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On current neural network applications involving spatial modelling of property prices

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Abstract. In recent years, the neural network modelling technique has become a serious alternative to and extension of more conventional property value modelling approaches. The neural network is a nonlinear and flexible (i.e., model-free, non/semi-parametric) regression technique that does not require *a priori* specified formal theory to work on. Instead, the idea – although not confined to this particular group of methods – is to allow for only *a posteriori* support for theory. The aim of the article is to evaluate the pros and cons of neural network models of property valuation (particularly the 'self-organizing map', SOM) in comparison with hedonic models, and to provide some examples of the application of the SOM method. Of particular interest is how different locational, environmental, and social factors impact housing market segments and house price levels. It is argued that these objectives are conveniently handled with a method based on the SOM. Some ideas for follow-up are also presented for this method.

Key words: house prices, market segments, neural network modelling, property valuation, the 'self-organizing map'

1. Introduction

Isolating the impact of different physical and locational characteristics on the formation of house or land prices at a given location has been the subject of many rigorous studies (e.g., Laakso, 1997; Lake et al., 1998; Orford, 1999). In these studies, the most important determinants of property value, such as house size and type as well as the attractiveness of the area, are recognised and their impact on value is investigated. The empirical model to be estimated is called the 'value model' in the literature. This type of research has various practical applications in fields such as tax assessment, market research, site selection and land-use planning.

Most of the price studies are conducted with hedonic modelling and other methods based on multiple regression analysis. Basically, these methods are appropriate to a straightforward estimation of the relationship between price and the various characteristics used as independent variables. However, these techniques might become problematic if the agenda of the appraisal is widened to include aspects such as outliers, nonlinearity, spatial and other kind of dependence between observations, discontinuity, and fuzziness. There are, however, some plausible alternatives, one being the use of neural networks, which are better suited to deal with these aspects. It is apparent that these alternatives can be useful in the appraisal practice. (See e.g., Worzala et al., 1995)

The aim of this article is twofold: to evaluate the pros and cons of neural network modelling in property valuation, including examples of application; and to develop an adequately valid method for capturing the house price effect attributable to the location. The article addresses two questions: What is the added value of the neural network approach in terms of uncovering aspects that go unobserved in the hedonic price model? Can the method be applied to real-world problems of valuation, such as the calculation of urban land prices for taxation purposes, or comparative evaluation of attractiveness of locations? Thus, the article seeks to explain the value modelling applications based on neural networks and – when necessary – comment on the similarities and differences of this approach compared to other kinds of methods.

The paper is organised in eight sections. The second one briefly discusses the relevant conceptual model behind the role of location and vicinity in forming the house price (and the land value). The third section presents some alternative solutions to capture this influence empirically. The next one introduces different neural network algorithms and their architectures. This is followed, in the fifth section, by a survey of prior neural network applications in property valuation and related urban assessment research. The sixth section examines the neural network technique from the perspective of more commonplace statistical methods. Some pitfalls of the method are reviewed in the seventh section. The final section presents a summary of the study. It also positions the suggested improvement within the wider modelling literature as a spatial, fuzzy, and nonlinear *complement* and *alternative* to hedonic modelling.

2. Conceptual issues in residential value modelling

The residential valuation literature recognises that the land value and the environmental qualities of the vicinity contribute to price. However, it is hard to isolate the effects of these factors on prices. The most neglected factors in value models are locational, environmental and social. This also applies to an enlargement of the spatial scale. It is widely known that certain socioeconomic indicators such as the level of income as well as the educational and professional distribution exert an influence, through an increase in potential demand, on the property prices of a given locality (Adair et al., 1996; McGreal et al., 1998; Jenkins et al., 1999).

To choose an overall theoretical framework that could provide useful guidelines for any kind of modelling of locational value formation, let us assume that the price of a given dwelling, the value allocated to the land share of the real property, and the quality of its vicinity are connected. Furthermore, let us assume that their reciprocal connections are explained by two well-known theories: the *'capitalization' theory* and the *theory of hedonic prices*. According to the former, an environmental improvement or a public good provided by the local government leads to higher housing prices in the vicinity, unless the *good* causes significant negative externalities and becomes *bad*. The benefits can be measured as the difference in price per housing unit before and after the improvements, expressed as the 'shadow price' (e.g., Laakso, 1997). Moreover, when a given proportion of the price of the dwelling is connected to the price of the land below it, another type of 'capitalization' (or allocation) occurs over time. This happens when the price fluctuations caused by volatile markets and urban development are shifted to the land prices (e.g., Boyce and Kinnard, 1984). The latter theory, developed by Rosen in 1974, states that the market implicitly reveals the function which connects the market price and the prices of the features of a given dwelling (Laakso, 1997). Both of these theories are extensions of the theory of residential location elaborated by Alonso in the 1960s and the earlier theory of bid rent advanced by Ricardo in the 1820s (e.g., Laakso, 1997).

This theoretical framework provides a background for the analysis presented in the following sections. What is important is that the reciprocal relationships between house price, land value, and quality of the vicinity can be conceptualised as a setting of monetary values for various factors. Given this limited tradition of including the locational component in house price analysis, a recurring question in the literature is how to measure the share of the vicinity in the house price and the land value. So far, this has been answered by hedonic regression models with extensions (see e.g., Lake et al., 1998, for a GIS-based analysis). A multitude of possible types of price association have been hypothesised and tested; each study usually isolates one particular type of influence on property value or estimates a model for the total housing market.

How well, then, do hedonic models that utilise locational proxies capture the discontinuous and fragmented nature of the market? The evidence is not entirely convincing, even in cases where discrete variables have been used successfully and certain aspects of data noise or incoherence are controlled for. Local externalities are indeed capitalised in land values and house prices, but what is the spatial and contextual extent of it? The methodology based on the assumption of a single value model operating on data from a uniform housing market is not necessary valid, given the idiosyncrasies pertaining to a certain area, group of people, or both. It may be argued that the hedonic regression models only trace the average estimates and fail to consider the effects of the uncontrolled variables (see Grigsby et al., 1987; Orford, 1999). Therefore, a variety of alternative approaches are suggested, some of which build upon the paradigm of machine learning and artificial intelligence. Many of them can also be seen as extensions of the hedonic model (Kauko, 2000).

3. Hedonic models and alternative value modelling approaches

In property valuation and housing market research, the locational value is usually analysed by hedonic methods. These use multiple regression techniques on large data sets and require a formality based on microeconomic theory in the analyses. Instead of just heuristics – that is, an *ad hoc* assessment of all factors contributing to the price formation at a certain location – the analysis involves a mathematical rigour, thus satisfying the need for a more 'scientific' analysis (see e.g., Adair et al., 1996). Besides the 'scientificity' argument, the underpinnings of the hedonic models are fairly easy to demonstrate for the end user. For these reasons, hedonic models have become the established tool for isolating the different value determinants. It has also become common to include a limited number of locational influences in hedonic models.

In many situations, exogenous factors or lack of information constrain an individual's participation in segments of a larger market (Michaels and Smith, 1990). Additionally, different buyers may have different housing preferences. This has led to the assertion that 'persistent localised disequilibrium' is caused by both spatial and sectoral factors and either supply- or demand-side diversification (Maclennan and Tu, 1996). To be fair, hedonic analysis has not ignored market segmentation completely. The simplest solution is to construct separate models for separate subsets of the data, with each subset, usually comprising all transactions within a region, having its specific hedonic equation (i.e., the partitioning approach).

Usually the spatial element is made explicit by supporting the analysis with a GIS interface (e.g., Lake et al., 1998; Orford, 1999). This enables data *visualisation* and *storage*, the possibility to construct *more efficient accessibility measures*, and basic *spatial analysis*. When the spatial analysis system is 'loosely coupled', the statistical analyses may be performed separately from the GIS interface. Both packages thus have their own function in the system. However, problems still remain due to the spatial dependence of the property values and to the spatial dependence of the characteristics.

Recently, the hedonic modelling approach has undergone substantial improvement in the direction of capturing spatial dependence and heterogeneity (see Orford, 1999; Dubin et al., 1999; Pavlov, 2000; Meen, 2001). Generally, when talking about spatial house price models with a basis in hedonic price theory, we may distinguish two principal lines of research: *spatial lag models* and *spatial error models* (Meen, 1996, 2001).[1] Models of the first type allow for spatial drift and decay effects, whereas those of the latter type allow for spatial autocorrelation of residuals. Local spatial errors or spatially lagged variables effectively proxy for omitted variables correlated with location (Pace et al., 1998). Within this genre, Pavlov's (2000) semi-parametric approach based on space-varying regression coefficients (SVC) is ingenious, in the sense that the model combines both spatial elements. Nevertheless, all these methods are based on *a priori* formal model selection and an assumption of a smooth price formation surface across space.

In order to capture the more discontinuous price formation structure, further improvement has therefore been made in the form of flexible (i.e., model-free, semi/non-parametric) regression (see Meese and Wallace, 1991; Pace, 1995; Mason and Quigley, 1996; Verkooijen, 1996). The neural network is, in fact, an example of a flexible regression approach. These methods are basically different from the standard methods. Specifically, they allow for a broader range of variation in the output than the hedonic regression model, with its spatial extensions. It is not clear how the coefficients in the model vary in space. Thus, there is good reason to assume that location is better treated as a non-parametric than as a parametric component of the model (see e.g., Pavlov, 2000).

A distinction may now be made between two broad types of methods: (1) the hedonic regression model, with spatial expansions; and (2) flexible regression methods. In the hedonic regression -based paradigm, the model predictions are exact. On the other hand, they may not be the correct ones. In the flexible regression paradigm, the results are not exact, but a broad variation is allowed (e.g., Verkooijen, 1996). The methods of type (1) require formal ties to theory and strict *a priori* assumptions. Their consequent lack of flexibility is an inevitable drawback. The methods of type (2) are plagued by a certain lack of transparency; that is to say, it is unclear how to explain the computations behind the results. The literature refers to this as the 'black box' problem. There is no straightforward functional relationship between the input and output values. Consequently, such methods only permit *a posteriori* support for a certain loosely formulated theory. That theory may be the equilibrium framework (e.g., Laakso, 1997), but it could also be a multiple equilibrium framework, depending on which one the evidence supports better.

Apart from neural networks, other 'intelligent' (i.e., learning) approaches that have been considered as extensions of or alternatives to the standard value/hedonic modelling paradigm include fuzzy logic (Bagnoli and Smith, 1998), the genetic algorithm (Cooley et al., 1994), rule-based expert systems (Scott and Gronow, 1990), case-based reasoning (Gonzalez and Laureano-Ortiz, 1992; O'Roarty et al., 1997), and miscellaneous computer-assisted techniques of mass appraisal (see McCluskey and Anand, 1999). By using all types of specifications, the user amasses a much better arsenal to combat problems of inefficiency and misspecification (Pace, 1995). At least, various modelling techniques provide more options to study the location/locality issues presented above. Having more options is preferable, given that submarkets or nonlinearity in the price formation exists in a given spatially defined context.

The benefit of using a more refined approach rather than the standard hedonic approach depends on the trade-off between three evaluation criteria: conceptual soundness, modelling performance, and feasibility of use. Of course, one needs to have some idea of the object of study and the geographical context, but different methods also tend to be adapted to different fields. From the perspective of urban and land economics, the more flexible systems are perhaps not rigorous enough, unless the evidence strongly supports the notions of multiple equilibria (i.e., the total demand and/or supply is differentiated across space), fuzziness (i.e., value is determined by a bundle of non-quantifiable concepts such as image), nonlinearity (compared to a linear or log-linear relationship between house or plot size and price), and residual price effects (i.e., not fully captured by the defined demand and supply proxies). Such requirements of rigour do not necessarily exist within the theoretically less developed field of property valuation.

4. Neural networks

Research on applied neural networks has a short history, going back only as far as the end of the 1980s. The underlying idea of the (artificial) neural network was developed as early as the 1940s by McCulloch and Pitts. But it took four decades before there were computers capable of handling the complex computational processes involved. This section provides some basic detail on the structure and typology of neural networks.

The basic structural elements of a neural network are called *neurons* or *nodes*, the connections among which are determined by *weights*. Together, the neurons process a numerical signal coming from outside the network in such a manner that a connection is made between input and output information. The connection is referred to as the 'intelligence of the network'. The various types of networks can be classified according to their *network architecture* (feed forward, feedback, or competitive) and the nature of the *learning process* (supervised or unsupervised). Figure 1 depicts the principles of the three basic types of network architecture. The arrows stand for the connections between the layers of nodes for each type. The direction of the calculation process can be input-hidden-output (the feed forward network), input-output (the competitive network) or unspecified (the feedback network[2]).

The architecture of the feed forward network consists of an input layer of nodes connected to the observation vector, an output layer of nodes, and one or more hidden layers (i.e., a predefined number of nodes that mediate between the input signals and output response and thereby provide the nonlinear relationship between input and output). Like the synapses in the brain, the weights determine the strength of the impulses between the layers. As the training proceeds, the weights are adjusted endogenously until the divergence between the observed output-value and the value estimated by the network is at the minimum.

The *multilayer-Perceptron (MLP) network*, or the *backpropagation algorithm*, was developed in 1986 by Rumelhart, Hinton, and Williams. It is by far the most popular neural network -based method This technique is based on a supervised learning process and a feed forward network architecture. The idea is a back propagation of errors, after which the algorithm corrects the error – hence the name 'backpropagation algorithm'[3]. The error is the actual output less the output calculated by the network (y_k). In a two-layer network, the output is

$$y_k = \sum_j \left[w_{kj}\sigma\left(\sum_i w_{ji}x_i\right) + w_{jH} \right] \tag{1}$$

w_{kj} = the weights between the hidden layer (j) and the output layer (k)
$\sigma(\cdot)$ = the nonlinear activation function of the neuron
w_{ji} = the weights between the input layer (i) and the hidden layer (j)
x_i = the input vector
w_{jH} = a bias-term, where H is a constant.

According to the experts, the method is considered a very useful option for multiple regression analysis, though it suffers from many of the same limitations as the latter. (e.g., Tay and Ho, 1992.) The '*self-organizing map*' (*SOM*), invented by Kohonen in 1982, is different in this respect. The SOM

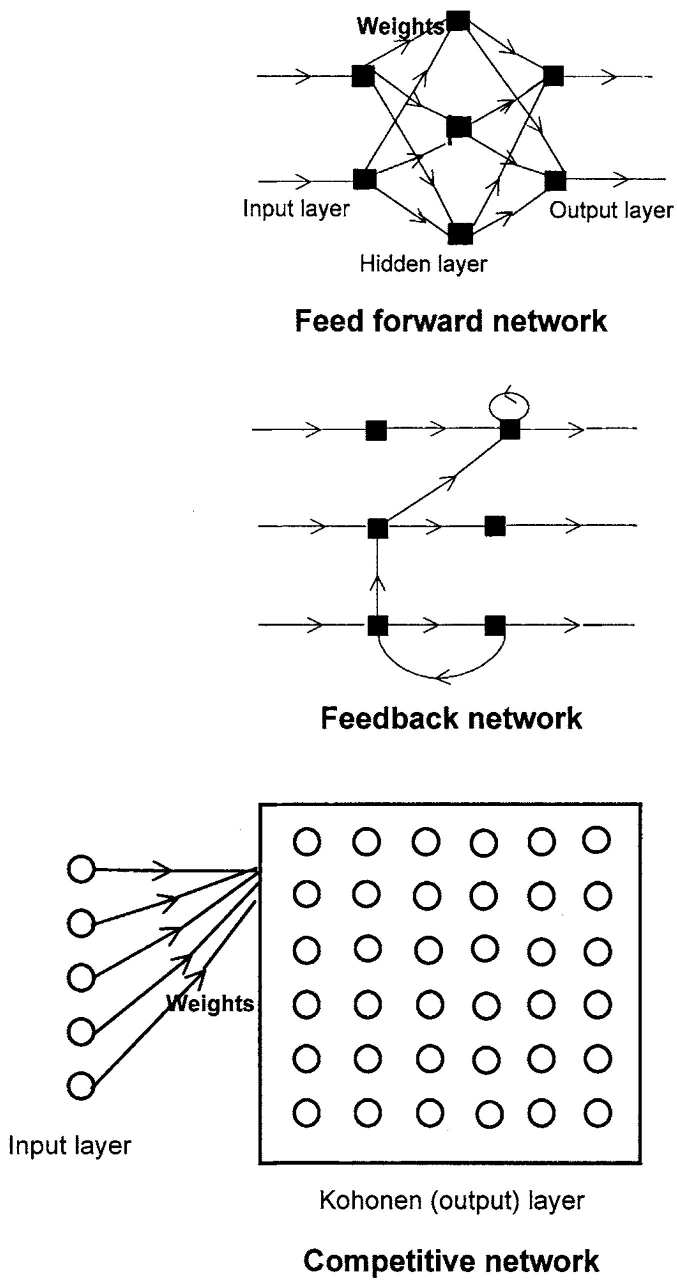

Figure 1. The principles of the three basic types of network architectures. *Source*: modified illustration based on Kathmann, 1993; James et al., 1994.

is best defined as the result of mapping from a high-dimensional data space onto a (usually) two-dimensional lattice of points (Kohonen et al., 1996a). In other words, disordered information is profiled and analysed into visual patterns, thus forming a landscape of the phenomenon described by the data set (see Kohonen, 1995).

The starting point for using the SOM is to initialise the map by generating random values for each node. Then, the training procedure of the algorithm proceeds in three stages: first, select (randomly) a training vector x; then find the best matching neuron, node c, that is closest to x; finally, adjust the node c and its neighbours towards the observation x (e.g., Koikkalainen, 1994). Usually the *matching* is determined by the smallest Euclidean distance between node c and vector x, when m_i defines a parametric reference vector (codebook vector) of every node on map i. This can be written as follows (e.g., Kohonen et al., 1996a):

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

The technique is based on the principle of unsupervised competitive learning, which could be described as 'the winner takes all'. Thus, the winner is the node with shortest distance to the observation vector, and its weights are adapted towards the observation (see Figure 1). This goes on until all desired observations are used for training – usually more than once. Neighbouring nodes on the map are similarly adapted towards the observation, but the extent of this depends on the selected parameters. As a result of these mechanics, the multidimensional input data set is processed into a 2-D projection, where each response is a combination of variable levels that is close to the observation vector (Euclidean distance).

Usually, discernible patters may emerge on one layer or in all layers. They appear when similar categories of observations, which are clearly different from others, form 'patches' on the map surface. The challenge then is to look for associations. The resulting patterns may reveal outliers or clusters, and some areas may stick out and make interesting cases worthy of a closer look. Based on theory and local expertise, the clusters may then be interpreted as submarkets. The question then becomes: How can we determine the most meaningful criteria for discrimination – that is, submarket formation? Are the best criteria any of the input variables? Or are they found in an unanticipated combination of the most important variables affecting the structure of the map in relation to location?

The SOM algorithm generates a projection of the data set, identifies potential clusters based on the defined dimensions, and calculates a 'typical value' for each node (a certain combination of input variables) and with regard to each input variable. Thus, the main properties of the SOM-based methodology concern visualisation of patterns, classification, and price estimation. This way, the SOM also allows for some qualitative analysis on top of the quantitative exercise. Furthermore, it connects the best of both worlds, simulation and spatial analysis, and contains a non-parametric element. The SOM may also be used for pre-processing only, before switching to more analytical computational techniques.

The 'learning vector quantization' (LVQ), an extension of the SOM, is based on the principle of supervised competitive learning (Kohonen et al., 1996b). The basic idea of this algorithm is that the observations are approximated into various classes of the input vector x, and x is then allocated to the class to which the nearest codebook vector m_i belongs. The classes are determined by giving each observation a label as a basis for calibration of the feature map. Finally, the accuracy of the classification is determined, preferably with a set-aside sample. The classification performance is evaluated by the recognition accuracy, which is the percentage ratio of successful hits averaged over all classes.

Summarising, the neural network arrives at results through an iterative process, where the input is linked with the output and the linkage is adjusted by weights. The results are strongly dependent on the data – nearly all necessary guidance for the analyses is obtained from the sample we feed the network. In other words, 'neural network theory' is essentially not theory at all, unless we conceive of the theory in a highly context-sensitive and open sense, which means working from the empirical towards a generalisation. Thus, it is experience that gives 'intelligence' to the model. Unfortunately, the lack of a straightforward functional relationship between input and output creates a problem of explainability; this is the classic 'black box' argument. On the other hand, we notice some connections to statistics (see section 6); in particular, supervised learning is equivalent to parameter estimation.

5. Applications

This section provides a summary of (to my knowledge) existing studies based on neural networks closely related to property valuation. The emphasis is on the general design and findings of these studies. In most of them, the aim is to estimate the price of either the apartment or the real property, based on its floor space and other structural factors. The questions pertain to comparing the performance of multiple regression and neural network models. These straightforward studies will be discussed first, beginning with the MLP applications and then moving to the SOM ones. Subsequently, some more advanced studies will be introduced.

5.1. *Technical comparison*

Tay and Ho (1992) as well as Do and Grudnitski (1992) have compared the MLP to multiple regression analysis. The mean percentage error (both studies), the coefficient of determination (Tay and Ho, 1992), and the number of sales within a five per cent error margin (Do and Grudnitski, 1992) were used as criteria indicators. In both of these studies, the neural network proved to be almost twice as accurate as the regression model. Furthermore, in Do and Grudnitski's study, the appraising view was deepened by applying a sensitivity study on the determination of marginal adjustment factors to comparable sales.

Evans et al. (1991), Kathmann (1993), and Borst (1995) also drew conclusions about the superiority of the neural network, although they did not provide empirical evidence themselves. These studies are based on the same idea as Do and Grudnitski (1992) about the price sensitivity profile of a given input-variable to be applied in the appraisal practice. Borst (1995) concluded that neural networks are at least as accurate as the linear model calibrated by multiple regression analysis.

In a study by Worzala et al. (1995), the results diverge from those reported above, although they used the same criteria for comparison as Do and Grudnitski (1992). This was, in fact, the first openly critical comment on neural networks. Worzala et al. (1995) conducted an exercise with three samples drawn from the same basic data set, in each case comparing the performance of two neural network programs and a regression model. In the light of the results achieved, the neural networks did not prove to be significantly better than the statistical approach, in contrast to the conclusions drawn by Borst (1995) as well as by Do and Grudnitski (1992).[4]

McGreal et al. (1998) ended up close to the position taken by Worzala et al. (1995), noting that the accuracy of the neural networks is beyond the bounds of acceptability by the valuation profession (cf. Adair et al., 1996). Their comparison of performances between rule- and net-based models gave varying outcomes, and the outputs from two successive cross-sections were of a contrasting nature. While reinforcing the 'black box' argument, McGreal et al. (1998) encouraged further research on the subject.

All the studies mentioned above were carried out with the MLP. However, in a number of Finnish studies, these two methods of appraisal, namely statistics and neurocomputing, have been compared using the SOM instead.[5] The results of research conducted so far are quite similar to those presented above; a neural network -based approach to mass appraisal is recommended. The Kohonen map has been applied in the UK as well (see Lam, 1994; James et al., 1994; Jenkins et al., 1999), where it has been used specifically for clustering and detecting outlier objects.

In research conducted with neural networks, outliers may remain in the data set, since the method does not require as homogeneous a data set as multiple regression (e.g., Tay and Ho, 1992). Consequently, this means that the 'thinner' the market – that is, the less there are transactions of homogeneous dwellings – the bigger the difference between neural network and multiple regression. This is because in the latter, only the average dependencies are traced and thus a homogeneous sample is required.[6] However, according to some studies (e.g., Lenk et al., 1997; McGreal et al., 1998) also the neural network analysis should be performed without outliers, since homogeneous data might lead to an improvement in the results. Regardless of which one is the correct procedure, in all types of samples, a sufficient variance is required if the calculations by the network are to have any relevance.

5.2. *Incorporating market segmentation and locational value*

In the studies discussed so far comparison is made on a technical level. In very recent studies, the emphasis has been shifted towards more complex problems. Specifically, they address meaningful ways to link different techniques together and/or to develop a link to value formation theory in search of true 'intelligibility'.

Linking different techniques together is not an unfamiliar procedure within the more conventional approach to residential appraisal. For instance, Bourassa et al. (1997) used three statistical techniques to analyse housing submarkets in Sydney and Melbourne, Australia. They used principal component analysis to extract some factors from the original variables. They applied cluster analysis to determine the most appropriate market segmentation. And multiple regression was used to estimate the hedonic price equations for all the submarkets and each city as a whole. They applied two types of cluster analysis: the hierarchical Ward's method, and the partitional k-means method. By and large, the same analysis can be performed with the SOM.

Jenkins et al. (1999) first used the SOM for stratification of the data set. That is, they used it to uncover submarkets within a large data set and construct independent MLP networks for each data set. Then they added census variables in order to improve the modelling accuracy of the MLP estimation. Finally, they made the method more transparent by adding some intelligibility through the use of *a posteriori* created rules for the partitioning by the SOM. Later, Jenkins et al. attempted to add an MLP link for prediction of property values. Actually, the MLP is an excellent alternative for that purpose, as demonstrated by Connellan and James (1998).

Moreover, Jenkins et al. (1999) is arguably the valuation-based neural network application accommodating the most comprehensive locality-specific perspective (cf. Feng and Xu, 1996; and Raju et al., 1998, for such urban planning applications). In most of the studies, environmental and socioeconomic attributes describing the locality have *not* been included among the independent variables of the price model. Even if a larger residential area receives attention in some of the studies, it is treated in a less explicit way.

It may be argued that the SOM has an advantage over other modelling approaches in that it primarily deals with the idiosyncratic aspect of spatial housing market structure and property value formation. Following the guidelines presented above in section 4, Kauko (1997) showed an exploratory application with the SOM in the context of analysing housing markets in Finland and Helsinki. Recorded information on ca. 6200 observations regarding ten variables was used as input. This ten-dimensional matrix was projected to a 24-by-16 sized 2-D matrix (i.e. the map dimensions), where the units of analysis were measures of relative proximity across the sample. Patterns were formed on the basis of the input variables, where similar categories of observations, which are clearly different from others, form 'patches' on the map surface. A nearby situation on the feature map indicated some similarity, indirectly determined by the measures for the input variables, at each point of the map – that is, for each group of similar observations. (See Kauko, 2002, for a full documentation.)

Figures 2 and 3 show two feature map layers from this analysis: the price level and the age of the building. The circles represent nodes of similar observations that are different from others in terms of typical combinations of characteristics. The position of the nodes is fixed across all layers. The number in the circle is an indicator of the observations (label). The labels refer to subdistricts within Metropolitan Helsinki and are used for calibration of the feature map. In this way, a certain locational label becomes a symbol for a certain combination of variables and market structure. Each labelled node may represent one or more observations (and in case the node has no label, it does not represent any observations within the training data, but a combination of interpolated attribute levels). Some labels occur on the map more than once. That is because some locations are particularly well represented in the data set and represent a large variation in the measured dimensions.

The value variation of a certain input variable across the data set is indicated by various shades of grey. A light colour indicates areas with a high price per sq.m. (Figure 2) and old buildings (Figure 3), whereas a dark colour indicates areas with a low price per sq.m. (Figure 2) and new buildings (Figure 3). At a glance, it can be seen which areas have a high unit price level,

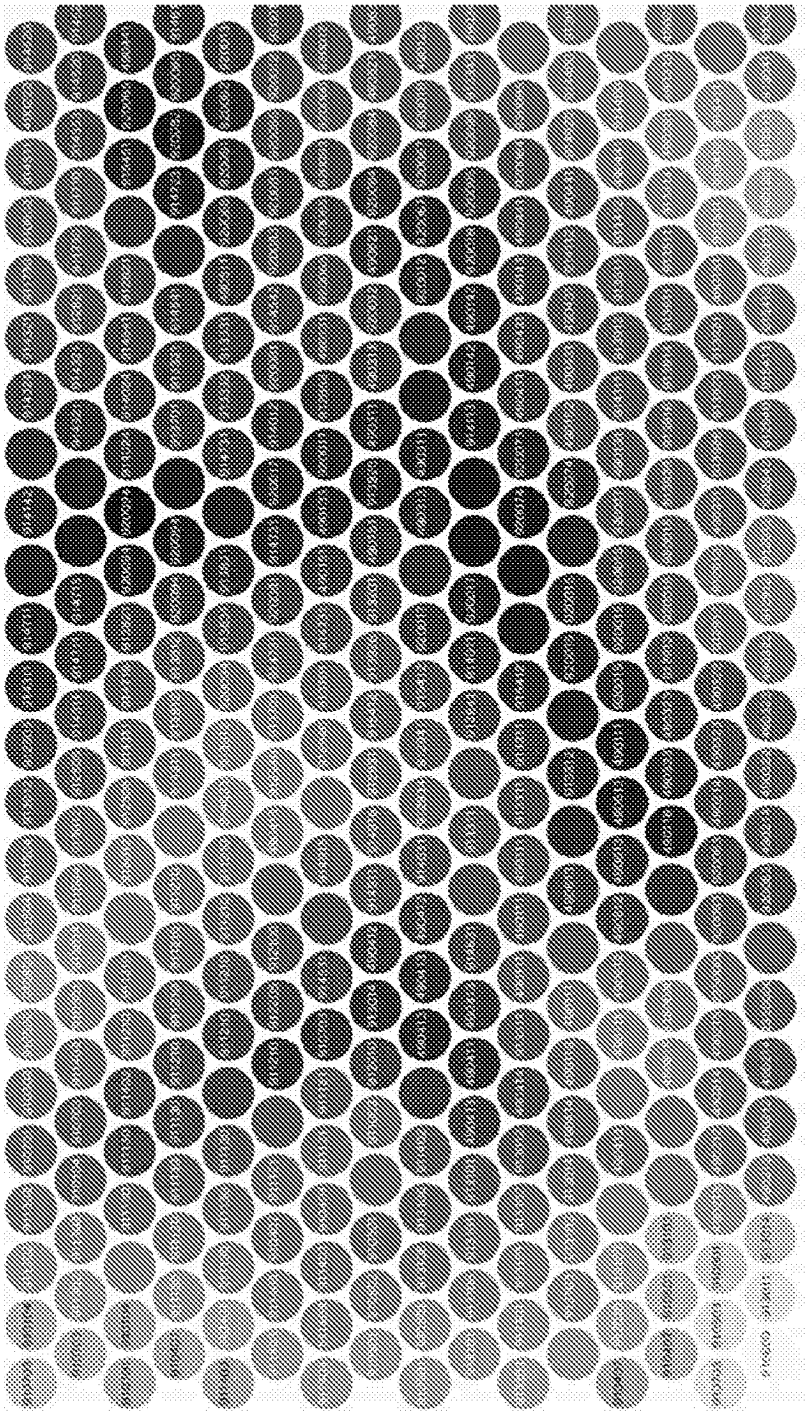

Figure 2. Feature map illustrating price levels in Helsinki subareas (dark colour = cheap area; light colour = expensive area).

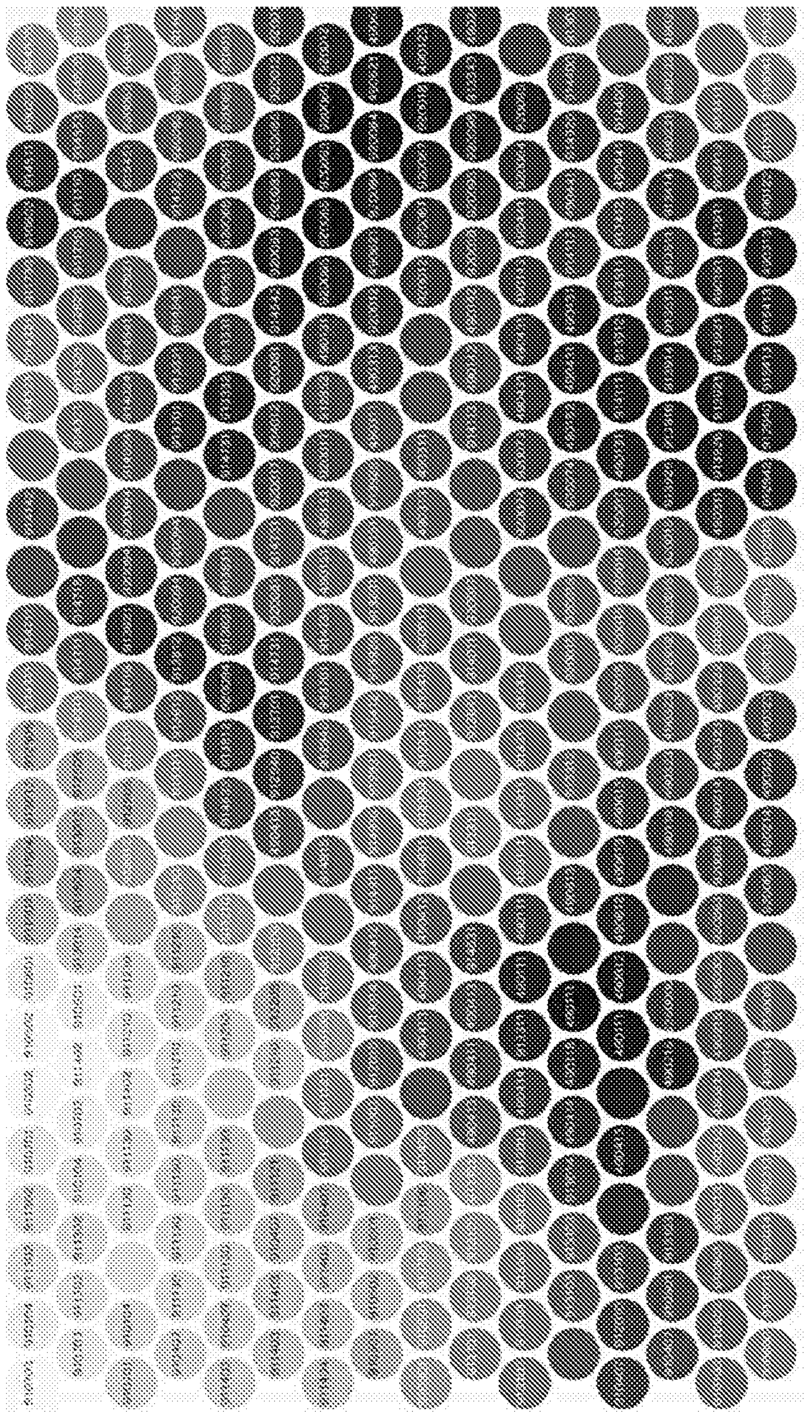

Figure 3. Feature map illustrating age of the building in Helsinki subareas (dark colour = new buildings; light colour = old buildings).

which areas have an old building stock, and to what extent these two layers overlap – in other words, whether these two factors show any associations. We see that the old buildings contribute to the segmentation of the data set and that some of these areas are among the more expensive cases. Similar visual analysis can be undertaken for all input variables. For a more quantitative analysis, the 'typical values' of the nodes may be examined.

The LVQ was described above in section 4. This method requires a small number of meaningful labels to provide a more formal measure for the success of the SOM analysis. In particular, it may be used to evaluate the most important criteria for segmentation – is it price or any other factor? For the feature map of Helsinki (see Figures 2 and 3), it turned out that the segmentation depended primarily on relative location and house type. Price level clearly played a lesser role in this respect.

Apart from the more obvious aim of detecting and visualising submarkets, the methodology also provides a means to make the various price factors commensurable. Depending on the context, this calculation is called the 'shadow price' or the marginal adjustment. However, this kind of analysis of the price effect requires solving the price association of a given input variable, either graphically or statistically. Apart from the graphical approach, it is possible to post-process the numerical values of the neurons by OLS techniques as 'smoothed' data in order to estimate a price effect. This exercise was, in fact, conducted in Kauko and Peltomaa (1998).

6. Statistical implications of neural networks

Are artificial neural networks merely an extension of statistics, or do they represent a whole new paradigm in modelling data? The answer is: both. According to White (1989), "learning methods in neural networks are sophisticated statistical procedures" and "neural network models provide a novel, elegant, and extremely valuable class of mathematical tools of data analysis", and eventually "statistics and neural network modelling must work together, hand in hand". Furthermore, White (1989) showed that the process of network learning is in fact the same as the process of computing a particular statistic.

It is clear that neural networks and statistics can be applied to similar problems. Certain neural network applications have been successfully applied in the fields of economics and finance. Among others, Yoon et al. (1993) compared the MLP with statistical discriminant analysis using a numerical multidimensional data set. In order to assess the descriptive and predictive power of these two methods, a test sample of half of the observations was classified on the basis of the trained MLP network and the statistical method.

The MLP outperformed the quadratic model estimated with discriminant analysis (see also Donaldson and Kamstra, 1996; Fish et al., 1995).

It needs to be noted that, whereas the MLP seems to be a suitable substitute for linear regression analysis, the SOM has more in common with factor and cluster analysis. The similarities to these two methods are notable, as the SOM is more apt for detecting rather than estimating purposes. One option is, in fact, to restrict the application of the SOM to detecting outliers among the data (e.g., James et al., 1994). If one draws an analogy with statistical cluster analysis (e.g., Kaski, 1997), an especially relevant question arises: How does the SOM differ from the *k*-means classifier? The crucial difference is the 'neighbourhood' concept – that is, the node that gives the closest response to each observation vector (the 'winner' node) with its adjacent nodes (see e.g., Openshaw et al., 1994). Nevertheless, usually the comparison – for some unknown reason – is made strictly between neural networks (either MLP or SOM) and multiple regression. Comparisons between the SOM and cluster analysis are rare.[7]

Another way of positioning the neural network tool is to consider it as a form of computer simulation instead of as a form of regression. Nowadays, the lack of data no longer restricts the operative use of heavy models. Thus, many GIS-enthusiasts actually argue in favour of advanced computer simulation approaches such as the use of cellular automata for modelling the complexity of urban spatial growth processes (see Wu and Webster, 1998).

7. Problems and caveats

There are several problems with the technical presumptions of the analysis that the user of the SOM needs to be aware of. The first question is how to preprocess the data, and especially how to determine the field range of a given variable (scaling, cf. McCluskey and Anand, 1999, who call this "assignment of attribute weights"). If one variable is given a larger range than the others, it will have more weight in the calculations and the map will primarily be organised on the basis of the variation in this particular factor. The second question is how to select optimal network parameters.[8] The selection might have a substantial effect on the outcome (e.g., Kohonen et al., 1996a). This is another exogenous variable that may lead to sub-optimal maps. Kohonen and others make only certain general recommendations regarding these parameters. The outcome also largely depends on the available computing resources and desired accuracy, and it often involves a process of trial and error. One suggestion for using the SOM is to conduct several runs with different parameters, to visually select a well-structured feature map, and to compare values relatively within it.

Despite the evolving tradition of neural network -based economic and spatial research and the amount of promising work being conducted, one should remember that the neural network does not enjoy an established position in this area. Its marginal status is due to the fact that the method remains too much of a 'black box' activity. Most of the studies conducted throughout the nineties in order to demonstrate the validity of the neural network as an assessment method used the neural network as a simple substitute for the linear regression model. These studies produced mixed results. Some of them argued for and others against the approval of neurocomputing within the appraisal industry. Most of the applications are based on the MLP, but the SOM has also been applied. Notwithstanding the general problems associated with neural networks, the SOM seems to offer plenty of possibilities. One lies in the locational value aspect, while an explicit treatment of this aspect was neglected by most of the studies discussed above.

8. Conclusions

Traditionally, property prices and environmental 'shadow prices' have been estimated with the hedonic price model and other regression-based approaches. This contribution has demonstrated how very recently interest has been drawn to the neural network as an alternative modelling technique. Most of the research conducted so far has been based on a comparison between these two techniques. However, neural network techniques might also be seen as complementary to the hedonic regression approaches rather than as substitutes for them.

The introduction formulated two questions: the first concerns the added value of the method, the second its validity and feasibility for practical application. Indeed, when studying empirically the formation of a price for land and real property as well as the segmentation of the housing market, the neural network has some advantages over standard hedonic models, since it can deal with imprecision and nonlinearity. Even compared to sophisticated spatial regression techniques, this method has some benefits: it does not require *a priori* specified models and it does not assume a smooth relationship between the price and location variables. The inductive approach based on the feature maps may help us analyse possible residual aspects of the price formation. Considering the demands of today, an important aspect of the SOM is its capability to detect submarkets. In this respect, the method may be seen as an alternative to the partitioning approach to hedonic price modelling. Furthermore, because of its capability to generate a partly qualitative outcome, it may be argued that it can handle discontinuities better than they can be handled by hedonic regression with extensions. Actually, the most interesting objects to study from the feature maps seem to be the *marginal* cases and, more generally, those variables whose impact on the price deviates from the expected. This assertion seems justified, if it is argued that the new approach to real estate appraisal needs to take into consideration an outlier type of location-specific price formation.

To answer the practical question, it seems that the neural network provides a relevant tool for mass appraisal. That is, it seems to be applicable to a situation where a large number of houses or sites have to be valued quickly and within a predefined range of error tolerance. Having said that, the problem is to validate the quantitative output of the neural network model, as running it seems to be a matter of trial and error. For this reason, care has to be taken to perform sensitivity analysis on the resulting price estimates. This means that a loosely formulated theory, along with some additional knowledge of the local market context, is always required to guide the analyses. One way to proceed further and to optimise the use of the method might be to generalise from the results of the SOM processing *a posteriori* and to perform the analysis with similar types of input in a different context, with the aim of extracting an institutionally sensitive new theory.

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Notes

[1] Also other spatial statistical methods have been applied within economic property research, such as two-dimensional spline polynomials (Colwell, 1998); stochastic hierarchical trends and Kalman filter (Francke and de Vos, 1998); and stochastic hierarchical trends and Gibbs sampler (Gelfand et al., 1998).

[2] In feedback networks (the Hopfield Net and the Bolzmann Machine), the neurons are connected in all directions. So far, there have not been any applications based on them within this realm (e.g. James et al., 1994). Therefore, they are not discussed here.

[3] It is worth noting that in the U.S., the MLP (or backpropagation) is used as a synonym for the neural network. In Europe, neural networks have a wider definition.

[4] Also Brunson, Buttimer and Rutherford, cited in Worzala et al. (1995), Collins and Evans, cited in James et al. (1994), McCluskey, cited in McGreal et. al. (1998), as well as Rayburn

and Tosh (1995) all take the position that neural networks are a viable alternative to multiple regression. Lenk, Worzala, and Silva (1997), in turn, disagree strongly with that and infer that substantial value estimation errors are possible with the neural network.

[5] Studies by Carlson (1991, 1992), Kauko (1996, 1997), Tulkki (1996), Airaksinen and Carlson (1996), and Lehtonen, cited in Kauko (1997) were directly related to mass appraisal. A more experimental study by Kauko and Peltomaa (1998), in turn, applied the SOM for smoothing of the data set, which is an alternative way of pre-processing the data before an explicit estimation takes place.

[6] Some might disagree that it is usual to exclude outliers from multiple regression applications in general. Within the property valuation discipline, however, this is usually the case as the valuation is based on a limited number of reasonably comparable observations.

[7] To my knowledge only Kaski (1997) has used this perspective to evaluate (in a strict sense) the methodology of using SOMs for exploratory data analysis.

[8] It has to be noted that the tree-structured SOM (TS-SOM) developed by Lappeenranta University of Technology does not require any network parameters (e.g. Koikkalainen, 1994).

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