

# **Design replication in partial-profile choice experiments**

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# Outline

- ▶ Motivation
- ▶ Technical background
- ▶ Design replication
- ▶ Simulation study

# Motivating example

## Question 1

Which of the two explanations below would help you most to understand and manage your own osteoarthritis?

Explanation 1A	Explanation 1B
<p>Osteoarthritis is the most common form of arthritis in the UK</p> <p>Pain, stiffness, and limitation in full movement of the joint are typical</p> <p>You can take steps to improve your osteoarthritis, by being physically active, maintaining a healthy weight and thinking positively. This can help how you feel and what you can do now, and may help to avoid the need for more treatments in future. Support is available to help you to achieve this</p> <p>Even a modest weight loss can make quite a difference</p>	<p>You have osteoarthritis, a condition which can affect the whole joint and surrounding muscles</p> <p>Osteoarthritis can affect your joints in different ways at different times, sometimes you may not have any difficulties but at other times you might</p> <p>There is no cure for osteoarthritis but there are a number of things that can be done to ease symptoms</p> <p>Even a modest weight loss can make quite a difference</p>

Please tick one box only

Explanation 1A

Explanation 1B

R3-S253-Q2017-B2C01MDP163

# Motivating example

## Question 5

Which of the two explanations below would help you most to understand and manage your own osteoarthritis?

Explanation 5A	Explanation 5B
<p>Osteoarthritis is caused by an ongoing process of wear and the joint trying to heal itself</p>	<p>Osteoarthritis occurs perhaps because of severe wear and tear to the joints or a problem with the repair process, and osteoarthritis develops</p>
<p>It is mild in many cases; however, about 1 in 10 people aged over 65 years have a major disability due to osteoarthritis</p>	<p>It is mild in many cases; however, about 1 in 10 people aged over 65 years have a major disability due to osteoarthritis</p>
<p>Many people can manage a regular walk</p>	<p>It can be easier to keep moving if you build up from where you are now and put new activities to improve your osteoarthritis in to your daily routine</p>
<p>Keeping active and maintaining a healthy weight are best for your osteoarthritis in the long run, even though some social activities can make this difficult</p>	<p>Many people are afraid to exercise because they believe, mistakenly, that it'll cause further damage to their joints</p>

Please tick one box only

Explanation 5A

Explanation 5B

R1-S022-Q0173-B1C10MDP170

# Partial profiles

Full profiles ...

... use **all** factors

A2	A1
B1	B2
C2	C1
D1	D1

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Profile strength  $S$ :

Comparison depth  $d$ :

Number of factors **shown**

Number of shown factors where  
alternatives **differ**



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$K$  factors with levels  $1, \dots, v_k$ ,  $k = 1, \dots, K$ , of interest  
and extra level 0 to indicate factor is not shown

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MNL probability of choosing  $\mathbf{s}$  from pair  $(\mathbf{s}, \mathbf{t})$ :

$$P(\mathbf{s}; (\mathbf{s}, \mathbf{t})) = \frac{\exp[\mathbf{f}^\top(\mathbf{s})\boldsymbol{\beta}]}{\exp[\mathbf{f}^\top(\mathbf{s})\boldsymbol{\beta}] + \exp[\mathbf{f}^\top(\mathbf{t})\boldsymbol{\beta}]}$$

# Design efficiency

Exact partial-profile designs  $\xi_N$ : pairs  $(\mathbf{s}_1, \mathbf{t}_1), \dots, (\mathbf{s}_N, \mathbf{t}_N)$

Fisher information matrix of  $\xi_N$  in MNL Model:  $\mathbf{M}_{\xi_N, \beta}$

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▶  $\mathbf{M}_{\xi_N, \beta} = \mathbf{M}_{\xi_N, \mathbf{0}} = \frac{1}{4} \mathbf{X}^\top \mathbf{X}$

where  $\mathbf{X}$  has rows  $\mathbf{f}^\top(\mathbf{s}_n) - \mathbf{f}^\top(\mathbf{t}_n)$ ,  $n = 1, \dots, N$

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▶  $D$ -efficiency of  $\xi$

$$\text{eff}_D(\xi_N) = 100 \times \left( \frac{\det(\mathbf{M}_{\xi_N, \mathbf{0}}/N)}{D_{\text{opt}}} \right)^{1/p}$$

where  $D_{\text{opt}}$  is determinant of information matrix of  $D$ -optimal approximate design



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▶  $D_{\text{opt}}$  for ME and ME + 2FI models: GGHS

# The question of replication

Given

- ▶ maximum number of respondents  $T$
- ▶  $q$  choice questions per respondent
- ▶ exact base design  $\xi_N$  of size  $N < qT$

How to replicate  $\xi_N$  ?

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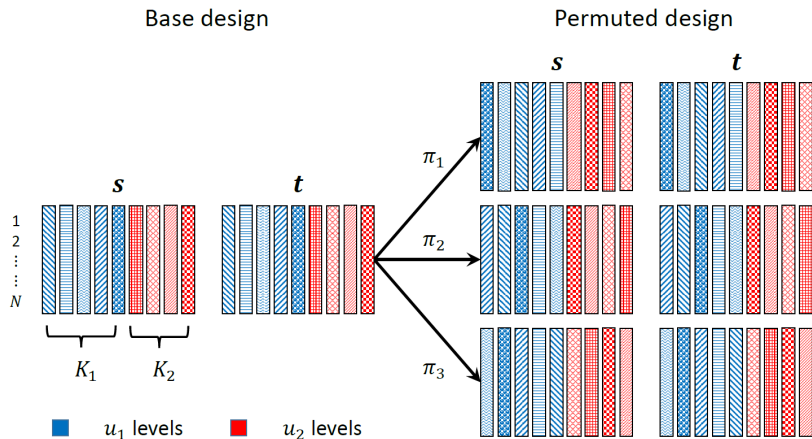
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# Illustration of factor permutation



# Properties of factor permutation

Consider exact base design  $\xi_N$  and design  $\xi_{RN}$  consisting of  $R$  factor-permuted replicates of  $\xi_N$  for ME or ME + 2FI model

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Justification: equivariance of  $\mathbf{f}$ , convexity and invariance under orthogonal transformations of (appropriate) criterion function for  $D$ -optimality

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▶  $\mathbf{M}_{\xi_N,0}$  block diagonal  $\Rightarrow \mathbf{M}_{\xi_{RN},0}$  block diagonal

# Example for simulation study

Entscheidung 1 von 10:

	Operation A	Operation B
Wahrscheinlichkeit für dauerhafte Inkontinenz. 🚰	0 von 100 Personen 	1 von 100 Personen 
Häufigkeit des Wasserlassens in der Nacht. 🌙	1 Mal pro Nacht	3 Mal pro Nacht
Dringlichkeit des Wasserlassens. 🚽	Sofort auf Toilette müssen	30 Minuten einhalten können
Dauer des Wasserlassens. ⏱	6 Minuten	3 Minuten
Wahrscheinlichkeit einer erneuten Operation. 🏠	20 von 100 Personen 	10 von 100 Personen 
Würden Sie Operation A oder B wählen?	<input type="radio"/>	<input type="radio"/>

Entscheidung 2 von 10:

	Operation A	Operation B
Wahrscheinlichkeit für dauerhafte Inkontinenz. 🚰	0 von 100 Personen 	5 von 100 Personen 
Häufigkeit des Wasserlassens in der Nacht. 🌙	3 Mal pro Nacht	5 Mal pro Nacht
Veränderung der Erektionsfähigkeit. 📈	➡️ Nimmt sehr gering ab	↔️ Unverändert
Wahrscheinlichkeit einer erneuten Operation. 🏠	10 von 100 Personen 	0 von 100 Personen 
Wahrscheinlichkeit für eine Funktionsstörung des Samenergusses. 🧠	65 von 100 Personen 	5 von 100 Personen 
Würden Sie Operation A oder B wählen?	<input type="radio"/>	<input type="radio"/>

# Simulation study



# Simulation study

- ▶  $3^5 \times 4^4$  main-effects model
  - ▶  $p = 22$  parameters
  - ▶  $S = d = 5$  factors with distinct levels per question

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- ▶ Survey
  - ▶ Maximum sample size: 200 respondents
  - ▶ Expected response rate: 25%
  - ▶ 8 choice pairs per person

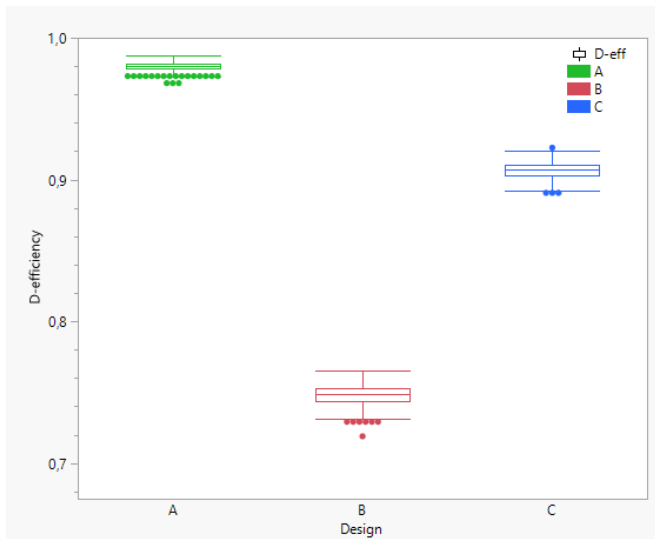
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- ▶ Base designs and replication
  - A  $D$ -opt. (GGS09,  $N = 528$  pairs, D-eff: 100%), 3 permuted reps
  - B  $D$ -eff. (JMP,  $N = 44$  pairs, D-eff:  $\approx 77\%$ ), 36 non-permuted reps
  - C B, 36 permuted reps

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  - C B, 36 permuted reps
- ▶ Simulation of 1000 surveys
  - ▶ Per survey:  $200/4 = 50$  respondents with 8 pairs each
  - ▶ For each of A, B, C and each survey: realized design with 400 pairs
  - ▶ Compare  $D$ -efficiencies of 1000 realized designs

# Results



# Conclusions

- ▶ When applicable, replication with factor permutation preferable to simple repetition of base design
- ▶ Factor permutation increases  $D$ -efficiency
- ▶ Permutation approach works well with both analytical and algorithmic  $D$ -optimal or  $D$ -efficient base designs
- ▶ Suggestion for algorithmic designs: Use larger number of choice sets than “usual”

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