An Empirical Study of Generating Texts for Search Engine Advertising

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Abstract

Although there are many studies on neural language generation (NLG), few trials are put into practice, particularly in the advertising domain. Generating ads with NLG models can help copywriters in their creation. However, few studies have adequately evaluated the effect of generated ads with actual serving because this requires a large amount of training data and a particular environment. In this study, we demonstrate a practical use case of generating ad-text with an NLG model. Particularly, we show how to improve the ads’ impact, deploy models to a product, and evaluate the generated ads.

1 Introduction

Search engine advertising (SEA) displays ads relevant to the queries that users have searched on search engines as a part of the search results. On the ad creation side, ad copywriters develop keywords and ad-texts that are likely to be searched by users, and ad-texts are attractive to users based on the keywords and landing page (LP) contents. Advertisers or advertising agencies then submit these keywords and ad-texts to the ad delivery service. After submission, if the user’s search queries and the submitted keywords match, the service selects an ad-text from the submissions through an auction and displays it to the user. SEA plays an important role in the advertising market because it can mutually satisfy users’ and advertisers’ respective demands. Advertising agencies have many copywriters on staff; however, manual creation will eventually reach its limit with the ever-increasing content. Therefore, auto-generating ads are expected to be a great support for ad creation.

Fill templates with words and phrases extracted from web search results or LPs are commonly used in ad-text generation (Bartz et al. (2008), Fujita et al. (2010), Fujita et al. (2011), Thomaidou et al. (2013)). These approaches create limited ad-text because they strongly rely on a pre-built list of templates or an LP containing ad-related texts. Hughes et al. (2019) proposed a method to incorporate a reinforcement learning (RL) framework into an end-to-end sequence-to-sequence (Seq2Seq) model for generating effective search engine ad-text considering feedback regarding ad effectiveness from ad delivery services.

However, unlike typical natural language generation tasks, ad-texts are determined from input and characteristics such as previous ad delivery performance, the contexts in overall ads, and the relevance between the search queries and the results. Diversity is also an importance factor in this task because readers can be bored if a model generates ad-text that has already been used. Therefore, to make ad-texts more attractive, the model must generate ad-texts that were not used previously. In addition, the model must consider the ad-text’s length because ads are presented in a limited space, which imposes a limitation on the length in practical usage. The addition of important keywords in the ad-text is also necessary to enhance user engagement because the search result page highlights the searched keyword in the user query and the ad-text. Furthermore, few ad-text generation models are used in real-world applications notwithstanding the commercial domain of advertising. Therefore, few studies have evaluated all end-to-end processes from generation to actual delivery.

Considering these requirements, we propose a
method for generating ad-text by utilizing RL with rewards. This approach enables using ad-texts not included in the original training dataset through sampling from the training model. Therefore, we can expect improvements in diversity for generated ad-texts. We compared models specifically constructed for ad-text generation to determine the important factors for this task. We investigated our models in a real-world application, and performed an ad-delivery evaluation. The evaluation results showed that the proposed method improved the both human-rated attractiveness and relevance scores and the ad-delivery results compared to other approaches, while also maintaining diversity of the generated ad-texts.

Our contributions are as follows.

- We present a case study of ad-text generation as a real-world application. This study confirmed that the automatic generation of ad-texts using the RL-based encoder-decoder model is effective in actual advertisement creation.

- We propose a method for generating ad-text that utilizes RL with rewards to improve advertising performance. We performed automated evaluations on different types of metrics, as well as human evaluations involving crowdsourcing workers and professional copywriters. The results showed the usefulness of the methods.

- We describe how to incorporate our model into an ad-delivery service and performed an online evaluation to compare the performance of ad-texts generated by the model with traditional ads written by a human.

2 Generating Ad-text with RL

As shown in Table 1, Seq2Seq generates ad-texts from the given keywords and contents of LPs. Note that we concatenated these elements as sequences for each side by a separator symbol \(<\text{SEP}>\). Figure 1 presents an overview of the proposed ad-text generation method. We use a model proposed by Paulus et al. (2018) as our Seq2Seq. In our method, Seq2Seq is trained using RL to capture useful features for generating effective ad-texts. In Sections 2.1 and 2.2, we describe each part of the proposed ad-text generation method.

2.1 RL for Seq2Seq

In Seq2Seq, for the input sequence \(x = x_1 \cdots x_n\), the ad-text \(y = y_1 \cdots y_m\) is generated by maximizing the output probability, which is calculated by the following formula:

\[
y = \arg\max_y \prod_{t=1}^{m} P(y_t|x, y_{t-1} \cdots y_1). \tag{1}
\]

For training Seq2Seq in consideration of the characteristics of an effective ad, we use RL in training. Because considering all possible outputs in the decoder is intractable, we use an approach based on a policy gradient method called self-critical sequence training (SCST) (Rennie et al., 2017), which can train models on sampled output sequences. In SCST, using \(y^* = y_1^* \cdots y_m^*\) (a sequence obtained by greedy decoding), the RL loss \(L_{rl}\) is calculated as follows:

\[
L_{rl} = (r(\hat{y}) - r(y^*)) \sum_{t=1}^{m} \log P(y_t^*|y_{t-1}^* \cdots y_1^*, x), \tag{2}
\]

where \(r(\hat{y})\) and \(r(y^*)\) are the rewards of \(\hat{y}\) and \(y^*\), respectively. It is difficult to optimize the model using only RL owing to its instability. We must, therefore, use maximum likelihood estimation (MLE), which maximizes the probability of the reference sequence \(y_1^* \cdots y_m^*\) as follows:

\[
L_{mle} = -\sum_{t=1}^{m} \log P(y_t^*|y_{t-1}^* \cdots y_1^*, x). \tag{3}
\]

Considering \(L_{rl}\) and \(L_{mle}\), our final loss function \(L_{mix}\) is defined as follows:

\[
L_{mix} = \gamma L_{rl} + (1 - \gamma) L_{mle}, \tag{4}
\]

where \(\gamma\) is a hyperparameter weighting the importance of \(L_{rl}\).

2.2 Rewards

To explicitly capture the characteristics of effective ad-text, we use the following three rewards: fluency, relevance, and ad quality. These rewards are summed and incorporated in the loss function of Eq.(2) to enhance the effectiveness of the ad. Thus, the reward for the generated text \(y\) is calculated as follows:

\[
r(y) = r^F(y) + r^R(x, y) + r^Q(x, y), \tag{5}
\]

where \(r^F(y)\) is a reward for fluency, \(r^R(x, y)\) is a reward for relevance, and \(r^Q(y)\) is a reward for ad quality. In Sections 2.2.1 through 2.2.3, we discuss these rewards in detail.
2.2.1 Fluency

Fluency is an essential factor in generating natural language texts. In addition, the length limitation of the text must be considered, as space for advertising is limited. If the ad-text is truncated owing to space limitations, its fluency is significantly degraded. To address these problems, our fluency reward consists of two types of scores as follows:

\[ r^F = s^{LM}(y) + s^{\text{Len}}(y), \quad (6) \]

where \( s^{LM}(y) \) is a grammatical score and \( s^{\text{Len}}(y) \) scores the fidelity of \( |y| \) to the given desired length. We use the function described in Eq. (10) of Zhang and Lapata (2017) as the first score \( s^{LM}(y) \).

The second score, \( s^{\text{Len}}(y) \), measures the appropriateness of the length of the generated text. The length of the generated text must not exceed the length limit. However, to maintain informativeness, it should not be significantly shorter than the limit. We incorporate these factors into \( s^{\text{Len}} \). Let \( y_{\text{title}} \) be the title part of \( y \), \( y_{\text{desc}} \) be the description part of \( y \), \( C_{\text{title}} \) be the length limit of the title part, \( C_{\text{desc}} \) be the length limit of the description part, and \( s^l \) be a score function for each part of the generated text. The score \( s^{\text{Len}} \) is calculated as follows:

\[ s^{\text{Len}}(y) = \frac{s^l(y_{\text{title}}, C_{\text{title}}) + s^l(y_{\text{desc}}, C_{\text{desc}})}{2}, \quad (7) \]

where \( s^l(\cdot, C) \) is a function that returns \( \exp(|\cdot| - C) \) when \( |\cdot| \leq C \), whereas it returns 0 when \( |\cdot| > C \).

2.2.2 Relevance

Effective ad-text is generally consistent with what it advertises. Therefore, we consider the relevance between the input text and output ad-text as a reward. In ad-text generation, the input text includes important keywords that should be emphasized in the generated ad-text. For the generated ad-text to be relevant to the input, the ad-text should contain keywords from the input text as important words\(^1\). Therefore, we focus on the use of important keywords in the generated ad-text for building a reward to measure relevance. In addition to the coverage of keywords, the positions of keywords in the generated ad-text are also important, because keywords should appear at the beginning of ad-text. Considering these factors, we calculate \( r^R(x, y) \), the reward of the relevance for input \( x \) and the generated ad-text \( y \) as follows:

\[ r^R(x, y) = s^{\text{cov}}(x, y) + s^{\text{pos}}(x, y), \quad (8) \]

where \( s^{\text{cov}}(x, y) \) scores the coverage of keywords in \( x \) and \( s^{\text{pos}}(x, y) \) scores the position of keywords in \( y \). The first score \( s^{\text{cov}}(x, y) \) calculates the proportion of keywords in \( x \) that are covered by \( y \). The second score \( s^{\text{pos}}(x, y) \) calculates the average position of keywords in \( y \). To prevent this reward from reducing the coverage of keywords, we impose the length of the generated ad-text as a score of a keyword not included in the ad-text. Then,

\(^1\)Actually, Google Ads recommends to include at least one of advertisement keywords as described in the support page: https://support.google.com/google-ads/answer/1704392?hl=en
We prepared a dataset that contained pairs consisting of an input and ad-text in Japanese for training and evaluating our models. This dataset consisted of eight clients (one real estate company, one health food company, one media service company, two cosmetic companies, one job recruiting company, and three financial companies). We carefully split the dataset into 713,928, 8,000, and 8,000 pairs for training, development, and the test set, respectively.

In this dataset, we used the meta-description as the content of the LP. In addition to the ad-texts, we prepared Japanese Wikipedia articles\(^2\) to pre-train the language model. The fine-tuning of LM was performed on the ad-text dataset. All texts in this dataset were tokenized by MeCab\(^3\) with the Neologd dictionary (Sato et al., 2017).

### 3.2 Models

The baselines are as follows:

**Separated (Sep):** This baseline trains the models for different clients separately. Therefore, it is necessary to build as many models as the number of clients, which can be significantly high. In addition, the diversity of the ad-text generated from this model was considerably low. Such unpractical features are not suitable for automatic ad-text generation; however, this model can generate ad-text that is highly similar to the given dataset. Therefore, we treated this model as a type of upper limit for generating ad-texts.

**Mixed without Domain Tags (Mix w/o tag):** This model was trained on the entire dataset with the MLE loss of Eq. (3).

**Mixed (Mix):** Similar to Mix w/o tag, this model was trained on the entire dataset with the MLE loss of Eq. (3). However, in this model, we included additional labels to identify the domain and the client of the input in both the training and the prediction steps. Particularly, we added the tags `<domain_id>` and `<client_id>` to the beginning of the input.

The methods employed are as follows:

**Mixed with Rewards (Mix+Rewards):** This model was trained on the mixed loss function, which is a combination of the RL loss and MLE loss, as defined in Eq. (4). The data format used in this model is similar to that in the Mixed model. We combined several rewards: reward of the fluency \(r^F\) in Eq. (6) (Flu), the reward of the relevance \(r^R\) in Eq. (8) (Rel), and reward of the ad quality \(r^Q\) discussed in Section 2.2.3 (QS). The combinations of Flu, Rel, and QS are represented by the + symbol. It should be noted that Mix+QS is the model proposed by Hughes et al. (2019); thus, it is categorized as a baseline.

Table 2 presents the parameter settings. We adapted to the settings used in previous research (Paulus et al., 2018) and choose \(\lambda\) as 0.98 for the re-
Gradient normalization cut word its freq. <2

10 0.98 0.25 -50,000 20

LR decay

Batch size

Optimizer

Max length

180 60

Epoch (pretrain)

300

Adam SGD

Epoch (fine-tuning)

50

Dropout

0.2

Learning rate (LR)

200

200

0.3

We used BLEU, F1 whether the keywords were included in the generated ad-text, and that the lengths of these parts did not exceed the length limit. The percentage of generated ad-texts contained the title and description parts, and that the lengths of these parts did not exceed the length limit. The percentage of generated ad-texts with the appropriate format was reported.

### Table 2: Parameter settings.

| Seq2Seq | Data | Vocab | Optimizer | Learning rate (LR) | LR decay | Dropout | Batch size | Epoch | LM | Vocab | Optimizer | Learning rate (LR) | LR decay | Dropout | Batch size | Epoch | Div | Cov | R-1 | R-2 | R-L |
|---------|------|-------|-----------|-------------------|----------|---------|-----------|-------|-----|-------|-----------|-------------------|----------|---------|-----------|-------|-----|-----|-----|-----|-----|
|         | train | 250   | Adam      | 0.0001            | 0.25     | 0.2     | 10        | 10    | 20  | 20    | SGD        | 0.0001            | 0.25     | 0.2     | 10        | 10    | 20 | 20 | 20 | 20 | 20 |
| Seq2Seq | dev   | 50    | Adam      | 0.0001            | 0.25     | 0.2     | 10        | 10    | 20  | 20    | SGD        | 0.0001            | 0.25     | 0.2     | 10        | 10    | 20 | 20 | 20 | 20 | 20 |

### Diversity (Div): This metric evaluates the diversity of the generated ad-text by calculating the percentage of generated ad-texts excluded from the training dataset for each model.

### 3.4 Human Evaluation

We hired 10 annotators through Lancers⁴, a crowdsourcing service in Japan, and 3 professional copywriters to evaluate the quality of ad-texts that were generated by the seven models: ad-text written by a human (Reference), Sep, Mix, Mix+QS, Mix+Flu+QS, Mix+Flu+Rel, and Mix+Flu+QS+Rel. It should be noted that, for this human evaluation, we omitted some models that performed poorly in the automatic evaluation.

We generated ad-texts from randomly sampled 240 ads in the test set and performed two tasks to evaluate three criteria: (i) fluency, (ii) attractiveness, and (iii) relevance. In the first task, annotators were instructed to evaluate the fluency of a displayed single ad-text. In the second task, the annotators were instructed to select one of the two ad-texts displayed side-by-side from the perspective of the ad-texts’ attractiveness and relevance to the keywords⁵. We generated 11,760 questions in total, including 1,680 questions for the first task and 10,080 questions for the second task.

In the first task, fluency scores were obtained by calculating the percentage of annotators who answered “yes” to all questions. All answers were represented as a relation of each pair such as “win,” “lose,” and “tie” in the second task. We then scored each method’s performance through these relation pairs using TrueSkill™ (Herbrich et al., 2007), a widely used rating system that incorporates a Bayesian inference algorithm⁶. This algorithm treats the performance of each method as a standard distribution, where the mean \(\mu\) represents the performance, and variance \(\sigma\) represents confidence. These are updated by repeating the pairwise comparison through the annotators’ evaluations. We used the \(\mu\) value of each method as the final result.

### 3.5 Deployment and Ad-delivery Evaluation

We deployed the baselines and our models to an ad-text generation tool, as shown in Figure 2. In

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⁴https://www.lancers.jp

⁵There was also the option “same,” but it was explicitly stated in the tutorial that this was deprecated.

⁶Following the official settings, the parameters were initialized as follows: \(\mu = 25.0, \sigma = 8.33\). The draw probability was set to the ratio of the number of “same” options selected out of all answers.
addition to the generated ad-texts, the tool also dis-
plays currently serving ads, other ads in the search
result, and the non-ad search results on the same
screen. Besides, we predict the quality scores for
all items using the method described in Section
2.2.3. This tool aids copywriters to edit the gener-
ated ad-text effectively and obtain a comprehensive
understanding of market trends.

We also performed an ad-delivery evaluation us-
ing the deployed tool. We gathered the ad-texts
generated by the different models\(^7\), including those
written by copywriters, into the same ad-group per
product and served each ad-group for one to two
weeks. In total, we served 104 ads, 11 ad-groups,
and 1,568 keywords for three weeks. In the re-
sult section, we show the number of impressions,
click-through rates (CTRs), and costs averaged by
ad-groups from the serving result. The Impression
is the number of times an ad is displayed, the CTR
is the percentage of clicks that out of impressions,
and the Cost is the budget spent; the higher, the
better for all metrics.

\(^7\)Mix+Flu+QS was not included because it had a high
percentage of output overlap with the other models, and we
filtered out ad-texts that could cause legal problems.

4 Results and Discussions

4.1 Automatic Evaluation

Table 3 presents the results of the automatic evalu-
ation. Mix achieved the best diversity among the
three models Sep, Mix, and Mix w/o tag. The di-
versity of Mix w/o tag was also better than that
of Sep. This result indicates that a dataset cov-
ering many domains is useful for improving di-
versity. Furthermore, a comparison between Mix
and Mix w/o tag illustrated that discriminating
domains and clients is useful in terms of diver-
sity. Mix+Flu+Rel improved R-1, R-2, and R-L
by 0.7, 2.0, and 0.7 points, respectively, whereas
Mix+Flu+QS achieved the best BLEU score. Be-
cause Rouge uses the F\(_1\) score and BLEU uses the
precision of overlapped words between references
and system outputs, we conclude that Rel gener-
ated ad-texts with words that were not included in
the references. This is consistent with the improve-
ments of Mix+Rel and Mix+Flu+Rel in Div. In
EQ, Rel improved EQ similar to QS. This result
is consistent with our expectation that Rel is an
important factor for the effectiveness of ad-texts.
In both LM and Pos, QS achieved the best scores.
This result indicates that LM and Pos are corre-
lated with EQ. In Cov, only Mix+Flu+Rel+QS

| Model             | R-1 | R-2 | R-L | BLEU | EQ  | LM  | Cov | Pos | FC | Div |
|-------------------|-----|-----|-----|------|-----|-----|-----|-----|----|-----|
| Mix w/o tag       | 36.8| 17.9| 36.8| 43.7 | 64.0| 10.4| 51.6| 10.8| 99.3| 36.0|
| Mix               | 35.6| 18.5| 35.6| 44.7 | 64.3| 12.4| 55.6| 12.1| 99.6| 40.6|
| Mix+QS            | 35.8| 18.0| 35.8| 44.2 | 64.6| 13.4| 55.6| 11.0| 99.2| 42.0|
| Mix+Flu           | 36.8| 17.9| 36.8| 44.9 | 64.2| 12.1| 54.4| 10.8| 99.5| 40.6|
| Mix+Flu+QS        | 36.3| 16.9| 36.3| 45.4 | 64.5| 12.9| 52.2| 10.8| 99.3| 37.4|
| Mix+Flu+Rel       | 37.5| 20.5| 37.5| 44.4 | 64.9| 13.3| 53.2| 11.9| 99.6| 40.8|
| Mix+Flu+Rel+QS    | 35.3| 18.4| 35.2| 43.1 | 64.9| 13.1| 52.8| 11.3| 99.4| 42.7|

Table 3: Results of automatic evaluation.

| Model          | Copywriter | Crowdsourcing |
|----------------|------------|--------------|
|                | (1) Flu.  | (2) Att.  | (3) Rel. | (1) Flu. | (2) Att. | (3) Rel. |
| Reference      | 87.5      | 25.5      | 24.4     | 75.6     | 26.8     | 29.1     |
| Sep            | 82.1      | 25.2      | 24.0     | 65.7     | 24.6     | 28.4     |
| Mix            | 83.3      | 25.1      | 23.7     | 64.5     | 23.8     | 26.1     |
| Mix+QS         | 80.8      | 25.0      | 23.7     | 64.0     | 23.2     | 26.5     |
| Mix+Flu+QS     | 81.7      | 25.3      | 22.8     | 64.3     | 24.4     | 26.6     |
| Mix+Flu+Rel    | 77.5      | 24.2      | 23.7     | 60.9     | 24.8     | 26.2     |
| Mix+Flu+Rel+QS | 81.2      | 23.9      | 24.3     | 62.7     | 25.4     | 26.9     |

Table 4: Results of human evaluation. Flu., Attr., and Rel. refer to Fluency, Attractiveness, and Relevance, re-
spectively.
achieved a score comparable to that of Mix. The results for each metric suggest the importance of a combination of rewards. However, the importance of each metric in ad-text generation is uncertain. To clarify this concept, we performed additional human evaluations.

4.2 Human Evaluation

Table 4 presents the results of these human evaluations. Our methods achieved better scores than all other methods in terms of the attractiveness and relevance criteria by both the copywriter’s and crowdsourcing’s evaluations. Particularly, Mix+Flu+QS+Rel improved attractiveness and relevance scores by 1.6 and 0.4 points, respectively. Considering the attractiveness evaluation results, there are some differences between the annotations by copywriters and crowdsourcing workers. This is due to the stance of each annotator, where copywriters evaluate ad-texts as editable sources. By contrast, crowdsourcing workers treat ad-texts as a part of completed ads. In other words, copywriters rate an ad-text highly if they regard that they can fix it to a good one, whereas crowdsourcing workers evaluate ad-texts in their current form. This trend also appears in the fluency task, as presented in Table 4; overall, the score of the fluency task in the copywriter section is higher than that in the crowdsourcing section. Mix produced the best score for the fluency task; however, the proposed Mix+Flu+QS had a highly competitive result with a difference of just 0.2 points.

4.3 Ad-Delivery Evaluation

Table 5 presents the result of the ad-delivery evaluation. Mix+Flu+Rel achieved the best score in terms of impression and cost, whereas Sep achieved the best score in CTR. Because Sep and Reference have similar ad-texts, their CTRs are almost identical. These results indicate that considering the relevance between ad-texts and user queries is important to enhance user recognition for the ad-texts.

Based on these results, we used linear regression to investigate if the evaluation metrics are related to each ad-delivery evaluation metric. Figure 3 shows the results. With regard to impression and cost, considering the coverage of keywords in generated ad-texts is important. In CTR, it is necessary to focus on the fluency rated by crowdsourcing workers. The attractiveness of crowdsourcing workers is counterproductive. This is because people avoid clicking on an ad-text that looks like an ad-text. Based on the result, we conclude that the keyword-related automatic evaluation metric and evaluations via crowdsourcing are important for generating effective ad-texts.

5 Conclusion

In this paper, we proposed several rewards based on RL, which can consider the various characteristics of ad-texts. In experiments, ad-texts generated from Seq2Seq incorporated with these rewards achieved better automatic, human, and ad-delivery evaluation results than the basic Seq2Seq methods. Our analysis showed that considering results from the keyword-related automatic evaluation metric and the fluency by crowdsourcing workers is important for generating effective ad-texts. As further work, we plan to consider diversity as a reward to generate more diverse ad-texts.

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| Model            | Impression | CTR (%) | Cost  |
|------------------|------------|---------|-------|
| Reference        | 1.33       | 7.82    | 23.79 |
| Sep              | 3.96       | 7.98    | 47.43 |
| Mix              | 4.71       | 5.18    | 78.80 |
| Mix+QS           | 2.77       | 7.01    | 51.89 |
| Mix+Flu+Rel      | **5.06**   | 4.10    | **86.01** |
| Mix+Flu+QS+Rel   | 1.75       | 5.53    | 61.48 |

Table 5: Results of ad-delivery evaluation.

Figure 3: The weights for each metric. All weights are scaled by maximum values for each row.

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⁷CW and CS denote the copywriter and the crowdsourcing results, respectively.
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