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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

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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.

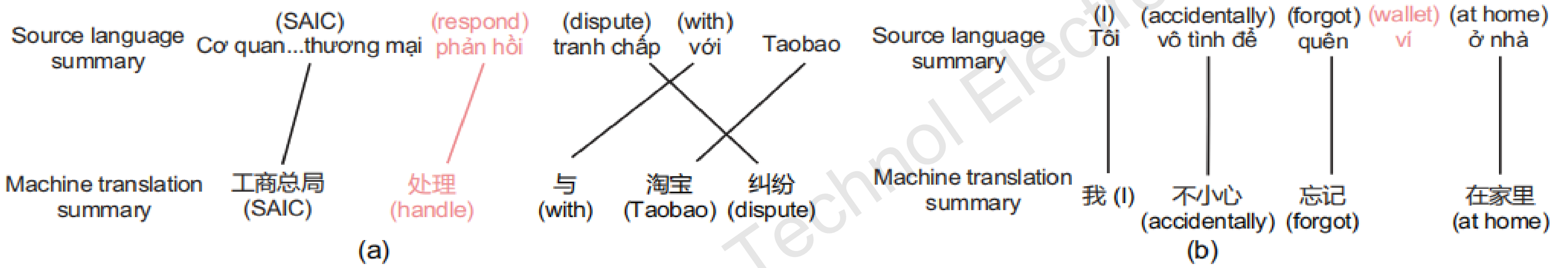

Fig. 1 Common translation errors: (a) improper choice of words; (b) missing content word

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 dateset. 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

```
Input: Y_idf, Y_align^{A→B} /* Input TF–IDF values of source language summary words and correlation table */
score ← 0 /* Total reward score */
sum_wd ← 0 /* Total word missingness penalty score */
Count_cor ← 0 /* Count the number of times y_{j,sim}^B being greater than 0 */
sum_cor ← 0 /* Total word correlation score */
for y_{j,idf}^A in Y_idf^A do
    y_{j,sim}^B ← sim(y_j^A, Y_align^{A→B})_sum
    if y_{j,sim}^B = 0 then
        sum_wd ← sum_wd − y_{j,idf}^A
    else
        score_cor ← y_{j,sim}^B · y_{j,idf}^A
        score ← score + score_cor
        sum_cor ← sum_cor + y_{j,sim}^B
        Count_cor ← Count_cor + 1
    end if
end for
if Count_cor ≠ 0 then
    avg_cor ← sum_cor / Count_cor
    score ← score + sum_wd · avg_cor
end if
return score
```

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

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

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

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

Method

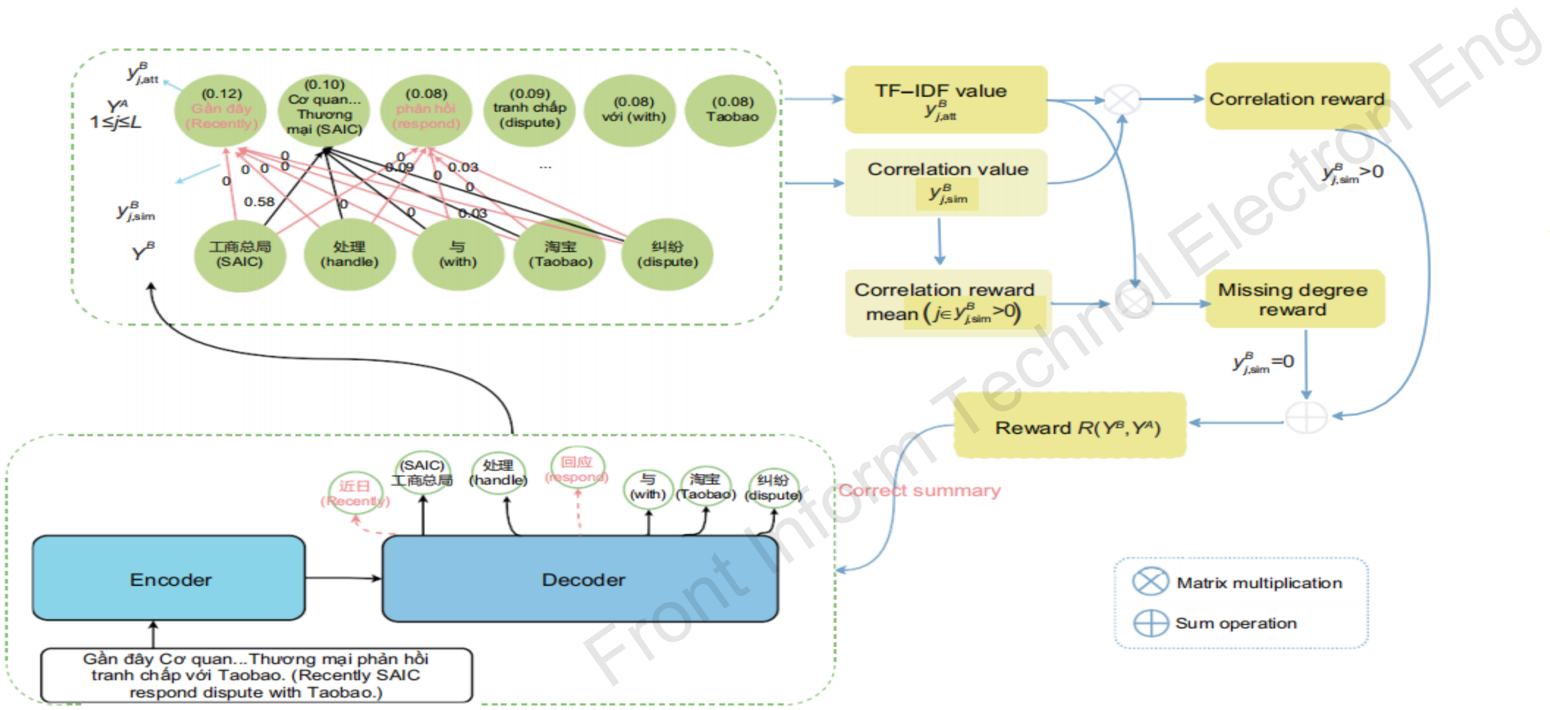

Fig. 2 Fine-grained reinforcement learning model structure to improve the quality of model-generated summary by computing word correlation and missingness between decoder-generated summary and source language summary (Words in red represent the updated words. References to color refer to the online version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

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

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

Method

Table 4 Results of comparison with baseline models

Model	Zh-Visum$_{\text{Filter}}$				Vi-Zhsum$_{\text{Filter}}$			
	RG-1	RG-2	RG-L	BERTScore	RG-1	RG-2	RG-L	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.

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