Picking Stocks

with Emergent Self-organizing Value maps

Abstract

Picking stocks that are suitable for portfolio management is a complex task. The most common criteria are the price earnings ratio, the price book ratio, price sales ratio, the price cash flow ratio, and market capitalization. Another approach called CAN SLIM relies on earnings growth (quarterly and annual earnings growth) of companies; the relative strength of the stock prices; the institutional sponsorship; the debt capital ratio, the shares outstanding, market capitalization, and the market direction. The main issue with the traditional approaches is the proper weighting of criteria to obtain a list of stocks that are suitable for portfolio management. This paper proposes an improved method for stock picking using the CAN SLIM system in conjunction with emergent self-organizing value maps to assemble a portfolio of stocks that outperforms a relevant benchmark. The neural network approach discussed in this paper finds structures in sets of stocks that fulfill the CAN SLIM criteria. These structures are visualized using U-Matrix and used to construct portfolios. Portfolios constructed in this way perform better the more the CAN SLIM criteria were fulfilled. The best of the portfolios constructed by emergent self-organizing value maps outperformed the S&P500 Index by about 12% based on two months of out-of-sample testing.

1. Introduction

Picking stocks that are suitable for portfolio management is a complex challenge as continued changes in computers, technology and communications are creating an increasing number of innovative companies. Furthermore, changes in medicine, retail, leisure and entertainment industries are complicating this challenge for all investors.

One of the best know methods for picking stocks is a method, called the CANSLIM system. This system is based on multiple criteria for the selection of a stock. These criteria are evaluated for each stock and compared in order to obtain a list of stocks that are suitable for portfolio management. It turns out, however, that given the same importance to all criteria and applied to all stocks listed on the three major US exchanges, that no single stock would be selected.

The purpose of this paper is to expand the CANSLIM system and enrich it with the use of emergent self-organizing maps. This paper proposes an improved method for stock picking using criteria from the best-know system for picking stocks in conjunction with emergent self-organizing value maps to assemble a portfolio of stocks. This paper is based on the work on "Value Maps" as well as "Emergent Self-Organizing feature maps", presented elsewhere. Section two describes the CAN SLIM approach. Section three elaborates the methodology we used. Section four discusses the preprocessing of data. Section five contains the main results from using self-organizing maps in conjunction with the CAN SLIM system. Section six contains a discussion of these results. Main conclusions from this study can be found in section seven.

2. The CAN SLIM Approach

One of the best know methods for picking stocks, invented by William J. O'Neil, founder of the Investor's Business Daily, is described in *How to Make Money with Stocks: A Winning System in Good Times or Bad* [1]. The Investor's Business Daily (see http://www.investors.com) founded in 1984, is the fastest growing financial newspaper in the US with daily readership of over 800,000 and is specifically designed to highlight potential winning stocks based on evaluative tables, screens and graphs. In *How to Make Money with Stocks*, O'Neil describes the CAN SLIM system, which is a system based on multiple criteria each of which is identified by one letter from its most salient feature. In a nutshell, the system is based on picking stocks based on

C = Current quarterly earnings per share
A = Annual earnings increases
N = New products, new management, new highs
S = Supply and Demand: small capitalization plus big volume demand
L = Leader or Laggards
I = Institutional sponsorship
M = Market direction
Readers who are not familiar with the CAN SLIM system can find a brief summary of the rational for each outline in Box 1. A more detailed tutorial on the CAN SLIM system can be found at http://www.investors.com/educate/edumod15.html/ .

The main issues with the CAN SLIM system are (i) the comparability of the criteria and (ii) the weighting of criteria to obtain a list of stocks that are suitable for portfolio management. If someone is right on every one of the first six sets of criteria, but is wrong about the market direction of the general market, that three out of four stocks will slump and produce losses. Furthermore, while the first two criteria are easy to quantify (since both are based on earnings growth) the degree of innovation or newness of products or services, the degree of leadership, and the quality of institutional sponsorship are qualitative calls.

One of the biggest shortcomings of this system is that it lacks guidance on the appropriate weighting of criteria in order to produce short of stocks. In fact, when all criteria would somehow be quantified, be given the same importance and applied to all stocks listed on the three major US exchanges, then a zero set would be derived. In other words with equal weighting of all criteria and applying the most stringent limits of each there would be no single stock that would be selected. In sum, the CAN SLIM system by itself does not provide for an automatic selection of stocks. In this paper, we propose to enrich and enhance the CAN SLIM system with emergent self-organizing value maps.

Box 1: Criteria of the CAN SLIM System

Current quarterly earnings per share: pick stocks that show a major percentage increase in the current quarterly earnings per share (the most recent quarter) when compared to the prior year's same quarter. Earnings per share are calculated by dividing a company's total after tax profits by the company's number of common shares outstanding. The percentage increase in earnings per share is the single most important element in stock selection. Current quarterly earnings per share should be up at least 25 to 50% or more over the same quarter last year.

Annual earnings increases: Profitable growth is reflected in annual earnings. The annual compounded growth rate of earnings should exceed 25% per year over four to five years. Each year's annual earnings per share for the last five years should show an increase over the prior year's earnings. Hence, stability and consistency in earnings in the past five years provides additional value. The unique combination of a sound growth record during recent years and strong current earnings record in the past few quarters, rather than one or the other, creates a superb stock pick, or one that has higher chance of success.

[1] First published in 1988 and in its second edition sold more than 500,000 copies.

New products, new management, new highs: pick stocks of companies whose stocks are merging from price consolidation patterns and close to or actually reaching new highs in price; also look for companies that have a key new product or service, new management, or changes in conditions in their industry.

Supply and demand: pick stocks with small capitalization, for which there is big volume demand, that have a large percentage of ownership by top management, and have low debt ratio. Stocks with small number of shares outstanding will usually outperform older, large capitalization companies. More than 95% of companies have their greatest period of earnings growth and stock market performance when they have fewer than 25 million shares outstanding. In addition, companies that have been reducing their debt as a percentage of equity over the past few years are worth considering.

Leader or Laggards: pick market leaders i.e. the top two or three stocks action wise in a strong industry group. It seldom pays to invest in laggard performing stocks even if they look tantalizing cheap. Out of 500 best performing stocks from 1953 through 1993 the average relative price strength rating was 87 just before their major increase in price actually begun.

Institutional sponsorship: sponsorship may be by mutual funds, corporate pension funds, insurance companies, large investment counselors, hedge funds, bank trusts, state-, charitable or educational institutions. Pick stocks that have at least a few institutional sponsors that have better than average recent performance records.

Market direction: the general market direction determines whether picking stocks according to the above criteria will produce profit or losses. The price and volume changes in the general market indices should be interpreted together with the action of individual market leaders to determine the overall market's direction.

3. Method

What are *emergent self-organizing value maps*? This section explains in detail the methodology we used.

Self-organizing maps (SOM) belong to a general class of neural network methods, which are non-linear regression techniques that can be applied to find relationships between inputs and outputs or organize data so as to disclose so far unknown patterns or structures. This approach has been demonstrated to be highly relevant to many financial, economic and marketing applications.[2] SOM, developed by Teuvo Kohonen in 1982, exhibit the interesting and non-trivial ability of emergence through self-organization. This ability applied to finding value in stock markets will be called *emergent self-organizing value maps*.

Self-organization means the ability of a system to adapt its internal structure to structures sensed in the input of the system. This adaptation should be performed in such a way that firstly, no intervention from the environment is necessary (unsupervised learning) and secondly, the internal structure of the self-organizing system represents features of the input-data that are relevant to the system.

Emergence means the ability of a system to produce a phenomenon on a new, higher level. This change of level is termed in physics „mode"- or „phase-change". It is produced by the cooperation of many elementary processes. A further elaboration of the emergence ability can be found in Box 2.

Emergence happens in natural, technical as well as in human systems. The formation of cumulus cloud streets and LASERs are examples of natural and technical nature. Emergent phenomena can also happen in crowds of human beings. An example is the „La-Ola Wave" in football stadiums. Participating human beings function as the elementary processes, which can produce a large wave by rising from their places and throwing their arms up in the air. This wave can be observed on a macroscopic scale and could,

[2] For a detailed technical discussion of this approach we refer the novice reader to the literature.

be described in terms of wavelength, velocity and repetition rate. Similar phenomena can be observed in the financial markets where once lots of individuals start committing or withdrawing money to/from the market, a large wave may emerge lifting the markets up or bringing them down.

By *value maps* we mean applying self-organizing principles, in this case enlarged to detect emergence of new, higher level phenomena, to high-dimensional data that contains relevant indicators of the value of companies. The resulting maps seek to identify the companies based primarily on how well or how badly companies treat their shareholders. The main yardstick used for creating these *value maps* is the total return to stockholders. Total return includes the changes in share prices; the reinvestment of any dividends, rights and warrant offerings and cash equivalents (such as stocks received in spin offs). Returns are also adjusted for stock splits, stock dividends and re-capitalization. Although there are many ways to assess value the total return to shareholders that companies provide is the one true measure important to investors.

Box 2: Emergence in self-organizing maps.

For emergence to occur it is absolutely necessary that a huge number of elementary processes cooperate. A new, higher level phenomena can only be observed when elementary processes are disregarded and only structures formed by the cooperation of many elementary processes, are considered. In typical applications of SOM the number of nodes in the maps are to few to show emergence. In typical applications a single node may be regarded as a cluster, i.e. all data, whose best matches fall on this node, are members of this cluster. This type of applications performs clustering in a way that is similar to statistical clustering algorithms like, for example, k-means or single-linkage.

Emergence can only be expected to happen with a large number of nodes. Such maps, which we call ***emergent self-organizing maps***, have typically at least thousands (if not tens of thousands) of nodes. In particular the number of nodes may be much bigger than the number of data points in the input data. Consequently most of the nodes of emergent SOM will represent few input points if at all. Clusters are detected on emergent SOM not by regarding single nodes but by regarding the overall structure of the whole map. The latter can be done using U-Matrix methods.

The simplest of the U-matrix methods is to sum up the distances between the node weights and those of its immediate neighbors. This sum of the distances to its neighbors is displayed as elevations at the position of each node. The elevation values of all nodes produce a three-dimensional landscape, the U-Matrix. U-Matrices have the following properties: i/ best matches that are neighbors in the high-dimensional input data space lie in a common valley; ii/ gaps in the distribution of input points and hills can be seen on the U-Matrix; iii/ elevations or hills are proportional to the gap distances in the input-space. The principal properties of SOM in conserving the overall topology of the input space, is inherited by an U-Matrix. Data closest in the input-space can also be found at neighboring places on the U-Matrix. Topological relations between the clusters are also represented on the two dimensional layout of the nodes.

With U-Matrix methods emergence in SOM can be observed. The cluster-structure of the input dataset is detected in the U-Matrix as valleys surrounded by hills with more or less elevation, i.e. clusters are detected, for example, by raising a virtual water level up to a point, where the water floods a valley on the U-Matrix. The user can grasp the high-dimensional structure of the data: nodes that lie in a common valley are subsumed to a cluster; regions of a feature map that have high elevations in an U-Matrix are not identified with a cluster; nodes that lie in a valley but are not best matches are interpolations of the input-data. This approach has been extensively tested over the last few years on many different applications. It can be shown that this method gives a good picture of the high-dimensional and otherwise invisible structure of the data. In many applications meanings for clusters could be detected.

Emergent SOM can be easily used to construct classifiers. If the U-Matrix has been separated into valleys corresponding to clusters and hills corresponding to gaps in the data, then an input data point can be easily classified by looking at the best match of this data point. If the point's best match lies inside a cluster-region on the U-Matrix the input-data is in that cluster. If the best match lies on a hill in the U-Matrix, no classification of this point can be assigned. This is in particular the case if the dataset possesses new features, i.e. aspects that were not included in the data learned so far. With this approach, for example, outliers and errors in the data are easily detected.

4. Data

The data used for this study was derived from Morningstar™, a Chicago-based company that provides data on all stocks and funds listed on US exchanges. Morningstar™ publishes monthly and quarterly fundamental and technical information on over 7700 stocks listed on the NYSE, AMEX and NASDAQ exchanges. This study is based on data published as off the third quarter of 1999, or the last day of September 30, 1999. Morningstar Principia Pro™ was used to select the stocks for each of the maps in this paper.[3] The Morningstar™ data as of the third quarter of 1999 contained 7730 stocks. From this we created five data files based on quantitative interpretations of the criteria described above. Specifically, we selected:

1. all stocks with EPS (earning per share) percentage change between current quarter and same quarter of last year EQUAL OR GREATER than 50% . This produced **631 records** out of 7730.

2. all stocks with annual growth in earnings between year 1 to year 2, year 2 to year 3, year 3 to year 4 EQUAL OR GREATER than 25% . This produced **148 records** out of 7730.

3. all stocks with relative strength GREATER than 80% which produced **678 records** out of 7730.

4. all stocks with percentage held by funds GREATER than 30% which produced **350 records** out of 7730.

5. all stocks with LESS than 25 million shares outstanding AND market capitalization EQUAL OR GREATER than 5 million and debt to equity less than 3. This produced **1551 records** out of 7730.

There are quite a number of records with missing values for one or more columns; these incomplete records were included in the subsequent analysis.

In sum 3358 records are identified by all five sets of criteria. Since among these there are 601 duplicate records, the O'Neil criteria identify **2757 out of 7730 stocks** *when applied separately*. Most interesting however is that *when all criteria are applied cumulatively* then not a single stock survives the selection criteria. Note that we applied the strictest interpretation of O'Neil criteria for EPS growth from the current quarter to four quarters ago. We selected only stocks whose EPS growth quarter-to-quarter was equal or greater to 50%. **Nevertheless, the CAN SLIM system, when applied to the letter does not produce a manageable shortlist of stocks based on the available database from Morningstar™.**

[3] Principia Pro's key features include filtering, custom tailored reporting, detailed individual-stock summary pages, graphic displays, and portfolio monitoring. Principia Pro does not however provide exploratory data analysis nor does it allow data mining based on the principles of self-organization. Our use of emergent SOM on the Morningstar™ data demonstrates how tabular data can be translated into colorful maps to enhance stock picking and portfolio monitoring.

5. Main Findings

A mechanical application of the CANSLIM system produces a zero set of stocks meaning no stocks are selected out of all those included in the Morningstar™ database. To remedy this we applied first emergent self-organizing maps to the individual data sets described above.

For each of the files described above an emergent self-organizing value map of 64 by 64 = 4096 neurons was created. Each neuron had a weight vector of dimension 17 corresponding to the variables in the training sets. The values for each stock were presented 2000 times to the network. During the presentation the radius of neighborhood was linearly diminished from 60 neurons in the beginning to 2 neurons in the end. The learning rate of the weights was set to 0.01. A U-matrix was then calculated for each learned network (see Figure 1).

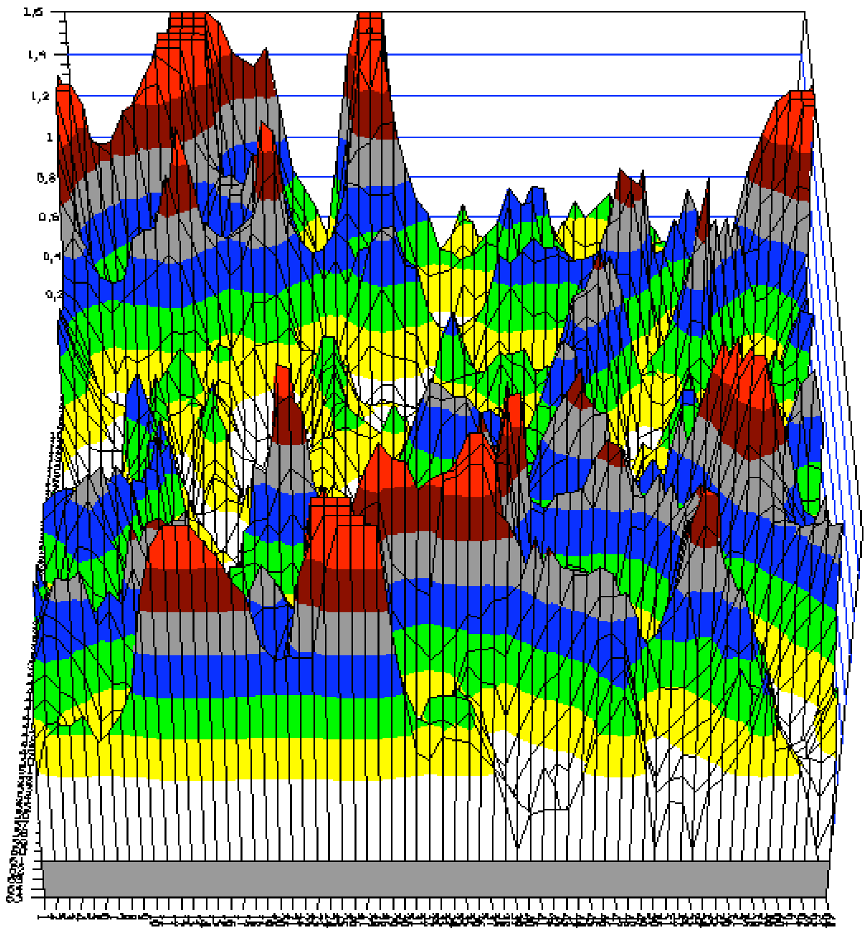

Figure 1: U-Matrix of stocks with EPS growth quarter-to-quarter equal or greater 50%.

In Figure 1 on top of the 64 by 64 Neurons a 3 dimensional U-matrix can be seen. Thru emergence walls or hills separating valleys are constructed. In these valleys lie data points that have common features. This allowed to identify clusters of stocks that have common properties.

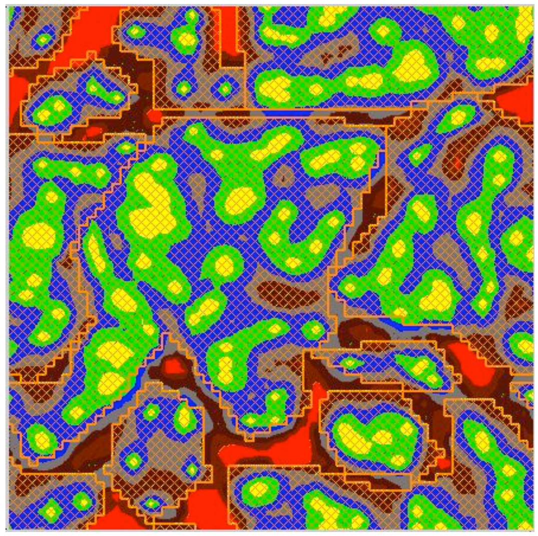

Figure 2 U-Matrix of an emergent self-organizing value map with cluster borders

Figure 2 shows a U-Matrix of one of the files including the borders of the clusters found. Note that the topology of the network is toroid i.e. the leftmost and rightmost as well as topmost and bottom neurons are connected.

The summary statistics of SOM applied to the data set that required annual earnings per share growth of more than 25% is shown in Table 1. The columns in this table contain the O'Neil criteria, the rows show for each class or cluster identified by SOM, the mean, the minimum and the maximum value of the records captured by a cluster. The highlighted values show the ones that meet the criteria of the CAN SLIM system, which are summarized in the first row under the column headings.

Table 1: Median values of clusters of stocks grouped by SOM

Class	**Records**	**EPS Q1Q5**	**EPS Y1Y2**	**EPS Y2Y3**	**EPS Y3Y4**	**RSI**	**Held**	**Fund Owned**	**Shares Out**	**Market Cap**	**Debt to cap**
		>= 50%	**>=25%**	**>=25%**	**>=25%**	**> 80%**	**> 30%**	**> 30%**	**< 25 mil**	**>= 5 mil**	**< 3**
1	29	30.1	**52.3**	**46.6**	**60**	-16	27.7	4	5.9	87.1	28.75
2	10	-89.7	**44.45**	**46.4**	**41.15**	-38.5	**32.8**	14.5	38.3	632.4	3.3
3	31	21.75	**39.4**	**53.8**	**55.6**	4	23.1	14	32.6	889.9	**0**
4	17	24.7	**42.7**	**40.7**	**56.1**	-19	10.8	9	122.4	1963.5	37.3
5	29	21.2	**50.7**	**42.2**	**86.2**	-35	9.3	21	**19.7**	417.8	34
6	10	39.75	**34.95**	**31.95**	**39.55**	8.5	11.4	19	311.55	10041.1	**0**
7	15	25	**37**	**48.5**	**110**	-24	**62.1**	7	**19.3**	327.8	**0**
8	7	**71.4**	**53.8**	**76.9**	**600**	**90**	9.4	25	76.7	5440.1	3.65

From table 1 we note that eight clusters of stocks are identified by SOM, however the median values of none meet all the criteria. Cluster 8 meets most of the criteria, specifically those regarding EPS change, quarter to quarter and over three years and the relative strength requirements. Cluster 7 meets the annual EPS criteria, the share outstanding, the institutional sponsorship and the debt-to-equity criteria but does not meet the important criteria of 50% or greater change in quarter-to-quarter growth. Cluster 6 meets the annual EPS criteria and the debt-to-equity criteria. The degree to which various clusters of stocks meet the O'Neil criteria was then used to narrow down the list of potential candidate portfolios.

Table 2 shows the stocks identified by the clusters obtained via SOM. The table shows the company names, the stock ticker or symbol as well as the sector and industry classification for each. It is interesting to note that cluster 8 selection is dominated by technology, the fastest growing sector in the markets, while the selections identified by cluster 7 and 6 are more diversified and include companies from service, retail, consumer staples, industrial cyclical sectors.

Table 2: Stocks identified in clusters obtained from self-organizing map of all stocks with highest EPS growth both over last four quarters and over the past three years

Class	Company_Name	Ticker	Sector	Industry
8	Biogen	BGEN	Health	Biotech
8	Citrix_Systems	CTXS	Technology	Software
8	Metris_Companies	MXT	Financial	Finance
8	Qlogic	QLGC	Technology	Semiconductors
8	Veritas_Software	VRTS	Technology	Software
8	Vitesse_Semiconductor	VTSS	Technology	Semiconductors
8	Williams-Sonoma	WSM	Retail	Furniture_Retail

The out-of-sample performance of the above portfolios of stocks, obtained by applying SOM to data files based on single criteria selections, is provided in Tables 3.

Table 3 provides the out-of-sample performance of the portfolio that met the most of O'Neil's criteria. The out-of-sample performance is measured by comparing the most recent available price –as of the day of this writing- with the price of the stock on September 30th, 1999, which was the day of record of all the information used for this analysis.

Table 3: Out-of Sample Performance of "star" portfolio obtained via SOM

Companies in Class 8	Symbol	Sector	Industry	Price 9/30/99	Price 11/30/99	Differ-ence	% Change
Biogen	BGEN	Health	Biotech	$ 78.81	$ 72.6250	($6.19)	-7.85%
Citrix_Systems	CTXS	Technology	Software	$ 61.94	$ 94.5000	$32.56	52.57%
Metris_Companies	MXT	Financial	Finance	$ 29.50	$ 31.0000	$1.50	5.08%
Qlogic	QLGC	Technology	Semiconductors	$ 69.81	$ 112.1875	$42.38	60.70%
Veritas_Software	VRTS	Technology	Software	$ 75.94	$ 90.1250	$14.19	18.68%
Vitesse_Semiconductor	VTSS	Technology	Semiconductors	$ 85.38	$ 45.2500	$2.56	3.00%
Williams-Sonoma	WSM	Retail	Furniture_Retail	$ 48.56	$ 54.3125	$5.75	11.85%
Average Change						$13.25	**20.58%**
S&P 500			…	1,282	1,389	106.20	**8.28%**
							12.30%

Performance versus S&P 500

The average change in price among all stocks identifies the total portfolio result assuming equal dollar amount of investments in each stock. Hence, if one had put equal dollar amounts in each stock, which implies variable number of shares given the different stock prices, then the total portfolio result in the period since 9/30/1999 would have been 20.58 %. In the same period the S&P 500, a standard benchmark for comparing the performance of stock portfolios increased by 8.28 %. In consequence, the portfolio of stocks identified by SOM based on records selected out of 7730 stocks using the O'Neil criteria, outperformed the S&P500 by 12.3 % over a period of two months. In comparison with the Dow Jones

Index the value added was 15.34%; compared to the Russell 2000 the value added was 14.69% and compared to the composite of all stocks traded on the New York stock exchange the SOM identified portfolio outperformed the NYSE composite by 14.1%.

Comparable information for two other portfolios identified by SOM (cluster 6 and 7 who based on Table 1 were next in line in meeting the CAN SLIM criteria) shows that cluster 6 over two months of out-sample-testing achieved 10.7 % and that the portfolio identified by cluster 7 achieved only 5.7% over two months. Hence two other SOM defined portfolios which ranked lower in meeting the CAN SLIM criteria were either close or marginally under performing against all the benchmarks used above (S&P 500, Dow Jones, Russell 2000 and NYSE composite index).

6. Discussion

The CAN SLIM system, when applied to the letter does not produce a manageable shortlist of stocks based on the available database from Morningstar™. In the Investor's Business Daily separate columns are provided on each criteria; for each all stocks are ranked and the percentile ranking for each stock is provided. Hence the IBD recommends to only pick stock with percentile ranking 85 or above on EPS growth etc. The IBD then leaves it up to the user on how to combine the selections of stocks based on percentile rankings from various criteria. It is this gap in the CAN SLIM system that this paper specifically addresses.

Finally on the validity of the use of the Morningstar™ data: the Investor's Business Daily has announced that the IBD database will eventually become available in electronic form to the public, but until it does, the test of the O'Neil criteria can only be applied to the best available alternative(s).

In consequence the CAN SLIM by itself is insufficient to create a "winning system in good or bad times" as advertised in the second edition of *How to make money in stocks*. It requires to be augmented by human interpretation and it lacks a systematic approach to combining various highly valuable criteria for stock picking.

In this paper we demonstrated how these shortcomings of the CANSLIM system can be overcome by merging the criteria from the CAN SLIM system with an emergent self-organizing map for finding clusters or classes of stocks that meet most of the criteria to the largest possible extend.

We used single criteria data files to create emergent self-organizing maps, which then identified clusters that grouped stocks with similar features. The cluster(s) that came closed to asserting all the criteria of the CAN SLIM system were selected for further testing. The out-of-sample testing of these showed various degrees of out performance compared to a standard benchmark i.e. the S&P 500 index. Clusters or stocks that asserted less of the criteria from the CAN SLIM system underperformed the benchmark.

Common structures among different stocks were found by emergent self-organizing value map using U-matrices. This method produced portfolios of stocks and allowed the ranking of clusters according to how well the CAN SLIM criteria were met. The results show the effectiveness of the merger between traditional criteria and the use of emergent self-organizing value maps for picking stocks.

7. Conclusions

In sum,

- The CAN SLIM system requires a lot of human interpretation and cannot be use as mechanical system for picking stocks.
- The CAN SLIM system does not provide guidance on how to combine or weight the various criteria.
- *Self-organizing maps* provide the ability for system to detect internal structures based on similarity or dissimilarity of values in high dimensional data sets.
- *Emergent self-organizing maps* allow to detect new, higher level phenomena based on the use of much lager number of nodes or neurons in the map.

- When emergent self-organizing maps are applied to company data to identify which companies provide value we consider them to be *value maps* or roadmaps to finding value in the stock markets
- The application of *emergent self-organizing value maps* to subsets of data obtained via the criteria from the CAN SLIM system, produced several clusters that grouped stocks based on common features or degree of adherence to the CAN SLIM criteria.
- Based on the median values of all attributes for all clusters it was feasible to identify from among these one or more clusters that meet most criteria; these then identified selections of stocks for portfolio management.
- The out-of-sample performance of the best among these portfolios showed that it gained 20.6% in the period from September 30th to November 30th, 1999. In comparison the return of the S&P 500, index in the same period was 8.28%, which implied that the portfolio selected through the use of emergent self-organizing maps exceeded the S&P 500 performance by about 12.3 %.
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Emergent self-organizing value maps used in conjunction with established criteria for picking stocks can overcome the problems associated with the use of a mixture of criteria as well as weighting of different criteria. It has been demonstrated that this approach adds real value and has the potential to reduce the complexity of picking stocks.

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