Neural Networks - intro

Part 1 - XOR

1. Using the XOR dataset below, train (400 epochs) a neural network (NN) using 2, 3, 4, and 5 hidden layers (where each layer has only 2 neurons). For each n layers, store the resulting accuracy along with n. Plot the results to find what the optimal number of layers is.
2. Repeat the above with 3 neurons in each Hidden layers. How do these results compare to the 2 neuron layers?
3. Repeat the above with 4 neurons in each Hidden layers. How do these results compare to the 2 and 3 neuron layers?
4. Using the most optimal configuraion (n-layers, k-neurons per layer), compare how `tanh`, `sigmoid`, `softplus` and `relu` effect the loss after 400 epochs. Try other Activation functions as well (https://keras.io/activations/)
5. Again with the most optimal setup, try other optimizers (instead of `SGD`) and report on the loss score. (https://keras.io/optimizers/)

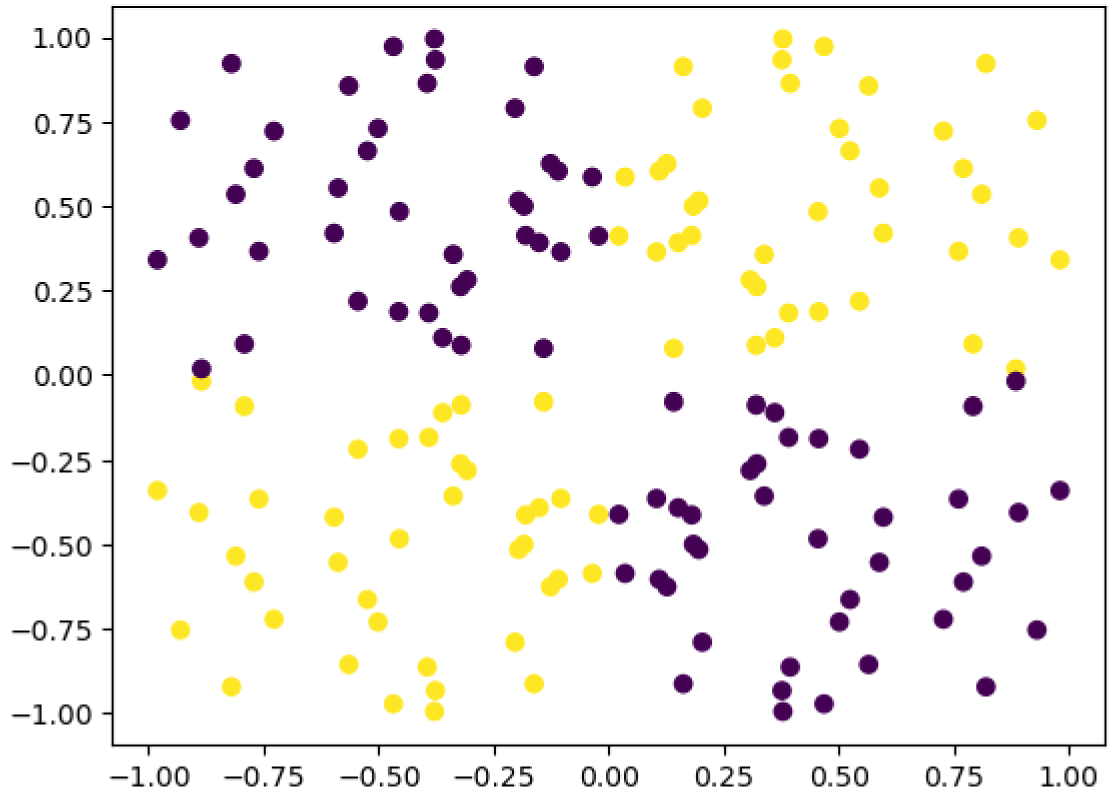
In [1]:
```
# Import Libraries Etc
from keras.models import Sequential
from keras.layers import Dense
from keras.optimizers import SGD  #Stochastic Gradient Descent

import numpy as np
# fix random seed for reproducibility
np.random.seed(2023)

import matplotlib.pyplot as plt
%matplotlib inline

from IPython.display import display
```

In [2]:
```
# Using Provided XOR Dataset
n = 40
xx = np.random.random((n,1))
yy = np.random.random((n,1))
```

In [3]:
```
X = np.array([np.array([xx,-xx,-xx,xx]),np.array([yy,-yy,yy,-yy])]).reshape(2,4*n).T
y = np.array([np.ones([2*n]),np.zeros([2*n])]).reshape(4*n)
```

In [4]:
```
# Visualizing for Own Benefit
plt.scatter(*zip(*X), c=y)
```

Out[4]:
```
<matplotlib.collections.PathCollection at 0x174e2bc7d60>
```



In [5]:
```
# 1. Using the XOR dataset below, train (400 epochs) a neural network (NN) using 2, 3,
# (where each layer has only 2 neurons). For each n layers, store the resulting accurc
# results to find what the optimal number of layers is.

## Two Hidden Layers
model_two_layer = Sequential()
model_two_layer.add(Dense(2, input_dim=2, activation='relu')) # Keeping Dense layers j
model_two_layer.add(Dense(2, activation='relu')) # First argument '2' Keeps two neuror

## Three Hidden Layers
model_three_layer = Sequential()
model_three_layer.add(Dense(2, input_dim=2, activation='relu')) # Keeping Dense layers
model_three_layer.add(Dense(2, activation='relu'))
model_three_layer.add(Dense(2, activation='relu'))

## Four Hidden Layers
model_four_layer = Sequential()
model_four_layer.add(Dense(2, input_dim=2, activation='relu')) # Keeping Dense layers
model_four_layer.add(Dense(2, activation='relu')) # Add another layer; three total lay
model_four_layer.add(Dense(2, activation='relu'))
model_four_layer.add(Dense(2, activation='relu'))

## Five Hidden Layers
## Four Hidden Layers
model_five_layer = Sequential()
model_five_layer.add(Dense(2, input_dim=2, activation='relu')) # Keeping Dense layers
model_five_layer.add(Dense(2, activation='relu')) # Add another layer; three total lay
model_five_layer.add(Dense(2, activation='relu'))
model_five_layer.add(Dense(2, activation='relu'))
model_five_layer.add(Dense(2, activation='relu'))
```

In [6]:
```
sgd = SGD(lr=0.1)
model_two_layer.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accura
```

```
model_three_layer.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accu

model_four_layer.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accur
model_five_layer.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accur
```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use
the legacy optimizer, e.g.,tf.keras.optimizers.legacy.SGD.
```

In [7]:

```
%%capture
# The training cells result in the html/pdf downloads becoming very long (>400 pages),
# 400 Epoch Training
model_two_layer.fit(X, y, batch_size=12, epochs=400)
model_three_layer.fit(X, y, batch_size=12, epochs=400)
model_four_layer.fit(X, y, batch_size=12, epochs=400)
model_five_layer.fit(X, y, batch_size=12, epochs=400)
```

In [66]:

```
# Accuracy & n
scores_two_layer = model_two_layer.evaluate(X, y)
scores_three_layer = model_three_layer.evaluate(X, y)
scores_four_layer = model_four_layer.evaluate(X, y)
scores_five_layer = model_five_layer.evaluate(X, y)

# Comparison
(scores_two_layer, scores_three_layer, scores_four_layer, scores_five_layer)
```

```
5/5 [==============================] - 0s 2ms/step - loss: 4.1732 - accuracy: 0.5188
5/5 [==============================] - 0s 2ms/step - loss: 3.8243 - accuracy: 0.5000
5/5 [==============================] - 0s 2ms/step - loss: 3.9813 - accuracy: 0.8000
5/5 [==============================] - 0s 2ms/step - loss: 4.0526 - accuracy: 0.5000
```

Out[66]:

```
([4.1732258796691895, 0.518750011920929],
 [3.8243298530578613, 0.5],
 [3.9812514781951904, 0.800000011920929],
 [4.0525898933410645, 0.5])
```

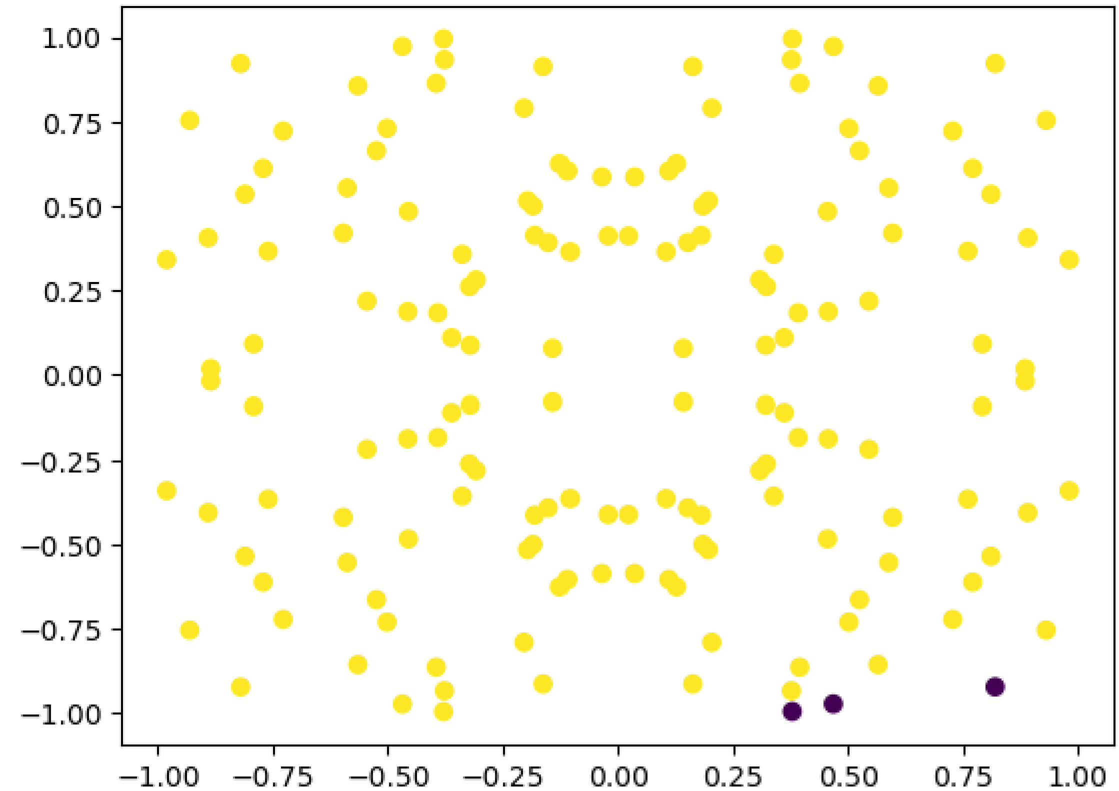
In [67]:

```
plt.scatter(*zip(*X), c=model_two_layer.predict(X).argmax(axis=-1))
```

```
5/5 [==============================] - 0s 1ms/step
```

Out[67]:

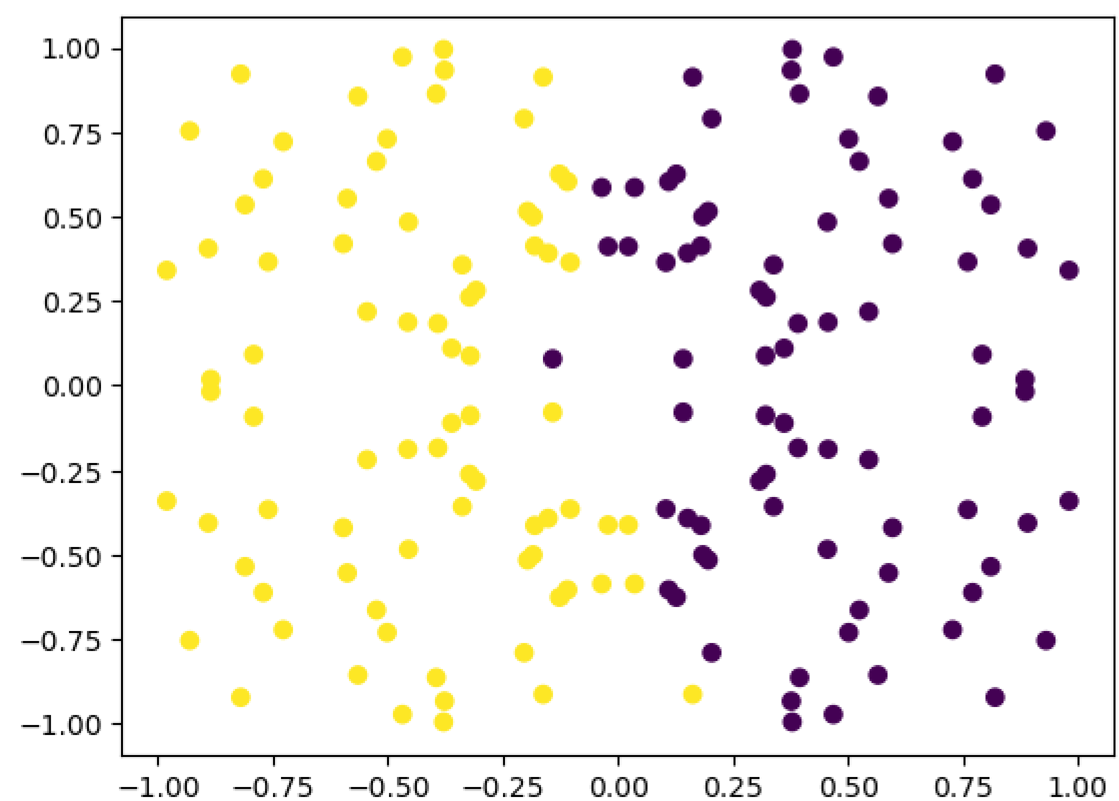
```
<matplotlib.collections.PathCollection at 0x1748ce81bd0>
```



In [68]:
```
plt.scatter(*zip(*X), c=model_three_layer.predict(X).argmax(axis=-1))
```

```
5/5 [==============================] - 0s 998us/step
```

Out[68]:
```
<matplotlib.collections.PathCollection at 0x1748cde1d80>
```

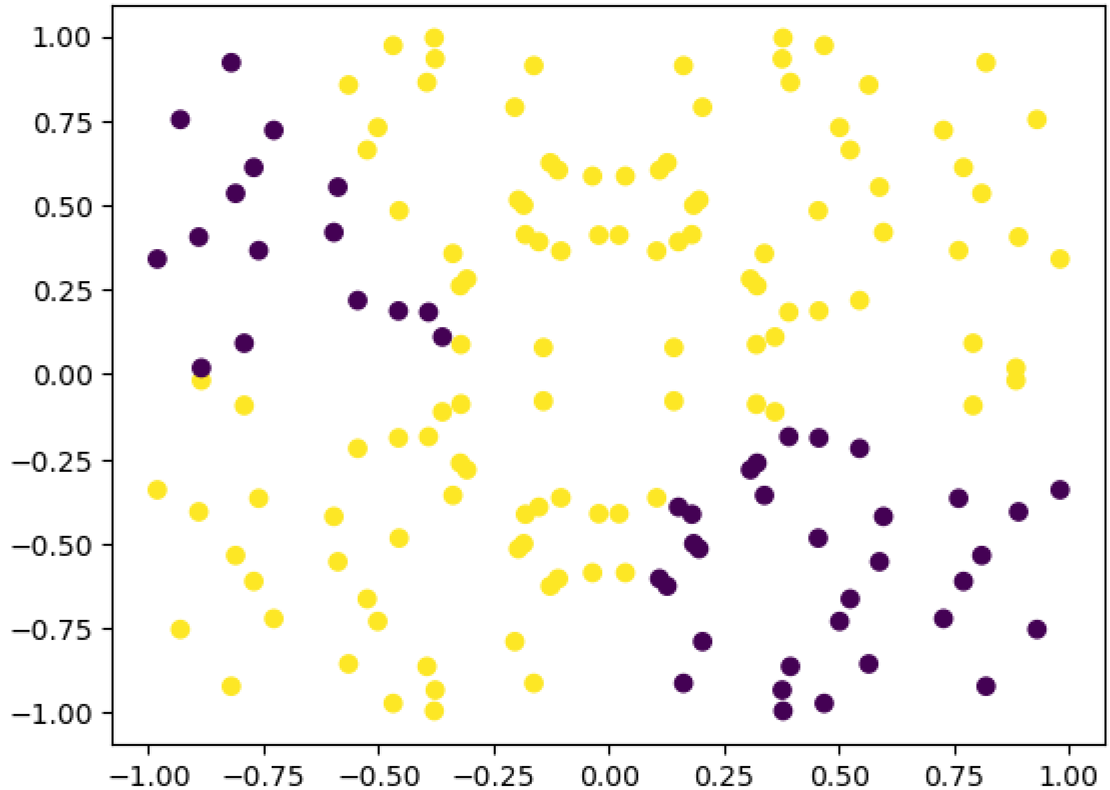


In [69]:
```
plt.scatter(*zip(*X), c=model_four_layer.predict(X).argmax(axis=-1))
```

```
5/5 [==============================] - 0s 2ms/step
```

Out[69]:

```
<matplotlib.collections.PathCollection at 0x1748cf13430>
```



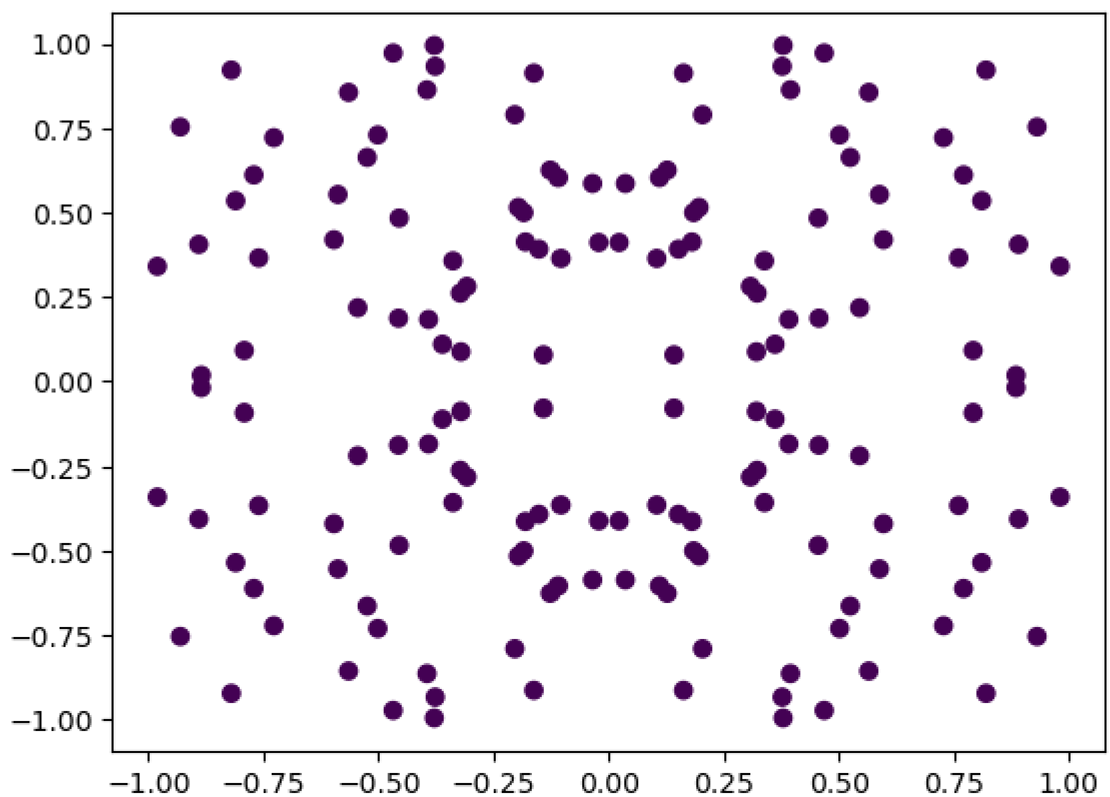
In [70]:

```
plt.scatter(*zip(*X), c=model_five_layer.predict(X).argmax(axis=-1))
```

```
5/5 [==============================] - 0s 1ms/step
```

Out[70]:

```
<matplotlib.collections.PathCollection at 0x1748d0e6680>
```



In [13]:
```
# In the two-neuron setup, the three four-layer model works best, with an accuracy of
# predicting the dataset.
```

In [14]:
```
# 3. Repeat the above with 3 neurons in each Hidden layers. How do these results compa
neurons = 3
neurons
```

Out[14]:
```
3
```

In [15]:
```
# 1. Using the XOR dataset below, train (400 epochs) a neural network (NN) using 2, 3,
# (where each layer has only 2 neurons). For each n layers, store the resulting accura
# results to find what the optimal number of layers is.

## Two Hidden Layers
model_two_layer_3n = Sequential()
model_two_layer_3n.add(Dense(neurons, input_dim=2, activation='relu')) # Keeping Dense
model_two_layer_3n.add(Dense(neurons, activation='relu')) # First argument '2' Keeps t

## Three Hidden Layers
model_three_layer_3n = Sequential()
model_three_layer_3n.add(Dense(neurons, input_dim=2, activation='relu')) # Keeping Der
model_three_layer_3n.add(Dense(neurons, activation='relu'))
model_three_layer_3n.add(Dense(neurons, activation='relu'))

## Four Hidden Layers
model_four_layer_3n = Sequential()
model_four_layer_3n.add(Dense(neurons, input_dim=2, activation='relu')) # Keeping Dens
model_four_layer_3n.add(Dense(neurons, activation='relu')) # Add another layer; three
model_four_layer_3n.add(Dense(neurons, activation='relu'))
model_four_layer_3n.add(Dense(neurons, activation='relu'))

## Five Hidden Layers
## Four Hidden Layers
model_five_layer_3n = Sequential()
model_five_layer_3n.add(Dense(neurons, input_dim=2, activation='relu')) # Keeping Dens
model_five_layer_3n.add(Dense(neurons, activation='relu')) # Add another layer; three
model_five_layer_3n.add(Dense(neurons, activation='relu'))
model_five_layer_3n.add(Dense(neurons, activation='relu'))
model_five_layer_3n.add(Dense(neurons, activation='relu'))
```

In [16]:
```
sgd = SGD(lr=0.1)
model_two_layer_3n.compile(loss='binary_crossentropy', optimizer='adam', metrics=['acc
model_three_layer_3n.compile(loss='binary_crossentropy', optimizer='adam', metrics=['a
model_four_layer_3n.compile(loss='binary_crossentropy', optimizer='adam', metrics=['ac
model_five_layer_3n.compile(loss='binary_crossentropy', optimizer='adam', metrics=['ac
```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use
the legacy optimizer, e.g.,tf.keras.optimizers.legacy.SGD.
```

In [17]:
```
%%capture
# 400 Epoch Training
model_two_layer_3n.fit(X, y, batch_size=12, epochs=400)
model_three_layer_3n.fit(X, y, batch_size=12, epochs=400)
model_four_layer_3n.fit(X, y, batch_size=12, epochs=400)
model_five_layer_3n.fit(X, y, batch_size=12, epochs=400)
```

In [71]:
```
# Accuracy & n
scores_two_layer_3n = model_two_layer_3n.evaluate(X, y)
```

```
scores_three_layer_3n = model_three_layer_3n.evaluate(X, y)
scores_four_layer_3n = model_four_layer_3n.evaluate(X, y)
scores_five_layer_3n = model_four_layer_3n.evaluate(X, y)

# Comparison
(scores_two_layer_3n,
 scores_three_layer_3n,
 scores_four_layer_3n,
 scores_five_layer_3n)
```

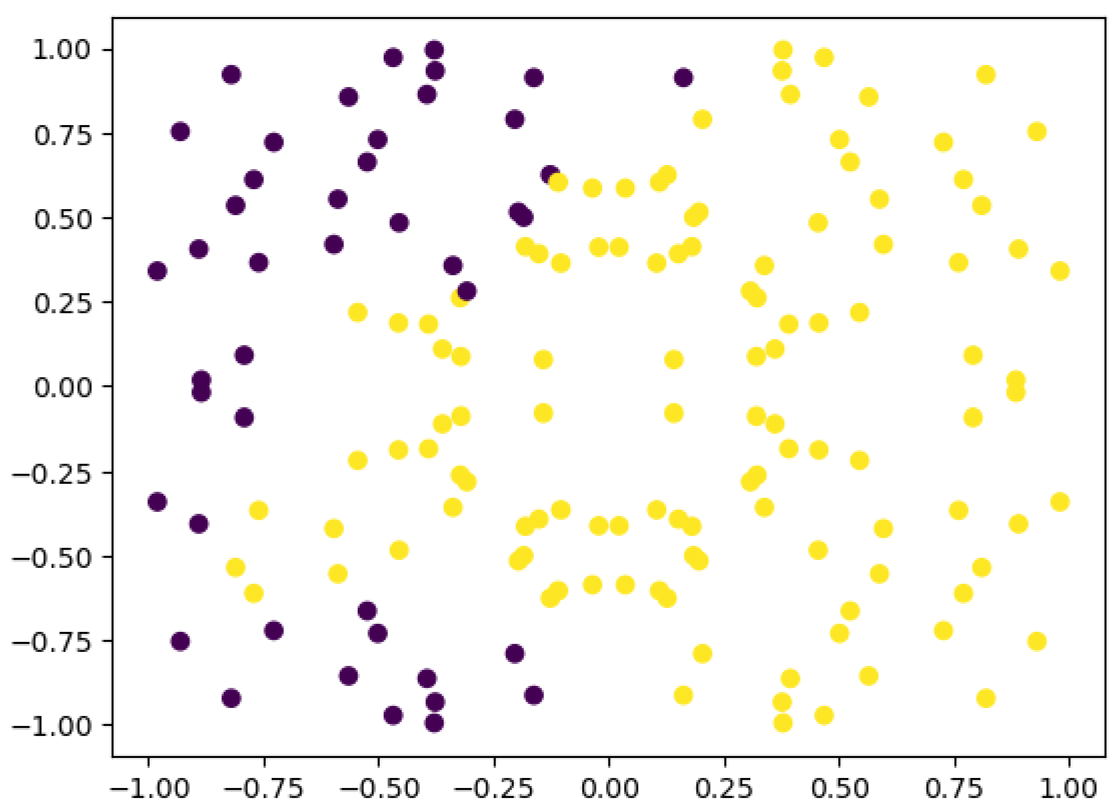
```
5/5 [==============================] - 0s 2ms/step - loss: 2.8514 - accuracy: 0.1688
5/5 [==============================] - 0s 2ms/step - loss: 4.1569 - accuracy: 0.5000
5/5 [==============================] - 0s 2ms/step - loss: 0.0626 - accuracy: 0.4625
5/5 [==============================] - 0s 1ms/step - loss: 0.0626 - accuracy: 0.4625
```

Out[71]:
```
([2.851390838623047, 0.16875000298023224],
 [4.156896114349365, 0.5],
 [0.0625719279050827, 0.4625000059604645],
 [0.0625719279050827, 0.4625000059604645])
```

In [72]:
```
plt.scatter(*zip(*X), c=model_two_layer_3n.predict(X).argmax(axis=-1))
```

```
5/5 [==============================] - 0s 997us/step
```

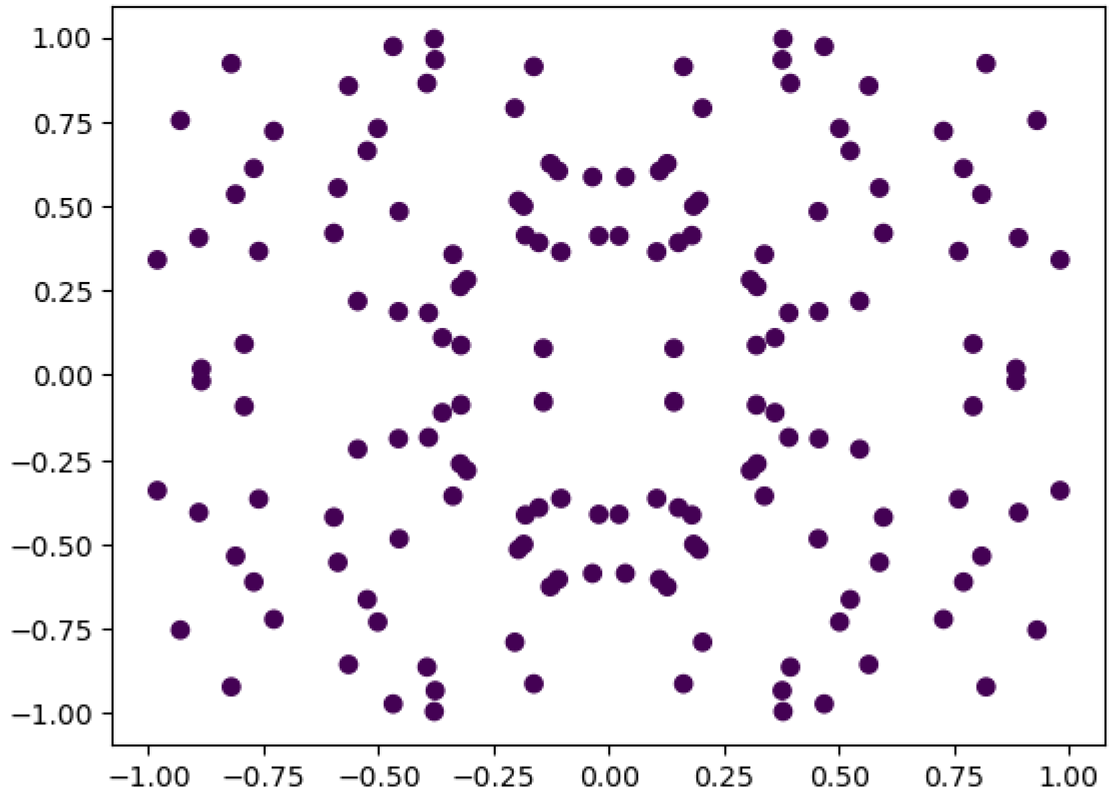
Out[72]:
```
<matplotlib.collections.PathCollection at 0x1748d19cb50>
```



In [73]:
```
plt.scatter(*zip(*X), c=model_three_layer_3n.predict(X).argmax(axis=-1))
```

```
5/5 [==============================] - 0s 2ms/step
```

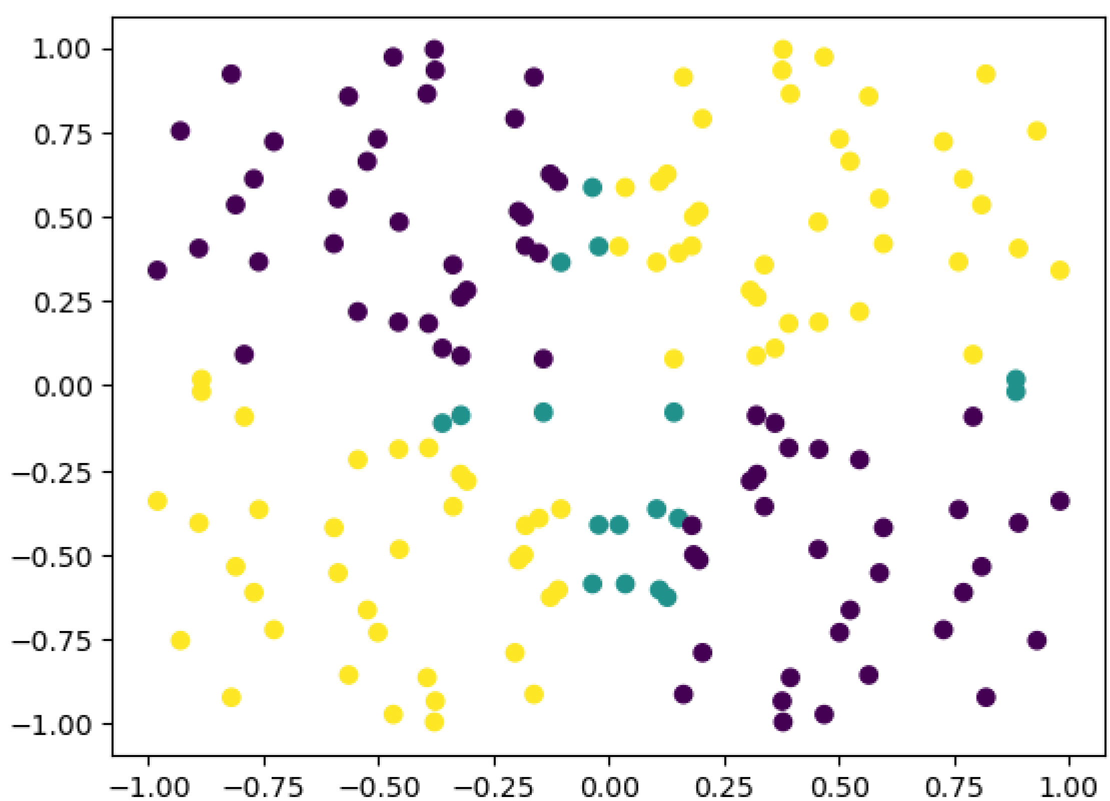
Out[73]:
```
<matplotlib.collections.PathCollection at 0x1748d168760>
```



In [74]:
```
plt.scatter(*zip(*X), c=model_four_layer_3n.predict(X).argmax(axis=-1))
```

```
5/5 [==============================] - 0s 1ms/step
```

Out[74]:
```
<matplotlib.collections.PathCollection at 0x1748d1d0940>
```

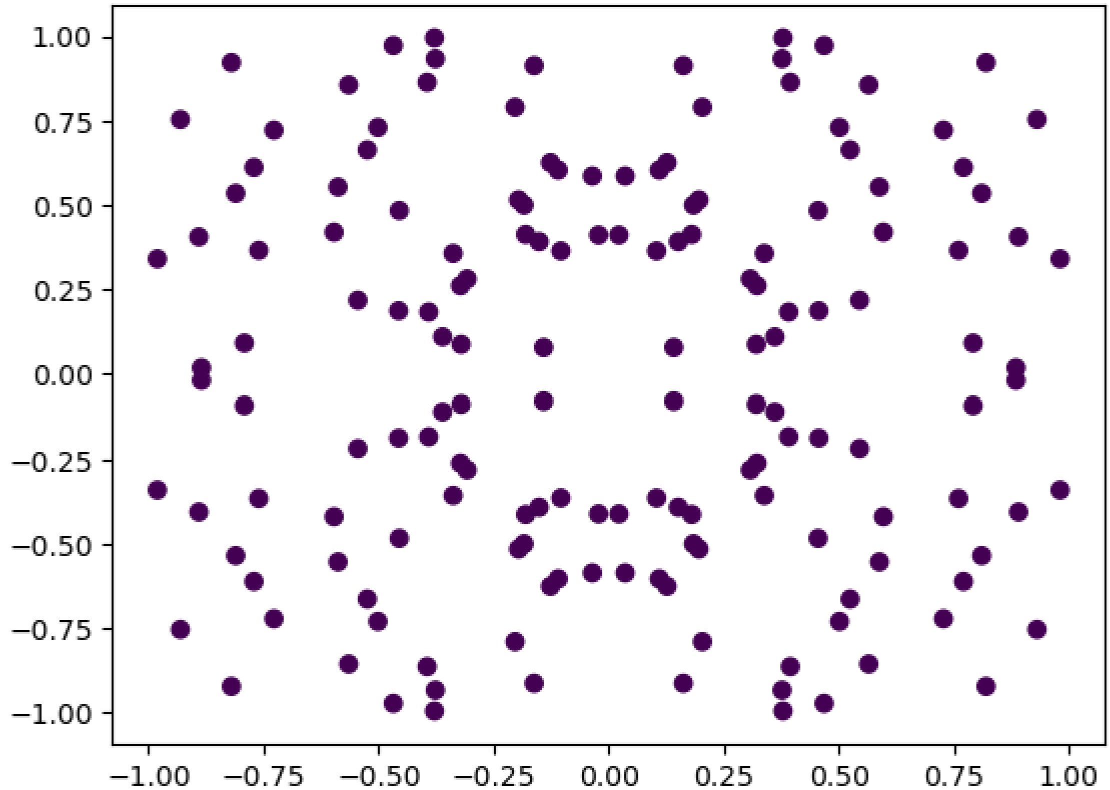


In [76]:
```
plt.scatter(*zip(*X), c=model_five_layer_3n.predict(X).argmax(axis=-1))
```

```
5/5 [==============================] - 0s 1ms/step
```

Out[76]:

```
<matplotlib.collections.PathCollection at 0x174837aeda0>
```



In [23]:

```
# None off the models in the three-neuron setup performs as well as the two-neuron, fo
# these are the three neuron, four layer setup.
```

In [24]:

```
# 2. Repeat the above with 4 neurons in each Hidden layers. How do these results compa
neurons = 4
neurons
```

Out[24]:

```
4
```

In [25]:

```
# 1. Using the XOR dataset below, train (400 epochs) a neural network (NN) using 2, 3,
# (where each layer has only 2 neurons). For each n layers, store the resulting accura
# results to find what the optimal number of layers is.

## Two Hidden Layers
model_two_layer_4n = Sequential()
model_two_layer_4n.add(Dense(neurons, input_dim=2, activation='relu')) # Keeping Dense
model_two_layer_4n.add(Dense(neurons, activation='relu')) # First argument '2' Keeps t

## Three Hidden Layers
model_three_layer_4n = Sequential()
model_three_layer_4n.add(Dense(neurons, input_dim=2, activation='relu')) # Keeping Den
model_three_layer_4n.add(Dense(neurons, activation='relu'))
model_three_layer_4n.add(Dense(neurons, activation='relu'))

## Four Hidden Layers
model_four_layer_4n = Sequential()
model_four_layer_4n.add(Dense(neurons, input_dim=2, activation='relu')) # Keeping Dens
model_four_layer_4n.add(Dense(neurons, activation='relu')) # Add another layer; three
model_four_layer_4n.add(Dense(neurons, activation='relu'))
model_four_layer_4n.add(Dense(neurons, activation='relu'))
```

```
## Five Hidden Layers
## Four Hidden Layers
model_five_layer_4n = Sequential()
model_five_layer_4n.add(Dense(neurons, input_dim=2, activation='relu')) # Keeping Dens
model_five_layer_4n.add(Dense(neurons, activation='relu')) # Add another layer; three
model_five_layer_4n.add(Dense(neurons, activation='relu'))
model_five_layer_4n.add(Dense(neurons, activation='relu'))
model_five_layer_4n.add(Dense(neurons, activation='relu'))
```

In [26]:

```
sgd = SGD(lr=0.1)
model_two_layer_4n.compile(loss='binary_crossentropy', optimizer='adam', metrics=['acc
model_three_layer_4n.compile(loss='binary_crossentropy', optimizer='adam', metrics=['a
model_four_layer_4n.compile(loss='binary_crossentropy', optimizer='adam', metrics=['ac
model_five_layer_4n.compile(loss='binary_crossentropy', optimizer='adam', metrics=['ac
```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use
the legacy optimizer, e.g.,tf.keras.optimizers.legacy.SGD.
```

In [27]:

```
%%capture
# 400 Epoch Training
model_two_layer_4n.fit(X, y, batch_size=12, epochs=400)
model_three_layer_4n.fit(X, y, batch_size=12, epochs=400)
model_four_layer_4n.fit(X, y, batch_size=12, epochs=400)
model_five_layer_4n.fit(X, y, batch_size=12, epochs=400)
```

In [77]:

```
# Accuracy & n
scores_two_layer_4n = model_two_layer_4n.evaluate(X, y)
scores_three_layer_4n = model_three_layer_4n.evaluate(X, y)
scores_four_layer_4n = model_four_layer_4n.evaluate(X, y)
scores_five_layer_4n = model_five_layer_4n.evaluate(X, y)

# Comparison
(scores_two_layer_4n, scores_three_layer_4n, scores_four_layer_4n, scores_five_layer_4
```

```
5/5 [==============================] - 0s 1ms/step - loss: 0.6874 - accuracy: 0.2812
5/5 [==============================] - 0s 1ms/step - loss: 5.8000 - accuracy: 0.9125
5/5 [==============================] - 0s 1ms/step - loss: 0.0077 - accuracy: 0.4938
5/5 [==============================] - 0s 1ms/step - loss: 1.9381 - accuracy: 0.4750
```

Out[77]:

```
([0.6874362230300903, 0.28125],
 [5.800013542175293, 0.9125000238418579],
 [0.007748936302959919, 0.4937500059604645],
 [1.938126564025879, 0.4749999940395355])
```

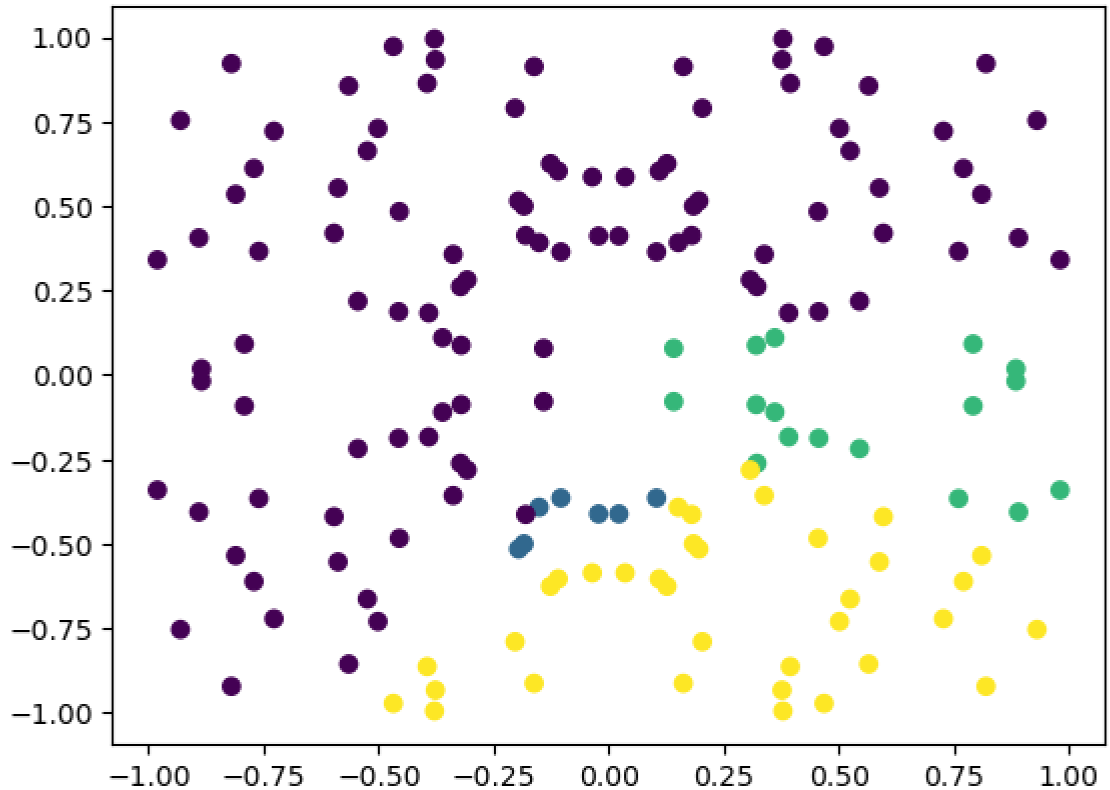
In [78]:

```
plt.scatter(*zip(*X), c=model_two_layer_4n.predict(X).argmax(axis=-1))
```

```
5/5 [==============================] - 0s 998us/step
```

Out[78]:

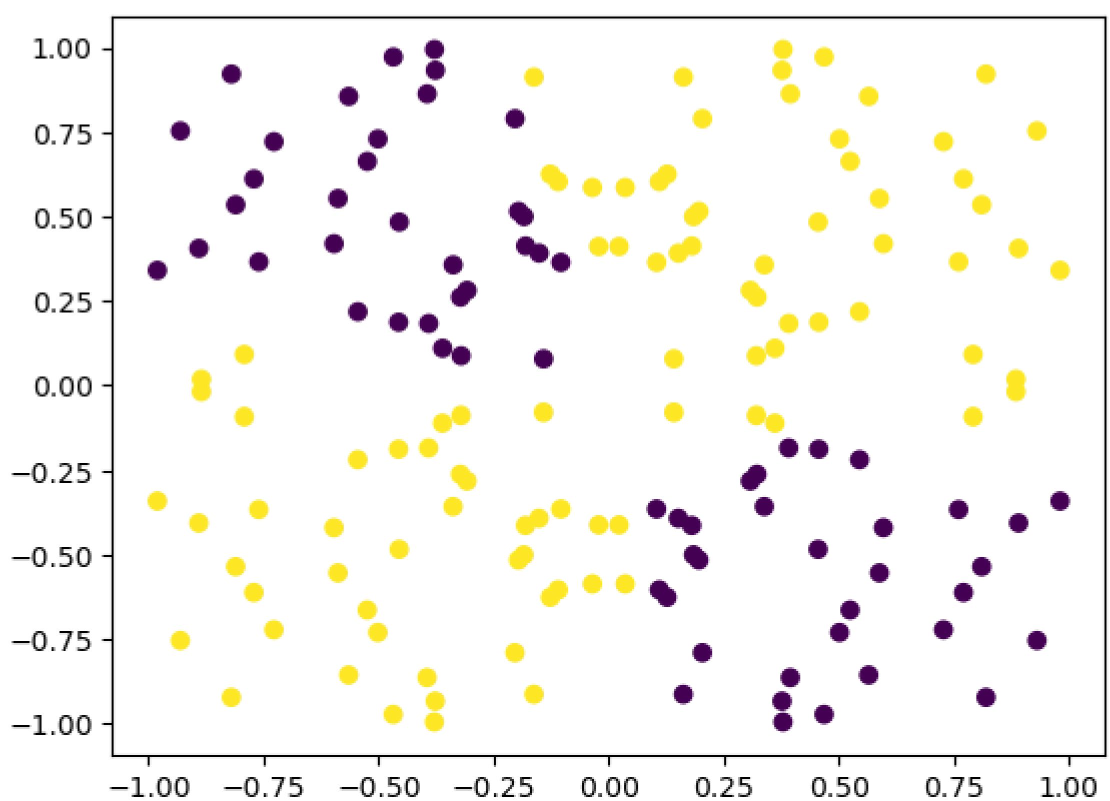
```
<matplotlib.collections.PathCollection at 0x174ff92b340>
```



In [79]:
```
plt.scatter(*zip(*X), c=model_three_layer_4n.predict(X).argmax(axis=-1))
```

```
5/5 [==============================] - 0s 998us/step
```

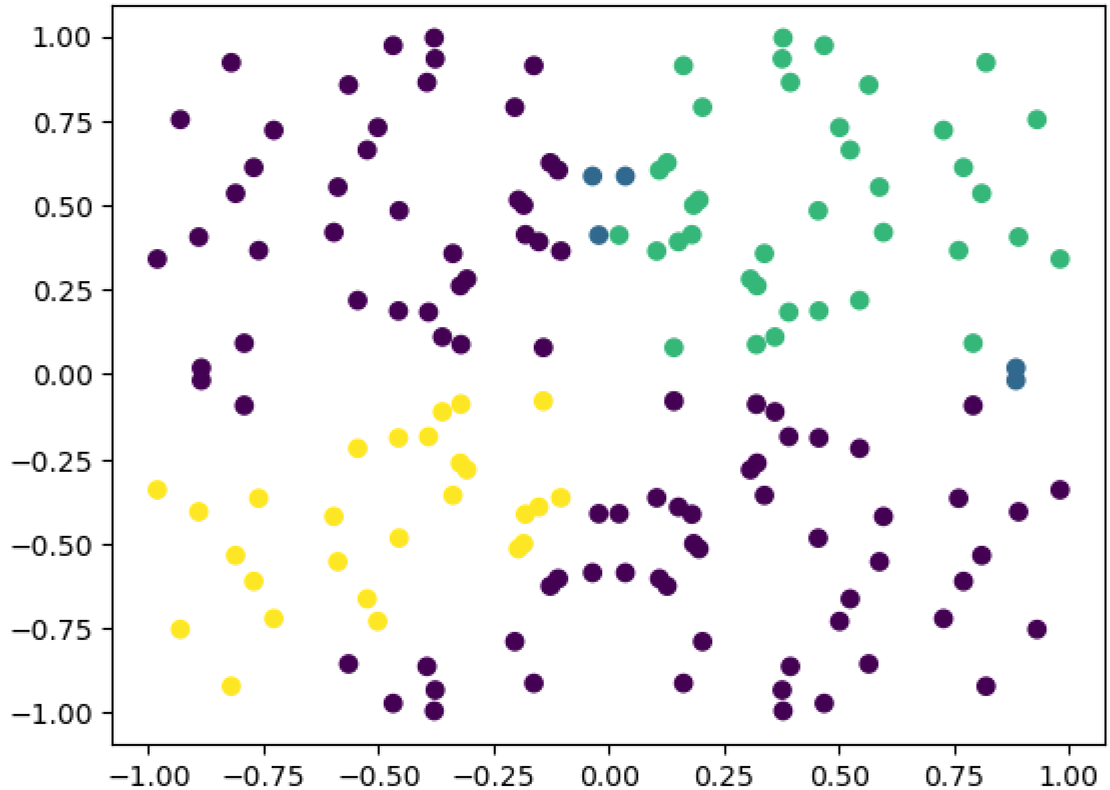
Out[79]:
```
<matplotlib.collections.PathCollection at 0x174fbf56650>
```



In [80]:
```
plt.scatter(*zip(*X), c=model_four_layer_4n.predict(X).argmax(axis=-1))
```

```
5/5 [==============================] - 0s 1ms/step
```

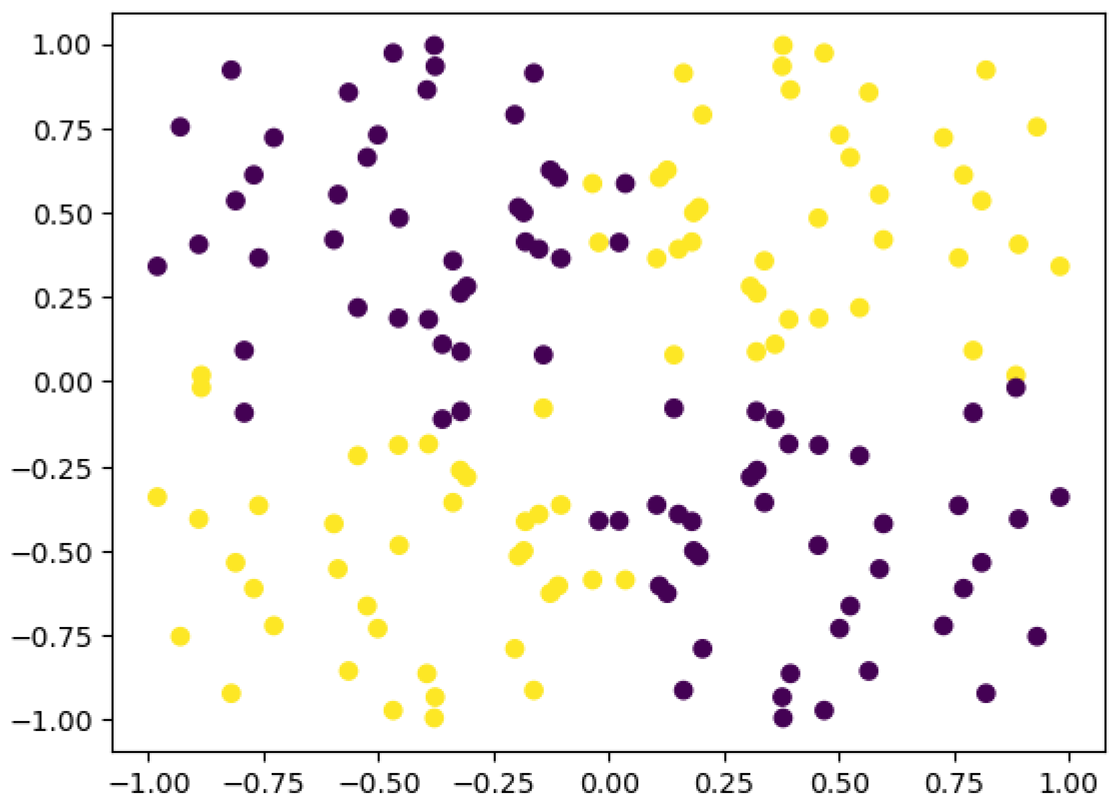
Out[80]: <matplotlib.collections.PathCollection at 0x174f6eb8e20>



In [81]:
```
plt.scatter(*zip(*X), c=model_five_layer_4n.predict(X).argmax(axis=-1))
```

```
5/5 [==============================] - 0s 1ms/step
```

Out[81]: <matplotlib.collections.PathCollection at 0x1748e47b0d0>



In [33]:
```
# The models for the four neuron setup show increased accuracy, with the four-neuron,
# of .912 (the best so far).
```

In [83]:
```
# Full Comparison of Neuron Values

# Comparison
(scores_two_layer, scores_three_layer, scores_four_layer, scores_five_layer,
scores_two_layer_3n, scores_three_layer_3n, scores_four_layer_3n, scores_five_layer_3n
scores_two_layer_4n, scores_three_layer_4n, scores_four_layer_4n, scores_five_layer_4n
```

Out[83]:
```
([4.1732258796691895, 0.518750011920929],
 [3.8243298530578613, 0.5],
 [3.9812514781951904, 0.800000011920929],
 [4.0525898933410645, 0.5],
 [2.851390838623047, 0.16875000298023224],
 [4.156896114349365, 0.5],
 [0.0625719279050827, 0.4625000059604645],
 [0.0625719279050827, 0.4625000059604645],
 [0.6874362230300903, 0.28125],
 [5.800013542175293, 0.9125000238418579],
 [0.007748936302959919, 0.4937500059604645],
 [1.938126564025879, 0.4749999940395355])
```

In [84]:
```
# 3. Using the most optimal configuraion (n-layers, k-neurons per layer), compare how
# Using four-neuron, three-layers setup
neurons = 4
## Four Hidden Layers
model_3l_4n_relu = Sequential()
model_3l_4n_relu.add(Dense(neurons, input_dim=2, activation='relu')) # Keeping Dense l
model_3l_4n_relu.add(Dense(neurons, activation='relu')) # Add another layer; three tot
model_3l_4n_relu.add(Dense(neurons, activation='relu'))
# model_4l_4n_relu.add(Dense(neurons, activation='relu'))

# tanh

## Four Hidden Layers
model_3l_4n_tanh = Sequential()
model_3l_4n_tanh.add(Dense(neurons, input_dim=2, activation='tanh')) # Keeping Dense l
model_3l_4n_tanh.add(Dense(neurons, activation='tanh')) # Add another layer; three tot
model_3l_4n_tanh.add(Dense(neurons, activation='tanh'))
# model_4l_4n_tanh.add(Dense(neurons, activation='tanh'))

# sigmoid

## Four Hidden Layers
model_3l_4n_sigmoid = Sequential()
model_3l_4n_sigmoid.add(Dense(neurons, input_dim=2, activation='sigmoid')) # Keeping D
model_3l_4n_sigmoid.add(Dense(neurons, activation='sigmoid')) # Add another layer; thr
model_3l_4n_sigmoid.add(Dense(neurons, activation='sigmoid'))
# model_4l_4n_sigmoid.add(Dense(neurons, activation='sigmoid'))

# softplus

## Four Hidden Layers
model_3l_4n_softplus = Sequential()
model_3l_4n_softplus.add(Dense(neurons, input_dim=2, activation='softplus')) # Keeping
model_3l_4n_softplus.add(Dense(neurons, activation='softplus')) # Add another layer; t
model_3l_4n_softplus.add(Dense(neurons, activation='softplus'))
# model_4l_4n_softplus.add(Dense(neurons, activation='softplus'))
```

```
# relu - Already used in above models

# Additional Activation Functions
# elu
model_3l_4n_elu = Sequential()
model_3l_4n_elu.add(Dense(neurons, input_dim=2, activation='softplus')) # Keeping Dens
model_3l_4n_elu.add(Dense(neurons, activation='softplus')) # Add another layer; three
model_3l_4n_elu.add(Dense(neurons, activation='softplus'))
# model_4l_4n_elu.add(Dense(neurons, activation='softplus'))

#exponential
model_3l_4n_exp = Sequential()
model_3l_4n_exp.add(Dense(neurons, input_dim=2, activation='softplus')) # Keeping Dens
model_3l_4n_exp.add(Dense(neurons, activation='softplus')) # Add another layer; three
model_3l_4n_exp.add(Dense(neurons, activation='softplus'))
# model_4l_4n_elu.add(Dense(neurons, activation='softplus'))
```

In [85]:

```
sgd = SGD(lr=0.1) # Keeping this in incase adjustments are needed
model_3l_4n_relu.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accur
model_3l_4n_tanh.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accur
model_3l_4n_sigmoid.compile(loss='binary_crossentropy', optimizer='adam', metrics=['ac
model_3l_4n_softplus.compile(loss='binary_crossentropy', optimizer='adam', metrics=['a
model_3l_4n_elu.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accura
model_3l_4n_exp.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accura
```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use
the legacy optimizer, e.g.,tf.keras.optimizers.legacy.SGD.
```

In [88]:

```
%%capture
# 400 Epoch Training
model_3l_4n_relu.fit(X, y, batch_size=12, epochs=400)
model_3l_4n_tanh.fit(X, y, batch_size=12, epochs=400)
# model_4l_4n_sigmoid.fit(X, y, batch_size=12, epochs=400)
    # Sigmoid Training is throwing an error - trying with other activation models
model_3l_4n_softplus.fit(X, y, batch_size=12, epochs=400)
model_3l_4n_elu.fit(X, y, batch_size=12, epochs=400)
model_3l_4n_exp.fit(X, y, batch_size=12, epochs=400)
```

In [89]:

```
# Accuracy Comparisons
model_3l_4n_relu_scores = model_4l_4n_relu.evaluate(X, y)
model_3l_4n_tanh_scores = model_4l_4n_tanh.evaluate(X, y)
model_3l_4n_softplus_scores = model_4l_4n_softplus.evaluate(X, y)
model_3l_4n_elu_scores = model_4l_4n_elu.evaluate(X, y)
model_3l_4n_exp_scores = model_4l_4n_exp.evaluate(X, y)

# Comparison
(model_3l_4n_relu_scores,
 model_3l_4n_tanh_scores,
 model_3l_4n_softplus_scores,
 model_3l_4n_elu_scores,
 model_3l_4n_exp_scores)
```

```
5/5 [==============================] - 0s 2ms/step - loss: 7.7125 - accuracy: 0.5000
5/5 [==============================] - 0s 1ms/step - loss: 1.5049 - accuracy: 0.2750
5/5 [==============================] - 0s 2ms/step - loss: 1.9509 - accuracy: 0.5000
5/5 [==============================] - 0s 1ms/step - loss: 0.0696 - accuracy: 0.2062
5/5 [==============================] - 0s 3ms/step - loss: 0.6844 - accuracy: 0.3125
```

Out[89]:
```
([7.7124738693237305, 0.5],
 [1.504901647567749, 0.2750000059604645],
 [1.9508568048477173, 0.5],
 [0.06959564983844757, 0.20624999701976776],
 [0.6844061613082886, 0.3125])
```

In [94]:
```
# Comparing Accuracy, relu and softplus are providing the best results, with .500 accu
# vs sub-.500 for the other models. Using relu for simplicity
```

In [95]:
```
model_3l_4n_relu_sgd = model_3l_4n_relu
model_3l_4n_relu_RMSprop = model_3l_4n_relu
model_3l_4n_relu_Adadelta = model_3l_4n_relu
model_3l_4n_relu_Nadam = model_3l_4n_relu
model_3l_4n_relu_Ftrl = model_3l_4n_relu
```

In [96]:
```
# 4. Again with the most optimal setup, try other optimizers (instead of `SGD`) and re

model_3l_4n_relu_sgd.compile(loss='binary_crossentropy', optimizer='SGD', metrics=['ac
model_3l_4n_relu_RMSprop.compile(loss='binary_crossentropy', optimizer='RMSprop', metr
# model_4l_4n_relu_adamW = model_4l_4n_relu.compile(loss='binary_crossentropy', optimi
model_3l_4n_relu_Adadelta.compile(loss='binary_crossentropy', optimizer='Adadelta', me
model_3l_4n_relu_Nadam.compile(loss='binary_crossentropy', optimizer='Nadam', metrics=
model_3l_4n_relu_Ftrl.compile(loss='binary_crossentropy', optimizer='Ftrl', metrics=['
```

In [97]:
```
%%capture
# 400 Epoch Training
np.random.seed(2023)
model_3l_4n_relu_sgd.fit(X, y, batch_size=12, epochs=400)
model_3l_4n_relu_RMSprop.fit(X, y, batch_size=12, epochs=400)
model_3l_4n_relu_Adadelta.fit(X, y, batch_size=12, epochs=400)
model_3l_4n_relu_Nadam.fit(X, y, batch_size=12, epochs=400)
model_3l_4n_relu_Ftrl.fit(X, y, batch_size=12, epochs=400)
```

In [98]:
```
# Accuracy Comparisons
model_3l_4n_relu_sgd_scores = model_4l_4n_relu_sgd.evaluate(X, y)
model_3l_4n_relu_RMSprop_scores = model_4l_4n_relu_RMSprop.evaluate(X, y)
model_3l_4n_relu_Adadelta_scores = model_4l_4n_relu_Adadelta.evaluate(X, y)
model_3l_4n_relu_Nadam_scores = model_4l_4n_relu_Nadam.evaluate(X, y)
model_3l_4n_relu_Ftrl_scores = model_4l_4n_relu_Ftrl.evaluate(X, y)
```

```
5/5 [==============================] - 0s 1ms/step - loss: 7.7125 - accuracy: 0.5000
5/5 [==============================] - 0s 2ms/step - loss: 7.7125 - accuracy: 0.5000
5/5 [==============================] - 0s 2ms/step - loss: 7.7125 - accuracy: 0.5000
5/5 [==============================] - 0s 1ms/step - loss: 7.7125 - accuracy: 0.5000
5/5 [==============================] - 0s 2ms/step - loss: 7.7125 - accuracy: 0.5000
```

In [45]:
```
# The differences in accuracy is relatively minimal between the various classifiers.
```

Part 2 - BYOD (Bring your own Dataset)

Using your own dataset, experiment and find the best Neural Network configuration. You may use any resource to improve results, just reference it.

While you may use any dataset, I'd prefer you didn't use the diabetes dataset used in the lesson.

https://stackoverflow.com/questions/34673164/how-to-train-and-tune-an-artificial-multilayer-perceptron-neural-network-using-k

https://keras.io/

In [99]:
```
# BYOD Info
# Source: https://www.kaggle.com/datasets/fedesoriano/stellar-classification-dataset-s
# Column meanings for reference:
    # alpha = Right Ascension angle (at J2000 epoch)
    # delta = Declination angle (at J2000 epoch)
    # u = Ultraviolet filter in the photometric system
    # g = Green filter in the photometric system
    # r = Red filter in the photometric system
    # i = Near Infrared filter in the photometric system
    # z = Infrared filter in the photometric system
    # redshift = redshift value based on the increase in wavelength
```

In [100…
```
import pandas as pd
stars = pd.read_csv('../data/star_classification.csv')
stars.head()
```

Out[100]:

	obj_ID	alpha	delta	u	g	r	i	z	run_ID	rer
0	1.237661e+18	135.689107	32.494632	23.87882	22.27530	20.39501	19.16573	18.79371	3606	
1	1.237665e+18	144.826101	31.274185	24.77759	22.83188	22.58444	21.16812	21.61427	4518	
2	1.237661e+18	142.188790	35.582444	25.26307	22.66389	20.60976	19.34857	18.94827	3606	
3	1.237663e+18	338.741038	-0.402828	22.13682	23.77656	21.61162	20.50454	19.25010	4192	
4	1.237680e+18	345.282593	21.183866	19.43718	17.58028	16.49747	15.97711	15.54461	8102	

In [101…
```
stars_classes = stars['class'].drop_duplicates()
stars_classes
```

Out[101]:
```
0    GALAXY
5       QSO
9      STAR
Name: class, dtype: object
```

In [102…
```
from sklearn.preprocessing import OneHotEncoder
enc = OneHotEncoder()
enc.fit(stars[['class']])
```

Out[102]:
```
▾ OneHotEncoder
OneHotEncoder()
```

In [103…
```
encoded_values = enc.transform(stars[['class']])
encoded_dataframe = pd.DataFrame(encoded_values.toarray())
encoded_dataframe.shape
```

Out[103]:
```
(100000, 3)
```

In [105…

```
encoded_dataframe[1].sum()
# There are just under 19k stars out of 100k rows
is_star = encoded_dataframe[1]
is_star
```

Out[105]:

```
0        0.0
1        0.0
2        0.0
3        0.0
4        0.0
        ...
99995    0.0
99996    0.0
99997    0.0
99998    0.0
99999    0.0
Name: 1, Length: 100000, dtype: float64
```

In [106…

```
stars_lean = stars[['alpha', 'delta','u','g','r','i','z', 'redshift']]
stars_lean
```

Out[106]:

	alpha	delta	u	g	r	i	z	redshift
0	135.689107	32.494632	23.87882	22.27530	20.39501	19.16573	18.79371	0.634794
1	144.826101	31.274185	24.77759	22.83188	22.58444	21.16812	21.61427	0.779136
2	142.188790	35.582444	25.26307	22.66389	20.60976	19.34857	18.94827	0.644195
3	338.741038	-0.402828	22.13682	23.77656	21.61162	20.50454	19.25010	0.932346
4	345.282593	21.183866	19.43718	17.58028	16.49747	15.97711	15.54461	0.116123
...	...	...	...	...	...	...	...	...
99995	39.620709	-2.594074	22.16759	22.97586	21.90404	21.30548	20.73569	0.000000
99996	29.493819	19.798874	22.69118	22.38628	20.45003	19.75759	19.41526	0.404895
99997	224.587407	15.700707	21.16916	19.26997	18.20428	17.69034	17.35221	0.143366
99998	212.268621	46.660365	25.35039	21.63757	19.91386	19.07254	18.62482	0.455040
99999	196.896053	49.464643	22.62171	21.79745	20.60115	20.00959	19.28075	0.542944

100000 rows × 8 columns

In [107…

```
stars_nn = pd.concat([stars_lean, encoded_dataframe[1]], axis=1)
stars_nn.rename(columns={1: 'is_star'}, inplace=True)
stars_nn
```

Out[107]:

	alpha	delta	u	g	r	i	z	redshift	is_star
0	135.689107	32.494632	23.87882	22.27530	20.39501	19.16573	18.79371	0.634794	0.0
1	144.826101	31.274185	24.77759	22.83188	22.58444	21.16812	21.61427	0.779136	0.0
2	142.188790	35.582444	25.26307	22.66389	20.60976	19.34857	18.94827	0.644195	0.0
3	338.741038	-0.402828	22.13682	23.77656	21.61162	20.50454	19.25010	0.932346	0.0
4	345.282593	21.183866	19.43718	17.58028	16.49747	15.97711	15.54461	0.116123	0.0
...	...	...	...	...	...	...	...	...	...
99995	39.620709	-2.594074	22.16759	22.97586	21.90404	21.30548	20.73569	0.000000	0.0
99996	29.493819	19.798874	22.69118	22.38628	20.45003	19.75759	19.41526	0.404895	0.0
99997	224.587407	15.700707	21.16916	19.26997	18.20428	17.69034	17.35221	0.143366	0.0
99998	212.268621	46.660365	25.35039	21.63757	19.91386	19.07254	18.62482	0.455040	0.0
99999	196.896053	49.464643	22.62171	21.79745	20.60115	20.00959	19.28075	0.542944	0.0

100000 rows × 9 columns

In [137…

```
# Normalize Data
stars_lean_normal = (stars_lean-stars_lean.mean())/stars_lean.std()
stars_lean_normal
```

Out[137]:

	alpha	delta	u	g	r	i	z	redshift
0	-0.434601	0.425527	0.059754	0.054926	0.403960	0.046007	0.003937	0.079557
1	-0.339920	0.363400	0.088045	0.072456	1.584398	1.185091	0.092834	0.277095
2	-0.367249	0.582710	0.103326	0.067165	0.519743	0.150018	0.008808	0.092422
3	1.669515	-1.249099	0.004921	0.102209	1.059899	0.807606	0.018321	0.486768
4	1.737301	-0.150241	-0.080055	-0.092947	-1.697412	-1.767878	-0.098468	-0.630263
...	...	...	...	...	...	...	...	...
99995	-1.430106	-1.360643	0.005890	0.076991	1.217558	1.263230	0.065143	-0.789182
99996	-1.535045	-0.220743	0.022371	0.058421	0.433624	0.382694	0.023526	-0.235068
99997	0.486603	-0.429358	-0.025538	-0.039729	-0.777180	-0.793287	-0.041496	-0.592981
99998	0.358950	1.146625	0.106075	0.034840	0.144546	-0.007005	-0.001386	-0.166443
99999	0.199653	1.289375	0.020184	0.039876	0.515101	0.526047	0.019287	-0.046142

100000 rows × 8 columns

In [138…

```
## First NN
stars_nn_two_layers_two_neurons = Sequential()
stars_nn_two_layers_two_neurons.add(Dense(2, input_dim=8, activation='relu')) # Keepir
stars_nn_two_layers_two_neurons.add(Dense(2, activation='relu'))
```

In [139…
```
%%capture
sgd = SGD(lr=0.1)
stars_nn_two_layers_two_neurons.compile(loss='binary_crossentropy', optimizer='adam',
# Dataset is really big, so I am cutting the epochs down to a manageable size
stars_nn_two_layers_two_neurons.fit(stars_lean_normal, is_star, batch_size=12, epochs=
```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use
the legacy optimizer, e.g.,tf.keras.optimizers.legacy.SGD.
```

In [140…
```
# Accuracy
# Used a validation split (as per Stackoverflow thread)
stars_nn_two_layers_two_neurons_scores = stars_nn_two_layers_two_neurons.evaluate(star
(stars_nn_two_layers_two_neurons_scores)
```

```
3125/3125 [==============================] - 3s 1ms/step - loss: 2.7931 - accuracy:
0.6767
```

Out[140]:
```
[2.793077230453491, 0.6767299771308899]
```

In [141…
```
## Second NN - Adding Layers
stars_nn_three_layers_three_neurons = Sequential()
stars_nn_three_layers_three_neurons.add(Dense(3, input_dim=8, activation='relu')) # Ke
stars_nn_three_layers_three_neurons.add(Dense(3, activation='relu'))
stars_nn_three_layers_three_neurons.add(Dense(3, activation='relu'))
```

In [142…
```
%%capture
sgd = SGD(lr=0.1)
stars_nn_three_layers_three_neurons.compile(loss='binary_crossentropy', optimizer='ada
# Dataset is really big, so I am cutting the epochs down to a manageable size
stars_nn_three_layers_three_neurons.fit(stars_lean_normal, is_star, batch_size=12, epo
```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use
the legacy optimizer, e.g.,tf.keras.optimizers.legacy.SGD.
```

In [143…
```
# Accuracy
stars_nn_three_layers_three_neurons = stars_nn_two_layers_three_neurons.evaluate(stars
(stars_nn_three_layers_three_neurons)
```

```
3125/3125 [==============================] - 3s 879us/step - loss: 9.2134 - accuracy:
0.1906
```

Out[143]:
```
[9.21337890625, 0.19062000513076782]
```

In [144…
```
# This model performed worse; trying a model with mixed neurons next
```

In [145…
```
%%capture
# Third NN - Mixing Neurons
stars_nn_three_layers_mixed_neurons = Sequential()
stars_nn_three_layers_mixed_neurons.add(Dense(3, input_dim=8, activation='relu')) # Ke
stars_nn_three_layers_mixed_neurons.add(Dense(2, activation='relu'))
stars_nn_three_layers_mixed_neurons.add(Dense(3, activation='relu'))
sgd = SGD(lr=0.1)
stars_nn_three_layers_mixed_neurons.compile(loss='binary_crossentropy', optimizer='ada
# Dataset is really big, so I am cutting the epochs down to a manageable size
stars_nn_three_layers_mixed_neurons.fit(stars_lean_normal, is_star, batch_size=12, epo
```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use
the legacy optimizer, e.g.,tf.keras.optimizers.legacy.SGD.
```

In [146…

```
# Accuracy
stars_nn_three_layers_mixed_neurons_scores = stars_nn_three_layers_mixed_neurons.evalu
(stars_nn_three_layers_mixed_neurons)
```

```
3125/3125 [==============================] - 3s 978us/step - loss: 1.5917 - accuracy:
0.0000e+00
```

Out[146]:

```
<keras.src.engine.sequential.Sequential at 0x1749570b2e0>
```

In [147…

```
## The Mixed neuron model (3 layers, 1st and 3rd layer with 3 neurons and middle with
```

In [148…

```
%%capture
# Fourth NN - Changing Configurations
stars_nn_mixed_neurons_softplus = Sequential()
stars_nn_mixed_neurons_softplus.add(Dense(3, input_dim=8, activation='softplus')) # Ke
stars_nn_mixed_neurons_softplus.add(Dense(2, activation='softplus'))
stars_nn_mixed_neurons_softplus.add(Dense(3, activation='softplus'))
sgd = SGD(lr=0.1)
stars_nn_mixed_neurons_softplus.compile(loss='binary_crossentropy', optimizer='adam',
# Dataset is really big, so I am cutting the epochs down to a manageable size
stars_nn_mixed_neurons_softplus.fit(stars_lean_normal, is_star, batch_size=12, epochs=
```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use
the legacy optimizer, e.g.,tf.keras.optimizers.legacy.SGD.
```

In [149…

```
# Accuracy
stars_nn_mixed_neurons_softplus_scores = stars_nn_mixed_neurons_softplus.evaluate(star
(stars_nn_mixed_neurons_softplus_scores)
```

```
3125/3125 [==============================] - 3s 1ms/step - loss: 2.9248 - accuracy:
0.8104
```

Out[149]:

```
[2.9248480796813965, 0.8103899955749512]
```

In [150…

```
# The results of the softplus model were a improvement, with accuracy of .810
```

In [151…

```
%%capture
# Fifth NN - Adding Layers
stars_nn_mixed_neurons_five_layers = Sequential()
stars_nn_mixed_neurons_five_layers.add(Dense(3, input_dim=8, activation='softplus')) #
stars_nn_mixed_neurons_five_layers.add(Dense(2, activation='softplus'))
stars_nn_mixed_neurons_five_layers.add(Dense(3, activation='softplus'))
stars_nn_mixed_neurons_five_layers.add(Dense(2, activation='softplus'))
stars_nn_mixed_neurons_five_layers.add(Dense(2, activation='softplus'))
sgd = SGD(lr=0.1)
stars_nn_mixed_neurons_five_layers.compile(loss='binary_crossentropy', optimizer='adam
# Dataset is really big, so I am cutting the epochs down to a manageable size
stars_nn_mixed_neurons_five_layers.fit(stars_lean_normal, is_star, batch_size=12, epoc
```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use
the legacy optimizer, e.g.,tf.keras.optimizers.legacy.SGD.
```

In [152…

```
# Accuracy
stars_nn_mixed_neurons_five_layers_scores = stars_nn_mixed_neurons_five_layers.evaluat
(stars_nn_mixed_neurons_five_layers_scores)
```

```
3125/3125 [==============================] - 4s 1ms/step - loss: 7.6413 - accuracy:
0.8104
```

Out[152]:

```
[7.641303062438965, 0.8103799819946289]
```

In [ ]:
```
# Additional layers stayed in the same general area of accuracy, but with a greater lo
```