Defining the Problem — Machine Learning

How do we make machine learn to do something without explicitely programming it to do that thing?

Example tasks:

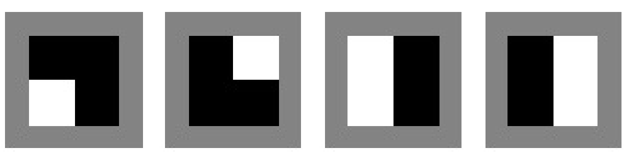
- Identify if image contains a cat
- Classify handwritten characters
- Generate music
- Play go
- Translation
- Write an essay (not for submission of course)
- ...

We could programme a computer to do these thigns, but it gets harder the less we know how to write such programme. (Imagine someone asking you to handcraft a translator)

Consider this trivial task:

We have four-pixel images, and we want to classify them as 1, 7, or L.

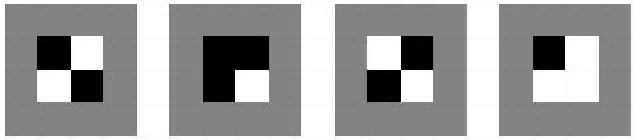
Left to right: 7, L, 1, 1



Okay, maybe you wrote a bunch of if else statements and got something to work

What if... new language with other ways of writing 1, 7, L—

Left to right: 7, L, 1, 1

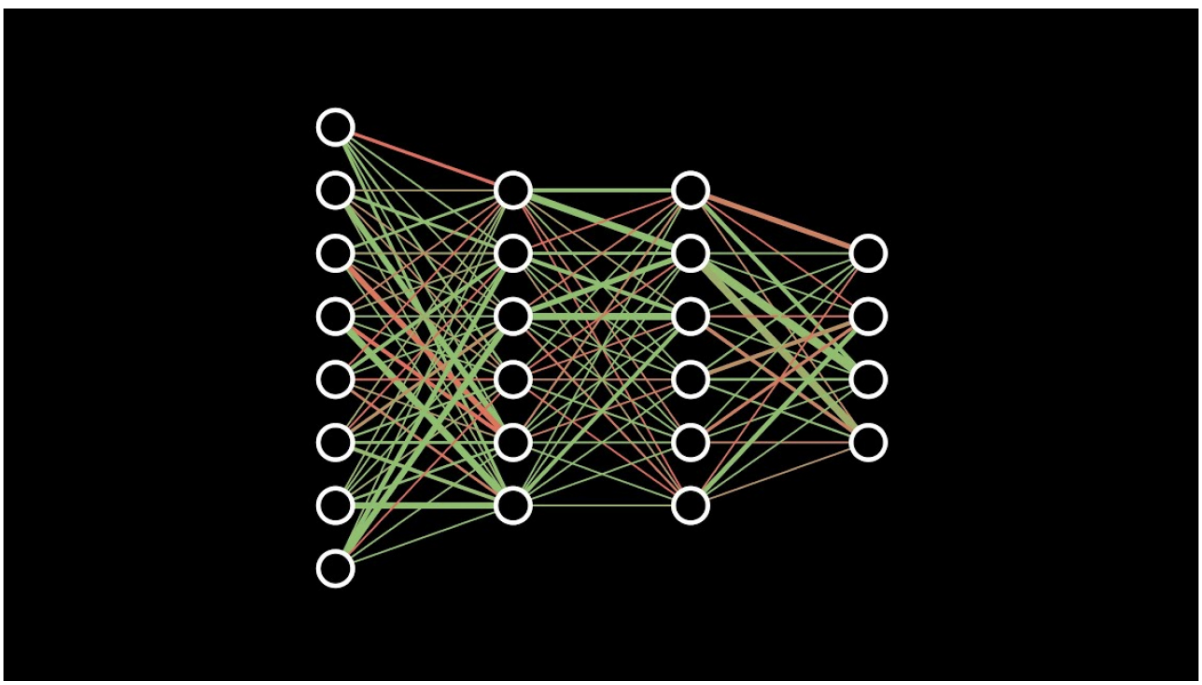


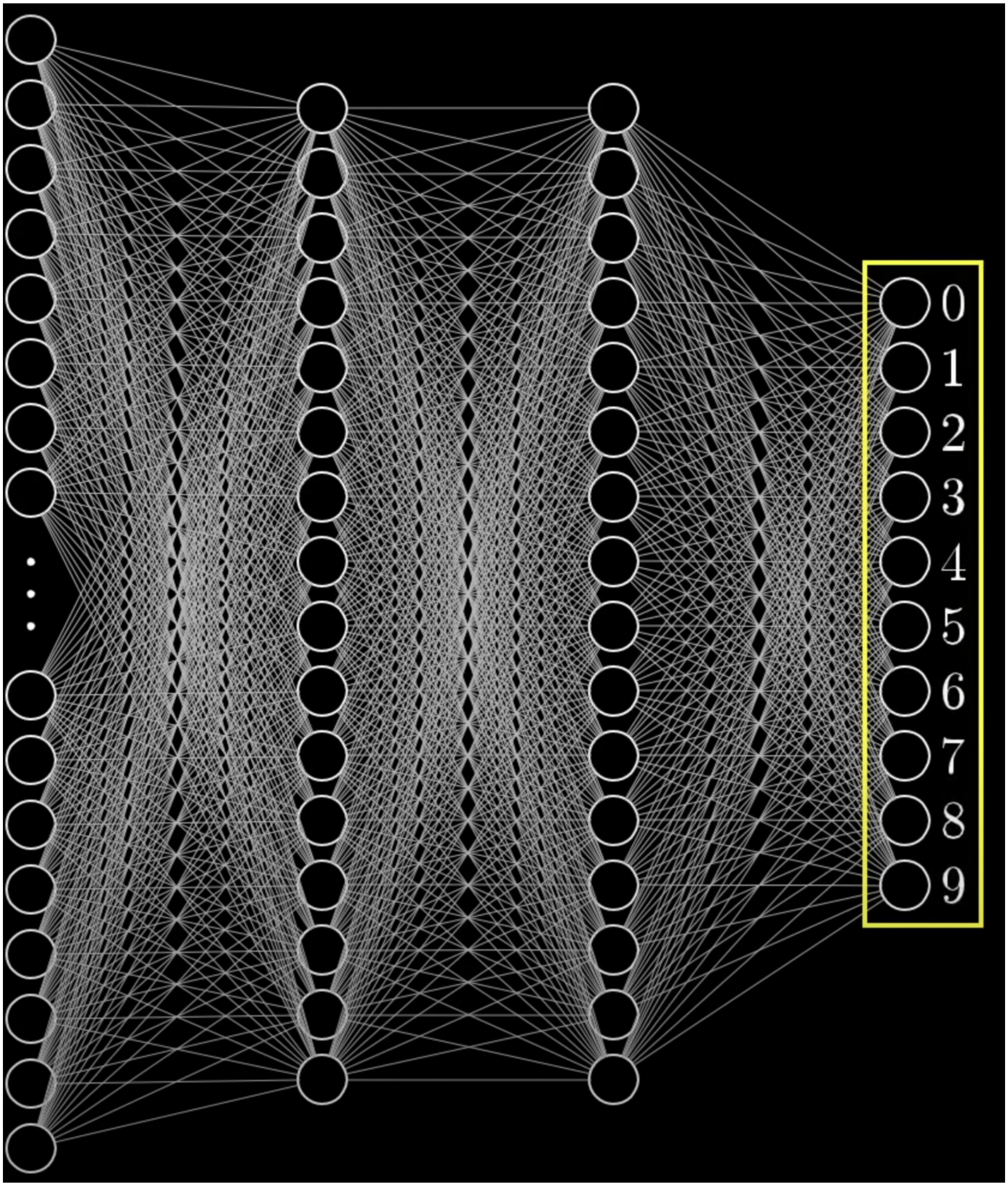
...That just broke our programme

Ideas:

- Decision tree?
- Neural network!

Overview of Neural Network




0
1
2
3
4
5
6
7
8
9

- Intuition for understanding neural network: it resembles how neurons in our brain are connected
- Input: some representations of our data
- Output: some predictions based on the input data

Question to ask:

- How can we communicate our goal with the machine?
- How does these neural nodes or layers transmit information from one to the other?
- How does it make predictions and adjust its predictions?

Consider the image below. How do we represent an image so that machine can understand it?

```
0000000000000000000000000000
0000000000000000000000000000
0000000000000011111000000000
0000000000111111111000000000
0000000011111110000000000000
0000000011111110000000000000
0000001111111100000000000000
0000111111000000000000000000
0011111100000000000000000000
0011111100000000000000000000
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1111110000000000000000011111
1111110000000000000000011111
0011110000000000000000011111
0011111100000000000001111111
0011111100000000000001111111
0000111111111111111111111110
0000001111111111111111111000
0000000011111111111110000000
```
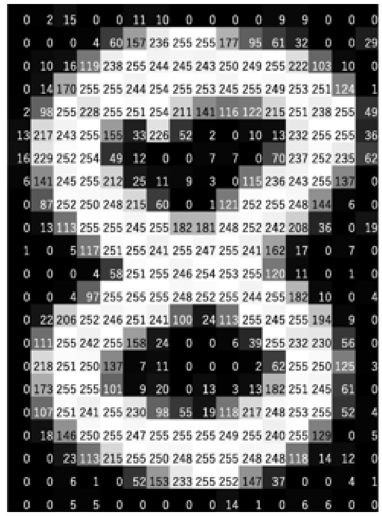

We can represent this 6 as some **vector/matrix** consisted of 0 and 1.

What if my picture has shadows?

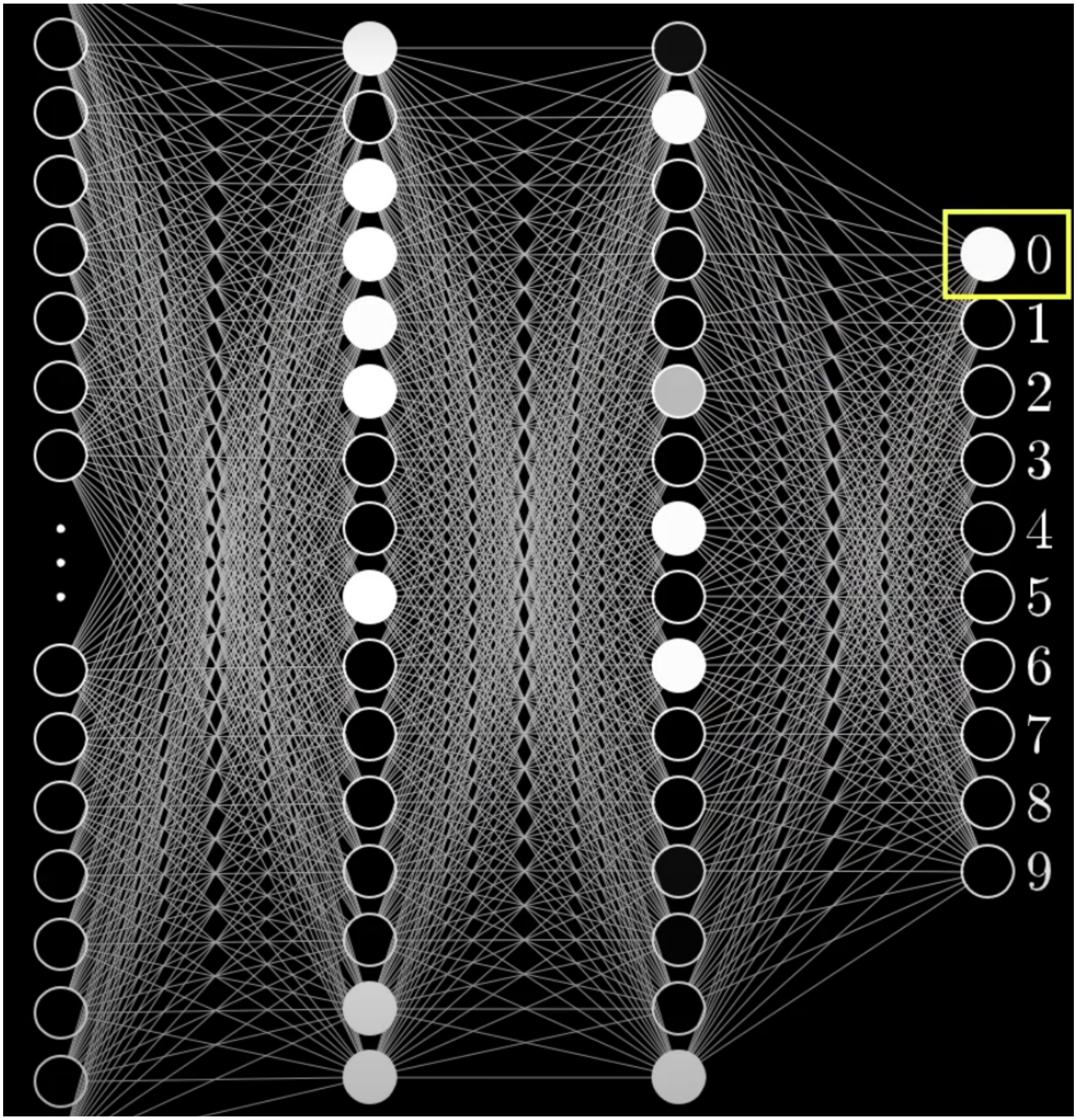


0	2	15	0	0	11	10	0	0	0	0	9	9	0	0	0
0	0	0	4	60	157	236	255	255	177	95	61	32	0	0	29
0	10	16	119	238	255	244	245	243	250	249	255	222	103	10	0
0	14	170	255	255	244	254	255	253	245	255	249	253	251	124	1
2	98	255	228	255	251	254	211	141	116	122	215	251	238	255	49
13	217	243	255	155	33	226	52	2	0	10	13	232	255	255	36
16	229	252	254	49	12	0	0	7	7	0	70	237	252	235	62
6	141	245	255	212	25	11	9	3	0	115	236	243	255	137	0
0	87	252	250	248	215	60	0	1	121	252	255	248	144	6	0
0	13	113	255	255	245	255	182	181	248	252	242	208	36	0	19
1	0	5	117	251	255	241	255	247	255	241	162	17	0	7	0
0	0	0	4	58	251	255	246	254	253	255	120	11	0	1	0
0	0	4	97	255	255	255	248	252	255	244	255	182	10	0	4
0	22	206	252	246	251	241	100	24	113	255	245	255	194	9	0
0	111	255	242	255	158	24	0	0	6	39	255	232	230	56	0
0	218	251	250	137	7	11	0	0	0	2	62	255	250	125	3
0	173	255	255	101	9	20	0	13	3	13	182	251	245	61	0
0	107	251	241	255	230	98	55	19	118	217	248	253	255	52	4
0	18	146	250	255	247	255	255	255	249	255	240	255	129	0	5
0	0	23	113	215	255	250	248	255	255	248	248	118	14	12	0
0	0	6	1	0	52	153	233	255	252	147	37	0	0	4	1
0	0	5	5	0	0	0	0	0	14	1	0	6	6	0	0

We can then represent this 8 by some **matrix/vector** with the rgb values at each pixel

---

How can we know which output it generates?



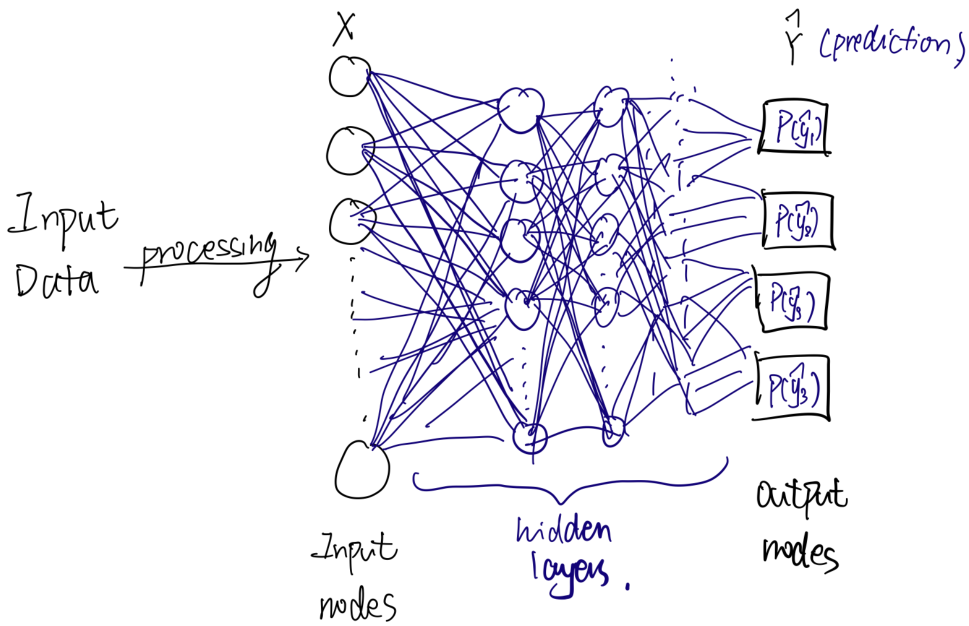
One common way is to use probability. The output with the highest probabilities is what our neural network thinks the input is.

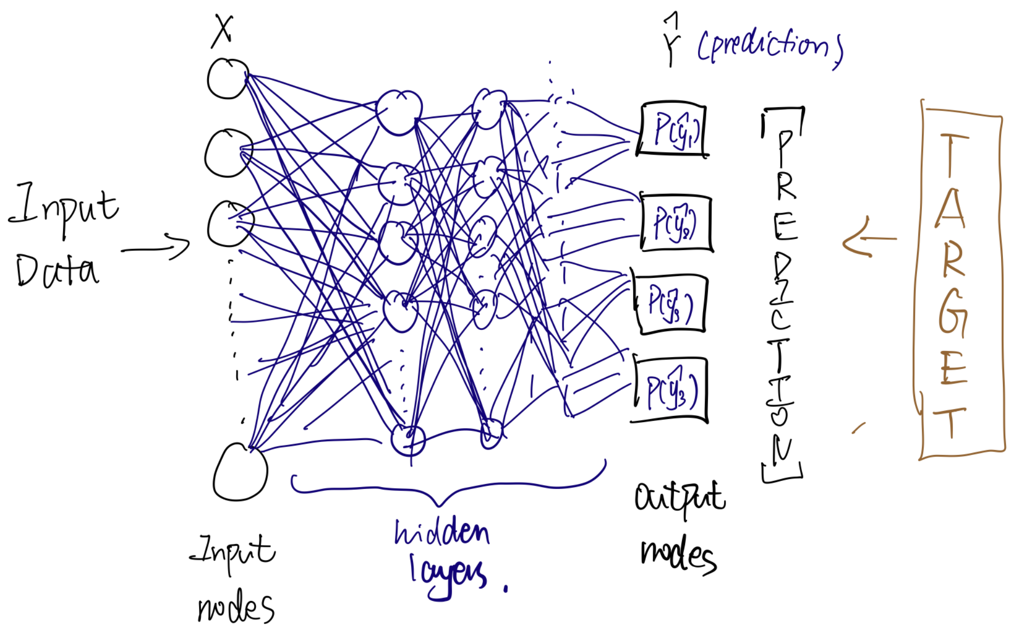
Key takeaways

- In our simple neural network, we *input* some **vector** representations of our data to the model, or our neural network, and ask it to do its magic and *output* some **predictions** about what the input is.

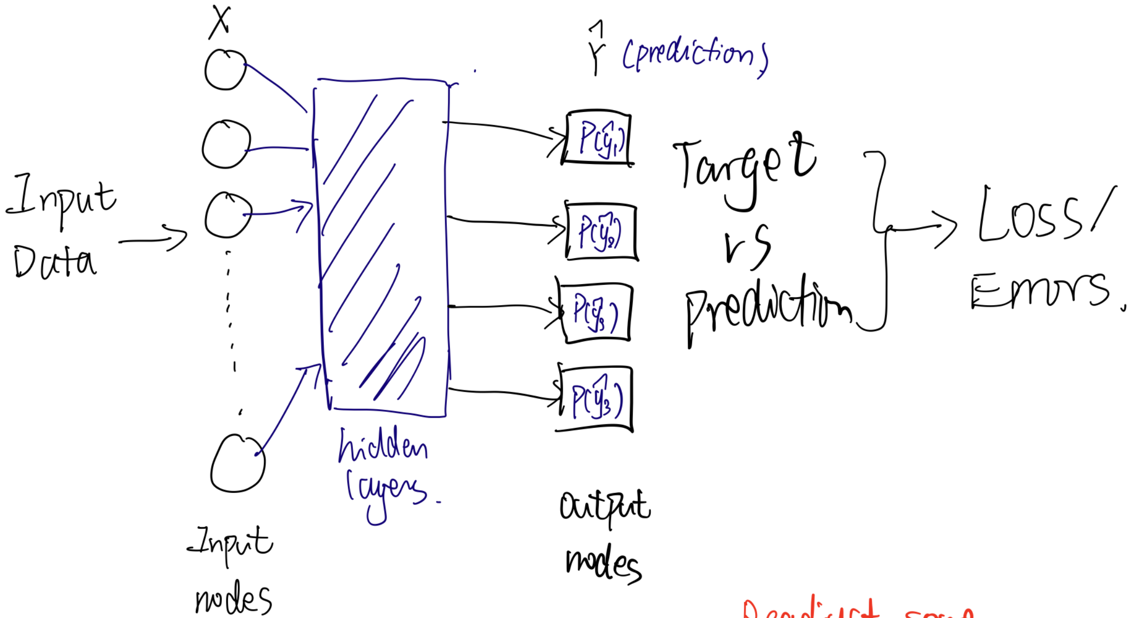
Basic Architecture of a Neural Network

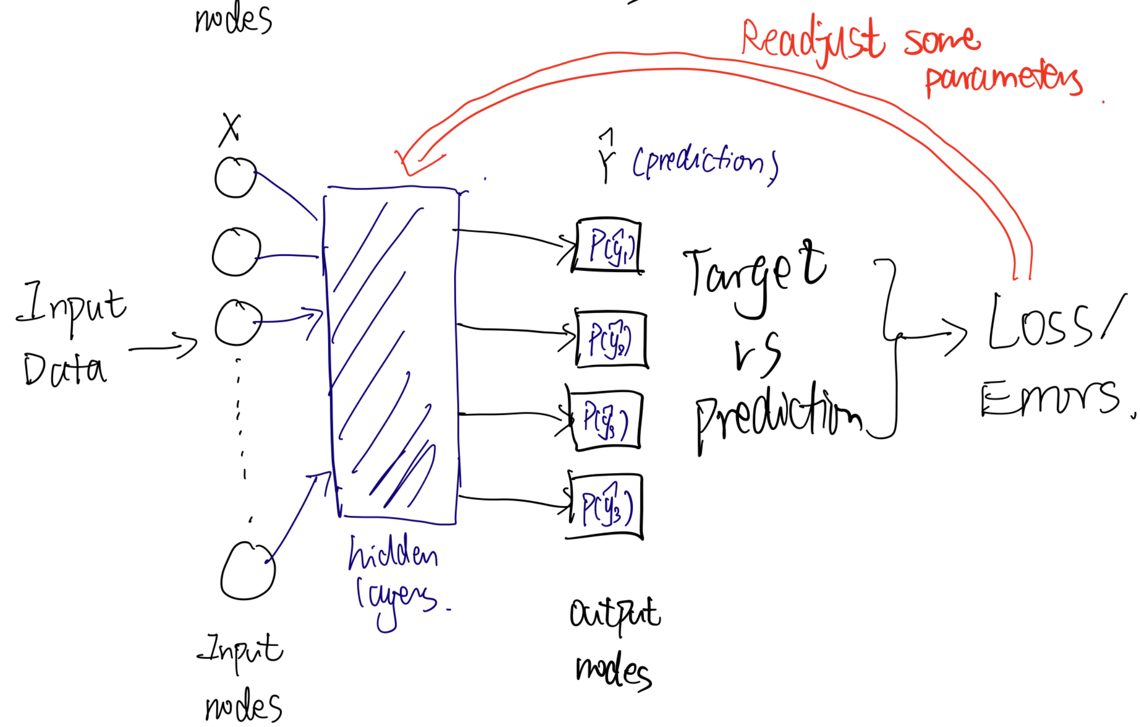
Forward Propogation:





Calculating Loss & Propagate backward





Key Takeaway

After we do adjust the model, we start from the left again.

Repeating the process described above for some large number of times, our model will be able to predict the results with more accuracy.

Terminology

- Forward Propagation: the process of going from input and prediction. During forward propagation, we do some transformations/calculation with our input vectors.
- Loss: the quantified difference between our predictions and the target.
- Backward Propagation: the process of re-calculating and updating the parameters in the model

Building the Model

Structure

- **Propagation**
- **Optimization**

In [ ]:
```
import numpy as np
import matplotlib.pyplot as plt
import h5py  # Library to load dataset for our cats
```

In [ ]:
```
# This just downloads the dataset we're using
!wget https://github.com/rvarun7777/Deep_Learning/raw/master/Neural%20Networks%
!wget https://github.com/rvarun7777/Deep_Learning/raw/master/Neural%20Networks%
```

```
--2023-04-02 20:00:42--  https://github.com/rvarun7777/Deep_Learning/raw/maste
r/Neural%20Networks%20and%20Deep%20Learning/Week%202/Logistic%20Regression%20a
s%20a%20Neural%20Network/datasets/test_catvnoncat.h5
Resolving github.com (github.com)... 140.82.112.4
Connecting to github.com (github.com)|140.82.112.4|:443... connected.
HTTP request sent, awaiting response... 302 Found
Location: https://raw.githubusercontent.com/rvarun7777/Deep_Learning/master/Neu
ral%20Networks%20and%20Deep%20Learning/Week%202/Logistic%20Regression%20as%20a%
20Neural%20Network/datasets/test_catvnoncat.h5 [following]
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ning/master/Neural%20Networks%20and%20Deep%20Learning/Week%202/Logistic%20Regre
ssion%20as%20a%20Neural%20Network/datasets/test_catvnoncat.h5
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 185.199.108.
133, 185.199.110.133, 185.199.109.133, ...
Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|185.199.10
8.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 616958 (602K) [application/octet-stream]
Saving to: 'test_catvnoncat.h5'

test_catvnoncat.h5  100%[===================>] 602.50K  --.-KB/s    in 0.1s

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r/Neural%20Networks%20and%20Deep%20Learning/Week%202/Logistic%20Regression%20a
s%20a%20Neural%20Network/datasets/train_catvnoncat.h5
Resolving github.com (github.com)... 140.82.112.4
Connecting to github.com (github.com)|140.82.112.4|:443... connected.
HTTP request sent, awaiting response... 302 Found
Location: https://raw.githubusercontent.com/rvarun7777/Deep_Learning/master/Neu
ral%20Networks%20and%20Deep%20Learning/Week%202/Logistic%20Regression%20as%20a%
20Neural%20Network/datasets/train_catvnoncat.h5 [following]
--2023-04-02 20:00:43--  https://raw.githubusercontent.com/rvarun7777/Deep_Lear
ning/master/Neural%20Networks%20and%20Deep%20Learning/Week%202/Logistic%20Regre
ssion%20as%20a%20Neural%20Network/datasets/train_catvnoncat.h5
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 185.199.108.
133, 185.199.110.133, 185.199.109.133, ...
Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|185.199.10
8.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 2572022 (2.5M) [application/octet-stream]
Saving to: 'train_catvnoncat.h5'

train_catvnoncat.h5 100%[===================>]   2.45M  6.36MB/s    in 0.4s

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```

In [ ]:

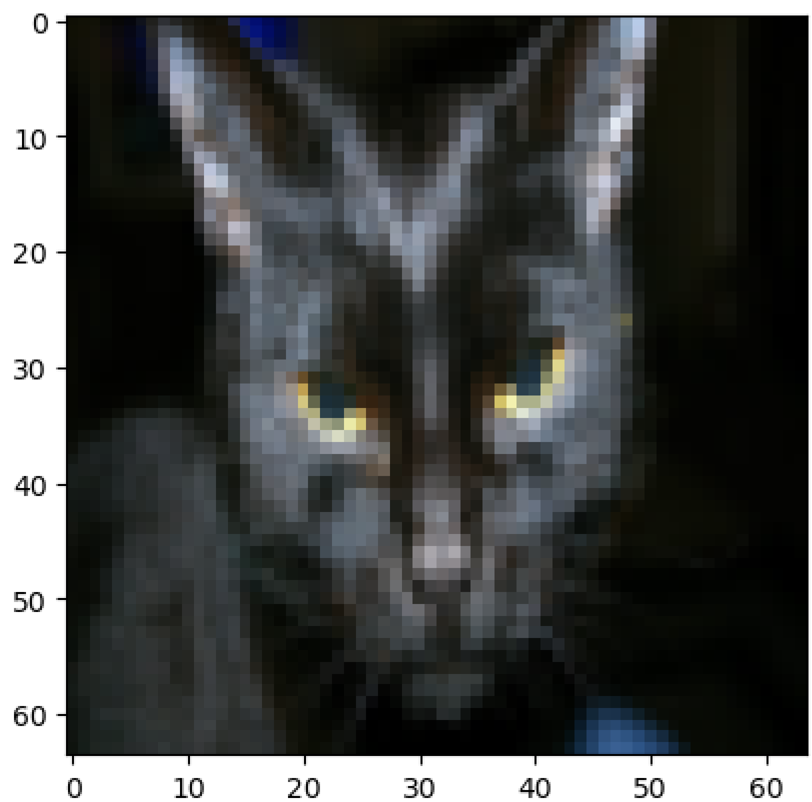
```python
# Load dataset: Numpy version

device = "cpu"

def load_dataset_np():
    train_dataset = h5py.File('train_catvnoncat.h5','r')
    #
    train_set_x_orig = np.array(train_dataset["train_set_x"][:])
    train_set_y_orig = np.array(train_dataset["train_set_y"][:])
```

```
    test_dataset = h5py.File("test_catvnoncat.h5",'r')
    test_set_x_orig = np.array(test_dataset["test_set_x"][:])
    test_set_y_orig = np.array(test_dataset["test_set_y"][:])

    classes = np.array(test_dataset["list_classes"][:])

    train_set_y_orig = train_set_y_orig.reshape((1, train_set_y_orig.shape[0]))
    test_set_y_orig = test_set_y_orig.reshape((1, test_set_y_orig.shape[0]))

    return train_set_x_orig, train_set_y_orig, test_set_x_orig, test_set_y_orig

# Loading the data (cat/non-cat)
train_set_x_orig, train_set_y, test_set_x_orig, test_set_y, classes = load_data

# flatten train set and test set
train_set_x = train_set_x_orig.reshape(-1,train_set_x_orig.shape[0])
test_set_x = test_set_x_orig.reshape(-1,test_set_x_orig.shape[0])

# standardize
train_set_x = (train_set_x/255)
test_set_x = test_set_x/255
```

In [ ]:

```
# Example of a picture
index = 25
plt.imshow(train_set_x_orig[index])
print ("y = " + str(train_set_y[:, index]) + ", it's a '" + classes[np.squeeze(
```

```
y = [1], it's a 'cat' picture.
```



Propagatioin

At each layer during forward propogation

X_{m*n}: Input where m = number of inputs, n = input size.

Y_{m*1}: Target

W_{k*n} and b: weights where n = input size, k = output layer size

---

Step 1: Give a prediction

Prediction: $Z = (W)^T \cdot X + b = (y'_1, y'_2, \ldots, y'_n)$ (Matrix multiplication)

Activation: $A = \sigma(Z) = (a_1, a_2, \ldots, a_n)$ (We chose sigmoid act. function)

where $n =$ input size. The dimension of A = dimemsion of X.

- Linear Combination!

Step 2: Calculates the loss

$J = \sum_1^m [y^i * \log(a^i) + (1 - y^i) \log(1 - a^i)]$

Calculate the difference between the activations and the target through what's called the loss function.

Step 3: Update the gradients

Use the Loss to update gradients, which in the optimazation step later on, will be used to update weights

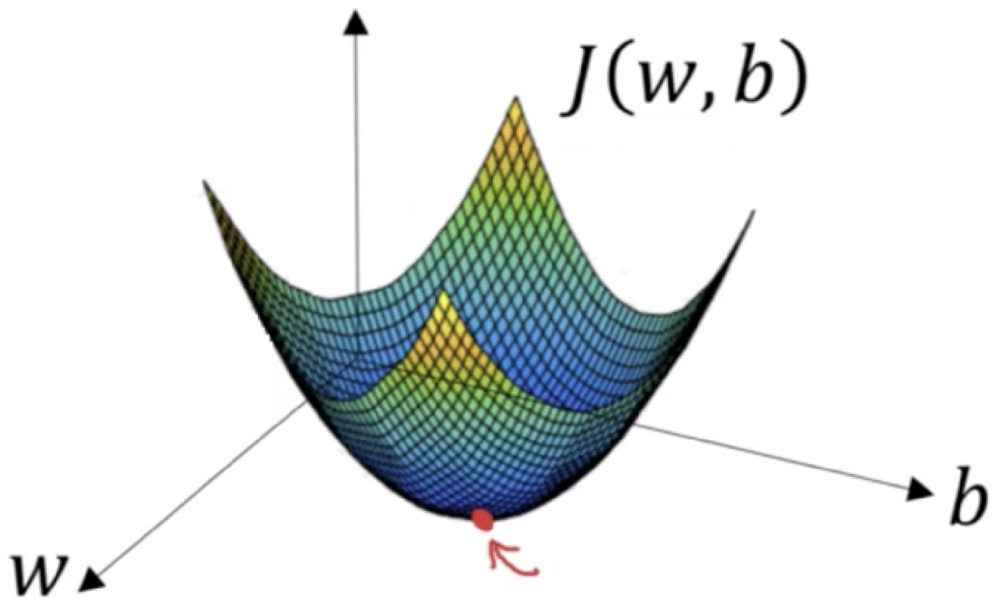
Difference $= [(a^1 - y^1), \ldots., (a^n - y^n)] = A - Y$

$\frac{dJ}{dW} = \frac{1}{m} * \sum_{i=1}^m X * (A - Y)^T$

$\frac{dJ}{db} = \frac{1}{m} * \sum_{i=1}^m \frac{dJ}{db^i} = \frac{1}{m} * \sum_{i=1}^m (a^i - y^i)$

Gradients Descent

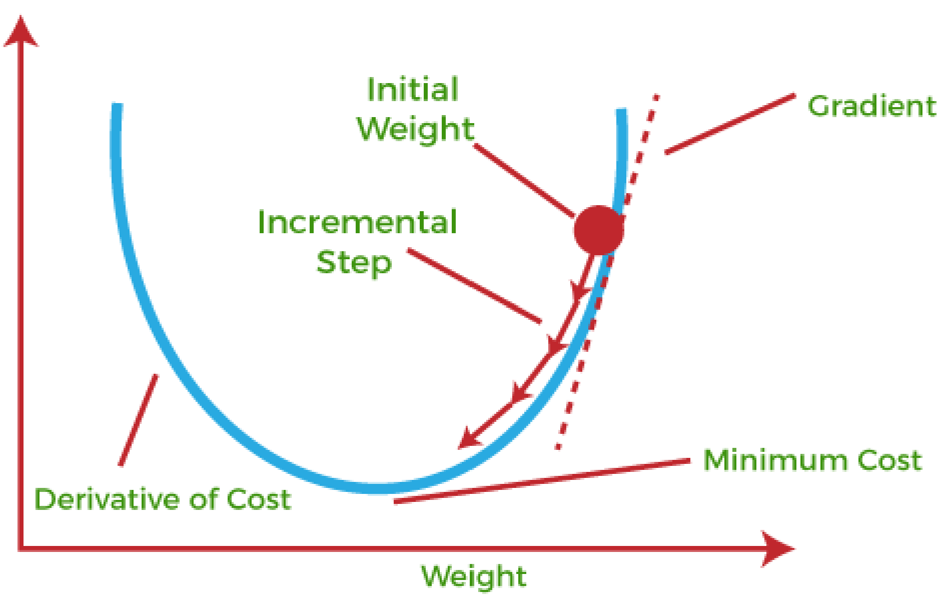
- An optimiazation algorithm that allows us to get closer to the optimal prediction.



- Gradient is the derivative of Loss with respect to weights, i.e. how does our loss changes according the change in weights.

$\frac{dJ}{dw} = \frac{1}{m} * X(A - Y)$

$\frac{dJ}{db} = \frac{1}{m} * \sum_{1}^{m}(a^i - y^i)$



Gradient descent allows us to lower cost through iterations of training.

Two common types of Gradient Descent

1. Stochastic Gradient Descent (SGD)
2. Mini-batch gradient descent (batch)

Let's Implement Forward propagation

- Load data

```
def propagate(w,b,X,Y)
```

In [ ]:
```
# FORWARD PROPAGATION (FROM X TO COST)
def propagate(w, b, X, Y):
    # X: n*m
    # Y: k'*m
    # W: n * output_layer_size
    # b: constant/number
    m = X.shape[1]                  # m = number of inputs
    z = np.dot(w.T, X) + b          # Make Prediction
    A = 1/(1 + np.exp(-z))          # Activation to add non-linearity
    cost = -1/m * np.sum(Y * np.log(A) + (1-Y)*np.log(1-A))   # cost function

    # BACKWARD PROPAGATION (TO FIND GRAD)
    dw = 1/m * np.dot(X,(A-Y).T)
    db = 1/m * np.sum(A-Y)

    cost = np.squeeze(np.array(cost))   # do some dimension work

    # return cost and gradients
    grads = {"dw": dw,
             "db": db}

    return grads, cost
```

Optimization

The goal of optimzation is to learn the "best" parameters W and b such that we can minmize the loss function J.

```
def optimize(w, b, X, Y, epochs, learning_rate)
```

W: initial weights (usually some matrix of zeros or ones)

b: initial bias

X_{n*m}: inputs

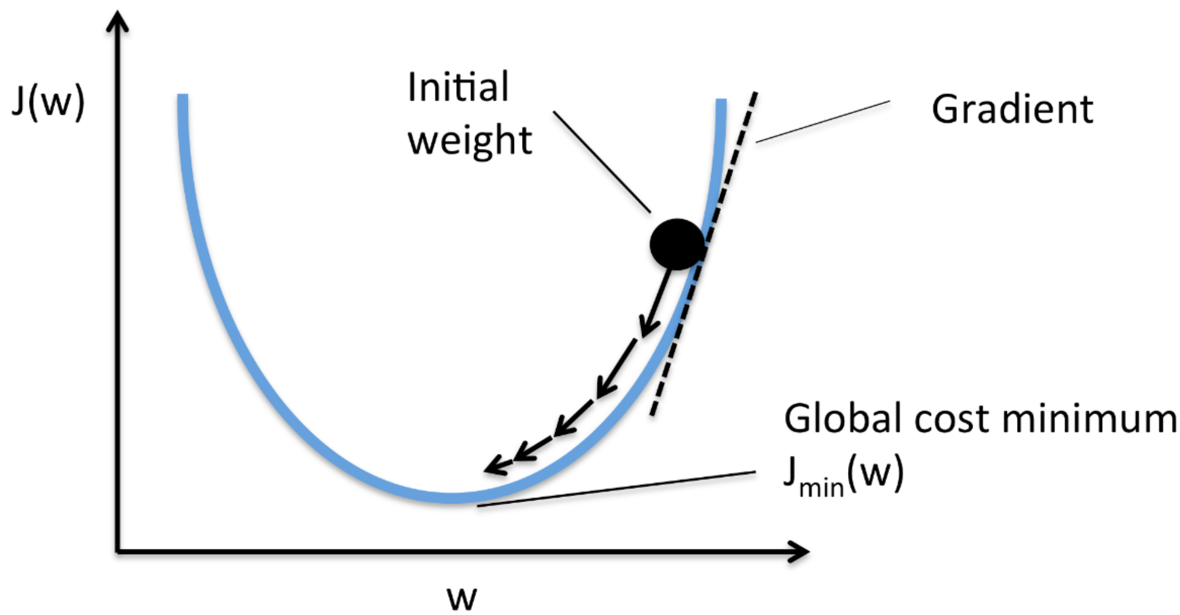
Y_m: target/label

α: learning rate

Formulas for updating the variables:

$W = W - \alpha * dw$

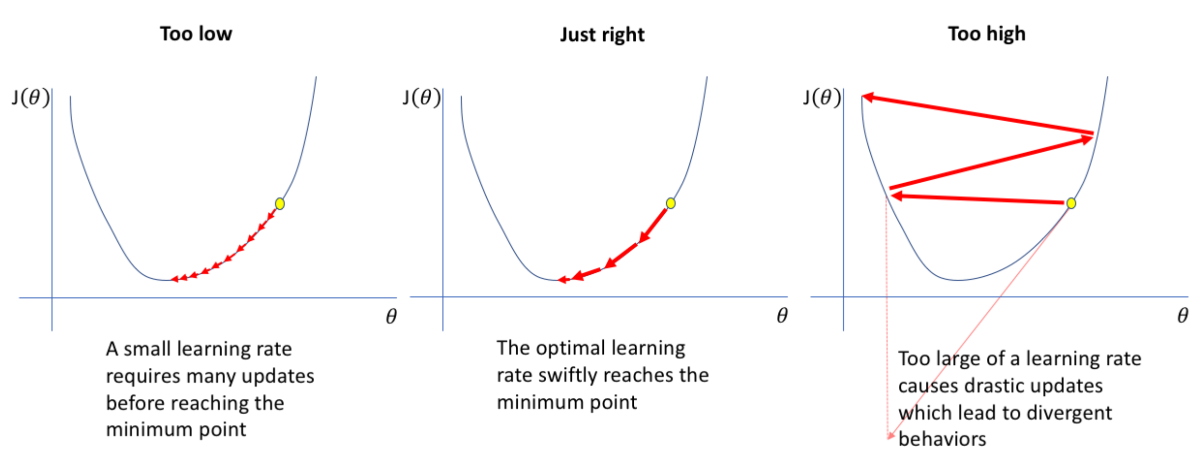
$b = b - \alpha * db$



Learning rate

The learning rate defines how frequently the model will update its weights. The idea is that we want the model to update the weight at such a frequency that it can reaches its optimal performance.

- If the learning rate is too small, it might take thousands of years to train a model.
- If the learning rate is too high, we are at risk of missing the global minimum(i.e. overfitting)



In [ ]:
```
import copy

def optimize(w, b, X, Y, num_iterations=100, learning_rate=0.009, print_cost=Fa
    w = copy.deepcopy(w)
    b = copy.deepcopy(b)

    costs = []

    for i in range(num_iterations):
        grads,cost = propagate(w,b,X,Y)

        # Retrieve derivatives
        dw = grads["dw"]
        db = grads["db"]

        # update parameters
        w = w - learning_rate * dw
        b = b - learning_rate * db

        # Record the costs
        if i % 100 == 0:
            costs.append(cost)

            # Print the cost every 100 training iterations
            if print_cost:
                print ("Cost after iteration %i: %f" %(i, cost))

    params = {"w": w,
              "b": b}

    grads = {"dw": dw,
             "db": db}

    return params, grads, costs
```

Put pieces together

1. Initialize weights
2. Train the model with training dataset(propagation and optimization)
3. Make prediction on the test set

Prediction function:

if the predicted probability for an test sample is greater than 0.5, it is a cat. Otherwise, the model thinks that it is not a cat.

In [ ]:
```
# Prediciton given test-set

def predict(w, b, X):
    # w,b: weights after training
    # X: test_X_dataset
    m = X.shape[1]
    Y_prediction = np.zeros((1, m))
```

```
    w = w.reshape(X.shape[0], 1)

    #Make prediction:
    A = 1/(1+ np.exp(-(np.dot(w.T,X)+b)))

    for i in range(A.shape[1]):
        if A[0,i]>0.5:
          Y_prediction[0,i] = 1
        else:
          Y_prediction[0,i] = 0


    return Y_prediction
```

In [ ]:

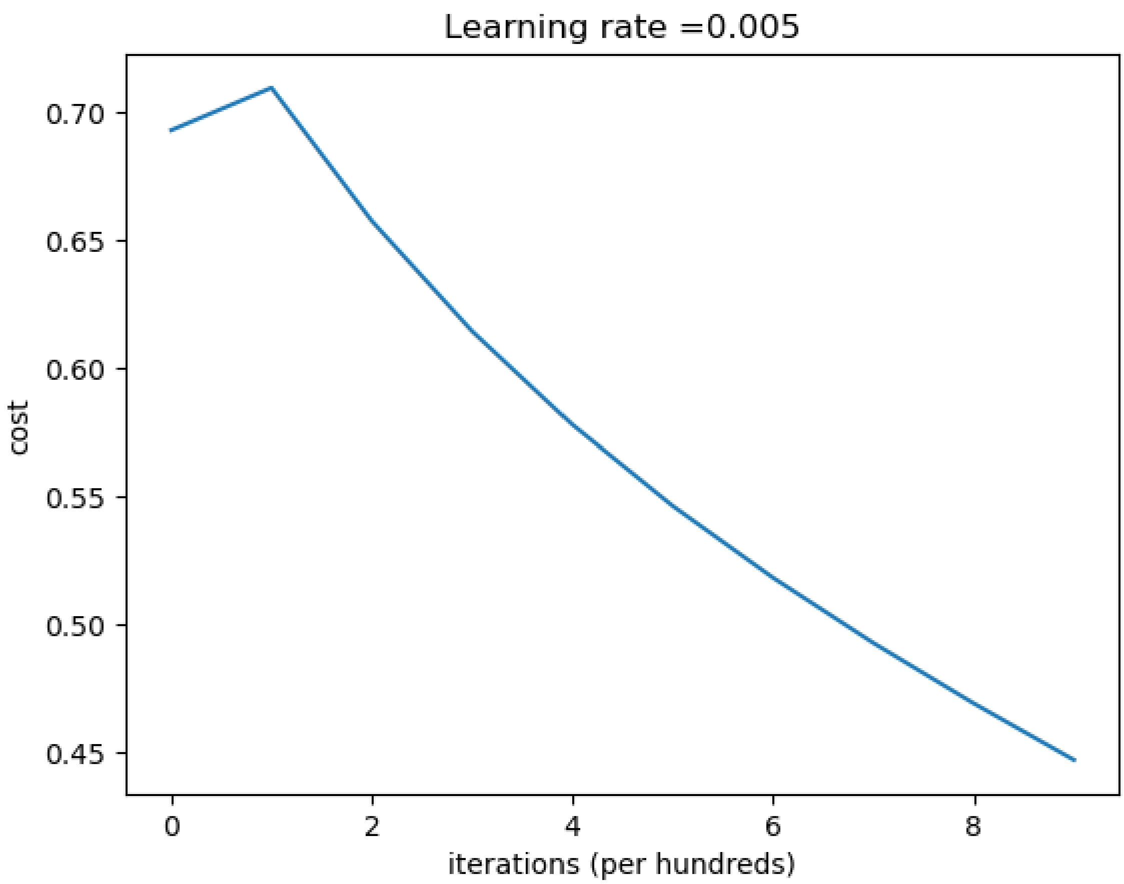
```
def model(X_train, Y_train, X_test, Y_test, num_iterations=2000, learning_rate=

    #initialize weights
    w,b = np.zeros((X_train.shape[0],1)),0.0

    # train model with train data set
    params,grads,costs = optimize(w,b,X_train,Y_train,num_iterations,learning_r
    w,b = params['w'],params['b']

    # make prediction
    Y_prediction_test = predict(w,b,X_test)
    Y_prediction_train = predict(w,b,X_train)
    # YOUR CODE ENDS HERE

    # Print train/test Errors
    if print_cost:
        print("train accuracy: {} %".format(100 - np.mean(np.abs(Y_prediction_t
        print("test accuracy: {} %".format(100 - np.mean(np.abs(Y_prediction_te


    d = {"costs": costs,
         "Y_prediction_test": Y_prediction_test,
         "Y_prediction_train" : Y_prediction_train,
         "w" : w,
         "b" : b,
         "learning_rate" : learning_rate,
         "num_iterations": num_iterations}

    return d
```

In [ ]:

```
logistic_regression_model = model(train_set_x, train_set_y, test_set_x, test_se
```

```
Cost after iteration 0: 0.693147
Cost after iteration 100: 0.709726
Cost after iteration 200: 0.657712
Cost after iteration 300: 0.614611
Cost after iteration 400: 0.578001
Cost after iteration 500: 0.546372
Cost after iteration 600: 0.518331
Cost after iteration 700: 0.492852
Cost after iteration 800: 0.469259
Cost after iteration 900: 0.447139
train accuracy: 84.21052631578948 %
test accuracy: 34.0 %
```

```
# Plot learning curve (with costs)
costs = np.squeeze(logistic_regression_model['costs'])
plt.plot(costs)
plt.ylabel('cost')
plt.xlabel('iterations (per hundreds)')
plt.title("Learning rate =" + str(logistic_regression_model["learning_rate"]))
plt.show()
```



---END of First lecture ---- See you next time~

Cat Classifier PyTorch Version

```
# Import several PyTorch libraries
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
```

```
device = "cpu"

def load_dataset():
    train_dataset = h5py.File('train_catvnoncat.h5','r')
    #
    train_set_x_orig = torch.tensor(train_dataset["train_set_x"][:])
    train_set_y_orig = torch.tensor(train_dataset["train_set_y"][:])
```

```
    test_dataset = h5py.File("test_catvnoncat.h5",'r')
    test_set_x_orig = torch.tensor(test_dataset["test_set_x"][:])
    test_set_y_orig = torch.tensor(test_dataset["test_set_y"][:])

    classes = np.array(test_dataset["list_classes"][:])

    train_set_y_orig = train_set_y_orig.reshape((1, train_set_y_orig.shape[0]))
    test_set_y_orig = test_set_y_orig.reshape((1, test_set_y_orig.shape[0]))

    return train_set_x_orig, train_set_y_orig, test_set_x_orig, test_set_y_orig
```

In [ ]:

```
# Loading the data (cat/non-cat)
train_set_x_orig, train_set_y, test_set_x_orig, test_set_y, classes = load_data

# flatten train set and test set
train_set_x = train_set_x_orig.reshape(train_set_x_orig.shape[0],-1)
test_set_x = test_set_x_orig.reshape(test_set_x_orig.shape[0],-1)

# standardize
train_set_x = (train_set_x/255)
test_set_x = test_set_x/255

print(train_set_y.squeeze().shape)
print(train_set_x.shape)
```

```
torch.Size([209])
torch.Size([209, 12288])
```

In [ ]:

```
# Hyperparameters

# train_set_x.shape == (209,12288)
input_size = train_set_x.shape[1] # size of one image
num_epochs = 3000
learning_rate = .001
hidden1_size = 128
hidden2_size = 64
```

In [ ]:

```
class CatClassifier(nn.Module):
    def __init__(self,input_size,hidden1_size,hidden2_size):
        super(CatClassifier,self).__init__()
        self.layer1 = nn.Linear(input_size,1)
        self.activate1 = nn.Sigmoid()

    def forward(self,inputs):
        output = self.layer1(inputs.float())
        output = self.activate1(output)
        return output

model = CatClassifier(input_size,hidden1_size,hidden2_size)
criterion = nn.BCELoss()
# Note: SGD performs better on image classification task than Adam.
# SGD, stochastic gradient descent is precisely substrating weights * learning
optimizer = optim.SGD([p for p in model.parameters() if p.requires_grad], lr=le
```

In [ ]:

```
losses = []
target = train_set_y.float().squeeze()

for epoch in range(num_epochs):
```

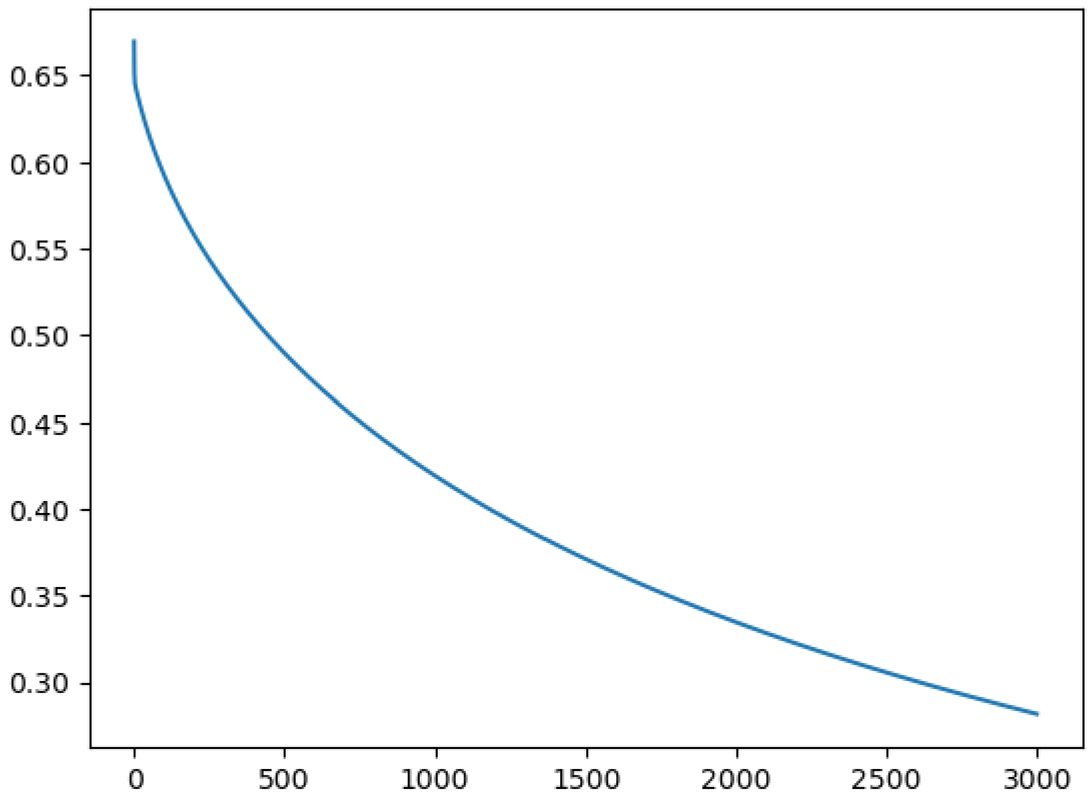
```python
    #output weights
    outputs = model(train_set_x).squeeze()
    #calculate binary cross entropy loss
    loss = criterion(outputs,target)
    #Clear out gradients from previous epoch
    optimizer.zero_grad()
    # do backward propogation
    loss.backward()
    # using SGD to do gradient descent
    optimizer.step()
    losses.append(loss.item())
```

In [ ]:

```python
plt.plot(losses)
```

Out[ ]:

```
[<matplotlib.lines.Line2D at 0x169034af0>]
```



In [ ]:

```python
# test size: 50 * 12288
labels = test_set_y.squeeze()
outputs = model(test_set_x).squeeze()
predictions = torch.maximum(outputs,torch.ones(outputs.shape))
n_correct = (predictions==labels).sum().item()
accuracy = n_correct/50
print(f'accuracy: {(accuracy*100):.3}%')
```

```
accuracy: 66.0%
```

Some fun things you can do

- play around with https://playground.tensorflow.org
- Watch the neural network series by 3b1b

- Explore this an interactive visualization of what we are trying to make

An Introduction to Pytorch

In [ ]:
```
from matplotlib import pyplot as plt
import torch # you can't pytorch without importing it
torch.manual_seed(0) # this is just to keep random things consistent for demo
```

Out[ ]:
```
<torch._C.Generator at 0x117050f10>
```

Tensor Operations

One thing you will be working with a lot is tensor. A tensor can be thought of as a high-dimensional matrix (which itself could be though of as a higher dimensional vector).

Let's try making some vectors and matrices first.

In [ ]:
```
v = torch.tensor([1,2]) # you can create a vector this way
v, v.shape
```

Out[ ]:
```
(tensor([1, 2]), torch.Size([2]))
```

In [ ]:
```
A = torch.tensor([[2, 1], [3, 4]]) # now let's create a square matrix
B = torch.tensor([[-1, 4], [2, 0]]) # one more
print(A)
print(B)
```

```
tensor([[2, 1],
        [3, 4]])
tensor([[-1,  4],
        [ 2,  0]])
```

And we can do matrix operations on them

In [ ]:
```
torch.matmul(A, v) # this is a matrix-vector multiplication!
```

Out[ ]:
```
tensor([ 4, 11])
```

In [ ]:
```
torch.matmul(A, B)
```

Out[ ]:
```
tensor([[ 0,  8],
        [ 5, 12]])
```

In [ ]:
```
A.T # this is how you take a transpose
```

Out[ ]:
```
tensor([[2, 3],
        [1, 4]])
```

In [ ]:
```
torch.det(A.float()) # even take the determinant (doesn't work for int matrix,
```

Out[ ]:
```
tensor(5.)
```

A very powerful thing torch lets you do is tensor calculus. Let's create a random tensor with gradient enabled.

In [ ]:
```
x = torch.randn((2,3,4), requires_grad = True) # track gradients
print(x.shape)
print(x)
```

```
torch.Size([2, 3, 4])
tensor([[[-1.1258, -1.1524, -0.2506, -0.4339],
         [ 0.8487,  0.6920, -0.3160, -2.1152],
         [ 0.4681, -0.1577,  1.4437,  0.2660]],

        [[ 0.1665,  0.8744, -0.1435, -0.1116],
         [ 0.9318,  1.2590,  2.0050,  0.0537],
         [ 0.6181, -0.4128, -0.8411, -2.3160]]], requires_grad=True)
```

Now, if we do a bunch of calculations based on the tensor... Notice we get a single tensor that's the mean of w after all these business

In [ ]:
```
y = x + 3.0
z = y*y
w = z.mean()
w
```

Out[ ]:
```
tensor(10.1019, grad_fn=<MeanBackward0>)
```

Watch the magic as we call `w.backward` — it calculates the partial derivative of values in the tensors that lead to the value of `w` and eventually goes back to `x`, which we said `requires_grad=True`

In [ ]:
```
w.backward()
print(x.grad) # each element is ∂w/∂x
```

```
tensor([[[0.1562, 0.1540, 0.2291, 0.2138],
         [0.3207, 0.3077, 0.2237, 0.0737],
         [0.2890, 0.2369, 0.3703, 0.2722]],

        [[0.2639, 0.3229, 0.2380, 0.2407],
         [0.3277, 0.3549, 0.4171, 0.2545],
         [0.3015, 0.2156, 0.1799, 0.0570]]])
```

Another example that shows the partial derivative relation more clearly

In [ ]:
```
x = torch.tensor([2.0, 6.0], requires_grad = True) # track gradients
y = x**3
z = y.sum()
z.backward()
x.grad
```

Out[ ]:
```
tensor([ 12., 108.])
```

There are ways to stop torch from keeping track of gradient when you don't want it to. Examples are as follows, but we won't go into detail right now

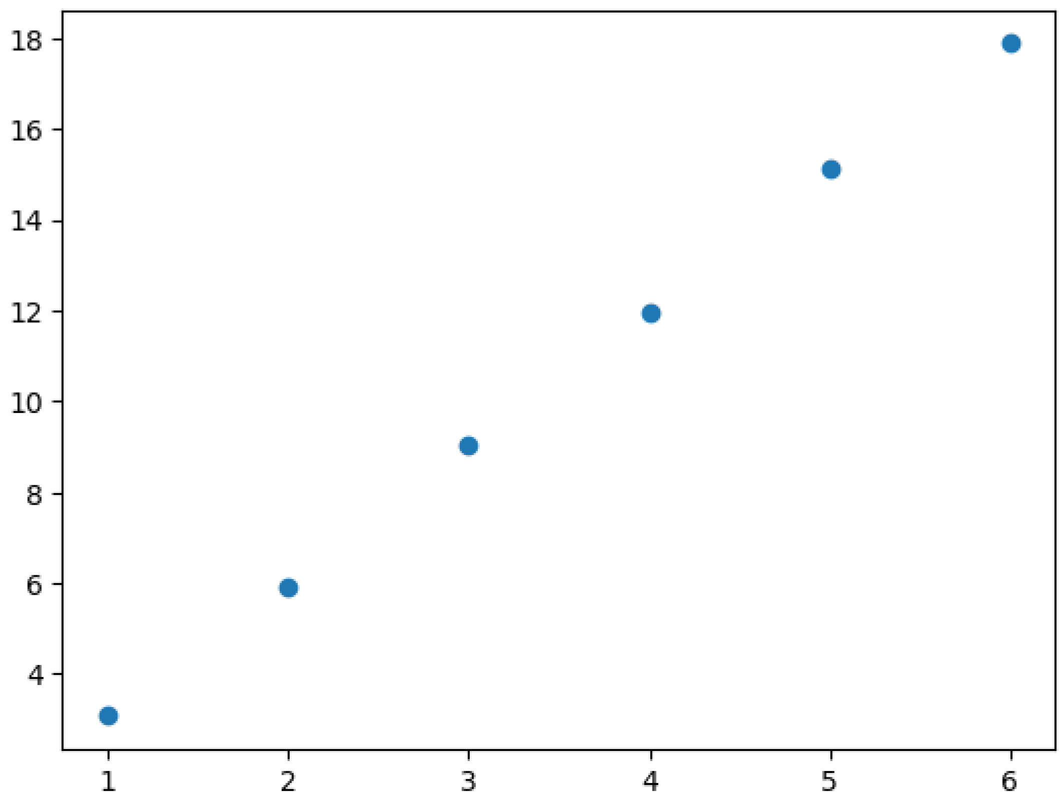
```python
x.requires_grad_(False)
y = x.detach() + 2
with torch.no_grad():
  y = x.detach() + 2
```

Some linear regression — optimizing one variable

In [ ]:
```python
# we are trying to fit f(x) = 3 * x
X = torch.tensor([1, 2, 3, 4, 5, 6], dtype=torch.float32)
Y = torch.tensor([3.07, 5.93, 9.04, 11.97, 15.12, 17.89], dtype=torch.float32)
```

In [ ]:
```python
plt.scatter(X, Y) # looks linear enough!
```

Out[ ]:
```
<matplotlib.collections.PathCollection at 0x116e4ddf0>
```



In [ ]:
```python
# we try to learn this c in f(x) = c * x
c = torch.tensor(0.0, dtype=torch.float32, requires_grad=True)

def predict(x):
  return c * x

# Mean squared error
def calc_loss(y, y_hat):
  return ((y_hat - y)**2).mean()

# training params
learning_rate = 0.01
n_iters = 100

for epoch in range(n_iters):
```

```
    # do prediction
    y_hat = predict(X)

    # calculate loss
    loss = calc_loss(Y, y_hat)

    # calculate partial derivatives
    loss.backward()

    # optimize using those partial derivatives
    with torch.no_grad():
        c -= learning_rate * c.grad

    # clear gradient (for next round)
    c.grad.zero_()

    if epoch % 10 == 0:
        print(f'<epoch {epoch+1}> c = {c.item():.4f}, loss = {loss.item():.4f},
```

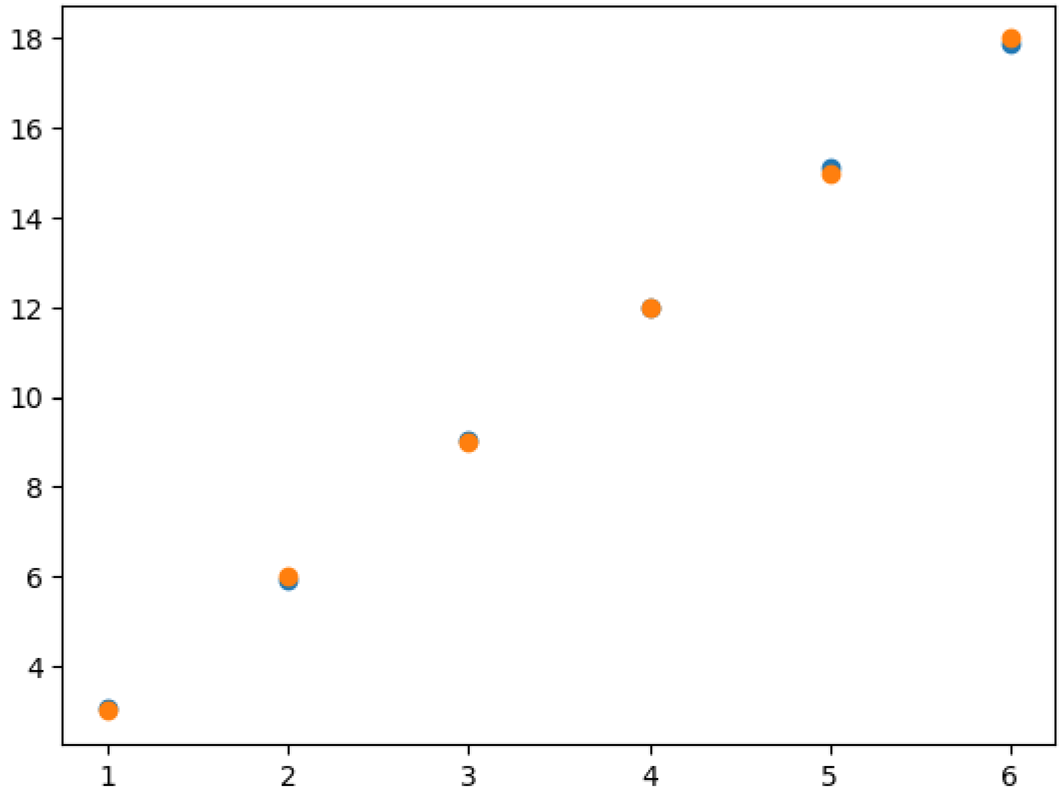
```
<epoch 1> c = 0.9096, loss = 136.3765, f(5) prediction = 4.548
<epoch 11> c = 2.9423, loss = 0.1053, f(5) prediction = 14.712
<epoch 21> c = 2.9971, loss = 0.0065, f(5) prediction = 14.985
<epoch 31> c = 2.9985, loss = 0.0064, f(5) prediction = 14.993
<epoch 41> c = 2.9986, loss = 0.0064, f(5) prediction = 14.993
<epoch 51> c = 2.9986, loss = 0.0064, f(5) prediction = 14.993
<epoch 61> c = 2.9986, loss = 0.0064, f(5) prediction = 14.993
<epoch 71> c = 2.9986, loss = 0.0064, f(5) prediction = 14.993
<epoch 81> c = 2.9986, loss = 0.0064, f(5) prediction = 14.993
<epoch 91> c = 2.9986, loss = 0.0064, f(5) prediction = 14.993
```

In [ ]:

```
# examine the predictions
plt.scatter(X, Y) # original
with torch.no_grad():
    Y_hat = [predict(x) for x in X]
plt.scatter(X, Y_hat)
```

Out[ ]:

```
<matplotlib.collections.PathCollection at 0x16912dc10>
```



MNIST Digit Classifier

—The Hello World of neural networks (...?)

In [ ]:
```
import torch
import torch.nn as nn
import torchvision
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
import torch.nn.functional as F
from tqdm.notebook import tqdm
```

In [ ]:
```
# this lets us use GPU, if one is available
if torch.cuda.is_available():
    device = torch.device("cuda:0")
    print("Running on gpu")
# this is Apple's GPU, if there exists one
elif torch.backends.mps.is_available():
    device = torch.device("mps")
    print("Running on mps")
# Otherwise CPU, which will be much slower
else:
    device = torch.device("cpu")
    print("Running on cpu")
```

```
Running on mps
```

In [ ]:
```
# constants. don't touch or things may break
input_size = 784 # (28 * 28) images
```

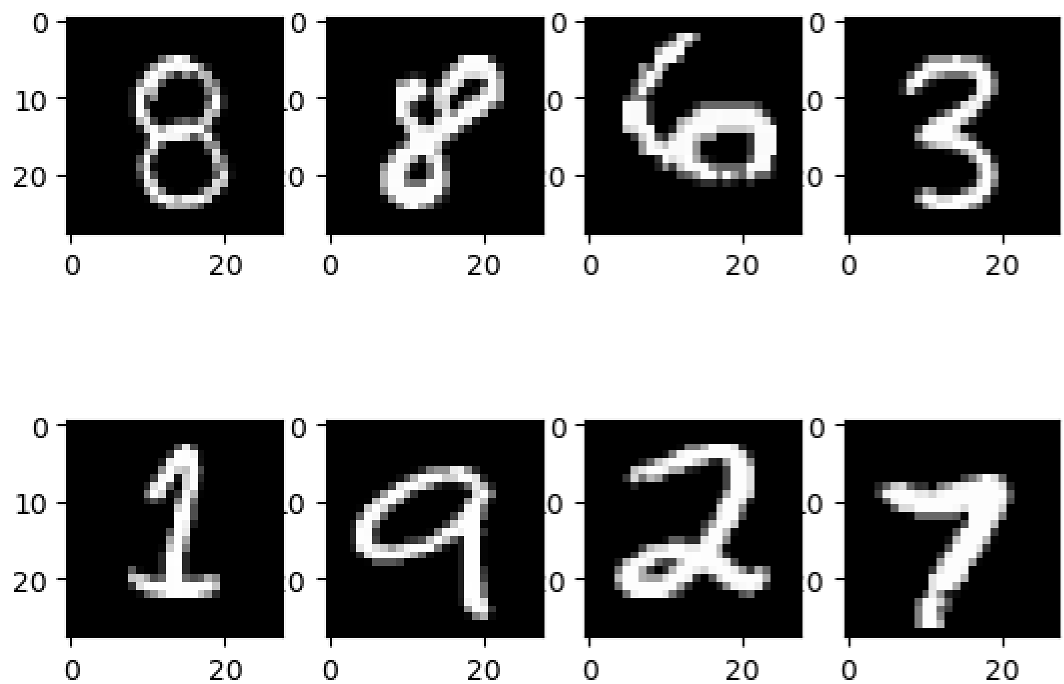
```
num_classes = 10

# hyperparams. You can play around with these
hidden1_size = 256
hidden2_size = 64
num_epochs = 10
batch_size = 128
learning_rate = .0001
```

In [ ]:
```
train_dataset = torchvision.datasets.MNIST(root = './data', train = True, trans
test_dataset = torchvision.datasets.MNIST(root = './data', train = False, trans
```

In [ ]:
```
train_loader = torch.utils.data.DataLoader(dataset = train_dataset, batch_size
test_loader = torch.utils.data.DataLoader(dataset = test_dataset, batch_size =
```

In [ ]:
```
samples, labels = next(iter(train_loader))
print(samples.shape, labels.shape)

for i in range(8):
    plt.subplot(2,4,i+1)
    plt.imshow(samples[i][0], cmap='gray')
plt.show()
```

```
torch.Size([128, 1, 28, 28]) torch.Size([128])
```



In [ ]:
```
class NeuralNet(nn.Module):
    def __init__(self, input_size, num_classes, hidden1_size, hidden2_size):
        super(NeuralNet, self).__init__()

        self.network = nn.Sequential(
            nn.Linear(input_size, hidden1_size),
            nn.ReLU(),
            nn.Linear(hidden1_size, hidden2_size),
            nn.ReLU(),
            nn.Linear(hidden2_size, num_classes),
            nn.Sigmoid()
```

```
        )

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

In [ ]:
```
model = NeuralNet(input_size, num_classes, hidden1_size, hidden2_size).to(devic
```

In [ ]:
```
loss_fn = nn.CrossEntropyLoss()
optimiser = torch.optim.Adam(model.parameters(), lr = learning_rate)
losses = []
```

In [ ]:
```
n_total_steps = len(train_loader)
for epoch in range(num_epochs):
    for i, (images, labels) in enumerate(train_loader):
        images = images.reshape(-1, 28*28).to(device)
        labels = labels.to(device)

        outputs = model(images)
        loss = loss_fn(outputs, labels)

        optimiser.zero_grad()
        loss.backward()
        optimiser.step()

        if (i + 1) % 100 == 0:
            print (f'epoch = [{epoch+1}/{num_epochs}], step = [{i+1}/{n_total_s
    losses.append(loss.item())
```

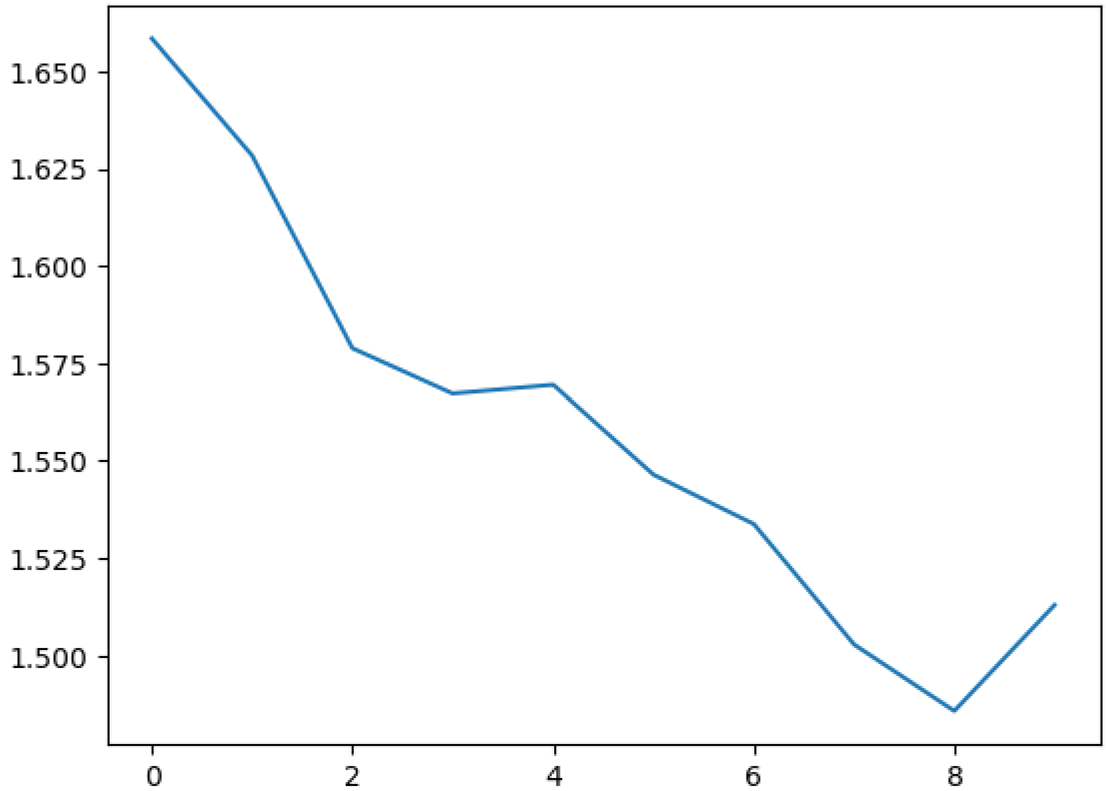
```
epoch = [1/10], step = [100/469], loss = 2.124385118484497
epoch = [1/10], step = [200/469], loss = 1.855729579925537
epoch = [1/10], step = [300/469], loss = 1.757800817489624
epoch = [1/10], step = [400/469], loss = 1.6989238262176514
epoch = [2/10], step = [100/469], loss = 1.646148920059204
epoch = [2/10], step = [200/469], loss = 1.654342532157898
epoch = [2/10], step = [300/469], loss = 1.5765453577041626
epoch = [2/10], step = [400/469], loss = 1.6063997745513916
epoch = [3/10], step = [100/469], loss = 1.6199983358383179
epoch = [3/10], step = [200/469], loss = 1.5985586643218994
epoch = [3/10], step = [300/469], loss = 1.5651957988739014
epoch = [3/10], step = [400/469], loss = 1.5614111423492432
epoch = [4/10], step = [100/469], loss = 1.5597553253173828
epoch = [4/10], step = [200/469], loss = 1.5576527118682861
epoch = [4/10], step = [300/469], loss = 1.5752973556518555
epoch = [4/10], step = [400/469], loss = 1.5659799575805664
epoch = [5/10], step = [100/469], loss = 1.5647411346435547
epoch = [5/10], step = [200/469], loss = 1.5742769241333008
epoch = [5/10], step = [300/469], loss = 1.5521223545074463
epoch = [5/10], step = [400/469], loss = 1.5499091148376465
epoch = [6/10], step = [100/469], loss = 1.5868661403656006
epoch = [6/10], step = [200/469], loss = 1.5591518878936768
epoch = [6/10], step = [300/469], loss = 1.5384305715560913
epoch = [6/10], step = [400/469], loss = 1.5775145292282104
epoch = [7/10], step = [100/469], loss = 1.520632028579712
epoch = [7/10], step = [200/469], loss = 1.5483708381652832
epoch = [7/10], step = [300/469], loss = 1.5502614974975586
epoch = [7/10], step = [400/469], loss = 1.5184895992279053
epoch = [8/10], step = [100/469], loss = 1.5154091119766235
epoch = [8/10], step = [200/469], loss = 1.5130215883255005
epoch = [8/10], step = [300/469], loss = 1.5256640911102295
epoch = [8/10], step = [400/469], loss = 1.5348907709121704
epoch = [9/10], step = [100/469], loss = 1.5189883708953857
epoch = [9/10], step = [200/469], loss = 1.5316388607025146
epoch = [9/10], step = [300/469], loss = 1.5024809837341309
epoch = [9/10], step = [400/469], loss = 1.527031421661377
epoch = [10/10], step = [100/469], loss = 1.5116820335388184
epoch = [10/10], step = [200/469], loss = 1.509131669998169
epoch = [10/10], step = [300/469], loss = 1.5189975500106812
epoch = [10/10], step = [400/469], loss = 1.526064395904541
```

In [ ]:

```
plt.plot(losses)
```

Out[ ]:

```
[<matplotlib.lines.Line2D at 0x16c4e3ca0>]
```



In [ ]:
```
with torch.no_grad():
    n_correct = 0
    n_samples = 0
    for images, labels in test_loader:
        images = images.reshape(-1, 28*28).to(device)
        labels = labels.to(device)
        outputs = model(images)

        _, predictions = torch.max(outputs, 1)
        n_samples += len(labels)
        n_correct += (predictions == labels).sum().item()
    accuracy = n_correct / n_samples
    print(f'{(accuracy*100):.3}%')
```

```
94.0%
```

What to do next

More fun things to look at

- CNN on MNIST visualized
- https://poloclub.github.io/cnn-explainer/
- RNN..? Maybe too complicated
- Different activation functions

MNIST Classifier, CNN version

if time, else take home