runs

Filter tags (regular expressions supported)

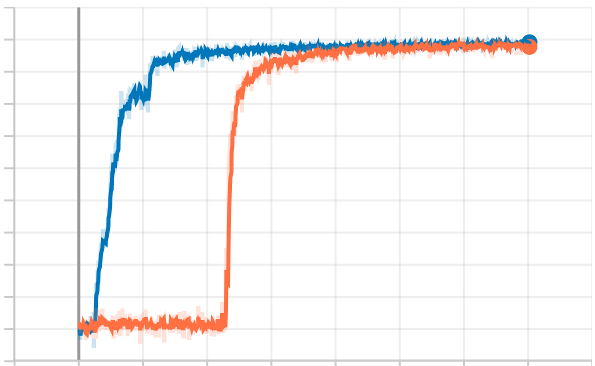
Accuracy 2

test
tag: Accuracy/test



run to download

train
tag: Accuracy/train



run to download

Loss

TensorBoard TIME SERIES SCALARS INACTIVE

Show data download links

Ignore outliers in chart scalin

Tooltip sorting method: default

Smoothing

0.6

Horizontal Axis

STEP RELATIVE

WALL

Runs

Write a regex to filter runs

LeNet-mnist-e-30-lr-1.3-20250508_202812

relu-LeNet-mnist-e-30-lr-0.05-20250508_204535

relu-LeNet-cifar10-e-30-lr-0.05-20250508_205420

TOGGLE ALL RUNS

/home/jose-roberto/Documents/Disciplinas/INF492/assignment/a5/train_runs

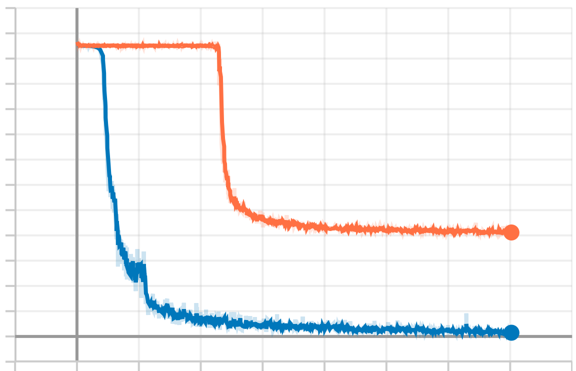
Filter tags (regular expressions supported)

Accuracy 2

Loss

train

tag: Loss/train



run to download