Towards Better Question Generation in QA-based Event Extraction

Zijin Hong, Jian Liu
Jinan University, Beijing Jiaotong University

Introduction

Context:
Marines$_{attacker}$ were involved in a firefight in the center of Baghdad. They used rocket-propelled grenades and semi-automatic weapons, causing some injuries.

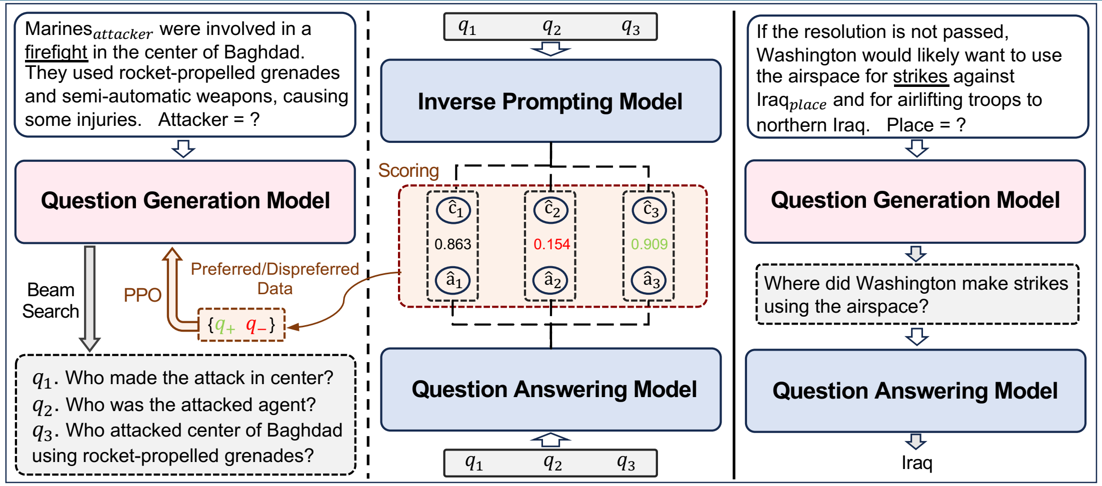
Template Q1: Who is the attacker in firefight?
A1. None ✗

Template Q2: Who was the attacking agent?
A2. weapons ✗

Human-Written Q3: Who was involved in the firefight in the center of Baghdad using grenades and weapons?
A3. Marines ✓

- The QA-based event extraction method first proposes a question based on the given context and the target role, then uses a QA model to obtain the result.
- The quality of the proposed question significantly affects the accuracy of extracting the required argument.
- Previous methods improve the question through well-designed templates, which are rigid and less context-dependent.
- We propose a novel framework towards generate better questions with more context-dependent and clear guidance.

Proposed Method



- **QG**: Given an event context, the QG model is fine-tuned based on the template questions and then uses beam search to generate multiple question candidates.
- **RL**: Each question will be rephrased through inverse prompting and then answered. The preferred question pair will be collected based on quality to conduct RL refinement.
- **QA**: An off-the-shelf QA model is utilized to answer the questions generated by the RL-refined QG model to extract the corresponding argument.

Reinforcement Learning for Question Generation Refinement

Algorithm 1 RL for QG Refinement

for each $(c', t', r') \in$ training set D **do**
  Generate question set $\mathcal{Q}$ with f_{SFT}
  for each question $q \in \mathcal{Q}$ **do**
    Generate recovered context $\hat{c}$
    Generate predicted answer $\hat{a}$
    Compute score using Eq. 6
  end for
  return Reward score set $S_{\mathcal{Q}}$
  if Condition in Eq. 7 satisfied **then**
    return (q_+, q_-) as Eq. 8
  end if
end for
Reward modeling $r(p, q)$ with Eq. 9
PPO training with objective function Eq. 10
return RL-refined model f_{RL}

- Based on the SFT model, the preferred question pairs are first collected for further RL refinement:
  - Given an event context c', trigger t' and the required role r', the SFT model generates a question q and the score S_q is computed by:
  $$S_q = \lambda_1 \operatorname{SemSim}(c, \hat{c}) + \lambda_2 \operatorname{COR}(a, \hat{a}), \quad (6)$$
  - Then, preferred/dispreferred questions are obtained with condition:
  $$\begin{cases} \max(S_{\mathcal{Q}}) > \alpha \\ \max(S_{\mathcal{Q}}) - \min(S_{\mathcal{Q}}) > \beta, \end{cases} \quad (7)$$
  $$(q_+, q_-) = (q_{\max(S_{\mathcal{Q}})}, q_{\min(S_{\mathcal{Q}})}), \quad (8)$$
- Given the preference dataset, a reward model $r(p, q)$ is constructed by:
$$\mathcal{L}_{\mathrm{RM}} = -\mathbb{E}\left[\log\left(\sigma\left(r\left(p, q^+\right) - r\left(p, q^-\right)\right)\right)\right], \quad (9)$$
- Finally, the PPO training is conducted as RL refinement with the objective function:
$$\mathcal{L}_{\mathrm{RL}} = \mathbb{E}\left[r\left(p, q\right)\right] - \mu \mathbb{E}\,\mathrm{KL}\left(f_{RL} \mid f_{SFT}\right), \quad (10)$$

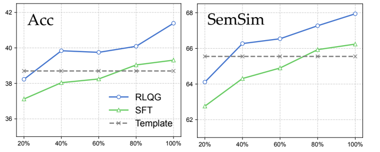
Experiments

Methods	Practical Eval. EM	Practical Eval. COR	Practical Eval. SemSim	Full Eval. EM	Full Eval. COR	Full Eval. SemSim
Template						
Simple-Q (Liu et al., 2020)	35.41	40.23	60.93	14.38	16.17	24.55
Standard-Q (Du and Cardie, 2020)	37.42	43.87	63.70	15.60	17.36	25.92
Back-Trans-Q	36.13	41.39	62.41	15.14	16.67	25.28
Guideline-Q (Du and Cardie, 2020)	38.51	45.28	65.54	17.61	19.96	28.14
Dynamic-Q (Lu et al., 2023)	38.70	45.79	65.55	20.45	23.12	30.79
Supervised Fine-tuning						
SFT (*Standard*)	37.63	42.95	62.36	15.31	17.13	25.72
SFT (*Back-Trans*)	38.24	43.56	64.11	17.47	18.90	27.32
SFT (*Guideline*)	38.62	44.69	64.66	17.33	19.61	27.77
SFT (*Dynamic*)	39.31	46.78	66.24	20.35	23.05	30.53
In-context learning						
LLaMA-2-13b-Chat (*0shot*)	1.21	3.50	35.88	0.43	1.25	21.78
LLaMA-2-13b-Chat (*5shot*)	27.97	33.04	53.69	13.01	14.93	23.54
GPT-4 (*0shot*)	28.97	35.83	57.90	11.14	13.54	23.35
GPT-4 (*5shot*)	39.24	47.59	65.92	16.32	19.37	27.46
RLQG (Ours)	**41.39**	**48.58**	**67.94**	**21.71**	**24.19**	**31.80**

- Performance of QA-based event extraction on ACE2005

Methods	EM	COR	SemSim
Template			
Standard-Q	17.65	23.02	47.96
Back-Trans-Q	16.45	21.47	46.43
Supervised Fine-tuning			
SFT (*Standard*)	18.10	23.84	48.79
SFT (*Back-Trans*)	18.29	24.11	49.32
RLQG (Ours)	**19.61**	**25.43**	**50.69**

- Performance on RAMS



- In data-scarce scenario

Context:
Former senior banker Callum McCarthy$_{person}$ **begins** what is one of the most important jobs in London's financial world in September, when incumbent Howard Davies steps down.

Template Question:
Who is the employee?
Answer: Davies ✗

SFT Question:
Who was hired by banker?
Answer: Howard Davies ✗

RLQG Question:
Who was hired as one of the most important jobs?
Answer: Callum McCarthy ✓

Human-Written Question:
Who was the former senior banker that began an important job in September?
Answer: Callum McCarthy ✓

- A case study of RLQG

➢ Contact: hongzijin@stu2020.jnu.edu.cn, jianliu@bjtu.edu.cn (corresponding author)
➢ Code: https://github.com/Rcrossmeister/RLQG Paper: https://arxiv.org/pdf/2405.10517