# A coupon effect model considering behavior data

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**Abstract.** Along with the market expansion of the EC sites in recent years, it has become possible to make use of a great number of users' access log data. Therefore, web marketing techniques based on analyzing the accumulated data have become more important. The discount coupon is one of effective ways and many EC sites introduce the system issuing discount coupons to active users. If an appropriate targeting method is not installed, coupons must be issued to customers who will purchase items even without coupons. Therefore, it is desirable to identify customers who are motivated to purchase items by issued coupons (coupon-motivated customers). On the other hand, in EC site, we can observe the data of each customer's behavior of their item purchase. In this paper, we combine a latent class model to take into account the heterogeneity of customers' purchase behavior and the logit model to predict coupon-motivated customers. For showing an example of the application, we analyze actual customers' behaviors data for predicting the coupon-motivated customers and representing the difference of customers' purchase behaviors.

**Keywords**: EC site, Web marketing, a latent class model, the logit model, coupon-motivated purchasing users

## 1. INTRODUCTION

Along with the market expansion of the EC sites in recent years, it has become possible to make uses of a great number of users' access log data. Therefore, web marketing techniques based on analyzing the accumulated data have become more important. The discount coupon is one of the effective ways for motivating users to purchase items and many EC sites introduce the system issuing discount coupons to active users. If an appropriate targeting method is not installed, coupons are issued to users who will purchase items even without coupons. That should be regarded as an opportunity loss because they only pay the discount price. Therefore, it is desirable to identify customers who are motivated to purchase items by issued coupons (coupon-motivated customers).

On the other hand, in EC sites, we can observe the data of each customer's behavior for their item purchase that is the Web page browsing history data. We can also obtain the data whether the users got coupon or not for each page browsing history. Through the preliminary data analysis, we found that there is the difference of purchasing behavior between the case of issuing the coupon and the case not issuing, which is shown in the section 2.2. Therefore, it is important to construct an analysis model to use the data of each customer's behavior of their item purchase.

In this paper, we propose a predictive model of coupon effects taking account of users' characteristics by using a great number of users' access log data. We combine a latent class model (Hofmann, 1999) to represent the heterogeneity of users' purchase behavior and the logit model (McFadden, 1973) to predict the purchasing rate by coupon-motivated users. Our proposal enables to make it easy to figure out the purchasing behavior of the coupon motivated users and helps constructing an appropriate strategy of coupon issuing.

## 2. RELATED MODELS

### 2.1 The Aspect Model

The aspect model (AM) (Hoffman 1999) is one of the latent class models which represent the user preferences and the features of the items. AM was proposed by Hofmann in 1999 to signify the joint probability of documents and words in the field of natural language processing. This model can be applied to the data analysis of EC sites. In the AM for the purchase history analysis on EC sites, the joint probability of customers and items are estimated by replacing documents and words with customers and items. In this section, a customer and a purchased item in AM are described respectively.

In the latent class model, similar users and items are assumed to belong to the same discrete class. The purchase action of a latent variable model is expressed by a general co-occurrence data which associates an unobserved class $z_c \in \mathcal{Z} = \{z_1, z_2, \dots, z_C\}$ with each observation, i.e., with each occurrence of a customer $x_i \in \mathcal{X} = \{x_1, x_2, \dots, x_I\}$ and each occurrence of a purchased item $y_j \in \mathcal{Y} = \{y_1, y_2, \dots, y_J\}$. The important assumption is that the customers who have same preference belong to the same latent class. The graphical model of the AM is described in Figure 1.

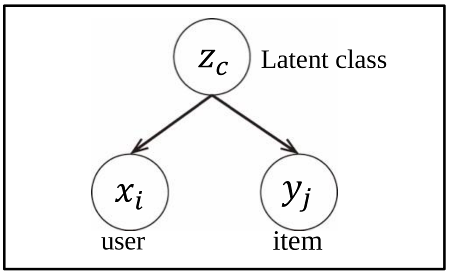


Figure1: Graphical model of AM for purchase data

In this model, customers and items are arisen from each class statistically and this model can express the differences of customers' preferences and features of items. The probabilistic model of AM is formulated as the following equation (1).

$$P(x_i, y_j) = \sum_{z \in Z} P(z_c) P(x_i|z_c) P(y_j|z_c). \qquad (1)$$

Latent classes express the latent features of users with regard to items. A customer$x_i$ and an item $y_j$are observed as data directly. Parameters which need to be estimated are $P(z_c)$, $P(x_j|z_c)$ and $P(y_i|z_c)$. These stochastic variables are assumed to follow a multinomial distribution respectively. These parameters can be estimated by maximizing the log likelihood for the set of all record data. The log likelihood function is defined as follows:

$$L = \sum_{i-1}^{I} \sum_{j=1}^{J} \delta(x_i, y_j) \log P(x_i, y_j). \qquad (2)$$

Here, $\delta(x_i, y_j)$ is an indicator function that takes 1 if the user $x_i$ has purchased the item $y_j$ and 0 if the user has not purchased the item yet. In addition, the equation (2) includes the latent class $z_c$ which can not be observed. Therefore, the maximum likelihood estimator cannot be formulated by a mathematical form, so that the parameters including a latent variable should be estimated by using a searching method, e.g. the EM algorithm.

The EM algorithm is an iterative method to maximize the likelihood of incomplete data with an unobservable variable. This algorithm consists of two steps; the expectation step (E step) and the maximizing step (M step). By iterating these steps, the log likelihood gradually increases and converges finally to a local-maximum. The procedure of the parameter estimation by the EM algorithm is formulated as the equations (3)-(6). In the E-step, the expectation of each latent class is estimated under the condition that the parameters $P(z_c)$, $P(x_j|z_c)$ and $P(y_i|z_c)$are given. In the second step (M step), the parameters $P(z_c)$, $P(x_j|z_c)$ and $P(y_i|z_c)$ are updated. By iterating these E and M steps, the log likelihood will converge and parameters can be estimated. The estimation of $P(z_c|x_i, y_j)$, $P(z_c)$, $P(x_j|z_c)$ and $P(y_i|z_c)$ are formulated as follows:

<E-step>

$$P(z_c|x_i, y_j) = \frac{P(z_c) P(y_i|z_c) P(x_j|z_c)}{\sum_{z \in Z} P(z_c) P(x_i|z_c) P(y_j|z_c)}, \qquad (3)$$

<M-step>

$$P(z_c) = \frac{\sum_{i-1}^{I} \sum_{j=1}^{J} \delta(x_i, y_j) P(z_c|x_i, y_j)}{\sum_{i-1}^{I} \sum_{j=1}^{J} \sum_{z \in Z} \delta(x_i, y_j) P(z_c|x_i, y_j)}, \qquad (4)$$

$$P(y_j|z_c) = \frac{\sum_{i-1}^{I} \delta(x_i, y_j) P(z_c|x_i, y_j)}{\sum_{i-1}^{I} \sum_{j=1}^{J} \delta(x_i, y_j) P(z_c|x_i, y_j)}, \qquad (5)$$

$$P(x_i|z_c) = \frac{\sum_{j-1}^{J} \delta(x_i, y_j) P(z_c|x_i, y_j)}{\sum_{i-1}^{I} \sum_{j=1}^{J} \delta(x_i, y_j) P(z_c|x_i, y_j)}. \qquad (6)$$

### 2.2 The Binomial logit model

The Binominal logit model is one of the probability selection models which can estimate the probability whether the user selects or not.

Let $P_{ci}$ be $i$-th user's choice probability on the $c$-th latent classes, and it is formulated as following.

$$P_{ci} = \frac{\exp\{V_{ci}\}}{\exp\{V_{ci}\}+1}\ . \tag{7}$$

In the equation (7), $V_{ci}$ represents the $i$-th user's selection utility formulated as follows;

$$V_{ci} = \boldsymbol{\beta}_c^{\mathrm{T}}\boldsymbol{w_i} + \varepsilon_{ci}\,, \tag{8}$$

where $\boldsymbol{w}_i = (w_1^i, w_2^i, \dots, w_K^i)^{\mathrm{T}}$ is the $K$-demensional vector of $K$ utility variables, $\boldsymbol{\beta}_c = (\beta_1^c, \beta_2^c, \dots, \beta_K^c)$ is the selection utility parameter vector of the $c$-th latent class, $\varepsilon_{ci}$ is a random utility, and T means the transpose symbol of matrixes.

In this study, since we deal with a EC site access log data, a customer has two selections which purchase the items in one access or not. Therefore, this model is useful for expressing the selection model for each user.

## 3. PRELIMINARY DATA ANALYSIS

### 3.1 Data Information

In this paper, we deal with the data of a Japanese largest EC site. It has session IDs data which can be observed in a browsing behavior of each user from visit to EC site to exit. For example, when a user visited the EC site twice in a day, the user generates two session IDs. Each session ID attaches the browsing URL, the number of browsing pages, the browsing time per page, browsing page types, purchase records, the amounts of each purchase item price, coupon records and so on. We focus on the relationship between the purchase behavior and coupons utility for each user. Note that we did not analyze the demographic data such as age, sex and occupation because of the privacy protection policy.

### 3.2. Basic Analysis

In this section, we carry out the basic analysis from the viewpoint of the difference between the coupon issue and the buying behavior.

The access log data has coupon IDs which represent the types of coupons. For simplifying of the argument, in this paper, we consider all types of coupons have same effect to users. In this section, we stratified the session data by sessions with issuing coupon and sessions without coupon (no coupon) and compared the statistics of the browsing time, the number of page views, the price of the browsing item and the conversion price in a session. The conversion price represents the total purchase amount of susers. The result of the basic analysis is shown in table 1.

First, looking at the column of browsing time, both "issuing coupon" and "no coupon" are almost the same behavior. However, the column of the number of page views, the group of "issuing coupon" has lower mean and standard deviation than the group of "no coupon". From these results, the coupon has the disposition which makes users' purchase a little shorter and more stable.

Second, we consider that the column of the average browsing item price and the conversion price in a session. The mean and median are almost the same between the groups of "issuing coupon" and "no coupon". However, the standard deviation of conversion price of "issuing coupon" group is about one-third as that of "not coupon" group. Therefore, it is suggested that the coupons have a high stabilization quality to user's conversion price. In summary, it is important to issue the coupons efficiently at the perspective of increasing sales in the EC site.

Table 1: Difference of buying behavior from the view point of the coupon issue

| | coupon | no coupon | coupon | no coupon | coupon | no coupon | coupon | no coupon |
|---|---|---|---|---|---|---|---|---|
| | browsing time (ms) | | the number of page views | | total browsing item price | | conversion price | |
| mean | 1347231.43 | 1344813.33 | 14.38 | 14.35 | 13410.79 | 13394.70 | 10099.64 | 9572.35 |
| median | 381103 | 381956 | 6 | 7 | 3990 | 3990 | 7311 | 7009 |
| std | 2529185.67 | 2510808.93 | 24.00 | 23.24 | 40395.70 | 33767.58 | 9386.59 | 8342.92 |

Then, we make the histogram showing the conversion prices which are stratified by the groups of "issuing coupons" and "no coupon". In Figure 2, the x-axis means the session's conversion price and the y-axis means the normalized frequency. This results show that the histograms are not so different; it is suggested that the effect of issued coupon is not so much. Therefore, there is room for improvement on the current system of coupons issue. Hence, it is important to issue the coupons without making errors.

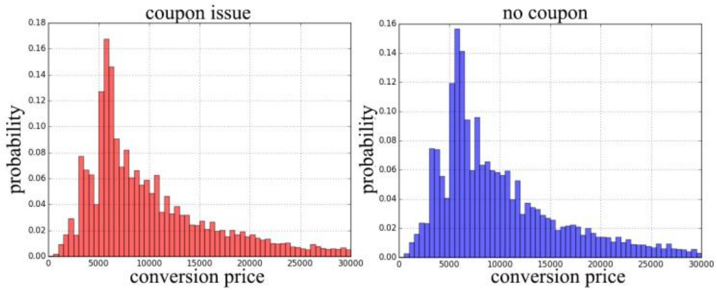


Figure 2: Comparison of issuing coupons (left figure) and not issuing coupons (right figure) of conversion price

## 4. THE PROPOSED MODEL

### 4.1. Overview

The purpose of our study is to construct the predictive model for the effect of the coupon considering customers' purchase behaviors for each session. We propose the following combined model to represent the heterogeneity of users' purchase behavior for issued coupons.

We apply the AM to analyze the co-occurrence of customer's purchase behavior and whether the user bought something or not. Moreover, for considering whether the customer bought something or not, we combine the binominal logit model including the information of coupon issue for one of the utility variables to the AM.

It is possible to cluster not only the co-occurrence of customer's buying behavior and browsed items in the session, but also cluster the effect of utility variables for the customer's purchase. Therefore, we can decide the effective customer for whom the coupons should be issued by using our model.

## 4.2. Formulation

In this section, we describe the formulation of our model.

Let $(r_s, \boldsymbol{y}_s)$ be the data of $s$-th session, where $r_s$ is a binary value if in the $s$-th session something is sold, it score 1, otherwise, 0, and $\boldsymbol{y}_s = (y_1^s, y_2^s, \dots, y_N^s)$ is also a binary vector if in the $s$-th session brows $n$-th item, $y_n^s$ score 1, otherwise, 0. Each data is drawn from the multinomial distribution. The data set is denoted by $= \{(r_s, \boldsymbol{y}_s)\}_{s=1}^{S}$ . Next, let $L$ be the number of latent classes that are not observed in the data, and $w_s \in \mathcal{Z} = \{z_1, \dots, z_l, \dots, z_L\}$ be the set of latent classes. For applying the logit model the $K$-demensional vector of $K$ utility variables $\boldsymbol{x}_s = (x_1^s, x_2^s, \dots, x_K^s)^{\mathrm{T}}$ is introduced in the model. The graphical model of our proposal is described as Figure 3.

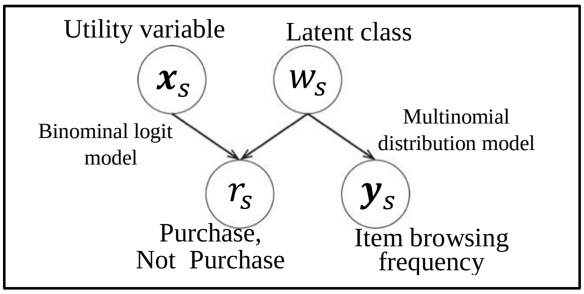


Figure 3: Graphical model of our proposal

Here, let the parameter vector of the multinomial distribution by $l$-th latent class and $n$-th item be $\boldsymbol{\theta}_l = (\theta_{l1}, \dots, \theta_{ln}, \dots, \theta_{lN})$, where the parameter vector satisfies the following restriction,

$$\sum_{n=1}^{N} \theta_{ln} = 1. \tag{9}$$

The joint probability $P(r_s, \boldsymbol{y}_s)$ is formulated as following.

$$P(r_s, \boldsymbol{y}_s) = \sum_{l=1}^{L} P(z_l) P(r_s|\boldsymbol{x}_s, z_l) P(\boldsymbol{y}_s|z_l)$$

$$= \sum_{l=1}^{L} P(z_l) P(r_s|\boldsymbol{x}_s, z_l) \frac{(\sum_{n=1}^{N} y_n^s)!}{\prod_{n=1}^{N} y_n^s\,!} \prod_{n=1}^{N} \theta_{ln}^{y_n^s} . \tag{10}$$

In the equation (10), $P(r_s|\boldsymbol{x}_s, z_l)$ is assumed to be estimated by the binominal logit model as follows:

$$P(r_s|\boldsymbol{x}_s, z_l) = P_{ls} = \frac{\exp\{V_{ls}\}}{\exp\{V_{ls}\} + 1}, \tag{11}$$

$$V_{ls} = \boldsymbol{\beta}_l^{\mathrm{T}} \boldsymbol{x}_s + \varepsilon_{ls}. \tag{12}$$

where, $V_{ls}$ represents the $s$-th user's selection in $l$-th latent class's utility, $\boldsymbol{\beta}_l = (\beta_1^l, \beta_2^l, \dots, \beta_K^l)$ is the $l$-th latent class's selection utility parameter vector, $\varepsilon_{ls}$ is a random utility.

## 4.3. Parameters Estimation

In order to estimate the parameters, we apply the EM algorithm (Dempster *et.al.* 1977) in this study.

The log likelihood function $LL$ for the set of the access log data is formulated as follows.

$$LL = \sum_{s=1}^{S} \log P(r_s, \boldsymbol{y}_s). \tag{13}$$

Since this equation includes the latent class $z_l$ which cannot be observed, the parameters of the log likelihood $LL$ are estimated by applying the EM algorithm. The EM algorithm is based on an iterative procedure to locally maximize the log likelihood of incomplete data. This algorithm consists of two steps, which are the expectation step (E-step) and the maximization step (M-step). The E-step calculates the posterior probability of the latent class under the condition that the parameters are given. The M-step estimates the parameters which maximize the conditional expectation of the log likelihood by using the posterior probability of the latent class.

By iterating the E-step and the M-step, the log likelihood finally converges to a local maximum and the parameters can be estimated.

In the E-step, the posterior probability of the latent class $z_l$ is calculated by using the data of each session $\mathcal{S}$ and the given parameters. The posterior probability $P(z_l|\boldsymbol{x}_s, r_s, \boldsymbol{y}_s)$ is formulated as follows:

<E-step>

$$P(z_l|\boldsymbol{x}_s, r_s, \boldsymbol{y}_s) = \frac{P(z_l) P(r_s|\boldsymbol{x}_s, z_l) P(\boldsymbol{y}_s|z_l)}{\sum_{l=1}^{L} P(z_l) P(r_s|\boldsymbol{x}_s, z_l) P(\boldsymbol{y}_s|z_l)} . \tag{14}$$

In the M-step, the parameters $P(z_l)$, $\theta_{ln}$, and $P(r_s|\boldsymbol{x}_s, z_l)$ are updated using $P(z_l|\boldsymbol{x}_s, r_s, \boldsymbol{y}_s)$ estimated in the equation (13) respectively. Each parameter is updated by the following equations. Note that $P(r_s|\boldsymbol{x}_s, z_l)$ is the logit model which is estimated by the non-liner optimization of the binominal logit model.

<M-step>

$$P(z_l) = \frac{\sum_{s=1}^{S} P(z_l|\boldsymbol{x}_s, r_s, \boldsymbol{y}_s)}{\sum_{l=1}^{L}\sum_{s=1}^{S} P(z_l|\boldsymbol{x}_s, r_s, \boldsymbol{y}_s)}. \quad (15)$$

$$\theta_{ln} = \frac{\sum_{s=1}^{S} P(z_l|\boldsymbol{x}_s, r_s, \boldsymbol{y}_s) y_n^s}{\sum_{n=1}^{N}\sum_{s=1}^{S} P(z_l|\boldsymbol{x}_s, r_s, \boldsymbol{y}_s) y_n^s}. \quad (16)$$

Then, the estimation flow of $P(r_s|\boldsymbol{x}_s, z_l)$ is formulated as follows.

The utility parameter vector in $l$-th latent class $\boldsymbol{\beta}_l = (\beta_1^l, \beta_2^l, \dots, \beta_K^l)$ which maximizes the log likelihood $LL_{logit}$ of the binomial logit model given $r_s$ and $\boldsymbol{x}_s$ is estimated as follows:

$$\begin{aligned} LL_{logit} &= \log \prod_{s=1}^{S} P_s^{r_s}(1-P_s)^{1-r_s} \\ &= \sum_{s=1}^{S}\left[ r_s \left( \sum_{l=1}^{L} \boldsymbol{\beta}_l^{\mathrm{T}} \boldsymbol{x}_s \right) - \log\left\{ \exp\left( \sum_{l=1}^{L} \boldsymbol{\beta}_l^{\mathrm{T}} \boldsymbol{x}_s \right) + 1 \right\} \right]. \end{aligned} \quad (17)$$

On the other hand, the purchase in $s$-th session in $l$-th latent class probability $P(r_s|\boldsymbol{x}_s, z_l)$ is defined as the equation (11). And $s$-th session's purchase probability $P_s$ is defined as follows.

$$\begin{aligned} P_s &= \sum_{l=1}^{L} P(z_l) P_{ls} \\ &= \sum_{l=1}^{L} P(z_l) \frac{\exp\{V_{ls}\}}{\exp\{V_{ls}\}+1}. \end{aligned} \quad (18)$$

# 5. DATA ANALYSIS USING PROPOSED METHOD

To verify the effectiveness of the proposed method, we analyze the real session's log data of an actual EC site.

## 5.1. Analysis Condition

In this analysis, the proposed model retrieves the session's lag data as following table 2. Conversion rate (CVR) in Table 2 means the ratio of the number of purchase sessions for the total sessions.

Table 2: Overview of using data

| period | 1 Apr. 2016 ~ 7 Apr. 2016 |
|---|---|
| the total number of Page Views | 16,806,439 |
| the total type of a good for browsing | 524,507 |
| the total number of Sessions | 1,888,572 |
| the total number of Purchase Sessions | 61,975 |
| CVR | 0.0328 |

For our proposal, we adopt the 9 utility variables in the binomial logit model as shown in Table 3. "Access from newsletter" means if users access in the EC site from E-mail which was sent by the EC site company, it tales 1, otherwise 0, "Access from advertisement" means if users access from the Internet advertisement of the EC site, it takes 1, otherwise 0. Because of preliminary experiments, the number of latent classes is set as 5.

Table 3: List of the utility variables

| utility variables | | |
|---|---|---|
| browsing time | number of cart botton clicks | Access from brand key word |
| page views | hour of day | Access from newsletter |
| device | Access from advertisment | coupon isue or not |

## 5.2. Results and Discussion

The result of experiment is shown as follow. Focusing on the parameter $\boldsymbol{\beta}_l$ which indicates how strong the effect of the utility vector $\boldsymbol{x}$ of $l$-th latent class is. Table 4 shows the result of that $\boldsymbol{\beta}_l$ in each latent class.

It shows that the largest coefficient of coupon issue is given on the latent class 4. In the latent class $z_4$, "coupon issue" shows a higher value as 13.408 than other latent classes and "device" also shows a high value as 12.712. This result means that the purchase probability is improved when the coupon is issued for sessions belonging to the latent class $z_4$ and accessing the EC site from a PC. Taking closer look at this row, the value of "page view" is higher than "browsing time". If we carry out the marketing promotion to this class, it can be expected to increase theirs page views.

Focusing on the latent class 2, the value of "coupon issue" is the smallest in the obtained result although the value of "browsing time" and "page views" are the highest in that result. It shows that the effect of issuing coupons to the sessions belonging to $z_2$ is weak. However, the "newsletter" like an E-mail sending items information works with effect.

From the above result, We can make clear understanding which utility variables are effective to each session. Based on an appropriate strategy by using the result of the analysis, it can be carried out to make different marketing approaches to users accessing the EC site.

# 6. CONCLUSION AND FUTURE WORK

We proposed a model combined a latent class model with the binomial logit model. In addition, we showed the effectiveness of the proposed model by simulating the data analysis on the case of a Japanese major EC site. Specifically, it is possible to decrease the number of sessions to issue coupons to

Table 4: The result of utility parameter vector $\boldsymbol{\beta}_l$

| latent class | browsing time | page views | device | cart button click count | hour of day | Access from advertisemen | Access from newsletter | Access from brand | coupon issue | mixture ratio |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 9.276 | 6.919 | 11.311 | 12.972 | 8.188 | 5.066 | 9.734 | 10.519 | 11.283 | 0.255 |
| 2 | 12.407 | 12.572 | 6.329 | 11.418 | 7.897 | 7.859 | 13.442 | 10.652 | 5.663 | 0.208 |
| 3 | 4.987 | 9.333 | 7.624 | 6.696 | 7.160 | 8.410 | 7.802 | 7.296 | 10.134 | 0.205 |
| 4 | 8.343 | 13.365 | 12.712 | 9.914 | 12.782 | 4.874 | 3.989 | 6.880 | 13.408 | 0.178 |
| 5 | 11.759 | 4.748 | 9.465 | 4.564 | 6.170 | 12.006 | 13.400 | 10.460 | 7.298 | 0.154 |

adopt the proposed model.

For more improvement, it is quite important to predict the sessions on which an item will be purchased in an instant to apply the actual EC site promotion. That is, it is an important future work to predict the user with the high coupons effect. And the variables selection in the model is also required. These tasks comprise our future work.

## ACKNOWLEDGMENTS

The authors would like to express our thanks to all members of Goto Laboratory. Waseda University for their helpful comments for this study. In addition, we wish to thank offering the access log data of the EC site and timely kind help given by Emotion Intelligence, Inc. A part of this study was supported by JSPS KAKENHI Grant Numbers 26282090 and 26560167.

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