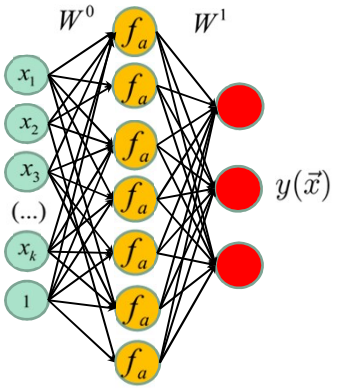
Réseaux de neurones

IFT 780

Réseaux récurrents

Par
Pierre-Marc Jodoin, Antoine Théberge

Réseau de neurones de base (régression)



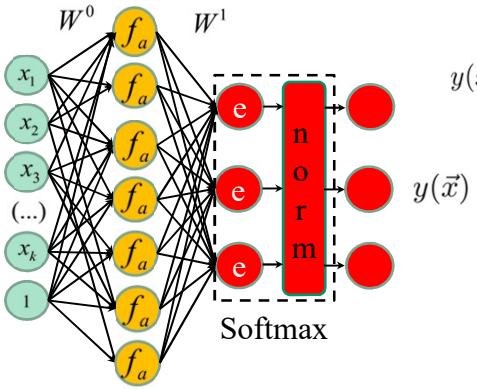
$$y(\vec{x}) = W^1 f_a(W^0 \vec{x})$$

$$\vec{h} = f_a(W^0 \vec{x})$$

$$y(\vec{x}) = W^1 \vec{h}$$

f_a : fonction d'activation

Réseau de neurones de base (classification)



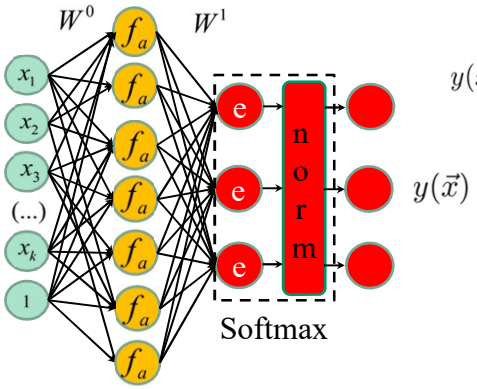
$$y(\vec{x}) = \text{softmax}(W^1 f_a(W^0 \vec{x}))$$

$$\vec{h} = f_a(W^0 \vec{x})$$

$$\hat{y} = W^1 \vec{h}$$

$$y(\vec{x}) = \text{softmax}(\hat{y})$$

Réseau de neurones de base (classification)



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$$\vec{h} = f_a(W^0 \vec{x})$$

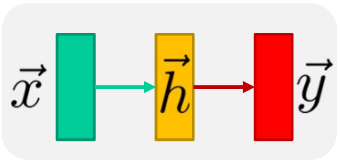
$$\hat{y} = W^1 \vec{h}$$

$$y(\vec{x}) = \text{softmax}(\hat{y})$$

Ne permettent que des tâches “1 pour 1”

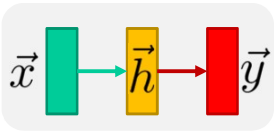
- Classification (1 image = 1 étiquette)
- Régression (1 donnée = 1 vecteur)
- Localisation (1 boîte = 1 classification + 1 régression)

Illustration simplifiée



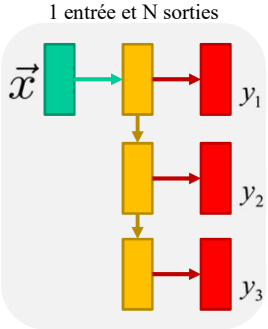
RN de base

Différentes configurations pour différentes applications



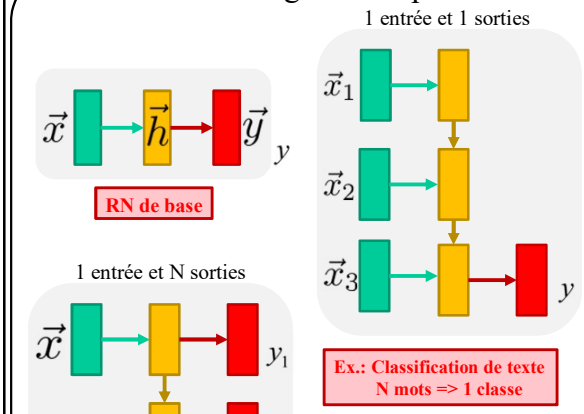
RN de base

1 entrée et N sorties



Ex.: description d'une image
1 image => N mots

Différentes configurations pour différentes applications



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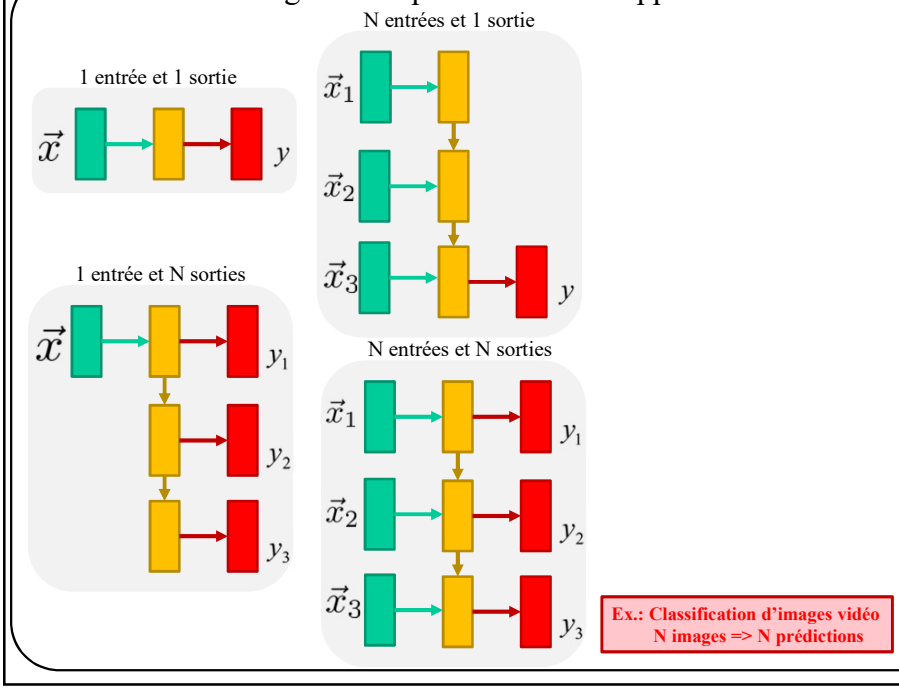
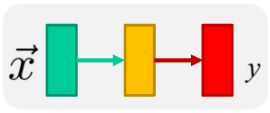
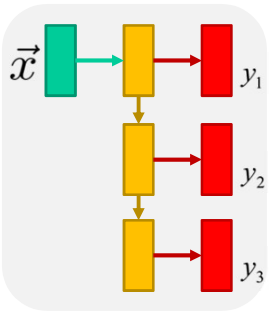


Différentes configurations pour différentes applications

1 entrée et 1 sortie



1 entrée et N sorties



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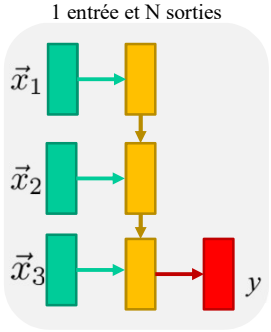
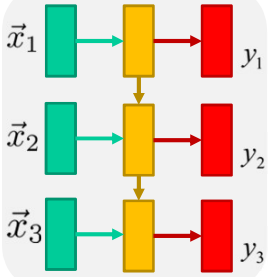
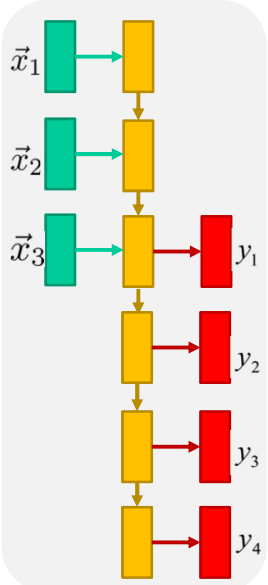


N entrées et N sorties

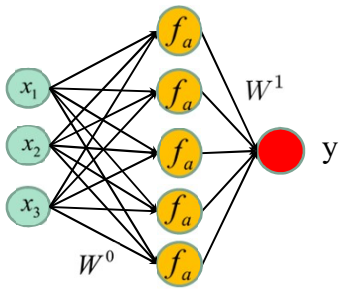


M entrées et N sorties



Ex.: Traduction d'un texte
N mots => N mots

Réseau récurrent : la sortie des neurones est réinjectée dans leur entrée



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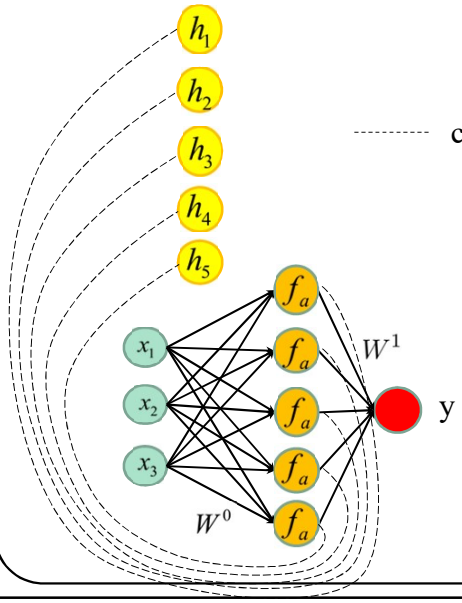

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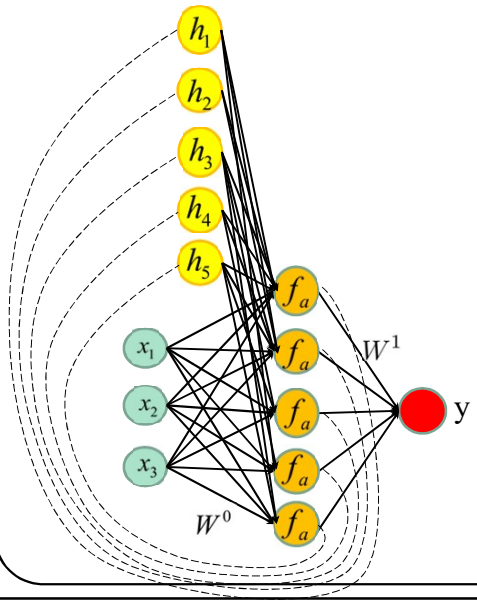
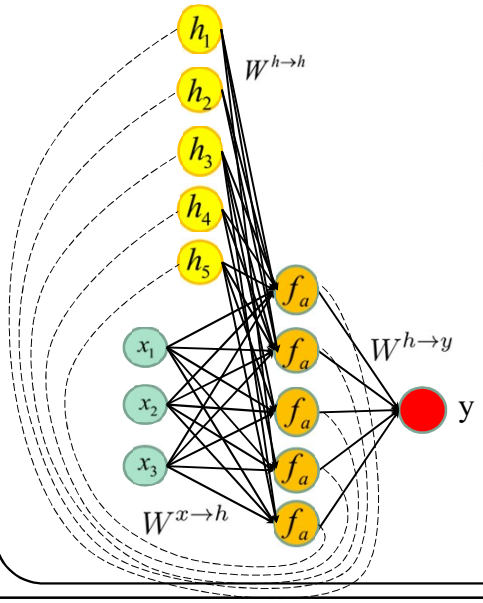


Ici, au lieu d'avoir 3 entrées, chaque neurone a **3+5=8 entrées.**

Réseau récurrent : la sortie des neurones est réinjectée dans leur entrée

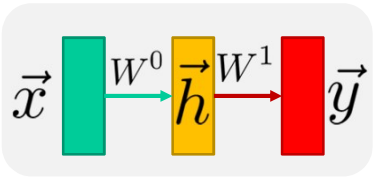


$$y(\vec{x}) = W^{h\to y} f_a(W^{x\to h}\vec{x} + W^{h\to h}\vec{h})$$

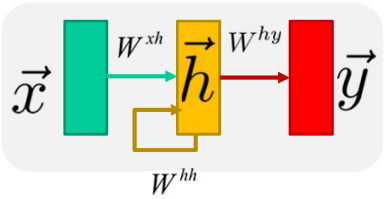
$$\vec{h} = f_a(W^{x\to h}\vec{x} + W^{h\to h}\vec{h})$$

$$y(\vec{x}) = W^{h\to y}\vec{h}$$

Illustration simplifiée

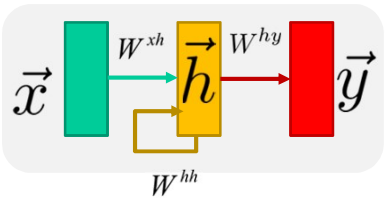


RN de base



RN récurrent

Dans le cas général avec K sorties (régression)



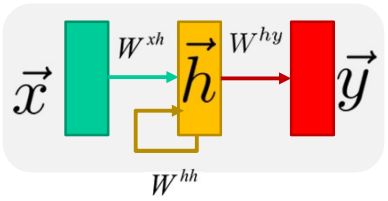
$$y(\vec{x}) = W^{hy} f_a(W^{xh}\vec{x} + W^{hh}\vec{h})$$

$$\downarrow$$

$$\vec{h} = f_a(W^{xh}\vec{x} + W^{hh}\vec{h})$$

$$\vec{y}(\vec{x}) = W^{hy}\vec{h}$$

Dans le cas général avec K sorties (classification)



$$y(\vec{x}) = W^{hy} f_a(W^{xh}\vec{x} + W^{hh}\vec{h})$$

$$\downarrow$$

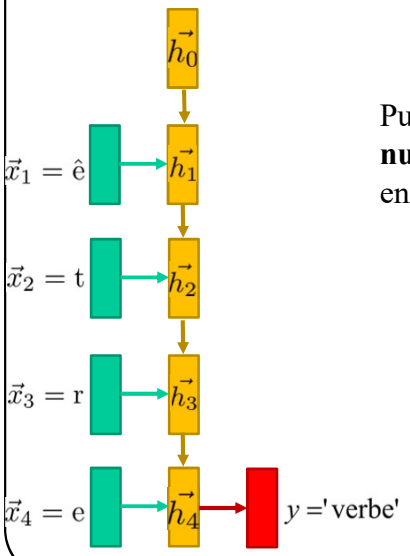
$$\vec{h} = f_a(W^{xh}\vec{x} + W^{hh}\vec{h})$$

$$\hat{y} = W^{hy}\vec{h}$$

$$\vec{y}(\vec{x}) = \text{softmax}(\hat{y})$$

Exemple pour N entrées et 1 sortie:

Analyse grammaticale (classification) : (ê.t.r.e)=>'verbe'



Puisque $\vec{x}, \vec{h}$ et y doivent être des **variables numériques** on utilise souvent un encodage de type « *one hot* ».

$'a' = [1,0,0,...,0]$
$'b' = [0,1,0,...,0]$
$'c' = [0,0,1,...,0]$
$\in R^{256}$

....

$'verbe' = [1,0,0...0]$
$'nom' = [0,1,0,...0]$
$'adjectif' = [0,0,1,...0]$
$\in R^{M}$

Exemple pour N entrées et 1 sortie:

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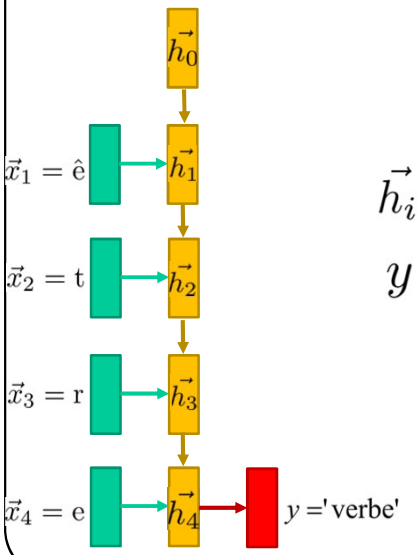

$$\vec{h_i} = f_a(W^{xh}\vec{x_i} + W^{hh}\vec{h_{i-1}})$$
$$y = \text{softmax}(W^{hy}\vec{h}_{i-1})$$

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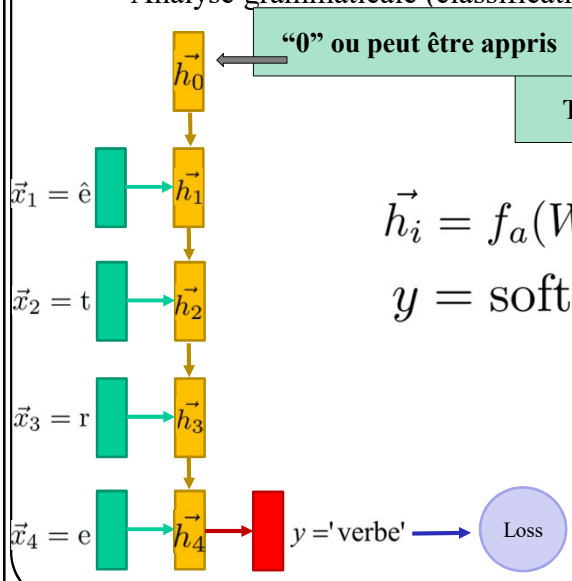

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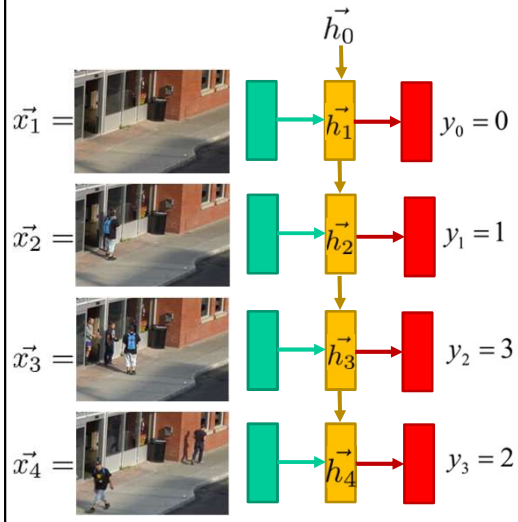
Même idée pour N entrées et N sorties:

ex.: Analyse vidéo (régression) : Images vidéo => nb_piétons



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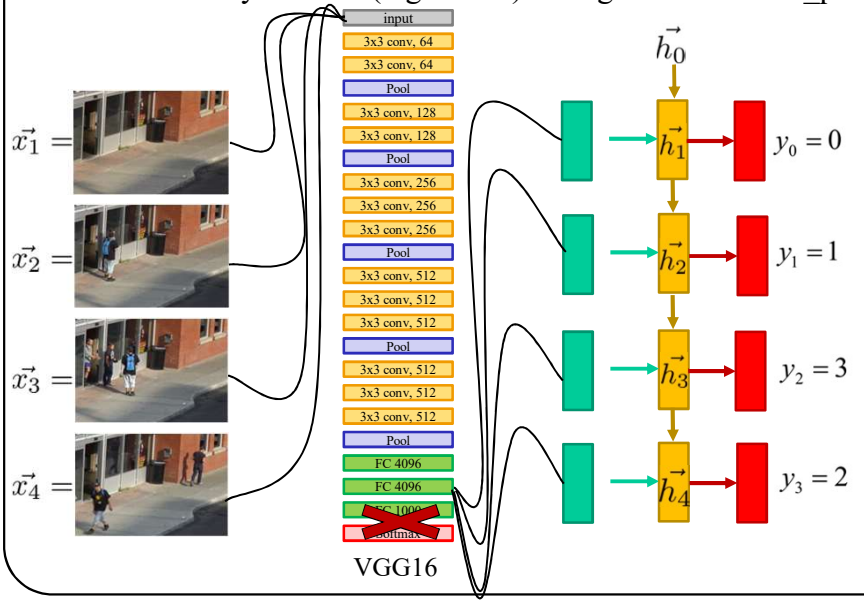

VGG16

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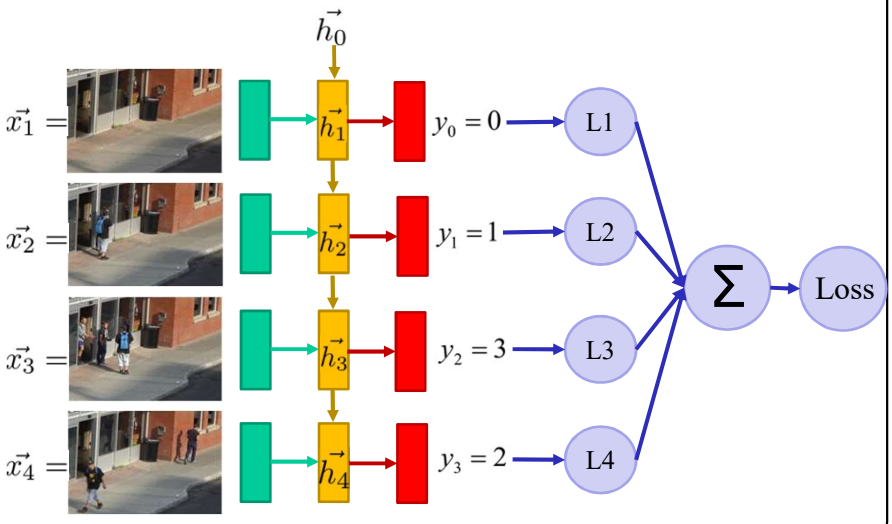

Autre exemple: **prédiction de caractères** (modèle de langue)

Alphabet jouet :[**a,e,m,s**]

Représentation « one hot » jouet:

‘a’ = [1, 0, 0, 0]
‘e’ = [0, 1, 0, 0]
‘m’ = [0, 0, 1, 0]
‘s’ = [0, 0, 0, 1]

But : Entraîner un modèle à prédire les lettres du mot « **masse** ».

Autre exemple: **prédiction de caractères** (modèle de langue)

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Entraîner un modèle à prédire les lettres du mot « **masse** ».

$\vec{x_1} = \mathrm{m}$ 

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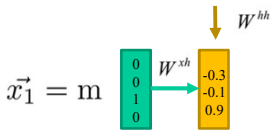

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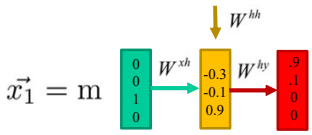

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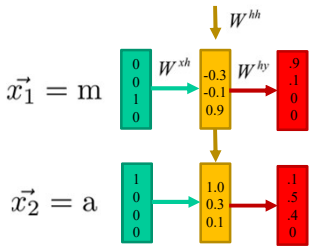

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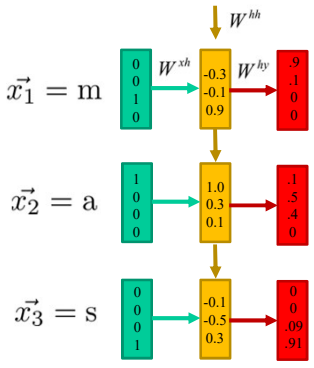

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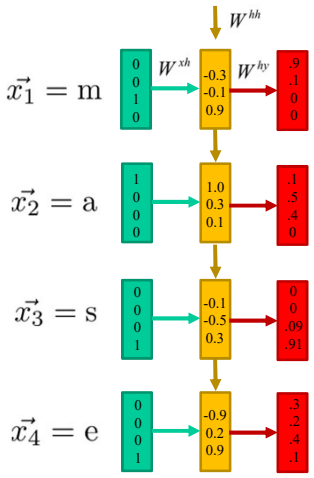

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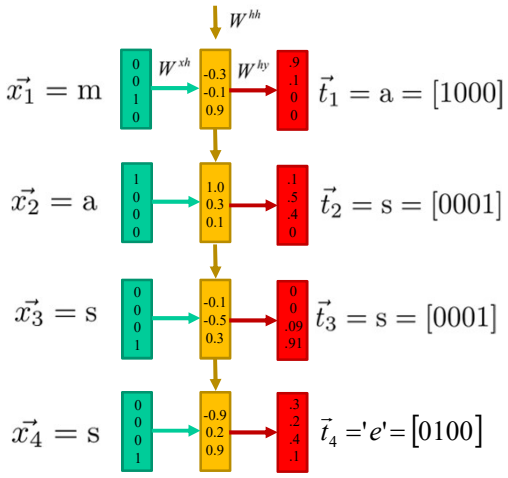

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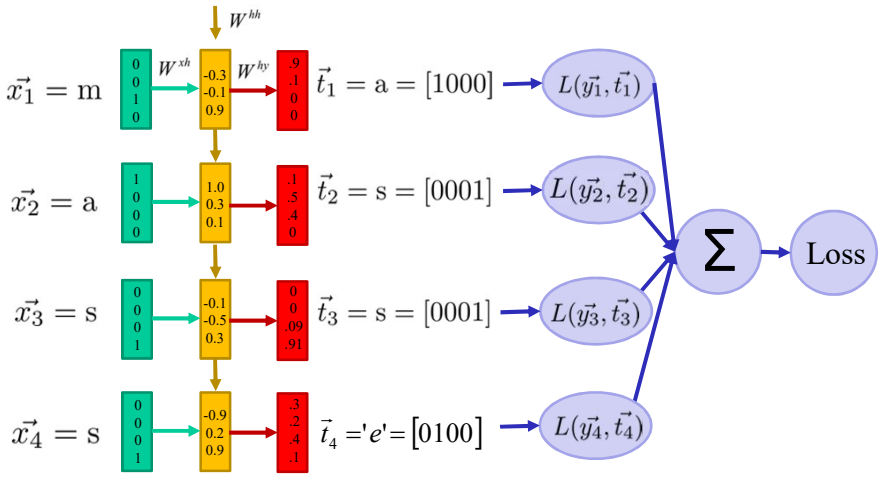

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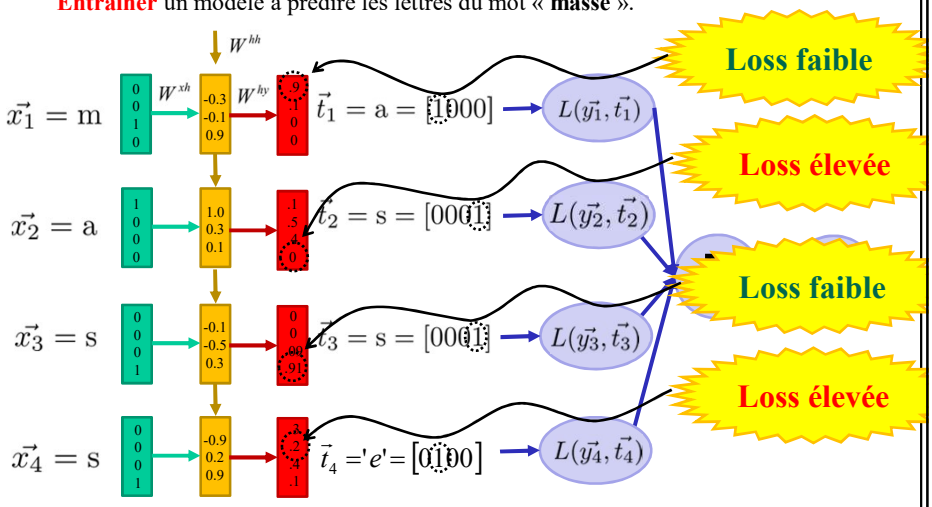
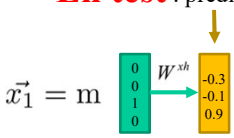


Autre exemple: **prédiction de caractères** (modèle de langue)

Alphabet :[**a,e,m,s**]

En test : prédire les lettres les unes après les autres



Étape 1 : Calcul de la couche cachée

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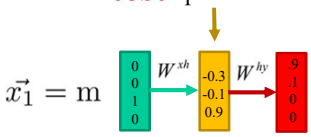
Alphabet :[**a,e,m,s**]

En test : prédire les lettres les unes après les autres

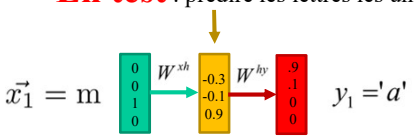


Étape 2 : Calcul de la sortie (softmax)

Autre exemple: **prédiction de caractères** (modèle de langue)

Alphabet :[**a,e,m,s**]

En test : prédire les lettres les unes après les autres

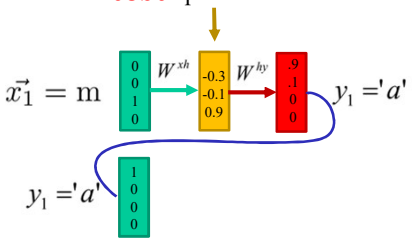


Étape 3 : Sélectionner le caractère le plus probable

Autre exemple: **prédiction de caractères** (modèle de langue)

Alphabet :[**a,e,m,s**]

En test : prédire les lettres les unes après les autres

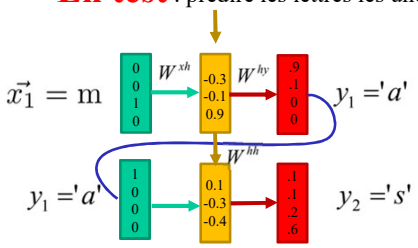


Étape 4 : Injecter le caractère prédit au début du réseau

Autre exemple: **prédiction de caractères** (modèle de langue)

Alphabet :[**a,e,m,s**]

En test : prédire les lettres les unes après les autres

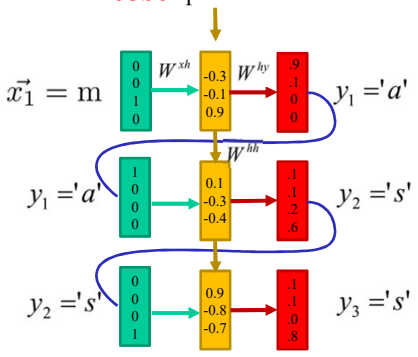


Et on recommence!

Autre exemple: **prédiction de caractères** (modèle de langue)

Alphabet :[**a,e,m,s**]

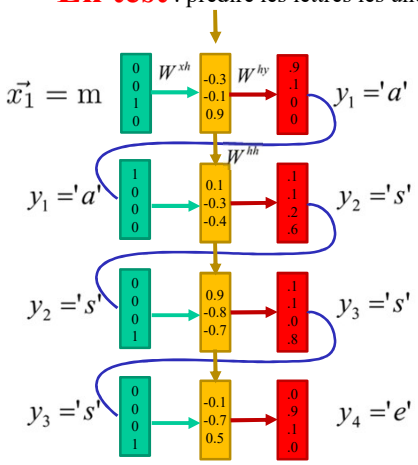
En test : prédire les lettres les unes après les autres



Autre exemple: **prédiction de caractères** (modèle de langue)

Alphabet :[**a,e,m,s**]

En test : prédire les lettres les unes après les autres

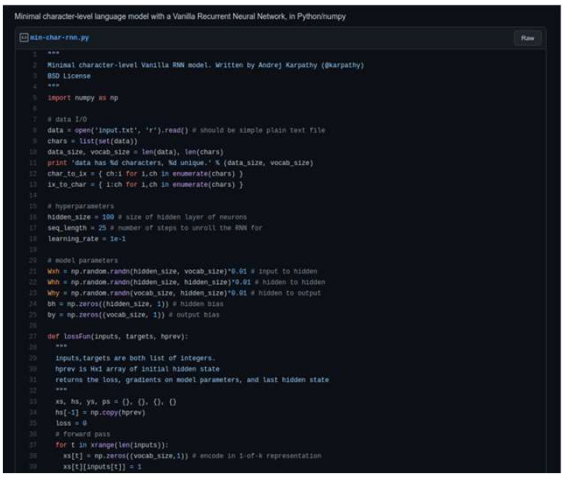


Autre exemple: **prédiction de caractères** (modèle de langue)

Code python: **"mini-char-RNN" de A. Karpathy**

https://gist.github.com/karpathy/d4dee566867f8291f086

Un RNN en 112 lignes !



$$'a' = [1,0,0,\ldots,0]$$
$$'b' = [0,1,0,\ldots,0]$$
$$'c' = [0,0,1,\ldots,0]$$
$$\in R^{256}$$

...

Autre exemple: **prédiction de caractères** (modèle de langue)

Code python: **"mini-char-RNN" de A. Karpathy**
https://gist.github.com/karpathy/d4dee566867f8291f086

THE SONNETS

by William Shakespeare

From fairest creatures we desire increase,
That thereby beauty's rose might never die,
But as the riper should by time decease,
His tender heir might bear his memory:
But thou, contracted to thine own bright eyes,
Feed'st thy light's flame with self-substantial fuel,
Making a famine where abundance lies,
Thyself thy foe, to thy sweet self too cruel:
Thou that art now the world's fresh ornament,
And only herald to the gaudy spring,
Within thine own bud buriest thy content,
And tender churl mak'st waste in niggarding:
Pity the world, or else this glutton be,
To eat the world's due, by the grave and thee.

When forty winters shall besiege thy brow,
And dig deep trenches in thy beauty's field,
Thy youth's proud livery so gazed on now,
Will be a tatter'd weed of small worth held:
Then being asked, where all thy beauty lies,
Where all the treasure of thy lusty days;
To say, within thine own deep sunken eyes,
Were an all-eating shame, and thriftless praise.
How much more praise deserv'd thy beauty's use,
If thou couldst answer 'This fair child of mine
Shall sum my count, and make my old excuse,'
Proving his beauty by succession thine!
This were to be new made when thou art old,
And see thy blood warm when thou feel'st it cold.

$$\left.\begin{array}{l} 'a' = [1,0,0,...,0] \\ 'b' = [0,1,0,...,0] \\ 'c' = [0,0,1,...,0] \end{array}\right\} \in R^{256}$$

...

Autre exemple: **prédiction de caractères** (modèle de langue)

```
tyntd-iafhatawiaoihrdemot  lytdws  e ,tfti, astai f ogoh eoase rrranbyne 'nhthnee e
plia tklrgd t o idoe ns,smtt   h ne etie h,hregtrs nigtike,aoaenns lng
```

train more

```
"Tmont thithey" fomesscerliund
Keushey. Thom here
sheulke, anmerenith ol sivh I lalterthend Bleipile shuwy fil on aseterlome
coaniogennc Phe lism thond hon at. MeiDimorotion in ther thize."
```

train more

```
Aftair fall unsuch that the hall for Prince Velzonski's that me of
her hearly, and behs to so arwage fiving were to it beloge, pavu say falling misfort
how, and Gogition is so overelical and ofter.
```

train more

```
"Why do what that day," replied Natasha, and wishing to himself the fact the
princess, Princess Mary was easier, fed in had oftened him.
Pierre aking his soul came to the packs and drove up his father-in-law women.
```

Crédit: A. Karpathy, CS231

Autre exemple: **prédiction de caractères** (modèle de langue)

Texte généré une fois le modèle entraîné

```
PANDARUS:
Alas, I think he shall be come approached and the day
When little srain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:
They are away this miseries, produced upon my soul,
Breaking and strongly should be buried, when I perish
The earth and thoughts of many states.

DUKE VINCENTIO:
Well, your wit is in the care of side and that.

Second Lord:
They would be ruled after this chamber, and
my fair nues begun out of the fact, to be conveyed,
Whose noble souls I'll have the heart of the wars.

Clown:
Come, sir, I will make did behold your worship.

VIOLA:
I'll drink it.
```

```
VIOLA:
Why, Salisbury must find his flesh and thought
That which I am not aps, not a man and in fire,
To show the reining of the raven and the wars
To grace my hand reproach within, and not a fair are hand,
That Caesar and my goodly father's world;
When I was heaven of presence and our fleets,
We spare with hours, but cut thy council I am great,
Murdered and by thy master's ready there
My power to give thee but so much as hell:
Some service in the noble bondman here,
Would show him to her wine.

KING LEAR:
O, if you were a feeble sight, the courtesy of your law,
Your sight and several breath, will wear the gods
With his heads, and my hands are wonder'd at the deeds,
So drop upon your lordship's head, and your opinion
Shall be against your honour.
```

Crédit: A. Karpathy, CS231

Autre exemple: **prédiction de caractères** (modèle de langue)

Entraînement sur le code source de Linux en C++

Texte généré une fois le modèle entraîné

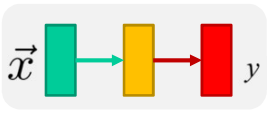
```
static void do_command(struct seq_file *m, void *v)
{
  int column = 32 << (cmd[2] & 0x80);
  if (state)
    cmd = (int)(int_state ^ (in_8(&ch->ch_flags) & Cmd) ? 2 : 1);
  else
    seq = 1;
  for (i = 0; i < 16; i++) {
    if (k & (1 << 1))
      pipe = (in_use & UMXTHREAD_UNCCA) +
        ((count & 0x00000000fffffff8) & 0x000000f) << 8;
    if (count == 0)
      sub(pid, ppc_md.kexec_handle, 0x20000000);
    pipe_set_bytes(i, 0);
  }
  /* Free our user pages pointer to place camera if all dash */
  subsystem_info = &of_changes[PAGE_SIZE];
  rek_controls(offset, idx, &soffset);
  /* Now we want to deliberately put it to device */
  control_check_polarity(&context, val, 0);
  for (i = 0; i < COUNTER; i++)
    seq_puts(s, "policy ");
}
```

```
#include <asm/io.h>
#include <asm/prom.h>
#include <asm/e820.h>
#include <asm/system_info.h>
#include <asm/setew.h>
#include <asm/pgproto.h>

#define REG_PG    vesa_slot_addr_pack
#define PFM_NOCOMP  AFSR(0, load)
#define STACK_DDR(type)     (func)

#define SNAP_ALLOCATE(nr)     (e)
#define emulate_sigs()  arch_get_unaligned_child()
#define access_rw(TST)  asm volatile("movd %%esp, %0, %3" : : "r" (0));   \
  if (__type & DO_READ)

static void stat_PC_SEC __read_mostly offsetof(struct seq_argsqueue, \
           pC>[1]);

static void
os_prefix(unsigned long sys)
{
#ifdef CONFIG_PREEMPT
  PUT_PARAM_RAID(2, sel) = get_state_state();
  set_pid_sum((unsigned long)state, current_state_str(),
           (unsigned long)-1->lr_full; low;
}
```

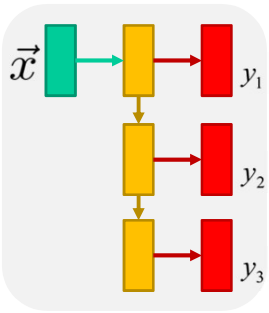
Crédit: A. Karpathy, CS231

Différentes configurations pour différentes applications

1 entrée et 1 sortie



1 entrée et N sorties



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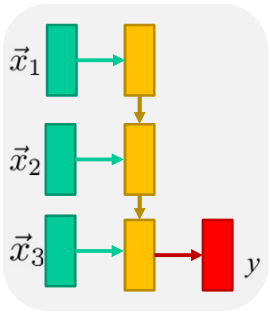
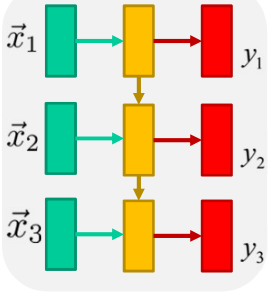
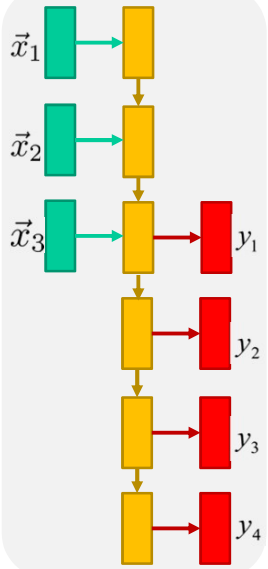


N entrées et N sorties



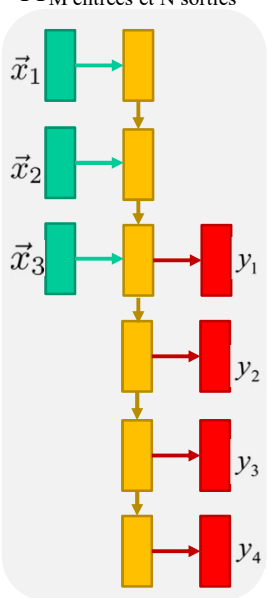
M entrées et N sorties



Ex.: Traduction Français-Anglais
N mots => M mots

Différentes configurations pour différentes applications

M entrées et N sorties



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Autre exemple: **traduction**

Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to sequence learning with neural networks. *Advances in neural information processing systems*, *27*.

Traduire ‘assez’ -> ‘enough’
Alphabet fr :[**<BoS>,a,e,s,z,<EoS>**]
Alphabet en: **[<BoS>,e,g,h,n,o,u,<EoS>]**

Pas le même nombre d’entrées que de sorties !
(BoS : Begining of Sentence, EoS:End of Sentence).

Autre exemple: **traduction**

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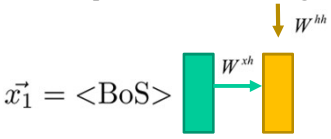

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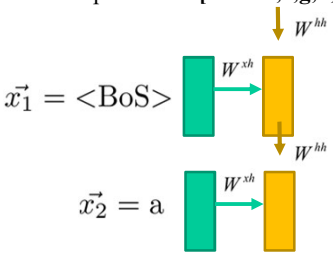

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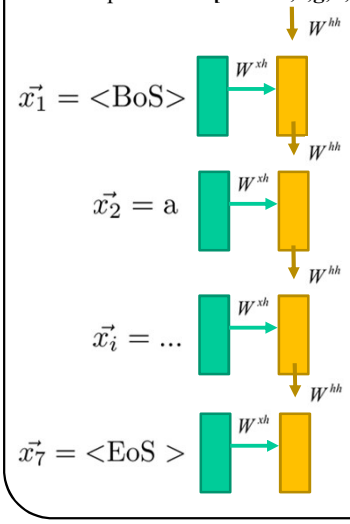

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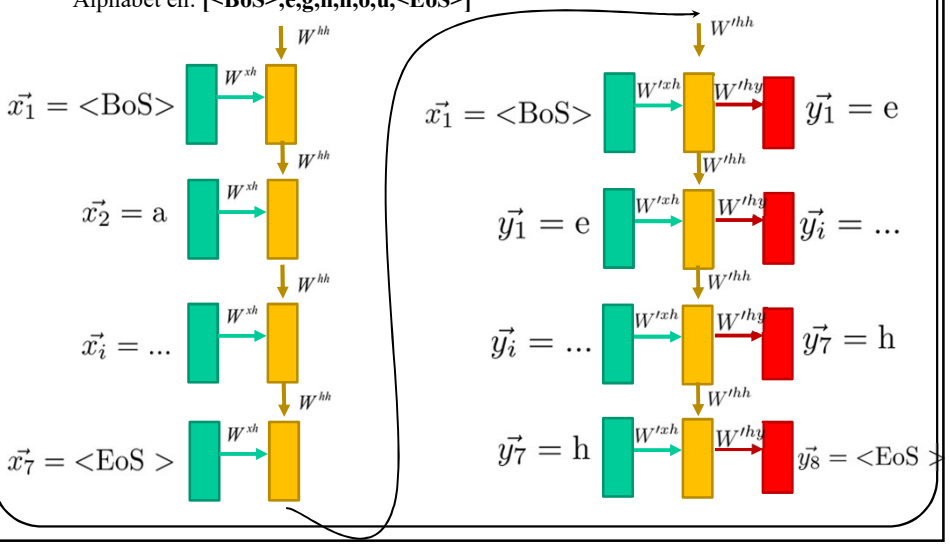

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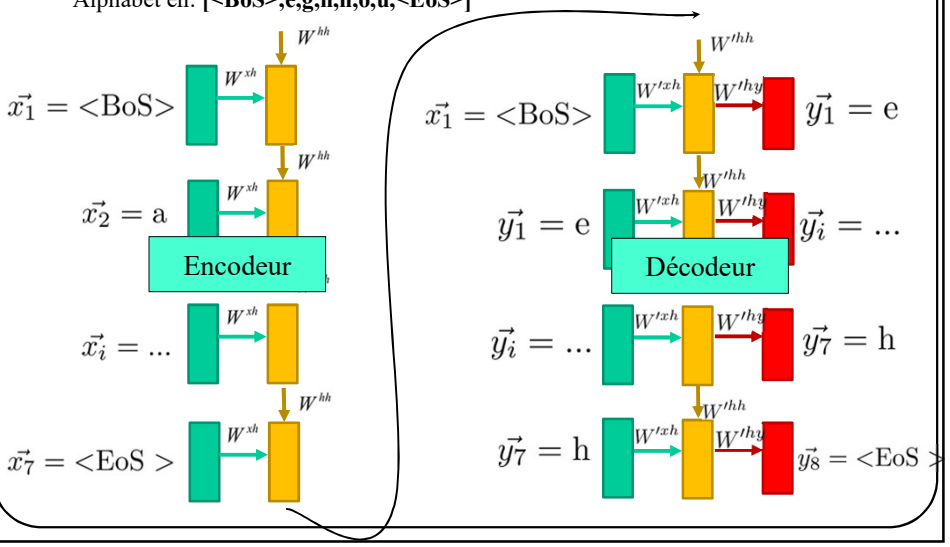
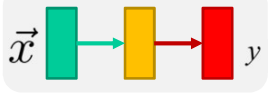
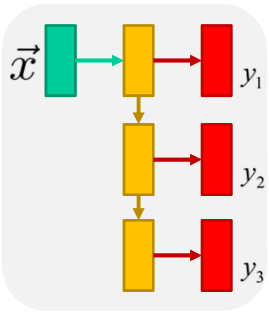


Différentes configurations pour différentes applications

1 entrée et 1 sortie



1 entrée et N sorties



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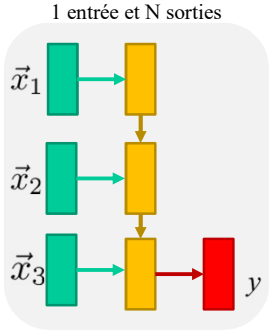
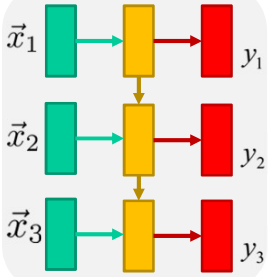
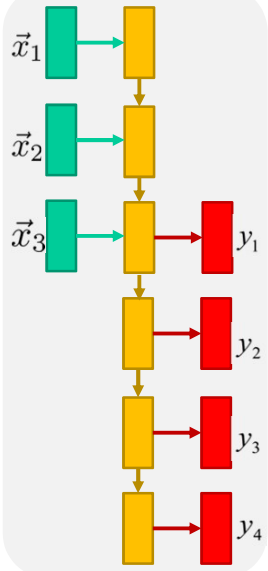


N entrées et N sorties



M entrées et N sorties



Ex.: Traduction Français-Anglais
N mots => M mots

Différentes configurations pour différentes applications

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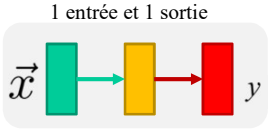

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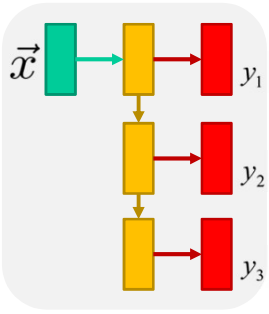
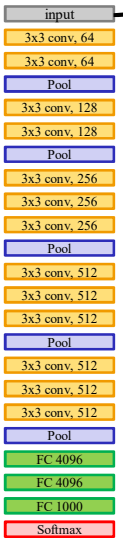


Captioning

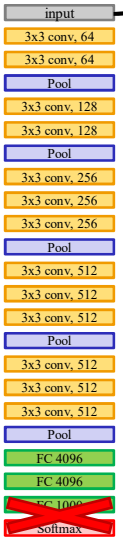


VGG16

Pré-entraîné sur *ImageNet*

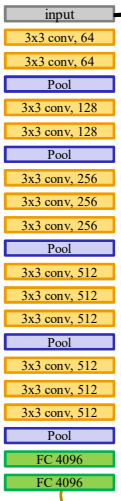
55

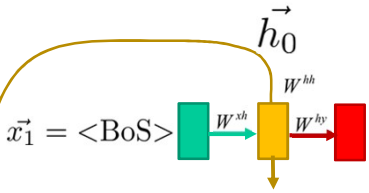
Captioning



VGG16

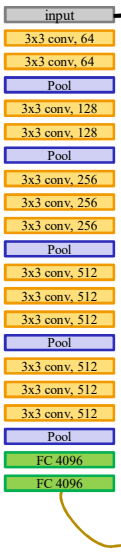
Captioning

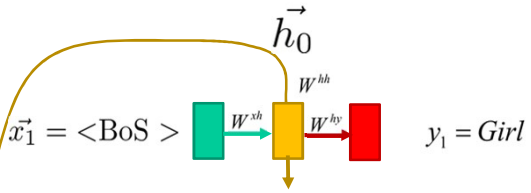




Étape 1 : Init + Propagation avant

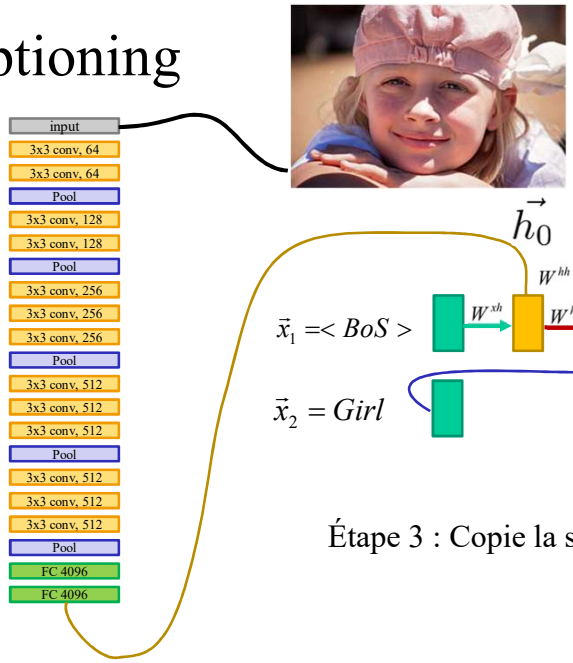
Captioning





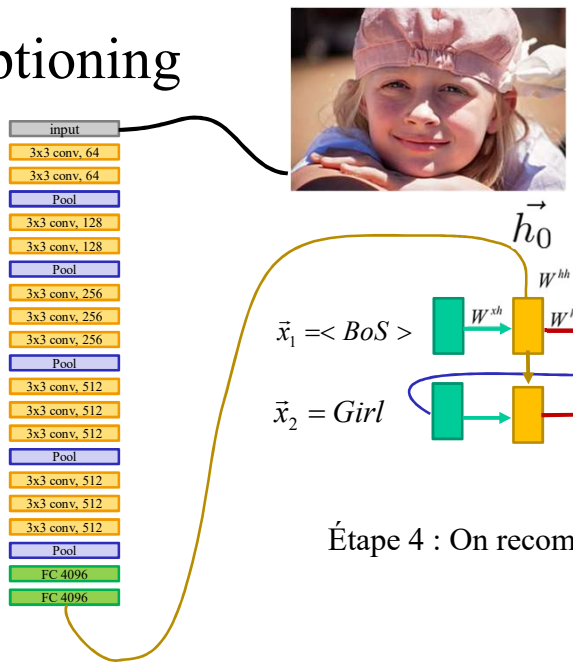
Étape 2 : Échantionnage

Captioning



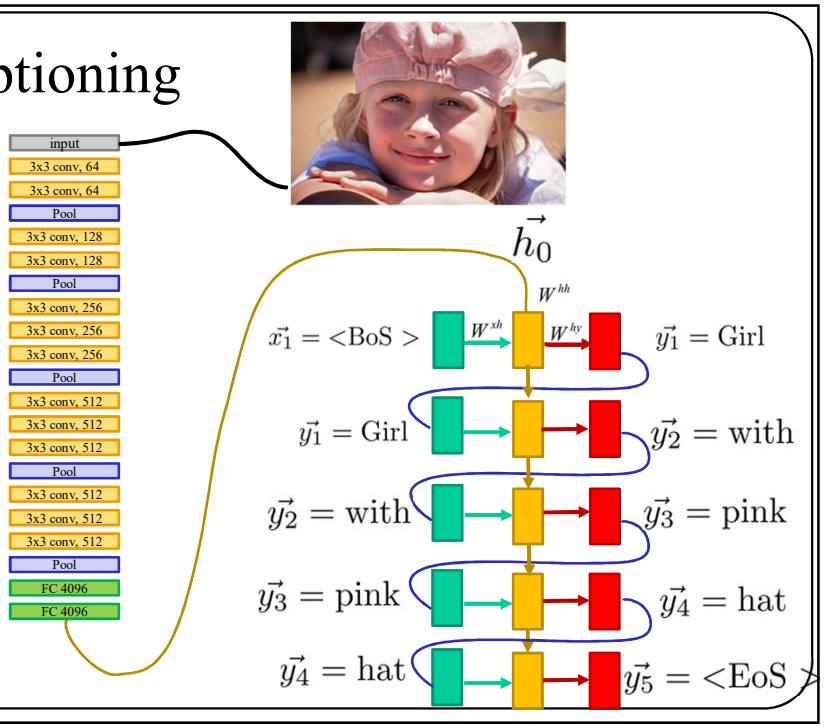
Étape 3 : Copie la sortie vers l'entrée

Captioning



Étape 4 : On recommence!

Captioning



Exemples de résultats

https://github.com/karpathy/neuraltalk2


an elephant standing in a grassy field with trees in the background


a man riding a wave on top of a surfboard

a street sign on a pole in front of a building


a group of people playing a game with nintendo wii controllers


a couple of zebra standing on top of a dirt field

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Exemples d'erreurs https://github.com/karpathy/neuraltalk2

a man is throwing a frisbee in a park

a man riding a skateboard down a street

a laptop computer sitting on top of a wooden desk

A woman is holding a cat in her hand

A woman standing on a beach holding a surfboard

63

NeuralTalk and Walk https://vimeo.com/146492001

64

Analyse de texte

Souvent les modèles de langue utilisent l'encodage « one hot »

Pour des **caractères**…

$$\left.\begin{array}{l} 'a' = [1,0,0,...,0] \\ 'b' = [0,1,0,...,0] \\ 'c' = [0,0,1,...,0] \end{array}\right\} \in R^{256}$$

...

65

Analyse de texte

Souvent les modèles de langue utilisent l'encodage « one hot »

Pour des **mots**…

...

$$\left.\begin{array}{l} 'grand' = [...,1,0,0,...,0] \\ 'grandement' = [...,0,1,0,...,0] \\ 'grandeur' = [...,0,0,1,...,0] \end{array}\right\} \in R^{10,000}$$

...

66

Prédiction sur des lettres vs. mots

$$\left.\begin{array}{l} 'a' = [1,0,0,...,0] \\ 'b' = [0,1,0,...,0] \\ 'c' = [0,0,1,...,0] \end{array}\right\} \in R^{256}$$

Prédiction sur des lettres

...

...

$$\left.\begin{array}{l} 'grand' = [...,1,0,0,...,0] \\ 'grandement' = [...,0,1,0,...,0] \\ 'grandeur' = [...,0,0,1,...,0] \end{array}\right\} \in R^{10,000}$$

Prédiction sur des mots

...

Prédiction sur des fractions de mots

$$\left.\begin{array}{r} ... \\ 'e' = [0,0,..,1,..,0] \\ ... \\ 'grand' = [0,0,..,1,..,0] \\ ... \\ 'ment' = [0,0,..,1,..,0] \\ ... \end{array}\right\} \in \mathbb{R}^m$$

'grand'
'grand'+'e'
'grand'+'e'+'ment'

Tokenization (jeton-isation ?)

Idée: à partir d'un dictionnaire qui ne contient que des caractères, combiner les séquences fréquentes en jetons (*tokens*)

Les séquences fréquentes (comme les mots ou sous-mots fréquents) se voient attribuer un jeton. Les séquences peu fréquentes peuvent être bâties à partir de jetons.

Sennrich, R., Haddow, B., & Birch, A. (2015). Neural machine translation of rare words with subword units. arXiv preprint arXiv:1508.07909.

Algorithm 1 Learn BPE operations

```
import re, collections

def get_stats(vocab):
  pairs = collections.defaultdict(int)
  for word, freq in vocab.items():
    symbols = word.split()
    for i in range(len(symbols)-1):
      pairs[symbols[i],symbols[i+1]] += freq
  return pairs

def merge_vocab(pair, v_in):
  v_out = {}
  bigram = re.escape(' '.join(pair))
  p = re.compile(r'(?<!\S)' + bigram + r'(?!\S)')
  for word in v_in:
    w_out = p.sub(''.join(pair), word)
    v_out[w_out] = v_in[word]
  return v_out

vocab = {'l o w </w>' : 5, 'l o w e r </w>' : 2,
         'n e w e s t </w>':6, 'w i d e s t </w>':3}
num_merges = 10
for i in range(num_merges):
  pairs = get_stats(vocab)
  best = max(pairs, key=pairs.get)
  vocab = merge_vocab(best, vocab)
  print(best)
```

r · → r·
l o → lo
lo w → low
e r· → er·

Limites des « one-hot vectors »

Bien que simple, cet encodage a plusieurs **inconvénients**

1- Peu efficace en mémoire lorsque non compressé
ex.: 10,000 bits pour encoder le mot « **je** » dans une langue à 10,000 mots!

2- Pas de distance sémantique entre les codes:

Ex.
distance[**one-hot**(‘**bon**’), **one-hot**(‘**bien**’)]= **distance**[**one-hot**(‘**bon**’), **one-hot**(‘**trottoir**’)]

Or, on souhaiterait un **code** tel que
distance[**code**(‘**bon**’), **code**(‘**bien**’)] << **distance**[**code**(‘**bon**’), **code**(‘**trottoir**’)]
distance[**code**(‘**Jean**’), **code**(‘**Chantal**’)] << **distance**[**code**(‘**bon**’), **code**(‘**trottoir**’)]
distance[**code**(‘**Inde**’), **code**(‘**Liban**’)] << **distance**[**code**(‘**bon**’), **code**(‘**trottoir**’)]

Word2Vec s'appuie sur 2 idées fondamentales

Un solution est d'utiliser l'encodage **Word2Vec** de [Mikolov et al. '13]

Idée 1: **Dictionnaire = matrice d'encodage**

Exemple jouet: on veut représenter ces 8 mots par des codes à 4 éléments

« one-hot »

'the'	1	0	0	0	0	0	0	0
'quick'	0	1	0	0	0	0	0	0
'brown'	0	0	1	0	0	0	0	0
'fox'	0	0	0	1	0	0	0	0
'jumps'	0	0	0	0	1	0	0	0
'over'	0	0	0	0	0	1	0	0
'lazy'	0	0	0	0	0	0	1	0
'dog'	0	0	0	0	0	0	0	1

Dictionnaire

2	3	4	5
-1	-3	-2	2
11	6	4	-3
-4	8	-4	4
24	-6	42	17
91	13	14	-5
0	36	4	56
-1	0	1	35

1 ligne = code pour 1 mot

Word2Vec s'appuie sur 2 idées fondamentales

Idée 1: **Dictionnaire = matrice d'encodage**

Comment sélectionner le code d'un mot? En multipliant son vecteur One-hot par la matrice d'encodage (le dictionnaire!)

Ex: sélectionner le code de « brown »

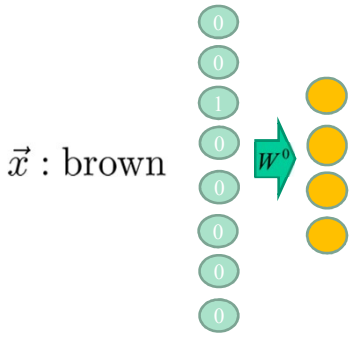
Dictionnaire (matrice d'encodage)

$$\begin{pmatrix} 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} 2 & 3 & 4 & 5 \\ -1 & -3 & -2 & 2 \\ 11 & 6 & 4 & -3 \\ -4 & 8 & -4 & 4 \\ 24 & -6 & 42 & 17 \\ 91 & 13 & 14 & -5 \\ 0 & 36 & 4 & 56 \\ -1 & 0 & 1 & 35 \end{pmatrix} = \begin{pmatrix} 11 & 6 & 4 & -3 \end{pmatrix}$$

Word2Vec s'appuie sur 2 idées fondamentales

Idée 1: **Dictionnaire = matrice d'encodage**

Première couche d'un réseau de neurones
=
matrice d'encodage



Word2Vec s'appuie sur 2 idées fondamentales

Idée 1: **Dictionnaire = matrice d'encodage**

Première couche d'un réseau de neurones
=
matrice d'encodage

$$code_{\vec{x}} = W^0 \vec{x}$$

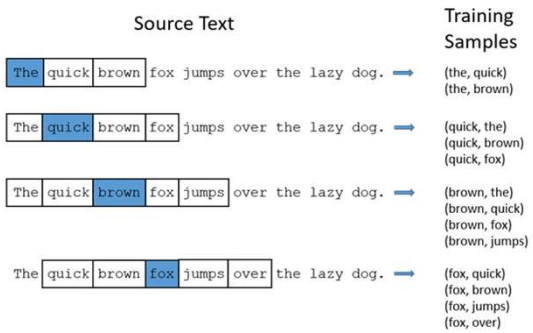
Word2Vec s'appuie sur 2 idées fondamentales

Idée 1: **Dictionnaire = matrice d'encodage**

On pourra donc utiliser un réseau de neurones pour calculer le contenu du dictionnaire

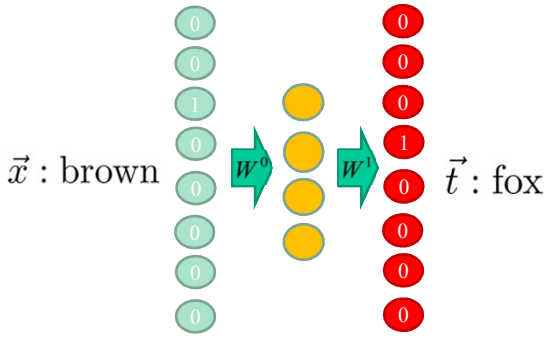
Word2Vec s'appuie sur 2 idées fondamentales

Idée 2: **2 mots proches dans un texte = 2 mots proches sémantiquement**



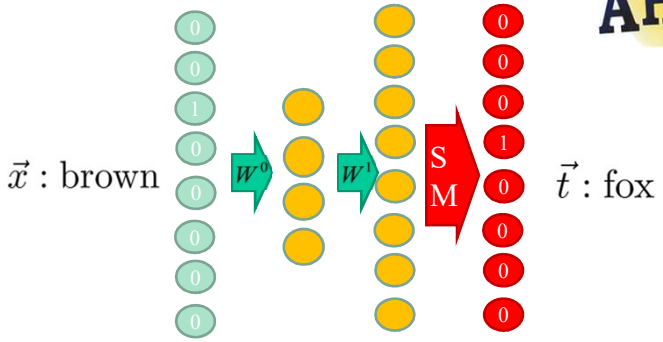
Basé sur un corpus de texte, on va créer des **millions de paires de mots**

Word2Vec [Mikolov et al. '13]



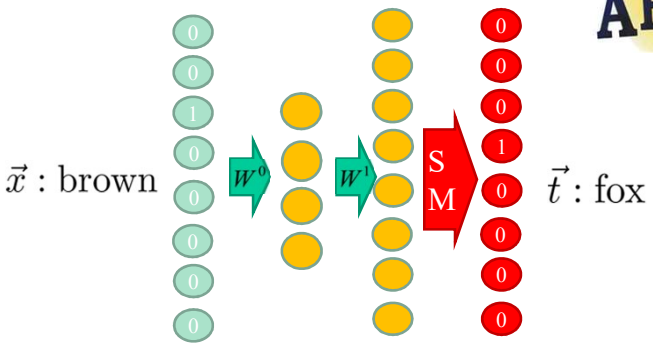
Entraîner un réseau de neurones
à reproduire le 2e mot partant du 1er

Word2Vec [Mikolov et al. '13]



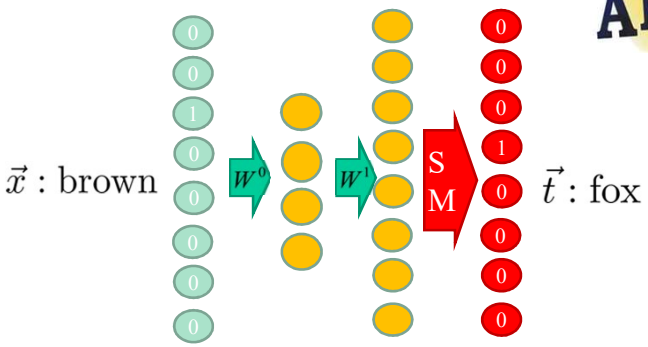
Puisque la sortie est de type « *one-hot* »
on utilise un softmax

Word2Vec [Mikolov et al. '13]



$$y(\vec{x}) = \text{softmax}(W^1 f_a(W^0 \text{x}))$$

Word2Vec [Mikolov et al. '13]



Lorsqu'entraîné, utiliser W^0
comme dictionnaire

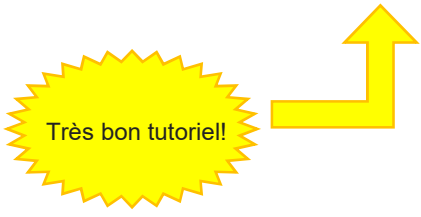
Word2Vec [Mikolov et al. '13]

Cet algorithme vient avec **d'autres détails**

- Réduire l'occurrence des mots fréquents et sémantiquement faibles (*the, of, for, this, or, and,…*)
- Combiner des mots qui forment une entité (ex: *nations unies*)
- Divers trucs pour simplifier/accélérer l'entraînement

Limites du « one-hot vector »

http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/

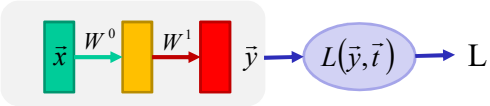


T.Mikolov et al. (2013). "Efficient Estimation of Word Representations in Vector Space", in ICLR 2013

Comment entraîner un RNN?

Histoire de gradients

RN de classification avec entropie croisée

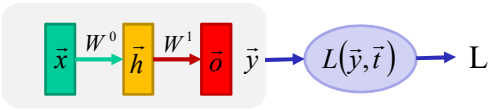


$$\vec{y}(\vec{x}) = S_M\left(W^1 \tanh\left(W^0 \vec{x}\right)\right)$$

$$L = L_{EC}\left(\vec{y},\vec{t}\right)$$

Histoire de gradients

Simple RN de classification avec entropie croisée

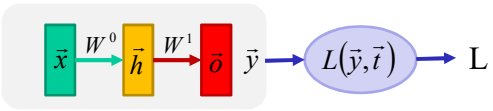


$$\vec{h} = \tanh\left(W^0 \vec{x}\right)$$
$$\vec{o} = W^1 \vec{h}$$
$$\vec{y} = S_M\left(\vec{o}\right)$$
$$L = L_{CE}\left(\vec{y},\vec{t}\right)$$

Propagation avant

Histoire de gradients

Simple RN de classification avec entropie croisée



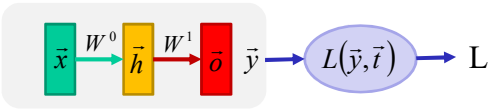
$$\vec{h} = \tanh\left(W^0 \vec{x}\right)$$
$$\vec{o} = W^1 \vec{h}$$
$$\vec{y} = S_M\left(\vec{o}\right)$$
$$L = L_{CE}\left(\vec{y},\vec{t}\right)$$

Pour entraîner le réseau il faut calculer

$\nabla_{W^o} L$ et $\nabla_{W^1} L$

Histoire de gradients

Simple RN de classification avec entropie croisée

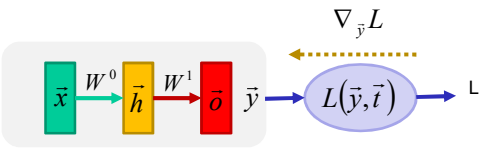


$$\vec{h} = \tanh\left(W^0\vec{x}\right)$$
$$\vec{o} = W^1\vec{h}$$
$$\vec{y} = S_M\left(\vec{o}\right)$$
$$L = L_{CE}\left(\vec{y},\vec{t}\right)$$

Dérivée en chaîne

$$\nabla_{W^1} L = \nabla_{\vec{y}} L \nabla_{\vec{o}} \vec{y} \nabla_{W^1} \vec{o}$$
$$\nabla_{W^0} L = \nabla_{\vec{y}} L \nabla_{\vec{o}} \vec{y} \nabla_{\vec{h}} \vec{o} \nabla_{W^0} \vec{h}$$

Histoire de gradients

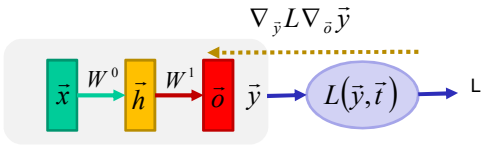


$$\vec{h} = \tanh\left(W^0\vec{x}\right)$$
$$\vec{o} = W^1\vec{h}$$
$$\vec{y} = S_M\left(\vec{o}\right)$$
$$L = L_{CE}\left(\vec{y},\vec{t}\right)$$

$$\nabla_{\vec{y}} L = -\frac{\vec{t}}{\vec{y}}$$

Rétro-propagation

Histoire de gradients

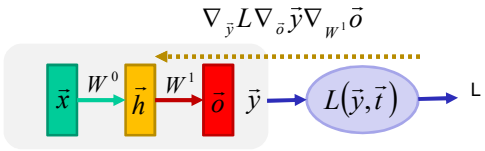


$$\vec{h} = \tanh\left(W^0 \vec{x}\right)$$
$$\vec{o} = W^1 \vec{h}$$
$$\vec{y} = S_M\left(\vec{o}\right)$$
$$L = L_{CE}\left(\vec{y},\vec{t}\right)$$

$$\nabla_{\vec{o}} \vec{y} = \mathrm{I}\vec{y}^T - \vec{y}^T \vec{y}$$
$$\nabla_{\vec{y}} L = -\frac{\vec{t}}{\vec{y}}$$

Rétro-propagation

Histoire de gradients



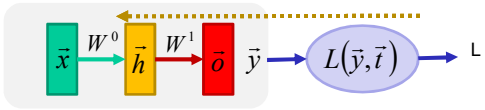
$$\vec{h} = \tanh\left(W^0 \vec{x}\right)$$
$$\vec{o} = W^1 \vec{h}$$
$$\vec{y} = S_M\left(\vec{o}\right)$$
$$L = L_{CE}\left(\vec{y},\vec{t}\right)$$

$$\nabla_{W^1} \vec{o} = \vec{h}$$
$$\nabla_{\vec{o}} \vec{y} = \mathrm{I}\vec{y}^T - \vec{y}^T \vec{y}$$
$$\nabla_{\vec{y}} L = -\frac{\vec{t}}{\vec{y}}$$

Rétro-propagation

Histoire de gradients

$$\nabla_{\vec{y}} L \nabla_{\vec{o}} \vec{y} \nabla_{\vec{h}} \vec{o}$$



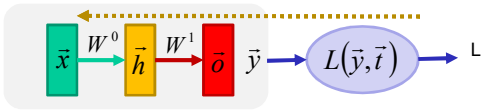
$$\vec{h} = \tanh\left(W^0 \vec{x}\right)$$
$$\vec{o} = W^1 \vec{h}$$
$$\vec{y} = S_M\left(\vec{o}\right)$$
$$L = L_{CE}\left(\vec{y},\vec{t}\right)$$

Rétro-propagation

$$\nabla_{\vec{h}} \vec{o} = W^1$$
$$\nabla_{W^1} \vec{o} = \vec{h}$$
$$\nabla_{\vec{o}} \vec{y} = \mathrm{I}\vec{y}^T - \vec{y}^T \vec{y}$$
$$\nabla_{\vec{y}} L = -\frac{\vec{t}}{\vec{y}}$$

Histoire de gradients

$$\nabla_{\vec{y}} L \nabla_{\vec{o}} \vec{y} \nabla_{\vec{h}} \vec{o} \nabla_{W^0} \vec{h}$$

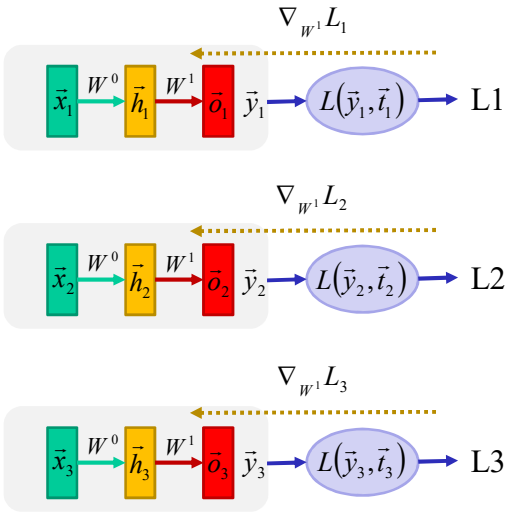


$$\vec{h} = \tanh\left(W^0 \vec{x}\right)$$
$$\vec{o} = W^1 \vec{h}$$
$$\vec{y} = S_M\left(\vec{o}\right)$$
$$L = L_{CE}\left(\vec{y},\vec{t}\right)$$

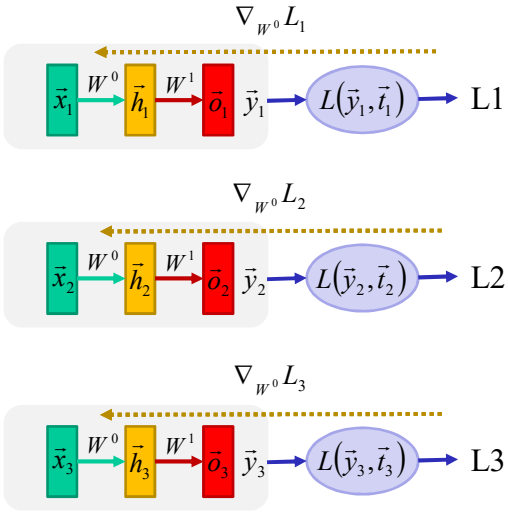
Rétro-propagation

$$\nabla_{W^0} \vec{h} = 1 - \tanh^2\left(W^1 \vec{x}\right)\vec{x}$$
$$\nabla_{\vec{h}} \vec{o} = W^1$$
$$\nabla_{W^1} \vec{o} = \vec{h}$$
$$\nabla_{\vec{o}} \vec{y} = \mathrm{I}\vec{y}^T - \vec{y}^T \vec{y}$$
$$\nabla_{\vec{y}} L = -\frac{\vec{t}}{\vec{y}}$$

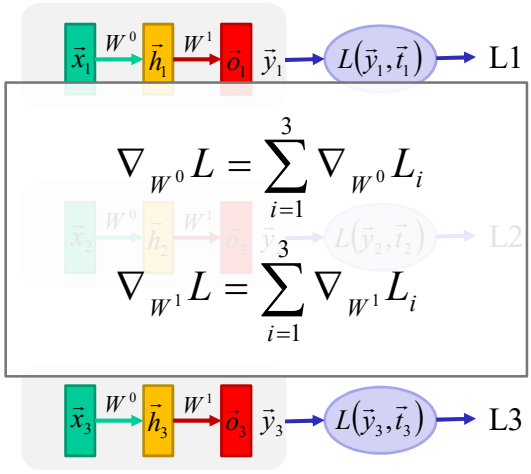
Ex.: 3 données, 3 rétro-propagations



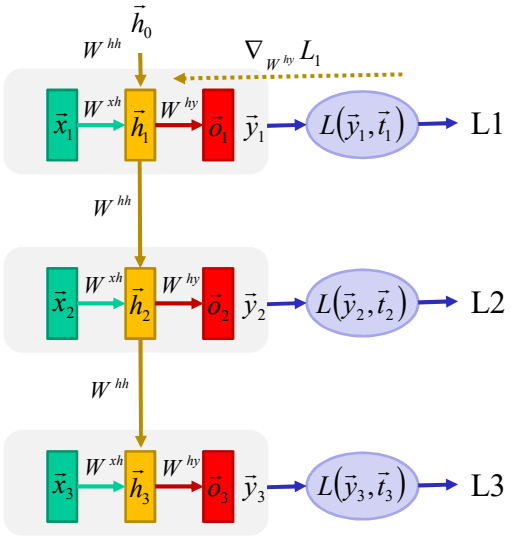
Ex.: 3 données, 3 rétro-propagations



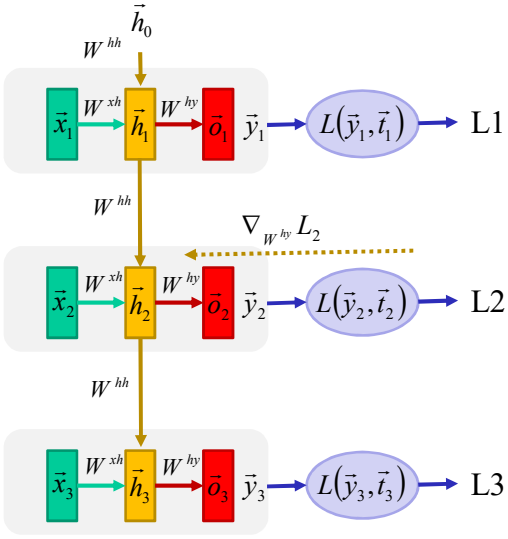
3 rétro-propagations



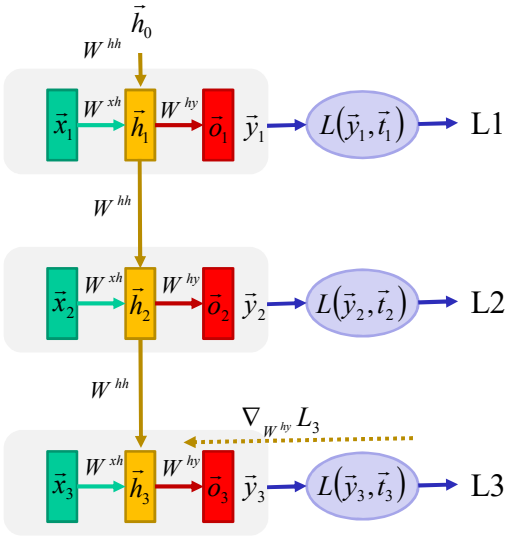
Réseau récurrent: gradient pour W^{hy}



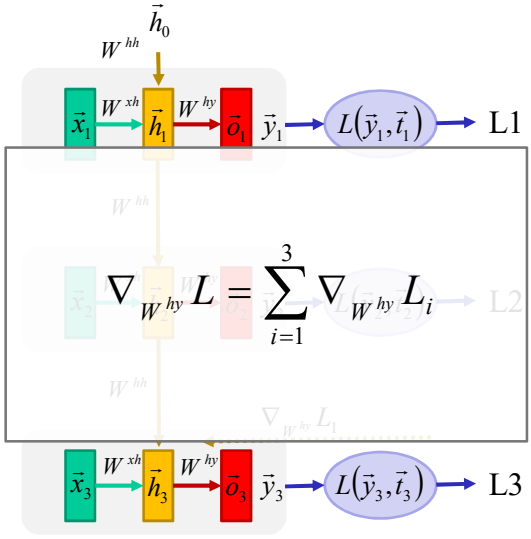
Réseau récurrent: gradient pour W^{hy}



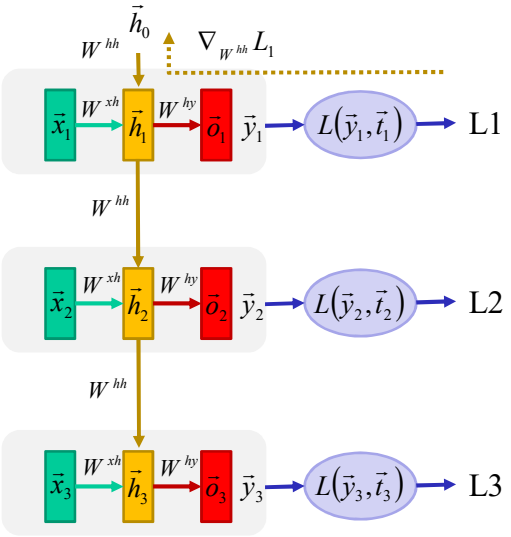
Réseau récurrent: gradient pour W^{hy}



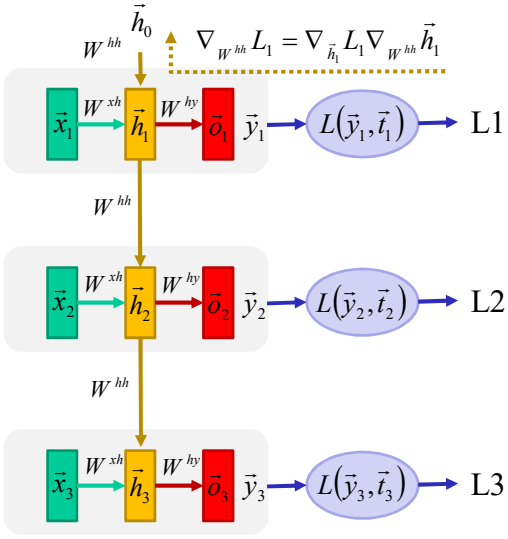
Réseau récurrent: gradient pour W^{hy}



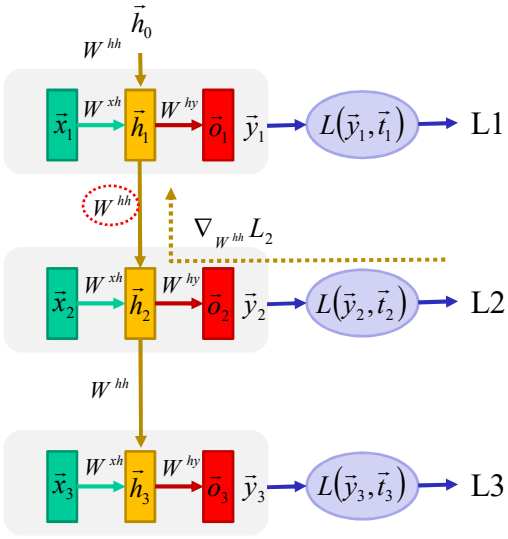
Réseau récurrent: gradient pour W^{hh}



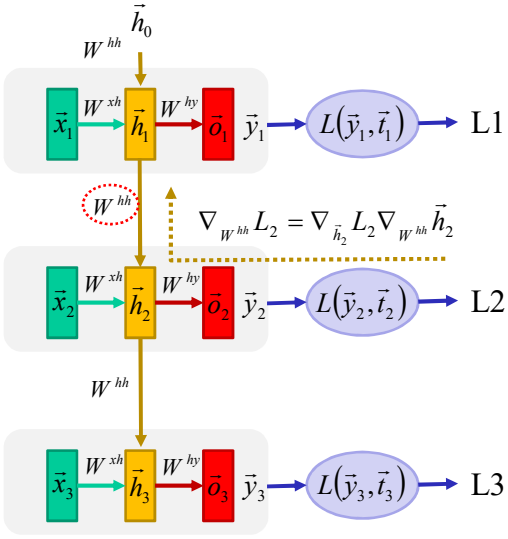
Réseau récurrent: gradient pour W^{hh}



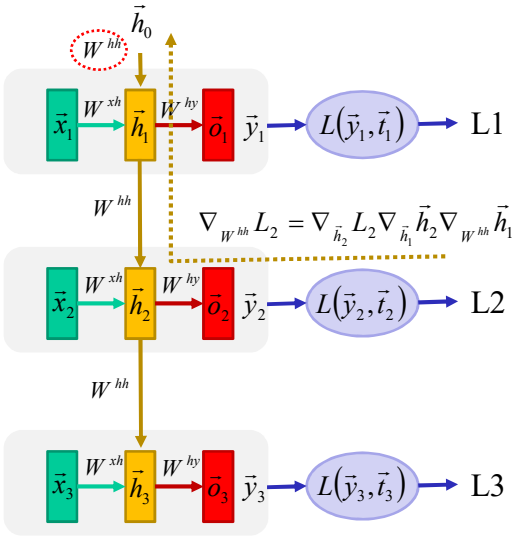
Réseau récurrent: gradient pour W^{hh}



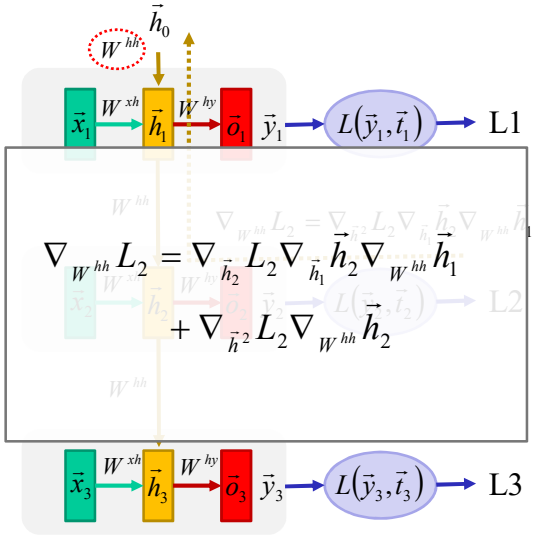
Réseau récurrent: gradient pour W^{hh}



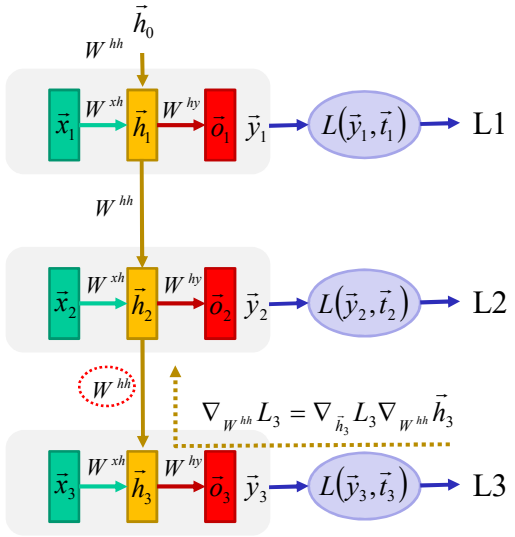
Réseau récurrent: gradient pour W^{hh}



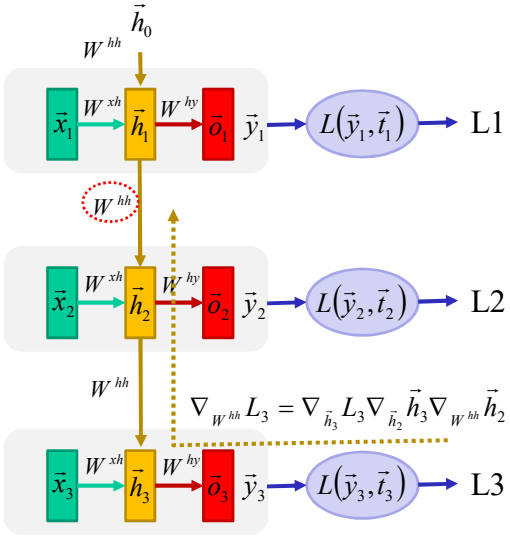
Réseau récurrent: gradient pour W^{hh}



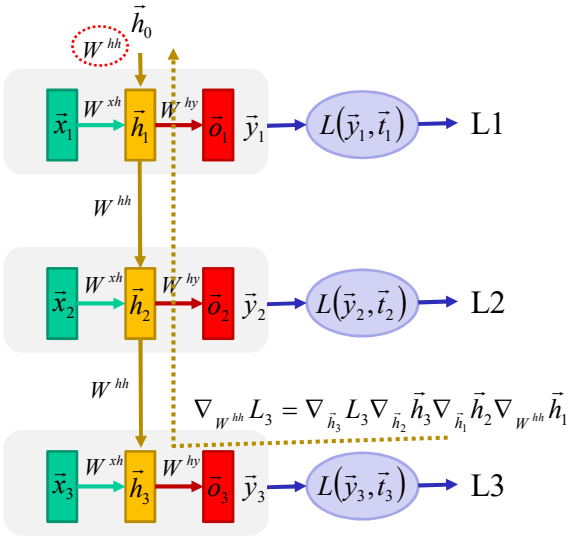
Réseau récurrent: gradient pour W^{hh}



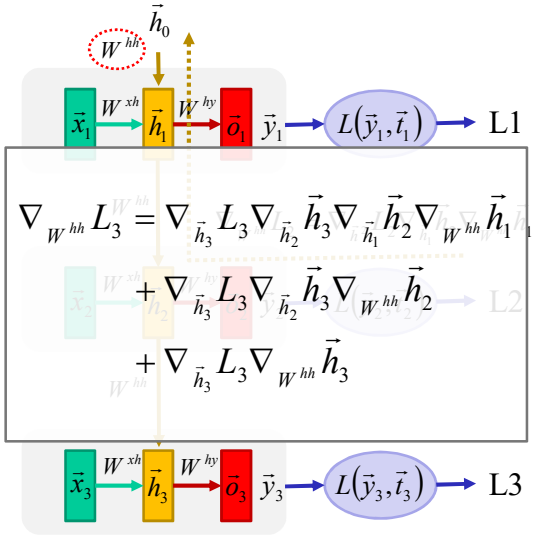
Réseau récurrent: gradient pour W^{hh}



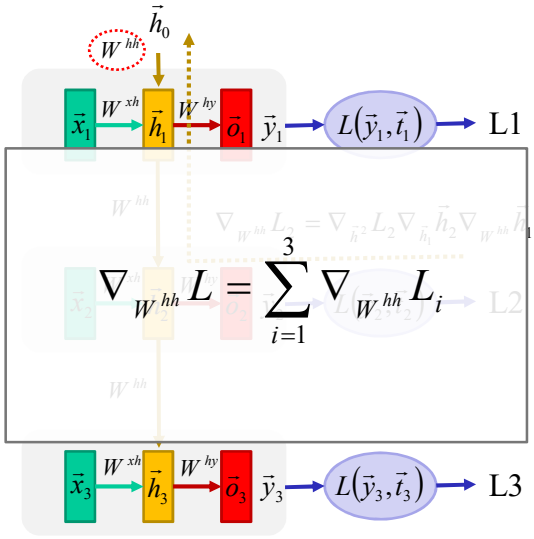
Réseau récurrent: gradient pour W^{hh}



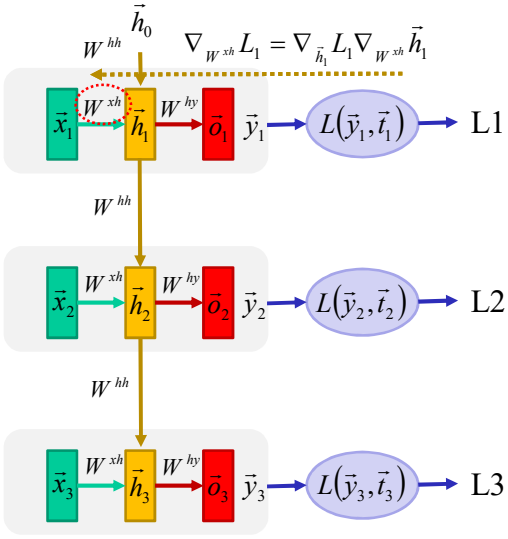
Réseau récurrent: gradient pour W^{hh}



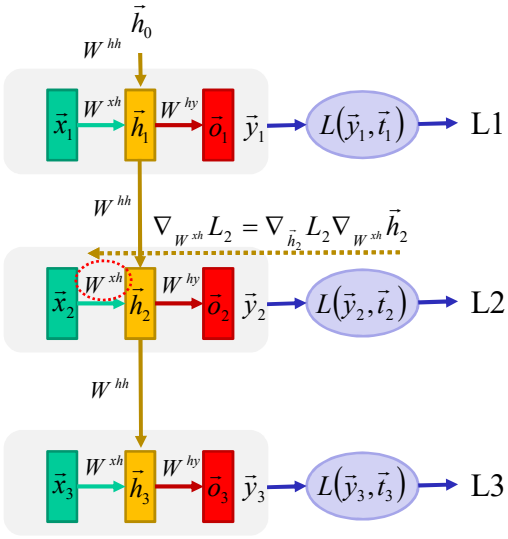
Réseau récurrent: gradient pour W^{hh}



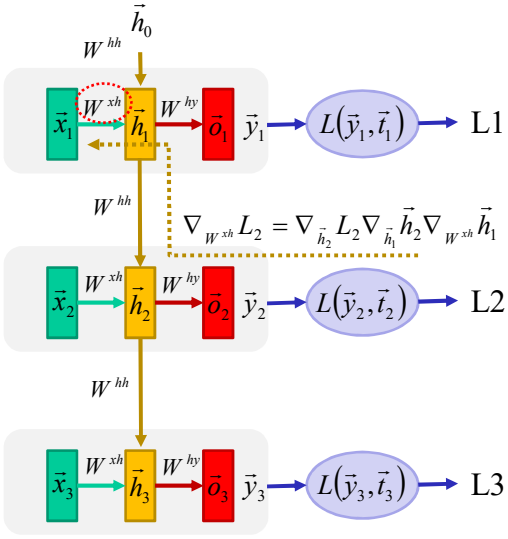
Réseau récurrent: gradient pour W^{xh}



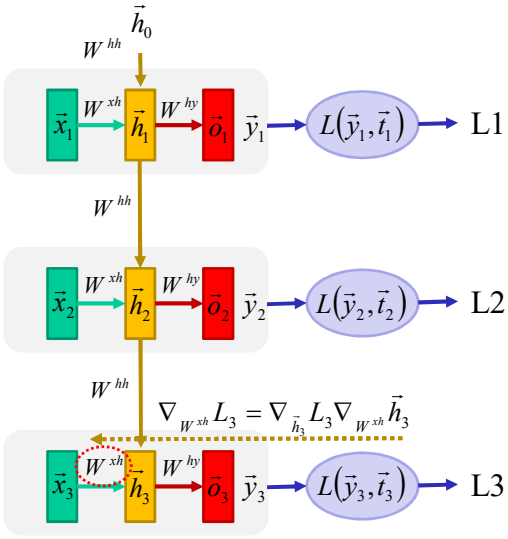
Réseau récurrent: gradient pour W^{xh}



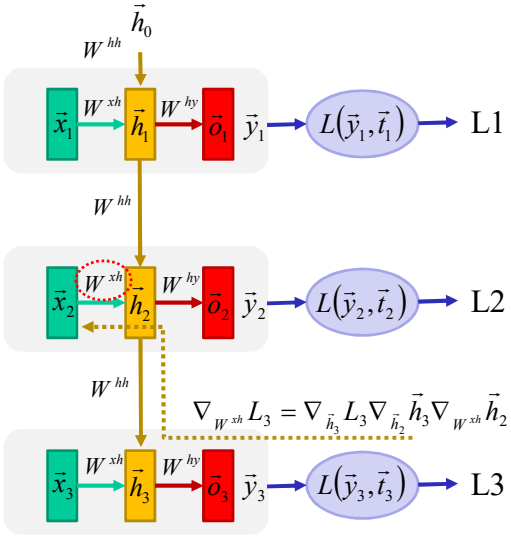
Réseau récurrent: gradient pour W^{xh}



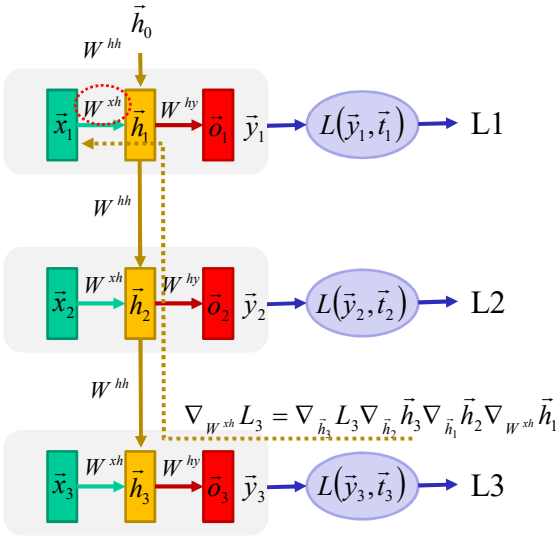
Réseau récurrent: gradient pour W^{xh}



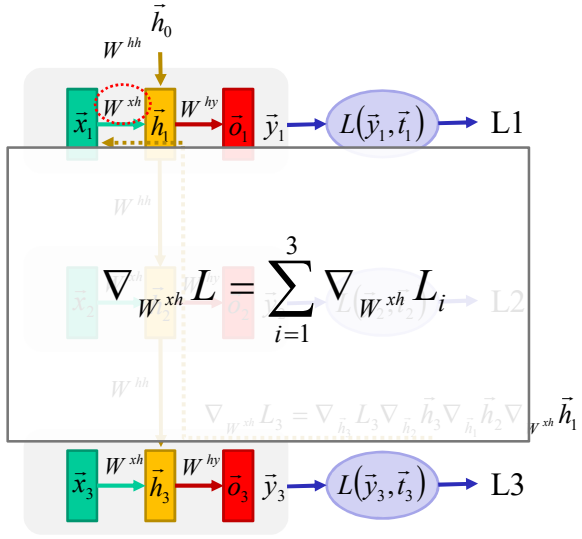
Réseau récurrent: gradient pour W^{xh}



Réseau récurrent: gradient pour W^{xh}



Réseau récurrent: gradient pour W^{xh}



Réseau récurrent: calcul du gradient

Moins difficile qu'il n'y paraît.

```
44    # backward pass: compute gradients going backwards
45    dWxh, dWhh, dWhy = np.zeros_like(Wxh), np.zeros_like(Whh), np.zeros_like(Why)
46    dbh, dby = np.zeros_like(bh), np.zeros_like(by)
47    dhnext = np.zeros_like(hs[0])
48    for t in reversed(xrange(len(inputs))):
49      dy = np.copy(ps[t])
50      dy[targets[t]] -= 1 # backprop into y. see http://cs231n.github.io/neural-networks-case-study/#grad if confused here
51      dWhy += np.dot(dy, hs[t].T)
52      dby += dy
53      dh = np.dot(Why.T, dy) + dhnext # backprop into h
54      dhraw = (1 - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
55      dbh += dhraw
56      dWxh += np.dot(dhraw, xs[t].T)
57      dWhh += np.dot(dhraw, hs[t-1].T)
58      dhnext = np.dot(Whh.T, dhraw)
59    for dparam in [dWxh, dWhh, dWhy, dbh, dby]:
60      np.clip(dparam, -5, 5, out=dparam) # clip to mitigate exploding gradients
61    return loss, dWxh, dWhh, dWhy, dbh, dby, hs[len(inputs)-1]
```

Voir https://d2l.ai/chapter_recurrent-neural-networks/bptt.html pour plus d'informations

Les réseaux récurrents ont un inconvénient majeur:

difficile à établir des
relations à longue distance

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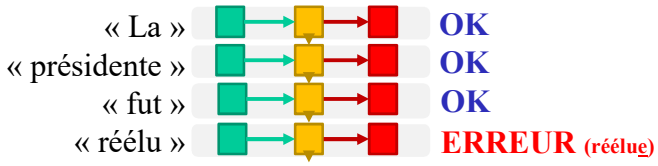
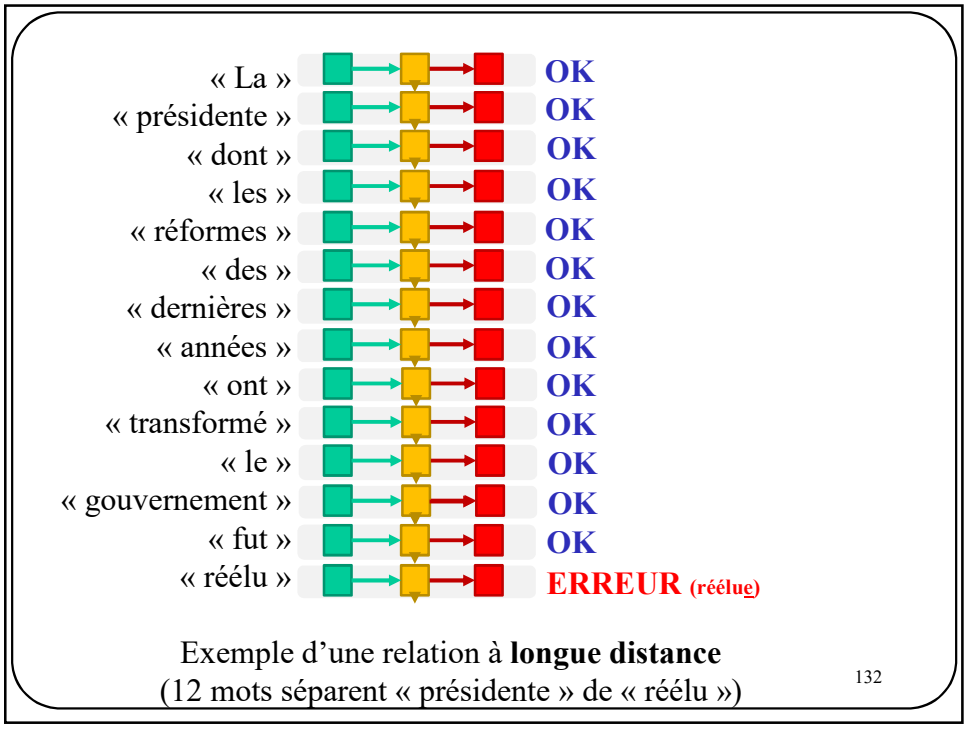
Exemples: analyse grammaticale

Entraîner un réseau à détecter des erreurs grammaticales



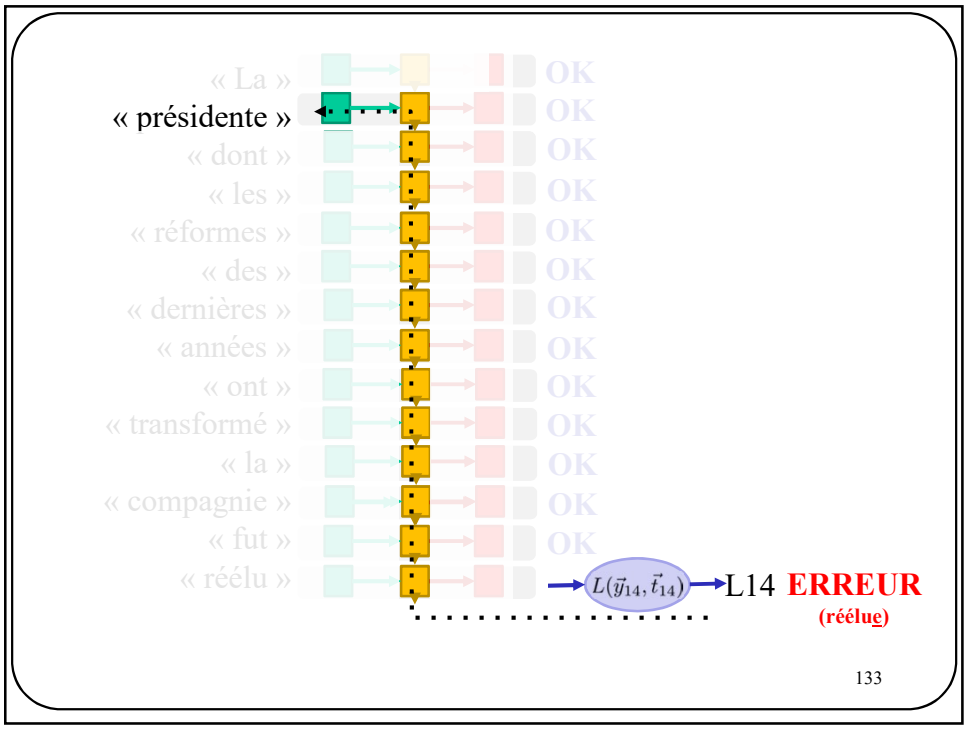
Exemple d'une relation à **courte distance**
(1 mot sépare « présidente » de « réélu »)

131

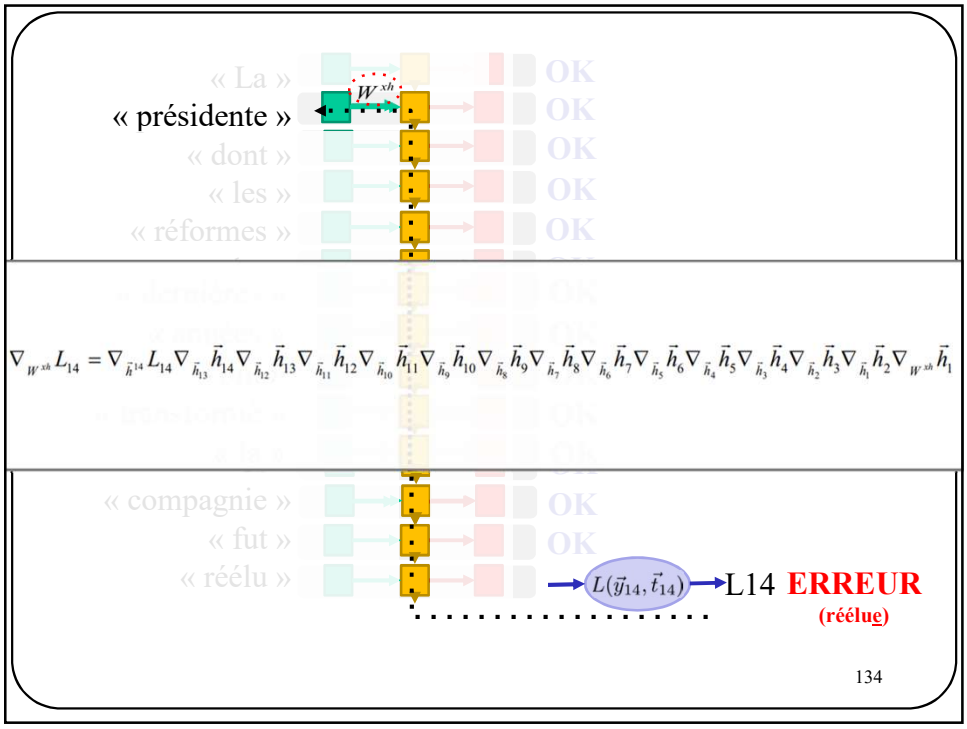


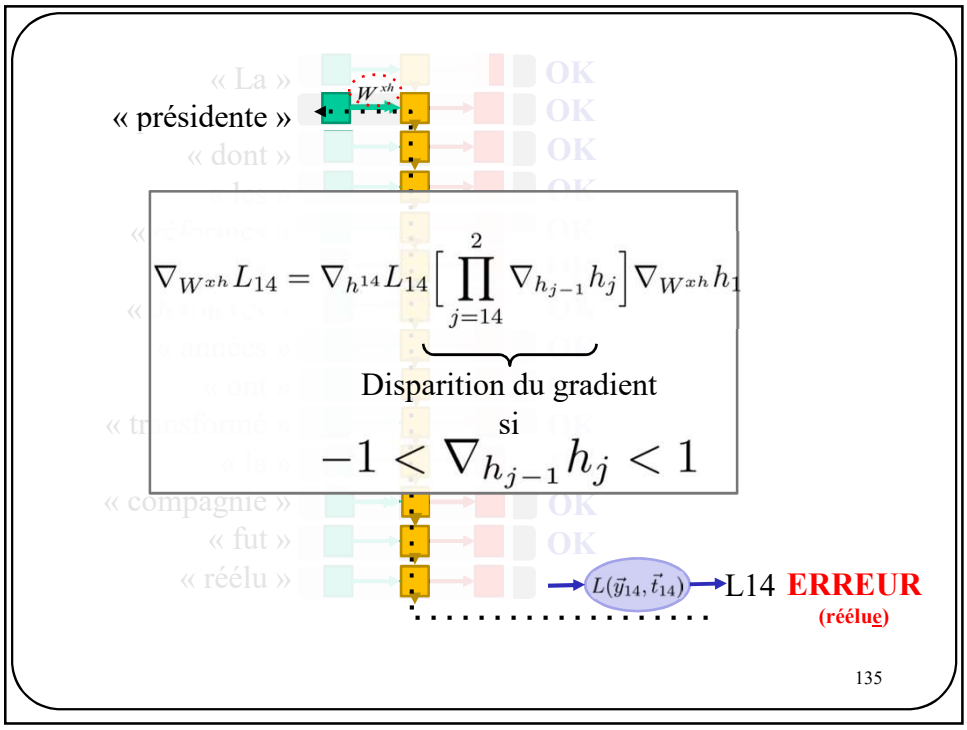
Exemple d'une relation à **longue distance**
(12 mots séparent « présidente » de « réélu »)

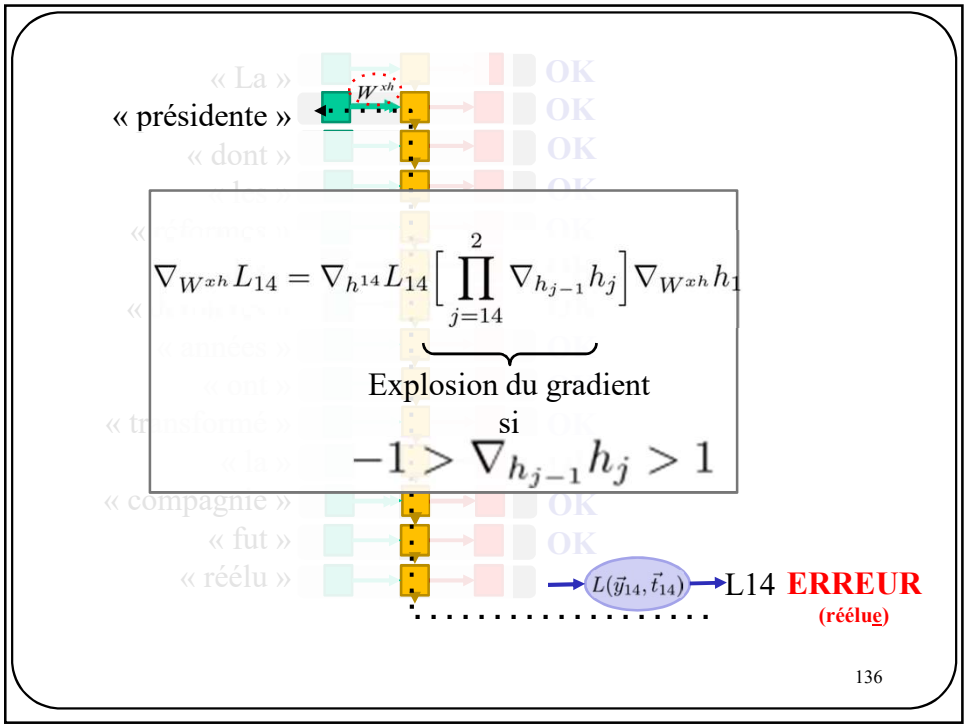
132



133


« La »
« présidente »
« dont »
« les »
« réformes »
« compagnie »
« fut »
« réélu »
OK
W^{xh}
$\nabla_{W^{xh}} L_{14} = \nabla_{\vec{h}^{14}} L_{14} \nabla_{\vec{h}_{13}} \vec{h}_{14} \nabla_{\vec{h}_{12}} \vec{h}_{13} \nabla_{\vec{h}_{11}} \vec{h}_{12} \nabla_{\vec{h}_{10}} \vec{h}_{11} \nabla_{\vec{h}_9} \vec{h}_{10} \nabla_{\vec{h}_8} \vec{h}_9 \nabla_{\vec{h}_7} \vec{h}_8 \nabla_{\vec{h}_6} \vec{h}_7 \nabla_{\vec{h}_5} \vec{h}_6 \nabla_{\vec{h}_4} \vec{h}_5 \nabla_{\vec{h}_3} \vec{h}_4 \nabla_{\vec{h}_2} \vec{h}_3 \nabla_{\vec{h}_1} \vec{h}_2 \nabla_{W^{xh}} \vec{h}_1$
$L(\vec{y}_{14}, \vec{t}_{14})$
L14 ERREUR
(réélue)
134


« La »
« présidente »
« dont »
« compagnie »
« fut »
« réélu »
OK
W^{xh}
$\nabla_{W^{xh}} L_{14} = \nabla_{h^{14}} L_{14} \left[\prod_{j=14}^{2} \nabla_{h_{j-1}} h_j \right] \nabla_{W^{xh}} h_1$
Disparition du gradient
si
$-1 < \nabla_{h_{j-1}} h_j < 1$
$L(\vec{y}_{14}, \vec{t}_{14})$
L14 ERREUR
(réélue)
135



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Problème connexe

Gestion de la mémoire

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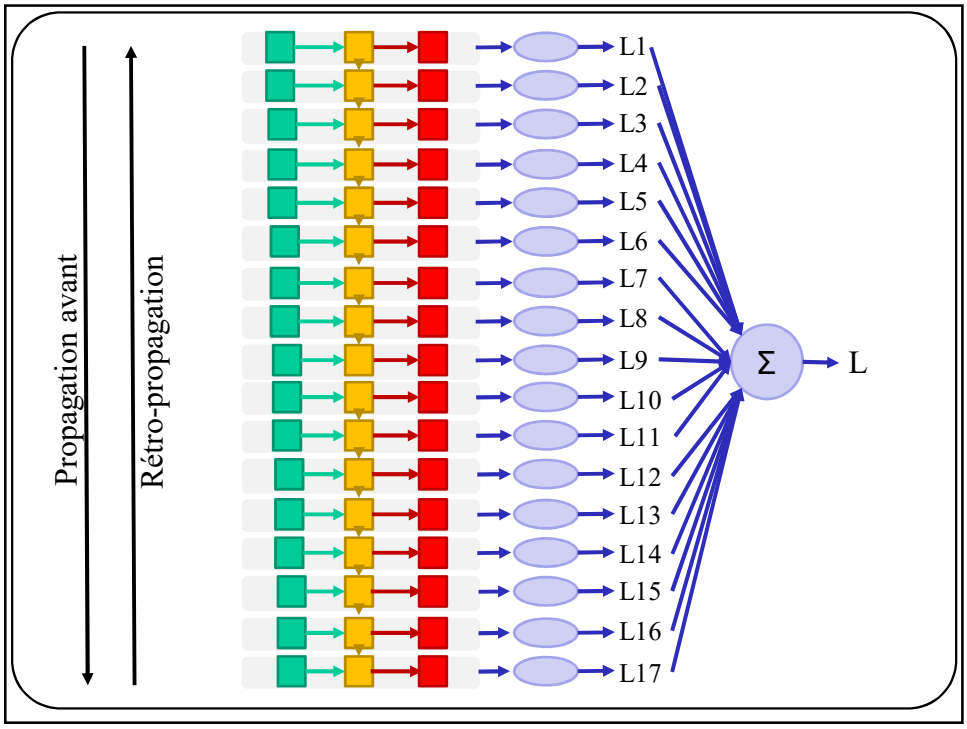
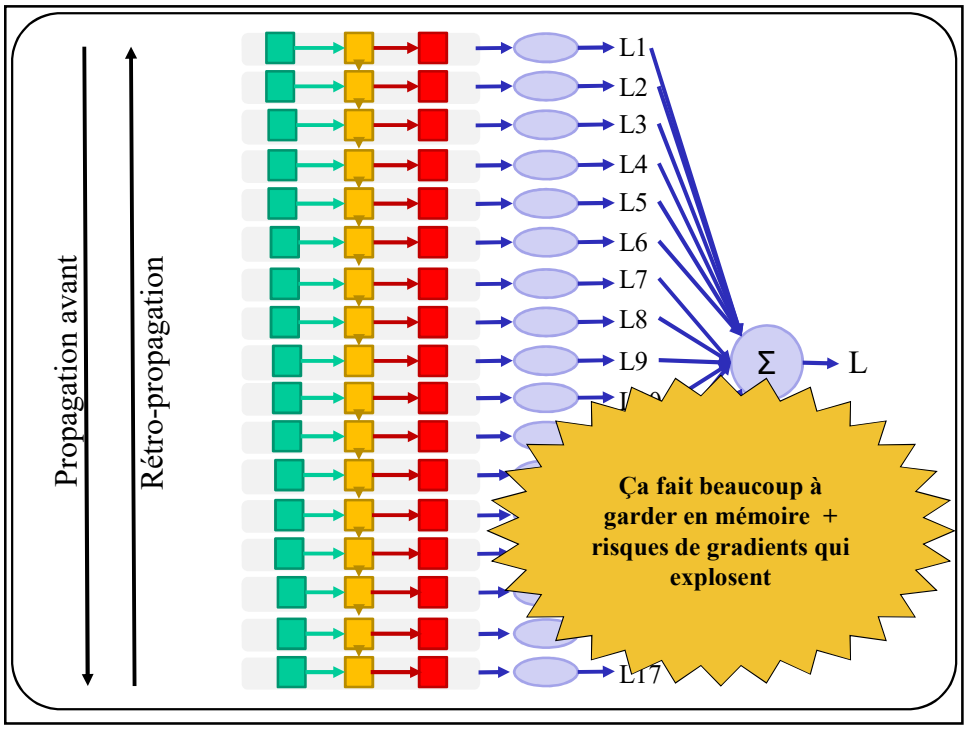

Propagation avant
Rétro-propagation
L1
L2
L3
L4
L5
L6
L7
L8
L9
L10
L11
L12
L13
L14
L15
L16
L17
Σ
L


Propagation avant
Rétro-propagation
L1
L2
L3
L4
L5
L6
L7
L8
L9
L17
Σ
L
Ça fait beaucoup à garder en mémoire + risques de gradients qui explosent

Solution pour la gestion de la mémoire
Fenêtres coulissantes

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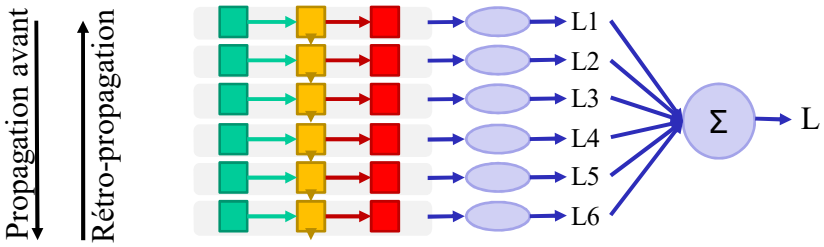
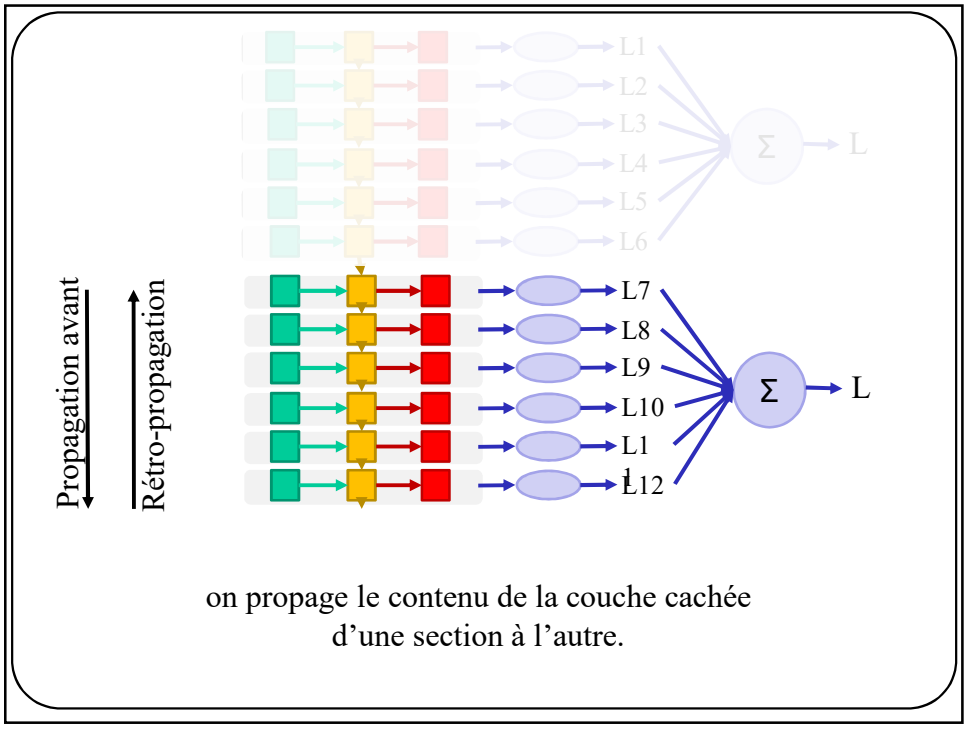
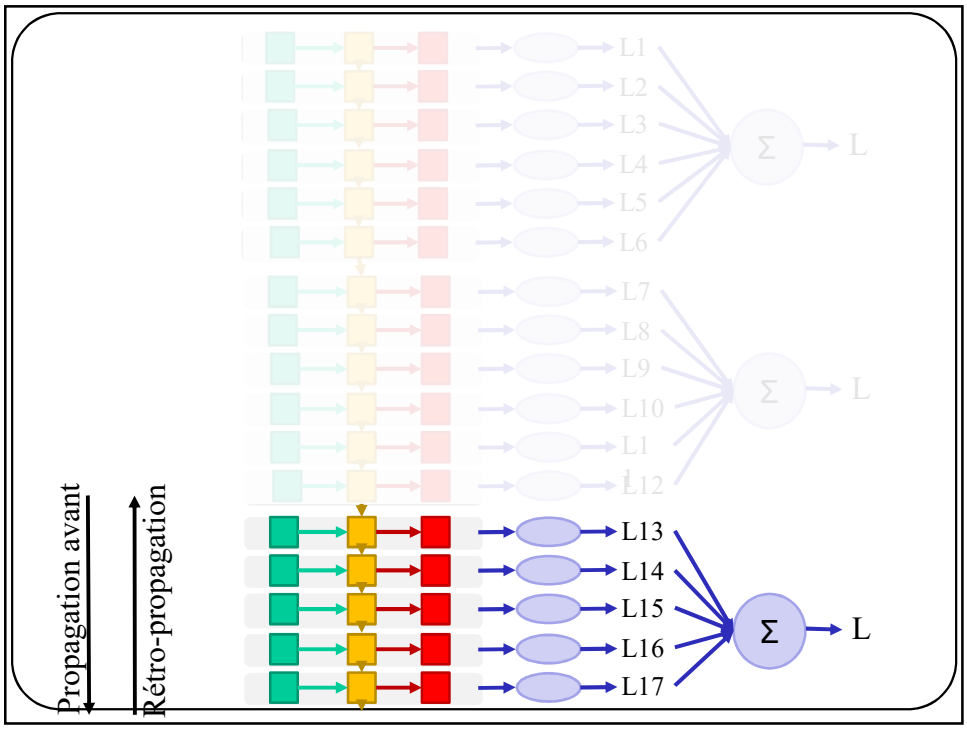


Lorsque les séquences sont trop longues
On entraîne le réseau par fenêtres coulissantes



on propage le contenu de la couche cachée
d'une section à l'autre.



Solution à la disparition du gradient:

Gated Recurrent Unit : GRU
Long-Short Term Memory : LSTM

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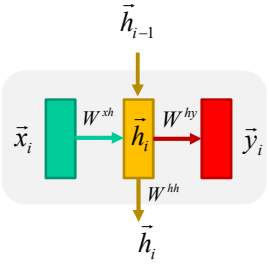
Illustration + formulation d'un RNN



$$\vec{h}_i = f_a\left(W^{xh}\vec{x}_i + W^{hh}\vec{h}_{i-1}\right)$$
$$\hat{y}_i = W^{hy}\vec{h}_i$$
$$\vec{y}_i = SMAX\left(\hat{y}_i\right)$$

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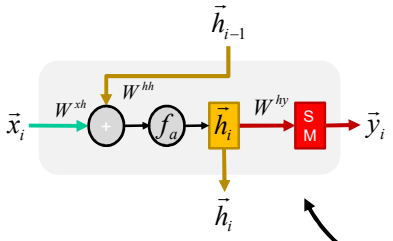
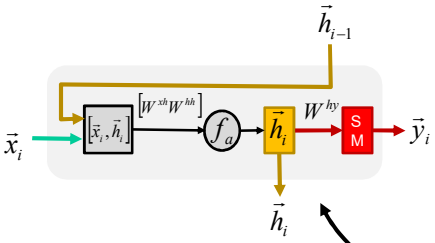
Autre illustration du même RNN



$$\vec{h}_i = f_a\left(W^{xh}\vec{x}_i + W^{hh}\vec{h}_{i-1}\right)$$
$$\hat{y}_i = W^{hy}\vec{h}_i$$
$$\vec{y}_i = SMAX\left(\hat{y}_i\right)$$

Identique

Autre illustration du même RNN



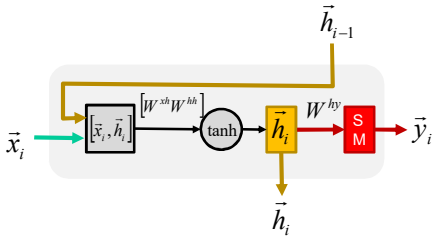
$$\vec{h}_i = f_a\left(W^{xh}\vec{x}_i + W^{hh}\vec{h}_{i-1}\right)$$
$$\hat{y}_i = W^{hy}\vec{h}_i$$
$$\vec{y}_i = SMAX\left(\hat{y}_i\right)$$

Encore identique

GRU (Gated Recurrent Unit)

Modif 1

$$f_a = \tanh$$



$$\vec{h}_i = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\vec{h}_{i-1}\right)$$
$$\hat{y}_i = W^{hy}\vec{h}_i$$
$$\vec{y}_i = SMAX\left(\hat{y}_i\right)$$

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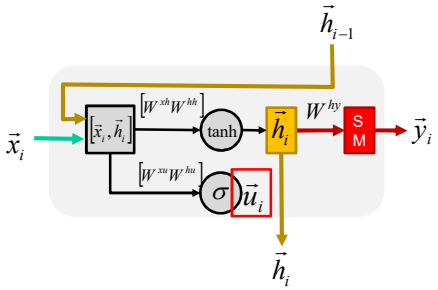
GRU (Gated Recurrent Unit)

Modif 2

Update gate

$$\sigma = \text{sigmoid}$$



$$\vec{u}_i = \sigma\left(W^{xu}\vec{x}_i + W^{hu}\vec{h}_{i-1}\right)$$
$$\vec{h}_i = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\vec{h}_{i-1}\right)$$
$$\hat{y}_i = W^{hy}\vec{h}_i$$
$$\vec{y}_i = SMAX\left(\hat{y}_i\right)$$

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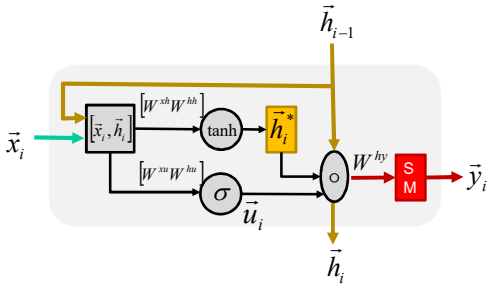
GRU (Gated Recurrent Unit)

Modif 2

Update gate



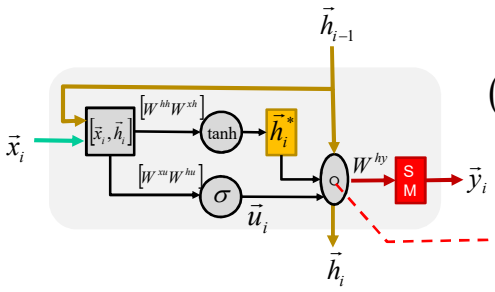
$$\vec{u}_i = \sigma\left(W^{xu}\vec{x}_i + W^{hu}\vec{h}_{i-1}\right)$$
$$\vec{h}_i^* = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\vec{h}_{i-1}\right)$$
$$\vec{h}_i = \vec{u}_i \circ \vec{h}_i^* + \left(1-\vec{u}_i\right)\circ \vec{h}_{i-1}$$
$$\hat{y}_i = W^{hy}\vec{h}_i$$
$$\vec{y}_i = SMAX\left(\hat{y}_i\right)$$

150

GRU (Gated Recurrent Unit)

Modif 2

« element-wise product »
ou
« Hadamard product »



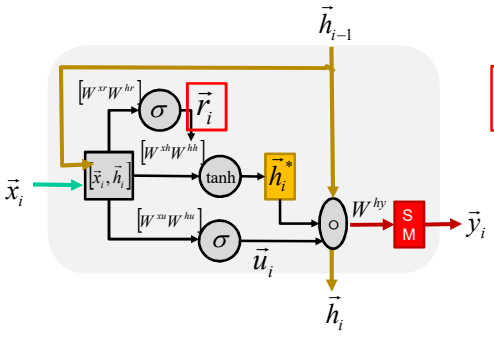
$$(a,b,c)\circ(x,y,z) = (ax, by, cz)$$

151

GRU (Gated Recurrent Unit)

Modif 3

Reset gate



$$\vec{u}_i = \sigma\left(W^{xu}\vec{x}_i + W^{hu}\vec{h}_{i-1}\right)$$

$$\vec{r}_i = \sigma\left(W^{xr}\vec{x}_i + W^{hr}\vec{h}_{i-1}\right)$$

$$\vec{h}_i^* = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\left(\vec{r}_i \circ \vec{h}_{i-1}\right)\right)$$

$$\vec{h}_i = \vec{u}_i \circ \vec{h}_i^* + \left(1 - \vec{u}_i\right) \circ \vec{h}_{i-1}$$

$$\hat{y}_i = W^{hy}\vec{h}_i$$

$$\vec{y}_i = SMAX\left(\hat{y}_i\right)$$

152

Comprendre les gates

$$SI \quad \begin{matrix} u_i & = 1 \\ r_i & = 1 \end{matrix} \Bigg\}$$

$$\vec{u}_i = \sigma\left(W^{xu}\vec{x}_i + W^{hu}\vec{h}_{i-1}\right)$$

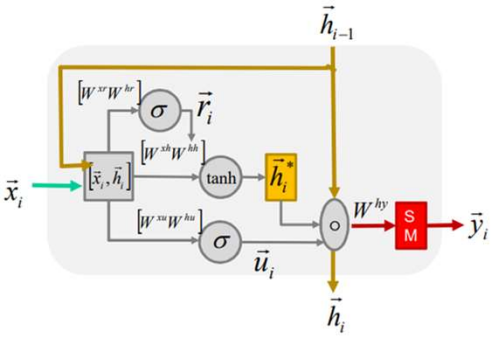
$$\vec{r}_i = \sigma\left(W^{xr}\vec{x}_i + W^{hr}\vec{h}_{i-1}\right)$$

$$\vec{h}_i^* = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\left(\vec{r}_i \circ \vec{h}_{i-1}\right)\right)$$

$$\vec{h}_i = \vec{u}_i \circ \vec{h}_i^* + \left(1 - \vec{u}_i\right) \circ \vec{h}_{i-1}$$

$$\hat{y}_i = W^{hy}\vec{h}_i$$

$$\vec{y}_i = SMAX\left(\hat{y}_i\right)$$

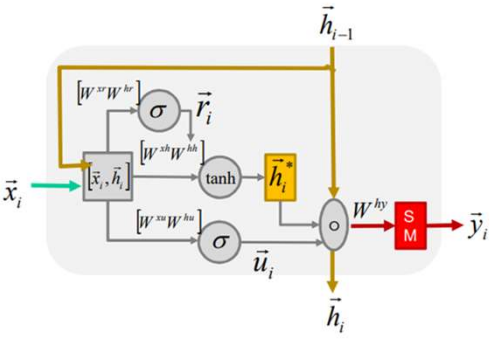


153

Comprendre les gates

SI $u_i = 1$, $r_i = 1$

$$\vec{u}_i = \sigma\left(W^{xu}\vec{x}_i + W^{hu}\vec{h}_{i-1}\right)$$
$$\vec{r}_i = \sigma\left(W^{xr}\vec{x}_i + W^{hr}\vec{h}_{i-1}\right)$$
$$\vec{h}_i^* = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\left(\vec{r}_i \circ \vec{h}_{i-1}\right)\right)$$
$$\vec{h}_i = \vec{u}_i \circ \vec{h}_i^* + (1 - \vec{u}_i) \circ \vec{h}_{i-1}$$
$$\hat{y}_i = W^{hy}\vec{h}_i$$
$$\vec{y}_i = SMAX\left(\hat{y}_i\right)$$

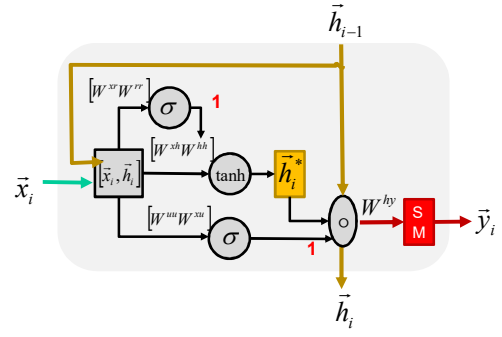


154

Comprendre les gates

SI $u_i = 1$, $r_i = 1$

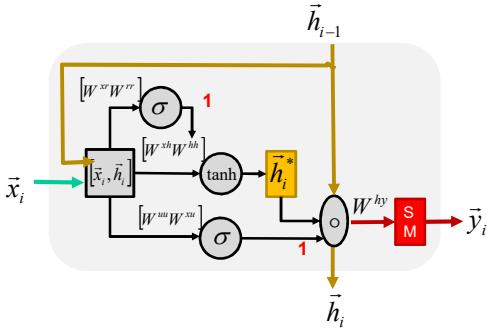
$$\vec{u}_i = \sigma\left(W^{xu}\vec{x}_i + W^{hu}\vec{h}_{i-1}\right)$$
$$\vec{r}_i = \sigma\left(W^{xr}\vec{x}_i + W^{hr}\vec{h}_{i-1}\right) \rightarrow 1$$
$$\vec{h}_i^* = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\left(\vec{r}_i \circ \vec{h}_{i-1}\right)\right)$$
$$\vec{h}_i = \vec{u}_i \circ \vec{h}_i^* + (1 - \vec{u}_i) \circ \vec{h}_{i-1}$$
$$\hat{y}_i = W^{hy}\vec{h}_i$$
$$\vec{y}_i = SMAX\left(\hat{y}_i\right)$$



155

Comprendre les gates

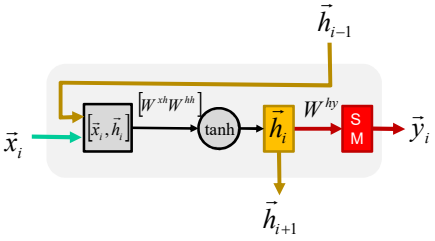
$$\textit{SI} \quad \begin{matrix} \vec{u}_i = 1 \\ \vec{r}_i = 1 \end{matrix} \Bigg\{ \begin{matrix} \vec{h}_i^{*} = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\vec{h}_{i-1}\right) \\ \vec{h}_i = \vec{h}_i^{*} \\ \hat{y}_i = W^{hy}\vec{h}_i \\ \vec{y}_i = SMAX\left(\hat{y}_i\right) \end{matrix}$$



156

Comprendre les gates

$$\textit{SI} \quad \begin{matrix} \vec{u}_i = 1 \\ \vec{r}_i = 1 \end{matrix} \Bigg\{ \begin{matrix} \vec{h}_i^{*} = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\vec{h}_{i-1}\right) \\ \vec{h}_i = \vec{h}_i^{*} \\ \hat{y}_i = W^{hy}\vec{h}_i \\ \vec{y}_i = SMAX\left(\hat{y}_i\right) \end{matrix}$$

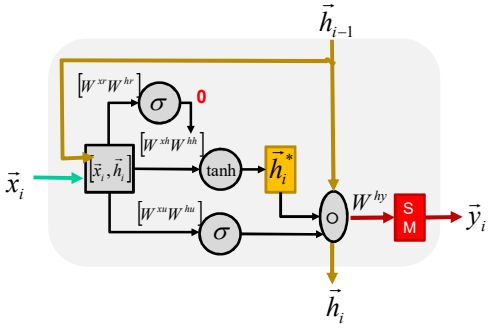


RNN de base!

157

SI $\vec{u}_i \neq 1$, $\vec{r}_i = 0$

$$\vec{u}_i = \sigma\left(W^{xu}\vec{x}_i + W^{hu}\vec{h}_{i-1}\right)$$
$$\vec{r}_i = \sigma\left(W^{xr}\vec{x}_i + W^{hr}\vec{h}_{i-1}\right)$$
$$\vec{h}_i^{*} = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\left[\vec{r}_i \circ \vec{h}_{i-1}\right]\right)$$
$$\vec{h}_i = \vec{u}_i \circ \vec{h}_i^{*} + (1-\vec{u}_i)\circ \vec{h}_{i-1}$$
$$\hat{y}_i = W^{hy}\vec{h}_i$$
$$\vec{y}_i = SMAX(\hat{y}_i)$$

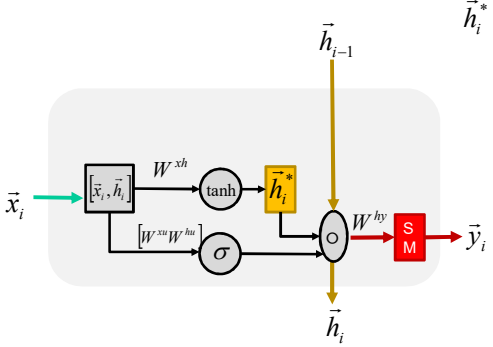


158

SI $\vec{u}_i \neq 1$, $\vec{r}_i = 0$

$$\vec{u}_i = \sigma\left(W^{xu}\vec{x}_i + W^{hu}\vec{h}_{i-1}\right)$$
$$\vec{h}_i^{*} = \tanh\left(W^{xh}\vec{x}_i\right)$$
$$\vec{h}_i = \vec{u}_i \circ \vec{h}_i^{*} + (1-\vec{u}_i)\circ \vec{h}_{i-1}$$
$$\hat{y}_i = W^{hy}\vec{h}_i$$
$$\vec{y}_i = SMAX(\hat{y}_i)$$

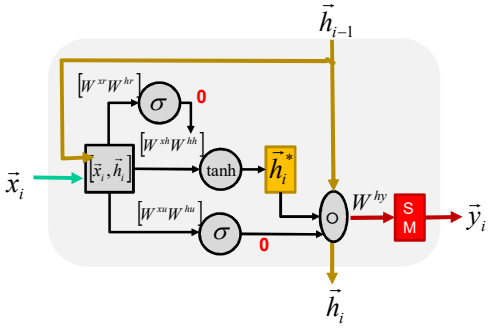
$\vec{h}_i^{*}$ **ne dépend que de** $\vec{x}_i$ **et non de** $\vec{h}_{i-1}$



159

SI $\vec{u}_i = 0$, $\vec{r}_i = 0$

$$\vec{u}_i = \sigma\left(W^{xu}\vec{x}_i + W^{hu}\vec{h}_{i-1}\right)$$
$$\vec{r}_i = \sigma\left(W^{xr}\vec{x}_i + W^{hr}\vec{h}_{i-1}\right)$$
$$\vec{h}_i^{*} = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\left(\vec{r}_i \circ \vec{h}_{i-1}\right)\right)$$
$$\vec{h}_i = \vec{u}_i \circ \vec{h}_i^{*} + \left(1 - \vec{u}_i\right) \circ \vec{h}_{i-1}$$
$$\hat{y}_i = W^{hy}\vec{h}_i$$
$$\vec{y}_i = SMAX\left(\hat{y}_i\right)$$



160

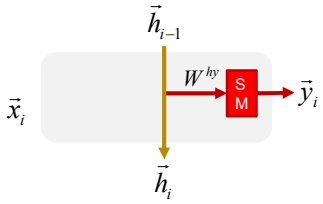
SI $\vec{u}_i = 0$, $\vec{r}_i = 0$

$$\vec{h}_i = \vec{h}_{i-1}$$
$$\hat{y}_i = W^{cy}\vec{h}_i$$
$$\vec{y}_i = SMAX\left(\hat{y}_i\right)$$

$\vec{h}_{i-1}$ **est recopié**

$\vec{x}_i$ **est ignoré**

Aucune disparition de gradient

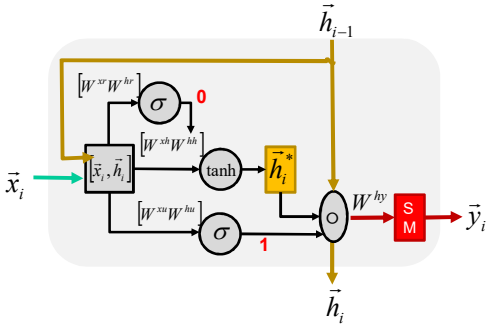


161

SI

$$\left.\begin{array}{l}\vec{u}_i = 1\\ \vec{r}_i = 0\end{array}\right\}$$

$$\vec{u}_i = \sigma\left(W^{xu}\vec{x}_i + W^{hu}\vec{h}_{i-1}\right)$$
$$\vec{r}_i = \sigma\left(W^{xr}\vec{x}_i + W^{hr}\vec{h}_{i-1}\right)$$
$$\vec{h}_i^{*} = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\left(\vec{r}_i \circ \vec{h}_{i-1}\right)\right)$$
$$\vec{h}_i = \vec{u}_i \circ \vec{h}_i^{*} + \left(1 - \vec{u}_i\right) \circ \vec{h}_{i-1}$$
$$\hat{y}_i = W^{hy}\vec{h}_i$$
$$\vec{y}_i = SMAX\left(\hat{y}_i\right)$$



162

SI

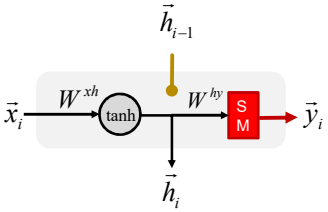
$$\left.\begin{array}{l}\vec{u}_i = 1\\ \vec{r}_i = 0\end{array}\right\}$$

$$\vec{h}_i = \tanh\left(W^{xh}\vec{x}_i\right)$$
$$\hat{y}_i = W^{hy}\vec{h}_i$$
$$\vec{y}_i = SMAX\left(\hat{y}_i\right)$$

$\vec{h}_{i-1}$ **est ignoté**

$\vec{x}_i$ **est le seul utilisé**

Gradient temporel bloqué



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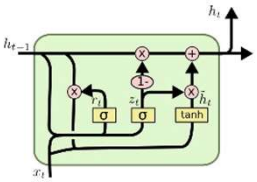
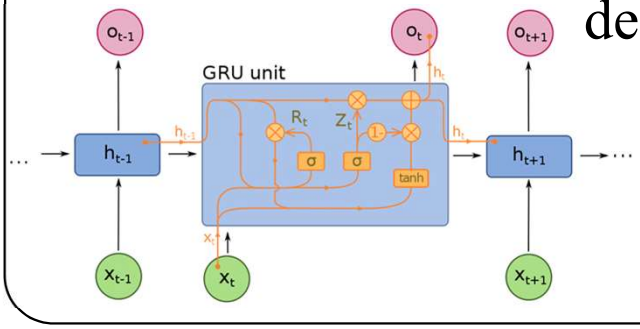
Gated Recurrent Unit (GRU)



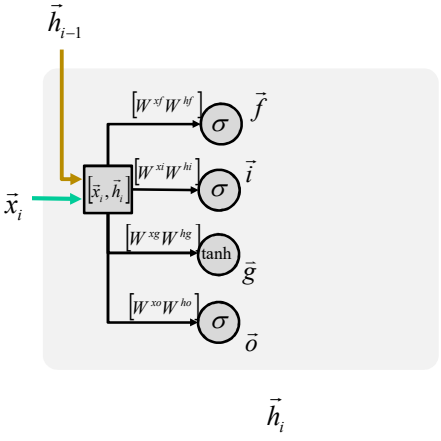
$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$
$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Figure: Cristopher Olah, "Understanding LSTM Networks" (2015) / Slide: Alberto Montes



Le web regorge d'illustrations de GRU!

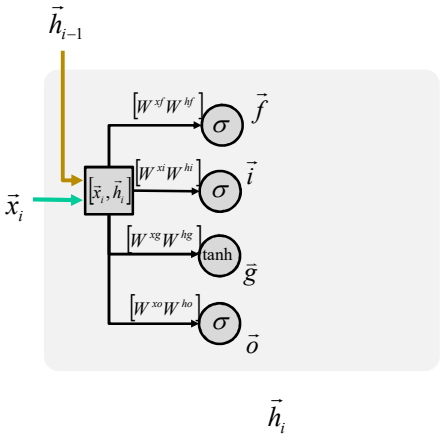
LSTM (Long Short Term Memory)



$\vec{f}$: forget gate
$\vec{i}$: input gate
$\vec{g}$: gate gate
$\vec{o}$: output gate

Hochreiter and Schmidhuber, "Long Short Term Memory", Neural Computation, 1997

LSTM (Long Short Term Memory)



$\vec{f}$: forget gate

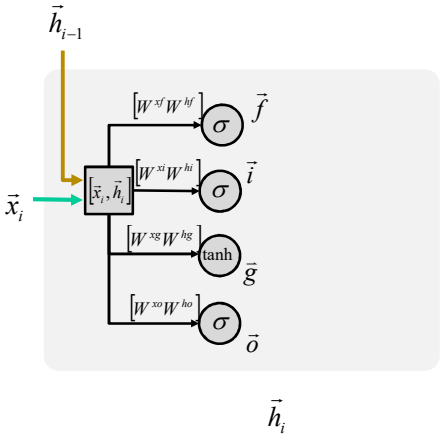
$\vec{i}$: input gate

$\vec{g}$: gate gate

Modèle récurrent le plus utilisé. À bien comprendre !

Hochreiter and Schmidhuber, "Long Short Term Memory", Neural Computation, 1997

LSTM (Long Short Term Memory)



$$\vec{f} = \sigma\left(W^{xf}\vec{x}_i + W^{hf}\vec{h}_{i-1}\right)$$
$$\vec{i} = \sigma\left(W^{xi}\vec{x}_i + W^{hi}\vec{h}_{i-1}\right)$$
$$\vec{g} = \tanh\left(W^{xg}\vec{x}_i + W^{hg}\vec{h}_{i-1}\right)$$
$$\vec{o} = \sigma\left(W^{xo}\vec{x}_i + W^{ho}\vec{h}_{i-1}\right)$$

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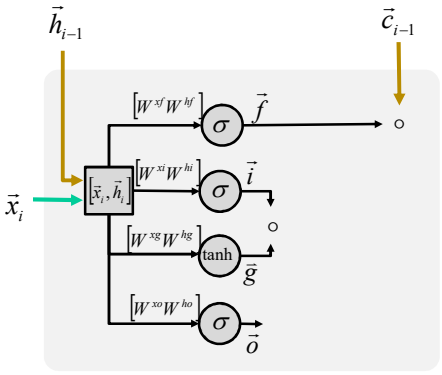
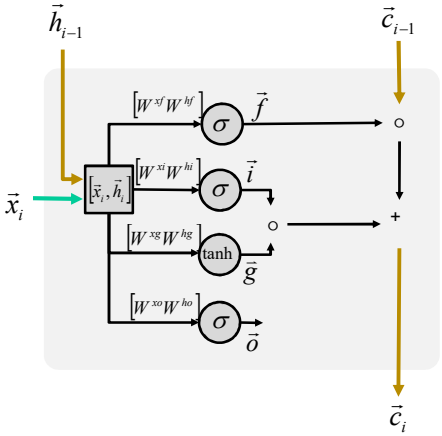
LSTM (Long Short Term Memory)



$\vec{f} \circ \vec{c}_i$

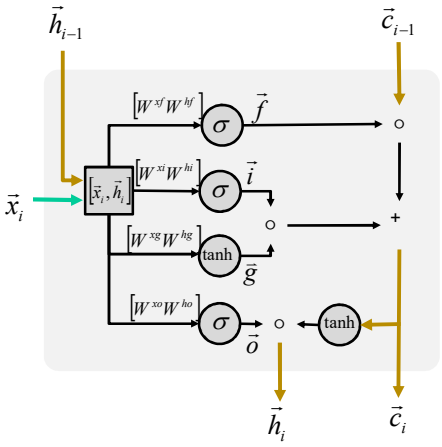
$\vec{i} \circ \vec{g}$

LSTM (Long Short Term Memory)



$$\vec{c}_i = \vec{f} \circ \vec{c}_i + \vec{i} \circ \vec{g}$$

LSTM (Long Short Term Memory)



$$\vec{c}_i = \vec{f} \circ \vec{c}_i + \vec{i} \circ \vec{g}$$
$$\vec{h}_i = \vec{o} \circ \tanh(\vec{c}_i)$$

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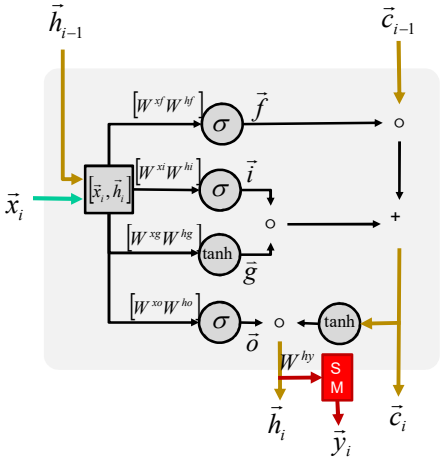
LSTM (Long Short Term Memory)



$$\vec{c}_i = \vec{f} \circ \vec{c}_i + \vec{i} \circ \vec{g}$$
$$\vec{h}_i = \vec{o} \circ \tanh(\vec{c}_i)$$
$$\vec{y}_i = SMAX(W^{hy} \vec{h}_i)$$

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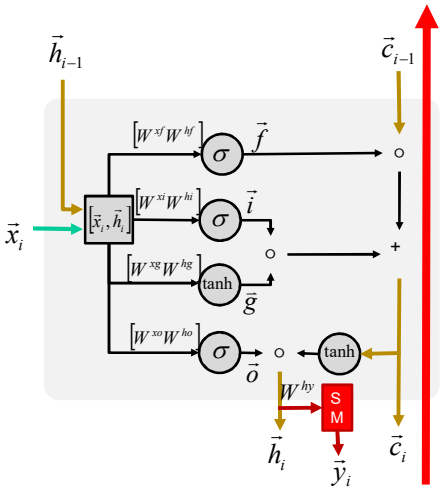
LSTM (Long Short Term Memory)



Gradient simplifié

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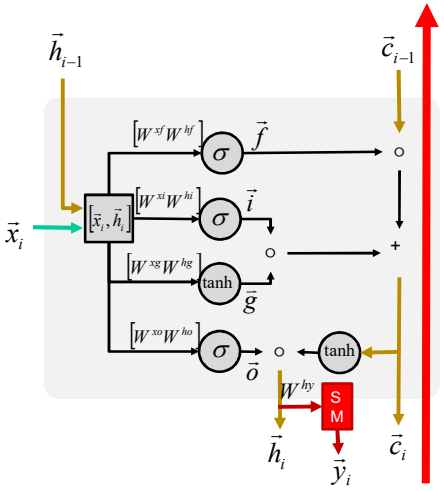
LSTM (Long Short Term Memory)



Gradient simplifié

Ça vous rappelle quelque chose ?
Le Resnet !

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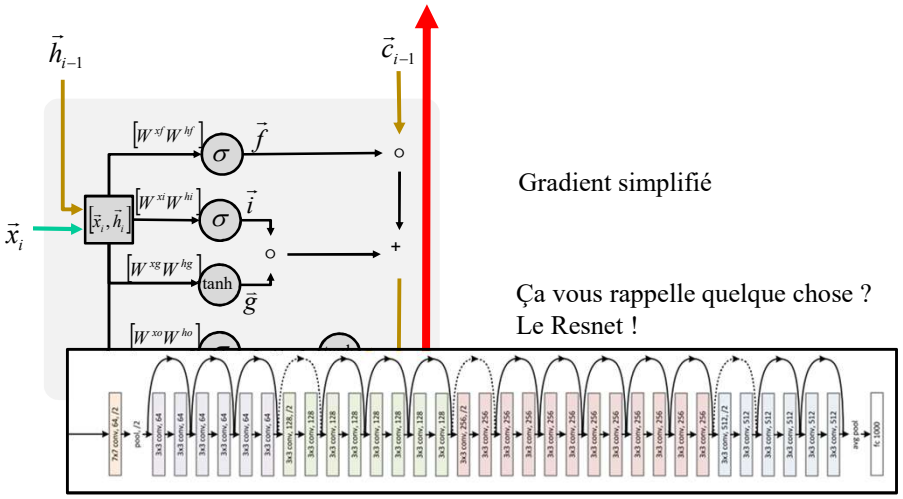
LSTM (Long Short Term Memory)

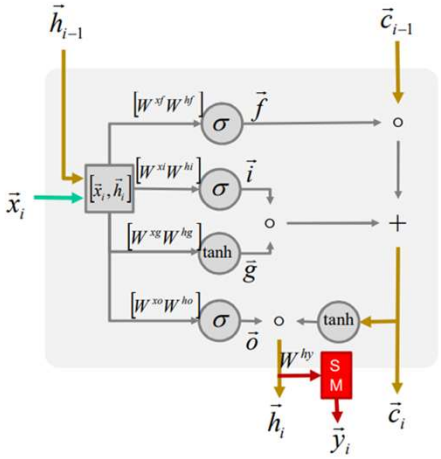


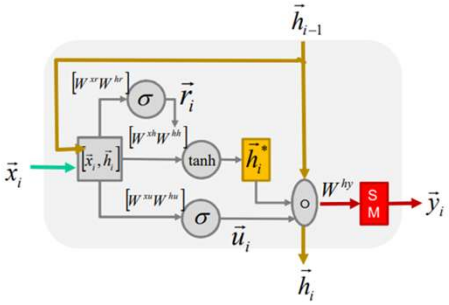
Gradient simplifié

Ça vous rappelle quelque chose ?
Le Resnet !

ResNET

LSTM et GRU





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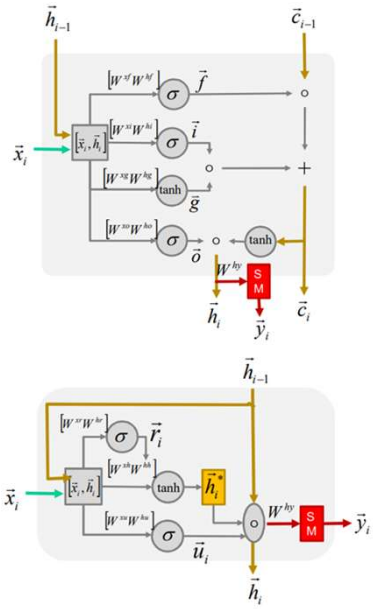
LSTM et GRU

- Servent à protéger le gradient
- Conçus empiriquement
- GRU légèrement plus simple
- Les “gates” ne servent qu’à bloquer ou permettre à l’information (données ou temporelle) de passer



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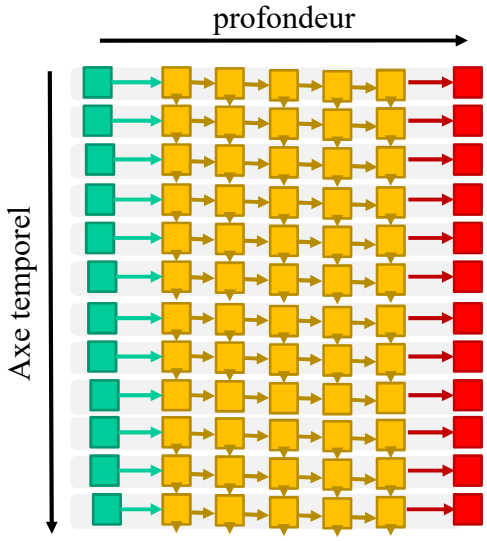
RNN multi-couches



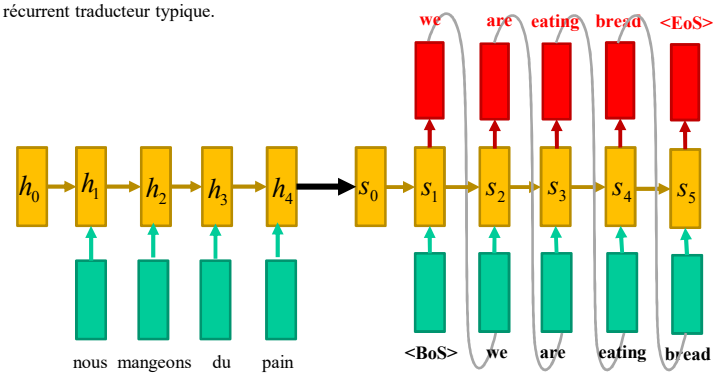
Modèles d'attention

Seq2Seq:

Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to sequence learning with neural networks. *Advances in neural information processing systems*, *27*.

'**nous mangeons du pain**' -> '**we are eating bread**'

Réseau récurrent traducteur typique.



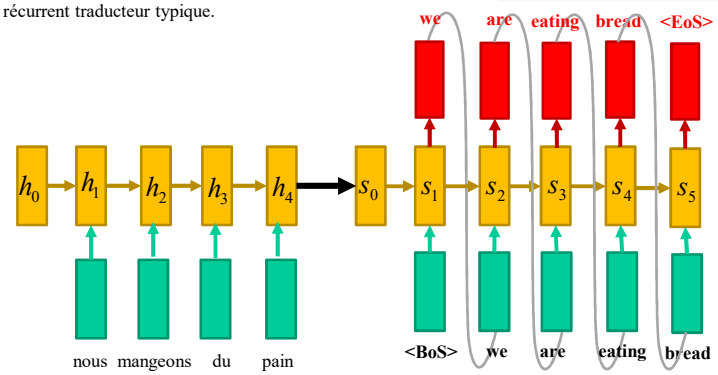
Seq2Seq:

Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to sequence learning with neural networks. *Advances in neural information processing systems*, 27.

'nous mangeons du pain' -> 'we are eating bread'

Problème avec cette formulation ?

Réseau récurrent traducteur typique.



Seq2Seq:

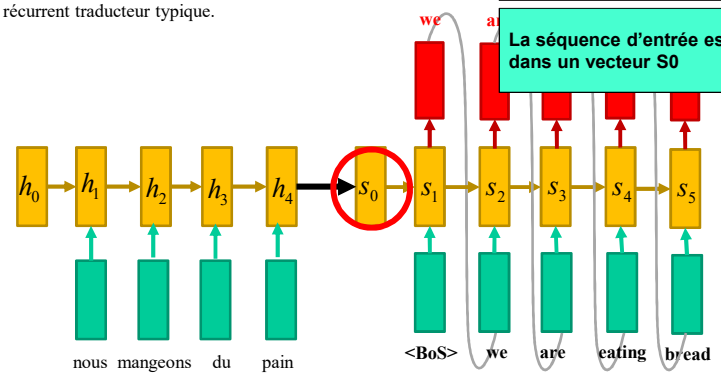
Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to sequence learning with neural networks. *Advances in neural information processing systems*, 27.

'nous mangeons du pain' -> 'we are eating bread'

Problème avec cette formulation ?

La séquence d'entrée est résumée dans un vecteur S0

Réseau récurrent traducteur typique.



Seq2Seq:

Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to sequence learning with neural networks. *Advances in neural information processing systems*, 27.

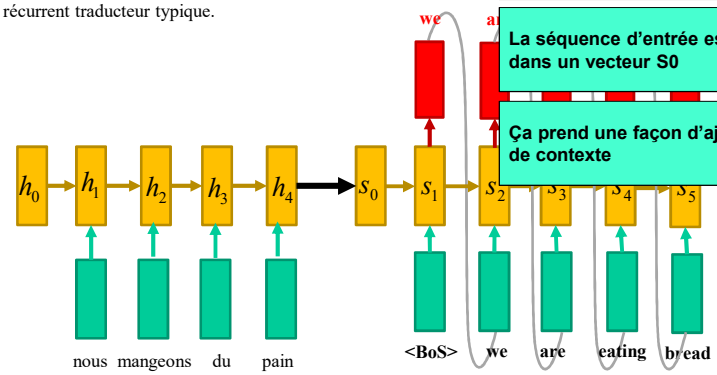
'nous mangeons du pain' -> 'we are eating bread'

Réseau récurrent traducteur typique.

Problème avec cette formulation ?

La séquence d'entrée est résumée dans un vecteur S0

Ça prend une façon d'ajouter plus de contexte

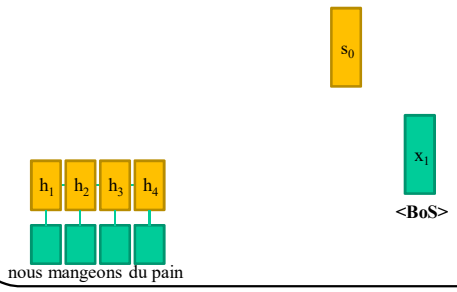


Seq2Seq avec attention

(version simplifiée)

Bahdanau, D., Cho, K., & Bengio, Y. (2014). Neural machine translation by jointly learning to align and translate. arXiv preprint arXiv:1409.0473.

$$\vec{h}_i = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\vec{h}_{i-1}\right) \quad \in R^D$$

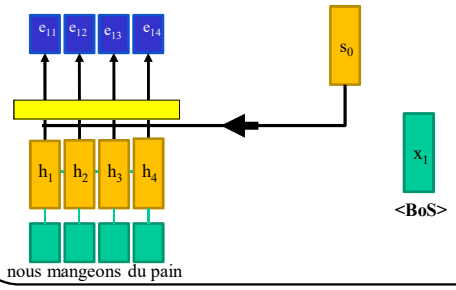


s_0 = init value

Seq2Seq avec attention
(version simplifiée)

$$\vec{h}_i = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\vec{h}_{i-1}\right) \quad \in R^D$$

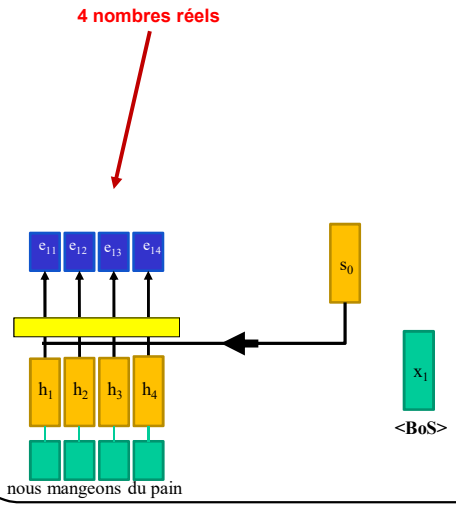
$$e_{1i} = \vec{w}^{saT}\vec{s}_0 + \vec{w}^{haT}\vec{h}_i \quad \in R$$



Seq2Seq avec attention
(version simplifiée)

$$\vec{h}_i = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\vec{h}_{i-1}\right) \quad \in R^D$$

$$e_{1i} = \vec{w}^{saT}\vec{s}_0 + \vec{w}^{haT}\vec{h}_i \quad \in R$$

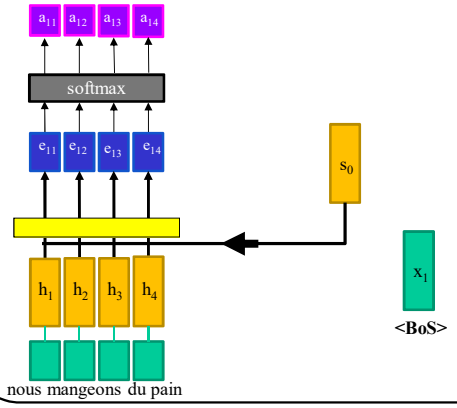


Seq2Seq avec attention
(version simplifiée)

$$\vec{h}_i = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\vec{h}_{i-1}\right) \quad \in R^D$$

$$e_{1i} = \vec{w}^{saT}\vec{s}_0 + \vec{w}^{haT}\vec{h}_i$$

$$a_{1i} = \frac{\exp(e_{1i})}{\sum_{t=1}^{4}\exp(e_{1t})}$$



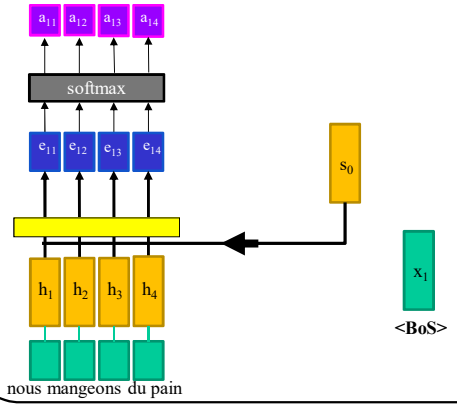
Seq2Seq avec attention
(version simplifiée)

$$\vec{h}_i = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\vec{h}_{i-1}\right) \quad \in R^D$$

$$e_{1i} = \vec{w}^{saT}\vec{s}_0 + \vec{w}^{haT}\vec{h}_i$$

$$a_{1i} = \frac{\exp(e_{1i})}{\sum_{t=1}^{4}\exp(e_{1t})}$$

4 nombres réels
dont la somme est 1



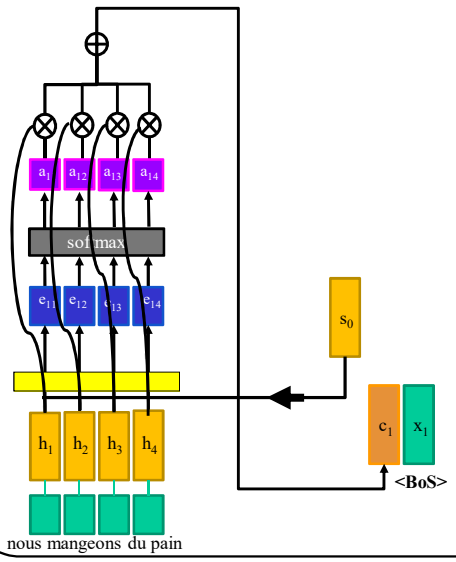
Seq2Seq avec attention
(version simplifiée)

$$\vec{h}_i = \tanh\left(W^{xh}\vec{x}_i + W^{hh}\vec{h}_{i-1}\right) \quad \in R^D$$

$$e_{1i} = \vec{w}^{sa\,T}\vec{s}_0 + \vec{w}^{ha\,T}\vec{h}_i$$

$$a_{1i} = \frac{\exp(e_{1i})}{\sum_{t=1}^{4}\exp(e_{1t})}$$

$$\vec{c}_1 = \sum_{t=1}^{4} a_{1t}\vec{h}_t$$



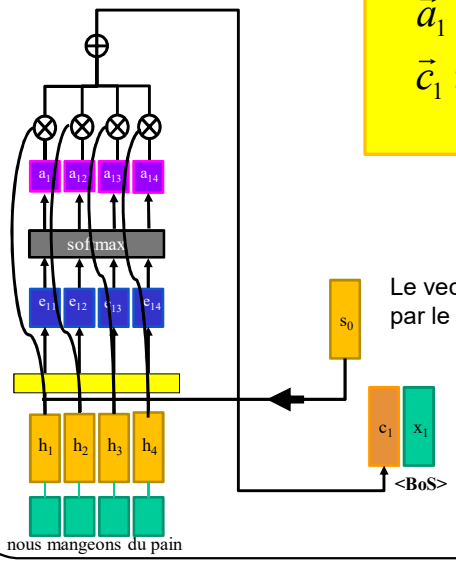
Seq2Seq avec attention
(version simplifiée)

$\vec{a}_1$: vecteur d'attention

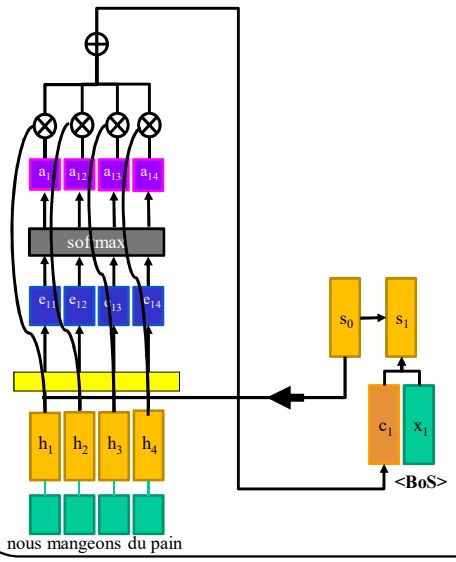
$\vec{c}_1$: vecteur de context

$$\vec{c}_1 = \sum_{t=1}^{4} a_{1t}\vec{h}_t$$

Le vecteur de contexte est la somme pondérée par le vecteur d'attention des représentations hi



Seq2Seq avec attention
(version simplifiée)



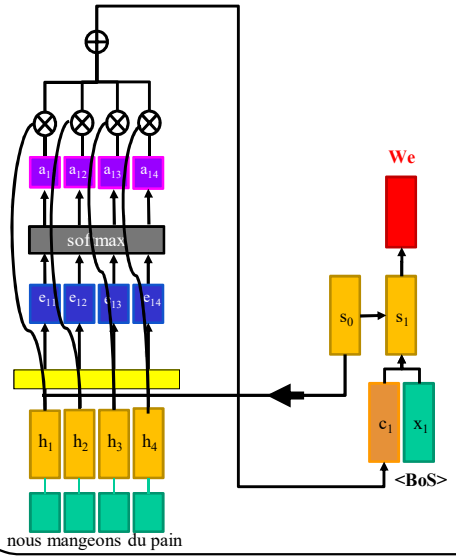
$$e_{1i} = \vec{w}^{sa^T}\vec{s}_0 + \vec{w}^{ha^T}\vec{h}_i$$

$$a_{1i} = \frac{\exp(e_{1i})}{\sum_{t=1}^{4}\exp(e_{1t})}$$

$$\vec{c}_1 = \sum_{t=1}^{4} a_{1t}\vec{h}_t$$

$$s_1 = \tanh\left(W^{ss}\vec{s}_0 + W^{cs}\vec{c}_1 + W^{xs}\vec{x}_1\right)$$

Seq2Seq avec attention
(version simplifiée)



$$e_{1i} = \vec{w}^{sa^T}\vec{s}_0 + \vec{w}^{ha^T}\vec{h}_i$$

$$a_{1i} = \frac{\exp(e_{1i})}{\sum_{t=1}^{4}\exp(e_{1t})}$$

$$\vec{c}_1 = \sum_{t=1}^{4} a_{1t}\vec{h}_t$$

$$s_1 = \tanh\left(W^{ss}\vec{s}_0 + W^{cs}\vec{c}_1 + W^{xs}\vec{x}_1\right)$$

$$y_1 = \text{softmax}\left(W^{sy}\vec{s}_1\right)$$

Seq2Seq avec attention
(version simplifiée)

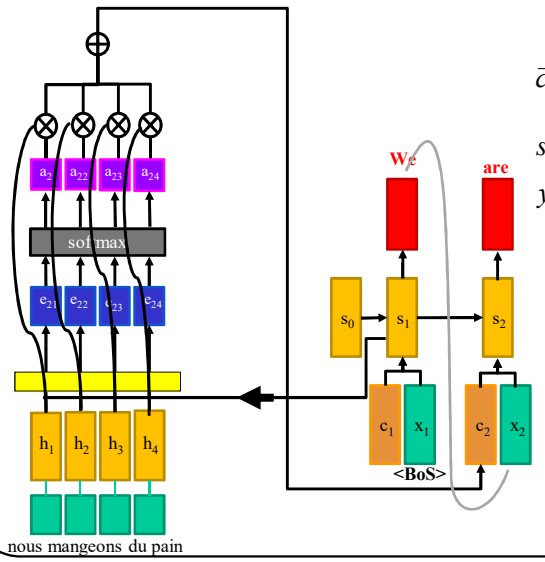
$$e_{2i} = \vec{w}^{sa\,T}\vec{s}_1 + \vec{w}^{ha\,T}\vec{h}_i$$

$$a_{2i} = \frac{\exp(e_{2i})}{\sum_{t=1}^{4}\exp(e_{2t})}$$

$$\vec{c}_2 = \sum_{t=1}^{4} a_{2t}\vec{h}_t$$

$$s_2 = \tanh\left(W^{ss}\vec{s}_1 + W^{cs}\vec{c}_2 + W^{xs}\vec{x}_2\right)$$

$$y_2 = \text{softmax}\left(W^{sy}\vec{s}_2\right)$$



Seq2Seq avec attention
(version simplifiée)

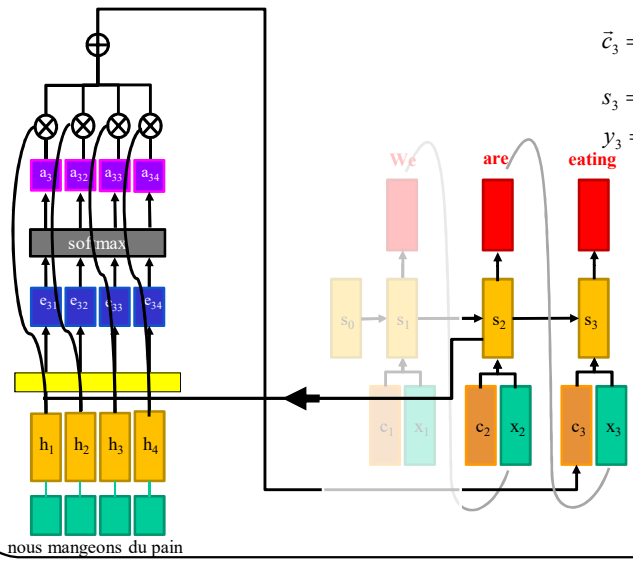
$$e_{3i} = \vec{w}^{sa\,T}\vec{s}_2 + \vec{w}^{ha\,T}\vec{h}_i$$

$$a_{3i} = \frac{\exp(e_{3i})}{\sum_{t=1}^{4}\exp(e_{3t})}$$

$$\vec{c}_3 = \sum_{t=1}^{4} a_{3t}\vec{h}_t$$

$$s_3 = \tanh\left(W^{ss}\vec{s}_2 + W^{cs}\vec{c}_3 + W^{xs}\vec{x}_3\right)$$

$$y_3 = \text{softmax}\left(W^{sy}\vec{s}_3\right)$$



Seq2Seq avec attention
(version simplifiée)

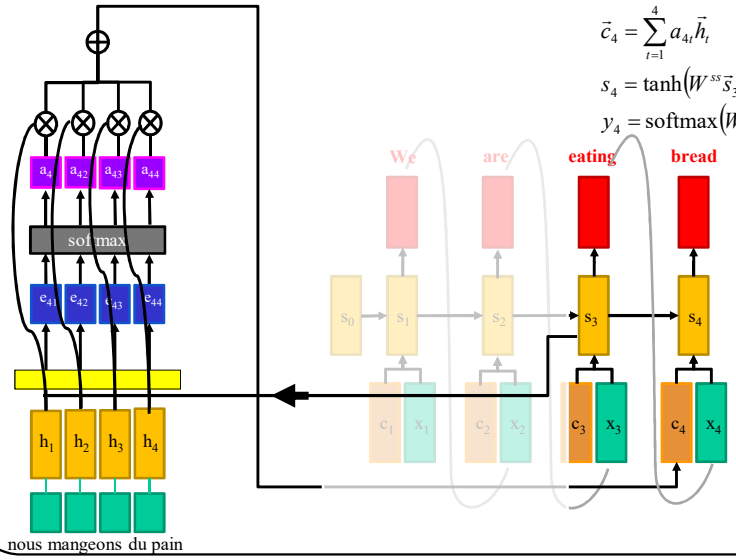
$$e_{4i} = \vec{w}^{sa\,T}\vec{s}_3 + \vec{w}^{ha\,T}\vec{h}_i$$

$$a_{4i} = \frac{\exp(e_{4i})}{\sum_{t=1}^{4}\exp(e_{4t})}$$

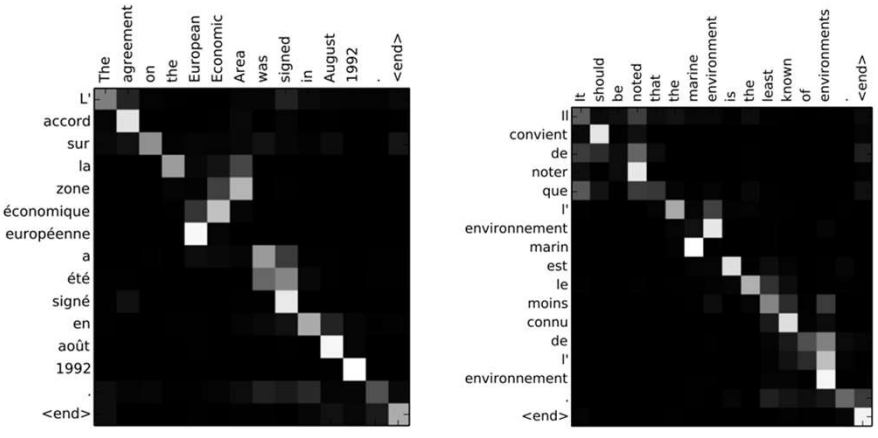
$$\vec{c}_4 = \sum_{t=1}^{4} a_{4t}\vec{h}_t$$

$$s_4 = \tanh\left(W^{ss}\vec{s}_3 + W^{cs}\vec{c}_4 + W^{xs}\vec{x}_4\right)$$

$$y_4 = \mathrm{softmax}\left(W^{sy}\vec{s}_4\right)$$

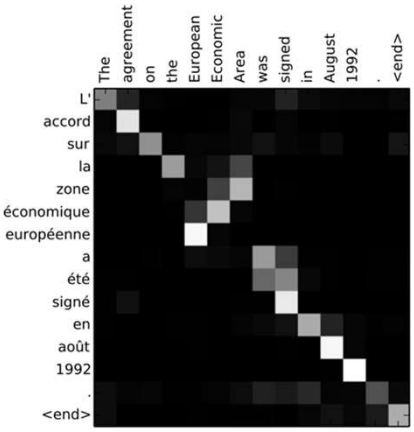


Un vecteur d'attention pour chaque mot

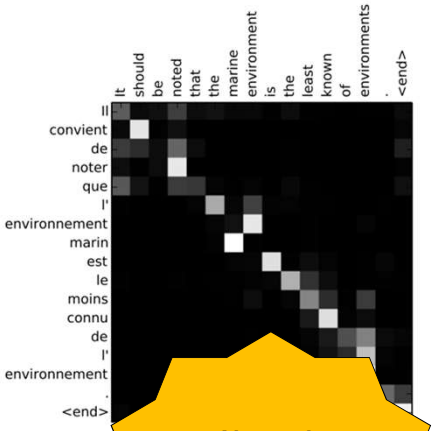


Bahdanau, D., Cho, K., & Bengio, Y. (2014). Neural machine translation by jointly learning to align and translate. arXiv preprint arXiv:1409.0473.

Seq2Seq avec attention



(a)

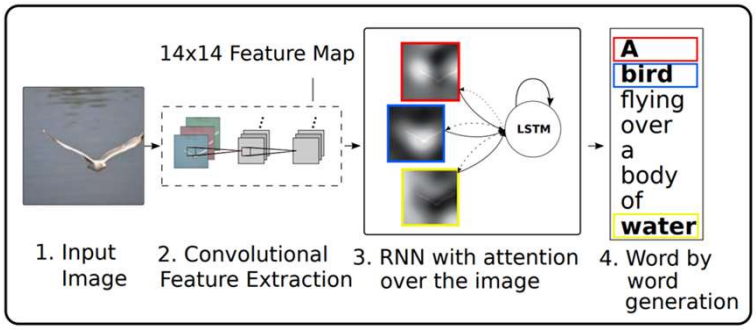


Ajoute de l'interprétabilité au modèle !

Bahdanau, D., Cho, K., & Bengio, Y. (2014). Neural machine translation by jointly learning arXiv:1409.0473.

Modèles d'attention pour la description d'images

Réseau récurrent pour du captioning capable de « concentrer son attention » sur les zones de l'image associés aux mots.



Xu, K., Ba, J., Kiros, R., Cho, K., Courville, A., Salakhudinov, R., ... & Bengio, Y. (2015, June). Show, attend and tell: Neural image caption generation with visual attention. In International conference on machine learning (pp. 2048-2057). PMLR.

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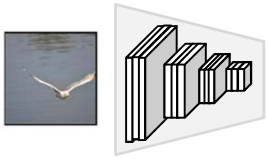
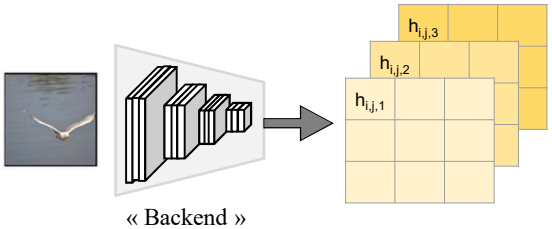
Modèles d'attention pour la description d'images

(version simplifiée)

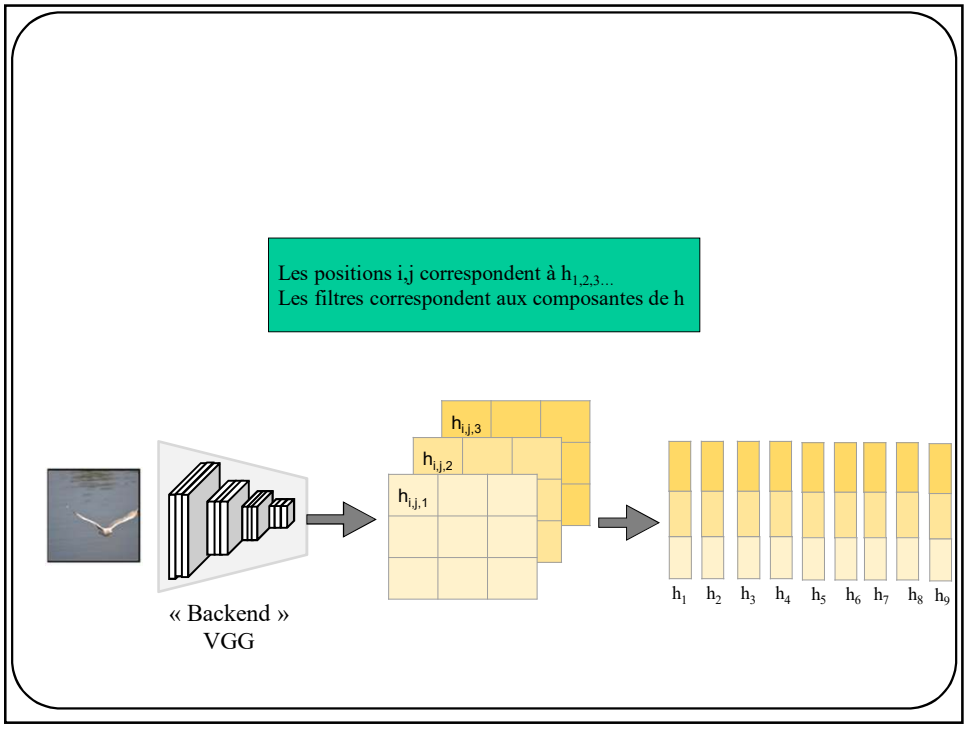


« Backend »
VGG

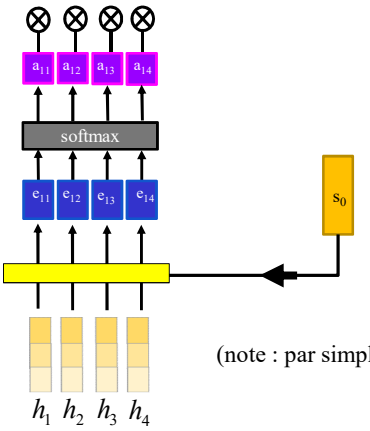
198



« Backend »
VGG

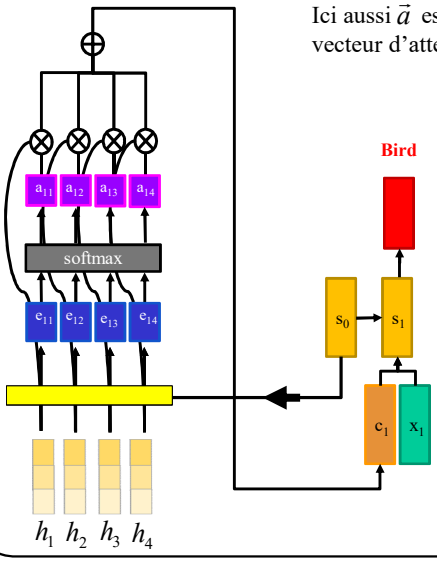


Seq2Seq avec attention
(version simplifiée)



(note : par simplicité, nous avons mis que 4 vecteurs latents)

Seq2Seq avec attention
(version simplifiée)



$$e_{1i} = \vec{w}^{sa^T}\vec{s}_0 + \vec{w}^{ha^T}\vec{h}_i$$

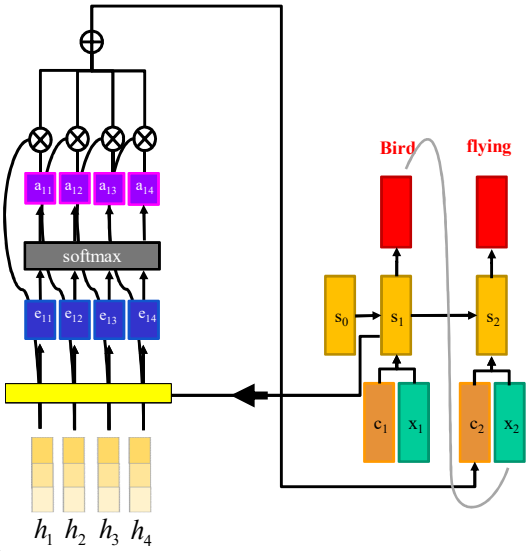
$$a_{1i} = \frac{\exp(e_{1i})}{\sum_{t=1}^{4}\exp(e_{1t})}$$

$$\vec{c}_1 = \sum_{t=1}^{4} a_{1t}\vec{h}_t$$

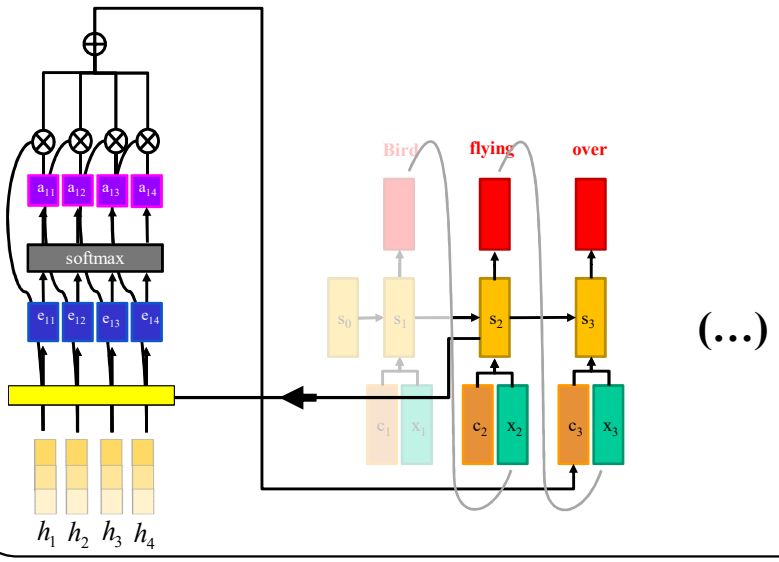
$$s_1 = \tanh\left(W^{ss}\vec{s}_0 + W^{cs}\vec{c}_1 + W^{xs}\vec{x}_1\right)$$

$$y_1 = \text{softmax}\left(W^{sy}\vec{s}_1\right)$$

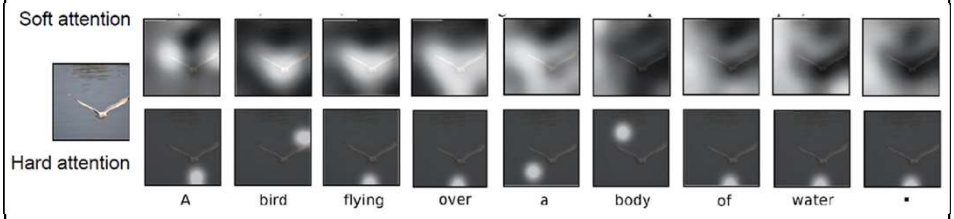
Seq2Seq avec attention
(version simplifiée)



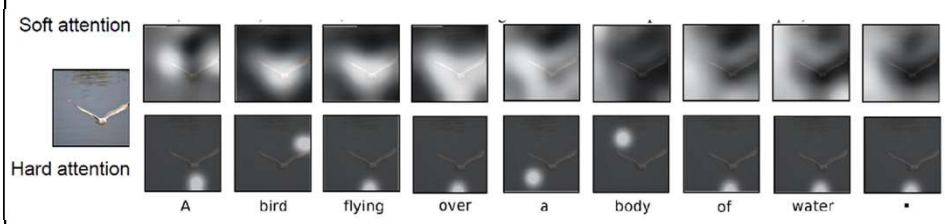
Seq2Seq avec attention
(version simplifiée)



Cartes d'attention superposées à l'image d'entrée



Kelvin Xu, Jimmy Lei Ba, Jamie Kiros, Kyunghyun Cho, Aaron Courville, Ruslan Salakhutdinov, Richard S. Zemel, and Yoshua Benchio "Show, Attend, and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015



Attention portée initialement sur l'oiseau, puis autour de l'oiseau

Kelvin Xu, Jimmy Lei Ba, Jamie Kiros, Kyunghyun Cho, Aaron Courville, Ruslan Salakhutdinov, Richard S. Zemel, and Yoshua Benchio "Show, Attend, and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Kelvin Xu, Jimmy Lei Ba, Jamie Kiros, Kyunghyun Cho, Aaron Courville, Ruslan Salakhutdinov, Richard S. Zemel, and Yoshua Bengio "Show, Attend, and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

L'auto-attention
(self attention)

Revenons à la base : **multiplication matricielle**

Considérons les 4 matrices suivantes

$$X = \begin{pmatrix} x_{11} & x_{12} & x_{13} & x_{14} \\ x_{21} & x_{22} & x_{23} & x_{24} \\ x_{31} & x_{32} & x_{33} & x_{34} \end{pmatrix} \in R^{3x4}$$

$$W^q = \begin{pmatrix} W^q{}_{11} & W^q{}_{12} & W^q{}_{13} \\ W^q{}_{21} & W^q{}_{22} & W^q{}_{23} \\ W^q{}_{31} & W^q{}_{32} & W^q{}_{33} \end{pmatrix} \in R^{3x3}$$

$$W^k = \begin{pmatrix} W^k{}_{11} & W^k{}_{12} & W^k{}_{13} \\ W^k{}_{21} & W^k{}_{22} & W^k{}_{23} \\ W^k{}_{31} & W^k{}_{32} & W^k{}_{33} \end{pmatrix} \in R^{3x3}$$

$$W^V = \begin{pmatrix} W^V{}_{11} & W^V{}_{12} & W^V{}_{13} \\ W^V{}_{21} & W^V{}_{22} & W^V{}_{23} \end{pmatrix} \in R^{2x3}$$

Revenons à la base : **multiplication matricielle**

$$X = \begin{pmatrix} x_{11} & x_{12} & x_{13} & x_{14} \\ x_{21} & x_{22} & x_{23} & x_{24} \\ x_{31} & x_{32} & x_{33} & x_{34} \end{pmatrix} \in R^{3x4}$$

$$W^q = \begin{pmatrix} W^q{}_{11} & W^q{}_{12} & W^q{}_{13} \\ W^q{}_{21} & W^q{}_{22} & W^q{}_{23} \\ W^q{}_{31} & W^q{}_{32} & W^q{}_{33} \end{pmatrix} \in R^{3x3}$$

$$W^k = \begin{pmatrix} W^k{}_{11} & W^k{}_{12} & W^k{}_{13} \\ W^k{}_{21} & W^k{}_{22} & W^k{}_{23} \\ W^k{}_{31} & W^k{}_{32} & W^k{}_{33} \end{pmatrix} \in R^{3x3}$$

$$W^V = \begin{pmatrix} W^V{}_{11} & W^V{}_{12} & W^V{}_{13} \\ W^V{}_{21} & W^V{}_{22} & W^V{}_{23} \end{pmatrix} \in R^{2x3}$$

Leur multiplication donne:

$$W^q X = Q = \begin{pmatrix} Q_{11} & Q_{12} & Q_{13} & Q_{14} \\ Q_{21} & Q_{22} & Q_{23} & Q_{24} \\ Q_{31} & Q_{32} & Q_{33} & Q_{34} \end{pmatrix} \in R^{3x4}$$

$$W^K X = K = \begin{pmatrix} K^x{}_{11} & K^x{}_{12} & K^x{}_{13} & K^x{}_{14} \\ K^x{}_{21} & K^x{}_{22} & K^x{}_{23} & K^x{}_{24} \\ K^x{}_{31} & K^x{}_{32} & K^x{}_{33} & K^x{}_{34} \end{pmatrix} \in R^{3x4}$$

$$W^V X = V = \begin{pmatrix} V^x_{11} & V^x_{12} & V^x_{13} & V^x_{14} \\ V^x_{21} & V^x_{22} & V^x_{23} & V^x_{24} \end{pmatrix} \in R^{2x4}$$

210

Auto attention

X est une matrice de données pour laquelle chaque colonne *i* correspond à un vecteur en entrée $\vec{x}_i$

$$X = \begin{pmatrix} x_{11} & x_{12} & x_{13} & x_{14} \\ x_{21} & x_{22} & x_{23} & x_{24} \\ x_{31} & x_{32} & x_{33} & x_{34} \end{pmatrix} \in R^{3x4}$$

Nous mangeons du pain

Dans cet exemple, 4 mots en entrée donc 4 colonnes dans X
Les vecteurs 3D peuvent être obtenus par **Word2Vec**

211

Auto attention

$$X = \begin{pmatrix} x_{11} & x_{12} & x_{13} & x_{14} \\ x_{21} & x_{22} & x_{23} & x_{24} \\ x_{31} & x_{32} & x_{33} & x_{34} \end{pmatrix} \in R^{3x4}$$

Nous mangeons du pain

$$W^q = \begin{pmatrix} W^q_{11} & W^q_{12} & W^q_{13} \\ W^q_{21} & W^q_{22} & W^q_{23} \\ W^q_{31} & W^q_{32} & W^q_{33} \end{pmatrix} \in R^{3x3}$$

$$W^k = \begin{pmatrix} W^k_{11} & W^k_{12} & W^k_{13} \\ W^k_{21} & W^k_{22} & W^k_{23} \\ W^k_{31} & W^k_{32} & W^k_{33} \end{pmatrix} \in R^{3x3}$$

$$W^V = \begin{pmatrix} W^V_{11} & W^V_{12} & W^V_{13} \\ W^V_{21} & W^V_{22} & W^V_{23} \end{pmatrix} \in R^{2x3}$$

W : Matrices de paramètres appris par **rétropropagation**

212

Auto attention

$$X = \begin{pmatrix} x_{11} & x_{12} & x_{13} & x_{14} \\ x_{21} & x_{22} & x_{23} & x_{24} \\ x_{31} & x_{32} & x_{33} & x_{34} \end{pmatrix} \in R^{3x4}$$

Nous mangeons du pain

$$W^q = \begin{pmatrix} W^q_{11} & W^q_{12} & W^q_{13} \\ W^q_{21} & W^q_{22} & W^q_{23} \\ W^q_{31} & W^q_{32} & W^q_{33} \end{pmatrix} \in R^{3x3}$$

$$W^k = \begin{pmatrix} W^k_{11} & W^k_{12} & W^k_{13} \\ W^k_{21} & W^k_{22} & W^k_{23} \\ W^k_{31} & W^k_{32} & W^k_{33} \end{pmatrix} \in R^{3x3}$$

$$W^V = \begin{pmatrix} W^V_{11} & W^V_{12} & W^V_{13} \\ W^V_{21} & W^V_{22} & W^V_{23} \end{pmatrix} \in R^{2x3}$$

Matrices de paramètres appris par rétropropagation

Pour ces 3 matrices, le nombre de colonnes (3) doit être égale au nombre de lignes dans X (3)

213

Auto attention

$$X = \begin{pmatrix} x_{11} & x_{12} & x_{13} & x_{14} \\ x_{21} & x_{22} & x_{23} & x_{24} \\ x_{31} & x_{32} & x_{33} & x_{34} \end{pmatrix} \in R^{3x4}$$

Nous mangeons du pain

$$W^q = \begin{pmatrix} W^q_{11} & W^q_{12} & W^q_{13} \\ W^q_{21} & W^q_{22} & W^q_{23} \\ W^q_{31} & W^q_{32} & W^q_{33} \end{pmatrix} \in R^{3x3}$$

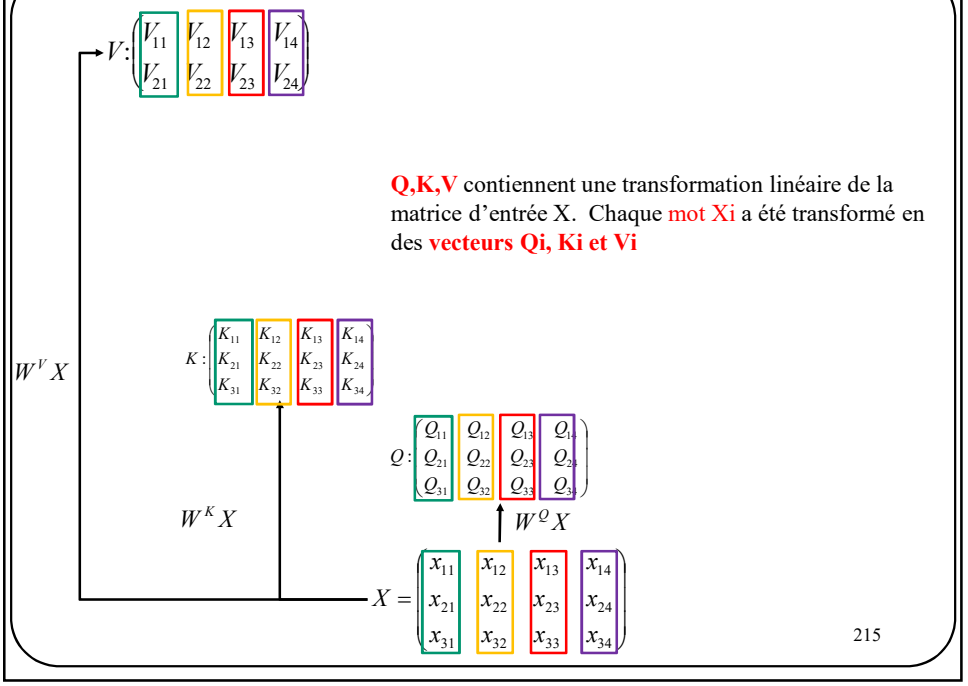
$$W^k = \begin{pmatrix} W^k_{11} & W^k_{12} & W^k_{13} \\ W^k_{21} & W^k_{22} & W^k_{23} \\ W^k_{31} & W^k_{32} & W^k_{33} \end{pmatrix} \in R^{3x3}$$

$$W^V = \begin{pmatrix} W^V_{11} & W^V_{12} & W^V_{13} \\ W^V_{21} & W^V_{22} & W^V_{23} \end{pmatrix} \in R^{2x3}$$

Matrices de paramètres appris par rétropropagation

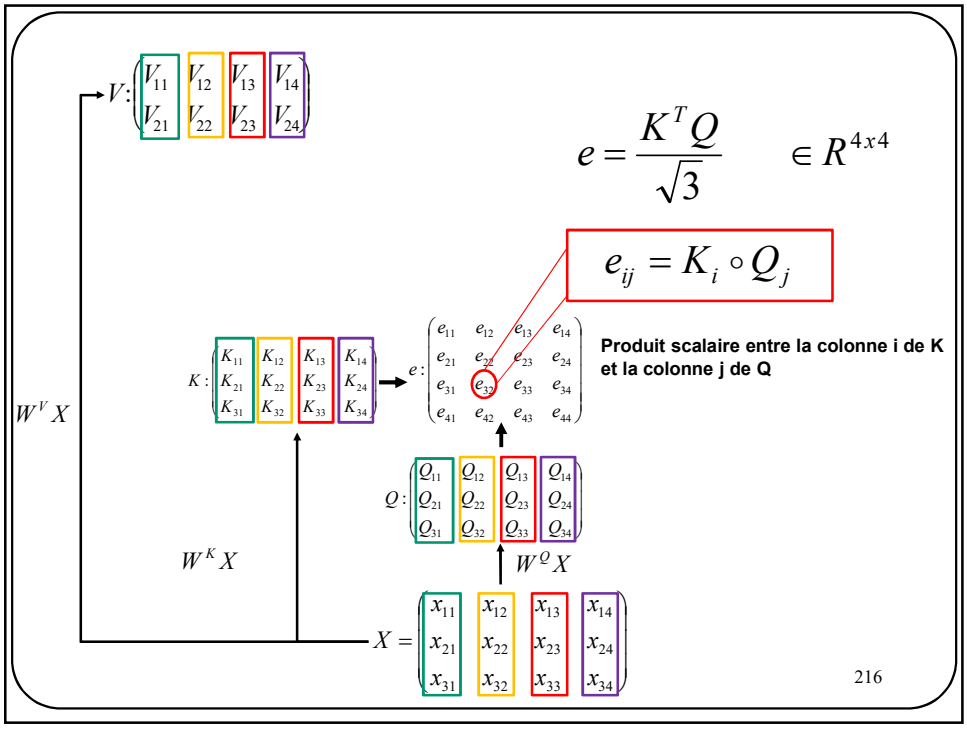
Pour ces 3 matrices, le nombre de ligne (3,3,2) est arbitraire

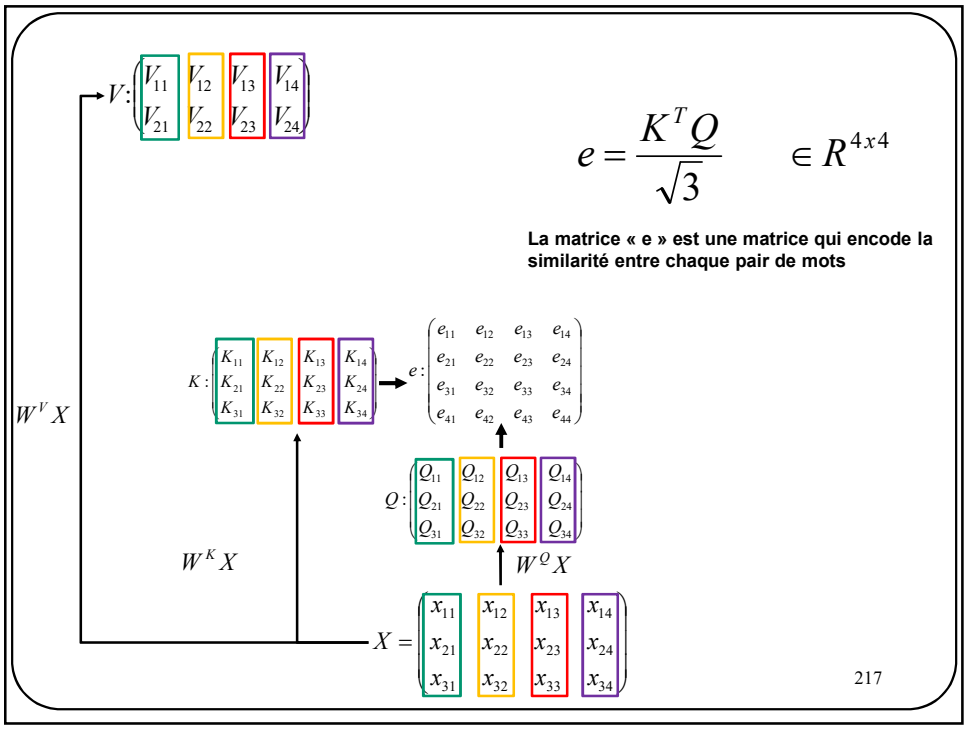
214

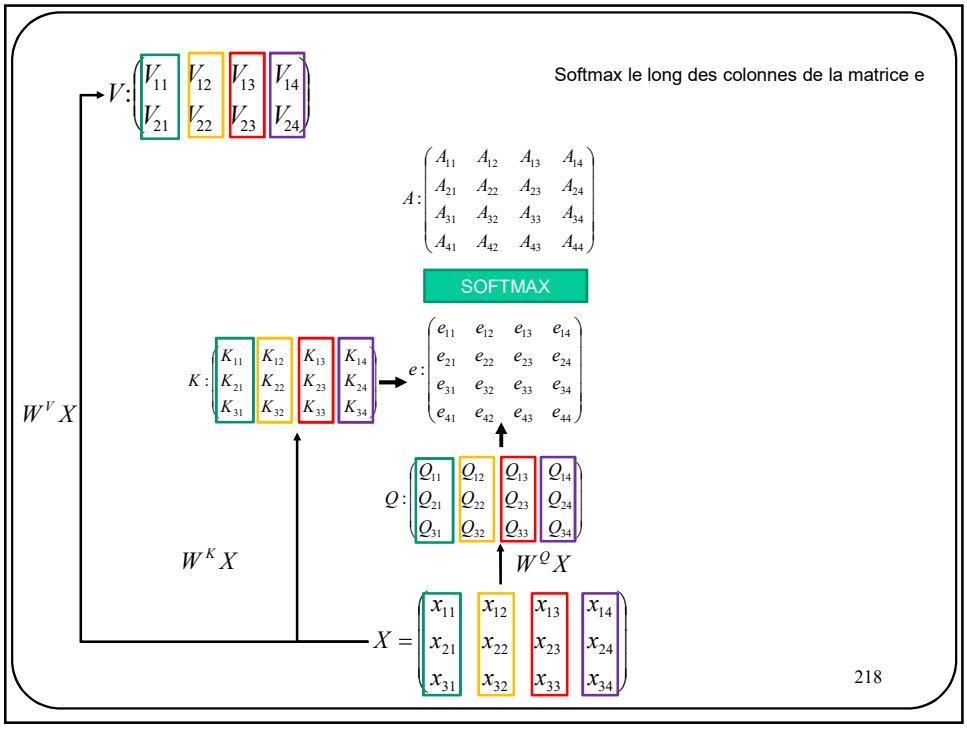


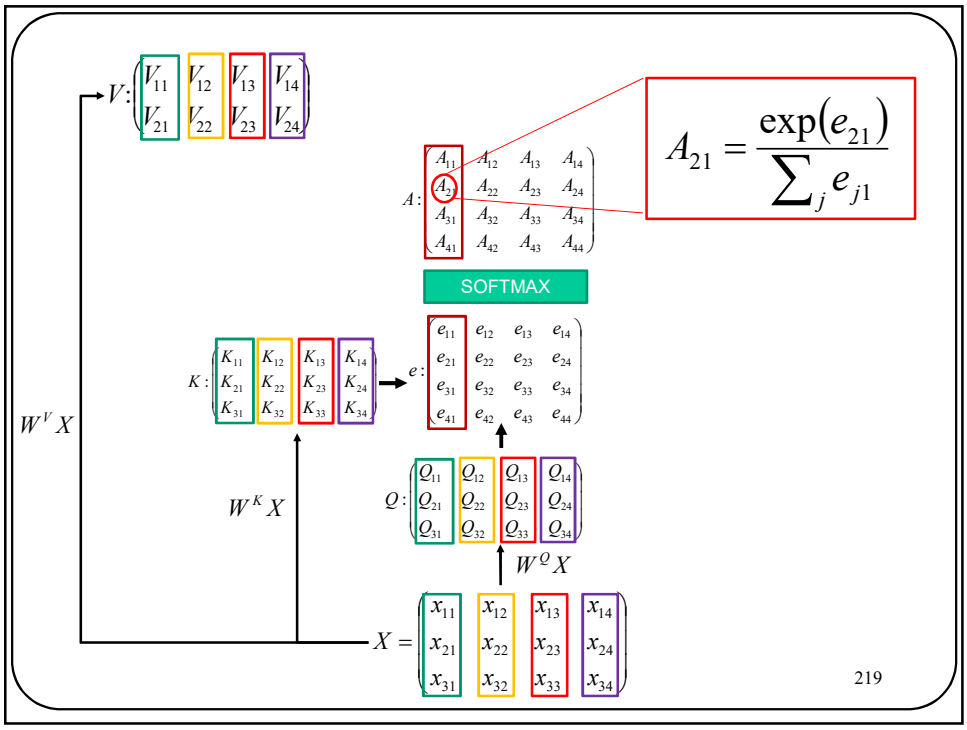
Q,K,V contiennent une transformation linéaire de la matrice d'entrée X. Chaque mot Xi a été transformé en des **vecteurs Qi, Ki et Vi**

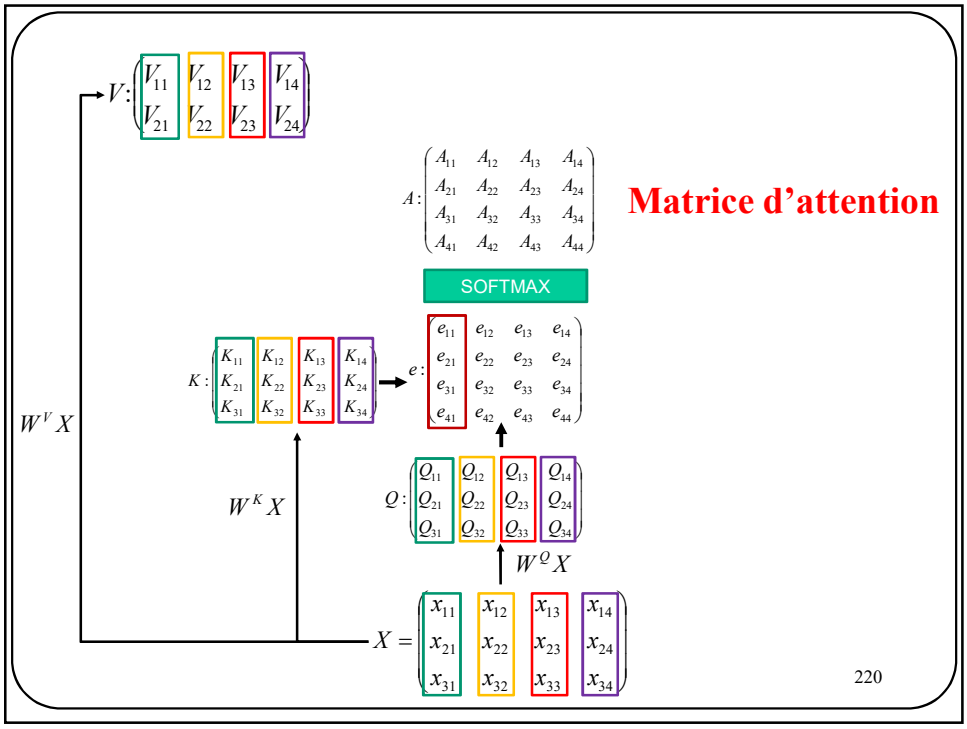
215

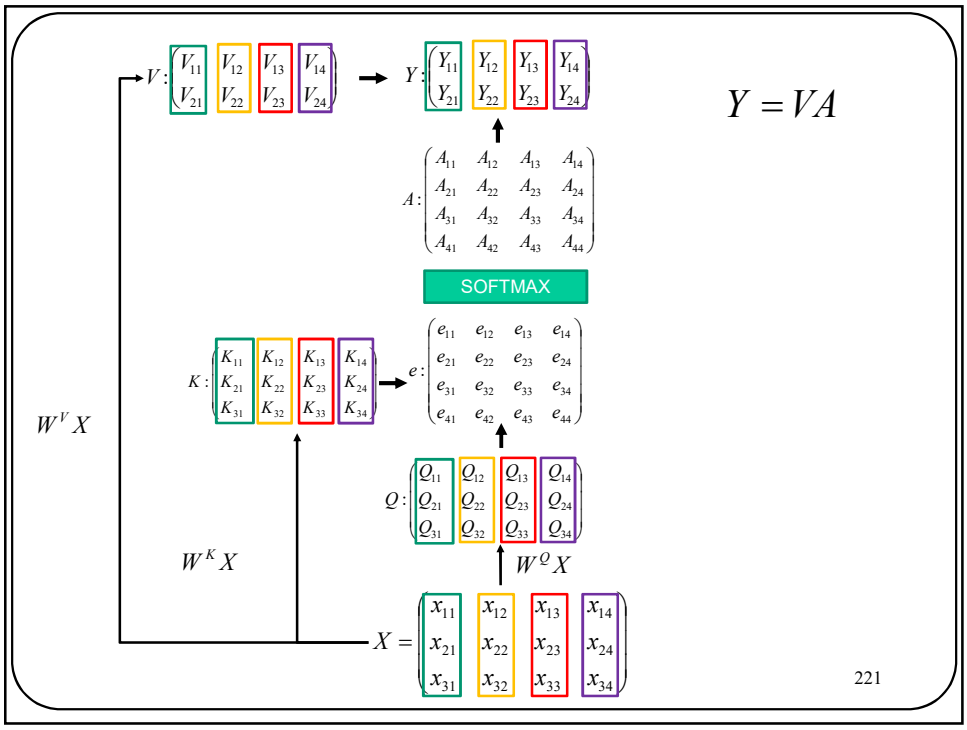

$e = \frac{K^T Q}{\sqrt{3}} \quad \in R^{4x4}$
$e_{ij} = K_i \circ Q_j$
Produit scalaire entre la colonne i de K et la colonne j de Q
V:
K:
e:
Q:
$W^V X$
$W^K X$
$W^Q X$
$X =$
216


$e = \frac{K^T Q}{\sqrt{3}} \quad \in R^{4x4}$
La matrice « e » est une matrice qui encode la similarité entre chaque pair de mots
V:
K:
e:
Q:
$W^V X$
$W^K X$
$W^Q X$
$X =$
217

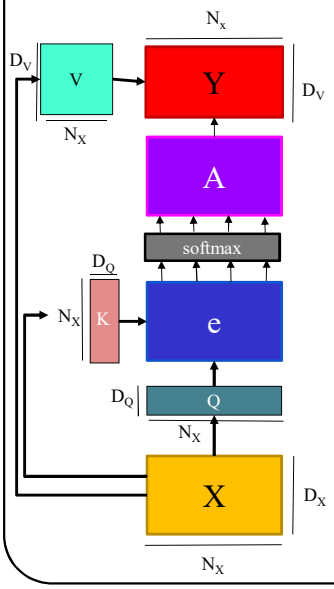

Softmax le long des colonnes de la matrice e
SOFTMAX
218


SOFTMAX
219


V:
A:
Matrice d'attention
SOFTMAX
K:
e:
W^V X
W^K X
Q:
W^Q X
X =
220


V:
Y:
Y = VA
A:
SOFTMAX
K:
e:
W^V X
W^K X
Q:
W^Q X
X =
221

Couche d'auto-attention *(Self-attention layer)*



X données
Query: que chercher dans nos données
Key: la "clé" des données
Value: la "valeur" des données
Entries: le "contenu" des données
Attention: la pertinence des entrées

$$Q = W^Q X$$
$$K = W^K X$$
$$V = W^V X$$
$$e = \frac{K^T Q}{\sqrt{D_Q}}$$
$$A_{ji} = \frac{\exp(e_{ji})}{\sum_j e_{ji}}$$
$$Y = VA$$

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

Autre façon d'illustrer la couche d'auto-attention

$$Attention(Q, K, V) = V \cdot \text{softmax}\left(\frac{K^T Q}{\sqrt{D_Q}}\right)$$

X

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

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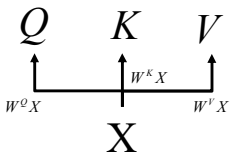

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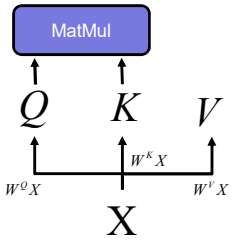
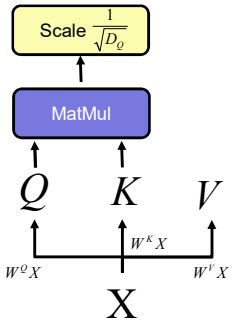


Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

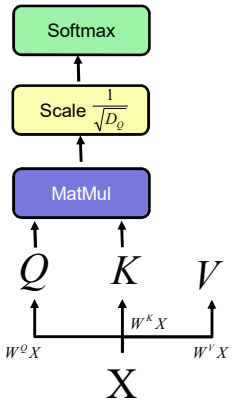
Autre façon d'illustrer la couche d'auto-attention



$$Attention(Q,K,V) = V \cdot \text{softmax}\left(\frac{K^T Q}{\sqrt{D_Q}}\right)$$

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

Autre façon d'illustrer la couche d'auto-attention



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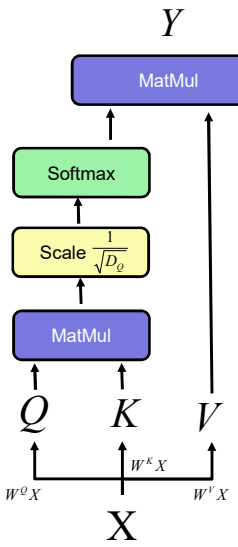
Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

Autre façon d'illustrer la couche d'auto-attention

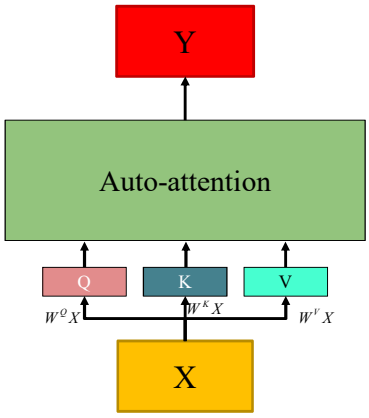


$$Attention(Q,K,V) = V \cdot \text{softmax}\left(\frac{K^T Q}{\sqrt{D_Q}}\right)$$

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

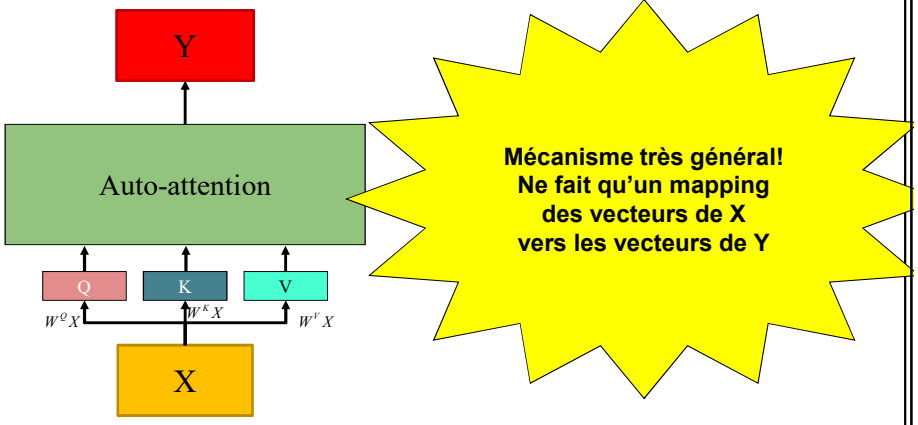
Couche d'auto-attention *(Self-attention layer)*

Autre représentation schématique



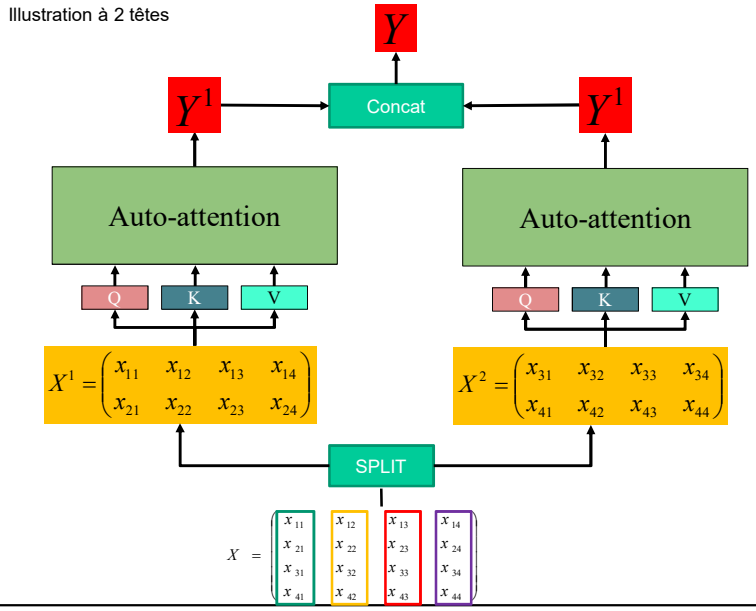
Couche d'auto-attention *(Self-attention layer)*

Autre représentation schématique



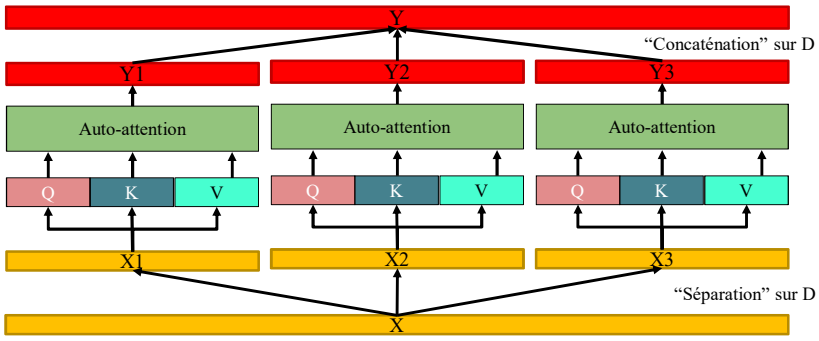
Auto-attention multi-têtes *(Multi-head Self-attention)*

Illustration à 2 têtes



231

Auto-attention multi-tête *(Multi-head Self-attention)*



Très bon résumé de l'auto-attention multi-tête :

https://towardsdatascience.com/transformers-explained-visually-part-3-multi-head-attention-deep-dive-1c1ff1024853

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

L'apothéose des réseaux de neurones

Transformer

(Attention is all you need)

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

Transformer

Implique ***aucune notion de récurrence***

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

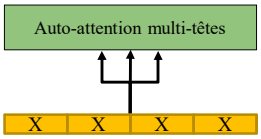
Transformer (Attention is all you need)

X	X	X	X

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

Transformer (Attention is all you need)

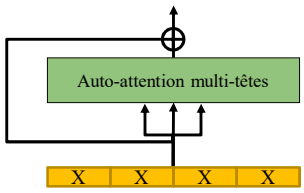
- Auto-attention multi-têtes sur les dimensions de X



Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

Transformer (Attention is all you need)

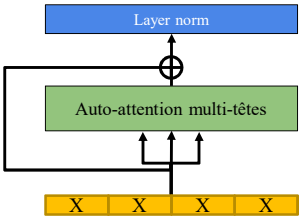
- Auto-attention multi-têtes sur les dimensions de X
- "+ " = connexion résiduelle



Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

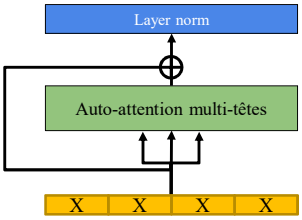
Transformer (Attention is all you need)

- Auto-attention multi-têtes sur les dimensions de X
- "+ " = connexion résiduelle
- "Layer-norm"

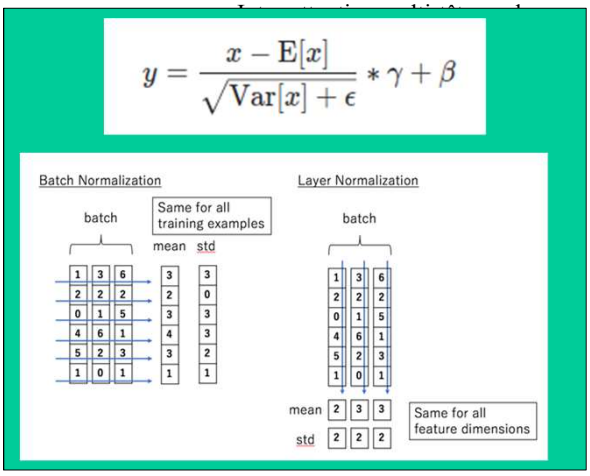


Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

Transformer (Attention is all you need)



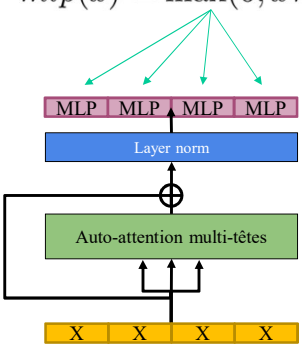
$$y = \frac{x - \mathrm{E}[x]}{\sqrt{\mathrm{Var}[x] + \epsilon}} * \gamma + \beta$$



Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

Transformer (Attention is all you need)

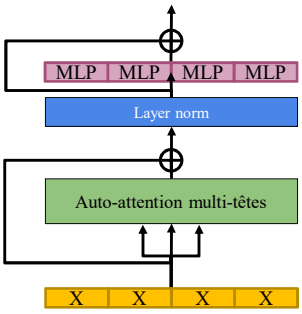
$$mlp(x) = \max(0, xW^1)W^2$$



- Auto-attention multi-têtes sur les dimensions de X
- "+ " = connexion résiduelle
- "Layer-norm"
- MLP par entrée

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

Transformer (Attention is all you need)

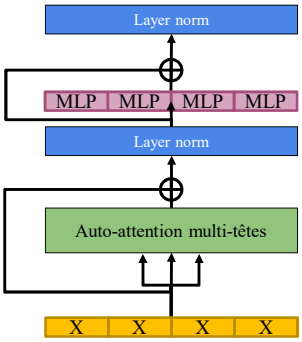


- Intra-attention multi-tête sur les dimensions de X
- "+ " = connexion résiduelle
- "Layer-norm"
- MLP par entrée

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

Transformer (Attention is all you need)

- Auto-attention multi-têtes sur les dimensions de X
- "+ " = connexion résiduelle
- "Layer-norm"
- MLP par entrée



Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

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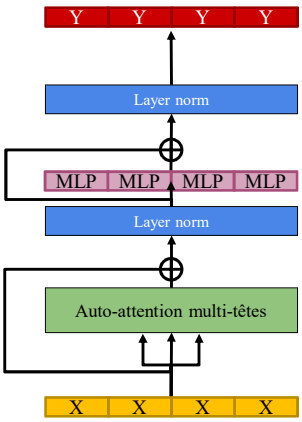

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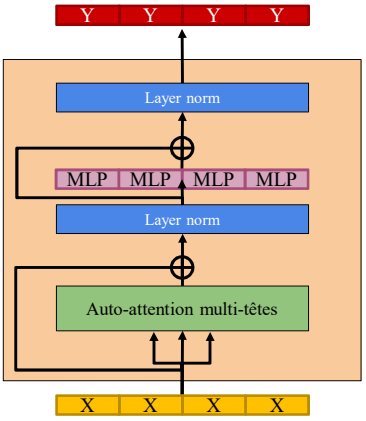
Transformer (Attention is all you need)



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- "Layer-norm"
- MLP par entrée

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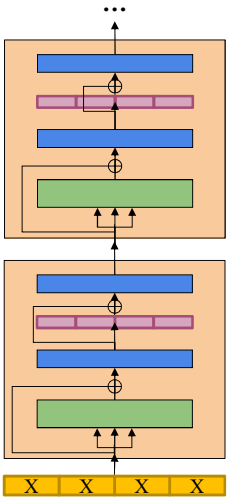
Transformer (Attention is all you need)



x6

- Intra-attention multi-tête sur les dimensions de X
- "+ " = connexion résiduelle
- "Layer-norm"
- MLP par entrée

Le bloc est répété 6 fois pour l'encodeur

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

Transformer (Attention is all you need)

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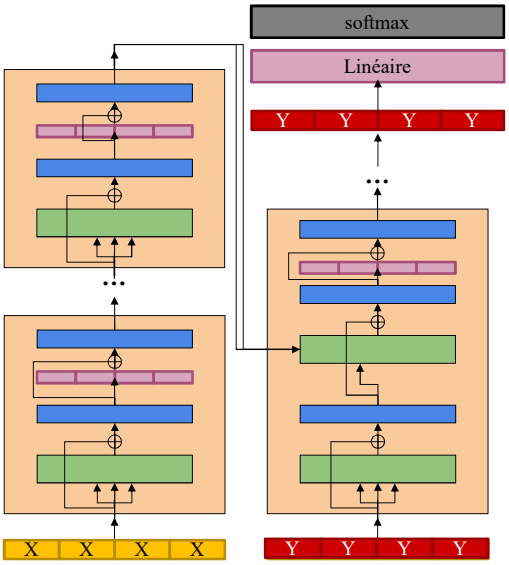

- Intra-attention multi-tête sur les dimensions de X
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- MLP par entrée

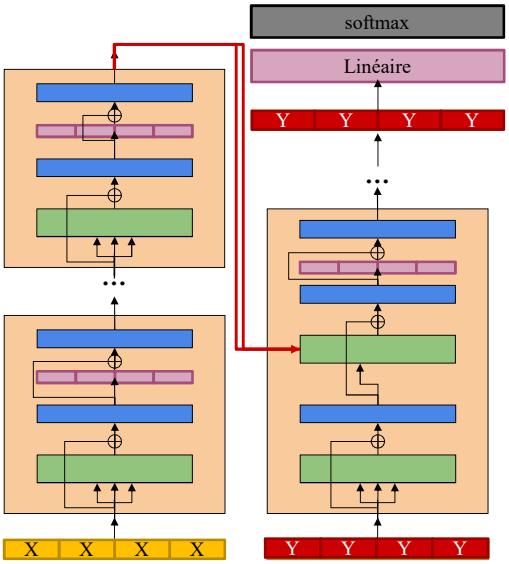
Le bloc est répété 6 fois pour l'encodeur

La sortie de l'encodeur sert de K,V pour tous les décodeurs

Le décodeur est répété 6 fois

Transformer (Attention is all you need)

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.



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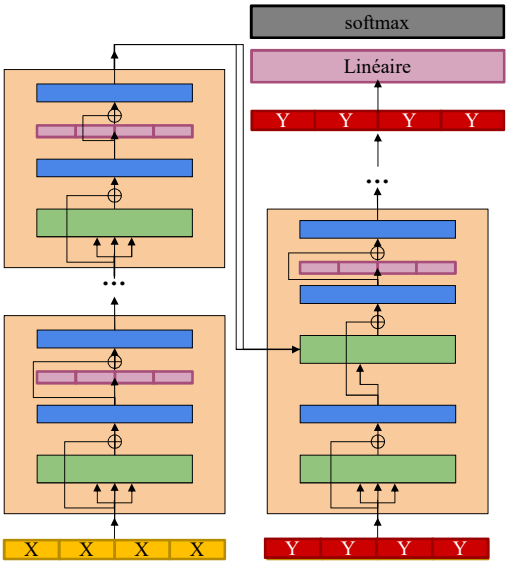


- Intra-attention multi-tête sur les dimensions de X
- "+ " = connection résiduelle
- "Layer-norm"
- MLP par entrée

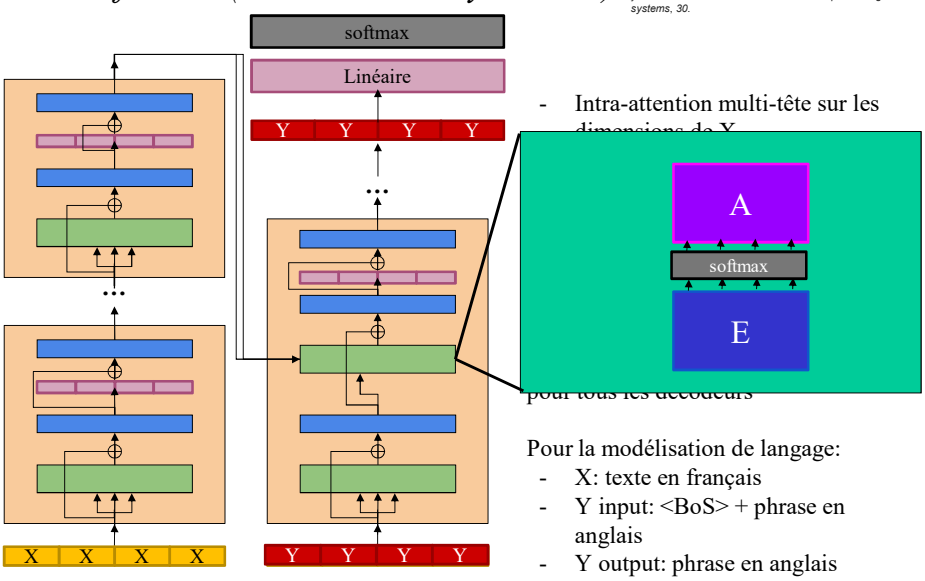
Le bloc est répété 6 fois pour l'encodeur

La sortie de l'encodeur sert de K,V pour tous les décodeurs

Pour la modélisation de langage:
- X: texte en français
- Y input: <BoS> + phrase en anglais
- Y output: phrase en anglais

Transformer (Attention is all you need)

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems, 30.*



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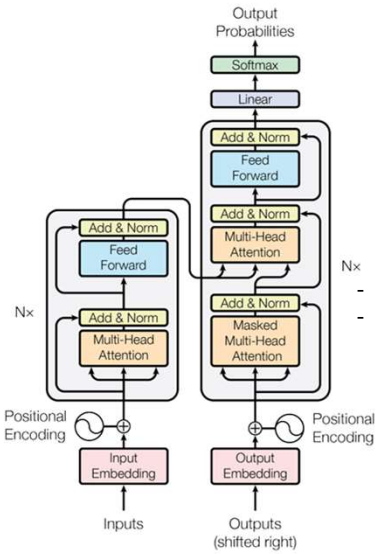

Supers bons tutoriels:

- https://jalammar.github.io/illustrated-transformer/
- https://data-science-blog.com/blog/2021/04/07/multi-head-attention-mechanism/

Transformer (Attention is all you need)

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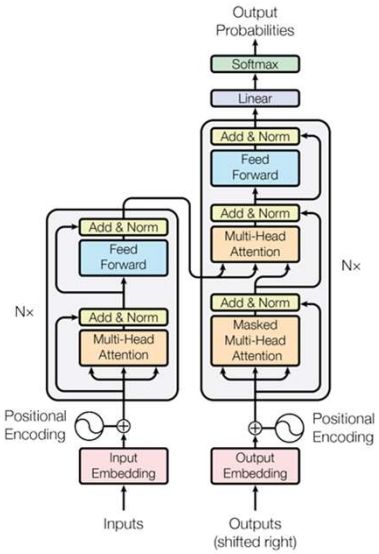


Très gourmand en mémoire:

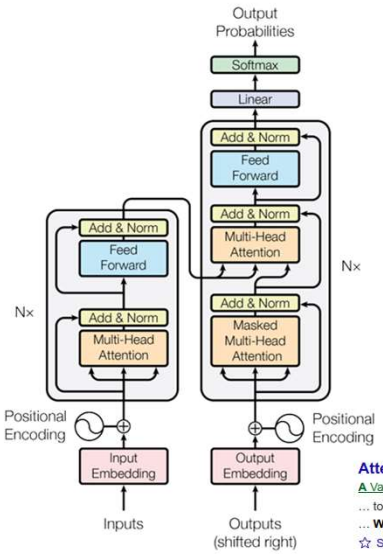
- Matrices de poids W^Q,W^K,W^V
- Couches pleinement connectées
- “Répétition” de paramètres par les multi-têtes

Très demandants en opérations

- Complexité quadratique

Transformer (Attention is all you need)

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.



Très gourmand en mémoire:

- Matrices de poids W^Q,W^K,W^V
- Couches pleinement connectées
- "Répétition" de paramètres par les multi-têtes

Aussi très populaires !

Attention is all you need
A Vaswani, N Shazeer, N Parmar… - Advances in neural …, 2017 - proceedings.neurips.cc
… to attend to **all** positions in the decoder up to and including that position. **We need** to prevent … **We** implement this inside … scaled dot-product **attention** by masking out (setting to $-\infty$) …
☆ Save 99 Cite Cited by 65964 Related articles All 46 versions »

Différentes version de transformers

Pour rappel: Resnet-50: 23M de paramètres

Model	Layers	Width	Heads	Params	Data	Training
Transformer-Base	12	512	8	65M		8x P100 (12 hours)
Transformer-Large	12	1024	16	213M		8x P100 (3.5 days)

crédit: Justin Johnson

Transformers

Model	Layers	Width	Heads	Params	Data	Training
Transformer-Base	12	512	8	65M		8x P100 (12 hours)
Transformer-Large	12	1024	16	213M		8x P100 (3.5 days)
BERT-Base	12	768	12	110M	13 GB	
BERT-Large	24	1024	16	340M	13 GB	

crédit: Justin Johnson

Transformers

Model	Layers	Width	Heads	Params	Data	Training
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BERT-Base	12	768	12	110M	13 GB	
BERT-Large	24	1024	16	340M	13 GB	
XLNet-Large	24	1024	16	~340M	126 GB	512x TPU-v3 (2.5 days)
RoBERTa	24	1024	16	355M	160 GB	1024x V100 GPU (1 day)

crédit: Justin Johnson

Transformers

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GPT-2	12	768	?	117M	40 GB	
GPT-2	24	1024	?	345M	40 GB	
GPT-2	36	1280	?	762M	40 GB	
GPT-2	48	1600	?	1.5B	40 GB	

crédit: Justin Johnson

Transformers

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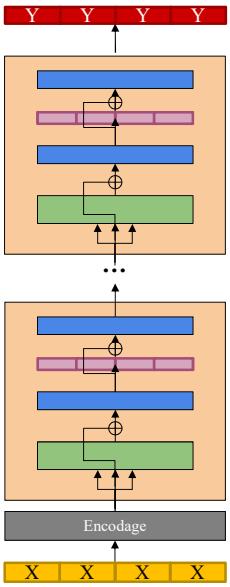
GPT-2	24	1024	?	345M	40 GB	
GPT-2	36	1280	?	762M	40 GB	
GPT-2	48	1600	?	1.5B	40 GB	
Megatron-LM	40	1536	16	1.2B	174 GB	64x V100 GPU
Megatron-LM	54	1920	20	2.5B	174 GB	128x V100 GPU
Megatron-LM	64	2304	24	4.2B	174 GB	256x V100 GPU (10 days)
Megatron-LM	72	3072	32	8.3B	174 GB	512x V100 GPU (9 days)

crédit: Justin Johnson

GPT1-2-3



Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving language understanding by generative pre-training.
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Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., ... & Amodei, D. (2020). Language models are few-shot learners. Advances in neural information processing systems, 33, 1877-1901.

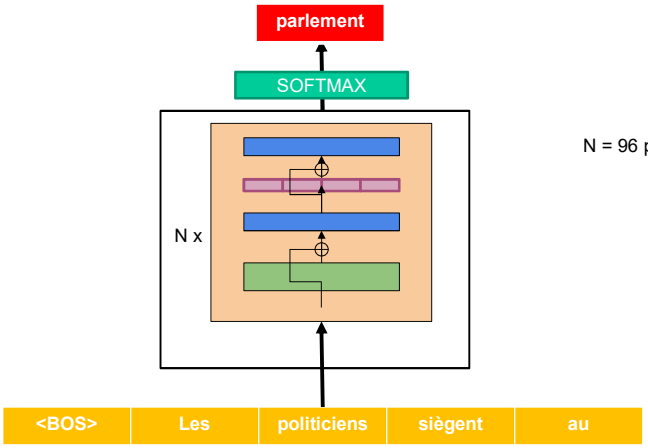
Generative-Pre-Training

GTP 1,2,3 entraînent l'encodeur du transformer sur des données non annotée (d'où le « pre-training »)

GPT3 a 96 blocks d'auto-attention!

GPT1-2-3

Pré-entraînement : le but estd'entraîner un réseau **à prédire le prochain mot**.

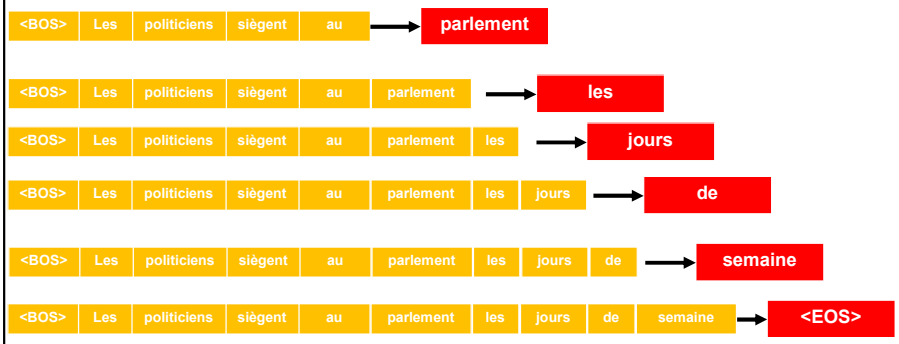


N = 96 pour GPT3

262

GPT1-2-3

Et on recommence:



263

Transformers

Les transformers sont *vraiment bons* pour générer du texte

SYSTEM PROMPT (HUMAN-WRITTEN)

Recycling is good for the world.

NO! YOU COULD NOT BE MORE WRONG!!

MODEL COMPLETION (MACHINE-WRITTEN, 25 TRIES)

Recycling is NOT good for the world. It is bad for the environment, it is bad for our health, and it is bad for our economy. I'm not kidding. Recycling is not good for the environment. It is destructive to the earth and it is a major contributor to global warming. Recycling is not good for our health. It contributes to obesity and diseases like heart disease and cancer. Recycling is bad for our economy. It increases the cost of a product, and in turn, the price of everything that is made with that product. Recycling is not good for our nation. We pay a tremendous price for the privilege of having the world's most advanced and efficient recycling system. Recycling is a huge, colossal waste of time, energy, money, and resources. And THAT is why we need to get back to basics and get back to basics in our recycling efforts. One of the best ways to start is to look at the process of creating a paper product. When you make a paper product, it is basically a long chain of materials. Everything from the raw materials (wood, cardboard, paper, etc.), to the reagents (dyes, solvents, etc.) to the printing equipment (chemicals, glue, paper, ink, etc.), to the packaging, to the packaging materials (mercury, chemicals, etc.) to the processing equipment (heating, cooling, etc.), to the packaging materials, to the packaging materials that are shipped overseas and to the packaging materials that are used in the United States. Each step along the way creates tons of waste that we constantly have to clean up. The process of making a paper product is a very wasteful one. But the end result is something that all of us need to consume. And if we want to keep the recycling process running efficiently, then we really need to think about each and every step that goes into making a paper product.

https://openai.com/blog/better-language-models/#sample8

Transformers

Les transformers sont *vraiment bons* pour générer du texte sémantiquement viable

I really like the IFT780 course on neural networks offered at the Université de Sherbrooke, because

the teacher uses examples from video games, which I find a nice contrast to the theory.

I think I would like a course on AI to really understand how it works, but when we are in class, the prof speaks in a rapid French, and I can't really process what he's saying.

Having started a course on it at a different time, I understand more this time, but I still don't know where I stand.

My "new" plan for next year is to do all of the tutorials and classes I've been wanting to take, but I'm still stuck on one big, heavy, headachey decision: how do I want to spend my post - masters year?

With a lot of math and statistics classes, it's not a hard choice.

I'm on the fence with what I want to spend my summer doing: a lot of analysis and research work or do some volunteering?

I've applied to several volunteer programs: naturis and Vert directeur de la santé, which are essentially summer internships for dentists and health care professionals to do a bit of volunteer work.

https://app.inferkit.com/demo

GPT-1-2-3

Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving language understanding by generative pre-training.
Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). Language models are unsupervised multitask learners. OpenAI blog, 1(8), 9.
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GPT-2

Parameters	Layers	d_{model}
117M	12	768
345M	24	1024
762M	36	1280
1542M	48	1600

Table 2. Architecture hyperparameters for the 4 model sizes.

GPT-3

Model Name	n_{params}	n_{layers}	d_{model}	n_{heads}	d_{head}	Batch Size	Learning Rate
GPT-3 Small	125M	12	768	12	64	0.5M	6.0×10^{-4}
GPT-3 Medium	350M	24	1024	16	64	0.5M	3.0×10^{-4}
GPT-3 Large	760M	24	1536	16	96	0.5M	2.5×10^{-4}
GPT-3 XL	1.3B	24	2048	24	128	1M	2.0×10^{-4}
GPT-3 2.7B	2.7B	32	2560	32	80	1M	1.6×10^{-4}
GPT-3 6.7B	6.7B	32	4096	32	128	2M	1.2×10^{-4}
GPT-3 13B	13.0B	40	5140	40	128	2M	1.0×10^{-4}
GPT-3 175B or "GPT-3"	175.0B	96	12288	96	128	3.2M	0.6×10^{-4}

Table 2.1: Sizes, architectures, and learning hyper-parameters (batch size in tokens and learning rate) of the models which we trained. All models were trained for a total of 300 billion tokens.

GPT1-2-3

Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving language understanding by generative pre-training.
Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). Language models are unsupervised multitask learners. OpenAI blog, 1(8), 9.
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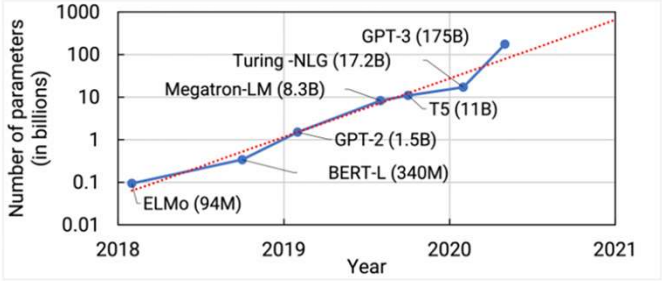


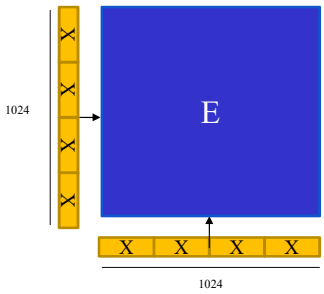
Figure 1. Trend of state-of-the-art NLP model sizes with time.

https://developer.nvidia.com/blog/scaling-language-model-training-to-a-trillion-parameters-using-megatron/

"355 years on a V100 GPU server with 28 TFLOPS capacity and would cost ***$4.6 million at $1.5 per hour****"*

https://bdtechtalks.com/2020/09/21/gpt-3-economy-business-model/

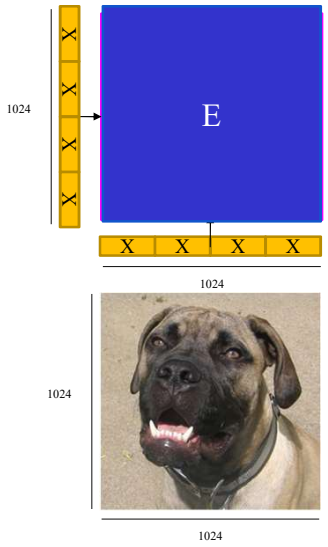
Vision Transformers (ViT)



Opération (au moins) quadratique = 1024^2 opérations et composantes à garder en mémoire

Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., ... & Houlsby, N. (2020). An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929.

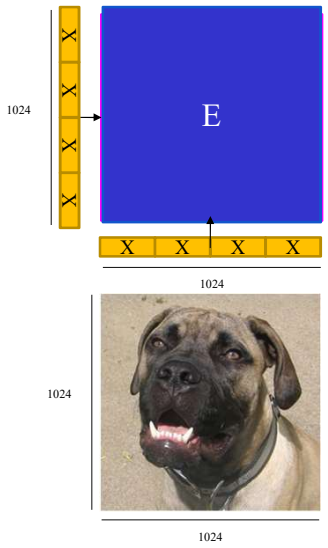
Vision Transformers (ViT)



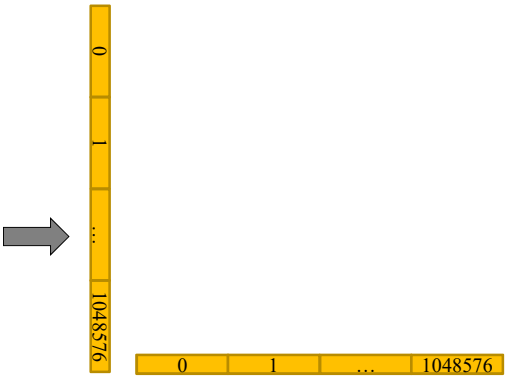
Opération (au moins) quadratique

Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., ... & Houlsby, N. (2020). An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929.

Vision Transformers (ViT)



Opération (au moins) quadratique



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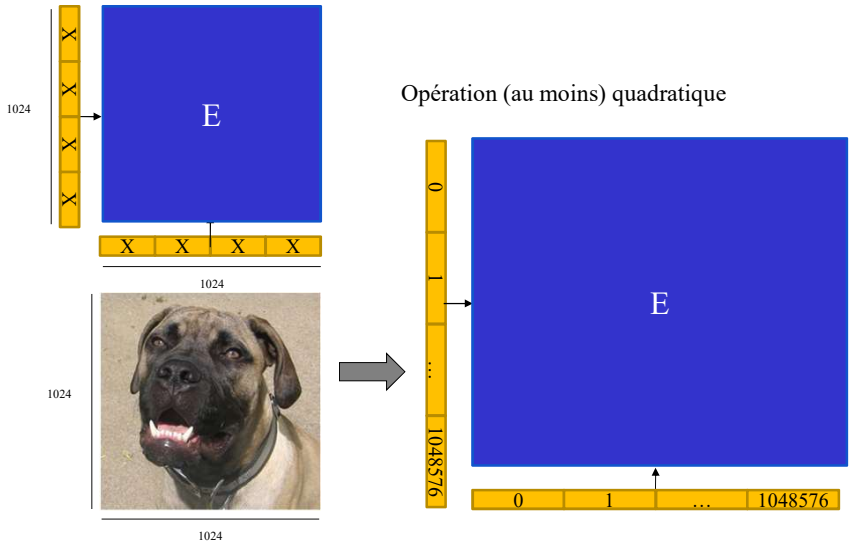
Vision Transformers (ViT)



Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., ... & Houlsby, N. (2020). An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929.

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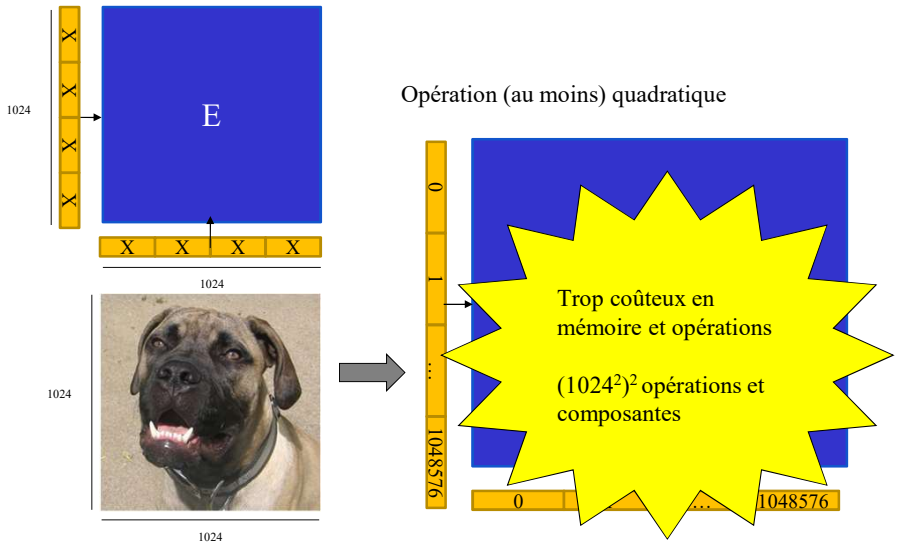

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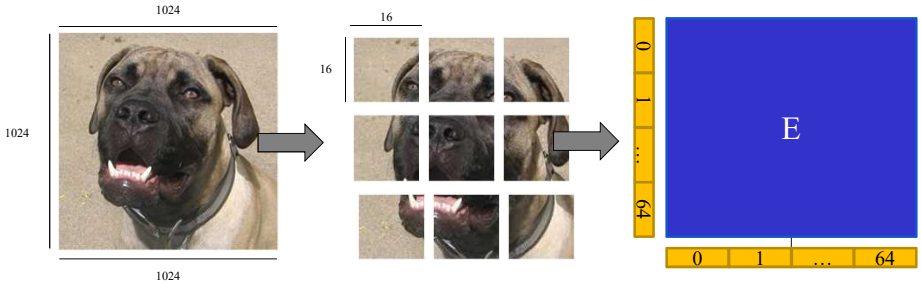

Chaque “patch” est un token de (par exemple) 256 composantes

Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., ... & Houlsby, N. (2020). An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929.

Vision Transformers (ViT)

- L’image est séparée en patch

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Vision Transformers (ViT)

- L'image est séparée en patch
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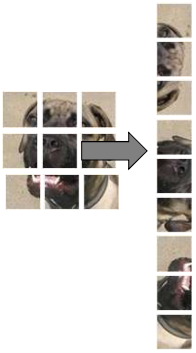

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Vision Transformers (ViT)

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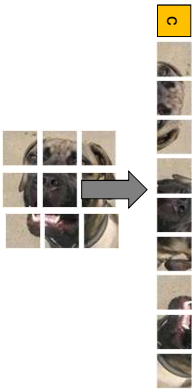
- Un token spécial représentant la classe est ajouté



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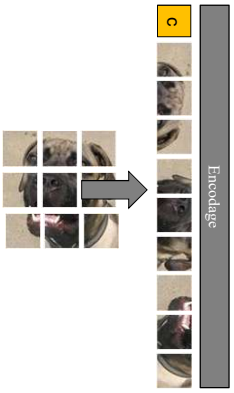

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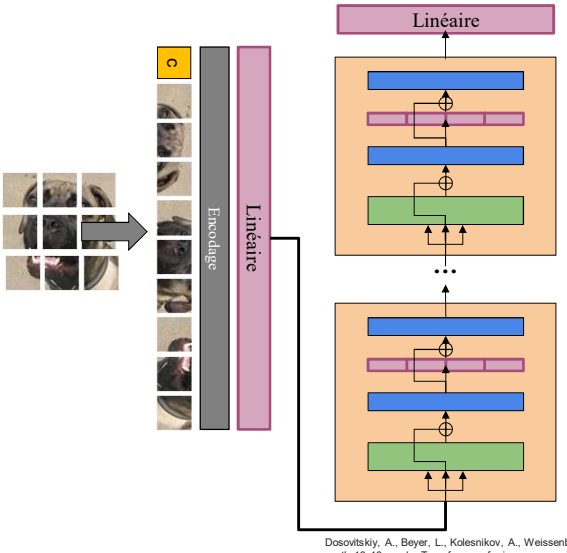

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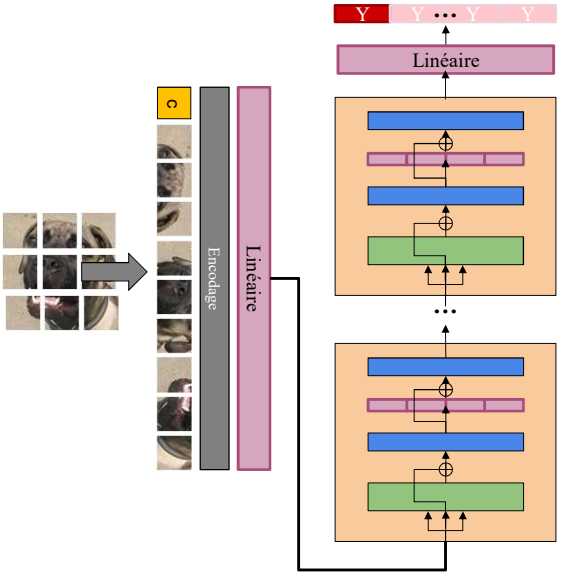

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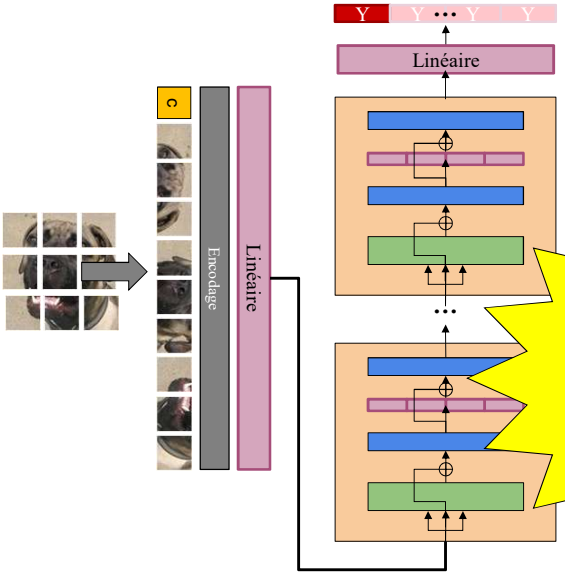

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Vision Transformers (ViT)

	Ours-JFT (ViT-H/14)	Ours-JFT (ViT-L/16)	Ours-I21k (ViT-L/16)	BiT-L (ResNet152x4)	Noisy Student (EfficientNet-L2)
ImageNet	**88.55** ± 0.04	87.76 ± 0.03	85.30 ± 0.02	87.54 ± 0.02	88.4/88.5*
ImageNet ReaL	**90.72** ± 0.05	90.54 ± 0.03	88.62 ± 0.05	90.54	90.55
CIFAR-10	**99.50** ± 0.06	99.42 ± 0.03	99.15 ± 0.03	99.37 ± 0.06	–
CIFAR-100	**94.55** ± 0.04	93.90 ± 0.05	93.25 ± 0.05	93.51 ± 0.08	–
Oxford-IIIT Pets	**97.56** ± 0.03	97.32 ± 0.11	94.67 ± 0.15	96.62 ± 0.23	–
Oxford Flowers-102	99.68 ± 0.02	**99.74** ± 0.00	99.61 ± 0.02	99.63 ± 0.03	–
VTAB (19 tasks)	**77.63** ± 0.23	76.28 ± 0.46	72.72 ± 0.21	76.29 ± 1.70	–
TPUv3-core-days	2.5k	0.68k	0.23k	9.9k	12.3k

Table 2: Comparison with state of the art on popular image classification benchmarks. We report mean and standard deviation of the accuracies, averaged over three fine-tuning runs. Vision Transformer models pre-trained on the JFT-300M dataset outperform ResNet-based baselines on all datasets, while taking substantially less computational resources to pre-train. ViT pre-trained on the smaller public ImageNet-21k dataset performs well too. *Slightly improved 88.5% result reported in Touvron et al. (2020).

Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., ... & Houlsby, N. (2020). An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929.

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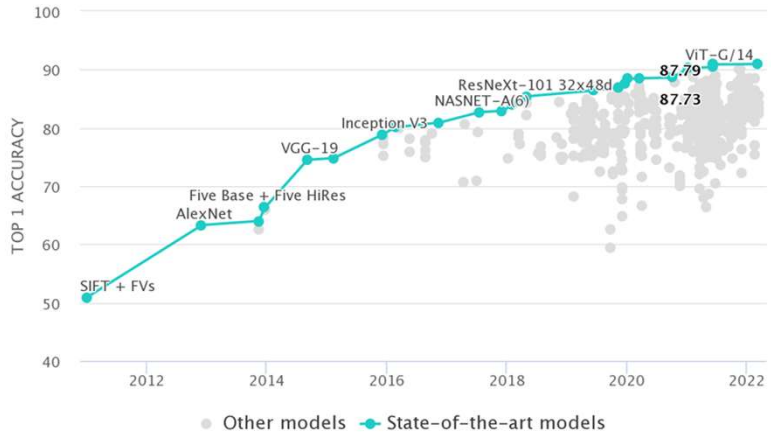
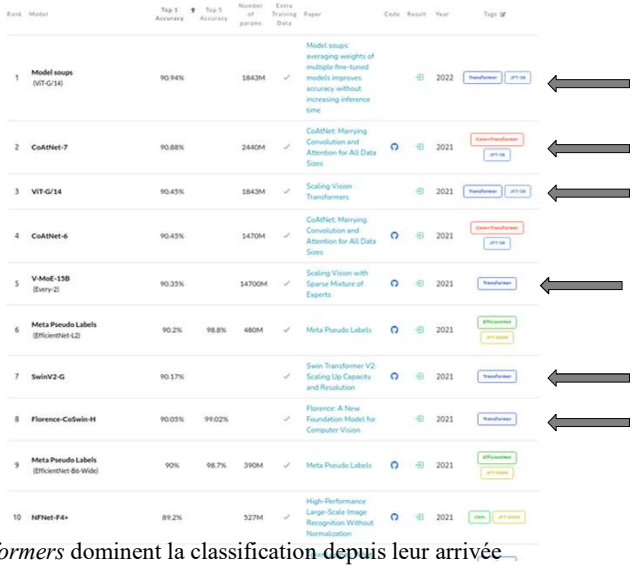


Les *vision transformers* dominent la classification depuis leur arrivée

https://paperswithcode.com/sota/image-classification-on-imagenet

Vision Transformers (ViT)



Rank	Model	Top 1 Accuracy	Top 5 Accuracy	Number of params.	Extra Training Data	Paper	Code	Result	Year	Tags
1	**Model soups** (ViT-G/14)	90.94%		1843M	✓	Model soups: averaging weights of multiple fine-tuned models improves accuracy without increasing inference time			2022	Transformer
2	**CoAtNet-7**	90.88%		2440M	✓	CoAtNet: Marrying Convolution and Attention for All Data Sizes			2021	Conv+Transformer
3	**ViT-G/14**	90.45%		1843M	✓	Scaling Vision Transformers			2021	Transformer
4	**CoAtNet-6**	90.45%		1470M	✓	CoAtNet: Marrying Convolution and Attention for All Data Sizes			2021	Conv+Transformer
5	**V-MoE-15B** (Every-2)	90.35%		14700M	✓	Scaling Vision with Sparse Mixture of Experts			2021	Transformer
6	**Meta Pseudo Labels** (EfficientNet-L2)	90.2%	98.8%	480M	✓	Meta Pseudo Labels			2021	EfficientNet
7	**SwinV2-G**	90.17%			✓	Swin Transformer V2: Scaling Up Capacity and Resolution			2021	Transformer
8	**Florence-CoSwin-H**	90.05%	99.02%		✓	Florence: A New Foundation Model for Computer Vision			2021	Transformer
9	**Meta Pseudo Labels** (EfficientNet-B6-Wide)	90%	98.7%	390M	✓	Meta Pseudo Labels			2021	EfficientNet
10	**NFNet-F4+**	89.2%		527M	✓	High-Performance Large-Scale Image Recognition Without Normalization			2021	ResNet

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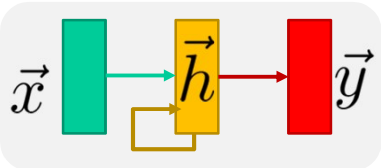
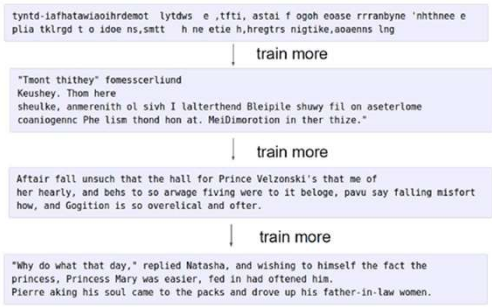
Sommaire

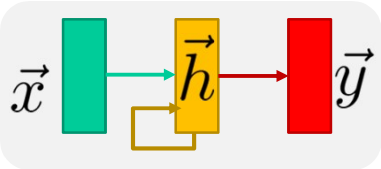


- Les réseaux récurrents peuvent traiter des séquences
- Ils ne requièrent que de légères modifications à des réseaux pleinement connectés
- Ils sont instables sur de longues séquences
- LSTM/GRU sont utilisés en pratique



Modélisation de langage

Sommaire



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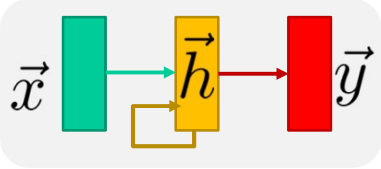
a group of people playing a game with nintendo wii controllers

Description d'images

Sommaire



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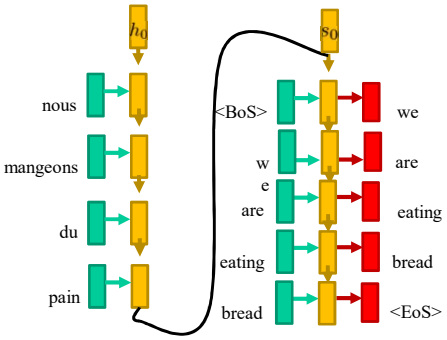
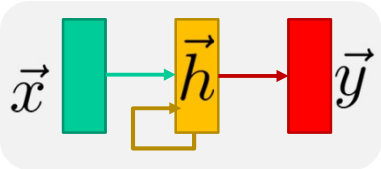


Traduction

Sommaire



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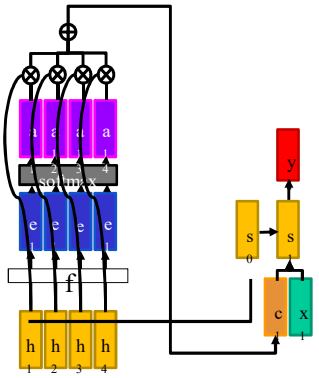

- L'attention est un mécanisme très puissant permettant aux réseaux d'apprendre quelle partie des données utilisées pour faire une prédiction
- L'attention n'est pas limitée au texte, ou même aux séquences

Sommaire

- Un *Transformer* sont un modèle extrêmement puissant pour les tâches liées au *langage naturel*
- Les *transformers* n'utilisent *que* l'attention (pas un modèle récurrent)
- Les *transformers* sont demandant en ressources
- Ceux-ci ne sont pas limités au langage!