Towards Human-Friendly Referring Expression Generation

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Abstract

This paper addresses the generation of referring expressions that not only refer to objects correctly but also ease human comprehension. As the composition of an image becomes more complicated and a target becomes relatively less salient, identifying referred objects comes more difficult. However, the existing studies regarded all sentences that refer to objects correctly as equally good, ignoring whether they are easily understood by humans. If the target is not salient, humans utilize relationships with the salient contexts around it to help listeners to comprehend it better. To derive these information from human annotations, our model is designed to extract information from the inside and outside of the target. Moreover, we regard that sentences that are easily understood are those that are comprehended correctly and quickly by humans. We optimized it by using the time required to locate the referred objects by humans and their accuracies. To evaluate our system, we created a new referring expression dataset whose images were acquired from Grand Theft Auto V (GTA V), limiting targets to persons. Our proposed method outperformed previous methods both on machine evaluation and on crowd-sourced human evaluation. The source code and dataset will be available soon.

1. Introduction

With the popularization of intelligent agents such as robots, symbiosis with them becomes more important. Sharing what humans and agents see naturally is particularly an essential aspect for a smooth communication in the symbiosis environment. In daily life, people often use referring expressions to indicate specific targets such as “a man wearing a red shirt.” Further, communicating with agents by a natural language is an intuitive method of interaction. When referring to a specific object by a natural language, many expressions can be used that are equally correct from a semantic standpoint such that one can locate the target. However, it may not always be equally easy to locate the target. As shown in Fig. 1, it is important for the expression to be comprehended correctly and quickly by humans regardless of whether the target is salient. We call this type of expression as “human-friendly referring expressions.” Generating them is more difficult than merely generating the correct referring expressions, in that the type of sentences that are easily understood by humans must be considered. Recently, the generation of correct referring expressions has demonstrated significant progress. Considering an agent’s views that are automatically captured such as in-vehicle images, the compositions of the images are more complex than images from MSCOCO [32], which are typically used in the existing works of referring expression generation. The existing studies regard all referring expressions as equally good. However, in these images, the target objects often become relatively less salient and identifying the referred objects sometimes becomes difficult even if the sentences are correct.

For the agents to refer to objects by natural language in a real world, they must be described clearly for an easier comprehension. Therefore, expressions utilizing relationships between the targets and other salient contexts such as “a woman by the red car” would help listeners to identify the referred object. Thus, human-friendly expressions demand the following requirements:

\begin{itemize}
  \item If the target is salient, brief description suffices.
  \item If the target is less salient, utilizing relationships with salient contexts around it is required.
\end{itemize}
If these sentences can be generated, drivers can be navigated by utilizing in-vehicle images such as, “please turn right at the alley where the person in white is standing.”

We herein propose a new approach to generate human-friendly referring expressions that are brief and sufficiently easy for a human to locate a target object in an image without sacrificing the semantic validity. To utilize salient contexts around the target, our model is designed to extract information from the inside and outside of the target. Moreover, we perform optimization to generate sentences that can be comprehended correctly and quickly using the time required to locate it by human, and its accuracy. Although these quantities by themselves do not tell the absolute level of the goodness of the generated sentences, comparing them among candidate sentences helps to identify a preferable one. We adopt a ranking learning technique in this respect.

To evaluate our system, we constructed a new referring expression dataset whose images from GTA V [1], limiting targets to humans. We included the time required to locate the referred objects by humans, and their correct answer rates in the dataset for the ranking method above.

Overall, our primary contributions are as follows.
- We propose a novel task that we call “human-friendly referring expression generation.” In this task, sentences that are comprehended by humans correctly and quickly are regarded as good.
- We propose a novel method to optimize the task above by utilizing the time required to locate referred objects by humans, and their accuracy with ranking learning.
- We propose a novel referring expression generation model that can extract information from the inside and outside of the targets.
- We created a new large-scale referring expression dataset based on GTA V (RefGTA), which contains more images with more complex compositions than the existing referring expression datasets.
- We outperformed the previous methods both on automatic evaluation metrics and human evaluation.

2. Related work

First, we introduce image captioning. Next, we explain referring expression generation that describes specific objects. Finally, we refer to datasets used for referring expression generation and comprehension.

2.1. Image Captioning

Following the advent in image recognition and machine translation with deep neural network, the encoder–decoder model improved the quality of image caption generation significantly, which encodes a image by deep the convolutional neural network (CNN), and subsequently decodes it by a long term-short memory (LSTM) [24]. Many recent approaches use the attention model that extracts local image features dynamically while generating each word of a sentence [10, 16, 29, 18, 25, 11, 33]. Lu et al. [10] introduced a new hidden state of the LSTM called the “visual sentinel” vector. It controls the instant to attend the image by holding a sentence context under generation, because words such as “the” and “of” depend on the sentence context rather than the image information. Recently, researchers have applied reinforcement learning to directly optimize automatic evaluation metrics that are non-differentiable [29, 25, 11, 33].

2.2. Referring Expression Generation

While image captioning describes a full image, referring expression generation is to generate a sentence that distinguishes a specific object from others in an image. Referring expressions have been studied for a long time as a NLP problem [31, 5]. Recently, large-scale datasets (ReFCOCO, RefCOCO+, RefCOCOg, etc.) were constructed, and both referring expression generation and comprehension have been developed in pictures acquired in the real world [9, 19, 21, 27, 26, 7]. As these problems are complementary, recent approaches of referring expression generation solve both problems simultaneously [9, 12, 20, 19, 27]. Mao et al. [12] introduced max-margin Maximum Mutual Information (MMI) training that solves comprehension problems with a single model to generate disambiguous sentences. Liu et al. [9] focused on the attributes of the targets and improved the performance. Yu et al. [19] proposed a method that jointly optimizes the speaker, listener, and reinforcer models, and acquired state-of-the-art performance. Each role of them is to generate referring expressions, comprehend the referred object in the image, and reward the speaker for generating discriminative expressions.

2.3. Referring Expression Datasets

The initial datasets consist of simple computer graphics [13] or small natural objects [22, 23]. Subsequently, first large-scale referring expression dataset RefClef [30] was constructed using images from ImageClef [6]. By extending images from MSCOCO, other large-scale datasets such as RefCOCO, RefCOCO+ [20] and RefCOCOg [12] were collected. The average sentence lengths of RefCOCO and RefCOCO+ are 3.61 and 3.53, respectively; therefore, each sentence typically consists of one phrase. In particular, RefCOCO+ forbid annotators from using location words such as “right man,” and focuses on appearance. Meanwhile, the average sentence length of RefCOCOg is 8.3; therefore, each sentence typically consists of a full sentence. These useful datasets consist of many images captured by humans, whose compositions are simple with some subjects in the center. For visions of robots or other intelligent agents, handling more complex images is important. Thus, we extended our study to images from GTA V, whose compositions are more complex.
3. Model

To generate human-friendly referring expressions, the model should be able to utilize relationships between targets and the salient context around them. Similar to normal image captioning, we consider generating sentences word by word, and the sentence information under generation is also a context. We refer to this context as the sentence context. We assumed the necessary information to generate the sentences as follows, and propose a model that satisfies them.

(A) Salient features of the target
(B) Relationships between the target and salient context around it
(C) Sentence context under generation

We propose a model comprising a novel context-aware speaker and reinforcer. As reported in [19], joint optimization using both a listener and reinforcer achieves similar performance to using either one in isolation. This is mainly because both of them provide feedback to the neural network based on the same ground truth captions. Instead, we aim to generate more appropriate captions by modifying the speaker given the above assumptions (A), (B) and (C).

Moreover, human-friendly expressions should ease a human in locating the referred objects correctly and quickly. If the targets are sufficiently salient, brief expressions are required to satisfy the rapidity. We optimized them by comparing the time required to locate the referred objects by human, and their accuracies among sentences annotated to the same instance.

First, we introduce a state-of-the-art method to generate referring expressions, i.e., the speaker-listener-reinforcer [19]. Next, we explain our generation model. Finally, we introduce the optimization of a human-friendly expressions directory and describe compound loss.

3.1. Baseline Method

We explain a state-of-the-art method [19]. Three models, speaker, listener, and reinforcer were used. Herein, we explain only the speaker and reinforcer that are used in our proposed model.

**Speaker:** For generating referring expressions, the speaker model should extract target image features that are distinguished from other objects. Yu *et al.* [19] used the CNN to extract image features and generate sentences by LSTM. First, Yu *et al.* [19] extracted the following five features: (1) target image feature vector $o_i$, (2) whole image feature vector $g_i$, (3) the feature encoding the target’s coordinate $(x, y)$ and the size $(w, h)$ as $l_i = \frac{x}{w}, \frac{y}{h}, \frac{x}{w}, \frac{y}{h}, l_i$, (4) difference in target image feature from others $\delta l_i = \frac{1}{n} \sum_{j \neq i} o_{ij} - o_{ii}$, (5) difference in target coordinate from others $\delta v_{ij} = (\Delta x_{ij}, \Delta y_{ij}, \Delta s_{ij}, \Delta v_{ij}, w_{ij}, h_{ij})$. Applying one fully connected layer to this, $v_i = W_m o_i, g_i, l_i, \delta v_i, \delta l_i$, obtained feature $v_i$ is fed into the LSTM and learned to generate sentences $r_i$ by minimizing the negative log-likelihood with model parameters $\theta$:

$$L_i^1(\theta) = -\sum_i \log P(r_i | o_i ; \theta)$$  \hspace{1cm} (1)

To generate discriminative sentences, they generalized the MMI [12] to enforce the model, to increase the probability of generating sentences $r_i$ if the given positive pairs as $(r_i, o_i)$ than if the given negative pairs as $(r_j, o_k)$ where $r_j$ and $o_k$ are sampled randomly from other objects, and optimized by following the max-margin loss ($\lambda_1$, $\lambda_2$, $M_1$ and $M_2$ are hyper-parameters):

$$L_i^2(\theta) = \sum_i \{ \lambda_i^1 \max(0, M_1 + \log P(r_i | o_i) - \log P(r_j | o_i)) + \lambda_i^2 \max(0, M_1 + \log P(r_j | o_i) - \log P(r_i | o_i)) \}$$  \hspace{1cm} (2)

**Reinforcer:** Next, we explain the reinforcer module that rewards the speaker model for generating discriminative sentences. First, the reinforcer model is pretrained by classifying whether the input image feature and sentence feature are paired by logistic regression. The reinforcer extracts image features by the CNN and sentence features by LSTM and subsequently, feed into mlp by concatenating both features to output a scalar. Next, it rewards the speaker model while fixing its parameters. Because the sampling operation of sentences $w_{1:T}$ is non-differentiable, they used policy-gradient to train the speaker to maximize the reward $F(w_{1:T} | o_i)$ by the following loss:

$$\nabla_{\theta} J = -E_{P(w_{1:T} | o_i)}[F(w_{1:T} | o_i)] \nabla_{\theta} \log P(w_{1:T} | o_i ; \theta)$$  \hspace{1cm} (3)
3.2. Context-aware speaker model

Our speaker model (in Fig. 2) generates referring expressions that can utilize relationships between targets and salient contexts around the target. Similar to Yu [19], we encoded image features by the CNN, and decoded it into a language by LSTM. In extracting the global features from whole images whose compositions are complex, information around the target objects is more important. We replace global features $g_i$ with $g'_i$ that weight Gaussian distributions whose centers are the center of the targets (variance is a learnable parameter). We used $v_i = W_m [o_i; g'_i; l_i; \delta v_i; \delta l_i]$ as a target image feature to feed into the LSTM.

Next, we introduce the attention module that satisfies the requirements. We begin by defining the notations: $V_{\text{global}}, V_{\text{local}}$ are spatial features extracted by the CNN. Each feature contains $k,l$ features, respectively ($V_{\text{global}} = \{f^g_1, \cdots , f^g_k\}, V_{\text{local}} = \{f^l_1, \cdots , f^l_l\}$, $V_{\text{global}} \in \mathbb{R}^{d \times k}, V_{\text{local}} \in \mathbb{R}^{d \times l}$). To extract the required information: (A) salient features of the target, (B) relationships with salient context around it, and (C) sentence context under generation, we can use $V_{\text{local}}, V_{\text{global}}$ for (A) and (B), respectively. As for (C), we used a sentinel vector $s_t$ proposed by Lu et al. [10], which is a hidden state of the LSTM calculated as follows: ($h_t$: hidden state of LSTM, $m_t$: memory cell of LSTM):

$$s_t = \sigma(W_x x_t + W_h h_{t-1}) \odot \tanh (m_t) \tag{4}$$

For focusing more around the target, we introduce target-centered weighting $G_i (G_i \in \mathbb{R}^{1 \times k})$ with Gaussian distribution, similar as in the feature $g'_i$. Using four weights, $W_{\text{global}} \in \mathbb{R}^{d \times d}, W_{\text{local}} \in \mathbb{R}^{d \times d}, W_s \in \mathbb{R}^{d \times d}, w_h \in \mathbb{R}^{d \times 1}$, and defining $V_t = [V_{\text{global}}; V_{\text{local}}; s_t]$, our attention $\alpha_t$ is calculated as follows::

$$v_t = [W_{\text{global}} V_{\text{global}}; W_{\text{local}} V_{\text{local}}; W_s s_t] \tag{5}$$

$$z_t = w_h^T \tanh (v_t + W_g h_t 1^T) \tag{6}$$

$$\alpha_t = \text{Softmax}([z_t; [...] : k] + \log G_i); [z_t; [...] : k]) \tag{7}$$

([: ] implies concatenation, and [...] : $k$) implies to extract the partial matrix up to column $k$.

Finally, we can obtain the probability of possible words as follows:

$$c_t = \sum_{n=1}^{k+l+1} \alpha_{tn} V_{tn} \tag{8}$$

$$p(w_t | w_1, \cdots , w_{t-1}, o_i) = \text{Softmax}(W_p (c_t + h_t)) \tag{9}$$

3.3. Optimization of human-friendly referring expressions

In our task, sentences to be generated should be comprehended by humans (1) correctly and (2) quickly. Although (1) can be learned by the baseline method, (2) is difficult to optimize because defining an absolute indicator that can measure it is difficult. However, we can determine which sentence is better than the others by human annotations. In our task, we used the time required by humans to identify the referred objects and its accuracy for the annotations.

We now consider ranking labels as teacher information. For a target $o_i$, sentences $\{r_{i1}, \cdots , r_{im}\}$ are annotated. We denote a set of pairs satisfying $\text{rank}(r_{ip}) < \text{rank}(r_{iq})$ ($p \neq q, 1 \leq p,q \leq m$) as $\Omega_i$. In this case, the probability of generating $r_{ip}$ should be higher than one of generating $r_{iq}$. We sample $(r_{ip}, r_{iq})$ randomly from $\Omega_i$ and perform optimization by the max margin loss as follows ($\lambda_3^G$ and $M_3$ are hyper-parameters):

$$L_3^G(\theta) = \sum_i [\lambda_3^G \max(0, M_3 + \log P(r_{iq}|o_i) - \log P(r_{ip}|o_i))] \tag{10}$$

Moreover, we applied this ranking loss to the reinforcer model. We used the output before the last sigmoid activation to calculate the loss similar to the above Eqn. 10. The final loss function of the reinforcer is both the ranking loss and logistic regression. Similar to Eqn. 3, we can train the speaker to generate sentences to maximize the new reward $F'(w_{1:T}, o_i)$, which estimates how easily the generated expressions can be comprehended by humans as follows:

$$\nabla_{\theta} J' = -EP(w_{1:T}|o_i)[F'(w_{1:T}, o_i)] \nabla_{\theta} \log P(w_{1:T}|o_i; \theta) \tag{11}$$

We also introduced sentence attention [34] into the sentence encoder of the model to capture the words that would facilitate a human’s comprehension of a sentence.

**Compund loss**: The final loss of our speaker model $L_s$ is a combination of Eqn. 1, Eqn. 2, Eqn. 10 and Eqn. 11 as follows ($\lambda^c$ is a hyper-parameter):.

$$L_s(\theta) = L_s^1 + L_s^2 + L_s^3 - \lambda^c J' \tag{12}$$

4. Dataset Construction

For the agents to refer to objects in the real world, generating expressions that can be comprehended correctly and quickly by humans is important even when the image compositions are complex. To acquire more images with more complex compositions we utilized images from GTA V because referring expression generation requires a large-scale dataset. We can use the realistic images for applications to real world problems as in [8]. In this study we constructed a new referring expression dataset, RefGTA, limiting the target type to humans only. This is because identifying human targets is of primary importance for the symbiosis of humans and robots as well in designing safe mobile agents.

We collected images and information such as a person’s bounding boxes automatically, and subsequently annotated the referring expression by humans. (GTA V is allowed for use in non-commercial and research uses [2]).
4.1. Image Collection

First, we extracted images and persons’ bounding box information once every few seconds using a GTA V mod that we created (PC single-player mods are allowed [3]). Moreover, even when multiple persons whose appearances are similar exist, the system should be able to generate expressions where humans can identify referred objects easily by utilizing the relationships between the targets and other objects etc. Therefore, we further collected images in which only either white-clothed or black-clothed persons exist, by setting them when the mod starts, as in Fig. 3.

Finally, we deleted duplicate images by the average hash. We also deleted images comprising combinations of the same IDs. We set the obtained images and bounding box information as a dataset.

4.2. Sentence Annotation

We annotate sentences to each instance obtained in Sec. 4.1 by the following two steps. We requested the annotations of the Amazon Mechanical Turk (AMT) workers. **Annotating sentences:** First, we requested the AMT workers to annotate five descriptions that are distinguished from the others for each instance. We instructed the workers to annotate a sentence that refers only to the target and is easy to distinguish from others at a glance. We also instructed the workers to use not only the target attributes but also the relative positions to other objects in the image. We instructed them not to use absolute positions inside the image and allowed the relative positions to other objects.

**Validating sentences:** Next, we assigned five AMT workers to obtain the referred person in each description to verify whether it is an appropriate referring expression. If a referred person does not exist, we allow them to check the box, “impossible to identify.” We instructed the workers to obtain the referred objects as soon as possible, and also reminded the workers by displaying the elapsed time on the task screen. We set the sentences where more than half of the workers accurately obtained the referred persons as a dataset. We also left the time and accuracy of five workers for each sentence.

**Examples:** We show the annotation examples in Fig. 4. The rightmost column is the ranking we used in Sec. 3.3. This is calculated as follows: first, all sentences are ranked by humans’ comprehension accuracy; subsequently, sentences that are comprehended correctly by all workers are ranked by time. This ranking is performed as follows. When comparing the times of two sentences we take the three middle times for each. We consider sentence “A” as better than sentence “B” if the mean of “B” substracted by the mean of “A” is greater than the sum of their standard errors. For each sentence we count the number of sentences that it is better than and rank the sentence according to this number.

4.3. Statistical Information

We show the statistics of our dataset, RefGTA. The scale of RefGTA is presented in Table 1. The resolution of the image is 1920 1080. The mean length of annotated sentences is 4.21 ± 0.60 seconds.

As shown in Fig. 5, RefGTA consists of many objects that occupy smaller proportions of the area in the images than RefCOCO. In this case, the target objects often become less salient and the relationships between the targets and salient context around them becomes more important.
Table 2. Comprehension evaluation on RefCOCO, RefCOCO+ and RefCOCOg. () implies the model used for comprehension. ensemble* implies to use both speaker and listener or reinforcer. Our speaker demonstrates comparable or better performance in most cases.

Table 3. Comprehension evaluation of our dataset (RefGTA). Our speaker model exhibits high comprehension performance, and its ensembling exceeds that of re-SLR.

Table 4. Accuracy of classifying ranked pairs. Ranking loss improved its performance.

Figure 6. Generation example on RefCOCOg and each attention transition. The sum of global, local, and sentinel attention is 1 for each word.

5. Experiments

First, we explain the datasets used in our study. Next, we describe the results of comprehension, ranking, and generation evaluation in this order. Finally, we evaluate the generated sentences by humans.

We refer to the state-of-the-art method of referring expression generation, i.e., the speaker-listener-reinforcer as “SLR”. The SLR originally used VGGNet [15] as its image feature encoder. We also used ResNet152 [14] that achieved better performance on image classification. We compared re-implemented SLR and our model that we refer as “re-SLR”, and “our SR” respectively. We set re-SLR with ResNet as a baseline. Our SLR implies our SR with the re-implemented listener.

5.1. Datasets

We conducted experiments on both existing datasets (RefCOCO, RefCOCO+ [20] and RefCOCOg [12]) and our dataset (RefGTA). The experiments on the former datasets are to evaluate our system on various objects, and the experiments on the latter are to evaluate ours on images with complex compositions. Yu et al. [19] collected more sentences for the test sets of RefCOCO and RefCOCOg; therefore, we used these when evaluating the generation quality.

5.2. Comprehension Evaluation

We compared comprehension performance of the speaker, listener, and reinforcer. Given a sentence $r$, each comprehension by reinforcer and speaker is calculated by $o^* = \arg \max_i F(r, o_i)$ and $o^* = \arg \max_i P(r|o_i)$, respectively.

Results on existing datasets: First, we demonstrate the comprehension performance of the system on RefCOCO, RefCOCO+, and RefCOCOg in Table 2. Although our speaker demonstrates comparable or better performance in most cases, we focus on the sentence generation, and the model with higher comprehension performance does not always generate better sentences. Because both the listener and reinforcer used in [19] has a similar role as described in Sec. 3, we obtained similar results from our SR and our SLR.

Results on our datasets: Next, we demonstrate the comprehension performance of the system in RefGTA in Table 3. Although the listener’s comprehension accuracy is better for re-SLR, our speaker’s comprehension accuracy is higher than that of the re-SLR, and our model is best when ensembling a speaker and listener models.

5.3. Ranking Evaluation

We evaluated the ranking accuracy by classifying a given pair into two classes; whether the given two expressions are correctly ranked or not. First, we extracted the set of ranking pair as described in Sec. 4.2. The number of all pairs is 13,023. The results are shown in Table 4. “Rank loss” implies to adopt the ranking loss to both speaker and reinforcer as we explain in Sec. 3.3. Both of them improved the ranking performance by rank loss. This implies that rank loss helps our model learning expressions comprehended by humans correctly and quickly.

5.4. Generation Evaluation

Qualitative results on existing datasets: Generated sentence example on RefCOCOg is shown in Fig. 6. While the value of local attention is high when explaining the target car, the value of global attention becomes high when men-
tioning outside of the target. When switching from local attention to global attention, the value of sentinel attention that holds the sentence context becomes higher.

### Quantitative results on existing datasets:
Next, we discuss the quantitative evaluation based on the automatic evaluation metric, CIDEr [28] and Meteor [4]. Because ground-truth sentences are referring expressions, we can evaluate them to some extent. Our re-implemented rerank did not improve the generation performance although Yu et al. [19] reported that reranking improves performance. In RefCOCO and RefCOCO+, the generation qualities are high by the speaker only. Meanwhile, in RefCOCOg, rerank helped to improve the performance. This is because while the model should generate one phrase in RefCOCO and RefCOCO+, the model should generate a full sentence in RefCOCOg and has to solve more complex problems including satisfying language structures.

### Qualitative results on RefGTA:
Next, we demonstrate the generated sentence examples on RefGTA in Fig. 7. While the baseline method (re-SLR) demonstrates lower capability in capturing outside of the target than our method, our method can generate sentences that can identify the target easier especially in the right-side examples. As shown in the left-bottom example, while the baseline method generates a brief and enough description, our SR+rerank also generates the same one. Attention visualization is shown in Fig. 8. While the local attention value is high when describing the target, the global attention value is high when mentioning “building,” which is outside of the target.

### Quantitative results on RefGTA:
Finally, we demonstrate the quantitative evaluation on RefGTA. To evaluate human-friendly referring expressions, the ideal metric should assign a high score to a sentence that can be easily comprehended by humans correctly and quickly. While CIDEr calculates the average similarity between a generated sentence from an object $o_i$ and ground-truth sentences $\{r_{ik}, \ldots , r_{im}\}$; we define the ranking-weighted CIDEr (R-CIDEr) which utilizes weighted similarity scores between them by the inverse of their rank. The weight of the sentence $r_{ij}$ is calculated as $w(r_{ij}) = \frac{1}{\text{rank}(r_{ij}) \sum_{j} \text{rank}(r_{ij})^{-1}}$. This metric assigns a high score to sentences where a human identified the referred objects correctly and quickly. In Table 6, R1-CIDEr implies using ranking by humans’ comprehension accuracy and time required, and R2-CIDEr implies using ranking by only humans’ comprehension accuracy. In particular, R1-CIDEr that we optimized is improved by the ranking loss. Rerank was not applicable in our dataset.

### 5.5. Human Evaluation

#### Human comprehension evaluation:
First, we evaluated human comprehension for the generated sentences by each method. We used 600 targets extracted randomly from the test data, and requested 10 AMT workers to identify the referred persons while measuring the time. If no referred target exists, we allow them to check a box, “impossible to identify.” The results are shown in Table 7. Our model outperformed the baseline method, and the rank loss improved the performance.

#### Time evaluation:
Next, we evaluated whether our method improved performance based on the time required by humans to locate referred objects. We evaluated as follows: first, all sentences are ranked by humans’ comprehension
accuracy; subsequently, sentences that are comprehended correctly by all workers (i.e., comprehension accuracy is 100%) are ranked by the average time; finally, for the remaining sentences, we calculated the ratio of the number of instances that are ranked first in each method (if there are 2 or 3 instances ranked first, the number is counted as 1/2, and 1/3 respectively.) The obtained results (see Table 8) show that rank loss improved not only human comprehension accuracy but also the time.

As shown in Table 9, SR+rank generates sentences that are longer compared to the baseline method, and shorter than those by SR.

### Human comprehension evaluation considering saliency

Finally, we evaluated our method when the saliency of the target changes. We used 2,000 targets extracted randomly from the test data and requested five AMT workers to identify the referred objects. We evaluated the relationship between humans’ comprehension accuracy and targets’ saliency. We used a saliency model proposed by Itti et al. [17]. First, we calculated a saliency map of a whole image, and we used the value in a bounding box of a target. We present the results in Fig. 9. As shown, our model performs better on the lower saliency area because mentioning salient contexts around the targets helped humans to comprehend them. The difference between the methods becomes smaller as the saliency becomes higher.

### 6. Conclusions

We herein focused on generating referring expressions that allowed for humans to identify referred objects correctly and quickly, which we called human-friendly referring expressions. We proposed a model that could utilize relationships between targets and contexts around them to generate better sentences even when the compositions of the images were complex, and the targets were not sufficiently salient. We also proposed a method to optimize a human-friendly referring expressions directory. To evaluate our system, we constructed a new dataset, RefGTA. We demonstrated that our method improved referring expression generation not only on the existing automatic evaluation metric, but also on the newly proposed automatic evaluation metric and human evaluation.
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