Autonomous Restructuring Portfolios in Credit Cards

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Abstract

This paper proposes the novel concept of Autonomous Restructuring Portfolios which would enable financial portfolios to re-adjust themselves to cater with the highly volatile customer behavior pattern. It investigates the possibility of using Kohonen's Self Organizing Maps in analyzing, categorizing & modifying strategies applied on financial portfolios according to the its behavior patterns. It also puts forth a design which could enhance the effectiveness of the strategy assignment to different areas of portfolios. This model would introduce new strategies to meet new scenarios as well as to drop off obsolete strategies. This model is also applicable to any financial portfolio where dynamic business decisions needs to be made based on the portfolio's behavior.

1. Introduction

"Know the Customer" – is the motto of any business. The extent to which its process 'knows' the customer & predicts his/her behavior is where the success of a business lies. In order to retain its customers, it should be able to adapt itself to the changes in the customer behavior.

In the current world of sheer competition, with a highly dynamic customer base, retention of customers is becoming a major concern for all financial institutions. Towards this end, businesses try to offer a multitude of offers which is expected to give them an edge over their competitors. But the vastness of available options in the market & the dynamism of customer base cause these offers to fail at times. Mostly the issue would be with identifying the correct customers for an offer or the correct offers for a customer. Both need some sort of a prediction on customer's preferences which is highly volatile.

The main deterrent of having an accurate prediction of customer behavior & preferences is that they are ever changing in the current market scenario & businesses cannot categorize them statically to specific behavior groups. To cater with this, it needs an adaptive system which would categorize the customers based on their spending habits, repaying schedules & other factors which are subject to change over a period of time.

This paper discusses the novel concept of Autonomous Restructuring Portfolios (ARP) – an approach of incorporating Kohonen's Self Organizing maps with financial portfolios to have them dynamically classified into different behavior groups. This paper discusses the applicability of ARP in relation with Credit Card Portfolios; but it is equally applicable in any other financial portfolio where decisions need to be made dynamic. In this model, the portfolio would restructure itself to form new strategies & drop obsolete ones according to changing socio-economic scenarios. It relies on the basic principle of business – "Know your Customer" as he changes with time.

2. Credit Card Industry

In this paper, we would take the Credit Card industry, being one of the fastest growing industries where customer base is ever expanding & rapidly changing, as an example to discuss the concept of Autonomous Restructuring Portfolios

The growth of the Credit Card industry had been tremendous in the last couple of decades. From being an accessory of the rich, it has now found its place in the wallet of any middle class person. Also the places where one can use his credit card has expanded from few five star hang outs to street shops & taxi cabs. As the market has expanded over a larger population, the diversity of cards available in the market in turn increased. Currently, credit cards are being custom made to suit the usual spending outlets of each customer. Special purpose credit cards are now available for customer groups - from drivers to frequent flyers to shoppers to executives to military personals.

To start with, the main objective for most credit card issuers was account acquisition & all their strategies revolved around it. But as the market base became a sizable population, there was a gradual, but major shift in the drastic account acquisition strategies to involve account retention tactics as well. As a result, a wide variety of rewards cards & offers are being floated in the market & are made available for existing as well as new customers.

These rewards & offers eventually became the trump cards of card issuers to attract & retain customers. As per a 2007 survey conducted by CNNMoney.com, approximately 85% of American households have at least one rewards card. In its recent survey of 83 credit cards, Consumer Action found that 62 cards offered rewards of one sort or another. Many people make many everyday purchases using rewards cards. They seek to earn a solid return, such as 1% or 2% cash back. This shows how vital a role rewards & offers play in this industry; and how important it is to offer the apt rewards to the apt people.

3. Business Strategies

In the credit card industry, like any industry, business decisions drive the growth path. For enabling the system to consider & process the accounts with respect to its behavior, each account would be tied to many different strategies which would drive the way it will be processed. For example, the pricing of an account would be driven by a pricing strategy; Authorizations happening on an account would be driven by an Auth Strategy etc. Whether it is the pricing parameters or the account offers or promotions, there will be a pool of strategies present in the system & accounts will be assigned these strategies, based on pre determined business policies. This enables the business to treat customers differently within the same system, based on their features.

As the diversity of portfolios to be handled intensified, the complexity to manage them also increased to higher levels. For e.g. a retail private label card cannot be given the same options as a frequent flyer card or Oil Card. Apart from the categorization of cards based on the customer usage, there could be numerous sub categories as a result of various business strategies.

Currently credit card processing systems uses various techniques to manage this diversity, all of which is more or less the implementation of parameters grouping to form strategies & assigning them to accounts. TSYS, one of the largest credit card processing vendors in US & UK, uses a mechanism based on "Option Sets" which is a set of "Options" which would be assigned to an account. In FDR, another leading credit card processing system, the processing options are driven by "Strategies" assigned to different processing areas. A strategy would comprise of a various "Sections" each of which would be a group of processing "Parameters".

In either case, as well as in any other major credit card processing systems like Vision PLUS, Card Pac etc, the processing parameters are statically set by a strategy which would be a collection of attributes. This strategy will be assigned to an account & it drives the processing of that account.

Even though this approach offers flexibility to manage diversified portfolios to a certain extent, it is limited in two main aspects.

1. Static Allocation
2. Manual Decision Making
3. Limited Strategy Pool

The strategies once assigned, will remain in an account until business selects that account for an upgrade, or an account activity forces a strategy change based on the programmed rules. Mostly, upgrade/downgrade decisions are made by business which limits its effectiveness to the extent to which the business can perceive the patterns.

Also, these strategies are limited to a certain set which business has already designed. Any new sub categorization formed within the customer behavior pattern would be oblivious to the business. Also, any existing strategies which no longer hold well would not be noticed by business.

4. Current strategy assignment

The strategy assignment to an account mostly happens as a response for some event happening on an account – account opening, a credit line increase, being delinquent for more than a stipulated time etc. Another way these strategies could change is a system wide upgrade which would design & apply some new strategies on a selected population based on various account criteria.

In most cases, the strategy assignment on an account happens at any of the following events

1. New Account Opening
2. Special offer Upgrades
3. System-wide Upgrades
4. Punitive downgrades

All these strategy assignment-reassignments are more or less manually driven. The manual decision is coming into play in either assigning the strategy for new accounts or for selecting the accounts for a special offer.

These actions may even consider the account behavior over a period of time. For a decision to be made on whether a promotional offer needs to be extended to a customer will be made based on his past behavior. But the decision to extend a better strategy or assign a more restrictive strategy is normally made based on the stipulated parameters or as per programmed rules.

But as discussed in *Section-3,* this approach is limited in its adaptability to readjust with new scenarios as it doesn't take into consideration the volatility of the customer behavior & it solely depends on the decision made by business. It is highly impossible for business to select the apt population which would embrace an offer, considering the vastness of the customer base we are talking about. Secondly, as discussed earlier, once a decision is made & a strategy is assigned to an account & remains there until an event triggers a change or it gets selected in a population which business decides.

Here, the missing part is that, the flexibility provided by strategies to the business is not really adaptable to the rapidly changing behavior pattern of the customer base. The customer behavior & spending habits may even be affected by various factors other than what a business could imagine, like the economic state of the whole country, the market growth, natural disaster etc. It would take time for the business to identify these re-categorizations & act accordingly. And it may incur loss to the portfolio. But if a self re-organizing structure is in place which would identify the change in behavior patterns & adapt itself to suit new scenarios, business can rest assured.

This paper proposes an autonomous structure for credit card portfolios which would restructure itself based on changing customer behavior pattern. It would automatically incorporate the socio-economic state of the external world into the portfolio management there by detaching the business from the burden of identifying ditches & making decisions. This model has its base on the concept of Self Organizing Maps proposed by Kohonen in 1982.

5. Neural Networks for Decision Making

Most Credit Card issuer institutions now rely on various behavioral scores, like FICO score etc., for their business decision making. Various neural models are in place which helps evaluating these scores for the accounts. But the main limitation with this approach is that it would reduce the adaptability of portfolios to a single dimension. It would encode or rather try to represent the whole of an account's characteristic in terms of a single score & use this score value to take decisions.

For obvious reasons, this approach is highly limited & lacks the reliability which a neural model in its basic form can offer.

6. Kohonen's Self Organizing Maps

The Self-Organizing Map (SOM), commonly also known as Kohonen network (Kohonen 1982, Kohonen 2001) is a computational method for the visualization and analysis of high-dimensional data.

The Self-Organizing Map defines an ordered mapping; a kind of projection from a set of given data items onto a regular, usually two-dimensional grid. A model is associated with each grid node. These models are computed by the SOM algorithm. A data item will be mapped into the node whose model which is most similar to the data item, e.g., has the smallest distance from the data item in some metric.

SOMs are used for different purposes; however their main application is data visualization. If the data are high dimensional or non-numerical, a SOM can be used to represent the data in a two-dimensional space, often called 'latent' space. Nearby locations in the latent space represent similar data. For example, the SOM can be used to represent images in a two-dimensional space, such that similar images are nearby. This latent representation can then be used to browse a large image database.

Like a codebook vector in vector quantization, the model is then usually a certain weighted local average of the given data items in the data space. But in addition to that, when the models are computed by the SOM algorithm, they are more similar at the nearby nodes than between nodes located farther away from each other on the grid. In this way the set of the models can be regarded to constitute a similarity graph, and structured 'skeleton' of the distribution of the given data items.

The SOM was originally developed for the visualization of distributions of metric vectors, such as ordered sets of measurement values or statistical attributes, but it can be shown that a SOM-type mapping can be defined for any data items, the mutual pair wise distances of which can be defined. Examples of non-vectorial data that are feasible for this method are strings of symbols and sequences of segments in organic molecules (Kohonen and Somervuo 2002).

SOMs are mainly used for dimensionality reduction rather than expansion. There are two ways to interpret a SOM. Because in the training phase weights of the whole neighborhood are moved in the same direction, similar items tend to excite adjacent neurons. Therefore, SOM forms a semantic map where similar samples are mapped close together and dissimilar apart.

The other way to perceive the neuronal weights is to think them as pointers to the input space. They form a discrete approximation of the distribution of training samples. More neurons point to regions with high training sample concentration and fewer where the samples are scarce.

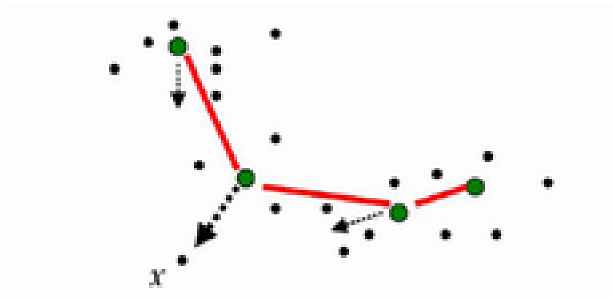
6. SOM Algorithm

A detailed discussion on the concept of Self Organizing Maps is out of the scope of this paper. A basic implementation of SOM is given below. This can be extended to suit any specific scenarios.

6.1 Basic SOM algorithm

1. Initialize the prototype vectors as randomly selected data points.
2. Iterate these steps:
   <u>Assignment</u>: Assign the current data item to its nearest (typically in terms of Euclidean distance) prototype 'X' in the data space, this prototype is called the 'winner'.
   <u>Update</u>: Move the each prototype 'S' towards the data vector by an amount proportional to N(X, S), the

value of the neighborhood function evaluated at the winner X and prototype S



7. SOM in Credit Cards

Artificial Neural Networks have found its firm place in the field of credit cards way before. Applications of neural networks have been implemented & are in use in a wide variety of credit card areas life credit evaluation, fraud detection etc.

Mostly, these applications are in the field of fraud detection. They would observe, & learn from past experiences & build a knowledge base which in turn would help in future cases. Credit evaluation is another area in which lots of neural network enabled applications are in use.

Martin-del-Prio and Serrano-Cinca [7] have been one of the first who applied SOM to the financial analysis. They generated SOMs of the Spanish banks and subdivided them into two large groups and this allo-wed establishing root causes of the banking crisis. Kiviluoto [10] made a SOM-map which included 1137 companies, 304 companies from them were crashed. The created SOM was able to give useful qualitative information about similar input vectors. Visual exploration allowed seeing the distribution of important indicator – bankrupt – on the map, thus, it was possibly to apply that map for the forecasting of companies bankrupt. The mentioned authors have estimated only a current situation of credit state and afterwards they have interpreted it for forecasting bankrupt, causes of crisis period or market segmentation of banks. But no major advancements have happened in the research of predicting a new customer class based on these past interpretations.

Self Organizing Maps being a fairly new technology is yet to find its real application in this field. There is various fraud detection methods which would self organize transactions based on their behavior, which would help to predict the behavior of a new transaction at the door based on its features & past experiences. But the vast applicability of SOM is yet to be unraveled in this field.

8. Autonomous Restructuring Portfolios

Autonomous Restructuring Portfolios, as its name suggests, is a novel model for financial portfolios in which the portfolio would manage itself to meet the changing business environment. It takes care of creating new strategy groups, dropping off obsolete ones & conditioning existing ones to cater with a changing world.

8.1 Deciding Parameters

The first step for modeling an Autonomous Restructuring Portfolio is to identify the deciding parameters for the portfolio. In case of a credit card portfolio these parameters could include directives of customer spending habits, repaying habits, risk evaluation indicators etc. In case of an insurance portfolio, these parameters would be completely different & may include the risk of the item insured, age of the person/item insured etc. Having the flexibility to select the ARP parameters makes it suitable for any business & gives the implementing organization the choice to decide between efficiency & robustness depending on its constraints.

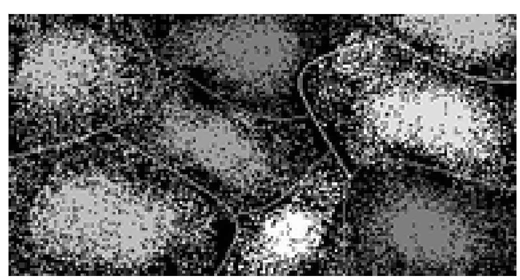
Once the parameters are selected, this paper proposes two alternatives to restructure the portfolio. Any one of this or both can be implemented on any portfolio & can even be given a choice between the 2 based on portfolio size & dynamism.

8.2 Basic Model

The basic model would be to have a pool of strategies (similar to the existing systems) & each strategy would define a set of parameters which would drive the processing of an account. This pool would be distributed along the two dimensional latent plane where the portfolio clustering is to happen. As the accounts get clustered & re organized along the latent space, the portfolio will automatically reassign the strategies making it adaptable to the changing behavior patterns.

This model needs manual intervention to monitor the portfolio's clustering & to define new strategies in case if a considerable cluster is formed in the pattern due to some external impact.

Basic ARP - Strategy Structure



The above figure shows a snap shot of a possible portfolio clustering pattern. And the business has to identify the clustering pattern & has to design strategies which best suit that part of the cluster. It should also define directives which would guide the portfolio to readjust the strategies itself as the portfolio restructures. As shown in the above figure, the two dimensional latent space is divided into different strategy areas based on the clusters developed. And the appropriate strategy would be placed on the account. If the behavior of the account causes it to re-organize to another cluster, then the strategy would be automatically re assigned.

Even though this model enables the portfolio to restructure itself based on its own behavior, it is limited by the fact that the choice of strategies is limited to a predefined pool which is statically maintained. This pool and any new additions to it are designed by the business which means the portfolio is robust only to the extent business identifies the diversity of its portfolio. So, even though an ARP basic model would re-organize itself based on customer behavior, it would not be able to introduce new strategies & drop off obsolete ones. Business has to monitor the clustering plane to identify any possibility of a new strategies or the worthlessness of an obsolete strategy. Apart from this, designing of the new strategy would be the responsibility of the business. An advanced model can be proposed which will take care of this drawback.

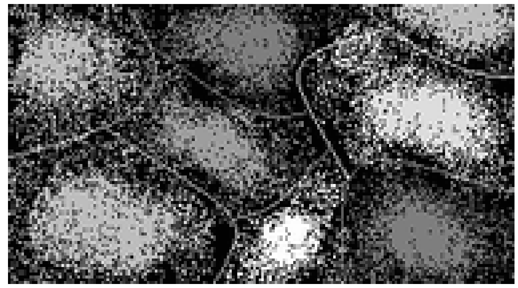
8.3 Advanced Model

An advanced model can be envisioned by adding another level of adaptability by having the ARP design its own strategies rather than having the business supply the strategy pool. Based on the portfolio’s behavior, the ARP would automatically create new strategies or drop off obsolete strategies.

For this, instead of assigning the strategies across the two dimensional clustering plane, basic rules or directives would be represented within the ARP to have the parameters distributed over the two dimensional plane on which the ARP would cluster the accounts. Parameters would be selected automatically by the ARP system for clusters. So, if due to some external effects, a considerable population of the portfolio clusters in a region which was earlier sparsely populated, the ARP would automatically generate a new strategy for that cluster based on the directives on parameters. Similarly, if a bigger population develops an internal sub clustering into 2 different groups, the ARP would drop off the old strategy & create two new strategies which would be processed differently then onwards.

An example of the above mentioned scenario is depicted below in the figure.

Advanced ARP - Initial Strategy Structure



Advanced ARP - Strategy Structure after Restructuring

As shown in the figure, the ARP initial strategy structure re-adjusts itself over a period of time to incorporate the changes in the behavior pattern & forms a new structure. This will be an ongoing process which will keep the structure catered to the changing environment.

This would save the processing cost by optimizing the number of strategies to manage. At any point of time, one can be sure that there exist only those strategies which are really required. If the density in a specific region goes below a specified limit, strategies can be re-allocated to nearby strategies & have the strategy deleted from the system. This threshold level of population for a strategy can be defined by the business based on how small a population of accounts it can afford to have a separate strategy.

9. Alternate Designs

The concept of ARP can be extended in many ways than jus the 2 models discussed in this paper. An exploration of all the different ways to implement this concept is out of the scope of this paper. But in this section we will consider few alternate designs of ARP

9.1 ARP with No strategies

One alternate approach of implementing ARP is to completely eliminate the concept of strategies. In this model an account would have its own set of processing parameters. In that way, each account would be processed in its optimal way. The main drawback of this design is that it would increase the storage requirement for each account. But in this age of easy availability of cheap storage, that wouldn't seem to be a major deterrent. But the elimination of strategies would take away an easy pointer to refer how an account is processed. This will reduce he control business can exercise over its portfolios. A strategy based structure would also give the business an idea of the degree of diversity of its portfolio, which is lacking in this model.

9.2 Layered ARP

Another alternate design of ARP is to have a layered approach for parameter assignment. The system would define a layer of processing parameters in the 2D categorization/latent plane. An account falling into a cluster in the latent plane can either chose to have the absolute parameters based on the layer of each parameter or a clustered strategy into which that area of the latent plane falls into. This choice can be represented at the account level by a flag within the account record.

This model offers a way for the system to have a pointer to the strategy assigned to an account; at the same time there would be an unlimited pool of strategies that can be assigned to an account

10. Concluding Remarks

In this paper, ARP is discussed in its conceptual level giving less emphasis to its implementation details. Credit card portfolios were taken as an instrument to better discuss the concepts & to analyze its advantages in comparison with existing techniques. ARP in its basic form unearths hidden patterns in customer behavior & categorizes customers dynamically based on that. So it stands good for any financial portfolio where customer behavior plays a key role in driving business.

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