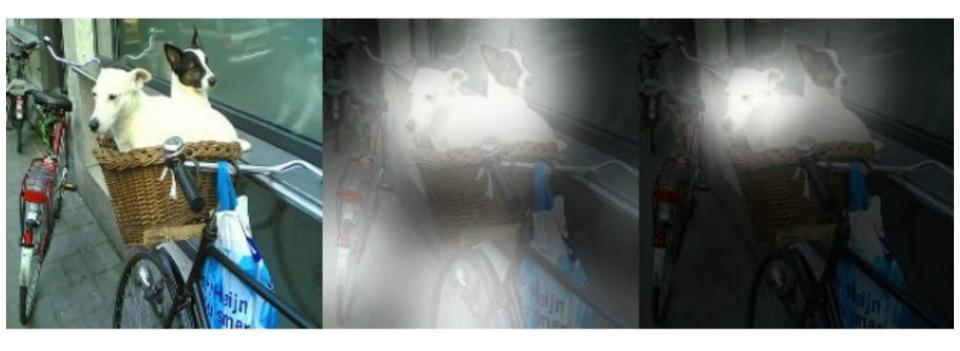
3. Iterative Pooling



original image

first attention layer

second attention layer aws

Question Answering

Joe went to the kitchen.

Fred went to the kitchen.

Joe picked up the milk.

Joe travelled to the office.

Joe left the milk.

Joe went to the bathroom.

Where is the milk?



Question Answering

Joe went to the kitchen.

Fred went to the kitchen.

Joe picked up the milk.

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Question Answering

Joe went to the kitchen. Fred went to the kitchen.

Joe picked up the milk.

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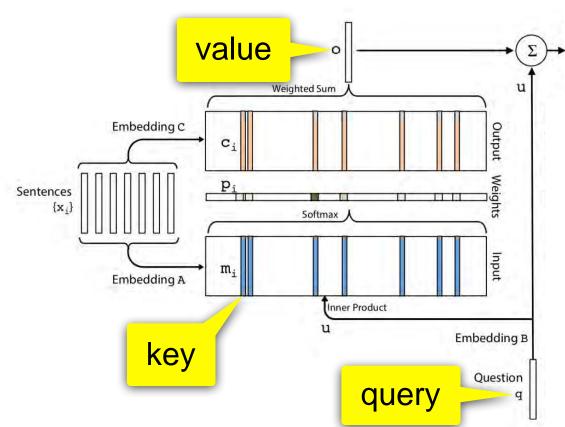
Joe left the milk.

Joe went to the bathroom.

Where is the milk?

- Simple attention selects sentences with 'milk'.
- Attention pooling doesn't help much since it misses intermediate steps.

Question Answering with Pooling (Sukhbaatar et al., '15)



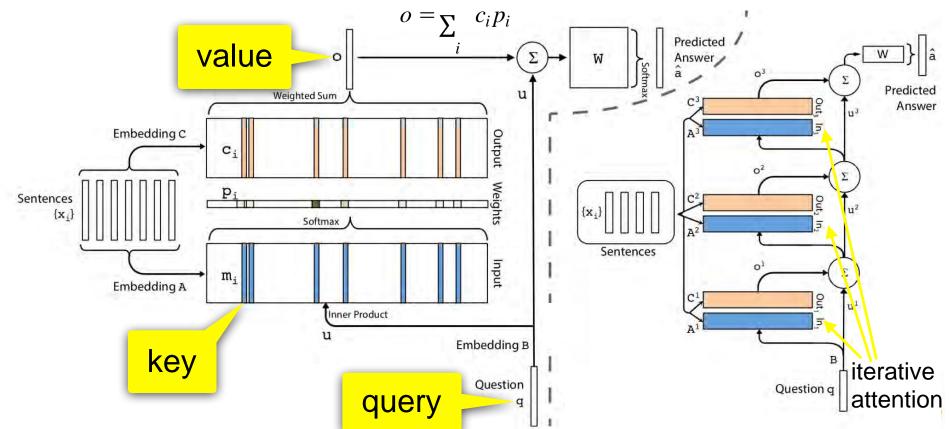
 Simple attention selects sentences with 'milk'.

Predicted

Answer

 Attention pooling doesn't help much since it misses intermediate steps.

Question Answering with Pooling and Iteration (Sukhbaatar et al., '15)



Question Answering with Pooling and Iteration (Sukhbaatar et al., '15)

Sam walks into the kitchen.
Sam picks up an apple.
Sam walks into the bedroom.
Sam drops the apple.

Q: Where is the apple?

A. Bedroom

Brian is a lion.

Julius is a lion.

Julius is white.

Bernhard is green.

Q: What color is Brian?

A. White

Mary journeyed to the den.

Mary went back to the kitchen.

John journeyed to the bedroom.

Mary discarded the milk.

O: Where was the milk before the den?

A. Hallway



Question Answering with Pooling and Iteration (Yang et al., '16) feature vectors of different parts of image key & value input都是一樣的(每-Query **Question: Answer** Softmax What are sitting CNN/ dogs in the basket on **LSTM** a bicycle? Attention layer 1 Attention layer 2

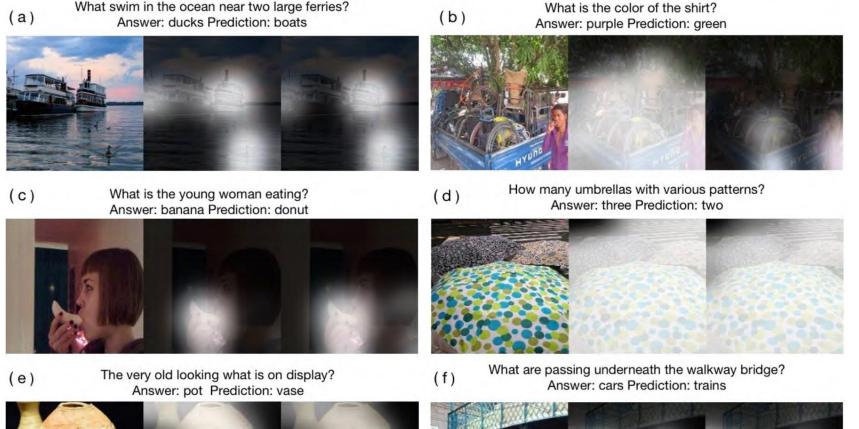
Question Answering with Pooling and Iteration (Yang et al., '16)

- Encode image via CNN
- Encode text query via LSTM
- Weigh patches according to attention and iterate

- Improving it (2019 tools)
 - Convolutionalize CNN (e.g. ResNet)
 - BERT for query encoding
 - Convolutional weighting (a la SE-Net)



What is the color of the box? What are pulling a man on a wagon down on dirt road? (b) (a) Answer: red Prediction: red Answer: horses Prediction: horses (d) How many people are going up the mountain with walking sticks? What next to the large umbrella attached to a table? (c) Answer: four Prediction: four Answer: trees Prediction: tree What is the color of the horns? What is sitting on the handle bar of a bicycle? (e) (f) Answer: red Prediction: red Answer: bird Prediction: bird aws







Iterative Attention Summary

Pooling

$$f(X) = \rho \left(\sum_{x \in X} \phi(x) \right)$$

Attention pooling

$$f(X) = \rho \sum_{x \in X} \alpha(x, w) \phi(x)$$

Iterative Attention pooling

Repeatedly update internal state

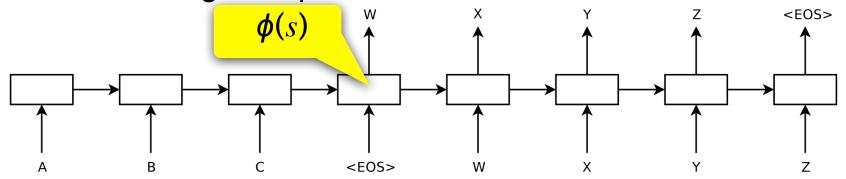
$$q_{t+1} = \rho \sum_{\substack{x \in X}} \alpha(x, q_t) \phi(x)$$





Seq2Seq for Machine Translation, Sutskever, Vinyals, Le '14

- Encode source sequence s via LSTM to representation $\phi(s)$
- Decode to target sequence one character at a time

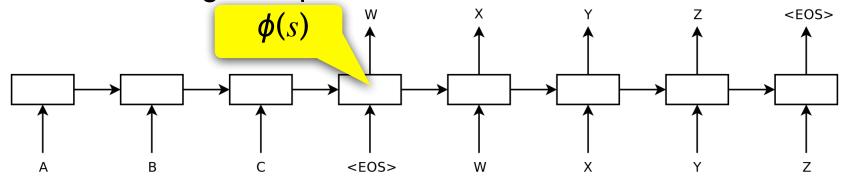


- 'The table is round.' 'Der Tisch ist rund.'
- 'The table is very beautiful with many inlaid patterns, blah blah blah '- 'Error ...'



Seq2Seq for Machine Translation, Sutskever, Vinyals, Le '14

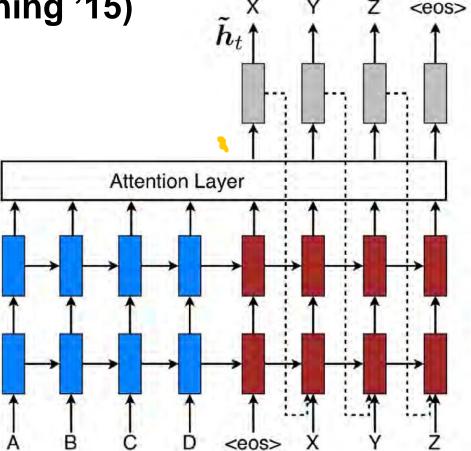
- Encode source sequence s via LSTM to representation $\phi(s)$
- Decode to target sequence one character at a time



- 'The table is round.' 'Der Tisch ist ru
- 'The table is very beautiful with mablah blah blah blah' 'Error ...'

Representation not rich enough





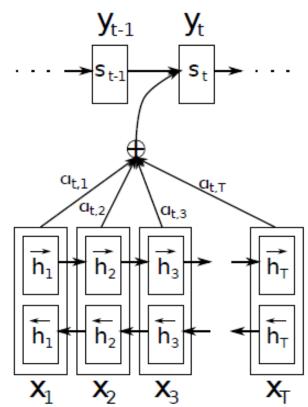


$$e_{ij} = a(s_{i-1}, h_j)$$

$$\alpha_{ij} = \frac{\exp\left(e_{ij}\right)}{\sum_{k=1}^{T_x} \exp\left(e_{ik}\right)},$$

$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j.$$

$$s_i = f(s_{i-1}, y_{i-1}, c_i).$$



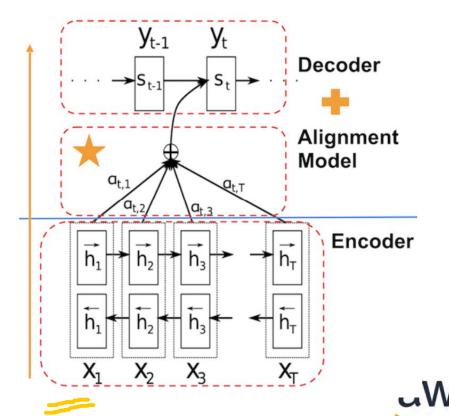


$$e_{ij} = a(s_{i-1}, h_j)$$

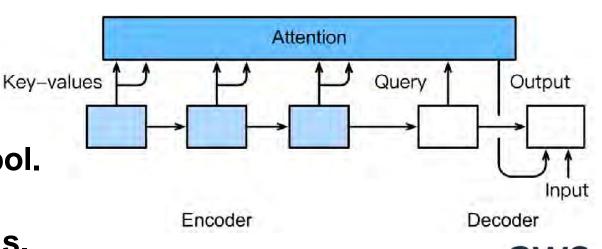
$$\alpha_{ij} = \frac{\exp\left(e_{ij}\right)}{\sum_{k=1}^{T_x} \exp\left(e_{ik}\right)},$$

$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j.$$

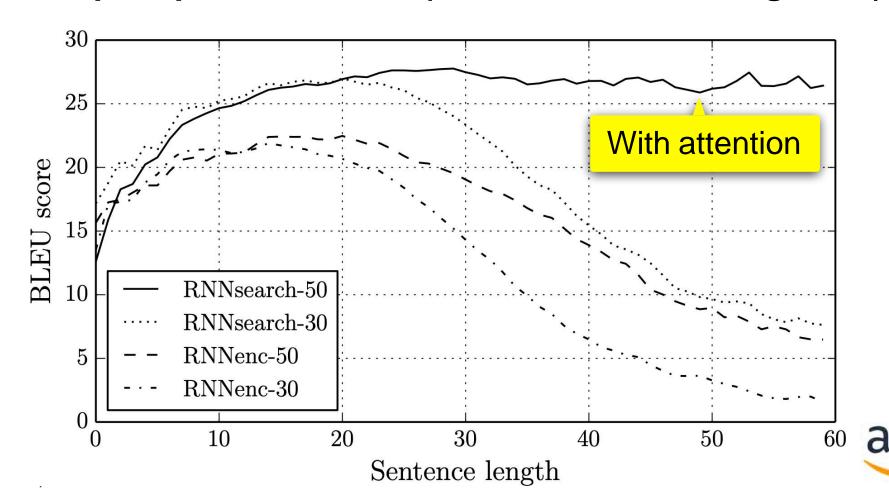
$$s_i = f(s_{i-1}, y_{i-1}, c_i).$$



- Iterative attention model
 - Compute (next) attention weights
 - Aggregate next state
 - Emit next symbol
- Repeat
- Memory networks emit only one symbol.
- NMT with attention emits many symbols.



Seq2Seq with attention (Bahdanau, Cho, Bengio '14)



Variations on a Theme

BWV 988

(PART I)

J.S.Bach (1685-1750)

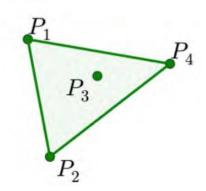




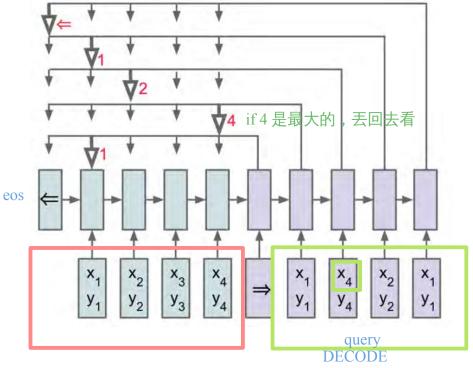
Pointer networks for finding convex hull (Vinyals et al., '15)

Input $P = \{P_1, ...P_4\}$ Output $O = \{1,4,2,1\}$

INPUT OUTPUT不固定 -> SEQ2SEQ



ENCODE (latent) value/key





Pointer networks for finding convex hull (Vinyals et al., '15)

Input
$$P = \{P_1, ...P_4\}$$

Output $O = \{1,4,2,1\}$

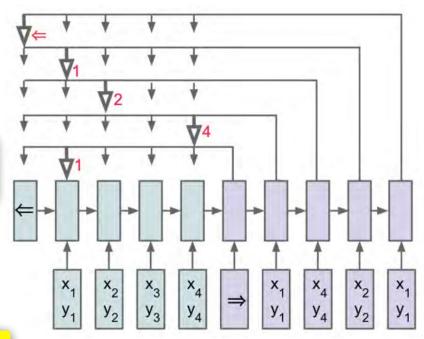
key

query

$$u_{ij} = v^{\top} \tanh(W[e_j, d_i])$$

$$p(C_i \mid C_{[1:i-1]}, P) = \operatorname{softmax}(u_i)$$

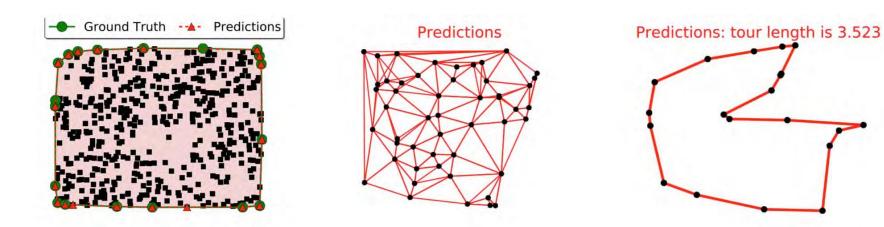
attention weight as prediction distribution



encoder state: *e_i* decoder state: *d_i*



Convex hulls, Delaunay triangulation, and TSP

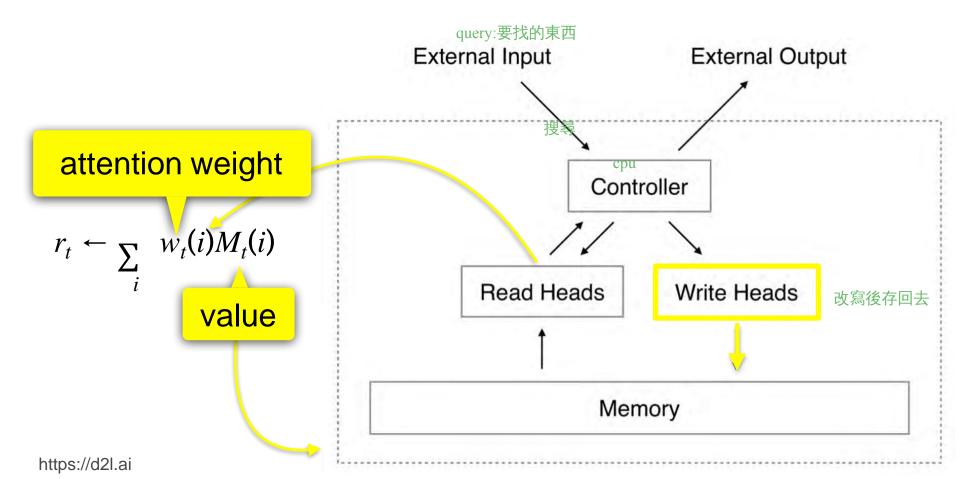


2019 style improvements

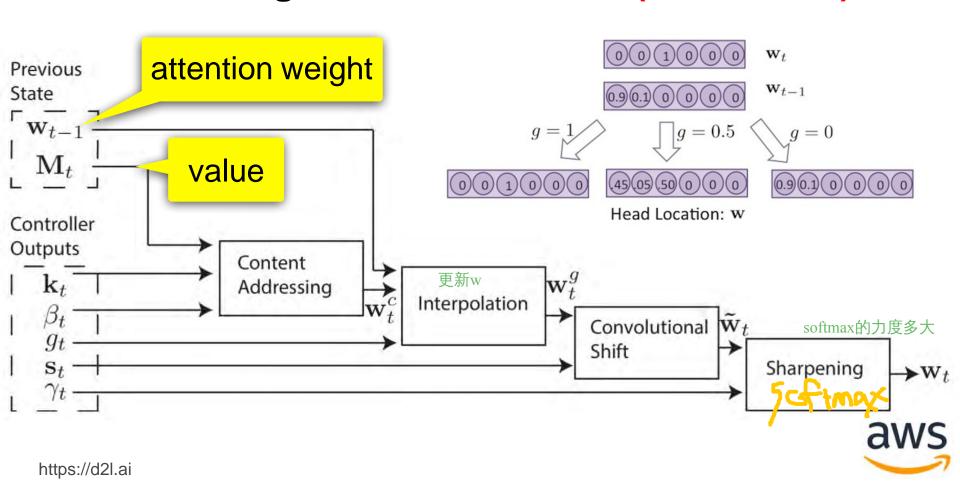
- Transformer to encode inputs (and outputs)
- Graph neural networks for local interactions



Neural Turing Machines (Graves et al., '14)

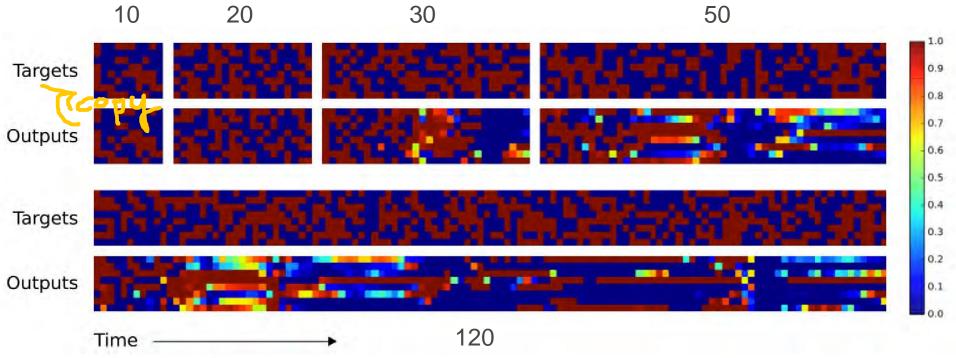


Attention weights can be stateful (values, too)



Copying a sequence (with LSTM)

lstm在短的interval時候是表現不錯的,長的就不行





Copying a sequence (with NTM)

