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validateHOT - an R package for holdout task validation and market simulations

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Software

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Summary

validateHOT is an R package that provides functions to both validate a validation/holdout task and run market simulations for results obtained in a (adaptive) choice-based conjoint analysis (hereafter ACBC and CBC, respectively) and maximum difference scaling (hereafter MaxDiff) using, for example, ChoiceModelR (Sermas, 2022) or Sawtooth's Lighthouse Studio.

Statement of need

The aim of preference measurement techniques' (e.g., (A)CBC or MaxDiff) is to predict behavior (Green & Srinivasan, 1990). Hence, it is essential for both researchers and practitioners to ensure that the data collected is valid and predicts outside tasks (i.e., the model has external validity) well.[1] The simplest way for testing validity is to include so-called validation or holdout tasks (Orme, 2015; e.g., Rao, 2014), which are tasks that are fixed (i.e., same across participants) and are typically not used for estimating the part-worth utilities (raw logit utilities) in hierarchical Bayes estimation. Despite the importance of validation/holdout tasks, practitioners do not always include them (Yang et al., 2018). This is unsatisfactory given the fact that the model is used to estimate market shares which poses the basis for relevant marketing decisions.

validateHOT combines both validation and market simulation in one package and has three main advantages, it (1) helps to opt for the best model and (2) performs relevant market simulations that help, for example, to find the right product combination or assortment, and (3) is an open source tool that helps especially researchers to report accompanied scripts for their research.

State of the field in R

Other packages provide functions to calculate validation metrics, however, these are not specified for individual raw logit coefficients which are usually the output when running random parameter logit / hierarchical Bayes models. Metrics (Hamner & Frasco, 2018), for example, provides functions to run validation metrics such as *mean absolute error*, *root mean squared error*, or the five metrics of the confusion matrix. However, to get the output of, for example, Sawtooth Software or ChoiceModelR (Sermas, 2022) into the right format, the user needs some data wrangling. The conjoint (Bak & Bartlomowicz, 2012) package provides functions that are most similar to those of validateHOT. However, it does not include any functions for validation and moreover, conjoint (Bak & Bartlomowicz, 2012) focuses on classical conjoint

[1] In terms of external validity, we refer to the generalizations to different settings (see, Calder et al., 1982, p. 240).

analysis and is therefore limited when using more common conjoint methods, for example, (A)CBC. support.BWS (Aizaki & Fogarty, 2023) only covers best-worst scaling case 1 (also known as MaxDiff) and provides market simulations based on conditional logit rule. logitr (Helveston, 2023), besides running multinomial and mixed logit models, also offers functions to run market simulations tools. However, it currently does not provide validation metrics such as mean hit probability (Voleti et al., 2017) or hit rate (Netzer & Srinivasan, 2011).

A comparison of validateHOT's functions with current R packages is shown in Figure 1. To the best of our knowledge, a package that converts raw utility scores into validation metrics or running a variety of marketing simulations (especially TURF) is missing.

Key functionalities	validateHOT (v 1.0.0)	Metrics (v 0.1.4)	caret (v 6.0-94)	conjoint (v 1.4)	philentropy (v 0.7.0)	logitr (v 1.1.1)	mlogit (v 1.1-1)	support.bws (v 0.4-6)
Confusion matrix	✓	✓	✓					
Creating design matrix				✓		✓	✓	✓
Creating holdout / market scenario	✓			✓		✓		
Estimate utilities				✓		✓	✓	✓
Estimate WTP						✓		
Hit rate	✓							
Kullblack-Leibler-Divergence	✓				✓			
MAE, MedAe, RMSE	✓	✓	✓					
Market Shares	✓		✓	✓		✓		✓
Mean hit probability	✓							
TURF	✓							

Figure 1: Comparison of validateHOT's function to existing R packages

validateHOT is introduced with data estimated using Lighthouse Studio. It, however, can easily be used with data estimated with ChoiceModelR (Sermas, 2022), bayesm (Rossi, 2023), or STAN (2023).

Key functions

validateHOT's functions can be categorized into four main components, see Table 1. To bring the data into the right format, users can run the `createHOT()` function, which creates the total utility of each alternative by applying the additive utility model (Rao, 2014, p. 82). `turf()` as well as the four rescaling functions, however, are not dependent on `createHOT()` and can be run using the raw logit scores.

Table 1: Overview of validateHOT's main four components and their corresponding functions

Validation metrics	Confusion matrix	Market simulations	Rescaling scores
hitrate()	accuracy()	freqassort()	att_imp()
kl()	f1()	marksim()	prob_scores()
mae()	precision()	reach()	zc_diffs()
medae()	recall()	turf()	zero_anchored()
mhp()	specificity()		
rmse()			

Typical workflow

In the following, we provide the workflow for a MaxDiff study and a CBC study with only part-worth coded attributes (the vignette also provides detailed examples for a CBC including linear-coded attributes as well as an ACBC).

MaxDiff

Creating Holdout Task / Market Scenario

After running the hierarchical Bayes estimation (Allenby & Ginter, 1995; Lenk et al., 1996), the **raw** utility scores have to be exported and read into an R data frame. This data frame must contain the actual choice in the validation/holdout task (if only a market scenario is created, the `choice` argument can be left empty).

Suppose you have a validation/holdout task with a total of 7 alternatives plus the no-buy alternative (`none`). To create this validation task in R, we use the `createHOT()` function.

```
HOT <- createHOT(
  data = MaxDiff,
  id = "ID",
  none = "none",
  prod.levels = list(3, 10, 11, 15, 16, 17, 18),
  method = "MaxDiff",
  choice = "HOT",
  varskeep = "Group"
)
```

Validating Holdout Task

In the following, we provide the hitrate, a metric that is often reported as validation metric (see, e.g., Ding et al. (2005); Sablotny-Wackershauser et al. (2024)). `hitrate()` requires the data, the alternatives in the validation/holdout task (`opts`), and the actual choice (`choice`). The input can be implemented using the tidyverse (Wickham et al., 2019) logic. The setup is the same for other metrics that are often reported, for example, mean hit probability (mhp, Voleti et al., 2017) or mean absolute error (mae, Wlömert & Eggers, 2014).

```r
hitrate(
  data = HOT,
  opts = c(Option_1:None),
  choice = choice
) %>%
  round(2)
```

```
## # A tibble: 1 x 5
##      HR    se chance   cor     n
##   <dbl> <dbl>  <dbl> <dbl> <dbl>
## 1  55.7  5.98   12.5    39    70
```

validateHOT also includes the Confusion Matrix. The underlying logic in validateHOT is that the user must provide a no-buy alternative (`none`). validateHOT calculates how often a buy or no-buy was correctly predicted and, therefore, tests whether the model correctly predicts the general demand (here by applying `accuracy()`).

```r
accuracy(
  data = HOT,
  group = Group,
  opts = c(Option_1:None),
  choice = choice,
  none = None
) %>%
  round(2)
```

```
## # A tibble: 3 x 2
##   Group accuracy
##   <dbl>    <dbl>
## 1     1     73.9
## 2     2     72
## 3     3     63.6
```

Market Simulations

Lastly, two functions for market simulations are introduced, namely `marksim()` and `turf()`. In the following example, the market share is calculated according to the multinomial logit model (McFadden, 1974).

```r
marksim(
  data = HOT,
  opts = c(Option_1:None),
  method = "sop"
) %>%
  mutate_if(is.numeric, round, 2)
```

```
## # A tibble: 8 x 5
##   Option      mw    se lo.ci up.ci
##   <chr>    <dbl> <dbl> <dbl> <dbl>
## 1 Option_1 18.3   4.12 10.2   26.4
## 2 Option_2 11.3   2.69  6.05 16.6
## 3 Option_3  4.08  1.49  1.16  6.99
## 4 Option_4 32.5   4.45 23.8   41.2
## 5 Option_5  1.93  0.92  0.13  3.72
## 6 Option_6 10.4   2.68  5.12 15.6
## 7 Option_7  5.58  1.75  2.15  9.01
## 8 None     16.0   3.29  9.53 22.4
```

Next, turf(), a "product line extension model" (Miaoulis et al., 1990, p. 29), is a tool to find the perfect assortment that creates the highest reach and is particularly powerful for MaxDiff studies (Chrzan & Orme, 2019, p. 108). To optimize the search for the optimal bundle, we also add the arguments fixed, to define alternatives that have to be part of the assortment, and prohib, to prohibit certain item combinations of being part of the assortment (see the vignette for more details and the application of turf() with data obtained using a Likert scale).

For the following example, let's assume that the user conducted an anchored MaxDiff analysis with 10 items (opts) and now wants to find the best assortment with a size of 3 items. The user uses the anchor (no-buy alternative) as a threshold.

```
turf(
  data = MaxDiff,
  opts = c(Option_01:Option_10),
  none = none,
  size = 3,
  approach = "thres"
) %>%
  head(., n = 5) %>%
  mutate_if(is.numeric, round, 2) %>%
  t() %>%
  as.data.frame() %>%
  slice(-1) %>%
  rename_all(., ~ paste0("Combo ", c(1:5)))
```

```
##           Combo 1 Combo 2 Combo 3 Combo 4 Combo 5
## reach       82.86   81.43   81.43   81.43   80.00
## freq         1.46    1.57    1.43    1.41    1.44
## Option_01       1       1       1       1       1
## Option_02       0       0       1       0       0
## Option_03       0       1       0       0       0
## Option_04       1       0       1       1       0
## Option_05       0       0       0       0       0
## Option_06       1       1       0       0       1
## Option_07       0       0       0       0       0
## Option_08       0       0       0       0       1
## Option_09       0       0       0       0       0
## Option_10       0       0       0       1       0
```

CBC

Creating Holdout Task / Market Scenario

The setup is almost the same, only the arguments prod.levels, coding, and method are different or new, respectively.

```r
HOT_CBC <- createHOT(
  data = CBC,
  id = "ID",
  none = "none",
  prod.levels = list(c(4, 9, 19), c(8, 12, 17), c(5, 10, 17)),
  coding = c(0, 0, 0),
  method = "CBC",
  choice = "HOT"
)
```

Validating Holdout Task

This time we calculate the mean hit probability (i.e., MHP).

```r
HOT_CBC %>%
  mhp(
  data = .,
  opts = c(Option_1:None),
  choice = choice
) %>%
  round(2)
```

```
## # A tibble: 1 x 2
##     MHP    se
##   <dbl> <dbl>
## 1  40.6  3.53
```

Rescaling Scores

Finally, we can also display the attributes importance scores. Therefore, we need to define the attribute levels as well as the coding of the attributes.

```r
att_imp(
  data = CBC,
  attrib = list(
    c(4:8),
    c(9:13),
    c(14:20)
  ),
  coding = c(rep(0, 3)),
  res = "agg"
) %>%
  mutate_if(is.numeric, round, 2)
```

```
## # A tibble: 3 x 3
##   Option        mw   std
##   <chr>      <dbl> <dbl>
## 1 att_imp_1   35.7 11.3
## 2 att_imp_2   27.7 10.0
## 3 att_imp_3   36.6  9.32
```

Availability

validateHOT is available on [Github](https://github.com).

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