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Urban Pastures: A Computational Approach to Identify the Barriers of Segregation

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An Honors Paper for the Department of Sociology

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Abstract

Urban Sociology is concerned with identifying the relationship between the built environment and the organization of residents. In recent years, computational methods have offered new techniques to measure segregation, including using road networks to measure marginalized communities' institutional and social isolation. This paper contributes to existing computational and urban inequality scholarship by exploring how the ease of mobility along city roads determines community barriers in Atlanta, GA. I use graph partitioning to separate Atlanta’s road network into isolated chunks of intersections and residential roads, which I call urban pastures. Urban pastures are social communities contained to residential road networks because movement outside of a pasture requires the need to use larger roads. Urban pastures fences citizens into homogenous communities. The urban pastures of atlanta have little (<1) standard deviation along dimensions of race, educational attainment, and poverty levels. Scholars have long identified the role roads have in displacing urban communities, reducing hosing value, and acting as static physical barriers between communities. This paper identifies new approaches to consider how the movement along roads networks also segregates cities.

Key Words: *Network, Graph, Graph Partition, Urban Inequality, Segregation, Subgraph*

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Introduction

American cities are hypersegregated (Glaser 2001). Research on segregation investigates various structural causes for the persistence of urban segregation in cities, including the uneven spatial proximity of racial groups, the effects of infrastructure on segregation, and the unequal access to place-based resources (Alba and Logan, 1993; Massey and Denton 1993, Logan 2013). Sociologists have long been concerned with identifying, measuring, and diagnosing residential segregation (Dubois 1903; Massy and Denton 1993; Sampson 2012; Sampson and Sharkey 2008). From the early days of Sociology, researchers have drawn on different methods to measure and identify further nuances of segregation and urban inequality, from walking urban streets (Simmel 1902), examining census data (Glaeser and Vigdor 2001), and surveying citizens on the conditions of their life (Sampson 2011). Although these studies may examine the effects of segregation over time, much of these data focus on a single point, treating residents within communities as static actors confined to their local environment.

Over the last fifty years, scholars have used computer modeling to develop and test existing theories related to segregation (Shelling 1971). Computational Sociology can analyze online interactions, apply machine learning to existing datasets to anticipate future outcomes, or build simulated social environments to run experiments (Evans & Foster 2019, p. 11). Shelling's foundational models of segregation revealed the persistence of racial segregation in communities despite individual preferences to live in racially integrated neighborhoods (1971). More recent models have highlighted how social performances among individuals produce segregated social performance spaces (Shaw 2015). Spatial Proximity and Connectivity (*SPC)* (Roberto 2018), the most contemporary segregation model, identifies how the built environment disrupts residential proximity to each other, and therefore it identifies segregation. These methods, however, lack the nuance of the experience of accessing urban amenities through traveling on different sizes of roads.

This paper uses computational methods to determine spatial segregation by modeling the effect of transportation on separating communities. I construct a digital model of the city of Atlanta, GA using spatial, demographic, and transportation data to understand how people move through their environment. Using graph partitioning, a computer algorithm, Atlanta's Road network is split up into smaller chunks so that only the residential roads remain. Each chunk is a collection of intersections held together only by residential roads, which I call *urban pastures*. To leave and urban pasture requires movement along a larger faster road (i.e., highways). An individual in one of these pastures can travel everywhere within the same pasture without using a highway, interstate, or any significant road. Transitions to large roads from residential roads are the fences that compose these pastures and hold citizens to space and community.

Urban pastures show that large roads create space between and discourage the mixing of varying residents. Mobility is an integral part of engaging with other people, whether on the street, stores, or public spaces. Atlanta's roads inhibit movement, and the road network of Atlanta produces the fences that isolate citizens into homogonous communities. Roads block people from accessing different communities because the difficulty of walking, biking, and driving on large roads discourages mobility and limits people to their local areas. Urban pastures show that considering human movement when analyzing spatial data produces novel findings about how infrastructure constricts communities from moving freely throughout cities.

Urban Pastures offer a new level of nuance in road data by accounting for the experience of movement along a road. As SPC only accounts for the distance along a road, this paper argues that the size of the roads also produces structural boundaries in the city of Atlanta. Like SPC this paper combines large datasets with individual agent-based thinking to better capture experiences on the ground with a model. While SPC utilized roads to calculate proximity, this paper considers the experience of traveling large roads as a processes that segregates urban communities. Relative to previous studies that observed infrastructure acting as static barriers, urban pastures arise from identifying barriers as a combination of infrastructure and dynamic human movement. Considering the complexity of human movement in these large models produces more detailed findings reflective of actual life on the streets.

The next section of this paper will review the literature on urban inequality and modeling in calculating segregation. Section 3 will provide background on the methodology and structures used from computer science to aid in understanding the methods and results of this paper. The driving questions will be drawn in the fourth section. The fifth section will provide an overview of the data used, the computational methods applied to the data structure, and why Atlanta was selected as the case study city. Section six will display the results of these computational tests. The following section discusses the results, the methodology, and their placements in the literature and field. The final section will conclude the paper.

SOCIAL RELATIONS AND THE URBAN ENVIRONMENT

Scholars have long examined how the built environment of cities has shaped the social lives of the people who inhabit them. Classical scholars explored how the growth of modern cities resulted in increased segregation among their inhabitants. In his investigation of the city, Park (1915: 608) reflects how the "big, booming confusion of city life" created "moral distances which make the city a mosaic of little worlds which touch but do not interpenetrate." Park's discussion emphasizes how the city's size, density, and heterogeneity (Wirth 1929) result in the moral and social breakdown of urban communities. Conversely, Simmel (1902-3) observes that “bodily closeness and lack of space” make for a “swift and continuous shift of external and internal stimuli,” which produce “a rational manner” and “intensification of consciousness” in urbanites (16). The complexity of moving parts of a city produces a shield to block residents from the onslaught of stimulation. Simmel connects residents' lived experiences to their movement within and between urban spaces. Answering Simmel's concerns using computational methods, this thesis considers how the built environment affects the conditions of life on the streets.

Sociologists have also investigated how the spatial layout of infrastructure results in different socializing and relationship building among residents. The physical layout of a city yields different social conditions from a Suburb, which, in turn, produces different social conditions than a rural town. In his famous study *The Levittowners*, Gans (1967) highlighted how the proximity of homes within a suburb “discourage[s] visiting the less adjacent” neighbors, which results in reduced connectivity (Gans, 158). Gans measured how likely residents of a suburb were to interact and build connections with neighbors in all directions (1967). The layout, down the individual building, type of building, and design of a building, affects the lifestyles of those who interact with them. Understanding how physical building impact people's socialization has been done on small scales, but with more current data and computation, these findings are expandable to the scope of entire cities.

The structure of cities organizes people into specific places that align with their objectives, opportunities, and abilities to navigate cities physically. Burgess’ concentric circle city model (1925) examines how the built environment organizes people based on accesses to labor, similar identities, and cost of living. This organization however separates people on the dimensions above which creates segregated spaces. More recently, Sampson’s *Great American*

City presents a thorough analysis of the relation between society and time and space (2011). Sampson connected infrastructure to social conditions of space, showed that previous neighborhood conditions predict current conditions, and displayed the effect neighborhoods have on adjacent neighborhoods (206, 114, 241). He used novel methods to measure trust, collective efficacy, and disadvantage to understand how proximity, infrastructure, history, and movement affected people's nature in Chicago (Sampson 2011). Sampson's data effectively highlighted the degree to which granular infrastructure impacted residents' attributes like trust, but his dataset was an expensive, laborious, and timely to produce. Computation provides a much faster way to analyze spatial data and it can holistically consider both citizens and city infrastructure. Like Chicago, Atlanta has a complex relationship with its people and infrastructure.

Scholars have also debated on how the construction of various roads exacerbate or ameliorate residents' sense of social and institutional isolation. Webber (1963) theorized how the construction of interstate highways facilitated residents to seek communities of interest beyond their residential neighborhoods. In his study of sex between men in rest stop bathrooms, Humphreys (1975) also found that interstate highways created the social distance necessary for married men to explore their sexualities away from their families and communities. Conversely, scholars have also considered how the implementation of large roads and highways facilitated the social and residential isolation of marginalized communities. Massey and Denton (1991) explores the central role of highways in constructing the urban ghetto. As the expansion of urban slums around central social and cultural institutions threatened middle- and upper-class whites' sense of safety, containing urban ghettos within highways ensured that Blacks and lower-class residents could not easily access urban spaces valuable to whites.

Debates over the role of roads within cities have also emphasized their role in complicating residents' access to other communities. In her famous challenge to Robert Moses' efforts of clearing historical buildings to construct highways Jacobs (1961), highlight how large roads prevent the kind of contact necessary to create and facilitate strong communities. Supporting the importance of sidewalks and public parks for contact, she emphasizes how healthy communities depend on the ability of residents to move freely throughout the urban landscape. Postmodern urbanisms, which reflect the decentralization of cities due to the connection of various communities through large roads and highway systems, also draws attention to how communities have further insulated themselves from one another, due in large part to the relative difficulty of traveling on highways.

Roads have been studied as static delineations in the urban landscape and as tool to segregate cities, but not as dynamic integrated features. In Atlanta, highways were used to "clear slums and blacks out of downtown" to create an intentional segregated urban landscape (Bayor 1988). In Atlanta large interstates are placed in-between black and white communities, and if viewed from above, act as static separators. Roads, however, are dynamic networks that move people around cities because of the way they are constructed. Computational methods can analyze road networks dynamically to show how road infrastructure organizes people into space.

Urban Sociology and Computation

Identifying segregation through computational methods has been around for the last half-century. Shelling's *Dynamic Models of Segregation* (1971) simulated the development of segregation in abstracted societies. In his models, members of the simulated society had individual preferences for neighborhood composition, and even with preferences for diversity, the simulated individuals self-segregated (Shelling, 1971). Shelling's simple model defined individual interaction to show the natural emergence of segregation as a social phenomenon. In his simple abstracted world, a single person or agent's complexity is reduced to make a connection between individual and society abundantly clear. Shelling's model stands as the foundation for social simulation and modeling and, specifically, as the father of agent-based modeling (ABM).

More recently, ABMs have represented the more complex elements of societies, foreshadowing their integration into more complex, accurate models representative of actual human life. Shaw's *Mechanics and Dynamics of Social Construction: Modeling the Emergence of Culture from Individual Mental Representation* uses psychological findings of social interaction to show how social performance homogenizes around social groups and space. Her model grows out of the psychological idea that humans "are inherently skilled at and oriented toward ''matching'' the representations of each other" (Shaw, 79). She models simple interactions between individual agents who impart their performances to their proximate peers. When individuals in her model follow this rule, patterns emerge. Individuals or agents matched the social performances of those around them, resulting in spatial groupings of social performances. Shelling and Shaw's agent-based models (ABM) simulate individual interaction and show that replicating individual action through modeling produces understandings of society-wide dynamics.

Despite abstracting society, Agent-Based Models (ABM) show the relationship between the individual and the emergence of society, and agent-based thinking is starting to enter segregation modeling. These models reduce the complexity of real life "to perform highly abstract thought experiments that explore plausible mechanisms that may underlie observed patterns" (Macy, Michael W., and Robert Willer). The goal is not to "provide an accurate representation of a particular empirical application" (Macy, Michael W., and Robert Willer). ABMs achieve an ideal understanding of how individuals contribute to and construct their greater society. They achieve this by abstracting the complexities of both the individual and environment. Shown later SPC is the first paper to think about proximity through the road network, and by which is a step towards approaching segregation modeling by thinking about it on an individual level. People obviously travel along the road network, so proximity should be calculated via that network.

Accessible satellite spatial data sets provide promising new pathways for thinking about infrastructure and create digital models that better represent cities. Unlike Sampson's intensive survey dataset, free spatial data does not require querying people on their experiences (Lazer, et al). Like other large datasets, spatial data, with the correct synthesis, can reveal "novel patterns that challenge existing theories or call out for new ones" (Evans, Foster, 11). Large location data sets can provide insight in to how much, when, and where people spend time with others. They could allude to how people build their social networks (Lazer, et al). Big data unlike previous data sets are comprehensive and detailed enabling the application on both the individual and system wide scale. With infrastructure data, one can know the amenities on a given street and the number of homes in a neighborhood. This data combined with appropriate computer science methodology can allude to the daily life of residents. When spatial datasets are combined with information about the people that inhabit the space, it becomes possible to model the relationship between structure and people.

Large scale segregation models have gone through many iterations methodology and have increased in accuracy as data nuance increases. I've found the spatial proximity and connectivity method (SPC) proposed by Elizabeth Roberto to be at the forefront of segregation modeling.[1] Her paper covers the progression of segregation modeling leading up to her implementation of SPC, and I highly recommend reading her paper if you're interested in computational Sociology. The novelty of SPC is achieved because of the advent of spatial datasets that describe road networks which allows for new, more intimate analysis.

SPC measures how segregated a specific road intersection's proximate space/neighborhood is relative to the citywide racial or attribute composition (could be poverty, education, or another demographic variable). SPC, unlike previous segregation models, thinks proximity as a function of movement pathways not Euclidian distance. Roberto's model works in 6 steps: "(1) linking the geographic data for blocks and roads, (2) estimating the population count and composition at locations on the road network, (3) calculating the distance of the shortest path between all locations, (4) constructing local environments around each location, (5) calculating proximity weights, and (6) measuring segregation."

Measuring how segregated a neighborhood is, is a tricky calculation. Fortunately, Roberto developed an equation for doing so in an earlier 2016 paper, *The Divergence Index: A Decomposable Measure of Segregation and Inequality*. The divergence index compares the racial or other attribute compositions of a neighborhood with the respective compositions of the city. The divergence index, in the case of SPC, compares the ratio of a given group (race, education attainment level, ect) to the same group's composition ratio at the city level. If these two compositions are the same, then the egocentric neighborhood is determined to not be

[1] SPC

segregated, and if the two blocks have different compositions, the divergence index goes up. The Divergence Index is used to calculate how segregated each egocentric neighborhood. This process is repeated for every egocentric neighborhood of each intersection. The result is value that describes how segregated the intersections of a city are. Each index of each intersection can be multiplied by the proportion of the population at that intersection to determine a wholistic segregation measure for a city.

Roberto outlines the equation as:

"The divergence index for location (i.e., node) i's local environment with a reach of r km is

$$\tilde{D}_{ri} = \sum_{m} \tilde{\pi}_{rim} \log \frac{\tilde{\pi}_{rim}}{\pi_m},$$

where π_m is group m's proportion of the region's (e.g., a city's) overall population and $\tilde{\pi}_{rim}$ is group m's proportion of the proximity-weighted population in location i's local environment with reach r." $\tilde{D}_{ri}$ represents the divergence index of an egocentric neighborhood.

SPC uses road networks travel distance to determine proximity and the bounds of egocentric neighborhoods which is a huge shift in thinking about segregation modeling. Previous models measured segregation by calculating proximity via Euclidian distances. Figure 3 shows how this process results in different egocentric neighborhood extent. Using road networks to calculate proximity accounts for the barriers in infrastructure that divide people through movement pathways. Figure 3 shows how the presence of a railroad results in drastically different neighborhood calculations than previous models which used straight line distance. Roberto's model begins to approach calculating citywide segregation by imagining individual life. Instead of using straight line distances which have no representative connection to a person walking through an enviroment, the road network better represents an individual on the street and is more like Agent based modeling. Agent based segregation calculation has become possible because of the nuanced detailed datasets modern technologies have given accesses to.

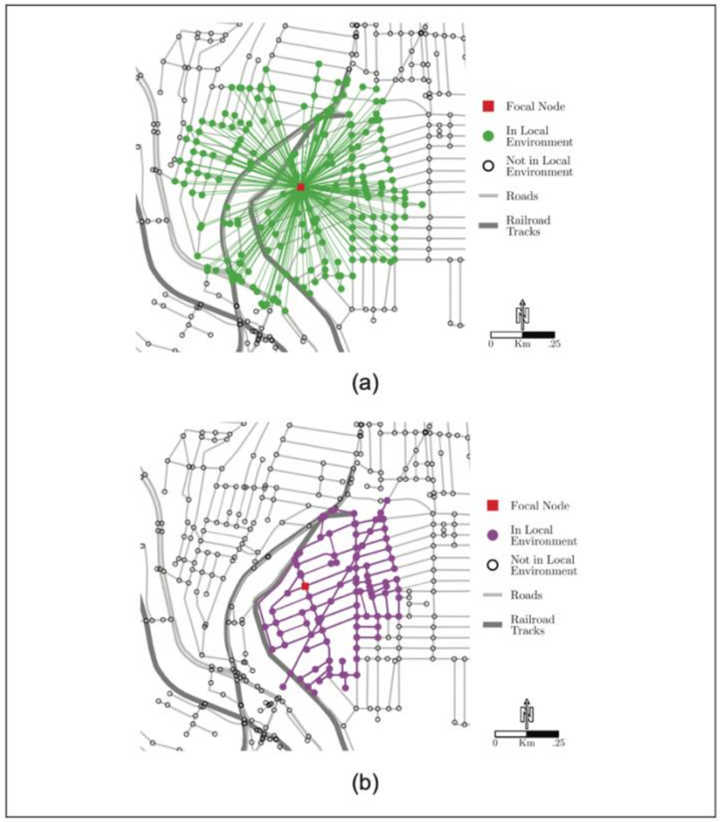

Figure 3. "Comparing a local environment constructed with straight line distance and road network distance (reach of the local environment = .5 km). (a) Local environment constructed with straight line distance. (b) Local environment constructed with road network distance."

Future citywide computational models should continue to approach identifying social dynamics through the simulation and representation of individual life. Large datasets, better modeling tools, and individual data are making this task more achievable. The model described in this paper will push the representation of individual life in computation further than Roberto's.

Multiple computational modeling techniques will be used to identify boundaries of segregation and analyze inequality.

Preliminaries and Background

Computer scientists are concerned with using the appropriate data structure for the given task. Different problems require different structures to represent the data. For the problems presented in this paper, a graph data structure was the best option for representing Atlanta. Graphs are great for representing networks making it perfect for representing the road, walk, and bike transportation networks of the city. It's critical to understand what this data structure looks like so that assumptions made are clearly understood.

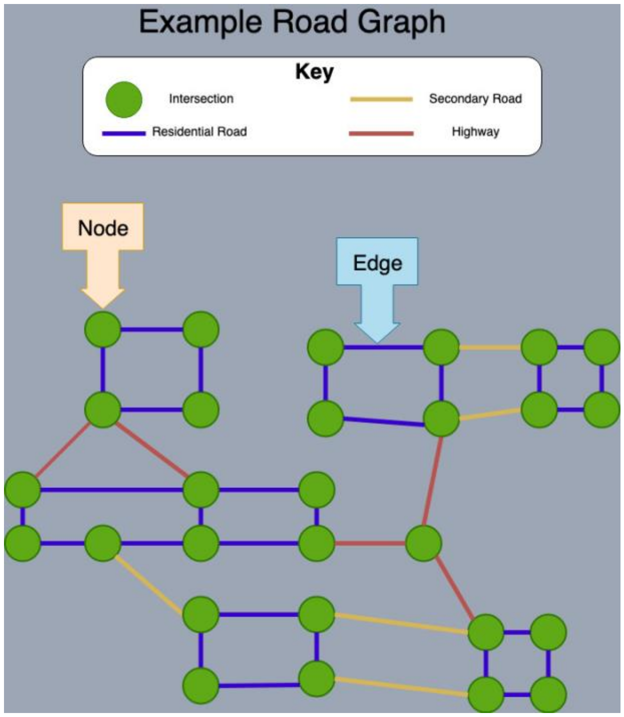

Figure 1. Example Road Graph

Graphs are collections of nodes and edges. Figure one shows an example naive graph that represents a road network. Each green dot is a node that represents an intersection in the road network. Each edge connects one edge to another and may have other information associated with it. In Figure 1, the edges have types of residential, secondary, and highway that describe what type of road it is. It's very common for an edge to have a weight associated with it that describes the cost of traveling that edge. In most cases the weight of an edge is the length of the edge. Graphs are also referred to as networks.

Questions and Objectives

Graph Partitioning is an established algorithmic process in computer science. It will be used to this paper to partition the road network to determine sub-graphs or, in other words, to distinguish the smaller groups of the road network. These subgraphs will represent the *Urban Pastures* and provide new understandings for how infrastructure produces segregated places.

Methods and Setting

Setting

Building a model of a real space requires information about the built environment and the people that inhabit the space. Population dense areas are the best real environments to replicate in computer models because they provide the highest resolution. Resolution, in this model, is the accuracy of locating people to a specific spatial area. Higher resolutions provide more certainty in connecting people to a specific location. Spatial certainty is critical when trying to assess the effect space has on people. If demographic data is known for a city block as opposed to a wider neighborhood level, relationships drawn between space and person will be more accurate. Better resolution will reflect how a person's more proximate infrastructure affects them as opposed to a building on the other side of the neighborhood. Thus, to create the most accurate model, individual data should be collected for the smallest spatial unit possible.

Census data provides information on the type of people living in a given spatial delineation. The census block group is the smallest unit of spatial analysis the census provides for Atlanta. Each census block group—regardless of area covered—tries to encompass a residing population of 600 to 3000 people (US Census 2022). Because population determines the geometries (area covered) of these spatial delineations, the denser the place, the smaller the block groups are. In rural areas, census tracts (typically block groups are not collected for rural areas) can be hundreds of miles across, but in a city, a block group may represent a few hundred yards.

This allows for more accurate placement of a person to a specific intersection. The granularity of a block group increases the accuracy of identifying people to a space. The census only collects block groups for cities, and their density makes these spatial units small and therefore precise.

On top of the data resolution reasons listed above, cities have more diversity in the people and structures they house. Diversity in the modeled population allows for comparative analysis based on race, education attainment, poverty, and other demographic measures. Similarly, cities have complexity and variability in their built landscape. This allows for analysis on the effect of multiple types of infrastructure on the condition of people. Equally important to diversity is the prevalence of datapoints within each of these categories. If there was only one census block group that contained people representing an important cohort of the population, it would prohibit accurate analysis because of the small sample size. Cities, however, are heterogenous, populated, and dense, making them great candidates for modeling.

Atlanta was chosen because it accentuated the properties above and has a history of segregation supported through road development. Segregation and inequality problems in Atlanta have been perpetuated through the infrastructure of the city (Bruce Katz et al. 2000). The city is racially divided between the north and the south. The northern census tracts and counties are predominantly white, and the urban center and Sothern tracks are predominantly black. Atlanta has three major interstates running through downtown, and another circling the entirety of the city. I-20 cuts the city in half spatially and the northern region is over 80 percent white (Bruce Katz et al. 2000). Atlanta’s road network covers the whole city, but many of these roads enable access primarily in the northern half of the city. Outside of roads, Atlanta’s public transportation has a tumultuous history improving the mobility of marginalized people.

Throughout the 80’s and 90’s the city invested heavily in its road network but failed to financially support the Metropolitan Atlanta Rapid Transit Authority (MARTA). The metro lines of MARTA only serve two counties, both of which are predominantly black. In turn, because metro riders are majority African American, it has “limited MARTA’s growth [into] predominantly white and well-off suburban areas” (Bruce Katz et al. 2000). Furthermore, MARTA fails to incorporate Cobb, Gwinnett, and Clayton County which contain concentrated employment (Bruce Katz et al. 2000). Other studies have shown that in Atlanta, “residents with the highest need for high quality public transportation have access to some of the lowest levels of transit connectivity” (Bayor 1988). Although this paper does not directly address MARTA, MARTA’s bus lines use the road network of Atlanta and thus it is important context to have for this discussion. Atlanta’s diverse, complex, and vast built environment, and the history of how infrastructure has been used to segregate citizens makes it a great case study city for modeling.

Data Collection

After selecting Atlanta as the city, a spatial boundary that defined the extent of Atlanta for data collection was set. There is a defined geometry for the city limits of Atlanta, but a larger extent that included surrounding areas and suburbs of Atlanta was used. A bounding box from (33.9, -84.5) and (33.6, -84.25) defined the extent of data collection. This area sufficiently includes the city limits of Atlanta and surrounding suburbs and is broadly defined to follow the bounding interstate of 285. All data was collected within this geographic box.

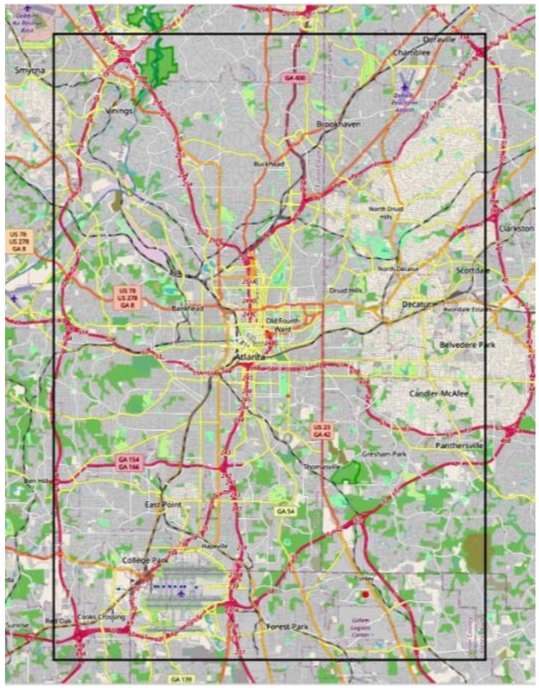

Fig. 4. The bounding box and city limits of Atlanta

Demographic data representing the people of Atlanta was produced by the American Community Survey (ACS). The ACS 2019 five-year estimate dataset represents many dimensions of individual life ranging from race to method of commute. The five-year estimate data set compiles previous years of data and current data to estimate the current conditions. The 2019 ACS demographic datasets were collected through Social Explorer. Social Explorer is a web driven software for interfacing with, selecting, and filtering spatial data into usable data sheets. Social Explorer was used to produce data sheets containing the demographic data for Atlanta. Race, education attainment, and poverty level data was downloaded for all census blocks that were contained or intersected by the bounding box. This data sheet is accessed by the model whenever citizen data is needed.

Retrieving spatial data that represents infrastructure is more complex than querying Social Explorer, but is relatively easy with the use of open-source tools. Although spatial data is accessible to an average person through platforms like Google Maps, downloading and manipulating this data is difficult and expensive. Fortunately, inaccessibility to private spatial datasets has been mitigated through community action. Open Street Maps (OSM) is the standard open-source spatial dataset for researchers, businesses, and mapping enthusiasts.

OSM enables the free use of a global spatial dataset. The OSM dataset is like those provided by Google Maps or Apple, but downloading, manipulating, and accessing them has been made easier. OSM is user-constructed in a manner similar to Wikipedia where any individual can go to the OSM website and add roads, buildings, cafes, or any another spatial element to the dataset. Any person can log on and record a building and this setting generates a dataset that is built by community members and GIS professionals. Although OSM is the best viable option for opensource spatial data, it lacks the detail of privately owned datasets. Despite this clear disadvantage, the accessibility of OSM makes it the best option for building the digital representation of Atlanta.

OSMNX is a Python library made to download, processes, and visualize road and other transportation networks from OSM. OSMX is dependent on the python libraries of GeoPandas, NetworkX, and Matplotlib, which were also used in the organization of road networks. OSMNX works with the OSM API to retrieve network data for a selected area. The road network data was retrieved for the bounding box, compressed, and stored as graphs.

Graphs function well with networks and spatial data, and there are hundreds of algorithms that partition, traverse, and describe properties of graphs. Graphs are collections of nodes connected to other nodes by edges. In this dataset nodes are intersections of the road network and the edges represent the road length connecting each intersection to its proximate intersections.

Graph Partitioning

Graph partitioning is an effective way to determine the natural sub-graphs of a graph. In the case of Atlanta's road network, the sub-graphs become the urban pastures of Atlanta. There are many algorithms that separate graphs, and the one used here removes high weight edges until smaller chunks of the graph are discontinuous from each other. The road network was separated because road edges have different types that distinguish the difficulty of movement along a road edge. The weight (difficulty of movement) of a road edge used here is the average speed limit. In Atlanta, the OSM road network has fourteen different types of roads which have different average speed limits across the city. These road types and respective speed limits are shown in Table 1. The average speed of each type of road for Atlanta was calculated by recording the speed limit, if given, for each road of each type and finding the mean. Two types, "disused" and "living street," had no roads in the road network with given speed limits, so no average was found.

Road Type	Average Speed
Residential	25.6349539
Tertiary	34.1242284
Secondary ink	41.11111111
Tertiary link	30
Trunk link	30
Motorway link	58.36134454
Motorway	60.460199
Secondary	36.49489322
Unclassified	24.07594937
Trunk	39.37967115
Primary	38.09659091
Primary link	31
Disused	N/A
Living street	N/A

Table. 1. The roads and their speed limits of Atlanta, GA

The speeds of each road type are a proxy for the difficulty of moment to, along, and off each road type. Motorways average speed limit is highest, thus suggesting that it would require an individual more effort both to get to and to drive this larger road. Removing road types from the road network that have more extreme speed limits results in sub-graphs that are connected by easier to move along roads. These subgraphs then represent the urban pastures of Atlanta.

The graph partitioning algorithm used here removed all road types from the Atlanta Road network besides residential roads. Although unclassified roads on average have a lower speed limit, they were removed because their addition had little influence on the subgraphs produced and there were very of them. Typically, their presence was removed when trimming the subgraphs of size <10. Each road of each type was removed from the large graph until only intersections that were connected by residential road types remained.

Removing all edges besides those labeled as residential produced a total of 5733 sub graphs. Most of these subgraphs contain a small number (<10) of intersections. The average size of the connected components was 4.989 nodes, and only the subgraphs containing more than 10 nodes were saved for analysis. All 357 of the subgraphs greater than ten intersections in size were saved to a file for further analysis.

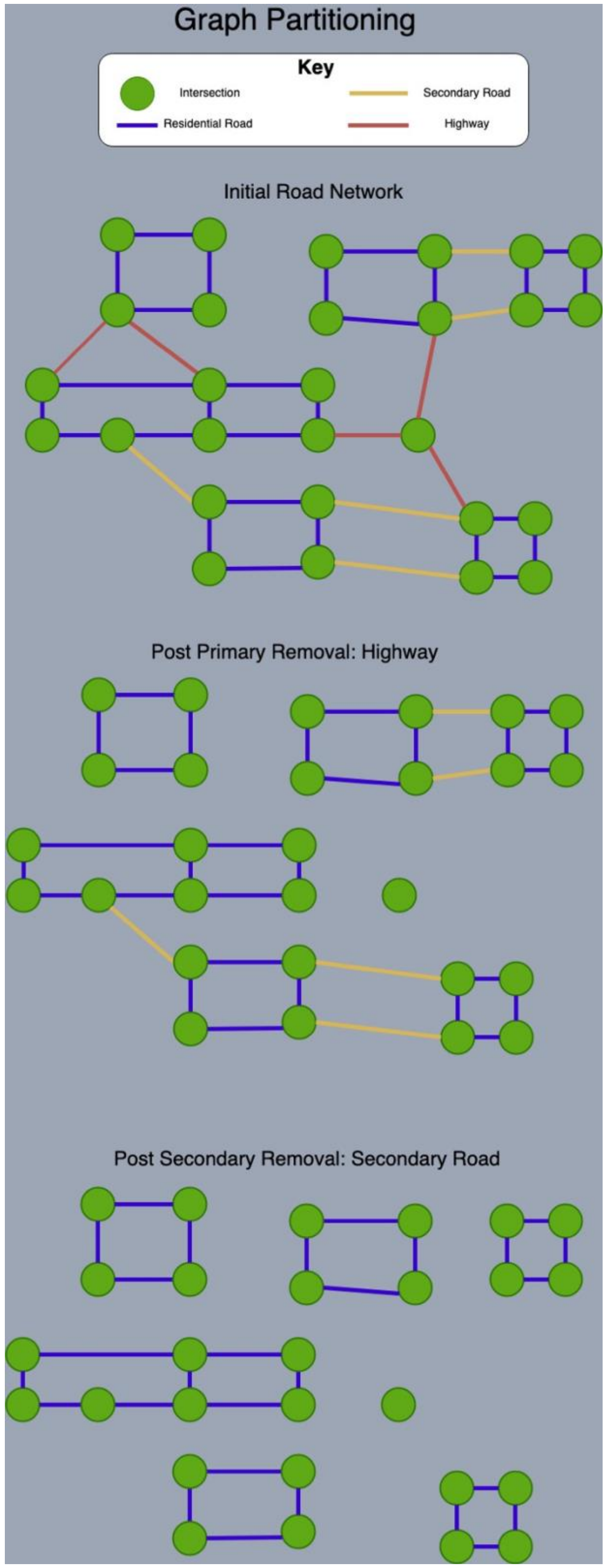

Figure. 6. Graph Partitioning example

Homogeneity and Content Analysis

The homogeneity of each subgraph was tested for race, education attainment, and poverty levels. For race, only the percent black and white was tested for homogeneity because these two racial groups make up most of the population in each census block. The homogeneity of each sub graph was determined by iterating through each intersection, retrieved data from the census block that the intersection fell within. The demographic data of the census block was recorded for each intersection and the number of census blocks queried was recorded for each subgraph. After recording demographic data for a whole subgraph, the standard deviation was calculated to determine the variance demographic data from the census blocks the subgraphs covered.

Results

Figure 7 shows all the intersections in the road network of Atlanta. Figure 8 displays the urban pastures (Sub Graphs) made through the graph partitioning algorithm described above. The intersections of the urban pastures have been assigned different colors so one can be seen from others. Only networks with greater than 10 intersections are shown in Figure 8. There are 357 subgraphs of size greater that 10 intersections, and the largest subgraph contains 935 intersections. The average size of these subgraphs is 54.4 intersection with a median of 19. Each of these subgraphs cover an average of 1.98 census blocks; 133 of the 357 subgraphs shown only contain nodes within a single census block. The density of all subgraphs, measured by road length, was 137 meters and varied by about 10%. This information along with the respective racial, poverty, and education data is displayed in Table 1.

Each subgraph of Atlanta is extremely homogonous in each demographic variable tested. For every demographic variable the standard deviation of each graph was calculated. The average of the standard deviations of every graph is less than 1, and no individual standard deviation exceeded 1 (see appendix for tables). The variation in demographic data for each node was extremely low.

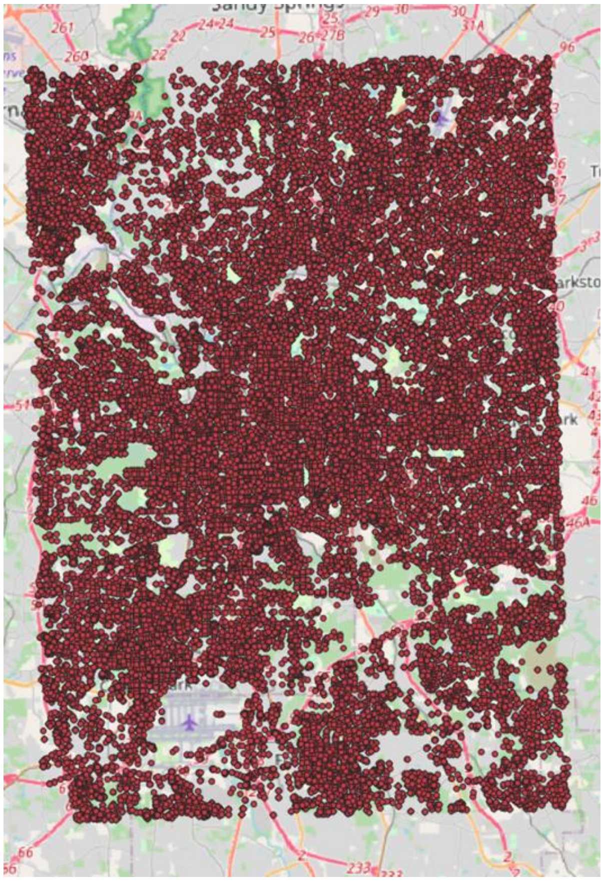

Figure 7. All of the intersections of Atlanta's road network

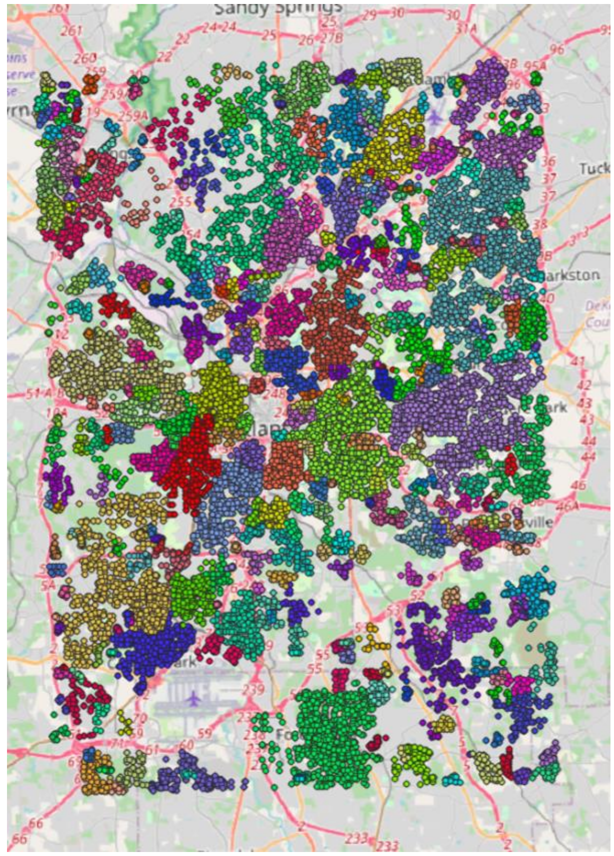

Figure 8. The connected components after partition

Discussion

Figure 8 shows the urban pastures of Atlanta. The delineations, or fences, of these pastures, represent the limits reachable by residential roads without needing to enter a larger road. Scholars have largely conceptualized roads as static barriers. However, this paper accounts for how the movement of people along roads also creates barriers and results in separation, nuancing our understanding of urban roads in scholarly literature. Drawing on computational methods allows us to view roads as complex systems that interact with and impact the movement of residents. Larger roads act as fences that discourage the residents in Atlanta from accessing other communities, which perpetuates a segregated built environment.

These findings depend on the reality that higher-speed roads increase the difficulty of movement. This idea may seem counterintuitive because urban scholarship has emphasized the role of larger roads in allowing quick movement over far distances. However, entering and traveling these large roads poses a challenge for specific communities. Large roads pose barriers as inaccessible movement pathways. To reach a destination outside of a pasture requires the energy to enter and exit a highway. When accounting for traffic flows and congestion, entering and exiting takes up valuable time in a person's day. Staying within a residential system allows for slow yet more straightforward access to their community. Residential roads are also more conducive to other more accessible forms of commuting like walking and riding a bike. Changes from residential to highways or other significant roads are the fences of urban pastures.

The tension created by the connectivity of residential roads also bounds residents to urban pastures. The speed of travel along a road is a proxy for a person's connection to their environment. Residential roads are the slowest prevalent roads in Atlanta and thus act as the fabric connecting communities. People moving along these roads see the streets, interface with the people, and, in turn, are more impacted by the environment than an individual speeding down the interstate. These roads hold space together because they are the most intimately tied to space and act as a glue holding urban pastures together.

The containment of residents to urban pastures produces communities. Restricting the movement of people out of pastures forces residents to interact with each other, build connections to space, and develop relationships with accessible amenities. Residents will walk the streets of their pasture and run into familiar faces and develop community. Residents of urban pasture will frequent the same grocery stores and local institutions. Social life is a product of space and iterative interaction, and thus the physical and dynamic space of an urban pasture is a cement mixer of socializing and community-building. Proximity creates connections due to the ease of movement through residential roads, and urban pastures force proximity.

The communities contained within the pastures are homogenous. This is not surprising given that most urban pastures fall within a single census block. The culture, residential composition, and spaces may not vary in these pastures because of their homogeneity. The Urban Pastures are homogonous communities with less than one standard deviation in the three demographic variables tested. Due to this homogeneity, to reach a demographically different group, an individual needs to travel along a larger road showing that road mobility further accentuates segregation. Communities are isolated and inaccessible to other communities because of the road network, and casual social interactions that may lead to community building will not happen across two different pastures. Roads are barriers to integration, and urban pastures are the spatial areas that the road network organizes people into.

The final element of this urban pasture analysis is that movement on these large roads is not equivalently easy and accessible for every citizen. Highways and larger roads require time and a car to travel. They are not built to be movement pathways for those without the capacity to buy a car. This makes urban pastures one-way valves for those privileged enough to use large roads. Individuals without the means to travel large roads are stuck in their pastures, while those who have the means of travel can leave and enter other pastures on their own will. This makes pastures passible barriers to less marginalized residents and accentuates their bounding effect on those who are marginalized. Urban pastures are infrastructural boundaries that scale with the privilege of those being contained. Those who are privileged can escape, and those who are marginalized are stuck. In this way, urban pastures fully embody their analogy and act as tools to fence marginalized people to certain parts of a city.

Outside of this study, urban pastures are valuable units of measurement for future research. Instead of researching at the neighborhood level, the subgraphs prove to be a new spatial unit to conducted research on. Neighborhoods of cities may be socially or historically constructed, but urban pastures are physical delineations in the urban landscape. Urban pastures may prove to be a better unit to conduct research because their extent is dilinated by the urban landscape. Further explorations of the ecological conditions that shape individual urban pastures will deepen our understanding of the separation of people, how movement plays into interaction, and how placemaking occurs on residential roads.

Future computational research should continue to integrate nuance into modeling. This model, SPC, and multiple transit networks should be combined to make a more accurate segregation model. SPC only thinks about proximity in terms of the road network, but people move along public transport, bike and walking networks which changes how proximity should be calculates. Likewise, SPC should consider nuance the speed along larger roads that this analysis explores. Again, proximity along a road network varies by the nature of the road, and this change in proximity should figure in the calculation of an egocentric neighborhood. Combining all the elements into one model will better calculate proximity and therefore produce a more accurate understanding of segregation.

Conclusion

The way road networks are constructed discourages travel which creates barriers in the built enviroment. Accounting for the way people move produces delineations in roads networks resulting urban landscape. These delineations arise because the effort required to leave an urban pasture necessitates traveling along larger roads and interstate highways, which may not even be feasible if an individual does not own a car. The urban pastures of Atlanta are homogenous along the three demographic variables tested, which means there are making for isolated homogenous communities splattered across the city.

Urban pastures are social and community-building venues. Residents share the same spaces, amenities, and homes. The internal proximity and accessibility to nearby residents result in community and place-making development. These communities reflect constructs of the built environment and the movement of residents. Urban pastures also act as a one-way valve allowing those who have cars and the time to spend traveling these larger roads to mobilize and access communities of interest (Webber 1963). Marginalized residents may not have the time or resources, like a vehicle, to travel these larger roads. Urban pastures embody their analogy by fully acting as fenced-off city areas, thereby trapping residents. Urban pastures add another dimension to urban inequality literature by describing how road networks produce unequal urban landscapes.

Above all, urban pastures provide new ways of thinking about space and people. They illustrate how urban landscapes limit the movement and actions of residents. Residents remain heavily impacted by the construction of urban spaces and infrastructure, which shapes their social lives within cities. Analyzing urban pastures allows us to study the city of Atlanta under a different lens by assessing how infrastructure interacts with the movement of people. Analyzing these infrastructure elements can be done on the ground or through interviewing. Still, computational methods can consider even more subtle elements of daily life and create models that provide a complex analysis of systemic inequity that would otherwise be unseen.

Computation enables city-wide analysis at a granular level which produces a better understanding of the entirety of a city as a system. It is challenging to have a holistic view of a city as accurately as the modeling extensive data and computation can produce. Urban pastures require the analysis of thousands of different roads, all with different characteristics, which is an impossible task for an individual. These spatial datasets open new methods to analyze cities at both a system-wide and individual level. However, current spatial datasets lack the nuance and detail of targeted surveys and previous empirical methods that scholars have used to measure the presence and persistence of community segregation.

Researchers have been measuring segregation for the last 100 years. Studies have involved surveying, interviews, and observation simply through walking the streets as ways to study and prove that people are separated from different people. This literature shows that the built environment organizes people into spaces for pursuing various opportunities that improve their lived experiences, including housing, social relationships, access to culture and leisure, and many other reasons. Urban pastures contribute to this overwhelming finding by suggesting that the way people interact with roads separates them into fenced-off communities. People are stuck in place because roads partition people into pastures. Our understanding of the urban environment will only increase, and computation provides many valuable methods to better understand this process.

Looking through the lens of urban pastures encourages us to understand segregation through new methods and provides a new segregation unit in cities. Computational methods of measuring segregation will enable scholars to consider new forms of movements, thus increasing our understanding of life on the ground for an entire city. As data quality increases, these city-wide models will only get better at simulating the conditions on the ground in a city.

References

Alba, Richard D. and John R. Logan. 1992. "Assimilation and Stratification in the Homeownership Patterns of Racial and Ethnic Groups." *International Migration Review* 26(4):1314–41.

Bayor, Ronald H. 1988. "Roads to Racial Segregation." *Journal of Urban History* 15(1):3–21.

Du Bois, W. E. B. 1903. *The Souls of Black Folk: Essays and Sketches*. A. C. McClurg & Co., Chicago.

Evans, James and Jacob G. Foster. 2019. "Computation and the Sociological Imagination." *Contexts* 18(4):10–15.

Gans, Herbert J. 1967.in *The levittowners, ways of life and politics in a new Surburban*. Allen Lane the Penguin Press.

Glaeser, Edward, and Jacob Vigdor. 2001. *Racial Segregation in the 2000 Census: Promising News.* Washing- ton, DC: The Brookings Institution

Humphreys, Laud. 1970. "Tearoom Trade: Impersonal Sex in Public Places." *Society* 7(3):10–25.

Jacobs, Jane. 1961. *The Death and Life of Great American Cities*. New York: Random House.

Katz, Bruce and Amy Liu. 2000. "Moving beyond Sprawl: Toward a Broader Metropolitan Agenda." *The Brookings Review* 18(2):31.

Lazer, David et al. 2009. "Computational Social Science." *Science* 323:721–23.

Logan, John R. 2013. "The Persistence of Segregation in the 21st Century Metropolis." *City & Community* 12(2):160–68.

Macy, Michael W. and Robert Willer. 2002. "From Factors to Actors: Computational Sociology and Agent-Based Modeling." *Annual Review of Sociology* 28(1):143–66.

Massey, Douglas and Nancy Denton. 1992. *American Apartheid Segregation and the Making of the Underclass*. Harvard University Press.

Massey, Douglas S. 1990. "American Apartheid: Segregation and the Making of the Underclass." *American Journal of Sociology* 96(2):329–57.

Park, Robert Ezra, E. W. Burgess, and Roderick Duncan McKenzie. 1974. "The Growth of the City: An Introduction to a Research Project." Pp. 47–62 in *The City*. Chicago: University of Chicago Press.

Park, Robert Ezra, Ernest Watson Burgess, and Robert J. Sampson. 1915. *The City*. Chicago: The University of Chicago Press.

Roberto, Elizabeth. 2016. "The Divergence Index: A Decomposable Measure of Segregation and Inequality."

Roberto, Elizabeth. 2018. "The Spatial Proximity and Connectivity Method for Measuring and Analyzing Residential Segregation." *Sociological Methodology* 48(1):182–224.

Sampson, Robert J. 2013. *Great American City: Chicago and the Enduring Neighborhood Effect*. Chicago: The University of Chicago Press.

Sampson, Robert J. and Patrick Sharkey. 2008. "Neighborhood Selection and the Social Reproduction of Concentrated Racial Inequality." *Demography* 45(1):1–29.

Schelling, Thomas C. 1971. "Dynamic Models of Segregation." *The Journal of Mathematical Sociology* 1(2):143–86.

Shaw, Lynette. 2015. "Mechanics and Dynamics of Social Construction: Modeling the Emergence of Culture from Individual Mental Representation." *Poetics* 52:75–90.

Simmel, Georg. 1903. *The Metropolis and Mental Life*. Europaconcorsi.

Appendix

Table 2.1 - Race

id	Number of Intersections in Urban Pasture	Census Blocks Covered	%White	Standard Deviation	%Black or African American Alone	Standard Deviation
0	11	1	0.19794345	0	0.633836761	0
1	694	6	0.25052947	0.097757658	0.482826397	0.151303286
2	16	1	0.18896408	0	0.718375846	0
3	19	2	0.17947855	0.023925669	0.705105764	0.027042624
4	183	3	0.0381038	0.03529663	0.874613461	0.105808851
5	26	1	0.30009234	0	0.471375808	0
6	28	1	0.1656051	0	0.527600849	0
7	11	2	0.16854495	0.009750379	0.537258659	0.032031333
8	83	1	0.18896408	0	0.718375846	0
9	13	1	0.04417865	0.006667001	0.888426978	0.002376088
10	230	2	0.09110071	0.076905001	0.832566527	0.144324958
11	15	2	0.15667199	0.015402601	0.745610682	0.033980362
12	83	3	0.17111297	0.032889562	0.763353154	0.036262964
13	29	2	0.12996306	0.127459039	0.830021586	0.142990391
14	21	1	0.19794345	0	0.633836761	0
15	48	3	0.20231771	0.03538187	0.627108506	0.034542863
16	48	2	0.0500389	0.024246195	0.931063452	0.017065074

17	15	1	0.19562888	0.003388179	0.690690458	0.083225291
18	51	2	0.19452178	0.023205694	0.606272867	0.064671706
19	25	2	0.50123725	0.02298667	0.459225945	0.015870624
20	346	5	0.29959809	0.223820133	0.564123051	0.277785353
21	14	2	0.04752535	0.113032986	0.764410604	0.099958142
22	30	2	0.05581672	0.048332337	0.901823842	0.077369041
23	14	2	0.15422001	0.012584471	0.741411598	0.030962168
24	111	3	0.53209264	0.214020186	0.133579639	0.034753221
25	20	1	0.51786415	0	0.406360424	0
26	14	2	0.54512553	0.097784788	0.347445686	0.075299263
27	161	1	0.43597227	0	0.4122583	0
28	14	1	0.60649086	0.11508929	0.191470399	0.010430819
29	21	2	0.55182652	0.051336015	0.35495143	0.032386177
30	133	3	0.7897465	0.204002017	0.126137523	0.195240077
31	28	1	0.26661952	0	0.497878359	0
32	17	1	0.42051282	0	0.447985348	0
33	16	2	0.44232609	0.05960519	0.422374294	0.069982723
34	165	3	0.45183112	0.169092629	0.432919365	0.220828356
35	13	1	0.42051282	0	0.447985348	0
36	18	2	0.43693593	0.034450253	0.184188899	0.034456341
37	12	2	0.4327833	0.036803106	0.180035528	0.03680961

38	29	1	0.63568521	0	0.171641791	0
39	15	2	0.45324507	0.121483185	0.417143171	0.076639684
40	12	1	0.54133333	0	0.404	0
41	22	1	0.33080885	0	0.265980006	0
42	115	3	0.62364712	0.118823877	0.24177172	0.093430564
43	16	1	0.57125961	0	0.327321112	0
44	13	1	0.58766626	0	0.31076179	0
45	13	2	0.32894357	0.001534841	0.407713108	0.116625187
46	16	1	0.58766626	0	0.31076179	0
47	13	1	0.57125961	0	0.327321112	0
48	19	1	0.559172	0.084302108	0.303656166	0.069688221
49	28	2	0.51050546	0.027019002	0.399720462	0.024380038
50	29	1	0.57125961	0	0.327321112	0
51	18	1	0.5272788	0.040904712	0.39393344	0.029297993
52	21	3	0.29516696	0.117582586	0.571518973	0.106885662
53	17	2	0.48867848	0.049470077	0.246993527	0.067128943
54	19	1	0.34432766	0.058927133	0.268336942	0.010273646
55	15	1	0.53983177	0	0.319643741	0
56	135	2	0.72840776	0.174475707	0.096726732	0.067148938
57	204	4	0.86188025	0.069543935	0.087328786	0.052873403
58	870	4	0.52774415	0.25308582	0.406756943	0.264904455

59	178	4	0.09750683	0.072681159	0.855285472	0.100894141
60	59	3	0.68319947	0.116135733	0.11072146	0.087517026
61	13	1	0.58328096	0	0.188560654	0
62	18	1	0.43327126	0	0.360024829	0
63	137	3	0.01509429	0.008287611	0.93859349	0.025933078
64	50	2	0.76692389	0.118504172	0.101469322	0.066604751
65	797	5	0.75652749	0.12222905	0.108322057	0.076740832
66	18	1	0.02495345	0	0.879702048	0
67	15	3	0.88735386	0.034308576	0.029252497	0.018479586
68	64	3	0.75138197	0.185352953	0.148511312	0.205068563
69	120	4	0.78271762	0.204228695	0.134350062	0.20385252
70	112	2	0.24891109	0.072633139	0.642713532	0.073363862
71	314	4	0.80987678	0.081412654	0.058488133	0.035996387
72	13	1	0.75561798	0	0.040449438	0
73	76	4	0.2967669	0.107646107	0.63352755	0.116378039
74	12	1	0.49425287	0	0.41954023	0
75	38	2	0.73923848	0.204719052	0.191445354	0.17877882
76	935	4	0.65332828	0.182381982	0.273675104	0.183162918
77	27	3	0.39354833	0.132481715	0.182011463	0.128382989
78	96	3	0.68786762	0.198614653	0.169765965	0.186535982
79	254	3	0.68672445	0.144232694	0.094739386	0.074393845

80	14	2	0.74025776	0.133007672	0.133956903	0.098948946
81	20	1	0.03726708	0	0.962732919	0
82	18	2	0.44930706	0.089476646	0.047667425	0.014222472
83	17	2	0.01809729	0.001766792	0.950481357	0.01823941
84	352	5	0.87518324	0.073835739	0.044659855	0.05050167
85	168	3	0.49279941	0.20121163	0.083279658	0.037179171
86	45	1	0.0148	0	0.9368	0
87	119	3	0.73594843	0.118775547	0.099097318	0.015727158
88	14	2	0.56957308	0.017803813	0.198456044	0.054279919
89	25	2	0.48046234	0.031791535	0.402065623	0.071270746
90	63	4	0.73206517	0.128224049	0.11439534	0.063031044
91	16	2	0.07930461	0.013097049	0.909039848	0.01366282
92	13	1	0.02767135	0	0.97232865	0
93	62	2	0.04719114	0.011258271	0.930928137	0.00565362
94	19	1	0.0275283	0.00062353	0.967453566	0.02125
95	95	4	0.15681109	0.101686414	0.795044944	0.100558653
96	78	3	0.08128988	0.00803715	0.907185654	0.009707342
97	11	1	0.89389175	0.00482494	0.032077654	0.005093642
98	13	3	0.08274466	0.069223599	0.900703849	0.075746599
99	18	2	0.07966842	0.012348016	0.908660325	0.01288143
100	28	3	0.82653947	0.137384903	0.105712293	0.058884521
101	14	2	0.08957281	0.04604861	0.896485672	0.045373116

102	50	2	0.60860046	0.065282553	0.202197584	0.046836387
103	11	2	0.64978704	0.276766092	0.201804916	0.188617552
104	13	1	0.0735768	0	0.906015038	0
105	158	4	0.76512763	0.152945805	0.099893139	0.106821661
106	75	3	0.72001309	0.108565524	0.148622813	0.06401368
107	52	3	0.89782836	0.020501056	0.036659779	0.009173902
108	14	2	0.01624399	0.011524453	0.973080562	0.002871795
109	16	2	0.91649975	0.007511267	0.0194667	0.00225338
110	20	1	0.30341879	0.050368589	0.634916867	0.068059267
111	12	2	0.47164232	0.078325245	0.443862338	0.084254255
112	37	3	0.71337061	0.114455072	0.178143313	0.037189752
113	14	1	0.01624008	0.005388295	0.938341398	0.005767385
114	24	1	0.75298508	0	0.186567164	0
115	19	1	0.00466805	0	0.952282158	0
116	25	2	0.58346723	0.030527181	0.156095842	0.093070673
117	33	2	0.02381037	0.006926007	0.959566316	0.021033106
118	15	3	0.39162464	0.048158245	0.023045876	0.009280866
119	18	3	0.10253925	0.03398291	0.840662799	0.020165241
120	26	2	0.03220561	0.010274171	0.958173451	0.010717998
121	11	2	0.79281359	0.070387901	0.115785295	0.06972276
122	12	2	0.56408028	0.092044222	0.190819404	0.033992128

123	11	2	0.48790091	0.296689457	0.046095429	0.018687482
124	11	2	0.77582806	0.037791558	0.104498514	0.045259596
125	19	2	0.38427569	0.048087826	0.52514896	0.027534229
126	21	1	0.06601863	0	0.820980154	0
127	21	3	0.8589006	0.093361949	0.061513799	0.040196579
128	12	1	0.12178388	0	0.838765009	0
129	11	1	0.02767135	0	0.97232865	0
130	14	2	0.16785554	0.040347786	0.82336779	0.042873885
131	11	1	0.00466805	0	0.952282158	0
132	52	2	0.11401945	0.07541672	0.878409754	0.071002462
133	19	3	0.55146178	0.168303401	0.267149173	0.087850108
134	15	2	0.0616236	0.026565665	0.927484655	0.027713258
135	17	2	0.0253865	0.005540582	0.964352757	0.016825805
136	25	2	0.62788505	0.096711554	0.280277033	0.093776358
137	16	2	0.77916534	0.043106899	0.119884926	0.029955338
138	20	2	0.31158392	0.112382444	0.28382722	0.031846195
139	24	1	0.84520124	0	0.07120743	0
140	22	2	0.72565215	0.021793875	0.098426859	0.002433396
141	12	1	0.36696005	0	0.201083277	0
142	15	2	0.5540796	0.142119947	0.166886016	0.056982498
143	44	3	0.54852699	0.043981635	0.331788817	0.037603272

144	19	3	0.33035403	0.08115074	0.630859162	0.0855746
145	18	2	0.19685232	0.054600523	0.72466194	0.084614959
146	28	2	0.88368275	0.014821683	0.032901116	0.009073518
147	28	3	0.44162667	0.121530024	0.339722571	0.086054244
148	16	2	0.07699931	0.013148944	0.899362473	0.021535438
149	33	2	0.10015324	0.019365343	0.858495956	0.029011551
150	12	3	0.40767577	0.150909968	0.269285512	0.123814138
151	12	1	0.89243698	0	0.033613445	0
152	43	2	0.90856306	0.038515804	0.030438811	0.026209533
153	13	1	0.39816031	0.103545149	0.363311817	0.07154878
154	17	2	0.54744087	0.037229167	0.268906584	0.033616927
155	11	1	0.27406199	0	0.032626427	0
156	15	2	0.57299867	0.263559	0.273388864	0.195761332
157	11	1	0.03354037	0	0.90931677	0
158	18	2	0.74057146	0.018334416	0.103841005	0.002265548
159	12	1	0.5342723	0	0.269483568	0
160	11	2	0.94564299	0.05435737	0.010879587	0.024205553
161	20	3	0.18312706	0.046235251	0.805646438	0.043307946
162	24	2	0.10738304	0.125291627	0.871791289	0.153665759
163	18	1	0.75257025	0	0.084989719	0
164	42	1	0.52521219	0.062156235	0.217644329	0.030011607

165	13	1	0.63829906	0.024764628	0.020321183	0.037696328
166	29	1	0.82753101	0.022643452	0.081424314	0.038019519
167	11	1	0.92389172	0	0.020007846	0
168	23	1	0.72561863	0	0.040029112	0
169	14	1	0.0148	0	0.9368	0
170	14	1	0.0735768	0	0.906015038	0
171	12	2	0.04104306	0.013080388	0.957973855	0.016485884
172	22	1	0.59627413	0.107129975	0.210872385	0.049737957
173	11	1	0.57880435	0	0.207201087	0
174	14	1	0.92529631	0.005255492	0.021064939	0.00395528
175	102	5	0.07501725	0.087276097	0.908175327	0.098108066
176	31	1	0.61182878	0.022497145	0.277423957	0.041945377
177	27	1	0.36014615	0.047160771	0.487765712	0.145594546
178	52	2	0.80165297	0.055610241	0.092236872	0.018955355
179	383	3	0.10976664	0.107113636	0.829533885	0.14104398
180	372	4	0.14506249	0.090208885	0.806488218	0.08867985
181	170	3	0.77464679	0.13007334	0.149943805	0.164440936
182	44	2	0.80398452	0.035541365	0.083361073	0.014171491
183	95	2	0.03878258	0.042610234	0.956570636	0.040892325
184	203	6	0.34637807	0.169600379	0.534593916	0.189915946
185	27	4	0.02202571	0.011799495	0.928323495	0.037112005
186	554	4	0.86797059	0.108123764	0.067950377	0.069011505

187	23	1	0.01942857	0	0.901714286	0
188	80	3	0.03101746	0.02622458	0.942180801	0.048551441
189	19	1	0.03254113	0	0.949908592	0
190	13	1	0.03311966	0	0.905270655	0
191	160	3	0.74530194	0.119627301	0.160367501	0.097802814
192	37	2	0.76756528	0.014815189	0.11931809	0.030122388
193	17	1	0	0	1	0
194	46	3	0.41909648	0.099768326	0.525923056	0.137639402
195	16	1	0.79598662	0	0.080267559	0
196	50	4	0.06505517	0.04388418	0.934555533	0.044656653
197	25	1	0.02831595	0	0.970193741	0
198	16	2	0.06816314	0.134907775	0.902300505	0.131256787
199	17	1	0.47870765	0.018176042	0.222764189	0.030896523
200	12	1	0.05165637	0	0.941605839	0
201	101	3	0.05757921	0.016157806	0.920919309	0.016943649
202	73	2	0.34825147	0.007994365	0.312357551	0.010254123
203	22	3	0.95068157	0.088071539	0.01553132	0.047913622
204	188	3	0.66794203	0.24624545	0.246717439	0.261703986
205	46	2	0.01743867	0.000353599	0.977822156	0.00101068
206	39	2	0.03414997	0.006297701	0.872273395	0.014488473
207	171	4	0.8656407	0.122262799	0.083390501	0.090051109
208	26	1	0	0	1	0

209	45	2	0.0845554 2	0.0016553 22	0.8951438 29	0.0119338 45
210	11	2	0.0191195 1	0.0107912 58	0.9650202 95	0.0077656 96
211	697	6	0.1545205 6	0.1621510 96	0.7897136 41	0.1951221 23
212	421	4	0.0323128 4	0.0472067 73	0.9541453 08	0.0575121 89
213	29	2	0.0416920 1	0.0089260 32	0.9565093 83	0.0075915 08
214	40	1	0.5619341 1	0.0481181 59	0.2156815 9	0.0126459 29
215	76	1	0.0758534 5	0.0237542 97	0.8695164 62	0.0253294 18
216	11	1	0.8230251 1	0	0.0496019 6	0
217	204	4	0.3047326 8	0.1700936 57	0.6115628 74	0.2340197 85
218	309	4	0.0435607 7	0.0631385 39	0.9314830 7	0.0765493 87
219	39	2	0.5347231 8	0.0982230 84	0.3500542 45	0.1102304 32
220	67	2	0.4996966 5	0.0148700 77	0.2060140 99	0.0449108 74
221	59	3	0.0304334 1	0.0319075 59	0.9358241 96	0.0527479 31
222	12	1	0.0379752 2	0.0082500 47	0.9554503 6	0.0083485 6
223	224	3	0.4715247 7	0.2836855 23	0.4700451 7	0.2897142 07
224	28	2	0.6653407 8	0.0228289 53	0.2416515 32	0.0195538 9
225	14	1	0.6828597 6	0	0.2719981 67	0
226	24	3	0.8511715 8	0.0646915 3	0.0941067 31	0.0323635 8
227	21	1	0.4576317 6	0	0.2585900 07	0
228	35	2	0.2775194	0.1363267 71	0.6954189 74	0.1460658 61
229	153	4	0.0356227 8	0.0248475 36	0.9438138 25	0.0361635 69

230	12	1	0.05165637	0	0.941605839	0
231	100	4	0.06505425	0.049951368	0.887504153	0.037069429
232	12	1	0.06226523	0.002545309	0.924896373	0.007287178
233	19	2	0.36496209	0.001944867	0.562527241	0.042022952
234	34	1	0.01068091	0	0.943257677	0
235	14	2	0.67446826	0.087691728	0.255262194	0.093582922
236	23	3	0.03951615	0.009372524	0.931064233	0.02206125
237	64	1	0.48347644	0.043459534	0.205564939	0.018361854
238	39	2	0.85856066	0.069286174	0.042750273	0.060182016
239	156	2	0.05785869	0.033528556	0.941771267	0.033927453
240	34	3	0.86101509	0.046888893	0.128916992	0.055645285
241	58	4	0.93963716	0.066046776	0.033237314	0.031300779
242	60	3	0.62000296	0.049742648	0.243522724	0.059311709
243	14	1	0.20843686	0.084737722	0.700856964	0.094045463
244	28	3	0.81208114	0.058384749	0.060251278	0.042228714
245	14	2	0.45845362	0.119446422	0.439488688	0.143473647
246	11	2	0.45891779	0.136254604	0.4801976	0.178471751
247	94	2	0.59365817	0.035899357	0.323262084	0.035086325
248	18	2	0.98947723	0.038253861	0	0
249	32	2	0.12419232	0.081561885	0.780076683	0.074191365
250	12	1	0	0	0.905966021	0

251	38	2	0.00507107	0.003925085	0.961168439	0.025957276
252	41	2	0.01702951	0.019489093	0.960350321	0.039315786
253	18	2	0.79416801	0.060678038	0.124035682	0.06923659
254	55	1	0.62710084	0	0.24894958	0
255	18	1	0.35339656	0.068991941	0.613305716	0.077301956
256	32	3	0.58637006	0.054731536	0.370239456	0.080745932
257	38	2	0.69148579	0.036349425	0.215639658	0.018805583
258	48	2	0.67059366	0.159978242	0.251377674	0.180338359
259	23	3	0.39928023	0.050304455	0.567479488	0.025851711
260	12	2	0.3733334	0.01273154	0.592666268	0.008380362
261	37	2	0.07546799	0.036323921	0.915425753	0.038596166
262	13	3	0.01007088	0.005239452	0.988638934	0.008080264
263	17	2	0.03700608	0.042865598	0.957255039	0.039047157
264	23	3	0.001344	0.006445577	0.997849607	0.010312923
265	42	2	0.4505032	0.018296639	0.507320786	0.019862665
266	30	2	0.09910268	0.084767603	0.843612392	0.130423206
267	19	3	0.8323677	0.128480969	0.047106157	0.085029276
268	28	3	0.02268268	0.009825777	0.839271078	0.065990394
269	26	2	0.04640452	0.012390624	0.944923006	0.014943732
270	12	2	0.60951756	0.0506272	0.209820396	0.050318434
271	33	4	0.2741239	0.202731318	0.68887203	0.244087805

272	17	1	0.03878584	0	0.952782462	0
273	11	2	0.83342966	0.072917915	0.074745732	0.035139917
274	29	2	0.13719467	0.048199404	0.849981432	0.040852183
275	91	2	0.14582233	0.019439077	0.85041307	0.020138014
276	18	3	0.64340489	0.034988955	0.163696277	0.024759799
277	19	3	0.75400518	0.050659448	0.156797001	0.034181343
278	18	1	0.68149325	0	0.163224782	0
279	18	2	0.6437939	0.067258905	0.172084824	0.057779646
280	20	3	0.79045967	0.0244997	0.053689086	0.011979461
281	15	2	0.47842745	0.092494556	0.48124904	0.083979878
282	34	2	0.16290361	0.073997517	0.83709639	0.073997517
283	15	1	0.0206379	0	0.979362101	0
284	15	2	0.05851284	0.019886622	0.903343459	0.021965736
285	23	3	0.63837168	0.060230154	0.304608313	0.086371026
286	12	1	0.0455259	0	0.916797488	0
287	16	1	0.10372461	0.018628963	0.879442838	0.044414471
288	14	2	0.98846188	0.043171678	0	0
289	38	2	0.44043916	0.06535731	0.290095149	0.048542485
290	15	1	0.08986487	0	0.842567568	0
291	11	2	0.84117756	0.016086345	0.113434137	0.032015453
292	12	1	0.00884467	0	0.991155334	0

293	20	2	0.83287767	0.017201666	0.008879136	0.027329403
294	25	2	0.03407691	0.016082512	0.952421153	0.015345646
295	18	1	0.36609337	0	0.538083538	0
296	23	2	0.74203138	0.089470832	0.155047206	0.08662006
297	17	2	0.01832208	0.013948214	0.980713597	0.01468233
298	13	2	0.01790281	0.020126846	0.958588577	0.04060234
299	31	1	0.83846637	0	0	0
300	14	2	0.12842844	0.007670335	0.821554834	0.022066139
301	15	2	0.08961619	0.029995653	0.878447886	0.040437832
302	11	1	0.07559032	0.026934187	0.909752554	0.005675864
303	14	1	0.86311942	0	0.075142161	0
304	19	2	0.84696814	0.037058356	0	0
305	27	2	0.95375676	0.030609375	0.006773101	0.007716809
306	15	2	0.79199083	0.015120861	0.142162674	0.021265605
307	14	2	0.04634678	0.013339522	0.944929117	0.015850491
308	12	1	0.68149325	0	0.163224782	0
309	12	2	0.07780303	0.027222415	0.901883025	0.020825182
310	28	1	0.62710084	0	0.24894958	0
311	14	2	0.01331998	0.025197963	0.974865238	0.046569775
312	11	1	0.04305284	0	0.933463796	0
313	12	2	0.01253849	0.000736072	0.954272949	0.010480969

314	15	1	0.04761905	0	0.913165266	0
315	19	2	0.80946228	0.022617345	0.106498052	0.008931194
316	19	2	0.05943913	0.011755038	0.875808697	0.027435492
317	16	1	0.02111324	0	0.898272553	0
318	18	1	0.01753105	0	0.978086194	0
319	17	1	0.16424581	0	0.83575419	0
320	22	1	0.29017341	0	0.650289017	0
321	14	1	0.1919917	0.002521511	0.780031982	0.061936961
322	23	1	0.19099974	0	0.804397852	0
323	11	2	0.4910672	0.075567226	0.219815251	0.005302921
324	14	2	0.54664822	0.093201262	0.126747055	0.033249174
325	18	1	0.56317555	0	0.226239284	0
326	22	1	0.03878584	0	0.952782462	0
327	21	1	0.03205674	0	0.939858156	0
328	12	1	0.03328106	0.005820024	0.95658128	0.006229488
329	14	2	0.74948674	0.006869715	0.080240175	0.01157354
330	33	1	0.37002212	0	0.558628319	0
331	14	1	0.03878584	0	0.952782462	0
332	12	2	0.03491784	0.030823194	0.950704225	0.043515097
333	11	2	0.20671698	0.10488463	0.732423329	0.111621867
334	17	1	0.134273	0	0.848664688	0

335	16	2	0.01676777	0.002612718	0.968070118	0.023869931
336	27	1	0.05165637	0	0.941605839	0
337	11	1	0.13047842	0	0.815657411	0
338	16	1	0.03311966	0	0.905270655	0
339	16	1	0.08753568	0	0.876308278	0
340	26	1	0.42051282	0	0.447985348	0
341	27	2	0.55805612	0.040433157	0.135910075	0.051304683
342	13	1	0.63568521	0	0.171641791	0
343	11	1	0.18896408	0	0.718375846	0
344	18	3	0.78017777	0.05322237	0.121403463	0.075027963
345	24	1	0.84664949	0	0.065292096	0
346	14	1	0.84664949	0	0.065292096	0
347	12	1	0.44360603	0.082102402	0.337971704	0.000453205
348	12	2	0.41195002	0.009710549	0.024516992	0.012773703
349	15	1	0.03530167	0	0.949293967	0
350	12	1	0.94191729	0.00567658	0.033573874	0.004272191
351	12	1	0.46828283	0	0.221414141	0
352	12	1	0.0735768	0	0.906015038	0
353	20	2	0.02030868	0.007309023	0.816866648	0.062867942
354	14	1	0.56481482	0	0.212962963	0
355	14	1	0.57125961	0	0.327321112	0

356	14	1	0.07469103	0	0.86351424	0

Table 2.2 - Poverty

id	Number of Intersections in Urban Pasture	Census Blocks Covered	% Population for Whom Poverty Status Is Determined: Under 1.00 (Doing Poorly)	Standard Deviation	% Population for Whom Poverty Status Is Determined: 1.00 to 1.99 (Struggling)	Standard Deviation	% Population for Whom Poverty Status Is Determined: 2.00 and Over (Doing Ok)'	Standard Deviation
0	11	1	6.76	0	26.9	0	66.4	0
1	694	6	24.3	0.15	37	0.14	38.8	0.13
2	16	1	9.21	0	36.2	0	54.6	0
3	19	2	8.89	0.01	34.6	0.03	56.5	0.04
4	183	3	15.6	0.06	32.6	0.1	51.8	0.11
5	26	1	31.8	0	35.7	0	32.5	0
6	28	1	42.3	0	2.02	0	55.7	0
7	11	2	39	0.11	4.28	0.07	56.7	0.03
8	83	1	9.21	0	36.2	0	54.6	0
9	13	1	20.9	0.02	48.6	0.09	30.5	0.07
10	230	2	4.28	0.02	15.5	0.09	80.2	0.11
11	15	2	8.73	0.01	19.8	0.02	71.4	0.01
12	83	3	9.78	0.03	18.9	0.01	71.3	0.02
13	29	2	11.1	0.11	20.4	0.06	68.5	0.05
14	21	1	6.76	0	26.9	0	66.4	0
15	48	3	7.53	0.05	26.8	0.05	65.7	0.04
16	48	2	11.3	0.03	26.1	0.03	62.6	0.05
17	15	1	7.61	0.01	24.3	0.04	68.1	0.03
18	51	2	11.3	0.06	17.8	0.12	70.9	0.06

19	25	2	18.6	0.04	30.8	0.07	50.7	0.03
20	346	5	23.6	0.21	19.8	0.12	56.6	0.23
21	14	2	21.8	0.04	22.6	0.07	55.6	0.03
22	30	2	3.9	0.03	24	0.02	72.1	0
23	14	2	8.69	0.01	19.9	0.02	71.4	0.01
24	111	3	6.7	0.01	4.68	0.03	88.6	0.02
25	20	1	4.75	0	13.5	0	81.7	0
26	14	2	2.52	0.01	6.37	0	91.1	0.01
27	161	1	4.66	0	6.63	0	88.7	0
28	14	1	2.29	0.02	10.5	0.02	87.2	0.04
29	21	2	2.74	0.01	7.48	0	89.8	0.01
30	133	3	3.93	0.02	5.7	0.08	90.4	0.1
31	28	1	11.3	0	22.9	0	65.9	0
32	17	1	7.07	0	19.9	0	73	0
33	16	2	6.61	0.01	18.6	0.04	74.8	0.05
34	165	3	5.01	0.03	11.4	0.07	83.6	0.1
35	13	1	7.07	0	19.9	0	73	0
36	18	2	5.59	0.01	10.3	0.04	84.1	0.03
37	12	2	5.7	0.01	9.84	0.04	84.5	0.03
38	29	1	6.24	0	14.9	0	78.8	0
39	15	2	4.96	0.03	7.5	0	87.5	0.03
40	12	1	14.7	0	26.4	0	58.9	0
41	22	1	23	0	31.7	0	45.3	0
42	115	3	9.07	0.03	4.03	0.01	86.9	0.02
43	16	1	2.19	0	6.35	0	91.5	0
44	13	1	9.43	0	7.86	0	82.7	0
45	13	2	13.6	0.08	16.8	0.12	69.5	0.2
46	16	1	9.43	0	7.86	0	82.7	0
47	13	1	2.19	0	6.35	0	91.5	0
48	19	1	2.87	0	3.62	0.01	93.5	0.01
49	28	2	5.28	0.02	13.8	0.01	80.9	0.03
50	29	1	2.19	0	6.35	0	91.5	0
51	18	1	14.4	0.01	25.4	0.03	60.2	0.04
52	21	3	12.1	0.04	18.1	0.02	69.8	0.06
53	17	2	4.28	0.01	11.2	0.02	84.5	0.04
54	19	1	22.3	0.03	30.4	0.05	47.3	0.09
55	15	1	2.87	0	3.76	0	93.4	0
56	135	2	10.9	0.09	10.8	0.01	78.3	0.1
57	204	4	4.22	0.04	5.77	0.02	90	0.05

58	870	4	11	0.11	13.8	0.08	75.2	0.16
59	178	4	19.4	0.06	26.7	0.09	53.9	0.1
60	59	3	17.9	0.11	9.12	0.03	73	0.12
61	13	1	19.9	0	4.65	0	75.4	0
62	18	1	9.87	0	15.9	0	74.2	0
63	137	3	19.1	0.04	19	0.04	61.9	0.08
64	50	2	3.72	0	8.74	0.04	87.5	0.04
65	797	5	7.6	0.07	6.26	0.07	86.1	0.13
66	18	1	1.4	0	21.8	0	76.8	0
67	15	3	2.03	0.01	2	0.02	96	0.03
68	64	3	7.55	0.16	2.44	0.05	90	0.21
69	120	4	11.3	0.16	5.34	0.05	83.4	0.2
70	112	2	22.5	0.03	23.8	0.05	53.7	0.08
71	314	4	6.38	0.05	8.18	0.06	85.4	0.09
72	13	1	6.46	0	12.5	0	81	0
73	76	4	10.2	0.01	24.2	0.1	65.6	0.09
74	12	1	19.2	0	10.6	0	70.2	0
75	38	2	7.73	0.06	12.9	0.04	79.4	0.08
76	935	4	11	0.08	8.62	0.06	80.3	0.11
77	27	3	25.6	0.15	20.7	0.16	53.7	0.3
78	96	3	20.8	0.11	23.4	0.14	55.8	0.18
79	254	3	11.3	0.09	11.3	0.1	77.4	0.17
80	14	2	4.55	0.03	8.02	0.02	87.4	0.01
81	20	1	2.15	0	5.42	0	92.4	0
82	18	2	39.7	0.06	47.2	0.01	13.1	0.06
83	17	2	33	0.08	25.3	0.01	41.8	0.09
84	352	5	5.82	0.05	5.03	0.07	89.2	0.1
85	168	3	22.7	0.05	25.6	0.08	51.7	0.06
86	45	1	24.1	0	31.9	0	44	0
87	119	3	11.5	0.04	10.8	0.03	77.6	0.05
88	14	2	17.4	0.04	22.4	0.03	60.2	0.01
89	25	2	26.2	0.04	26.7	0.01	47.1	0.05
90	63	4	10.7	0.08	8.56	0.03	80.8	0.05
91	16	2	15.6	0.02	13.6	0.07	70.9	0.09
92	13	1	16.9	0	27	0	56	0
93	62	2	11.9	0.02	26	0	62	0.01
94	19	1	16.1	0.04	26.8	0.01	57.1	0.05
95	95	4	13.7	0.1	26	0.11	60.3	0.13
96	78	3	15	0.02	11.8	0.01	73.2	0.02

97	11	1	10.9	0.03	0.18	0.01	88.9	0.02
98	13	3	30.9	0.09	29.1	0.04	40.1	0.07
99	18	2	15.5	0.02	13.4	0.06	71.1	0.08
100	28	3	5.53	0.06	6.92	0.04	87.5	0.1
101	14	2	19.4	0.11	35.1	0.08	45.5	0.09
102	50	2	5.55	0.07	3.85	0.05	90.6	0.11
103	11	2	6.03	0.05	4.76	0.03	89.2	0.07
104	13	1	24.4	0	34.7	0	40.9	0
105	158	4	2.55	0.03	5.26	0.04	92.2	0.06
106	75	3	7.29	0.02	12	0.08	80.7	0.1
107	52	3	6.99	0.05	1.7	0.01	91.3	0.05
108	14	2	16.9	0.01	15.5	0	67.7	0.01
109	16	2	5.66	0.01	3.38	0.01	91	0.02
110	20	1	50.7	0.04	17	0.03	32.2	0.01
111	12	2	19.8	0.02	11.3	0.02	68.9	0.04
112	37	3	8.83	0.05	11.3	0.07	79.9	0.1
113	14	1	23.8	0.01	32.2	0.01	44	0
114	24	1	9.22	0	10.7	0	80.1	0
115	19	1	17.6	0	24.8	0	57.5	0
116	25	2	20.4	0.06	20.4	0.04	59.2	0.02
117	33	2	18.5	0.01	16.5	0.03	65	0.04
118	15	3	41.4	0.04	46.8	0.01	11.8	0.03
119	18	3	24.1	0.06	28.2	0.04	47.6	0.1
120	26	2	22.1	0.01	37.6	0.05	40.3	0.07
121	11	2	4.59	0.01	2.39	0.06	93	0.06
122	12	2	17	0.07	6.38	0.09	76.7	0.16
123	11	2	20.1	0.14	33.1	0.23	46.8	0.37
124	11	2	11.5	0.02	16.2	0.05	72.2	0.07
125	19	2	8.37	0.03	12.3	0.03	79.3	0.06
126	21	1	30.5	0	32.3	0	37.2	0
127	21	3	11.4	0.02	6.29	0.05	82.3	0.06
128	12	1	15.3	0	27.4	0	57.3	0
129	11	1	16.9	0	27	0	56	0
130	14	2	18.6	0	14.7	0.04	66.7	0.03
131	11	1	17.6	0	24.8	0	57.5	0
132	52	2	9.72	0.03	23.3	0.08	67	0.07
133	19	3	15.1	0.1	15.9	0.14	69	0.24
134	15	2	18	0.04	22.6	0.14	59.4	0.17
135	17	2	18.3	0.01	15.9	0.02	65.8	0.03

136	25	2	6.04	0.01	15.6	0.07	78.4	0.08
137	16	2	11.7	0.03	16.4	0.06	71.9	0.08
138	20	2	36.9	0.1	29.8	0.05	33.2	0.16
139	24	1	9.75	0	3.72	0	86.5	0
140	22	2	3.77	0	1.39	0	94.8	0
141	12	1	4.48	0	37.9	0	57.6	0
142	15	2	26	0.13	8.29	0.04	65.7	0.17
143	44	3	15.2	0.04	15.1	0.02	69.7	0.04
144	19	3	19	0.08	15.6	0.04	65.4	0.11
145	18	2	31.2	0.14	20.1	0	48.8	0.14
146	28	2	9.5	0.04	2.62	0.01	87.9	0.04
147	28	3	6.71	0.07	3.81	0.02	89.5	0.09
148	16	2	23.5	0.05	35	0.06	41.6	0.02
149	33	2	15.6	0.09	40.7	0.1	43.8	0.01
150	12	3	3.11	0.02	20.7	0.18	76.2	0.2
151	12	1	11.8	0	0	0	88.2	0
152	43	2	1.63	0.01	8.91	0.03	89.5	0.02
153	13	1	15.2	0.02	20.6	0.01	64.3	0.03
154	17	2	15.6	0.04	6.55	0.02	77.9	0.06
155	11	1	30.5	0	49.4	0	20.1	0
156	15	2	13.1	0.03	11.5	0.08	75.4	0.11
157	11	1	3.35	0	13.6	0	83.1	0
158	18	2	14.7	0.03	10.3	0.02	75	0.05
159	12	1	16.1	0	6.43	0	77.5	0
160	11	2	0.42	0.01	5.32	0.01	94.3	0
161	20	3	18	0.02	17	0.09	65	0.08
162	24	2	14.6	0.22	8.8	0.05	76.6	0.27
163	18	1	0	0	5.14	0	94.9	0
164	42	1	49.2	0.07	9.9	0.01	40.9	0.08
165	13	1	28.5	0.08	14.7	0.05	56.8	0.03
166	29	1	3.78	0	9.6	0.03	86.6	0.03
167	11	1	1.18	0	10.2	0	88.6	0
168	23	1	8.08	0	13.8	0	78.2	0
169	14	1	24.1	0	31.9	0	44	0
170	14	1	24.4	0	34.7	0	40.9	0
171	12	2	3.23	0.04	5.96	0.02	90.8	0.06
172	22	1	13.2	0.01	6.71	0.01	80.1	0.02
173	11	1	3.47	0	2.27	0	94.3	0
174	14	1	1.41	0.01	9.68	0.02	88.9	0.01

175	102	5	15.3	0.07	33.1	0.11	51.6	0.11
176	31	1	15.7	0.09	3.95	0.02	80.3	0.07
177	27	1	44.9	0.08	18.1	0.07	37	0.15
178	52	2	1.41	0.02	2.24	0.02	96.4	0.03
179	383	3	32.6	0.1	29.1	0.13	38.3	0.14
180	372	4	28.8	0.08	26.9	0.06	44.3	0.08
181	170	3	10.3	0.12	6.13	0.04	83.5	0.15
182	44	2	3.13	0	2.4	0.01	94.5	0.01
183	95	2	30.4	0.1	33	0.12	36.7	0.08
184	203	6	27.7	0.15	17.2	0.12	55.1	0.2
185	27	4	28.4	0.2	40	0.1	31.6	0.1
186	554	4	5.01	0.04	5.4	0.05	89.6	0.06
187	23	1	16.3	0	46.5	0	37.1	0
188	80	3	21.5	0.08	29.1	0.07	49.4	0.13
189	19	1	27.9	0	36.4	0	35.7	0
190	13	1	15.5	0	35.9	0	48.5	0
191	160	3	5.86	0.05	15.6	0.08	78.6	0.1
192	37	2	5.3	0.02	6.27	0.03	88.4	0.06
193	17	1	36.5	0	12.7	0	50.8	0
194	46	3	33.7	0.11	13.9	0	52.4	0.11
195	16	1	7.8	0	12.5	0	79.7	0
196	50	4	37.1	0.14	26	0.05	36.9	0.15
197	25	1	22.7	0	45.4	0	31.9	0
198	16	2	74.7	0.16	7.96	0	17.3	0.16
199	17	1	41.3	0.01	18.3	0.07	40.4	0.06
200	12	1	13.9	0	19.5	0	66.6	0
201	101	3	35.7	0.08	24.3	0.04	39.9	0.09
202	73	2	31.4	0.02	7.12	0.01	61.5	0.03
203	22	3	1.45	0.01	1.15	0.04	97.4	0.05
204	188	3	12.1	0.16	8.68	0.05	79.2	0.17
205	46	2	30.8	0.06	23.5	0.01	45.7	0.07
206	39	2	33.4	0.05	24.1	0.03	42.5	0.05
207	171	4	11.4	0.06	7.19	0.04	81.4	0.07
208	26	1	36.5	0	12.7	0	50.8	0
209	45	2	38.8	0.01	17.2	0.02	44	0.03
210	11	2	34.4	0.07	26.9	0.02	38.7	0.09
211	697	6	25.7	0.16	21	0.13	53.2	0.19
212	421	4	29.9	0.15	31.4	0.12	38.7	0.14
213	29	2	14.7	0.06	24.5	0.05	60.9	0.07

214	40	1	20.3	0.15	9.83	0.02	69.8	0.17
215	76	1	51.3	0.03	26.6	0	22.1	0.03
216	11	1	5.33	0	4.1	0	90.6	0
217	204	4	30.4	0.23	15.1	0.08	54.5	0.23
218	309	4	31.1	0.12	28.6	0.13	40.3	0.15
219	39	2	14.5	0	5.76	0	79.8	0
220	67	2	17	0.02	12.8	0.03	70.2	0.05
221	59	3	21.4	0.08	28.1	0.05	50.5	0.13
222	12	1	7.23	0.04	26.5	0.04	66.2	0
223	224	3	23.7	0.16	14.8	0.09	61.5	0.22
224	28	2	4.58	0.02	5.64	0.05	89.8	0.07
225	14	1	6.39	0	8.85	0	84.8	0
226	24	3	2.23	0.03	6.33	0.03	91.4	0.05
227	21	1	39.7	0	26.9	0	33.4	0
228	35	2	33.7	0.03	25.2	0.23	41.1	0.21
229	153	4	32.7	0.14	24.7	0.09	42.6	0.13
230	12	1	13.9	0	19.5	0	66.6	0
231	100	4	25.2	0.06	24.9	0.04	49.9	0.09
232	12	1	10	0	23.6	0.03	66.3	0.03
233	19	2	27.7	0.1	24.4	0.02	47.8	0.08
234	34	1	20.8	0	21.4	0	57.8	0
235	14	2	6.92	0.02	3.65	0.01	89.4	0.02
236	23	3	21.9	0.06	35.7	0.08	42.4	0.11
237	64	1	39.2	0.08	14.5	0.05	46.2	0.1
238	39	2	3.93	0.04	3.9	0.02	92.2	0.05
239	156	2	43.7	0.04	27.1	0.07	29.2	0.03
240	34	3	3.66	0.01	0.99	0.02	95.4	0.03
241	58	4	2.5	0.01	2.19	0.01	95.3	0.01
242	60	3	8.81	0.02	6.46	0.02	84.7	0.04
243	14	1	51.2	0.02	17.2	0.03	31.7	0.02
244	28	3	2.99	0.01	2.36	0.01	94.7	0.01
245	14	2	17.4	0.06	17.5	0.12	65.1	0.16
246	11	2	24.3	0.11	8.29	0.05	67.5	0.09
247	94	2	25.5	0.08	1.25	0.01	73.3	0.07
248	18	2	0.48	0.01	4.42	0.01	95.1	0.01
249	32	2	36	0.06	10.6	0.08	53.5	0.08
250	12	1	89.8	0	5.85	0	4.35	0
251	38	2	19.5	0.15	39.6	0.05	40.8	0.1
252	41	2	10.9	0.12	43.8	0.03	45.3	0.1

253	18	2	9.54	0.09	11.4	0.03	79.1	0.08
254	55	1	9.64	0	5.41	0	85	0
255	18	1	30.5	0.03	27.3	0.01	42.3	0.04
256	32	3	18	0.09	11.4	0.09	70.6	0.07
257	38	2	4.11	0.03	7.49	0.01	88.4	0.02
258	48	2	4.02	0.06	9.31	0.05	86.7	0.11
259	23	3	30.9	0.06	10.2	0.06	58.9	0.09
260	12	2	30.1	0.01	25.5	0.05	44.4	0.04
261	37	2	6.97	0.02	17.9	0.09	75.1	0.08
262	13	3	13.4	0.08	9.51	0.13	77.1	0.21
263	17	2	10.8	0.04	49.8	0	39.4	0.04
264	23	3	42.7	0.15	14.4	0.08	43	0.2
265	42	2	12.9	0.04	5.41	0.05	81.7	0.09
266	30	2	37.2	0.09	29.8	0.05	33.1	0.1
267	19	3	6.87	0.01	5.33	0.04	87.8	0.05
268	28	3	55.2	0.12	26.8	0.05	17.9	0.08
269	26	2	22.5	0.06	40.4	0.01	37.1	0.04
270	12	2	9.68	0	8.34	0.01	82	0.01
271	33	4	22.9	0.1	32.7	0.09	44.4	0.18
272	17	1	39.1	0	27.9	0	33	0
273	11	2	5.01	0.04	8.5	0.03	86.5	0.07
274	29	2	45.9	0.14	22.3	0.06	31.9	0.08
275	91	2	11.5	0.07	18.7	0.01	69.8	0.08
276	18	3	9.03	0.03	8.69	0.01	82.3	0.03
277	19	3	16.8	0.07	6.52	0.03	76.7	0.04
278	18	1	4.37	0	12.7	0	83	0
279	18	2	7.61	0.01	6.35	0.03	86	0.03
280	20	3	8.06	0.02	5.95	0.04	86	0.05
281	15	2	12.2	0.01	5.01	0.03	82.8	0.03
282	34	2	24.8	0.02	40.6	0.1	34.5	0.07
283	15	1	22.3	0	33.8	0	43.9	0
284	15	2	28	0.15	31.7	0.07	40.3	0.21
285	23	3	10.8	0.08	7.88	0.08	81.3	0.11
286	12	1	37.9	0	36.3	0	25.8	0
287	16	1	44.7	0.01	22.3	0.05	33	0.04
288	14	2	2.95	0	0	0	97	0
289	38	2	14.8	0.04	11.6	0.03	73.7	0.06
290	15	1	7.16	0	19.1	0	73.8	0
291	11	2	5.89	0.01	3.61	0.01	90.5	0.02

292	12	1	75	0	21.8	0	3.23	0
293	20	2	3.81	0	0.3	0.01	95.9	0.01
294	25	2	37.5	0.05	32.2	0.06	30.3	0.08
295	18	1	33.5	0	23.4	0	43.2	0
296	23	2	7.84	0.03	2.6	0	89.6	0.03
297	17	2	20.3	0.03	29.4	0.22	50.3	0.26
298	13	2	11.5	0.13	43.6	0.03	44.9	0.1
299	31	1	3.9	0	0	0	96.1	0
300	14	2	41.3	0.09	29	0.02	29.7	0.11
301	15	2	27.4	0.03	32.3	0.02	40.3	0.05
302	11	1	41.9	0.08	11.4	0.09	46.7	0.01
303	14	1	3.53	0	0.97	0	95.5	0
304	19	2	3.85	0	0	0	96.2	0
305	27	2	2.06	0.01	0	0	97.9	0.01
306	15	2	4.23	0.02	5.41	0.04	90.4	0.06
307	14	2	20.3	0.02	39.4	0.05	40.2	0.07
308	12	1	4.37	0	12.7	0	83	0
309	12	2	31	0.04	36.2	0.05	32.8	0.01
310	28	1	9.64	0	5.41	0	85	0
311	14	2	9.13	0.04	4.32	0.11	86.5	0.07
312	11	1	7.24	0	27.6	0	65.2	0
313	12	2	22.2	0.03	29.5	0.01	48.3	0.04
314	15	1	22.4	0	33.6	0	44	0
315	19	2	2.05	0	0.39	0.02	97.6	0.01
316	19	2	45.6	0.05	32.5	0.04	21.9	0.08
317	16	1	25.9	0	29.8	0	44.3	0
318	18	1	29.2	0	23.3	0	47.5	0
319	17	1	43.4	0	21.7	0	34.9	0
320	22	1	25	0	12.7	0	62.3	0
321	14	1	8.95	0.01	20.2	0.03	70.8	0.02
322	23	1	9.31	0	19.1	0	71.6	0
323	11	2	30.6	0.08	35.1	0.11	34.3	0.18
324	14	2	14.3	0	30.5	0.09	55.2	0.09
325	18	1	13.5	0	7	0	79.5	0
326	22	1	39.1	0	27.9	0	33	0
327	21	1	2.67	0	25.1	0	72.2	0
328	12	1	20.3	0.01	36	0.01	43.7	0
329	14	2	10.7	0.01	19.9	0.02	69.4	0.03
330	33	1	11.1	0	18.8	0	70.1	0

331	14	1	39.1	0	27.9	0	33	0
332	12	2	20.9	0.07	31.2	0.08	47.9	0.15
333	11	2	9.73	0.01	32.3	0.09	57.9	0.08
334	17	1	20.9	0	22.3	0	56.8	0
335	16	2	52.9	0.03	26.6	0	20.5	0.03
336	27	1	13.9	0	19.5	0	66.6	0
337	11	1	43.6	0	29.6	0	26.8	0
338	16	1	15.5	0	35.9	0	48.5	0
339	16	1	23.1	0	38.3	0	38.5	0
340	26	1	7.07	0	19.9	0	73	0
341	27	2	19.5	0.01	30	0.02	50.4	0.03
342	13	1	6.24	0	14.9	0	78.8	0
343	11	1	9.21	0	36.2	0	54.6	0
344	18	3	3.32	0.02	1.94	0.04	94.7	0.07
345	24	1	12.4	0	19.6	0	68	0
346	14	1	12.4	0	19.6	0	68	0
347	12	1	14.1	0.09	29.1	0.17	56.7	0.08
348	12	2	42.8	0.01	46.5	0	10.7	0.01
349	15	1	40	0	34	0	26	0
350	12	1	4.07	0.01	3.01	0.02	92.9	0.01
351	12	1	32.9	0	38.3	0	28.8	0
352	12	1	24.4	0	34.7	0	40.9	0
353	20	2	19.7	0.08	18.4	0.06	61.9	0.13
354	14	1	16.4	0	23.1	0	60.5	0
355	14	1	2.19	0	6.35	0	91.5	0
356	14	1	41	0	23.5	0	35.5	0

Table 2.3.1 - Education

id	Number of Intersections in Urban Pasture	Census Blocks Covered	% Population 25 Years and Over: Less than High School	Standard Deviation	% Population 25 Years and Over: High School Graduate (Includes Equivalency)'	Standard Deviation	% Population 25 Years and Over: Some College'	Standard Deviation
0	11	1	0.22	0	0.265282584	0	0	0
1	694	6	0.3	0.08	0.369241777	0.08	0	0.095
2	16	1	0.18	0	0.413849959	0	0	0
3	19	2	0.19	0.02	0.395994589	0.04	0	0.025
4	183	3	0.12	0.06	0.373646434	0.07	0	0.072
5	26	1	0.28	0	0.208955224	0	0	0
6	28	1	0.31	0	0.055749129	0	1	0
7	11	2	0.3	0.03	0.074797625	0.06	1	0.079
8	83	1	0.18	0	0.413849959	0	0	0
9	13	1	0.13	0.02	0.386662351	0	0	0.012
10	230	2	0.09	0.1	0.242683376	0.04	0	0.021
11	15	2	0.15	0.02	0.291795835	0.03	0	0.029
12	83	3	0.14	0.03	0.321424346	0.05	0	0.054

13	29	2	0.12	0.1	0.328327634	0.01	0	0.008
14	21	1	0.22	0	0.265282584	0	0	0
15	48	3	0.23	0.01	0.263276519	0.03	0	0.039
16	48	2	0.18	0.06	0.363455724	0.04	0	0.052
17	15	1	0.19	0.05	0.305285645	0.06	0	0.049
18	51	2	0.21	0.03	0.277743314	0.02	0	0.033
19	25	2	0.3	0.03	0.237217865	0.05	0	0.038
20	346	5	0.16	0.12	0.213799295	0.15	0	0.125
21	14	2	0.35	0.03	0.373818801	0	0	0.033
22	30	2	0.06	0.05	0.325132502	0.02	0	0.019
23	14	2	0.15	0.02	0.285117555	0.01	0	0.004
24	111	3	0.01	0.01	0.062738966	0.02	0	0.016
25	20	1	0.02	0	0.051491819	0	0	0
26	14	2	0	0	0.06430494	0.03	0	0.002
27	161	1	0.06	0	0.141994633	0	0	0
28	14	1	0.02	0.01	0.079573258	0.02	0	0.006
29	21	2	0.02	0	0.135804076	0.02	0	5E-04
30	133	3	0.01	0	0.056190703	0.02	0	0.082
31	28	1	0.22	0	0.12507238	0	0	0
32	17	1	0.01	0	0.102809325	0	0	0
33	16	2	0.01	0	0.094334353	0.02	0	0.053

34	165	3	0.03	0.04	0.082134903	0.05	0	0.071
35	13	1	0.01	0	0.102809325	0	0	0
36	18	2	0.02	0.01	0.096829213	0.02	0	0.011
37	12	2	0.02	0.01	0.094181004	0.02	0	0.012
38	29	1	0	0	0.121444201	0	0	0
39	15	2	0.02	0	0.098349829	0.05	0	0.001
40	12	1	0	0	0.2	0	0	0
41	22	1	0.16	0	0.298695457	0	0	0
42	115	3	0.02	0.02	0.090785118	0.03	0	0.034
43	16	1	0	0	0.056175729	0	0	0
44	13	1	0	0	0	0	0	0
45	13	2	0.08	0.07	0.146071044	0.13	0	0.025
46	16	1	0	0	0	0	0	0
47	13	1	0	0	0.056175729	0	0	0
48	19	1	0	0	0.064767254	0	0	0.04
49	28	2	0.03	0.04	0.05931209	0.03	0	0.047
50	29	1	0	0	0.056175729	0	0	0
51	18	1	0.02	0.05	0.195663957	0.01	0	0.05
52	21	3	0.06	0.03	0.23449619	0.09	0	0.042
53	17	2	0.03	0	0.118890841	0.01	0	0.083
54	19	1	0.15	0.04	0.282974643	0.07	0	0.038
55	15	1	0	0	0.065688776	0	0	0
56	135	2	0	0.01	0.070463373	0.01	0	0.019

57	204	4	0.02	0.01	0.050059796	0.06	0	0.028
58	870	4	0.08	0.06	0.172776705	0.11	0	0.078
59	178	4	0.15	0.04	0.357997261	0.07	0	0.06
60	59	3	0.03	0.01	0.054633234	0.05	0	0.038
61	13	1	0	0	0.070634921	0	0	0
62	18	1	0.07	0	0.16303584	0	0	0
63	137	3	0.1	0.05	0.214332493	0.06	0	0.053
64	50	2	0.02	0.01	0.082494493	0.03	0	0.024
65	797	5	0.05	0.06	0.087242945	0.06	0	0.062
66	18	1	0.05	0	0.150148368	0	0	0
67	15	3	0	0	0.024885015	0	0	0.017
68	64	3	0.03	0.06	0.072220073	0.1	0	0.02
69	120	4	0.03	0.06	0.082595603	0.1	0	0.039
70	112	2	0.08	0.02	0.220547479	0.08	0	0.043
71	314	4	0.05	0.08	0.073414627	0.06	0	0.038
72	13	1	0.07	0	0.159887798	0	0	0
73	76	4	0.13	0.07	0.203172823	0.03	0	0.025
74	12	1	0.01	0	0.15912031	0	0	0
75	38	2	0.02	0.03	0.113628424	0.04	0	0.06
76	935	4	0.06	0.05	0.130406157	0.1	0	0.054
77	27	3	0.32	0.3	0.158271169	0.04	0	0.052

78	96	3	0.36	0.24	0.162591461	0.07	0	0.062
79	254	3	0.13	0.16	0.077847974	0.06	0	0.033
80	14	2	0.01	0	0.044977001	0.04	0	0.054
81	20	1	0.01	0	0.17973462	0	0	0
82	18	2	0.61	0.07	0.273508861	0.02	0	0.033
83	17	2	0.13	0.02	0.357787328	0.05	0	0.05
84	352	5	0.03	0.06	0.064445672	0.06	0	0.046
85	168	3	0.28	0.06	0.239926638	0.03	0	0.051
86	45	1	0.18	0	0.33819797	0	0	0
87	119	3	0.04	0.03	0.095383619	0.04	0	0.032
88	14	2	0.07	0.03	0.137887488	0.08	0	0.059
89	25	2	0.04	0.01	0.214878138	0.04	0	0.014
90	63	4	0.01	0.01	0.089322181	0.02	0	0.008
91	16	2	0.09	0.01	0.244842599	0.04	0	0.036
92	13	1	0.16	0	0.45911215	0	0	0
93	62	2	0.14	0.01	0.403734084	0	0	0.015
94	19	1	0.16	0.03	0.442850898	0.07	0	0.041
95	95	4	0.17	0.06	0.363659136	0.03	0	0.05
96	78	3	0.09	0.01	0.234840202	0.01	0	0.009
97	11	1	0	0	0.06566381	0.01	0	0.008
98	13	3	0.15	0.03	0.41480761	0.05	0	0.068

99	18	2	0.09	0.01	0.243724419	0.04	0	0.034
100	28	3	0.02	0.02	0.026224893	0.01	0	0.041
101	14	2	0.13	0.02	0.42932374	0.03	0	0.016
102	50	2	0.05	0.03	0.075217143	0.09	0	0.047
103	11	2	0.15	0.18	0.175486688	0.11	0	0.042
104	13	1	0.16	0	0.326963907	0	0	0
105	158	4	0.02	0.02	0.111429687	0.04	0	0.038
106	75	3	0.04	0.09	0.077116532	0.04	0	0.059
107	52	3	0.01	0.01	0.067041127	0.03	0	0.043
108	14	2	0.15	0.01	0.299575513	0.01	0	0.007
109	16	2	0.01	0	0.059129888	0.01	0	0.03
110	20	1	0.17	0	0.398324365	0.03	0	0.004
111	12	2	0.02	0.02	0.168891083	0.03	0	0.044
112	37	3	0.02	0.03	0.116830477	0.02	0	0.058
113	14	1	0.17	0.03	0.332313397	0.02	0	0.041
114	24	1	0.04	0	0.240231548	0	0	0
115	19	1	0.09	0	0.414049587	0	0	0
116	25	2	0.09	0.05	0.197229939	0.13	0	0.102
117	33	2	0.15	0.04	0.269345686	0.05	0	0.047
118	15	3	0.72	0.05	0.250299525	0.02	0	0.023
119	18	3	0.14	0.03	0.291840122	0.01	0	0.065

120	26	2	0.05	0.01	0.389603853	0.03	0	0.029
121	11	2	0.02	0.02	0.068223446	0.01	0	0.064
122	12	2	0.08	0.03	0.148142253	0.05	0	0.011
123	11	2	0.43	0.31	0.143774695	0.1	0	0.091
124	11	2	0.03	0.02	0.114683697	0.06	0	0.054
125	19	2	0.09	0.01	0.226364324	0.07	0	0.033
126	21	1	0.17	0	0.302163833	0	0	0
127	21	3	0.02	0.01	0.073958221	0.04	0	0.029
128	12	1	0.15	0	0.261829653	0	0	0
129	11	1	0.16	0	0.45911215	0	0	0
130	14	2	0.09	0.02	0.470000209	0	0	0.003
131	11	1	0.09	0	0.414049587	0	0	0
132	52	2	0.1	0.04	0.323847257	0.06	0	0.091
133	19	3	0.13	0.12	0.125972069	0.05	0	0.003
134	15	2	0.07	0.02	0.299186129	0.08	0	0.074
135	17	2	0.16	0.03	0.280592709	0.04	0	0.037
136	25	2	0.06	0.01	0.064055763	0.04	0	0.044
137	16	2	0.03	0.01	0.13898101	0.03	0	5E-04
138	20	2	0.08	0.02	0.278483464	0.07	0	0.049
139	24	1	0.02	0	0.101178782	0	0	0
140	22	2	0.02	0.01	0.075224479	0.02	0	0.019

141	12	1	0.21	0	0.325704225	0	0	0
142	15	2	0.01	0.01	0.041741709	0	0	0.029
143	44	3	0.19	0.05	0.137877283	0.03	0	0.04
144	19	3	0.13	0.01	0.247235463	0.02	0	0.043
145	18	2	0.19	0.04	0.231919778	0.03	0	0.018
146	28	2	0.01	0.01	0.07027449	0.03	0	0.028
147	28	3	0.23	0.13	0.112282281	0.07	0	0.017
148	16	2	0.17	0.02	0.338160012	0.03	0	0.032
149	33	2	0.2	0.04	0.376114976	0.02	0	0.053
150	12	3	0.25	0.09	0.189574735	0.14	0	0.053
151	12	1	0	0	0.069943289	0	0	0
152	43	2	0.01	0	0.079671315	0	0	0.043
153	13	1	0.17	0.07	0.12253329	0.01	0	0.038
154	17	2	0.07	0.01	0.179509055	0.04	0	0.025
155	11	1	0.66	0	0.212616822	0	0	0
156	15	2	0.1	0.08	0.120452015	0.02	0	0.003
157	11	1	0.03	0	0.278959811	0	0	0
158	18	2	0.12	0.03	0.188564185	0.03	0	0.045
159	12	1	0.07	0	0.19047619	0	0	0
160	11	2	0.02	0	0.048298024	0	0	0.018
161	20	3	0.1	0.04	0.452926214	0.04	0	0.011

162	24	2	0.05	0.07	0.230838319	0.09	0	0.046
163	18	1	0.02	0	0.141544118	0	0	0
164	42	1	0.04	0.01	0.141688265	0.02	0	0.016
165	13	1	0.17	0.02	0.384253423	0.06	0	0.038
166	29	1	0.03	0.01	0.104926808	0	0	0.044
167	11	1	0.01	0	0.081205312	0	0	0
168	23	1	0.09	0	0.030176899	0	0	0
169	14	1	0.18	0	0.33819797	0	0	0
170	14	1	0.16	0	0.326963907	0	0	0
171	12	2	0.02	0.02	0.18432165	0.02	0	0.007
172	22	1	0.03	0.01	0.061917637	0.01	0	0.016
173	11	1	0	0	0.03125	0	0	0
174	14	1	0.01	0	0.077393478	0.01	0	0.022
175	102	5	0.12	0.07	0.316456823	0.08	0	0.086
176	31	1	0.05	0.03	0.095126811	0.03	0	0.077
177	27	1	0.14	0.12	0.261970964	0	0	0.034
178	52	2	0.06	0.09	0.029859245	0.02	0	0.036
179	383	3	0.12	0.05	0.294205362	0.12	0	0.055
180	372	4	0.16	0.07	0.292348948	0.1	0	0.05
181	170	3	0.01	0.02	0.059900914	0.01	0	0.052
182	44	2	0.01	0	0.020527044	0	0	0.006
183	95	2	0.22	0.09	0.292874048	0.04	0	0.035

184	203	6	0.21	0.11	0.299224718	0.09	0	0.092
185	27	4	0.24	0.05	0.398159023	0.04	0	0.045
186	554	4	0.01	0.03	0.048164046	0.06	0	0.056
187	23	1	0.21	0	0.392183288	0	0	0
188	80	3	0.18	0.09	0.337417021	0.03	0	0.036
189	19	1	0.11	0	0.33583691	0	0	0
190	13	1	0.08	0	0.395718654	0	0	0
191	160	3	0.1	0.06	0.110490514	0.06	0	0.044
192	37	2	0.01	0	0.043315135	0.02	0	0.017
193	17	1	0.1	0	0.189376443	0	0	0
194	46	3	0.15	0.01	0.145449104	0.09	0	0.083
195	16	1	0.01	0	0.098249027	0	0	0
196	50	4	0.19	0.11	0.409324267	0.1	0	0.076
197	25	1	0.14	0	0.356182796	0	0	0
198	16	2	0.24	0.06	0.388656527	0.03	0	0.004
199	17	1	0.02	0	0.038193396	0.01	0	0.06
200	12	1	0.07	0	0.344036697	0	0	0
201	101	3	0.15	0.04	0.321895194	0.08	0	0.035
202	73	2	0.28	0	0.201592955	0	0	6E-04
203	22	3	0.01	0	0.057461428	0.02	0	0.004
204	188	3	0.06	0.08	0.066718987	0.07	0	0.046

205	46	2	0.05	0.07	0.183451613	0	1	0.035
206	39	2	0.15	0.04	0.391604879	0.02	0	0.021
207	171	4	0.02	0.04	0.059036822	0.04	0	0.081
208	26	1	0.1	0	0.189376443	0	0	0
209	45	2	0.24	0.02	0.266824396	0.03	0	0.012
210	11	2	0.14	0.02	0.449755944	0.04	0	0.006
211	697	6	0.1	0.07	0.350090586	0.13	0	0.091
212	421	4	0.18	0.1	0.363848226	0.09	0	0.063
213	29	2	0.15	0.04	0.415906077	0.18	0	0.084
214	40	1	0.01	0.01	0.082362374	0.04	0	0.009
215	76	1	0.19	0	0.342334984	0.05	0	0.028
216	11	1	0.02	0	0.0925	0	0	0
217	204	4	0.23	0.16	0.26120063	0.1	0	0.061
218	309	4	0.18	0.09	0.32365369	0.12	0	0.077
219	39	2	0.12	0.05	0.151409694	0.06	0	0.018
220	67	2	0	0	0.06859488	0.01	0	0.028
221	59	3	0.07	0.02	0.340493227	0.03	0	0.072
222	12	1	0.09	0.01	0.199938547	0.09	0	0.082
223	224	3	0.07	0.06	0.173781643	0.11	0	0.077
224	28	2	0.04	0.06	0.076003283	0.02	0	0.009
225	14	1	0	0	0.03758967	0	0	0
226	24	3	0.01	0.01	0.0723078	0.03	0	0.024

227	21	1	0.02	0	0.052373159	0	0	0
228	35	2	0.11	0.06	0.245766058	0.07	0	0.128
229	153	4	0.14	0.07	0.290525822	0.15	0	0.058
230	12	1	0.07	0	0.344036697	0	0	0
231	100	4	0.11	0.07	0.337696899	0.05	0	0.086
232	12	1	0.22	0.03	0.348867646	0.03	0	0.019
233	19	2	0.09	0.05	0.328915402	0.07	0	0.023
234	34	1	0	0	0.265044814	0	0	0
235	14	2	0.02	0.02	0.075541978	0.03	0	0.023
236	23	3	0.22	0.05	0.44142065	0.07	0	0.045
237	64	1	0.01	0.01	0.034576466	0.02	0	0.036
238	39	2	0.03	0.01	0.007395779	0.02	0	0.012
239	156	2	0.18	0.02	0.369700867	0.03	0	0.01
240	34	3	0	0	0.047055904	0.02	0	0.045
241	58	4	0.01	0.01	0.010850971	0.01	0	0.033
242	60	3	0	0.01	0.065518454	0.02	0	0.076
243	14	1	0.17	0.02	0.203057162	0	0	0.059
244	28	3	0	0	0.019709735	0.01	0	0.028
245	14	2	0.08	0.03	0.167030173	0.05	0	0.031
246	11	2	0.08	0.02	0.172298119	0.03	0	0.044
247	94	2	0	0.01	0.051174744	0.01	0	0.026

248	18	2	0	0	0.003292909	0.01	0	0.016
249	32	2	0.13	0.02	0.183060021	0.07	0	0.061
250	12	1	0.31	0	0.325675676	0	0	0
251	38	2	0.17	0.08	0.281642041	0.06	0	0.013
252	41	2	0.15	0.09	0.299434994	0.1	0	0.066
253	18	2	0.04	0.03	0.088330553	0.06	0	0.047
254	55	1	0.07	0	0.115623705	0	0	0
255	18	1	0.28	0.03	0.240321122	0.03	0	0.013
256	32	3	0.04	0.03	0.117135031	0.06	0	0.007
257	38	2	0.02	0.03	0.041967197	0.04	0	0.076
258	48	2	0.01	0.02	0.045036654	0.1	0	0.043
259	23	3	0.13	0.07	0.304131381	0.08	0	0.014
260	12	2	0.27	0.05	0.239873582	0.02	0	0.011
261	37	2	0.14	0.04	0.295992921	0.12	0	0.169
262	13	3	0.07	0.02	0.225147195	0.07	0	0.107
263	17	2	0.13	0.14	0.419944069	0.09	0	0.022
264	23	3	0.2	0.04	0.368620221	0.1	0	0.142
265	42	2	0.21	0.02	0.152365149	0.02	0	0.012
266	30	2	0.16	0.15	0.167863021	0.13	0	0.178
267	19	3	0.03	0.02	0.043373976	0.02	0	0.089
268	28	3	0.23	0.05	0.435518792	0.07	0	0.064

269	26	2	0.27	0.04	0.249830996	0.09	0	0.047
270	12	2	0	0	0.102915098	0.02	0	0.021
271	33	4	0.16	0.06	0.369633362	0.09	0	0.109
272	17	1	0.16	0	0.4771529	0	0	0
273	11	2	0.01	0.02	0.043554621	0.04	0	0.01
274	29	2	0.19	0.03	0.470275437	0.03	0	0.003
275	91	2	0.06	0.04	0.15548235	0.06	0	0.045
276	18	3	0	0.01	0.062774183	0.01	0	0.045
277	19	3	0.01	0.01	0.132462439	0.05	0	0.113
278	18	1	0.01	0	0.017673888	0	0	0
279	18	2	0.02	0.02	0.056279145	0.02	0	0.03
280	20	3	0.01	0.01	0.044269104	0.01	0	0.051
281	15	2	0.2	0.02	0.141067086	0.03	0	0.039
282	34	2	0.17	0.06	0.320311947	0.08	0	0.013
283	15	1	0.06	0	0.233292831	0	0	0
284	15	2	0.08	0.01	0.328496066	0.02	0	0.059
285	23	3	0.02	0.03	0.077384007	0.06	0	0.017
286	12	1	0.09	0	0.333333333	0	0	0
287	16	1	0.06	0	0.432140905	0.06	0	0.046
288	14	2	0	0	0.002106307	0.01	0	0.017
289	38	2	0.08	0.04	0.094027793	0.05	0	0.033

290	15	1	0.09	0	0.340425532	0	0	0
291	11	2	0	0	0.001884126	0.01	0	0.03
292	12	1	0.36	0	0.292647059	0	0	0
293	20	2	0	0	0.028357644	0	0	0.012
294	25	2	0.18	0.03	0.408944242	0.08	0	0.036
295	18	1	0.06	0	0.368107303	0	0	0
296	23	2	0.01	0.01	0.02030879	0.01	0	0.064
297	17	2	0.15	0.01	0.292423661	0.09	1	0.102
298	13	2	0.16	0.1	0.304052086	0.11	0	0.068
299	31	1	0	0	0.029488291	0	0	0
300	14	2	0.06	0.01	0.349783976	0.01	0	0.009
301	15	2	0.23	0.03	0.210197365	0.03	0	0.022
302	11	1	0.04	0.02	0.399674777	0.11	0	0.038
303	14	1	0.01	0	0.02653486	0	0	0
304	19	2	0	0	0.027936276	0.01	0	0.014
305	27	2	0.01	0.01	0.047164881	0.02	0	4E-04
306	15	2	0.04	0.03	0.108999866	0.01	0	0.029
307	14	2	0.27	0.05	0.233498941	0.03	0	0.01
308	12	1	0.01	0	0.017673888	0	0	0
309	12	2	0.18	0.01	0.385850905	0.02	0	0.037
310	28	1	0.07	0	0.115623705	0	0	0

311	14	2	0.19	0.07	0.304551368	0.05	0	0.013
312	11	1	0.08	0	0.186131387	0	0	0
313	12	2	0.06	0.01	0.332740123	0.01	0	0.042
314	15	1	0.23	0	0.34375	0	0	0
315	19	2	0.01	0	0.016138637	0.02	0	5E-04
316	19	2	0.19	0.02	0.390152904	0.01	0	0.003
317	16	1	0	0	0.185053381	0	1	0
318	18	1	0.03	0	0.184431138	0	1	0
319	17	1	0.14	0	0.332197615	0	0	0
320	22	1	0.25	0	0.317810458	0	0	0
321	14	1	0.14	0.04	0.368147598	0.04	0	0.036
322	23	1	0.12	0	0.385291767	0	0	0
323	11	2	0.3	0.09	0.195241815	0.03	0	0.002
324	14	2	0.33	0.13	0.151793142	0.03	0	0.026
325	18	1	0.03	0	0.059367397	0	0	0
326	22	1	0.16	0	0.4771529	0	0	0
327	21	1	0.04	0	0.334754797	0	0	0
328	12	1	0.07	0.03	0.262679288	0.02	0	0.045
329	14	2	0.22	0.04	0.114408782	0.02	0	0.019
330	33	1	0.08	0	0.215909091	0	0	0
331	14	1	0.16	0	0.4771529	0	0	0
332	12	2	0.21	0.1	0.320652579	0.02	0	0.038

333	11	2	0.19	0.07	0.188346458	0.02	0	0.002
334	17	1	0.18	0	0.400289017	0	0	0
335	16	2	0.29	0.03	0.181971678	0.05	0	0.001
336	27	1	0.07	0	0.344036697	0	0	0
337	11	1	0.06	0	0.347556779	0	0	0
338	16	1	0.08	0	0.395718654	0	0	0
339	16	1	0.09	0	0.256449165	0	0	0
340	26	1	0.01	0	0.102809325	0	0	0
341	27	2	0.37	0.05	0.270619752	0.03	0	0.007
342	13	1	0	0	0.121444201	0	0	0
343	11	1	0.18	0	0.413849959	0	0	0
344	18	3	0.02	0.01	0.031190448	0.04	0	0.009
345	24	1	0.16	0	0.055851064	0	0	0
346	14	1	0.16	0	0.055851064	0	0	0
347	12	1	0.1	0.06	0.174775689	0.07	0	0.016
348	12	2	0.72	0.06	0.258687908	0.01	0	0.034
349	15	1	0.17	0	0.455122393	0	0	0
350	12	1	0	0	0.032286783	0.02	0	0.024
351	12	1	0.33	0	0.205755396	0	0	0
352	12	1	0.16	0	0.326963907	0	0	0
353	20	2	0.3	0.13	0.344398465	0.07	0	0.075

354	14	1	0.06	0	0.117564731	0	0	0
355	14	1	0	0	0.056175729	0	0	0
356	14	1	0.21	0	0.466622604	0	0	0

Table 2.3.2 - Education

id	Number of Intersections in Urban Pasture	Census Blocks Covered	% Population 25 Years and Over: Bachelor's Degree	Standard Deviation	"% Population 25 Years and Over: Master's Degree"	Standard Deviation	'% Population 25 Years and Over: Professional School Degree	Standard Deviation
0	11	1	0.111880046	0	0.035755479	0	0.008765859	0
1	694	6	0.079208536	0.042311742	0.013984059	0.017142237	0.002528131	0.005688106
2	16	1	0.110469909	0	0.044517725	0	0	0
3	19	2	0.103947976	0.015686902	0.047211526	0.007946634	0.000461361	0.002011026
4	183	3	0.118966805	0.060724804	0.055111418	0.0287692	0.00433751	0.005247645
5	26	1	0.09141791	0	0.024253731	0	0	0
6	28	1	0.033101045	0	0	0	0	0
7	11	2	0.040262773	0.023752762	0.003250498	0.010780682	0.000796896	0.002643006
8	83	1	0.110469909	0	0.044517725	0	0	0
9	13	1	0.078539802	0.02770022	0.03412927	0.003556563	0	0
10	230	2	0.19599871	0.104717234	0.066572177	0.045509059	0.020413736	0.010834084
11	15	2	0.094191765	0.028850639	0.066171574	0.010390802	0.053249892	0.017893381
12	83	3	0.121731425	0.052970465	0.061390814	0.011172172	0.040594356	0.024685513
13	29	2	0.198613208	0.099513299	0.033558266	0.018150429	0.006365593	0.002735442
14	21	1	0.111880046	0	0.035755479	0	0.008765859	0

15	48	3	0.110122372	0.011382218	0.034265667	0.007220495	0.008400615	0.001770186
16	48	2	0.121368367	0.036313416	0.036998128	0.020798589	0.001432981	0.009927981
17	15	1	0.139734579	0.040774861	0.039291289	0.005175896	0.009041348	0.000403275
18	51	2	0.115574081	0.022787301	0.066246277	0.040686941	0.005411883	0.004257985
19	25	2	0.279763428	0.065380005	0	0	0	0
20	346	5	0.205998884	0.097812086	0.117755607	0.052786162	0.031486503	0.025070199
21	14	2	0.115065736	0.002525637	0	0	0	0
22	30	2	0.237051148	0.077303627	0.029699967	0.020512294	0.015417517	0.02268758
23	14	2	0.086959487	0.00717263	0.067586479	0.009161592	0.05636829	0.013700922
24	111	3	0.484132676	0.032254908	0.257858098	0.026488544	0.048801386	0.043278685
25	20	1	0.367661213	0	0.204042348	0	0.017805582	0
26	14	2	0.471645743	0.02996529	0.216838877	0.021775667	0.070632308	0.013277131
27	161	1	0.316413238	0	0.176878354	0	0.03667263	0
28	14	1	0.475238802	0.031651659	0.222414685	0.018786757	0.053500623	0.03015129
29	21	2	0.332448011	0.012046373	0.157023744	0.0179238	0.033945305	0.007777846
30	133	3	0.435528408	0.047363656	0.202323042	0.037722244	0.093078628	0.02112497
31	28	1	0.218297626	0	0.218297626	0	0.027793862	0
32	17	1	0.330543933	0	0.108786611	0	0.063359235	0
33	16	2	0.35470971	0.066033473	0.118660595	0.026980862	0.058303748	0.01381422
34	165	3	0.405935386	0.105452837	0.221471403	0.058005495	0.036743174	0.023470522
35	13	1	0.330543933	0	0.108786611	0	0.063359235	0

36	18	2	0.512465046	0.00612942	0.219938853	0.036191094	0.016409058	0.003134479
37	12	2	0.511726205	0.006548042	0.224301331	0.038662842	0.016786888	0.003348555
38	29	1	0.476203501	0	0.201586433	0	0.035010941	0
39	15	2	0.355580871	0.028506921	0.19144313	0.042415453	0.019009371	0.018405744
40	12	1	0.385294118	0	0.066666667	0	0.009803922	0
41	22	1	0.196131354	0	0.062977958	0	0	0
42	115	3	0.382310641	0.037801847	0.199979844	0.018799594	0.086667459	0.027266751
43	16	1	0.479654303	0	0.211019085	0	0.074180771	0
44	13	1	0.514705882	0	0.371323529	0	0	0
45	13	2	0.312372178	0.095648847	0.168991289	0.087233148	0	0
46	16	1	0.514705882	0	0.371323529	0	0	0
47	13	1	0.479654303	0	0.211019085	0	0.074180771	0
48	19	1	0.362927288	0.02243384	0.224871313	0.003896824	0.044162295	0.014584737
49	28	2	0.366387254	0.004677613	0.200020409	0.014767411	0.018375467	0.002092455
50	29	1	0.479654303	0	0.211019085	0	0.074180771	0
51	18	1	0.381353192	0.011469779	0.075674281	0.026216007	0.011579483	0.005167642
52	21	3	0.268833146	0.054684048	0.073803139	0.069077223	0.004619348	0.008616445
53	17	2	0.461353376	0.087517963	0.184887048	0.021141652	0.020732455	0.009920644
54	19	1	0.212898434	0.073086009	0.079206672	0.070739326	0	0
55	15	1	0.357780612	0	0.225765306	0	0.040816327	0
56	135	2	0.438959965	0.123994027	0.171245719	0.051002412	0.066928922	0.030218107

57	204	4	0.441415221	0.096656119	0.269984101	0.066695583	0.082403745	0.051689389
58	870	4	0.279766104	0.0874435	0.172668122	0.071191103	0.057033638	0.044971694
59	178	4	0.180930212	0.059875174	0.046212606	0.016052381	0.00364905	0.006963444
60	59	3	0.32444147	0.048399506	0.250282895	0.060104159	0.134805342	0.061975294
61	13	1	0.555555556	0	0.231746032	0	0.025396825	0
62	18	1	0.278988053	0	0.138439916	0	0.117357695	0
63	137	3	0.203206963	0.049891411	0.051049675	0.031134285	0.033323359	0.022406072
64	50	2	0.44481703	0.171666749	0.241874499	0.040516331	0.094635563	0.052456383
65	797	5	0.35335835	0.075360155	0.197704652	0.062666124	0.094888631	0.055202397
66	18	1	0.248664688	0	0.074183976	0	0.013649852	0
67	15	3	0.395783306	0.028738488	0.246642381	0.040433676	0.161789128	0.055637974
68	64	3	0.351898154	0.070160186	0.263295911	0.077993368	0.067761034	0.027754631
69	120	4	0.347875038	0.096328273	0.175369492	0.049041521	0.157527514	0.078632418
70	112	2	0.157391817	0.054166673	0.148887301	0.034151481	0.030005066	0.019679883
71	314	4	0.445914405	0.098194003	0.231417177	0.079777737	0.054649088	0.035689196
72	13	1	0.298737728	0	0.244039271	0	0.064516129	0
73	76	4	0.261286561	0.02427741	0.182164499	0.046429191	0.023475977	0.00918272
74	12	1	0.381630013	0	0.122897801	0	0.113842173	0
75	38	2	0.354468472	0.071822357	0.212955561	0.021840914	0.078171245	0.029234702
76	935	4	0.347426101	0.071030113	0.193332605	0.069753417	0.068142912	0.045707902
77	27	3	0.238866429	0.179189901	0.078861582	0.0778449	0.025557954	0.025265508

78	96	3	0.192908444	0.130994077	0.101275557	0.065822818	0.016255781	0.01387626
79	254	3	0.388979727	0.12755393	0.195309076	0.083190375	0.06563294	0.056214946
80	14	2	0.487003375	0.030203044	0.259028034	0.05209135	0.063693861	0.006928665
81	20	1	0.349819059	0	0.031363088	0	0.017490953	0
82	18	2	0.007130694	0.030252972	0.039719165	0.024244604	0	0
83	17	2	0.141727158	0.027557171	0.062674793	0.002965849	0.014014025	9.38E-05
84	352	5	0.389123712	0.083987598	0.234195423	0.053279002	0.128707843	0.062899505
85	168	3	0.210401897	0.030318768	0.074158055	0.019400098	0.009510849	0.005755769
86	45	1	0.109137056	0	0.027918782	0	0	0
87	119	3	0.451741141	0.134840391	0.181796946	0.048730234	0.088061734	0.021734419
88	14	2	0.281742508	0.02982317	0.098819937	0.002058853	0.087227634	0.014012785
89	25	2	0.2563952	0.012557151	0.118828126	0.007333486	0.010916725	0.030172234
90	63	4	0.433333405	0.109943268	0.2495503	0.022607234	0.083283798	0.05011147
91	16	2	0.157786873	0.002290109	0.087345528	0.012434654	0.035897042	0.006536935
92	13	1	0.066004673	0	0.02978972	0	0	0
93	62	2	0.1149805	0.003035642	0.040392744	0.006099298	0.007602339	0.000175302
94	19	1	0.075618358	0.041905082	0.032126259	0.010184741	0.000718413	0.003131491
95	95	4	0.128736036	0.05048285	0.06270057	0.034675058	0.006322988	0.006480215
96	78	3	0.159481346	0.02190436	0.083294555	0.006397871	0.036838738	0.004441077
97	11	1	0.350208061	0.014169726	0.232639046	0.000414143	0.167276243	0.009336283
98	13	3	0.090216501	0.054216563	0.038365838	0.041704713	0.000865926	0.00312214

99	18	2	0.157723258	0.002159135	0.087000121	0.011723505	0.036078624	0.006163081
100	28	3	0.522030657	0.133414451	0.262204794	0.073413734	0.058986314	0.049414455
101	14	2	0.076004916	0.019085544	0.034150934	0.011615116	0	0
102	50	2	0.441216416	0.086552367	0.182945306	0.003567638	0.092652242	0.039122871
103	11	2	0.297340158	0.00176016	0.111172473	0.025604864	0.022019503	0.025298483
104	13	1	0.136588818	0	0.094125973	0	0	0
105	158	4	0.385683946	0.130286565	0.186531571	0.042758079	0.080305803	0.028905244
106	75	3	0.432537598	0.061308439	0.287341873	0.081396489	0.029785541	0.032402063
107	52	3	0.350524513	0.082069749	0.254479309	0.041201019	0.115306553	0.073205115
108	14	2	0.140969017	0.000484278	0.072621586	0.009351226	0.00177683	0.001843904
109	16	2	0.374690857	0.008654971	0.26687806	0.003704377	0.160522258	0.0077626
110	20	1	0.087157828	0.007686665	0.052130921	0.014668301	0.020689655	0.007075713
111	12	2	0.361751742	0.068860351	0.123354055	0.001580512	0.104355326	0.032863405
112	37	3	0.375262195	0.053428794	0.186384934	0.041154898	0.093404191	0.039297134
113	14	1	0.109188957	0.000194197	0.029590524	0.006255087	0.001202887	0.004500791
114	24	1	0.351664255	0	0.094548963	0	0.031355523	0
115	19	1	0.126446281	0	0.017355372	0	0.008264463	0
116	25	2	0.258468422	0.051136085	0.097213203	0.003530197	0.076292017	0.024026922
117	33	2	0.162349587	0.040931233	0.057628193	0.011708188	0.013394055	0.01925893
118	15	3	0.010280374	0.027129838	0.006613717	0.014082292	0	0
119	18	3	0.123348174	0.016966005	0.126043056	0.050485915	0.009827503	0.008367838

120	26	2	0.166022457	0.001796509	0.132062458	0.009754545	0.01238922	0.005127993
121	11	2	0.340277242	0.059728323	0.22536358	0.021453194	0.148632684	0.039550352
122	12	2	0.33485311	0.019948617	0.140122179	0.033807481	0.054047036	0.017142847
123	11	2	0.223116612	0.202585937	0.078565713	0.070105213	0.013062665	0.018123713
124	11	2	0.35368223	0.027320382	0.161584042	0.095579261	0.110335498	0.030535612
125	19	2	0.323532079	0.021565523	0.15662357	0.04304314	0.050795121	0.013129784
126	21	1	0.139103555	0	0.111282844	0	0.017774343	0
127	21	3	0.355883174	0.049387523	0.260559499	0.03704577	0.103631483	0.059269076
128	12	1	0.128286015	0	0.041009464	0	0.011566772	0
129	11	1	0.066004673	0	0.02978972	0	0	0
130	14	2	0.077582367	0.00333229	0.047424004	0.005075496	0	0
131	11	1	0.126446281	0	0.017355372	0	0.008264463	0
132	52	2	0.184422978	0.027941908	0.060500424	0.015124237	0.009475231	0.004844365
133	19	3	0.325519663	0.111559211	0.173517585	0.04201757	0.038443751	0.019641733
134	15	2	0.16087852	0.004645189	0.104132311	0.025222083	0.027072181	0.013259323
135	17	2	0.153034989	0.032743664	0.06029259	0.009366172	0.009011358	0.015406521
136	25	2	0.190725987	0.063261044	0.267384318	0.050775376	0.040618965	0.023007229
137	16	2	0.350148261	0.028906156	0.124560057	0.046406069	0.09660298	0.006981893
138	20	2	0.292590901	0.058747399	0.095861502	0.084598379	0.000890736	0.002741629
139	24	1	0.333988212	0	0.270137525	0	0.030451866	0
140	22	2	0.384895756	0.018729455	0.170902939	0.00381909	0.112933862	0.005663923

141	12	1	0.201584507	0	0.167253521	0	0	0
142	15	2	0.306157113	0.014065031	0.279356102	0.054604298	0.062259316	0.062959199
143	44	3	0.267569956	0.030547286	0.26897834	0.034603811	0.033302807	0.012123176
144	19	3	0.292827784	0.077438496	0.053166177	0.05720324	0.008339337	0.01983477
145	18	2	0.227184844	0.030773134	0.124858645	0.025347116	0.042845894	0.015946423
146	28	2	0.423005845	0.030420198	0.216805845	0.025925886	0.10138714	0.062563768
147	28	3	0.308713469	0.017806005	0.120064845	0.045891713	0.044318962	0.009269205
148	16	2	0.130974832	0.023176286	0.079985142	0.030403777	0.000944584	0.003778338
149	33	2	0.123670599	0.034155178	0.021270737	0.013091918	0.002289902	0.005502915
150	12	3	0.256928131	0.064096528	0.133579315	0.043476914	0.022877681	0.024303659
151	12	1	0.345935728	0	0.232514178	0	0.164461248	0
152	43	2	0.309275531	0.01996978	0.226543231	0.003116263	0.101945866	0.023881887
153	13	1	0.255656316	0.020953748	0.14817089	0.039997906	0.058973513	0.008608047
154	17	2	0.348681327	0.047739243	0.17478737	0.020197139	0.043896872	0.022094135
155	11	1	0.077102804	0	0.028037383	0	0	0
156	15	2	0.300905006	0.032032677	0.212852705	0.055465788	0.027764148	0.002602372
157	11	1	0.138888889	0	0.130023641	0	0.03427896	0
158	18	2	0.334458769	0.005946495	0.068498873	0.037533975	0.008919865	0.037843781
159	12	1	0.332157554	0	0.17930629	0	0.041740153	0
160	11	2	0.588139113	0.0453099	0.187004961	0.021326627	0.059457042	0.001793271
161	20	3	0.084120821	0.016995699	0.046101507	0.010489123	0.000628141	0.001933376

162	24	2	0.280563322	0.114442149	0.039530658	0.013423462	0.018705295	0.002643298
163	18	1	0.291360294	0	0.231617647	0	0.079963235	0
164	42	1	0.330168097	0.002541853	0.211445282	0.006057248	0.055403987	0.033984367
165	13	1	0.183333744	0.018780393	0.099487836	0.028199627	0.039221166	0.00244997
166	29	1	0.341705345	0.005169734	0.255317721	0.020873055	0.109629452	0.031374213
167	11	1	0.301327886	0	0.227783453	0	0.092441267	0
168	23	1	0.46930281	0	0.222684703	0	0.046826223	0
169	14	1	0.109137056	0	0.027918782	0	0	0
170	14	1	0.136588818	0	0.094125973	0	0	0
171	12	2	0.333768666	0.055600192	0.035769236	0.015263344	0.01916098	0.005785143
172	22	1	0.36789321	0.00790753	0.215240746	0.016253927	0.088637059	0.007640242
173	11	1	0.717329545	0	0.177556818	0	0.011363636	0
174	14	1	0.305814647	0.016787922	0.224080816	0.013853996	0.090849455	0.005956014
175	102	5	0.178291909	0.098014793	0.059782252	0.038352741	0.015155092	0.018020634
176	31	1	0.320622829	0.113954249	0.207131392	0.018197263	0.060225223	0.011186136
177	27	1	0.152244899	0.017142923	0.142584546	0.061877939	0.016749494	0.009123529
178	52	2	0.551253956	0.030756136	0.236734908	0.044794172	0.086412274	0.033634699
179	383	3	0.19820298	0.096114968	0.081506826	0.072884088	0.007021163	0.012484076
180	372	4	0.156337922	0.05247636	0.062923476	0.037015159	0.009440317	0.014404493
181	170	3	0.306561512	0.089793508	0.292013214	0.119165716	0.148849565	0.074275262
182	44	2	0.460711745	0.007818539	0.242801296	0.019650661	0.115057969	0.005342455

183	95	2	0.116604856	0.064660313	0.080802368	0.014397677	0	0
184	203	6	0.216658142	0.127910157	0.047998579	0.039331653	0.0034764	0.006213152
185	27	4	0.086686788	0.044571157	0.01743271	0.008752841	0	0
186	554	4	0.444022785	0.073261485	0.214798034	0.063938543	0.129772123	0.06063799
187	23	1	0.095687332	0	0.017520216	0	0	0
188	80	3	0.132118436	0.051500296	0.034971596	0.028043972	0.002940454	0.00701416
189	19	1	0.192060086	0	0.033798283	0	0.004291845	0
190	13	1	0.168807339	0	0.063608563	0	0	0
191	160	3	0.396125803	0.046885642	0.180706674	0.033386455	0.06841713	0.024619109
192	37	2	0.354405166	0.100230263	0.283575966	0.029118115	0.144852748	0.031983232
193	17	1	0.227482679	0	0.031177829	0	0	0
194	46	3	0.160855359	0.02246929	0.078688075	0.008311368	0.002322161	0.005800077
195	16	1	0.421206226	0	0.247081712	0	0.062256809	0
196	50	4	0.090475492	0.072194064	0.045442145	0.028279591	0.002501525	0.007580767
197	25	1	0.044354839	0	0.010752688	0	0	0
198	16	2	0.054966094	0.026534464	0.038508738	0.037411534	0.002376426	0.006493632
199	17	1	0.390550353	0.000883956	0.302342287	0.057490861	0.031835797	0.021809603
200	12	1	0.174311927	0	0.110856269	0	0.019877676	0
201	101	3	0.116431951	0.033045181	0.098608234	0.063066374	0.01216688	0.013444648
202	73	2	0.204954997	0.003726014	0.087721296	0.004047223	0.016535647	0.002134456
203	22	3	0.355518367	0.073192866	0.182156414	0.033857087	0.254925488	0.074386228

204	188	3	0.424803976	0.131588149	0.213564962	0.090351473	0.060848065	0.04055687
205	46	2	0.206375178	0.030607183	0.056913181	0.002395253	0	0
206	39	2	0.127544761	0.013648322	0.057636307	0.005039498	0.000736313	0.004598275
207	171	4	0.427040008	0.079408055	0.217802905	0.080521771	0.095624651	0.039200372
208	26	1	0.227482679	0	0.031177829	0	0	0
209	45	2	0.105186486	0.00278906	0.113521837	0.016187992	0.029916547	0.004787357
210	11	2	0.079631934	0.031401801	0.051806606	0.019584558	0.023267568	0.0011243
211	697	6	0.178826489	0.083217292	0.08688071	0.0659117	0.013995205	0.017031307
212	421	4	0.127706241	0.064426214	0.054677065	0.051805689	0.008244721	0.015949877
213	29	2	0.099358603	0.075204314	0.047847723	0.041877752	0.008230284	0.016684248
214	40	1	0.376361793	0.010474904	0.275334903	0.051771077	0.070837432	0.014967572
215	76	1	0.126420735	0.049553536	0.044930816	0.022071428	0.000110881	0.000966639
216	11	1	0.339166667	0	0.225833333	0	0.125	0
217	204	4	0.182144328	0.150137868	0.063621044	0.043685744	0.01075558	0.022287738
218	309	4	0.104652938	0.095496779	0.057839142	0.042932903	0.007791066	0.017647456
219	39	2	0.229067764	0.049488078	0.10911183	0.024595141	0.065882974	0.018091856
220	67	2	0.528923328	0.048296299	0.207856729	0.02388701	0.052616935	0.023316521
221	59	3	0.169696464	0.043487544	0.032987138	0.019178604	0.003950614	0.011645413
222	12	1	0.199968116	0.015471264	0.087411377	0.014137802	0.019683545	0.000117066
223	224	3	0.340566797	0.111710273	0.152636701	0.082004159	0.043747714	0.034343954
224	28	2	0.501602111	0.048528475	0.17200024	0.015370242	0.038736806	0.006281798

225	14	1	0.417790531	0	0.227833572	0	0.079770445	0
226	24	3	0.338588092	0.060568663	0.223835793	0.057226264	0.205395202	0.031476848
227	21	1	0.389525368	0	0.235679214	0	0.006546645	0
228	35	2	0.181911222	0.059691576	0.222324122	0.164491033	0.016545893	0.016516055
229	153	4	0.215918315	0.109933136	0.067556286	0.053082113	0.007958227	0.009799804
230	12	1	0.174311927	0	0.110856269	0	0.019877676	0
231	100	4	0.170724557	0.019218473	0.047832519	0.039967753	0.013828425	0.02285255
232	12	1	0.116585167	0.017058587	0.029122064	0.017645424	0.000743052	0.002574009
233	19	2	0.19607259	0.037316321	0.079125733	0.00232289	0	0
234	34	1	0.1446863	0	0.103713188	0	0.051216389	0
235	14	2	0.419968216	0.071961112	0.22651246	0.036834519	0.06608765	0.020911893
236	23	3	0.111645664	0.057681733	0.020095911	0.025058381	0.004568644	0.003411452
237	64	1	0.390623308	0.006055436	0.317295138	0.049274841	0.04873727	0.015811809
238	39	2	0.598996035	0.036620183	0.225638642	0.016132153	0.01203001	0.032821629
239	156	2	0.106420576	0.01931438	0.043839892	0.026695094	0.015981653	0.009353251
240	34	3	0.620137117	0.061520685	0.084916966	0.056749743	0.064195902	0.011076967
241	58	4	0.401805467	0.051340482	0.269313636	0.051045539	0.149970186	0.034744228
242	60	3	0.438062743	0.04514033	0.215143597	0.038377368	0.046648999	0.044126132
243	14	1	0.168595301	0.02893504	0.090824242	0.016638305	0.013869626	0.035255973
244	28	3	0.452887889	0.027872154	0.260517632	0.025358122	0.120773297	0.040816876
245	14	2	0.248272438	0.051785986	0.231499462	0.062175719	0.072782997	0.011732135

246	11	2	0.242501618	0.036265713	0.330291214	0.077965444	0.039733362	0.044312233
247	94	2	0.474310551	0.035704678	0.234478613	0.00849273	0.073836079	0.00595688
248	18	2	0.378159102	0.065818257	0.335459502	0.044757376	0.245135715	0.056351232
249	32	2	0.2872962	0.083557292	0.145337561	0.038703152	0.020894706	0.006355447
250	12	1	0	0	0	0	0	0
251	38	2	0.195375172	0.095755822	0.067664784	0.047961715	0	0
252	41	2	0.234615646	0.096673142	0.077075987	0.060144016	0.003075477	0.003519671
253	18	2	0.450742818	0.027424357	0.177484863	0.041144677	0.058104691	0.051254758
254	55	1	0.243265644	0	0.194778284	0	0.052631579	0
255	18	1	0.143918985	0.006514831	0.095625048	0.009660705	0.018341641	0.000678069
256	32	3	0.459426376	0.03351941	0.181269813	0.042632509	0.056045155	0.017115855
257	38	2	0.530741036	0.162298261	0.193578341	0.000677445	0.0513524	0.000722178
258	48	2	0.590251072	0.116270169	0.183882146	0.036493056	0.047770701	0.012464868
259	23	3	0.123456365	0.039310159	0.116474009	0.037457556	0.018931561	0.006371108
260	12	2	0.143578369	0.006499265	0.100939196	0.010520816	0.018250951	0.000239482
261	37	2	0.212578534	0.007780746	0.069390829	0.011883746	0.008490816	0.009861718
262	13	3	0.190104152	0.052667629	0.191517539	0.066272951	0.065991788	0.03011369
263	17	2	0.146953152	0.082510773	0.076620519	0.010085366	0.005205622	0.00346363
264	23	3	0.074255083	0.074418728	0.002388915	0.011456836	0	0
265	42	2	0.202245212	0.012852709	0.091829075	0.00137443	0.033149901	0.003387536
266	30	2	0.241337318	0.091398406	0.057457957	0.072157795	0.001415094	0.002878571
267	19	3	0.393697139	0.036708754	0.26172469	0.036847416	0.121657999	0.022209809

268	28	3	0.079587189	0.02102766	0.028247143	0.015692404	0.022624265	0.011880799
269	26	2	0.050139265	0.021943805	0.063605645	0.018724995	0.000795071	0.000234062
270	12	2	0.374144933	0.017182383	0.24206555	0.007628393	0.083620388	0.008756457
271	33	4	0.147499284	0.11586746	0.069835027	0.020011598	0.018497966	0.019847213
272	17	1	0.108084359	0	0.007908612	0	0	0
273	11	2	0.493013165	0.057128179	0.211413959	0.028701451	0.099532343	0.033383659
274	29	2	0.062002242	0.006817277	0.011388836	0.005466551	0	0
275	91	2	0.189392374	0.031851807	0.122492554	0.017393753	0.024190575	0.004491226
276	18	3	0.471937915	0.040143822	0.229904508	0.033784161	0.104850146	0.017953646
277	19	3	0.391201183	0.044658416	0.166293894	0.080991301	0.067965018	0.049419676
278	18	1	0.543329532	0	0.268529076	0	0.054732041	0
279	18	2	0.469252101	0.088102789	0.192431236	0.043383453	0.06979034	0.059574698
280	20	3	0.413229459	0.071615621	0.223979583	0.021611262	0.149195612	0.042014476
281	15	2	0.209955476	0.018864256	0.10415599	0.048917973	0.040090011	0.023980372
282	34	2	0.17233872	0.019433618	0.053424354	0.006597899	0	0
283	15	1	0.114216282	0	0.092345079	0	0.008505468	0
284	15	2	0.083060886	0.038809843	0.039485975	0.020422879	0.016443196	0.025035641
285	23	3	0.450358535	0.015355453	0.216997277	0.049090729	0.058327348	0.009460357
286	12	1	0.061050061	0	0.030525031	0	0	0
287	16	1	0.106397303	0.065368241	0.018496215	0.028334044	0.007527529	0.011531297
288	14	2	0.653478533	0.052287034	0.207464837	0.012928936	0.08834112	0.004029649

289	38	2	0.414550066	0.151947467	0.173737918	0.035733081	0.05253356	0.030646629
290	15	1	0.247340426	0	0.029255319	0	0	0
291	11	2	0.480140194	0.011742128	0.16989393	0.031293938	0.082488221	0.002010986
292	12	1	0.186764706	0	0	0	0	0
293	20	2	0.470229482	0.004872926	0.252553273	0.000517679	0.103351565	0.003108245
294	25	2	0.103241826	0.035265194	0.067730869	0.012697911	0	0
295	18	1	0.174366617	0	0.0804769	0	0	0
296	23	2	0.440241695	0.107304542	0.259992716	0.017587956	0.070419612	0.042992726
297	17	2	0.02870019	0.021848847	0.006957622	0.00529669	0	0
298	13	2	0.230283714	0.099836635	0.074380928	0.062112144	0.003233194	0.003634848
299	31	1	0.471812663	0	0.252385082	0	0.102341717	0
300	14	2	0.196885909	0.012681913	0.060418178	0.004603327	0.022367515	0.006437814
301	15	2	0.177373217	0.043489792	0.026310023	0.035122704	0.016156798	0.00794045
302	11	1	0.100946721	0.009912847	0.022646393	0.050385043	0.011646716	0.025912308
303	14	1	0.47346514	0	0.209157128	0	0.123829344	0
304	19	2	0.482109514	0.044882933	0.249838996	0.011098135	0.101548161	0.003459031
305	27	2	0.412340325	0.097055759	0.208937926	0.045469003	0.207191681	0.086978389
306	15	2	0.354901096	0.016228557	0.215308771	0.01413087	0.0578715	0.011213049
307	14	2	0.054576325	0.039843699	0.06398425	0.018415934	0.000799803	0.000230199
308	12	1	0.543329532	0	0.268529076	0	0.054732041	0
309	12	2	0.05090425	0.038691073	0.064113557	0.007314827	0.008375923	0.029015048

310	28	1	0.243265644	0	0.194778284	0	0.052631579	0
311	14	2	0.14892306	0.024395701	0.08778439	0.057488488	0.003637098	0.009245343
312	11	1	0.175182482	0	0.109489051	0	0	0
313	12	2	0.138267085	0.010375802	0.022226668	0.007465621	0.004604052	0.00215055
314	15	1	0.08203125	0	0.0546875	0	0.01953125	0
315	19	2	0.285370086	0.024939339	0.259058527	0.0195482	0.259950588	0.015659798
316	19	2	0.127478759	0.003903681	0.043111797	0.020571718	0.001113586	0.004854008
317	16	1	0.120996441	0	0.12455516	0	0.06405694	0
318	18	1	0.214371257	0	0.056287425	0	0	0
319	17	1	0.173764906	0	0.04088586	0	0.100511073	0
320	22	1	0.073529412	0	0.056372549	0	0.009803922	0
321	14	1	0.183505988	0.030344994	0.044847562	0.003851946	0.009474259	0.00030012
322	23	1	0.195443645	0	0.04636291	0	0.009592326	0
323	11	2	0.19582304	0.079202969	0.11394662	0.031939339	0.011714624	0.007834221
324	14	2	0.214470085	0.046086356	0.115461675	0.026081354	0.010682005	0.003074493
325	18	1	0.365450122	0	0.210218978	0	0.090997567	0
326	22	1	0.108084359	0	0.007908612	0	0	0
327	21	1	0.275053305	0	0.019616205	0	0.004264392	0
328	12	1	0.109803121	0.000209756	0.049372809	0.006756267	0.015437049	0.00486141
329	14	2	0.254210069	0.061907949	0.157177197	0.018854357	0.030071704	0.004822282
330	33	1	0.25	0	0.220588235	0	0.022058824	0

331	14	1	0.108084359	0	0.007908612	0	0	0
332	12	2	0.129708074	0.055878037	0.033341617	0.029431807	0	0
333	11	2	0.255303597	0.003406297	0.149913607	0.045391602	0.018527092	0.002268296
334	17	1	0.170520231	0	0	0	0	0
335	16	2	0.088344227	0.013681917	0.064740896	0.004565826	0	0
336	27	1	0.174311927	0	0.110856269	0	0.019877676	0
337	11	1	0.200275292	0	0.059187887	0	0.024088094	0
338	16	1	0.168807339	0	0.063608563	0	0	0
339	16	1	0.171471927	0	0.071320182	0	0.042488619	0
340	26	1	0.330543933	0	0.108786611	0	0.063359235	0
341	27	2	0.171838705	0.018466686	0.030506385	0.026790278	0.014260957	0.00964067
342	13	1	0.476203501	0	0.201586433	0	0.035010941	0
343	11	1	0.110469909	0	0.044517725	0	0	0
344	18	3	0.540599012	0.028465206	0.195702384	0.014815793	0.024352472	0.014304338
345	24	1	0.41356383	0	0.164228723	0	0.098404255	0
346	14	1	0.41356383	0	0.164228723	0	0.098404255	0
347	12	1	0.323212971	0.096399174	0.248656709	0.00939738	0.029592198	0.028088602
348	12	2	0	0	0.007188498	0.016788715	0	0
349	15	1	0.090661831	0	0.060743427	0	0	0
350	12	1	0.358907985	0.018133029	0.18026629	0.014964025	0.072013016	0.006433231
351	12	1	0.171942446	0	0.104316547	0	0.009352518	0

352	12	1	0.136588818	0	0.094125973	0	0	0
353	20	2	0.150852488	0.085754018	0.004704463	0.01148979	0.002623643	0.006407768
354	14	1	0.289713086	0	0.099370189	0	0.090972708	0
355	14	1	0.479654303	0	0.211019085	0	0.074180771	0
356	14	1	0.097157964	0	0.009253139	0	0	0

Table 2.3.3 - Education

id	Number of Intersections in Urban Pasture	Census Blocks Covered	'% Population 25 Years and Over: Doctorate Degree'	Standard Deviation
0	11	1	0.015916955	0
1	694	6	0.003807303	0.006958358
2	16	1	0.001648805	0
3	19	2	0.002139422	0.003392495
4	183	3	0.001664078	0.003964478
5	26	1	0	0
6	28	1	0	0
7	11	2	0.001446996	0.004799143
8	83	1	0.001648805	0
9	13	1	0.000649444	0.002341605
10	230	2	0.020444291	0.01953512
11	15	2	0.001247648	0.004121612
12	83	3	0.001376928	0.002166447
13	29	2	0.020084079	0.008828595
14	21	1	0.015916955	0
15	48	3	0.015253749	0.003214285
16	48	2	0.00989527	0.004379049
17	15	1	0.011543891	0.006401511
18	51	2	0.01020179	0.008084176
19	25	2	0	0
20	346	5	0.016213558	0.015502212
21	14	2	0	0
22	30	2	0.021492537	0.010929979
23	14	2	0.001136925	0.004253985
24	111	3	0.022131906	0.005559797
25	20	1	0	0
26	14	2	0.02039714	0.005870701
27	161	1	0.021243292	0
28	14	1	0.017272099	0.007925465
29	21	2	0.014343087	0.003286414
30	133	3	0.026698169	0.015705154
31	28	1	0.001158078	0

32	17	1	0	0
33	16	2	0	0
34	165	3	0.01817368	0.039715182
35	13	1	0	0
36	18	2	0.012152222	0.008505818
37	12	2	0.013177514	0.009086741
38	29	1	0.025984683	0
39	15	2	0.008032129	0.007777075
40	12	1	0.024509804	0
41	22	1	0.029689609	0
42	115	3	0.024264382	0.002256806
43	16	1	0.021966151	0
44	13	1	0.029411765	0
45	13	2	0.01141908	0.015033918
46	16	1	0.029411765	0
47	13	1	0.021966151	0
48	19	1	0.001887749	0.008228509
49	28	2	0	0
50	29	1	0.021966151	0
51	18	1	0.021786492	0.007926001
52	21	3	0.015501623	0.00887967
53	17	2	0.009388843	0.00377354
54	19	1	0.029674985	6.37E-05
55	15	1	0	0
56	135	2	0.050557129	0.031537826
57	204	4	0.055083885	0.022487597
58	870	4	0.04073533	0.038343998
59	178	4	0.004779662	0.007632741
60	59	3	0.071577213	0.04450752
61	13	1	0.027777778	0
62	18	1	0.019676739	0
63	137	3	0.009242094	0.004929881
64	50	2	0.041915549	0.011192675
65	797	5	0.075493128	0.031783193
66	18	1	0.00652819	0
67	15	3	0.083307974	0.015208012
68	64	3	0.094174918	0.023894681
69	120	4	0.090499159	0.03788181
70	112	2	0.03995675	0.020583177

71	314	4	0.023699651	0.01771291
72	13	1	0	0
73	76	4	0.007902959	0.008197205
74	12	1	0.010349288	0
75	38	2	0.037411877	0.01392201
76	935	4	0.043169834	0.035250007
77	27	3	0.014868687	0.016940368
78	96	3	0.018541605	0.017258834
79	254	3	0.039567597	0.038101815
80	14	2	0.041781795	0.004512926
81	20	1	0.047647768	0
82	18	2	0	0
83	17	2	0.024072867	0.00452116
84	352	5	0.05775971	0.037048945
85	168	3	0.022611106	0.006603374
86	45	1	0.009517766	0
87	119	3	0.007825209	0.013059438
88	14	2	0.033720405	0.000488218
89	25	2	0.022282643	0.004261592
90	63	4	0.038778202	0.01198409
91	16	2	0.009382819	0.002502085
92	13	1	0	0
93	62	2	0.007069148	0.001871604
94	19	1	0.000343589	0.001497669
95	95	4	0.007239385	0.005978667
96	78	3	0.010563048	0.004301008
97	11	1	0.080888865	0.001315303
98	13	3	0.000899685	0.003243861
99	18	2	0.009452321	0.002358988
100	28	3	0.046940056	0.031785169
101	14	2	0.006683375	0.006006463
102	50	2	0.064502438	0.02874304
103	11	2	0.029325437	0.018138279
104	13	1	0.019815994	0
105	158	4	0.078461038	0.031922012
106	75	3	0.031662316	0.022718501
107	52	3	0.080699659	0.055083322
108	14	2	0.011350235	0.004447658
109	16	2	0.076677585	0.001895002

110	20	1	0.000513347	0.001580049
111	12	2	0.011735417	0.00480169
112	37	3	0.034523364	0.010783429
113	14	1	0.010040813	0.001957061
114	24	1	0.038109021	0
115	19	1	0	0
116	25	2	0.034101411	0.000837119
117	33	2	0.013742457	0.003706115
118	15	3	0	0
119	18	3	0.016528603	0.015316411
120	26	2	0.000384936	0.001962797
121	11	2	0.100576252	0.003109785
122	12	2	0.040305887	0.00630926
123	11	2	0.020123566	0.027920314
124	11	2	0.068477091	0.023624954
125	19	2	0.023915709	0.009532647
126	21	1	0.032457496	0
127	21	3	0.06017313	0.00972138
128	12	1	0.012618297	0
129	11	1	0	0
130	14	2	0.017724587	0.005101487
131	11	1	0	0
132	52	2	0.002987136	0.002994875
133	19	3	0.040236498	0.02950557
134	15	2	0.006005004	0.005075155
135	17	2	0.014585847	0.002964772
136	25	2	0.100563381	0.020599612
137	16	2	0.068755847	0.026839534
138	20	2	0.050963822	0.000979488
139	24	1	0.035363458	0
140	22	2	0.118190413	0.014173068
141	12	1	0.018485915	0
142	15	2	0.206715353	0.046753344
143	44	3	0.003079744	0.01010974
144	19	3	0.005521955	0.014079932
145	18	2	0.015914352	0.013063316
146	28	2	0.057070202	0.010733176
147	28	3	0.016941994	0.009068808
148	16	2	0.018406029	0.004930374

149	33	2	0.015691248	0.00673778
150	12	3	0.020108691	0.018821773
151	12	1	0.081285444	0
152	43	2	0.087732552	0.004851238
153	13	1	0.068281402	0.030304152
154	17	2	0.02730017	0.016058362
155	11	1	0	0
156	15	2	0.020545152	0.014347763
157	11	1	0	0
158	18	2	0.019619986	0.019970018
159	12	1	0.025279248	0
160	11	2	0.015682422	0.005530871
161	20	3	0.018063627	0.002787813
162	24	2	0.034022511	0.021726697
163	18	1	0.090073529	0
164	42	1	0.04900053	0.013234659
165	13	1	0.035154634	0.000944772
166	29	1	0.045047695	0.006815441
167	11	1	0.085801839	0
168	23	1	0.020811655	0
169	14	1	0.009517766	0
170	14	1	0.019815994	0
171	12	2	0.044511149	0.010865567
172	22	1	0.070748023	0.002540234
173	11	1	0.024147727	0
174	14	1	0.084922897	0.003288698
175	102	5	0.005865686	0.007971001
176	31	1	0.028193604	0.0024229
177	27	1	0.004294742	0.002339366
178	52	2	0.012955708	0.014009289
179	383	3	0.007600283	0.01108238
180	372	4	0.016340768	0.022920367
181	170	3	0.051573975	0.033302579
182	44	2	0.034771846	0.006025511
183	95	2	0.000502689	0.00489961
184	203	6	0.000524348	0.002595159
185	27	4	0	0
186	554	4	0.028173502	0.01666439
187	23	1	0	0

188	80	3	0.009422492	0.011921048
189	19	1	0.012339056	0
190	13	1	0	0
191	160	3	0.017626827	0.014035102
192	37	2	0.024201174	0.00728005
193	17	1	0.006928406	0
194	46	3	0.003808315	0.009941682
195	16	1	0.023346304	0
196	50	4	0.000661939	0.003275746
197	25	1	0	0
198	16	2	0.007287706	0.019913804
199	17	1	0.032966675	0.005444558
200	12	1	0.059633028	0
201	101	3	0.005831735	0.00653802
202	73	2	0.01309072	0.001689778
203	22	3	0.065578683	0.013053015
204	188	3	0.037912828	0.029231356
205	46	2	0	0
206	39	2	0.000779626	0.004868761
207	171	4	0.034584426	0.028135964
208	26	1	0.006928406	0
209	45	2	0.000389869	0.001874485
210	11	2	0.011382436	0.016002911
211	697	6	0.012705325	0.017302737
212	421	4	0.002837063	0.008228775
213	29	2	0.011356917	0.017550236
214	40	1	0.039239505	0.007513618
215	76	1	0.011913384	0.00522098
216	11	1	0.033333333	0
217	204	4	0.00558088	0.010683322
218	309	4	0.011663845	0.018200767
219	39	2	0.01036312	0.001985756
220	67	2	0.026278517	0.010224733
221	59	3	0.002734704	0.005188353
222	12	1	0.043916104	0.009477661
223	224	3	0.03464767	0.020758346
224	28	2	0.00707077	0.000528732
225	14	1	0.065136298	0
226	24	3	0.044144092	0.017040799

227	21	1	0.039279869	0
228	35	2	0.011547002	0.019912658
229	153	4	0.005005825	0.006493049
230	12	1	0.059633028	0
231	100	4	0.016551669	0.012917212
232	12	1	0.009759167	0.001981078
233	19	2	0.005857967	0.010070858
234	34	1	0	0
235	14	2	0.037848308	0.013316188
236	23	3	0.030838346	0.0230273
237	64	1	0.039412899	0.021799958
238	39	2	0.036180437	0.01111052
239	156	2	0.004991025	0.003039194
240	34	3	0.063427518	0.019043106
241	58	4	0.025846936	0.019201135
242	60	3	0.060331366	0.034985083
243	14	1	0.031110672	0.000804545
244	28	3	0.036823194	0.016693543
245	14	2	0.018374022	0.005520935
246	11	2	0.010392147	0.012500395
247	94	2	0.025787356	0.00265892
248	18	2	0.00453793	0.015000825
249	32	2	0.003974449	0.010472103
250	12	1	0	0
251	38	2	0.030161363	0.023345345
252	41	2	0.020759472	0.023757783
253	18	2	0.036016477	0.015628257
254	55	1	0.029838375	0
255	18	1	0.000379435	0.001609805
256	32	3	0.01104039	0.012745073
257	38	2	0.007066984	0.012855908
258	48	2	0	0
259	23	3	0.046655512	0.021649184
260	12	2	0.004858471	0.016830236
261	37	2	0.068779818	0.025702657
262	13	3	0.017707251	0.004431283
263	17	2	0	0
264	23	3	0	0
265	42	2	0.033898305	0.007671772

266	30	2	0.012222971	0.017194114
267	19	3	0.100342615	0.052785633
268	28	3	0.023889961	0.012705064
269	26	2	0	0
270	12	2	0.046039536	0.005722691
271	33	4	0.005533801	0.01107174
272	17	1	0.012302285	0
273	11	2	0.016547416	0.006910959
274	29	2	0.004425405	0.001801495
275	91	2	0	0
276	18	3	0.029056631	0.0186257
277	19	3	0.021382742	0.025776145
278	18	1	0.052451539	0
279	18	2	0.034425455	0.012573188
280	20	3	0.040583117	0.012869012
281	15	2	0.034103341	0.005770277
282	34	2	0.011194549	0.007858172
283	15	1	0.012150668	0
284	15	2	0.000549828	0.002129475
285	23	3	0.021746943	0.014948235
286	12	1	0	0
287	16	1	0	0
288	14	2	0.024108706	0.010784546
289	38	2	0.037314718	0.004639973
290	15	1	0.012411348	0
291	11	2	0.052965182	0.017566564
292	12	1	0	0
293	20	2	0.058578537	0.009233665
294	25	2	0	0
295	18	1	0	0
296	23	2	0.015090683	0.014246351
297	17	2	0	0
298	13	2	0.02182406	0.024535223
299	31	1	0.061578491	0
300	14	2	0.001305173	0.004883511
301	15	2	0	0
302	11	1	0	0
303	14	1	0.041623309	0
304	19	2	0.059454697	0.009257401

305	27	2	0.044002537	0.029383669
306	15	2	0.032515084	0.002557222
307	14	2	0.001736865	0.006498754
308	12	1	0.052451539	0
309	12	2	0.000993754	0.003442463
310	28	1	0.029838375	0
311	14	2	0.008486563	0.021572467
312	11	1	0	0
313	12	2	0	0
314	15	1	0	0
315	19	2	0.067558163	0.005474308
316	19	2	0.001465244	0.006386852
317	16	1	0	0
318	18	1	0	0
319	17	1	0.011925043	0
320	22	1	0.008986928	0
321	14	1	0.004671932	0.004764058
322	23	1	0.002797762	0
323	11	2	0.008456068	0.006571057
324	14	2	0.019075009	0.005490165
325	18	1	0.071532847	0
326	22	1	0.012302285	0
327	21	1	0.026865672	0
328	12	1	0.016230196	0.002113867
329	14	2	0.03890431	0.005207424
330	33	1	0.00868984	0
331	14	1	0.012302285	0
332	12	2	0.010131712	0.012521061
333	11	2	0.002369956	0.004059019
334	17	1	0.033236994	0
335	16	2	0	0
336	27	1	0.059633028	0
337	11	1	0	0
338	16	1	0	0
339	16	1	0	0
340	26	1	0	0
341	27	2	0.013376698	0.013453939
342	13	1	0.025984683	0
343	11	1	0.001648805	0

344	18	3	0.025882057	0.007216013
345	24	1	0.023271277	0
346	14	1	0.023271277	0
347	12	1	0.014724748	0.006039173
348	12	2	0	0
349	15	1	0	0
350	12	1	0.074522091	0.003552199
351	12	1	0.00647482	0
352	12	1	0.019815994	0
353	20	2	0.007147165	0.017455643
354	14	1	0.033589923	0
355	14	1	0.021966151	0
356	14	1	0	0