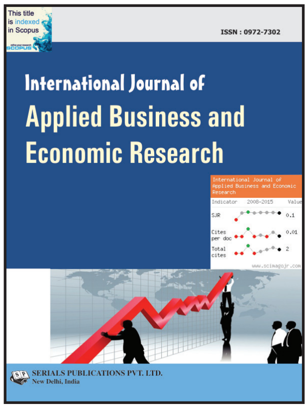

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Market of Luxury Goods and Sales Forecasting Using the Network Analysis

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ABSTRACT

The article substantiates the need to revise the sales planning in the luxury segment, forecasting and assessing the efficiency of the sales planning methods. The fashion industry (clothes, footwear, accessories) develops complex methods and systems of interaction with the customer. Companies invest considerable funds in the development of the forecasting models as part of improving the quality of medium-term planning (month-year). A number of objective factors in the industry do not allow obtaining a fairly accurate result using simple mathematical estimates and methods. The industry behavior is pro-cyclical in its nature (sales of clothing, footwear and accessories drop during the crisis and rocket during the boom). Specific factors of the sector can include a pronounced seasonality associated with weather deviations relative to the average statistical values, constant updating of the product range (textures and colors area factor of fashion trends), and lack of long-term historical statistics at the level of a specific item. Both complex hierarchical forecasting systems and the simplest models can serve as a response of companies to these limitations in information. Demand in the luxury goods market in the categories of clothing, footwear and accessories is described by a significant degree of volatility. Lots of factors have a high degree of influence on the seasonal demand structure and the actual sales volume of trading companies. Short periods of seasonal goods sales do not allow to determine the trends in the dynamics of sales at the commodity level with a high degree of accuracy. The fundamental distinctive feature of the horizons is the availability of remaining productsat the suppliers. As a rule, only a small number of seasonal items and the entire volume of off-season items can be refilled in the short-term period of the current season, whereas in the long run, the entire volume of items in all categories is available. This product limitation directly affects the sales forecasting in the short term. Various methods of planning and forecasting sales should be used depending on the type of goods.

Keywords: Models using network analysis, hybrid approach application. This method is a combination of the K-means cluster approach and the fuzzy neural network (KFNN) of assessment of the efficiency of the methods of sales planning. Complex economic systems of the luxury segment, development of the optimal structure of the neural network for sales forecasting in the clothing industry.

1. INTRODUCTION

The fashion industry (clothing, footwear, accessories) develops complex methods and systems of interaction with the customer. Companies invest considerable means in the development of the forecasting models as part of improving the quality of medium-term planning (month-year). In the traditional supply chain, each party has its own goals, which often conflict with each other. Often decisions on the volume of stock reserves are made without assessing the impact on counterparties. As a result, financial difficulties and uncertainties can emerge in the supply chain at the level of certain counterparty. Each company has to make numerous regular decisions on the order of goods. The accuracy of the forecast for demand is important in determining the volume of the order. Large international companies in particular industries set up integrated databases with their counterparties and build general forecasting models on the basis of the ERP system (Enterprise Resource Planning system).

2. METHOD

First of all, let's reveal the basic trends in the market for luxury goods. Shrinking aggregate demand, increased price competition and subsequent withdrawal of inefficient companies from the market should be considered as the basic scenario for the Russian market for luxury goods. Development scenarios shape in the company after considering the variety of external and internal factors. The company can miss real market opportunities and lose the strategic struggle for a market share if its planning relies upon the basic scenario of the aggregate decline in demand and does not provide for an optimistic scenario that takes into consideration the development through additional sources of growth (Au, et.al. 2008; Boradeand Bansod, 2011).

Let's resort to the study of the international consulting company Bain "LUXURY GOODS WORLDWIDE MARKET STUDY Fall-Winter 2015. Atimetoact: Howluxurybrandscanrebuildtowin" (D'Arpizio, Levato, Zito and Montgolfier, 2015; Banica, et. al. 2014).

Figure 1 and Table 1, which present data on the Bain research in 2015, allow to conclude that the Russian market is relatively small judging by the scale of the global or European markets, as well as the market for luxury goods in neighboring countries in the Asian region. The top ten countries show a steady growth in sales in the European currency (except for Hong Kong), which is largely related to the depreciation of the euro exchange rate. Considering the growth indicators in local currency, one can speak of a moderate growth in aggregate demand for luxury goods by country. The euro rate fall against world currencies allowed the Chinese market of personal luxury goods to outrun Italy and France.

The Russian market for luxury goods is actually determined and formed by the Moscow market. As such, Moscow is at the endof the top 20 of the world's "fashionable" capitals in terms of aggregate sales of luxury fashion goods. The top twenty cities in the world by sales volume can be seen in Table1. According to the Bain study, New York, like the US, is the leader of the rating with a significant separation from competitors. The US, unlike the European countries, is represented by 5 cities (New York, Las Vegas, Los Angeles, Honolulu andMiami). The European markets, like the Russian one, are highly concentrated and centered on the capitals and major cities of countries (France, England – capitals, Italy – 2 cities, Germany – one city, not capital).

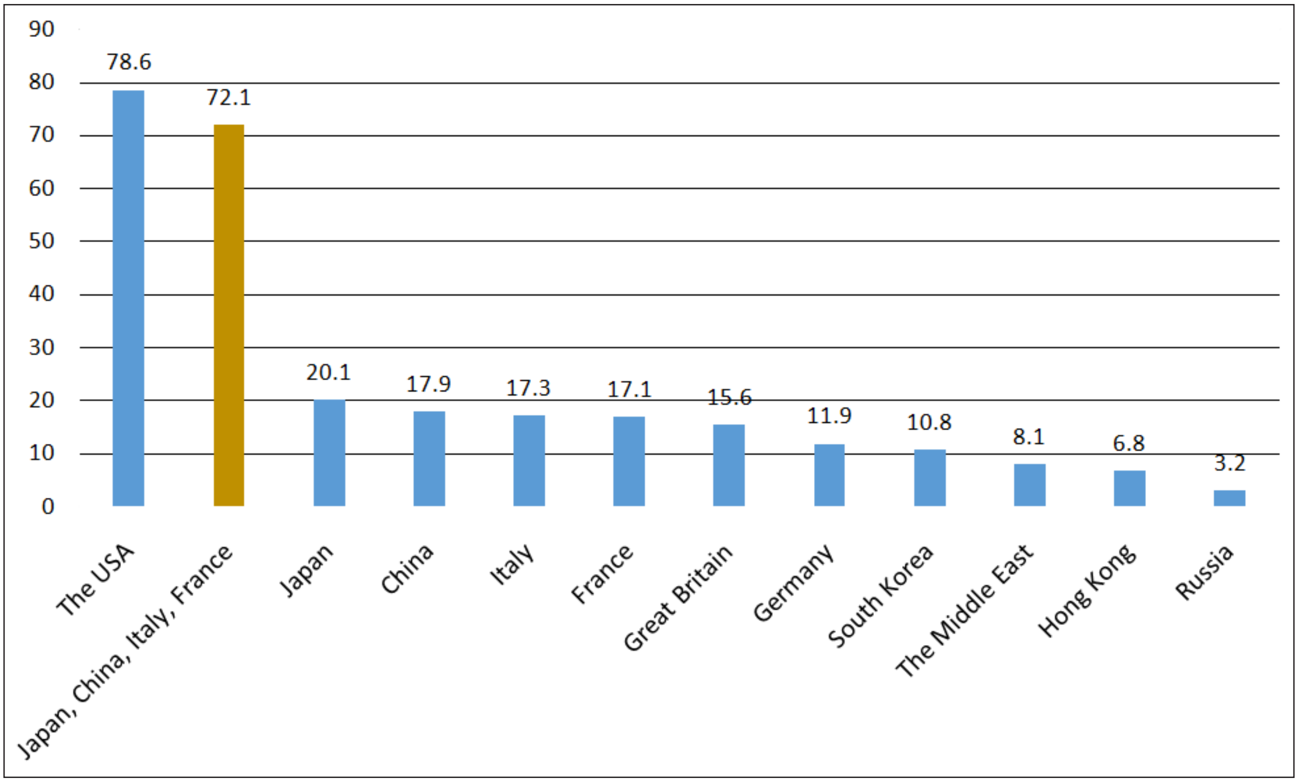


Figure 1: Consumption of personal luxury goods (clothing, footwear, accessories, beauty care, etc., cars, boats, other equipment, real estate and luxury services are excluded) by country in bln Eurosin 2015 (Bain & Company estimates)

Table 1
Consumption of personal luxury goods (clothing, footwear, accessories, beauty care, etc., cars, boats, other equipment, real estate and luxury services are excluded) by country in bln Eurosin 2015 (Bain & Company estimates)

Country	*Sales in bln euros in 2015*	*Country ranking in 2014*	*Growth in euro 2015* to 2014*	*Growth in local currency 2015* to 2014*
USA	78.6	1	20%	0%
Japan	20.1	2	13%	9%
China	17.9	5	17%	-1%
Italy	17.3	3	6%	6%
France	17.1	4	10%	10%
Great Britain	15.6	6	16%	5%
Germany	11.9	7	14%	14%
South Korea	10.8	8	16%	4%
Near East	8.1	10	19%	0%
Hong Kong	6.8	9	-11%	-25%
Russia	3.2	11	-25%	-2%

Judging from the above data, one can see at least two growth points in the Russian shrinking market. First of all, it could be assumed that some Russian citizens shop in the world fashion capitals – in particular, the main expenses occur in European capitals (Milan, London, Paris). Russian citizens shop during business trips and vacations, and the main reason used to be smaller price markups compared to those in Russia, which include additional customs, tax and transport costs. It can be assumed that in the current economic climate and with other things being equal, the number of business trips and vacations in the world capitals will fall and people will face a choice between buying luxury goods in Moscow or looking for alternatives more often (e-commerce with its limitations in fitting, refund and limit of the amount of duty-free import of goods for an individual within a month). Other things being equal, a consumer considers the retail price as the final and decisive argument. As such, it can be concluded that sales in the Russian market can grow thanks tobringingprice markups down to the European level. This decrease in price markups and subsequent sales to "returned" domestic consumers ultimately constitute import substitution, keeping more than half of the value of sold products in the country (taxes, wages, orders for contractors, company profits reinvested in business growth and development).

Foreign citizens shopping for goods in the world fashion capitals can be identified as another source of the sales growth (Figure 2). European consumers have a developed market of luxury goods and competitive prices and therefore are less likely to be the target audience. In the Chinese market, the increased price markup is applied to luxury goods due to the customs policy of the state. As such, Chinese tourists and citizens on business trips are active consumers of luxury goods in the world capitals of the fashion industry. Russia has become an attractive place for tourist trips of Chinese citizens due to the ruble depreciation. A significant increase in sales can be expected if Chinese consumers are provided prices for luxury goods at the European level.

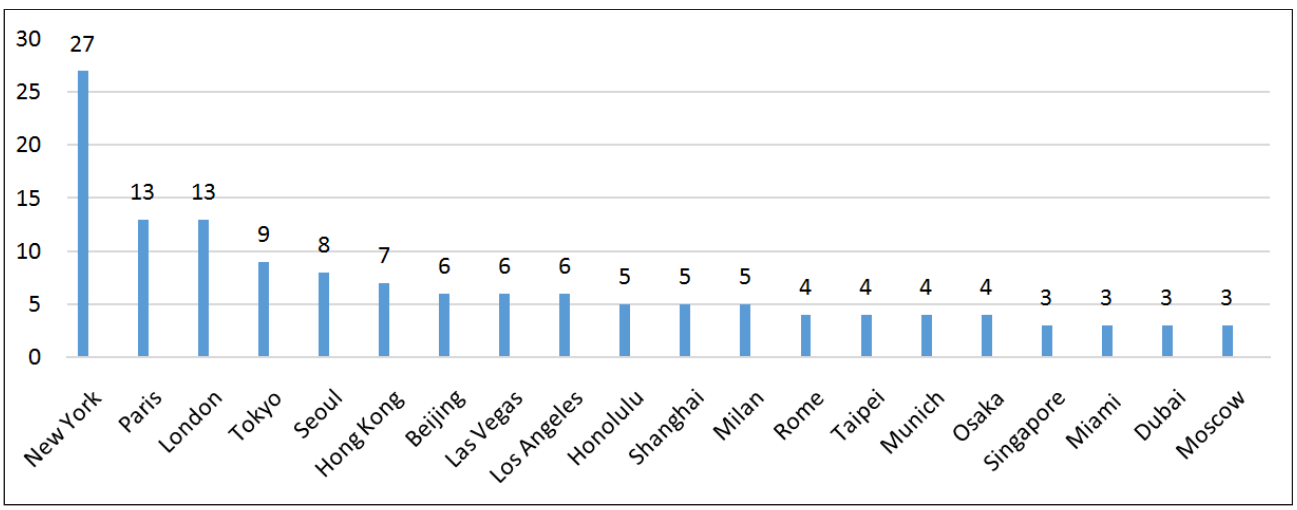


Figure 2: Consumption of personal luxury goods (clothing, footwear, accessories, beauty care, etc.) by city in bln euros in 2015 (Bain & Company estimates)

These macro parameters are directly applied to the forecasting models.

For the purpose of the research topic, we set the objective to figure out the practice of forecasting sales in the fashion industry using network analysis. It must be realized that for middle and small players of the global market, the alignment of such systems is economically unjustified and can actually be unattainable due to limitations on obtaining the standardized information from counterparties(Borade and Bansod, 2011). As a rule, such enterprises rely on traditional methods of demand assessment (classical statistical approaches, expert opinion). Examples of building forecasting models based on artificial neural networks (ANN) can be found in the literature. In many studies, ANNs are used along with fuzzy logic, genetic algorithm and symbiosis with classical models (Au, et.al. 2008).The Borade and Bansod study (2011) can serve as an example of such work, in which the forecast was built on the basis of various ANNs, where the result was derived on the basis of various accuracy parameters (Banica, et. al. 2008).

Let's take a closer look at the work "ComparisonofNeuralNetwork-BasedForecastingMethodsUsingMulti-CriteriaDecision-Making Tools" by AtulB.Borade and Satish V. Bansod (2011) (comparison of ANN forecasting methods using multiple criteria in decision-making tools) (Ekimova, et. al. 2016). The forecasts in the article are compared on the basis of costs and profits derived from various ANNs. TOPSIS, MAPPAC and ELECTRE were used to compare and choose the best forecast. TOPSIS stands for "Technique for Order of Preference by Similarity to Ideal Solution". MAPPAC stands for"Multi-criterion Analysis of Preferences by Means of Pair wise Actions and Criterion Comparisons". ELECTRE methods stand for "Elimination and Choice Expressing the Reality". These methods can be used to choose an efficient strategy that defines the behavioral resistance of the individual and the technical elements of the system.

Overall, there is a wide range of papers on the use of ANN for forecasting sales today (Danko, et. al. 2016). Let's refer to recent studies in this area. Yu et al. (2011)conducted comparisons of ANN models with traditional methods and came to a conclusion that ANN results are more accurate in most situations. It must be noted that many authors, including Borade and Bansod (2011) note that despite better accuracy, ANN methods require large initial investment to obtain the first positive outcomes. They offer a new model based on the combination of ELM (Extreme Learning Machine) and traditional statistical methods in their work. Simulations were applied to a real set of data, rather than to a simulated set. Comparisons with other traditional methods have shown the efficiency and speed of ELM-FF (where FF isFast Forecasting). Dr. Canan Efendigil Karatay(Dr. Canan, n.d) proposed a new forecasting mechanism based on approaches to the use of artificial intelligence, including the comparison of ANN and an adapted network model with fuzzy logic. This approach was used to define fuzzy demand in conditions of incomplete information. The efficiency of the method of demand forecasting was demonstrated on the real data of the Turkey-based company operating in the industry oflong-lived commodities.According to the work of Doganis.(Plan de Sécurité Alimentaire Commune Rurale de Dogani-bere 2006-2010, 2006), a successful forecasting model can be very useful for the food industry due to the short shelf life of the product and the importance of quality and freshness of the product for human health. The paper presented a full template, which can be used to develop the models of nonlinear time series. The method was a combination of two techniques of artificial intelligence RBF (Radial Basis Function) of the neural network architecture and a specially generated genetic algorithm (GA). A company producing dairy products successfully used the approach to forecast the sales of fresh milk. Chen and Ou(Kaya, et. al. 2014)determined the importance of managing the sales spots by placing balanced orders for them as a thesis of their work. The balance of the order determines success and sustainability of the company in its product segment. The GMFLN (Gray Relation Analysis Multilayer Functional Link Network) model was introduced in the article, consisting of the GRA (Gray Ratio Analysis), which sifts out the most significant factors from the source data. Then these data are transformed in order to enter the model of a multilayer functional link network to ensure better accuracy of result within the support and decision-making system. The proposed system assessed the real data provided by the franchising company. The GMFLN model demonstrated better accuracy in regard to the time series analysis methods; in particular, it performed better than the following methods: MA (Moving Average method), ARIMA (Autoregressive Integrated Moving Average), GARCH (Generalized Auto Regressive Conditional Heteroscedasticity) in terms of the mean absolute deviation (MAD) and TI indices (Theil indices to measure disproportion, inequality).

For example, applied a hybrid approach in forecasting the sales of printed circuit boards. This method is a combination of a K-means cluster approach and a fuzzy neural network (KFNN). Historical data were classified into different clusters based on the K-means of the cluster technique. Accuracy of the forecasting model improved thanks to the use of regionally focused data. The numerical values of various influencing factors and actual demand over the last five years of the printed circuit boards plant operation were used as input data for a hybrid model that forecasted future monthly sales. The forecast generated by this model proved the efficiency of the hybrid approach in comparison with other methods. In previous studiesworked with learning neural networks ENN (genetic algorithm and neural networks). Together with the identification of the trend and seasonal factors through the Holt-Winters model,the efficient economic factors were identified through the GRA (Gray Ratio Analysis). Data of the factors and demand for the last five years were taken as a training set for ENN, while comparison with other models was carried out on a test set.The outcomes showed the advantage of ENN over traditional statistical methods. Zhang, 2012]combined the approaches of fuzzy logic and artificial neural networks. Fuzzy logic has been added to the neural network for the purpose of taking into account the opinion of the expert on production control, thereby improving the accuracy of the model. The model was tested on real data provided by the company manufacturing printed circuit boards. The outcomesproved that the chosen model demonstrated the best accuracy in comparison with other models in terms of MAPE (Mean Absolute Percentage Error). One can also refer to other hybrid approaches. Wong and Guo(2010) developed a hybrid intelligent (HI) model, including preprocessing data and a prognostic approach, in order to evaluate mid-term sales in the fashion industry. HI forecasting approach was first trained on the set to determine the initial parameters of sales in the neural network. Then the heuristic method was used to obtain more forecasts. The outcomes demonstrated a significant superiority of the method over the traditional approaches to ARIMA sales forecasting in the fashion industry.

Khashei and Bijari(2011) (Zhang, 2012) proposed a new hybrid of the artificial neural networks and the ARIMA model to overcome the ANN constrains while obtaining more accurate forecasts than traditional ARIMA-ANN hybrids. Advantage of the ARIMA model in linear modeling in the proposed model was used to determine and strengthen the linear data structure. Then the neural network was used to determine the model of the data generation process and to determine the use of the processed data. (Au, et al. 2008; Borade and Bansod, 2011) presented evolutionary calculations for an ideal network structure for the forecasting system. As a result, the optimal structure of the neural network was developed to forecast sales in the clothing industry. The study revealed that the proposed algorithms are superior to traditional SARIMA for products featuring low demand uncertainty and weak seasonal trends. Method of decomposition is also used in the literature. Guo (Hess, n.d) proposed a modified EMD-FNN (*empirical* mode*decomposition*(EMD) based feed-forward *neural network* (FNN))model. This model demonstrated high accuracy of forecasts on the data from the fashion industry.

Companies build forecasts on the basis of historical data. Borade and Bansod (2011) examined five key approaches from a large number of network methods. The methods considered included MLPNN (multilayer perception neural network), Jordan-ElmanNN (neural network), SOFMNN (self-organizing feature mapping neural network or Kohonenself-organizing feature maps), RBFNN (radial basis function neural network) and FTLRNN (focused time-lagged recurrent neural network).

Forecast accuracy between the network models was compared using MCDM (Multi Criteria Decision Making methods) tools. The parameters under study included the supplier's costs of the stock reserves, seller's costs of the stock reserves, total costs of the entire supply chain, profit of the supplier and the seller.

It is recommended to examine each of the networks considered in the work of Borade and Bansod (2011). Figure 3 shows MLPNN (multilayer perceptron neural network).

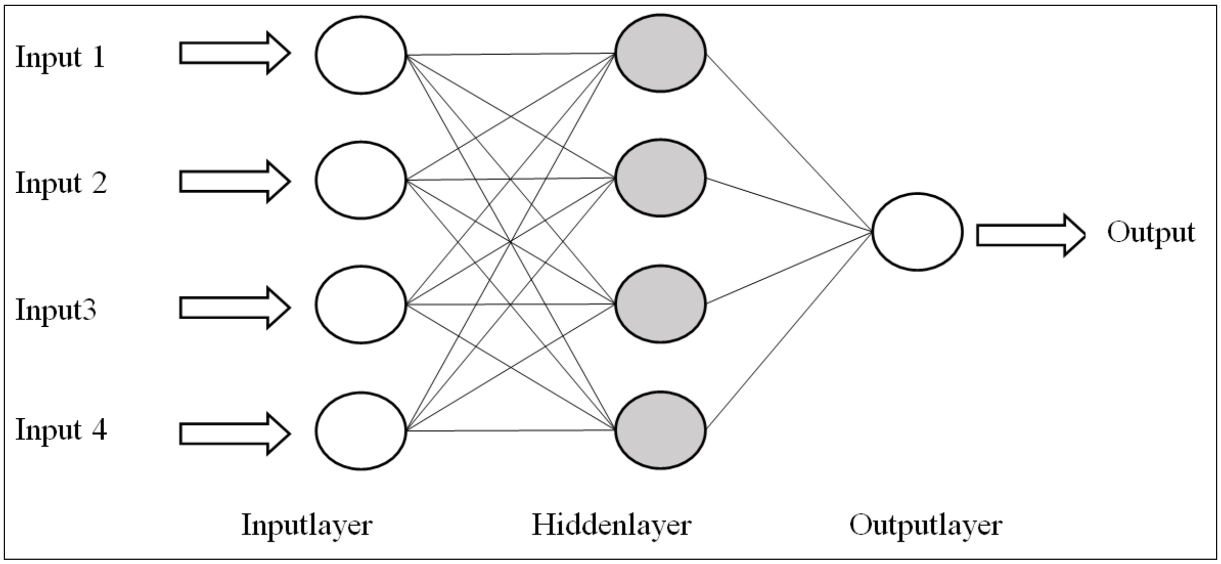


Figure 3: Fully related multilayer perceptron

Figure 3 demonstrates a three-layer model used for forecasting. Input elements are sales statistics for previous periods (for example, the previous year), the output node represents the forecast for the future period. Hidden nodes are used to process information from the input nodes. The k-foldcross-validation method was used for the construction of the optimal neural network architecture. The data in the work (Borade&Bansod, 2011) werebroken into three sets: learning, verifying and test.

The Jordan-Elemanmodelsrepresent a type of neural networks with reverse causality. In this case, reverse causality refers to a connection from a logically more remote element to a less remote one. Availability of reverse causality makes it possible to memorize and reproduce entire sequences of reactions to a single stimulus.

3. DISCUSSION AND RESULTS

As such, an analog of cyclic execution is found in these networks from the standpoint of programming. It must be noted that most of the features are currently poorly understood due to the ability of construction of a variety of architectures and the complexity of their analysis. The first work with Jordan's neural network (Jordan 1997) was published in 1986 (Figure 4).

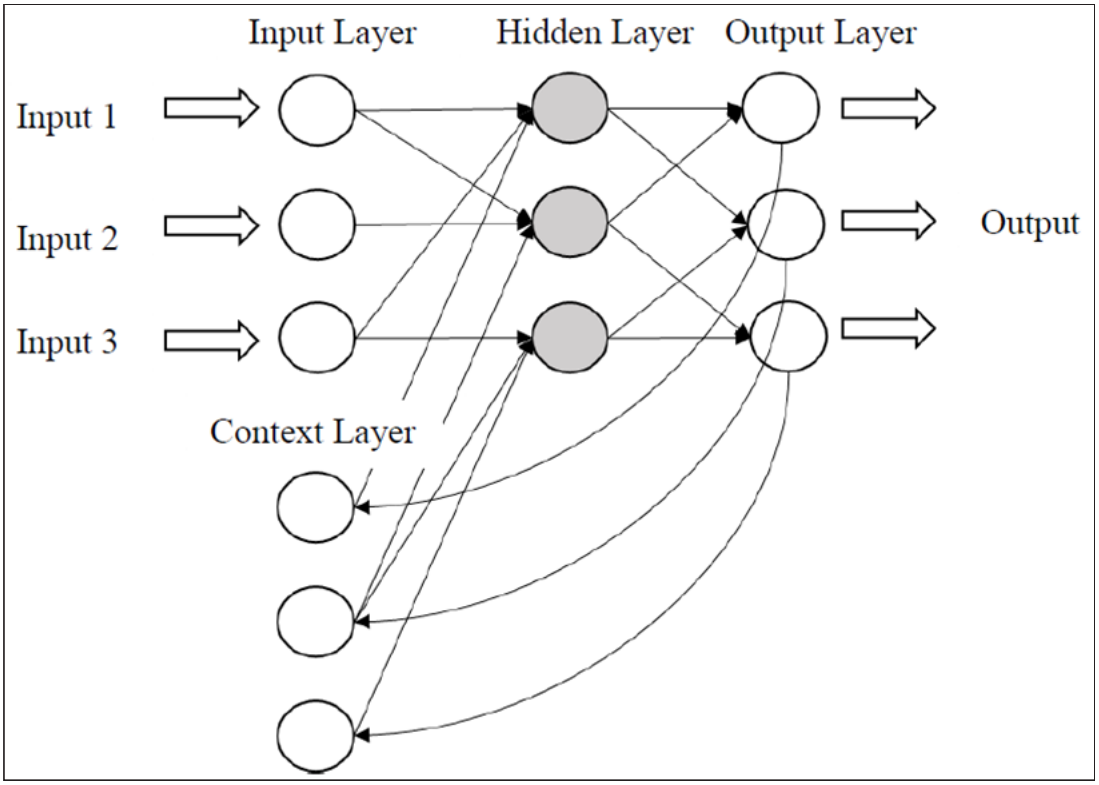


Figure 4: Architecture of Jordan's recurrent network

A new stage in the development of neural networks with reverse causality began at that moment. S. Sangwongwanish et al.(1990) proposed the modification of Jordan's network, which is the most known today (Figure 5).

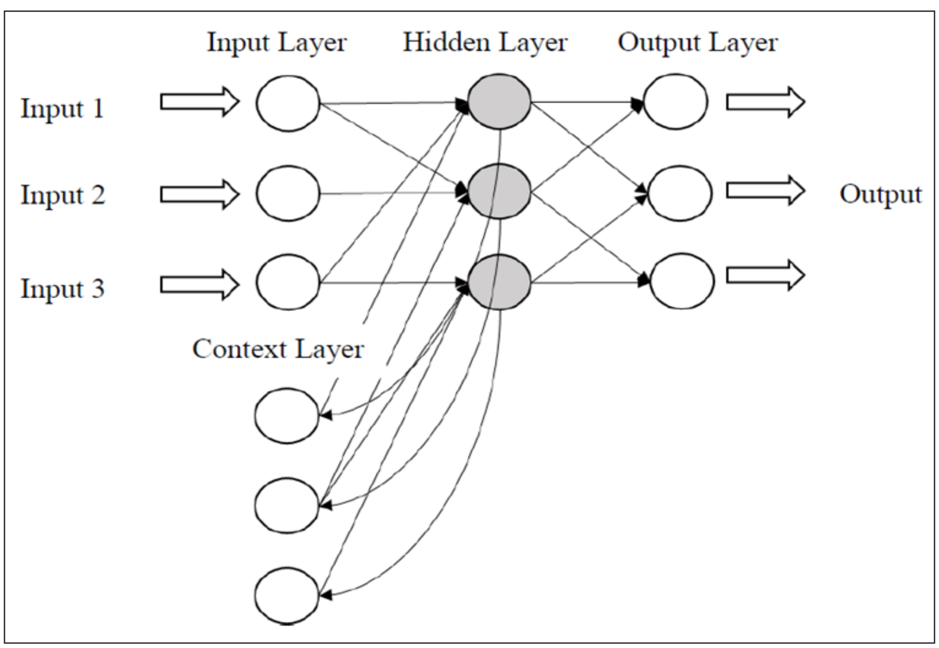
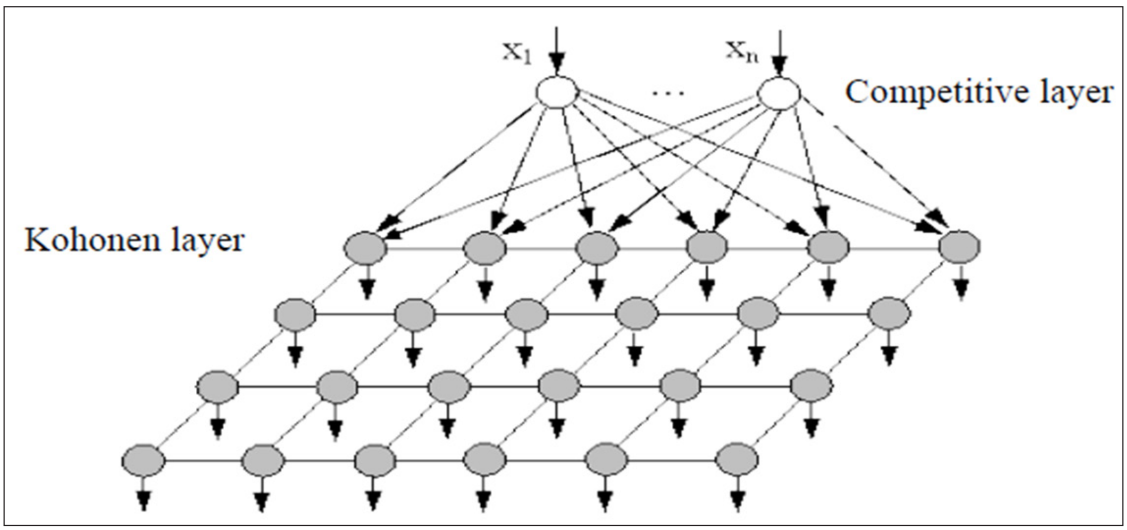


Figure 5: Architecture of Eleman's recurrent network

This type of network is called recurrent. They are based on a multilayer perceptron in most cases. The type of recurrent networks is simplified by their structure and variety in relation to their predecessors. The advantage of these networks is the ability to memorize sequences without problems with stability. This effect can be achieved thanks to the fact that the signal from the output layer has only a single delay and thus goes to additional inputs (Jordan's network) and does not go to the original inputs (as in Hopfield network). Since the signals aren't mixed, the problem of stability does not arise. Eleman's network is distinguished by a signal from the inner layer, which goes straight to additional inputs. These additional inputs are called context. Contexts serve as a place to store data about the previous stimulus, due to which the network reveals a response not only to the current stimulus, but also to the previous one (Mankar& Ghatol, 2009; Banica, et. al. 2014).

Kohonen self-organizing feature maps (SOFMs) in the neural network are a competitive model of the neural network, in which the neurons are located on a two-dimensional grid (in the basic version). This Kohonenlayer consists of the adaptive linear adders ("linear formal neurons"). The output signals of the Kohonen layer in most cases are transformed according to the rule "Winner takes all": the largest signal turns into a singular signal, the others turn into zero (Figure 6).



Source: Kohonen Self-organizing Maps

Figure 6: Topology of the Kohonenself-organizing feature map

The Kohonen neural network performs the visualization and clustering tasks. The network model was proposed by the Finnish scientist T. Kohonen in 1984. It is actually an attempt to project a multidimensional space into a space with a lower dimension (normally two-dimensional). This network is used in the area of solving modeling and forecasting objectives.

The radial basis function network is an artificial neural network of direct signal propagation, which contains an intermediate (hidden) layer of radially symmetric neurons (Figure 7). The network uses radial basis functions as activation functions. Such symmetric neurons transform the distance from a given input vector to the corresponding "center",according to some nonlinear law (as a rule, the Gaussian function is used). The network output is a linear combination of the radial basis functions of the inputs and parameters of the neuron.

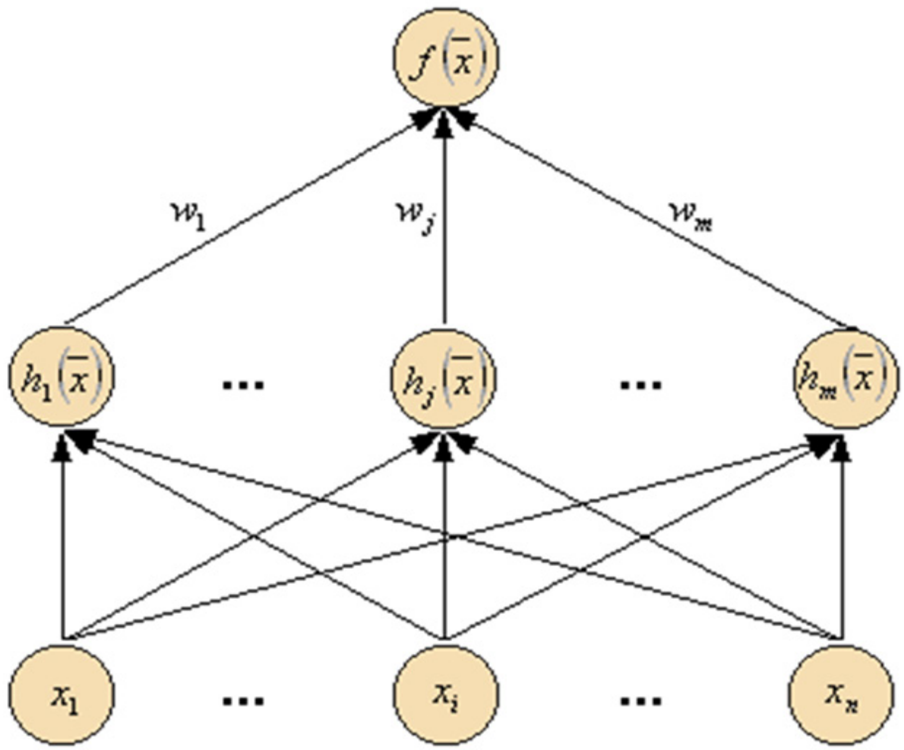


Figure 7: Radially symmetric functions in single-layer networks

As such, each of the n components of the input vector is fed to the input m of the basic functions, and their outputs are linearly summed with the weights: $\{w_j\}^m_{j=1}$. In other words, the output of the RBF network represents a linear combination of some set of basic functions:

$$f(x\square) = \sum^m_{j=1} w_j * h_j(x\square)$$

where, as indicated above, the Gaussian function is normally used as h. The radial basis function networks have many applications, including approximation functions, time series forecasting, classification and control systems.

FTLRNN (focused time-lagged recurrent neural network) model is an extension of the multilayer perceptron model with a short-term memory structure. In some cases, this extension allows to get better forecasts(Wang 2009).

According to the outcomes of the Borade and Bansod study (2011), the vendor's costs of stock reserves are the highest in the Jordan-Eleman recurrence network model and are the lowest in the FTLRNN model. On the contrary, the seller's costs of stock reserves are the highest with FTLRNN and the lowest with Jordan-Eleman. The total costs of stock reserves are the highest with Jordan-Eleman and are the lowest with FTLRNN. The largestsupplier's profit is achieved in the FTLRNN model, while the lowest profit is in the MLPNN model. The seller's profit is the largest in the Jordan-Eleman model and is the lowest in the FTLRNN model. The MCDM technique was used to compare these models.

Similar to construction ofthe forecasting models using the panel data method, neural networks are resource-consuming methods.

4. CONCLUSIONS

Clarification of the basic trends in the market for luxury goods has demonstrated great opportunities for its development for Russia.

Many technical improvements in the IT architecture are required in order to introduce the methods of network analysis in the assessment and forecasting of this market. These improvements require a team of highly qualified IT specialists and analysts possessing relevant experience.

It must be noted that the number of such specialists in the labor market today is limited, and therefore the wage rates are at high levels. Introduction of the network analysis for a large enterprise must be made in a comprehensive manner.

This entails a separate task to calculate the payback of an investment project for the introduction of network analysis at a retail enterprise – in other words, to find out how long it will take for the project to reach a breakeven point and begin to bring a net profit, at what volume of the seasonal order it will occur, at what net profitability of the business, and what are the project costs in terms of the payroll budget of the new research team.

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