Attention Mechanism

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8.11

Outline

- History of Attention
 - End-to-End Attention
 - Attention with Deep Learning
- Attention with Image Caption
- Attention with Computer Vision
 - Image classification
 - Fine-grained classification

End-To-End Memory Networks

Sainbayar Sukhbaatar, Arthur Szlam, Jason Weston, Rob Fergus FAIR
In NIPS 2015, cited by 322

Question Answering

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

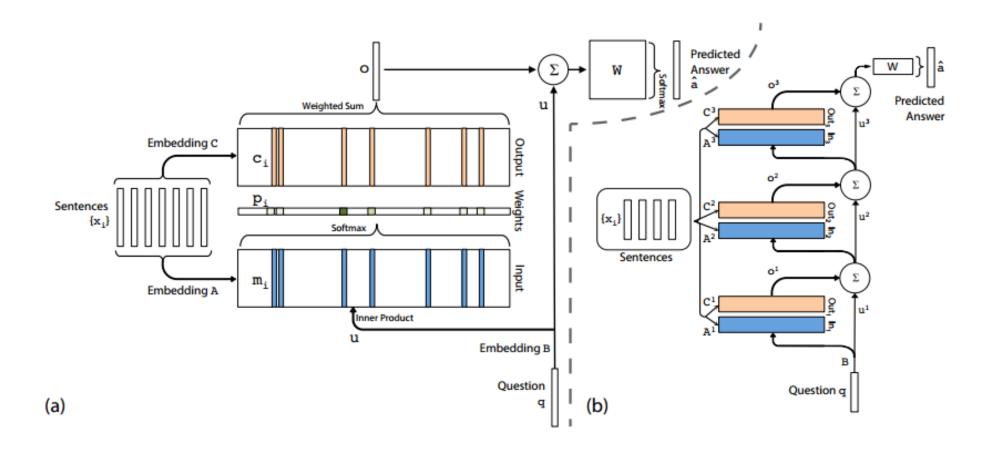
Q: Where is the apple?

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.
Q: Where was the milk before the den?
A. Hallway
```

End-to-End Model



$$p_i = \text{Softmax}(u^T m_i).$$

$$o = \sum_{i} p_i c_i.$$

$$\hat{a} = \mathrm{Softmax}(W(o+u))$$

Extensions

- Weight tying
- Sentence representation: position encoding

$$x_{i} = \{x_{i1}, x_{i2}, ..., x_{in}\}$$

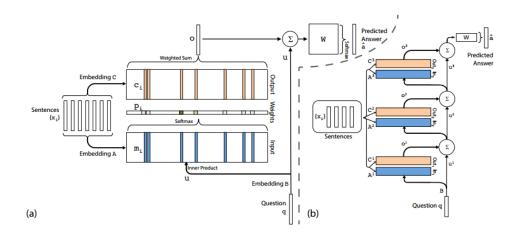
$$m_{i} = \sum_{j} l_{j} \cdot Ax_{ij}$$

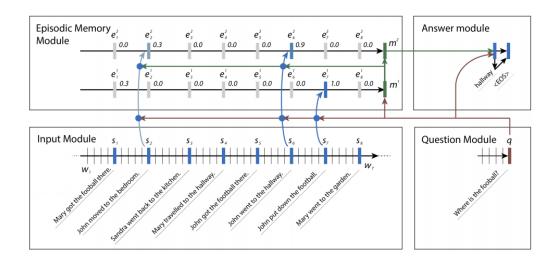
• Linear start

Ask Me Anything: Dynamic Memory Networks for Natural Language Processing

Ankit Kumar, Peter Ondruska, Mohit Iyyer, James Bradbury, Ishaan Gulrajani, Victor Zhong, Romain Paulus, Richard Socher Metamind In ICML 2016, cited by 133

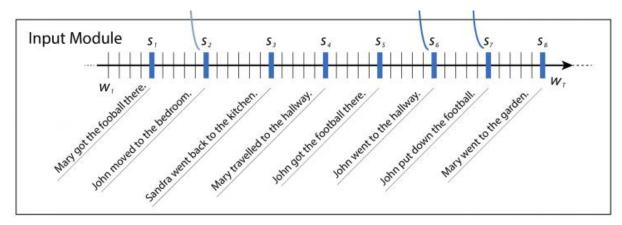
A deep version of end-to-end memory network





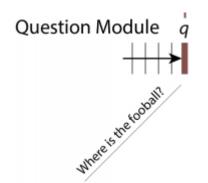
Modules

• Input Module:



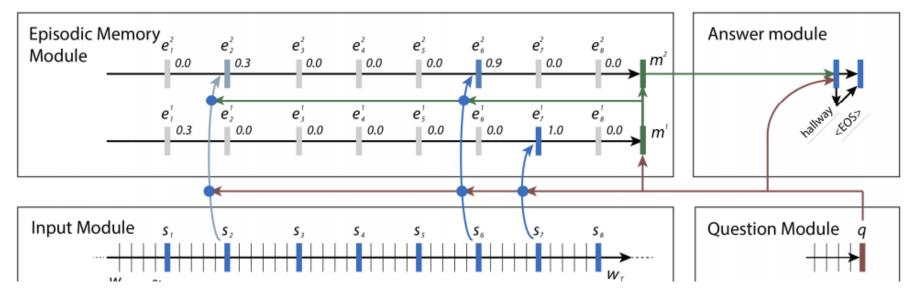
$$h_t = RNN(L[w_t], h_{t-1}),$$

Question Module:



$$q_t = GRU(L[w_t^Q], q_{t-1})$$

Episodic Memory

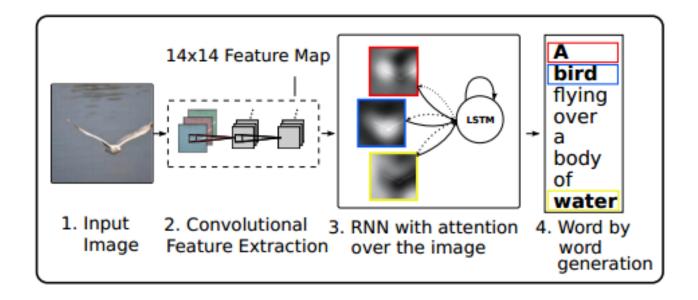


- Two layer feedforward neural network $g_t^i = G(c_t, m^{i-1}, q)$
- Input: $\left[c,m,q,c\circ q,c\circ m,|c-q|,|c-m|,c^TW^{(b)}q,c^TW^{(b)}m\right]$
- Memory update: $h^i_t = g^i_t GRU(c_t, h^i_{t-1}) + (1-g^i_t)h^i_{t-1}$ $e^i = h^i_{T_C}$

Show, Attend and Tell: Neural Image Caption Generation with Visual Attention

Kelvin Xu, Jimmy Lei Ba, Ryan Kiros, Kyunghyun, Aaron Courville, Ruslan Salakhutdinov, Richard S. Zemel, Yoshua Bengio UoT, UMontreal In ICML 2015, cited by 902

Image Caption



Model

• Encoder: CNN

$$a = \{\mathbf{a}_1, \dots, \mathbf{a}_L\}, \ \mathbf{a}_i \in \mathbb{R}^D$$

• Decoder: LSTM

• Input: $e_{ti} = f_{\text{att}}(\mathbf{a}_i, \mathbf{h}_{t-1})$ $\alpha_{ti} = \frac{\exp(e_{ti})}{\sum_{k=1}^{L} \exp(e_{tk})}.$ $\hat{\mathbf{z}}_t = \phi\left(\left\{\mathbf{a}_i\right\}, \left\{\alpha_i\right\}\right)$

Output: word probability

Attention Mechanism

Hard Attention

$$p(s_{t,i} = 1 \mid s_{j < t}, \mathbf{a}) = \alpha_{t,i}$$
$$\hat{\mathbf{z}}_t = \sum_i s_{t,i} \mathbf{a}_i.$$

Soft Attention

$$\mathbb{E}_{p(s_t|a)}[\hat{\mathbf{z}}_t] = \sum_{i=1}^{L} \alpha_{t,i} \mathbf{a}_i$$

Doubly Stochastic Attention

$$\hat{\phi}(\{\mathbf{a}_i\}, \{\alpha_i\}) = \beta \sum_{i=1}^{L} \alpha_i \mathbf{a}_i \qquad \sum_{t=1}^{L} \alpha_{ti} \approx 1$$

Results



A woman is throwing a frisbee in a park.



A dog is standing on a hardwood floor.



A <u>stop</u> sign is on a road with a mountain in the background.



A little <u>girl</u> sitting on a bed with a teddy bear.



A group of <u>people</u> sitting on a boat in the water.



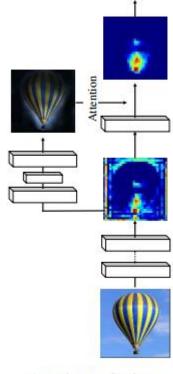
A giraffe standing in a forest with <u>trees</u> in the background.

Residual Attention Network for Image Classification

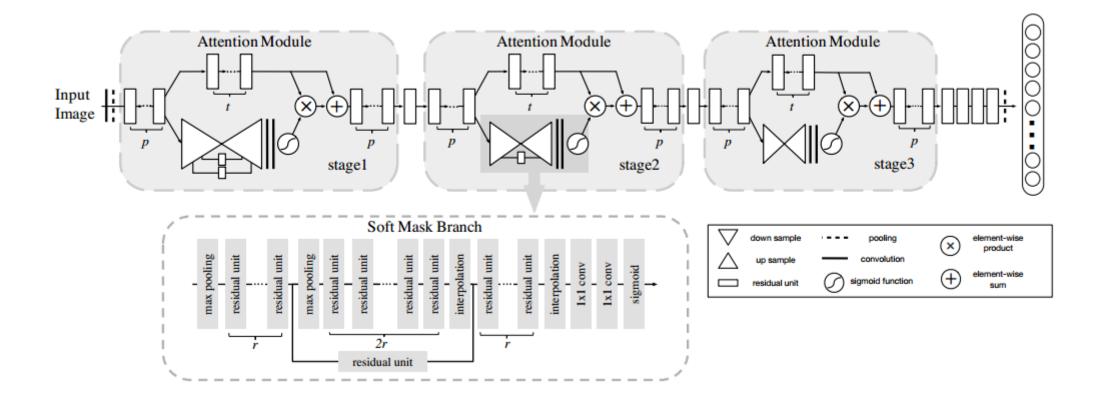
Fei Wang, Mengqing Jiang, Chen Qian, Shuo Yang, Cheng Li, Honggang Zhang, Xiaogang Wang, Xiaoou Tang SenseTime In CVPR 2017, SpotLight, cited by 1

Intuition

- Attention will help for classification
- Direct attention will diminish information



Model



Attention

- Mixed attention
- Channel attention
- Spatial attention

$$f_1(x_{i,c}) = \frac{1}{1 + exp(-x_{i,c})}$$

$$f_2(x_{i,c}) = \frac{x_{i,c}}{\|x_i\|}$$

$$f_3(x_{i,c}) = \frac{1}{1 + exp(-(x_{i,c} - \text{mean}_c)/\text{std}_c)}$$

Look Closer to See Better: Recurrent Attention Convolutional Neural Network for Fine-grained Image Recognition

Jianlong Fu, Heliang Zheng, Tao Mei MSRA In CVPR Oral