Using Attributes for Better Forecasting and Product Insight

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Agenda

- Introduction
- Benefits of Utilizing Product Attribution
- Identifying Attributes
- Use Cases
- History and Genealogy
- Model Overview

WE OPERATE FOUR DIVERSIFIED AGRIBUSINESSES, DRIVEN BY INSIGHTS AND INNOVATION

Crop Inputs & Insights
Agricultural products, data, technology tools and services

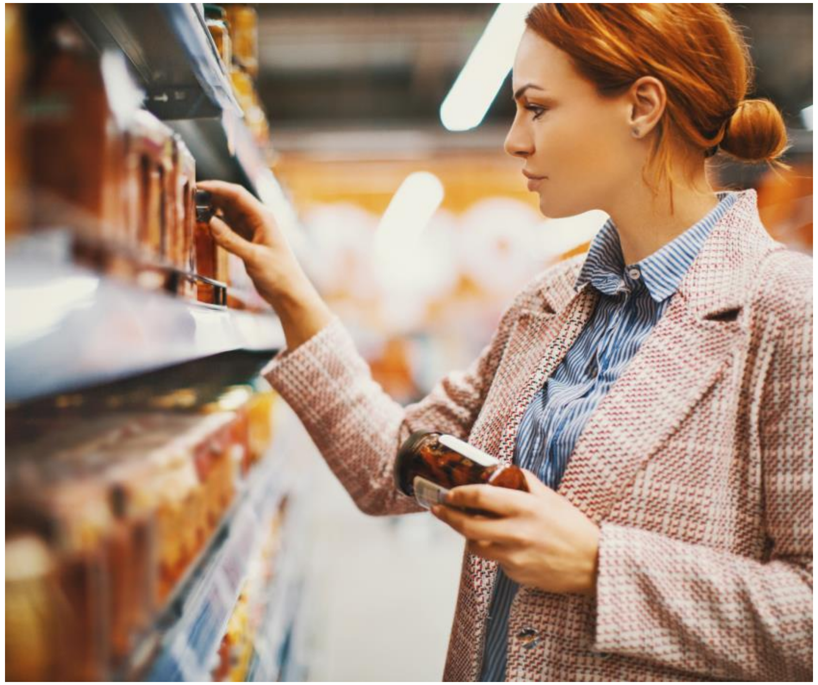
Animal Nutrition
Solutions that enhance performance and well-being

Dairy Foods
Milk-based products and ingredients

Sustainability
Environmental sustainability solutions

Planning Processes and Product Evaluation

- Attributes provide a consistent approach for evaluating all products
- Utilizing product attributes improves the planning process by providing a data-driven approach
  - Offers a framework for harder to forecast products like innovation
- Provides a consumer-driven view of important features for all products in our categories
- Allows assessment at different levels of product granularity



Identify Product Attributes

- Attributes can be obtained from internal and external sources
- Internal sources can include internal research, brand and size information, health profiles, and historical performance groupings
- External sources can include consumer preferences, external attribution, external research about brand preferences
- Focus on consumer needs and behavior to determine relevant attributes

High Level Product Trends

- Product attributes provides a high-level view of the product and category trends
- Product trends including how existing products are performing and how new products will perform
- Category trends include new trending flavors, formats, or sizes which resonate with consumers

Key Concepts for the Model: Product Attributes

- Products can be defined by their constituent attributes
- Consumers form preferences for these underlying attributes, rather than for each individual SKU
- The needs at time of purchase are the most important

Attributes of a Product

Type:	Lubricants
Brand:	Wiley
Size:	10 oz
Form:	Liquid
Formula:	Synthetic blend
Strength:	Max strength
Package:	Pourable bottle
Multipack:	No

Attributes of a Product

Type: Butter

Brand: Land O'Lakes

Size: 453.6 g or 1 lb.

Form: Stick

Salt Content: Unsalted

Package: Box

Multipack: No

Use Cases

- New Product Performance is one area where product attribution can be utilized
  - Such as estimating new product sales

Product Name	Product Number	Brand	Type	Size	Form	Package	Multipack
Product A	21000012	Brand 1	Type 1	8 oz	Form 1	Box	No
Product B	21000014	Brand 1	Type 1	8 oz	Form 2	Box	No
Product C	21000015	Brand 2	Type 1	10 oz	Form 2	Bag	No
Product L	41000014	Brand 3	Type 2	16 oz	Form 3	Box	Yes
Product M	41000016	Brand 1	Type 2	8 oz	Form 4	Box	No
Product N	41000018	Brand 3	Type 2	8 oz	Form 4	Box	No
New Product Q	21000312	Brand 1	Type 3	8 oz	Form 1	Box	No
New Product X	41000411	Brand 3	Type 2	16 oz	Form 4	Box	No

	Unit Sales	Volume Sales	Projected Unit Sales
	400,000	3,200,000	320,000
	200,000	1,600,000	200,000
	700,000	7,000,000	700,000
	300,000	4,800,000	300,000
	1,000,000	8,000,000	1,000,000
	500,000	4,000,000	375,000
	-	-	200,000
	-	-	300,000
Total:	3,100,000		3,395,000

Use Cases

- Another use case that can leverage product attribution is category assortment

Product Name	Product Number	Brand	Type	Size	Form	Package	Multipack	Unit Sales	Volume Sales	Projected Unit Sales
Product A	21000012	Brand 1	Type 1	8 oz	Form 1	Box	No	400,000	3,200,000	400,000
Product B	21000014	Brand 1	Type 1	8 oz	Form 2	Box	No	200,000	1,600,000	200,000
Product C	21000015	Brand 2	Type 1	10 oz	Form 2	Bag	No	700,000	7,000,000	700,000
Product L	41000014	Brand 3	Type 2	16 oz	Form 3	Box	Yes	300,000	4,800,000	300,000
Product M	41000016	Brand 1	Type 2	8 oz	Form 4	Box	No	1,000,000	8,000,000	1,000,000
Product N	41000018	Brand 3	Type 2	8 oz	Form 4	Box	No	500,000	4,000,000	375,000
New Product X	41000411	Brand 3	Type 2	16 oz	Form 4	Box	No	-	-	250,000
							Total:	3,100,000		3,225,000

Caution: Product Master Data Issues

- Missing attributes
  – It is not unusual for less common fields to have missing data
- Incorrect data
  – Data will need to be cleansed
- Inconsistency
  – Not all fields use consistent abbreviations
  – Example : “32 Oz” vs “32 oz”
- Statistical imputation and ML tools can help patch the holes

History and Genealogy

1983

A LOGIT MODEL OF BRAND CHOICE CALIBRATED ON SCANNER DATA*

PETER M. GUADAGNI† AND JOHN D. C. LITTLE‡

A multinomial logit model of brand choice, calibrated on 32 weeks of purchases of regular ground coffee by 100 households, shows high statistical signficance for the explanatory variables of brand loyalty, size loyalty, presence/absence of store promotion, regular shelf price and promotional price cut. The model is parsimonious in that the coefficients of these variables are modeled to be the same for all coffee brand-sizes. The calibrated model predicts remarkably well the share of purchases by brand-size in a hold-out sample of 100 households over the 32-week calibration period and a subsequent 20-week forecast period. The success of the model is attributed in part to

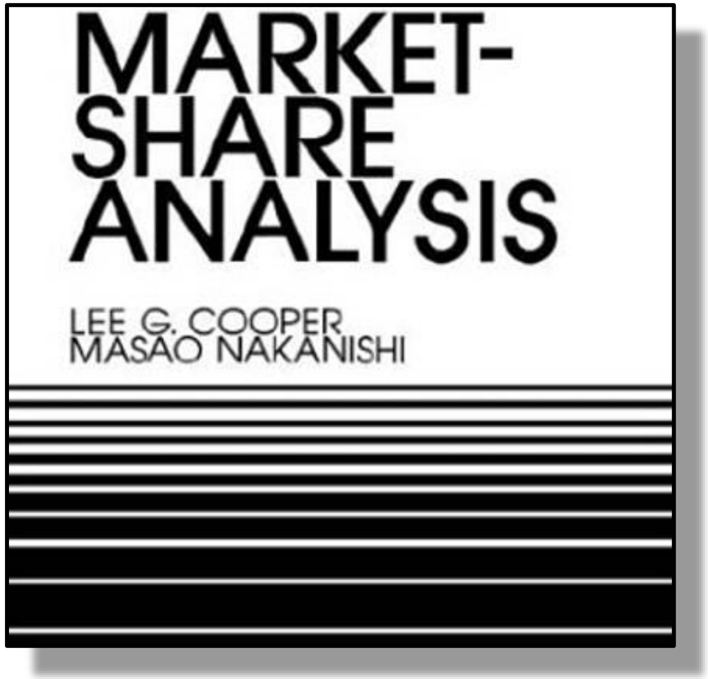
- A consumer choice model: the Multinomial Logit
- Used consumer panel shopping data (only 100 households!)

Key point:

choice probabilities modeled as a function of price, promotion, and brand loyalty.

History and Genealogy

1988



- Textbook with various econometric approaches to modeling market (category) share as a function of price and promotion.
- “Attraction models” or “multiplicative competitive interaction” models (MCI)
- Used aggregate (e.g. POS) sales data, not consumer choice data

Key point to come later:

Shares can be thought of as an aggregation of individual shopper choice probabilities

History and Genealogy

1996

PETER S. FADER and BRUCE G. S. HARDIE*

Most choice models in marketing implicitly assume that the fundamental unit of analysis is the brand. In reality, however, many more of the decisions made by consumers, manufacturers, and retailers occur at the level of the stock-keeping unit (SKU). The authors address a variety of issues involved in defining and using SKUs in a choice model, as well as the unique benefits that arise from doing so. They discuss how a set of discrete attributes (e.g., brand name, package size, type) can be used to characterize a large set of SKUs in a parsimonious manner. They postulate that consumers do not form preferences for each individual SKU, per se, but instead evaluate the underlying attributes that describe each item. The model is shown to be substantially superior to a more traditional framework that does not emphasize the complete use of SKU attribute information. Their analysis also highlights several other benefits associated with the proposed modeling approach, such as the ability to forecast sales for imitative line extensions that enter the market in a future period. Other implications and extensions also are discussed.

Modeling Consumer Choice Among SKUs

- Modifies the 1983 consumer brand choice model and makes it SKU-centric
- SKUs can be represented parsimoniously through their attributes (brand, pack, size)
- Used consumer panel shopping data

Key point :

Consumers form preferences for the underlying attributes of a SKU. These preferences can be recombined to forecast sales for imitative line extensions

History and Genealogy

1998

Attribute-based Market Share Models: Methodological Development and Managerial Applications

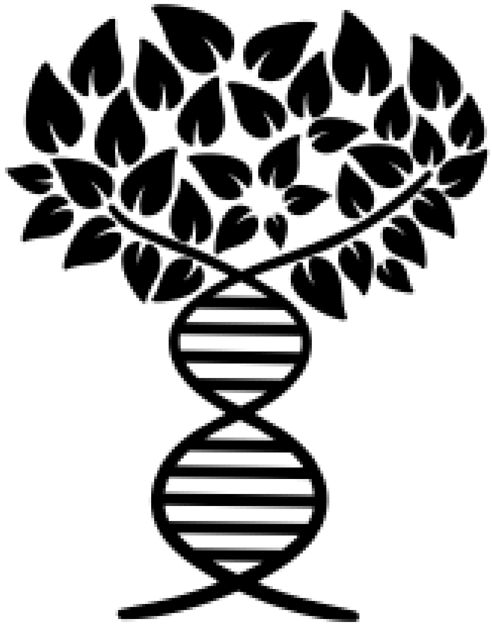
Bruce G.S. Hardie
Leonard M. Lodish
Peter S. Fader
Alistair P. Sutcliffe
William T. Kirk

February 1998

- Merged concepts from 1996 SKU-oriented choice model with 1988 Market Share Modeling approach
- Enabled ability to (implicitly) model consumer choice through aggregate sales data making this approach scalable
  - Data more plentiful, with broader coverage of products and geographies.

Our work largely derived from this model

History and Genealogy



- Extensive progeny stemming from these and related papers
- Several commercial adaptations created by analytics firms

Model Overview

Inputs

Product attributes

Price, promo, etc

$\rightarrow f(x) \rightarrow$

Outputs

Attribute attractiveness

Lifts and elasticities

Forecasts

Simulations

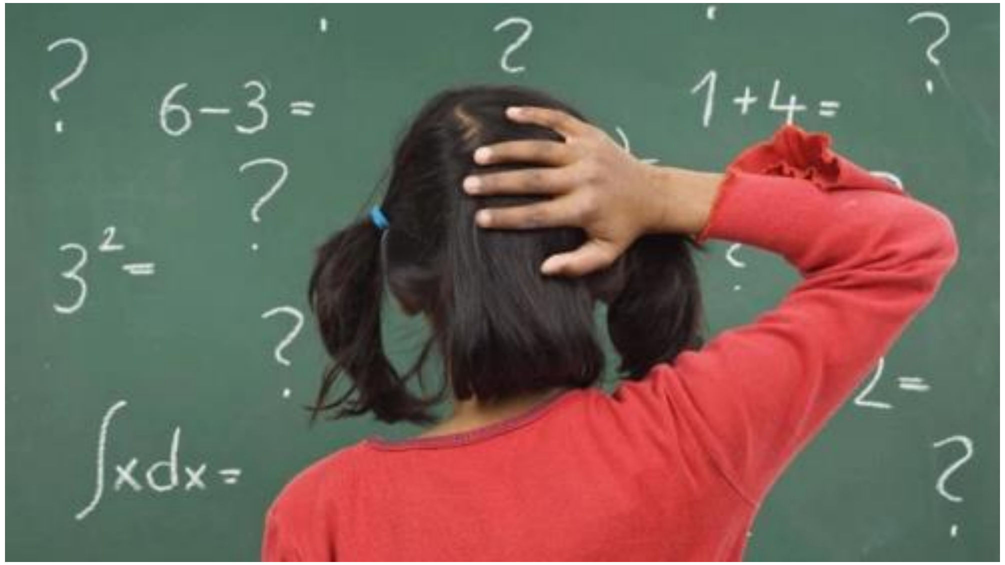
Applications

- Forecast new line extensions by recombining weights of component attributes
- Portfolio optimization (SKU rationalization) by understanding transferrable and non-transferrable demand

APPENDIX

Trigger Warning: Math Ahead!

But it’s simple and high level – this isn’t a modeling course!



Main Generalized Equation

Market (category) share for SKU i

Attraction term for SKU i

$$MS_i = \frac{A_i}{\sum_j A_j}$$

Sum of attractions for all SKUs

- Follows a methodology in the 1988 textbook. Analogous to a multinomial logit
- Calibrated on store-week data (subscripts not shown)

SKU Attraction

Attraction for SKU i

Item-specific intercept for SKU i

$$A_i = \exp(\alpha_i + \beta' X_i + \varepsilon_i)$$

Marketing variables (price, promotion, etc)

- This expands the numerator from the main equation.
- But it is still SKU-, not attribute-oriented.
- Not parsimonious

Attribute Attraction

Attraction for SKU i

Attribute levels
for SKU i

$$A_i = \exp(g(l_1,l_2,\ldots,l_N) + \beta' X_i + \varepsilon_i)$$

$$g(l_1,l_2,\ldots,l_N) = \sum_{n=1}^{N} m_{i'n}\,\alpha_n$$

Vector of attractiveness over
L levels of the n^{th} attribute

- Replace the SKU intercept with a structure to estimate attribute-level attractiveness.
- Though non-linear in the parameters, a linearizing transformation makes it possible to estimate via ordinary least squares regression.

But That's the Easy Part!

Special constructs and transformation of input variables to account for:

- Overcoming the IIA property
- Price effects for each product
- Cross-price effects in a parsimonious way

To get forecasted volumes, a separate category volume model is used