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Understanding neighborhood isolation through spatial interaction network analysis using location big data

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Abstract
Hidden biases of racial and socioeconomic preferences shape residential neighborhoods throughout the USA. Thereby, these preferences shape neighborhoods composed predominantly of a particular race or income class. However, the assessment of spatial extent and the degree of isolation outside the residential neighborhoods at large scale is challenging, which requires further investigation to understand and identify the magnitude and underlying geospatial processes. With the ubiquitous availability of location-based services, large-scale individual-level location data have been widely collected using numerous mobile phone applications and enable the study of neighborhood isolation at large scale. In this research, we analyze large-scale anonymized smartphone users' mobility data in Milwaukee, Wisconsin, to understand neighborhood-to-neighborhood spatial interaction patterns of different racial classes. Several isolated neighborhoods are successfully identified through the mobility-based spatial interaction network analysis.

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Narrative

Residential segregation within neighborhoods continues to decline. Yet, the segregation, especially in urban areas, still warrants attention (Amini et al., 2014; Clark, 1986; Jarvis, 2015). A growing body of scientific literature argues that disadvantaged neighborhoods of minority and/or poor residents face challenges to access what many experts refer to as social or opportunity isolation (Acevedo-Garcia et al., 2003; Saenz, 2005; Wilson, 2012). Among these opportunities includes a lack of safe and healthy living environment, a lack of access to higher-paying jobs, and education. However, the assessment of spatial extent and the degree of isolation outside the residential neighborhoods at large scale is challenging, which requires further investigation to understand and identify the magnitude and underlying geospatial processes.

Neighborhood isolation is thought to be prevalent in metropolitan Milwaukee, Wisconsin, as Milwaukee has suffered from systemic racism such as redlining for years. In June 2019, the city government declared racism as a public-health crisis (Pierre, 2019). According to the recent American Community Survey, Milwaukee is the most segregated area in the USA (Frey, 2019). The primary focus of our analysis evaluates the extent of race as a limiting or privileging role for Milwaukee neighborhood mobility.

In order to investigate race's role in mobility, we first apply graph theory to construct spatial interaction communities (Gao et al., 2013; Shi et al., 2015). Specifically, an undirected and weighted graph from a three-column data frame in the form of (*V1*, *V2*, weight), where *V1* and *V2* are the origin and destination neighborhoods obtained through the SafeGraph database[1] and the weight representing the total number of visits between two census block groups (CBG) *V1* and *V2* during the one-month data collection period in October 2018. SafeGraph aggregates anonymized location data from numerous mobile applications covering millions of users in order to provide insights about physical places. These data consist of "pings," each identifying the coordinates of a smartphone at a moment in time. To enhance privacy, SafeGraph excludes CBG information if fewer than five devices visited an establishment in a month from a given CBG. We then use the Louvain method of community detection to assign community membership to the graph's edges such that each community is densely connected internally (Blondel et al., 2008). The result is shown by the colored flows in Figure 1, which represent different communities identified through the community detection. For each community, we extract all the census block groups whose origin and thereby destination correspond to the respective community. Next, each CBG identifier is linked to its corresponding demographic information, which comes from the American Community Survey. We sum up the demographic data for all census block groups in each community separately to obtain the comprehensive demographic composition per community. The community flows are overlaid on top of a cartogram of the census block groups to promote a more socially just map (Dorling, 1993). Accordingly, the map is a contiguous cartogram, which preserves the important topology of Milwaukee County while distorting shape to represent the percent of the census block population that is non-white (i.e. Black, Hispanic, Asian, Native American, other). Accordingly, larger census block groups indicate areas with higher proportions of non-white residents, whereas smaller areas indicate areas with lower proportions of non-white residents.

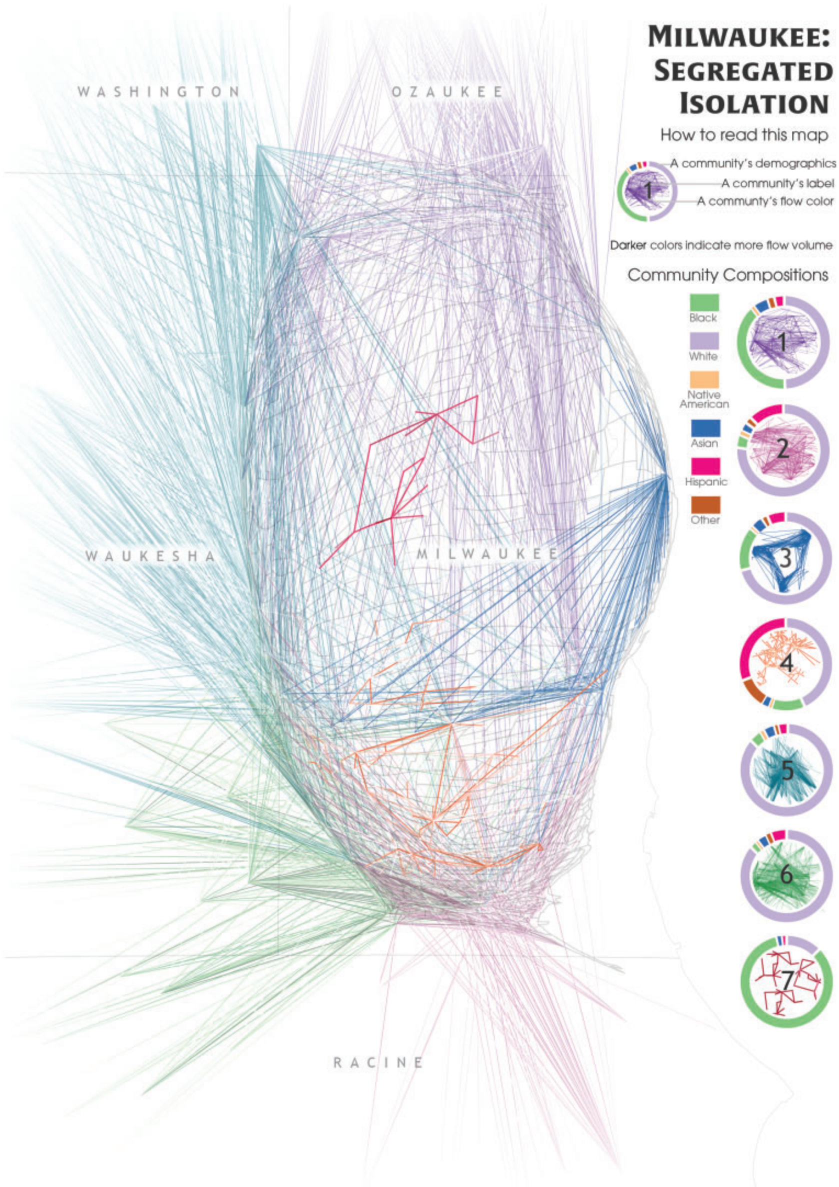

Figure 1. Spatial interactions between Milwaukee communities and their demographic composition with a cartogram base distorted by the percent of the non-white population. (Note: a dark background version of this map without a cartogram base can be accessed online via the link: https://geods.geography.wisc.edu/mke_isolation_dark).

To illustrate our findings, we examine two very different communities in our study area. Community 5 is shown in the figure as teal blue. This community consists of 87.5% White followed by 4.3% Black, 3.5% Hispanic, 3.4% Asian, 0.8% Native American, and 0.5% other. Most of the flows' origins for community 5 reside in counties outside of Milwaukee County. Why do so many white people live outside of Milwaukee, particularly in Waukesha

Table 1. Shannon entropy diversity results for the selected seven communities.

Community	1	2	3	4	5	6	7
Ln Entropy	1.07581	0.81266	0.96382	1.34810	0.54506	0.53424	0.54772

County? The answer is the "white flight." White flight explains a phenomenon in which whites leave places (particularly urban) that are increasingly populated by other races. In Milwaukee, this practice began in the 1950s as legal segregation policies went away and were replaced with so-called practical segregation. In 2002, "less than 1% of residents in the metro area outside the City of Milwaukee lived on integrated blocks," which include both white and black people (Quinn and Pawasarat, 2002: 11). Thus, community 5 represents white flight and an environment of opportunity outside of the inner parts of Milwaukee. In addition, community 7 is shown in the figure in red. This community consists of 84.2% black followed by 12.5% white, 1.8% Hispanic, 1.2% Asian, 0.2% other, and less than 0.1% Native American. Most of this community's travels mainly occur within the black-dominated census-block groups. Moreover, community 7 does not often travel to environments of opportunity throughout Milwaukee, including the central business district and the downtown area.

Moreover, we utilize the Shannon entropy based on natural logarithm (Ln) to measure the racial diversity of each community (Shannon, 1948). As shown in Table 1, the entropy results coincide with demographic composition patterns that communities 1 and 4 with higher entropy have more diverse racial group spatial interactions, while communities 5, 6, and 7 with lower entropy have primarily one dominated racial group spatial interactions within their own community.

Altogether, our computations and the featured graphic show how location big data can help study, quantify, and visualize neighborhood spatial isolation with regards to race. Examining how neighborhood disparities of wealth affect travel to a neighborhood of a different income class warrants future analysis.

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Note

1. https://www.safegraph.com/

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