DISJUNCTIVE MAPPING: CHANGING THE WAY WE UNDERSTAND AND PREDICT CUSTOMER BEHAVIOR

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ABSTRACT

Relative to the traditional statistical techniques that we have come to rely on, this article presents a fundamentally different way to analyze and predict customer behavior. In addition, new analytical tools are described that highlight promising opportunities to modify customer behavior to better achieve desired outcomes.

Many commonly used techniques to understand and predict consumer behavior presume an underlying functional relationship – a model - buried in confusing data. We take the position that these models are generally not good representations of human behavior. Furthermore, with desktop computing having become so powerful, it is now practical to challenge whether the modeling approaches that we have come to rely on represent the best paradigm for understanding and predicting consumer behavior.

Underlying our approach, termed Disjunctive Mapping (DM), is the notion that there are generally multiple routes (sets of influences and decisions) leading to any outcome and their effects can be measured in terms of change in an outcome's probabilities. Rather than attempt to capture central tendencies or capitalize on dominant patterns, DM obtains its power by focusing on the multiple ways events occur. DM metrics enable users to measure the change in probability of an outcome due to the influence of any factor or set of factors in the data, *without* building models. A structured inquiry process allows it to offer direct, accessible, comprehensive, and prioritized measures in answer to practical questions.

Veritec has developed software, termed *Customer Behavior Mapping* (*CuBe Mapping*), to implement the concepts introduced here.

Key Words: disjunctive mapping, forecasting, customer behavior, elasticity, pricing, probability, regression

INTRODUCTION

In the Fall of 2008 at a Congressional hearing, the following exchange took place between Alan Greenspan, the former Chairman of the United States Federal Reserve Board, and Senator Waxman. Mr. Greenspan, who had presided over the build-up to the recent financial collapse, testified:

> "I made a mistake in presuming that the self-interests of organizations, specifically banks and others, were such as that they were best capable of protecting their own shareholders and their equity in the firms"

Seeking clarification of Mr. Greenspan's comments, Mr. Waxman responded, "In other words, you found that your view of the world, your ideology, was not right, it was not working," Mr. Waxman said.

> "Absolutely, precisely," Mr. Greenspan replied. "You know, that's precisely the reason I was shocked, because I have been going for 40 years or more with very considerable evidence that it was working exceptionally well." (Drum, 2008)[1]

There was, Mr. Greenspan acknowledged, an error in his thinking and in the models he relied upon. Although he did not say it specifically, it appears that in his view, the error was that his model had missed variables or relationships that accounted for the limited effects of the "self-interests of organizations."

While we agree that Mr. Greenspan erred in his thinking and in his models, we believe the error is bigger than that. Indeed, as described more fully in this article, we believe the error is inherent in the analytical methods we have come to rely upon for understanding and predicting human decision-making. And if we are right, the catastrophic breakdown of Mr. Greenspan's models could have, and should have, been expected.

Relative to the traditional statistical techniques that we have grown accustomed to using to explain, forecast, and affect customer behavior during the past 50 years (or even more), we propose an alternative approach that we've termed *Disjunctive Mapping.* Disjunctive Mapping begins with a different set of assumptions about how we should think about and measure human behavior. At the heart of the approach is the notion that there are generally multiple routes or paths leading to an outcome (i.e., there are different ways an outcome can happen) and the likelihood of an outcome occurring is the sum of the probabilities of those routes. Traditional statistical methods such as regression aim at identifying central tendencies and dominant patterns.

Disjunctive Mapping (DM) creates metrics that enable users to measure the change in probability of an outcome due to the influence of any factor or set of factors in the data by summing their effects across relevant routes. Both allow making predictions from the data, but only DM uses

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[1]Testimony to the House Oversight and Government Reform Committee, October 23, 2008, as reported by Kevin Drum at www.motherjones.com.

the full range of information available and recognizes disjunctive mechanisms. A structured inquiry process allows DM to offer direct, accessible, comprehensive, and prioritized measures to answer practical questions.

Potential application areas include:

- Direct and immediate "plug-in" to analyzing virtually any type of survey data
- Consumer buying analyses and prediction, including price/demand elasticity ranges
- Medical research and diagnoses
- Internet Search and ad placement prioritization
- Financial markets
- Program evaluation

Returning to the situation faced by Mr. Greenspan, he was, we suspect, thinking that there was some factor or interaction his thinking and models had not addressed. As we try to show in this article, however, all such corrections to our traditional models can do is formulate a new set of "right for the wrong reasons" rules that fit the current situation better, and hope it proves durable. The real error, as we hope to show, is in the nature of the thinking and models that he, and we, generally rely upon.

A MORE DIRECT WAY TO ANSWER PRACTICAL QUESTIONS

Many of the methods commonly used to understand and predict consumer behavior are grounded in statistical techniques that were developed prior to the availability of computers. These techniques presume there is an underlying functional relationship buried in confusing data—mathematical signals to be teased out of noisy measurements. For many years, in part due to the limits on our computing power, this only allowed a narrow range of functional relationships to be captured. Much of the history of statistics can be seen as a struggle to expand what these models can handle without abandoning the basic underlying mathematics and principles that have given us regression, factor analysis, and so forth. In the process, methods have become very complicated and require increasing levels of sophistication to apply correctly.[2]

But are the underlying mathematics and principles a good representation of human behavior? And if not, do we need to rely on them any longer? Only in recent years, with desktop computing having become so powerful, has it become practical to challenge whether the modeling approaches that we have come to rely on truly represent the best paradigm for understanding and predicting consumer behavior. And, as is detailed further in this article, we think the answer is a

[2] For the reader who has not personally faced the complications involved, Peter Kennedy's *A Guide to Econometrics* (originally published by the MIT Press, Cambridge MA in 1979 and now in its 5th edition, published by Blackwell, Malden, MA) particularly the general and technical notes at the ends of the chapters, give an idea of what is involved at a level that advanced undergraduates are expected to understand.

resounding, “No, they are not.”

Different people often do the same thing for different reasons and the same person may do the same thing for different reasons at different times—whether making a purchase, taking a political stance, choosing a profession, and so on. Such an observation may seem obvious, even trite; yet, traditional analytic methods are typically designed to find underlying relationships as if that diversity was merely appearances, not genuine differences, or as if only shared characteristics are important. What has been done, and what we now generally take for granted, is accept that an analytical methodology, whose origins can be traced to finding insights into biological processes, is also the most appropriate way to understand and predict human behavior.[3] It’s a leap that we rarely give much thought. Our contention is that by guiding us to try to capture the variety of reasons in a single or a few functional forms, looking for essences where there is in fact diversity, it is quite likely that we will lose information that is crucial to understanding decision processes and behaviors more generally. The ultimate effect, when relying on those methods, is undermining the quality of the decision process.

Consider an alternative way of thinking about consumer behavior: one that does not try to find the essence or underlying patterns of decision processes, but rather explains behavior by the variety of ways consumers make choices. Each of us makes decisions for combinations of reasons. A natural consequence of this is that as a greater number of *combinations lead to the same outcome,* the likelihood of that outcome also increases. The logic here is *disjunctive*. If one combination of inputs *or* another (*or* another, etc.) occurs, the behavior of interest (e.g., a purchase) occurs. The probability or likelihood of the outcome is the sum of the probabilities that the various combinations occur. No underlying consistency (no “essence”) is required.

To fit this way of thinking about consumer behavior, rather than developing a functional form to model consumer behavior, we propose using historical transaction data to develop a *map* of consumer behavior—all the various routes to an outcome—and then analyzing the information contained in this map. Combining consumer demographic, psychographic, and other data with data about the products and/or outcomes of interest enables creating metrics that identify and rank the most important influences on the outcomes, as well as tracing their interrelationships.

How does a map of customer behavior differ from a model of customer behavior? As is familiar to us all, a map simply shows various ways to get from here to there. A model, however, is fundamentally different. By their very nature, models have to find or impose an underlying logic and are a poor fit when there are many distinctive underlying logics—typical for situations where behaviors arise for a variety of reasons.

If our conjecture is right, we believe that this fundamentally different way of analyzing consumer behavior, and ultimately using this information to predict future behavior, will offer new insights into how and why consumers make choices. From a strategic as well as tactical perspective, this could lead us to take different actions as we strive to achieve our objectives more frequently, and/or more profitably.

[3] The initial conceptualization of linear regression has been associated with work conducted by Sir Francis Galton to understand the inherited characteristics of sweet peas.

BASIC CONCEPTS IN DISJUNCTIVE MAPPING

Multiple Reasons

Consider the variety of reasons someone might buy a car. Michelle buys a car because the dealer has one in stock and is nearby, its price is acceptable, it can carry five people comfortably, and it has a good consumer magazine rating. Jim buys the same model because his children like it, it is the cheapest car that looks like a BMW, and it is almost affordable. Jerry buys the same model because you can fit a half keg in the trunk and has the highest wattage stereo of the cars he can afford. Dianne buys the same model because it meets her well-researched requirement for fuel efficiency and emissions, has exceptional no-skid brakes, and comes in a glorious shade of red. And so on.

These are genuinely different combinations of reasons. There are shared elements but the shared elements do not necessarily drive the process: no parsimonious description or model can do them justice. Yet our analytic methods and traditions are generally aimed at producing parsimonious representations based on finding consistencies across instances, even though current computers can handle a more accurate description. In short, our traditional methods waste valuable information.

Or, more informally, as noted previously, most everyone knows people often do the same thing—whether making a purchase, taking a political stance, choosing a profession—for different reasons. Yet traditions and methods all but beg us, 'Believe the models, not your lying eyes.'

Combinations and Disjunctions

The car-buying example illustrates a common feature of decision-making: we do things for combinations of reasons and there are apt to be a large number of combinations. If cars can carry 2 through 7 people, trunks come in three sizes, automotive status symbols come in 5 varieties, and stereo wattage comes in 3 levels, we are already at 270 combinations and we are just beginning to list criteria.[4] Thinking in terms of these combinations, if we ask what would make buying a particular model more likely, the answer would be: the presence of more combinations that leads to buying the car, or increases in the likelihood of those combinations.

The logic here is disjunctive. If combination A or B or C or D, and so forth occurs, the purchase is made. The probability of the purchase is the sum of the probabilities of the various combinations. The question is how to capture as much of the disjunction as possible, and report it in a form we can use.

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[4] Even if not all combinations are available (e.g., cars able to carry only 2 passengers may not be made with the largest size trunk), the number of available combinations will typically be quite large.

Categories Not Continua

The combinations are made of categorical variables, not continuous scales, although categories can represent ranges on those scales. This may seem to be a limitation since we often measure behavior on continuous scales, but on the whole, using categories pushes us in a useful direction. Since Miller's classic paper, *The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information,* there have been a series of demonstrations that we break continua into a rather limited number of categories, and that there are cognitive limitations that force such strategies upon us (Miller, 1956). The tendency to stereotype, to create dichotomies, to consider only a few options when making decisions, and so forth, seems to be more than just a bad habit or *satisficing.* Thus a model of human behavior that tracks how one thing leads to another, if it works from continua, is using a surrogate for the information that actually influences responses—the categorical interpretations we impose on ranges of continua. Breaking continua into these categories can add that information. Using categories is a feature not a bug.

The choice of categories, and more generally, the degree to which factors should be aggregated or disaggregated, depends on whether there is information to be gained by further subdivision. (Our software implementation of DM provides support for finding the most informative level of aggregation.)

Maps Not Models

A map shows various ways to get from here to there, and has no difficulty if each of the routes has its own logic—go through the pass, follow the river valley, take the coastal route but avoid the marshes, take the scenic highway, get on a train. But models have to find or impose an underlying logic. Thus models are a poor fit when there are multiple underlying logics, as there can easily be when behaviors arise from various combinations of reasons. Maps, on the other hand, simply show them.

If we think of each combination as a route to a behavior—purchasing a car, selecting a flight, taking out a loan, voting for a candidate—and each route having a probability, we have a straightforward and detailed (to the limits of the relevant data) description of the various ways behaviors happen and their likelihoods. It allows us to see which routes are frequently used (and by whom) and which are not. And we can examine selected routes or sets of routes to see what characteristics are present or absent. Mapping routes and measuring probabilities is the foundation of Disjunctive Mapping.

Commonalities Are Not the Basis for Explanations

The way we generally go from the diversity we observe to the uniformities of our explanations and models is to find or hypothesize commonalities across instances of a phenomenon. Consider a sample of consumers who have some preferences in common but far from all. For example, they are all concerned about price, comfort, and reliability. But there are only scattered concerns about the quality of the sound system, the number of cup holders, the high speed handling, how sporty it looks, if a manual transmission is available, and so on across the sample.

Data representing the common and idiographic preferences could look something like what is displayed in Table 1, with three shared concerns (A, B, C) and somewhat larger overlapping sets of concerns whose combinations are unique to an individual or smaller set of individuals.

Consumer	Common Factors	Idiographic Factors
1	A B C	G H P Q R X
2	A B C	E F I N P R
3	A B C	F K M N P X
4	A B C	D E G I K M P

Table 1: Illustrative display of common and ideographic preferences

In a conventional statistical analysis the three factors in common (A, B and C) would be the only ones that are likely to account for a substantial percentage of the variance, and would be understood as driving the consumer's choice. Nothing else is consistent enough to compete. The idiographic factors would be largely treated as noise, and tend to fall out of the model because they would not increase its predictive power. In this the analysis is only doing what it is supposed to do, identify reliable predictors—but that is not the same thing as measuring their influence, even when there is no question of spurious correlation (the relationship between the common factors and purchasing the car is genuine).

Does treating the common factors as the major if not sole determinants of consumer choice make sense? We should ask ourselves: How likely is it that someone would buy a car which met their desires for price, comfort, and reliability versus buying a car that met those desires and a host of idiographic ones, such as such as the quality of the sound system, the number of cup holders, the high speed handling, how sporty it looks, and if a manual transmission is available. The answer seems obvious; why buy less of what you want when you can get more? What we are actually doing is attributing to the common factors what is actually explained by the common factors and various combinations of idiographic ones. It may even turn out that some combinations of idiosyncratic behavior can be the stronger influence—such as buying the car of your dreams in spite of its costing too much, being uncomfortable, and being unreliable. In no way are the common factors the sole, or even necessarily, the major determinants.

It would be more consistent with the data to recognize that consumer choices are due to combinations of reasons, containing both common and idiographic elements, with no prior assumptions about their relative impacts. A factor's or set of factors' influence can be measured by comparing routes with and without that factors or set of factors, as is done in the measures of factor influence discussed below.

This kind of route based analysis, which can require keeping thousands if not hundreds of thousands of routes in a database, and making rapid searches and computations, was not a practical possibility until recently. But now that it is possible we have far less reason to rely on earlier methods and assumptions—as brilliant as they were —given the limitations then at hand.

Probabilities are the Measure of Effect Size

From a practical perspective, our ability to understand, to predict, and ultimately to influence the decision-making process hinges on our ability to estimate the likelihood of events. Although it seems we sometimes forget, when interpreting traditional statistical analyses of customer behavior, measures of a model's reduction in prediction errors (such as R^2), mean differences, and deviations from a central tendency, all familiar in statistical practice, do not actually measure likelihood directly. Probabilities do. Although we do need to exercise care in how we interpret probabilities when using them as a basis for forecasting, probabilities are also simple to calculate and understand, requiring only counting and division—the same calculations as percentages.

Probabilities can be obtained using a number of statistical and decision-making programs, spreadsheet calculations, to say nothing of doing them by hand. The issue is not how to calculate them but being able to efficiently identify the probabilities that are telling in complex disjunctive systems. After that, it is only a matter of arithmetic.

By organizing data into maps that identify the routes to outcomes and by using the measures and procedures discussed below, DM is, in effect, a system to identify and readily calculate those probabilities.

THE TOOLS FOR THE JOB

Prior to presenting the details underlying Disjunctive Mapping, it is useful to define a number of terms to facilitate the discussion.

Routes

We can describe the events and conditions that lead to human behaviors—motivations, habits, events, beliefs, conventions, feelings, influences, perceptions, social pressures, circumstances and so forth—quite simply as routes or paths. For example, a sequence or combination of three input events, A, B, and C, leading to an output behavior X is a route through A, B, and C to X.

$$A \quad B \quad C \rightarrow X$$

If there is uncertainty associated with the output, for example, if two outcomes are possible, we might have X1 represent when X occurs and the other X2 when X does not.

$$A \quad B \quad C \rightarrow X1, X2$$

If there is uncertainty about both the inputs and the outcomes we could represent each possible set of events, behaviors, and outcomes by a stack of routes, one for each combination of inputs.[5]

$$A1 \quad B1 \quad C1 \rightarrow X1, X2$$
$$A1 \quad B1 \quad C0 \rightarrow X1, X2$$
$$A1 \quad B0 \quad C1 \rightarrow X1, X2$$
$$A1 \quad B0 \quad C0 \rightarrow X1, X2$$
$$A0 \quad B1 \quad C1 \rightarrow X1, X2$$
$$A0 \quad B1 \quad C0 \rightarrow X1, X2$$
$$A0 \quad B0 \quad C1 \rightarrow X1, X2$$
$$A0 \quad B0 \quad C0 \rightarrow X1, X2$$

We refer to the various states that a variable can take as *factors.* The probabilities associated with the routes, and the factors they contain, can be computed directly from the data.

The Map

The behavioral map shown in Figure 1 contains one row for each route and one column for each input variable. The five input variables in this map are age category, sex, reviews, style, and dealer. To the right of the input variables are the three output columns, with one column for each factor; these columns are labeled Other, Zoom, and None. As each row in the map describes a set of behaviors and the frequency with which that behavioral combination leads to the various outputs, an input variable has only one column regardless of the number of factors; an output variable has as many columns as it has factors. The column following the output columns, labeled N, contains the frequency with which the specific combination of behaviors (i.e., the route) occurred. So, looking at any row we see the elements of a route, the frequency with which the route occurs, and the frequency of its outcomes.

[5] To keep the example simple, each input (like the output) has only two states, they either happen or they don't. A map can be constructed with any number of input and output states for each input and output variable, and any number of inputs and outputs.

The routes and their outcomes, taken together, along with a few basic statistics, describe the disjunction.

age category	sex	reviews	style	dealer	Other	Zoom	None	N	route probability	route potential	route contribution	%route contribution
26 - 35	Female	Read	Innocuous	Good	10	10	4	24	0.079	0.417	0.033	3.300
26 - 35	Male	Read	Innocuous	Good	8	7	2	17	0.056	0.412	0.023	2.310
26 - 35	Male	Read	Ugly	Good	9	5	2	16	0.053	0.313	0.017	1.650
26 - 35	Male	Ignored	Ugly	Poor	9	1	1	11	0.036	0.091	0.003	0.330
26 - 35	Male	Read	Ugly	Poor	4	3	4	11	0.036	0.273	0.010	0.990
26 - 35	Female	Read	Ugly	Good	5	4	0	9	0.030	0.444	0.013	1.320
18 - 25	Male	Ignored	Ugly	Poor	6	2	1	9	0.030	0.222	0.007	0.660
26 - 35	Male	Read	Attractive	Good	1	7	0	8	0.026	0.875	0.023	2.310
>=36	Female	Read	Innocuous	Good	2	4	1	7	0.023	0.571	0.013	1.320
18 - 25	Female	Ignored	Ugly	Poor	5	2	0	7	0.023	0.286	0.007	0.660
26 - 35	Female	Read	Ugly	Poor	6	0	1	7	0.023	0.000	0.000	0.000
>=36	Female	Read	Attractive	Good	0	6	0	6	0.020	1.000	0.020	1.980
>=36	Male	Read	Innocuous	Good	2	3	1	6	0.020	0.500	0.010	0.990
26 - 35	Female	Ignored	Innocuous	Good	3	2	1	6	0.020	0.333	0.007	0.660
26 - 35	Female	Read	Ugly	Satisfactory	5	1	0	6	0.020	0.167	0.003	0.330
26 - 35	Male	Ignored	Innocuous	Poor	2	2	2	6	0.020	0.333	0.007	0.660
26 - 35	Male	Read	Innocuous	Poor	4	1	0	5	0.017	0.200	0.003	0.330
26 - 35	Male	Read	Innocuous	Satisfactory	3	2	0	5	0.017	0.400	0.007	0.660
18 - 25	Female	Ignored	Innocuous	Poor	2	2	1	5	0.017	0.400	0.007	0.660
26 - 35	Male	Read	Ugly	Satisfactory	4	0	1	5	0.017	0.000	0.000	0.000

Figure 1. Partial Listing of Routes in a Map

The remaining columns in the map, and we shall discuss these shortly, are computed statistics that describe the likelihood that a car named the *SuperZoom 4000* is purchased. Although not included in this map, the same statistics can be computed for the other outcomes, such as purchasing a different car or no purchase.

Given the map, the core problem is how do we extract useful information without collapsing the diversity of routes it contains, and thereby throwing away potentially valuable information.

Basic Statistics

To enable us to extract useful information, we introduce four key statistics:

Route Probability of Route i is defined as the probability that route i occurs, a relative frequency, namely:

$$N_i / \sum N$$

where the summation is taken over the frequency of all routes.

Route Potential of Route i is the probability of the outcome of interest given the route:

$$(\text{Frequency of Outcome of interest on Route i})/N_i$$

Route Contribution for Route i is the probability of the outcome of interest accounted for by the route, relative to all possible routes:

$$(\text{Route Probability})_i * (\text{Route Potential})_i$$

Route Contribution Percentage of Route i describes the frequency percentage of the outcome of interest accounted for by route i relative to all routes:

$$(\text{Route Contribution})_i / \sum \text{Route Contribution}$$

where the summation is taken over all routes.

It is worth making a few comments about Route Potential and Route Contribution.

Route Potential

Route Potential shows the strength of the relationship between the factors on a given route and the outcome of interest; in this example, it is the likelihood that each combination of factors results in the purchase of the *SuperZoom 4000*. Sorting the behavioral map by Route Potential, as shown in Figure 2, enables us to identify quickly those routes with the strongest input-output relationships.

age category	sex	reviews	style	dealer	Other	Zoom	None	N	route probabilit	route potential	route contributio	%route contributio
>=36	Female	Read	Attractive	Good	0	6	0	6	0.020	1.000	0.020	1.980
>=36	Male	Read	Attractive	Good	0	5	0	5	0.017	1.000	0.017	1.650
26 - 35	Male	Ignored	Attractive	Good	0	5	0	5	0.017	1.000	0.017	1.650
18 - 25	Female	Read	Innocuous	Poor	0	3	0	3	0.010	1.000	0.010	0.990
>=36	Female	Ignored	Innocuous	Good	0	2	0	2	0.007	1.000	0.007	0.660
26 - 35	Male	Read	Attractive	Satisfactory	0	2	0	2	0.007	1.000	0.007	0.660
>=36	Female	Read	Innocuous	Poor	0	2	0	2	0.007	1.000	0.007	0.660
18 - 25	Male	Read	Innocuous	Good	0	2	0	2	0.007	1.000	0.007	0.660
26 - 35	Female	Read	Attractive	Satisfactory	0	2	0	2	0.007	1.000	0.007	0.660
>=36	Male	Ignored	Attractive	Good	0	1	0	1	0.003	1.000	0.003	0.330
>=36	Female	Ignored	Ugly	Satisfactory	0	1	0	1	0.003	1.000	0.003	0.330
>=36	Male	Read	Ugly	Satisfactory	0	1	0	1	0.003	1.000	0.003	0.330
>=36	Female	Read	Innocuous	Satisfactory	0	1	0	1	0.003	1.000	0.003	0.330
18 - 25	Male	Read	Ugly	Satisfactory	0	1	0	1	0.003	1.000	0.003	0.330
18 - 25	Female	Read	Attractive	Good	0	1	0	1	0.003	1.000	0.003	0.330
>=36	Male	Ignored	Attractive	Poor	0	1	0	1	0.003	1.000	0.003	0.330
>=36	Male	Ignored	Innocuous	Good	0	1	0	1	0.003	1.000	0.003	0.330
>=36	Female	Ignored	Attractive	Satisfactory	0	1	0	1	0.003	1.000	0.003	0.330
26 - 35	Male	Read	Attractive	Good	1	7	0	8	0.026	0.875	0.023	2.310
26 - 35	Female	Read	Attractive	Good	0	3	1	4	0.013	0.750	0.010	0.990

FIGURE 2. Behavioral Map, sorted by Route Potential

Figure 3 displays the Route Potential distribution. For a given Route Potential, Figure 3 displays the total number of routes having that Route Potential and the proportion (i.e., the probability) of the routes in the map with that Route Probability. For example, 18 routes had a Route Potential of 1 and these 18 routes comprised approximately 24 percent of the routes in the map.

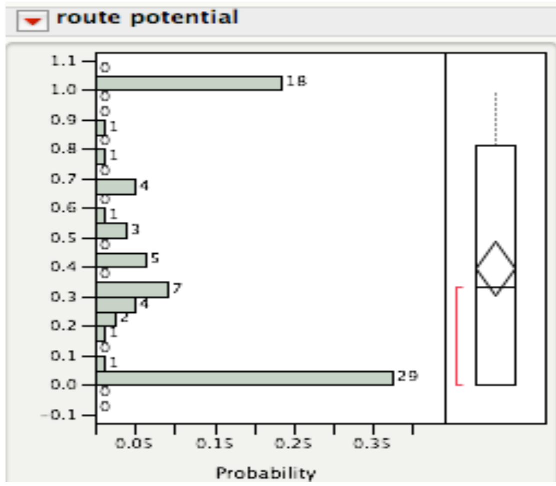

FIGURE 3. Route Potential Distribution

The Route Potential ranking and distribution give a sense of the possibilities available in the data. The presence of high-Potential routes, for example, indicates strong relationships, even if they are few in number. Fairly even potential across a range of routes might indicate either that a large number of reasons for a behavior can be substituted for one another, or that the data has not picked up the factors that differentiate the probability of behaviors. Depending on the context of the behavior being explored, analyzing the distribution of Route Potential offers an excellent opportunity to obtain a comprehensive view of the behavior and insights into strategies and tactics that could be effective ways to exert influence to increase the likelihood that the outcome of interest occurs.

Route Contribution

Route Potential, a measure of the strength of a relationship, does not indicate the extent to which a relationship plays a role in the probability of the outcome. That depends on how frequently the route occurs. Strong relationships may be infrequent, weaker ones common, and all possibilities in between.

Figure 4 lists the routes in order of their contribution to the probability of the outcome of interest, purchasing the *SuperZoom.* When routes have a high Route Contribution, fewer routes are required to lead to the behavior of interest.

age category	sex	reviews	style	dealer	Other	Zoom	None	N	route probabilit	route potential	route contributio	%route contributio
26 - 35	Female	Read	Innocuous	Good	10	10	4	24	0.079	0.417	0.033	3.300
26 - 35	Male	Read	Attractive	Good	1	7	0	8	0.026	0.875	0.023	2.310
26 - 35	Male	Read	Innocuous	Good	8	7	2	17	0.056	0.412	0.023	2.310
>=36	Female	Read	Attractive	Good	0	6	0	6	0.020	1.000	0.020	1.980
26 - 35	Male	Read	Ugly	Good	9	5	2	16	0.053	0.313	0.017	1.650
>=36	Male	Read	Attractive	Good	0	5	0	5	0.017	1.000	0.017	1.650
26 - 35	Male	Ignored	Attractive	Good	0	5	0	5	0.017	1.000	0.017	1.650
26 - 35	Female	Read	Ugly	Good	5	4	0	9	0.030	0.444	0.013	1.320
>=36	Female	Read	Innocuous	Good	2	4	1	7	0.023	0.571	0.013	1.320
26 - 35	Male	Read	Ugly	Poor	4	3	4	11	0.036	0.273	0.010	0.990
>=36	Male	Read	Innocuous	Good	2	3	1	6	0.020	0.500	0.010	0.990
26 - 35	Female	Read	Attractive	Good	0	3	1	4	0.013	0.750	0.010	0.990
18 - 25	Female	Read	Innocuous	Poor	0	3	0	3	0.010	1.000	0.010	0.990
26 - 35	Female	Ignored	Innocuous	Good	3	2	1	6	0.020	0.333	0.007	0.660
26 - 35	Male	Ignored	Innocuous	Poor	2	2	2	6	0.020	0.333	0.007	0.660
26 - 35	Male	Read	Innocuous	Satisfactory	3	2	0	5	0.017	0.400	0.007	0.660
18 - 25	Female	Ignored	Innocuous	Poor	2	2	1	5	0.017	0.400	0.007	0.660
>=36	Male	Ignored	Innocuous	Poor	0	2	1	3	0.010	0.667	0.007	0.660
>=36	Female	Read	Ugly	Satisfactory	1	2	0	3	0.010	0.667	0.007	0.660
18 - 25	Female	Ignored	Innocuous	Good	1	2	0	3	0.010	0.667	0.007	0.660

FIGURE 4. Behavioral Map, Sorted by Route Contribution

Just as in the Route Potential ranking, the Route Contribution distribution shown in Figure 5 highlights the range and quantities of route contribution.

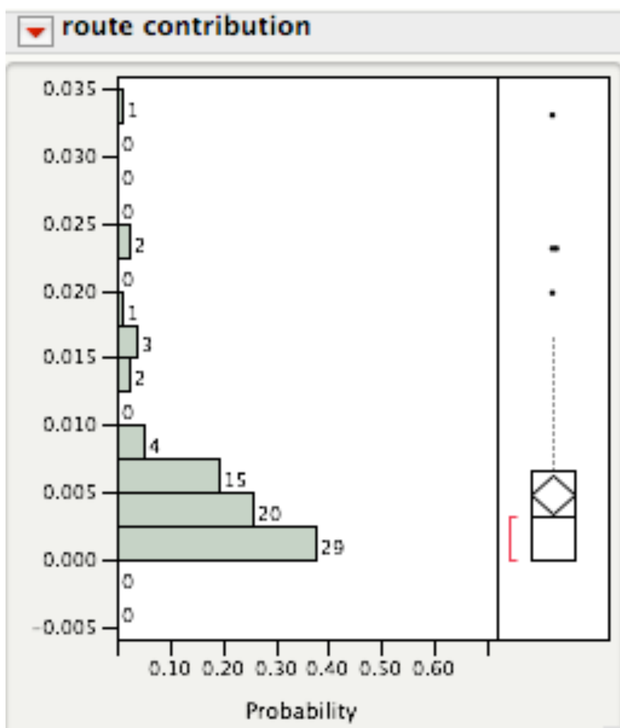

FIGURE 5. Route Contribution Distribution

Taken together, Figure 4, the Route Contribution Ranking, and Figure 5, the Route Contribution Distribution, show the role each route plays in producing the outcome of interest. They can indicate, by inspection, the extent to which high contribution routes contribute to the outcome, the number of routes required to account for any percentage of the outcome (this would be the cumulative sum of Route Contribution), and more generally, the degree to which the probability of the outcome is spread across the routes.

The sum of the Route Contributions is the observed probability of the outcome. Although the calculations are not shown here, the probability of purchasing the *SuperZoom 4000* is .38. The sum of Route Contributions should not be interpreted as if the Map is a model—as a measure of the Map's ability to account for the outcome. The Map is a reorganization of the data into a useful form, and as such must account for 100% of the outcome's probability of .38. The quality of the map is gauged by *how well it identifies routes and factors that make a difference in the outcome's probability.* Wholly random variables and factors would produce a map that accounts for the same probability as a map containing strong systematic effects, but the routes and factors it contained would all have approximately the same statistics. Consequently, it is through analyzing the key statistics that we have defined that one can evaluate how well the Behavioral Map provides insight into the behavior of interest.

Route Potential by Route Contribution Scatterplot

Figure 6, the scatterplot of Route Potential by Route Contribution combines information on the strength and likelihood of relationships.

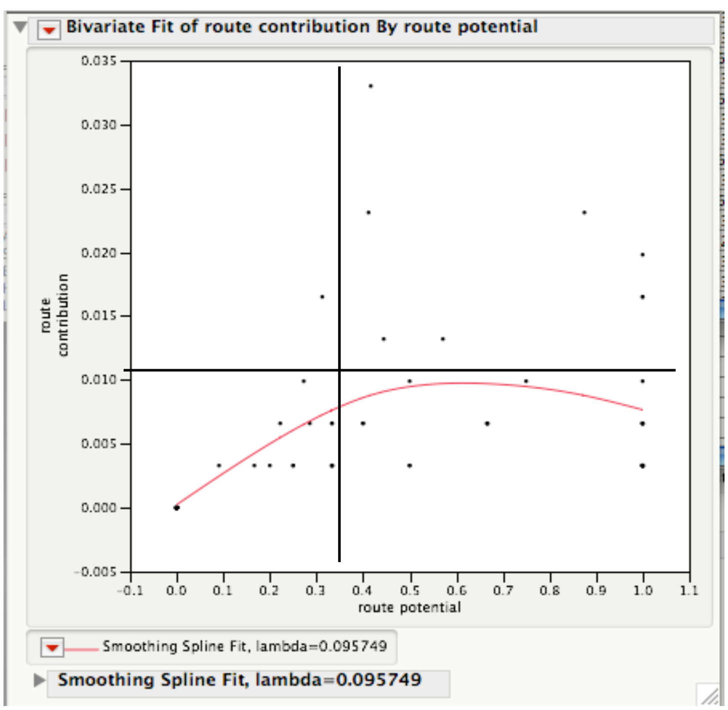

FIGURE 6. Scatterplot of Route Potential by Route Contribution

It can be useful to think of this plot in quadrants. The lines creating the quadrants here are drawn at the medians of Route Potential and Route Contribution. The placement of the lines creating the quadrants, however, will depend on the nature of the problem being analyzed. For example, if we were interested in relationships with higher Potential, we could move the vertical line to the right. Regardless of where the lines are drawn, however, the upper right quadrant contains the routes with high-Potential and high-Contribution.

The smoother is primarily used to clarify the massing of the distributions. In this case, which we think is likely to be fairly typical, it also shows that increases in Route Potential do not necessarily lead to increases in Route Contribution. The smoother is particularly useful in scatter plots whose numerous overlapping points are hard to read by eye. (A non-parametric density plot and other devices can also used to clarify these distributions.)

Interactive Displays in DM

All the graphics shown can take advantage of the interactive capabilities of modern statistical software. For example, selecting bars and routes in the displays can simultaneously select them in the data used to build that display, and vice versa. By selecting the points in the upper right quadrant of the Route Potential by Route Contribution plot, we would be able to examine the factors that are most likely to lead to the purchase of the *SuperZoom 4000,* as the selected routes would have both high-Potential and high-Contribution. Such knowledge might then lead to identifying strategies and tactics to increase the likelihood of consumers purchasing that car. It may be worth noting that relative to more conventional statistical analyses, the identification of sets of factors that lead to the purchase of the *SuperZoom* is a much easier and more comprehensive process. Consequently, determining appropriate tactics and strategies to take to increase the likelihood that a *SuperZoom* is purchased is also facilitated. The process of examining sets of routes so that appropriate action can be taken is at the core of DM, and is discussed in the next sections.

Prediction

The structure of the Map lends itself to making predictions when faced with a variety of possible futures. Each route contains a prediction about a distribution of outcomes if it occurs—a different future. Thus, we can use the Map as a reference work, looking up what to expect given any set of conditions its routes describe. The prediction can be made from the Route Potentials of a single route, or the average Route Potential of a set of routes. The average may be weighted by the Route Probabilities in the data, or externally supplied information.

An example of a single route prediction: we would predict that males, aged between 25 and 35, who considered reviews, found the styling innocuous but the dealer good, would have a .41 probability of purchasing the *SuperZoom.* This is the route potential of Route 3 in the Map shown in Figure 4.

An example of a multiple route prediction: we would predict that females with satisfactory dealers would have a .38 probability of purchasing the car. As shown in Figure 7, this is the weighted average (Route Potential*N/∑N) of the Route Potentials of the 12 routes that contain both females and satisfactory dealers.

age category	sex	reviews	style	dealer	Other	Zoom	None	N	route probabilit	route potential	route contributio	%route contributio	(RP*N)/ΣN
26 - 35	Female	Read	Ugly	Satisfactory	5	1	0	6	0.020	0.167	0.003	0.330	0.048
>=36	Female	Read	Ugly	Satisfactory	1	2	0	3	0.010	0.667	0.007	0.660	0.095
26 - 35	Female	Ignored	Ugly	Satisfactory	2	0	0	2	0.007	0.000	0.000	0.000	0.000
26 - 35	Female	Read	Attractive	Satisfactory	0	2	0	2	0.007	1.000	0.007	0.660	0.095
>=36	Female	Ignored	Ugly	Satisfactory	0	1	0	1	0.003	1.000	0.003	0.330	0.048
26 - 35	Female	Ignored	Attractive	Satisfactory	0	0	1	1	0.003	0.000	0.000	0.000	0.000
>=36	Female	Read	Attractive	Satisfactory	0	0	1	1	0.003	0.000	0.000	0.000	0.000
>=36	Female	Read	Innocuous	Satisfactory	0	1	0	1	0.003	1.000	0.003	0.330	0.048
18 - 25	Female	Read	Attractive	Satisfactory	1	0	0	1	0.003	0.000	0.000	0.000	0.000
18 - 25	Female	Read	Innocuous	Satisfactory	1	0	0	1	0.003	0.000	0.000	0.000	0.000
18 - 25	Female	Read	Ugly	Satisfactory	1	0	0	1	0.003	0.000	0.000	0.000	0.000
>=36	Female	Ignored	Attractive	Satisfactory	0	1	0	1	0.003	1.000	0.003	0.330	0.048

FIGURE 7.   Prediction Subset for Females with Satisfactory Dealer Ratings

These predictions, like any data-based prediction, presume a continuity of behavior from past to future; although examining route frequency and changes to these frequencies over time allows us to evaluate the robustness of our predictions to a greater extent than is typically done and also provides an early warning system for when behavioral changes may be occurring.

Maintaining numerous and diverse routes puts DM in a position to make close, nuanced, matches with anticipated circumstances and what if scenarios. Further, because we do not have to make any behavioral suppositions prior to creating and analyzing the Map, as is typically a practical requirement with more conventional analyses, *DM is far more likely to enable the discovery of factor combinations that influence behavior in ways we may not have anticipated;* possessing that information enables us to identify tactics and strategies for influencing the behavior of interest that we would otherwise not have done, or would have been arrived at much later.

Operational Applications and Sequences

Predictions can be made from any subset of a route, so if the factors occur in a sequence, we can make predictions from each step along the way. Predictions can be made of the likelihood of each outcome as well as of Route Potential and Route Contribution and their distributions. Such information can be useful in terms of making appropriate decisions about the best actions to take to influence behavior in the most desirable ways.

DM can be built into a decision making system, with routes representing various courses of actions available and their outcome probabilities, given the events that have already occurred.

Leverage

Generally, a DM-based analysis is structured by a series of inquiries. For example, one key practical inquiry is, "How do we change things: what are the levers we can use to exert influence in a disjunctive system?"

In DM terms, these are questions of a factor or a set of factors' influence, whether on Route Potential or Route Contribution. The *Factor Influence* for a route or set of routes can be visualized at the route level and factor level with simple charts. Figure 8 shows the influence of the Style variable, measured by Route Contribution. We can see that Attractive and Innocuous judgments are associated with a greater Contribution than if the car is perceived as Ugly, but the horizontal comparison bars in the diamonds allow a visual check on whether the means are different at the .05 level, showing that we cannot statistically differentiate the effects of Attractive and Innocuous. When analytically useful, additional distributional information such as box plots, histograms, might also be reviewed.

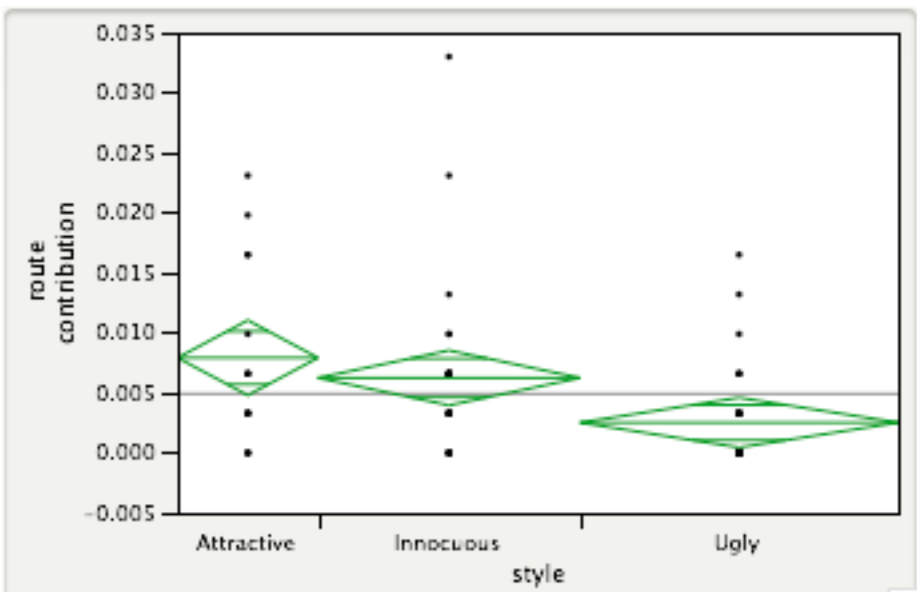

FIGURE 8. Route Contribution by Factor: Style Variable

Conventional measures mix the strength and frequency of effects into one overall measure. DM, however, enables us to isolate the effects of the factors using the Route Potential measure, as shown in Figure 9, Route Potential by Factor, again for the variable Style.

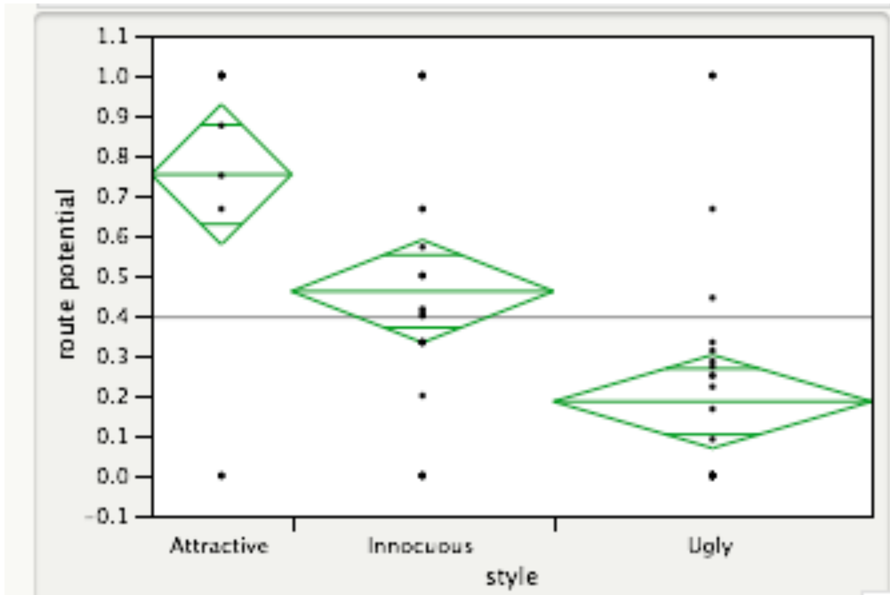

FIGURE 9. Route Potential by Factor: Style Variable

Whereas the influence of the factors for Style were relatively similar when analyzing Route Contribution, greater differentiation occurs when we analyze the influence of these factors via Route Potential. Figure 9 makes it clear that the car's being perceived as attractively styled is a powerful factor, with a probability of purchase well above the effect of when style is judged merely Innocuous, but concealed in a view that does not isolate the size of effect from its frequency.

We can use DM to take this analysis further by asking under what conditions does Attractiveness makes a difference? Figure 10, a display of Factor Potential by Route, provides the basis for answering that question, as it shows Factor Influence under various conditions. This transparency, which is generally either very difficult to carry out or simply not possible from a practical perspective with conventional methods, is one of the key reasons we believe that DM-based analysis is able to provide much deeper insight, and a broader base for action, than more standard statistical approaches

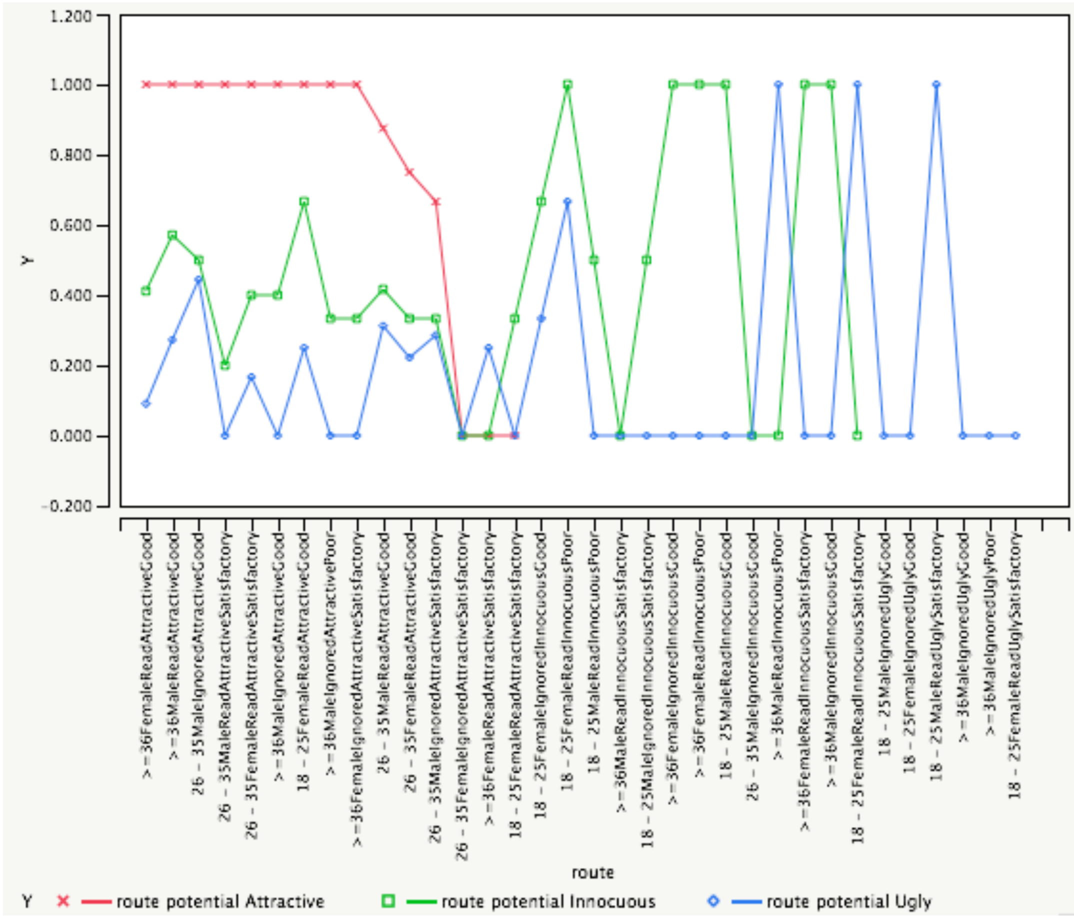

FIGURE 10. Factor Potential by Route

The sub-routes listed on the horizontal axis of Figure 10 contain all the variables except for Style. Completing the routes with the three alternatives for Style gives rise to the three lines. The routes on the left of Figure 10 are those where Attractiveness has a powerful effect on raising the probability of purchase, compared to the other two factors. Moving to the right we see its effect diminishing, and then routes when it never occurs. (In a larger sample the effects would probably be less extreme.) This allows us to ask, what makes these routes different?

Figure 11 compares the distributions of the variables in the two groups, with the top showing the distributions of the variables on high-Potential routes that contain the factor Attractive and the bottom showing the distributions of the variables on all other routes. By this comparison, we see that the high-Potential routes containing Attractive tend to be over age 25, slightly more likely to be male, very slightly more likely to read reviews, and disinclined to purchase from dealers they judge as Poor and to some extent, dealers they judge as Satisfactory.

FIGURE 11. Comparing Distributions on High-Potential and Low-Potential Routes

Using the same approach, we could explore apparent anomalies. For example, Figure 10 contains a route where the car is considered Ugly but the probability of purchase is 1. Simply drawing the conclusion that the likelihood of purchasing the *SuperZoom* is high when potential customers do not think well of the car's design would be risky at best, and more likely to be an incorrect interpretation. Analyzing this anomaly further, it would be discovered that in this data set, that particular route occurred only once. Drawing any conclusion on purchase behavior from such sparse routes would likely be foolhardy. If, however, a larger sample had been available and such purchase behavior continued to be present, it could be worthwhile comparing the distributions of variables on low-Potential and high-Potential routes where the factor ugly is present, seeking a substantive explanation.

The interactive capabilities of statistical software programs allow exploring the interrelationships among these factors in each set of routes. For example, Figure 12 facilitates a deeper analysis of high-Potential routes that contain the factor Attractive. Of these routes, the darker areas show the distributions of variables on routes that contain consumers age 36 or older. We can see that on high-Potential routes containing Attractive, these consumers are less likely to read reviews than the younger age groups.

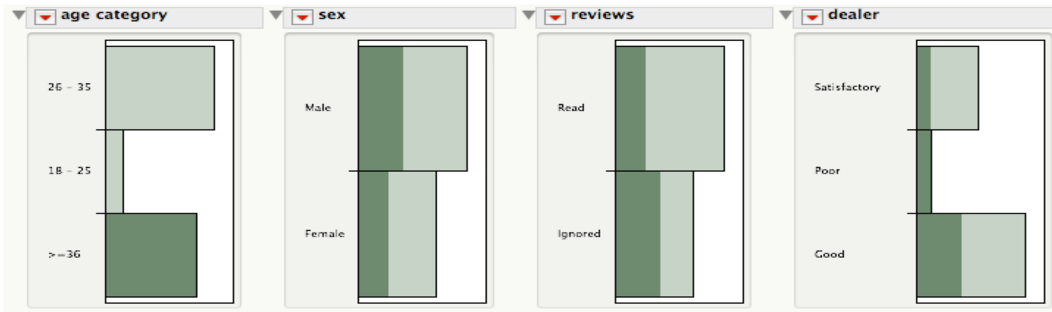

FIGURE 12. Exploring Relationships Among Factors for High-Potential Routes with Attractive

Confidence intervals and summary statistics would typically be available for these distributions.

Multiple Approaches to Analysis

The example we have followed illustrates one way DM may be used, but many other routes could have been taken. We could, for example, just have easily have begun by selecting the routes in the high-Potential, high-Contribution quadrant, and explored their factor influences. We could have pursued multiple predictions to judge the effects of various marketing proposals. We could have drilled down further into the relationships between factors, by examining factor influence on routes with and without selected factors. The choices depend on the purposes of the analysis. DM itself allows a wide range of exploratory possibilities.

Because DM uses likelihoods to measure effects and is map-based so that it does not require the potentially time consuming effort of building and re-building models, DM provides analysts with a more efficient way of pursuing a wider range of questions than conventional statistics. In practice, this means that analysts would be likely to explore relationships and questions that they simply do not have the time or resources to investigate. Consequently, DM provides a more direct path to behavioral understandings and ultimately to the tactics and strategies to influence these behaviors.

CONTRASTING DISJUNCTIVE MAPPING WITH CONVENTIONAL STATISTICS

This paper's primary purpose is to introduce a new method of data analysis, whose virtues include its ability to get at questions of prediction and leverage, with the advantage of using all the information available about the variety of ways consumers behave, and without the complications introduced by modeling. Current technology allows a far more direct approach to data analysis then was previously possible and it is our view that this approach provides a more realistic portrayal of human decision making than is offered by conventional statistical modeling.

It is not our intention, nor would it be appropriate in this article, to carry out a comprehensive comparison of conventional statistical methods and Disjunctive Mapping. But it may be worth making a few comments on some of the differences between Disjunctive Mapping and more traditional methods used in market segmentation analyses.

Disjunctive Mapping is based on a logical rather than a mathematical representation of behavior, even though probability calculations are used to measure effects. Its basic structures are along the lines of, 'If *A and B and C*, then *Y*,' rather than, $y = f(x)$. Propositions rather than functions provide the foundation for Disjunctive Mapping. In a number of ways this simplifies the analyst's task.

Because DM seeks to map observations rather than tease underlying patterns out of the noise, there is no model, no goodness of fit, to evaluate. There is no model that must, of necessity, drop out relationships that are too noisy, weak, or infrequent to earn a seat at the table—the map merely *organizes* what has been observed in a way that makes relationships clear and accessible for analysis. With no model there is no need to measure a model's goodness of fit (there is no equivalent to R^2), compare models by various criteria, worry about appropriate mathematical forms, violations of assumptions, distributions of errors (no model, no errors), or outliers (a route can only be especially influential if it represents both a strong relationship and occurs frequently). For such reasons, the value of 'merely' organizing information should not be underestimated.

In DM there is less need to simplify to gain insights because we do not expect to comprehend the entire map, only to look things up as we need to know them. Just as with a road map, we do not need to understand or keep in mind all the possible routes available to travel from one place to another. We only need to concern ourselves with the ones of interest; and the ones of interest change over time as well as with the questions we ask.

Disjunctive Mapping does not try to capture human behavior in a way we can comprehend or state verbally—we are using computers and computations precisely because understanding disjunctive systems under uncertainty are not the kind of things our brains are good at. Indeed, one of the inherent virtues of DM is that it provides a method to effectively influence behavior in desired ways without requiring that we comprehend it.

Theory testing is less of a concern in DM than conventional methods because with multiple explanations, any individual explanation accounts for much less. Moreover, once we are not seeking more universal theories, credible explanations are not that hard to come by.

Partitioning of variance, a key method for determining the impact of individual variables but often difficult to interpret as each variable's contribution depends on the contributions of other variables in the model, how well the model fits the data, and the degree of inter-correlation, is supplanted. Since the routes are never folded into a model, their effects are already partitioned. All DM has to do is sum or average the effects of a set of routes to determine any partition's impact on the outcome.

Disjunctive Mapping replaces model building by identifying influential factors and combinations of factors and providing quantified estimates of these influences; the estimates are both meaningful and intuitive because they are expressed as changes in the likelihood of an outcome associated with a change in conditions. Because influences can depend on the state of a variable (i.e., a factor), factors can be thought of as levers on the system. Change one small thing (e.g., a factor or set of factors) and a lot of larger ones can move (routes and the probabilities of outcomes).

Let's be clear. When outcomes do, in fact, result from an underlying relationship (whether or not we know what that relationship is) rather than the sum of the effect of multiple routes, conventional statistical methods not only work well, they are wholly appropriate. Many biological and physical processes, for example, fall into this mode and we have many reasons to believe that our models in these areas provide an accurate portrayal of the underlying relationships. Not only are we not questioning the use of conventional statistical approaches for such analyses, indeed we would advocate for them. But with human behavior, there is no particular reason to believe that outcomes are, in fact, best described as the result of any single or even a few underlying relationships. Thus, for the analysis of human behavior, conventional methods put us in an uphill struggle against the mismatch between the nature of the methods and the nature of subject matter.

As we will soon discuss in more detail, it is our view that conventional methods are often right for the wrong reasons, as highlighted by Mr. Greenspan's recent experience. But there is no reason to continue to rely on those methods when there is an alternative that gets us closer to being right for the right reasons.

Before we enter into that discussion, however, we first provide a brief case study in the use of Disjunctive Mapping techniques.

CASE STUDY: USING SURVEY DATA TO DECIDE WHERE TO INVEST

In the interests of simplicity we have been using hypothetical data in our example. In this section we provide an overview of an actual application.

A hotel wanted to identify those areas in which investments to improve the customer experience would yield the greatest benefits. Benefit was defined as increasing the frequency of repeat stays of customers or past customers recommending that others choose to try the product. The hotel identified over 20 potential areas in which they could invest. Traditional market research methods had been used, enabling hotel management to understand what factors were of greatest perceived importance to customers as well as the level of customer satisfaction with each area. But traditional methods were less successful in helping hotel staff estimate the incremental change in customer behavior that would result from investing in an area.

By employing the techniques and metrics of DM described in this article, we estimated the impacts of the factors and enabled hotel staff to visualize their impacts as well as better understand some of the ways in which the factors interacted. Further, the areas identified by DM where improvements would have the greatest incremental impact differed from those that they previously thought were the best candidate areas. The level of effort and time required to carry out the analysis was also significantly less than what have been required using traditional techniques.

Additionally, in carrying out a variety of exploratory analyses on customer demographics (much easier to do with DM than with the more traditional approaches they were accustomed to using), we identified trends in customer experience that could have a major impact on departmental performance. Prior to our analysis, hotel staff were unaware of these impacts; possibly because the analytical techniques that they had come to rely on did not make it easy for them to pursue such questions. For example, departments were evaluated each month on the level of customer satisfaction that guests reported. As a by-product of our DM-based analysis, we discovered that first time guests provided lower customer satisfaction ratings than return guests and that there were strong reasons to believe that these guests would provide a lower rating even if their actual experience was identical to that of a returning guest. Therefore, departmental satisfaction ratings might "naturally" be lower during months when the hotel had a higher percentage of first-time guests even if the department was doing a great job. This could result when the hotel offered incentives to individuals who had never stayed at the hotel. Such incentives were periodically offered to drive new customer acquisition. This finding was important to the hotel because its performance system had not been designed to correct for this naturally and periodically occurring variation (and staff compensation levels could also be affected by this variation).

By developing a map, rather than a model of customer behavior, and following the analytic procedure outlined above, the DM approach enabled identifying patterns that were being missed. Conventional statistics, if pushed hard enough and in enough ways, might have been capable of revealing similar information. In fact, the hotel was employing experienced and qualified staff to getting at these questions, but the level of effort required was simply beyond what was available. Indeed, we have found that the level of resources, both time and money, required to get at such information through conventional statistics is often beyond what firms in many industries are prepared to devote. DM provides a way to make additional progress because it is more naturally attuned to the way we make decisions.

STRATEGIC IMPLICATIONS OF DISJUNCTIVE MAPPING

In the beginning of this article, we conjectured that Mr. Greenspan erred in the nature of his thinking and that the models and analytical methods we generally rely on to understand and predict human decision-making are inherently flawed. Further, if we are not blinded by thinking we are right for the right reasons, when we are right for the wrong reasons, there are apt to be signs of emerging problems and opportunities well before they become obvious. In the case of the recent financial collapse that Mr. Greenspan was discussing, there were, close in, a housing bubble and a proliferation of dubious and opaque financial instruments, and in recent years major scandals where regulation was inadequate (Savings and Loan, Junk Bond, and Enron). In addition, it can be argued that since the 1980's there has been a growing and visible anything goes, grab the money while you can, business culture. See, for example, *Liar's Poker* by Michael Lewis, and Tom Wolfe's 1987 novel, Bonfire of the Vanities.

We would argue that the traditional prudent self-interested behaviors that Mr. Greenspan trusted to a single overarching cause, self-interest, were more likely the product of a disjunction. Contrary to what Mr. Greenspan's comments imply, we do not believe an additional factor, or set of factors, if incorporated into Mr. Greenspan's models, would provide a suitable correction.

The disjunction's combinations would be likely to consist of self-interest and, among other factors:

- A business culture that frowned upon making risky loans and innovative, complex, financial instruments
- A business environment where jobs were focused on following conventional practices rather than aggressively increasing revenue
- An industry where people attracted to investment banking were of cautious dispositions
- An industry where regulatory measures prohibited some risky practices, or at least made them more difficult to pursue
- An industry where the long term viability of a firm was given greater weight relative to short term profits
- A business culture where promotions and remuneration were more dependent on pleasing the boss and the appearance of rectitude than on spectacular increases in revenue
- A business environment where making money was more closely associated with producing and selling goods rather than manipulating money and government.

The list of factors forming the disjunction could likely go on. In short, looking at these factors and the shifts that have occurred, there was reason to suspect that the forces for prudence were visibly, even dramatically, slackening, and were we open to acknowledging the importance of how such factors could influence decision-making, this could be seen without any explicitly disjunctive thinking.

Interestingly, these factors are the type of social, cultural, and political factors economists sometimes point to after the fact—when things do not go as they expected. What this kind of second-guessing typically misses, however, is that these factors do not simply help explain how and why things go wrong but are also central to the explanation of how things go right. Commonalities like self-interest, are only a part, and possibly only a small, if more or less necessary part, of the mechanism. As a result, when Mr. Greenspan talks about a flaw in his model, he is probably on the wrong track.

The error was not a flaw, something that at least in principle can be corrected without much alteration of the rest of the model—an ill chosen parameter value, a crucial factor missing, an incorrectly defined function. The greater error was that *the model itself was of the wrong logical type*—a conjunctive model of a disjunctive phenomenon. All corrections to such models can do is formulate a new set of right for the wrong reasons rules and functions that fit the current situation better, and hope that they prove durable.

Note that the error here is not oversimplification—all explanations simplify and whether an oversimplification is at the root of the problem depends on how the explanation is being used. Rather, the error is the mismatch of the logic of the explanatory model and the phenomena. Not understanding the nature of what had been modeled or why the model worked while it did, Mr. Greenspan did not understand what could be expected from it, or the need to pay closer attention to what the model excluded — both the excluded factors and the disjunctive nature of the phenomena that made the various factors more important than his model would show.

Using historical data, we suspect that the probabilities of financial implosions would be higher on routes where factors such as those noted above are present. Had Mr. Greenspan taken a disjunctive mapping approach as the basis for his analysis and predictions, it is quite likely that he would more readily, and somewhat naturally, have observed the increased prevalence of those factors and realized that we had reason to worry.

This does not imply that Mr. Greenspan would simply have been able to "read the signs" and fix the problem. Although the routes would show an increasing probability of financial implosion given the conditions (i.e., factors) occurring, there would be a range of probabilities of potential outcomes. Further, our prior experience might not contain a mix that produces as high a probability of financial disaster as the situation warrants. But this is as it should be, as in the real world we rarely have unambiguous indications. A critical strategic (and even tactical) value of DM, by keeping information on what may have been low probability combinations in the past, is that it provides warnings that more parsimonious models cannot. These warnings can be used to take early and possibly relatively minor actions that could prevent (or at least reduce the likelihood of) later breakdowns. If we had taken these warnings as reasons to investigate, to look closely at lending practices, the information being concealed by the new financial instruments (e.g., leverage ratios, rating agency practices, junk mortgages)— places where the effects of a lack of prudence would be manifest—there would have been better grounds to oppose some of the deregulation, and better justification for proposing regulations. And it is worth noting that there would be quantitative grounds, as well as qualitative, to justify these actions.

A tool like DM allows tracking not only what is most likely given past information, but what happens in less likely cases, recognizing that what was unlikely yesterday may become tomorrow's reality; or that today's events are themselves unlikely and there is a good chance that things will soon revert to more likely patterns. This is not a matter of certainties, as even high probability events do not always happen. It is a matter of having a better of chance of avoiding being blind-sided, of knowing that more information is needed, and taking actions to minimize threats and maximize opportunities.

None of this can be done, of course, if we mistake being right for the wrong reasons for being right for the right reasons.

CONCLUSION

In the end, we hope that what comes through here, is not so much all the details of the method, which are still evolving, but that we can address a far more realistic representation of human behavior, in all its variety, more realistically and effectively than current methods allow.

Prior to DM, we have tried, of necessity, to understand disjunctive phenomena with inappropriate tools and methods, and the distortion thus introduced runs through our everyday thinking as well as through more formal and mathematical methods. In the process we confuse ourselves and resort to ever more arcane methods because the fundamental assumptions wrong-foot us, and we must struggle against them to succeed. That we often do succeed is as much testimony to our perseverance and ingenuity as to the methods themselves.

ACKNOWLEDGEMENTS

We would like to express our appreciation to Michael Gordon for his efforts and expertise in working with us to create the CuBe Mapping software that allowed us to test our theory and enabled us to better understand some of the new insights that could be obtained from analyses of customer behavior.

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