Generating Distractors for Reading Comprehension Questions from Real Examinations

Yifan Gao[1], Lidong Bing[2], Piji Li[3], Irwin King[1], Michael R. Lyu[1]
[1]Department of Computer Science and Engineering, The Chinese University of Hong Kong
[2]R&D Center Singapore, Machine Intelligence Technology, Alibaba DAMO Academy [3]Tencent AI Lab
[1]{yfgao, king, lyu)@cse.cuhk.edu.hk [2]l.bing@alibaba-inc.com [3]pijili@tencent.com

code & data

What is 'Distractor Generation'?

A New Task: Generate reasonable distractors (wrong options) for multiple choices questions (MCQs) in reading comprehension

Definition: Given an article P containing multiple sentences $s_1, s_2, \ldots, s_n$, a pair of question q and its correct option a originated from the article, the goal is to generate the distractor d:

$$\overline{d} = \arg\max_{d} \log \mathrm{P}(d|P, a, q)$$

Example:

Article:

. . .
The Yanomami live along the rivers of the rainforest in the north of Brazil. They have lived in the rainforest for about 10,000 years and they use more than 2,000 different plants for food and for medicine. But in 1988, someone found gold in their forest, and suddenly 45,000 people came to the forest and began looking for gold. They cut down the forest to make roads. They made more than a hundred airports. The Yanomami people lost land and food. Many died because new diseases came to the forest with the strangers.
. . .
In 1987, they closed fifteen roads for eight months. No one cut down any trees during that time. In Panama, the Kuna people saved their forest. They made a forest park which tourists pay to visit. The Gavioes people of Brazil use the forest, but they protect it as well. They find and sell the Brazil nuts which grow on the forest trees.

Question:

Those people built roads and airports in order to _____ .

A. carry away the gold conveniently (**Answer**)
B. make people there live a better life (**Distractor**)
C. stop spreading the new diseases (**Distractor**)
D. develop the tourism there (**Distractor**)

Real-world Applications:

- Help the preparation of MCQ reading comprehension datasets
  - The existence of distractors fail existing content-matching SOTA reading comprehension on MCQs like RACE dataset (Lai et al. 2017)
  - Large datasets can boost the performance of MCQ reading comprehension systems
- Alleviate instructors' workload in designing MCQs for students
  - Poor distractor options can make the questions almost trivial to solve
  - Reasonable distractors are time-consuming to design

Difference with Previous Works

Previous:

- Extract a fixed distractor candidate set (usually word phrases)
- Use similarity-based methods or learning-based methods to select the distractors (a classification or ranking problem)

Our Goal:

- Generate longer and semantic-rich distractors (8.1 tokens on avg.)
- The generated distractors should semantically related to the reading comprehension question
- The distractors should not be paraphrases of the correct answer option
- The generated distractors should be grammatically consistent with the question, especially for questions with a blank in the end

Dataset

RACE Reading Comprehension Dataset:

- A large-scale **Re**A**d**ing **C**omprehension dataset from **E**xaminations (RACE) that are created for middle school and high school students

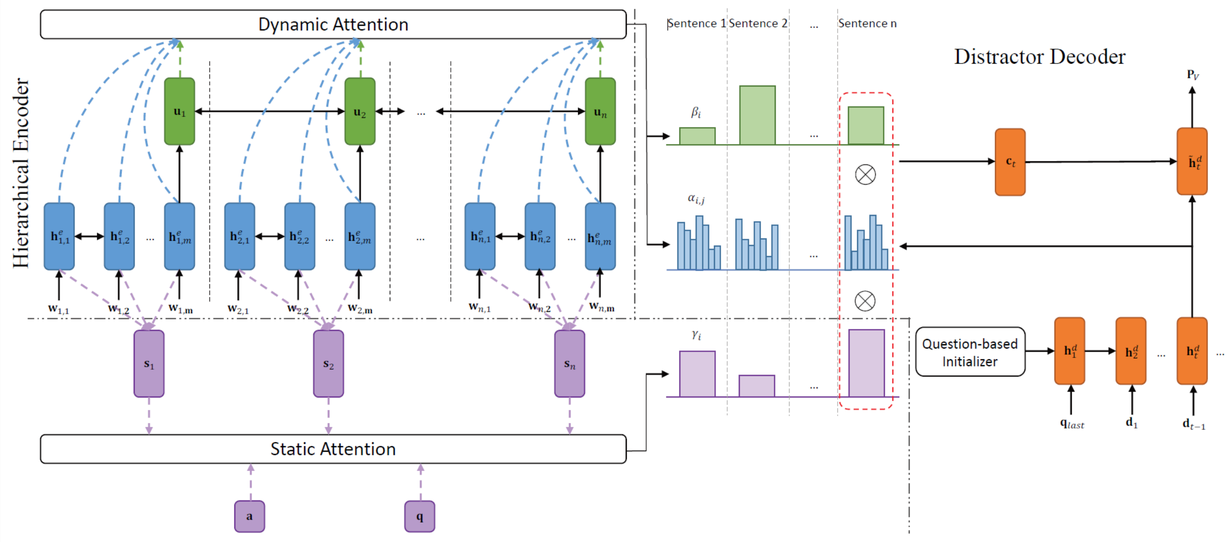
Pruning for our Distractor Generation Task:

- Some distractors have no semantic relevance with the article, which can be easily excluded
- Some distractors require some world knowledge outside the article
- Pruning Constraint: Keep a distractor if its *weighted frequency* of *meaningful tokens* is larger than 5

Our Dataset Statistics:

# Train Samples	96501
# Dev Samples	12089
# Test Samples	12284
Avg. article length (tokens)	347.0
Avg. distractor length	8.5
Avg. question length	9.9
Avg. answer length	8.7
Avg. # distractors per question	2.1

Model



1. **Static Attention**: learn an importance distribution $(\gamma_1, \gamma_2, \ldots, \gamma_n)$ of the sentences $(s_1, s_2, \ldots, s_n)$ in the article
   - Encoding: $\mathbf{a} = \frac{1}{k}\sum_{t=1}^{k}\mathbf{a}_t$, $\mathbf{q} = \frac{1}{l}\sum_{t=1}^{l}\mathbf{q}_t$, $\mathbf{s}_i = \frac{1}{m}\sum_{t=1}^{m}\mathbf{h}_{i,t}^{e}$
   - Matching: $o_i = \lambda_q \mathbf{s}_i^{\top}\mathbf{W}_m\mathbf{q} - \lambda_a \mathbf{s}_i^{\top}\mathbf{W}_m\mathbf{a} + \mathbf{b}_m$
   - Normalization: $\tau = \mathrm{sigmoid}(\mathbf{w}_{\mathrm{q}}^{\top}\mathbf{q} + b_q)$, $\gamma_i = \mathrm{softmax}(\frac{o_i}{\tau})$
2. **Dynamic Attention**: $\alpha_{i,j} = \mathbf{h}_{i,j}^{e\,\top}\mathbf{W}_{d_2}\mathbf{h}_t^d$, $\beta_i = \mathbf{u}_i^{\top}\mathbf{W}_{d_1}\mathbf{h}_t^d$
3. **Modulation**: use the static attention to modulate the dynamic hierarchical attention $\tilde{\alpha}_{i,j} = \frac{\alpha_{i,j}\beta_i\gamma_i}{\Sigma_{ij}\alpha_{i,j}\beta_i\gamma_i}$
4. **Question-based Initializer**:
   - Use the last token in the question as the initial input of the decoder
   - Use the final cell state and hidden state of the question LSTM to initialize the decoder
5. **Generate Diverse Distractors**: Use beam search to receive k candidate distractors, select top 3 with predefined Jaccard distance

Experiment Results

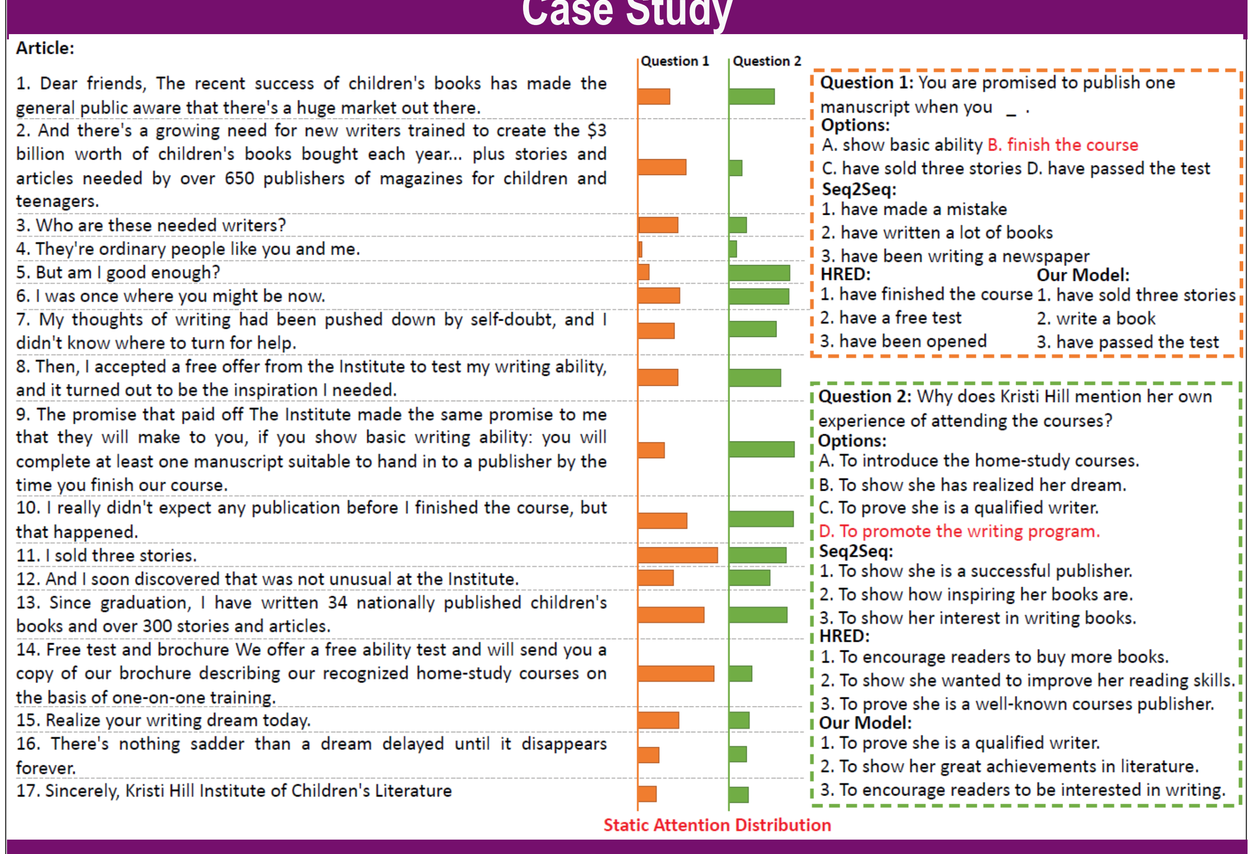
Automatic Evaluation:

		$BLEU_1$	$BLEU_2$	$BLEU_3$	$BLEU_4$	$ROUGE_1$	$ROUGE_2$	$ROUGE_L$
1st Distractor	Seq2Seq	25.28	12.43	7.12	4.51	14.12	3.35	13.58
	HRED	26.10	13.96	8.83	6.21	14.83	4.07	14.30
	Our Model	**27.32**	**14.69**	**9.29**	**6.47**	**15.69**	**4.42**	**15.12**
2nd Distractor	Seq2Seq	25.13	12.02	6.56	3.93	13.72	3.09	13.20
	HRED	25.18	12.21	6.94	4.40	13.94	3.11	13.40
	Our Model	**26.56**	**13.14**	**7.58**	**4.85**	**14.72**	**3.52**	**14.15**
3rd Distractor	Seq2Seq	25.34	11.53	5.94	3.33	13.78	2.82	13.23
	HRED	25.06	11.69	6.26	3.71	13.65	2.84	13.04
	Our Model	**26.92**	**12.88**	**7.12**	**4.32**	**14.97**	**3.41**	**14.36**
Avg. Performance	Seq2Seq	25.25	11.99	6.54	3.92	13.87	3.09	13.34
	HRED	25.45	12.62	7.34	4.77	14.14	3.34	13.58
	Our Model	**26.93**	**13.57**	**8.00**	**5.21**	**15.13**	**3.78**	**14.54**

Manual Evaluation:

	Annotator 1	Annotator 2	Annotator 3	# Selected
Seq2Seq	31	35	30	96
HRED	33	40	35	108
Our Model	43	45	36	124
Human	75	70	79	224

Case Study



Reference

1. Lai, Guokun et al. "RACE: Large-scale ReAding Comprehension Dataset From Examinations." EMNLP (2017).