Radiology Report Generation with a Learned Knowledge Base and Multi-modal Alignment

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Abstract

In clinics, a radiology report is crucial for guiding a patient’s treatment. Unfortunately, report writing imposes a heavy burden on radiologists. To effectively reduce such a burden, we hereby present an automatic, multi-modal approach for report generation from chest x-ray. Our approach, motivated by the observation that the descriptions in radiology reports are highly correlated with the x-ray images, features two distinct modules: (i) Learned knowledge base. To absorb the knowledge embedded in the above-mentioned correlation, we automatically build a knowledge base based on textual embedding. (ii) Multi-modal alignment. To promote the semantic alignment among reports, disease labels and images, we explicitly utilize textual embedding to guide the learning of the visual feature space. We evaluate the performance of the proposed model using metrics from both natural language generation and clinic efficacy on the public IU and MIMIC-CXR datasets. Our ablation study shows that each module contributes to improving the quality of generated reports. Furthermore, with the aid of both modules, our approach clearly outperforms state-of-the-art methods.

Introduction

The radiology report is crucial for assisting clinic decision making (Zhou, Rueckert, and Fichtinger 2019). It describes some observations on images such as diseases’ degree, size, and location. However, the process of writing reports is time-consuming and tedious for radiologists (Bruno, Walker, and Abujudeh 2015). With the advancement of deep learning and natural language processing, automatic radiology report generation has attracted growing research interests.

Many radiology report generation approaches follow the practice of image captioning models (Xu et al. 2015, Lu et al. 2017, Anderson et al. 2018). For example, (Jing, Xie, and Xiong 2018, Yuan et al. 2019) employ the encoder-decoder architecture and propose the hierarchical generator as well as the attention mechanism to generate long reports. However, radiology report generation task is different from image captioning task. In image captioning, the model is required to cover the details of the input image, while for radiology report generation, the model is required to focus on the abnormal regions and infer potential diseases. Therefore, to generate a correct radiology report, the model needs to identify the abnormal regions and provide proper descriptions. To this end, the medical background knowledge needs to be included in modeling.

Recently, some works attempt to integrate medical knowledge in modeling: MKG (Zhang et al. 2020) and PPKED (Liu et al. 2021) incorporate manual pre-constructed knowledge graphs to enhance the generation, HRGR (Li et al. 2018) builds a template database based on prior knowledge by manually filtering a set of sentences in the training corpus. These methods achieve improved performance over image captioning models. However, these models need to build the knowledge graph or template database in advance which is still laborious. In addition, when applying these models to images of other diseases, the knowledge graph or template database needs to be updated as well.

In this paper, we propose a knowledge base updating mechanism to store medical knowledge automatically. It learns a knowledge base from training data. Firstly, we initialize a memory as a knowledge base and use CNN/BERT model to extract visual features and textual embeddings from the input images and corresponding reference reports. Next, the knowledge base is updated by the report embeddings during the training phase. At the end of training, we fix the knowledge base as the model’s parameter and use it for report generation. To acquire the related knowledge of the input image, we propose a visual-knowledge attention module that queries knowledge base with visual features. Finally, we employ the standard Transformer model with the help of the visual features and acquired knowledge to generate radiology reports.

Since the critical clinical information usually comes from descriptions of abnormalities, where such sentences are rare and diverse in radiology datasets, we need to enable the knowledge base to focus on the knowledge of abnormalities. To this end, we propose a multi-modal alignment mechanism. It consists of visual-textual alignment and visual-label alignment. The intuition is that the reports and disease labels describe the same observations on the images, so the semantic features among images, reports, and disease labels should be consistent. Specifically, we adapt the triplet margin loss (Balntas et al. 2016) to align the visual features and
textual embeddings, as well as the binary cross-entropy loss to align the visual features and disease labels. Guided by the proposed multi-modal alignment, the proposed knowledge base can store the knowledge of abnormalities which works together with the visual encoder to generate accurate descriptions of abnormalities.

We evaluate our proposed methods on the publicly accessible IU and MIMIC-CXR datasets. Besides natural language generation (NLG) metrics, we adopt clinical efficacy (CE) metrics to analyze the quality of generation reports in clinics. The results show that the proposed method achieves state-of-the-art performance on NLG and CE metrics. It also indicates that the radiology report generation benefits from the multi-modal alignment mechanism and the learned knowledge base, avoiding laborious manual construction. Furthermore, the proposed methods boost the quality of generated reports in both language and clinical correctness.

The main contributions are as follows:

- We propose a novel radiology generation framework with a knowledge base, which could be learned automatically from the training data by a novel updating mechanism.
- We propose a multi-modal alignment mechanism that promotes the semantic alignment among images, reports, and disease labels to guide the learning of visual features.
- Our experiments demonstrate consistent performance improvements of our proposed methods. Furthermore, our model achieves state-of-the-art performance on various metrics for both the public IU and MIMIC-CXR datasets.

Related Work

With the advancement of computer vision and natural language processing, many works exploit to combine radiology images and free-text for automatically generating reports to assist radiologists in the clinic (Zhou et al. 2021). Inspired by image captioning, (Shin et al. 2016) adopts the CNN-RNN framework to describe the detected diseases based on visual features on a chest x-ray dataset. The work is restricted to the categories of predefined diseases. The Co-Att (Jing, Xie, and Xing 2018) and (Xue et al. 2018; Yuan et al. 2019) propose different attention mechanisms and hierarchical LSTM to generate radiology reports. However, most reports generated by such works tend to describe normal observations, and pose a knowledge-enhancing generator without manual labor to build a knowledge base.

As revealed by recent studies (Graves et al. 2016; Wu et al. 2018; Chen et al. 2020a), the memory mechanism can provide prior knowledge to boost the generation model. The R2Gen (Chen et al. 2020b) proposes a relational memory in the decoder to learn the order of words or sentences. Nevertheless, the order relies on the radiologist’s personal style. The KVMN (Miller et al. 2016) proposes a key-value structured memory that automatically encodes prior knowledge into the memory for question and answer tasks (QA). Our work is different from KVMN in three aspects. First, KVMN deals with a different task (QA) which is a classification problem. As a result, their framework cannot be directly applied to medical report generation. Second, the knowledge source of KVMN is pre-defined by a manually prepared database, while our knowledge base is learned from scratch during training. Third, we propose a multi-head updating mechanism that has more expressive ability than the KVMN model.

Method

In this section, we introduce the proposed method. Firstly, we provide the notation and formulate the radiology report generation task; Secondly, we propose the framework of our method; Thirdly, we describe the proposed knowledge base updating and multi-modal alignment mechanism in detail.

Notation and Problem Formulation

Let $Img$ denote a radiology image, $Y = \{y_1, \ldots, y_{N_Y}, |y_i| = 0/1\}$ denote the class label of this image, $W^* = \{w_1^*, w_2^*, \ldots, w_{N_W}^* | w_i^* \in \mathcal{V}\}$ denote the reference report, $W = \{w_1, w_2, \ldots, w_{N_W} | w_i \in \mathcal{V}\}$ denote the report generated by the model. Here $w_i^*$ and $w_i$ refer to the index of word in vocabulary $\mathcal{V}$, $N_L$ is the number of labels, $N_R$ and $N_W$ are the length of the reference and generated reports. In the training stage of the proposed model, we need $Img$, $Y$ and $W^*$; In the testing stage, we only need $Img$ to generate $W$.

Framework

Figure 1 displays the framework of the proposed model: a knowledge-enhancing generator, a knowledge-updating module, and a multi-modal alignment module. All three modules are used in the training stage, and only the knowledge-enhancing generator is used in the testing stage. In training, the knowledge-updating module and the multi-modal alignment module work together to restore learned knowledge into the knowledge base; In prediction, the knowledge base is fixed. The knowledge-enhancing generator extracts related knowledge from the knowledge base to generate radiology reports.

Firstly, we extract visual features from the input radiology image. Following previous works (Jing, Xie, and Xing 2018; Wang et al. 2018; Chen et al. 2020b), the convolution neural...
During training, we also extract report embeddings from reference reports to update the knowledge base and guide the learning of visual features. Similar to BERT model (Devlin et al. 2019), we employ the encoder of Transformer (Vaswani et al. 2017) as our report encoder to extract report embeddings. The report embeddings are acquired from the hidden states of the last layer:

\[ T = BERT(W^*), \]  

(3)

where \( W^* \) denotes the reference reports written by radiologists, \( BERT(\cdot) \) refers to the report encoder, and \( T \in \mathbb{R}^{N \times D} \) is extracted textual embedding.

In BERT, the first token (CLS) of a sentence is regarded as the aggregate representation of the entire sequence. Based on the report embedding acquired in Eq. (3), the aggregated textual feature of the report \( z_{txt} \) is acquired by Eq. (4):

\[ z_{txt} = T_{[CLS]}W^Z + b^Z \]  

(4)

where \( T_{[CLS]} \) denotes the embedding of CLS in report embeddings \( T \), \( W^Z \) is a learnable affine transformation, and \( b^Z \) is a bias. Thus, \( z_{txt} \) has the dimension of \( D \).

Knowledge Base Updating

Different from image captioning, radiology report generation requires professional medical domain knowledge. The radiologists need to examine diseases’ degree, size, and location before writing reports. To distill the domain knowledge
conceived in the pairs of radiology images, we introduce the memory mechanism. As revealed by recent studies (Graves et al. 2016, Wu et al. 2018, Chen et al. 2020a), the memory mechanism can provide prior knowledge to boost the generation model. Inspired by this, we initialize a memory as a radiology knowledge base and propose an updating mechanism to learn from training data.

In our implementation, we use a matrix to initialize the knowledge base \( M_0 \in \mathbb{R}^{N_m \times D} \), where \( N_m \) is the base size and \( D \) is the dimension. In initialization, the diagonal element of \( M_0 \) is set 1, and other elements are set to 0.

To model the relationship among the knowledge base, the textual features from the reference reports, and the visual features from input images, we use the multi-head attention (MHA) (Vaswani et al. 2017) mechanism. The MHA consists of \( n \) parallel heads and each head is defined as a scaled dot-product attention:

\[
\text{Att}_i(X, Y) = \text{softmax}\left(\frac{XW^Q_i(YW^K_i)^T}{\sqrt{d_n}}\right)YW^V_i
\]

MHA(X, Y) = \[\text{Att}_1(X, Y); \ldots; \text{Att}_n(X, Y)\]W^O \tag{5}

where \( X \in \mathbb{R}^{l_x \times d} \) and \( Y \in \mathbb{R}^{l_y \times d} \) denote the Query matrix and the Key/Value matrix, respectively; \( W^Q_i, W^K_i, W^V_i \in \mathbb{R}^{d \times d_n} \) and \( W^O \in \mathbb{R}^{dx \times d} \) are learnable parameters, where \( d_n = \frac{d}{n} \). \([\cdot, \cdot] \) stands for concatenation operation.

To update the knowledge base \( M_{t-1} \) at the training step \( t-1 \), we use the textual features extracted from the reference reports identifying the knowledge that is missing in \( M_{t-1} \).

\[
\Delta M_t = \text{MHA}(M_{t-1}, T) \tag{6}
\]

where \( \Delta M_t \) stands for the incremental knowledge acquired at the training step \( t \) and \( T \) denotes the textual features acquired in Eq. (3). By integrating the incremental knowledge, we can acquire the updated knowledge base at training step \( t \).

\[
M_t = M_{t-1} + \text{Norm}(\Delta M_t) \tag{7}
\]

where \( \text{Norm} \) refers to layer normalization to normalize the incremental knowledge.

Next, we acquire supporting knowledge regarding the current image by multi-head attention.

\[
M^S = \text{MHA}(z_{img}, M_t) \tag{8}
\]

where \( M^S \) refers to the supporting knowledge, \( z_{img} \) refers to the pooled visual feature acquired from Eq. (2). The report generator automatically generates a medical report using visual features and the learned knowledge base. The Transformer-based model has proven effective in natural language processing (Devlin et al. 2019). Thus, we employ a standard Transformer model as our report generator (Vaswani et al. 2017) which includes a stack of self-attention layers and masked self-attention layers. The generator decodes the concatenation of visual features and the supporting knowledge to a sequence of hidden representation and follows the auto-regressive decoding process generating the radiology report \( W \) from the conditional distribution:

\[
p_0(W|V; M^S) = \prod_{t=1}^{N_W} p_0(w_t| w_{<t}, V; M^S), \tag{9}
\]

where \( \theta \) refers to the model’s parameters, \( w_{<t} \) denotes the generated words before time step \( t \), and \( V \) refers to visual features acquired in Eq. (1).

### Multi-Modal Alignment

In this section, we introduce the Multi-Modal Alignment module which aligns the visual, textual, and disease labels to guide the learning of the proposed model.

#### Textual-Textual Alignment

Following the paradigm of natural language generation, our basic model maximizes the likelihood of generated reports by minimizing the cross-entropy loss. The model is optimized by the consistency between generated and reference reports, so we name it textual-textual (T-T) alignment.

\[
\mathcal{L}_{T-T} = -\frac{1}{N_w} \sum_{i=0}^{N_w} \log p_0(W|[V; M]) \tag{10}
\]

where \( W \) is the generated sequence.

Besides the general textual-textual alignment, we propose two extra multi-modal alignments. The radiology report generation is a multi-modal task that aims to transform radiology images into reports. Since reports and disease labels describe the observations on the x-ray image, the semantic features among images, reports, and disease labels should be consistent. Following this intuition, we proposed visual-textual (V-T) alignment and visual-label (V-L) alignment to encourage our model to be consistent among different modalities and guide the learning of the proposed model.

#### Visual-Textual Alignment

The visual-textual alignment module tries to make the features in radiology images and reference reports to be close. Firstly, we extract the pooled textual feature \( z_{txt} \) from the reference report and the pooled visual features \( z_{img} \) from the input image. As illustrated in Chauhan et al. (2020), the triplet margin loss (Balntas et al. 2016) model performs well for joining image learning and report in the radiology image classification task. We adapt the image-to-text and text-to-image triplet margin loss losses which force the paired features closer than unpaired features in latent space. This helps to model the bidirectional inter-relationship between image and report. Given a target pair \( \{z_{img}, z_{txt}\} \), we sample an negative pair \( \{z_{img}, z_{txt}^{(n)}\} \) from the training set, and the visual-textual alignment is formulated as:

\[
\mathcal{L}_{V-T} = \max(0, \mu + d(z_{img}, z_{txt}) - d(z_{img}, z_{txt}^{(n)})) + \max(0, \mu + d(z_{txt}, z_{img}) - d(z_{txt}, z_{txt}^{(n)})) \tag{11}
\]

where \( d(z_1, z_2) = 1 - \frac{z_1 \cdot z_2}{||z_1|| \cdot ||z_2||} \tag{12} \)

\[
L = \max(0, \mu + d(z_{img}, z_{txt}) - d(z_{img}, z_{img}^{(n)})) \tag{13}
\]

In our implementation, \( d(\cdot, \cdot) \) is a distance function to quantify the closeness of two modalities, and \( \mu \) is a margin parameter defined as Eq. (14), which is determined by the difference of disease labels between the target image and negative image.

\[
\mu = \max(0, 1 - \sum_{y \in Y} \sum_{y' \in Y^{(n)}} ||y - y'||) \quad Y = Y^{(n)} \tag{14}
\]
Table 1: The performances of our model compared with baselines on IU and MIMIC-CXR datasets. The best results are highlighted in bold. For the baselines marked by *, we cite the results reported in (Jing, Wang, and Xing 2019). For the baselines marked by #, we replicate results by their codes; the rests are cited from the original paper.

| Dataset       | Model       | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | CIDEr | ROUGE-L |
|---------------|-------------|--------|--------|--------|--------|-------|---------|
| IU            | S&T*        | 0.216  | 0.124  | 0.087  | 0.066  | 0.294 | 0.306   |
|               | SA&T#       | 0.399  | 0.251  | 0.168  | 0.118  | 0.302 | 0.323   |
|               | AdaAtt*     | 0.220  | 0.127  | 0.089  | 0.068  | 0.295 | 0.308   |
|               | CMAS*       | 0.464  | 0.301  | 0.210  | 0.154  | 0.275 | 0.362   |
|               | KERP        | 0.482  | 0.325  | 0.226  | 0.162  | 0.351 | 0.376   |
|               | R2Gen       | 0.470  | 0.304  | 0.219  | 0.165  | /     | 0.371   |
|               | PPKED       | 0.483  | 0.315  | 0.224  | 0.168  | 0.351 | 0.376   |
|               | Our         | 0.497  | 0.319  | 0.230  | 0.174  | 0.407 | 0.399   |
| MIMIC-CXR     | S&T#        | 0.256  | 0.157  | 0.102  | 0.070  | 0.063 | 0.249   |
|               | SA&T#       | 0.304  | 0.177  | 0.112  | 0.077  | 0.083 | 0.249   |
|               | AdaAtt#     | 0.311  | 0.178  | 0.111  | 0.075  | 0.084 | 0.246   |
|               | TopDown#    | 0.280  | 0.169  | 0.108  | 0.074  | 0.073 | 0.250   |
|               | R2Gen       | 0.353  | 0.218  | 0.145  | 0.103  | /     | 0.277   |
|               | PPKED       | 0.360  | 0.224  | 0.149  | 0.106  | /     | 0.284   |
|               | Our         | 0.386  | 0.237  | 0.157  | 0.111  | 0.111 | 0.274   |

where $Y \in \mathbb{R}^{N_L}$ and $Y^{(n)} \in \mathbb{R}^{N_L}$ denote the disease labels of input image and negative sampled image, respectively.

**Visual-Label Alignment.** Let $Y' \in \mathbb{R}^{N_L}$ denote the predicted labels of current input image by the proposed model. Then the visual-label alignment is calculated as follows.

$$Y' = z_{img} W^L + b^L$$  \hspace{1cm} (15)

where $W^L$ is a learnable affine transformation, and $b^L$ is a bias.

Next, we adopt binary cross entropy loss to optimize the model on the consistency between visual and disease labels:

$$\mathcal{L}_{V-L} = -\frac{1}{N_L} \sum_{i=0}^{N_L} y_i \log \phi(y'_i)$$  \hspace{1cm} (16)

where $y_i$ and $y'_i$ are ground-truth label and the predicted label in Eq. (15), respectively, and $\phi(\cdot)$ denotes a sigmoid function.

Finally, we optimize the proposed model with the textual-textual alignment $\mathcal{L}_{T-T}$, the visual-textual alignment $\mathcal{L}_{V-T}$, and the visual-label alignment $\mathcal{L}_{V-L}$. It is formulated as:

$$\mathcal{L} = \lambda_1 \mathcal{L}_{T-T} + \lambda_2 \mathcal{L}_{V-T} + \lambda_3 \mathcal{L}_{V-L},$$  \hspace{1cm} (17)

where $\lambda_1$, $\lambda_2$, and $\lambda_3$ are coefficients to balance the three constraint terms.

**Experiment**

In this section, we evaluate the proposed model on MIMIC-CXR and IU datasets and conduct some ablation studies to analyze the performance of the proposed model and the effectiveness of each component.

**Dataset**

**MIMIC-CXR.** MIMIC-CXR (Johnson et al. 2019) is a large dataset that contains 377,110 chest x-ray images and 227,827 free-text radiology reports associated with these images for 65,379 patients. The dataset contains multi-view images, and we filter frontal and lateral view images following previous works (Chen et al. 2020b). The dataset is labeled for 14 common chest radiology observations derived from the free-text radiology reports by a label tool CheXpert (Irvin et al. 2019).

**IU.** Indiana University Chest X-ray Collection (Demner-Fushman et al. 2016) is a public radiology examination dataset containing 3,955 radiology reports and 7,470 posterior-anterior/lateral view chest x-ray images. Each report consists of MeSH, indication, comparison, findings, and impression. For consistency, we employ the CheXpert to extract the labels as to the IU dataset.

The finding section in both datasets is used as the ground-truth reference report since it directly describes the observations on x-ray images. First, we filter out the reports without x-ray images or images missing findings section. Then, each report is converted to lower case and filtered out with a minimum frequency of three, which results in 760/7866 unique words on IU and MIMIC-CXR datasets, respectively. The labels include 12 disease labels and 2 individual labels indicating "No finding" and "Support device". There is no official split of the dataset for the IU dataset, so we follow the data split of previous SOTA work R2Gen (Chen et al. 2020b) which splits the data into training, validation, and testing set using a ratio 7:1:2 without overlap in patients. For the MIMIC-CXR dataset, the official split is adopted.
Implementation Detail

In our implementation, we employ the ResNet-101 (He et al. 2016) model as our visual encoder pre-trained on ImageNet. The report encoder and generator are implemented by ourselves and trained from scratch. All hyper-parameters are selected by the performances on the validation set. The layer of report encoder is set to 3. The dimension of the model is set to 512. All images are resized to 224×224, and we use zero-padding for each mini-batch reports to keep the same length. Except for the visual encoder with an initial learning rate of 5e-5, we use the Adam optimizer with an initial learning rate of 1e-4 and weight decay of 5e-5 for training. We train the model with epochs of 50 and 30 for the IU and MIMIC-CXR datasets, respectively. The coefficients of multi-modal alignment \(\lambda_1, \lambda_2,\) and \(\lambda_3\) are set to 1, 0.1, and 0.1. We evaluate the proposed model on the validation set and report the test set results when the performance of the validation set achieves the best BLEU-4 score.

Quantitative Results

We adopt the widely used NLG metrics and clinical efficacy metrics to evaluate the performance of the proposed model. The NLG metrics include BLEU-n (Papineni et al. 2002), CIDEr (Vedantam, Lawrence Zitnick, and Parikh 2015), and ROUGE-L (Lin 2004) score. We compute these metrics using MSCOCO caption evaluation tool[1]. The clinical efficacy (CE) metrics are proposed in R2Gen (Chen et al. 2020b), including precision, recall, and F1 score of the disease labels described in reference and generated radiology reports. Since the IU dataset does not provide consistent labels, we only report CE metrics on the MIMIC-CXR dataset. For consistency, we employ the CheXpert to extract the labels from generated reports.

We compare our proposed model with general image captioning works, e.g., S&T (Vinyals et al. 2015), SA&T (Xu et al. 2015), AdaAtt (Lu et al. 2017), and TopDown (Anderson et al. 2018), and specific medical report generation works, e.g., CMAS (Jing, Wang, and Xing 2019), KERP (Li et al. 2019), R2Gen (Chen et al. 2020b), and PPKE-D (Liu et al. 2021).

Table 2: The results of clinical efficacy metrics on the MIMIC-CXR dataset. The ACC, P, R, F1 denote accuracy, precision, recall, and F1 score, respectively.

| Model     | ACC  | P    | R    | F1  |
|-----------|------|------|------|-----|
| S&T       | 0.423| 0.084| 0.066| 0.072 |
| SA&T      | 0.703| 0.181| 0.134| 0.144 |
| AdaAtt    | 0.741| 0.265| 0.178| 0.197 |
| TopDown   | 0.743| 0.166| 0.121| 0.133 |
| R2Gen     | /    | 0.333| 0.273| 0.276 |
| Ours      | 0.795| 0.420| 0.339| 0.352 |

The NLG and CE results are shown in Table 1 and Table 2 respectively. First, as we can see from the NLG results, our proposed method outperforms almost previous works except for slightly lower Rouge-L score on the MIMIC-CXR dataset and BLEU-2 score on the IU dataset. The results prove the effectiveness of the proposed method for radiology report generation. Second, in terms of CE metrics, our method remarkably outperforms the previous works, which indicates that our model generates more accurate reports than others in clinics. The potential reason for this might come from two aspects. On the one hand, guided by the reference reports and disease labels in training via semantic alignment, the visual feature space is better learned. On the other hand, the learned knowledge base can provide useful knowledge about observations on radiology images.

Ablation Study

We conduct experiments to analyze the effectiveness of the multi-modal alignment mechanism and the impact of the knowledge base size.

Table 3: The performance of different alignments on both datasets. The V-T and V-L refer to visual-textual alignment and visual-label alignment, respectively.

| Dataset | Alignment | BLUE-3 | BLUE-4 | ROUGE-L |
|---------|-----------|--------|--------|---------|
| IU      | V-L       | 0.207  | 0.157  | 0.356   |
|         | V-T       | 0.215  | 0.163  | 0.371   |
|         | V-T + V-L | 0.230  | 0.174  | 0.399   |
| MIMIC   | V-L       | 0.141  | 0.099  | 0.270   |
|         | V-T       | 0.149  | 0.105  | 0.271   |
|         | V-T + V-L | 0.157  | 0.111  | 0.274   |

Table 3 shows the performances of our model using different alignments on both datasets. The first three rows show that our model benefits from any alignment, which proves the effectiveness of the proposed two alignments. Furthermore, the model that combines two alignments achieves the best performance. This indicates that the alignments enforcing among different modalities in the model can boost the quality of radiology reports.

Table 4: The performance of different head size in knowledge base updating. #Head refers to the size of head. The BL-n, CDr, and RG-L denote BLEU-n, CIDEr, and ROUGE-L scores, respectively.

| Dataset | #Head | BL-3 | BL-4 | CDr  | RG-L |
|---------|-------|------|------|------|------|
| IU      | 1     | 0.205| 0.149| 0.289| 0.372|
|         | 2     | 0.216| 0.158| 0.379| 0.379|
|         | 4     | 0.225| 0.164| 0.371| 0.379|
|         | 8     | 0.230| 0.174| 0.407| 0.399|
| MIMIC   | 1     | 0.131| 0.090| 0.109| 0.259|
|         | 2     | 0.144| 0.101| 0.103| 0.271|
|         | 4     | 0.149| 0.105| 0.120| 0.271|
|         | 8     | 0.157| 0.111| 0.111| 0.274|

[1]https://github.com/tylin/coco-caption
To validate the impact of head size in knowledge base updating, we conduct experiments to evaluate the performance of models with different head sizes. As shown in Table 4, as the number of heads increases, the model’s performance improves consistently, showing enhanced expressive ability of using the multi-head mechanism to learn the features from different subspaces.

Table 5: The performance of our model with different size of knowledge bases. The #KB denotes the size of knowledge base, where 0 refers to the model without knowledge base. The BL-n, CDr, and RG-L denote BLEU-n, CIDEr, and ROUGE-L scores, respectively.

| Dataset | #KB | BL-3 | BL-4 | CDr  | RG-L |
|---------|-----|------|------|------|------|
| IU      | 0   | 0.197| 0.149| 0.366| 0.376|
|         | 1   | 0.206| 0.154| 0.386| 0.371|
|         | 10  | 0.211| 0.155| 0.375| 0.368|
|         | 30  | 0.230| 0.174| 0.407| 0.399|
|         | 60  | 0.227| 0.173| 0.416| 0.395|
| MIMIC   | 0   | 0.126| 0.091| 0.104| 0.269|
|         | 1   | 0.138| 0.092| 0.109| 0.267|
|         | 10  | 0.148| 0.104| 0.106| 0.270|
|         | 30  | 0.152| 0.107| 0.108| 0.272|
|         | 60  | 0.157| 0.111| 0.111| 0.274|

The size of the knowledge base determines the capacity of the knowledge learning from reference reports. We train five models with sizes of 0, 1, 10, 30, and 60, where 0 means not using the knowledge base. As shown in Table 5, the performance of our model goes up as the size rises, but it achieves the best when the size is 30 on the IU dataset. The potential reason is that the IU dataset is relatively small, so the diversity is limited. As the size goes up, the redundant information stored may distract the model, leading to declined performance. The performance improves continuously on the MIMIC-CXR dataset, showing that the model benefits from the large knowledge base on a large dataset.

**Qualitative Results**

In Figure 3 we visualize two images with reports. Compared with the basic model, our model generates more accurate descriptions from the x-ray image. For example, in the first row, our model generates the descriptions of *pleural effusions, atelectasis, and cardiomegaly*, while the basic model lacks the key descriptions of *pleural effusions, atelectasis*. The potential reason may be the guiding of the multi-modal alignment mechanism, which helps the model better learn visual feature space and capture the subtle changes in radiology images. Furthermore, as we can see, our model outputs the descriptions with support devices with the same sentence “the monitoring and support devices are in constant position“, which are confirmed by the underlined sentences in the ground truth reports with similar meanings. However, the basic model only correctly describes the support device in the first row while omitting it in the second row. This clearly demonstrates the superiority of our model to use the knowledge base to learn a template representation from training reports about *support devices*, showing the advantage of report generation through utilizing a learned knowledge base.

**Conclusion**

We proposed a knowledge augment generation model with an automatic knowledge base and a semantic consistency mechanism for radiology report generation. We conducted experiments to validate the proposed model and demonstrated the effectiveness of each component on IU and MIMIC-CXR datasets. The results show that our model achieves state-of-the-art performances in terms of NLG and CE metrics on both
datasets. The ablation studies show that our model learns visual features well guided by semantic consistency constraints. Besides, the model benefits from the large size of the knowledge base on a large dataset. The proposed knowledge base updating method is easily applied to other datasets without extra labor, such as constructing a template database. In the future, we will apply the method to other generation systems.

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