杜岳華

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About me

- Julia Taiwan 社群發起人
- AI Tech 社群常規成員與講師
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- 著作:《Julia程式設計》

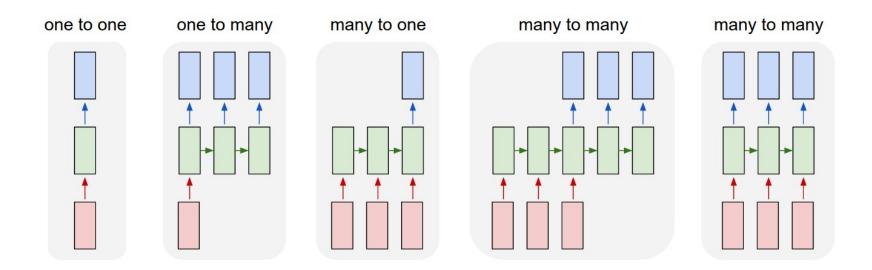
- 專長:系統生物學、計算生物學、機器學習
- 碩論:Identification of cell state using super-enhancer RNA

- 陽明生物醫學資訊所碩士
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Outline

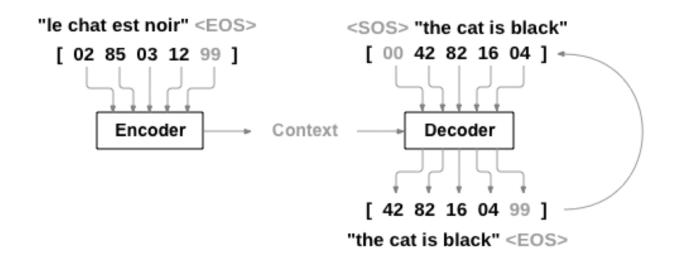
- RNN 的問題
- Seq2Seq encoder-decoder 架構
- Attention model 解決的問題
- Attention types
- Applications of attention
 - Translation
 - Summarization
 - Image caption
- Transformer

RNN 的問題



<u>picture source (http://karpathy.github.io/2015/05/21/rnn-effectiveness/)</u>

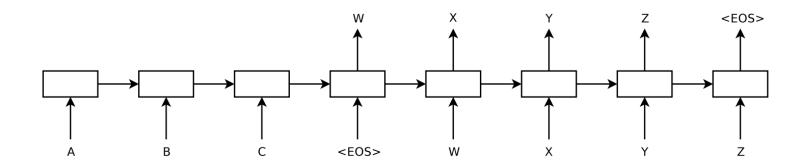
Seq2Seq encoder-decoder 架構



picture source

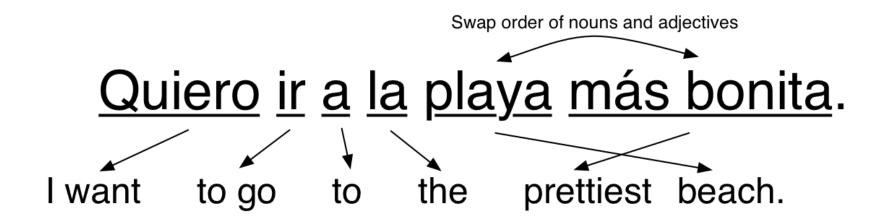
(https://pytorch.org/tutorials/intermediate/seq2seq translation tutorial.html)

Seq2Seq encoder-decoder 架構



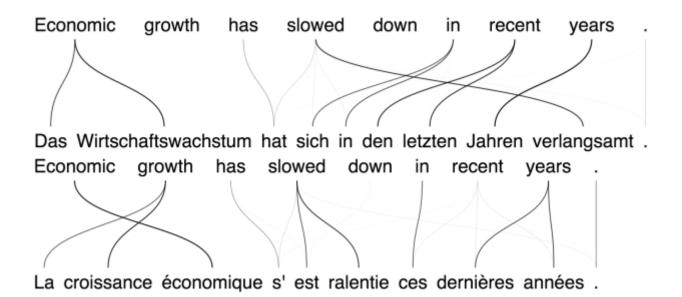
<u>picture source (https://machinelearningmastery.com/encoder-decoder-recurrent-neural-network-models-neural-machine-translation/)</u>

Attention model 解決的問題

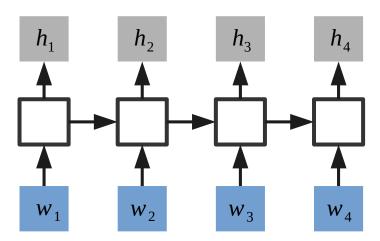


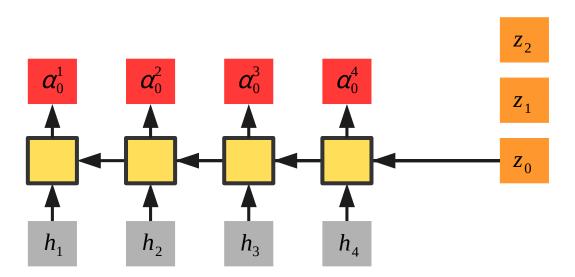
<u>picture source (https://medium.com/@ageitgey/machine-learning-is-fun-part-5-language-translation-with-deep-learning-and-the-magic-of-sequences-2aceOaccaOaa)</u>

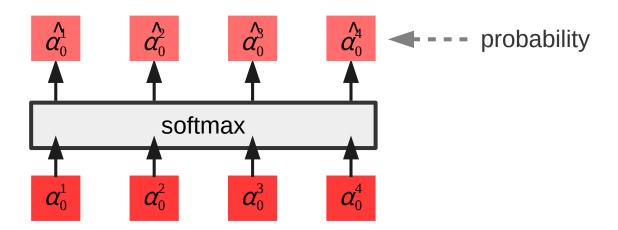
How to solve the problem?

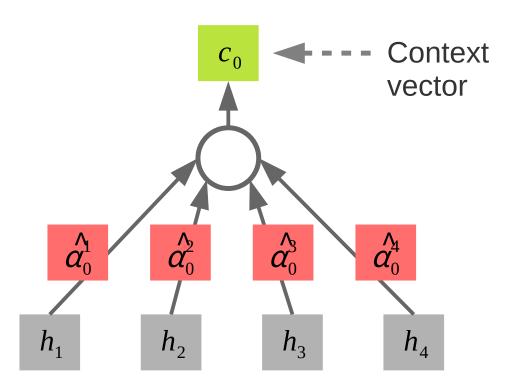


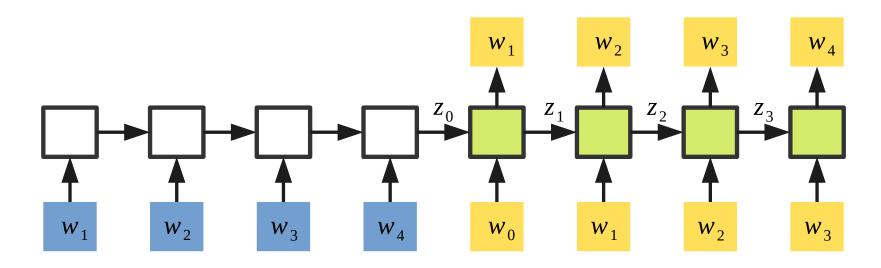
<u>picture source (https://devblogs.nvidia.com/introduction-neural-machine-translation-gpus-part-3/)</u>

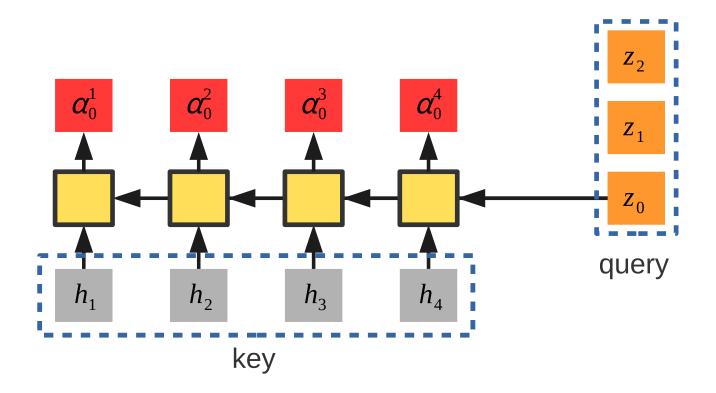


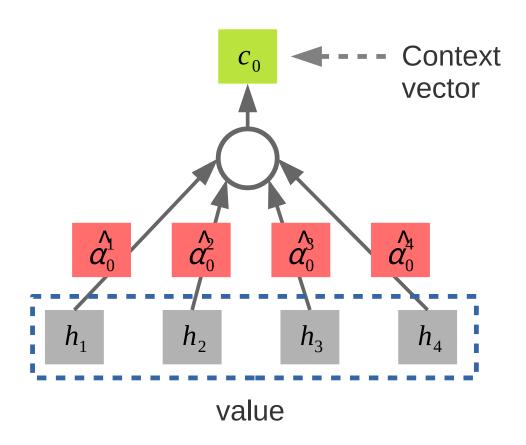


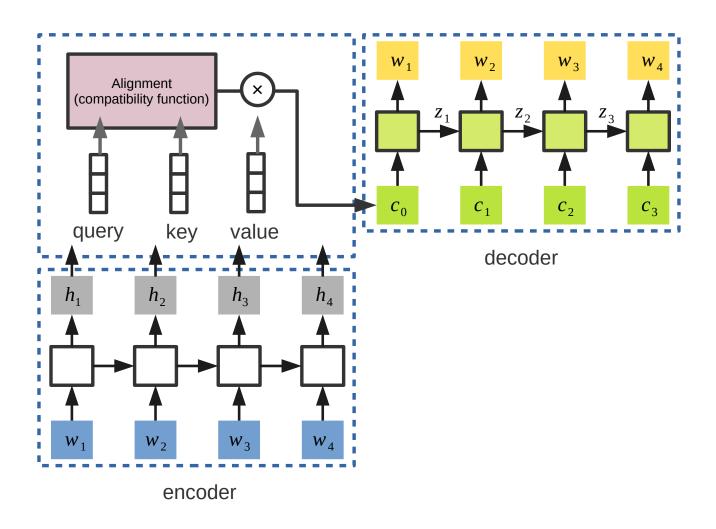








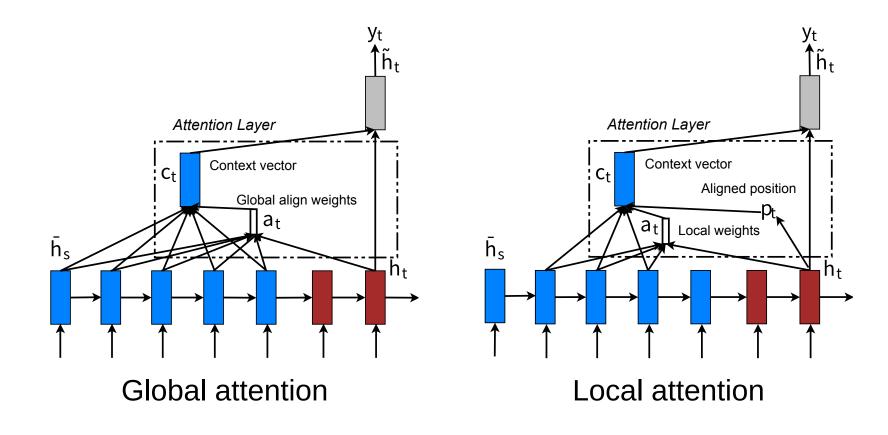




Attention types

- Global/local attention
- Hard/soft attention
- Self-attention

Global/local attention



Hard/soft attention

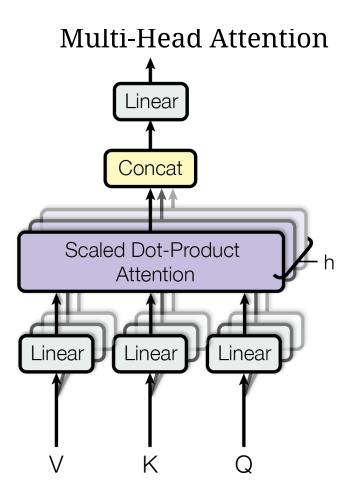
Soft attention

- Alignment weights are learned to attend over all data
- $0 \le w \le 1$
- Pro: model is smooth and differentiable
- Con: large computation if input is large

Hard attention

- Select part of data to attend or not at a time
- 0 or 1
- Pro: less inference time
- Con: model is non-differentiable

Self-attention



Alignment (compatibility function)

query: q_j , key: k_i

Location-based

$$lpha^i_j = softmax(W_lpha q_j)$$

Content-based

$$score(q_j, k_i) = cos([q_j; k_i])$$

Additive

$$score(q_j, k_i) = v_{lpha}^T tanh(W_{lpha}[q_j; k_i])$$

Alignment (compatibility function)

General

$$score(q_j, k_i) = q_j^T W_{lpha} k_i$$

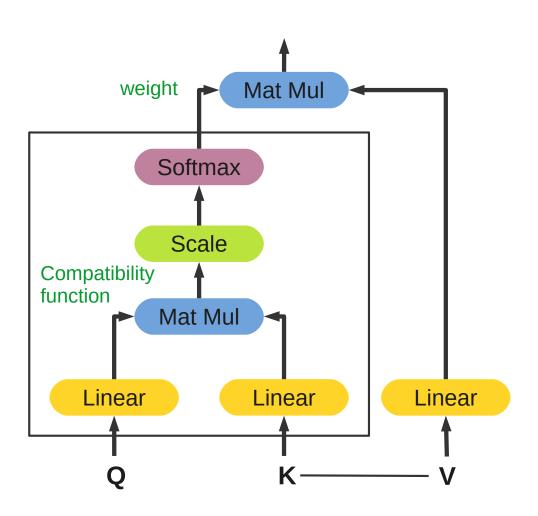
Dot-product

$$score(q_j, k_i) = q_j^T k_i$$

Scaled dot-product

$$score(q_j, k_i) = rac{q_j^T k_i}{\sqrt{n}}$$

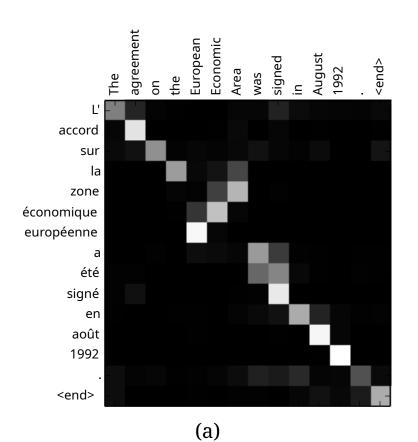
Scaled dot-product attention

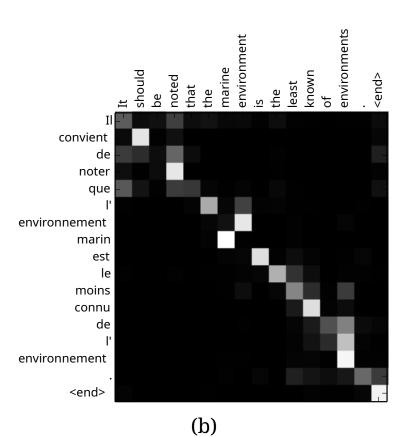


Applications of attention

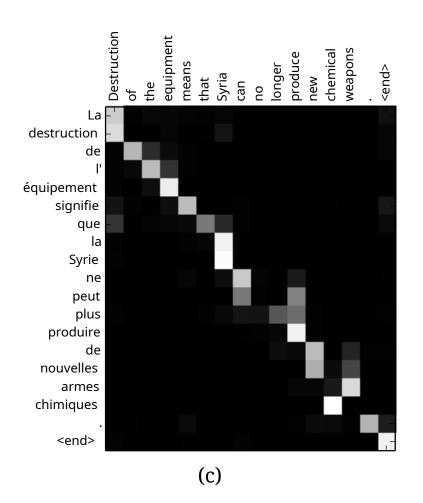
- Summarization: Rush 2015 (https://arxiv.org/abs/1509.00685)
- Translation: <u>Bahdanau 2014 (https://arxiv.org/abs/1409.0473)</u>, <u>Luong 2015 (https://arxiv.org/abs/1508.04025)</u>
- Image caption: Xu 2015 (https://arxiv.org/abs/1502.03044)
- ...

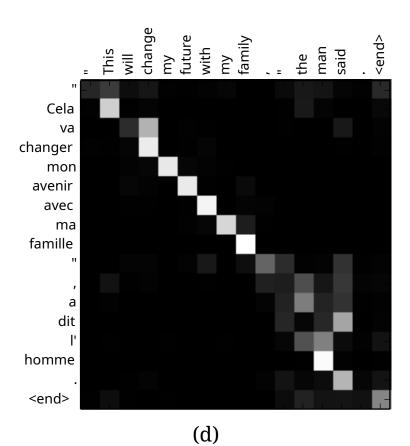
Translation





Translation





Summarization

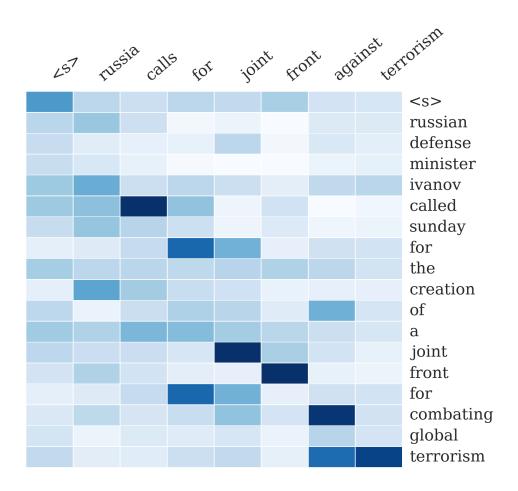


Image caption

Figure 5.Examples of mistakes where we can use attention to gain intuition into what the model saw.



A large white bird standing in a forest.



A woman holding a clock in her hand.



A man wearing a hat and a hat on a skateboard.



A person is standing on a beach with a <u>surfboard.</u>

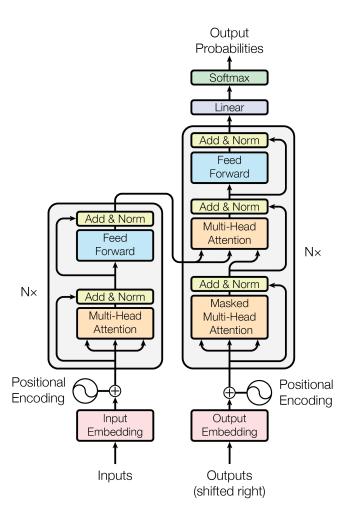


A woman is sitting at a table with a large pizza.



A man is talking on his cell <u>phone</u> while another man watches.

Transformer



The era of Transformer

Why self-attention?

• More or equal efficient than RNN/CNN

Integration of RNN/CNN into Transformer

Thank you for attention.

References

- Attention? Attention! (https://lilianweng.github.io/lil-log/2018/06/24/attentionattention.html)
- 放棄幻想,全面擁抱 Transformer:自然語言處理三大特徵抽取器 (CNN/RNN/TF) 比較 (http://bangqu.com/f7t7X5.html)

Papers