

FusionNet

Motivation

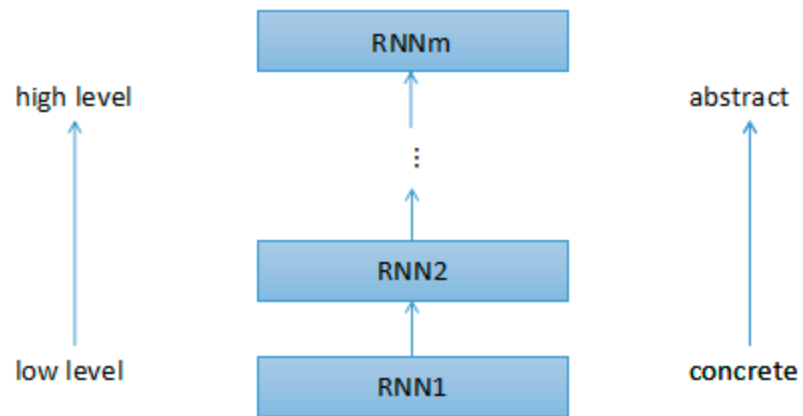
- 1.The encoding for word of the whole history procedure is important.
- 2.The fully-aware multi-level attention fusion is important.

Contributions

This paper proposes a novel attention mechanism with following three contributions:

- 1.The concept of "history of words" to build the attention using complete information from lowest word-level embedding up to the highest semantic-level representation.
- 2.It proposes a novel attention scoring function.
- 3.It proposes a fully-aware multi-level fusion to exploit information layer by layer.

Multi-Level



Scoring Function

$$S_{ij} = f(U(\text{HoW}_i^A))^T D f(U(\text{HoW}_j^B))$$

Fully-Aware Fusion Network

Input Vectors

context: 921-dim {300-dim GloVe embedding, 600-dim contextualized vector, 12-dim POS embedding, 8-dim NER embedding, 1-dim normalized term frequency}

question: 900-dim {300-dim GloVe embedding, 600-dim contextualized vector}

$$C : \{w_1^C, \dots, w_m^C\} \in R^{900+20+1}$$

$$Q : \{w_1^Q, \dots, w_n^Q\} \in R^{900}$$

Fully-aware Multi-level Fusion: Word-level

$$\hat{g}_i^C = \sum_j \alpha_{ij} g_j^Q, \quad \alpha_{ij} \propto \exp(S(g_i^C, g_j^Q)), \quad S(x, y) = \text{ReLU}(Wx)^T \text{ReLU}(Wy)$$

em_i is created for each word in C to indicate whether the word occurs in the question Q.

$$\tilde{w}_i^C = [w_i^C; em_i; \hat{g}_i^C]$$

Reading

$$h_1^{Cl}, \dots, h_m^{Cl} = \text{BiLSTM}(\tilde{w}_1^C, \dots, \tilde{w}_m^C), \quad h_1^{Ql}, \dots, h_n^{Ql} = \text{BiLSTM}(w_1^Q, \dots, w_n^Q),$$

$$h_1^{Ch}, \dots, h_m^{Ch} = \text{BiLSTM}(h_1^{Cl}, \dots, h_m^{Cl}), \quad h_1^{Qh}, \dots, h_n^{Qh} = \text{BiLSTM}(h_1^{Ql}, \dots, h_n^{Ql}).$$

Hence low-level and high-level concept $h^l, h^h \in \mathbb{R}^{250}$ are created for each word.

Question Understanding

$$U_Q = \{u_1^Q, \dots, u_n^Q\} = \text{BiLSTM}([h_1^{Ql}; h_1^{Qh}], \dots, [h_n^{Ql}; h_n^{Qh}]).$$

where $\{u_i^Q \in \mathbb{R}^{250}\}_{i=1}^n$ are the understanding vectors for Q .

Fully-aware Multi-level Fusion: Higher-level

$$\text{HoW}_i^C = [g_i^C; c_i^C; h_i^{Cl}; h_i^{Ch}], \quad \text{HoW}_i^Q = [g_i^Q; c_i^Q; h_i^{Ql}; h_i^{Qh}] \in \mathbb{R}^{1400},$$

1. Low-level fusion: $\hat{h}_i^{Cl} = \sum_j \alpha_{ij}^l h_j^{Ql}$, $\alpha_{ij}^l \propto \exp(S^l(\text{HoW}_i^C, \text{HoW}_j^Q))$.
2. High-level fusion: $\hat{h}_i^{Ch} = \sum_j \alpha_{ij}^h h_j^{Qh}$, $\alpha_{ij}^h \propto \exp(S^h(\text{HoW}_i^C, \text{HoW}_j^Q))$.
3. Understanding fusion: $\hat{u}_i^C = \sum_j \alpha_{ij}^u u_j^Q$, $\alpha_{ij}^u \propto \exp(S^u(\text{HoW}_i^C, \text{HoW}_j^Q))$.

$$V_C = \{v_1^C, \dots, v_m^C\} = \text{BiLSTM}([h_1^{Cl}; h_1^{Ch}; \hat{h}_1^{Cl}; \hat{h}_1^{Ch}; \hat{u}_1^C], \dots, [h_m^{Cl}; h_m^{Ch}; \hat{h}_m^{Cl}; \hat{h}_m^{Ch}; \hat{u}_m^C]).$$

Fully-aware Self-boosted Fusion

$$\text{HoW}_i^C = [g_i^C; c_i^C; h_i^{Cl}; h_i^{Ch}; \hat{h}_i^{Cl}; \hat{h}_i^{Ch}; \hat{u}_i^C; v_i^C] \in \mathbb{R}^{2400}.$$

Then perform fully-aware attention,

$$\hat{v}_i^C = \sum_j \alpha_{ij}^s v_j^C, \quad \alpha_{ij}^s \propto \exp(S^s(\text{HoW}_i^C, \text{HoW}_j^C)).$$

The final context representation is

$$U_C = \{u_1^C, \dots, u_m^C\} = \text{BiLSTM}([v_1^C; \hat{v}_1^C], \dots, [v_m^C; \hat{v}_m^C]).$$

Output

Through the above operations, we can get

$$U_C = u_1^C, \dots, u_m^C,$$

$$U_Q = u_1^Q, \dots, u_n^Q$$

Then we get the vector representation of Q

$$u^Q = \sum_i \beta_i u_i^Q$$

For start,

$$P_i^S \propto \exp((u^Q)^T W_S u_i^C),$$

For end,

$$v^Q = \text{GRU}(u^Q, \sum_i P_i^S u_i^C)$$

$$P_i^E \propto \exp((v^Q)^T W_E u_i^C)$$

Experiments

Attention Function	EM / F1
Additive (MLP)	71.8 / 80.1
Multiplicative	72.1 / 80.6
Scaled Multiplicative	72.4 / 80.7
Scaled Multiplicative + ReLU	72.6 / 80.8
Symmetric Form	73.1 / 81.5
Symmetric Form + ReLU	75.3 / 83.6

Configuration		Dev EM / F1
<i>C</i> , <i>Q</i> Fusion	Self <i>C</i>	
High-level	None	64.6 / 73.2
FA High-level		73.3 / 81.4
FA All-level		72.3 / 80.7
FA Multi-level		74.6 / 82.7
FA Multi-level	Normal	74.4 / 82.6
	FA	75.3 / 83.6