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Chapter 1 : A Brief History of Spatial Analysis | GIS and Science

In recent years, spatial analysis has become an increasingly active field, as evidenced by the establishment of educational and research programs at many universities. Its popularity is due mainly to new technologies and the development of spatial data infrastructures.

By far the most common type of analysis used to achieve this aim is that of regression in which relationships between one or more independent variables and a single dependent variable are estimated. In spatial analysis, the data are drawn from geographical units and a single regression equation is estimated. That is, the relationships being measured are assumed to be stationary over space. Relationships which are not stationary, and which are said to exhibit spatial non- stationarity, create problems for the interpretation of parameter estimates from a regression model. It is the intention of this paper to describe a statistical technique, which we refer to as Geographically Weighted Regression GWR , which can be used both to account for and to examine the presence of spatial non-stationarity in relationships. It would seem reasonable to assume that relationships might vary over space and that parameter estimates might exhibit significant spatial variation in some cases. There are three reasons why parameter estimates from a regression model might exhibit spatial variation: The first and simplest is that parameter estimates will vary due to random sampling variations in the data used to calibrate the model. The contribution ofthis source of variation is not of interest here but needs to be eliminated by significance testing. That is, in this paper we want to concentrate on large-scale, statistically significant variations in parameter estimates over space, the source ofwhich cannot be attributed solely to sampling. The second is that, for whatever reason, some relationships are intrinsically different across space. This is a situation where we throw away a great of interesting spatial detail in relationships. The third reason why some relationships might exhibit spatial variation is that the model from which the relationships are being estimated is a gross misspecification ofreality and that one or more relevant variables have either been omitted from the model or represented by an incorrect functional form and are making their presence felt through the parameter estimates. Given that ali models, by their nature, are likely to be misspecifications ofreality, the potential for this misspecification to be sufficiently gross as to cause spatial non-stationarity in parameter estimates would seem quite high. Ifmisspecification is the cause of spatial non-stationarity, GWR has two roles to play. The first is in an exploratory mode when it can help to identify the nature of the misspecification by an examination of the spatial pattern of the locali sed parameter estimates. This would be particularly important when a global estimate is insignificant, and when the variable associated with this estimate is often excluded from the analysis, but when some ofthe localised estimates from GWR are statistically significant. The latter two reasons for thinking that spatial non-stationarity might be a possibility in regression modelling are interesting in that they retlect opposite views of modelling. The belief that some relationships are intrinsically different across space is consistent with a post-modernist view of spatial analysis where striving to identifY global relationships is seen as having little relevance to real-world situations where relationships are very complex and are likely to be highly contextual. We do not take sides on this debate in this paper; we merely note that GWR is consistent with either view and that it can be seen as a possible bridge between them. In this framework, parameters ofa global model can be made functions of 62 s. Brunsdon other attributes including geographic space so that trends in parameter estimates over space can be measured Fotheringham and Pitts ; Eldridge and Jones While this is a useful and easy-to-apply framework in which improved models can be developed, it is essentially a trend-fitting exercise in which complex pattems of relationships will be hidden. The output from the expansion model is essentially a second order set of relationships describing how the first order relationships vary across space. The output from GWR, on the other hand, is a set of parameter estimates which describe the ftrst order relationships. These parameter estimates can be mapped to show their exact spatial distributions rather than just any trends that might exist in them. At least three other statistical methods to handle varying parameter estimates have been proposed but which are of limited use in a spatial context: The first incorporates spatial relationships in a rather ad hoc manner and produces parameter estimates which cannot be tested statistically and so has found very limited applicability. In the latter two techniques the parameter estimates in a regression model are assumed to be random variables. In multilevel modelling the distribution of the estimates is assumed to be Gaussian, while in the random coefficients model, the parameter estimates are modelled as finite mixture distributions. Although geographical variations of multilevel modelling have been attempted Jones they rely heavily on a pre-defined hierarchy of spatial units which again probably represents an unrealistically discrete view of spatial dependency. In contrast, the GWR procedure described below utilises a distance- decay-based spatial weighting structure which is probably more reasonable in most spatial applications. Usually the least squares method is used to estimate the aks and using matrix notation the estimator can be expressed as: It is important to note that this matrix is constant with respect to i and that only one set of parameter estimates is obtained for all points i. That is, the effect of any x on y is assumed constant across the space. GWR is a relatively simple technique that extends the traditional regression framework of equations 4. That is, the parameter estimates become specific to location i and the model is rewritten as: Note that equation 4. The GWR equation in 4. As is shown in the empirical example below, the point i in equation 4. This makes it possible to produce parameter estimates for a sample set of points defined by the user as a precursor to mapping. As it stands, equation 4. There are more unknowns than observed variables. However, many models ofthis kind have been proposed before and they are reviewed by Rosenberg , and Spjotvoll J More recent work has been carried out by Hastie and Tibshirani J Our approach borrows from the latter particularly in the fact that we do not assume the coefficients to be random, but rather that they are deterministic functions of some other variables - in our case location in space. The general approach when handling such models is to note that although an unbiased estimate is not possible, estimates with a small amount of bias can be provided. We argue here that the estimat ion process in G WR can be thought of as a trade-off between bias and standard error. Assuming the parameters exhibit some degree of spatial consistency then values near to the one being estimated should have relatively similar magnitudes and signs. Thus, when estimating a parameter for a given point i, one can approximate 4. However, if the local sample is large enough, this will allow a calibration to take place - albeit a biased one. To reduce this effect one final adjustment to this approach may also be made. Assuming that points in the calibration subset further from i are more likely to to have differing coefficients, a weighted OLS calibration is used, so that more 64 S. Brunsdon influence in the calibration is attributable to the points closer to i. As noted above, the calibration of equation 4. In essence, the equation measures the relationships inherent in the model araund each paint i. Hence weighted least squares provides a basis for understanding how GWR operates. In ordinary least squares, the sum of squared differences between predicted and observed YiS is minimized by the parameter estimates. In weighted least squares a weighting factor w is applied to each squared difference before minimizing so that the inaccuracy of some predictions carries more of a penalty than others. The weighted least squares estimator for equation 4. Note that the weight of each observation is a constant and that only one set of parameter estimates is obtained for aII points in the space. In GWR the weighted least squares approach is taken one step further by weighting an observat ion in accordance with its proximity to point i so that the weighting of an observation is no longer constant in the calibration but varies with i. Data from observations c10se to iare weighted more than data from observations farther away. In this way, the estimator for the parameters in equation 4. There are parallels between GWR and that ofkemel regression and kemel density estimation Parzen ; Cleveland ; Cleveland and Devlin ; Silverman ; Brunsdon , ; Wand and Jones In kemel regression, y is mode led as a non-linear function ofx by weighting data in attribute space rather than geographic space. That is data points c10ser to Xi are weighted more heavily than data points farther away and the output is a set of localized parameter estimates in X space. It should be noted that as well as produc ing localized parameter estimates, the GWR technique described above will produce localized versions of aII standard regression diagnostics includ ing goodness-of-fit measures such as r-squared. The latter can be particularly informative in understanding the application of the model being calibrated and for exploring the possibility of adding additional explanatory variables to the model. Measuring Spatial Variations 65 4. The choice of such a relationship will be considered here. Firstly, consider the implicit weighting scheme ofthe OLS framework in equations 4. That is, in the global model each observation has a weight of unity. An initial step towards weighting based on locality might be to exclude from the model calibrat ion observations that are further than some distance d from the locality. However, the spatial weighting function in 4. As i varies around the study area, the regression coefficients could change drastically as one sample point moves in to or out of the circular buffer around i and which defines the data to be included in the calibration for location i. Although sudden changes in the parameters over space might genuinely occur, in this case changes in their estimates would be artefacts of the arrangement of sample points, rather than any underlying process in the phenomena under investigation. One way to combat this is to specity w ij as a continuous function of d ij ,the distance between i andj. One obvious choice is: For data a long way from i the weighting will fali to virtually zero, effectively excIuding these observations from the estimation of parameters for location i. A problem common to most weighting functions and aII distance-based weighting functions is determin ing the steepness of the decay curve, p, around each point and this topic is now addressed. Conversely, as the distance-decay becomes greater, the parameter estimates wiII increasingly depend on observations in close proximity to i and hence will have increased variance. The problem is therefore how to select an appropriate decay function in GWR. Consider the selection of p in equation 4. One way to proceed would be to minimise the quantity. In order to find the fitted value ofYi it is necessary to estimate the a,ks at each ofthe sample points and then combine these with the x-values at these points. However, when minimising the sum of squared errors suggested above, a problem is encountered. Suppose P is made very large so that the weighting of aII points except for i itself become negligible. Then the fitted values at the sampled points will tend to the actual values, so that the value of 4. This suggests that under such an optimising criterion the value of P tends to infinity but c1early this degenerate case is not helpful. Firstly, the parameters of such a model are not defined in this limiting case and secondly, the estimates will tluctuate wildly throughout space in order to give locally good fitted values at each i. Here, a score ofthe form. Plotting the CV score against the required parameter ofwhatever weighting function is selected wiII therefore provide guidance on selecting an appropriate value of that parameter. If it is desired to automate this process, then the CV score could be maximised using an optimisation technique such as a Golden Section search Greig, However, it is useful to assess the question: In general terms, this could be thought ofas a variance measure. As there are n values ofthis parameter estimate one for each point i within the region , an estimate ofvariability is given by the standard deviation of these values. This statistic will be referred to as Sk. The next stage is to determine the sampling distribution of Sk under the null hypothesis that the global model in equation 4.

Chapter 2 : Spatial analysis - Wikipedia

This book illustrates some recent developments in spatial analysis, behavioural modelling, and computational intelligence. World renown spatial analysts explain and demonstrate their new and insightful models and methods.

The value of q is within [0, 1], 0 indicates no spatial stratified heterogeneity, 1 indicates perfect spatial stratified heterogeneity. The value of q indicates the percent of the variance of an attribute explained by the stratification. The q follows a noncentral F probability density function. A hand map with different spatial patterns. Spatial interpolation[edit] Spatial interpolation methods estimate the variables at unobserved locations in geographic space based on the values at observed locations. Basic methods include inverse distance weighting: Kriging is a more sophisticated method that interpolates across space according to a spatial lag relationship that has both systematic and random components. This can accommodate a wide range of spatial relationships for the hidden values between observed locations. Kriging provides optimal estimates given the hypothesized lag relationship, and error estimates can be mapped to determine if spatial patterns exist. Local regression and Regression-Kriging Spatial regression methods capture spatial dependency in regression analysis , avoiding statistical problems such as unstable parameters and unreliable significance tests, as well as providing information on spatial relationships among the variables involved. The estimated spatial relationships can be used on spatial and spatio-temporal predictions. Geographically weighted regression GWR is a local version of spatial regression that generates parameters disaggregated by the spatial units of analysis. Spatial stochastic processes, such as Gaussian processes are also increasingly being deployed in spatial regression analysis. Model-based versions of GWR, known as spatially varying coefficient models have been applied to conduct Bayesian inference. Factors can include origin propulsive variables such as the number of commuters in residential areas, destination attractiveness variables such as the amount of office space in employment areas, and proximity relationships between the locations measured in terms such as driving distance or travel time. In addition, the topological, or connective , relationships between areas must be identified, particularly considering the often conflicting relationship between distance and topology; for example, two spatially close neighborhoods may not display any significant interaction if they are separated by a highway. After specifying the functional forms of these relationships, the analyst can estimate model parameters using observed flow data and standard estimation techniques such as ordinary least squares or maximum likelihood. Competing destinations versions of spatial interaction models include the proximity among the destinations or origins in addition to the origin-destination proximity; this captures the effects of destination origin clustering on flows. Computational methods such as artificial neural networks can also estimate spatial interaction relationships among locations and can handle noisy and qualitative data. This characteristic is also shared by urban models such as those based on mathematical programming, flows among economic sectors, or bid-rent theory. An alternative modeling perspective is to represent the system at the highest possible level of disaggregation and study the bottom-up emergence of complex patterns and relationships from behavior and interactions at the individual level. Two fundamentally spatial simulation methods are cellular automata and agent-based modeling. Cellular automata modeling imposes a fixed spatial framework such as grid cells and specifies rules that dictate the state of a cell based on the states of its neighboring cells. As time progresses, spatial patterns emerge as cells change states based on their neighbors; this alters the conditions for future time periods. For example, cells can represent locations in an urban area and their states can be different types of land use. Patterns that can emerge from the simple interactions of local land uses include office districts and urban sprawl. Agent-based modeling uses software entities agents that have purposeful behavior goals and can react, interact and modify their environment while seeking their objectives. Unlike the cells in cellular automata, simulysts can allow agents to be mobile with respect to space. For example, one could model traffic flow and dynamics using agents representing individual vehicles that try to minimize travel time between specified origins and destinations. While pursuing minimal travel times, the agents must avoid collisions with other vehicles also seeking to minimize their travel times. Cellular automata and agent-based modeling are complementary modeling strategies. They can be integrated into a common geographic automata system where some agents are fixed while others are mobile. Initial approaches to CA proposed robust calibration approaches based on stochastic, Monte Carlo methods. The method analyzes the spatial statistics of the geological model, called the training image, and generates realizations of the phenomena that honor those input multiple-point statistics. A recent MPS algorithm used to accomplish this task is the pattern-based method by Honarkhah. This allows the reproduction of the multiple-point statistics, and the complex geometrical features of the training image. Each output of the MPS algorithm is a realization that represents a random field. Together, several realizations may be used to quantify spatial uncertainty. One of the recent methods is presented by Tahmasebi et al. This method is able to quantify the spatial connectivity, variability and uncertainty. Furthermore, the method is not sensitive to any type of data and is able to simulate both categorical and continuous scenarios. CCSIM algorithm is able to be used for any stationary, non-stationary and multivariate systems and it can provide high quality visual appeal model. Geospatial analysis, or just spatial analysis, [33] is an approach to applying statistical analysis and other analytic techniques to data which has a geographical or spatial aspect [34]. Such analysis would typically employ software capable of rendering maps processing spatial data, and applying analytical methods to terrestrial or geographic datasets, including the use of geographic information systems and geomatics. Basic applications[edit] Geospatial analysis, using GIS , was developed for problems in the environmental and life sciences, in particular ecology , geology and epidemiology. It has extended to almost all industries including defense, intelligence, utilities, Natural Resources i. Oil and Gas, Forestry Spatial statistics typically result primarily from observation rather than experimentation. Basic operations[edit] Vector-based GIS is typically related to operations such as map overlay combining two or more maps or map layers according to predefined rules , simple buffering identifying regions of a map within a specified distance of one or more features, such as towns, roads or rivers and similar basic operations. Descriptive statistics, such as cell counts, means, variances, maxima, minima, cumulative values, frequencies and a number of other measures and distance computations are also often included in this generic term spatial analysis. Spatial analysis includes a large variety of statistical techniques descriptive, exploratory , and explanatory statistics that apply to data that vary spatially and which can vary over time. Advanced operations[edit] Geospatial analysis goes beyond 2D and 3D mapping operations and spatial statistics. GIS-based network analysis may be used to address a wide range of practical problems such as route selection and facility location core topics in the field of operations research , and problems involving flows such as those found in hydrology and transportation research. In many instances location problems relate to networks and as such are addressed with tools designed for this purpose, but in others existing networks may have little or no relevance or may be impractical to incorporate within the modeling process. Problems that are not specifically network constrained, such as new road or pipeline routing, regional warehouse location, mobile phone mast positioning or the selection of rural community health care sites, may be effectively analysed at least initially without reference to existing physical networks. Locational analysis "in the plane" is also applicable where suitable network datasets are not available, or are too large or expensive to be utilised, or where the location algorithm is very complex or involves the examination or simulation of a very large number of alternative configurations. Geovisualization â€” the creation and manipulation of images, maps, diagrams, charts, 3D views and their associated tabular datasets. GIS packages increasingly provide a range of such tools, providing static or rotating views, draping images over 2. This latter class of tools is the least developed, reflecting in part the limited range of suitable compatible datasets and the limited set of analytical methods available, although this picture is changing rapidly. All these facilities augment the core tools utilised in spatial analysis throughout the analytical process exploration of data, identification of patterns and relationships, construction of models, and communication of results Mobile Geospatial Computing[edit] Traditionally geospatial computing has been performed primarily on personal computers PCs or servers. Due to the increasing capabilities of mobile devices, however, geospatial computing in mobile devices is a fast-growing trend. In addition to the local processing of geospatial information on mobile devices, another growing trend is cloud-based geospatial computing. In this architecture, data can be collected in the field using mobile devices and then transmitted to cloud-based servers for further processing and ultimate storage. In a similar manner, geospatial information can be made available to connected mobile devices via the cloud, allowing access to vast databases of geospatial information anywhere where a wireless data connection is available. Geographic information science and spatial analysis[edit] Further information: The increasing ability to capture and handle geographic data means that spatial analysis is occurring within increasingly data-rich environments. Geographic data capture systems include remotely sensed imagery, environmental monitoring systems such as intelligent transportation systems, and location-aware technologies such as mobile devices that can report location in near-real time. GIS provide platforms for managing these data, computing spatial relationships such as distance, connectivity and directional relationships between spatial units, and visualizing both the raw data and spatial analytic results within a cartographic context. Content[edit] Spatial location: Transfer positioning information of space objects with the help of space coordinate system. Projection transformation theory is the foundation of spatial object representation. Geovisualization GVis combines scientific visualization with digital cartography to support the exploration and analysis of geographic data and information, including the results of spatial analysis or simulation. GVis leverages the human orientation towards visual information processing in the exploration, analysis and communication of geographic data and information. In contrast with traditional cartography, GVis is typically three- or four-dimensional the latter including time and user-interactive. Geographic knowledge discovery GKD is the human-centered process of applying efficient computational tools for exploring massive spatial databases. GKD includes geographic data mining , but also encompasses related activities such as data selection, data cleaning and pre-processing, and interpretation of results. GVis can also serve a central role in the GKD process. GKD is based on the premise that massive databases contain interesting valid, novel, useful and understandable patterns that standard analytical techniques cannot find. GKD can serve as a hypothesis-generating process for spatial analysis, producing tentative patterns and relationships that should be confirmed using spatial analytical techniques. Spatial decision support systems SDSS take existing spatial data and use a variety of mathematical models to make projections into the future. This allows urban and regional planners to test intervention decisions prior to implementation.

Chapter 3 : Recent Developments in Spatial Analysis - - Buchzentrum

Spatial Analysis (Statistics) Recent Developments in Spatial Analysis: Spatial Statistics, Behavioural Modelling, and Computational Intelligence.

Chapter 4 : Recent Developments in Spatial Analysis : Manfred M. Fischer :

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In recent years, spatial analysis has become an increasingly active field, as evidenced by the establishment of educational and research programs at many universities. Its popularity is due mainly to new technologies and the development of spatial data infrastructures. This book illustrates some.