lecture_10

October 7, 2019

1 Neural Network - Practical Lesson 10

1.1 Overview

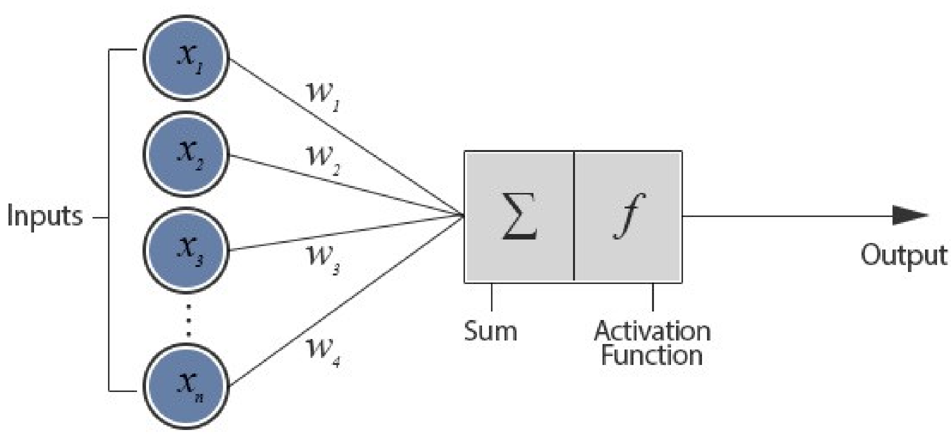
In this lesson we will see how machine learning techniques can be successfully applied to solve financial problems. We will first do a quick tour on the theory behind neural networks and then we will see an example and two practical applications: regression and classification.

1.2 Neural networks

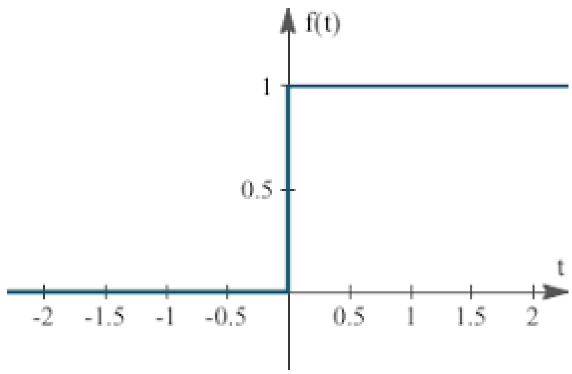
1.2.1 Definition

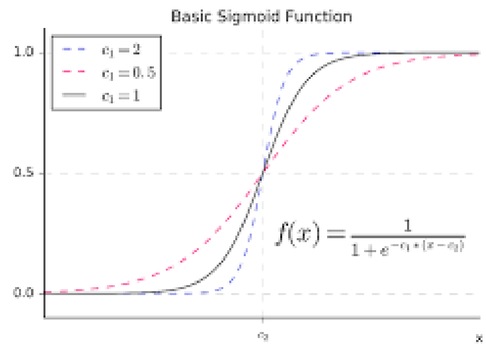
Artificial Neural Networks (ANN) are information processing models that are developed by inspiring from the working principles of human brain. Their most essential property is the ability of learning from sample sets. The basic process units of ANN architecture are neurons which are internally in connection with other neurons.

A neuron (or more generally a perceptron) consists of weights (w_i) and real (x_i) numbers. All the inputs are individually weighted, added together and passed into the activation function. There are many different types of activation function but one of the simplest would be step function (another is the sigmoid).



Model of an artificial neuron.





1.2.2 Training of perceptrons

When teaching children how to recognize a bus, we just tell them, showing an example: "This is a bus. That is not a bus." until they learn the concept of what a bus is. Furthermore, if the child sees new objects that she hasn't seen before, we could expect her to recognize correctly whether the new object is a bus or not. This is exactly the idea behind the perceptron. Similarly, inputs from a *training* set are presented to the perceptron one after the other and weights are modified according to the expected output.

When an entire pass through all of the input training vectors is completed the perceptron has learnt ! At this time, if an input vector P (already in the training set) is given to the perceptron, it will output the correct value. If P is not in the training set, the network will respond with an output similar to other training vectors close to P.

Unfortunately using just a perceptron is not too useful since it is not possible to solve the interesting problems we would like to face. The next step is then to put together more perceptron together in *layers*.

1.2.3 Multi-layered neural networks

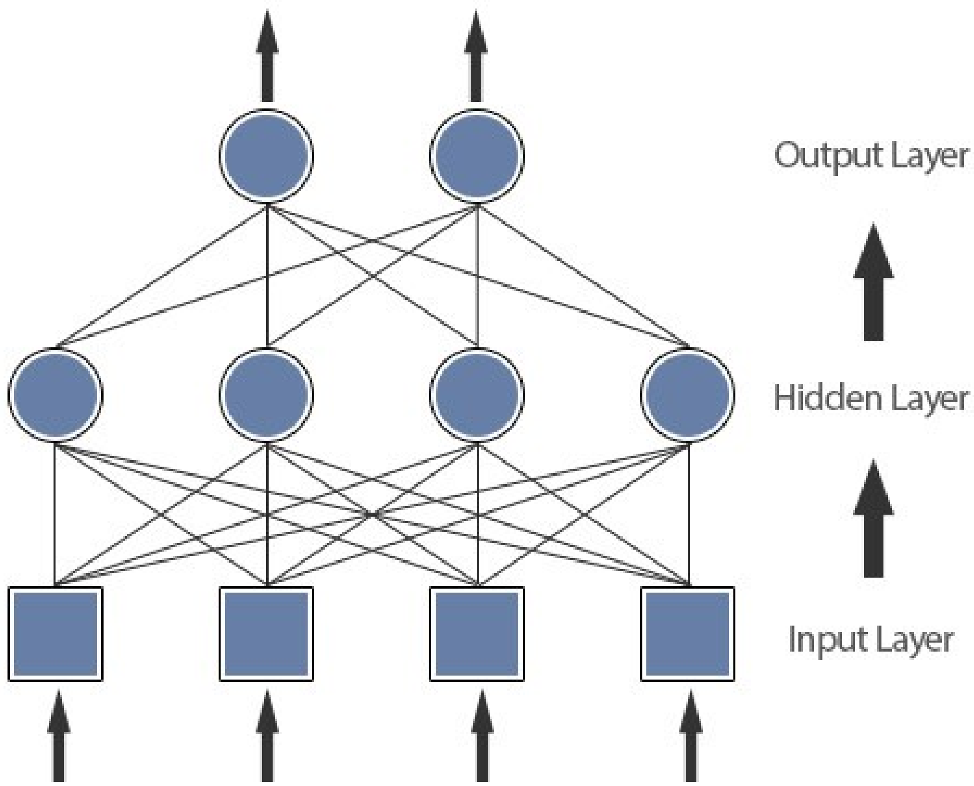
Each input from the *input layer* is fed up to each node in the hidden layer, and from there to each node on the output layer. We should note that there can be any number of nodes per layer and there are usually multiple hidden layers to pass through before ultimately reaching the output layer. But to train this network we need a learning algorithm which should be able to tune not only the weights between the output layer and the hidden layer but also the weights between the hidden layer and the input layer.

1.2.4 Back propagation

First of all, we need to understand what do we lack. To tune the weights between the hidden layer and the input layer, we need to know the error at the hidden layer, but we know the error only at the output layer (We know the correct output from the training sample and we also know the output predicted by the network.) So, the method that was suggested was to take the errors at the output layer and proportionally propagate them backwards to the hidden layer.

So, what we are doing is:

- We present a training sample to the neural network (initialised with random weights)
- Compute the output received by calculating activations of each layer and thus calculate the error



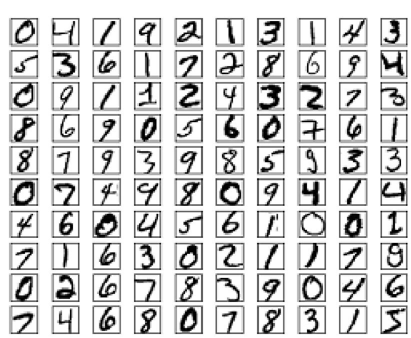
A multi-layered neural network.

- Having calculated the error, we readjust the weights such that the error decreases
- We continue the process for all training samples several times until the weights are not changing too much

1.3 Neural net to recognize handwritten digits

We don't usually appreciate how tough a problem our visual system solve (it involves 5 visual cortices containing 140 million neurons each). The difficulty of visual pattern recognition becomes apparent if you attempt to write a computer program to recognize digits like those below.

Simple intuitions about how we recognize shapes - "a 9 has a loop at the top, and a vertical



The so-called MNIST training sample

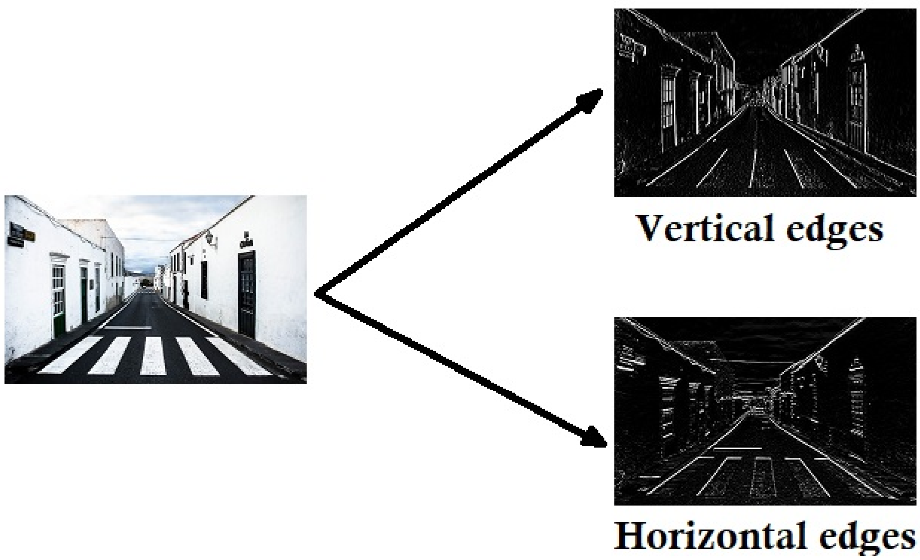
stroke in the bottom right" - turn out to be not so simple to express algorithmically. When you try to make such rules precise, you quickly get lost in a morass of exceptions and caveats and special cases. It seems hopeless.

Neural networks approach the problem in a different way. The idea is to take a large number of handwritten digits and then develop a system which can learn from those training examples. By increasing the number of training examples, the network can learn more about handwriting, and so improve its accuracy. So while I've shown just 100 training digits above, perhaps we could build a better handwriting recognizer by using thousands or even millions or billions of training examples (**remember that neural nets are not capable of extrapolating results !!!**).

Let's try to implement an ANN that is capable of recognize handwritten digits. To start we need to install two new modules (from the command line type the following):

`pip install keras, mnist, tensorflow`

Our program will be based on a Convolutional Neural Network (CNN, will see later other two types of NN) which is designed for image/pattern recognition. It works essentially by applying on top of an image a series of filters (matrices) that works as edge detectors and with them it classifies images according to their features.




```
In [2]: import numpy as np
        # contains our dataset for training
        import mnist
        # keras gives us all the tools to work with NN
        from keras.models import Sequential
        from keras.layers import Conv2D, MaxPooling2D, Dense, Flatten
        from keras.utils import to_categorical

        # load the training and testing set
        train_images = mnist.train_images() # the actual images
        train_labels = mnist.train_labels() # the truth (it is 0, 1, 2...)
        test_images = mnist.test_images()
        test_labels = mnist.test_labels()
```

```python
# transform data for convenience
train_images = (train_images / 255) - 0.5
test_images = (test_images / 255) - 0.5
train_images = np.expand_dims(train_images, axis=3)
test_images = np.expand_dims(test_images, axis=3)

# definition of the actual network
num_filters = 8
filter_size = 3
pool_size = 2

# the input size reflects the size of the image with
# the numbers 28x28 pixels
# the output is given by 10 neurons returning the
# probability that image is in each class.
model = Sequential([
    Conv2D(num_filters, filter_size, input_shape=(28, 28, 1)),
    MaxPooling2D(pool_size=pool_size),
    Flatten(),
    Dense(10, activation="softmax")
])

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

model.fit(train_images,
          to_categorical(train_labels),
          epochs=3,
          validation_data=(test_images, to_categorical(test_labels)))
```

```
Using TensorFlow backend.


Train on 60000 samples, validate on 10000 samples
Epoch 1/3
60000/60000 [==============================] - 13s 222us/step - loss: 0.3369 - acc: 0.9025 - val
Epoch 2/3
60000/60000 [==============================] - 14s 228us/step - loss: 0.1633 - acc: 0.9531 - val
Epoch 3/3
60000/60000 [==============================] - 14s 226us/step - loss: 0.1211 - acc: 0.9649 - val
```

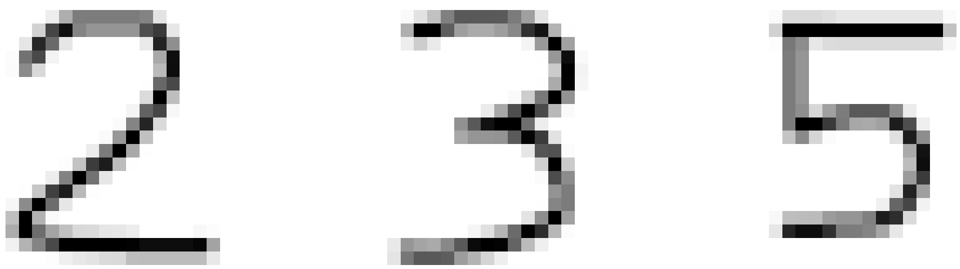
Out[2]: <keras.callbacks.History at 0x7f3bd6db5390>

In [10]:
```python
predictions = model.predict(test_images[0:2])
for p in predictions:
    print (["{:.2f}".format(i) for i in p])

for i in range(2):
```

```
            print("The CNN predicted {} and it was {}".format( \
                  np.argmax(predictions[i], axis=0), test_labels[i]))
```

```
['0.00', '0.00', '0.00', '0.00', '0.00', '0.00', '0.00', '1.00', '0.00', '0.00']
['0.00', '0.00', '0.99', '0.00', '0.00', '0.00', '0.01', '0.00', '0.00', '0.00']
The CNN predicted 7 and it was 7
The CNN predicted 2 and it was 2
```

I have tested the NN using digits written by me:



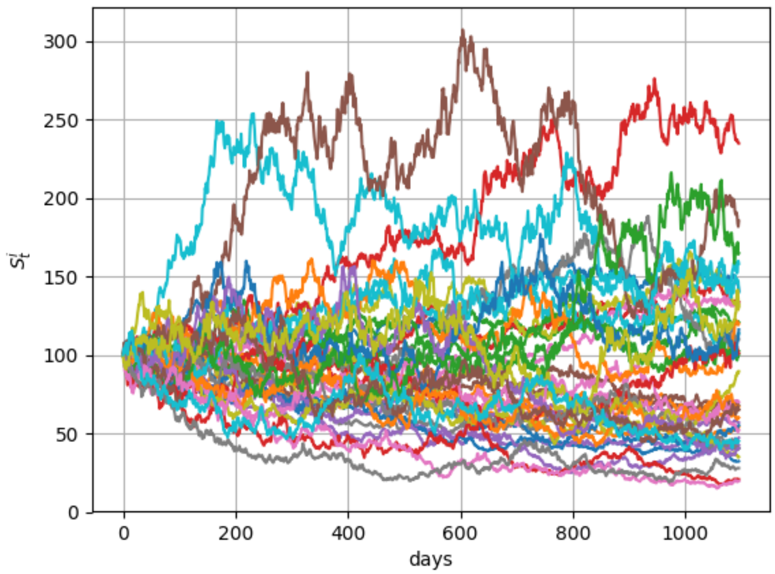
and the ANN worked with the three of them. This is the result with my 5:

```
[5]
[0.00, 0.00, 0.00, 0.10, 0.00, 0.89, 0.00, 0.00, 0.00, 0.00]
```

Smaller probability *only* 89.4% (confused by the 3 10%) **but still it works**.

1.4 Black-Scholes call options

The first practical application concerns the pricing of european call options. In this case I have generated by myself a large number of call options with different strikes, maturity, underlying development and trained the NN using as inputs: volatility, strike, maturity and underlying price. The truth is the price of the call computed using the Black-Scholes formula.



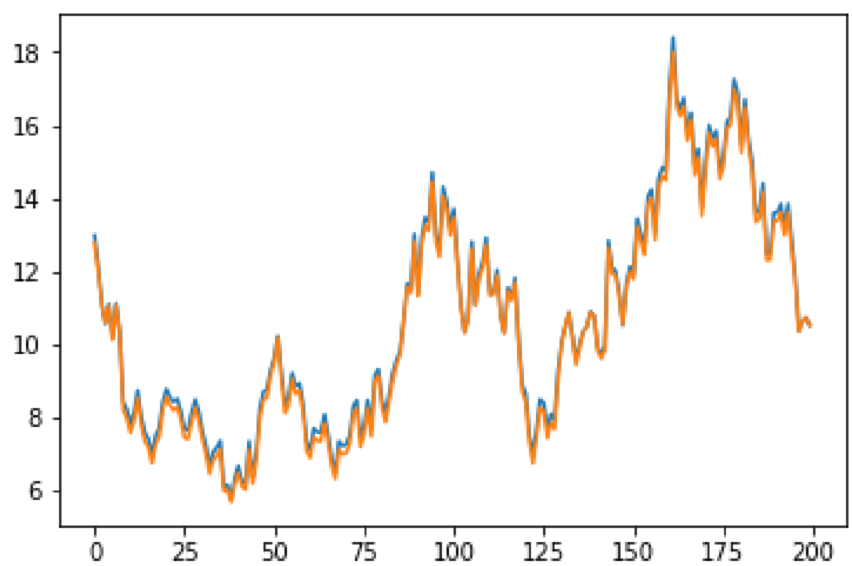
In this case I have used a *traditional* NN with an input layer with 5 neurons (the number of inputs), an hidden layer with 8 neurons and an output layer with 1 single neuron (since I need just a number, the price of the call).

```
In [ ]: # Regression Example
        from keras.models import Sequential, load_model
        from keras.layers import Dense
        from keras.optimizers import SGD
        from keras.wrappers.scikit_learn import KerasRegressor
        from sklearn.model_selection import cross_val_score
        from sklearn.model_selection import train_test_split
        from sklearn.metrics import accuracy_score
        import pandas as pd
        import matplotlib.pyplot as plt

        ## just a way to load the dataset
        dataset = pd.read_csv("training.csv")
        X_train = dataset.iloc[:, :5].values
        Y_train = dataset.iloc[:, 5].values

        # NN defintion
        model = Sequential()
        model.add(Dense(8, input_dim=5,
                        kernel_initializer='normal',
                        activation='relu'))
        model.add(Dense(11, kernel_initializer='normal',
                        activation='relu'))
        model.add(Dense(1, kernel_initializer='normal'))

        # Compile model
```

```
model.compile(loss='mean_absolute_error',
              optimizer='adam',
              metrics=['mse'])

# perform the actual training
history = model.fit(X_train,
                    Y_train,
                    epochs=100,
                    verbose=1,
                    batch_size=100)
```

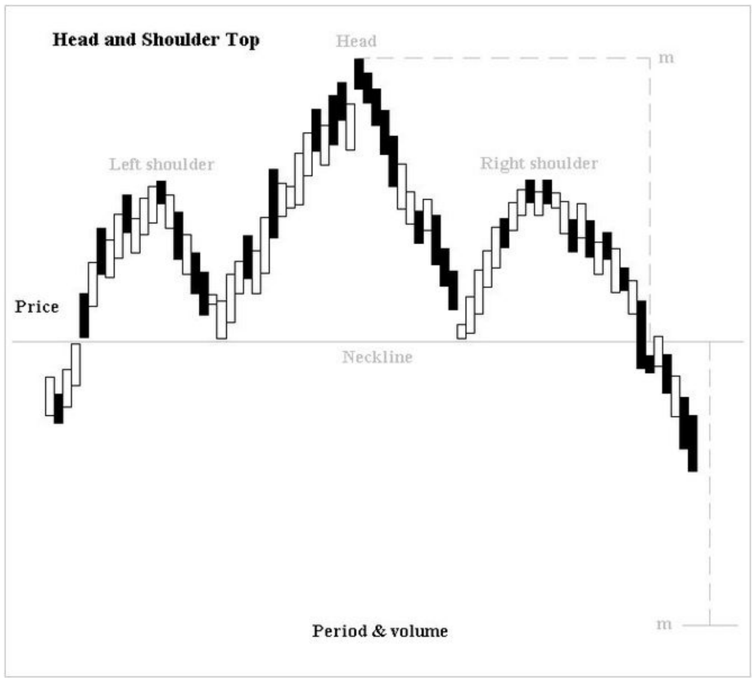
The training of a neural net is stochastic so it should be run multiple times to asses its performance.

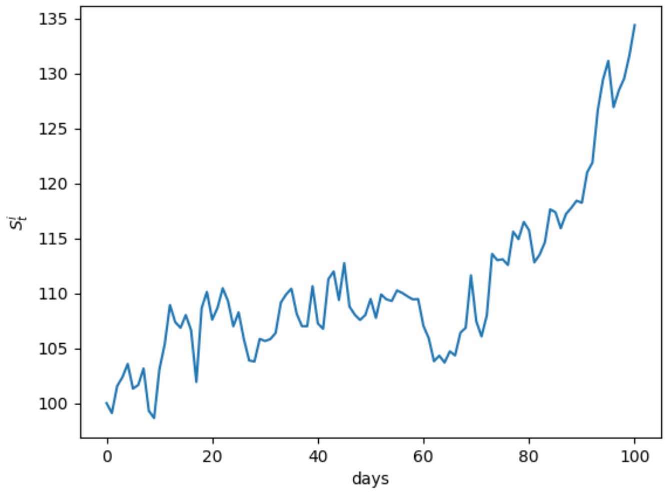
```
In [13]: import pandas as pd
         from keras.models import load_model
         import matplotlib.pyplot as plt

         model = load_model('bs_model.h5.very_very_good')

         dataset = pd.read_csv("testing.csv")
         X_test = dataset.iloc[:, :5].values
         Y_test = dataset.iloc[:, 5].values

         plt.plot(model.predict(X_test[0:200]))
         plt.plot(Y_test[0:200])
         plt.show()
```



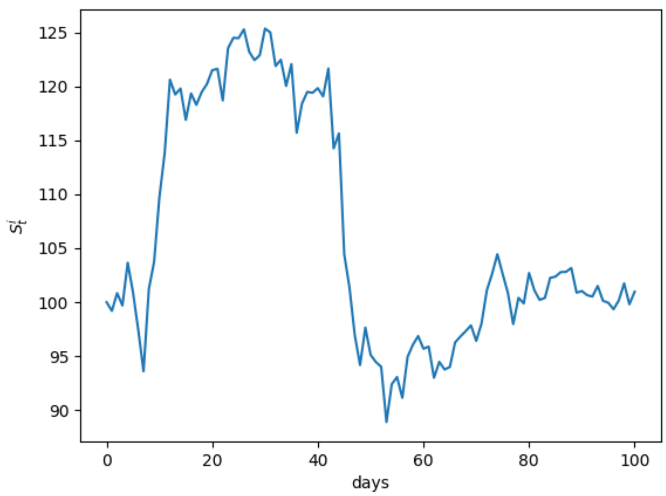
1.5 Technical Analysis

In finance, technical analysis is a security analysis discipline for forecasting the direction of prices through the study of past market data, primarily price and volume. Essentially the analyst looks for particular patterns in the price time series that are *known* to develop in predictable ways to take profit of it.

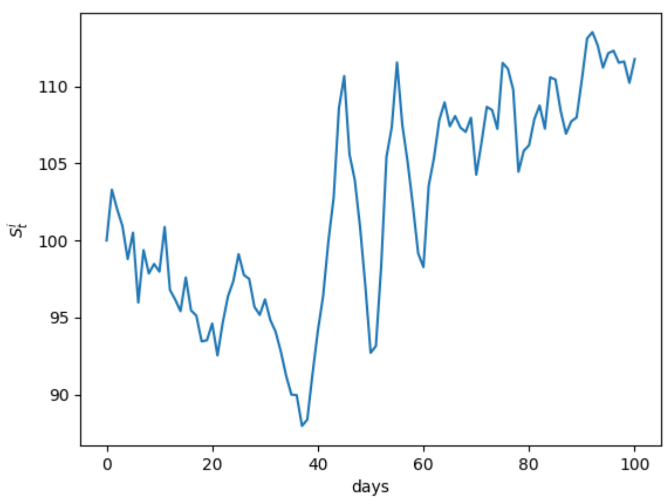




135
130
125
120
115
110
105
100
S_t^i
0
20
40
60
80
100
days



125
120
115
110
105
100
95
90
S_t^i
0
20
40
60
80
100
days



110
105
100
95
90
S_t^i
0
20
40
60
80
100
days

As you may imagine we will try to develop a CNN (like in the handwriting case) capable of classifying features in time series to be used in a technical analysis (this is much faster than having somebody looking at thousands of time series by eye...).

As in the previous application I have generated by myself the training set simulating 9000 time series (1/3 with head and shoulder patter, 1/3 with triangle pattern and 1/3 with no pattern). To make the training easier the features have been exagerated.

No pattern

Head and shoulder pattern

Tringle pattern

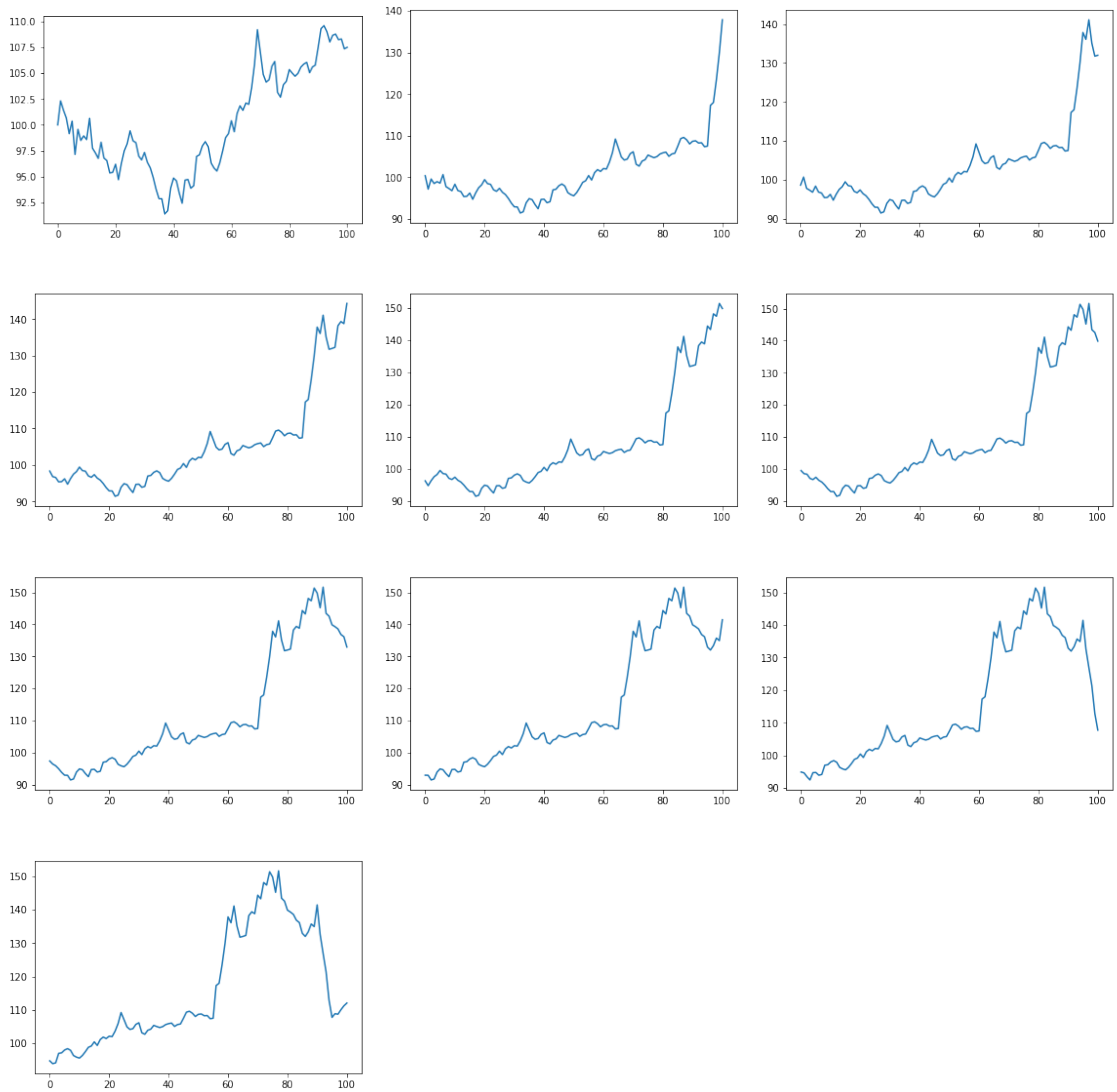
In [17]:
```
import numpy as np
import json
from keras.models import Sequential, load_model
from keras.layers import Dense, Conv1D, Dropout
from keras.layers import MaxPooling1D, GlobalAveragePooling1D
from keras.utils import to_categorical

# load the training set
with open("training_tech_ana_labels.json", "r") as f:
    train_labels = json.load(f)

train_labels = train_labels[:900]
train_images = []

with open("training_tech_ana_images.json", "r") as f:
    train_images = json.load(f)
train_images = train_images[:900]

train_images = np.array(train_images)
train_images = np.expand_dims(train_images, axis=3)

# define the CNN
model = Sequential()
model.add(Conv1D(filters=80, kernel_size=20,
                 activation='relu', input_shape=(101, 1)))
model.add(Conv1D(filters=80, kernel_size=15,
                 activation='relu'))
model.add(MaxPooling1D(3))
model.add(Conv1D(filters=100, kernel_size=10,
                 activation='relu'))
model.add(Conv1D(filters=100, kernel_size=5,
                 activation='relu'))
model.add(GlobalAveragePooling1D())
model.add(Dropout(0.5))
model.add(Dense(3, activation="softmax"))
model.compile(loss='categorical_crossentropy',
              optimizer='adam', metrics=['accuracy'])
```

```
# make the training
model.fit(train_images, to_categorical(train_labels),
          epochs=150, batch_size=35, verbose=2)

model.save('tech_ana.h5')
```

```
/usr/lib/python3/dist-packages/ipykernel_launcher.py:20: DeprecationWarning: Both axis > a.ndim


Epoch 1/150
 - 1s - loss: 2.0686 - acc: 0.3522
 ...
Epoch 46/150
 - 1s - loss: 0.4162 - acc: 0.7789
...
Epoch 150/150
 - 1s - loss: 0.1258 - acc: 0.9444
```

To test the perfomance I have created a longer time series and passed as input to the CNN a sliding time window to simulate the evolution of the price and a feature that is coming. The goal is to check when the neural net is capable of predicting the incoming pattern.

```
In [12]: import numpy as np
         import json
         from keras.models import Sequential, load_model
         from keras.layers import Dense, Conv1D, Dropout, MaxPooling1D, GlobalAveragePooling1D
         from keras.utils import to_categorical
         from matplotlib import pyplot as plt

         test_images = []

         with open("testing_tech_ana_images_frames.json", "r") as f:
             test_images = json.load(f)

         test_images = np.array(test_images)
         for i in range(test_images.shape[0]):
             plt.plot(test_images[i, :])
             plt.show()
         test_images = np.expand_dims(test_images, axis=3)

         model = load_model('tech_ana_10000.h5')

         predictions = model.predict(test_images)
         for i in range(len(predictions)):
             print (np.argmax(predictions[i]), max(predictions[i]))
```



```
0 0.9059956
0 0.9251846
0 0.9130782
0 0.93703276
0 0.96242875
1 0.56031984
1 0.95728
1 0.88402504
1 1.0
1 1.0
```

So at the 6th sample the CNN start recognizing the *head and shoulder* pattern in the price evolution.