Lab 8

In [1]:
```
import seaborn as sns
from keras.models import Sequential
from keras.layers import Dense, Activation
import seaborn as sns
import numpy as np
import pandas as pd

from sklearn.datasets import load_iris
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from keras.utils import np_utils



import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Dropout
from keras.optimizers import RMSprop

import scipy.io as scipy_io
from scipy import sparse
```

```
Using TensorFlow backend.
```

We are running tensorflow through keras. The swiss/swedish/norwegian roll does not perform well for us at all. It does not pick up the structure even when I expand the input features to include sin(x), sin(y), x*y, x**2, and y**2. I thought that would help. The loss function does not go down monotonically, which I think is to be expected with the peceptron algorithm and the neural net. These jumps in the loss functions are seen in the test and training data.

The learning rate impacts how quickly it settles in on a pattern. When the learning rate is large the model 'settles down' quickly, but can miss the pattern (especially when the pattern is more complex, it seems). A small learning rate leads to a model which more slowly changes the loss function, but seems more likely to eventually identify the pattern.

The epoch seems to be the number of iterations the model goes through. I don't quite follow what happens at each epoch, but the more epochs you go through the better the model gets, unless the learning rate is too high.

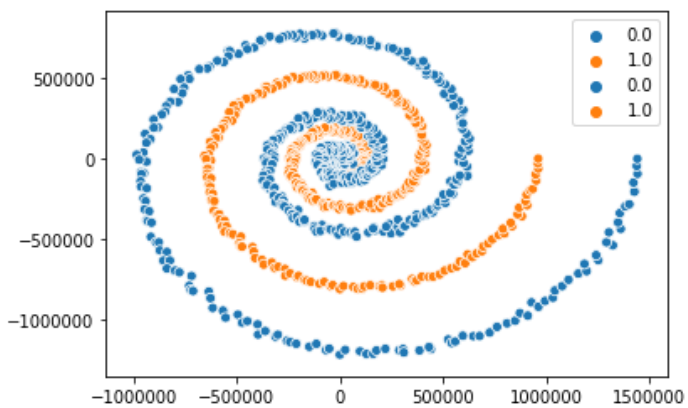
SGD refers to stochastic gradient descent. Adam, ' adaptive moment estimation' is an alternative which can be faster I read.

Adding nodes and layers slows down our models, but in the more complex patterns I looked at more layers and nodes helped to identify the pattern.

I've included some of our code below along side an exploration of the MNIST dataset. We went a little off script for this lab, but it was easier to adapt some of the excersies to python than others.

*note, I am also using [http://playground.tensorflow.org (http://playground.tensorflow.org)](http://playground.tensorflow.org) to explore the models. I could get the swiss roll neural net in tensor flow playground to work, but could not achieve anything close to accurate when I coded it up myself.

In [2]:
```
XTrain_spiral = []
YTrain_spiral = []
for theta in np.linspace(0,10*np.pi, num = 1000):
    r = ((theta)**4)
    XTrain_spiral.append(r*np.cos(theta) + 100*np.random.normal(0, 100, 1) )
    YTrain_spiral.append(r*np.sin(theta) + 100*np.random.normal(0, 100, 1))


XTrain_spiral = np.reshape(XTrain_spiral, 1000)
YTrain_spiral = np.reshape(YTrain_spiral, 1000)

x = np.concatenate([XTrain_spiral,1.5*XTrain_spiral])
y = np.concatenate([YTrain_spiral, 1.5*YTrain_spiral])
cl = (np.concatenate([np.ones(1000), np.zeros(1000)]))

sns.scatterplot(x,y,hue = cl)

#cl = np_utils.to_categorical(cl)
data = np.vstack([x,y]).T
#sns.scatterplot(x,y,hue = cl[:,1])
sns.scatterplot(x,y,hue = cl)

#now build neural net


train_X, test_X, train_y, test_y = train_test_split(data, cl,
                                                    train_size=0.5,
                                                    test_size=0.5)
```



The first model is a classification model

In [3]:
```
model = Sequential()
model.add(Dense(8, activation='tanh', kernel_initializer='random_normal', input_sh
ape=(2,)))
model.add(Dense(8, activation='tanh', kernel_initializer='random_normal'))
model.add(Dense(1, activation='sigmoid', kernel_initializer='random_normal'))
```

In [4]:
```
model.summary()

model.compile(optimizer ='adam',loss='binary_crossentropy', metrics =['accuracy'])

model.fit(train_X, train_y,
          epochs=100,
          batch_size=128, verbose = 0)
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 8)                 24
_________________________________________________________________
dense_2 (Dense)              (None, 8)                 72
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 9
=================================================================
Total params: 105
Trainable params: 105
Non-trainable params: 0
_________________________________________________________________
```

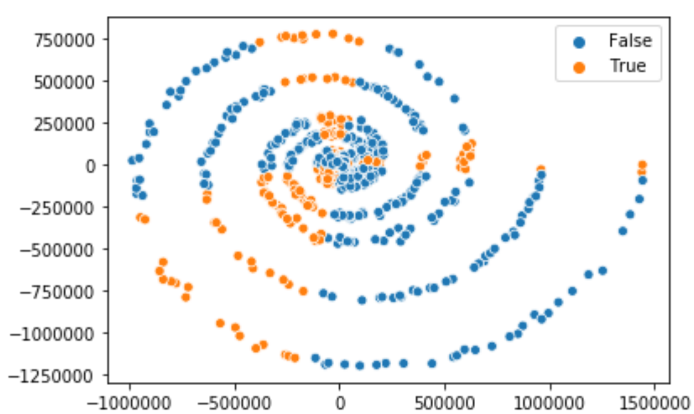
Out[4]: <keras.callbacks.callbacks.History at 0x13e9822d0>

Now I can plot the neural net predictions.

In [5]:
```
score = model.evaluate(test_X, test_y, batch_size=128)
score
predict = model.predict(test_X)

y_pred=model.predict(test_X)
y_pred =(y_pred>0.5)

sns.scatterplot(test_X[:,0], test_X[:,1], hue =y_pred[:,0])
```

```
1000/1000 [==============================] - 0s 31us/step
```

Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x13ec442d0>



In [6]:
```
model.summary()

model.compile(optimizer ='adam',loss='binary_crossentropy', metrics =['accuracy'])

model.fit(train_X, train_y,
          epochs=1000,
          batch_size=128, verbose = 0)
```

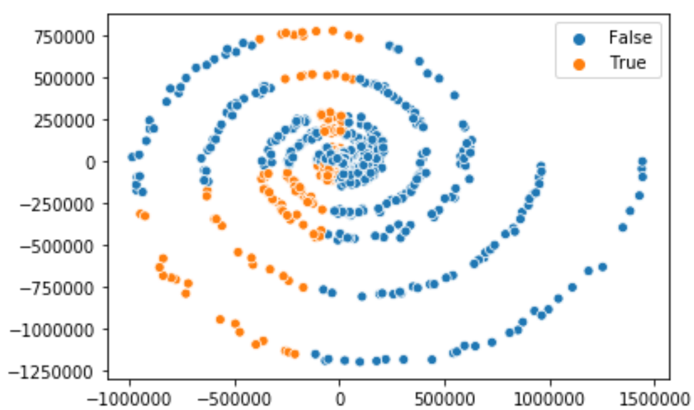
```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 8)                 24
_________________________________________________________________
dense_2 (Dense)              (None, 8)                 72
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 9
=================================================================
Total params: 105
Trainable params: 105
Non-trainable params: 0
_________________________________________________________________
```

Out[6]: `<keras.callbacks.callbacks.History at 0x13f3d8f50>`

In [7]:
```
score = model.evaluate(test_X, test_y, batch_size=128)
score
predict = model.predict(test_X)

y_pred=model.predict(test_X)
y_pred =(y_pred>0.5)

sns.scatterplot(test_X[:,0], test_X[:,1], hue =y_pred[:,0])
```

```
1000/1000 [==============================] - 0s 26us/step
```

Out[7]: `<matplotlib.axes._subplots.AxesSubplot at 0x13f362e10>`



In [8]:
```
print(score)
```

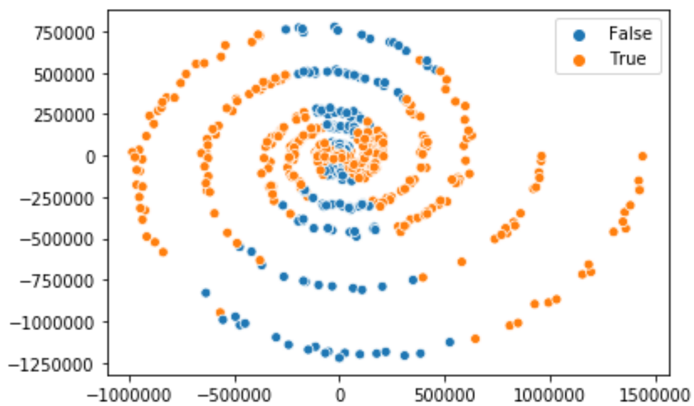
```
[0.7023964176177978, 0.4650000035762787]
```

So clearly our neural net for the swiss/swedith/german roll is not working very well. I am going to try a basis expansion and see if that helps, since we clearly do not have a linear decision boundary.

In [9]:
```
data = np.vstack([x,y,x**2,y**2, x*y, np.sin(x), np.sin(y)]).T


train_X, test_X, train_y, test_y = train_test_split(data, cl,
                                                    train_size=0.5,
                                                    test_size=0.5)

model = Sequential()
model.add(Dense(10, activation='tanh', input_shape=(7,)))
model.add(Dropout(0.1))
model.add(Dense(10, activation='tanh'))
model.add(Dense(1, activation='sigmoid'))

model.summary()

adam = keras.optimizers.Adam(learning_rate=0.1, beta_1=0.9, beta_2=0.999, amsgrad=
False)

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

model.fit(train_X, train_y,
          epochs=100,
          batch_size=128, verbose = 0)

score = model.evaluate(test_X, test_y, batch_size=128)
score
predict = model.predict(test_X)

y_pred=model.predict(test_X)
#print(y_pred)
y_pred =(y_pred>0.5)

sns.scatterplot(test_X[:,0], test_X[:,1], hue =y_pred[:,0])
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (None, 10)                80
_________________________________________________________________
dropout_1 (Dropout)          (None, 10)                0
_________________________________________________________________
dense_5 (Dense)              (None, 10)                110
_________________________________________________________________
dense_6 (Dense)              (None, 1)                 11
=================================================================
Total params: 201
Trainable params: 201
Non-trainable params: 0
_________________________________________________________________
1000/1000 [==============================] - 0s 34us/step
```

Out[9]: `<matplotlib.axes._subplots.AxesSubplot at 0x13f6b0150>`



So, including more 'features' did not seem to help. Trying to get this to work is probably not the best use of my time at the moment, but I am pretty frustrated...

News Prediction

In [10]:
```
news = scipy_io.loadmat('news.mat')
X = news["X"]
l = news["L"]

X = X.T
train_X, test_X, train_y, test_y = train_test_split(X, l,
                                                    train_size=0.9,
                                                    test_size=0.1)
```

In [11]:
```
model = Sequential()
model.add(Dense(10, activation='tanh', input_shape=(9656,)))
model.add(Dropout(0.1))
model.add(Dense(10, activation='tanh'))
model.add(Dense(1, activation='sigmoid'))

model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_7 (Dense)              (None, 10)                96570
_________________________________________________________________
dropout_2 (Dropout)          (None, 10)                0
_________________________________________________________________
dense_8 (Dense)              (None, 10)                110
_________________________________________________________________
dense_9 (Dense)              (None, 1)                 11
=================================================================
Total params: 96,691
Trainable params: 96,691
Non-trainable params: 0
_________________________________________________________________
```

In [12]:
```
model.compile(optimizer ='adam',loss='binary_crossentropy', metrics =['accuracy'])

model.fit(train_X, train_y,
          epochs=100,
          batch_size=128, verbose = 0)
```

Out[12]: `<keras.callbacks.callbacks.History at 0x13f48cc10>`

In [13]:
```
score = model.evaluate(test_X, test_y, batch_size=128)
score
predict = model.predict(test_X)
y_pred =(predict>0.5)
pd.crosstab(y_pred[:,0], test_y[:,0])
```

```
180/180 [==============================] - 0s 212us/step
```

Out[13]:

col_0	-1	1
row_0		
False	83	17
True	0	80

We have correctly predicted 100% of the "-1s" and 78% of the "1s".

If we use less training data the accuracy gets better, which is confusing to me. I would have assumed less training data would have resulted into pooring testing results.

In [14]:
```
train_X, test_X, train_y, test_y = train_test_split(X, l,
                                                    train_size=0.5,
                                                    test_size=0.5)

model.fit(train_X, train_y,
          epochs=100,
          batch_size=128, verbose = 0)

score = model.evaluate(test_X, test_y, batch_size=128)
score
predict = model.predict(test_X)

y_pred =(predict>0.5)
pd.crosstab(y_pred[:,0], test_y[:,0])
```

```
900/900 [==============================] - 0s 17us/step
```

Out[14]:

col_0	-1	1
row_0		
False	439	4
True	0	457

MNIST

The following is different than the class assignment, but seemed relevant. Plus I found documentation on Keras for the MNIST dataset so I am more confident the activations I am using are appropriate.

In [15]:

```python
#''Trains a simple deep NN on the MNIST dataset.

#Gets to 98.40% test accuracy after 20 epochs
#(there is *a lot* of margin for parameter tuning).
#2 seconds per epoch on a K520 GPU.
#''


batch_size = 128
num_classes = 10
epochs = 20

# the data, split between train and test sets
(x_train, y_train), (x_test, y_test) = mnist.load_data()

x_train = x_train.reshape(60000, 784)
x_test = x_test.reshape(10000, 784)
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
x_train /= 255
x_test /= 255
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')

# convert class vectors to binary class matrices
y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)

model = Sequential()
model.add(Dense(512, activation='relu', input_shape=(784,)))
model.add(Dropout(0.2))
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(num_classes, activation='softmax'))

model.summary()
```

```
60000 train samples
10000 test samples
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_10 (Dense)             (None, 512)               401920    
_________________________________________________________________
dropout_3 (Dropout)          (None, 512)               0         
_________________________________________________________________
dense_11 (Dense)             (None, 512)               262656    
_________________________________________________________________
dropout_4 (Dropout)          (None, 512)               0         
_________________________________________________________________
dense_12 (Dense)             (None, 10)                5130      
=================================================================
Total params: 669,706
Trainable params: 669,706
Non-trainable params: 0
_________________________________________________________________
```

In [16]:
```
#model.compile(loss='categorical_crossentropy',
#              optimizer=RMSprop(),
#              metrics=['accuracy'], verbose = 0)

#history = model.fit(x_train, y_train,
#                    batch_size=batch_size,
#                    epochs=epochs,
#                    verbose=1,
#                    validation_data=(x_test, y_test))

#score = model.evaluate(x_test, y_test)
#print('Test loss:', score[0])
#print('Test accuracy:', score[1])
```

In [ ]:
```

```