# **KU LEUVEN**

# **Extending Idefix package**

Intermediate presentation

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#### 0 Outline

- 1 Introduction
- 2 Modified Fedorov Algorithm
- 3 Kullback-Leibler criterion
- 4 Coordinate Exchange Algorithm
- 6 Simulation study

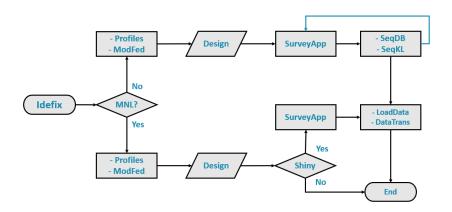
#### Outline

- Introduction

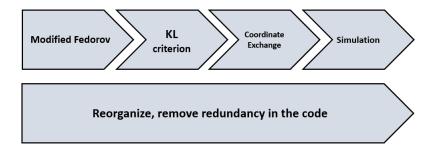
### 1 What is *idefix* R package for?

- ► To create optimal designs for discrete choice experiments (DCEs) based on the multinomial logit model (MNL) and
- Individually adapted designs for the mixed multinomial logit model (MIXL).
- Available on CRAN (v 0.3.3).

### 1 Current state of the package



#### 1 Objectives



### 1 Multinomial Logit Model

- ▶ Respondent's utility is  $u_{js} = \mathbf{x}_{js}' \boldsymbol{\beta} + \epsilon_{js}$ , where  $\boldsymbol{\beta}$  is a vector of parameters and  $\epsilon_{js}$  is an i.i.d. extreme value error term.
- lacktriangle Probability a respondent chooses alternative j in choice set s is

$$p_{js} = \frac{e^{\mathbf{x}'_{js}\beta}}{\sum_{t=1}^{J} e^{\mathbf{x}'_{ts}\beta}}$$

Information Matrix is

$$\mathbf{M}(\mathbf{X}, \boldsymbol{\beta}) = N \sum_{s=1}^{S} \mathbf{X}_{s}' (\mathbf{P}_{s} - \mathbf{p}_{s} \mathbf{p}_{s}') \mathbf{X}_{s}$$

### 1 D-optimality

- ightharpoonup To obtain precise estimates of  $oldsymbol{eta}$
- ▶ In OLS, minimize  $D = |M^{-1}(\mathbf{X})| = |(\mathbf{X}'\mathbf{X})^{-1}|$
- $\triangleright$  In MNL is defined adopting the prior distribution of  $\beta$

$$D_B = \int_{\mathcal{R}^k} \left\{ \det \left( \mathbf{M}^{-1}(\mathbf{X}, \boldsymbol{\beta}) \right) \right\}^{1/k} \pi(\boldsymbol{\beta}) d\boldsymbol{\beta}$$

Where k is the number of unknown parameters in the model and  $\pi(\beta)$  is the prior distribution of  $\beta$ . This criterion is also called Bayesian D-optimality criterion or just  $D_B$ .

### 1 Mixed Multinomial Logit model

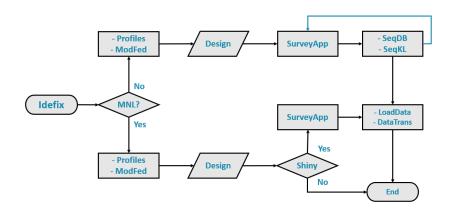
- MNL models assume that the respondents have the same preferences,  $\beta$ , for the attributes studied in the experiment.
- MIXL models assume that the individual preferences,  $\beta_n$ , follow a certain distribution across respondents  $(\beta_n \sim f(\mu_\beta, \sigma_\beta))$ .

#### Individually Adapted designs

The proper name of the methodology is *Individually adapted* sequential Bayesian design. It consists in two stages:

- Initial static design
- Adaptative sequential design

### 1 Current state of the package

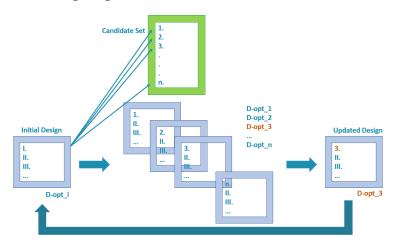


#### Outline

- 2 Modified Fedorov Algorithm

### 2 Modified Fedorov Algorithm

#### Point exchange algorithm



# First activity: Improve processing time in individually adapted designs.

SeqDB function selects the next DB-efficient choice set given parameter values and an initial design.

#### Example

Considering  $3^3/2/8$  design:



#### How to make it faster?

Using Hadley Wickham approach in his book Advanced R:

- 1 Find the biggest bottleneck (the slowest part of the code).
- 2 Try to eliminate it (you may not succeed but that is ok).
- 3 Repeat until your code is **fast enough**.

#### How to make it faster?

Using Hadley Wickham approach in his book *Advanced R*:

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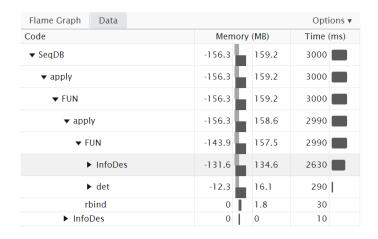
#### But, how to make it faster?

- Using faster functions in R and avoiding loops using vectorized functions.
- Implementing parts of the code in C++.

#### Find the biggest bottleneck

- ▶  $4 \times 3 \times 2/2/8$  design.
- ▶ 10 draws from  $\beta$  distribution.
- Pre-defined initial design and alternatives chosen (1st stage of IASB approach).

#### **Profiling SeqDB function**



#### Implementation in C++

- ► Use of Rcpp package
- ▶ Use of Rcpp Armadillo: C++ linear algebra library

#### Implementation in C++

- Use of Rcpp package
- Use of Rcpp Armadillo: C++ linear algebra library

```
InfoDes <- function(par, des, n.alts)</pre>
  group <- rep(seg(1, nrow(des) / n.alts, 1), each = n.alts)
  # probability
  u <- des %*% diag(par)
  u <- .rowSums(u, m = nrow(des), n = length(par))
  p <- exp(u) / rep(rowsum(exp(u), group), each = n.alts)</pre>
  # information matrix
  info.des <- crossprod(des * p, des) - crossprod(rowsum( des * p, group))
  return(info.des)
```

10 lines of code

#### Implementation in C++

- Use of Rcpp package
- Use of Rcpp Armadillo: C++ linear algebra library

```
InfoDes <- function(par, des, n.alts) {
  group <- rep(seq(1, nrow(des) / n.alts, 1), each = n.alts)
  # probability
  u <- des %*% diag(par)
  u <- .rowSums(u, m = nrow(des), n = length(par))
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  # information matrix
  info.des <- crossprod(des * p, des) - crossprod(rowsum( des * p, group))
  return(info.des)
}

// [[Rcpp::depends(RcppArmadillo)]]

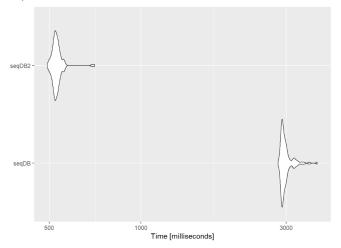
// using namespace Rcpp;</pre>
```

10 lines of code

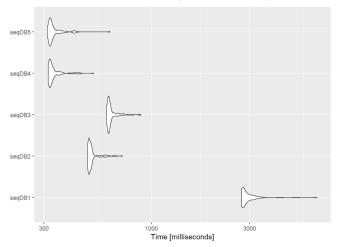
lines of code

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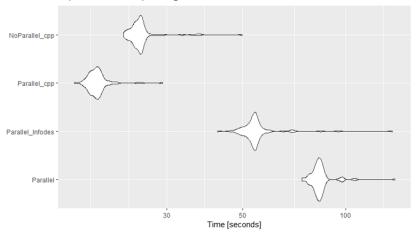
**Result:** Implementation in C++ is almost 6x faster.



Find next bottleneck and improve it (multiple times)



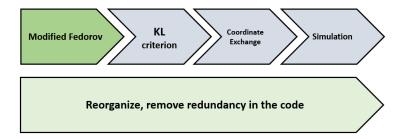
### What about parallel computing?



#### Second activity: Improve processing time in MNL designs

- The hardest work had already been done
  - Find bottlenecks
  - Improve functions in C++
- ModFed processing time was also improved by using the same functions as in SeqDB.

# 2 Progress



#### Outline

- Kullback-Leibler criterion

#### 3 Kullback-Leibler criterion

- It was developed under individually adapted designs for the MIXL.
- It is an alternative to D-optimal criterion.
- It is faster to compute and it provides equally efficient designs.
- ▶ It is based on the Kullback-Leibler information:

$$KL(f,g) = \int f(x)log\frac{f(x)}{g(x)}dx$$

Where f and g are continuous densities of X.

#### 3 Kullback-Leibler criterion

#### Implementation in DCEs

- $\blacktriangleright$  Maximize the KL between the current posterior of  $\beta$  and the updated posterior one can obtain with the additional response from the next choice set.
- Since there are multiple alternatives, the expectation over all possible choices is maximized.

$$KLP = \sum_{j=1}^{J} \pi(y_{jsn}|\mathbf{y}_n^{s-1})KL\left[f(\boldsymbol{\beta}_n|\mathbf{y}_n^{s-1}), f(\boldsymbol{\beta}_n|\mathbf{y}_n^{s-1}, y_{jsn})\right]$$

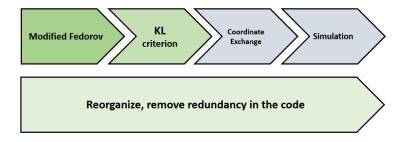
- Modified Fedorov algorithm.
- Simulations in R are not consistent with results obtained in the paper that proposed the criterion.

#### 3 Kullback-Leibler criterion

#### Third activity: Check why SeqKL function is not working

- Check code of simulations done in the paper that proposed the criterion.
  - Made in SAS. Proc IML.
  - 490 lines of code. No comments, no indentation.
- Check code of implementation in R
- Comparison of results from each function in both implementations.
- List differences.
- Discussion.

#### 3 Progress

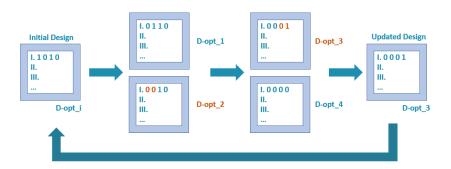


#### Outline

- 4 Coordinate Exchange Algorithm

### 4 Coordinate Exchange Algorithm

- ▶ Compute optimality criterion  $\sum_{j=1}^{J} l_j$  times for each row.
- Point exchange algorithm: Compute optimality criterion  $\prod_{j=1}^{J} l_j$  times for each row.



### **Coordinate Exchange Algorithm**

#### Fourth activity: Implement the Coordinate Exchange algorithm

- Implementation with only categorical factors/attributes.
- Implementation with continuous attributes.
- 3 Implementation with both categorical and continuous.
- Improve processing time, if possible (parallel computing, C++).

#### Note:

D-optimality criterion is going to be used, so the implementation of the information matrix in C++ is also going to be used here.

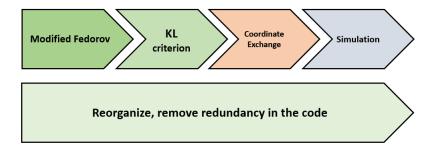
#### Outline

- Simulation study

### 5 Simulation study

- Compare the processing time of Modified Fedorov algorithm and the Coordinate Exchange algorithm.
  - Determine the scenarios where one outperforms the other.
  - Determine in which situations parallel computing is needed.
- lacktriangle Compare efficiency of designs found with D-optimality criterion and KL criterion.
  - Determine the scenarios where one outperforms the other.

### 5 Objectives



### 5 Optimality criteria

- ightharpoonup To obtain precise estimates of eta
  - D—optimality: minimize the determinant of the variance-covariance matrix of β
  - A-optimality: minimize the trace of the variance-covariance matrix of  $oldsymbol{\beta}$
- ► To obtain precise response predictions
  - ullet G-optimality: minimize the maximum prediction variance
  - ullet V-optimality: minimize the average prediction variance

#### Note:

These criteria are based on the information matrix, which depends on the unknown values in  $\beta$  through the probabilities  $p_{js}$ . Therefore, a Bayesian strategy that integrates the design criteria over a prior parameter distribution  $\pi(\beta)$  is adopted. Usually, the prior is a multivariate normal distribution.

### 5 Modified Fedorov Algorithm

#### Example

- ▶ Design  $3^3/2/8 \Rightarrow$  Design matrix  $16 \times 6$  (dummy coding).
- ▶ Candidate set has  $3^3 = 27$  rows/profiles
- ▶ In each iteration,  $D_B$  is computed  $16 \times 27 = 432$  times.
- Assuming just 10 draws,  $D_B$  is computed 4320.
- Assuming 10 initial designs, the final number of  $D_B$  computed is 43200.

# 5 Coordinate Exchange Algorithm

#### Example

- ▶ Design  $3^3/2/8 \Rightarrow$  Design matrix  $16 \times 6$  (dummy coding).
- No Candidate set is needed.
- ▶ In each iteration,  $D_B$  is computed  $16 \times 9 = 144$  times.
- Assuming just 10 draws,  $D_B$  is computed is 1440.
- Assuming 10 initial designs, the final number of  $D_B$  computed is 14400.

As a reminder, in Modified Fedorov the final number was 43200.

### 5 Parallel computing

- 1 Create set of copies of R running in parallel
- 2 Send data required to those copies
- 3 Split the task in chunks and send each chunk to each copy
- 4 Wait for all copies to complete their tasks
- 5 Combine results
- 6 Close and delete these copies

This procedure is used to compute the  $D_B$ , where for each draw from the prior a correspondent D-optimality value is computed.

#### 5 KL criterion

#### List of differences

- ► A minus sign missing in a function. ✓
- Number of degrees of freedom for the multivariate t distribution (importance distribution).  $\checkmark$
- ▶ Difference in the density of the multivariate *t* distribution.
- Generation of lattice points.

### 5 Objectives

- 1 Improve processing time of the **Modified Fedorov algorithm** by implementing some parts of the algorithm in C++.  $\checkmark$
- 2 Implement the **KL criterion** and compare it with the function that is already available in the package. ✓
- 3 Implement the Coordinate Exchange algorithm to create optimal designs.
- 4 Make a **simulation study** to compare processing times and optimality of designs between the Modified Fedorov algorithm, the Coordinate Exchange algorithm and the use of DB and KL criteria.
- 5 Reorganize some functions inside the package, remove possible redundancy in code and implement parts of the code in C++. ✓