

Session 2: Conjoint Design

Fall 2018

A. Lemmens

Random Utility Theory

Decompositional view of conjoint

Decompositional View

Price = 24,895 EUR

Consumption = 5.1 L/100km



Brand = Fiat

Trunk size = 185 L

CO-emission = 116 g/km



Decompositional View

Price = 24,420 EUR

Consumption = 5.0 L/100km



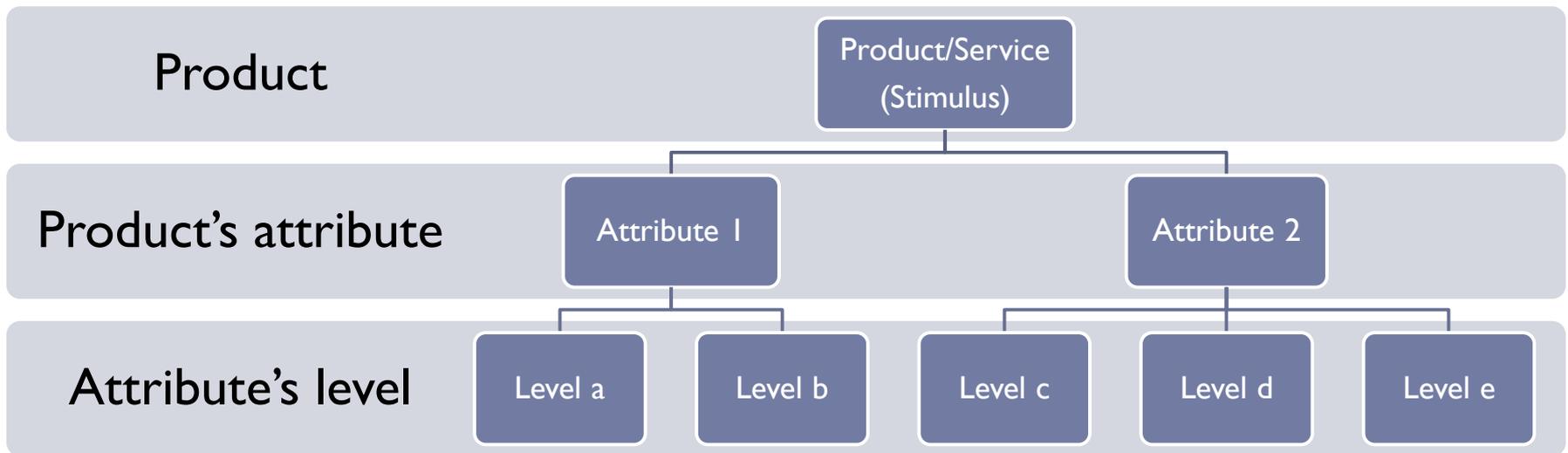
Brand = Skoda

Trunk size = 610 L

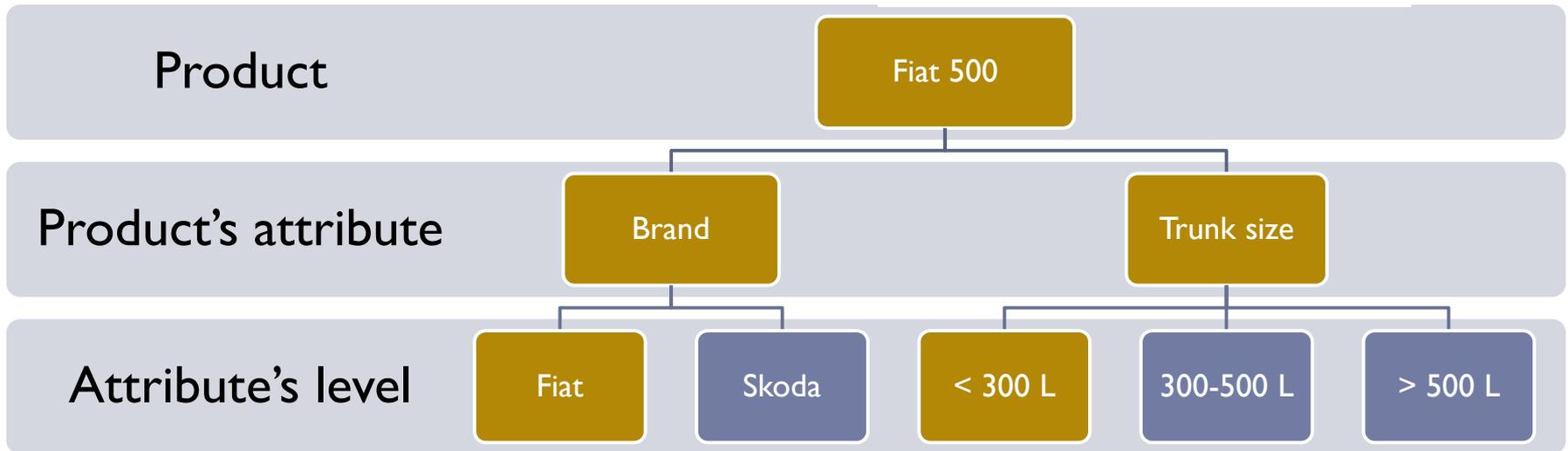
CO-emission = 109 g/km



Decompositional View

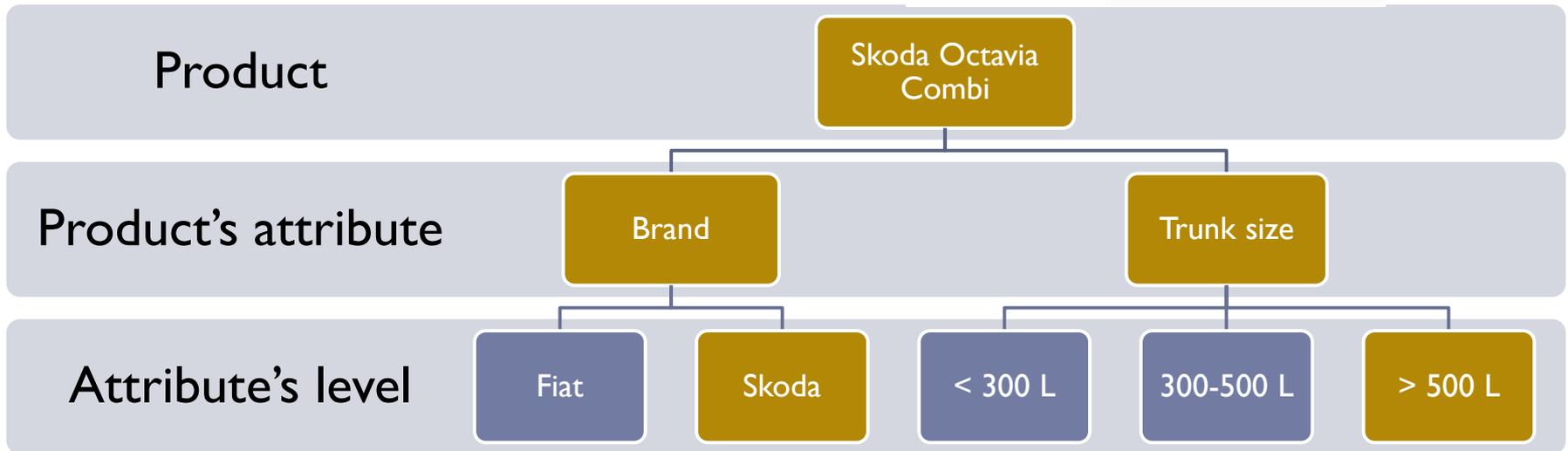


Decompositional View



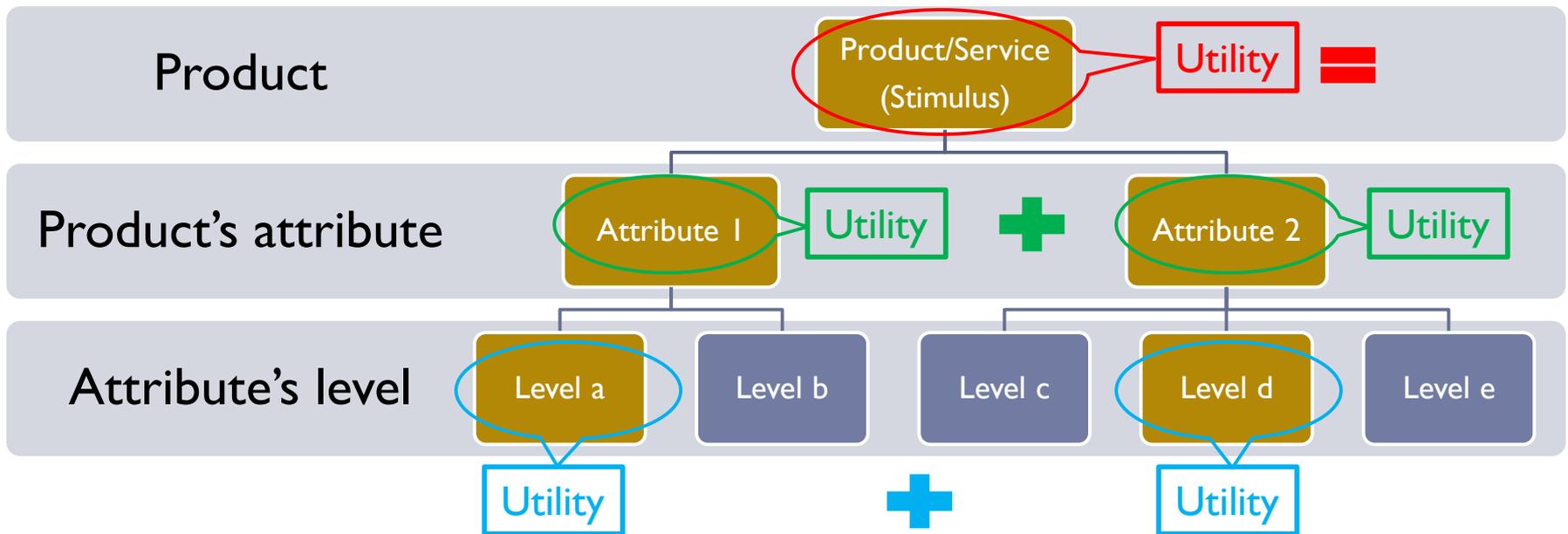
... and many more attributes...

Decompositional View



... and many more attributes...

Decompositional View



Utilities

The utility of a stimulus = the sum of the utilities of the various attributes' levels



- + Utility (brand = Fiat)
- + Utility (trunk size = <300L)
- + ...



- + Utility (brand = Skoda)
- + Utility (trunk size = >500L)
- + ...

Total Utility Fiat 500

Total Utility Skoda Octavia Combi



From Utilities to Choice

In general, customers pick the stimulus with the highest utility



Total Utility Fiat 500



Total Utility Skoda Octavia Combi

Random Utility Theory

▶ Thurstone (1927)

- ▶ A consumer generally chooses the alternative that she likes the most, subject to constraints such as income and time.
- ▶ Sometimes, they don't because of random factors

▶ **Example:**

Trade-off!

Choose Fiat if (Utility Fiat 500 > Utility Skoda Octavia)

That is, everything else equal, if

$U(\text{brand} = \text{Fiat}) + U(\text{trunk size} = <300\text{L}) > U(\text{brand} = \text{Skoda}) + U(\text{trunk size} = >500\text{L})$



Random Utility Theory

- ▶ Sometimes, a customer does not choose the stimulus with the highest utility
 - ➔ some randomness involved

- ▶ Unobservable, true utility
= Observable & systematic utility + random component

Tiredness, uncertainty, distraction, context, ...

Noise: Example of Context Effect

Compromise effect

Which one do you prefer?



€ 2,50



€ 3,50

Random Utility Theory

- ▶ Let C be a choice set composed of n stimuli (e.g. products)
- ▶ The probability of choosing stimulus i among the choice set C is equal to

$$P(i|C) = P[U_i > U_j], \text{ for all } j \in C$$

U_i = Utility of stimulus i

U_j = Utility of stimulus j

Random Utility Theory

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- ▶ The probability of choosing stimulus i among the choice set C is equal to

$$P(i|C) = P[U_i > U_j], \text{ for all } j \in C$$

- ▶ The utility of stimulus i is the sum of the utilities of all attributes x_i and some random noise ε_i

$$U_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_k x_{ik} + \varepsilon_i$$

with $\beta_1 \dots \beta_k$ the vector of preferences for each attribute called *part-worths* and $x_{i1} \dots x_{ik}$ the k attributes of stimulus i

Random Utility Theory

- ▶ In matrix notation, we can re-write

$$U_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} + \varepsilon_i$$

price

Trunk size

Brand

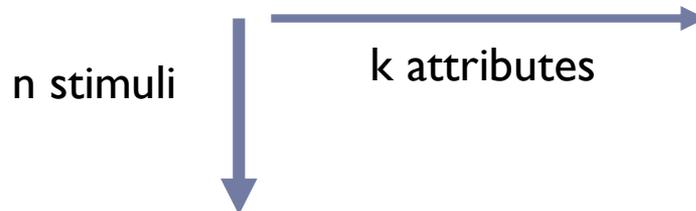
Random Utility Theory

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$$U_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} + \varepsilon_i$$

as follows

$$\begin{bmatrix} U_1 \\ \vdots \\ U_n \end{bmatrix} = \begin{bmatrix} x_{11} & \cdots & x_{1k} \\ & \ddots & \\ x_{n1} & \cdots & x_{nk} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_k \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$



Random Utility Theory

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$$U = X\beta + \varepsilon$$

Back to the Example

Price = 24,895 EUR

Consumption = 5.1 L/100km

$$\beta_1 x_1 = -.5$$

$$\beta_2 x_2 = -.2$$

$U_{fiat} = 2.0$



Brand = Fiat

$$\beta_3 x_3 = 1.7$$

$$\beta_5 x_5 = -0.1$$

Trunk size = 185 L

$$\beta_4 x_4 = 1.1$$

CO-emission = 116 g/km

PAUL E. GREEN and VITHALA R. RAO*

Conjoint measurement is a new development in mathematical psychology that can be used to measure the joint effects of a set of independent variables on the ordering of a dependent variable. In this (primarily expository) article, the techniques are applied to illustrative problems in marketing. In addition, a number of possible areas of application to marketing research are discussed, as well as some of the methodology's limitations.

Conjoint Measurement for Quantifying Judgmental Data

The quantification of managerial or consumer judgment has long posed problems for marketing researchers, irrespective of their interest in normative or descriptive decision making. For example, most media selection models reflect some dependence on media planners' judgmental estimates [4, 5], which are often used in evaluating target populations in terms of households' or individuals' product usage or demographic and socioeconomic characteristics [6]. Moreover, subjective weights are frequently used in appraising vehicle appropriateness and advertising message perception.

Further, the study of consumer decision making requires ascertaining how buyers trade off conflicting criteria in making purchase decisions [8]. Finally, recent studies in public administration attest to a growing interest in the modeling of administrators' evaluations involving multiattribute alternatives in which the analyst must rely on judgmental estimates to a large extent [10].

The purpose of this article is to describe a new approach to quantifying judgmental data, conjoint measurement. Its procedures require only rank-ordered input, yet yield interval-scaled output.¹ The principles of conjoint measurement are discussed and synthetic data are used in solving some typical problems. The conclusion is a discussion of limitations of these techniques and possible application to marketing planning and

CONJOINT MEASUREMENT

As the name suggests, conjoint measurement is concerned with the joint effect of two or more independent variables on the ordering of a dependent variable. For example, one's preference for various houses may depend on the joint influence of such variables as nearness to work, tax rates, quality of school system, anticipated resale value, and so on. Starting with the theoretical work of Luce and Tukey [14], mathematical psychologists have developed procedures for simultaneously measuring the joint effects of two or more variables at the level of interval scales (with common unit) from rank-ordered data alone.

An important special case of conjoint measurement is the additive model, which is analogous to the absence of interaction in the analysis of variance involving two (or more) levels of two (or more) factors in a completely crossed design [2]. In the latter procedure one tests whether or not original cell values can be portrayed as additive combinations of row and column effects. In additive conjoint measurement, however, one asks if the cell values can be monotonically transformed so that additivity can be achieved.²

Since the work of Luce and Tukey, mathematical psychologists have extended additive conjoint models to deal with nonadditivity, partially ordered data, and any polynomial type of function. Analogous to our discussion of the additive model, a data matrix satisfies the (more

¹In the case of finite data, the scale is technically an ordered scale. As the number of input values increases, however, a level is approached.

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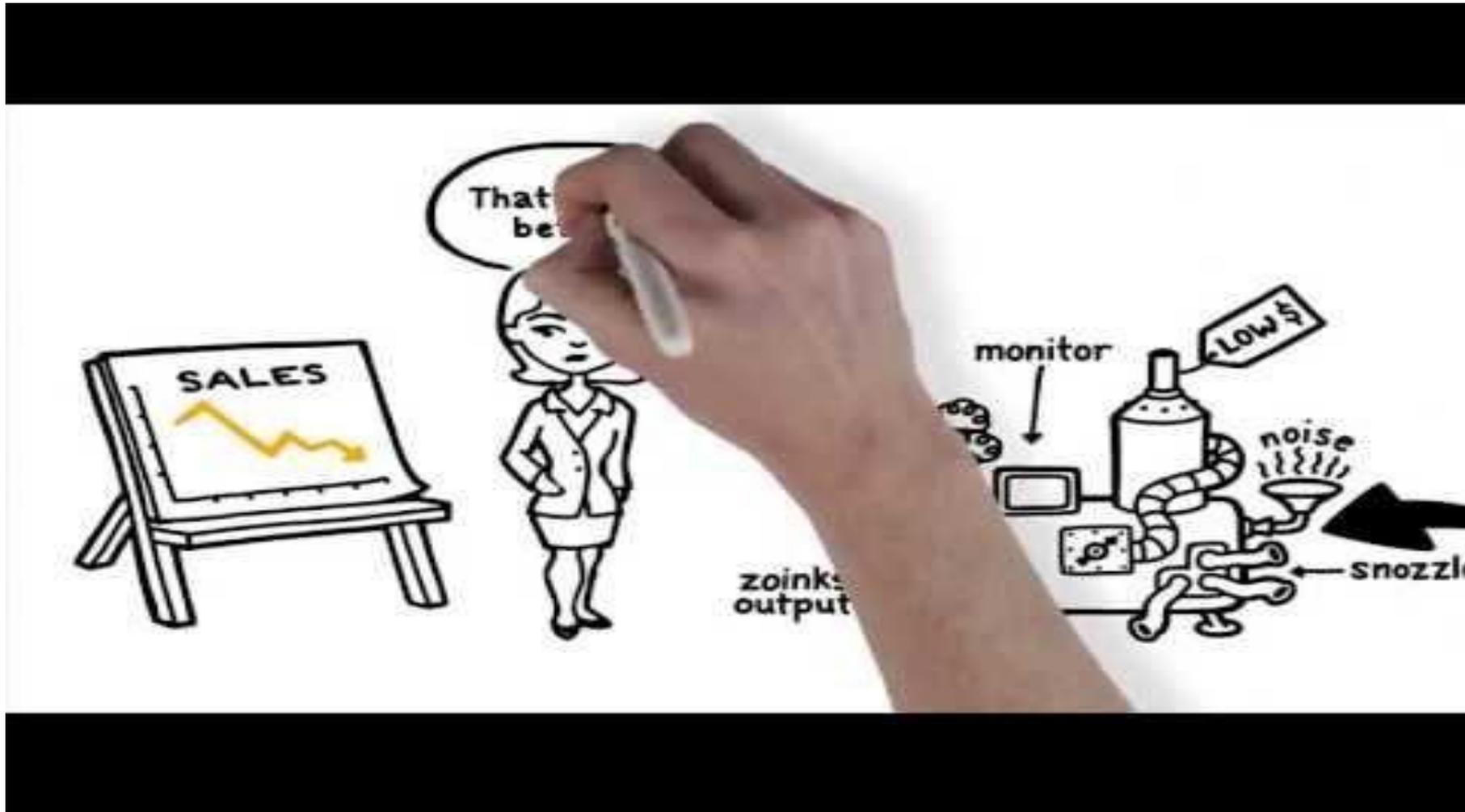
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Seven Steps of Conjoint Analysis

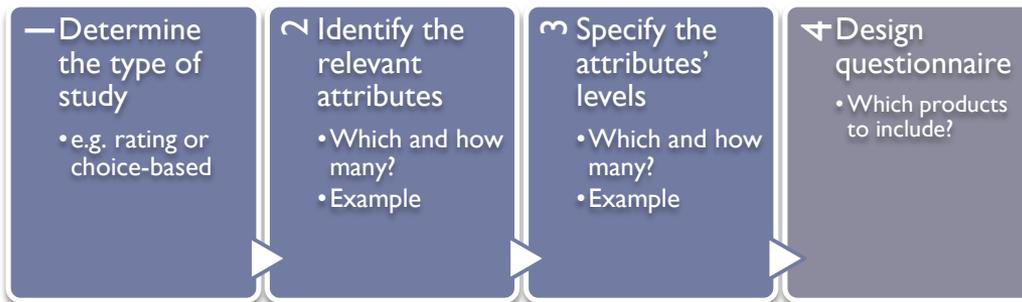
From design to optimization

Interesting Video on Conjoint Analysis

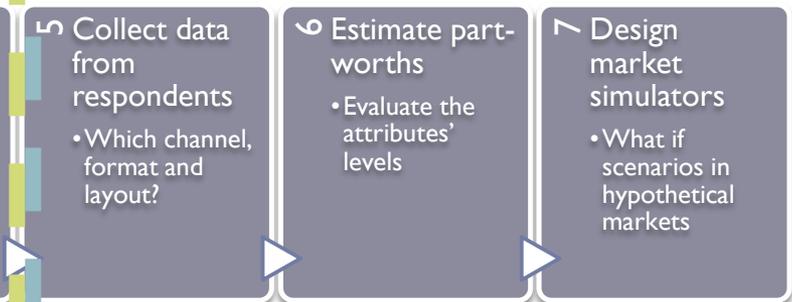


Steps in Conjoint Analysis

Conjoint Design

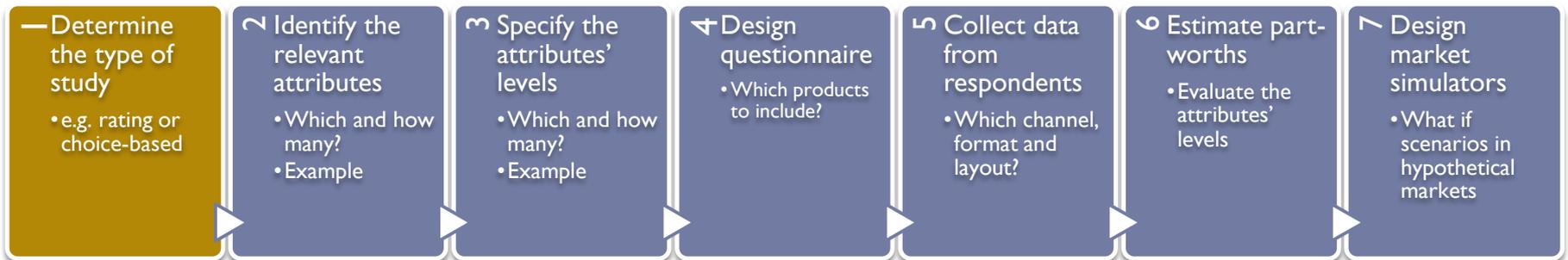


Conjoint Analysis



! In Grey: different for RBC and CBC

Step 1: Ratings vs. Choices



Some History

- ▶ Ranking-based conjoint (seventies, early 80s)
 - ▶ Dependent variable: ordinal responses
 - ▶ Method of estimation: monotonic regression
- ▶ Rating-based conjoint (eighties, early 90s)
 - ▶ Dependent variable: ratings responses
 - ▶ Method of estimation: linear regression (OLS)
- ▶ Choice-based conjoint (nineties, new millennium)
 - ▶ Dependent variable: qualitative responses (choices)
 - ▶ Method of estimation: maximum likelihood (conditional logit)

Choice-Based Conjoint

Rating-based Conjoint

▶ Please rate (scale from 0 to 10):

- ▶  Rating: 8
- ▶  Rating: 3
- ▶  Rating: 5
- ▶  Rating: 7
- ▶  Rating: 8
- ▶ ...

Choice-based Conjoint

▶ Please choose (check box)

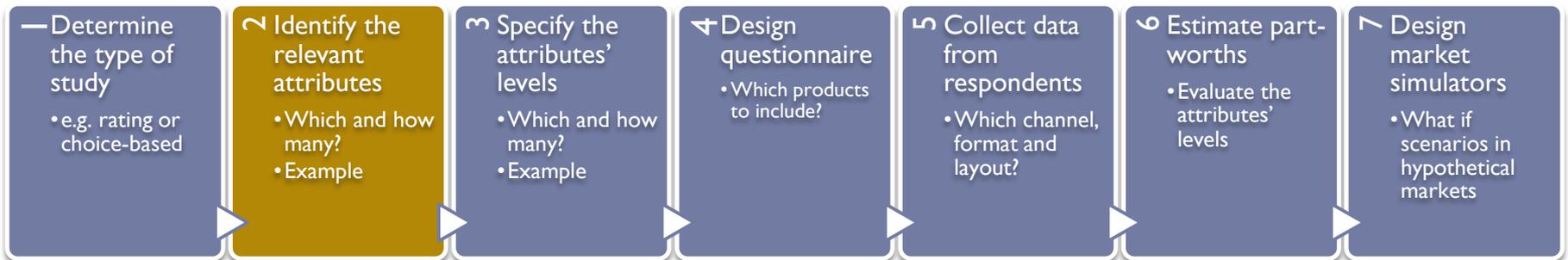
- ▶   none
- ▶   none
- ▶   none
- ▶ ...

Examples: Respondents are asked to choose between stimuli in choice sets

Welches der folgenden Angebote würden Sie auswählen?
Sie können auch angeben, keines der Angebote auszuwählen.

 <p>SONY HD Ready</p>	 <p>TOSHIBA HD Ready</p>	 <p>Panasonic</p>	<p>Keines</p> <input type="radio"/>
<p>66cm Diagonale WXGA 3000:1 Kontrast</p> <p>MediaMarkt</p> <p>€ 1.599,-</p> <input type="radio"/>	<p>81cm Diagonale WXGA 1000:1 Kontrast</p> <p>CONRAD</p> <p>€ 1.399,-</p> <input type="radio"/>	<p>106cm Diagonale WXGA 4500:1 Kontrast</p> <p>SATURN</p> <p>€ 1.999,-</p> <input type="radio"/>	

Step 2: Choosing Attributes



Desirable Properties of Attributes

- ▶ Attributes in conjoint analysis should
 - ▶ be relevant for the management (discuss with them!)
 - ▶ have varying levels in real-life (4 wheels for a car)
 - ▶ be expected to influence preferences (theory, qualitative research)
 - ▶ be clearly defined and communicable (respondent should understand correctly, e.g., verbal descriptions, pictures, intro movie)
 - ▶ preferably not exhibit strong correlations (but price, brand name)

Number of Attributes

- ▶ Green & Srinivasan (1990):
 - ▶ full-profile conjoint if # attributes ≤ 6

- ▶ Techniques for large numbers of attributes do not outperform conjoint:
 - ▶ Direct survey (see problems discussed earlier)
 - ▶ Partial-profile conjoint (only subsets of attributes)
 - ▶ Hybrid conjoint (direct survey, small full-profile conjoint)
 - ▶ Adaptive conjoint (direct survey, dynamic paired comparisons)



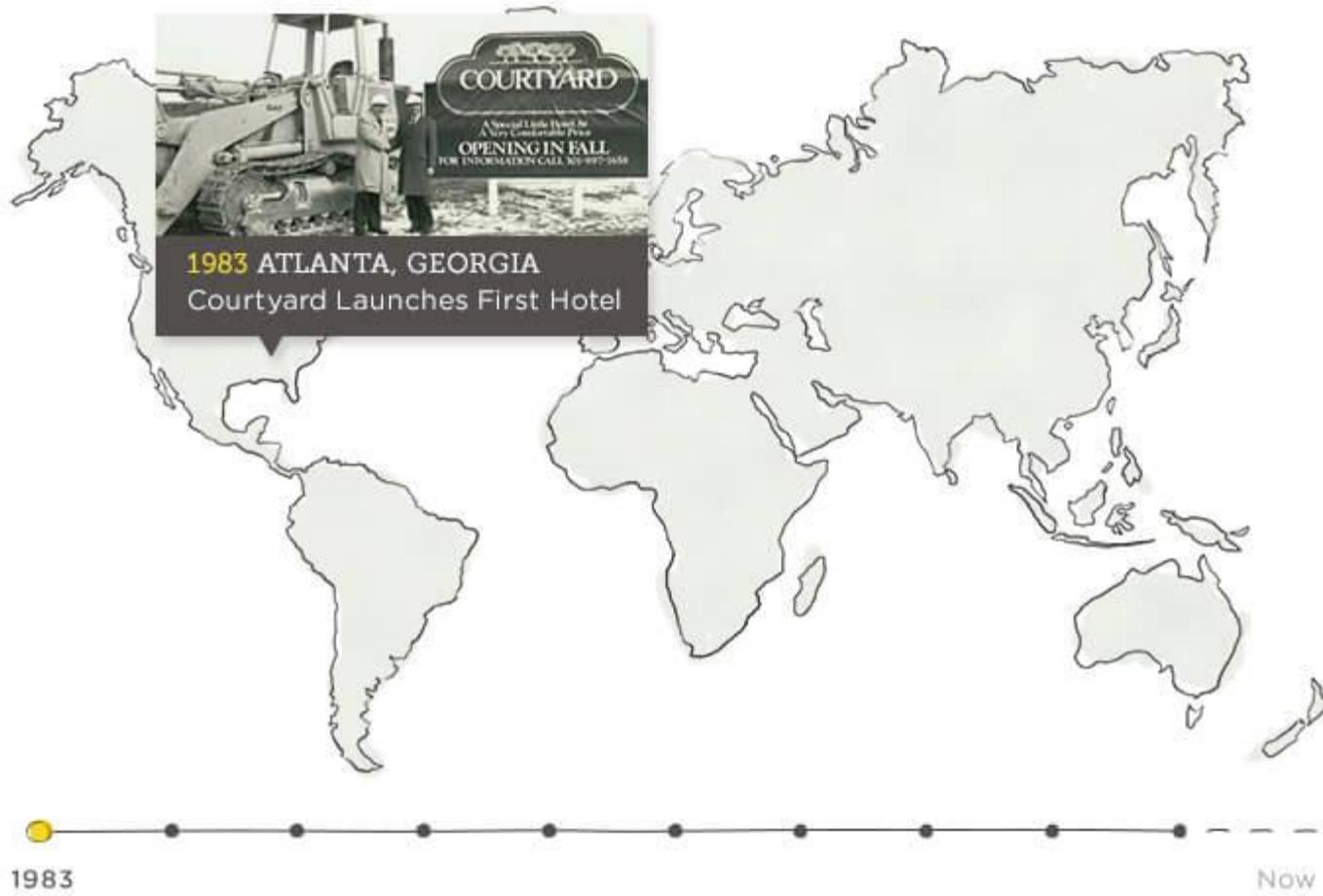


Case Study

Courtyard by Marriott



Courtyard by Marriott



Courtyard by Marriott

Courtyard by Marriott: Designing a Hotel Facility with Consumer-Based Marketing Models

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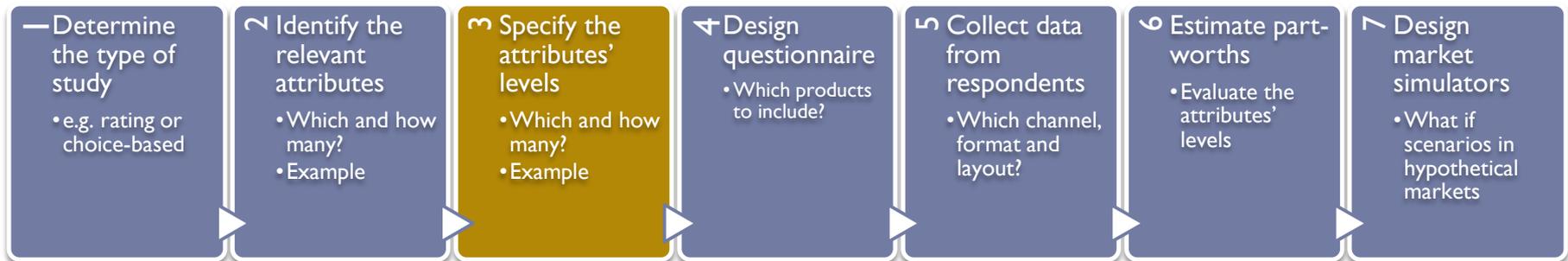
Marriott used conjoint analysis to design a new hotel chain. The study provided specific guidelines for selecting target market segments, positioning services, and designing an improved facility in terms of physical layout and services. Based on these strategy and design recommendations, Marriott developed the *Courtyard by Marriott* concept, which it has successfully test marketed and subsequently introduced nationally. The effectiveness of the study and associated processes also changed Marriott's approach to new product development. Marriott has since developed additional lodging and related products successfully using similar procedures.

Case Study: Which Attributes to Include?

- (1) External factors — building shape, landscape design, pool type and location, hotel size;
- (2) Rooms — room size and decor, type of heating and cooling, location and type of bathroom, amenities;
- (3) Food-related services — type and location of restaurant, room service, vending services and stores, in-room kitchen facilities;
- (4) Lounge facilities — location, atmosphere and type of people (clientele);
- (5) Services — including reservations, registration and check-out, limo to airport, bellman, message center, secretarial services, car rental and maintenance;
- (6) Facilities for leisure-time activities — sauna, exercise room, racquetball courts, tennis courts, game room, children's playroom and yard; and
- (7) Security factors — security guards, smoke detectors, 24-hour video camera, and so forth.



Step 3: Choosing Levels



Desirable Properties of the Levels

- ▶ Levels of attributes should be
 - ▶ interesting for the management (discuss with them!)
 - ▶ unambiguous (“low” versus “high” is too imprecise)
 - ▶ separated enough (otherwise too little weight)
 - ▶ realistic (but allowed to be little bit outside current range)
 - ▶ such that no attribute can a priori be expected to be clear winner



Number of Levels

- ▶ Two levels is minimum
- ▶ In case of linearity, two levels is both sufficient and efficient
- ▶ In case of nonlinearity (e.g. quadratic), more than two levels are needed
- ▶ More levels than necessary is inefficient:
 - ▶ More parameters need to be estimated, and complexity for respondent increases
- ▶ Equal number of levels:
 - ▶ Attributes with more levels are found to be more important (Wittink, Krishnamurthi and Reibstein, 1990)
- ▶ Question Case Study: which levels should we consider?

Case Study: Which Levels?

Attribute

Hotel Size

Corridor/View

Pool Location

Pool Type

Landscaping

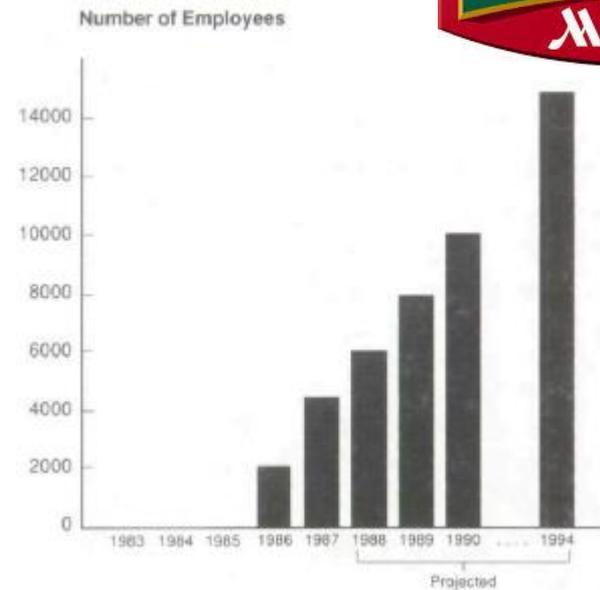
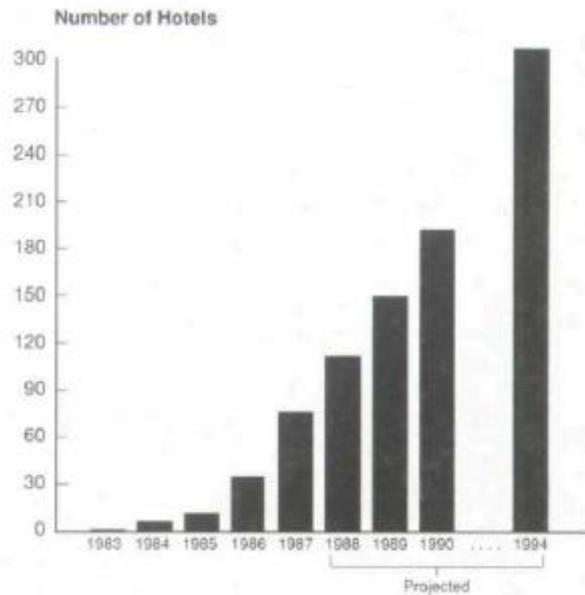
Building Shape

*Figure in parentheses after each description = price premium.

“a special little hotel at a very comfortable price”

Case Study: Was It a Success?

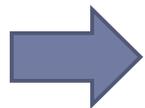
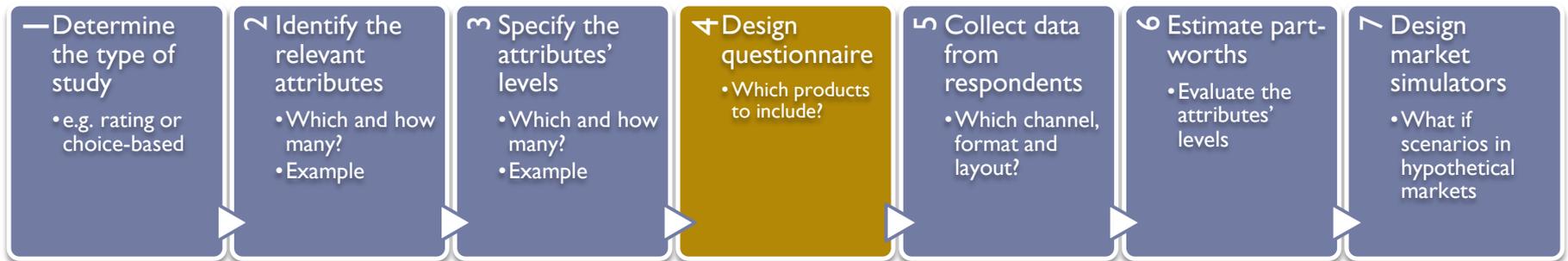
▶ Courtyard by Marriott



Case Study: Was It a Success?

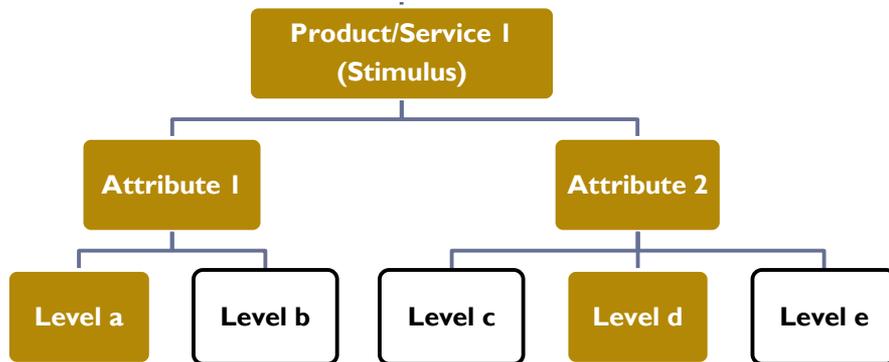


Step 4: Questionnaire Design

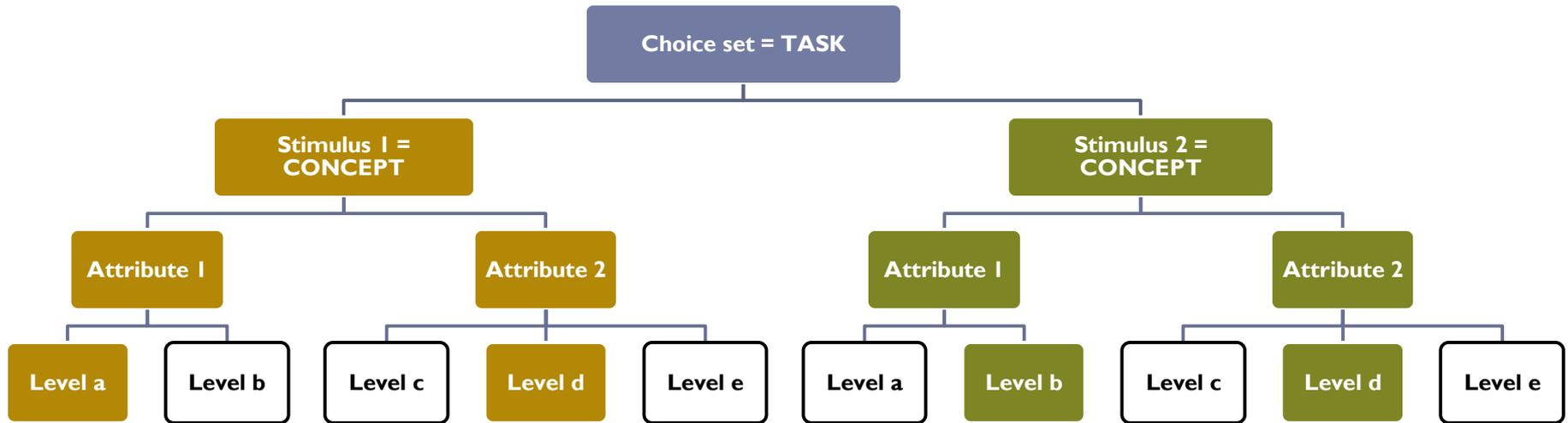


Let's focus here on choice-based conjoint only

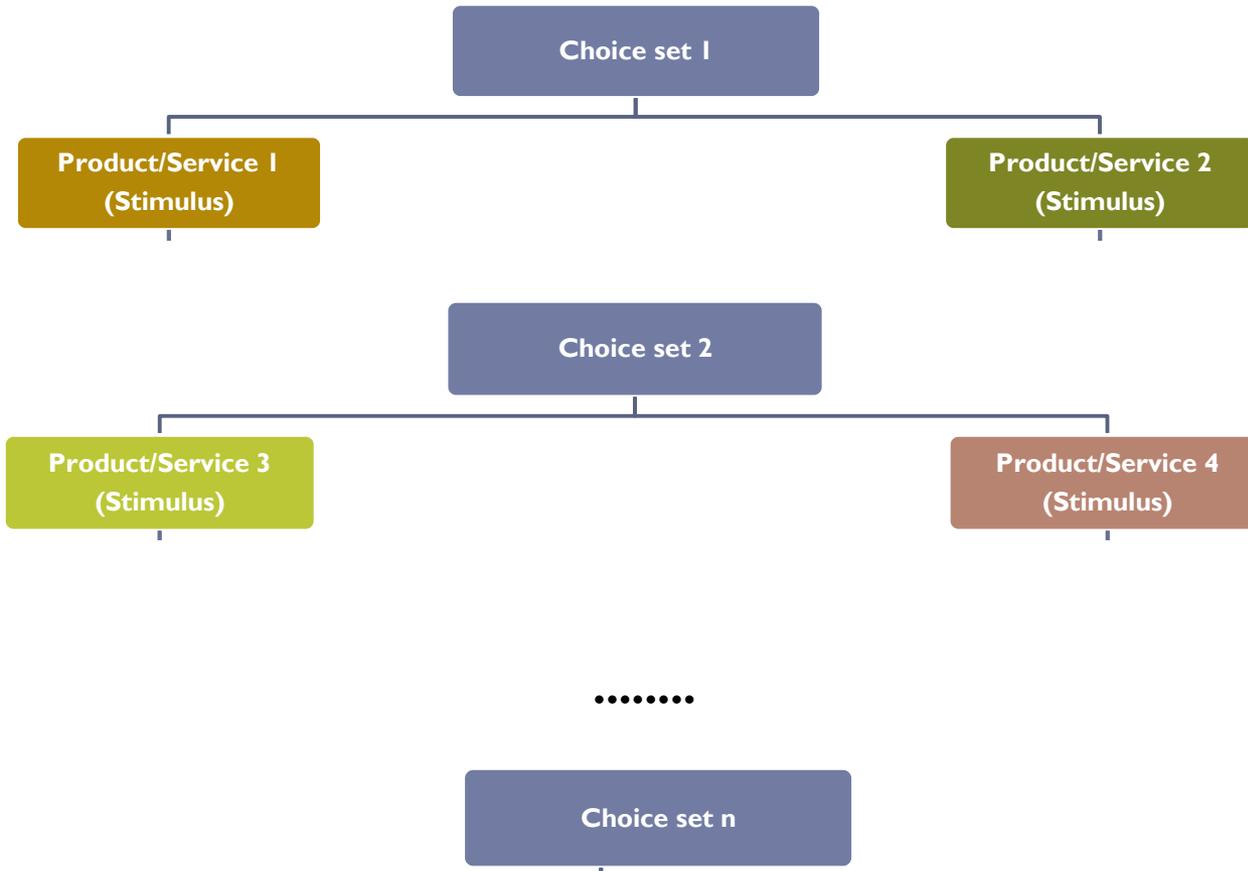
Choice Sets



Sawtooth Terminology



Choice Sets



Key Aspects for a Good Design

- ▶ How many stimuli (CONCEPTS) to include?
- ▶ Which stimuli to include?
- ▶ How to combine them in choice sets (TASKS)?
 - ▶ How many choice sets?
 - ▶ How many stimuli per choice sets?

For instance, there is > 34 million ways to combine 18 stimuli in
9 choice sets!

