CS 541-A-Homework 3

Neural networks

Fill your details below

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References: ***Cite your references here***

Submission guidelines:

1. Submit this notebook along with its PDF version. You can do this by clicking File->Print->"Save as PDF"

2. Name the file as "<mailID_HWnumber.extension>". For example, mailID is abcdefg @stevens.edu then name the files as abcdefg_HW1.ipynb and abcdefg_HW1.pdf.

3. Please do not Zip your files.

```
#@title Installing Pytorch

!pip install torch
!pip install torchvision
```

```
Requirement already satisfied: torch in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (2.2.0)
Requirement already satisfied: filelock in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from torch) (3.13.1)
Requirement already satisfied: typing-extensions>=4.8.0 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from torch) (4.9.0)
Requirement already satisfied: sympy in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from torch) (1.12)
```

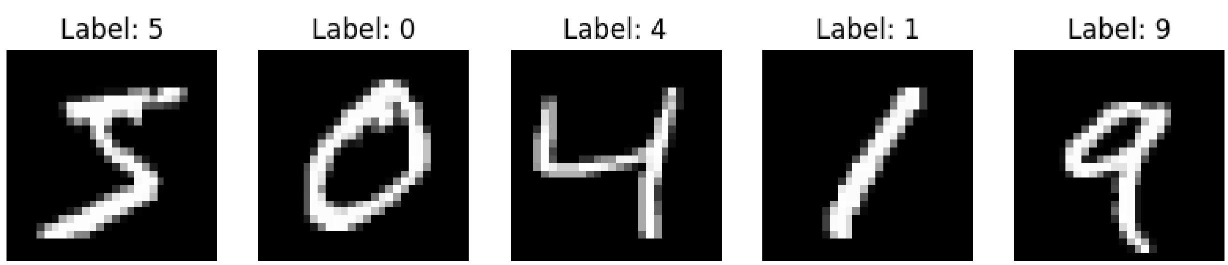
```
Requirement already satisfied: networkx in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from torch) (3.2.1)
Requirement already satisfied: jinja2 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from torch) (3.1.3)
Requirement already satisfied: fsspec in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from torch) (2023.10.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from jinja2->torch) (2.1.5)
Requirement already satisfied: mpmath>=0.19 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from sympy->torch) (1.3.0)
Requirement already satisfied: torchvision in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (0.17.0)
Requirement already satisfied: numpy in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from torchvision) (1.26.4)
Requirement already satisfied: requests in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from torchvision) (2.31.0)
Requirement already satisfied: torch==2.2.0 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from torchvision) (2.2.0)
Requirement already satisfied: pillow!=8.3.*,>=5.3.0 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from torchvision) (10.2.0)
Requirement already satisfied: filelock in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from torch==2.2.0->torchvision) (3.13.1)
Requirement already satisfied: typing-extensions>=4.8.0 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from torch==2.2.0->torchvision) (4.9.0)
Requirement already satisfied: sympy in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from torch==2.2.0->torchvision) (1.12)
Requirement already satisfied: networkx in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from torch==2.2.0->torchvision) (3.2.1)
Requirement already satisfied: jinja2 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from torch==2.2.0->torchvision) (3.1.3)
Requirement already satisfied: fsspec in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from torch==2.2.0->torchvision) (2023.10.0)
Requirement already satisfied: charset-normalizer<4,>=2 in
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from requests->torchvision) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from requests->torchvision) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from requests->torchvision) (2.2.1)
Requirement already satisfied: certifi>=2017.4.17 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from requests->torchvision) (2024.2.2)
Requirement already satisfied: MarkupSafe>=2.0 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from jinja2->torch==2.2.0->torchvision) (2.1.5)
Requirement already satisfied: mpmath>=0.19 in
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages (from sympy->torch==2.2.0->torchvision) (1.3.0)
```

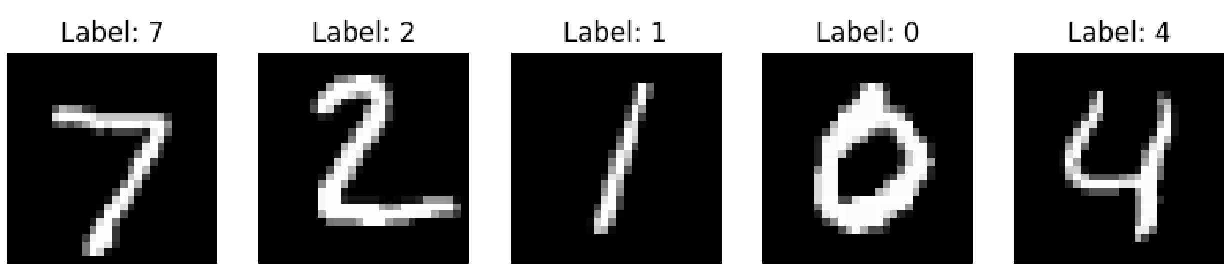
```python
#@title Import Dependencies

import torch
import torch.nn as nn
import torchvision.datasets as dsets
import torchvision.transforms as transforms
from torch.autograd import Variable

#@title Define Hyperparameters

input_size = 784 # img_size = (28,28) ---> 28*28=784 in total
hidden_size = 500 # number of nodes at hidden layer
num_classes = 10 # number of output classes discrete range [0,9]
num_epochs = 5 # number of times which the entire dataset is passed
throughout the model
batch_size = 100 # the size of input data took for one iteration
lr = 1e-3 # size of step

#@title Downloading MNIST data

train_data = dsets.MNIST(root = './data', train = True,
                        transform = transforms.ToTensor(), download =
True)

test_data = dsets.MNIST(root = './data', train = False,
                       transform = transforms.ToTensor())

#@title Loading the data

train_gen = torch.utils.data.DataLoader(dataset = train_data,
                                        batch_size = batch_size,
                                        shuffle = True)
```

```
test_gen = torch.utils.data.DataLoader(dataset = test_data,
                                      batch_size = batch_size,
                                      shuffle = False)

import matplotlib.pyplot as plt

transform = transforms.ToTensor()

print("First 5 images in train dataset:")
fig, axes = plt.subplots(1, 5, figsize=(10, 2))
for i in range(5):
    image, label = train_data[i]
    axes[i].imshow(image.squeeze().numpy(), cmap='gray')
    axes[i].set_title('Label: {}'.format(label))
    axes[i].axis('off')
plt.show()

print("\nFirst 5 images in test dataset:")
fig, axes = plt.subplots(1, 5, figsize=(10, 2))
for i in range(5):
    image, label = test_data[i]
    axes[i].imshow(image.squeeze().numpy(), cmap='gray')
    axes[i].set_title('Label: {}'.format(label))
    axes[i].axis('off')
plt.show()
```

```
First 5 images in train dataset:
```




```

First 5 images in test dataset:
```



Q1. (50 points): design a neural network, provide justification.

PyTorch neural network documentation: https://pytorch.org/docs/stable/nn.html

```
#@title Define model class

class Net(nn.Module):
  def __init__(self, input_size, hidden_size, num_classes):
    super(Net,self).__init__()
    ''' code to build the model '''
    self.fc1 = nn.Linear(input_size, hidden_size)
    self.relu = nn.ReLU()
    self.fc2 = nn.Linear(hidden_size, num_classes)


  def forward(self,x):
    ''' code to define the forward pass '''
    out = self.fc1(x)
    out = self.relu(out)
    output = self.fc2(out)
    return output

#@title Build the model

net = Net(input_size, hidden_size, num_classes)
if torch.cuda.is_available():
  net.cuda()

#@title Define loss-function & optimizer

loss_function = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(net.parameters(), lr=lr)
```

##Q2.

##a) In the code provided below, What is the meaning of the "loss.backward()" step? Please explain the functionality. (15 pts)

##b) What is the meaning of "optimizer.step()" and what does it do? (15 pts)

```
#@title Training the model

for epoch in range(num_epochs):
  for i ,(images,labels) in enumerate(train_gen):
    images = Variable(images.view(-1,28*28))
    labels = Variable(labels)

    optimizer.zero_grad()
    outputs = net(images)
```

```
    loss = loss_function(outputs, labels)
    loss.backward() #Q2a (15 points): What is the meaning of this
step? Please explain the functionality.
    optimizer.step() #Q2b (15 points): What is the meaning of this
step? Please explain the functionality.

    if (i+1) % 100 == 0:
      print('Epoch [%d/%d], Step [%d/%d], Loss: %.4f'%(epoch+1,
num_epochs, i+1, len(train_data)//batch_size, loss.item()))
```

```
Epoch [1/5], Step [100/600], Loss: 0.4093
Epoch [1/5], Step [200/600], Loss: 0.2264
Epoch [1/5], Step [300/600], Loss: 0.2733
Epoch [1/5], Step [400/600], Loss: 0.2714
Epoch [1/5], Step [500/600], Loss: 0.1924
Epoch [1/5], Step [600/600], Loss: 0.1618
Epoch [2/5], Step [100/600], Loss: 0.1369
Epoch [2/5], Step [200/600], Loss: 0.1461
Epoch [2/5], Step [300/600], Loss: 0.0674
Epoch [2/5], Step [400/600], Loss: 0.0785
Epoch [2/5], Step [500/600], Loss: 0.0352
Epoch [2/5], Step [600/600], Loss: 0.1625
Epoch [3/5], Step [100/600], Loss: 0.0242
Epoch [3/5], Step [200/600], Loss: 0.0697
Epoch [3/5], Step [300/600], Loss: 0.2257
Epoch [3/5], Step [400/600], Loss: 0.1261
Epoch [3/5], Step [500/600], Loss: 0.1763
Epoch [3/5], Step [600/600], Loss: 0.0440
Epoch [4/5], Step [100/600], Loss: 0.0742
Epoch [4/5], Step [200/600], Loss: 0.0387
Epoch [4/5], Step [300/600], Loss: 0.1057
Epoch [4/5], Step [400/600], Loss: 0.0249
Epoch [4/5], Step [500/600], Loss: 0.0534
Epoch [4/5], Step [600/600], Loss: 0.0379
Epoch [5/5], Step [100/600], Loss: 0.0238
Epoch [5/5], Step [200/600], Loss: 0.0518
Epoch [5/5], Step [300/600], Loss: 0.0205
Epoch [5/5], Step [400/600], Loss: 0.0530
Epoch [5/5], Step [500/600], Loss: 0.0465
Epoch [5/5], Step [600/600], Loss: 0.0280
```

loss.backward() - computes gradients of loss function with respect to the model parameters and are later used for updating parameters during training via gradient descent or other similar algorithms.

optimizer.step() - This will update the model parameters based on the computed gradients and the chosen optimization algorithm (Adam optimizer in above case). It's essentially performing a gradient descent step to minimize the loss.

#Q3 (20 points): Discuss the results. Is the neural network doing a good job?

```python
#@title Evaluating the accuracy of the model

correct = 0
total = 0
for images,labels in test_gen:
  images = Variable(images.view(-1,28*28))
  labels = labels

  output = net(images)
  _, predicted = torch.max(output,1)
  correct += (predicted == labels).sum()
  total += labels.size(0)

print('Accuracy of the model: %.3f %%' %((100*correct)/(total+1)))
#Q3 (20 points): How to interpret the results? Is the neural network
does a good job?
```

```
Accuracy of the model: 97.920 %
```

accuracy is around 97.3 to 98.3 using above model

Above is a neural network model with one hidden layer and ReLU activation function

```python
def build_model(input_size, hidden_size, num_classes, num_layers,
activations):
    layers = []
    layers.append(nn.Linear(input_size, hidden_size))
    for i in range(num_layers):
        activation = activations[i] if i < len(activations) else
'relu'
        if activation == 'relu':
            layers.append(nn.ReLU())
        elif activation == 'sigmoid':
            layers.append(nn.Sigmoid())
        elif activation == 'tanh':
            layers.append(nn.Tanh())
        elif activation == 'softmax':
            layers.append(nn.Softmax())
        layers.append(nn.Linear(hidden_size, hidden_size))
    layers.append(nn.Linear(hidden_size, num_classes))
    return nn.Sequential(*layers)

activations = ['relu', 'relu', 'relu', 'relu']
net = build_model(input_size, hidden_size, num_classes, num_layers=1,
activations=activations)

if torch.cuda.is_available():
  net.cuda()
```

```python
#@title function to evaluate different activation functions and
different number of layers

loss_function = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(net.parameters(), lr=lr)

#@title Training the model

for epoch in range(num_epochs):
  for i ,(images,labels) in enumerate(train_gen):
    images = Variable(images.view(-1,28*28))
    labels = Variable(labels)

    optimizer.zero_grad()
    outputs = net(images)
    loss = loss_function(outputs, labels)
    loss.backward() #Q2a (15 points): What is the meaning of this
step? Please explain the functionality.
    optimizer.step() #Q2b (15 points): What is the meaning of this
step? Please explain the functionality.

    if (i+1) % 100 == 0:
      print('Epoch [%d/%d], Step [%d/%d], Loss: %.4f'%(epoch+1,
num_epochs, i+1, len(train_data)//batch_size, loss.item()))


#@title Evaluating the accuracy of the model

correct = 0
total = 0
for images,labels in test_gen:
  images = Variable(images.view(-1,28*28))
  labels = labels

  output = net(images)
  _, predicted = torch.max(output,1)
  correct += (predicted == labels).sum()
  total += labels.size(0)

print('Accuracy of the model: %.3f %%' %((100*correct)/(total+1)))
```

```
Epoch [1/5], Step [100/600], Loss: 0.3478
Epoch [1/5], Step [200/600], Loss: 0.1650
Epoch [1/5], Step [300/600], Loss: 0.1820
Epoch [1/5], Step [400/600], Loss: 0.0816
Epoch [1/5], Step [500/600], Loss: 0.1511
Epoch [1/5], Step [600/600], Loss: 0.1417
Epoch [2/5], Step [100/600], Loss: 0.0391
Epoch [2/5], Step [200/600], Loss: 0.0725
Epoch [2/5], Step [300/600], Loss: 0.0300
```

```
Epoch [2/5], Step [400/600], Loss: 0.1114
Epoch [2/5], Step [500/600], Loss: 0.0522
Epoch [2/5], Step [600/600], Loss: 0.0707
Epoch [3/5], Step [100/600], Loss: 0.0159
Epoch [3/5], Step [200/600], Loss: 0.0361
Epoch [3/5], Step [300/600], Loss: 0.0106
Epoch [3/5], Step [400/600], Loss: 0.0616
Epoch [3/5], Step [500/600], Loss: 0.1423
Epoch [3/5], Step [600/600], Loss: 0.0725
Epoch [4/5], Step [100/600], Loss: 0.0285
Epoch [4/5], Step [200/600], Loss: 0.0408
Epoch [4/5], Step [300/600], Loss: 0.0471
Epoch [4/5], Step [400/600], Loss: 0.0116
Epoch [4/5], Step [500/600], Loss: 0.0177
Epoch [4/5], Step [600/600], Loss: 0.0930
Epoch [5/5], Step [100/600], Loss: 0.0029
Epoch [5/5], Step [200/600], Loss: 0.0084
Epoch [5/5], Step [300/600], Loss: 0.0094
Epoch [5/5], Step [400/600], Loss: 0.0276
Epoch [5/5], Step [500/600], Loss: 0.0103
Epoch [5/5], Step [600/600], Loss: 0.0742
Accuracy of the model: 97.790 %
```

activations = ['relu', 'sigmoid', 'tanh', 'softmax'] net = build_model(input_size, hidden_size, num_classes, num_layers=4, activations=activations) Accuracy of the model: 97.120 %

activations = ['relu', 'sigmoid', 'tanh', 'softmax'] net = build_model(input_size, hidden_size, num_classes, num_layers=3, activations=activations) Accuracy of the model: 97.600 %

activations = ['relu', 'relu', 'relu', 'relu'] net = build_model(input_size, hidden_size, num_classes, num_layers=3, activations=activations) Accuracy of the model: 97.740 %

activations = ['relu', 'relu', 'relu', 'relu'] net = build_model(input_size, hidden_size, num_classes, num_layers=4, activations=activations) Accuracy of the model: 97.850 %

activations = ['relu', 'relu', 'relu', 'relu'] net = build_model(input_size, hidden_size, num_classes, num_layers=6, activations=activations) accuracy - 97.660%

relu with 1 layer; accuracy - 97.680%

above code checks model for different layers and activation functions. Model can be updated accordingly as below which has 3 layers and 'relu' on each layer. Functions and number of layers can be added accordingly.

```python
class Net(nn.Module):
    def __init__(self, input_size, hidden_size, num_classes):
        super(Net, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.relu1 = nn.ReLU()
```

```
        self.fc2 = nn.Linear(hidden_size, hidden_size)
        self.relu2 = nn.ReLU()
        self.fc3 = nn.Linear(hidden_size, num_classes)

    def forward(self, x):
        out = self.fc1(x)
        out = self.relu1(out)
        out = self.fc2(out)
        out = self.relu2(out)
        output = self.fc3(out)
        return output

import torch
import torch.nn as nn
import torchvision.datasets as dsets
import torchvision.transforms as transforms
from torch.autograd import Variable

#@title CNN implementation

input_size = 784 # img_size = (28,28) ---> 28*28=784 in total
num_classes = 10 # number of output classes discrete range [0,9]
num_epochs = 5 # number of times which the entire dataset is passed
throughout the model
batch_size = 100 # the size of input data took for one iteration
lr = 1e-3 # size of step

#@title Downloading MNIST data

train_data = dsets.MNIST(root = './data', train = True,
                        transform = transforms.ToTensor(), download =
True)

test_data = dsets.MNIST(root = './data', train = False,
                       transform = transforms.ToTensor())

#@title Define model class

class Net(nn.Module):
    def __init__(self, num_classes):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 16, kernel_size=5, stride=1,
padding=2)
        self.relu = nn.ReLU()
        self.maxpool = nn.MaxPool2d(kernel_size=2, stride=2)
        self.conv2 = nn.Conv2d(16, 32, kernel_size=5, stride=1,
padding=2)
        self.fc1 = nn.Linear(7 * 7 * 32, 128)
        self.fc2 = nn.Linear(128, num_classes)
```

```python
    def forward(self, x):
        out = self.conv1(x)
        out = self.relu(out)
        out = self.maxpool(out)
        out = self.conv2(out)
        out = self.relu(out)
        out = self.maxpool(out)
        out = out.view(out.size(0), -1)
        out = self.fc1(out)
        out = self.relu(out)
        out = self.fc2(out)
        return out

#@title CNN implementation

net = Net(num_classes)
if torch.cuda.is_available():
  net.cuda()

#@title Define loss-function & optimizer

loss_function = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(net.parameters(), lr=lr)

#@title Training the model

train_loader = torch.utils.data.DataLoader(dataset=train_data,
                                           batch_size=batch_size,
                                           shuffle=True)

total_step = len(train_loader)
for epoch in range(num_epochs):
    for i, (images, labels) in enumerate(train_loader):
        images = Variable(images)
        labels = Variable(labels)

        optimizer.zero_grad()
        outputs = net(images)
        loss = loss_function(outputs, labels)
        loss.backward()
        optimizer.step()

        if (i+1) % 100 == 0:
            print('Epoch [%d/%d], Step [%d/%d], Loss: %.4f'
                  %(epoch+1, num_epochs, i+1, total_step,
loss.item()))

#@title Evaluating the accuracy of the model

test_loader = torch.utils.data.DataLoader(dataset=test_data,
```

```
                                          batch_size=batch_size,
                                          shuffle=False)

correct = 0
total = 0
for images, labels in test_loader:
    images = Variable(images)
    labels = labels

    output = net(images)
    _, predicted = torch.max(output.data, 1)
    correct += (predicted == labels).sum()
    total += labels.size(0)

print('Accuracy of the model on the 10000 test images: %d %%' % (100 *
correct / total))
```

```
Epoch [1/5], Step [100/600], Loss: 0.2079
Epoch [1/5], Step [200/600], Loss: 0.0920
Epoch [1/5], Step [300/600], Loss: 0.0469
Epoch [1/5], Step [400/600], Loss: 0.0560
Epoch [1/5], Step [500/600], Loss: 0.0944
Epoch [1/5], Step [600/600], Loss: 0.0161
Epoch [2/5], Step [100/600], Loss: 0.0877
Epoch [2/5], Step [200/600], Loss: 0.0248
Epoch [2/5], Step [300/600], Loss: 0.1439
Epoch [2/5], Step [400/600], Loss: 0.0775
Epoch [2/5], Step [500/600], Loss: 0.0538
Epoch [2/5], Step [600/600], Loss: 0.1182
Epoch [3/5], Step [100/600], Loss: 0.0519
Epoch [3/5], Step [200/600], Loss: 0.0154
Epoch [3/5], Step [300/600], Loss: 0.0112
Epoch [3/5], Step [400/600], Loss: 0.0476
Epoch [3/5], Step [500/600], Loss: 0.0091
Epoch [3/5], Step [600/600], Loss: 0.0200
Epoch [4/5], Step [100/600], Loss: 0.0204
Epoch [4/5], Step [200/600], Loss: 0.0508
Epoch [4/5], Step [300/600], Loss: 0.0470
Epoch [4/5], Step [400/600], Loss: 0.0452
Epoch [4/5], Step [500/600], Loss: 0.0829
Epoch [4/5], Step [600/600], Loss: 0.0114
Epoch [5/5], Step [100/600], Loss: 0.0075
Epoch [5/5], Step [200/600], Loss: 0.0276
Epoch [5/5], Step [300/600], Loss: 0.0247
Epoch [5/5], Step [400/600], Loss: 0.0457
Epoch [5/5], Step [500/600], Loss: 0.0019
Epoch [5/5], Step [600/600], Loss: 0.0125
Accuracy of the model on the 10000 test images: 99 %
```

CNN model with 2 convolutional layers; used ReLU activation functions and max pooling layers.
initial accuracy - 98%

```
import torch
import torch.nn as nn
import torchvision.datasets as dsets
import torchvision.transforms as transforms
from torch.autograd import Variable

#@title Define Hyperparameters

input_size = 784 # img_size = (28,28) ---> 28*28=784 in total
num_classes = 10 # number of output classes discrete range [0,9]
num_epochs = 5 # number of times which the entire dataset is passed
throughout the model
batch_size = 100 # the size of input data took for one iteration
lr = 1e-3 # size of step

#@title Downloading MNIST data

train_data = dsets.MNIST(root = './data', train = True,
                        transform = transforms.ToTensor(), download =
True)

test_data = dsets.MNIST(root = './data', train = False,
                       transform = transforms.ToTensor())

#@title Define model class

class Net(nn.Module):
    def __init__(self, num_classes, activation='relu', pooling='max'):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 16, kernel_size=5, stride=1,
padding=2)
        if activation == 'relu':
            self.activation = nn.ReLU()
        elif activation == 'sigmoid':
            self.activation = nn.Sigmoid()
        elif activation == 'tanh':
            self.activation = nn.Tanh()
        elif activation == 'softmax':
            self.activation = nn.Softmax()
        self.maxpool = nn.MaxPool2d(kernel_size=2, stride=2) if
pooling == 'max' else nn.AvgPool2d(kernel_size=2, stride=2)
        self.conv2 = nn.Conv2d(16, 32, kernel_size=5, stride=1,
padding=2)
        self.fc1 = nn.Linear(7 * 7 * 32, 128)
        self.fc2 = nn.Linear(128, num_classes)
```

```python
    def forward(self, x):
        out = self.conv1(x)
        out = self.activation(out)
        out = self.maxpool(out)
        out = self.conv2(out)
        out = self.activation(out)
        out = self.maxpool(out)
        out = out.view(out.size(0), -1)
        out = self.fc1(out)
        out = self.activation(out)
        out = self.fc2(out)
        return out

#@title Build and Train the model

def train_model(activation, pooling):
    net = Net(num_classes, activation, pooling)
    if torch.cuda.is_available():
        net.cuda()

    loss_function = nn.CrossEntropyLoss()
    optimizer = torch.optim.Adam(net.parameters(), lr=lr)

    train_loader = torch.utils.data.DataLoader(dataset=train_data,
                                               batch_size=batch_size,
                                               shuffle=True)

    total_step = len(train_loader)
    for epoch in range(num_epochs):
        for i, (images, labels) in enumerate(train_loader):
            images = Variable(images)
            labels = Variable(labels)

            optimizer.zero_grad()
            outputs = net(images)
            loss = loss_function(outputs, labels)
            loss.backward()
            optimizer.step()

            if (i+1) % 100 == 0:
                print('Epoch [%d/%d], Step [%d/%d], Loss: %.4f'
                      %(epoch+1, num_epochs, i+1, total_step,
loss.item()))

    test_loader = torch.utils.data.DataLoader(dataset=test_data,
                                              batch_size=batch_size,
                                              shuffle=False)

    correct = 0
    total = 0
```

```
    for images, labels in test_loader:
        images = Variable(images)
        labels = labels

        output = net(images)
        _, predicted = torch.max(output.data, 1)
        correct += (predicted == labels).sum()
        total += labels.size(0)

    accuracy = 100 * correct / total
    print('Accuracy of the model on the 10000 test images with
activation {} and pooling {}: {} %'.format(activation, pooling,
accuracy))

# Try different combinations of activation functions and pooling
layers
activations = ['relu', 'sigmoid', 'tanh', 'softmax']
poolings = ['max', 'avg']

for activation in activations:
    for pooling in poolings:
        print("Training model with activation: {}, pooling:
{}".format(activation, pooling))
        train_model(activation, pooling)
```

```
Training model with activation: relu, pooling: max
Epoch [1/5], Step [100/600], Loss: 0.2634
Epoch [1/5], Step [200/600], Loss: 0.0862
Epoch [1/5], Step [300/600], Loss: 0.0988
Epoch [1/5], Step [400/600], Loss: 0.2082
Epoch [1/5], Step [500/600], Loss: 0.0707
Epoch [1/5], Step [600/600], Loss: 0.0395
Epoch [2/5], Step [100/600], Loss: 0.1340
Epoch [2/5], Step [200/600], Loss: 0.0217
Epoch [2/5], Step [300/600], Loss: 0.0446
Epoch [2/5], Step [400/600], Loss: 0.0615
Epoch [2/5], Step [500/600], Loss: 0.0481
Epoch [2/5], Step [600/600], Loss: 0.0185
Epoch [3/5], Step [100/600], Loss: 0.1353
Epoch [3/5], Step [200/600], Loss: 0.0249
Epoch [3/5], Step [300/600], Loss: 0.0586
Epoch [3/5], Step [400/600], Loss: 0.0469
Epoch [3/5], Step [500/600], Loss: 0.0870
Epoch [3/5], Step [600/600], Loss: 0.0232
Epoch [4/5], Step [100/600], Loss: 0.0475
Epoch [4/5], Step [200/600], Loss: 0.0792
Epoch [4/5], Step [300/600], Loss: 0.0196
Epoch [4/5], Step [400/600], Loss: 0.0069
Epoch [4/5], Step [500/600], Loss: 0.0340
Epoch [4/5], Step [600/600], Loss: 0.0246
```

```
Epoch [5/5], Step [100/600], Loss: 0.0356
Epoch [5/5], Step [200/600], Loss: 0.0452
Epoch [5/5], Step [300/600], Loss: 0.0481
Epoch [5/5], Step [400/600], Loss: 0.0520
Epoch [5/5], Step [500/600], Loss: 0.0056
Epoch [5/5], Step [600/600], Loss: 0.0472
Accuracy of the model on the 10000 test images with activation relu
and pooling max: 99.12999725341797 %
Training model with activation: relu, pooling: avg
Epoch [1/5], Step [100/600], Loss: 0.2264
Epoch [1/5], Step [200/600], Loss: 0.3562
Epoch [1/5], Step [300/600], Loss: 0.0640
Epoch [1/5], Step [400/600], Loss: 0.1025
Epoch [1/5], Step [500/600], Loss: 0.1144
Epoch [1/5], Step [600/600], Loss: 0.0838
Epoch [2/5], Step [100/600], Loss: 0.0536
Epoch [2/5], Step [200/600], Loss: 0.0965
Epoch [2/5], Step [300/600], Loss: 0.0533
Epoch [2/5], Step [400/600], Loss: 0.0550
Epoch [2/5], Step [500/600], Loss: 0.0551
Epoch [2/5], Step [600/600], Loss: 0.0597
Epoch [3/5], Step [100/600], Loss: 0.0565
Epoch [3/5], Step [200/600], Loss: 0.0669
Epoch [3/5], Step [300/600], Loss: 0.1003
Epoch [3/5], Step [400/600], Loss: 0.0324
Epoch [3/5], Step [500/600], Loss: 0.0350
Epoch [3/5], Step [600/600], Loss: 0.0916
Epoch [4/5], Step [100/600], Loss: 0.0343
Epoch [4/5], Step [200/600], Loss: 0.0443
Epoch [4/5], Step [300/600], Loss: 0.0388
Epoch [4/5], Step [400/600], Loss: 0.0506
Epoch [4/5], Step [500/600], Loss: 0.0274
Epoch [4/5], Step [600/600], Loss: 0.0947
Epoch [5/5], Step [100/600], Loss: 0.0109
Epoch [5/5], Step [200/600], Loss: 0.0097
Epoch [5/5], Step [300/600], Loss: 0.0064
Epoch [5/5], Step [400/600], Loss: 0.0405
Epoch [5/5], Step [500/600], Loss: 0.0125
Epoch [5/5], Step [600/600], Loss: 0.0127
Accuracy of the model on the 10000 test images with activation relu
and pooling avg: 98.95999908447266 %
Training model with activation: sigmoid, pooling: max
Epoch [1/5], Step [100/600], Loss: 2.2943
Epoch [1/5], Step [200/600], Loss: 1.9212
Epoch [1/5], Step [300/600], Loss: 0.5494
Epoch [1/5], Step [400/600], Loss: 0.4647
Epoch [1/5], Step [500/600], Loss: 0.4137
Epoch [1/5], Step [600/600], Loss: 0.4385
Epoch [2/5], Step [100/600], Loss: 0.2556
```

```
Epoch [2/5], Step [200/600], Loss: 0.4516
Epoch [2/5], Step [300/600], Loss: 0.1736
Epoch [2/5], Step [400/600], Loss: 0.1035
Epoch [2/5], Step [500/600], Loss: 0.1683
Epoch [2/5], Step [600/600], Loss: 0.2033
Epoch [3/5], Step [100/600], Loss: 0.1520
Epoch [3/5], Step [200/600], Loss: 0.1440
Epoch [3/5], Step [300/600], Loss: 0.1222
Epoch [3/5], Step [400/600], Loss: 0.1249
Epoch [3/5], Step [500/600], Loss: 0.0784
Epoch [3/5], Step [600/600], Loss: 0.0808
Epoch [4/5], Step [100/600], Loss: 0.0681
Epoch [4/5], Step [200/600], Loss: 0.0919
Epoch [4/5], Step [300/600], Loss: 0.1561
Epoch [4/5], Step [400/600], Loss: 0.0501
Epoch [4/5], Step [500/600], Loss: 0.1328
Epoch [4/5], Step [600/600], Loss: 0.0614
Epoch [5/5], Step [100/600], Loss: 0.0346
Epoch [5/5], Step [200/600], Loss: 0.1494
Epoch [5/5], Step [300/600], Loss: 0.0177
Epoch [5/5], Step [400/600], Loss: 0.1604
Epoch [5/5], Step [500/600], Loss: 0.0421
Epoch [5/5], Step [600/600], Loss: 0.1305
Accuracy of the model on the 10000 test images with activation sigmoid
and pooling max: 98.23999786376953 %
Training model with activation: sigmoid, pooling: avg
Epoch [1/5], Step [100/600], Loss: 2.3028
Epoch [1/5], Step [200/600], Loss: 2.2841
Epoch [1/5], Step [300/600], Loss: 1.0302
Epoch [1/5], Step [400/600], Loss: 0.4151
Epoch [1/5], Step [500/600], Loss: 0.4250
Epoch [1/5], Step [600/600], Loss: 0.3971
Epoch [2/5], Step [100/600], Loss: 0.2560
Epoch [2/5], Step [200/600], Loss: 0.1762
Epoch [2/5], Step [300/600], Loss: 0.2541
Epoch [2/5], Step [400/600], Loss: 0.1848
Epoch [2/5], Step [500/600], Loss: 0.1346
Epoch [2/5], Step [600/600], Loss: 0.2151
Epoch [3/5], Step [100/600], Loss: 0.2522
Epoch [3/5], Step [200/600], Loss: 0.3217
Epoch [3/5], Step [300/600], Loss: 0.1766
Epoch [3/5], Step [400/600], Loss: 0.1475
Epoch [3/5], Step [500/600], Loss: 0.1381
Epoch [3/5], Step [600/600], Loss: 0.1324
Epoch [4/5], Step [100/600], Loss: 0.0580
Epoch [4/5], Step [200/600], Loss: 0.1158
Epoch [4/5], Step [300/600], Loss: 0.0860
Epoch [4/5], Step [400/600], Loss: 0.0682
Epoch [4/5], Step [500/600], Loss: 0.1718
```

```
Epoch [4/5], Step [600/600], Loss: 0.1266
Epoch [5/5], Step [100/600], Loss: 0.1057
Epoch [5/5], Step [200/600], Loss: 0.1326
Epoch [5/5], Step [300/600], Loss: 0.1515
Epoch [5/5], Step [400/600], Loss: 0.0942
Epoch [5/5], Step [500/600], Loss: 0.0973
Epoch [5/5], Step [600/600], Loss: 0.1332
Accuracy of the model on the 10000 test images with activation sigmoid
and pooling avg: 97.56999969482422 %
Training model with activation: tanh, pooling: max
Epoch [1/5], Step [100/600], Loss: 0.1959
Epoch [1/5], Step [200/600], Loss: 0.1846
Epoch [1/5], Step [300/600], Loss: 0.1010
Epoch [1/5], Step [400/600], Loss: 0.0629
Epoch [1/5], Step [500/600], Loss: 0.1392
Epoch [1/5], Step [600/600], Loss: 0.0684
Epoch [2/5], Step [100/600], Loss: 0.0691
Epoch [2/5], Step [200/600], Loss: 0.0167
Epoch [2/5], Step [300/600], Loss: 0.0698
Epoch [2/5], Step [400/600], Loss: 0.0435
Epoch [2/5], Step [500/600], Loss: 0.0316
Epoch [2/5], Step [600/600], Loss: 0.0133
Epoch [3/5], Step [100/600], Loss: 0.1031
Epoch [3/5], Step [200/600], Loss: 0.0263
Epoch [3/5], Step [300/600], Loss: 0.0941
Epoch [3/5], Step [400/600], Loss: 0.0533
Epoch [3/5], Step [500/600], Loss: 0.0136
Epoch [3/5], Step [600/600], Loss: 0.0075
Epoch [4/5], Step [100/600], Loss: 0.0426
Epoch [4/5], Step [200/600], Loss: 0.0065
Epoch [4/5], Step [300/600], Loss: 0.0083
Epoch [4/5], Step [400/600], Loss: 0.0253
Epoch [4/5], Step [500/600], Loss: 0.0063
Epoch [4/5], Step [600/600], Loss: 0.0206
Epoch [5/5], Step [100/600], Loss: 0.0017
Epoch [5/5], Step [200/600], Loss: 0.0127
Epoch [5/5], Step [300/600], Loss: 0.0041
Epoch [5/5], Step [400/600], Loss: 0.0777
Epoch [5/5], Step [500/600], Loss: 0.0227
Epoch [5/5], Step [600/600], Loss: 0.0185
Accuracy of the model on the 10000 test images with activation tanh
and pooling max: 98.91000366210938 %
Training model with activation: tanh, pooling: avg
Epoch [1/5], Step [100/600], Loss: 0.4282
Epoch [1/5], Step [200/600], Loss: 0.3099
Epoch [1/5], Step [300/600], Loss: 0.1676
Epoch [1/5], Step [400/600], Loss: 0.2217
Epoch [1/5], Step [500/600], Loss: 0.1322
Epoch [1/5], Step [600/600], Loss: 0.0761
```

```
Epoch [2/5], Step [100/600], Loss: 0.0480
Epoch [2/5], Step [200/600], Loss: 0.1465
Epoch [2/5], Step [300/600], Loss: 0.0863
Epoch [2/5], Step [400/600], Loss: 0.0267
Epoch [2/5], Step [500/600], Loss: 0.2406
Epoch [2/5], Step [600/600], Loss: 0.0361
Epoch [3/5], Step [100/600], Loss: 0.1034
Epoch [3/5], Step [200/600], Loss: 0.0736
Epoch [3/5], Step [300/600], Loss: 0.0702
Epoch [3/5], Step [400/600], Loss: 0.0766
Epoch [3/5], Step [500/600], Loss: 0.0485
Epoch [3/5], Step [600/600], Loss: 0.0725
Epoch [4/5], Step [100/600], Loss: 0.1222
Epoch [4/5], Step [200/600], Loss: 0.0254
Epoch [4/5], Step [300/600], Loss: 0.0240
Epoch [4/5], Step [400/600], Loss: 0.0674
Epoch [4/5], Step [500/600], Loss: 0.0770
Epoch [4/5], Step [600/600], Loss: 0.0654
Epoch [5/5], Step [100/600], Loss: 0.0059
Epoch [5/5], Step [200/600], Loss: 0.0170
Epoch [5/5], Step [300/600], Loss: 0.0452
Epoch [5/5], Step [400/600], Loss: 0.0813
Epoch [5/5], Step [500/600], Loss: 0.0240
Epoch [5/5], Step [600/600], Loss: 0.0472
Accuracy of the model on the 10000 test images with activation tanh
and pooling avg: 98.58999633789062 %
Training model with activation: softmax, pooling: max

/usr/local/lib/python3.10/dist-packages/torch/nn/modules/
module.py:1511: UserWarning: Implicit dimension choice for softmax has
been deprecated. Change the call to include dim=X as an argument.
  return self._call_impl(*args, **kwargs)

Epoch [1/5], Step [100/600], Loss: 2.3073
Epoch [1/5], Step [200/600], Loss: 2.1499
Epoch [1/5], Step [300/600], Loss: 1.9291
Epoch [1/5], Step [400/600], Loss: 1.7264
Epoch [1/5], Step [500/600], Loss: 1.6367
Epoch [1/5], Step [600/600], Loss: 1.5525
Epoch [2/5], Step [100/600], Loss: 1.3800
Epoch [2/5], Step [200/600], Loss: 1.3266
Epoch [2/5], Step [300/600], Loss: 1.2881
Epoch [2/5], Step [400/600], Loss: 1.2172
Epoch [2/5], Step [500/600], Loss: 1.2184
Epoch [2/5], Step [600/600], Loss: 1.0739
Epoch [3/5], Step [100/600], Loss: 1.1657
Epoch [3/5], Step [200/600], Loss: 1.1278
Epoch [3/5], Step [300/600], Loss: 1.1744
Epoch [3/5], Step [400/600], Loss: 1.1106
Epoch [3/5], Step [500/600], Loss: 1.1071
```

```
Epoch [3/5], Step [600/600], Loss: 1.0743
Epoch [4/5], Step [100/600], Loss: 0.9926
Epoch [4/5], Step [200/600], Loss: 0.9965
Epoch [4/5], Step [300/600], Loss: 1.0429
Epoch [4/5], Step [400/600], Loss: 0.9816
Epoch [4/5], Step [500/600], Loss: 0.9818
Epoch [4/5], Step [600/600], Loss: 0.9236
Epoch [5/5], Step [100/600], Loss: 0.9665
Epoch [5/5], Step [200/600], Loss: 0.9473
Epoch [5/5], Step [300/600], Loss: 0.9554
Epoch [5/5], Step [400/600], Loss: 0.9297
Epoch [5/5], Step [500/600], Loss: 0.8637
Epoch [5/5], Step [600/600], Loss: 0.8805
Accuracy of the model on the 10000 test images with activation softmax
and pooling max: 50.75 %
Training model with activation: softmax, pooling: avg
Epoch [1/5], Step [100/600], Loss: 2.3030
Epoch [1/5], Step [200/600], Loss: 2.1887
Epoch [1/5], Step [300/600], Loss: 1.9355
Epoch [1/5], Step [400/600], Loss: 1.7694
Epoch [1/5], Step [500/600], Loss: 1.6624
Epoch [1/5], Step [600/600], Loss: 1.5159
Epoch [2/5], Step [100/600], Loss: 1.4562
Epoch [2/5], Step [200/600], Loss: 1.3378
Epoch [2/5], Step [300/600], Loss: 1.2458
Epoch [2/5], Step [400/600], Loss: 1.1820
Epoch [2/5], Step [500/600], Loss: 1.1994
Epoch [2/5], Step [600/600], Loss: 1.1897
Epoch [3/5], Step [100/600], Loss: 1.1513
Epoch [3/5], Step [200/600], Loss: 1.1231
Epoch [3/5], Step [300/600], Loss: 1.1452
Epoch [3/5], Step [400/600], Loss: 1.1741
Epoch [3/5], Step [500/600], Loss: 1.1515
Epoch [3/5], Step [600/600], Loss: 1.0100
Epoch [4/5], Step [100/600], Loss: 0.9501
Epoch [4/5], Step [200/600], Loss: 0.9848
Epoch [4/5], Step [300/600], Loss: 1.1054
Epoch [4/5], Step [400/600], Loss: 0.9482
Epoch [4/5], Step [500/600], Loss: 1.0657
Epoch [4/5], Step [600/600], Loss: 1.0135
Epoch [5/5], Step [100/600], Loss: 0.9469
Epoch [5/5], Step [200/600], Loss: 0.8603
Epoch [5/5], Step [300/600], Loss: 0.8846
Epoch [5/5], Step [400/600], Loss: 0.8474
Epoch [5/5], Step [500/600], Loss: 1.0053
Epoch [5/5], Step [600/600], Loss: 0.9385
Accuracy of the model on the 10000 test images with activation softmax
and pooling avg: 50.86000061035156 %
```

only thing to be modified is modeland based on above values, ReLu activation function with max pooling worked best. If needed, changes can be made accordingly.

```
class Net(nn.Module):
    def __init__(self, num_classes):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 16, kernel_size=5, stride=1,
padding=2)
        self.relu = nn.ReLU()
        # changes for different activation functions accordingly;
nn.Softmax() - softmax function
        # nn.Sigmoid() -- sigmod function; nn.Tanh() -- hyperbolic
tangent function
        self.maxpool = nn.MaxPool2d(kernel_size=2, stride=2)
        #self.maxpool = nn.AvgPool2d(kernel_size=2, stride=2)  --
average pooling
        self.conv2 = nn.Conv2d(16, 32, kernel_size=5, stride=1,
padding=2)
        self.fc1 = nn.Linear(7 * 7 * 32, 128)
        self.fc2 = nn.Linear(128, num_classes)

    def forward(self, x):
        out = self.conv1(x)
        out = self.relu(out)
        out = self.maxpool(out)
        out = self.conv2(out)
        out = self.relu(out)
        out = self.maxpool(out)
        out = out.view(out.size(0), -1)
        out = self.fc1(out)
        out = self.relu(out)
        out = self.fc2(out)
        return out
```