Plotting Banknote Prediction

This notebook is a tutorial of how we can modify the predictor python script to show a visualization of the data in the hidden space and how the predictor classifies each point. Each dimension of the hidden space corresponds to a neuron from the predictor. Because only three neurons are used for the banknote data, we can plot it in the hidden space. The banknote data is used to distinguish genuine and forged banknotes. *Note: This isn't part of Daimensions. We are going to manually edit the python script to output a png of the model's results in the hidden space.

1. Build Predictor

In [2]:

```
! btc https://www.openml.org/data/get_csv/1586223/php50jXam -f NN -e 10
```

```
Brainome Daimensions(tm) 0.97 Copyright (c) 2019, 2020 by Brainome, Inc. All Rights Reser
ved.
Licensed to: Ariana Park
Expiration date: 2020-11-30 (131 days left)
Number of threads: 1
Maximum file size: 4GB
Connected to: https://beta.brainome.ai:8080

Running btc will overwrite existing a.py. OK? [y/N] yes
Download from https://www.openml.org/data/get_csv/1586223/php50jXam overwrites existing f
ile php50jXam.csv. OK? [y/N] yes
Downloading php50jXam.csv...done.
Input: php50jXam.csv
Sampling...done.
Cleaning...done.
Note: Class labels required remapping onto contiguous integers. Mapped as follows: {'1':
0, '2': 1}
Splitting into training and validation...done.
Pre-training measurements...done.
Data:
Number of instances: 1372
Number of attributes: 4
Number of classes: 2
Class balance: 55.54% 44.46%

Learnability:
Best guess accuracy: 55.54%
Capacity progression (# of decision points): [2, 7, 7, 8, 10, 10]
Decision Tree: 44 parameters
Estimated Memory Equivalent Capacity for Neural Networks: 37 parameters

Risk that model needs to overfit for 100% accuracy...
using Decision Tree: 6.41%
using Neural Networks: 60.66%

Expected Generalization...
using Decision Tree: 31.18 bits/bit
using a Neural Network: 37.08 bits/bit

Recommendations:
Note: Maybe enough data to generalize. [yellow]
Warning: Cannot find numpy. The output predictor may not run on this machine.
Warning: Remapped class labels to be contiguous. Use -cm if DET/ROC-based accuracy measur
ements are wrong.

Time estimate for a Neural Network:
Estimated time to architect: 0d 0h 0m 1s
Estimated time to prime (subject to change after model architecting): 0d 0h 3m 13s
Note: Machine learner type NN given by user.
Architecting model...done.
Model capacity (MEC):    10 bits
```

```
Model capacity (MEC):      19 bits
Architecture efficiency:    1.0 bits/parameter

Estimating time to prime model...done.
Estimated time to prime model: 0d 0h 2m 24s

Priming model...done.
Estimating training time...done.
Estimated training time: 0d 0h 15m 39s

Training...done.
Model created:
Sequential(
  (0): Linear(in_features=4, out_features=3, bias=True)
  (1): ReLU()
  (2): Linear(in_features=3, out_features=1, bias=True)
)

Compiling predictor...done.
Validating predictor...done.
Classifier Type:                    Neural Network
System Type:                        Binary classifier
Best-guess accuracy:                55.53%
Model accuracy:                     100.00% (1372/1372 correct)
Improvement over best guess:        44.47% (of possible 44.47%)
Model capacity (MEC):               19 bits
Generalization ratio:               72.21 bits/bit
Model efficiency:                   2.34%/parameter
System behavior
True Negatives:                     55.54% (762/1372)
True Positives:                     44.46% (610/1372)
False Negatives:                    0.00% (0/1372)
False Positives:                    0.00% (0/1372)
True Pos. Rate/Sensitivity/Recall:  1.00
True Neg. Rate/Specificity:         1.00
Precision:                          1.00
F-1 Measure:                        1.00
False Negative Rate/Miss Rate:      0.00
Critical Success Index:             1.00
Overfitting:                        No

Output: a.py
READY.
```

2. Make Changes to Python Script

The previous line of code should output a python script 'a.py' with the model's predictor. Next, we'll manually edit the code by adding and removing a few lines so that it will output the desired png when we run -validate. I'll show you the section of code we'll change with the modified lines highlighted.

In [ ]:

```
# Classifier
def single_classify(row, ax):
    x = row
    o = [0] * num_output_logits
    h_0 = max((((-22.079895 * float(x[0]))+ (-15.1198225 * float(x[1]))+ (-5.914762 * float(x[2]))+ (-2.156884 * float(x[3]))) + 10.891173), 0)
    h_1 = max((((2.4272702 * float(x[0]))+ (5.21773 * float(x[1]))+ (4.5376763 * float(x[2]))+ (1.6435318 * float(x[3]))) + -1.4549569), 0)
    h_2 = max((((3.2089252 * float(x[0]))+ (-8.139707 * float(x[1]))+ (11.706116 * float(x[2]))+ (-4.6293216 * float(x[3]))) + 0.7604494), 0)
    o[0] = (3.3051527 * h_0)+ (-0.9237582 * h_1)+ (-1.8347793 * h_2) + 7.872639
    ax.scatter(h_0, h_1, h_2, marker=('o' if o[0] >= 0 else '^'), c=('r' if o[0] >= 0 else 'b'))
    if num_output_logits == 1:
        return o[0] >= 0
    else:
        return argmax(o)
```

```
#for classifying batches
def classify(arr):
    outputs = []
    for row in arr:
        outputs.append(single_classify(row))
#removed four lines here**
    return outputs

def Validate(cleanvalfile):
    #Binary
    import matplotlib.pyplot as plt
    from mpl_toolkits.mplot3d import Axes3D
    fig = plt.figure()
    ax = fig.add_subplot(111, projection='3d')
    if n_classes == 2:
        with open(cleanvalfile, 'r') as valcsvfile:
            count, correct_count, num_TP, num_TN, num_FP, num_FN, num_class_1, num_class
_0 = 0, 0, 0, 0, 0, 0, 0, 0
            valcsvreader = csv.reader(valcsvfile)
            for valrow in valcsvreader:
                if len(valrow) == 0:
                    continue
                if int(single_classify(valrow[:-1], ax)) == int(float(valrow[-1])):
                    correct_count += 1
                    if int(float(valrow[-1])) == 1:
                        num_class_1 += 1
                        num_TP += 1
                    else:
                        num_class_0 += 1
                        num_TN += 1
                else:
                    if int(float(valrow[-1])) == 1:
                        num_class_1 += 1
                        num_FN += 1
                    else:
                        num_class_0 += 1
                        num_FP += 1
                count += 1
                ax.set_xlabel('h0')
                ax.set_ylabel('h1')
                ax.set_zlabel('h2')
                plt.savefig('bank_note_authentication.png')
        return count, correct_count, num_TP, num_TN, num_FP, num_FN, num_class_1, num_cl
ass_0

    #Multiclass
    else:
        with open(cleanvalfile, 'r') as valcsvfile:
            count, correct_count = 0, 0
            valcsvreader = csv.reader(valcsvfile)
            numeachclass = {}
            preds = []
            y_trues = []
            for i, valrow in enumerate(valcsvreader):
                pred = int(single_classify(valrow[:-1]))
                preds.append(pred)
                y_true = int(float(valrow[-1]))
                y_trues.append(y_true)
                if len(valrow) == 0:
                    continue
                if pred == y_true:
                    correct_count += 1
                #if class seen, add to its counter
                if y_true in numeachclass.keys():
                    numeachclass[y_true] += 1
                #initialize a new counter
                else:
                    numeachclass[y_true] = 0
                count += 1
        return count, correct_count, numeachclass, preds,  y_trues
```

3. Run -validate

You can make this modification in your own python script most easily by replacing lines 317-395 with the code above. Below I'm using an already modified version of the script called 'a_mod.py', but you would use your edited 'a.py'. We simply have to run the following line of code and it will output our desired png.

In [3]:

```
! python3 a_mod.py php50jXam.csv -validate
```

```
Classifier Type:                    Neural Network
System Type:                        Binary classifier
Best-guess accuracy:                55.53%
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Precision:                          1.00
F-1 Measure:                        1.00
False Negative Rate/Miss Rate:      0.00
Critical Success Index:             1.00
```
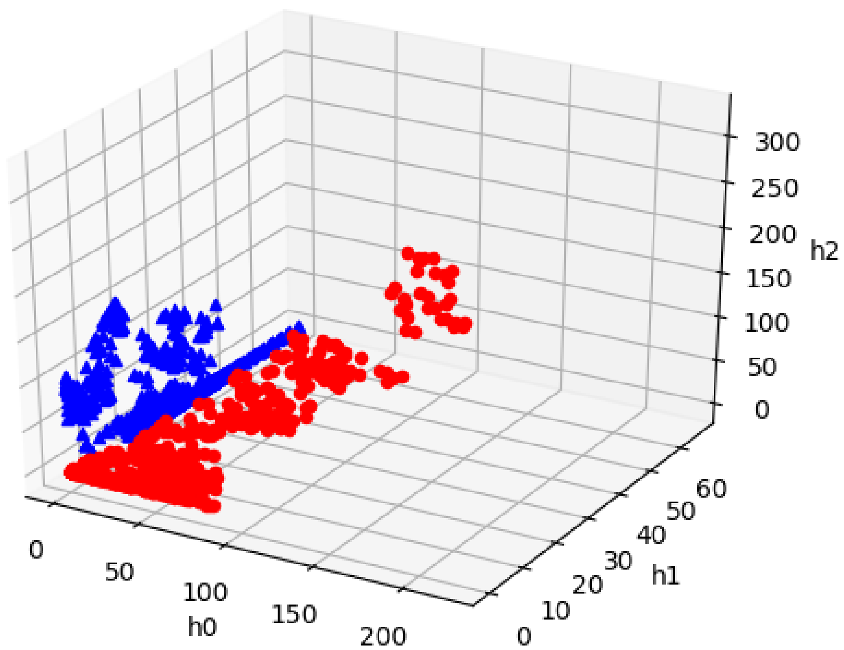

Your current directory should now have a png called 'bank_note_authentication.png' in it that looks like the following:



Here we see the 3D hidden space that corresponds to the three neurons the model uses. The blue triangles represent data points that are classified as forgeries; and the red circles are data points that are classified as authentic. Because our model is 100% accurate, there is a clear plane separating the two classifications. This is the plane that the predictor uses to distinguish between the two classes.