Visual Conjoint Experiments

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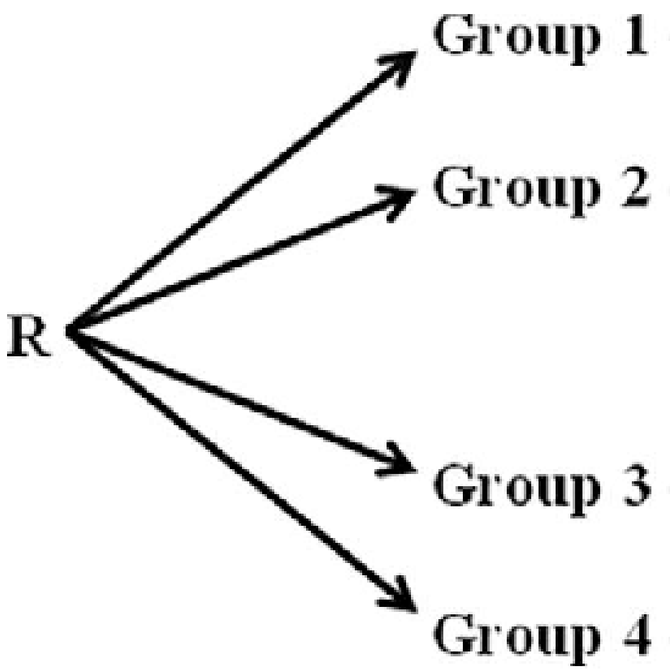
60 YEARS IDOS

Main messages

1. If you work on research questions that involve **multiple explanatory factors** or **trade-offs**, consider using conjoint experiments.

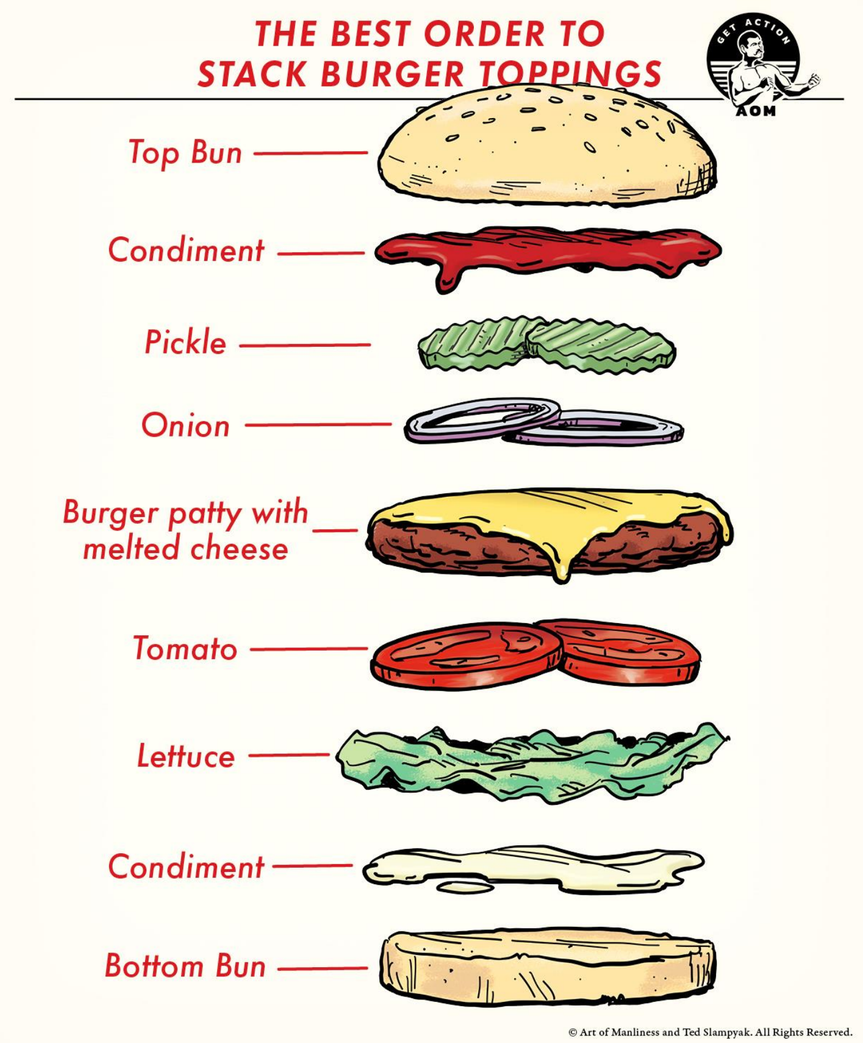
2. To make your design more realistic, use **visuals** in a **standardized** way.

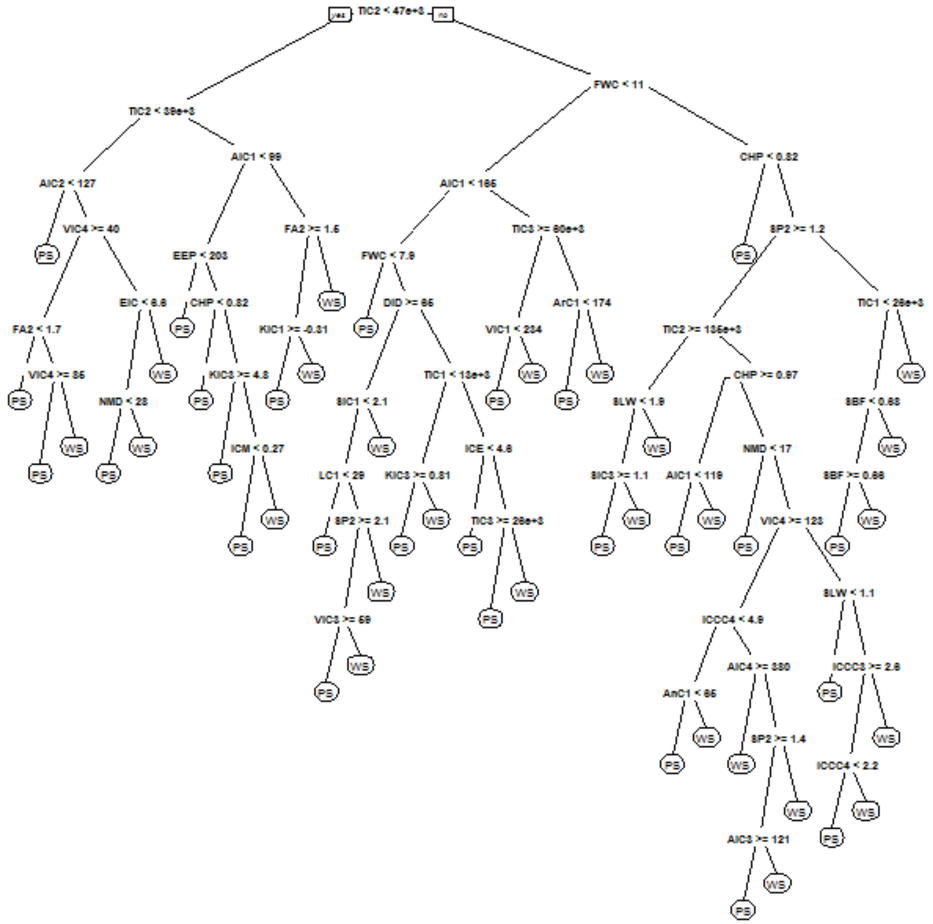
Experimental interventions



N = 800 with 200 respondents to each category.
e.g. the level of education on the vote choice for a political candidate

Life is more complex





…here come conjoints!

Attribute	Profile1	Profile2
Level of Education	High School	Bachelor's
Age	45	50
Years in Politics	5	10
Political Party	Conservative	Progressive
Gender	Male	Female

…here come conjoints!

Attribute	Profile1	Profile2
Level of Education	Master's	PhD
Age	55	40
Years in Politics	20	3
Political Party	Liberal	Green
Gender	Female	Male

N=Number of Respondents×Number of Tasks per Respondent×Number of Profiles per Task

e.g. N = 800 respondents x 5 comparisons x 2 profiles = 8000

…here come conjoints!

Attribute	Profile1	Profile2
Level of Education	Master's	PhD
Age	55	40
Years in Politics	20	3
Political Party	Liberal	Green
Gender	Female	Male

Causal effect: the marginal effect of level of education == PhD compared to the baseline on the probability of choosing one profile over the other, controlled for other attributes,

Conjoints are widely used

public support for democratic backsliding (Gidengil, Stolle, and Bergeron-Boutin 2022; Lewandowsky and Jankowski 2022; Saikkonen and Christensen 2023),

electoral sanctioning of corruption (Klašnja, Lupu, and Tucker 2020),

public support for incumbent autocratic regimes (Malesky and Schuler 2020),

repression, censorship, and policing (Curtice 2022; Kobayashi, Song, and Chan 2021; Springman et al. 2022; Ward and Denney 2023)

Ecological validity!

AI-generated Linkedin

Sinanoglu 2025

Twitter Profiles

Figure 1. Visual conjoint task with two hypothetical twitter profiles. The figure shows two random social media profiles as they would appear to respondents. On the left, Candidate A is characterized by the following features: White, Woman, Millennial, with High Feedback, an Ivy League Graduate, Jewish, and a Doctor (no military service). On the right, Candidate B is characterized by the following features: Black, Man, Boomer, with Low Feedback, and a College graduate working as a lawyer that served the military (no religion).

Vecchiato and Munger 2024

Twitter Profiles

ConjointTweets: Generating image-based conjoint tweets programmatically

This repository implements a python program to generate conjoint image-based tweets programatically and at scale.

The purpose of this tool is to facilitate the work for researchers interested in running survey experiments using images as conjoints, instead of text-based implementations.

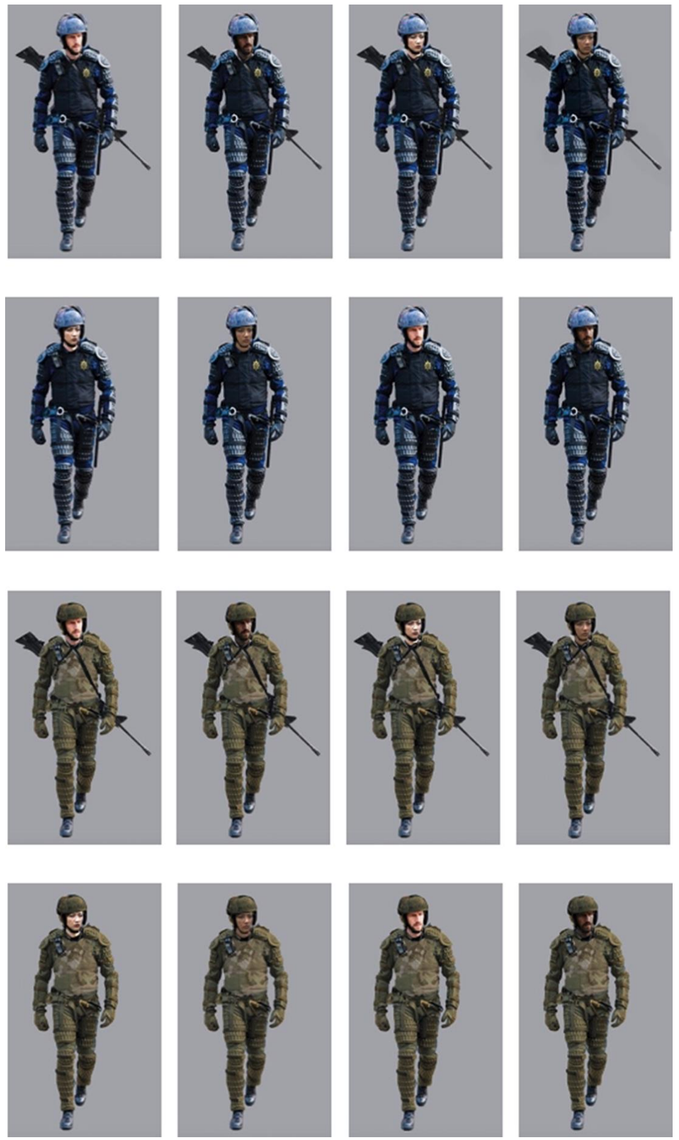
This is a work in progress and part of my ongoing collaboration with Kevin Munger (Penn State), Katherine McCabe (Rutger University) and Keng-Chi Chang (UCSD) -- who wrote a big part of this code.

Demos

In addition to this readme, we prepared two demos explaining how to use our functions. See below for R and Python users:

- demo to use in R
- demo to use in python

Appearances



[Flores-Macias & Zarkin 2021]

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Best practices and suggestions

1. Report both AMCEs and MMs, with forced and scale outcomes.
2. Write up and report the results properly: The AMCE of an attribute value is always defined with respect to a particular reference value of the same attribute, or the “baseline” value of the attribute, given the distribution of other attributes (see Leeper et al. 2020).
3. Use available cutting-edge tools to detect heterogeneity.
4. Identify and report the most important attribute.
5. Analyze AMCIE (interaction effects).

Heterogeneity

Robinson & Duch 2024

cjbart: Heterogeneous Effects Analysis of Conjoint Experiments

A tool for analyzing conjoint experiments using Bayesian Additive Regression Trees ('BART'), a machine learning method developed by Chipman, George and McCulloch (2010) <doi:10.1214/09-AOAS285>. This tool focuses specifically on estimating, identifying, and visualizing the heterogeneity within marginal component effects, at the observation- and individual-level. It uses a variable importance measure ('VIMP') with delete-d jackknife variance estimation, following Ishwaran and Lu (2019) <doi:10.1002/sim.7803>, to obtain bias-corrected estimates of which variables drive heterogeneity in the predicted individual-level effects.

Version:	0.3.2
Depends:	R (≥ 3.6.0), BART
Imports:	stats, rlang, tidyr, ggplot2, randomForestSRC (≥ 3.2.2), Rdpack
Suggests:	testthat (≥ 3.0.0), knitr, parallel, rmarkdown
Published:	2023-09-06
DOI:	10.32614/CRAN.package.cjbart

Thanks!

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