Conversion Prediction Using Multi-task Conditional Attention Networks to Support the Creation of Effective Ad Creatives

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ABSTRACT

Accurate predicting of conversions in advertisement is generally a challenging task because such conversions do not occur frequently. In this paper, we propose a new framework to support creating high-performance ad creatives including accurate prediction of ad creative text conversions before delivering to consumer. Our framework includes three key ideas, as follows: multi-task learning, conditional attention, and attention highlighting. Multi-task learning is an idea for improving the prediction accuracy of conversion, that predict the clicks and the conversion simultaneously to solve the difficulty of data imbalance. Furthermore, conditional attention focuses attention of each ad creative with the consideration of its genre and target gender, thereby improving conversion prediction accuracy. The attention highlighting visualizes important words and/or phrases based on the conditional attention. We evaluated our proposed framework with actual delivery history data (14,000 creatives displayed more than a certain amount of times from Gunosy Inc.) and confirmed that our ideas improve the prediction performance of conversion and visualize noteworthy words according to creatives' attributes.

CCS CONCEPTS

• **Information systems → Online advertising**; • **Computing methodologies → Multi-task learning**; *Neural networks.*

KEYWORDS

Online Advertising, Supporting Ad Creative Creation, Recurrent Neural Network, Multi-task Learning, Attention Mechanism

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Figure 1: The example of an ad creative in digital advertising: an ad creative is constructed by an image and two short texts. These short texts are called title and description.

1 INTRODUCTION

In display advertisements, ad creatives, such as images and texts, play an important role in delivering product information to customers efficiently [6]. Figure 1 shows the example of an ad creative which is constructed by two short texts and an image. The performance of these advertisements are generally defined by *revenue of conversions* per *cost of advertisement*. Conversions are user actions like the purchase of an item or download of an application, and they represent a known metric that the advertisers try to maximize through their ad creatives. The costs of advertisements are generally calculated by the cost per click (CPC), where an advertiser pays for the number of times their advert had been clicked on. Therefore, the high performance of an ad is determined by minimizing the amount payed the maximum number of conversions. Creating high performance ad creatives is a difficult but crucial task for advertisers.

Our purpose is to supporting the creation of ad creatives with many conversions, and we propose a new framework to support creating high-performance ad creatives including accurate prediction of ad creative text conversions before delivering to consumer[1]. If conversions of ad creatives can be predicted before delivery to consumers, advertisers can avoid the losses incurred by the high cost of ineffective advertisements. Morever, since ad creatives with high click through rates (CTR) and low conversions have a tendency of deceiving users, we also expect to improve the user experience

[*]This work was done while the first author was doing internship at Gunosy Inc. Thanks for the support of Ad engineering team who provides useful comments.
[1]We have also achieved the improvement of CVR prediction using the result of conversion prediction.

on media displaying those ads. As a result, advertisers will be able to focus on improving the CTR of ad creatives.

Some attempts to support high-performance creatives creation by predicting ad creative conversions have been reported in the industry,[2,3,4], but as far as we know, no academic research has been published in this area. Thomaidou et al. [34, 35] have proposed a framework for generating ad creatives automatically. However this framework focuses on search ads and generates ad text according to set rules, so this framework can't be applied for our purpose. Some studies have reported that ad creatives affect the CTR of advertisements [1, 3, 8], but they do not predict the conversions. Prediction of a user's CTR or conversion rate (CVR) is a general task undertaken by many studies in this research area, but there are no studies that have predicted these rates for ad creatives. The prediction of an ad creative's performance is another important issue, but to the best of our knowledge, no study has examined this.

Although ad creatives are mainly image and text, we focus on the latter and predicting its conversions. Because it is difficult to replace ad images but easy to replace text, in this work, we propose a recurrent neural network (RNN)-based framework that predicts the performance of an ad creative text before delivery. Our framework includes three key ideas, namely the multi-task learning, conditional attention, and attention highlighting. Multi-task learning is an idea for improving the prediction accuracy of conversion, that predict the clicks and the conversion simultaneously to solve the difficulty of data imbalance. Conditional attention focuses on the feature representation of each creative based on its genre and target gender, thereby improving conversion prediction accuracy. The attention highlighting visualizes important words and/or phrases based on the conditional attention. We confirm that the proposed framework outperforms some baselines and the proposed ideas are valid for prediction. These ideas are expected to be useful for supporting ad creatives' creation.

Our research is motivated to support the creation of high performance creative text. Our contributions are summarized as follows:

(1) We propose a new framework that accurately predicts ad creative performance.

In order to realize this, we propose two key strategies to improve the prediction performance of advertisement conversion.

(a) Multi-task learning predicts conversion together with prior click actions by learning common feature representations.
(b) Conditional attention mechanism focuses attention on the feature representation of each creative text considering with target gender and genre.

(2) We propose an attention highlighting that offers important words and/or phrases using conditional attention.

A prototype implementation of our proposed framework is released on GitHub[5].

[2]https://www.facebook.com/business/m/facebook-dynamic-creative-ads
[3]https://www.adobe.com/en/advertising/creative-management.html
[4]https://support.google.com/google-ads/answer/2404190?hl=en
[5]https://github.com/shunk031/Multi-task-Conditional-Attention-Networks

2 RELATED WORK

Our study focuses on ad creatives. First, we describe existing studies that analyze high performance ad creatives and discuss how to generate them. Many studies about advertising creatives focus on images, and offering few results on texts. Furthermore, these studies focus on the CTR rather than the conversions. Second, we introduce studies on performance prediction for ads. In contrast to our study, which aims to predict performance for new ads, these studies also focus on images. Finally, highlighting studies related to our ideas, we introduce multi-task learning and RNN-based attention mechanisms.

2.1 Analysis and Generation of Effective Advertisements

Since ad creatives play an important role in the performance of ads, some studies analyze ad creative performance [1, 3, 8]. For example, Azimi et al. [1] tried to predict some features of the CTR using ad creative images and evaluate the effectiveness of visual features. The motivation of their study is similar to ours, but we focus on text instead of images in ad creatives and predict conversions rather than the CTR. Cheng et al. [8] proposed a model for predicting the CTR of new ads and reported some knowledge using feature importance, but text features of this study is based on fixed rules. With the development of deep learning, especially convolutional neural networks (CNNs) [21], visual features can be easily and effectively used for machine learning. Chen et al. [7] proposed Deep CTR, showing that using the features of ad images can significantly improve CTR prediction.

Thomaidou et al. [34] developed GrammaAds, which automatically generates keywords for search ad. In addition, they proposed an integrated framework for the automated development and optimization of search ads [35]. These studies can support text ad creative creation, since these methods are rule-based, focusing only on search ads, they cannot be applied to display advertising.

2.2 CTR and Conversion Prediction in Display Advertising

CTR prediction of display advertising is important not only in the industry but also academia. In [5, 31], a CTR prediction model was proposed using logistic regression (LR), and factorization machines (FMs) have also proposed to predict advertising performance [18, 19, 30]. In industry, LR and FMs are mainly used because, in display advertising, the prediction response time needs to be short to display an advertisement smoothly. In recent years, deep neural networks (DNNs) have been applied for predicting the advertisement CTR [7, 9, 13, 14, 23], and especially, some models combining DNNs with FMs have been proposed and have improved predictions [9, 14, 23, 26]. The improvements achieved by these models show that explicit interaction between variables is important for advertisement performance prediction, so we adopted explicit interaction in our idea as a conditional attention mechanism.

There are several studies on CVR prediction [27, 29, 38], but there are not as many as the studies on CTR prediction. CVR prediction is difficult because the number of conversions is imbalanced data that almost ad creative's conversions is zero. Existing studies tackled this difficulty. Yang et al. [39] adopted dynamic transfer learning for predicting the CVR and demonstrating feature importance. Punjobi et al. [29] proposed robust FMs for overcoming user response noise. In our study, we tackle this difficulty using multi-task learning.

2.3 Background of the Proposal Strategies

In this paper, we propose two key strategies to improve prediction performance of advertisement conversion, namely multi-task learning and a conditional attention mechanism. As the background of these strategies, we describe multi-task learning and the RNN-based attention mechanism.

Multi-task Learning. Multi-task learning [4] is a method that involves learning multiple related tasks; It improves the prediction performance by learning common feature representations. Recently, multi-task learning has been used in various research areas, especially natural language processing (NLP) [12, 28] and computer vision [10, 25, 40], and has achieved significant improvements. Conversions represent extremely imbalanced data, so conversion prediction is difficult. Since ad click actions represent a pre-action of conversion actions, click prediction may be related to conversion prediction. Therefore, we adopt multi-task learning, which predicts clicks and conversions simultaneously.

RNN-based Attention Mechanism. For supporting ad creative text creation, we use the knowledge of NLP. RNN-based models, such as long short-term memory (LSTM) [16], gated recurrent unit (GRU) [11], and attention mechanisms [2], which have made breakthroughs in various NLP tasks, for example, machine translation [2], document classification [24, 39], and image captioning [37]. An RNN is a deep learning model for learning sequential data, and, in NLP, this model can learn word order. Attention mechanisms compute an alignment score between two sources and make significant improvements in some NLP tasks. Recently, self-attention [24], which computes alignment in a single source, was proposed. In addition, visual analysis using attention can highlight important phrases and/or words using the attention result, so the attention mechanism is also attractive for interpretability. In this study, we adopt a self-attention mechanism for improving conversion prediction performance and visualizing word importance.

3 METHODOLOGY

The outline of our proposed framework for ad creative evaluation is shown in Figure 2. In the framework, we propose two strategies as follows: multi-task learning, which simultaneously predicts conversions and clicks, and a conditional attention mechanism, which detects important representations in ad creative text according to the text's attributes.

Conversion prediction using ad creatives with an imbalanced number of conversions is a challenging task. Therefore, in multi-task learning, we expect to improve the model accuracy by predicting conversions along with clicks. Conditional attention mechanism makes it possible to dynamically compute attention according to the attributes of ad creatives, its genre and target gender.

3.1 Framework Overview

The input of our framework is ad creative text and ad creative attribute values. Figure 1 shows the example of an ad creative, and these are two short texts which are called titles and descriptions. The ad attribute values are gender of the delivery target and genre of the ad creative, and they are related to ad creatives.

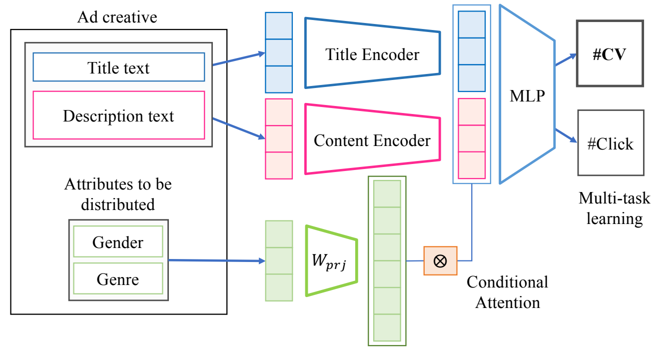


Figure 2: Outline of the our framework used in this paper. In the framework, we propose two strategies as follows: multi-task learning, which simultaneously predicts conversions and clicks, and a conditional attention mechanism, which detects important representations in ad creative text according to the text's attributes.

Specifically, the input of the framework we propose is an ad creative text $S = \{\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_n\}$ consisting of n word embeddings, where $\mathbf{w}_i \in \mathbb{R}^{d_w}$ represents the word vector at the i-th position in the ad creative text. Therefore, $S \in \mathbb{R}^{n \times d_w}$ is a two-dimensional matrix of the word sequence.

Incidentally, in the practical situation, a number of ad creative texts that have title and description texts are created for the target product. These texts often have different contexts for maximizing the amount of information empirically. Therefore, our proposed framework uses two *text encoders*, which learn individual context from the title and description.

As a *text encoder*, we adopted the GRU, which can extract features from ad creative text considering word order. Specifically, title text $S^{\text{title}} = \{\mathbf{w}_1^{\text{title}}, \mathbf{w}_2^{\text{title}}, \cdots, \mathbf{w}_n^{\text{title}}\}$ and description text $S^{\text{desc}} = \{\mathbf{w}_1^{\text{desc}}, \mathbf{w}_2^{\text{desc}}, \cdots, \mathbf{w}_n^{\text{desc}}\}$ are input from the ad creative into title and description encoders, respectively, and are encoded into feature representations as $\mathbf{h}_t^{\text{title}} \in \mathbb{R}^{u_{\text{title}}}$ and $\mathbf{h}_t^{\text{desc}} \in \mathbb{R}^{u_{\text{desc}}}$; $t = 1, 2, \cdots, n$:

$$\begin{aligned} \mathbf{h}_t^{\text{title}} &= \text{title encoder}(\mathbf{w}_t^{\text{title}}, \mathbf{h}_{t-1}^{\text{title}}), \\ \mathbf{h}_t^{\text{desc}} &= \text{description encoder}(\mathbf{w}_t^{\text{desc}}, \mathbf{h}_{t-1}^{\text{desc}}) \end{aligned} \tag{1}$$

Let u_{title} and u_{desc} be the number of hidden units of the title and description encoders obtained here. The n hidden states can be expressed as $H^{\text{title}} = \{\mathbf{h}_1^{\text{title}}, \cdots, \mathbf{h}_n^{\text{title}}\}$ and $H^{\text{desc}} = \{\mathbf{h}_1^{\text{desc}}, \cdots, \mathbf{h}_n^{\text{desc}}\}$, respectively. Compute a vector $\mathbf{x}_{\text{feats}}$ that concatenates these hidden states, H^{title}, H^{desc}, one-hot vectors of gender features $\mathbf{x}_{\text{gender}} \in \mathbb{R}^{d_{\text{gender}}}$ and genre features $\mathbf{x}_{\text{genre}} \in \mathbb{R}^{d_{\text{genre}}}$:

$$\mathbf{x}_{\text{feats}} = \text{concat}(H^{\text{title}}, H^{\text{desc}}, \mathbf{x}_{\text{genre}}, \mathbf{x}_{\text{gender}}) \tag{2}$$

Note here $\mathbf{x}_{\text{feats}} \in \mathbb{R}^{d_{\text{feats}}}$;$d_{\text{feats}} = n \times (u_{\text{title}} + u_{\text{desc}}) + d_{\text{gender}} + d_{\text{genre}}$. These concatenated vectors are input to a multi-layer perceptron (MLP) which is an output layer of our proposed framework. In order to predict both conversions $\hat{y}^{(\text{cv})}$ and clicks $\hat{y}^{(\text{click})}$, multi-task learning described later predicted $\hat{\mathbf{y}}_{\text{multi}} = \{\hat{y}^{(\text{cv})}, \hat{y}^{(\text{click})}\}$ through the MLP:

$$\hat{\mathbf{y}}_{\text{multi}} = \text{MLP}(\mathbf{x}_{\text{feats}}) \tag{3}$$

To improve the performance of the model robustness, we use wildcard training [32] with dropout [15] for the input word embeddings.

3.2 Multi-task Learning

Conversion prediction is difficult due to the imbalanced data, so we use the strategy of multi-task learning. Multi-task learning is a method that solve multiple tasks related to each other and that improve the prediction performance by learning common feature representations. We adapt multi-task learning and predict clicks and conversion prediction simultaneously. Since click prediction may be related to conversion prediction, we expect to improve prediction performance by learning common feature representations using multi-task learning.

In multi-task learning, the input is a feature vector of a training sample denoted by $\mathbf{x}$, and the ground truth is y. For training samples $\mathbf{x} = \{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_N\}$, the single model, f, learns to generate predictions $\hat{y} = \{\hat{y}_1, \hat{y}_2, \cdots, \hat{y}_N\}$:

$$\hat{y} = f(\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_N) \tag{4}$$

We minimize the mean squared error (MSE) over all samples, N, in $l = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$. In K supervised tasks, the multi-task model, $F = \{f_1, f_2, \cdots, f_K\}$, learns to generate predictions $\hat{\mathbf{y}} = \{\hat{y}^{(1)}, \hat{y}^{(2)}, \cdots, \hat{y}^{(K)}\}$:

$$\hat{\mathbf{y}} = F(\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_N) \tag{5}$$

The total loss is calculated from the sum of loss in each task,

$$\mathcal{L} = \frac{1}{N}\sum_{k=1}^{K}\sum_{i=1}^{N}\left(y_i^{(k)} - \hat{y}_i^{(k)}\right)^2. \tag{6}$$

In our task, for ground truth of y_{cv} and y_{click}, we minimize losses for predicted conversions $\hat{y}_{\text{cv}}$ and clicks $\hat{y}_{\text{click}}$:

$$\mathcal{L}_{\text{multi}} = \frac{1}{N}\sum_{i=1}^{N}\left(y_i^{(\text{cv})} - \hat{y}_i^{(\text{cv})}\right)^2 + \lambda\frac{1}{N}\sum_{i=1}^{N}\left(y_i^{(\text{click})} - \hat{y}_i^{(\text{click})}\right)^2, \tag{7}$$

where $\lambda > 0$ is the hyper-parameter to control the effect of the click loss.

3.3 Conditional Attention

We propose the strategy of conditional attention mechanism. Supporting the ad creative creation considering attribute values is useful, but the conventional attention mechanism learns keywords or key phrases, depending on calculating the alignment score using only the input sentence.

In this paper, we propose a conditional attention mechanism to calculate self-attention using feature vectors obtained from attribute values of the ad creative. Figure 3 illustrates conditional attention mechanism. The conditional attention mechanism can consider ad creative attributes against the conventional attention mechanism.

The conditional attention mechanism is calculated from attention of *text encoder* and feature vector obtained from attribute values of ad creative text. Each word in the word sequence S is independent of the others. To capture these word order relations, we apply a *text encoder* to the text to obtain the hidden state $\mathbf{h}_t \in \mathbb{R}^u$. The n hidden states of these $u \times n$ dimensions can be expressed as $H = \{\mathbf{h}_1, \mathbf{h}_2, \cdots, \mathbf{h}_n\}$.

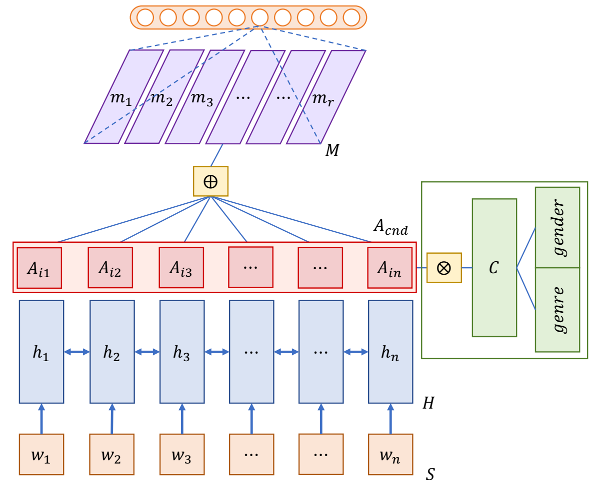


Figure 3: Example of conditional attention mechanism. Conditional attention is calculated from the element-wise product of the attention matrix A and the feature vector $\mathbf{c}$ consisting of gender and genre.

To consider ad attribute values, a *conditional* vector, $\mathbf{c} \in \mathbb{R}^n$, is calculated by performing a linear combination of $\mathbf{x}_{\text{feats}} \in \mathbb{R}^{d_{\text{feats}}}$ and trainable parameters $W_{\text{prj}} \in \mathbb{R}^{n \times d_{\text{feats}}}$:

$$\mathbf{c} = W_{\text{prj}}\mathbf{x}_{\text{feats}}. \tag{8}$$

Here, we use *self-attention* [24] for computing the linear combination. The attention mechanism takes the entire hidden state H of the *text encoder* as input and outputs the attention vector $\mathbf{a}$:

$$\mathbf{a} = \text{softmax}(\mathbf{w}_{s2}^T \tanh(W_{s1}H)), \tag{9}$$

where $W_{s1} \in \mathbb{R}^{n \times u}$ and $\mathbf{w}_{s2} \in \mathbb{R}^n$ are trainable parameters. Since H is an $n \times u$ dimension, the size of the attention vector $\mathbf{a}$ is n. The softmax$(\cdot)$ is calculated so that the sum of all the weight is 1.

Furthermore, we calculate the *conditional attention vector* using the attributes given to the ad creative. The *conditional attention* vector, $\mathbf{a}_{\text{cnd}}$, is calculated using conditional vector $\mathbf{c}$ and attention vector $\mathbf{a}$:

$$\mathbf{a}_{\text{cnd}} = \mathbf{a} \odot \mathbf{c} \tag{10}$$

Here, $\odot$ is an element-wise product. We want r different parts to be extracted from the ad creative texts, *conditional attention* vector $\mathbf{a}_{\text{cnd}}$ becomes *conditional attention* matrix $A_{\text{cnd}} \in \mathbb{R}^{n \times r}$. Therefore, sentence vector $\mathbf{m}$ with embedded ad creative text becomes sentence matrix $M \in \mathbb{R}^{u \times r}$. The *conditional attention* matrix, A_{cnd}, is multiplied by hidden state H of the *text encoder*, and the r-weighted sentence matrices are calculated as follows:

$$M = HA_{\text{cnd}} \tag{11}$$

In our framework, the model predicts based on the calculated M and ad creative attributes such as $\mathbf{x}_{\text{gender}}$ and $\mathbf{x}_{\text{genre}}$.

Table 1: Features included in the ad creative dataset. It contains 1,694 campaigns, some of which were part of campaigns delivered by Gunosy. The average lengths of the title and description text are about 15 characters and, 32 respectively. The Campaign ID feature is not directly input into the model because it is used for evaluations with cross-validation based on the ID.

	Features	Feature Description	Details
	Campaign ID	Campaign ID in Gunosy Ads	1,694 campaigns
Texts	Title	Title texts	Avg. 15.44±3.16 chars
	Description	Description texts	Avg. 32.69±5.43 chars
Attrs	Genre	Genre of the creatives	20 types
	Gender	Gender of delivery target	3 types

4 EXPERIMENTS

4.1 Dataset

We use real-world data from a Japanese digital advertising program, Gunosy Ads[6], provided by Gunosy Inc.[7]. Gunosy Inc. is provider of several news delivery applications, and Gunosy Ads delivers digital advertisements for these applications. Gunosy is a news delivery application achieved over 24 million downloads in January 2019.

For evaluation, we used 14,000 ad creatives delivered by Gunosy Ads from August 2017 to August 2018. In digital advertising, the cost of acquiring a conversion is called the cost per acquisition (CPA). Advertisers set target CPAs for a product and manage its ad creatives to improve their performance. When target CPAs for creatives are different, the trend of conversions may also vary, and for this reason the dataset we selected comprises ad creatives where the target CPA was within a certain range. In addition, we removed creatives with a low amount of impressions[8] from the dataset. As shown in Table 1, the title, description, and genre of the ad creative, as well as the gender to which the ad is delivered, are used as an input features. Note that campaign ID is not a feature directly used as an input to the model because it is used for evaluating with cross-validation based on the ID.

Creative texts written in Japanese are split into words using MeCab [22], a morphological analysis engine for Japanese texts, and mecab-ipadic-neologd [36], which is a customized system dictionary that includes many neologisms for MeCab. The number of clicks and conversions are log-normalized.

Figure 4 shows a histogram of the number of clicks and conversions. The number of conversions is concentrated on zero, and in relation, the number of clicks is a long-tailed distribution. Therefore, the ad creative dataset is definitely imbalanced. Figure 5 shows the distribution between the number of clicks and conversions in the dataset. The correlation coefficient between the number of clicks and conversions is 0.816, which is a strong correlation. As a reminder, we hide the number of clicks and conversions, and also their frequencies for confidentiality reasons.

[6] https://gunosy.co.jp/ad/
[7] https://gunosy.co.jp/en/
[8] An occasion when a particular advertisement is seen by someone on the application.

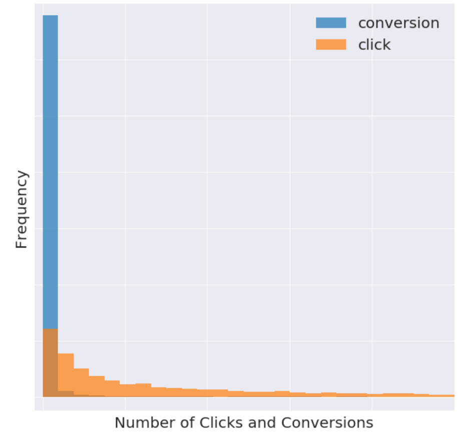


Figure 4: Distribution of clicks and conversions in dataset. The number of conversions is concentrated on zero. Compared with conversions, the number of clicks indicates a long-tail distribution.

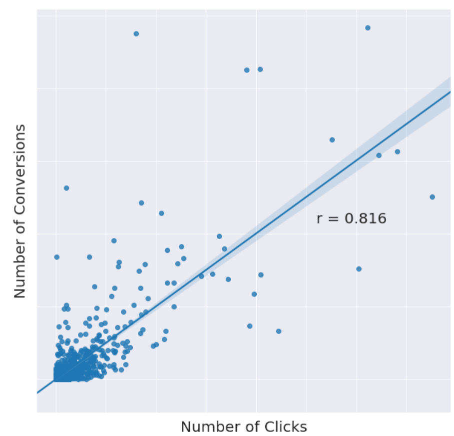


Figure 5: Linear relationship between clicks and conversions in the dataset (correlation coefficient $r = 0.816$)

4.2 Experimental Settings

In these experiments, support vector regression (SVR) and an MLP-based *text encoder* were used as a baseline model. When inputting creative text into the SVR model, we used average-pooled sentence representations computed from word representations using pre-trained word2vec (w2v) [33]. The same pre-trained w2v was used as word embedding for the proposed model.

We compared and examined the following models: MLP (not considering word order) and GRU (considering word order) as the *text encoder* in the proposed framework. LSTM was also considered as a candidate for the baseline model; however, it showed no improvement in performance, so it was excluded from the experiment. In addition, CNNs are known to be capable of training at high speed because they can perform parallel calculation compared with LSTM and GRU, and the performance is also known to be

Table 2: Comparison of prediction performance of CVs in mean squared error (MSE) criteria. The proposed multi-task learning and conditional attention reduced MSE in almost all the categories, especially estimating cases where number of conversion (#CV) is one ore more (#CV > 0). However, "All predicted as zero" showed sufficiently low MSE in this category due to too many $\mathrm{CV} = 0$ in this dataset. Therefore, we conclude using MSE as an evaluation metric is not suitable in this study.

Model		MSE			
		All		#CV >0	
		Single-task	**Multi-task**	Single-task	**Multi-task**
MLP		0.01712	0.01698	0.04735	0.03199
GRU	Vanilla	0.01696	0.01695	0.04657	0.04355
	Attention	0.01685	0.01688	0.04695	0.03105
	Conditional attention	**0.01683**	**0.01675**	**0.04641**	**0.02825**
All predicted as zero		**0.02148**		–	

equal. Nevertheless, it was excluded in these experiments, because we were targeting an RNN-based model that can apply attention for visualizing the contributions of words to ad creative evaluation.

We compared proposed models used in our framework. The following models were compared and examined for confirming the effect of multi-task learning in conversion prediction:

- **Single-task** : A commonly known model that predicts conversions only; and
- **Multi-task** : A model that simultaneously predicts the number of clicks and the number of conversions.

To confirm the effect of the conditional attention mechanism, we compared the following models:

- **Vanilla** : A simple *text encoder* without an attention mechanism. It is a baseline in the proposed model;
- **Attention** : A mechanism that introduced self-attention to the *text encoder*. It makes it possible to visualize which word contributed to prediction during creative evaluation; and
- **Conditional Attention** : A mechanism introduced to the *text encoder* of the proposed method. Conditional attention can be computed and visualized considering attribute values of ad creative. Different attentions can be visualized by changing the attribute value for the same creative text.

In addition, hyper-parameter setting is described below. The mini-batch size was set to be 64, and the number of epochs was set to be 50. For multi-task learning, we used a fix value of $\lambda = 1$. In the *text encoder*, the number of hidden units were set to be 200 for u_{title} and u_{desc} respectively. For all models, we use Adam [20] with a weight decay of $1\mathrm{e}^{-4}$ for parameter optimization.

4.3 Evaluation Metrics

First, as evaluation metrics, we adopt not only MSE but also normalized discounted cumulative gain (NDCG) [17] which is evaluation metrics for ranking. The MSE measures the average of the squares of the errors, which is the average squared difference between the estimated values and what is estimated. The reason we adopted ranking evaluation metrics is that the number of conversions is imbalanced. As shown in Figure 4, most ad creative conversions are zero and imbalance, a high evaluation score can be achieved by an overfit model that predicts all outputs as zero when such metrics are used. For high-performance ad creatives creation, rather than predicting zero conversions, we would like to accurately predict high-conversion creatives as such.

As for NDCG is mainly used in the experiments. NDCG is the discounted cumulative gain (DCG) normalized score. In DCG, the score decreases as the evaluation of an advertisement declines, so a penalty is imposed if a low effect is predicted for highly effective creatives. At the time of NDCG calculation, after obtaining the rank of ground truth and its predicted value respectively, evaluation scores were calculated for all the evaluation data, as well as those restricted to the top 1% of conversions.

For ad creative evaluation, the metrics are computed by cross-validation. In most advertising system, advertisements are delivered in units of campaigns. In a campaign, target gender and its genre are set, and multiple ad creatives are developed.

In this paper, we predict the number of conversions for ad creative text in unknown campaigns and confirm the generalization performance of our proposed framework. Therefore, at the time of evaluation, five-fold cross validation was performed in such a manner that the delivered campaign did not overlap.

4.4 Experimental Results

For confirming the accuracy of the proposed framework compared with the baselines, we compared single-task and multi-task learning, and the results of applying conditional attention mechanism are described. Through almost all the results, the proposed framework applying multi-task learning and the conditional attention mechanism achieved better performance than others. Especially, when focusing on ad creatives with many conversions, our proposed framework achieved high prediction accuracy.

Table 2 shows the MSE score both with all the evaluations in each model and with conversion of one or more in each model. Almost all the results show that the model applying the multi-task learning and conditional attention mechanism had a smaller MSE score than the other models did. Overall, the RNN-based GRU showed better performance than the baseline models. Therefore, the results suggest that it is important to properly capture word order when evaluating creative texts. Compared with *vanilla* and *attention*, the *conditional attention* in the proposed model showed better performance.

Table 3: Comparison of normalized discounted cumulative gain (NDCG) in the proposed model. When calculating NDCG scores, the results for all data and the scores restricted to the top 1% of conversions (#CV) were calculated.

Model		NDCG [%]			
		All		#CV top 1 %	
		single	**multi-task**	single	**multi-task**
SVM		96.72		83.73	
MLP		96.68	97.18	82.97	84.12
GRU	Vanilla	96.54	97.00	76.39	78.51
	Attention	96.76	97.11	83.00	85.49
	Conditional Attention	**96.77**	**97.20**	**87.11**	**87.14**

Although improvement of all dataset is weak, because as shown in Figure 4, the number of conversions of many ad creatives is zero, the MSE is small even if the conversion of most ad creatives is predicted to be zero. Therefore, we evaluated data with conversions other than zero. As a result, we found that the proposed model exhibits much better performance than the baseline model for data with a number of conversions of one or more. The proposed model was able to predict creatives with more conversions than the baseline models.

To evaluate ad creatives with many conversions as such, we evaluated using the ranking algorithm NDCG. The NDCG result in the proposed model is shown in Table 3[9]. The NDCG score (regarded as *All* in Table 3) for all the datasets is shown for reference, since, as noted above, the most samples have zero conversions. The performance of the GRU model that considers word order compared with the baseline model has improved by an average of approximately 3-5%, with many conversions.

In the NDCG result (Table 3) the multi-task model realized higher prediction accuracy than the single-task model predicting only conversions did. A score improvement of approximately 1-2% was confirmed when compared with the baselines. Because clicks are highly correlated with target ad conversions, as shown in Figure 5, rather than predicting conversions alone, training the model to multi-task by predicting clicks simultaneously can improve prediction accuracy. By training clicks and conversions, the proposed model seems to implicitly learn features that contribute to conversion prediction.

Since several previous studies predicted the CVR directly, we also calculated it using the prediction of the multi-task learning model and compared accuracy. In a multi-task model, the CVR can be calculated by dividing conversions by clicks. In Table 4, the multi-task model is compared with the single-task model by directly estimating the CVR. The prediction performance of the multi-task model is higher than that of the single-task model. Although the number of clicks and conversions predicted by multi-task learning may not always be close to the ground truth, the ratio of the number of clicks to the conversion number is properly captured.

In Table 3, the conditional attention mechanism achieved better result with the NDCG metric. Especially, the conditional attention mechanism showed better results than the conventional attention mechanism did. In the conventional attention mechanism, the training was focused solely on the co-occurrence relationship between words in the input text, but the conditional attention mechanism can predict conversion by using the attribute value.

[9]The same tendency was observed even when mean average precision (MAP) was used as an evaluation metric.

Table 4: Comparison of NDCG between the CVR directly predicted by the single-task model and the CVR (#conversions / #clicks) calculated from the multi-task GRU model's predicted conversions and clicks. The threshold value for calculating NDCG is assumed to be a CVR of 0.5 or more.

Model		NDCG [%]
Single-task	Vanilla	80.54
	Attention	82.58
	Conditional attention	83.89
Multi-task	Vanilla	82.63
	Attention	84.27
	Conditional attention	**85.61**

Table 5: Comparison of GRU models for creative texts and their attribute value interactions. Performance is improved using conditional attention rather than giving attribute values directly to word vectors.

Model		NDCG [%]	
		Single-task	**Multi-task**
w2v + attributes	Vanilla	77.84	78.03
	Attention	80.39	83.52
w2v	**Conditional attention**	**87.11**	**87.14**

Table 5 shows the result comparing feature interaction between w2v-based embeddings and ad attribute values. In our framework, this interaction is realized by conditional attention mechanism, explicitly. Since attention computed by input variables, this interaction is implicitly expressed by inputting both variables to the *text encoder*. For confirming the effect of this explicit interaction in conditional attention mechanism, we compare the model that input both variables to the *text encoder* with conditional attention mechanism. The conditional attention mechanism showed the best performance in the single-task and multi-task model. Introducing vanilla model and conventional attention model to the word representation with ad attribute values resulted in poor performance, mainly because the duplicate interactions were calculated excessively. It is suggested that it is better to introduce the explicit interaction of attribute values.

5 DISCUSSION

5.1 Advantages of the Proposed Framework

Our proposed framework aim to predict not the CVR but conversions. However, in CVR prediction, we also achieved high-performance using the result of multi-task learning. From the business perspective, we assume that predicting conversions can evaluate high-performance ad creative rather than prediction CVR. In the process of advertising management, advertisers stop low performance creatives and focus cost on high performance creatives, so there are few conversions of low performance creative and many conversions of high performance creatives. For that reason, the number of conversion seems to be good metrics for evaluating ad creative, and conversion prediction may be learn good representation of high performance ad creatives.

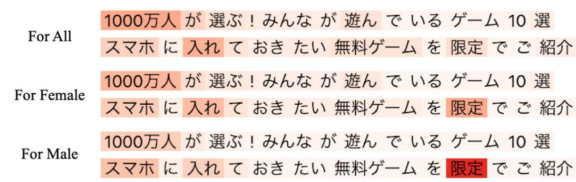
We proposed an RNN-based framework and achieved high performance conversion prediction. Normally, when advertiser create the creative text, words are selected in such a way as to change the word order or emphasize the characteristics of the product. Then, we let the model learn feature representation so that it could properly capture the features between words in the creative text.

We achieved high-performance conversion prediction by predicting the clicks and conversions simultaneously; this method is called multi-task learning. Many ad creative conversions are zero, which is imbalanced data, so predicting this number correctly is a difficult task. Multi-task learning is a method that learns multiple tasks related to each other and improves prediction performance. Since ad click actions represent pre-action of conversion actions, we assumed that click prediction may be related to conversion prediction and that improved conversion prediction would be obtained using multi-task learning. We expect that this achievement can be applied to various prediction tasks with imbalanced data.

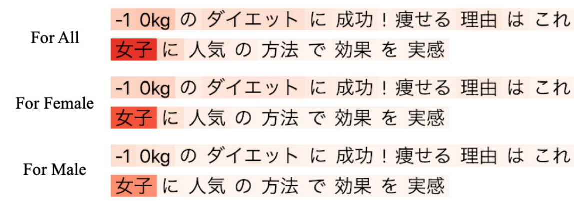
High accuracy was achieved by conditional attention in our experiment. When predicting the CTR or CVR of advertisements, it is important to properly capture the explicit feature interactions [23]. The conditional attention mechanism seems to capture the explicit interactions between the attention gained from creative text and feature representations consisting of the text's attribute values. It is also possible to visualize different forms of attention by controlling different attribute values in the same creative texts. This can greatly support ad creative creation.

5.2 Visualization for High-Performance Ad Creative Creation

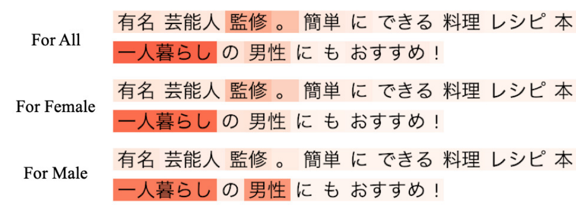
We attempt to highlight important words using attention. If the words contributing to conversions are clarified, advertisers will be able to easily create high-performance ad creatives. Attention is a mechanism that focuses on words contributing to prediction, and the results predicted by these mechanisms are useful for ad creatives' creation. Our proposed conditional attention mechanism



(a) Title text: "Chosen by 10 million people! The 10 games played by everyone." Description text: "Exclusively introducing free games that you will want to install on mobile phone."



(b) Title text: "Success in -10 kg weight loss! This is the reason for getting slim." Description text: "Realizing the effects popular among girls."



(c) Title text: "Supervised by a famous celebrity; easy cook book." Description text: "Recommended for men living alone!"

Figure 6: Heatmap showing the change in conditional attention when the distribution target is changed.

can compute attention based on ad creative attributes, as well as the genre and target gender, so conditional attention highlight important words according to their attribute values.

Figure 6 shows examples of the visualization of attention when modifying the attributes of gender for three Japanese ad creative texts for different groups (for all audiences, for females, and for males). Different types of attention were gained using conditional attention mechanism.

Figure 6a shows an ad creative for a mobile games. The word "1000万" (*10 million*), a concrete numerical value, and the word "限定" (*exclusively*) contribute to predicting conversion. Especially for male, the word "限定" contributes more to the prediction than it does for females.

Figure 6b is an ad creative in the beauty genre for females. The word "女性" (*girls*) contributes to the conversion prediction. More attention is also given to "ダイエット" (*weight loss*) for females than males. When setting the delivery target to males in this ad creative, the attention score and the number of predicted conversions are smaller than that of all targets or female targets.

Figure 6c is an ad creative in the health food genre for males. The words "一人暮らし" (*living alone*) and "監修" (*supervised by*) are being closely highlighted. The word "lived alone" is an expression that narrows down the delivery target. When proposing ad creative text, the term "supervised by" is often used in conjunction with the names of celebrities, and the effect is high. Moreover, it was confirmed that the word "男性" (*men*) is an important factor when the delivery target is male.

Overall, most words that are highlight by attention are concrete numerical values and expressions focusing on the delivery target. We believe that this knowledge is also empirically correct. In this way, visualization of important words using the conditional attention mechanism of the proposed method can be expected to greatly contribute to supporting the creation of ad creatives. This result is a good example of interpretability.

6 CONCLUSION

In this paper, we propose a new framework to support the creation of high-performance ad creative text. The proposed framework includes three key ideas, the multi-task learning and conditional attention are to improve prediction performance of advertisement conversion and the attention highlighting is to offer important words and/or phrases in text creative. We confirmed that our framework realizes excellent performance thanks to these ideas through our experiments with actual delivery history data.

In the future, we will build a framework that simultaneously uses images attached to ad creatives and aim to improve the accuracy of conversion prediction.

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