Leveraging Discourse Rewards for Document-Level Neural Machine Translation

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Introduction

Document-level machine translation is widely regarded as a challenging task since the translation of the individual sentences in the document needs to retain aspects of the **discourse** at document level.

Related work

Most existing document-level NMT approaches aim to implicitly teach the model the discourse of a document by encoding the context from surrounding sentences with **multiple encoders**, **extra attention layers** and **memory caches**...

Our Approach

Instead, we have proposed to **explicitly** teach the model what good document structure is, by using discourse rewards in the objective function.

Lexical Cohesion and Coherence

Lexical Cohesion (LC):

A measure of the frequency of semantically-similar words co-occurring in a document (or block of sentences)

$$LC = \frac{\#\ of\ cohesion\ devices\ in\ document}{\#\ of\ words\ in\ document} \quad (1)$$

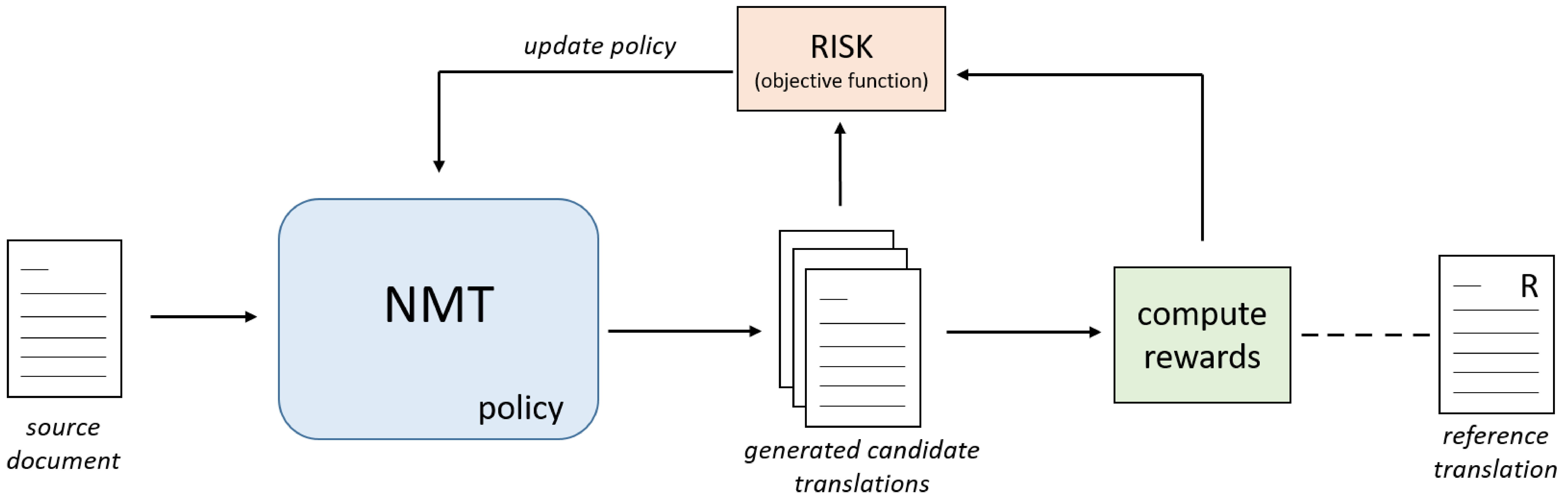
Coherence (COH):

A measure of how well adjacent sentences in a text are linked to each other. We have used a *topic-based* coherence metric, and uses a Latent Semantic Analysis (LSA) pretrained model to compute the topic vectors of each sentence ($\mathbf{t}_i$) and measure the cosine distance.

$$COH = \frac{1}{k-1}\sum_{i=2}^{k}\cos(\mathbf{t}_i, \mathbf{t}_{i-1}) \quad (2)$$

Expected Risk Minimization (Risk) Training

We have used reinforcement learning style training (**Risk**[1]) in order to be able to use discontinuous reward functions (LC and COH) during training. NLL has been used for pre-training to avoid a *cold-start* and as a mixed objective with Risk.



Experiments

TED talks (IWSLT Workshop):

Model	Zh-En (TED talks) BLEU	LC	COH	F_{BERT}	Cs-En (TED talks) BLEU	LC	COH	F_{BERT}	Es-En (TED talks) BLEU	LC	COH	F_{BERT}
Sentence-level NMT	16.94	55.39	28.02	66.94	22.74	55.62	27.72	69.60	39.55	56.67	28.27	79.5
HAN_{join}	17.52	55.02	28.15	67.21	23.44	55.63	27.62	69.87	39.89	56.25	28.56	**79.88**
Human reference	–	55.13	29.33	–	–	55.91	29.7	–	–	57.84	30.79	–
Risk(1.0)-$\text{BLEU}_{\text{doc}} + \text{LC}_{\text{doc}} + \text{COH}_{\text{doc}}$	**18.15**	**57.48***	**29.32***	67.69	23.40	**58.31***	**28.17**	**70.09**	37.4	59.41†	28.92	78.86
Risk(0.8)-$\text{BLEU}_{\text{doc}} + \text{LC}_{\text{doc}} + \text{COH}_{\text{doc}}$	17.82	55.18	28.68	67.60	23.43	56.03*	27.62	70.01*	39.52	**57.53**	**28.79**	79.11
Risk(0.5)-$\text{BLEU}_{\text{doc}} + \text{LC}_{\text{doc}} + \text{COH}_{\text{doc}}$	17.83	54.70	28.30	**67.73**	23.42	56.07	27.78	69.95*	**40.1**	57.4	28.78	79.61
Risk(0.2)-$\text{BLEU}_{\text{doc}} + \text{LC}_{\text{doc}} + \text{COH}_{\text{doc}}$	17.80	55.10	28.35	67.62	**23.48**	55.85	27.62	69.95	40.07	56.83	28.61	79.62

Movie subtitles (OpenSubtitles):

Model	Eu-En (movie subtitles) BLEU	LC	COH	F_{BERT}	Es-En (movie subtitles) BLEU	LC	COH	F_{BERT}
Sentence-level NMT	9.12	37.08	19.34	59.18	29.34	58.31	22.70	67.57
HAN_{join}	9.74	37.19	19.63	59.72	**30.14**	58.11	22.58	**67.73**
Human reference	–	41.83	21.93	–	–	57.28	24	–
Risk(1.0)-$\text{BLEU}_{\text{doc}} + \text{LC}_{\text{doc}} + \text{COH}_{\text{doc}}$	1.19	72.51†	27.67†	36.72	3.37	67.82†	19.53	48.07
Risk(0.8)-$\text{BLEU}_{\text{doc}} + \text{LC}_{\text{doc}} + \text{COH}_{\text{doc}}$	9.67	**40.66***	19.60	**59.76**	29.51	58.34	22.82	67.51
Risk(0.5)-$\text{BLEU}_{\text{doc}} + \text{LC}_{\text{doc}} + \text{COH}_{\text{doc}}$	9.77	38.85*	**19.80**	59.62	29.79	**58.44**	22.76	67.53
Risk(0.2)-$\text{BLEU}_{\text{doc}} + \text{LC}_{\text{doc}} + \text{COH}_{\text{doc}}$	**9.99**	37.53	19.42	59.72	29.70	58.39	**22.96**	67.50

News (WMT Workshop):

Model	Es-En (news) BLEU	LC	COH	F_{BERT}
Sentence-level NMT	21.79	32.97	28.1	67.88
HAN_{join}	22.16	32.87	28.15	**68.28**
Human reference	–	38.66	30.97	–
Risk(1.0)-$\text{BLEU}_{\text{doc}} + \text{LC}_{\text{doc}} + \text{COH}_{\text{doc}}$	20.67	32.81	28.14	67.84
Risk(0.8)-$\text{BLEU}_{\text{doc}} + \text{LC}_{\text{doc}} + \text{COH}_{\text{doc}}$	22.26	**33.70***	**28.45***	68.14
Risk(0.5)-$\text{BLEU}_{\text{doc}} + \text{LC}_{\text{doc}} + \text{COH}_{\text{doc}}$	22.34	33.51*	28.39	68.02
Risk(0.2)-$\text{BLEU}_{\text{doc}} + \text{LC}_{\text{doc}} + \text{COH}_{\text{doc}}$	**22.45***	33.32*	28.25	68.13

(*) means that the differences are statistically significant with respect to the HAN_{join} baseline with a p-value < 0.05 over a one-tailed Welch's t-test.

References

[1] Sergey Edunov, Myle Ott, Michael Auli, David Grangier, and Marc'Aurelio Ranzato. Classical structured prediction losses for sequence to sequence learning. *Proceedings of the North American Chapter of the Association for Computational Linguistics (NAACL)*, 2018.

Conclusion

Consistent improvement in LC and COH, while retaining **comparable values of accuracy metrics such as BLEU and F_{BERT}**. The best combination of discourse rewards, accuracy rewards and NLL has had to be selected by validation for each dataset.

In the **future** we plan to investigate how to automate this selection, and also explore the applicability of the proposed approach to other **natural language generation** tasks.

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