Heart logistic regression

Hyperparameters of the logistic regression model:

- Since it is similar to linear regression, the network is already defined as a 1 neuron combining all the features of the input with an activation function that is sigmoid so layer number and number of units are not hyperparameters in this specific problem.
- Regularization type, and term is a hyper parameter to be tuned(We will find that we need to use regularization due to overfitting).
- The type of optimizer and its parameters.
- Learning rate (We will need to tune it so we reach convergence).

In [0]:

```
# %xmode Plain
# %pdb on
import pandas as pd
import seaborn as sns
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegressionCV
from keras.models import Sequential
from keras.layers.core import Dense, Activation
from keras.regularizers import l1,l2
from keras.optimizers import Adam, SGD
from keras.utils import np_utils
from matplotlib import pyplot as plt
from sklearn.preprocessing import StandardScaler
```

In [0]:

```
dataset = pd.read_csv("heart.csv")

X = dataset.iloc[:, 0:13].values
y = dataset.iloc[:, 13].values
```

In [5]:

```
train_X, test_X, train_y, test_y = train_test_split(X, y, train_size=0.75, random_state=0)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_split.py:2179: FutureWarning: F
rom version 0.21, test_size will always complement train_size unless both are specified.
  FutureWarning)
```

In [0]:

```
def test_model(reg, opt, loss, train_X, train_y, verbose = 0):
  ## START CODE HERE
  def Model(input_shape):
    model = Sequential()
    model.add(Dense(1, input_shape = input_shape, kernel_initializer = 'normal' , kernel_regularizer=reg))
    model.add(Activation('sigmoid'))
    return model
  model = Model(train_X.shape[1:])
  ## END CODE HERE
  model.compile(loss=loss, metrics=['accuracy'], optimizer=opt)
  history = model.fit(train_X, train_y, verbose=verbose, batch_size=1, epochs=150, validation_split=0.1 )
  # Plot training & validation accuracy values
  plt.plot(history.history['acc'])
  plt.plot(history.history['val_acc'])
  plt.title('Model accuracy')
  plt.ylabel('Accuracy')
  plt.xlabel('Epoch')
  plt.legend(['Train', 'Test'], loc='upper left')
  plt.show()

  # Plot training & validation loss values
  plt.plot(history.history['loss'])
  plt.plot(history.history['val_loss'])
  plt.title('Model loss')
  plt.ylabel('Loss')
  plt.xlabel('Epoch')
  plt.legend(['Train', 'Test'], loc='upper left')
  plt.show()
  print('Last validation loss : ', history.history['val_loss'][-1], ' | last training loss : ', history.hist
ory['loss'][-1])
  print('Last validation accuracy : ', history.history['val_acc'][-1], ' | last training accuracy : ', histo
ry.history['acc'][-1])
  return model
```

Model Configurations

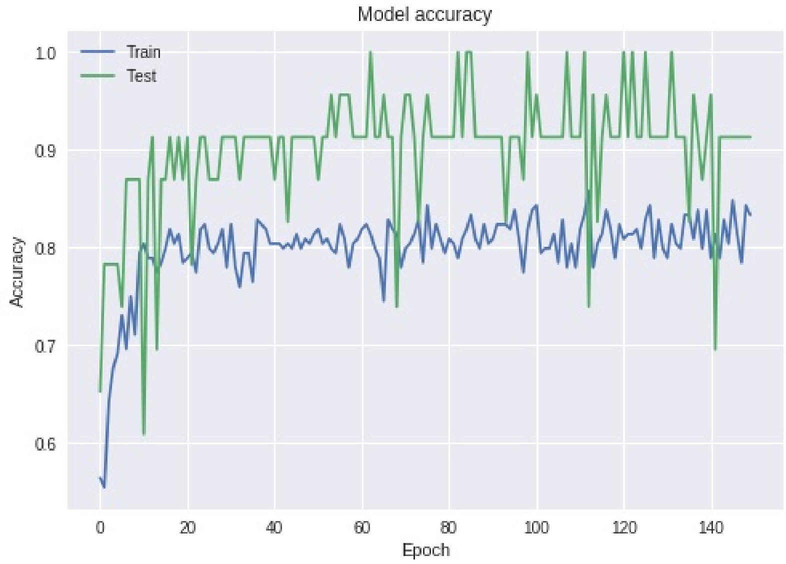
Default logistic regression without regularization and no artificial variables with Adam optimizer with default values with binary crossentropy as loss

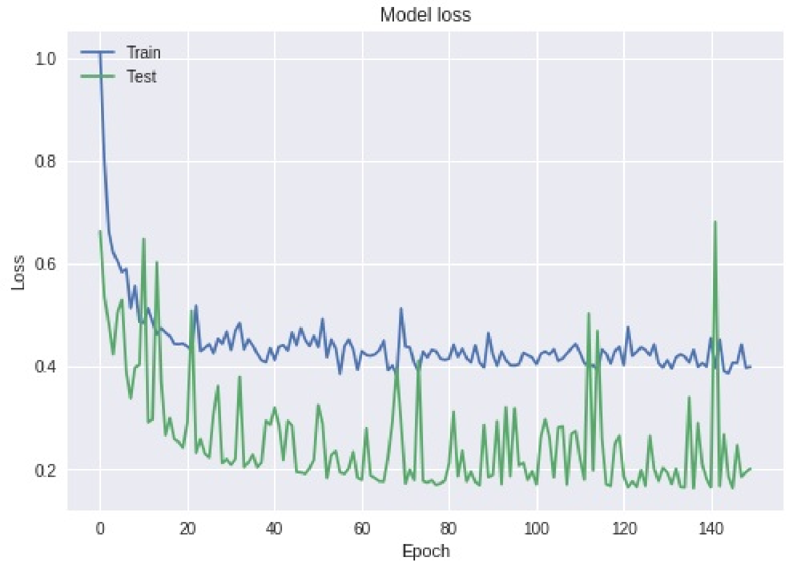
In [0]:

```
models = []
```

In [127]:

```
models.append(test_model(None, 'Adam', 'binary_crossentropy', train_X, train_y))
```



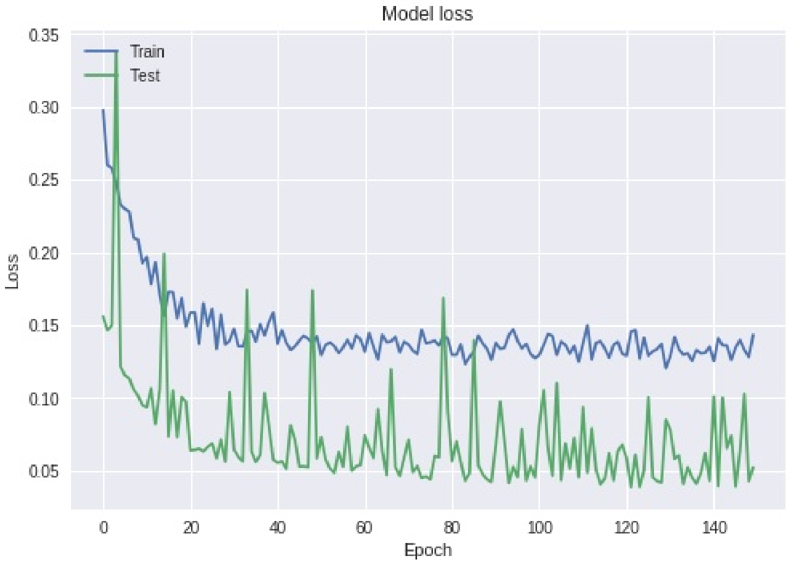



```
Last validation loss :  0.2007818983503334  | last training loss :  0.3991374346272399
Last validation accuracy :  0.9130434782608695  | last training accuracy :  0.8333333333333334
```

Default logistic regression with no regularization and no artificial variables with Adam optimizer with default values with mse as loss

In [20]:

```
models.append(test_model(None, 'Adam', 'mse', train_X, train_y))
```

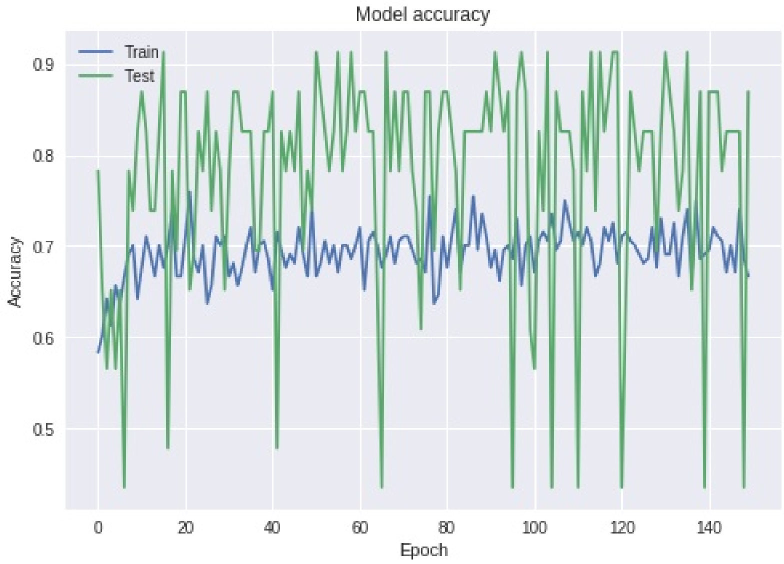


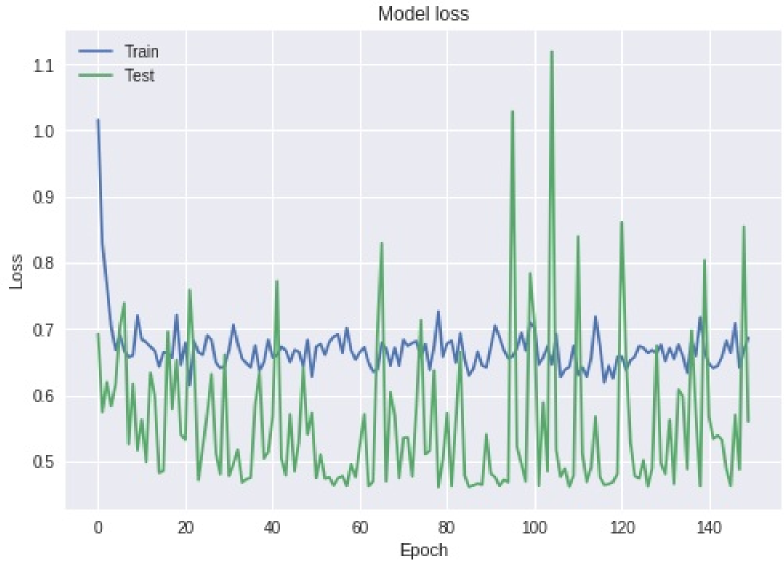

```
Last validation loss :  0.05239429693742058  | last training loss :  0.1432699806389326
Last validation accuracy :  0.9130434782608695  | last training accuracy :  0.8088235294117647
```

Default logistic regression with l1 regularization (0.1) and no artificial variables with Adam optimizer with default values with binary crossentropy as loss

In [129]:

```
models.append(test_model(l1(0.1), 'Adam', 'binary_crossentropy', train_X, train_y))
```



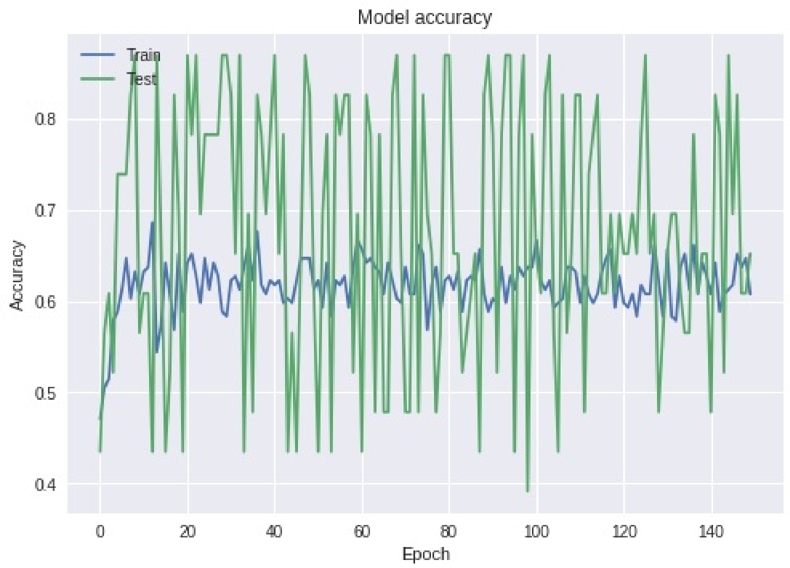


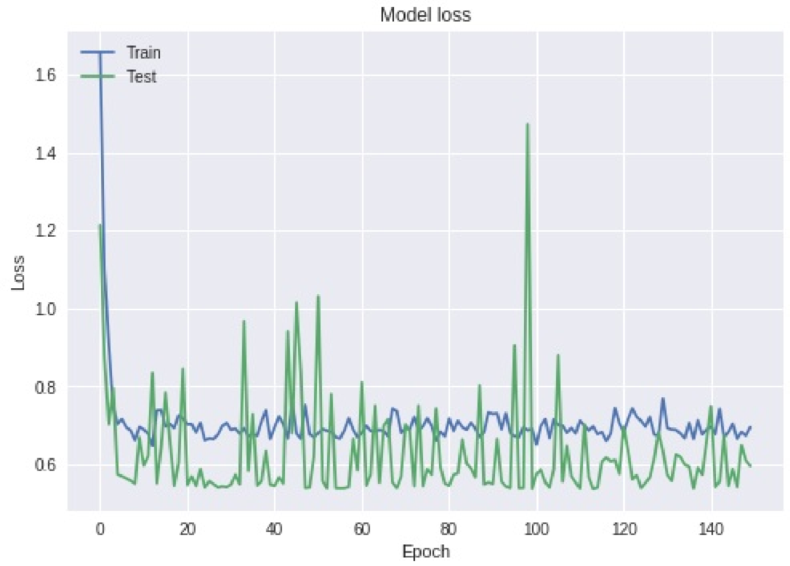

```
Last validation loss :  0.5601213062586992  | last training loss :  0.6862971161072161
Last validation accuracy :  0.8695652173913043  | last training accuracy :  0.6666666666666666
```

Default logistic regression with l1 regularization (0.2) and no artificial variables with Adam optimizer with default values with binary crossentropy as loss

In [130]:

```
models.append(test_model(l1(0.2), 'Adam', 'binary_crossentropy', train_X, train_y))
```





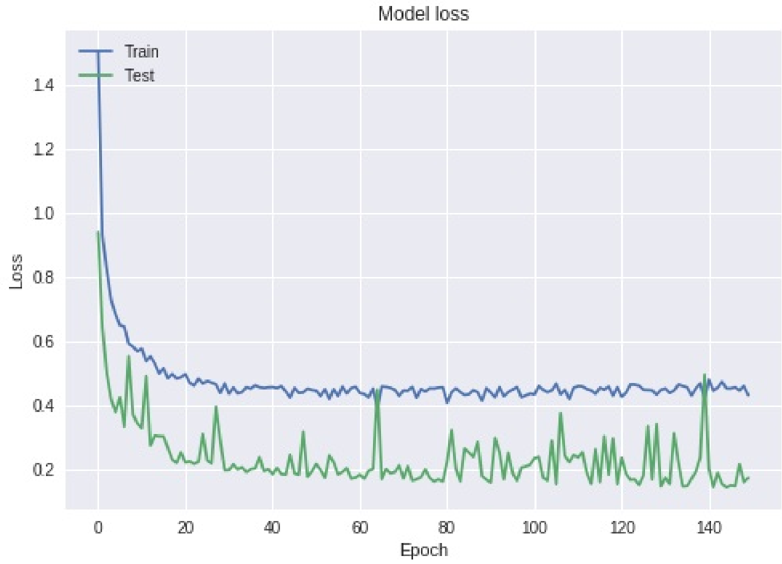

```
Last validation loss :  0.5953691841467567  | last training loss :  0.6944774019659734
Last validation accuracy :  0.6521739130434783  | last training accuracy :  0.6078431372549019
```

Regularization lowers performance, and since overfitting doesn't seem to be problem, it is better not to use it.

Default logistic regression with no regularization and no artificial variables with RMSprop optimizer with default values with binary crossentropy as loss

In [136]:

```
models.append(test_model(None, 'RMSprop', 'binary_crossentropy', train_X, train_y))
```

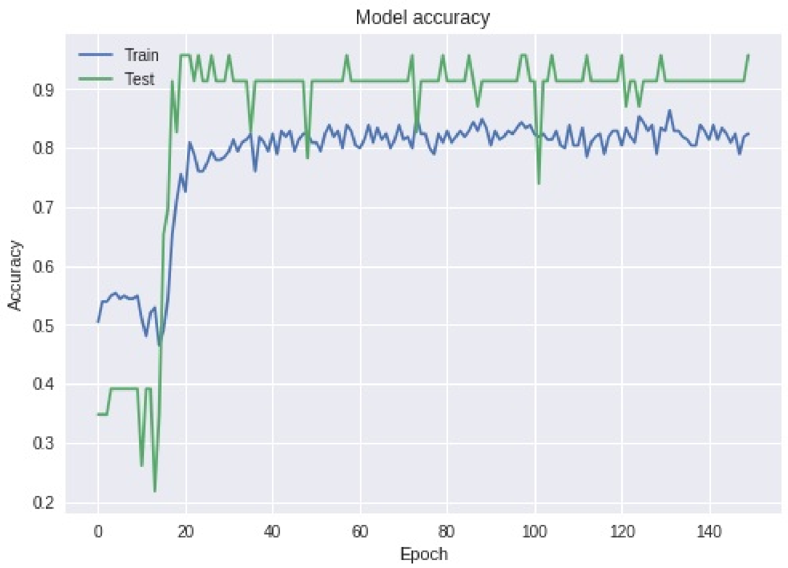


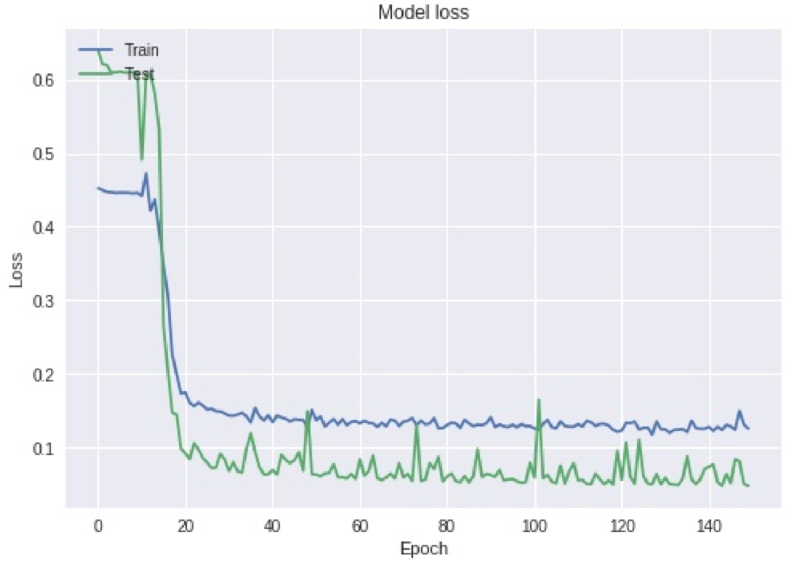

```
Last validation loss :  0.17339704824616606  | last training loss :  0.4318031250157076
Last validation accuracy :  0.9130434782608695  | last training accuracy :  0.7892156862745098
```

Default logistic regression with no regularization and no artificial variables with Adam optimizer with learning rate of 0.0005 with mse as loss

In [17]:

```
models.append(test_model(None, Adam(0.0005), 'mse', train_X, train_y))
```






```
Last validation loss :  0.047804697226163866  | last training loss :  0.12585188889365251
Last validation accuracy :  0.9565217391304348  | last training accuracy :  0.8235294117647058
```

Adding artifical variable combinations

Add 3 features which are the product of some of the continous features, and a relation between age and sex.

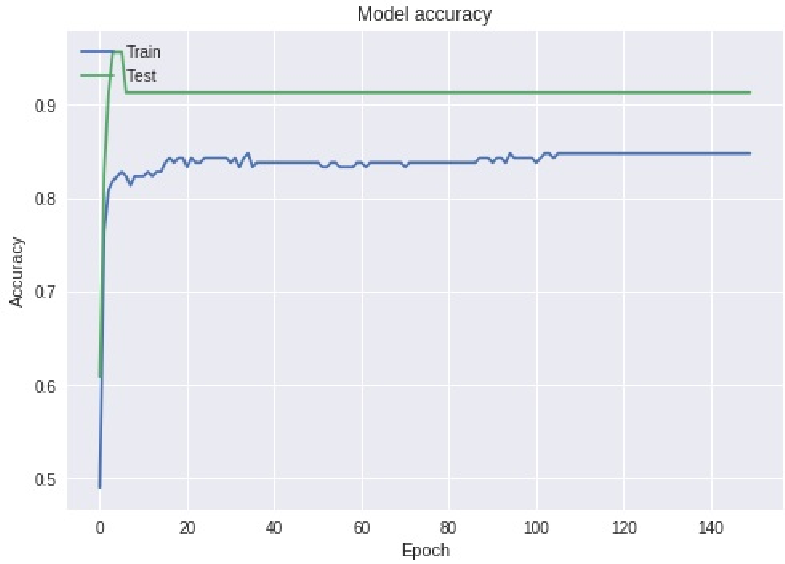
In [45]:

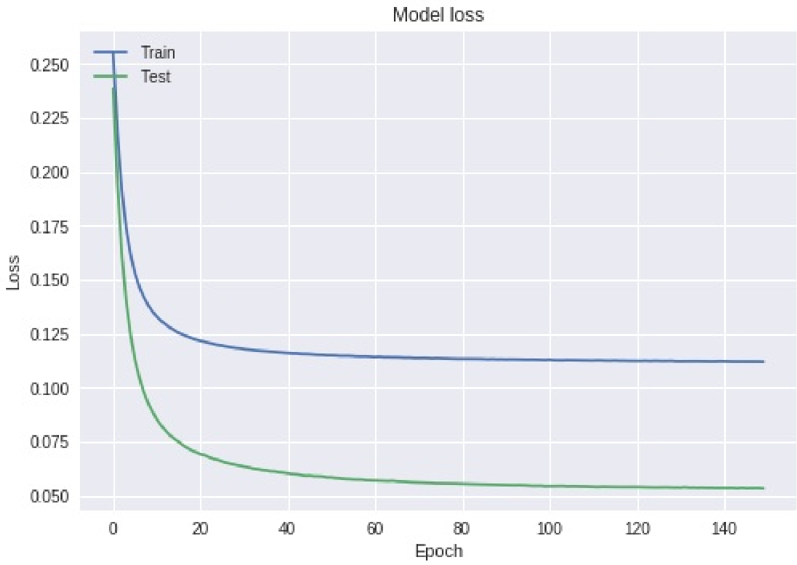
```
dataset.plot.scatter(x=0, y=1, c=13)
plt.show()
scaler = StandardScaler()
mod_train_x_std = scaler.fit_transform(train_X)
mod_train_x = np.zeros((train_X.shape[0], train_X.shape[1] + 3))
mod_train_x[:,:-3] = mod_train_x_std
for i in range(len(mod_train_x)):
  if train_X[i,1] == 1:
    mod_train_x[i, 13] = mod_train_x[i, 0]
  else:
    mod_train_x[i, 13] = -mod_train_x[i, 0]
  mod_train_x[i, 14] = mod_train_x[i, 3] * mod_train_x[i,7]
  mod_train_x[i, 15] = mod_train_x[i, 4] * mod_train_x[i,7]
def artificial_data(x_data):
  data_x_std = scaler.transform(x_data)
  data_x = np.zeros((x_data.shape[0], x_data.shape[1] + 3))
  data_x[:,:-3] = data_x_std
  for i in range(len(data_x)):
    if x_data[i,1] == 1:
      data_x[i, 13] = data_x[i, 0]
    else:
      data_x[i, 13] = -data_x[i, 0]
    data_x[i, 14] = data_x[i, 3] * data_x[i,7]
    data_x[i, 15] = data_x[i, 4] * data_x[i,7]
  return data_x
```

Default logistic regression with no regularization and artificial variables with Adam optimizer with learning rate of 0.0007 with mean square error as loss

In [48]:

```
models.append(test_model(None, Adam(0.0007), 'mse', mod_train_x, train_y))
```






```
Last validation loss :  0.0532132143220738  | last training loss :  0.11195896770893807
Last validation accuracy :  0.9130434782608695  | last training accuracy :  0.8480392156862745
```

Best configuration performance on test data

In [49]:

```
model = models[-1]
test_X_mod = artificial_data(test_X)
score, accuracy = model.evaluate(test_X_mod, test_y, batch_size=16, verbose=0)
print("Test fraction correct (NN-Score) = {:.2f}".format(score))
print("Test fraction correct (NN-Accuracy) = {:.2f}".format(accuracy))
```

```
Test fraction correct (NN-Score) = 0.12
Test fraction correct (NN-Accuracy) = 0.83
```

Conclusion

- Adam optimizer worked the best for this data.
- No regularization needed since the network is already low capacity
- Artifical variables helped elevate model performance since it is a shallow network.
- Mean squared error worked as nice and even better than binary entropy for this task