January 2020.

Modeling High Resolution Socio-Spatial Neighborhood Dynamics in America's 15 Largest Metros

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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 on gentrification 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 thus develop a spatial Markov Chain to examine the ways in which neighborhoods transition between states as a function of their previous state and the states of the surrounding neighborhoods. We develop our model 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 using data with high spatial and temporal resolution and we incorporate concepts of neighborhood spillovers into our model. 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 of neighborhood change.

INTRODUCTION

Gentrification has been a topic of lively interest in the urban studies since the concept's introduction by Ruth, 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 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).

[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."

[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.

To measure gentrification, we thus develop a spatial Markov Chain to examine the ways in which neighborhoods transition between states as a function of their previous state and the states of the surrounding neighborhoods. We develop our model 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 using data with high spatial and temporal resolution and we incorporate concepts of neighborhood spillovers into our model. 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 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) 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). Ruth, 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 has poor temporal resolution, most studies resort to the latter” (Ley 1986).

Others such as 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.

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 quanttitative techniques to identidy empirical social areas, first using principal components and factor analysis, and later using multivariate clustering analysis (Shevky and Williams 1949; Shevsky 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 (Alexander D Singleton and Longley 2009; Alexander D. Singleton and Longley 2009; 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 the explicit application in human geography, many have nonetheless been employed for geodemographic research. Various authors have turned to kmeans, hierarchical clustering (Alexander D Singleton and Longley 2009; Spielman and Singleton 2015), or self-organizing maps (SOMs) (Singleton and Spielman 2014), each of which have particular strengths in differentiating different sizes and shapes of multivariate clusters. While several authors have devised geodemographic typologies for studying urban areas, the concept of developing and analyzying *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; **???**; **???**; 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 nothing to describe why these trajectories emerge or which neighborhoods might be likely to diverge in the future. Neither does the sequence cluster methodology provide any insight into the underlying reasons or processes that define the trajectories.

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, educational levels, and industrial classification of each worker. 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 along with high accuracy, and it is possible to examine both the residential characteristics and the 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 being 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)[3], 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 $3333/month and share with earnings

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

less than 1250 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).

Clustering Approach

As discussed above, dozens of clustering algorithms have been developed in applied in the statistical literature, many of which have appeared wiith success in the geodemographic literature. In this study, we elect to use a Gaussian Mixture Model 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. For each metro region, we choose the best fitting cluster model for clusters ranging from two through seven. 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.

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. 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 model neighbor. 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 surrounded by a different type of neighbor.

As a result, we can see how likely neighborhoods are to transition between types, and we can see how that probability changes under different conditions of spatial context. In practical terms, this means we we can see if a neighborhood is likely to gentrify, then we can see how that likelihood differs if the focal neighborhood is surrounded by others that have already gentrified. Finally, because the LEHD data lack information in development, we construct models for both workplace areas and residential areas. By examining relationships between the residential and workplace transition matrices, we can begin to intuit whether these processes of change are related, for example if downtown reinvestment triggers changes in the employment structure prior to neighborhood change, or if the reverse process is observed.

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[4]. 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.

[4] detailed tables and figures for each metro are available in the appendix

	name	pop	wac_stability	rac_stability	lr_pval	q_p_val
24	Portland-Vancouver-Hillsboro, OR-WA	2,478,810	0.574127	0.436857	0	0
23	San Antonio-New Braunfels, TX	2,518,036	0.539252	0.455045	0	0
22	Charlotte-Concord-Gastonia, NC-SC	2,569,213	0.558599	0.416939	0	0
21	Orlando-Kissimmee-Sanford, FL	2,572,692	0.559719	0.437269	0	0
20	Baltimore-Columbia-Towson, MD	2,802,789	0.633107	0.438312	0	0
19	St. Louis, MO-IL	2,805,465	0.55002	0.413238	0	0
18	Denver-Aurora-Lakewood, CO	2,932,415	0.587632	0.433425	0	0
17	Tampa-St. Petersburg-Clearwater, FL	3,142,663	0.541407	0.434045	0	0
16	San Diego-Chula Vista-Carlsbad, CA	3,343,364	0.576992	0.48199	0	0
15	Minneapolis-St. Paul-Bloomington, MN-WI	3,629,190	0.6395	0.422106	0	0
14	Seattle-Tacoma-Bellevue, WA	3,939,363	0.579002	0.463316	0	0
13	Detroit-Warren-Dearborn, MI	4,326,442	0.59858	0.424298	0	0
12	Riverside-San Bernardino-Ontario, CA	4,622,361	0.614707	0.457217	0	0
11	San Francisco-Oakland-Berkeley, CA	4,729,484	0.640516	0.495937	0	0
10	Phoenix-Mesa-Chandler, AZ	4,857,962	0.594854	0.423039	0	0
9	Boston-Cambridge-Newton, MA-NH	4,875,390	0.403386	0.456491	0	0
8	Atlanta-Sandy Springs-Roswell, GA	5,949,951	0.582577	0.483736	0	0
7	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	6,096,372	0.616822	0.45001	0	0
6	Miami-Fort Lauderdale-Pompano Beach, FL	6,198,782	0.530239	0.481383	0	0
5	Washington-Arlington-Alexandria, DC-VA-MD-WV	6,249,950	0.627447	0.504891	0	0
4	Houston-The Woodlands-Sugar Land, TX	6,997,384	0.582445	0.507484	0	0
3	Dallas-Fort Worth-Arlington, TX	7,539,711	0.626968	0.452897	0	0
2	Chicago-Naperville-Elgin, IL-IN-WI	9,498,716	0.654814	0.550459	0	0
1	Los Angeles-Long Beach-Anaheim, CA	13,291,486	0.628102	0.555388	0	0
0	New York-Newark-Jersey City, NY-NJ-PA	19,979,477	0.613401	0.488283	0	0

Table 1: MSA Summary: Average Stability Rate and ‘p‘ value by Metro Region

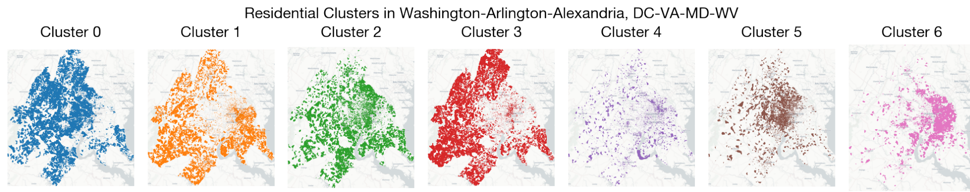

Figure 1: D.C. Residential Clusters

Washington DC

Residential clusters in the Washington D.C. region are visualized in fig. 1, from which it is immediately apparent 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 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.

Residential neighborhood types in the Washington D.C. metropolitan region follow predictable patterns of race and class segregation

- Cluster 0: white with some diversity, highest education, highest earning,
- Cluster 1: black/white, lower education, lower income
- Cluster 2: white/black, high education, high income
- Cluster 3: white segregated, high education, high income
- Cluster 4: racially diverse, lower education, lower income
- Cluster 5: white/asian, high education high income
- Cluster 6: black/racially diverse, lower education, lower income

Transition rates between neighborhoods also show important patterns about the stickiness of segregation. Type 6, for example, which has the largest share of minority residents, as well as the lowest educational attainment and earnings has a 68% chance of remaining Type 6 in successive time periods. It has less than a 1% chance of becoming Type 0 or Type 3–the two neighborhood types with the smallest shares of minority residents. There is, however, an 8.7% chance of transitioning into Type 4, a highly transitional neighborhood type that has a high probability of transitioning into many other neighborhood types. Put differently, without considering spatial effects, it is virtually impossible for Type 6 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.

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.852	0.045	0.09	0.04	0.061	0.387	0.165	0.639
1	0.489	0.479	0	0.055	0.101	0.247	0.208	0.497
2	0.745	0.171	0.067	0.097	0.084	0.325	0.182	0.578
3	0.934	0.066	0	0.053	0.072	0.319	0.194	0.551
4	0.584	0.263	0.08	0.286	0.165	0.242	0.222	0.446
5	0.616	0.092	0.256	0.092	0.087	0.39	0.169	0.607
6	0.446	0.444	0.088	0.181	0.132	0.242	0.207	0.47

Table 2: Residential Clusters in the Washington D.C. metro

	0	1	2	3	4	5	6
0	0.59	0.036	0.133	0.099	0.009	0.125	0.007
1	0.062	0.477	0.09	0.113	0.053	0.03	0.175
2	0.162	0.069	0.487	0.059	0.028	0.098	0.096
3	0.21	0.141	0.107	0.452	0.028	0.04	0.022
4	0.028	0.107	0.066	0.034	0.342	0.095	0.328
5	0.186	0.025	0.121	0.026	0.046	0.505	0.09
6	0.006	0.1	0.066	0.009	0.087	0.051	0.681

Table 3: Aspatial Residential Transition Rates in D.C.

	0	1	2	3	4	5	6
0	0.621	0.031	0.123	0.094	0.008	0.118	0.005
1	0.21	0.233	0.142	0.263	0.039	0.084	0.029
2	0.285	0.047	0.416	0.077	0.019	0.122	0.034
3	0.301	0.104	0.1	0.425	0.018	0.043	0.01
4	0.118	0.132	0.125	0.084	0.204	0.216	0.121
5	0.319	0.036	0.126	0.036	0.028	0.427	0.027
6	0.041	0.055	0.219	0.032	0.055	0.152	0.446

Table 4: Residential Transitions in D.C. with Modal Neighbor Type 0

	0	1	2	3	4	5	6
0	0.537	0.074	0.13	0.159	0.011	0.085	0.005
1	0.042	0.541	0.073	0.088	0.048	0.021	0.186
2	0.104	0.157	0.442	0.075	0.045	0.051	0.126
3	0.174	0.188	0.115	0.45	0.034	0.022	0.017
4	0.014	0.275	0.049	0.024	0.269	0.049	0.319
5	0.2	0.099	0.169	0.07	0.093	0.264	0.105
6	0.002	0.264	0.043	0.008	0.054	0.013	0.616

Table 5: Residential Transitions in D.C. with Modal Neighbor Type 1

	0	1	2	3	4	5	6
0	0.523	0.038	0.206	0.087	0.013	0.124	0.01
1	0.1	0.347	0.217	0.146	0.055	0.047	0.088
2	0.148	0.067	0.532	0.053	0.024	0.089	0.086
3	0.194	0.146	0.168	0.358	0.034	0.061	0.039
4	0.05	0.126	0.136	0.054	0.234	0.144	0.256
5	0.206	0.036	0.197	0.033	0.043	0.399	0.086
6	0.013	0.071	0.184	0.018	0.072	0.092	0.55

Table 6: Residential Transitions in D.C. with Modal Neighbor Type 2

	0	1	2	3	4	5	6
0	0.54	0.069	0.111	0.199	0.011	0.065	0.004
1	0.147	0.315	0.114	0.316	0.035	0.044	0.03
2	0.208	0.107	0.428	0.118	0.018	0.081	0.04
3	0.198	0.146	0.09	0.495	0.024	0.033	0.014
4	0.087	0.174	0.095	0.164	0.202	0.107	0.171
5	0.258	0.082	0.165	0.098	0.048	0.312	0.036
6	0.018	0.143	0.163	0.069	0.087	0.091	0.43

Table 7: Residential Transitions in D.C. with Modal Neighbor Type 3

	0	1	2	3	4	5	6
0	0.483	0.03	0.183	0.087	0.017	0.167	0.033
1	0.035	0.417	0.087	0.083	0.097	0.031	0.248
2	0.1	0.073	0.434	0.058	0.057	0.084	0.194
3	0.148	0.151	0.165	0.347	0.062	0.048	0.08
4	0.022	0.088	0.057	0.03	0.39	0.082	0.33
5	0.096	0.036	0.122	0.026	0.096	0.436	0.188
6	0.002	0.068	0.051	0.013	0.164	0.052	0.649

Table 8: Residential Transitions in D.C. with Modal Neighbor Type 4

	0	1	2	3	4	5	6
0	0.525	0.02	0.134	0.047	0.011	0.246	0.017
1	0.168	0.205	0.145	0.186	0.069	0.117	0.11
2	0.216	0.032	0.4	0.047	0.028	0.188	0.087
3	0.246	0.106	0.145	0.344	0.039	0.091	0.029
4	0.045	0.039	0.105	0.039	0.293	0.228	0.251
5	0.17	0.016	0.105	0.02	0.039	0.568	0.083
6	0.024	0.028	0.102	0.012	0.087	0.211	0.537

Table 9: Residential Transitions in D.C. with Modal Neighbor Type 5

	0	1	2	3	4	5	6
0	0.447	0.038	0.227	0.062	0.031	0.153	0.042
1	0.011	0.506	0.06	0.025	0.078	0.013	0.307
2	0.058	0.067	0.448	0.035	0.054	0.089	0.249
3	0.099	0.166	0.189	0.278	0.087	0.044	0.137
4	0.007	0.088	0.041	0.015	0.369	0.056	0.424
5	0.061	0.019	0.113	0.011	0.097	0.449	0.25
6	0.004	0.091	0.054	0.006	0.088	0.04	0.717

Table 10: Residential Transitions in D.C. with Modal Neighbor Type 6

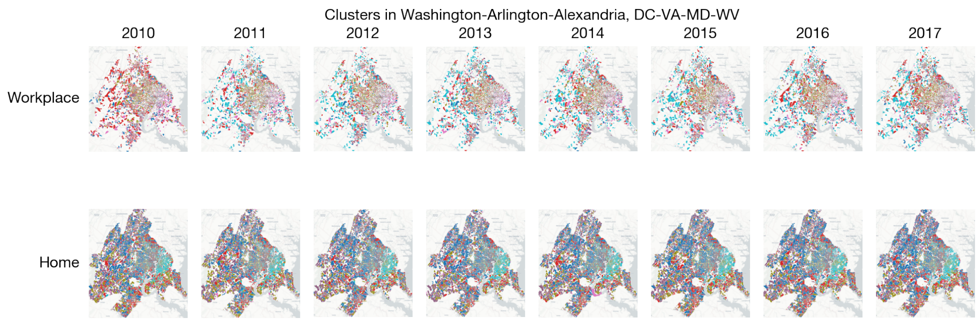

Figure 2: D.C. Clusters Over Time

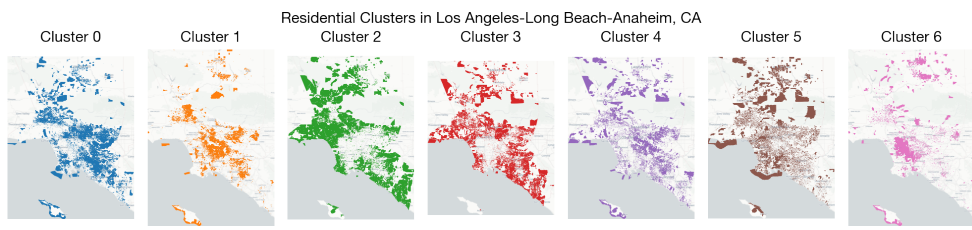

Figure 3: L.A. Residential Clusters

The transitions also show important spatial dynamics that affect gentrification and other important processes of neighborhood change. For example neighborhood Type 6 (characterized by racially-concentrated disadvantage) has only a 5% chance of gentrifying into Type 5 (characterized by the highest earnings and education) without considering spatial effects. But if that same neighborhood already has many Type 5 neighbors, then its probability of transitioning into Type 5 during the next year raises from 5% to 21%. 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 invasion and succession processes change shape.

Los Angeles

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.609	0.05	0.313	0.335	0.149	0.258	0.243	0.408
1	0.842	0.056	0.068	0.745	0.242	0.133	0.252	0.299
2	0.809	0.056	0.105	0.158	0.089	0.324	0.252	0.496
3	0.747	0	0.234	0.158	0.097	0.332	0.234	0.499
4	0.858	0	0.085	0.571	0.194	0.193	0.245	0.369
5	0.581	0.159	0.165	0.328	0.151	0.24	0.258	0.401
6	0.574	0.36	0.031	0.477	0.207	0.146	0.281	0.296

	0	1	2	3	4	5	6
0	0.537	0.068	0.089	0.132	0.075	0.081	0.018
1	0.084	0.608	0.008	0.005	0.155	0.046	0.095
2	0.071	0.005	0.631	0.179	0.037	0.068	0.008
3	0.128	0.004	0.216	0.529	0.083	0.037	0.002
4	0.114	0.178	0.067	0.118	0.424	0.065	0.033
5	0.129	0.061	0.135	0.057	0.071	0.431	0.115
6	0.024	0.109	0.013	0.002	0.029	0.095	0.727

These results largely confirm those reported by Hwang and Sampson (2014) "that racial heterogeneity works in a particular way to shape neighborhood trajectories among gentrifying tracts and their initially low-income adjacent tracts."

DISCUSSION

Following the predictions of the early Chicago School, we find strong evidence for the spatial pattern of residential succession and invasion. 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 not far apart in multivariate space. And when they do transition, they are influence strongly by the neighborhoods around them. 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 now possible to construct an information system that identifies neighborhoods at an increased risk for gentrification based on their prior trajectories and those of their neighbors[5]/spatialucr/geosnap)] python package].

Our finding that neighborhoods tend toward stability over time also provides evidence that NIMBY fears of massive neighborhood tipping are vastly overblown. It is difficult to generate a significant change in most established neighborhoods and absent such a major change, neighborhood stability is nearly guaranteed. 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

[5] We are developing the software infrastructure for such an information system as part of the [geosnap](http://github.com

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 the tip of the iceberg for studies of neighborhood dynamics seeking to leverage temporal geodemographics and spatial Markov chains. In future work, there are several ways to extend this study. This study leverages Gaussian Mixture Modeling as the clustering algorithm because it allows fo the use of the Bayesian Information Citerion to assess model fit and guide the selection of an optimal *k* parameter, but alternative methods, such as a silhouette score (Rousseeuw 1987), that may be used to judge model fit 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 useful to use a geosilhouette score (Wolf, Knaap, and Rey 2019).

Another area for exploration includes different operationalizations 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 hand, however, it builds in spatial dependence into the neighborhood identification process by definition, and it is unclear how to model this. Including a kernel function or spatial constraint would also require the specification of a threshold distance and/or kernel function, for which the analyst may have little guidance.

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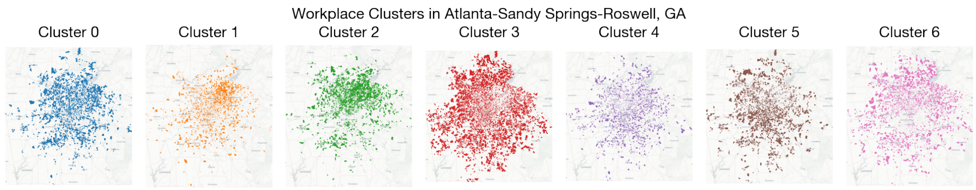

Figure 4: Atlanta Workplace Clusters

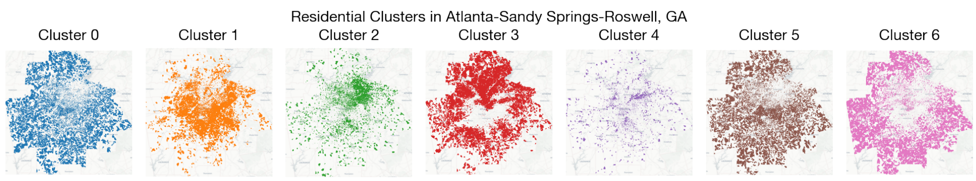

Figure 5: Atlanta Residential Clusters

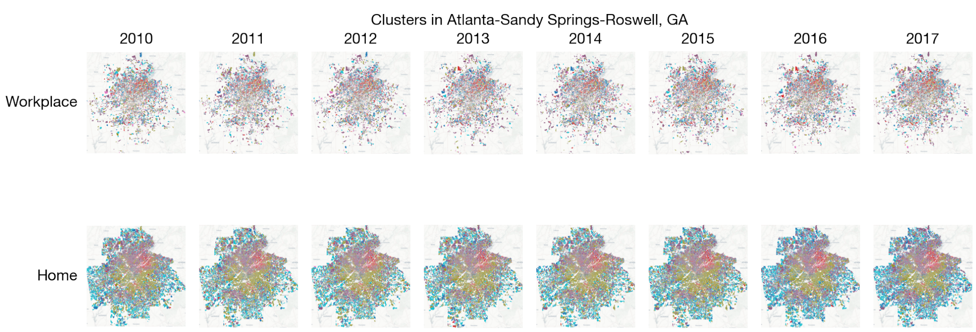

Figure 6: Atlanta Clusters Over Time

APPENDIX

Atlanta

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.628	0.319	0.038	0.073	0.092	0.154	0.436	0.191
1	0.515	0.243	0.212	0.098	0.118	0.267	0.279	0.343
2	0.732	0.207	0.051	0.052	0.077	0.305	0.141	0.556
3	0.758	0.242	0	0.038	0.097	0.199	0.292	0.319
4	0.509	0.385	0.083	0.043	0.11	0.157	0.477	0.128
5	0.574	0.398	0.016	0.03	0.093	0.226	0.17	0.438
6	0.802	0.124	0.031	0.181	0.136	0.182	0.231	0.321

	0	1	2	3	4	5	6
0	0.684	0.018	0.065	0.059	0.076	0.059	0.04
1	0.07	0.558	0.103	0.049	0.121	0.034	0.064
2	0.078	0.035	0.691	0.051	0.015	0.095	0.036
3	0.089	0.018	0.063	0.609	0.045	0.11	0.067
4	0.246	0.096	0.038	0.093	0.446	0.044	0.039
5	0.085	0.011	0.117	0.121	0.021	0.616	0.028
6	0.14	0.051	0.088	0.145	0.039	0.064	0.474

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.635	0.33	0	0.103	0.1	0.213	0.24	0.397
1	0.415	0.536	0.037	0.057	0.099	0.205	0.246	0.383
2	0.538	0.254	0.189	0.068	0.092	0.291	0.212	0.459
3	0.851	0.089	0.052	0.03	0.066	0.307	0.19	0.546
4	0.575	0.308	0.059	0.257	0.148	0.193	0.26	0.339
5	0.451	0.549	0	0.034	0.1	0.198	0.256	0.363
6	0.884	0.116	0	0	0.071	0.253	0.215	0.457

	0	1	2	3	4	5	6
0	0.367	0.126	0.045	0.106	0.063	0.196	0.097
1	0.095	0.593	0.072	0.077	0.033	0.116	0.014
2	0.058	0.13	0.508	0.154	0.074	0.046	0.029
3	0.067	0.068	0.08	0.638	0.009	0.07	0.069
4	0.174	0.119	0.147	0.037	0.445	0.061	0.018
5	0.19	0.133	0.031	0.103	0.018	0.418	0.108
6	0.159	0.031	0.034	0.175	0.01	0.175	0.417

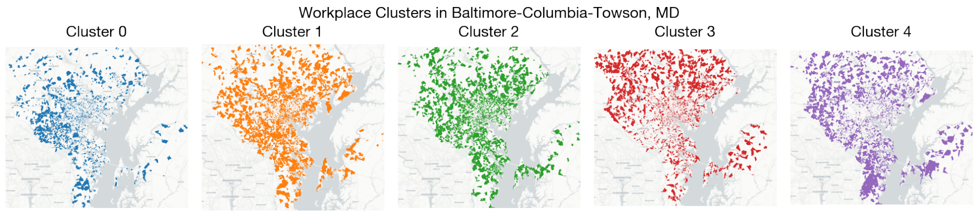

Figure 7: Baltimore Workplace Clusters

Figure 8: Baltimore Residential Clusters

Baltimore

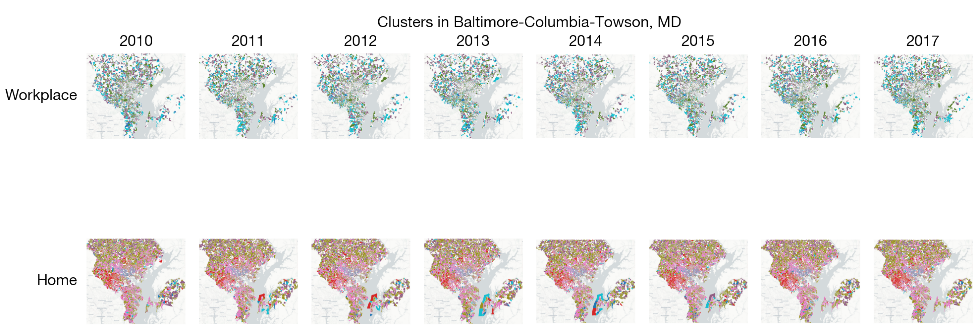

Figure 9: Baltimore Clusters Over Time

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.541	0.246	0.174	0.074	0.119	0.231	0.331	0.302
1	0.736	0.221	0.033	0.028	0.074	0.28	0.148	0.57
2	0.64	0.3	0.044	0.042	0.091	0.162	0.415	0.204
3	0.803	0.197	0	0	0.087	0.206	0.285	0.35
4	0.841	0.111	0.018	0.131	0.129	0.199	0.199	0.401

	0	1	2	3	4
0	0.565	0.096	0.227	0.032	0.08
1	0.019	0.785	0.099	0.041	0.055
2	0.06	0.113	0.733	0.043	0.052
3	0.031	0.186	0.156	0.541	0.087
4	0.055	0.186	0.146	0.071	0.542

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.303	0.668	0	0.055	0.112	0.173	0.256	0.334
1	0.905	0.049	0.045	0.019	0.063	0.294	0.201	0.539
2	0.659	0.149	0.169	0.049	0.075	0.307	0.202	0.528
3	0.638	0.362	0	0	0.082	0.229	0.231	0.429
4	0.577	0.364	0.043	0.03	0.083	0.242	0.223	0.46
5	0.917	0.057	0	0.063	0.074	0.259	0.212	0.497
6	0.506	0.371	0.062	0.158	0.128	0.208	0.244	0.387

	0	1	2	3	4	5	6
0	0.445	0.01	0.019	0.237	0.179	0.027	0.083
1	0.007	0.395	0.099	0.163	0.176	0.147	0.013
2	0.02	0.139	0.484	0.041	0.18	0.065	0.071
3	0.132	0.133	0.021	0.478	0.089	0.122	0.024
4	0.089	0.116	0.088	0.076	0.537	0.051	0.043
5	0.029	0.208	0.069	0.203	0.104	0.344	0.043
6	0.15	0.028	0.126	0.077	0.157	0.077	0.385

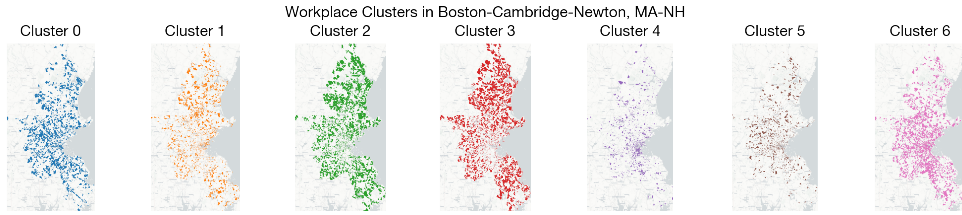

Figure 10: Boston Workplace Clusters

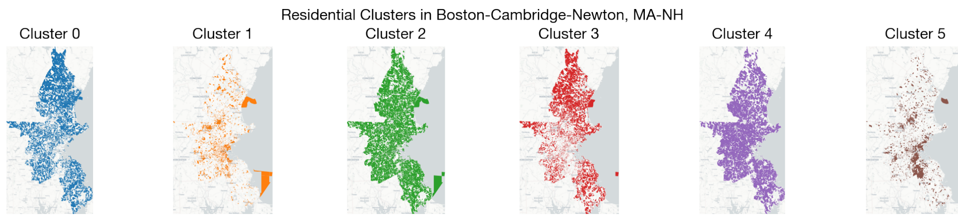

Figure 11: Boston Residential Clusters

Boston

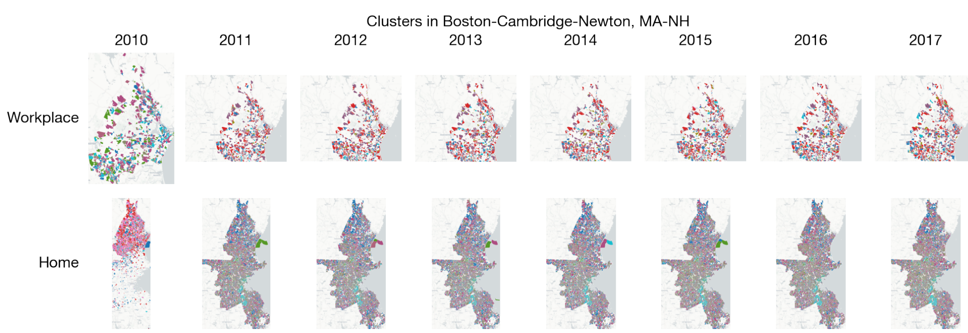

Figure 12: Boston Clusters Over Time

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.904	0.037	0.049	0.037	0.056	0.37	0.119	0.691
1	0.877	0.058	0.014	0.23	0.13	0.204	0.314	0.314
2	0.935	0.028	0.022	0.044	0.061	0.224	0.376	0.296
3	1	0	0	0.029	0.066	0.264	0.293	0.399
4	0.596	0.289	0.076	0.192	0.126	0.214	0.348	0.221
5	0.655	0.038	0.282	0.063	0.107	0.292	0.334	0.342
6	0.825	0.102	0.06	0.097	0.082	0.249	0.298	0.358

	0	1	2	3	4	5	6
0	0.652	0.009	0.201	0.12	0.001	0.002	0.016
1	0.061	0.225	0.332	0.309	0.003	0.017	0.052
2	0.079	0.022	0.747	0.118	0	0.003	0.03
3	0.071	0.028	0.225	0.652	0	0.004	0.019
4	0.119	0.067	0.396	0.201	0.015	0.037	0.164
5	0.134	0.028	0.317	0.092	0.028	0.254	0.148
6	0.106	0.03	0.435	0.111	0.009	0.03	0.278

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.973	0	0.027	0	0.052	0.344	0.209	0.566
1	0.656	0.116	0.173	0.249	0.117	0.269	0.245	0.42
2	0.912	0.047	0.041	0.041	0.06	0.337	0.209	0.559
3	0.978	0	0	0.07	0.061	0.32	0.218	0.54
4	0.839	0.029	0.109	0.039	0.058	0.351	0.196	0.586
5	0.646	0.289	0.042	0.156	0.097	0.262	0.244	0.432

	0	1	2	3	4	5
0	0.574	0.003	0.14	0.202	0.079	0.002
1	0.127	0.37	0.106	0.089	0.21	0.097
2	0.236	0.01	0.333	0.156	0.244	0.022
3	0.284	0.012	0.168	0.387	0.14	0.008
4	0.096	0.014	0.184	0.092	0.595	0.018
5	0.086	0.056	0.133	0.072	0.174	0.479

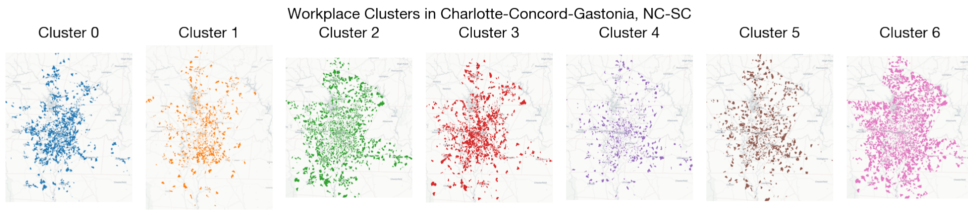

Figure 13: Charlotte Workplace Clusters

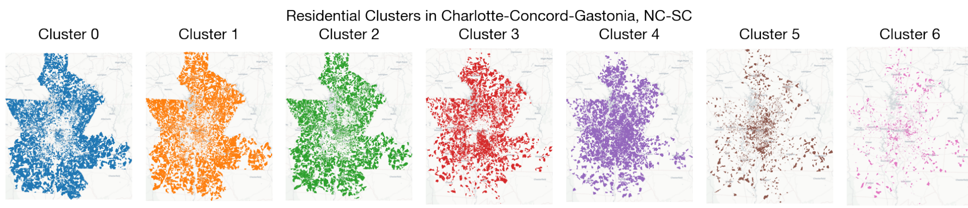

Figure 14: Charlotte Residential Clusters

Charlotte

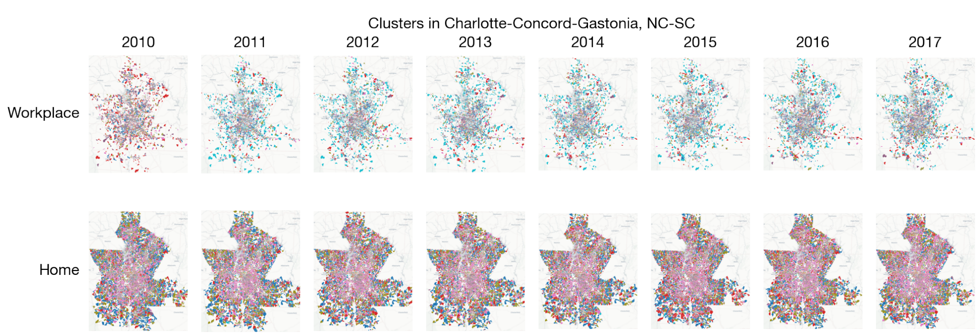

Figure 15: Charlotte Clusters Over Time

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.707	0.249	0.029	0.054	0.092	0.142	0.464	0.172
1	0.735	0.109	0.14	0.045	0.095	0.265	0.27	0.405
2	0.694	0.277	0	0.043	0.108	0.153	0.35	0.226
3	0.791	0.182	0.018	0.031	0.081	0.25	0.131	0.502
4	0.646	0.234	0.065	0.201	0.158	0.144	0.362	0.177
5	0.818	0.132	0.033	0.126	0.135	0.161	0.131	0.379
6	0.893	0.107	0	0.03	0.095	0.195	0.265	0.328

	0	1	2	3	4	5	6
0	0.726	0.025	0.067	0.059	0.028	0.03	0.064
1	0.14	0.489	0.041	0.079	0.068	0.093	0.091
2	0.142	0.017	0.408	0.084	0.032	0.048	0.268
3	0.073	0.018	0.042	0.685	0.003	0.063	0.116
4	0.185	0.073	0.125	0.013	0.388	0.134	0.082
5	0.073	0.04	0.051	0.142	0.036	0.572	0.085
6	0.071	0.021	0.121	0.094	0.014	0.037	0.642

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.905	0.095	0	0	0.078	0.222	0.222	0.415
1	0.69	0.31	0	0.059	0.102	0.188	0.253	0.35
2	0.673	0.285	0	0.09	0.107	0.182	0.254	0.344
3	0.869	0.077	0.053	0.024	0.077	0.26	0.204	0.482
4	0.674	0.277	0.032	0.057	0.092	0.216	0.231	0.415
5	0.537	0.287	0.158	0.048	0.102	0.236	0.235	0.406
6	0.641	0.233	0.047	0.268	0.14	0.175	0.257	0.322

	0	1	2	3	4	5	6
0	0.464	0.207	0.137	0.115	0.051	0.02	0.006
1	0.17	0.38	0.204	0.089	0.108	0.034	0.015
2	0.129	0.237	0.344	0.054	0.151	0.035	0.048
3	0.155	0.143	0.072	0.326	0.222	0.076	0.006
4	0.032	0.091	0.096	0.114	0.584	0.061	0.021
5	0.04	0.09	0.089	0.124	0.182	0.423	0.052
6	0.027	0.078	0.218	0.03	0.147	0.104	0.397

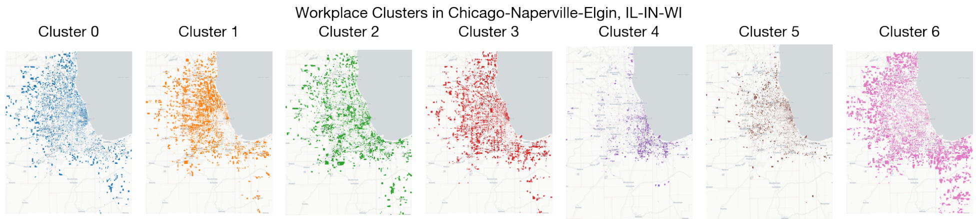

Figure 16: Chicago Workplace Clusters

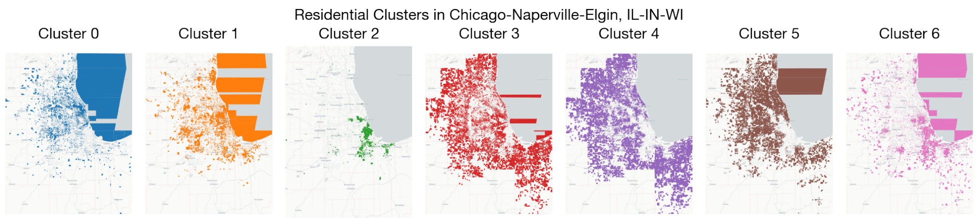

Figure 17: Chicago Residential Clusters

Chicago

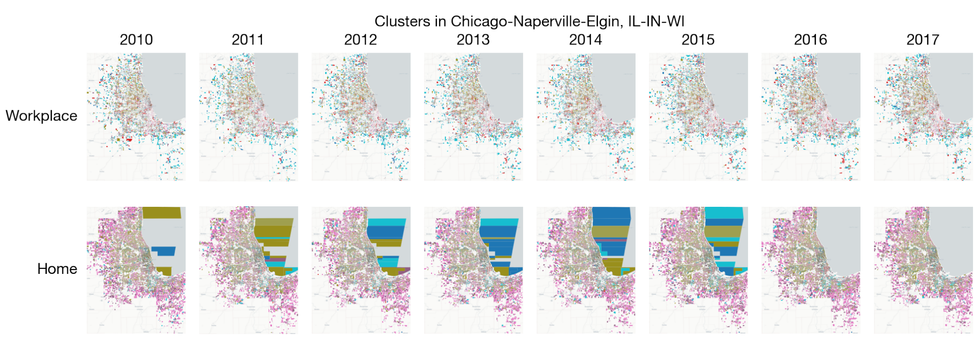

Figure 18: Chicago Clusters Over Time

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.835	0.046	0.068	0.303	0.151	0.195	0.326	0.241
1	0.883	0.046	0.062	0.093	0.068	0.313	0.205	0.498
2	0.841	0.11	0.031	0.213	0.131	0.222	0.097	0.543
3	0.82	0.114	0.045	0.161	0.088	0.158	0.48	0.151
4	0.435	0.538	0.017	0.1	0.125	0.167	0.357	0.222
5	0.532	0.188	0.249	0.159	0.12	0.259	0.35	0.26
6	0.963	0.036	0	0.127	0.096	0.216	0.307	0.347

	0	1	2	3	4	5	6
0	0.49	0.084	0.104	0.149	0.008	0.065	0.101
1	0.039	0.705	0.086	0.08	0.005	0.021	0.064
2	0.06	0.123	0.678	0.038	0.024	0.014	0.063
3	0.066	0.079	0.032	0.697	0.032	0.028	0.067
4	0.009	0.017	0.053	0.084	0.75	0.06	0.027
5	0.094	0.059	0.03	0.094	0.07	0.636	0.017
6	0.065	0.103	0.075	0.106	0.014	0.009	0.628

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.63	0.057	0.264	0.181	0.106	0.312	0.23	0.441
1	0.72	0.187	0.076	0.316	0.139	0.218	0.237	0.387
2	0.062	0.92	0.011	0.02	0.122	0.155	0.283	0.316
3	0.935	0.05	0	0.279	0.119	0.226	0.237	0.419
4	0.983	0.001	0.016	0.058	0.062	0.295	0.227	0.501
5	0.854	0.032	0.1	0.069	0.063	0.327	0.21	0.53
6	0.51	0.443	0	0.227	0.134	0.174	0.27	0.34

	0	1	2	3	4	5	6
0	0.51	0.172	0.001	0.052	0.041	0.189	0.035
1	0.093	0.538	0.015	0.147	0.026	0.082	0.099
2	0.002	0.059	0.695	0.002	0	0	0.243
3	0.026	0.123	0.001	0.47	0.196	0.107	0.078
4	0.021	0.026	0	0.216	0.532	0.192	0.014
5	0.079	0.067	0	0.095	0.164	0.586	0.009
6	0.032	0.161	0.095	0.149	0.021	0.019	0.523

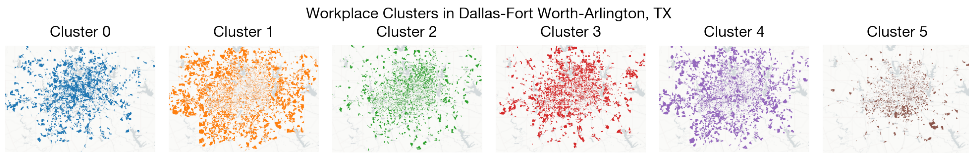

Figure 19: Dallas Workplace Clusters

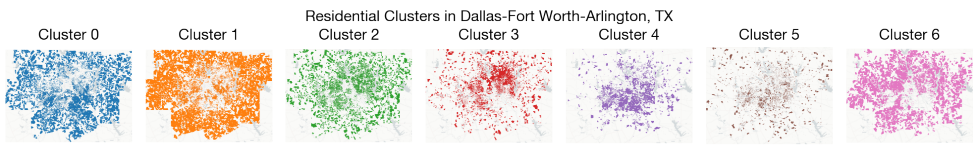

Figure 20: Dallas Residential Clusters

Dallas

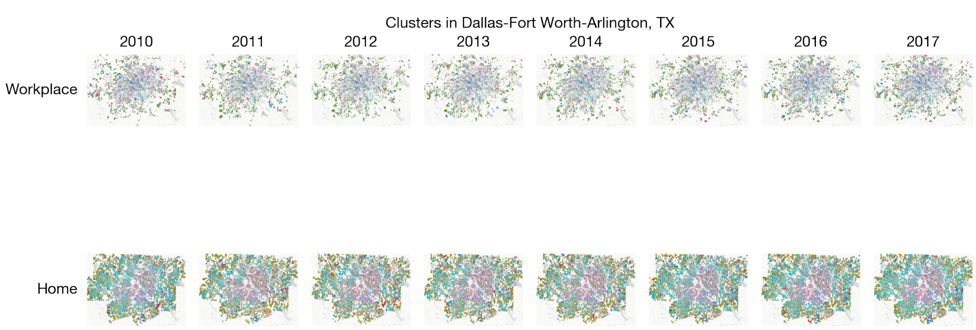

Figure 21: Dallas Clusters Over Time

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.816	0.119	0.048	0.176	0.105	0.248	0.119	0.577
1	0.923	0.077	0	0.209	0.128	0.172	0.252	0.348
2	0.656	0.113	0.178	0.239	0.141	0.209	0.33	0.276
3	0.788	0.138	0.05	0.23	0.111	0.131	0.444	0.162
4	0.867	0.064	0.03	0.315	0.174	0.152	0.162	0.372
5	0.529	0.425	0.03	0.162	0.138	0.163	0.409	0.195

	0	1	2	3	4	5
0	0.769	0.04	0.026	0.055	0.091	0.019
1	0.115	0.511	0.038	0.128	0.171	0.038
2	0.09	0.048	0.547	0.17	0.103	0.042
3	0.064	0.049	0.048	0.735	0.064	0.04
4	0.176	0.107	0.048	0.101	0.557	0.011
5	0.079	0.051	0.054	0.149	0.025	0.643

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.665	0.296	0	0.268	0.14	0.171	0.237	0.377
1	0.955	0.044	0	0.229	0.115	0.218	0.203	0.468
2	0.835	0.094	0.071	0.147	0.096	0.259	0.192	0.519
3	0.661	0.093	0.218	0.103	0.087	0.311	0.182	0.559
4	0.638	0.288	0.05	0.33	0.151	0.166	0.234	0.368
5	0.594	0.181	0.129	0.338	0.164	0.185	0.234	0.37
6	0.885	0.054	0.036	0.106	0.081	0.261	0.187	0.549

	0	1	2	3	4	5	6
0	0.487	0.182	0.073	0.026	0.139	0.041	0.052
1	0.193	0.486	0.147	0.026	0.048	0.014	0.086
2	0.093	0.18	0.321	0.141	0.093	0.031	0.142
3	0.043	0.048	0.17	0.531	0.054	0.052	0.103
4	0.193	0.063	0.088	0.04	0.528	0.058	0.03
5	0.182	0.06	0.094	0.119	0.193	0.332	0.019
6	0.079	0.128	0.162	0.099	0.039	0.008	0.485

Figure 22: Denver Workplace Clusters

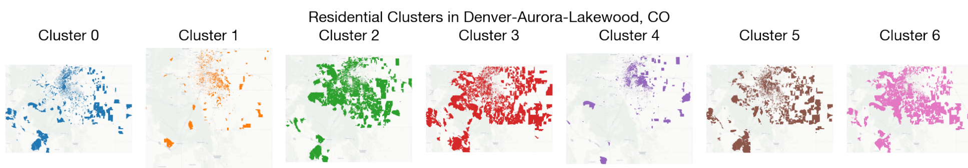

Figure 23: Denver Residential Clusters

Denver

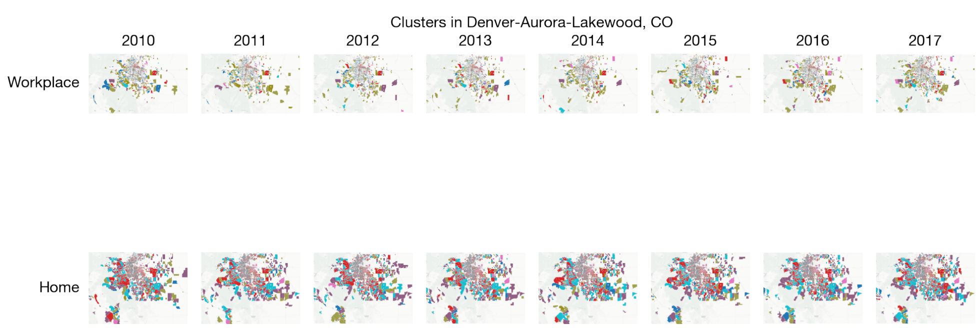

Figure 24: Denver Clusters Over Time

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.906	0.036	0.03	0.158	0.077	0.185	0.373	0.219
1	0.913	0.033	0.033	0.118	0.071	0.31	0.099	0.635
2	0.915	0.059	0.009	0.216	0.118	0.21	0.155	0.463
3	0.842	0.068	0.052	0.253	0.117	0.169	0.379	0.187
4	0.725	0.191	0.048	0.273	0.171	0.175	0.234	0.373
5	0.976	0	0	0.147	0.088	0.245	0.247	0.411
6	0.716	0.04	0.179	0.16	0.104	0.285	0.285	0.369

	0	1	2	3	4	5	6
0	0.711	0.062	0.046	0.127	0.003	0.043	0.008
1	0.067	0.751	0.093	0.028	0.013	0.034	0.015
2	0.115	0.177	0.498	0.099	0.033	0.068	0.01
3	0.171	0.036	0.07	0.572	0.044	0.058	0.049
4	0.017	0.067	0.116	0.208	0.506	0.046	0.039
5	0.113	0.088	0.096	0.098	0.017	0.56	0.028
6	0.047	0.083	0.024	0.216	0.034	0.081	0.515

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.853	0	0.084	0.271	0.111	0.244	0.214	0.435
1	0.656	0.118	0.16	0.177	0.102	0.266	0.216	0.44
2	0.9	0.04	0.04	0.093	0.066	0.298	0.194	0.527
3	1	0	0	0.14	0.075	0.286	0.202	0.498
4	0.72	0.207	0.042	0.266	0.122	0.199	0.234	0.359
5	0.891	0.073	0	0.235	0.101	0.235	0.218	0.424
6	0.943	0	0.036	0.077	0.059	0.314	0.19	0.546

	0	1	2	3	4	5	6
0	0.365	0.058	0.058	0.119	0.082	0.166	0.151
1	0.121	0.336	0.113	0.02	0.238	0.123	0.049
2	0.033	0.032	0.527	0.056	0.065	0.106	0.181
3	0.077	0.007	0.068	0.421	0.019	0.175	0.233
4	0.049	0.075	0.076	0.018	0.577	0.189	0.016
5	0.094	0.03	0.105	0.138	0.139	0.394	0.1
6	0.087	0.013	0.176	0.194	0.013	0.102	0.414

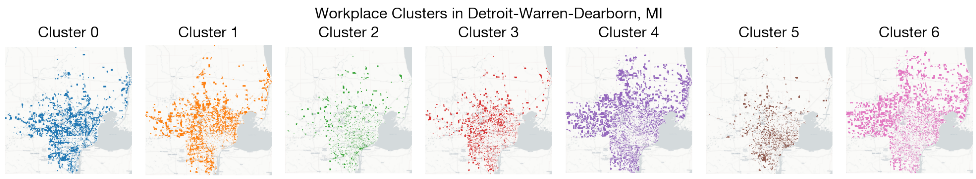

Figure 25: Detroit Workplace Clusters

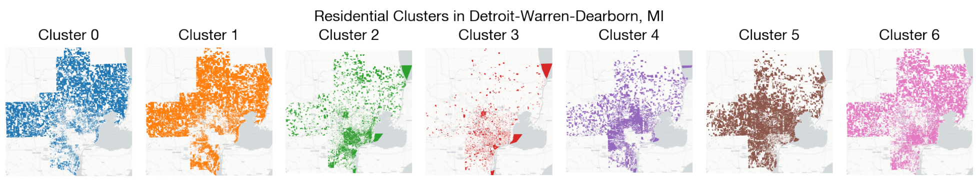

Figure 26: Detroit Residential Clusters

Detroit

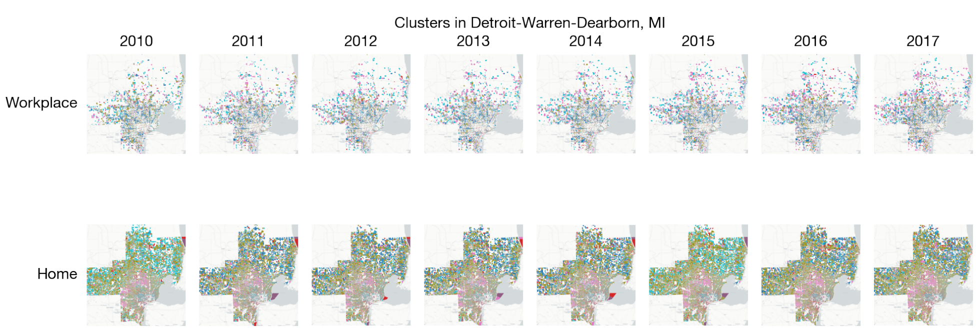

Figure 27: Detroit Clusters Over Time

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.852	0.109	0.029	0.022	0.056	0.306	0.134	0.593
1	0.844	0.109	0.031	0.027	0.061	0.166	0.455	0.184
2	0.594	0.302	0.052	0.139	0.125	0.168	0.413	0.183
3	0.746	0.072	0.159	0.036	0.079	0.27	0.322	0.342
4	0.906	0.065	0	0.051	0.073	0.195	0.337	0.303
5	0.455	0.52	0.011	0.029	0.097	0.162	0.385	0.203
6	0.931	0.068	0	0	0.067	0.223	0.316	0.331

	0	1	2	3	4	5	6
0	0.755	0.062	0.006	0.036	0.07	0.028	0.043
1	0.069	0.661	0.015	0.055	0.123	0.039	0.038
2	0.03	0.072	0.513	0.087	0.111	0.151	0.037
3	0.106	0.156	0.051	0.523	0.09	0.025	0.049
4	0.092	0.129	0.025	0.036	0.551	0.036	0.131
5	0.078	0.09	0.059	0.023	0.064	0.653	0.033
6	0.084	0.076	0.008	0.032	0.236	0.03	0.534

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.989	0	0.011	0	0.05	0.28	0.229	0.485
1	0.957	0.023	0	0.044	0.056	0.259	0.236	0.459
2	0.531	0.424	0	0.08	0.089	0.193	0.287	0.339
3	0.547	0.301	0.094	0.179	0.108	0.212	0.287	0.345
4	0.789	0.05	0.139	0.036	0.058	0.319	0.226	0.503
5	0.746	0.203	0.044	0.015	0.06	0.264	0.241	0.457
6	0.592	0.407	0	0	0.073	0.22	0.272	0.38

	0	1	2	3	4	5	6
0	0.365	0.251	0.024	0.004	0.088	0.107	0.16
1	0.145	0.422	0.082	0.012	0.095	0.133	0.112
2	0.023	0.116	0.432	0.069	0.048	0.117	0.195
3	0.01	0.041	0.186	0.41	0.143	0.157	0.052
4	0.064	0.111	0.039	0.042	0.505	0.202	0.037
5	0.056	0.114	0.071	0.034	0.153	0.475	0.097
6	0.132	0.154	0.16	0.016	0.044	0.134	0.361

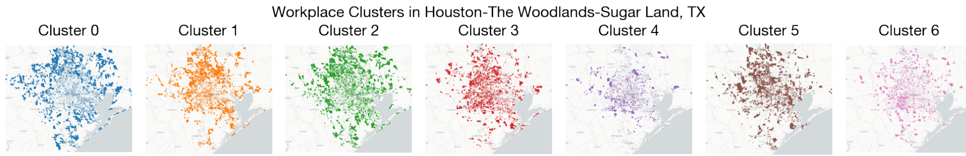

Figure 28: Houston Workplace Clusters

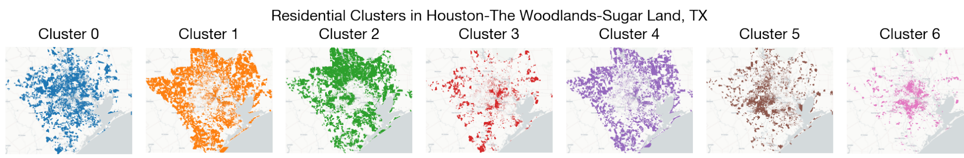

Figure 29: Houston Residential Clusters

Houston

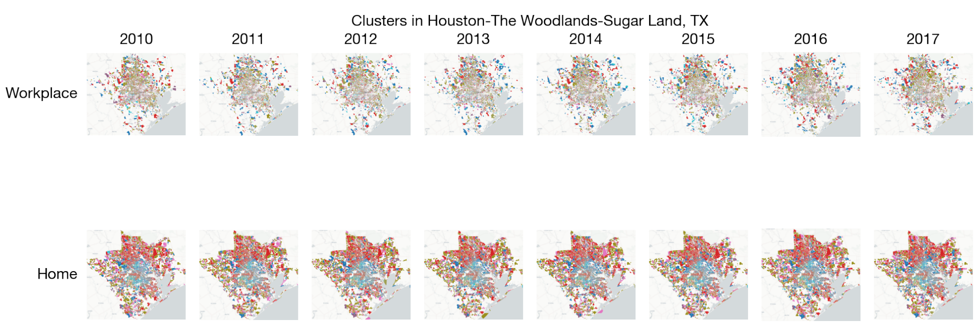

Figure 30: Houston Clusters Over Time

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.927	0.073	0	0.304	0.155	0.158	0.227	0.376
1	0.765	0.164	0.049	0.301	0.132	0.12	0.43	0.169
2	0.864	0.066	0.034	0.398	0.196	0.145	0.161	0.386
3	0.681	0.217	0.092	0.233	0.129	0.197	0.208	0.413
4	0.566	0.333	0.072	0.321	0.18	0.118	0.503	0.107
5	0.828	0.108	0.047	0.258	0.132	0.222	0.083	0.654
6	0.587	0.093	0.262	0.261	0.167	0.214	0.304	0.289

	0	1	2	3	4	5	6
0	0.51	0.1	0.191	0.055	0.03	0.095	0.02
1	0.04	0.704	0.067	0.08	0.056	0.038	0.015
2	0.119	0.105	0.504	0.053	0.028	0.163	0.029
3	0.032	0.125	0.049	0.556	0.057	0.121	0.059
4	0.042	0.183	0.063	0.108	0.528	0.009	0.066
5	0.038	0.032	0.098	0.077	0.003	0.742	0.009
6	0.035	0.065	0.084	0.159	0.092	0.033	0.533

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.755	0.181	0.046	0.397	0.161	0.171	0.21	0.441
1	0.957	0.043	0	0.329	0.14	0.194	0.199	0.485
2	0.877	0.045	0.069	0.123	0.087	0.274	0.167	0.605
3	0.465	0.534	0	0.25	0.158	0.136	0.271	0.342
4	0.861	0.068	0	0.418	0.159	0.171	0.212	0.443
5	0.598	0.128	0.244	0.162	0.117	0.278	0.188	0.544
6	0.457	0.418	0.082	0.332	0.175	0.149	0.258	0.343

	0	1	2	3	4	5	6
0	0.546	0.086	0.081	0.048	0.083	0.056	0.1
1	0.107	0.487	0.163	0.03	0.169	0.029	0.017
2	0.085	0.128	0.605	0.005	0.053	0.12	0.005
3	0.134	0.075	0.015	0.482	0.048	0.015	0.23
4	0.167	0.272	0.107	0.032	0.333	0.043	0.046
5	0.095	0.037	0.178	0.009	0.031	0.57	0.081
6	0.172	0.024	0.007	0.151	0.039	0.077	0.53

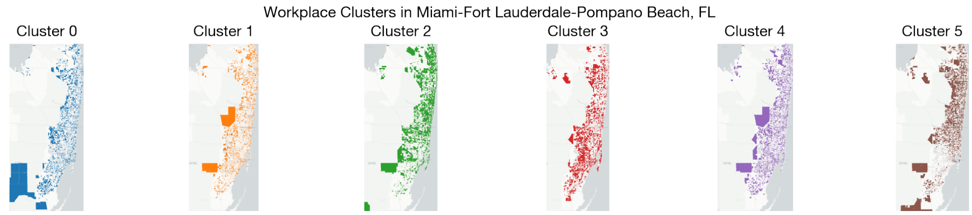

Figure 31: Miami Workplace Clusters

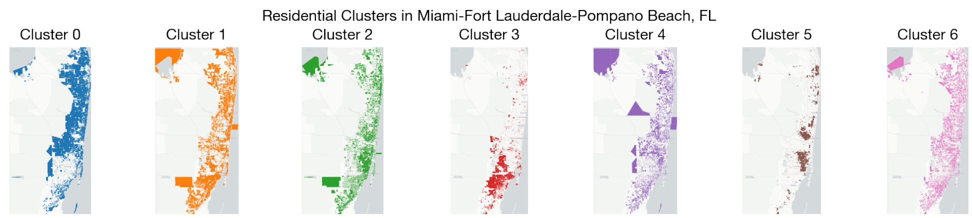

Figure 32: Miami Residential Clusters

Miami

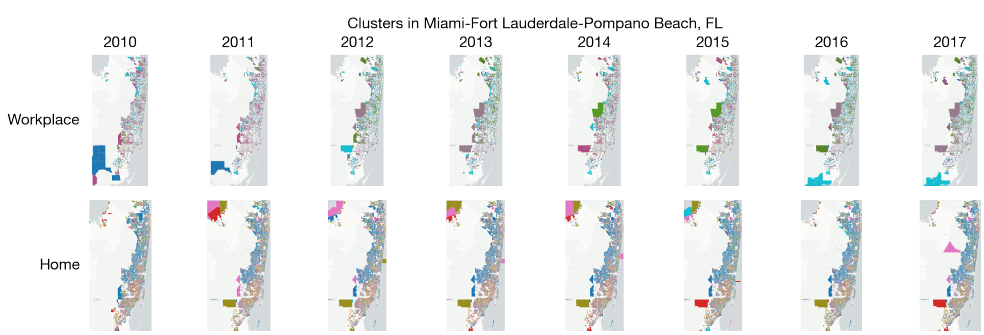

Figure 33: Miami Clusters Over Time

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.745	0.112	0.093	0.426	0.188	0.203	0.291	0.263
1	0.878	0.122	0	0.413	0.171	0.19	0.274	0.278
2	0.807	0.152	0.027	0.309	0.131	0.236	0.156	0.464
3	0.806	0.154	0.024	0.512	0.18	0.149	0.329	0.19
4	0.839	0.161	0	0.44	0.177	0.186	0.282	0.26
5	0.627	0.308	0.039	0.229	0.156	0.16	0.366	0.173

	0	1	2	3	4	5
0	0.485	0.039	0.1	0.13	0.113	0.132
1	0.087	0.19	0.134	0.147	0.353	0.089
2	0.034	0.018	0.757	0.08	0.049	0.063
3	0.04	0.022	0.087	0.703	0.073	0.074
4	0.073	0.131	0.102	0.131	0.465	0.099
5	0.073	0.021	0.111	0.123	0.09	0.581

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.805	0.136	0.041	0.227	0.113	0.246	0.223	0.431
1	0.915	0.085	0	0.46	0.147	0.218	0.225	0.387
2	0.596	0.35	0	0.348	0.161	0.179	0.252	0.308
3	0.907	0.047	0.028	0.755	0.187	0.183	0.222	0.339
4	0.589	0.234	0.134	0.304	0.149	0.22	0.24	0.358
5	0.167	0.823	0.004	0.103	0.17	0.125	0.286	0.221
6	0.713	0.226	0.061	0.324	0.142	0.216	0.228	0.387

	0	1	2	3	4	5	6
0	0.616	0.121	0.067	0.021	0.081	0.008	0.086
1	0.085	0.564	0.136	0.102	0.038	0.002	0.073
2	0.072	0.206	0.398	0.051	0.08	0.119	0.075
3	0.034	0.248	0.071	0.548	0.045	0	0.053
4	0.137	0.091	0.135	0.052	0.402	0.055	0.129
5	0.013	0.013	0.236	0	0.065	0.615	0.058
6	0.17	0.219	0.13	0.064	0.137	0.053	0.227

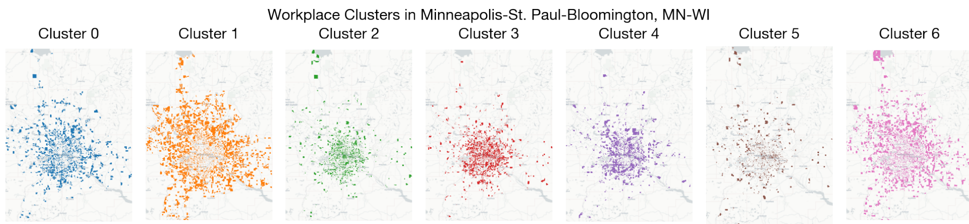

Figure 34: Minnesota Workplace Clusters

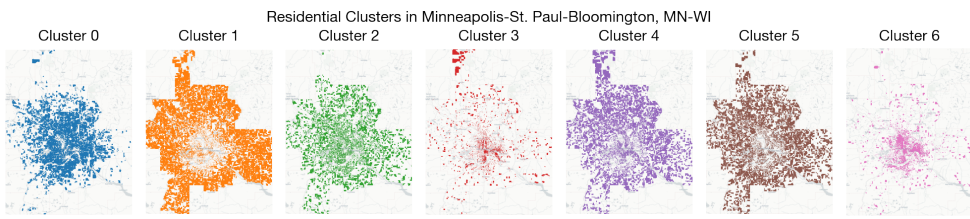

Figure 35: Minnesota Residential Clusters

Minnesota

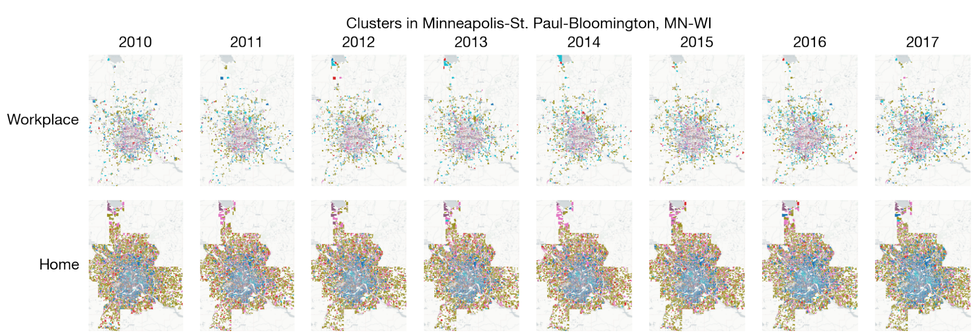

Figure 36: Minnesota Clusters Over Time

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.936	0.021	0.025	0.025	0.048	0.192	0.424	0.249
1	1	0	0	0.01	0.054	0.201	0.331	0.359
2	0.657	0.254	0.051	0.064	0.077	0.17	0.452	0.142
3	0.837	0.065	0.08	0.043	0.064	0.231	0.251	0.405
4	0.932	0.025	0.031	0.019	0.047	0.308	0.088	0.684
5	0.625	0.098	0.211	0.141	0.117	0.196	0.33	0.25
6	0.921	0.044	0	0.047	0.063	0.18	0.373	0.286

	0	1	2	3	4	5	6
0	0.664	0.051	0.039	0.104	0.065	0.002	0.075
1	0.1	0.628	0.014	0.029	0.062	0.005	0.162
2	0.069	0.011	0.647	0.135	0.007	0.061	0.069
3	0.103	0.019	0.081	0.617	0.099	0.035	0.046
4	0.057	0.03	0.003	0.089	0.787	0.003	0.031
5	0.013	0.011	0.135	0.133	0.013	0.641	0.054
6	0.143	0.144	0.068	0.072	0.057	0.024	0.492

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.892	0.035	0.052	0.028	0.049	0.285	0.217	0.528
1	1	0	0	0	0.044	0.263	0.23	0.507
2	0.885	0.058	0.058	0	0.048	0.287	0.223	0.508
3	0.76	0.095	0.058	0.164	0.092	0.228	0.267	0.395
4	0.919	0.042	0	0.041	0.052	0.262	0.233	0.49
5	0.974	0	0.026	0.051	0.052	0.276	0.224	0.518
6	0.609	0.201	0.162	0.054	0.073	0.243	0.259	0.394

	0	1	2	3	4	5	6
0	0.561	0.028	0.09	0.03	0.121	0.089	0.081
1	0.063	0.429	0.13	0.012	0.168	0.188	0.011
2	0.186	0.116	0.274	0.026	0.152	0.13	0.116
3	0.101	0.018	0.043	0.382	0.145	0.062	0.249
4	0.182	0.113	0.11	0.061	0.344	0.132	0.057
5	0.175	0.173	0.124	0.032	0.169	0.295	0.031
6	0.099	0.006	0.067	0.088	0.05	0.021	0.669

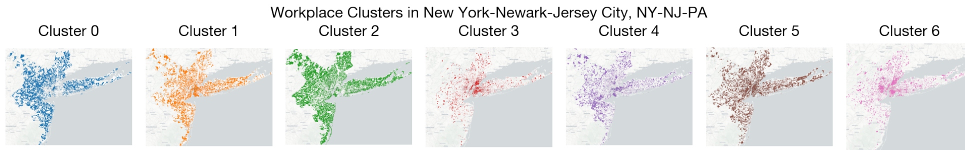

Figure 37: New York Workplace Clusters

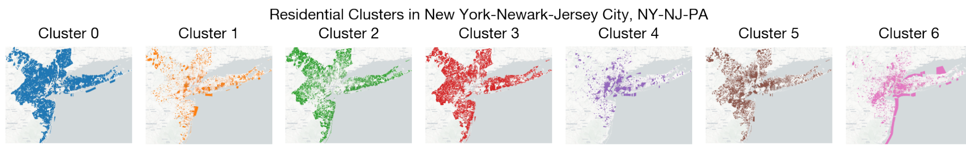

Figure 38: New York Residential Clusters

New York

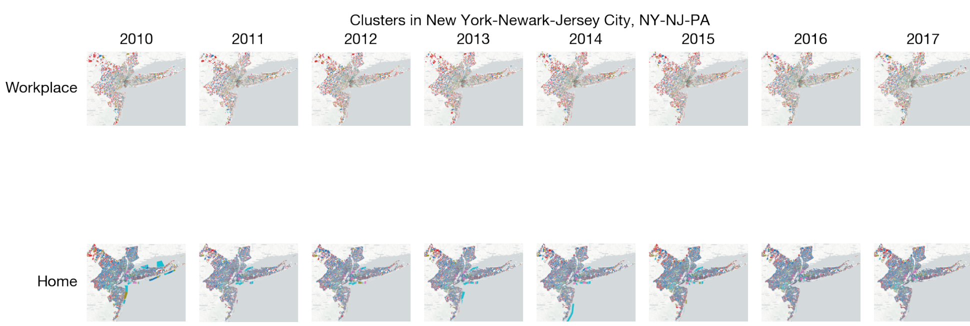

Figure 39: New York Clusters Over Time

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.851	0.072	0.066	0.098	0.06	0.371	0.191	0.57
1	0.728	0.139	0.11	0.176	0.098	0.208	0.436	0.213
2	0.917	0.043	0.04	0.134	0.095	0.261	0.312	0.337
3	0.603	0.184	0.15	0.399	0.2	0.193	0.364	0.184
4	0.598	0.046	0.32	0.122	0.119	0.299	0.339	0.296
5	0.752	0.175	0.05	0.203	0.108	0.275	0.142	0.531
6	0.573	0.37	0.035	0.305	0.157	0.19	0.31	0.245

	0	1	2	3	4	5	6
0	0.692	0.077	0.105	0.002	0.023	0.099	0.004
1	0.063	0.614	0.103	0.041	0.073	0.062	0.044
2	0.107	0.129	0.537	0.019	0.059	0.113	0.036
3	0.005	0.119	0.046	0.532	0.086	0.051	0.162
4	0.041	0.143	0.094	0.061	0.602	0.049	0.009
5	0.093	0.066	0.101	0.017	0.026	0.634	0.062
6	0.005	0.063	0.046	0.093	0.008	0.103	0.683

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.859	0.057	0.073	0.095	0.063	0.359	0.205	0.559
1	0.644	0.307	0	0.281	0.126	0.236	0.24	0.415
2	0.948	0.051	0	0.074	0.06	0.339	0.223	0.528
3	0.953	0	0.047	0.073	0.058	0.358	0.219	0.542
4	0.504	0.424	0.049	0.313	0.136	0.214	0.238	0.395
5	0.689	0.021	0.261	0.074	0.071	0.384	0.215	0.538
6	0.553	0.187	0.213	0.237	0.116	0.297	0.225	0.459

	0	1	2	3	4	5	6
0	0.564	0.021	0.07	0.152	0.037	0.099	0.056
1	0.07	0.365	0.066	0.048	0.334	0.029	0.088
2	0.236	0.073	0.246	0.325	0.028	0.066	0.026
3	0.221	0.021	0.132	0.471	0.009	0.127	0.02
4	0.04	0.111	0.008	0.007	0.732	0.004	0.098
5	0.188	0.017	0.034	0.16	0.008	0.493	0.1
6	0.102	0.05	0.013	0.025	0.17	0.094	0.547

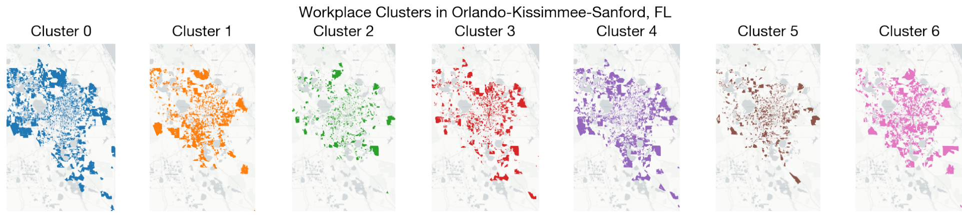

Figure 40: Orlando Workplace Clusters

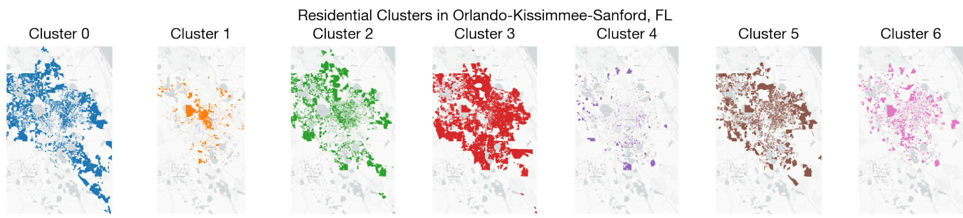

Figure 41: Orlando Residential Clusters

Orlando

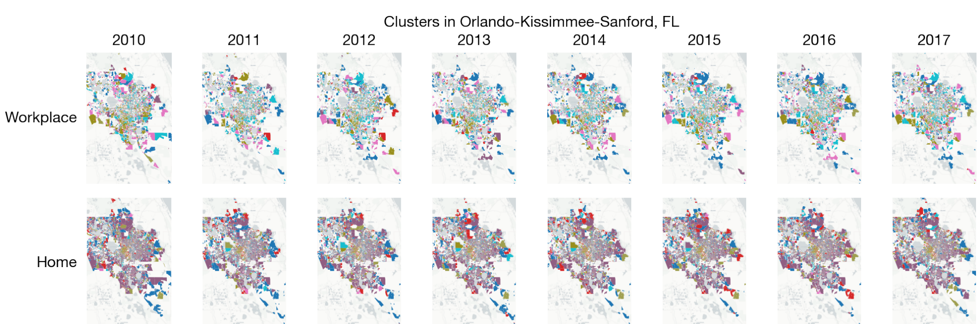

Figure 42: Orlando Clusters Over Time

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.906	0.094	0	0.181	0.123	0.181	0.294	0.269
1	0.801	0.149	0.031	0.209	0.107	0.123	0.461	0.13
2	0.672	0.106	0.161	0.231	0.14	0.229	0.282	0.312
3	0.86	0.078	0.042	0.143	0.092	0.26	0.13	0.502
4	0.847	0.084	0.026	0.314	0.158	0.156	0.332	0.188
5	0.625	0.282	0.072	0.182	0.135	0.149	0.406	0.146
6	0.821	0.139	0.024	0.209	0.124	0.195	0.197	0.363

	0	1	2	3	4	5	6
0	0.551	0.079	0.023	0.076	0.127	0.032	0.112
1	0.056	0.681	0.006	0.025	0.064	0.062	0.108
2	0.07	0.028	0.468	0.121	0.121	0.146	0.045
3	0.082	0.034	0.029	0.552	0.053	0.028	0.222
4	0.155	0.128	0.041	0.073	0.418	0.053	0.132
5	0.058	0.135	0.06	0.046	0.054	0.584	0.062
6	0.055	0.078	0.008	0.12	0.051	0.025	0.664

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.933	0.067	0	0.184	0.104	0.212	0.245	0.373
1	0.419	0.512	0.048	0.169	0.144	0.146	0.294	0.231
2	0.636	0.321	0	0.203	0.13	0.17	0.277	0.289
3	0.837	0.1	0.038	0.258	0.114	0.204	0.248	0.365
4	0.724	0.091	0.064	0.445	0.165	0.17	0.276	0.279
5	0.842	0.096	0.062	0.203	0.109	0.219	0.241	0.381
6	0.668	0.13	0.169	0.177	0.111	0.233	0.243	0.381

	0	1	2	3	4	5	6
0	0.517	0.007	0.166	0.095	0.017	0.168	0.031
1	0.02	0.554	0.234	0.073	0.006	0.049	0.064
2	0.194	0.095	0.451	0.099	0.034	0.089	0.037
3	0.085	0.023	0.076	0.616	0.021	0.13	0.049
4	0.115	0.017	0.195	0.188	0.249	0.117	0.119
5	0.237	0.025	0.105	0.202	0.027	0.301	0.103
6	0.083	0.066	0.082	0.146	0.048	0.203	0.371

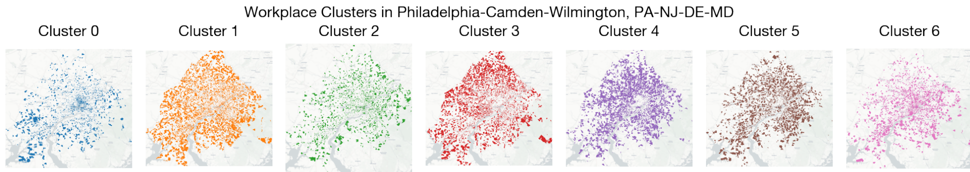

Figure 43: Philadelphia Workplace Clusters

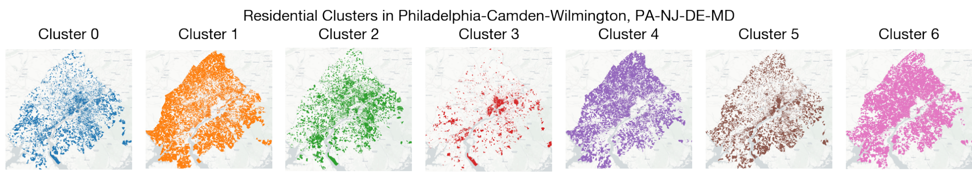

Figure 44: Philadelphia Residential Clusters

Philadelphia

Figure 45: Philadelphia Clusters Over Time

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.568	0.337	0.053	0.219	0.146	0.152	0.376	0.193
1	0.861	0.12	0	0.083	0.087	0.203	0.303	0.343
2	0.621	0.105	0.252	0.068	0.109	0.261	0.325	0.316
3	0.956	0.044	0	0	0.066	0.241	0.288	0.393
4	0.887	0.074	0.032	0.031	0.057	0.306	0.169	0.565
5	0.802	0.127	0.058	0.055	0.07	0.174	0.464	0.197
6	0.599	0.362	0.026	0.067	0.09	0.236	0.196	0.419

	0	1	2	3	4	5	6
0	0.598	0.092	0.063	0.006	0.008	0.097	0.135
1	0.043	0.498	0.021	0.104	0.135	0.108	0.09
2	0.066	0.041	0.589	0.02	0.067	0.167	0.051
3	0.005	0.18	0.015	0.558	0.156	0.065	0.021
4	0.003	0.065	0.018	0.048	0.726	0.072	0.069
5	0.035	0.071	0.053	0.024	0.092	0.673	0.053
6	0.057	0.068	0.021	0.012	0.107	0.06	0.676

gaussian_mixture	emp_white	emp_black	emp_asian	emp_hisp	edu_lths	edu_bachelor	earn_under_1250	earn_over_3333
0	0.632	0.332	0.035	0.096	0.09	0.235	0.244	0.422
1	0.944	0.056	0	0.034	0.059	0.287	0.218	0.511
2	0.665	0.133	0.178	0.055	0.075	0.303	0.223	0.491
3	0.462	0.428	0.058	0.255	0.127	0.178	0.27	0.32
4	0.958	0.016	0.026	0	0.05	0.315	0.211	0.544
5	0.484	0.482	0	0.057	0.092	0.206	0.258	0.377
6	0.896	0.043	0.048	0.029	0.054	0.314	0.207	0.549

	0	1	2	3	4	5	6
0	0.348	0.109	0.114	0.126	0.049	0.171	0.084
1	0.11	0.32	0.04	0.008	0.259	0.091	0.17
2	0.118	0.041	0.508	0.064	0.071	0.053	0.145
3	0.177	0.011	0.083	0.559	0.005	0.157	0.009
4	0.04	0.222	0.053	0.002	0.437	0.047	0.198
5	0.191	0.087	0.049	0.102	0.055	0.46	0.055
6	0.059	0.118	0.098	0.005	0.164	0.038	0.518