Aspect-based Analysis of Advertising Appeals for Search Engine Advertising

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Abstract

Writing an ad text that attracts people and persuades them to click or act is essential for the success of search engine advertising. Therefore, ad creators must consider various aspects of advertising appeals (A^3) such as the *price*, *product features*, and *quality*. However, products and services exhibit unique effective A^3 for different industries. In this work, we focus on exploring the effective A^3 for different industries with the aim of assisting the ad creation process. To this end, we created a dataset of advertising appeals and used an existing model that detects various aspects for ad texts. Our experiments demonstrated that different industries have their own effective A^3 and that the identification of the A^3 contributes to the estimation of advertising performance.

1 Introduction

Search engine advertising (SEA) displays an ad text that consists of a title and a description that are relevant to search queries in search engines, as illustrated in Figure 1. SEA plays an important role in sales promotion and marketing as it allows advertisers to approach users who are interested in specific search queries effectively (Fain and Pedersen, 2006). Ad creators write an ad text that attracts the attention of users and persuades them to click or act by introducing various aspects of advertising appeals (denoted as A^3 in this paper for short), such as *special deals*, as shown in Figure 1. However, products and services exhibit unique effective A^3 for different industries. For example, *limited offers* may be attractive to users in the e-commerce (EC) industry, whereas the *quality of products* may be more important in the automobile industry.

Thus, we argue that the suggestion of effective A^3 for various industries can offer assistance to ad creators. Therefore, we need to discover the effective aspects. However, although aspect-based text analysis has attracted significant attention in the review analysis for products and services (Akhtar et al., 2017; Chen et al., 2019), it has received less focus in the advertisement field.

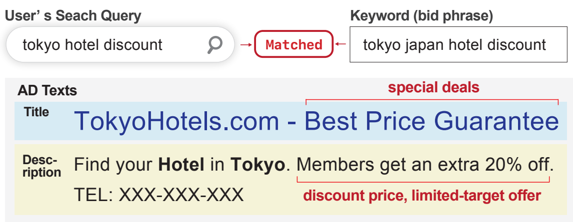

Figure 1: Example ad text and its corresponding A^3.

In this work, to deal with this problem, we defined the A^3 and constructed a dataset of ad texts that are annotated with A^3 in various industries as a first attempt towards assisting ad creators with A^3. Subsequently we developed an aspect detection model to identify different A^3 and performed correlation analysis between A^3 and the click-through rate (CTR), which is used for supporting ad creation, as an advertising performance metric to explore the effective aspects in different industries. Furthermore, we investigated the effectiveness of A^3 in CTR prediction as a potential application for ad creation support.

Through correlation analysis in our experiments, we found that different industries exhibit unique effective A^3. Furthermore, we found that the identification of the A^3 contributes to the CTR prediction.

2 Related Work

Ad Creation Support Attempts have been made to perform automatic generation of ad texts and keywords (Ravi et al., 2010; Hughes et al., 2019; Kamigaito et al., 2021) as well as the estimation of advertising performance metrics such as the CTR (Richardson et al., 2007; Zhang et al., 2014; Mishra et al., 2021) to support the ad creation process. In this work, we tackle the discovery of the effective A^3 for various industries and apply the A^3 to CTR prediction with the goal of improving the efficiency

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Labels	#spans	Labels	#spans
(1) Special deals	343	(12) Limited offers	52
(2) Discount price	120	(13) Limited time	61
(3) Reward points	85	(14) Limited target	114
(4) Free	430	(15) First-time limited	25
(5) Special gift	126	(16) Track record	75
(6) Features	1,360	(17) Largest/no. 1	141
(7) Quality	65	(18) Product lineup	258
(8) Problem solving	17	(19) Trend	99
(9) Speed	142	(20) Others	182
(10) User-friendliness	337	(21) Story	98
(11) Transportation	89		

Table 1: A^3 and statistics of annotated dataset, where “#spans” represents the number of span texts annotated with each label.

of the ad creation process.

Aspect-based Text Analysis Although aspect-based text analysis has attracted significant attention, the majority of studies have been limited to specific domains such as hotels, restaurants, and home appliances (Pontiki et al., 2016; Akhtar et al., 2017; Chen et al., 2019). Moreover, as the product review analysis focuses on the aspects of each product, the defined aspects are extremely fine grained (e.g., the *modes*, *energy efficiency*, and *noise* for refrigerators (Li et al., 2020)). These aspects are not suitable for ad creation because ad creators must deal with ad texts for various products in multiple industries. Therefore, ad creators are required to consider numerous A^3. In this study, we carefully designed labels that cover the A^3 for the general purpose of exploring these in a wide range of industries. Furthermore, we explored methods for aspect detection, as in the previous work (Bagheri et al., 2013), as well as the identification of the effective aspects in terms of advertising performance metrics such as the CTR.

3 Construction of A^3 Dataset

3.1 Data Collection

We constructed a dataset of advertising appeals to understand the A^3 in ad texts. Many A^3 exist in real-world advertisements, including product features, price, and campaigns. We collected 782,158 ads from March 1, 2020 to February 28, 2021 through Google Ads,[1] which is an online advertising platform, to cover the expressions of advertising appeals in a wide range of industries. In this work, we used ads in Japanese. Each ad consists of a title, a description, and a landing page (LP), which is a web page for a specific advertising campaign. We used the meta-description[2] of each LP as the LP content. We sampled 5,000 ad texts for each advertiser to alleviate the bias owing to a different quantity of ad texts for the advertisers. Moreover, we excluded ad texts that comprised less than 15 characters or more than 200 characters. The aforementioned two steps yielded 34,952 ad texts. Furthermore, we excluded duplicates and highly similar texts using the normalized Levenshtein distance metric (Levenshtein, 1966; Greenhill, 2011), because the majority of the ad texts were created from templates for the sake of cost efficiency (Fujita et al., 2010). As a result, we collected 2,738 ad texts consisting of 666 titles, 1,532 descriptions, and 440 LP contents from 13 types of industries.[3] We provide the detailed statistics of the collected ad texts in Appendix A.

3.2 Label Types and Annotation Scheme

Owing to the existence of various A^3, we believe that the systematic organization of the A^3 can aid the ad creation process. We manually defined aspect labels in the following two phases. First, we conducted a preliminary analysis of the collected ad texts and found that approximately eight aspects appeared: *special deals*, *quality*, *problem solving*, *speed*, *user-friendliness*, *limited offers*, *product lineup*, and *trend*. Second, we presented these aspects and the collected ad texts to experienced ad creators and asked for their opinions on the A^3 with the aim of refining the aspect labels. Consequently, the ad creators suggested that we further subdivide *special deals* and *limited offers*. For example, *special deals* was subdivided into *discount price*, *reward points*, *free*, and *special gift*. The reason for this is that there are differences in the strength of the aspects between *free* and *special gift*, even though they appear to be similar. Furthermore, *largest/no.1* was added as another aspect label because it attracts a lot of users.

Table 1 lists the A^3 that we manually defined. Detailed descriptions and examples are provided in Appendix B. Finally, we carefully designed a hierarchical scheme for A^3 to help ad creators and annotators to understand the differences between

[1] https://ads.google.com/

[2] A meta-description is an HTML attribute that provides a brief summary of a web page, such as an LP.

[3] *EC*, *Media*, *Finance*, *VOD&eBook*, *Cosmetics*, *Human resources*, *Education*, *Travel*, *Automobile*, *Entertainment*, *Real estate*, and *Beauty&health*

the labels. The aspect hierarchy consists of five types of coarse-grained labels including *special deals*, which are underlined in Table 1, and 16 types of fine-grained labels such as *discount price*.

Because an ad text often contains multiple expressions of advertising appeals, as depicted in Figure 1, we defined an advertising expression as a span text to be annotated. For example, annotators provide the aspect label (e.g., *special deals*) for the span text "*best price guarantee*." Each span was annotated during the annotation work. Moreover, we allowed the annotators to provide multiple labels for each span because an expression of advertising appeals may contain multiple aspects. For example, the advertising expression "*members get an extra 20% off*" contains two aspects *discount price* and *limited-target offer*, because it means that only users belonging to a membership program can receive an extra 20% discount.

3.3 Annotation Process

We recruited six participants who worked at an advertising agency. We separated 2,738 collected ad texts into two sets consisting of 1,100 and 1,638 texts, and assigned three participants to each set. We presented a one-hour lecture to the participants to explain the detailed definitions of the labels and to provide annotation examples. Furthermore, we asked them to annotate 30 ad texts that were separated from the collected dataset as a practice session. After the session, we answered questions from the participants. During the annotation, we answered any additional questions from them and shared information when a difficult case appeared, which was relatively rare.

3.4 Annotated Dataset Statistics

Table 1 displays the statistics of the annotated dataset. We adopted annotated spans only if at least two of the three annotators for each span text agreed with their boundaries and labels. The annotation work for the 2,738 ad texts required a total of 42 hours; thus, the average time per ad text was 55.2 seconds. A single ad text contains 1.54 spans on average. Furthermore, we calculated the Cohen's Kappa coefficients (κ) between the tokens annotated by different pairs of annotators to determine the inter-annotator agreement. Moreover, following the previous work (Brandsen et al., 2020), we also report the F_1 scores that were calculated between the spans annotated by different pairs of annotators, where we considered one annotation as the ground truth and another as the prediction. We obtained relatively high agreement among the annotators: $\kappa = 0.612, F_1 = 0.451$.

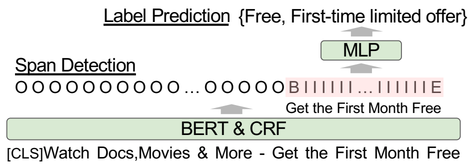


Figure 2: Overview of the span-based model.

4 Aspect Detection Model

We investigate two existing models for aspect detection, i.e., the span-based (Zheng et al., 2019) and document-based (doc-based) models (Devlin et al., 2019). These models receive an ad text $\boldsymbol{x} = (x_i)_{i=1}^{|\boldsymbol{x}|}$ as an input and predict aspect labels $\boldsymbol{y} = (y_i)_{i=1}^{K}$, where x_i and y_i represent a token of an ad text and a binary label for each aspect label, respectively. As each span may contain multiple aspects, both models perform label prediction in the form of multi-label classification (Kurata et al., 2016). K is the number of aspect labels defined in Table 1. We consider an expression of the advertising appeals in an ad text, such as "*best price guarantee*" in Figure 1, to be a *span*. We use $S(i, j)$ to represent the span from i to j, where $1 \leq i < j \leq |\boldsymbol{x}|$. The span-based model consists of two steps: (i) extracting a span $S(i, j)$ from $\boldsymbol{x}$ and (ii) predicting the aspect labels $\boldsymbol{y}$ for each span. In contrast, the doc-based model predicts the aspect labels $\boldsymbol{y}$ for an entire ad text $\boldsymbol{x}$. We employed a pre-trained BERT (Devlin et al., 2019) for both models owing to the limited amount of the annotated dataset.

4.1 Span-Based Model

Figure 2 presents an overview of the span-based model. The task of extracting a span from an ad text can be considered as named entity recognition, and we introduce the boundary-aware neural model proposed by Zheng et al. (2019). We consider characters as a unit (token) in the span-based model. We use the BIOE scheme to create boundary labels $\boldsymbol{l} = (l_i)_{i=1}^{|\boldsymbol{x}|}$ for the input tokens $\boldsymbol{x}$. We feed $\boldsymbol{x}$ into the BERT to obtain a vector h_i for x_i for span detection. Subseqently, we obtain the distribution of the boundary labels $v_i \in \mathbb{R}^L$ by applying a multilayer perceptron (MLP) $v_i = \mathtt{MLP}(h_i)$, where L is the number of boundary types (BIOE). We also use a linear-chain conditional random field (CRF)

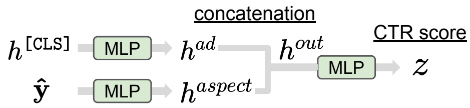


Figure 3: Overview of the CTR prediction model.

(Lafferty et al., 2001) to model the dependencies of the boundary labels (e.g., label E must appear after B or I). As a result, we can obtain the boundary labels $\boldsymbol{l}$ that are predicted by viterbi decoding for the input $\boldsymbol{x}$.

For label prediction, we create a vector representation $h^{avg}_{(i,j)}$ for a span $S(i,j)$ using the average of the output vectors of the BERT (i.e., $h_i, h_{i+1} \cdots h_j$). Thereafter, we obtain the probability that each span $S(i,j)$ belongs to the aspect labels $\boldsymbol{y}$ by applying an MLP and a sigmoid function $\boldsymbol{m} = \mathtt{Sigmoid}(\mathtt{MLP}(h^{avg}_{(i,j)}))$, where $\boldsymbol{m} = (m_k)^K_{k=1}$ and $m_k = p(y_k = 1|S(i,j))$. For example, in Figure 2, the expression "*Get the First Month Free*" is detected as a span, and the model predicts two aspect labels *free* and *first-time limited offer* for the detected span.

4.2 Doc-Based Model

Although the span-based model offers the advantage of detecting a specific expression using span detection, we are concerned that errors in span detection could affect label prediction. Therefore, we also introduce the doc-based model as an alternative to the span-based model.

The doc-based model is a BERT-based classification model. Following the original BERT-based classifier (Devlin et al., 2019), the doc-based model consists of a BERT and an MLP, which take an entire ad text $\boldsymbol{x}$ as an input and outputs labels $\boldsymbol{y}$. Specifically, we first input the ad text $\boldsymbol{x}$ into the BERT and obtain the vector representation $h^{[\mathtt{CLS}]}$ for a [CLS] token. Subsequently, we feed the vector $h^{[\mathtt{CLS}]}$ into the MLP to obtain the probability that the ad text $\boldsymbol{x}$ belongs to the aspect labels $\boldsymbol{y}$ as a multi-label classification task $\boldsymbol{m} = \mathtt{Sigmoid}(\mathtt{MLP}(h^{[\mathtt{CLS}]}))$, where $\boldsymbol{m} = (m_k)^K_{k=1}$ and $m_k = p(y_k = 1|\boldsymbol{x})$.

5 CTR Prediction with A^3

Within the context of ad creation support, the estimation of advertising performance for an ad text (e.g., the CTR) plays a key role in both the improvement and cost efficiency of the ad creation because it helps us understand the user's interest. Therefore, we also investigate whether the A^3 contributes to the prediction of the advertising performance. For this task, we input an ad text $\boldsymbol{x}$ consisting of a title and description, an industry type of the ad $\boldsymbol{t}$ (e.g., EC), and keywords $\boldsymbol{k}$ (e.g., *tokyo* and *hotel*). We also introduce the predicted aspect labels $\hat{\boldsymbol{y}}$ (e.g., *features*) for $\boldsymbol{x}$ as additional features, which were detected by either the span-based or doc-based model. In this case, we use the CTR $\boldsymbol{z} \in [0,1]$ as the advertising performance (CTR = clicks ÷ impressions).

Figure 3 presents an overview of the regression model. Similarly to recent work (Mishra et al., 2021), we design this regression model based on the BERT. In the model, we feed the three types of tokens $\boldsymbol{x}$, $\boldsymbol{t}$, $\boldsymbol{k}$ into the BERT to obtain the vector $h^{[\mathtt{CLS}]}$ for a [CLS] token. Subsequently, we input $h^{[\mathtt{CLS}]}$ and the aspect labels $\hat{\boldsymbol{y}}$ for the ad text $\boldsymbol{x}$ into the following MLP. Thereafter, we obtain the concatenated vector $h^{out} = [h^{ad}; h^{aspect}]$, where ";" is a concatenation operator. The final MLP then predicts a CTR score $\boldsymbol{z}$ from h^{out} as $\boldsymbol{z} = \mathtt{Sigmoid}(\mathtt{MLP}(h^{out}))$.

6 Experiments

We conducted experiments on three tasks: (1) aspect detection for the A^3, (2) correlation analysis between the A^3 and CTR, and (3) CTR prediction.

6.1 Experimental Settings

Dataset We used the annotated dataset in Table 1 for the aspect detection. We separated the dataset into 1,857 samples for training, 465 for development, and 410 for testing after excluding 6 ad texts that we determined were inappropriately annotated. We collected 168,412 pairs of ad texts, keywords, and industry types from March 1, 2020 to February 28, 2021 through Google Ads for the CTR prediction. We carefully separated the dataset into 136,352, 16,084, and 15,976 samples for training, development, and testing, respectively. The detailed statistics of the dataset for the CTR prediction are presented in Appendix C. We used the training dataset for the CTR prediction for the correlation analysis between the CTR and A^3. We used the campaign ID of each ad for data division to prevent leakage between the datasets.

Implementation We used the character-level BERT[4] for the span-based model, and the word-

[4]https://huggingface.co/cl-tohoku/bert-base-japanese-char

Labels		Span-based Pred	Span-based Orac	Doc-based
(1)	Special deals	0.11	0.19	0.70
(2)	Discount price	0.00	0.00	0.57
(3)	Reward points	0.62	0.74	0.75
(4)	Free	0.68	0.88	0.94
(5)	Special gift	0.28	0.40	0.65
(6)	Features	0.50	0.70	0.72
(7)	Quality	0.00	0.00	0.44
(8)	Problem solving	0.00	0.00	0.00
(9)	Speed	0.51	0.66	0.92
(10)	User-friendliness	0.46	0.59	0.56
(11)	Transportation	0.91	1.00	0.53
(12)	Limited offers	0.38	0.53	0.62
(13)	Limited time	0.00	0.00	0.47
(14)	Limited target	0.26	0.57	0.44
(15)	First-time limited	0.00	0.00	0.00
(16)	Performance	0.27	0.50	0.48
(17)	Largest/no. 1	0.67	0.80	0.82
(18)	Product lineup	0.42	0.67	0.67
(19)	Trend	0.41	0.56	0.47
(20)	Others	0.00	0.00	0.39
(21)	Story	0.32	0.83	0.53
Macro average		0.32	0.46	0.56

Table 2: Results of the aspect detection (F_1 scores)

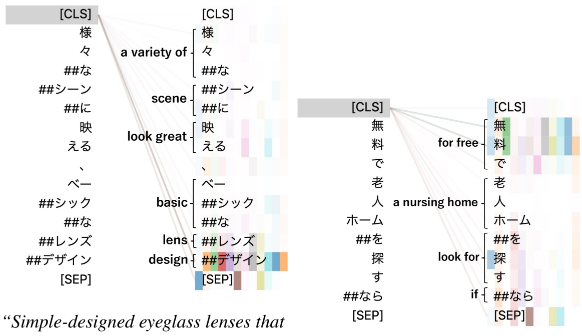
level BERT[5] for the doc-based model and CTR prediction. We fine-tuned the models on the dataset and applied an early stopping strategy with 10 epochs. The training was stopped if there was no improvement in the validation loss for three consecutive epochs in all experiments. Further implementation details are described in Appendix D.

Evaluation Metrics We calculated the F_1 scores of the aspect labels for the aspect detection. For the span-based model, a detected label was considered as a true positive if both its span and label were correctly detected. We used the area under the receiver operating characteristic curve (AUC) (Fawcett, 2006), which is a widely used metric in the field of CTR prediction (Zhou et al., 2018; Xiao et al., 2020). Moreover, we used the root-mean-squared error (RMSE) and mean absolute error (MAE) to measure the differences between the ground-truth and predicted scores.

6.2 Aspect Detection

In this experiment, we evaluated two models, the span-based and doc-based models. As errors in the span prediction may affect the label prediction in the span-based model, we also introduced the `Oracle` model, which predicts their labels, provided with *oracle* spans, in addition to the `Pred` model, which predicts both the spans and labels.

[5]https://huggingface.co/cl-tohoku/bert-base-japanese



"Simple-designed eyeglass lenses that look great in a variety of scenes"

(a) Ad text labeled as *features*

"Find a nursing home for free"

(b) Ad text labeled as *free*

Figure 4: Visualization of attention weights in the doc-based model. Each example consists of the original Japanese ad text with the literal translation for each subword and the corresponding English ad text.

The evaluation results for the aspect detection are presented in Table 2. The doc-based model outperformed the span-based model, including the `Oracle` model, for most A[3]. As the `Pred` model is required to predict both the spans and labels correctly, its task is relatively more difficult than that of other models. In fact, we found that the F_1 score for the span detection is 0.69 for the `Pred` model. Therefore, we conclude that it is the reason why the macro-average F_1 score of `Pred` was lower than those of the doc-based and `Oracle` models.

In the comparison between the `Oracle` and doc-based models, the doc-based model outperforms the `Oracle` model. We hypothesize that its training objective for the span-based model is more difficult as it is more fine grained than the doc-based model.

We observed that the scores for *free*, *speed*, and *largest/no. 1* are high in the doc-based model. This implies that the advertising expressions for these aspects are relatively monotonous and easy to detect compared to the other aspects. For example, the advertising expression "*free shipping*," which belongs to *free*, often occurs frequently in ad texts for a wide range of industries. The aspect detection was difficult for several aspects in which the numbers of annotated cases were limited, such as (8) and (15), as indicated from Tables 1 and 2. Hence, they exhibited an F_1 score of 0.00.

We also conducted an analysis of the attention in the doc-based model to understand to which signals the model attended in the aspect detection. Figure

Labels	eBook	EC	Fin	HR	Travel
(1)	0.229	0.011	-0.171	–	0.017
(2)	-0.135	-0.166	-0.128	–	-0.176
(3)	0.183	0.000	**0.443**	–	**0.377**
(4)	-0.126	-0.163	-0.052	0.116	–
(5)	0.086	0.122	**0.339**	-0.024	**-0.332**
(6)	-0.128	-0.121	-0.094	-0.040	0.050
(7)	-0.001	-0.081	-0.034	–	–
(8)	–	–	–	–	–
(9)	-0.017	0.065	-0.109	0.024	–
(10)	-0.236	0.053	**-0.252**	-0.004	0.205
(11)	–	–	–	–	–
(12)	-0.036	-0.149	-0.044	0.003	0.221
(13)	-0.090	0.186	0.014	-0.006	-0.184
(14)	-0.020	-0.162	-0.011	0.023	–
(15)	-0.165	–	–	–	–
(16)	0.108	-0.161	-0.099	0.237	-0.148
(17)	**0.283**	-0.073	0.143	0.102	–
(18)	-0.206	0.044	-0.005	-0.159	-0.195
(19)	-0.074	-0.007	0.157	–	–
(20)	0.022	-0.083	0.134	-0.042	**0.268**
(21)	-0.093	–	–	–	–
#cases	30,536	20,671	20,183	10,823	8,093

Table 3: Point-biserial correlation coefficient **r**, where "# cases" denotes the number of ad texts for each industry type and "–" indicates that the corresponding labels were not found.

4 depicts the visualized attention patterns with respect to the [CLS] token of the final layer of the BERT. We found that many of the attention heads attend to the words "*design*" and "*for free*" for the ad text (a) and (b), respectively. This suggests that the doc-based model classified the ad text (a) and (b) as *features* and *free*, respectively, because these words were related to the aspects.

6.3 Correlation between Aspects and CTR

To realize the ad creation process considering the A^3, we analyzed which A^3 were effective in each industry through correlation analysis between the CTR[6] and the aspect labels that were predicted by the doc-based model. Because the aspect labels are binary for each aspect (e.g., whether or not each aspect is included in an ad text) and the CTR is continuous, we used the point-biserial correlation coefficient **r** for the analysis. Table 3 lists the point-biserial correlation coefficients **r** between the aspect labels and the CTR. We investigated the correlation among the industry types *VOD&eBook (eBook)*, *EC*, *Finance (Fin)*, *Human resources (HR)*, and *Travel*. As indicated in **bold text** in Table 3, we observed a weak correlation

[6]We used the *actual* CTR for each ad rather than the *predicted* CTR.

	AUC (↑)	RMSE (↓)	MAE (↓)
BERT	0.683	0.220	0.142
+ $\mathbf{l}_{span}$	0.709	0.218	0.137
+ $\mathbf{l}_{doc}$	**0.713**	**0.217**	**0.136**

Table 4: Results of CTR prediction

($0.25 < |\mathbf{r}| < 0.5$) between the CTR and the labels, such as (3) *reward points* for *Finance*. This implies that ad texts that include effective A^3 tend to attract more attention from users. However, there was no correlation with regard to the other aspects. This may be because (1) *features*, for example, is considered to be a general-purpose aspect and can be used in any situation.

Based on the above insights, we also investigated the expressions for the effective A^3 in our annotated dataset. For example, regarding the *VOD&eBook* industry, we found that the expression "*one of the largest websites in Japan*" (国内最大級サイト) was annotated as (17) *largest/no. 1*. Furthermore, the expressions for *Finance* "*get* [N] *points for new membership*" (新規入会&利用で[N]ポイント) and "*earn* [N] *points per* [N] *yen*" ([N]円につき[N]ポイント貯まる) were labeled with (3) *reward points*.[7] We believe that the presentation of these effective expressions to ad creators may provide actionable insights and aid in the ad creation process.

6.4 CTR Prediction

We investigated whether the identification of the A^3 contributes to the estimation accuracy of the CTR. Table 4 presents the results of the CTR prediction. For comparison with a baseline (BERT), that does not use A^3, we introduced two models that consider A^3 predicted by the span-based model (+$\mathbf{l}_{span}$) or the doc-based model (+$\mathbf{l}_{doc}$). It can be observed that the aspect-aware models that leverage the A^3 outperformed the baseline model in terms of all evaluation metrics. This suggests that the identification of the A^3 that are included in ad texts can contribute to the improvement of CTR prediction. In the comparison between the two models, +$\mathbf{l}_{doc}$ improved the performance of the CTR prediction more than the +$\mathbf{l}_{span}$. This is likely because the doc-based model predicted the aspect labels more accurately than the span-based model, as indicated in Table 2. We believe that improving the aspect detection with more refined methods will lead to

[7]Numbers (e.g., price, points) are masked with [N].

better correlation and prediction for the CTR.

7 Conclusions

In this work, we have explored the effective A^3 by means of aspect detection and correlation analysis towards ad creation support with the A^3. Our experimental results demonstrated that each industry exhibits unique effective A^3 and that identification of the A^3 can contributes to CTR prediction.

We demonstrate two possible directions for future studies. First, we will investigate whether introducing the effective A^3 in the ad creation process can help ad creators write effective ad texts in real-world applications. Second, we will develop an aspect-aware model to automatically generate ad texts to support the ad creation process. For the latter, we will train the model with a dataset that includes pairs of ad texts and their corresponding aspect labels predicted using aspect detection.

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A Collected Ad Texts for Annotation

Table 7 lists the detailed statistics of the collected ad text. We collected 2,738 ad texts comprising 666 titles $\boldsymbol{x}^{title}$, 1,532 descriptions $\boldsymbol{x}^{desc}$, and 440 LP contents $\boldsymbol{x}^{lp}$ from 13 industries: *EC*, *Media*, *Finance*, *VOD&eBook*, *Cosmetics*, *Human resources*, *Education*, *Travel*, *Automobile*, *Entertainment*, *Real estate*, and *Beauty&Health*.

B Descriptions and Examples of A^3

Table 5 lists the detailed descriptions and examples of A^3 that we have defined. For example, the expression "*enjoy free shipping*" is labeled with (4) *free*, as it represents free offers for products or services. In the table, "#spans" represents the number of span texts annotated with each label.

C Dataset for CTR Prediction

Table 8 lists the detailed statistics of the datasets used for CTR prediction. We carefully separated the dataset into 136,352, 16,084, and 15,976 samples for training, development, and testing, respectively. For correlation analysis between the CTR and aspect labels of advertising appeals, we used the training dataset for CTR prediction.

D Additional Implementation Details

Table 6 lists the implementation details, e.g., hyperparameters, for the aspect detection and CTR prediction models. We developed our models using pre-trained BERT models, which are publicly available from the Transformers library (Wolf et al., 2020).[8] The framework is available under the Apache 2.0 license. We trained the models with a Tesla V100 GPU on the Google Cloud Platform, which is the cloud computing infrastructure. Moreover, we performed a hyperparameter search, using Optuna (Akiba et al., 2019) with default parameters for the aspect detection models on the validation set. In the experiment, the hyperparameter search is limited to 30 trials. Therefore, we performed our experiments in a single run.

We used CRF and binary cross-entropy (BCE) loss for span detection and label prediction in the span-based model, respectively. We used the mean squared error (MSE) as an objective function to train the CTR prediction model. Furthermore, we applied an early stopping strategy to all the models. Specifically, we stopped training if there was no improvement in the validation loss after three consecutive epochs.

[8] https://huggingface.co/cl-tohoku

	Aspect labels	Description & Example	#spans
(1)	Special deals	Expressions representing special deals (e.g., *Compare hotels and save money*)	343
(2)	Discount price	Specific discount rate or amount (e.g., *Buy 1 get 1 50% off*)	120
(3)	Reward points	Customers can earn points (e.g., *Use our app to earn points*)	85
(4)	Free	Free offer for products or services (e.g., *Enjoy free shipping*)	430
(5)	Special gift	Special gifts or presents for customers (e.g., *Join today and get a free brush set*)	126
(6)	Features	Features of services or products (e.g., *Ergonomically designed to protect children*)	1,360
(7)	Quality	Top-quality or high-grade services (e.g., *Find premium kitchen appliances*)	65
(8)	Problem solving	Solutions to customer problems (e.g., *Get bright, clear skin*)	17
(9)	Speed	Speed of delivery and services (e.g., *Fast & free shipping*)	142
(10)	User friendliness	Usability of services and products (e.g., *Quick, simple, and easy to use*)	337
(11)	Transportation	Convenience of transportation (e.g., *Centrally located in the heart of Tokyo*)	89
(12)	Limited offers	Limited availability of services and products (e.g., *Limited to 1,000 items per day*)	52
(13)	Limited-time offer	Offers available for a limited time only (e.g., *Three days only at 20% off*)	61
(14)	Limited-target offer	Offers available for target customers only (e.g., *Discount for members only*)	114
(15)	First-time limited offer	Limited offers for first-time customers (e.g., *Take 15% off your first order*)	25
(16)	Track record	Track records of services or companies (e.g., *45M+ users worldwide*)	75
(17)	Largest/no. 1	Largest/No. 1 products or services (e.g., *Boston's no. 1 hair salon*)	141
(18)	Product lineup	Wide range of products or stores (e.g., *Large selection of hotels*)	258
(19)	Trend	Popularity or favorable reputation (e.g., *Top trending shoes and boots*)	99
(20)	Others	Other advertising appeals (e.g., *An experience like no other*)	182
(21)	Story	Synopsis of a movie or drama (e.g., *After Peter Parker is bitten by a$\cdots$*)	98

Table 5: A^3 and statistics of annotated dataset.

	Aspect Detection Model		CTR Prediction Model
	Span-based	Doc-based	
Pre-trained model	`bert-base-japanese-char`	`bert-base-japanese`	`bert-base-japanese`
Number of heads	12	12	12
Number of hidden layers	12	12	12
Hidden layer size	768	768	768
Dropout probability	0.1	0.1	0.1
Vocab size	4,000	32,000	32,000
Batch size	10	10	30
Max sequence length	512	512	512
Number of epochs	10	10	10
Learning rate	8.6×10^{-5}	5.5×10^{-5}	2.0×10^{-5}
Optimizer	Adam	Adam	Adamax
Loss	CRF loss, BCE loss	BCE loss	MSE loss

Table 6: Hyperparameters and implementation details.

Industry	Title	Desc.	LP	Sub-total
EC	131	314	87	532
Others	137	272	123	532
Media	119	250	27	396
Finance	105	203	56	364
VOD&eBook	38	112	78	228
Cosmetics	43	110	20	173
Human resources	72	75	8	155
Education	58	50	10	118
Travel	23	62	18	103
Automobile	18	32	5	55
Entertainment	14	36	3	53
Real estate	5	12	2	19
Beauty&Health	3	4	3	10
Total	766	1,532	440	2,738

Table 7: Statistics of collected ad texts.

Industry	Train	Dev	Test
VOD&eBook	30,536	3,823	3,812
EC	20,671	2,584	2,583
Finance	20,183	2,521	2,521
Others	15,526	1,936	1,936
Human resources	10,823	1,348	1,348
Media	10,434	1,295	1,274
Education	9,592	1,344	1,228
Travel	8,093	1,002	1,042
Cosmetics	5,584	231	232
Entertainment	2,455	0	0
Automobile	1,697	0	0
Beauty&Health	445	0	0
Real estate	313	0	0
Total	136,352	16,084	15,976

Table 8: Statistics of dataset for CTR prediction.