论文阅读笔记

Step6

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1 Cognitive Graph for Multi-Hop Reading Comprehension at Scale

这篇文章基于Bert和GNN，在迭代中逐步构建出cognitive graph：$\mathcal{G}$，图中的每一个节点都和一个实体或者一个可能的答案有关。由两部分组成：implicit extraction（System 1）和explicit reasoning（System 2）。

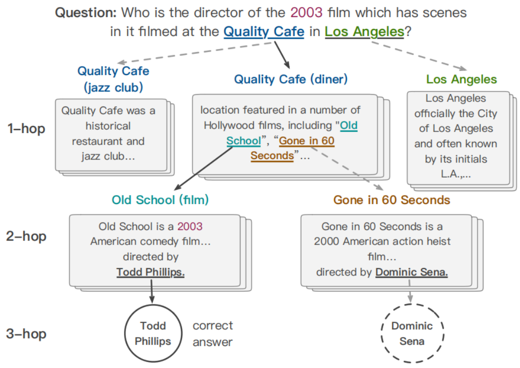


Figure 1: An example of cognitive graph for multi-hop QA. Each *hop node* corresponds to an entity (e.g., "Los Angeles") followed by its introductory paragraph. The circles mean *ans nodes*, answer candidates to the question. Cognitive graph mimics human reasoning process. Edges are built when calling an entity to "mind". The solid black edges are the correct reasoning path.

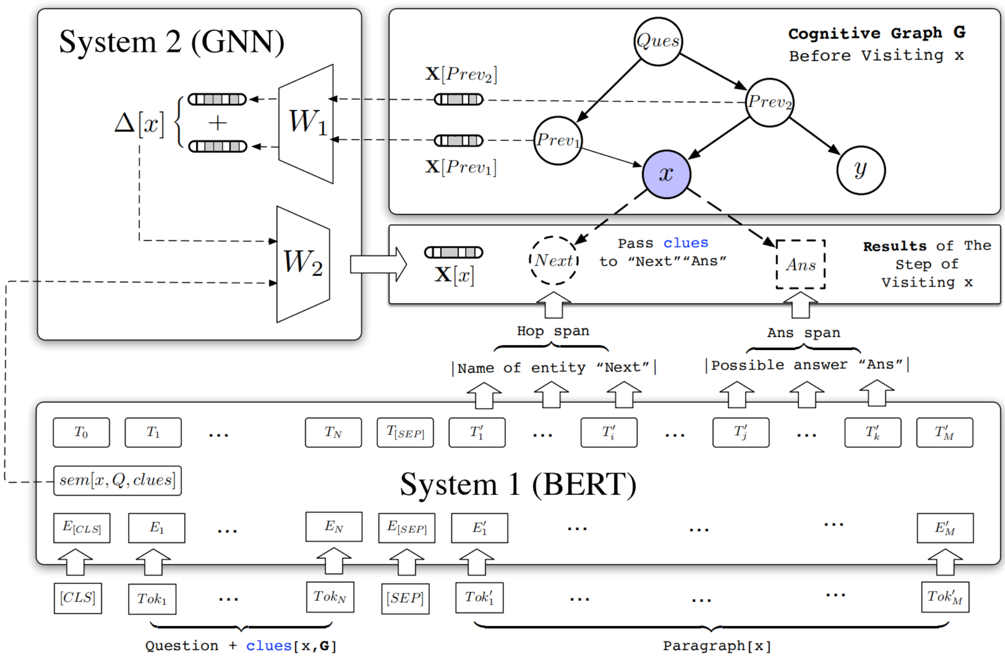


Figure 2: Overview of CogQA implementation. When visiting the node x, System 1 generates new hop and answer nodes based on the $clues[x, \mathcal{G}]$ discovered by System 2. It also creates the inital representation $sem[x, Q, clues]$, based on which the GNN in System 2 updates the hidden representations $\mathbf{X}[x]$.

Algorithm 1: Cognitive Graph QA

Input:
System 1 model $\mathcal{S}_1$, System 2 model $\mathcal{S}_2$,
Question Q, Predictor $\mathcal{F}$,Wiki Database $\mathcal{W}$

Initialize cognitive graph $\mathcal{G}$ with entities mentioned in Q and mark them *frontier nodes*
repeat
  pop a node x from frontier nodes
  collect $clues[x, \mathcal{G}]$ from predecessor nodes of x
   // eg. $clues$ can be sentences where x is mentioned
  fetch $para[x]$ in $\mathcal{W}$ if any
  generate $sem[x, Q, clues]$ with $\mathcal{S}_1$ // initial $\mathbf{X}[x]$
  if *x is a hop node* **then**
    find hop and answer spans in $para[x]$ with $\mathcal{S}_1$
    for *y in hop spans* **do**
      if *$y \notin \mathcal{G}$ and $y \in \mathcal{W}$* **then**
        create a new hop node for y
      if *$y \in \mathcal{G}$ and edge$(x, y) \notin \mathcal{G}$* **then**
        add edge (x, y) to $\mathcal{G}$
        mark node y as a frontier node
    end
    for *y in answer spans* **do**
      add new answer node y and edge (x, y) to $\mathcal{G}$
    end
  end
  update hidden representation $\mathbf{X}$ with $\mathcal{S}_2$
until *there is no frontier node in $\mathcal{G}$ or $\mathcal{G}$ is large enough*;
Return $\underset{\text{answer node } x}{\arg\max}\ \mathcal{F}(\mathbf{X}[x])$

[注] 本文选取的数据集是HotpotQA，HotpotQA 是一个大型问答数据集，它包含约 11.3 万个具备上述特征的问答对。也就是说，这些问题要求问答系统能够筛选大量的文本文档，以找到与生成答案相关的信息，并对找到的多个支撑性事实进行多步推理，从而得出最终答案。

System 1从段落中提取与问题相关的实体和answer candidate，并对其语义信息进行编码。提取的实体被组织成一个Cognitive Graph。然后，系统2对图进行推理，并收集线索指导系统1更好地提取下一跳实体。

System 1(Bert)：

$$\underbrace{[CLS]Question[SEP]\,\text{clues}[x, \mathcal{G}][SEP]}_{\text{Sentence } A}\ \underbrace{\text{Para}[x]}_{\text{Sentence } B} \tag{1.1}$$

System 2(GNN)：

$$\begin{aligned} \Delta &= \sigma\left(\left(AD^{-1}\right)^{T} \sigma\left(\mathbf{X} W_1\right)\right) \\ \mathbf{X}' &= \sigma\left(\mathbf{X} W_2 + \Delta\right) \end{aligned} \tag{1.2}$$

2 Exploiting Explicit Paths for Multi-hop Reading Comprehension

本文基于WikiHop数据集，在该数据集中问题以三元组的形式出现$(h_e, r, ?)$，h_e代表head entity，r代表head entity和未知的tail entity之间的关系。任务是从给定的candidates集合中选出一个答案:$(c_1, c_2, \ldots, c_N)$。

所做的工作是在预测答案的同时，将推理的path展示出来。方法很intuitive，但难的是想到并去做这个工作。

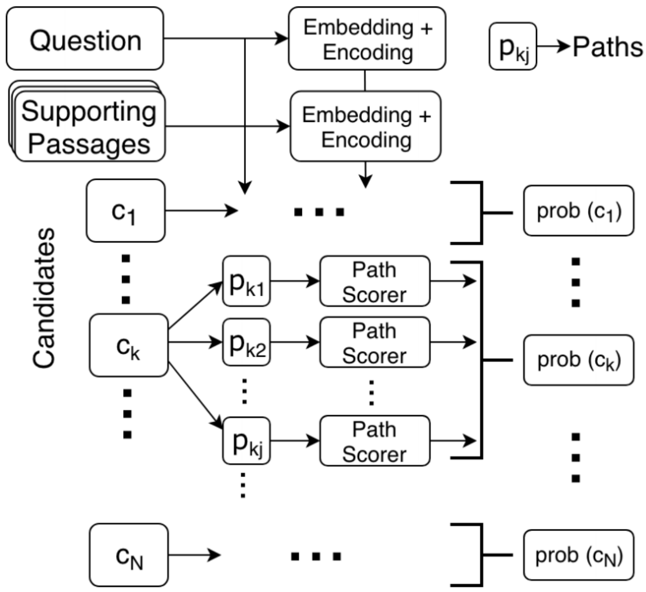


图 1: Architecture of the proposed model

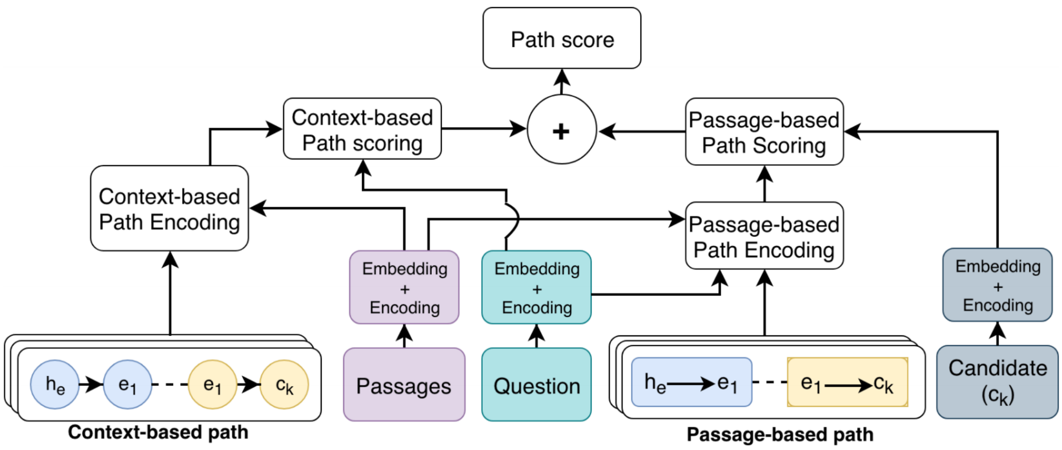


图 2: Architecture of the proposed path scoring module

模型的流程是：

1. 提取Path 在含有h_e的第一篇文章中，找出在那句话或者下一句话中出现的所有实体，然后在其它的passage中寻找这些实体，如果该passge也包含candidate中的单词那么则构建出了一个path。为每一个candidate构建一个从h_e的路径。

2. 对所有的path进行encoding以及score，选出answer以及输出path。

[1] Context-based Path Encoding:

对于2-hop的path：$(h_e, e_1), (e_1, c_k)$:

$$\mathbf{g}_{h_e} = \mathbf{s}_{p_1,i_1} \| \mathbf{s}_{p_1,i_2} \tag{2.1}$$

$$\mathrm{FFL}(\mathbf{a}, \mathbf{b}) = \tanh\left(\mathbf{a}\mathbf{W}_a + \mathbf{b}\mathbf{W}_b\right) \tag{2.2}$$

$$\mathbf{r}_{h_e,e_1} = \mathrm{FFL}\left(\mathbf{g}_{h_e}, \mathbf{g}_{e_1}\right) \tag{2.3}$$

$$\mathbf{x}_{ctx} = \mathrm{FFL}\left(\mathbf{r}_{h_e,e_1}, \mathbf{r}_{e_1,c_k}\right) \tag{2.4}$$

[2] Passage-based Path Encoding:

首先计算相似矩阵：$\mathbf{A}_p \in \mathbb{R}^{T\times U}$，然后分别计算question-aware passage和passage-aware question：$\mathbf{S}_p^{q_1} = \mathbf{A}\mathbf{Q}$和$\mathbf{Q}_p = \mathbf{A}^\top \mathbf{S}_p$，根据更新的question表示再计算$\mathbf{S}_p^{q_2} \in \mathbb{R}^{T\times H}$，其中$\mathbf{S}_p^{q_2} = \mathbf{A}\mathbf{Q}_p$

然后将两次计算的结果拼接：$S_p^q \in \mathbb{R}^{T\times 2H} = \mathbf{S}_p^{q_1} \| \mathbf{S}_p^{q_2}$。

$$\begin{aligned} a_t^p &\propto \exp\left(\mathbf{s}_{p,t}^q \mathbf{w}^\top\right) \\ \tilde{\mathbf{s}}_p &= \mathbf{a}^p \mathbf{S}_p^q \end{aligned} \tag{2.5}$$

$$\mathbf{x}_{psg} = \mathrm{FFL}\left(\tilde{\mathbf{s}}_{p1}, \tilde{\mathbf{s}}_{p_2}\right) \tag{2.6}$$

[3] Path Scoring:

$$\tilde{\mathbf{q}} = \left(\mathbf{q}_0 \| \mathbf{q}_U\right) \mathbf{W}_q \tag{2.7}$$

$$\mathbf{y}_{x_{ctx},q} = \mathrm{FFL}\left(\mathbf{x}_{ctx}, \tilde{\mathbf{q}}\right) \tag{2.8}$$

$$z_{ctx} = \mathbf{y}_{x_{ctx},q} \mathbf{w}_{ctx}^\top \tag{2.9}$$

$$z_{psg} = \tilde{\mathbf{c}}_k \mathbf{x}_{psg}^\top \tag{2.10}$$

$$z = z_{ctx} + z_{psg} \tag{2.11}$$

3 Relational inductive biases, deep learning, and graph networks

主要介绍了一些GNN的相关应用方法，是Section 1 的论文中System 2的组成部分。

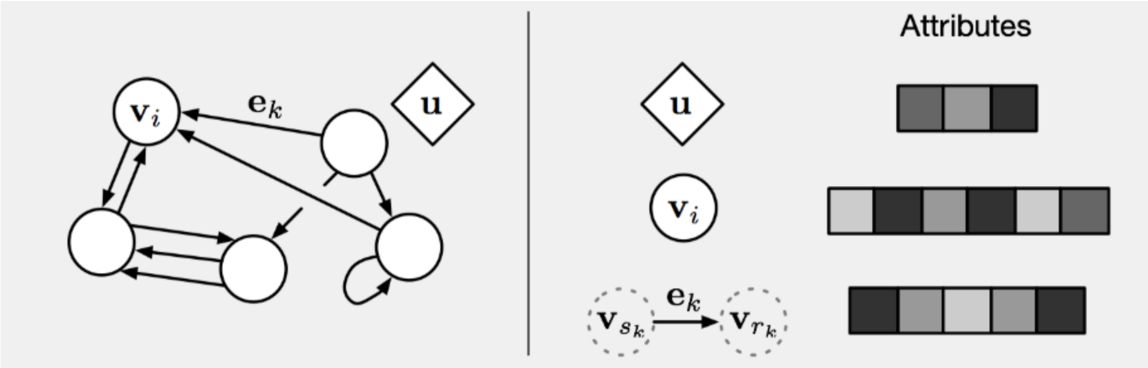


图 3: GNN的定义

GNN中节点更新方式：

$$\begin{aligned} \mathbf{e}'_k &= \phi^e\left(\mathbf{e}_k, \mathbf{v}_{r_k}, \mathbf{v}_{sk}, \mathbf{u}\right) & \overline{\mathbf{e}}'_i &= \rho^{e\rightarrow v}\left(E'_i\right) \\ \mathbf{v}'_i &= \phi^v\left(\overline{\mathbf{e}}'_i, \mathbf{v}_i, \mathbf{u}\right) & \overline{\mathbf{e}}' &= \rho^{e\rightarrow u}\left(E'\right) \\ \mathbf{u}' &= \phi^u\left(\overline{\mathbf{e}}', \overline{\mathbf{v}}', \mathbf{u}\right) & \overline{\mathbf{v}}' &= \rho^{v\rightarrow u}\left(V'\right) \end{aligned} \tag{3.1}$$

Algorithm 1 Steps of computation in a full GN block.

function GraphNetwork(E, V, $\mathbf{u}$)
  for $k \in \{1 \ldots N^e\}$ **do**
    $\mathbf{e}'_k \leftarrow \phi^e\left(\mathbf{e}_k, \mathbf{v}_{r_k}, \mathbf{v}_{s_k}, \mathbf{u}\right)$ ▷ 1. Compute updated edge attributes
  end for
  for $i \in \{1 \ldots N^n\}$ **do**
    let $E'_i = \{(\mathbf{e}'_k, r_k, s_k)\}_{r_k=i,\, k=1:N^e}$
    $\overline{\mathbf{e}}'_i \leftarrow \rho^{e\rightarrow v}\left(E'_i\right)$ ▷ 2. Aggregate edge attributes per node
    $\mathbf{v}'_i \leftarrow \phi^v\left(\overline{\mathbf{e}}'_i, \mathbf{v}_i, \mathbf{u}\right)$ ▷ 3. Compute updated node attributes
  end for
  let $V' = \{\mathbf{v}'\}_{i=1:N^v}$
  let $E' = \{(\mathbf{e}'_k, r_k, s_k)\}_{k=1:N^e}$
  $\overline{\mathbf{e}}' \leftarrow \rho^{e\rightarrow u}\left(E'\right)$ ▷ 4. Aggregate edge attributes globally
  $\overline{\mathbf{v}}' \leftarrow \rho^{v\rightarrow u}\left(V'\right)$ ▷ 5. Aggregate node attributes globally
  $\mathbf{u}' \leftarrow \phi^u\left(\overline{\mathbf{e}}', \overline{\mathbf{v}}', \mathbf{u}\right)$ ▷ 6. Compute updated global attribute
  return $(E', V', \mathbf{u}')$
end function

4 BAM! Born-Again Multi-Task Networks for Natural Language Understanding

多任务模型的性能通常比它们的单任务对应对象差,本文就提出了了一种通用的解决方案。通过Knowledge Distillation，Multi-Task Distillation和Teacher Anneall来解决这个问题。主要思想是对于每一个Task，由Teacher(Teacher的结构和student一样)来“教导”它们该如何去做，在训练一定时间之后，“student”再去向golden answer学习。理由是teacher提供的answer的预测是一个分布，比golden answer的one-hot能够提供更多的信息。比如在图像分类的时候，该图片为马，one-hot只会标注这是一只马，而Teacher预测的distribution不仅能知道是马，还能够知道，相比于自行车飞机什么的，更有可能是一只驴。

1.Kownledge Distillation:

传统的one-hot：$\mathcal{L}(\theta)=\sum_{x_{\tau}^{i}, y_{\tau}^{i} \in \mathcal{D}_{\tau}} \ell\left(y_{\tau}^{i}, f_{\tau}\left(x_{\tau}^{i}, \theta\right)\right)$

Distillation:$\mathcal{L}(\theta)=\sum_{x_{\tau}^{i}, y_{\tau}^{i} \in \mathcal{D}_{\tau}} \ell\left(f_{\tau}\left(x_{\tau}^{i}, \theta^{\prime}\right), f_{\tau}\left(x_{\tau}^{i}, \theta\right)\right)$

2.Multi-Task Distillation:

$$\mathcal{L}(\theta)=\sum_{\tau \in \mathcal{T}} \sum_{x_{\tau}^{i}, y_{\tau}^{i} \in \mathcal{D}_{\tau}} \ell\left(f_{\tau}\left(x_{\tau}^{i}, \theta_{\tau}\right), f_{\tau}\left(x_{\tau}^{i}, \theta\right)\right)$$

3.Teacher Annealing:

$$\ell\left(\lambda y_{\tau}^{i}+(1-\lambda) f_{\tau}\left(x_{\tau}^{i}, \theta_{\tau}\right), f_{\tau}\left(x_{\tau}^{i}, \theta\right)\right)$$

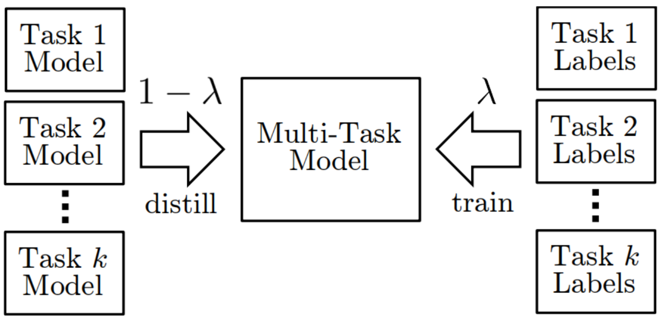
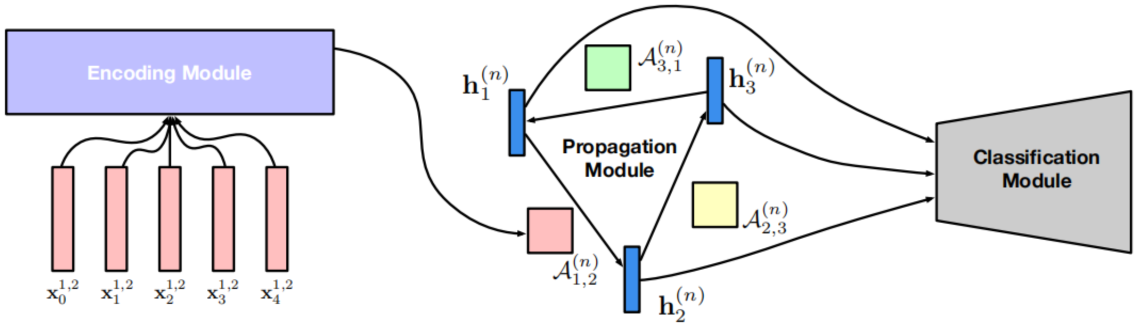


Figure 1: An overview of our method. λ is increased linearly from 0 to 1 over the course of training.

5 Graph Neural Networks with Generated Parameters for Relation Extraction

本文是刘知远老师组里的工作，是GNN在推理和关系抽取上的一次应用：Graph Neural Network with Generated Parameter（GP-GNNs）。



结构分为三部分：

1. Encoding Module:

$$s=(x_0,x_1,\ldots,x_{l-1}) \tag{5.1}$$

$$E\left(x_t^{i,j}\right)=\left[\boldsymbol{x}_t;\boldsymbol{p}_t^{i,j}\right] \tag{5.2}$$

$$\mathcal{A}_{i,j}^{(n)}=f\left(E\left(x_0^{i,j}\right),E\left(x_1^{i,j}\right),\cdots,E\left(x_{l-1}^{i,j}\right);\theta_e^n\right) \tag{5.3}$$

i,j分别是对应的entity的索引，x_t是一个sequence中t位置的word。p_t是相对位置向量，即表示该单词是否在实体i，实体j中还是都不在。

2. Propagation Module:

$$\mathbf{h}_i^{(n+1)}=\sum_{v_j\in\mathcal{N}(v_i)}\sigma\left(\mathcal{A}_{i,j}^{(n)}\mathbf{h}_j^{(n)}\right) \tag{5.4}$$

3. Classification Module:

$$\mathcal{L}=g\left(\mathbf{h}_{0:|\mathcal{V}|-1}^0,\mathbf{h}_{0:|\mathcal{V}|-1}^1,\ldots,\mathbf{h}_{0:|\mathcal{V}|-1}^K,Y;\theta_c\right) \tag{5.5}$$

$$\boldsymbol{r}_{v_i,v_j}=\left[\left[\boldsymbol{h}_{v_i}^{(1)}\odot\boldsymbol{h}_{v_j}^{(1)}\right]^\top;\left[\boldsymbol{h}_{v_i}^{(2)}\odot\boldsymbol{h}_{v_j}^{(2)}\right]^\top;\ldots;\left[\boldsymbol{h}_{v_i}^{(K)}\odot\boldsymbol{h}_{v_j}^{(K)}\right]^\top\right] \tag{5.6}$$

$$\mathcal{L}=\sum_{s\in S}\sum_{i\neq j}\log\mathbb{P}\left(r_{v_i,v_j}|i,j,s\right) \tag{5.7}$$

6 Multi-hop Reading Comprehension across Multiple Documents by Reasoning over Heterogeneous Graphs

本文所解决的问题是跨文档的多跳阅读理解，提出的模型是Heterogeneous Document-Entity Graph（HDEGraph）。

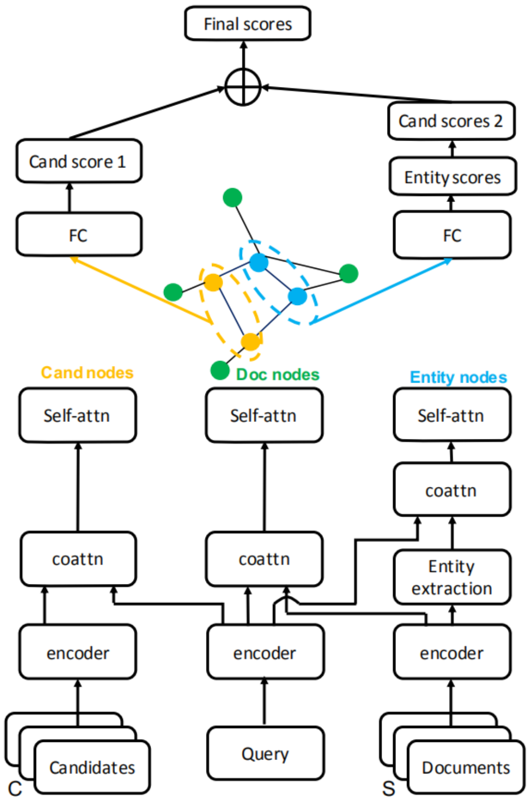


Figure 2: System diagram. S and C are the number of support documents and candidates respectively. We use yellow nodes to represent query-aware candidate representation, blue nodes to represent extracted query-aware entity representation and green nodes to represent query-aware document representation.

1. Context Encoding

   以support document的encoding距离，candidates和query的情况类似。

$$\mathbf{A}_{qs}^{i}=\mathbf{H}_{s}^{i}\left(\mathbf{H}_{q}\right)^{\top}\in\mathbb{R}^{l_{s}^{i}\times l_{q}} \tag{6.1}$$

$$\begin{aligned}\mathbf{C}_{q}&=\operatorname{softmax}\left(\mathbf{A}_{qs}^{\top}\right)\mathbf{H}_{s}\in\mathbb{R}^{l_{q}\times h}\\ \mathbf{C}_{s}&=\operatorname{softmax}\left(\mathbf{A}_{qs}\right)\mathbf{H}_{q}\in\mathbb{R}^{l_{s}\times h}\end{aligned} \tag{6.2}$$

$$\mathbf{D}_{s}=f\left(\operatorname{softmax}\left(\mathbf{A}_{qs}\right)C_{q}\right)\in\mathbb{R}^{l_{s}\times h} \tag{6.3}$$

$$\mathbf{S}_{ca}=\left[\mathbf{C}_{s};\mathbf{D}_{s}\right]\in\mathbb{R}^{l_{s}\times 2h} \tag{6.4}$$

$$\begin{aligned}\mathbf{a}_{s}&=\operatorname{softmax}\left(MLP\left(\mathbf{S}_{ca}\right)\right)\in\mathbb{R}^{l_{s}\times 1}\\ \mathbf{s}_{sa}&=\mathbf{a}_{s}^{\top}\mathbf{S}_{ca}\in\mathbb{R}^{1\times 2h}\end{aligned} \tag{6.5}$$

2. Reasoning over HDE graph

$$\mathbf{z}_i^k=\sum_{r\in\mathcal{R}}\frac{1}{|\mathcal{N}_i^r|}\sum_{j\in\mathcal{N}_i^r}f_r\left(\mathbf{h}_j^k\right) \tag{6.6}$$

$$\mathbf{u}_i^k=f_s\left(\mathbf{h}_i^k\right)+\mathbf{z}_i^k \tag{6.7}$$

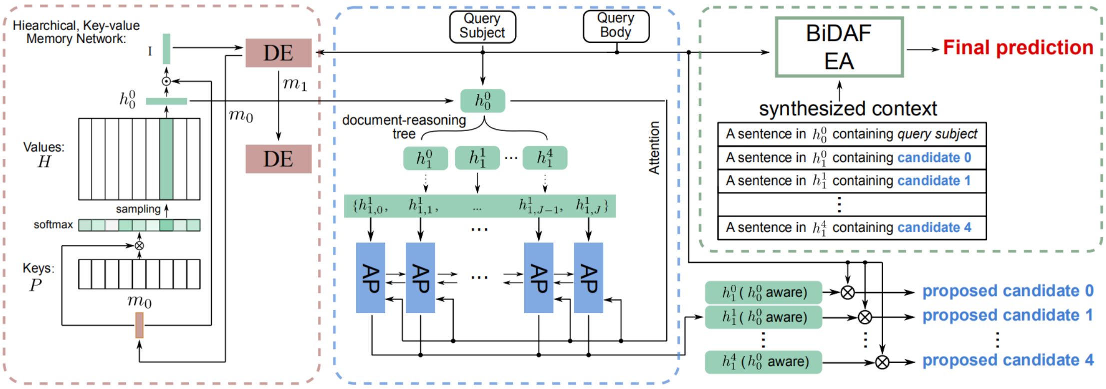
$$\begin{gathered}\mathbf{g}_i^k=\operatorname{sigmoid}\left(f_g\left(\left[\mathbf{u}_i^k;\mathbf{h}_i^k\right]\right)\right)\\ \mathbf{h}_i^{k+1}=\tanh\left(\mathbf{u}_i^k\right)\odot\mathbf{g}_i^k+\mathbf{h}_i^k\odot\left(1-\mathbf{g}_i^k\right)\end{gathered} \tag{6.8}$$

3. Score accumulation

$$\mathbf{a}=f_C\left(\mathbf{H}^C\right)+ACC_{\max}\left(f_E\left(\mathbf{H}^E\right)\right) \tag{6.9}$$

7 Explore, Propose, and Assemble: An Interpretable Model for Multi-Hop Reading Comprehension

本文也是应用于multi-hop multi-document的一篇文章，提出了Explore-Propose-Assemble reader (EPAr)模型。首先，Document Explorer迭代地选择相关文档并在树结构中表示不同的推理链，以便吸收来自所有链的信息。然后，Answer-Proposer从推理树中的每个根到叶路径提出一个答案。最后Evidence Assembler从每个路径中提取包含建议答案的关键语句，并将它们组合以预测最终答案。



1. Retrieval and Encoding:
   使用TF-IDF算法来先筛选出一部分的document，减少计算量。

2. Document Explorer：
   用document-level的representation和word-level的representation分别作为Memory Network的Key和value。

   Read：

$$x_n = p_n^T \mathbf{W_r} m^t \quad \chi = \operatorname{softmax}(x) \quad P(d_i) = \chi_i \tag{7.1}$$

   Write：

$$\begin{aligned} w_k &= h_k^T \mathbf{W_w} m & \tilde{h} &= \textstyle\sum_{k=1}^K h_k \omega_k \\ \omega &= \operatorname{softmax}(w) & m^{t+1} &= \mathbf{GRU}\left(\tilde{h}, m^t\right) \end{aligned} \tag{7.2}$$

3. Answer Proposer

$$\begin{aligned} e_i^k &= \mathbf{v}^T \tanh\left(\mathbf{W_h} \hat{h}_{cct}^i + \mathbf{W_s} s^k + \mathbf{b}\right) \\ a^k &= \operatorname{softmax}\left(e^k\right); \quad c^k = \sum_i a_i^k h_{cct}^i \\ y^k &= \mathbf{LSTM}\left(\hat{h}_T^{k-1}, s^{k-1}, c^{k-1}\right) \\ w^k &= \boldsymbol{\alpha}\left(y^k, u_s\right) + \boldsymbol{\alpha}\left(y^k, u_b\right); \epsilon = \operatorname{softmax}(w) \end{aligned} \tag{7.3}$$

$$a = \sum_{k=1}^K \hat{h}_T^k \epsilon_k; \quad \text{Score }_l = \boldsymbol{\beta}\left(c_l, a\right) \tag{7.4}$$

4. Evidence Assembler：
   将相关的sentence拼接起来，送入传统的单document算法模型。

5. Joint Optimization

8 Multi-hop Reading Comprehension through Question Decomposition and Rescoring

本文提出了一种创新的方法来解决multi-hop的阅读理解问题，没有在神经网络的结构上做文章，而是在数据上做文章，将原始的mult-hop的question分解文多个single-hop的问题，然后用传统的RC模型去回答问题，然后将答案再进行整合。代码地址：`https://github.com/shmsw25/DecompRC`

Type	**Bridging (47%)** requires finding the first-hop evidence in order to find another, second-hop evidence.
Q	Which team does the **player** named 2015 Diamond Head Classic's MVP play for?
Q1	Which player named 2015 Diamond Head Classic's MVP?
Q2	Which team does ANS play for?
Type	**Intersection (23%)** requires finding an entity that satisfies two independent conditions.
Q	Stories USA starred ✓ which actor and comedian ✓ from 'The Office'?
Q1	Stories USA starred which actor and comedian?
Q2	Which actor and comedian from 'The Office'?
Type	**Comparison (22%)** requires comparing the property of two different entities.
Q	Who was born earlier, Emma Bull or Virginia Woolf?
Q1	Emma Bull was born when?
Q2	Virginia Woolf was born when?
Q3	Which is smaller (Emma Bull, ANS) (Virgina Woolf, ANS)

图 4: 原问题分解的三种目标子类型

Type	**Bridging (47%)** requires finding the first-hop evidence in order to find another, second-hop evidence.
Q	Which team does the **player** named 2015 Diamond Head Classic's MVP play for?
Q1	Which player named 2015 Diamond Head Classic's MVP?
Q2	Which team does ANS play for?
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Q3	Which is smaller (Emma Bull, ANS) (Virgina Woolf, ANS)

图 5: 整体的目标结构

$$U = \mathrm{BERT}(S) \in \mathbb{R}^{n \times h} \tag{8.1}$$

$$Y = \mathrm{softmax}(UW) \in \mathbb{R}^{n \times c} \tag{8.2}$$

$$\mathrm{ind}_1, \ldots, \mathrm{ind}_c = \underset{i_1 \leq \cdots \leq i_c}{\mathrm{argmax}} \prod_{j=1}^{c} \mathbb{P}\left(i_j = \mathrm{ind}_j\right) \tag{8.3}$$

Algorithm 1 Sub-questions generation using Pointer_c.[2]

procedure GENERATESUBQ(Q : question, Pointer_c)

    / Find q_1^b and q_2^b for Bridging */*
    $\text{ind}_1, \text{ind}_2, \text{ind}_3 \leftarrow \text{Pointer}_3(Q)$
    $q_1^b \leftarrow Q_{\text{ind}_1:\text{ind}_3}$
    $q_2^b \leftarrow Q_{:\text{ind}_1} : \texttt{ANS} : Q_{\text{ind}_3:}$
    article in $Q_{\text{ind}_2-5:\text{ind}_2} \leftarrow$ 'which'
    / Find q_1^i and q_2^i for Intersecion */*
    $\text{ind}_1, \text{ind}_2 \leftarrow \text{Pointer}_2(Q)$
    $s_1, s_2, s_3 \leftarrow Q_{:\text{ind}_1}, Q_{\text{ind}_1:\text{ind}_2}, Q_{\text{ind}_2:}$
    if s_2 starts with wh-word **then**
        $q_1^i \leftarrow s_1 : s_2,\ q_2^i \leftarrow s_2 : s_3$
    else
        $q_1^i \leftarrow s_1 : s_2,\ q_2^i \leftarrow s_1 : s_3$
    / Find q_1^c, q_2^c and q_3^c for Comparison */*
    $\text{ind}_1, \text{ind}_2, \text{ind}_3, \text{ind}_4 \leftarrow \text{Pointer}_4(Q)$
    $\text{ent}_1, \text{ent}_2 \leftarrow Q_{\text{ind}_1:\text{ind}_2}, Q_{\text{ind3}:\text{ind}_4}$
    $op \leftarrow \text{find\_op}(Q, \text{ent}_1, \text{ent}_2)$
    $q_1^c, q_2^c \leftarrow \text{form\_subq}(Q, \text{ent}_1, \text{ent}_2, op)$
    $q_3^c \leftarrow op\ (\text{ent}_1, \texttt{ANS})\ (\text{ent}_2, \texttt{ANS})$

图 6: 生成分割点的算法

9 Dynamically Fused Graph Network for Multi-hop Reasoning

本文也是一篇关于Mult-hop的用GNN来处理的文章。亮点在于GNN推理的时候，使用了一个soft-mask，可以理解为只做了一个局部的信息传播。模型可以划分为以下步骤：

1. Paragraph Selection:
   分别将paragraph和Query作为输入送入Bert，然后通过一个SIGMOD来预测其相关性，筛选出部分最相关的paragraph。

2. Constructing Entity Graph:
   用Stanford coreNLP工具来做实体抽取，作为node，然后以下三种情况nodes间有边：

   [1] 两个实体出现在同一句话中。

   [2] 对于在上下文中具有相同提及文本的每对实体。

   [3] 在同一段中的中央实体节点和其他实体之间。

3. Encoding Query and Context:使用bert即可。

4. Reasoning with the Fusion Block：
   Document to Graph flow:
   将entity含有的word的embedding通过max和mean池化层得到所需向量。
   Dynamic Graph Attention：

$$\begin{aligned}\tilde{\mathbf{q}}^{(t-1)} &= \operatorname{MeanP}\text{ooling}\left(\mathbf{Q}^{(t-1)}\right)\\ \gamma_i^{(t)} &= \tilde{\mathbf{q}}^{(t-1)}\mathbf{V}^{(t)}\mathbf{e}_i^{(t-1)}/\sqrt{d_2}\\ \mathbf{m}^{(t)} &= \sigma\left(\left[\gamma_1^{(t)},\cdots,\gamma_N^{(t)}\right]\right)\\ \tilde{\mathbf{E}}^{(t-1)} &= \left[m_1^{(t)}\mathbf{e}_1^{(t-1)},\ldots,m_N^{(t)}\mathbf{e}_N^{(t-1)}\right]\end{aligned} \tag{9.1}$$

$$\begin{aligned}&\mathbf{h}_i^{(t)} = \mathbf{U}_t\tilde{\mathbf{e}}_i^{(t-1)} + \mathbf{b}_t\\ &\beta_{i,j}^{(t)} = \text{ LeakyReLU }\left(\mathbf{W}_t^{\top}\left[\mathbf{h}_i^{(t)},\mathbf{h}_j^{(t)}\right]\right)\\ &\alpha_{i,j}^{(t)} = \frac{\exp\left(\beta_{i,j}^{(t)}\right)}{\sum_k \exp\left(\beta_{i,k}^{(t)}\right)}\end{aligned} \tag{9.2}$$

$$\mathbf{e}_i^{(t)} = \operatorname{ReLU}\left(\sum_{j\in B_i}\alpha_{j,i}^{(t)}\mathbf{h}_j^{(t)}\right) \tag{9.3}$$

$$\mathbf{Q}^{(t)} = \mathrm{Bi}-\mathrm{Attention}\left(\mathbf{Q}^{(t-1)},\mathbf{E}^{(t)}\right) \tag{9.4}$$

5. Graph to Document Flow:

$$\mathbf{C}^{(t)} = \operatorname{LSTM}\left(\left[\mathbf{C}^{(t-1)},\mathbf{M}\mathbf{E}^{(t)\top}\right]\right) \tag{9.5}$$

6. Prediction:

$$
\begin{aligned}
\mathbf{O}_{sup} &= \mathcal{F}_0\left(\mathbf{C}^{(t)}\right) \\
\mathbf{O}_{start} &= \mathcal{F}_1\left(\left[\mathbf{C}^{(t)}, \mathbf{O}_{sup}\right]\right) \\
\mathbf{O}_{end} &= \mathcal{F}_2\left(\left[\mathbf{C}^{(t)}, \mathbf{O}_{sup}, \mathbf{O}_{start}\right]\right) \\
\mathbf{O}_{type} &= \mathcal{F}_3\left(\left[\mathbf{C}^{(t)}, \mathbf{O}_{sup}, \mathbf{O}_{end}\right]\right)
\end{aligned} \tag{9.6}
$$

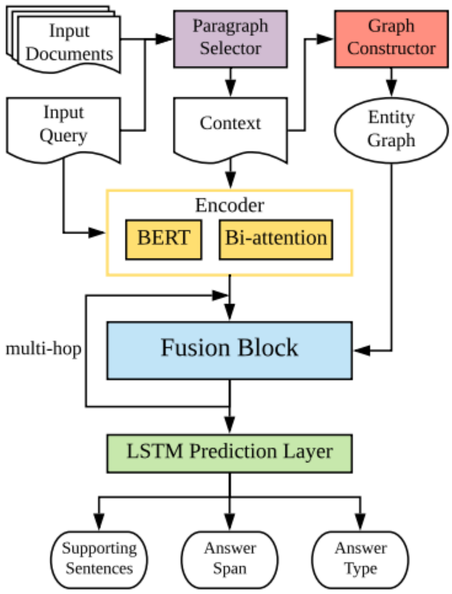

Figure 3: Overview of DFGN.

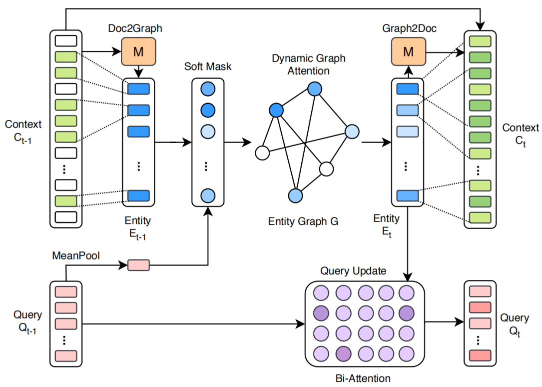

Figure 4: Reasoning with the fusion block in DFGN