RMM: An R Package for Customer Choice-Based Revenue Management Models for Sales Transaction Data

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Abstract  We develop an R package RMM to implement a Conditional Logit (CL) model using the Robust Demand Estimation (RDE) method introduced in Cho et al. (2020), a customer choice-based Revenue Management Model. In business, it is important to understand customers’ choice behavior and preferences when the product prices change over time and across various customers. However, it is difficult to estimate actual demand because of unobservable no-purchase customers (i.e., truncated demand issue). The CL model fitted using the RDE method, enables a more general utility model with frequent product price changes. It does not require the aggregation of sales data into time windows to capture each customer’s choice behavior. This study uses real hotel transaction data to introduce the R package RMM to provide functions that enable users to fit the CL model using the RDE method along with estimates of choice probabilities, size of no-purchase customers, and their standard errors.

1 Introduction

There is an extensive history of research on techniques used to estimate product or service demand across a wide area of industries. However, in practice, it is very challenging to estimate demand because of unobservable no-purchase customers (i.e., truncated demand issue). Although customers may visit a physical store or online website, they may not purchase products from the offered portfolios because of the following reasons: (1) their willingness-to-pay is lower than the offered prices; (2) the case of unintentional product out-of-stocks (or sell-outs); (3) the case of intentionally forcing lower-price options to be unavailable (Ferguson, 2020). Unobserved no-purchase customers provide a distorted view of demand, resulting in a lower estimated mean and variance. Basing demand estimates on censored data will result in biased forecasts for future demand, which will lead to a profit spiral down.

To resolve this issue, the Revenue Management Model (RMM) has been developed. Specifically, Conditional Logit (CL) modeling has been receiving attention in academia and practice. Talluri and Van Ryzin (2004) developed the expectation-maximization (EM) method to estimate parameters associated with purchase probability and arrival rates, based solely on observed sales data. Some other methods have been proposed, including a variant of the EM method (Vulcano et al., 2012), two-step estimation method (Newman et al., 2014) and maximize-minorize optimization method (Abdallah and Vulcano, 2021). However, these methods require a data aggregation process for product attributes including the prices and choice sets by each time window. They also require the use of a cell mean utility model, assuming that the product attributes remain constant across customers and time periods. Namely, it is difficult to fit choice models by capturing the varying product attributes and available choice sets over time. This leads to a loss of information and potentially biased estimates. As an alternative, we use the Robust Demand Estimation (RDE) method proposed by Cho et al. (2020), which is a customer choice-based RMM and enables a more general utility model with frequent price changes in the products. Additionally, it does not require aggregating sales data into time windows to capture each customer’s choice behavior. The ability to manage frequent price changes is vital for demand estimation, especially in the areas of airlines, hotels, and e-commerce, where dynamic pricing is prevalent.

To apply the RDE method to censored data, Cho et al. (2020) employs a CL model to fit the censored transaction data. Although the parameters of the CL model for the available products can be consistently estimated using conventional maximum likelihood estimation, the no-purchase utility cannot be estimated without further information. Cho et al. (2020) considered the following two additional types of information to identify the model parameters: 1) additional assumptions on customers’ utility function, and 2) external information about a firm’s market share. Afterwards, Cho et al. (2020) developed robust estimation algorithm to address the inaccuracies in the information type and let the data decide the most appropriate approach.

Various CL modeling approaches are already accessible in R, such as, for instance, mlogit (Croissant, 2020), Rchoice (Sarrias, 2016), and mixl (Molloy et al., 2021). However, there is no suitable R package to implement the handling of censored sales data by employing the CL model. To the best of our knowledge, other publicly available software, including SAS and Python, do not provide this function either.
The source codes of the RMM package are accessible in Kim et al. (2022). It is available after installation in R 4.1.0 or later versions. There are three main functions in RMM. First, the function `rmm reshape()` should be used by all users to fit the CL model, by changing the data to a wide format and defining information such as the response and alternative specific variables from the given data. The function `rmm()` fits a CL model using the RDE method. This function estimates the parameters, their standard error and size of the no-purchase. Finally, the function `predict()` produces a prediction value, which is the choice probability for each alternative in the fitted model. The customer’s decision can be confirmed by this prediction value.

2 Conditional Logit Model using the Robust Demand Estimation Method

The CL model using the robust demand estimation proposed by Cho et al. (2020) uses the concept of random utility maximization. It captures each customer’s choice behavior where customer \(i\) is assumed to choose product \(j\) from the choice set \(S_i\) having the maximum utility. The choice set \(S_i\) can include up to \(J\) products in total. Consider the mean utility of customer \(i\) for product \(j\),

\[v_{ij} = \alpha_i + \beta x_{ij}, \quad i = 1, \ldots, n, \quad j \in S_i\]

where \(\alpha_i\) is a fixed utility associated with the product \(j\), \(x_{ij}\) is a vector attributes of product \(j\) exposed to customer \(i\), \(\beta\) is a vector of regression slope coefficients corresponding to the product attributes \(x_{ij}\). Utilities can be vary across customers of the same product.

The CL model is a common RMM derived by assuming random utility \(U_{ij}\),

\[U_{ij} = v_{ij} + \epsilon_{ij}\]

where \(v_{ij}\) are mean utilities (systematic component) and \(\epsilon_{ij}\) are random errors (i.e., an unobserved component) which follow i.i.d. the Gumbel distribution. Under this assumption, the choice probability for product \(j\) for a customer \(i\) and the no-purchase probability are respectively given as:

\[p_{ij} = \frac{\exp(v_{ij})}{1 + \sum_{j \in S_i} \exp(v_{ij})}, \quad p_{i0} = 1 - \sum_{j \in S_i} p_{ij}\]  \hspace{1cm} (1)

Using the choice probabilities in (1), the complete log-likelihood is given by

\[l_{\text{comp}}(\alpha, \beta) = \sum_{i=1}^{n} \left\{ (1 - \delta_i) \log p_{i0} + \sum_{j \in S_i} \delta_i \log p_{ij} \right\}\]  \hspace{1cm} (2)

where \(\alpha = (\alpha_1, \ldots, \alpha_J)\), \(\delta_i\) represents the indicator function if customer \(i\) purchases product \(j\) and \(\delta_i = \sum_{j \in S_i} \delta_{ij}, \quad \text{for } i = 1, \ldots, n\). Because the no-purchase records are unobservable, the complete-data likelihood function (2) should be written again in a reduced form, initially discussed in McFadden et al. (1973), as follows:

\[l_{\text{obs}}(\alpha^*, \beta) = \sum_{i=1}^{n} \delta_i \sum_{j \in S_i} \delta_{ij} \log \left( \frac{\exp(\alpha^*_j + \beta x_{ij})}{\sum_{j \in S_i} \exp(\alpha^*_j + \beta x_{ij})} \right)\]  \hspace{1cm} (3)

where \(\alpha^* = (\alpha^*_1, \ldots, \alpha^*_J)\) and \(x_{ij}^*\) are normalized parameters and covariates, respectively, defined as

\[\alpha^*_j = \alpha_j - \alpha_K, \quad x_{ij}^* = x_{ij} - x_K,\]

for a fixed baseline product \(k \in S_i\). For parameter identification, we reduce the dimension of \(\alpha\) from \(K\) to \(K - 1\) possible choices. Similarly, the covariate \(x\) sharing the same model parameter \(\beta\), is normalized to be compatible across different sets of available products. To find the fixed baseline product \(k\) with the smallest value among all \(\alpha_k\) values, Cho et al. (2020) developed a grid searching algorithm presented in 1.

Cho et al. (2020) defined instant loss rate, evaluated at purchase by the customer \(i\), as the odds of no-purchase probability given by

\[l_i = \frac{p_{i0}}{1 - p_{i0}} = \frac{1 - p_i}{p_i} = \frac{\exp (v_{i0})}{\sum_{j \in S_i} \exp (v_{ij})}\]  \hspace{1cm} (4)

where the utility of customer \(i\) from no-purchase is \(v_{i0}\) and probability of purchasing at least one of the available products is \(p_j = \sum_{j \in S_i} p_{ij}\). The instant loss rate in (4) is a relative ratio of no-purchase against purchase given choice set and product attributes, according to \(S_i\). Thus, it can be understood
Algorithm 1

**Input:** $S$: a set of products.

**Output:** Baseline product $k^*$

1: for $k \in S$ do
2: Obtain MLE $\hat{\eta}_k^*$ by maximizing (3)
3: if $\hat{\alpha}_i^j \geq 0$ for all $j \neq k$ then
4: $k^* = k$
5: else $k^* = j$, where $\hat{\alpha}_i^j$ satisfies $\hat{\alpha}_i^j \leq \hat{\alpha}_i^l$ for all $l \in S$.
6: end if

as the number of no-purchase customers exposed to the same choice set with customer $i$. Because customers are independent of each other but share the same choice model, the loss rate on customer $i$ is the expected number of no-purchase customers. Accordingly, the total number of no-purchase customers, indicated by $L$, in the observed time period can be defined as

$$L = \sum_{i=1}^{n} \delta_i l_i.$$  

Considering the choice model parameters and definition of instant loss rate (4), we can rewrite the total number of no purchases as

$$L = \exp(\gamma) \sum_{i=1}^{n} \delta_i \left( \sum_{j \in S_i} v_{ij}(\eta_{-k}^*) \right)^{-1},$$  

where $\gamma = -\alpha_k$ is the model parameter corresponding to the baseline product $k$, and $\eta_{-k}^*$ is the normalized vector of model parameters excluding $\alpha_k$. However, the parameter estimate $\gamma$ is not generally identifiable and estimable from the observed log-likelihood (3). Thus, we cannot obtain a consistent estimator of $L$ despite the consistent maximum likelihood estimates $\hat{\eta}_{-k}^*$. To estimate no-purchase utility $\gamma$, Cho et al. (2020) considered additional information of market share as applied in Vulcano et al. (2012) and Abdallah and Vulcano (2021). To identify and estimate $\gamma$, we incorporate market share information $s$ where $s \in (0, 1)$. We construct an estimation function in which the ratio between the size of no-purchases and purchases is equal to the inverted odds of the market share, that is,

$$\frac{\text{No purchases (L)}}{\text{Purchases (NR)}} = \frac{1 - s}{s}.$$  

From the Equations (5) and (6), we derive the estimation of $\gamma$,

$$U(\gamma | \hat{\eta}_{-k}^*) = \frac{1}{n_R} \exp(\gamma) \left[ \sum_{i=1}^{n} \delta_i \left( \sum_{j \in S_i} v_{ij}(\eta_{-k}^*) \right)^{-1} \right]^{-1} - \frac{1 - s}{s} = 0.$$  

The asymptotic properties of the MLE estimates $\hat{\eta}_{-k}^*$ obtained by maximizing the observed log-likelihood (3) with the baseline product $k$, are well-known along with the likelihood theory. The variance of $\hat{\eta}_{-k}^*$ can be estimated using the Hessian of the observed log-likelihood (3). The asymptotic properties of the no-purchase parameter estimator $\hat{\gamma}$ are presented in Theorem 1 in Cho et al. (2020).

3 Implementation of the RMM package

In this section, we explain how to fit the CL model using the RDE method discussed in the previous section, through the data of Hotel_Long and Hotel_Wide, contained in the RMM package. Usually, two formats of customers’ transaction data are generated from a hotel, airline, or e-commerce field, namely, long or wide format. The long format data corresponding to Hotel_Long records the attributes of each alternative in a single row (many rows are required to represent each customer’s decision situation). The wide format data corresponding to Hotel_Wide records each customer’s decision situation in a single row (this format requires more columns than the long format). Here, we start by introducing the sources of the two data (Hotel_Long, Hotel_Wide).
Hotel_Long and Hotel_Wide data

Hotel_Long and Hotel_Wide are preprocessing datasets derived from the publicly available “Hotel 1” data introduced in Bodea et al. (2009). In the “Hotel 1” data, customers are exposed to several types of rooms, that is, the choice sets are made available to them at the time of their visit. The room prices are recorded according to the characteristics of the customers (for example, party size or VIP status) and date. Cho et al. (2020) used this data to study robust demand estimation, Berbeglia et al. (2021) and Subramanian and Harsha (2021) used it to develop their revenue management models.

For illustration purposes, we performed the following preprocessing on the “Hotel 1” data.

1. Customers’ booking transactions with only one room type available in their choice set, were discarded.
2. Duplicate transactions were removed.
3. Choice sets with less than 33 observations representing rare cases were discarded.

As a result of the above preprocessing, the data contains 1,100 transactions from 2007-02-12 to 2007-04-15 (62 days). Hotel_Long is a long format and Hotel_Wide is a wide format of this data.

Hotel_Long can be loaded as follows. Note: 1,100 transactions are recorded in 8,318 rows because the data is in a long format. Table 1 represents the description of the 11 variables of Hotel_Long.

```r
> library(RMM) # Load the RMM package
> data(Hotel_Long) # Load the long format example data
> dim(Hotel_Long) # 8,318 observations, 11 variables
[1] 8318 11
> head(Hotel_Long) # First 6 observations out of 8,318
```

| Booking_ID | Purchase | Room_Type | Price | Party_Size | Membership_Status |
|------------|----------|-----------|-------|------------|-------------------|
| 1          | 10       | King Room | 329   | 1          | 1                 |
| 2          | 10       | Queen Room| 329   | 1          | 1                 |
| 3          | 10       | King Room | 359   | 1          | 1                 |
| 4          | 10       | 2 Double Beds Room | 359 | 1 | 1 |
| 5          | 10       | Queen Room | 359   | 1          | 1                 |
| 6          | 10       | Special Type Room | 359 | 1 | 1 |

VIP_Membership_Status Booking_Date Check_In_Date Check_Out_Date Length_of_Stay
1 02007-04-08 2007-04-09 2007-04-10 1
2 02007-04-08 2007-04-09 2007-04-10 1
3 02007-04-08 2007-04-09 2007-04-10 1
4 02007-04-08 2007-04-09 2007-04-10 1
5 02007-04-08 2007-04-09 2007-04-10 1
6 02007-04-08 2007-04-09 2007-04-10 1

| Name                  | Description                                                                 |
|-----------------------|-----------------------------------------------------------------------------|
| Booking_Id            | ID associated with a booking.                                               |
| Purchase              | Indicator variable equals to one if the product identified is purchased by Room_Type, zero otherwise. |
| Room_Type             | Indicating a room type exposed to customers.                                |
| Price                 | The average nightly rate paid by the customer in USD.                      |
| Party_Size            | The number of people associated with the booking.                          |
| Membership_Status     | Status in rewards program (0—not a member, 1—basic, 2—elevated, 3—premium).|
| VIP_Membership_Status | Membership status of a VIP rewards program member (0—not a VIP, 1—basic VIP, 2—premium VIP member). |
| Booking_Date          | The date the booking was created.                                          |
| Check_In_Date         | The date the customer checked in.                                          |
| Check_Out_Date        | The date the customer checked out.                                         |
| Length_of_Stay        | Length of stay (the number of nights).                                     |

**Table 1:** Description of Hotel_Long Data
The same data as above, but converted to a wide format is `Hotel_Wide` given below. Because one transaction is expressed in each row, 1,100 rows are recorded, and the number of variables is 22, which is more than that of `Hotel_Long`. Where `Decis_Alts_Code` is a numeric coded variable of `Room_Type` selected by the customer, and `Choice_Set` is a variable that expresses `Room_Type` exposed to the customer as `Decis_Alts_Code`.

```r
> dim(Hotel_Wide)  # 1,100 observations, 22 variables
[1] 1100 22
> head(Hotel_Wide)

| Booking_ID | Party_Size | Membership_Status | VIP_Membership_Status | Booking_Date       |
|------------|------------|-------------------|-----------------------|--------------------|
| 1          | 22         | 1                 | 0                     | 2007-04-05         |
| 2          | 23         | 1                 | 0                     | 2007-04-05         |
| 3          | 24         | 1                 | 0                     | 2007-04-05         |
| 4          | 30         | 1                 | 0                     | 2007-04-05         |
| 5          | 32         | 1                 | 0                     | 2007-04-09         |
| 6          | 37         | 1                 | 3                     | 2007-04-06         |

| Check_In_Date | Check_Out_Date | Length_of_Stay | Room_Type |
|---------------|----------------|---------------|-----------|
| 2007-04-10    | 2007-04-11     | 1             | King Room 4 |
| 2007-04-10    | 2007-04-11     | 1             | King Room 4 |
| 2007-04-10    | 2007-04-11     | 1             | Special Type Room 1 |
| 2007-04-09    | 2007-04-11     | 2             | King Room 4 |
| 2007-04-10    | 2007-04-11     | 1             | Suite 1   |
| 2007-04-13    | 2007-04-14     | 1 2           | Double Beds Room 1 |

| Decis_Alts_Code | Choice_Set | Choice_Set_Code | Price_1  | Price_2  | Price_3  |
|-----------------|------------|-----------------|---------|---------|---------|
| 1               | 5          | 1|5|7|8|9|10 | 6       | 399     | 0       |
| 2               | 5          | 1|5|7|8|9|10 | 6       | 399     | 0       |
| 3               | 8          | 1|5|8   | 7       | 399     | 0       |
| 4               | 5          | 1|4|5|7|8|9|10 | 4       | 359     | 0       |
| 5               | 9          | 1|4|5|8|9|10 | 5       | 399     | 0       |
| 6               | 1          | 1|2|3|4|5|7|8|9|10 | 2       | 299     | 279     |

| Price_4 | Price_5 | Price_6 | Price_7 | Price_8 | Price_9 | Price_10 |
|---------|---------|---------|---------|---------|---------|---------|
| 1       | 0       | 439     | 0       | 399     | 399     | 499     |
| 2       | 0       | 439     | 0       | 399     | 399     | 499     |
| 3       | 0       | 439     | 0       | 399     | 399     | 499     |
| 4       | 359     | 399     | 0       | 359     | 359     | 459     | 559    |
| 5       | 399     | 439     | 0       | 399     | 399     | 499     |
| 6       | 299     | 339     | 0       | 299     | 299     | 379     | 479    |
```

The “Alternative Specific Variables” (ASV) and “Individual Specific Variables” (ISV) are present in the data in which the CL model can be fitted. The former is a variable indicating the characteristics of each product (alternatives) such as "Price", and the latter is a variable indicating the attributes of a customer (individual) such as "Party_Size", "Membership_Status", and "VIP status". The RMM package can only use ASV to model customers’ choice probabilities based on the RDE method in Cho et al. (2020).

To apply the proposed RDE method, users must first use the `rmm_reshape()` function to reshape the data into a wide format and organize the information required by the `rmm()` model fitting function. Once the model parameters are estimated from `rmm()`, the users obtain predict values of unobserved customer demand using `predict()`. The next subsections have detailed descriptions of each step.

### `rmm_reshape()` for preparing data

The `rmm()` function for fitting the model requires an S3 class called `rmm_data` as the input object, which the user can prepare using the `rmm_reshape()` function. Table 2 describes arguments used in `rmm_reshape()`.

`rmm_reshape(data, idvar, resp, alts, asv, 
aelts_code = NULL, choice_set = NULL, choice_set_code = NULL, 
min_obs = 30)`

Let us consider the case where the user has either the long or wide format data. If the user has long format data such as `Hotel_Long` and inserts it into the `rmm_reshape()`, the function automatically converts the data into wide format and defines the information. Accordingly, it codes all the alternatives in the data as numbers and specifies the choice sets exposed to customers, as follows.
| Argument   | Explanation                                                                 | Default value                  |
|------------|-----------------------------------------------------------------------------|-------------------------------|
| data       | data frame, a long or wide format data                                      |                               |
| idvar      | character, variable name representing each individual’s id in the transaction data. |                               |
| resp       | character, variable name representing result of an individual choice.       |                               |
| alts       | character vector, variable names representing alternatives.                 |                               |
| asv        | character vector, variable names representing alternative specific variables. |                               |
| alts_code  | character, variable name representing numerically coded alternatives.       | NULL                          |
| choice_set | character, variable name representing a set of alts_code exposed to individuals. The delimiter for each alternative must be ‘|’. For example, “1|2|5.” | NULL                          |
| choice_set_code | character, variable name representing a numerically coded choice set. | NULL                          |
| min_obs    | numeric, specify the minimum observations for each choice set in the transaction data. | 30                            |

*Only used when data is in wide format.*

### Table 2: Arguments to the function `rmm_reshape()`

# When data is in the long format.
```r
rst_reshape <- rmm_reshape(data=Hotel_Long,
  idvar="Booking_ID",
  resp="Purchase",
  alts="Room_Type",
  asv="Price",
  min_obs=30)
```

However, if the user has wide format data such as `Hotel_Wide`, three more arguments, namely, `alts_code`, `choice_set`, and `choice_set_code`, must be specified when using the `rmm_reshape()` function, unlike in the long format.

# When data is in the wide format.
```r
rst_reshape <- rmm_reshape(data=Hotel_Long,
  idvar="Booking_ID",
  resp="Purchase",
  alts="Room_Type",
  asv="Price",
  alts_code="Decis_Alts_Code",
  choice_set="Choice_Set",
  choice_set_code="Choice_Set_Code",
  min_obs=30)
```

Note that, only one variable should be specified for the response variable, but ASV can specify multiple variables as a character vector in the `asv` argument. Here, we used “Purchase” as the response variable and “Price” as ASV.

The output of `rmm_reshape()` is a list, which is the S3 class “rmm_data” required as input by `rmm()`.

```r
> class(rst_reshape) # S3 class ‘rmm_data’
[1] "rmm_data"
```

```r
> ls(rst_reshape)
[1] "Alts_Code_Desc" "ASV" "asv_name"
[4] "data_wide" "Rem_Choice_Set" "Removed_Choice_Set"
```
The output `rst_reshape$Alts_Code_Desc`, represents all alternatives that exist in the transaction, by numerical coding. As shown below, our `Hotel_Long` data has 10 alternatives, coded using numbers from 1 to 10.

```r
> rst_reshape$Alts_Code_Desc
# A tibble: 10 x 2
  Alts_Code Room_Type
       <int> <chr>
 1         1 Double Beds Room 1
 2         2 King Room 1
 3         3 King Room 2
 4         4 King Room 3
 5         5 King Room 4
 6         6 Queen Room 1
 7         7 Queen Room 2
 8         8 Special Type Room 1
 9         9 Suite 1
10        10 Suite 2
```

The output `rst_reshape$Rem_Choice_Set`, shows the remaining choice sets expressed as a set of `Alts_Code`. Similar to `Room_Type`, each choice set is coded using numbers, starting from 1. The `Observation` column indicates how often each choice set was exposed in the transaction. Because we set the value of the `min_obs` argument to 30, only the choice set that is exposed more than 30 times, appears here. This is why the second column is labeled as “Remaining.”

```r
> rst_reshape$Rem_Choice_Set
# A tibble: 12 x 3
  Choice_Set_Code Remaining_Choice_Set Observation
       <int> <chr>                 <int>
 1         1 1|2|3|4|5|6|7|8|9|10 150
 2         2 1|2|3|4|5|7|8|9|10  62
 3         3 1|3|4|5|7|8|9|10  75
 4         4 1|4|5|7|8|9|10 341
 5         5 1|4|5|8|9|10  34
 6         6 1|5|7|8|9|10  87
 7         7 1|5|8  37
 8         8 1|5|8|9|10  36
 9         9 2|5|8  32
10        10 4|5|7|8|9|10  34
11        11 4|5|8 127
12        12 5|9|10  85
```

The removed choice sets are listed in `rst_reshape$Removed_Choice_Set`. These are not used in the model because they contain fewer than 30 observations. As a result of `rmr_reshape()`, 34 choice sets are removed from `Hotel_Long`.

```r
> rst_reshape$Removed_Choice_Set
# A tibble: 34 x 2
  Removed_Choice_Set Observation
        <chr>       <int>
 1 1|2|3|4|5|6|7|8|9|10    1
 2 1|2|3|4|5|7|8|9|10    5
 3 1|2|3|5|6|7|8|9|10    8
 4 1|2|4|5|6|7|8|9|10   12
 5 1|2|4|5|7|8|9|10    3
 6 1|2|5|7|8|9|10    2
 7 1|3|4|5|6|7|8|9|10  26
 8 1|3|4|5|6|8|9|10    3
 9 1|3|4|5|7|8|10    8
10 1|4|5|6|7|8|9|10    9
# ... with 24 more rows
```
In rst reshape$ASV, user-specified ASV is stored as wide format.

```r
> rst reshape$ASV

$ASV
# A tibble: 1,100 × 10

Price_1 Price_2 Price_3 Price_4 Price_5 Price_6 Price_7 Price_8 Price_9
 <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1 399 0 0 0 439 0 399 399 499
2 399 0 0 0 439 0 399 399 499
3 399 0 0 0 439 0 0 399 0
4 399 0 0 0 439 0 0 399 0
5 399 0 0 0 439 0 0 399 0
6 399 0 0 0 439 0 0 399 0
7 399 0 0 0 439 0 0 399 0
8 399 0 0 0 439 0 0 399 0
9 0 0 0 319 349 0 0 319 0
10 379 0 0 0 419 0 0 379 479

# ... with 1,090 more rows
```

Data preparation for fitting the CL model is now complete. The following subsection introduces the \texttt{rmm()} function to fit the CL model using the RDE method developed by Cho et al. (2020).

\textbf{rmm()} for fitting the model

The CL model using the RDE method discussed in the previous section is implemented through the main function \texttt{rmm()}. For a detailed description of arguments, see Table \ref{table:3}.

\begin{verbatim}
rmm(rmm_data, prop=0.7)
\end{verbatim}

| Argument   | Explanation                                                                 | Default value |
|------------|-----------------------------------------------------------------------------|---------------|
| \texttt{rmm_data} | S3 class \texttt{rmm_data} which is output of \texttt{rmm reshape()} function. |               |
| \texttt{prop} | numeric, an user-assumed market share.                                       | 0.7           |

\textbf{Table 3:} Arguments to the main function \texttt{rmm()}

The \texttt{rmm()} function allows only the output of \texttt{rmm reshape}, \texttt{rmm_data} S3 class, as an input. The \texttt{prop} argument refers to the market share, additional assumption, as mentioned in Eq. (7). Therefore, it indicates the proportion of the given transaction details to the total market transaction details. As previously discussed, in \texttt{RMM} package, the customer’s choice probability is modeled as a CL model of the mean utility $\nu_i$, as shown in Eq. (1).

Here, we would like to fit the conditional logit model using the robust demand estimation introduced in Cho et al. (2020). Examine the code below:

```r
# Fitting the conditional logit model with a market share of 0.7
rst_rmm <- rmm(rmm_data = rst reshape,
               prop = 0.7)
```

The result of the \texttt{rmm()} function is S3 object class ”\texttt{rmm},” which uses the \texttt{predict.rmm()} method.
The first and second outputs of the `rmm()` function are `rst_rmm$Model`, `rst_rmm$Estimation_Method`, respectively. They indicate that we fitted the CL model using the RDE method. In the third and fourth output, `rst_rmm$Response_Variable`, `rst_rmm$Alternative_Specific_Variables` indicate the response variable and ASVs in our model. The fifth output `rst_rmm$Baseline_Product` is the result of the Baseline Product Search Algorithm mentioned in Algorithm (1). In our example, out of 10 alternatives, the third alternative, "King Room 3," was searched as a baseline product. In `rst_rmm$Coefficient`, we can check the estimated values, standard errors, and P-values of each parameter in the model. Additionally, following the robust demand estimation procedure, it is possible to estimate the number of customers who have returned without purchasing products, with `rst_rmm$No_Purchase` and `rst_rmm$Total_Arrivals` indicating these estimates.

```r
> class(rst_rmm) # S3 class "rmm"
[1] "rmm"
```

The next subsection demonstrates how to make predictions when new data are given. We use the model estimated in this subsection.

**predict() for prediction**

The `predict()` function allows users to obtain predictions from the estimated model. See table 4 for a detailed description of the arguments.
predict(object, newdata, Rem_Choice_Set, Choice_Set_Code, fixed = TRUE, ...)  

| Argument        | Explanation                                                                 | Default value |
|-----------------|-----------------------------------------------------------------------------|---------------|
| object          | Object of class inheriting from ‘rmm’.                                       |               |
| newdata         | new data to be used for prediction.                                         |               |
| Rem_Choice_Set  | List of choice sets remaining in the data.                                  |               |
| Choice_Set_Code | Specifies the choice set of new data.                                       |               |
| fixed            | If fixed=TRUE, the alternative with the highest prediction probability is determined as decision. Otherwise (fixed=FALSE), one of the alternatives is sampled in proportion to the predictive probability. | TRUE          |
| ...             | further arguments passed to or from other methods.                         |               |

**Table 4: Arguments to the function predict()**

In the object argument, we insert the output object of the rmm() function. Note that, the Rem_Choice_Set argument must specify the remaining choice set which is the output of the rmm_reshape() function. As discussed earlier, this can be seen as rst.reshape$Rem_Choice_Set.

```r
> Rem_Choice_Set <- rst_reshape$Rem_Choice_Set
> Rem_Choice_Set
```

# A tibble: 12 x 3

| Choice_Set_Code | Remaining_Choice_Set | Observation |
|-----------------|----------------------|-------------|
| <int>           | <chr>                | <int>       |
| 1               | 1|2|3|4|5|6|7|8|9|10 | 150 |
| 2               | 1|2|3|4|5|7|8|9|10 | 62  |
| 3               | 1|3|4|5|7|8|9|10 | 75  |
| 4               | 1|4|5|7|8|9|10 | 341 |
| 5               | 1|4|5|8|9|10 | 34  |
| 6               | 1|5|7|8|9|10 | 87  |
| 7               | 7|1|5|8  | 37  |
| 8               | 8|1|5|8|9|10 | 36  |
| 9               | 9|2|5|8  | 32  |
| 10              | 10|4|5|7|8|9|10| 34  |
| 11              | 11|4|5|8  | 127 |
| 12              | 12|5|9|10 | 85  |

Suppose that the new data for prediction is given as follows. According to the Choice_Set_Code, this data assumes the situation exposed to Choice_Set_Code 7. Because products numbered 1, 5, and 8 belong to Choice_Set_Code 7, their attributes, Price (alternative specific variable) can be seen in the new data. newdata1 has five observations or five situations in which each individual is exposed to different prices.

```r
> newdata1 <- data.frame(Price_1=c(521, 321, 101, 234, 743),
+                       Price_5=c(677, 412, 98, 321, 382),
+                       Price_8=c(232, 384, 330, 590, 280))
> print(newdata1)
```

| Price_1 | Price_5 | Price_8 |
|---------|---------|---------|
| 521     | 677     | 232     |
| 321     | 412     | 384     |
| 101     | 98      | 330     |
| 234     | 321     | 590     |
| 743     | 382     | 280     |

To predict the choice probability with this newdata1, the arguments of the predict() function can be specified as follows. The first output rst.pred1$Model indicates the type of prediction model. The second and third outputs are the prediction results, with rst.pred1$Decision showing the code number of the product selected from the products exposed to each individual. rst.pred1$Probability
represents the probability of each individual choosing one of the exposed products. Because the value of the fixed argument is TRUE, the product corresponding to the highest choice probability is determined as Decision.

```r
> rst_pred1 <- predict(object = rst_rmm,
+                     newdata = newdata1,
+                     Rem_Choice_Set = Rem_Choice_Set,
+                     Choice_Set_Code = 7,
+                     fixed = TRUE)
> print(rst_pred1)

$Model
[1] "Prediction by Conditional Logit Model."

$Decision
[1] 8 1 5 1 8

$Probability
   Alts_1 Alts_5 Alts_8
[1,] 0.032273722 0.006073611 0.961652667
[2,] 0.573101692 0.251077881 0.175820427
[3,] 0.396453969 0.589491288 0.014054743
[4,] 0.681064726 0.314302956 0.004632318
[5,] 0.002256071 0.352244224 0.645499705

To examine the case where fixed=FALSE, suppose that newdata2 is given. These data are of three people exposed to Choice_Set_Code 3.

```r
newdata2 <- data.frame(Price_1=c(232, 122, 524), Price_3=c(152, 531, 221),
   Price_4=c(123, 743, 192), Price_5=c(139, 535, 325),
   Price_7=c(136, 276, 673), Price_8=c(387, 153, 454),
   Price_9=c(262, 163, 326), Price_10=c(421, 573, 472))
```  

Similar to prediction with newdata1, arguments can be set as follows. However, fixed = FALSE determines the product in proportion to each choice probability. In rst_pred2$Probability, it can be seen that the first customer has the highest choice probability for the fourth product (Alt_4), which is 0.4887, but the final decision is the third product. This is the difference between fixed = TRUE and fixed = FALSE.

```r
> rst_pred2 <- predict(object = rst_rmm,
+                     newdata = newdata2,
+                     Rem_Choice_Set = Rem_Choice_Set,
+                     Choice_Set_Code = 3,
+                     fixed = FALSE)
> print(rst_pred2)

$Model
[1] "Prediction by Conditional Logit Model."

$Decision
[1] 3 8 4

$Probability
   Alts_1 Alts_3 Alts_4 Alts_5 Alts_7 Alts_8
[1,] 0.059017764 0.0439933498 0.4887438272 0.282743835 0.0761297013 0.005475253
[2,] 0.514723134 0.0006655305 0.0003222683 0.003429207 0.0257447096 0.239374472
[3,] 0.004973822 0.0673153629 0.7478395764 0.094527281 0.0002654811 0.008598506

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## 4 Conclusion

The **RMM** is a useful package for estimating the following factors: (1) the customer’s choice probability and (2) the number of no-purchase customers given censored transaction data with different choice sets and product prices exposed to each individual. Accordingly, **RMM** uses a CL model with robust demand estimation procedure, introduced in Cho et al. (2020). To the best of our knowledge, **RMM** is the only package useful for handling censored sales data by employing a CL model. **RMM** package can be applied without limitation as long as the data can be fitted using the CL model even if it is not transaction data. Therefore, ASVs, which indicate the characteristics of each attribute, exist as independent variables.

The current version of the **RMM** has some limitations. If multiple attributes are used to fit the model using the `rmm()` function, only a no-interaction model can be used. For example, if there are two ASVs as an independent variable, a linear additive model such as $ASV_1 + ASV_2$, can be used. However, if a model includes an interaction effect such as $ASV_1 \times ASV_2$, it cannot be fitted. Also, a multinomial logit model, which is another popular customer’s choice model, is not yet covered by **RMM**. However, the second issue will be resolved in the next version of **RMM**.

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