“Advanced spatial analytics and management: models, methods and applications”

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SECTION 3. General issues in management

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Advanced spatial analytics and management: models, methods and applications

Abstract

In this contribution, a concept of the integration of spatial predictive analytics and mathematical programs for spatial decision making – namely, advanced spatial analytics and management – is outlined. In particular, selected methods for spatial predictive analytics are discussed, including spatial econometrics and discrete choice analysis. Then, the integration of spatial predictive models in mathematical programs (prescriptive analytics) for facility location and districting is demonstrated. The paper includes illustrative applications which stem from health care, retail, marketing, logistics, and transportation. Based on the discussion, future research perspectives are developed.

Keywords: advanced spatial analytics and management, discrete choice, predictive analytics, spatial econometrics, mathematical programming, prescriptive analytics.
JEL Classification: C44, C35, C21, R41, M31, M21, C53.

Introduction

Geographical or spatial factors – such as location and distance – play an important role in everyday decision making of organizations, since the data used for decision making have a geographic component in nearly all cases (Day et al., 1987; Crossland et al., 1995; Benoit and Clarke, 1997; Vlachopoulou et al., 2001; Grimshaw, 2000; Porter and Stern, 2001; Graf and Mudambi, 2005; and Miller et al., 2006). For many operations, such as health care, finance, energy, insurance, communications, transportation, logistics and retail, location intelligence or spatial analytics provide very specific benefits, which translate into increased revenues, reduced costs, and improved efficiency for any organization. For example, a retail chain may be interested in analyzing the shopping destination choice behavior of their customers to estimate branch patronization of existing and potential branch locations. Based on these estimates, the retail chain might modify its network of branches to increase patronage, revenues, and profits. Using tailored spatial models and methods helps the management to make better locational decisions. In particular, the endogenous incorporation of predictive analytics (choice models, for example) in mathematical decision models (i.e., prescriptive analytics) seems to be beneficial for many decision processes in many operations (MaseTshaba and Seeletse, 2014). For example, in planning of the network of lines for a public transport service provider one usually employs customer demand as an input factor (i.e., a parameter). However, a given network of public transport lines (i.e., a solution) yields a specific demand by public transport users. Thus, demand must be treated endogenously, i.e., as a variable. As a consequence, reliable demand models need to be incorporated in public transport line planning models. The same is true for locating preventive health care facilities, for example (Krohn et al., 2016). A given set of located facilities triggers the participation of (potential) clients. If we do not consider the choice (decision) behavior directly within the facility location model by adequate spatial choice models, we might end up with bad locational decisions and, as a consequence, with low participation rates (and the corresponding effects).

This leads us to two crucial questions: (i) what are adequate spatial predictive models, and (ii) how can we incorporate them in mathematical models for decision making? To answer these questions, we, first, discuss selected spatial predictive models and how these might be applied in management and economics. Since these models are based on empirical data, we distinguish between (spatially) aggregated data and disaggregated (or individual-level) data. This discrimination is meaningful, because spatial aggregation usually comes along with continuous measures of the dependent variable of the predictive models, while individual-level (choice) data yield categorical dependent variables. Of course, we might further distinguish between cross-sectional and longitudinal data. The predictive models considered here stem from the realm of spatial econometrics (spatial error models, for example) and discrete choice analysis (multinomial logit model, for example). Second, the description of the spatial predictive models and the discussion of illustrative applications is followed by an elaboration of how the spatial predictive models are incorporated in mathematical spatial decision models (i.e., prescriptive analytics). In particular, we consider facility location models and districting models. The applications presented here range from the analysis of destination choice behavior and service quality to the planning of facility locations of retail branches and the alignment of sales territories.

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1. Spatial predictive analytics

Predictive analytics can be seen as an arsenal of statistical techniques that enable to analyze current and historical data to make predictions about unknown (future) events (Shmueli and Koppius, 2011; Hair, 2007). In business applications, predictive analytics exploit patterns found in historical and transactional data to support decision makers in their tasks to identify risks and opportunities of unknown events. The respective methods and models disclose relationships between the variable of interest (revenue, for example) and a variety of explaining attributes (service quality, for example) and characteristics. This empirical relationship is, then, used to make – hopefully good – predictions about the future (Taylor, 2012). Now, the crucial point with spatial predictive analytics is to explicitly account for spatial effects in the relationship between the dependent variable (the variable of interest) and the explanatory variables.

1.1. Aggregate data. Assume your variable of interest can take any value. Then, a simple predictive model would consist of a dependent variable and a set of independent or rather predictor variable X. This relationship is expressed as an equation that predicts the dependent variable y as a linear function of the model parameters β:

$$y = X\beta + \varepsilon. \tag{1}$$

These parameters are adjusted so that a measure of fit (a function related to ε) is optimized. Unfortunately, it is well evidenced that the relationship of (1) suffers from bias due to spatial effects underlying the data generating process (Anselin, 2003). So, in presence of space in our data, we might be better off choosing a formal relationship that enables to account for these spatial effects. One such spatial effect occurs if we omit variables from the model which are actually spatially correlated. As a consequence, the errors of our model are spatially correlated. In such a case, the spatial error model

$$y = X\beta + (I - \lambda W)^{-1}\varepsilon \tag{2}$$

would be a good choice, because the correlation is captured via the spatial weights matrix W and the parameter λ (Anselin, 1988; Bradlow et al., 2005; Bronnenberg, 2005)[1]. A second spatial effect is that the relationship in (1) and (2) is not constant over space, i.e., the parameter β might be a function of location. This phenomenon is known as spatial non-stationarity (Wheeler and Paez, 2010). For example, Müller and Haase (2015) show that neglecting spatial effects is likely to yield revenue response functions that produce bad predictions. In particular, they study the relationship between revenue and service quality of a local public transport service provider in Munich, Germany. The study reveals that simple linear regression models suffer from biased parameter estimates due to spatially correlated error terms. The authors employ a spatial error model of (2) to account for this spatial effect. Further, they define the parameters β in (2) as a function of the location of the observations (districts) in order to account for spatial non-stationarity. The findings illustrate that addressing spatial effects of service data can improve management ability to implement programs aimed at enhancing seasonal ticket revenue. The corresponding spatial revenue response function enables managers to identify small scale areas that are most efficient in terms of increasing revenue by service improvement. These findings are confirmed by Mittal et al. (2004) and Müller et al. (2013). Müller et al. (2013) and Müller (2012) employ the geographically weighted regression (GWR) technique (Fotheringham et al., 1997)

$$y = (\beta \otimes X)1 + \varepsilon \tag{3}$$

with

$$\hat{\beta}_i = (X'W_iX)^{-1}X'W_iy \tag{4}$$

to account for spatial non-stationarity. The results of the GWR are included in (2) such that the resulting predictive model (revenue response function) is able to simultaneously account for spatial dependencies (correlated error terms, for example) and spatial non-stationarity. The resulting simultaneous model is new to the literature and shows statistically significant better estimates compared to traditional models.

1.2. Disaggregate data. So far, the data we considered are characterized by a dependent variable that can take any value. In spatial analysis, we usually observe this kind of data, if the underlying data is spatially aggregated: for example, the sum of revenues of public transport customers within a zip-code area. Now, we turn to this underlying data. If we stick to the revenue example, the sum of revenues within a zip-code area is the result of decisions of individuals to choose public transportation for their trips and to pay a certain amount of money for this service. Aggregating this data might yield a loss in information due to aggregation (Müller and Rode, 2013; Rode and Müller, 2016). Therefore, we are interested in analyzing individual-level data. The best method for this kind of analysis is discrete choice analysis (McFadden, 2001): an individual (customer) n chooses an alternative j from the set of all alternatives M,[2] if

[1] I is the identity matrix.

[2] The choice set M must be exhaustive, and the alternatives have to be mutually exclusive. Roughly speaking, all alternatives the individuals face have to be included in the choice set.

$$u_{nj} > u_{nm} \ \forall m \in M, m \neq j. \tag{5}$$

Utility u_{nj} consists of a deterministic component v_{nj} and a stochastic component ε_{nj}, i.e.,

$$u_{nj} = v_{nj} + \varepsilon_{nj}. \tag{6}$$

Usually, the deterministic component is modeled as a linear function:

$$v_{nj} = \sum_{l \in L} \beta_{jl} c_{njl}, \tag{7}$$

where L is the set of attributes or characteristics (attractiveness determinants), c_{njl} is the value of attribute l concerning individual n and alternative j, and the coefficient β_{jl} is the utility contribution per unit of attribute l related to alternative j. β_{jl} are the model coefficients (parameters) to be estimated by maximum likelihood (Ben-Akiva and Lerman, 1985). Since u_{nj} of (6) is stochastic, we can only make probabilistic statements about (5):

$$P_{nj} = Prob(u_{nj} > u_{nm} \ \forall m \in M, m \neq j). \tag{8}$$

Assuming that the stochastic component ε_{nj} is independent, identically extreme value distributed (iid EV), the probability (8) that individual n chooses alternative j is determined by

$$P_{nj} = \frac{e^{v_{nj}}}{\sum_{m \in M} e^{v_{nm}}}, \tag{9}$$

which is the well-known multinomial logit model (Ben-Akiva and Bierlaire, 2003). For example, Müller et al. (2008) employ the multinomial logit model (MNL) to analyze and forecast the mode choice behavior of students in Dresden, Germany. The authors found ranges of commuting distances for which a given transport mode is dominant. This dominance depends on further attributes and characteristics, such as weather and car availability. The specified and validated model is, then, used to predict the changes in market shares of the transport modes due to school closures. Further, they quantified scenarios of school closures by the change in transport cost. However, closing a certain school not only yields a change in the students mode choice behavior, but also shifts the students to the remaining school (van Wyk and Van der Westhuizen, 2015). This, in turn, needs the school choice behavior of students (or their parents, respectively) to be understood (Müller, 2011). Müller et al. (2012) analyzed the school choice behavior of students in Dresden, Germany. Since choosing one school location from a set of spatially dispersed school locations is truly a spatial choice, we might presume that spatial effects underlie this specific choice process (Müller, 2010). The authors, indeed, find strong empirical evidence that the simplifying assumptions that underlie the MNL are breached (i.e., iid EV). They propose a sophisticated spatial nesting structure to relax the independence from irrelevant alternatives property (which stems from the iid assumption) and to reveal the underlying spatial correlations between school locations. In particular, they employ the general nested logit model (GNL)

$$P_n(i|C_n) = \sum_{k=1}^{K} \frac{\left(\sum_{j \in C_{nk}} \alpha_{jk}^{\mu_k/\mu} e^{\mu_k v_{nj}}\right)^{\mu/\mu_k}}{\sum_{m=1}^{K} \left(\sum_{j \in C_{nm}} \alpha_{jm}^{\mu_m/\mu} e^{\mu_m v_{nj}}\right)^{\mu/\mu_m}} \times \frac{\alpha_{ik}^{\mu_k/\mu} e^{\mu_k v_{nj}}}{\sum_{j \in C_{nk}} \alpha_{jk}^{\mu_k/\mu} e^{\mu_k v_{nj}}} \tag{10}$$

with C_n as the choice set (of school locations), K the set of nests (subsets of school locations), C_{nk} as the set of schools that belong to the choice set of n and to nest k, α_{ik} as an allocation parameter that reflects the extent to which alternative i is a member of nest k, and scale parameters μ and μ_k. Although (10) is not a straightforward formulation, it exhibits the advantage of a closed-form model, while allowing flexible correlation – and, thus, substitution patterns – between alternatives (here: school locations). The mixed multinomial logit model (MXL) allows for an even greater flexibility at the cost of a non-closed-form model, though (Seidel et al., 2016)[3]. It is easy to imagine that having a school choice model as (10) at hand would be very important when planning the locations of school facilities in a city, or region (see Section 2.1).

2. Spatial management and planning

In this section, we consider selected spatial decision problems that occur in management and the business industry. First, we show how the MNL can be incorporated into the well-known general maximum capture problem (ReVelle, 1986). This is followed by some extensions (considering capacities and heterogeneous customers) and applications to health care, retail, and school location. Second, we present the integration of revenue response functions in the sales force deployment problem (Drexl and Haase, 1999). The ultimate goal is to illustrate the benefit for researchers and practitioners integrating predictive analytics and mathematical programs for spatial business decision making.

2.1. Location planning. In discrete facility location planning, we are faced with the problem to select locations from a given set of potential facilities with respect to an objective that is optimized. Let us assume that we aim to select r locations from a set

[3] In case of a non-closed-form, the choice probabilities have to be simulated.

of potential facility locations J so that the total customer patronage of the selected facilities is maximized. Further, we assume that the customer choice is modeled by the MNL. Then, we might formulate the problem as

$$\text{maximize} \sum_{i \in I} \frac{\sum_{j \in J} e^{v_{ij}} y_j}{\sum_{j \in M \setminus j} e^{v_{ij}} + \sum_{j \in J} e^{v_{ij}} y_j} \tag{11}$$

subject to

$$\sum_{j \in J} y_j = r \tag{12}$$

$$y_j \in \{0,1\} \quad \forall j \in J \tag{13}$$

with v_{ij} as the deterministic utility of customers located in $i \in I$ choosing facility location $j \in M$. y_j is the decision variable that equals one, if the location $j \in J$ is selected, and zero, otherwise. $M \setminus j$ denotes the set of locations that are not under decision (locations of competitors, for example). Haase and Müller (2014) present a mixed-integer linear reformulation to the non-linear program (11)-(13) that is superior to other reformulations in terms of solvability using a standard integer program solver. The reformulation is based on the constant substitution pattern inherent to the MNL. Haase and Müller (2015) discuss an application to preventive health care facility location planning, where the linear reformulation of (11)-(13) is enhanced by capacity constraints. It is shown that the original formulation proposed by Zhang et al. (2012) might yield suboptimal results, if the utility function of (7) is not specified in an adequate manner. In particular, Zhang et al. (2012) consider the quality of care exogenously to the choice model. That is, they consider a corresponding constraint within the mathematical program instead of considering this important attribute within the utility function.

Müller and Haase (2014) address the impact of the predictive bias of the MNL due to the independence from irrelevant alternatives property (IIA) of the MNL. They show that this bias can be reduced by more than 15% (based on their studies of retail facility location), if customer segmentation is used. That is, for each demand node i, a set of customer segments S is used. In fact, the IIA applies to each segment S, but not to demand point i over all segments S. However, the predictive bias of the MNL due to the IIA can only be completely eliminated by either a perfect specification of the deterministic utility function or an adequate modeling of the stochastic part of utility in (6). While the former is usually impossible (Ben-Akiva et al., 2002) – in particular, in a spatial context (Hunt et al., 2004) – the latter one is achieved by more sophisticated choice models (see Section 2.2). In Haase and Müller (2013), a MXL is incorporated in a school location planning approach to maximize students utility, while a certain budget must not be exceeded. The MXL does not provide closed-form choice probabilities and, as a consequence, simulation procedures are used to compute the MXL choice probabilities. From a mathematical programming perspective, this yields a stochastic problem (Müller et al., 2009). The authors propose an intelligible Monte-Carlo simulation-based mixed-integer program as the corresponding deterministic equivalent. The problem can be easily solved by standard integer program solvers.

2.2. Districting. Roughly speaking, the districting problem is to partition a set of areas (census blocks, for example) into larger areas, "regions", given an optimization criterion (minimization of the perimeter of the regions, for example) and some feasibility constraints (contiguity, for example). A prominent application of districting appears in sales force deployment (Zolterns and Sinah, 2005; Georgi and Lachmann, 2014). Sales force deployment involves the concurrent resolution of four interrelated subproblems (Drexl and Haase, 1999): (i) sizing of the sales force, (ii) locations of the sales representatives (location planning), (iii) sales territory alignment (districting), and (iv) sales resource allocation. The objective is to maximize profit (Skiera and Albers, 1998). Haase and Müller (2014) propose explicit contiguity constraints to guarantee contiguous sales territories as demanded by many sales organizations. Haase et al. (2016c) propose general model formulations for random utility models. Further, they introduce a semidefinite mixed-integer program to account for the continuous domain of the selling time variable (denoted as t). The problem is solved by a branch-and-price algorithm. The authors consider a general concave profit contribution function

$$p_{ij}(t) = c_{ij} t^b - o_{ij} t, \tag{14}$$

where i is the location of the sales representative, j is the accounts' location, c_{ij} is a profitability parameter dependent on account j and travel time from i to j, o_{ij} is a travel cost parameter, and b is the selling time elasticity ($0 < b < 1$)[4]. The selling time elasticity b is estimated by the methods mentioned in Section 1.1. Now, Haase and Müller (2014) found that the objective function value (i.e., the profit)

[4] To be correct: b is the calling time (time for presenting a product, for example) elasticity. Selling time is the sum of travel time and calling time. Generally, it is assumed that the calling time is a constant fraction of the selling time.

heavily depends on the value of *b*, as shown in Figure 1. Obviously, biased estimates of the selling time elasticity are likely to yield remarkably biased solutions to the sales force deployment problem.

Conclusion

In this contribution, we address the questions such as: what are adequate spatial predictive analytical models and methods, and how can we implement them in mathematical programs for spatial decision making? We delineated selected methods for spatial predictive analytics and we showed how they can be incorporated in facility location problems and districting problems. This integrated approach might be defined as advanced spatial analytics and management. An excerpt of the constitutive work towards advanced spatial analytics and management has been discussed here. However, from this point, several new and demanding challenges appear. For example, the integration of decision variables into the utility function of locational choice models (waiting time and quality of care in preventive health care facility planning). The consideration of multiple choices of customers (i.e., a customer is choosing more than one location, for example) may be an interesting endeavor as well.

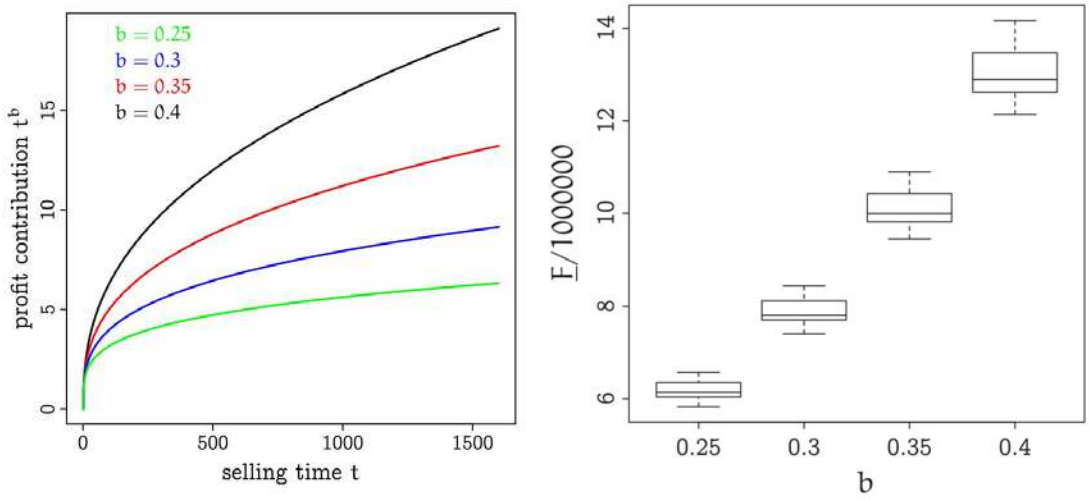

Fig. 1. Profit contribution, profit *F*, and elasticity *b*. Assuming c_{ij} = 1 and o_{ij} = 0

Figure (a) shows that the profit contribution remarkably varies in *b*. The same is true for the coherence of the objective function value *F* and elasticity *b* (Figure (b)). The box blots summarize results over 30 randomly generated instances.

Source: Haase and Müller (2014).

Although we have outlined a wide range of applications (health care, retail, transportation etc.), the use of advanced spatial analytics and management in further applications might be fruitful (Kassens-Noor et al., 2015; Haase et al., 2016a; Haase et al., 2016b; Müller and Haase, 2016b). Moreover, applying this approach in other domains within management and business industry would help to establish the idea of integrating (spatial) analytics and mathematical programming. For example, we might consider a social space (social distance) instead of a geographical space in predictive models ("socio-spatial error models"). Or we might consider predictive models forecasting the choice of products instead of locations to be selected according to an optimization principle (assortment optimization).

One final insight can be gained from this contribution: researchers and practitioners benefit from having expertise in both fields – predictive analytics and mathematical programming – to adequately tackle problems that arise in management and business industry.

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