

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/> (<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/> (<https://keras.io/optimizers/>))

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

<https://keras.io/> (<https://keras.io/>)

```
In [34]: !pip3 install tensorflow keras
```

```
Requirement already satisfied: tensorflow in /Users/obelisk/anaconda3/lib/python3.10/site-packages (2.13.0)
```

```
Requirement already satisfied: keras in /Users/obelisk/anaconda3/lib/python3.10/site-packages (2.13.1)
```

```
Requirement already satisfied: tensorboard<2.14,>=2.13 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (2.13.0)
```

Requirement already satisfied: tensorflow-io-gcs-filesystem<=0.23.1 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (0.32.0)

Requirement already satisfied: six<=1.12.0 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (1.16.0)

Requirement already satisfied: opt-einsum<=2.3.2 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (3.3.0)

Requirement already satisfied: termcolor<=1.1.0 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (2.3.0)

Requirement already satisfied: astunparse<=1.6.0 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (1.6.3)

Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.4,!=4.21.5,<5.0.0dev,>=3.20.3 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (4.23.4)

Requirement already satisfied: grpcio<2.0,>=1.24.3 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (1.56.0)

Requirement already satisfied: wrapt<=1.11.0 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (1.14.1)

Requirement already satisfied: packaging in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (22.0)

Requirement already satisfied: numpy<=1.24.3,>=1.22 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (1.23.5)

Requirement already satisfied: typing-extensions<4.6.0,>=3.6.6 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (4.4.0)

Requirement already satisfied: gast<=0.4.0,>=0.2.1 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (0.4.0)

Requirement already satisfied: h5py<=2.9.0 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (3.7.0)

Requirement already satisfied: absl-py<=1.0.0 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (1.4.0)

Requirement already satisfied: setuptools in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (65.6.3)

Requirement already satisfied: tensorflow-estimator<2.14,>=2.13.0 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (2.13.0)

Requirement already satisfied: flatbuffers<=23.1.21 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (23.5.26)

Requirement already satisfied: libclang<=13.0.0 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (16.0.0)

Requirement already satisfied: google-pasta<=0.1.1 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorflow) (0.2.0)

Requirement already satisfied: wheel<1.0,>=0.23.0 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from astunparse<=1.6.0->tensorflow) (0.38.4)

Requirement already satisfied: google-auth-oauthlib<1.1,>=0.5 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorboard<2.14,>=2.13->tensorflow) (1.0.0)

Requirement already satisfied: markdown<=2.6.8 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorboard<2.14,>=2.13->ten

sorflow) (3.4.1)

Requirement already satisfied: werkzeug>=1.0.1 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorboard<2.14,>=2.13->tensorflow) (2.2.2)

Requirement already satisfied: requests<3,>=2.21.0 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorboard<2.14,>=2.13->tensorflow) (2.28.1)

Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorboard<2.14,>=2.13->tensorflow) (0.7.1)

Requirement already satisfied: google-auth<3,>=1.6.3 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from tensorboard<2.14,>=2.13->tensorflow) (2.21.0)

Requirement already satisfied: urllib3<2.0 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from google-auth<3,>=1.6.3->tensorboard<2.14,>=2.13->tensorflow) (1.26.14)

Requirement already satisfied: rsa<5,>=3.1.4 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from google-auth<3,>=1.6.3->tensorboard<2.14,>=2.13->tensorflow) (4.9)

Requirement already satisfied: pyasn1-modules>=0.2.1 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from google-auth<3,>=1.6.3->tensorboard<2.14,>=2.13->tensorflow) (0.2.8)

Requirement already satisfied: cachetools<6.0,>=2.0.0 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from google-auth<3,>=1.6.3->tensorboard<2.14,>=2.13->tensorflow) (5.3.1)

Requirement already satisfied: requests-oauthlib>=0.7.0 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from google-auth-oauthlib<1.1,>=0.5->tensorboard<2.14,>=2.13->tensorflow) (1.3.1)

Requirement already satisfied: certifi>=2017.4.17 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from requests<3,>=2.21.0->tensorboard<2.14,>=2.13->tensorflow) (2022.12.7)

Requirement already satisfied: charset-normalizer<3,>=2 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from requests<3,>=2.21.0->tensorboard<2.14,>=2.13->tensorflow) (2.0.4)

Requirement already satisfied: idna<4,>=2.5 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from requests<3,>=2.21.0->tensorboard<2.14,>=2.13->tensorflow) (3.4)

Requirement already satisfied: MarkupSafe>=2.1.1 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from werkzeug>=1.0.1->tensorboard<2.14,>=2.13->tensorflow) (2.1.1)

Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from pyasn1-modules>=0.2.1->google-auth<3,>=1.6.3->tensorboard<2.14,>=2.13->tensorflow) (0.4.8)

Requirement already satisfied: oauthlib>=3.0.0 in /Users/obelisk/anaconda3/lib/python3.10/site-packages (from requests-oauthlib>=0.7.0->google-auth-oauthlib<1.1,>=0.5->tensorboard<2.14,>=2.13->tensorflow) (3.2.2)

```
In [2]: from keras.models import Sequential
        from keras.layers import Dense
        from keras.optimizers import SGD #Stochastic Gradient Descent

        import pandas as pd
        import numpy as np
        # fix random seed for reproducibility
        np.random.seed(7)

        import matplotlib.pyplot as plt
        %matplotlib inline
```

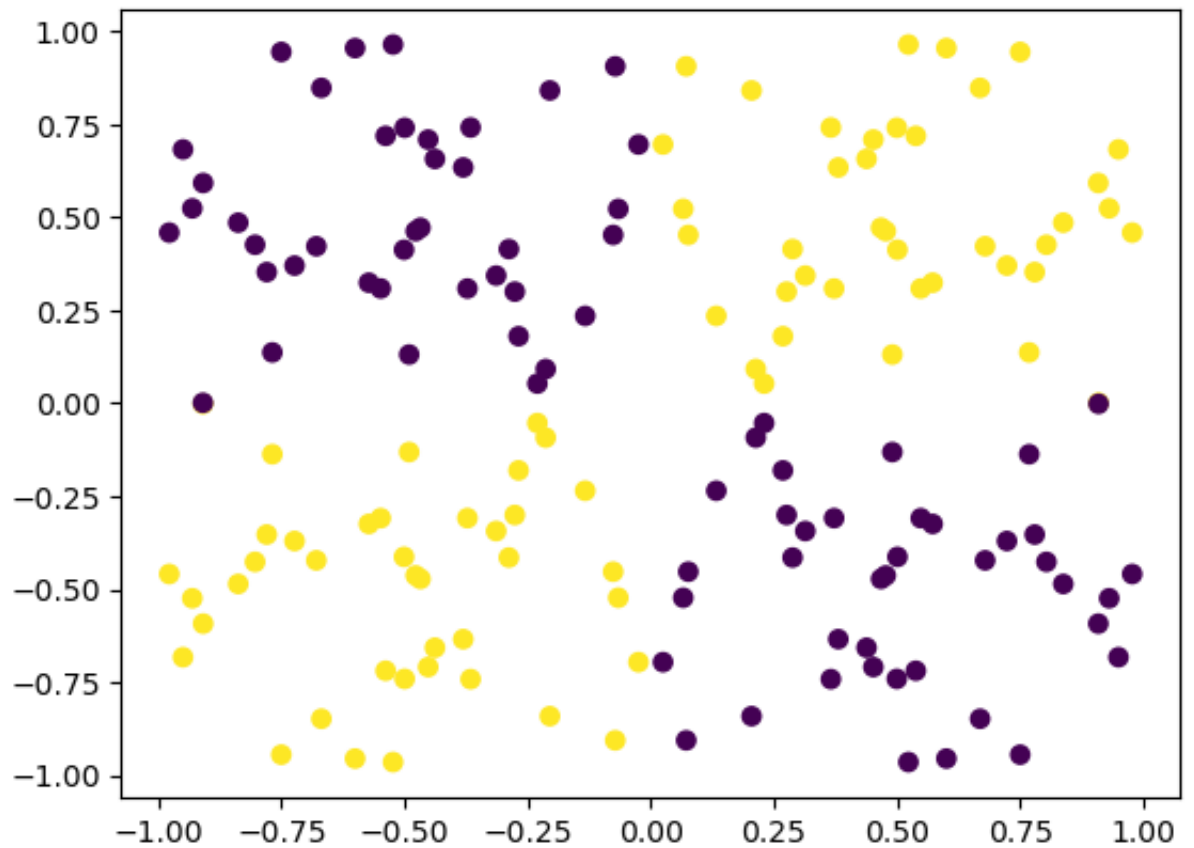
2023-07-16 14:23:05.935864: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.

```
In [3]: n = 40
        xx = np.random.random((n,1))
        yy = np.random.random((n,1))
```

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

```
In [5]: plt.scatter(*zip(*X), c=y)
```

```
Out[5]: <matplotlib.collections.PathCollection at 0x7fda2b1930d0>
```



```
In [6]:
```

```

num_layers = [1,2,3,4,5]
scores = []
plt.figure(figsize=(12, 8))
model = Sequential()
model.add(Dense(2, input_dim=2, activation='tanh'))
sgd = SGD(learning_rate=0.1)

for num_layer in num_layers:
    # for the first iteration, the model will only have the base layer
    if num_layer > 1:
        model.add(Dense(2, activation='tanh'))

    model.compile(loss='binary_crossentropy', optimizer='Adam')

    history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

    plt.plot(history.history['loss'], label=f'{num_layer} layers')

    model.summary()

    score = model.evaluate(X, y)
    scores.append(score)

plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Loss vs. Epochs for Different Number of Layers')
plt.legend()
plt.show()
printout = [item for sublist in zip(num_layers, scores) for item in sublist]
print("2 Neurons per layer:", printout)

```

Model: "sequential"

| Layer (type) | Output Shape | Param # |
|---------------|--------------|---------|
| dense (Dense) | (None, 2) | 6 |

```

Total params: 6 (24.00 Byte)
Trainable params: 6 (24.00 Byte)
Non-trainable params: 0 (0.00 Byte)

```

5/5 [=====] - 0s 1ms/step - loss: 0.6931
Model: "sequential"

| Layer (type) | Output Shape | Param # |
|-----------------|--------------|---------|
| dense (Dense) | (None, 2) | 6 |
| dense_1 (Dense) | (None, 2) | 6 |

```

=====
Total params: 12 (48.00 Byte)
Trainable params: 12 (48.00 Byte)
Non-trainable params: 0 (0.00 Byte)

```

```

5/5 [=====] - 0s 1ms/step - loss: 4.0120
Model: "sequential"

```

| Layer (type) | Output Shape | Param # |
|-----------------|--------------|---------|
| dense (Dense) | (None, 2) | 6 |
| dense_1 (Dense) | (None, 2) | 6 |
| dense_2 (Dense) | (None, 2) | 6 |

```

=====
Total params: 18 (72.00 Byte)
Trainable params: 18 (72.00 Byte)
Non-trainable params: 0 (0.00 Byte)

```

```

5/5 [=====] - 0s 1ms/step - loss: 4.0095
Model: "sequential"

```

| Layer (type) | Output Shape | Param # |
|-----------------|--------------|---------|
| dense (Dense) | (None, 2) | 6 |
| dense_1 (Dense) | (None, 2) | 6 |
| dense_2 (Dense) | (None, 2) | 6 |
| dense_3 (Dense) | (None, 2) | 6 |

```

=====
Total params: 24 (96.00 Byte)
Trainable params: 24 (96.00 Byte)
Non-trainable params: 0 (0.00 Byte)

```

```

5/5 [=====] - 0s 1ms/step - loss: 4.0093
Model: "sequential"

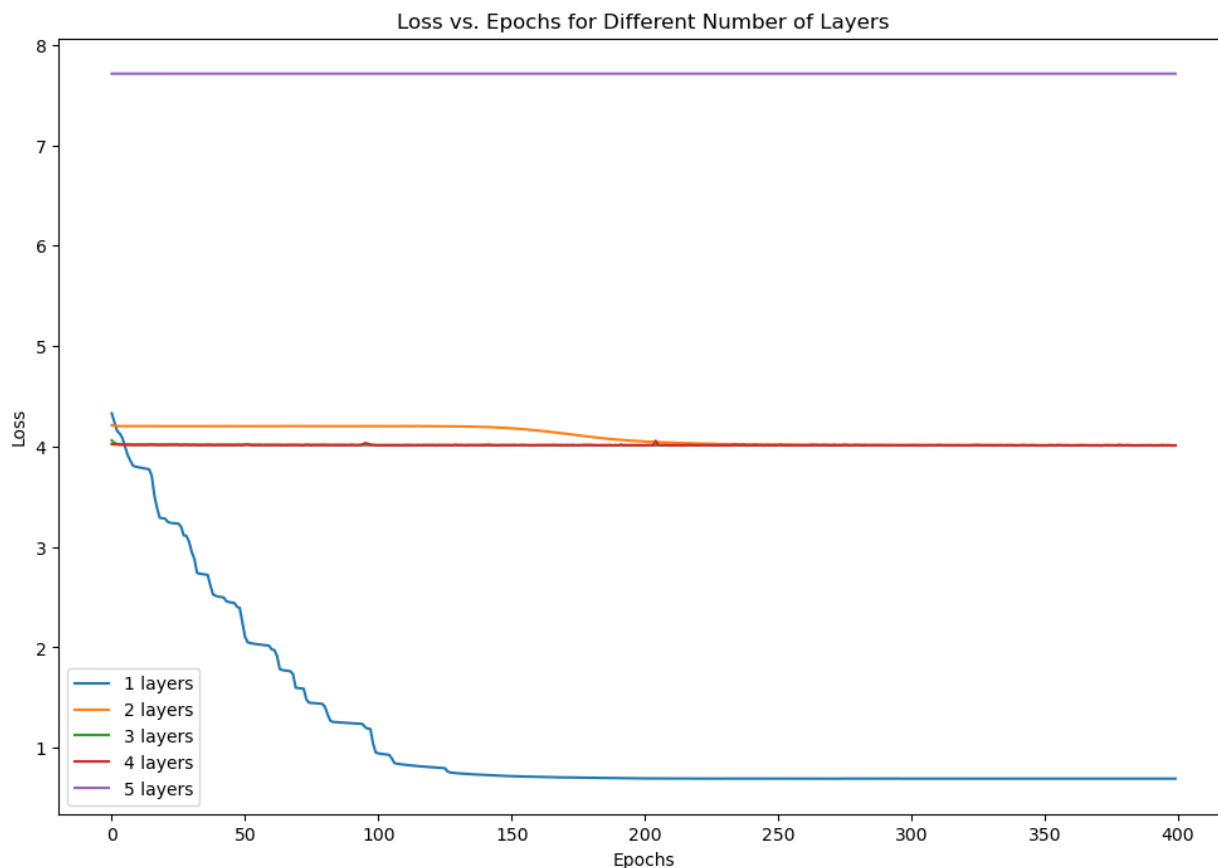
```

| Layer (type) | Output Shape | Param # |
|-----------------|--------------|---------|
| dense (Dense) | (None, 2) | 6 |
| dense_1 (Dense) | (None, 2) | 6 |
| dense_2 (Dense) | (None, 2) | 6 |

| | | |
|-----------------|-----------|---|
| dense_3 (Dense) | (None, 2) | 6 |
| dense_4 (Dense) | (None, 2) | 6 |

```
=====
Total params: 30 (120.00 Byte)
Trainable params: 30 (120.00 Byte)
Non-trainable params: 0 (0.00 Byte)
```

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



2 Neurons per layer: [1, 0.693149745464325, 2, 4.012002944946289, 3, 4.009472846984863, 4, 4.009335041046143, 5, 7.7124738693237305]

In [7]:


```

scores2 = []
plt.figure(figsize=(12, 8))
model = Sequential()
model.add(Dense(3, input_dim=2, activation='tanh'))

for num_layer in num_layers:

    if num_layer > 1:
        model.add(Dense(3, activation='tanh'))

    model.compile(loss='binary_crossentropy', optimizer='Adam')

    history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

    plt.plot(history.history['loss'], label=f'{num_layer} layers')

    model.summary()

    score = model.evaluate(X, y)
    scores2.append(score)

plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Loss vs. Epochs for Different Number of Layers')
plt.legend()
plt.show()
printout2 = [item for sublist in zip(num_layers, scores2) for item in
print("2 Neurons per layer:", printout)
print("3 Neurons per layer:", printout2)

```

Model: "sequential_1"

| Layer (type) | Output Shape | Param # |
|-----------------|--------------|---------|
| dense_5 (Dense) | (None, 3) | 9 |

```

=====
Total params: 9 (36.00 Byte)
Trainable params: 9 (36.00 Byte)
Non-trainable params: 0 (0.00 Byte)

```

5/5 [=====] - 0s 1ms/step - loss: 1.7975
Model: "sequential_1"

| Layer (type) | Output Shape | Param # |
|-----------------|--------------|---------|
| dense_5 (Dense) | (None, 3) | 9 |
| dense_6 (Dense) | (None, 3) | 12 |

```
=====
Total params: 21 (84.00 Byte)
Trainable params: 21 (84.00 Byte)
Non-trainable params: 0 (0.00 Byte)
```

```
5/5 [=====] - 0s 2ms/step - loss: 2.7003
Model: "sequential_1"
```

| Layer (type) | Output Shape | Param # |
|-----------------|--------------|---------|
| dense_5 (Dense) | (None, 3) | 9 |
| dense_6 (Dense) | (None, 3) | 12 |
| dense_7 (Dense) | (None, 3) | 12 |

```
=====
Total params: 33 (132.00 Byte)
Trainable params: 33 (132.00 Byte)
Non-trainable params: 0 (0.00 Byte)
```

```
5/5 [=====] - 0s 1ms/step - loss: 0.0573
Model: "sequential_1"
```

| Layer (type) | Output Shape | Param # |
|-----------------|--------------|---------|
| dense_5 (Dense) | (None, 3) | 9 |
| dense_6 (Dense) | (None, 3) | 12 |
| dense_7 (Dense) | (None, 3) | 12 |
| dense_8 (Dense) | (None, 3) | 12 |

```
=====
Total params: 45 (180.00 Byte)
Trainable params: 45 (180.00 Byte)
Non-trainable params: 0 (0.00 Byte)
```

```
5/5 [=====] - 0s 1ms/step - loss: 5.1497
Model: "sequential_1"
```

| Layer (type) | Output Shape | Param # |
|-----------------|--------------|---------|
| dense_5 (Dense) | (None, 3) | 9 |
| dense_6 (Dense) | (None, 3) | 12 |
| dense_7 (Dense) | (None, 3) | 12 |

| | | |
|-----------------|-----------|----|
| dense_8 (Dense) | (None, 3) | 12 |
| dense_9 (Dense) | (None, 3) | 12 |

```

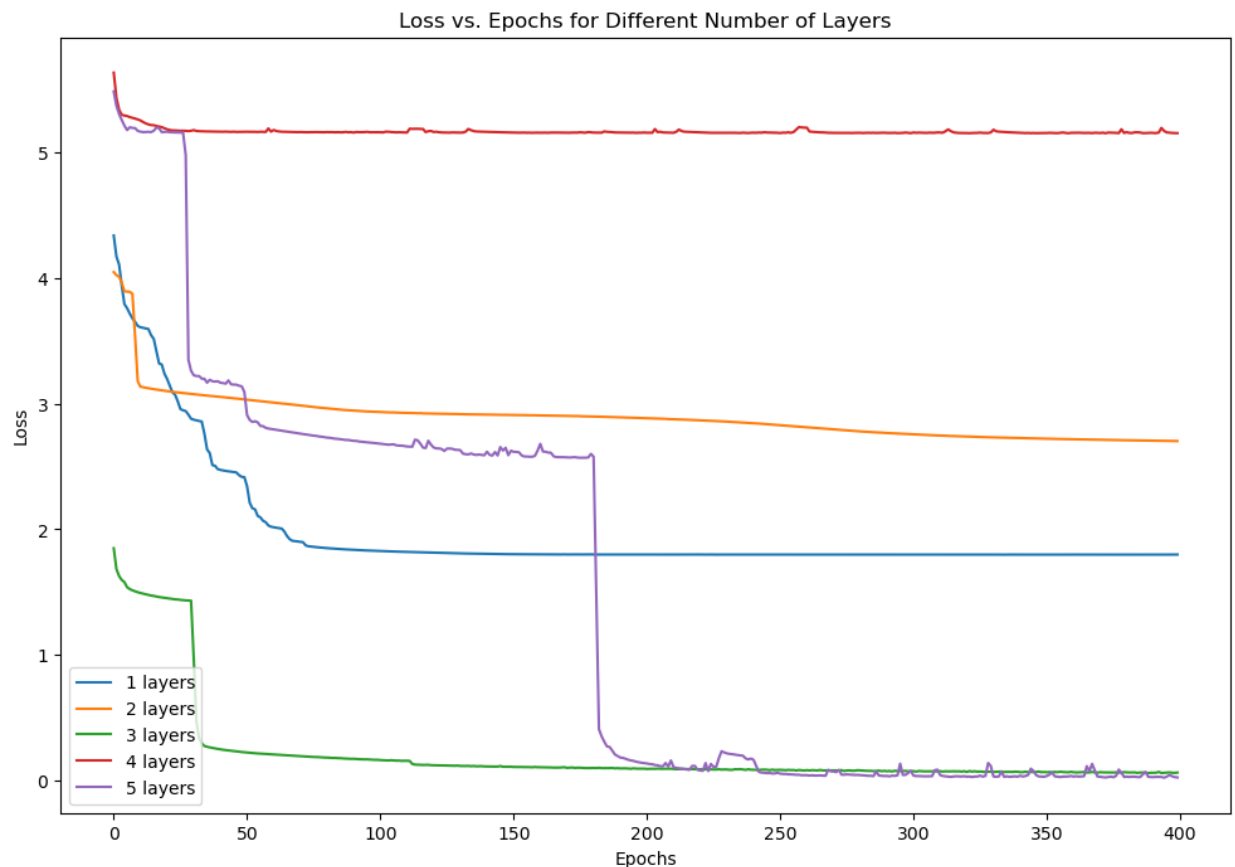
=====
Total params: 57 (228.00 Byte)
Trainable params: 57 (228.00 Byte)
Non-trainable params: 0 (0.00 Byte)

```

```

5/5 [=====] - 0s 1ms/step - loss: 0.0218

```



2 Neurons per layer: [1, 0.693149745464325, 2, 4.012002944946289, 3, 4.009472846984863, 4, 4.009335041046143, 5, 7.7124738693237305]
 3 Neurons per layer: [1, 1.797528862953186, 2, 2.700294017791748, 3, 0.057295072823762894, 4, 5.149728775024414, 5, 0.021826880052685738]

Over all the 3 neuron layers appear to perform generally better to the 2 neuron layers. The loss scores are lower than the 2 neuron layers. The best performance so far is 5 layer 3 neuron model with a loss of 0.022.

In [8]:

```

scores3 = []
plt.figure(figsize=(12, 8))
model = Sequential()
model.add(Dense(4, input_dim=2, activation='tanh'))

for num_layer in num_layers:

    if num_layer > 1:
        model.add(Dense(4, activation='tanh'))

    model.compile(loss='binary_crossentropy', optimizer='Adam')

    history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

    plt.plot(history.history['loss'], label=f'{num_layer} layers')

    model.summary()

    score = model.evaluate(X, y)
    scores3.append(score)

plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Loss vs. Epochs for Different Number of Layers')
plt.legend()
plt.show()
printout3 = [item for sublist in zip(num_layers, scores3) for item in
print("2 Neurons per layer:", printout)
print("3 Neurons per layer:", printout2)
print("4 Neurons per layer:", printout3)

```

Model: "sequential_2"

| Layer (type) | Output Shape | Param # |
|-------------------------------------|--------------|---------|
| dense_10 (Dense) | (None, 4) | 12 |
| Total params: 12 (48.00 Byte) | | |
| Trainable params: 12 (48.00 Byte) | | |
| Non-trainable params: 0 (0.00 Byte) | | |

5/5 [=====] - 0s 1ms/step - loss: 4.0063
Model: "sequential_2"

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_10 (Dense) | (None, 4) | 12 |
| dense_11 (Dense) | (None, 4) | 20 |

```

=====
Total params: 32 (128.00 Byte)
Trainable params: 32 (128.00 Byte)
Non-trainable params: 0 (0.00 Byte)

```

```

5/5 [=====] - 0s 1ms/step - loss: 3.0856
Model: "sequential_2"

```

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_10 (Dense) | (None, 4) | 12 |
| dense_11 (Dense) | (None, 4) | 20 |
| dense_12 (Dense) | (None, 4) | 20 |

```

=====
Total params: 52 (208.00 Byte)
Trainable params: 52 (208.00 Byte)
Non-trainable params: 0 (0.00 Byte)

```

```

5/5 [=====] - 0s 1ms/step - loss: 4.9333
Model: "sequential_2"

```

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_10 (Dense) | (None, 4) | 12 |
| dense_11 (Dense) | (None, 4) | 20 |
| dense_12 (Dense) | (None, 4) | 20 |
| dense_13 (Dense) | (None, 4) | 20 |

```

=====
Total params: 72 (288.00 Byte)
Trainable params: 72 (288.00 Byte)
Non-trainable params: 0 (0.00 Byte)

```

```

5/5 [=====] - 0s 1ms/step - loss: 0.1448
Model: "sequential_2"

```

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_10 (Dense) | (None, 4) | 12 |
| dense_11 (Dense) | (None, 4) | 20 |
| dense_12 (Dense) | (None, 4) | 20 |

| | | |
|------------------|-----------|----|
| dense_13 (Dense) | (None, 4) | 20 |
| dense_14 (Dense) | (None, 4) | 20 |

```

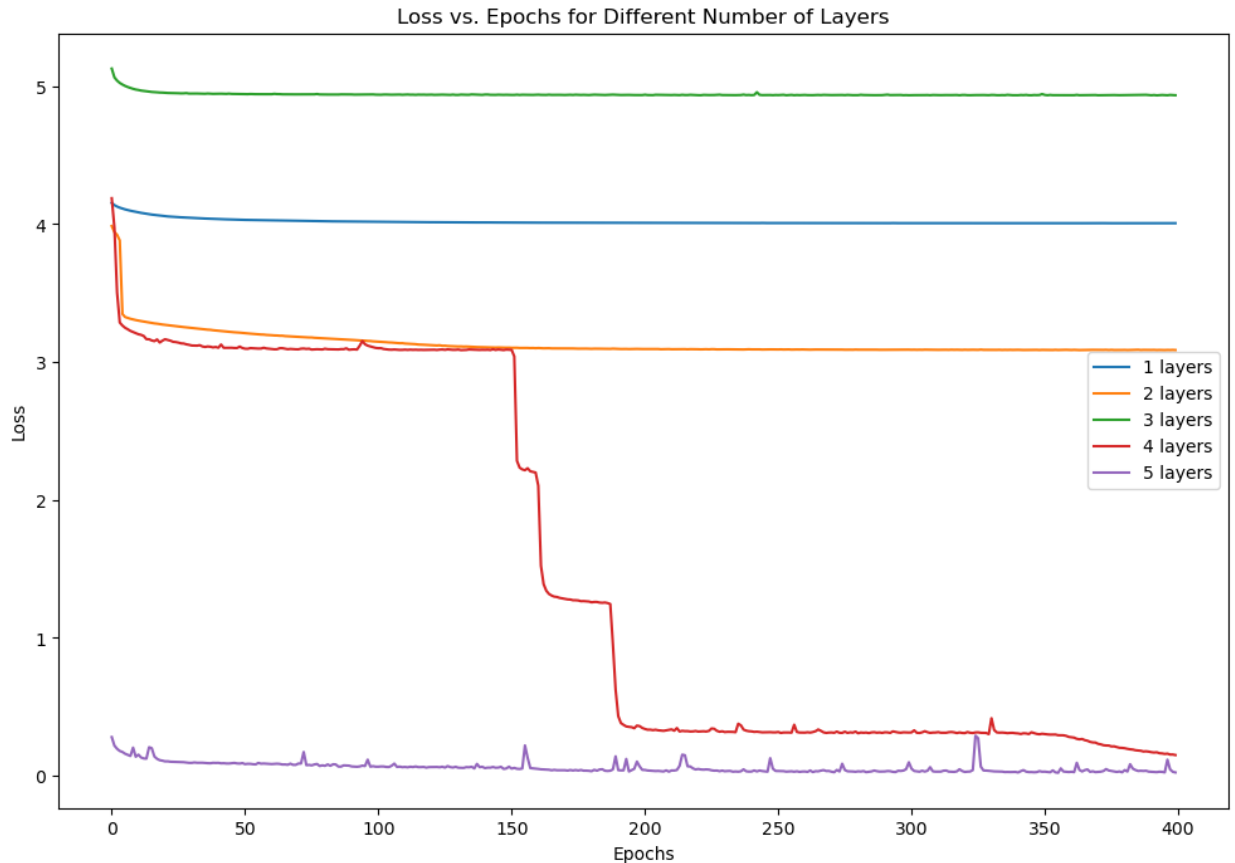
=====
Total params: 92 (368.00 Byte)
Trainable params: 92 (368.00 Byte)
Non-trainable params: 0 (0.00 Byte)

```

```

5/5 [=====] - 0s 1ms/step - loss: 0.0231

```



```

2 Neurons per layer: [1, 0.693149745464325, 2, 4.012002944946289, 3,
4.009472846984863, 4, 4.009335041046143, 5, 7.7124738693237305]
3 Neurons per layer: [1, 1.797528862953186, 2, 2.700294017791748, 3,
0.057295072823762894, 4, 5.149728775024414, 5, 0.021826880052685738]
4 Neurons per layer: [1, 4.006335735321045, 2, 3.0856049060821533, 3,
4.933342456817627, 4, 0.14478500187397003, 5, 0.023132342845201492]

```

Generally similar results to the 3 neuron models here. Seems to have more noise in the results of the loss scores.

Best results are 3 neurons and 5 layers from this iteration with a loss score of 0.022. Even after switching to the Adam optimizer from SGD I am seeing somewhat erratic results between each execution of the for-loop.

In [9]: # *tanh*

```
model = Sequential()

model.add(Dense(3, input_dim=2, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))

model.compile(loss='binary_crossentropy', optimizer='Adam')

history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

plt.plot(history.history['loss'], label='Tanh')

model.summary()

score_tanh = model.evaluate(X, y)

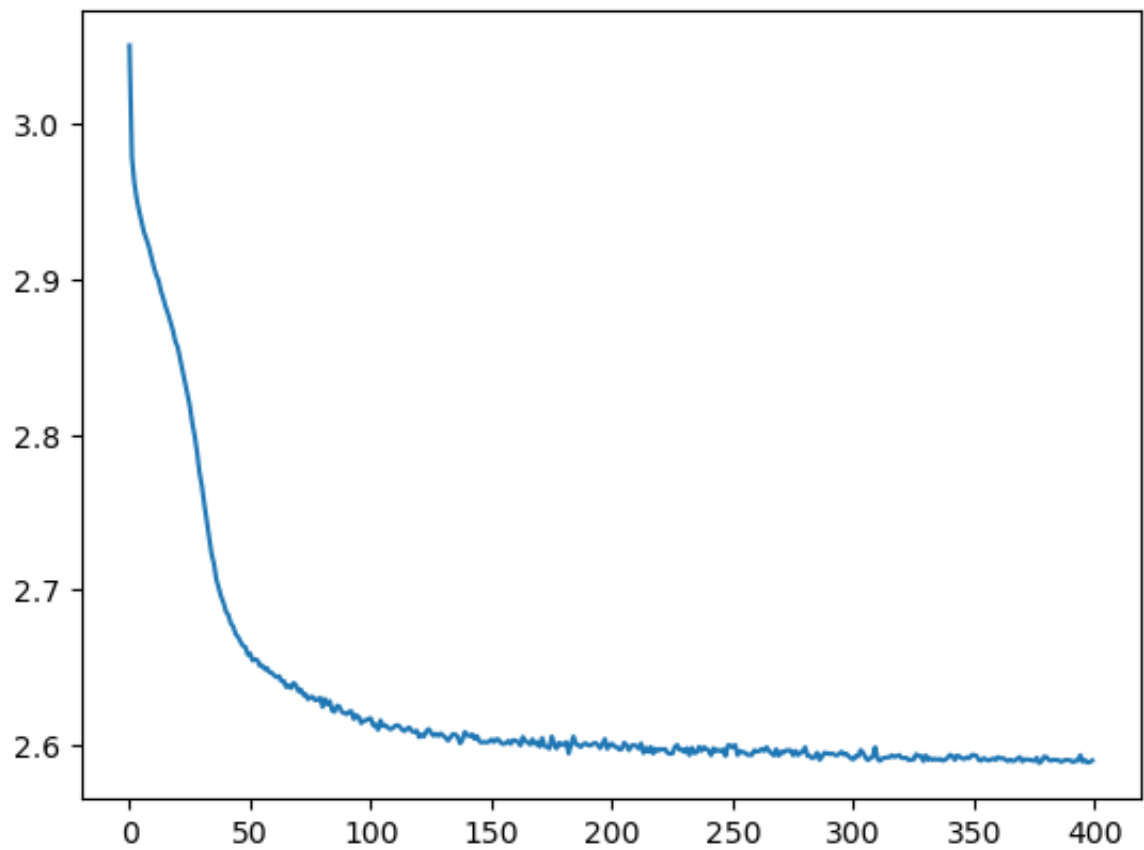
print("Tanh Loss Score:", score_tanh)
```

Model: "sequential_3"

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_15 (Dense) | (None, 3) | 9 |
| dense_16 (Dense) | (None, 3) | 12 |
| dense_17 (Dense) | (None, 3) | 12 |
| dense_18 (Dense) | (None, 3) | 12 |
| dense_19 (Dense) | (None, 3) | 12 |

```
=====
Total params: 57 (228.00 Byte)
Trainable params: 57 (228.00 Byte)
Non-trainable params: 0 (0.00 Byte)
=====
```

5/5 [=====] - 0s 1ms/step - loss: 2.5861
Tanh Loss Score: 2.5861058235168457



In [10]:


```

# sigmoid

model = Sequential()

model.add(Dense(3, input_dim=2, activation='sigmoid'))
model.add(Dense(3, activation='tanh')) # If I have more than 1 sigmoid
model.add(Dense(3, activation='tanh')) # If I have all sigmoid layers
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))

model.compile(loss='binary_crossentropy', optimizer='Adam')

history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

plt.plot(history.history['loss'], label='Sigmoid')

model.summary()

score_sigmoid = model.evaluate(X, y)

print("Sigmoid Loss Score:", score_sigmoid)

```

Model: "sequential_4"

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_20 (Dense) | (None, 3) | 9 |
| dense_21 (Dense) | (None, 3) | 12 |
| dense_22 (Dense) | (None, 3) | 12 |
| dense_23 (Dense) | (None, 3) | 12 |
| dense_24 (Dense) | (None, 3) | 12 |

```

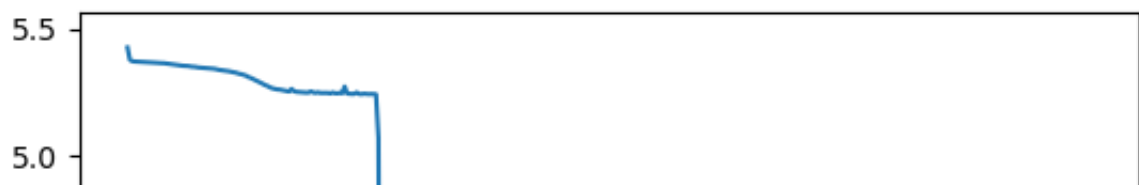
=====
Total params: 57 (228.00 Byte)
Trainable params: 57 (228.00 Byte)
Non-trainable params: 0 (0.00 Byte)

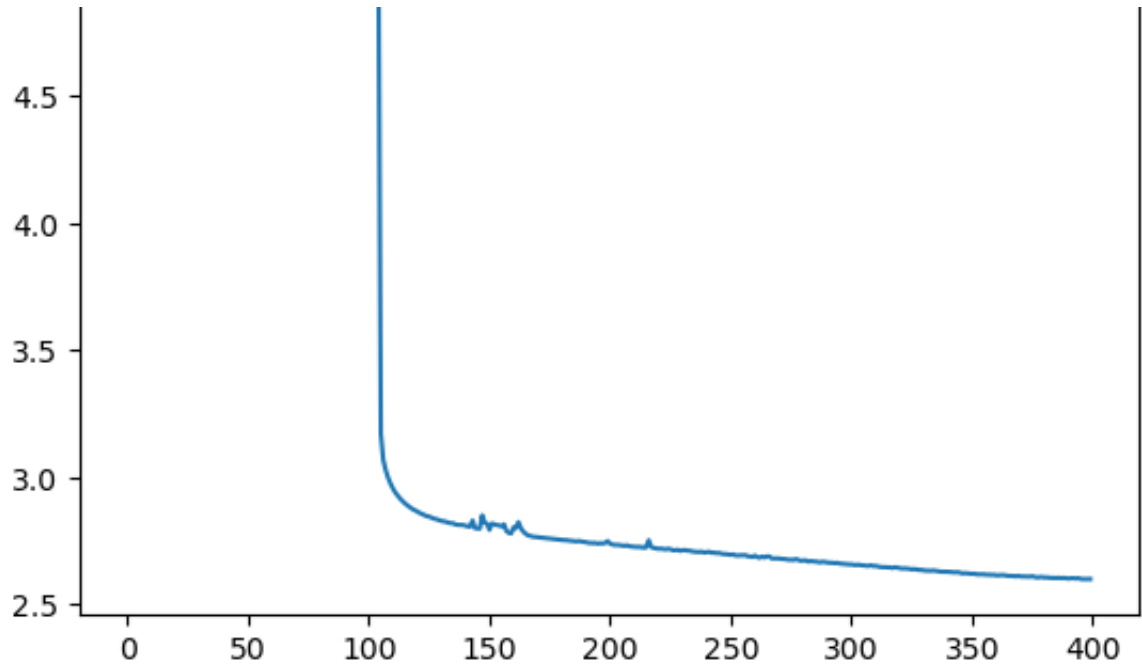
```

```

5/5 [=====] - 0s 1ms/step - loss: 2.5952
Sigmoid Loss Score: 2.595248222351074

```





In [12]: `# softplus`

```
model = Sequential()

model.add(Dense(3, input_dim=2, activation='softplus'))
model.add(Dense(3, activation='softplus'))
model.add(Dense(3, activation='softplus'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='softplus'))

model.compile(loss='binary_crossentropy', optimizer='Adam')

history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

plt.plot(history.history['loss'], label='Softplus')

model.summary()

score_soft_plus = model.evaluate(X, y)

print("Softplus Loss Score:", score_soft_plus)
```

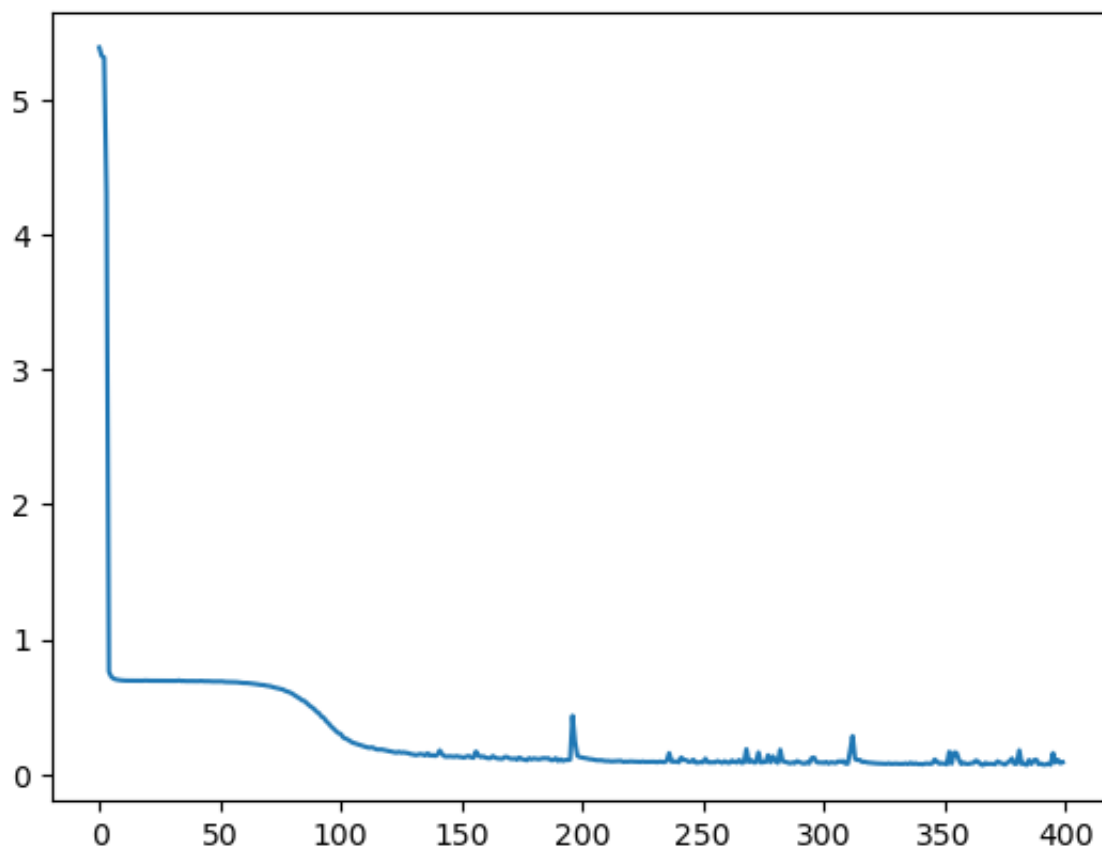
Model: "sequential_6"

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_30 (Dense) | (None, 3) | 9 |
| dense_31 (Dense) | (None, 3) | 12 |

| | | |
|------------------|-----------|----|
| dense_32 (Dense) | (None, 3) | 12 |
| dense_33 (Dense) | (None, 3) | 12 |
| dense_34 (Dense) | (None, 3) | 12 |

```
=====
Total params: 57 (228.00 Byte)
Trainable params: 57 (228.00 Byte)
Non-trainable params: 0 (0.00 Byte)
```

```
5/5 [=====] - 0s 1ms/step - loss: 0.0670
Softplus Loss Score: 0.06703799217939377
```



In [14]:

```

# relu

model = Sequential()

model.add(Dense(3, input_dim=2, activation='relu'))
model.add(Dense(3, activation='relu'))
model.add(Dense(3, activation='relu'))
model.add(Dense(3, activation='tanh')) # If I have 4 relu weird things
model.add(Dense(3, activation='tanh')) # If I have all relu weird things

model.compile(loss='binary_crossentropy', optimizer='Adam')

history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

plt.plot(history.history['loss'], label='Relu')

model.summary()

score_relu = model.evaluate(X, y)

print("Relu Loss Score:", score_relu)

```

Model: "sequential_8"

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_40 (Dense) | (None, 3) | 9 |
| dense_41 (Dense) | (None, 3) | 12 |
| dense_42 (Dense) | (None, 3) | 12 |
| dense_43 (Dense) | (None, 3) | 12 |
| dense_44 (Dense) | (None, 3) | 12 |

```

=====
Total params: 57 (228.00 Byte)
Trainable params: 57 (228.00 Byte)
Non-trainable params: 0 (0.00 Byte)

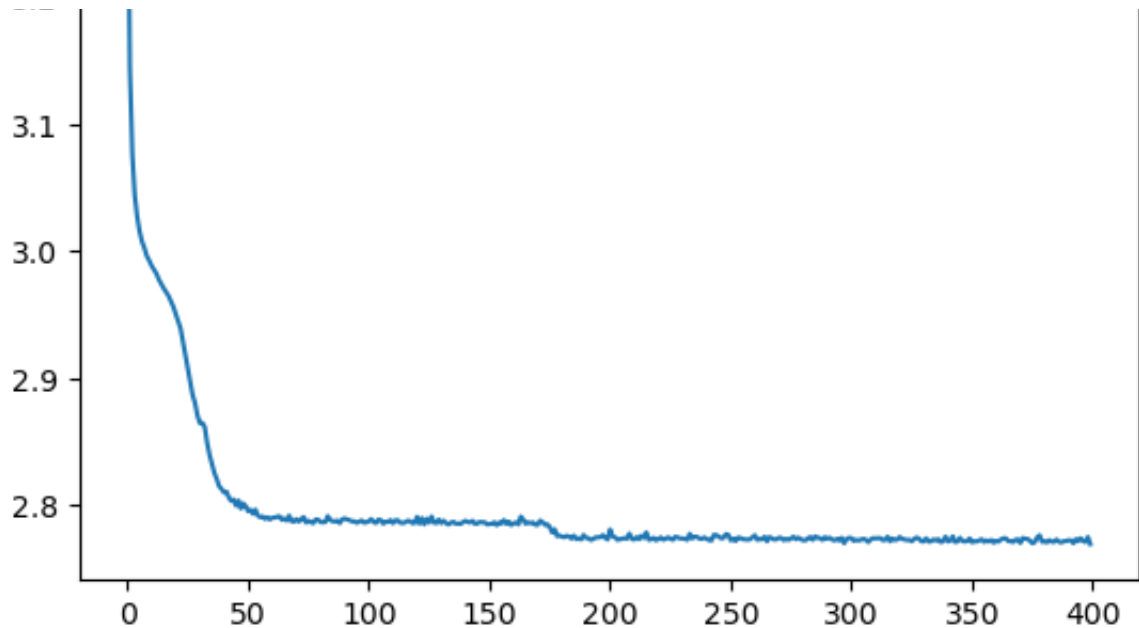
```

```

5/5 [=====] - 0s 1ms/step - loss: 2.7737
Relu Loss Score: 2.773733139038086

```





In [15]: `# softmax`

```
model = Sequential()

model.add(Dense(3, input_dim=2, activation='softmax'))
model.add(Dense(3, activation='tanh')) # Two softmax layers was less c
model.add(Dense(3, activation='tanh')) # If I have all softmax layers
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))

model.compile(loss='binary_crossentropy', optimizer='Adam')

history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

plt.plot(history.history['loss'], label='Softmax')

model.summary()

score_softmax = model.evaluate(X, y)

print("Softmax Loss Score:", score_softmax)
```

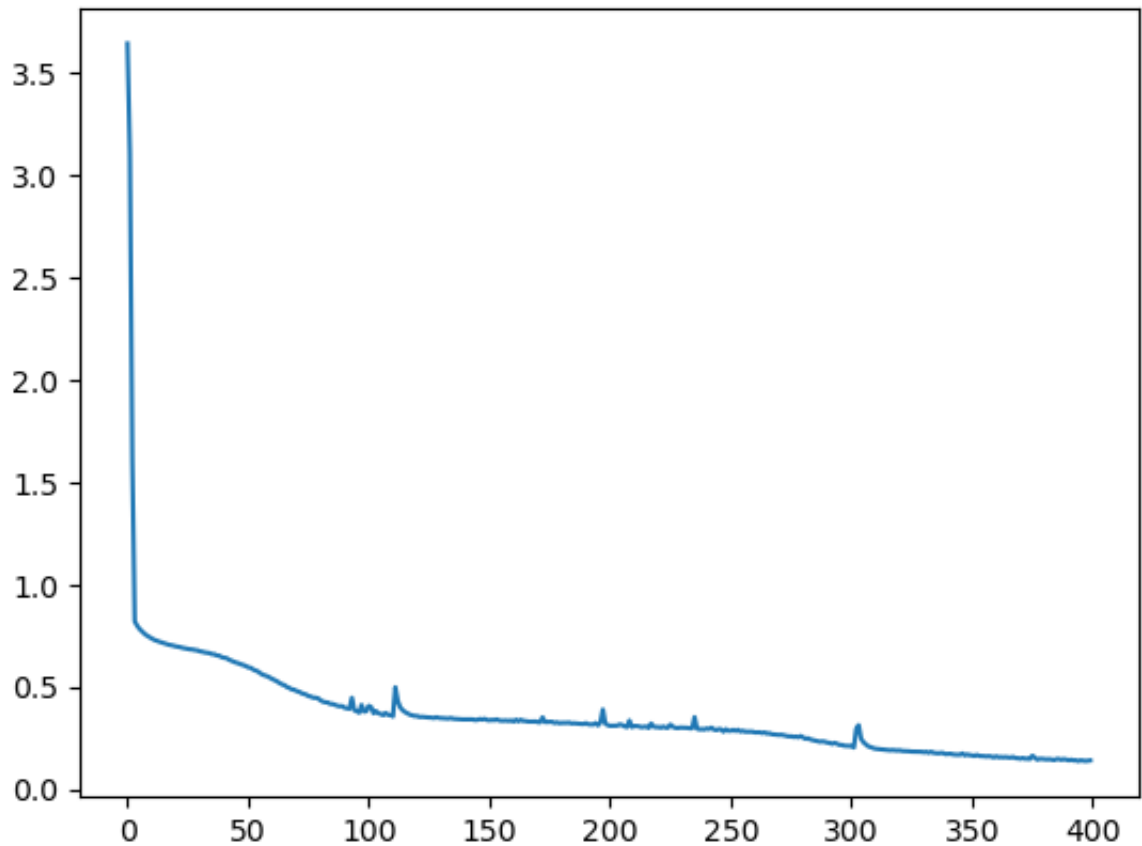
Model: "sequential_9"

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_45 (Dense) | (None, 3) | 9 |
| dense_46 (Dense) | (None, 3) | 12 |
| dense_47 (Dense) | (None, 3) | 12 |

| | | |
|------------------|-----------|----|
| dense_48 (Dense) | (None, 3) | 12 |
| dense_49 (Dense) | (None, 3) | 12 |

```
=====
Total params: 57 (228.00 Byte)
Trainable params: 57 (228.00 Byte)
Non-trainable params: 0 (0.00 Byte)
```

```
5/5 [=====] - 0s 1ms/step - loss: 0.1529
Softmax Loss Score: 0.15287908911705017
```



In [16]:

```

# softsign

model = Sequential()

model.add(Dense(3, input_dim=2, activation='softsign'))
model.add(Dense(3, activation='softsign'))
model.add(Dense(3, activation='softsign'))
model.add(Dense(3, activation='softsign'))
model.add(Dense(3, activation='tanh')) # 4 softsign layers with 1 tanh

model.compile(loss='binary_crossentropy', optimizer='Adam')

history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

plt.plot(history.history['loss'], label='Softsign')

model.summary()

score_softsign = model.evaluate(X, y)

print("Softsign Loss Score:", score_softsign)

```

Model: "sequential_10"

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_50 (Dense) | (None, 3) | 9 |
| dense_51 (Dense) | (None, 3) | 12 |
| dense_52 (Dense) | (None, 3) | 12 |
| dense_53 (Dense) | (None, 3) | 12 |
| dense_54 (Dense) | (None, 3) | 12 |

```

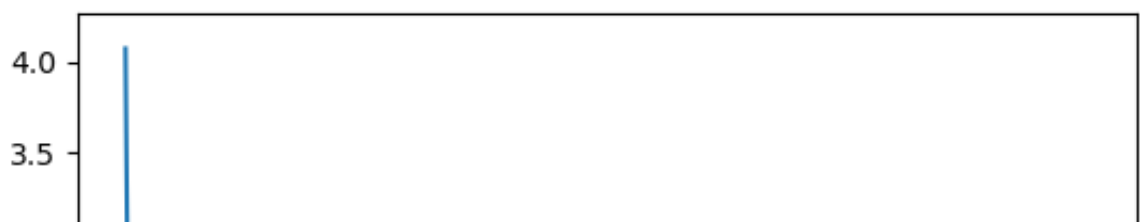
=====
Total params: 57 (228.00 Byte)
Trainable params: 57 (228.00 Byte)
Non-trainable params: 0 (0.00 Byte)

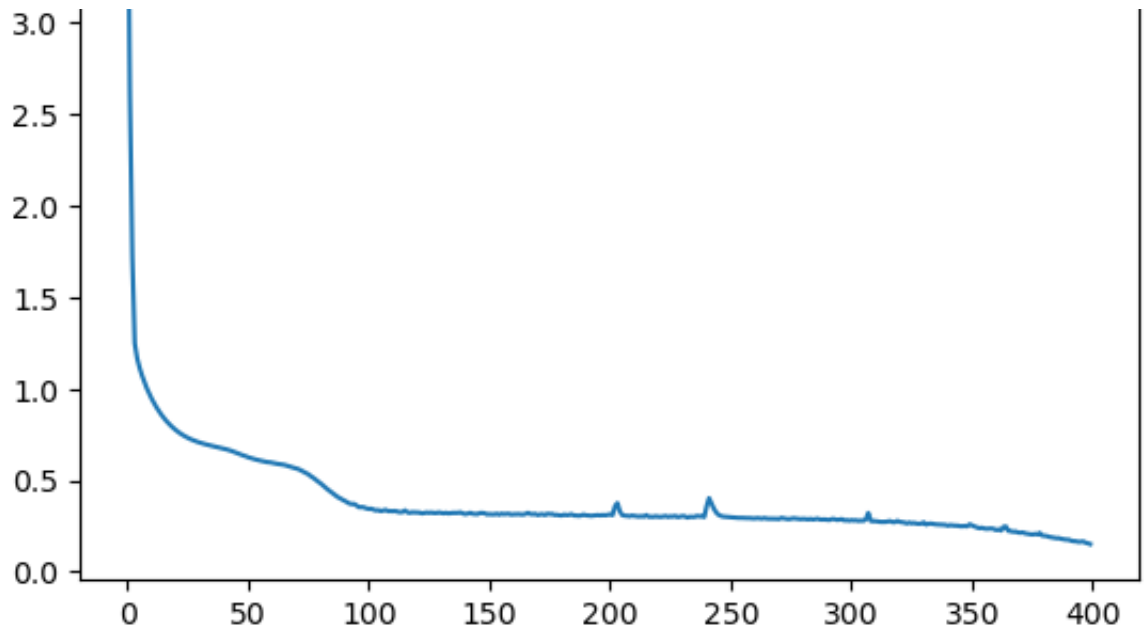
```

```

5/5 [=====] - 0s 1ms/step - loss: 0.1448
Softsign Loss Score: 0.14476850628852844

```





In [17]: `# elu`

```
model = Sequential()

model.add(Dense(3, input_dim=2, activation='elu'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh')) # Diminishing returns with elu.

model.compile(loss='binary_crossentropy', optimizer='Adam')

history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

plt.plot(history.history['loss'], label='Elu')

model.summary()

score_elu = model.evaluate(X, y)

print("Elu Loss Score:", score_elu)
```

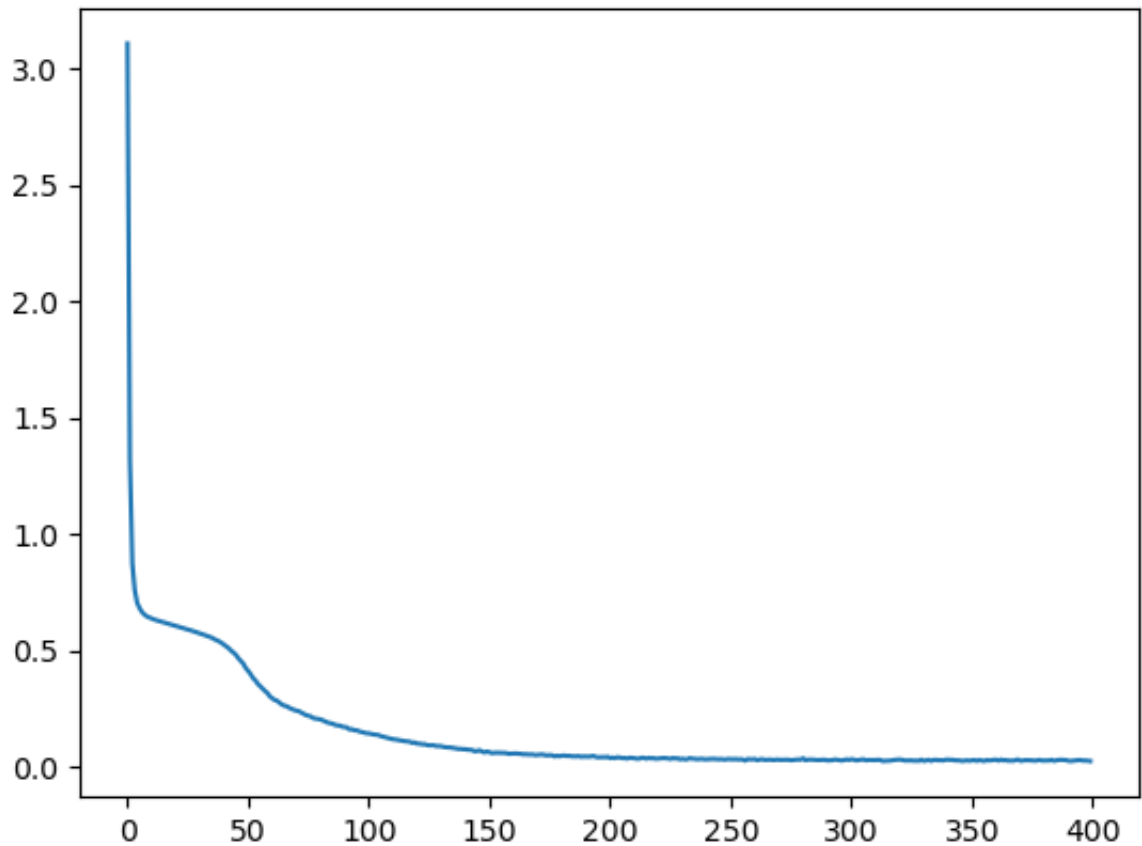
Model: "sequential_11"

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_55 (Dense) | (None, 3) | 9 |
| dense_56 (Dense) | (None, 3) | 12 |
| dense_57 (Dense) | (None, 3) | 12 |

| | | |
|------------------|-----------|----|
| dense_58 (Dense) | (None, 3) | 12 |
| dense_59 (Dense) | (None, 3) | 12 |

```
=====
Total params: 57 (228.00 Byte)
Trainable params: 57 (228.00 Byte)
Non-trainable params: 0 (0.00 Byte)
```

```
5/5 [=====] - 0s 1ms/step - loss: 0.0192
Elu Loss Score: 0.019223075360059738
```



In [18]:

```
# selu

model = Sequential()

model.add(Dense(3, input_dim=2, activation='selu'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh')) # Diminishing returns with selu

model.compile(loss='binary_crossentropy', optimizer='sgd')

history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

plt.plot(history.history['loss'], label='Selu')

model.summary()

score_selu = model.evaluate(X, y)

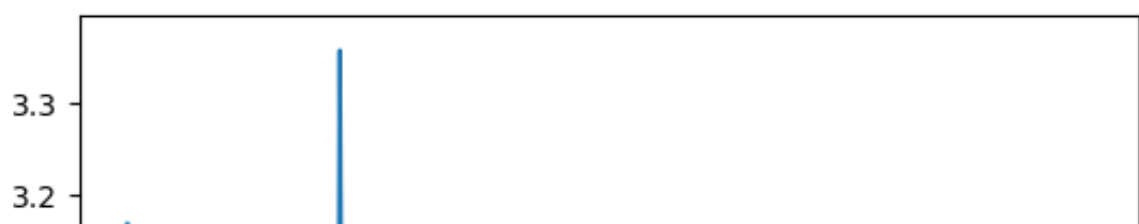
print("Selu Loss Score:", score_selu)
```

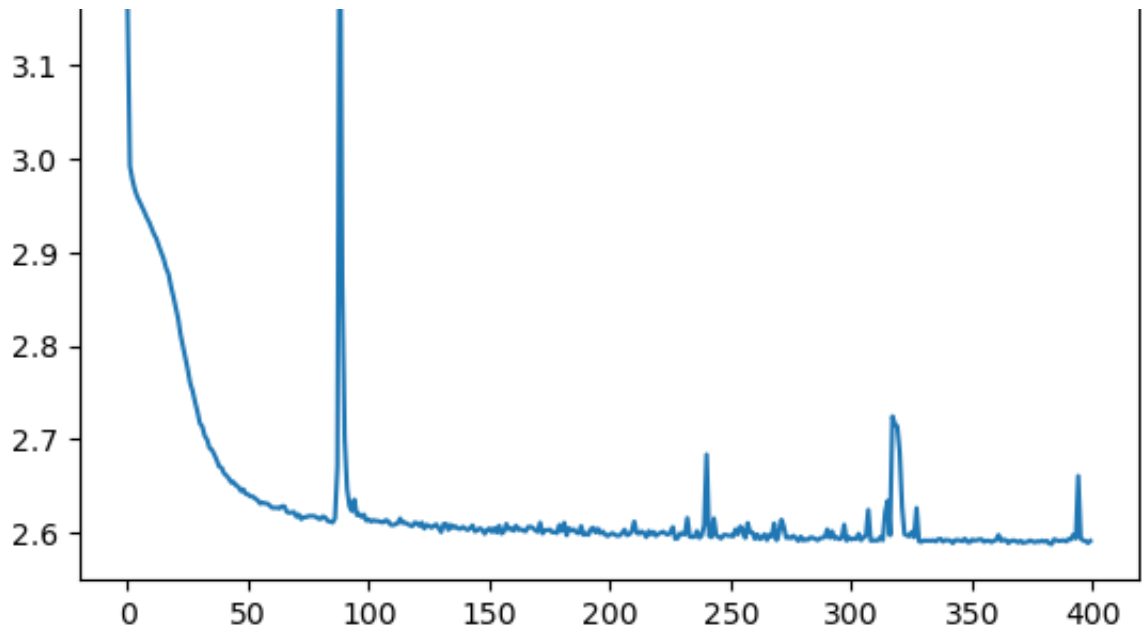
Model: "sequential_12"

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_60 (Dense) | (None, 3) | 9 |
| dense_61 (Dense) | (None, 3) | 12 |
| dense_62 (Dense) | (None, 3) | 12 |
| dense_63 (Dense) | (None, 3) | 12 |
| dense_64 (Dense) | (None, 3) | 12 |

```
=====
Total params: 57 (228.00 Byte)
Trainable params: 57 (228.00 Byte)
Non-trainable params: 0 (0.00 Byte)
```

```
5/5 [=====] - 0s 2ms/step - loss: 2.5857
Selu Loss Score: 2.5857462882995605
```





```
In [19]: # RMSprop

from keras.optimizers import RMSprop

model = Sequential()

model.add(Dense(3, input_dim=2, activation='elu'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh')) # Diminishing returns with elu.

model.compile(loss='binary_crossentropy', optimizer='RMSprop')

history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

plt.plot(history.history['loss'], label='RMSprop')

model.summary()

score_rmsprop = model.evaluate(X, y)

print("RMSprop Loss Score:", score_rmsprop)
```

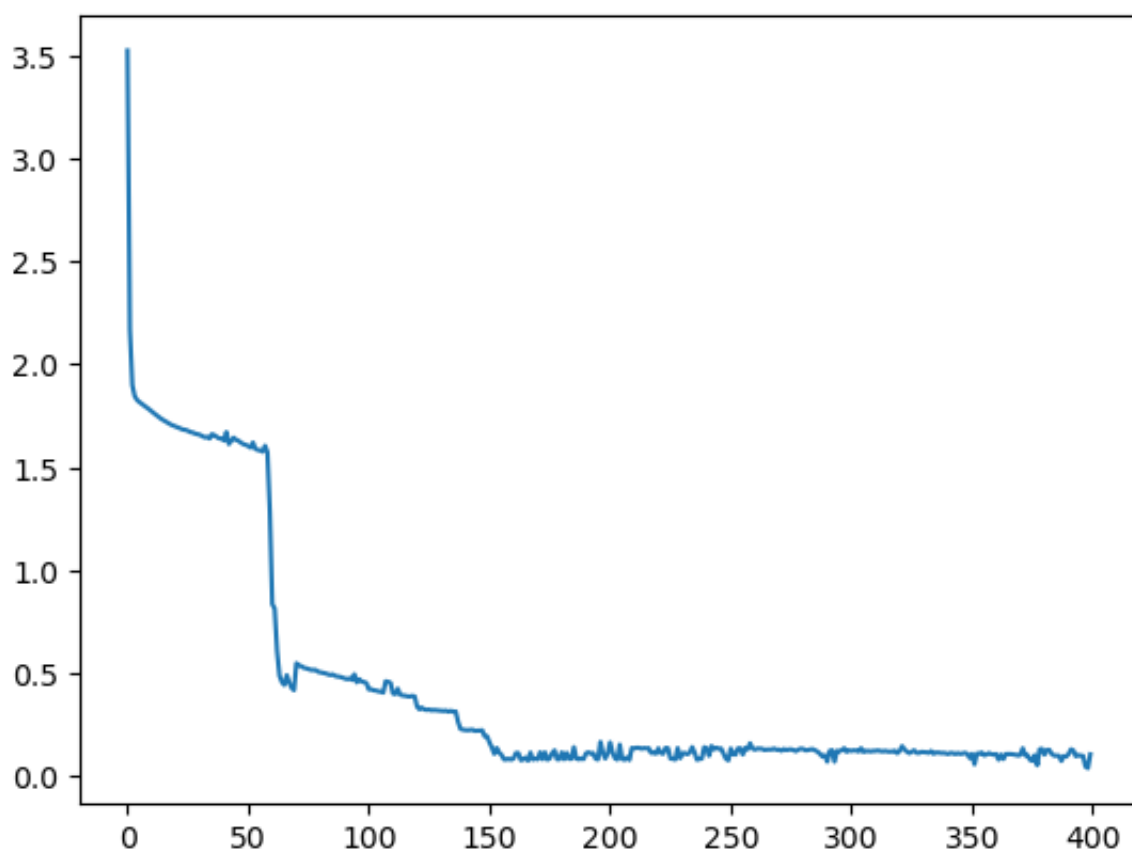
Model: "sequential_13"

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_65 (Dense) | (None, 3) | 9 |
| dense_66 (Dense) | (None, 3) | 12 |

| | | |
|------------------|-----------|----|
| dense_67 (Dense) | (None, 3) | 12 |
| dense_68 (Dense) | (None, 3) | 12 |
| dense_69 (Dense) | (None, 3) | 12 |

```
=====  
Total params: 57 (228.00 Byte)  
Trainable params: 57 (228.00 Byte)  
Non-trainable params: 0 (0.00 Byte)
```

```
5/5 [=====] - 0s 1ms/step - loss: 0.0671  
RMSprop Loss Score: 0.067109614610672
```



In [20]:

```
# SGD

from keras.optimizers import Adam

model = Sequential()

model.add(Dense(3, input_dim=2, activation='elu'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh')) # Diminishing returns with elu.

model.compile(loss='binary_crossentropy', optimizer='sgd')

history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

plt.plot(history.history['loss'], label='SGD')

model.summary()

score_SGD = model.evaluate(X, y)

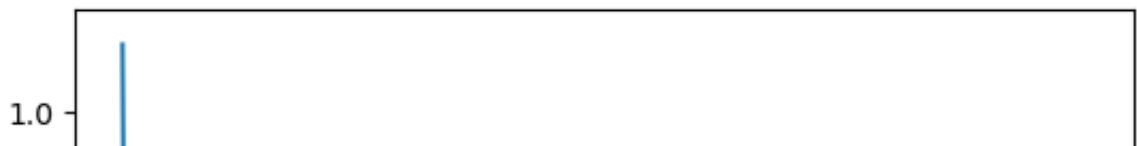
print("SGD Loss Score:", score_SGD)
```

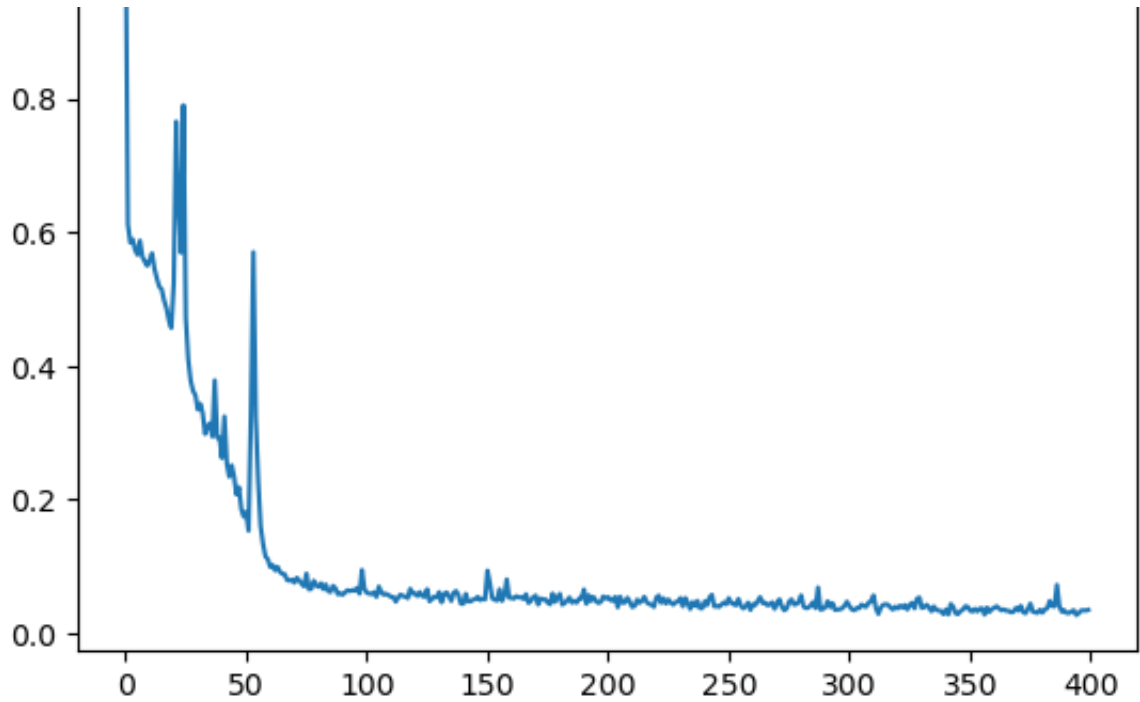
Model: "sequential_14"

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_70 (Dense) | (None, 3) | 9 |
| dense_71 (Dense) | (None, 3) | 12 |
| dense_72 (Dense) | (None, 3) | 12 |
| dense_73 (Dense) | (None, 3) | 12 |
| dense_74 (Dense) | (None, 3) | 12 |

```
=====
Total params: 57 (228.00 Byte)
Trainable params: 57 (228.00 Byte)
Non-trainable params: 0 (0.00 Byte)
```

```
5/5 [=====] - 0s 1ms/step - loss: 0.0232
SGD Loss Score: 0.023236945271492004
```





```
In [21]: # Adadelta

from keras.optimizers import Adadelta

model = Sequential()

model.add(Dense(3, input_dim=2, activation='elu'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh')) # Diminishing returns with elu.

model.compile(loss='binary_crossentropy', optimizer='Adadelta')

history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

plt.plot(history.history['loss'], label='Adadelta')

model.summary()

score_Adadelta = model.evaluate(X, y)

print("Adadelta Loss Score:", score_Adadelta)
```

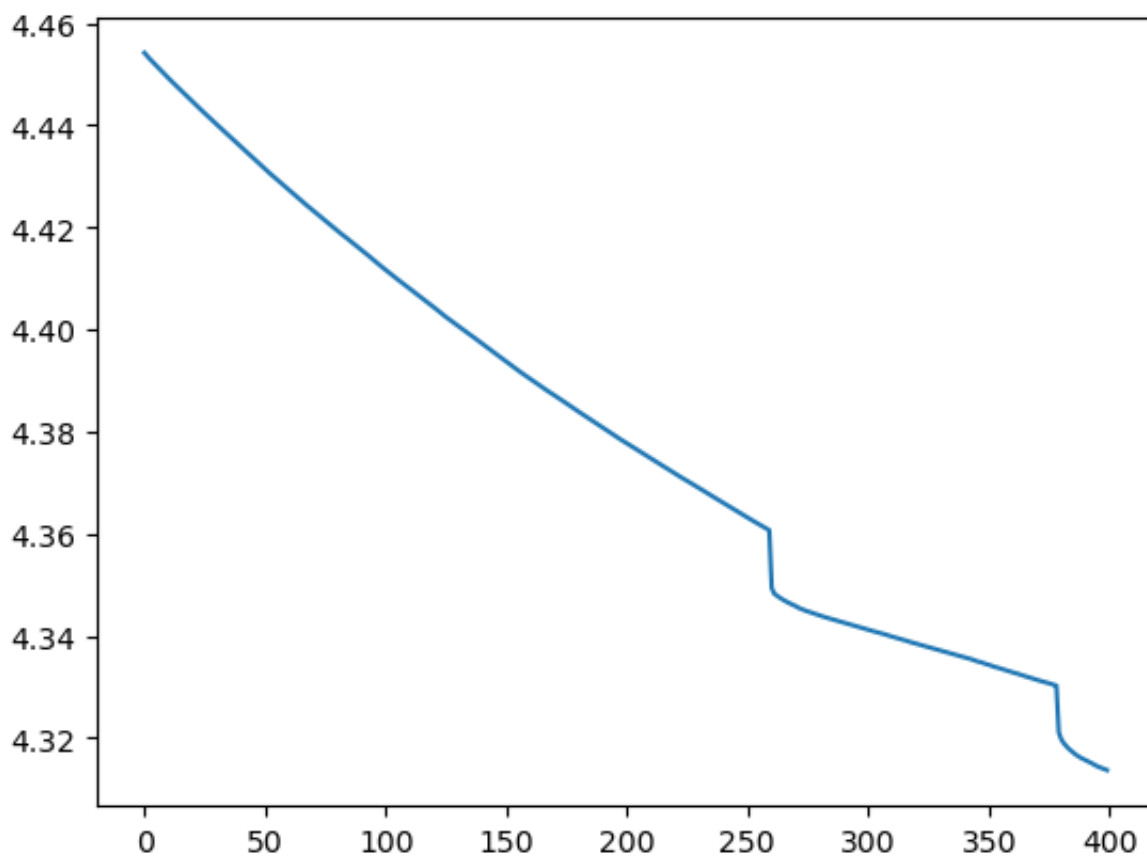
Model: "sequential_15"

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_75 (Dense) | (None, 3) | 9 |

| | | |
|------------------|-----------|----|
| dense_76 (Dense) | (None, 3) | 12 |
| dense_77 (Dense) | (None, 3) | 12 |
| dense_78 (Dense) | (None, 3) | 12 |
| dense_79 (Dense) | (None, 3) | 12 |

```
=====
Total params: 57 (228.00 Byte)
Trainable params: 57 (228.00 Byte)
Non-trainable params: 0 (0.00 Byte)
```

```
5/5 [=====] - 0s 1ms/step - loss: 4.3135
Adadelta Loss Score: 4.313548564910889
```



In [22]:

```
# Adagrad

from keras.optimizers import Adagrad

model = Sequential()

model.add(Dense(3, input_dim=2, activation='elu'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh')) # Diminishing returns with elu.

model.compile(loss='binary_crossentropy', optimizer='Adagrad')

history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

plt.plot(history.history['loss'], label='Adagrad')

model.summary()

score_Adagrad = model.evaluate(X, y)

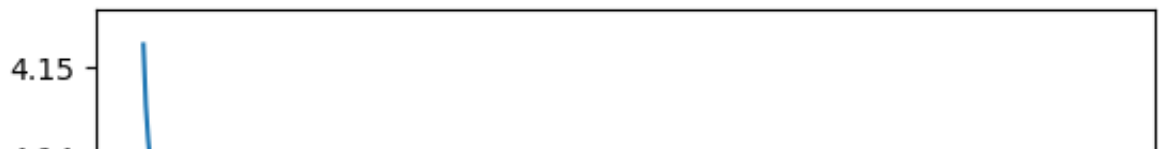
print("Adagrad Loss Score:", score_Adagrad)
```

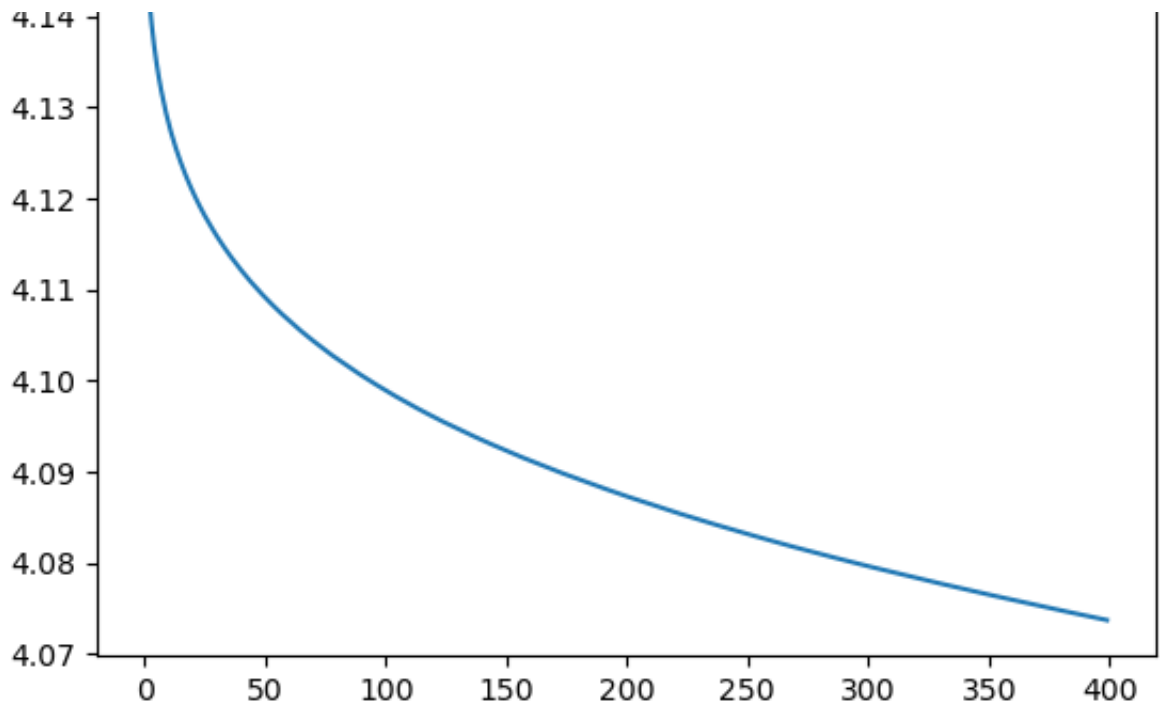
Model: "sequential_16"

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_80 (Dense) | (None, 3) | 9 |
| dense_81 (Dense) | (None, 3) | 12 |
| dense_82 (Dense) | (None, 3) | 12 |
| dense_83 (Dense) | (None, 3) | 12 |
| dense_84 (Dense) | (None, 3) | 12 |

```
=====
Total params: 57 (228.00 Byte)
Trainable params: 57 (228.00 Byte)
Non-trainable params: 0 (0.00 Byte)
```

```
5/5 [=====] - 0s 1ms/step - loss: 4.0737
Adagrad Loss Score: 4.073662757873535
```





```
In [23]: # Adamax

from keras.optimizers import Adamax

model = Sequential()

model.add(Dense(3, input_dim=2, activation='elu'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh')) # Diminishing returns with elu.

model.compile(loss='binary_crossentropy', optimizer='Adamax')

history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

plt.plot(history.history['loss'], label='Adamax')

model.summary()

score_Adamax = model.evaluate(X, y)

print("Adamax Loss Score:", score_Adamax)
```

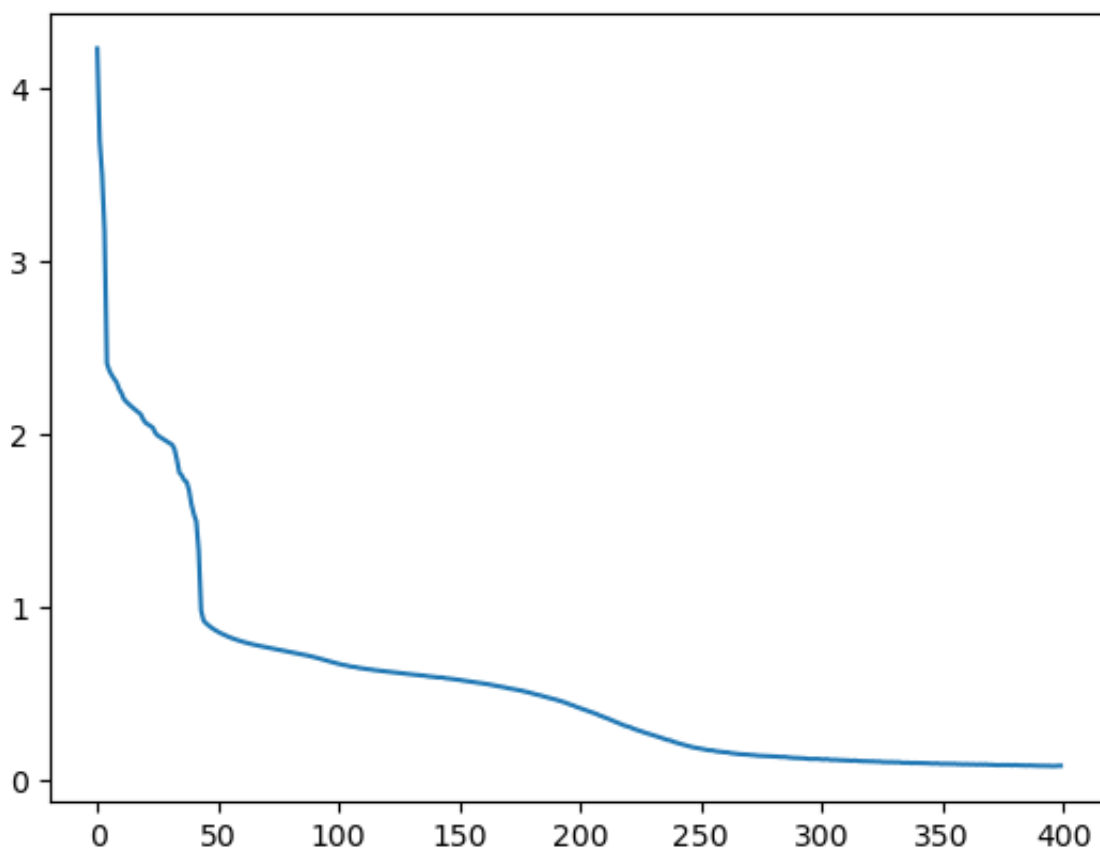
Model: "sequential_17"

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_85 (Dense) | (None, 3) | 9 |

| | | |
|------------------|-----------|----|
| dense_86 (Dense) | (None, 3) | 12 |
| dense_87 (Dense) | (None, 3) | 12 |
| dense_88 (Dense) | (None, 3) | 12 |
| dense_89 (Dense) | (None, 3) | 12 |

```
=====
Total params: 57 (228.00 Byte)
Trainable params: 57 (228.00 Byte)
Non-trainable params: 0 (0.00 Byte)
```

```
5/5 [=====] - 0s 1ms/step - loss: 0.0772
Adamax Loss Score: 0.07723230123519897
```



In [27]:

```
# Nadam

from keras.optimizers import Nadam

model = Sequential()

model.add(Dense(3, input_dim=2, activation='elu'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh')) # Diminishing returns with elu.

model.compile(loss='binary_crossentropy', optimizer='Nadam')

history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

plt.plot(history.history['loss'], label='Nadam')

model.summary()

score_Nadam = model.evaluate(X, y)

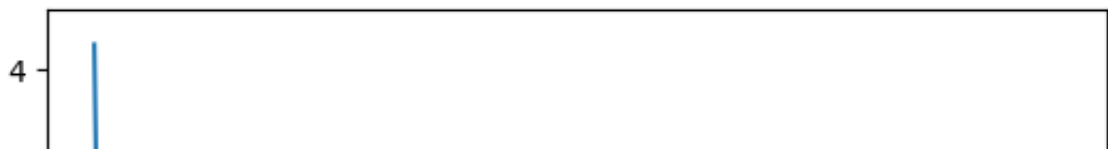
print("Nadam Loss Score:", score_Nadam)
```

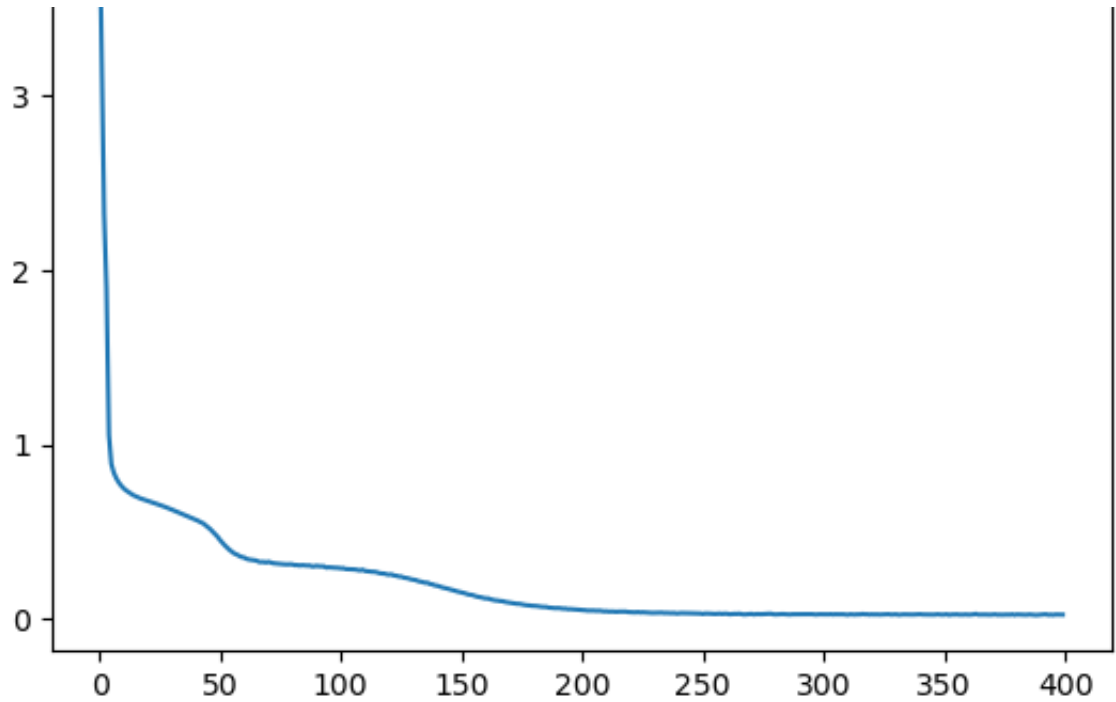
Model: "sequential_21"

| Layer (type) | Output Shape | Param # |
|-------------------|--------------|---------|
| dense_103 (Dense) | (None, 3) | 9 |
| dense_104 (Dense) | (None, 3) | 12 |
| dense_105 (Dense) | (None, 3) | 12 |
| dense_106 (Dense) | (None, 3) | 12 |
| dense_107 (Dense) | (None, 3) | 12 |

```
=====
Total params: 57 (228.00 Byte)
Trainable params: 57 (228.00 Byte)
Non-trainable params: 0 (0.00 Byte)
```

```
5/5 [=====] - 0s 1ms/step - loss: 0.0171
Nadam Loss Score: 0.017082305625081062
```





```
In [25]: # Ftrl

from keras.optimizers import Ftrl

model = Sequential()

model.add(Dense(3, input_dim=2, activation='elu'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh')) # Diminishing returns with elu.

model.compile(loss='binary_crossentropy', optimizer='Ftrl')

history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

plt.plot(history.history['loss'], label='Ftrl')

model.summary()

score_Ftrl = model.evaluate(X, y)

print("Ftrl Loss Score:", score_Ftrl)
```

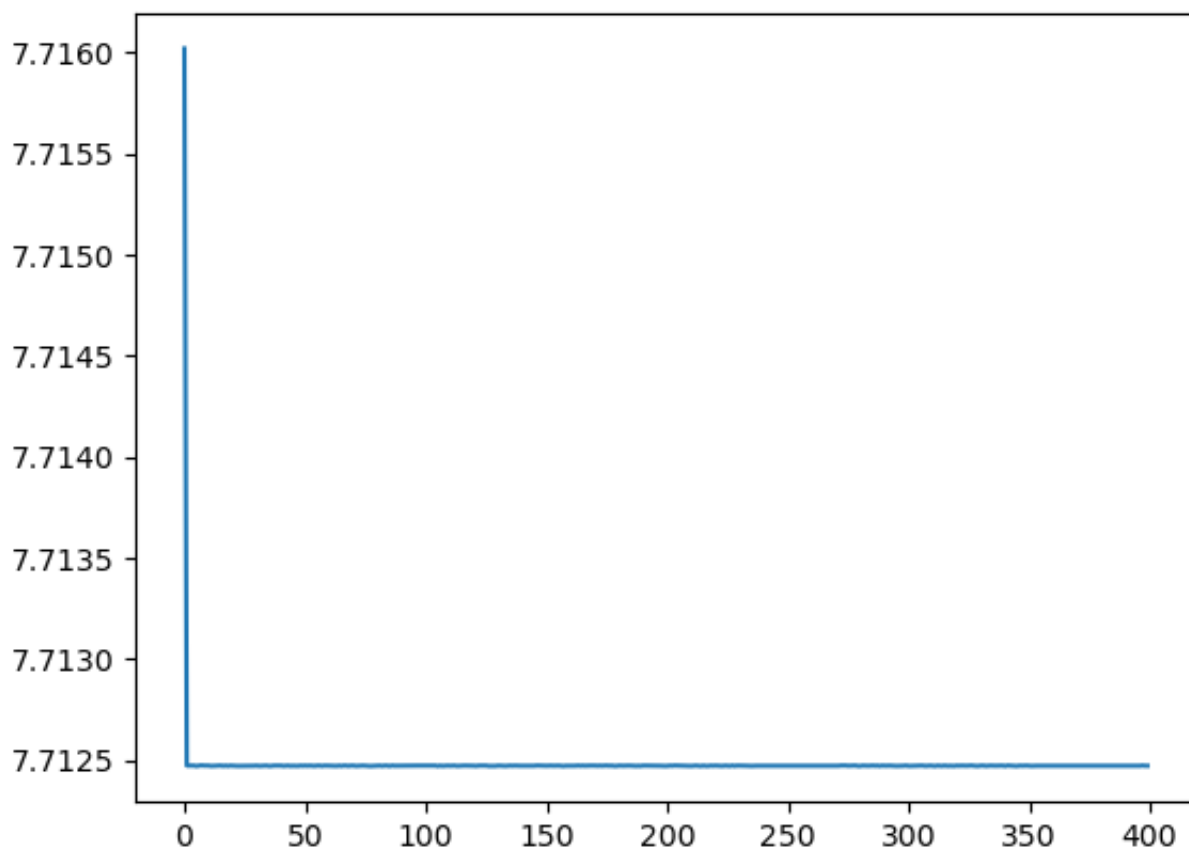
Model: "sequential_19"

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_93 (Dense) | (None, 3) | 9 |

| | | |
|------------------|-----------|----|
| dense_94 (Dense) | (None, 3) | 12 |
| dense_95 (Dense) | (None, 3) | 12 |
| dense_96 (Dense) | (None, 3) | 12 |
| dense_97 (Dense) | (None, 3) | 12 |

```
=====
Total params: 57 (228.00 Byte)
Trainable params: 57 (228.00 Byte)
Non-trainable params: 0 (0.00 Byte)
```

```
5/5 [=====] - 0s 1ms/step - loss: 7.7125
Ftrl Loss Score: 7.7124738693237305
```



In [26]:

All Optimizers on One Graph

As noted elsewhere the results between looped execution and

```
scores_opt = []
optimizers = ['Adam', 'RMSprop', 'sgd', 'Adadelata', 'Adagrad', 'Adamax', 'Na
plt.figure(figsize=(12, 8))
model = Sequential()
model.add(Dense(3, input_dim=2, activation='elu'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh'))
model.add(Dense(3, activation='tanh')) # Diminishing returns with elu.

for opt in optimizers:

    model.compile(loss='binary_crossentropy', optimizer=opt)

    history = model.fit(X, y, batch_size=2, epochs=400, verbose=0)

    plt.plot(history.history['loss'], label=f'{opt} used')

    model.summary()

    score = model.evaluate(X, y)
    scores_opt.append(score)

plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Loss vs. Epochs for Different Optimizers')
plt.legend()
plt.show()
printout_opt = [item for sublist in zip(optimizers, scores_opt) for item in sublist]
print("Optimizers:", printout_opt)
```

Model: "sequential_20"

| Layer (type) | Output Shape | Param # |
|-------------------|--------------|---------|
| dense_98 (Dense) | (None, 3) | 9 |
| dense_99 (Dense) | (None, 3) | 12 |
| dense_100 (Dense) | (None, 3) | 12 |
| dense_101 (Dense) | (None, 3) | 12 |
| dense_102 (Dense) | (None, 3) | 12 |

Total params: 57 (228.00 Byte)
 Trainable params: 57 (228.00 Byte)
 Non-trainable params: 0 (0.00 Byte)

5/5 [=====] - 0s 1ms/step - loss: 3.8654
 Model: "sequential_20"

| Layer (type) | Output Shape | Param # |
|-------------------|--------------|---------|
| dense_98 (Dense) | (None, 3) | 9 |
| dense_99 (Dense) | (None, 3) | 12 |
| dense_100 (Dense) | (None, 3) | 12 |
| dense_101 (Dense) | (None, 3) | 12 |
| dense_102 (Dense) | (None, 3) | 12 |

Total params: 57 (228.00 Byte)
 Trainable params: 57 (228.00 Byte)
 Non-trainable params: 0 (0.00 Byte)

5/5 [=====] - 0s 1ms/step - loss: 3.8650
 Model: "sequential_20"

| Layer (type) | Output Shape | Param # |
|-------------------|--------------|---------|
| dense_98 (Dense) | (None, 3) | 9 |
| dense_99 (Dense) | (None, 3) | 12 |
| dense_100 (Dense) | (None, 3) | 12 |
| dense_101 (Dense) | (None, 3) | 12 |
| dense_102 (Dense) | (None, 3) | 12 |

Total params: 57 (228.00 Byte)
 Trainable params: 57 (228.00 Byte)
 Non-trainable params: 0 (0.00 Byte)

5/5 [=====] - 0s 1ms/step - loss: 0.6815
 Model: "sequential_20"

| Layer (type) | Output Shape | Param # |
|------------------|--------------|---------|
| dense_98 (Dense) | (None, 3) | 9 |

| | | |
|-------------------|-----------|----|
| dense_99 (Dense) | (None, 3) | 12 |
| dense_100 (Dense) | (None, 3) | 12 |
| dense_101 (Dense) | (None, 3) | 12 |
| dense_102 (Dense) | (None, 3) | 12 |

```

=====
Total params: 57 (228.00 Byte)
Trainable params: 57 (228.00 Byte)
Non-trainable params: 0 (0.00 Byte)

```

```

5/5 [=====] - 0s 1ms/step - loss: 0.6807
Model: "sequential_20"

```

| Layer (type) | Output Shape | Param # |
|-------------------|--------------|---------|
| dense_98 (Dense) | (None, 3) | 9 |
| dense_99 (Dense) | (None, 3) | 12 |
| dense_100 (Dense) | (None, 3) | 12 |
| dense_101 (Dense) | (None, 3) | 12 |
| dense_102 (Dense) | (None, 3) | 12 |

```

=====
Total params: 57 (228.00 Byte)
Trainable params: 57 (228.00 Byte)
Non-trainable params: 0 (0.00 Byte)

```

```

5/5 [=====] - 0s 1ms/step - loss: 0.6801
Model: "sequential_20"

```

| Layer (type) | Output Shape | Param # |
|-------------------|--------------|---------|
| dense_98 (Dense) | (None, 3) | 9 |
| dense_99 (Dense) | (None, 3) | 12 |
| dense_100 (Dense) | (None, 3) | 12 |
| dense_101 (Dense) | (None, 3) | 12 |
| dense_102 (Dense) | (None, 3) | 12 |

Total params: 57 (228.00 Byte)
 Trainable params: 57 (228.00 Byte)
 Non-trainable params: 0 (0.00 Byte)

5/5 [=====] - 0s 1ms/step - loss: 0.6711
 Model: "sequential_20"

| Layer (type) | Output Shape | Param # |
|-------------------|--------------|---------|
| dense_98 (Dense) | (None, 3) | 9 |
| dense_99 (Dense) | (None, 3) | 12 |
| dense_100 (Dense) | (None, 3) | 12 |
| dense_101 (Dense) | (None, 3) | 12 |
| dense_102 (Dense) | (None, 3) | 12 |

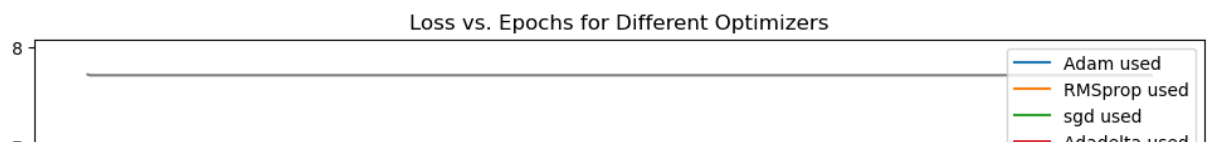
Total params: 57 (228.00 Byte)
 Trainable params: 57 (228.00 Byte)
 Non-trainable params: 0 (0.00 Byte)

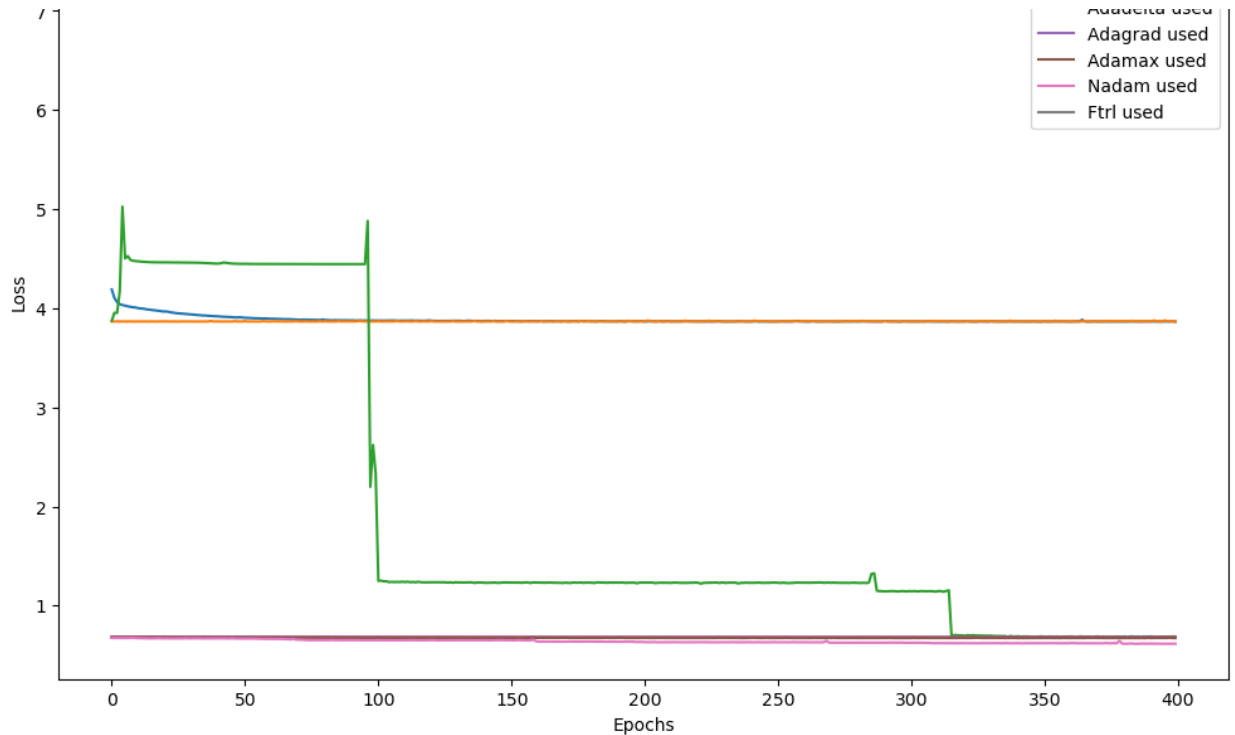
5/5 [=====] - 0s 1ms/step - loss: 0.6133
 Model: "sequential_20"

| Layer (type) | Output Shape | Param # |
|-------------------|--------------|---------|
| dense_98 (Dense) | (None, 3) | 9 |
| dense_99 (Dense) | (None, 3) | 12 |
| dense_100 (Dense) | (None, 3) | 12 |
| dense_101 (Dense) | (None, 3) | 12 |
| dense_102 (Dense) | (None, 3) | 12 |

Total params: 57 (228.00 Byte)
 Trainable params: 57 (228.00 Byte)
 Non-trainable params: 0 (0.00 Byte)

5/5 [=====] - 0s 1ms/step - loss: 7.7125





Optimizers: ['Adam', 3.8653903007507324, 'RMSprop', 3.865039825439453, 'sgd', 0.6815272569656372, 'Adadelta', 0.6806966066360474, 'Adagrad', 0.6800661683082581, 'Adamax', 0.6711133718490601, 'Nadam', 0.6132935881614685, 'Ftrl', 7.7124738693237305]

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

<https://keras.io/> (<https://keras.io/>)

In [29]: *# BYOD Import*

```
heart = pd.read_csv('../data/heart+disease/processed.cleveland.data',
                    names=["age", "sex", "cp", "trestbps", "chol", "fbs",
                          "exang", "oldpeak", "slope", "ca", "thal", "r"],
                    delimiter=',')

heart_clean = heart[pd.to_numeric(heart["ca"], errors='coerce').notnull()]

heart_clean = heart_clean[pd.to_numeric(heart_clean["oldpeak"], errors='coerce').notnull()]

heart_clean = heart_clean[pd.to_numeric(heart_clean["thal"], errors='coerce').notnull()]

heart_clean["heart_disease"] = heart_clean['num'].astype(bool)
heart_clean["heart_disease"], heart_clean['num']
heart_clean = heart_clean.dropna()
```

In [30]: heart_clean

Out[30]:

| | age | sex | cp | trestbps | chol | fbs | restecg | thalach | exang | oldpeak | slope | ca | thal | r |
|-----|------|-----|-----|----------|-------|-----|---------|---------|-------|---------|-------|-----|------|---|
| 0 | 63.0 | 1.0 | 1.0 | 145.0 | 233.0 | 1.0 | 2.0 | 150.0 | 0.0 | 2.3 | 3.0 | 0.0 | 6.0 | |
| 1 | 67.0 | 1.0 | 4.0 | 160.0 | 286.0 | 0.0 | 2.0 | 108.0 | 1.0 | 1.5 | 2.0 | 3.0 | 3.0 | |
| 2 | 67.0 | 1.0 | 4.0 | 120.0 | 229.0 | 0.0 | 2.0 | 129.0 | 1.0 | 2.6 | 2.0 | 2.0 | 7.0 | |
| 3 | 37.0 | 1.0 | 3.0 | 130.0 | 250.0 | 0.0 | 0.0 | 187.0 | 0.0 | 3.5 | 3.0 | 0.0 | 3.0 | |
| 4 | 41.0 | 0.0 | 2.0 | 130.0 | 204.0 | 0.0 | 2.0 | 172.0 | 0.0 | 1.4 | 1.0 | 0.0 | 3.0 | |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| 297 | 57.0 | 0.0 | 4.0 | 140.0 | 241.0 | 0.0 | 0.0 | 123.0 | 1.0 | 0.2 | 2.0 | 0.0 | 7.0 | |
| 298 | 45.0 | 1.0 | 1.0 | 110.0 | 264.0 | 0.0 | 0.0 | 132.0 | 0.0 | 1.2 | 2.0 | 0.0 | 7.0 | |
| 299 | 68.0 | 1.0 | 4.0 | 144.0 | 193.0 | 1.0 | 0.0 | 141.0 | 0.0 | 3.4 | 2.0 | 2.0 | 7.0 | |
| 300 | 57.0 | 1.0 | 4.0 | 130.0 | 131.0 | 0.0 | 0.0 | 115.0 | 1.0 | 1.2 | 2.0 | 1.0 | 7.0 | |
| 301 | 57.0 | 0.0 | 2.0 | 130.0 | 236.0 | 0.0 | 2.0 | 174.0 | 0.0 | 0.0 | 2.0 | 1.0 | 3.0 | |

297 rows × 15 columns

In [31]: *# Setting up the target and dataset.*

```
xray = heart_clean.copy()
yankee = heart_clean['heart_disease'].copy()
xray = xray.drop(columns=['num', 'heart_disease'], axis=1)

xray = np.asarray(xray).astype('float32') # Issues with 'float' data t
```

In [32]: *# NN Model Build*

```
byod = Sequential()

byod.add(Dense(24, input_dim=13, activation='elu')) # Exponential Linear
#byod.add(Dense(12, activation='sigmoid')) # From what I can see sigmoid
byod.add(Dense(24, activation='selu')) # Scaled Exponential Linear Uni
byod.add(Dense(24, activation='softsign')) # Softmax converts a vector
# Softsign activation funct

byod.add(Dense(24, activation='tanh'))

byod.compile(loss='binary_crossentropy', optimizer='Nadam') # Much lik
# Nadam is
history = byod.fit(xray, yankee, batch_size=2, epochs=400, verbose=0)

plt.plot(history.history['loss'], label='BYOD')

byod.summary()

score_byod = byod.evaluate(xray, yankee)

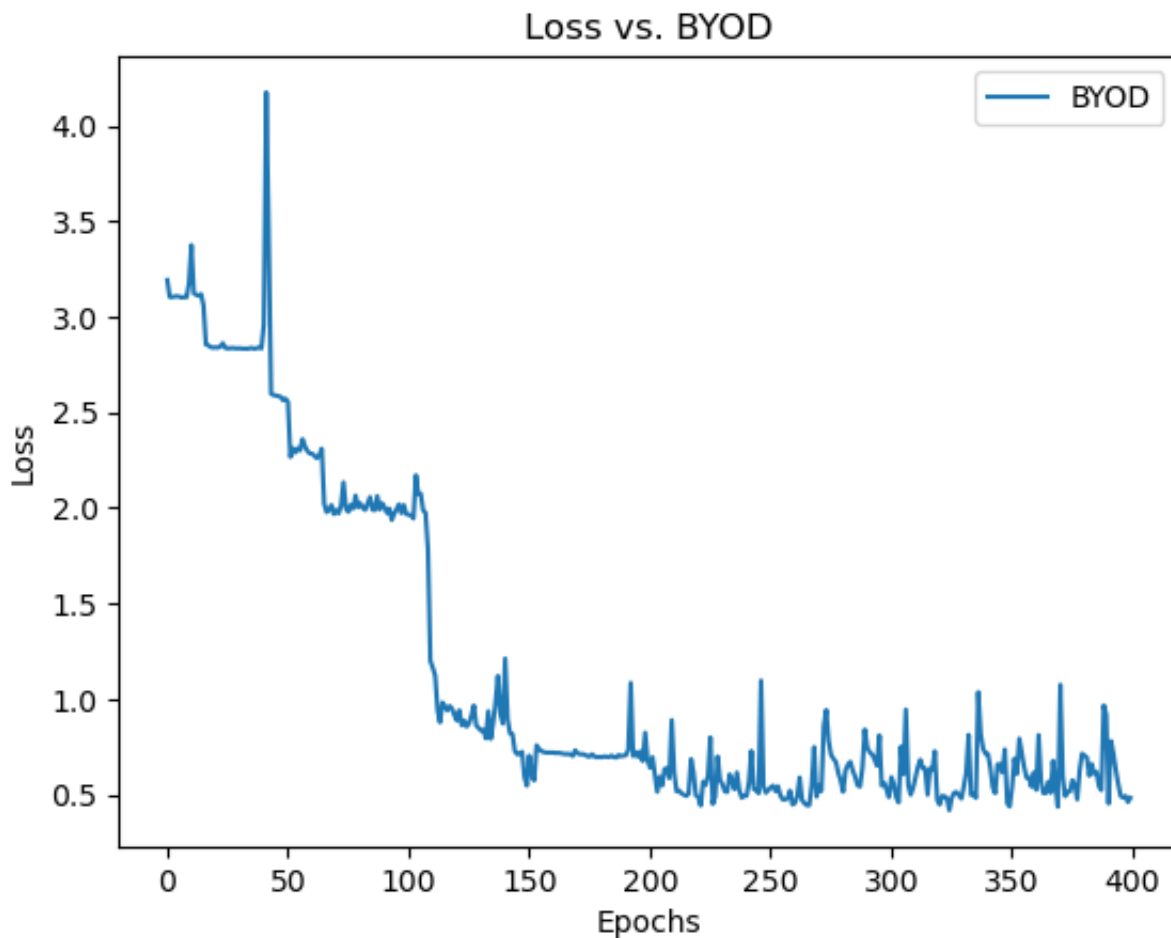
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Loss vs. BYOD')
plt.legend()
plt.show()
print("BYOD Loss Score:", score_byod)
```

Model: "sequential_23"

| Layer (type) | Output Shape | Param # |
|-------------------|--------------|---------|
| ===== | | |
| dense_112 (Dense) | (None, 24) | 336 |
| dense_113 (Dense) | (None, 24) | 600 |
| dense_114 (Dense) | (None, 24) | 600 |
| dense_115 (Dense) | (None, 24) | 600 |

```
=====
Total params: 2136 (8.34 KB)
Trainable params: 2136 (8.34 KB)
Non-trainable params: 0 (0.00 Byte)
```

```
10/10 [=====] - 0s 891us/step - loss: 0.4335
```



BYOD Loss Score: 0.4335453510284424

0.43 loss score was the best I was able to optimize for with the data I brought. The Heart dataset only has 297 observations once it has been cleaned which is a fairly small training size for a neural net. With that in mind I am fairly happy with the results.

```
In [73]: model = Sequential()

model.add(Dense(2, input_dim=2, activation='tanh')) #sigmoid, relu
model.add(Dense(2, activation='tanh'))
model.add(Dense(1, activation='sigmoid'))
model.add(Dense(1, input_dim=2, activation='sigmoid'))

sgd = SGD(lr=0.1)
model.compile(loss='binary_crossentropy', optimizer='sgd')

model.fit(X, y, batch_size=2, epochs=400) #160/4 = 40 per epoch
#print(model.predict_proba(X).reshape(4*n))

# evaluate the model
scores = model.evaluate(X, y)
```

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

```
Epoch 1/400
80/80 [=====] - 0s 1ms/step - loss: 0.7131
Epoch 2/400
80/80 [=====] - 0s 820us/step - loss: 0.7043
Epoch 3/400
80/80 [=====] - 0s 790us/step - loss: 0.6985
Epoch 4/400
80/80 [=====] - 0s 772us/step - loss: 0.6949
Epoch 5/400
80/80 [=====] - 0s 805us/step - loss: 0.6925
Epoch 6/400
80/80 [=====] - 0s 754us/step - loss: 0.6908
Epoch 7/400
80/80 [=====] - 0s 737us/step - loss: 0.6898
Epoch 8/400
80/80 [=====] - 0s 713us/step - loss: 0.6888
```

```
In [52]: print(model.predict_proba(X).reshape(4*n))
```

```
-----
AttributeError                                Traceback (most recent call
last)
Cell In[52], line 1
----> 1 print(model.predict_proba(X).reshape(4*n))

AttributeError: 'Sequential' object has no attribute 'predict_proba'
```

```
In [53]: scores = model.evaluate(X, y)
scores, model.metrics_names
```

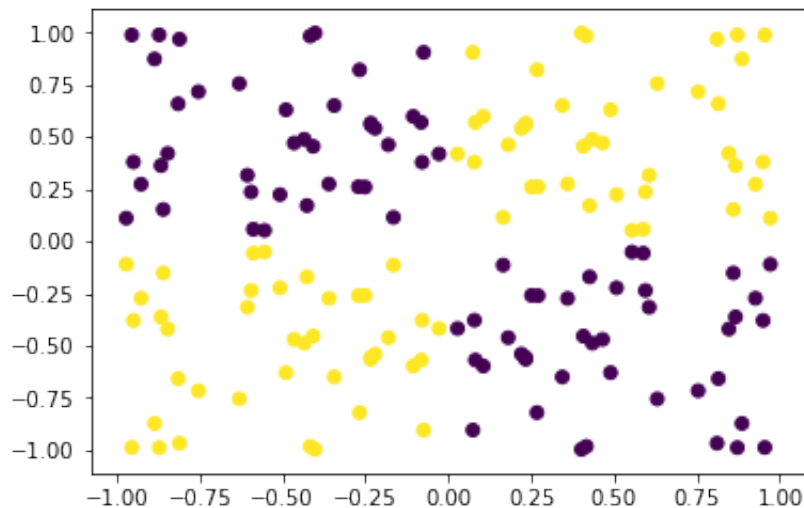
```
5/5 [=====] - 0s 1ms/step - loss: 2.3497
```

```
Out[53]: (2.349733829498291, ['loss'])
```

```
In [127]: plt.scatter(*zip(*X), c=model.predict_classes(X))
```

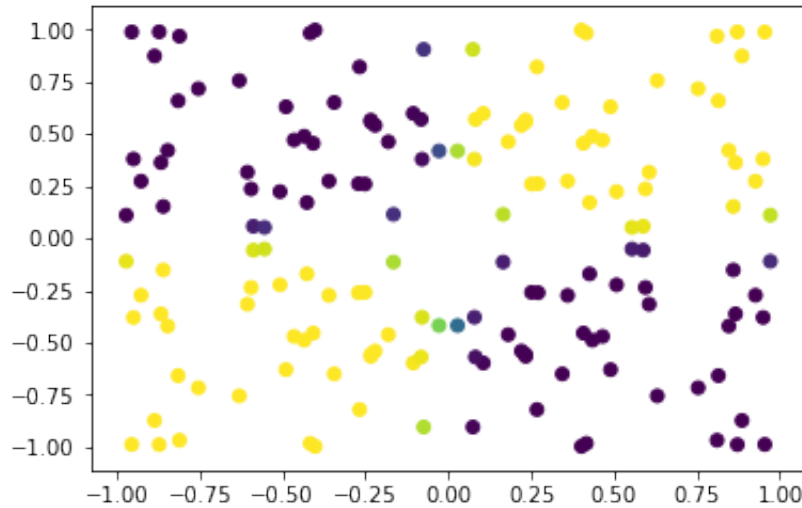
```
32/160 [=====>.....] - ETA: 0s
```

```
Out[127]: <matplotlib.collections.PathCollection at 0x121aed828>
```



```
In [128]: plt.scatter(*zip(*X), c=model.predict(X))
```

```
Out[128]: <matplotlib.collections.PathCollection at 0x120f4ee80>
```



Using Diabetes data

<http://archive.ics.uci.edu/ml/machine-learning-databases/pima-indians-diabetes/pima-indians-diabetes.data> (<http://archive.ics.uci.edu/ml/machine-learning-databases/pima-indians-diabetes/pima-indians-diabetes.data>)

1. Number of times pregnant
2. Plasma glucose concentration a 2 hours in an oral glucose tolerance test
3. Diastolic blood pressure (mm Hg)
4. Triceps skin fold thickness (mm)
5. 2-Hour serum insulin (mu U/ml)
6. Body mass index (weight in kg/(height in m)²)
7. Diabetes pedigree function
8. Age (years)
9. Class variable (0 or 1)

```
In [135]: # load pima indians dataset
dataset = np.loadtxt("../data/pima-indians-diabetes.data", delimiter="
# split into input (X) and output (Y) variables
Z = dataset[:,0:8]
W = dataset[:,8]
```


In [144]: dataset.head()

```
-----
-----
AttributeError                                Traceback (most recent call
last)
Cell In[144], line 1
----> 1 dataset.head()

AttributeError: 'numpy.ndarray' object has no attribute 'head'
```

```
In [136]: # create model
model = Sequential()
model.add(Dense(16, input_dim=8, activation='tanh'))
model.add(Dense(16, activation='tanh'))
model.add(Dense(1, activation='sigmoid'))
# Compile model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['
# Fit the model
model.fit(Z, W, epochs=1000, batch_size=10)
# evaluate the model
scores = model.evaluate(Z, W)
print("\ns: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

```
Epoch 1/1000
768/768 [=====] - 1s - loss: 0.6821 - acc: 0
.5820
Epoch 2/1000
768/768 [=====] - 0s - loss: 0.6273 - acc: 0
.6536
Epoch 3/1000
768/768 [=====] - 0s - loss: 0.6122 - acc: 0
.6719
Epoch 4/1000
768/768 [=====] - 0s - loss: 0.6111 - acc: 0
.6680
Epoch 5/1000
768/768 [=====] - 0s - loss: 0.6065 - acc: 0
.6862
Epoch 6/1000
768/768 [=====] - 0s - loss: 0.6049 - acc: 0
.6745
Epoch 7/1000
768/768 [=====] - 0s - loss: 0.5978 - acc: 0
.6880
```

Type Markdown and LaTeX: α^2

In []: