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Measuring segregation using patterns of daily travel behavior: A social interaction based model of exposure

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ABSTRACT

Recent advances in transportation geography demonstrate the ability to compute a metropolitan scale metric of social interaction opportunities based on the time-geographic concept of *joint accessibility*. The method we put forward in this article decomposes the social interaction potential (SIP) metric into interactions within and between social groups, such as people of different race, income level, and occupation. This provides a novel metric of exposure, one of the fundamental spatial dimensions of segregation. In particular, the SIP metric is disaggregated into measures of inter-group and intra-group exposure. While activity spaces have been used to measure exposure in the geographic literature, these approaches do not adequately represent the dynamic nature of the target populations. We make the next step by representing both the source and target population groups by space–time prisms, thus more accurately representing spatial and temporal dynamics and constraints. Additionally, decomposition of the SIP metric means that each of the group-wise components of the SIP metric can be represented at zones of residence, workplace, and specific origin–destination pairs. Consequently, the spatial variation in segregation can be explored and hotspots of segregation and integration potential can be identified. The proposed approach is demonstrated for synthetic cities with different population distributions and daily commute flow characteristics, as well as for a case study of the Detroit–Warren–Livonia MSA.

1. Introduction

Residential segregation refers to the sorted patterning of population groups into different neighborhoods, and measures of segregation attempt to quantify the degree of separation between two or more population groups (Massey and Denton, 1988). Decades of research have shown that residential segregation is associated with spatial inequalities in service provision causing racial disparities in health (Williams and Collins, 2001), economic outcomes (Massey et al., 1987), educational achievement of youth (Card and Rothstein, 2006), and spatial mismatch between the locations of low-wage workers and employment opportunities (Kain, 1968). Measuring the degree to which minority groups are concentrated in their own neighbourhoods (i.e. ghettoization) is an appropriate way to quantify segregation if the research goal is to identify the existence of segregation or to determine whether it is statistically associated with socioeconomic and health inequalities. For this reason, the Duncan Dissimilarity Index (DI) was the most commonly applied method for measuring racial segregation for many decades (Duncan & Duncan, 1955). The DI is interpreted as the percentage of the minority population that would need to relocate in order to perfectly integrate the residential distributions in a region. In addition to individual or neighbourhood level outcomes, segregation is also theorized to be associated with societal outcomes of the region like social cohesion (Tumin, 1953; Wilkinson, 2002). Defined as the degree to which different members of society work together for their common good (OECD, 2011), social cohesion depends on bridging network relations across social groups, requiring the existence of opportunities for communication and social interaction (Forrest and Kearns, 2001). Notwithstanding the societal implications of bridging social interactions, social networks may also be of interest for their production of social capital (Coleman, 1988). In either case, exposure has evolved as a dimension of segregation that is better suited to the measurement of interaction opportunities.

Following a decade of heightened criticism of the DI and the development of more than 20 new segregation indices, Massey and Denton (1988) determined that segregation could be explained by a set of five principal dimensions: evenness, exposure, concentration, centralization and clustering. Of these, we highlight the particular salience of exposure in this research. It “refers to the degree of potential contact, or the possibility of interaction, between minority and majority group members within geographic areas of a city” (Massey and Denton, 1988, 278).

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The interaction index is the archetypical measure of exposure cited in the literature (Bell, 1954; Lieberson, 1981). Massey and Denton eloquently describe it as “the minority-weighted average of each spatial unit's majority proportion” (Massey and Denton, 1988, 288). Borrowing notation from Wong and Shaw (2011) we can measure the exposure of group a to group b as:

$$P_{a\times b} = \sum_{i=1}^{n}\left(\frac{a_i}{A}\right)\left(\frac{b_i}{t_i}\right) \tag{1}$$

where a_i, b_i and t_i are the population counts of the two groups and the total population in zone i respectively, A is the total population of group a in the region, and n is the number of residential zones in the region. This interaction index evaluates the contact probability of the majority to the minority group within each residential zone, ignoring the potential for contact with members of the majority group living and working in different zones as people go about their daily activities. Importantly, this index is extendable to three or more population groups, and reversible, so that measures of isolation can also be obtained. A number of authors have sought to expand potential interaction spaces to areas outside of the residential zone by fusing segregation measures with spatial statistics (Morgan, 1983; Wong, 1993; Wong, 2002; Reardon and O'Sullivan, 2004), or by adopting more explicit activity–space approaches to measuring segregation (Schnell and Yoav, 2001; Wong and Shaw, 2011) and there is now a call for research that continues to move beyond measuring segregation within residential neighbourhoods to better capture people's experience of segregation over the course of their daily lives (Kwan, 2009, 2013).

The goal of this article is to draw on research developments in measuring metropolitan scale social interaction potential (Farber et al., 2012) and to quantify exposure using a time-geographic approach (Hägerstrand, 1970). Moreover, we are interested in developing a metric that is readily computable and comparable between regions so that hypotheses regarding the impacts of the spatial structure of regions (i.e. the patterns of where people live, work, and conduct their daily activities) on social contact opportunities can be explored. Specifically, we would like to extend this line of inquiry into an improved understanding of the relationship between spatial structure of regions and opportunities for between-group and within-group interaction potentials.

The rest of the article is organized as follows. First, we review the recent advances in segregation research, focusing on activity-based measurement approaches. Next we put forward our proposed measure of exposure that is based on the concept of social interaction potential. Following this, we describe the results of a simulation experiment designed to test the behaviour of the new metric with respect to its input parameters. After, the metric is applied in an empirical case study focussing on Detroit, Michigan, the most residentially segregated city in the US according to a recent study (Logan and Stults, 2011). Finally, we discuss the results, contextualize the knowledge gained through this research, and provide our thoughts on future research in this area.

2. Literature review

Our paper is part of a wider discourse aimed at using daily activity patterns to address the Uncertain Geographic Context Problem (UGCoP) which states that relationships between neighbourhood units and individual behaviours and outcomes are inherently fraught with errors associated with the unknown definitions of relevant spatial and temporal contexts (Kwan, 2012b, 2012a). By using activity patterns of individuals in a city, we are more succinctly defining a relevant spatiotemporal context in which to measure opportunities for social interaction between social groups.

Although this line of inquiry is recent, there has been a flurry of research activity using activity patterns to measure aspects of segregation. The existing research can be grouped into three categories. First are the papers that describe and visualize activity spaces belonging to members of different social groups in order to discover evidence of isolation, limited mobility, and ethnic partitions of activity spaces. For example, Lee and Kwan (2011) developed four visual methods to identify and describe socio-spatial isolation amongst South Koreans living in Columbus, Ohio. Similar work investigates three-way separation between activity spaces belonging to Palestinians, secular Jews and ultra-orthodox Jews living in Jerusalem (Greenberg Raanan and Shoval, 2014). Wang et al. (2012), for their part, visualize activity spaces of residents of different urban enclaves in Beijing and find statistical differences between spatiotemporal characteristics of activity patterns. These works are based on relatively small samples and are primarily visual and descriptive in nature. Importantly, there is no attempt to generalize findings into a replicable or transferable measure of segregation or exposure.

The second category of work in this area includes attempts at measuring exposure by better defining individuals' geographic context using travel behaviour data, and measuring exposure through the intersection of the derived activity spaces of individuals with static census-based residential population counts. Wong and Shaw (2011) evaluated individual-level exposure measures using the collection of administrative zones visited by respondents of a travel diary survey. Each individual in the survey was considered potentially exposed to the residential population in the administrative zones visited. From this, an index of white–black exposure was built on the propensity of white respondents to visit zones in which black populations reside. Farber and Páez (2012) extend this approach by implementing a model-based activity space, and by placing the exposure measurement within a statistical inferential framework based on the G_i^* local statistic (Getis and Ord, 1992). While both approaches use sophisticated conceptualizations of the activity space, neither of them adequately represents the dynamic nature of the target population. In both cases, the measure of exposure is based on a simple static target population aggregated to zonal centroids. In other words, while activity spaces are used to generate more realistic representations of the geometries of the geographic context a person is exposed to, the context itself is still merely attributed with static residential population counts.

A third group of papers address this shortcoming by representing both source and target populations with detailed spatiotemporal activity patterns. In a methodologically innovative study, mobile phone location data was used to build activity spaces for ethnic Russians and Estonians living in Estonia (Silm and Ahas, 2014a, 2014b). Using location data of nearly half of the country's population, over a three-year period, the researchers developed a time series of Russian and Estonian concentrations in neighbourhoods throughout Estonia. This data was then analyzed for temporal shifts in segregation on daily, weekly, and seasonal scales. The research identified that workday levels of segregation are far lower than evening and weekend levels, when people have more discretion to self-sort themselves into households and discretionary activity locations. In a similar vein, Palmer (2014) developed a spatial proximity index for grouped GPS trajectory data. Importantly, through spatial Monte Carlo simulations, it was demonstrated that the small sample bias of the proximity estimator disappears when the sample of trajectories approaches several hundred.[1]

Analyzing spatio-temporal activity patterns using mobile phone and GPS data allows very accurate measurement of the spatiotemporal contexts of both source and target populations. However, these data are often semantically poor. Mobile phone and GPS trajectory data are seldom associated with socioeconomic attributes of the phone's owner or user. One could quite readily establish the phone's home location,

[1] Palmer computes a proximity index using a sample of GPS trajectories. The index is a sample estimate of the true population index that could only be computed if we had trajectories for the entire population of the city. Palmer shows that as the sample size gets larger and larger, the difference between the sample estimate and population index shrinks, and for samples of several hundred respondents, there is essentially no bias in the estimate.