8 Principles of Neural Spatial Interaction Modeling

Manfred M. Fischer

Department of Economic Geography & Geoinformatics, Vienna University of Economics and Business Administration, Nordbergstr. 15/4/A, A-1090 Vienna, Austria.

e-mail: Manfred.Fischer@wu-wien.ac.at

8.1 Introduction

Regional science is a rich discipline at the cross-roads of economics and geography. A closer look at the history of the discipline teaches us that the field of spatial interaction has a long and deep intellectual tradition. That there have been relatively few papers in this field in recent years is merely a function of the hiatus that followed a very active period of theory development in the 1960s and 1970s, the heady days of Stewart and Warntz, Stouffer, Isard, Wilson and Alonso. The empiricism that emanated from their theoretical and methodological contributions filled regional science and geography journals. The lull came not so much because interest decreased, but very little theoretical progress has been achieved. One exception was the excitement over the work of Fotheringham on competing destinations in the early 1980s when several new models were developed and new perspectives added (Fischer & Getis, 1999).

In more recent years, the major influence stems both from the emerging data-rich environment and from technological innovations. The powerful and fast computing environment now available has brought many scholars to spatial interaction theory once again, either by utilizing evolutionary computation to breed novel forms of spatial interaction models (see Openshaw, 1988; Turton, Openshaw & Diplock, 1997) or applying neural network theory to spatial interaction, first proposed by Fischer and Gopal (1994) and later extended by many others (including Fischer & Leung, 1998; Bergkvist, 2000; Reggiani & Tritapepe, 2000; Mozolin, Thill & Usery, 2000; Fischer & Reismann, 2002a, b; Fischer, 2000, 2002a, b; Fischer, Reismann & Hlavackova-Schindler, 2003).

This chapter is intended as a convenient resource for regional scientists interested in a statistical view of the neural spatial interaction modelling approach. We

---

1 It is beyond the scope of this contribution to offer a survey of this tradition. The reader is referred to the wealth of historical material in Carrothers (1956), Isard and Bramhall (1956), Olsson (1965), Wilson (1967, 1970), Batten and Boyce (1986), Fotheringham and O’Kelly (1989), Sen and Smith (1995), among others.
view neural spatial interaction models as an example of non-parametric estimation that makes few, if any, a priori assumptions about the nature of the data-generating process to approximate the true, but unknown spatial interaction function of interest. We limit the scope of this chapter to unconstrained spatial interaction and use appropriate statistical arguments to gain important insights into the problems and properties of this modelling approach that may be useful for those interested in application development.²

The remainder of this chapter is structured as follows. The next section introduces the class of neural spatial interaction models of interest, and sets forth the context in which spatial interaction modelling will be considered. The sections that follow present important components of a methodology for neural spatial interaction modelling.

Section 8.3 discusses the notion of model performance and shows a way how to choose the best approximation and, moreover, formalizes the requirement that a novel spatial interaction model shows good generalization (out-of-sample) performance. Given a sufficiently complex model (that is, sufficiently many hidden units) the role of learning is viewed to find suitable values for the model parameters to approximate the particular function relevant for a given application context.

Section 8.4 defines learning as an optimization problem and briefly reviews two alternative approaches to learning: Gradient descent based local search and global search procedures that are expected to allow the network to escape from local minima during learning.

Motivated by the desire to obtain distributional results for the approximation that rely neither on large scale sample size nor on artificial data-generating assumptions, Section 8.5 shows how the bootstrapping pairs approach provides an unconditional bootstrap distribution and can give trustworthy estimates even if the model is wrong. One of the most important factors in the success of a practical application of neural spatial interaction models is the search for an appropriate technique for determining model complexity. Section 8.6 addresses this issue and provides insights into current best practice to optimize complexity so to perform well on generalization tasks.

Section 8.7 discusses the standard approach for assessing the generalization (out-of-sample) performance of a neural spatial interaction model and suggests the use of bootstrapping to overcome the problem of static data splitting. Finally, Section 8.8 contains some concluding remarks. The references included are intended to provide useful pointers to the literature rather than a complete record of the historical development of the field.

² The reader interested in benchmark comparisons against the classical gravity models is referred to a series of papers by the author (see Fischer, 2002a, b; Fischer & Reismann, 2002b; Fischer et al., 2003).