The Fifth Quadrant:

Using Data Mining technologies and tools to bring efficiency, effectiveness, and accountability to current marketing practices.

By Keith White

"Advertising is a ten billion dollar a year misunderstanding with the public."

--Chester L. Posey, Senior VP and Creative Director, McCann Erickson

Introduction

A television program fades to a scene of Chinese elementary school children sitting in class. We see them from the teacher's point of view from the front. We hear the teacher ask, "Who is the President of the United States?" All children raise their hands in unison and exclaim, "George Bush!" All but one, that is. The camera zooms in to see an Internet downloading bar on his forehead. The teacher asks, "Who is the President of China?" All children raise their hands and answer, "Jiang Zemin!" The boy still sits, sweating and gulping in embarrassment, as the download bar progresses painfully slow. The teacher asks, "Who is the British Prime Minister?" All children raise their hands and yell, "Tony Blair!" as the one boy yawns and taps his desk, the internet download bar still not yet at 100%. There is a cut to same scene later that day. All children have gone home and the young boy is still seated at his desk as a janitor cleans in the background. Suddenly, the download bar flashes as complete and the boy's hand jolts up and he exclaims, "George Bush!" The message "Kids can learn faster than 56k" flashes on the screen and then the name of the broadband service company Oxygen (Saatchi). End of commercial.

Created by worldwide advertising agency, Saatchi & Saatchi, the commercial aired in China in 2002. It won awards like the Cannes Silver Lion, the Adfest Bronze, and the Media and Marketing Spike. Oxygen predicted that after two months of the ad launch their hotline should receive twenty thousand calls of interest. They reached that number within the first week, with a conversion rate of 40% (Saatchi). There is no doubt that the product succeeded in being sold, but did the ad truly stimulate demand, or were sales affected by other, outside forces? What aspects of this campaign succeeded? Which ones failed? Why? How? These questions remain unasked and unanswered by current advertising/marketing practices.

As Michael Schudson states, "[C]hances are that neither the client nor the agency will ever know very much about what role the ad played in sales or profits of the client, either short-term or long-term." In analyzing a brief history of advertising/marketing we see that these practices have not evolved or addressed shortcomings since the early 20th Century. Current advertising/marketing practices, at best, employ the techniques of description, interpretation, evaluation, and prediction to produce campaigns. Advertising agencies are complacent. Failures are blamed loosely on poor creativity, botched visions, and market dynamics. Successes are due to bold visions that come to imaginative realization. But, in looking at other sectors of the business world, the tools and techniques to bring not only effective and efficient campaigns, but also accountability, are available to the advertising/marketing industry.

These tools and techniques can be found in Data Mining technologies. Once integrated into advertising/marketing practices, the merger would result in significant increases in revenue, satisfaction, retainment, and attainment, unquestionably due to the campaigns. Beyond current description, interpretation, evaluation and prediction, the use of Data Mining to produce useful knowledge would create the next step in advertising/marketing to consumers and B2B—that of control. In analyzing current Data Mining technology, we find that this control is possible in creating straightforward, individualized solutions, backed by solid, relevant, data-based reasoning, to guide sure advertising/marketing campaign content success.

Creating Advertising Success

Many advertising and business scholars have given their theoretical and experiential insight on this topic. The past and present techniques can be categorized using Longwood's Quadrant Map (LQ MAP), which was developed for the classification of the level and quality of marketing and communications efforts (Pettite 2). It is useful for framing the strengths and weaknesses of a wide variety of methods, tools, and techniques. In the first quadrant is Description. Companies in the past, and still even today, relied in large measure on anecdotal evidence, advertiser's experience and erroneously used tools to predict sales or behavior (Pettit 2). Take for example Dial Soap advertising success Ed Wilson. He stuck with his campaign because "When in doubt the best possible answer is *Don't*" (Cone 204).

Many successful advertising moguls have written "How-To Rules" on correct advertising/marketing, and these rules in their many variations exemplify the first quadrant of Description.

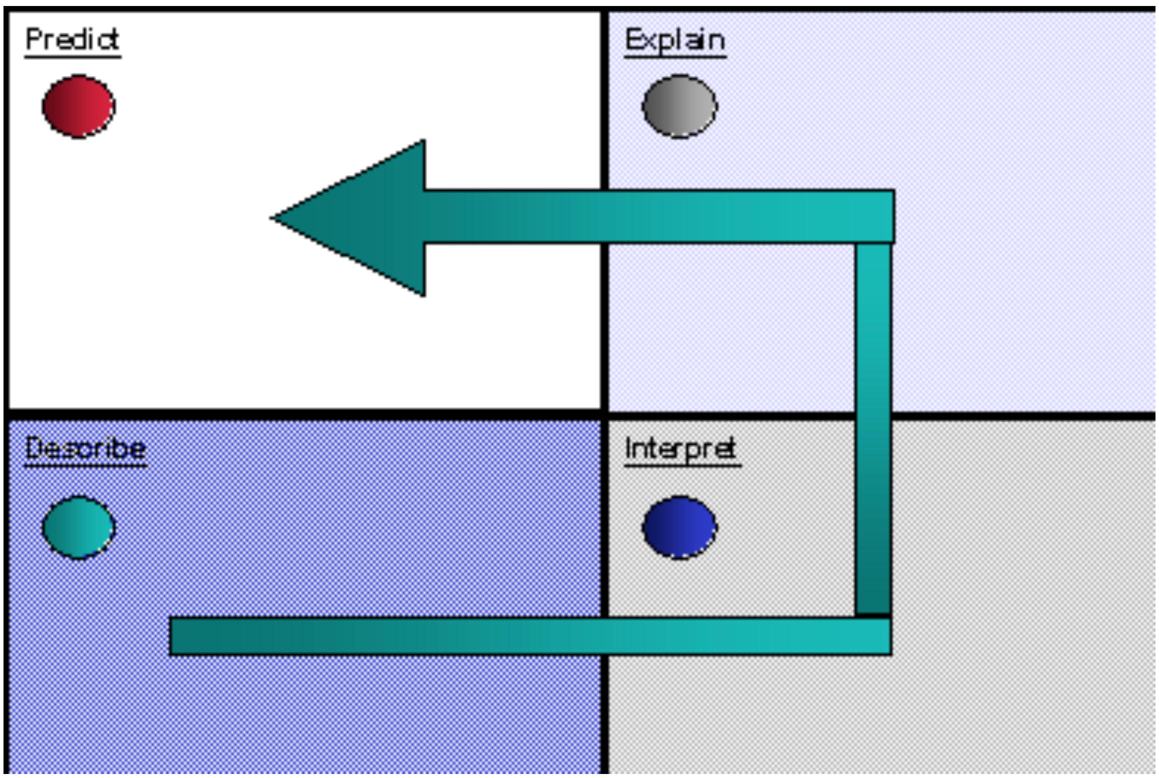

Figure 1.2 Longwood's Quadrant Map (Pettite 3)

Based on anecdotal evidence and unproven correlation to success, these rules are deceptive in their commonsensical appearance. Is it proven, as Fairfax Cone states, that successful advertisements "will always express the personality of the advertiser, for a promise is only as good as its maker" or that "good advertising/marketing must immediately make clear what the basic proposition is"? (58). Or, for instance, that the unwavering trust in Hallmark's Joyce Hall's taste seen in the comment "It was plain that he felt entirely capable of passing judgement…and I have no doubt that he was; his instincts are not impaired by the ravages of time" is justified based on his past? (208). These "instincts" whether solely based on an advertisers opinion or backed by erroneous data is not only unwise, but can also be a serious waste of money.

The second quadrant, Interpretation, is where advertisers seek to interpret basic measurement and observations of consumer tendencies, intent, or behavior (Pettit 2). As Michael Schudson states, advertising/marketing may improve consumers' attitude towards a brand or product, but using that data to then say an ad was successful is faulty (Schudson 25). Take for example the recent milk ads. Though widely popular, milk consumption is still at a decline (25). Much of marketing research's work is done in the second quadrant of Interpretation, and more often than not, result-to-action are weakly presented, sometimes based on the experience, intuition, or pure guessing found in the first quadrant. In-market test would fall under this quadrant, which can be valuable but are more often than not dismissed because of their expense (Pettit 2). This traditional technique, even when based on measured success can only repeat past successes. Campaign success is determined in terms of the past. Any information gleaned and applied is still an accountability leap of faith.

The next quadrant is Explanation. It is the least used, in general, by marketers but considered to be the most dynamic, actionable, and understandable guide to the assessment and evaluation of advertising's impact (Pettit 3). Some agencies are research intensive, such as Grey Advertising and Ogilvy & Mather, but most remain hostile toward asking what, why and how much success a campaign will have. One advertiser stated that research is commonsensical and merely “something that tells you that a jackass has two ears” (Schudson 57). William Bernbach, when told his Avis “We’re number two, we try harder” research report said the campaign would do poorly because it tested as contra to the American “number one” ideology, replied “Get some other research” (57). This aspect of research versus creative has been hotly debated within the advertising field for campaign success. Regardless, the Explanation quadrant is important in that it marks the beginning of serious consideration on the success of campaigns. It encompasses Description, Interpretation, and Explanation of successful campaigns (Pettit 3).

John Philip Jones’ academic work falls within this quadrant. He describes successful campaigns are those that have been proven to have a powerful effect on consumer purchasing in the short-term (short-term being the easiest situation to gauge impact without the contamination of outside forces). He interprets these campaigns to have three similar characteristics. They are likeable in their entertainment value, visual rather than verbal, and say something important about the product being advertised (89). He explains these conclusions using the experiments on relationship of likeability and effectiveness performed by The Ogilvy Center for Research & Development in San Francisco. The Ogilvy & Mather advertising agency owns such centers all over the world, including the acquired New York Decisions Center Inc. and collaboration with Peking University’s China Center for Economic Research). The Center produces work for the agency on such topics as “Conceptualizing and measuring product attitudes and their accessibility from memory 1985-87," "Category-memory associations and their activation from memory 1987-88," and "Principles of persuasion 1988-90" (Fazio 1). Before this research, it was standard practice for advertising creatives to work from effectiveness folklore, as outlined above.

One such belief was that there was no evidence that likeability had any relation with effectiveness. Therefore, a campaign that was hated could still be effective. Not so. In 1985 The Ogilvy Center for Research & Development conducted a study on likeability, spanning over fifty-seven products in eleven categories (Jones 112). They found that when an advertisement was liked, the brand preference went up 16.2% (114). A campaign was found to be "likeable" when it was Meaningful (71%), Energetic (50%), Ingenious (28%), Didn't Rub the Wrong Way (24%), and Warm (18%) (116). But, even in the face of advertising/marketing effectiveness, Jones favors creative over research and states that it is the creative edge that is assumed to give the cognitive nudge to buy. Jones states, "[I]f the advertisement is creatively ineffective, repeated exposures will not bring it to life" (90).

This leads into the fourth and final quadrant on the Longwood's Map, Prediction. If advertising agencies could predict when an ad would be viewed as "likeable" or "meaningful" or any other qualifier for ultimate effectiveness, the creative leap of faith that is commonly accepted in advertising/marketing would be eliminated. This is stated as the final goal of advertisers—to gather converging evidence for the success or failure of a marketing campaign, while also helping to discriminate between these success and failure factors. Companies involved in direct marketing use econometric modeling to organize data into overall marketing planning and "what-if" decision-making. But even then, advertisers hurry to claim that these models are not a substitute for grounded testing and evaluation by those in charge of creative decisions. Return On Investment (ROI), the rational behind high cost expenditures for advertising/marketing based on the even higher income result, is the generative force. This quadrant is basically still using past successes or failures to guide decision-making in the creation of future campaigns. It gives no new insight as to what about a campaign, what within it made it successful, and thus gives no assurance of accountability of efficiency of processes or campaign effectiveness.

What current advertising agencies and academia leave us with is the idea that research is limited to such fields as direct marketing demographics, that research is limited to focusing on the past, that campaigns can only strive to reach past successes, products and past consumers because that is all we know until we try (as in test audiences and focus groups, or even so far as scanner data). This attitude can be summed up in the common mentality that "There is no 'silver bullet' tool or technique to handle the complexity and sophistication of today's marketing realities" (Pettit 4). Advertising progress is accepted as basically shot-in-the-dark guesstimates. However, current marketing and advertising have the technology and processes available to create straightforward, individualized solutions for extreme effectiveness. By utilizing such technological processes currently used by direct marketers and applying them to specific campaign details, revolutionary advertising/marketing can create a fifth quadrant never before realized—that of Control.

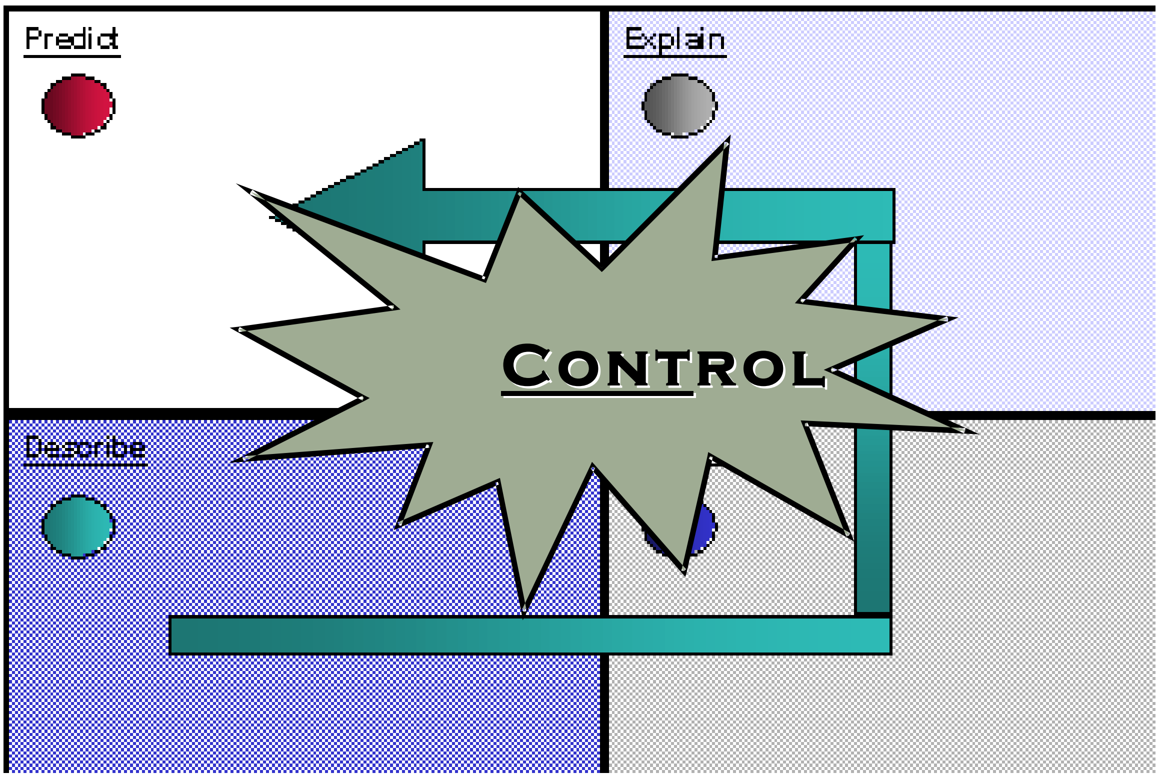

Figure 1.3: Fifth Quadrant of Control.

IV. Data Mining

These technological processes are not obscure, untested theories, but rather the common practice of Data Mining. The ideas and ideals behind Data Mining (DM) are not new. In the 1960's data collection was implemented, and in the 1970's the first Relational Database Management Systems (RDBMS) were developed. In the 80's enhanced data access techniques and suitable programming languages were developed. In the 90's there was the development of Data Warehouses (DW) and Decision Support Systems (DSS) (Symeonidis 11). Data Warehouses are Databases in which data from many sources are gathered together and organized in a consistent and useful way (Berry).

But companies who had invested in this new technology still had no way to glean information from the constantly growing data volumes. This need for data analysis tools for knowledge discovery led to what we now know as Data Mining. Data Mining in the 2000's is characterized by being computer-driven and fully automated, solving query formulation problems of previous systems, and confronting visualization and understanding of large data sets efficiently (Symeonidis 12). Data mining is the combination of several decades' disciplines and technologies, including Database Technology, Machine Learning, Information Technology, Visualization, and Statistics (17).

Therefore, Data Mining is "the application of data analysis and discovery algorithms that, under acceptable computational efficiency limitations, produce a particular enumeration of patterns over the data" (13). In layman's terms, Data Warehousing provides the memory through which the intelligence of Data Mining processes combs, noticing patterns, devising rules, coming up with new ideas, figuring out the right questions, and making predictions about the future (Berry). This is the fundamental step of Knowledge Discovery in Databases (KDD), the overall process of extracting interesting, nontrivial, implicit, previously unknown and potentially useful information or patterns from raw data (Tan 3, Symeonidis 13). DM and KDD are often used interchangeably, as they are two facets of the same process.

There are many examples of Data Mining methodology. A useful one is found in Berry and Linoff's second edition of <u>Data Mining Techniques</u>:

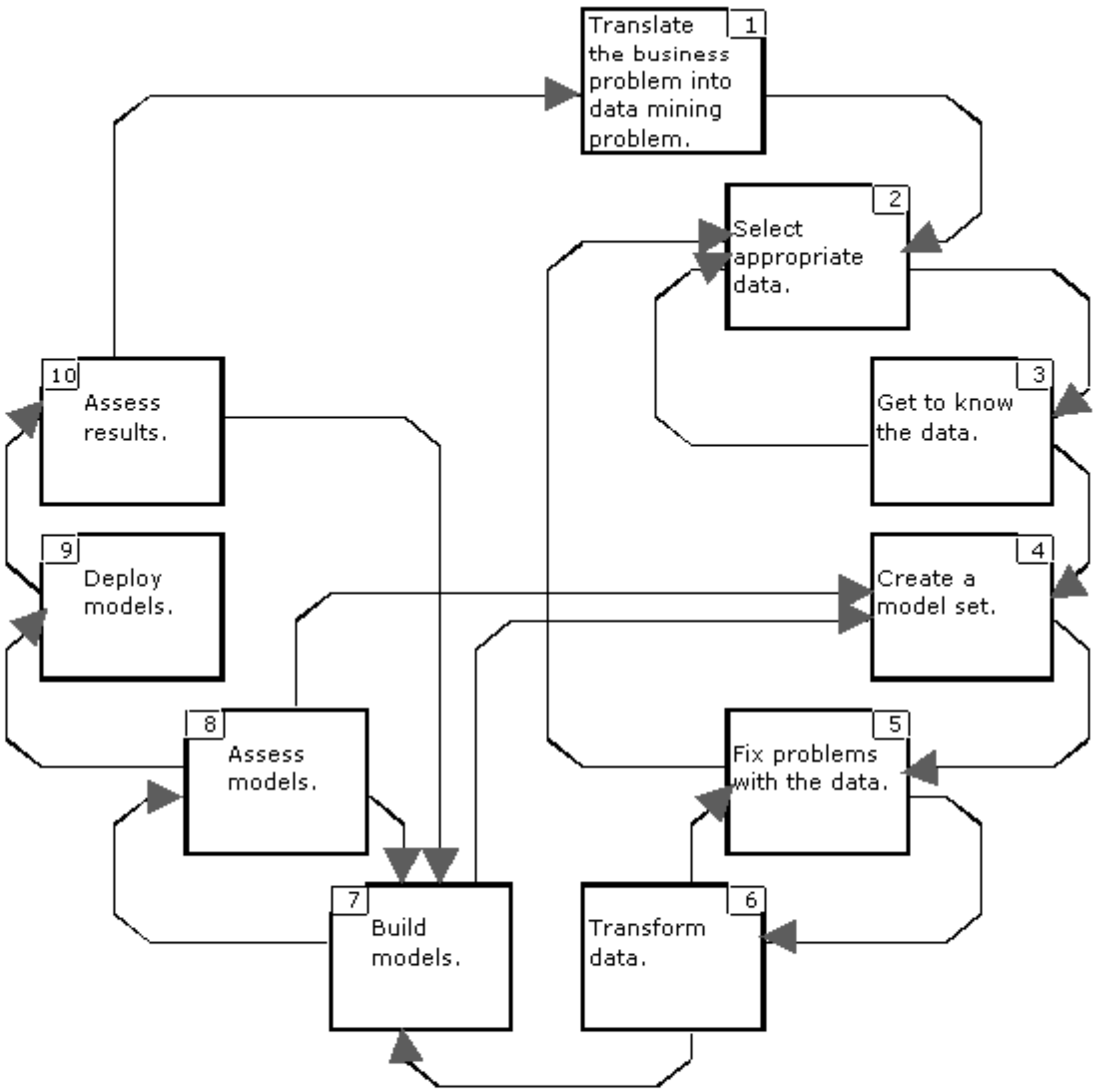

Figure 1.4: Data Mining Methodology (Berry).

The first step is to translate a business problem into a Data Mining problem. Data mining can be divided into two categories: directed and undirected. Directed data mining attempts to explain or categorize some particular target field, or question, such as “how much income” or “what response.” Classification, Estimation, and Prediction are all directed data mining tasks. Undirected data mining attempts to find patterns or similarities among groups of records without the use of a particular target field or collection of predefined classes. Undirected data mining tasks include Affinity Grouping and Clustering. Description and Profiling can be either directed or undirected (Berry).

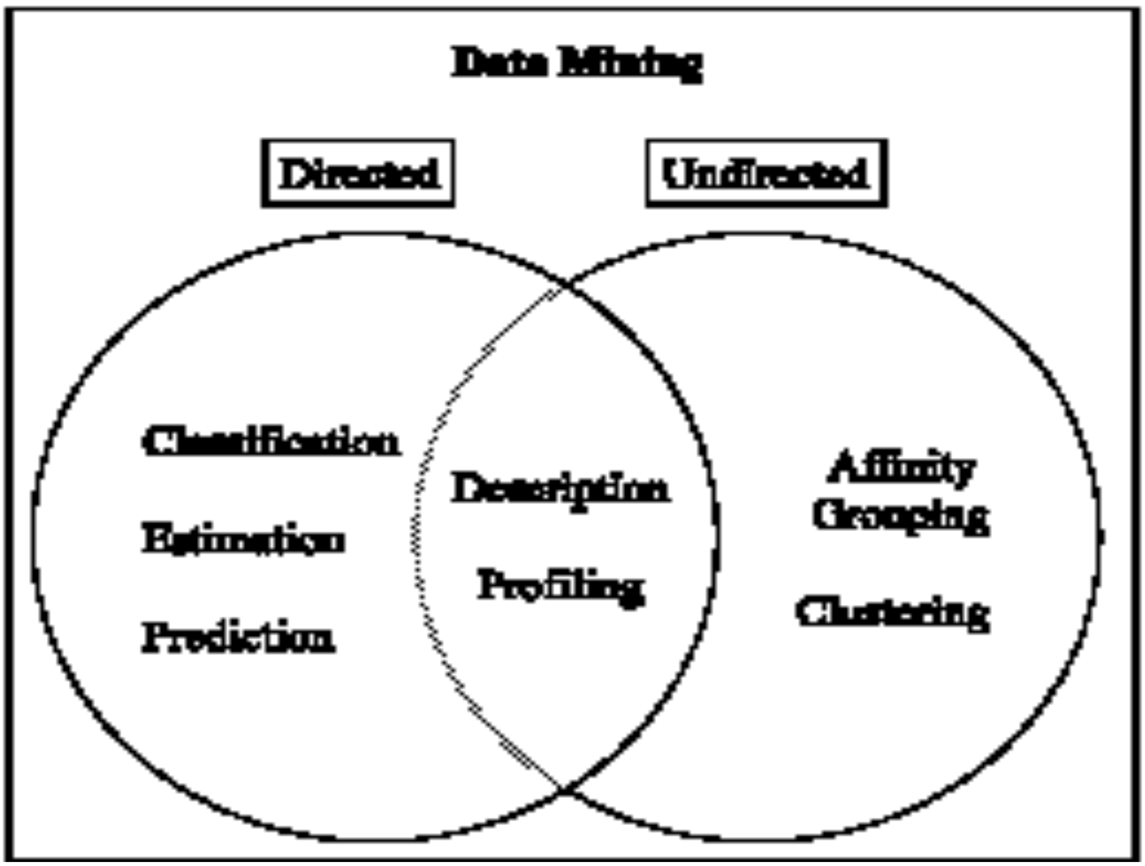

Figure 1.5: Directed and Undirected Data Mining Tasks

The second step is to select the appropriate data from Data Warehouses. Many corporations have already invested in Data Warehousing technology but have not successfully mined the data-rich resource at their disposal. Others without such a resource can find available Databases and Data Warehouses online, from Data Warehousing companies, from Data Mining companies, or from government sources, such as the U.S. Consensus. What is important is to acknowledge that there are different types of data, some better suited to a company's needs than others. Data can be either quantitative or qualitative. Some data can contain time series or objects with explicit relationships to one another. The type of data dictates which Data Mining tools and techniques can be applied.

Steps 3-6 involve getting to know the data, creating a model set, fixing problems with the data, and thus capturing trends, creating ratios, and converting counts to proportions. Data is far from perfect. Most Data Mining techniques can accommodate a certain amount of imperfection, but an understanding of the data leads to the improvement of data quality and resulting analysis quality. Raw data must sometimes be processed, whether it is to improve data quality or to modify it to suit a certain Data Mining technique or tool. For example a data set of continuous attributes such as degree of temperature may need to be modified to discreet categories like cold, warm, and hot. Data can also be preprocessed to make it more suitable for Data Mining through aggregation (combining two or more objects into a single object), sampling (using a smaller subset of data to avoid expensive or time consuming processing), dimensionality reduction (creating new attributes that are a combination of the old), feature subset selection (eliminating redundant or irrelevant features of objects), feature creation (extracting features creating a new set from raw data, re-mapping data to a new space, and creating new forms in which to showcase data present), discretization and binarization (transforming continuous attributes into categorical attributes and both continuous and discrete attributes into one or more binary attributes), and variable transformation (applying variables to simple functions or normalizing it) (Tan 45-65).

Data can be cleaned, ordered, and applied in various ways crucial to reaching optimal, accurate results.

Having completed these, the next steps of Data Mining is assessing what models are useful in the situation, deploying those models, and then assessing the results. Models are simply algorithms—sets of rules—that connect a collection of inputs to a particular target or outcome. There are a variety of different models used in data mining. The three that are most applicable to advertising/marketing, the ultimate aim of this paper, are Regression, Artificial Neural Networks, and Decision Trees. Regression is the process of using the value of a correlated pair to predict the value of the second (Berry). Take for example, a data sample containing information on a user of eBay's online auction bidding. If value one is the amount of hours a person spends browsing items on eBay (X), and value two is how much money they spend (Y). X and Y are in the data set. Once a line is established between X and Y, it can be used to predict Y when given X, and to predict X when given Y.

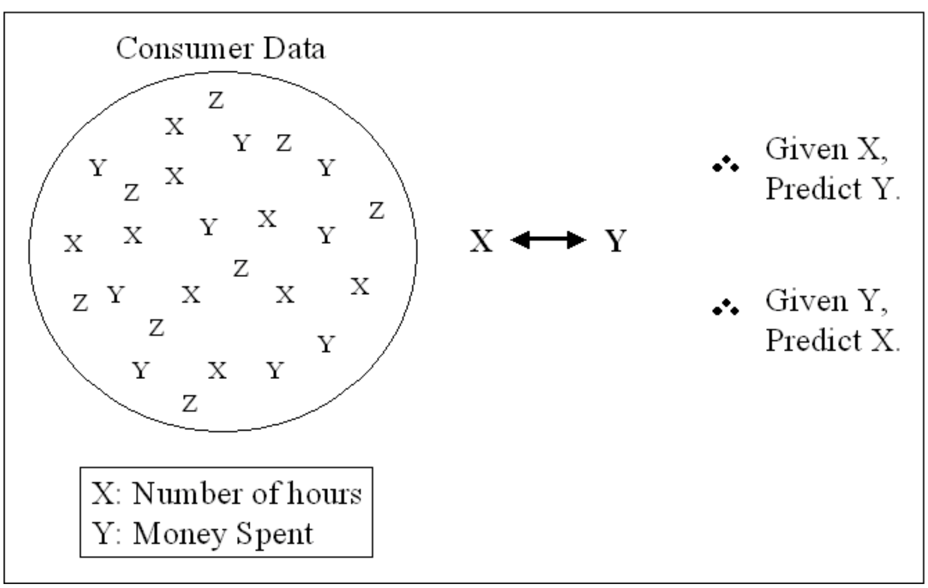

Figure 1.6: Regression Model (Berry).

Artificial Neural Networks (ANN) are a class of powerful, general-purpose tools readily applied to prediction, classification, and clustering. They are modeled after the neural connections in the human brain. An ANN is made up of an interconnected assembly of nodes and directed links. Much like biological neuron networks, an ANN learns by changing the strength of the connection between inputs upon repeated stimulus by the same connection. While this may seem confusing, most non-technological data mining users approach Artificial Neural Networks not as an overwhelmingly complex process, but rather as 'black boxes.' Data goes in as inputs and results come out as outputs. It is not important to most users how or why ANN models work, only that they do. In fact, artificial neural networks are over ninety percent accurate. In the example below, the inputs are various positive features of a house being sold. Plugged into the Artificial Neural Network, an accurate appraisal value is the output. This example is overly simple, but imagine thousands of inputs of data producing not only the classification of worth, but also predicting behavior, and clustering together important facts about consumers as outputs.

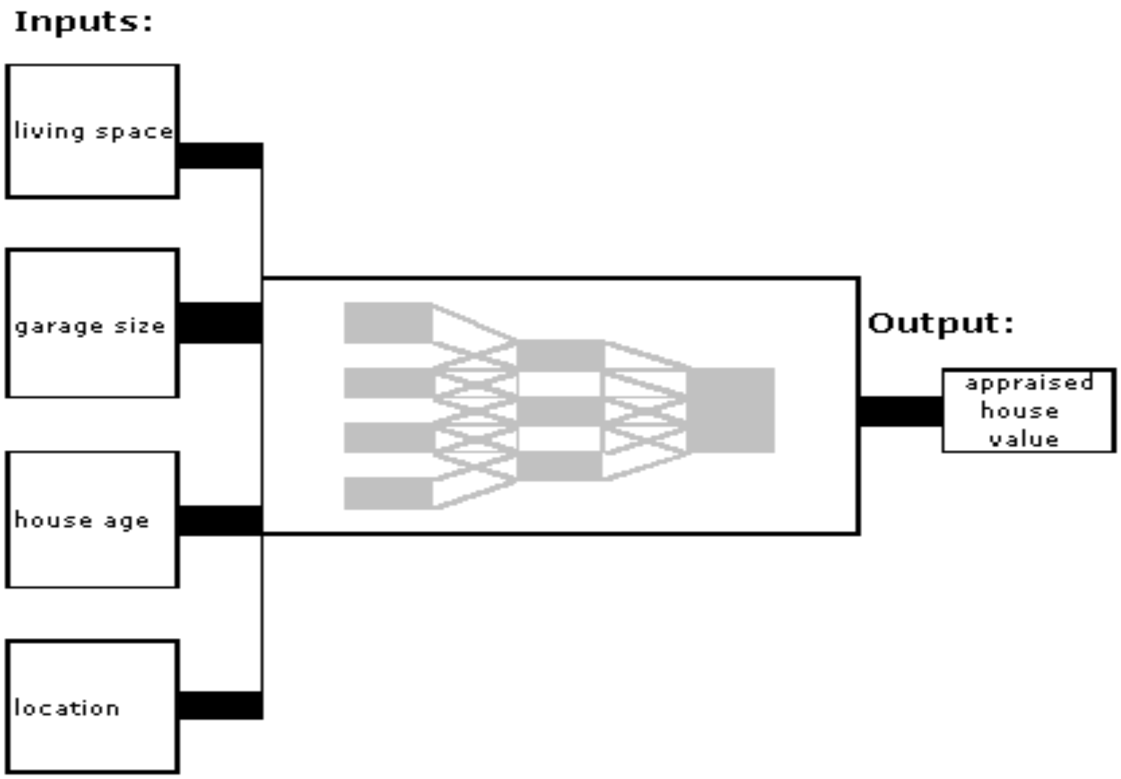

Figure 1.7: Artificial Neural Network (Berry).

Decision Trees are powerful for both classification and prediction, as well. They are attractive to businesses because they represent algorithms and rules as expressed in English. They are also useful for exploring data to gain insight into the relationships of a large number of candidate input variable to a target output variable (Symeonidis 22). Decision Tree classification can be likened to a game of Twenty Questions. A customer's record enters at the root node and is asked a question that determines which internal node it will encounter next. Non-terminal nodes, the root and internal nodes, contain attribute test conditions to separate records that have different characteristics. This process is repeated until the record reaches a leaf node, where all the records are classified in the same way. The path the record took is an expression of the rule used to classify it. An example of a Decision Tree model for classification would be running an organism's characteristics through a mammal or non-mammal series of nodes, such as body temperature or giving live birth. In the prediction Decision Tree example I have provided below, a company is trying to predict what catalog customers are more likely to respond to their mailings. The rule for leaf 11 is based on its path: If the customer has made more than 6.5 orders and it has been fewer than 765 days since their last order, the customer is likely to respond.

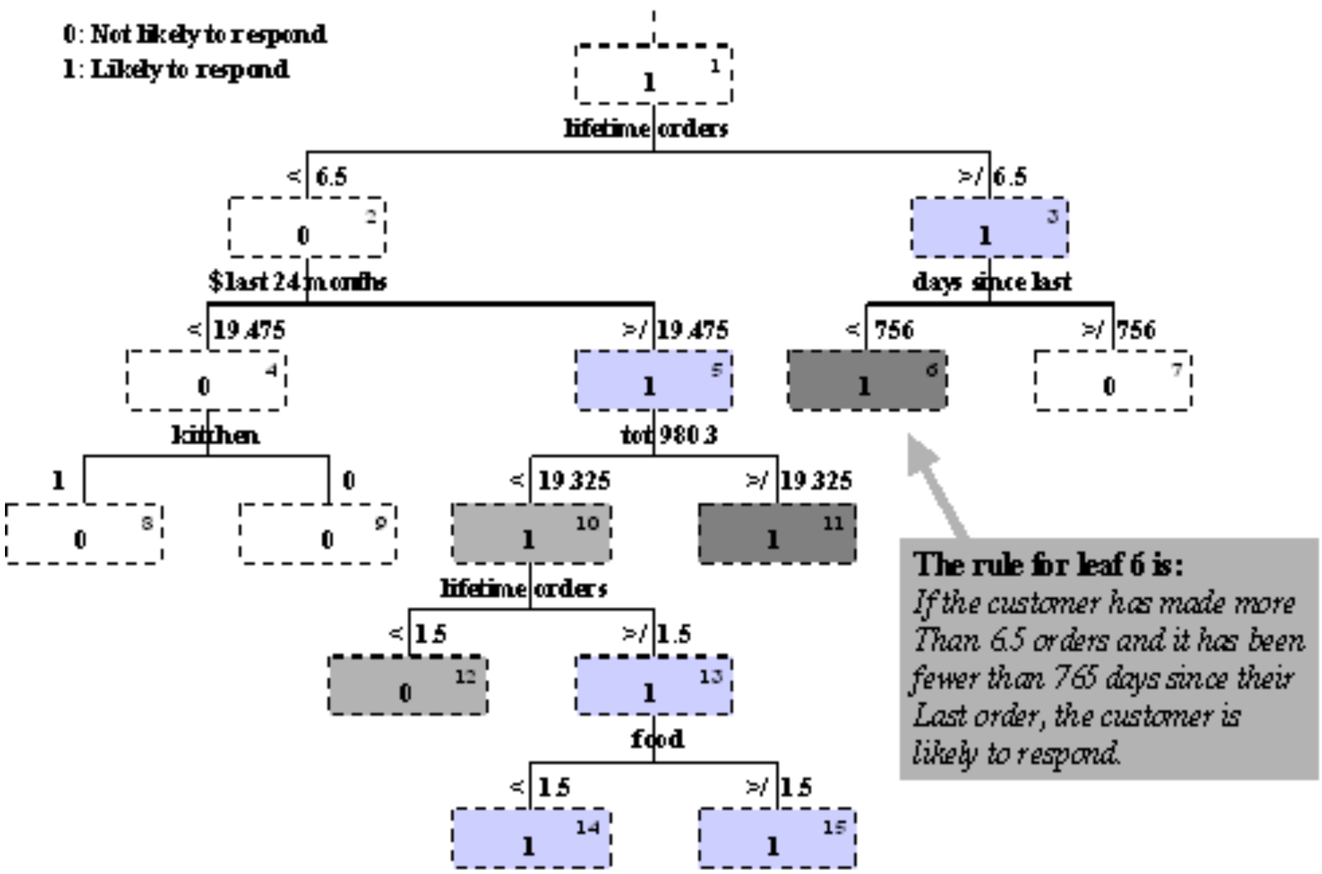

Figure 1.8: Decision Tree Model (Berry).

V. Data Mining in Current Practice

Data mining, its models, and its resulting scores are widely used by a wide array of corporations. Online companies use data mining in the form of Active Server Page Analytics (ASP), which store and apply Internet users' data from applications, requests, responses, servers, and sessions. An example of this is seen when a user searches a certain book on Amazon.com. Automatically the ASP recommends books similar to the book requested. When the user revisits the site, Amazon.com advertises the certain genre the user had previously expressed interest in, maintaining user variables from page to page. Bank and credit companies use data mining to decrease customer fraud and delinquency, score customers, and increase profitability. A credit company recently used directed data mining techniques to ask, "Would credit card usage and interest earned increase significantly if the bank halved its minimum required payment?" Looking at two years of warehoused data, they found the change would generate more than twenty five million dollars additional interest (Berry).

In bioinformatics and pharmaceuticals, data mining is used to analyze sequence data, drug discovery, and clinical trials. Merck-Medco, a small mail order business that sells drugs to Blue Cross and Blue Shield (the United States largest health care providers), large HMOs, and state governments, used warehoused data in an undirected search to uncover a link between known illnesses and their drug treatments to spot trends that help pinpoint which drugs are the most effective for what types of patients. The result was more effective treatments at ten to fifteen percent lower costs for patients (Berry). Other specific industries that are currently utilizing the advantages of data mining include Ecommerce, Email, Human Resources, Privacy, Investment Analysis and Prediction, Survey, Telecommunications, Travel, Reporting, and even Sports. Brian James, coach of the Toronto Raptors, uses data mining to "rack and stack" his team against the rest of the NBA (Berry). But it is in Marketing and Customer Relationship Management (CRM) that data mining has taken its recent application step.

Customer Relationship Management is a learning relationship based on noticing what a company's customer is doing, remembering what it and its customer have done over time, learning from what is remembered, and acting on what has been learned to make the customer more profitable (Berry). 7-Eleven recently updated their store strategy to utilizing data mining to improve CRM. Using scanner data, or point-of-sale data that can be collected literally every hour, 7-Eleven found that their old "space selling" approach, big displays that the customer would literally trip over, was unnecessary for it to sell well. So instead of stacking Coca-Cola Classic at the front of the store, 7-Eleven was able to introduce a new product, Red Bull Energy Drinks in the freed up space without affecting Coca-Cola sales (Koch 1). And they were able to take subsequent scanning data, converting it into friendlier, visual model formats, and present them to store managers to aid their future stock buying and presentation decisions.

Another way in which Data Mining is used to improve Customer Relationship Management can be seen in the CRM services of KnowledgeBase Marketing, a subsidiary of the advertising firm Young & Rubicam Inc. They state, "If you are not aggressively managing your customer relationships, then you're already losing revenue and market share to your competitors" (KnowledgeBase 1). They promise to "drill down into your data, analyze your successes and failures, and apply our real-life business experience to help you uncover new profitable marketing strategies" (1) These strategies might be in the form of a custom model of such things as acquisition propensity, in-market timing, potential revenue, or analysis and evaluation of marketing programs.

KnowledgeBase also provide lists of American consumer data, created from data collected by Yankelovich, a consumer research company. KnowledgeBase has taken this data, applied various Data Mining models, and come up with Lists With Attitude. These lists include categories like "Adventure Seekers" or "Patriotic Loyalists." There are also lists based on demographics, cataloged in such groups as "Estimated household income" or "Race code" (29). They can provide consumer data based on neighborhoods, businesses, or lifestyles. There are even NationsBest Lists, where companies can purchase information on "Active singles," "Outdoor enthusiasts," or "Hispanic credit card prospects" (20). This information is a large part of their company marketing and advertising mentality—the mentality that if you "reach the right person at the right time with the right message, you can motivate them to action" (KnowledgeBase 1). But, this is deceptive in its claim to seemingly surefire success.

VI. The Future

Like advertising's past and present, as seen by the Longwood's Quadrant Map, this "reach the right person at the right time with the right message, [and] you can motivate them to action" mentality is reliant on past successes and blind prediction based on consumer data. The most that Data mining is being used for now is targeting known consumers and providing knowledge to somewhat guide blind acquisition of consumers.

Data Mining technology has the potential to be used much more effectively. Having analyzed Data Mining and its processes, how can they translate into revolutionary advertising? The use of Data Mining can go beyond this ‘blind acquisition’ and ‘intelligent retention’ of consumers to create campaigns of ‘intelligent acquisition,’ as well. This can be accomplished by applying currently used Knowledge Discovery Database technologies to the campaign creation process, of which Data Mining is integral. Rather than “reaching the *right* person at the *right* time with the *right* message,” advertisers can “*create* the right campaign to *make* a person a consumer at *any* time.”

Collecting data on why and how campaigns are successful is crucial to implementing Data Mining into advertising/marketing processes. If agencies and data mining marketers continue their current practices of pre-testing, research, and post-testing, but also begin asking and recording consumer information on what within a commercial or advertisement motivates or motivated or doesn’t, then massive amounts of useful data can be warehoused in a relatively short time. US Consensuses, marketing attribute lists, penetration equations, ARS Persuasion, AD*VANTAGE/ACT, People Meters and Audiometers, the Starch method, point-of-sale scanner data, and all forms of measurement asking relevant questions about campaigns themselves could amass incredible amounts of information about consumers in one Data Warehouse—the more data the better. Once enough data is present on consumer preference, agencies will be able to apply Data Mining algorithms and models to glean knowledge. While continuously streaming in more data, refreshing, cleaning, adding, Data Mining models can be instantaneously produced, with not only up-to-date knowledge, but answers as well. An agency faced with the task of creating a car commercial can get answers to questions like, “What color car in a print ad would consumers to be more likely enticed to buy?” Not just answers to questions, agencies would receive information on unknown trends, such as “In soda commercials, the use of African American males as the protagonist corresponds with a 7% growth in sales.” In this way advertising creatives are able to make informed decisions on campaign details—details that are now left to personal preference and guessing which can result in costly, labor-intensive ad production that is sent back to the drawing board after a poor test run.

As more data is gathered about what motivates consumers and then is applied to the next campaigns, data can then be collected from the results of *those* campaigns, and so on. This process hones in on the consumer psyche, creating extremely specific knowledge on what works and what doesn’t, what causes what emotions, and what causes what actions. This knowledge is not limited to specific campaigns and those consumers affected by them. Knowledge on industries, products, brands, and the people who are targeted and who are not can be readily available to agencies and clients. This perfection of knowledge and process brings the control lacking in current advertising/marketing. Advertising/marketing would no longer be hit-or-miss, leap-of-faiths to be at best tested, but would produce what moves audiences from the start. Advertising/marketing becomes efficient, effective, and accountable.

This control may be objected to by the critics of advertising in society now. They claim that advertising/marketing has negative effects on society by creating demand and manipulating the consumer in a chain effect of awareness, interest, invoked desire, and then action to buy. In this informational role, there is the incorrect inflection that there are no deeper benefits or reasons to guide brand choice other than the weight of advertising. On this assumption, a consumer would be moved by the last advertisement seen or by the general weight of past advertising (Jones 68). But, advertising, like all media, is not a one-way flow to passive audiences. Consumers are able to reject ideas, compare messages, turn off or tune out, and invoke other experiences or knowledge. In fact, the use of Data Mining in advertising/marketing plays upon this. Gathering data from many sources and on many different categories, attributes, and objects, it is the ultimate acknowledgment that advertising/marketing works within a multitude of cultural influences. In running Undirected Data Mining algorithms, the advertiser is opening the door to new ideas and possibilities for campaign content based on topics never before considered or even thought of as logical. By focusing on the consumer psyche, control is not what critics claim as propaganda of capitalism. Rather, it is stimulating sales based on what the consumer already demands and demands to see. Data Mining merely figures what that is better than advertising has ever done before.

Another objection might be raised on the initial costs of accruing data in data warehouses with campaign specific details. But, as already mentioned, the addition of campaign specific questions, observations, and research to testing already in use would be relatively costless. Once in place, the spiral of honing in on details, campaign after campaign, would be based on the accumulation of data in Data Warehouses from the very campaigns they produce. Also, the Return on Investment would be larger than any advertising/marketing expenditure, as the cost put in would decrease over time.

This is opposed to current advertising research costs that are accrued every time a campaign is created, never learning any information to be applied to the next campaign, depending upon pre-testing *after* the labor and costs to make a campaign have already been generated**.** The main objection against Data Mining knowledge guiding advertising creative decisions will come from the creatives. Already briefly mentioned in the beginning of this paper, most creatives, and advertisers in general, harbor a dislike and distrust to what they see as trying to "create advertising scientifically" (Rothenberg 110). William Bernbach states, "There are a lot of technicians in advertising…They know all the rules…but there's one little rub. They forget advertising is persuasion, and persuasion is not a science, but an art" (Fox 257). But, in advertising /marketing the call for research is increasing. Already utilized in such external ways as demographics and sample group tests, research is becoming an art itself. This is seen in the prominent David Ogilvy Award, which now in 2006 is being focused on the best ROI campaign (ARF 1). Still, creatives will see the use of Data Mining as impinging on their 'genius.' David Ogilvy once said, "Shakespeare wrote his sonnets within a strict discipline of fourteen lines of iambic pentameter, rhyming in three quatrains and a couplet. Were his sonnets dull? Mozart wrote his sonnets with an equally rigid discipline" (Harris 1). As Vincent Van Gogh said, "Great thing are not done by impulse, but by a series of small things put together" (Quotes.com). Those series of small things can be guided by signs as to the most effective path to reaching consumers. Whether it be the color of a car, the age of the spokesperson, the time of day, or any other minute details that are randomly decided upon, when backed by solid data, meaning gets put into every decision, maximizing a campaign's effect. And when a client asks "Why this? Why there?" the agency has accountable reasoning to explain creatives' ultimate creation.

The introduction of Data Mining to advertising/marketing is not the abandonment of other practices. Like the steps before the present, Data Mining would be part of a

larger web of processes built up by the various technologies and tools available today. The result of this merger would not only be significant increases in revenue, satisfaction, retainment, and attainment, but also accountable, effective, efficient campaigns from knowledge. The resulting campaign content would be created from solid, relevant, data-based reasoning honed in on consumer psyche. In this way, advertisers can give their clients results of not only gambling acquisition and intelligent retention, but also intelligent acquisition of previously unreachable consumers. The possibilities of this future are currently untapped and unrealized, but the potential and trend toward advertising research is promising.

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