Lesson_Two

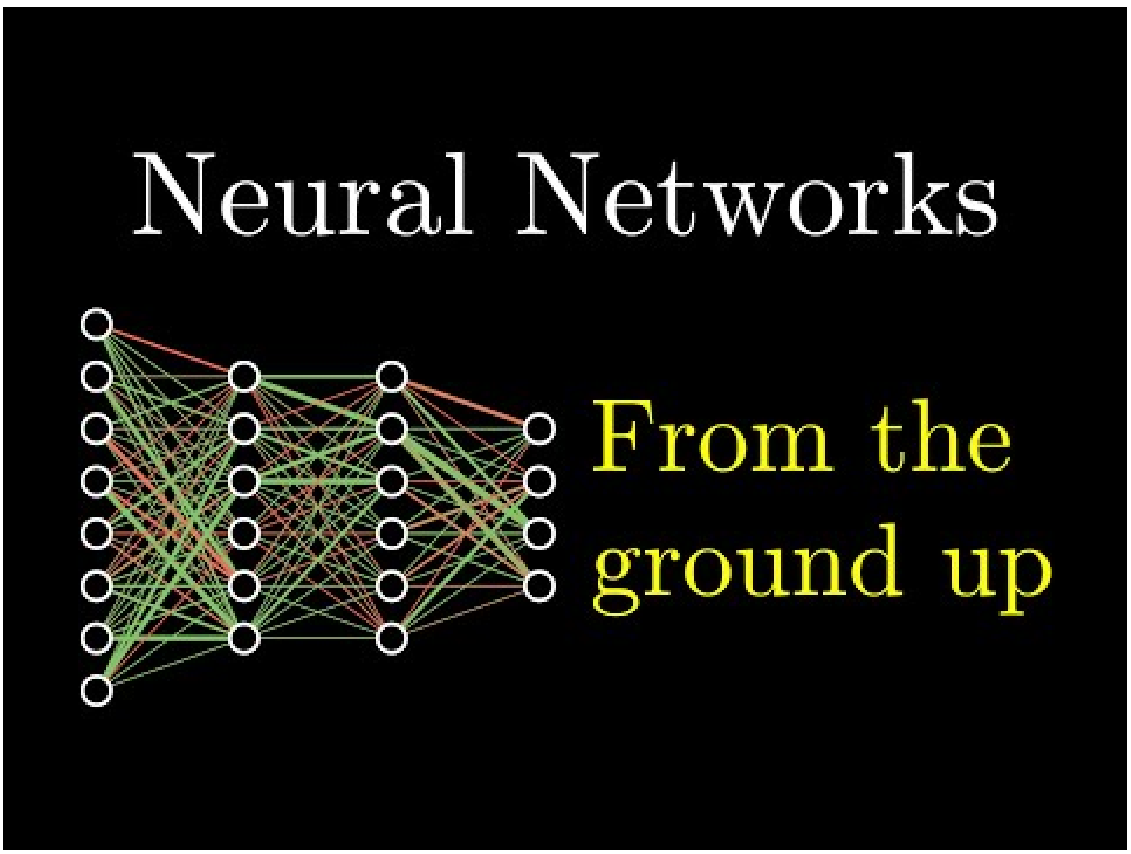
May 6, 2020

1 Introduction

We presume a CS 1301-level understanding of Python. This notebook will cover the very essentials of neural networks and Pytorch. Before you can begin to understand the given code, it is important that you have a solid understanding of the mechanics of neural networks and convolutions. Hence, watch the videos and visit the link provided in this section.

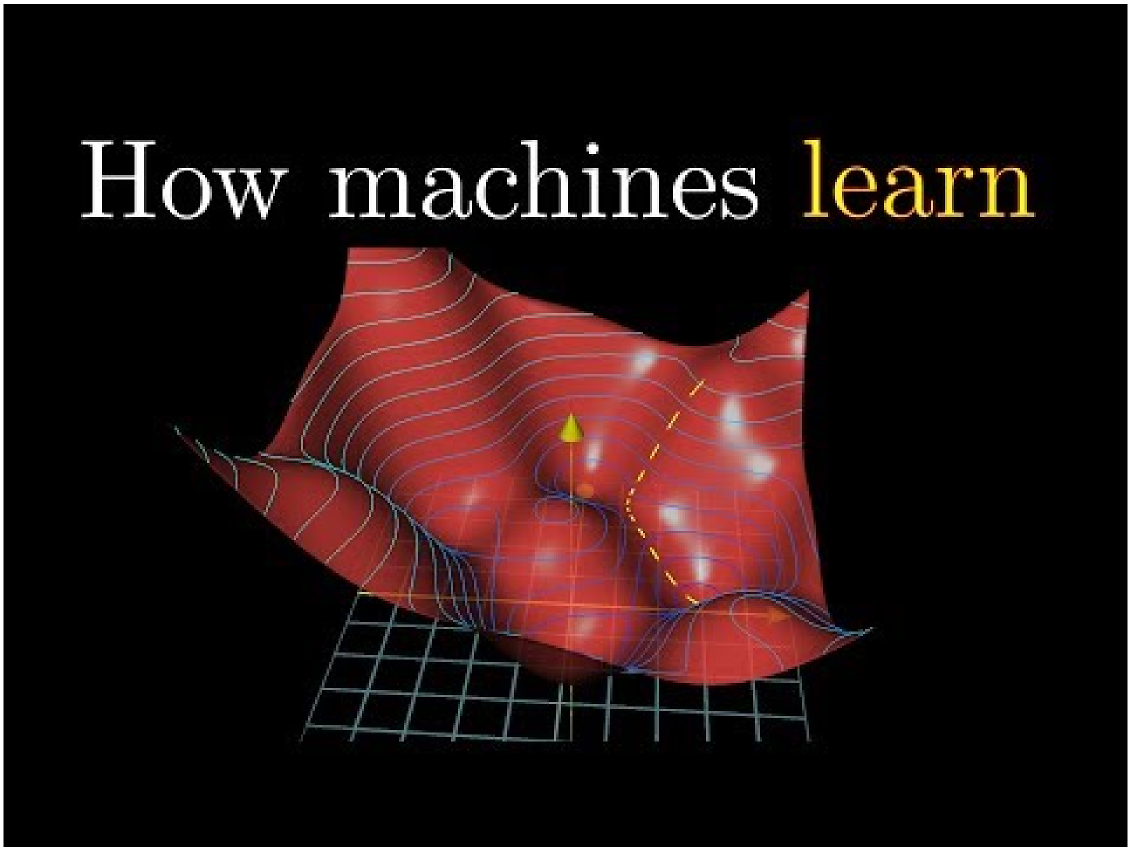
[0]:
```
from IPython.display import YouTubeVideo
YouTubeVideo("aircAruvnKk")
```

[0]:



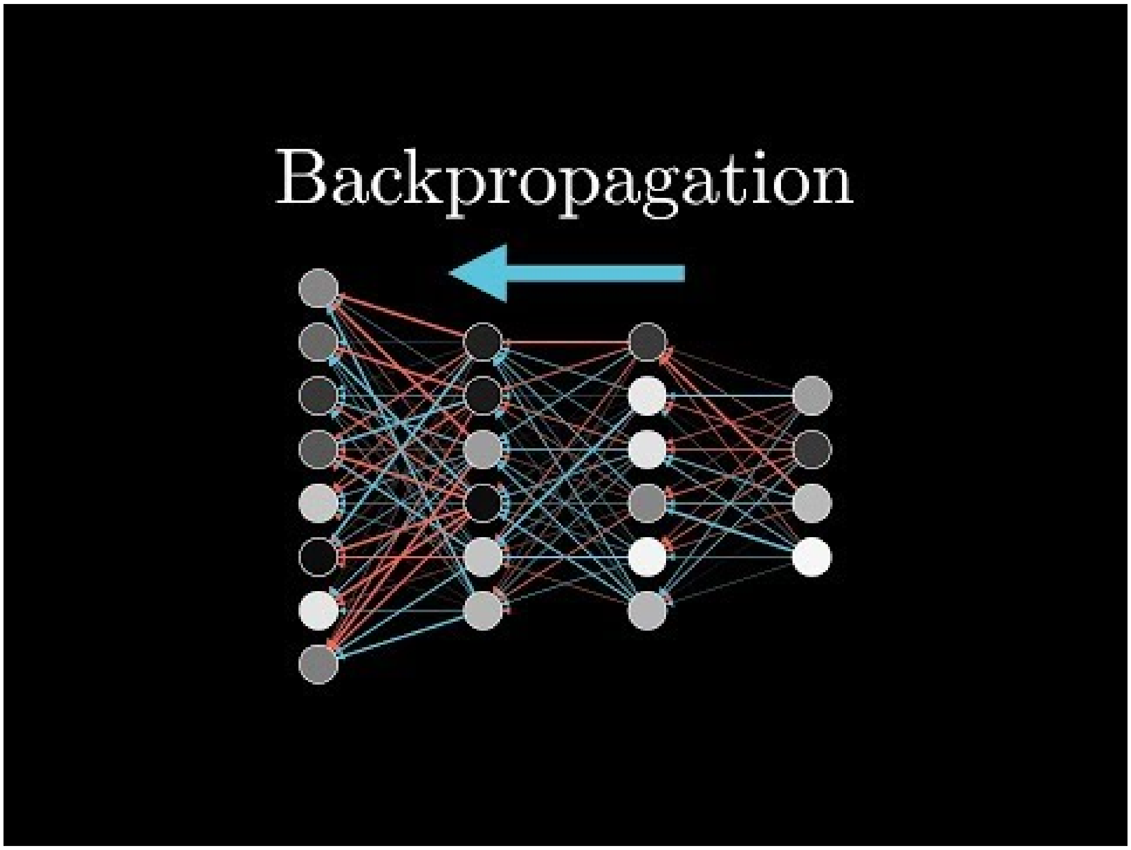
[0]:
```
YouTubeVideo("IHZwWFHWa-w")
```

[0]:



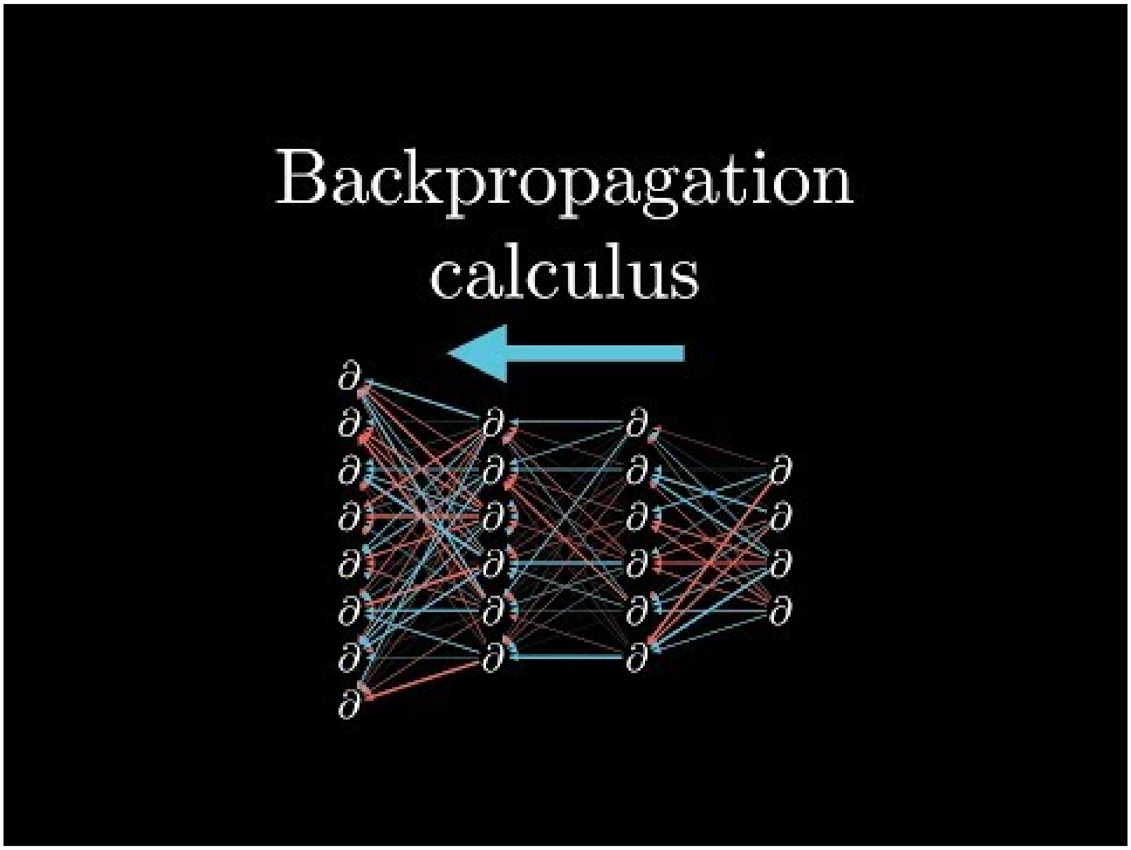
[0]:
```
YouTubeVideo("Ilg3gGewQ5U")
```

[0]:



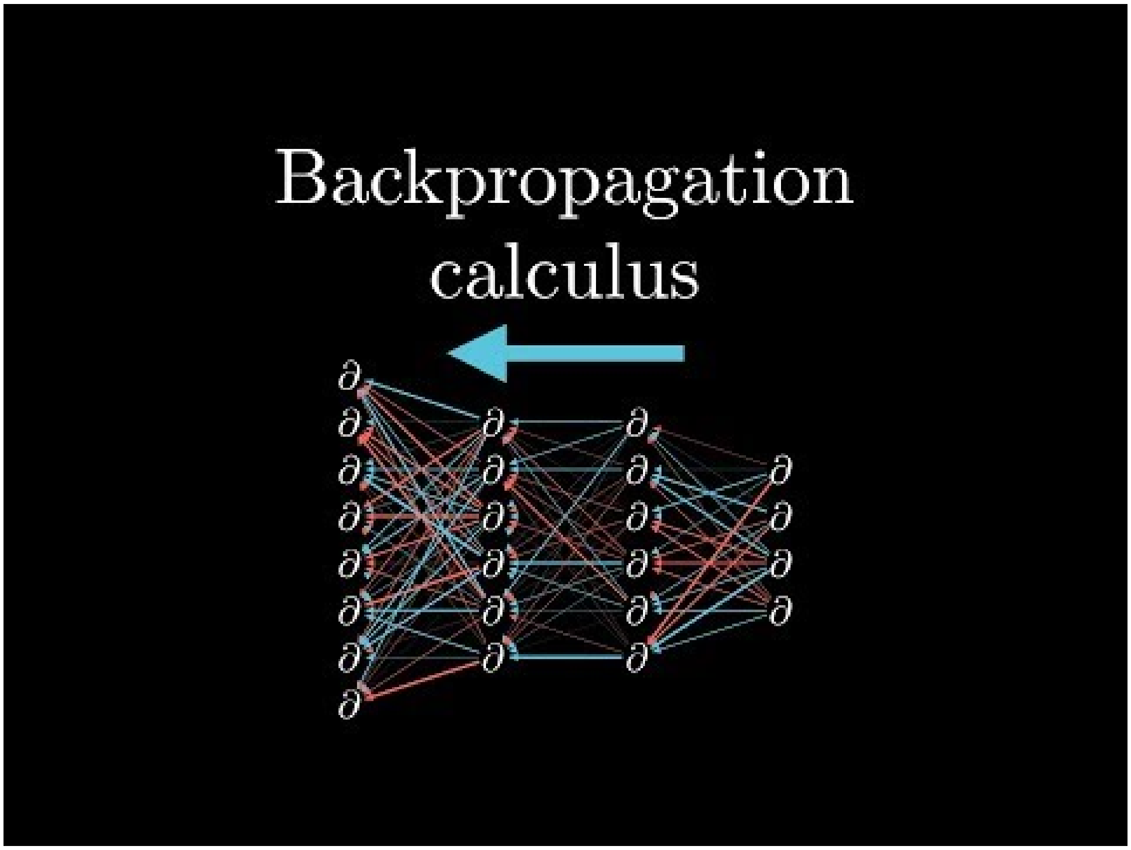
[0]:
```
YouTubeVideo("tIeHLnjs5U8")
```

[0]:



[0]:
```
YouTubeVideo("tIeHLnjs5U8")
```

[0]:



2 Neural Network for KMNIST

We're going to be utilizing PyTorch to build a simple classifier known as Mendes_NN (completely arbitrary name) for the KMNIST dataset (a collection of images of Hiranga characters).

Go to 'Runtime' and 'Change Runtime Type' to run this code on a GPU from Google. Make sure to carefully read the comments. Also, note that you can go into settings and change features such as key bindings, font, theme, and whitespace (set indent to 4 spaces for PEP8 compliance). Also, look at the drag from the left arrow toward the top for file structure (not necessary for lesson one).

[0]:
```
device = 'cuda' #Enables GPU use
!pip3 install torch torchvision


#Dependencies
import numpy as np
import matplotlib.pyplot as plt
import torch
```

```python
import torch.nn.functional as F
import torch.nn as nn
import torch.optim as optim
import torchvision.transforms as transforms
from torchvision.datasets import KMNIST
from torch.utils.data import DataLoader
```

```
Requirement already satisfied: torch in /usr/local/lib/python3.6/dist-packages
(1.1.0)
Requirement already satisfied: torchvision in /usr/local/lib/python3.6/dist-
packages (0.3.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages
(from torch) (1.16.4)
Requirement already satisfied: pillow>=4.1.1 in /usr/local/lib/python3.6/dist-
packages (from torchvision) (4.3.0)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages
(from torchvision) (1.12.0)
Requirement already satisfied: olefile in /usr/local/lib/python3.6/dist-packages
(from pillow>=4.1.1->torchvision) (0.46)
```

As you know from watching the videos, a neural network initializes the weights and biases with random variables before optimization. Setting a random seed stablizes the initialization, which means that the same random numbers are chosen and you can rerun the code with the same results. Try changing the seed slightly to see what happens. Note the form field syntax.

[0]:
```python
#Set seeds for reproducibility
seed = 42042069 #@param {type: "integer"}
torch.manual_seed(seed)
np.random.seed(seed)
```

Before we utilize the data, we transform it. First, we take the files and turn them into tensors (they're somewhat like fancy matrices). Then, we normalize it, which, in this case, is just changing the ranges of pixel intensity. The parameters of that can be played with as I'm quite sure the current ones are suboptimal. Knowing what transformations to use comes more from experience in my opinion.

[0]:
```python
#Define transformations; Convert data to tensors and normalize
train_transform = transforms.Compose([transforms.ToTensor(), transforms.
 ↪Normalize([0.1307], [0.3081])])
valid_transform = train_transform
```

Thankfully, KMNIST comes with PyTorch. We will cover how to load your own data later on.

[0]:
```python
#Download KMNIST data
```

```
train_set = KMNIST('./data/kmnist', train=True, download=True,␣
 ↪transform=train_transform)
valid_set = KMNIST('./data/kmnist', train=False, download=True,␣
 ↪transform=valid_transform)
```

```
  0%|          | 0/18165135 [00:00<?, ?it/s]

Downloading http://codh.rois.ac.jp/kmnist/dataset/kmnist/train-images-
idx3-ubyte.gz to ./data/kmnist/KMNIST/raw/train-images-idx3-ubyte.gz

18169856it [00:02, 6951652.86it/s]

Extracting ./data/kmnist/KMNIST/raw/train-images-idx3-ubyte.gz

32768it [00:00, 284949.15it/s]
0it [00:00, ?it/s]

Downloading http://codh.rois.ac.jp/kmnist/dataset/kmnist/train-labels-
idx1-ubyte.gz to ./data/kmnist/KMNIST/raw/train-labels-idx1-ubyte.gz
Extracting ./data/kmnist/KMNIST/raw/train-labels-idx1-ubyte.gz
Downloading http://codh.rois.ac.jp/kmnist/dataset/kmnist/t10k-images-
idx3-ubyte.gz to ./data/kmnist/KMNIST/raw/t10k-images-idx3-ubyte.gz

3047424it [00:00, 5062569.13it/s]
8192it [00:00, 103547.14it/s]

Extracting ./data/kmnist/KMNIST/raw/t10k-images-idx3-ubyte.gz
Downloading http://codh.rois.ac.jp/kmnist/dataset/kmnist/t10k-labels-
idx1-ubyte.gz to ./data/kmnist/KMNIST/raw/t10k-labels-idx1-ubyte.gz
Extracting ./data/kmnist/KMNIST/raw/t10k-labels-idx1-ubyte.gz
Processing…
Done!
```

How large do you think your data is now? In production code, you might want to convert this format to assertations instead for better automation.

[0]:
```
#Print shapes of the dataset
print(train_set.train_data.shape)
print(valid_set.test_data.shape)
```

```
torch.Size([60000, 28, 28])
torch.Size([10000, 28, 28])

/usr/local/lib/python3.6/dist-packages/torchvision/datasets/mnist.py:53:
UserWarning: train_data has been renamed data
  warnings.warn("train_data has been renamed data")
/usr/local/lib/python3.6/dist-packages/torchvision/datasets/mnist.py:58:
UserWarning: test_data has been renamed data
  warnings.warn("test_data has been renamed data")
```

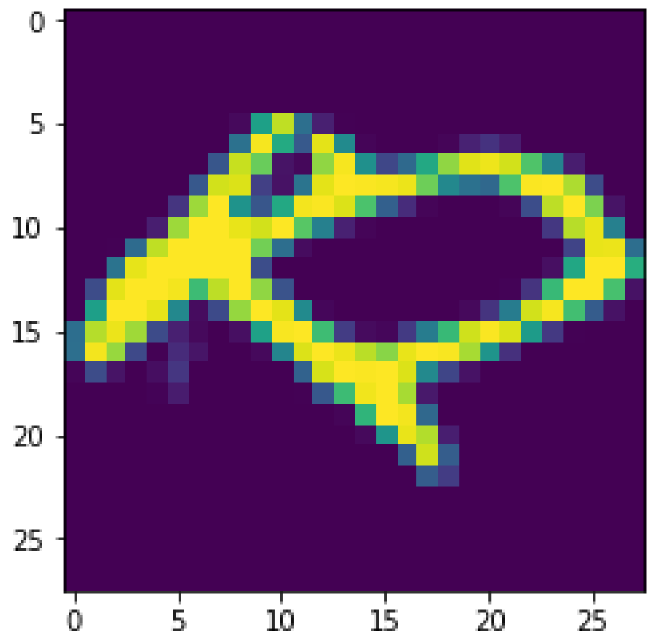
Let's take a look at what this data actually looks like. Change the number '20' to see other digits.

[0]:
```
#Display a single digit
plt.figure()
plt.imshow(train_set.train_data[20])
print(train_set.train_labels[20])
```

```
/usr/local/lib/python3.6/dist-packages/torchvision/datasets/mnist.py:53:
UserWarning: train_data has been renamed data
  warnings.warn("train_data has been renamed data")
```

```
tensor(7)
```

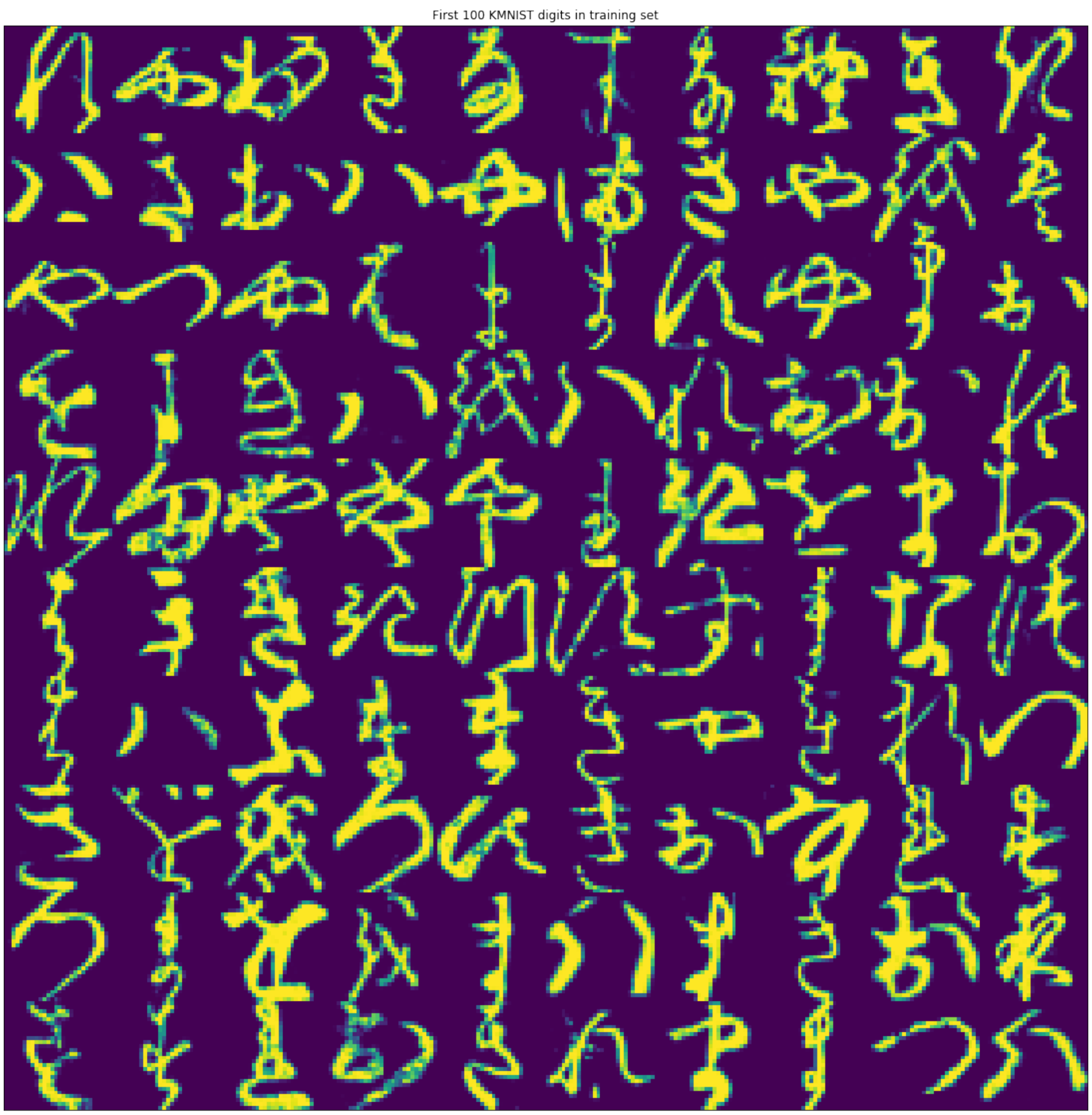
```
/usr/local/lib/python3.6/dist-packages/torchvision/datasets/mnist.py:43:
UserWarning: train_labels has been renamed targets
  warnings.warn("train_labels has been renamed targets")
```



[0]:
```
plt.figure(figsize=(20,20))

sample = train_set.train_data[:100] #See the first 100 images
# shape (64, 28, 28)
sample = sample.reshape(10,10,28,28) #Resize them so they can actually fit on␣
↪the screen
# shape (8, 8, 28, 28)
sample = sample.permute(0,2,1,3)
# shape (8, 28, 8, 28)
sample = sample.reshape(10*28,10*28)
# shape (8*28, 8*28)
```

```
plt.imshow(sample)
plt.xticks([])
plt.yticks([])
plt.grid(True)
plt.title('First 100 KMNIST digits in training set')
plt.show()

print('Labels:', train_set.train_labels[:100].numpy())
```

```
/usr/local/lib/python3.6/dist-packages/torchvision/datasets/mnist.py:53:
UserWarning: train_data has been renamed data
  warnings.warn("train_data has been renamed data")
```



```
Labels: [8 7 0 1 4 2 4 8 1 1 5 1 0 5 7 6 1 7 9 5 7 3 7 5 6 6 2 7 6 0 9 6 1 5 9 5
8
 0 0 8 8 6 7 7 7 8 1 9 6 0 5 1 1 1 3 2 2 6 4 3 5 5 4 6 6 1 7 8 8 3 1 9 9 3
 2 1 0 4 8 2 3 6 9 9 6 5 6 1 0 7 2 2 8 0 1 8 6 6 3 5]
```

```
/usr/local/lib/python3.6/dist-packages/torchvision/datasets/mnist.py:43:
UserWarning: train_labels has been renamed targets
  warnings.warn("train_labels has been renamed targets")
```

```
A data loader is ...
```

[0]:

```
#Initialize data loaders
train_loader = DataLoader(train_set, batch_size=269, num_workers=0,␣
 ↪shuffle=True)
valid_loader = DataLoader(valid_set, batch_size=690, num_workers=0,␣
 ↪shuffle=False)
```

[0]:

```
#Create neural network
class Mendes_NN(nn.Module):

  def __init__(self, num_channels=1, num_classes=10):
    super(Mendes_NN, self).__init__()
    hidden_1 = 420
    hidden_2 = 420
    hidden_3 = 420
    self.fc1 = nn.Linear(28 * 28, hidden_1)
    self.fc2 = nn.Linear(hidden_1, hidden_2)
    self.fc3 = nn.Linear(hidden_2, hidden_3)
    self.fc4 = nn.Linear(hidden_3, 10)
    self.dropout = nn.Dropout(0.4)

  def forward(self, x):
    x = x.view(-1, 28 * 28)
    x = F.relu(self.fc1(x))
    x = self.dropout(x)
    x = F.relu(self.fc2(x))
    x = F.relu(self.fc3(x))
    x = self.dropout(x)
    x = self.fc4(x)
    return x #logits
```

[0]:

```
#Elucidates progress
class AverageBase(object):

    def __init__(self, value=0):
        self.value = float(value) if value is not None else None
```

```
    def __str__(self):
        return str(round(self.value, 4))

    def __repr__(self):
        return self.value

    def __format__(self, fmt):
        return self.value.__format__(fmt)

    def __float__(self):
        return self.value


class RunningAverage(AverageBase):
    """
    Keeps track of a cumulative moving average (CMA).
    """

    def __init__(self, value=0, count=0):
        super(RunningAverage, self).__init__(value)
        self.count = count

    def update(self, value):
        self.value = (self.value * self.count + float(value))
        self.count += 1
        self.value /= self.count
        return self.value


class MovingAverage(AverageBase):
    """
    An exponentially decaying moving average (EMA).
    """

    def __init__(self, alpha=0.99):
        super(MovingAverage, self).__init__(None)
        self.alpha = alpha

    def update(self, value):
        if self.value is None:
            self.value = float(value)
        else:
            self.value = self.alpha * self.value + (1 - self.alpha) *␣
 ↪float(value)
        return self.value
```

```
from IPython.display import HTML, display

#Creates a progress bar
class ProgressMonitor(object):
    """
    Custom IPython progress bar for training
    """

    tmpl = """
        <p>Loss: {loss:0.4f}   {value} / {length}</p>
        <progress value='{value}' max='{length}', style='width: 100%'>{value}</
→progress>
    """

    def __init__(self, length):
        self.length = length
        self.count = 0
        self.display = display(self.html(0, 0), display_id=True)

    def html(self, count, loss):
        return HTML(self.tmpl.format(length=self.length, value=count,␣
→loss=loss))

    def update(self, count, loss):
        self.count += count
        self.display.update(self.html(self.count, loss))


#Creates checkpoints for the model
def save_checkpoint(optimizer, model, epoch, filename):
    checkpoint_dict = {
        'optimizer': optimizer.state_dict(),
        'model': model.state_dict(),
        'epoch': epoch
    }
    torch.save(checkpoint_dict, filename)


def load_checkpoint(optimizer, model, filename):
    checkpoint_dict = torch.load(filename)
    epoch = checkpoint_dict['epoch']
    model.load_state_dict(checkpoint_dict['model'])
    if optimizer is not None:
        optimizer.load_state_dict(checkpoint_dict['optimizer'])
    return epoch
```

[0]:
```python
#Initialize neural network
model = Mendes_NN()
model.to(device)
```

[0]:
```
Mendes_NN(
  (fc1): Linear(in_features=784, out_features=420, bias=True)
  (fc2): Linear(in_features=420, out_features=420, bias=True)
  (fc3): Linear(in_features=420, out_features=420, bias=True)
  (fc4): Linear(in_features=420, out_features=10, bias=True)
  (dropout): Dropout(p=0.4)
)
```

[0]:
```python
#Utilizes the Adadelta algorithm for optimization
optimizer = optim.Adadelta(model.parameters(), lr=0.01)
```

[0]:
```
!mkdir -p checkpoints
```

[0]:
```python
#Creates a function for training the model
def train(optimizer, model, num_epochs=9, first_epoch=1 ):

  criterion = nn.CrossEntropyLoss()

  train_losses = []
  valid_losses = []

  for epoch in range(first_epoch, first_epoch + num_epochs):
    print("Epoch", epoch)

    #training phase

    model.train()

    #create a progress bar
    progress = ProgressMonitor(length=len(train_set))

    train_loss = MovingAverage()

    for batch, targets in train_loader:

      #Move to GPU
      batch = batch.to(device)
      targets = targets.to(device)

      #clear out
      optimizer.zero_grad()

      #run forward prop
```

```
      predictions = model(batch)

      #calculate loss
      loss = criterion(predictions, targets)

      #backprop
      loss.backward()

      #update parameters
      optimizer.step()

      #update average loss
      train_loss.update(loss)

      #update progress bar
      progress.update(batch.shape[0], train_loss)

    print('Training loss:', train_loss)
    train_losses.append(train_loss.value)


    #validation phase
    model.eval()

    valid_loss = RunningAverage()

    #keep track of predictions'
    y_pred = []


    with torch.no_grad():

      for batch, targets in valid_loader:

        #Move to GPU
        batch = batch.to(device)
        targets = targets.to(device)

        #clear out
        optimizer.zero_grad()

        #running forward prop
        predictions = model(batch)

        #calculate loss
        loss = criterion(predictions, targets)
```

```
        #update average loss
        valid_loss.update(loss)

        y_pred.extend(predictions.argmax(dim=1).cpu().numpy())

    print('validation loss', valid_loss)
    valid_losses.append(valid_loss.value)

    #Calculate validation accuracy
    y_pred = torch.tensor(y_pred, dtype=torch.int64)
    accuracy = torch.mean((y_pred == valid_set.test_labels).float())
    print('Validation accuracy: {:.4f}%'.format(float(accuracy) * 100))

    # Save a checkpoint
    checkpoint_filename = 'checkpoints/kmnist-{:03d}.pkl'.format(epoch)
    save_checkpoint(optimizer, model, epoch, checkpoint_filename)

  return train_losses, valid_losses, y_pred
```

[0]:
```
train_losses, valid_losses, y_pred = train(optimizer, model, num_epochs=10)␣
 ↪#Train
```

```
Epoch 1
```

```
<IPython.core.display.HTML object>
```

```
Training loss: 2.2468
validation loss 2.2137
Validation accuracy: 32.4700%
Epoch 2
```

```
/usr/local/lib/python3.6/dist-packages/torchvision/datasets/mnist.py:48:
UserWarning: test_labels has been renamed targets
  warnings.warn("test_labels has been renamed targets")
```

```
<IPython.core.display.HTML object>
```

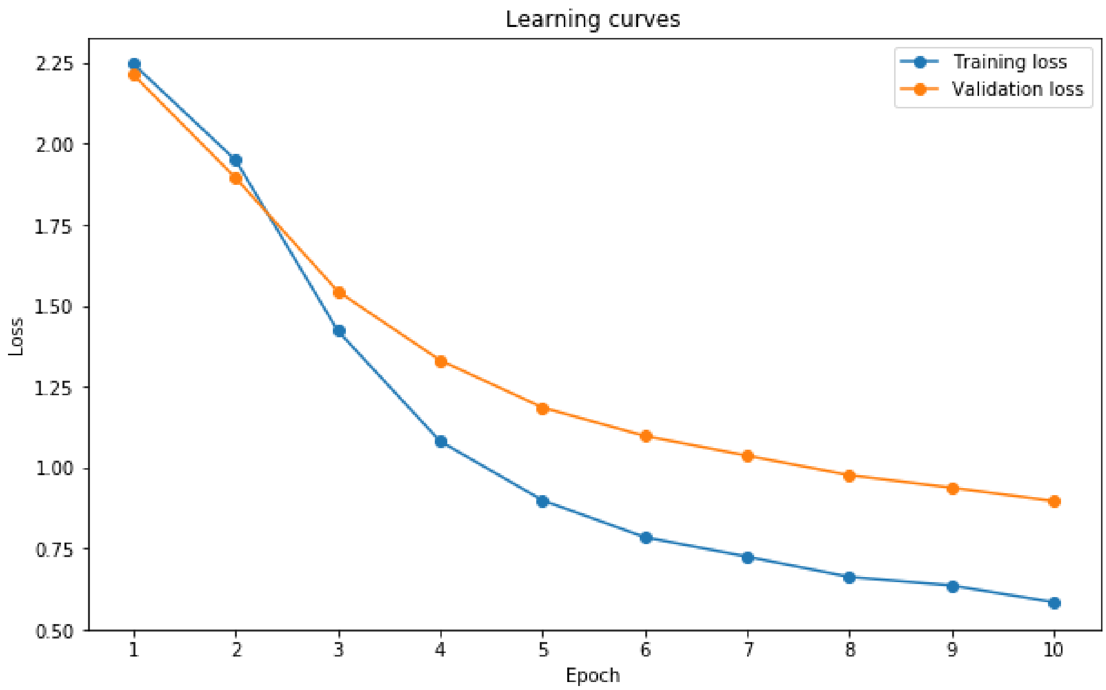
```
Training loss: 1.9499
validation loss 1.8951
Validation accuracy: 44.2100%
Epoch 3
```

```
<IPython.core.display.HTML object>
```

```
Training loss: 1.4226
validation loss 1.5445
Validation accuracy: 52.7200%
Epoch 4
```

```
<IPython.core.display.HTML object>


Training loss: 1.0816
validation loss 1.3317
Validation accuracy: 58.5200%
Epoch 5

<IPython.core.display.HTML object>


Training loss: 0.8994
validation loss 1.1862
Validation accuracy: 63.2100%
Epoch 6

<IPython.core.display.HTML object>


Training loss: 0.7855
validation loss 1.0983
Validation accuracy: 65.0700%
Epoch 7

<IPython.core.display.HTML object>


Training loss: 0.7255
validation loss 1.0373
Validation accuracy: 66.8500%
Epoch 8

<IPython.core.display.HTML object>


Training loss: 0.6628
validation loss 0.977
Validation accuracy: 68.6800%
Epoch 9

<IPython.core.display.HTML object>


Training loss: 0.6364
validation loss 0.9383
Validation accuracy: 69.6600%
Epoch 10

<IPython.core.display.HTML object>


Training loss: 0.5846
validation loss 0.897
Validation accuracy: 70.7600%
```

[0]:
```
#Graph training and validation loss
epochs = range(1, len(train_losses) + 1)

plt.figure(figsize=(10,6))
plt.plot(epochs, train_losses, '-o', label='Training loss')
plt.plot(epochs, valid_losses, '-o', label='Validation loss')
plt.legend()
plt.title('Learning curves')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.xticks(epochs)
plt.show()
```



3 Exercises

The comments in the code below provide you with instructions on how to modify the code to create a new neural network for the Fashion-MNIST dataset.

[0]:
```
import numpy as np
import matplotlib.pyplot as plt
import torch
import torch.nn.functional as F
import torch.nn as nn
```

```
import torch.optim as optim
import torchvision.transforms as transforms
#Import the Fashion-MNIST dataset
from torch.utils.data import DataLoader
```

[0]:
```
#Set seeds for reproducibility
#
#
#
```

[0]:
```
train_transform = transforms.Compose(
    #Add in three new transformations
valid_transform = train_transform
```

[0]:
```
#Download data
#
#
#
```

[0]:
```
#Fix up the assert statements for the shapes of the data
assert #
assert #
```

[0]:
```
train_loader = DataLoader(train_set, batch_size=269, num_workers=0,␣
 ↪shuffle=True)
valid_loader = DataLoader(valid_set, batch_size=690, num_workers=0,␣
 ↪shuffle=False)
```

```
  File "<ipython-input-5-686410b9c325>", line 3
    num_workers=0 #@param {type: "integer"},
              ^
SyntaxError: invalid syntax
```

[0]:
```
class New_NN(nn.Module):

  def __init__(self, num_channels=1, num_classes=10):
    super(New_NN, self).__init__()
    hidden_1 = 420 #@param {type: "integer"}
    hidden_2 = 420 #@param {type: "integer"}
    hidden_3 = 420 #@param {type: "integer"}
    #Replace these layes with conulutional layers
    #Does there need to be a change in the forward function?
    #Run the code and see
    self.dropout = nn.Dropout(0.4)
```

```
  def forward(self, x):
    x = #What goes here?
    x = F.relu(self.fc1(x))
    x = self.dropout(x)
    x = F.relu(self.fc2(x))
    x = F.relu(self.fc3(x))
    # Fill in the blanks
    return x
```

[0]:

```

```

[0]:

```
class AverageBase(object):

    def __init__(self, value=0):
        self.value = float(value) if value is not None else None

    def __str__(self):
        return str(round(self.value, 4))

    def __repr__(self):
        return self.value

    def __format__(self, fmt):
        return self.value.__format__(fmt)

    def __float__(self):
        return self.value


class RunningAverage(AverageBase):

    def __init__(self, value=0, count=0):
        super(RunningAverage, self).__init__(value)
        self.count = count

    def update(self, value):
        self.value = (self.value * self.count + float(value))
        self.count += 1
        self.value /= self.count
        return self.value


class MovingAverage(AverageBase):

    def __init__(self, alpha=0.99):
        super(MovingAverage, self).__init__(None)
```

```
        self.alpha = alpha

    def update(self, value):
        if self.value is None:
            self.value = float(value)
        else:
            self.value = self.alpha * self.value + (1 - self.alpha) *␣
↪float(value)
        return self.value


from IPython.display import HTML, display

class ProgressMonitor(object):


    tmpl = """
        <p>Loss: {loss:0.4f}   {value} / {length}</p>
        <progress value='{value}' max='{length}', style='width: 100%'>{value}</
↪progress>
    """

    def __init__(self, length):
        self.length = length
        self.count = 0
        self.display = display(self.html(0, 0), display_id=True)

    def html(self, count, loss):
        return HTML(self.tmpl.format(length=self.length, value=count,␣
↪loss=loss))

    def update(self, count, loss):
        self.count += count
        self.display.update(self.html(self.count, loss))


def save_checkpoint(optimizer, model, epoch, filename):
    checkpoint_dict = {
        'optimizer': optimizer.state_dict(),
        'model': model.state_dict(),
        'epoch': epoch
    }
    torch.save(checkpoint_dict, filename)


def load_checkpoint(optimizer, model, filename):
    checkpoint_dict = torch.load(filename)
```

```
    epoch = checkpoint_dict['epoch']
    model.load_state_dict(checkpoint_dict['model'])
    if optimizer is not None:
        optimizer.load_state_dict(checkpoint_dict['optimizer'])
    return epoch
```

[0]:
```
#Initialize neural network
```

[0]:
```
#Create a optimizer; Pick something other than Adadelta after referring to the␣
↪PyTorch documentation
```

[0]:
```
!mkdir -p checkpoints
```

[0]:
```
def train(optimizer, model, num_epochs=9, first_epoch=1 ):

  criterion = nn.CrossEntropyLoss()

  train_losses = []
  valid_losses = []

  for epoch in range(first_epoch, first_epoch + num_epochs):
    print("Epoch", epoch)

    model.train()

    progress = ProgressMonitor(length=len(train_set))

    train_loss = MovingAverage()

    for batch, targets in train_loader:

      batch = batch.to(device)
      targets = targets.to(device)

      optimizer.zero_grad()

      predictions = model(batch)

      loss = criterion(predictions, targets)

      loss.backward()

      optimizer.step()

      train_loss.update(loss)

      progress.update(batch.shape[0], train_loss)
```

```
    print('Training loss:', train_loss)
    train_losses.append(train_loss.value)

    model.eval()

    valid_loss = RunningAverage()

    y_pred = []


    with torch.no_grad():

      for batch, targets in valid_loader:

        batch = batch.to(device)
        targets = targets.to(device)

        optimizer.zero_grad()

        predictions = model(batch)

        loss = criterion(predictions, targets)

        valid_loss.update(loss)

        y_pred.extend(predictions.argmax(dim=1).cpu().numpy())

    print('validation loss', valid_loss)
    valid_losses.append(valid_loss.value)

    y_pred = torch.tensor(y_pred, dtype=torch.int64)
    accuracy = torch.mean((y_pred == valid_set.test_labels).float())
    print('Validation accuracy: {:.4f}%'.format(float(accuracy) * 100))

    # Save a checkpoint

  return train_losses, valid_losses, y_pred
```

[0]:
```
train_losses, valid_losses, y_pred = train(optimizer, model, num_epochs=10)
```

[0]:
```
#Integrate TensorBoard here in less than 15 lines
```

Optional Exercise: Implement named tensors in the code above.