

AN ANALYSIS OF BRAND INTERDEPENDENCIES USING ARTIFICIAL NEURAL NETWORKS

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Abstract

The purpose of this article is to present the abilities of Artificial Neural Networks in analyzing the existing structure of brand interdependencies compared to DE-MCI model. To achieve this purpose a comparative study is done based on POS data used by Cooper and Nakanishi in their monograph.

The results suggest that ANN model outperform DE-MCI model with regards to model fit and they offer face valid estimates of self and cross-elasticities. Based on the transformed cross-elasticity estimates, a MDS map is produced. This competitive map is used to identify the existing interdependencies among the brands in the market.

Key words: market response models, artificial neural networks, MCI market share models, cross-elasticities, competitive market structure, competitive map

JEL classification: C45, C53, M39

1. Introduction

One of the major challenges facing brand managers is to find an answer to the question concerning the effects of marketing mix changes on their own brand performance and the performance of the competitive brands. In finding answer to this question they often rely on self and cross-elasticity estimates derived from some type of market response models. With regard to this, the main objective of this article is to define a quantitative model that allows to gain knowledge about the existing structure of interdependencies between the brands in the industry¹.

There is abundant marketing literature exploring the empirical application and validation of the market share response models [Buzzell, 1964; Buzzell, Kolin, and Murphy, 1965; Fothergill and Ehrenberg, 1965; Kotler, 1965; Weiss, 1968, 1969; Little, 1970; Beckwith, 1972, 1973; Naert and Bultez, 1973; McGuire and Weiss, 1976; Naert and Weverbergh, 1981; Ghosh, Neslin, and Shoemaker, 1984; Leeflang and Reuyl, 1984; Brodie and de Kluyver, 1984; Cooper and Nakanishi, 1988; Farris, Olver, and de Kluyver, 1989; Verbeke, Clement, and Farris, 1994; Reibstein, and Farris, 1995; Fok and Franses, 2000; Fok, 2003;

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Fok, Paap, and Franses, 2003 and many others²]. Some of the models are very simplified and they don't account for the existing interaction effects between marketing mix variables. Others, with higher level of complexity, account for the behaviour of the own brand and the other brands in the market place.

The present article compares and contrasts Artificial Neural Networks³ (ANNs) to the Multiplicative Competitive Interaction (MCI) model – the most popular and considered as a favourite in competitive market structure analyzing model, which not only ensures logical consistency (that is market shares lie between 0 and 1 and they sum to 1), but also lets to account for the existing nonlinearity, interactions and asymmetric cross-effects among the brands. Due to the shorter and shorter product life cycle, non-stability of the market environment and non-regularity of marketing activities, which result in too limited data samples, the fully-extended MCI (FE-MCI) model can't be estimated. In such situation the best possible form of market share attraction model that can be identified is differential-effect MCI (DE-MCI) model, but its application reduces the knowledge about the market structure that can be gained from the model and thereby presents a distorted picture of the market.

A relatively new data-driven modeling technique which overcomes all these problems without compromises with model richness is the application of ANNs. In the last ten years, there are many empirical studies on the application of ANNs in market share predictive modeling. Some of the examples are the empirical studies of Van Wezel and Baets [1995], Gruca and Klemz [1998], Gruca, Klemz, and Ann Furr Peterson [1999], Hruschka [2000], Ivanova [2007], who are trying to find out a "niche" where ANNs might be a successful substitute for MCI models.

2. Distinguishing features of ANNs in market share modeling

Artificial Neural Networks could be defined as an advanced, computer-based method for knowledge discovery from vast and semi-structured databases by building of nonparametric models for decision support. Generally speaking, the neural network model is a hierarchical system of interconnected elements (neurons, nodes, elements) for simultaneous data processing which is analogous to the human data processing and decision-making.

ANNs are very good alternative to the traditional attraction models, since, analogous to DE-MCI models, ANNs account for the competitive asymmetry and the inherent nonlinearity and interdependence of marketing data, while they demonstrate greater flexibility, effectiveness and relative tolerance to zero values (zero market share and/or lack of marketing activities). By ex post normalization the derived from ANN model market share estimates could be easily transformed into a logically consistent form. The most serious disadvantage of ANNs is the lack of well-established methodology for model building, model validation and testing, choosing of model parameters, etc.

The ANN model building process consists of the following stages: (1) choice of learning approach; (2) choice of modeling approach; (3) definition of the number of input nodes and their connections with the next layer neurons; (4) definition of the number of hidden layers and nodes and their connections with the other neurons in the system; (5) definition of the number of output nodes; (6) choice of learning algorithm; (7) choice of activation functions for the hidden and output neurons; (8) choice of learning parameters; (9) choice of stopping criterion.

The following generalizations can be made based on previous research on ANNs applications and adapting the results to the market share features:

- ▶▶ The choice of learning approach depends on the type of the marketing problem being solved. The supervised learning approach is used in the case of solving a predictive problem.
- ▶▶ Depending on the modeling approach – a separate model for each brand (or SKU) or a single architecture for all the competitive brands – ANNs models could be classified as single and multiple. Previous research shows more accurate results in favour of single ANN models [Van Wezel and Baets, 1995; Gruca and Klemz, 1998].
- ▶▶ The number of input nodes could be defined by: (1) the used modeling approach (single or multiple); (2) the number and the type of variables, included in the model. The wish for presenting the abilities of ANNs in modeling the competitive asymmetries lead to the need of including of input nodes that accounts not only for the variety of marketing activities, but also the competitive brands these activities are applied to.
- ▶▶ From a theoretical point of view, a neural network with one hidden layer and sufficient number of hidden units can approximate any continuous function to a desired degree of accuracy. The presence of hidden layers and nodes in neural network architecture is an indicator of nonlinear nature of a given phenomenon.
- ▶▶ In spite of the abundance of theoretical rules for determination of the proper number of hidden nodes, there isn't a universal approach. The best approach is to base the choice of hidden neurons on experiments with different architectures. That's the way to account for the features of a given marketing phenomenon, rather than blindly rely on rules of thumb, defined under different circumstances.
- ▶▶ The number of output nodes could be defined by: (1) the used modeling approach (single or multiple); (2) the length of forecast horizon.
- ▶▶ The choice of learning algorithm could be defined by: (1) the type of the marketing problem being solved by using ANN architecture and the chosen learning approach; (2) the abilities of the available ANN software; (3) the wish for the researcher to overcome some typical problems addressed by ANN building, validation and testing. The most suitable learning algorithm in the case of market share predictive modeling is Backpropagation with momentum [Ivanova, 2007, 69-70].
- ▶▶ The type of the activation function depends on the type of the marketing problem being solved by using ANN architecture. The interval restriction of the market share estimates makes the sigmoid function a very attractive one in the case of market share modeling.
- ▶▶ The type of the basic learning parameters that must be set directly corresponds to the chosen learning algorithm. There is abundance of theoretical rules of thumb for determination of their values, but the "best" approach is the grid-based search.
- ▶▶ Since all of the known stopping criteria (a priori defined error level in the validation set; a priori defined number of iterations/epochs; when the error in the validation sample starts to increase) have advantages and disadvantages, only by their combined use could be made the best of them.

These are the rules that will be applied in the case of market share predictive modeling using ANNs.

3. ANNs vs DE-MCI: Cooper and Nakanishi case

To demonstrate the relative abilities of ANNs in competitive market structure analysis the present study is based on POS data used by Cooper and Nakanishi in their monograph

[Cooper and Nakanishi, 1988, 112-113]. The data are obtained at a single store in 14 weeks and characterize a very price-sensitive market. Data sample contains market shares of five national and two regional brands of margarine and their prices. All these brands account for 70% of total margarine sales.

Based on the 90% of the data sample, seven DE-MCI models and seven 3-layer feed-forward ANNs are constructed and trained/estimated, one for each brand⁴. The DE-MCI models are built as a kind of compromise for the lack of enough data to estimate the FE-MCI model.

Every ANN model consists of 7 inputs (price for 7 brands) and 1 output (market share for each brand). The fixed approach⁵ is used to determine the number of hidden neurons. In defining the values of the basic learning parameters a grid search approach is applied. The best-fit model configurations contain from 3 to 5 hidden nodes, a learning constant of 0.1, a momentum of 0.7, and a sigmoid activation function in every node. The training is realized in three passes. To stop the training either the fixed epoch number criterion (epochs=1000) or the lack of error improvement criterion is used.

Before analyzing the competitive market structure, the out-of-sample predictive power of both types of models is estimated, based on the adjusted Mean Absolute Percentage Error (aMAPE). The research results suggest that for each of the analyzed brands ANNs have better predictive accuracy than DE-MCI model. The values of aMAPE vary from 0.39% to 18.41% for ANN models, compared to 25.85% to 123.6% for DE-MCI models.

The self and cross-elasticities are computed as a basis for analyzing the competitive market structure, both for DE-MCI and ANNs models. In the case of DE-MCI models, the elasticities are computed directly from the model parameters. Because of the nonparametric nature of the ANNs, their parameters (synaptic weights) couldn't be directly interpreted as well a quite different procedure for elasticity obtaining is applied. This procedure is based on the definition of the elasticities. Its detailed description can be found in the article of Gruca and Klemz [1998, 52-53]. Shortly, the elasticity of a given independent variable is estimated setting all other independent variables to their mean level. Using the trained ANN and fixing the values of its weights, the market share corresponding to the any level of the given variable is obtained. Both single and mean arc elasticities⁶ are computed for each independent variable.

A matrix with 49 elements is constructed, including 7 self and 42 cross-elasticities. ANN models offer face valid estimates of elasticities (all the diagonal elements are negative and all the off-diagonal elements are positive). The cross-elasticities estimated for ANNs are bigger in their magnitude and one of the reasons might be the incapability of DE-MCI models to detect the cross-effects in data.

Since the cross-elasticity matrix is informative, it couldn't directly reveal the relative price sensitivity among brands. That's why, using standard transformations of the cross-elasticity estimates, a "similarities matrix" is computed⁷. Based on it, a MDS map is produced (Fig. 1).

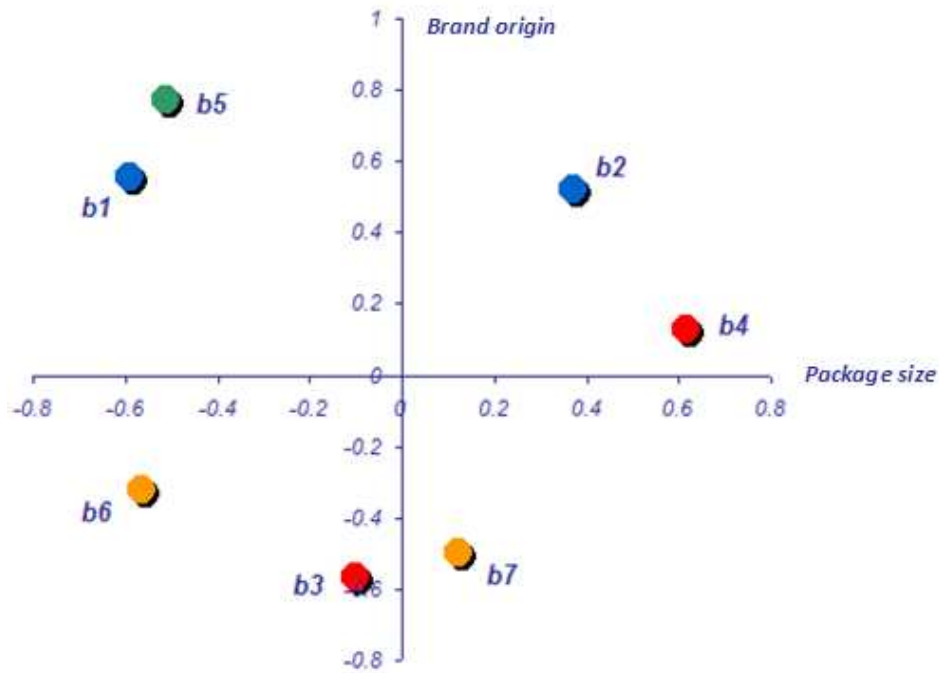


Fig. 1. MDS map

Based on this map, some conclusions about the competitive market structure are made. There aren't cannibalistic effects between smaller ($b1$ and $b3$) and larger packages (respectively, $b2$ and $b4$) of the same brand (their vectors are orthogonal). Furthermore, the competition among the national brands ($b1$ and $b5$; $b2$ and $b4$) is more intense (their vectors are closer). There isn't a competition between the two regional brands ($b6$ and $b7$). Based on the location of the positive part of the vectors, the horizontal axis is named as "package size" and the vertical axis is named as "brand origin".

4. Conclusions

The research results above illustrate not only the better approximation abilities of ANNs compared to the DE-MCI models, but also their flexibility and ability to account for asymmetric cross-elasticities, even when there is not sufficient data to estimate the FE-MCI model. Also the results present ANNs as a basis for analysis of the existing structure of interdependencies among the brands (the intensity of competition, presence or lack of cannibalization), which is very helpful for brand managers' decision-making process.

Rereferences

Beckwith, N., "Multivariate Analysis of Sales Responses of Competing Brands to Advertising", *Journal of Marketing Research*, Vol. 9, 1972, pp. 168-176.

- Beckwith, N., "Concerning the Logical Consistency of Multivariate Market Share Models", *Journal of Marketing Research*, Vol. X, August 1973, pp. 341-344.
- Brodie, R., de Kluyver, C., "Attraction versus Linear and Multiplicative Market Share Models: an Empirical Evaluation", *Journal of Marketing Research*, Vol. XXI, May 1984, pp. 194-201.
- Buzzell, R., "Predicting Short-Term Changes in Market Shares as a Function of Advertising Strategy", *Journal of Marketing Research*, Vol. I, August 1964, pp. 27-31.
- Buzzell, R., Kolin, M., and Murphy, M., "Television Commercial Test Scores and Short-Term Changes in Market Shares", *Journal of Marketing Research*, Vol. II, August 1965, pp. 307-313.
- Cooper, L., Nakanishi, M., *Market-Share Analysis: Evaluating Competitive Marketing Effectiveness*, Kluwer Academic Publishers, Boston, 1988.
- Farris, P., Olver, J., and de Kluyver, C., "The Relationship between Distribution and Market Share", *Marketing Science*, Vol. 8, No. 2, Spring 1989, pp. 107-128.
- Fok, D., *Advanced Econometric Marketing Models*, ERIM Ph.D. Series research in Management, No. 27, 2003.
- Fok, D., Franses, Ph., "Forecasting Market Shares from Models for Sales", *ERIM Report Series Research in Management*, ERS-2000-03-MKT, February 2000, pp. 1-16.
- Fok, D., Paap, R., and Franses, Ph., "Modeling Dynamic Effects of the Marketing Mix on Market Shares", *ERIM Report Series Research in Management*, ERS-2003-044-MKT, May 2003, pp. 1-28.
- Fothergill, J., Ehrenberg, A., "On the Schwerin Analysis of Advertising Effectiveness", *Journal of Marketing Research*, Vol. II, August 1965, pp. 298-306.
- Fothergill, J., Ehrenberg, A., "Concluding Comments on the Schwerin Analysis of Advertising Effectiveness", *Journal of Marketing Research*, Vol. II, November 1965, pp. 413-414.
- Ghosh, A., Neslin, S., and Shoemaker, R., "A Comparison of Market Share Models and Estimation Procedures", *Journal of Marketing Research*, Vol. XXI, May 1984, pp. 202-210.
- Gruca, T., Klemz, B., "Using Neural Networks to Identify Competitive Market Structures from Aggregate Market Response Data", *Omega, International Journal of Management Science*, Vol. 26, No. 1, 1998, pp. 49-62.
- Gruca, T., Klemz, B., and Ann Furr Peterson, E., "Mining Sales Data Using a Neural Network Model of Market Response", *ACM SIGKDD Explorations*, Vol. 1, Iss. 1, June 1999, pp. 39-43.
- Hruschka, H., "An Artificial Neural Net Attraction Model (ANNAM) to Analyze Market Share Effects of Marketing Instruments", *Report Series Adaptive Information Systems and Modelling in Economics and Management Science*, Report No. 48, Vienna University of Economics and Business Administration, University of Vienna, Vienna University of Technology, November 2000, pp. 1-20.
- Ivanova, M., *Prediktivno modelirane na pazarnia dyal s izkustveni nevronni mrezi*, Stopanski sviat, Svishtov, No. 87, 2007a.
- Ivanova, M., "Genezis and evolyutsia na agregiranite modeli na pazarnia dyal", *Ikonomicheski izsledvania*, No. 2, 2007b, pp. 117-148.
- Kaastra, I., Boyd, M., "Designing a Neural Network for Forecasting Financial and Economic Time Series", *Neurocomputing*, No. 10, 1996, pp. 215-236.
- Kotler, Ph., "Competitive Strategies for New Product Marketing Over the Life Cycle", *Management Science*, Vol. 12, No. 4, December 1965, pp. B104-B119.
- Leefflang, P., Reuyl, J., "On the Predictive Power of Market Share Attraction Models", *Journal of Marketing Research*, Vol. XXI, May 1984, pp. 211-215.
- Little, J., "Models and Managers: The Concept of a Decision Calculus", *Management Science*, Vol. 16, No. 8, April 1970, pp. B465-B485.

- McGuire, T., Weiss, D., "Logically Consistent Market Share Models II", *Journal of Marketing Research*, Vol. XIII, August 1976, pp. 296-302.
- Naert, Ph., Bultez, A., "Logically Consistent Market Share Models", *Journal of Marketing Research*, Vol. X, August 1973, pp. 334-340.
- Naert, Ph., Weverbergh, M., "On the Prediction Power of Market Share Attraction Models", *Journal of Marketing Research*, Vol. XVIII, May 1981, pp. 146-153.
- Pilon, T., *Extensions to the Analysis of Choice Studies*, Sawtooth Software Research Paper Series, 1998, at <http://www.sawtoothsoftware.com/download/techpap/extend.pdf>, accessed on October 14, 2008.
- Reibstein, D., Farris, P., "Market share and Distribution: A Generalization, a Speculation, and Some Implications", *Marketing Science*, Vol. 14, No. 3, Part 2 of 2, 1995, pp. G190-G202.
- Verbeke, W., Clement, F., and Farris, P., "Product Availability and Market Share in an Oligopolistic Market: The Dutch Detergent Market", *The International Review of Retail, Distribution and Consumer Research*, Vol. 4, No. 3, 1994, pp. 277-296.
- Van Wezel, M., Baets W., "Predicting Market Responses with a Neural Network: The Case of Fast Moving Consumer Goods", *Marketing Intelligence & Planning*, Vol.13, No.7, 1995, pp. 23-30.
- Weiss, D., "Determinants of Market Share", *Journal of Marketing Research*, Vol. V, August 1968, pp. 290-295.
- Weiss, D., "An Analysis of the Demand Structure for Branded Consumer Products", *Applied Economics*, Vol. I, No. 1, 1969, pp. 37-49.

Notes

1. Cooper and Nakanishi [1988, 56] use the term competitive market structure to designate the structure of interdependencies existing among the competitors in the industry, expressed by grouping patterns of brands.
2. A synopsis of the theoretical and empirical research on market share response modeling can be found in Ivanova [2007b, 117-148].
3. In this paper Back-propagation with momentum algorithm is used.
4. All ANNs are trained using NeuroSolutions for Excel v5.07. For all other computations SPSS 16.0 is used.
5. Kaastra and Boyd [1996, 226] define as a fixed the approach where some ANNs with different number of hidden nodes (1, 2, 3 and so on nodes) are trained simultaneously. The choice of the "best" architecture is based on the minimum of the error function in the validation set towards the number of hidden nodes.
6. For their computation midpoint elasticity formula is used.
7. The transformation procedure is described by Pilon [1998, 4-5].