

Supplementary Document: Visual-Textual Attentive Semantic Consistency for Medical Report Generation

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A. Discussion of disease and description pattern labels.

The disease labels and description pattern labels (DPLs) are extracted from the medical reports using CheXpert Labeler. Someone might wonder if the description pattern labels are associated with the disease labels, or they are not related. In the current version, once the disease and DPLs are extracted, they are treated independently. When we were selecting the DPLs according to the MIMIC-CXR and IU X-ray datasets, we didn't observe many duplicated DPLs in a report. Moreover, since the DPLs contain useful information like lesion location and size, they are very helpful to train the image encoder and MMSA module. However, the concern for more open-world medical reports is insightful, where duplicated DPLs may appear for multiple diseases in a report (maybe severely ill patients). The relationships between disease labels and DPLs could be exploited in the decoder design to generate more accurate sentences.

B. Training if some report parts are missing.

We can consider what happens if the finding part or the indication parts are missing in the original report. Will that affect the training? First, the finding part, which contains detailed sentence descriptions, is usually the main part of a report. This is our target to generate. It is hard to implement a medical report generator without any training report data. Second, if the indication part is missing, we can detach the clinical feature encoding part, which will decrease the performance to some extent. However, the indication part is usually available in reports' raw data from a hospital. Most existing public datasets contain the indication part together with the finding part.

C. Discussion of \mathcal{L}_{ISM} and \mathcal{L}_{DA} .

Here we further discuss \mathcal{L}_{ISM} and \mathcal{L}_{DA} with their individual contributions. As shown in Eq. 10 in the original paper, since $\{\mathcal{L}_{sent} + \mathcal{L}_{stop} + \mathcal{L}_{word}\}$ is the basic loss function used in the medical report generation framework, we set it as the baseline(B). We show the effectiveness of \mathcal{L}_{ISM} and \mathcal{L}_{DA} in the following table on MIMIC-CXR, when other modules are fully deployed. E.g. BLEU-1 shows that $B + \mathcal{L}_{ISM}(\sim 97.8\%)$ contributes more than $B + \mathcal{L}_{DA}(\sim 94.4\%)$. Although the two losses totally bring around 3% additional training time, there is no extra cost in the testing.

Methods	BLEU-1	CIDEr	ROUGE	METEOR	nKTD
Baseline(B)	0.345	0.898	0.321	0.168	0.169
$B + \mathcal{L}_{ISM}$	0.364	1.029	0.325	0.179	0.132
$B + \mathcal{L}_{DA}$	0.351	0.954	0.320	0.173	0.155
$B + \mathcal{L}_{ISM} + \mathcal{L}_{DA}$	0.372	1.121	0.335	0.190	0.106

D. Qualitative Results.

We demonstrate more results showing the reports generated by our method, compared with ground-truths and some baselines in Fig. 1.

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Figure 1. Illustration of generated sentences by our method and comparisons with baselines. For reports by **Ours**, the key findings correctly mentioned in the report are highlighted by **green**, and those wrongly described are in **red**. The **blue** texts are input clinical information.