ATTENTIVE CONVOLUTIONAL LSTM

AImage Lab

UNIMORE UNIVERSITÀ DEGLI STUDI DI MODENA E REGGIO EMILIA

RECALL….

```
ssh -p port user@YourAzureVM
pip freeze | grep torch==0.4.0
git pull https://github.com/aimagelab/aidlda_tutoral
```

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

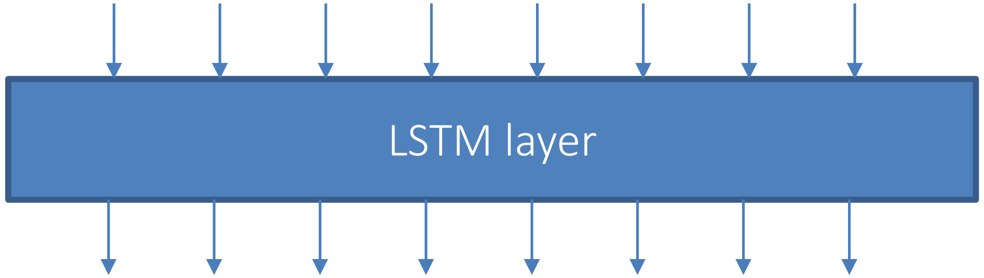
Don't get lost:

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

LSTM

A recurrent layer.

$$\mathbf{X} = \{X_1, X_2, ..., X_T\}$$



$$\mathbf{Y} = \{Y_1, Y_2, ..., Y_T\}$$

From the exterior

Takes as input a sequence.

Outputs a sequence with the same length.

LSTM

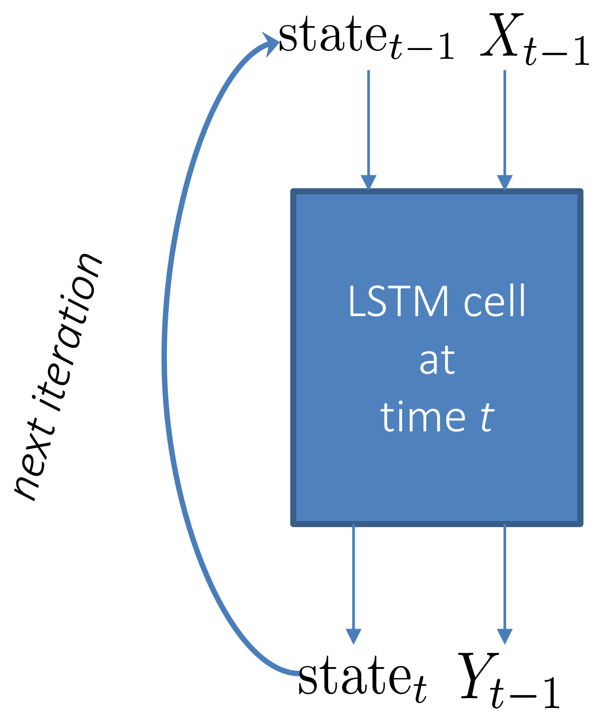
A recurrent layer.

Inside, at each timestep:

Takes the current input

Combines it with current state

Produces output and next states



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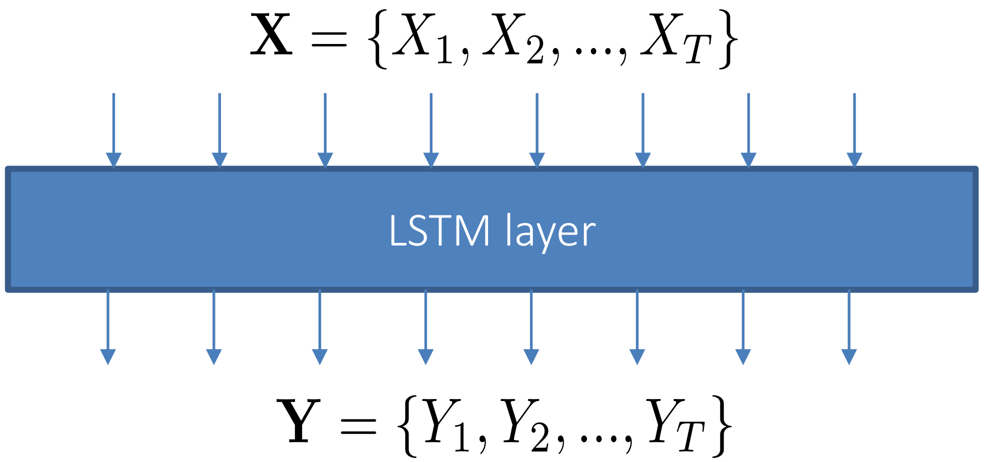
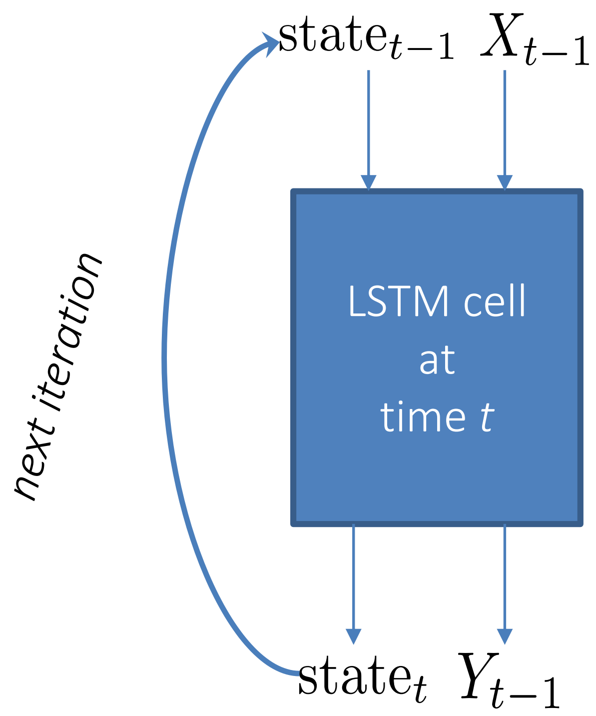


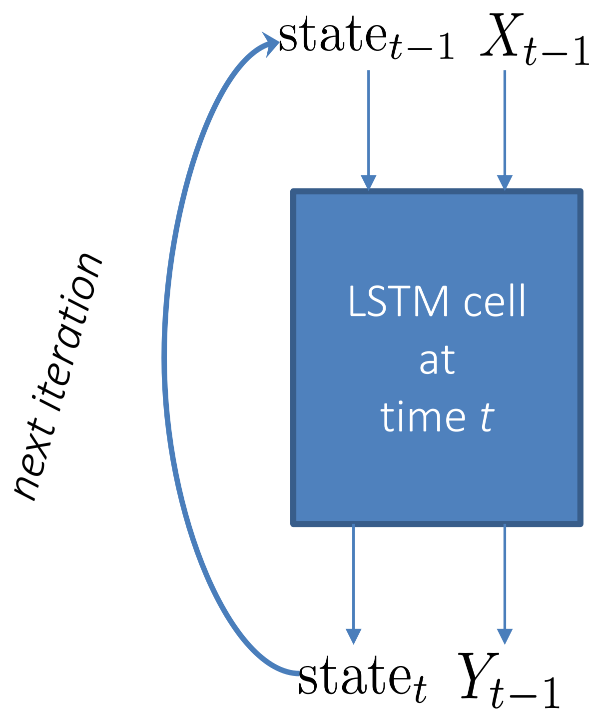
Repeat *T* times



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 (Ht, Ct). The “output” is Ht

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?

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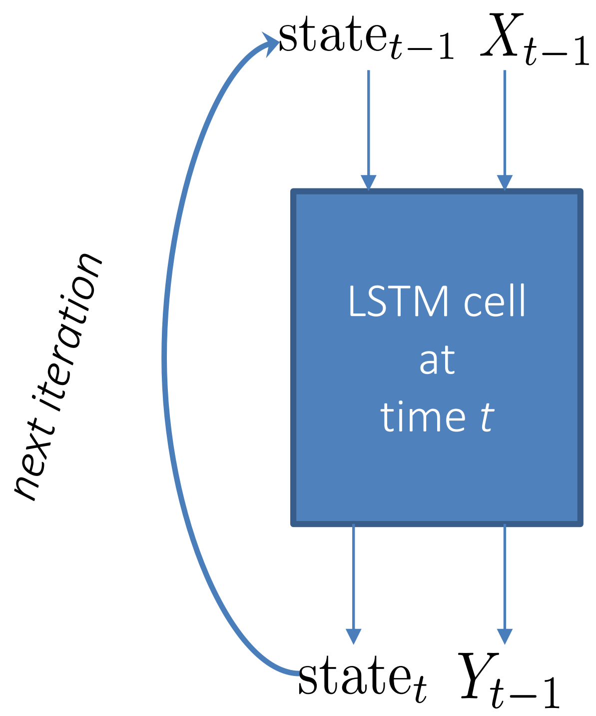

The “state” is given by (Ht, Ct). The “output” is Ht

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:**

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

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

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

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:

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

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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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

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If you still have questions…

- Marcella will be around in the next days
- Or, drop us a line! ☺

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THANK YOU!

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