UNIVERSITÉ LAVAL

GLO-4030/7030 APPRENTISSAGE PAR RÉSEAUX DE NEURONES PROFONDS

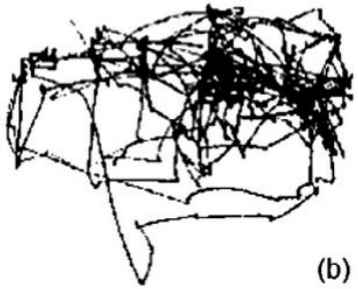
Attention

(image et texte)

Philippe Giguère

Attention visuelle humaine

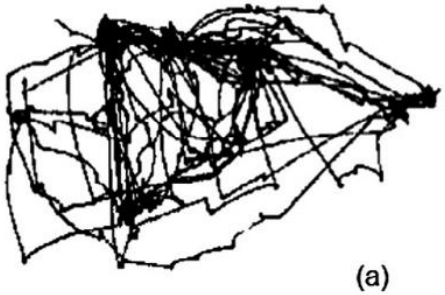
Position du regard en fonction de la question posée



Estimate the wealth of the family

Summarize what the family had been doing before the arrival of the "unexpected visitor"

Remember the position of the people and objects in the room



No specific task

Give the ages of the people

Remember the clothes worn by the people

Estimate how long the "unexpected visitor" had been away from the family

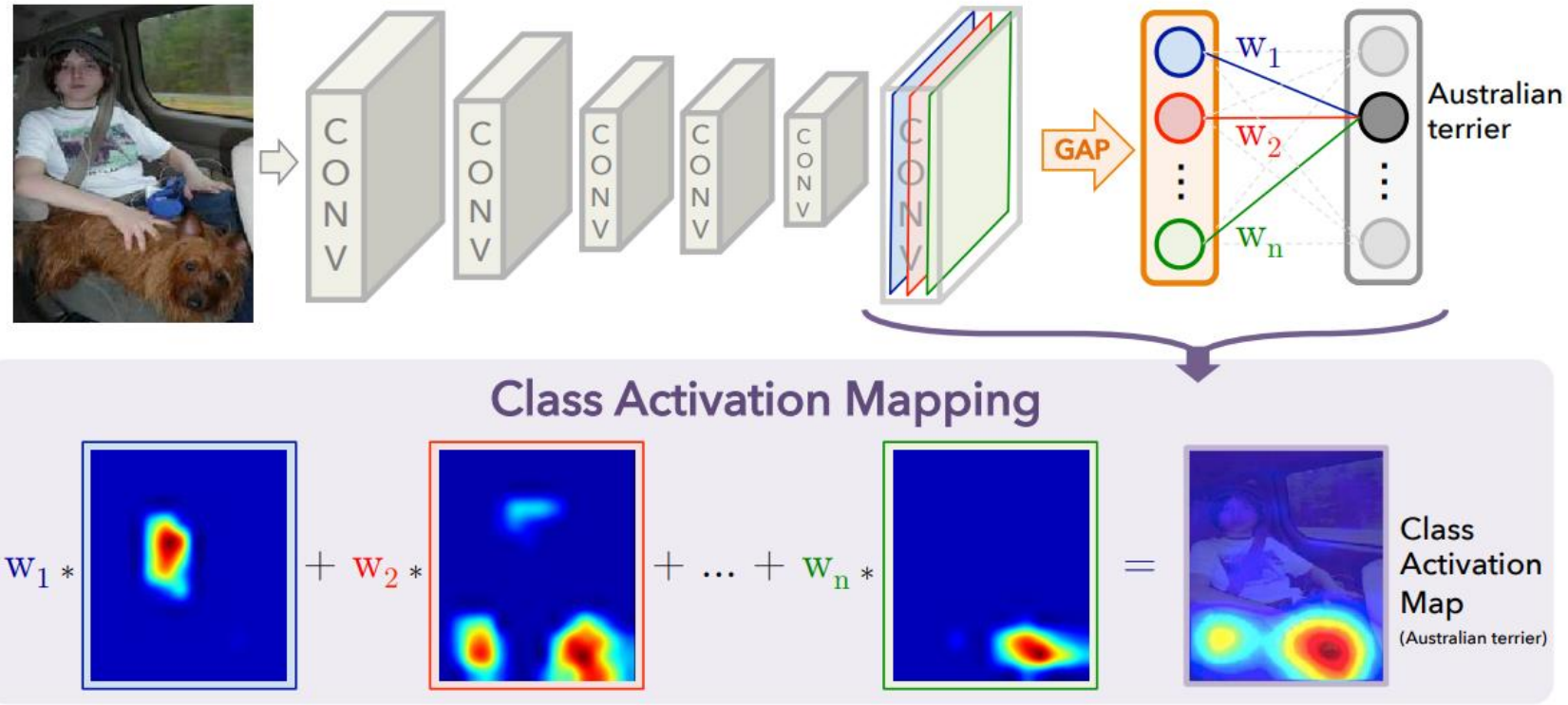
Yarbus, A. (1967). Eye movements and vision. New York: Plenum Press (Translated from the Russian edition by Haigh, B).

Attention visuelle humaine

- Fovéa dans l'oeil

Globlal average pooling

- Vers la localisation et l'attention visuelle



- Donne une certaine interprétabilité aux résultats

Zhou et al., Learning Deep Features for Discriminative Localization, CVPR 2016.

Image captioning

- Attention séquentielle sur l'image

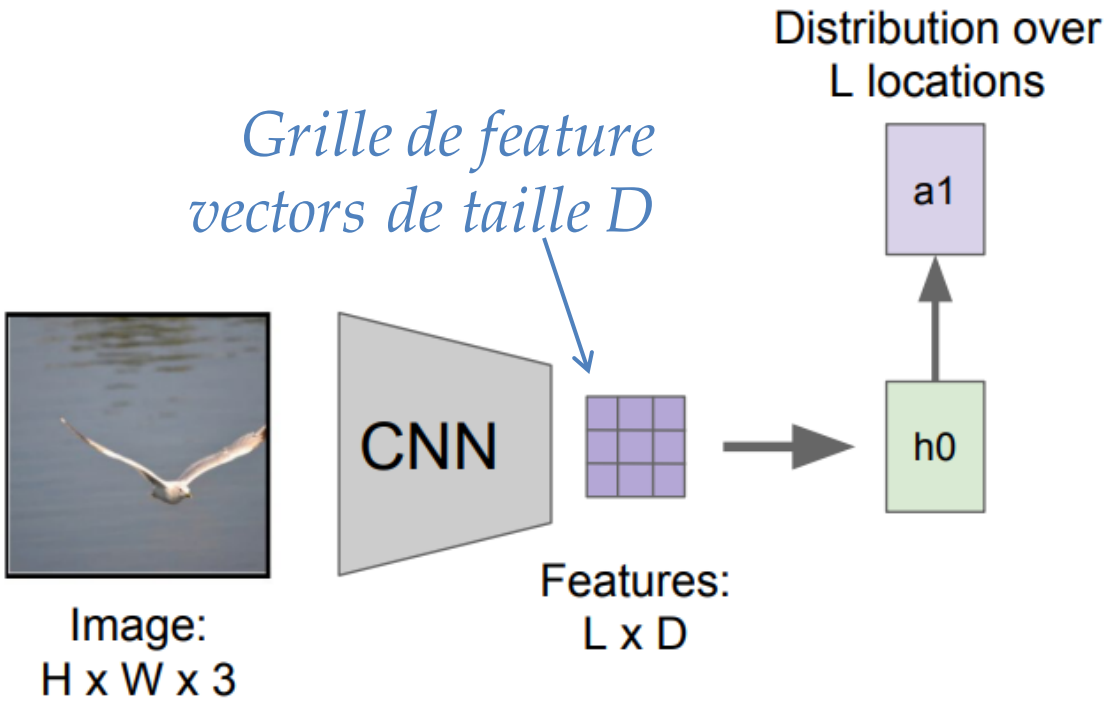
A dog is running in the grass with a frisbee

A woman is holding a cat in her hand

A cat is sitting on a tree branch

A man in a baseball uniform throwing a ball

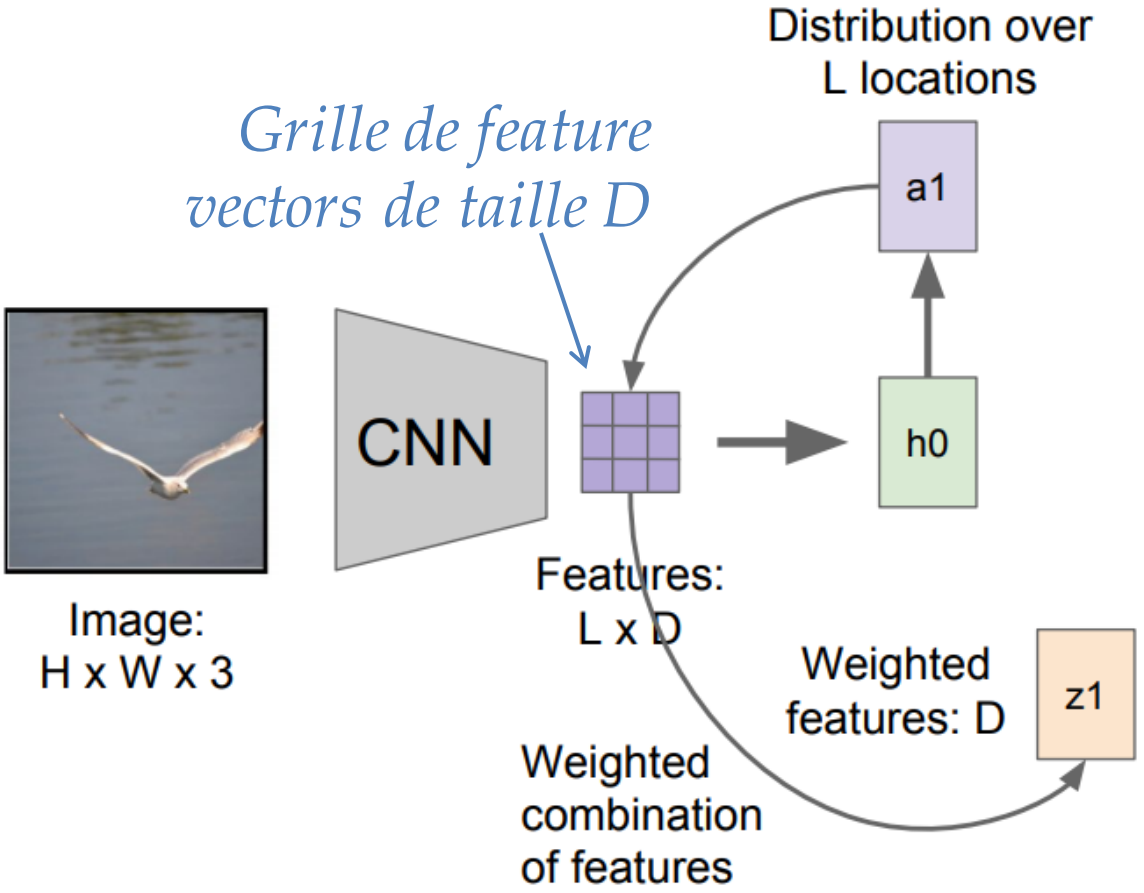
Image captioning avec attention



Xu et al., Show, Attend and Tell: Neural Image Caption Generation with Visual Attention, ICML 2015.

Tiré de cs231n

Image captioning avec attention



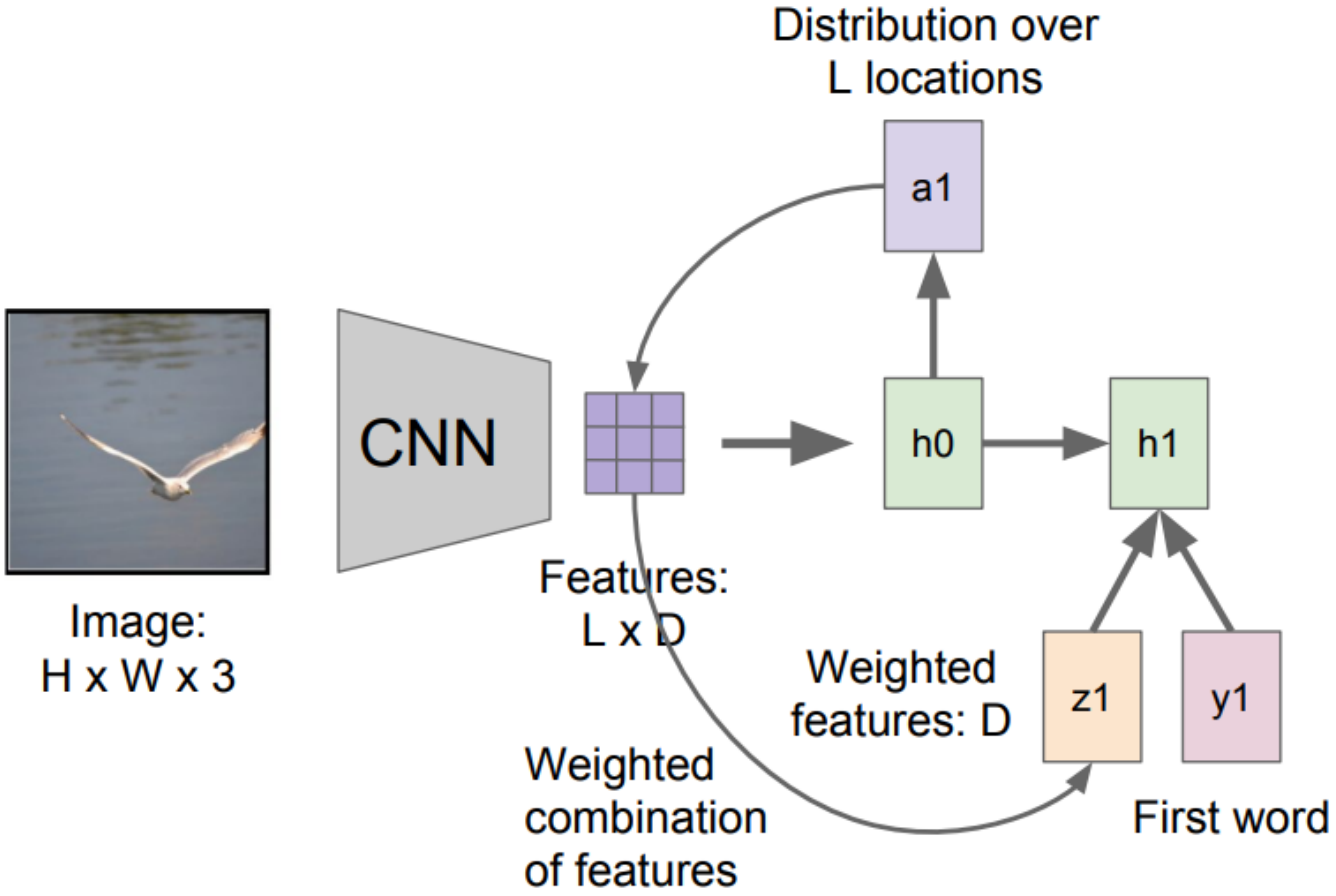
$$z = \sum_{i=1}^{L} p_i v_i$$

(soft attention)

Xu et al., Show, Attend and Tell: Neural Image Caption Generation with Visual Attention, ICML 2015.

Tiré de cs231n

Image captioning avec attention



Xu et al., Show, Attend and Tell: Neural Image Caption Generation with Visual Attention, ICML 2015.

Tiré de cs231n

Image captioning avec attention

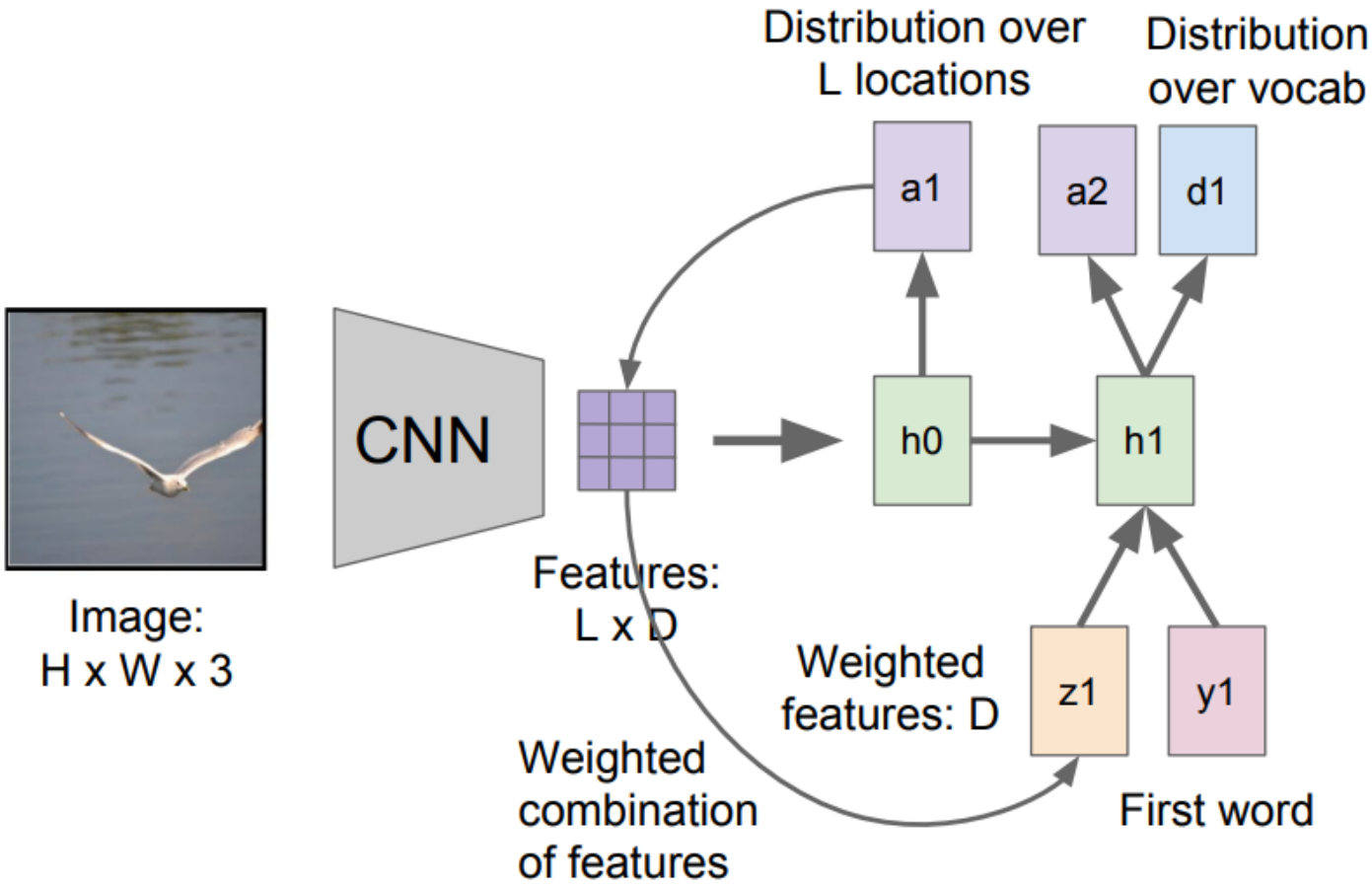


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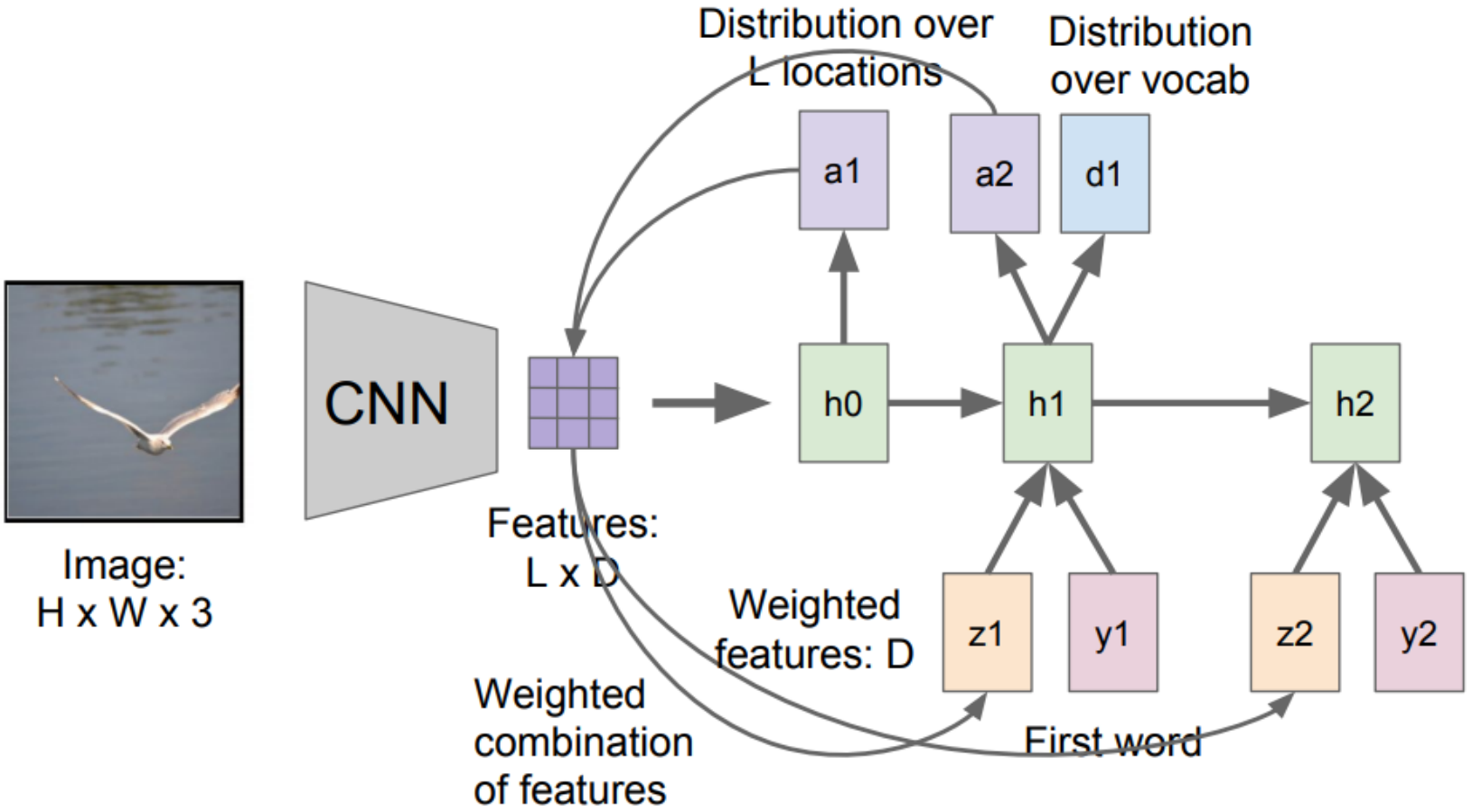
Image captioning avec attention



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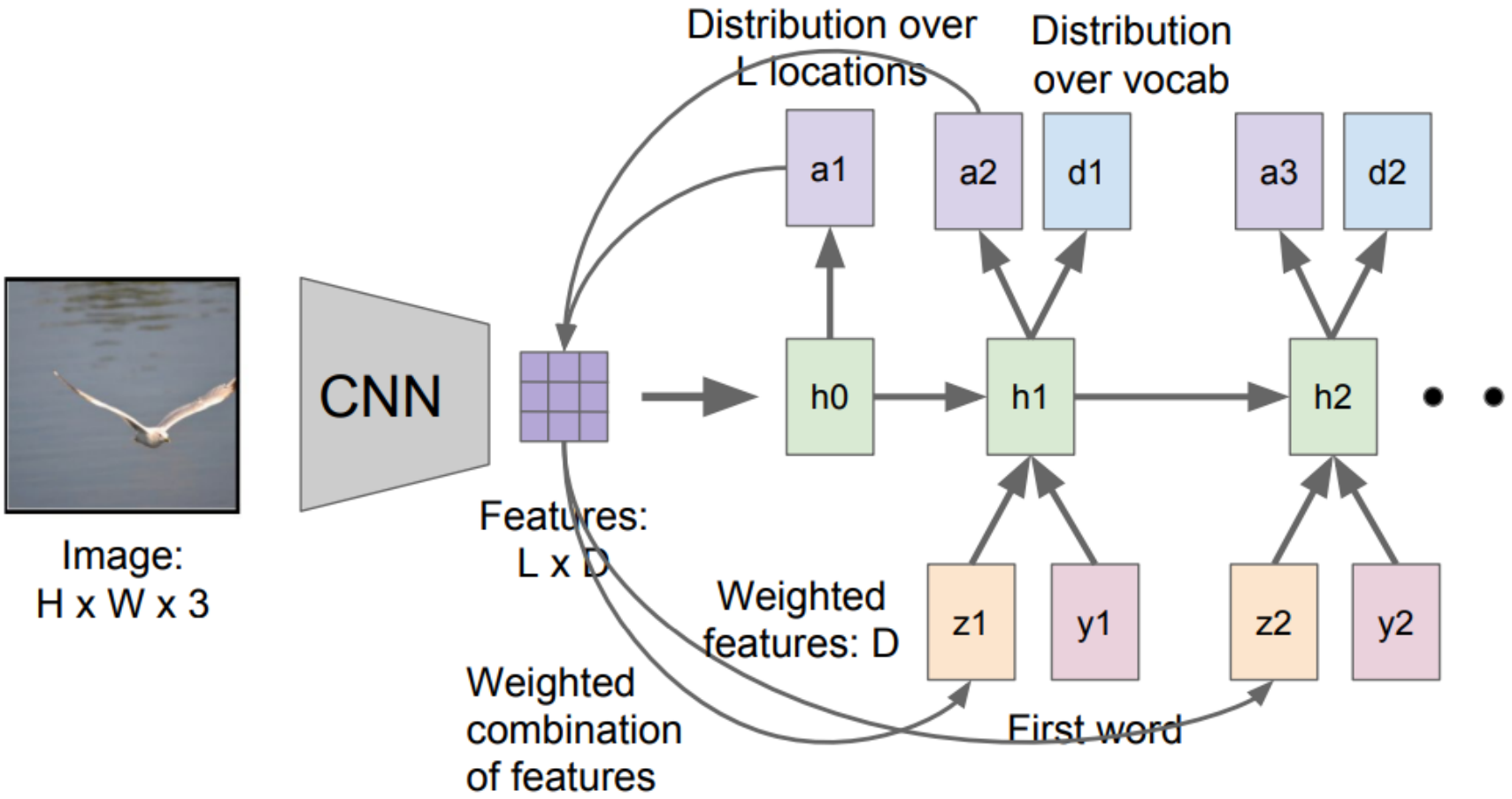
Tiré de cs231n

Image captioning avec attention



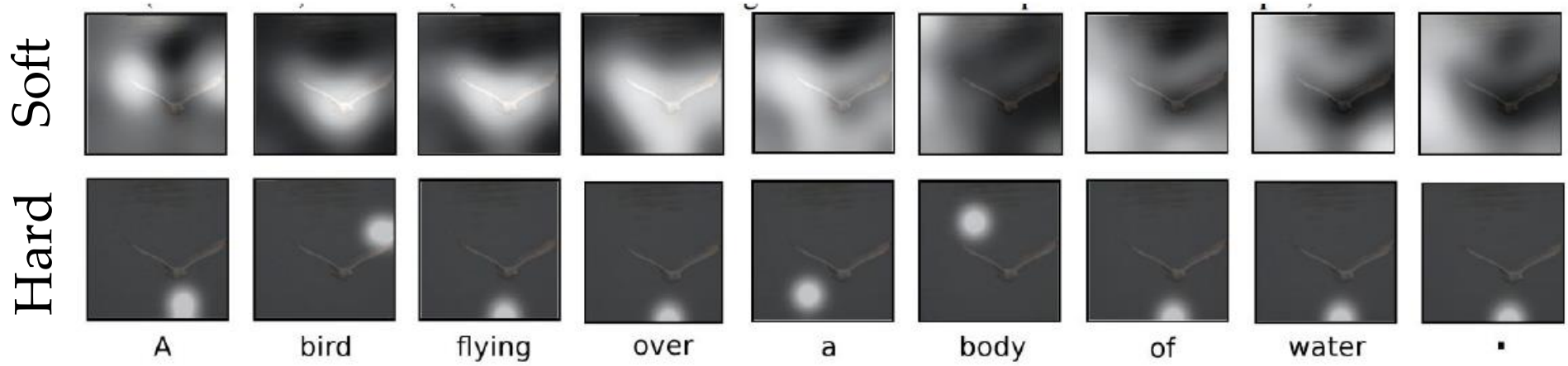
Xu et al., Show, Attend and Tell: Neural Image Caption Generation with Visual Attention, ICML 2015.

Tiré de cs231n

Soft vs. hard attention

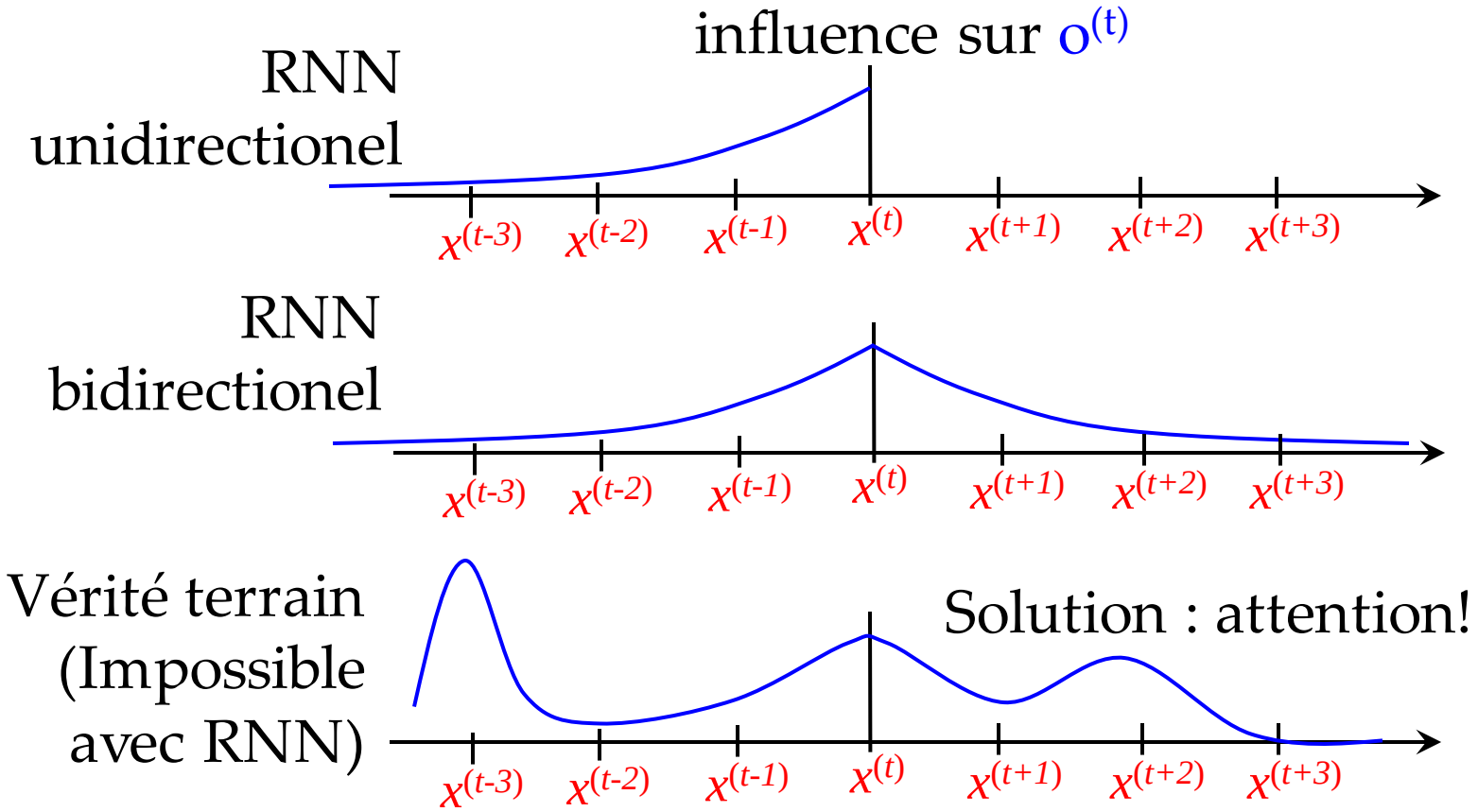
- Soft
  - Sommes pondérées
  - Poids calculés par une softmax (cas d'utilisation qui n'est pas en sortie)
  - dérivable end-to-end
- Hard
  - Softmax : distribution de probabilité de piger
  - pige un élément sur lequel diriger l'attention
  - non-dérivable + difficile à entrainer (question de la semaine passée sur VAE)

Soft vs. hard attention



Rappel : longue portée

- Influence à longue portée difficile dans RNN
- RNN : décroissance exponentielle de l'influence



Published as a conference paper at ICLR 2015

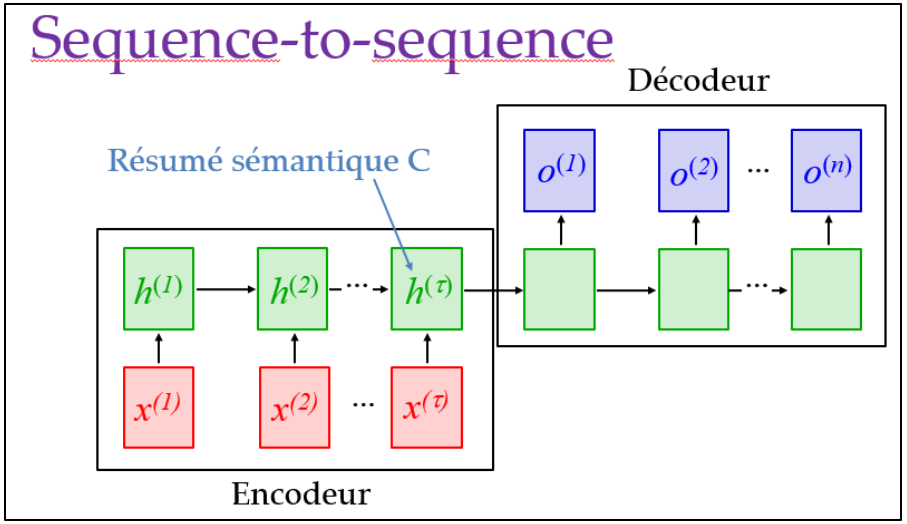
NEURAL MACHINE TRANSLATION BY JOINTLY LEARNING TO ALIGN AND TRANSLATE

Dzmitry Bahdanau
Jacobs University Bremen, Germany

KyungHyun Cho **Yoshua Bengio***
Université de Montréal

Attention pour traduction

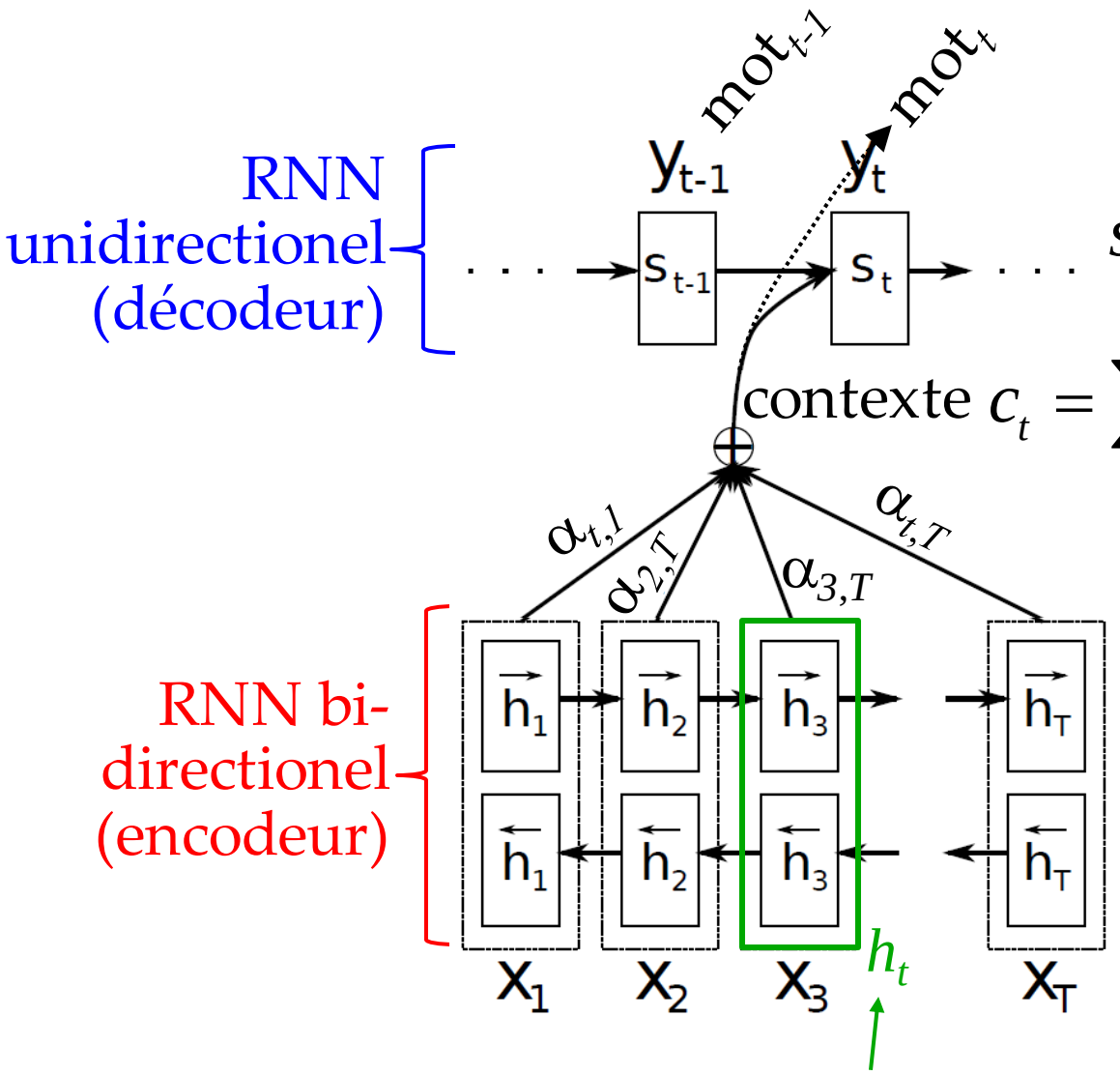
- Résumé sémantique d'une phrase en un seul vecteur <u>est trop restrictif</u>



- Propose plutôt d'associer un vecteur supplémentaire (état caché) à chaque mot
- Mécanisme d'**attention** *soft* sur les états des mots en entrée pour aider à la prédiction en sortie
- Généralise mieux pour des phrases longues

Bahdanau et al., Neural Machine Translation by Jointly Learning to Align and Translate, ICLR 2015.

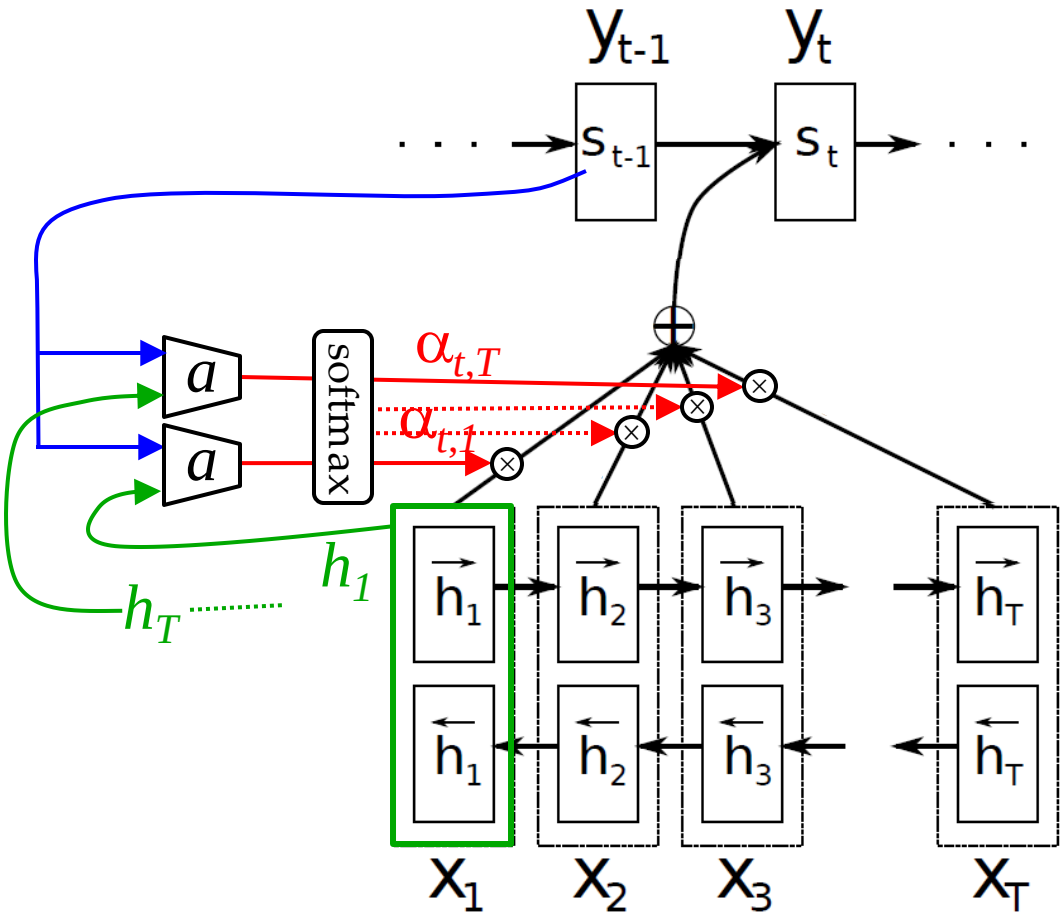
Architecture



$\alpha_{t,i}$ encode la probabilité que le mot t en sortie soit relié au mot i en entrée (alignement)

Architecture : réseau *a* d'attention

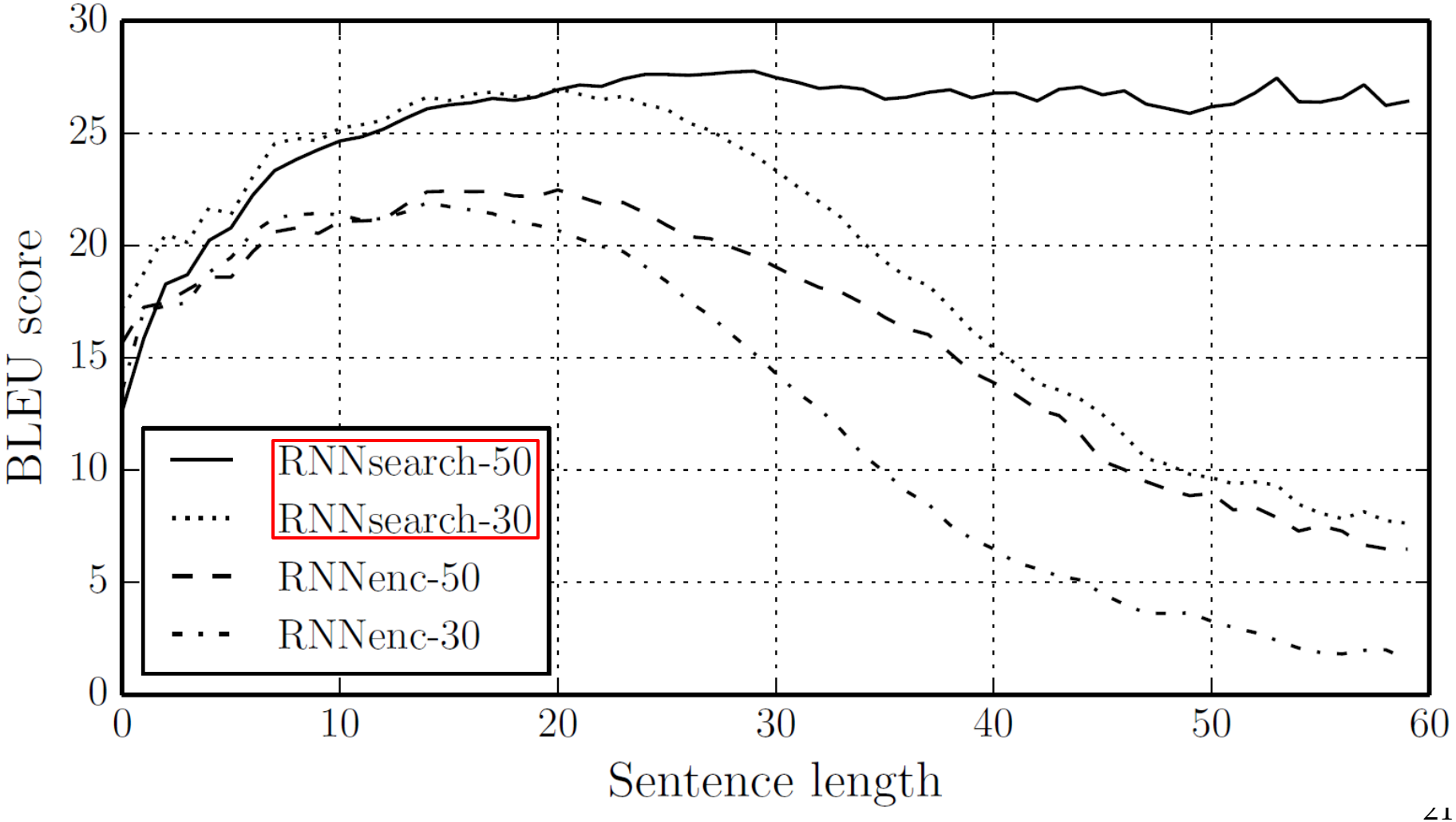
Réseau *a* peu profond



Bahdanau et al., Neural Machine Translation by Jointly Learning to Align and Translate, ICLR 2015.

Résultats

- Fonctionne bien pour de longues phrases

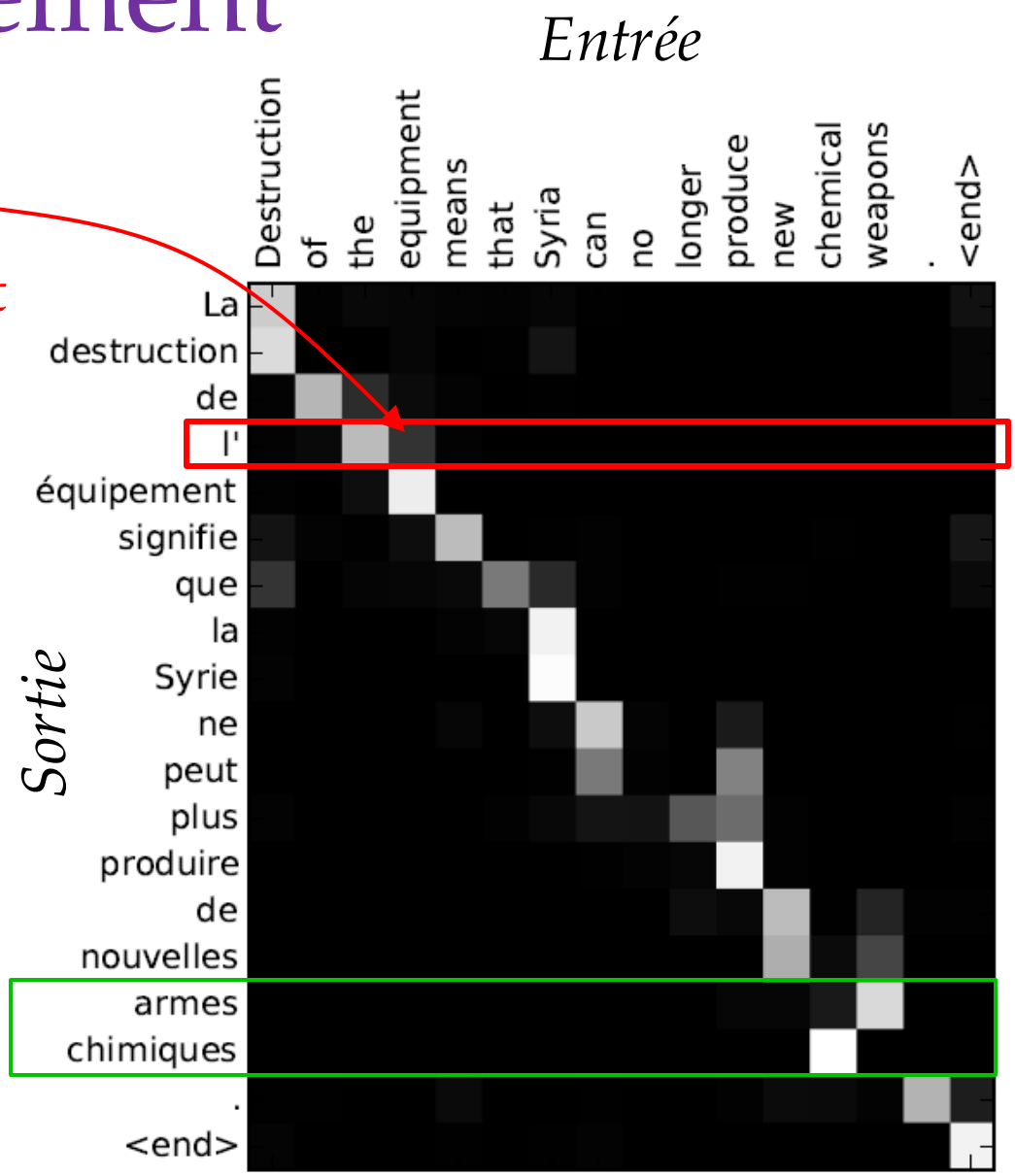


Exemple alignement

- Pour le choix de l'article {le, la, l'}, le réseau regarde un mot en avant

Donne une certaine interprétabilité aux résultats

- Inversion de l'ordre des mots pour l'adjectif



Attention Is All You Need

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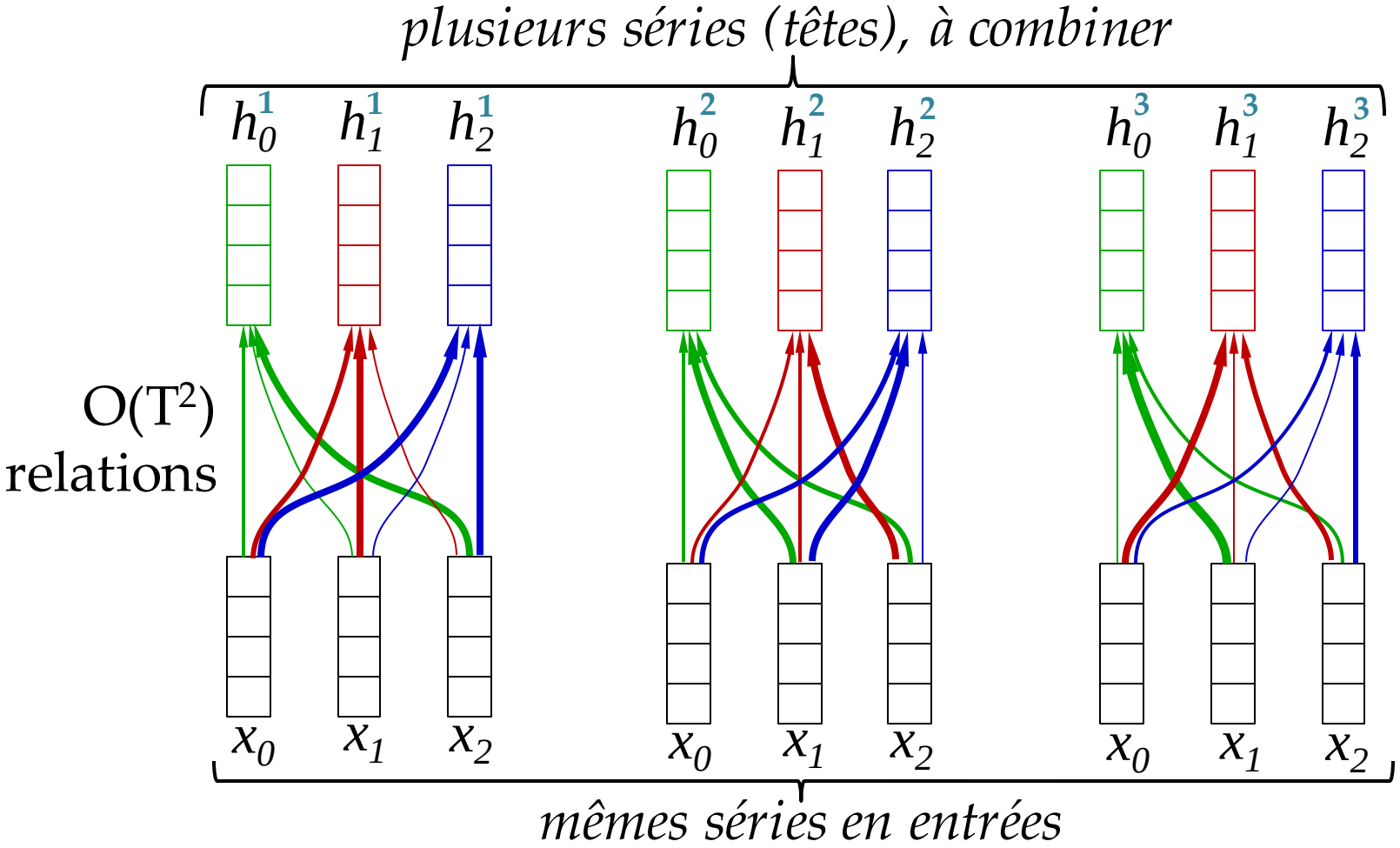
NIPS 2017

Évolution

- *Word alignment* (précédent)
  - attention input-output
  - réseau *a*( ) calculant l'attention peu profond
- *Attention is all you need*
  - attention input-input, input-output, output-output
  - beaucoup plus de profondeur
  - Aucune récurrence
  - Plus facile à entraîner
    - Gradient se propage bien
    - Facilité à paralléliser (car non-séquentiel)
  - Utilise le self-attention

Multi-head : attentions combinées

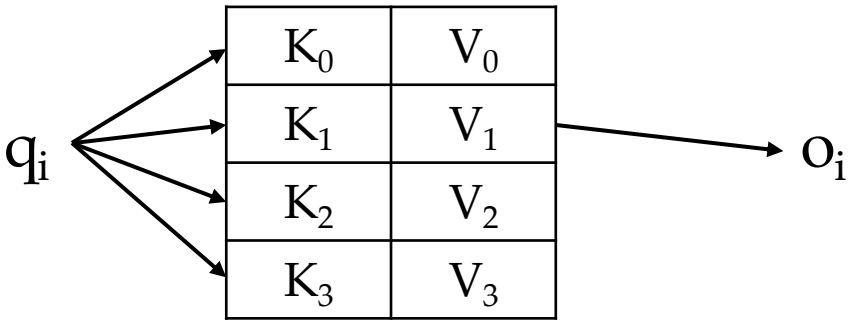


- Chaque tête peut apprendre des relations temporelles différentes (+ grande flexibilité)
- Interprétabilité des résultats

Single-head : mémoire associative

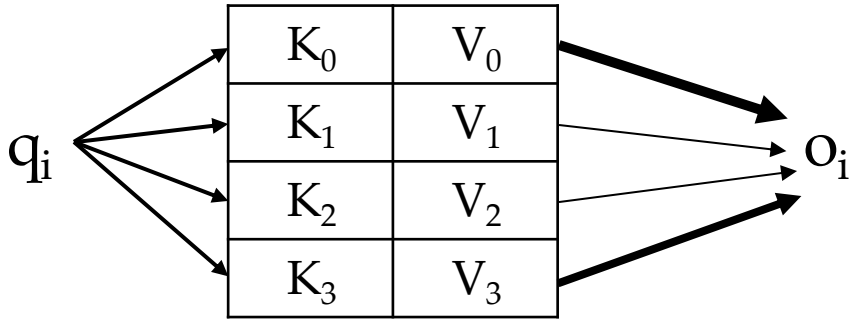
- Voir comme une mémoire associative, version *soft* d'un dictionnaire Python
  - clefs + valeurs
  - requête
  - fonction de distance requête-clefs

Python : hard



si $q_i = K_1$

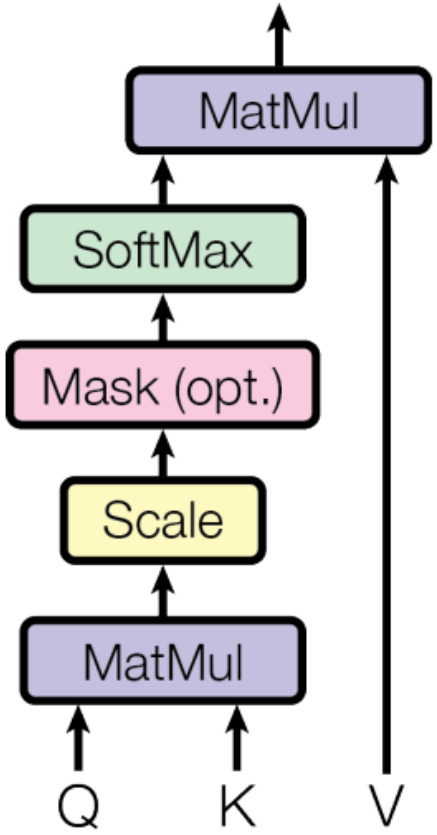
soft



Single-head : mémoire associative

- Similarité cosinus (*cosine distance*)
- Utilisation du softmax pour les pondérations
- Compacter toutes les requêtes q_i dans une matrice Q
  - optimisation GPU pour matrice-matrice malgré le facteur $O(T^2)$

$$sortie = \text{Softmax}\left(\frac{QK}{\sqrt{d_k}}\right)V$$

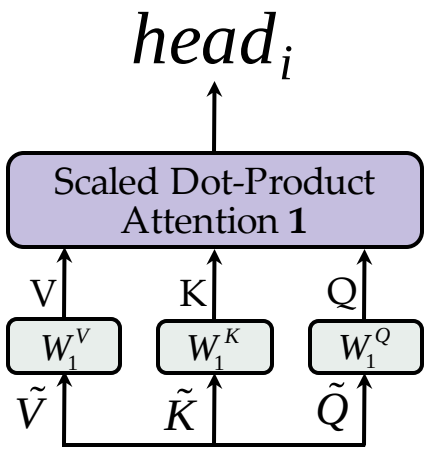


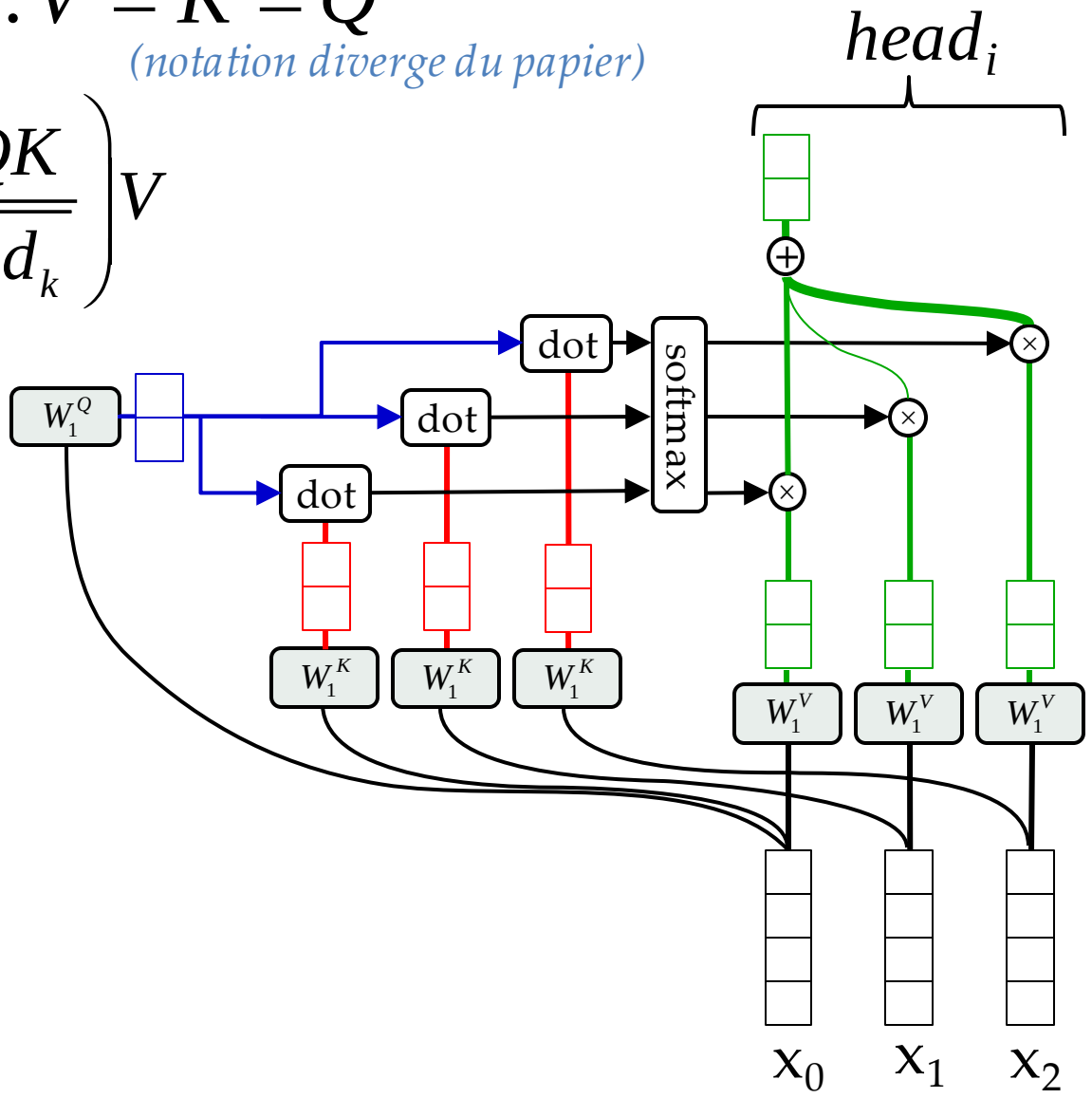
$head_i$: Scaled Dot-Product Attention

- Self-attention : $\tilde{V} = \tilde{K} = \tilde{Q}$

(notation diverge du papier)

$$sortie = \text{Softmax}\left(\frac{QK}{\sqrt{d_k}}\right)V$$





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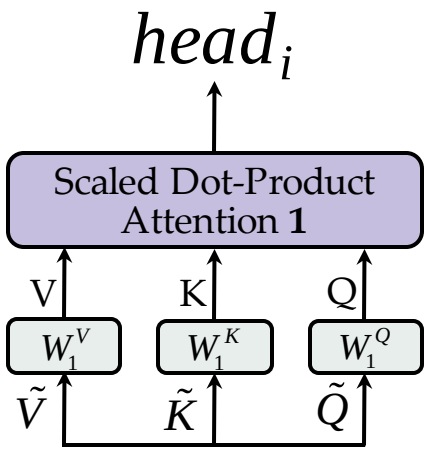

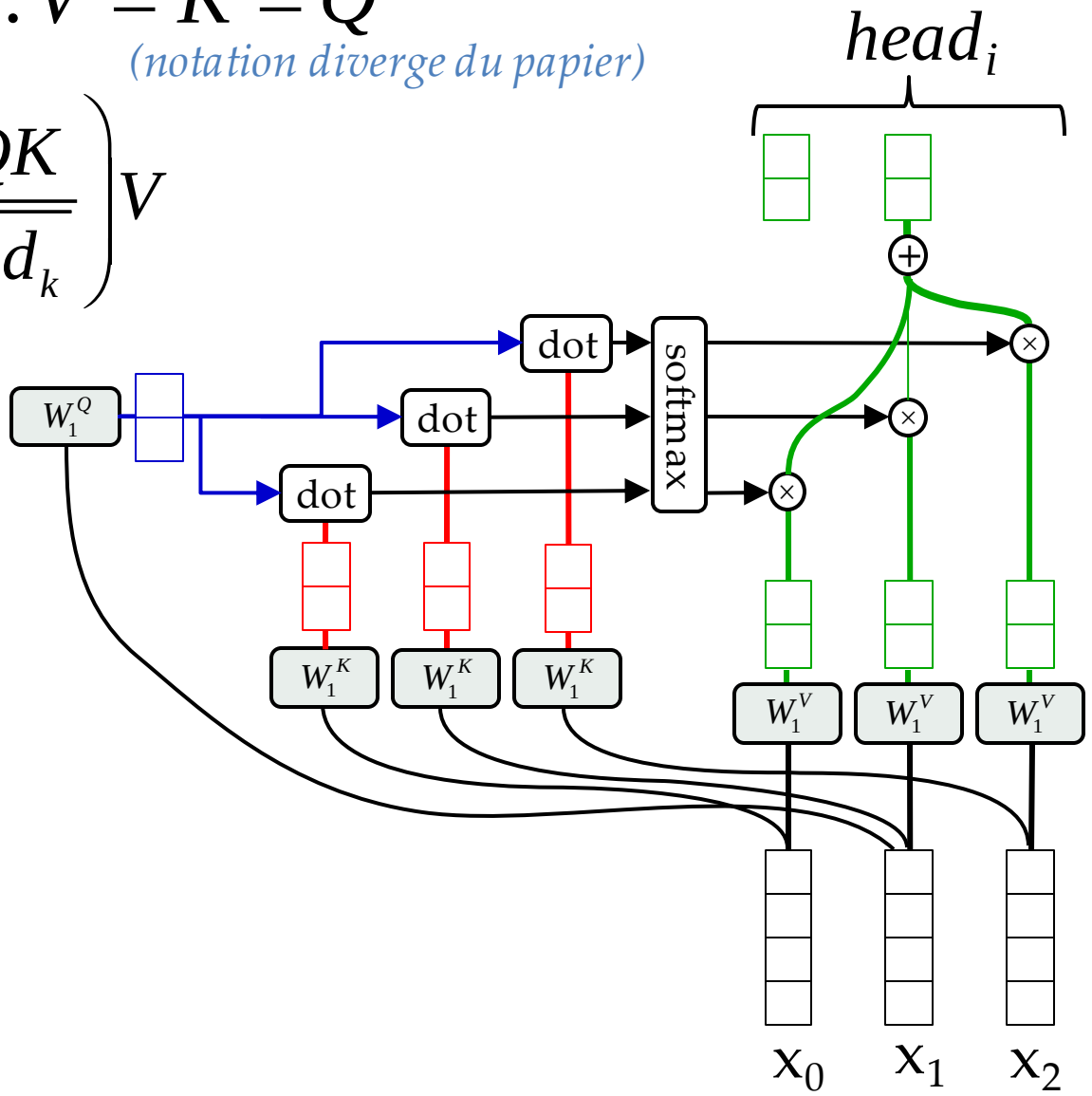

$head_i$: Scaled Dot-Product Attention

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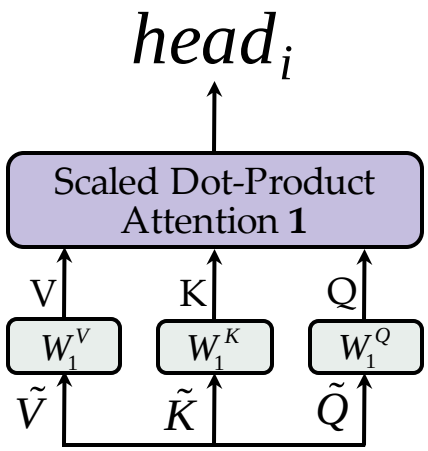
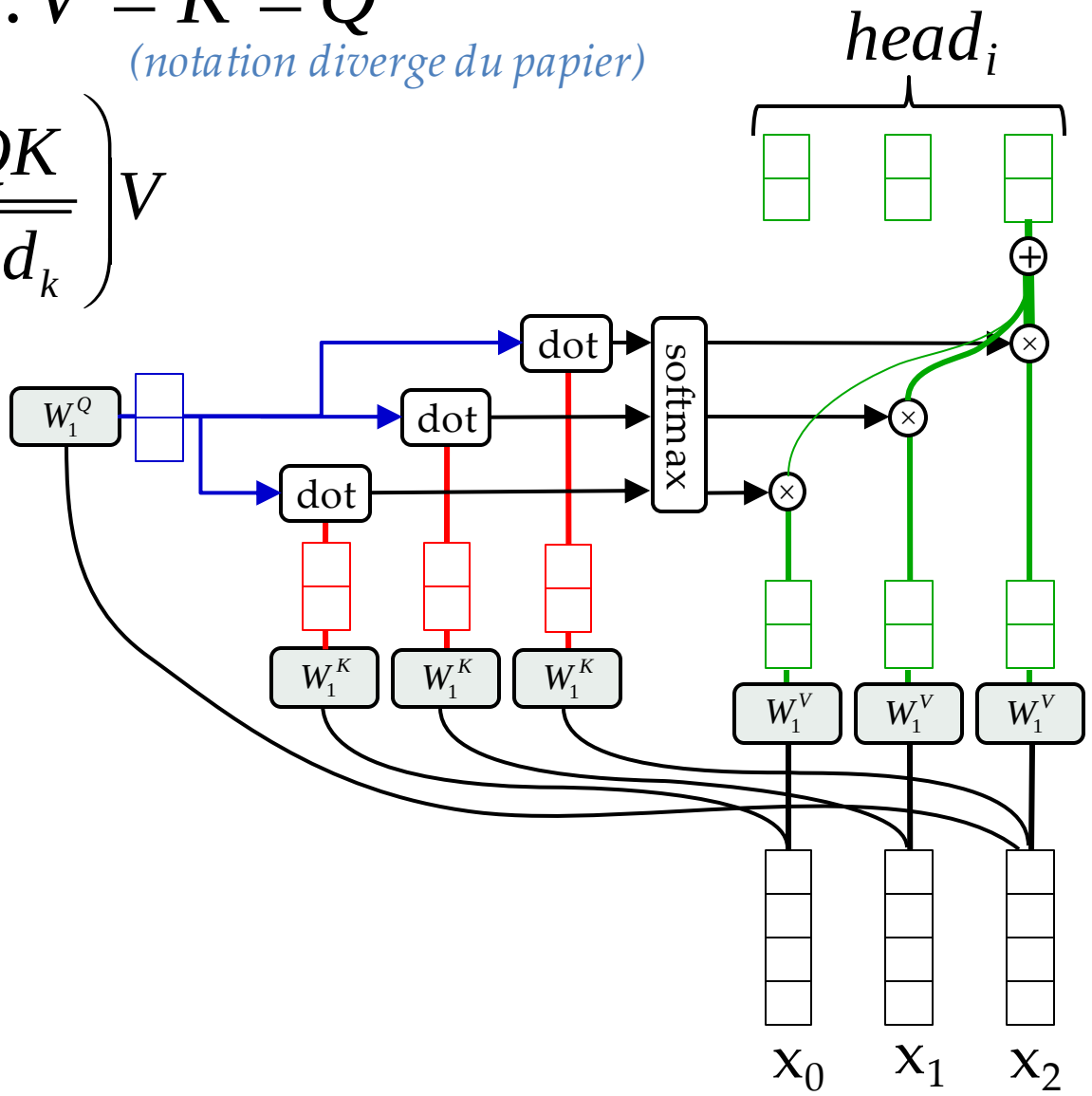
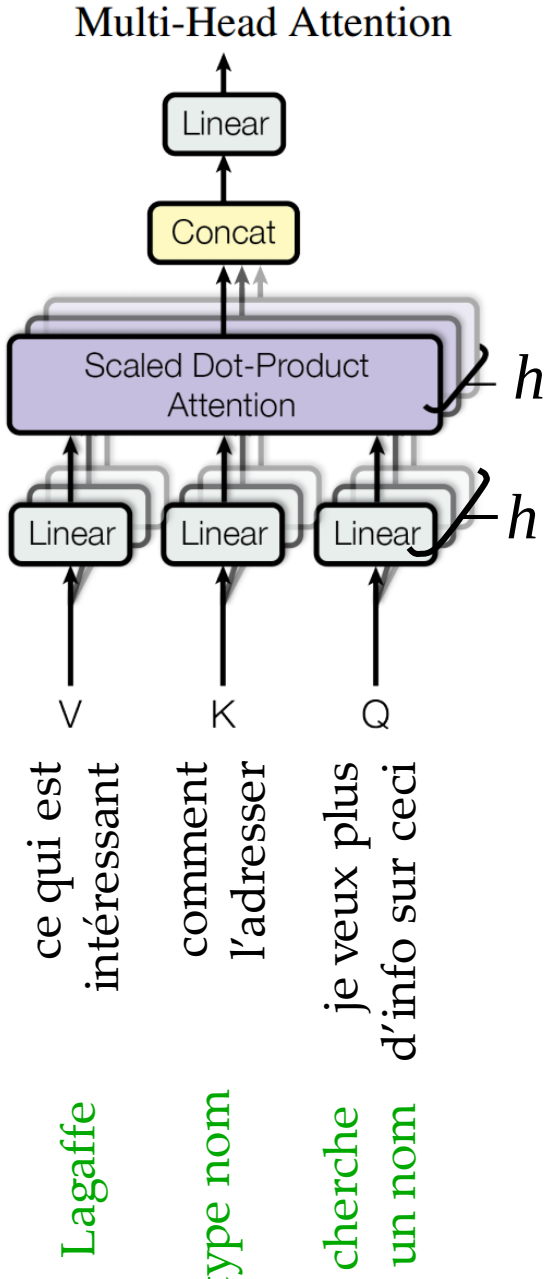
(notation diverge du papier)

$$sortie = \text{Softmax}\left(\frac{QK}{\sqrt{d_k}}\right)V$$





Attention


Multi-Head Attention
Linear
Concat
Scaled Dot-Product Attention
h
Linear
Linear
Linear
h
V
K
Q
ce qui est intéressant
comment l'adresser
je veux plus d'info sur ceci
Lagaffe
type nom
cherche un nom

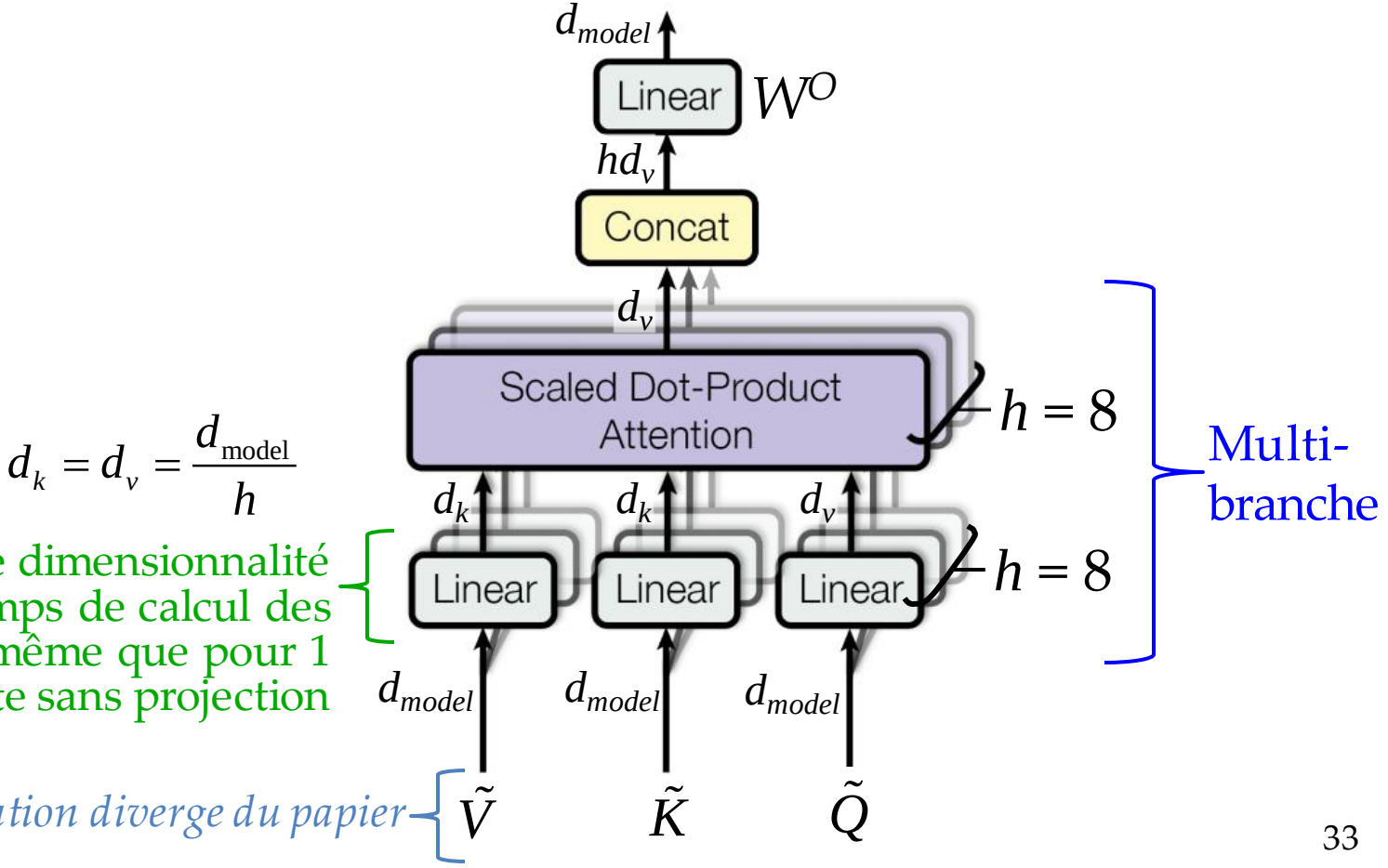
Avantages du self-attention

- Facilité à paralléliser le calcul
  - RNN est fondamentalement séquentiel
- Longueur **fixe** du chemin dans le graphe de calcul pour les dépendances à longue-portée
  - plus de vanishing gradient
  - RNN : longueur dépend du nombre d'itérations

Multi-head attention

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_h)W^O$$
$$\text{where head}_i = \text{Attention}(\downarrow QW_i^Q, \downarrow KW_i^K, \downarrow VW_i^V)$$

notation diverge du papier



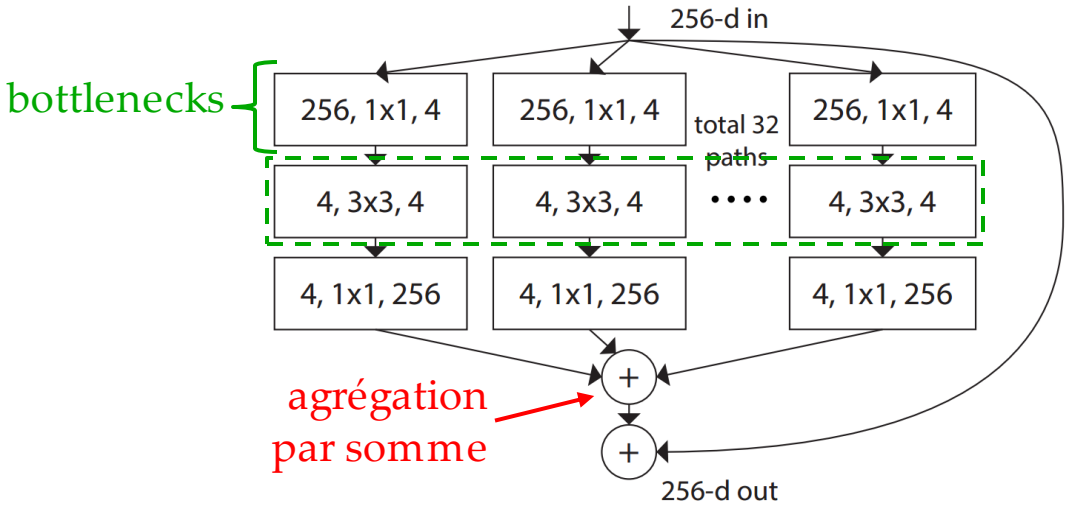
$$d_k = d_v = \frac{d_{\text{model}}}{h}$$

Réduction de dimensionnalité linéaire : temps de calcul des têtes est le même que pour 1 tête sans projection

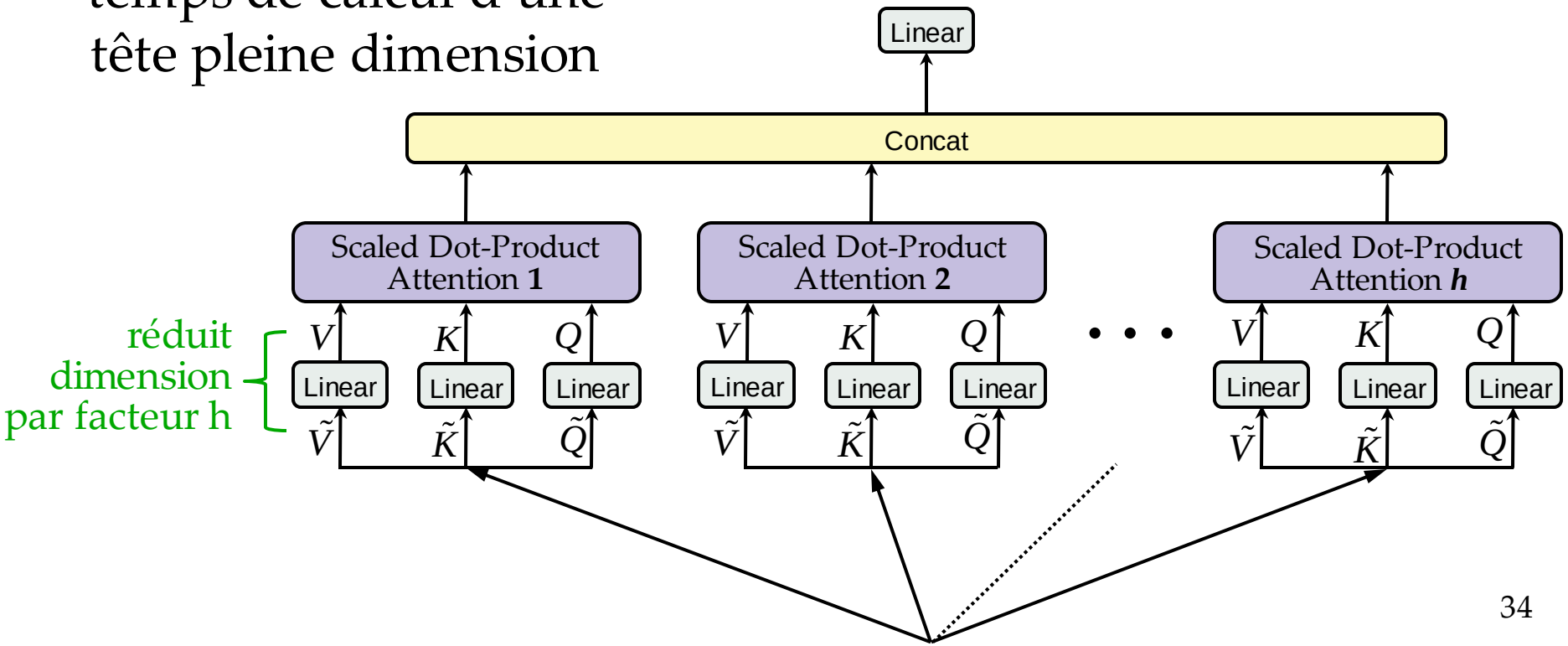
Multi-branche

notation diverge du papier

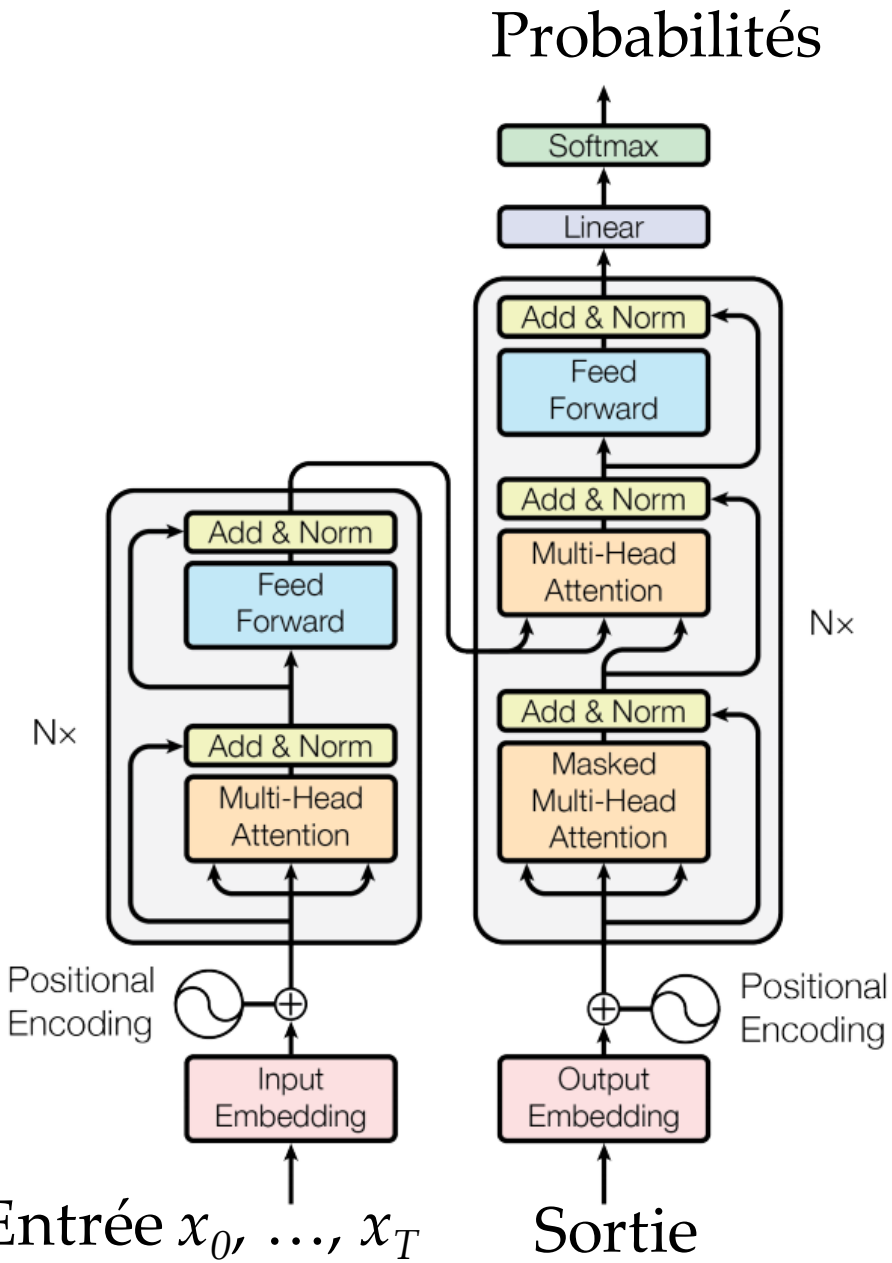
Similarité avec ResNext



Temps de calcul de h têtes sur dimension 1/h *égale* temps de calcul d'une tête pleine dimension

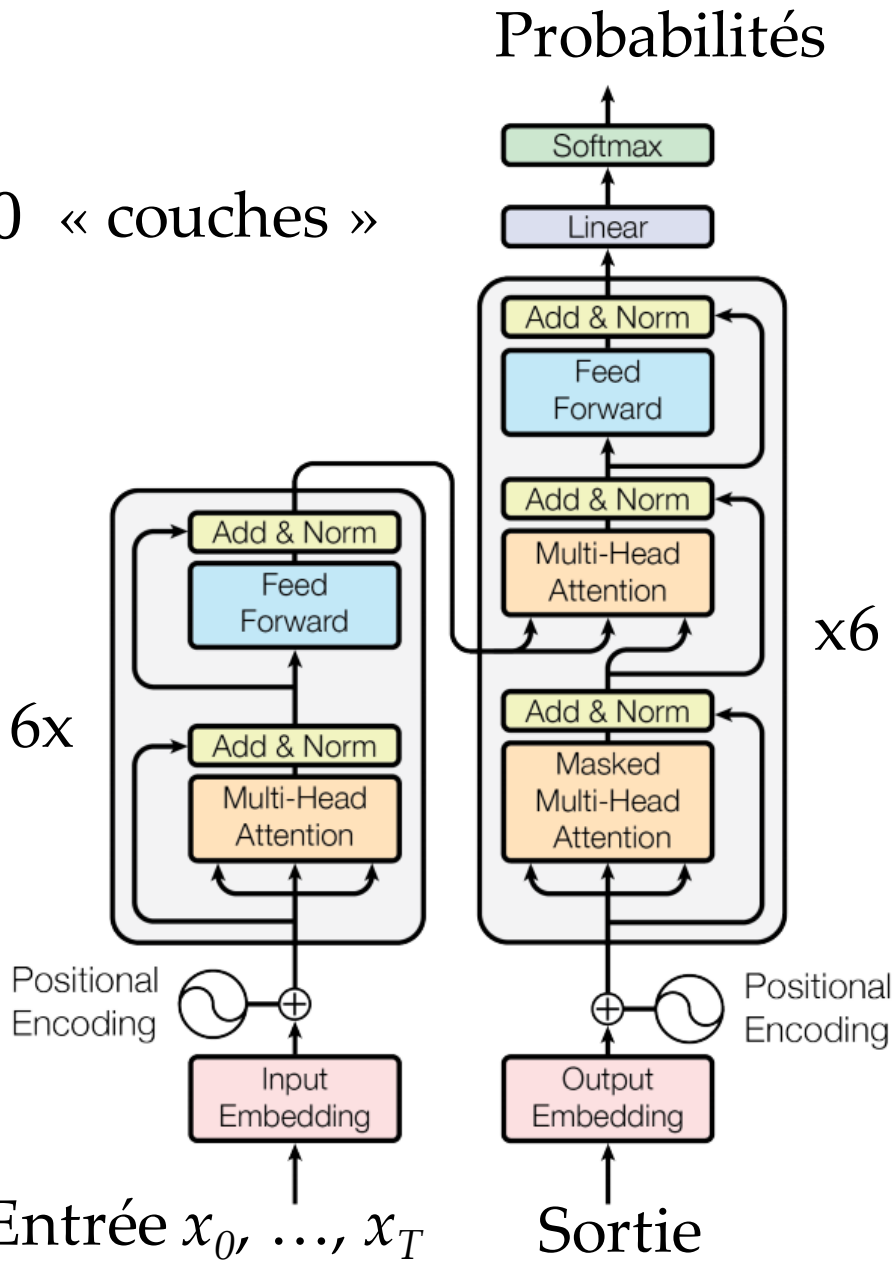


Architecture complète

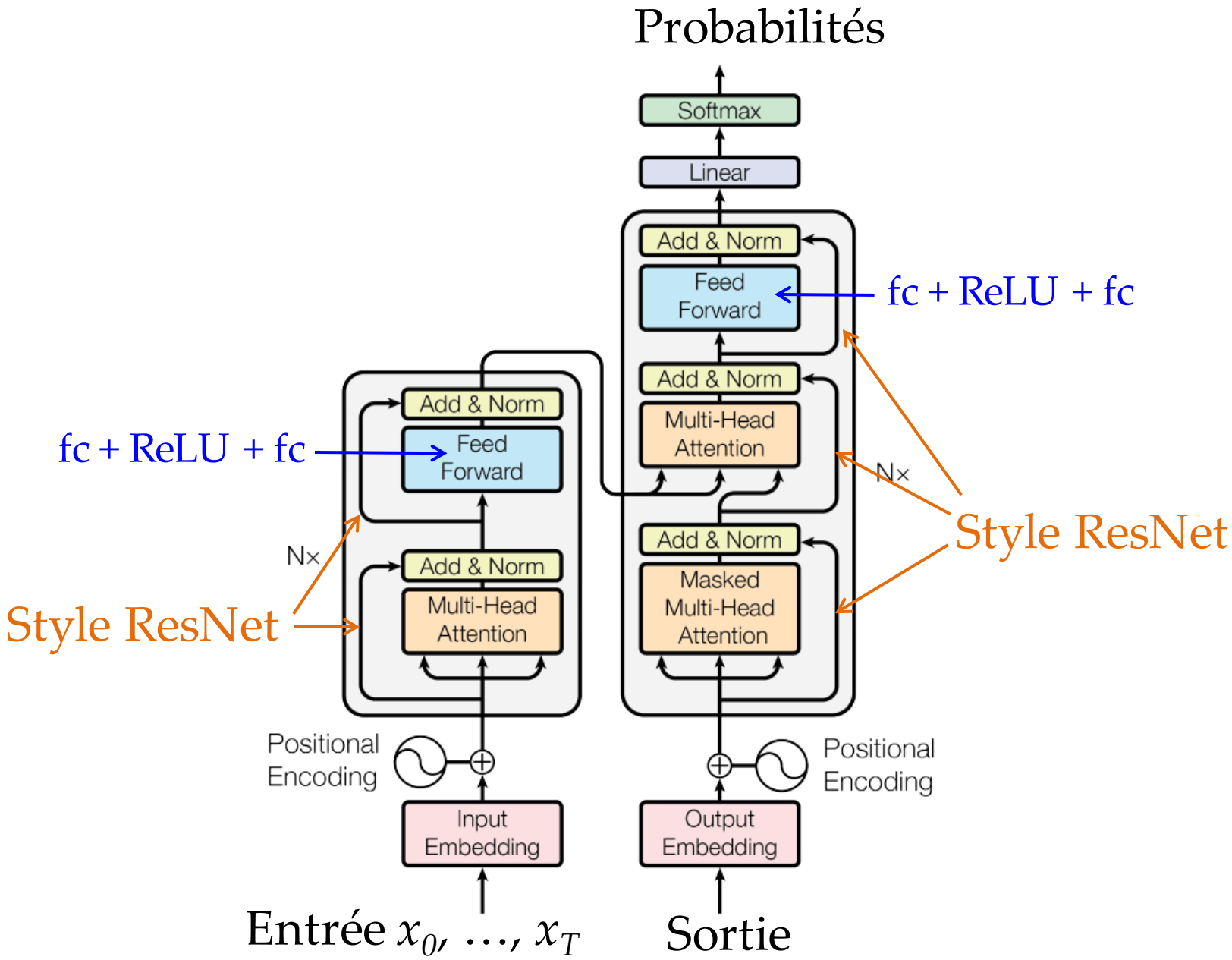


Profondeur

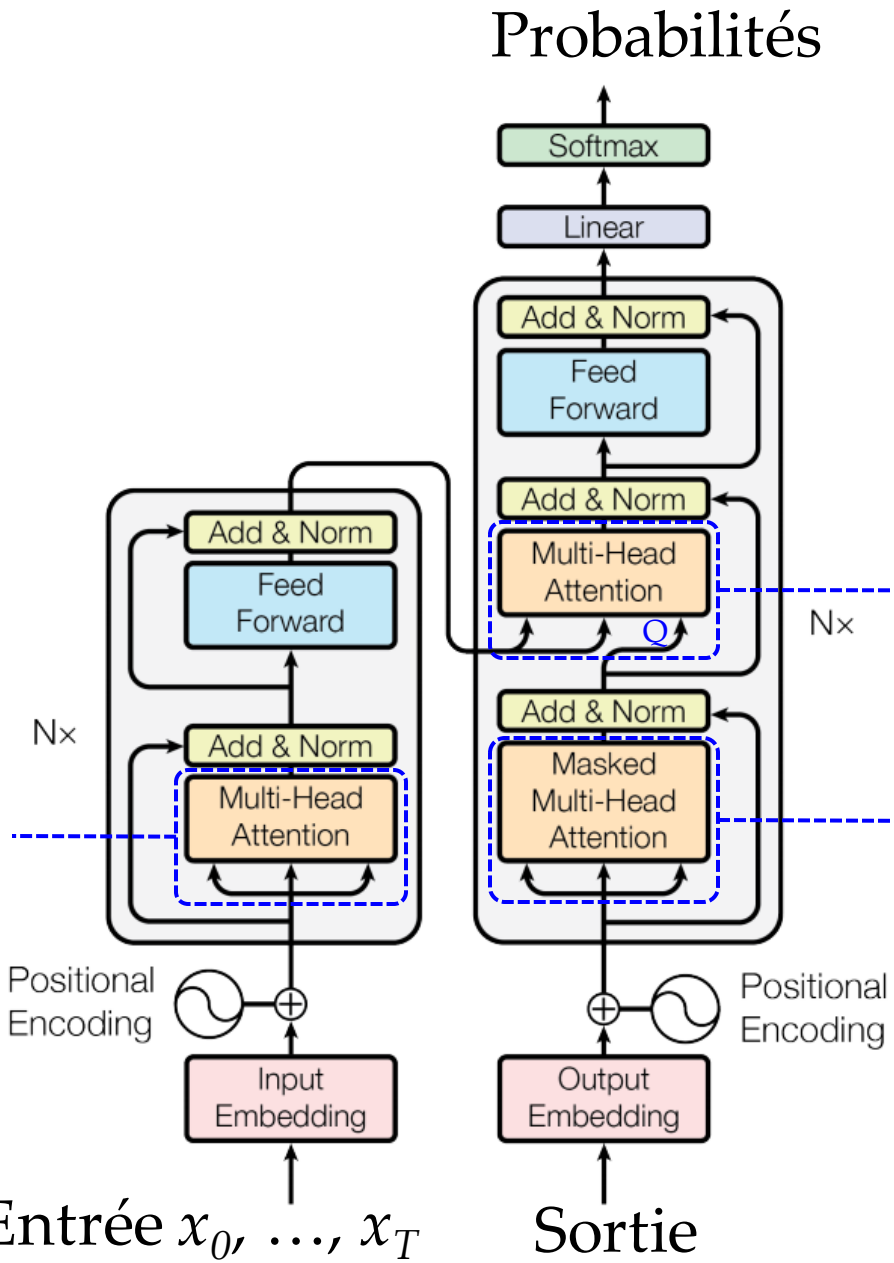
$6 \times 2 + 6 \times 3 = 30$ « couches »



Architecture



Répartition de l'attention



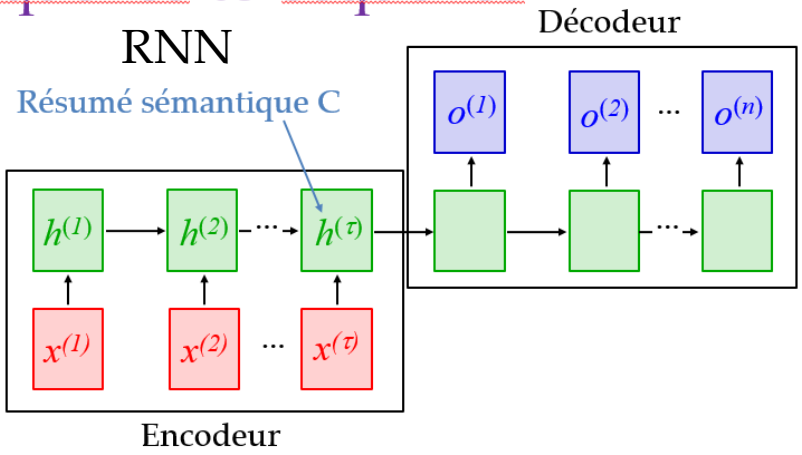
Attention Input-Output

Attention Output-Output

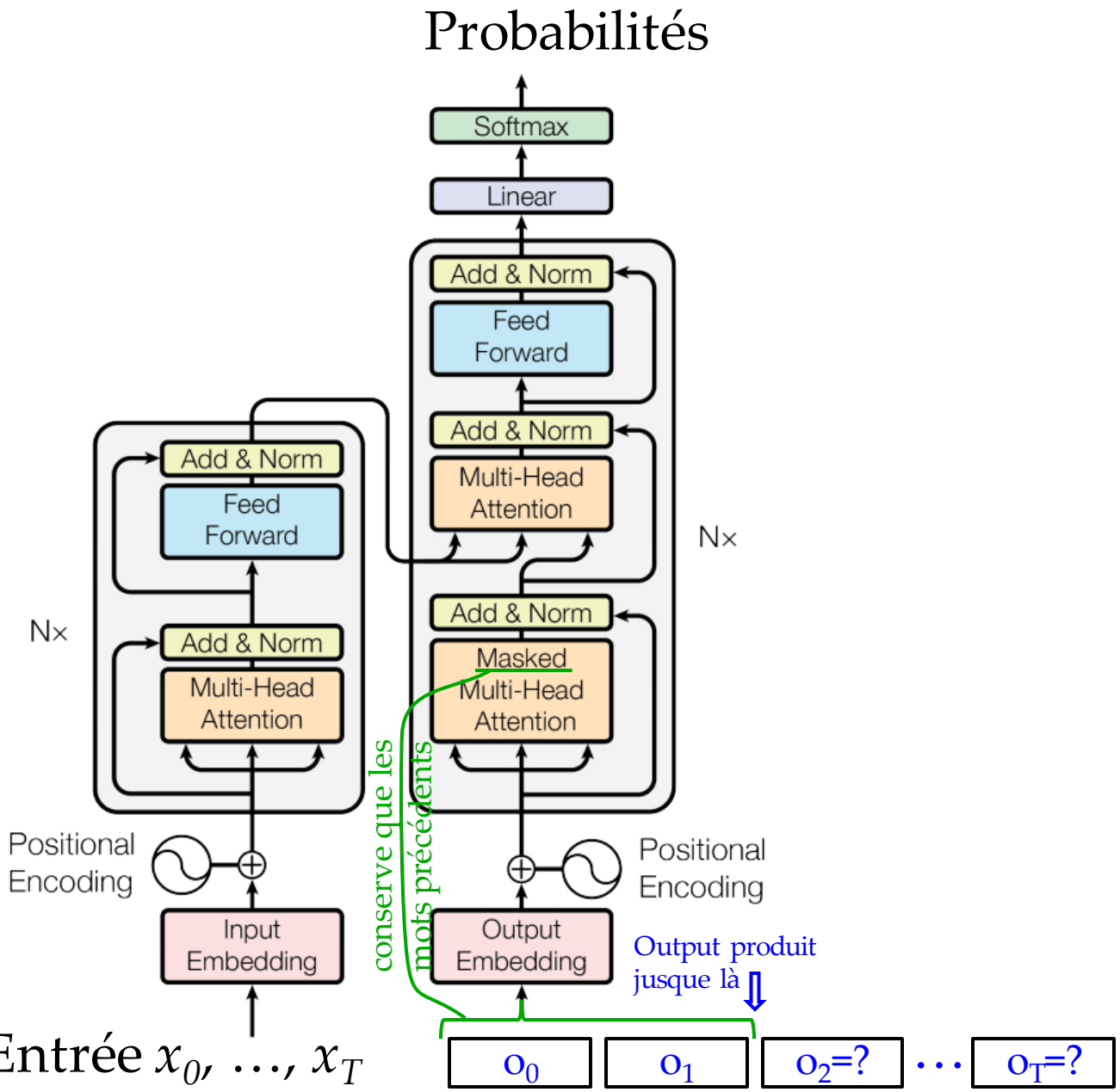
Attention Input-Input

Vue encodeur-décodeur

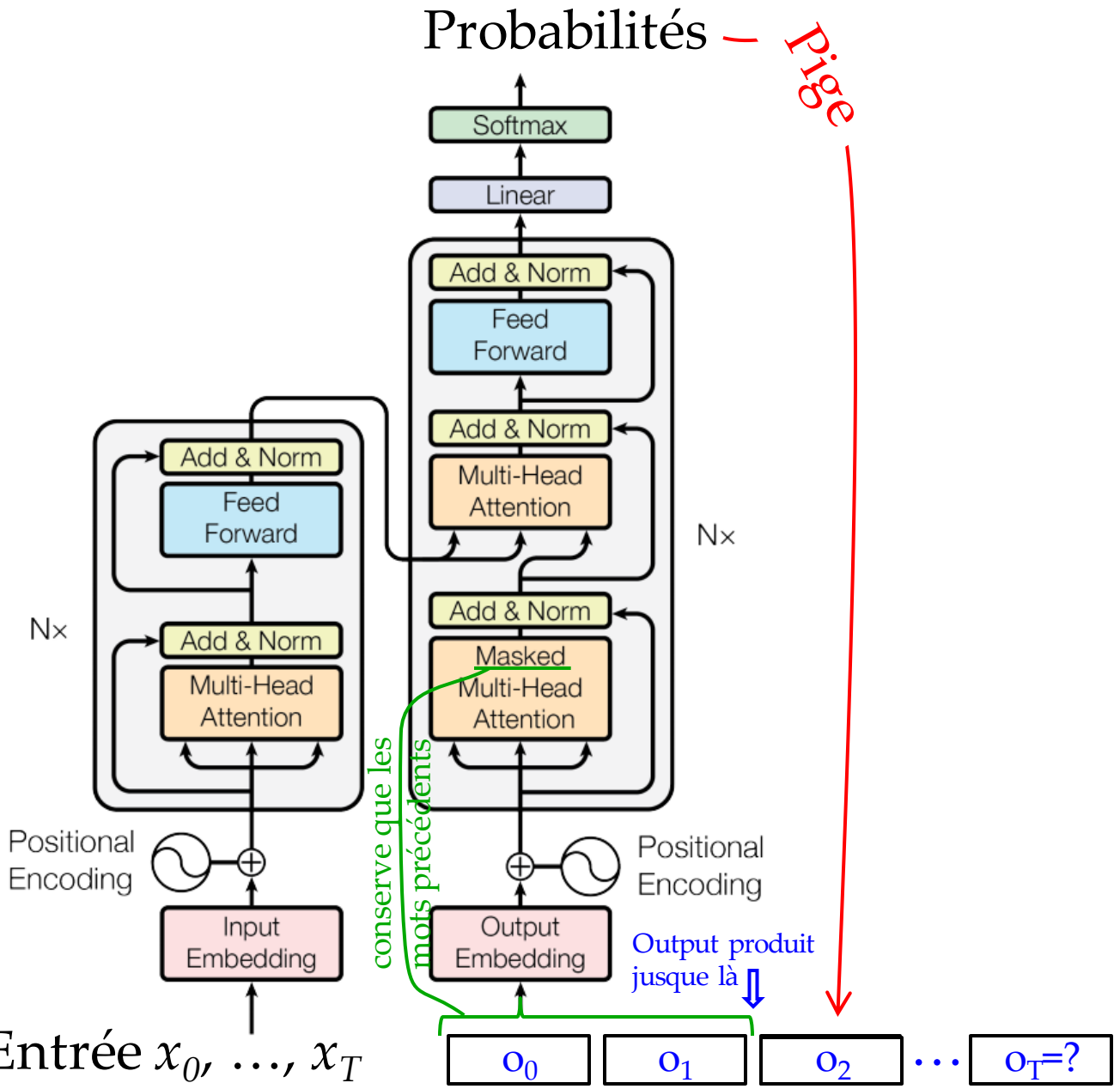
Sequence-to-sequence



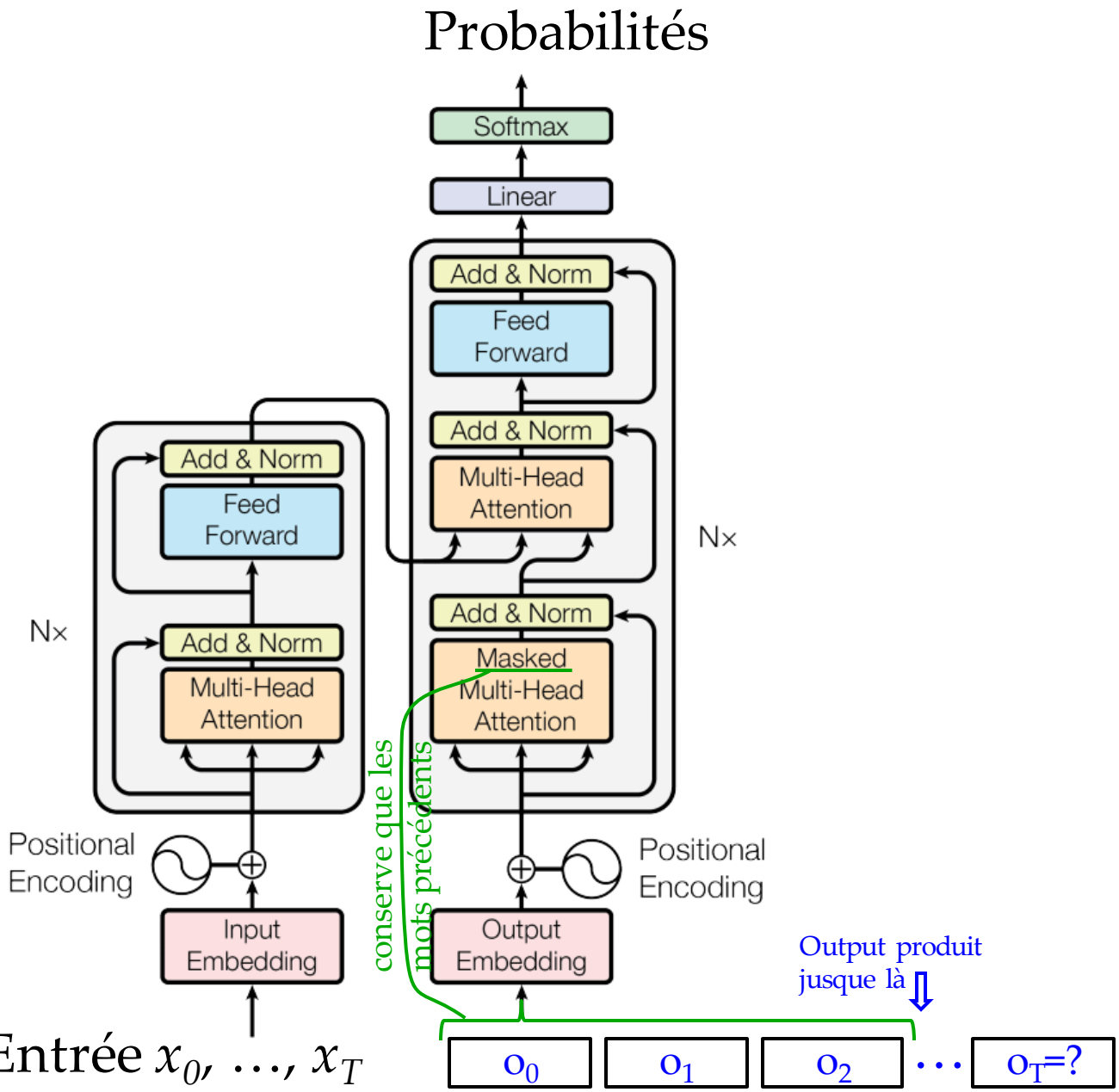
Génération séquence de sortie o



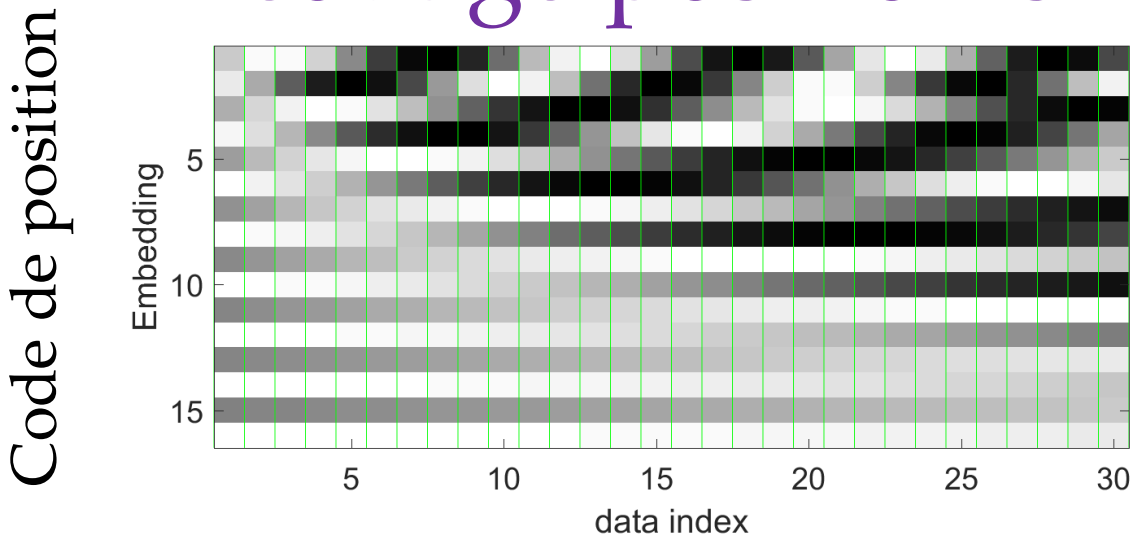
Génération séquence de sortie o



Génération séquence de sortie o



Encodage position sinus/cosinus

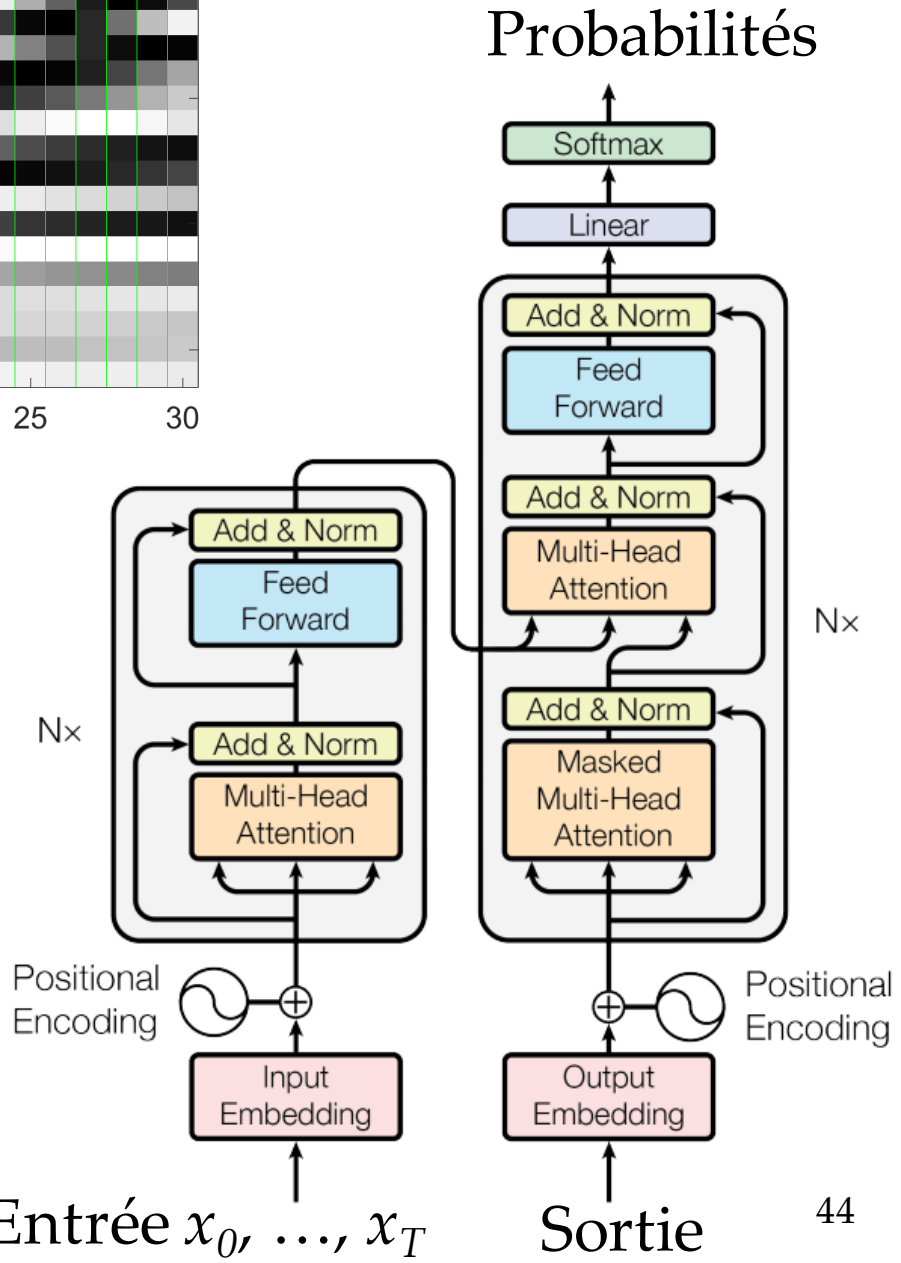


- Perte de l'ordre car l'approche est similaire à CBOW (continuous bag-of-words)
- Additionne à l'*embedding* un vecteur encodant les positions

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$

$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

- Redonne un signal sur l'ordre des mots



Résultats

Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [18]	23.75			
Deep-Att + PosUnk [39]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [38]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [32]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [39]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [38]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	**$3.3 \cdot 10^{18}$**	
Transformer (big)	**28.4**	**41.8**	$2.3 \cdot 10^{19}$	