

Case-Based Reasoning (CBR) Inference Based Electronic Goods Production

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Abstract:

The system can provide the user to forecast the electronic goods production for future in business application within acceptable time. By using this system, user can obtain the desired solution for producing such as profit, products and general expenses for future. Electronic goods producing are the act of determining the future value of business sectors on time series historical data. The ability to accurately forecast long-term future sales of specific items is highly desirable capability for many business areas. New product sales forecasting must deal with major problems caused by lack of data and the uncertainty of how breakthrough technologies and products will be accepted by consumers. It is then matched with previous stored cases and retrieved the most similar cases. The nearest-neighbor concept is employed to match cases and the similarity percentages are shown as a result.

Keywords —CBR Inference and CBR cycle, Similarity measure, the local-global principle

The system can provide the user to forecast the product's markets for future in business application within acceptable time. By using this system, user can obtain the desired solution for market such as profit, products and general expenses for future.

They may need to forecast the size and growth of a market or product category. When strategic issues are being considered, they need to forecast the actions and reactions of key decision makers such as competitors, suppliers, distributors, governments, their own actions, and complementors' (organizations with whom they cooperate) actions. These actions can help to forecast market share.

This system is based on historical data such as data Investment income, Order quantity, Sale amount, Net Income, total assets, and total liabilities and number of expense of past time. In this system, Case-Based Reasoning (CBR) is used to forecast future market. Time series methods use known historical sales and data to predict future sales. Hence, storing and retrieving information on previous dataset are the most important tasks to provide business organization [3].

In this system, the features of electronic product market data are represented in attribute-value pairs. A similarity table is constructed for local similarity measure of each attribute. The values of the system user entered are considered as a new problem case. It is then matched with all the stored cases in historical database by using the local-global similarity measure. As a result, the system outputs the ranked similar cases. Based on the retrieved cases, the system user can modify or reuse it as the market case solution.

The main objectives of the system are: to predict the accurate forecasting result by using Knowledge base and four procedure, to gain the net profit from market forecasting, to support the business environment, and to determine products manufacturing or not by using forecasting result.

The other objects for new product forecasting are: to eliminate an unprofitable product is an equally useful reason to forecast as introducing a successful product, manufacturing decisions on raw materials procurement, manufacturing schedules, and finished goods inventory levels and marketing decisions on marketing budgets and promotion schedules.

Hence, storing and retrieving information on previous dataset are the most important tasks to provide business organization.

This paper is organized into five sections including this section. Section 2 presents the background theory, CBR cycle and the similarity measure utilized in this system. Section 3 illustrates the system design and dataset. Section 4 describes the system implementation and conclusion is given in section 5.

I. BACKGROUND THEORY OF CBR

Case-based reasoning (CBR) is a problem-solving paradigm that remembers previous similar situations (or cases) and reuses the information and knowledge about the stored cases for dealing with new problems. CBR systems have intuitive appeal because much of human problem solving capability is experience based, that is, humans draw on past experience when solving problems and can readily solve problems that are similar to ones encountered in the past [2, 6].

On the other hand, the case-based reasoning is performed by the concept of parallel instead of serial chain like rule-base. The knowledge is stored in case like slots. The CBR works in cyclic form as the following procedures. When the user inputs new problems to be solved, the system first of all searches the case base for the same case or similar cases. If the retrieved case meets with the user needs, reuse it as the current problem solution. Otherwise, modify the necessity parts to produce an optimal solution and output this case. At the same time, store the solution in case base to be capitalized and eventually reused as reference for a new problem [2, 6].

A. CBR inference engine

CBR module contains five parts: description of the issues, case retrieval, case assessment, case amendment, and case learning.

(1) Problem Description: User describes the problem to solve in functions, parameters and other elements.

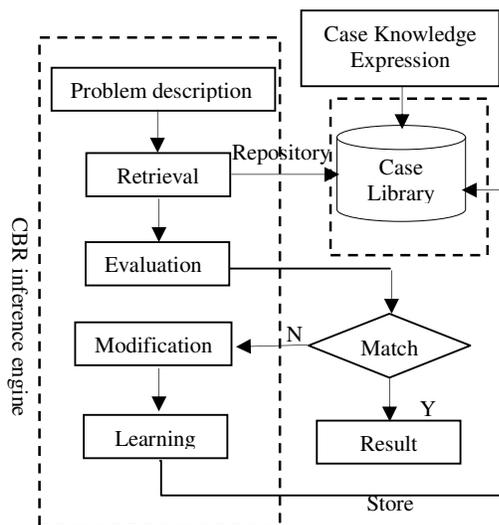


Figure 1. CBR Inference Engine

(2) Case Retrieval: When initiating a case-based problem solving process, the first phase is the retrieval of useful cases providing solutions to be reused easily for solving the problem at hand. The quality of the case retrieval strongly depends on the quality of the used similarity measures.

(3) Case Assessment: The output of this module is the list of cases retrieved according to the ranked similarity of the matched case.

(4) Case Amendment: If instances are similar to the problem, but some aspects are still not suitable after assessment, the case amendment module can be used to amend the case, and create a new instance and store it.

(5) Case Learning: Methods of solving problems can be obtained from past experience. Case learning module can store the knowledge and experience gained in the previous steps [2, 6].

B. Similarity measure

A similarity measure is a function $Sim: D_D \times D_D \rightarrow [0,1]$. By computing the similarity between the query, q and the case characterizations of the cases contained in CB, the retrieval mechanism has to identify a list of cases, called retrieval result, ordered by the computed similarity values. The number of cases to be retrieved may be specified by an integer value which denotes the maximal number of cases to be retrieved.[1]

C. The Local-Global Principle

A similarity measure that can be adapted on a particular attribute-value based case representation is called the local-global principle. According to this principle it is possible to decompose the entire similarity computation in a local part only considering local similarities between single attribute, and a global part computing the global similarity for whole cases based on the local similarity assessments.

A local similarity measure for an attribute A is a function $Sim_A: A_{range} \times A_{range} \rightarrow [0,1]$, where A_{range} is the value range of A . For unordered symbol types, the only feasible way to represent local similarities is an explicit enumeration in form of a lookup table, called similarity tables. [1]

Table 1. Example: Similarity table for color

	red	green	blue
red	1.0	0.0	0.0
green	0.0	1.0	0.0
blue	0.0	0.0	1.0

The second important part of similarity measures defined according to the local-global principle is attribute weights.

They are used to express the different importance of individual attributes for the entire utility approximation.

Global similarity measure is represented by an aggregation function computing the final similarity based on the local similarity values computed previously and the attribute weights defined:

A global similarity measure for D is a function

Sim: $D_D \times D_D \rightarrow [0, 1]$, of the following form:

$$\text{Case Sim (query, case)} = \frac{\sum_{i=1}^n w_i * sim_i}{\sum_{i=1}^n w_i}$$

where, sim_i is similarity of i^{th} feature, w_i is weight of i^{th} feature [1]

II. SYSTEM BACKGROUND AND DESIGN

The method of forecasting new product depletions is *historical review*. If a company has introduced similar new products into similar markets in the past, these histories can often be good predictors of future outcomes. If a company has no such history, then histories of similar new products introduced by competitors or other companies can serve as historical guidelines to help derive a new product sales forecast [4]. Sales forecasting is the activity of predicting the future level of demand of products.

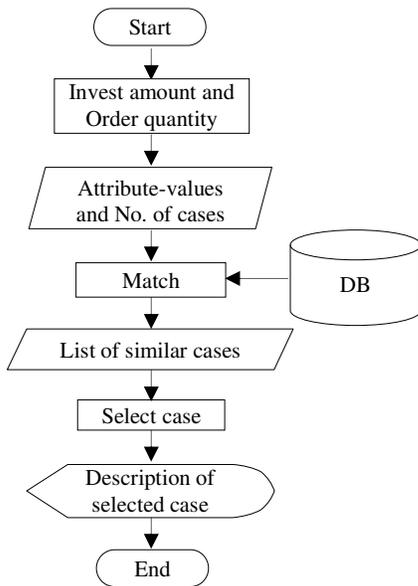


Figure 2. System flow for case retrieval

Sales forecasting plays a significant role in making decisions regarding new products and older products. For older products, there are several quantitative methods for sales forecasting such as moving average, percent rate of change, unit rate of change, exponential smoothing and line extension. For new products, with the lack of historical data, a few

simple routines can be employed, requiring more creativity in order come up with useful predictions of the future level of demand [5, 7]

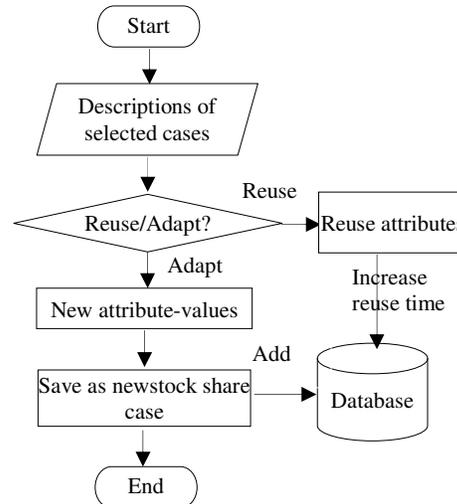


Figure 3. System flow for case adaptation

For retrieval of useful cases for customer requirements, the matching of query case and the stored cases in the case base is performed by the similarity measure discussed in section 2.2. The computed similarity result is ranked and shown in percentage form. The user makes selection on one of the retrieved cases and views the detail description of the selected case. If the user meets with their needs, reuse the selected case as the current investment amount and increase the reuse times. Otherwise, modify the necessity parts and re-input new attribute values. The system flow diagrams of retrieval and adaptation processes are illustrated in Figure 2 and 3 respectively.

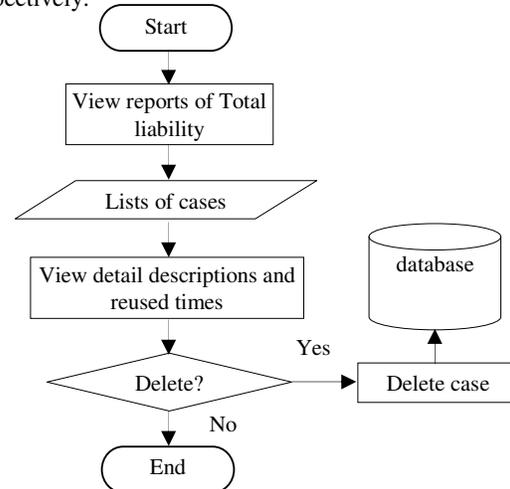


Figure 4. System flow for case maintenance

As the case-base becomes grow, the searching time of the relevant cases gets slow. Therefore, we need to maintain the case-base. We will use the case addition and deletion policy. Case-addition option of case retain step is described in Figure 3, in which the new stock share case is added to the database for future use. However, if some stock share cases are not convenient for later use and the reuse time is low, we need to decide whether to delete it or not. The process of case-deletion is shown in Figure 4.

Table 1. Sample database

Month	Investment	Order quantity	Sale Amounts	Net Income	Total Assets	Total Liabilities	Target Class
Jan	2760	75	2810	2800	2800	510	1
Feb	2870	80	2900	2410	2410	620	0
Mar	2900	80	3030	2970	2970	550	1
April	2890	86	2990	2910	2910	500	1
May	2940	81	3020	2800	2800	610	1
June	3030	85	3060	3050	2050	630	0
July	3050	74	3100	3010	2040	580	0
Aug	3010	68	3030	3110	3110	600	1
Sept	3130	70	3080	3130	3130	610	0
Oct	3020	76	3100	2670	2670	700	1
Nov	3170	72	3230	2670	2670	710	1
Dec	3160	81	3110	2990	2990	720	1

III. SYSTEM IMPLEMENTATION

This system used time series historical data (investment income, Order quantity, Sale amount, Net Income, total assets, and total liabilities). In this testing phase, the system will show the percentage of increase Profit (1) or percentage of decrease Profit (0). The system calculates the testing data with updated input values and then forecast of production may be increased or decreased.

The proposed system is tested by the customer requirements. A production forecasting is the main business sectors of a company, derivative or other financial asset. The system forecasts the electronic market situation that will increase or decrease with Profit amount.

The user then browses the ranked similar cases and makes selection on the top-level one. The retrieved product case is decorated with sequence, the common popular product, especially for celebrities and grooms.

For adding new Investment and Profit amount in the design database, the system user can substitute the attribute values or input new values. And then, the new forecasting result is made. Not only new forecasting case, the system

enables the user to modify the retrieved Profit amount. The new successful forecasting case is stored in the forecasting database.

Fig. 5 Similarity Result

IV. CONCLUSION

Case-based reasoning concept is reviewed and applied in forecasting electronic market. A specific attributes case has better ability to improve the new attributes efficiency than clear rules. The reusable and adaptable ability of CBR is mainly utilized in this system. The work flow of the system is discussed with case study. As a result, the system user can get an exposure to the past remarkable attributes to produce new innovative Profit amount.

In business application, there can have difficulty to forecast the products manually if there are too large amount of datasets. So, this system can produce the result effectively and quickly by using GGA. Because electronic products in business products are using as data sets in this system, user want to perform in practical that gets result within a short time.

The system can provide the user to forecast the products for future in business application within acceptable time. By using this system, user can obtain the desired solution for market such as profit, products and general expenses for future.

History is not always a good predictor of the future; it is often difficult to find accurate historical data relevant to the new product under consideration; and what other companies have been able to do does not necessarily tell us what the next company can do. This system will be extended to forecast large numbers of data sets such as cosmetic products, entertainment products and telecommunication products for long-term. This system can only be solved to forecast electronic products for monthly.

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