Strategic Marketing Analytics

Session 3
Conjoint Analysis

Today's agenda

- Conjoint analysis
  - Understanding preferences and choices
- Case study and software demonstration
  - In-classe exercise, or OfficeStar
- Video
  - Courtyard by Marriott

Article

Psychology

The price of prejudice

It's what you do that counts—not what you say you'd do

NOBODY likes to admit an uncomfortable truth about himself, especially when charged issues such as race, sex, age and even supersized waistlines come into play. That makes the task of the behavioural scientist a difficult one. Not only may participants in a study be lying to those running a test, but they may also, fundamentally, be lying to themselves.

Prising the lid off human assumptions and hidden biases thus requires clever tools. One of the most widely deployed, known as the implicit-association test, measures how quickly people associate words describing facial characteristics with different types of faces that display those characteristics. When such characteristics are favourable—"laughter" or "joy", for example—it often takes someone longer to match them with faces that they may, unconsciously, view unfavourably (old, if the participant is young, or non-white if he is white). This procedure thus picks up biases that the participants say they are not aware of having.

Whether these small differences in what are essentially artificial tasks really reflect day-to-day actions and choices was, until recently, untested. But that has changed. In a paper to be published next month in Social Cognition, a group of researchers led by Eugene Caruso of the University of Chicago report their use of a technique called conjoint analysis, which they have adopted from the field of market research and adapted to study implicit biases in more realistic situations.

Conjoint analysis, they think, lets them quantify what has been dubbed the "stereotype tax"—the price that the person doing the stereotyping pays for his preconceived notions. In two studies, they turn their new tool loose on questions of the perception of weight and sex.

Know thyself not

Conjoint analysis asks participants to evaluate a series of products that vary in several important attributes, such as televisions of various screen sizes, brands and prices. By varying these attributes in a systematic way market researchers can measure with reasonable precision how much each trait is worth. They can then calculate how big a premium people are willing to pay in one attribute (price) to get what they want in another (a larger screen).

In their first study, Dr Caruso and his team recruited 101 students and asked them to imagine they were taking part in a team trivia game with a cash prize. Each student was presented with profiles of potential team-mates and asked to rate them on their desirability.

The putative team-mates varied in several ways. Three of these were meant to correlate with success at trivia: educational level, IQ and previous experience with the game. In addition, each profile had a photo which showed whether the team-mate was slim or fat. After rating the profiles, the participants were asked to say how important they thought each attribute was in their decisions.

Not surprisingly, they reported that weight was the least important factor in their choice. However, their actual decisions revealed that no other attribute counted more heavily. In fact, they were willing to sacrifice quite a bit to have a thin team-mate. They would trade 11 IQ points—about 50% of the range of IQs available—for a colleague who was suitably slender.

In a second study the team asked another group, this time of students who were about to graduate, to consider hypothetical job opportunities at consulting firms. The positions varied in starting salary, location, holiday time and the sex of the potential boss.

When it came to salary, location and holiday, the students' decisions matched their stated preferences. However, the boss's sex turned out to be far more important than they said it was (this was true whether a student was male or female). In effect, they were willing to pay a 22% tax on their starting salary to have a male boss.

A black and white answer

A recent paper in Science adds further fuel to the notion that implicit biases and inaccurate self-perceptions do indeed exist and need further study. A team led by Kerry Kawakami from York University in Canada conducted an experiment to try to understand how racism persisted despite most people roundly condemning it.

Dr Kawakami, too, used students. She recruited 120 who identified themselves as not being black, and then divided them into two equal groups. Members of one ▸▸

Understanding preferences and choices

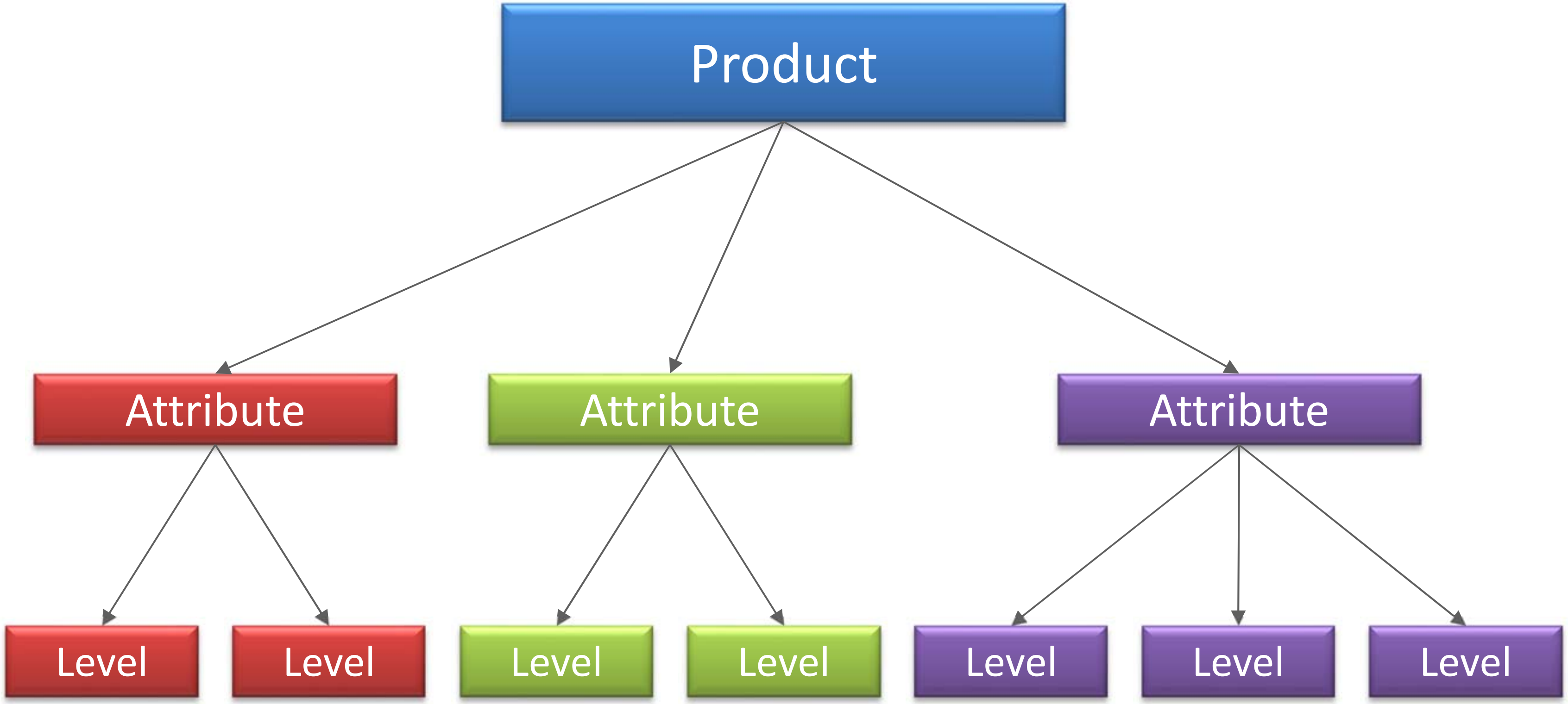
CONJOINT ANALYSIS

Managerial issues

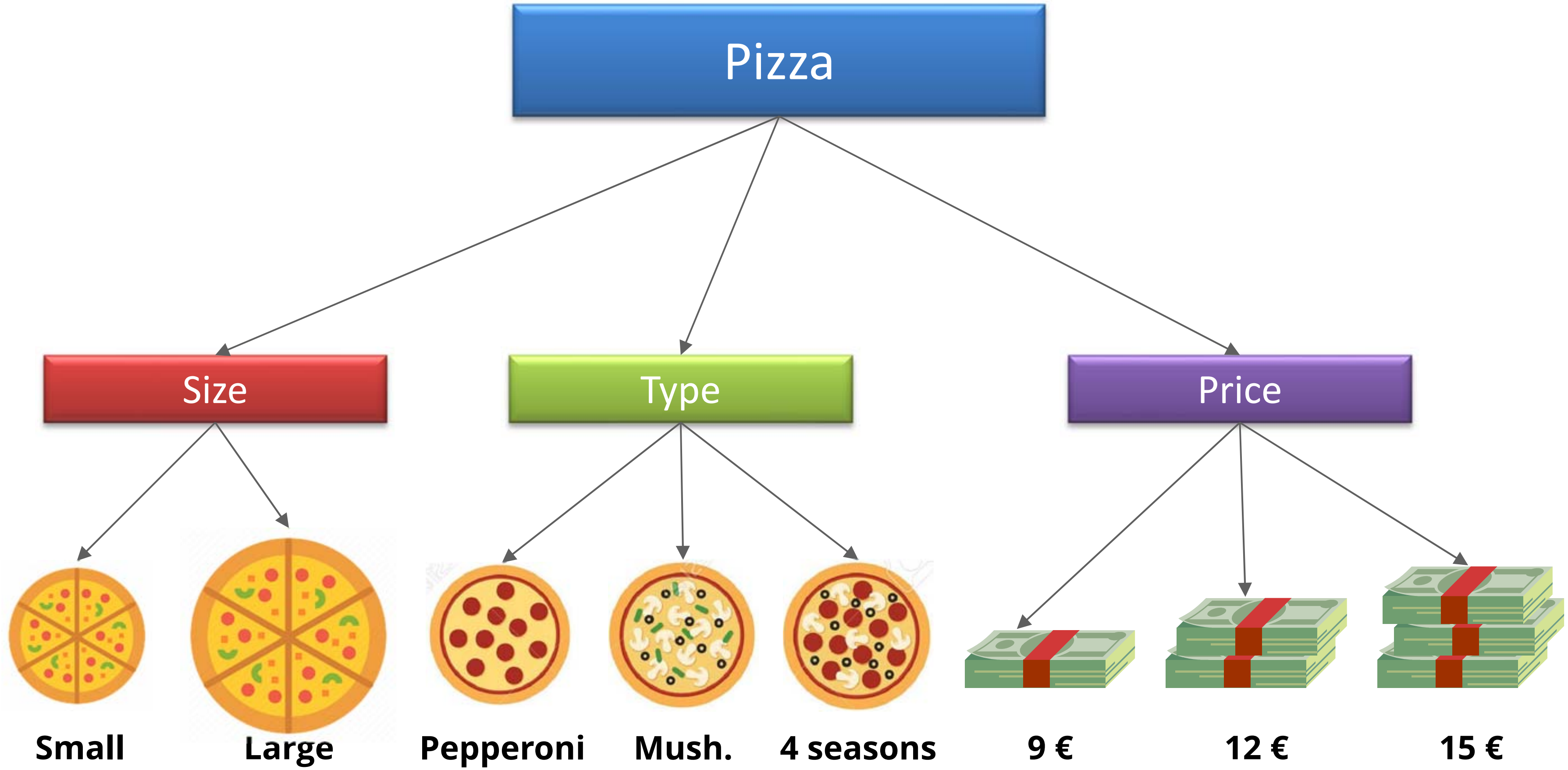
Managerial issues we will address today:

- How to understand and quantify what consumers value, like, dislike and prefer?
- How to link consumers' preferences to consumers' choices?
- How to evaluate potential market shares of new product offerings, and product cannibalization?
- How to identify market opportunities for new product offerings?

Products, attributes, and attribute levels



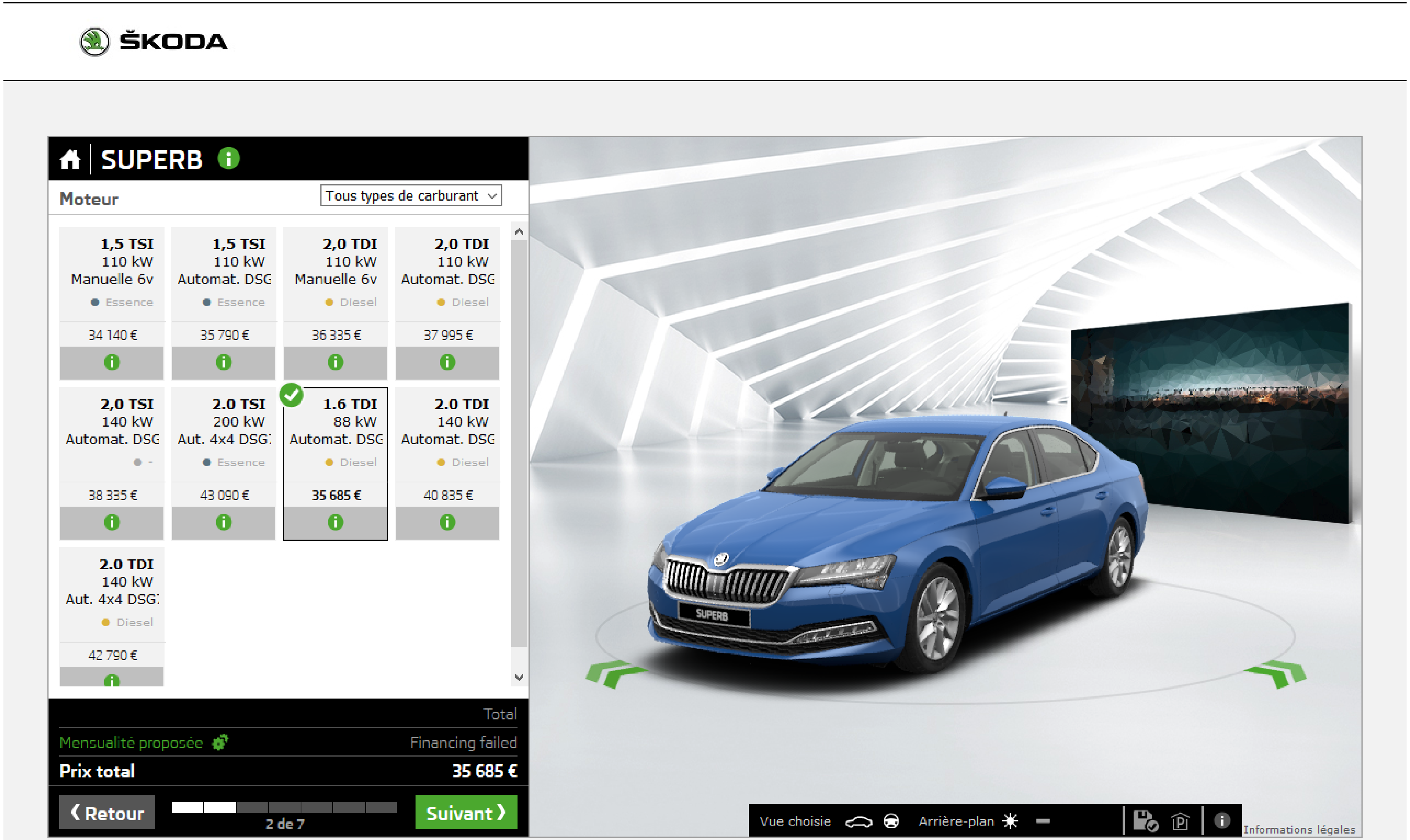
Products, attributes, and attribute levels



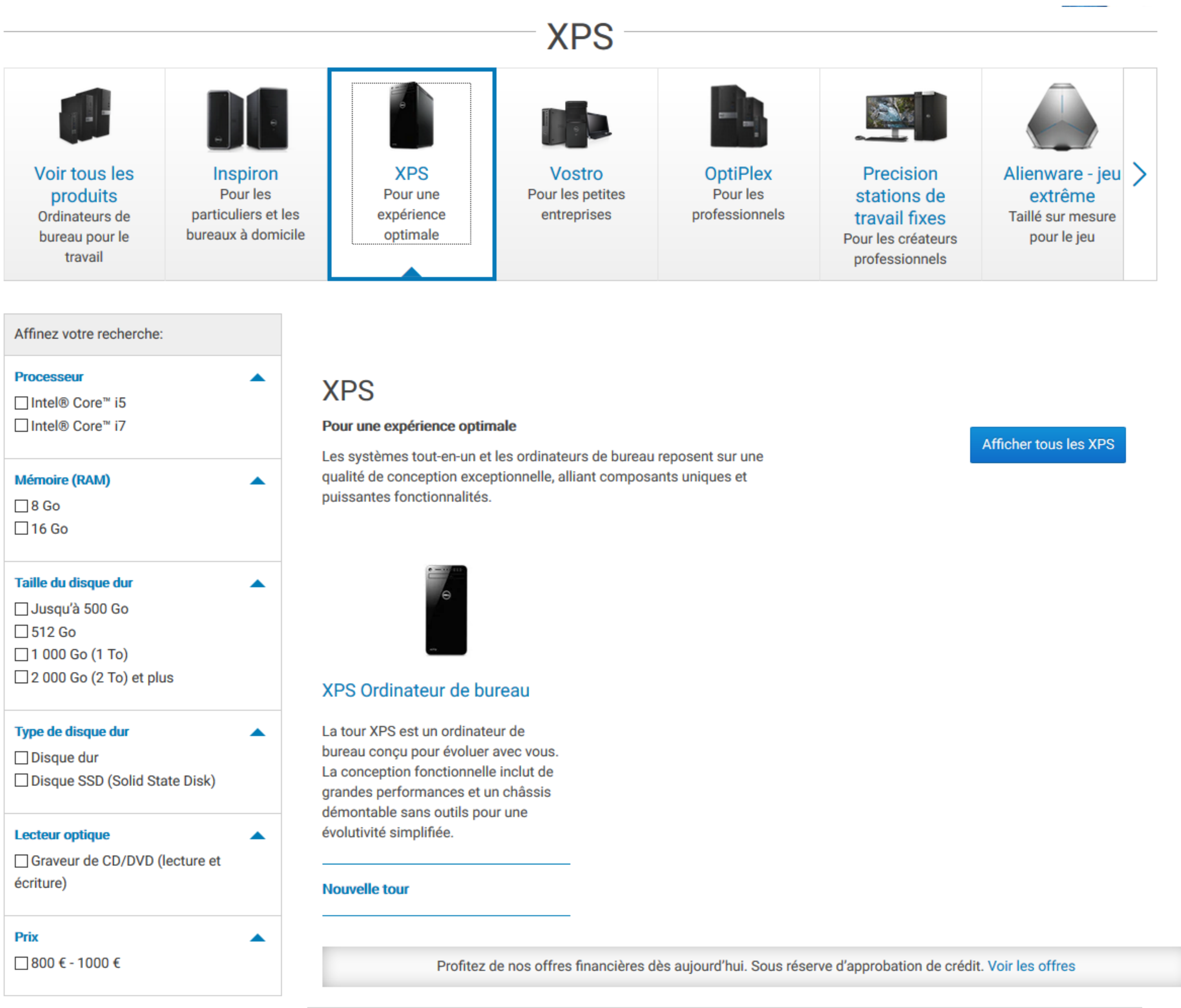
Example of attributes, levels

- Color
  - Red
  - Blue
  - Green
  - Black
- Warranty
  - No warranty
  - 1-year warranty
  - 3-year warranty
- Brand
  - Samsung
  - Acer
  - HP
- Number of stops
  - Non-stop flight
  - 1 stop
  - 2 stops or more
- Meat cooking
  - Rare
  - Medium-rare
  - Medium
  - Well done
- Customer ratings
  - 5 stars
  - 4 stars
  - …

Example of attributes, levels

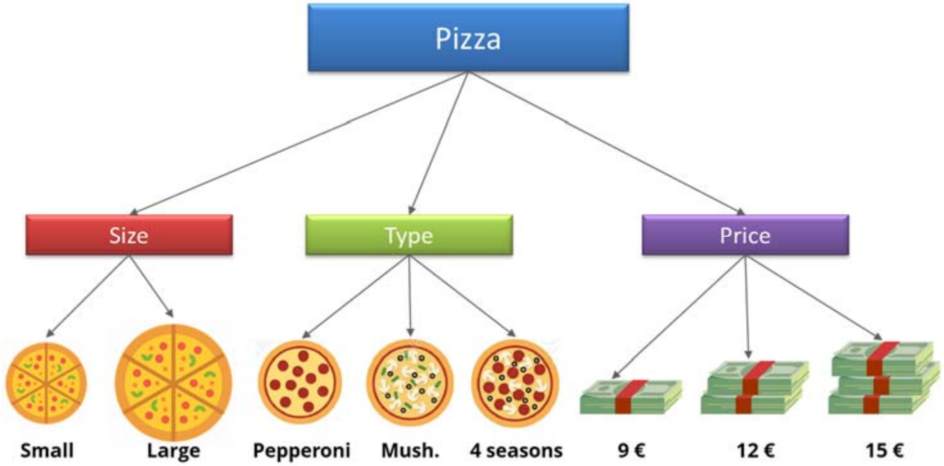


Example of attributes, levels



Products are bundles of attribute levels

A product is simply a bundle of attribute levels

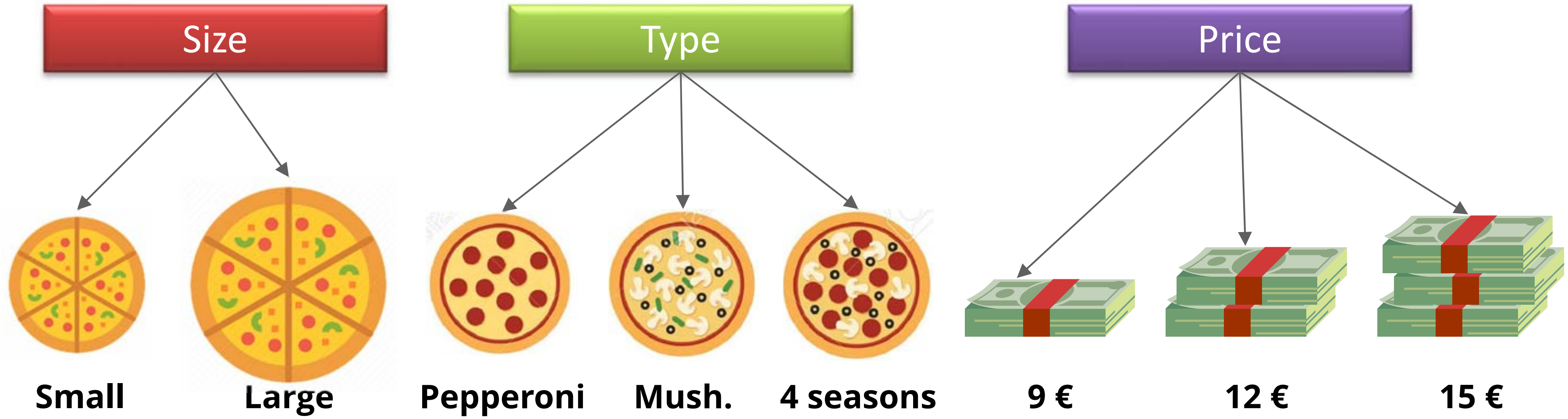


- Product 1 Small pepperoni pizza for 9€
- Product 2 Large mushroom pizza for 15€
- Product 3 Small 4 seasons pizza for 12€
- Etc.

2 × 3 × 3 = 18 different products (and nothing more!)

Preference partworths

A value is associated with each level to indicate preference



0	10	40	0	30	50	30	0

From preference partworths to product preferences

- The preference score for a product becomes the **sum** of the preference scores of the levels of that product

Product 1	Large (10) pepperoni (40) at 9€ (50) =	100
Product 2	Small (0) four seasons (30) at 12€ (30) =	60
Product 3	Small (0) mushrooms (0) at 15€ (0) =	0

- Since Product 1 is preferred to Product 2, it is "**more likely**" to be purchased.
(later, we will see exactly how preferences are translated into choices)

Comments

- For simplicity, preference for products are scaled between 0 and 100
  - Worst levels = 0
  - Sum of most preferred levels = 100
  - (done automatically by the software)

- Of course, people prefer to pay less!
  - What's important is how strong these preferences for low prices are, compared to preference for other attributes

- Preferences vary across customers
  - Later, we will see customers can be segmented based on their preference partworths, to build segments of customers who share similar preferences

Preference partworth estimation

- The question then becomes "how to estimate these preference partworths?"
- You can't ask → not reliable
- You have to estimate it indirectly through

conjoint analysis

("considered jointly")

Preference partworth estimation

Steps 1 & 2 - profile generation and rating

- First, create a **list** of products
  - Also referred to as "bundles" or "profiles"

- Ask respondents to **rate** them on a scale (e.g., 0-100, 1-10)
  - Also referred to as "preference scores"

Profile #1
- Small
- Pepperoni
- 12 €

70

Profile #2
- Large
- Mushroom
- 15€

10

Profile #3
- Small
- Four seasons
- 9€

?

…

(NB: other conjoint estimation techniques exist: choice-based conjoint, ranking, etc.)

Preference partworth estimation

Steps 3 – regression analysis

- Third, run a **regression analysis** to estimate each attribute level's contribution to the overall preference score

Preference partworth estimation

Steps 3 – regression analysis

Small	Large	Pepperoni	Mushrooms	4 seasons	9 €	12 €	15 €	Score
	●	●			●			100
●				●		●		60
●			●				●	45
	●	●				●		80
	●		●		●			…

Preference partworth estimation

Steps 3 – regression analysis

Small		Large		Pepperoni		Mushrooms		4 seasons		9 €		12 €		15 €		Score
$ß_1X_1$	+	$ß_2X_2$	+	$ß_3X_3$	+	$ß_4X_4$	+	$ß_5X_5$	+	$ß_6X_6$	+	$ß_7X_7$	+	$ß_8X_8$	=	100
$ß_1X_1$	+	$ß_2X_2$	+	$ß_3X_3$	+	$ß_4X_4$	+	$ß_5X_5$	+	$ß_6X_6$	+	$ß_7X_7$	+	$ß_8X_8$	=	60
$ß_1X_1$	+	$ß_2X_2$	+	$ß_3X_3$	+	$ß_4X_4$	+	$ß_5X_5$	+	$ß_6X_6$	+	$ß_7X_7$	+	$ß_8X_8$	=	45
$ß_1X_1$	+	$ß_2X_2$	+	$ß_3X_3$	+	$ß_4X_4$	+	$ß_5X_5$	+	$ß_6X_6$	+	$ß_7X_7$	+	$ß_8X_8$	=	80
$ß_1X_1$	+	$ß_2X_2$	+	$ß_3X_3$	+	$ß_4X_4$	+	$ß_5X_5$	+	$ß_6X_6$	+	$ß_7X_7$	+	$ß_8X_8$	=	…

X_y: is this attribute level present in that profile? 1=yes, 0=no

Preference partworth estimation

Steps 3 – regression analysis

Small	Large	Pepperoni	Mushrooms	4 seasons	9 €	12 €	15 €	Score
	β_2	$+ \beta_3$			$+ \beta_6$			$= 100$
β_1				$+ \beta_5$		$+ \beta_7$		$= 60$
β_1			$+ \beta_4$				$+ \beta_8$	$= 45$
	β_2	$+ \beta_3$				$+ \beta_7$		$= 80$
	β_2		$+ \beta_4$		$+ \beta_6$			$=$ …

β_y: contribution of that attribute level to the overall score

Preference partworth estimation

Steps 3 – regression analysis

Intercept		Small		Large		Pepperoni		Mushrooms		4 seasons		9 €		12 €		15 €		Score
$ß_0$	+	$ß_1X_1$	+	$ß_2X_2$	+	$ß_3X_3$	+	$ß_4X_4$	+	$ß_5X_5$	+	$ß_6X_6$	+	$ß_7X_7$	+	$ß_8X_8$	=	100
$ß_0$	+	$ß_1X_1$	+	$ß_2X_2$	+	$ß_3X_3$	+	$ß_4X_4$	+	$ß_5X_5$	+	$ß_6X_6$	+	$ß_7X_7$	+	$ß_8X_8$	=	60
$ß_0$	+	$ß_1X_1$	+	$ß_2X_2$	+	$ß_3X_3$	+	$ß_4X_4$	+	$ß_5X_5$	+	$ß_6X_6$	+	$ß_7X_7$	+	$ß_8X_8$	=	45
$ß_0$	+	$ß_1X_1$	+	$ß_2X_2$	+	$ß_3X_3$	+	$ß_4X_4$	+	$ß_5X_5$	+	$ß_6X_6$	+	$ß_7X_7$	+	$ß_8X_8$	=	80
$ß_0$	+	$ß_1X_1$	+	$ß_2X_2$	+	$ß_3X_3$	+	$ß_4X_4$	+	$ß_5X_5$	+	$ß_6X_6$	+	$ß_7X_7$	+	$ß_8X_8$	=	...

$ß_y$: contribution of that attribute level to the overall score

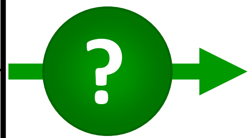
Comments

- Once you have computed preference partworths (ß's), you can estimate how much a profile will be liked by the respondent
  - Even products he did not rate
  - Even products that do not exist yet
- Let the software determine the list of profiles that will be rated
  - Will ensure that statistical prerequisites of regression analysis are met (enough profiles to estimate everything, multicollinearity, etc.)

From preferences to choices

How to go from preferences to choices?

Profile	Preference score
Product A	**70**
Product B	**20**
Product C	**10**



Probability of choice?

From preferences to choices

How to go from preferences to choices?

Profile	Preference score
Product A	70
Product B	20
Product C	10

?

First choice	Logit	Share of preference	Random
100%	83%	70%	33%
0%	13%	20%	33%
0%	4%	10%	33%

- Choice rule depends on the context
  - High-stake decision? (house, a car) → First choice
  - High variety seeking? (meals)? → Share of preference
  - In-between? (clothes)? → Logit

(NB: if current market shares are known, the alpha-rule provides yet another rule, more precise and versatile)

Running simulations

- Once you have…
  - Defined attributes, levels
  - Collected data (ratings) from a sample of your target customers
  - Estimated preferences
  - Linked preferences to choices

- …You simulate and estimate market shares if
  - You increase price? Change characteristics of a product?
  - You introduce a new product?
  - Competition introduces a new product?
  - Are there opportunities to introduce new products? Which ones?
  - Cannibalization?
  - Etc.

Simulation: example #1

What if we changed an existing product?

- Profile #3
- People prefer planes to buses
- Let's do it by plane, and slightly increase price to cover additional costs

Profile	Preference score	Market share
Beach, 800 € by Plane	45	31%
Beach, 600 € by Bus	40	26%
Mountain 450 €, by Bus	55	42%

Simulation: example #1

What if we changed an existing product?

- Profile #3
- People prefer planes to buses
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Profile	Preference score	Market share
Beach, 800 € by Plane	45	31%
Beach, 600 € by Bus	40	26%
Mountain 450 €, by Bus	55	42%

Profile	Preference score	Market share	Delta
Beach, 800 € by Plane	45	35%	+4%
Beach, 600 € by Bus	40	30%	+3%
Mountain 600 €, Plane	45	35%	-7%

Simulation: example #2

What if there were a new entrant?

- Low-cost company

Profile	Preference score	Market share
Beach, 800 € by Plane	**45**	**31%**
Beach, 600 € by Bus	**40**	**26%**
Mountain 450 €, by Bus	**55**	**42%**

Simulation: example #2

What if there were a new entrant?

- Low-cost company

Note: of the third product (Mountain, 450 €, by Bus) is offered by the same company, there is significant cannibalization

Profile	Preference score	Market share
Beach, 800 € by Plane	45	31%
Beach, 600 € by Bus	40	26%
Mountain 450 €, by Bus	55	42%

Profile	Preference score	Market share	Delta
Beach, 800 € by Plane	45	15%	-16%
Beach, 600 € by Bus	40	13%	-13%
Mountain 450 €, by Bus	55	21%	-22%
Beach, 450 € by Plane	100	51%	+51%

Running a conjoint study

Stage 1 — **Design the conjoint study**

- Select relevant Attributes
- Select relevant Levels for each Attribute
- Develop the product bundles to be evaluated

Stage 2 — **Collect data and estimate preferences**

- Collect data
- Estimate preference partworths (regression)

Stage 3 — **Exploit the results**

- From preferences to choices: choice rule
- Run simulations (market shares, new products)
- Segment customers based on preferences

Stage 1

Design the conjoint study

- **Select relevant Attributes**
  - Ask consumers, managers, experts
  - Analyze secondary sources (public media, brochures)
  - Select between 4 and 6 attributes maximum

- **Select relevant Levels for each Attribute**
  - Ask managers, experts (product managers, manufacturers)
  - Analyze secondary sources (public media, brochures)
  - Be realistic, try to span all options present in the market
  - Select between 2 and 4 levels maximum per attribute
  - (Try to) include the same number of levels for each attribute

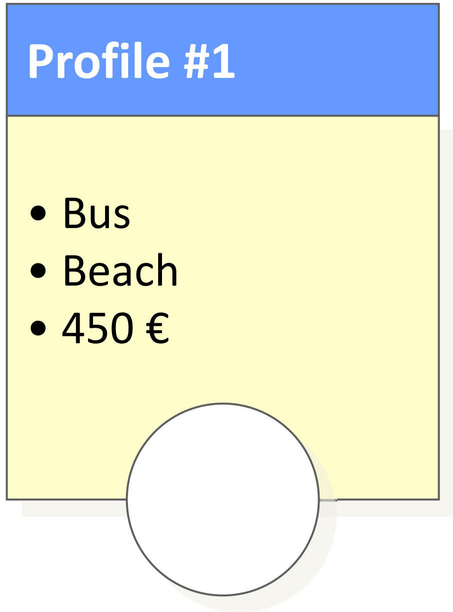
- **Develop the product bundles to be evaluated**
  - Let the software decide
  - If some profiles do not make sense, review your design

Stage 2

Collect data and estimate preferences

- Collect data
  - Develop a survey (design, scale, prototypes)
  - Select sample of respondents
  - Collect data

- Estimate preference partworths (regression)
  - Run a regression analysis on collected data



Stage 3

Exploit the results

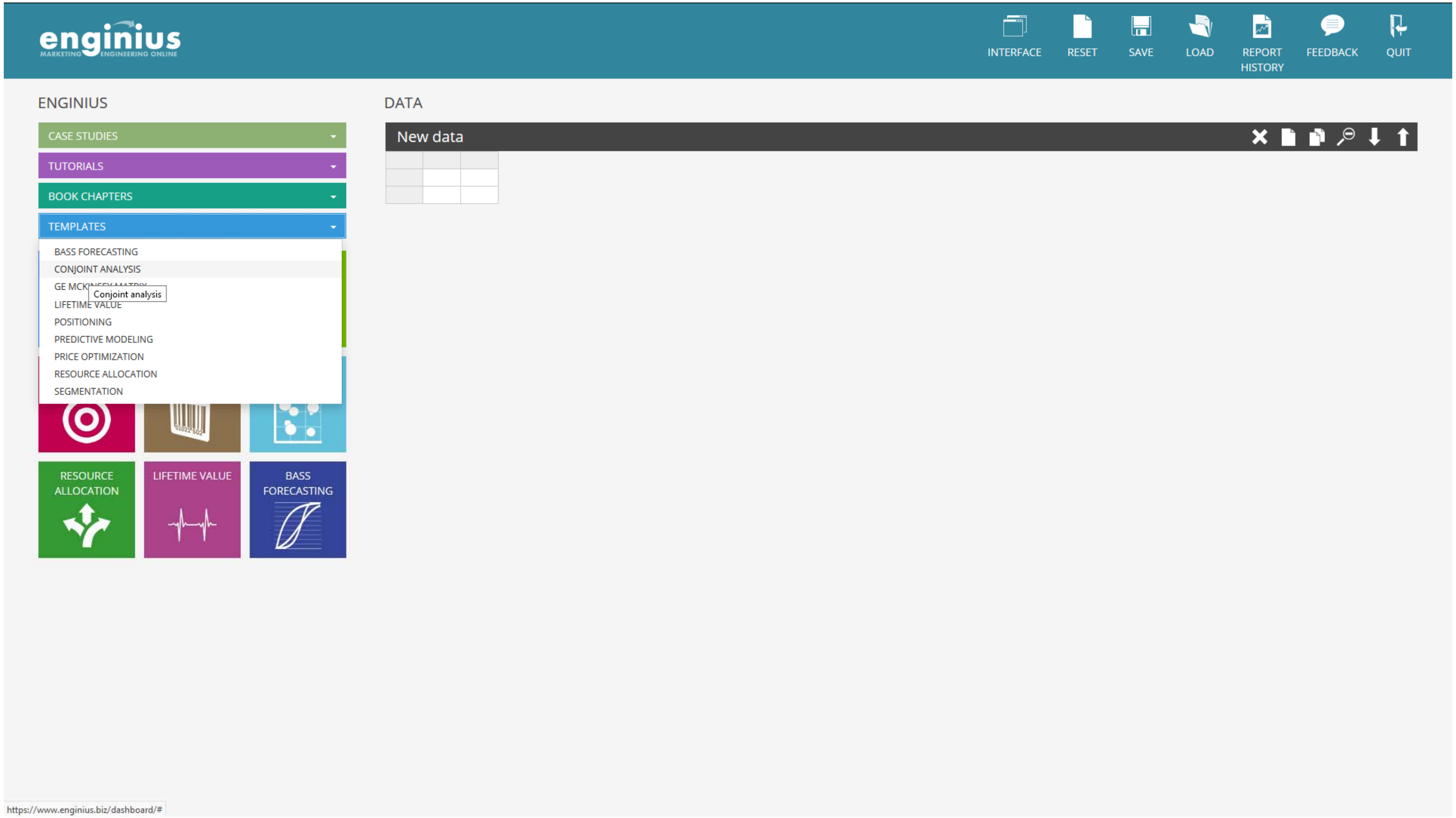
- From preferences to choices: choice rule
  - What choice rule? (first-choice, share of preferences, etc.)
  - Do you have market shares to estimate alpha-rule? (*advanced*)
- Run simulations (market shares, new products)
  - Replicate the existing market
  - Select scenarios (new product, new entrant, changes)
  - Run simulations
- Segment customers based on preferences
  - Preferences are heterogeneous in the population
  - Regrouping similar customers might lead to great insights
  - A new offering might have low global market shares, but dominate a specific niche or segment (e.g., those who hate flying)

Enginius

SOFTWARE DEMONSTRATION

Conjoint study

1. Create a study design
   - Attributes
   - Levels
2. Create a data collection template
3. Collect data
4. Estimate preference partworths
5. Create an analysis template
6. Enter your analysis parameters
   - Existing products
   - New product ideas…
7. Run analysis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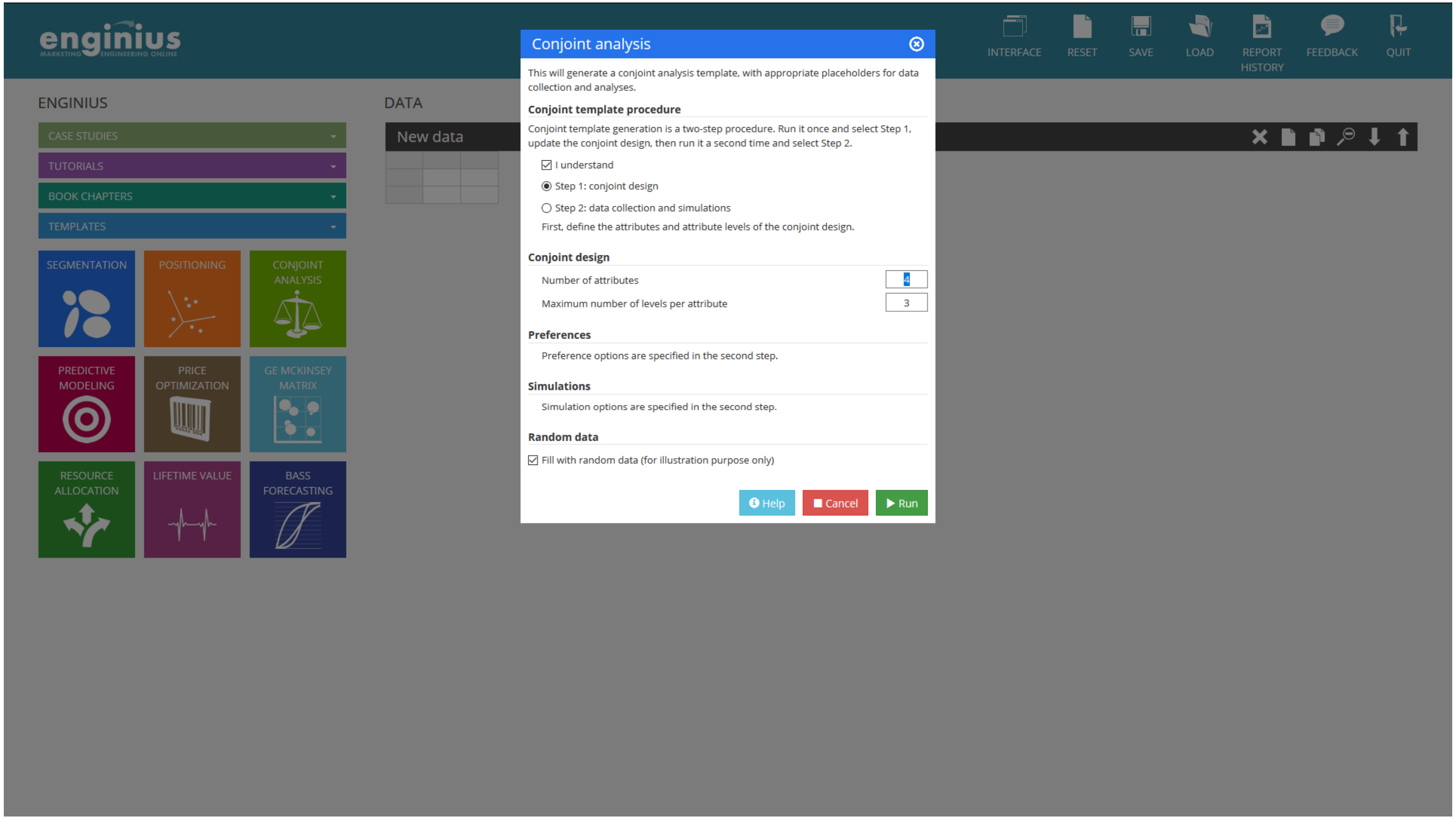
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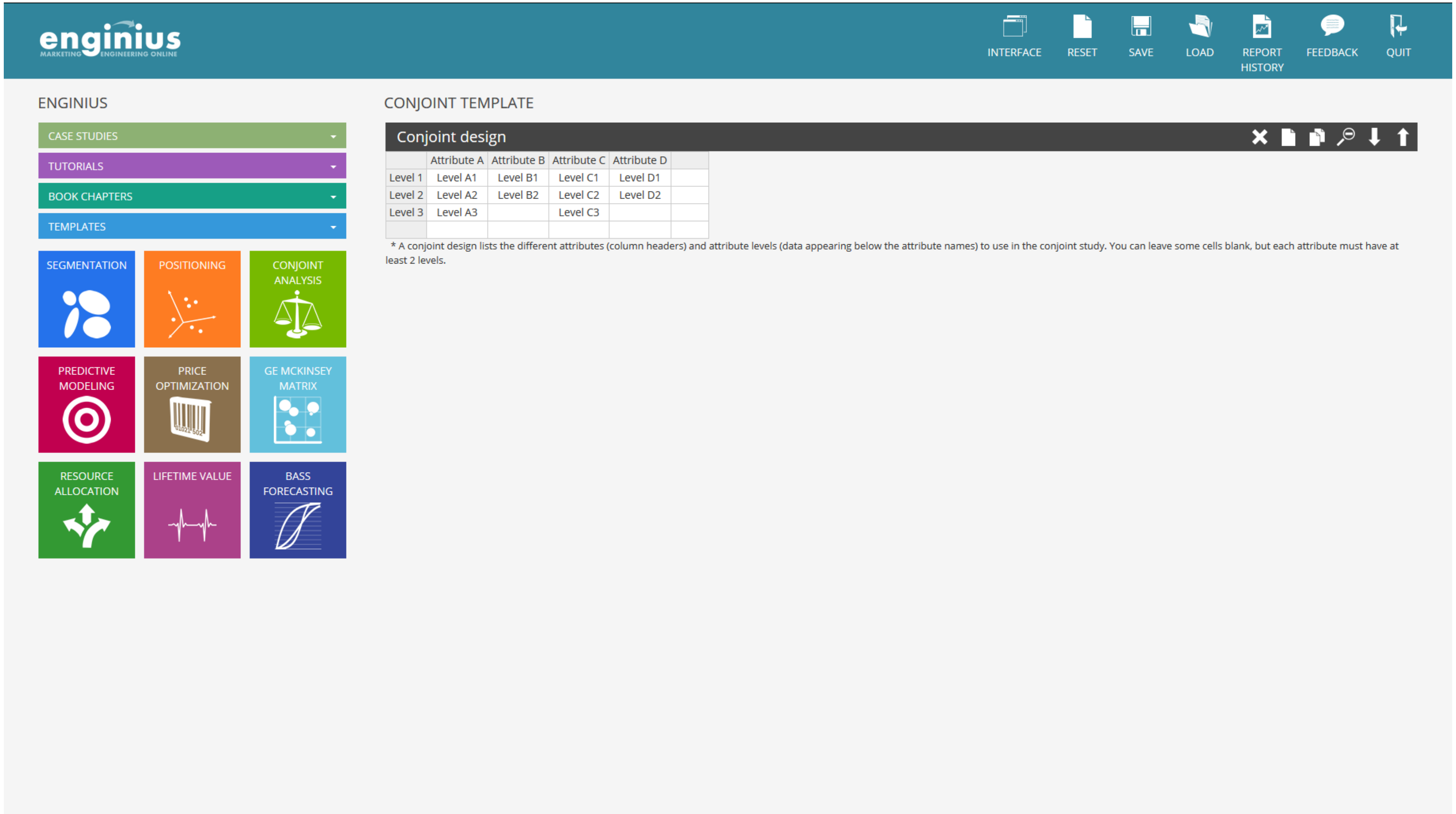
DATA
New data
Conjoint analysis
This will generate a conjoint analysis template, with appropriate placeholders for data collection and analyses.
Conjoint template procedure
Conjoint template generation is a two-step procedure. Run it once and select Step 1, update the conjoint design, then run it a second time and select Step 2.
I understand
Step 1: conjoint design
Step 2: data collection and simulations
First, define the attributes and attribute levels of the conjoint design.
Conjoint design
Number of attributes
4
Maximum number of levels per attribute
3
Preferences
Preference options are specified in the second step.
Simulations
Simulation options are specified in the second step.
Random data
Fill with random data (for illustration purpose only)
Help
Cancel
Run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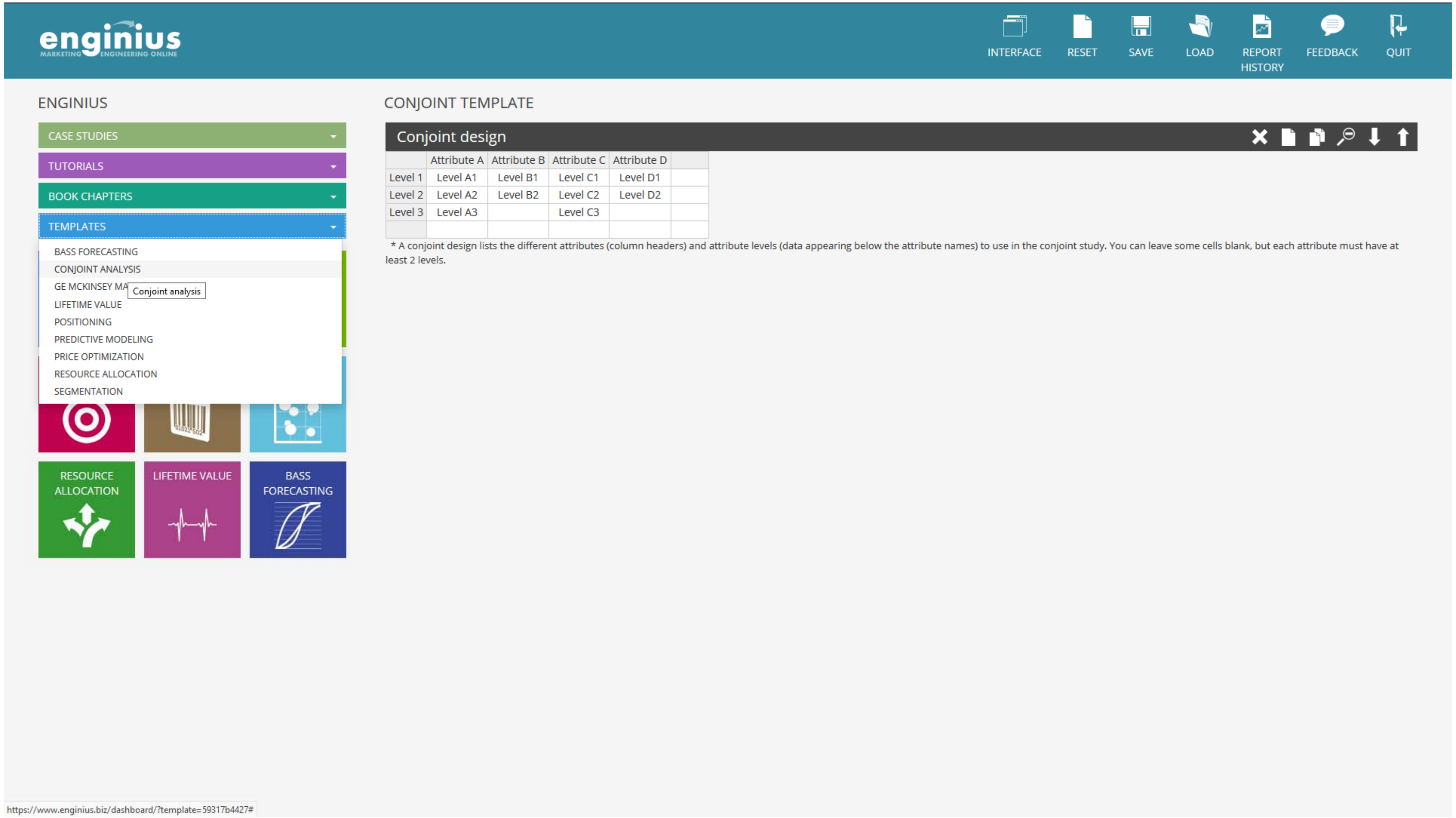
RESOURCE ALLOCATION
LIFETIME VALUE
BASS FORECASTING
CONJOINT TEMPLATE
Conjoint design
Attribute A Attribute B Attribute C Attribute D
Level 1 Level A1 Level B1 Level C1 Level D1
Level 2 Level A2 Level B2 Level C2 Level D2
Level 3 Level A3 Level C3
* A conjoint design lists the different attributes (column headers) and attribute levels (data appearing below the attribute names) to use in the conjoint study. You can leave some cells blank, but each attribute must have at least 2 levels.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* A conjoint design lists the different attributes (column headers) and attribute levels (data appearing below the attribute names) to use in the conjoint study. You can leave some cells blank, but each attribute must have at least 2 levels.
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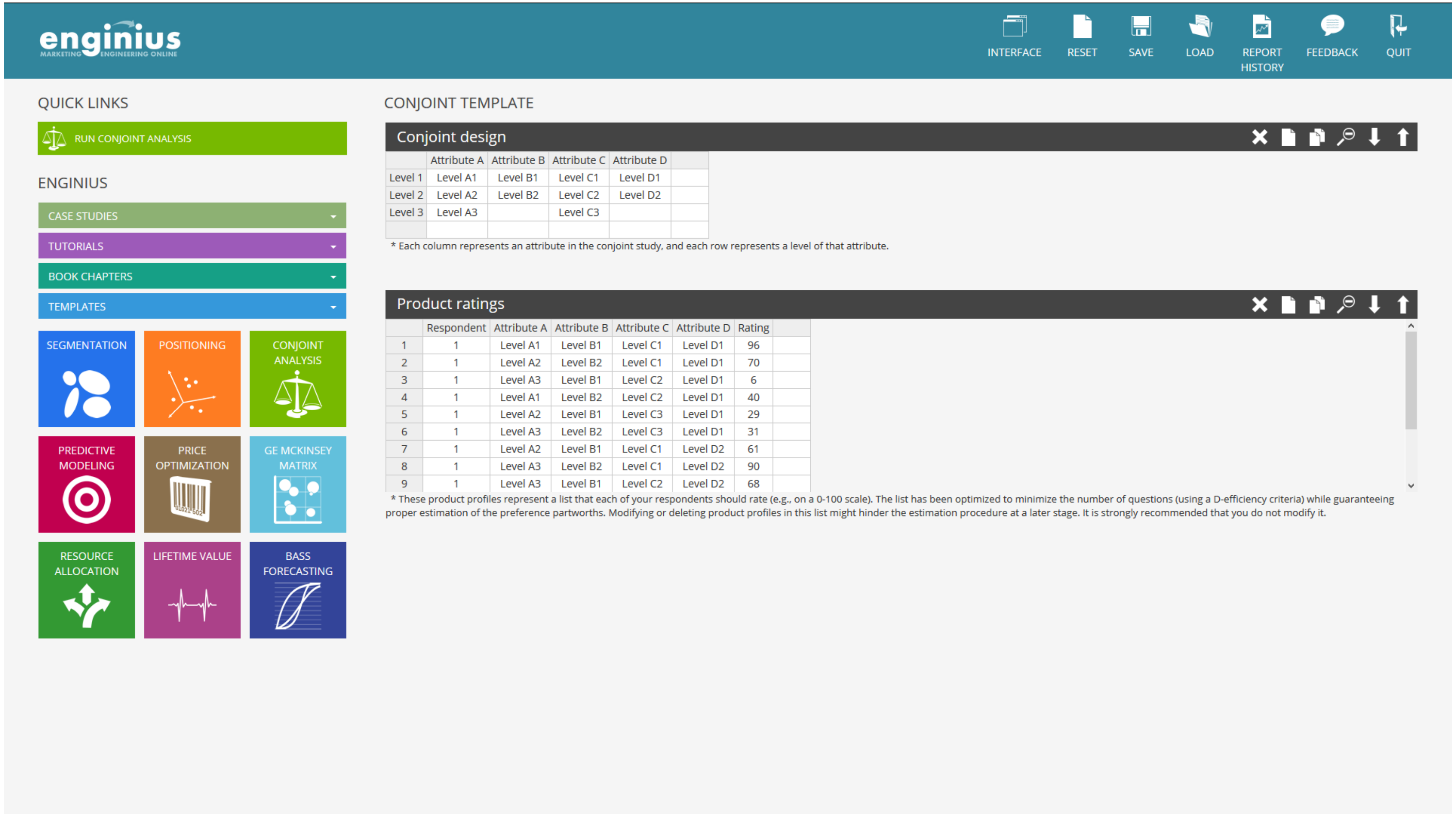

	Attribute A	Attribute B	Attribute C	Attribute D
Level 1	Level A1	Level B1	Level C1	Level D1
Level 2	Level A2	Level B2	Level C2	Level D2
Level 3	Level A3		Level C3	

* Each column represents an attribute in the conjoint study, and each row represents a level of that attribute.

Product ratings

	Respondent	Attribute A	Attribute B	Attribute C	Attribute D	Rating
1	1	Level A1	Level B1	Level C1	Level D1	96
2	1	Level A2	Level B2	Level C1	Level D1	70
3	1	Level A3	Level B1	Level C2	Level D1	6
4	1	Level A1	Level B2	Level C2	Level D1	40
5	1	Level A2	Level B1	Level C3	Level D1	29
6	1	Level A3	Level B2	Level C3	Level D1	31
7	1	Level A2	Level B1	Level C1	Level D2	61
8	1	Level A3	Level B2	Level C1	Level D2	90
9	1	Level A3	Level B1	Level C2	Level D2	68

* These product profiles represent a list that each of your respondents should rate (e.g., on a 0-100 scale). The list has been optimized to minimize the number of questions (using a D-efficiency criteria) while guaranteeing proper estimation of the preference partworths. Modifying or deleting product profiles in this list might hinder the estimation procedure at a later stage. It is strongly recommended that you do not modify it.

Historical video

COURTYARD BY MARRIOTT

Next week…

Case study #1 - KIRIN