Abstract

Generating long and coherent reports to describe medical images poses challenges to bridging visual patterns with informative human linguistic descriptions. We propose a novel Hybrid Retrieval-Generation Reinforced Agent (HRGR-Agent) which reconciles traditional retrieval-based approaches populated with human prior knowledge, with modern learning-based approaches to achieve structured, robust, and diverse report generation. HRGR-Agent employs a hierarchical decision-making procedure. For each sentence, a high-level retrieval policy module chooses to either retrieve a template sentence from an off-the-shelf template database, or invoke a low-level generation module to generate a new sentence. HRGR-Agent is updated via reinforcement learning, guided by sentence-level and word-level rewards. Experiments show that our approach achieves the state-of-the-art results on two medical report datasets, generating well-balanced structured sentences with robust coverage of heterogeneous medical report contents. In addition, our model achieves the highest detection precision of medical abnormality terminologies, and improved human evaluation performance.

1 Introduction

Beyond the traditional visual captioning task [41, 28, 43, 40, 18] that produces one single sentence, generating long and topic-coherent stories or reports to describe visual contents (images or videos) has recently attracted increasing research interests [19, 35, 22], posed as a more challenging and realistic goal towards bridging visual patterns with human linguistic descriptions. Particularly, report generation has several challenges to be resolved: 1) The generated report is a long narrative consisting of multiple sentences or paragraphs, which must have a plausible logic and consistent topics; 2) There is a presumed content coverage and specific terminology/phrases, depending on the task at hand. For example, a sports game report should describe competing teams, winning points, and outstanding players [38]. 3) The content ordering is very crucial. For example, a sports game report usually talks about the competition results before describing teams and players in detail.

As one of the most representative and practical report generation task, the desired medical image report generation must satisfy more critical protocols and ensure the correctness of medical term usage. As shown in Figure 1, a medical report consists of a findings section describing medical observations in details of both normal and abnormal features, an impression or conclusion sentence...
Our main contribution is to bridge rule-based (retrieval) and learning-based generation via reinforcement learning, which can achieve plausible, correct and diverse medical report generation. Moreover, our HRGR-Agent has several technical merits compared to existing retrieval-generation-based models: 1) our retrieval and generation modules are updated and benefit from each other via policy learning; 2) the retrieval actions are regarded as a part of the generation whose selection of templates directly influences the final generated result. 3) the generation module is encouraged to learn diverse and complicated sentences while the retrieval policy module learns template-like sentences, driven by distinct word-level and sentence-level rewards, respectively. Other work such as [24] still enforces the generative model to predict template-like sentences.
We conduct extensive experiments on two medical image report dataset [8]. Our HRGR-Agent achieves the state-of-the-art performance on both datasets under three kinds of evaluation metrics: automatic metrics such as CIDEr [33], BLEU [25] and ROUGE [20], human evaluation, and detection precision of medical terminologies. Experiments show that the generated sentences by HRGR-Agent shares a descent balance between concise template sentences, and complicated and diverse sentences.

2 Related Work

Visual Captioning and Report Generation. Visual captioning aims at generating a descriptive sentence for images or videos. State-of-the-art approaches use CNN-RNN architectures and attention mechanisms [27, 41, 43, 28]. The generated sequence is usually short, describing only the dominating visual event, and is primarily rewarded by language fluency in practice. Generating reports that are informative and have multiple sentences [38, 16] poses higher requirements on content selection, relation generation, and content ordering. The task differs from image captioning [43, 23] and sentence generation [14, 6] where usually single or few sentences are required, or summarization [2, 44] where summaries tend to be more diverse without clear template sentences. State-of-the-art methods on report generation [16] are still remarkably cloning expert behaviour, and incapable of diversifying language and depicting rare but prominent findings. Our approach prevents from mimicking teacher behaviour by sparing the burden of automatic generative model with a template selection and retrieval mechanism, which by design promotes language diversity and better content selection.

Template Based Sequence Generation. Some of the recent approaches bridged generative language approaches and traditional template-based methods. However, state-of-the-art approaches either treat a retrieval mechanism as latent guidance [44], the impact of which to text generation is limited, or still encourage the generation network to mimic template-like sequences [24]. Our method is close to previous copy mechanism work such as pointer-generator [2], however, we are different in that: 1) our retrieval module aims to retrieve from an external common template base, which is particularly effective to the task, as opposed to copying from a specific source article; 2) we formulate the retrieval-generation choices as discrete actions (as opposed to soft weights as in previous work) and learn with hierarchical reinforcement learning for optimizing both short- and long-term goals.

Reinforcement Learning for Sequence Generation. Recently, reinforcement learning (RL) has been receiving increasing popularity in sequence generation [27, 3, 13] such as visual captioning [21, 28, 18], text summarization [26], and machine translation [39]. Traditional methods use cross entropy loss which is prone to exposure bias [27, 31] and do not necessarily optimize evaluation metrics such as CIDEr [33], ROUGE [20], BLEU [25] and METEOR [3]. In contrast, reinforcement learning can directly use the evaluation metrics as reward and update model parameters via policy gradient. There has been some recent efforts [42] devoted in applying hierarchical reinforcement learning (HRL) [7] where sequence generation is broken down into several sub-tasks each of which targets at a chunk of words. However, HRL for long report generation is still under-explored.

3 Approach

Medical image report generation aims at generating a report consisting of a sequence of sentences $Y = (y_1, y_2, \ldots, y_M)$ given a set of medical images $I = \{I_j\}_{j=1}^K$ of a patient case. Each sentence comprises a sequence of words $y_i = (y_{i,1}, y_{i,2}, \ldots, y_{i,N})$, $y_{i,j} \in V$ where $i$ is the index of sentences, $j$ the index of words, and $V$ the vocabulary of all output tokens. In order to generate long and topic-coherent reports, we formulate the decoding process in a hierarchical framework that first produces a sequence of hidden sentence topics, and then predicts words of each sentence conditioning on each topic.

It is observed that doctors writing a report tend to follow certain patterns and reuse templates, while adjusting statements for each individual case when necessary. To mimic the procedure, we propose to combine retrieval and generation for automatic report generation. In particular, we first compile an off-the-shelf template database $T$ that consists of a set of sentences that occur frequently in the training corpus. Such sentences describe general observations, and are often inserted into medical reports, e.g., "the heart size is normal" and "there is no pleural effusion or pneumothorax". (Table 1 provides more examples.)
As described in Figure 2, a set of images for each sample is first fed into a CNN to extract visual features which is then transformed into a context vector by an image encoder. Then a sentence decoder recurrently generates a sequence of hidden states $q = \{q_1, q_2, \ldots, q_M\}$ which represent sentence topics. Given each topic state $q_i$, a retrieval policy module decides to either automatically generate a new sentence by invoking a generation module, or retrieve an existing template from the template database. Both the retrieval policy module (that determines between automatic generation or template retrieval) and the generation module (that generates words) are making discrete decisions and be updated via the REINFORCE algorithm [37, 30]. We devise sentence-level and word-level rewards accordingly for the two modules, respectively.

3.1 Hybrid Retrieval-Generation Reinforced Agent

Image Encoder. Given a set of images $\{I_j\}^K_{j=1}$, we first extract their features $\{v_j\}^K_{j=1}$ with a pretrained CNN, and then average $\{v_j\}^K_{j=1}$ to obtain $v$. The image encoder converts $v$ into a context vector $h^v \in \mathbb{R}^D$ which is used as the visual input for all subsequent modules. Specifically, the image encoder is parameterized as a fully-connected layer, and the visual features are extracted from the last convolution layer of a DenseNet [15] or VGG-19 [29].

Sentence Decoder. Sentence decoder comprises stacked RNN layers which generates a sequence of topic states $q$. We equip the stacked RNNs with attention mechanism to enhance text generation, inspired by [32, 41, 23]. Each stacked RNN first generates an attentive context vector $c^s_i$, where $i$ indicates time steps, given the image context vector $h^v$ and previous hidden state $h^s_{i-1}$. It then generates a hidden state $h^s_i$ based on $c^s_i$ and $h^s_{i-1}$. The generated hidden state $h^s_i$ is further projected into a topic space as $q_i$ and a stop control probability $z_i \in [0, 1]$ through non-linear functions respectively. Formally, the sentence decoder can be written as:

$$c^s_i = F_{\text{attn}}(h^v, h^s_{i-1})$$  \hspace{1cm} (1)  
$$h^s_i = F_{\text{RNN}}(c^s_i, h^s_{i-1})$$ \hspace{1cm} (2)  
$$q_i = \sigma(W_q h^s_i + b_q)$$ \hspace{1cm} (3)  
$$z_i = \text{Sigmoid}(W_z h^s_i + b_z),$$ \hspace{1cm} (4) 

where $F_{\text{attn}}$ denotes a function of the attention mechanism [28], $F_{\text{RNN}}$ denotes the non-linear functions of Stacked RNN, $W_q$ and $b_q$ are parameters which project hidden states into the topic space while $W_z$ and $b_z$ are parameters for stop control, and $\sigma$ is a non-linear activation function. The stop control probability $z_i$ greater than or equal to a predefined threshold (e.g. 0.5) indicates stopping generating topic states, and thus the hierarchical report generation process.

Retrieval Policy Module. Given each topic state $q_i$, the retrieval policy module takes two steps. First, it predicts a probability distribution $u_i \in \mathbb{R}^{1+|T|}$ over actions of generating a new sentence and retrieving from $|T|$ candidate template sentences. Based on the prediction of the first step, it triggers different actions. If automatic generation obtains the highest probability, the generation module is activated to generate a sequence of words conditioned on current topic state (the second row on the right side of Figure 2). If a template in $T$ obtains the highest probability, it is retrieved from the off-the-shelf template database and serves as the generation result of current sentence topic (the first row on the right side of Figure 2). We reserve $0$ index to indicate the probability of selecting automatic generation and positive integers in $\{1, |T|\}$ to index the probability of selecting templates.
in T. The first step is parameterized as a fully-connected layer with Softmax activation:

\[ u_i = \text{Softmax}(W_u q_i + b_u) \]  
\[ m_i = \text{argmax}(u_i), \]  

where \( W_u \) and \( b_u \) are network parameters, and the resulting \( m_i \) is the index of highest probability in \( u_i \).

**Generation Module.** Generation module generates a sequence of words conditioned on current topic state \( q_i \) and image context vector \( h^i \) for each sentence. It comprises RNNs which take environment parameters and previous hidden state \( h^i_{i,t-1} \) as input, and generate a new hidden state \( h^i_{i,t} \) which is further transformed to a probability distribution \( a_{i,t} \) over all words in \( V \), where \( t \) indicates \( t \)-th word.

We define environment parameters as a concatenation of current topic state \( q_i \) and image context vector \( c^g_{i,t} \) encoded by following the same attention paradigm in sentence decoder, and embedding of previous word \( e_{i,t-1} \). The procedure of generating each word is written as follows, which is an attentional decoding step:

\[ c^g_{i,t} = F^g_{\text{att}}(h^i, [e_{i,t-1}; q_i], h^i_{i,t-1}) \]  
\[ h^i_{i,t} = F^g_{\text{RNN}}([c^g_{i,t}; e_{i,t-1}; q_i], h^i_{i,t-1}) \]  
\[ a_t = \text{Softmax}(W_y h^i_{i,t} + b_y) \]  
\[ y_t = \text{argmax}(a_t) \]  
\[ e_{i,t} = W_e \odot (y_{i,t}) \]  

where \( F^g_{\text{att}} \) denotes the attention mechanism of generation module, \( F^g_{\text{RNN}} \) denotes non-linear functions of RNNs, \( W_y \) and \( b_y \) are parameters for generating word probability distribution, \( y_{i,t} \) is index of the maximum probable word, \( W_e \) is a learnable word embedding matrix initialized uniformly, and \( \odot \) denotes one hot vector.

**Reward Module.** We use automatic metrics CIDEr for computing rewards since recent work on image captioning [28] has shown that CIDEr performs better than many traditional automatic metrics such as BLEU, METEOR and ROUGE. We consider two kinds of reward functions: sentence-level reward and word-level reward. For the \( i \)-th generated sentence \( y_i = (y_{i,1}, y_{i,2}, \ldots, y_{i,N}) \) either from retrieval or generation outputs, we compute a delta CIDEr score at sentence level, which is

\[ R_{\text{sent}}(y_i) = f(y_{1:k}, \text{gt}) - f(y_{1:k-1}, \text{gt}) \]  

where \( f \) denotes CIDEr evaluation, and \( \text{gt} \) denotes ground truth report. This assesses the advantages the generated sentence brings in to the existing sentences when evaluating the quality of the whole report. For a single word input, we use reward as delta CIDEr score which is

\[ R_{\text{word}}(y_i) = f(y_{1:k}^{*}, \text{gt}^{*}) - f(y_{1:k-1}^{*}, \text{gt}^{*}) \]  

where \( \text{gt}^{*} \) denotes the ground truth sentence. The sentence-level and word-level rewards are used for computing discounted reward for retrieval policy module and generation module respectively.

### 3.2 Hierarchical Reinforcement Learning

Our objective is to maximize the reward of generated report \( Y \) compared to ground truth report \( Y^{*} \). Omitting the condition on image features for simplicity, the loss function can be written as:

\[ \mathcal{L}(\theta) = -\mathbb{E}_{z,m,y}[R(Y, Y^{*})] \]  
\[ \nabla_{\theta} \mathcal{L}(\theta) = -\mathbb{E}_{z,m,y} \left[ \nabla_{\theta} \log p(z, m, y) R(Y, Y^{*}) \right] \]  
\[ = -\mathbb{E}_{z,m,y} \left[ \sum_{i=1}^{N} \mathbb{I}(z_i < \frac{1}{2} | z_{i-1}) \left( \nabla_{\theta \mu} \mathcal{L}(\theta_{\mu}) + \mathbb{I}(m_i = 0) \nabla_{\theta_y} \mathcal{L}(\theta_y) \right) \right], \]  

where \( \theta, \theta_{\mu}, \text{and } \theta_y \) denote parameters of the whole network, retrieval policy module, and generation module respectively; \( \mathbb{I} (\cdot) \) is binary indicator; \( z_i \) is the probability of topic stop control in Equation 4; \( m_i \) is the action chosen by retrieval policy module among automatic generation \( m_i = 0 \) and all templates \( m_i \in [1, |T|] \) in the template database. The loss of HRGR-Agent comes from two parts: retrieval policy module \( \mathcal{L}(\theta_{\mu}) \) and generation module \( \mathcal{L}(\theta_y) \) as defined below.

**Policy Update for Retrieval Policy Module.** We define the reward for retrieval policy module \( R^{*} \) at sentence level. The generated sentence or retrieved template sentence is used for computing the
We further group candidates that express the same meaning but have a little linguistic variations. For example, "no pleural effusion or pneumothorax" and "there is no pleural effusion or pneumothorax" are grouped as one template. This results in 97 templates with greater than 500 document frequency for CX-CHR and 28 templates with greater than 100 document frequency for IU X-Ray. Upon retrieval, only the most frequent sentence of a template group will be retrieved for HRGR-Agent or CX-CHR datasets. Please see Supplementary Material for more details.

Policy Update for Generation Module. We define the word-level reward $R^g(y_t)$ for each word generated by generation module as discounted reward of all generated words after the considered word. The discounted reward function and its policy update for generation module can be written as:

$$R^g(y_t) = \sum_{j=0}^{\infty} \gamma^j R_{word}(y_{t+j})$$

(15)

$$\mathcal{L}(\theta_g) = -E_{y_t}[R^g(y_t, y_t^*)]$$

(16)

$$\nabla_{\theta_g}\mathcal{L}(\theta_g) = -E_{y_t} \sum_{t=1}^{\infty} \nabla_{\theta_g} \log p(y_t|y_{t-1}) R^g(y_t, y_t^*)]$$

(17)

where $\gamma$ is a discount factor; $y_t$ is the $i$-th generated sequence; and $\theta_g$ represents parameters of retrieval policy module which are $W_u$ and $b_u$ in Equation 5.

Datasets. We conduct experiments on two medical image report datasets. First, Indiana University Chest X-Ray Collection (IU X-Ray) [8] is a public dataset consists of 7,470 frontal and lateral-view chest x-ray images paired with their corresponding diagnostic reports. Each patient has 2 images and a report which includes impression, findings, comparison and indication sections. We preprocess the reports by tokenizing, converting to lower-cases, and filtering tokens of frequency no less than 3 as vocabulary, which results in 1185 unique tokens covering over 99.0% word occurrences in the corpus.

CX-CHR is a proprietary internal dataset of chest X-ray images with Chinese reports collected from a professional medical institution for health checking. The dataset consists of 35,500 patients. Each patient has one or multiple chest x-ray images in different views such as posteroanterior and lateral, and a corresponding Chinese report. We select patients with no more than 2 images and obtained 33,236 patient samples in total which covers over 93% of the dataset. We preprocess the reports through tokenizing by Jieba [1] and filtering tokens of frequency no less than 3 as vocabulary, which results in 1282 unique tokens.

On both datasets, we randomly split the data by patients into training, validation and testing by a ratio of 7:1:2. There is no overlap between patients in different sets. We predict the ‘findings’ section as it is the most important component of reports. On CX-CHR dataset, we pretrain a DenseNet with public available ChestX-ray8 dataset [36] on classification, and fine-tune it on CX-CHR dataset on 20 common thorax disease labels. Then we extract image features from the last convolutional layer, which yields 16 $\times$ 16 $\times$ 256 feature maps. As IU X-Ray dataset is relatively small, we do not directly fine-tune the pretrained DenseNet on it, and instead extract visual features of size 16 $\times$ 16 $\times$ 256 from the last convolutional layer of a DenseNet pretrained jointly on ChestX-ray8 dataset [36] and CX-CHR datasets. Please see Supplementary Material for more details.

Template Database. We select sentences in the training set whose document frequencies (the number of occurrence of a sentence in training documents) are no less than a threshold as template candidates. We further group candidates that express the same meaning but have a little linguistic variations. For example, "no pleural effusion or pneumothorax" and "there is no pleural effusion or pneumothorax" are grouped as one template. This results in 97 templates with greater than 500 document frequency for CX-CHR and 28 templates with greater than 100 document frequency for IU X-Ray. Upon retrieval, only the most frequent sentence of a template group will be retrieved for HRGR-Agent or
any rule-based models that we compare with. Although this introduces minor but inevitable error in
the generated results, our experiments show that the error is negligible compared to the advantages
that a hybrid of retrieval-based and generation-based approaches brings in. Besides, separating
templates of the same meaning into different categories diminishes the capability of retrieval policy
module to predict the most suitable template for a given visual input, as multiple templates share the
exact same meaning. Table 1 shows examples of templates for IU X-Ray dataset. More template
examples are provided in supplementary materials.

| Template | df(%) |
|----------|-------|
| No pneumothorax or pleural effusion. No pleural effusion or pneumothorax. There is no pleural effusion or pneumothorax. | 18.36 |
| The lungs are clear Lungs are clear The lung are clear bilaterally. | 23.60 |
| No evidence of focal consolidation, pneumothorax, or pleural effusion. No focal consolidation, pneumothorax or large pleural effusion. No focal consolidation, pleural effusion, or pneumothorax identified. | 6.55 |
| Cardiomiadiastin silhouette is within normal limit. The cardiomiadiastin silhouette is within normal limit. The cardiomiadiastin silhouette is within normal limit for size and contour. | 5.12 |

Table 1: Examples of template database of IU X-Ray dataset. Each template is constructed by a group
of sentences of the same meaning but slightly different linguistic variations. Top 3 most frequent
sentences for a template are displayed in the first and third column. The second column shows
document frequency (in percentage of training corpus) of each template.

**Evaluation Metrics.** We use three kinds of evaluation metrics: 1) automatic metrics including
CIDEr, ROUGE, and BLEU; 2) medical abnormality terminology detection accuracy: we select 10
most frequent medical abnormality terminologies in medical reports and evaluate average precision
and average false positive (AFP) of compared models; 3) human evaluation: we randomly select
100 samples from testing set for each method and conduct surveys through Amazon Mechanical
Turk. Each survey question gives a ground truth report, and ask candidate to choose among reports
generated by different models that matches with the ground truth report the best in terms of language
fluency, content selection, and correctness of medical abnormal finding. A default choice is provided
in case of no or both reports are preferred. We collect results from 20 participants and compute the
average preference percentage for each model excluding default choices.

**Training Details.** We implement our model on PyTorch and train on a GeForce GTX TITAN GPU.
We first train all models with cross entropy loss for 30 epochs with an initial learning rate of 5e-4,
and then fine-tune the retrieval policy module and generation module of HRGR-Agent via RL with
a fixed learning rate 5e-5 for another 30 epochs. We use 512 as dimension of all hidden states and
word embeddings, and batch size 16. We set the maximum number of sentences of a report and
maximum number of tokens in a sentence as 18 and 44 for CX-CHR and 7 and 15 for IU X-Ray.
Besides, as observed from baseline models which overly predict most popular and normal reports
for all testing samples and the fact that most medical reports describe normal cases, we add post-
processing to increase the length and comprehensiveness of the generated reports for both datasets
while maintaining the design of HRGR-Agent to better predict abnormalities. The post-processing
we use is that we first select 4 most commonly predicted key words with normal descriptions by
other baselines, then for each key word, if the generated report does not describe any abnormality
nor normality of these key words, we add the a corresponding sentence of these key words that
describe their normal cases respectively. The key words for IU X-Ray are ‘heart size and mediastinal
contours’, ‘pleural effusion or pneumothorax’, ‘consolidation’, and ‘lungs are clear’. As observed
in our experiments, this step maintains the same medical abnormality term detection results, and
improves the automatic report generation metrics, especially on BLEU-n metrics.

**Baselines.** On both datasets, we compare with four state-of-the-art image captioning models: CNN-
RNN [34], LRCN [9], AdaAtt [23], and Att2in [28]. Visual features for all models are extracted
from the last convolutional layer of pretrained denseNets respectively as mentioned in 4, yielding
16 × 16 × 256 feature maps for both datasets. We use greedy search and argmax sampling for
HRGR-Agent and the baselines on both datasets. On IU X-Ray dataset, we also compare with
CoAtt [16] which uses different visual features extracted from a pretrained ResNet [11]. The authors
of CoAtt [16] re-trained their model using our train/test split, and provided evaluation results for automatic report generation metrics using greedy search and sampling temperature 0.5 at test time. We further evaluated their prediction to obtain medical abnormality terminology detection precision and AFP. Due to the relatively large size of CX-CHR, we conduct additional experiments on it to compare HRGR-Agent with its different variants by removing individual components (Retrieval, Generation, RL). We train a hierarchical generative model (Generation) without any template retrieval or RL fine-tuning, and our model without RL fine-tuning (HRG). To examine the quality of our pre-defined templates, we separately evaluate the retrieval policy module of HRGR-Agent by masking out the generation part and only use the retrieved templates as prediction (Retrieval). Note that Retrieval uses the same model as HRG-Agent whose training involves automatic generation of sentences, thus the results of which may be higher than a general retrieval-based system (e.g. directly perform classification among a list of majority sentences given image features).

### 4.1 Results and Analyses

**Automatic Evaluation.** Table 2 shows automatic evaluation comparison of state-of-the-art methods and our model variants. Most importantly, HRGR-Agent outperforms all baseline models that have no retrieval mechanism or hierarchical structure on both datasets by great margins, demonstrating its effectiveness and robustness. On IU X-Ray dataset, HRGR-Agent achieves slightly lower BLEU-1,4 and ROUGE score than that of CoAtt [16]. However, CoAtt uses different pre-processing of reports and visual features, jointly predicts ‘impression’ and ‘findings’, and uses single-image input while our method focuses on ‘findings’ and use combined frontal and lateral view of patients. On CX-CHR, HRGR-Agent increases CIDEr score by 0.73 compared to HRG, demonstrating that reinforcement fine-tuning is crucial to performance increase since it directly optimizes the evaluation metric. Besides, Retrieval surpasses Generation by relatively large margins, showing that retrieval-based method is beneficial to generating structured reports, which leads to boosted performance of HRGR-Agent when combined with neural generation approaches (generation module). To better understand HRGR-Agent’s performance, each generated report at testing has on average 7.2 and 4.8 sentences for CX-CHR and IU X-Ray dataset, respectively. The percentages of retrieval vs generation are 83.5 vs 16.5 on the CX-CHR data, and 82.0 vs 18.0 on IU X-Ray, respectively.

**Medical Abnormality Terminology Evaluation.** Table 3 shows evaluation results of average precision (Prec.) and average false positive (AFP) of medical abnormality terminology detection, and human evaluation (Hit). The higher Prec. and the lower AFP, the better.
In this paper, we introduce a novel Hybrid Retrieval-Generation Reinforced Agent (HRGR-Agent) to perform robust medical image report generation. Our approach is the first attempt to bridge human prior knowledge and generative neural network via reinforcement learning. Experiments show that HRGR-Agent does not only achieve state-of-the-art performance on two medical image report datasets, but also generates robust reports that have high precision on medical abnormal findings detection and best human preference.
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