



ATTENTIVE CONVOLUTIONAL LSTM

RECALL....

```
ssh -p port user@YourAzureVM
```

```
pip freeze | grep torch==0.4.0
```

```
git pull https://github.com/aimagelab/aidlda_tutorial
```

You have all the slides and the code in the Github repo!

Don't get lost:

- if you don't understand something: **ask!**
- If you can't do something: **the solution is in the repo!**



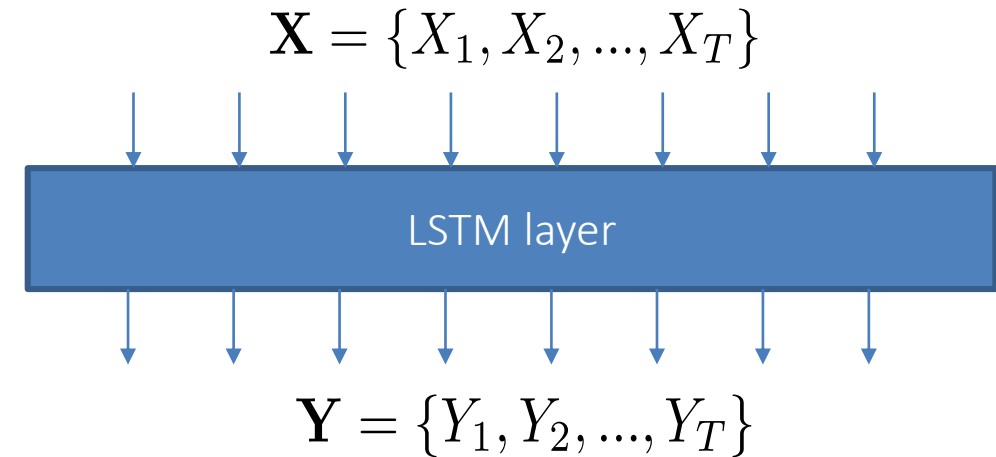
LSTM

A recurrent layer.

From the exterior

Takes as input a sequence.

Outputs a sequence with the same length.



LSTM

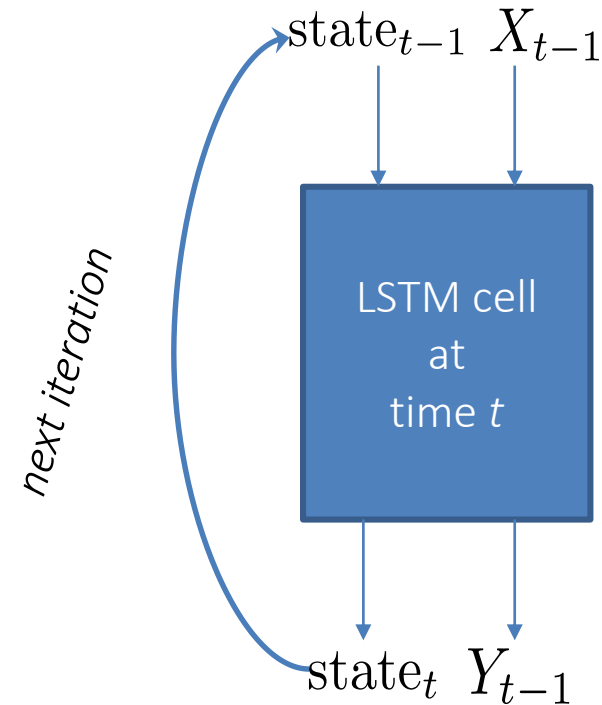
A recurrent layer.

Inside, at each timestep:

Takes the current input

Combines it with current state

Produces output and next states



LSTM

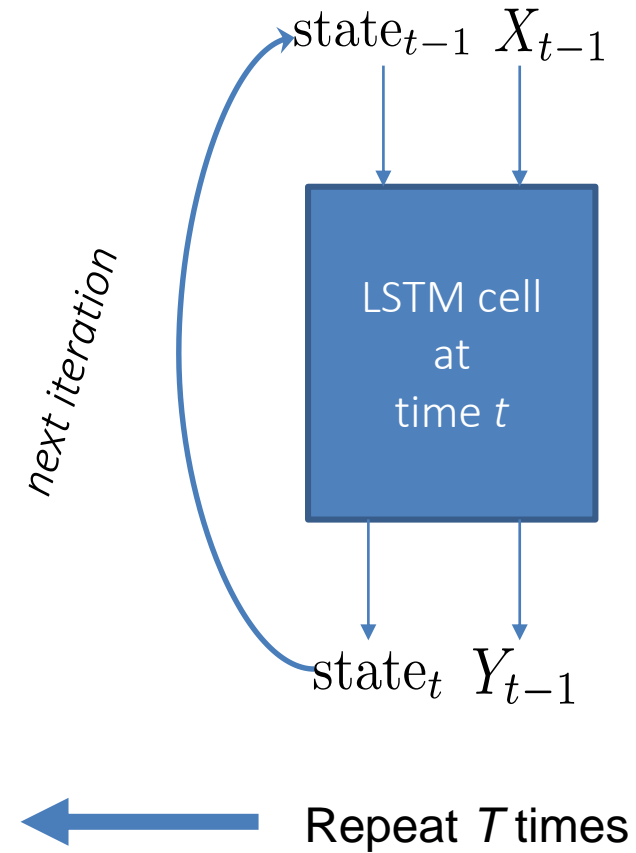
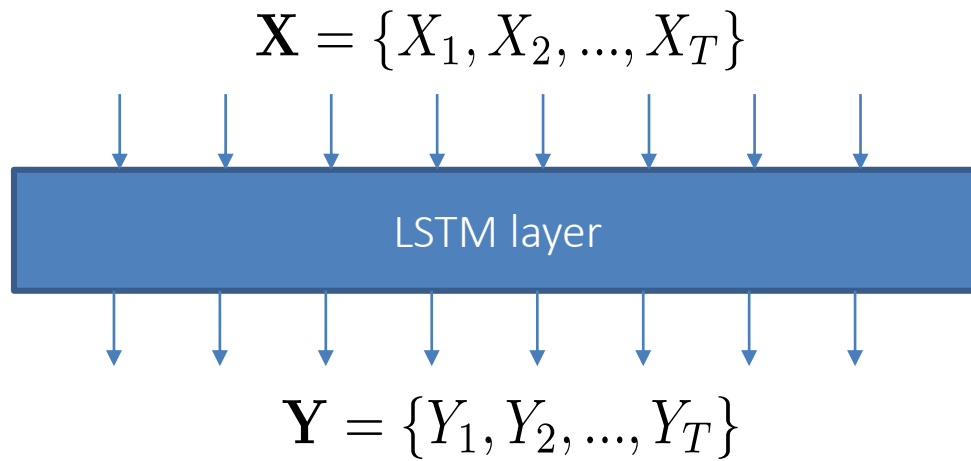
A recurrent layer.

Inside, at each timestep:

Takes the current input

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Produces output and next states



LSTM

For the LSTM, the actual equations are:

$$I_t = \sigma(W_i * \tilde{X}_t + U_i * H_{t-1} + b_i)$$

$$F_t = \sigma(W_f * \tilde{X}_t + U_f * H_{t-1} + b_f)$$

$$O_t = \sigma(W_o * \tilde{X}_t + U_o * H_{t-1} + b_o)$$

$$G_t = \tanh(W_c * \tilde{X}_t + U_c * H_{t-1} + b_c)$$

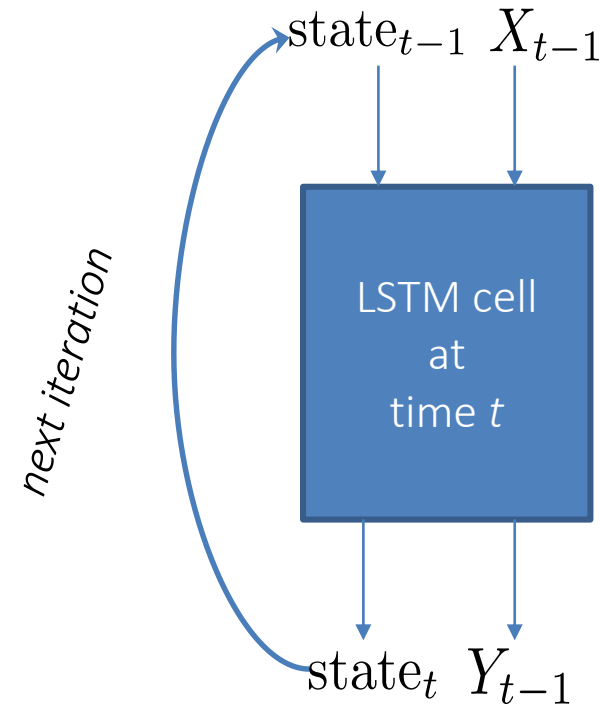
$$C_t = F_t \odot C_{t-1} + I_t \odot G_t$$

$$H_t = O_t \odot \tanh(C_t)$$

The “state” is given by (H_t, C_t) . The “output” is H_t

Notice that, beside the activation function, all gates are computed in the same way.

→ Any ideas on how to exploit this to speed up the computation?



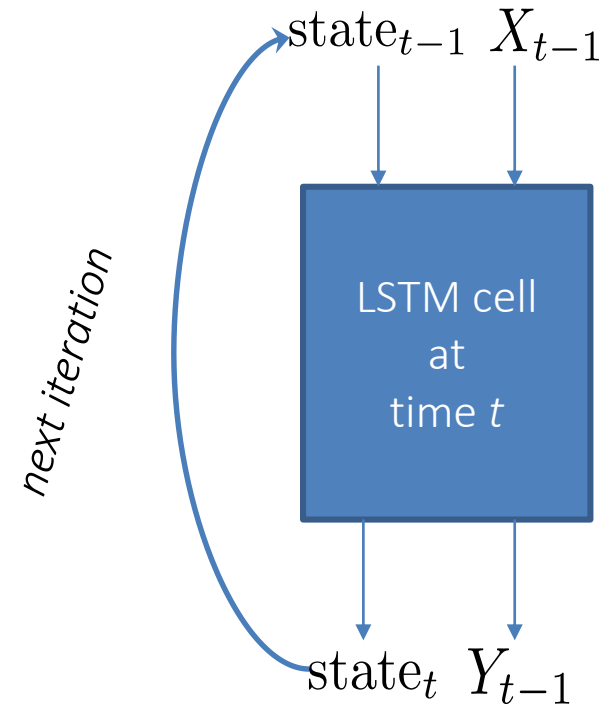
LSTM

For the LSTM, the actual equations are:

$$\begin{aligned} I_t &= \sigma(W_i * \tilde{X}_t + U_i * H_{t-1} + b_i) \\ F_t &= \sigma(W_f * \tilde{X}_t + U_f * H_{t-1} + b_f) \\ O_t &= \sigma(W_o * \tilde{X}_t + U_o * H_{t-1} + b_o) \\ G_t &= \tanh(W_c * \tilde{X}_t + U_c * H_{t-1} + b_c) \\ C_t &= F_t \odot C_{t-1} + I_t \odot G_t \\ H_t &= O_t \odot \tanh(C_t) \end{aligned}$$

The “state” is given by (H_t , C_t). The “output” is H_t

We are going to implement an LSTM on images. So inputs, states and outputs will be 3-d tensors (channels x h x w), and operations between them will be convolutions!



ATTENTION

The input of the network is replaced by an element-wise multiplication between the input and an **attentive map**:

$$Z_t = V_a * \tanh(W_a * X + U_a * H_{t-1} + b_a). \quad (7)$$

The output of this operations is a 2-d map from which we can compute a normalized spatial attention map through the *softmax* operator:

$$A_t^{ij} = p(att_{ij}|X, H_{t-1}) = \frac{\exp(Z_t^{ij})}{\sum_i \sum_j \exp(Z_t^{ij})} \quad (8)$$

where A_t^{ij} is the element of the attention map in position (i, j) . The attention map is applied to the input X with an element-wise product between each channel of the feature maps and the attention map:

$$\tilde{X}_t = A_t \odot X. \quad (9)$$

CODING TIME!

Implement a Convolutional Attentive LSTM, following the equations of the previous slides.

Follow the schema in the Github repo:

1. Implement an LSTM Cell
2. Implement an LSTM Module, which calls (1) at each iteration
3. Plug the attention equations in
4. Test it!



CONCLUSIONS

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What you should have learned

- Some theory on human fixation and saliency prediction
- Two state of the art approaches, for task agnostic and task-driven saliency
- You should be a quasi-guru of PyTorch programming 1-0-1 😊
- How to implement forward/backward passes of the essential building blocks of a CNN
- How an attentive LSTM works, and how it can be applied for saliency prediction

CONCLUSIONS

If you still have questions...

- Marcella will be around in the next days
- Or, drop us a line! 😊
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 - marcella.cornia@unimore.it



THANK YOU!