CNN_Keras

January 10, 2018

1 Neural Networks using Keras

- Most *object detection/labeling/segmentation/classification* tasks now have neural network equivalent algorithms that perform on-par with or better than hand-crafted methods.
- One library that gives Python users particularly easy access to deep learning is Keras: https://github.com/fchollet/keras/tree/master/examples (it works with both Theano and TensorFlow).

1.0.1 Configurations

From http://www.asimovinstitute.org/neural-network-zoo/:

1.0.2 Preliminary: Installing Keras

Generic instructions to install Keras with TensorFlow can be found here: - https://keras.io/#installation - https://www.pyimagesearch.com/2016/11/14/installing-keras-with-tensorflow-backend/

If you use Anaconda, you can replace the `pip` installer with `conda`, although both should work. You should already have: `numpy scipy scikit-learn scikit-image pillow h5py` installed. Keras and tensorflow are available from conda-forge for the major systems/OS:

```
conda install -c conda-forge tensorflow
conda install -c conda-forge keras
conda install -c conda-forge graphviz pydot
```

Test if installation was successfull in python:

```
Python 3.5.1 |Continuum Analytics, Inc.| (default, Jun 15 2016, 16:14:02)
...

In [1]: import keras
Using TensorFlow backend.
W tensorflow/core/platform/cpu_feature_guard.cc:45] The TensorFlow library wasn't compiled to us
...
In [2]:
```

You can ignore such warnings, these simply indicate that the base library for tensorflow was installed, which will work just fine, maybe not as fast as it could be. You may want to install the GPU version `tensorflow-gpu`, much faster, but will require some tuning specific to your system. If a GPU version is installed, Keras should normally use it automatically. - https://www.tensorflow.org/install/ - MacOS support has been dropped recently, workaround: https://stackoverflow.com/questions/44744737/tensorflow-mac-os-gpu-support - Windows: http://inmachineswetrust.com/posts/deep-learning-setup/ and https://blog.paperspace.com/running-tensorflow-on-windows/

In the Keras docs, you may read about `image_data_format`. By default, this is `channels-last`, which is compatible with scikit-image's storage of `(row, cols, ch)` and the most efficient when using TensorFlow. Check your config `~/.keras/keras.json`, which should look like:

```
{
    "image_data_format": "channels_last",
    "epsilon": 1e-07,
    "backend": "tensorflow",
    "floatx": "float32"
}
```

```
In [3]: # Test your installation:
        import tensorflow
        import keras
        import pydot
```

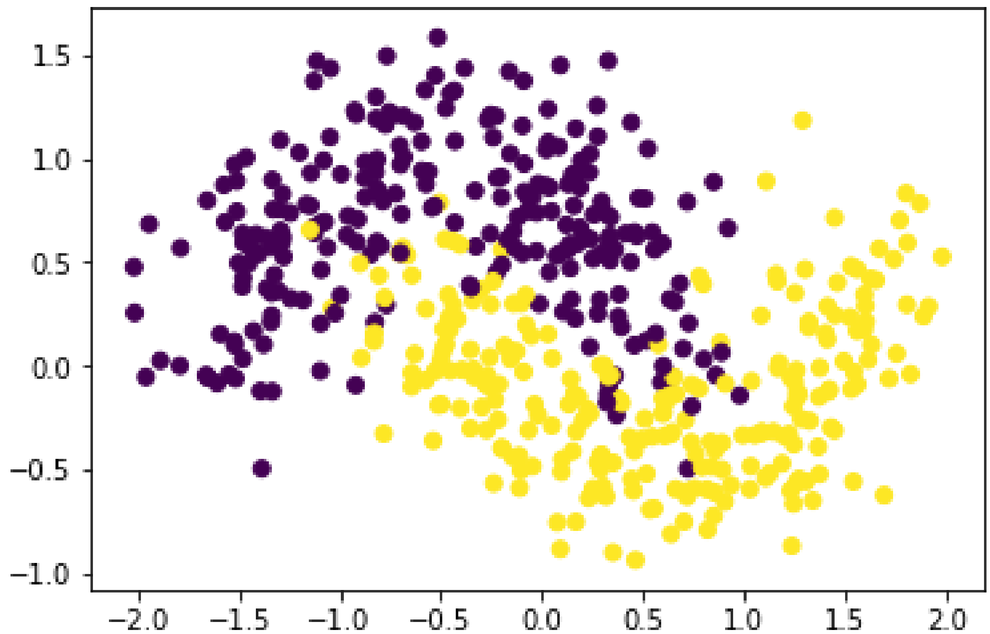
```
In [5]: import numpy as np
        import matplotlib.pyplot as plt
        %matplotlib inline
```

1.1 Keras basics

In this section, we apply a simple NN to simple 2D data to introduce the basic elements of Keras: - Creating a neural-network model - Training it and evaluating the accuracy - Plotting the learning curves

```
In [192]: ## Generate dummy data with some structure
          from sklearn import datasets
          from sklearn.model_selection import train_test_split

          # X, y = datasets.make_classification(n_features=2, n_samples=200, n_redundant=0, n_in
          #                                     n_clusters_per_class=1, random_state=42, class_s

          X, y = datasets.make_moons(n_samples=500, noise=0.25)
          X[:,0]-=0.5 # Center the moons

          X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5, random_state=
          #X_test[:,1]+=15

          plt.scatter(X[:,0],X[:,1], c=y)
          #plt.plot(X_train[:,0],X_train[:,1], 'r.', markersize=1)
          #plt.plot(X_test[:,0],X_test[:,1], 'b.', markersize=1)
```

Out[192]: <matplotlib.collections.PathCollection at 0x16e93fac8>



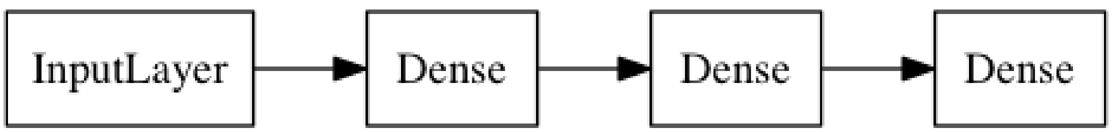
In [193]:
```
# Create a Neural Network with two hidden layers

from keras.models import Sequential
from keras.layers import Dense, Dropout, InputLayer

N=64

model = Sequential()
model.add(InputLayer(input_shape=[2]))
model.add(Dense(N, activation='relu'))
model.add(Dense(N, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

model.compile(loss='binary_crossentropy',
#model.compile(loss='mse',
              optimizer='rmsprop',
              metrics=['accuracy'])
```

In [194]:
```
model.summary(line_length=100)

# Visualize the network
from IPython.display import SVG, Image
from keras.utils.vis_utils import model_to_dot # need pydot and graphviz packages
```

```
Image(model_to_dot(model,rankdir='LR',show_layer_names=False, show_shapes=False).creat
#SVG(model_to_dot(model,rankdir='LR',show_layer_names=False).create(prog='dot', format
#plot_model(model, to_file='model.png') # Save to an image file
```

```
_______________________________________________________________________________________
Layer (type)                           Output Shape                      Param #
=======================================================================================
input_125 (InputLayer)                 (None, 2)                         0
_______________________________________________________________________________________
dense_338 (Dense)                      (None, 64)                        192
_______________________________________________________________________________________
dense_339 (Dense)                      (None, 64)                        4160
_______________________________________________________________________________________
dense_340 (Dense)                      (None, 1)                         65
=======================================================================================
Total params: 4,417
Trainable params: 4,417
Non-trainable params: 0
_______________________________________________________________________________________
```

Out[194]:



In [195]:
```
# Train the network
epochs=100
history = model.fit(X_train, y_train, epochs=epochs,
          batch_size=100, validation_data=(X_test,y_test),verbose=1)
score = model.evaluate(X_test, y_test)

print('\n\nAccuracy:', score[1])
score
```

```
Train on 250 samples, validate on 250 samples
Epoch 1/100
250/250 [==============================] - 4s 16ms/step - loss: 0.6617 - acc: 0.7560 - val_loss:
Epoch 2/100
250/250 [==============================] - 0s 54us/step - loss: 0.6006 - acc: 0.8440 - val_loss:
Epoch 3/100
250/250 [==============================] - 0s 49us/step - loss: 0.5603 - acc: 0.8440 - val_loss:
Epoch 4/100
250/250 [==============================] - 0s 48us/step - loss: 0.5264 - acc: 0.8480 - val_loss:
```

```
Epoch 5/100
250/250 [==============================] - 0s 55us/step - loss: 0.4971 - acc: 0.8480 - val_loss:
Epoch 6/100
250/250 [==============================] - 0s 50us/step - loss: 0.4712 - acc: 0.8520 - val_loss:
Epoch 7/100
250/250 [==============================] - 0s 54us/step - loss: 0.4485 - acc: 0.8520 - val_loss:
Epoch 8/100
250/250 [==============================] - 0s 50us/step - loss: 0.4265 - acc: 0.8560 - val_loss:
Epoch 9/100
250/250 [==============================] - 0s 50us/step - loss: 0.4071 - acc: 0.8560 - val_loss:
Epoch 10/100
250/250 [==============================] - 0s 51us/step - loss: 0.3910 - acc: 0.8560 - val_loss:
Epoch 11/100
250/250 [==============================] - 0s 50us/step - loss: 0.3761 - acc: 0.8600 - val_loss:
Epoch 12/100
250/250 [==============================] - 0s 55us/step - loss: 0.3634 - acc: 0.8560 - val_loss:
Epoch 13/100
250/250 [==============================] - 0s 57us/step - loss: 0.3524 - acc: 0.8600 - val_loss:
Epoch 14/100
250/250 [==============================] - 0s 53us/step - loss: 0.3430 - acc: 0.8640 - val_loss:
Epoch 15/100
250/250 [==============================] - 0s 63us/step - loss: 0.3344 - acc: 0.8640 - val_loss:
Epoch 16/100
250/250 [==============================] - 0s 57us/step - loss: 0.3265 - acc: 0.8640 - val_loss:
Epoch 17/100
250/250 [==============================] - 0s 54us/step - loss: 0.3193 - acc: 0.8720 - val_loss:
Epoch 18/100
250/250 [==============================] - 0s 51us/step - loss: 0.3132 - acc: 0.8720 - val_loss:
Epoch 19/100
250/250 [==============================] - 0s 59us/step - loss: 0.3081 - acc: 0.8720 - val_loss:
Epoch 20/100
250/250 [==============================] - 0s 55us/step - loss: 0.3025 - acc: 0.8720 - val_loss:
Epoch 21/100
250/250 [==============================] - 0s 52us/step - loss: 0.2977 - acc: 0.8720 - val_loss:
Epoch 22/100
250/250 [==============================] - 0s 55us/step - loss: 0.2939 - acc: 0.8720 - val_loss:
Epoch 23/100
250/250 [==============================] - 0s 54us/step - loss: 0.2890 - acc: 0.8800 - val_loss:
Epoch 24/100
250/250 [==============================] - 0s 55us/step - loss: 0.2861 - acc: 0.8840 - val_loss:
Epoch 25/100
250/250 [==============================] - 0s 54us/step - loss: 0.2824 - acc: 0.8880 - val_loss:
Epoch 26/100
250/250 [==============================] - 0s 55us/step - loss: 0.2793 - acc: 0.8880 - val_loss:
Epoch 27/100
250/250 [==============================] - 0s 52us/step - loss: 0.2775 - acc: 0.8880 - val_loss:
Epoch 28/100
250/250 [==============================] - 0s 52us/step - loss: 0.2733 - acc: 0.8920 - val_loss:
```

```
Epoch 29/100
250/250 [==============================] - 0s 54us/step - loss: 0.2711 - acc: 0.8960 - val_loss:
Epoch 30/100
250/250 [==============================] - ETA: 0s - loss: 0.2319 - acc: 0.920 - 0s 52us/step -
Epoch 31/100
250/250 [==============================] - 0s 50us/step - loss: 0.2668 - acc: 0.8960 - val_loss:
Epoch 32/100
250/250 [==============================] - 0s 53us/step - loss: 0.2649 - acc: 0.8960 - val_loss:
Epoch 33/100
250/250 [==============================] - ETA: 0s - loss: 0.2728 - acc: 0.900 - 0s 48us/step -
Epoch 34/100
250/250 [==============================] - 0s 54us/step - loss: 0.2598 - acc: 0.9040 - val_loss:
Epoch 35/100
250/250 [==============================] - 0s 52us/step - loss: 0.2581 - acc: 0.9040 - val_loss:
Epoch 36/100
250/250 [==============================] - 0s 62us/step - loss: 0.2573 - acc: 0.9000 - val_loss:
Epoch 37/100
250/250 [==============================] - 0s 52us/step - loss: 0.2547 - acc: 0.9040 - val_loss:
Epoch 38/100
250/250 [==============================] - 0s 61us/step - loss: 0.2516 - acc: 0.9080 - val_loss:
Epoch 39/100
250/250 [==============================] - 0s 60us/step - loss: 0.2500 - acc: 0.9120 - val_loss:
Epoch 40/100
250/250 [==============================] - 0s 52us/step - loss: 0.2476 - acc: 0.9120 - val_loss:
Epoch 41/100
250/250 [==============================] - 0s 50us/step - loss: 0.2463 - acc: 0.9120 - val_loss:
Epoch 42/100
250/250 [==============================] - 0s 47us/step - loss: 0.2436 - acc: 0.9120 - val_loss:
Epoch 43/100
250/250 [==============================] - 0s 48us/step - loss: 0.2422 - acc: 0.9120 - val_loss:
Epoch 44/100
250/250 [==============================] - 0s 51us/step - loss: 0.2396 - acc: 0.9120 - val_loss:
Epoch 45/100
250/250 [==============================] - 0s 59us/step - loss: 0.2371 - acc: 0.9160 - val_loss:
Epoch 46/100
250/250 [==============================] - 0s 47us/step - loss: 0.2372 - acc: 0.9160 - val_loss:
Epoch 47/100
250/250 [==============================] - 0s 51us/step - loss: 0.2336 - acc: 0.9120 - val_loss:
Epoch 48/100
250/250 [==============================] - 0s 49us/step - loss: 0.2315 - acc: 0.9160 - val_loss:
Epoch 49/100
250/250 [==============================] - 0s 58us/step - loss: 0.2301 - acc: 0.9200 - val_loss:
Epoch 50/100
250/250 [==============================] - 0s 51us/step - loss: 0.2287 - acc: 0.9200 - val_loss:
Epoch 51/100
250/250 [==============================] - 0s 57us/step - loss: 0.2274 - acc: 0.9240 - val_loss:
Epoch 52/100
250/250 [==============================] - 0s 55us/step - loss: 0.2245 - acc: 0.9160 - val_loss:
```

```
Epoch 53/100
250/250 [==============================] - 0s 56us/step - loss: 0.2231 - acc: 0.9160 - val_loss:
Epoch 54/100
250/250 [==============================] - 0s 53us/step - loss: 0.2215 - acc: 0.9240 - val_loss:
Epoch 55/100
250/250 [==============================] - 0s 55us/step - loss: 0.2202 - acc: 0.9160 - val_loss:
Epoch 56/100
250/250 [==============================] - 0s 56us/step - loss: 0.2171 - acc: 0.9240 - val_loss:
Epoch 57/100
250/250 [==============================] - 0s 52us/step - loss: 0.2158 - acc: 0.9200 - val_loss:
Epoch 58/100
250/250 [==============================] - 0s 50us/step - loss: 0.2135 - acc: 0.9240 - val_loss:
Epoch 59/100
250/250 [==============================] - 0s 55us/step - loss: 0.2116 - acc: 0.9240 - val_loss:
Epoch 60/100
250/250 [==============================] - 0s 53us/step - loss: 0.2097 - acc: 0.9240 - val_loss:
Epoch 61/100
250/250 [==============================] - 0s 53us/step - loss: 0.2080 - acc: 0.9240 - val_loss:
Epoch 62/100
250/250 [==============================] - 0s 66us/step - loss: 0.2053 - acc: 0.9240 - val_loss:
Epoch 63/100
250/250 [==============================] - 0s 61us/step - loss: 0.2030 - acc: 0.9240 - val_loss:
Epoch 64/100
250/250 [==============================] - 0s 56us/step - loss: 0.2006 - acc: 0.9240 - val_loss:
Epoch 65/100
250/250 [==============================] - 0s 61us/step - loss: 0.1998 - acc: 0.9240 - val_loss:
Epoch 66/100
250/250 [==============================] - 0s 56us/step - loss: 0.1981 - acc: 0.9240 - val_loss:
Epoch 67/100
250/250 [==============================] - 0s 48us/step - loss: 0.1965 - acc: 0.9280 - val_loss:
Epoch 68/100
250/250 [==============================] - 0s 55us/step - loss: 0.1945 - acc: 0.9280 - val_loss:
Epoch 69/100
250/250 [==============================] - 0s 64us/step - loss: 0.1910 - acc: 0.9280 - val_loss:
Epoch 70/100
250/250 [==============================] - 0s 51us/step - loss: 0.1896 - acc: 0.9280 - val_loss:
Epoch 71/100
250/250 [==============================] - 0s 51us/step - loss: 0.1874 - acc: 0.9280 - val_loss:
Epoch 72/100
250/250 [==============================] - 0s 53us/step - loss: 0.1867 - acc: 0.9240 - val_loss:
Epoch 73/100
250/250 [==============================] - 0s 49us/step - loss: 0.1842 - acc: 0.9280 - val_loss:
Epoch 74/100
250/250 [==============================] - 0s 53us/step - loss: 0.1829 - acc: 0.9280 - val_loss:
Epoch 75/100
250/250 [==============================] - 0s 50us/step - loss: 0.1801 - acc: 0.9280 - val_loss:
Epoch 76/100
250/250 [==============================] - 0s 48us/step - loss: 0.1788 - acc: 0.9280 - val_loss:
```

```
Epoch 77/100
250/250 [==============================] - 0s 47us/step - loss: 0.1795 - acc: 0.9280 - val_loss:
Epoch 78/100
250/250 [==============================] - 0s 52us/step - loss: 0.1755 - acc: 0.9320 - val_loss:
Epoch 79/100
250/250 [==============================] - 0s 51us/step - loss: 0.1739 - acc: 0.9360 - val_loss:
Epoch 80/100
250/250 [==============================] - 0s 52us/step - loss: 0.1732 - acc: 0.9320 - val_loss:
Epoch 81/100
250/250 [==============================] - 0s 49us/step - loss: 0.1707 - acc: 0.9360 - val_loss:
Epoch 82/100
250/250 [==============================] - 0s 58us/step - loss: 0.1691 - acc: 0.9320 - val_loss:
Epoch 83/100
250/250 [==============================] - 0s 52us/step - loss: 0.1679 - acc: 0.9360 - val_loss:
Epoch 84/100
250/250 [==============================] - 0s 49us/step - loss: 0.1661 - acc: 0.9320 - val_loss:
Epoch 85/100
250/250 [==============================] - 0s 47us/step - loss: 0.1646 - acc: 0.9320 - val_loss:
Epoch 86/100
250/250 [==============================] - 0s 50us/step - loss: 0.1627 - acc: 0.9320 - val_loss:
Epoch 87/100
250/250 [==============================] - 0s 54us/step - loss: 0.1621 - acc: 0.9320 - val_loss:
Epoch 88/100
250/250 [==============================] - 0s 49us/step - loss: 0.1610 - acc: 0.9360 - val_loss:
Epoch 89/100
250/250 [==============================] - 0s 52us/step - loss: 0.1576 - acc: 0.9320 - val_loss:
Epoch 90/100
250/250 [==============================] - 0s 46us/step - loss: 0.1573 - acc: 0.9360 - val_loss:
Epoch 91/100
250/250 [==============================] - 0s 50us/step - loss: 0.1566 - acc: 0.9360 - val_loss:
Epoch 92/100
250/250 [==============================] - 0s 48us/step - loss: 0.1551 - acc: 0.9360 - val_loss:
Epoch 93/100
250/250 [==============================] - 0s 49us/step - loss: 0.1530 - acc: 0.9320 - val_loss:
Epoch 94/100
250/250 [==============================] - 0s 49us/step - loss: 0.1530 - acc: 0.9280 - val_loss:
Epoch 95/100
250/250 [==============================] - 0s 55us/step - loss: 0.1507 - acc: 0.9360 - val_loss:
Epoch 96/100
250/250 [==============================] - 0s 50us/step - loss: 0.1498 - acc: 0.9360 - val_loss:
Epoch 97/100
250/250 [==============================] - 0s 52us/step - loss: 0.1496 - acc: 0.9320 - val_loss:
Epoch 98/100
250/250 [==============================] - 0s 48us/step - loss: 0.1466 - acc: 0.9360 - val_loss:
Epoch 99/100
250/250 [==============================] - 0s 46us/step - loss: 0.1459 - acc: 0.9360 - val_loss:
Epoch 100/100
250/250 [==============================] - 0s 47us/step - loss: 0.1455 - acc: 0.9280 - val_loss:
```

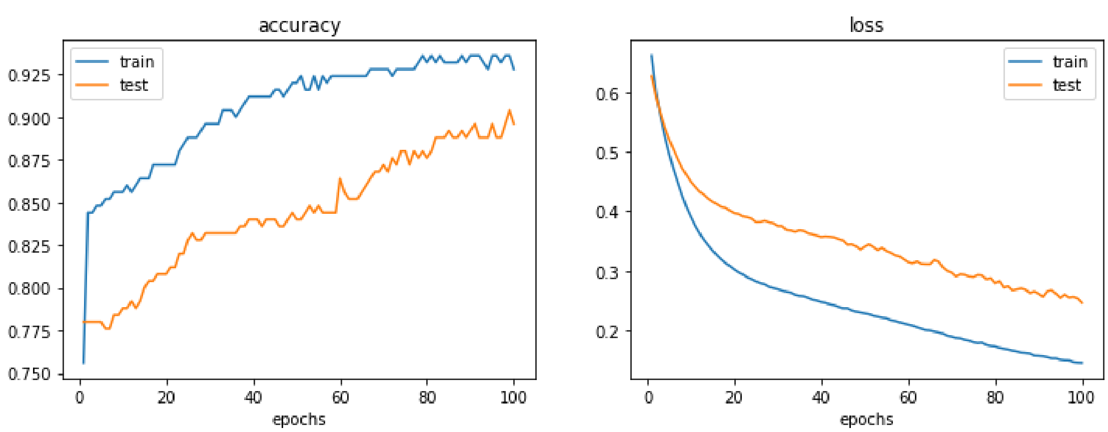
```
250/250 [==============================] - 0s 43us/step


Accuracy: 0.896000000954
```

```
Out[195]: [0.2463931860923767, 0.89600000095367427]
```

1.1.1 Plotting learning curve

```
In [196]: def plot_history(history):
              epochs = len(history.history['acc'])
              fig,axes = plt.subplots(1,2,figsize=(12,4))
              ticks=range(1,epochs+1)
              axes[0].plot(ticks,history.history['acc'], label='train')
              axes[0].plot(ticks,history.history['val_acc'], label='test')
              axes[0].legend()
              axes[0].set_title('accuracy')
              axes[0].set_xlabel('epochs')
              axes[1].plot(ticks,history.history['loss'], label='train')
              axes[1].plot(ticks,history.history['val_loss'], label='test')
              axes[1].legend()
              axes[1].set_title('loss')
              axes[1].set_xlabel('epochs')
              #plt.xticks(range(0,nepochs,5));
```

```
In [197]: plot_history(history)
```



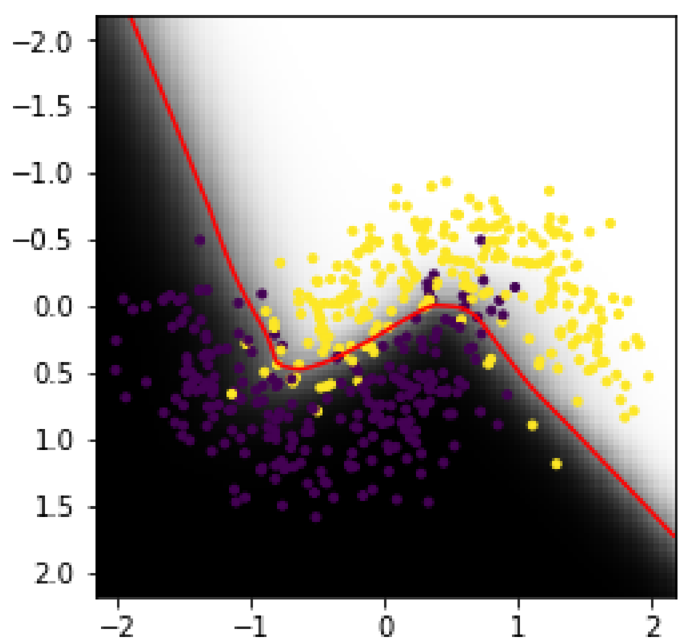
For simple problems, classifiers such as random forests can actually provide same or better performance faster than neural networks. Let's see with more challenging problem in next section.

1.1.2 Debugging the decision function (in 2D)

```
In [198]: # Visualize the decision function
```

```
def plot_2d_decision(model, X, y):
    assert X.shape[1]==2, 'X should have 2 columns, got {}'.format(X.shape[1])

    # Generate a 2D grid of input samples
    B=np.max(X)*1.1
    gridy, gridx = np.mgrid[-B:B:100j,-B:B:100j]
    X_grid = np.concatenate((gridx.reshape(-1,1),gridy.reshape(-1,1)),axis=1)

    # Apply the network to this input
    out = model.predict(X_grid)
    out_im = out.reshape(gridx.shape)

    # Visualize the result overlayed with the dataset
    plt.imshow(out_im, extent=(-B,B,B,-B), cmap='gray')
    plt.contour(out_im, levels=[0.5], colors=['r'], extent=(-B,B,-B,B))
    plt.scatter(X[:,0],X[:,1], c=y, marker='.')
```

In [199]: plot_2d_decision(model, X, y)



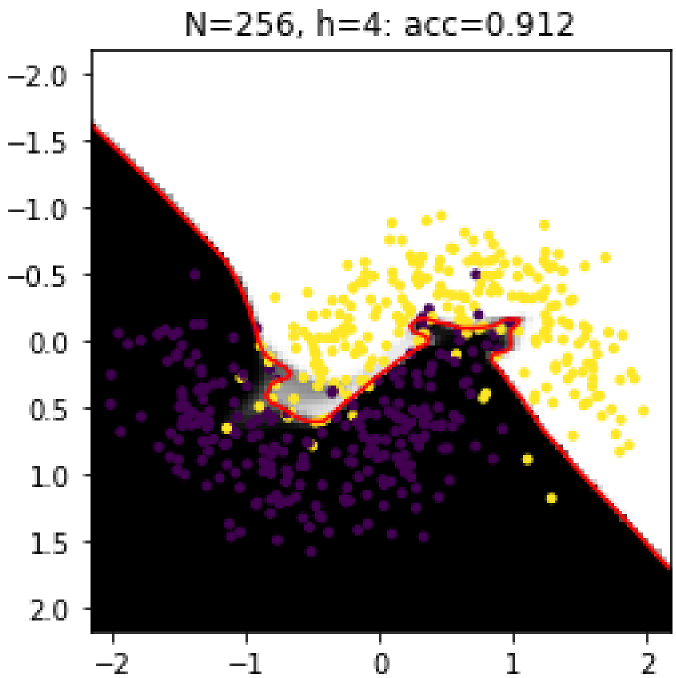
1.1.3 Evaluating the meta-parameters (number of nodes, layers...)

In [200]:
```
# Function that evaluates a network created according to meta-parameters
def evaluate_perf(N=64, hidden=2, epochs=50):
    print('evaluate_perf: N={}, hidden={}...'.format(N, hidden))

    model = Sequential()
```

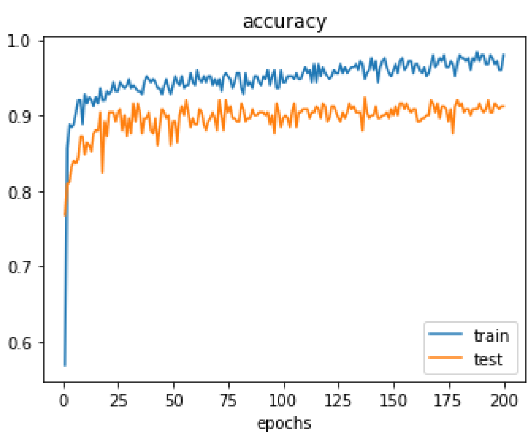
```
        model.add(InputLayer(input_shape=[2]))
        for i in range(hidden):
            model.add(Dense(N, activation='relu'))
        model.add(Dense(1, activation='sigmoid'))

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

        history = model.fit(X_train, y_train, epochs=epochs,
                  batch_size=100, verbose=0, validation_data=(X_test, y_test))
        loss, acc = model.evaluate(X_test, y_test)

        print('  accuracy={:.3f}'.format(acc))
        plot_2d_decision(model, X, y)

        plt.title('N={}, h={}: acc={:.3f}'.format(N, hidden, acc))

        perf = {'acc':acc, 'history':history}

        return perf
```

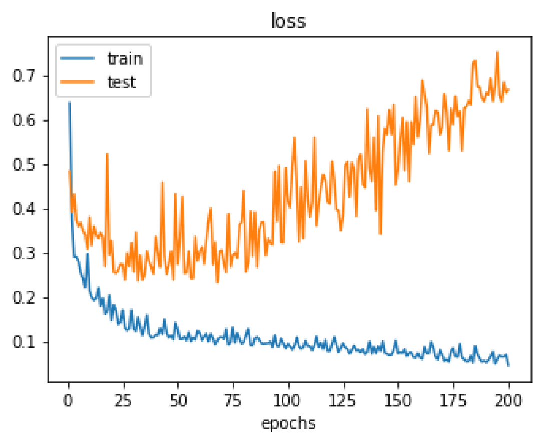
In [201]:
```
# Illustration of over-fitting: too many parameters
perf = evaluate_perf(N=256, hidden=4, epochs=200)
fig = plt.figure()
plot_history(perf['history']);
```

```
evaluate_perf: N=256, hidden=4...
250/250 [==============================] - 0s 68us/step
  accuracy=0.912
```



<matplotlib.figure.Figure at 0x16f37f390>

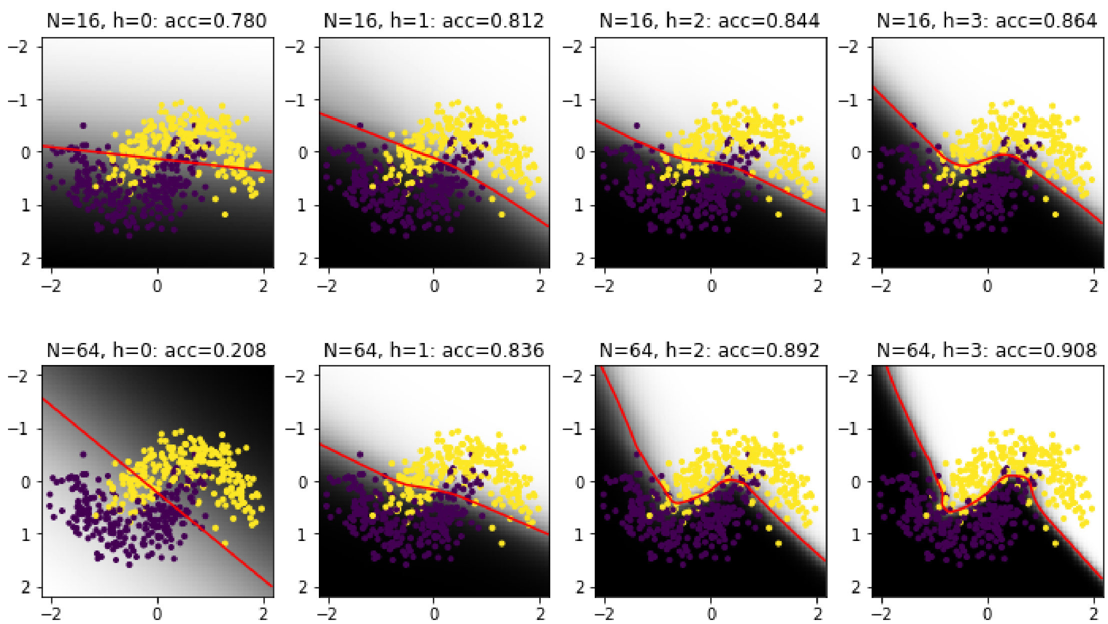





```
In [206]: params=[(16,0),(16,1),(16,2),(16,3),
                  (64,0),(64,1),(64,2),(64,3)]
          nx=4
          ny=(len(params)+nx-1)//nx

          acc_array = np.zeros(len(params))
```

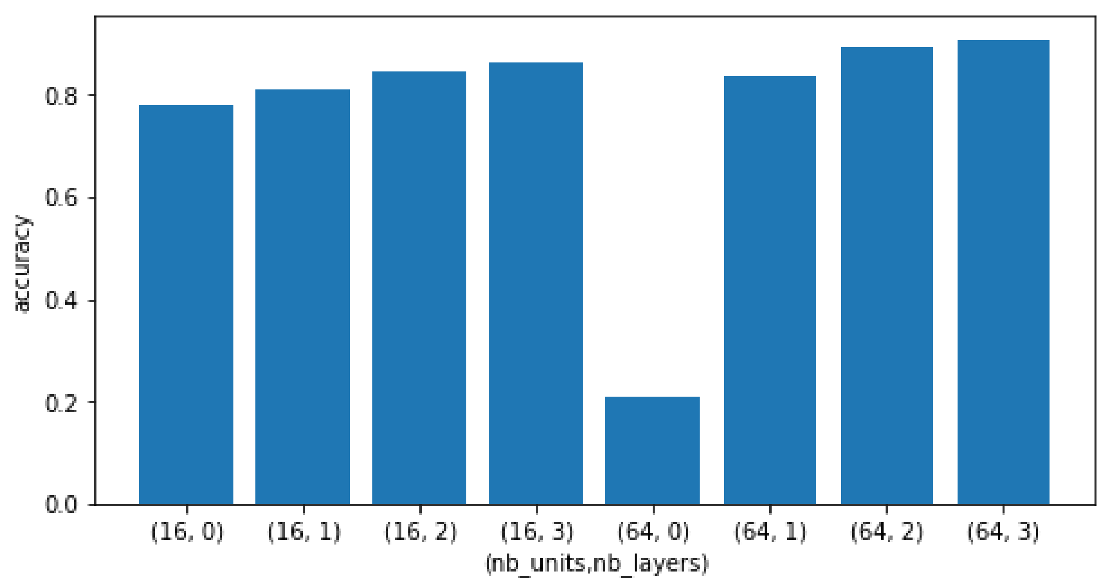
```python
        fig,axes = plt.subplots(ny,nx,figsize=(12,7))
        axes=axes.ravel()
        for i,(N,h) in enumerate(params):
            plt.sca(axes[i])
            perf = evaluate_perf(N,h, 100)
            acc_array[i] = perf['acc']
```

```
evaluate_perf: N=16, hidden=0...
250/250 [==============================] - 0s 40us/step
  accuracy=0.780
evaluate_perf: N=16, hidden=1...
250/250 [==============================] - 0s 38us/step
  accuracy=0.812
evaluate_perf: N=16, hidden=2...
250/250 [==============================] - 0s 42us/step
  accuracy=0.844
evaluate_perf: N=16, hidden=3...
250/250 [==============================] - 0s 44us/step
  accuracy=0.864
evaluate_perf: N=64, hidden=0...
250/250 [==============================] - 0s 42us/step
  accuracy=0.208
evaluate_perf: N=64, hidden=1...
250/250 [==============================] - 0s 44us/step
  accuracy=0.836
evaluate_perf: N=64, hidden=2...
250/250 [==============================] - 0s 47us/step
  accuracy=0.892
evaluate_perf: N=64, hidden=3...
250/250 [==============================] - 0s 58us/step
  accuracy=0.908
```




```
In [208]: fig2 = plt.figure(figsize=(8,4))
          plt.bar(range(len(params)),acc_array, tick_label=[str(p) for p in params])
          plt.ylabel('accuracy')
          plt.xlabel('(nb_units,nb_layers)')
```

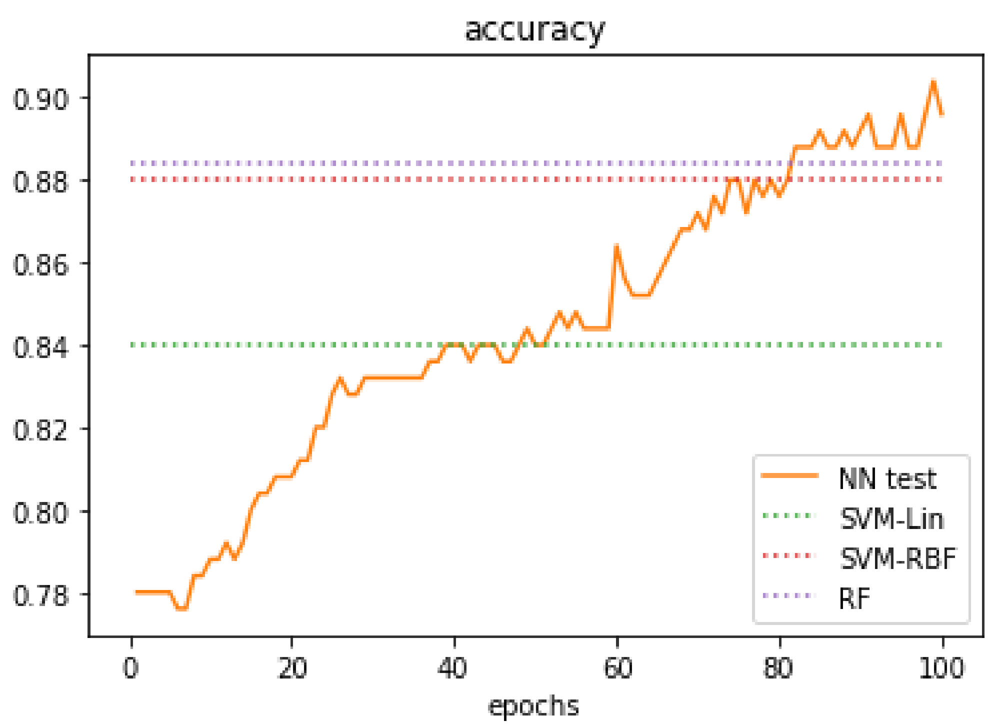
```
Out[208]: Text(0.5,0,'(nb_units,nb_layers)')
```



1.1.4 Comparing to sklearn classifiers

In [204]:
```
def plot_history_compare(history, acc_dict):
    """
    Plot NN fit history (test accuracy) and overlay fixed accuracy from other classifi

    history: output of model.fit()
    acc_dict: dictionnary of the form {'approach_name': accuracy, ...}
    """
    epochs = len(history.history['acc'])

    plt.plot([],[],label='_nolegend_')

    ticks=range(1,epochs+1)
    plt.plot(ticks,history.history['val_acc'], label='test')
    plt.legend()
    plt.title('accuracy')
    plt.xlabel('epochs')

    epochs = len(history.history['acc'])
    for label in acc_dict:
        acc = acc_dict[label]
        plt.gcf().axes[0].plot([0,epochs],[acc,acc], ":")
    plt.gcf().axes[0].legend(['NN test'] + list(acc_dict.keys()))
```

In [205]:
```
# Compare to RandomForest and SVM

from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from collections import OrderedDict

perfs=OrderedDict()

svm = SVC(kernel='linear')
svm.fit(X_train, y_train)
perfs['SVM-Lin'] = svm.score(X_test, y_test)

svm = SVC()
svm.fit(X_train, y_train)
perfs['SVM-RBF'] = svm.score(X_test, y_test)

rf = RandomForestClassifier()
rf.fit(X_train, y_train)
perfs['RF'] = rf.score(X_test, y_test)

plot_history_compare(history, perfs)
```



1.2 Simple CNN for object recognition

When dealing with images, Convolutional Neural Network offer the advantage of computing visual features from the image using Convolutional Layers, which can be trained at the same time as the dense layers that perform the classification.

In this section, we use the Fashion-MNIST dataset to recognize pieces of clothes shown as 28x28 pixel gray-scale images.

Dataset from https://github.com/zalandoresearch/fashion-mnist. The training set contains 60,000 samples and the test set 10,000 samples. Each training and test example is assigned to one of the following labels:

```
0 T-shirt/top
1 Trouser
2 Pullover
3 Dress
4 Coat
5 Sandal
6 Shirt
7 Sneaker
8 Bag
9 Ankle boot
```

```
In [155]: from keras.datasets import fashion_mnist, mnist
          from keras.utils import np_utils
```

```
data=fashion_mnist.load_data()
# Download will be done only once:
# By default, the dataset will be cached inside ~/.keras/datasets/

#data=mnist.load_data() # Uncomment to use original MNIST instead

((X_train,y_train),(X_test,y_test))=data

# To go faster, reduce the amount of training data
X_train=X_train[:2500]
y_train=y_train[:2500]

# Prepare datasets
# This step contains normalization and reshaping of input.
# For output, it is important to change number to one-hot vector.
X_train = X_train.astype('float32') / 255
X_train = X_train.reshape(X_train.shape[0], 1, 28, 28)
X_test = X_test.astype('float32') / 255
X_test = X_test.reshape(X_test.shape[0], 1, 28, 28)
y_train = np_utils.to_categorical(y_train, 10)
y_test = np_utils.to_categorical(y_test, 10)
```

In [156]:

```
fig,axes = plt.subplots(4,10, figsize=(12,4))
axes=axes.ravel()
for i in range(len(axes)):
    axes[i].imshow(X_train[i,0,:,:], cmap='gray')
    axes[i].set_xticks([]); axes[i].set_yticks([])
#a.set_xtick(None)
```

In [157]:

```
import numpy as np
from keras.models import Sequential
from keras.layers import Dense, Dropout, InputLayer, BatchNormalization, Conv2D, MaxPo
from keras.initializers import Constant
```

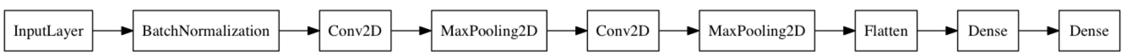
```
model = Sequential()
model.add(InputLayer(input_shape=(1, 28, 28)))
model.add(BatchNormalization())
model.add(Conv2D(32, (2, 2),
        padding='same',
        bias_initializer=Constant(0.01),
        kernel_initializer='random_uniform'
    ))
model.add(MaxPool2D(padding='same'))
model.add(Conv2D(32, (2, 2),
        padding='same',
        bias_initializer=Constant(0.01),
        kernel_initializer='random_uniform',
        input_shape=(1, 28, 28)
    ))
model.add(MaxPool2D(padding='same'))
model.add(Flatten())
model.add(Dense(128,
        activation='relu',
        bias_initializer=Constant(0.01),
        kernel_initializer='random_uniform',
    ))
model.add(Dense(10, activation='softmax'))

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

```
In [163]: model.summary()

          from IPython.display import SVG, Image
          from keras.utils.vis_utils import model_to_dot # need pydot and graphviz packages

          Image(model_to_dot(model,rankdir='LR',show_layer_names=False).create(prog='dot', forma
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_120 (InputLayer)       (None, 1, 28, 28)         0
_________________________________________________________________
batch_normalization_1 (Batch (None, 1, 28, 28)         112
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 1, 28, 32)         3616
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 1, 14, 32)         0
```

```
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 1, 14, 32)         4128
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 1, 7, 32)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 224)               0
_________________________________________________________________
dense_332 (Dense)            (None, 128)               28800
_________________________________________________________________
dense_333 (Dense)            (None, 10)                1290
=================================================================
Total params: 37,946
Trainable params: 37,890
Non-trainable params: 56
_________________________________________________________________
```

Out[163]:



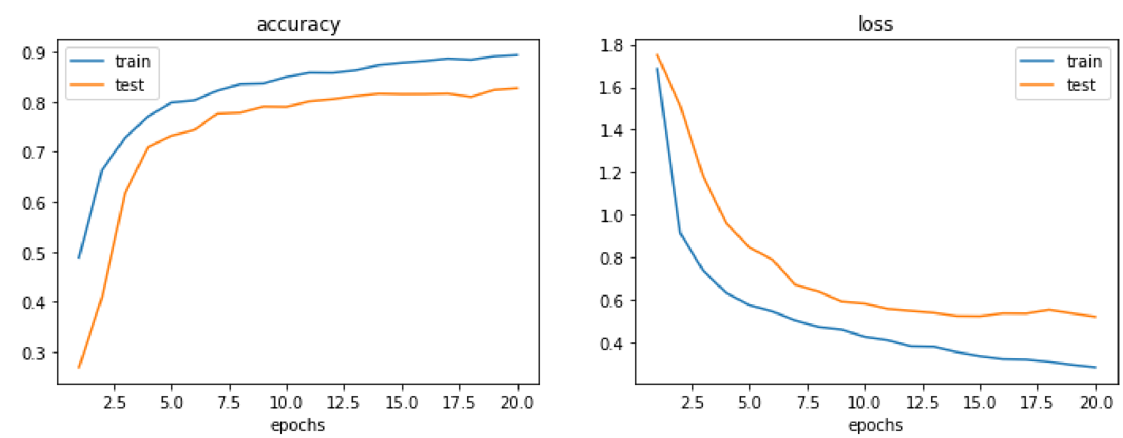
In [159]:
```
history = model.fit(
    X_train,
    y_train,
    epochs=20,
    batch_size=100,
    validation_data=(X_test, y_test),
    verbose=1,
)
model.evaluate(X_test,y_test)
```

```
Train on 2500 samples, validate on 10000 samples
Epoch 1/20
2500/2500 [==============================] - 3s 1ms/step - loss: 1.6851 - acc: 0.4884 - val_loss
Epoch 2/20
2500/2500 [==============================] - 1s 212us/step - loss: 0.9128 - acc: 0.6636 - val_lo
Epoch 3/20
2500/2500 [==============================] - 1s 211us/step - loss: 0.7357 - acc: 0.7276 - val_lo
Epoch 4/20
2500/2500 [==============================] - 1s 208us/step - loss: 0.6314 - acc: 0.7704 - val_lo
Epoch 5/20
2500/2500 [==============================] - 1s 221us/step - loss: 0.5740 - acc: 0.7980 - val_lo
Epoch 6/20
2500/2500 [==============================] - 1s 215us/step - loss: 0.5446 - acc: 0.8024 - val_lo
Epoch 7/20
```

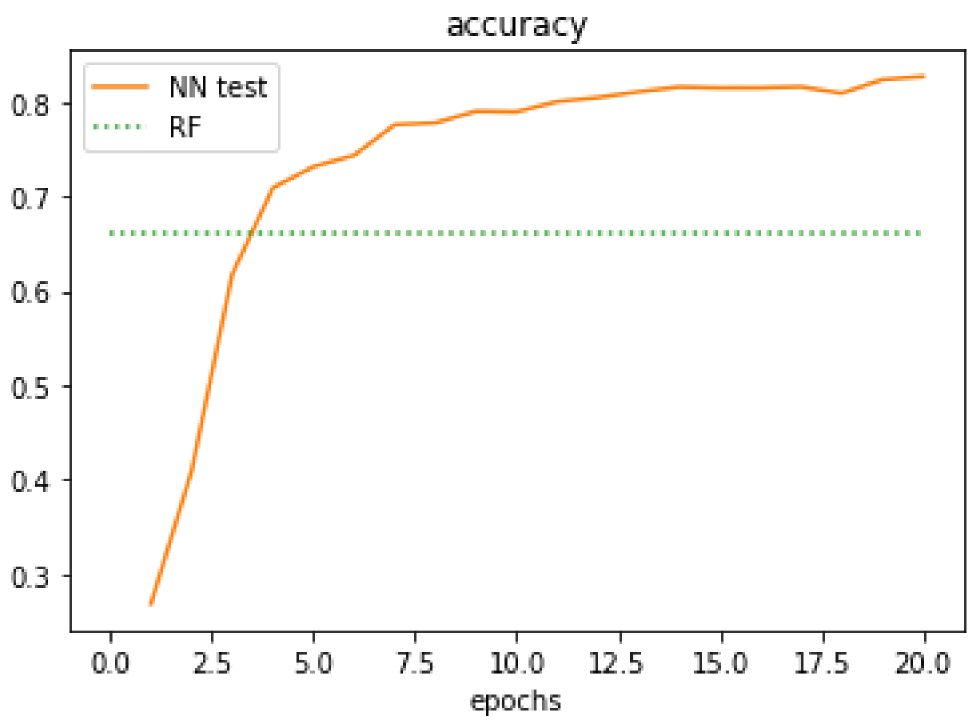
```
2500/2500 [==============================] - 1s 217us/step - loss: 0.5015 - acc: 0.8220 - val_lo
Epoch 8/20
2500/2500 [==============================] - 1s 215us/step - loss: 0.4714 - acc: 0.8348 - val_lo
Epoch 9/20
2500/2500 [==============================] - 1s 215us/step - loss: 0.4591 - acc: 0.8360 - val_lo
Epoch 10/20
2500/2500 [==============================] - 1s 210us/step - loss: 0.4253 - acc: 0.8492 - val_lo
Epoch 11/20
2500/2500 [==============================] - 1s 228us/step - loss: 0.4094 - acc: 0.8580 - val_lo
Epoch 12/20
2500/2500 [==============================] - 1s 211us/step - loss: 0.3809 - acc: 0.8576 - val_lo
Epoch 13/20
2500/2500 [==============================] - 1s 214us/step - loss: 0.3788 - acc: 0.8628 - val_lo
Epoch 14/20
2500/2500 [==============================] - 1s 212us/step - loss: 0.3533 - acc: 0.8728 - val_lo
Epoch 15/20
2500/2500 [==============================] - 1s 209us/step - loss: 0.3341 - acc: 0.8772 - val_lo
Epoch 16/20
2500/2500 [==============================] - 1s 214us/step - loss: 0.3207 - acc: 0.8808 - val_lo
Epoch 17/20
2500/2500 [==============================] - 1s 221us/step - loss: 0.3184 - acc: 0.8856 - val_lo
Epoch 18/20
2500/2500 [==============================] - 1s 223us/step - loss: 0.3074 - acc: 0.8832 - val_lo
Epoch 19/20
2500/2500 [==============================] - 1s 212us/step - loss: 0.2929 - acc: 0.8904 - val_lo
Epoch 20/20
2500/2500 [==============================] - 1s 217us/step - loss: 0.2811 - acc: 0.8932 - val_lo
10000/10000 [==============================] - 1s 68us/step
```

```
Out[159]: [0.5192161620616913, 0.82699999999999996]
```

```
In [160]: plot_history(history)
```



In [161]:
```
# Compare to RandomForest

from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier()
rf.fit(X_train.reshape((X_train.shape[0],-1)), y_train)
acc=rf.score(X_test.reshape((X_test.shape[0],-1)), y_test)

plot_history_compare(history, {'RF':acc})
```



It is clear that CNN outperform RF on this dataset. Their architecture is better at extracting the relevant information from the image compared to passing the raw image data to the random forest. Improving the performance of the RF would require designing better features to be fed to the RF classifier, which the CNN includes in the first layers.

1.3 Object recognition using Inception-v3

In this section, we use the pre-trained model Inception-v3 for object recognition.

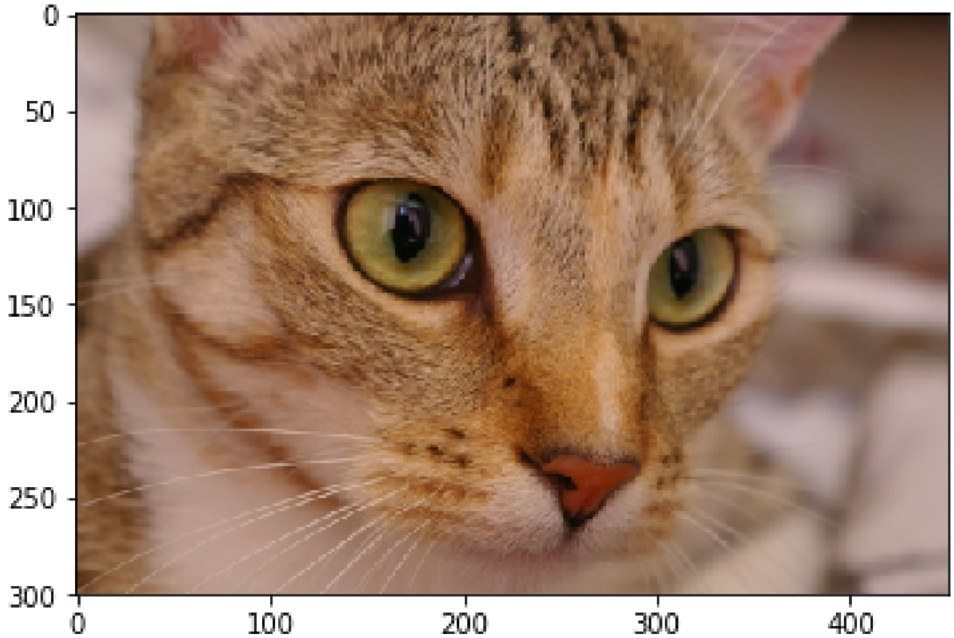
In [164]:
```
from keras.applications.inception_v3 import InceptionV3, preprocess_input, decode_pred

# Loading the pre-trained model
# (takes a few seconds, may need downloading the first time)
net = InceptionV3()
```

```
In [167]: if False: # Change to true to display Inception structure (very large)
              net.summary(line_length=100, positions=[0.35,0.65,0.7,1.0])
              Image(model_to_dot(net,rankdir='TB',show_layer_names=False).create(prog='dot', for
```

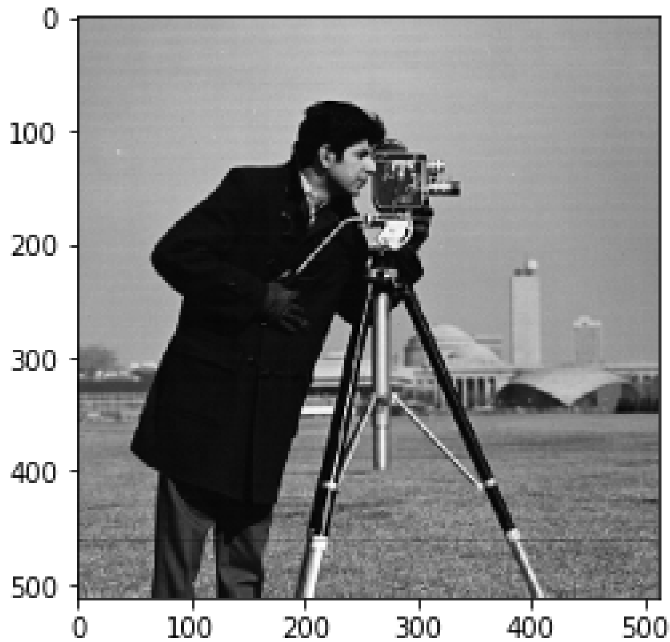
```
In [168]: from skimage import transform

          def inception_predict(image):
              # Rescale image to 299x299, as required by InceptionV3
              image_prep = transform.resize(image, (299, 299, 3), mode='reflect')

              # Scale image values to [-1, 1], as required by InceptionV3
              image_prep = (img_as_float(image_prep) - 0.5) * 2

              predictions = decode_predictions(
                  net.predict(image_prep[None, ...])
              )

              plt.imshow(image, cmap='gray')

              for pred in predictions[0]:
                  (n, klass, prob) = pred
                  print('{klass:>15} ({prob:.3f})'.format(klass=klass, prob=prob))
```

```
In [169]: from skimage import data, img_as_float
          inception_predict(data.chelsea())
```

```
   Egyptian_cat (0.897)
          tabby (0.056)
      tiger_cat (0.039)
           lynx (0.000)
    plastic_bag (0.000)
```




```
In [170]: inception_predict(data.camera())

        tripod (0.929)
        crutch (0.002)
    binoculars (0.002)
  reflex_camera (0.001)
     overskirt (0.000)
```



```
In [171]: inception_predict(data.coffee())
```

```
       espresso (0.984)
            cup (0.001)
     coffee_mug (0.001)
         eggnog (0.001)
 espresso_maker (0.001)
```

```
In [172]: inception_predict(data.stereo_motorcycle()[1])

          moped (0.700)
  motor_scooter (0.186)
     disk_brake (0.049)
   crash_helmet (0.004)
      car_wheel (0.001)
```

You can fine-tune Inception to classify your own classes, as described at https://keras.io/applications/#fine-tune-inceptionv3-on-a-new-set-of-classes

---

Extra topics: - Many examples provided with Keras (ResNet, OCR, AutoEncoders, ...): https://github.com/fchollet/keras/tree/master/examples - Using Keras as a Scikit-learn classifier: https://keras.io/scikit-learn-api/

1.3.1 ResNet for object recognition

We can also try ResNet, which is included in Keras distribution.

In [174]:
```
from keras.applications.resnet50 import ResNet50
from keras.applications import resnet50

# Loading the pre-trained model
# (may take a few minutes to download for the first time)
resnet = ResNet50()
```

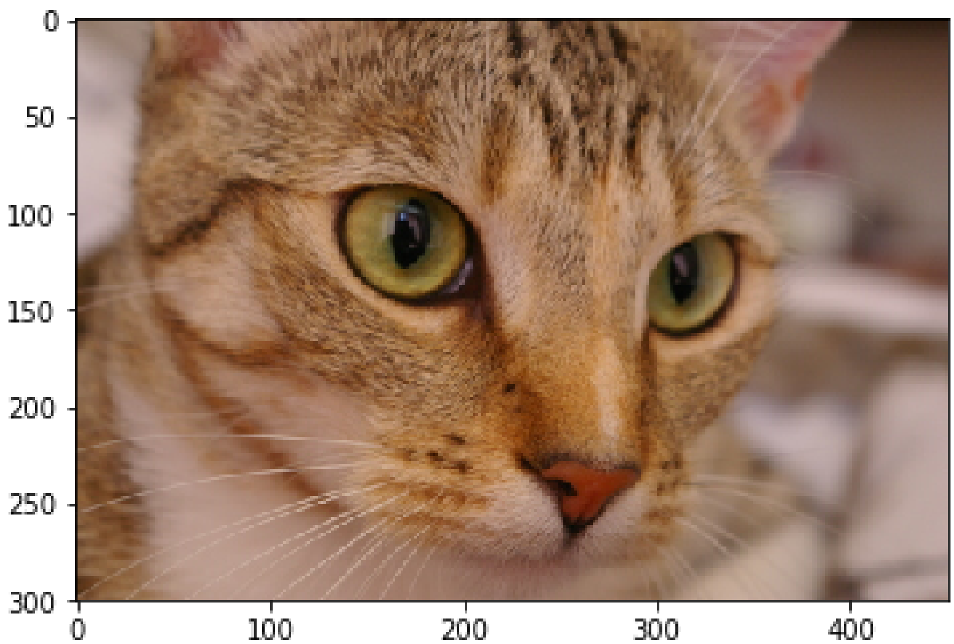
In [175]:
```
if False:
    resnet.summary()
    Image(model_to_dot(resnet,rankdir='TB',show_layer_names=False).create(prog='dot',
```

In [176]:
```
def resnet_predict(image):
    # Rescale image to 224x224, as required by ResNet50
    image_prep = transform.resize(image, (224, 224, 3), mode='reflect')
```

```
    # Scale image values to [-128, 128]
    image_prep = img_as_float(image_prep)*256 - 128

    predictions = resnet50.decode_predictions(
        resnet.predict(image_prep[None, ...])
    )

    plt.imshow(image, cmap='gray')

    for pred in predictions[0]:
        (n, klass, prob) = pred
        print('{klass:>15} ({prob:.3f})'.format(klass=klass, prob=prob))
```

In [177]: `resnet_predict(data.chelsea())`

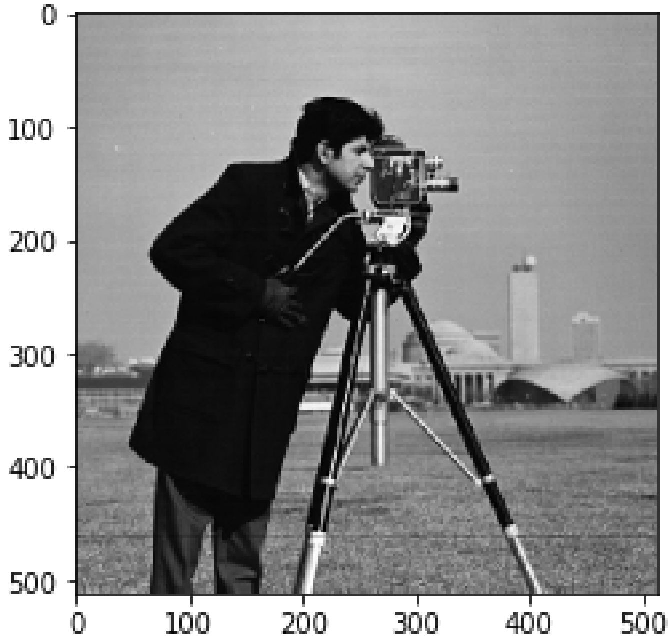
```
  Egyptian_cat (0.993)
     tiger_cat (0.002)
         tabby (0.002)
          lynx (0.002)
  snow_leopard (0.001)
```



In [510]: `resnet_predict(data.camera())`

```
        tripod (0.996)
 reflex_camera (0.002)
```

```
binoculars (0.001)
    crutch (0.000)
 harmonica (0.000)
```




```
In [511]: resnet_predict(data.coffee())
```

```
  espresso (0.453)
       cup (0.084)
      tray (0.069)
 water_jug (0.032)
  milk_can (0.028)
```

```
In [513]: resnet_predict(data.stereo_motorcycle()[1])

          moped (0.594)
  motor_scooter (0.308)
        Model_T (0.052)
       tricycle (0.022)
    crash_helmet (0.010)
```

In [184]:
```
resnet_predict(data.rocket())
```

```
         obelisk (0.614)
           crane (0.144)
            pole (0.078)
drilling_platform (0.035)
      totem_pole (0.029)
```


0
50
100
150
200
250
300
350
400
0
100
200
300
400
500
600