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Martin Raubal is Professor of Geoinformation Engineering at the Swiss Federal Institute of Technology (ETH) Zurich. He also serves as Director of Studies for Spatial Engineering, as Deputy Academic Director of the MAS (Master of Advanced Studies) Future Mobility and he is a member of the Energy Science Center at ETH Zurich. He was previously Associate Professor and Vice-Chair at the Department of Geography, University of California, Santa Barbara, and Junior Professor at the University of Münster. Raubal received his Dr. techn. in Geoinformation from Vienna University of Technology in 2001 with honors. He holds a M.S. in Spatial Information Science and Engineering from the University of Maine and a Dipl.-Ing. in Surveying Engineering from Vienna University of Technology.

Raubal's research interests lie in the areas of Mobility & Energy, more specifically in mobile Geographic Information Systems (GIS) & Location Based Services (LBS), spatial cognitive engineering, mobile eye-tracking, and GIS for renewable energy analysis. His teaching includes courses on GIS, cartography, geovisualization, location-based services, temporal aspects of GIS, spatial cognition and wayfinding, and research methods. Raubal was Co-Chair of AGILE (Association of Geographic Information Laboratories in Europe) from 2014-19 and he was a board member of UCGIS (University Consortium for Geographic Information Science) from 2008-11. He serves as Associate Editor of the *Journal of Location Based Services*, and on the editorial boards of Transactions in GIS, *Journal of Spatial Information Science, Spatial Cognition and Computation, Annals of the AAG*, *and Geography Compass*. Raubal was the General Chair of the 14th International Conference on Location Based Services in 2018. In 2008 he won the U.V. Helava Award. He has authored and co-authored more than 170 books and research papers published in refereed journals and conference proceedings.

It's the Spatial Data Science, stupid![1]

The long-standing debate of whether Geographic Information Science (GIScience) is a Science or not (Goodchild, 1992; Reitsma, 2012) has made me think about two questions, namely "why do we care?" and more importantly "why don't we strive for something bigger?" With the latter I am implicitly considering Spatial Data Science. Why? Because GIScience is only a part—although an important one—of the big picture that encompasses space and spatial data at a wide spectrum of scales. For this big picture we need Spatial Data Science, including its representations, models, and analysis methods. These are essential for solving many of the world's challenging problems, which do

[1] A snowclone based on the phrase "The economy, stupid,, which James Carville coined as a campaign strategist of Bill Clinton's successful 1992 presidential campaign (https://en.wikipedia.org/wiki/It's_the_economy,_stupid).

not only occur at the geographic scale, e.g., in the domains of mobility, transport, or climate. Examples are manifold, such as in particle physics (creating quantum computers), biology (human genome), or cognitive science (simulating and modeling the human brain). Spatial Data Science is an interdisciplinary endeavor—in fact, one has a hard time thinking of disciplines and domains that should or could not be a part of it—and I find it both necessary and exciting to set an interdisciplinary research agenda that strongly integrates theory, methods, and practice.

Spatial Data Science gives and takes. Being truly interdisciplinary, it certainly draws knowledge, and utilizes methods and insights from other fields, but it also enhances and widens these. Geostatistics with its focus on spatial and spatio-temporal data sets is an early example. It resulted from applying mathematical statistics to the spatial evaluation of mineral resources for mining purposes (Krige, 1951). Spatial dependency, famously expressed through Tobler's First Law of Geography (Tobler, 1970), is now the basis for solving different problems in hydrology, oceanography, or epidemiology.

The recently unprecedented acquisition of spatial data—made possible by the rapid progress of computing, communication, and information technologies—has also led to the application of various machine learning methods in diverse "spatial disciplines," such as geography, transportation science, or environmental science (Raubal, Wang, Guo, Jonietz, & Kiefer, 2018). On the one hand, machine learning is applied to spatial big data in CyberGIS analytics, for spatio-temporal outlier and anomaly detection, and for predicting human spatial behavior. On the other hand, Spatial Data Science contributes to machine learning by proposing methods for spatio-temporal modeling and context integration to achieve better results and higher performance. For example, in the area of mobility and transport, it has recently been demonstrated how graph convolutional neural networks (GCNs) can be used for imputing human activity purposes from GPS trajectory data (Martin et al., 2018). Multiple personalized graphs were utilized to model human mobility behavior and to embed a large variety of spatio-temporal information and structure in the graphs' weights and connections. These graphs served as input to the GCNs, which in turn exploited such structure.

I also find it fascinating how spatio-temporal analysis methods that were developed for a particular geographic domain can be transferred to and utilized in other domains and for different scales. Take, for example, computational movement and trajectory analysis. As defined in (Andrienko et al., 2011), movement data involve geographical space, time, objects in space, and multidimensional attributes. A comprehensive set of methods for computational movement analysis has been developed over time, which allow for trajectory clustering, similarity measurement, movement prediction, or interpolation. But movement data does not necessarily come from geographic space. Studying visual attention and its connection to cognitive processes often happens by analyzing eye-tracking data (Kiefer, Giannopoulos, Raubal, & Duchowski, 2017). More specifically, eye movement data allow for tracking overt visual attention associated with a viewer's point of gaze. Such data consist of fixations and saccades, resulting in so-called scanpaths, which are similar to geographic movement trajectories, but represented at a different scale. These trajectories also consist of pairs (s, t), having a particular position s in space and t in time. The so-called spatial events in geographic trajectories are the fixations in scanpaths. Applying known techniques from computational movement analysis, such as clustering, similarity measurement, or movement prediction, to the analysis of scanpaths will show if such transfer works or whether these two domains require fundamentally different algorithms. In any case, both Spatial Data Science and Cognitive Science will benefit from such methodological exchange.

In conclusion, I strongly believe that setting an interdisciplinary research agenda for Spatial Data Science will benefit not only GIScience by extending its applicability and reach towards other disciplines. It will also facilitate addressing and solving the grand challenges of our society. Therefore, it's the Spatial Data Science, stupid!

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