Introduction to Deep Learning

Convolution (part 2) and (gated) recurrent Network

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MILES Machine Intelligence and Learning Systems

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Outline

Outline

Sequence of discrete symbols classification

Movie review classification

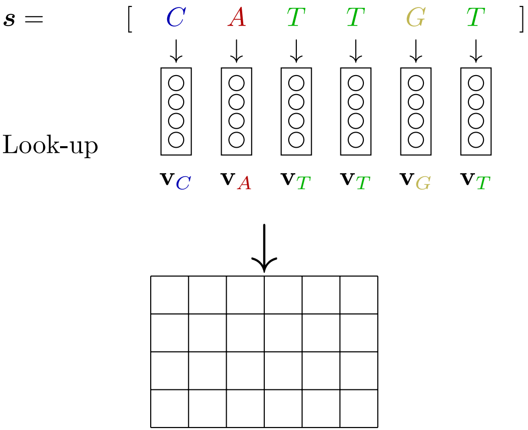
my wonderful friend took me to see this movie for our anniversary. it was terrible.	$: \; \boldsymbol{x} \in \mathbb{R}^D \longrightarrow c \in \{0,1\}$

Enhancer Identification in DNA Sequences

A T C G A T C G ... G T A A T C G	$: \; \boldsymbol{x} \in \mathbb{R}^D \longrightarrow c \in \{0,1\}$

- $\mathcal{D} = (\boldsymbol{x}_{(i)}, c_{(i)})_{i=1}^{N}$
- The input is a sequence $\rightarrow$ how to build $\boldsymbol{x}$?
- A sequence of discrete symbols $\in \mathcal{V}$
- Symbols interact with each other, the neighborhood is important

Embedding of discrete symbols



Convolution 1D

Extract a frame, or a window, and apply a “filter”

The input sequence of $L = 6$ vectors in $\mathbb{R}^D$, $D = 4$

$x_{1,4}$	$x_{2,4}$	$x_{3,4}$	$x_{4,4}$	$x_{5,4}$	$x_{6,4}$
$x_{1,3}$	$x_{2,3}$	$x_{3,3}$	$x_{4,3}$	$x_{5,3}$	$x_{6,3}$
$x_{1,2}$	$x_{2,2}$	$x_{3,2}$	$x_{4,2}$	$x_{5,2}$	$x_{6,2}$
$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	$x_{4,1}$	$x_{5,1}$	$x_{6,1}$

The filter: kernel size of $ks = 2$

$w_{1,4}$	$w_{2,4}$
$w_{1,3}$	$w_{2,3}$
$w_{1,2}$	$w_{2,2}$
$w_{1,1}$	$w_{2,1}$

The output value (output channel)

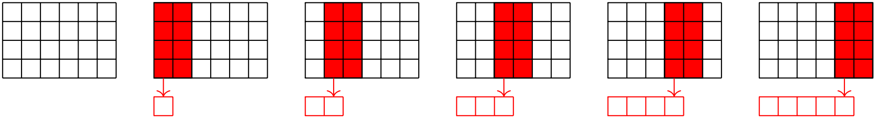
$$\text{At time } t = 1,\ h_1 = \sum_{i,j} w_{i,j} \times x_{i,j}$$

Convolution 1D

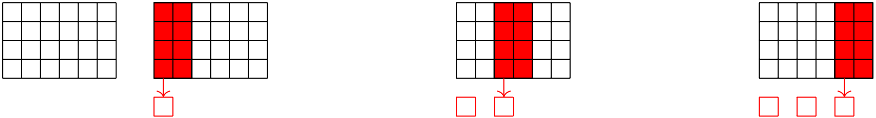
Stride, or a sliding window

The input is a matrix $(L = 6, d = 4)$, one filter of kernel size $= 2$:

With a stride $= 1$



With a stride $= 2$



Convolution 1D

With 2 output channels

$L = 6,\ D = 4$

$x_{1,4}$	$x_{2,4}$	$x_{3,4}$	$x_{4,4}$	$x_{5,4}$	$x_{6,4}$
$x_{1,3}$	$x_{2,3}$	$x_{3,3}$	$x_{4,3}$	$x_{5,3}$	$x_{6,3}$
$x_{1,2}$	$x_{2,2}$	$x_{3,2}$	$x_{4,2}$	$x_{5,2}$	$x_{6,2}$
$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	$x_{4,1}$	$x_{5,1}$	$x_{6,1}$

Filters:kernel size of $ks = 2$

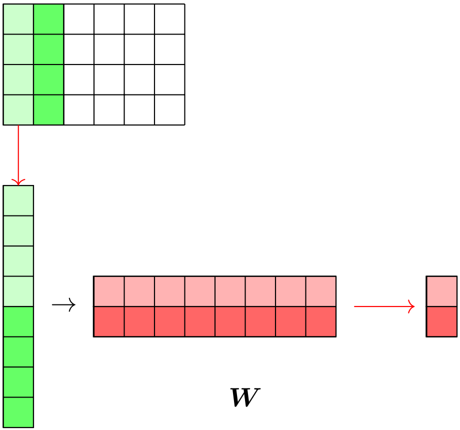
$w^{(2)}_{1,4}$	$w^{(2)}_{2,4}$
$w^{(2)}_{1,3}$	$w^{(2)}_{2,3}$
$w^{(2)}_{1,2}$	$w^{(2)}_{2,2}$
$w^{(2)}_{1,1}$	$w^{(2)}_{2,1}$

The output value (output channel)

$$h_{1,1} = \sum_{i,j} w^{(1)}_{i,j} \times x_{i,j}$$

$$h_{2,1} = \sum_{i,j} w^{(2)}_{i,j} \times x_{i,j}$$

Another wiew for two output channels



- Two filters applied to the same frame (or window)
- Each filter generates one feature

$\rightarrow$ a vector of two values, two features $(h_{1,1}, h_{2,1})$

- $h_{c,t}$ is the feature extracted for the channel c at time t.
- $\boldsymbol{W}$ gathers the parameters of the filters in one matrix
- The parameters $\boldsymbol{W}$ are learnt

Exercise

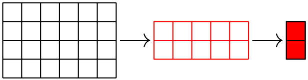
Stride

- With an input of length L, a kernel size of ks and a stride $= 1$, what is the output dimension ?
- And with a stride $= 2$, what is the output dimension ?
- With a stride of s ?

Side effect

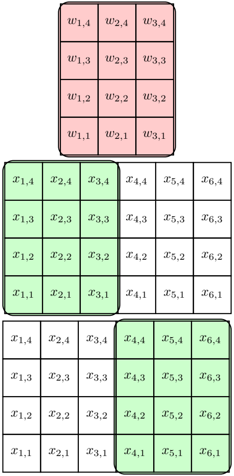
- The first (and last) time steps are not processed as the others. How to correct this aspects ?
- How to ensure the same length in output (assuming a stride of 1) ?
- How to ensure that every inputs are “seen” equally ?

Pooling over time



- Mean pooling
- Max pooling, and k-max pooling

Exercise



The convolution filter generates h_1 and h_2, and the pooling operation: $o = f(h_1, h_2)$. During training the loss gradient should be back-propagated:

$$\frac{\partial l}{\partial \boldsymbol{\theta}} = \frac{\partial l}{\partial o} \times \frac{\partial o}{\partial h_i} \times \frac{\partial h_i}{\partial \boldsymbol{\theta}}$$

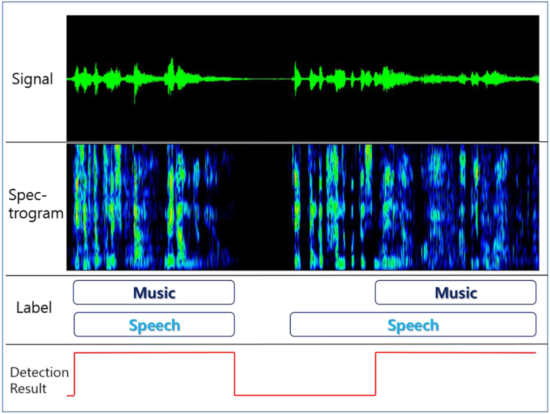
With mean-pooling:

1. Write f and $\frac{\partial l}{\partial h_i}$ given $\frac{\partial l}{\partial o}$
2. With 2 output channels, at time 1 $\rightarrow (h_{1,1}, h_{1,2})$ and at time 2 $\rightarrow (h_{2,1}, h_{2,2})$, and the pooling $\rightarrow (o_1, o_2)$. Compute the back-prop. gradient.
3. For an input of length L, how many updates for one filter ?

Reconsider the questions for the max-pooling !

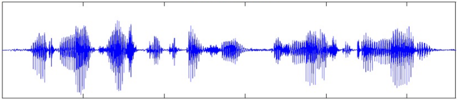
Audio classification / segmentation

(Jang et al.2019)



- Classification at each time step
- But the context is crucial (for the input and the output) !
- **Spectrogram ?**

Interlude: the input spectrogram



↓

Segmentation in frames (Hamming window)

↓

F.F.T

↓

Mel Filters

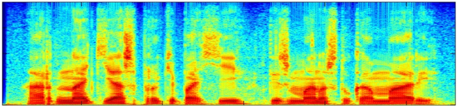
↓

Log

↓

D.C.T

↓



Human activity Recognition

The data

10k samples of fixed length (128 points at 50kHz) [a]:

- x, y, and z accelerometer data (linear acceleration)
- and the three gyroscopic data (angular velocity)

The classes are: Walking, Upstairs, Downstairs, Sitting, Standing, Laying.

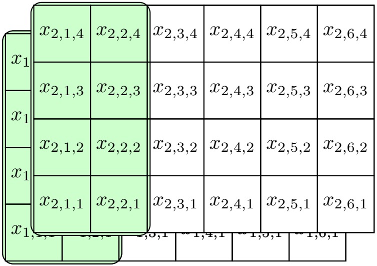
[a] https://archive.ics.uci.edu/ml/datasets/human+activity+recognition+using+smartphones

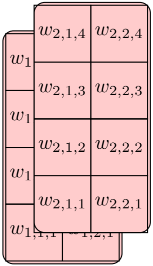
→ Two different input channels (accelerometer and gyroscopic).

→ How to define a convolution filter for two input channels ?

→ The sequence is long but of fixed size, the overall max-pooling is maybe not the best option.

Convolution 1D with 2 input channels





The output value (output channel)

$$\text{At time } t = 1,\ h_1 = \sum_{k,i,j} w_{k,i,j} \times x_{k,i,j}$$

We can have multiple input and output channels.

Convolution 1D and max-pooling in pytorch

Convolution 1D

torch.nn.Conv1d(

- in_channels,
- out_channels,
- kernel_size,
- stride=1,
- padding=0,
- dilation=1, ...

)

Max-Pooling 1D

torch.nn.MaxPool1d(

- kernel_size,
- stride=None,
- padding=0,
- dilation=1,
- return_indices=False,
- ceil_mode=False

)

Outline

Image classification

An image = (2D array of values) × (number of channels)

2D array

The spatial structure:

- A 2D real space
- With distance

Channels

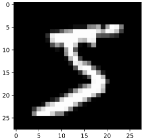
- For image : R,G,B
- In fluid mechanics: pression, velocity, ...
- In general: different measures on the same spatial domain

Sources

Many figures and examples are inspired by, or extracted from the course of the Stanford course of Fei-Fei Li.

http://cs231n.stanford.edu/

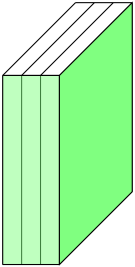
Image classification



$\rightarrow$

$\boldsymbol{x} \in \mathbb{R}^{784} \longrightarrow c \in \{0, 1, 2, \ldots, 9\}$

Another example with a color image (3 channels) of 32×32 pixels

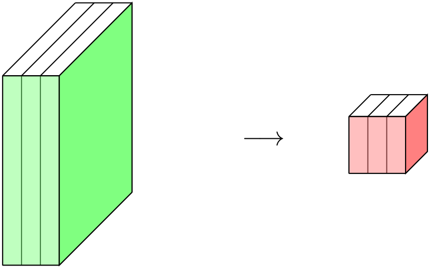


$\rightarrow$

$\boldsymbol{x} \in \mathbb{R}^{3072} \longrightarrow c \in \{0, 1, 2, \ldots, 9\}$

Convolution in 2D

The basics



$3 \times 32 \times 32$ image

$3 \times 5 \times 5$ filter

Convolution of the filter with the image:

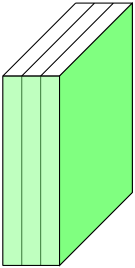
- Sliding the filter along the two axis
- Computing the “dot product” at each step

→ preserve the spatial structure along the channels

→ each step extract a “local” and spatial feature

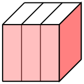
Convolution in 2D

With a single output channel



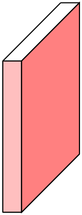
$3 \times 32 \times 32$ image

$\longrightarrow$



$3 \times 5 \times 5$ filter

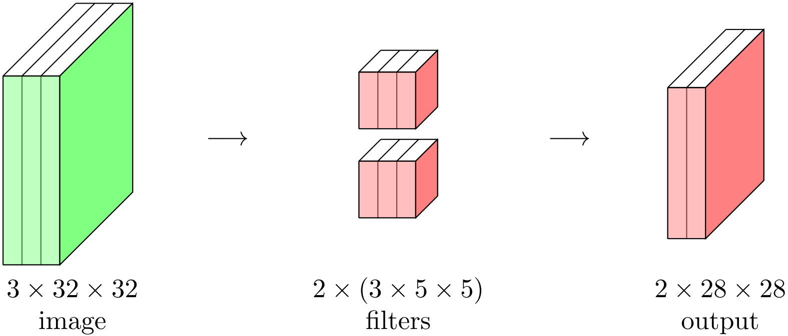
$\longrightarrow$



$1 \times 28 \times 28$ output

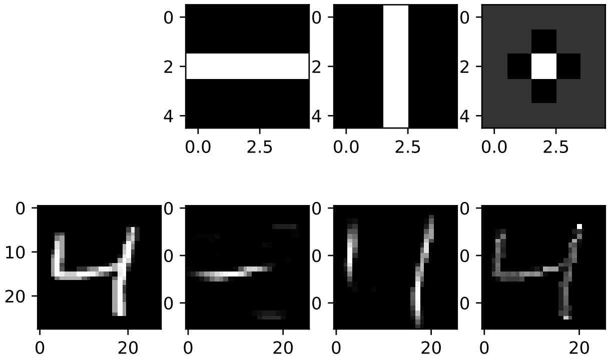
Convolution in 2D

Add a second output channel



Motivation for convolution

Extract "low level" features



Motivation for convolution

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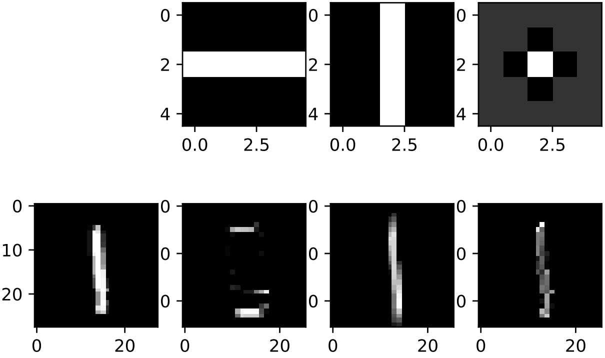

Motivation for convolution

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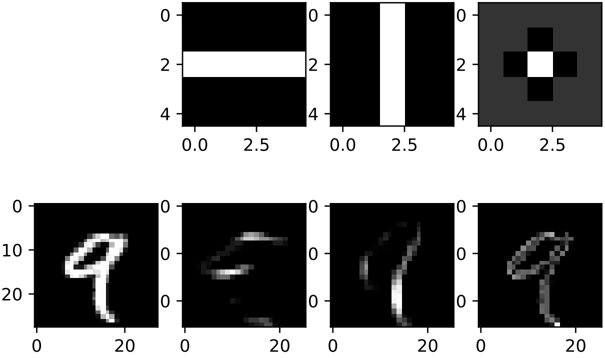
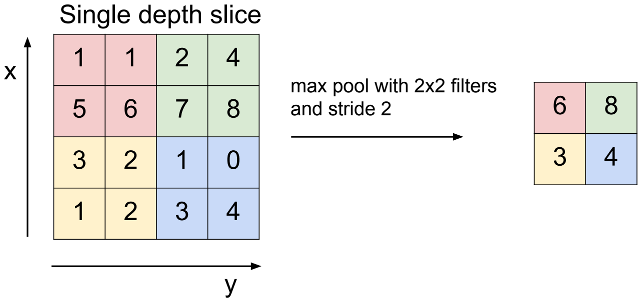


Max-pooling or Downsampling in 2D

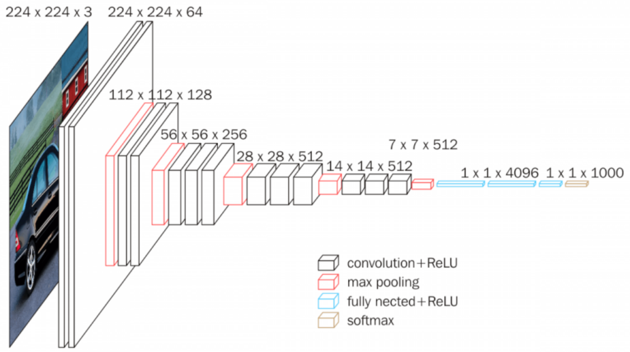
The goal

- Convolution extracts local features (followed by non-linearity)
- Max-pooling acts as a selection, compression, or contraction operator
- The back-propagation promote feature saliency for each channel



Architecture of deep convolution NNet for image processing

VGGNet (Simonyan and Zisserman2015)



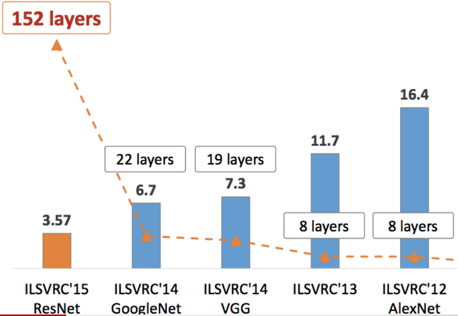
Conv. layers with kernel size of 3×3, stride and padding, followed by pooling layers (max on 2×2 with stride 2).

Architecture of deep convolution NNet for image processing

A summary

The basic block

- A convolution layer with a ReLU activation followed by a max-pooling layer
- An alternative is two convolution layers in a Residual block (ResNet (He et al.2015))



Outline

Sequence processing

Sequence generation model

$$P(w_1^L) = P(w_1, w_2, ...w_L) = \prod_{i=1}^{L} P(w_i|w_1^{i-1}), \quad \forall i, w_i \in \mathcal{V}$$

with the n**-gram assumption** (convolution):

$$P(w_1^L) = \prod_{i=1}^{L} P(w_i|w_{i-n+1}^{i-1}), \quad \forall i, w_i \in \mathcal{V},$$

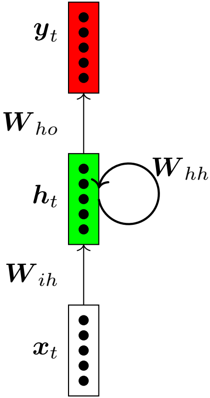
in the **recurrent** way

$$P(w_i|w_1^{i-1})$$

Sequence representation

$$\boxed{\begin{array}{c} \text{A T C G A T C G} \\ \cdots \text{ G T A A T C G} \end{array}} \; : \; \boldsymbol{x} \in \mathbb{R}^D \longrightarrow c \in \{0, 1\}$$

Recurrent Cell



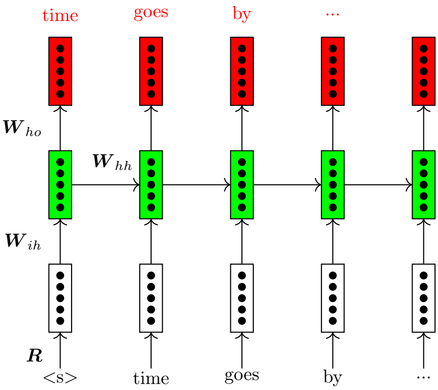
A dynamic system, at time t:

- maintains a hidden representation, the internal state: $\boldsymbol{h}_t$
- Updated with the observation of $\boldsymbol{x}_t$ and the previous state $\boldsymbol{h}_{t-1}$
- The prediction $\boldsymbol{y}_t$ depends on the internal state ($\boldsymbol{h}_t$)
- For a language model, $\boldsymbol{x}_t$ comes from word embeddings

The same parameter set is shared across time steps

Recurrent network sequence model

Unfolding the structure: a deep-network



At each step t

- Read the word $w_t \rightarrow \boldsymbol{x}_t$ from $\boldsymbol{R}$
- Update the hidden state $\boldsymbol{h}_t = f(\boldsymbol{W}_{ih}\boldsymbol{x}_t + \boldsymbol{W_{hh}h_{t-1}})$
- The word at $t+1$ can be predicted from $\boldsymbol{h}_t$:

$$\boldsymbol{y}_t = g(\boldsymbol{W}_{ho}\boldsymbol{h}_t)$$

- g is the softmax function over the vocabulary

Training recurrent language model

Training algorithm

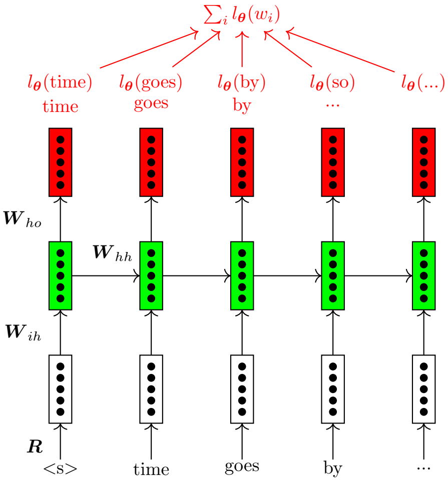
Back-Propagation through time or BPTT
(Rumelhart et al.1986; Mikolov et al.2011):

- for each step t
  - compute the loss gradient
  - Back-Propagation through the unfolded structure

Inference

- Cannot be easily integrated to conventional approaches (ASR, SMT, ...)
- A powerful device for end-to-end system

Training recurrent language model - 2



Mini-batching for RNN

Mini-batching makes things much faster!

Mini-batch

- Add a dimension to your input example $\boldsymbol{x}$
- Forward propagation of the whole mini-batch at a time
- Compute the loss and back-propagation

But

- mini-batching in RNNs is harder than in feed-forward networks
- Each word depends on the previous word
- Sequences are of various length

Batching / Padding / Masking

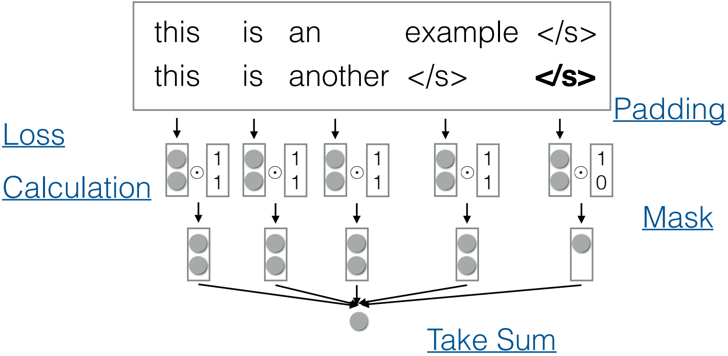
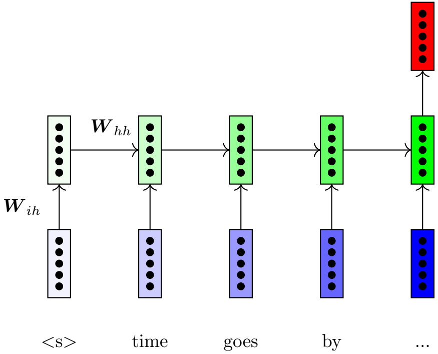


Figure from G. Neubig

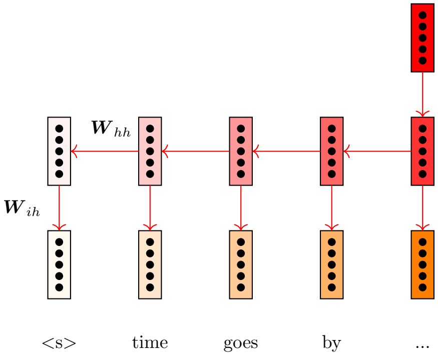
Short term memory



During inference :

- With the distance, the influence of observations reduces
- The memory is limited
- No way to keep/skip information

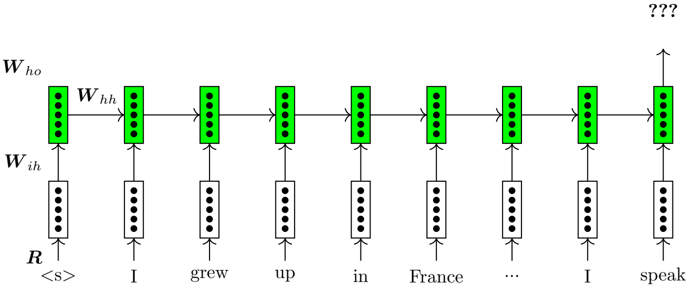
Vanishing gradient issue



During training:

- The gradient diminishes at each backward step
- No long term propagation of the gradient

The Problem of Long-Term Dependencies



- Recent observations hide the older ones (Bengio et al.1994)
- The vanishing (exploding) gradient is a real issue (Pascanu et al.2013)

Solutions

Improved optimization

- Gradient clipping (Pascanu et al.2013)
- Hessian-Free optimzation (Martens and Sutskever2012) or natural gradient (Desjardins et al.2013; Ollivier2015)

Modified unit

A recurrent network should be able to mitigate the observations *vs* its internal state:

- LSTM or Long-Short-Term-Memory cell (Hochreiter and Schmidhuber1997; Graves and Schmidhuber2009)
- Gated Recurrent Unit or GRU (Cho et al.2014)

Gradient clipping

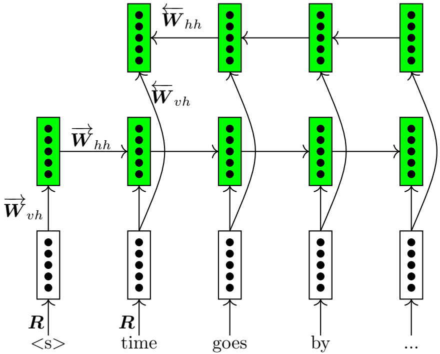
A simple and efficient trick

Given a threshold γ, before each update:

- Compute the norm of the gradient (at each time step) : $||\nabla_{\boldsymbol{\theta}}||$
- If $||\nabla_{\boldsymbol{\theta}}|| > \gamma$:

$$\nabla_{\boldsymbol{\theta}} \leftarrow \frac{\gamma}{||\nabla_{\boldsymbol{\theta}}||}\nabla_{\boldsymbol{\theta}}$$

Sentence encoder: the bi-recurrent solution



A each step t, from left to right

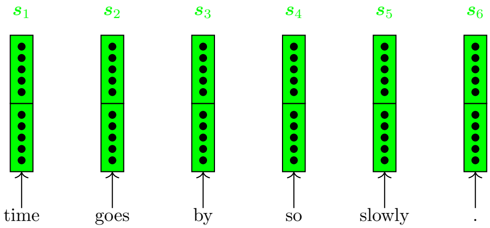
- $w_t \rightarrow \boldsymbol{x}_t$
- $\overrightarrow{\boldsymbol{h}}_t = f(\overrightarrow{\boldsymbol{W}}_{vh}\boldsymbol{x}_t + \overrightarrow{\boldsymbol{W}}_{hh}\overrightarrow{\boldsymbol{h}}_{t-1})$

A each step t, from right to left

- $w_t \rightarrow \boldsymbol{x}_t$
- $\overleftarrow{\boldsymbol{h}}_t = f(\overleftarrow{\boldsymbol{W}}_{vh}\boldsymbol{x}_t + \overleftarrow{\boldsymbol{W}}_{hh}\overleftarrow{\boldsymbol{h}}_{t-1})$

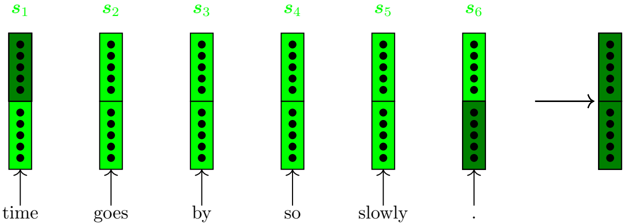
$[\overrightarrow{\boldsymbol{h}}_t; \overleftarrow{\boldsymbol{h}}_t]$ **: contextualized representation of** w_t

Sequence representation



- A bi-recurrent encoder
- Each observation is associated to a vector: a contextualised representation s_t

Sequence representation



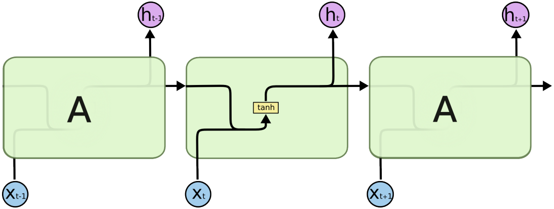
- A bi-recurrent encoder
- Each observation is associated to a vector: a contextualised representation s_t

Outline

Introduction to LSTM

The standard recurrent cell

- A recurrent cell is neural network layer
- Conveyor belt : the hidden state

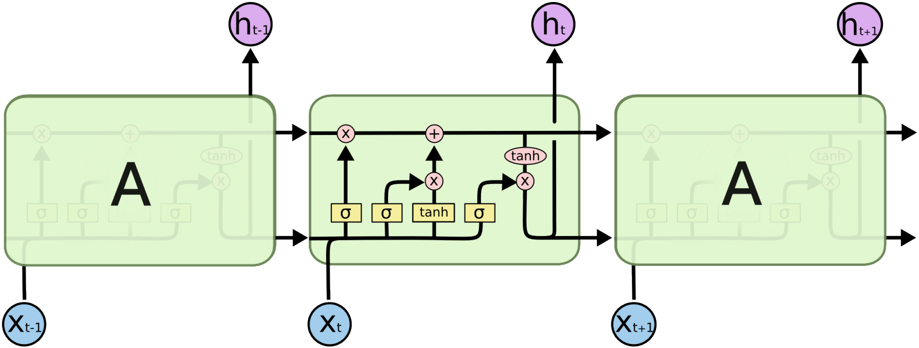


Lines carry a vectors

Based on `http://colah.github.io/posts/2015-08-Understanding-LSTMs/`

Introduction to LSTM

The LSTM cell



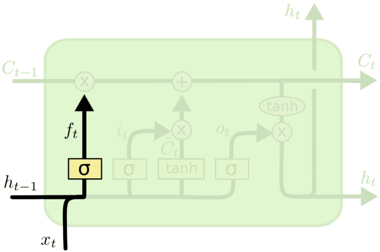
- LSTM introduces a second channel:
  the cell state
- The cell is now four neural layers, interacting in a very special way
- It acts as a memory
- Gates control the memory

Roadmap of inference

1. Memory organization
   1. what should be kept ?
   2. what shoud be updated ?
2. Update the cell state
3. Filter the state to provide the "hidden" state

LSTM : Control flow - 1

What should be forgotten from the previous cell state ?



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

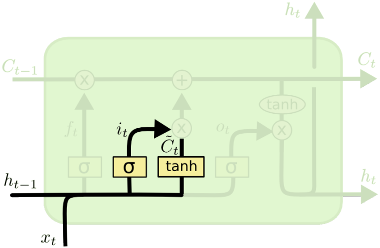
Action

The sigmoid (forget gate) answers for each component:

- 1: to keep it,
- 0 to forget it, or
- a value in-between to mitigate its influence

LSTM : Control flow - 2

What should be taken into account ?



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

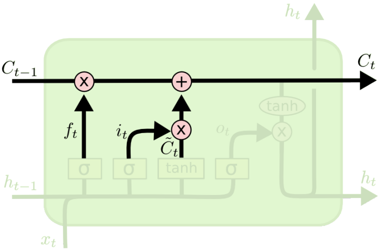
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

Actions

- Create the update $\tilde{C}_t$ of the cell state
- and its contribution i_t (the input gate with a sigmoid activation)

LSTM : Control flow - 3

Write the new state



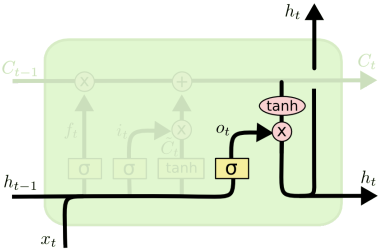
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Actions

- Merge the old cell state modified by the forget gate
- with the new input

LSTM : Control flow - 4

Write the new hidden state



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

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

Actions

- Decide what parts of the (filtered) cell state to output o_t
- Compute the hidden state

LSTM summary

A special kind of recurrent architecture

- keep or skip information in memory
- to reset or mitigate the long-term memory

Consequences: an efficient model of sequences

- Overcome the vanishing gradient issue
- Very promising results in generation

State of the art

- Stacked LSTM and Bi-recurrent encoder
- Variants: Gated recurrent units (GRU) (Cho et al.2014) or a more complicated one (Gers and Schmidhuber2000)

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