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# Attention mechanism



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- encoder decoder networks
- attention mechanism

### **Recurrent Neural Networks**

 Recurrent Neural Networks are networks with loops in them, allowing information to persist.





Recurrent Neural Networks have loops.

In the above diagram, a chunk of neural network, A, looks at some input  $X_t$  and outputs a value  $h_t$ .

A loop allows information to be passed from one step of the network to the next. An unrolled recurrent neural network.

A recurrent neural network can be thought of as multiple copies of the same network, each passing a message to a successor.

The diagram above shows what happens if we unroll the loop.

#### **Examples of Recurrent Neural Networks**



- Each rectangle is a vector and arrows represent functions (e.g. matrix multiply).
- Input vectors are in red, output vectors are in blue and green vectors hold the RNN's state
- 1. Standard mode of processing without RNN, from fixed-sized input to fixed-sized output (e.g. image classification).
- 2. Sequence output (e.g. image captioning takes an image and outputs a sentence of words).
- 3. Sequence input (e.g. sentiment analysis where a given sentence is classified as expressing positive or negative sentiment).
- 4. Sequence input and sequence output (e.g. Machine Translation: an RNN reads a sentence in English and then outputs a sentence in French).
- Synced sequence input and output (e.g. video classification where we wish to label each frame of the video).

### Seq2Seq model



Videos by Jay Alammar: <u>Visualizing A Neural Machine Translation Model</u> (Mechanics of Seq2seq Models With Attention), 2018

# Seq2Seq for NMT

#### Neural Machine Translation SEQUENCE TO SEQUENCE MODEL



#### **Encoder-Decoder model**

• encode into a latent space



#### **Encoder-decoder for sequences**



#### Encoder-decoder for NMT





#### Encoder-decoder hidden states



# Unrolled encoder-decoder

#### **Neural Machine Translation**

**SEQUENCE TO SEQUENCE MODEL** 



Je suis étudiant

#### Problems of encoder-decoder models

- long dependencies that would require larger networks and many more training data
- the information of different length sentences is stored in the fixed length hidden layer (migh be too long or to short)
- solution: attention mechanism

# NMT with attention

#### **Neural Machine Translation**

SEQUENCE TO SEQUENCE MODEL WITH ATTENTION



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# Attention mechanism implementation for RNNs 1/2

- for all input words, we store their hidden layer weights
- during decoding, we add these vectors to the decoder input
- we use bidirectional encoding (forward and backward LM) and concatenate both weight vectors
- vectors are stored into a matrix

$$\overrightarrow{\boldsymbol{h}}_{j}^{(f)} = \text{RNN}(\text{embed}(f_{j}), \overrightarrow{\boldsymbol{h}}_{j-1}^{(f)}) \overleftarrow{\boldsymbol{h}}_{j}^{(f)} = \text{RNN}(\text{embed}(f_{j}), \overleftarrow{\boldsymbol{h}}_{j+1}^{(f)}). \qquad \boldsymbol{h}_{j}^{(f)} = [\overleftarrow{\boldsymbol{h}}_{j}^{(f)}; \overrightarrow{\boldsymbol{h}}_{j}^{(f)}].$$

$$H^{(f)} = \operatorname{concat\_col}(\boldsymbol{h}_1^{(f)}, \dots, \boldsymbol{h}_{|F|}^{(f)}).$$

# Attention mechanism implementation for RNNs 2/2

- we train the attention which stored vectors are more or less important for decoding certain words
- the importance is determined with the attention vector  $\alpha_t$  (between 0 and 1, sums to 1), applied to stored hidden weights and given as additional input to the decoder

$$\boldsymbol{c}_t = H^{(f)} \boldsymbol{\alpha}_t$$

### Illustration of attention

Attention at time step 4

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## Decoder with attention

**Neural Machine Translation** SEQUENCE TO SEQUENCE MODEL WITH ATTENTION



#### Attention produces alignments



# Illustration of attention



### Attention illustration



# **Problems with RNNs**

- We want parallelization but RNNs are inherently sequential
- Despite GRUs and LSTMs, RNNs still need attention mechanism to deal with long range dependencies – path length between states grows with sequence
- If attention gives us access to any state... maybe we can just use attention and don't need the RNN?