Large Scale Machine Learning

Natural Language Processing

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Acknowledgement

Slides inspired by

- Édouard Grave
- Claire Boyer
- fidle-cnrs
- Charles Deledalle's lectures

Motivation

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  - information retrieval, web search
  - medical records, scientific articles
- Large scale? Wikipedia: 3B words, Common Crawl: 24TB

Text classification: is this spam?

Text classification: is this review positive?

Text classification: what is this article about?

Enriching Word Vectors with Subword Information

Piotr Bojanowski* and **Edouard Grave*** and **Armand Joulin** and **Tomas Mikolov**
Facebook AI Research
{bojanowski,egrave,ajoulin,tmikolov}@fb.com

Abstract

Continuous word representations, trained on large unlabeled corpora are useful for many natural language processing tasks. Popular models that learn such representations ignore the morphology of words, by assigning a distinct vector to each word. This is a limitation, especially for languages with large vocabularies and many rare words. In this paper, we propose a new approach based on the skipgram

et al., 2010; Baroni and Lenci, 2010). In the neural network community, Collobert and Weston (2008) proposed to learn word embeddings using a feed-forward neural network, by predicting a word based on the two words on the left and two words on the right. More recently, Mikolov et al. (2013b) proposed simple log-bilinear models to learn continuous representations of words on very large corpora efficiently.

Large Language Models: ChatGPT

AD

Hello ChatGPT! What are you useful for?

Hello! As a language model, I am designed to be useful for a wide variety of tasks that involve natural language processing, such as:

1. Answering questions: I can provide information on a broad range of topics, from science and history to entertainment and current events.
2. Generating text: I can help generate text for a variety of purposes, such as writing essays, creating social media posts, or even composing poetry.
3. Translation: I can translate text from one language to another, although my proficiency may vary depending on the language pair.
4. Personalized Assistance: I can provide personalized assistance such as setting up reminders, scheduling appointments and more.
5. Learning: I can help people learn new things through answering questions, providing explanations, and suggesting resources.

Overall, I am designed to be a helpful resource for anyone who needs assistance with tasks that involve natural language processing.

Sommaire

Word representation

Recurrent NN

Transformers

Tokenization

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  - Some arbitrary choices: be consistent!
  - Language-dependant!

One-hot encoding

Dictionary

0	a
1	before
2	fantastic
3	i’ve
4	is
5	like
6	movie
7	never
8	seen
9	this

[“I’ve”, “never”,“seen”, “a”,“movie”, “like”, “this”, “before”]

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- Solution: vectorize!

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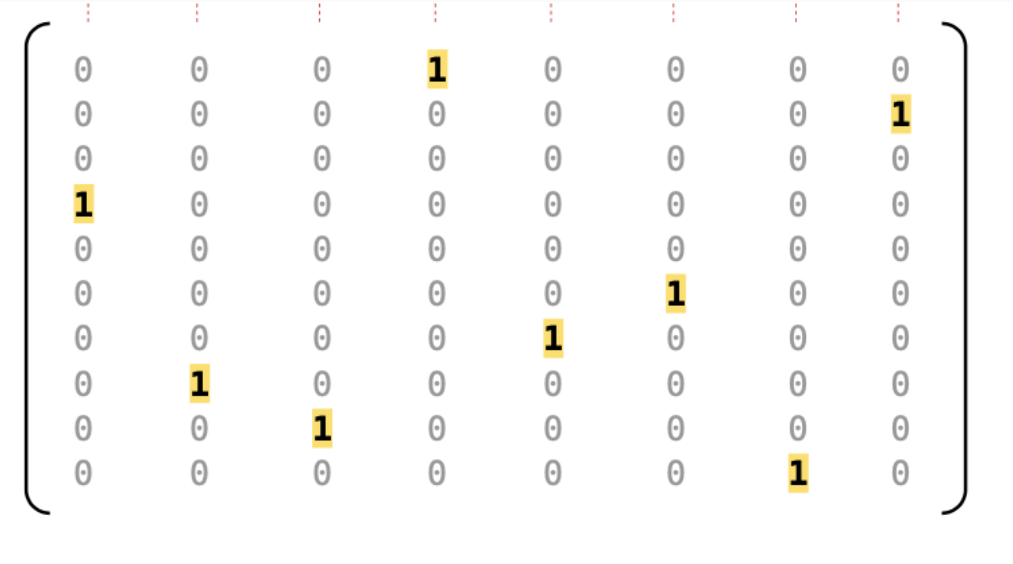

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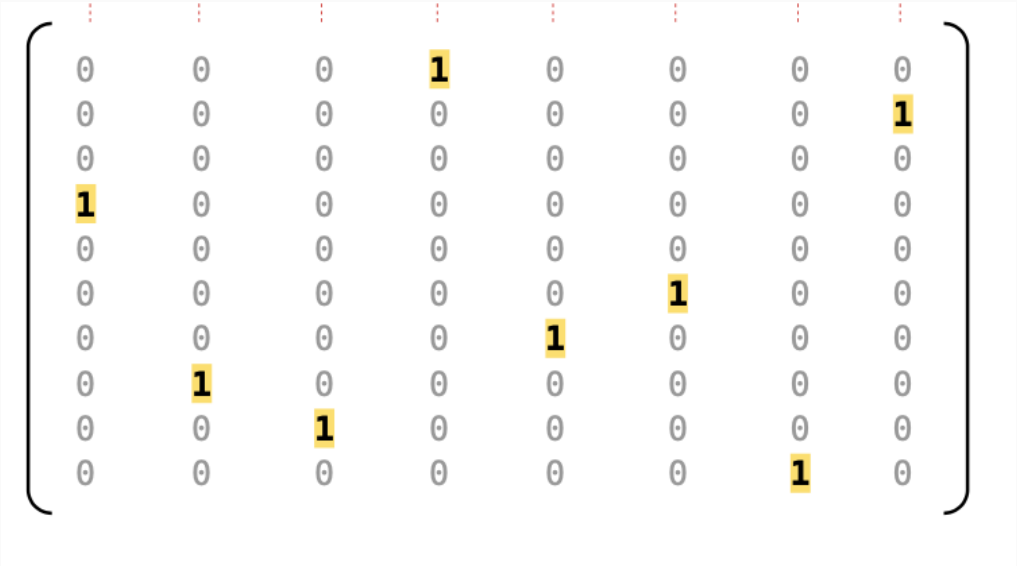

- Each word has its own dimension. Limits: size!

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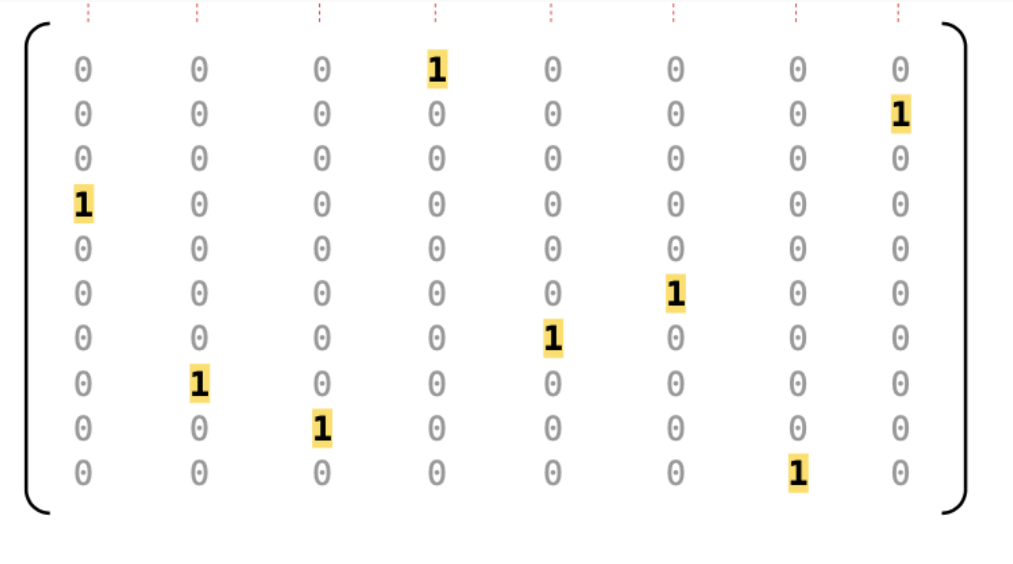

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Example

- Dictionary of 80 000 words, text of 300 words

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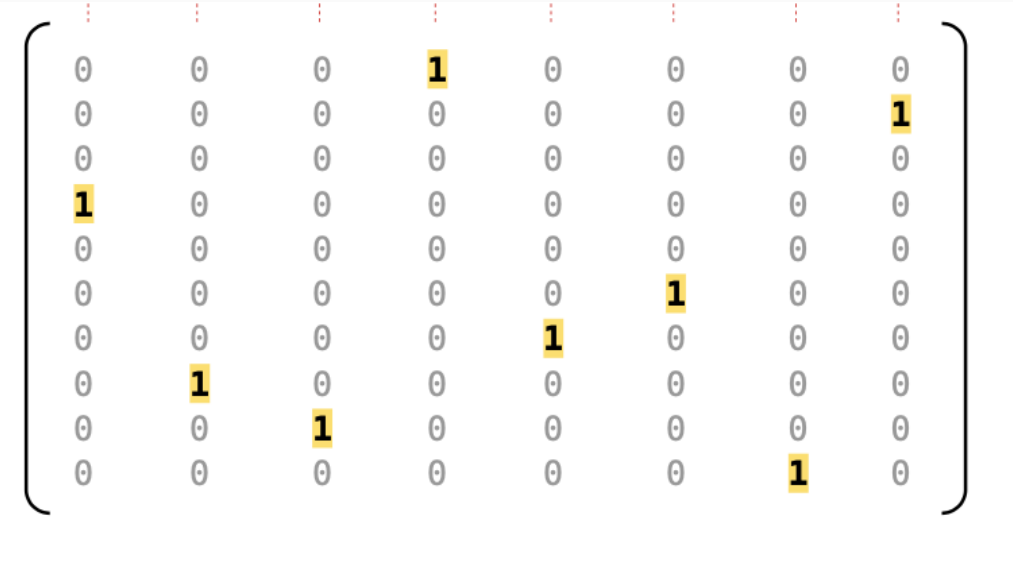

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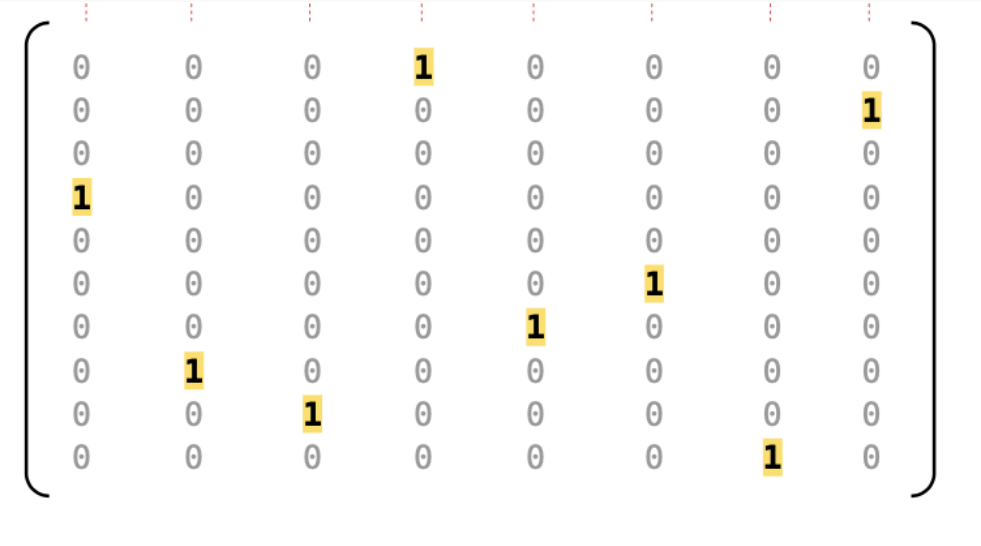
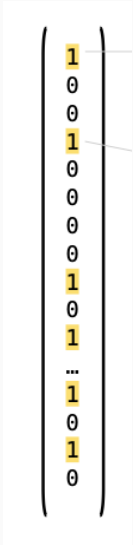
Example

- Dictionary of 80 000 words, text of 300 words
- Memory: 24.10^6 parameters to store the text!

One-hot vector





- 1 if word is present in the sentence

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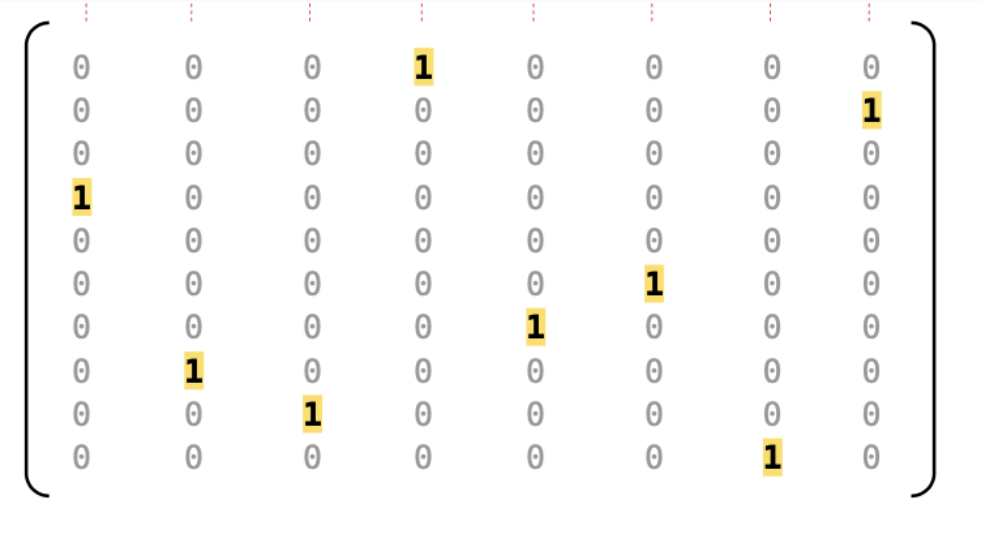

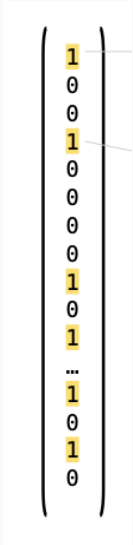

- 1 if word is present in the sentence
- Size does not depend on length of the sentence

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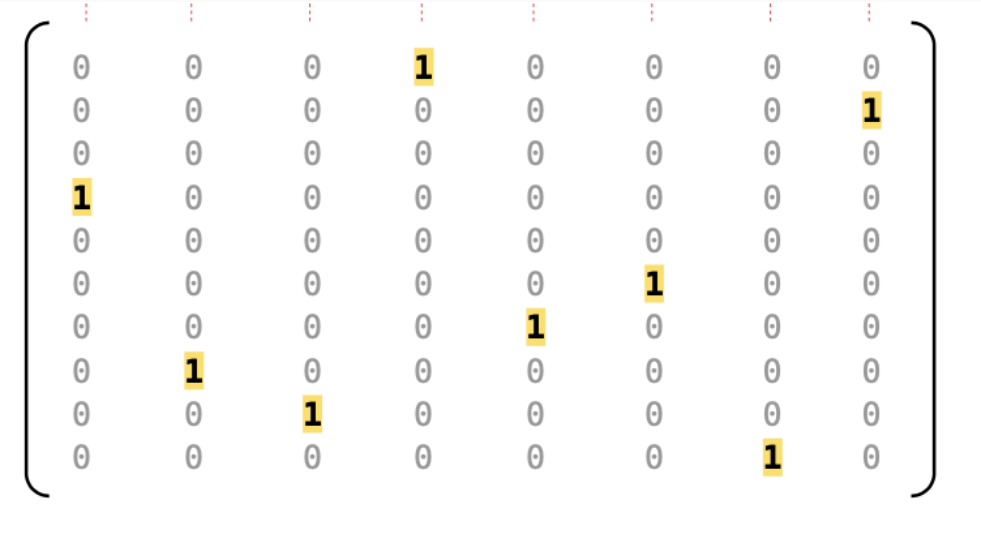

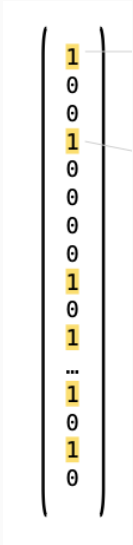

- 1 if word is present in the sentence
- Size does not depend on length of the sentence
- But: lose the words order

Embedding layer

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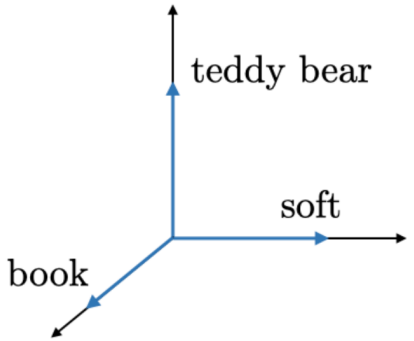
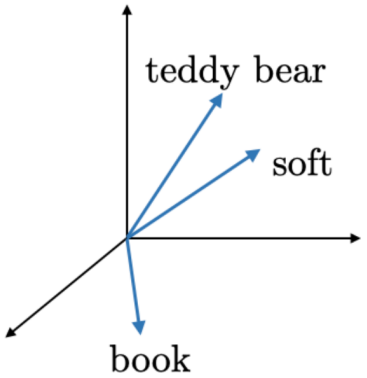
Example

- Text of 300 words
- Embedding size: 200
- Memory: 60 000 parameters to store the text!

Word embedding

- Goal: obtain a word embedding with semantic meaning (and not on a classification task)

1-hot representation	Word embedding
	

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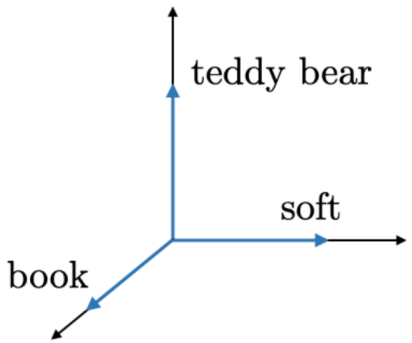	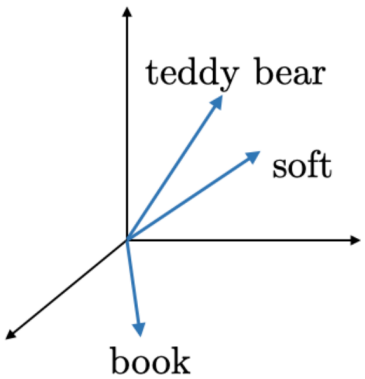

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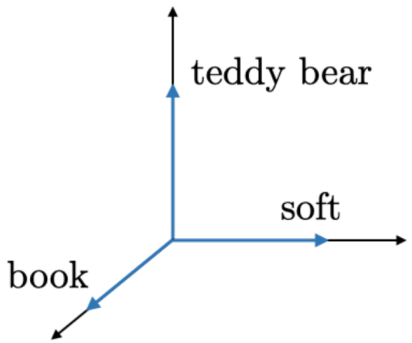	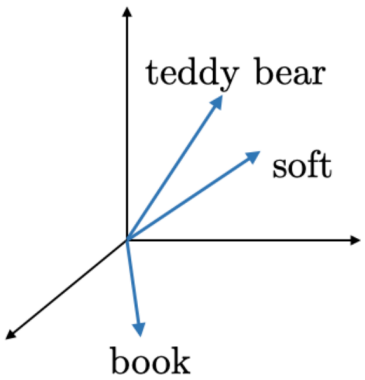

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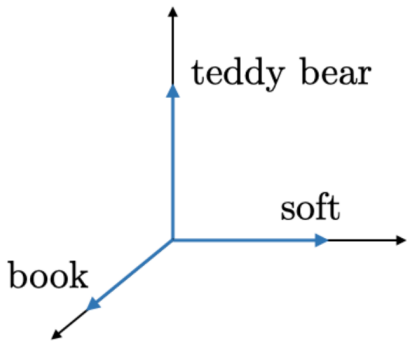	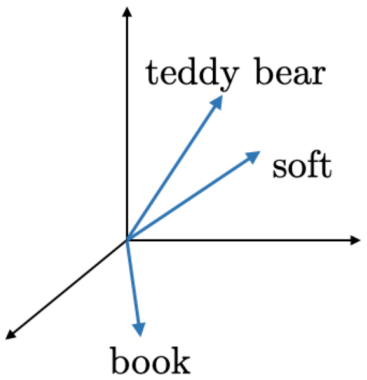

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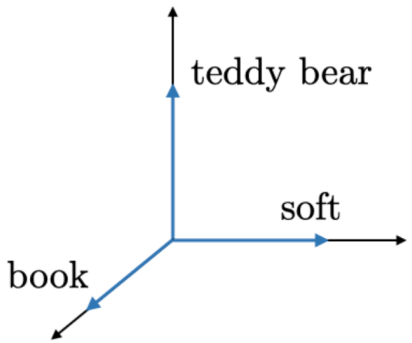
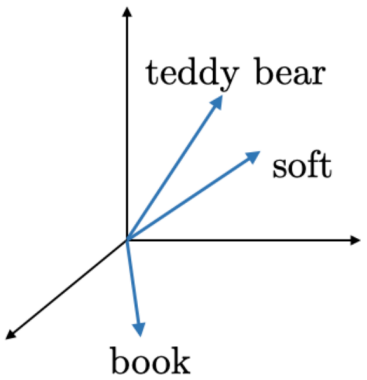
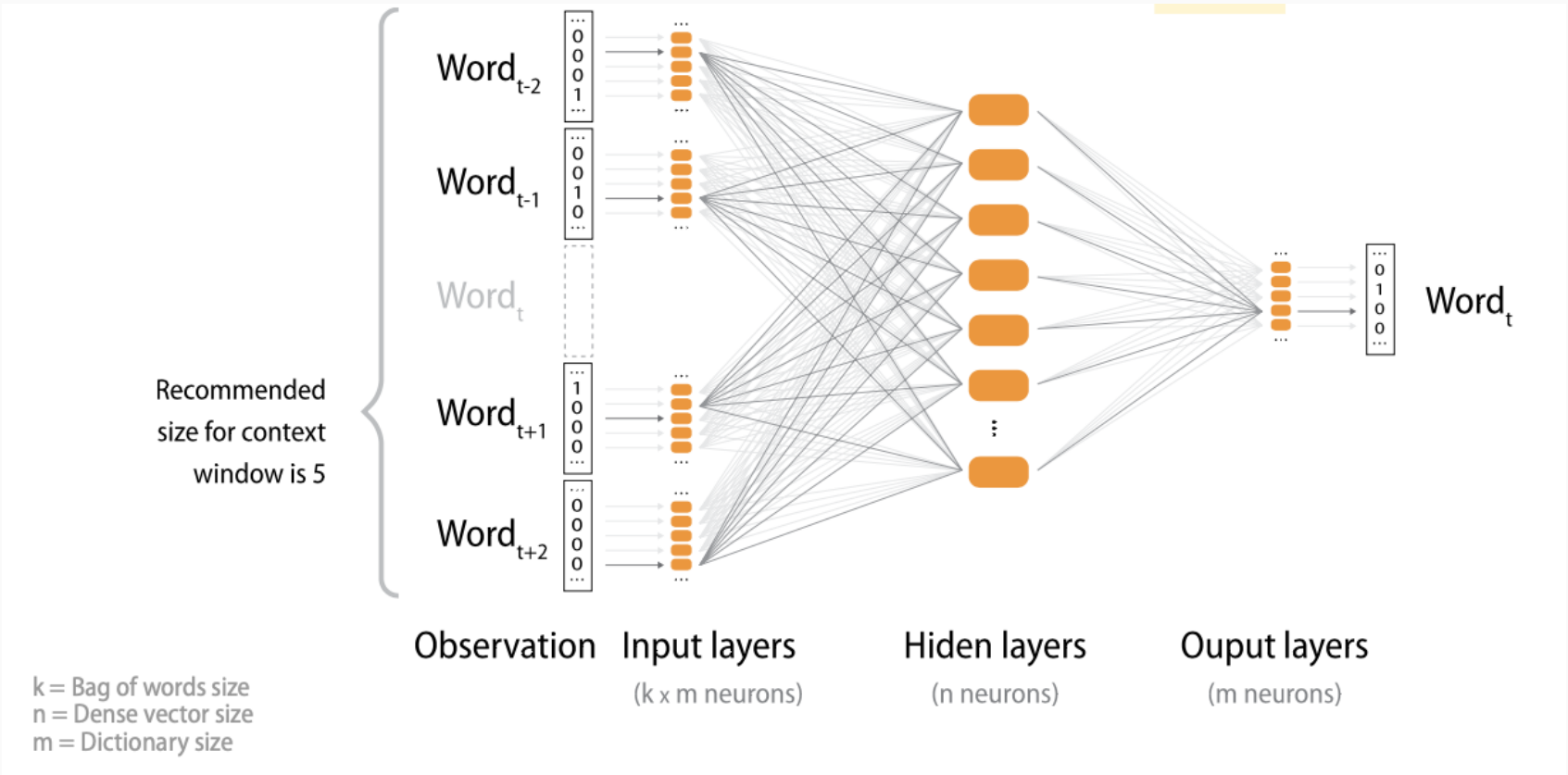
	

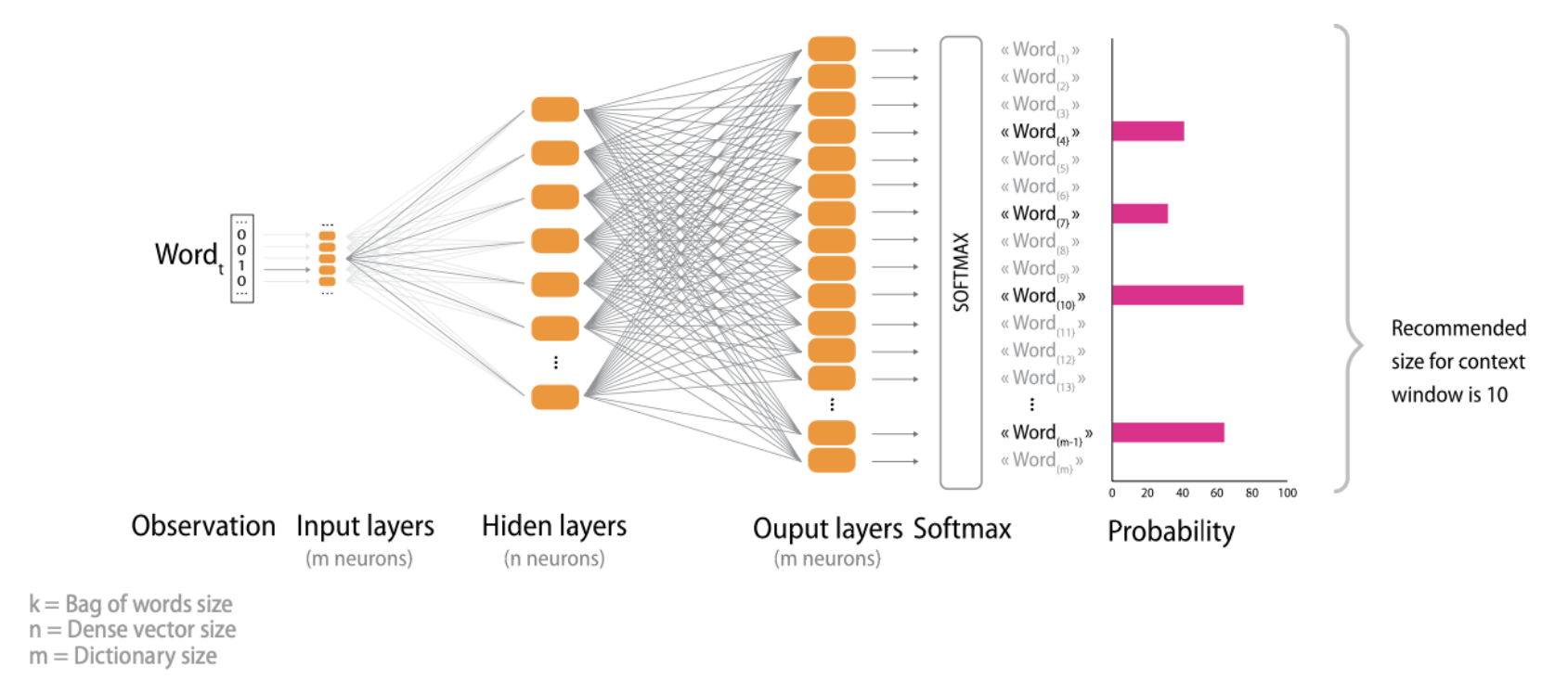
CBOW



source: fidle-cnrs

- Objective: find a word from its context

Skip-Gram



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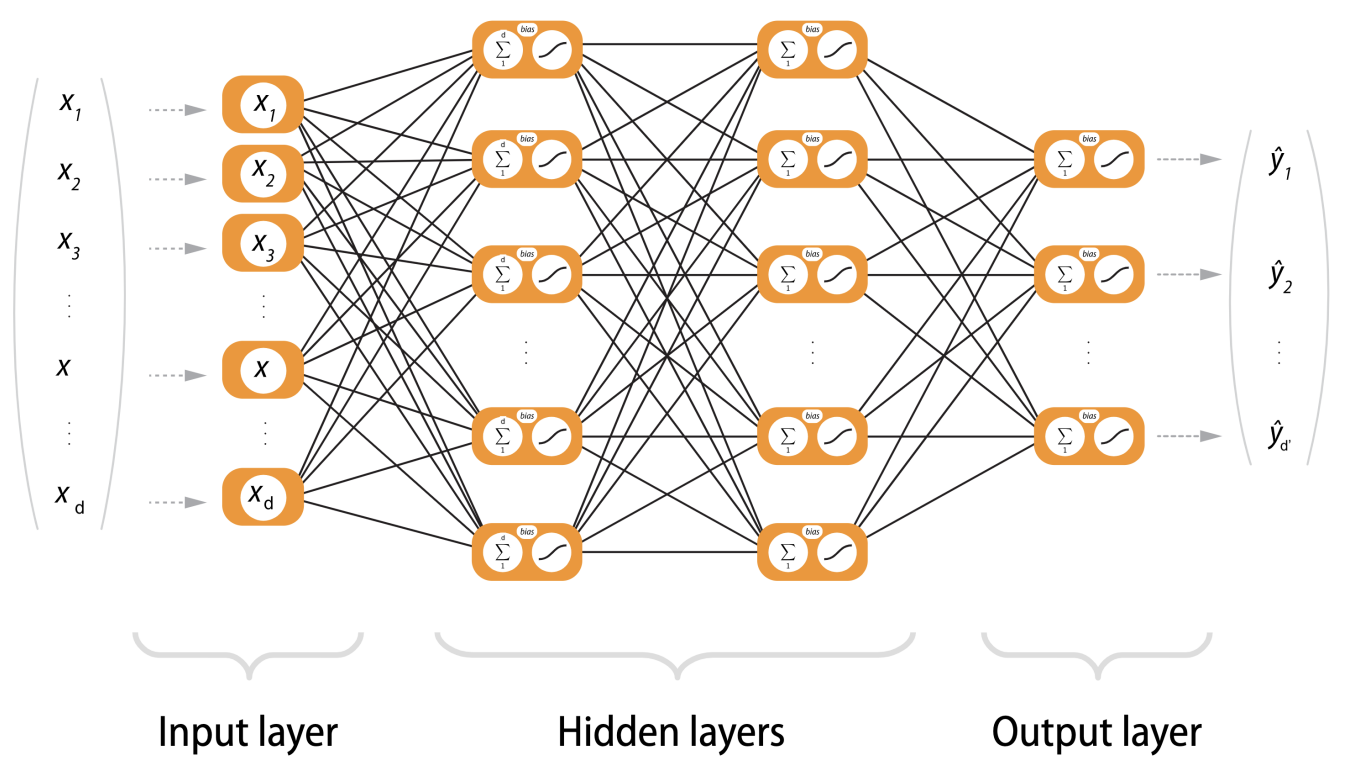
Sommaire

Word representation

Recurrent NN

Transformers

Recall: neural networks



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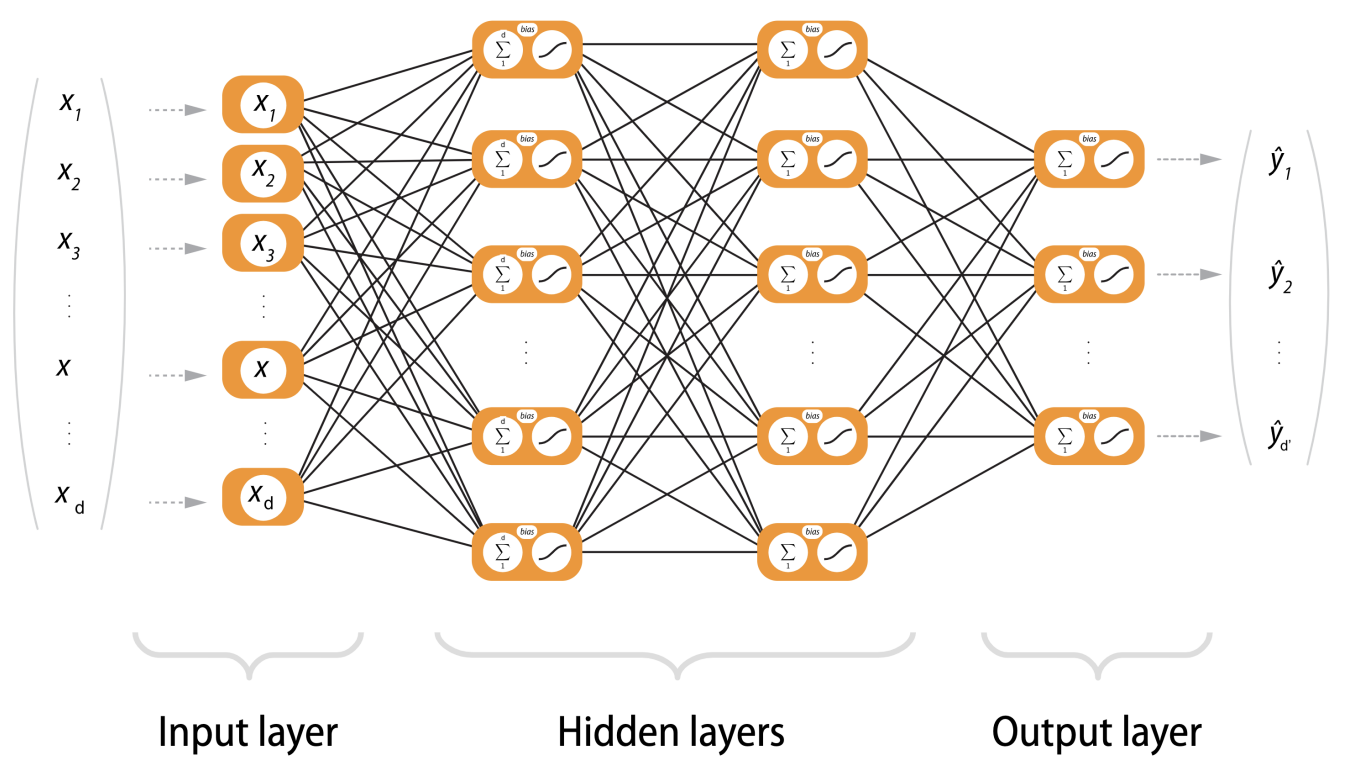
Recall: neural networks



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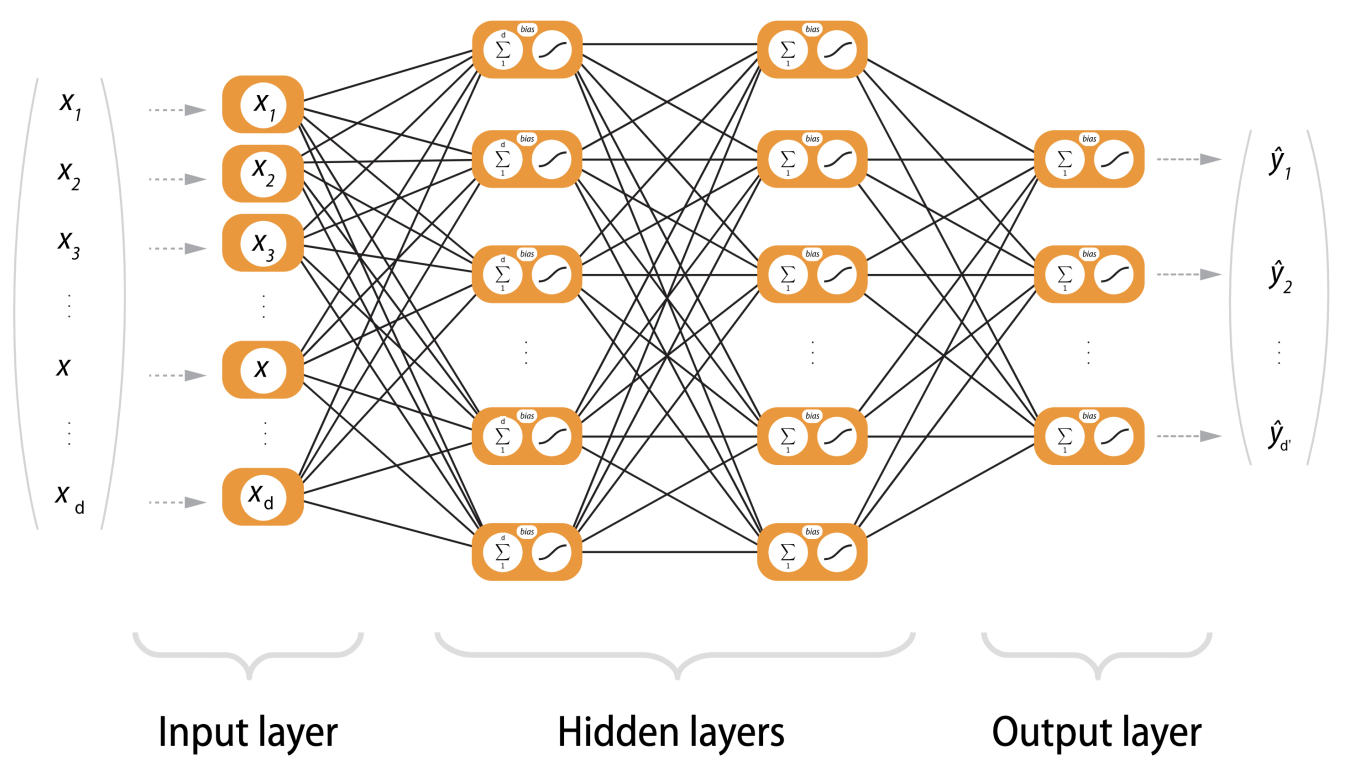

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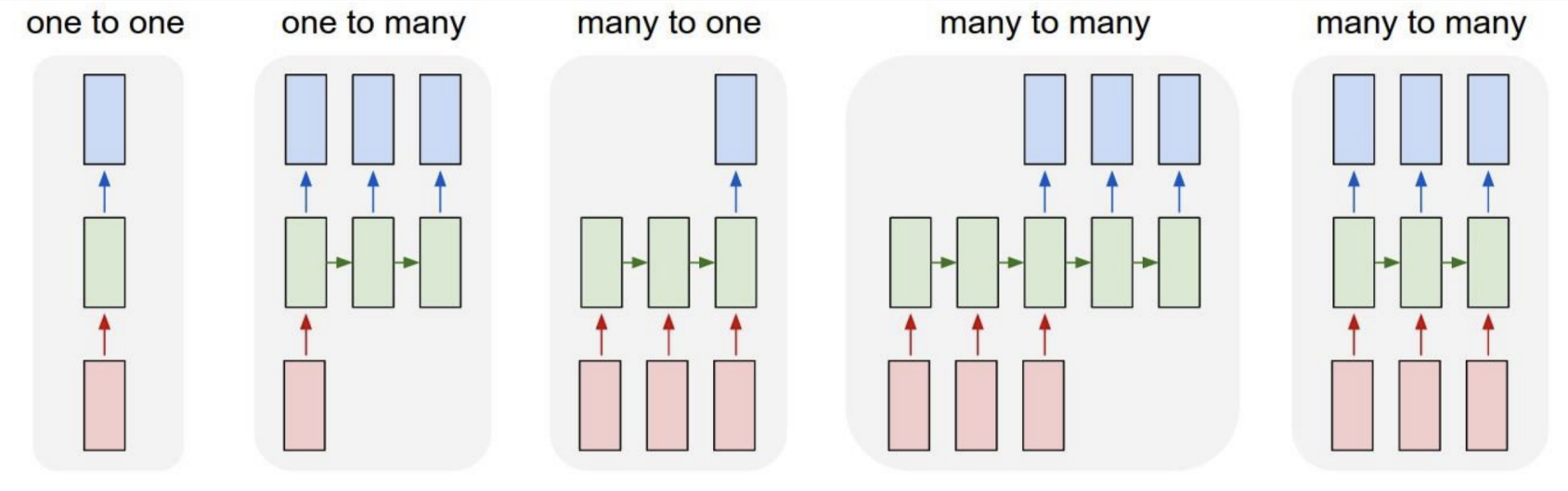
- Cascade of linear and nonlinear functions
- Formally

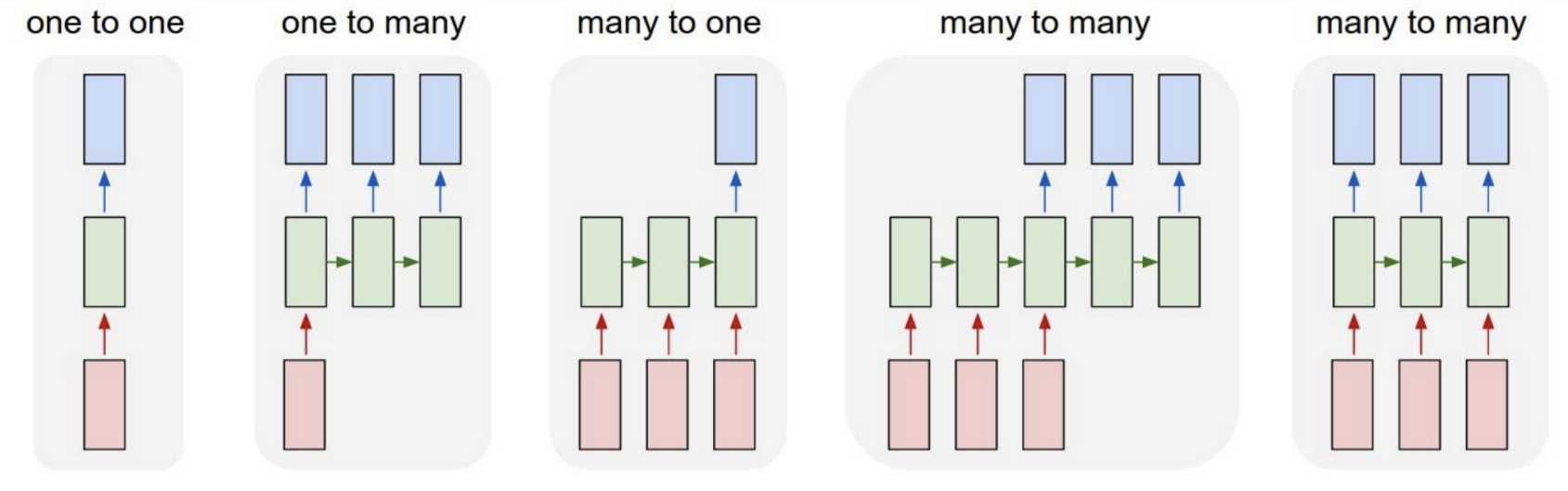
$$\hat{y} = \sigma\left(W_L \sigma\left(W_{L-1} \sigma\left(\ldots \sigma\left(W_1 x\right)\right)\right)\right)$$

Recurrent neural networks

- Recurrent Neural Networks (RNNs) are Artificial Neural Networks that can deal with sequences of variable size.



Different uses of recurrent neural networks



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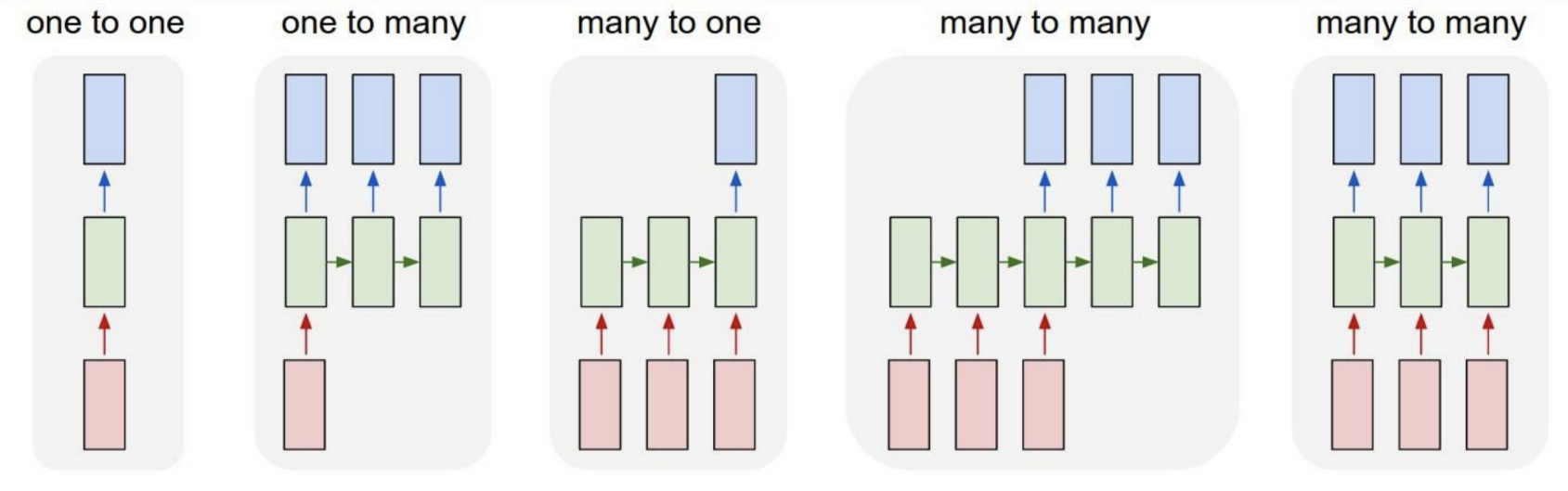

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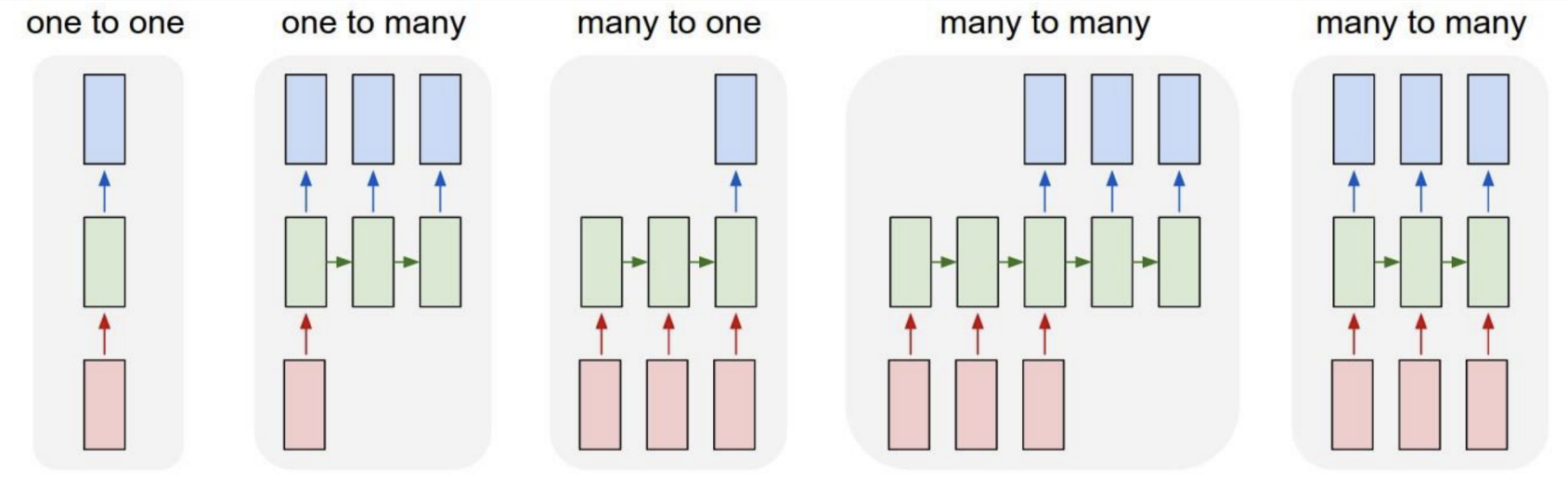

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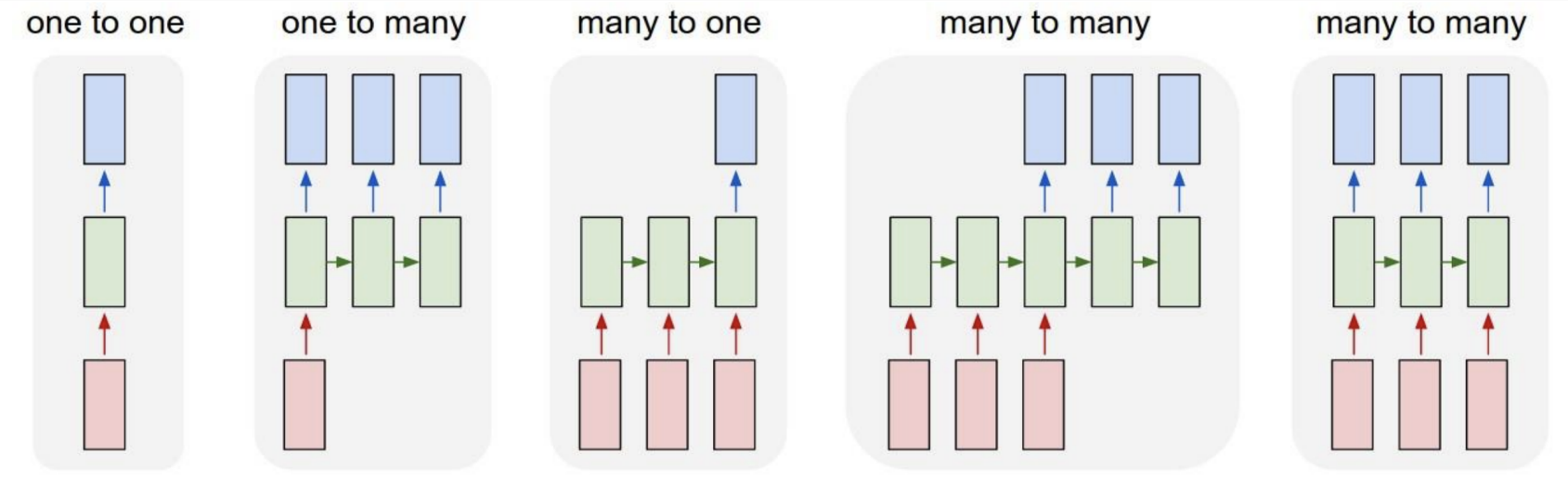

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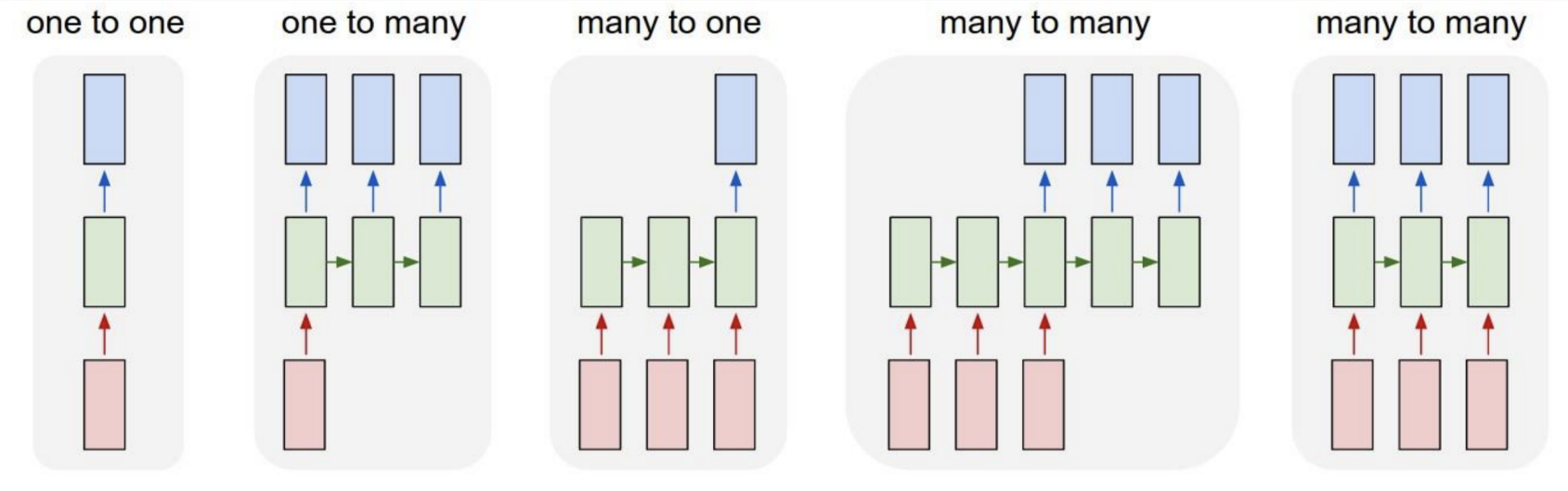

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- Translation (many-to-many): sequence of words/sequence of words
- Video classification on frame level (many-to-many): sequence of image/sequence of label

Language generating NN: training

How to learn “`The cat is in the kitchen drinking milk.`”?

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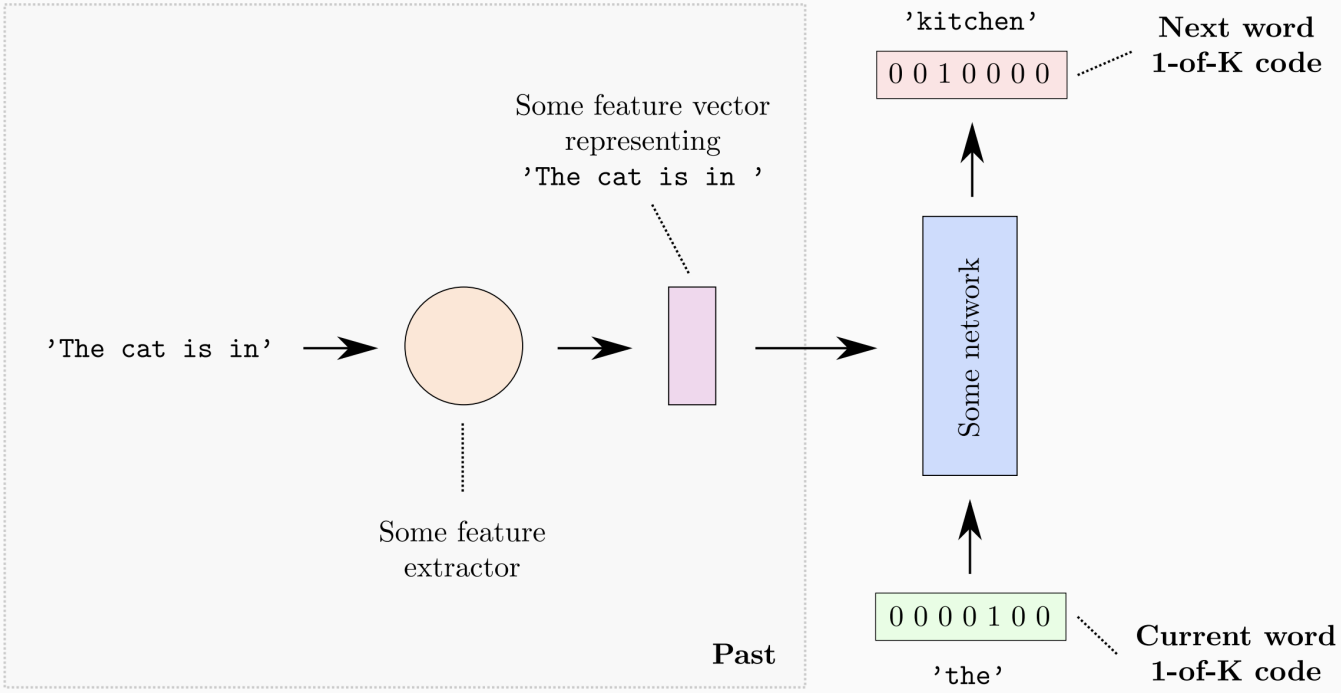

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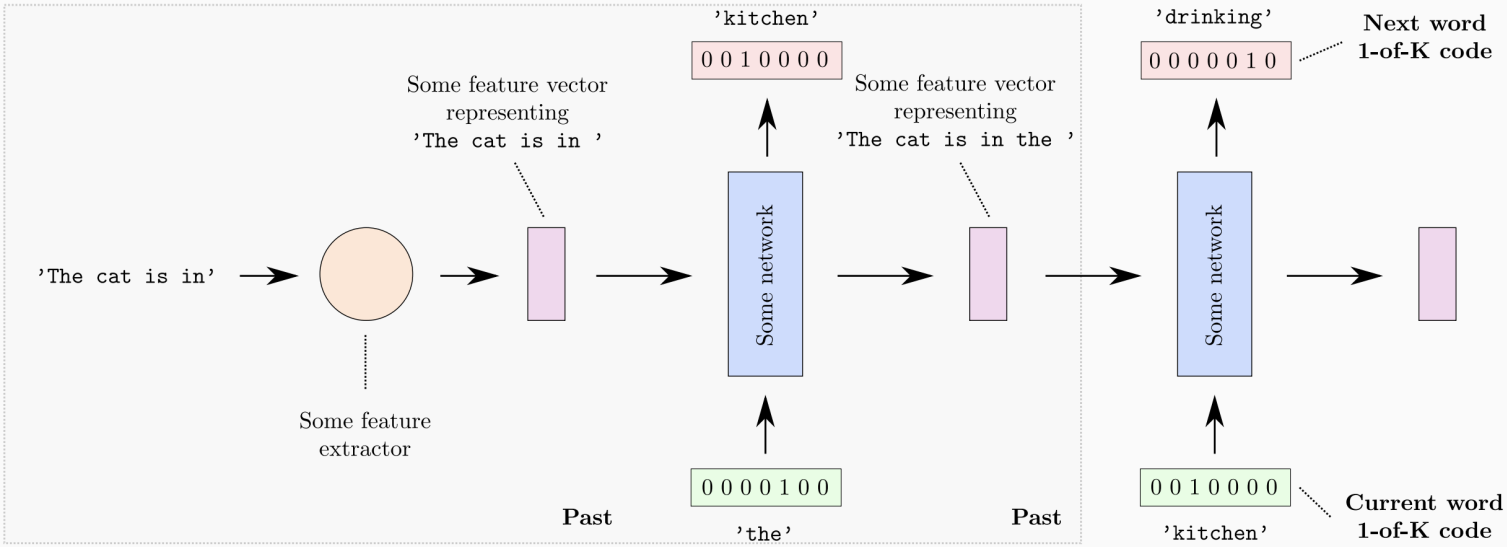
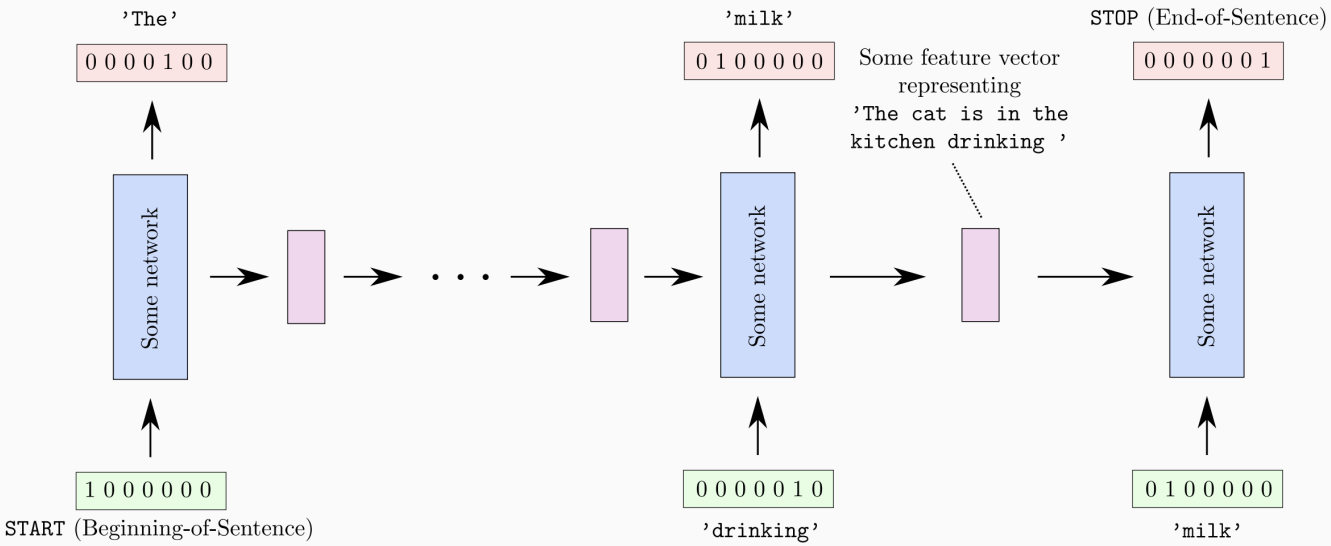


- Learn also how to represent the current sentence
- Repeat for the next word

Language generating NN: training

- Add two words: START and STOP to delimitate the sentence



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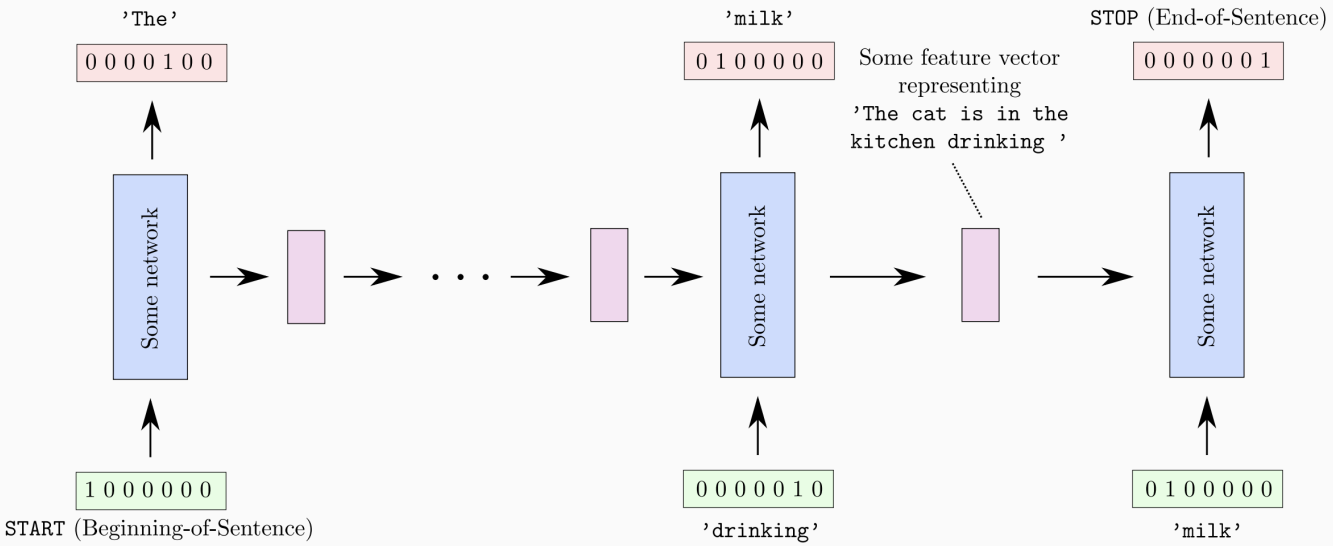

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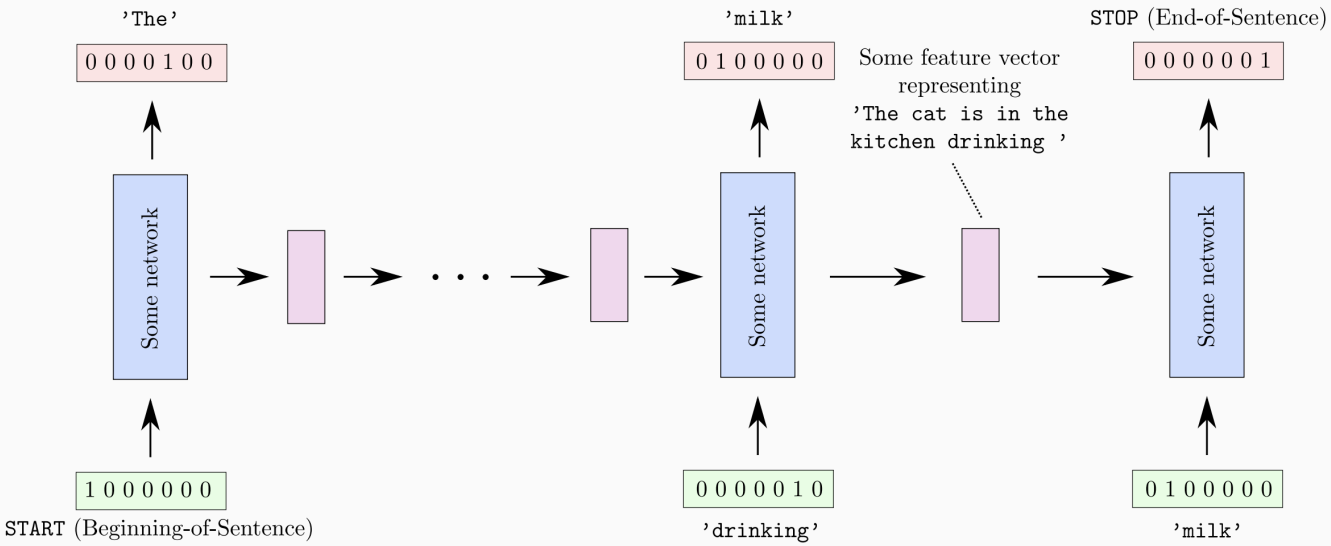

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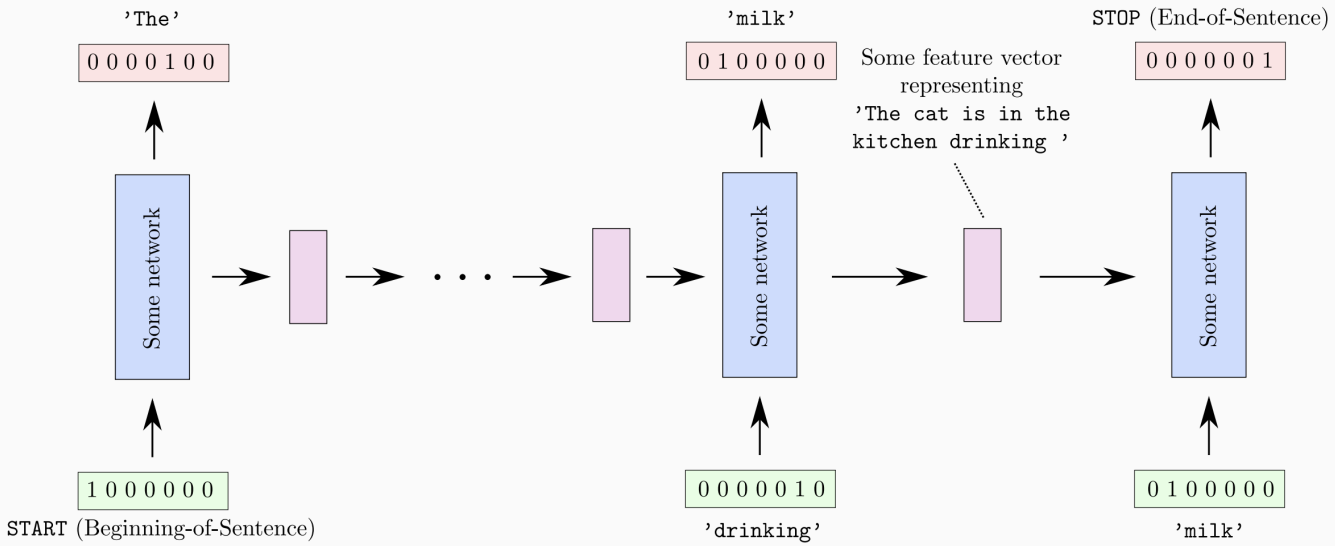

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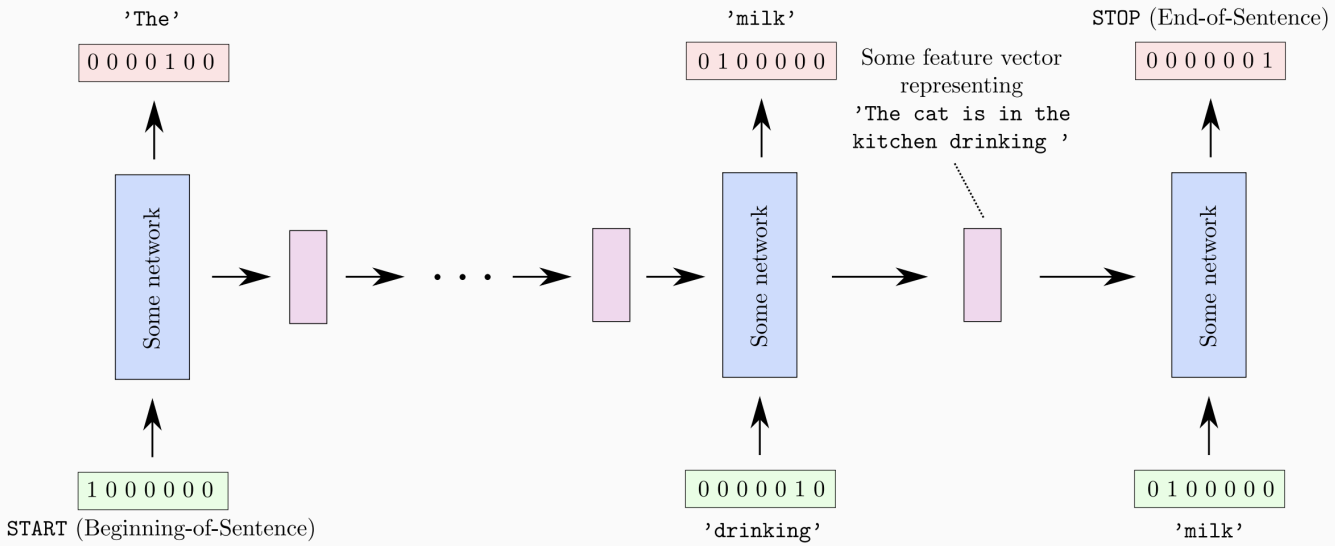
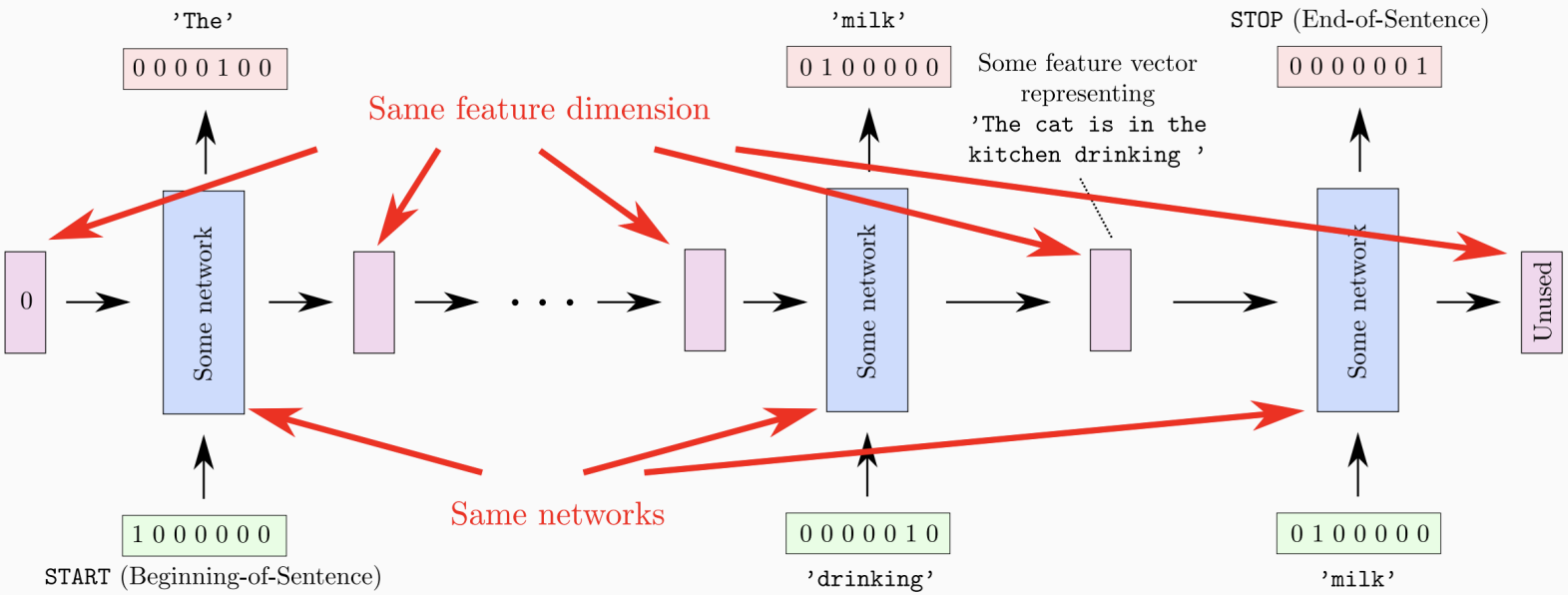


▷ *How should the network architecture and size of intermediate features evolve with the location in the sequence?*

Language generating NN: training

from Charles Deledalle's lectures

- Use the same networks and the same feature dimension



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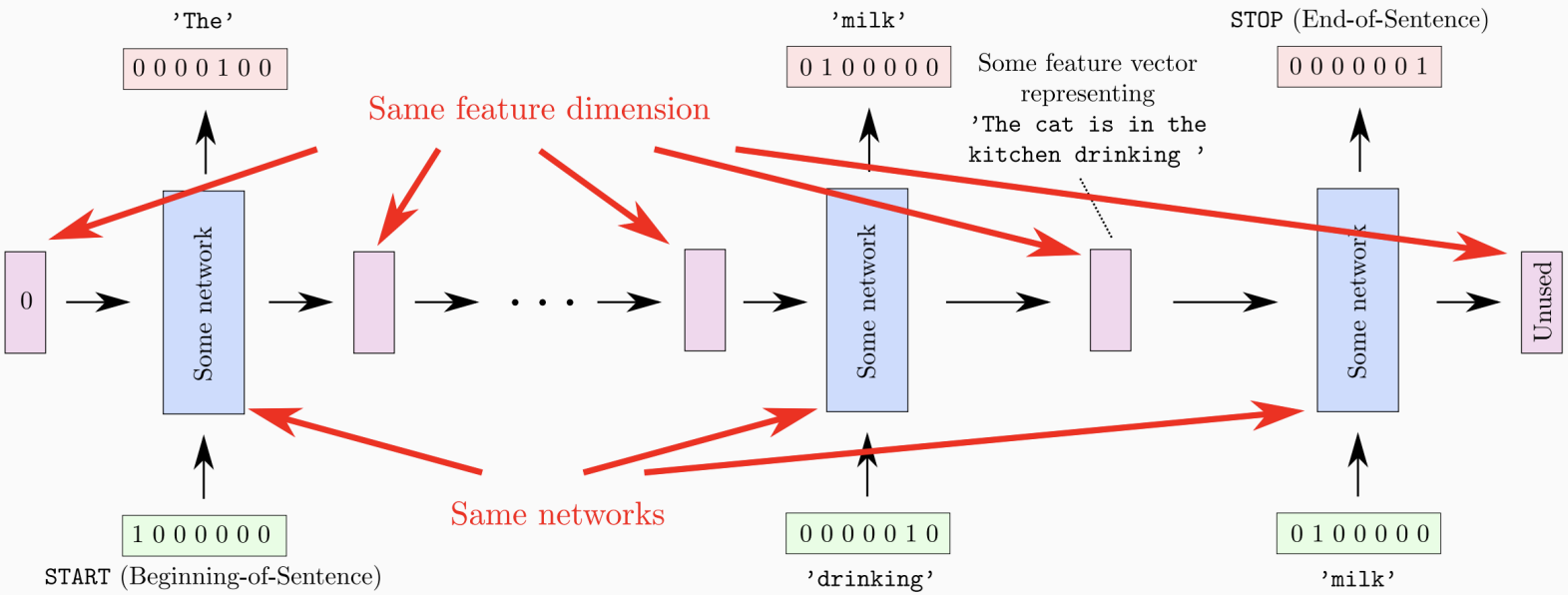

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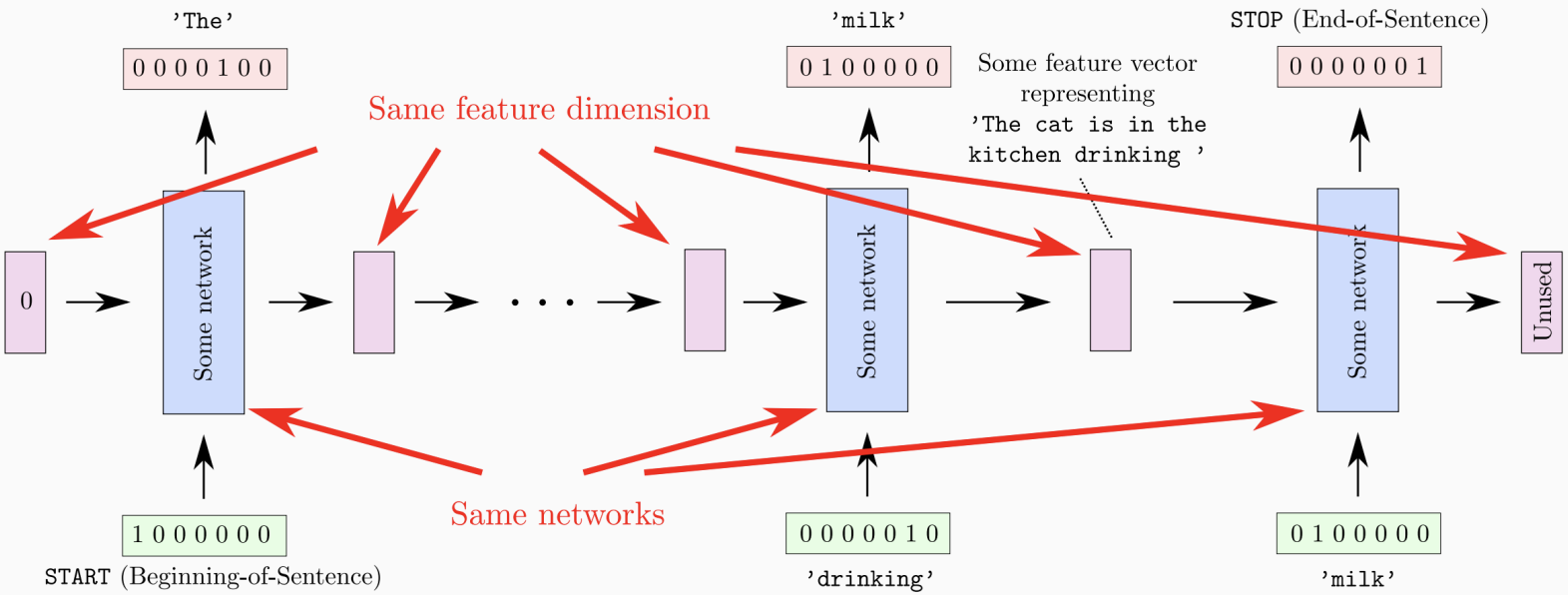

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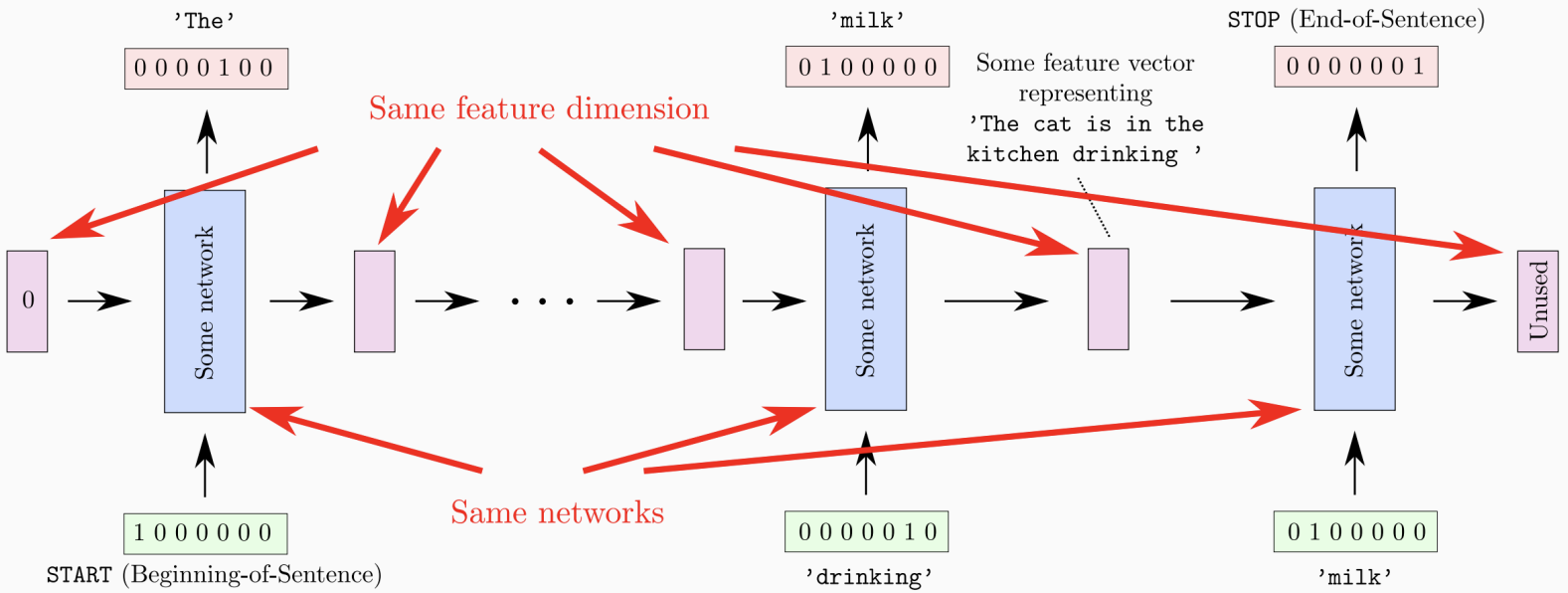

- ▷ Allows you to learn from arbitrarily long sequences

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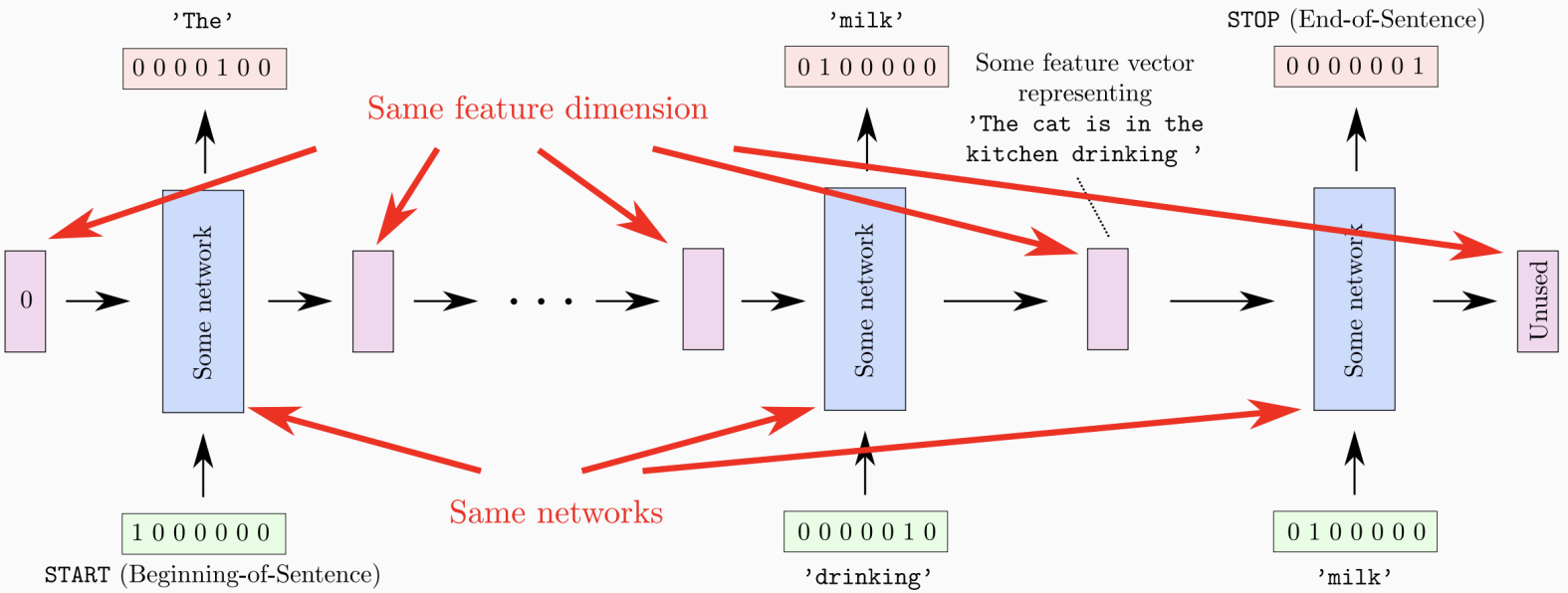
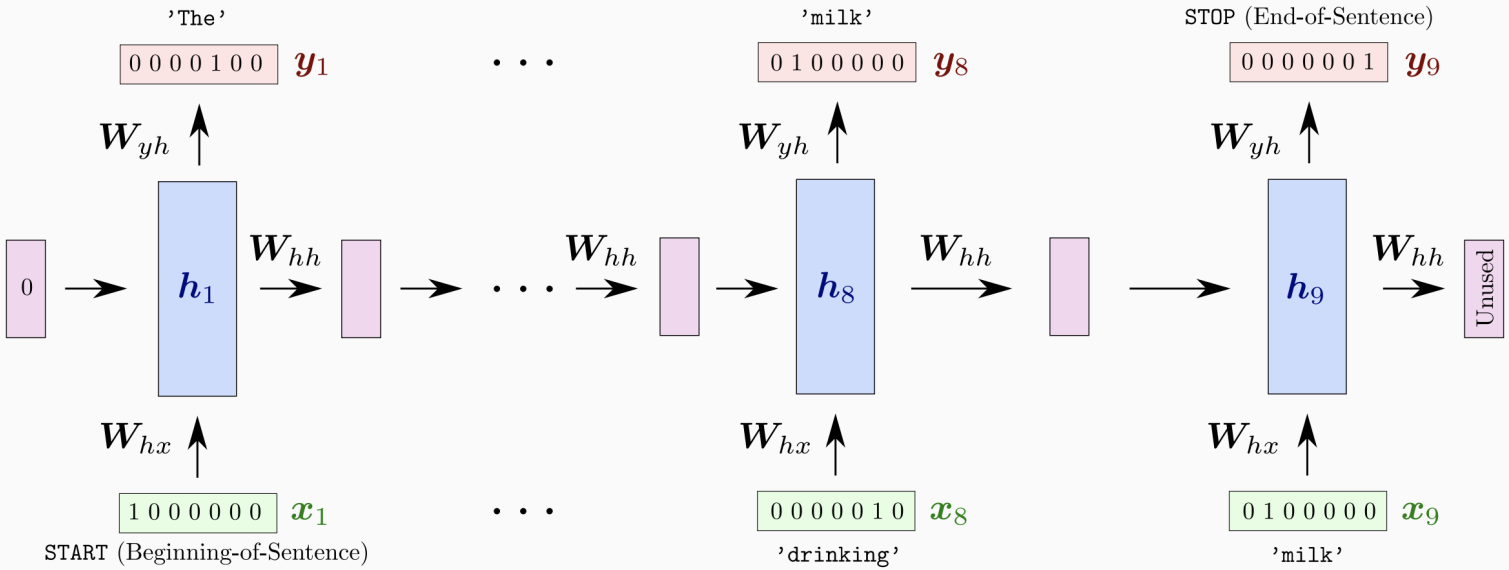


- Allows you to learn from arbitrarily long sequences
- Sharing the architecture $\Rightarrow$ fewer parameters $\Rightarrow$ training requires less data and the final prediction can be expected to be more accurate

A simple shallow RNN for sentence generation

- This is an unfolded representation of an RNN



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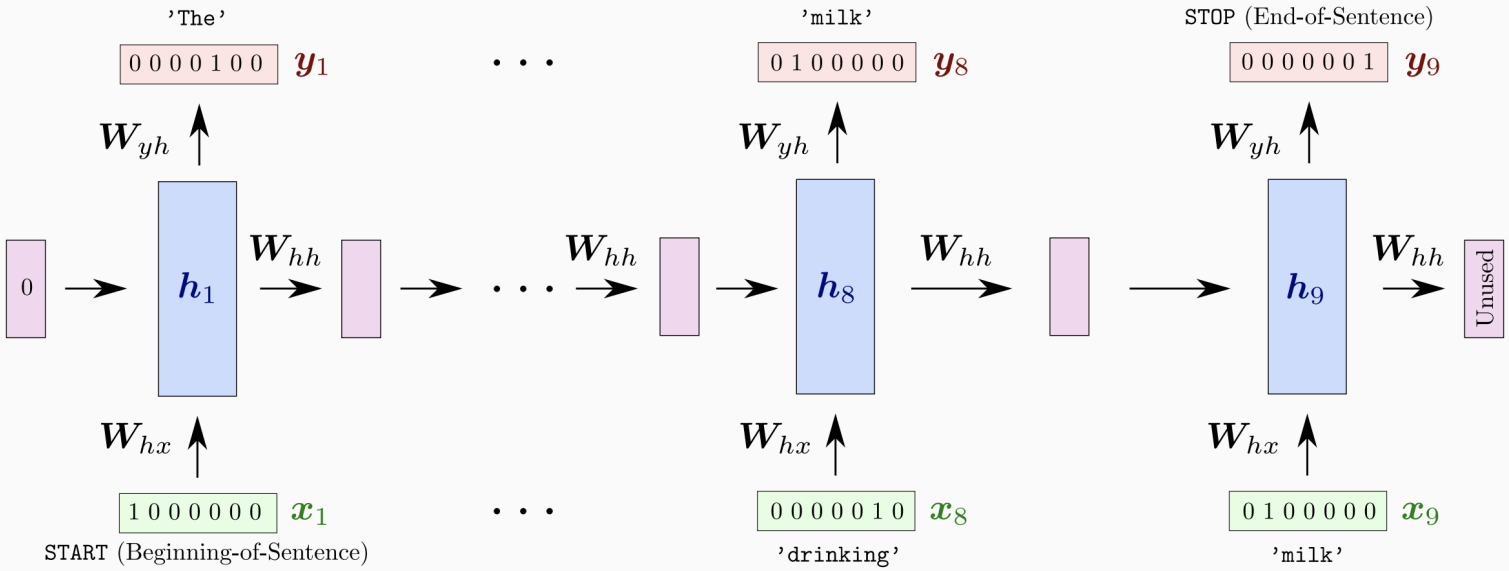

Vanilla RNN

$$h_t = g\left(W_{hx}x_t + W_{hh}h_{t-1} + b_h\right)$$

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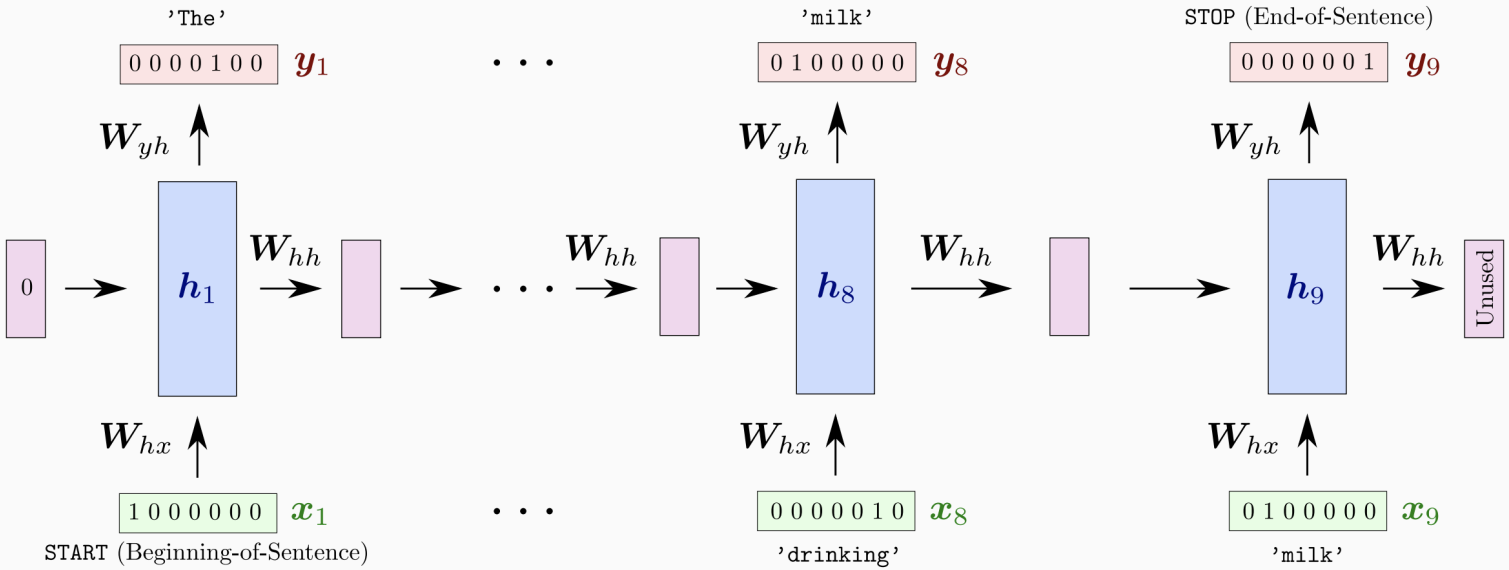

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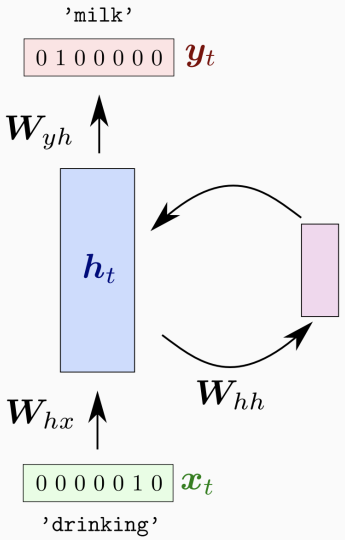
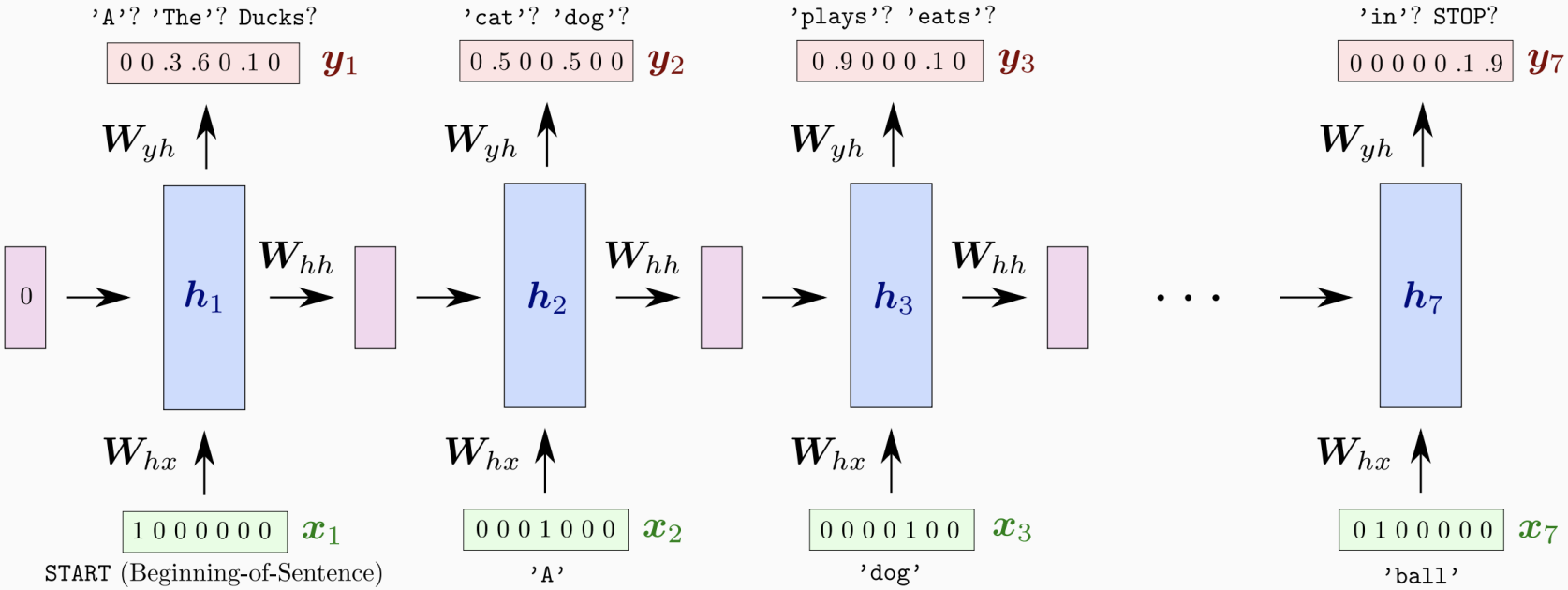


- Folded representation: RNN ≈ ANN with loops

Generate a sentence in practice



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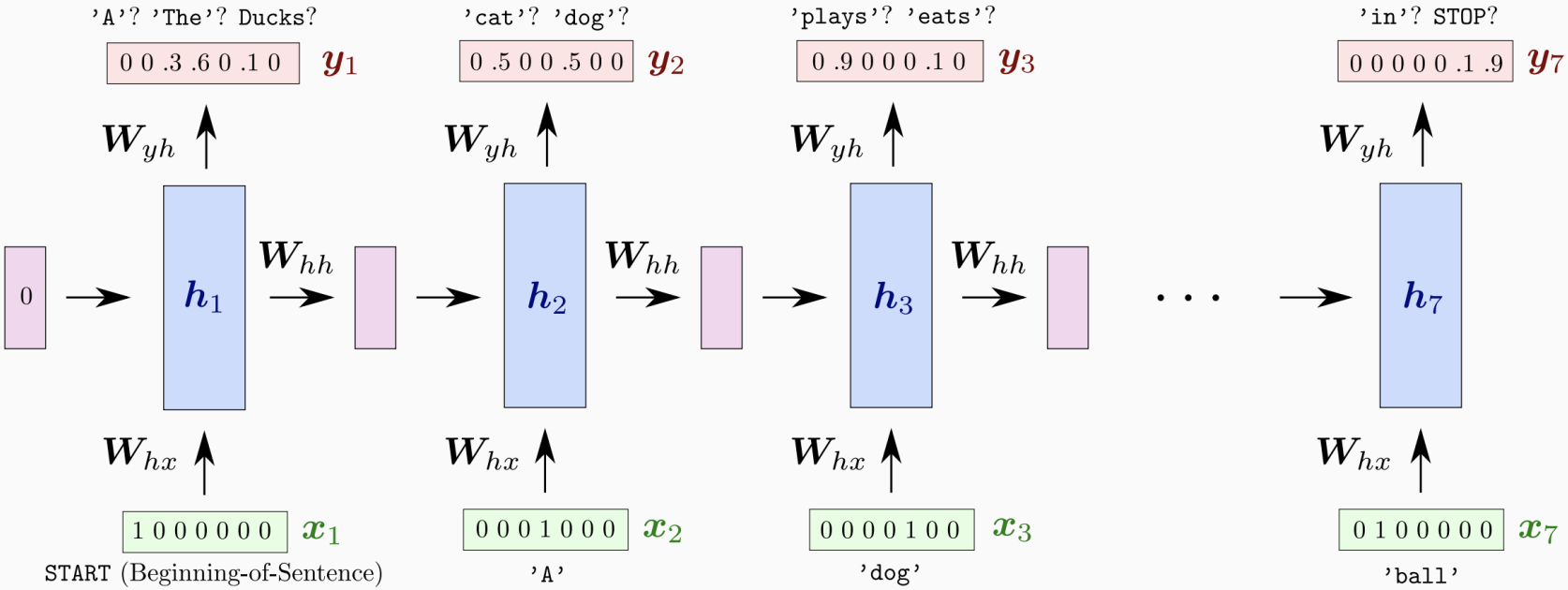

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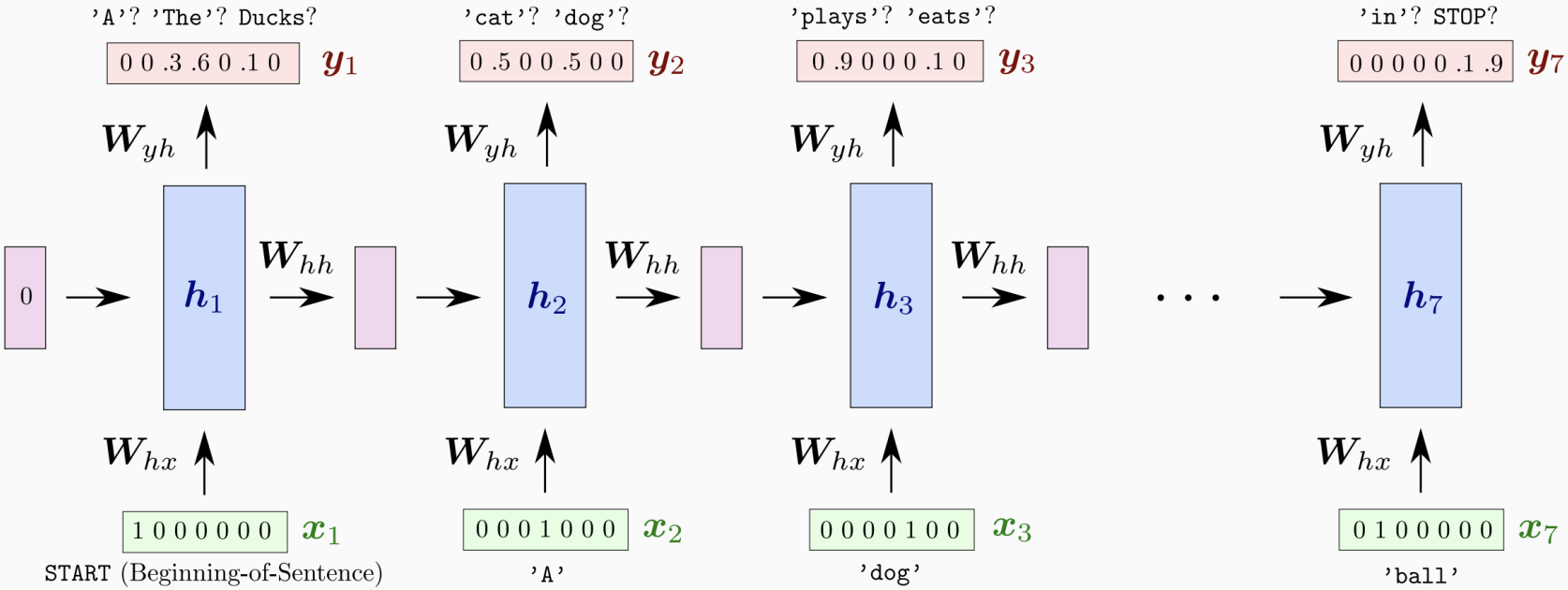

- Provide START, get all the probabilities
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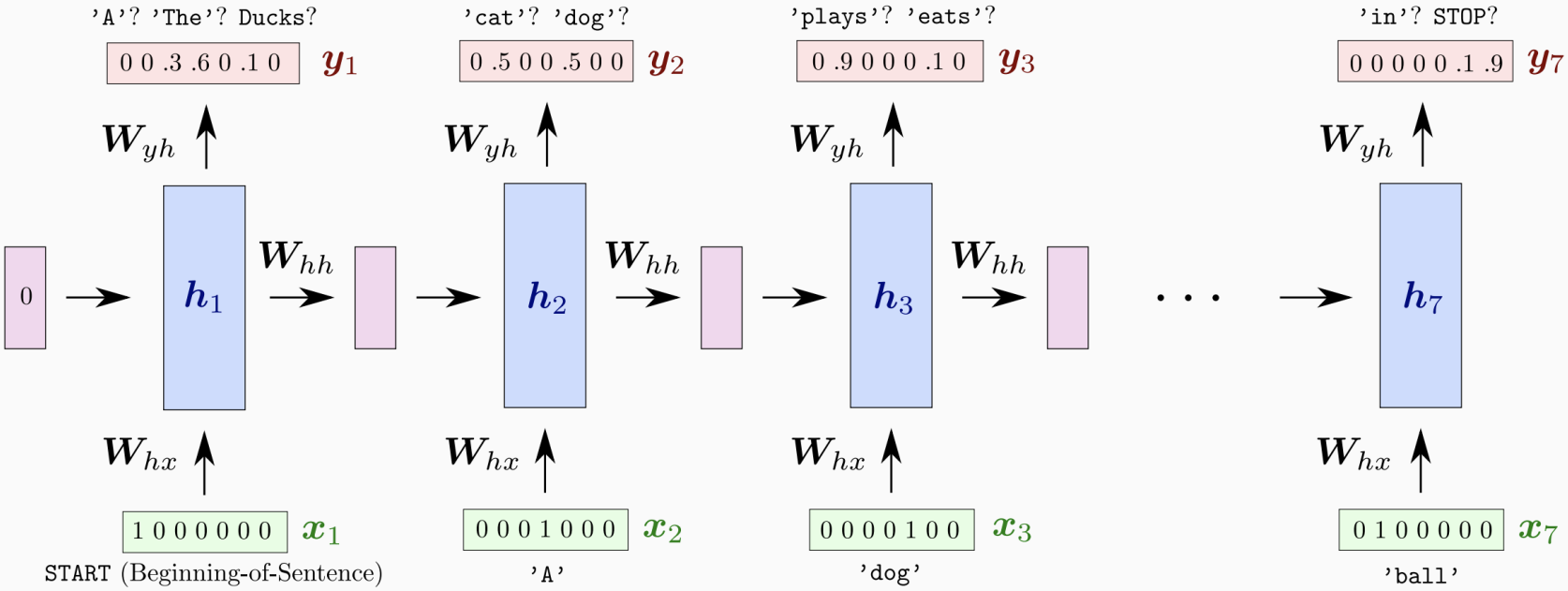

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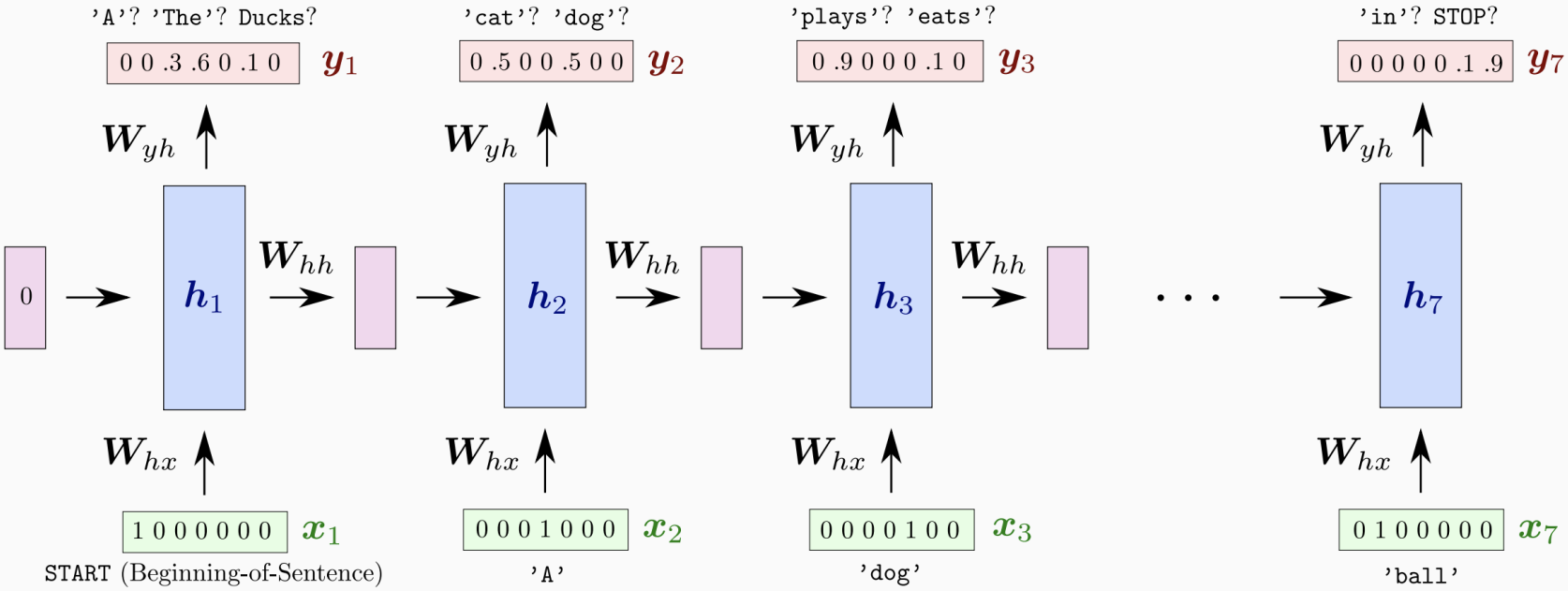

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- Repeat while generating the sentence 'A dog plays with a ball'
- Stop as soon as you have picked STOP.

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- Output at time t may not only depend on the previous elements, but also on future elements

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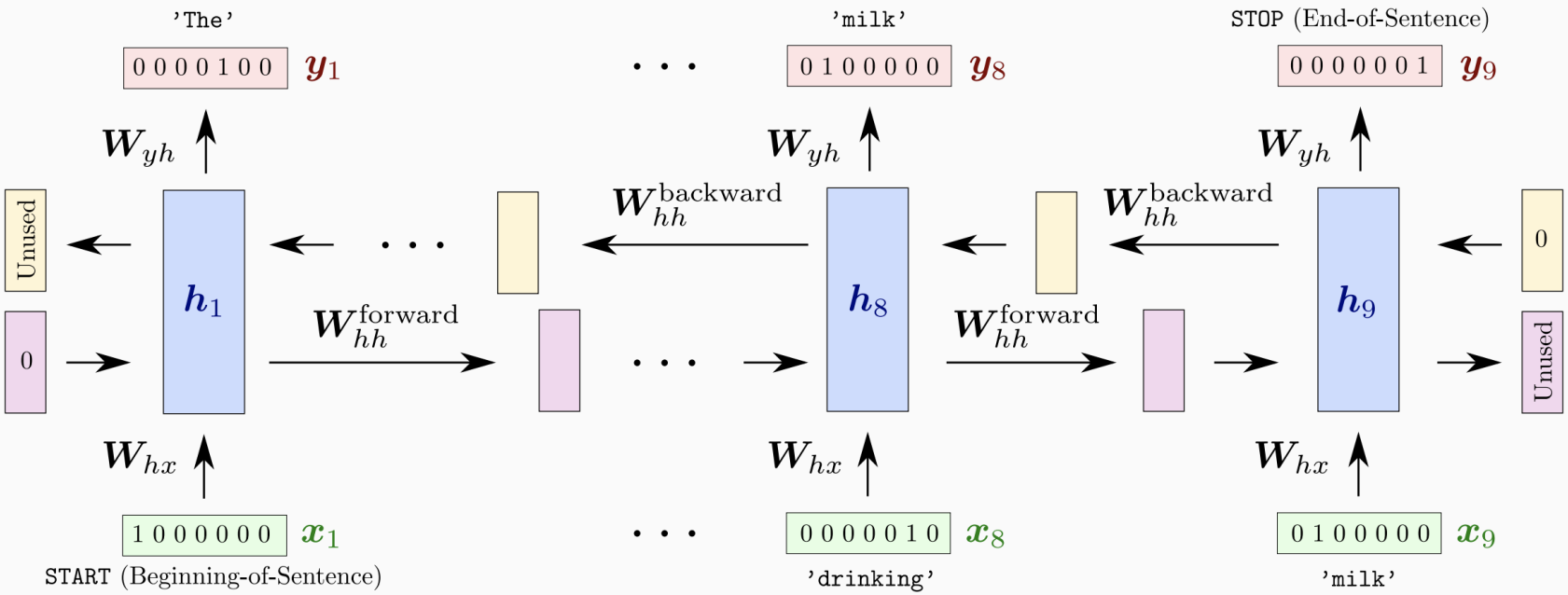

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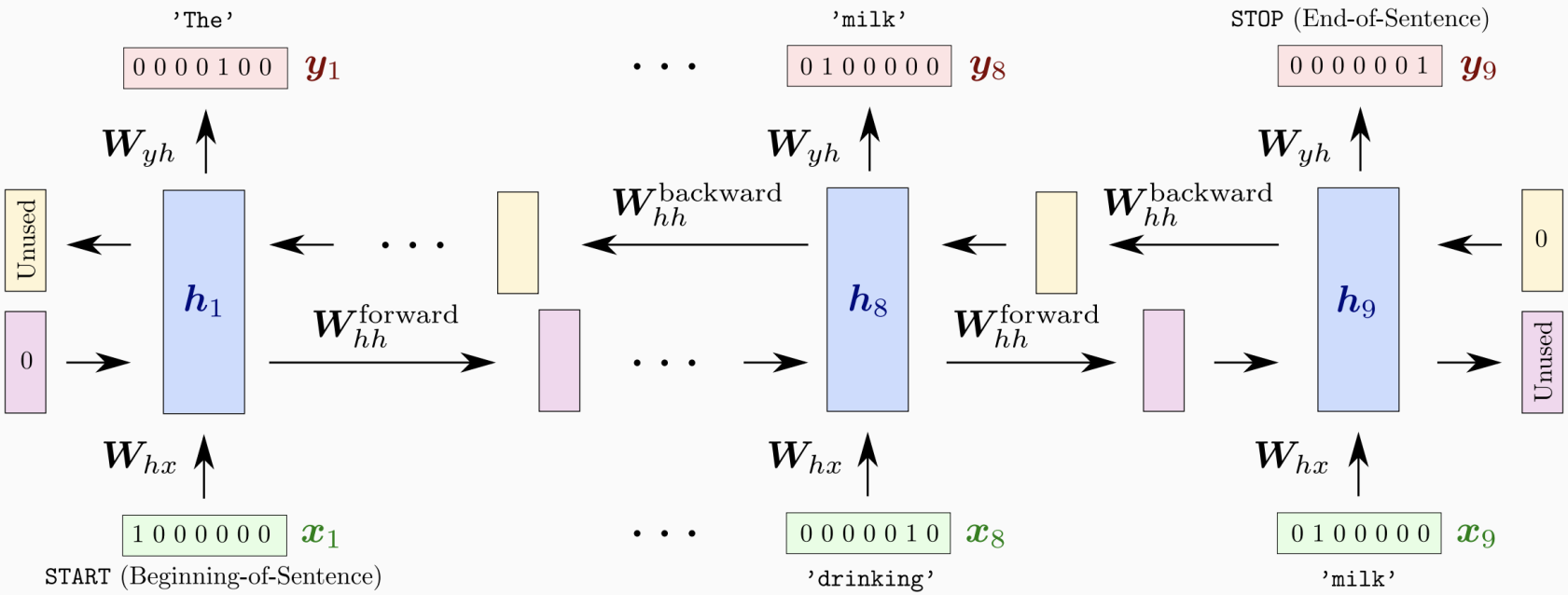

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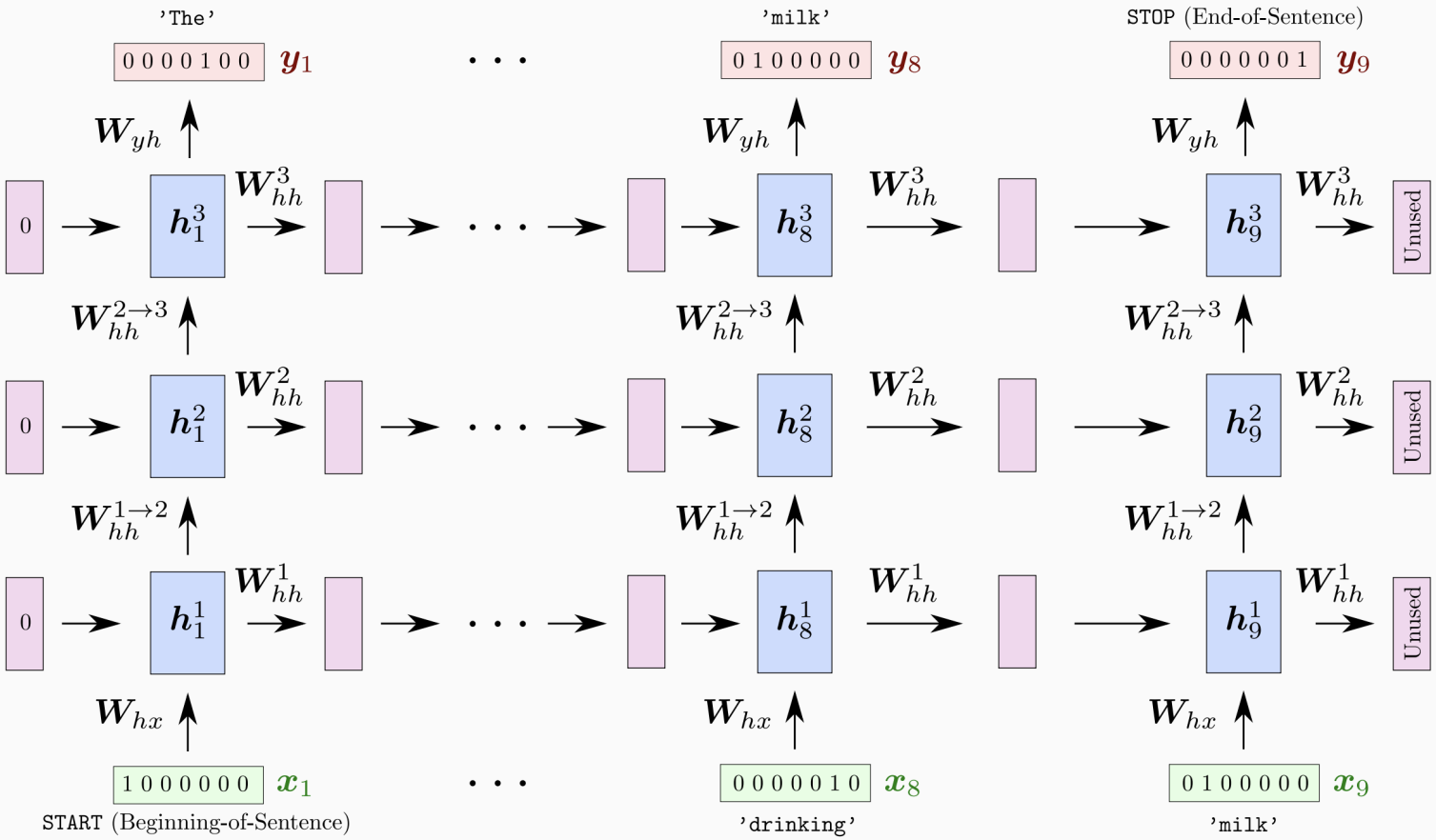
Deep RNN

- Multiple layers per time step (a feature hierarchy)



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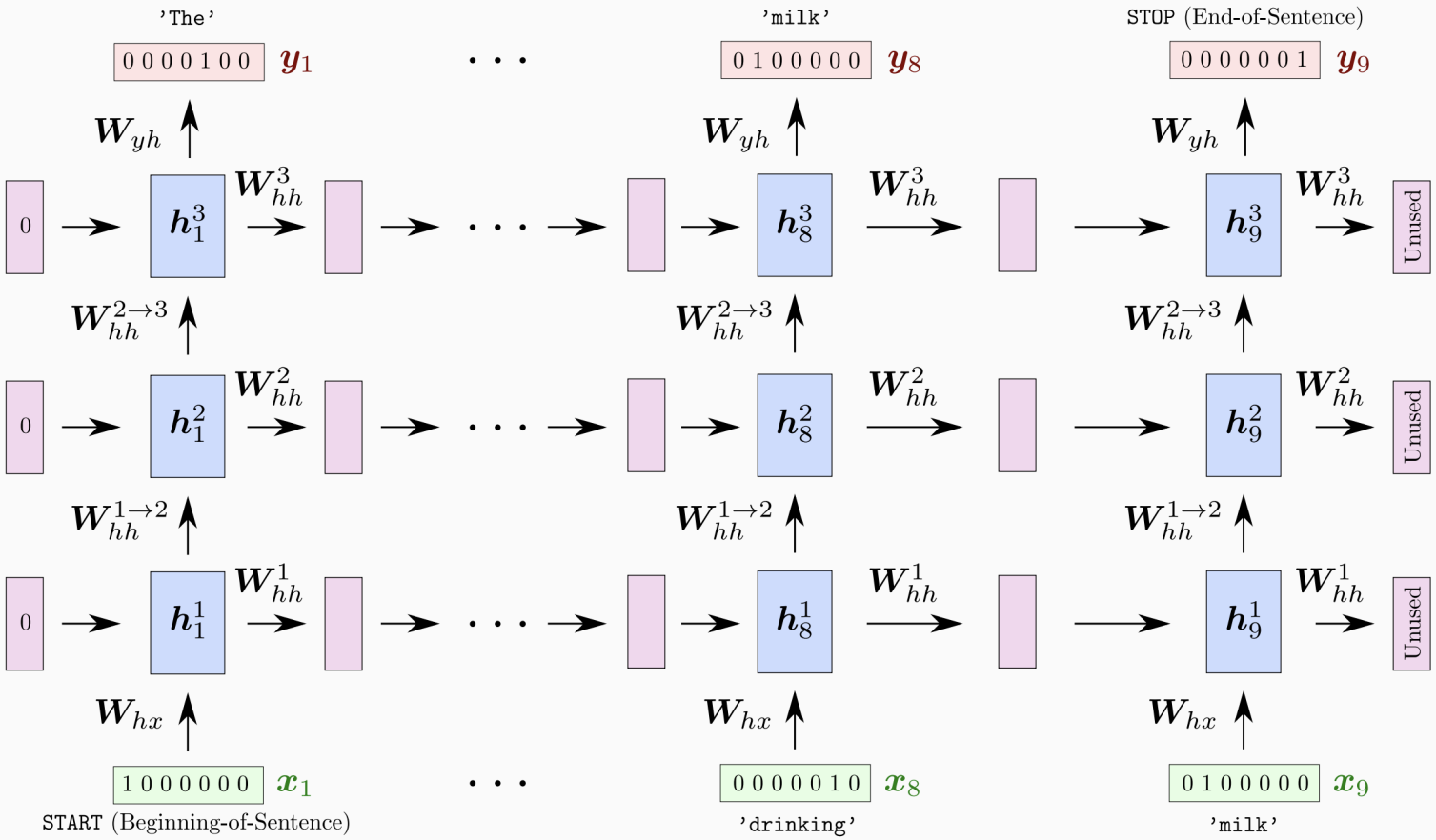

Deep RNN

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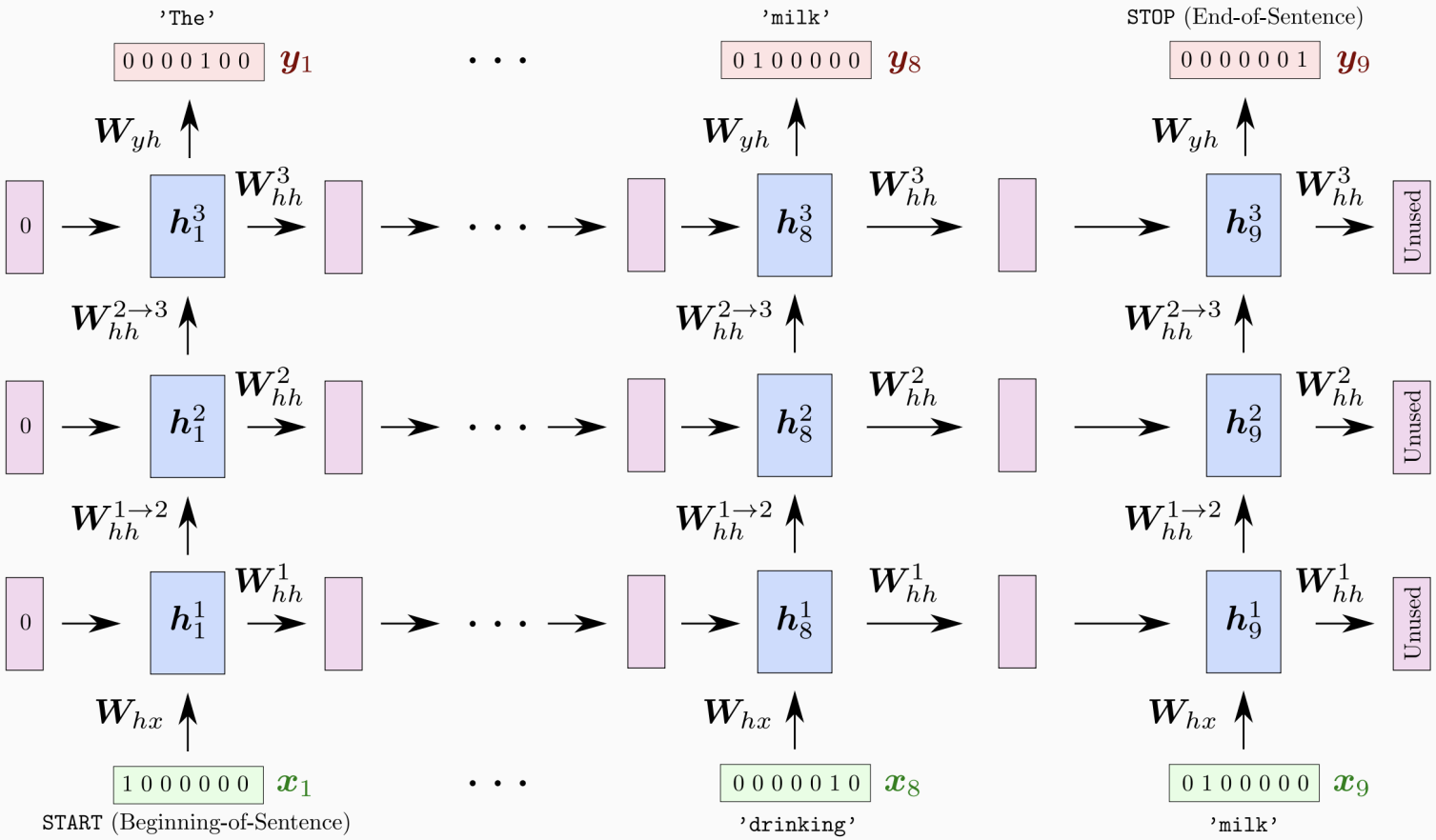
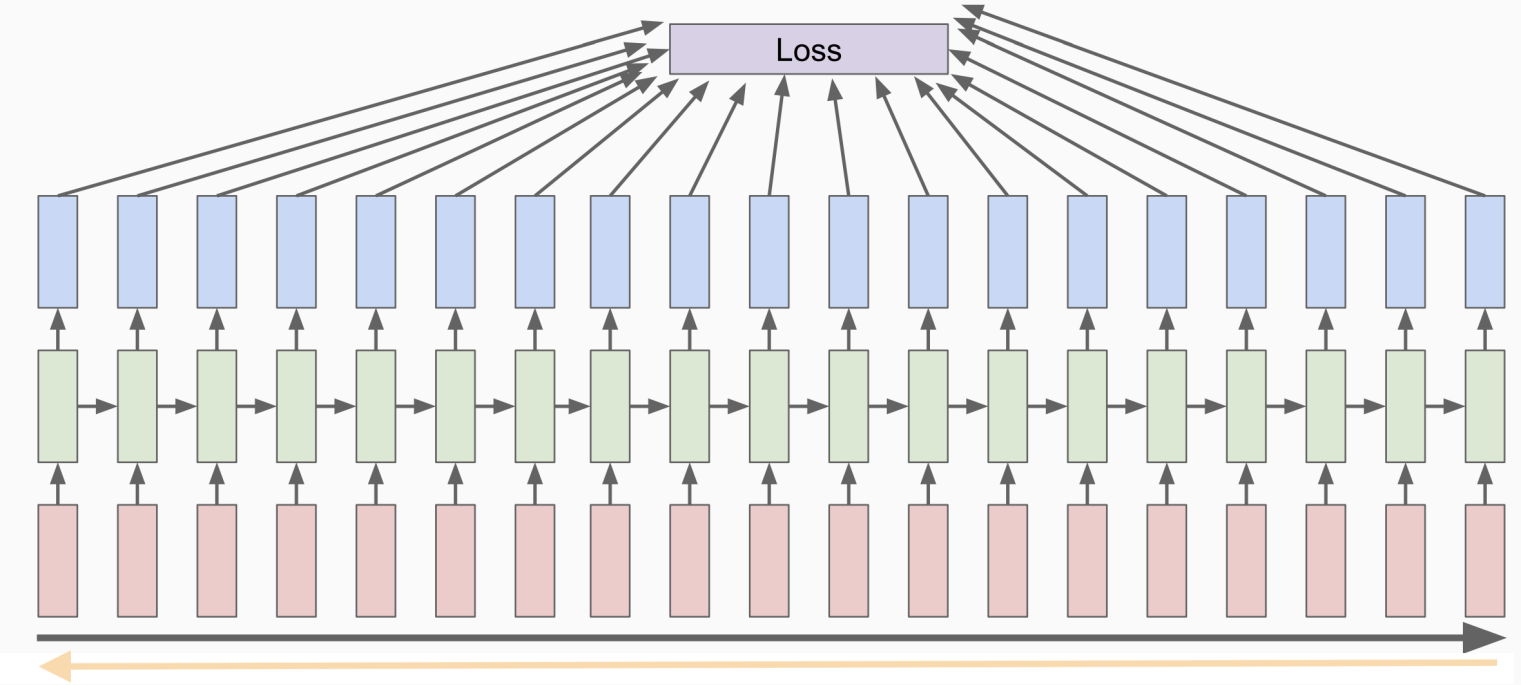
- Requires a lot more training data



Learning phase for RNN



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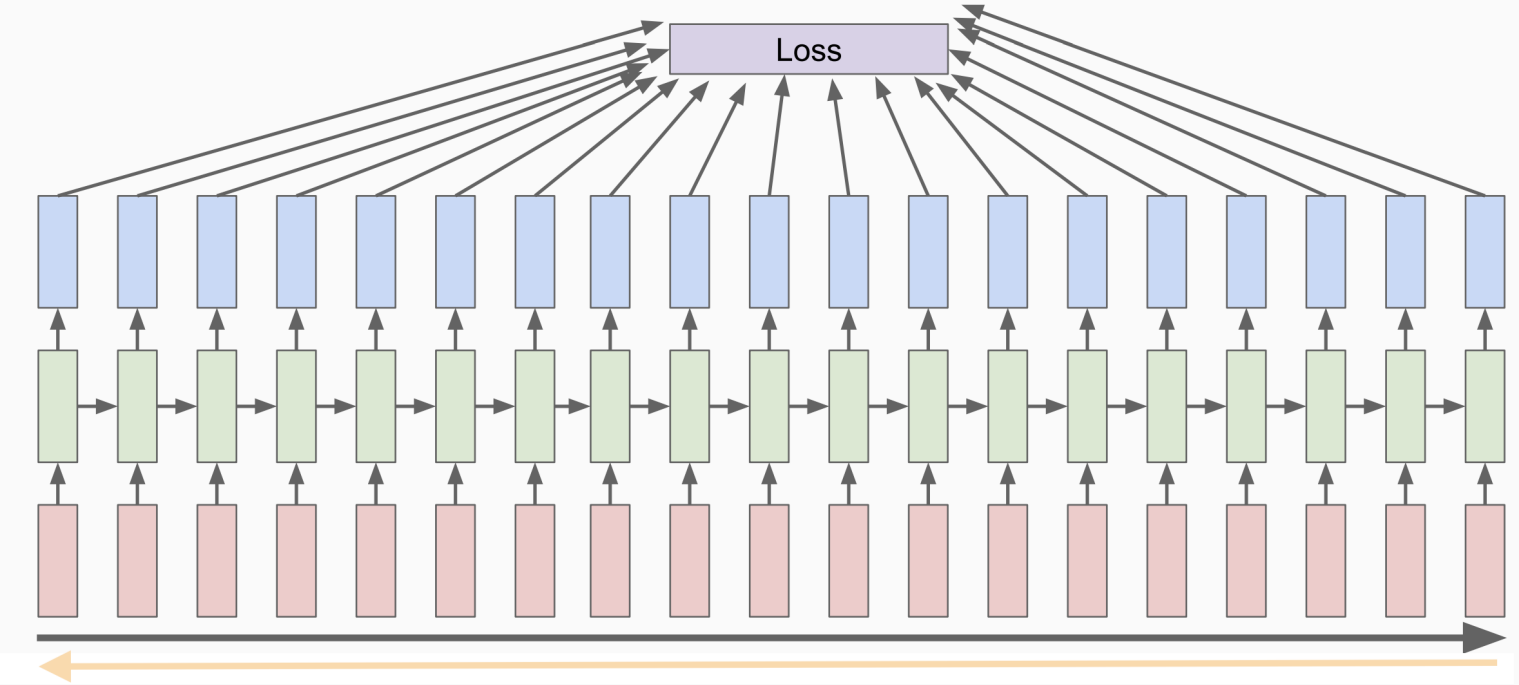

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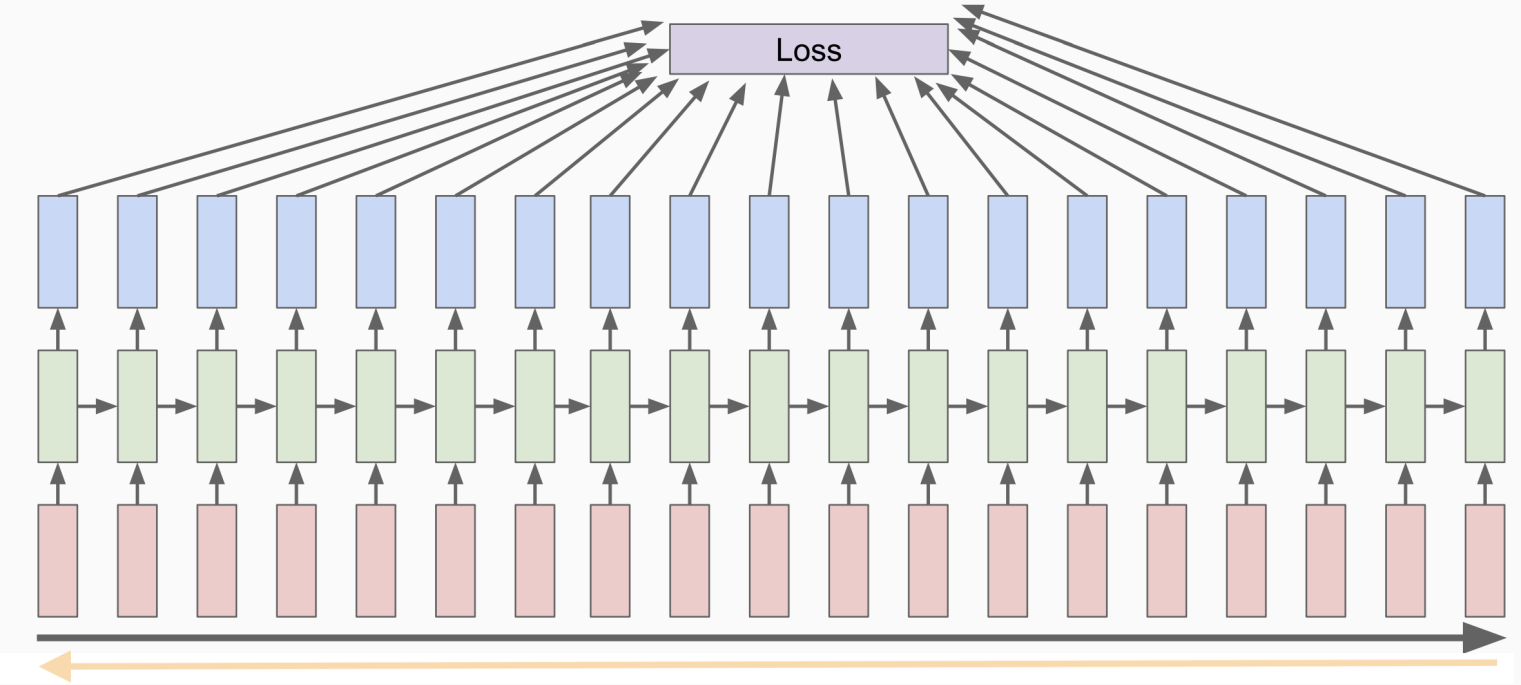

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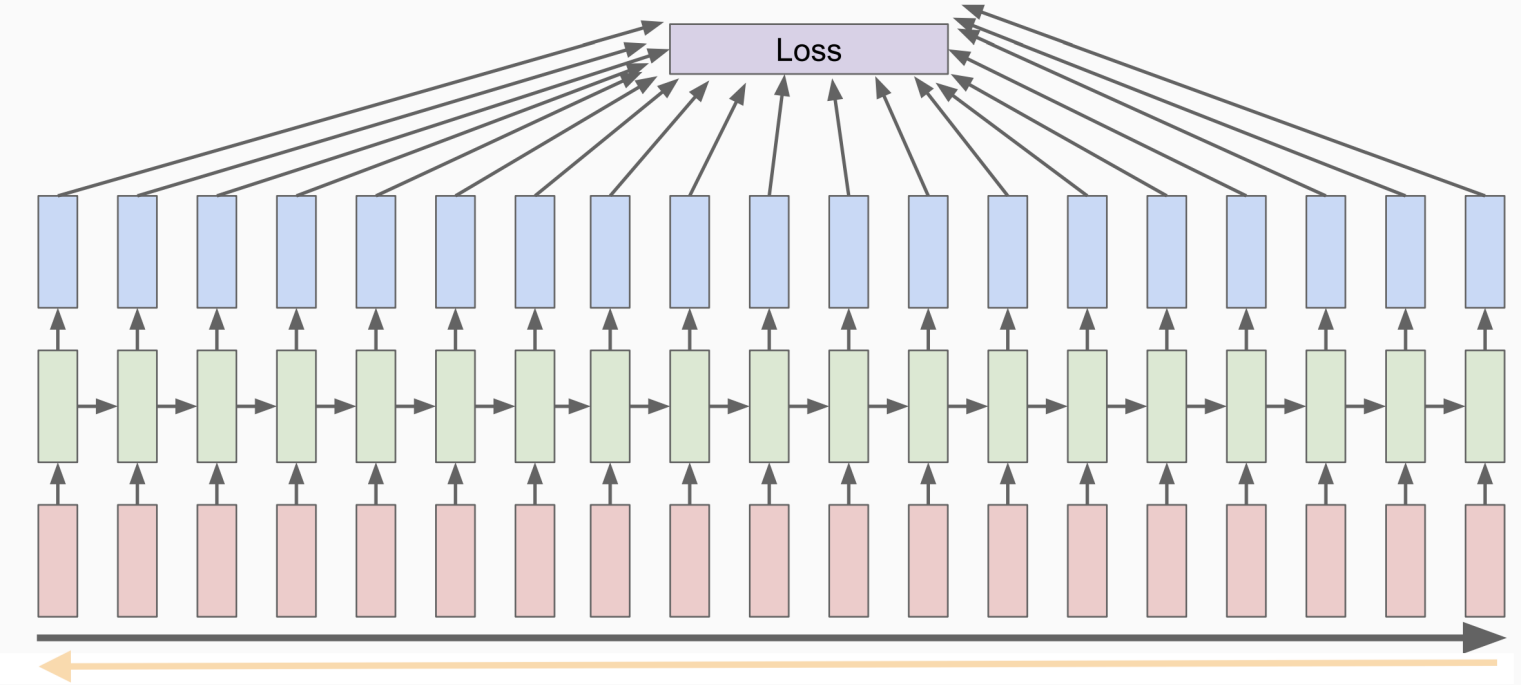

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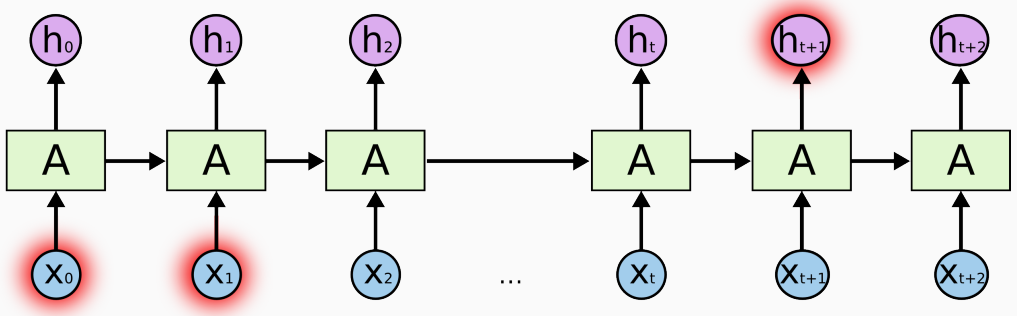
- Backward through the entire sequence to compute gradients

Language generating RNN: limitations

- Vanilla RNN have difficulties learning long-term dependencies



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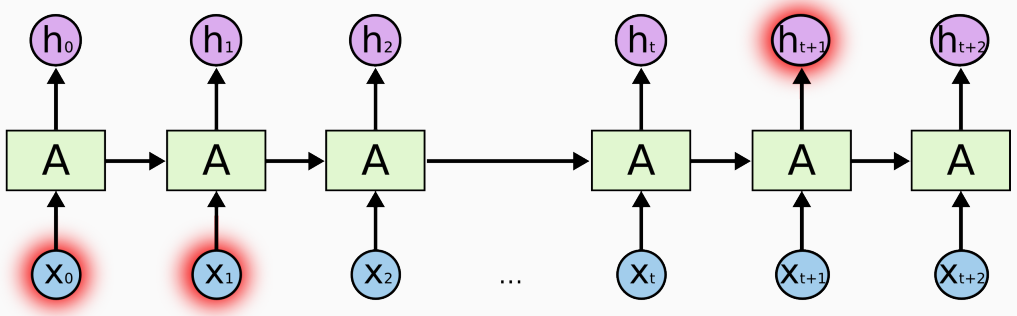

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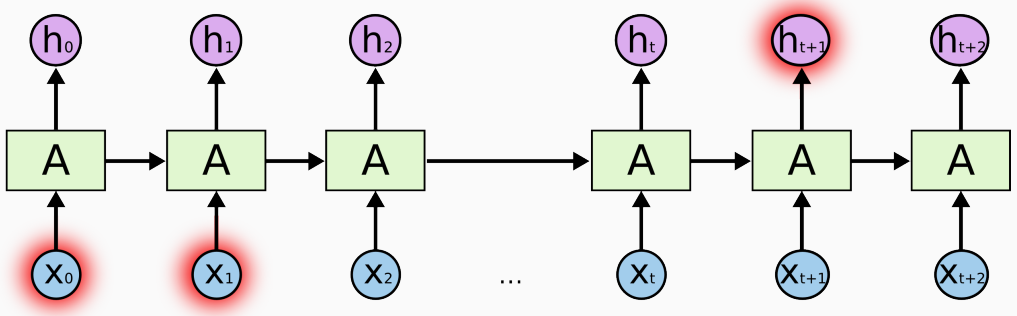

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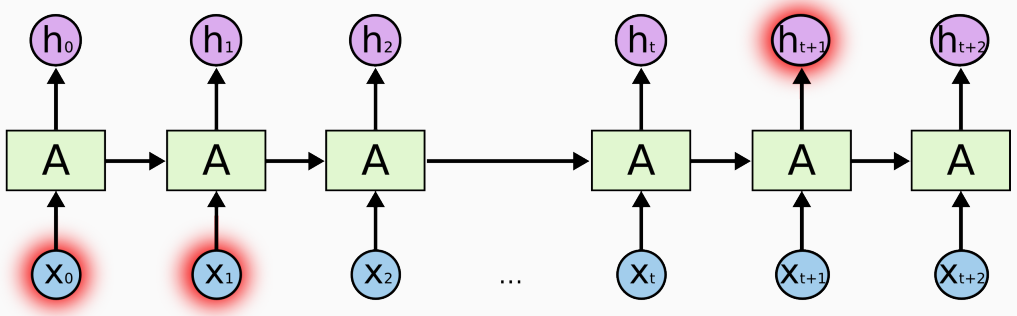

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- Certain types of RNNs are specifically designed to get around them

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- the update gate tells us how much memory retention versus forgetting needs to happen

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

Long-Short Term Memory

$$h_t = g\left(W_{hx}x_t + W_{hh}h_{t-1} + b_h\right) \qquad \text{(memory)}$$

$$y_t = \text{softmax}\left(W_{yh}h_t + b_y\right) \qquad \text{(used as feature for prediction)}$$

Long-Short Term Memory

$$g_t = g\left(W_{cx}x_t + W_{ch}h_{t-1} + b_c\right) \quad \text{(input modulation gate)}$$

$$c_t = g_t \quad \text{(place memory in a cell unit c)}$$

$$h_t = c_t$$

$$y_t = \text{softmax}\left(W_{yh}h_t + b_y\right) \quad \text{(use } h_t \text{ for prediction)}$$

Long-Short Term Memory

$$g_t = g\left(W_{cx}x_t + W_{ch}h_{t-1} + b_c\right) \qquad \text{(input modulation gate)}$$

$$c_t = c_{t-1} + g_t \qquad \text{(the cell keeps track of long term)}$$

$$h_t = c_t$$

$$y_t = \text{softmax}\left(W_{yh}h_t + b_y\right)$$

Long-Short Term Memory

$$f_t = \text{sigm}\,(W_{fx}x_t + W_{fh}h_{t-1} + b_f) \qquad \text{(forget gate)}$$

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$$c_t = f_t \odot c_{t-1} + g_t \qquad \text{(but can forget some of its memories)}$$

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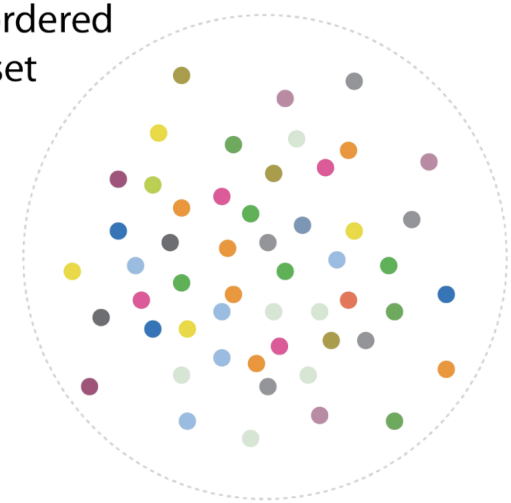
$$y_t = \text{softmax}\,(W_{yh}h_t + b_y)$$

- There are many variants, but this is the general idea

Preparation of sequence data

Not ordered
Dataset



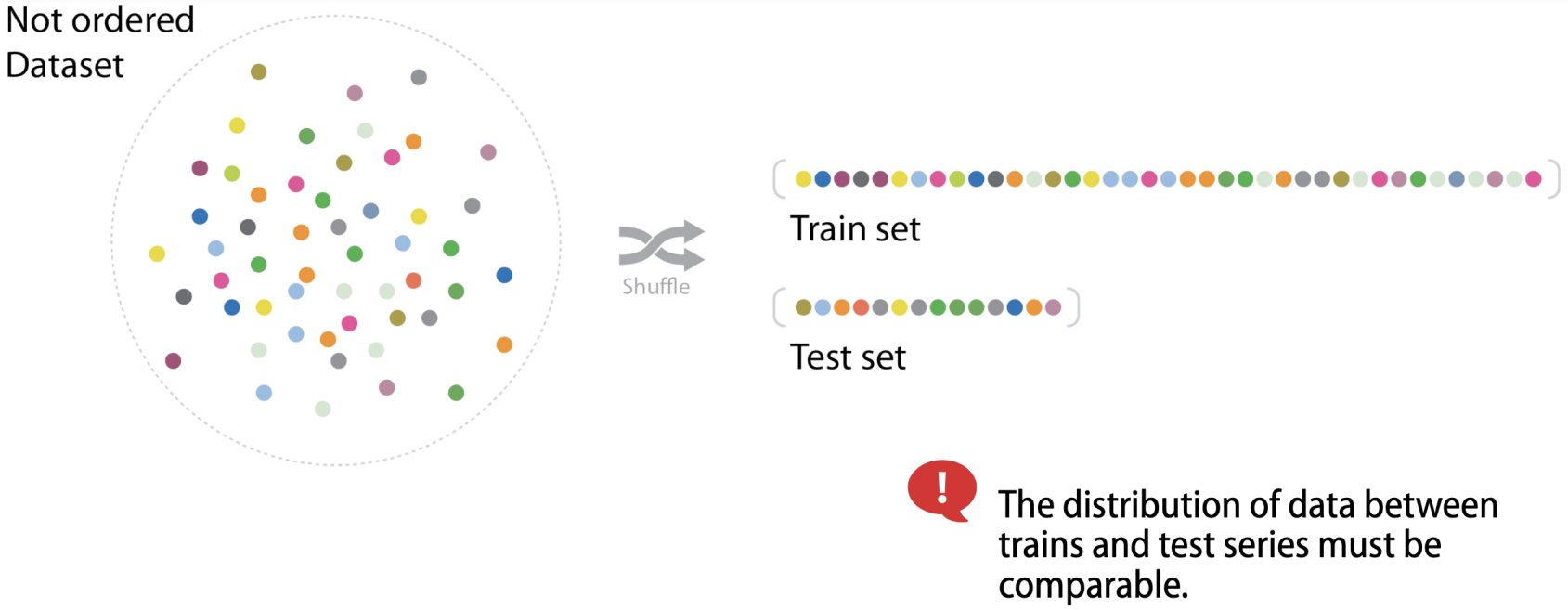
Shuffle

Train set

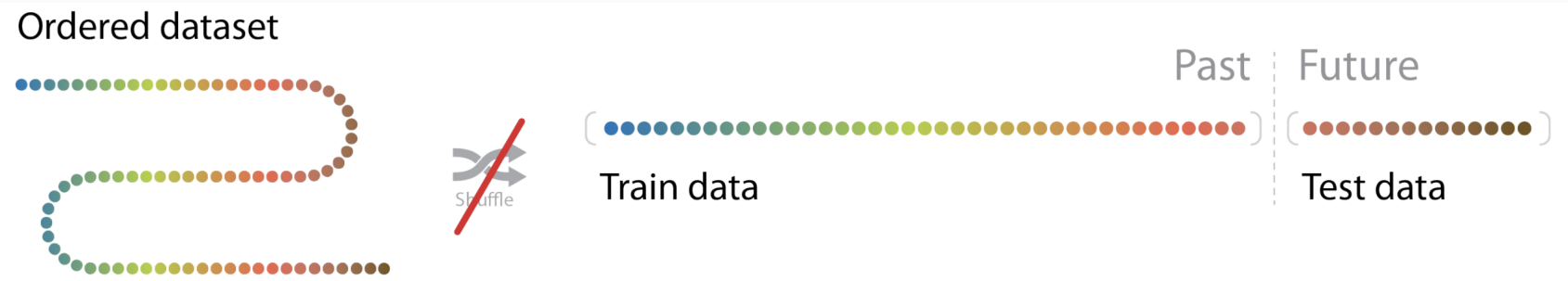
Test set

The distribution of data between trains and test series must be comparable.

Preparation of sequence data

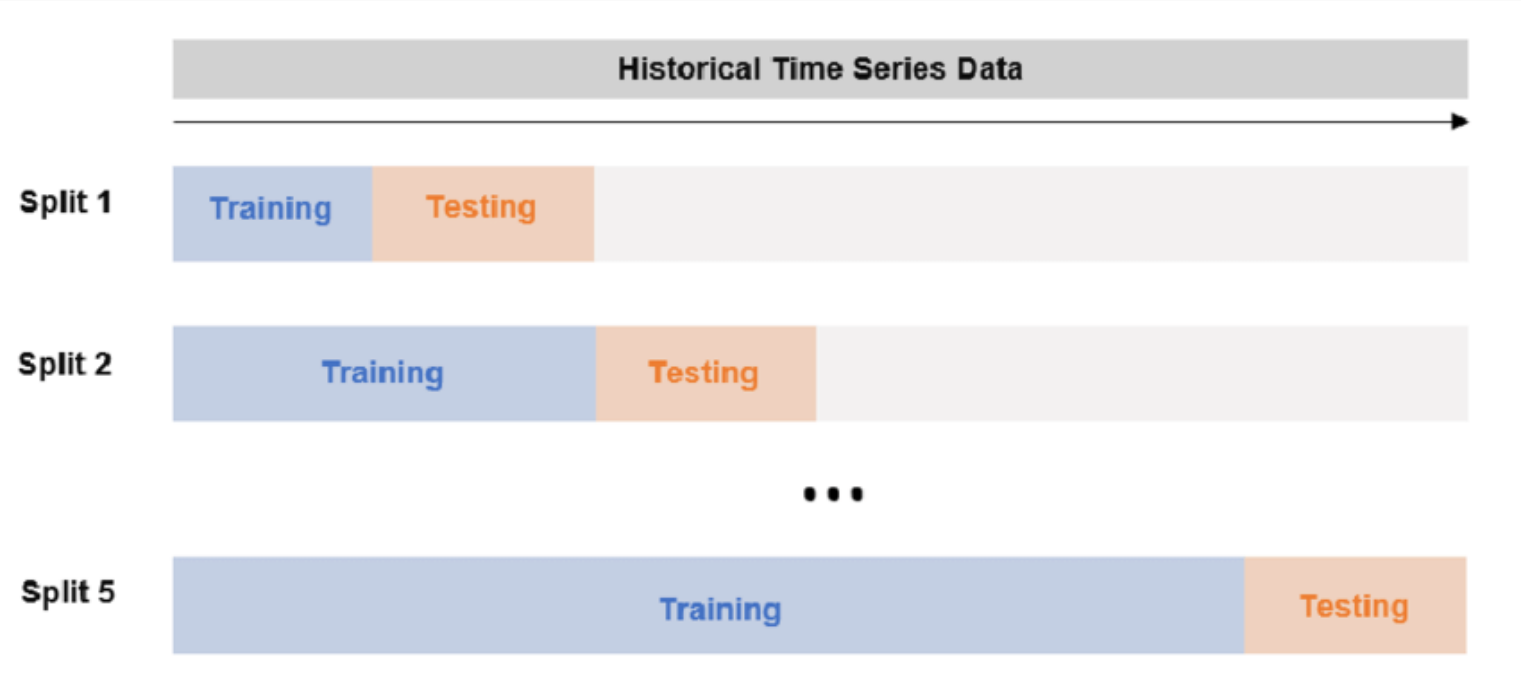


- Can you predict the past with the future? Beware of splitting time series!



source: fidle-cnrs

Cross-validation for time series



Sommaire

Word representation

Recurrent NN

Transformers

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- RNN maps a sequence to a single output or a sequence

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- This is an embedding

A preliminary version of self-attention

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  - *The operation is permutation-invariant (but this can be fixed, see later)*

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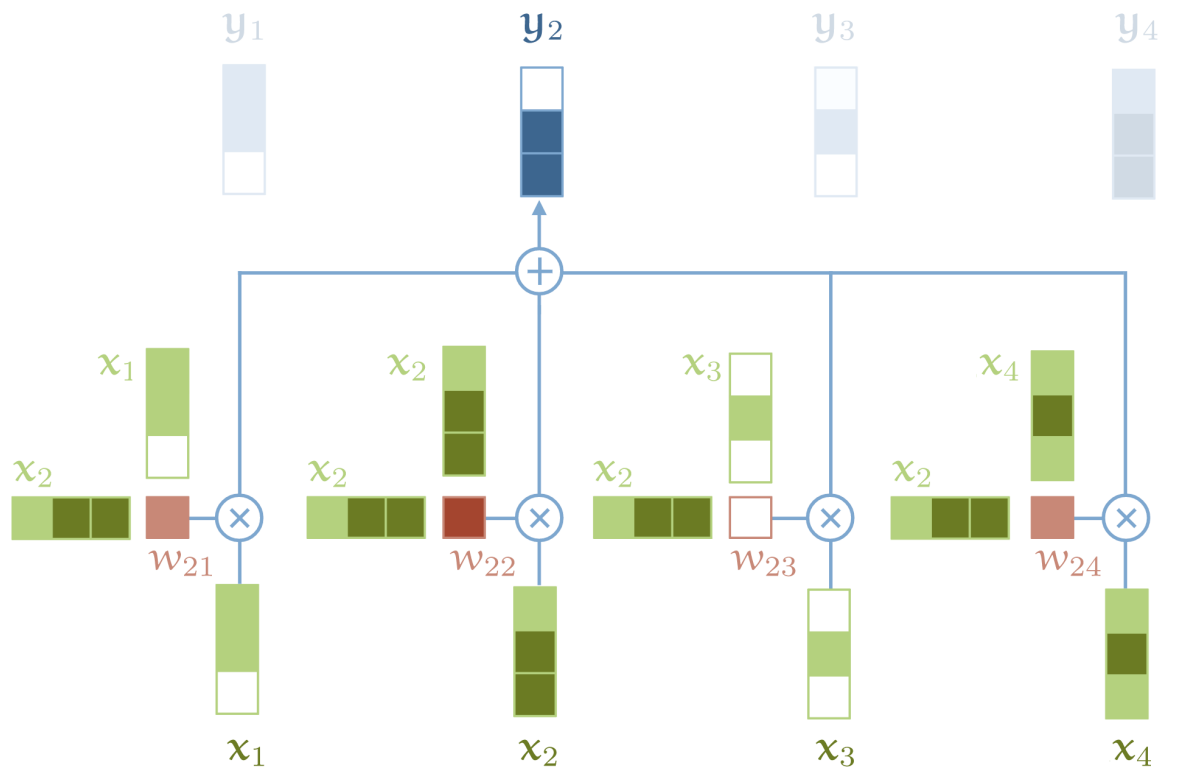
from http://peterbloem.nl/blog/transformers



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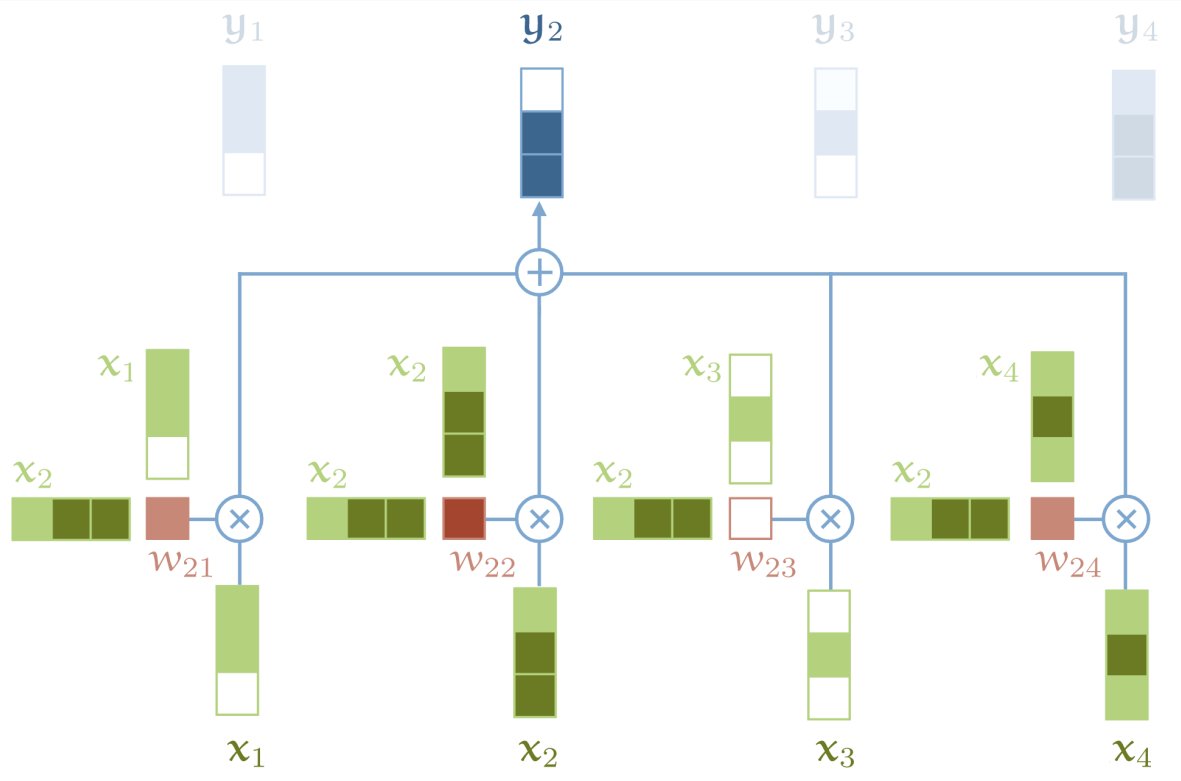

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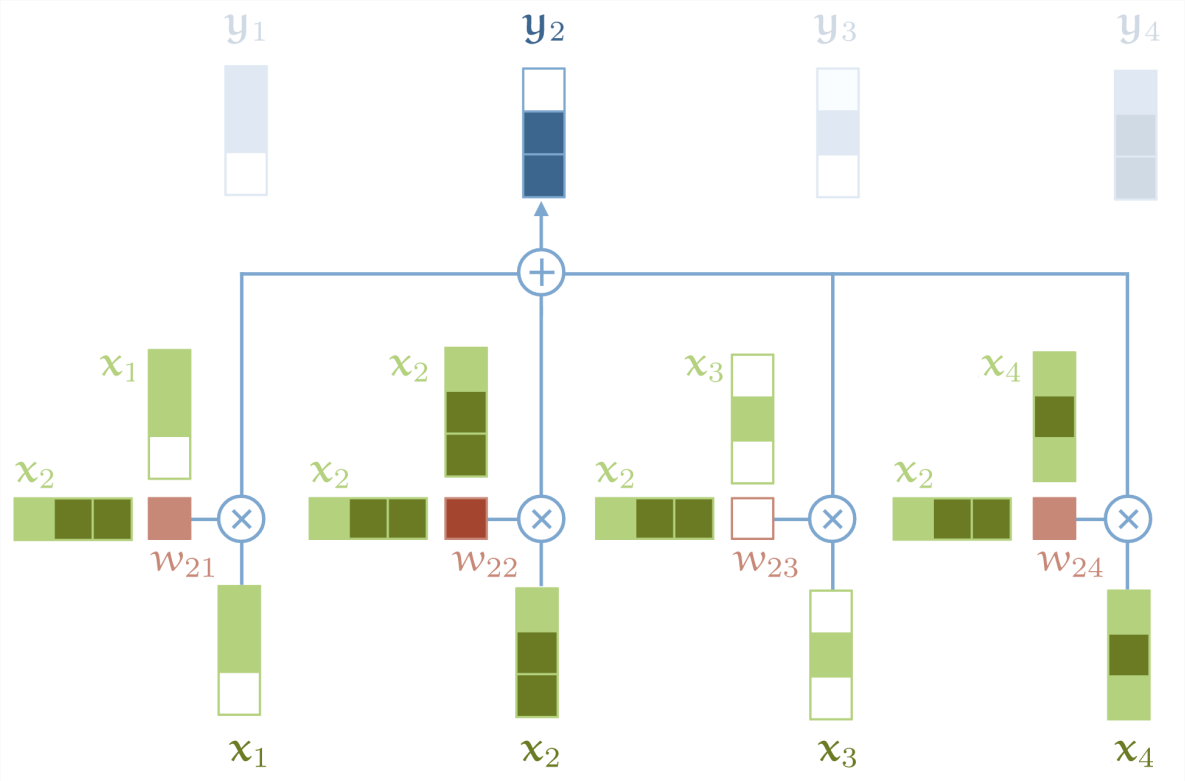

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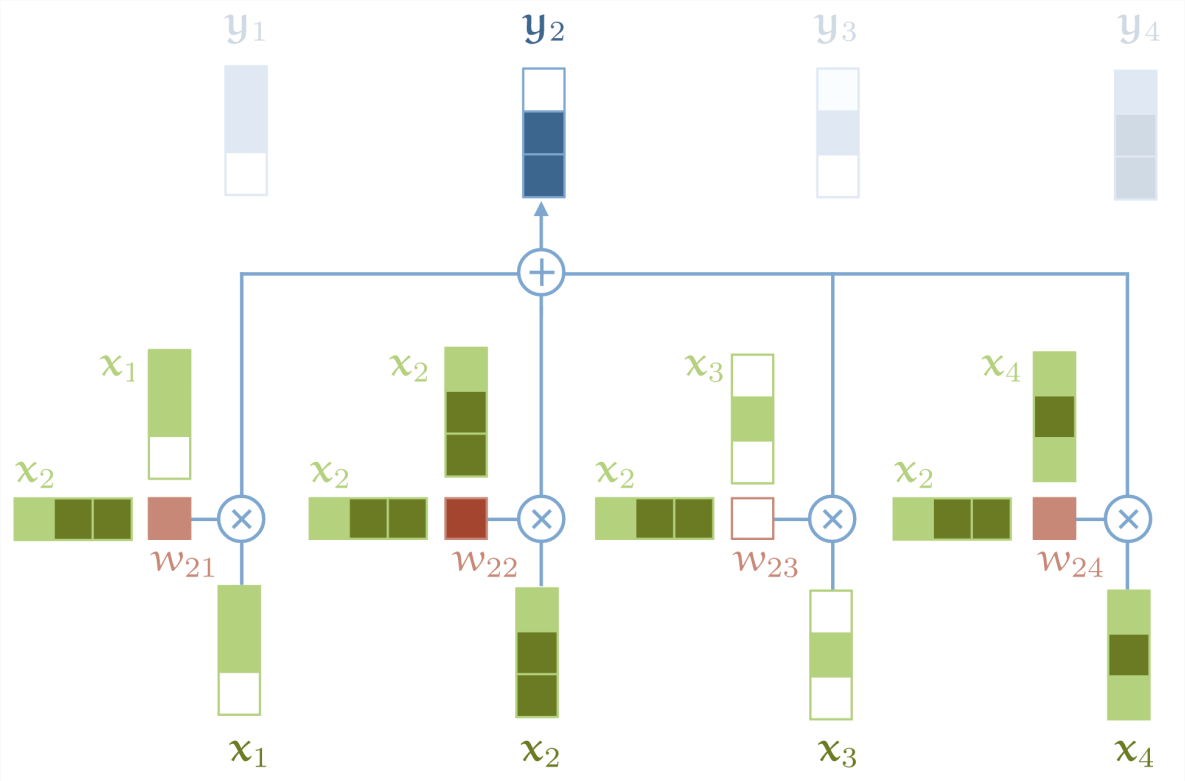

- A few other ingredients are needed for a complete transformer
- But this is the only operation in the whole architecture that propagates information between vectors
  - ▷ *Every other operation in the transformer is applied to each vector in the input sequence without interactions between vectors*

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- Possible by the scalar products

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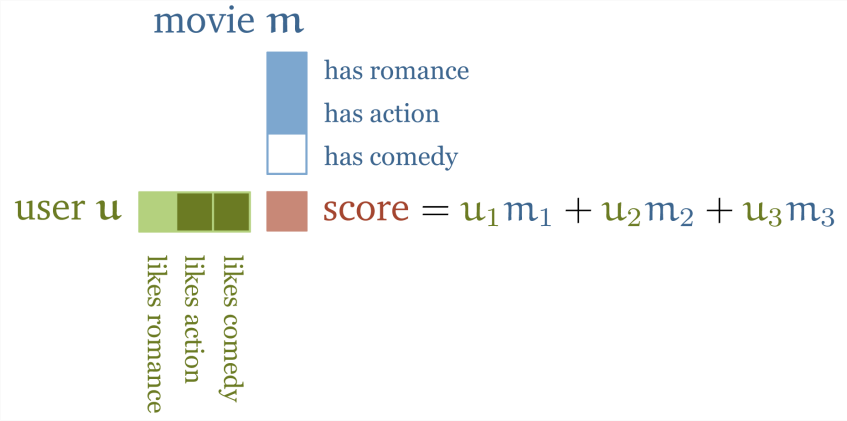
Another example: movie recommendation

1. create manual features for movies and for users



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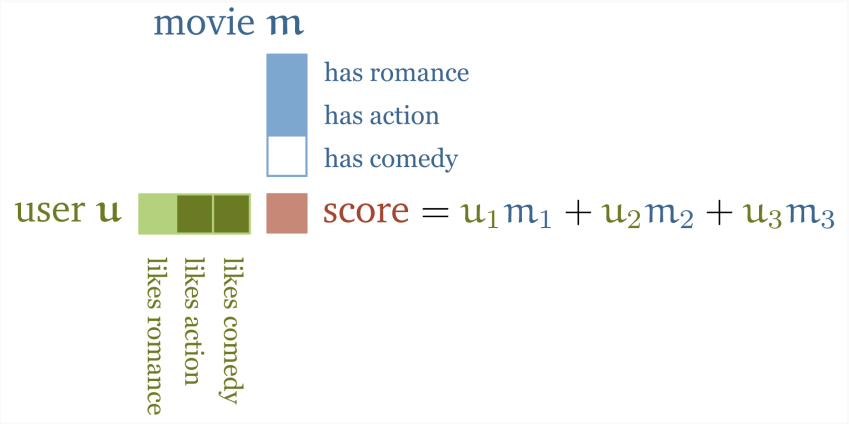

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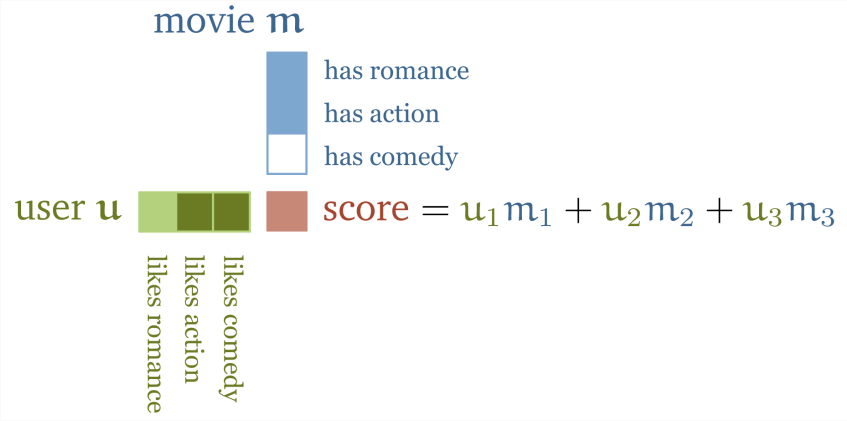

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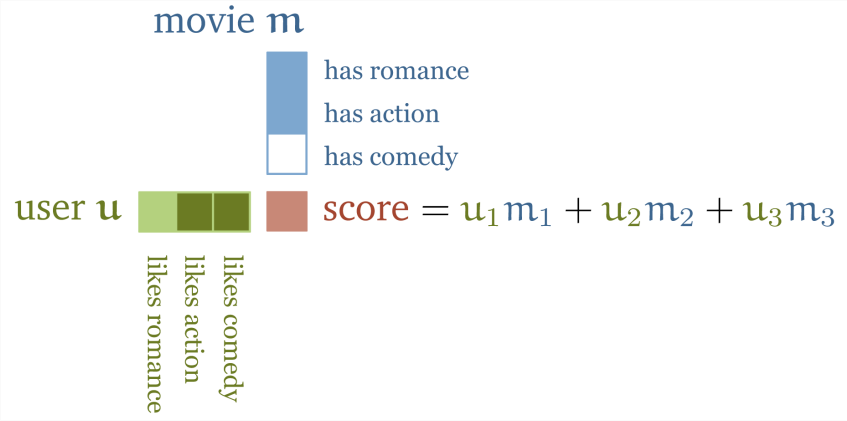

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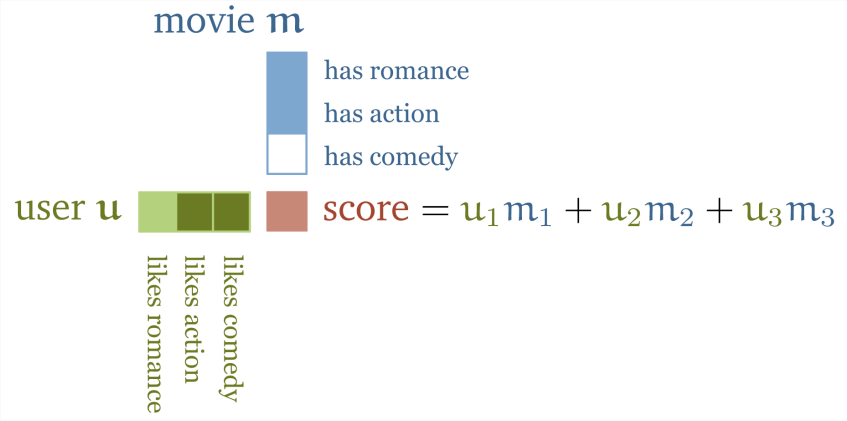

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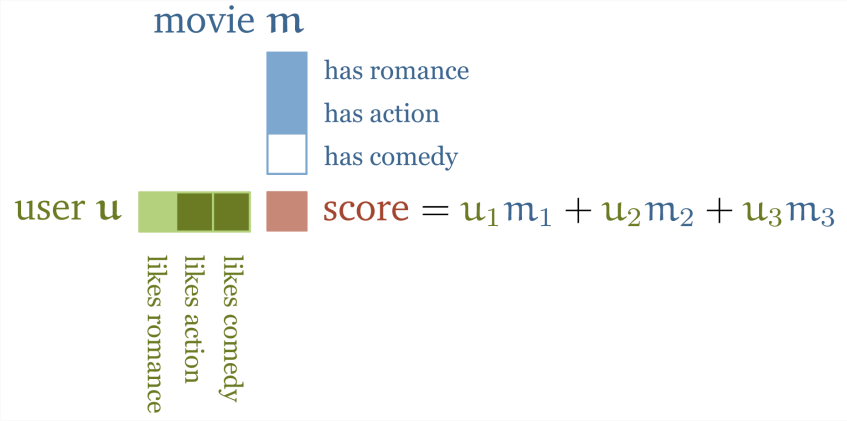

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Dot product $\approx$ relations between objects

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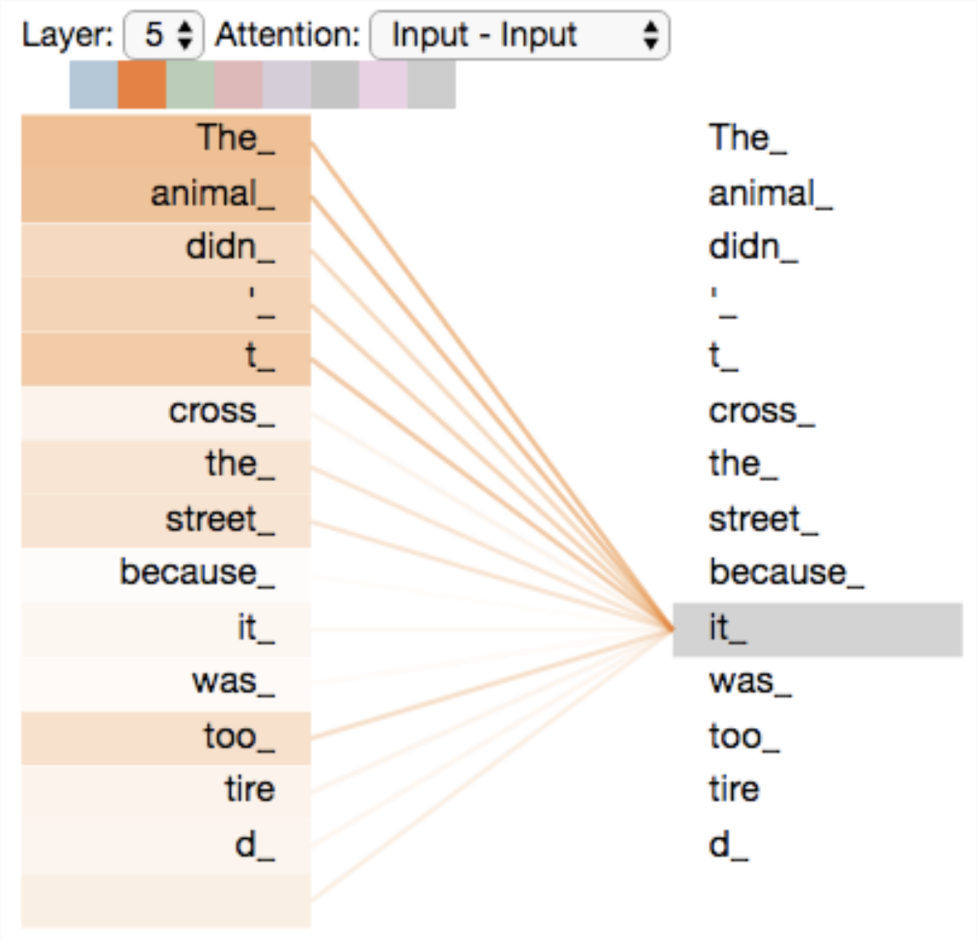
▷ Desire 1: the embedding $v_{\texttt{The}}$ should have a zero or negative scalar product with the other words

- Helpful to interpret who sleeps

▷ Desire 2: for nouns like '`dog`' and verbs like '`sleeps`', learn an embedding $v_{\texttt{dog}}$ and $v_{\texttt{sleeps}}$ that have a high, positive dot product

Learning the embedding: attention weights



- Showing the scalar products between the learned embedding v
- As we are encoding the word "`it`", part of the attention mechanism was focusing on "`the animal`"

Towards a real self-attention layer

In the toy self-attention version, every input vector x_i is used in three different ways in the self attention operation

$$w'_{ij} = x_i{}^\top x_j, \quad w_{ij} = \text{softmax}((w'_{ij})_j), \quad y_i = \sum_{j=1}^{N} w_{ij} x_j$$

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These three roles are called the query, key, and value.

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Make these roles distinct by adding a few dummy variables:

$$q_i = x_i \qquad \text{(Query)}$$
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Then, we can use learnable parameters for each of these roles, for instance:

$$q_i = W_q x_i \qquad \text{(Query)}$$
$$k_i = W_k x_i \qquad \text{(Key)}$$
$$v_i = W_v x_i \qquad \text{(Value)}$$

where W_q, W_k, W_v are learnable projection matrices that defines the roles of each data point

An attention head

from http://peterbloem.nl/blog/transformers

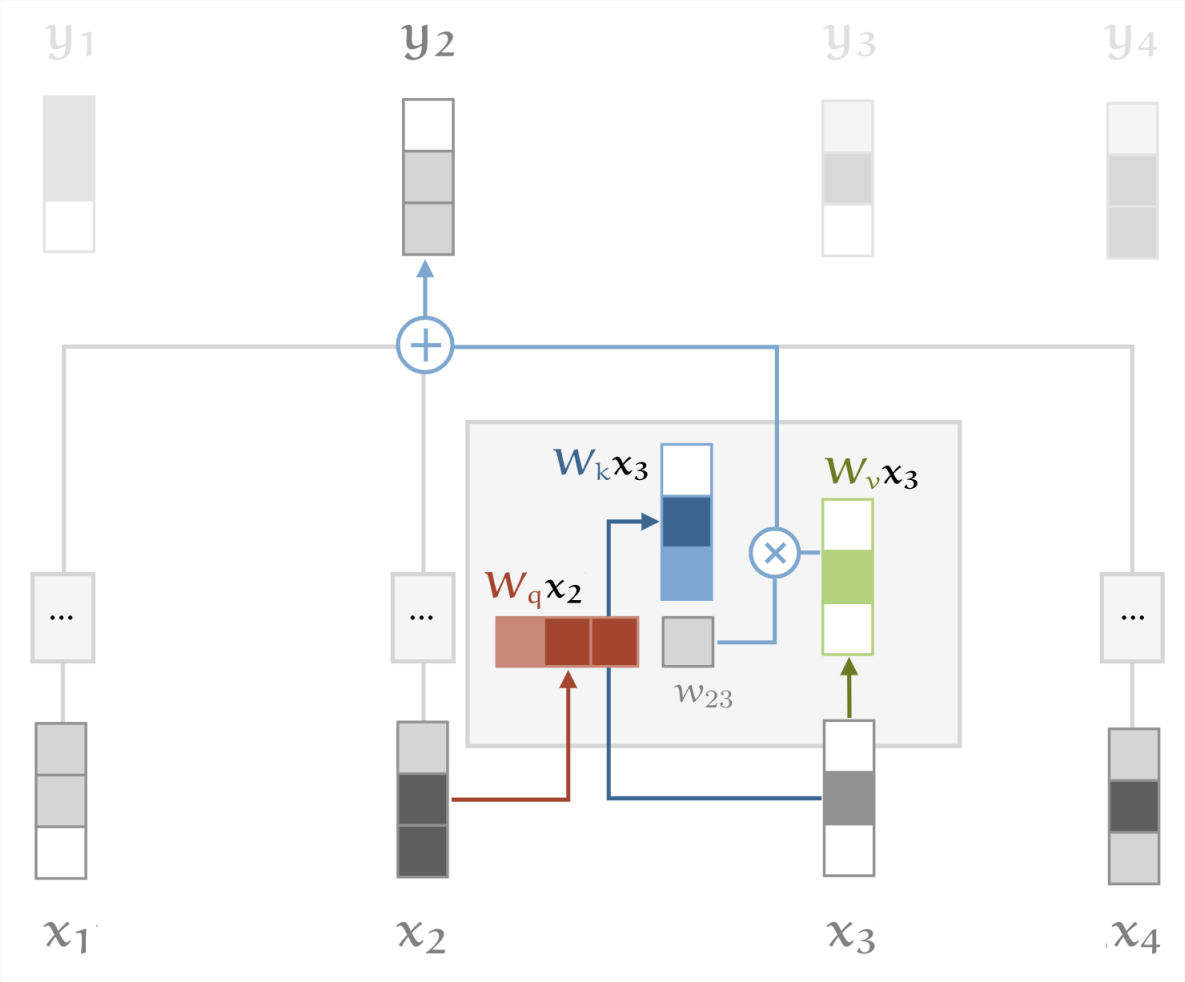

Figure 1: Illustration of the self-attention with key, query and value transformations

Scaling the dot product

- The dot product in attention weights is usually scaled

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- The average value of the dot product grows with the embedding dimension

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$$y_i = W_y \text{concat}\left(y_i^1, y_i^2, \ldots\right)$$

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$$y_i = W_y \text{concat}\left(y_i^1, y_i^2, \ldots\right)$$

$$(y_1, \ldots, y_N) = \textbf{Attn}\,(x_1, \ldots, x_N)$$

Multi-head self attention layer

- Concatenate different self-attention mechanisms to give it more flexibility
- Index each head with $r = 1, 2, \ldots$

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- Trick to reduce dimension: use lower-dimensional matrices W_q^r, W_k^r and W_v^r: $\dim(x) \times h$ intead of $\dim(x) \times \dim(x)$

A multi-head attention

from http://peterbloem.nl/blog/transformers

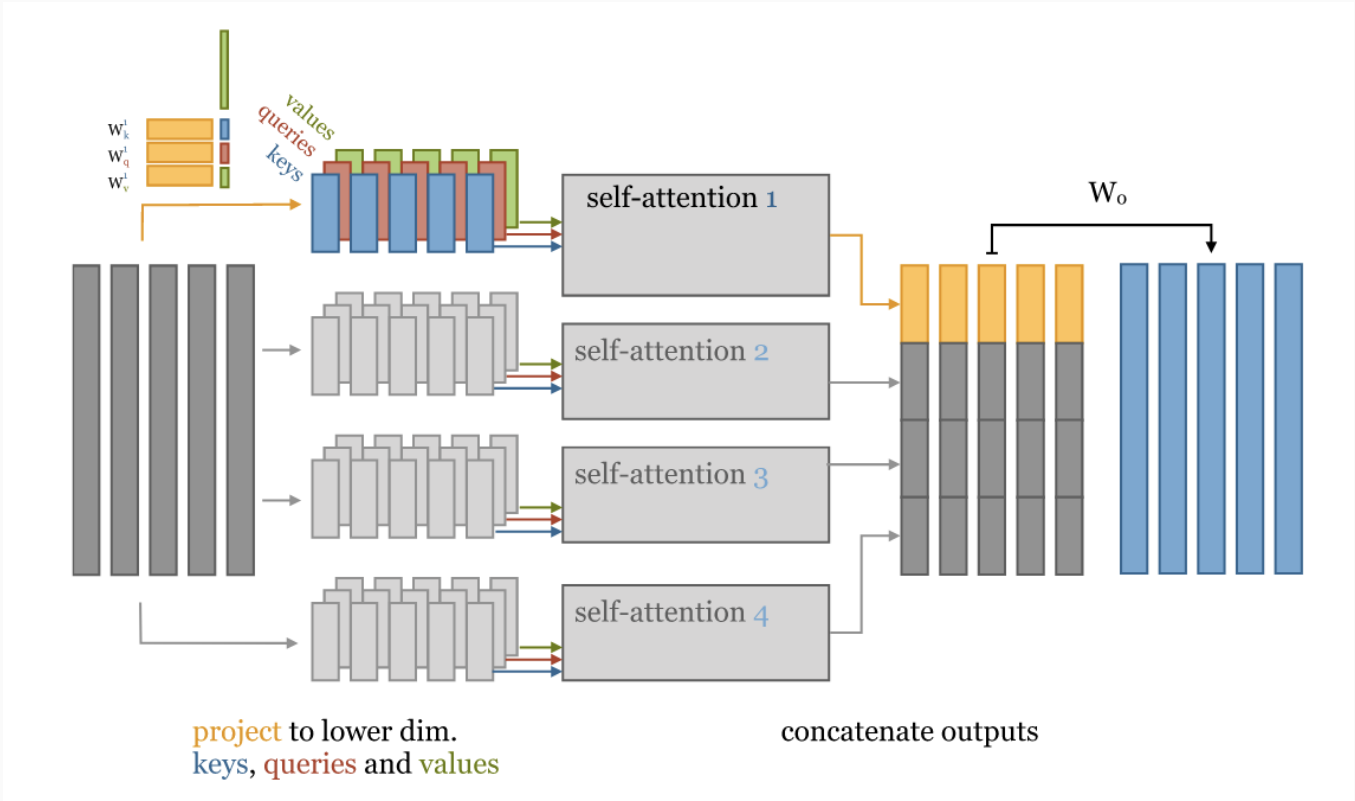

Figure 2: Illustration of multi-head self-attention with 4 heads. To get our keys, queries and values, we project the input down to vector sequences of smaller dimension.

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  The outputs are aggregates of these interactions and attention scores.

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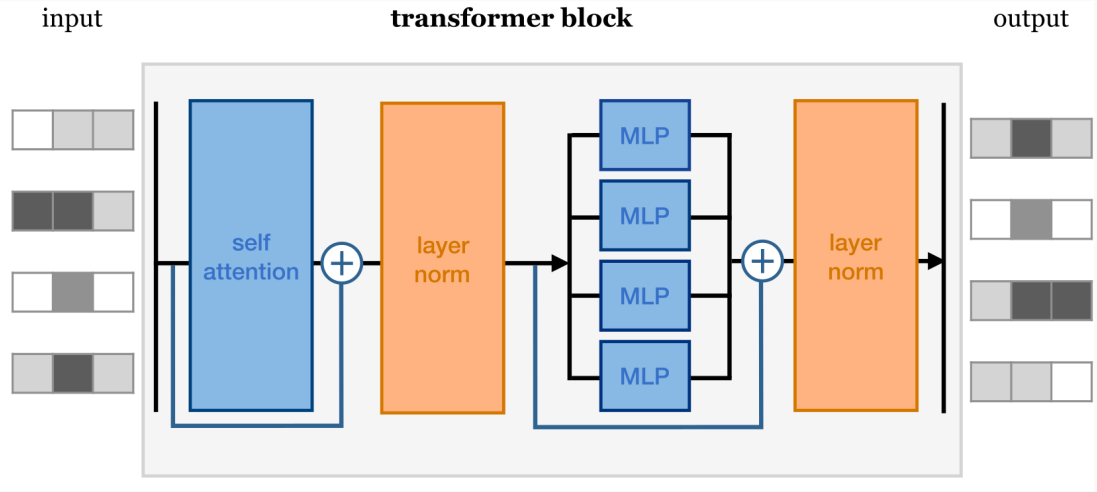

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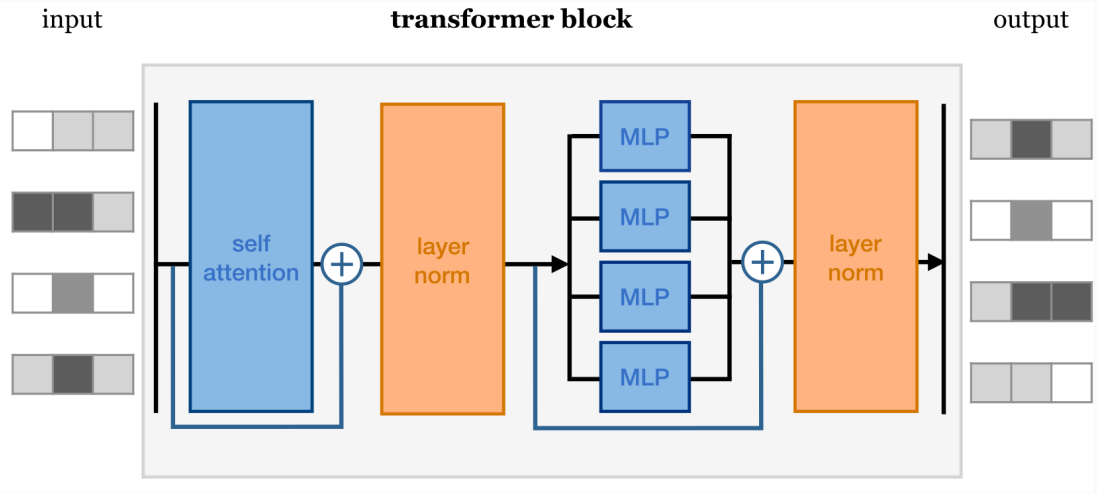

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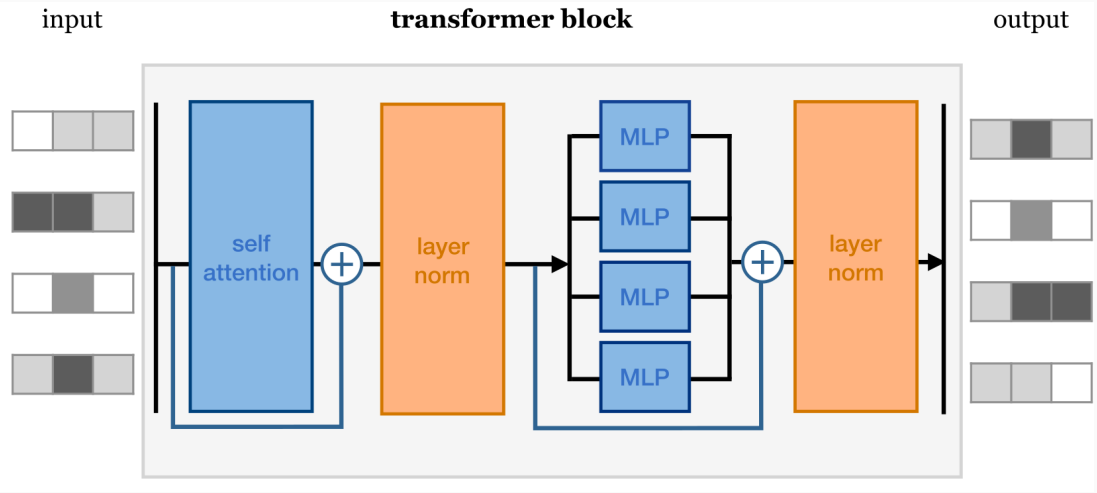

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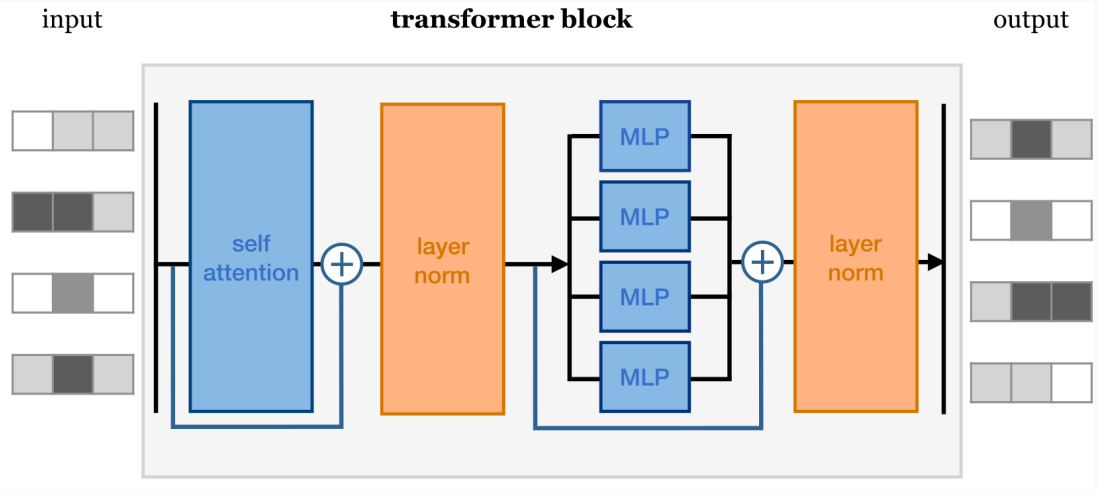

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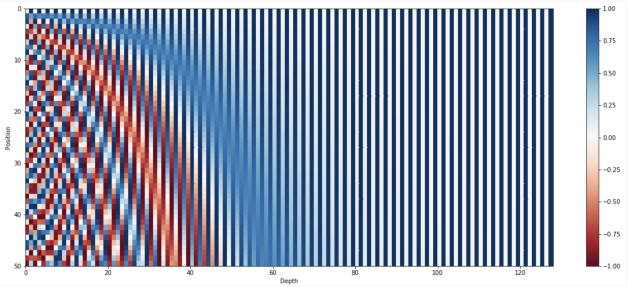

The 128-dimensional positional encoding for a sentence with a maximum length of 50. Each row represents the encoding vector.

Simple sequence classification transformer

- Goal: build a sequence classifier for sentiment analysis
- IMDb sentiment classification dataset
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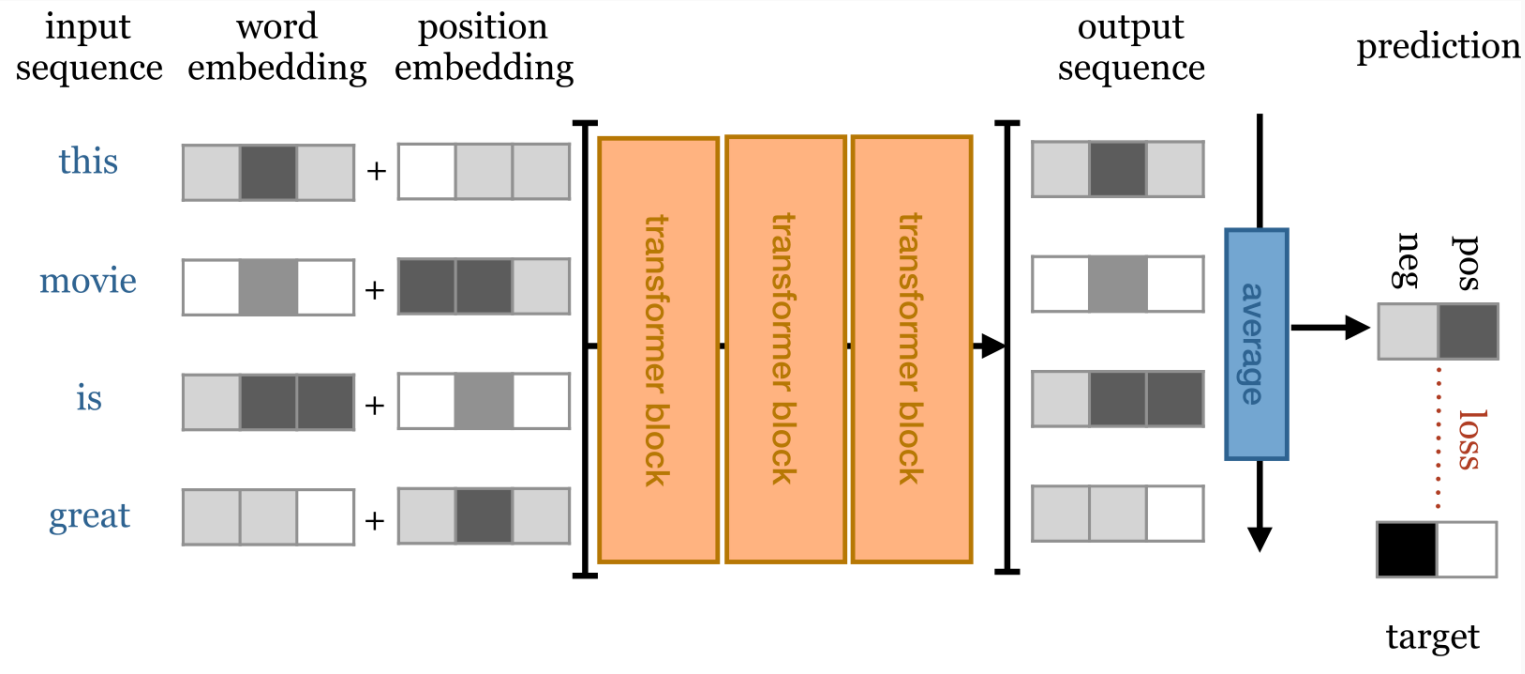

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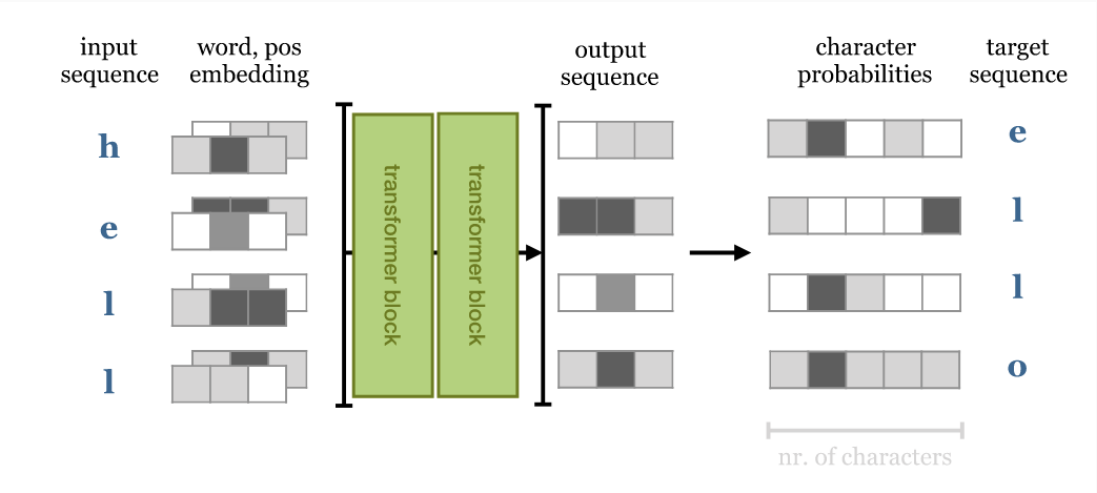

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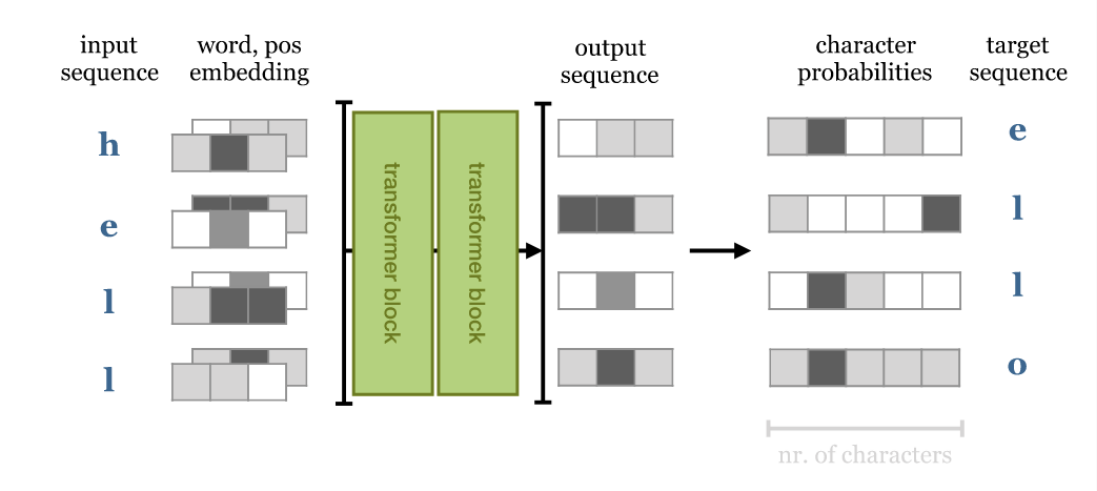

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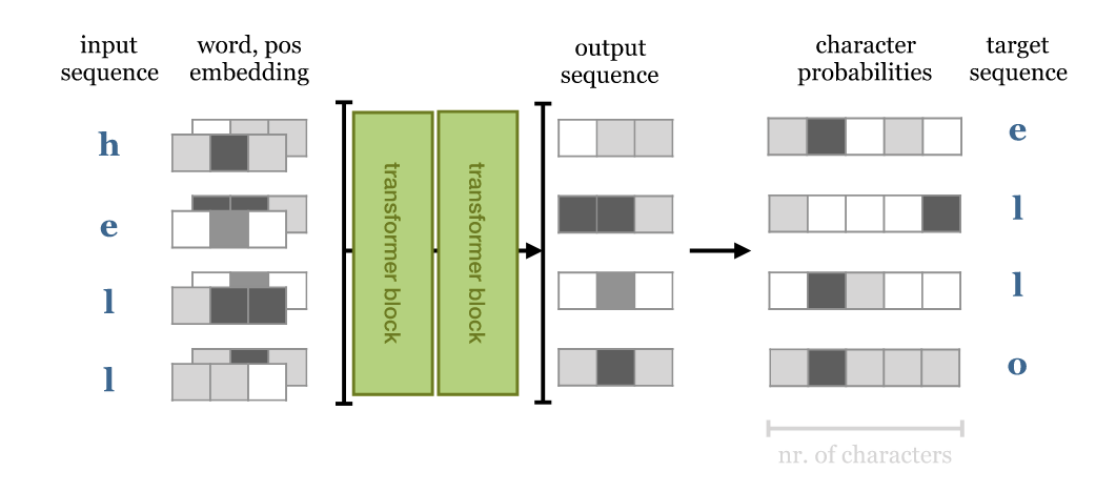

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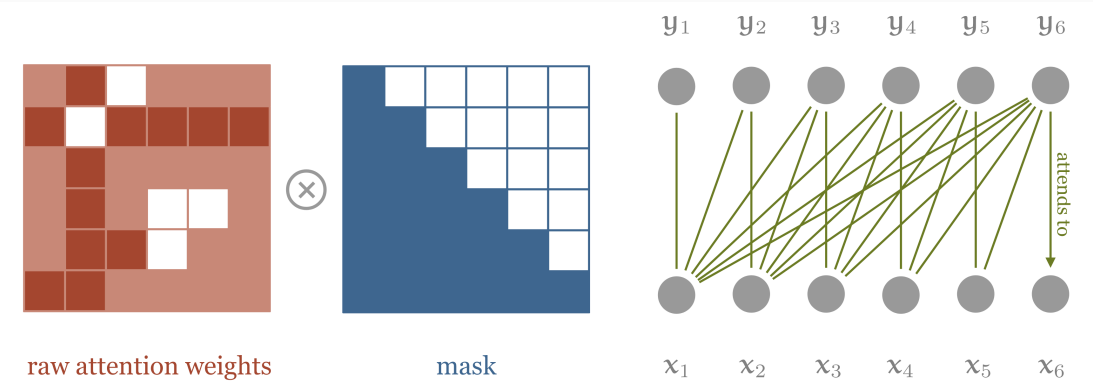

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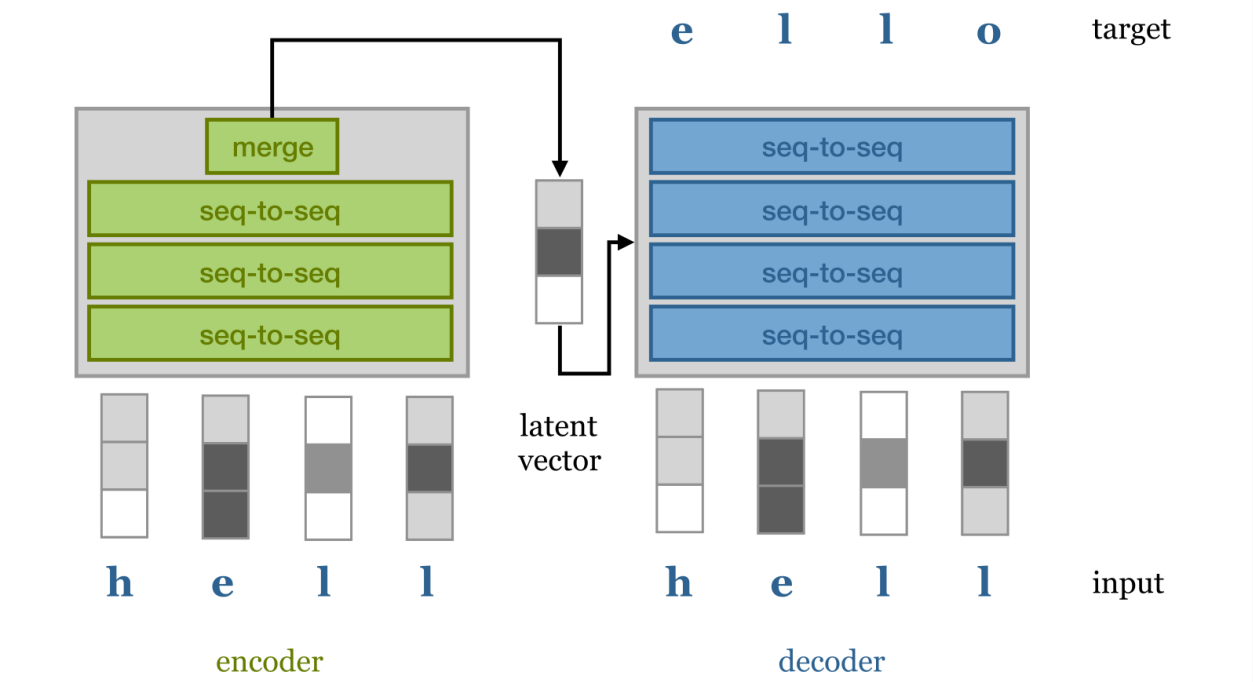

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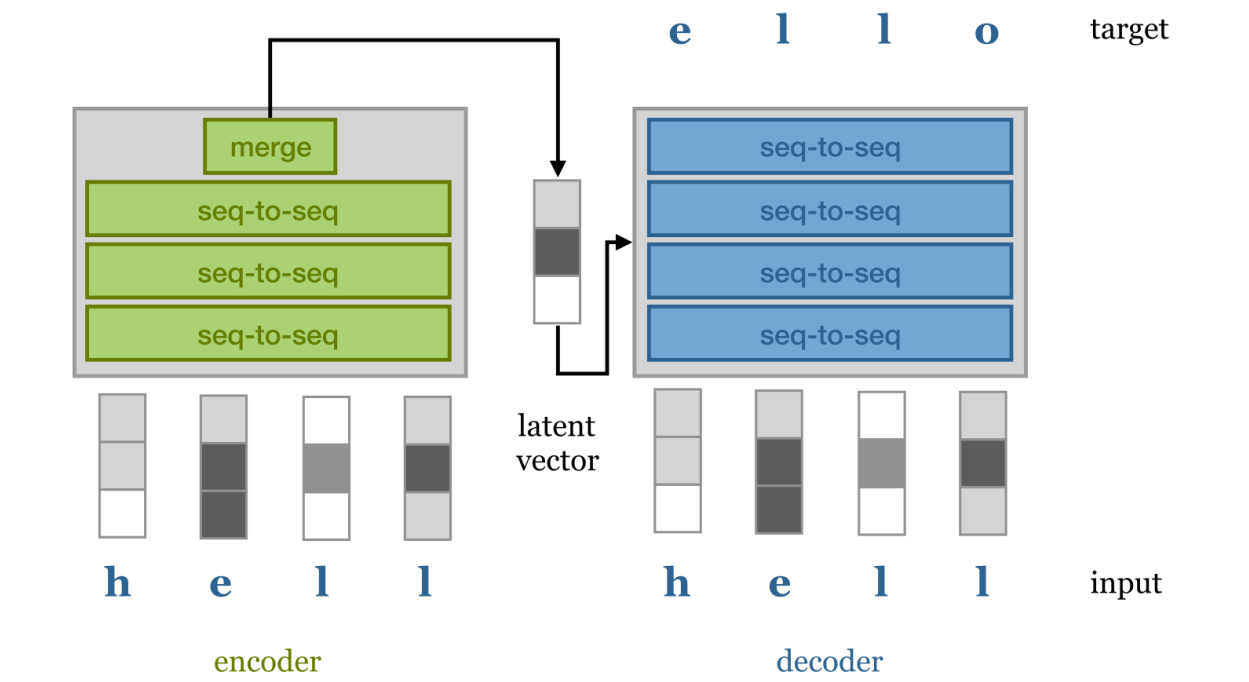

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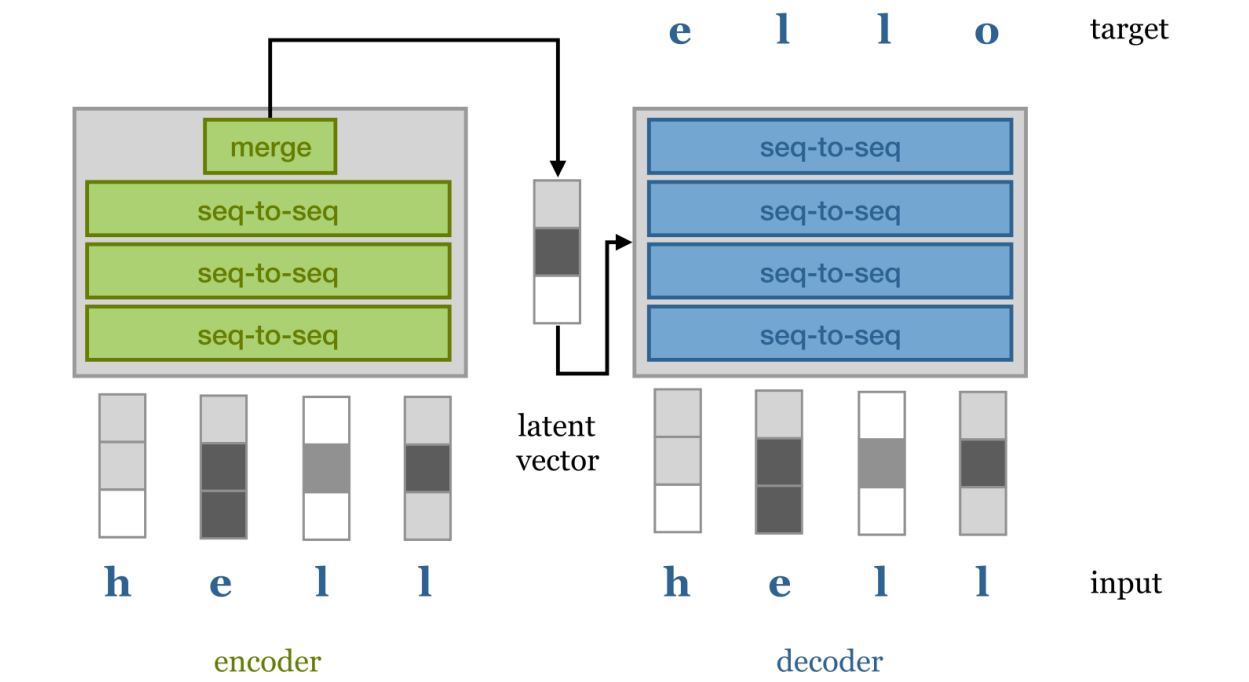

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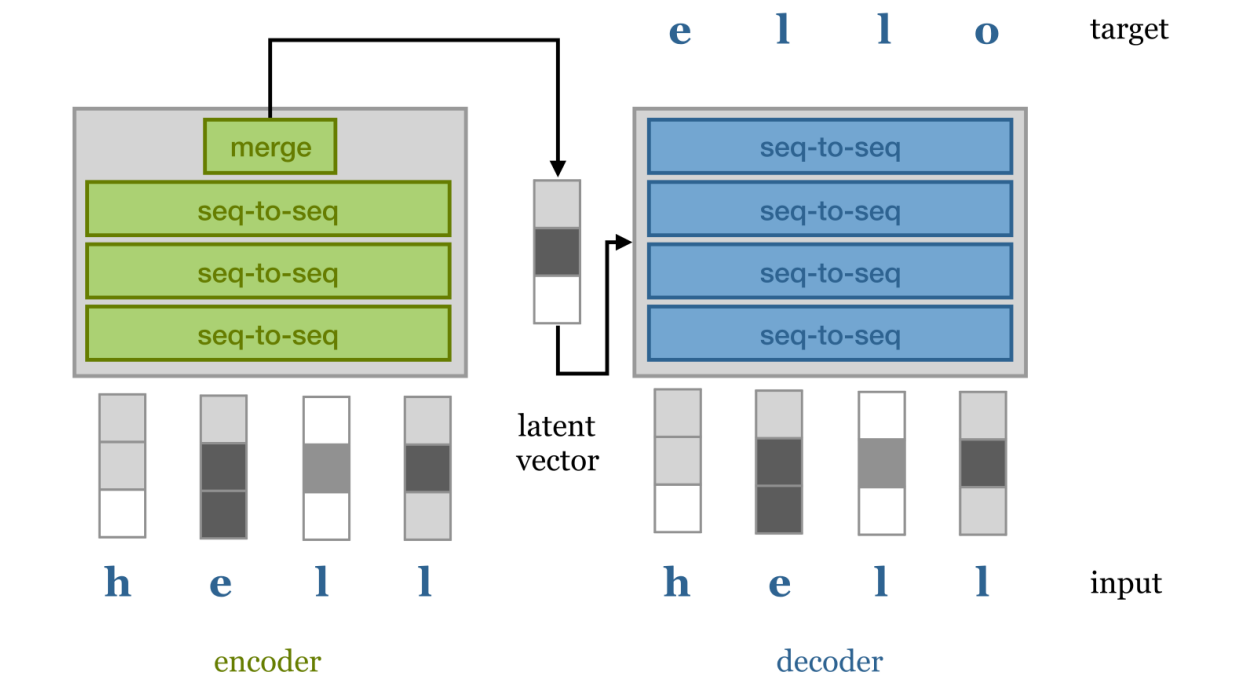

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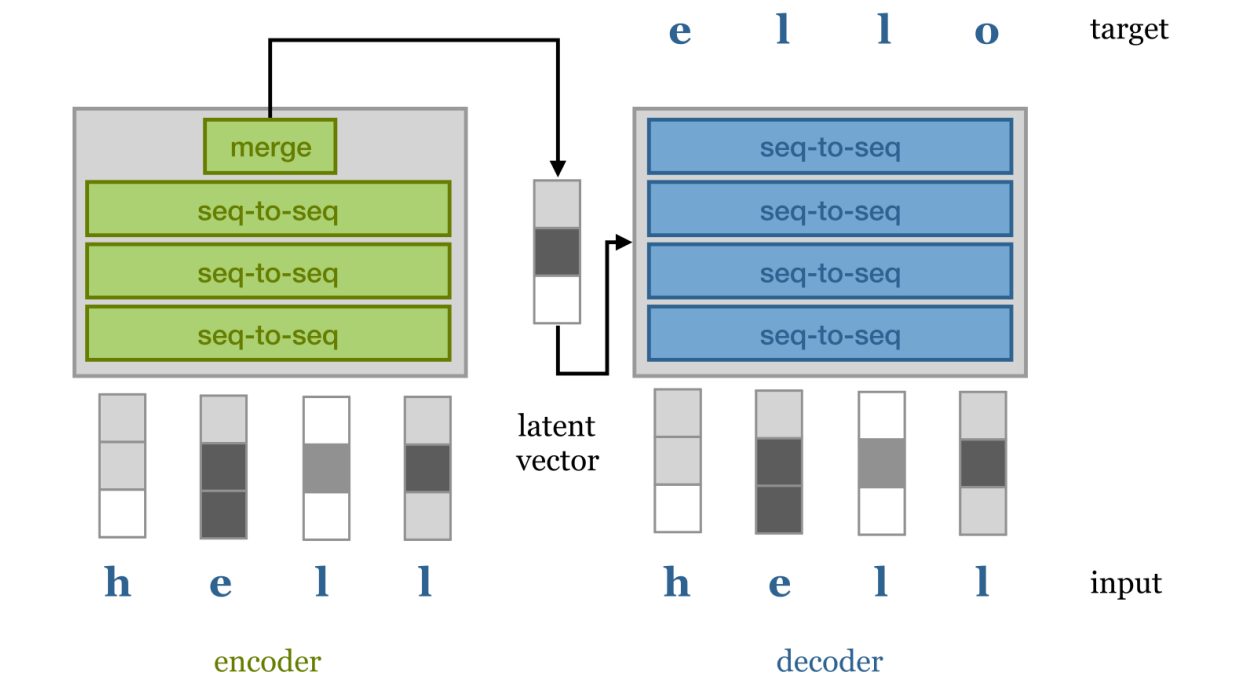

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- The decoder can use
  - word-for-word sampling to take care of the low-level structure like syntax and grammar
  - the latent vector to capture more high-level semantic structure

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References i

 Mikolov, Tomas et al. (2013). “Distributed representations of words and phrases and their compositionality”. In: *Advances in neural information processing systems* 26.

 Vaswani, Ashish et al. (2017). “Attention is all you need”. In: *Advances in neural information processing systems* 30.