May 2020.

Machine Learning in the Chicago School: Modeling Multidimensional Neighborhood Change as a Spatial Markov Process

Despite lively interest and much active research, there remains little consensus on the appropriate ways to measure gentrification and neighborhood change, and even less on the best ways to model the phenomenon. In this paper, we enter the debate by considering a novel model of neighborhood change. Drawing from regional science, social theory, and unsupervised machine learning, we construct a model of gentrification that accounts simultaneously for multiple dimensions of change and incorporates both spatial and temporal effects. The crux of our approach is the consideration of a neighborhood as a bundle of demographic attributes which together describe a discrete 'neighborhood state' rather than a single or series of continuous variable(s). To measure gentrification, we then use spatial Markov Chain models to examine the ways in which neighborhoods transition between states as a function of their previous state and the states of the surrounding neighborhoods. As a result, we capture the nuanced process of demographic change in concert with economic restructuring, while incorporating neighborhood spillover mechanisms, using data with high spatial and temporal resolution. We develop such models for the 15 largest metros in the U.S. and describe how classic social theory can compliment the application of modern geographic data science together lending both insight and forewarning into the process of neighborhood change.

INTRODUCTION

Gentrification has been a topic of lively interest in the urban studies since the concept's introduction by Glass and Rodgers (1964). Despite this interest, empirical work on gentrification remains a major challenge, in large part because "gentrification" is uncannily similar to pornography in its ability to be known only when seen (Vile, Hudson, and Schultz 2014).[1]Post-hoc gentrification is easily identified according to a common narrative, in which a

[1]In the landmark Supreme Court Case Jacobellis v. Ohio 378 U.S. 184 (1964) Justice Potter Stewart famously penned in his concurring opinion that, "I shall not today attempt further to define the kinds of material I understand to be embraced within that shorthand description 'hard-core pornography'; and perhaps I could never succeed in intelligibly doing so. But I know it when I see it, and the motion picture involved in this case is not that."

formerly distressed neighborhood "median family income skyrocketed, minorities virtually disappeared, and educated professionals became dominant in the resident work force. As for the housing stock, the apartments and town houses… appeared in the census data along with a significant percentage of new housing units constructed on the empty lots left after the demolition of structurally unsound housing and nonresidential buildings. Turnover increased as numerous new households moved into the neighborhood, and the value of owner-occupied units tripled" (Beauregard 1990).[2] When so many indictors point in the same direction, gentrification is easily identified, but when neighborhood attributes change simultaneously at different rates and scales, the task of identifying neighborhoods in transition, or those having passed the tipping point of change, becomes much more difficult.

Thus, despite lively interest and much active research, there remains little consensus on the appropriate ways to meaure gentrification and even less on the best ways to model the phenomenon (Freeman 2005; Hwang and Lin 2016). In this paper, we enter the debate by considering a novel model of neighborhood change. Drawing from regional science, social theory, and simple unsupervised machine learning, we construct a model of gentrification that accounts simultaneously for multiple dimensions of change and incorporates both spatial and temporal effects. The crux of our approach is the consideration of a neighborhood as a bundle of demographic attributes which together describe a discrete 'neighborhood state' rather than a single or series of continuous variable(s).

To measure gentrification, we thus treat neighborhood change as a spatial Markov process and develop models to examine the ways in which neighborhoods transition between discrete states as a function of their previous state and the states of the surrounding neighborhoods. We develop our models using annual, block-level LEHD data which include information about the location of both workers and employers in the USA. As a result, our model captures a wide variety of crucial information often overlooked in quantitative studies of neighborhood change. We model the nuanced process of residential turnover in concert with economic restructuring, leveraging data with high spatial and temporal resolution and incorporating concepts of neighborhood spillovers and spatial dependence. We develop such models for the 15 largest metros in the U.S. and describe how the application of modern geographic data science can lend both insight and forewarning into the process

[2] In this particular example, Beauregard is describing the Society Hill neighborhood in Pittsburgh, but this description could likely be applied to nearly any city undergoing gentrification.

of neighborhood change.

MEASURING NEIGHBORHOOD CHANGE

Although the gentrification literature began to emerge in the 1970s, scholarly work on neighborhoods and neighborhood change more broadly extends back 100 years to the formation of the fabled Chicago School of urban sociology and its study of ethnic enclaves, invasion, and succession. Early concepts of neighborhood change were explicitly spatial, with "invasion" and "succession" drawing from the ecological concepts of adjacent wildlife habitats. Much of today's gentrification literature, however, is *aspatial* in that most studies eschew formal analyses of spatial relationships in their models. Furthermore, a singular focus on "gentrification," while often necessary from a methodological (or workload) perspective, nonetheless restricts analyses of neighborhood change to a specific (if ill–defined) form thereof, possibly overlooking important substantive changes elsewhere. For that reason, we are concerned with gentrification as a particular process of specific concern, but we also situate this article within the broader literature on neighborhood change.

Neighborhoods, Social Areas, Urban Spatial Structure

Urban sociologists have defined a neighborhood as a population which resides in an identifiable section of a city. One lasting perspective of classification of neighborhoods is that of the "natural area," organized according to the Chicago School framework of Park, Burgess, and McKenzie (1925). The natural area is geographically distinct; has a unique social, demographic or ethnic composition; a social system that functions as a mechanism of social control; and emergent behaviors or ways of life that distinguish it from other areas (Schwirian 1983). Within this framework, Park and the Chicago School popularized the use of the terms invasion and succession, borrowed from the then-growing field of ecology, to describe neighborhood change. Invasion refers to in-movement of newcomers of different social backgrounds into a social area. This can result in a new neighborhood equilibrium, or a process of succession, by which the original population withdraws and is replaced by additional newcomers (Park 1952).

Early neighborhood change research in the 1960s and 70s attempted to classify and predict neighborhood invasion and succession patterns. This empirical work aimed to understand the ongoing process of white flight from central cities by identifying "tipping points," or the point at which white flight occurs in a neighborhood (Schelling 1972). That research, though descriptive, was not theoretically fruitful. Goering (1978, 77) concluded that "There is currently no a priori basis for predicting what will happen when a specific area begins to experience racial transition... All data and analyses to date suggest it is incorrect to postulate an iron law of demographic change as the key to the process of racial transition," and in doing so helped cement that invasion and succession, while observable processes, were not predictable social laws.

Another early school of neighborhood change was the life-cycle model, advanced by (Hoover and Vernon 1959). In Anatomy of a Metropolis, Hoover and Vernon described a five stage process for neighborhoods, in this sequential order: development, transition, downgrading, thinning out, and renewal (Hoover and Vernon 1959). This model was used to describe the ongoing processes of abandonment and renewal ongoing in central cities across the US in the 1960s and 1970s (Muth 1969). Glass and Rodgers (1964) coined the term "gentrification" to describe invasion and reinvestment in working class neighborhoods in London. Fascination with a similar pattern in some American inner cities in the 1970s spawned an energetic flurry of multidisciplinary research that sought to empirically and theoretically ground the gentrification processes ongoing therein (Henig 1980; London, Lee, and Lipton 1986; Smith 1979; Sumka 1979; Ley 1986).

These early studies of gentrification sought to identify or explain the neighborhood renewal and upgrading process, without simultaneously measuring neighborhood change more broadly. We follow these authors and posit that gentrification as a neighborhood change process can rest within a framework of Chicago School succession and invasion, through invasion and succession by middle-income families; and also within the life-cycle model, through the renewal stage.

Defining Gentrification and Relevant Neighborhood Change

One of the most vexing issues in neighborhood change research is that important terms like "decline", "disinvestment", or "gentrification", while generally understood, are ill-defined, with fuzzy boundaries that define where they begin and end. For that reason, "the term gentrification inevitably generates controversy and disagreement. People disagree about its definition, its causes, and, above all, its consequences. All seem to agree, however, that whatever gentrification is, it is becoming more prevalent in U.S. cities" (Ellen and Ding 2016). Despite the difficulty, it is clear that any study of gentrification or neighborhood change must begin by specifying a research question that defines precisely what "gentrification" means. In the American context, gentrification is most closely associated with neighborhoods like Brooklyn that have experienced simultaneous change in racial, economic, housing market, and employment firm makeup.

Despite its usage in today's parlance, the term "gentrification" has certainly evolved in its academic use over time, since, "At the theoretical level, Glass's (1964) original formulation of the concept of gentrification occurred in the East End of London, a conglomeration of working-class neighborhoods that were at that time populated predominantly by Whites. Hence, at its inception, the concept of gentrification was silent on ethnoracial factors" (Timberlake and Johns-Wolfe 2017). In many contexts racial turnover is considered an explicit and necessary part of gentrification, whereas elsewhere it is considered a byproduct, if anything.

Thus in some cases, it has been defined broadly; Freeman (2005) defines gentrification simply as "the process by which decline and disinvestments in inner-city neighborhoods are reversed". Such definitions are useful in that they comport with our common understanding of the term and provide for general discussion without the need to quibble over terminology, but broad definitions also do little to advance a notion of the process that is quantifiable. This is in part because "more problematic is the operational definition of gentrification," for which early scholarship had "Two options… available: indicators of housing market activity (such as price changes, renovations, turnover rates, or building permits) or measures of changing household status drawn from the census", and since the former often requires prohibitively-difficult data collection efforts, most studies resort to the latter (Ley 1986, 526).

Others such as Freeman (2005) and Chapple (2009) are far more specific, defining gentrification as "a central city neighborhood with housing price appreciation above the regional average, increase in educational attainment above the regional average, and household income at or below the 40th percentile of regional household income". This is a sound definition but also constrains gentrification to to both a particular place (central cities) and socioeconomic thresholds that could also be up for debate. More precise definitions beg questions such as, can gentrification still occur in neighborhoods that do not exceed the income and housing price thresholds defined here? Or, does gentrification occur *solely* in central cities? Given the well-known pattern of urban disinvestment and suburban white flight that characterized American metropolitan regions through the last half-century, central cities were the first to exhibit signs of gentrification as the "back to the city" movement awoke, but suburban areas can also decline and revitalize, bringing along substantive socioeconomic change. Indeed recent work contests the notion that only central cities can gentrify, and has shown that suburban spaces can be similarly susceptible to rapid processes of change, gentrification, and displacement (W. Lung-Amam, Pendall, and Knaap 2019; Markley 2017; W. S. Lung-Amam 2019). As the gentrification literature continues to grow it is increasingly clear that while scholars agree on its importance as a topic of study, none have provided the penultimate and unassailable definition thereof.

NEIGHBORHOOD DYNAMICS AS TEMPORAL GEODEMOGRAPHICS

Apart from gentrification literature entirely, one of the oldest threads in neighborhood research is the concept of a spatially-defined "social area". Another tradition from the Chicago School, social areas consist "of all those urban subareas with similar combinations of residents' social characteristics on status, familism, and ethnicity. The subareas need not be contiguous. Their similarity arises from the social similarity, not the physical proximity of their residents" (Schwirian 1983). Since the 1950s, scholars in sociology and human geography have used various quantitative techniques to identify empirical social areas, first using principal components and factor analysis, and later using multivariate clustering analysis (Shevky and Williams 1949; Shevky and Bell 1955; Anderson and Bean 1961). The move from factor analysis to cluster analysis represents a shift in nomenclature from social area analysis to "geodemographics," but the theoretical underpinnings remain consistent. Geodemographics have a long history in geography and urban studies, and have been used in a variety of applications in both the public and private sectors, including urban planning, public health delivery, and targeted marketing (A. Singleton and Longley 2009b, 2009a; Longley 2012; Singleton and Spielman 2014; Webber and Burrows 2018).

Identifying Neighborhood Prototypes with Unsupervised Learning

Multivariate clustering is technique for unsupervised machine learning designed to collect observations into a set of groups, each of which share similarity in several variables. While certain longstanding ML techniques like cluster analysis are seeing a revival in the current era of data-science obsession, "cluster analysis is an established and appropriate approach to identifying the most substantial distinctions among a large number of diverse neighborhoods", and has been used in neighborhood analysis for decades (Owens 2012, 353).

There are a wide variety of clustering algorithms in today's machine learning toolbox, and while few were designed for explicit application in human geography, many have nonetheless been employed for geodemographic research. Various authors have turned to k-means, hierarchical clustering (A. Singleton and Longley 2009b; Spielman and Singleton 2015), or self-organizing maps (SOMs) (Singleton and Spielman 2014), each of which have particular strengths in differentiating a variety of sizes and shapes of multivariate clusters. While several authors have devised geodemographic typologies for studying urban areas, the concept of developing and analyzing *changes* in geodemographic typologies is a rather new pursuit in academia. This new trend is a useful addition to the literature on neighborhood dynamics, neighborhood change, and gentrification, however, since comparing successive geodemographic classifications facilitates the identification of many different types of neighborhood change beyond simple ascent, decline, or stagnation (Wei and Knox 2014; Ling and Delmelle 2016; Delmelle 2017).

Modeling Neighborhood Change as a Spatial Markov Process

Conceiving urban spatial change as a Markov process is not a novel idea and was first applied in the early 1970s to test the very theory of the Chicago School and the spatial structure it posits (Hagerty 1971; Bell 1974; Tang, Wang, and Yao 2007). Since Markov chains operate on discrete data, however, early work on urban transitions used quantization and pre-defined thresholds to turn continuous neighborhood variables into discrete categories. With the adoption of geodemographics and unsupervised learning, however, permits the analysis to proceed without forcing the analyst to make arbitrary decisions about cutoff criteria that distinguish neighborhood characteristics. Put differently, leveraging geodemographics means that researchers need not identify neighborhoods that are less than 30% of the area median income and instead these thresholds are endogenized through the model.

Apart from endogenized thresholds, another way to improve neighborhood modeling in the modern era is to include spatial effects in the modeling process. Spatial Markov chains developed to understand dynamics of spatial economies and the methodology necessary for developing them has been codified into the open-source pysal spatial analysis library (Hammond 2004; Rey and Janikas 2005; Bosker and Krugell 2008). Recent work has used geodemographics and Markov chain analysis to measure neighborhood change but it ignores issues of spatial dependence. Apart from a misspecified model, excluding spatial effects is conceptually inaccurate given the way the Chicago School describes the model of neighborhood change (Delmelle 2015, 2017, 2019)

Rather than Markov chains, Delmelle (2016) creates a temporal geodemographic classification, then uses an optimal matching algorithm to examine similarity between long-term neighborhood sequences. Following, she runs a second cluster analyses on the results of the optimal matching output. This process categorizes neighborhoods into types that have followed the same general trajectories over time (e.g. labelled persistently struggling or stable elite) but does not describe why these trajectories emerge or which neighborhoods might be likely to diverge in the future. Neither does the sequence cluster method provide any insight into the underlying reasons or processes that define the trajectories. Put differently, identifying sequence clusters provides a rich description of prototypical neighborhood evolutions in a given study area, but is not designed to probe the underlying logic of why different pathways emerge. By contrast, the spatial Markov method analyzes which neighborhood types transition into other types, and how these transitions differ under different conditions of socio-spatial fabric. This means the spatial Markov approach is well-positioned to examine whether sociological theories of neighborhood change (such as ecological invasion and succession) are borne out in the empirical data.

NEIGHBORHOOD CHANGE IN AMERICA'S 15 LARGEST METROS

As Hagerty (1971) describes, "As an ideal test of the statically interpreted Burgess formulation, it would be best to divide each city into five zones delimited by social area analysis and observe changes in the five zones over time". For our present work, we perform exactly such an analysis, save that we permit the zones to range from two to seven, depending on the best cluster model fit, and we expand on Hagerty's Markov chain analysis to text explicitly spatial relationships such as those implied by the succession and invasion model. In so doing, we examine two Chicago School school hypothesis of urban spatial structure and neighborhood dynamics: that social areas can be uncovered empirically in a given city, and that processes of invasion and succession help guide the transition between social areas in the city. Transitions between certain types of neighborhoods (e.g. types differentiated by SES indicators) will be taken as evidence of gentrification, but transitions of other types (e.g. between types differentiated solely by racial indicators) may also be taken as evidence of important substantive change, either constituent of, or related to gentrification

Study Data

As discussed above, gentrification studies in general, and modeling exercises in particular, tend to rely on decennial census data, typically at the tract level because it provides the greatest availability of important variables that could operationalize gentrification. While this is a reasonable strategy, the major limitation of tract-based census data is its coarse spatial and temporal resolution. Thus, here, we use annual data from the Census's Longitudinal-Employment Household Dynamics (LEHD) database. Unlike commonly-used decennial Census or American Community Survey (ACS) data which are collected by the Census Bureau through surveys and targeted sampling, LEHD data are built from ES202 unemployment insurance records collected annually by the Bureau of Labor Statistics (BLS) that include information about the race, ethnicity, wage levels[3], educational levels of each worker, as well as the industrial classification of the employee's job. Data are then tabulated by both workers' home census block and workplace census block.

As a result, these data have high spatial and temporal resolutions, and it is possible to examine both residential characteristics and workplace characteristics (which roughly translate as daytime and nighttime populations) in each metropolitan region. Despite these benefits, it is important to be clear that records drawn from unemployment insurance are not representative of the entire working and non-working population, so as with other data sources analyzed in novel combinations, we remain diligent about drawing conclusions within the scope of the data (Arribas-Bel 2014).

For ease of interpretation, we limit our analysis to the 15 largest Metropolitan Statistical Areas (MSAs) in the U.S., though all necessary code is available to generate results for any location in the country. In our cluster models we include variables on race (white, black, and asian), ethnicity (Hispanic population)[4], educational attainment (share or workers with a bachelors degree or greater and share with less than a high school diploma), and income (share of workers with earnings greater than $3,333 per month and share with earnings less than $1,250 per month.). Prior to 2010 the Census Bureau did not release demographic information as part of the LEHD data, so our data include every year between 2010 and 2017 (inclusive)[5].

[3]Unfortunately, the wage data in LEHD is rather coarse; it offers counts of workers in three wage brackets: Less than $1250 per month (which we term "low-wage)", $1,250 - $3,333 per month, and Greater than $3,333 per month (which we term "high-wage"))

[4]Note: unlike the decennial census, LEHD data do not tabulate race and ethnicity categories separately

[5]Because of differences in data availability, the Boston metropolitan region includes only

Clustering Approach

As discussed above, dozens of clustering algorithms have been developed in applied in the statistical literature, many of which have appeared with success in the geodemographic literature. In this study, we employ a Gaussian Mixture Modeling (GMM) approach to develop neighborhood clusters, which, while used only occasionally in the neighborhood literature provides the benefit of using the Bayesian Information Criterion (BIC) statistic as a measure of model fit (Fraley and Raftery 2002; Knaap 2017). To process the data, we first z-standardize each variable relative to its own year before running the clustering algorithm on the full dataset. In other words, we split the dataset by year, apply a z-score transformation, and recombine the data, which allows individual neighborhoods to move up or down the distribution of neighborhoods each year and keeps a consistent set of clusters over time. We then use a GMM to assign a cluster label to each neighborhood in each time period in each of the study areas. Formally, we follow Fraley and Raftery (2007), assuming that a vector of neighborhood data $y = (y_i, \ldots, y_n)$ are generated by a GMM:

$$f(y) = \prod_{i=1}^{n} \sum_{k=1}^{G} \tau_k f_k(y_i|\mu_k, \Sigma_k) \tag{1}$$

where f_k are multivariate normal distributions parameterized by their mean μ_k, and covariance Σ_k, and τ_k is the probability of belonging to the kth component. We use the `mixture` module from the Python machine learning library `scikit-learn` to fit the model via the Expectation-Maximization algorithm, assigning each block/year combination to a cluster label (Pedregosa et al. 2012). We allow k to vary between two and seven, and for each value of k, we allow the covariance matrix to vary between four different specifications[6]. Using this matrix of parameters, we choose the best-fitting model for each metropolitan area according to its BIC.

data from 2011 forward

[6]These include the full covariance, in which each component has its own general covariance matrix; "tied", in which all components share the same general covariance matrix; diagonal, in which each component has its own diagonal covariance matrix; and "spherical", in which each component has its own single variance. For more information, see the scikit-learn documentation (Pedregosa et al. 2012)

A Spatial Markov Chain Modeling Neighborhood Transitions

To construct a set of spatial Markov chain models, we first arrange the dataset in a wide-form such that each census block becomes a single observation, and their cluster labels are arranged in a temporal sequence by year. We then encode spatial relationships using a k-nearest neighbor weights matrix, using each block's five nearest neighbors. Because census blocks are small and some are unpopulated, using contiguity weights would result in a highly sparse connectivity matrix. Following Rey (2010), we proceed by computing the empirical transition matrix between neighborhood types for each pair of consecutive years in the dataset, conditioned by the modal spatial lag (Quah 1993; Rey 2004):

$$M_c = \begin{pmatrix} m_{11} & \dots & m_{1k} \\ m_{21} & \dots & m_{2k} \\ \vdots & \vdots & \vdots \\ m_{k1} & \dots & m_{kk} \end{pmatrix} \tag{2}$$

where $m_{i,j}$ are the probabilities of a neighborhood making the transition from cluster type i to cluster j over a one-year period, given that its most common neighbor is assigned to cluster type c. With this data structure in hand, neighborhood transitions are modeled as a series of spatial Markov chains, where an overall transition probability matrix is estimated, as are k other transition probability matrices (where k is the number of clusters in the solution), each of which is conditioned on a different modal neighbor c. In other words, we model the transition between every two neighborhood types in the absence of any spatial structure; we also model the transition probability between every pair neighborhood types when the origin type is characterized by a different spatial context.

As a result, we observe how likely neighborhoods are to experience demographic change, along which dimensions, and how that probability shifts under different conditions of spatial context. In practical terms, this we estimate the likelihood that a neighborhood will gentrify, as well as the ways in which that likelihood shifts if the focal neighborhood is surrounded by others that have already gentrified. Finally, because we situate the transitions within a spatial Markov framework, we conduct formal tests of spatial independence for each neighborhood transition. That is, for each metro we calculate Likelihood Ratio and Q Statistics to test whether neighborhood transitions under different spatial contexts differ significantly from overall (unconditioned) transition rates. Together these tests provide evidence of spatial dependence in neighborhood transitions (Rey and Janikas 2005).

RESULTS

Both the results from the cluster analysis and the spatial Markov model confirm results from prior studies and offer new insights. In general, there are many similar neighborhood types that occur across metropolitan areas, but each metro has nuance. On the one hand, this means it might be possible to apply a general classification system to the entire United States and examine nationwide transition dynamics. On the other hand, this would also mean that some important features unique to each metro would be overlooked by a more generalized cluster model. Here, we describe some overall trends drawn from the results from all 15 metropolitan areas[7]. We then examine the results from two metro areas in greater detail, Washington D.C. and Los Angeles, to provide greater context and describe the intuition behind the results. Since our primary interest is in residential change, we discuss briefly the relationship between residential change and workplace change via Table 1, but save further discussion, figures, and tables for the appendix.

Similar to Delmelle (2017), we find that neighborhood change is the exception, not the rule; the most likely transition between any two neighborhood types is remaining the same type–and this is especially true for neighborhoods on either end of the (correlated) economic or racial spectrums. Furthermore, every single neighborhood transition in every single metropolitan region shows significant spatial dependence, suggesting that neighborhood change models that exclude spatial effects are misspecified. Importantly, many of the most disadvantaged neighborhood types and the most privileged show are remarkably stable–in part because segregation by race and class help ensure they are typically surrounded by similar neighborhoods, further insulating their probability of transitioning away.

Washington DC

Residential neighborhood types in the Washington D.C. metropolitan region follow predictable patterns of race and class segregation. Figure 1 maps resulting neighborhood types in the Washington D.C. region, from which it is obvious that each neighborhood type tends toward a distinct spatial distribution. Type 0 appears in famously privileged neighborhoods like Georgetown in northwest D.C. as well as the Chinatown neighborhood in Southeast DC where the Nationals Stadium is credited for helping spur gentrification through the last decade. It also appears highly concentrated in D.C.'s wealthy suburbs in Maryland and Northern Virginia. Type 1 appears in Northeast

[7] Detailed tables and figures for each metro are available in the appendix

Name	Average Self-Transition	LR Stat	LR p-val	Q Stat	Q p-val
New York-Newark-Jersey City, NY-NJ-PA	0.572917	31128.7	0	41724.5	0
Los Angeles-Long Beach-Anaheim, CA	0.44332	22264.6	0	27734.9	0
Chicago-Naperville-Elgin, IL-IN-WI	0.662691	6930.29	0	9332.04	0
Dallas-Fort Worth-Arlington, TX	0.489182	8607.98	0	11364.9	0
Houston-The Woodlands-Sugar Land, TX	0.507039	8227.69	0	13067.5	0
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.558584	10336.3	0	13788.1	0
Miami-Fort Lauderdale-Pompano Beach, FL	0.516897	7014.55	0	9075.56	0
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	0.488	9244.27	0	12723.5	0
Atlanta-Sandy Springs-Roswell, GA	0.593011	5632.86	0	7255.76	0
Boston-Cambridge-Newton, MA-NH	0.649846	5364.17	0	7649.78	0
Phoenix-Mesa-Chandler, AZ	0.466593	3272.1	0	3901.08	0
San Francisco-Oakland-Berkeley, CA	0.510594	7772.72	0	10026.8	0
Riverside-San Bernardino-Ontario, CA	0.55438	2461.74	0	2856.91	0
Detroit-Warren-Dearborn, MI	0.527042	4518.02	0	6217.14	0
Seattle-Tacoma-Bellevue, WA	0.515062	3962.98	0	4515.37	0

Table 1: MSA Summary: Average Stability Rate and p-Value by Metro Region

DC and the DC suburbs in southeast Maryland. Type 2 is located throughout much of the city of DC, also the inner suburbs in Northern Virginia, and the exurbs. Type 3 appears in the inner north-western D.C. suburbs in well known enclaves of privilege like Bethesda and Potomac, and in the exurbs. Type 4 shows up in the inner suburb and college town of College Park, and tightly follow the I-270 transportation corridor in Montgomery county Maryland. Types 5 and 6 appear to show a macro geographic divide, where Type 5 essentially avoids all of the southeast part of the region and Type 6 essentially *only* appears in the eastern half of the region.

D.C. Neighborhood Types:

- Cluster 0: white segregated, moderate education and earnings
- Cluster 1: white/asian, high education, high income
- Cluster 2: racially diverse, lower education, lower income

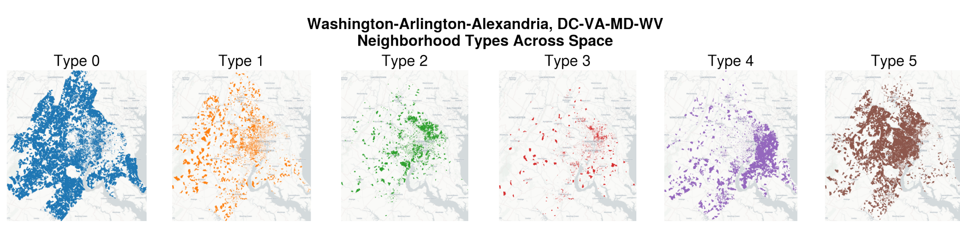

Figure 1: Neighborhood Types in the Washington D.C. Region

- Cluster 3: racially diverse, large Hispanic population, lowest education, lowest salary
- Cluster 4: predominantly black, moderate education, income diverse
- Cluster 5: white with some diversity, highest education, highest earning

Transition rates between neighborhoods also show important patterns about the stickiness of segregation. Type 4, for example, which has the largest share of black residents, 79 percent chance of remaining Type 4 in successive time periods. Meanwhile, Type 3 has less than a five percent chance of becoming either Type 1 or Type 5—the two neighborhood types with the smallest shares of minority residents. There is, however, an 8.2 percent percent chance of transitioning into Type 2, a more transitional neighborhood type that with high probabilities of transitioning into other neighborhood types. Put differently, without considering spatial effects, it is virtually impossible for Type 4 to gentrify without at least transitioning into a more diverse neighborhood first. This is an intuitive finding, since it is unlikely that complete race and class tipping can be reached in the span of a single year, but it is nonetheless important to see that some neighborhood types are highly transitional while others are not.

Employees (%)	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5
White	0.848	0.608	0.569	0.572	0.337	0.753
Black	0.102	0.086	0.281	0.3	0.606	0.088
Asian	0.036	0.258	0.128	0.057	0.034	0.135
Hispanic	0.061	0.089	0.238	0.348	0.074	0.094
Less Than HS	0.076	0.087	0.14	0.192	0.114	0.075
Bachelor's +	0.323	0.376	0.263	0.214	0.228	0.383
Low Salary	0.192	0.18	0.208	0.224	0.207	0.16
High Salary	0.566	0.583	0.461	0.421	0.486	0.636

Table 2: Mean Demographics by Neighborhood Type in Washington-Arlington-Alexandria, DC-VA-MD-WV

The transitions also show important spatial dynamics that affect gentrification and other important processes of neighborhood change. For example neighborhood Type 4 has only a seven percent chance of gentrifying into Type 0 (with higher earnings and education) without considering spatial effects. But if that same neighborhood already has many Type 0 neighbors, then its probability of transitioning into Type 0 during the next year raises from

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5
Type 0	0.645	0.031	0.035	0.007	0.057	0.225
Type 1	0.167	0.329	0.097	0.023	0.023	0.362
Type 2	0.061	0.033	0.608	0.084	0.114	0.1
Type 3	0.052	0.034	0.315	0.382	0.169	0.048
Type 4	0.072	0.005	0.082	0.029	0.792	0.02
Type 5	0.235	0.071	0.07	0.01	0.019	0.595

Table 3: Washington-Arlington-Alexandria, DC-VA-MD-WV Neighborhood Transition Matrix

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5
Type 0	0.696	0.03	0.026	0.005	0.048	0.194
Type 1	0.381	0.216	0.027	0.019	0.027	0.331
Type 2	0.169	0.039	0.443	0.045	0.105	0.198
Type 3	0.183	0.087	0.215	0.264	0.141	0.109
Type 4	0.302	0.015	0.067	0.023	0.524	0.069
Type 5	0.39	0.052	0.04	0.009	0.024	0.485

Table 4: Washington-Arlington-Alexandria, DC-VA-MD-WV Transitions: Modal Neighbor 0

7.2 percent to 30.2 percent. In other words, once the seed of neighborhood change has been planted, it will likely ripple through the urban social fabric, altering the transition dynamics of proximate neighborhoods, as processes like invasion, succession and redevelopment shape residential turnover.

Los Angeles

Results for the Los Angeles metro region are shown in Figure 3 and described in Tables 11, 12. Notably, the neighborhood types discovered by the model in Los Angeles are quite different from those discovered in Washington DC, reflecting both differences in regional demographic makeup and the flexibility of the modeling strategy. Since the cluster models are unique to each metropolitan region, we can make no direct comparisons between, e.g. the location and prevalence and transitive properties of neighborhood Type 1 in LA versus DC because Type 1 is unique in each case.

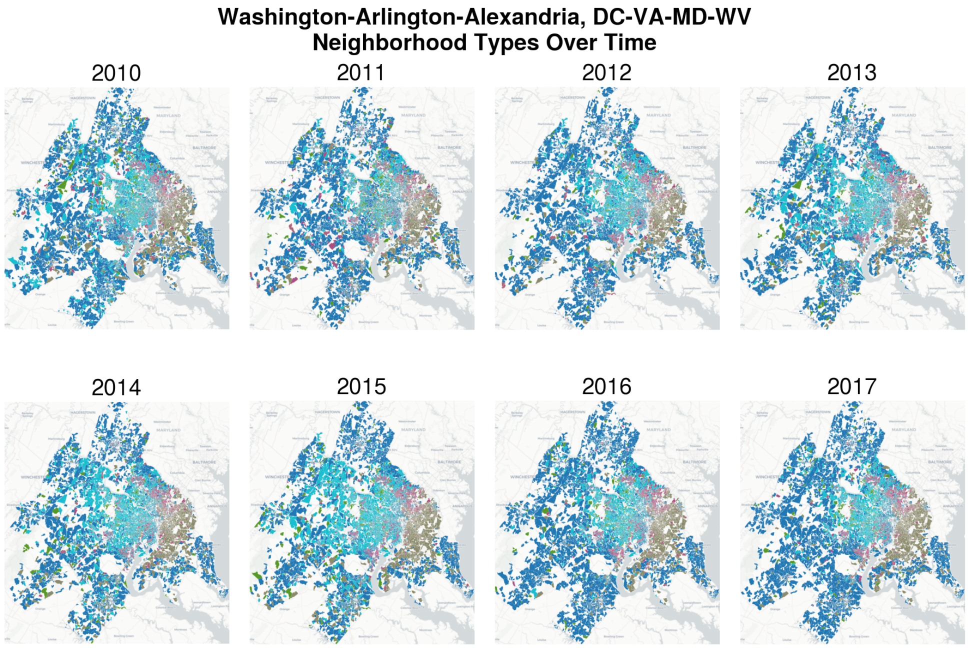

Figure 2: D.C. Clusters Over Time

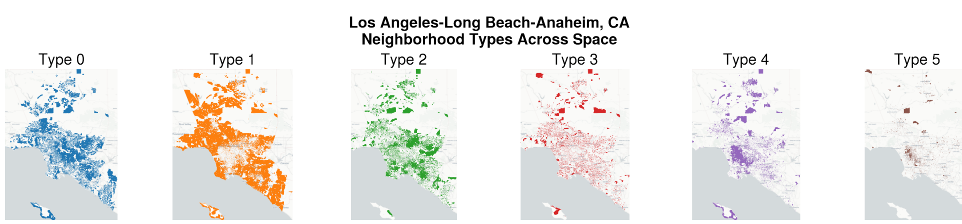

Figure 3: Neighborhood Types in the Washington Los Angeles Region

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5
Type 0	0.507	0.052	0.054	0.01	0.042	0.334
Type 1	0.112	0.394	0.099	0.018	0.018	0.358
Type 2	0.09	0.109	0.501	0.044	0.036	0.22
Type 3	0.024	0.133	0.422	0.265	0.036	0.12
Type 4	0.211	0.053	0.151	0.033	0.447	0.105
Type 5	0.168	0.119	0.075	0.009	0.014	0.615

Table 5: Washington-Arlington-Alexandria, DC-VA-MD-WV Transitions: Modal Neighbor 1

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5
Type 0	0.392	0.039	0.17	0.033	0.133	0.234
Type 1	0.063	0.35	0.229	0.062	0.039	0.257
Type 2	0.05	0.028	0.659	0.091	0.095	0.078
Type 3	0.045	0.025	0.405	0.378	0.102	0.045
Type 4	0.089	0.016	0.289	0.058	0.509	0.04
Type 5	0.155	0.078	0.245	0.041	0.033	0.448

Table 6: Washington-Arlington-Alexandria, DC-VA-MD-WV Transitions: Modal Neighbor 2

L.A. Neighborhood Types

- Cluster 0: white/hispanic low education and income
- Cluster 1: white, some diversity. highest education highest earning
- Cluster 2: mixed race asian, high education and income
- Cluster 3: mixed race white, moderate income and education
- Cluster 4: black/hispanic, lowest education, lowest income
- Cluster 5: black/hispanic moderate education, moderate income

Despite some differences in the resulting neighborhood types, Los Angeles is similar to Washington DC in the clear display of spatial patterning in neighborhood transitions. In Los Angeles, neighborhoods Type 4 and 5 (with large minority populations and low incomes) appear almost exclusively in the famous, historically black, south-central portion of the city, whereas Type 1 with high earnings and low minority shares is virtually non-existent in that region. Focusing on Type 5, we also observe some an invasion and succession process in Los Angeles region, where neighborhood Type 5 with

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5
Type 0	0.532	0.024	0.132	0.044	0.112	0.156
Type 1	0.097	0.262	0.272	0.078	0.029	0.262
Type 2	0.036	0.026	0.641	0.146	0.103	0.048
Type 3	0.034	0.022	0.33	0.464	0.114	0.036
Type 4	0.085	0.008	0.198	0.099	0.592	0.017
Type 5	0.214	0.077	0.199	0.031	0.051	0.429

Table 7: Washington-Arlington-Alexandria, DC-VA-MD-WV Transitions: Modal Neighbor 3

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5
Type 0	0.541	0.021	0.057	0.016	0.26	0.106
Type 1	0.243	0.217	0.247	0.055	0.077	0.162
Type 2	0.039	0.015	0.534	0.077	0.301	0.034
Type 3	0.034	0.015	0.195	0.282	0.464	0.01
Type 4	0.046	0.002	0.063	0.027	0.852	0.009
Type 5	0.307	0.04	0.149	0.011	0.101	0.392

Table 8: Washington-Arlington-Alexandria, DC-VA-MD-WV Transitions: Modal Neighbor 4

the largest black population has only a 15 percent chance of remaining type 5, but has a 37.8 percent chance of becoming Type 4 (a process suggesting the in-migration of Hispanic residents) and nearly a 20 percent chance of becoming Type 0 (suggesting the in-migration of white residents).[8] In less technical terms, these results suggest that neighborhoods with large shares of black residents are transitioning at a much higher rate in LA than they are in Washington DC, but the variety of change is not universal. Some neighborhoods are becoming whiter and wealthier—a process we would identify as gentrification, whereas others are becoming poorer and more Hispanic—a process that lacks a name in the popular lexicon but nonetheless conforms to spatial spillover and demographic succession. Together, these results largely confirm those reported by Hwang and Sampson (2014) "that racial heterogeneity

[8] Again, as with D.C., these likelihoods inflate when proximate neighborhoods have already made similar transitions. For further review, see the spatially-conditioned transition matrices in the appendix

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5
Type 0	0.471	0.038	0.037	0.006	0.024	0.425
Type 1	0.134	0.318	0.064	0.012	0.015	0.456
Type 2	0.111	0.068	0.426	0.045	0.064	0.286
Type 3	0.112	0.123	0.257	0.275	0.065	0.167
Type 4	0.23	0.032	0.166	0.029	0.392	0.151
Type 5	0.216	0.073	0.06	0.008	0.015	0.627

Table 9: Washington-Arlington-Alexandria, DC-VA-MD-WV Transitions: Modal Neighbor 5

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
Type 0	0.587	0.038	0.027	0.005	0.109	0.223	0.011
Type 1	0.082	0.321	0.127	0.007	0.06	0.328	0.075
Type 2	0.012	0.05	0.525	0.059	0.071	0.166	0.116
Type 3	0	0	0.333	0.381	0.107	0.012	0.167
Type 4	0.108	0.014	0.146	0.033	0.472	0.165	0.061
Type 5	0.102	0.039	0.141	0.015	0.08	0.563	0.059
Type 6	0.053	0.076	0.317	0.055	0.094	0.181	0.225

Table 10: Washington-Arlington-Alexandria, DC-VA-MD-WV Transitions: Modal Neighbor 6

works in a particular way to shape neighborhood trajectories among gentrifying tracts and their initially low-income adjacent tracts."

make te

DISCUSSION

Despite valid concerns about the rapid spread of gentrification, particularly in large American metros, most neighborhoods tend toward racial and economic homogeneity, and most neighborhoods remain the same over time. Neighborhoods that do transition tend to move between types that are nearby in multivariate space. And when they transition, they are influenced strongly by the neighborhoods around them. Thus, following the predictions of the early Chicago School, our models reveal strong evidence for the spatial pattern of residential succession and invasion. When neighborhoods experience demographic change, they rarely do so in dramatic and/or leapfrogging pat-

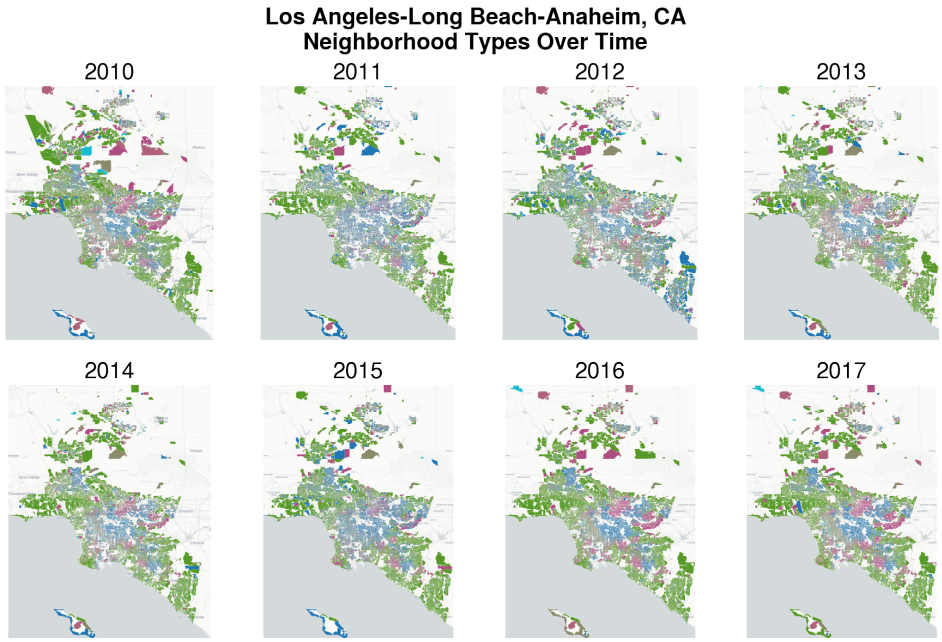

Figure 4: L.A. Clusters Over Time

terns. Rather, neighborhoods tend to transition between types that are nearby in both spatial and multivariate attribute space.

From a policy perspective, this study lends some new ways for thinking about which neighborhoods may be susceptible to gentrification risk. From our results, it is possible to identify which neighborhoods comprise one of the transitional neighborhood types, then among those types, which have an increased probability of "gentrification-style" transition given their proximity to other neighborhood types. Put differently, with these results in hand, it is conceivable to construct a generalized prediction engine for neighborhood change, in which a model is trained on prior neighborhood transitions to identify neighborhoods at an increased risk for gentrification based on their prior trajectories and those of their neighbors. We intend to explore such a model in future work.

Our finding that neighborhoods tend toward stability over time also provides evidence that wealthy neighborhoods resistant to infill development or up-zoning, driven by NIMBYism and fears of massive neighborhood tipping are similarly unlikely to undergo these types of transitions. It is difficult to generate a significant change in the racial and income mix of most estab-

Employees (%)	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5
White	0.82	0.789	0.498	0.659	0.597	0.441
Black	0.051	0.038	0.082	0.079	0.286	0.373
Asian	0.094	0.141	0.384	0.159	0.071	0.064
Hispanic	0.621	0.203	0.272	0.351	0.487	0.413
Less Than HS	0.21	0.102	0.147	0.153	0.204	0.183
Bachelor's +	0.171	0.308	0.27	0.253	0.156	0.186
Low Salary	0.252	0.243	0.245	0.263	0.275	0.259
High Salary	0.335	0.484	0.412	0.409	0.305	0.356

Table 11: Mean Demographics by Neighborhood Type in Los Angeles-Long Beach-Anaheim, CA

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5
Type 0	0.611	0.18	0.077	0.023	0.099	0.009
Type 1	0.13	0.747	0.077	0.026	0.017	0.002
Type 2	0.145	0.204	0.514	0.043	0.081	0.014
Type 3	0.194	0.322	0.187	0.148	0.115	0.034
Type 4	0.26	0.056	0.114	0.035	0.487	0.047
Type 5	0.199	0.072	0.118	0.08	0.378	0.152

Table 12: Los Angeles-Long Beach-Anaheim, CA Neighborhood Transition Matrix

lished neighborhoods–and absent such a major change, neighborhood stability is more than likely. Despite these intriguing results there are a number of additional extensions, caveats, and alternative specifications worthy of discussion.

First, it may be possible to capture important path dependencies by specifying a higher-order Markov process. Although we discuss how path dependencies already manifest somewhat, since some pathways of neighborhood change can only transpire by passing through certain "gateway" neighborhood types, it may also be possible to model this process directly by specifying a higher-order Markov chain that takes account of longer neighborhood histories. Second, novel concepts including space-time weights matrices or weights matrices based on street network distance open up new possibilities for incorporating more realistic neighborhood frameworks or testing how the shape, structure, and composition of different neighborhoods change over time. Finally it will be important to investigate scale effects and the universality of neighborhood types, for example examining the tradeoffs between developing a universal neighborhood typology using data for the entire country versus isolating typologies by region, since "the choice of one city with numerous gentrifying neighborhoods minimized the contextual differences across neighborhoods, further facilitating the focus on more contingent factors." (Beauregard 1990)

CONCLUSION

Prior to opining on novel extensions and future scholarship, it is useful to conclude this paper by reiterating an understated point in the gentrification literature; while gentrifying neighborhoods are critically important foci for scholars of urban inequality, neighborhoods of persistent and enduring racially concentrated poverty are far more common and affect more people. The results in this paper confirm that finding and make clear that neighborhoods tend toward stability rather than change–a trait which is especially true for neighborhoods on the poles of the economic and racial distributions (which, of course, are highly correlated). While it remains critically important to engage with ways to ensure that long term residents of revitalizing neighborhoods reap the benefits of revitalization, it is also important to remain focused on the fact that "the racialized social order of gentrification leads most poor minority neighborhoods to remain so" (Hwang and Sampson 2014, 37). Indeed, the findings in this paper suggest that neighborhood transitions that might be characterized as "gentrification" are fairly uncommon, and when they do occur, they appear to be heavily influenced by the neighborhoods (or, "racialized social order") nearby.

While intriguing, these findings are a whetting of the appetite for studies of neighborhood dynamics seeking to leverage temporal geodemographics and spatial Markov chains. In future work, there are a variety ways to extend this study. The present research leverages Gaussian Mixture Modeling as the clustering algorithm of choice because it allows for the use of the Bayesian Information Citerion to assess model fit and guide the selection of an optimal k parameter. But this choice is by no means definitive and alternative methods, such as a silhouette score (Rousseeuw 1987), could be used to judge model fit and the selection of k for other clustering algorithms. In future work it would be useful to explore how robust the results are to different clustering algorithms and different selections for k. If including space-time weights matrix, it might be also be preferable to leverage a geosilhouette score (Wolf, Knaap, and Rey 2019).

Another area for exploration includes different representations of urban space, such as applying a kernel function the observations prior to clustering, or include a spatial constraint during the clustering process, to examine how both the social composition and the spatial footprint of a neighborhood change over time (Rey et al. 2011). On the one hand, this is a more realistic concept of urban experience. On the other, however, it builds spatial dependence into the neighborhood identification process, by definition, and it remains unclear how to model this. Including a kernel function or spatial constraint would also require the specification of additional parameters such as a threshold distance and/or kernel function, for which the analyst may have little guidance. Again, these are ripe areas for future research.

REFERENCES

Anderson, T. R., and L. L. Bean. 1961. "The Shevky-Bell Social Areas: Confirmation of Results and a Reinterpretation." *Social Forces* 40 (2): 119–24. https://doi.org/10.2307/2574289.

Arribas-Bel, Daniel. 2014. "Accidental, open and everywhere: Emerging data sources for the understanding of cities." *Applied Geography* 49 (May): 45–53. https://doi.org/10.1016/j.apgeog.2013.09.012.

Beauregard, R A. 1990. "Trajectories of Neighborhood Change: The Case of Gentrification." *Environment and Planning A: Economy and Space* 22 (7): 855–74. https://doi.org/10.1068/a220855.

Bell, Earl J. 1974. "Markov analysis of land use change—an application of stochastic processes to remotely sensed data." *Socio-Economic Planning Sciences* 8 (6): 311–16. https://doi.org/10.1016/0038-0121(74)90034-2.

Bosker, Maarten, and Waldo Krugell. 2008. "Regional income evolution in {South} {Africa} after {Apartheid}." *Journal of Regional Science* 48 (3): 493–523.

Chapple, Karen. 2009. "Mapping Susceptibility to Gentrification: The Early Warning Toolkit." Berkeley, CA: Berkeley Center for Community Innovation. http://communityinnovation.berkeley.edu/reports/Gentrification-Report.pdf.

Delmelle, Elizabeth. 2019. "The Increasing Sociospatial Fragmentation of Urban America." *Urban Science* 3 (1): 9. https://doi.org/10.3390/urbansci3010009.

Delmelle, Elizabeth C. 2017. "Differentiating pathways of neighborhood change in 50 U.S. metropolitan areas." *Environment and Planning A* 49 (10): 0308518X1772256. https://doi.org/10.1177/0308518x17722564.

Delmelle, Elizabeth C. 2015. "Five decades of neighborhood classifications and their transitions: A comparison of four US cities, 1970–2010." *Applied Geography* 57 (February): 1–11. https://doi.org/10.1016/j.apgeog.2014.12.002.

———. 2016. "Mapping the DNA of urban neighborhoods: Clustering longitudinal sequences of neighborhood socioeconomic change." *Annals of the American Association of Geographers* 106 (1): 36–56. https://doi.org/10.1080/00045608.2015.1096188.

Ellen, Ingrid Gould, and Lei Ding. 2016. "Advancing Our Understanding of Gentrification." *Cityscape* 18 (3): 1–6.

Fraley, Chris, and Adrian E Raftery. 2002. "Model-Based Clustering, Discriminant Analysis, and Density Estimation." *Journal of the American Statistical Association* 97 (458): 611–31. https://doi.org/10.1198/016214502760047131.

———. 2007. "Bayesian Regularization for Normal Mixture Estimation and Model-Based Clustering." *Journal of Classification* 24 (2): 155–81. https://doi.org/10.1007/s00357-007-0004-5.

Freeman, Lance. 2005. "Displacement or Succession?" *Urban Affairs Review* 40 (4): 463–91. https://doi.org/10.1177/1078087404273341.

Glass, Ruth Lazerus, and H. B. Rodgers. 1964. *London: Aspects of Change*. London: MacGibbon & Kee. https://doi.org/10.1080/00420986420080381.

Goering, John M. 1978. "Neighborhood Tipping and Racial Transition: A Review of Social Science Evidence." *Journal of the American Institute of Planners* 44 (1): 68–78. https://doi.org/10.1080/01944367808976879.

Hagerty, Lee J. 1971. "Another Look at the Burgess Hypothesis: Time as an Important Variable." *American Journal of Sociology* 76 (6): 1084–93.

Hammond, George W. 2004. "Metropolitan/non-metropolitan divergence: a spatial {Markov} chains approach." *Papers in Regional Science* 83 (3): 543–63.

Henig, Jeffrey R. 1980. "Gentrification and Displacement Within Cities: A Comparative Analysis." *Social Science Quarterly* 61 (3/4): 638–52. https://doi.org/10.2307/42860776.

Hoover, Edgar M, and Raymond Vernon. 1959. *Anatomy of a Metropolis*. Cambridge, MA: Harvard University Press. https://doi.org/10.4159/harvard.9780674498617.

Hwang, Jackelyn, and Jeffrey Lin. 2016. "What have we learned about the causes of recent gentrification?" *Cityscape: A Journal of Policy Development and Research* 18 (3): 9–26.

Hwang, Jackelyn, and Robert J. Sampson. 2014. "Divergent Pathways of Gentrification." *American Sociological Review* 79 (4): 726–51. https://doi.org/10.1177/0003122414535774.

Knaap, Elijah. 2017. "The Cartography of Opportunity: Spatial Data Science for Equitable Urban Policy." *Housing Policy Debate* 27 (6): 913–40. https://doi.org/10.1080/10511482.2017.1331930.

Ley, David. 1986. "Alternative explanations for inner-city gentrification: a Canadian assessment." *Annals of the Association of American Geographers* 76 (4): 521–35.

Ling, Chenjun, and Elizabeth C. Delmelle. 2016. "Classifying multidimensional trajectories of neighbourhood change: a self-organizing map and k-means approach." *Annals of GIS* 22 (3): 173–86. https://doi.org/10.1080/19475683.2016.1191545.

London, Bruce, Barrett A. Lee, and S. Gregory Lipton. 1986. "The Determinants of Gentrification in the United States." *Urban Affairs Quarterly* 21 (3): 369–87. https://doi.org/10.1177/004208168602100307.

Longley, Paul A. 2012. "Geodemographics and the practices of geographic information science." *International Journal of Geographical Information Science* 26 (12): 2227–37. https://doi.org/10.1080/13658816.2012.719623.

Lung-Amam, Willow, Rolf Pendall, and Elijah Knaap. 2019. "Mi Casa no es Su Casa : The Fight for Equitable Transit-Oriented Development in an Inner-Ring Suburb." *Journal of Planning Education and Research*, October. https://doi.org/10.1177/0739456X19878248.

Lung-Amam, Willow S. 2019. "Surviving suburban redevelopment: Resisting the displacement of immigrant-owned small businesses in Wheaton, Maryland." *Journal of Urban Affairs*, January, 1–18. https://doi.org/10.1080/07352166.2018.1555439.

Markley, Scott. 2017. "Suburban gentrification? Examining the geographies of New Urbanism in Atlanta's inner suburbs." *Urban Geography* 39 (4): 1–25. https://doi.org/10.1080/02723638.2017.1381534.

Muth, Richard F. 1969. "Cities and housing; the spatial pattern of urban residential land use." *American Journal of Agricultural Economics* 91 (1): 19–41. http://trid.trb.org/view.aspx?id=545388.

Owens, Ann. 2012. "Neighborhoods on the rise: A typology of neighborhoods experiencing socioeconomic ascent." *City and Community* 11 (4): 345–69. https://doi.org/10.1111/j.1540-6040.2012.01412.x.

Park, Robert E., Ernest W Burgess, and Roderick D McKenzie. 1925. *The City*. Chicago: Chicago, IL: University of Chicago Press. http://www.jstor.org/stable/3004850?origin=crossref.

Park, Robert Ezra. 1952. *Human communities; the city and human ecology*. https://doi.org/10.2307/2087814.

Pedregosa, Fabian, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, et al. 2012. "Scikit-learn: Machine Learning in Python." *Journal of Machine Learning Research* 12 (January): 2825–30. http://jmlr.csail.mit.edu/papers/v12/pedregosa11a.html%7B/%%7D5Cnhttp://arxiv.org/abs/1201.0490%20http://arxiv.org/abs/1201.0490.

Quah, Danny T. 1993. "Empirical Cross-Section Dynamics in Economic Growth." *European Economic Review* 37 (2-3): 426–34.

Rey, Sergio J. 2004. "Spatial dependence in the evolution of regional income distributions." In *Spatial Econometrics and Spatial Statistics*, edited by A Getis, J Múr, and H Zoeller, 193–213. 217. Hampshire: Palgrave.

———. 2010. "Spatial Empirics for Economic Growth and Convergence." *Geographical Analysis* 33 (3): 195–214. https://doi.org/10.1111/j.1538-4632.2001.tb00444.x.

Rey, Sergio J., Luc Anselin, David C. Folch, Daniel Arribas-Bel, Myrna L. Sastré Gutiérrez, Lindsey Interlante, Myrna L Sastre Gutierrez, Lindsey Interlante, Myrna L. Sastré Gutiérrez, and Lindsey Interlante. 2011. "Measuring Spatial Dynamics in Metropolitan Areas." *Economic Development Quarterly* 25 (1): 54–64. https://doi.org/10.1177/0891242410383414.

Rey, Sergio J., and Mark V. Janikas. 2005. "Regional convergence, inequality, and space." *Journal of Economic Geography* 5 (2): 155–76. https://doi.org/10.1093/jnlecg/lbh044.

Rousseeuw, Peter J. 1987. "Silhouettes: A graphical aid to the interpretation and validation of cluster analysis." *Journal of Computational and Applied*

Mathematics. https://doi.org/10.1016/0377-0427(87)90125-7.

Schelling, Thomas. 1972. "A process of residential segregation: neighborhood tipping." In *Racial Discrimination in Economic Life*, 157–84. Lexington, Mass: Lexington Books.

Schwirian, Kent P. 1983. "Models of Neighborhood Change." *Annual Review of Sociology* 9 (1): 83–102. https://doi.org/10.1146/annurev.so.09.080183.000503.

Shevky, Eshref, and Wendell Bell. 1955. *Social Area Analysis; Theory, Illustrative Application and Computational Procedures*. Stanford University Press.

Shevky, E, and M Williams. 1949. *The social areas of Los Angeles: analysis and typology*. Published for the John Randolph Haynes; Dora Haynes Foundation by the University of California Press. https://books.google.com/books?id=nrUPAQAAMAAJ.

Singleton, Alexander D, and Seth E Spielman. 2014. "The Past, Present, and Future of Geodemographic Research in the United States and United Kingdom." *The Professional Geographer* 66 (4): 558–67. https://doi.org/10.1080/00330124.2013.848764.

Singleton, Alexander, and Paul Longley. 2009a. "Geodemographics, visualisation, and social networks in applied geography." *Applied Geography* 29 (3): 289–98. https://doi.org/10.1016/j.apgeog.2008.10.006.

———. 2009b. "Creating open source geodemographics: Refining a national classification of census output areas for applications in higher education." *Papers in Regional Science* 88 (3): 643–66. https://doi.org/10.1111/j.1435-5957.2008.00197.x.

Smith, Neil. 1979. "Toward a Theory of Gentrification A Back to the City Movement by Capital, not People." *Journal of the American Planning Association* 45 (4): 538–48. https://doi.org/10.1080/01944367908977002.

Spielman, Seth E, and Alex Singleton. 2015. "Studying {Neighborhoods} {Using} {Uncertain} {Data} from the {American} {Community} {Survey}: {A} {Contextual} {Approach}." *Annals of the Association of American Geographers* 105 (5): 1003–25.

Sumka, Howard J. 1979. "Neighborhood Revitalization and Displacement A Review of the Evidence." *Journal of the American Planning Association* 45 (4): 480–87. https://doi.org/10.1080/01944367908976994.

Tang, J, L Wang, and Z Yao. 2007. "Spatio-temporal urban landscape change analysis using the {Markov} chain model and a modified genetic algorithm." *International Journal of Remote Sensing* 28 (15): 3255–71.

Timberlake, Jeffrey M., and Elaina Johns-Wolfe. 2017. "Neighborhood Ethnoracial Composition and Gentrification in Chicago and New York, 1980 to 2010." *Urban Affairs Review* 53 (2): 236–72. https://doi.org/10.1177/1078087416636483.

Vile, John R., David L. Hudson, and David Schultz. 2014. "Jacobellis v. Ohio (1964)." In *Encyclopedia of the First Amendment*. 2300 N Street, NW, Suite 800, Washington DC 20037 United States: CQ Press. https://doi.org/10.4135/9781604265774.n722.

Webber, Richard, and Roger Burrows. 2018. *The Predictive Postcode: The Geodemographic Classification of British Society*. SAGE.

Wei, Fang, and Paul L. Knox. 2014. "Neighborhood Change in Metropolitan America, 1990 to 2010." *Urban Affairs Review* 50 (4): 459–89. https://doi.org/10.1177/1078087413501640.

Wolf, Levi John, Elijah Knaap, and Sergio Rey. 2019. "Geosilhouettes: Geographical measures of cluster fit." *Environment and Planning B: Urban Analytics and City Science*, September. https://doi.org/10.1177/2399808319875752.

APPENDIX

Employees (%)	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
White	0.853	0.568	0.835	0.385	0.176	0.706	0.532
Black	0.138	0.346	0.111	0.326	0.804	0.147	0.416
Asian	0.001	0.033	0.046	0.267	0.009	0.117	0.04
Hispanic	0.03	0.245	0.035	0.103	0.026	0.054	0.098
Less Than HS	0.077	0.138	0.068	0.115	0.111	0.073	0.102
Bachelor's +	0.248	0.194	0.303	0.265	0.165	0.314	0.216
Low Salary	0.216	0.257	0.192	0.232	0.279	0.194	0.236
High Salary	0.461	0.343	0.543	0.393	0.314	0.532	0.397

Table 13: Mean Demographics by Neighborhood Type in Atlanta-Sandy Springs-Roswell, GA

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
Type 0	0.555	0.012	0.268	0.001	0.025	0.054	0.085
Type 1	0.046	0.512	0.029	0.057	0.088	0.047	0.221
Type 2	0.154	0.005	0.652	0.002	0.003	0.12	0.064
Type 3	0.004	0.095	0.02	0.582	0.023	0.133	0.142
Type 4	0.025	0.024	0.005	0.004	0.826	0.002	0.114
Type 5	0.084	0.025	0.284	0.052	0.006	0.465	0.085
Type 6	0.089	0.064	0.09	0.024	0.118	0.055	0.559

Table 14: Atlanta-Sandy Springs-Roswell, GA Neighborhood Transition Matrix

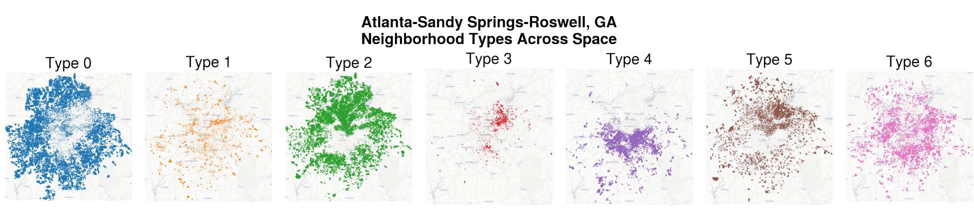

Figure 5: Atlanta Residential Clusters

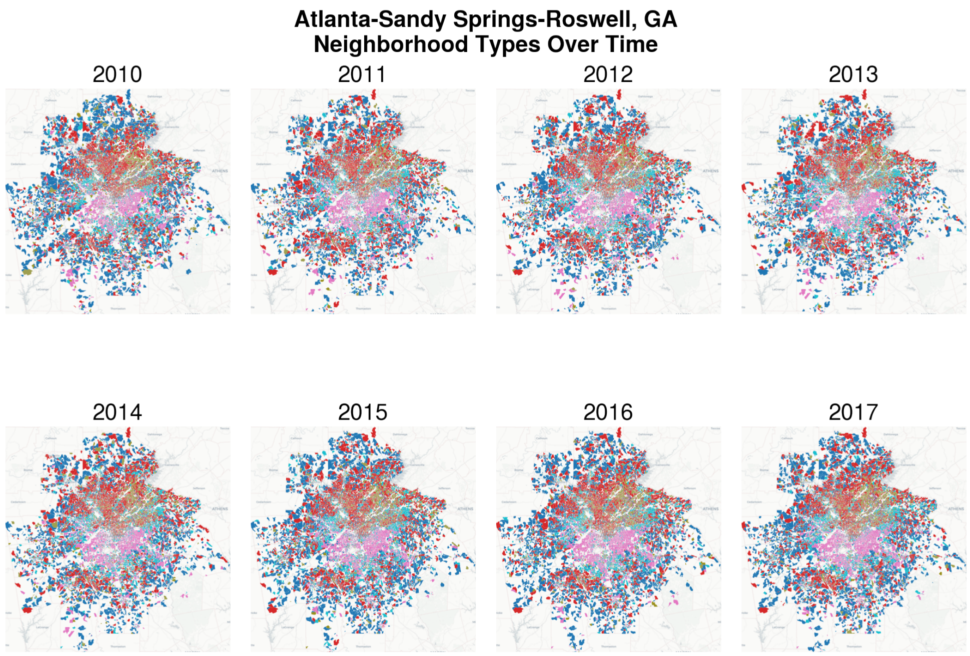

Figure 6: Atlanta Clusters Over Time

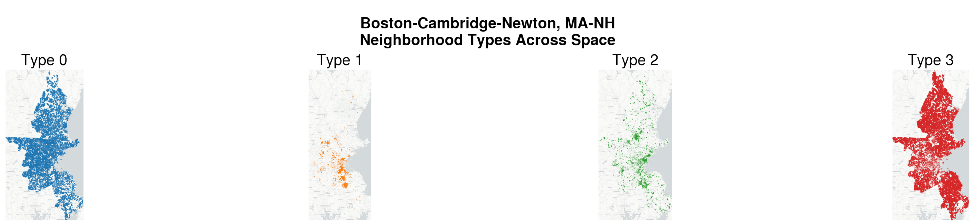

Figure 7: Boston Residential Clusters

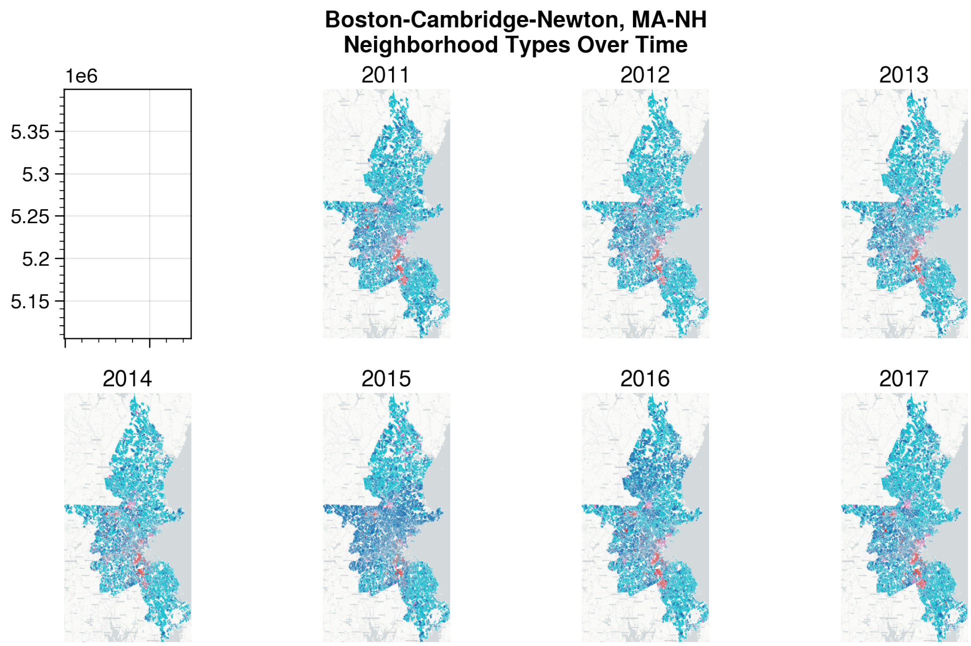

Figure 8: Boston Clusters Over Time

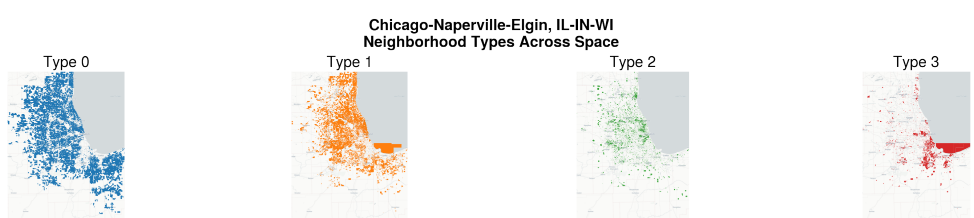

Figure 9: Chicago Residential Clusters

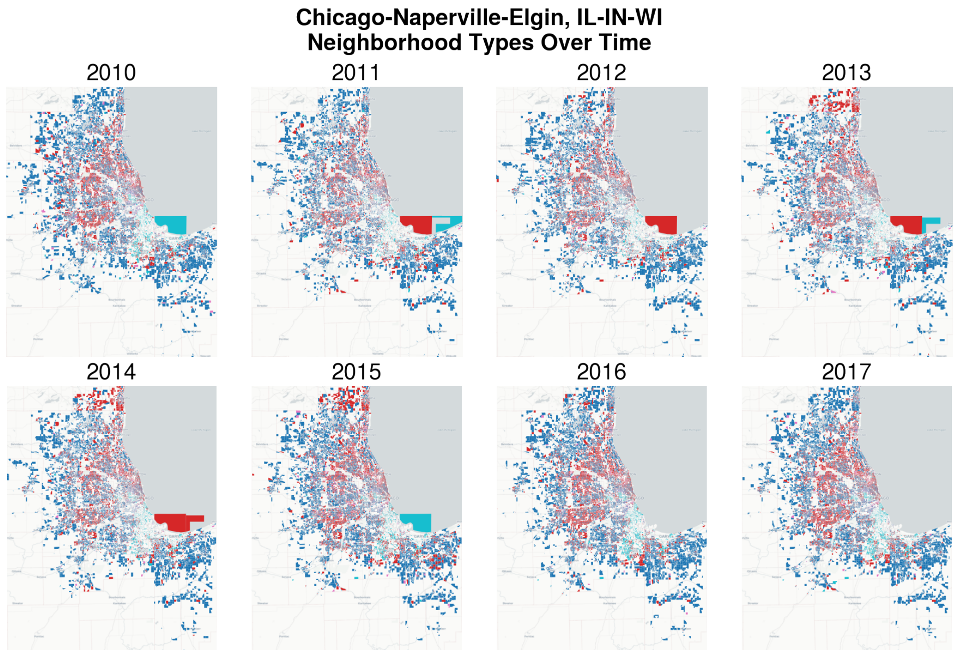

Figure 10: Chicago Clusters Over Time

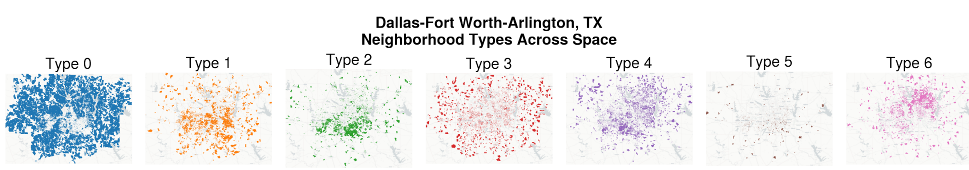

Figure 11: Dallas Residential Clusters

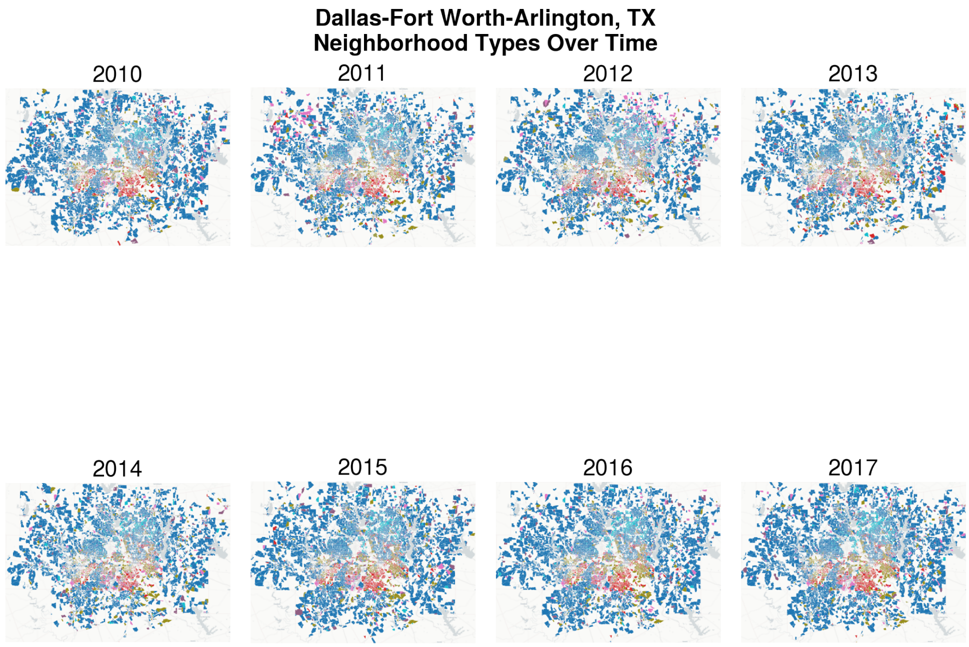

Figure 12: Dallas Clusters Over Time

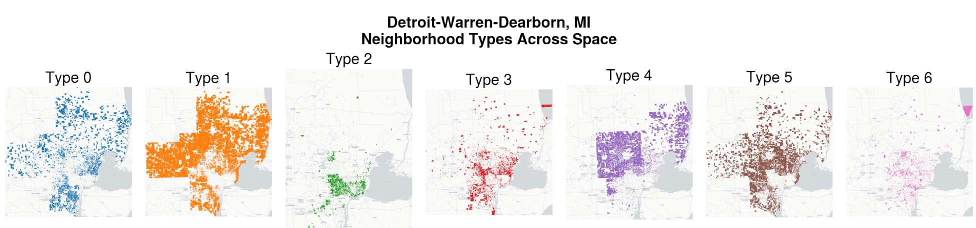

Figure 13: Detroit Residential Clusters

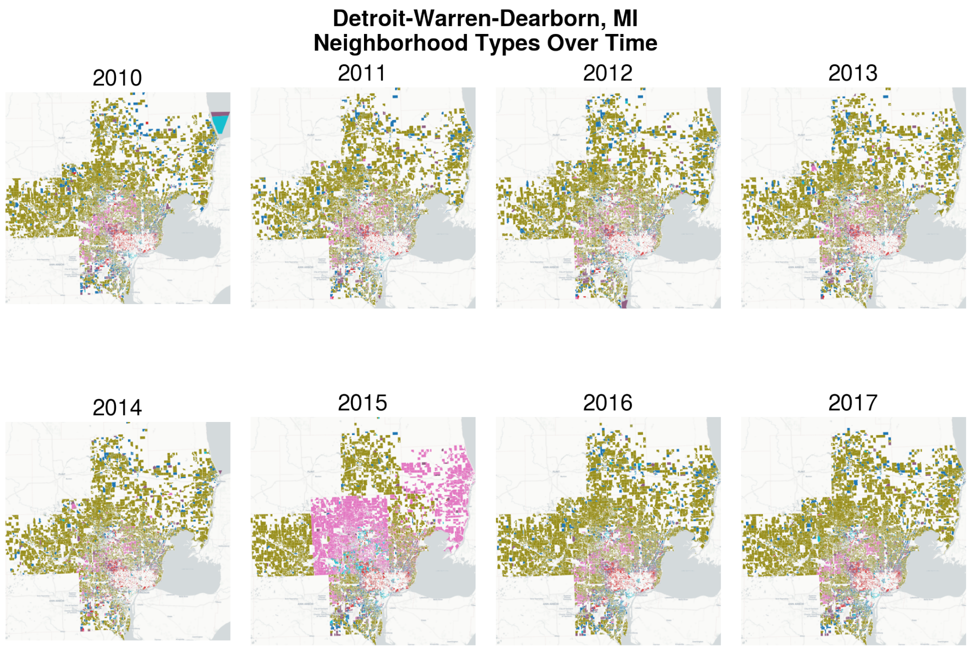

Figure 14: Detroit Clusters Over Time

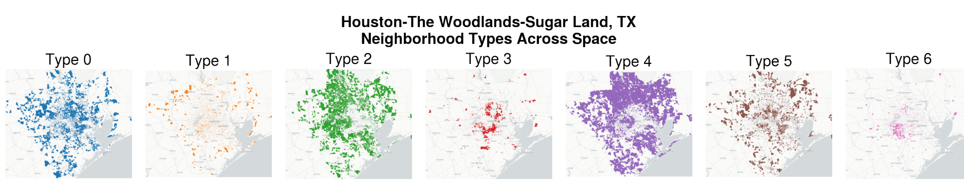

Figure 15: Houston Residential Clusters

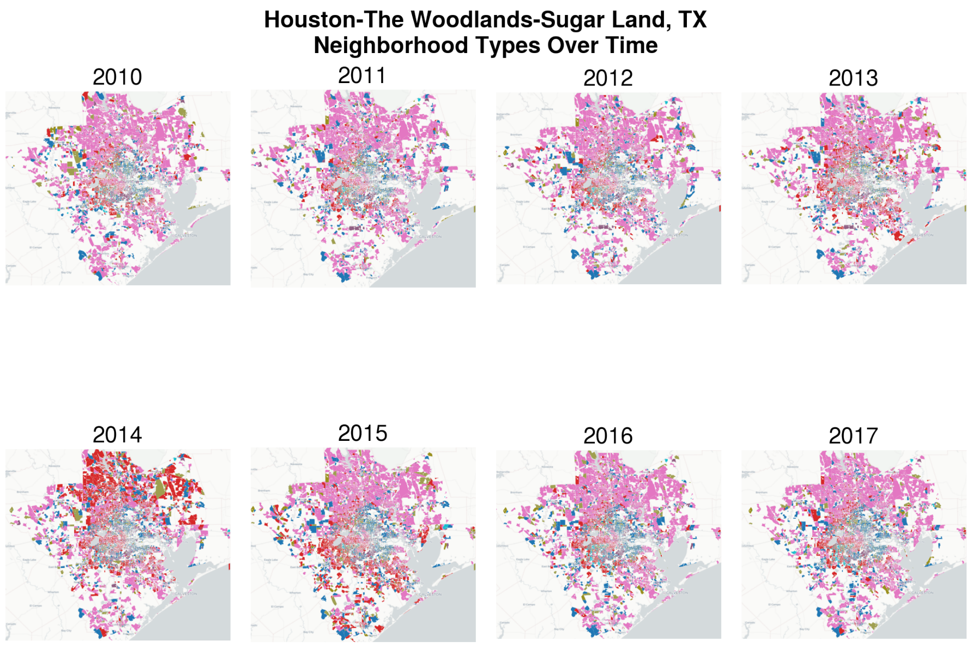

Figure 16: Houston Clusters Over Time

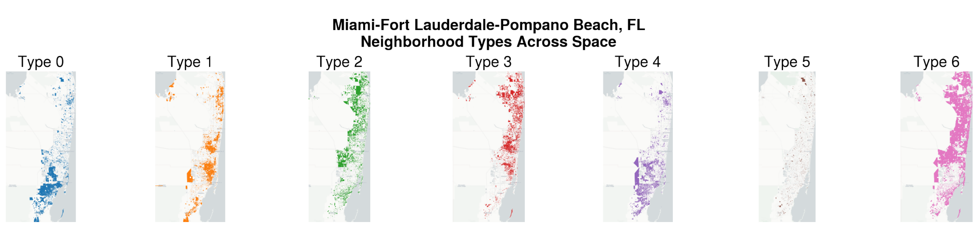

Figure 17: Miami Residential Clusters

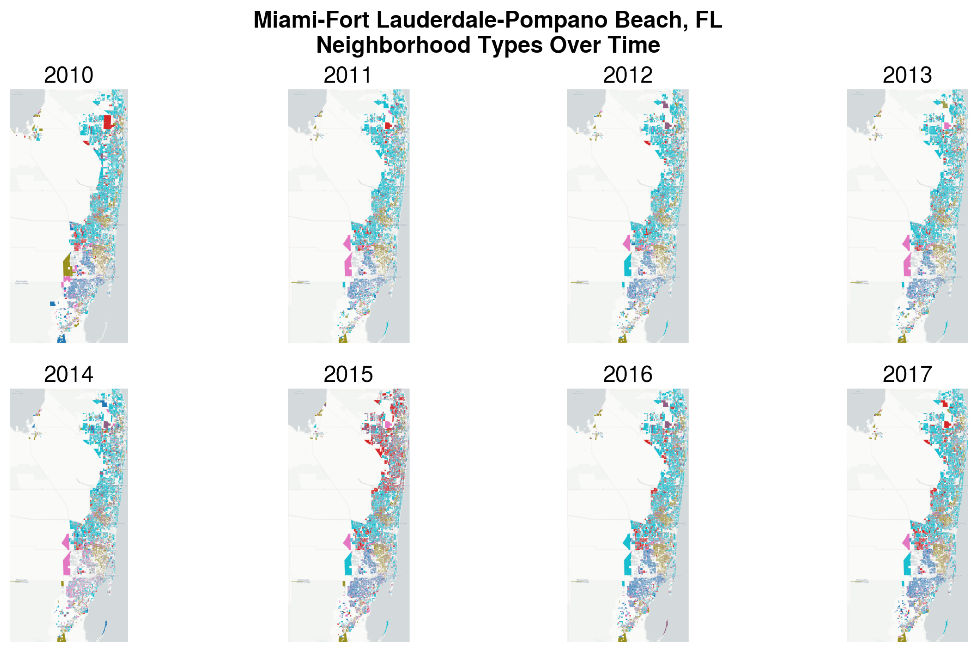

Figure 18: Miami Clusters Over Time

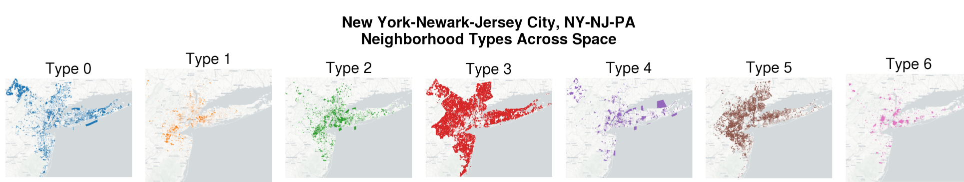

Figure 19: New York Residential Clusters

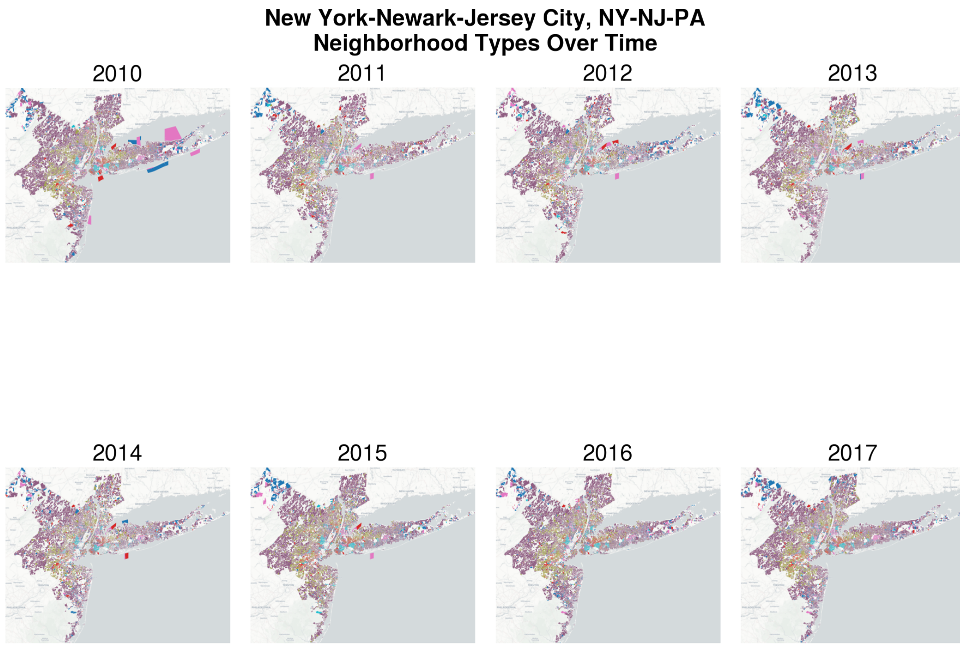

Figure 20: New York Clusters Over Time

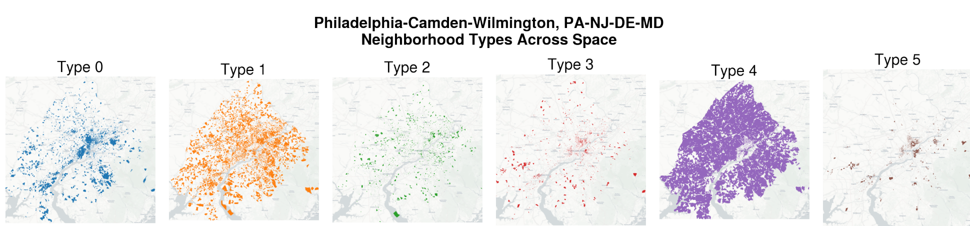

Figure 21: Philadelphia Residential Clusters

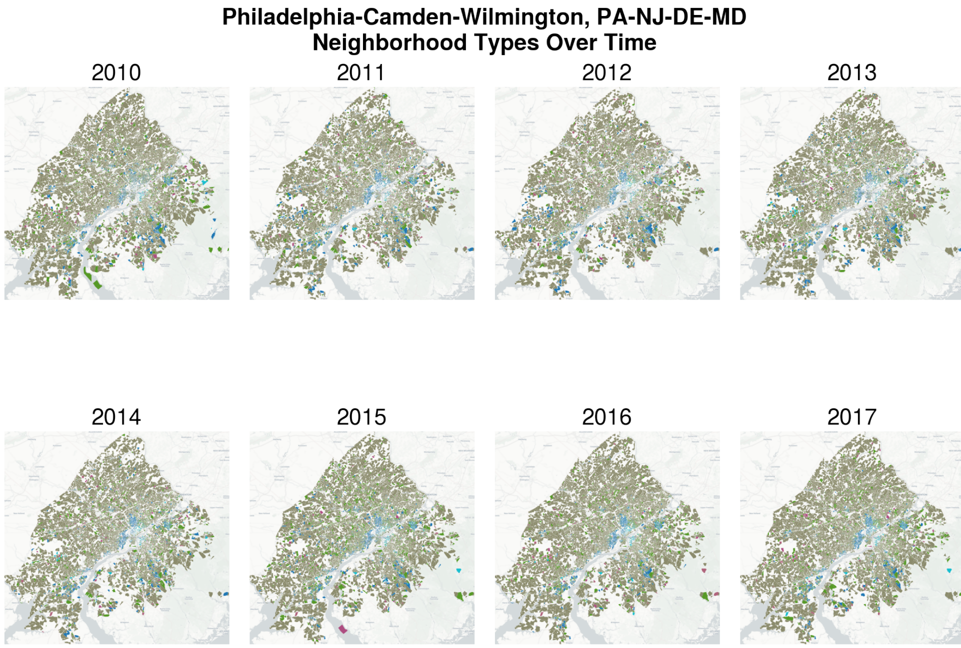

Figure 22: Philadelphia Clusters Over Time

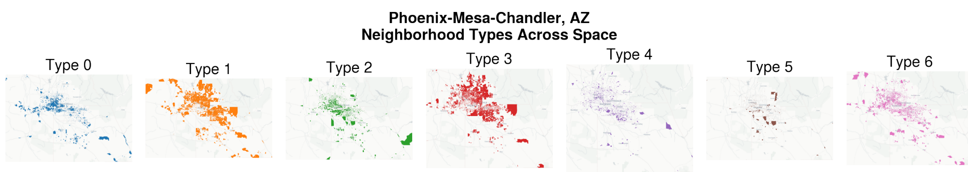

Figure 23: Phoenix Residential Clusters

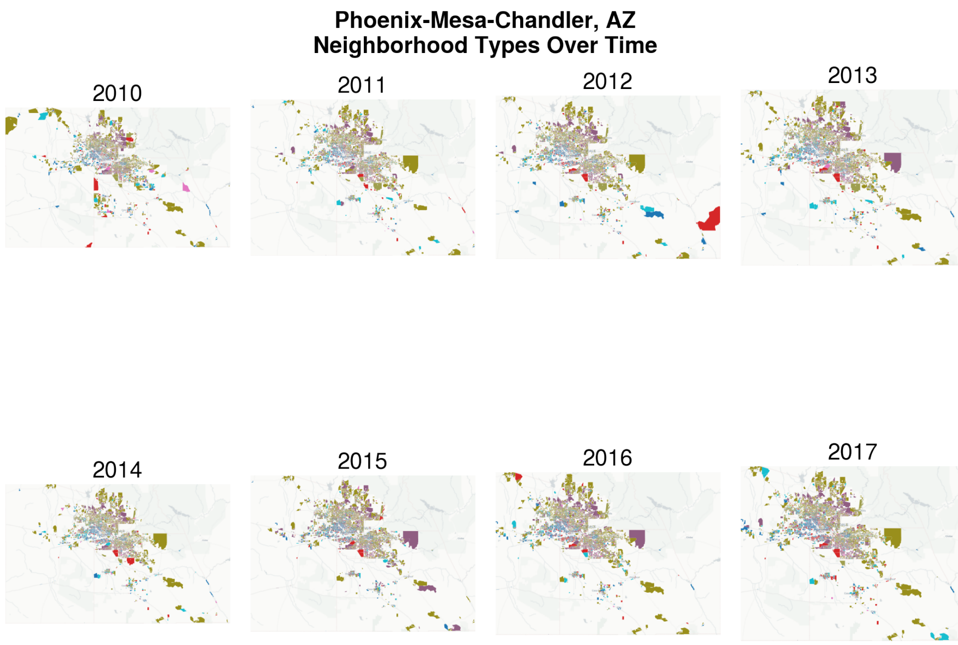

Figure 24: Phoenix Clusters Over Time

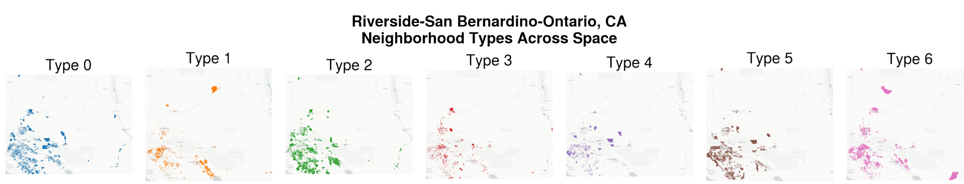

Figure 25: Riverside Residential Clusters

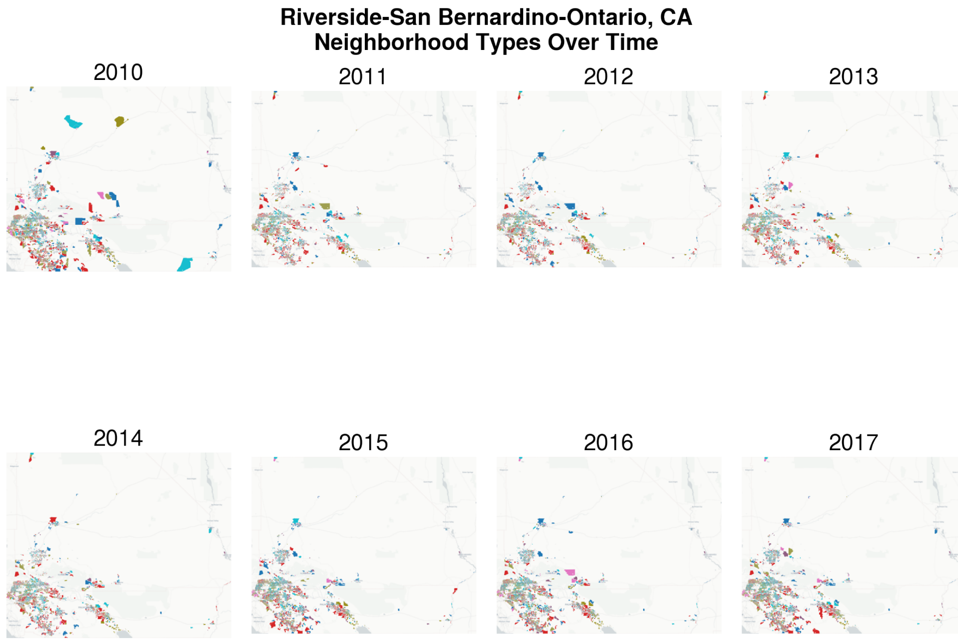

Figure 26: Riverside Clusters Over Time

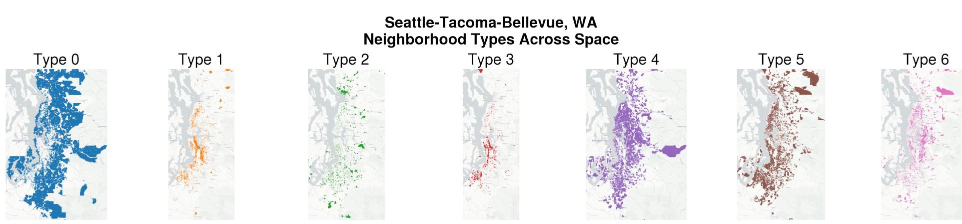

Figure 27: Seattle Residential Clusters

Employees (%)	Type 0	Type 1	Type 2	Type 3
White	0.852	0.455	0.78	0.943
Black	0.04	0.344	0.123	0.032
Asian	0.088	0.175	0.051	0.022
Hispanic	0.054	0.123	0.277	0.031
Less Than HS	0.061	0.104	0.112	0.059
Bachelor's +	0.342	0.265	0.257	0.33
Low Salary	0.198	0.248	0.242	0.212
High Salary	0.576	0.415	0.425	0.555

Table 15: Mean Demographics by Neighborhood Type in Boston-Cambridge-Newton, MA-NH

	Type 0	Type 1	Type 2	Type 3
Type 0	0.603	0.039	0.075	0.284
Type 1	0.111	0.735	0.101	0.053
Type 2	0.192	0.085	0.629	0.093
Type 3	0.305	0.02	0.043	0.631

Table 16: Boston-Cambridge-Newton, MA-NH Neighborhood Transition Matrix

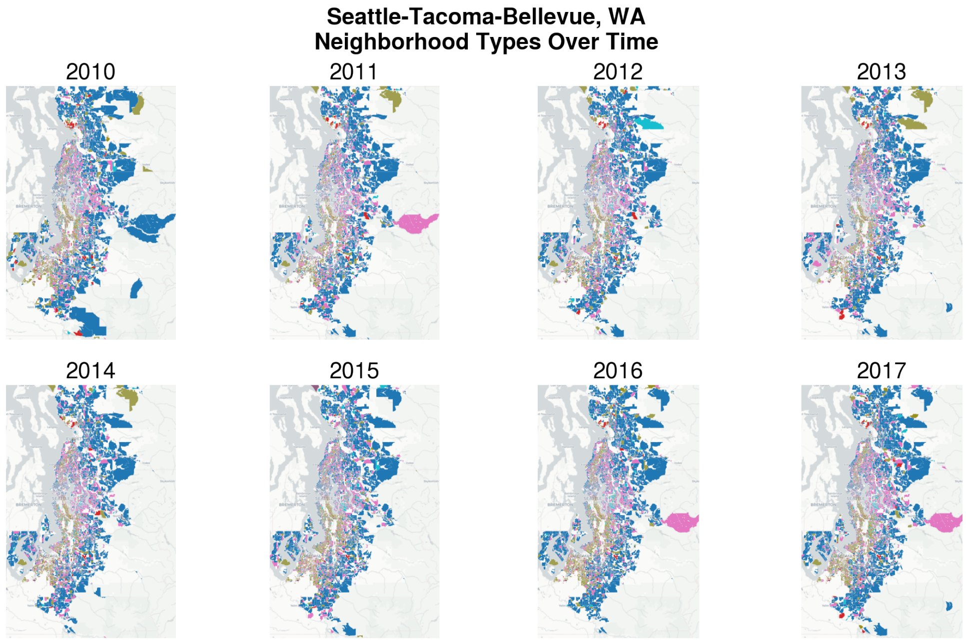

Figure 28: Seattle Clusters Over Time

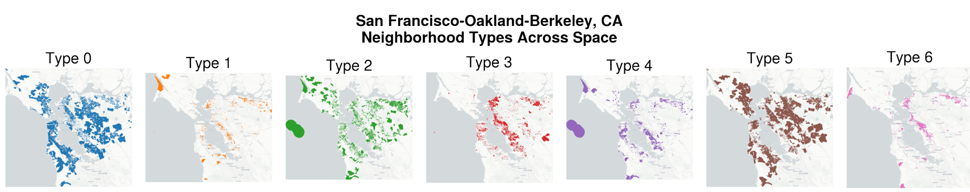

Figure 29: San Francisco Residential Clusters

Employees (%)	Type 0	Type 1	Type 2	Type 3
White	0.94	0.751	0.654	0.251
Black	0.026	0.115	0.111	0.711
Asian	0.022	0.116	0.177	0.019
Hispanic	0.183	0.14	0.343	0.097
Less Than HS	0.093	0.088	0.146	0.125
Bachelor's +	0.262	0.295	0.238	0.168
Low Salary	0.227	0.22	0.242	0.277
High Salary	0.467	0.481	0.377	0.331

Table 17: Mean Demographics by Neighborhood Type in Chicago-Naperville-Elgin, IL-IN-WI

	Type 0	Type 1	Type 2	Type 3
Type 0	0.801	0.165	0.029	0.005
Type 1	0.222	0.681	0.065	0.032
Type 2	0.202	0.355	0.402	0.042
Type 3	0.031	0.162	0.041	0.767

Table 18: Chicago-Naperville-Elgin, IL-IN-WI Neighborhood Transition Matrix

Employees (%)	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
White	0.883	0.817	0.367	0.73	0.661	0.584	0.63
Black	0.067	0.141	0.58	0.115	0.24	0.239	0.094
Asian	0.035	0.017	0.033	0.072	0.081	0.033	0.247
Hispanic	0.123	0.521	0.159	0.262	0.21	0.443	0.105
Less Than HS	0.087	0.191	0.131	0.133	0.122	0.192	0.086
Bachelor's +	0.255	0.137	0.158	0.202	0.211	0.149	0.328
Low Salary	0.19	0.237	0.259	0.219	0.217	0.25	0.177
High Salary	0.532	0.324	0.35	0.423	0.442	0.325	0.574

Table 19: Mean Demographics by Neighborhood Type in Dallas-Fort Worth-Arlington, TX

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
Type 0	0.797	0.049	0.011	0.023	0.061	0.001	0.058
Type 1	0.111	0.71	0.044	0.035	0.085	0.01	0.005
Type 2	0.053	0.087	0.661	0.027	0.142	0.011	0.019
Type 3	0.29	0.191	0.06	0.204	0.128	0.032	0.095
Type 4	0.257	0.157	0.122	0.042	0.345	0.004	0.073
Type 5	0.086	0.31	0.178	0.154	0.091	0.163	0.019
Type 6	0.298	0.011	0.019	0.04	0.085	0.002	0.545

Table 20: Dallas-Fort Worth-Arlington, TX Neighborhood Transition Matrix

Employees (%)	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
White	0.884	0.966	0.155	0.609	0.751	0.851	0.554
Black	0.087	0.014	0.821	0.337	0.083	0.068	0.323
Asian	0.005	0.009	0.007	0.031	0.149	0.064	0.092
Hispanic	0.07	0.021	0.015	0.027	0.029	0.022	0.156
Less Than HS	0.074	0.053	0.098	0.071	0.056	0.053	0.11
Bachelor’s +	0.214	0.273	0.159	0.224	0.34	0.308	0.195
Low Salary	0.271	0.229	0.327	0.26	0.205	0.22	0.308
High Salary	0.384	0.485	0.288	0.394	0.549	0.508	0.315

Table 21: Mean Demographics by Neighborhood Type in Detroit-Warren-Dearborn, MI

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
Type 0	0.384	0.275	0.004	0.1	0.042	0.173	0.022
Type 1	0.077	0.713	0.001	0.009	0.069	0.128	0.004
Type 2	0.004	0.001	0.803	0.123	0.006	0.017	0.046
Type 3	0.086	0.025	0.071	0.603	0.06	0.095	0.059
Type 4	0.04	0.233	0.002	0.058	0.344	0.281	0.041
Type 5	0.08	0.228	0.004	0.055	0.129	0.49	0.013
Type 6	0.068	0.031	0.098	0.211	0.16	0.08	0.352

Table 22: Detroit-Warren-Dearborn, MI Neighborhood Transition Matrix

Employees (%)	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
White	0.763	0.655	0.7	0.263	0.876	0.769	0.345
Black	0.201	0.138	0.133	0.688	0.072	0.126	0.263
Asian	0.022	0.101	0.144	0.032	0.039	0.063	0.365
Hispanic	0.493	0.336	0.171	0.177	0.157	0.49	0.154
Less Than HS	0.189	0.151	0.106	0.149	0.098	0.194	0.137
Bachelor's +	0.138	0.213	0.265	0.136	0.245	0.153	0.259
Low Salary	0.229	0.212	0.174	0.286	0.181	0.227	0.224
High Salary	0.386	0.454	0.574	0.315	0.564	0.387	0.453

Table 23: Mean Demographics by Neighborhood Type in Houston-The Woodlands-Sugar Land, TX

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
Type 0	0.613	0.011	0.051	0.053	0.099	0.167	0.005
Type 1	0.121	0.206	0.172	0.03	0.164	0.231	0.076
Type 2	0.066	0.017	0.477	0.014	0.334	0.057	0.036
Type 3	0.163	0.006	0.026	0.715	0.035	0.023	0.033
Type 4	0.071	0.008	0.184	0.007	0.682	0.045	0.003
Type 5	0.332	0.035	0.088	0.017	0.127	0.391	0.01
Type 6	0.062	0.043	0.231	0.099	0.05	0.05	0.465

Table 24: Houston-The Woodlands-Sugar Land, TX Neighborhood Transition Matrix

Employees (%)	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
White	0.927	0.366	0.753	0.491	0.773	0.502	0.868
Black	0.055	0.615	0.125	0.43	0.153	0.196	0.099
Asian	0.009	0.007	0.106	0.04	0.037	0.202	0.023
Hispanic	0.748	0.234	0.314	0.162	0.623	0.364	0.223
Less Than HS	0.188	0.171	0.122	0.145	0.184	0.161	0.109
Bachelor's +	0.181	0.143	0.269	0.183	0.174	0.214	0.25
Low Salary	0.229	0.274	0.21	0.256	0.234	0.251	0.221
High Salary	0.328	0.244	0.458	0.315	0.328	0.326	0.44

Table 25: Mean Demographics by Neighborhood Type in Miami-Fort Lauderdale-Pompano Beach, FL

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
Type 0	0.67	0.033	0.02	0.008	0.166	0.003	0.1
Type 1	0.043	0.686	0.008	0.141	0.07	0.003	0.049
Type 2	0.062	0.025	0.343	0.069	0.11	0.023	0.369
Type 3	0.02	0.258	0.051	0.405	0.039	0.014	0.213
Type 4	0.317	0.095	0.065	0.031	0.385	0.016	0.093
Type 5	0.042	0.043	0.141	0.143	0.182	0.403	0.047
Type 6	0.066	0.029	0.075	0.061	0.04	0.002	0.727

Table 26: Miami-Fort Lauderdale-Pompano Beach, FL Neighborhood Transition Matrix

Employees (%)	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
White	0.84	0.338	0.565	0.923	0.662	0.745	0.277
Black	0.08	0.208	0.171	0.026	0.237	0.06	0.657
Asian	0.056	0.431	0.235	0.039	0.063	0.177	0.037
Hispanic	0.283	0.124	0.198	0.078	0.469	0.086	0.174
Less Than HS	0.11	0.105	0.107	0.057	0.165	0.06	0.131
Bachelor's +	0.273	0.357	0.307	0.36	0.19	0.402	0.2
Low Salary	0.234	0.22	0.224	0.209	0.257	0.179	0.242
High Salary	0.461	0.49	0.471	0.559	0.345	0.604	0.381

Table 27: Mean Demographics by Neighborhood Type in New York-Newark-Jersey City, NY-NJ-PA

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
Type 0	0.423	0.003	0.088	0.227	0.168	0.084	0.007
Type 1	0.008	0.4	0.265	0.017	0.083	0.106	0.121
Type 2	0.065	0.07	0.562	0.028	0.124	0.112	0.038
Type 3	0.086	0.002	0.014	0.758	0.007	0.131	0.002
Type 4	0.124	0.019	0.113	0.014	0.599	0.014	0.117
Type 5	0.072	0.028	0.124	0.294	0.012	0.466	0.003
Type 6	0.005	0.028	0.037	0.003	0.121	0.003	0.803

Table 28: New York-Newark-Jersey City, NY-NJ-PA Neighborhood Transition Matrix

Employees (%)	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5
White	0.327	0.647	0.57	0.52	0.889	0.44
Black	0.633	0.222	0.107	0.337	0.071	0.484
Asian	0.024	0.103	0.266	0.119	0.032	0.027
Hispanic	0.054	0.09	0.098	0.196	0.034	0.351
Less Than HS	0.102	0.08	0.093	0.135	0.059	0.149
Bachelor’s +	0.189	0.267	0.301	0.204	0.297	0.146
Low Salary	0.265	0.23	0.242	0.251	0.215	0.295
High Salary	0.351	0.457	0.451	0.35	0.524	0.265

Table 29: Mean Demographics by Neighborhood Type in Philadelphia-Camden-Wilmington, PA-NJ-DE-MD

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5
Type 0	0.646	0.141	0.008	0.029	0.125	0.051
Type 1	0.132	0.429	0.034	0.03	0.348	0.027
Type 2	0.085	0.303	0.335	0.066	0.19	0.02
Type 3	0.246	0.256	0.085	0.169	0.123	0.121
Type 4	0.041	0.086	0.006	0.004	0.861	0.002
Type 5	0.245	0.145	0.02	0.077	0.026	0.488

Table 30: Philadelphia-Camden-Wilmington, PA-NJ-DE-MD Neighborhood Transition Matrix

Employees (%)	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
White	0.891	0.934	0.715	0.852	0.683	0.538	0.834
Black	0.057	0.026	0.15	0.041	0.064	0.218	0.086
Asian	0.006	0.015	0.035	0.079	0.206	0.05	0.03
Hispanic	0.573	0.149	0.358	0.146	0.214	0.423	0.29
Less Than HS	0.185	0.084	0.133	0.083	0.111	0.171	0.125
Bachelor’s +	0.125	0.232	0.165	0.265	0.25	0.14	0.193
Low Salary	0.258	0.221	0.243	0.199	0.214	0.269	0.212
High Salary	0.257	0.448	0.33	0.5	0.436	0.275	0.392

Table 31: Mean Demographics by Neighborhood Type in Phoenix-Mesa-Chandler, AZ

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
Type 0	0.643	0.095	0.104	0.04	0.007	0.008	0.103
Type 1	0.037	0.692	0.022	0.171	0.007	0.001	0.07
Type 2	0.183	0.087	0.435	0.074	0.034	0.035	0.151
Type 3	0.029	0.325	0.041	0.497	0.045	0.002	0.061
Type 4	0.033	0.092	0.102	0.315	0.359	0.016	0.082
Type 5	0.124	0.018	0.337	0.025	0.065	0.364	0.067
Type 6	0.152	0.282	0.132	0.128	0.025	0.006	0.276

Table 32: Phoenix-Mesa-Chandler, AZ Neighborhood Transition Matrix

Employees (%)	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
White	0.812	0.932	0.917	0.575	0.465	0.717	0.806
Black	0.034	0.025	0.026	0.274	0.118	0.088	0.123
Asian	0.082	0.012	0.035	0.031	0.364	0.168	0.041
Hispanic	0.438	0.772	0.232	0.472	0.254	0.302	0.536
Less Than HS	0.169	0.249	0.109	0.182	0.135	0.127	0.194
Bachelor’s +	0.186	0.108	0.23	0.141	0.257	0.237	0.141
Low Salary	0.256	0.264	0.232	0.271	0.229	0.217	0.255
High Salary	0.371	0.287	0.446	0.331	0.441	0.464	0.33

Table 33: Mean Demographics by Neighborhood Type in Riverside-San Bernardino-Ontario, CA

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
Type 0	0.399	0.081	0.16	0.04	0.017	0.122	0.18
Type 1	0.081	0.639	0.03	0.026	0.004	0.01	0.209
Type 2	0.132	0.022	0.65	0.007	0.005	0.101	0.085
Type 3	0.084	0.065	0.023	0.531	0.03	0.033	0.234
Type 4	0.062	0.008	0.031	0.048	0.524	0.25	0.076
Type 5	0.109	0.01	0.129	0.012	0.066	0.552	0.121
Type 6	0.102	0.119	0.06	0.053	0.01	0.071	0.585

Table 34: Riverside-San Bernardino-Ontario, CA Neighborhood Transition Matrix

Employees (%)	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
White	0.918	0.493	0.766	0.461	0.791	0.756	0.646
Black	0.008	0.148	0.04	0.25	0.038	0.083	0.026
Asian	0.043	0.326	0.054	0.196	0.143	0.092	0.284
Hispanic	0.042	0.04	0.256	0.147	0.041	0.103	0.067
Less Than HS	0.055	0.092	0.109	0.109	0.055	0.07	0.094
Bachelor's +	0.309	0.288	0.227	0.235	0.335	0.275	0.343
Low Salary	0.174	0.214	0.219	0.229	0.168	0.188	0.163
High Salary	0.57	0.45	0.445	0.396	0.584	0.501	0.561

Table 35: Mean Demographics by Neighborhood Type in Seattle-Tacoma-Bellevue, WA

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
Type 0	0.695	0.003	0.007	0.001	0.194	0.083	0.019
Type 1	0.013	0.517	0.005	0.095	0.103	0.166	0.102
Type 2	0.092	0.011	0.45	0.072	0.058	0.293	0.025
Type 3	0.008	0.139	0.048	0.55	0.027	0.189	0.038
Type 4	0.22	0.023	0.005	0.004	0.541	0.134	0.072
Type 5	0.136	0.051	0.032	0.038	0.184	0.512	0.048
Type 6	0.087	0.092	0.01	0.028	0.287	0.156	0.34

Table 36: Seattle-Tacoma-Bellevue, WA Neighborhood Transition Matrix

Employees (%)	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
White	0.565	0.674	0.702	0.429	0.525	0.803	0.448
Black	0.027	0.107	0.064	0.192	0.063	0.044	0.396
Asian	0.37	0.095	0.163	0.317	0.374	0.125	0.107
Hispanic	0.092	0.566	0.241	0.15	0.307	0.117	0.285
Less Than HS	0.079	0.19	0.113	0.106	0.144	0.07	0.144
Bachelor's +	0.391	0.188	0.307	0.308	0.276	0.37	0.21
Low Salary	0.173	0.227	0.196	0.205	0.22	0.163	0.245
High Salary	0.606	0.412	0.53	0.515	0.448	0.63	0.409

Table 37: Mean Demographics by Neighborhood Type in San Francisco-Oakland-Berkeley, CA

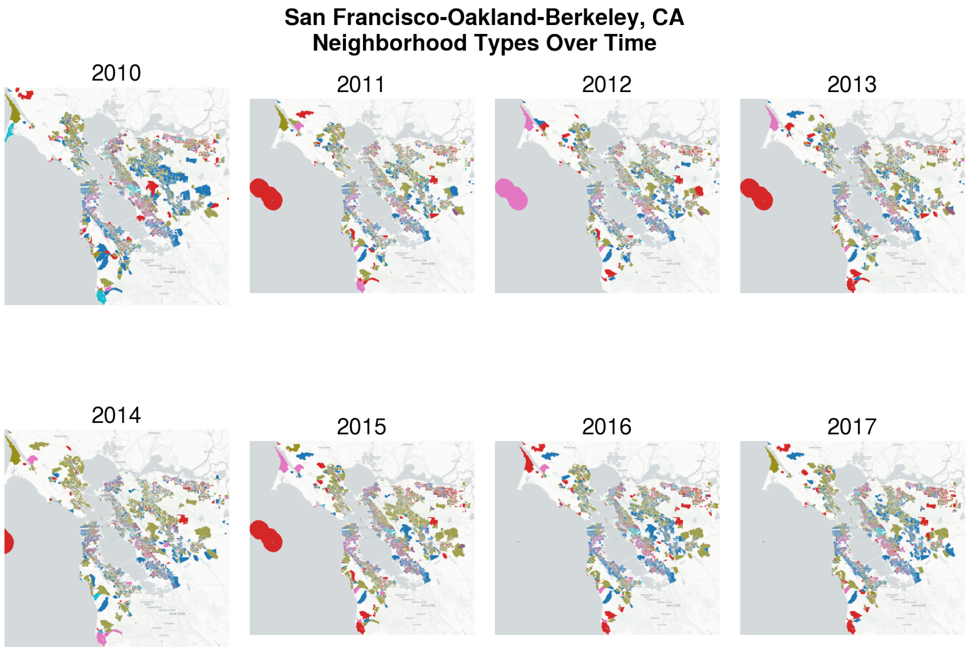

Figure 30: San Francisco Clusters Over Time

	Type 0	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
Type 0	0.615	0.004	0.055	0.047	0.073	0.199	0.008
Type 1	0.042	0.464	0.143	0.05	0.158	0.026	0.117
Type 2	0.154	0.039	0.308	0.075	0.161	0.235	0.027
Type 3	0.143	0.019	0.087	0.447	0.141	0.085	0.079
Type 4	0.166	0.038	0.12	0.086	0.525	0.04	0.024
Type 5	0.217	0.003	0.09	0.027	0.021	0.639	0.003
Type 6	0.038	0.067	0.069	0.16	0.07	0.019	0.576

Table 38: San Francisco-Oakland-Berkeley, CA Neighborhood Transition Matrix