**Greg Walsh**

**DSSA-5104-091 - DEEP LEARNING**

**Spring 2020**

**Pima Indians - diabetes prediction**

### Neural Network for binary classification ¶

In [1]:
```
# Import necessary libraries
from keras.models import Sequential
from keras.layers import Dense
from keras import optimizers
import numpy as np
from keras.callbacks import EarlyStopping
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt

# set random seed for reproducibility
np.random.seed(7)

# load pima indians dataset
dataset = np.loadtxt("pima-indians-diabetes.csv", delimiter=",")

# split into input (X) and output (Y) variables
X = dataset[:,0:8]
Y = dataset[:,8]
```

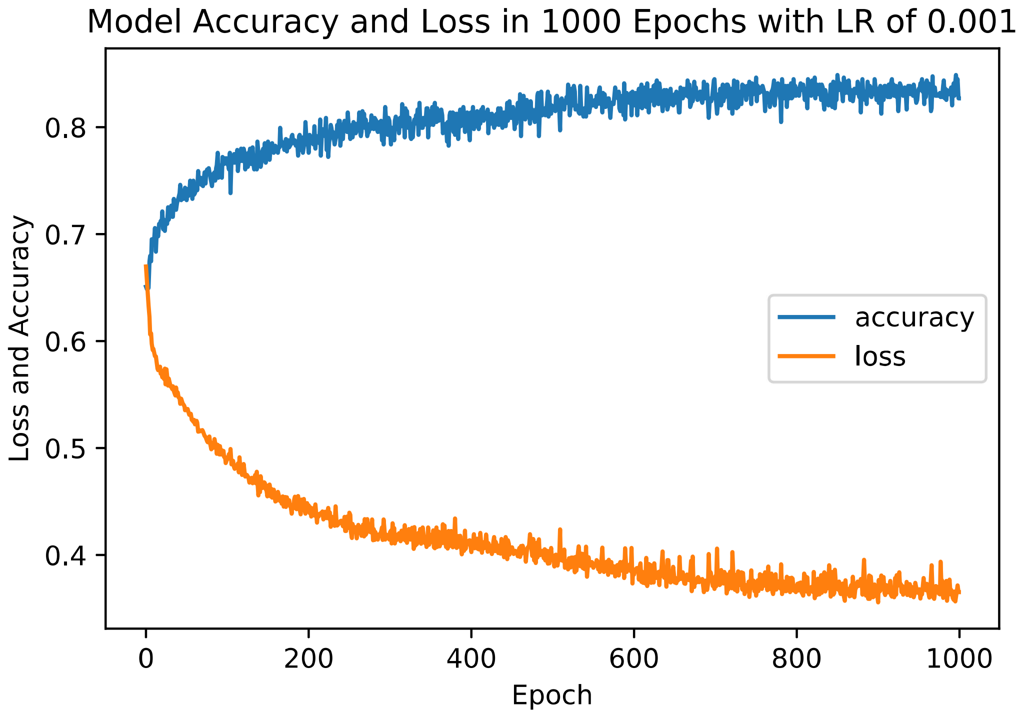
```
Using TensorFlow backend.
```

In [2]:
```
# LR 0.001
# Reset our variables
scores = None
Y_predict = None
adam = None
rounded = None
y_pred = None
history = None
model = None

# create model
model = Sequential()
#12 neurons using relu activation function
model.add(Dense(12, input_dim=8,activation='relu'))
# 8 neurons using relu activation function
model.add(Dense(8, kernel_initializer='uniform', activation='relu'))
#Single neuron used to produce a probability output in range of 0 to 1
model.add(Dense(1, kernel_initializer='uniform', activation='sigmoid'))

# Compile model
adam = optimizers.Adam(lr=0.001, beta_1=0.9, beta_2=0.999, epsilon=None, decay
=0.0, amsgrad=False)

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

# early stopping monitor is a keras lib that will see if the model is changing
and if not end it
early_stopping_monitor = EarlyStopping(monitor='val_loss', patience=1)

# Fit the model
history = model.fit(X,Y,epochs=1000,batch_size=10, verbose=0, callbacks=[early
_stopping_monitor])

# Evaluate the model
scores = model.evaluate(X, Y)
Y_predict = model.predict(X)

# Accuracy and loss
print("\n%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
print("\n%s: %.2f%%" % (model.metrics_names[0], scores[0]*100))

# Confusion Matrix
rounded = [round(i[0]) for i in Y_predict]
y_pred = np.array(rounded,dtype='int64')

# Confusion Matrix will look at the quality of our outputs from the NN. 0,0 an
d 1,1 are what we strive for.
print('================')
print('Confusion Matrix')
print('================')
CM = confusion_matrix(Y, y_pred)
print('True negatives:',CM[0,0])  # No and predicted No | we like this
print('False negatives:',CM[1,0]) # Yes but predicted No | This is horrible. W
e want least amount of these.
print('False positives:',CM[0,1]) # No but predicted Yes | This is okay for th
```

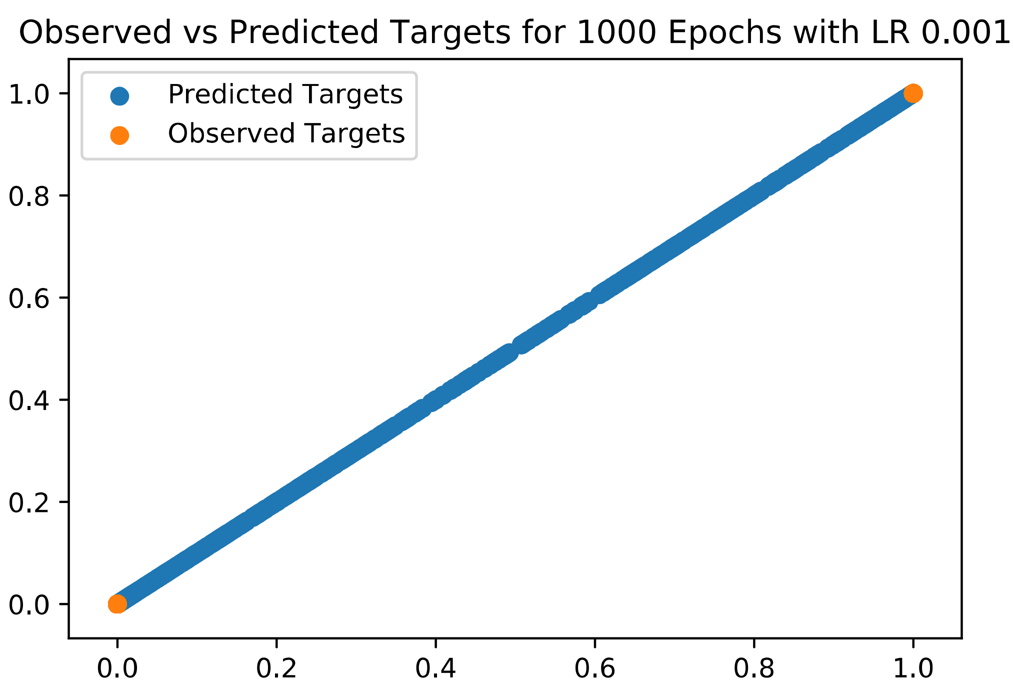
```
is use case.
print('True positives:',CM[1,1])  # Yes and predicted Yes | we like this
```

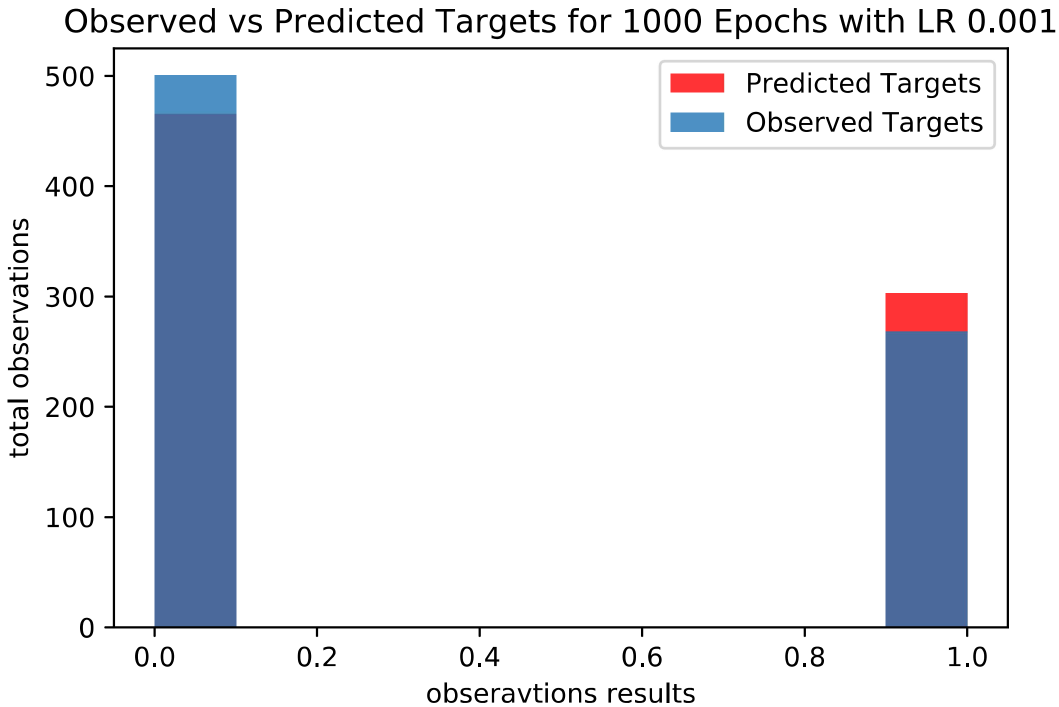
```
768/768 [==============================] - 0s 94us/step

accuracy: 83.98%

loss: 35.84%
================
Confusion Matrix
================
True negatives: 421
False negatives: 44
False positives: 79
True positives: 224
```

In [3]:
```
#Plot figure
plt.plot(history.history['accuracy'])
plt.plot(history.history['loss'])
plt.title('Model Accuracy and Loss in 1000 Epochs with LR of 0.001')
plt.ylabel('Loss and Accuracy')
plt.xlabel('Epoch')
plt.legend(['accuracy', 'loss'], loc='center right')
plt.text(0,0, 'Model Accuracy and Loss of the \nPima Indian Dataset.\nAccuracy
increases with more epochs.\nLoss decreases with more epochs')
plt.show()


plt.scatter(Y_predict,Y_predict, label = "Predicted Targets")
plt.scatter(Y,Y, label = "Observed Targets")
plt.legend()
plt.title('Observed vs Predicted Targets for 1000 Epochs with LR 0.001')
plt.show()

ax = plt.subplot(1,1,1)
plt.hist(y_pred,alpha=0.8,label="Predicted Targets",color='red')
ax.legend()
plt.hist(Y,alpha=0.8, label="Observed Targets")
ax.legend()
plt.ylabel("total observations")
plt.xlabel("obseravtions results")
plt.title("Observed vs Predicted Targets for 1000 Epochs with LR 0.001")
plt.show()
```




Model Accuracy and Loss of the
Pima Indian Dataset.
Accuracy increases with more epochs.
Loss decreases with more epochs



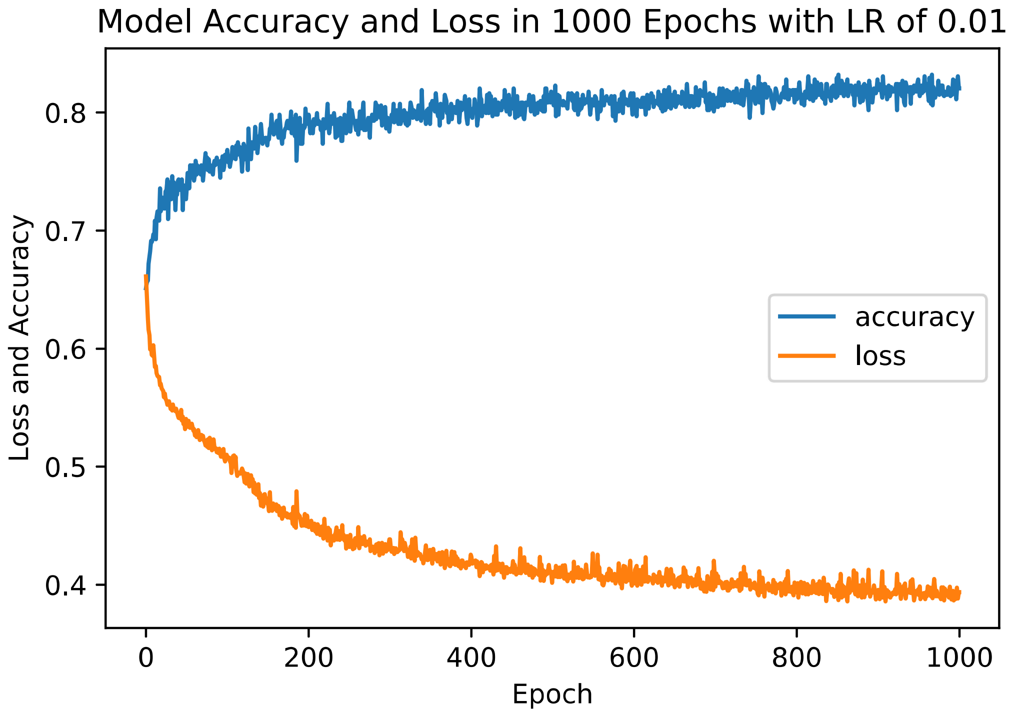


Observed vs Predicted Targets for 1000 Epochs with LR 0.001
Predicted Targets
Observed Targets
total observations
obseravtions results
0
100
200
300
400
500
0.0
0.2
0.4
0.6
0.8
1.0

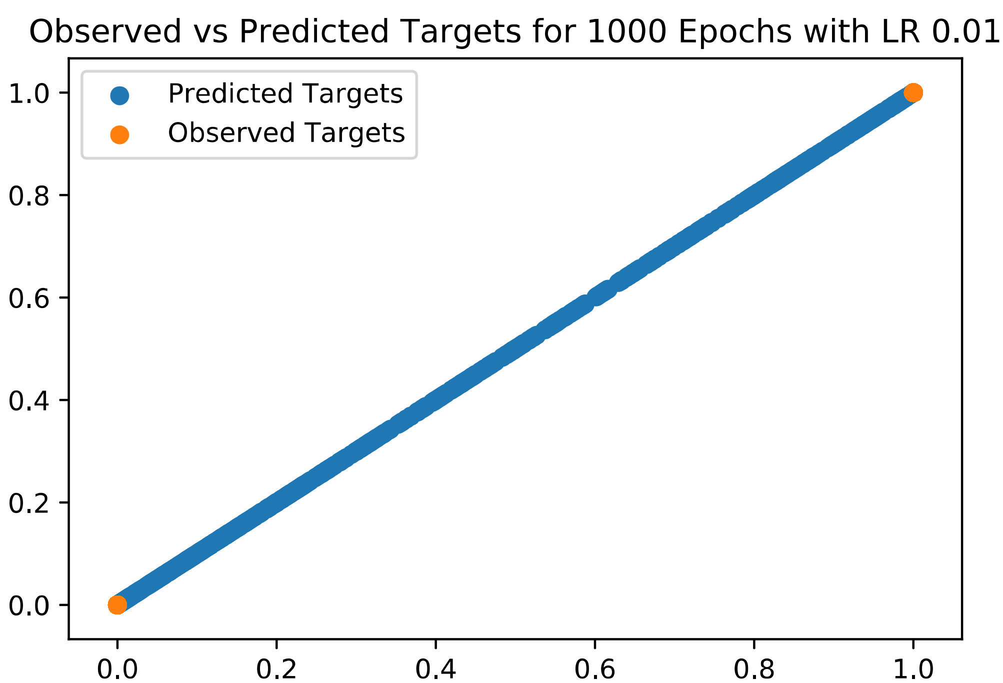
In [10]:
```
# Run for learning rate 0.5 and 1000 Epochs
# Reset our variables
scores = None
Y_predict = None
adam = None
rounded = None
y_pred = None
history = None
model = None

# create model
model = Sequential()
#12 neurons using relu activation function
model.add(Dense(12, input_dim=8,activation='relu'))
# 8 neurons using relu activation function
model.add(Dense(8, kernel_initializer='uniform', activation='relu'))
#Single neuron used to produce a probability output in range of 0 to 1
model.add(Dense(1, kernel_initializer='uniform', activation='sigmoid'))
# Compile model (requires completion)
adam = optimizers.Adam(lr=.5, beta_1=0.9, beta_2=0.999, epsilon=None, decay=0.
0, amsgrad=False)

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

# early stopping monitor is a keras lib that will see if the model is changing
and if not end it
early_stopping_monitor = EarlyStopping(monitor='val_loss', patience=1)

# Fit the model
history = model.fit(X,Y,epochs=1000,batch_size=10, verbose=0, callbacks=[early
_stopping_monitor])

# Evaluate the model
scores = model.evaluate(X, Y)
Y_predict = model.predict(X)

# Accuracy and loss
print("\n%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
print("\n%s: %.2f%%" % (model.metrics_names[0], scores[0]*100))

rounded = [round(i[0]) for i in Y_predict]
y_pred = np.array(rounded,dtype='int64')
print('================')
print('Confusion Matrix')
print('================')
CM = confusion_matrix(Y, y_pred)
print('True negatives:',CM[0,0])  # No and predicted No | we like this
print('False negatives:',CM[1,0]) # Yes but predicted No | This is horrible. W
e want least amount of these.
print('False positives:',CM[0,1]) # No but predicted Yes | This is okay for th
is use case.
print('True positives:',CM[1,1])  # Yes and predicted Yes | we like this
```

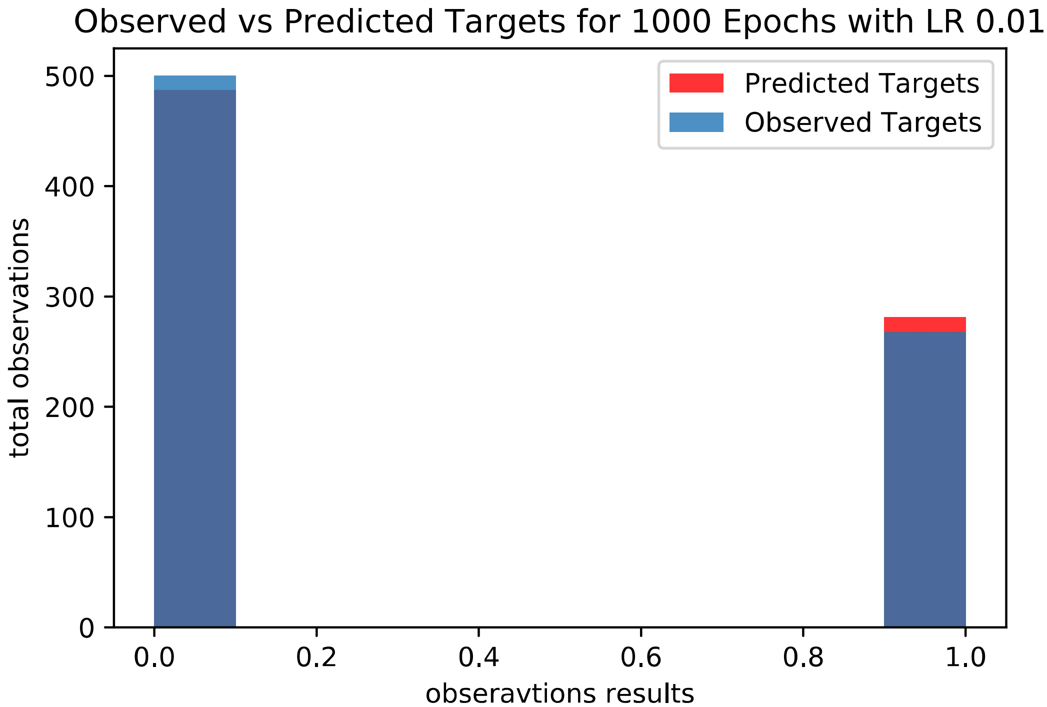
```
768/768 [==============================] - 0s 61us/step

accuracy: 81.64%

loss: 38.33%
================
Confusion Matrix
================
True negatives: 423
False negatives: 64
False positives: 77
True positives: 204
```

In [11]:
```
#Plot figure
plt.plot(history.history['accuracy'])
plt.plot(history.history['loss'])
plt.title('Model Accuracy and Loss in 1000 Epochs with LR of 0.5')
plt.ylabel('Loss and Accuracy')
plt.xlabel('Epoch')
plt.legend(['accuracy', 'loss'], loc='center right')
plt.text(0,0, 'Model Accuracy and Loss of the \nPima Indian Dataset.\nAccuracy increases with more epochs.\nLoss decreases with more epochs')
plt.show()


plt.scatter(Y_predict,Y_predict, label = "Predicted Targets")
plt.scatter(Y,Y, label = "Observed Targets")
plt.legend()
plt.title('Observed vs Predicted Targets for 1000 Epochs with LR 0.5')
plt.show()

ax = plt.subplot(1,1,1)
plt.hist(y_pred,alpha=0.8,label="Predicted Targets",color='red')
ax.legend()
plt.hist(Y,alpha=0.8, label="Observed Targets")
ax.legend()
plt.ylabel("total observations")
plt.xlabel("obseravtions results")
plt.title("Observed vs Predicted Targets for 1000 Epochs with LR 0.5")
plt.show()
```




Model Accuracy and Loss of the
Pima Indian Dataset.
Accuracy increases with more epochs.
Loss decreases with more epochs





Observed vs Predicted Targets for 1000 Epochs with LR 0.01
Predicted Targets
Observed Targets
total observations
obseravtions results
0
100
200
300
400
500
0.0
0.2
0.4
0.6
0.8
1.0

In [8]:

```
# Run for learning rate 0.1 and 1000 Epochs
# Reset our variables
scores = None
Y_predict = None
adam = None
rounded = None
y_pred = None
history = None
model = None

# create model
model = Sequential()
#12 neurons using relu activation function
model.add(Dense(12, input_dim=8,activation='relu'))
# 8 neurons using relu activation function
model.add(Dense(8, kernel_initializer='uniform', activation='relu'))
#Single neuron used to produce a probability output in range of 0 to 1
model.add(Dense(1, kernel_initializer='uniform', activation='sigmoid'))

# Compile model
adam = optimizers.Adam(lr=0.00001, beta_1=0.9, beta_2=0.999, epsilon=None, dec
ay=0.0, amsgrad=False)

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

# early stopping monitor is a keras lib that will see if the model is changing
and if not end it
early_stopping_monitor = EarlyStopping(monitor='val_loss', patience=1)

# Fit the model
history = model.fit(X,Y,epochs=1000,batch_size=10, verbose=0, callbacks=[early
_stopping_monitor])

# Evaluate the model efficiency and performance
scores= model.evaluate(X, Y)
Y_predict= model.predict(X)

# Accuracy and loss
print("\n%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
print("\n%s: %.2f%%" % (model.metrics_names[0], scores[0]*100))

rounded = [round(i[0]) for i in Y_predict]
y_pred = np.array(rounded,dtype='int64')
print('================')
print('Confusion Matrix')
print('================')
CM = confusion_matrix(Y, y_pred)
print('True negatives:',CM[0,0])  # No and predicted No | we like this
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is use case.
print('True positives:',CM[1,1])  # Yes and predicted Yes | we like this
```
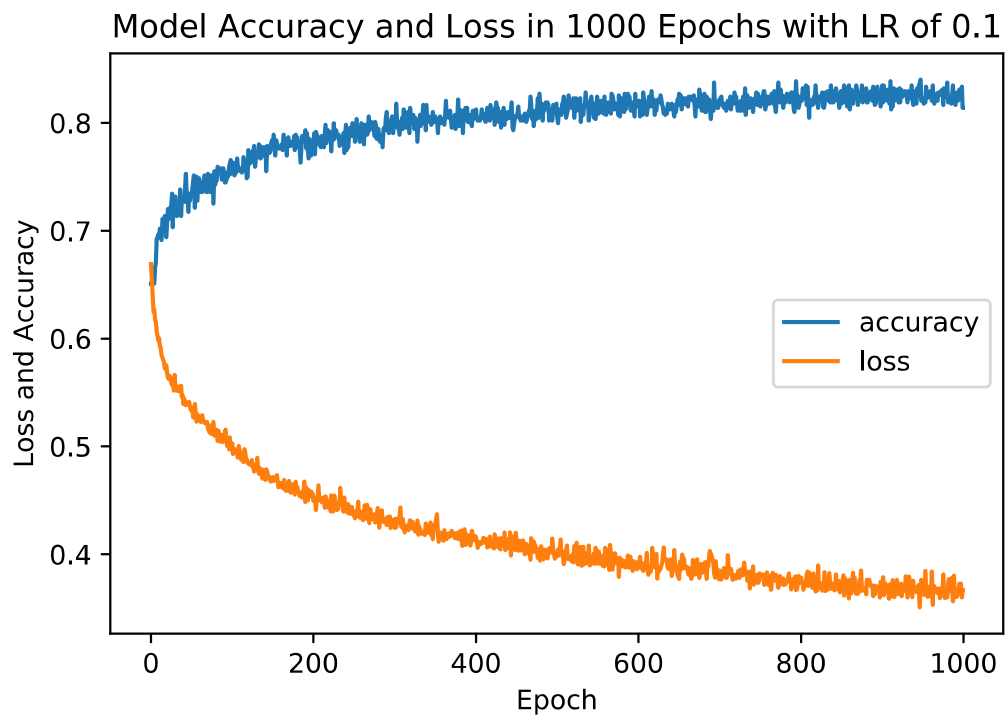
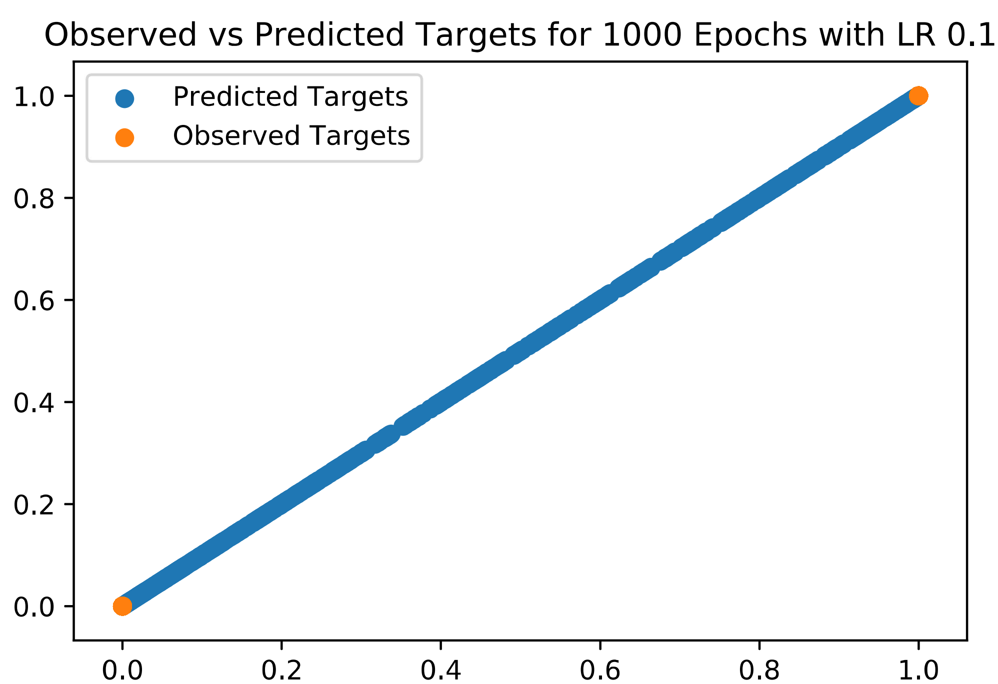
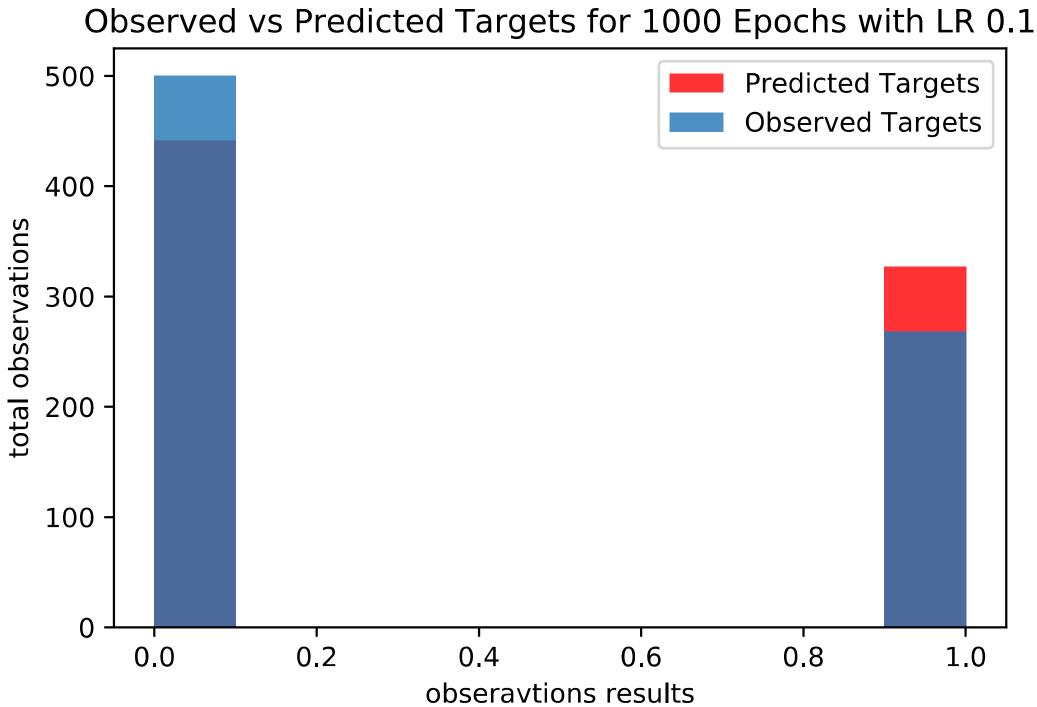

```
768/768 [==============================] - 0s 53us/step

accuracy: 80.08%

loss: 42.13%
================
Confusion Matrix
================
True negatives: 394
False negatives: 47
False positives: 106
True positives: 221
```

In [9]:
```
#Plot figure
plt.plot(history.history['accuracy'])
plt.plot(history.history['loss'])
plt.title('Model Accuracy and Loss in 1000 Epochs with LR of 0.00001')
plt.ylabel('Loss and Accuracy')
plt.xlabel('Epoch')
plt.legend(['accuracy', 'loss'], loc='center right')
plt.text(0,0, 'Model Accuracy and Loss of the \nPima Indian Dataset.\nAccuracy
increases with more epochs.\nLoss decreases with more epochs')
plt.show()


plt.scatter(Y_predict,Y_predict, label = "Predicted Targets")
plt.scatter(Y,Y, label = "Observed Targets")
plt.legend()
plt.title('Observed vs Predicted Targets for 1000 Epochs with LR 0.00001')
plt.show()

ax = plt.subplot(1,1,1)
plt.hist(y_pred,alpha=0.8,label="Predicted Targets",color='red')
ax.legend()
plt.hist(Y,alpha=0.8, label="Observed Targets")
ax.legend()
plt.ylabel("total observations")
plt.xlabel("obseravtions results")
plt.title("Observed vs Predicted Targets for 1000 Epochs with LR 0.00001")
plt.show()
```




Model Accuracy and Loss of the
Pima Indian Dataset.
Accuracy increases with more epochs.
Loss decreases with more epochs




Observed vs Predicted Targets for 1000 Epochs with LR 0.1
Predicted Targets
Observed Targets
total observations
0
100
200
300
400
500
0.0
0.2
0.4
0.6
0.8
1.0
oberavtions results

From my obersvations is seems the LR will affect the accuracy by a few percentages. It seems to have a greater impact on Loss. However from experimenting the major changes in accuracy and lower loss are running more epochs.

# 0.001

accuracy: 83.98%

loss: 35.84%

Confusion Matrix

True negatives: 421

False negatives: 44

False positives: 79

True positives: 224

# 0.5

accuracy: 81.64%

loss: 38.33%

Confusion Matrix

True negatives: 423

False negatives: 64

False positives: 77

True positives: 204

accuracy: 80.08%

# 0.00001

accuracy: 80.08%

loss: 42.13%

Confusion Matrix

True negatives: 394

False negatives: 47

False positives: 106

True positives: 221