Homework 5 (100 Points)

The focus of this homework will be Network and Graphs as well as Neural Networks.

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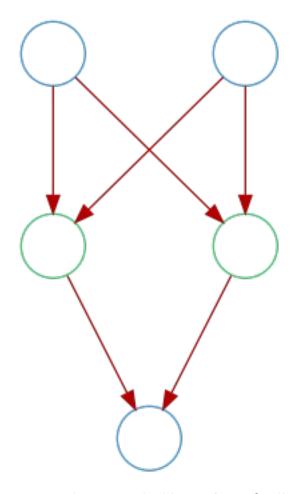
Exercise 1 [30pts]

This exercise will focus on Neural Networks and visualization.

a) Write a function that takes a keras network and outputs an image (png format) of the network. [5pts]

You can assume the model is sequential and only uses dense layers. The output image for

```
model = keras.models.Sequential()
  model.add(layers.Dense(2, input_dim=2))
  model.add(layers.Dense(1))
  model.compile(loss="binary_crossentropy")
should look something like this
from IPython.display import Image
Image(filename="example.png")
```



Hint: use the networkx library (specifically the to_agraph method)

```
!apt-get install graphviz -y
!pip install pydot
!pip install pydotplus
!apt-get install -y graphviz libgraphviz-dev pkg-config
!pip install pygraphviz
Reading package lists... Done
Building dependency tree
Reading state information... Done
graphviz is already the newest version (2.42.2-3build2).
0 upgraded, 0 newly installed, 0 to remove and 24 not upgraded.
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: pydot in
/usr/local/lib/python3.10/dist-packages (1.4.2)
Requirement already satisfied: pyparsing>=2.1.4 in
/usr/local/lib/python3.10/dist-packages (from pydot) (3.0.9)
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: pydotplus in
/usr/local/lib/python3.10/dist-packages (2.0.2)
```

```
Requirement already satisfied: pyparsing>=2.0.1 in
/usr/local/lib/python3.10/dist-packages (from pydotplus) (3.0.9)
Reading package lists... Done
Building dependency tree
Reading state information... Done
pkg-config is already the newest version (0.29.1-0ubuntu4).
graphviz is already the newest version (2.42.2-3build2).
The following additional packages will be installed:
  libgail-common libgail18 libgtk2.0-0 libgtk2.0-bin libgtk2.0-common
  libgvc6-plugins-gtk libxdot4
Suggested packages:
  avfs
The following NEW packages will be installed:
  libgail-common libgail18 libgraphviz-dev libgtk2.0-0 libgtk2.0-bin
  libgtk2.0-common libgvc6-plugins-gtk libxdot4
0 upgraded, 8 newly installed, 0 to remove and 24 not upgraded.
Need to get 2,148 kB of archives.
After this operation, 7,427 kB of additional disk space will be used.
Get:1 http://archive.ubuntu.com/ubuntu focal/main amd64 libgtk2.0-
common all 2.24.32-4ubuntu4 [126 kB]
Get:2 http://archive.ubuntu.com/ubuntu focal/main amd64 libgtk2.0-0
amd64 2.24.32-4ubuntu4 [1,791 kB]
Get:3 http://archive.ubuntu.com/ubuntu focal/main amd64 libgail18
amd64 2.24.32-4ubuntu4 [14.7 kB]
Get:4 http://archive.ubuntu.com/ubuntu focal/main amd64 libgail-common
amd64 2.24.32-4ubuntu4 [116 kB]
Get:5 http://archive.ubuntu.com/ubuntu focal/universe amd64 libxdot4
amd64 2.42.2-3build2 [15.4 kB]
Get:6 http://archive.ubuntu.com/ubuntu focal/universe amd64 libgvc6-
plugins-gtk amd64 2.42.2-3build2 [20.6 kB]
Get:7 http://archive.ubuntu.com/ubuntu focal/universe amd64
libgraphviz-dev amd64 2.42.2-3build2 [57.2 kB]
Get:8 http://archive.ubuntu.com/ubuntu focal/main amd64 libgtk2.0-bin
amd64 2.24.32-4ubuntu4 [7,728 B]
Fetched 2,148 kB in 1s (3,791 kB/s)
Selecting previously unselected package libgtk2.0-common.
(Reading database ... 122518 files and directories currently
installed.)
Preparing to unpack .../0-libgtk2.0-common 2.24.32-
4ubuntu4 all.deb ...
Unpacking libgtk2.0-common (2.24.32-4ubuntu4) ...
Selecting previously unselected package libgtk2.0-0:amd64.
Preparing to unpack .../1-libgtk2.0-0 2.24.32-4ubuntu4 amd64.deb ...
Unpacking libgtk2.0-0:amd64 (2.24.32-4ubuntu4) ...
Selecting previously unselected package libgail18:amd64.
Preparing to unpack .../2-libgail18_2.24.32-4ubuntu4_amd64.deb ...
Unpacking libgail18:amd64 (2.24.32-4ubuntu4) ...
Selecting previously unselected package libgail-common:amd64.
Preparing to unpack .../3-libgail-common 2.24.32-
4ubuntu4 amd64.deb ...
```

```
Unpacking libgail-common:amd64 (2.24.32-4ubuntu4) ...
Selecting previously unselected package libxdot4:amd64.
Preparing to unpack .../4-libxdot4 2.42.2-3build2 amd64.deb ...
Unpacking libxdot4:amd64 (2.42.2-3build2) ...
Selecting previously unselected package libgvc6-plugins-gtk.
Preparing to unpack .../5-libgvc6-plugins-gtk_2.42.2-3build2_amd64.deb
Unpacking libgvc6-plugins-qtk (2.42.2-3build2) ...
Selecting previously unselected package libgraphviz-dev:amd64.
Preparing to unpack .../6-libgraphviz-dev 2.42.2-3build2 amd64.deb ...
Unpacking libgraphviz-dev:amd64 (2.42.2-3build2) ...
Selecting previously unselected package libgtk2.0-bin.
Preparing to unpack .../7-libgtk2.0-bin 2.24.32-4ubuntu4 amd64.deb ...
Unpacking libgtk2.0-bin (2.24.32-4ubuntu4) ...
Setting up libxdot4:amd64 (2.42.2-3build2) ...
Setting up libgtk2.0-common (2.24.32-4ubuntu4) ...
Setting up libgtk2.0-0:amd64 (2.24.32-4ubuntu4) ...
Setting up libgvc6-plugins-gtk (2.42.2-3build2) ...
Setting up libgail18:amd64 (2.24.32-4ubuntu4) ...
Setting up libgtk2.0-bin (2.24.32-4ubuntu4) ...
Setting up libgail-common:amd64 (2.24.32-4ubuntu4) ...
Setting up libgraphviz-dev:amd64 (2.42.2-3build2) ...
Processing triggers for man-db (2.9.1-1) ...
Processing triggers for libc-bin (2.31-0ubuntu9.9) ...
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Collecting pygraphviz
 Downloading pygraphviz-1.10.zip (120 kB)

    120.6/120.6 kB 3.8 MB/s eta

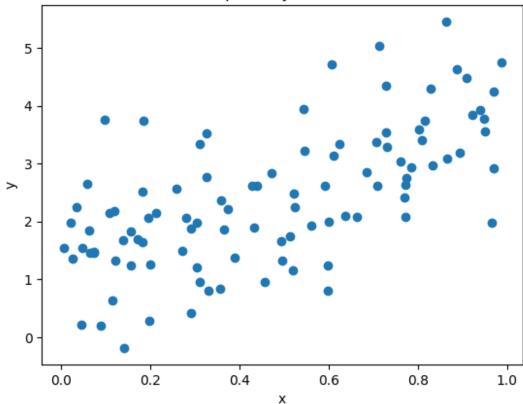
0:00:00
etadata (setup.py) ... e=pygraphviz-1.10-cp310-cp310-linux_x86_64.whl
size=184047
sha256=cb06878bc75face7c489b1d2d7694c80c522d3cc8c055e9846817a869cc8712
  Stored in directory:
/root/.cache/pip/wheels/e9/50/02/d9d68f6c947a928e517d5cd9af0ab007c1274
fdba95fa9cbe3
Successfully built pygraphviz
Installing collected packages: pygraphviz
Successfully installed pygraphviz-1.10
import networkx as nx
from networkx.drawing.nx agraph import to agraph
from networkx import DiGraph, set node attributes
from tensorflow.keras.layers import Dense
import keras
def unique index(layer, node):
    return str(layer) + " " + str(node)
```

```
def plot_keras_network(model, filename):
    graph = DiGraph(nodesep='1', ranksep='1')
    for l in range(len(model.layers)):
            layer = model.layers[l]
            for n in range(0, layer.input shape[1]):
                 if l == 0:
                     graph.add node(
                         unique index(l, n),
                         shape="circle",
                         color="#3498db",
                         label=''
                     )
                 else:
                     graph.add node(
                         unique index(l, n),
                         shape="circle",
                         color="#2ecc71",
                         label=''
                     )
                 for h in range(0, layer.output shape[1]):
                     if l == len(model.layers) - 1:
                         graph.add node(
                             unique_index(l + 1, h),
                              shape="circle",
                              color="#3498db",
                              label=''
                         )
                     graph.add edge(
                         unique index(l, n),
                         unique index(l + 1, h),
                         color="#B20000"
    agraph = to agraph(graph)
    agraph.draw(filename, prog='dot')
model = keras.models.Sequential()
model.add(keras.layers.Dense(2, input dim=2))
model.add(keras.layers.Dense(1))
model.compile(loss="binary_crossentropy")
plot_keras_network(model, "1_a_model.png")
b) Generate 100 datapoints of the form y = 3x + 1 + e where e \sim N(0, 1) and plot the data in
a scatter plot [2.5pts]
import numpy as np
import matplotlib.pyplot as plt
np.random.seed(42)
x = np.random.uniform(size=100)
```

```
e = np.random.normal(loc=0, scale=1, size=100)
y = 3 * x + 1 + e

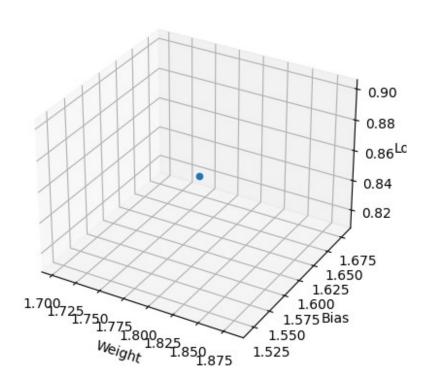
plt.scatter(x, y)
plt.title('Scatter plot of y = 3x + 1 + e')
plt.xlabel('x')
plt.ylabel('y')
plt.show()
```

Scatter plot of y = 3x + 1 + e



c) Create a Neural Network with no hidden layers (just input to ouput each with just one neuron), using the mean_squared_error loss and no activation function. Create an image of this model using a) then train this model on the dataset from b). In a 3D plot, plot the weight, the bias, and the loss value. [5pts]

```
model.compile(loss='mean_squared_error',
optimizer=keras.optimizers.SGD(lr=0.01))
plot keras network(model, "1 c model.png")
model.fit(x, y, epochs=100, batch size=30, verbose=0)
weight, bias = model.layers[0].get weights()
loss = model.evaluate(x, y)
fig = plt.figure()
ax = fig.add subplot(111, projection='3d')
ax.scatter(weight, bias, loss)
ax.set xlabel('Weight')
ax.set ylabel('Bias')
ax.set zlabel('Loss')
plt.show()
/usr/local/lib/python3.10/dist-packages/keras/optimizers/legacy/
gradient_descent.py:114: UserWarning: The `lr` argument is deprecated,
use `learning rate` instead.
  super(). init (name, **kwargs)
4/4 [============ ] - Os 4ms/step - loss: 0.8568
```

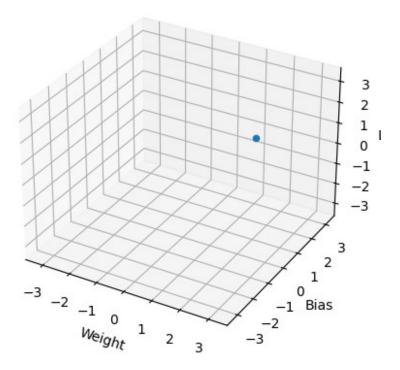


d) Re-train the model from c) and create an animation of the weight, bias, and loss at each training epoch. [5pts]

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
import keras
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
from matplotlib.animation import FuncAnimation
input shape = (1,)
model = Sequential([
    Input(shape=input shape),
    Dense(1, activation=None)
1)
model.compile(loss='mean squared error',
optimizer=keras.optimizers.SGD(lr=0.01))
def update(i):
 model.fit(x, y, epochs=1, batch size=32)
 weight, bias = model.layers[0].get weights()
  loss = model.evaluate(x, y)
  ax.clear()
  ax.scatter(weight, bias, loss)
  ax.set xlabel('Weight')
  ax.set ylabel('Bias')
  ax.set zlabel('Loss')
  ax.set title('Epoch {}'.format(i))
  ax.set xlim([-3.5, 3.5])
  ax.set ylim([-3.5, 3.5])
  ax.set zlim([-3.5, 3.5])
fig = plt.figure()
ax = plt.axes(projection='3d')
ani = FuncAnimation(fig, update, frames=100, interval=200,
repeat=True)
ani.save('1 d animation.gif', writer="pillow", fps=10)
/usr/local/lib/python3.10/dist-packages/keras/optimizers/legacy/
gradient descent.py:114: UserWarning: The `lr` argument is deprecated,
use `learning rate` instead.
  super(). init (name, **kwargs)
```

```
4/4 [============== ] - 0s 4ms/step - loss: 0.8666
```

Epoch 0

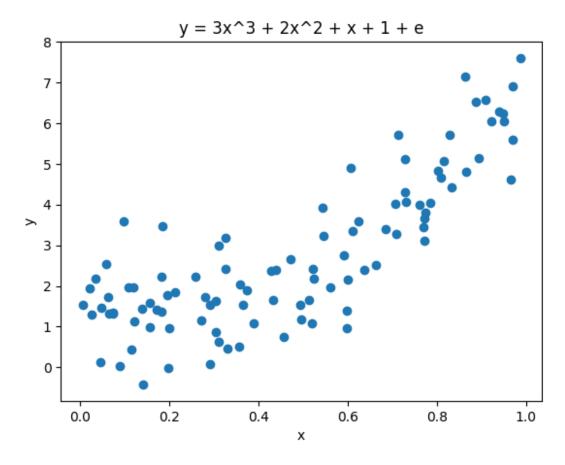


e) Generate data of the form $y = 3x^3 + 2x^2 + x + 1 + e$ where $e \sim N(0, 1)$ and plot the data in a scatter plot [2.5pts]

```
import numpy as np
import matplotlib.pyplot as plt

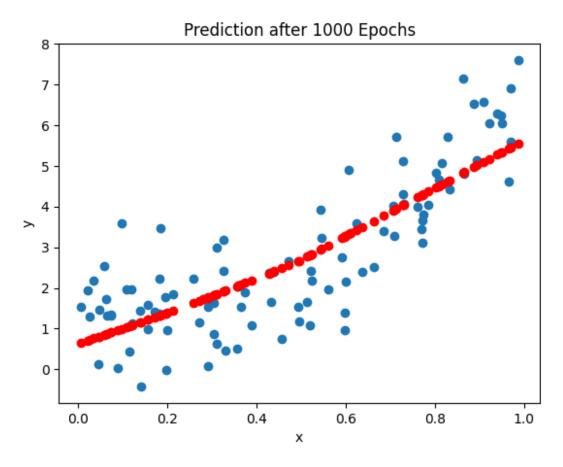
np.random.seed(42)
x = np.random.uniform(size=100)
e = np.random.normal(loc=0, scale=1, size=100)
y = 3 * x ** 3 + 2 * x ** 2 + x + 1 + e

plt.scatter(x, y)
plt.title('y = 3x^3 + 2x^2 + x + 1 + e')
plt.xlabel('x')
plt.ylabel('y')
plt.show()
```



f) Create and train a neural network on the dataset from b) and plot the resulting curve through the scatter plot. (you can use any number of epochs, hidden layers etc.) Also create an image of the network using the function from a) [5pts]

```
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from sklearn.metrics import mean squared error
model = Sequential()
model.add(Dense(100, input_shape=(1,), activation='relu'))
model.add(Dense(100, activation='relu'))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')
plot keras network(model, '1 f model.png')
model.fit(x, y, epochs=100, verbose=0)
y pred = model.predict(x)
mse = mean squared error(y, y pred)
y range = np.max(y) - np.min(y)
mse_norm = mse / y_range ** 2
```



g) Using matplotlib animation, create an animation of the resulting curve from your model at each training epoch (up to 100 epochs). [5pts]

```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.animation import FuncAnimation
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from sklearn.metrics import mean_squared_error

model = Sequential()
model.add(Dense(100, input_shape=(1,), activation='relu'))
```

```
model.add(Dense(100, activation='relu'))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')
fig, ax = plt.subplots()
ax.set xlabel('x')
ax.set ylabel('y')
ax.set_ylim(-110, 110)
def update(i):
  model.fit(x, y, epochs=1, verbose=0)
  y pred = model.predict(x)
  mse = mean squared error(y, y pred)
  y range = np.max(y) - np.min(y)
  mse norm = mse / y range ** 2
  ax.clear()
  ax.scatter(x, y)
  ax.scatter(x, y_pred, color='red')
  ax.set title(f'Epoch {i+1} - Normalized MSE: {mse norm:.4f}')
  ax.set xlabel('x')
  ax.set_ylabel('y')
  ax.set ylim(np.min(y) - 10, np.max(y) + 10)
  fig.tight layout()
ani = FuncAnimation(fig, update, frames=100, interval=200)
ani.save('1 g animation.gif', writer='pillow', fps=5)
4/4 [=======] - 0s 3ms/step
4/4 [=======] - 0s 6ms/step
4/4 [======= ] - 0s 4ms/step
4/4 [======] - 0s 4ms/step
4/4 [=======] - 0s 5ms/step
4/4 [=======] - 0s 3ms/step
4/4 [======= ] - 0s 3ms/step
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4/4 [======= ] - Os 3ms/step
```

4/4	[========]	-		3ms/step
4/4	[========]	-	0s	4ms/step
4/4	[========]		0s	3ms/step
•			0s	4ms/step
4/4	[========]	-	0s	3ms/step
4/4	[=========]	-	0s	4ms/step
4/4	[=========]	-	0s	4ms/step
4/4	[=========]	-	0s	3ms/step
4/4	[=========]	-	0s	3ms/step
4/4	[=========]	-	0s	6ms/step
4/4	[=========]	-	0s	3ms/step
4/4	[=========]	-	0s	3ms/step
4/4	[=========]	-	0s	3ms/step
4/4	[=========]	-	0s	4ms/step
4/4	[=========]	-	0s	3ms/step
4/4	[=========]	-	0s	3ms/step
4/4	[=========]	-	0s	3ms/step
4/4	[=========]	-	0s	5ms/step
4/4	[=========]	-	0s	3ms/step
4/4	[=========]	-	0s	5ms/step
4/4	[=========]	-	0s	4ms/step
4/4	[=========]	-	0s	3ms/step
4/4	[=========]	-	0s	2ms/step
4/4	[=========]	-	0s	3ms/step
4/4	[=========]	-	0s	3ms/step
4/4	[=========]	-	0s	3ms/step
4/4	[=========]	-	0s	3ms/step
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4/4	[=========]	-	0s	4ms/step
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4/4	[=========]	-	0s	3ms/step
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4/4	[=========]	-	0s	3ms/step
•				3ms/step
•	[=========]			4ms/step
	[=========]			
	[=========]			4ms/step
•	[========]			3ms/step
	[========]			
	[========]			
4/4	[=======]	-	0s	4ms/step

4/4	[========]	-	0s	5ms/step
4/4	[========]	-	0s	5ms/step
4/4	[========]	-	0s	5ms/step
4/4	[=======]	-	0s	5ms/step
4/4	[=======]	-	0s	4ms/step
4/4	[========]	-	0s	3ms/step
4/4	[========]	-	0s	3ms/step
4/4	[========]	-	0s	3ms/step
4/4	[========]	-	0s	3ms/step
4/4	[========]	-	0s	4ms/step
4/4	[========]	-	0s	3ms/step
4/4	[=======]	-	0s	3ms/step
4/4	[========]	-	0s	4ms/step
4/4	[========]	-	0s	3ms/step
4/4	[========]	-	0s	4ms/step
4/4	[========]	-	0s	3ms/step
4/4	[========]	-	0s	4ms/step
4/4	[========]	-	0s	3ms/step
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4/4	[========]	-	0s	3ms/step
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4/4	[========]	-	0s	3ms/step
4/4	[=======]	-	0s	4ms/step
4/4	[=======]	-	0s	3ms/step
4/4	[=======]	-	0s	4ms/step
4/4	[=======]	-	0s	3ms/step
4/4	[=======]	-	0s	4ms/step
				•

15 10 5 0 -5 -10 0.0 0.2 0.4 x 0.6 0.8 1.0

Epoch 1 - Normalized MSE: 0.0167

Exercise 2 [50pts]

In this excerise we will be implementing logic gates in various forms.

Part A: [25pts]

Recall in a logistic regression model we would find the weights and bias such that

$$P(y=1)=\sigma(w_1x_1+w_2x_2+b)$$

This means that when $w_1 x_1 + w_2 x_2 + b > 0$ we would predict y = 1. Moving b to the other side, we notice that only when $x_1 x_1 + w_2 x_2 < b$ do we predict y = 1. So the term b acts as a threshold past which the weighted sum of x's would cause the model to predict one class over the other.

In this part you are asked to find (not through gradient descent but through your own understanding of the functions below) the weights and threshold that appropriately describe the function being modeled.

Additional Resource/Hint: Realization of Logic Gates Using MccullochPitts Neuron Model

a) Implement the following logic gates - [20pts] 2 input AND gate 2 input OR gate 2 input NOR gate 1 input NOT gate 2 input NAND gate

by finding the correct weights and threshold.

Additional Resource: [Boolean Algebra Truth Tables for Logic Gate Functions] (https://www.electronics-tutorials.ws/boolean/bool_7.html#:~:text=The%20table%20used%20to%20represent,of%20these%20input(s).)

```
params
a = input 1
b = input 2
other definations
w1 = weight associated with input 1
w2 = weight associated with input 2
returns
Y = output of the gate
def and gate(a,b):
   w1 = 1 #TODO set weight w1
   w2 = 1 #TODO set weight w2
    g = w1*a + w2*b
    threshold = 1 #TODO: set threshold
    if g > threshold :
        return 1
    else:
        return 0
def or_gate(a,b):
    w1 = 1 #TODO set weight w1
    w2 = 1 #TODO set weight w2
    q = w1*a + w2*b
    threshold = 0.5 #TODO: set threshold
    if g > threshold :
        return 1
    else:
        return 0
def not_gate(a):
    w1 = -1 #TODO set weight w1
    threshold = -0.5 #TODO: set threshold
    if g > threshold :
        return 1
    else:
        return 0
def nor_gate(a,b):
    w1 = -1 #TODO set weight w1
```

```
w2 = -1 #TODO set weight w2
    q = w1*a + w2*b
    threshold = -1 #TODO: set threshold
    if q > threshold :
        return 1
    else:
        return 0
def nand gate(a,b):
    w1 = -1 #TODO set weight w1
    w2 = -1 #TODO set weight w2
    q = w1*a + w2*b
    threshold = -2 #TODO: set threshold
    if q > threshold :
        return 1
    else:
        return 0
# run this cell to check your fucntions
# the output provided it just a sample output. you can check for any
values of a and b
def gates(c, a, b=None):
    if c == 1:
        return and gate(a, b)
    elif c == 2:
        return or_gate(a, b)
    elif c == 3:
        return not gate(a)
    elif c == 4:
        return nor_gate(a, b)
    elif c == 5:
        return nand gate(a, b)
    else:
        return "Please check your choice"
def inputv(c):
    a = int(input(("Enter 1st value: ")))
    if (a>1 or a<0):
        print("Please check input")
    else:
        if c!=3:
            b = int(input(("Enter 2st value: ")))
            if (b>1 \text{ or } b<0):
                print("Please check input")
            return(a,b)
    return(a)
```

while True:

```
c = int(input("\n\nEnter your choice 1.AND 2.0R 3.NOT 4.NOR 5.NAND
6.exit\n"))
    if c == 6:
        break
    elif c not in range(1, 7):
        print("Please enter a valid choice")
        continue
    else:
        if c != 3:
            a = int(input("Enter 1st value: "))
            b = int(input("Enter 2nd value: "))
            if a not in [0, 1] or b not in [0, 1]:
                print("Please check input")
                continue
        else:
            a = int(input("Enter value: "))
            if a not in [0, 1]:
                print("Please check input")
                continue
        y = gates(c, a, b)
        print("Y =", y)
Enter your choice 1.AND 2.0R 3.NOT 4.NOR 5.NAND 6.exit
Enter 1st value: 0
Enter 2nd value: 1
Y = 1
Enter your choice 1.AND 2.0R 3.NOT 4.NOR 5.NAND 6.exit
5
Enter 1st value: 1
Enter 2nd value: 1
Y = 0
Enter your choice 1.AND 2.OR 3.NOT 4.NOR 5.NAND 6.exit
b) implement a XOR gate - [5pts]
Hint: XOR can be implemented as a combination of OR, NAND and AND gates. You can reuse
your functions from above
def xor gate(a,b):
    nand = nand gate(a,b)
    org = or gate(a,b)
```

```
andg = and_gate(nand,org)
return andg
```

Part B: Perceptron Learning Rule [25pts]

a) Inspired by the previous homework's implementation of logistic regression, implement a 2 input OR gate using perceptron learning rule - [20pts]

Recall: A perceptron is a no-hidden-layer neural network (like logistic regression) with a single output that is the activation of a weighted sum (plus a bias) of the inputs.

Your implementation should:

- use a bias
- have a configurable input size (the output size will always be 1)
- have a configurable learning rate
- have a configurable number of epochs
- have a configurable batch size
- support at least two types of activation functions
- support at least two types of losses / cost functions

```
import numpy as np
import matplotlib.pyplot as plt
class Perceptron:
    Implement a perceptron network
    def init (self, input size, learning rate=0.1, epochs=100,
batch_size=1, activation='step', loss='mse'):
        self.input size = input size
        self.learning_rate = learning_rate
        self.epochs = epochs
        self.batch size = batch size
        self.activation = activation
        self.loss = loss
        self.weights = np.random.rand(self.input size+1)
    def get activation(self):
        activation func=""
        if self.activation == 'step':
            activation func = lambda x: np.where(x > 0, 1, 0)
        elif self.activation == 'sigmoid':
            activation func = lambda x: 1 / (1 + np.exp(-x))
        else:
            raise ValueError("Invalid activation function")
        return activation func
    def get_loss(self):
        loss func=""
```

```
if self.loss == 'mse':
            loss func = lambda y true, y pred: np.mean((y true -
y_pred)**2)
        elif self.loss == 'mae':
            loss func = lambda y true, y pred: np.mean(np.abs(y true -
y_pred))
        else:
            raise ValueError("Invalid loss function")
        return loss func
    def fit(self, X, y):
        X = np.hstack([np.ones((X.shape[0],1)), X])
        activation func = self.get activation()
        loss func = self.get loss()
        loss values = []
        for epoch in range(self.epochs):
            for i in range(0, X.shape[0], self.batch size):
                X batch = X[i:i+self.batch size]
                y batch = y[i:i+self.batch size]
                y pred = activation func(np.dot(X batch,
self.weights))
                loss = loss_func(y_batch, y_pred)
                loss values.append(loss)
                grad = np.dot(X_batch.T, (y_pred - y_batch) * y_pred *
(1 - y_pred))
                self.weights -= self.learning rate * grad
    def predict(self, X):
        X = np.hstack([np.ones((X.shape[0],1)), X])
        activation func = self.get activation()
        return np.round(activation func(np.dot(X, self.weights)))
X = np.array([
    [0,0],
    [0,1],
    [1,0],
    [1,1]
])
y = np.array([0,1,1,1])
perceptron or = Perceptron(input_size=2, learning_rate=0.1,
epochs=100, batch size=1, activation='sigmoid', loss='mse')
perceptron or.fit(X, y)
print(perceptron or.predict(X))
[0. 1. 1. 1.]
```

b) How were the weights and biases you discovered in part B different from the ones you defined in part A for the OR gate? [5pts]

Exercise 3 [20pts]

This exercise will focus on Neural Networks.

```
from torch.utils.data import Dataset
from torchvision import datasets
from torchvision.transforms import ToTensor
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
import torch.nn.functional as F
import torchvision
import torchvision.transforms as transforms
from torch.optim import SGD, Adam
from tqdm import tqdm
```

a) Modify the number of layers to include at least 2 hidden layers with appropriate number of neurons that use the sigmoid function in the forward pass. Also change the epochs, criterion, batch size. [5pts]

Model which gave close to 77% testing accuracy

```
class NeuralNetwork(nn.Module):
    def init (self, input size):
        super(NeuralNetwork, self). init ()
        self.layer1 = nn.Linear(input size, 784)
        self.layer2 = nn.Linear(784, 400)
        self.layer3 = nn.Linear(400, 10)
        self.dropout = nn.Dropout(0.2)
    def forward(self, input):
        x = F.relu(self.layer1(input.view(-1, 28*28)))
        x = F.sigmoid(self.layer2(x))
        x = self.dropout(x)
        outputs = self.layer3(x)
        return F.softmax(outputs)
epochs = 10
device = torch.device("cuda" if torch.cuda.is available() else "cpu")
criterion = nn.CrossEntropyLoss()
batch size = 128
Model which improved testing performance on testing to ~89%
class NeuralNetwork(nn.Module):
  def init (self, input size):
    super(NeuralNetwork, self)._ init ()
```

```
self.layer1 = nn.Linear(input size, 800)
    self.layer2 = nn.Linear(800, 400)
    self.layer3 = nn.Linear(400, 10)
    self.dropout = nn.Dropout(0.2)
  def forward(self, input):
   x = F.relu(self.layer1(input))
   x = F.sigmoid(self.layer2(x))
   x = self.dropout(x)
   outputs = self.layer3(x)
    return F.softmax(outputs)
epochs = 20
device = torch.device("cuda" if torch.cuda.is available() else "cpu")
criterion = nn.MSELoss()
batch size = 500
Run the following cell everytime you update the above code
net = NeuralNetwork(784).to(device)
optimizer = Adam(net.parameters(), lr = 1e-2)
total loss = 0
### Downloading the data
training data = datasets.FashionMNIST(
    root="data",
   train=True,
   download=True,
   transform=ToTensor()
)
test data = datasets.FashionMNIST(
    root="data",
   train=False,
   download=True,
   transform=ToTensor()
)
train dataloader = torch.utils.data.DataLoader(training data,
batch size = batch size, shuffle = True, num workers=2)
train dataloader2 = torch.utils.data.DataLoader(training_data,
batch size = batch size, shuffle = True, num workers=2)
test dataloader = torch.utils.data.DataLoader(test data, batch size =
batch size, shuffle = True, num workers=2)
```

```
test_dataloader2 = torch.utils.data.DataLoader(test_data, batch_size =
batch size, shuffle = True, num workers=2)
```

b) You may change the architecture to increase the accuracy of this model. The goal is to attain the highest possible accuracy. You do not get marks for accuracies less than 83%. You may modify the values in part a [10pts]

```
for epoch in tqdm(range(epochs)):
  epoch_loss = 0
  for i, data in enumerate(train dataloader):
    inputs, labels = data
    optimizer.zero grad()
    outputs = net(inputs.view(batch size, -1).to(device))
    labels = F.one hot(labels, num classes= 10)
    loss = criterion(outputs, labels .to(device).float())
    loss.backward() # update network parameters
    optimizer.step() # update the optimizer parameters
    total loss += loss.item()
    epoch loss += loss.item()
 with torch.no grad():
    net.eval()
    correct = 0
    total = 0
    for i, data in enumerate(train dataloader2):
      input, labels = data
      outputs = net(input.view(batch size,-1).to(device))
      total+= len(labels)
      predictions = torch.argmax(outputs, dim = 1)
      predictions = predictions.to("cpu").numpy()
      correct += sum(1*(labels.numpy()==predictions))
 with torch.no grad():
    net.eval()
    correct test = 0
    total test = 0
    for i, data in enumerate(test_dataloader):
      input, labels = data
      outputs = net(input.view(batch size,-1).to(device))
      total test+= len(labels)
```

```
predictions = torch.argmax(outputs, dim = 1)
     predictions = predictions.to("cpu").numpy()
     correct test += sum(1*(labels.numpy()==predictions))
  print("epoch = ", epoch, " loss = ", epoch_loss, " training
accuracy = ", correct/total, "test accuracy = ",
correct test/total test)
               | 0/20 [00:00<?, ?it/s]<ipython-input-88-
  0%|
01cab3ebd345>:15: UserWarning: Implicit dimension choice for softmax
has been deprecated. Change the call to include dim=X as an argument.
  return F.softmax(outputs)
              | 1/20 [00:34<10:50, 34.24s/it]
 5%|
epoch = 0 loss = 8.6854855902493 training accuracy =
10%|
               | 2/20 [01:01<09:03, 30.17s/it]
epoch = 1 \text{ loss} = 7.1971323899924755 training accuracy = 0.54005
test accuracy = 0.5311
  15%|
               | 3/20 [01:29<08:13, 29.05s/it]
epoch = 2 loss = 7.045324757695198 training accuracy =
0.53496666666666667 test accuracy = 0.5261
               | 4/20 [01:56<07:33, 28.33s/it]
 20%|
epoch = 3 \log = 6.417871594429016 training accuracy = 0.6677
test accuracy = 0.6547
               | 5/20 [02:24<07:03, 28.23s/it]
 25%|
epoch = 4 \text{ loss} = 3.7952955327928066 training accuracy = 0.7844
test accuracy = 0.7648
               | 6/20 [02:54<06:42, 28.77s/it]
  30%|
epoch = 5 loss = 3.3493464402854443 training accuracy = 0.7909
test accuracy = 0.7713
               | 7/20 [03:23<06:16, 28.98s/it]
epoch = 6 loss = 3.257948087528348 training accuracy =
0.7970666666666667 test accuracy = 0.7766
               | 8/20 [03:53<05:50, 29.18s/it]
 40%|
epoch = 7 \text{ loss} = 3.0635340977460146 training accuracy = 0.89645
test accuracy = 0.8718
 45% | 9/20 [04:25<05:29, 29.96s/it]
```

```
epoch = 8 loss = 1.9454934252426028 training accuracy =
0.8980666666666667 test accuracy = 0.8729
            | 10/20 [04:57<05:06, 30.61s/it]
epoch = 9 loss = 1.834816343151033 training accuracy =
0.8958166666666667 test accuracy = 0.8723
 55%|
            | 11/20 [05:28<04:38, 30.89s/it]
epoch = 10 loss = 1.7833055071532726 training accuracy =
0.90883333333333334 test accuracy = 0.8802
            | 12/20 [06:02<04:14, 31.87s/it]
 60%
epoch = 11 loss = 1.7597284438088536
                                training accuracy =
| 13/20 [06:36<03:46, 32.29s/it]
epoch = 12 loss = 1.7457022368907928 training accuracy = 1.7457022368907928
70%| 14/20 [07:09<03:16, 32.74s/it]
epoch = 13 loss = 1.6854582568630576 training accuracy = 1.6854582568630576
75%|
           | 15/20 [07:45<02:48, 33.66s/it]
epoch = 14 loss = 1.626717634499073 training accuracy =
0.8998166666666667 test accuracy = 0.8682
 80%| | 16/20 [08:20<02:15, 33.96s/it]
epoch = 15 loss = 1.6478663124144077 training accuracy =
85%| | 17/20 [08:56<01:44, 34.73s/it]
epoch = 16 loss = 1.6200494412332773 training accuracy = 0.9149
test accuracy = 0.8841
 90%| | 18/20 [09:34<01:11, 35.57s/it]
epoch = 17 loss = 1.570212583988905 training accuracy =
95%| | 19/20 [10:12<00:36, 36.39s/it]
epoch = 18 loss = 1.576647930778563 training accuracy =
100% | 20/20 [10:50<00:00, 32.53s/it]
```

```
epoch = 19 loss = 1.5130695784464478 training accuracy =
0.9212333333333333 test accuracy = 0.8872
```

d) Explain in \sim 150 words your choice of architecture and parameters, and your general process. [5pts]

Firstly, I tried a neural network with 10 epochs, CrossEntropy Loss and 128 (default given) batch size which gave me close to 77% testing accuracy. I changed the parameters for the model with 20 epochs, MSE loss and 500 batch size, which improved the testing accuracy to $\sim 89\%$.