Disjunctive Mapping

Advances in understanding consumer behavior.

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The last time I went to a movie it was because the movie received good reviews, I liked two of the actors and my television was broken. The next time I go to a movie it might be because some friends ask me to join them and have dinner afterward; even though the movie may not interest me, enjoying dinner with my friends will be sufficiently appealing that I'll go anyway.

Customers' diverse desires, such as reasons for attending a movie, pose a problem for marketing, particularly for modeling consumer behavior.

The reasons we go to a movie are different, but the outcome (going to a movie) is the same. If we consider just 10 reasons that can influence going to movie – a good review, invited by friends, tired of hanging around the house, having a free pass that will expire soon, everyone else is seeing it, liking the genre, liking the cast, the TV is broken, the movie theatre is air conditioned, intrigued by the locale the movie is set in –1,024 possible combinations emerge. And many combinations of these reasons are genuinely diverse. Going to a movie for social reasons, not wanting a free pass to go to waste, having a love of cinema, having a taste for a particular genre and so on, in various combinations, are not all manifestations of a few underlying driving forces. Rather, the combinations are matches of diverse desires with products that can serve multiple purposes.

Different Reasons for Doing the Same Thing

CUSTOMERS' DIVERSE DESIRES coupled with multiple purposes pose a problem for marketing, particularly for modeling consumer behavior. In trying to identify cost-effective marketing tactics and strategies, we generally try to build models based on commonalities that define subgroups. For example, subgroups might include impulse buyers, style buyers, value buyers, status buyers and brand buyers, each representing a particular cluster of a few dimensions. Such categories, however, are rarely a good match to the reasons people give to explain a purchase; or if they are a good match, often individuals are members of different categories at different times.

A simple exercise in combinatorics, such as the one at the beginning of this article, suggests that an overwhelming number of categories might be needed to truly capture the diversity of reasons leading to a particular purchase. So, in the face of all these possibilities, we do the practical thing. We collapse a great deal of the diversity that we observe, trying to capture the most relevant aspects. Thus, an air of unreality permeates market research as in much of the social sciences. We look at a phenomenon where people do the same thing for a large number of different combinations of reasons and then do our best to explain it by using as few as possible of those reasons.

In effect, the inconsistent ways cooperate to achieve a consistent end.

Until recently we had no choice. We did not have the data processing capacity to do anything else. And now, in a time of micro-marketing and diverse sales channels, we continue to build increasingly complex models aimed at being smarter about matching diverse consumers with products. The question is whether we still need these models. Have we been using them for so long out of necessity that we have come to see them not as clever work-arounds but as accurate or at least as best attainable representations? Further, have we failed to realize that with increased data processing capabilities, we don't need to rely on our simplified models any longer? We can work with the diversity directly.

What this leads to computationally is fairly straightforward; once the data is structured to map the different ways an outcome can occur. The measure of effect size is familiar: probabilities. Understanding what these probabilities represent and how they can be used – what is implied by replacing conventional models with empirically based conditional probabilities – is the trickier part.

The basic, underlying paradigm in common sense and its extension into the natural and social sciences is that consistencies lead to other consistencies. Yet, for human behavior at least, this is clearly only a part of the story and possibly a minor part. As the movie example illustrates, numerous and diverse – inconsistent – reasons for a consistent outcome (people going to a movie) is implied by a simple listing of these reasons. They can, and do, act in various combinations. So the correct explanation of the behavior is not a signal and noise formulation, y = f(x) + e, but the sum of the probabilities that the combinations will occur, and given that they occur, that the behavior will occur:

$$P(y) = \sum P(\mathit{combinations} \mathbin{\&} \mathit{behavior} | \mathit{combinations})$$

However, to say this, even though it is a straightforward representation of what the example illustrates – and of numerous other examples that could just as easily be formulated illustrate – is to change the notion of what constitutes an explanation, and given that, how explanations should be pursued, and how the information should be applied in practice. We are now in the realm where inconsistencies lead to consistencies.

This turns some of our long-held beliefs and approaches to understanding and forecasting behavior upside-down. For example:

Common sense gains credibility. If explanations only have to cover one of the ways things happen, one of the inconsistent ways, each bears less of an explanatory burden. Understandings that seemed inadequate when the standard is consistencies leading to consistencies may well be adequate when the standard is inconsistencies leading to consistencies. They don't have to be right so often or explain so much. This lets in a great deal of common sense that would otherwise seem vulnerable to counterexamples (counterexamples are just evidence of the inconsistencies) or criticism for lack of universality. It allows us to pay analytic attention to low probability but high impact possibilities, the notorious Black Swans. That would seem like noise in conventional analyses. Further, it suggests that we know more than we think we do: no longer need it be the case that common sense understandings seem inadequate because they do not explain larger consistencies. We have mistakenly accepted that explaining larger consistencies requires powerful general understandings.

Research is organized around outcomes rather than relationships. When there are many ways an outcome can happen, particular ways (and the relationships they contain) become less important.

A cooperation of ideas more than a competition of ideas. Not only are we accustomed to looking for a best explanation, we believe doing so is appropriate and leads to the greatest insight. No longer. While the explanation of any particular outcome is whichever combination happened to hold in that instance, the explanation of the outcome in general is that if it doesn't happen one way it could happen in another way. In effect, the inconsistent ways cooperate to achieve a consistent end.

Base analyses on categorical variables. Humans "chunk" information. Continuous dimensions become categories. For example, income becomes rich and poor (or other categories that are appropriate toward understanding the behavior of interest); intelligence can become above average, average and below average; the names of colors cover ranges in the spectrum; and so forth. People respond not to a point on a continuum but to a range, a chunk of information containing that point. It's worth noting that that common sense understandings tend to be based on categorical understandings.

Historically, our most powerful quantitative methods require continuous variables, but these were aimed at unifying diverse phenomena. And that is exactly what we are not trying to do, and no longer need to do. As a practical matter categorical variables are better suited to describing the numerous inconsistencies that lead to consistencies. Would we want to model each one? How much could we gain from doing so?

Targeting cost-effective marketing tactics and strategies are generally based on commonalities that define subgroups.

Combinations, not individual categories, are the basic explanatory unit. Although we try not to worry about it, in market research (indeed, in the social sciences more generally) the meaning of terms is often highly variable and context dependent. Even in our simple movie example, the idea of liking the cast could refer to such different things as having feelings for them as individuals, appreciating previous performances, respecting a moral stand or a political position they have taken, or finding them physically attractive. Similarly, one could find dinner with friends appealing because of enjoying their company, or because they know good restaurants, or because they cover the bill. The same terms ("liking the cast," "appealing dinner invitations") can mean very different things. These terms rarely have unitary content.

We get around this, as best we can, by assuming there is some shared common core or that the differences do not matter for the question at hand. Otherwise, we are making the classic mistake of comparing apples with oranges – and risk fruitless results. The solution in everyday thinking is to use modifiers that provide a context. This cannot be done in parsimonious models, but it is a natural part of thinking in terms of combinations as the explanatory unit, where the meaning of the elements in the combination is understood as being defining in the context of the other elements.

Commonalities are not the basis for explanations. From a signal and noise point of view we can distinguish systematic or "real" effects by their consistency amidst more random events. This is a central device in everyday as well as experimental logic: checking whether an input is present when the outcome occurs and absent when it does not occur. Using statistical methods, we look for covariation, clustering and so forth. But as the movie example suggests, commonalities are of varying importance in explaining an outcome. I might go to movies that have the same director but the other reasons do not overlap. Or the commonalities might extend to enjoying the friends I go with, wanting to get out on a weekend night, looking forward to going to a restaurant afterwards and numerous other reasons. The degree to which those commonalities are important is an empirical question.

Commonalities may, however, be useful in making predictions, since they can be correlated with the outcome: a quality that is both useful and highly misleading.

The basic explanatory logic of human behavior is disjunctive, not conjunctive. Technically, this is just a shift from reasoning conjunctively to reasoning disjunctively. Rather than reasoning that A and B and C leads to D, we now reason that A or B or C leads to D (in the case of disjunctive explanations of human behavior the As and Bs are combinations). Substantively, it is a move to an entirely different mode of explanation and carries with it a number of important implications. Under uncertainty the probability of an outcome resulting from a disjunction is greater than the probability of that outcome due to any of its components. This is the logic of how many individual low probability inputs (inconsistencies, which given their number must mostly be low probability) can jointly explain high probability outcomes (consistencies). But once we adopt disjunctive logic, which makes it possible to use the information provided by the inconsistencies, the value of many prized intellectual traditions comes into question. Such traditions include commitments to:

- **Parsimony.** Disjunctions are anything but parsimonious.
- **Elegance.** Explanations that say it could happen this way, or maybe that, or maybe ... are anything but elegant.

- **Seeking powerful basic or underlying forces.** Such forces may be nothing more informative than the rules of chess, which simply describe the very large number of possible behaviors.
- **Theory development.** A disjunctive view suggests that our everyday insights, via a "sum of the probabilities of events" framework, can easily provide adequate explanations.
- **Hoping that once we have made enough progress the human world will become comprehensible.** Our minds are ill-suited to handling the number of possibilities, probability estimates and calculations required.

Disjunctive logic places all of these intellectual pursuits in a new and less flattering light.

For the most part, then, viewing behaviors as arising from the sum of the probabilities of diverse combinations – that is, the disjunctive approach – allows us to stay close to sensible everyday understandings, as much as it drives us away from many conventional analytic presumptions. Yet it supports a straightforward approach to quantitative analyses. Given the data and the power of personal computers we can map the disjunction. That is, we can structure the data to show each of the combinations (paths in the map) and calculate the probability of each leading to various outcomes (or, when appropriate, simply examine the counts).

Having constructed this map of paths and outcomes, we have, as we would with a geographic map, a reference work. We might ask, for example, what is the probability, based on previous behavior, that a customer with a certain demographic profile will purchase a particular brand of car in the next year. We would then look up (select) all the paths containing that profile and their car-buying history and compute the probability of the purchase. By itself this would be an unsatisfactory analysis, however, since it is likely that within this group the probability of purchase depends more on some factors than others. But we can take the next step and identify the paths associated with higher purchase probabilities and the factors they tend to contain. In Disjunctive Mapping, both of these steps are incorporated into a single graphic display. The display also provides a graphical display of significance tests for differences among the variables.

No model is constructed. Alternative explanations are not tested. With the possible exception of significance tests, depending on which are applied, the assumptions are only those required for basic arithmetic. The method is non-parametric. The effect size measure is easily interpreted (probabilities can be understood as percentages). It can be used with a minimum of mathematical training.

The map is a representation of empirical data, and we are simply looking up what it can tell us, yet we have answered, in an easily interpreted manner, exactly the kind of *how much* and *why* questions we generally pursue. The question for more conventional analysis is: When is its greater complexity and unreality justified?

Applications

WE'VE PUT the Disjunctive Mapping theory to the test in a few different scenarios. Although our first forecasting application did not leverage the fundamental strength of Disjunctive Mapping to sort out the complexities of disjunctive combinations because of a lack of much of the relevant data, we took advantage of the map's path structure to forecast demand for a hotel at alternative prices and in response to alternative competitive scenarios. The idea was that the disaggregated nature of our analysis would better capture the true variations in demand across alternative competitive scenarios, as we did not need to fit a functional form. Not only did our predictions tend to be more accurate than those that relied on aggregated price elasticity curves, our method did not exhibit the instabilities and extreme volume predictions that had plagued the conventional methods developed by the hotel's analysts.

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Because Disjunctive Mapping does not rely on a model, its forecasts were free to track discontinuities. Consequently, it was less likely to make errors on days that had unusually low or high demand. And, instead of being limited to sample sizes based on predefined day of week and seasonal considerations, it could increase sample sizes by combining data for days that show similar combinations of influential variables, and do so on the fly, That is, the forecast could be based on a selection of records chosen for the specifics of the day in question. This enabled optimal, and detailed, pricing strategies (e.g., which promotions and other controllable discounts to offer in addition to the publicly available rate) to be estimated for any given competitive scenario, considering how far in advance of check-in date as well as the number of rooms still available.

Further, if the competitive scenario was one that had not previously been experienced, it would be easily detected as that pathway would be devoid of observations. Analysts could be alerted that they were facing a new competitive situation. Such a level of specificity would not have been possible using typical price elasticity models.

In another application, we used Disjunctive Mapping to analyze the results of customer surveys for a hotel with a casino. The surveys contained a large number of items that reflected global responses, so many were highly correlated (although multicollinearity poses problems for regression-based analyses, this is not the case in Disjunctive Mapping). The hotel had found it difficult to identify which areas truly made a difference in the propensity for a customer to recommend and return to the property. Using conventional methods, its analysts were not able to determine the most cost-effective investments for increasing customer satisfaction and increasing customer return rates. By mapping instead of modeling customer survey responses, and carrying out analyses of frequency and likelihood of obtaining the desired outcome (i.e., receiving a high rating on the customer survey), Disjunctive Mapping enabled us to identify the specific areas that were most likely to make a difference in customer satisfaction and propensity to return.

As a side benefit, the analyses we conducted also led us to understand that certain customer segments responded to questions differently. For example, first-time visitors were systematically giving lower ratings. Because employee incentive compensation was tied directly to how customers responded to the surveys, it appeared that employees may have been unfairly penalized when promotions were run that led to higher percentages of first-time guests staying at the hotel.

Additional details on these applications will be provided in a future issue of *OR/MS Today.*

Other Potential Application Areas

THIS BASIC APPROACH to analysis described here can be extended in a number of directions. In health care, for example, a major impediment to progress has been the brilliantly successful infectious-disease model: find causative organism, defeat same, cure ailment. This approach, however, doesn't work for depression, obesity or diabetes, among others. Even some infectious ailments – AIDS, for instance, or drug-resistant tuberculosis – call for lifestyle changes along with attacking the organism. And some ailments interact; diabetes and obesity, for example, which in turn are often linked with respiratory problems such as sleep apnea. There's one primary path to getting strep throat; there are dozens of paths to diabetes and maybe thousands to depression. These seem a natural fit with the Disjunctive Mapping approach.

Other public policy areas, from analyzing crime patterns to economic development, where there are multiple paths to the same outcome, would also be good fits. Disjunctive Mapping has the potential to significantly improve the tactics and strategies employed in marketing, as well as in public policy.

For a more complete discussion, including practical strategies for a disjunctive human world and scripts for running Disjunctive Mapping's basic operations in JMP, see "The Arithmetic of Human Behavior," available as a PDF download from the Veritec Solutions website. (www.veritecsolutions.com). ORMS

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