Recurrent Neural Network

By Prof. Seungchul Lee
iSystems Design Lab
http://isystems.unist.ac.kr/
UNIST

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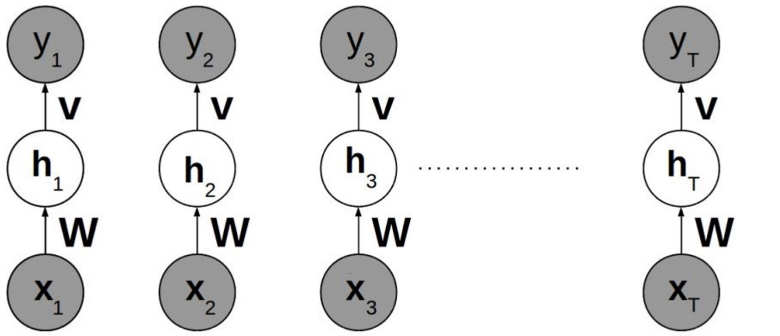
1. Recurrent Neural Network (RNN)

- RNNs are a family of neural networks for processing sequential data

1.1. Feedforward Network and Sequential Data



- Separate parameters for each value of the time index
    - Cannot share statistical strength across different time index

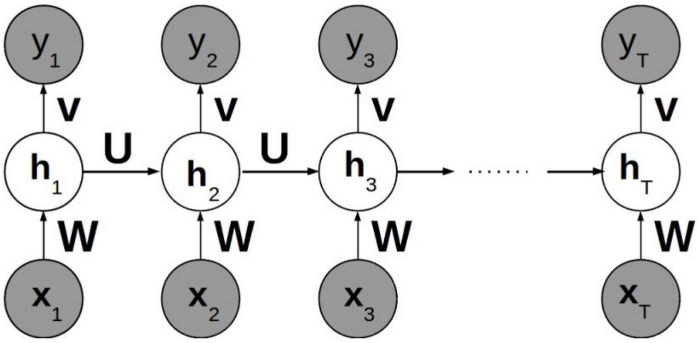
In [1]:

```
%%html
<center><iframe src="https://www.youtube.com/embed/oYglxfBtSQk"
width="560" height="315" frameborder="0" allowfullscreen></iframe></center>
```

1.2. Structure of RNN

Recurrence

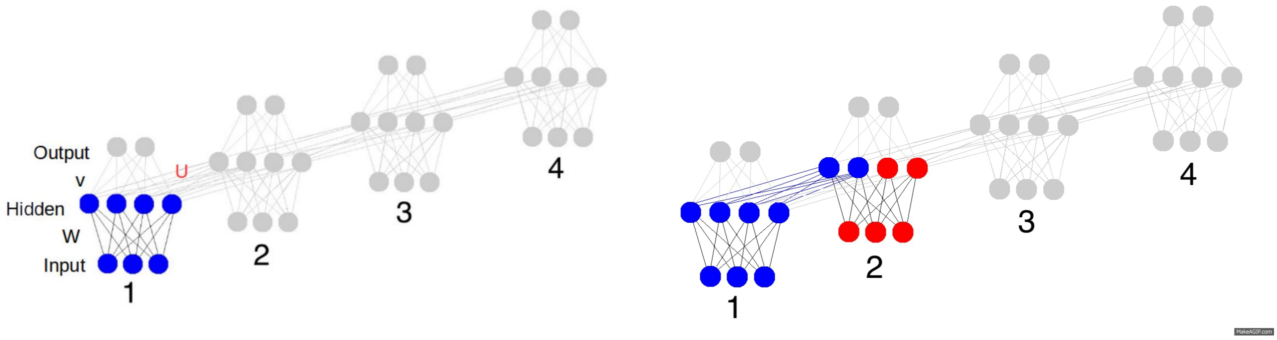
- It is possible to use the **same** transition function f with the same parameters at every time step



Hidden State

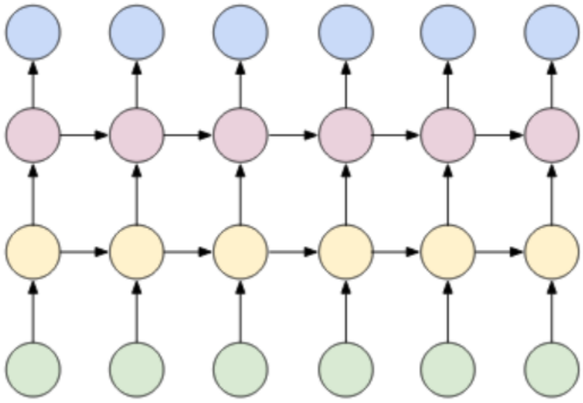
- Lossy summary of the the past sequence of inputs up to t
- Keep some aspects of the past sequence with more precision than other aspects
- Network learns the function f

$$h^{(t)} = f\left(h^{(t-1)}, x^{(t)}\right)$$
$$f\left(h^{(t-1)}, x^{(t)}\right) = g\left(Wx_t + Uh_{t-1}\right)$$



Deep Recurrent Networks

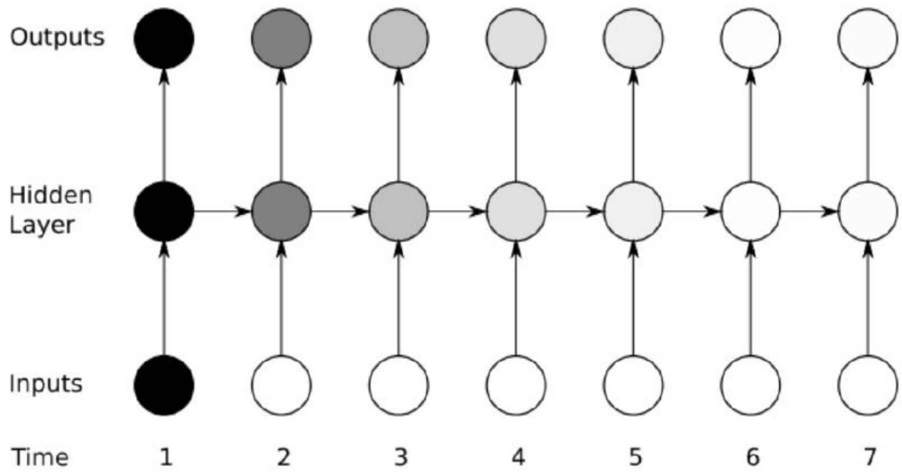
- Three blocks of parameters and associated transformation
  1. From the input to the hidden state (from green to yellow)
  2. From the previous hidden state to the next hidden state (from yellow to red)
  3. From the hidden state to the output (from red to blue)



1.3. RNN with LSTM

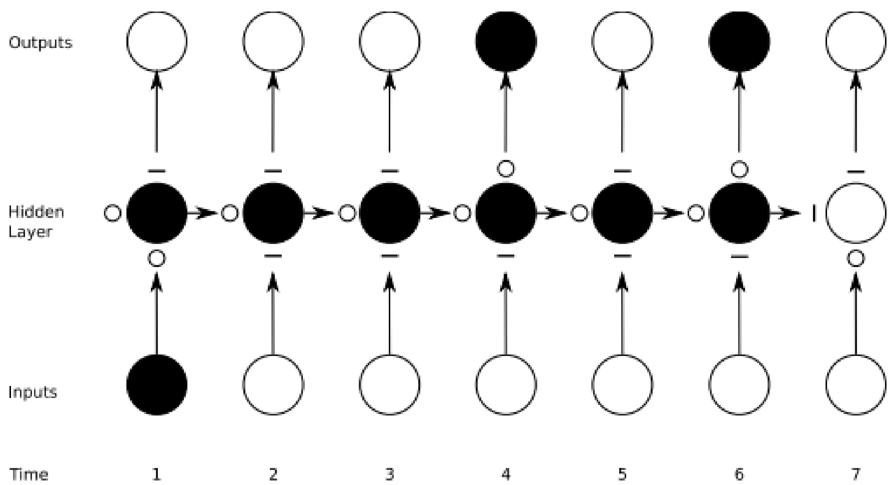
Long-Term Dependencies

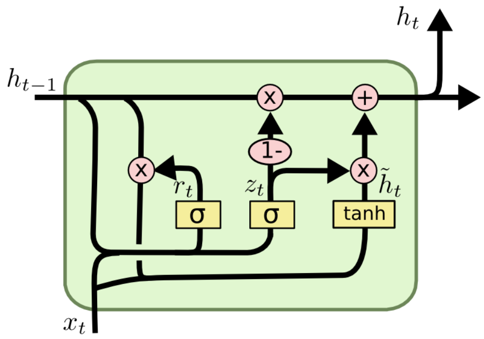
- Gradients propagated over many stages tend to either vanish or explode
- Difficulty with long-term dependencies arises from the exponentially smaller weights given to long-term interactions



Long Short-Term Memory (LSTM)

- Allow the network to **accumulate** information over a long duration
- Once that information has been used, it might be use for the neural network to **forget** the old state





$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

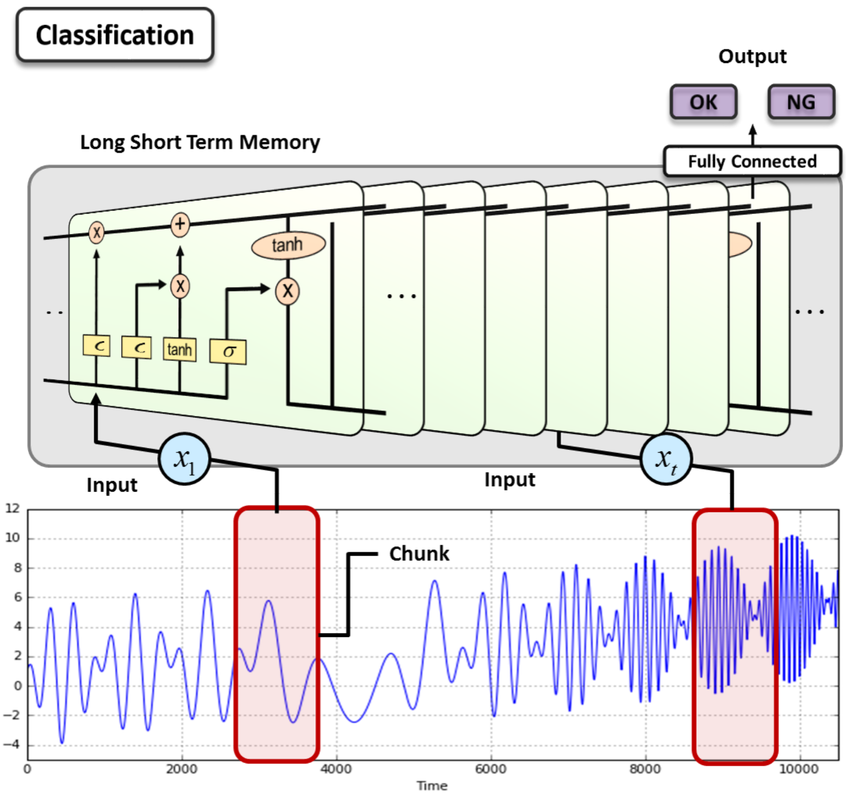
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Summary

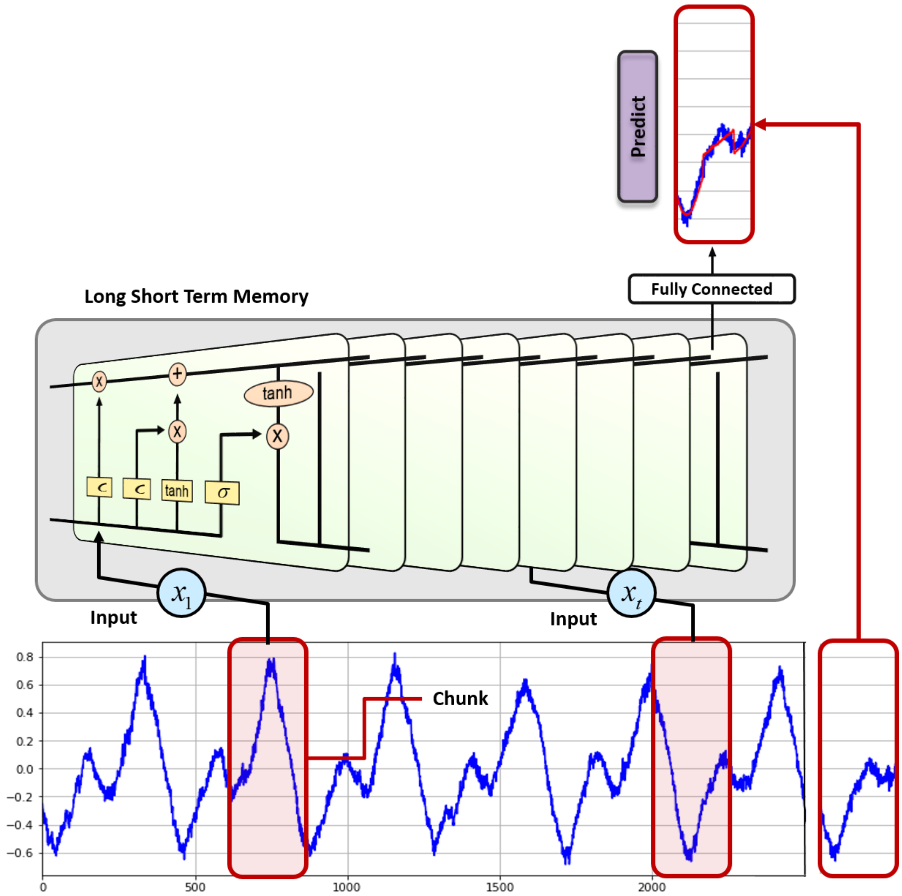
- Connect LSTM cells in a recurrent manner
- Train parameters in LSTM cells

1.4. RNN and Sequential Data

Time Series Data Classification



Time Series Data Prediction



2. RNN with Tensorflow

- Will predict a future time signal
- Regression problem

2.1. Import Library

In [2]:

```
import tensorflow as tf
from six.moves import cPickle
import numpy as np
import matplotlib.pyplot as plt
```

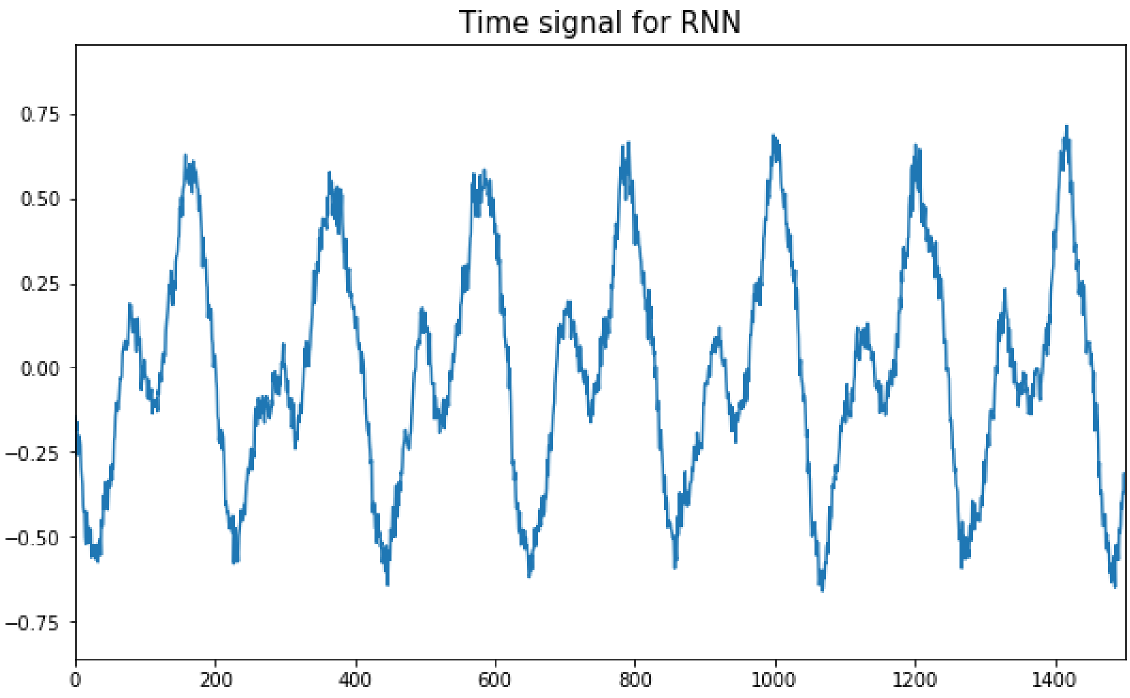
2.2. Load Time Signal Data

- Import acceleration data of rotation machinery

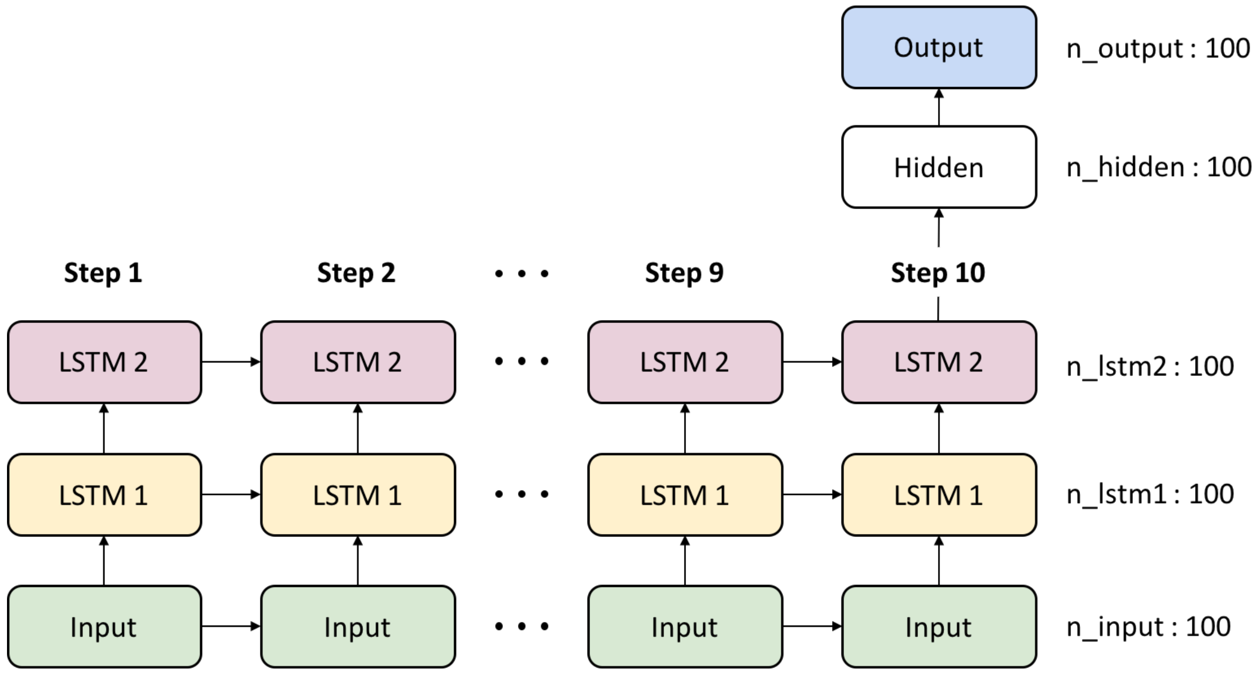
In [3]:

```
data =  cPickle.load(open('./data_files/rnn_time_signal_downsample.pkl', 'rb'))

print(data.shape)
plt.figure(figsize=(10, 6))
plt.title('Time signal for RNN', fontsize=15)
plt.plot(data)
plt.xlim(0,1500)
plt.show()
```

```
(41000,)
```



2.3. Define RNN Structure



In [4]:

```
## 1100 data points are used for each iteration
n_step = 10
n_input = 100

## LSTM shape
n_lstm1 = 100
n_lstm2 = 100

## Fully connected
n_hidden = 100
n_output = 100
```

2.4. Define Weights and Biases

LSTM Cell

- Do not need to define weights of lstm cells

Fully connected

- Define parameters based on the predefined layer size
- Initialize with a normal distribution with $\mu = 0$ and $\sigma = 0.01$

In [5]:

```
weights = {
    'hidden' : tf.Variable(tf.random_normal([n_lstm2, n_hidden], stddev=0.01)),
    'output' : tf.Variable(tf.random_normal([n_hidden, n_output], stddev=0.01))
}

biases = {
    'hidden' : tf.Variable(tf.random_normal([n_hidden], stddev=0.01)),
    'output' : tf.Variable(tf.random_normal([n_output], stddev=0.01))
}

x = tf.placeholder(tf.float32, [None, n_step, n_input])
y = tf.placeholder(tf.float32, [None, n_output])
```

2.5. Build Model

Build RNN Network

- First, define LSTM cell

```
lstm = tf.contrib.rnn.BasicLSTMCell(n_lstm)
```

- Second, compute hidden state (h) and lstm cell (c) with predefined lstm cell and input

```
h, c = tf.nn.dynamic_rnn(lstm, input_tensor, dtype=tf.float32)
```

In [6]:

```
def build_model(x, weights, biases):
    with tf.variable_scope('rnn'):
        # Build RNN network
        with tf.variable_scope('lstm1'):
            lstm1 = tf.contrib.rnn.BasicLSTMCell(n_lstm1)
            h1, c1 = tf.nn.dynamic_rnn(lstm1, x, dtype=tf.float32)
        with tf.variable_scope('lstm2'):
            lstm2 = tf.contrib.rnn.BasicLSTMCell(n_lstm2)
            h2, c2 = tf.nn.dynamic_rnn(lstm2, h1, dtype=tf.float32)

        # Build classifier
        hidden = tf.add(tf.matmul(h2[:,-1,:], weights['hidden']), biases['hidden'])
        hidden = tf.nn.relu(hidden)
        output = tf.add(tf.matmul(hidden, weights['output']), biases['output'])
        return output
```

2.6. Define Cost, Initializer and Optimizer

Loss

- Regression : Squared loss

$$\frac{1}{N}\sum_{i=1}^{N}(\hat{y}^{(i)} - y^{(i)})^2$$

Initializer

- Initialize all the empty variables

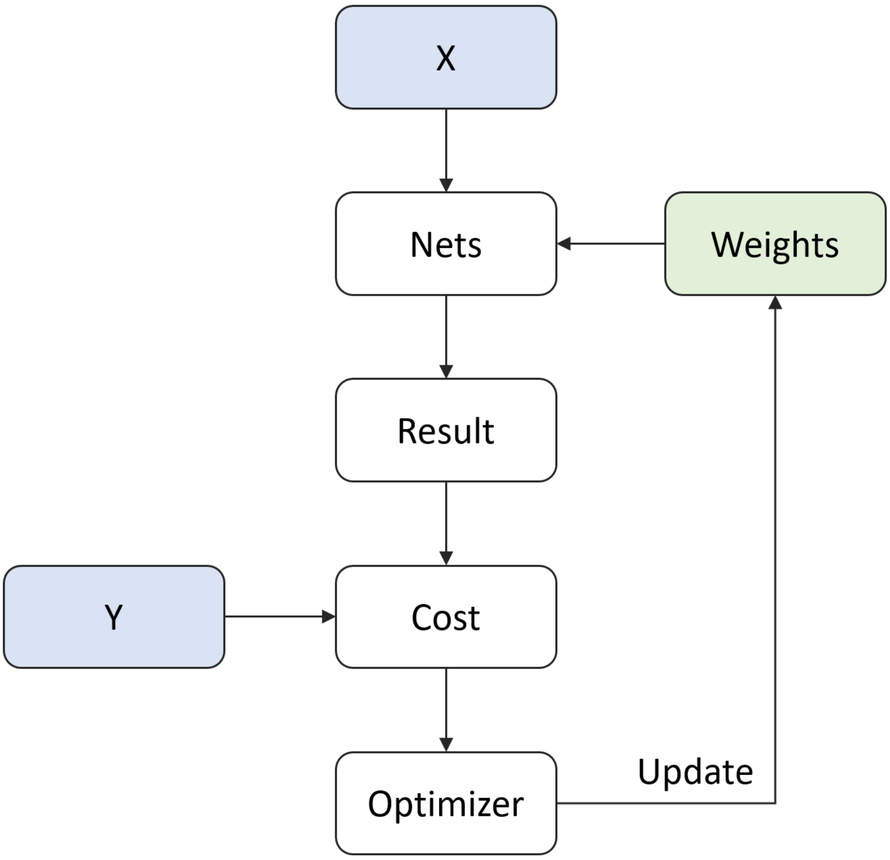
Optimizer

- AdamOptimizer : The most popular optimizer

In [7]:

```
LR = 0.0002

pred = build_model(x, weights, biases)
loss = tf.square(tf.subtract(y, pred))
loss = tf.reduce_mean(loss)

optm = tf.train.AdamOptimizer(LR).minimize(loss)

init = tf.global_variables_initializer()
```

2.7. Summary of Model



2.7. Define Configuration

- Define parameters for training RNN
  - n_iter : the number of training steps
  - n_prt : check loss for every n_prt iteration

In [8]:

```
n_iter = 2500
n_prt = 250
stride = 5
```

2.8. Optimization

In [9]:

```
# Run initialize
# config = tf.ConfigProto(allow_soft_placement=True)  # GPU Allocating policy
# sess = tf.Session(config=config)
sess = tf.Session()
sess.run(init)

for i in range(n_iter):
    train_x = data[i*stride:i*stride + n_step*n_input]
    train_x = train_x.reshape(n_step, n_input)
    train_x = train_x[np.newaxis,:]

    train_y = data[i*stride + n_step*n_input:i*stride + n_step*n_input + n_output]
    train_y = train_y[np.newaxis,:]

    sess.run(optm, feed_dict={x: train_x,  y: train_y})
    c = sess.run(loss, feed_dict={x: train_x,  y: train_y})
    if i % n_prt == 0:
        print ("Iter : {}".format(i))
        print ("Cost : {}".format(c))
```

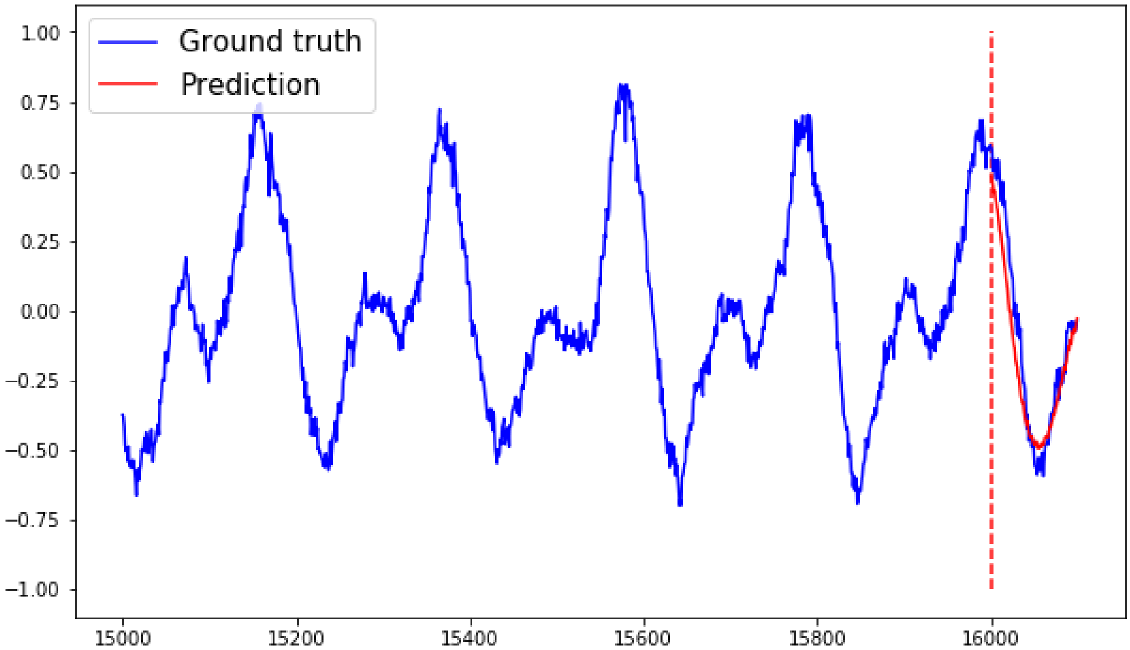
```
Iter : 0
Cost : 0.18020625412464142
Iter : 250
Cost : 0.15337766706943512
Iter : 500
Cost : 0.08356128633022308
Iter : 750
Cost : 0.07779762893915176
Iter : 1000
Cost : 0.03251627832651138
Iter : 1250
Cost : 0.0035845981910824776
Iter : 1500
Cost : 0.009463746100664139
Iter : 1750
Cost : 0.08887514472007751
Iter : 2000
Cost : 0.002686465624719858
Iter : 2250
Cost : 0.010863734409213066
```

2.9. Test

- Predict a future time signal
- `data[0:13600]` are used for learning ($5\times2500 + 1100 = 13600$)

In [10]:

```
start_pt = 15000

test_range = [start_pt, start_pt + n_step*n_input]
pred_range = [test_range[1], test_range[1] + n_input]
GT_range = [start_pt, pred_range[1]]

test_x = data[test_range[0]:test_range[1]]
test_x = test_x.reshape(n_step, n_input)
test_x = test_x[np.newaxis,:]

ground_truth = data[GT_range[0]:GT_range[1]]

test_pred = sess.run(pred, feed_dict={x : test_x})

plt.figure(figsize=(10, 6))
plt.plot(np.arange(GT_range[0], GT_range[1]), \
         ground_truth, 'b', label='Ground truth')
plt.plot(np.arange(pred_range[0], pred_range[1]), \
         test_pred.ravel(), 'r', label='Prediction')
plt.vlines(pred_range[0], -1, 1, colors = 'r', linestyles='dashed')
plt.legend(fontsize=15, loc='upper left')
plt.show()
```



In [11]:

```
start_pt = 15000

test_range = [start_pt, start_pt + n_step*n_input]
pred_range = [test_range[1], test_range[1] + n_step*n_input]
GT_range = [start_pt, pred_range[1]]

test_x = data[test_range[0]:test_range[1]]
test_x = test_x.reshape(n_step, n_input)
test_x = test_x[np.newaxis,:]

ground_truth = data[GT_range[0]:GT_range[1]]

gen_signal = []
for i in range(n_step):
    test_pred = sess.run(pred, feed_dict={x : test_x})
    gen_signal.append(test_pred.ravel())
    test_pred = test_pred[:,np.newaxis,:]

    test_x = test_x[:,1:,:]
    test_x = np.concatenate([test_x, test_pred], axis=1)

gen_signal = np.concatenate(gen_signal)

plt.figure(figsize=(10,6))
plt.plot(np.arange(GT_range[0], GT_range[1]), \
         ground_truth, 'b', label='Ground truth')
plt.plot(np.arange(pred_range[0], pred_range[1]), \
         gen_signal, 'r', label='Prediction')
plt.vlines(pred_range[0], -1, 1, colors = 'r', linestyles='dashed')
plt.legend(fontsize=15, loc='upper left')
plt.show()
```