Recurrent Neural Network

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1. Recurrent Neural Network (RNN)

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

ML RobotCop 2

2. Time Series Data

- For example

$$y[0] = 1, y[1] = \frac{1}{2}, y[2] = \frac{1}{4}$$

- Closed form

$$y[n] = \left(\frac{1}{2}\right)^n$$

- Linear difference equation (LDE) and initial condition

$$y[n] = \frac{1}{2}y[n-1], y[0] = 1$$
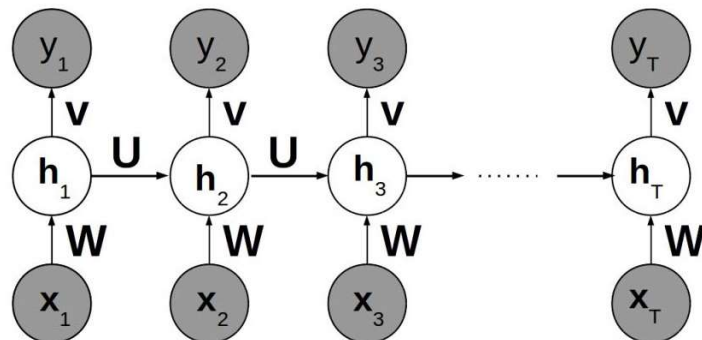
- High order LDEs

$$y[n] = \alpha_1 y[n-1] + \alpha_2 y[n-2]$$
$$y[n] = \alpha_1 y[n-1] + \alpha_2 y[n-2] + \cdots + \alpha_k y[n-k]$$

3. Recurrent Neural Network (RNN)

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

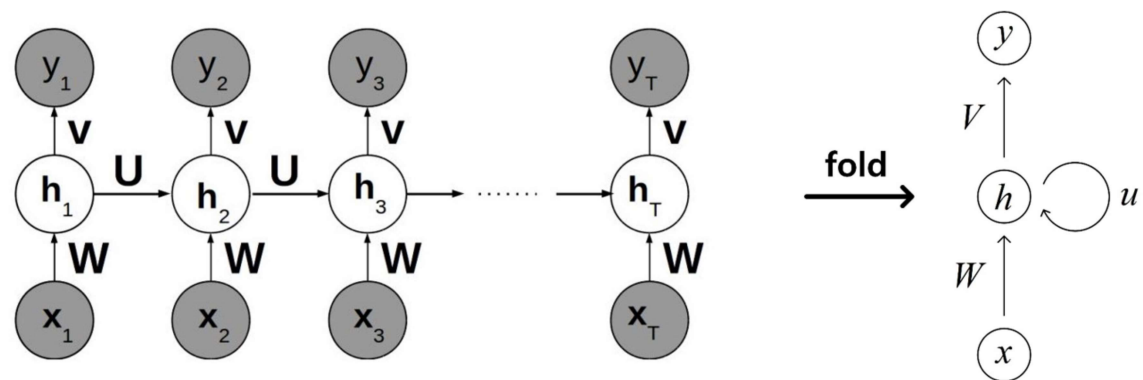## 3.1. Feedforward Network and Sequential Data

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

3.2. Structure of RNN

Recurrence

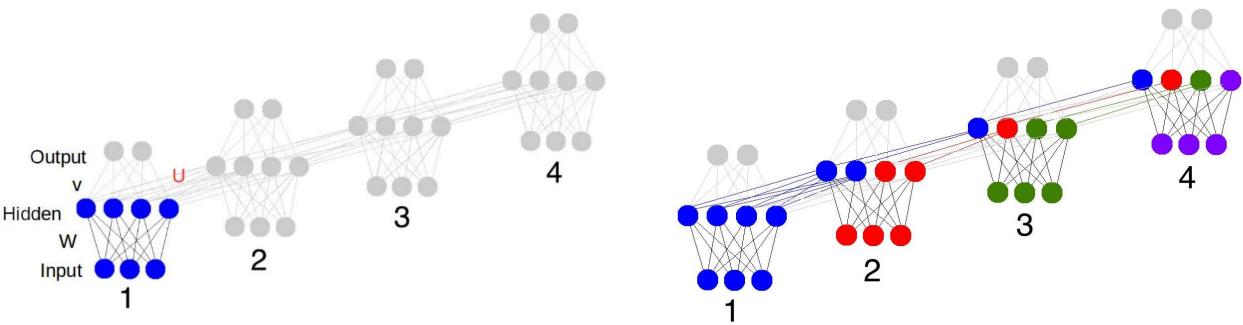- It is possible to use the **same** transition function f with the same parameters at every time step
- Order matters

Hidden State

- 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)
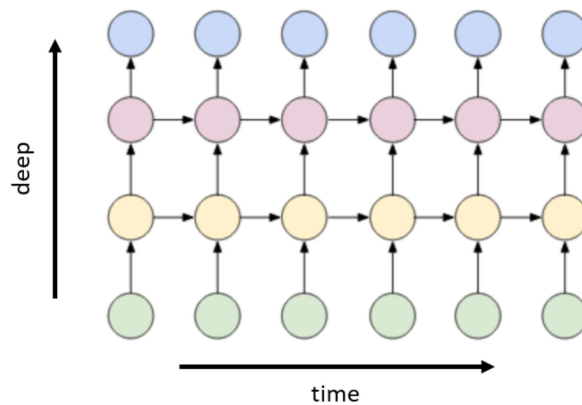
3.3. RNN with LSTM

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
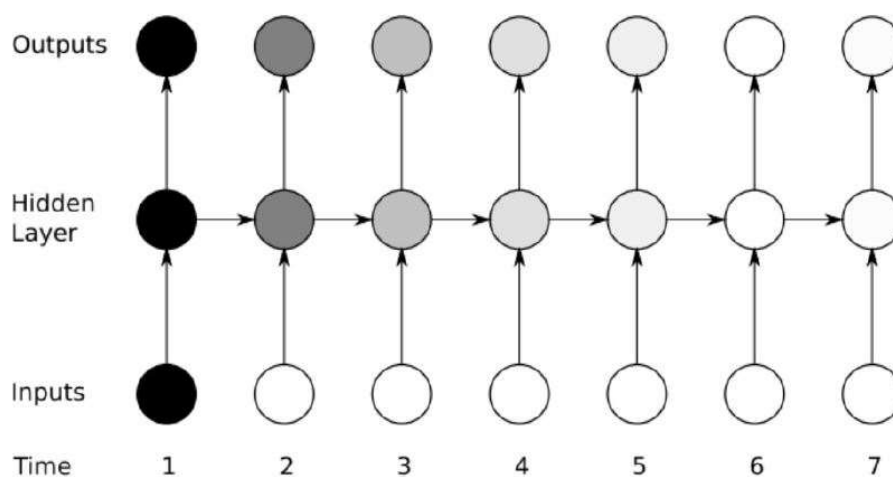
Long Short-Term Memory (LSTM)

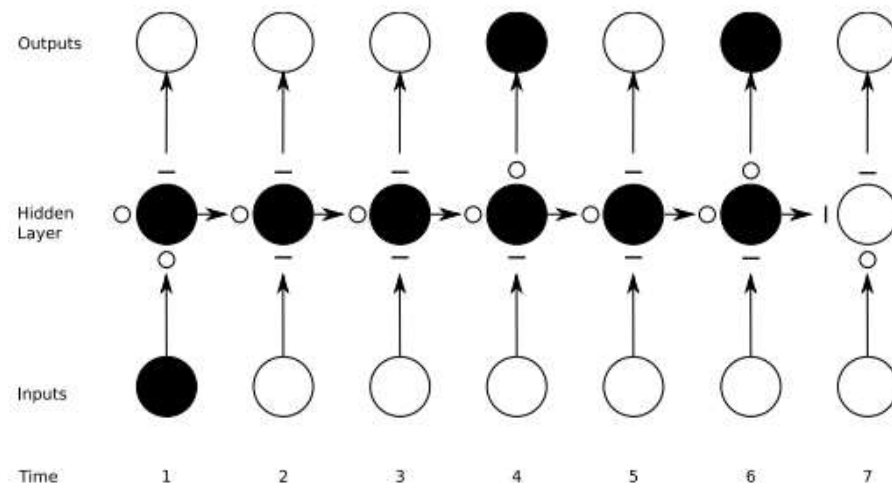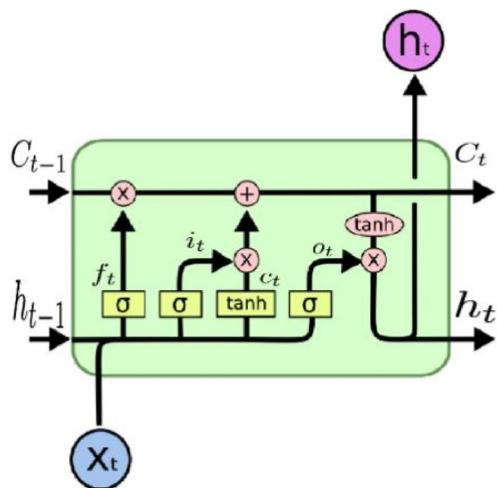- Allow the network to **accumulate** information over a long duration
- Once that information has been used, it might be used for the neural network to **forget** the old state

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

$$o_t = \sigma\left(W_o\, [h_{t-1}, x_t] + b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

- Time series data and RNN
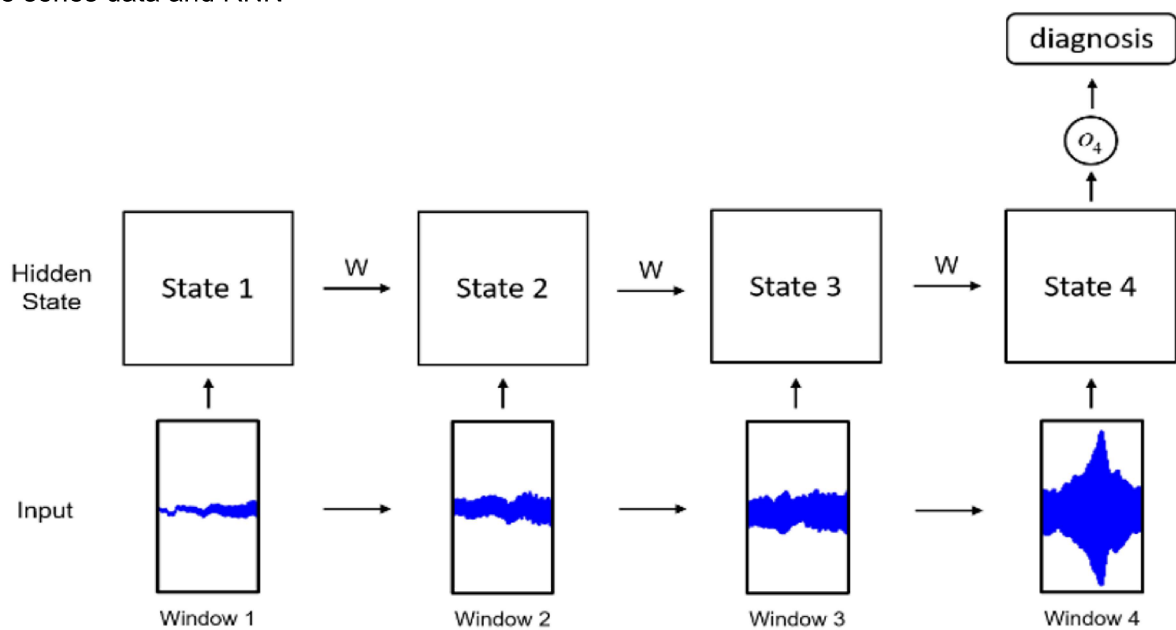
Summary

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

3.4. RNN and Sequential Data

RNN for Classification
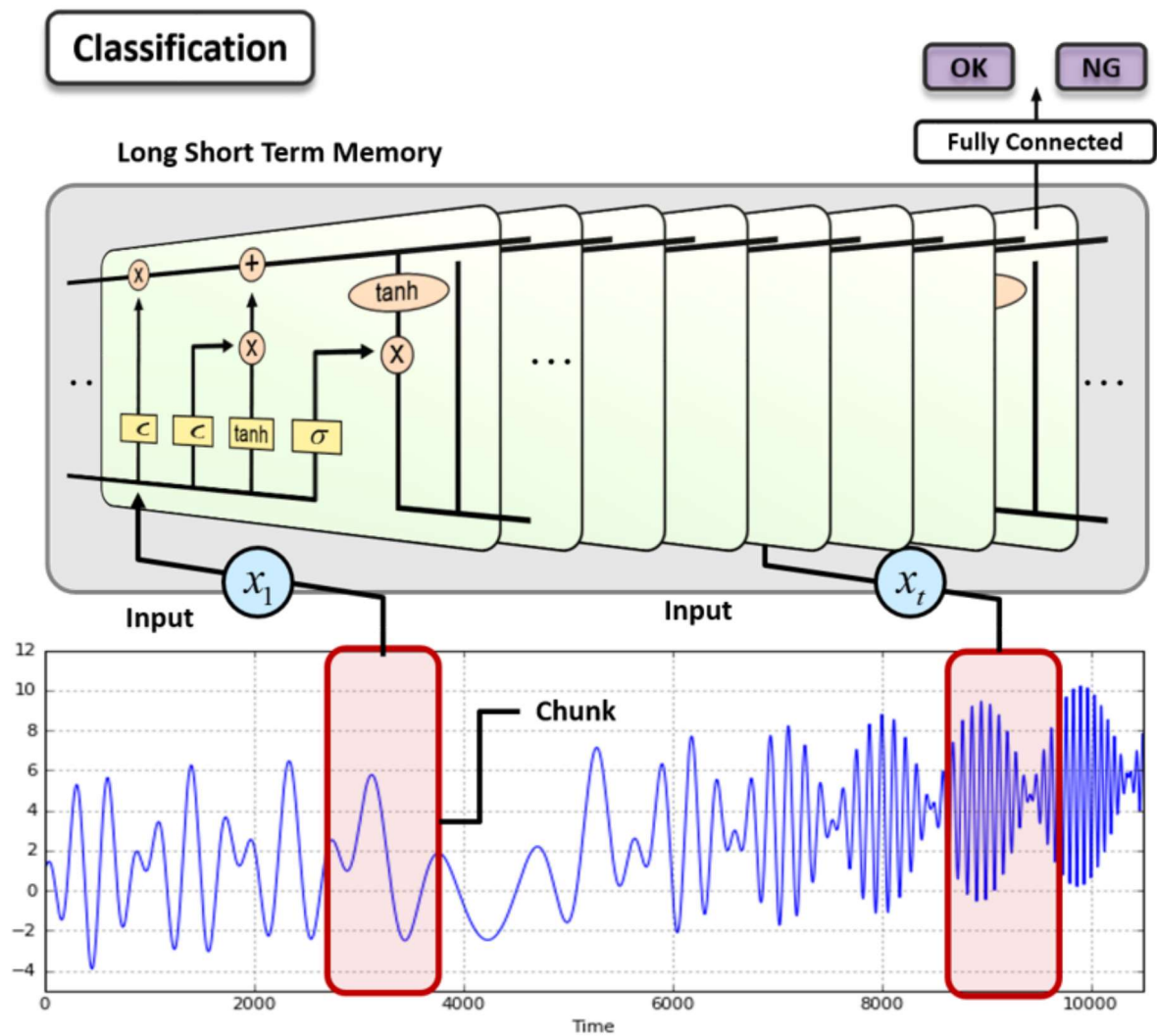
RNN for Prediction

Prediction

Long Short Term Memory

Fully Connected

Input x_1

Input x_t

Chunk

Prediction Example

Ground truth
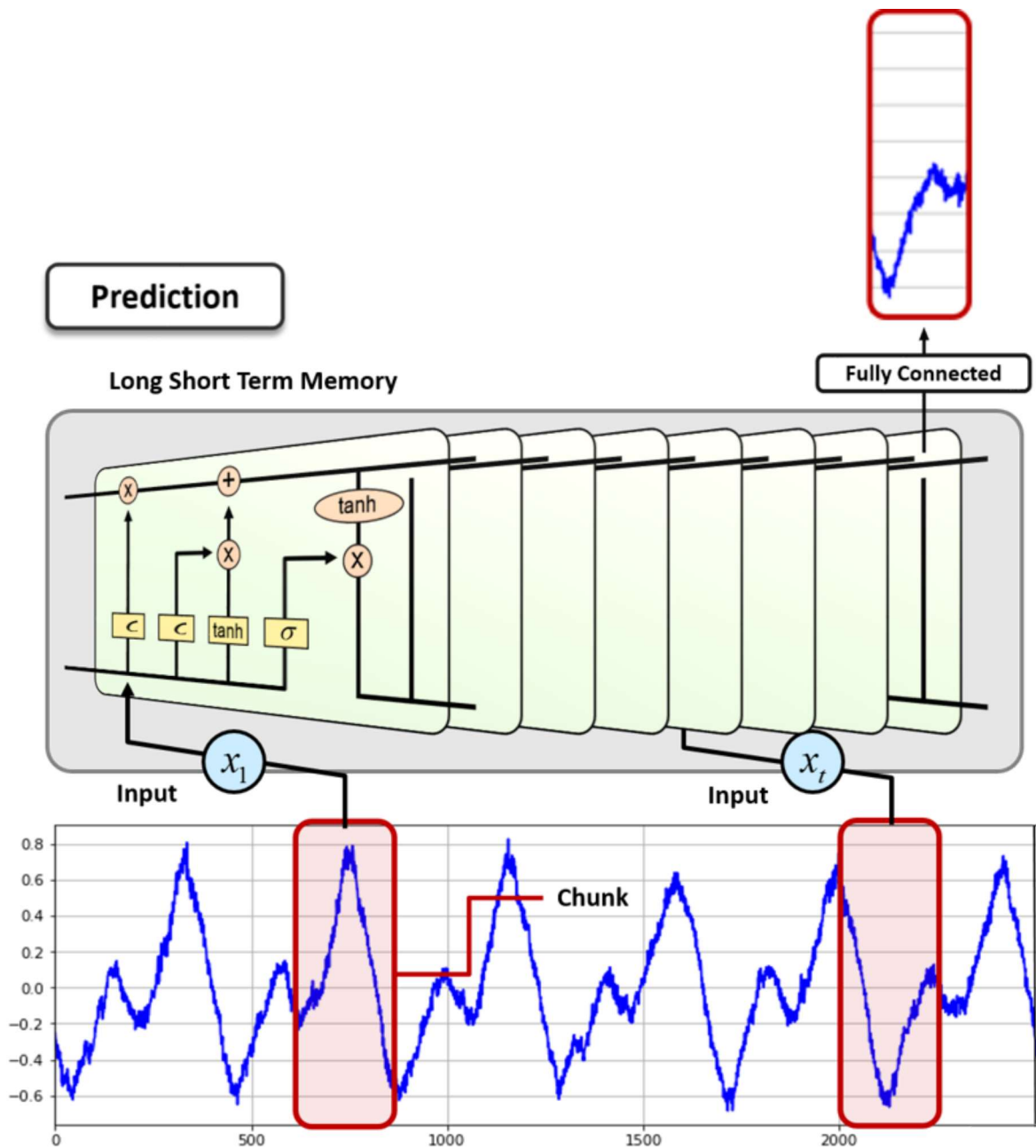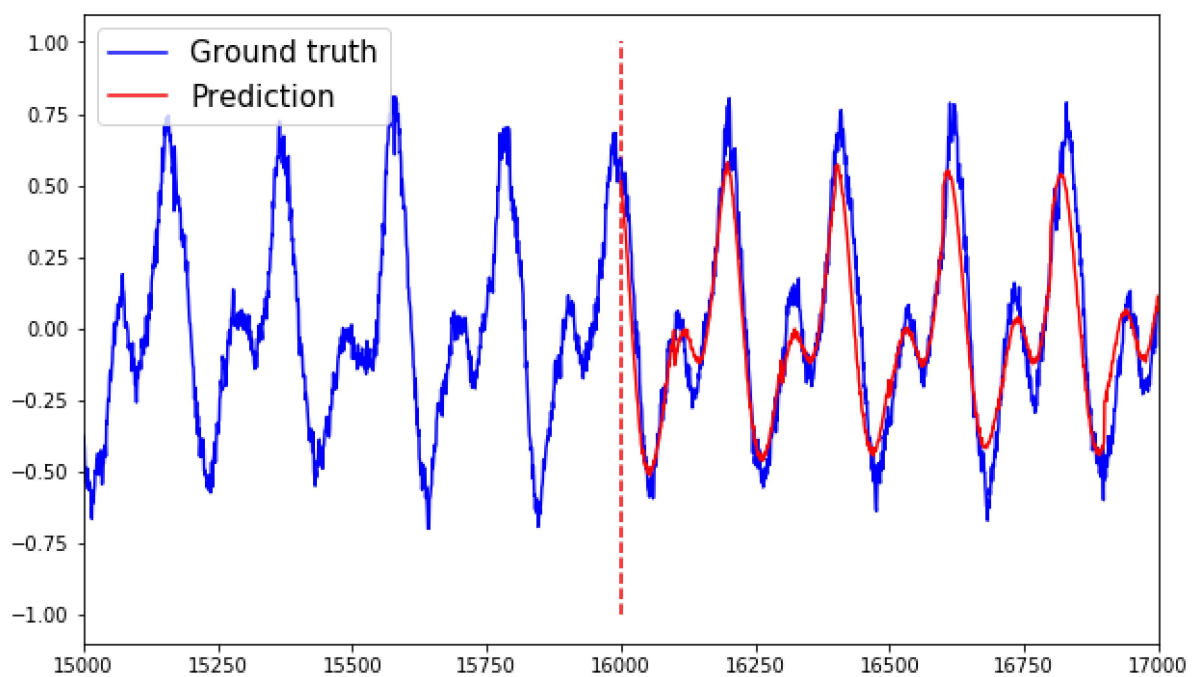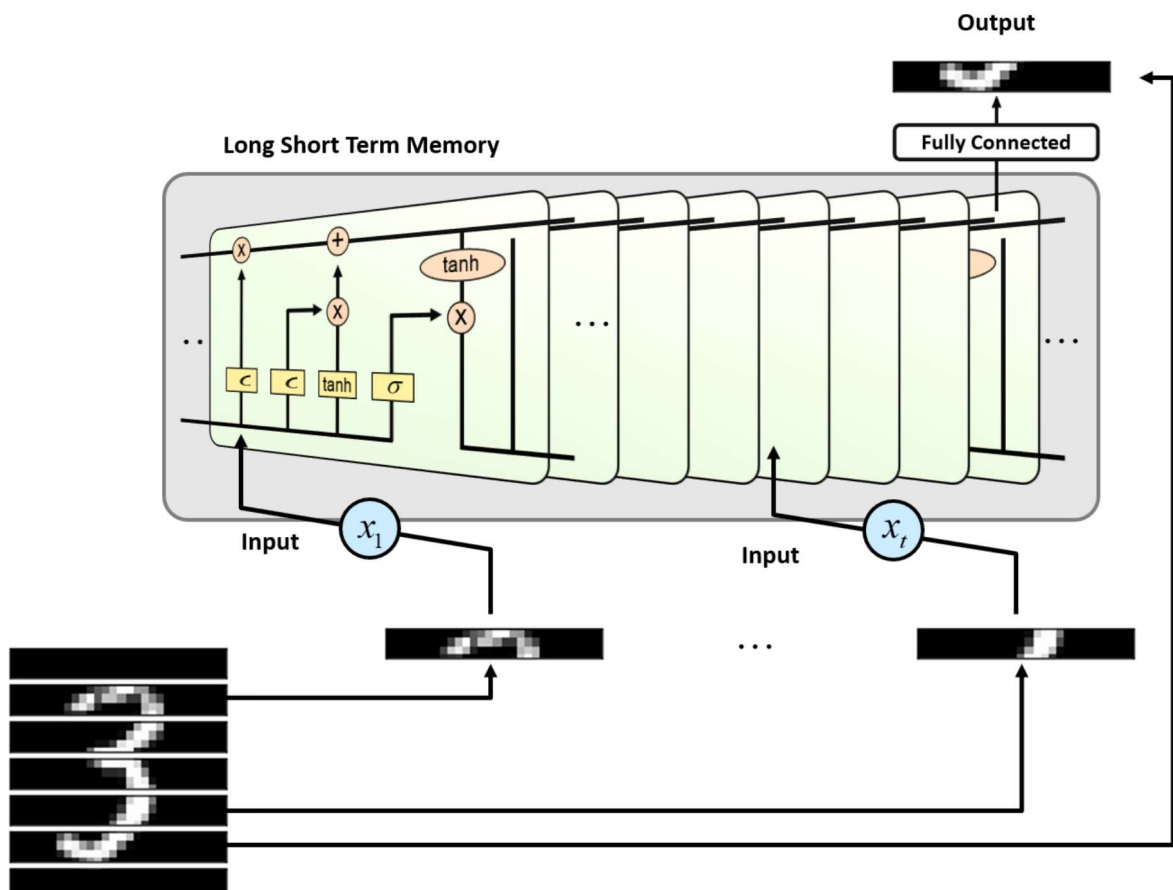
Prediction

4. RNN with Tensorflow

- An example for predicting a next piece of an image
- Regression problem

4.1. Import Library

In [2]:

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

4.2. Load MNIST Data

- Download MNIST data from the tensorflow tutorial example

In [3]:

```python
from tensorflow.examples.tutorials.mnist import input_data
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
```

```
Extracting MNIST_data/train-images-idx3-ubyte.gz
Extracting MNIST_data/train-labels-idx1-ubyte.gz
Extracting MNIST_data/t10k-images-idx3-ubyte.gz
Extracting MNIST_data/t10k-labels-idx1-ubyte.gz
```

In [4]:

```python
# Check data
train_x, train_y = mnist.train.next_batch(10)
img = train_x[9,:].reshape(28, 28)

plt.figure(figsize=(5, 3))
plt.imshow(img,'gray')
plt.title("Label : {}".format(np.argmax(train_y[9])))
plt.xticks([])
plt.yticks([])
plt.show()
```


Label : 2
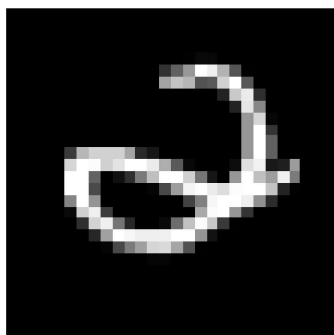
4.3. Define RNN Structure
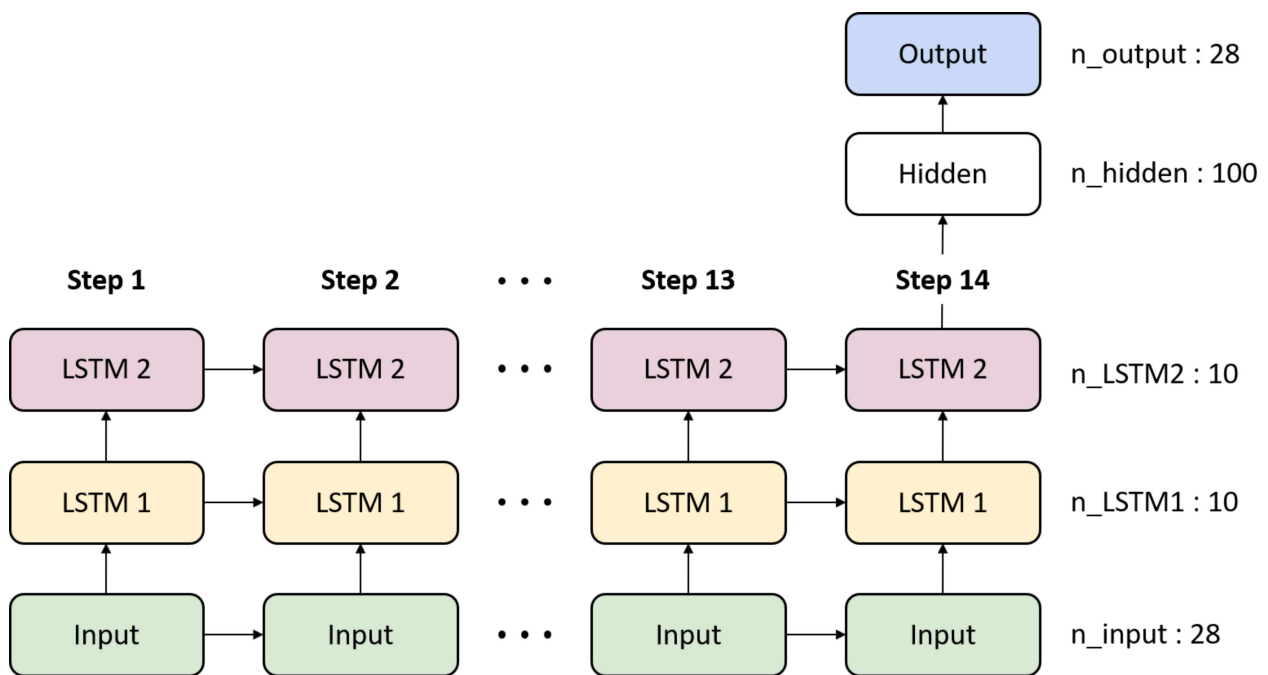
In [5]:

```
n_step = 14
n_input = 28

## LSTM shape
n_lstm1 = 10
n_lstm2 = 10

## Fully connected
n_hidden = 100
n_output = 28
```

4.4. Define Weights and Biases

LSTM Cell

- Do not need to define weights and biases 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 [6]:
```

```python
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])
```

4.5. Build a Model

Build the RNN Network

- First, define the LSTM cells


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

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


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

```
In [7]:
```

```python
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
```

4.6. 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

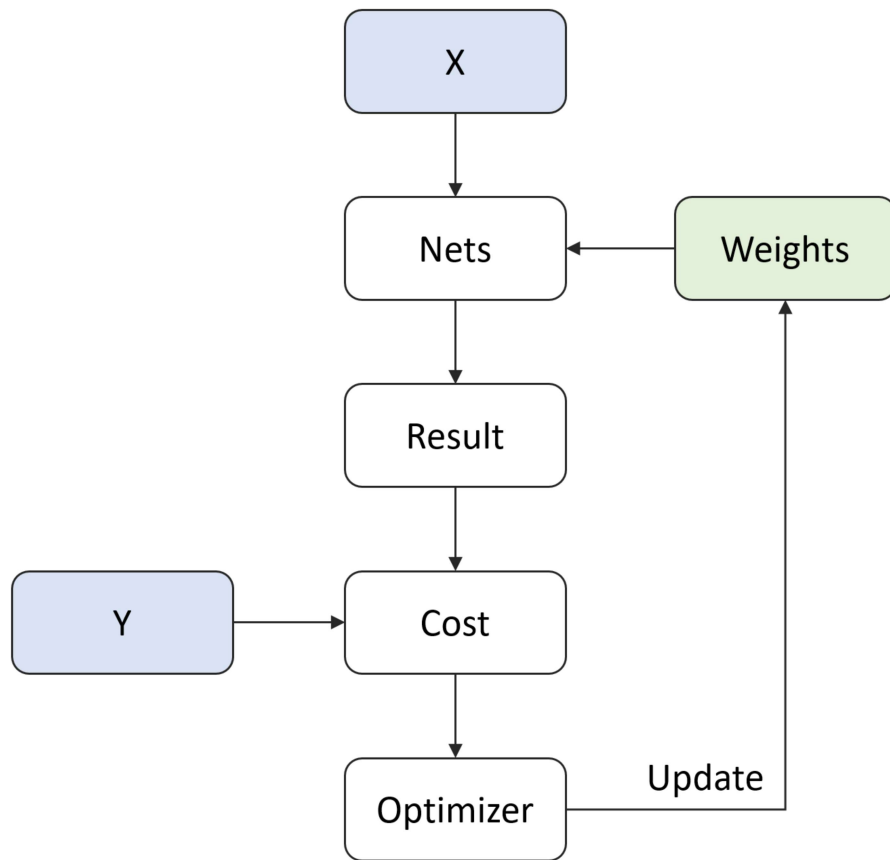- AdamOptimizer: the most popular optimizer

In [8]:

```
LR = 0.0005

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()
```

4.7. Summary of Model

4.8. Define Configuration

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

In [9]:

```python
n_iter = 2500
n_prt = 100
```

4.9. Optimization

Do not run on CPU. It will take quite a while.

In [ ]:

```python
# 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, train_y = mnist.train.next_batch(50)
    train_x = train_x.reshape(-1, 28, 28)

    for j in range(n_step):
        sess.run(optm, feed_dict={x: train_x[:,j:j+n_step,:],  y: train_x[:,j+n_step]})
    if i % n_prt == 0:
        c = sess.run(loss, feed_dict={x: train_x[:,13:13+n_step,:],  y: train_x[:,13+n_step]})
        print ("Iter : {}".format(i))
        print ("Cost : {}".format(c))
```

4.10. Test

- Do not run on CPU. It will take quite a while.

- Predict the MNIST image
- MNIST is 28 x 28 image. The model predicts a piece of 1 x 28 image.
- First, 14 x 28 image will be fed into a model, then the model predict the last 14 x 28 image, recursively.

```python
test_x, test_y = mnist.test.next_batch(10)
test_x = test_x.reshape(-1, 28, 28)

idx = 0
gen_img = []

sample = test_x[idx, 0:14, :]
input_img = sample.copy()

feeding_img = test_x[idx, 0:0+n_step, :]

for i in range(n_step):
    test_pred = sess.run(pred, feed_dict={x: feeding_img.reshape(1, 14, 28)})
    feeding_img = np.delete(feeding_img, 0, 0)
    feeding_img = np.vstack([feeding_img, test_pred])
    gen_img.append(test_pred)

for i in range(n_step):
    sample = np.vstack([sample, gen_img[i]])

plt.imshow(test_x[idx], 'gray')
plt.title('Original Img')
plt.xticks([])
plt.yticks([])
plt.show()

plt.figure(figsize=(4,3))
plt.imshow(input_img, 'gray')
plt.title('Input')
plt.xticks([])
plt.yticks([])
plt.show()

plt.imshow(sample, 'gray')
plt.title('Generated Img')
plt.xticks([])
plt.yticks([])
plt.show()
```

5. Load pre-trained Model

- We trained the model on GPU for you.

- You can load the pre-trained model to see RNN MNIST results

- LSTM size
  - n_lstm1 = 128
  - n_lstm2 = 256

In [10]:

```
from RNN import RNN
my_rnn = RNN()
my_rnn.load('./data_files/RNN_mnist/checkpoint/RNN_5000')
```

INFO:tensorflow:Restoring parameters from ./data_files/RNN_mnist/checkpoin
t/RNN_5000
Model loaded from file : ./data_files/RNN_mnist/checkpoint/RNN_5000

- Test with the pre-trained Model

In [11]:

```python
test_x, test_y = mnist.test.next_batch(10)
test_x = test_x.reshape(-1, 28, 28)

sample = test_x[0, 0:14,:]

gen_img = my_rnn.predict(sample)

plt.imshow(test_x[0], 'gray')
plt.title('Original Img')
plt.xticks([])
plt.yticks([])
plt.show()

plt.figure(figsize=(4,3))
plt.imshow(sample, 'gray')
plt.title('Input')
plt.xticks([])
plt.yticks([])
plt.show()

plt.imshow(gen_img, 'gray')
plt.title('Generated Img')
plt.xticks([])
plt.yticks([])
plt.show()
```
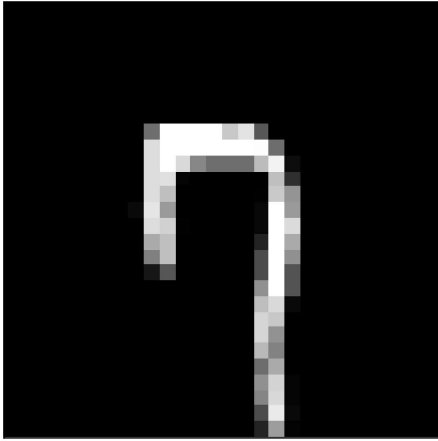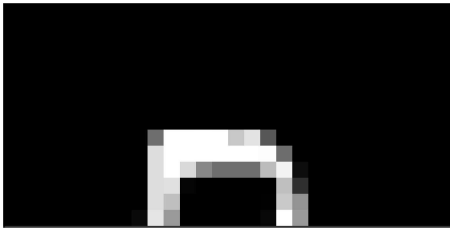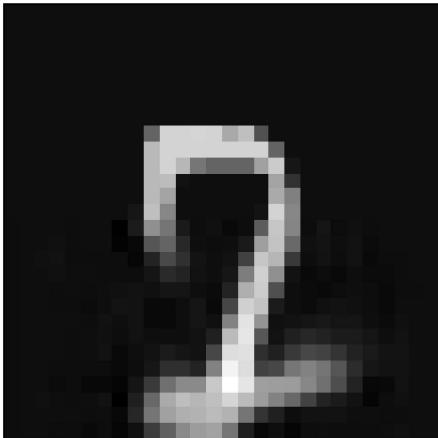
Original Img

Input

Generated Img

In [12]:

```javascript
%%javascript
$.getScript('https://kmahelona.github.io/ipython_notebook_goodies/ipython_notebook_toc.js')
```