Portfolio Analysis with Innovative Methods

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Özet

Bu çalışmanın amacı, optimum portföyün belirlenmesinde ya da yatırım kararı alınmasında kullanılan geleneksel yöntemlere yenilikçi açıdan bir bakış atmaktır Klasik yaklaşımlar insan gözü aracılığıyla karar vermeye dayalıyken, dünyada yeni trend halini alan bilgisayarlı sistemlerin karar verme güçleri her geçen gün artmaktadır. Bu çalışmada da yapay sinir ağları, davranışsal finans, veri madenciliği, nitel veri analizi gibi yöntemler bir arada kullanılarak elde edilen sonuçlar irdelenmiş, sonuçta 4. sanayi devriminin ekonomi ve finans alanlarına da etki edebileceği kanısına varılmıştır.

Anahtar Kelimeler: Yapay Sinir Ağları, Yapay Zeka, Davranışsal Finans, Nitel Veri Analizi, Veri Madenciliği.

Abstract

The aim of this study is to take an innovative perspective on the traditional methods used to determine the optimal portfolio or to make investment decisions. While classical approaches are based on decision making through the human eye, the decision-making power of new trends in computerized systems in the world is increasing day by day. In this study, the results obtained by using artificial neural networks, behavioral finance, data mining and qualitative data analysis together were examined and it was concluded that the 4th industrial revolution could also affect the economics and finance fields.

Keywords: Artificial Neural Networks, Artificial Intelligence, Behavioral Finance, Qualitative Data Analysis, Data Mining

INTRODUCTION

According to general acceptance, the first stock market was established in 1487 in Antwerp, Belgium. The first stock market to buy and sell securities began to develop in Lyon and London in the 16th century. The material that is based on the stock exchange for about 400 years after these dates is only "return & risk". The work published by Harry Markowitz in 1952 excludes the basic element from being merely the return. The definition of the relationship between risk and return has radically changed the buying and selling rationale. This method is still being used with improved versions.

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Similar to the exchange in the stock markets, the form of production factors varies from day to day. Until the oil revolution, the resources used in energy production were human and animal power, steam and coal. Nowadays, these resources are starting to give place to recyclable energy. Up to the 17th century, the use of gold and silver was common, and they left their place in banknotes. Today, this situation has changed and electronic money has started to be used as a means of exchange.

In summary;

- The first industrial revolution brought mechanization.
- The second industrial revolution brought electricity.
- The third industrial revolution brought computers.

The subject that is frequently mentioned today is the 4th industrial revolution. The fourth industrial revolution has changed the form of labor. Systems based on the human brain have begun to leave their place to artificial intelligence.

The purpose of this study is to examine the effect of this change in the form of labor on decision making through portfolio selection methods.

1. Literature Review

In this respect, the studies in the literature can be examined under two headings;

Models that only explain the movements of series

Behavioral models

Models that study the behavior of the series try to explain the series through their own movements with various mathematical calculations. For example, when examining portfolio movements, it is desirable that the average is high, variance and skewness is low. Over time, models based on this logic have been developed and the concept of "entropy" has been added. Such models have been criticized by some researchers, so some models have been put forward in which behavioral elements have been added. Some of the behavioral models include adding individual selection criteria, while others add psychological and sociological factors by converting them into numerical data in the form of indexes.

2. 1. Models That Only Explain The Movements of Series

Such models are usually based on CAPM and Markowitz models. However, the beginning of portfolio selection was made by "Traditional Portfolio Theory (TPT)". It is generally accepted that this theory is far from scientific, but the ease of its use makes this theory widespread.

TPT doesn't take into account the relationship between the securities to be acquired. It assumes that a diversification of business interests from different industries will reduce the risk. However, this may cause unnecessary instruments in the portfolio, incomplete information about some securities, increase in the number of research staff and swelling of commission expenses (Klein, 1970).

Markowitz brought the first solution to TPT's problems (Markowitz, 1952).

Markowitz's "mean variance model" is the basis for modern portfolio theory by defining the relationship between risk and return. The model has a mathematics that takes into account the correlation between securities. With the Markowitz model, the one-dimensional approach has left its place in a two-dimensional approach. But the model leads to some problems. It is very difficult to put the information that has been put into practice. In addition, the model is insufficient in terms of timing. For this reason, investors can not determine the most appropriate buying and selling time points. The model also considers basic and technical analysis information to be limited. One of the most important problems in the model is the large number of data required to find an effective portfolio. In a situation involving 10 investment papers, 65 parameters are required, while the number of data required for 100 investment papers is increased to 5150 (Fettahoğlu, 2003).

As a result, Capital Asset Pricing Model (CAPM) emerged as an alternative model.

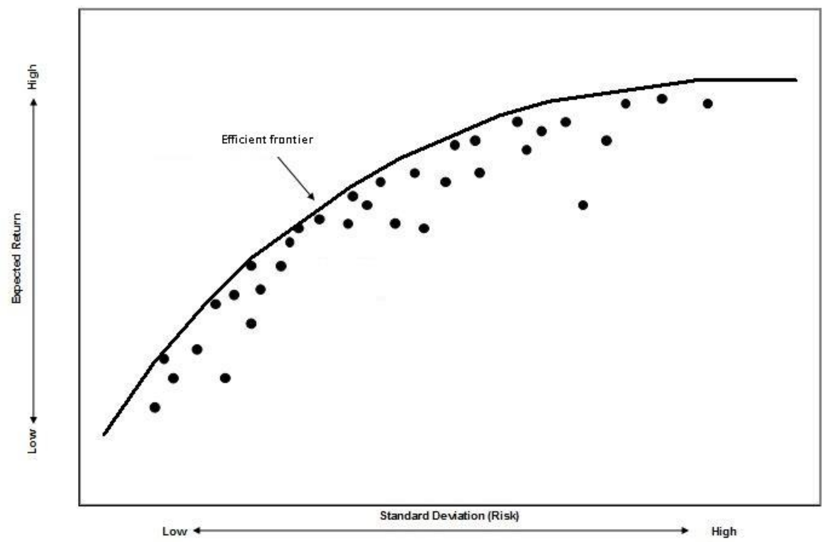


Figure 1: Efficient frontier

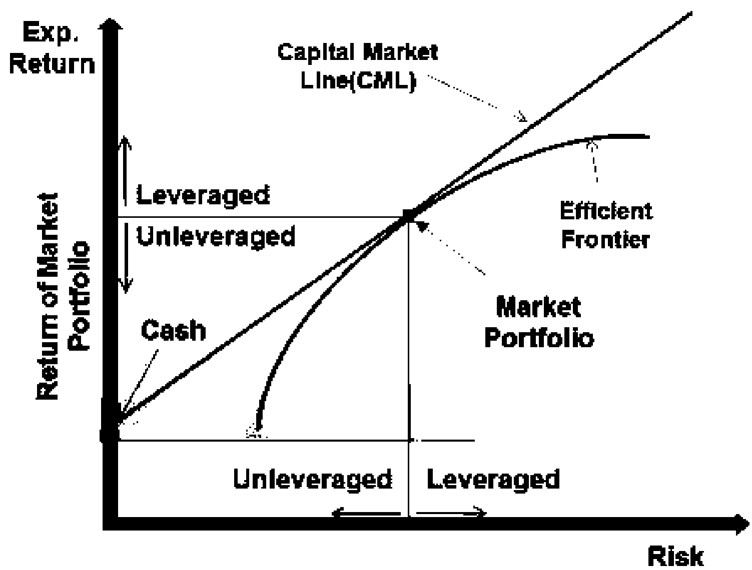


Figure 2: Capital asset pricing model

It started with a single index model developed by Sharp (1964) and switched to "Arbitrage Pricing Model" through other multiple index models.

These three basic models have been developed over time and continue to be used. In particular, the innovations brought about by the joint work of Fama (Fama & MacBeth, 1973; Fama & French, 1992, 1993, 1996) in CAPM model are widely used nowadays. Discussions on these developments also continue (Connor & Sehgal, 2001; Grauer, 2003; Diether, 2001; Chollette, 2004; Billou, 2004; Gökgöz, 2008; Gökbulut, 2010; Fama & French, 2017).

When discussions and developments are left on the edge, all such models operate on the motion range of the data. However, it is obvious that there are other values that affect the movement of the series. Their measurement has been tried with the methods given in the next section.

2.2 Behavioral Models

An exemplary study to start the division may be the work of Jin & Zhou (2008). In a number of other studies that have also been referenced in this study, behavioral items are included as mathematical constraints in models. The majority of these models are based on the "Continuous-time Portfolio Selection Model (CPSM)" and "Expected Utility" models. The main reference source for such studies is Tversky and Kahneman (1992).

To put it simply, without the specifics, the underlying rationale for behavioral models lies in the inclusion of individual expectations of investors into models with various tools. This is sometimes done in the form of maximization of expected utility, and sometimes in making personal preferences variables (Merton, 1969, 1971; Olsen, 1998; Shefrin & Statman, 2000; Crama & Schyns, 2003; Shefrin, 2007; Giorgi et al., 2008; Cui et al., 2017; Statman, 2017).

Another type of behavioral models are to convert some market and investor behaviors into series as numerical data. This is usually done with series like index. For example, Chicago Board Options Exchange (CBOE) Volatility Index (VIX) created by the Chicago Board Of Trade (CBT) in 1993, measures the degree of fear in the market over the volatility of option prices (Whaley, 2000). Other similar series are sometimes numerical data generated from questionnaires and sometimes from volatility changes (Shefrin, 2002; Barberis & Thaler, 2003; Baker et al, 2004; Jiang & Tian, 2007; Kliesen et al, 2012; Feldman & Liu, 2017).

Such models often include a wide range of mathematical modifications, such as the previous models. Recent years of development and demanding studies are using these models. But the complexity of the models and the controversial behavioral series lead to a mass audience of computerized methods. The desire to increase the capacity to control large-size data and qualitative data in this direction is also an important reason. Developments in qualitative data analysis also support this.

2.3. Section Breakdown

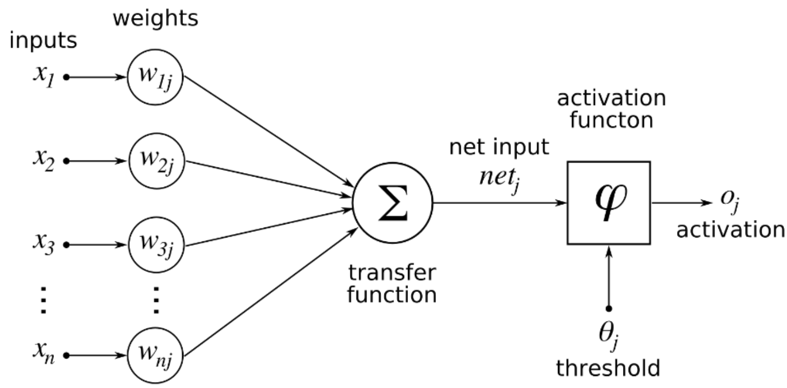
The two types of models mentioned generally focus on a narrow data set and do not have bidirectional or cyclic relationships. However, with the possibilities provided by the technology, a wider range of data is now available, and dynamic analysis is much easier. We can gather these possibilities in areas such as "big data" and "data mining". Such a simplification of data collection has led to the need for the analysis of these data to become more dynamic. This need is mostly met by computerized methods.

3. Artificial Intelligence

The most important of the computerized methods are artificial intelligence methods. In traditional models, complex mathematical methods have to go through long computation methods. However, artificial intelligence practices do these calculations on their own. In addition, the process does not require any changes in the structure of the series. Both the behavior of the series itself and the behavioral items can be involved in the process. This is an innovation that the 4th industrial revolution brings to this field.

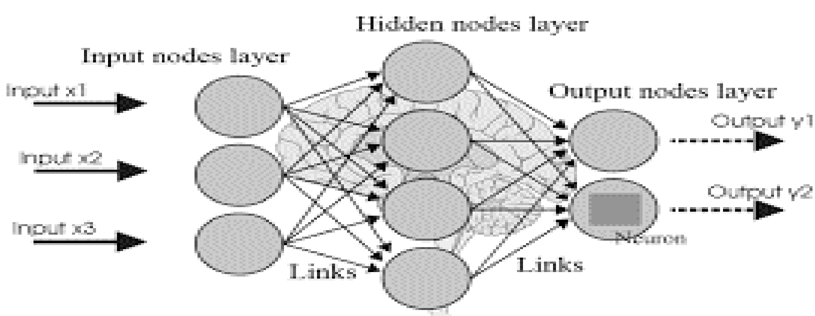
Trippi has done extensive work on this area (1992, 1995). It is stated that impressive results are obtained especially in the description of non-linear relations (Bell, 1997; Binner et al, 2004; Bahrammirzaee, 2010).

Figure 3: Structure of artificial neuron



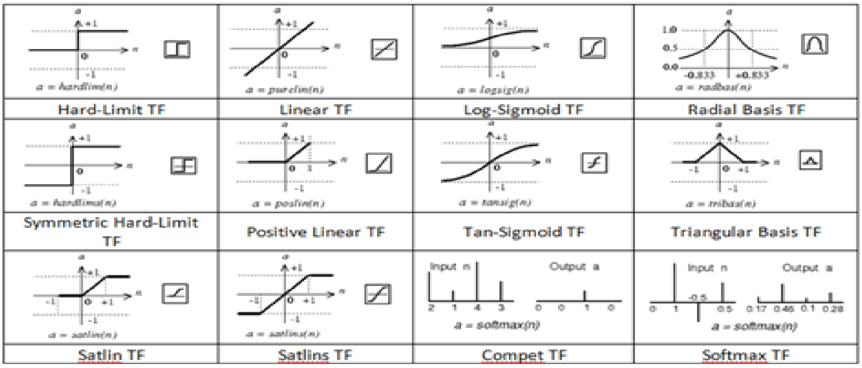
The structure of an artificial neuron is visible on the figure 3. The weighted data enters the transfer function, and the activation is given after the net output is passed through the threshold.

Figure 4: Artificial intelligence



Artificial intelligence also occurs when these networks are added together in a sequential manner according to an algorithm.

Table 1: Functions

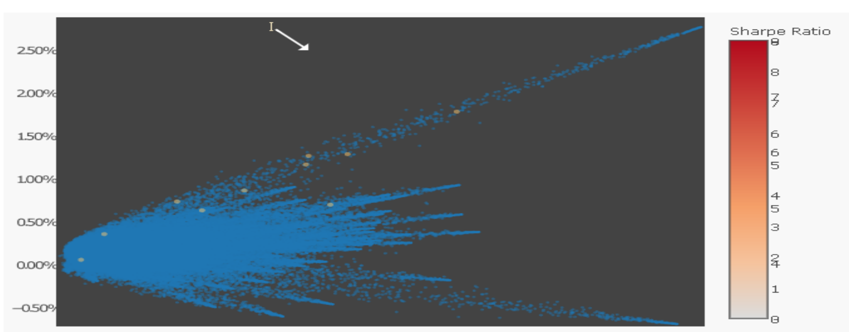


Some transfer functions for artificial neural networks are visible on the screen. Threshold and activation functions have the same structure with them.

4. Model Implementation

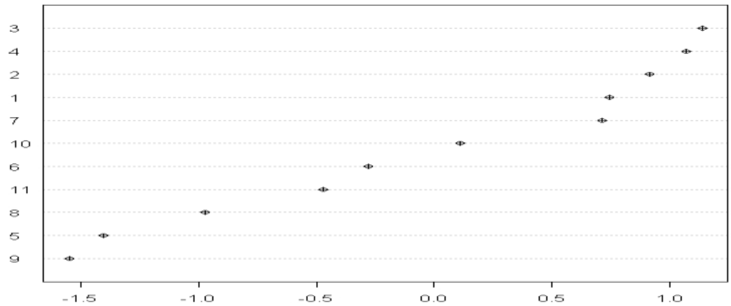
For this study, an algorithm which chooses the appropriate one according to individual preferences among the selected portfolios according to Markowitz model is examined. The artificial intelligence used is a cube-shaped 3D modification of the Hopfield algorithm (Hopfield, 1982; Li et al, 1989) and is specific to this work. It can also make inferences from qualitative data.

Figure 5: Portfolio distribution



With the integrated function of R software, the values of stocks, precious metals and currencies including 300 days before June 2nd have begun to be derived from the system. This gives 250000 portfolios randomly. Their distribution is seen in the picture. The bottom axis represents the risk and the left axis represents the return.

Figure 6: Wordfish distribution



Starting from the same dates, economic news on all online publications was monitored, and these reports were subjected to day-to-day Wordfish Analysis (Slapin & Proksch, 2008) and were observed to be more optimistic or pessimistic than the previous day. 11-day sample output is shown in the picture. One point is more pessimistic on the left than on the other, and more optimistic on the right. This method is also specific to this work.

In the third stage, the co-integration of all portfolios with stock market and similar values is examined.

Before deciding on artificial intelligence, the final capital and required funding data are entered. The decision logic of the algorithm operates as follows: On the days when the market improves, the ones with higher risk and return are selected from the co-integrated portfolios, and the ones with lower risk and lower risk from the co-integrated portfolios are selected on the days when the market goes bad. With this method, the selected portfolios perform 90% better than their counterparts (Kaastra & Boyd, 1996).

CONCLUSION

Nowadays, it is a fact that many investment institutions use self-buying virtual intelligence (Pau, 1991; Trippi & Jae, 1995; Goonatilake & Treleaven, 1995; Fethi & Pasiouras, 2010; The Financial Brand, 2017; Thapar, 2017; Forbes, 2017; Deloitte, 2017). This is a change that the 4th industrial revolution brings to this field.

A trend that has undergone deep-rooted changes in all areas of work can not be expected to escape the financial and economic spheres. It is possible to see this situation when we look at all the works mentioned in this work and other applications similar to the simply exemplified application.

APPENDIX

This study is composed of the contents of the graduation thesis entitled "Development of Financial Consciousness in the Industry (Sanayide Finansal Bilincin Geliştirilmesi)" which is supported by The Scientific and Technological Research Council of Turkey (TÜBİTAK) 2209B/2241A program and finalist of 2241B competition. In this context, we are grateful to TÜBİTAK.

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