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Recent Advances in Spatial Data Analysis

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Abstract

This article views spatial analysis as a research paradigm that provides a unique set of specialised techniques and models for a wide range of research questions in which the prime variables of interest vary significantly over space. The heart of spatial analysis is concerned with the analysis and modeling of spatial data. Spatial point patterns and area referenced data represent the most appropriate perspectives for applications in the social sciences. The researcher analysing and modeling spatial data tends to be confronted with a series of problems such as the data quality problem, the ecological fallacy problem, the modifiable areal unit problem, boundary and frame effects, and the spatial dependence problem. The problem of spatial dependence is at the core of modern spatial analysis and requires the use of specialised techniques and models in the data analysis. The discussion focuses on exploratory techniques and model-driven [confirmatory] modes of analysing spatial point patterns and area data. In closing, prospects are given towards a new style of data-driven spatial analysis characterized by computational intelligence techniques such as evolutionary computation and neural network modeling to meet the challenges of huge quantities of spatial data characteristic in remote sensing, geodemographics and marketing.

1. Introduction

The proliferation and dissemination of digital spatial databases, coupled with the ever wider use of Geographic Information Systems [GIS], is stimulating increasing interest in spatial analysis from outside the spatial sciences. The recognition of the spatial dimension in social science research sometimes yields different and more meaningful results than analysis that ignores it.

Spatial analysis is a research paradigm that provides a unique set of techniques and methods for analysing events – events in a very general sense – that are located in geographical space (see Table 1). Spatial analysis involves spatial modeling, which includes models of location-allocation, spatial interaction, spatial choice and search, spatial optimization, and space-time. Other entries in the encyclopedia take up these models (e.g. see *Location Theory; Spatial Interaction Models; Spatial Optimization Models; Spatial-Temporal Modeling*); this article concentrates on *spatial data analysis*, the heart of spatial analysis.

	Exploratory Spatial Data Analysis	Model-Driven Spatial Data Analysis
Object Data		
Point Pattern	quadrat methods kernel density estimation nearest neighbor methods *K* function analysis	homogeneous and heterogeneous Poisson process models, and multivariate extensions
Area Data	global measures of spatial associations: Moran's *I*, Geary's *c* local measures of spatial association: G_i and G_i^* statistics Moran's scatter plot	spatial regression models regression models with spatially autocorrelated residuals
Field Data	variogram and covariogram kernel density estimation Thiessen polygons	trend surface models spatial prediction and kriging spatial general linear modeling
Spatial Interaction Data	exploratory techniques for representing such data techniques to uncover evidence of hierarchical structure in the data such as graph-theoretic and regionalisation techniques	spatial interaction models location-allocation models spatial choice and search models modeling paths and flows through a network

Table 1: Popular Techniques and Methods in Spatial Data Analysis

2. Spatial Data and the Tyranny of Data

Spatial data analysis focuses on detecting patterns and exploring and modeling relationships between such patterns in order to understand processes responsible for observed patterns. In this way, spatial data analysis (SDA) emphasizes the role of space as a potentially important explicator of socioeconomic systems, and attempts to enhance understanding of the working and representation of space, spatial patterns, and processes.

2.1 Spatial data and data types

Empirical studies in the spatial sciences routinely employ data for which locational attributes are an important source of information. Such data characteristically consist of one or few cross-sections of observations for either micro-units such as individuals (households, firms) at specific points in space, or aggregate spatial entities such as census tracts, electoral districts, regions, provinces, or even countries. Observations such as these, for which the absolute location and/or relative positioning (spatial arrangement) is explicitly taken into account, are termed *spatial data* (e.g., see *Spatial Data*).

In the socioeconomic realm points, lines, and areal units are the fundamental entities for representing spatial phenomena. This form of spatial referencing is also a salient feature of GIS (e.g., see *GIS*; *Spatial Data Infrastructure*). Three broad classes of spatial data can be distinguished:

(a) *object data* where the objects are either *points* [spatial point patterns or locational data, i.e. point locations at which events of interest have occured] or *areas* [area or lattice data, defined as discrete variations of attributes over space],

(b) *field data* [also termed geostatistical or spatially continuous data], that is, observations associated with a continuous variation over space, given values at fixed sampling points, and

(c) *spatial interaction data* [sometimes called link or flow data] consisting of measurements each of which is associated with a link or pair of locations representing points or areas.

The analysis of spatial interaction data has a long and distinguished history in the study of a wide range of human activities, such as transportation movements, migration, and the transmission of information (see *Spatial Interaction; Spatial Interaction Models*). Field data play an important role in the environmental sciences, but are less important in the social sciences. This article therefore focuses on object data, the most appropriate perspective for spatial analysis applications in the social sciences. Object data include observations for micro-units at specific points in space, i.e. spatial point patterns, and /or observations for aggregate spatial entities, i.e. area data.

Of note is that point data can be converted to area data, and area data can be represented by point reference. Areas may be regularly shaped such as pixels in remote sensing or irregularly shaped such as statistical reporting units. When divorced from their spatial context such data lose value and meaning. They may be viewed as single realizations of a spatial stochastic process, similar to the approach taken in the analysis of time series.

2.2 The tyranny of data

Analysing and modeling spatial data present a series of problems. Solutions to many of them are obvious, others require extraordinary effort for their solution. Data exercise a power that can lead to misinterpretation and meaningless results; therein lies the tyranny of data.

Quantitative analysis crucially depends on *data quality*. Good data are reliable, contain few or no mistakes, and can be used with confidence. Unfortunately, nearly all spatial data are flawed to some degree (e.g., see *Spatial Data*). Errors may arise in measuring both the location and attribute properties, but may also be associated with computerised processes responsible for storing, retrieving, and manipulating spatial data. The solution to the data quality problem is to take the necessary steps to avoid having faulty data determining research results.

The particular form [i.e. size, shape and configuration] of the spatial aggregates can affect the results of the analysis to a varying, usually unknown, degree as evidenced in various types of analysis (see, e.g., Openshaw and Taylor 1979, Baumann et al. 1983). This problem has become generally recognized as the *modifiable areal units problem* (MAUP), the term stemming from the fact that areal units are not 'natural' but usually arbitrary constructs. For reasons of confidentiality, social science data (e.g., census data) are not often released for the primary units of observation (individuals), but only for a set of rather arbitrary areal aggregations (enumeration districts or census tracts). The problem arises whenever area data are analysed or modeled and involves two effects: one derives from selecting different areal boundaries while holding the overall size and the number of areal units constant (*the zoning effect*). The other derives from reducing the number but increasing the size of the areal units (*the scale effect*). There is no analytical solution to the MAUP, but questions of the following kind have to be considered in constructing an areal system for analysis: What are the basic spatial entities for defining areas? What theory guides the choice of the spatial scale? Should the definition process follow strictly statistical criteria and merge basic spatial entities to form larger areas using some regionalisation algorithms (see Wise et al. 1996)? These questions pose daunting challenges.

In addition, *boundary and frame effects* [i.e. the geometric structure of the study area] may affect spatial analysis and the interpretation of results. These problems are considerably more complex than in time series. Although several techniques, such as refined K-function analysis, take the effect of boundaries into account, there is a need to study boundary effects more systematically.

An issue that has been receiving increasing attention relates to the suitability of data. If the data, for example, are available only at the level of spatial aggregates, but the research question is at the individual respondent level, then the *ecological fallacy* (*ecological bias*) *problem* arises. Using area-based data to draw inferences about underlying individual–level processes and relationships poses considerable risks. This problem relates to the MAUP through the concept of spatial autocorrelation.

Spatial autocorrelation (also referred to as spatial dependence or spatial association) in the data can be a serious problem (e.g., see *Spatial Autocorrelation*), rendering conventional statistical analysis unsafe and requiring specialised spatial analytical tools. This problem refers to situations where the observations are non-independent over space. That is, nearby spatial units are associated in some way. Sometimes, this association is due to a poor match between the spatial extent of the phenomenon of interest (e.g., a labor or housing market) and the administrative units for which data are available. Sometimes, it is due to a spatial spillover effect. The complications are similar to those found in time series analysis, but are exacerbated by the multi-directional, two-dimensional nature of dependence in space rather than the uni-directional nature in time. Avoiding the pitfalls arising from spatially correlated data is crucial to good spatial data analysis, whether exploratory or confirmatory. Several scholars even argue that the notion of spatial autocorrelation is at the core of spatial analysis (see, e.g., Tobler 1979). No doubt, much of current interest in spatial analysis is directly derived from the monograph of Cliff and Ord (1973) on spatial autocorrelation that opened the door to modern spatial analysis.

3. Pattern Detection and Exploratory Analysis

Exploratory data analysis is concerned with the search for data characteristics such as trends, patterns and outliers. This is especially important when the data are of poor quality or genuine a priori hypotheses are lacking. Many such techniques emphasize graphical views of the data that are designed to highlight particular features and allow the analyst to detect patterns, relationships, outliers etc. Exploratory spatial data analysis (ESDA), an extension of exploratory data analysis (EDA) (Haining 1990, Cressie 1993), is especially geared to dealing with the spatial aspects of data.

3.1 Exploratory techniques for spatial point patterns

Point patterns arise when the important variable to be analysed is the location of events. At the most basic level, the data comprise only the spatial coordinates of events. They might represent a wide variety of spatial phenomena such as, cases of disease, crime incidents, pollution sources, or locations of stores (e.g., see *Spatial Pattern* ???). Research typically concentrates on whether the proximity of particular point events, their location in relation to each other, represents a significant (i.e., non-random) pattern. Exploratory spatial point pattern analysis is concerned with exploring the first and second order properties of spatial point pattern processes. First order effects relate to variation in the mean value of the process (a large scale trend), while second order effects result from the spatial correlation structure or the spatial dependence in the process.

Three types of methods are important: Quadrat methods, kernel estimation of the intensity of a point pattern, and distance methods. *Quadrat methods* involve collecting counts of the number of events in subsets of the study region. Traditionally, these subsets are rectangular (thus the name quadrat), although any shape is possible. The reduction of complex point patterns to counts of the number of events in quadrats and to one-dimensional indices is a considerable loss of information. There is no consideration of quadrat locations or of the relative positions of events within quadrats. Thus, most of the spatial information in the data is lost. Quadrat counts destroy spatial information, but they give a global idea of subregions with high or low numbers of events per area. For small quadrats more spatial information is retained, but the picture degenerates into a mosaic with many empty quadrats.

Estimating the intensity of a spatial point pattern is very like estimating a bivariate probability density, and bivariate *kernel estimation* can easily be adapted to give an estimate of intensity. Choice of the specific functional form of the kernel presents little practical difficulty. For most reasonable choices of possible probability distributions the kernel estimate will be very similar, for a given bandwidth. The bandwidth determines the amount of smoothing. There are techniques that attempt to optimize the bandwidth given the observed pattern of event location.

A risk underlying the use of quadrats is that any spatial pattern detected may be dependent upon the size of the quadrat. In contrast, *distance methods* make use of precise information on the locations of events and have the advantage of not depending on arbitrary choices of quadrat size or shape. *Nearest neighbor methods* reduce point patterns to one-dimensional nearest neighbor summary statistics (see Dacey 1960, Getis 1964). But only the smallest scales of patterns are considered. Information on larger scales of patterns is unavailable. These statistics indicate merely the direction of departure from Complete Spatial Randomness (CSR). The empirical *K* function, a reduced second-moment measure of the observed process, provides a vast improvement over nearest neighbor indices (see Ripley 1977, Getis 1984). It uses the precise location of events and includes all event-event distances, not just nearest neighbor distances, in its estimation. Care must be taken to correct for edge effects. *K* function analysis can be used not only to explore spatial dependence, but also to suggest specific models to represent it and to estimate the parameters of such models. The concept of *K* functions can be extended to the multivariate case of a marked point process [i.e. locations of events and associated measurements or marks] and to the time-space case.

3.2 Exploratory analysis of area data

Exploratory analysis of area data is concerned with identifying and describing different forms of spatial variation in the data. Special attention is given to measuring spatial association between observations for one or several variables. Spatial association can be identified in a number of ways, rigorously by using an appropriate spatial autocorrelation statistic (Cliff and

Ord 1981), or more informally, for example by using a scatter-plot and plotting each value against the mean of neighboring areas (Haining 1990).

In the rigorous approach to spatial autocorrelation the overall pattern of dependence in the data is summarized in a single indicator, such as *Moran's I* and *Geary's c*. While *Moran's I* is based on cross-products to measure value association, *Geary's c* employs squared differences. Both require the choice of a spatial weights or contiguity matrix that represents the topology or spatial arrangement of the data and represents our understanding of spatial association. Getis (1991) has shown that these indicators are special cases of a general formulation [called gamma] defined by a matrix representing possible spatial associations [the spatial weights matrix] among all areal units, multiplied by a matrix representing some specified non-spatial association among the areas. The non-spatial association may be a social, economic, or other relationship. When the elements of these matrices are similar, high positive autocorrelation arises. Spatial association specified in terms of covariances leads to *Moran's I* , specified in terms of differences, to *Geary's c*.

These *global measures of spatial association* can be used to assess spatial interaction in the data and can be easily visualized by means of a spatial variogram, a series of spatial autocorrelation measures for different orders of contiguity. A major drawback of global statistics of spatial autocorrelation is that they are based on the assumption of spatial stationarity, which implies inter alia a constant mean (no spatial drift) and constant variance (no outliers) across space. This was useful in the analysis of small data sets characteristic of pre-GIS times but is not very meaningful in the context of thousands or even millions of spatial units that characterize current, data-rich environments.

In view of increasingly data-rich environments a focus on *local patterns of association* ('hot spots') and an allowance for local instabilities in overall spatial association has recently been suggested as a more appropriate approach. Examples of techniques that reflect this perspective are the various geographical analysis machines developed by Openshaw and associates (see, e.g., Openshaw et al. 1990), the Moran scatter plot (Anselin 1996), and the distance-based G_i and G_i^* statistics of Getis and Ord (1992). This last has gained wide acceptance. These G-indicators can be calculated for each location i in the data set as the ratio of the sum of values in neighboring locations [defined to be within a given distance or order of contiguity] to the sum over all the values. The two statistics differ with respect to the inclusion of the value observed at i in the calculation [included in G_i^*, not included in G_i]. They can easily be mapped and used in an exploratory analysis to detect the existence of pockets of local non-stationarity, to identify distances beyond which no discernible association arises, and to find the appropriate spatial scale for further analysis (e.g., see *Spatial Association*).

No doubt, ESDA provides useful means to generate insights into global and local patterns and associations in spatial data sets. The use of ESDA techniques, however, is generally restricted to expert users interacting with the data displays and statistical diagnostics to explore spatial information, and to fairly simple low-dimensional data sets. In view of these limitations, there is a need for novel exploration tools sufficiently automated and powerful to cope with the data-richness-related complexity of exploratory analysis in spatial data environments (see, e.g., Openshaw and Fischer 1994).

4. Model Driven Spatial Data Analysis

ESDA is a preliminary step in spatial analysis to more formal modeling approaches. Model-driven analysis of spatial data relies on testing hypotheses about patterns and relationships, utilizing a range of techniques and methodologies for hypothesis testing, the determination of confidence intervals, estimation of spatial models, simulation, prediction, and assessment of model fit. Getis and Boots (1978), Cliff and Ord (1981), Upton and Fingleton (1985), Anselin (1988), Griffith (1988), Haining (1990), Cressie (1993), Bailey and Gatrell (1995) have helped to make model-driven spatial data analysis accessible to a wide audience in the spatial sciences.

4.1 Modelling spatial point patterns

Spatial point pattern analysis grew out of a hypothesis testing and not out of the pattern recognition tradition. The spatial pattern analyst tests hypotheses about the spatial characteristics of point patterns. Typically, Complete Spatial Random (CSR) represents the null hypothesis against which to assess whether observed point patterns are regular, clustered, or random. The standard model for CSR is that events follow a homogeneous Poisson process over the study region; that is, events are independently and uniformly distributed over space, equally likely to occur anywhere in the study region and not interacting with each other.

Various statistics for testing CSR are available. Nearest neighbor tests have their place in distinguishing CSR from spatially regular or clustered patterns. But little is known about their behavior when CSR does not hold. The *K* function may suggest a way of fitting alternative models. Correcting for edge effects, however, might provide some difficulty. The distribution theory for complicated functions of the data can be intractible even under the null hypothesis of CSR. Monte Carlo tests is a way around this problem.

If the null hypothesis of CSR is rejected, the next obvious step in model-driven spatial pattern analysis is to fit some alternative (parametric) model to the data. Departure from CSR is typically toward regularity or clustering of events. Clustering can be modeled through a heterogeneous Poisson process, a doubly stochastic point process, or a Poisson cluster process arising from the explicit incorporation of a spatial clustering mechanism. Simple inhibition processes can be utilized to model regular point patterns. Markov point processes can incorporate both elements through large-scale clustering and small-scale regularity. After a model has been fitted (usually via maximum likelihood or least squares using the *K* function), diagnostic tests have to be performed to assess its goodness-of-fit. Inference for the estimated parameters is often needed in response to a specific research question. The necessary distribution theory for the estimates can be difficult to obtain in which case approximations may be necessary. If, for example, clustering is found, one may be interested in the question whether particular spatial aggregations, or clusters, are associated with proximity to particular sources of some other factor. This leads to multivariate point pattern analysis, a special case of marked spatial point process analysis. For further details see Cressie (1993).

4.2 Modeling area data

Linear regression models constitute the leading modeling approach for analysing social and economic phenomena. But conventional regression analysis does not take into account problems associated with possible cross-sectional correlations among observational units caused by spatial dependence. Two forms of spatial dependence among observations may invalidate regression results: spatial error dependence and spatial lag dependence.

Spatial error dependence might follow from measurement errors such as a poor match between the spatial units of observation and the spatial scale of the phenomenon of interest. Presence of this form of spatial dependence does not cause ordinary least squares estimates to be biased, but it affects their efficiency. The variance estimator is downwards biased, thus inflating the R^2. It also affects the t- and F-statistics for tests of significance and a number of standard misspecification tests, such as tests for heteroskedasticity and structural stability (Anselin and Griffith 1988). To protect against such difficulties, one should use diagnostic statistics to test for spatial dependence among error terms and, if necessary, take action to properly specify the spatially autocorrelated residuals. Typically, dependence in the error term is specified as a spatial autoregressive or as a spatial moving average process. Such regression models require non-linear maximum likelihood estimation of the parameters (Cliff and Ord 1981, Anselin 1988).

In the second form, *spatial lag dependence*, spatial autocorrelation is attributable to spatial interactions in data. This form may be caused, for example, by significant spatial externalities of a socioeconomic process under study. Spatial lag dependence yields, biased and also inconsistent parameters. To specify a regression model involving spatial interaction, one must incorporate the spatial dependence into the covariance structure either explicitly or implicitly by means of an autoregressive and/or moving-average interaction structure. This constitutes the model identification problem that is usually carried out using the correlogram and partial correlogram. A number of spatial regression models, that is regression models with spatially lagged dependent variables [spatial autoregressive models], have been developed that include one or more spatial weight matrices which describe the many spatial associations in the data. The models incorporate either a simple general stochastic autocorrelation parameter or a series of autocorrelation parameters, one for each order contiguity (see Cliff and Ord 1981, Anselin 1988).

Maximum likelihood procedures are fundamental to spatial regression model estimation, but data screening and filtering can simplify estimation. Tests and estimators are clearly sensitive not only to the MAUP, but also to the specification of the spatial interaction structure represented by the spatial weights matrix. Recent advances in computation-intensive approaches to estimation and inference in econometrics and statistical modeling may yield new ways to tackle this specification issue. In practice, it is often difficult to choose between regression model specifications with spatially autocorrelated errors and regression models with spatially lagged dependent variables, though the 'common factor' approach (Bivand 1984) can be applied if the spatial lags are neatly nested.

Unlike linear regression, for which a large set of techniques for model specification and estimation now exist, the incorporation of spatial effects into non-linear models in general – and into models with limited dependent variables or count data (such as log-linear, logit and tobit models) in particular – is still in its infancy. The hybrid log-linear models of Aufhauser and Fischer (1985) are among the few exceptions. Similarly, this is true for the design of models that combine cross-sectional and time series data for areal units. See Hordijk and Nijkamp (1977) for dynamic spatial diffusion models.

5. Towards a New generation of Spatial Data Analysis Models

The next few years seem to provide a unique opportunity for spatial analysts to enter a new era in the development of novel SDA styles. The new analysis needs are being created and stimulated as a by-product of GIS-technology. GIS is creating extremely data rich and multi-domain, but theory poor and hypothesis-free environments, different from that within which computational SDA techniques have been normally applied.

5.1 Criteria for identifying future spatial data analysis

While there is a general consensus that the lack of SDA functionalities in current GIS seriously limits the usefulness of GIS as a research tool to analyze spatial data and relationships (Goodchild 1987, Openshaw 1991, Fischer and Nijkamp 1992, Anselin and Getis 1993), there is no agreement about what kinds of SDA techniques and methods are most relevant to GIS environments. (Openshaw 1991, 1994a) suggests several criteria that aim to distinguish between GISable and GIS irrelevant technology. These relevancy criteria are extremely useful to develop an improved understanding of the new analysis needs without being too concerned with how to achieve such SDA technology. The most important GIS relevancy criteria that SDA tools should ideally attempt to meet may be summarized as follows:

- A GISable SDA tool should be able to handle *large and very large numbers* (from a few tens to millions) *of spatial objects* without difficulties, and thus meet the large scale data processing needs in GIS.

- GIS relevant SDA techniques should be *sensitive to the special nature of spatial information*.

- The most useful GISable SDA techniques and models will be *frame independent* (i.e. invariant under alternative spatial partitionings of a study region).

- GIS relevant SDA should be a *safe technology* (i. e. the results should be reliable, robust, resilient, error and noise resistant, and not based in any important way on standard distributions).

- GISable SDA techniques should be *useful in an applied sense*, (i.e. focus on spatial analysis tasks that are relevant to GIS environments).

- The *results* of SDA operations should be *mappable* to afford understanding and insight, since GIS is a highly visual and graphics oriented technology.

These criteria make it apparent that future GISable spatial data analysis technology will be *data-driven* rather than theory-driven in nature, and essentially *exploratory* rather than inferential in a conventional spatial hypothesis testing sense. There is a clear need for a quantitative exploratory style of spatial analysis which can complement the map-oriented nature of GIS. Exploratory spatial data analysis (ESDA), provides useful means to generate insights into (global and local) patterns and associations in spatial data sets. The use of ESDA techniques, however, is generally restricted to both expert users interacting with the data displays and statistical diagnostics to explore spatial information, and to fairly simple low dimensional data sets.

In view of these limitations, it becomes evident that we urgently need novel exploration tools sufficiently automated and powerful to cope with the data-richness related complexity of exploratory analysis in spatial data environments (Openshaw 1995). The need is for tools that intelligently allow the user to sift through large quantities of spatial data, simplify multivariate data, and efficiently and comprehensively explore for patterns and relationships against a background of data uncertainty and noise, especially when the underlying database is of the order of multiple gigabytes.

From this perspective the question how to link SDA technology and GIS (see, e.g., Anselin and Getis 1993, Goodchild et al. 1992, Fischer et al. 1996) becomes less important than the need to fundamentally rethink spatial analysis technology, to adopt the most useful and relevant technologies for solving problems in data rich environments which are difficult or even impossible to tackle with conventional tools and to demonstrate the utility of novel approaches to spatial analysis (see also Openshaw and Fischer 1995).

5.2 Computational Intelligence - A new paradigm for spatial data analysis

Novel modes of computation which are collectively known as CI-technologies hold some promise to meet the need for novel styles that are relevant for SDA in data rich environments. Following Bezdek (1994) we use the term ‘computational intelligence’ in the sense that the lowest-level forms of intelligence stem from the ability to process numerical (low-level) data, without explicitly using knowledge in an artificial intelligence sense. CI tolerates imprecision and uncertainty in large-scale real world problems in order to achieve tractability, robustness, computational adaptivity, low cost, real-time speed approaching human-like turnaround and error rates which approximate human performance.

Artificial life, evolutionary computation and neural networks are the major representative components in this arena. The concept of *artificial life*, a methodological approach incorporating evolutionary principles and based on population rather than individual simulation, simple rather than complex specifications, bottom up rather than top down modelling and local rather than global control (see Langton 1989), shows a great potential to develop novel exploratory approaches able to efficiently and comprehensively explore large spatial databases for patterns and relationships, as illustrated, e.g., in Openshaw (1994b). Biologically inspired *evolutionary computation* (genetic algorithms, evolutionary programming, and evolutionary strategy) has proved its merit in treating hard optimization problems where classical optimization algorithms such as hill-climbers and simplex, and less classical ones such as simulated annealing tend to fail to be effective. Evolutionary computation might be adopted in SDA, for example, to improve the quality of results of spatial optimization problems, such as optimal sizing (see, e.g., Birkin et al. 1995), route choice and zone design problems.

No doubt, CI is currently best designed in capturing those systems which can efficiently process information in a massively parallel way and 'learn' by adjusting certain parameters. This neural network view is extremely attractive in a world where information abounds, as in the case of large spatial data volumes. Thus, we limit our discussion to neural networks which are likely to become the singly most important component of a CI-driven spatial analysis program, perceived from a methodological rather than a computer-based perspective. The recent re-emergence of neural network (NN) based approaches to computational intelligence has been accomplished by a virtual explosion of research, spanning a range of disciplines - computer science, statistics, mathematics, physics, neuroscience, cognitive science, electrical engineering, computational geography etc. - perhaps wider than any other contemporary intellectual endeavour. Much of the recent interest of computational geographers in neural network modelling (see, e.g. Openshaw 1993, Fischer and Gopal 1994a, 1994b, Leung 1997, Fischer 1998) stems from the growing realization of the limitations of conventional tools as vehicles for exploring patterns and relationships in GIS and RS (remote sensing) environments and from the consequent hope that these limitations may be overcome by judicious use of neural net approaches.

Although a vast variety of NN models exist, and more continue to appear as research continues, many of them have common topological characteristics, PE's properties, and training (learning) approaches. Basically three entities characterize a neural network (see Fischer and Gopal 1993):

- the network topology or interconnection of its PEs (called *architecture*),

- the characteristics of its PEs, and

- the method of determining the weights at the connections (called *training* or *learning strategy*).

Different interconnection strategies lead to different types of NN architectures (feedforward versus recurrent) which require different learning (training) strategies. At the most fundamental level two categories of training may be distinguished: Supervised and unsupervised. In *supervised learning* the network is trained on a training set consisting of a sequence of input and target output data. Training is accomplished by adjusting the network weights so as to minimize the difference between the desired and actual network outputs. Weight adjustment is based on the definition of a suitable error function which is then minimized with respect to the weights and biases in the network using stochastic or deterministic, pattern-based or batch versions of the gradient descent algorithm, or (scaled) conjugate gradient, quasi-Newton and global optimization algorithms like simulated annealing and genetic algorithms. *Unsupervised learning* (also called self-organization) requires only input data to train the network. During the training process the network weights are adjusted so that similar inputs produce similar outputs. This is accomplished by a training algorithm that extracts statistical regularities from the training set, representing them as the values of network weights (see Fischer and Gopal 1994b, Fischer 1998). It is important to note that results in statistics, econometrics and optimization literature can be applied directly to describe the properties of the network learning methods. Bootstrap techniques, for example, may be used for estimating the bias of network parameters.

The attraction of NN-based spatial analysis extends far beyond the high computation rates provided by massive parallelism. The advantages to be gained essentially stem from the following features:

- the greater representational flexibility and freedom from linear model design constraints;

- the built-in capability (via net representation, training) to incorporate rather than ignore the special nature of spatial data;

- the greater degree of robustness or fault tolerance to deal with noisy data, missing and fuzzy information;

- the ability to deal efficiently with very large spatial data sets, and thus the prospect to obtain better results by being able to process finer resolution data or real-time analysis;

- the built-in capability to dynamically adapt the connection weights to changes in the surrounding environment (learning);

- generalization (out-of-sample performance) capabilities in a very specific and generally satisfying sense, and

- the potential to improve the quality of results by reducing the number of rigid assumptions and shortcuts introduced by conventional methodologies.

5.3 Application domains and examples of NN-based spatial analysis

NN models in general and two-layered feedforward networks in particular, in combination with a wide variety of learning techniques, tend to provide spatial analysts with novel, elegant, and extremely valuable classes of mathematical tools for SDA based on sound theoretical concepts. They may be viewed as non-linear extensions of conventional spatial statistical models such as, e.g., regression models, spatial interaction models, linear discriminant functions and pattern recognition techniques (Fischer and Gopal 1994a) and are applicable, especially, to two major domains (see Fischer 1994):

- as *universal function approximators* to areas such as spatial regression, spatial interaction, spatial choice and space-time series analysis,

- as *pattern recognizers and classifiers* to intelligently allow the user to sift through the data, reduce dimensionality, and find patterns of interest in data-rich environments (e.g. census small area statistics, high-resolution remote sensing data).

Feedforward NN modelling as universal function approximators may be considered as a *three-stage process* as outlined in Fischer and Gopal (1994a) and applied to telecom traffic modelling by Gopal and Fischer (1996, 1997):

- The *first stage* refers to the identification of a model candidate from a family of two-layer feedforward (perceptron or radial basis function) networks with specific types of non-linear processing elements.

- The *second stage* involves the estimation of the network parameters of the selected neural network model and the optimization of the model complexity (via regularization theory, network pruning or cross-validation) for the given training set.

- The *third stage* is concerned with testing and evaluating the out-of-sample (generalization) performance of the model.

There is little doubt that neural pattern classifiers have an important role to play in high dimensional problems of *pattern recognition and classification of massive quantities of data*, for example, associated with national classifications based on census small area statistics or with spectral pattern classification problems using satellite imagery.

6. Conclusions and Outlook

GIS-technology is greatly increasing the need for spatial data analysis. Conventional SDA tools are generally not sufficiently powerful to cope with the new analysis needs. SDA is entering a new era of data-driven exploratory searches for patterns and relationships in the context of an analysis process increasingly driven by the availability of spatial data. CI-technologies in general and neural networks in particular provide an interesting and powerful paradigm to meet the new challenges, one that is likely to slowly evolve rather than revolutionize with major radical change over a short time frame. The driving force is a combination of large amounts of spatial data due to the GIS data revolution, the availability of attractive and novel CI-tools, the rapid growth in computational power (especially delivered through massively parallel computers), and the new emphasis on exploratory data analysis and modelling.

Neural networks provide not only novel and extremely valuable classes of data-driven mathematical tools for a series of spatial analysis tasks, but also an appropriate framework for re-engineering our well established SDA techniques to meet the new large scale data processing needs in GIS. Application of neural network models to spatial data sets holds the potential for fundamental advances in empirical understanding across a broad spectrum of application fields in spatial analysis. To realize these advances, it is important to adopt a principled rather than an ad hoc approach where spatial statistics and neural network modelling have to work together. The most important challenges in the next years will be twofold: first, to develop application domain specific methodologies relevant for SDA and, second, to gain deeper theoretical insights into the complex relationship between learning and generalization, which is of critical importance for the success of real world applications.

The mystique perceived by those outside the field which arises from the origins of neural network systems in the study of natural neural systems, and the associated metaphorical jargon may act to lessen the amount of serious attention given to the new paradigm. But - and this is important to note - many aspects of the study of neural networks lend themselves to rigorous mathematical analysis. This provides a sound foundation on which to base a study of the capabilities and limitations of these NN systems as well as applications. Casting the analysis in the universal language of mathematics makes it possible to dispel much unwarranted mystique. A start has been made for a NN-based SDA, but much remains to be done.

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