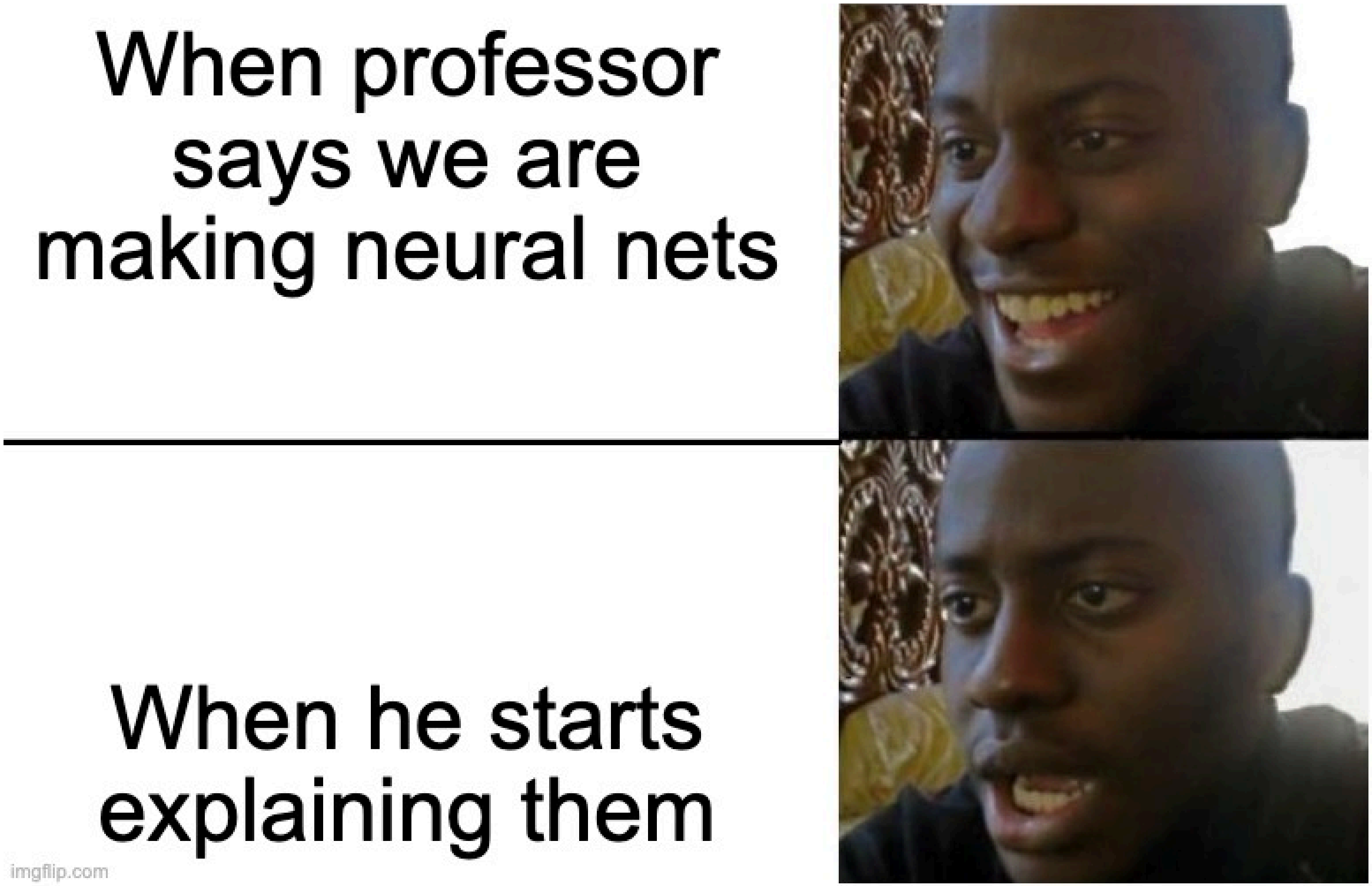
Neural Networks

For a great supplementary read, check this out!


When professor says we are making neural nets
When he starts explaining them
imgflip.com

Why?

Neural networks are a class of **advanced** machine learning models originally designed to replicate many observed characteristics of human brains

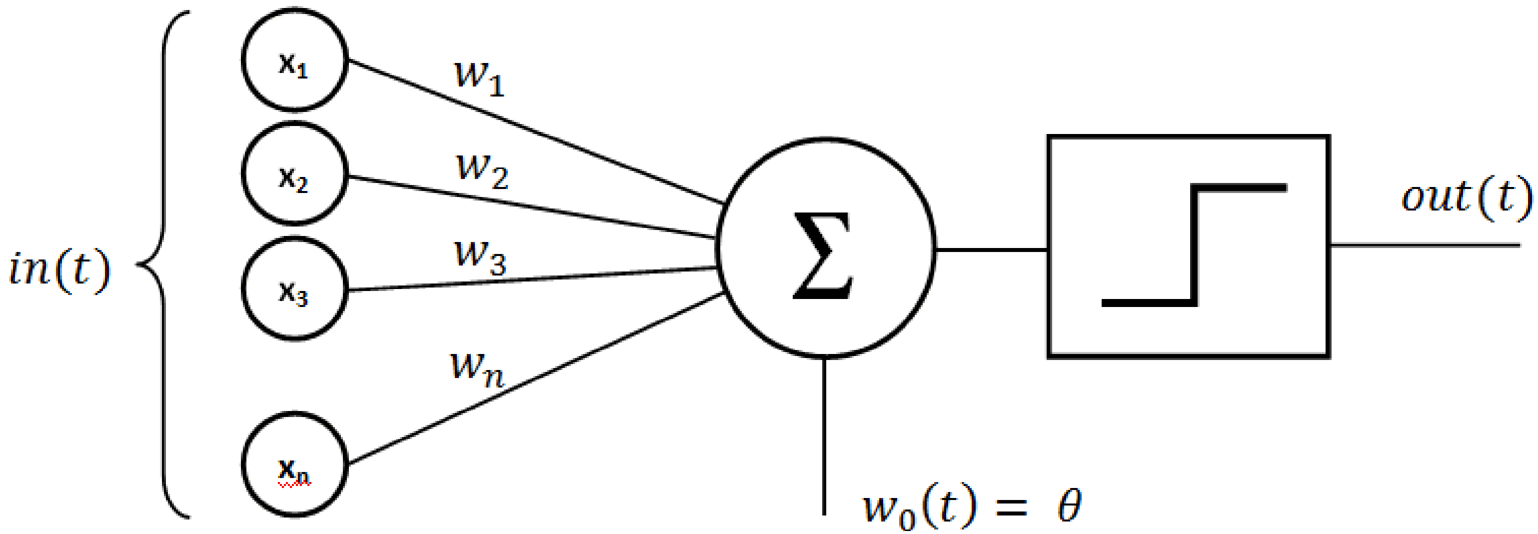
- Hard to use well (see statement on brains)
- Difficult to explain clearly (see above)
- Highly valuable **in specific contexts**

The basics - Perceptrons

A perceptron is the computational equivalent of a single neuron

Let's describe it with a visual

A perceptron



What is an Activation Function?

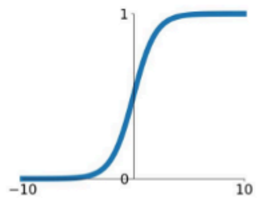
An activation function is a math function that determines when a perceptron moves from "off" to "on".

Again, let's describe this visually

Activation Functions

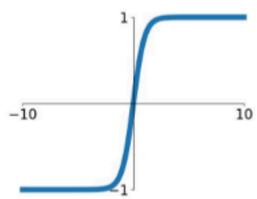
Sigmoid

$\sigma(x) = \frac{1}{1+e^{-x}}$



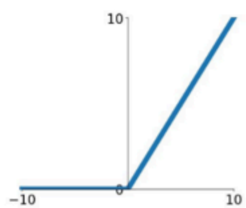
tanh

$\tanh(x)$



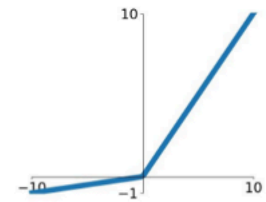
ReLU

$\max(0, x)$



Leaky ReLU

$\max(0.1x, x)$

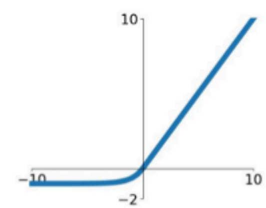


Maxout

$\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

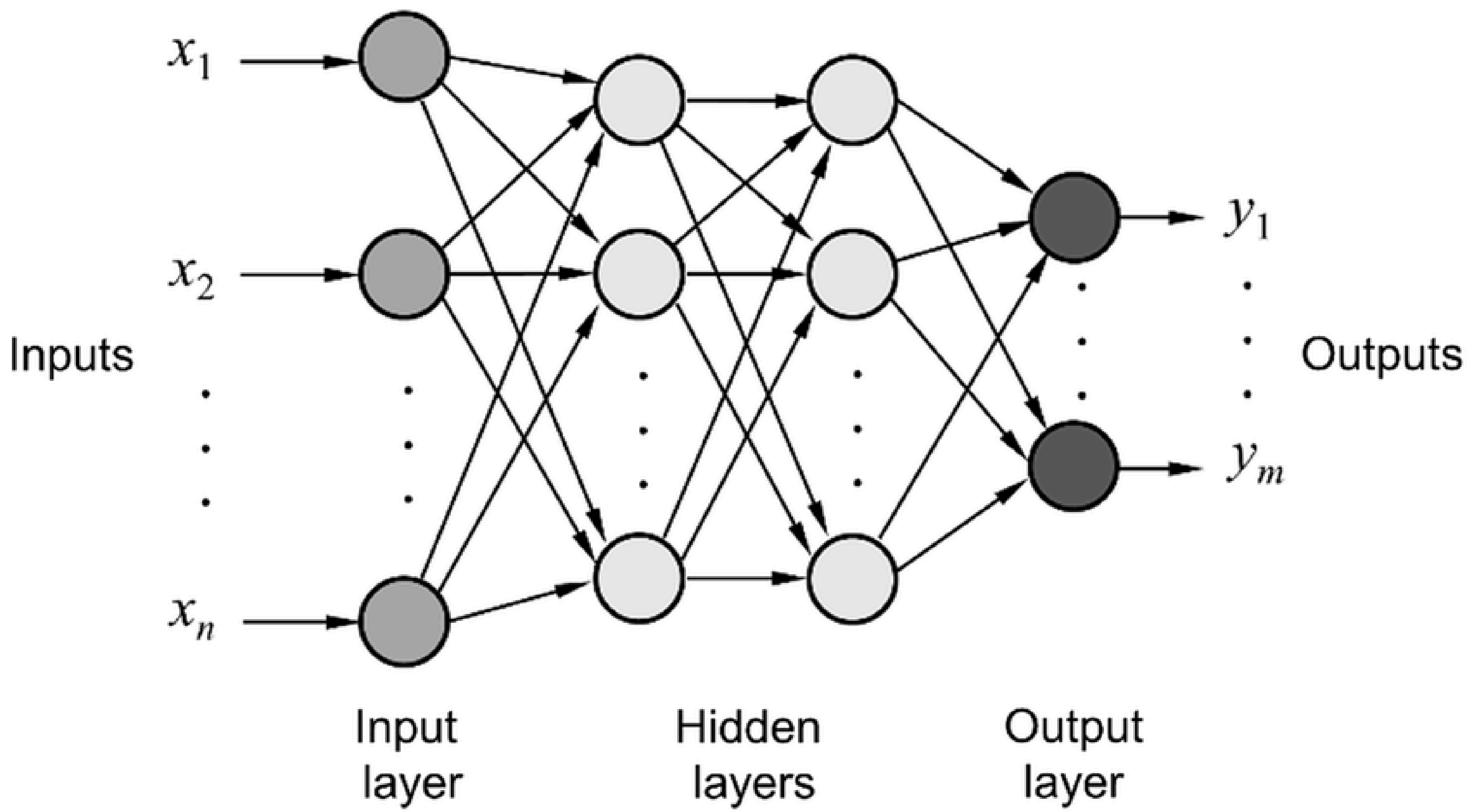
$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



How does this make a Neural Network?

Neural networks are made up of **layers** of perceptrons that are interconnected, leading from the **input layer** to the **output layer**.

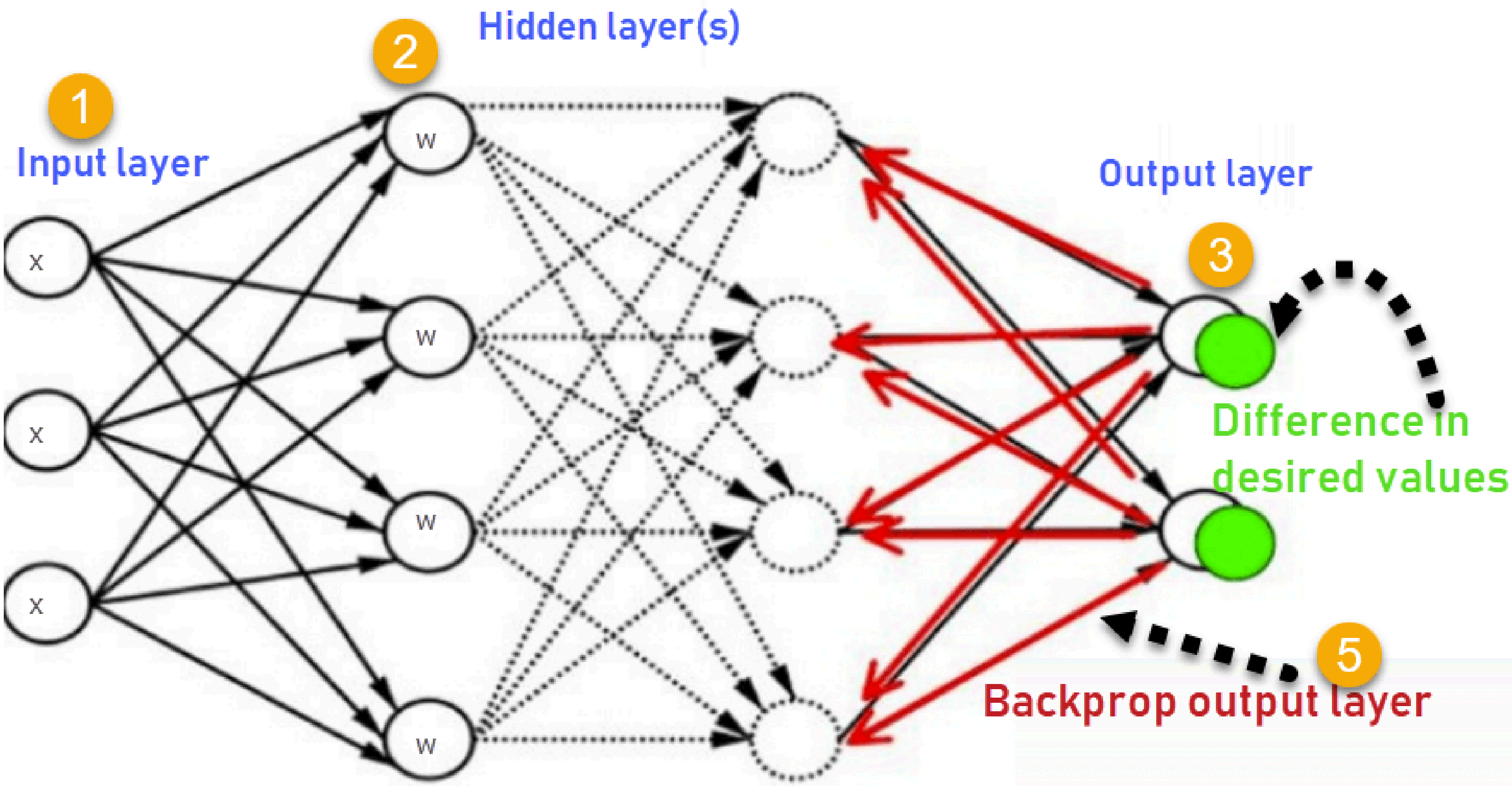
Any layer in between is called a **hidden layer**. Neural networks are often referred to as **deep learning** because of these hidden layers making the nerual network "deep".


x_1
x_2
x_n
Inputs
y_1
y_m
Outputs
Input layer
Hidden layers
Output layer

How do we use them?

Our goal with a neural network is to train our network with **weights** and **biases** (these are what trigger the activation functions, remember?) so that the network is able to represent the complex process of predicting our outcome of interest.

How we learn - Backpropagation



How we learn - Backpropagation

Through inputs and backpropagation, we train our model to perform as well as we can on our task.

How do we choose the right network?

Choosing the right network

1. Use one that someone else designed for the same (or similar) tasks
2. Evolutionary algorithms ("neuroevolution")
   - Here's an example: https://www.youtube.com/watch?v=qv6UVOQ0F44
3. Trial and error, called neural architecture search (NAS), not efficient!
4. Searching the design space efficiently (AnyNet did this)

Creating networks with `pytorch`

Why use `pytorch`?

- It is pythonic, so it makes sense (`tensorflow` feels like C++ and is really jarring for the typical Python user)
- It contains many prebuilt objects to speed up our construction
- Can easily be used with GPUs for acceleration of training (we won't do it this week, but it is trivially easy)

Setting up

```
pip3 install torch torchvision torchaudio
```

`torch` is the core library, while `torchvision` and `torchaudio` support specific tasks

Importing modules

```
# For reading data
import pandas as pd
from torch.utils.data import Dataset
from torch.utils.data import DataLoader

# For visualizing
import plotly.express as px

# For model building
import torch
import torch.nn as nn
import torch.nn.functional as F
```

Importing data

Using data in neural networks is not quite the same as using data for statistical models:

- Modern models have a LOT of parameters (ChatGPT-4 is believed to have over 1 TRILLION)
- We use **minibatches** of data to minimize memory use

We need to create a **class** object that can handle our data, and break it down as needed

Defining our data class

While some data can be imported straight from `pytorch` through its data library, real-world work requires us to be able to work with ANY data, so we will practice setting up our data input manually.

Defining our data class

```python
class CustomMNIST(Dataset):
    def __init__(self, url):
        # read in our raw data from the hosting URL
        self.raw_data = pd.read_csv(url)

    # return the length of the complete data set
    #   to be used in internal calculations for pytorch
    def __len__(self):
        return self.raw_data.shape[0]

    # retrieve a single record based on index position `idx`
    def __getitem__(self, idx):
        # extract the image separate from the label
        image = self.raw_data.iloc[idx, 1:].values.reshape(1, 28, 28)
        # Specify dtype to align with default dtype used by weight matrices
        image = torch.tensor(image, dtype=torch.float32)
        # extract the label
        label = self.raw_data.iloc[idx, 0]

        # return the image and its corresponding label
        return image, label
```

Importing the data

```
# Load our data into memory
train_data = CustomMNIST("https://github.com/dustywhite7/
Econ8310/raw/master/DataSets/mnistTrain.csv")
test_data = CustomMNIST("https://github.com/dustywhite7/
Econ8310/raw/master/DataSets/mnistTest.csv")

# Create data feed pipelines for modeling
train_dataloader = DataLoader(train_data, batch_size=64)
test_dataloader = DataLoader(test_data, batch_size=64)
```

Data vs `DataLoader`

Data

- Data is contained in instances of the class that we designed
- Can be used in many different ways, and is very flexible

`DataLoader`

- Takes a data class, and is the pipeline to create **minibatches** of that data source to be used at each step of training
- Wraps the data with the necessary functionality

Verify our data

```
# Check that our data look right when we sample

idx=1
print(f"This image is labeled a {train_data.__getitem__(idx)[1]}")
px.imshow(train_data.__getitem__(idx)[0].reshape(28, 28))
```

Does the number look like the label? Then you've got it set up correctly!

Building our first network

We are now ready to create a neural network using the data we have in memory!

In this case, let's walk through the most basic neural network that we can: a **linear neural network classifier**.

Building our first network

Steps:

1. Create a class to hold our network
    - Can you tell that `torch` is really focused on using class objects? So was `sklearn`!
2. Initialize our model (`__init__`)
    - We create the layers of our model in this stage, by declaring each layer and attaching it to the class object we created in (1)
3. Declare our `forward` method
    - This is where we construct our model and describe how to move from one layer to the next

Build it!

```python
class FirstNet(nn.Module):
    def __init__(self):
      # We define the components of our model here
      super(FirstNet, self).__init__()
      # Function to flatten our image
      self.flatten = nn.Flatten()
      # Create the sequence of our network
      self.linear_relu_model = nn.Sequential(
            # Add a linear output layer w/ 10 perceptrons
            nn.LazyLinear(10),
        )
```

Build it!

```
class FirstNet(nn.Module):
    ... # see last slide

    def forward(self, x):
      # We construct the sequencing of our model here
      x = self.flatten(x)
      # Pass flattened images through our sequence
      output = self.linear_relu_model(x)

      # Return the evaluations of our ten
      #   classes as a 10-dimensional vector
      return output

# Create an instance of our model
model = FirstNet()
```

Prepare to train the model

```
# Define some training parameters
learning_rate = 1e-2
batch_size = 64
epochs = 20

# Define our loss function
#   This one works for multiclass problems
loss_fn = nn.CrossEntropyLoss()
```

More definitions

Batch size: The number of image samples provided at once to our model. We have to keep this relatively small, since it takes a lot of computer memory to train the models on a set of images.

Epochs: The number of times we will loop over the **entire data set** as we train our model. More epochs leads to more refined models, but also takes a long time.

Learning Rate: How fast our model changes as it adapts to its mistakes.

Prepare to train the model

```
# Build our optimizer with the parameters from
#   the model we defined, and the learning rate
#   that we picked
optimizer = torch.optim.SGD(model.parameters(),
     lr=learning_rate)
```

Prepare to train the model

```
def train_loop(dataloader, model, loss_fn, optimizer):
    size = len(dataloader.dataset)
    # Set the model to training mode
    # important for batch normalization and dropout layers
    # Unnecessary in this situation but added for best practices
    model.train()
    # Loop over batches via the dataloader
    for batch, (X, y) in enumerate(dataloader):
        # Compute prediction and loss
        pred = model(X)
        loss = loss_fn(pred, y)

        # Backpropagation and looking for improved gradients
        loss.backward()
        optimizer.step()
        # Zeroing out the gradient (otherwise they are summed)
        #   in preparation for next round
        optimizer.zero_grad()

        # Print progress update every few loops
        if batch % 10 == 0:
            loss, current = loss.item(), (batch + 1) * len(X)
            print(f"loss: {loss:>7f}  [{current:>5d}/{size:>5d}]")
```

Prepare to train AND TEST the model

```
def test_loop(dataloader, model, loss_fn):
    # Set the model to evaluation mode
    # important for batch normalization and dropout layers
    # Unnecessary in this situation but added for best practices
    model.eval()
    size = len(dataloader.dataset)
    num_batches = len(dataloader)
    test_loss, correct = 0, 0

    # Evaluating the model with torch.no_grad() ensures
    # that no gradients are computed during test mode
    # also serves to reduce unnecessary gradient computations
    # and memory usage for tensors with requires_grad=True
    with torch.no_grad():
        for X, y in dataloader:
            pred = model(X)
            test_loss += loss_fn(pred, y).item()
            correct += (pred.argmax(1) == y).type(torch.float).sum().item()

    # Printing some output after a testing round
    test_loss /= num_batches
    correct /= size
    print(f"Test Error: \n Accuracy: {
        (100*correct):>0.1f}%, Avg loss: {
            test_loss:>8f} \n")
```

And now we train!

```
# Need to repeat the training process for each epoch.
#   In each epoch, the model will eventually see EVERY
#   observations in the data
for t in range(epochs):
    print(f"Epoch {t+1}\n-------------------------------")
    train_loop(train_dataloader, model, loss_fn, optimizer)
    test_loop(test_dataloader, model, loss_fn)
print("Done!")
```

Score the model

Take a look at the final testing score printed after the last epoch.

Does this model outperform our decision trees and random forests? Why?

Making more predictions

```
# Decide if we are loading for predictions or more training
model.eval()
# - or -
# model.train()

# Make predictions
pred = model(test_data.__getitem__(1)[0]).argmax()
truth = test_data.__getitem__(1)[1]
print(f"This image is predicted to be a {pred}, and is labeled as {truth}")
```

Where are we now?

- We have created a linear neural network classifier
- This is the foundation of neural network architecture
  - It is about 40 years out of date, though
- Remember, neural nets are a CLASS of models
  - We will explore variants of neural networks over the next two weeks

Before we go...

Training neural networks is time and resource intensive

According to these redditors, it would take 355 years to train GPT-3 on a single NVIDIA Tesla V100 GPU

So let's save our progress so that we can import it later

Saving a model

```
# Save our model for later, so we can train more or make predictions

EPOCH = epochs
# We use the .pt file extension by convention for saving
#    pytorch models
PATH = "model.pt"

# The save function creates a binary storing all our data for us
torch.save({
            'epoch': EPOCH,
            'model_state_dict': model.state_dict(),
            'optimizer_state_dict': optimizer.state_dict(),
            }, PATH)
```

Loading data back in

```
# Specify our path
PATH = "model.pt"

# Create a new "blank" model to load our information into
model = FirstNet()

# Recreate our optimizer
optimizer = torch.optim.SGD(model.parameters(), lr=0.001, momentum=0.9)

# Load back all of our data from the file
checkpoint = torch.load(PATH)
model.load_state_dict(checkpoint['model_state_dict'])
optimizer.load_state_dict(checkpoint['optimizer_state_dict'])
EPOCH = checkpoint['epoch']
```

Lab Time!

For homework assignment 3, you will work with Fashion MNIST, a more fancier data set.

- You must create a custom data loader [2 points]
- You must create a working neural network using only `pytorch` [2 points]
- You must store your weights and create an import script so that I can evaluate your model **without training it** [2 points]

Highest accuracy score gets some extra credit!