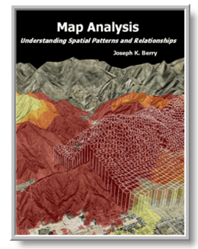
Beyond Mapping III

Topic 6: Analyzing In-Store Shopping Patterns



Map Analysis book with companion CD-ROM for hands-on exercises and further reading

Note: The processing and figures discussed in this topic were derived using MapCalc™ software. See www.innovativegis.com to download a free MapCalc Learner version with tutorial materials for classroom and self-learning map analysis concepts and procedures.

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GIS Analyzes In-Store Movement and Sales Patterns

(GeoWorld, February 1998, pg. 30-32)

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There are two fundamental types of people in the world: shoppers and non-shoppers. Of course, this distinction is a relative one, as all of us are shoppers to at least some degree. How we perceive stores and what prompts us to frequent them form a large part of retail marketing's GIS applications. Shoppers are seen as linked to stores by either simple buffers (as-the-crow flies distances), or more realistically as effective distances along a network of roads. Relative accessibility is a major ingredient in Competition Analysis and Targeted Marketing, and has received considerable attention in the GIS literature.

Movement within a store is conceptually similar, but the geographic factors and basic approach are different. The analysis scale collapses from miles along a road network, to feet through a maze of aisles and fixtures. Since the rules of the road and fixed widths of pavement don't exist, shoppers can (and do) move through capricious routes that are not amenable to traditional network analysis. However, at least for me, the objective is the same—get to the place(s) with the desired products, then get out and back home as easily as possible. What has changed in the process isn't the concept of movement, but how movement is characterized.

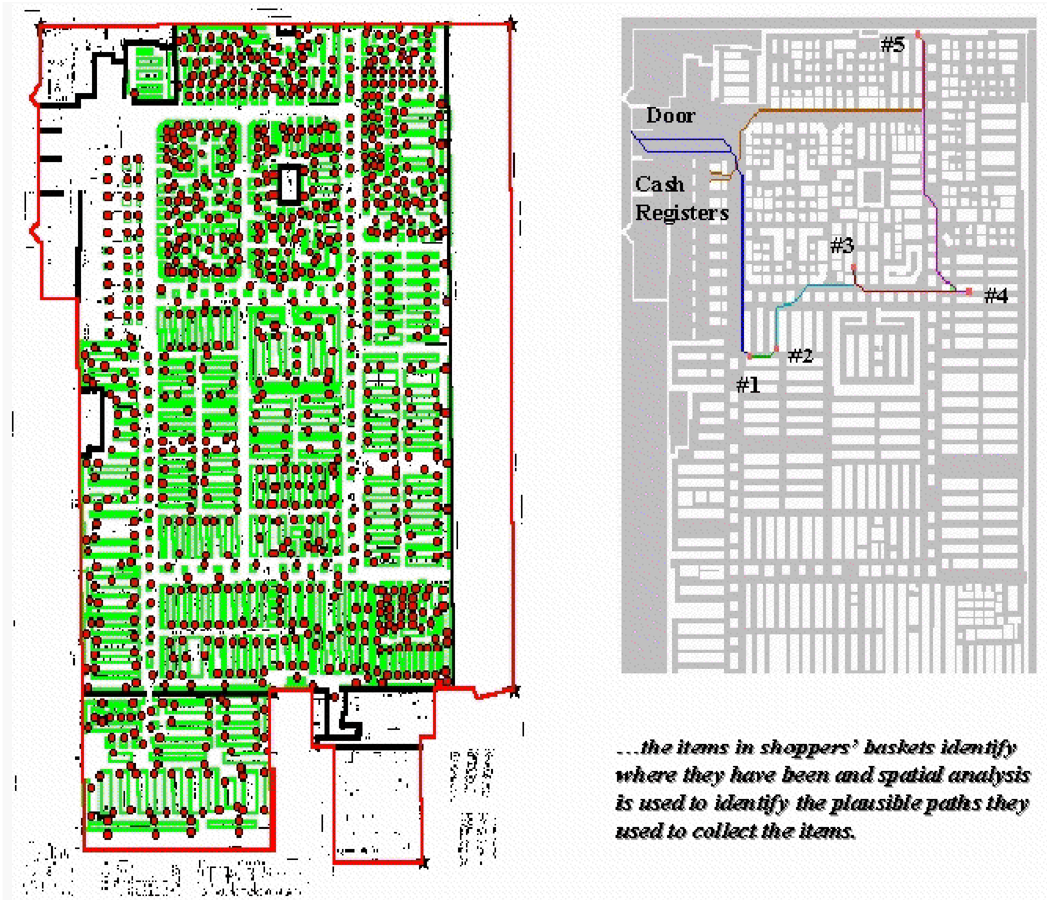

Figure 1. Establishing Shopper Paths. Stepped accumulation surface analysis is used to model shopper movement based on the items in a shopping cart.

The floor plan of a store is a continuous surface with a complex of array of barriers strewn throughout. The main aisles are analogous to mainline streets in a city, the congested areas are like secondary streets, and the fixtures form absolute barriers (can't climb over or push aside while maintaining decorum). Added to this mix are the entry doors, shelves containing the elusive items, cash registers, and finally the exit doors. Like an obstacle race, your challenge is to survive the course and get out without forgetting too much. The challenge to the retailer is to get as much information as possible about your visit.

For years, the product flow through the cash registers has been analyzed to determine what sells and what doesn't. Data analysis originally focused on reordering schedules, then extended to descriptive statistics and insight into which products tend to be purchased together (product affinities). However, mining the data for spatial relationships, such as shopper movement and sales activity within a store, is relatively new. The left portion of figure 1 shows a map of a retail superstore with fixtures (green) and shelving nodes (red). The floor plan was digitized and the fixtures and shelving spaces were encoded to form map features similar to buildings and addresses in a city. These data were gridded at a 1-foot resolution to form a continuous analysis space.

The right portion of figure 1 shows the plausible path a shopper took to collect the five items in a shopping cart. It was derived through stepped accumulation surface analysis described in last month's column. Recall that this technique constructs an effective proximity surface from a starting location (entry door) by spreading out (increasing distance waves) until it encounters the closest visitation point (one of the items in the shopping cart). The first leg of the shopper's plausible path is identified by streaming down the truncated proximity surface (steepest downhill path). The process is repeated to the establish the next tier of the surface by spreading from the current item's location until another item is encountered, then streaming over that portion of the surface for the next leg of the path. The spread/stream procedure is continued until all of the items in the cart have been evaluated. The final leg is delineated by moving to the checkout and exit doors.

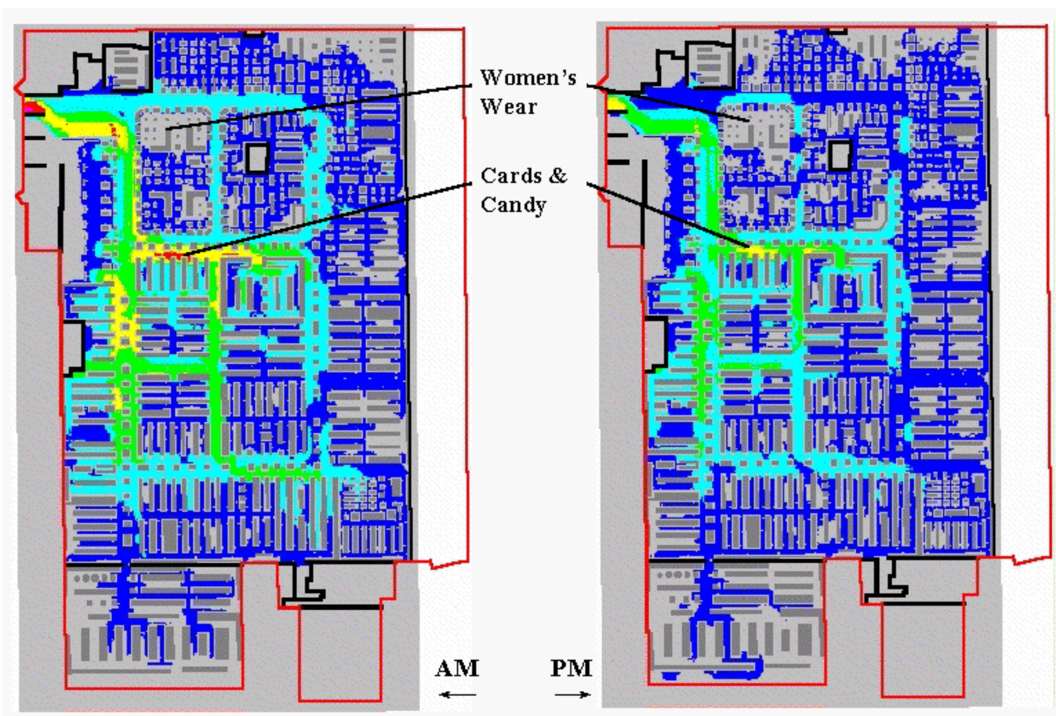

Figure 2. Shopper Movement Patterns. The paths for a set of shoppers are aggregated and smoothed to characterize levels of traffic throughout the store.

Similar paths are derived for additional shopping carts that pass through the cash registers. The paths for all of carts during a specified time period are aggregated and smoothed to generate an accumulated shopper movement surface. Although it is difficult to argue that each path faithfully tracks actual movement, the aggregate surface tends to identify relative traffic patterns throughout the store. Shoppers adhering to "random walk" or "methodical serpentine" modes of movement confound the process, but their presence near their purchase points are captured.

The left portion of figure 2 shows an aggregated movement surface for 163 shopping carts during a morning period; the right portion shows the surface for 94 carts during an evening period of the same day. The cooler colors (blues) indicate lower levels of traffic, while the warmer colors (yellow and red) indicate higher levels. Note the similar patterns of movement with the most traffic occurring in the left-center portion of the store during both periods. Note the dramatic falloff in traffic in the top portion.

The levels for two areas are particularly curious. Note the total lack of activity in the Women's Wear during both periods. As suspected, this condition was the result of erroneous codes linking the shelving nodes to the products. Initially, the consistently high traffic in the Cards & Candy department was thought to be a data error as well. But the data links held up. It wasn't until the client explained that the sample data was for a period just before Valentine's Day that the results made sense. Next month we will explore extending the analysis to include sales activity surfaces and their link to shopper movement.

***Author's Note**: the analysis reported is part of a pilot project lead by HyperParallel, Inc., San Francisco, California. A slide set describing the approach in more detail is available on the Worldwide Web at www.innovativegis.com*

Further Analyzing In-Store Movement and Sales Patterns

(GeoWorld, March 1998, pg. 28-30)

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The previous section described a procedure for deriving maps of shopper movement within a store by analyzing the items a shopper purchased. An analogy was drawn between the study of in-store traffic patterns and those used to connect shoppers from their homes to a store's parking lot… aisles are like streets and shelving locations are like street addresses. The objective of a shopper is to get from the entry door to the items they want, then through the cash registers and out the exit. The objective of the retailer is to present the items shoppers want (and those they didn't even know they wanted) in a convenient and logical pattern that insures sales.

Though conceptually similar, modeling traffic within a store versus within a town has some substantial differences. First the vertical component of the shelving addresses is important as it affects product presentation. Also, the movement options in and around store fixtures (verging on whimsy) is extremely complex, as is the characterization of relative sales activity. These factors suggest that surface analysis (raster) is more appropriate than the traditional network analysis (vector) for modeling in-store movement and coincidence among maps.

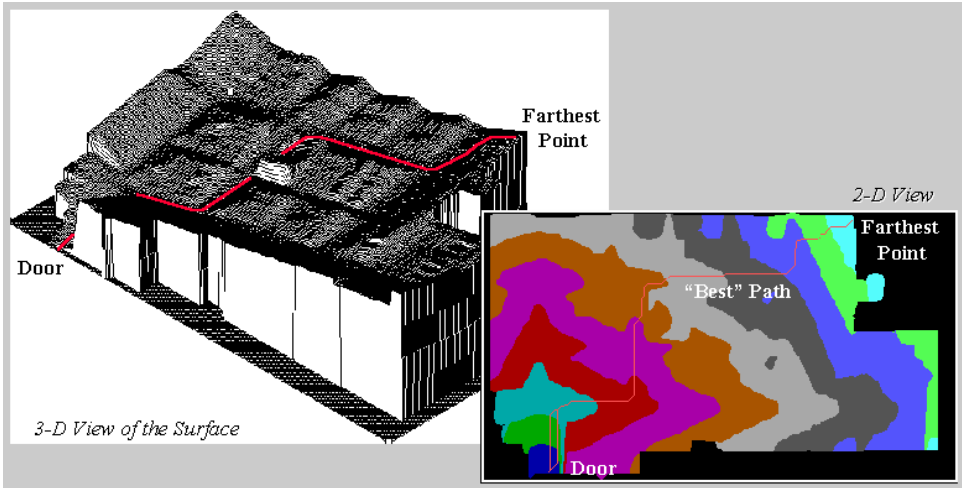

Figure 1. A shopper's route is the steepest downhill path over a proximity surface.

Path density analysis develops a "stepped accumulation surface" from the entry door to each of the items in a shopper's cart and then establishes the plausible route used to collect them by connecting the steepest downhill paths along each of the "facets" of the proximity surface. The figure 1 illustrates a single path superimposed on 2-D and 3-D plots of the proximity surface for an item at the far end of the store. The surface acts like mini-staircase guiding the movement from the door to the item.

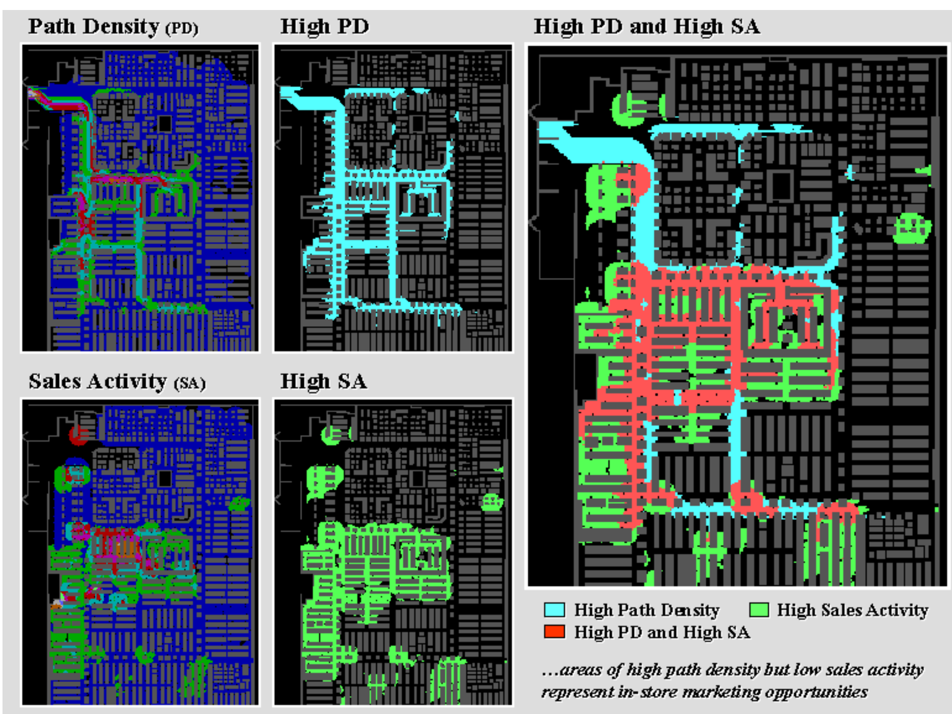

Figure 2. Analyzing coincidence between shopper movement/sales activity surfaces.

The procedure continues from item to item, and finally to the checkout and exit. Summing and smoothing the plausible paths for a group of shoppers (e.g., morning period) generates a continuous surface of shopper movement throughout the store— a space/time glimpse of in-store traffic. The upper left inset of figure 2 shows the path density for the morning period described last time.

OK, so much for review. The lower left inset identifies sales activity for the same period. It was generated by linking the items in all of the shopping carts to their appropriate shelving addresses and keeping a running count of the number of items sold at each location. This map summarizing sales points was smoothed into a continuous surface by moving a "roving window" around the map and averaging the number of sales within a ten-foot radius of each analysis grid cell (1 square foot). The resulting surface provides another view of the items passing through the checkouts— a space/time glimpse of in-store sales action.

The maps in the center identify locations of high path density and high sales activity by isolating areas exceeding the average for each mapped variable. As you view the maps note their similarities and differences. Both seem to be concentrated along the left and center portions of the store, however, some "outliers" are apparent, such as the pocket of high sales along the right edge and the strip of high traffic along the top aisle. However, a detailed comparison is difficult by simply glancing back and forth. The human brain is good at a lot of things, but summarizing the coincidence of spatially specific data isn't one of them.

The enlarged inset on the right is an overlay of the two maps identifying all combinations. The darker tones show where the action isn't (low traffic and low sales). The orange pattern identifies areas of high path density and high sales activity— what you would expect (and retailer hopes for). The green areas are a bit more baffling. High sales, but low traffic means only shoppers with a mission frequent these locations— a bit inconvenient, but sales are still high.

The real opportunity lies in the light blue areas indicating high shopper traffic but low sales. The high/low area in the upper left can be explained… entry doors and women's apparel with the data error discussed last time. But the strip in the lower center of the store seems to be an "expressway" simply connecting the high/high areas above and below it. The retailer might consider placing some end-cap displays for impulse or sale items along the route.

Or maybe not. It would be silly to make a major decision from analyzing just a few thousand shopping carts over a couple of days. Daily, weekly and seasonal influences should be investigated. That's the beauty of in-store analysis— its based on data that flows through the checkouts every day. It allows retailers to gain insight into the unique space/time patterns of their shoppers without being obtrusive or incurring large data collection expenses.

The raster data structure of the approach facilitates investigation of the relationships within and among mapped data. For example, differences in shopper movement between two time periods simply involve subtracting two maps. If a percent change map is needed, the difference map is divided by the first map and then multiplied by 100. If average sales for areas exceeding 50% increase in activity are desired, the percent change map is used to isolate these areas, then the values for the corresponding grid cells on the sales activity map are averaged. From this perspective, each map is viewed as a spatially defined variable, each grid cell is analogous to a sample plot, and each value at a cell is a measurement—all just waiting to unlock their secrets. Next time we will investigate more "map-ematical" analyses of these data.

Author's Note*: the analysis reported is part of a pilot project lead by HyperParallel, Inc., San Francisco, California. A slide set describing the approach in more detail is available on the Worldwide Web at www.innovativegis.com.*

Continued Analysis of In-Store Movement and Sales Patterns

(GeoWorld, April 1998, pg. 26-28)

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The first part of this series described a procedure for estimating shopper movement within a store, based on the items found in their shopping carts. The second part extended the discussion to mapping sales activity from the same checkout data and introduced some analysis procedures for investigating spatial relationships between sales and movement. Recall that the raster data structure (1-foot grids) facilitated the analysis as it forms a consistent "parceling" of geographic space. Within a "map-ematical" context, each value at a grid cell is a measurement, each cell itself is analogous to a sample plot, and each gridded map forms a spatially defined variable.

From this perspective, the vast majority of statistical and mathematical techniques become part of the GIS toolbox. For some, the thought of calculating a correlation coefficient or deriving a regression equation between two maps is as disgusting as it is intimidating. The graphical heritage of traditional mapping casts a colorful, yet qualitative, hue on spatial data processing. The thematic mapping and geo-query procedures of desktop mapping extends database management capabilities, but emphasizes the "repackaging" of information about predefined, discrete map objects.

The GIS procedures illustrated in this series touches on the vast potential of analytical capabilities for uncovering spatial relationships within data normally thought to be non-spatial. Until recently, analytic applications of GIS have been a trickle compared to the flood of mapping and data management applications. However, with the maturation of the technology and more powerful processors at ever lower costs, GIS modeling is beginning to capture the imagination of people outside its traditional realms.

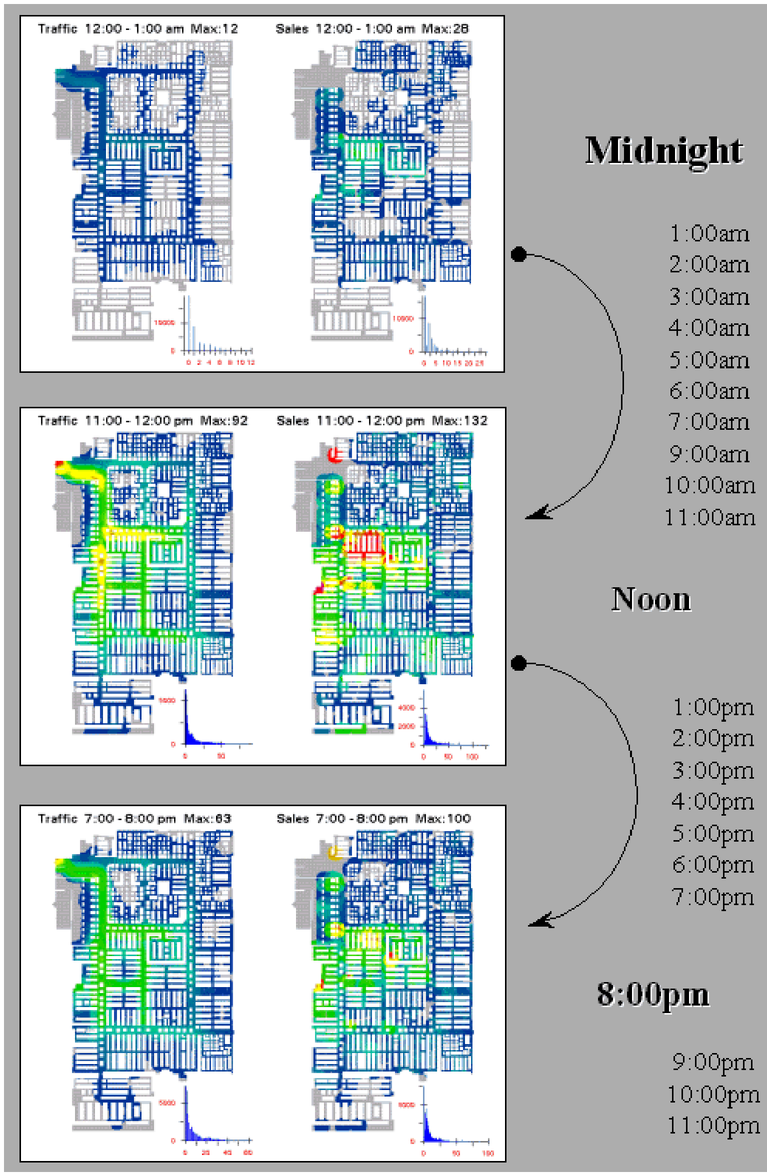

Figure 1. Snapshots from a movie of hourly maps of shopper movement and sales activity.

The recognition that maps are data as well as pictures fuels this "data mining" perspective. Cognitive abstractions of data coupled with physical features for geographic reference form new and useful views of the spatial relationships within a data set. For example, the insets in figure 1 show three "snapshots" of an animated sequence of the surfaces depicting shopper movement (left side) and sales activity (right side). The checkout data for a twenty-four hour period was divided into hourly segments and the movement and sales surfaces generated were normalized, and then assigned a consistent color ramp for display.

When viewed in motion, the warmer tones (reds) of higher activity appear to roll in and out like wisps of fog under the Golden Gate Bridge. The similarities and miss-matches in the ebb and flow provide a dramatic view (and new insights) of the spatial/temporal relationships contained in the data. Data visualization techniques, such as animation and 3-D datascapes, render complex and colorless tables of numbers into pictures more appropriate for human consumption.

Although the human brain is good at many things, detailed analysis of mapped data is not one of them. Visualizing the hourly changes provides a general impression of the timing and patterns in shopper movement and sales activity. However, additional insight results from further map-*ematics* identifying locations of "significant" difference at each time step. This is accomplished by subtracting two surfaces (e.g., movement at midnight minus movement at 1am), calculating the mean and standard deviation of the difference surface, then isolating and displaying the locations that are more than one standard deviation above and below the mean. When animated, the progression of th pockets of change around the store forms yet another view of the checkout data.

Segmentation of a data set forms the basis of many of the extended data mining procedures. In addition to time (e.g., hourly time steps) the data can be grouped through spatial partitioning. For example, each department's "footprint" can be summarized into an index of shopper "yield" as a ratio of its average sales to its average movement—calculated hourly shows which departments are performing best at each time step.

A third way to segment a data set is by data characteristics. For example, traditional product "affinity" analysis that notes which items tended to be purchased together can be extended to its spatial implications. Common sense suggests that items with a high product affinity, such as shampoo and conditioner, should have a high spatial affinity (shelved close together). Proximity analysis is used to determine effective distance between items, normalized to an affinity index, and then compared to the pair's product affinity index. Miss-matches identify inconveniently shelved items—similar products shelved far apart, or dissimilar products close together. The affinity information also assists in optimizing the shelving of impulse and sales items for frequently changed action aisle and end-cap displays.

Figure 2 shows another data characteristics segmentation analysis. The top left map summarizes all of the shopper paths that contained items from Department 5 (Electronics delineated by the dotted rectangle). Note the concentration of paths within the vicinity of the Department indicating that purchasers of these items tended not to venture into other departments. The bottom left inset is a similar map for Department 3 (Card & Candy). Note the larger number and greater dispersion of paths compared to Department 5.

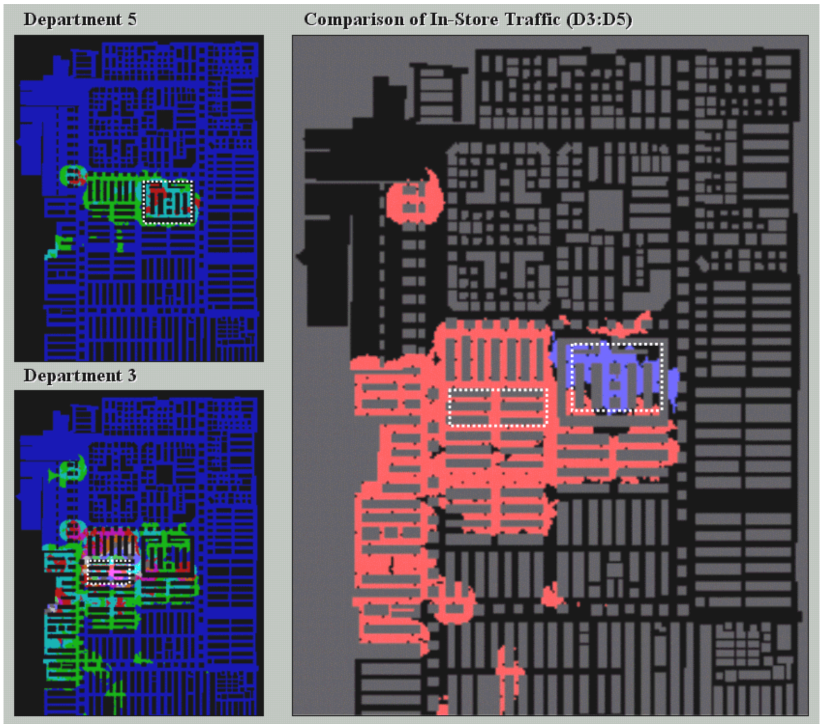

Figure 2. Departmental comparison of shopper movement patterns.

The large map on the right shows areas of large differences in path density between shopping carts containing items from Departments 3 (orange) and 5 (blue). It is expected that the areas within the departments (dotted rectangles) show large differences. The blue areas at the top, however, show more shoppers purchasing electronics traveled to men's wear that those purchasing cards & candy… a bit of common sense verified by empirical data. It leads one to wonder what insights might be gained from analysis of the orange area (more cards & candy traffic) or other departmental comparisons.

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