Generating Attractive Ad Text by Facilitating the Reuse of Landing Page Expressions

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Abstract

Ad text generation is vital for automatic advertising in various fields through search engine advertising (SEA) to avoid the cost problem caused by laborious human efforts for creating ad texts. Even though ad creators create the landing page (LP) for advertising and we can expect its quality, conventional approaches with reinforcement learning (RL) mostly focus on advertising keywords rather than LP information. This work investigates and shows the effective usage of LP information as a reward in RL-based ad text generation through automatic and human evaluations. Our analysis of the actually generated ad text shows that LP information can be a crucial reward by appropriately scaling its value range to improve ad text generation performance.

1 Introduction

With the growth of e-commerce, online advertising, which provides useful and appealing information about products or services to users becomes an important field. Search engine advertising (SEA) has played an important role as an online advertising approach. In SEA, an advertiser first specifies a landing page (LP), a Web page to be advertised, advertising keywords, and their ad text consisting of a title and description. Then, by taking into account the similarity between a search query entered by a user and the advertising keywords, a link to an LP considered appropriate for users' interests is presented to the users. At that time, SEA presents the ad text with the link so that the user can decide whether to click the link.

Although SEA has various advantages in automatically distributing advertisements that match users' interests, it has a cost problem for advertisers. In preparing ad texts, ad text writers need to create them for each advertising keyword for different LPs. To create ad texts that match users' interests for advertising the target LP, they must



Figure 1: An example of ad text generation for search engine advertising (SEA), that generates both title and description as a part of ad text based on the advertising keywords, meta title, description (Meta-TD), and the body of the landing page (LP).

investigate what kinds of ad texts attract users for each target product and service. Thus, it is not practical to manually create ad texts for a wide range of fields.

One solution to this issue is ad text generation. It automatically generates appropriate ad texts for an LP. In recent years, a lot of research (Murakami et al., 2023) has been conducted on ad text generation for SEA. After templatebased approaches (Bartz et al., 2008; Fujita et al., 2010, 2011; Thomaidou et al., 2013), sequenceto-sequence (seq2seq)-based generation methods (Bahdanau et al., 2016; Vaswani et al., 2017) have been widely used in ad text generation (Hughes et al., 2019; Kamigaito et al., 2021; Wang et al., 2021; Golobokov et al., 2022) as in other NLP fields. However, maximum likelihood estimation (MLE), commonly used for training seq2seq models by mimicking training data, is unsuitable for ad text generation, requiring originality and diversity



Figure 2: An example of the desired output in our proposed method. Keywords of the same color indicate the reuse from the landing page and advertising keywords. We aim to create a model that generates ad texts that are attractive and relevant to the input for readers by appropriately reusing expressions within the landing page, as demonstrated in this example.

for generating ad texts.

Some previous studies have relied on reinforcement learning (RL) to deal with this problem. In RL, models learn to follow rewards built explicitly for a target task rather than to mimic the training data. Thus, we can reflect specific characteristics for ad text into generated texts through the rewards. For the reward in ad text generation with seq2seq models, Hughes et al. (2019) focus on click-through rates for ad texts and Kamigaito et al. (2021) focus on feedback from SEA to enhance the quality of generated ad texts.

Although the advertising keywords, meta title and description, and body of an LP, like in Figure 1, are standard inputs in ad text generation and important for practical use, the introduced RL-based approaches focus on inserting advertising keywords into ad texts. Considering LPs themselves are written by professional ad creators and enriched more compared with advertising keywords, LPs have the potential to contribute to generating relevant and attractive ad texts.

In this work, we propose a method to facilitate a model to reuse expressions in LP texts by considering coverage of LP texts as rewards in RL. Figure 2 shows the desired ad text in our proposed method. As shown in the figure, reusing expressions in LP texts has the potential to improve relevance and attractiveness to LP texts in ad text generation. To use our proposed rewards with the conventional Client name ||| Advertising keywords ||| Meta title and description ||| Body

Table 1: The input format of our ad text generation.

rewards, we need to handle multiple rewards in RL for ad text generation. Even though this is a basic problem, there has been no investigation and discussion on how to treat them.

To appropriately use multiple rewards in RL for ad text generation, we also explore the usage of their effective combination in ad text generation by RL. We focus on the scaling of each reward as a solution and reveal that scaling is important to improve the coverage of LP texts.

Furthermore, we conducted automatic and human evaluations on our created ad text generation dataset with incorporating our rewards into T5, a pre-trained Transformer. Experimental results show that considering our proposed rewards increases LP text coverage in the test set, even compared with a large language model (LLM), Llama-2. Furthermore, our proposed method outperformed human-created reference of descriptions for ad texts in the attractiveness of human evaluation. These results indicate that LP information can be a crucial reward with its appropriate usage and scaling, even when used with other important information like advertising keywords and knowledge in a pre-trained language model.

2 Our Ad Text Generation Method

Figure 3 shows the overview of our ad text generation. The procedures of the generation process are as follows:

- 1. Transformer (Vaswani et al., 2017) generates and samples ad texts from input landing pages and their advertising keywords (See §2.1 for details).
- 2. To facilitate the reuse of expressions in landing pages, we treat the coverage of generated ad texts to the corresponding landing pages as rewards (See §2.2 for details).
- 3. The model parameters are updated to follow the rewards based on the manner of reinforcement learning (See §2.3 for details).
- 4. After the training, the model can generate ad texts trying to use expressions in landing page texts (See §3 for the effectiveness).



Figure 3: An overview of the training procedure in our ad text generation method.

We explain the details of each part in the following subsections.

2.1 Model and Generation

We use the pre-trained T5 (Raffel et al., 2020) as a Transformer-based seq2seq model to generate an ad text $\hat{\mathbf{y}} = \{\hat{y}_1, \dots, \hat{y}_m\}$ from an input text of an LP, $\mathbf{x} = \{x_1, \dots, x_n\}$, where the x_* and y_* are tokens. To input the text of an LP, as in Figure 1, to the model, we concatenate the title, meta title, description, body text of an LP, and keywords by using a separator symbol "III", as shown in Table 1.

Under the setting, by using the output probability $P_{\theta}(\mathbf{y}|\mathbf{x})$, the generation of our seq2seq model is represented as follows:

$$\hat{\mathbf{y}} = \underset{\mathbf{y}}{\operatorname{arg\,max}} P_{\theta}(\mathbf{y}|\mathbf{x})$$
$$= \underset{\mathbf{y}}{\operatorname{arg\,max}} \prod_{t=1}^{m} P_{\theta}(y_t|\mathbf{x}, y_{t-1} \cdots y_1). \quad (1)$$

Since exactly searching the ad text with the highest probability is computationally intractable, we use beam decoding in Eq. (1) for generating \hat{y} .

Similarly, we draw a sampled sequence $\mathbf{y}^s = \{y_1^s, \cdots, y_l^s\}$ by $P_{\theta}(\mathbf{y}|\mathbf{x})$ as follows:

$$\mathbf{y}^s \sim P_\theta(\mathbf{y}|\mathbf{x}). \tag{2}$$

For maintaining both diversity and fluency of the sampled sequence y^s , we use top-k (Fan et al., 2018) and top-p (Holtzman et al., 2020) sampling.

2.2 Reward Calculation

To enhance the coverage of generated ad texts to corresponding landing pages, we calculate rewards for generated $\hat{\mathbf{y}}$ and sampled \mathbf{y}^s (§2.2.1). Furthermore, to maintain the fluency and relevance of generated ad texts, we consider additional rewards (§2.2.2). We combine these rewards as the

final reward (§2.2.3) for conducting reinforcement learning.

2.2.1 Coverage to Landing Page Text

The purpose of distributing ad texts in SEA is to promote the contents of the corresponding LP. Therefore, the generated ad texts should be relevant to the contents of the LP. Furthermore, LP commonly contains high-quality promotional content created by professionals. Therefore, if we can utilize these expressions when generating ad texts, we can expect to produce ad texts that are more attractive to readers.

In this work, we treat coverage from an LP to its ad text as the reward for generating ad texts aligned to their LP texts. Because LP text consists of meta title/description (Meta-TD) and body content, we separately consider them as the following rewards:

Meta-TD (MTD) Letting W_{ad} and W_{mtd} be the sets of words in the ad text and Meta-TD, respectively, the reward of the coverage for the Meta-TD, $r_{mtd}(\mathbf{x}, \mathbf{y})$ is calculated as follows:

$$r_{mtd}(\mathbf{x}, \mathbf{y}) = \frac{|W_{ad} \cap W_{mtd}|}{|W_{mtd}|}.$$
 (3)

Body Similar to Eq. (3), letting W_{body} be the sets of words in the body of an LP, the reward of the coverage for the body, $r_{body}(\mathbf{x}, \mathbf{y})$ is calculated as follows:

$$r_{body}(\mathbf{x}, \mathbf{y}) = \frac{|W_{ad} \cap W_{body}|}{|W_{body}|}.$$
 (4)

Since the body of an LP is long, we split it into phrases by punctuation marks and picked up five phrases with the highest word coverage to other input parts.

2.2.2 Additional Rewards

In addition to the coverage of the LP text, we consider the following rewards used in the conventional approach of Kamigaito et al. (2021):

Fluency If the length of an ad text exceeds the predefined limit, we need to truncate the ad text to show it on SEA. Thus, to keep the fluency of ad texts, we need to generate them by following the predefined length limit. To include more information in ad texts, generating them exactly with the limit length is desirable. Letting $|\mathbf{y}|$ be the length of \mathbf{y} and C_{len} be a predefined length limit, $r_{flu}(\mathbf{y})$, the reward for fluency, is represented as follows:

$$r_{flu}(\mathbf{y}) = \begin{cases} \frac{|\mathbf{y}|}{C_{len}} & (|\mathbf{y}| \le C_{len}) \\ \frac{1}{\exp(|\mathbf{y}| - C_{len})} & (|\mathbf{y}| > C_{len}). \end{cases}$$
(5)

Eq. (5) assumes that ad texts should be as close to the limit length as possible without exceeding it.

Keyword (KW) Based on the insight of previous studies (Kamigaito et al., 2021; Murakami et al., 2022), we consider coverage of the advertising keywords. Letting W_{key} be the sets of words in the advertising keywords, $r_{key}(\mathbf{x}, \mathbf{y})$, the reward of the coverage for the advertising keyword, is represented as follows:

$$r_{key}(\mathbf{x}, \mathbf{y}) = \frac{|W_{ad} \cap W_{key}|}{|W_{key}|}.$$
 (6)

2.2.3 Final Reward

Finally, we can merge the rewards defined in §2.2.1 and §2.2.2 into a single reward that is used in reinforcement learning. However, even though all suggested rewards are important to generate ad texts, only summing them potentially results in underestimating each reward due to the different score ranges. To deal with this problem, we additionally propose a method to use scaling each reward by using the scaling function S for the final reward, r, as follows:

$$r(\mathbf{x}, \mathbf{y}) = S(r_{mtd}(\mathbf{x}, \mathbf{y})) + S(r_{body}(\mathbf{x}, \mathbf{y})) + S(r_{key}(\mathbf{x}, \mathbf{y})) + S(r_{flu}(\mathbf{x}, \mathbf{y}))$$
(7)

As far as we know, this is the first attempt to handle multiple rewards by scaling in ad text generation. Thus, which scaling method is suitable for ad text is uncertain.

To appropriately scale the rewards in Eq. (7) by S, we investigate the effectiveness of two types

of scaling approaches, min-max scaling in Equation (8) and z-score normalization in Equation (11). In both approaches, we scale values for each batch of training data. The details are explained in the following paragraphs.

Min-max Scaling Min-max scaling decides the value range of a set of values by their minimum and maximum values. Thus, it can emphasize value differences, whereas outliers easily influence them. When adopting min-max scaling, S is defined as follows:

$$S(r) = \frac{r - \min(\mathbf{r})}{\max(\mathbf{r}) - \min(\mathbf{r})},$$
(8)

where r is a reward, \mathbf{r} is a set of rewards in a batch, max is a function that returns the maximum reward in a given batch, and min is a function that returns the minimum one.

Z-score Normalization Z-score normalization decides the value range of a set of values by their mean and variance. Thus, it can mitigate the bias caused by outliers, whereas it underestimates the value differences. When adopting z-score normalization, S is defined as follows:

$$S(r) = \frac{r - \mu}{\sigma},\tag{9}$$

$$\mu = \frac{1}{|\mathbf{r}|} \sum_{r \in \mathbf{r}} r, \tag{10}$$

$$\sigma = \sqrt{\sum_{r \in \mathbf{r}} (r - \mu)^2} / |\mathbf{r}|, \qquad (11)$$

where μ is the mean of **r**, σ is the variance of **r**, and $|\mathbf{r}|$ is a batch size.

2.3 Reinforcement Learning

To train $P_{\theta}(\mathbf{y}|\mathbf{x})$ with a reward, we use self-critical sequence training (SCST) (Rennie et al., 2017), a kind of reinforcement learning (RL). In SCST, the loss L_{rl} of training $P_{\theta}(\mathbf{y}|\mathbf{x})$ is represented by using the decoded sequence $\hat{\mathbf{y}}$, the sampled sequence \mathbf{y}^s , and the reward function $r(\mathbf{x}, \mathbf{y})$ that returns rewards for given \mathbf{x} and \mathbf{y} as follows:

$$L_{rl} = r(\mathbf{x}, \hat{\mathbf{y}}) \sum_{t=1}^{m} log P(\hat{y}_t | \hat{y}_{t-1} \cdots \hat{y}_1, \mathbf{x})$$
$$-r(\mathbf{x}, \mathbf{y}^s) \sum_{t=1}^{l} log P(y_t^s | y_{t-1}^s \cdots y_1^s, \mathbf{x}). \quad (12)$$

Since RL sometimes traps a model in the loop of generating collapsed texts and then learning from

Domain	Title	Generat	ion	Descrip	eration	
2 0111111	Train	Valid	Test	Train	Valid	Test
EC	93,435	3,439	5,848	28098	1993	2531
Others	15,789	358	1,433	5715	36	470
Trip	10,682	-	1,189	4445	-	365
Education	10,333	22	219	3160	24	734
Job Hunting	5,529	-	40	2026	-	17
Media	4,421	-	-	1724	-	86
Finance	4,361	208	391	1868	34	268
Car	3,580	48	184	2016	33	-
Entertainment	3,409	-	91	857	-	37
Video On-demand	3,019	-	-	614	40	58
Fitness	2,866	-	71	930	-	-
Real Estate	2,320	83	161	948	46	223
Cosmetic	1,452	9	71	584	16	27
Healthcare	441	-	85	152	-	-
Total	161,637	4,167	9,783	53,137	2,222	4,816

Table 2: The statistics of our dataset for ad text generation.

it to regenerate another collapsed text, we utilize mixed loss of RL and MLE (Paulus et al., 2018) to stabilize the training as follows:

$$L_{mixed} = \gamma L_{rl} + (1 - \gamma) L_{mle}, \tag{13}$$

0

$$L_{mle} = -\sum_{t=1}^{5} log P(y_t^{\star} | y_{t-1}^{\star} \cdots y_1^{\star}, \mathbf{x}), \quad (14)$$

where γ is a hyperparameter to adjust the importance of RL and $\mathbf{y}^* = \{y_1^*, \cdots, y_o^*\}$ is the ad text in training data. In the training, we use L_{mixed} as the final loss.

3 Evaluation

3.1 Settings

3.1.1 Datasets

We gathered Japanese ad texts actually used in SEA. Table 2 shows the statistics for each setting. As shown in the table, this dataset covers 12 and 11 different domains in test split for title and description generation, respectively. These statistics show that our created dataset is practical and diversified. In the data, each domain consists of one client. During ad delivery, we deliver similar ads to each client based on groups. Considering this characteristic, we made splits, ensuring that the same groups do not appear in both training and testing. As a result, some domains do not have test splits. However, we did not remove the data of such domains in the training data because it is still effective in improving the generalization performance of the model through training. For the validation data, when the target domain has multiple groups in the training data, we created it by extracting the group with the lowest frequency. Therefore, some domains

have no validation data since these domains only have one group in their training data. Furthermore, we removed the same input-output pairs to prevent data leakage before the split.

3.1.2 Comparison Methods

In the evaluation, we compared all possible combinations of $\{W_{key}, W_{mtd}, W_{body}\}$ in Eqs. (3), (4), and (6) to investigate the effectiveness of each part of an input. We included the reward for fluency in Eq. (5) in all settings. We separately trained title and description generation models. We set the maximum length of titles and descriptions to 30 and 90 characters, respectively, excluding the endof-sentence tokens. Note that multi-byte characters are counted as two characters.

We used T5-base (Raffel et al., 2020) with T5 the weight and dictionary of t5-base-japanese¹ to handle Japanese texts. To calculate rewards and evaluation metrics for generated ad texts, we tokenized the ad texts into words by using MeCab² with the IPA dictionary (Kudo et al., 2004). We fine-tuned all T5-based methods by MLE on training data with one epoch. We used Adam with a learning rate of 0.001 for this training. After that, we conducted RL with five epochs using Adam with an initial learning rate of 0.0001. We saved models for each epoch and used the model that maximizes the chosen rewards on validation data. In RL, we set γ as 0.9984 following the setting by Paulus et al. (2018). We set the batch size to 8 throughout the training. For sampling and inference, we used the beam search with five candidates.

Llama-2 To compare T5-based models with the recent LLM, we also used Llama-2 (Touvron et al., 2023) 7B with the weight and dictionary of ELYZA-japanese-Llama-2-7b (Sasaki et al., 2023)³ to handle Japanese texts. Different from T5, LLMs require huge computational costs. As a solution, we fine-tuned Llama-2-based methods by LoRA (Hu et al., 2022) with 4-bit quantization through QLoRA (Dettmers et al., 2023) on one epoch using Adam with an initial learning rate of 0.0002 for each setting. We updated LoRA weights in all layers with setting the rank as 64 and scaling α as 16. We set the batch size to 16 during training.

t5-base-japanese

¹https://huggingface.co/sonoisa/

²https://github.com/taku910/mecab ³https://huggingface.co/elyza/

ELYZA-japanese-Llama-2-7b

Method				Fluenc	сy	Relevance				Diversity Average			
Rewards		Scaling		og Length		Rouge		Coverage					
KW	MTD	Body	Scanng	Prob.	Avg.	Correct	1	2	L	KW	MTD	Body	SBLEU
	Llama-2		,	-69.1	24.7	99.1	29.6	17.1	27.0	11.8	12.1	11.6	99.6
	T5-base	(MLE C	only)	-75.8	26.1	96.9	29.4	17.3	26.6	10.8	10.0	12.0	99.5
\checkmark			None	-78.1	23.9	95.9	18.9	7.1	17.5	65.9	7.9	9.6	98.1
1			Min-max	-79.3	26.1	95.7	20.0	8.8	18.8	47.9	7.3	9.2	98.9
v	-	-	Z-score	-81.0	26.0	90.4	19.4	7.9	18.2	59.1	7.7	9.4	98.6
			None	-74.5	27.0	96.3	30.5	17.7	27.5	8.5	11.2	12.2	99.6
-	\checkmark	-	Min-max	-70.9	26.8	93.1	<u>36.8</u>	23.1	32.4	9.5	<u>13.8</u>	14.9	99.6
			Z-score	-69.2	28.7	91.0	26.3	14.3	25.3	7.9	12.5	7.1	99.7
			None	-82.2	28.1	97.4	23.1	11.7	21.6	7.8	7.8	8.8	99.7
-	-	\checkmark	Min-max	-83.5	28.5	92.7	23.6	12.0	22.1	8.1	8.2	9.2	99.6
			Z-score	-85.0	28.1	90.9	28.6	16.3	26.1	8.9	9.7	13.2	99.7
			None	-86.6	24.8	95.1	22.1	9.0	19.8	45.3	9.0	13.5	99.2
\checkmark	\checkmark	-	Min-max	-82.4	28.2	95.2	23.4	11.6	22.0	10.2	8.0	9.0	99.6
			Z-score	-82.2	28.7	93.6	23.6	11.8	22.2	9.8	8.1	9.0	99.6
			None	-77.7	24.9	95.4	20.4	9.3	19.2	43.3	7.7	11.1	98.7
\checkmark	-	\checkmark	Min-max	-82.6	28.5	91.8	23.2	11.4	21.9	11.1	8.2	9.1	99.6
			Z-score	-82.6	28.5	91.5	24.1	12.3	22.5	8.9	8.3	9.3	99.8
			None	-76.0	27.9	93.7	33.5	20.9	29.4	8.0	13.5	15.0	100.0
-	\checkmark	\checkmark	Min-max	-77.9	27.5	94.7	27.3	15.2	24.9	8.9	9.6	10.8	99.6
			Z-score	-82.5	28.6	90.8	25.3	13.5	23.4	8.1	9.4	10.5	99.6
			None	-81.4	28.0	95.0	23.8	11.8	22.3	9.9	8.0	9.3	99.8
\checkmark	\checkmark	\checkmark	Min-max	-82.4	28.4	94.1	23.6	11.9	22.2	9.7	8.1	8.9	99.7
			Z-score	-67.0	<u>27.0</u>	97.5	<u>34.1</u>	21.2	<u>30.1</u>	7.8	12.9	13.3	99.6

Table 3: Evaluation results of title generation for ad texts. The result of the baseline methods is above the doublelined separator, whereas that of the proposed methods is under the separator. **Bold font** denotes the best score. <u>Underlined font</u> indicates the score is better than the best baseline score. KW, MTD, and Body denote the advertising keywords, meta title and description, and body of an LP, respectively.

In inference, ad text generation was conducted by greedy search. We describe the prompt used for ad text generation in Appendix A.

3.1.3 Automatic Evaluation Metrics

For the automatic evaluation, we considered the following aspects:

Fluency Since ad texts should be fluent within predefined length, we evaluated the fluency of generated ad texts by using the following metrics:

- Log probability with BERT (Log Prob.): We used the prediction probability from BERT in a manner of masked language models (Salazar et al., 2020). We used bert-base-japanese-v2⁴ in HuggingFace Transformers for this purpose.
- Average length: We checked the average length of generated ad texts. The closer this length is to the limit, the better, as long as the length does not exceed the limit.

• **Correct length**: This metric indicates the percentage of generated ad texts that do not exceed the limit length.

Relevance Ad texts should be along with given advertising keywords and LP information. To cover this aspect, we evaluated the relevance of generated ad texts to advertising keywords and LPs by using the following metrics:

- **Rouge**: Since reference ad texts include important parts of advertising keywords and LPs, we calculated Rouge-1, -2, -L (Lin, 2004) scores by comparing reference and generated ad texts.
- Coverage: Based on Eqs. (3), (4), and (6), we calculated each coverage by $r_{mtd}(\mathbf{x}, \mathbf{y})$, $r_{body}(\mathbf{x}, \mathbf{y})$, and $r_{key}(\mathbf{x}, \mathbf{y})$ as the metrics.

Diversity Because repeatedly used ad texts lack appealingness, considering how diversified ad texts are generated is essential in ad text generation. Hence, we calculated the diversity of

⁴https://huggingface.co/cl-tohoku/ bert-base-japanese-v2

Method					Fluenc	у	Relevance				Diversity		
	Rewards		Scaling	Log Length		Rouge		Coverage		Average			
KW	MTD	Body	0	Prob.	Avg.	Correct	1	2	L	KW	MTD	Body	SBLEU
	Llama-2 T5-base	7B (QLo (MLE C	/	-217.4 -200.9	77.8 67.2	95.8 99.9	42.0 34.6	29.2 21.7	38.2 31.0	18.8 22.0	31.9 23.4	19.3 19.4	97.3 96.4
\checkmark	-	-	None	-191.4	58.7	99.3	23.9	9.9	20.6	64.8	19.9	17.4	94.4
\checkmark	-	-	Min-max Z-score	-209.1 -211.5	70.9 70.8	96.3 95.4	37.4 35.1	24.1 22.6	33.9 31.8	24.9 34.6	28.9 25.8	$\frac{22.4}{21.4}$	97.4 95.7
-	\checkmark	-	None Min-max Z-score	-206.0 -367.0 -214.3	72.7 144.7 76.8	98.6 20.5 92.4	$\frac{42.2}{31.9}\\ \frac{44.2}{31.9}$	$\frac{29.8}{17.2}\\ \underline{32.9}$	39.0 28.3 41.5	16.1 23.2 14.2	$\frac{35.4}{41.6}$ $\frac{37.8}{37.8}$	$\frac{\frac{23.4}{30.6}}{\frac{26.3}{2}}$	98.8 96.8 99.5
-	-	\checkmark	None Min-max Z-score	-214.8 -215.2 -220.2	75.5 74.1 76.8	98.5 95.3 92.3	$\frac{43.8}{40.2}$ 41.5	$\frac{31.8}{27.1}$ 28.6	$\frac{40.6}{36.5}$ 37.8	11.8 15.6 15.7	$\frac{34.4}{31.2}$ $\frac{34.3}{34.3}$	$\frac{22.6}{23.1}$ $\frac{24.7}{24.7}$	99.4 98.7 99.0
\checkmark	\checkmark	-	None Min-max Z-score	-232.4 -281.7 -192.0	87.0 102.0 72.8	90.3 60.1 96.7	41.6 19.4 43.6	29.4 2.6 33.0	$\frac{38.4}{15.5} \\ \underline{41.0}$	16.2 19.3 29.1	$\frac{35.8}{16.0}$ <u>39.6</u>	$\frac{25.1}{18.9}\\ \underline{23.5}$	99.0 98.1 98.7
\checkmark	-	\checkmark	None Min-max Z-score	-208.4 -222.3 -218.0	72.8 76.7 77.2	97.9 95.7 91.0	40.5 44.2 42.3	27.8 30.8 29.2	$ \begin{array}{r} 37.1 \\ \underline{40.9} \\ \underline{38.5} \\ \end{array} $	19.4 16.7 16.4	$\frac{33.4}{39.2}\\ \frac{34.7}{34.7}$	$\frac{23.3}{26.0}$ $\frac{24.9}{24.9}$	98.6 99.2 99.1
-	\checkmark	~	None Min-max Z-score	-208.6 -474.4 -240.8	73.8 197.2 <u>85.3</u>	98.4 4.6 83.0	$\frac{43.1}{27.7}$ $\underline{43.8}$	$\frac{31.1}{13.9}\\ \underline{30.5}$	$\frac{40.0}{24.5}$ $\underline{40.3}$	12.1 20.6 13.9	$\frac{\frac{34.4}{41.1}}{\frac{40.2}{}}$	$\frac{22.4}{32.6}$ $\frac{28.0}{2}$	99.4 96.3 99.4
\checkmark	\checkmark	\checkmark	None Min-max Z-score	-212.0 -274.6 -240.4	74.6 137.2 <u>82.9</u>	98.7 47.0 86.8	$\frac{43.2}{17.6}$ 43.7	$\frac{31.0}{5.3}$ 30.3	$\frac{40.0}{15.2}\\ \underline{40.3}$	14.4 18.8 14.0	$\frac{36.1}{13.0}$ 39.2	$\frac{24.3}{16.8}$ 26.4	99.3 90.6 99.5

Table 4: Evaluation results of description generation for ad texts. The notations are the same as in Table 3.

	Not Fluent	Attractive	Relevant
Reference	16	126	33
None	8	134	109
KW-None	26	83	246
KW+LP-Z	15	74	29

Table 5: Human evaluation results for generated titles of ad texts. The numbers show the amount of selected times by three annotators in each metric. None denotes T5-base w/o any reward. KW-None denotes using advertising keywords as a reward w/o any scaling. KW+LP-Z denotes using advertising keywords, meta title and description, and bodies in LPs as rewards w/ z-score normalization.

generated ad texts. For this purpose, we averaged **Self-BLEU** (**SBLEU**) (Zhu et al., 2018) from one to four grams. The lower the SBLEU, the better the result. We used the implementation of TextGenerationEvaluationMetrics⁵ (Alihosseini et al., 2019).

3.1.4 Human Evaluation Metrics

Automatic evaluation is difficult to judge the attractiveness of the generated ad texts. To fill in this

	Not Fluent	Attractive	Relevant
Reference	22	101	30
None	10	50	19
KW-None	34	78	258
KW+LP-Z	28	131	76

Table 6: Human evaluation results for generated descriptions of ad texts. Other notations are the same as in Table 5.

weakness, we conducted human evaluation. We asked three annotators to select the ad texts generated by each method that best aligned with the measure for each pair. For this evaluation, we used not only **Attractive**, but also **Not Fluent** and **Relevant** to support the automatic evaluation. The measure **Relevant** indicates the relevance between generated ad texts and their corresponding input texts. We reported the amount of selected times by three annotators for each metric.

We created data consisting of 139 titles and their input and 140 descriptions and their input for the evaluation by selecting a maximum of three cases per domain (client) in the test set.

⁵https://github.com/IAmS4n/

TextGenerationEvaluationMetrics

Input		Output				
LP	Keyword	Reference	KW-None	KW+LP-Z		
App [Anonymized] is an application where anyone can create original t-shirt de- signs. It's easy to use. Once you've made a design you like, try sharing it with everyone! 	App [Anonymized], Handmade T-Shirt	You can create sweat- shirts and hoodies start- ing from [Anonymized] yen. Orders are possi- ble from just one cus- tom item.	Handmade t-shirts, with your very own original design.	We offer you a unique, original t-shirt. Get your favorite piece with App [Anonymized]'s origi- nal design.		
[Anonymized] Shopping a total sales of [Anonymized] bags, now delivering popular supplements "with free shipping". Voices of the buyers, tips on how to drink, and de- velopment behind-the-scenes stories are also available! I bag contains [Anonymized] pills, regular price [Anonymized] yen is now [Anonymized]% off Rich in nutrients	Care, Fatigue	With [Anonymized] shopping, get 1 bag of [Anonymized] pills at [Anonymized]% off. Special offers for buyers available!	Thanks to you, we've surpassed [Anonymized] ten thousand bags. Many happy voices published.	Get [Anonymized]'s supplement now, with 1 bag containing [Anonymized] pills at a spe- cial price. Made with whole [Anonymized], which has been a topic of discussion in buyer voices and reviews. Abundantly blended with nutrients!		

Table 7: Generated descriptions for ad texts. The methods are the same as in Table 6.

3.2 Automatic Evaluation Results

3.2.1 Title Generation

Table 3 shows the evaluation results for title generation for ad texts. From the results, we can see that the improvement in each coverage correlated to the part of the imposed rewards. Especially, MTD, which includes meta title information contributes to the improvement of title generation performances. Regarding coverage, scaling for combined rewards did not support performance improvement. On the other hand, scaling for rewards sometimes improved the Rouge scores. The scaling also works for emphasizing to generate appropriate length of ad texts based on Eq. (5). Considering the previous research (Kwon et al., 2023a) reports that predicting lengths of summaries can improve Rouge scores, we can estimate that Eq. (5) contributed to improving Rouge scores.

Excluding the improvement of the Rouge scores, the performance gain of using scaling is restricted. Furthermore, using a single reward outperforms combined rewards in many cases. Therefore, we can understand that using a single reward is strong enough in the title generation of ad texts.

3.2.2 Description Generation

Table 4 shows the evaluation results for generated descriptions. Unlike the title generation, we can see performance gains using both scaling and combined rewards. This is probably because the description is longer than the title and can be paraphrased in various ways. Especially in coverage for each part of LPs, we can see a large improvement.

Instead, rewards and scaling degrade fluency. Based on the result, we can understand that scaling and combined rewards can generate descriptions of ad texts with content similar to corresponding LPs at the expense of fluency. Since measuring fluency by automatic metrics is insufficient, we conduct human judgment as described in the next section.

3.3 Human Evaluation Results

To conduct further investigation, we conduct human evaluations for selected methods based on the results in §3.2 with the metrics in §3.1.4.

3.3.1 Title generation

Table 5 shows the result of the human evaluation on the generated titles. From the result, we can understand that in the title generation for ad texts, only fine-tuning pretrained T5 performs well and even surpasses human-created titles. Furthermore, the reward only for advertising keywords largely improves the relevance at the expense of fluency and attractiveness. In contrast, the information on LPs did not contribute to performance improvement. Considering that the limit of titles is short, we can assume that it restricts paraphrasing by words in LPs.

3.3.2 Description generation

Table 6 shows the result of the human evaluation on the generated descriptions. Unlike the title generation, only fine-tuning T5 is insufficient in performance, excluding fluency. The reward only for advertising keywords largely improves the relevance at the expense of fluency. This tendency is similar to title generation. As we anticipated, the information on LPs with z-score normalization drastically improves the attractiveness. Table 7 shows the anonymized and translated generated descriptions. From the table, we can understand that the performance improvement is based on the reuse of LP information. These results show the importance of scaling rewards to effectively use the information on LPs. In addition, the increase in attractiveness may have resulted from the reuse of ad text originally included in the LP. Moreover, as Kwon et al. (2023b) point out, we can consider text generation by extraction as a type of label embedding (Zhang et al., 2021; Xiong et al., 2021). Thus, this behavior matches with pre-trained models like T5.

4 Conclusion

In this paper, we propose a method to facilitate ad text generation models to use keywords in LP texts through word coverage-based rewards in RL. Furthermore, to handle multiple rewards for ad text generation, we introduce scaling of rewards into the ad text generation task. Moreover, we evaluated effective combinations of advertising keywords, meta title and description, and body of an LP as rewards in ad text generation by RL.

Through the evaluation of automatic and human evaluations, we revealed the importance of considering keywords in LP texts and scaling to the combined rewards to improve the performance of generated descriptions for ad texts.

In our future work, we plan to apply the RLbased approaches investigated in this work to LLMs.

5 Limitations

While the proposed method can generate more informative ad texts than the conventional approaches because it can effectively use information from the LP, its effectiveness is limited when the LP does not contain sufficient information. Furthermore, the dataset we created is restricted to internal use.

6 Ethical Considerations

We confirm that there is no license problem in the ad text data used for our experiment. In addition, inappropriate expressions in the ad texts have already been removed. Based on the above, there are no ethical considerations in this paper.

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A Prompt used in Llama-2

When generating title and descrptions, we instructed models to generate json style output from given json style data (Kawarada et al., 2024). After the generation, we extracted generated ad text part from the output by using a Python package jsonrepair⁶. The used prompts translated into English are as follows:

Prompt for Title Generation -

[INST] «SYS»You are a sincere and excellent Japanese assistant. «/SYS»

Please generate one advertisement title corresponding to the following WebPage content.

WebPage = {"Client": "*Client name*", "Keywords": ["*Keyword 1*", ..., "*Keyword N*"], "Abstract": "*Abstract*", "Texts": ["*Text from Body 1*", ..., "*Text from Body N*"]}

Also, when generating the advertisement title, follow the listed rules below:

- The length should be at most 30 characters. Note that fullwidth characters are counted as two characters.

- Do not include line breaks.
- Do not include paragraph breaks.
- Do not include URLs.
- Do not format in bullet points.
- Do not include a description in the advertisement title.

- The output should be in json format.

- The advertisement title should be outputted in the format {"Adtext": "*Adtext*"} as the value of Adtext.

- Output only the json format part. [/INST] - Prompt for Description Generation -

[INST] «SYS»You are a sincere and excellent Japanese assistant. «/SYS»

Please generate one advertisement text corresponding to the following WebPage content.

WebPage = {"Client": "*Client name*", "Keywords": ["*Keyword 1*", ..., "*Keyword N*"], "Abstract": "*Abstract*", "Texts": ["*Text from Body 1*", ..., "*Text from Body N*"]}

Also, when generating the advertisement text, follow the listed rules below:

- The length should be at most 90 characters. Note that fullwidth characters are counted as two characters.

- Do not include line breaks.
- Do not include paragraph breaks.
- Do not include URLs.

- Do not format in bullet points.

- Do not include a title in the advertisement text.

- The output should be in json format.

- The advertisement title should be outputted in the format {"Adtext": "*Adtext*"} as the value of Adtext.

- Output only the json format part.

[/INST]

⁶https://github.com/josdejong/jsonrepair