

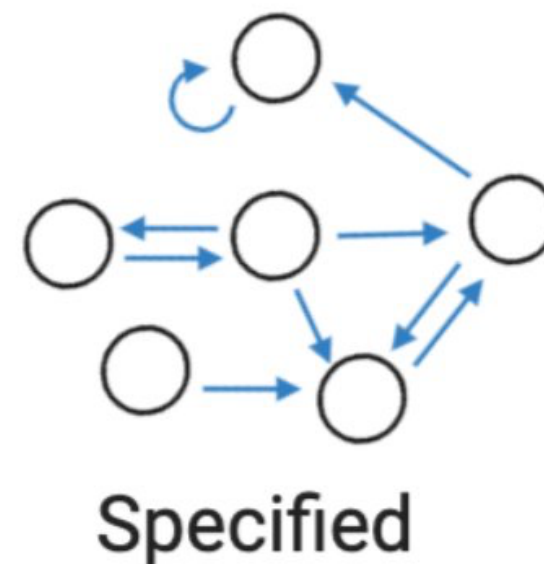
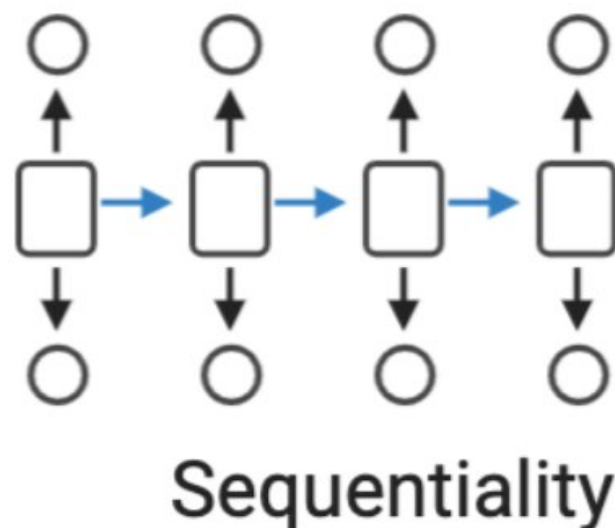
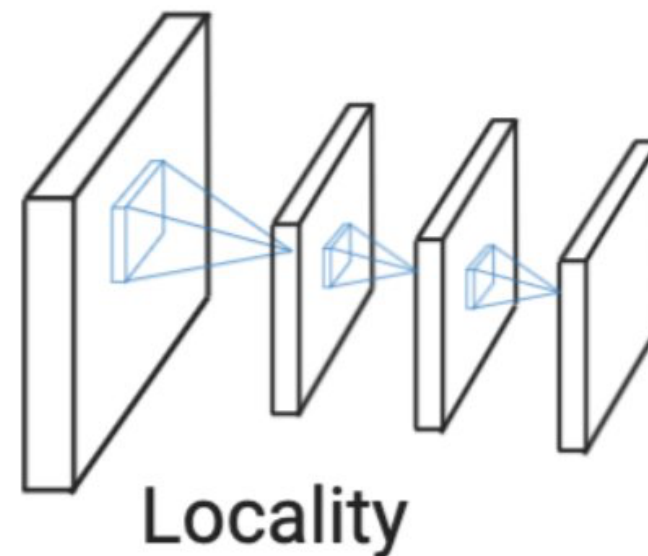
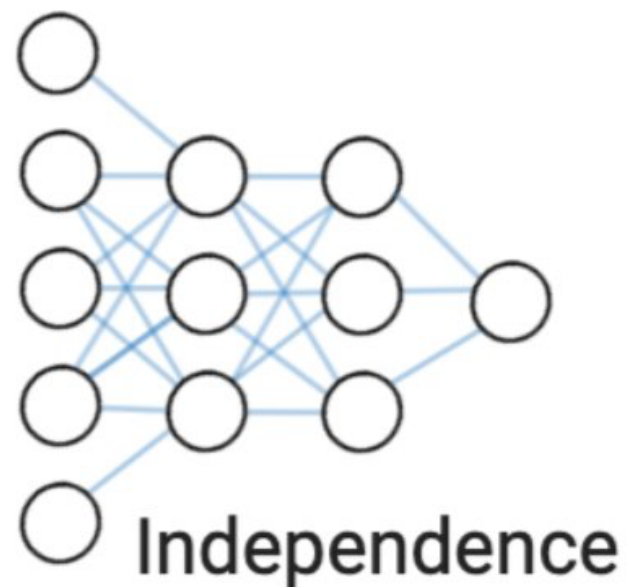
Deep Learning

5. Time series & sequences

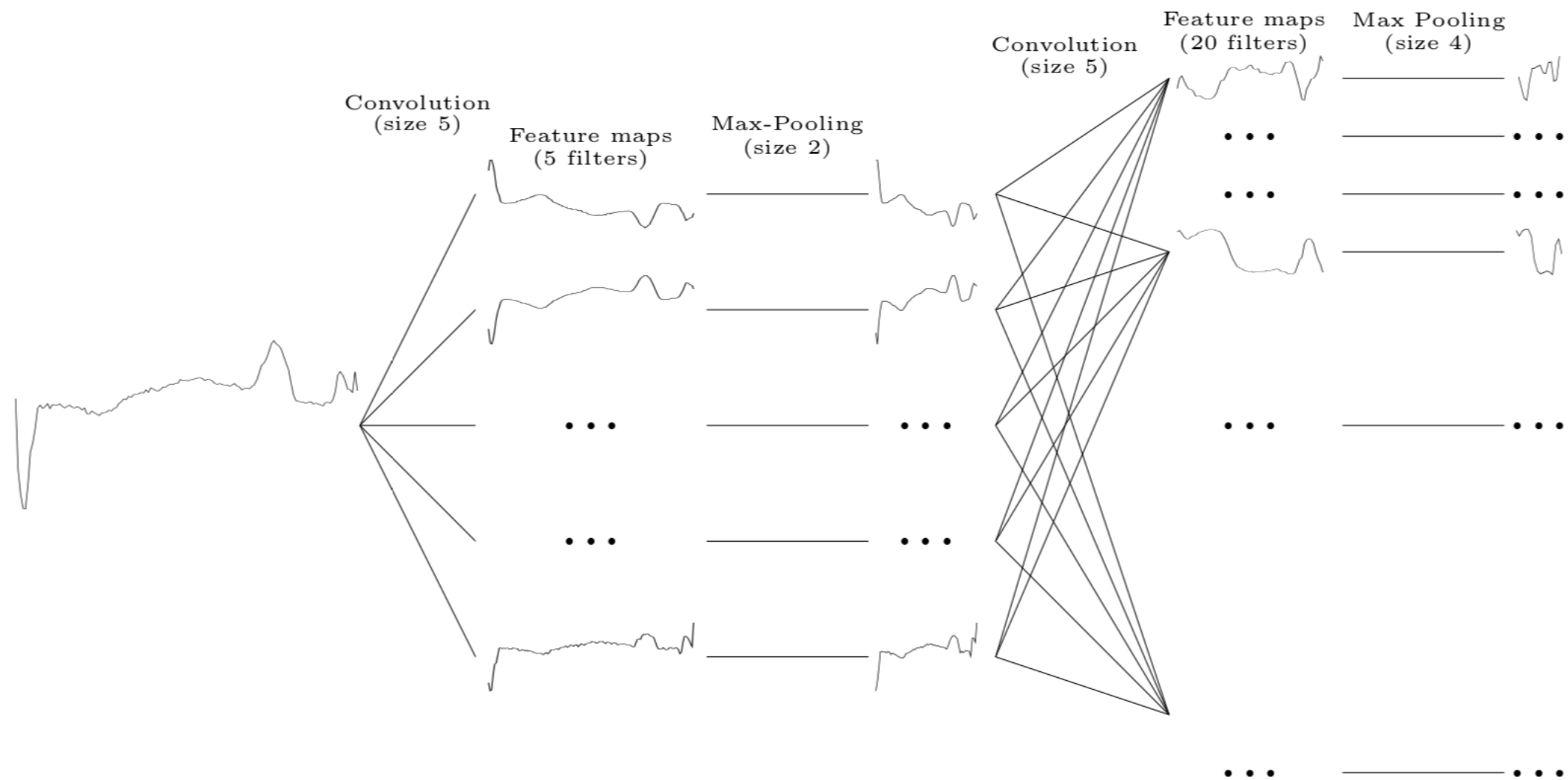
A course @EDHEC
by Romain Tavenard (Prof. @Univ. Rennes 2)

Neural network architectures and inductive biases

Relational Inductive Biases

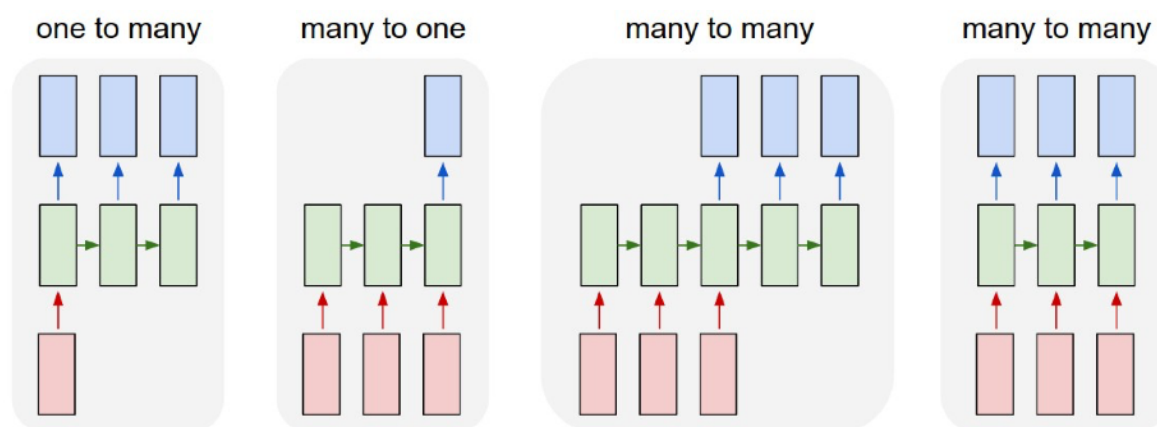


Convolutional neural nets for time series



Source: [Le Guennec *et al.*, 2014]

Recurrent neural nets



PANDARUS:

Alas, I think he shall be come approached and the day
When little strain 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 nudes begun out of the fact, to be conveyed,
Whose noble souls I'll have the heart of the wars.

Sample text generated by a RNN
trained on Shakespeare words

For $\bigoplus_{n=1,\dots,m} \mathcal{L}_{m,n} = 0$, hence we can find a closed subset \mathcal{H} in \mathcal{H} and any sets \mathcal{F} on X , U is a closed immersion of S , then $U \rightarrow T$ is a separated algebraic space.

Proof. Proof of (1). It also start we get

$$S = \text{Spec}(R) = U \times_X U \times_X U$$

and the comparicoly in the fibre product covering we have to prove the lemma generated by $\coprod Z \times_U U \rightarrow V$. Consider the maps M along the set of points Sch_{fppf} and $U \rightarrow U$ is the fibre category of S in U in Section, ?? and the fact that any U affine, see Morphisms, Lemma ?? . Hence we obtain a scheme S and any open subset $W \subset U$ in $Sh(G)$ such that $\text{Spec}(R') \rightarrow S$ is smooth or an

$$U = \bigcup U_i \times_{S_i} U_i$$

which has a nonzero morphism we may assume that f_i is of finite presentation over S . We claim that $\mathcal{O}_{X,x}$ is a scheme where $x, x', s'' \in S'$ such that $\mathcal{O}_{X,x'} \rightarrow \mathcal{O}'_{X',x'}$ is separated. By Algebra, Lemma ?? we can define a map of complexes $GL_{S'}(x'/S'')$ and we win. \square

To prove study we see that $\mathcal{F}|_U$ is a covering of \mathcal{X}' , and \mathcal{T}_i is an object of $\mathcal{F}_{X/S}$ for $i > 0$ and \mathcal{F}_p exists and let \mathcal{F}_i be a presheaf of \mathcal{O}_X -modules on \mathcal{C} as a \mathcal{F} -module. In particular $\mathcal{F} = U/\mathcal{F}$ we have to show that

$$\widetilde{M}^\bullet = \mathcal{I}^\bullet \otimes_{\text{Spec}(k)} \mathcal{O}_{S,s} - i_X^{-1} \mathcal{F}$$

is a unique morphism of algebraic stacks. Note that

$$\text{Arrows} = (Sch/S)_{fppf}^{opp}, (Sch/S)_{fppf}$$

and

$$V = \Gamma(S, \mathcal{O}) \mapsto (U, \text{Spec}(A))$$

is an open subset of X . Thus U is affine. This is a continuous map of X is the inverse, the groupoid scheme S .

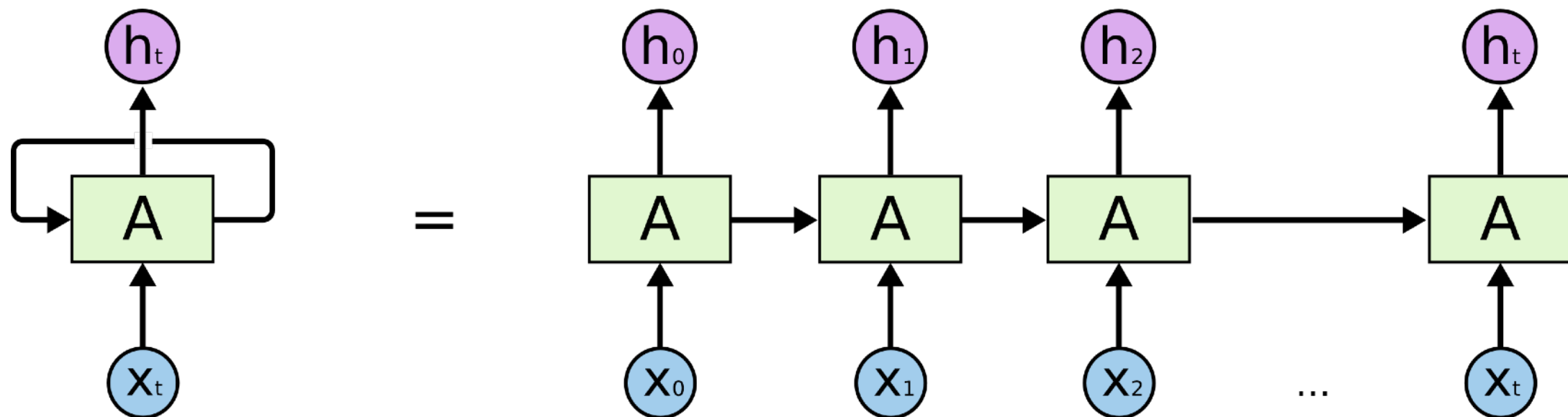
Proof. See discussion of sheaves of sets. \square

The result for prove any open covering follows from the less of Example ?? . It may replace S by $X_{spaces, \acute{e}tale}$ which gives an open subspace of X and T equal to S_{Zar} , see Descent, Lemma ?? . Namely, by Lemma ?? we see that R is geometrically regular over S .

Sample LaTeX generated by a RNN
trained on a book of algebraic geometry

Recurrent neural nets

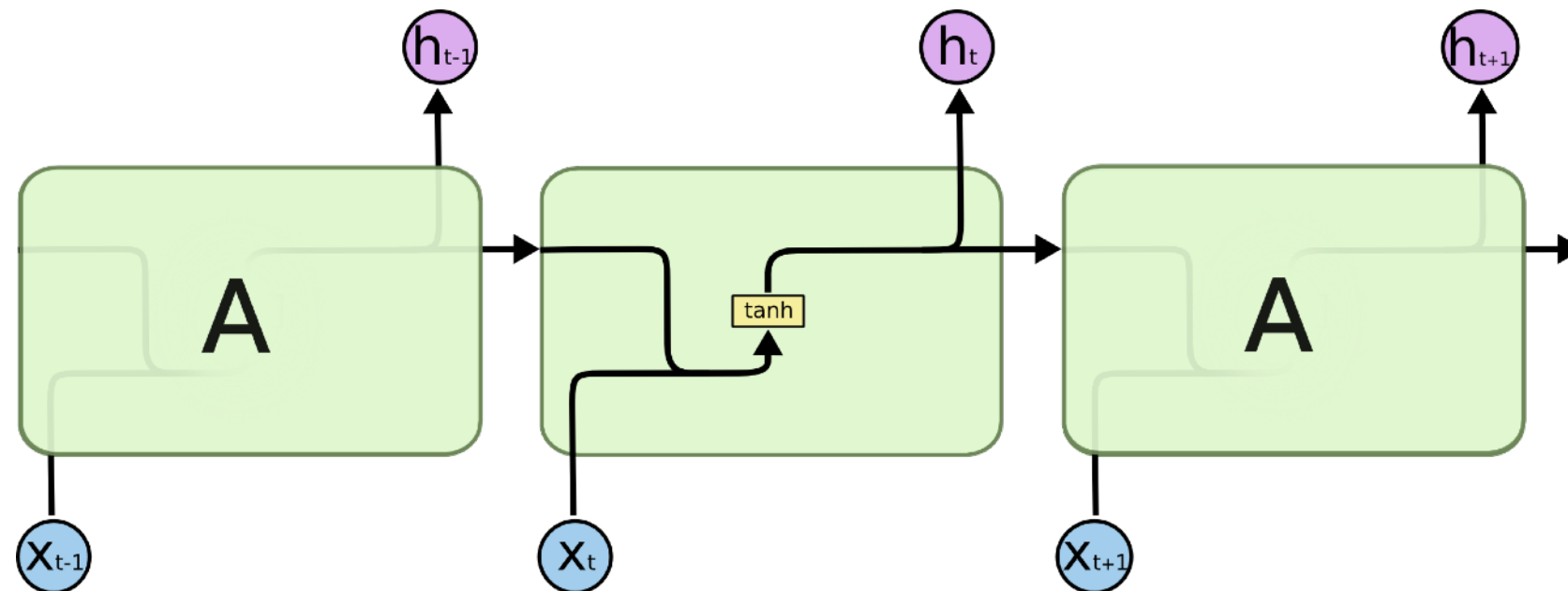
- Very flexible model (any length, let the model learn its memory needs, ...)



Source: [Christopher Olah's blog](#)

Recurrent neural nets

- "Vanilla" RNN in more details



$$h_t = \tanh(W_h h_{t-1} + W_x x_t + b)$$

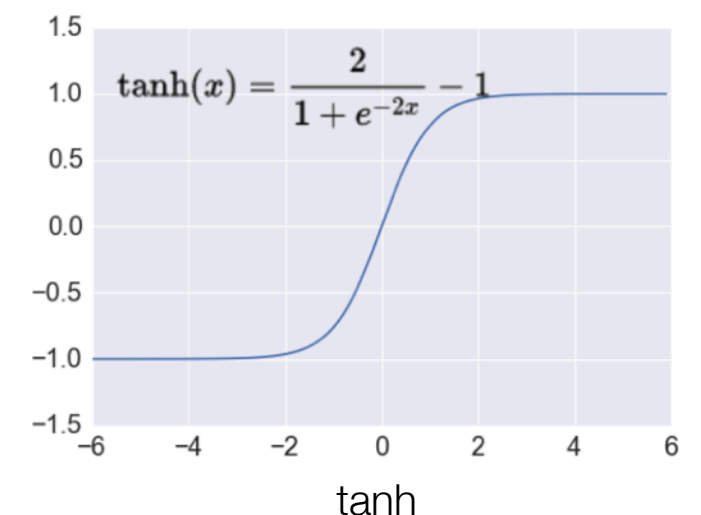
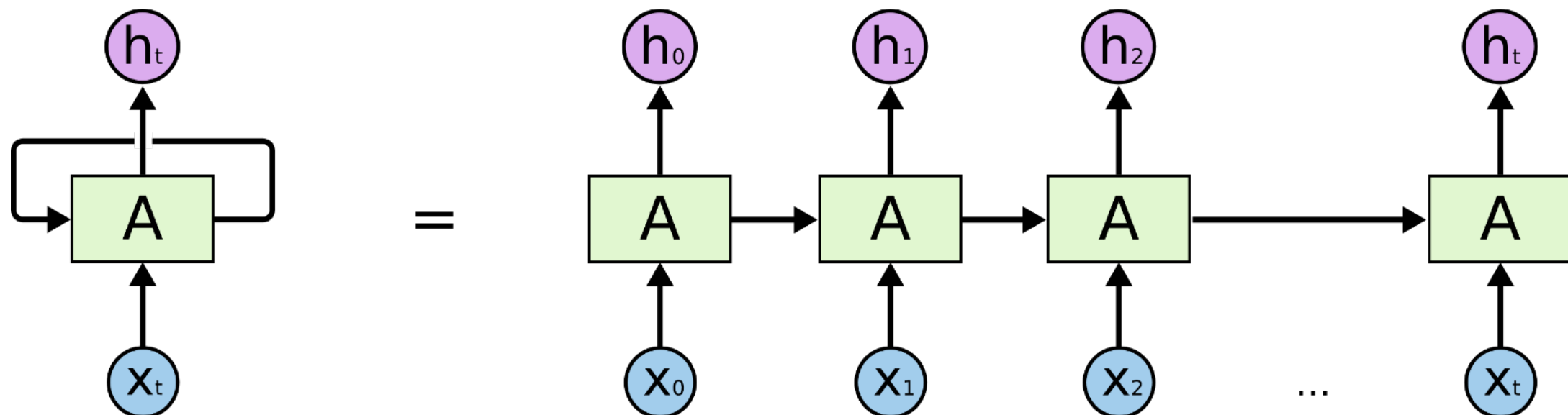


Illustration: RNN cell, source: [Christopher Olah's blog](#)

Recurrent neural nets

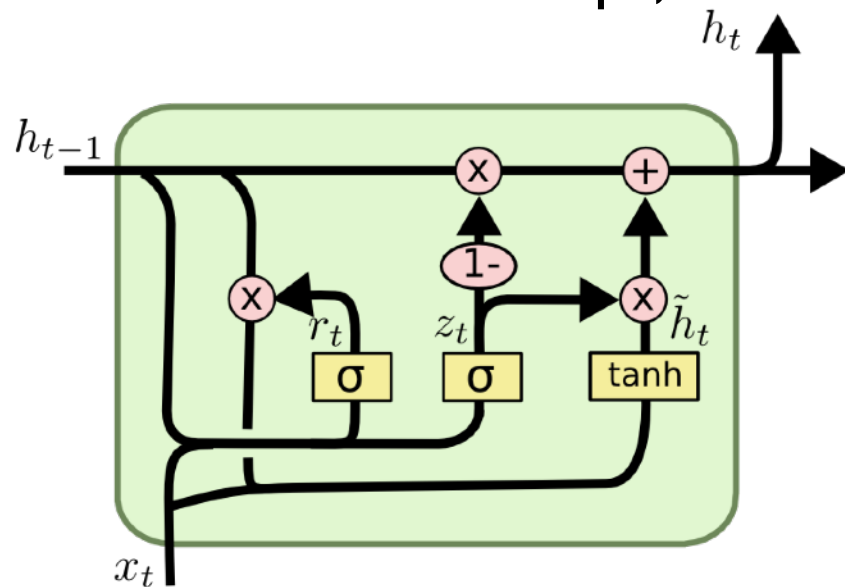
- Very flexible model (any length, let the model learn its memory needs, ...)
- Difficult to learn in practice
 - Slow (lack of parallelism)
 - Vanishing gradients (hard to learn long-term dependencies)



Source: [Christopher Olah's blog](#)

Recurrent neural nets

- Gated Recurrent Unit (GRU)
- Principle
 - At each time step, keep only part of the information



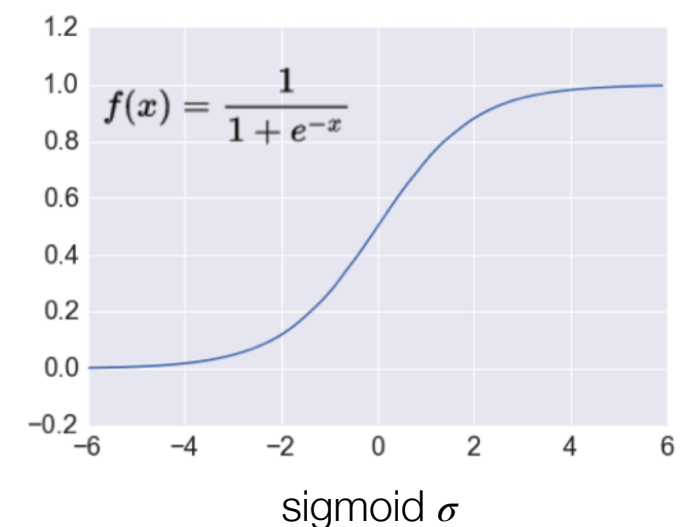
$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t])$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t])$$

$$\tilde{h}_t = \tanh(W \cdot [r_t * h_{t-1}, x_t])$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Illustration: GRU cell, source: [Christopher Olah's blog](#)



Recurrent neural nets

- Long Short-Term Memory (LSTM)
- Principle: similar to GRU

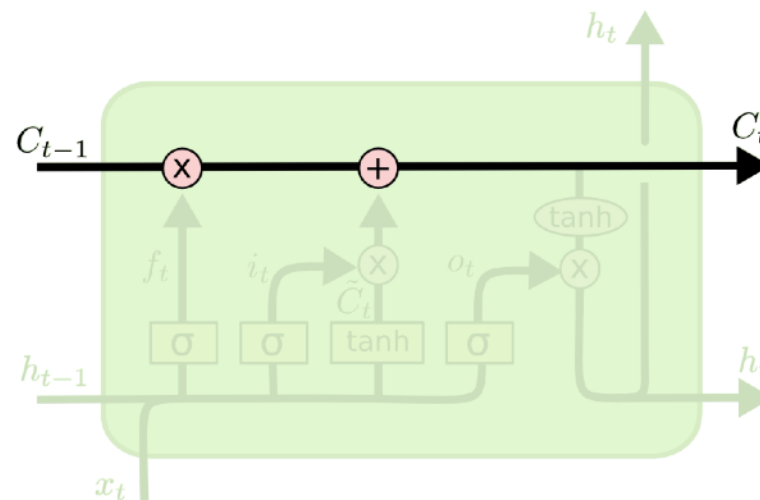
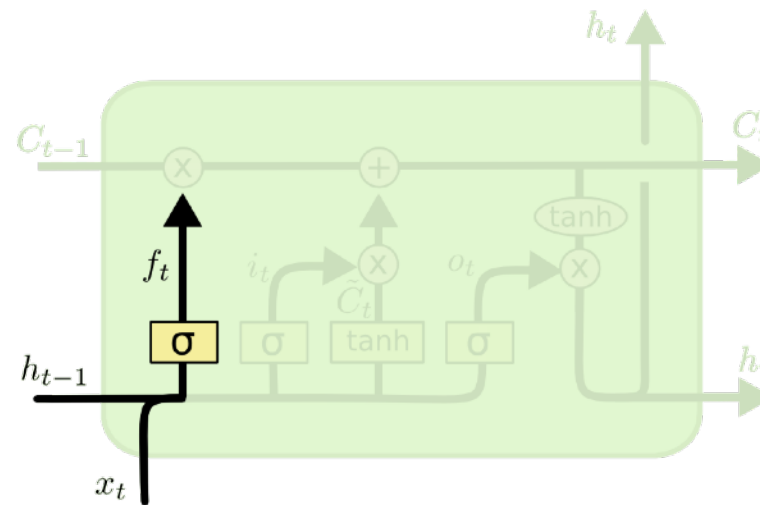


Illustration: LSTM cell, source: [Christopher Olah's blog](#)

Recurrent neural nets

- Long Short-Term Memory (LSTM)
- Principle: similar to GRU

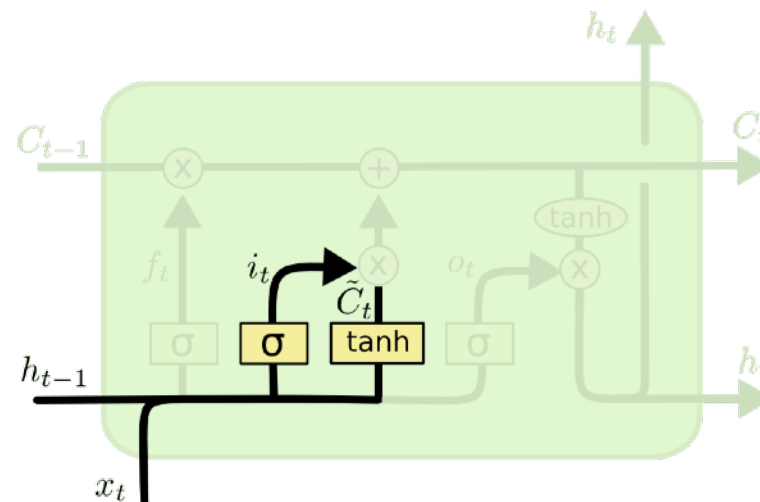


$$f_t = \sigma (W_f \cdot [h_{t-1}, x_t] + b_f)$$

Illustration: LSTM cell, source: [Christopher Olah's blog](#)

Recurrent neural nets

- Long Short-Term Memory (LSTM)
- Principle: similar to GRU

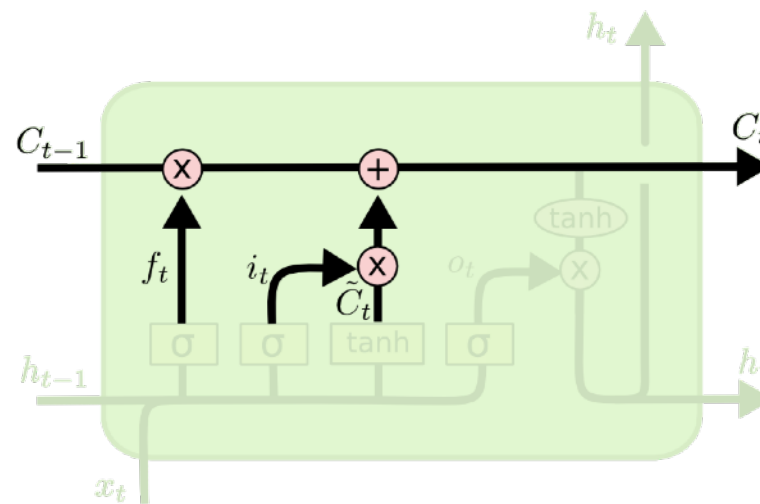


$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

Illustration: LSTM cell, source: [Christopher Olah's blog](#)

Recurrent neural nets

- Long Short-Term Memory (LSTM)
- Principle: similar to GRU

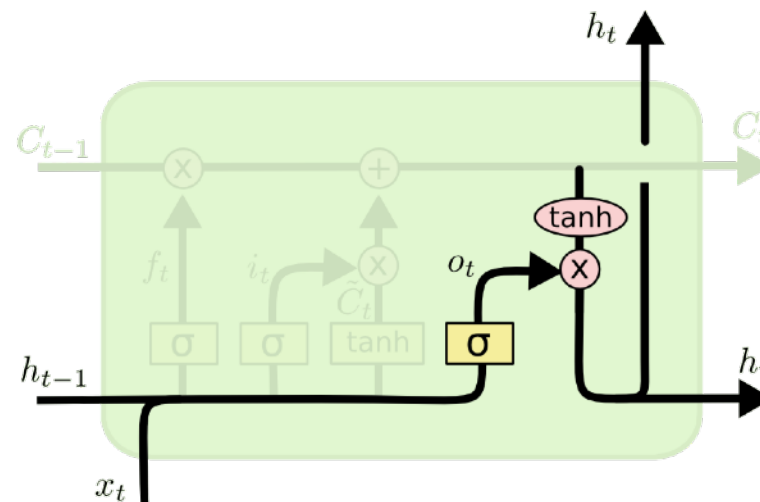


$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Illustration: LSTM cell, source: [Christopher Olah's blog](#)

Recurrent neural nets

- Long Short-Term Memory (LSTM)
- Principle: similar to GRU



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

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

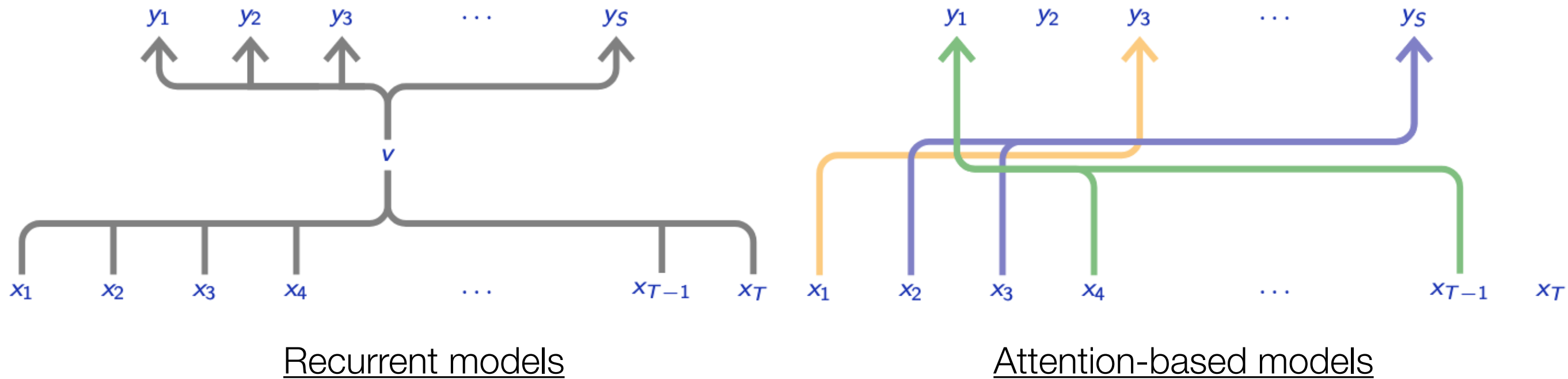
Illustration: LSTM cell, source: [Christopher Olah's blog](#)

Attention-based models

Motivating example

- Consider the following translation task:
 - From English: "**An apple** that had been on the tree in the garden for weeks had finally been **picked up**."
 - To French: "**Une pomme** qui était sur l'arbre du jardin depuis des semaines avait finalement été **ramassée**."
- Both recurrent and convolutional architectures fail at modelling long-range dependencies (for different reasons)
 - Attention aims at tackling this limitation

Attention for Sequence-to-Sequence (seq2seq) tasks



Recurrent models

- Compute a bottleneck representation
- Generate output sequence from this bottleneck

Attention-based models

- For each token in the output sequence, aggregate input features
- Aggregation is importance-based
- Importance depends on the features, not their localization

Assessing importance: Queries, Keys & Values

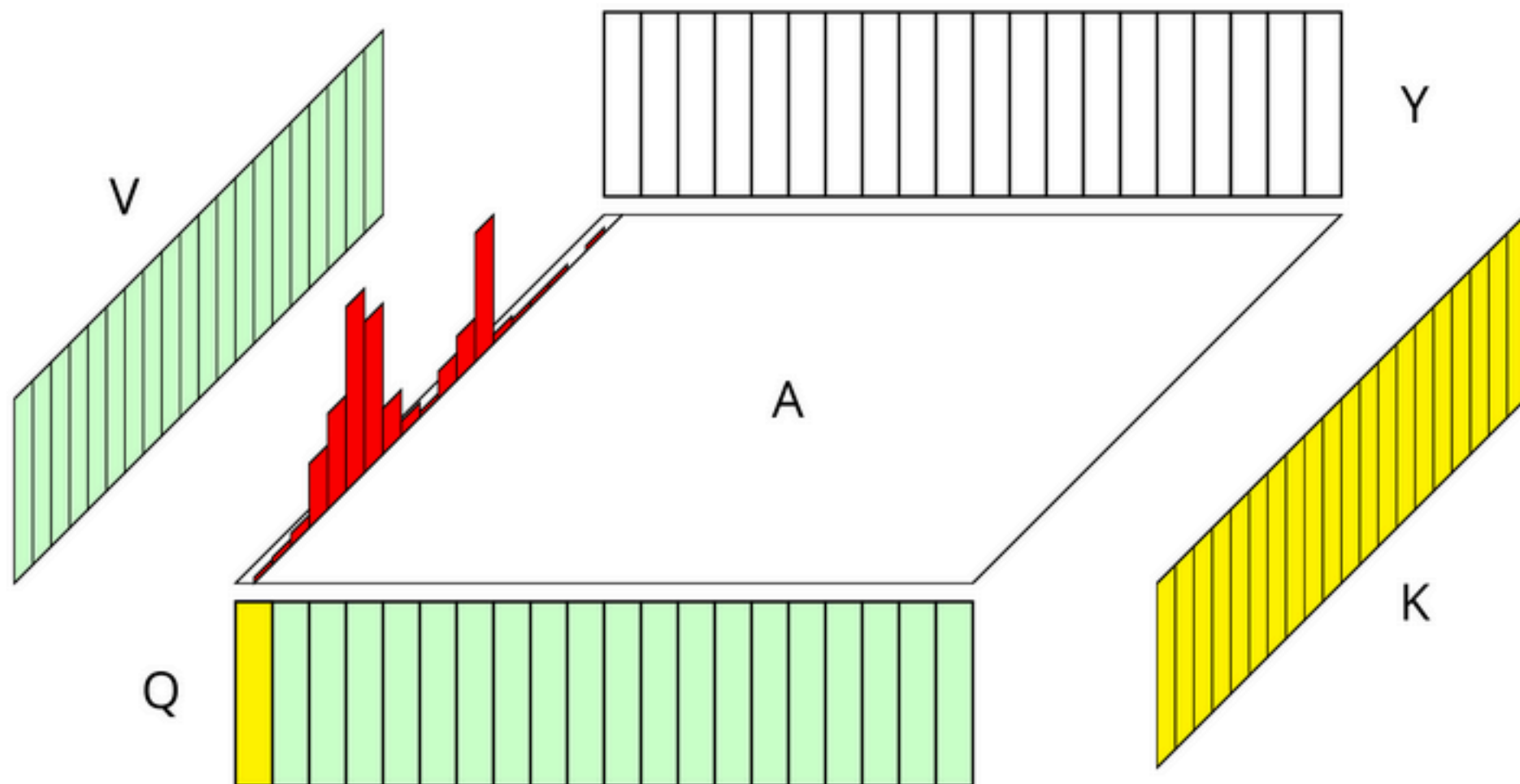
- The **Query** / **Key** / **Value** metaphor: Python dictionaries

```
d = {"a": 12, "b": 7}
print(d["a"])
```

- Queries, Keys & Values: the continuous case
 - Look for keys that are **similar** to the query (not equal)
 - Retrieved value is a weighted average of values associated to keys that are close to the query
 - Could be seen as weighted k-nearest neighbors

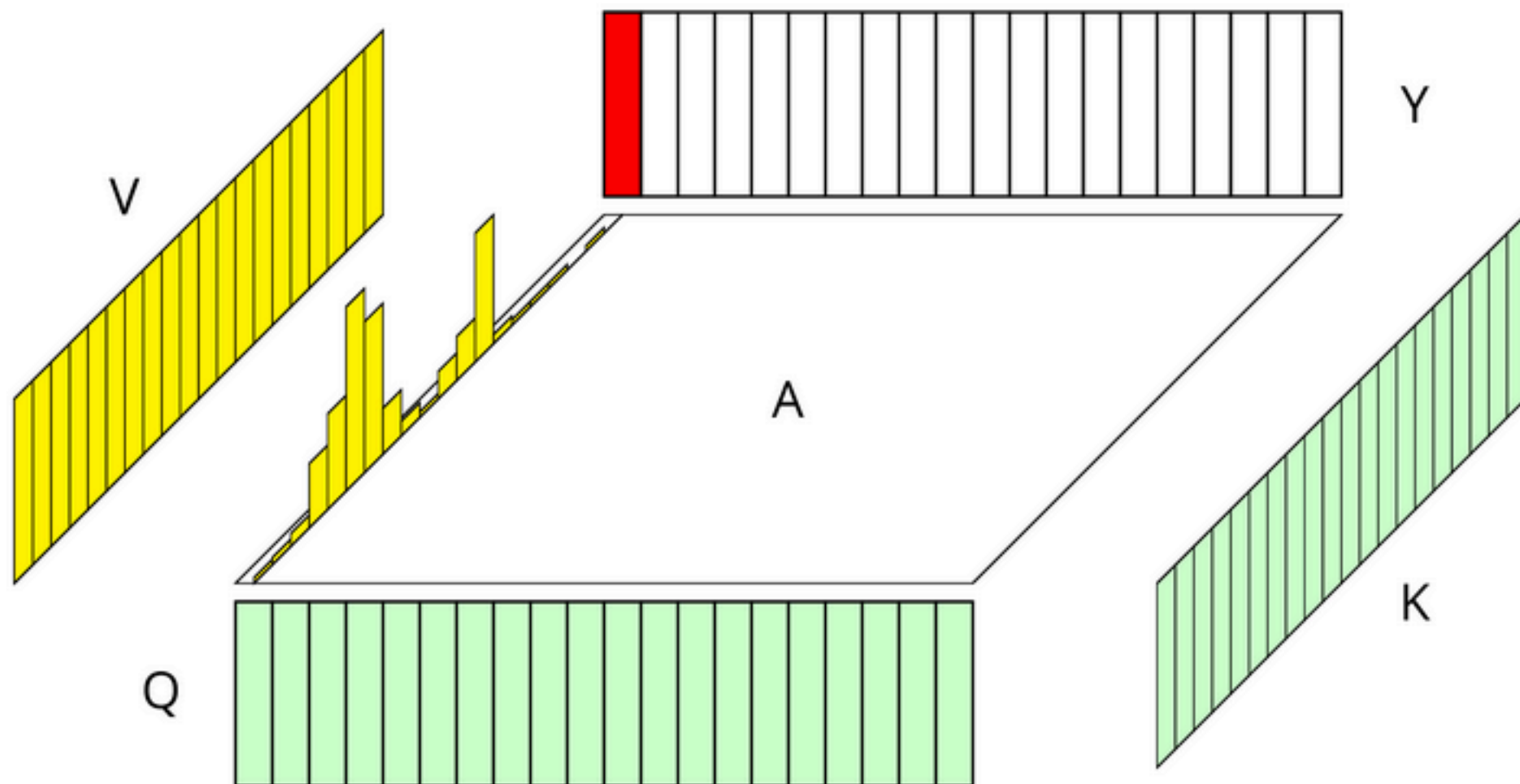
Visual explanation of the Attention mechanism

$$A_{i,j} = \text{softmax}(Q_i \cdot K_j)$$



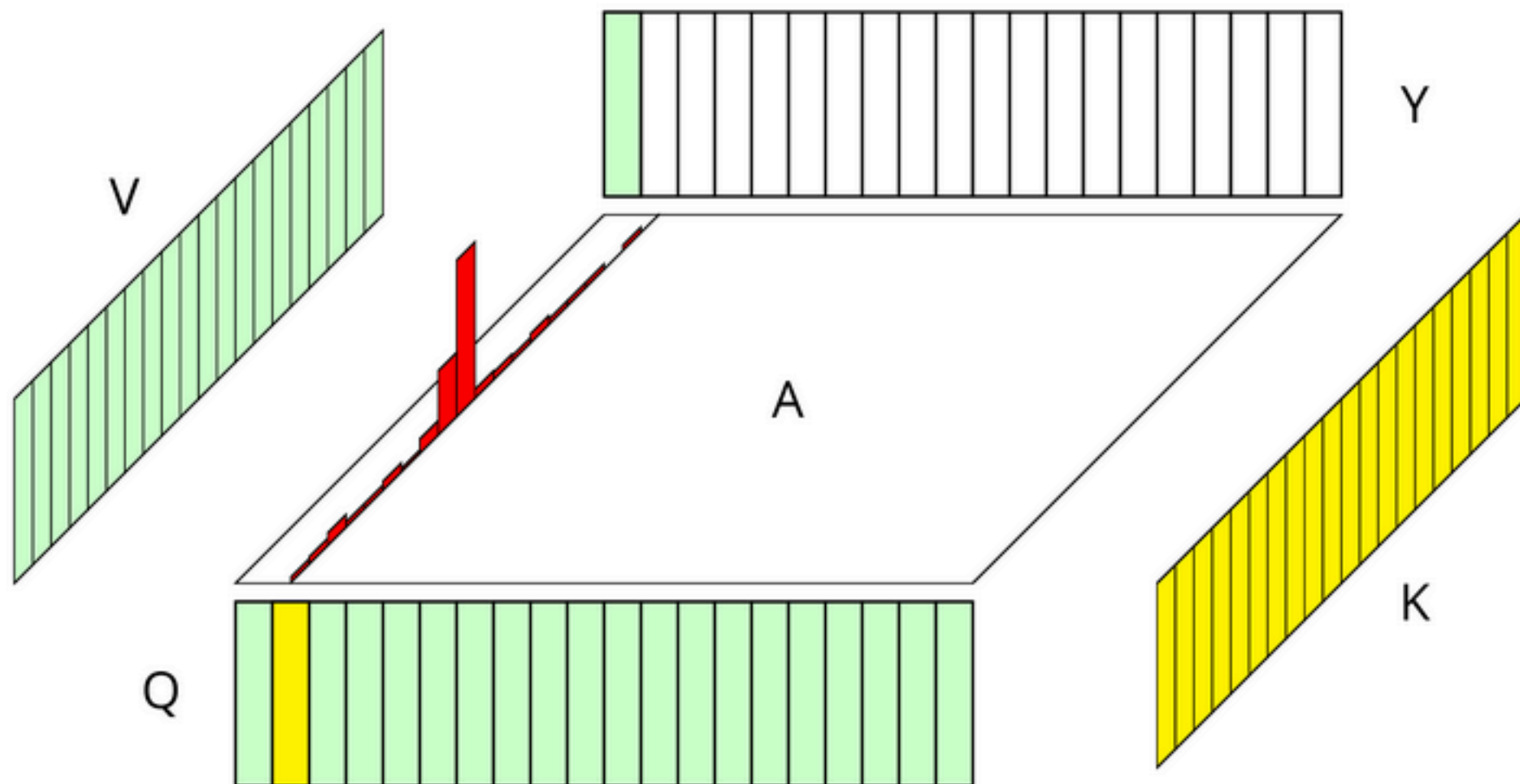
Visual explanation of the Attention mechanism

$$Y_i = \sum_j A_{i,j} V_j$$



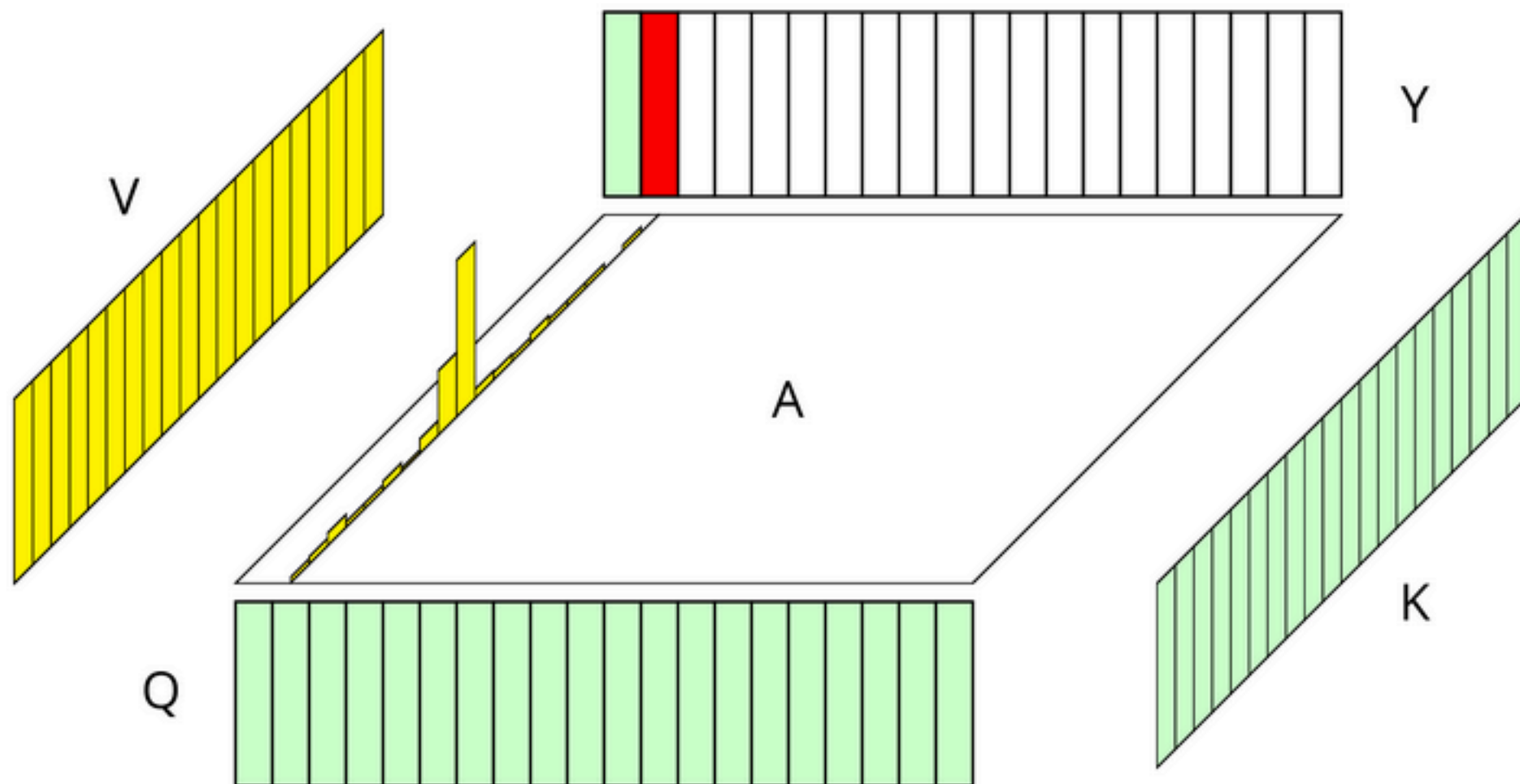
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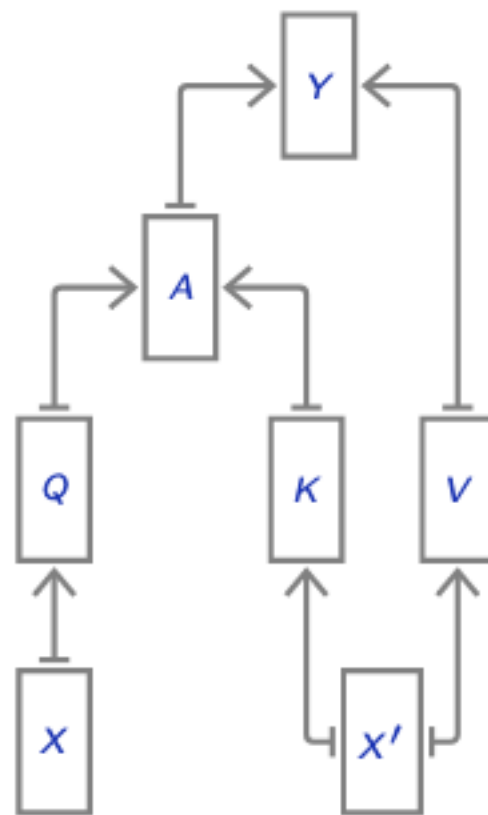
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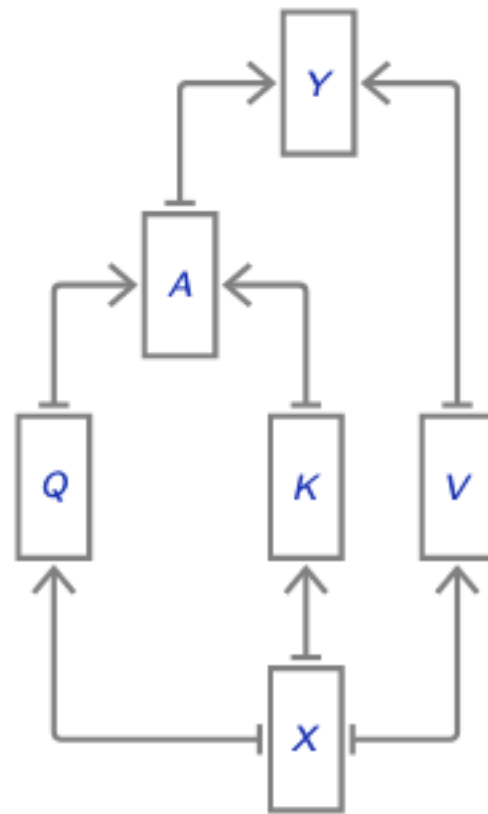
Standard attention layers

- Standard Attention layers
 - take as inputs 2 sequences X and X'
 - output a sequence Y



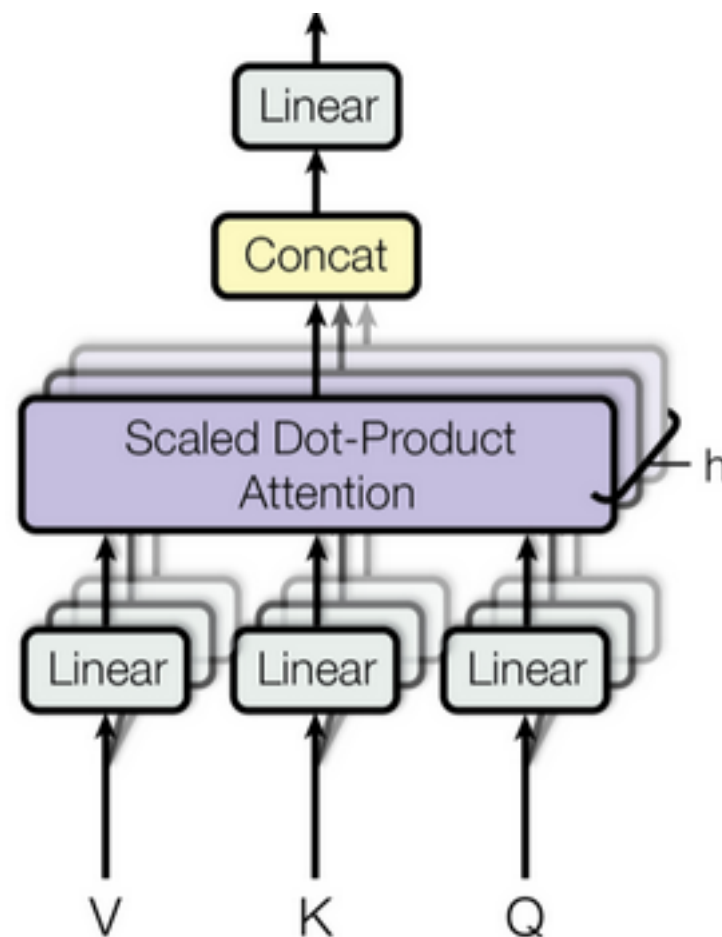
Standard attention layers

- In self-attention layers, we have $X=X'$



Standard attention layers

- In multi-head attention layers,
 - several (h here) such blocks operate in parallel
 - Their output is concatenated in feature dimension



Summary

- 1d-CNN, RNN and Attention-based models can be used
 - depends on the context
 - slightly different underlying assumptions
 - locality (ConvNets)
 - sequentiality (RNNs)
 - relationships between any set of items in the sequence (Attention-based models)
- 1d-CNN are faster to train