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Visualizing Human Movement in Attribute Space

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Summary

This chapter introduces a new method for visualizing the paths of point features moving across geographic space. It draws inspiration from two separate strands of research within Geographic Information Science. One relates to a renewed interest in the central notion of time geography, space-time paths, and the growing technological ability to determine such paths with high spatial and temporal resolution using the Global Positioning System (GPS). The second trend influencing the proposed methodology concerns methods for modeling multidimensional attribute data. Spatialization is one such approach. The chapter proposes to project a space-time path onto the spatialized representation of *n*-dimensional attributes associated with geographic features encountered along the path. First, a spatialized representation of geographic features based on their attributes is derived through the self-organizing map (SOM) method. Then, a spatio-temporal trajectory is projected on the SOM, leading to the visual emergence of an attribute space trajectory. This is implemented in two experiments, one involving long-distance travel on Interstate highways, the other concerned with journey-to-work paths in an urban environment.

1 Introduction

Imagine the following scenarios:

(1) You are on holiday driving on a country road somewhere in central Texas. As you come through a small town, you say to your passenger: “You know, I’ve never been here before, but what I saw for the last couple of miles looked familiar.” Then, you give a voice command to the vehicle’s navigation system: “Match last ten miles to similar locations outside of Texas!” The system responds with a list of five counties, one of which you recognize: “Ah yes, that’s where I spent the summer of ‘93.”

(2) You are a human geographer interested in finding out about differences in how men's and women's life experiences are shaped by their daily spatial routine. You know that researchers have used positional tracking with GPS to capture and compare space-time paths. However, you would like to have a convenient way of directly comparing paths captured in *different* cities. Luckily, a major GIS (geographic information system) software company has just released a product that allows such holistic comparison, generating a display of GPS tracks that looks a lot like a map, but is not based on geographic space. The direct visual comparison of male and female tracks will not only inform your research conclusions, but will also make for great poster presentations at professional meetings and may even catch the eye of policy makers.

(3) You are teaching an introductory college course in urban geography. You want to give your students some experiential sense of the structure of the city of New Orleans. A popular approach for doing this is to take students on an inexpensive city tour using public transport. Ideally, you would like to take a bus that starts at the Mississippi river, and runs northward, crossing the Irish Channel, the Garden District, and Central City in quick succession. These are three adjacent, yet racially and economically extremely diverse areas, illustrating the socio-economic patchwork that is typical for this city. There is just one problem: you and your students are in Philadelphia! To look for a solution, you start out with a "normal" geographic map display of New Orleans and draw a line following your chosen path. Then you turn to the same GIS software product mentioned in the previous scenario. It generates a single "map" showing both your New Orleans path and all the bus lines running in Philadelphia. From this map, you chose the bus path that provides the best visual match. For a more authentic New Orleans experience, you have the heat turned up in the bus, even in the middle of summer. As the bus drives through New Orleans in Philadelphia, you make sure to point out not only similarities but also differences between the two.

In all of these scenarios, one recognizes elements of contemporary geographic inquiry and one can imagine certain approaches to partially implement them. However, different methods for locating geographic features and performing computations on them are here combined in a novel way. The basic premise of this chapter is that as one moves across geographic space, one simultaneously passes through an n-dimensional attribute space of the geographic features encountered along the way. It is posited that explicitly visualizing these attribute-time paths as trajectories in a spatialization may be of value in the investigation of moving entities.

First, I will discuss some of the important developments within geographic information science informing this new way of looking at spatio-temporal trajectories. These range from early thoughts about time geography to its recent reemergence in the context of network accessibility modeling and feminist visualization. On the other hand, these scenarios only sound viable in the context of such computationally intense methods as artificial neural networks, Bayesian networks, or genetic algorithms. These methods are indicative of a growing awareness of a need to deal with high-dimensional attribute data beyond approaches rooted in the data-poor environment of traditional statistical inference (Openshaw 2000). The chapter argues that great synergistic potential may lie in a combination of time geography with methods designed to deal with high-dimensional attribute spaces. To that end, I first give a brief overview of some related techniques. After outlining a methodology aimed at combining space-time paths with self-organizing maps, two implementations are discussed and illustrated.

2 Relationship to other work

The last decade has seen a revived interest in early work on time geography (Hägerstrand 1970; Pred 1977), which deals with the movement of individuals in space over time. Hägerstrand and his contemporaries laid out the foundations of time geography with such notions as space-time paths and prisms, and envisioned a number of interesting applications of these concepts. However, technologies for detailed capture of space-time paths and their computational modeling were either not yet developed or were missing crucial components. By the early 1990's GIS had developed to a point were many of the database requirements and modeling aspirations of time geography could be supported. Harvey Miller's work on modeling network accessibility with space-time prisms exemplified this (Miller 1991).

It also became possible to deal with large amounts of disaggregate data, for example travel diaries, including the places of residence, employment, and other activities (Kwan 2000b). Toward the end of the 1990's, consumer-grade GPS receivers became available that made it feasible to capture detailed paths of individuals. It is not surprising that, at a time when many postmodern and feminist geographers looked upon maps, mapmakers, and mapmaking technology with great suspicion, similar criticism was extended to the integration of GIS and GPS in the implementation of time geography. Partly designed as constructive response to rightful social critique of unquestioned use of geospatial technology, a growing number of geographers have in recent years advanced geographic information science by actively engaging it from within, mostly under the heading of participatory GIS. In the context of time geography, Mei-Po Kwan's work on the development of 'feminist visualization' has been particularly significant

(Kwan 2000a, 2002), and is quite compatible with the methodology described later in this chapter.

Evidence for the resurgence of time geography can also be found in the evolution of the concept of 'geospatial lifelines' towards real-world application (Sinha and Mark 2005). As technology for capturing geographic location moves beyond dedicated devices (i.e., GPS receivers) towards ubiquity (e.g., in mobile phones), space-time paths will likely become an integral part of location-based services (Mountain and Raper 2001).

Apart from the ability to capture space-time paths, the scenarios described earlier make both overt and implicit reference to a capacity to assess *similarity* of space-time paths. The type of similarity referred to here is not based on low-dimensional, geometric characteristics, like shape. Instead, the focus is shifted to the attributes of geographic features. Most efforts at modeling similarity are purely computational (as opposed to involving a visualization component) and restricted to the spatial domain, with the temporal domain only gaining prominence recently (Yuan 2001). It is still rare to see the attribute domain explicitly considered. Indeed, while one would expect "multidimensional" modeling to include the added dimensionality of attributes, it typically refers to the combination of three spatial dimensions and one temporal dimension (Raper 2000). In the context of this chapter, the most important observation is that space-time paths have rarely been linked to representations of the attribute domain, even within the growing area of geographic data mining and knowledge discovery (Miller and Han 2001).

When looking for visual representations of the attribute domain, the self-organizing map is an obvious candidate. Most implementations of SOM trajectories involve objects whose attributes are changing and are therefore changing position with respect to a SOM in which each neuron has a fixed set of weights, one for each attribute. This has frequently been used in stock market and other financial analysis (Kohonen 2001; Deboeck and Kohonen 1998). In the context of spatio-temporal data, this approach has been used to depict counties as trajectories based on multi-year census attributes (Skupin and Hagelman 2005).

3 Methodology for visualizing movement in attribute space

As a *space-time path* (STP) runs through and past features located in geographic space, it can be conceptualized as simultaneously passing through and past these same features located in an *n*-dimensional attribute space as given by *n* attributes known for each feature. We can refer to the resulting trajectory as an *attribute-time path* (ATP). An STP can be easily displayed in either 3D − within a space-time cube, or 2D − when the cube is viewed orthogonally to the two spatial dimensions. However, an ATP cannot be directly displayed, since *n* will typically far exceed the number of available display dimensions. It is proposed here to first spatialize the attribute data and then project the ATP onto the spatialization to form a *spatialized attribute-time path* (SATP). Figure 1 illustrates this schematically with a trajectory traversing an area tessellated by polygonal features. Attributes of these features are spatialized using any suitable dimensionality reduction technique (e.g., SOM, MDS, PCA). Since every attribute has only one value for every polygon, each polygon becomes an individual point object in the spatialization. Polygons that are actually traversed become SATP vertices in the order of traversal (Figure 1). Notice how polygons E and G form the beginning and end points of the path, but are actually located relatively close in the spatialization. In other words, the SATP describes a circular route caused by the relative attribute similarity between those two polygon features.

When spatializing in two dimensions, the third dimension remains available to represent time, thus forming a *spatialized attribute-time cube* (SATC), which we will not deal with further in this chapter.

Insert Figure 1 approx. here

The following describes a specific methodology for implementing spatialized attribute-time paths, as pursued in this chapter (Figure 2). Spatialization of individual attribute-time paths is based on a single spatialization derived from a large number of geographic objects and their attributes. Choosing the geographic type, extent, and granularity of geographic objects is a crucial first step. Geographic type refers in particular to differences between objects conceptualized as points, lines, or areas. One could even spatialize individual cells or pixels, as provided, for example, by multispectral remote sensing. In this chapter, all examples are based on polygon objects. Specifically, we completely tessellate a given study area via administrative or enumeration areas (i.e., counties, census block groups, etc), thereby allowing unequivocal association of path vertices with geographic objects. Point and line objects could of course also be used, within certain proximity constraints. Objects to be spatialized must at least cover the expected extent of space-time paths, but one may want to go much beyond that in order to allow future paths to be easily spatialized, especially since one of the prime goals of this approach is to facilitate comparison of paths traversing different geographic areas. The granularity or density of geographic objects must be matched against characteristics of the captured paths and the purpose for spatializing them. For example, spatialization of paths based on counties (i.e., space-time paths spatialized as temporal sequence of counties) may be interesting for regional analysis. However, this would likely be too coarse when one wants to link a space-time path to the visual experience of someone following it on the ground.

Insert Figure 2 approx. here

When spatializing geographic objects, it is natural to want to include a great number of attributes, especially in an exploratory setting. Depending on the specific application, one may find it useful to include demographic, economic, or physical attributes. Those choices will often be limited by the actual availability of such attribute data, especially when dealing with a large geographic extent and fine granularity, as discussed above. Socio-demographic data, as published by the U.S. Census Bureau, are a rare exception, with dozens of attributes readily and at little cost available at multiple granularities. That was the main reason for using census attributes in the experiments described in this chapter.

The purpose of preprocessing is to turn raw attribute data into something suitable for neural network training using the SOM method. This may involve, for example, logarithmic transformation for highly skewed distributions and normalization of attribute ranges. After SOM training is completed, the same input data or other data (not illustrated in Figure 2) are mapped onto it to derive point coordinates for each input feature.

GPS is a logical choice for capturing STPs. Among dedicated devices, even consumer-grade receivers can now capture quasi-continuous paths with great spatial and temporal resolution. Standard GPS protocols, like NMEA, provide time stamps in Greenwich Mean Time for every observation. GIS overlay can be used to match a space-time path to the geographic objects encountered. This can be based on an exact or proximal match. After extracting the temporal sequence of objects, their corresponding point locations are found in the spatialization and linked to form a spatialized attribute-time path. Various layers could now be displayed within the same 2D geometric space that originated with the self-organizing map. Apart from the SOM and its immediate visual derivatives (e.g., U-Matrix, component planes, neuron clustering), one can display the SATP and the point locations of spatialized geographic objects simultaneously or in sequence.

4 Experiment 1: Travel on Interstate Highways

This section describes a first experiment for implementing the methodology laid out in the previous section. Traveling on U.S. interstate highways, especially in the western states, provides ample time for contemplating the geographic space one traverses. While traveling the United States by car, detailed geographic trajectories were captured by GPS, totaling over 6000 miles in length. The hardware used consisted of a Compaq iPAQ PocketPC paired with a CompactFlash

GPS card with external antenna and accompanying software, which stored track coordinates as a text file.

The chosen granularity of geographic base data was at the county level. For each of the 3140 counties, 40 socio-economic variables from the 1990 census were used, with a focus on race, marital status, age structure, and housing characteristics. Then a high-resolution SOM consisting of 10,000 neurons was trained (Figure 3). A selection of twelve of the forty component planes are shown here. As is typical with this form of SOM visualization, one can recognize major relationships between variables and one can also observe how prevalent certain portions of a variable's range are. For example, in the population density variable, few neurons have very high values. On the other hand, white population percentage shows high and medium values throughout, except in areas with large black population percentage and especially in SOM areas with a high percentage of households with children headed by a female (i.e., single mothers).

Insert Figure 3 approx. here

A SOM with a relatively large number of neurons allows discerning finer structures in the input space that would be lost to the aggregating effects of a coarser SOM. When *n*-dimensional observations are then mapped onto such a SOM, the resulting two-dimensional locations are spread throughout the finely grained display space. This is advantageous whenever geometric operations on individual objects are desired, for example to place multivariate point symbols or perform selections. Choosing SOM size in this experiment was thus driven by the goal of ideally establishing a unique two-dimensional location for each county. Despite the 3:1 neuron-to-county ratio (10,000 neurons versus 3,140 counties), some neurons became associated with multiple counties. To counter this remaining clustering effect, counties were randomly distributed within hexagonal polygons spanned around each node in the SOM (Skupin 2002). This allows generating unique county coordinates while still maintaining unequivocal links between neurons and counties.

Shown in this paper is one of the GPS tracks, in which a drive from Santa Barbara to New Orleans via San Francisco was documented with more than 25,000 vertices (Figure 4). GPS tracks were overlaid with county maps to produce a sequence of traversed counties and spatialized on the basis of that sequence (Figure 5).

Insert Figure 4 approx. here

Insert Figure 5 approx. here

As different as such cities as San Francisco and New Orleans might be and as far apart in geographic coordinate space they are, when arriving at one of these from the other, one realizes that – relative to the rest of the country as expressed by the involved attributes – one is back to where one started! The proposed method allows to spell this out, albeit visually, with the two cities appearing as neighbors in the SOM (lower right corner in main map in Figure 5). Notice how some geographically close portions of the path correspond to relatively compact portions of attribute space. One such region is entered when crossing from Smith County into Gregg County in Texas (see upper insert map in Figure 5). The path only leaves that region when crossing from St. Charles Parish into Jefferson Parish (not labeled here), just outside New Orleans.

Time stamps provided by GPS allow mapping the amount of time spent at certain locations, indicated here through graduated circles (Figure 6). Despite traversing huge portions of a very large country, the resulting visualization indicates that most time, and presumably money, was spent in a limited portion of attribute space (compare also to Figure 3).

Insert Figure 6 approx. here

5 Experiment 2: Journey to Work

One major goal driving the notion of attribute-time paths and their spatialization has been to allow exploring possible links between the *experience* of geographic space and the attributes of geographic features encountered along a trajectory. Ultimately, one would like to see (in a spatialization) trajectories that readily evoke the notion of traveling through attribute space. On the other hand, as one travels across geographic space, one should be able to experience patterns in attribute space as corresponding patterns in geographic space. County-level granularity combined with movement on the Interstate highway system (see previous section) does not really allow this, owing to the large size of counties and the homogenizing effects of Interstate highway routing.

For the second experiment, much finer granularity and shorter, urban paths were chosen. Census block groups, which typically contain around 500 persons, provide that fine granularity, yet their geometry and census attributes are readily available for the whole country, which allows keeping the geographic extent at the national level. The census data used here contained 208,671 block groups from the 2000 census, together with 32 socio-demographic attributes. Because many of the raw attributes were to be divided by either population size or household size, those block groups containing no population or no households were removed, yielding a final input data set of 207,933 block groups. Some highly skewed variables were logarithmically scaled and all variables eventually fitted into a 0-1 range. Given the large number of block groups and the goal of creating a point location for each of them (as discussed in previous section), a SOM consisting of 250,000 (500x500) neurons was created (Figure 7). Training took 92.5 hours (wall clock time) on a 2.8 GHz Xeon PC. Mapping of all 207,933 block groups onto the trained SOM took another 123 minutes.

Insert Figure 7 approx. here

Recent implementations of time-geography concepts have generally focused on urban environments, with travel on city streets. In deciding on a specific type of path to be captured, inspiration was drawn from the kind of socially critical analysis pursued by Mei-Po Kwan (Kwan 2002). Journey-to-work paths are a particularly worthwhile subject of inquiry, since the vast majority of employed persons have to travel a certain distance from their residence to the place of employment. Differences in the mode, duration, and routing of these paths provide an interesting subject of study, reflecting society's organization along lines of gender, race, age, and other factors. Travel mode, duration, and routing are of course interrelated, as already noted by Hägerstrand: "… the car-owner, because of his random access to transport, has much greater freedom to combine distant bundles than the person who has to walk or travel by public transportation" (Hägerstrand 1970). When pursuing the quickest route to work, private vehicles will tend to provide a more straightforward path and shorter overall travel time than public transport, at least in the New Orleans metro area. Perhaps more important with respect to the method proposed in this chapter is that different paths taken between residence and place of employment may entail differences in the geographic environment *experienced* en route.

The author's previous places of residence (Mid-City neighborhood in New Orleans) and employment (University of New Orleans) were chosen as origin and destination, respectively. Journey-to-work paths were captured using GPS on two subsequent mornings. Photos were also taken along the journey, to later allow juxtaposing visual impression (as one element of en route experience) with attribute space location. On the first day, a private vehicle was taken and the quickest route through the street network followed (from here on referred to as "private path"). On the next day, public transport with busses of the Regional Transit Authority was utilized and the path captured (from here on referred to as "public path"). Both tracks were started at approximately the same time of day (Figure 8). As expected, the private track was shorter in both space and time, running from Mid-City through the Bayou St. John neighborhood, then along City Park and the Mirabeau Gardens neighborhood, reaching the destination within about 18 minutes. The public path involved taking two buses, one connecting Mid-City with the Central Business District and the edge of the French Quarter, the second bus running first parallel to the Mississippi river and then following a straight northward path, toward Lake Pontchartrain. Following this path took 65 minutes, including transfers.

Insert Figure 8 approx. here

After intersecting the private and public paths with census block groups, the corresponding sequence of block groups was mapped onto the SOM (Figures 9, 10, 11). A total of 31 and 12 different block groups were traversed on the public and private path, respectively. In figure 9, block groups are labeled in the order of traversal. The origin in Mid-City is labeled “1” for both paths and the final vertex as “37” for the public path and “13” for the private path. Note that a new ID is created every time a census block boundary is crossed. Multiple entries into the same block group are possible, depending on how block groups and paths are shaped. The resulting duplicate labels for some block groups are kept in Figure 9, in order to allow tracking of the exact vertex sequence. Figure 10 shows both paths together and with respect to the complete 2-D SOM space. Finally, Figure 11 seeks to identify some of the specific attribute patterns common to neighborhoods along the public path. It shows the extreme diversity of neighborhoods encountered. Summary statistics for urban counties (like used in the first experiment) tend to hide internal urban heterogeneity. New Orleans, for example, can best be characterized as a patch work of often extremely different socio-demographic zones. The Mid-City origin of the public path is a bit of an exception, as it is actually quite integrated, thus mirroring a possible summary view of the city. However, once moving south along Canal Street, the city’s extremes become more apparent, at first in terms of gradually increasing percentage of black population. Just before reaching the CBD, this movement towards the extreme lower right corner of the SOM ends in a block group with 100% black population. Entering the CBD corresponds to a large jump upwards along the SOM’s right edge, followed by traversal of block groups on the edge of the French Quarter, and so forth.

What both Figure 9 and 11 illustrate is that named neighborhoods become manifested as regions in the SOM. For example, along the public path the French Quarter is the region with by far the highest percentage of white population (left portion of Figure 11), and large proportions of vacant housing, of households consisting of single males, and of persons in the 30 to 39 year age range (Figure 10). Compare this to Gentilly Woods, which is a middle-class area, with mixed racial composition and mostly owner-occupied housing. Traversing a geographic path means to either move within one of the neighborhoods or to move between them. Moving between named neighborhoods can occur rapidly, as seen when entering the CBD coming from Mid-City (see left portion of Figure 9), or it can involve intermediate block groups. Examples for the latter are seen in vertex “23” linking Faubourg-Marigny and New Marigny or vertex “29” between New Marigny and Gentilly.

6 Conclusions

This chapter argues that adding an attribute space representation to the mix of Hägerstrand’s original ideas with GPS, GIS, and geographic visualization may be an interesting and useful endeavor. While the early examples shown here are meant to illustrate the potential of this approach, they also convey a sense of the issues to be explored in future work. One of these relates to the choice of geographic data with which space-time paths are to be matched in order to generate attribute-time paths. While both examples used census data, the methodology accommodates other types of data. For example, when mapping out hiking trails in attribute space, one would want to focus on physical attributes, such as vegetation cover or slope steepness. With the emergence of wireless sensor networks, the on-the-fly “re-routing” of attribute-time paths based on changes in environmental factors (e.g., temperature, humidity) may become a valuable option. Today, hikers may look at Web sites displaying loops of NEXRAD data. Tomorrow, they might also see a looped animation of a spatialized ATP, possibly indicating a slow drift towards a danger zone.

For much of this chapter, spatialized attribute-time paths were treated (processed, stored, visualized) similar to space-time paths. Of course, there are important differences that remain to be investigated. For example, with space-time paths the notion of *bundles* (Hägerstrand 1970) has tangible, common sense implications. In a bundle, different STPs meet in geographic space for a period of time, the persons associated with them are enabled to directly communicate and interact. Similarly, making a phone call establishes a temporary bundle of trajectories in the virtual space of the phone system. But how are we to interpret a bundle of SATPs? What does it mean when two people moving through different cities are “meeting” in attribute space? Assuming that a sufficiently rich set of attributes drives the creation of a spatialization, SATP bundles may correspond to similar impressions and experiences. In turn, similar (or different) experiences may become manifested in similar (or different) social attitudes.

Whether or nor these speculations about SATPs hold true remains to be seen. In this context, it may be worthwhile linking attribute-time paths and their spatialized form to the investigation of activity spaces. Similarly, one might ask to what degree such notions as *domains* or *constraints* (e.g., those shaping space-time prisms) are transferable to attribute-time paths, thereby answering recent calls to rethink the concept and implications of individual accessibility in the light of technological advances and societal change (Kwan and Weber 2003). In approaching any of these issues, a major aim of future spatializations must be to incorporate multiple paths taken by multiple persons in multiple geographic areas, which was not demonstrated in this chapter. Such ability to visually compare paths covering separate study sites would truly demonstrate the usefulness of this method for time geography.

Some might argue that using a SOM for deriving a spatialization from only the non-spatial attributes of geographic features ignores important spatial relationships (e.g., topology, distance in geographic space) that may be very relevant for understanding a given domain. That is a valid argument, whenever such relationships are indeed ignored during training and use of a SOM. This is the case when individual geographic features are visualized as points in a spatialization or when trajectories are generated for features that are spatially fixed, but whose attributes are changing over time (Skupin and Hagelman 2005). However, the attribute-time paths described in this chapter are different in that neighboring vertices within a path correspond to topologically connected features in geographic space. Therefore, the length of a line segment in the spatialization gives some indication of spatial autocorrelation. Due to the distortion of *n*-dimensional proximities, this is only a rough approximation and quite dependent on the exact parameters of the spatialization method. The exact nature of the relationship between spatial autocorrelation and proximity in a spatialization is an interesting subject for future research.

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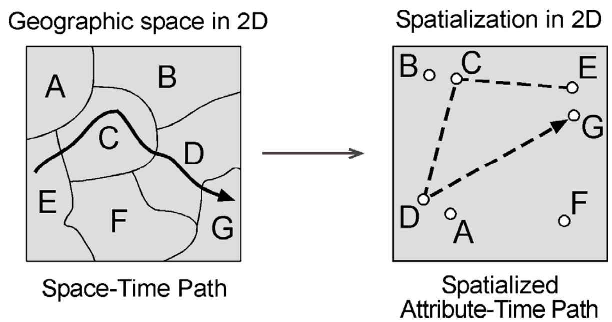

Figure 1. Space-time path transformed into an attribute-time path traversing a spatialization of attributes for polygon features.

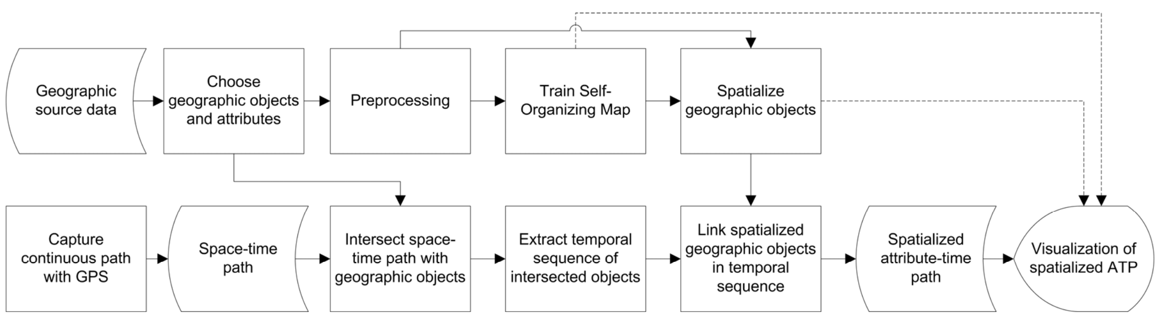

Figure 2. Methodology for creating a spatialized attribute-time path using GPS, GIS, and SOM.

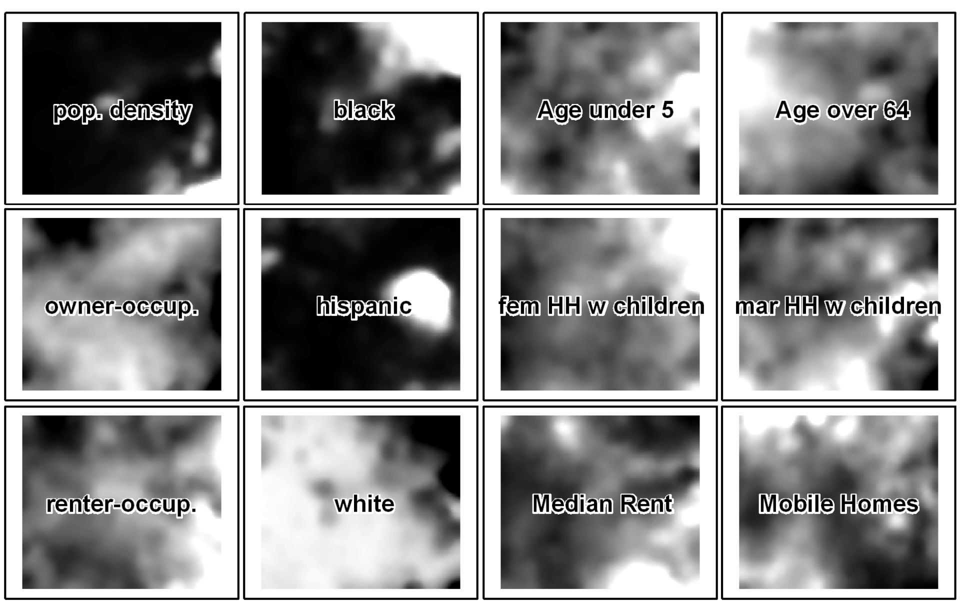

Figure 3. Several component planes from a 100-by-100 neuron SOM trained with socio-economic data for all U.S. counties. Lighter shading indicates higher values for a component layer.

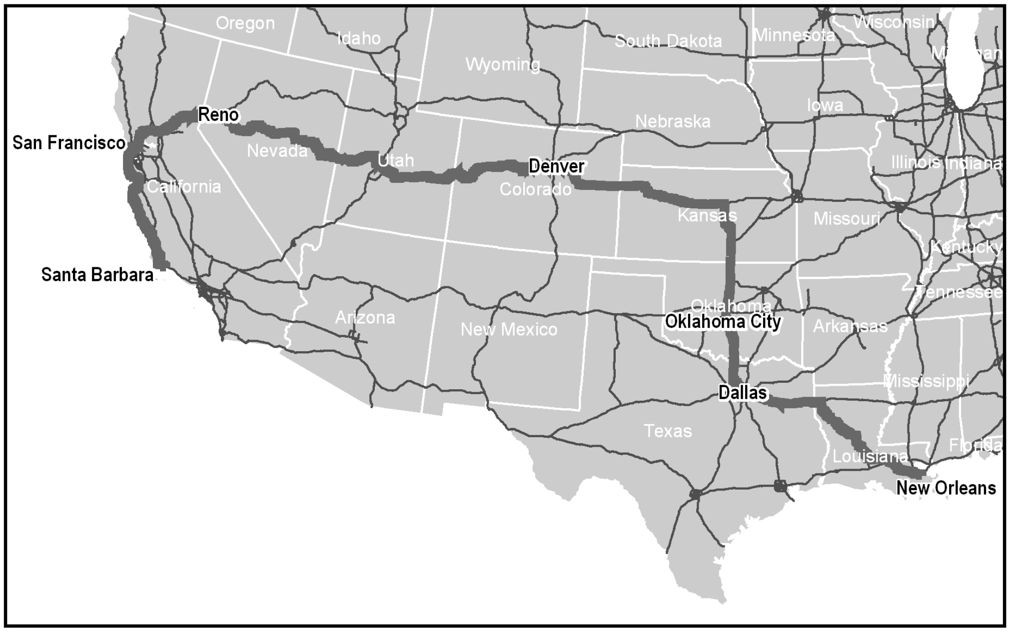

Figure 4. Experiment 1: Overview Map. Traveling from Santa Barbara to New Orleans, a track consisting of 25,000+ vertices was captured with a GPS receiver.

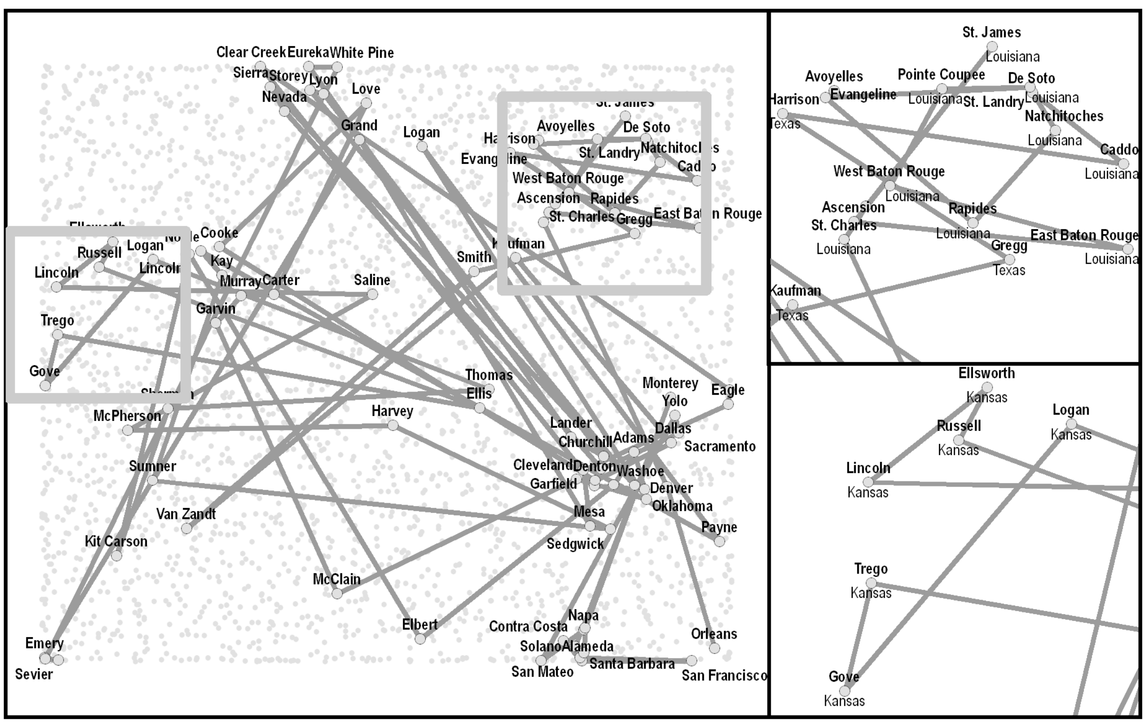

Figure 5. Space-time path for travel from Santa Barbara to New Orleans projected onto self-organizing map of 3,140 counties.

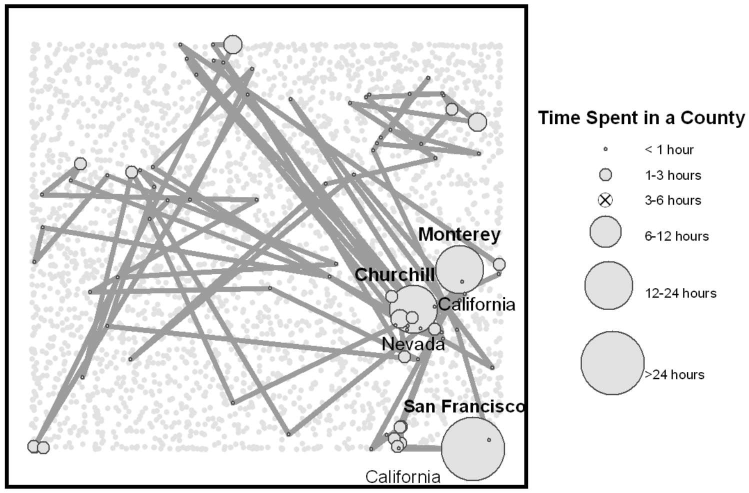

Figure 6. Visualization of time spent in each county during a multi-day drive from Santa Barbara to New Orleans.

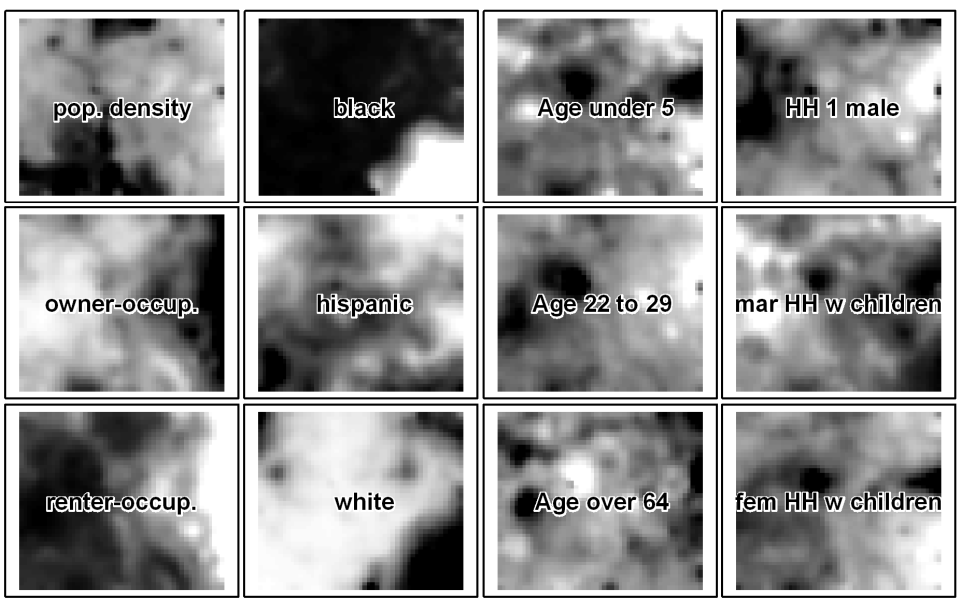

Figure 7. Several component planes of a SOM trained with socio-economic attributes for 200,000+ U.S. census block groups. Lighter shading indicates higher values.

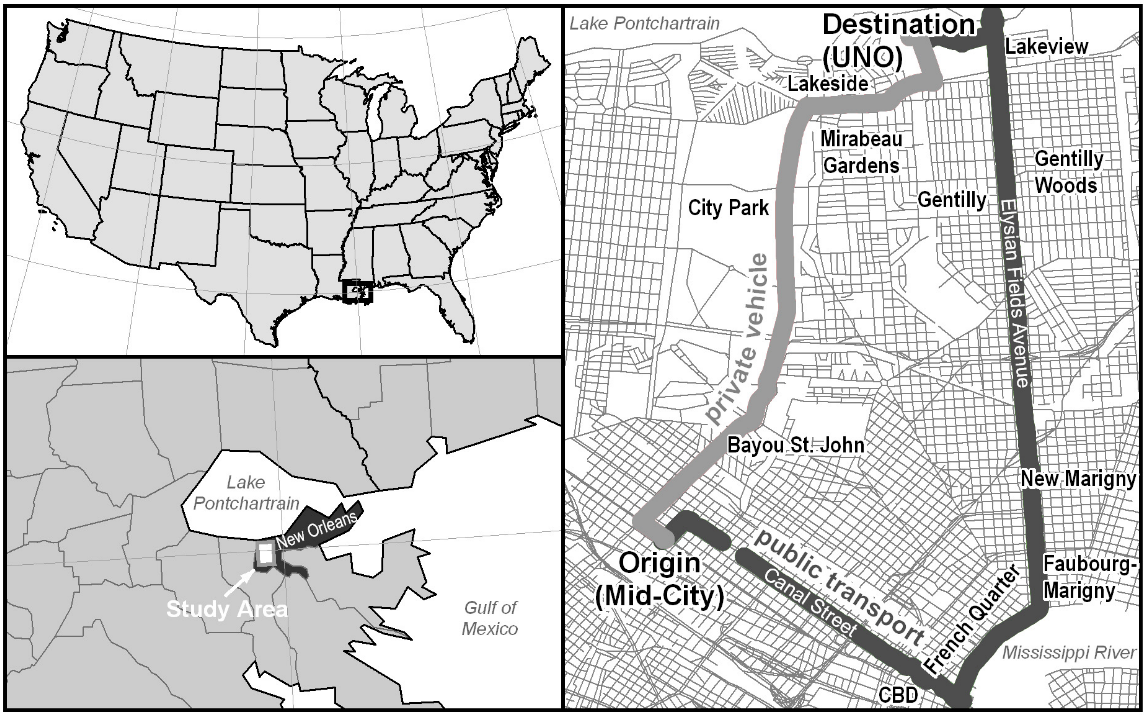

Figure 8. Experiment 2: Overview of study area. Two different journey-to-work paths were collected between origin and destination.

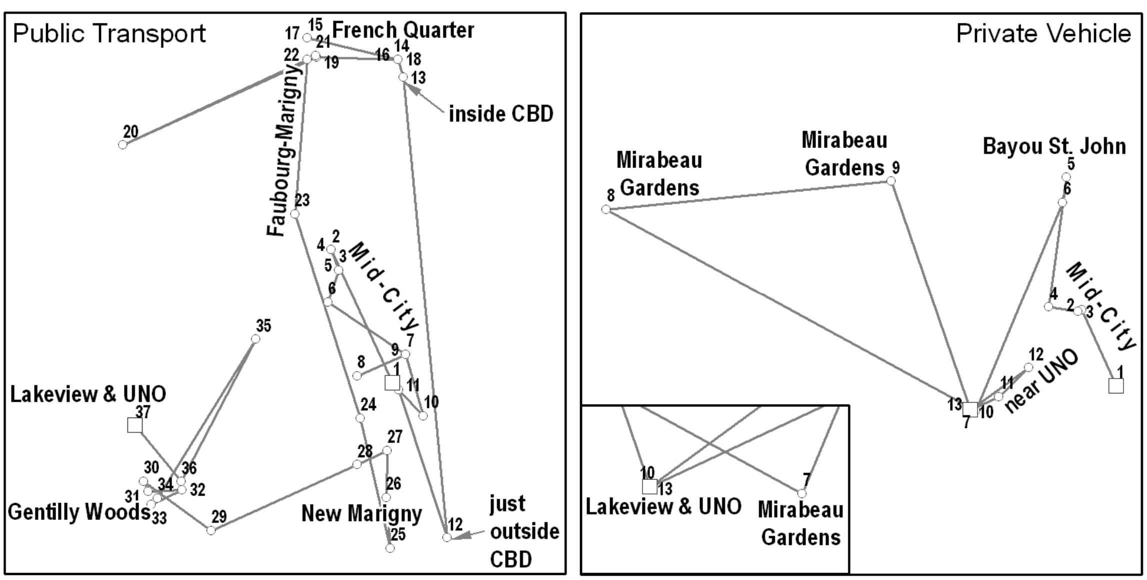

Figure 9. Journey-to-work paths traveled with private vehicle and public transport and visualized on spatialized block groups. Census block groups are labeled in order of traversal. Neighborhoods are also labeled.

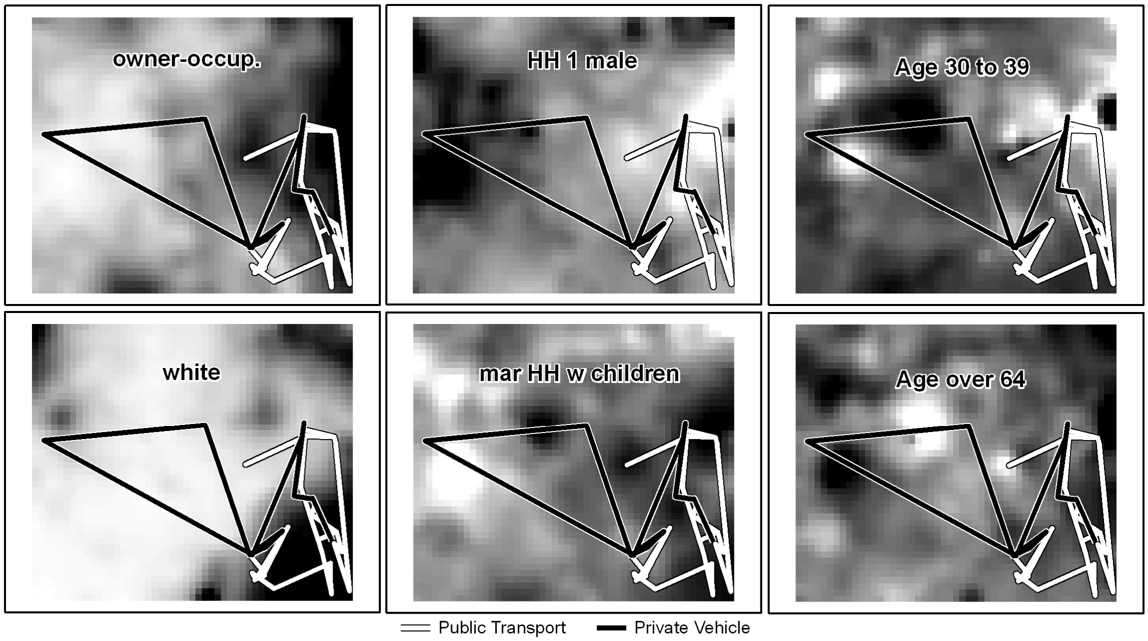

Figure 10. Journey-to-work paths overlaid on a spatialization of census block groups. Lighter shading indicates higher values in component planes.

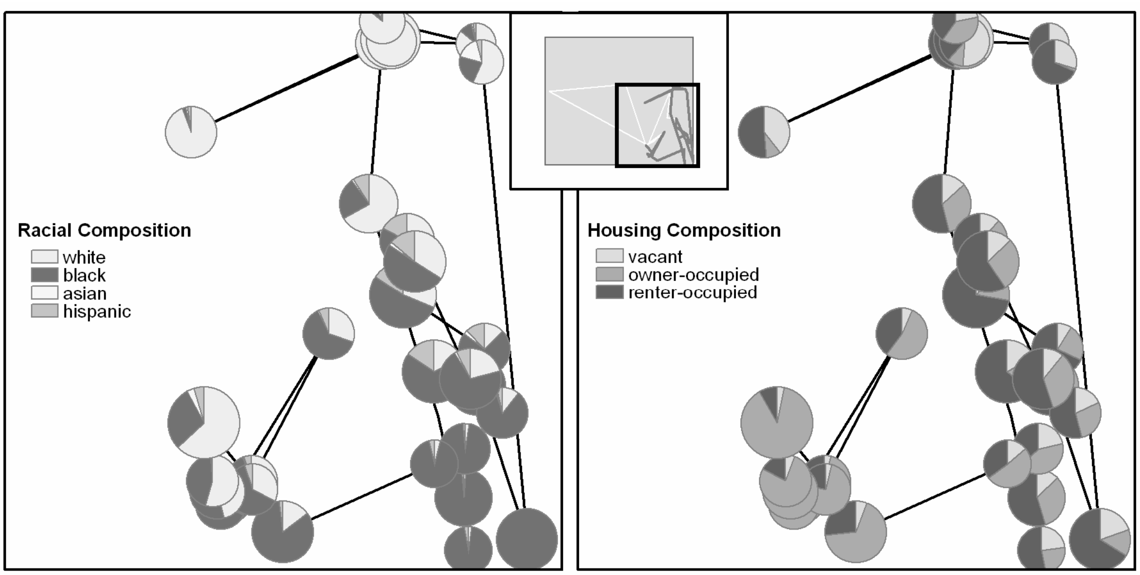

Figure 11. Visualization of attributes of block groups traversed during journey-to-work using public transport.

	Variable	Normalized by
1	Population size	Area
2	White population	Population size
3	Black	Population size
4	American Indian / Eskimo	Population size
5	Asian	Population size
6	Hawaiian / Pacific Islander	Population size
7	Other	Population size
8	Multi-race	Population size
9	Hispanic	Population size
10	Males	Population size
11	Females	Population size
12	Age < 5	Population size
13	Age 5-17	Population size
14	Age 18-21	Population size
15	Age 22-29	Population size
16	Age 30-39	Population size
17	Age 40-49	Population size
18	Age 50-64	Population size
19	Age >= 65	Population size
20	Median age	n/a
21	Average household size	n/a
22	Households w 1 male	Households
23	Households w 1 female	Households
24	Households married w/ children	Households
25	Households married w/o children	Households
26	Male head of household w/ children	Households
27	Female head of household w/ children	Households
28	Average family size	n/a
29	Vacant housing units	Housing units
30	Owner-occupied housing unit	Housing units
31	Renter-occupied housing unit	Housing units

Table 1. Experiment 2: Variables for 200,000+ census block groups used as input to SOM training.