Introduction to Transformers for NLP

where we are and how we got here

Olga Petrova
AI Product Manager

Preliminaries

- Who I am:
  - Product Manager for AI PaaS at Scaleway

    Scaleway: European cloud provider, originating from France

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  - Quantum physicist at École Normale Supérieure, the Max Planck Institute, Johns Hopkins University

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    - Enough intro for newcomers to NLP
    - Enough transformers for those who are used to RNNs

Outline

1. NLP 101: how do we represent words in machine learning
   🤖 Tokenization 🤖 Word embeddings
2. Order matters: Recurrent Neural Networks
   🤖 RNNs 🤖 Seq2Seq models
   🤖 What is wrong with RNNs
3. Attention is all you need!
   🤖 What is Attention 🤖 Attention, the linear algebra perspective
4. The Transformer architecture
   🤖 Mostly Attention
5. BERT: *contextualized* word embeddings

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Representing words

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I play with my dog.

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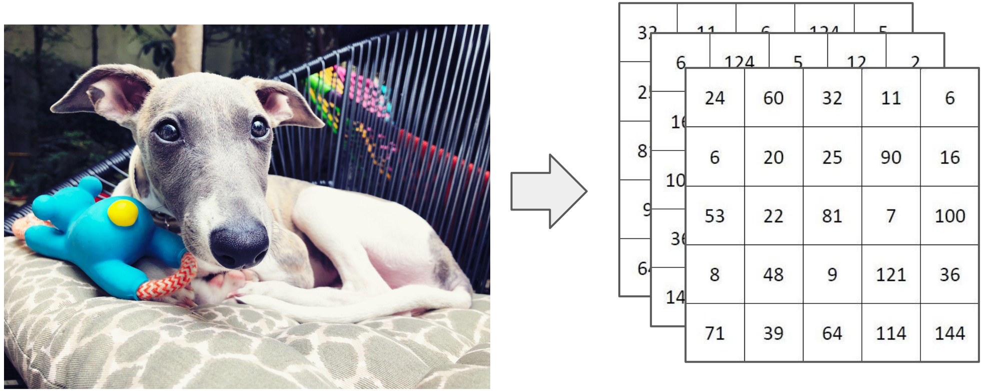

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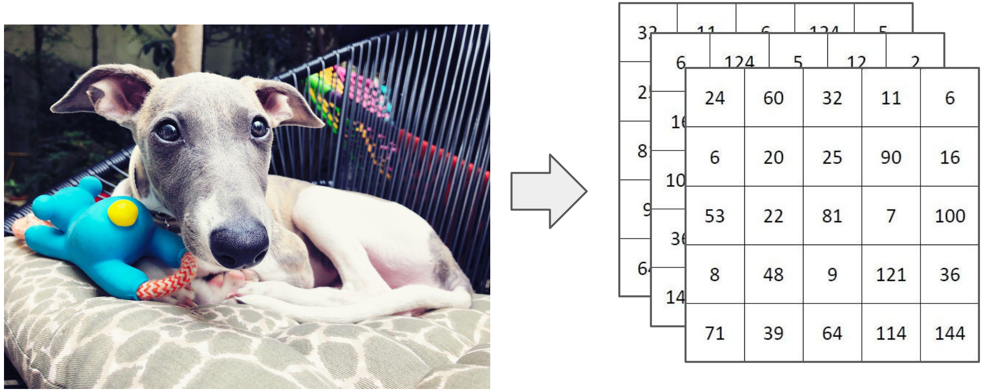

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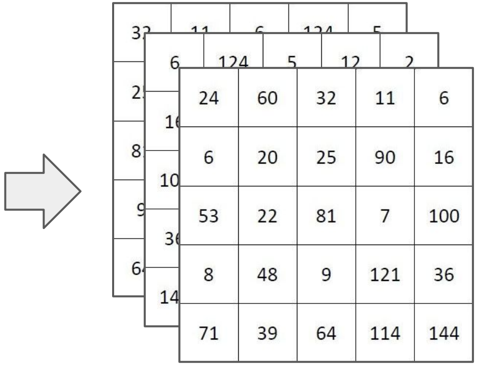

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- How do we convert “I play with my dog” into numerical values?

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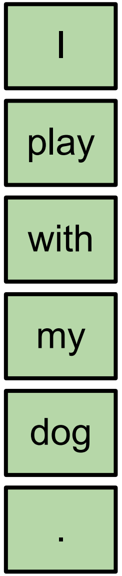

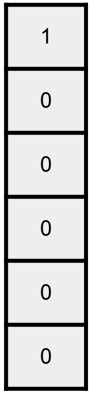

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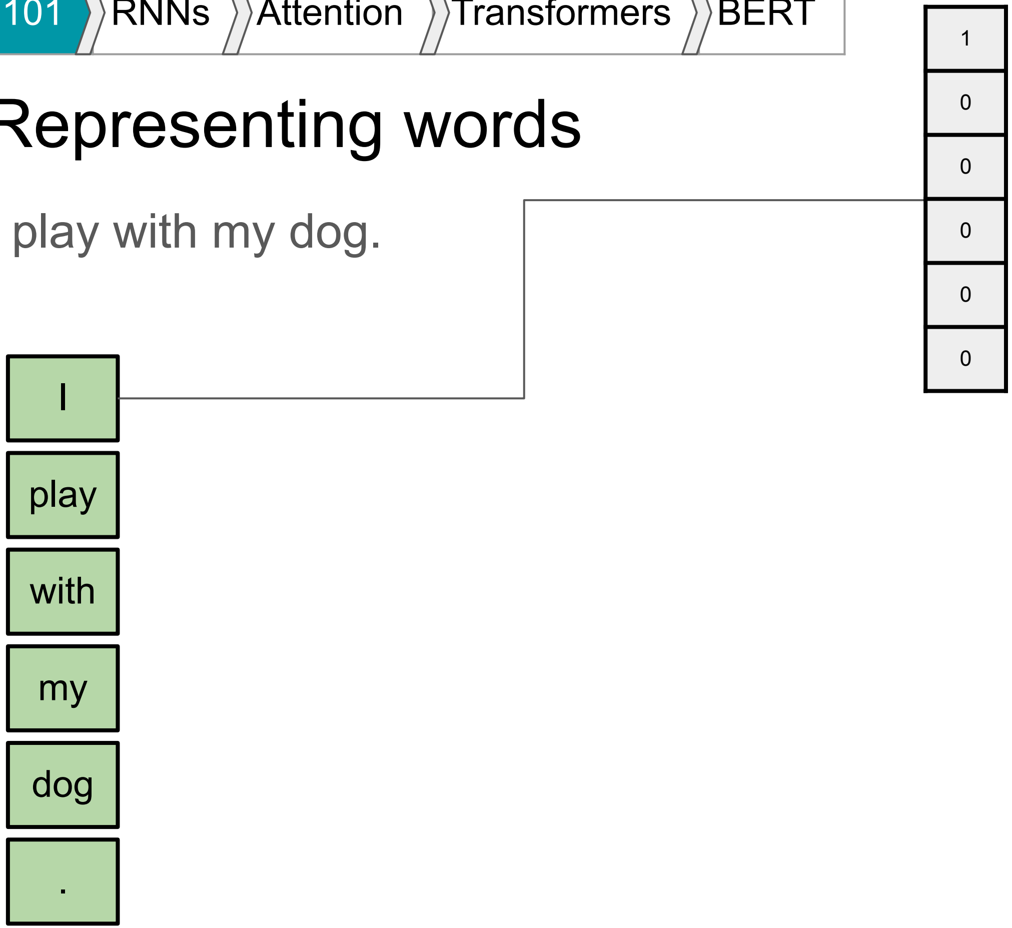

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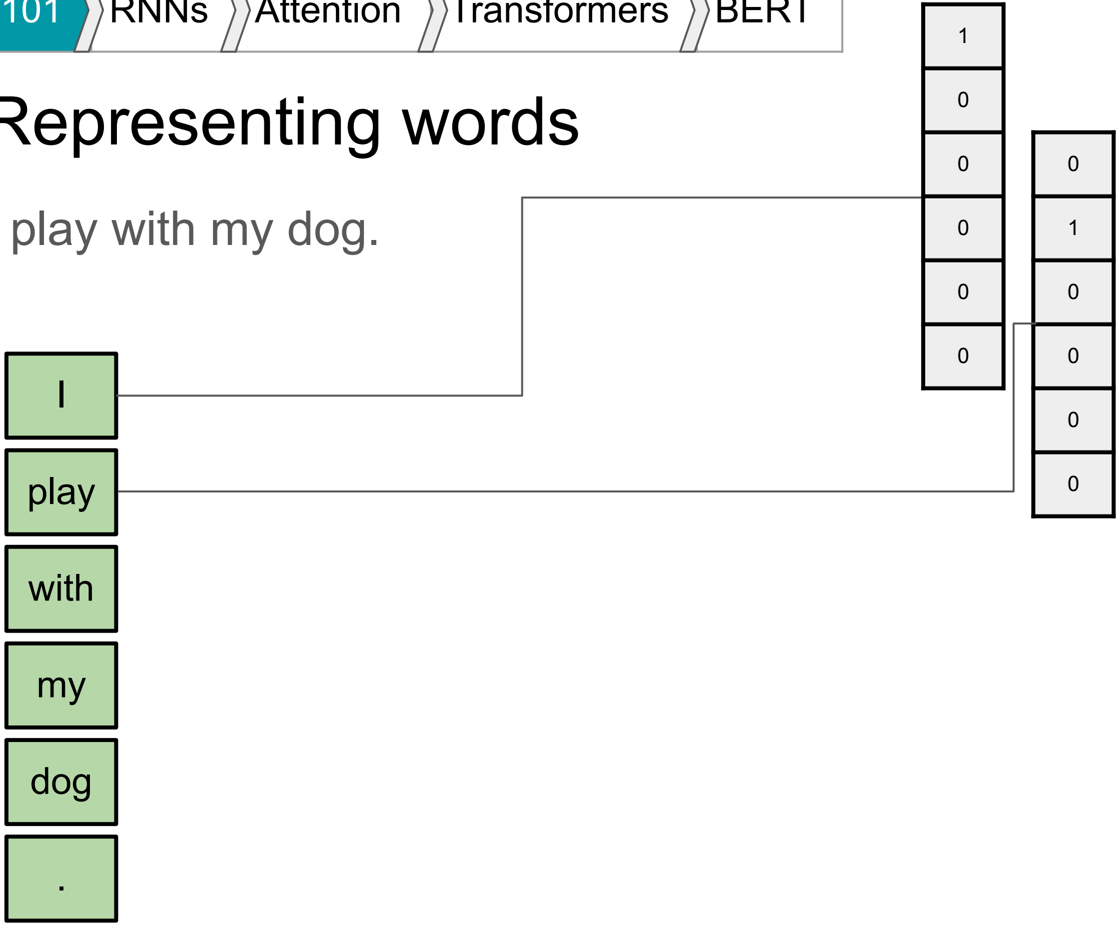

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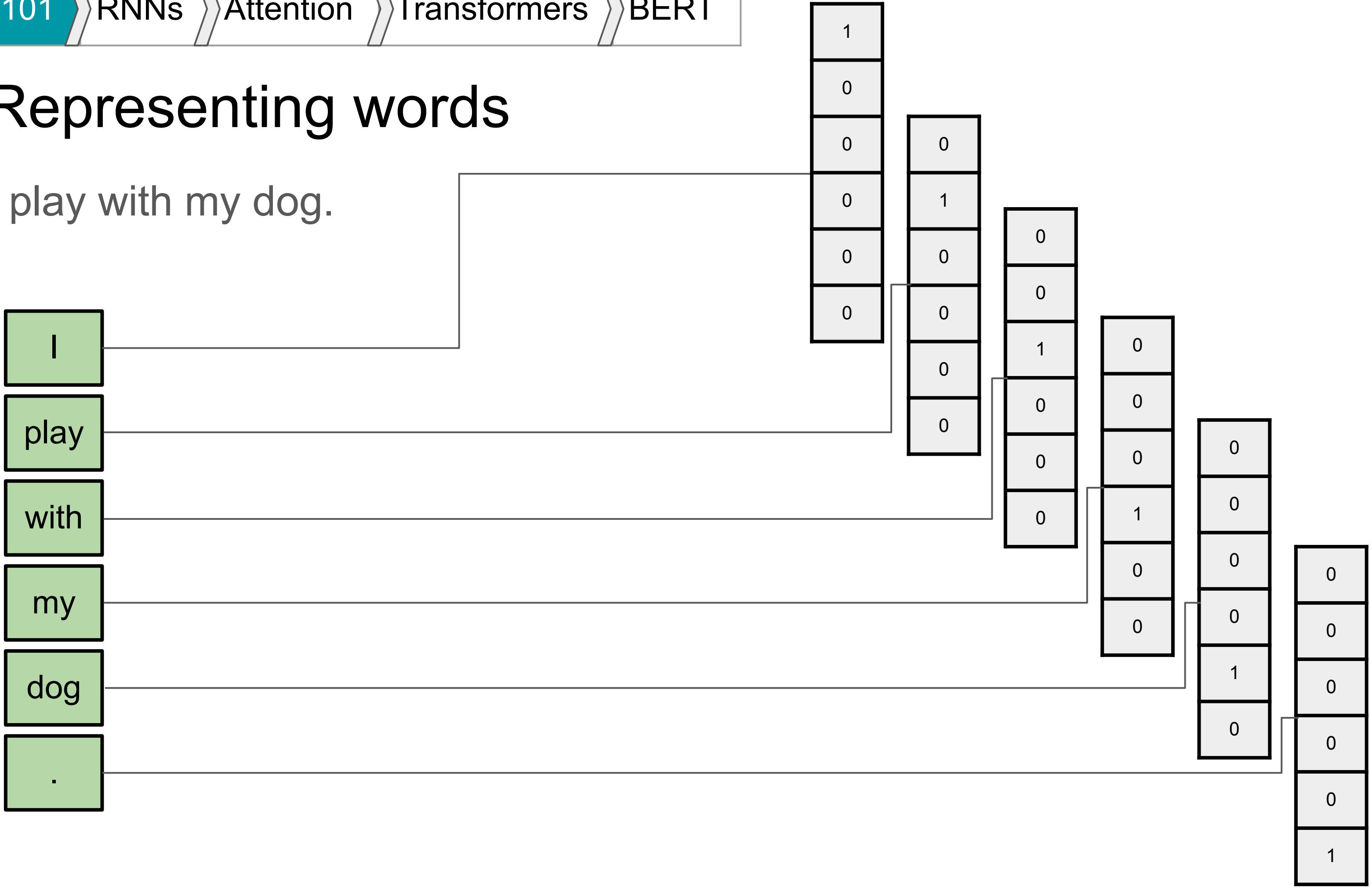

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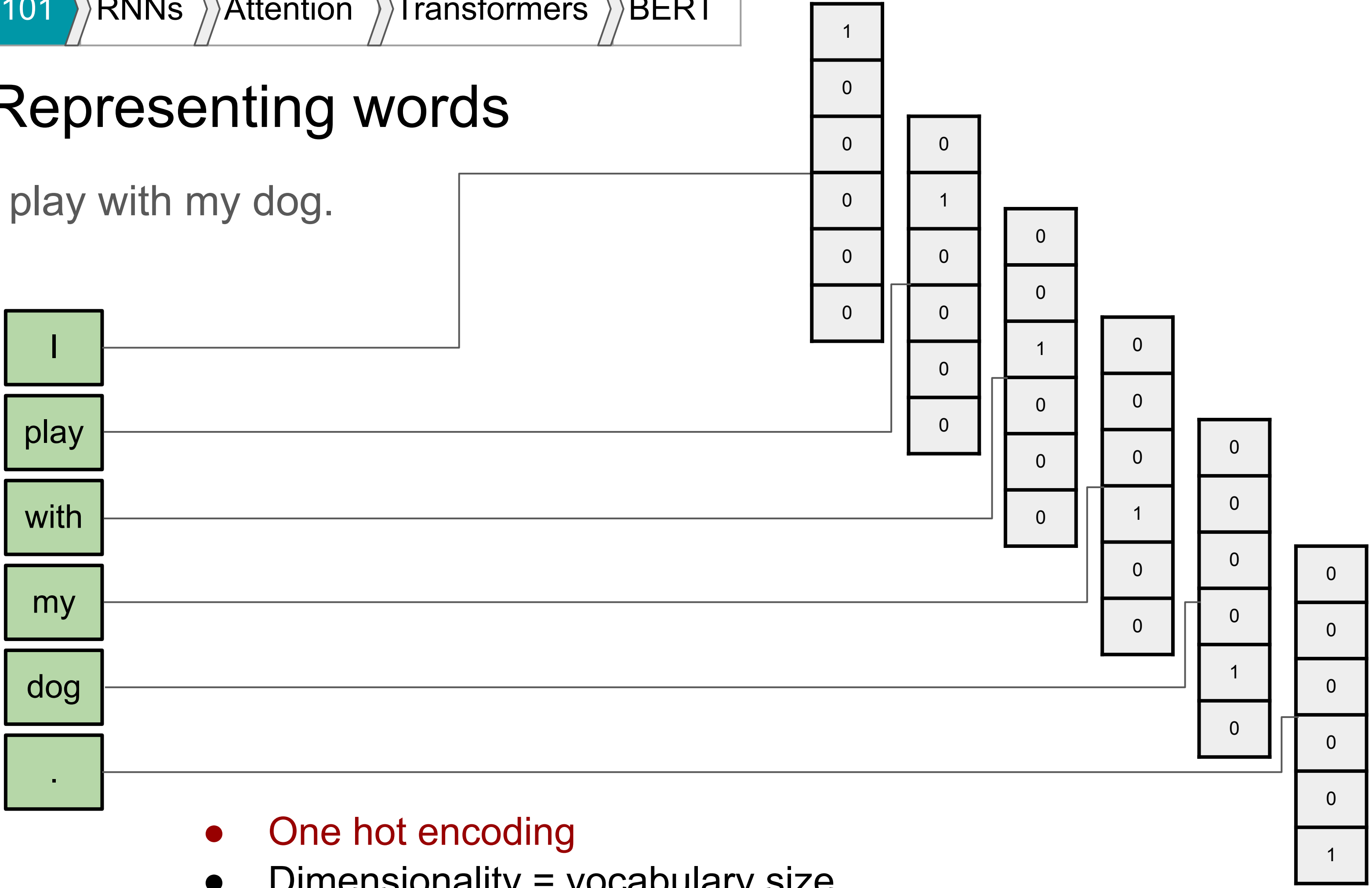

- One hot encoding
- Dimensionality = vocabulary size

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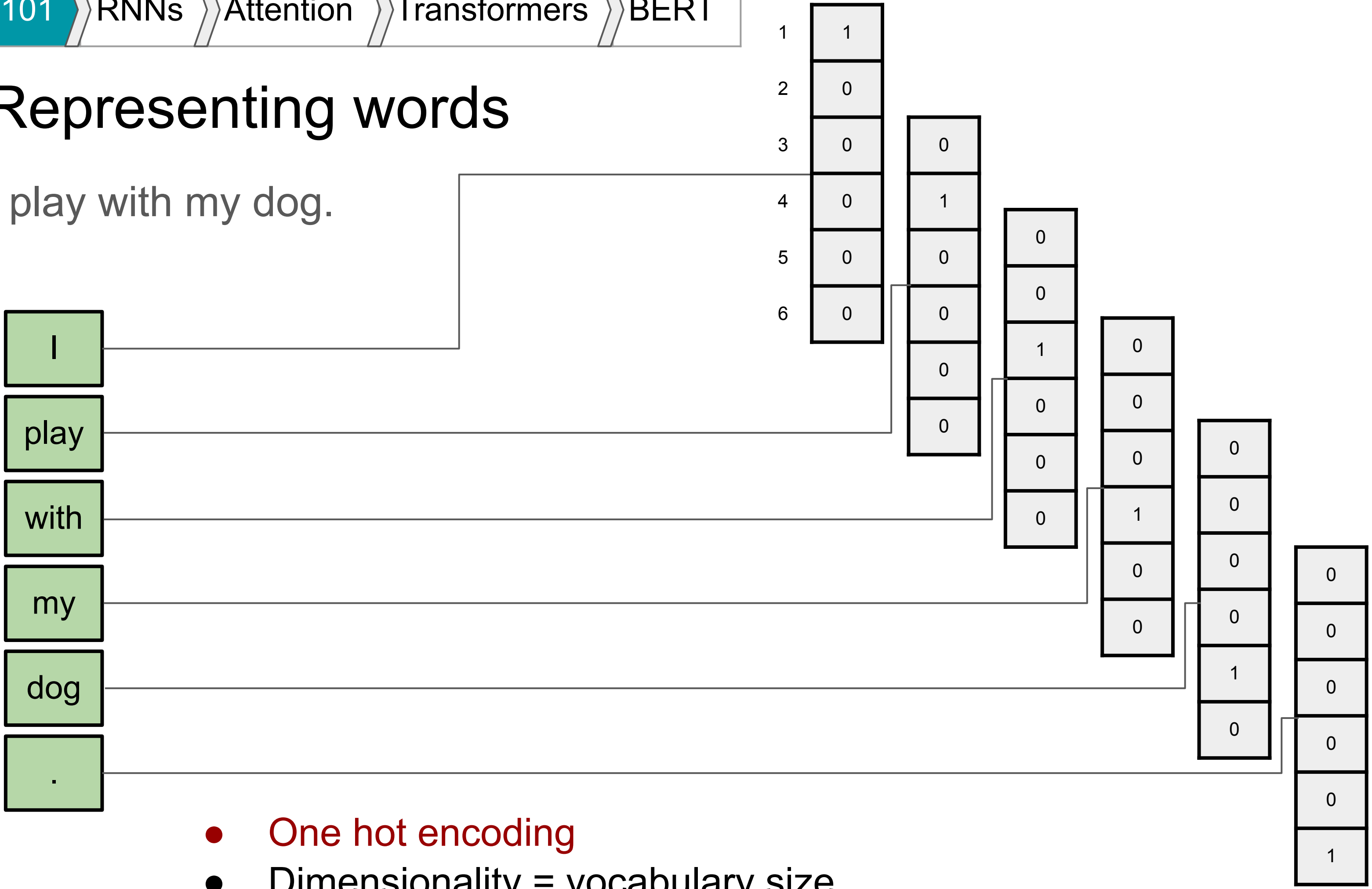

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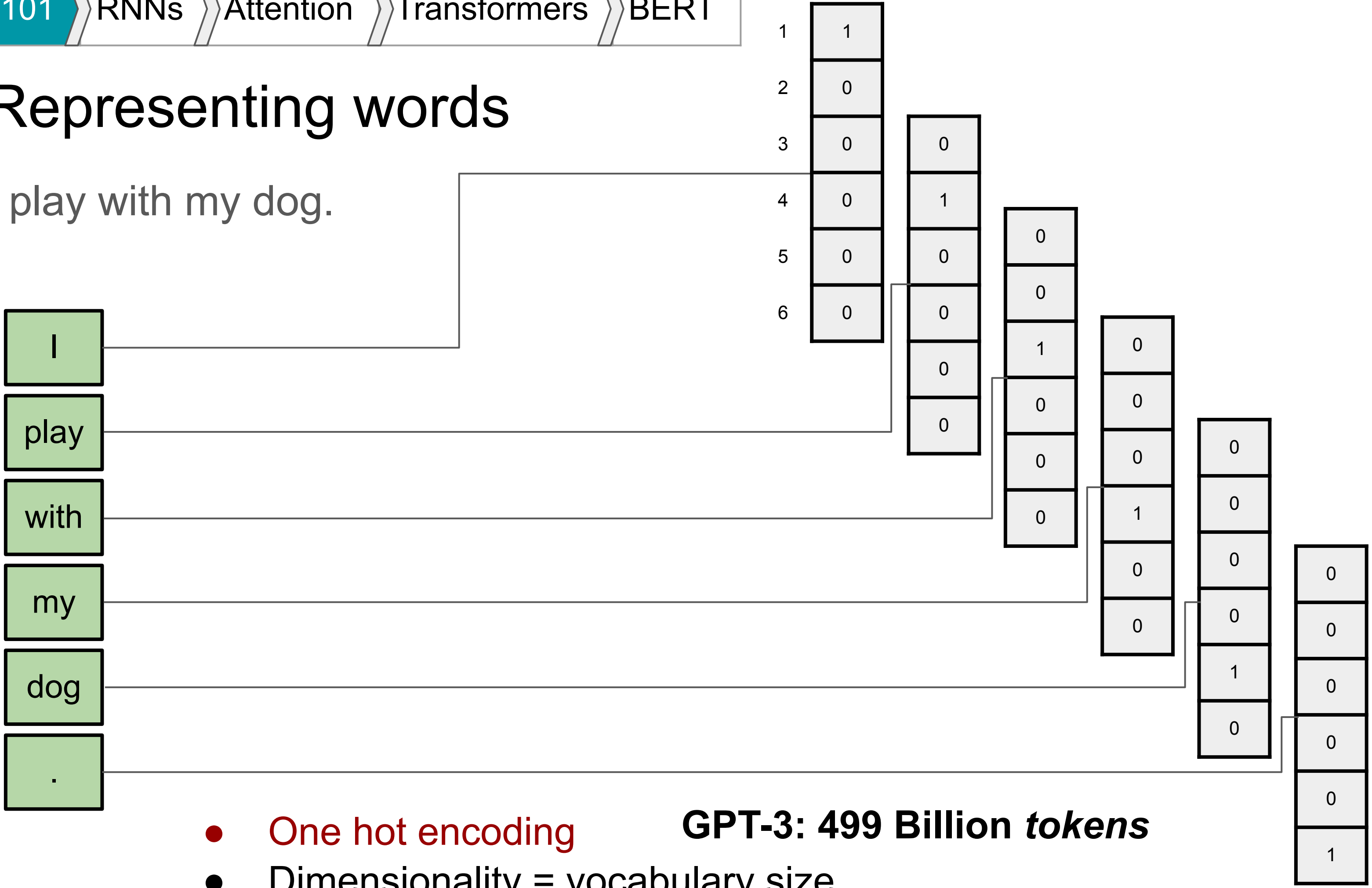

GPT-3: 499 Billion *tokens*

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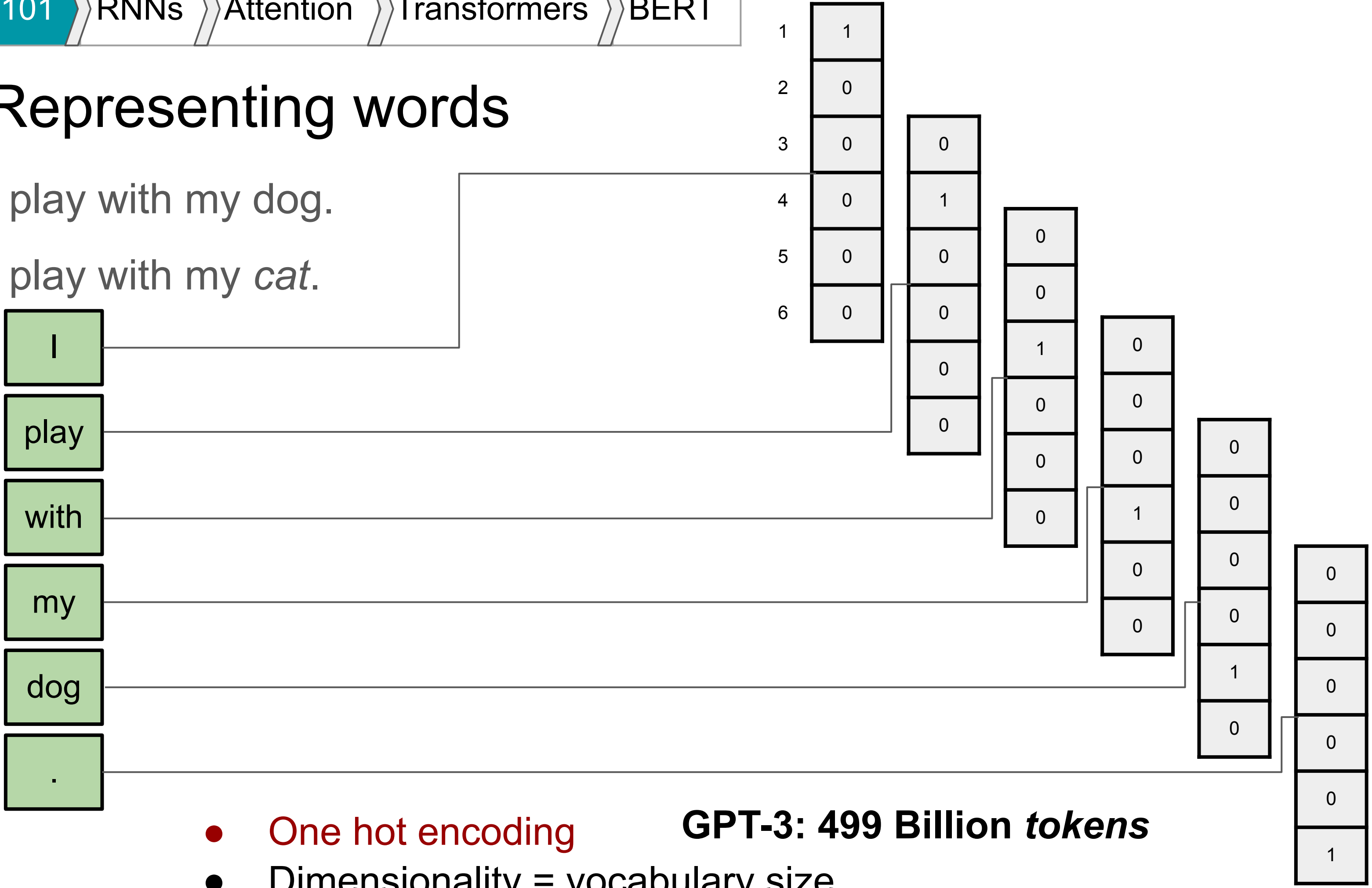

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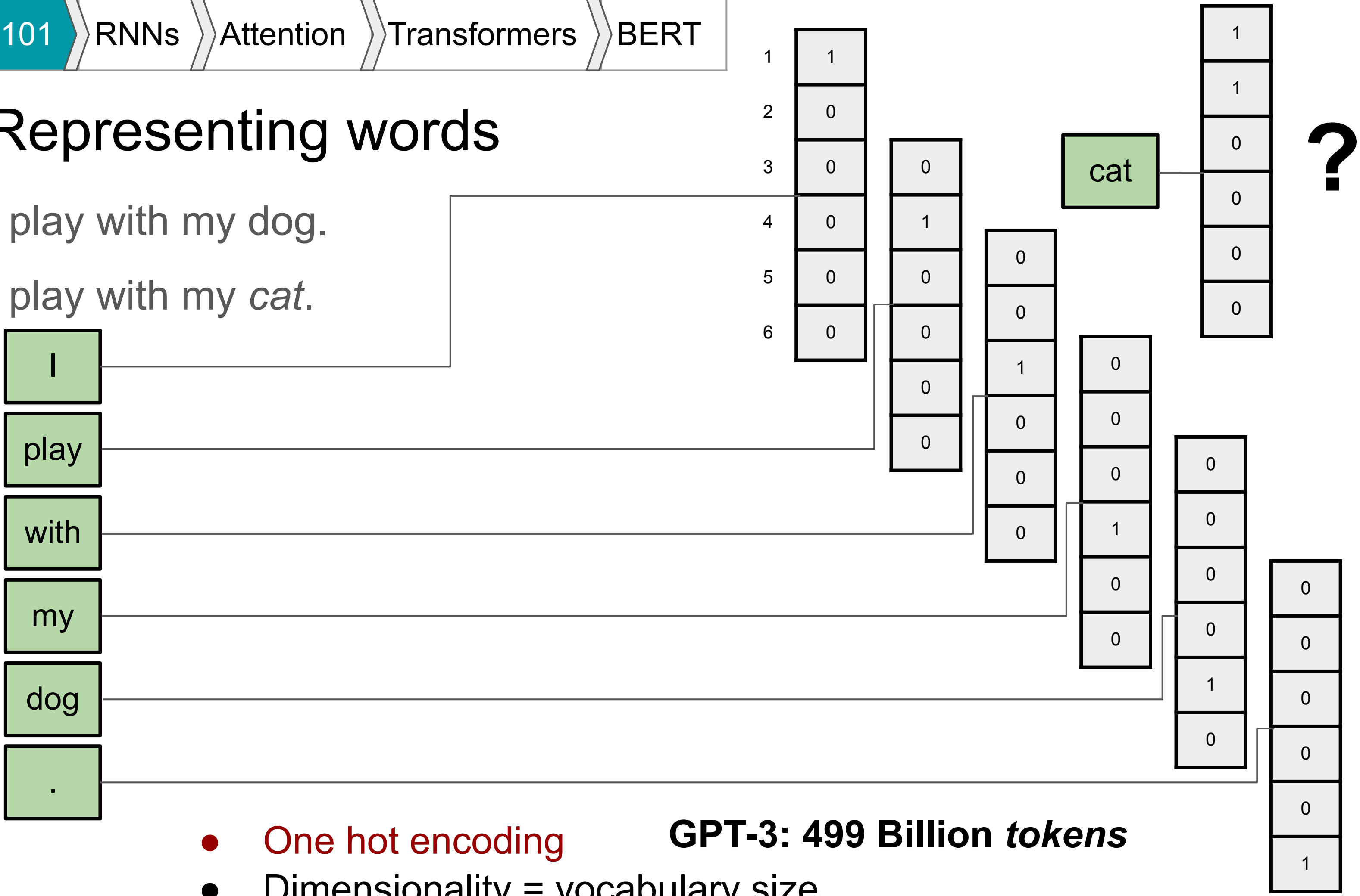

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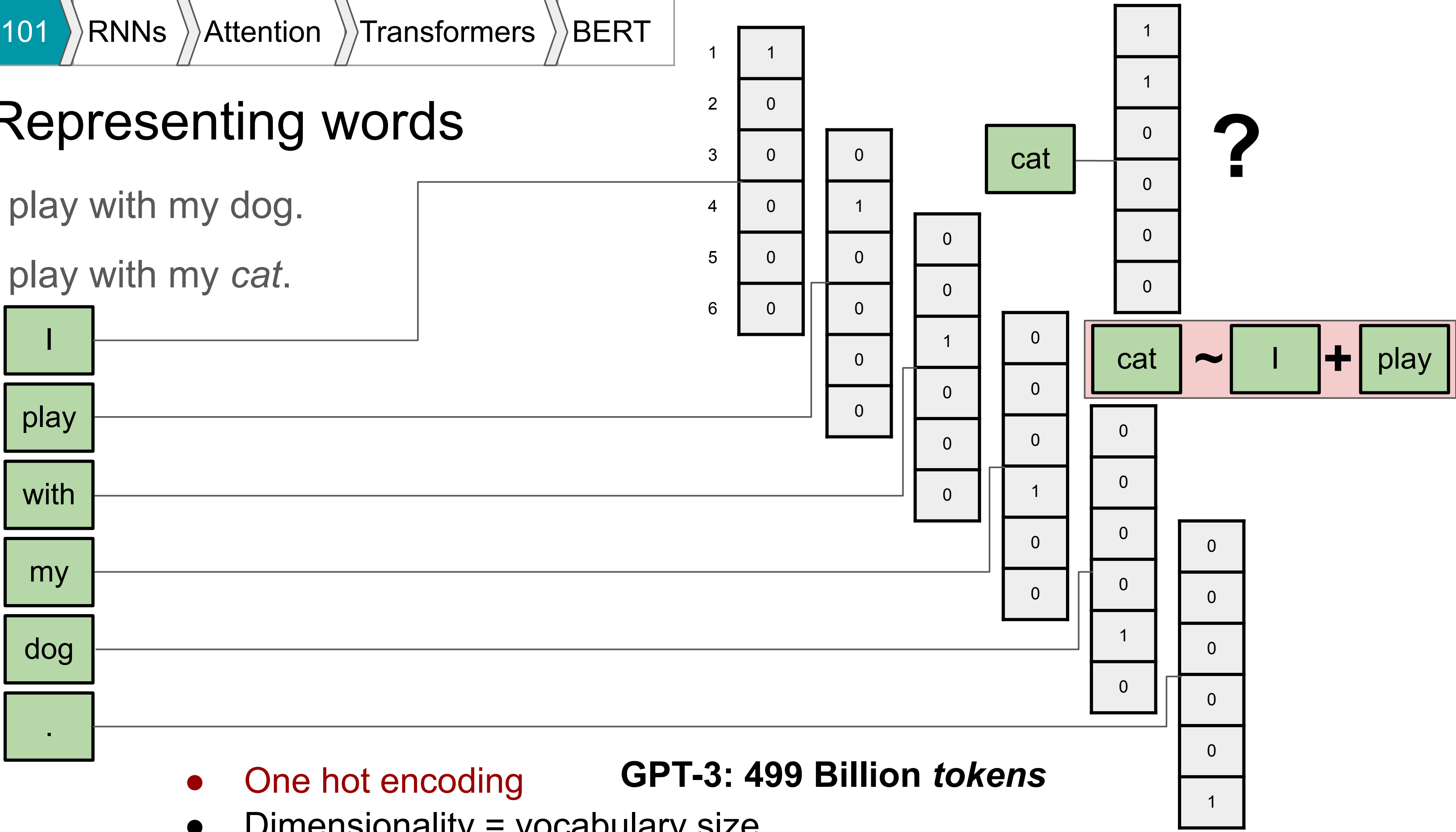

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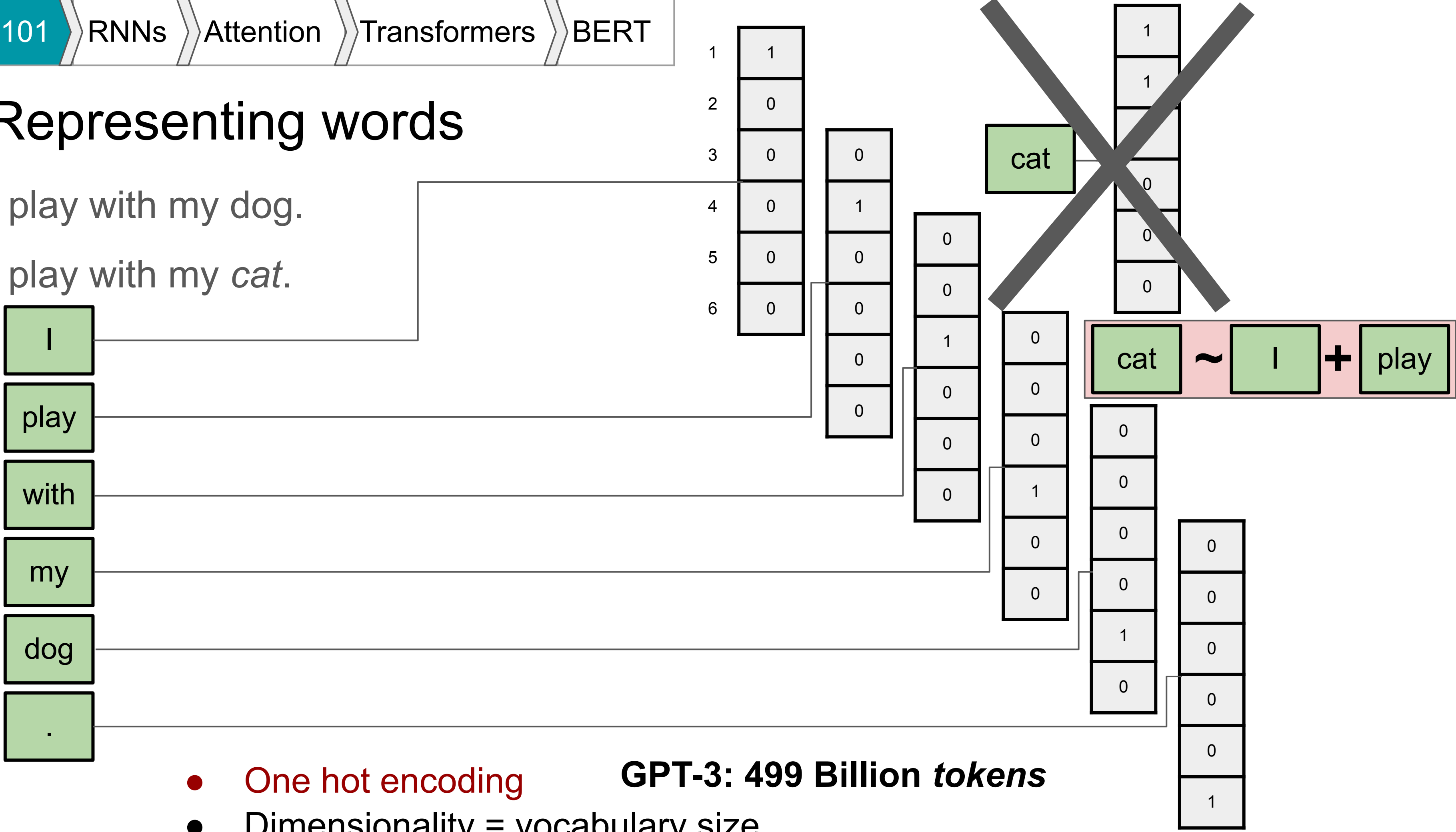

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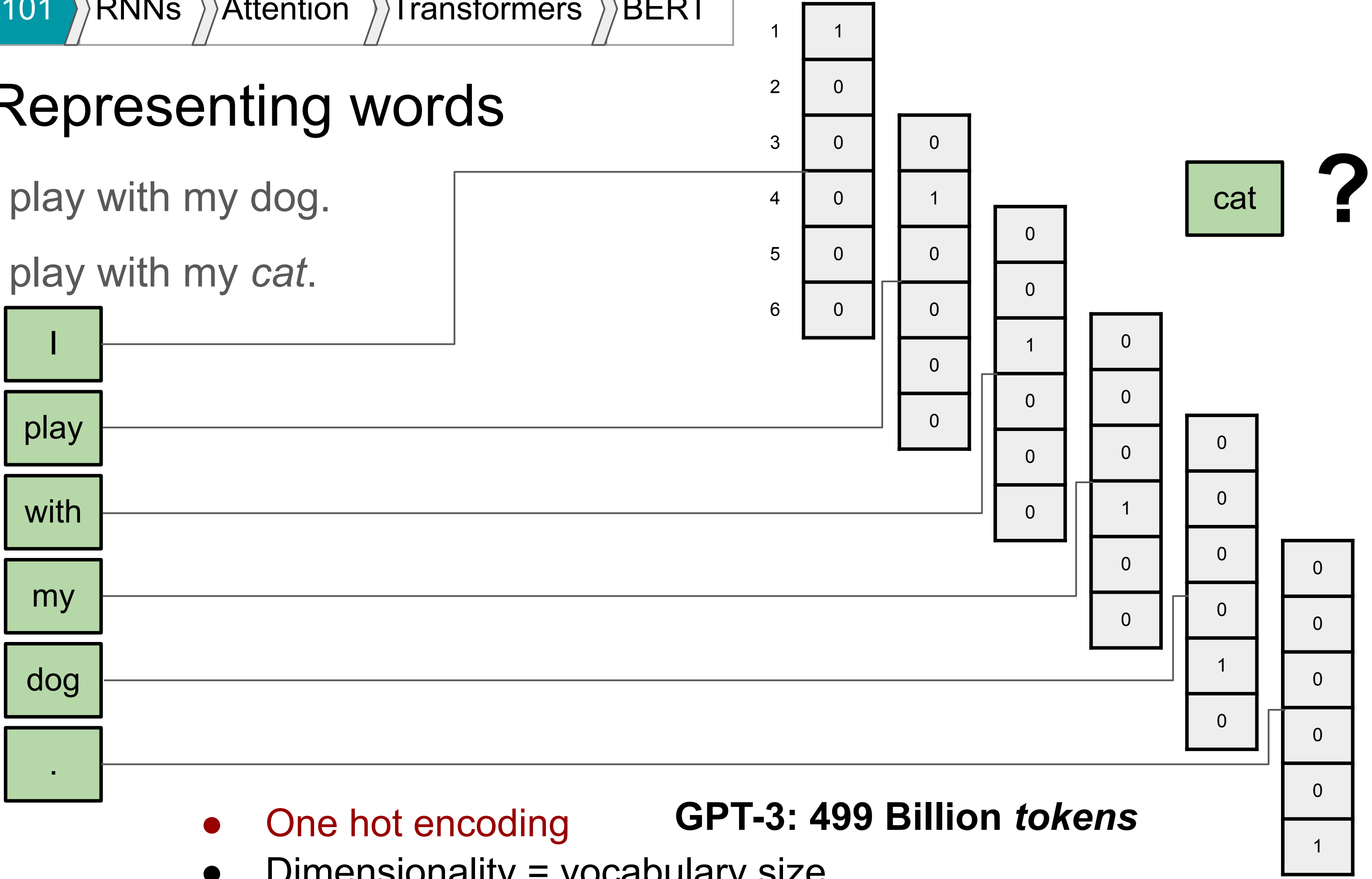

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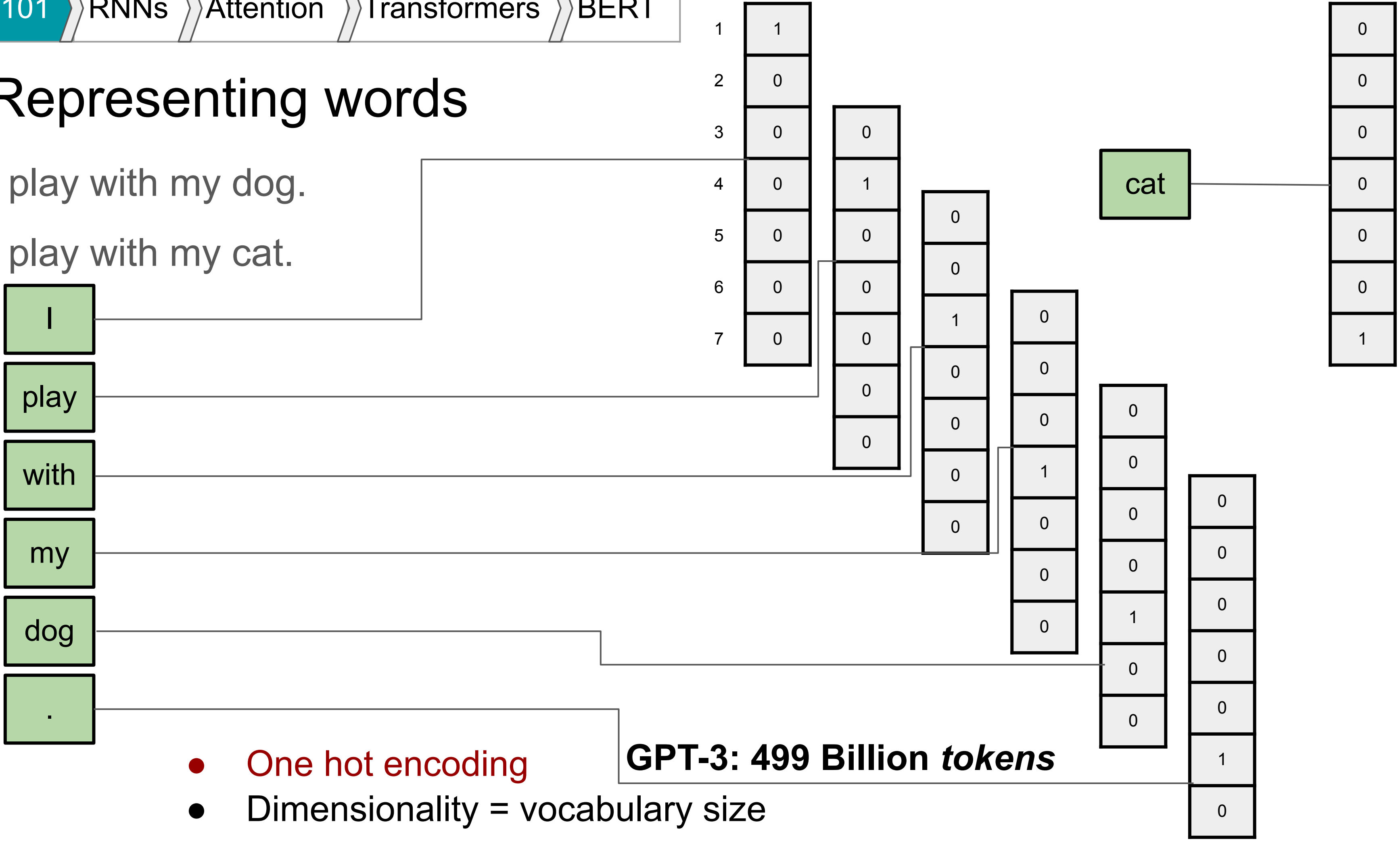

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👉 Tokenization, then word embeddings

Tokenization

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Why tokenize at subword level?

Tokenization

- Cut down on the size of the vocabulary:

play | played | playing   ask | asked | asking   call | called | calling   burn | burned | burning

vs.

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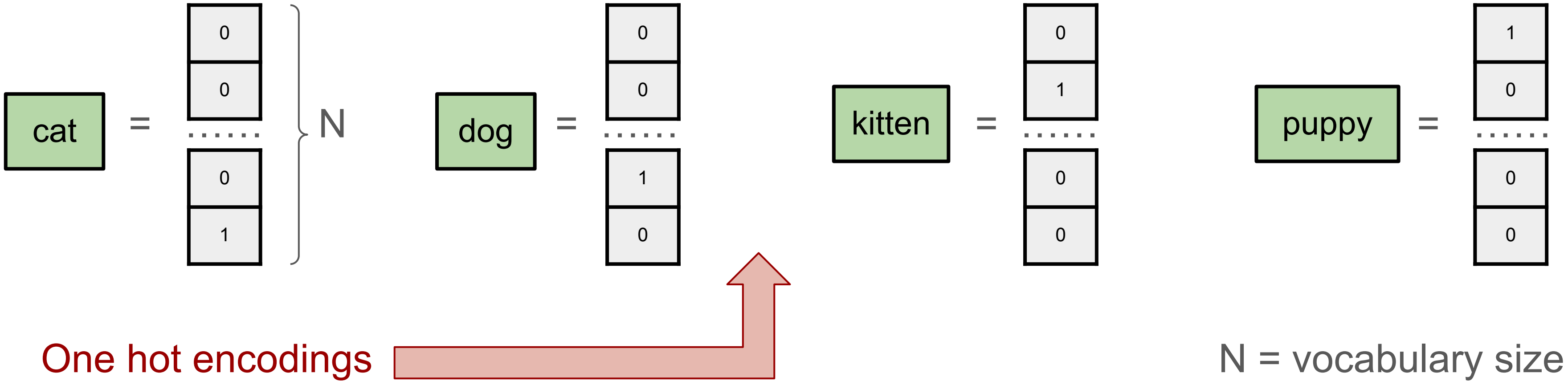
- Is there a way to encode semantic relations between words, **and** decrease the dimensions of the inputs?

Word embeddings



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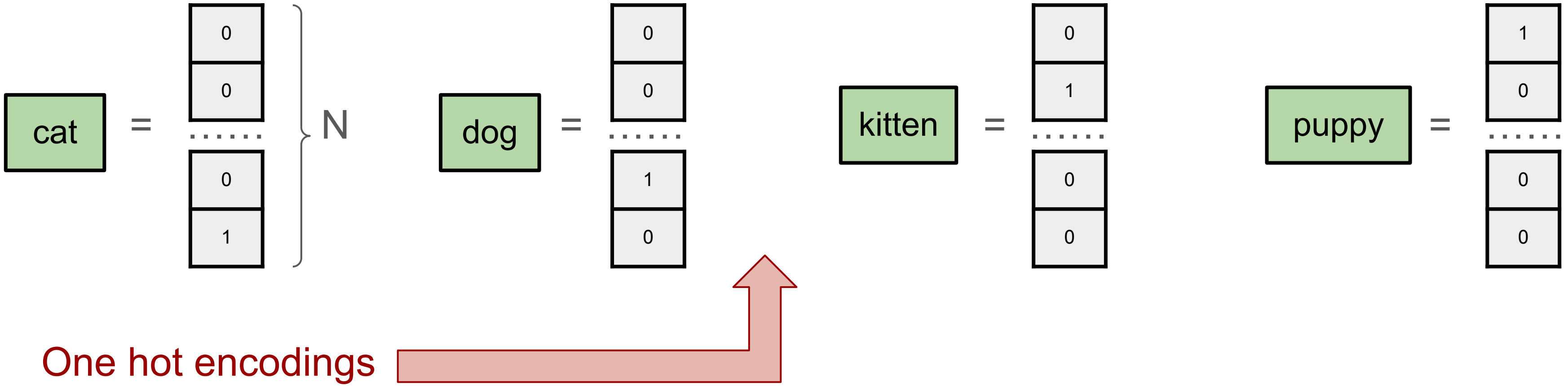

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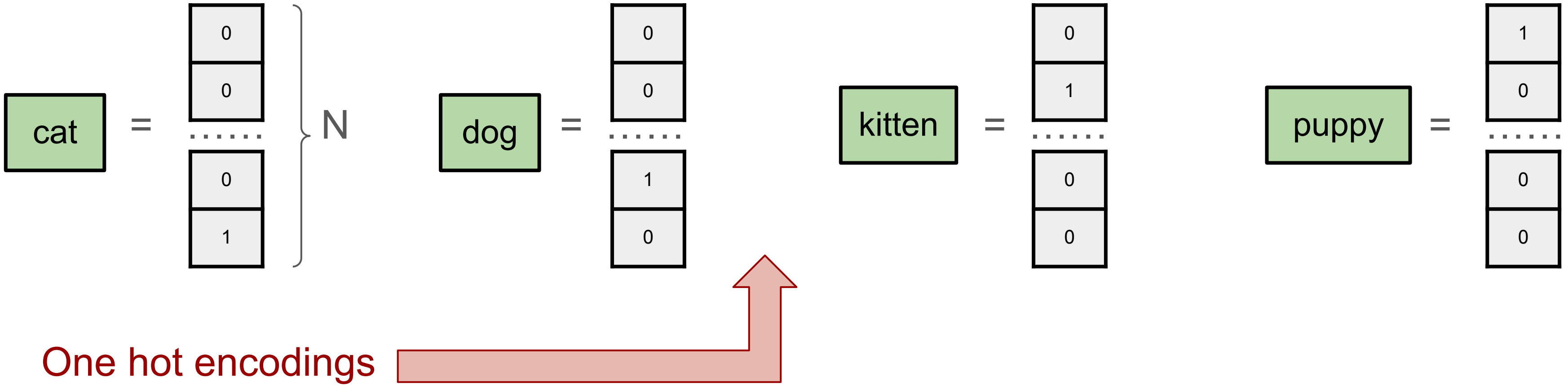

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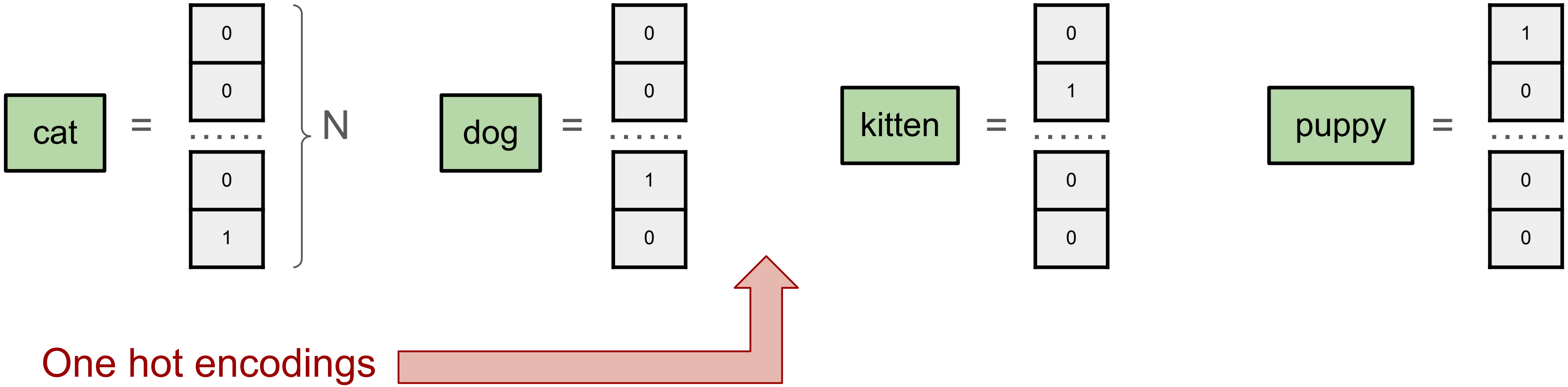

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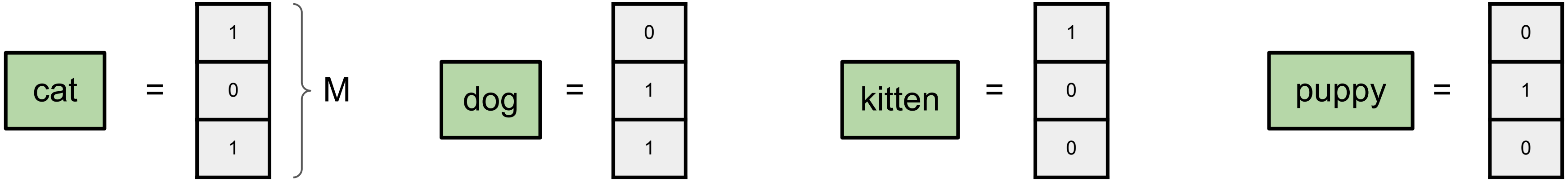

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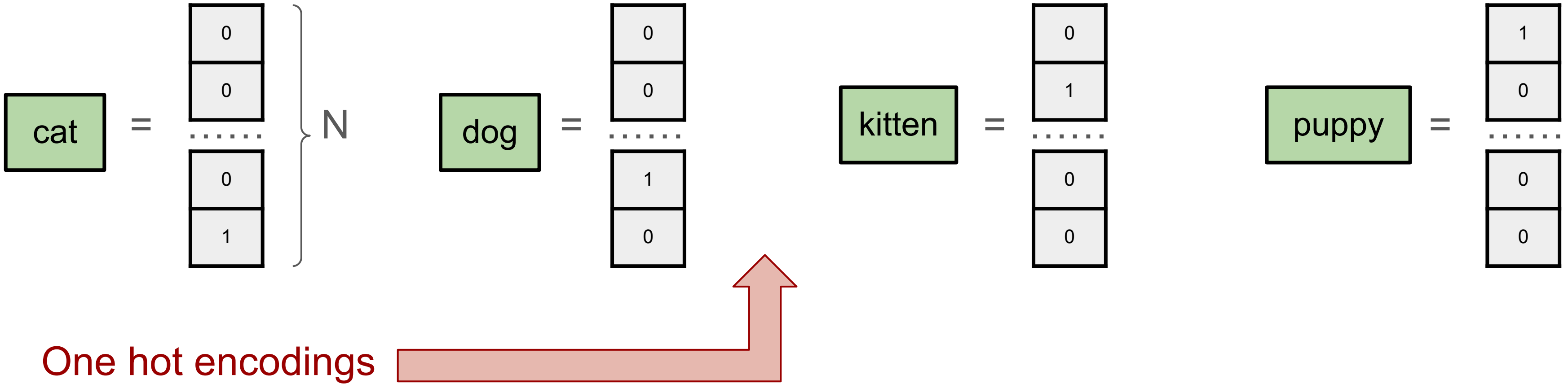

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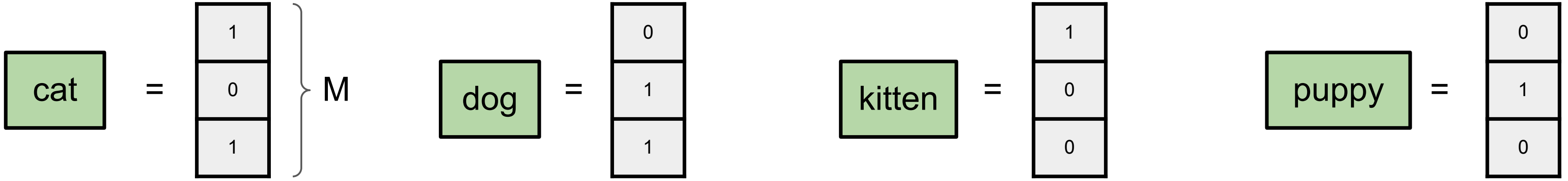

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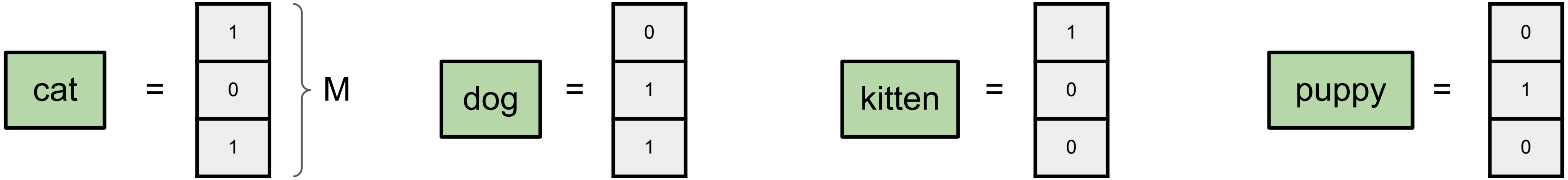

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Embedded vector

In practice:

- Embedding can be part of your model that you train for a ML task
- Or: use pre-trained embeddings (e.g. Word2Vec, GloVe, etc)

- Some information gets lost in the process
- Embedding matrix: through machine learning!

Further reading

Tokenization:

blog.floydhub.com/tokenization-nlp/

Word embeddings:

jalammar.github.io/illustrated-word2vec/

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2. Order matters: Recurrent Neural Networks

   🤖 RNNs 🤖 Seq2Seq models

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Sequence to Sequence models

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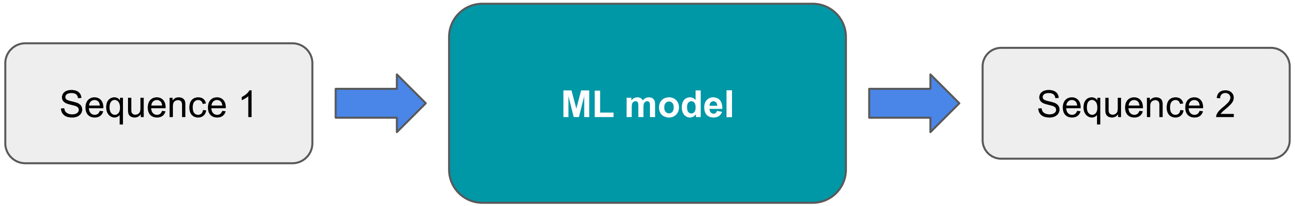

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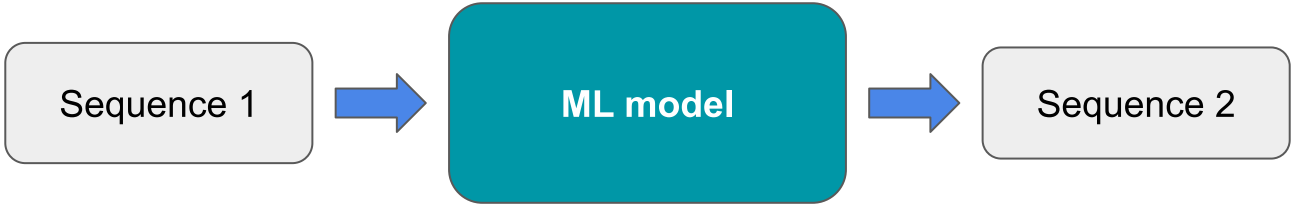

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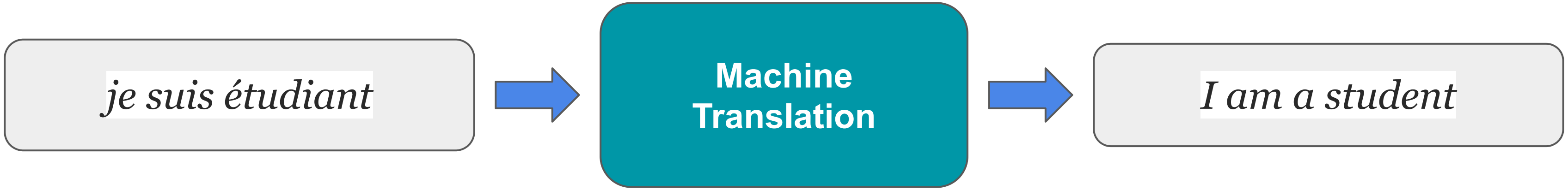

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Takeaways:

1. **Multiple elements in a sequence**
2. **Order of the elements matters**

Sequence 1 → **ML model** → Sequence 2

- Language modeling, question answering, machine translation, etc

je suis étudiant → **Machine Translation** → *I am a student*

RNNs: Recurrent Neural Networks

Recurrent neural network

From Wikipedia, the free encyclopedia

Not to be confused with recursive neural network.

A **recurrent neural network** (**RNN**) is a class of artificial neural networks where connections between nodes form a directed graph along a temporal sequence. This allows it to exhibit temporal dynamic behavior. Derived from

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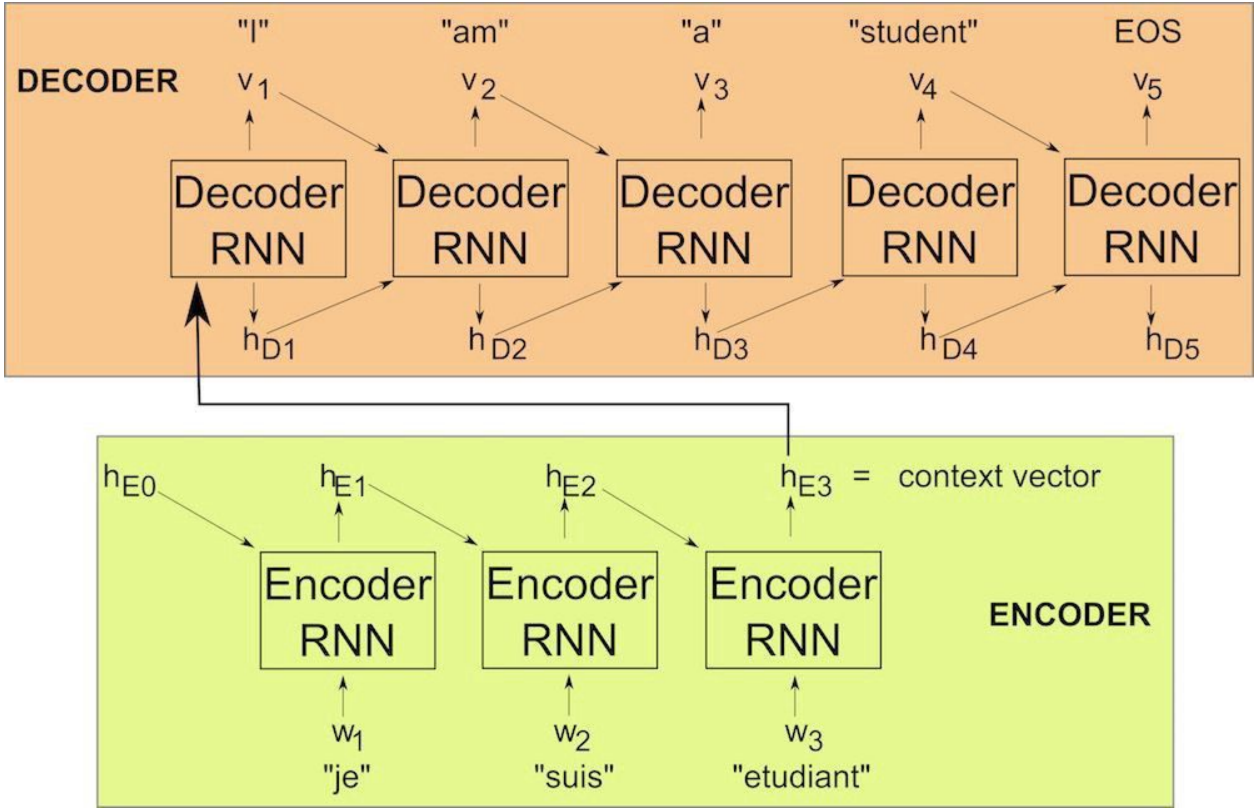
What does this mean???

RNNs: the seq2seq example



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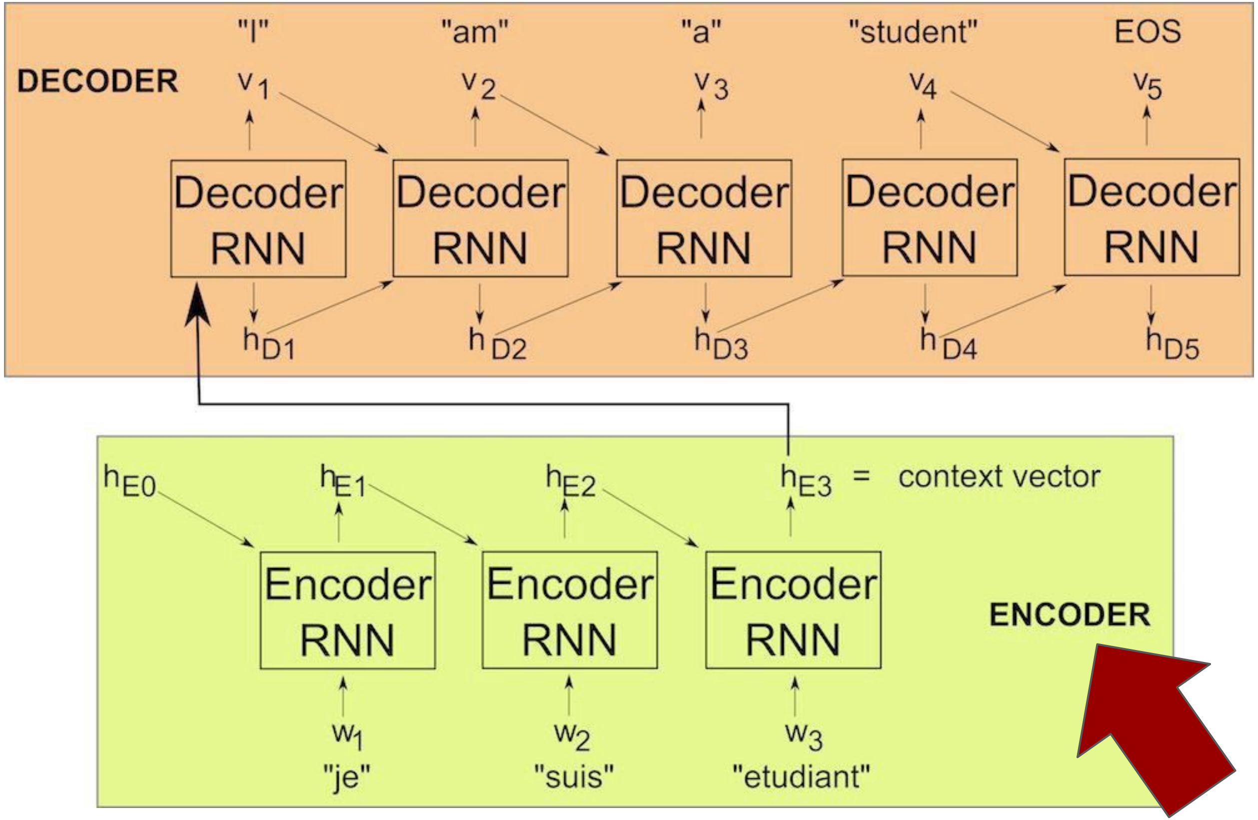

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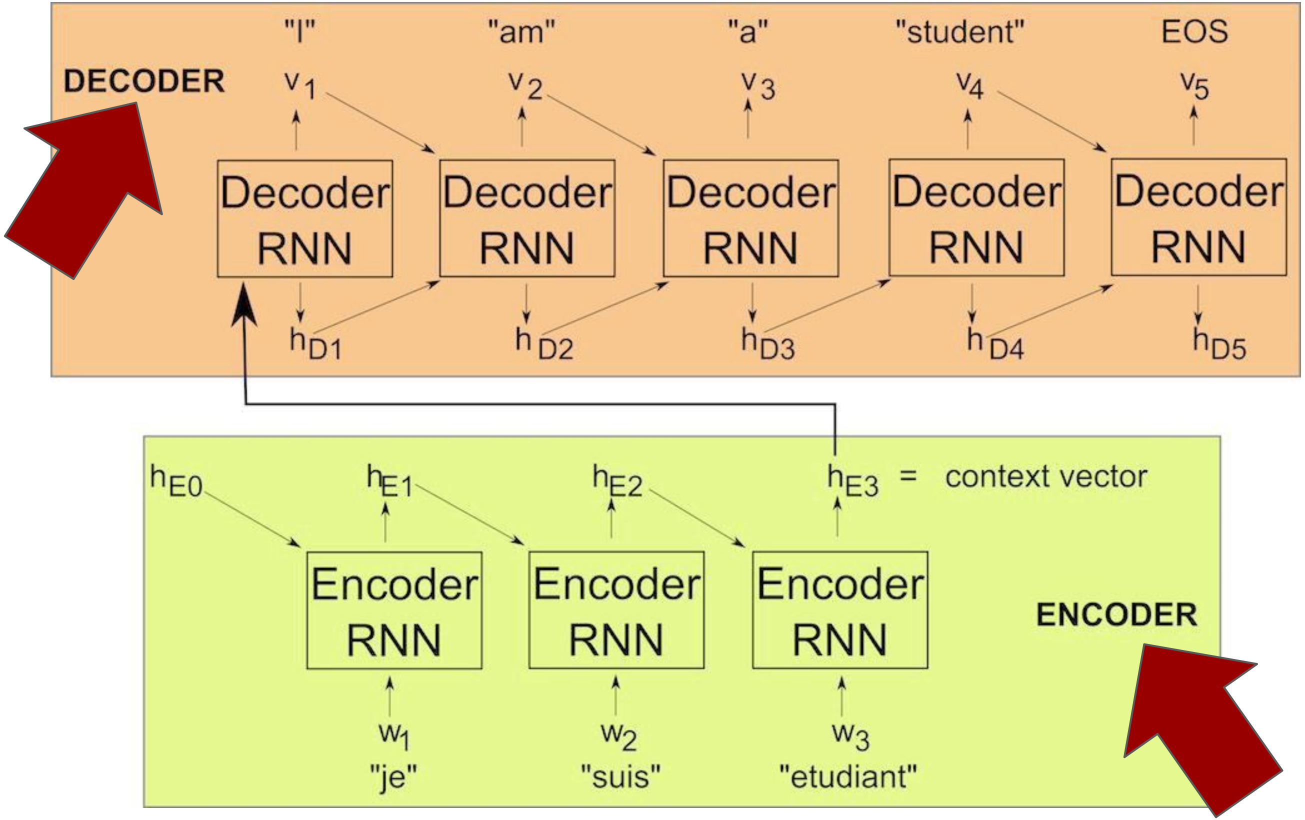

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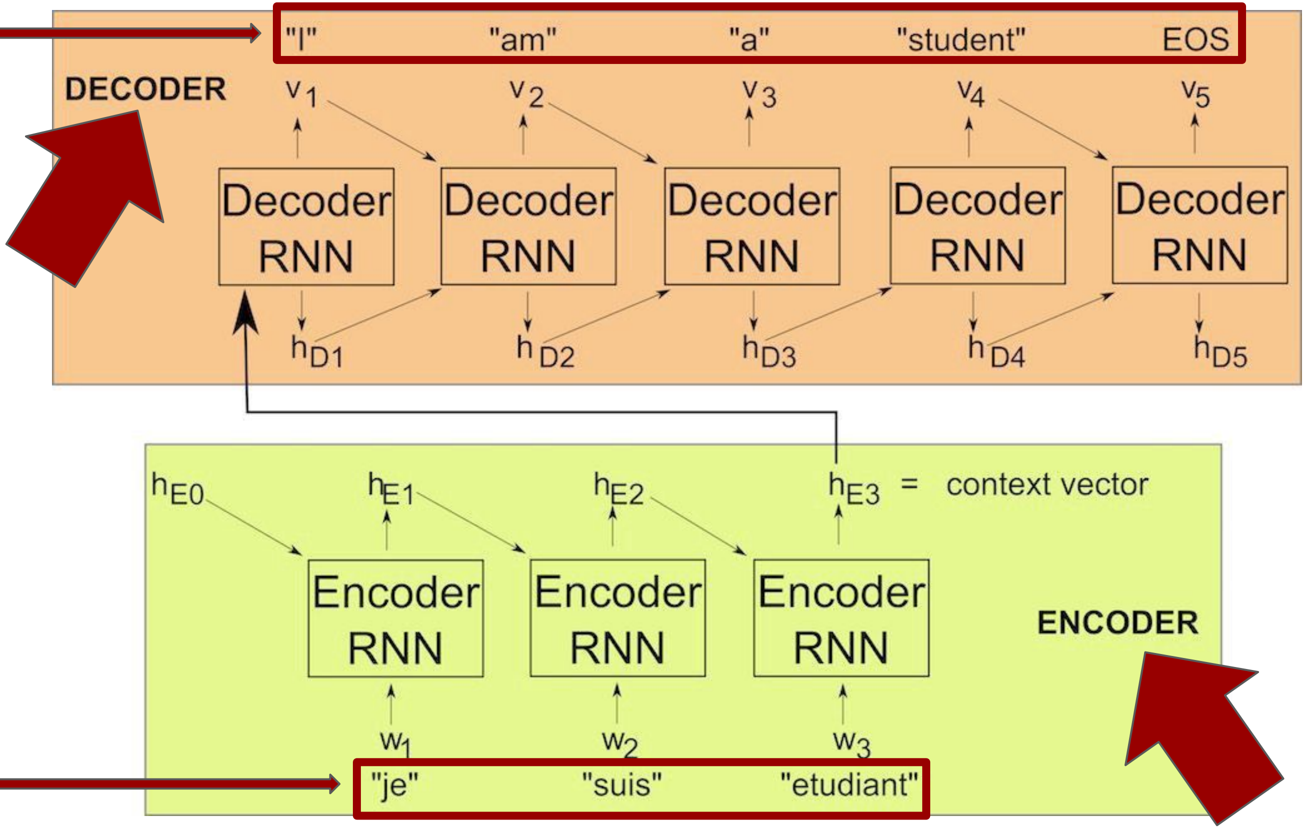
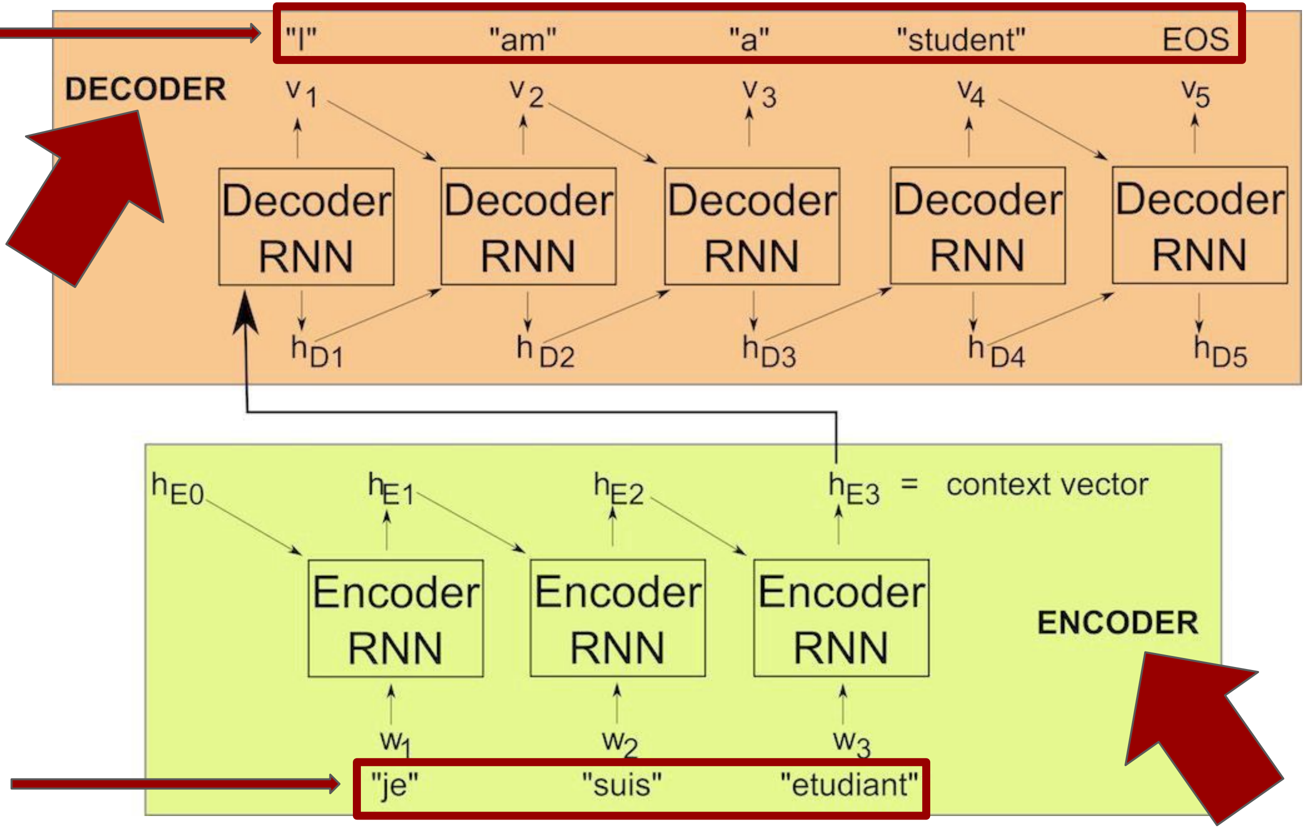


Input sequence

RNNs: the seq2seq example

Outputs (one-hot)

Inputs (word embeddings)



RNNs: the seq2seq example

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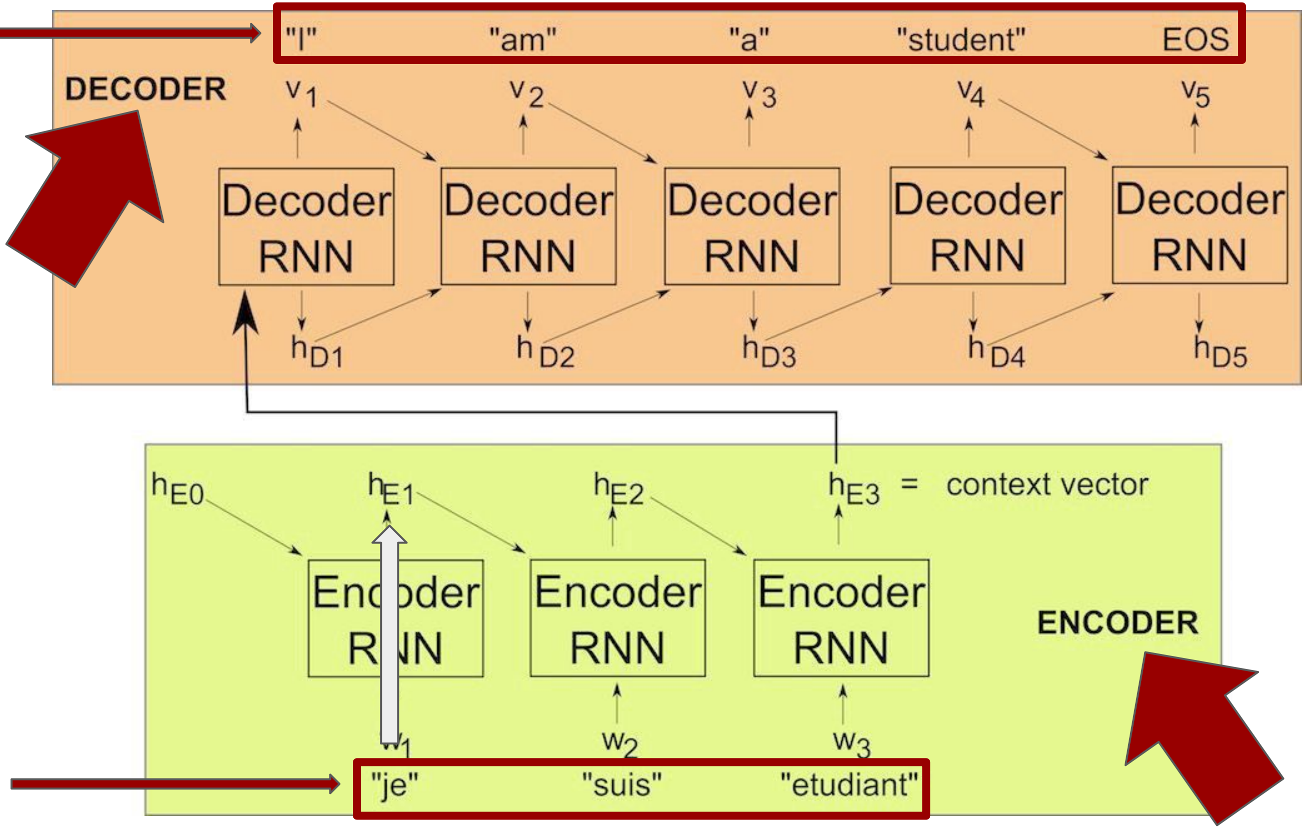

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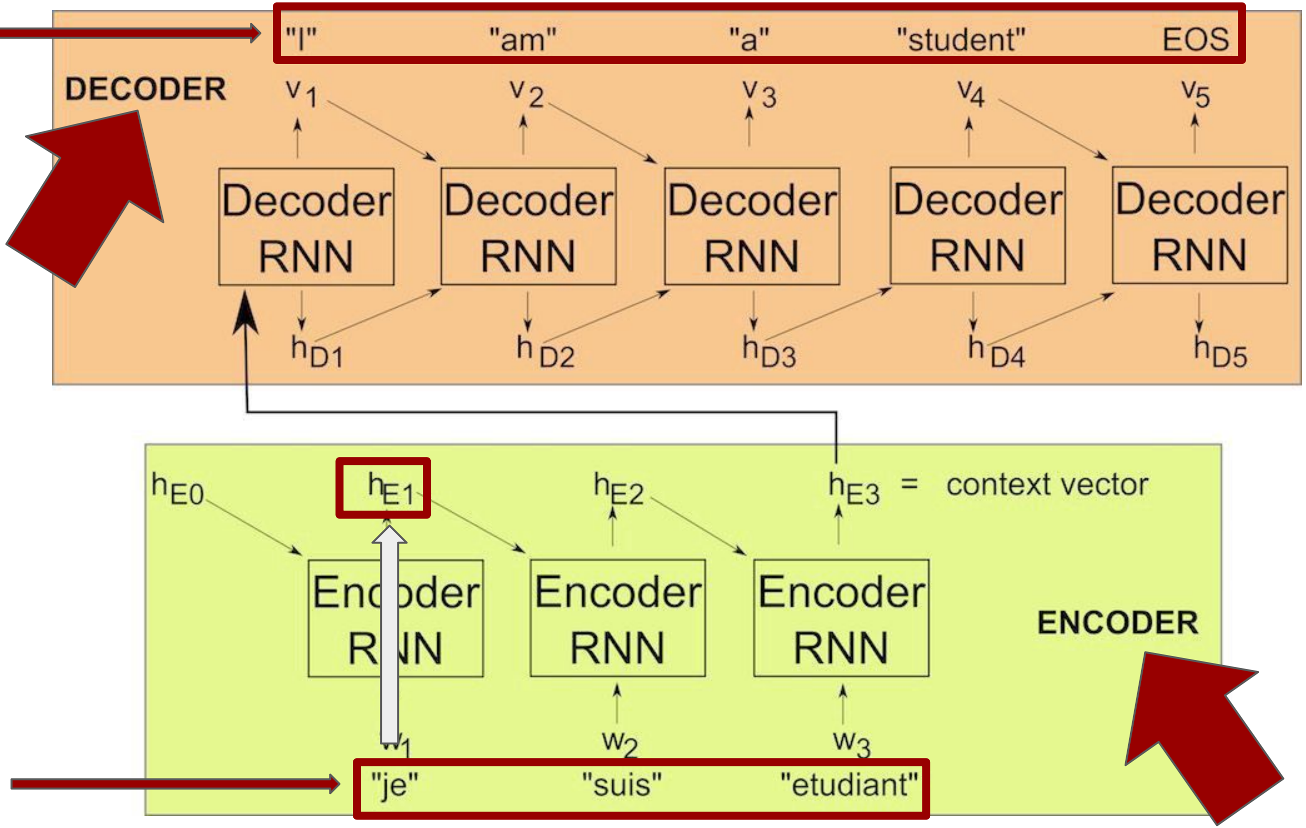

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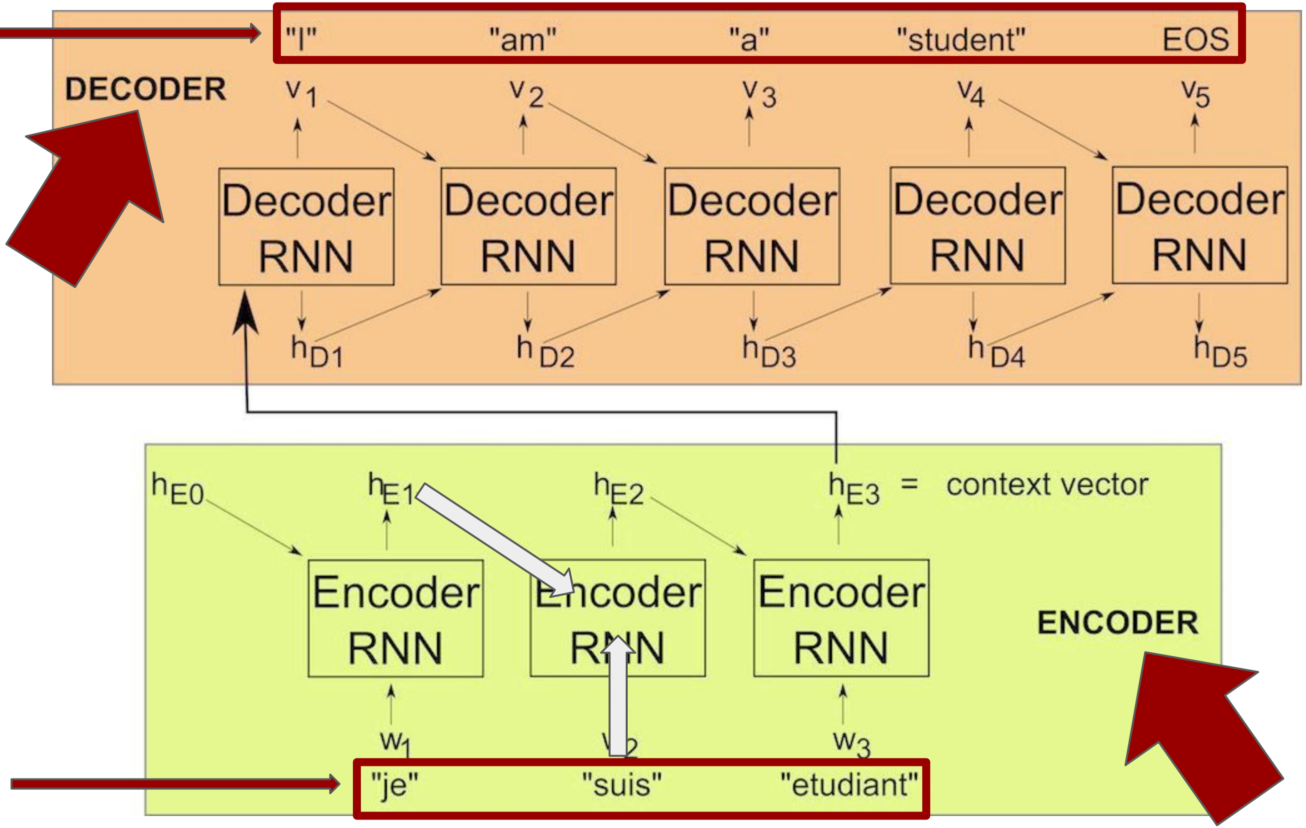

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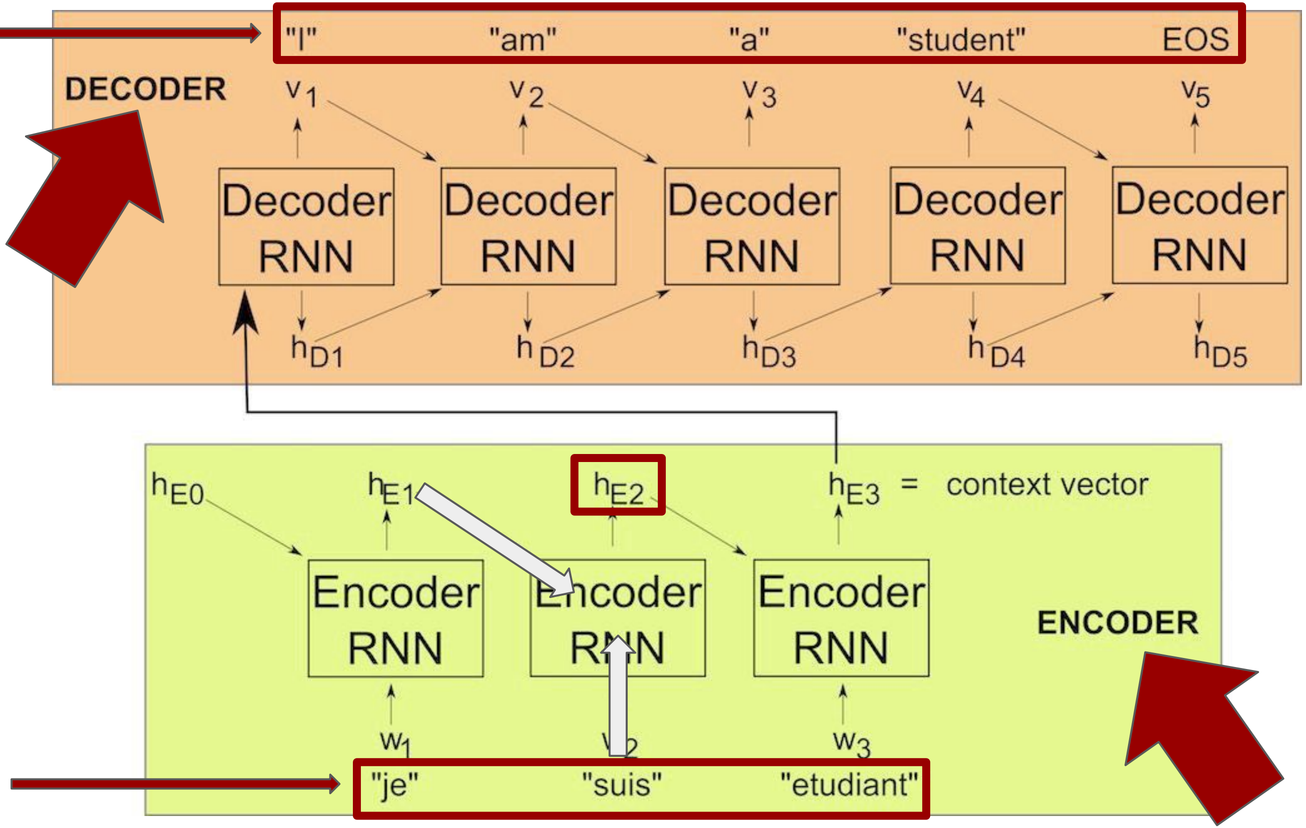

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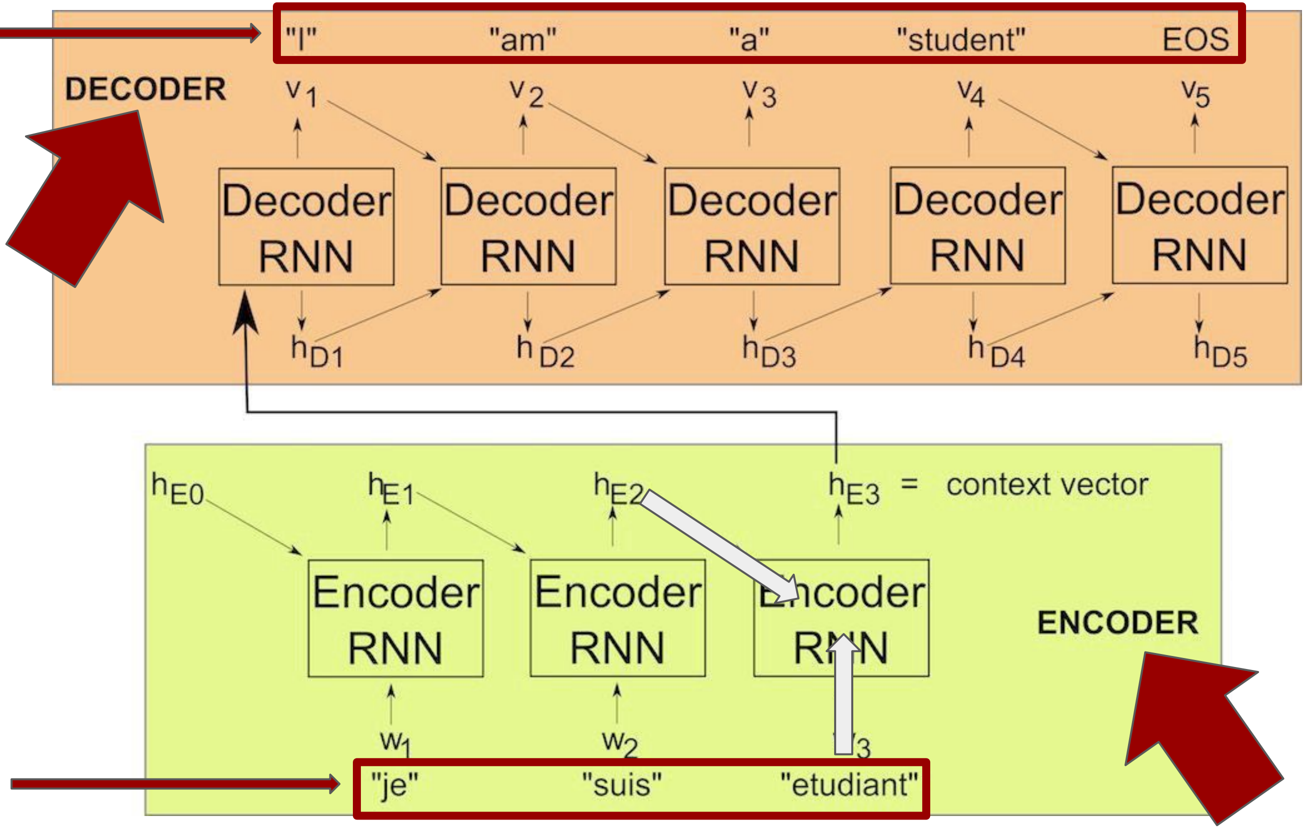

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Context vector: contains the meaning of the whole input sequence

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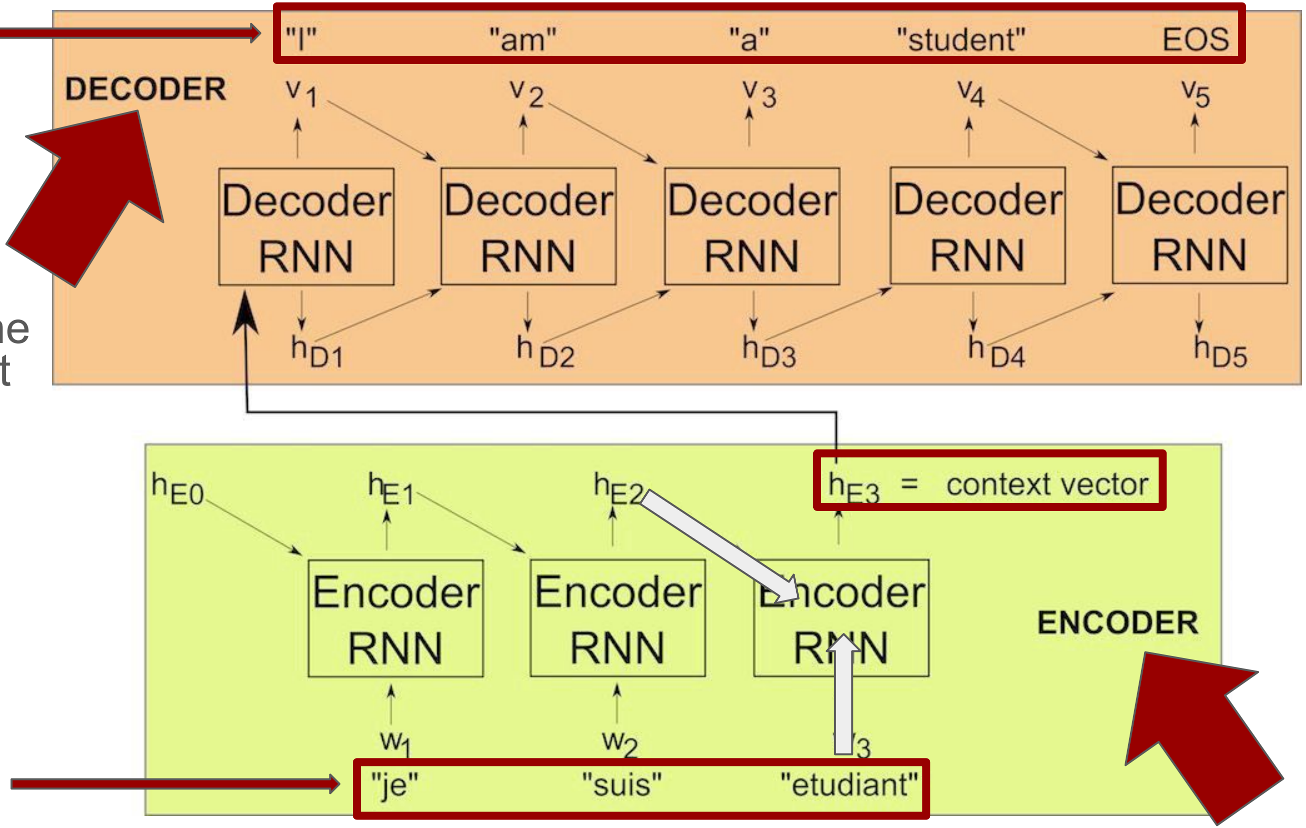

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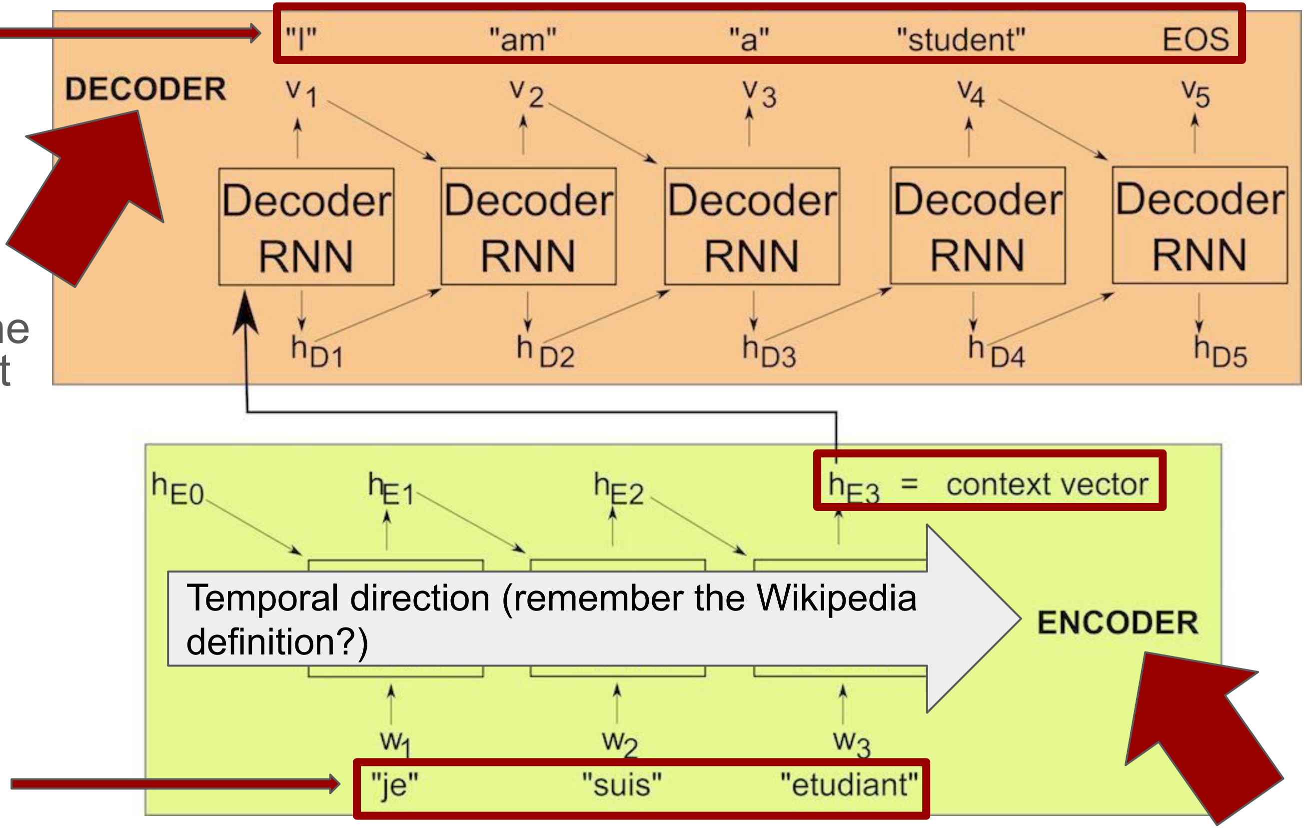

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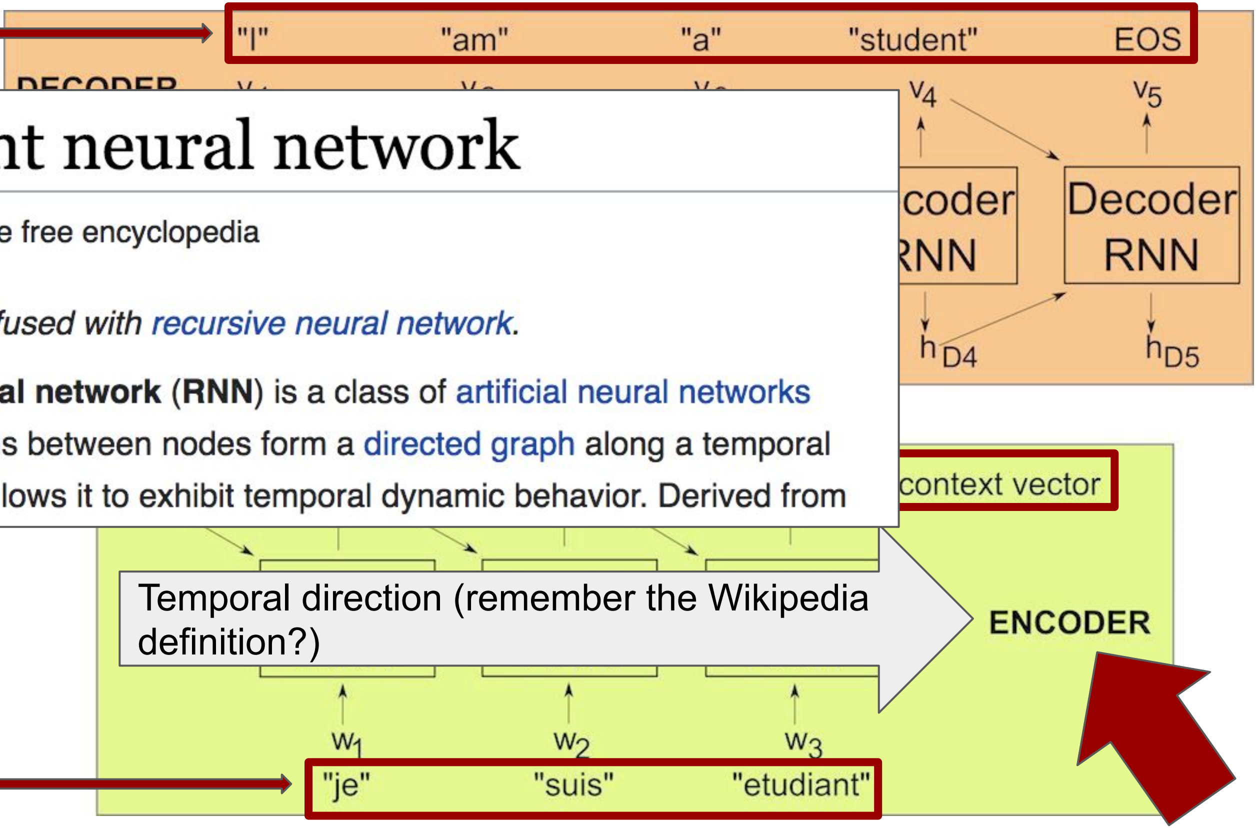

Recurrent neural network

From Wikipedia, the free encyclopedia

Not to be confused with recursive neural network.

A **recurrent neural network** (**RNN**) is a class of artificial neural networks where connections between nodes form a directed graph along a temporal sequence. This allows it to exhibit temporal dynamic behavior. Derived from

RNNs: the seq2seq example

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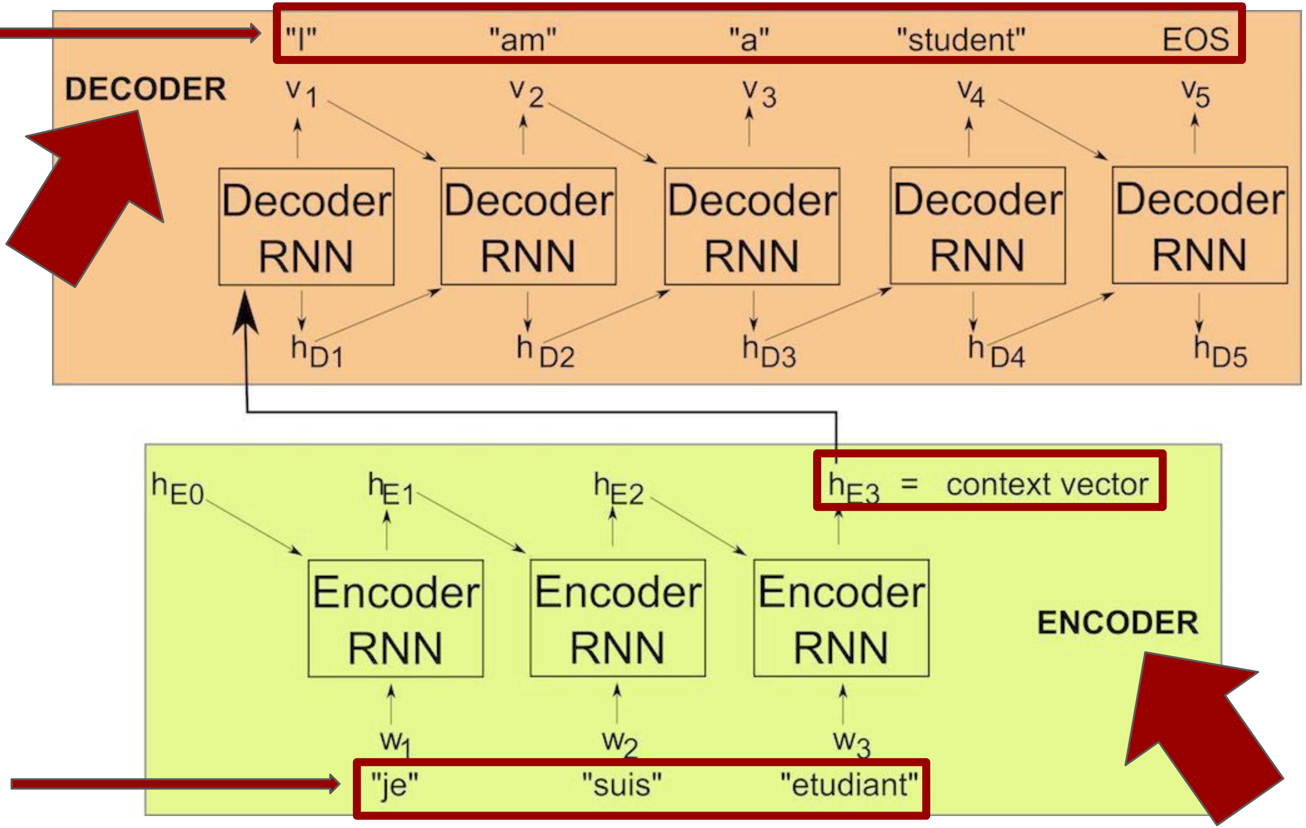

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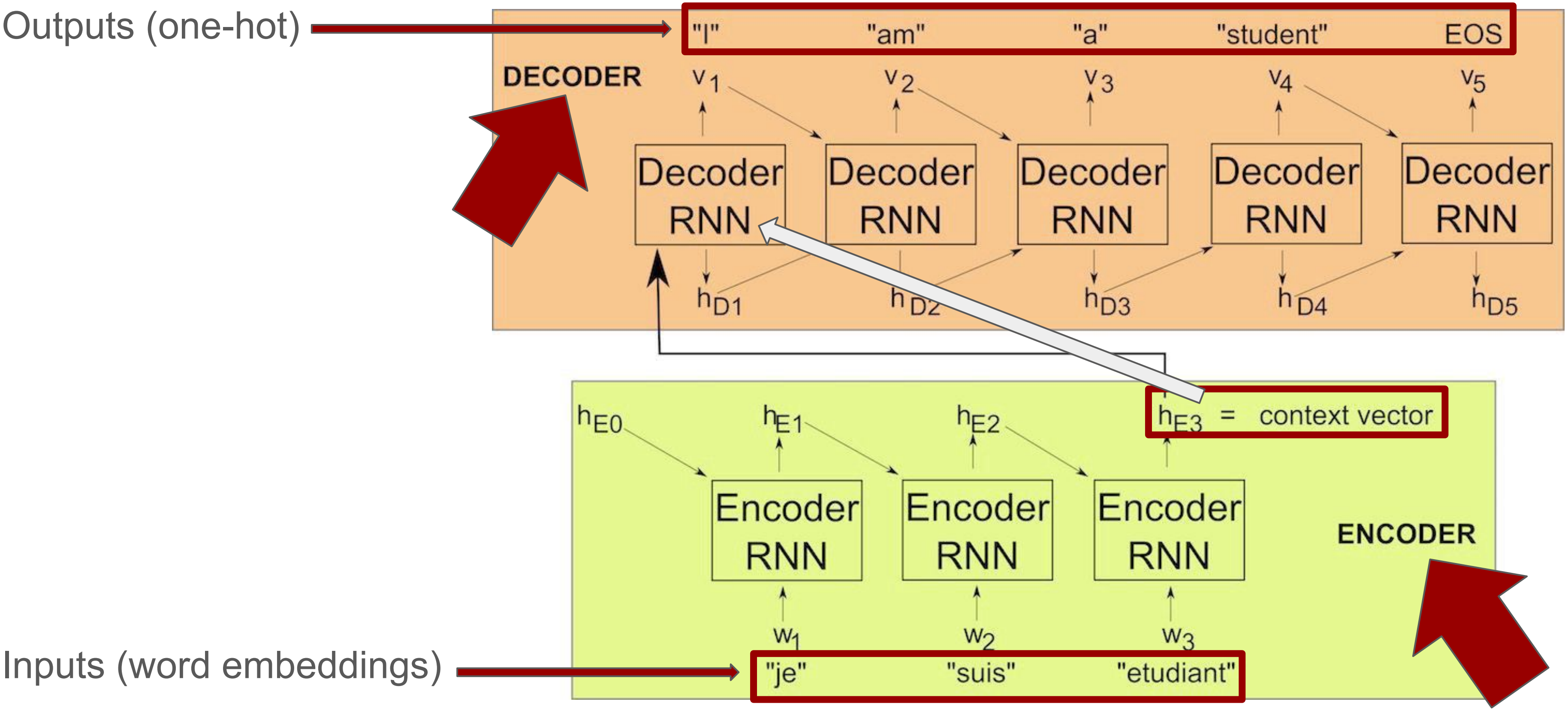

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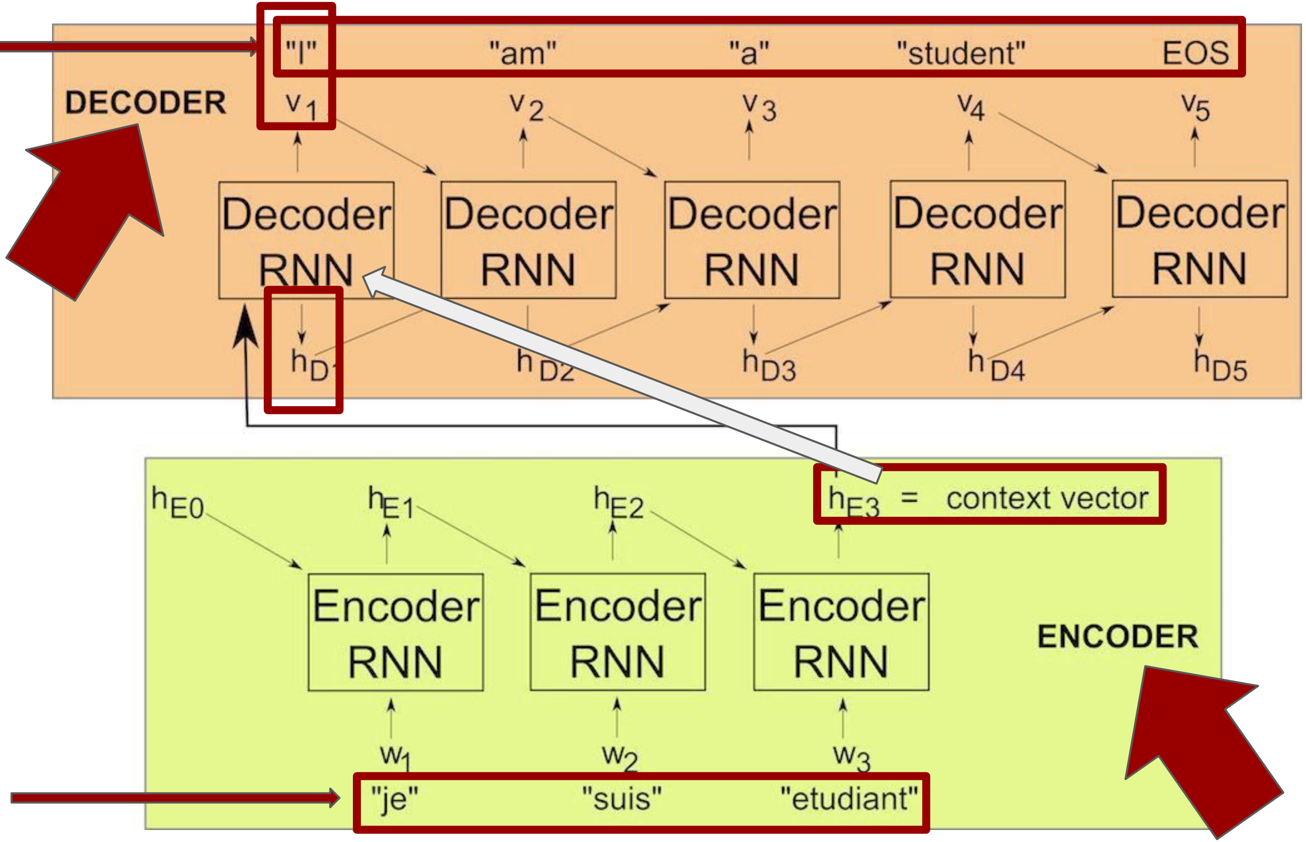

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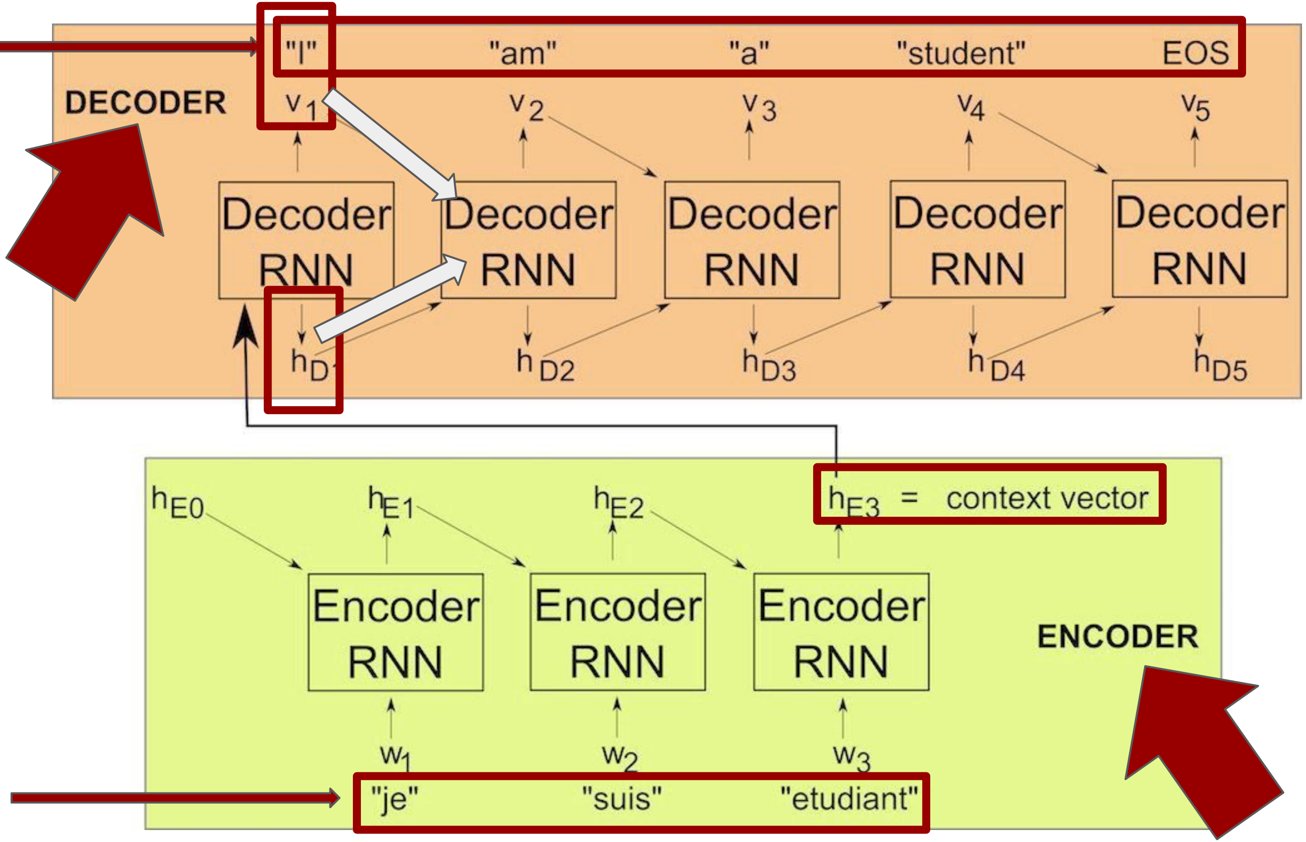

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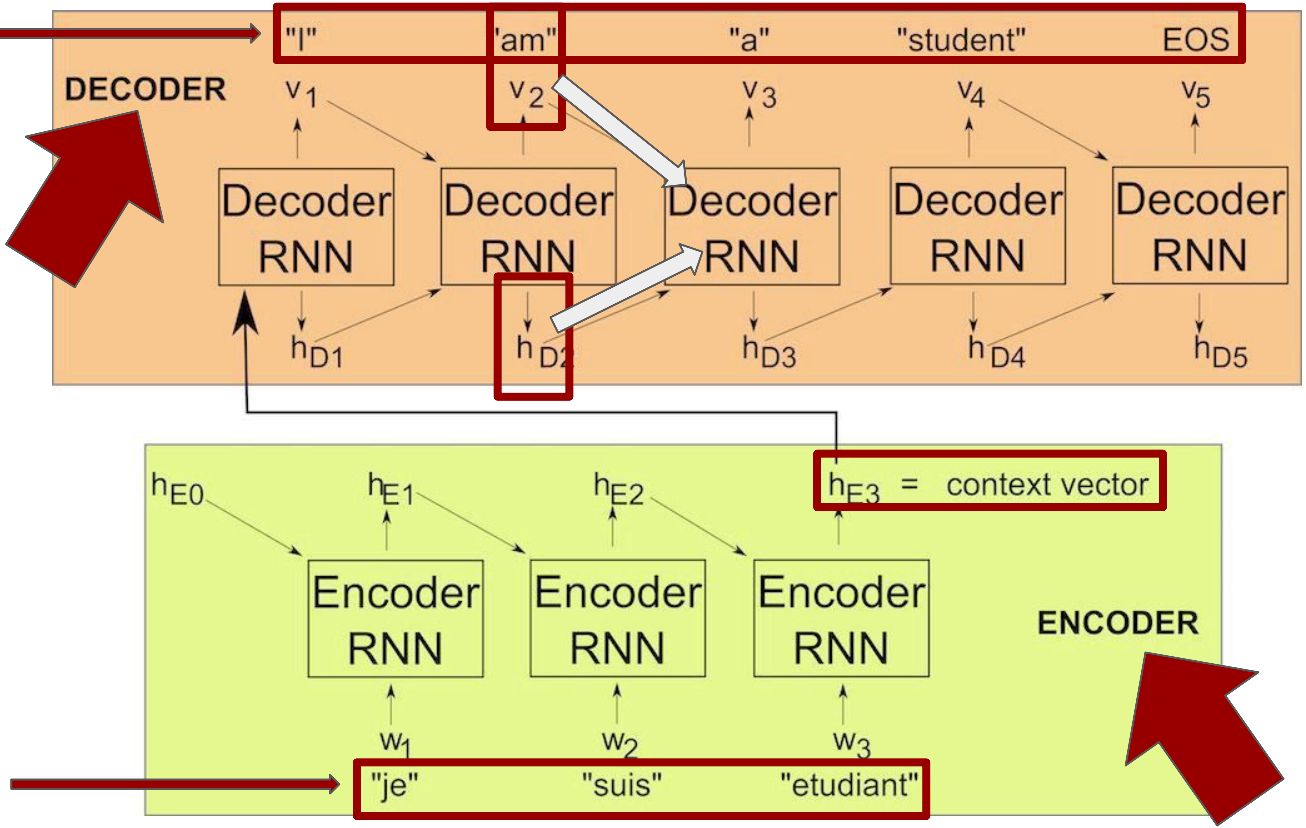

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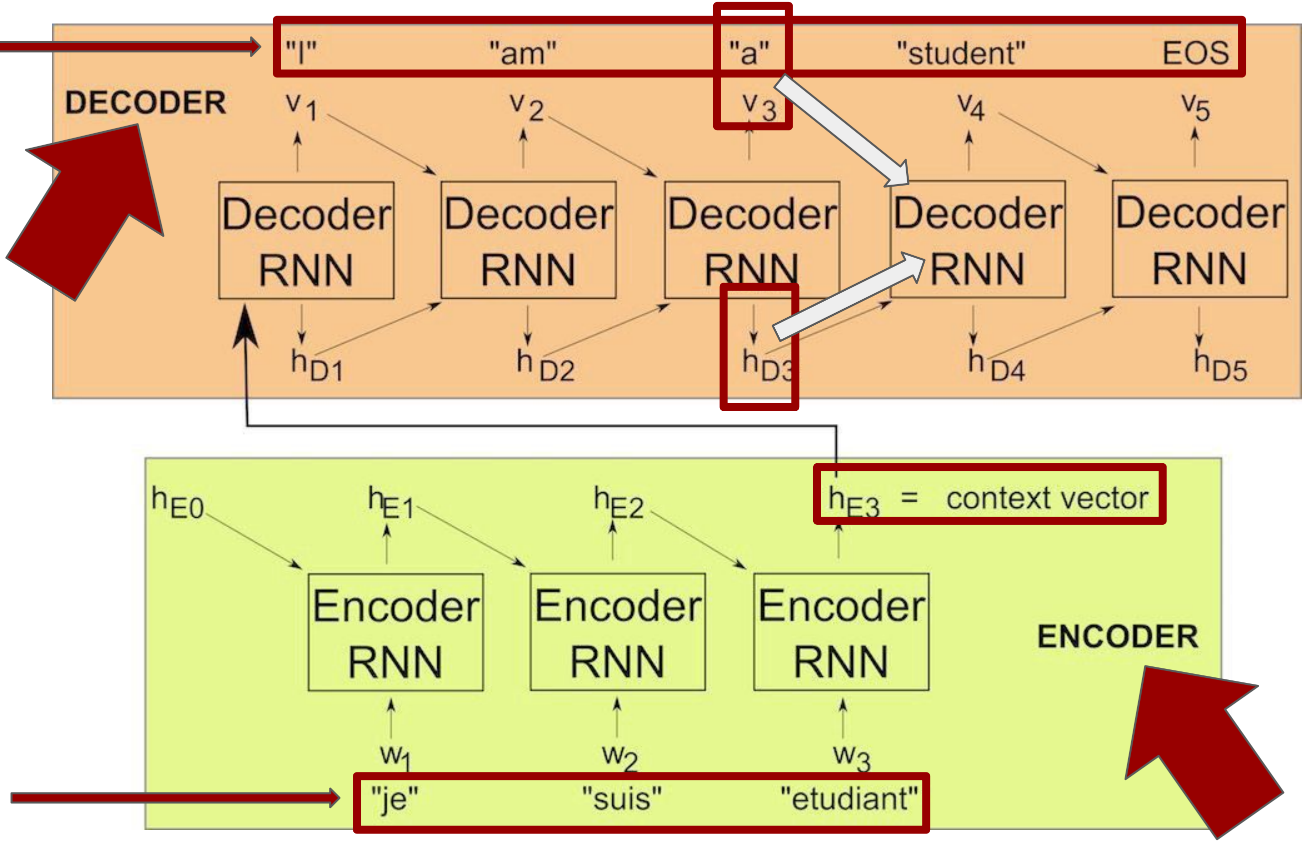

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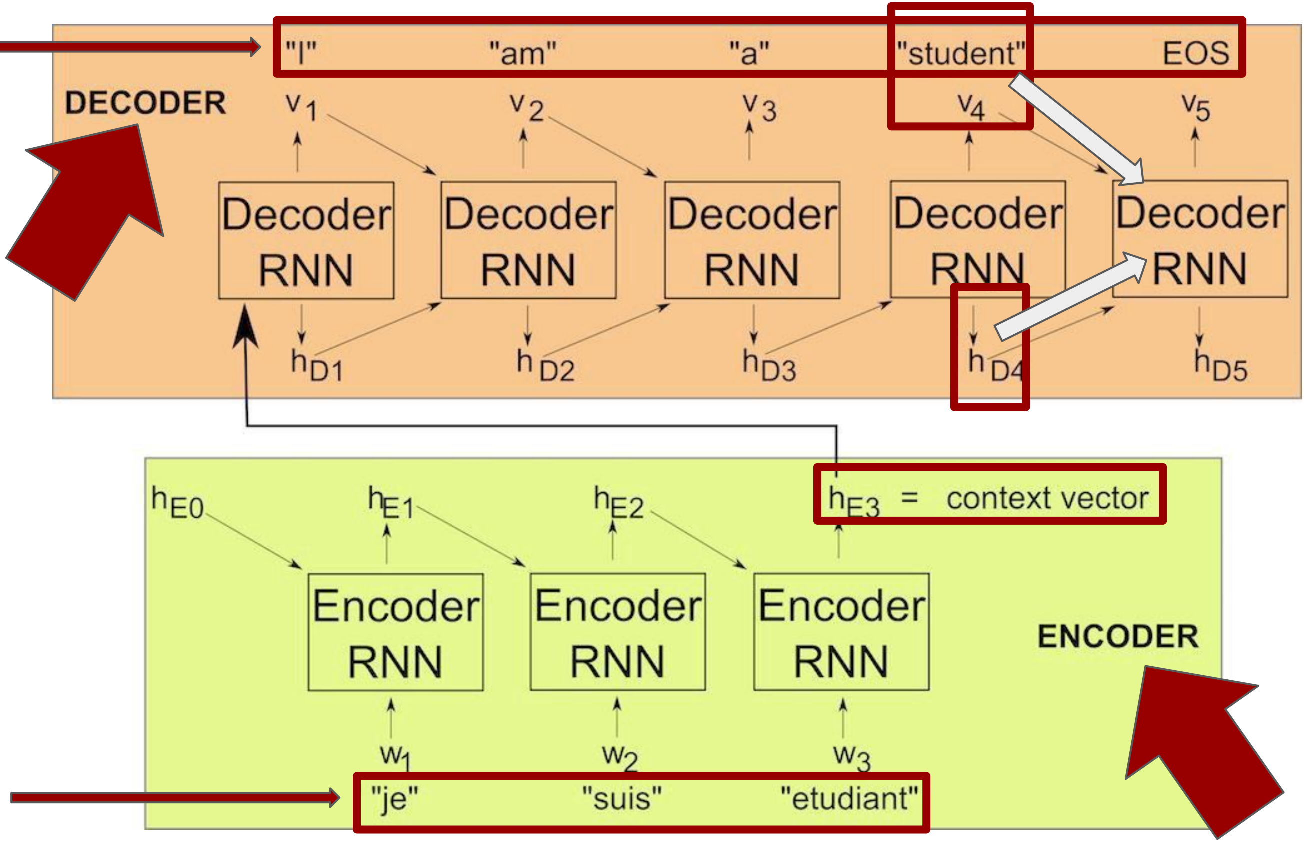

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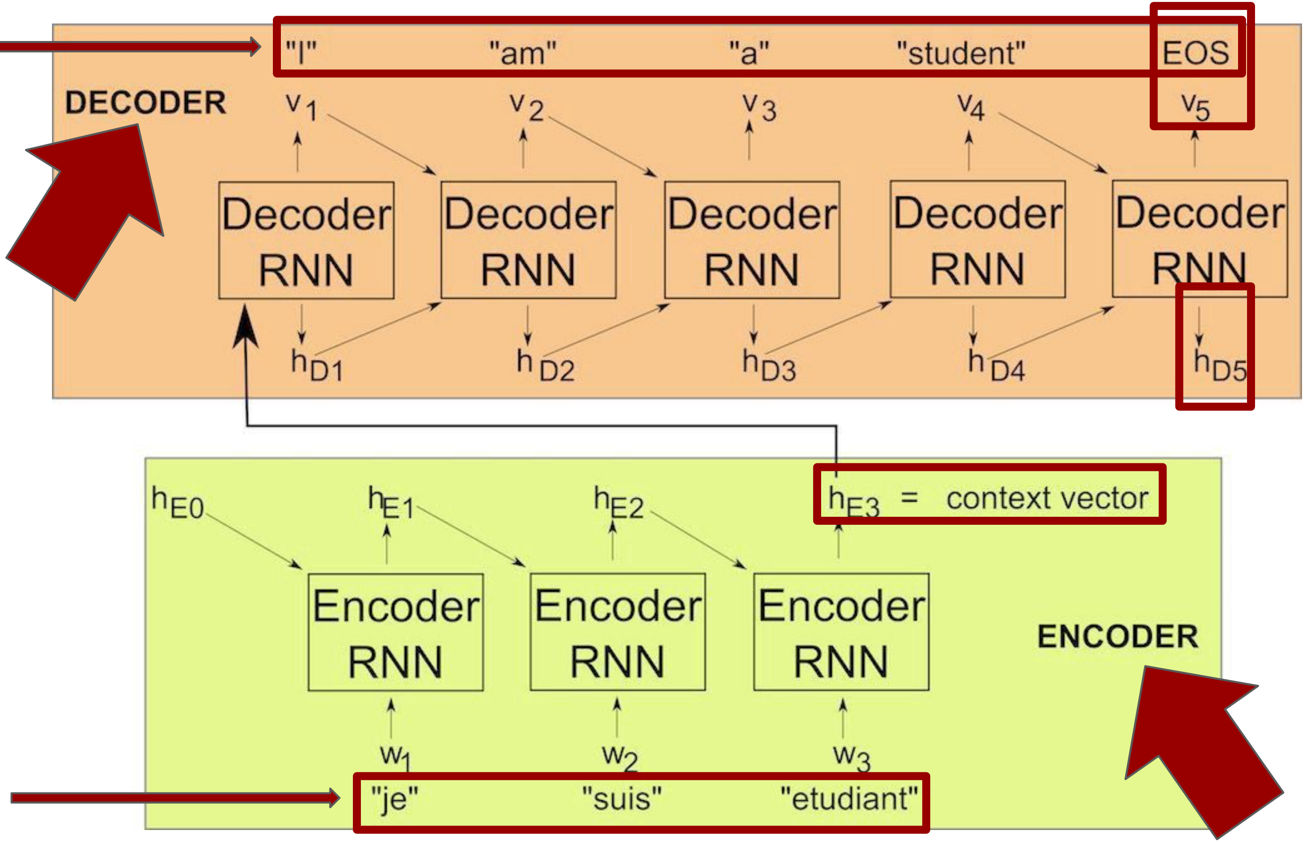

Inputs (word embeddings)

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Yes! (For the most part) Google Translate has been using these since ~ 2016

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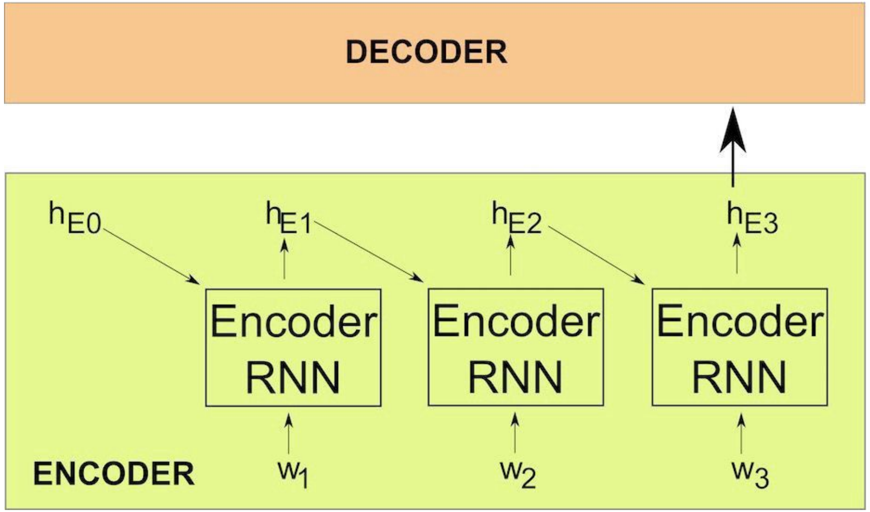
The Attention Mechanism



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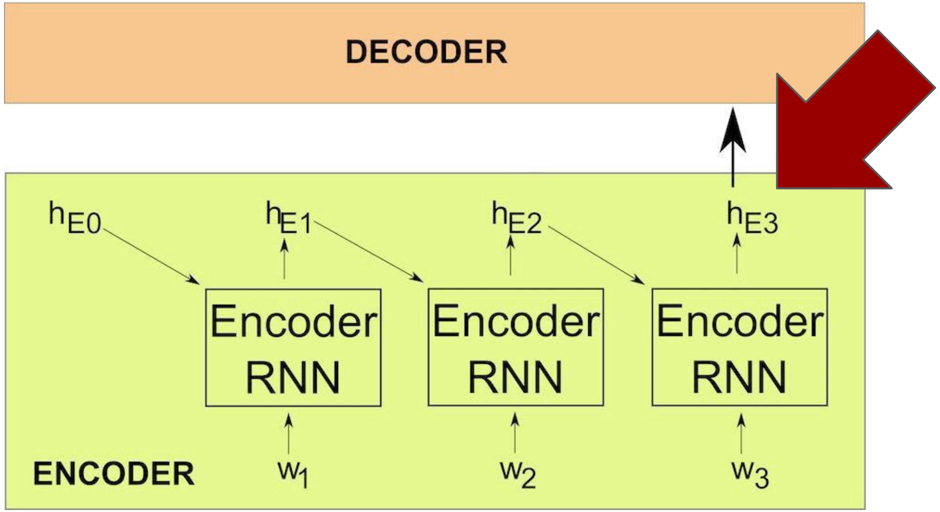

Recurrent NN from the previous section

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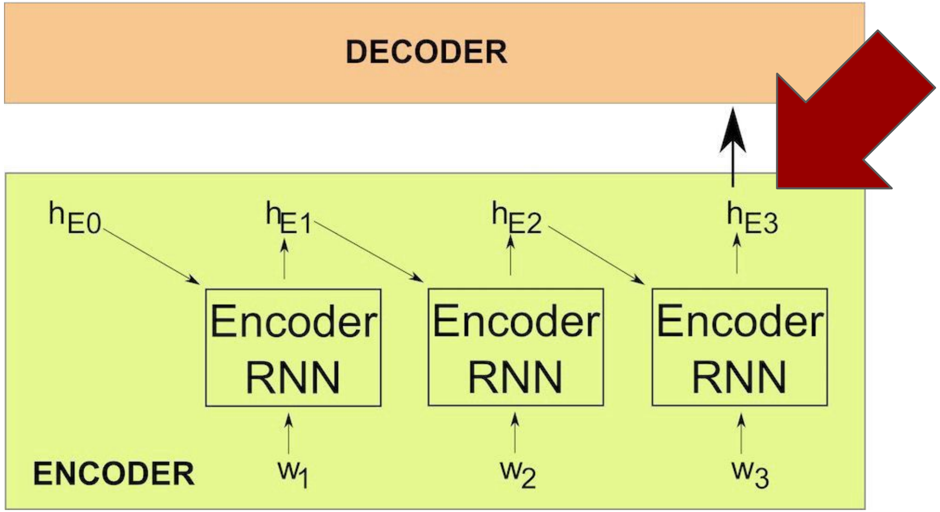

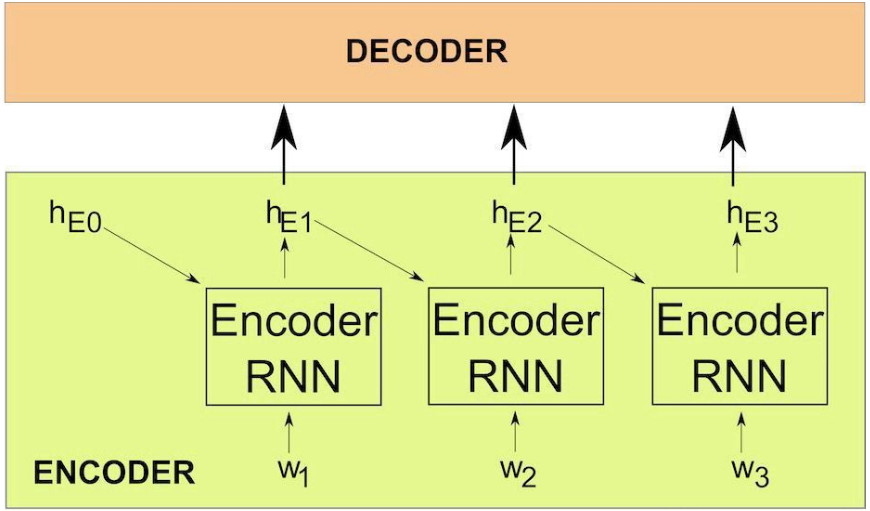

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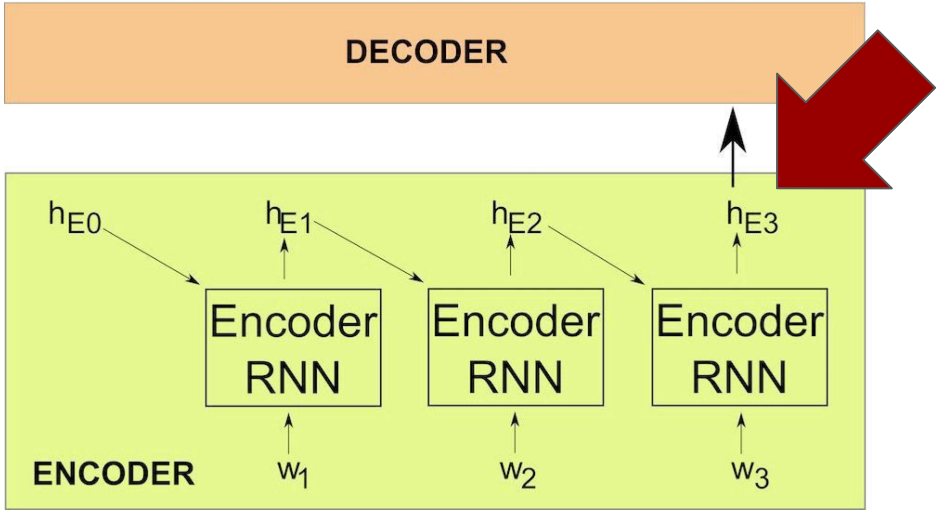

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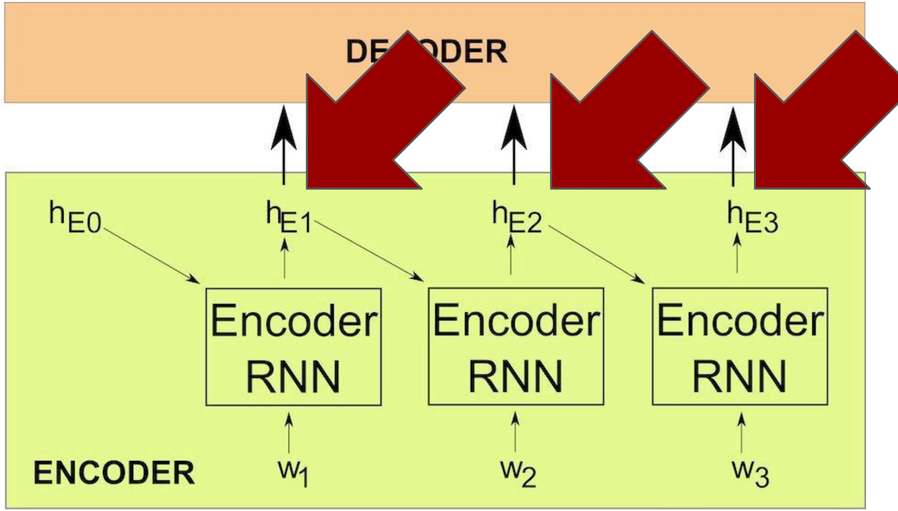

Send *all* of the hidden states to the Decoder, not just the last one

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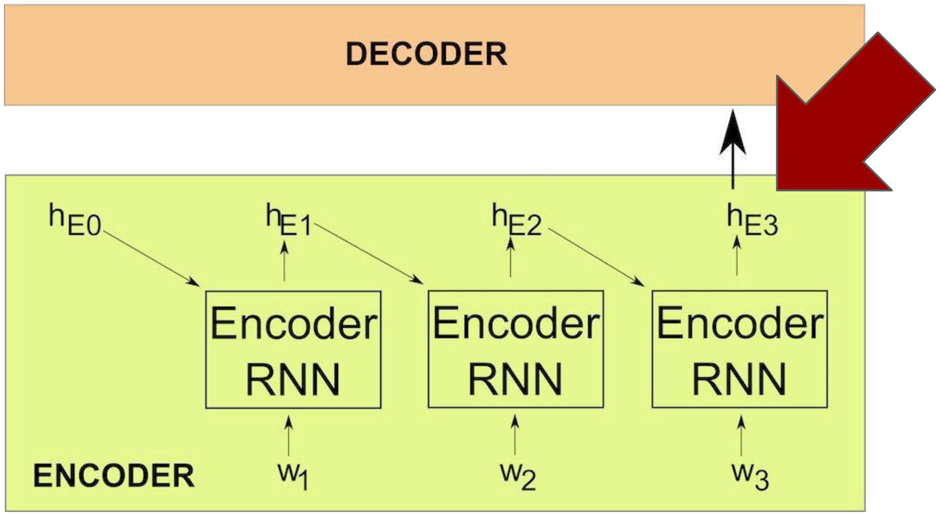

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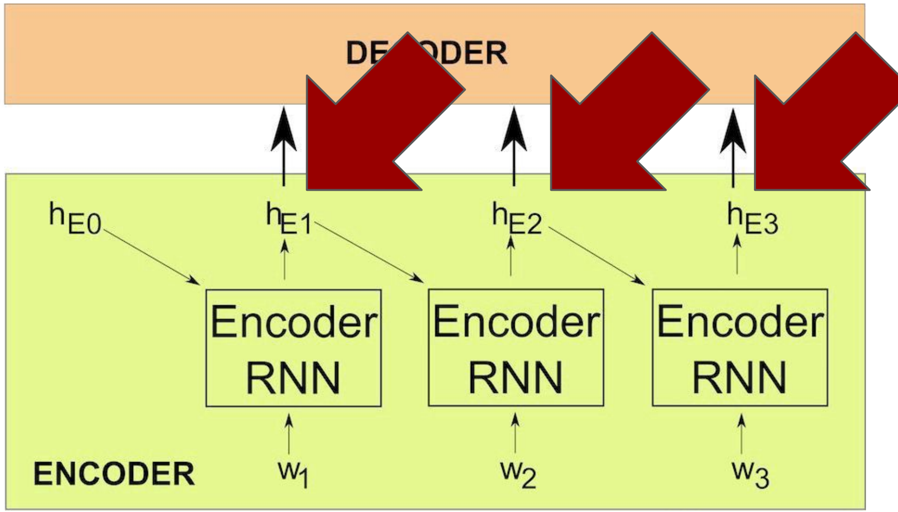

Send *all* of the hidden states to the Decoder, not just the last one

The Decoder determines which input elements get *attended* to via a softmax layer

Further reading

jalammar.github.io/illustrated-transformer/

My blog post that this talked is based on + the linear algebra perspective on Attention:

towardsdatascience.com/natural-language-processing-the-age-of-transformers-a36c0265937d

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Attention is All You Need © Google, 2017

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- Keep the Attention mechanism, throw away the sequential RNN
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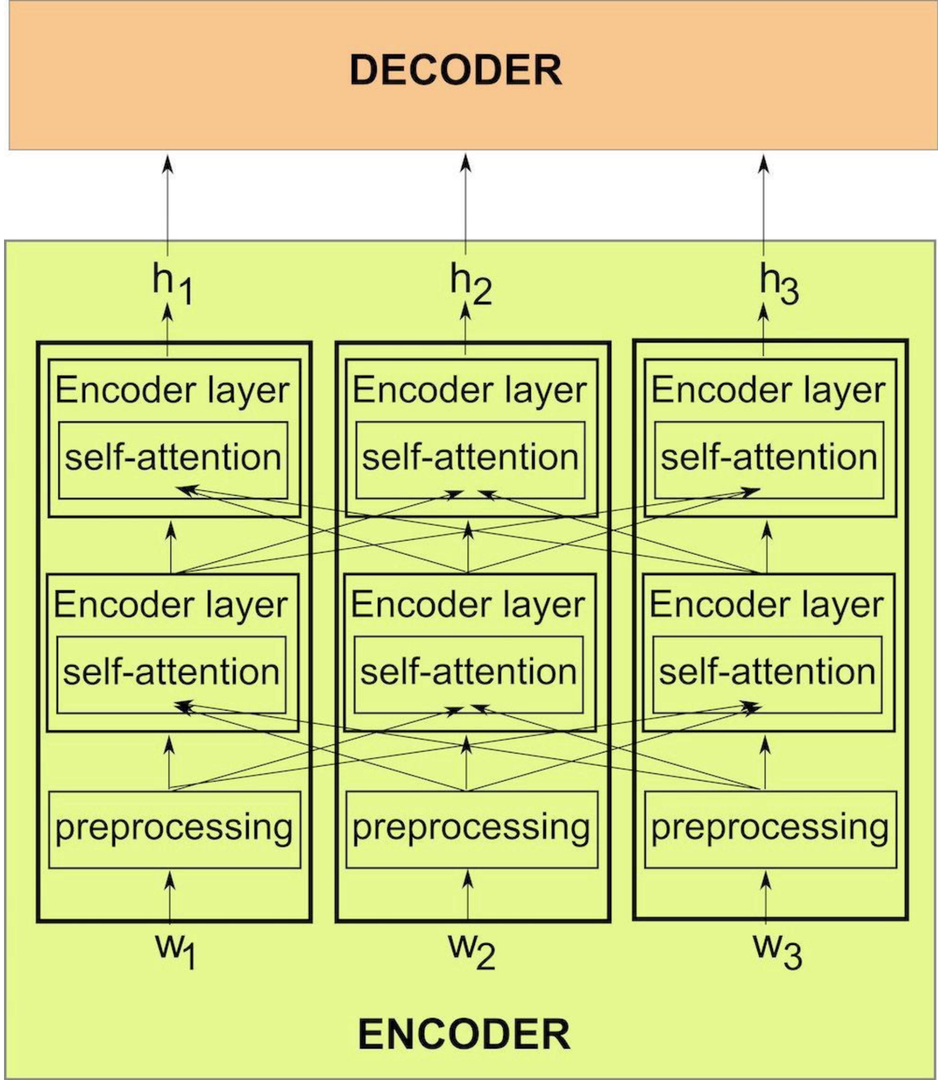
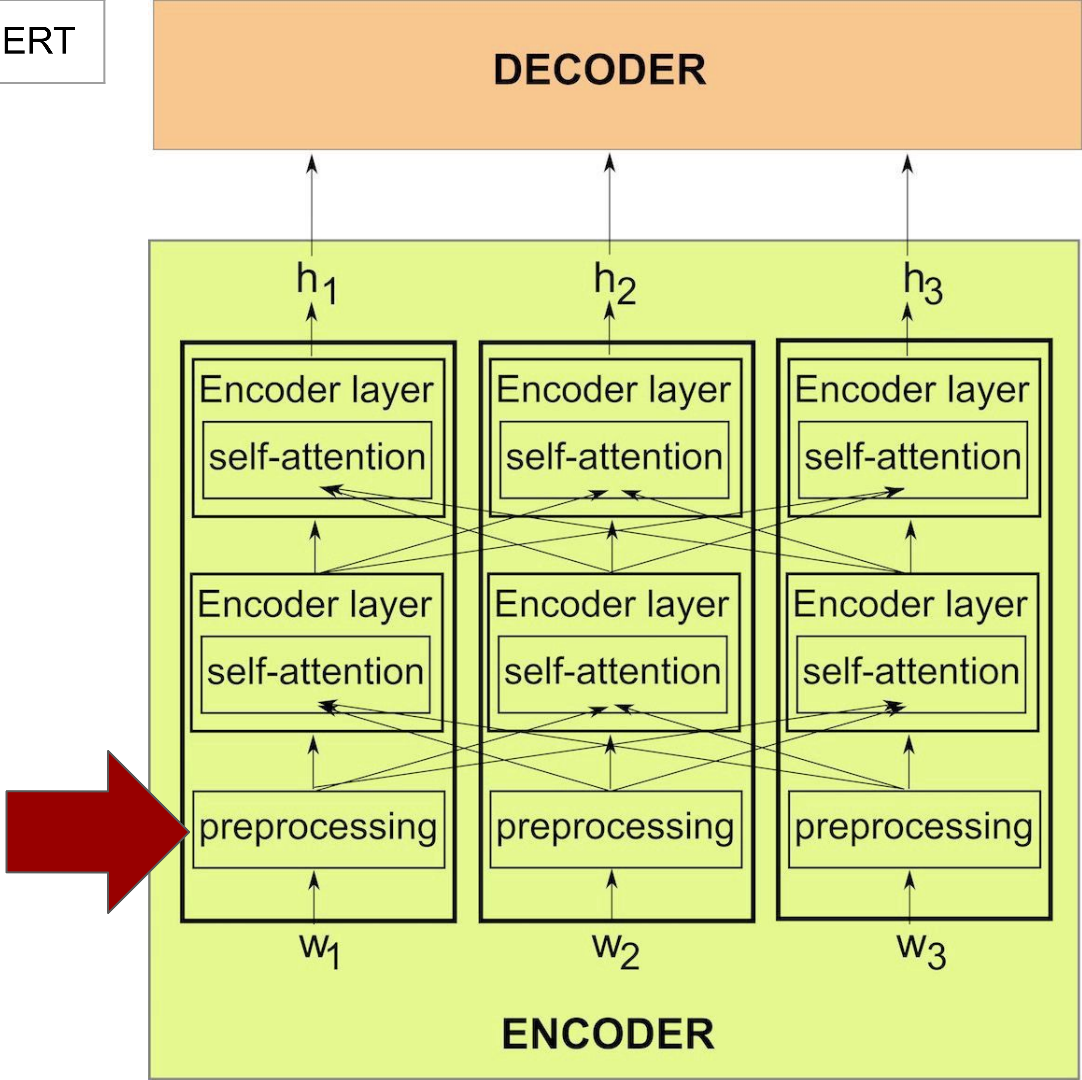
  - Also Self-Attention in the Decoder

Attention all around



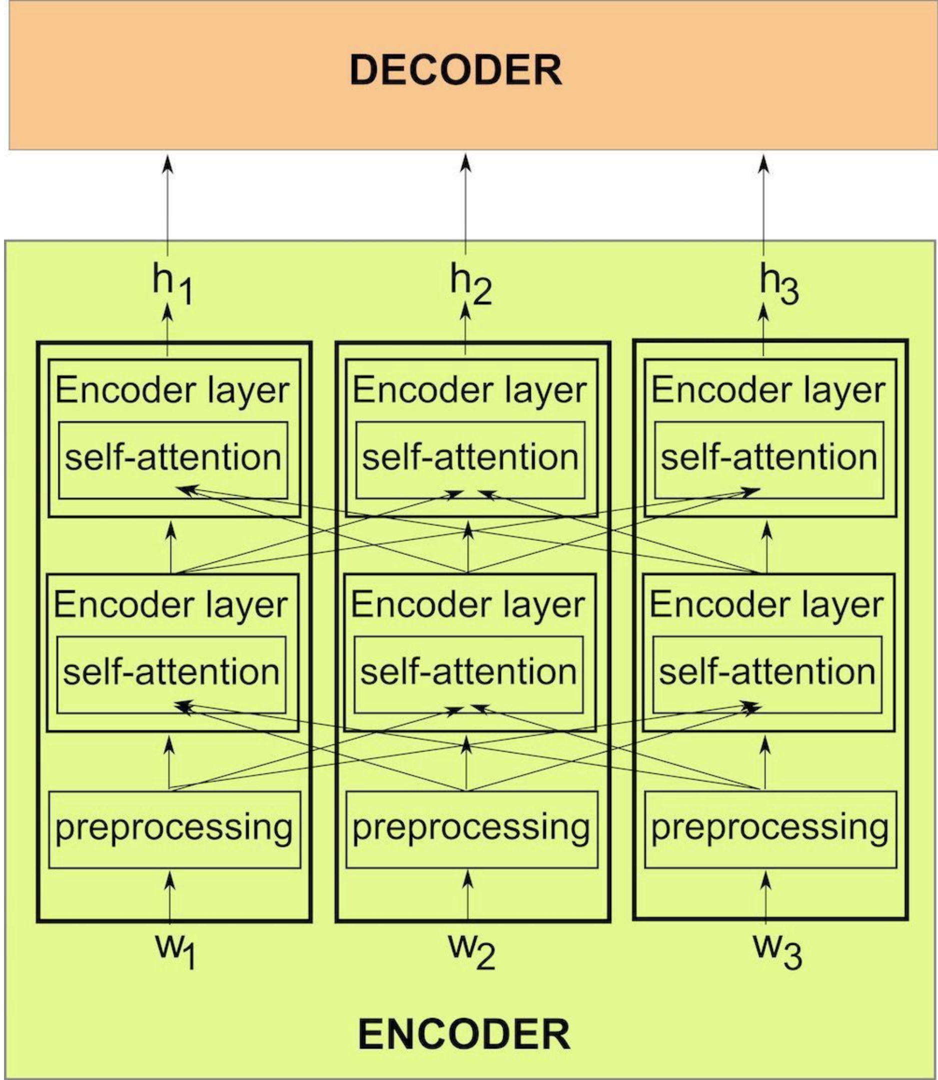
Attention all around

Word embedding + position encoding



Attention all around

- All of the sequence elements (w1, w2, w3) are being processed in parallel
- Each element's encoding gets information (through hidden states) from other elements
- Bidirectional by design 😍

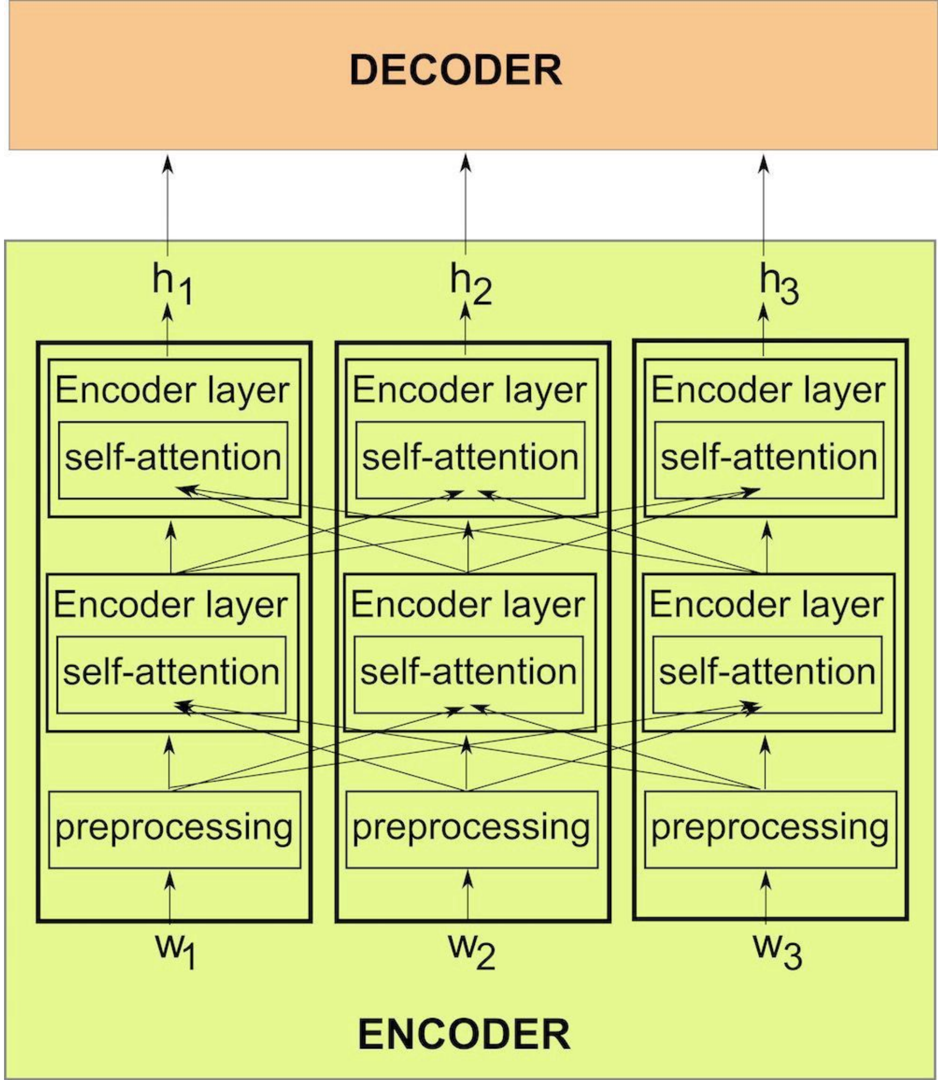


Why Self-Attention?

- “The **animal** did not cross the road because **it** was too tired.”

vs.

- “The animal did not cross the **road** because **it** was too wide.”



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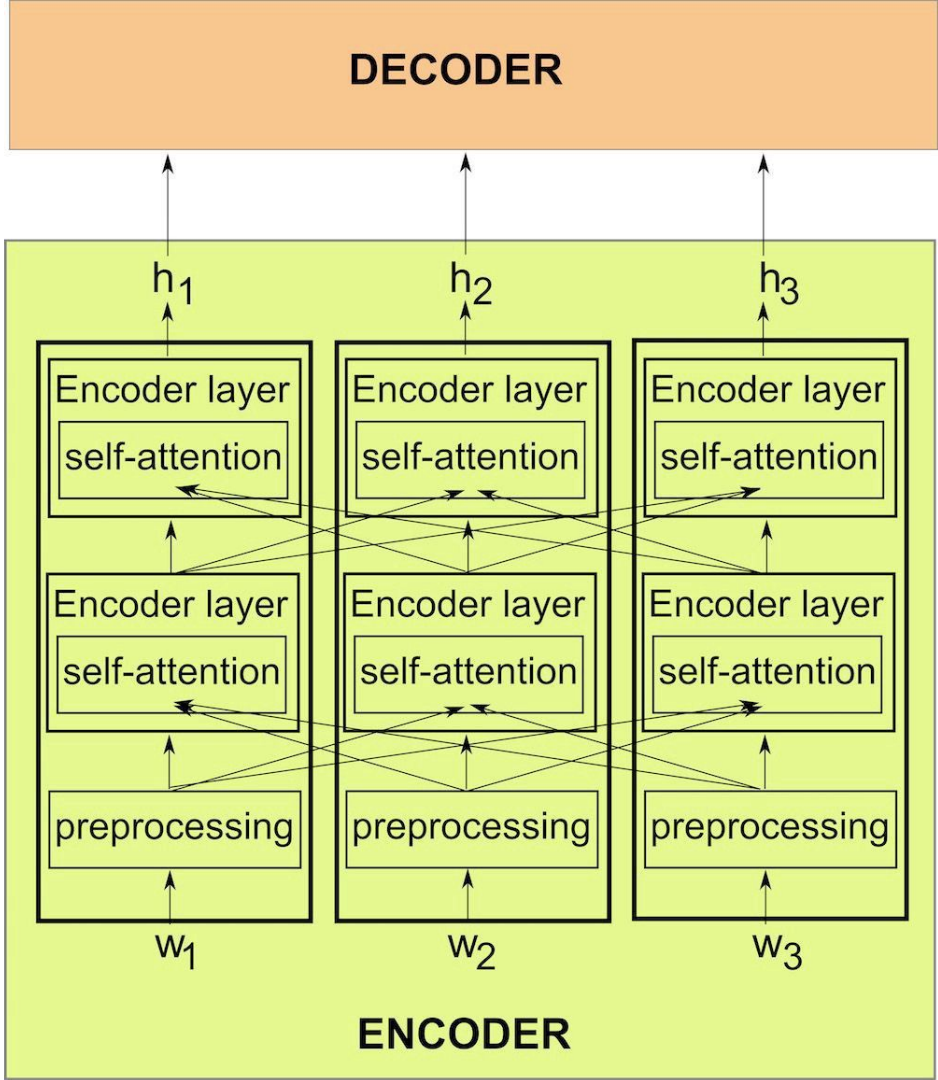
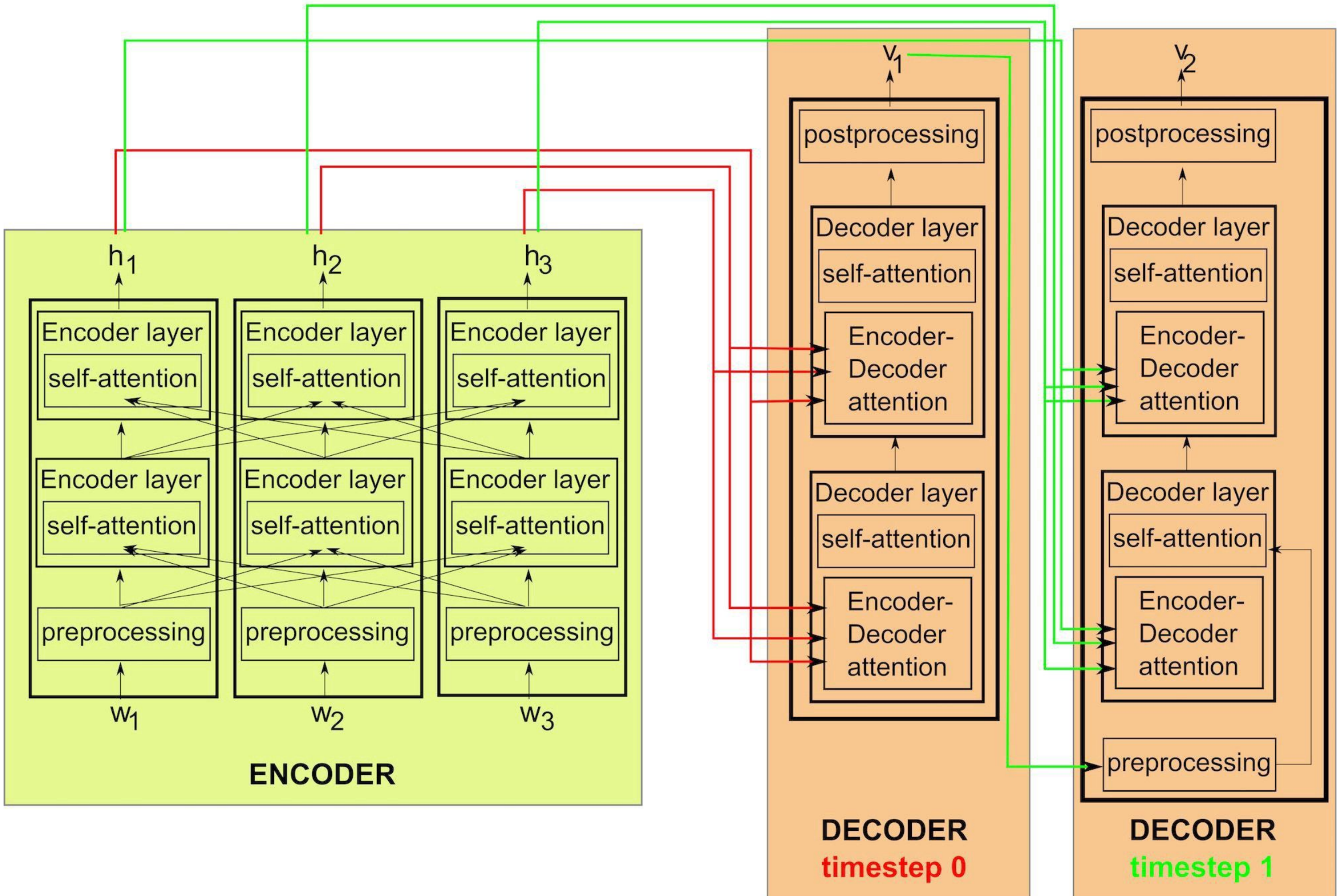
Uni-directional RNN would have missed this! Bi-directional is nice.



TRANSFORMER ARCHITECTURE



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- Dense (i.e. not sparse) vectors capturing the meaning of tokens/words

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BERT: Bidirectional Encoder Representations from Transformers

(Contextual) word embeddings

BERT: Bidirectional Encoder Representations from Transformers

Instead of Word2Vec, use pre-trained BERT for your NLP tasks ;)

What was BERT pre-trained on?

Task # 1: Masked Language Modeling

- Take a text corpus, randomly mask 15% of words
- Put a softmax layer (dim = vocab size) on top of BERT encodings for the words that are present to predict which word is missing

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Task # 2: Next Sentence Prediction

- Input sequence: two sentences separated by a special token
- Binary classification: are these sentences successive or not?

Further reading and coding

My blog posts:

towardsdatascience.com/natural-language-processing-the-age-of-transformers-a36c0265937d

blog.scaleway.com/understanding-text-with-bert/

The HuggingFace 🤗 Transformers library: huggingface.co/