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The power of market mood — Evidence from an emerging market

Timotej Jagric [a,*], Tanja Markovic-Hribernik [b], Sebastjan Strasek [c], Vita Jagric [b]

[a] Department for Quantitative Economic Analysis, Faculty of Economics and Business, University of Maribor, Razlagova 14, 2000, Maribor, Slovenia
[b] Department for Finance and Banking, Faculty of Economics and Business, University of Maribor, Razlagova 14, 2000, Maribor, Slovenia
[c] Department for Economic Policy, Faculty of Economics and Business, University of Maribor, Razlagova 14, 2000, Maribor, Slovenia

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ABSTRACT

This article focuses on investor behavior and, consequently, the mood in the market. By using a self-organizing network we develop a model which tries to capture the market mood and serves as an indicator of the reasonableness of selling or purchasing securities. In this sense, the final result of this model is the same as in the model-type prediction of future stock prices, with the only exception being that one is not required to know the concrete future values of the selected security. This will indirectly support the hypothesis that psychological factors are an important (if not key) market driving force.

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1. Introduction

The current global financial crisis began with reduced confidence among investors, which directly affected the price movement of securities listed on financial markets. The developments on international markets have confirmed the phenomenon of a "social infection," in which real estate owners, issuers and owners of mortgage securities, regulators, and credit-rating agencies contributed to the formation of a bubble and its "ex-post" burst. Although the crisis began with the collapse of the US mortgage market, this is not considered the main reason for the crisis, but merely a trigger. The main culprits for the great vulnerability of the financial system can be found elsewhere. However, it has been clearly demonstrated that an appropriate understanding of the risks and investor confidence are exceptionally important for today's financial markets.

This article presents the significance of understanding the market situation by using a model solution. Various approaches are used for modeling financial markets. The ones more commonly used include the agent and systemic approaches. The agent approach is used to model small individual units and simulate their interaction (Arthur et al., 1997; LeBaron, 2002). In contrast, the systemic approach is used to model the representative behavior of agents and simulate the behavior of a system (Andresen, 1997; Raczynski, 2000). This article uses the systemic approach and proceeds from the premise that the market mood provides key information about developments happening on the market, and that the market is thus not subject to factors arising from fundamental variables.

By using a self-organizing network (Kohonen variants)–a neural network model, which is used primarily in data mining–it will show a situation in a financial market in which the primary interest is placed on information that may refer to comprehending the market situation from a mood — that is, from a psychological perspective. This kind of approach will enable the development of a selected market model that may serve as an indicator of the reasonableness of selling or purchasing securities. In this sense, the final result of this model is the same as in the model-type prediction of future stock prices, with the only exception being that one is not required to know the concrete future values of the selected security. This will indirectly support the hypothesis that psychological factors are an important market driving force.

We believe that a model capable of describing the market situation can thus identify important changes in the market — that is, those having a direct impact on future stock price movements. This is especially important in emerging markets; therefore, the proposed model was tested on data from the Ljubljana Stock Exchange, a rapidly growing, small, open-economy market. This type of market is not only subject to influences from its own national economy, but also to developments on global financial markets.

This article has been divided into six sections. The introduction is followed by a section on the methodology. Section 3 presents the characteristics of the data used for testing the hypothesis. The development of the model is presented in Section 4, and the results

* Corresponding author. Tel.: +386 2 22 90 343; fax: +386 2 25 16 141.
E-mail address: timotej.jagric@uni-mb.si (T. Jagric).

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of the simulations performed in Section 5. The conclusion presents the article's key findings.

2. Methodological framework

Our main goal is to classify trading days based on the overall market mood. Therefore we have to apply cluster analysis. The objective of cluster analysis is to search inside data for patterns. Cluster analysis imposes no *a priori* restrictions on the structure of data and requires no assumptions about the probabilistic nature of the observations. However, the application of cluster analysis does have some limitations. For example, it may be difficult to determine the correct number of clusters, or whether the clusters formed from the data are statistically significant or just a result of randomly occurring concentrations of observations within an original distribution (Korobow and Stuhr, 1991). Hence, although cluster analysis is very useful for describing data, it should be characterized as a statistical exploratory technique (Hair et al., 1998).

When applying cluster analysis, it is important to select the appropriate type of clustering technique. The most commonly used technique has been the statistical technique of Principal Component Analysis (PCA), which is essentially a dimension reduction technique. Although standard statistical dimension reduction techniques boast the advantage of simplicity, they suffer from some important limitations, foremost their poor data visualization capabilities and their inability to appropriately account for possible nonlinear relationships among the indicators. We believe that the Self-Organizing Map (SOM) may provide a better classification of behavioral patterns.

The SOM belongs to the class of unsupervised and competitive learning algorithms. It is a neural network, with nodes arranged as a regular, usually two-dimensional grid (see Fig. 1). We usually think of the node connections as being associated with a vector of weights. In the case of SOM, it is easier to think of each node as being directly associated with a weight vector (Schatzmann, 2003). The items in the input data set are assumed to be in a vector format. If n is the dimension of the input space, then every node on the map grid holds an n-dimensional vector of weights.

$$m_i = [m_{i1} \dots m_{in}] \tag{1}$$

The basic principle of the SOM is to adjust these weight vectors until the map represents a picture of the input data set. Since the number of map nodes is significantly smaller than the number of items in the dataset, it is impossible to represent every input item from the data space on the map. Rather, the objective is to achieve a configuration in which the distribution of the data is reflected and the most important metric relationships are preserved. In particular, we are interested in obtaining a correlation between the similarity of items in the dataset and the distance of their most alike representatives on the map.

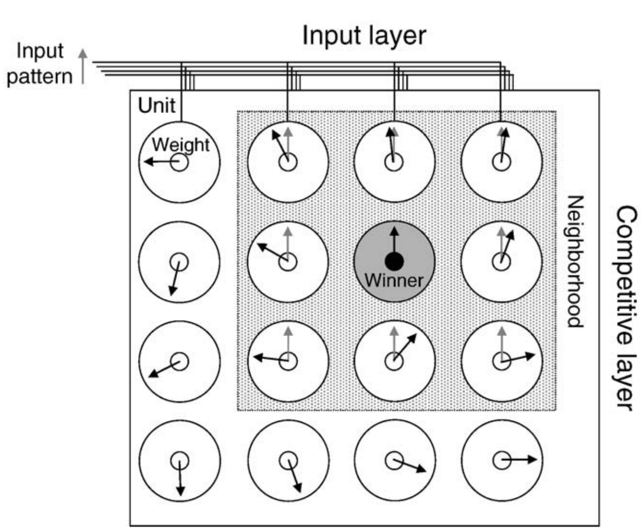

Fig. 1. A self-organizing map.

The algorithm proceeds iteratively. On each training step a data sample x from the input space is selected. The learning process is competitive, meaning that we determine a winning unit c on the map whose weight vector m_c is most similar to the input sample x.

$$||x - m_c|| = \min_i ||x - m_i|| \tag{2}$$

The weight vector m_c of the best matching unit is modified to match the sample x even closer. As an extension to standard competitive learning, the nodes surrounding the best matching unit are adapted as well. Their weight vectors m_i are also moved towards the sample x. The update rule is formulated as:

$$m_i(t+1) = m_i(t) + h_{ci}(t)(x - m_i(t)) \tag{3}$$

The scalar factor $h_{ci}(t)$ is often referred to as the neighborhood function. It is usually a Gaussian curve, decreasing from the neighborhood centre node c to the outer limits of the neighborhood.

$$h_{ci}(t) = \alpha(t) \exp\left(-\frac{||rc - ri||^2}{2o(t)^2}\right) \tag{4}$$

In the above equation, $\alpha(t)$ is scalar multiplier called the learning rate. It may be regarded as the height of the neighborhood kernel. $o(t)$ is the radius or the width the neighborhood kernel. It specifies the region of influence (Simula et al., 1999) that the input sample has on the map. Both the height and the width of the neighborhood function decrease monotonically with time. As can be seen from equation, nodes closer to the best matching unit will be more strongly adjusted than nodes further away. At the beginning of the learning process, the best matching unit will be modified very strongly and the neighborhood is fairly large. Towards the end, only very slight modifications will take place and the neighborhood includes little more than the best matching unit itself. This corresponds to rough ordering at the beginning of the training phase and fine tuning near the end.

Since not only the winning node is tuned towards the input pattern but also the neighboring nodes, it is probable that similar input patterns in future training cycles will find their best matching weight vector at nearby nodes on the map. In the run of the learning process, this leads to a spatial arrangement of the input patterns, thus inherently clustering the data. The more similar two patterns are, the closer their best matching units are likely to be on the final map. It is often said, that the SOM folds like an elastic net onto the cloud formed by the input data (Vesanto and Alhoniemi, 2000).

It is important to state that the SOM algorithm is not primarily a clustering algorithm. It is intended principally as a tool in reducing the dimensionality of the data and for information visualization. Of course, this includes the visualization of groups of similar items. But the SOM is not a tool that will produce an explicit partitioning of a dataset into a precise number of groups. This also explains why the concept of a cluster is not well defined for the SOM. The maps do not show sharp cluster borders and there is no obvious centroid.

To overcome this problem, we use each node on the map as a cluster centroid. The cluster corresponding to each node includes all dataset items mapping to this node. We checked the distribution of dataset across the nodes for all tested architecture of the map in order to ensure sufficient "hits" for every unit.

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