Reinforced Mnemonic Reader for Machine Reading Comprehension

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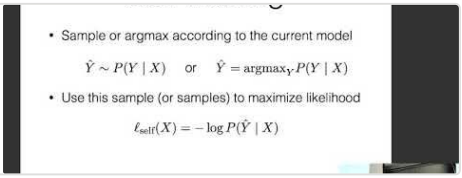
Reference

Reinforced Mnemonic Reader for Machine Reading Comprehension
In this paper, we introduce the Reinforced Mnemonic Reader for machine reading comprehension tasks, which enhances previous attentive readers in two aspects. First, a reattention mechanism is
https://arxiv.org/abs/1705.02798

CMU Neural Nets for NLP 2018 (14): Reinforcement
Uploaded by Graham Neubig on 2018-03-08.
https://www.youtube.com/watch?v=isxzsAelQX0&t=8s



MRC with Reattention (machine reading comprehension)

Alignment Architecture for MRC

Single-round alignment architecture

$$E_{ij} = f(v_i, u_j) \qquad (1)$$

- Vi: question
- Uj: context
- Eij: similarity matrix (similarity between i-th question word and j-th context word)

$$B_{ij} = \mathbb{1}_{\{i \neq j\}} f(h_i, h_j) \quad (2)$$

- Hij: question-aware context representation
- Bij: another similarity matrix

Single-round alignment architecture limited in its capability to capture complex interactions among question and context.

Multi-round alignment architectures

stacking several identical aligning layers

$$E_{ij}^t = f(v_i^t, u_j^t), \qquad B_{ij}^t = \mathbb{1}_{\{i \neq j\}} f(h_i^t, h_j^t) \qquad (3)$$

- Vt: t-th hidden representations of question
- Ut: t-th hidden representations of context
- Ht: t-th question-aware context representation

Reattention Mechanism

1. the *attention redundancy*: where multiple attention distributions are highly similar.

   $$D(\mathrm{softmax}(E_{:j}^t) \| \mathrm{softmax}(E_{:j}^k)) < \sigma(t \neq k)$$

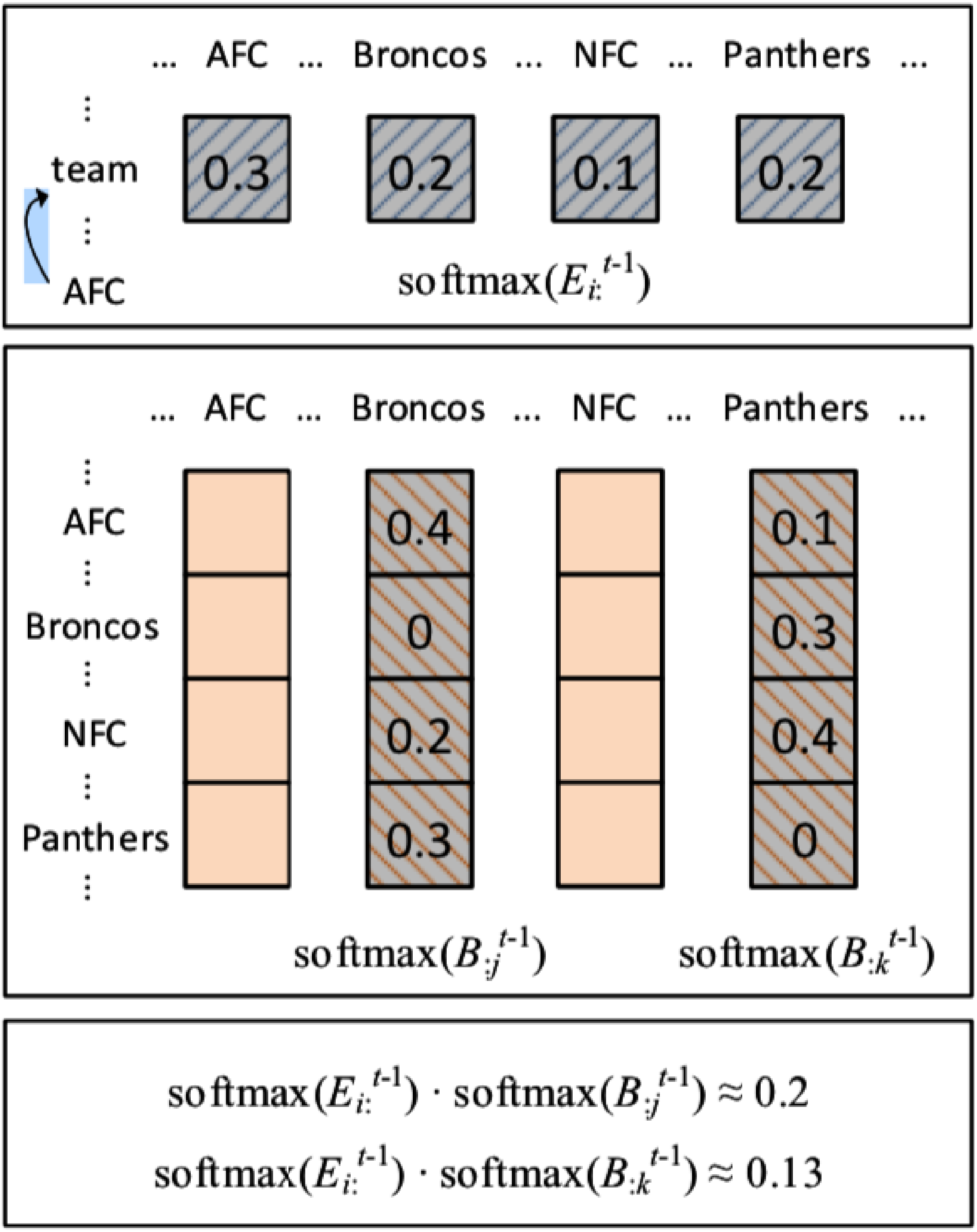
   - σ: is a small bound
   - D: is a function measuring the distribution distance

2. the *attention deficiency*: which means that the attention fails to focus on salient parts of the input

   $$D(\mathrm{softmax}(E_{:j}^{t\,*}) \| \mathrm{softmax}(E_{:j}^t)) > \delta$$

   - Et*: ground truth attention distribution.

We propose to temporally memorize past attentions and explicitly use them to refine current attentions.



- The similarity of word pair (*team*, *Broncos*) is higher than (*team*, *Panthers*).

$$
\begin{aligned}
\tilde{E}_{ij}^{t} &= \mathrm{softmax}(E_{i:}^{t-1}) \cdot \mathrm{softmax}(B_{:j}^{t-1}) \\
E_{ij}^{t} &= f(v_i^t, u_j^t) + \gamma \tilde{E}_{ij}^{t}
\end{aligned}
\qquad (4)
$$

- softmax(Et−1): the past context attention distribution for the i-th question word
- softmax(Bt−1): the past self attention distribution for the j-th context word
- γ: s a trainable parameter

$$
\begin{aligned}
\tilde{B}^t_{ij} =& \mathrm{softmax}(B^{t-1}_{i:}) \cdot \mathrm{softmax}(B^{t-1}_{:j}) \\
B^t_{ij} =& \mathbb{1}_{(i \neq j)} \left(f(h^t_i, h^t_j) + \gamma \tilde{B}^t_{ij} \right)
\end{aligned}
\tag{5}
$$

Dynamic-critical Reinforcement Learning

- standard maximum-likelihood (ML)

  $$p(A|C,Q;\theta) = p_1(i|C,Q;\theta)p_2(j|i,C,Q;\theta) \tag{6}$$

  - p1: predicting the start position i
  - p2: predicting the end position j
  - θ: all trainable parameters

  $$\mathcal{L}_{ML}(\theta) = -\sum_k \log p_1(y^1_k) + \log p_2(y^2_k|y^1_k) \tag{7}$$

- self-critical sequence training (SCST)

  $$\mathcal{L}_{SCST}(\theta) = -\mathbb{E}_{A^s \sim p_\theta(A)}[R(A^s) - R(\hat{A})] \tag{8}$$

  $$\hat{A} = \arg\max_A p(A|C,Q;\theta)$$

  - Rs: ampled answer
  - A^: A baseline is obtained by running greedy inference with the current model
  - R(As): F1 score between a sampled answer As and the ground truth A∗
  - R(A^): F1 score between a greedy inference answer As and the ground truth A∗

- Gradient

$$\nabla_\theta \mathcal{L}_{SCST}(\theta) = -\mathbb{E}_{A^s \sim p_\theta(A)}[(R(A^s) - b)\, \nabla_\theta \log p_\theta(A^s)]$$
$$\approx -\left(R(A^s) - R(\hat{A})\right) \nabla_\theta \log p_\theta(A^s) \qquad (9)$$

Context: The American Football Conference (AFC) champion Denver Broncos defeated the National Football Conference (NFC) champion Carolina Panthers 24–10 to earn their third Super Bowl title.

Question: Which NFL team represented the AFC at Super Bowl 50?
Answer: Denver Broncos

  - As: *champion Denver Broncos:*
  - Aˆ: *Denver Broncos*
  - the normalized reward would be negative and the prediction for end position would be suppressed. *convergence suppression* problem.
- dynamic-critical reinforcement learning (DCRL)

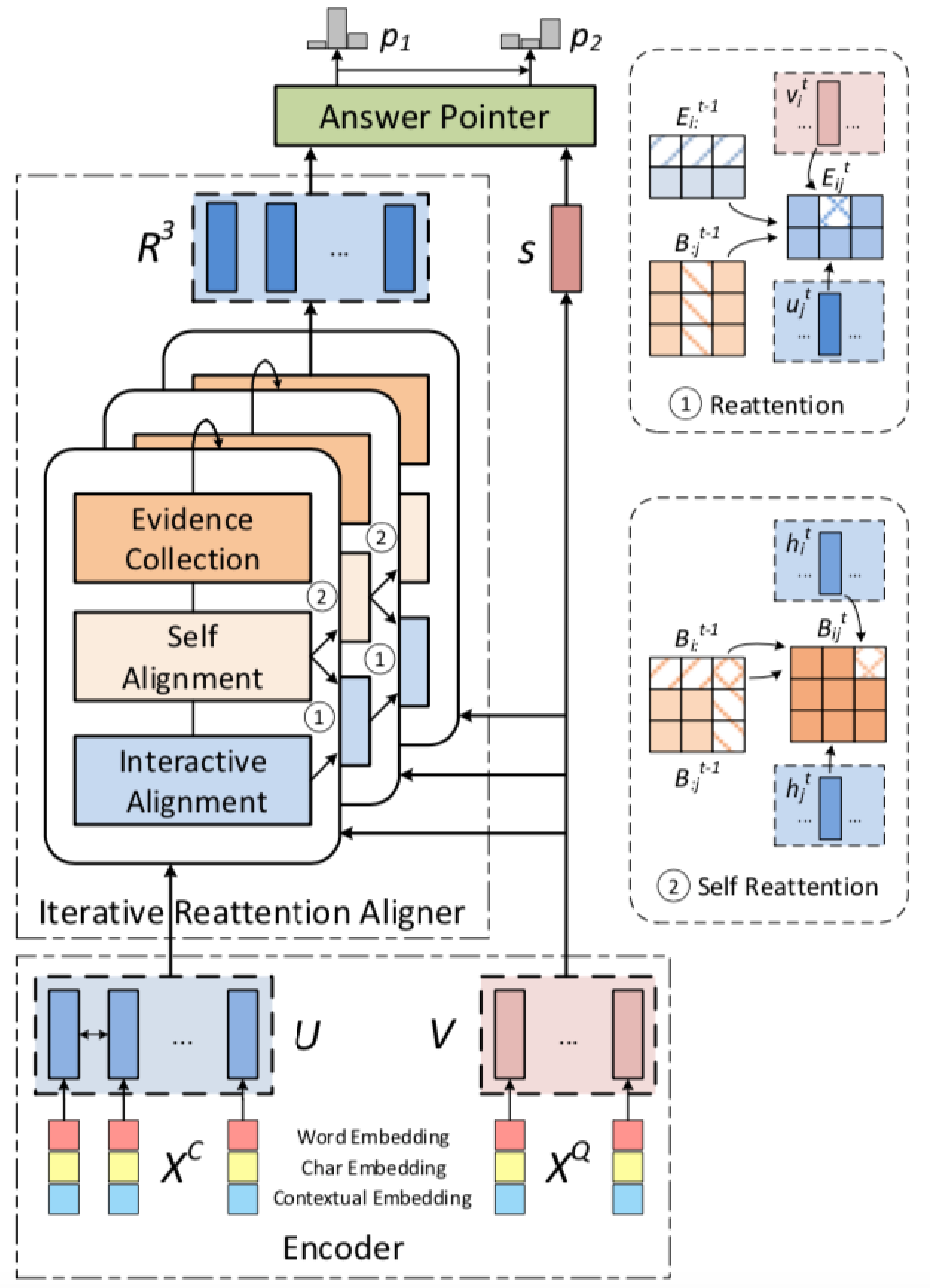
$$\nabla_\theta \mathcal{L}_{DCRL}(\theta) = -\mathbb{E}_{A^s \sim p_\theta(A)}[(R(A^s) - b)\, \nabla_\theta \log p_\theta(A^s)]$$
$$\approx -\mathbb{1}_{\{R(A^s) \geq R(\hat{A})\}} \left(R(A^s) - R(\hat{A})\right) \nabla_\theta \log p_\theta(A^s)$$
$$- \mathbb{1}_{\{R(\hat{A}) > R(A^s)\}} \left(R(\hat{A}) - R(A^s)\right) \nabla_\theta \log p_\theta(\hat{A}) \quad (10)$$

- combine ML and DCRL objectives

$$\mathcal{L} = \frac{1}{2\sigma_a^2}\mathcal{L}_{ML} + \frac{1}{2\sigma_b^2}\mathcal{L}_{DCRL} + \log \sigma_a^2 + \log \sigma_b^2 \qquad (11)$$

  - combine ML and DCRL objectives
  - σa, σb: trainable parameters

End-to-end Architecture



Encoder

builds contextual representations for question and context jointly

$$v_i = \mathrm{BiLSTM}(x_i^q), \quad u_j = \mathrm{BiLSTM}(x_j^c) \qquad (12)$$

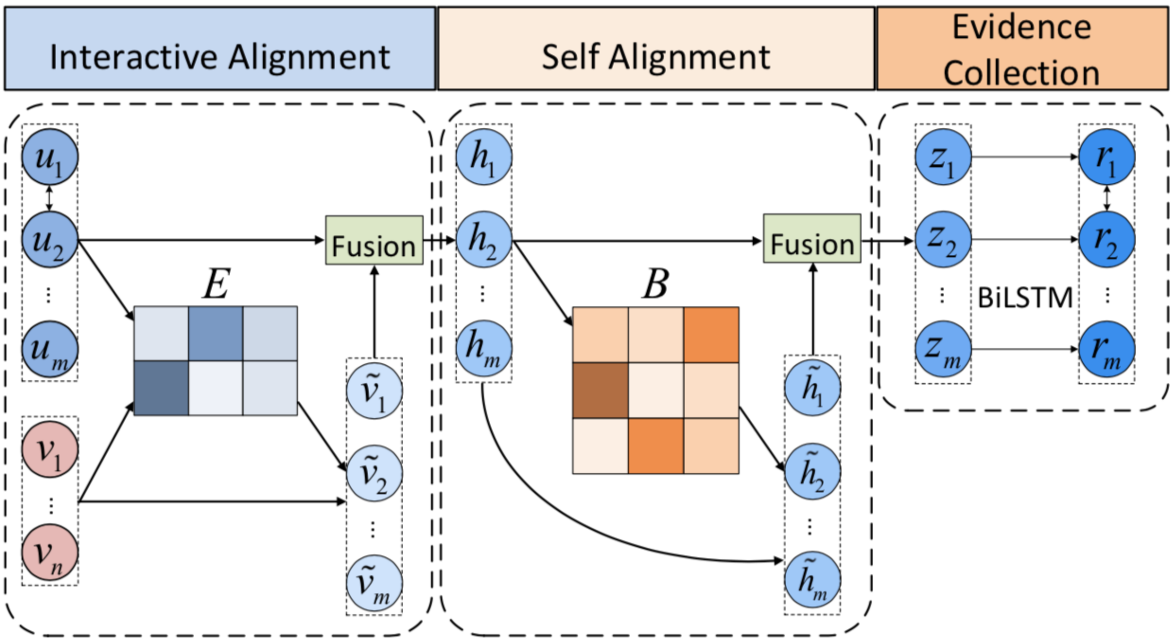
- 100-dim GloVe embedding (소스에는 CoVe?)
- 1024-dim ELMo embedding
- character-level embedding by encoding the character sequence with a BiLSTM
- POS embedding
- NER embedding
- weight-shared BiLSTM

Iterative Aligner

performs multi-round alignments between question and context with the reattention mechanism

1. interactive alignment: attend the question into the context;
2. self alignment: attend the context against itself;
3. evidence collection: model the context representation with a BiLSTM.

Single Aligning Block.



- compute question attention for the j-th context word is then: softmax(E:j)
    - $f(u,v) = relu(W_u u)^T relu(W_v v)$
    - $\tilde{v}_j = V \cdot softmax(E_{:j})$
    - heuristic fusion function: o = fusion(x, y)

$$\begin{aligned} \tilde{x} &= \text{relu}\left(W_r[x; y; x \circ y; x - y]\right) \\ g &= \sigma\left(W_g[x; y; x \circ y; x - y]\right) \\ o &= g \circ \tilde{x} + (1 - g) \circ x \end{aligned} \tag{13}$$

        - σ: sigmoid activation function
        - ∘: element-wise multiplication
        - bias term: omitted
        - gate g: similar to the highway networks, used to control the composition degree to which the intermediate vector (x, x˜) is exposed.
- self alignment: applied to capture the long-term dependencies among context words
    - $h_j = fusion(u_j, \tilde{v}_j)$
    - $\tilde{h}_j = H \cdot softmax(B_{:j})$
- BiLSTM is used to perform the evidence collection
    - $z_j = fusion(h_j, \tilde{h}_j)$
    - $r_j = BiLSTM(z_j)$

Multi-round Alignments with Reattention.

$$\begin{aligned} R^1, Z^1, E^1, B^1 &= \text{align}^1(U, V) \\ R^2, Z^2, E^2, B^2 &= \text{align}^2(R^1, V, E^1, B^1) \\ R^3, Z^3, E^3, B^3 &= \text{align}^3(R^2, V, E^2, B^2, Z^1, Z^2) \end{aligned} \tag{14}$$

Answer Pointer.

- p1

$$p_1(i) \propto \exp\left(w_1^{\mathrm{T}} \tanh(W_1[r_i^3; s; r_i^3 \circ s; r_i^3 - s])\right) \qquad (15)$$

  - $s = \sum_{i=1}^{n} a_i v_i$
  - $a_i \propto \exp(w^T v_i)$

- p2

$$p_2(j|i) \propto \exp\left(w_2^{\mathrm{T}} \tanh(W_2[r_j^3; \tilde{s}; r_j^3 \circ \tilde{s}; r_j^3 - \tilde{s}])\right) \qquad (16)$$

  - $\tilde{s} = fusion(s, l)$
  - $l = R^3 \cdot p_1$

Experiments

- The performance of Reinforced Mnemonic Reader and other competing approaches on the SQuAD dataset

Single Model	**Dev**		**Test**	
	EM	**F1**	**EM**	**F1**
LR Baseline[1]	40.0	51.0	40.4	51.0
DCN+[2]	74.5	83.1	75.1	83.1
FusionNet[3]	75.3	83.6	76.0	83.9
SAN[4]	76.2	84.1	76.8	84.4
AttentionReader+[†]	-	-	77.3	84.9
BSE[5]	77.9	85.6	78.6	85.8
R-net+[†]	-	-	79.9	86.5
SLQA+[†]	-	-	80.4	87.0
Hybrid AoA Reader+[†]	-	-	80.0	87.3
R.M-Reader	**78.9**	**86.3**	**79.5**	**86.6**
Ensemble Model				
DCN+[2]	-	-	78.8	86.0
FusionNet[3]	78.5	85.8	79.0	86.0
SAN[4]	78.6	85.8	79.6	86.5
BSE[5]	79.6	86.6	81.0	87.4
AttentionReader+[†]	-	-	81.8	88.2
R-net+[†]	-	-	82.6	88.5
SLQA+[†]	-	-	82.4	88.6
Hybrid AoA Reader+[†]	-	-	82.5	89.3
R.M-Reader	**81.2**	**87.9**	**82.3**	**88.5**
Human[1]	80.3	90.5	82.3	91.2

- Performance comparison on two adversarial datasets.

Model	**AddSent**		**AddOneSent**	
	EM	**F1**	**EM**	**F1**
LR Baseline	17.0	23.2	22.3	41.8
Match-LSTM[1*]	24.3	34.2	34.8	41.8
BiDAF[2*]	29.6	34.2	40.7	46.9
SEDT[3*]	30.0	35.0	40.0	46.5
ReasoNet[4*]	34.6	39.4	43.6	49.8
FusionNet[5*]	46.2	51.4	54.7	60.7
R.M-Reader	**53.0**	**58.5**	**60.9**	**67.0**

- AblationstudyonSQuADdevset.

Configuration	**EM**	**F1**	**ΔEM**	**ΔF1**
R.M-Reader	78.9	86.3	–	–
(1) - Reattention	78.1	85.8	-0.8	-0.5
(2) - DCRL	78.2	85.4	-0.7	-0.9
(3) - Reattention, DCRL	77.1	84.8	-1.8	-1.5
(4) - DCRL, + SCST	78.5	85.8	-0.4	-0.5
(5) Attention: Dot	78.2	85.9	-0.7	-0.4
(6) - Heuristic Sub	78.1	85.7	-0.8	-0.6
(7) - Heuristic Mul	78.3	86.0	-0.6	-0.3
(8) Fusion: Gate	77.9	85.6	-1.0	-0.7
(9) Fusion: MLP	77.2	85.2	-1.7	-1.1
(10) Num of Blocks: 2	78.7	86.1	-0.2	-0.2
(11) Num of Blocks: 4	78.8	86.3	-0.1	0
(12) Num of Blocks: 5	77.5	85.2	-1.4	-1.1

- Effectiveness of Reattention

KL divergence	**- Reattention**	**+ Reattention**
Redundancy		
E^1 to E^2	0.695 ± 0.086	$\mathbf{0.866} \pm 0.074$
E^2 to E^3	0.404 ± 0.067	0.450 ± 0.052
B^1 to B^2	0.976 ± 0.092	$\mathbf{1.207} \pm 0.121$
B^2 to B^3	1.179 ± 0.118	1.193 ± 0.097
Deficiency		
E^2 to E^{2*}	0.650 ± 0.044	$\mathbf{0.568} \pm 0.059$
E^3 to E^{3*}	0.536 ± 0.047	$\mathbf{0.482} \pm 0.035$

- Predictions with DCRL (red) and with SCST (blue) on SQuAD dev set

Context: Carolina's secondary featured Pro Bowl safety Kurt Coleman, who led the team with a career high seven interceptions, while also racking up 88 tackles and Pro Bowl cornerback Josh Norman, who developed into a shutdown corner during the season and had four interceptions, two of which were returned for touchdowns.

Question: How many interceptions did Josh Norman score touchdowns with in 2015?
Answer: two

Context: The further decline of Byzantine state-of-affairs paved the road to a third attack in 1185, when a large Norman army invaded Dyrrachium, owing to the betrayal of high Byzantine officials. Some time later, Dyrrachium—one of the most important naval bases of the Adriatic—fell again to Byzantine hands.

Question: Where was Dyrrachium located?
Answer: the Adriatic

Context: The motor used polyphase current which generated a rotating magnetic field to turn the motor (a principle Tesla claimed to have conceived in 1882). This innovative electric motor, patented in May 1888, was a simple self-starting design that did not need a commutator, thus avoiding sparking and the high maintenance of constantly servicing and replacing mechanical brushes.

Question: What high maintenance part did Tesla's AC motor not require?
Answer: mechanical brushes

Source Code

ewrfcas/Reinforced-Mnemonic-Reader
Reinforced Mnemonic Reader for Machine Reading Comprehension with reinforcement loss in tensorflow -
https://github.com/ewrfcas/Reinforced-Mnemonic-Rea...