

Yuxin HUANG, Huailing GU, Zhengtao YU, Yumeng GAO, Tong PAN, Jialong XU, 2023. Enhancing low-resource cross-lingual summarization from noisy data with fine-grained reinforcement learning. *Frontiers of Information Technology & Electronic Engineering*, 25(1):121-134. <https://doi.org/10.1631/FITEE.2300296>

Enhancing low-resource cross-lingual summarization from noisy data with fine-grained reinforcement learning

Key words: Cross-lingual summarization; Low-resource language; Noisy data; Fine-grained reinforcement learning; Word correlation; Word missing degree

Corresponding author: Zhengtao YU

E-mail: ztyu@hotmail.com

 ORCID: <https://orcid.org/0000-0002-4012-461X>

Motivation

1. **Low-resource cross-lingual summarization** aims to generate concise and informative summaries in the target language when faced with limited linguistic resources, making it highly meaningful.
2. Dealing with the challenge of **alleviating translation noise** becomes crucial due to the limited performance of low-resource translation models.
3. **Leveraging the source language summary** proves effective in alleviating noise issues. However, how to use this source language information requires careful design.

Method

Using the correspondence between source language summaries and target language summaries can effectively address the **noise issue**.

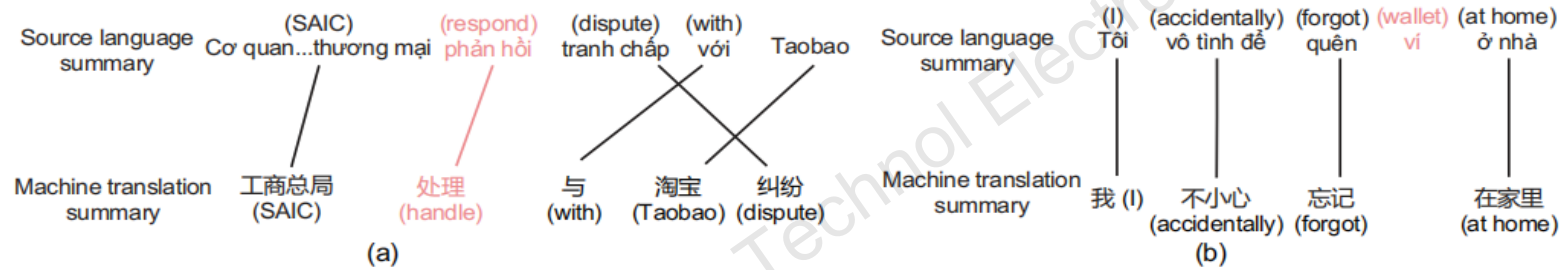


Fig. 1 Common translation errors: (a) improper choice of words; (b) missing content word

Table 2 The proportion of data of different noise types in Zh-Visum and Vi-Zhsum

Noise type	Proportion for Zh-Visum (%)			Proportion for Vi-Zhsum (%)		
	Filter-No	Filter-RG	Filter-BERT	Filter-No	Filter-BERT	Filter-MGF
Improper choice of words	37.00	30.67	29.34	28.25	23.58	22.38
Missing content words	17.50	18.67	18.32	12.75	15.71	15.95
Wrong word order	6.33	5.66	4.67	17.42	15.24	16.19
Named entity error	12.67	13.00	14.67	7.75	8.57	8.57
Other	6.50	8.00	7.00	4.83	5.47	4.05
No error	20.00	24.00	26.00	29.00	31.43	32.86

Filter-No: unfiltered dataset. Filter-RG/BERT/MGF: the use of ROUGE/BERTScore/MGFScore for filtering

Method

Carefully designing **reinforcement rewards** based on **word correlation** and **missing degree** between source language summaries and target language summaries

Algorithm 1 Reward function design

```

1: Input:  $Y_{\text{idf}}, Y_{\text{align}}^{A \rightarrow B}$  /* Input TF-IDF values of source
   language summary words and correlation table */
2: score  $\leftarrow 0$  /* Total reward score */
3: sumwd  $\leftarrow 0$  /* Total word missingness penalty score */
4: Countcor  $\leftarrow 0$  /* Count the number of times  $y_{j,\text{sim}}^B$  being
   greater than 0 */
5: sumcor  $\leftarrow 0$  /* Total word correlation score */
6: for  $y_{j,\text{idf}}^A$  in  $Y_{\text{idf}}^A$  do
7:    $y_{j,\text{sim}}^B \leftarrow \text{sim}(y_j^A, Y_{\text{align}}^{A \rightarrow B})_{\text{sum}}$ 
8:   if  $y_{j,\text{sim}}^B = 0$  then
9:     sumwd  $\leftarrow \text{sum}_{\text{wd}} - y_{j,\text{idf}}^A$ 
10:  else
11:    scorecor  $\leftarrow y_{j,\text{sim}}^B \cdot y_{j,\text{idf}}^A$ 
12:    score  $\leftarrow \text{score} + \text{score}_{\text{cor}}$ 
13:    sumcor  $\leftarrow \text{sum}_{\text{cor}} + y_{j,\text{sim}}^B$ 
14:    Countcor  $\leftarrow \text{Count}_{\text{cor}} + 1$ 
15:  end if
16: end for
17: if Countcor  $\neq 0$  then
18:   avgcor  $\leftarrow \frac{\text{sum}_{\text{cor}}}{\text{Count}_{\text{cor}}}$ 
19:   score  $\leftarrow \text{score} + \text{sum}_{\text{wd}} \cdot \text{avg}_{\text{cor}}$ 
20: end if
21: return score

```

$$y_{j,\text{sim}}^B = \text{sim}(y_j^A, Y_{\text{align}}^{A \rightarrow B})_{\text{sum}}$$

$$y_{j,\text{att}}^B = \begin{cases} y_{j,\text{idf}}^A, & y_{j,\text{sim}}^B > 0, \\ -y_{j,\text{idf}}^A, & y_{j,\text{sim}}^B = 0, \end{cases}$$

$$R(Y^B, Y^A) = \frac{1}{L} \sum_{j=1}^L \begin{cases} y_{j,\text{sim}}^B y_{j,\text{att}}^B, & y_{j,\text{sim}}^B > 0, \\ \frac{\sum_{j=1}^L y_{j,\text{sim}}^B}{\text{Count}(y_{j,\text{sim}}^B > 0)} y_{j,\text{att}}^B, & y_{j,\text{sim}}^B = 0, \end{cases} \quad (4)$$

$$L_{\text{rl}} = - \sum_{Y^B \in Y} \log P(Y^B | X^A; \theta) R(Y^B, Y^A),$$

Method

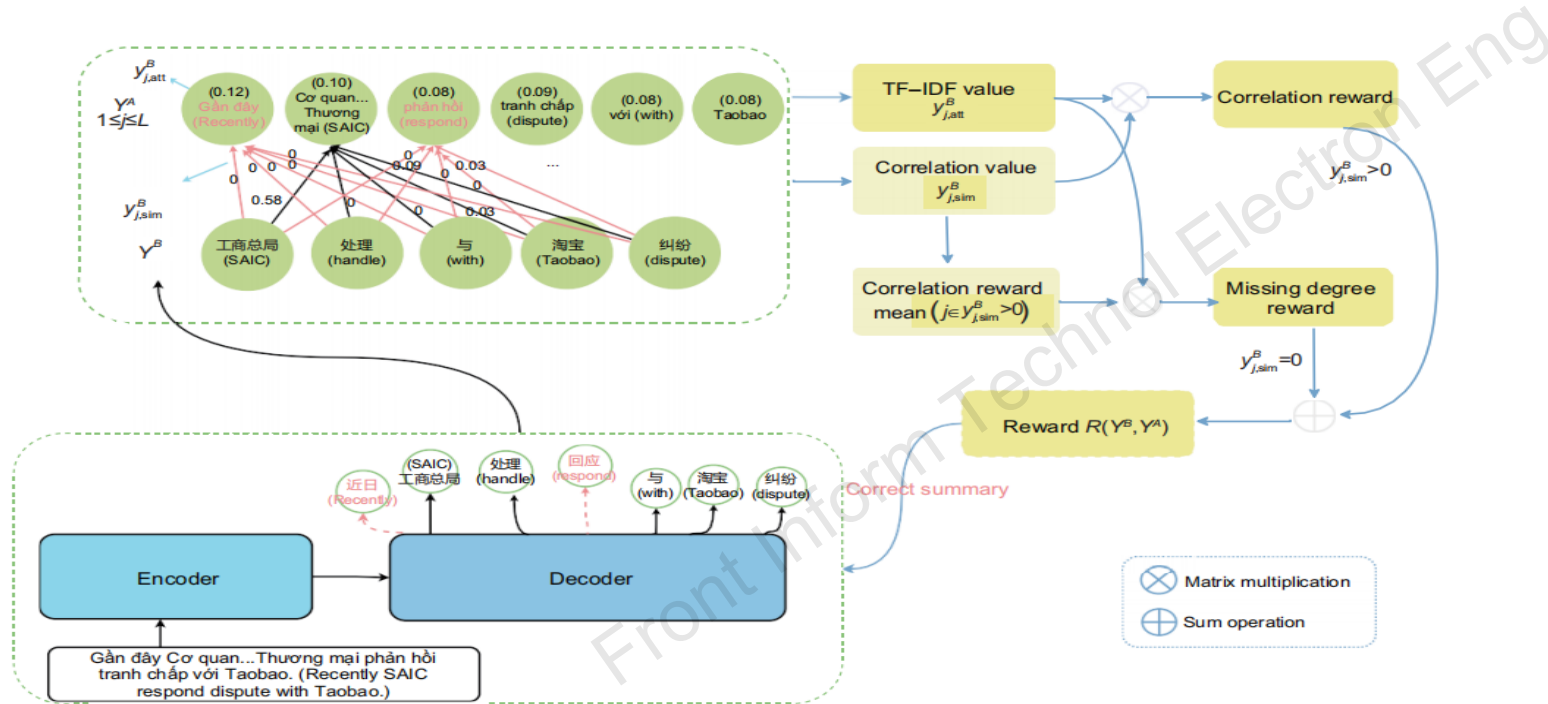


Fig. 2 Fine-grained reinforcement learning model structure to improve the quality of model-generated summary by computing word correlation and missingness between decoder-generated summary and source language summary (Words in red represent the updated words. References to color refer to the online version of this figure)

$$L_{\text{cls}} = \sum_{t=1}^M \log P(y_t^B | y_{<t}^B, X^A; \theta),$$

$$L_{\text{mix}} = \gamma L_{\text{cls}} + (1 - \gamma) L_{\text{rl}},$$

Method

Table 4 Results of comparison with baseline models

Model	Zh-Visum _{Filter}				Vi-Zhsum _{Filter}			
	RG-1	RG-2	RG- <i>L</i>	BERTScore	RG-1	RG-2	RG- <i>L</i>	BERTScore
Sum-Tra	17.78	8.13	16.54	63.29	19.65	6.76	15.70	60.59
Tra-Sum	20.92	10.24	18.97	65.36	22.61	8.24	16.89	61.61
NCLS (Zhu et al., 2019)	22.69	10.26	20.96	66.66	22.45	8.88	18.87	62.87
MCLAS (Bai et al., 2021)	23.19	10.88	21.35	66.81	22.71	9.30	19.36	62.82
KDCLS (Nguyen and Luu, 2022)	23.21	10.91	21.36	66.85	22.82	9.31	19.43	62.82
LR-ROUGE (Yoon et al., 2021)	23.16	10.83	21.36	66.79	22.63	9.30	19.31	62.81
XSIM (Dou et al., 2020)	22.89	10.53	20.96	66.76	22.76	9.25	19.23	62.71
LR-MC ($\gamma = 1$)	22.81	10.49	20.87	66.71	22.66	9.14	19.21	62.66
LR-MC ($\gamma = 0.6$)	23.40	10.93	21.60	66.91	23.29	9.32	19.57	62.87

Best results are in bold

Conclusions

1. The **correspondence** between **source language summaries** and **target language summaries** can effectively address the **noise issue**.
2. The combination of **reinforcement learning** loss and **cross-entropy loss** is used as the optimization objective for model training, reducing the negative impact of noisy data.
3. **High-quality data** are more conducive to model training.



Yuxin HUANG was born in 1983. He received the PhD degree from Kunming University of Science and Technology, in 2021. Now He is an associate professor at Kunming University of Science and Technology. His research interests include natural language processing and text generation.



Zhengtao YU Received his PhD degree in computer application technology from Beijing Institute of Technology, Beijing, China, in 2005. He is currently a professor with the School of Information Engineering and Automation, Kunming University of Science and Technology, China. His main research interests include natural language process, image processing, and machine learning.