

Spatio-temporal analysis of socioeconomic neighborhoods

Sergio Rey^{‡,*}, Elijah Knaap[‡], Su Han[‡], Levi Wolf[§], Wei Kang[‡]

Abstract—The neighborhood effects literature represents a wide span of the social sciences broadly concerned with the influence of spatial context on social processes. From the study of segregation dynamics, the relationships between the built environment and health outcomes, to the impact of concentrated poverty on social efficacy, neighborhoods are a central construct in empirical work. From a dynamic lens, neighborhoods experience changes not only in their socioeconomic composition, but also in spatial extent; however, the literature has ignored the latter source of change. In this paper, we discuss the development of novel, spatially explicit approaches to the study of longitudinal neighborhood dynamics using the scientific Python ecosystem.

Index Terms—neighborhoods, GIS, clustering, dynamics

Introduction (.5) (SR, EK, SH, LW, WK)

For social scientists in a wide variety of disciplines, neighborhoods are central thematic topics, focal units of analysis, and first-class objects of inquiry. Despite their centrality public health, sociology, geography, political science, economics, psychology, and urban planning, however, neighborhoods remain understudied because researchers lack appropriate analytical tools for understanding their evolution through time and space. Towards this goal we are developing the *open source longitudinal neighborhood analysis program* (OSLNAP). We envisage OSLNAP as a toolkit for better, more open and reproducible science focused on neighborhoods and their sociospatial ecology. In this paper we first provide an overview of the main components of OSLNAP. Next, we present an illustration of selected OSLNAP functionality. We conclude the paper with a road map for future developments.

OSLNAP

Neighborhood analysis involves a multitude of analytic tasks, and different types of enquiry lead to different analytical pipelines in which distinct tasks are combined in sequence. OSLNAP is designed in a modular fashion to facilitate the composition of different pipelines for neighborhood analysis. Its functionality is available through different interfaces from a web-based front end as a service to a library for scripting in Jupyter notebooks or at the shell. We first provide an overview of each of the main analytical components of OSLNAP before moving on to an illustration of

how selections of the analytical functionality can be combined for particular use cases.

OSLNAP's analytical components are organized into three core modules: [a] data layer; [b] neighborhood definition layer; [c] longitudinal analysis layer.

Data Layer

Like many quantitative analyses, one of the most important and challenging aspects of longitudinal neighborhood analysis is the development of a tidy and accurate dataset. When studying the socioeconomic makeup of neighborhoods over time, this challenge is compounded by the fact that spatial units whose composition is under study often change size, shape, and configuration over time. The *harmonize* module provides social scientists with a set of simple and consistent tools for building transparent and reproducible spatiotemporal datasets. Further, the tools in *harmonize* allow researchers to investigate the implications of alternative decisions in the data processing pipeline and how those decisions affect the results of their research.

Neighborhood demographic and socioeconomic data relevant to social scientists are typically collected via a household census or survey and aggregated to a geographic reporting unit such as a state, county or zip code which may be relatively stable. The boundaries of smaller geographies like census tracts, however, often are designed to encapsulate roughly the same number of people for the sake of comparability, which means that they are necessarily redrawn with each data release as population grows and fluctuates. Figure 1 illustrates the issues involved. Here two census tracts from 2000 have been merged to form a new tract in 2010. However, while one of the original tracts is completely contained in the new tracts, the second original tract is only partially contained in the new tract. In other words, since same physical location may fall within the boundary of different reporting units at different points in time, it is impossible to compare directly a single neighborhood with itself over time.

To facilitate temporal comparisons, research to date has proceeded by designating a “target” geographic unit or zone that is held constant over time, and allocating data from other zones using areal interpolation and other estimation techniques. This process is sometimes known as “boundary harmonization” [LSX16]. While “harmonized” data is used widely in neighborhood research, the harmonization process also has known shortcomings, since the areal interpolation of aggregate data is subject to the ecological fallacy—the geographic manifestation of which is known as the “Modifiable Areal Unit Problem” (MAUP) [Ope84]. Simply put, MAUP holds that areal interpolation introduces bias since the

* Corresponding author: sergio.rey@ucr.edu

‡ Center for Geospatial Sciences, University of California, Riverside

§ School of Geographical Sciences, University of Bristol



Fig. 1: Enumeration Unit Changes [U.S10].

spatial distribution of variables in each of the overlapping zones is unknown. A number of alternative approaches have been suggested to reduce the amount of error by incorporating auxiliary data such as road networks, which help to uncover the “true” spatial distribution of underlying variables, but this remains an active area of research [Sch17], [SQ13], [Tap10], [Xie95].

In practice, these challenges mean that exceedingly few neighborhood researchers undertake harmonization routines in their own research, and those performing temporal analyses typically use exogenous, pre-harmonized boundaries from a commercial source such as the Neighborhood Change Database (NCDB) [Tat], or the freely available Longitudinal Tract Database (LTDB) [LXS14]. The developers of creators of these products have published studies verifying the accuracy of their respective data, but those claims have gone untested because researchers are unable to fully replicate the underlying methodology.

To overcome the issues outlined above, OSLNAP provides a suite of functionality for conducting areal interpolation and boundary harmonization in the `harmonize` module. It leverages `geopandas` and `PySAL` for managing data and performing geospatial operations, and the `pydata` stack for attribute calculations [RA10]. The `harmonize` module allows a researcher to specify a set of input data (drawn from the space-time database described in the prior section), a set of target geographic units to remain constant over time, and an interpolation function that may be applied to each variable in the dataset independently. For instance, a researcher may decide to use different interpolation methods for housing prices than for the share of unemployed residents, than for total population; not only because the researcher may wish to treat rates and counts separately, but also because different auxiliary information might be applicable for different types of variables.

In a prototypical workflow, `harmonize` permits the end-user to:

- query the spatiotemporal database created via the `data` module
 - queries may have spatial, temporal, and attribute filters
- define the relevant variables to be harmonized and optionally apply a different interpolation function to each
- harmonize temporal data to consistent spatial units by either:

- selecting an existing native unit (e.g. zip codes in 2016)
- inputting a user-defined unit (e.g. a theoretical or newly proposed boundary)
- developing new primitive units (e.g. the intersection of all polygons)

Neighborhood Identification 1.5

Neighborhoods are complex social and spatial environments with multiple interacting individuals, markets, and processes. Despite hundreds of years of research it remains difficult to quantify neighborhood context, and certainly no single variable is capable of capturing the entirety of a neighborhood’s essential essence. For this reason, several traditions of urban research focus on the application of multivariate clustering algorithms to develop neighborhood typologies. Such typologies are sometimes viewed as more holistic descriptions of neighborhoods because they account for multiple characteristics simultaneously [Gal01].

One notable tradition from this perspective called “geodemographics”, is used to derive prototypical neighborhoods whose residents are similar along a variety of socioeconomic and demographic attributes [FG89], [SS14]. Geodemographics have been applied widely in marketing [FE05], education [SL09], and health research [PGL⁺11] among a wide variety of additional fields. The geodemographic approach as also been criticized, however, for failing to model geographic space formally. In other words, the geodemographic approach ignores spatial autocorrelation, or the “first law of geography”—that the attributes of neighboring zones are likely to be similar. Another tradition in urban research, known as “regionalization” has thus been focused on the development of multivariate clustering algorithms that account for spatial dependence explicitly. To date, however, these traditions have rarely crossed in the literature, limiting the utility each approach might have toward applications in new fields. In the `cluster` module, we implement both clustering approaches to (a) foster greater collaboration among weakly connected components in the field of geographic information science, and (b) to allow neighborhood researchers to investigate the performance of multiple different clustering solutions in their work, and evaluate the implications of including space as a formal component in their clustering models.

In OSLNAP, the `cluster` module leverages the scientific python ecosystem, building from `geopandas` <<http://geopandas.org/>>‘_, `PySAL` <<http://pysal.org/>>‘_, and `scikit-learn` <<http://scikit-learn.org/>>‘_. Using input from the Data Layer, the `cluster` module allows researchers to develop neighborhood typologies based on either attribute similarity (the geodemographic approach) or attribute similarity with incorporated spatial dependence (the regionalization approach). Given a space-time dataset, the `cluster` module allows users to cluster (a) a single time period, (b) a set of time periods cross-sectionally, or (c) a set of periods pooled as a time series. In (b), neighborhood clusters are independent from one time period to the next. This can be a useful approach if researchers are interested in the durability and permanence of certain kinds of neighborhoods. If similar types reappear in multiple cross sections (e.g. if the k-means algorithm places the k-centers in approximately similar locations each time period), then it may be inferred that the metropolitan dynamics are somewhat stable, at least at the macro level, since new kinds of neighborhoods do not appear to be evolving and old, established neighborhood types remain prominent. The drawback

of this approach is the type of a single neighborhood cannot be compared between two different time periods because the types are independent in each period.

In the third approach (c), clusters are defined from all observations in all time periods. The universe of potential neighborhood types is held constant over time, the neighborhood types are consistent across time periods, and researchers can examine how particular neighborhoods get classified into different neighborhood types as their composition transitions through different time periods. While comparatively rare in the research, this latter approach allows a richer examination of socio-spatial dynamics. By providing tools to drastically simplify the data manipulation and analysis pipeline, we aim to facilitate greater exploration of urban dynamics that will help catalyze more of this research.

To facilitate this work, the `cluster` module provides wrappers for several common clustering algorithms from `scikit-learn` that can be applied. Beyond these, however, it also provides wrappers for several *spatial* clustering algorithms from `PySAL`, in addition to a number of state-of-the-art algorithms that have recently been developed [Wol18].

In a prototypical workflow, `cluster` permits the end-user to:

- query the (tidy) space-time dataset created via the `harmonize` module
 - queries may have spatial, temporal, and attribute filters
- define the neighborhood attributes and time periods and on which to develop a typology
- run one or more clustering algorithms on the space-time dataset to derive neighborhood cluster membership
 - clustering may be applied cross-sectionally or on the pooled time-series
 - clustering may incorporate spatial dependence, in which case `cluster` provides options for users to parameterize a spatial contiguity matrix
- clustering results may be reviewed quickly via the builtin `plot()` method, or interactively by leveraging the `geovisualization` module.

Longitudinal Analysis (WK, SR, EK)

The third major analytical layer of OSLNAP provides a suite of functionalities for the longitudinal analysis of neighborhoods to uncover how neighborhoods evolve over time. Traditional analysis focuses solely on the changes in the socioeconomic composition, while it is argued that the geographic footprint should not be ignored [RAF⁺11]. Therefore, this component draws upon recent methodological developments from spatial inequality dynamics and implements two broad sets of spatially explicit analytics to provide deeper insights into the evolution of socioeconomic processes and the interaction between these processes and geographic structure.

Both sets of analytics take time series of neighborhood types assigned for all the spatial units of analysis (e.g. census tracts) based on adopting a spatial clustering algorithm as the input while they differ in how the time series are modeled and analyzed. The first set centers on *transition analysis* which treats each time series as stochastically generated from time point to time point. It is in the same spirit of the first-order Markov Chain analysis where a (k, k) transition matrix is formed by counting transitions across all

the k neighborhood types between any two consecutive time points for all spatial units. Drawbacks of such approach include that it treats all the time series as being independent of one another and following an identical transition mechanism. The spatial Markov approach was proposed by [Rey01] to interrogate potential spatial interactions by conditioning transition matrices on neighboring context while the spatial regime Markov approach allows several transition matrices to be formed for different spatial regimes which are constituted by contiguous spatial units. Both approaches together with inferences have been implemented in Python Spatial Analysis Library (PySAL)¹ [Rey15] and Geospatial Distribution Dynamics (giddy) package². Our module considers these packages as dependencies and wrap relevant classes/functions to make them consistent and efficient to the longitudinal neighborhood analysis.

The other set of spatially explicit approach to neighborhood dynamics is concerned with *sequence analysis* which treats each time series of neighborhood types as a whole in contrast to *transition analysis*. In this logic, demographic classifications are identified using some clustering method on demographic data alone. Then, the demographic experience of the neighborhood being studied is described by the demographic classifications it experiences over time. From here, neighborhoods can be further clustered or assigned based on how similar their demographic histories are. One method of building this measure of similarity focuses on the neighborhood's "demographic experience" using the optimal matching (OM) algorithm, which was originally used for matching protein and DNA sequences [AT00]. OM scores the similarity of neighborhoods' experiences by finding the minimum number of transformations required to shift one sequence to another using a combination of operations, including replacement, insertion, realignment, and deletion :cite: delmelle2016. Thus, OM is not explicitly "time sensitive," and similarities in demographic transitions are considered "near" regardless of whether or not they are contemporaneous. Another collection of methods does not allow for realignment, so edit distances capture areas' similarity in contemporary experience [LX]. We allow for both contemporaneous and experiential scoring methods and provide further tools to incorporate potential spatial dependence and spatial heterogeneity.

Empirical Illustration

In the following sections we demonstrate the utility of OSLNAP by presenting the results of several sample analyses conducted with the package. We begin with a series of cluster analyses, which are used in the proceeding section to analyze neighborhood dynamics. Typically, workflows of this variety would require extensive data collection, munging and recombination; with OSLNAP, however, we accomplish the same in just a few lines of code. Using the Los Angeles metropolitan area as our example, we present three neighborhood typologies, each of which leverages the same set of demographic and socioeconomic variables, albeit with different clustering algorithms. The results show similarities across the three methods but also several marked differences. This diversity of results can be viewed as either nuisance or flexibility, depending on the research question at hand, and highlights the need for research tools that facilitate rapid creation and exploration of different neighborhood clustering solutions. For each example, we prepare a cluster analysis for the Los Angeles metropolitan

1. <https://github.com/pysal/pysal>

2. <https://github.com/pysal/giddy>

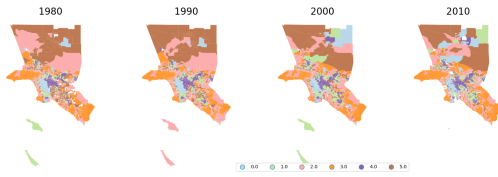


Fig. 2: Neighborhood Types in LA using Ward Clustering.

region using data at the census tract level. We show each clustering solution on a map, describe the resulting neighborhood types, and examine the changing spatial structure over time. For each of the examples, we cluster on the following variables: race categories (percent white, percent black, percent Asian, percent Hispanic), educational attainment (share of residents with a college degree or greater) and socioeconomic status (median income, median home value, percent of residents in poverty).

Agglomerative Ward

We begin with a simple example identifying six clusters via the agglomerative Ward method. Following the geodemographic approach, we aim to find groups of neighborhoods that are similar in terms of their residential composition, regardless of whether those neighborhoods are physically proximate. Initialized with the demographic and socioeconomic variables listed earlier, the Ward method identifies three clusters that are predominantly white on average but which differ with respect to socioeconomic status. The other three clusters, meanwhile, tend to be predominantly minority neighborhoods but are differentiated mainly by the dominant racial group (black versus Hispanic/Latino) rather than by class. The results, while unsurprising to most urban scholars, highlight the continued segregation by race and class that characterize American cities. For purposes of illustration, we give each neighborhood type a stylized moniker that attempts to summarize succinctly its composition (again, a common practice in the geodemographic literature). To be clear, these labels are oversimplifications of the socioeconomic context within each type, but they help facilitate rapid consumption of the information nonetheless. The resulting clusters are presented below in 2.

- Type 0. racially concentrated (black and Hispanic) poverty
- Type 1. minority working class
- Type 2. integrated middle class
- Type 3. white upper class
- Type 4. racially concentrated (Hispanic) poverty
- Type 5. white working class

When the neighborhood types are mapped, geographic patterns are immediately apparent, despite the fact that space is not considered formally during the clustering process. These visualizations reveal what is known as “the first law of geography”—that near things tend to be more similar than distant things (stated otherwise, that geographic data tend to be spatially autocorrelated) [Tob70]. Even though we do not include the spatial configuration as part of the modeling process, the results show obvious patterns, where neighborhood types tend to cluster together in euclidian space. The clusters for neighborhoods type zero and four are particularly compact and persistent over time (both types characterized by racially concentrated poverty), helping to shed light on the persistence of racial and spatial inequality. With these types of visualizations in hand, researchers are equipped not only with analytical tools to

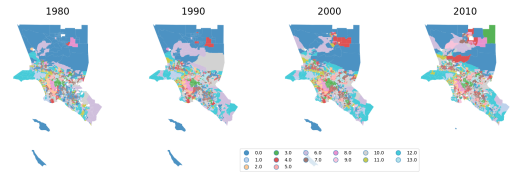


Fig. 3: Neighborhood Types in LA using Affinity Propagation.

understand how neighborhood composition can affect the lives of its residents (a research tradition known as neighborhood effects), but also how neighborhood identities can transform (or remain stagnant) over time and space. Beyond the simple diagnostics plots presented above, OSLNAP also includes an interactive visualization interface that allows users to interrogate the results of their analyses in a dynamic web-based environment where interactive charts and maps automatically readjust according to user selections.

Affinity Propagation

Affinity propagation is a newer clustering algorithm with implementations in scikit-learn that is capable of determining the number of clusters endogenously (subject to a few tuning parameters). Initialized with the default settings, OSLNAP discovers 14 neighborhood types in the Los Angeles region; in a way, this increases the resolution of the analysis beyond the Ward example, since increasing the number of clusters means neighborhoods are more tightly defined with lower variance in their constituent variables. On the other hand, increasing the number of neighborhood types also increase the difficulty of interpretation since the each type will be, by definition, less differentiable from the others. In the proceeding section, we discuss how researchers can exploit this variability in neighborhood identification to yield different types of dynamic analyses. Again, we find it useful to present stylized labels to describe each neighborhood type:

- Type 0. white working class
- Type 1. white extreme wealth
- Type 2. black working class
- Type 3. Hispanic poverty
- Type 4. integrated poverty
- Type 5. Asian middle class
- Type 6. white upper-middle class
- Type 7. integrated Hispanic middle class
- Type 8. extreme racially concentrated poverty
- Type 9. integrated extreme poverty
- Type 10. Asian upper middle class
- Type 11. integrated white middle class
- Type 12. white elite
- Type 13. Hispanic middle class

Despite having more than double the number of neighborhood types in the Ward example, many of the spatial patterns remain when using affinity propagation clustering, including concentrated racial poverty in South Central LA, concentrated affluence along much of the coastline, black and Hispanic enclaves in the core of the city, and white working class strongholds in more rural areas to the north of the region. Comparing these two examples makes clear that some of the sociodemographic patterns in the LA region are quite stable, and are somewhat robust to the clustering method or number of clusters. Conversely, by increasing the number of

clusters in the model, researchers can explore a much richer mosaic of social patterns and their evolution over time, such as the continued diversification of the I-5 corridor along the southern portion of the region.

SKATER

Breaking from the geodemographic approach, the third example leverages SKATER, a spatially-constrained clustering algorithm that finds groups of neighborhoods that are similar in composition, but groups them together if and only if they also satisfy the criteria for a particular geographic relationship¹. As such, the family of clustering algorithms that incorporate spatial constraints (from the tradition known as “regionalization”) must be applied cross-sectionally, and yield an independent set of clusters for each time period. The clusters, thus, depend not only on the composition of the census units, but also their spatial configuration and connectivity structure at any given time.

Despite the fact that clusters are independent from one year to the next (and thus, we lack appropriate space in this text for describing the SKATER results for each year) comparing the results over time nonetheless yield some interesting insights. Regardless of the changing spatial and demographic structure of the Los Angeles region, some of the of the neighborhood boundaries identified are remarkably stable, such as the area of concentrated affluence in Beverly Hills and its nearby communities that jut out to the region’s West. Conversely, there is considerable change among the predominantly minority communities in the center of the region, whose boundaries appear to be evolving considerably over time. In these places, a researcher might use the output from SKATER to conduct an analysis to determine the ways in which the empirical neighborhood boundaries derived from SKATER conform to residents’ perceptions of such boundaries, their evolution over time, and their social re-definition as developed by different residential groups [Hwang2016a]. Regardless of its particular use, the regionalization approach presents neighborhood researchers with another critical tool for understanding the bi-directional relationship between people and places.

In each of the sample analyses presented above, we use OSLNAP to derive a set of neighborhood clusters or types that can be used to analyze the demographic makeup of places over time. In some cases, these maps can serve as foundations for descriptive analyses or analyzed as research projects in their own right. In other cases, in which social processes rather than the demographic makeup of communities is the focus of study, the neighborhood types derived here can be used as input to dynamic analyses of neighborhood change and evolution, particularly as they relate to phenomena such as gentrification and displacement. In the following section, we demonstrate how the neighborhood typologies generated by OSLNAP’s `cluster` module can be used as input to dynamic models of urban spatial structure.

Neighborhood Dynamics

Wei’s Results

Conclusion (0.5)

In this paper we have presented the motivation for, and initial design and implementation of OSLNAP. At present, we are in the early phases of the project and moving we will be focusing on the following directions.

Parameter sweeps: In the definition of neighborhoods, a researcher faces a daunting number of decisions surrounding

treatment of harmonization, selection of variables, and choice of clustering algorithm, among others. In the neighborhood literature, the implications of these decisions remain unexplored and this is due to the computational burdens that have precluded formal examination. We plan on a modular design for OSLNAP that would support extensive parameter sweeps to provide an empirical basis for exploring these issues and to offer applied researchers computationally informed guidance on these decisions.

Data services: OSLNAP is being designed to work with existing harmonized data sets available from various firms and research labs. Because these fall under restrictive licenses, users must first acquire these sources - they cannot be distributed with OSLNAP. To address the limitations associated with this strategy, we are exploring interfaces to public data services such as CenPy and tigris so that users

Reproducible Urban Science: A final direction for future research is the development of reproducible workflows as part of OSLNAP. Here we envisage leveraging our earlier work on provenance for spatial analytical workflows [ARL14] and extending it to the full longitudinal neighborhood analysis pipeline.

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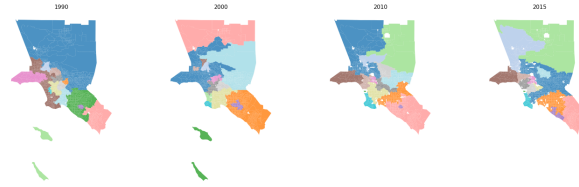


Fig. 4: Neighborhood Types in LA using Skater.

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