Modèle d'apprentissage pour la prévision du mildiou

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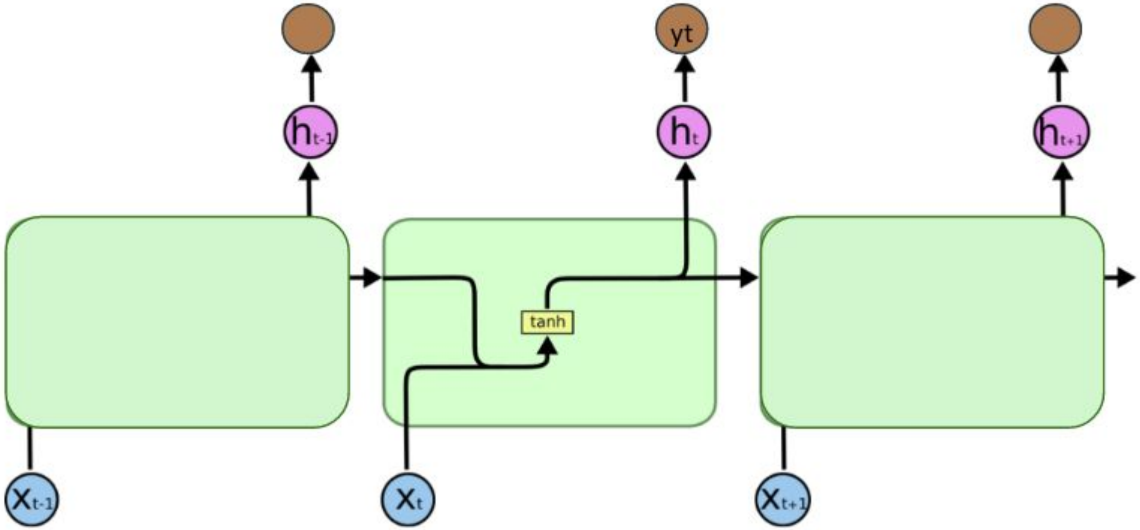
Introduction

Aujourd’hui, nous allons voir la structure exacte des Long Short Term Memory (LSTM) qui apportent une solution pour la prévision du Mildiou.

Recurrent Neural Network

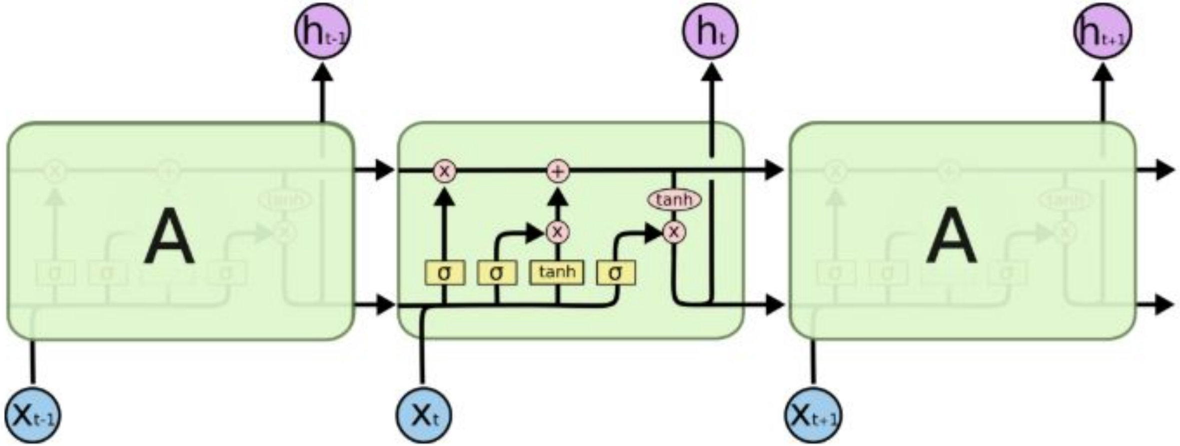


$$h_t = f_W(h_{t-1}, x_t)$$

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

$$y_t = W_{hy}h_t$$

Long Short Term Memory

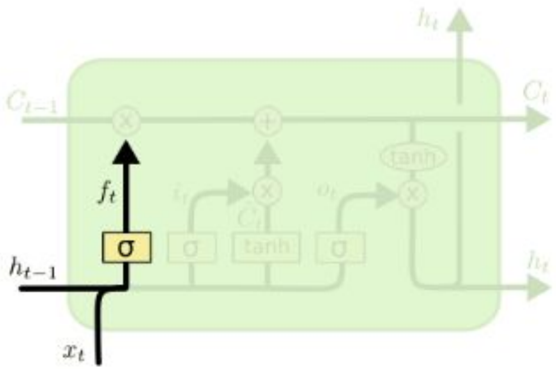


Forget Gate

Input Gate

Output Gate

Forget Gate



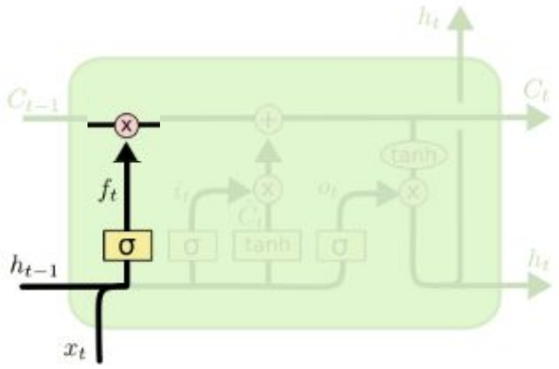
$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

```
>>> c_prev.shape
(5,)
>>> h_prev.shape
(5,)
>>> x.shape
(4,)
```

```
>>> x_h_prev = np.hstack((x, h_prev))
>>> x_h_prev.shape
(9,)
```

```
>>> Wf.shape
(9, 5)
>>> bf.shape
(5,)
>>> ft = sigmoid(np.dot(x_h_prev, Wf) + bf)
>>> ft.shape
(5,)
```

Forget Gate

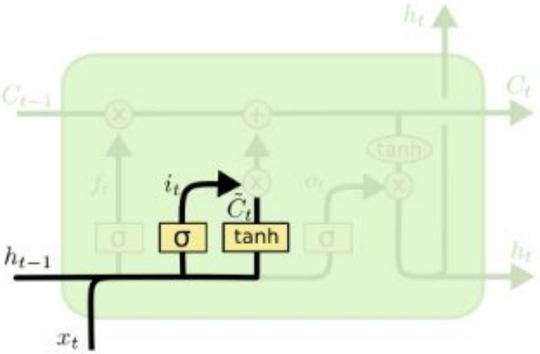


$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

```
>>> ft
array([0.00605241, 0.02419927, 0.12958965, 0.83141943,
0.5440948 ])
>>> c_prev
array([ 0.38000574,  1.13691447,  1.57618308, -1.01247179,
1.02257568])
```

```
>>> c_prev_forgot = ft*c_prev
>>> c_prev_forgot.shape
(5,)
>>> c_prev_forgot.shape
(5,)
>>>
```

Input Gate



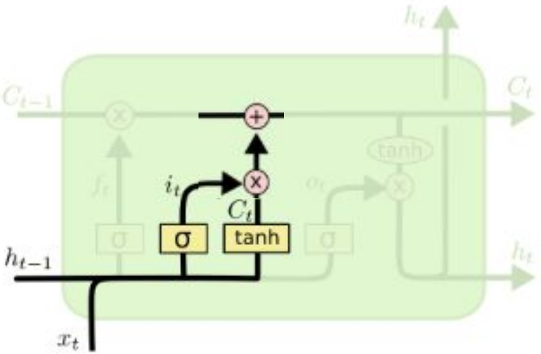
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

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

```
>>> Ĉt = np.tanh(np.dot(x_h_prev, Wc) + bc)
>>> Ĉt
array([-0.17806474, -0.99993564,  0.99164565,  0.92774236,
-0.99527522])
>>> Ĉt.shape
(5,)
>>>
```

```
>>> it = sigmoid(np.dot(x_h_prev, Wi) + bi)
>>> it
array([0.00798643, 0.92300084, 0.22905397, 0.27818745,
0.96195338])
>>> it.shape
(5,)
>>>
```

Input Gate



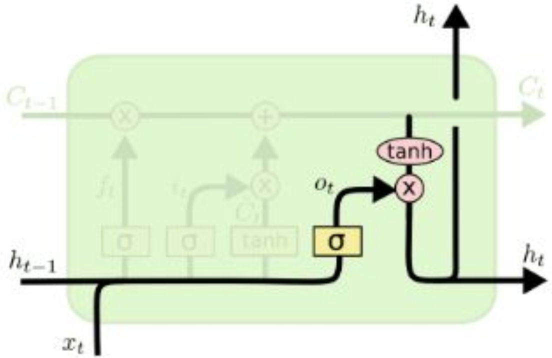
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

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

```
>>> new_c = it*Ĉt
>>> new_c
array([-0.0014221 , -0.92294144,  0.22714037,  0.25808628,
-0.95740836])
>>> new_c.shape
(5,)
```

```
>>> c = c_prev*ft + it*Ĉt
>>> c.shape
(5,)
>>> c
```

Output Gate



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

```
>>> ot = sigmoid(np.dot(x_h_prev, Wo) + bo)
>>> ot.shape
(5,)
>>> h = ot * np.tanh(c)
>>> h.shape
(5,)
```

Conclusion

Grâce à leur mémoire active, les LSTM seront utiles dans notre modèle d'apprentissage.

Elles apportent une solution pour la prévision du Mildiou.