



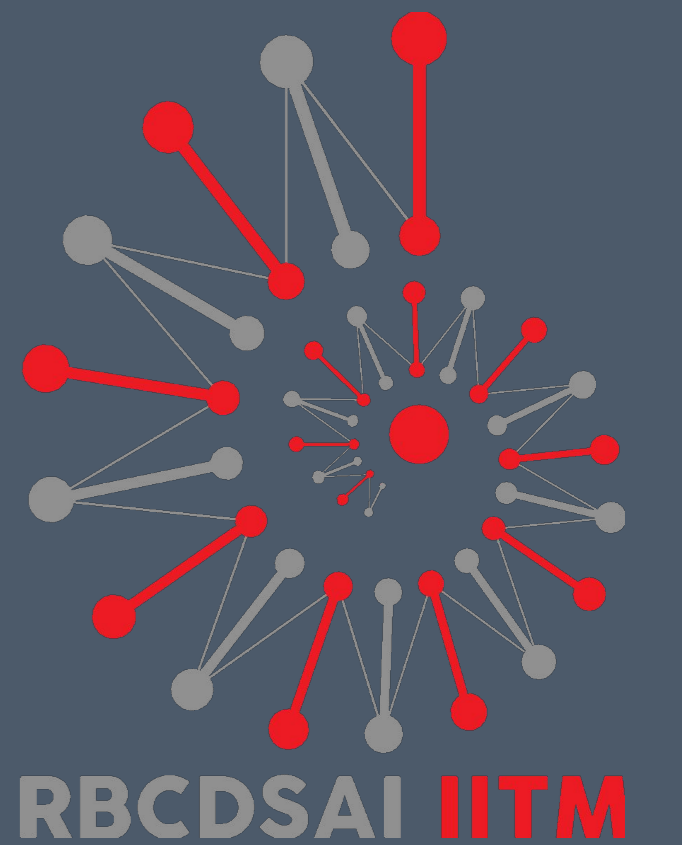
Let's Ask Again: Refine Network for Automatic Question Generation

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1. Motivation

- Existing Approaches focus on generating questions in *one single pass*. However, we observe that the generated questions look like an incomplete draft of the desired question with a clear scope for refinement.
- We propose a method which tries to mimic the human process of generating questions by first creating an initial draft and then refining it

Passage 1

Liberated by **Napoleon's** army in 1806, Warsaw was made the capital of the newly created Duchy of Warsaw.

Generated Questions

Baseline	What was the capital of the newly duchy of Warsaw?
RefNet	Who liberated Warsaw in 1806?
Reward-RefNet	Whose army liberated Warsaw in 1806?

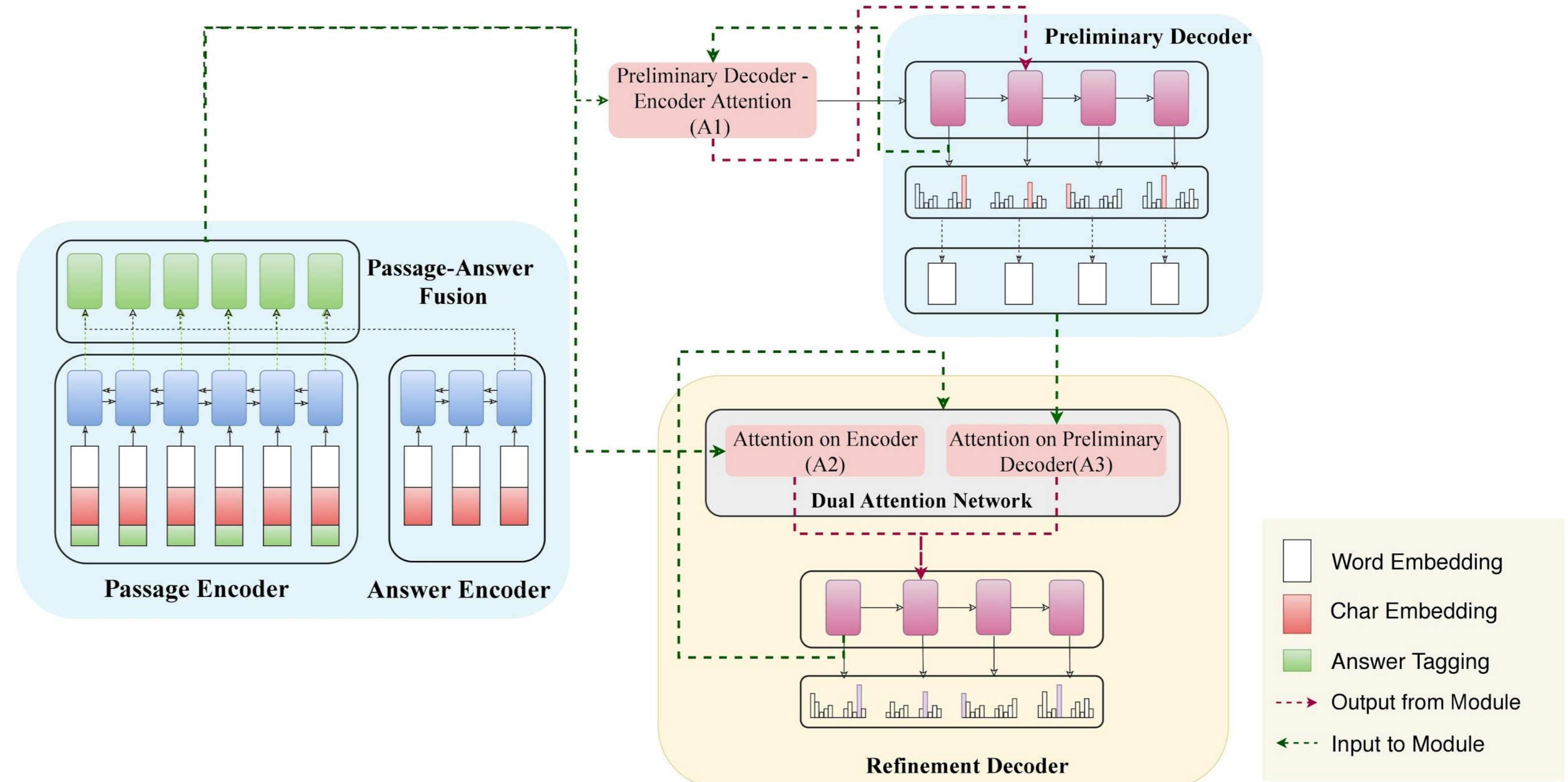
Passage 2

To fix carbon dioxide into sugar molecules in the process of photosynthesis, chloroplasts use **an enzyme called rubisco**

Generated Questions

Baseline	What does chloroplasts use?
RefNet	What does chloroplasts use to fix carbon dioxide into sugar molecules?
Reward-RefNet	What do chloroplasts use to fix carbon dioxide into sugar molecules?

2. Proposed Model

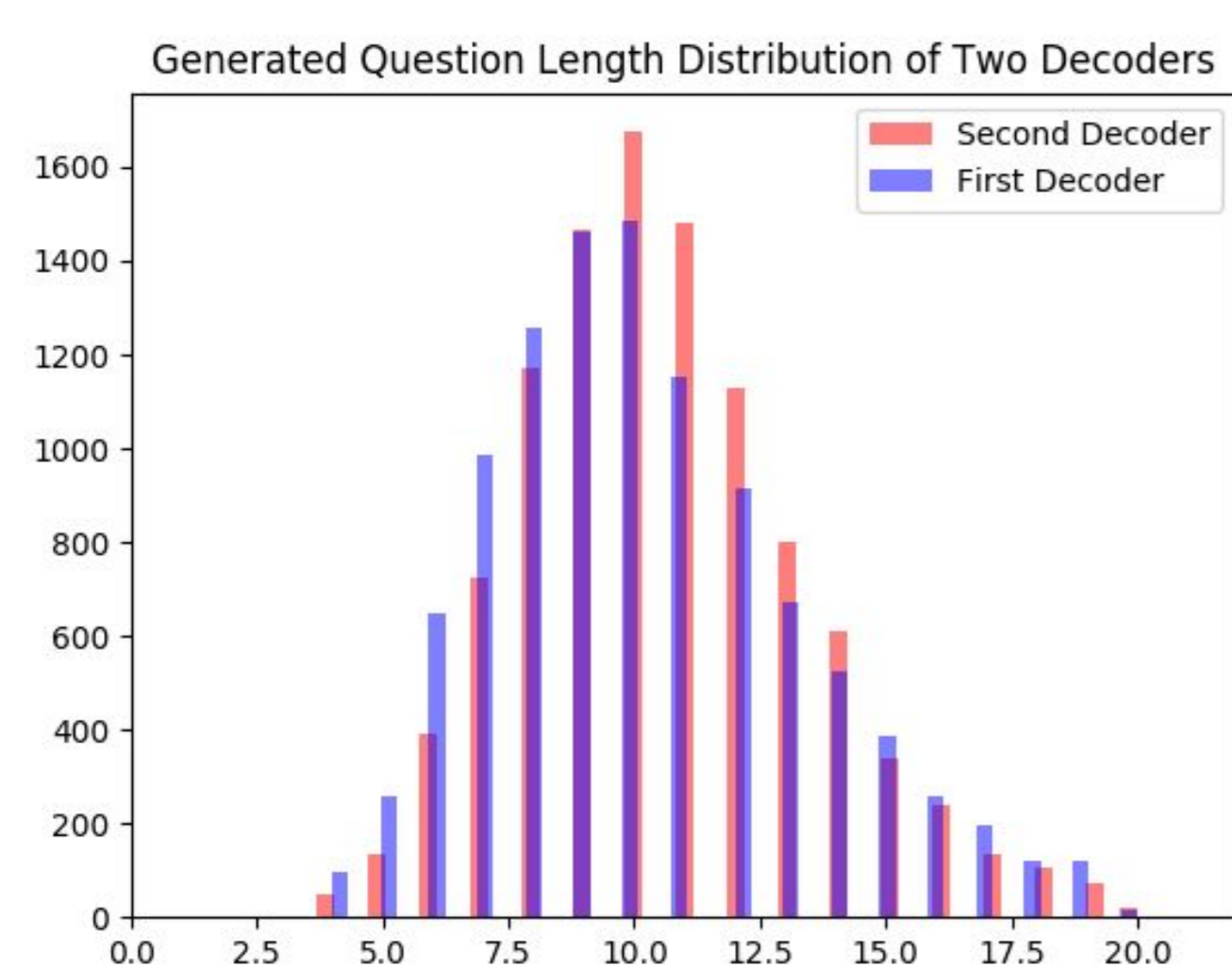


3. Results

Dataset	Model	n-gram						
		BLEU-1	BLEU-2	BLEU-3	BLEU-4	ROUGE-L	METEOR	QBLEU4
SQuAD (Sentence Level)	(Sun et al., 2018)	43.02	28.14	20.51	15.64	-	-	-
	(Zhao et al., 2018)	44.51	29.07	21.06	15.82	44.24	19.67	-
	(Kim et al., 2019)	-	-	-	16.17	-	-	-
	EAD	44.74	29.79	22.00	16.84	44.78	20.60	24.70
	RefNet	47.27	31.88	23.65	18.16	47.14	23.40	27.40
SQuAD (Passage Level)	(Zhao et al., 2018)*	45.07	29.58	21.60	16.38	44.48	20.25	-
	EAD	44.61	29.37	21.50	16.36	43.95	20.11	24.20
	RefNet	46.41	30.66	22.42	16.99	45.03	21.10	26.60
Hotpot QA	(Zhao et al., 2018)*	45.29	32.06	24.43	19.29	40.40	19.29	25.70
	EAD	46.00	32.47	24.82	19.68	41.52	23.27	26.20
	RefNet	45.45	33.13	26.05	21.17	43.12	25.81	28.70
Drop Dataset	(Zhao et al., 2018)*	39.56	29.19	22.53	18.07	45.01	19.68	31.40
	EAD	39.21	29.10	22.65	18.42	45.07	19.56	31.80
	RefNet	42.81	32.63	25.78	21.23	47.49	22.25	33.60

4. Discussions

Preliminary and Refinement Decoder



Model	Decoder	BLEU-4	QBLEU-4
without A_3	Refinement Decoder	17.16	25.80
	Preliminary Decoder	17.59	26.00
with A_3	Refinement Decoder	18.37	27.40
	Preliminary Decoder	17.89	26.00

Reward-RefNet

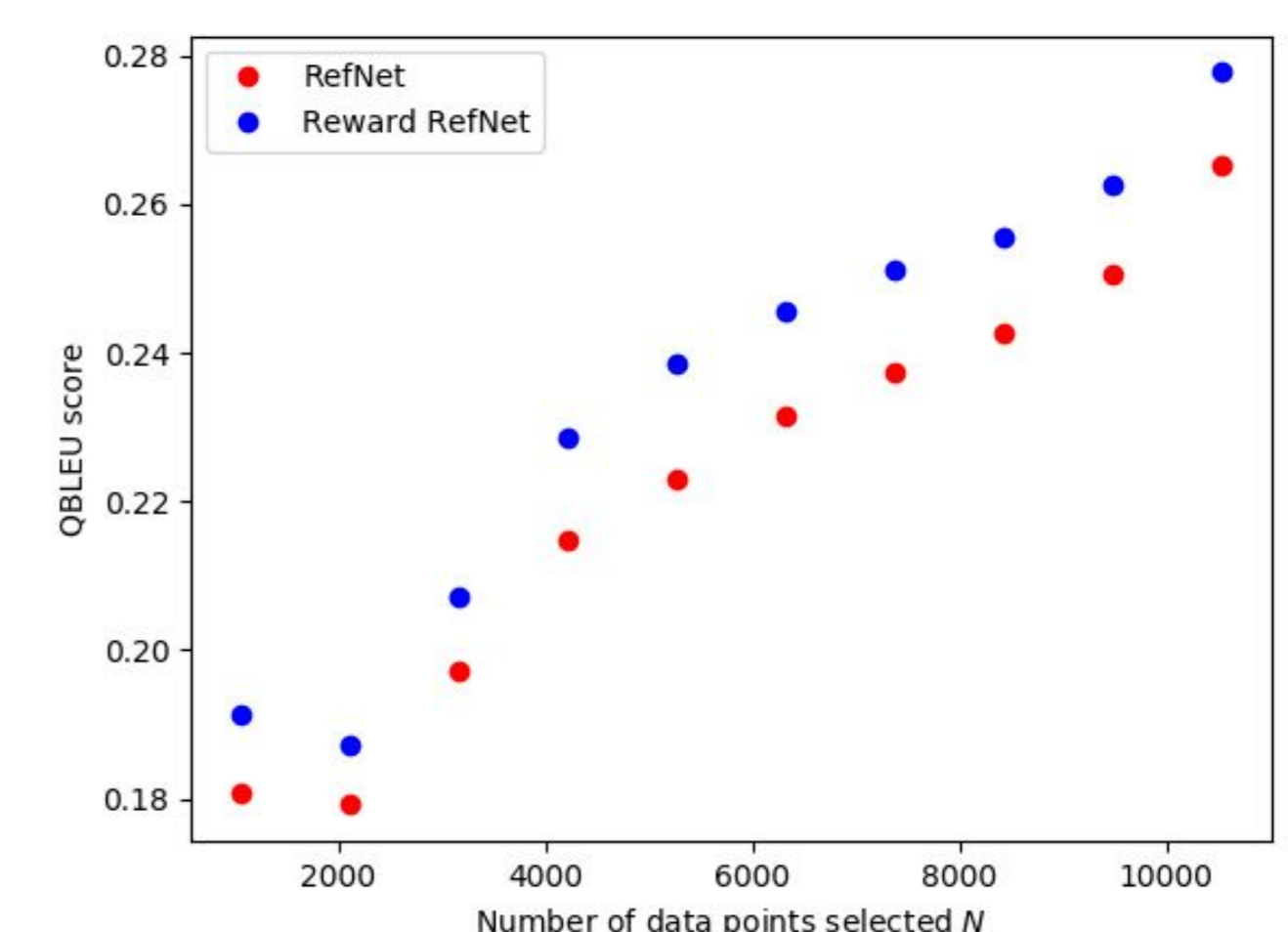
Given Preliminary & Refinement Decoder's Generated word sequence $\tilde{Q} = \{\tilde{q}_1, \tilde{q}_2, \dots, \tilde{q}_T\}$ and $Q = \{q_1, q_2, \dots, q_T\}$ respectively, the training loss is defined as follows:

$$L(Q) = (r(Q) - r(\tilde{Q})) \cdot \sum_{t=1}^T \log p(q_t | q_{t-1}, \dots, q_1, \tilde{Q}, U, h^a)$$

where $r(Q)$ and $r(\tilde{Q})$ are the rewards obtained by comparing with the reference question Q^* .

Model	BLEU Reward Signal		Answerability Reward Signal	
	BLEU-4	%preference	QBLEU-4	%preference
RefNet	18.37	32.9%	36.9	30%
Reward-RefNet	18.52	67.1%	37.5	70%

Analysis on Originality



Passage: McLetchie was elected on the Lothian regional list with Conservatives suffered a net loss of five seats, with leader **Annabel Goldie claiming that their support had held firm**, nevertheless, she too announced she would step down as leader of the party

Baseline	Who announced she would step down as leader of the Conservatives ?
RefNet	Who claiming that their support had held firm ?
Reward-RefNet	Who was the leader of the conservatives ?

5. Conclusion

- RefNet outperforms existing state-of-the-art models on the SQuAD, HOTPOT-QA and DROP datasets.
- We validate our empirical results using human evaluations.
- We show that Reward-RefNets improves the initial draft on specific aspects like Answerability, Fluency and Originality.

Acknowledgements

We thank Amazon Web Services for providing free GPU compute and Google for supporting Preksha Nema's contribution in this work through Google Ph.D. Fellowship programme. We would like to acknowledge Department of Computer Science and Engineering, IIT Madras and Robert Bosch Center for Data Sciences and Artificial Intelligence, IIT Madras (RBC-DSAI) for providing us sufficient resources. We would also like to thank Patanjali SLPSK, Sahana Ramnath, Rahul Ramesh, Anirban Laha, Nikita Moghe and the anonymous reviewers for their valuable and constructive suggestions.

References

- Xingwu Sun, Jing Liu, Yajuan Lyu, Wei He, Yan-jun Ma, and Shi Wang. 2018. Answer-focused and position-aware neural question generation.
- Yao Zhao, Xiaochuan Ni, Yuan Yuan Ding, and Qifa Ke. 2018. Paragraph-level neural question generation with maxout pointer and gated self-attention networks.
- Yanghoon Kim, Hwanhee Lee, Joongbo Shin, and Kyomin Jung. 2019. Improving neural question generation using answer separation

Code Available at :

<https://github.com/PrekshaNema25/RefNet-QG>