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A Case-Based New Financial Product Screening System

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Abstract

Initial screening is one of the most important and difficult processes in new product development. Many new product screening models have been developed in management and marketing. However, practical applications of these models have been limited in part due to their complexity and inflexibility, and in part due to their excessive data requirements. Thus, simple judgment models have been popular in practice. However, these models suffer from inaccuracy and inconsistency originating from human cognitive limitations. In light of the problems with traditional screening methods, we propose a new approach for screening based on managers' past experience and intuitive judgments-*screening by analogy*, and develop a computerized case-based system for screening new financial service concepts. Using the system, managers can predict the potential performance of a new product concept based on the performance of past products that are similar to it in terms of product characteristics, firm's resources, and market conditions. Based on this prediction, managers make a screening decision.

1. Introduction

The new product development process is characterized by a series of "Go/No-Go" decisions designed to weed out poor projects and to focus the firm's scarce resources on "best bet" projects. In such a decision context, screening is the first stage of a number of evaluations that a particular new product project must clear as it moves from a product idea to a commercialized product(Cooper 1982). This initial screening decision is very difficult because concrete financial and accurate resource data are either not availabel or very uncertain. It is also very important because it is the stage where management must commit the firm's scarce resources-money and manpower-to the most promising projects(Baker et al. 1976 ; Brentani 1986 ; Cooper 1985).

In the literature, a number of screening models and methods have been proposed to aid managers in selecting "successful" new product concepts at the early development stage. These models and methods can be categorized into three fundamental approaches : mathematical modeling, subjective judgment modeling, and statistical modeling. Several studies have indicated that mathematical models are not used in most actual new product development environments due to their incompleteness, complexity, and lack of evluation data at the early screening stage(Backer and Freeland 1975 ; Souder 1972). Subjective judgment models such as checklist and scoring models have been the most popular in practice, because they are simple and easy to apply(Cooper 1982 ; Souder 1972). However, the judgments required to develop and apply these models are often arbitray and inconsistent, thus affecting the models' performance and reliability(Backer and Freeland 1975 ; Cooper 1982). When there are enough empirical data, well-developed statistical techniques such as regression and discriminant analysis have been quite effective in predicting the potential performance of new product concepts. However, statistical models fail to capture the different characteristics of firms, important contextual factors, and manager's professional experience and knowledge. Decision makers are often uncomfortable using statistical models because these models use only a few quantifiable attributes to make predictions.

Recognizing the peculiar characteristics of screening decisions and the problems with traditional screening approaches, we propose a new approach which amplifies and extends the managers' own reasoning processes. In screening decisions, managers often use intuition about how a new product will perform based on similar past experiences or their professional knowledge. This process of applying intuition and heuristics from analogous experiences to solve new problems is called "analogical reasoning"(Gentner 1983 ; Gick and Holyoak 1980, 1983 ; Silverman 1985). When managers apply analogical reasoning to the task of screening new product concepts, they can make better screening decisions based on both qualitative and quantitative considerations about product characteristics, firm's resources, market conditions, and consumer demand.

This paper is structured as follows. In Section 2, we propose a new approach of *screening by analogy*. In Section 3, we discuss the development of a case-based system for screening new financial service concepts. This is followed by an illustrative example of screening using the system in Section 4. In Section 5, we address the benefits and disadvantages of the system. Section 6 demonstrates the effectiveness of the system in terms of its predictive accuracy over regression models. Then, in Section 7, we conclude the paper, suggesting some relevant future research directions.

2. Proposed New Approach : *Screening by Analogy*

Many behavioral studies of managers in various organizations have highlighted the importance of intuition and heuristics in problem solving and decision making(Peters and Waterman 1982 ; Silverman 1985). When considering a specific new problem, managers often understand it in terms of other past problems of a similar kind stored in their memory. They then solve the new problem by applying solutions and knowledge from the past through some mental simulation and adjustment(Carbonell 1986 ; Gentner 1989 ; Silverman 1983, 1985 ; Winston 1980). This whole process of knowledge transfer is termed analogical reasoning(Gentner 1983 ; Gick and Holyoak 1980, 1983).

Analogical reasoning is the principal means by which knowledge about the world is acquired, structured, and transferred(Carbonell 1983 ; Gentner 1989 ; Gick and Holyoak 1980 ; Palmer 1989). It can be used for screening new product ideas because products developed and marketed in similar situations are likely to perform similarly in the market(Choffray and Lilien 1986 : Wind, Mahajan and Cardozo 1981). The new product's performance can be predicted by investigating the performance of analogous products which have been marketed in the past. Thus, in screening a new product concept using analogical reasoning, managers first retrieve the "similar" product cases from their professional experience or knowledge. They then analogically predict the likely outcome for the new product concept. Based on this prediction, they can make a screening decision.

However, the effectiveness of this reasoning process is moderated by the managers' cognitive and situational limitations. Since managers can directly or indirectly encounter only a handful of new product introductions, their ability to retrieve analogous cases could be limited. managers also have various human cognitive limitations(Baron 1988). According to Hogarth (1980), there are four major consequences of limited human information-processing capacity on managers' judgment and decision-making processes : (1)selective information processing ; (2) sequential information processing ; (3) limited information-processig capacity ; and (4) limited capacity of memory. Managers are therefore subject to decisional biases, inconsistency, and incompleteness because of such cognitive limitations. Thus, they may not retrieve analogies nor have the ability to recall the best analogies consistently and correctly. In order to overcome these limitations, we propose to develop a computerized system which utilizes empirical data to identify the most similar past cases. In addition, the system provides an overall prediction on the questioned(target) attribute by combining the retrieved values of serveral most analogous cases.

3. Development of Case-Based New Financial Product Screening System(DB-NFPS[2])

In this section, we discuss the development of case-based new financial product screening system(CB-NFPS[2]). To develop such a system, we first create an extensive database of past product cases. Then we develop models to identify and retrieve the most relevant product cases and a system transferring appropriate knowledge to the target domain, including an overall prediction on the questioned(target) attribute by combining the retrieved values of several most similar product cases.

In order to collect these experiences from managers, a questionnaire was designed. The questionnaire asks for a detailed description and evaluation of a new product, from its development and marketing context to its performance and profitability in the market. Fifty questionnaires were distributed to product managers of a nation-wide brokerage company who personally participated in product development, marketing, or management. Data were obtained on various types of financial products such as annuities, bonds, CD's, mortgage backed securities, mutual funds, financial planning, limited partnerships, and financial planning. Two completed questionnaires were dropped from the analysis because of missing values, and 48 new product cases were used to create the system database. Any case in the database can potentially be used as an analog to screen new financial service concepts. Thus, it overcomes the disavantage of a limited number of personal new product experiences of each manager.

The variables in the questionnaire can be classified into "hard" variables, which can be used in the similarity calculation and prediction, and "soft" variables, which can be used as background information to inform managers. Soft variables, which are qualitative or quasi-qualitative, cannot be used in analytic models but are valuable for describing and understanding new product cases. They are reported to users at the time when individual cases are retrieved. Product performance is evaluated by five variables, each measured on a five-point ordinal scale : (1) "sales," (2) "product performed as anticipated," (3) "product perceived as a success by investor," (4) "product perceived as a success by IR (investment representative)", and (5) "produc perceived as a success by management." From these five measures, we extracted one factor[1](called "overall performance index") to represent the product's overall performance.

The second step in computerizing the analogical reasoning process is to evaluate a new prod-

1 *We conducted factor analysis using* 5 *performance measures and extracted one factor.* The factor loadings (1) sales, (2) product performed as anticipated, (3) evaluation by investor, (4) evaluation by IR and (5) evaluation by management are 0.67886, 0.82665, 0.66083, 0.90301, and 0.85513 respectively. The cronbach alpha of the composite measure's reliability is 0.8451.

uct concept by retrieving analogous product cases from the system's database. In this process, the system first selects a subset of attributes to be used in calculating the similarity between the new concept and past product cases. The system identifies the best analogies based on the similarity between the new product concept and each past product in the database. A mathematical programming model is employed to select the best set of independent(explanatory) attributes maximizing the correlation between the variable(performance of a new service concept) and the composite of explanatory attributes selected :

$$Max\ Z = \frac{\sum_{j=1}^{m} \rho_{tj} x_j}{\sqrt{\sum_{j=1}^{m} \sum_{l=1}^{m} \rho_{jl} x_j x_l}} \tag{1}$$

$$st.\ \sum_{j=1}^{m} x_j = k\ ;\ x_j = 1\ or\ 0$$

where m is the number of all independent(explanatory) attributes ; k is the number of attributes to select ; ρ_{tj} is the corrielation between the dependent(target) attribute and explanatory attribute j ; ρ_{jl} *is the correlation between explanatory attribute* j and l. The value of z represents the correlation between the target attrivute and the composite of explanatory attributes selected. The problem is to maximize z subject to the constraint that the number of selected attributes is k. The variable x_j represents attribute j and has a binary value of *0* or *1*. In the solution, if variable x_j is *1*, then attribute j is selected, otherwise it is left out.

Using the selected attributes, the system computes the similarity between the new service concept and each past product case in the database. A commonly used geometric model based on weighted Euclidean distance is employed, where attribute are weighted in proportion to the ratio of each selected attribute to the dependent target attribute. The similarity between target new product concept t and base product case b in the multi-dimensional space of the selected j attributes is represented by an inverse of an exponential decay function of the weighted metric distance as follows :

$$S_{tb} = \exp\left\{-\sqrt{\sum_{j=1}^{m_s} w_j (x_{bj} - x_{tj})^2}\right\} \tag{2}$$

where m_s is the number of explanatory attributes selected ; w_j represents the relative importance of feature j in measuring similarity ; x_{bj} and x_{tj} represent the values of base and target products on attribute j respectively.

The next step is to transfer relevant information from the source to the target domain. Information about similarities between the new product concept and the cases in the database provides a guideline for the manager to decide which cases(analogies) are most useful for understanding and predicting the performance of the new concept. The more similar cases are, the better analogies they are, and thus the more effective they should be in understanding the new situation. For the unknown(target) variable, the system provides an overall prediction combining the predictions(target values) of some useful analogies weighted in proportion to their relative similarities to the new product concept.

4. Illustrative Example of Making A Screening Decision Using The CB-NFPS^2

Once the system is developed, the manager can use the CB-NFPS^2 to make screening decisions. We illustrate the process using a concrete example. We take one historical new product from the database, and assume that this is the new product concept to be screened. At the first stage, the system presents the manager with a list of "hard" variables available in the system database. Then the manager is asked to specify the model by defining a dependent variable(target variable), feasible independent variables, and a set of constraints in selecting key independent variables. As constraints, the manager can specify the number of independent variables to select ; ask for the exclusion of any specific variable from the selection process ; and set a minimum correlation between the dependent target attribute and each independent variable to be selected. However, this process can also be done automatically by the system. With no specific instructions about constraints, the system uses its default settings : inclusion of all hard variables in the set of feasible independent variables ; select the number of variables maximizing the function value of the variable selection model ; and use the average correlation between each independent variables and the dependent target variable as a minimum correlation. Thus, all the manager has to do is to define the target variable. For the following example, we assume that the manager only specifies the target attribute of "sales" in this process.

Based on this specification, the system selects the optimal set of independent attributes to explain the target attribute of "sales" ; provides information about the selected attributes, and requests that the manager enter the values for the new product concept to evaluate, as shown in Figure 1. If the selected variables do not concur with the manager's intuition or expectation, or if the manager cannot provide the information about new product concept on the selected attributes, he/she can redo this selection process by specifying some constraints. This procedure can be repeated until the manager is satisfied with the variables selected and he/she can provide reliable information on the new product concept.

Figure 1 : List of Variables Selected by The System and Manager's Task

System Output					Manager's Task
Description of Key Attributes Selected(Independent Variables)	Scale of Variable	Mean of Variable	Variance of Variable	Correlation with Target Variable (Rank)	specify Levels of New Product
Product is superior with respect to yield	5 level ordinal	3.21	1.33	0.36(7)	—
Acceptance of product by salesforce	5 level ordinal	2.96	1.74	0.65(1)	—
Overall understanding of product by IR	5 level ordinal	2.83	1.01	0.47(6)	—
Ongoing marketing support throughout product life cycle	5 level ordinal	2.81	0.71	0.55(4)	—
Quality of ongoing marketing support of product	5 level ordinal	2.91	0.74	0.48(5)	—
Serve investor needs for growth	5 level ordinal	2.34	2.42	0.26(9)	—
Size of market during offering period	5 level ordinal	2.74	1.01	0.58(3)	—
Growth of market during offering period	5 level ordinal	2.85	1.46	0.59(2)	—
Product competes with established company's product	0 and 1 binary	0.88	0.11	0.35(8)	—

* The number in parentheses represents the rank of correlation size.

Once the manager has entered the attribute values of the new product concept on the selected variables, the system computes similarities between the new product concept and the cases in the system database. The system provides the list of historical cases ordered by their similarities to the new product concept as shown in Figure 2. Furthemore, the system can also provide various types of graphs locating the products in the database on the dependent variable of "sales" and similarity coordinates as shown in Figure 3. By reviewing this information, the manager can obtain an idea about the potential "sales" of the proposed new product. In addition, the system provides an overall prediction on the dependent variable of "sales" by combining the target values of "sales" of several most similar products in the list. If the manager's subjective prediction coincides with the system's and he/she does not need any additional information, he/she can make the screening decision on the new product concept. Otherwise, if the manager needs additional information, he/she can request the system to retrieve any historical product case of interest from the database. The system will then retrieve the complete information(including both hard and soft variables characterizing product development, management, sales, and performance) about the denoted historical product case, and present it to the manager for review as shown in Figure 4. By investigating each retrieved case in detail, the manager can evaluate whether the historical case would be an effective analogy for the new product concept. This process of making a screening decision using the CB-NFPS[2] is summarized in the flow chart shown in Figure 5.

Figure 2 : List of Historical Products Ordered by Similarities to New Product Concept

Case ID of Base Product	Target Value of Base Product (1-5 Scale)	Similarity between New Target Product and Bast product (0min-1max)	Predicted Value Combining Target Values of Base Products (1min-5max)	Average Similarity of Combining Base Products with Target Product (0min-1max)	Variance of Target Values of Combining Base Product	Number of Base Products Combined
12	4	0.63	4.00	0.63	0.00	1
48	4	0.52	4.00	0.58	0.00	2
7	4	0.52	4.00	0.56	0.00	3
22	3	0.52	3.76	0.55	0.19	4
30	5	0.52	4.00	0.54	0.40	5
26	3	0.51	3.84	0.54	0.47	6
31	2	0.49	3.60	0.53	0.82	7
25	3	0.48	3.53	0.52	0.75	8
36	4	0.47	3.57	0.52	0.69	9
38	4	0.47	3.61	0.51	0.64	10
..	..	...	...	...	...	...
..	..	...	...	...	...	...
1	1	0.20	3.38	0.35	1.27	38
28	1	0.20	3.35	0.34	1.37	39
33	1	0.20	3.32	0.34	1.46	40
23	1	0.19	3.28	0.33	1.54	41
9	3	0.19	3.28	0.33	1.50	42
32	1	0.17	3.25	0.33	1.57	43
45	1	0.17	3.22	0.32	1.63	44
40	4	0.15	3.23	0.32	1.62	45
27	1	0.13	3.21	0.32	1.67	46
39	2	0.11	3.20	0.31	1.66	47

Figure 3 : Similarity and Target Value Plot

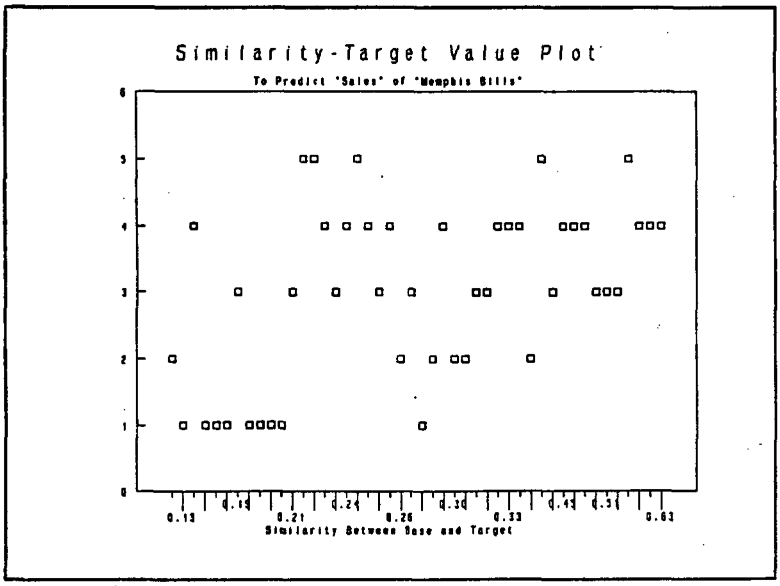


Figure 2 : Information of A Similar Product Case Retrieved(System Output)

Product Name : Memphis Bills Product Leader : James Bond Date : June 25, 1990

Brief Description of Product :

This Product was developed by a newly organized, closed-end diversified management investment company. The company's primary objectives are current income and long-term growth of income. They will seek to achieve their objectives by investing primarily in a diversified portfolio of equity and fixed income securities of companies n the public utilities industry.

Rationale for introducing this product :

Closed-end funds become a big product idea. Memphis Bills is well known name and a good way to introduce the salesforce to the new product idea.

Who initiated this product idea? Citibank

Major strengths : Strong management team with well-known name ; utility stocks ; NYS listed ; Borrow underwriting expenses
Major weaknesses : Limited supply ; Not much knowledge of how closed-end funds would perform in secondary-new concept

Objectives for this product :

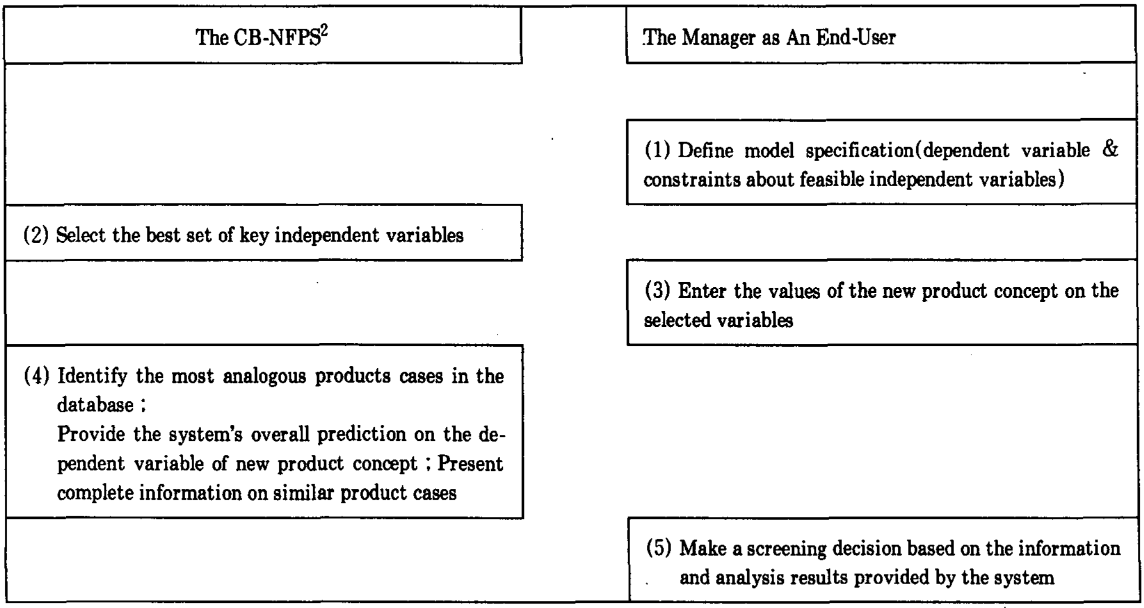
Total Sales :	150,000 shares($ 1,500,000)
IR participation(% of salesforce) :	7%
Amount sold per IR :	1500 shares
Commission revenue generated :	$ 64,500
Profitability :	$ 58,200

Target customer segment :

Customers needing diversification ; seeking current income as well as long-term growth of income

---------- continue ----------

Figure 5 : Process of Making Screening Decision Using The CB-NFPS[2]



5. Benefits and Limitations of The CB-NFPS^2

Benefits

There are some notable advantages of the CB-NFPS^2 over traditinal screening methods or systems. First, using the CB-NFPS^2, managers can learn by reviewing many historical new product cases, and eventually improve their new product management and concept screening skills. Managers' field experiences and professional knowledge are critical to the quality of screening decisions.

Unfortunately, managers' experiences tend to be limited to at most a handful of new product projects(Cooper 1982). The CB-NFPS^2 enables managers to indirectly experience many new product cases which have been described in detail by other managers who developed, advertised, sold, and managed them. By systematically sharing their experiences with each other, managers can better understand the new product development problem, and increase their professional knowledge and management skill.

Second, the CB-NFPS^2 incorporates managers' professional experience and knowledge in the decision process at various points, including : (1) creating the system's database ; (2) defining model specification ; (3) judging the importance of key attritutes ; (4) reviewing the validity of the system's prediction ; and (5) incorporating qualitative information to verify or adjust the system's predictions by exploring similar product cases in detail. Furthermore, since the system is based on a fundamental human reasoning process(analogical reasoning), it is simple and easy for managers to understand, to communicate with, and to control. A high level of involvement on their part will also increase the chance of their accepting the system's recommendations.

Third, the CB-NFPS^2 encourages managers to use both qualitative and quantitative information in screening descisions. Qualitative information is very important not only to understand the product case but also to correctly appreciate the quantiative information. Thus, in evaluating new product ideas, quantitative information can never be complete without qualitative decriptions about the product development, marketing, and management. Most screening methods, however, have not incorporated qualitative variables simply because they cannot be effectively and efficiently quantified. This has been a mojor limitation of traditional screening approaches. Using the CB-NFPS^2, however, managers can incorporate both quantitative data and qualitative information, which is usually overlooked in mathematical analysis, to reach better screening decisions.

Fourth, the CB-NFPS^2 can provide more information useful for screening decisions. It not only identifies important attributes in screening decisions, but also locates the relation of historical products with the proposed new product on the measure of similarity. Statistical models are quite proficient in providing summary information about key variables affecting product performance and their relative importance. However, they do not provide information about the relationship between each historical product and the present product. This information helps managers to understand the general performance of past products in the market as well as to make better screening decisions. Based on information about the performance distribution of both similar and dissimilar products, managers can more confidently judge the potential of a proposed new product in the market. If most highly-related(similar) products are relatively poor performers and least similar products show relatively good performance, the proposed new product is likely to be unsuccessful.

Fifth, the CB-NFPS^2 is quite effective and efficient in prediction and forecasting. Unlike most forecasting models and techniques, the system is not so sensitive to model mis-specification, the types of variables, number of variables, and minimum number of observations, as long as it can compute similarities among cases. We can thus easily apply the system and obtain qualified predictions, especially when there are no other appropriate tools available, the problem domain is complex, and relationships are highly context-dependent involving many variables.

Finally, as managers learn from experience and enhance their skills in prediction and decision making, the CB-NFPS^2 also evolves as more and diverse new product cases are added to its database. With an increased system database, the CB-NFPS^2 can identify better key attributes, select better analogies, and provide better predictions.

Limitations

While there are many benefits of the CB-NFPS^2, there are limitations as well. First, like most mathematical and statistical models, the models used in the CB-NFPS^2 do not use qualitative, non-quantifiable data. Thus, the selection of the best analogies depends only on the quantifiable variables. Although managers can incorporate qualitative information in selecting best analogous product cases, if these variables are not used to search for these cases, managers might be misled in their reasoning and decision making usint the system.

Second, the current CB-NFPS^2 cannot incorporate past product cases drawn from conceptually remote domains such as consumer package goods. That is, all the cases in the system database must be described and evaluated in terms of the same set of attributes measured on the same scale. This restricts the system from the creative application of analogies to solving novel problems in other domains. To solve such between-domain problems, the manager must still rely on his/her creative reasoning by analogy, and the system can, at best, only provide a possible clue about possible analogies.

Finally, the system's overall prediction completely relies on the composition of the system's database. For example, if there are only successful product cases in the database, the system's overall prediction on any new product concept will always be biased to "success," although the degree of its similarity with base cases will be different(successful and unsuccessful concepts show high and low levels of similarities respectively). It is similar to the case where a new product manager who has experienced only succcessful products is likely to evaluate a new product concept as "successful." In order to prevent such a biased decision, the system provides information about the distribution of the target values of base cases in the database along with the probability of yieding the overall prediction value given such a distribution. To make the most effective use of the CB-NFPS^2 and achieve high quality predictions, it is essential to build a database with a diversified set of cases.

6. Comparison between the CB-NFPS^2 and Statistical Techniques in Prediction

In making a screening decision using the CB-NFPS^2, the manager's professional knowledge, experience, and intuition are critical to the quality of the decision. However, in order to assess the internal validity of the system's overall predictions, we compared the performance of the CB-NFPS^2 with statistical techniques such as regression and discriminant analyses in predicting the performance of new product concepts.

We conducted split sample tests where the available 48 new product data were split into two subsets-an estimaiton sample and a holdout sample. The estimation sample was used to construct statistical models and estimate their parameters. Thus it was also used to construct the database of the CB-NFPS^2. The holdout sample is assumed to consist of new product ideas or concepts to be evaluated and screened. In order to investigate the relationship between the model's predictive accuracy and the size of the estimation sample, we varied the size of the estimation sample as well as the holdout sample. We selected 30%, 40%, 50%, 60%, 70%, and 80% of the past product cases randomly from the original data set(48 products) to create the estimation samples. The product cases left over were used as the corresponding holdout samples. By this selection procedure, 14, 21, 24, 28, 34, 38 product cases constitute estimation samples and the remaining 34, 27, 24, 20, 14, and 10 cases constitute the corresponding holdout samples respectively.

In addition, we used several dependent variables in order to enhance the validity of comparison results. The five variables representing product performance(i. e., sales, product performed as anticipated, evalution by inverstor, evaluation by IR, and evaluation by management) and a factor extracted from them are used as the dependent(target) variables to be predicted for the new product concepts(i. e., holdout sample). Predictions of these target variables are generated both by the statistical models and by the CB-NFPS[2]. They are compared with the known true values, and their absolute and squared differences are measured. These prediction errors are used to compare the performances of the regression model and the CB-NFPS[2]. In case of comparison between the CB-NFPS[2] and discriminant function, the correct classification rates are used to compare the performance.

Using each estimation sample(i. e., 30%, 40%, 50%, 60%, 70%, or 80% of cases selected from the total set of 48 product cases), we developed regression models for five performance measures and the overall performance index by stepwise regression analysis[2]. Totally, 36 regression models were developed for the six dependent variables and the six sample sets. We applied these linear regression models to the holdout sample and obtained forecasts. We compared these forecasts against their known true values, and measured the absolute differences(absolute prediction errors) as well as the squared differences(squared prediction errors). We summed these prediction errors across the entire holdout sample for each of the six dependent variables in the six sample sets. Each total prediction error was divieded by the number of cases in the holdout sample, to yield the average prediction error(mean absolute error(MAE)) for each new product concept.

We followed a similar procedure for the CB-NIFPS[2]. Using each estimation sample in its database, the CB-NIFPS[2] provides the overall prediction on the target variables of the corresponding holdout sample. These predictions are compared with their true known values of the holdout sample to compute their prediction errors. Then, we compute the mean prediction errors for each target variable of each holdout sample in the same way as we did for regression model. These MAEs are compared with those of the regression model. The results are summarized in Table 1.

Under varied conditions of different dependent variables(performance measures), and different sizes of estimation and holdout samples, the CB-NIFPS[2] significantly and consitently outperformed linear regression models. For example, while the average MAE's across six variables of the regression models are 1.18, 0.89, 1.22, 0.93, 0.86, and 1.15 in the six sample sets

2 The SAS's default significance levels(i. e., p=0.15 for both entry and staying) are used for stepwise regression.s

respectively, the corresponding average MAE's of the CB-NIFPS^2 are 1.00, 0.79, 0.80, 0.84, 0.69, and 0.90 respectively. Only in 4 comparisons out of 36, regression models showed slightly smaller MAEs than the CB-NIFPS^2 by 0.04 on average. Thus, the CB-NIFPS^2 is found to be superior to regression models in predicting the performances of new financial service concepts.

Table 1 : Summary Table Comparing MAEs of Regression Model and The CB-NIFPS^2

Six Split Samples by Random Selection	Methods	Sales	Product Performed as Anticipated	Evaluation by Investor	Evaluation by IR	Evaluation by Management	Overall Performance Index	Average Across Six Variables
Sample Set 1	Regression Model	1.43	1.18	0.82	1.26	1.38	1.01	1.18
	CB-NIFPS^2	0.77	1.19	0.83	1.09	1.19	0.91	1.00
Sample Set 2	Regression Model	0.85	0.86	0.88	0.87	1.14	0.75	0.89
	CB-NIFPS^2	0.89	0.64	0.57	0.84	1.14	0.67	0.79
Sample Set 3	Regression Model	1.31	1.43	0.71	1.24	1.58	1.03	1.22
	CB-NIFPS^2	0.94	0.65	0.62	0.79	1.05	0.76	0.80
Sample Set 4	Regression Model	0.99	0.72	0.92	0.92	1.15	0.89	0.93
	CB-NIFPS^2	0.96	0.72	0.71	0.83	1.15	0.68	0.84
Sample Set 5	Regression Model	0.87	1.03	0.61	1.02	0.97	0.64	0.86
	CB-NIFPS^2	0.74	0.65	0.67	0.63	0.85	0.57	0.69
Sample Set 6	Regression Model	1.25	0.96	0.84	1.32	1.68	0.86	1.15
	CB-NIFPS^2	1.06	0.65	0.57	1.06	1.34	0.69	0.90
Average of MAE's Across Six Sample Sets	Regression Model	1.12	1.03	0.80	1.11	1.32	0.85	1.04
	CB-NIFPS^2	0.89	0.75	0.66	0.87	1.12	0.71	0.83

7. Summary and Future Research

Many new product screening models have been developed in management and marketing science. However, practical applications of these models have been limited in part due to their complexity and inflexbility, and in part due to their excessive data requirements at the early screening stage. Thus, simple judgment models have been popular in practice. However, they suffer from inaccuracy and inconsistency originating from human cognitive limitations. In light of the problems with traditional screening approaches, we propose a new approach based on analogical reasoning. In this approach, the potential performance of a new product concept is predicted based on the success of past product that are similar to it in product characteristics, firm's resources, and market conditions. We formalize this approach, and demonstrate its potential by developing a computerized case-based new financial product screening system(CB-NFPS^2). Using this system, mangers could make better screening decisions by effectively exploiting both qualitative inputs from their own experience and empirical case descriptions, and quantitative inputs from models.

It is the managerial inputs that maximize the effectivenss of the CB-NFPS^2. However, in an attempt to demonstrate its predictive validity, we compared its accuracy with those of regression models in predicting the performnaces of new financial service product concepts. In most comparisons, the CB-NFPS^2 outperformed regression models.

Having demonstrated the effectiveness of the analogical reasoning approach in prediction, we first invite future research to investigate its potential in many business applications besides the screening of new product concepts. Second, additional research is required to improve the models used in the current system. Various approaches are available for selecting attributes and cases and for estimating similarities. Research should be conducted to identify which of these models is best able to identify relevant past cases and, at the same time, present its results in a manner comprehensible to managers.

Third, it would be valuable to develop a system that can effectively deal with multiple goals and multiple projects simultaneously. Screening decisions usually involve the consideration of multiple goals, and several product ideas would be considered based on their relative merits for achieving these goals. In screening a new financial service concept, for example, several dependent performance measures are identified, such as "sales", "evaluation by investor," "evaluation by investment representative," and "evaluation by management." Although they are correlated, they show differences as well. Thus, the screening decision cannot be made based on any one of these criterion variables alone. Instead, it should be made based on an overall consideration of all these criterion variables. It is desirable that the CB-NFPS^2 have a capability to evaluate multiple new product ideas by appraising multiple goals to pursue.

Reference

[1] Baker, N. R. and J. Freeland, "Recent Advances in R & D Benefit Measurement and Project Selection Methods," *Management Science*, Vol. 21, No. 18(1975), pp. 1164-1175.

[2] Baker, N. R., W. E. Souder, C. R. Shumway, P. M. Maher and A. H. Rubenstein, "A Budget Allocation Model for Large Hierarchical R&D Organization," *Management Science*, Vol. 23, No. 1(1976), pp. 59-70.

[3] Baron, J., *Thinking and Deciding*, Cambridge University Press(1988).

[4] Brentani, U. de, "Do Firms Need a Custom-Designed New Product Screening Model?" *Journal of Product Innovation Management*, Vol. 3(1986), pp. 108-119.

[5] Carbonell, J. G., "Learning by Analogy : Formulating and Generalizing Plan from Past Experience," *Machine Learning : An Artificial Intelligence Approach*, Vol. 2, eds. R. S. Michalski, J. G. Carbonell and T. M. Mitchell, Los Altos, CA : Morgan Kaufmann Publishers, Inc(1983).

[6] Carbonell, J. G., "Derivational Analogy : A Theory of Recontructive Problem Solving and Expertise Acquisition," *Machine Learning : An Artificial Intelligence Approach*, Vol. 2, eds. R. S. Michalski, J. G. Carbonell and T. M. Mitchell, los Altos, CA : Morgan Kaufmann Publishers, Inc(1986).

[7] Choffray, J. M. and G. L. Lilien, "A Decision-Support System for Evaluating Sales Prospects and Launch Strategies for New Products," *Industrial Marketing Management*, Vol. 15(1986), pp. 75-85.

[8] Cooper, R. G., *Guide to the Evaluation of New Industrial Products for Development*, Industrial Innovation Center, Montreal, Canada(1982).

[9] Cooper, R. G., "Overall Corporate Strategies for New Product Programs," *Industrial Marketing Management*, Vol. 14(1985), pp. 179-193.

[10] Gentner, D., "Structure-Mapping : A Theoretical Franework for Analogy," *Cognitive Science*, Vol. 7(1983), pp. 155-170.

[11] Gentner, D., "The Mechanisms of Analogical Learning," *Similarity and Analogical Reasoning*, Cambridge University Press, eds. Vosniadou, Stella and Ortony, Andrew(1989), pp. 199-233.

[12] Gick, M. and K. Holyoak, "Analogical Problem Solving," *Cognitive Psychology*, Vol. 12 (1980), pp. 306-355.

[13] Gick, M. and K. Holyoak, "Schema Induction and Analogical Transfer," *Cognitive Psychology*, Vol. 15(1983), pp. 1-38.

[14] Hogarth, R. M., *Judgement and Choice : The Psychology of Decision*, Wiley, Chichester, England(1980).

[15] Palmer, S. E., "Levels of Description in Information-Processing Theories of Analogy," *Similarity and Analogical Reasoning*, Cambridge University Press, eds. Vosniadou, Stella and Ortony, Andrew(1989), pp. 332-345.

[16] Peters, J. T. and R. H. Waterman, *In Search of Excellence : Lessons From America's Best-Run Companies*, Harper and Row Publishers, New York(1982).

[17] Silverman, B. G., "Analogy in Systems Management : A Theoretical Inquiry," *IEEE Transactions on systems, Man, and Cybernetics*, SMC-13, No. 6(1983), pp. 1049-1075.

[18] Silverman, B. G., "Expert intuition and Ill-Structured Problem Solving," *IEEE Transactions on Engineering Management*, EM-32, No. 1(1985), pp. 29-33.

[19] Souder, W. E., "A Scoring Methodology for Assessing the Suitability of Management Science Models," *Management Science*, Vol. 18, No. 10(1972), pp. B526-B543.

[20] Wind, Y., A. Mahajan and R. Cardozo, *New Product Forecasting: Models and Applications*, Lexington, Mass(1981).

[21] Winston, P. H., "Learning and Reasoning by Analogy," *Communications of the ACM*, Vol. 23, No. 12(1980), pp. 689-703.