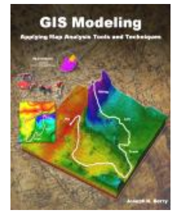
Beyond Mapping IV



GIS Modeling book

Topic 7 – Spatial Data Mining in Geo-business (Further Reading)

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Interpreting Interpolation Results (and why it is important)

(GeoWorld, August 2008)

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For some, previous discussion on generating map surfaces from point data (*"Myriad Techniques Help to Interpolate Spatial Distributions,"* GeoWorld, July 2008) might have been too simplistic—enter a few things then click on a data file and, *viola*, you have a equity loan percentage surface artfully displayed in 3D with a bunch of cool colors.

Actually, it is that easy to create one. The harder part is figuring out if the map generated makes sense and whether it is something you ought to use in analysis and important business decisions. This section discusses the relative amounts of information provided by the non-spatial arithmetic average versus site-specific maps by comparing the average and two different interpolated map surfaces. The discussion is further extended to describe a procedure for quantitatively assessing interpolation performance.

The top-left inset in figure 1 shows the map of the loan data's average. It's not very exciting and looks like a pancake but that's because there isn't any information about spatial variability in an average value—it assumes 42.88 percent is everywhere. The non-spatial estimate simply adds up all of the sample values and divides by the number of samples to get the average disregarding any geographic pattern.

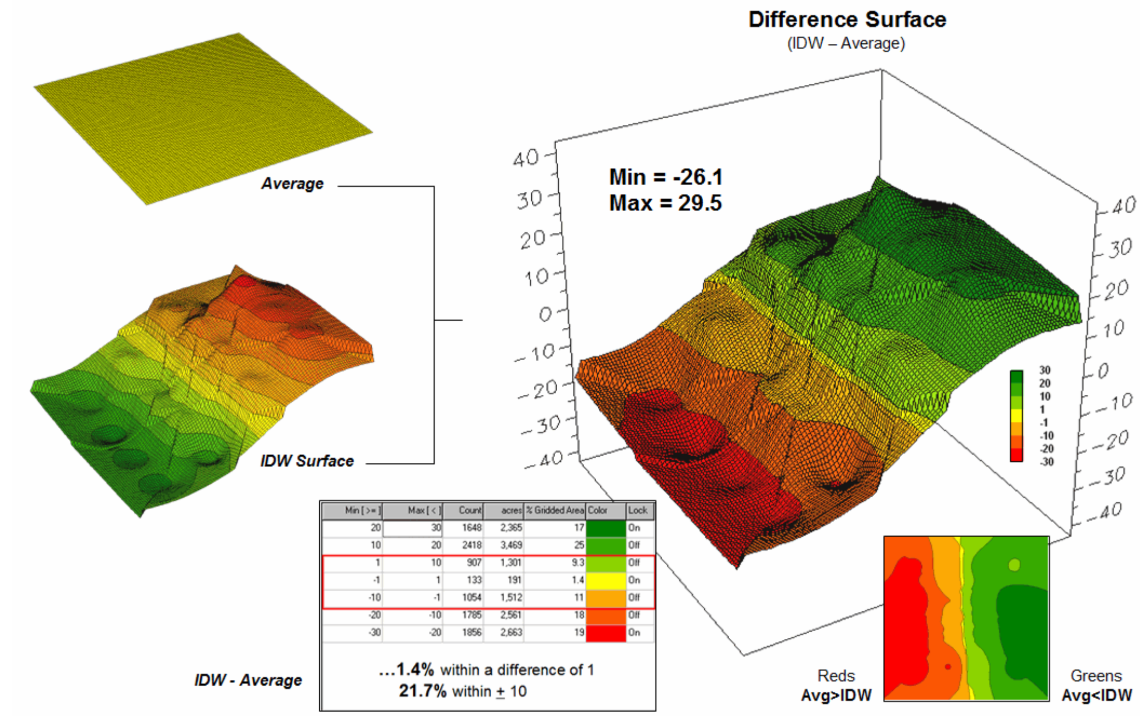


Figure 1. Spatial comparison of the project area average and the IDW interpolated surface.

The spatially-based estimates comprise the map surface just below the pancake. As described last month, *Spatial Interpolation* looks at the relative positioning of the samples values as well as their measure of loan percentage. In this instance the big bumps were influenced by high measurements in that vicinity while the low areas responded to surrounding low values.

The map surface in the right portion of figure 1 compares the two maps by simply subtracting them. The colors were chosen to emphasize the differences between the whole-field average estimates and the interpolated ones. The thin yellow band indicates no difference while the progression of green tones locates areas where the interpolated map estimated higher values than the average. The progression of red tones identifies the opposite condition with the average estimate being larger than the interpolated ones.

The difference between the two maps ranges from –26.1 to +29.5. If one assumes that a difference of +/- 10 would not significantly alter a decision, then about one-quarter of the area (9.3+1.4+11= 21.7%) is adequately represented by the overall average of the sample data. But that leaves about three-fourths of the area that is either well-below the average (18 + 19 = 37%) or well-above (25+17 = 42%). The upshot is that using the average value in either of these areas could lead to poor decisions.

Now turn your attention to figure 2 that compares maps derived by two different interpolation techniques—IDW (inverse distance weighted) and Krigging (an advanced spatial statistics technique using data trends). Note the similarity in the two surfaces; while subtle differences are visible, the overall trend of the spatial distribution is similar.

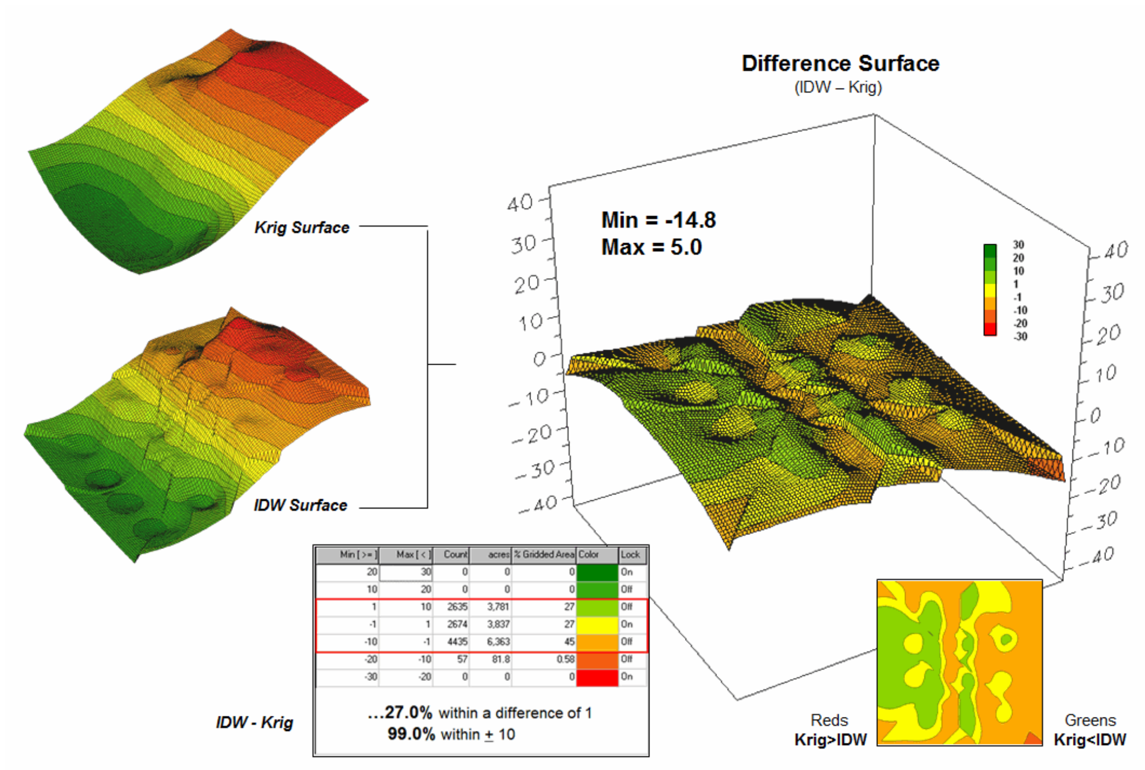


Figure 2. Spatial comparison of IDW and Krig interpolated surfaces.

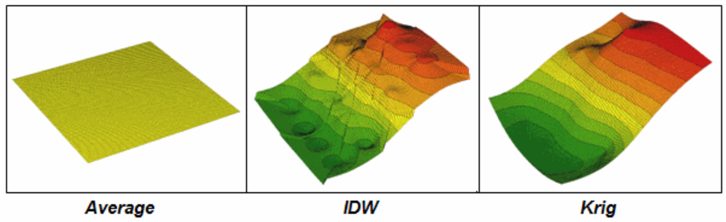
The difference map on the right confirms the similarity between the two map surfaces. The narrow band of yellow identifies areas that are nearly identical (within +/- 1.0). The light red locations identify areas where the IDW surface estimates a bit lower than the Krig ones (within -10); light green a bit higher (within +10). Applying the same assumption about plus/minus 10 difference being negligible for decision-making, the maps are effectively the same (99.0%).

So what's the bottom line? First, that there are substantial differences between an arithmetic average and interpolated surfaces. Secondly, that quibbling about the best interpolation technique isn't as important as using any interpolated surface for decision-making.

But which surface best characterizes the spatial distribution of the sampled data? The answer to this question lies in ***Residual Analysis***—a technique that investigates the differences between *estimated* and *measured* values throughout an area.

The table in figure 3 reports the results for twelve randomly positioned test samples. The first column identifies the sample ID and the second column reports the actual measured value for that location. Column C simply depicts the assumption that the project area average (42.88) represents each of the test locations. Column D computes the difference of the “estimate minus actual”—formally termed the *residual*. For example, the first test point (ID#1) estimated the average of 42.88 but was actually measured as 55.2, so -12.32 is the residual (42.88 - 55.20= -12.32) …quite a bit off. However, point #6 is a lot better (42.88-49.40= -6.52).

…Residual Analysis
is used to evaluate
interpolation performance
(Krig at .03 Normalized Error is best)



A	B	C	D	E	F	G	H
Test Set (randomly selected)							
ID	**Actual**	Average	**Avg-Actual**	IDW	**IDW-Actual**	Krig	**Krig-Actual**
1	55.20	42.88	**-12.32**	53.50	**-1.70**	53.60	**-1.60**
2	31.40	42.88	**11.48**	29.50	**-1.90**	30.60	**-0.80**
3	50.30	42.88	**-7.42**	50.60	**0.30**	49.20	**-1.10**
4	17.90	42.88	**24.98**	21.90	**4.00**	18.20	**0.30**
5	65.10	42.88	**-22.22**	63.90	**-1.20**	67.50	**2.40**
6	49.40	42.88	**-6.52**	51.20	**1.80**	50.30	**0.90**
7	17.80	42.88	**25.08**	20.40	**2.60**	16.40	**-1.40**
8	68.50	42.88	**-25.62**	66.50	**-2.00**	69.00	**0.50**
9	33.70	42.88	**9.18**	34.20	**0.50**	34.40	**0.70**
10	67.80	42.88	**-24.92**	64.90	**-2.90**	70.90	**3.10**
11	22.40	42.88	**20.48**	23.60	**1.20**	21.30	**-1.10**
12	55.60	42.88	**-12.72**	54.90	**-0.70**	57.40	**1.80**
Average values=	**44.59**	**42.88**		**44.59**		**44.90**	
Residual sum=			-20.54		0.00		3.70
Average error=			16.91		1.73		1.31
Normalized error=			$\boxed{0.38}$		$\boxed{0.04}$		$\boxed{0.03}$

Figure 3. A residual analysis table identifies the relative performance of average, IDW and Krig estimates.

The residuals for the IDW and Krig maps are similarly calculated to form columns F and H, respectively. First note that the residuals for the project area average are considerably larger than either those for the IDW or Krig estimates. Next note that the residual patterns between the IDW and Krig are very similar—when one is off, so is the other and usually by about the same amount. A notable exception is for test point #4 where the IDW estimate is dramatically larger.

The rows at the bottom of the table summarize the residual analysis results. The *Residual Sum* characterizes any bias in the estimates—a negative value indicates a tendency to underestimate with the magnitude of the value indicating how much. The –20.54 value for the whole-field average indicates a relatively strong bias to underestimate.

The *Average Error* reports how typically far off the estimates were. The 16.91 figure for area average is about ten times worse than either IDW (1.73) or Krig (1.31). Comparing the figures to the assumption that a plus/minus10 difference is negligible in decision-making, it is apparent that 1) the project area average is inappropriate and that 2) the accuracy differences between IDW and Krig are very minor.

The *Normalized Error* simply calculates the average error as a proportion of the average value for the test set of samples (1.73/44.59= 0.04 for IDW). This index is the most useful as it allows you to compare the relative map accuracies between different maps. Generally speaking, maps with normalized errors of more than .30 are suspect and one might not want to use them for important decisions.

So what's the bottom-bottom line? That Residual Analysis is an important component of geo-business data analysis. Without an understanding of the relative accuracy and interpolation error of the base maps, one cannot be sure of the recommendations and decisions derived from the interpolated data. The investment in a few extra sampling points for testing and residual analysis of these data provides a sound foundation for business decisions. Without it, the process becomes one of blind faith and wishful thinking with colorful maps.

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Author's Note: *Related discussion and hands-on exercises are in Topic 6, Surface Modeling in the workbook Analyzing Geo-Business Data (Berry, 2003; available at* ***www.innovativegis.com/basis/Books/AnalyzingGBdata/****).*

Get "Map-ematical" to Identify Data Zones

(GeoWorld, October 2008)

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Previous discussion introduced the concept of *Data Distance* as a means to measure data pattern similarity within a stack of map layers (*"Use Map Analysis to Characterize Data Groups,"* GeoWorld, September 2008). One simply mouse-clicks on a location, and all of the other locations are assigned a similarity value from 0 (zero percent similar) to 100 (identical) based on a set of specified map layers. The statistic replaces difficult visual interpretation of a series of side-by-side map displays with an exact quantitative measure of similarity at each location.

An extension to the technique allows you to circle an area then compute similarity based on the typical data pattern within the delineated area. In this instance, the computer calculates the average value within the area for each map layer to establish the comparison data pattern, and then determines the normalized data distance for each map location. The result is a map showing how similar things are throughout a project area to the area of interest.

The link between *Geographic Space* and *Data Space* is the keystone concept. As shown in figure 1, spatial data can be viewed as either a map, or a histogram. While a map shows us "*where is what*," a histogram summarizes "*how often*" data values occur (regardless where they occur). The top-left portion of the figure shows a 2D/3D map display of the relative housing density within a project area. Note that the areas of high housing Density along the northern edge generally coincide with low home Values.

The histogram in the center of the figure depicts a different perspective of the data. Rather than positioning the measurements in geographic space it summarizes the relative frequency of their occurrence in data space. The X-axis of the graph corresponds to the Z-axis of the map—relative level of housing Density. In this case, the spikes in the graph indicate measurements that occur more frequently. Note the relatively high occurrence of density values around 2.6 and 4.7 units per acre. The left portion of the figure identifies the data range that is unusually high (more than one standard deviation above the mean; 3.56 + .80 = 4.36 or greater) and mapped onto the surface as the peak in the NE corner. The lower sequence of graphics in the figure depicts the histogram and map that identify and locate areas of unusually low home values.

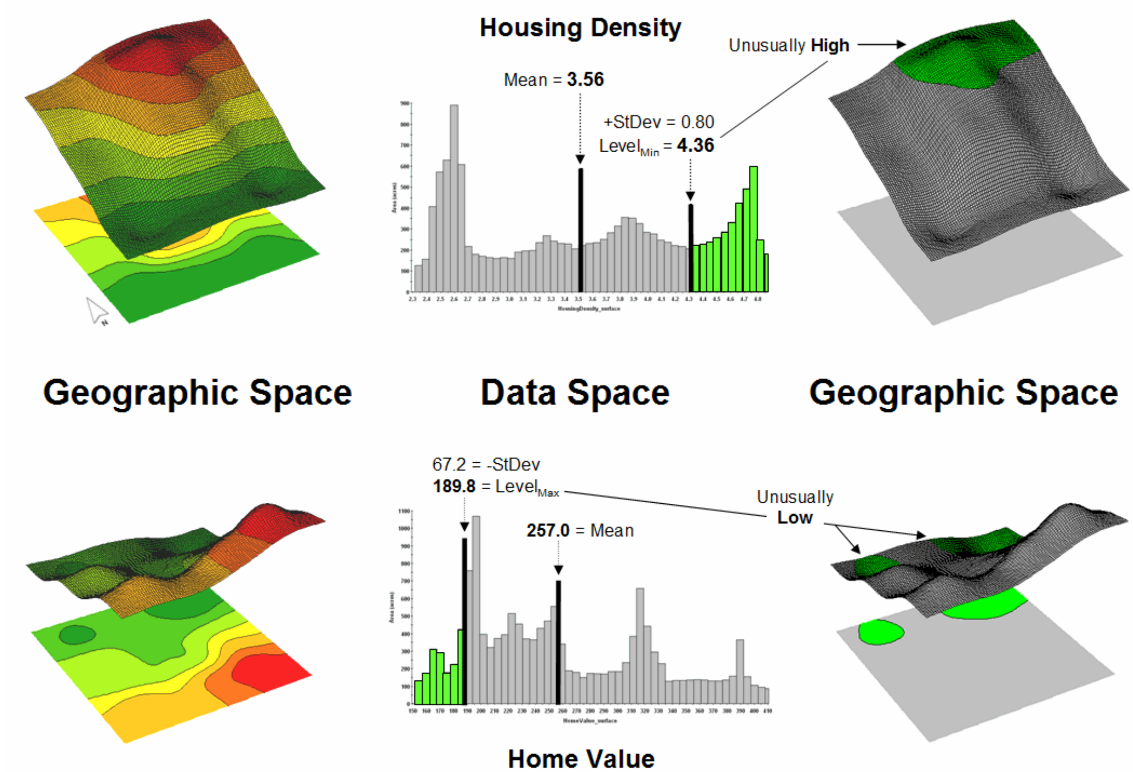

Figure 1. Identifying areas of unusually high measurements.

Figure 2 illustrates combining the housing Density and Value data to locate areas that have high measurements in both. The graphic in the center is termed a *Scatter Plot* that depicts the joint occurrence of both sets of mapped data. Each ball in the scatter plot schematically represents a location in the field. Its position in the scatter plot identifies the housing Density and home Value measurements for one of the map locations—10,000 in all for the actual example data set. The balls shown in the light green shaded areas of the plot identify locations that have high Density <u>or</u> low Value; the bright green area in the upper right corner of the plot identifies locations that have high Density <u>and</u> low Value.

The aligned maps on the right side of figure 2 show the geographic solution for the high D and low V areas. A simple map-*ematical* way to generate the solution is to assign 1 to all locations of high Density and Value map layers (green). Zero (grey) is assigned to locations that fail to meet the conditions. When the two binary maps (0 and1) are multiplied, a zero on either map computes to zero. Locations that meet the conditions on both maps equate to one (1*1 = 1). In effect, this "level-slice" technique locates any data pattern you specify—just assign 1 to the data interval of interest for each map variable in the stack, and then multiply.

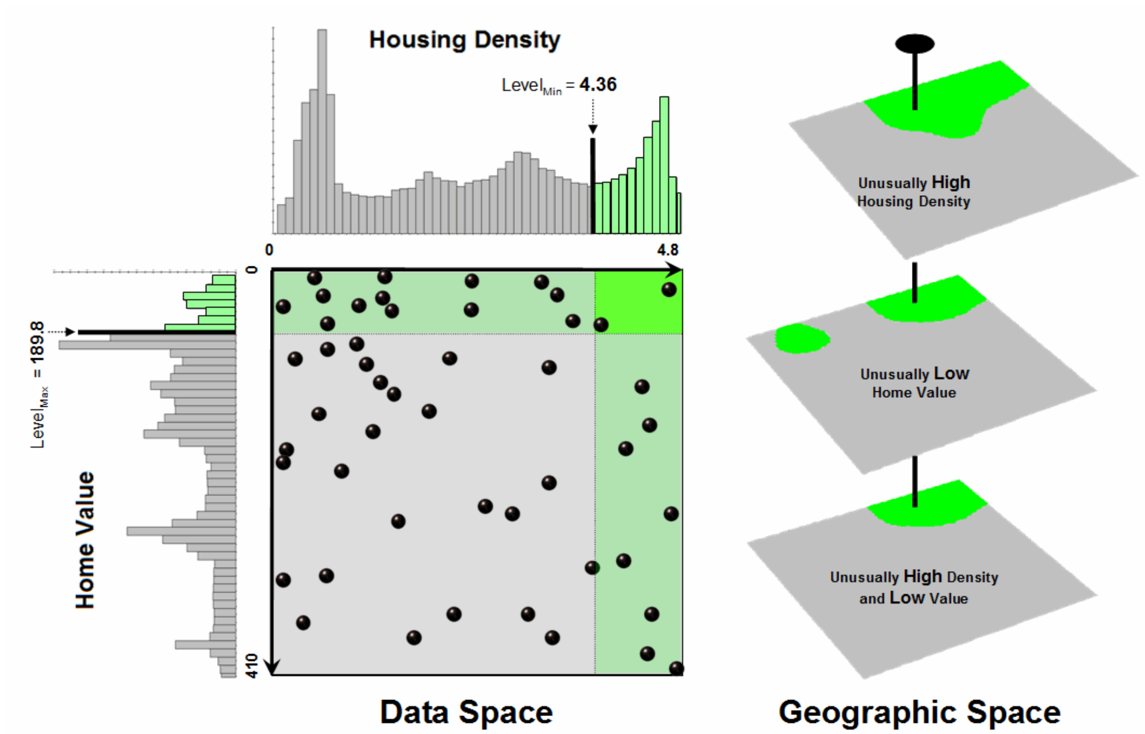

Figure 2. Identifying joint coincidence in both data and geographic space.

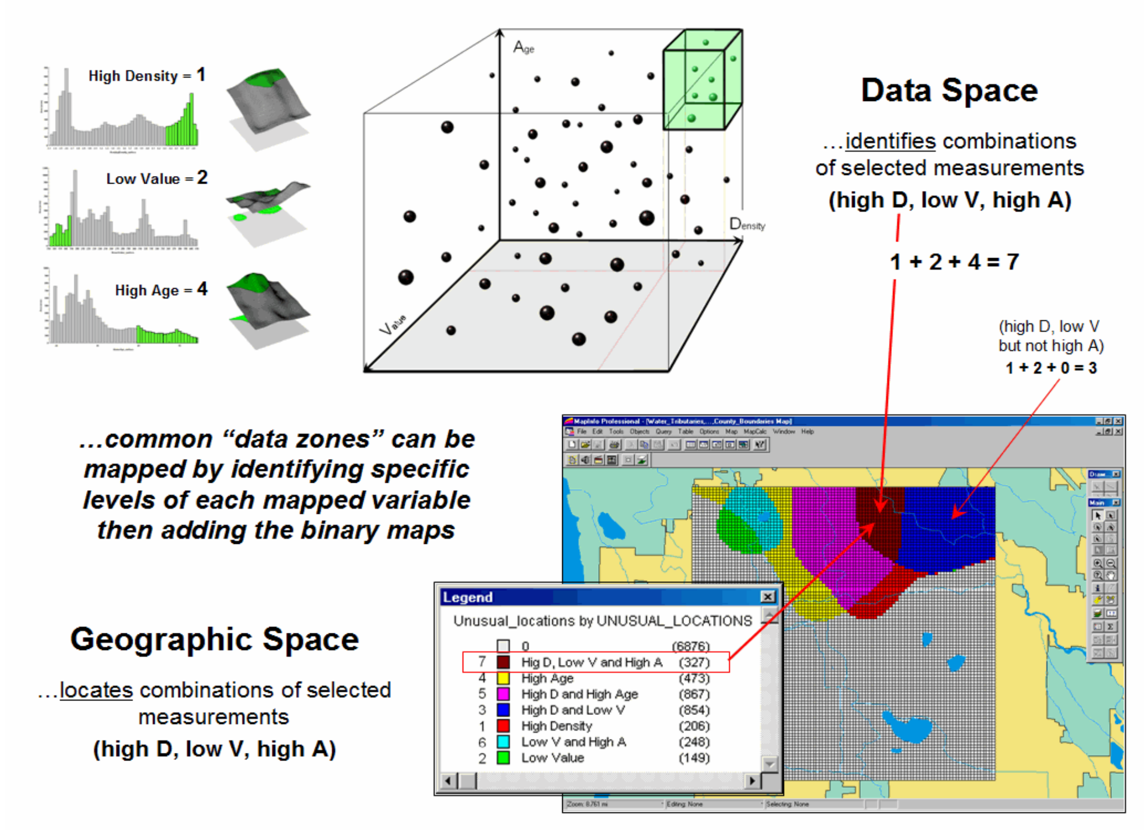

Figure 3. Level-slice classification using three map variables.

Figure 3 depicts level slicing for areas that are unusually low housing Density, high Value and low Age. In this instance the data pattern coincidence is a box in 3-dimensional scatter plot space (upper-right corner toward the back). However a slightly different map-*ematical* trick was employed to get the detailed map solution shown in the figure.

On the individual maps, areas of high Density were set to D= 1, low Value to V= 2 and high Age to A= 4, then the binary map layers were added together. The result is a range of coincidence values from zero (0+0+0= 0; gray= no coincidence) to seven (1+2+4= 7; dark red for location meeting all three criteria). The map values in between identify the areas meeting other combinations of the conditions. For example, the dark blue area contains the value 3 indicating high D and low V but not high A (1+2+0= 3) that represents about three percent of the project area (327/10000= 3.27%). If four or more map layers are combined, the areas of interest are assigned increasing binary progression values (…8, 16, 32, etc)—the sum will always uniquely identify all possible combinations of the conditions specified.

While level-slicing isn't a very sophisticated classifier, it illustrates the usefulness of the link between Data Space and Geographic Space to identify and then map unique combinations of conditions in a set of mapped data. This fundamental concept forms the basis for more advanced geo-statistical analysis—including map clustering that will be the focus of next month's column.

Author's Note: *Related discussion and hands-on exercises are in Topic 7, Spatial Data Mining in the workbook Analyzing Geo-Business Data (Berry, 2003; available at* ***www.innovativegis.com/basis/Books/AnalyzingGBdata/****).*

Can We Really Map the Future?

(GeoWorld, December 2008)

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Talk about the future of geo-business—how about mapping things yet to come? Sounds a bit farfetched but spatial data mining and predictive modeling is taking us in that direction. For years non-spatial statistics has been predicting things by analyzing a sample set of data for a numerical relationship (equation) then applying the relationship to another set of data. The drawbacks are that a non-spatial approach doesn't account for geographic patterns and the result is just summary of the overall relationship for an entire project area.

Extending predictive analysis to mapped data seems logical because maps at their core are just organized sets of numbers and the GIS toolbox enables us to link the numerical and geographic distributions of the data. The past several columns have discussed how the computer can "see" spatial data relationships including "descriptive techniques" for assessing *map similarity*, *data zones*, and *clusters*. The next logical step is to apply "predictive techniques" that generates mapped forecasts of conditions for other areas or time periods.

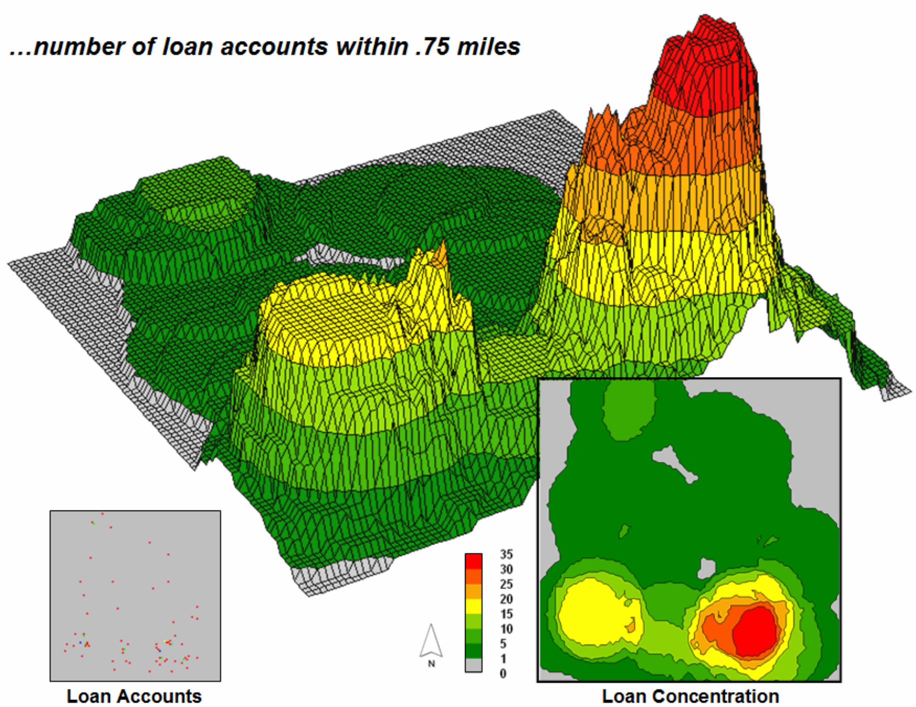

Figure 1. A loan concentration surface is created by summing the number of accounts for each map location within a specified distance.

To illustrate the process, suppose a bank has a database of home equity loan accounts they have issued over several months. Standard geo-coding techniques are applied to convert the street address of each sale to its geographic location (latitude, longitude). In turn, the geo-tagged data is used to "burn" the account locations into an analysis grid as shown in the lower left corner of figure 1. A roving window is used to derive a Loan Concentration surface by computing the number of accounts within a specified distance of each map location. Note the spatial distribution of the account density— a large pocket of accounts in the southeast and a smaller one in the southwest.

The most frequently used method for establishing a quantitative relationship among variables involves ***Regression***. It is beyond the scope of this column to discuss the underlying theory of regression; however in a conceptual nutshell, a line is "fitted" in data space that balances the data so the differences from the points to the line (termed the residuals) are minimized and the sum of the differences is zero. The equation of the best-fitted line becomes a prediction equation reflecting the spatial relationships among the map layers.

To illustrate predictive modeling, consider the left side of figure 2 showing four maps involved in a regression analysis. The loan Concentration surface at top is serves as the *Dependent Map Variable* (to be predicted). The housing Density, Value, and Age surfaces serve as the *Independent Map Variables* (used to predict). Each grid cell contains the data values used to form the relationship. For example, the "pin" in the figure identifies a location where high loan Concentration coincides with a low housing Density, high Value and low Age response pattern.

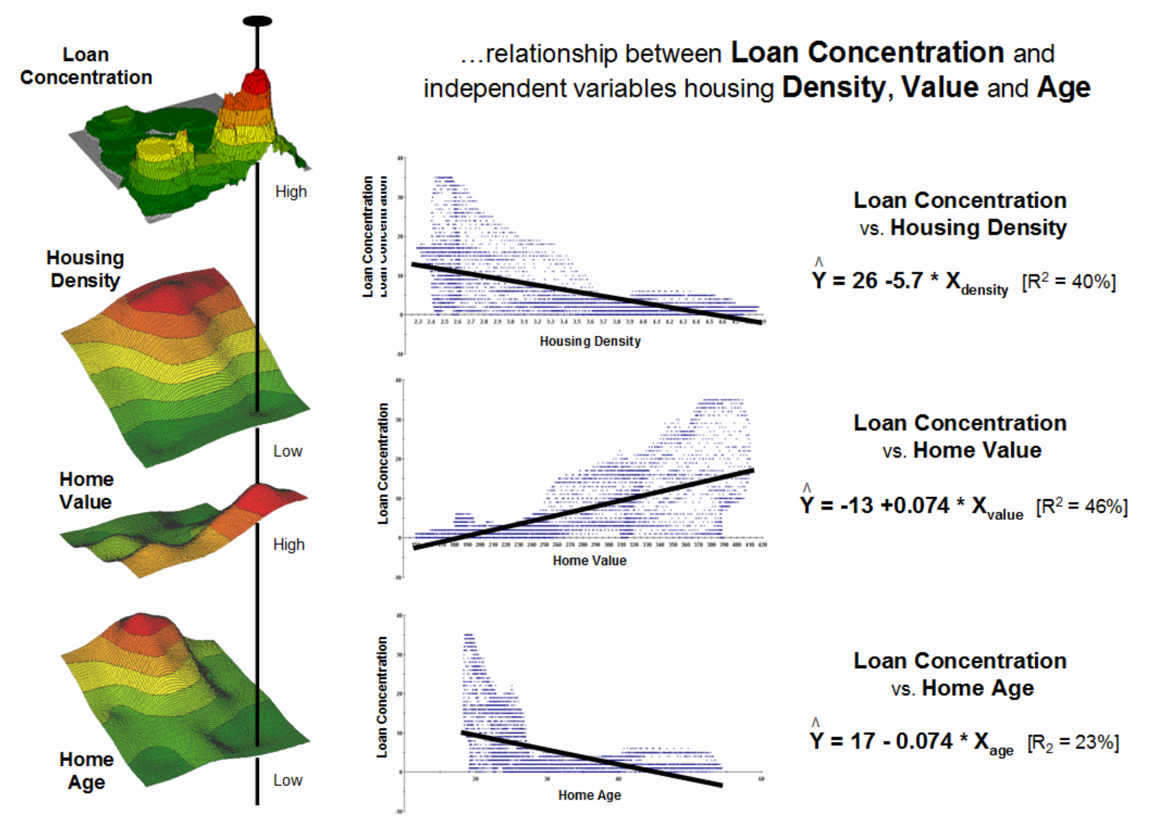

Figure 2. Scatter plots and regression results relate Loan Density to three independent variables (housing Density, Value and Age).

The scatter plots in the center of the figure graphically portray the consistency of the relationships. The Y axis tracks the dependent variable (loan Concentration) in all three plots while the X axis follows the independent variables (housing Density, Value, and Age). Each plotted point represents the joint condition at one of the grid locations in the project area— 10,000 dots in each scatter plot. The shape and orientation of the cloud of points characterizes the nature and consistency of the relationship between the two map variables.

A plot of a perfect relationship would have all of the points forming a line. An upward directed line indicates a *positive correlation* where an increase in X always results in a corresponding increase in Y. A downward directed line indicates a *negative correlation* with an increase in X resulting in a corresponding decrease in Y. The slope of the line indicates the extent of the relationship with a 45-degree slope indicating a 1-to-1 unit change. A vertical or horizontal line indicates *no correlation*— a change in one variable doesn't affect the other. Similarly, a circular cloud of points indicates there isn't any consistency in the changes.

Rarely does the data plot into these ideal conditions. Most often they form dispersed clouds like the scatter plots in figure 2. The general trend in the data cloud indicates the amount and nature of correlation in the data set. For example, the loan Concentration vs. housing Density plot at the top shows a large dispersion at the lower housing Density ranges with a slight downward trend. The opposite occurs for the relationship with housing Value (middle plot). The housing Age relationship (bottom plot) is similar to that of housing Density but the shape is more compact.

Regression is used to quantify the trend in the data. The equations on the right side of figure 2 describe the "best-fitted" line through the data clouds. For example, the equation Y= 26.0 – 5.7X relates loan Concentration and housing Density. The loan Concentration can be predicted for a map location with a housing Density of 3.4 by evaluating Y= 26.0 – (5.7 * 3.4) = 6.62 accounts estimated within .75 miles. For locations where the prediction equation drops below 0 the prediction is set to 0 (infeasible negative accounts beyond housing densities of 4.5).

The "R-squared index" with the regression equation provides a general measure of how good the predictions ought to be— 40% indicates a moderately weak predictor. If the R-squared index was 100% the predicting equation would be perfect for the data set (all points directly falling on the regression line). An R-squared index of 0% indicates an equation with no predictive capabilities.

In a similar manner, the other independent variables (housing Value and Age) can be used to derive a map of expected loan Concentration. Generally speaking it appears that home Value exhibits the best relationship with loan Concentration having an R-squared index of 46%. The 23% index for housing Age suggests it is a poor predictor of loan Concentration.

Multiple regression can be used to simultaneously consider all three independent map variables as a means to derive a better prediction equation. Or more sophisticated modeling techniques, such as Non-linear Regression and Classification and Regression Tree (CART) methods, can be used that often results in an R-squared index exceeding 90% (nearly perfect).

The bottom line is that predictive modeling using mapped data is fueling a revolution in sales forecasting. Like parasailing on a beach, spatial data mining and predictive modeling are affording an entirely new perspective of geo-business data sets and applications by linking data space and geographic space through grid-based map analysis.

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Author's Note: *Related discussion and hands-on exercises on spatial regression are in Topic 8, Predictive Modeling in the workbook* Analyzing Geo-Business Data *(Berry, 2003; available at* ***www.innovativegis.com/basis/Books/AnalyzingGBdata/****).*

Follow These Steps to Map Potential Sales

(GeoWorld, January 2009)

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My first sojourn into geo-business involved an application to extend a test marketing project for a new phone product (nick-named "teeny-ring-back") that enabled two phone numbers with distinctly different rings to be assigned to a single home phone—one for the kids and one for the parents. This pre-Paleolithic project was debuted in 1991 when phones were connected to a wall by a pair of copper wires and street addresses for customers could be used to geo-code the actual point of sale/use. Like pushpins on a map, the pattern of sales throughout the city emerged with some areas doing very well (high sales areas), while in other areas sales were few and far between (low sales areas).

The assumption of the project was that a relationship existed between conditions throughout the city, such as income level, education, number in household, etc. could help explain sales pattern. The demographic data for the city was analyzed to calculate a prediction equation between product sales and census data.

The prediction equation derived from test market sales in one city could be applied to another city by evaluating exiting demographics to "solve the equation" for a predicted sales map. In turn, the predicted sales map was combined with a wire-exchange map to identify switching facilities that required upgrading before release of the product in the new city. Although GIS systems were crude at the time, the project was deemed a big success.

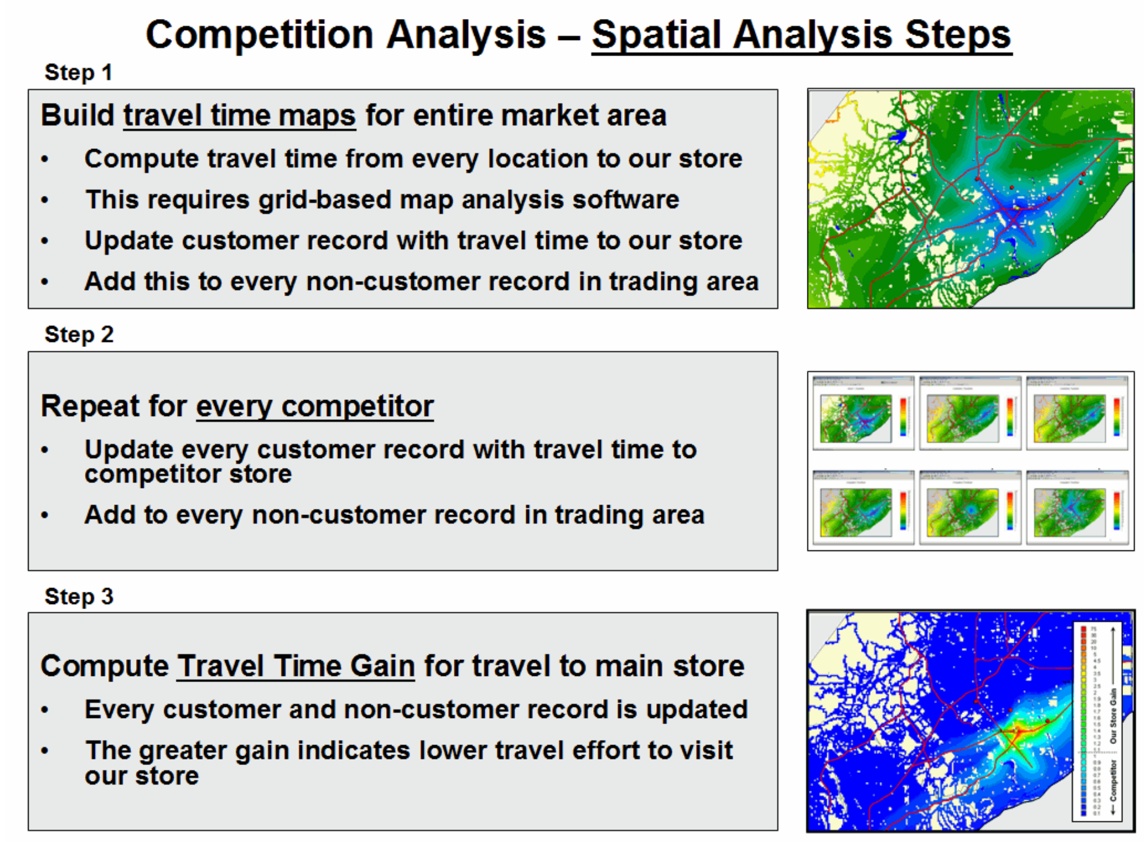

Figure 1. Spatial Modeling derives the relative travel time relationships for a store and each competitor store for all locations and then links this information to customer records.

Now fast-forward to more contemporary times. A GeoWorld feature article described a similar, but much more thorough analysis of retail sales competition (*Beyond Location, Location, Location: Retail Sales Competition Analysis*, GeoWorld, March 2006; see Author's Note). Figure 1 outlines the steps for determining competitive advantage for various store locations.

Most GIS users are familiar with network analysis that accepts starting and ending locations and then determines the best route between the two points along a road network. However the complexity of retail competition analysis with tens of thousands of customers and dozens of competitor locations makes the traditional point-to-point navigational solution impractical. A more viable approach uses grid-based map analysis involving continuous surfaces (steps 1 and 2 in figure 1).

Step 1 map shows the grid-based solution for travel-time from "Our Store" to all other grid locations in the project area. The blue tones identify grid cells that are less than twelve minutes away assuming travel on the highways is four times faster than on city streets. Note the star-like pattern elongated around the highways and progressing to the farthest locations (warmer tones). In a similar manner, competitor stores are identified and the set of their travel time surfaces forms a series of geo-registered maps supporting further analysis (Step 2).

Step 3 combines this information for a series of maps that indicate the relative cost of visitation between our store and each of the competitor stores (pair-wise comparison as a normalized ratio). The derived “Gain” factor for each map location is a stable, continuous variable encapsulating travel-time differences that is suitable for mathematical modeling. A Gain of less than 1.0 indicates the competition has an advantage with larger values indicating increasing advantage for our store. For example, a value of 2.0 indicates that there is a 200% lower cost of visitation to our store over the competition.

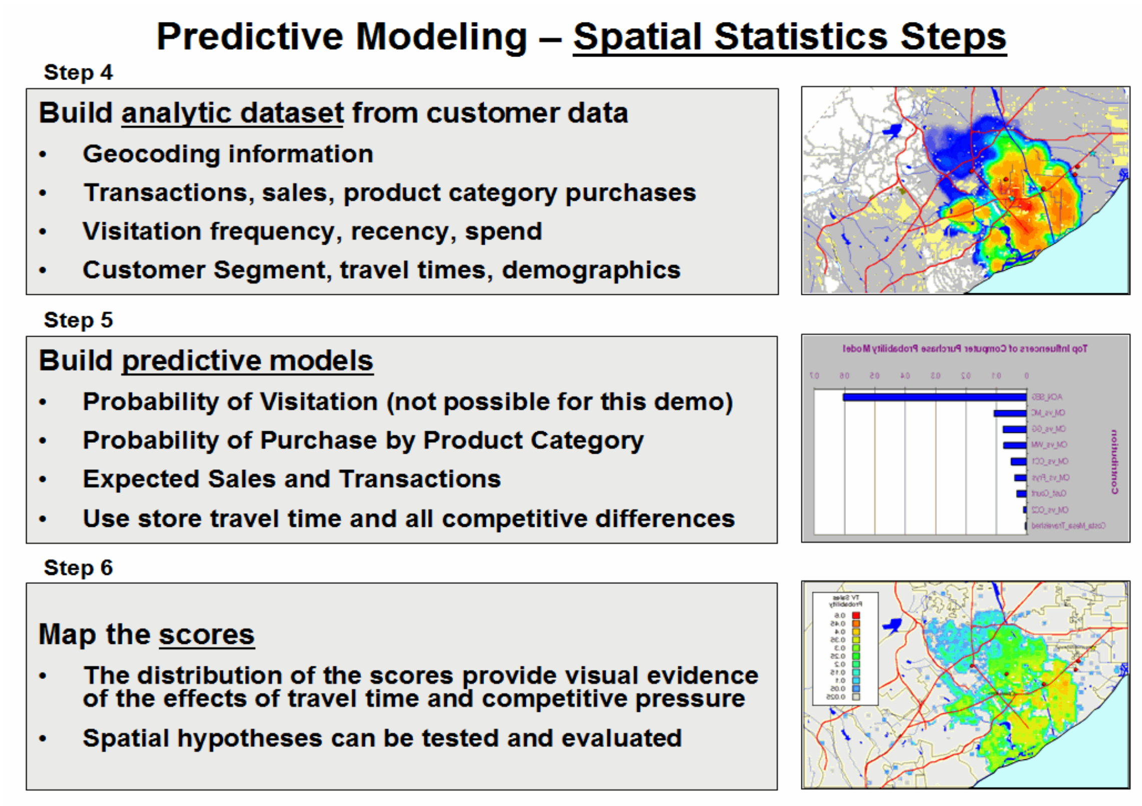

Figure 2. Predictive Modeling steps use spatial data mining procedures for relating spatial and non-spatial factors to sales data to derive maps of expected sales for various products.

Figure 2 summarizes the predictive modeling steps involved in competition analysis of retail data. The geo-coding link between the analysis frame and a traditional customer dataset containing sales history for more than 80,000 customers was used to append travel-times and Gain factors for all stores in the region (Step 4).

The regression hypothesis was that sales would be predictable by characteristics of the customer in combination with the travel-time variables (Step 5). A series of mathematical models are built that predict the probability of purchase for each product category under analysis (see Author’s Note). This provides a set of model scores for each customer in the region. Since a number of customers could be found in many grid cells, the scores were averaged to provide an estimate of the likelihood that a person from each grid cell would travel to our store to purchase one of the analyzed products. The scores for each product are mapped to identify the spatial distribution of probable sales, which in turn can be “mined” for pockets of high potential sales.

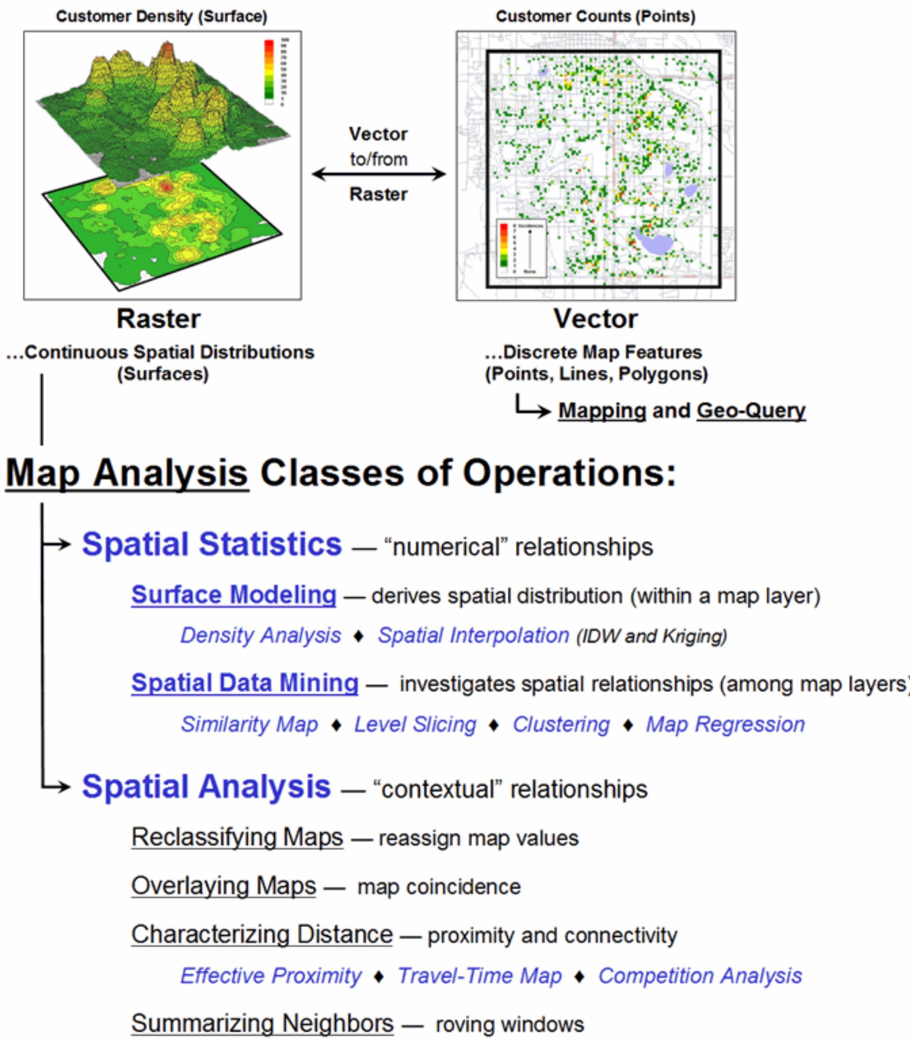

Figure 3. Map Analysis exploits the digital nature of modern maps to examine spatial patterns and relationships within and among mapped data.

Targeted marketing, retail trade area analysis, competition analysis and predictive modeling provide examples applying sophisticated *Spatial Analysis* and *Spatial Statistics* to improve decision making. The techniques described in the past nine Beyond Mapping columns on Geo-business applications have focused on Map Analysis— procedures that extend traditional mapping and geo-query to map-ematically based analysis of mapped data. Figure 3 outlines the classes of operations described in the series (blue highlighted techniques were specifically discussed).

Recall that the keystone concept is an *Analysis Frame* of grid cells that provides for tracking the continuous spatial distributions of mapped variables and serves as the primary key for linking spatial and non-spatial data sets. While discrete sets of points, lines and polygons have served our mapping demands for over 8,000 years and keep us from getting lost, the expression of mapped data as continuous spatial distributions (surfaces) provides a new foothold for the contextual and numerical analysis of mapped data— in many ways, “thinking with maps” is more different than it is similar to traditional mapping.

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Author’s Note: *a copy of the article Beyond Location, Location, Location: Retail Sales Competition Analysis, is posted online at www.innovativegis.com/basis/present/GW06_retail/GW06_Retail.htm. The predictive modeling used a specialized data mining technology, KXEN K2R, based on Vapnik Statistical Learning Theory (www.kxen.com).*

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