Visual Data Mining in Large Geospatial Point Sets

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The Wide Area Layout Data Observer (Waldo) complements uniquely human abilities with current computing technologies to find location-related patterns in large geospatial data sets.

Many existing and emergent applications collect and reference data by geospatial location. Credit card transactions, for example, include addresses of both the place of purchase and the purchaser; telephone records include addresses and sometimes cell phone zones and geocoordinates; and population census tables contain addresses and other location information. These data sets are sources of potentially valuable information that can give their holders a competitive advantage. Government agencies also publish a wealth of statistical information that data analysts can apply to key problems in public health and safety or combine with proprietary data. The difficulty lies in finding the details that reveal the fine structures hidden in this data.

Many approaches to analyzing such data exist—for example, statistical models, clustering, and association rules. Effective spatial data mining, however, must focus on finding location-related patterns and relationships. Interactive visual data exploration is important to spatial data mining.[1,2] The wide area layout data observer (Waldo) involves the analyst in data exploration, thus complementing human perceptual skills, imagination, and flexibility with current computer systems to process large volumes of data and generate sophisticated displays. In this setting, the analyst directly interacts with the data, solving problems by applying domain expertise and general background knowledge to form and validate new hypotheses.

In recent decades, visual data-mining techniques have proven valuable in exploratory data analysis, and they have strong potential in the exploration of large databases.[3] Visual data exploration is particularly useful when little is known about the data and when goals are indistinct. Because users directly guide the exploration process, they can easily shift or adjust the goals as needed. However, analyzing the torrent of spatial details available in these large (terabytes and beyond) databases to extract interesting knowledge or general characteristics is almost impossible for users. Thus we need new, more scalable visual techniques.

Visualizing geospatial data

Geospatial data describe real-world objects or phenomena with specific locations and associated statistical values or attributes. By considering just one statistical attribute at a time, we can interpret geospatial data sets as points in a 3D data space—that is, two geographical dimensions and a statistical dimension. Because real-world data set distributions are often nonuniform, the data points form readily identifiable 3D point clouds. Figure 1a shows a household income distribution in a 3D data space spanned by longitude, latitude, and median household income. Figure 1b shows an *xy*-plot of the 3D point clouds.

Visualizing large geospatial data sets involves mapping the two geographical dimensions to screen coordinates and encoding the statistical value by color. (Keim et al. give a good overview of visual data-mining techniques for geospatial data sets.[4]) The difficulty is finding a useful mapping function *f*.

When using a simple dot plot mapping function *f*, developers encounter two important visualization challenges:

- Overplotting obscures data points in densely populated areas; however, sparsely populated areas waste space while conveying scant detailed information.
- Small clusters are difficult to find. In general, they aren't noticeable enough in conventional maps and are often occluded by large clusters.

These difficulties lead to three important visual exploration goals for geospatial data, which we express as mapping constraints: *no overlap*, *position preservation*, and *clustering.* (The "Visual Exploration Goals" sidebar describes these goals.)

We bring visualization to data analysts' desktops to

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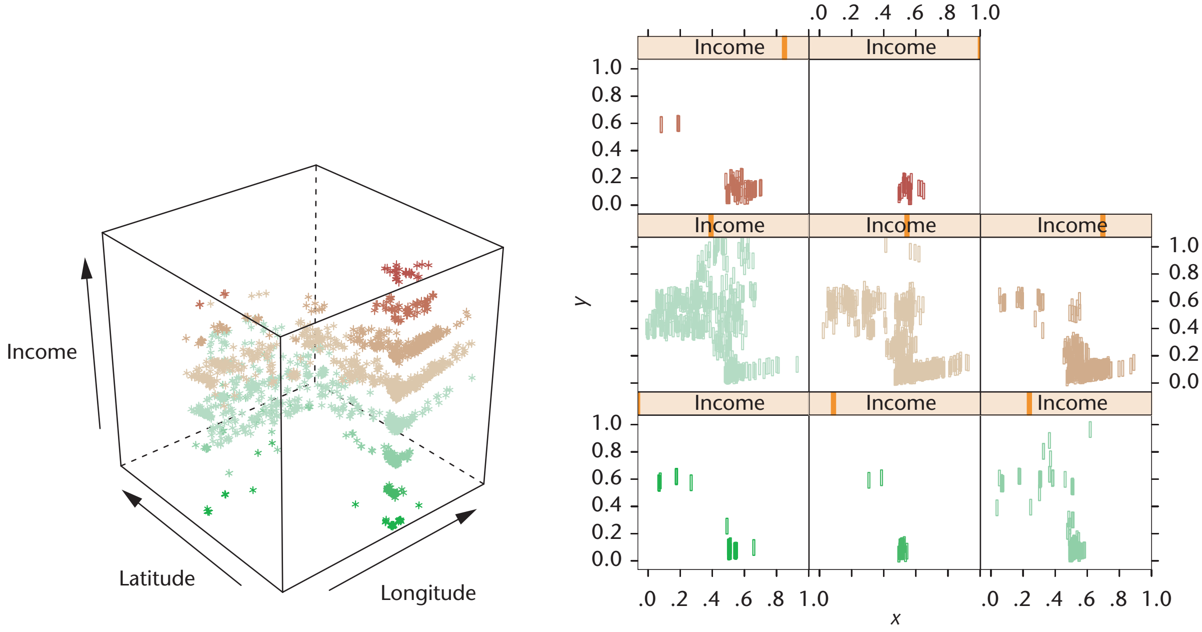

(a) (b)

1 Plotting of geospatial data points on (a) longitude, latitude, and statistical attribute (income in this example) 3D-point clouds arises even in small real-world data sets (1 percent of the data); and (b) an *xy*-plot of the 3D-point clouds. The goal is to display all 3D-point clouds in a single continuous display without overlap. (Example shows a small sample, 1 percent, from the US Census; see http://www.census.gov, *1999 New York Household Income* data set.)

Visual Exploration Goals

We define the visualization of georeferenced data as a mapping of input data points, with their associated positions and statistical attributes, to unique positions on an output map. The mapping function must satisfy three main constraints: *no overlap*, *position preservation*, and *clustering*. We formally define these constraints as follows.

Let A be the set of input points $A = \{a_0, \ldots, a_{N-1}\}$, where $a_i = a_i^x, a_i^y$ is each point's original position and $S_1(a_i), \ldots, S_k(a_i)$ are its associated statistical parameters. We assume A is large, so we will likely have many data points i and j for which the original positions are very close or even identical—that is, $a_i \approx a_j$. We define the data display space (screen or window space) $DS \subset INT^2$ as $DS = \{0, \ldots, x_{\max} - 1\} \times \{0, \ldots, y_{\max} - 1\}$, where $x_{\max}$ and $y_{\max}$ are the display bounds. The algorithm attempts to determine a mapping function f of the original data set to a solution set $B = \{b_0, \ldots, b_{N-1}, 0 \leq b_i^x \leq x_{max} = 1, 0 \leq b_i^y \leq y_{max} = 1$ such that $f : A \to B$, $f(a_i) = b_i \; \forall i = \{0, \ldots, N - 1\}$—that is, f determines the new position b_i of a_i.

Figure A shows graphical representations of the mapping constraints. Visual exploration techniques aim to balance the position preservation and clustering constraints under the condition that the no-overlap constraint is always satisfied.

No overlap. All data points are individually visible, with each assigned a unique pixel position (Figure A1). We express this formally as $i \neq j \Rightarrow b_i \neq b_j \; \forall i, j \in \{1, \ldots, N - 1\}$.

Position preservation. New positions should be as close as possible to the original positions. We measure this constraint using the points' absolute distance from their original positions (Figure A2) or their relative distance from each other (Figure A3). This gives us the following optimization goals:

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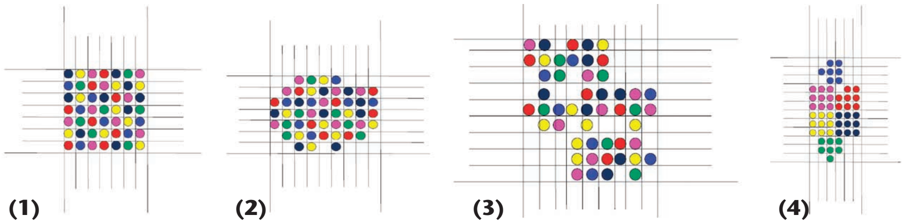
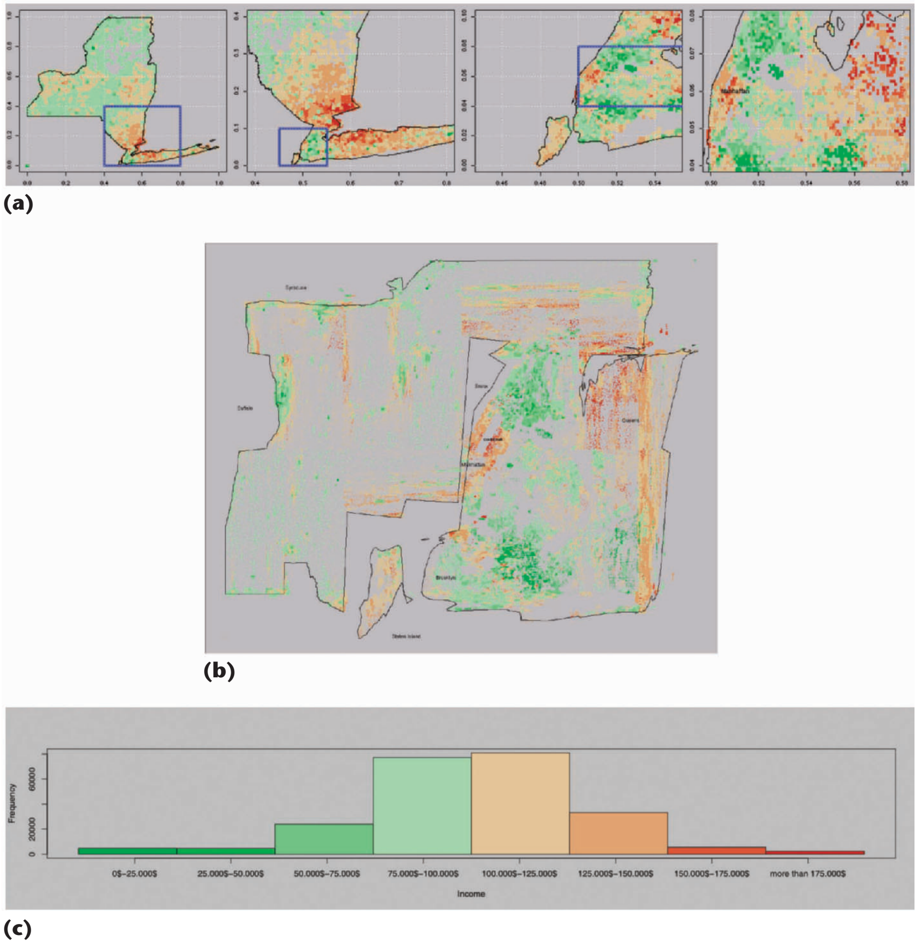


A Problem definition constraints: (1) no overlap, (2) absolute position preservation, (3) relative position preservation, and (4) clustering constraint. Visual exploration aims to find a good tradeoff between 2, 3, and 4 such that 1 is always satisfied.



2 **Zooming solves neither the overplotting nor pixel coherence problems. (a) Overplotting on a conventional map with interactive zooming, showing only a small sample of the data. (b) PixelMap showing 100 percent of the data without overplotting. (c) Household income histogram. Green represents low income and red represents high income.**

encourage more intuitive and productive exploration of large geospatial data resources. High-resolution pixilated displays are increasingly available in both wall-sized and desktop units. Although extra display pixels let us show more data, this technology alone doesn't eliminate overplotting. Figure 2 shows the resulting visualization in case of zoom in. Figure 3 shows how the degree of overlap—that is, the degree to which data points share a pixel position—varies with screen resolution. Although the number of points assigned to the same position decreases as resolution increases, even large, high-resolution displays, such as the display in Figure 4a, can't achieve a zero overlap and could lose potentially interesting patterns.

Another common solution is to aggregate all data points in each region and only show a summary. With this approach, the visualization reflects all the data points but doesn't show all available information in the dense regions. (See the "Related Work" sidebar for a discussion of other approaches.)

Wide area layout data observer

In addition to a basic visualization technique, successful data exploration often involves adjusting the

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- absolute position preservation,

$$\sum_{i=0}^{N-1} d\left(a_i, b_i\right) \to \min$$

- relative position preservation,

$$\sum_{i=0}^{N-1} \sum_{j=0, i\neq j}^{N-1} \left(d\left(b_i, b_j\right) - d\left(a_i, a_j\right)\right)^2 \to \min$$

The application determines the weighting between absolute and relative position preservation to be used.

We define the distance function d by an L^m – norm (m = 1 or 2):

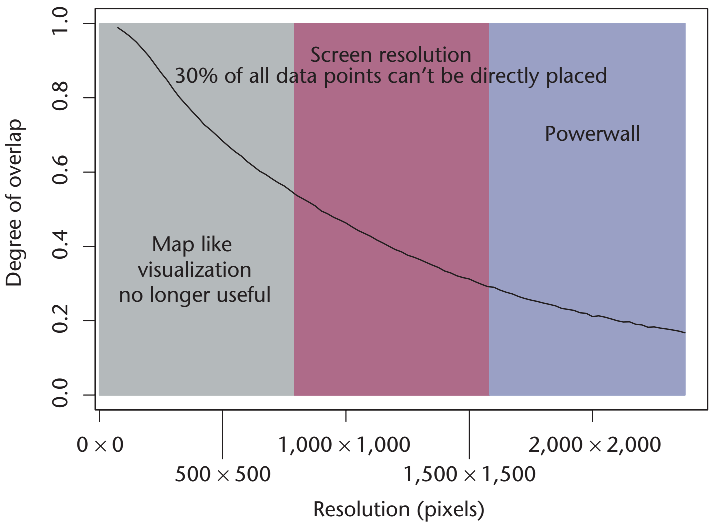
$$d\left(b_i, b_j\right) = \sqrt[m]{\left(b_i^x - b_j^x\right)^m + \left(b_i^y - b_j^y\right)^m}$$

Clustering. The clustering constraint involves repositioning the data points so those with high similarity in statistical attribute S_i (where S_i, $i \in \{0, \ldots, k\}$) are near each other (Figure A4). (We assume clustering depends on the statistical attribute $S \in \{S_0, \ldots, S_k\}$.) In other words, other points in the neighborhood of any given data point should have similar values, yielding pixel coherence. To formalize this constraint, we define the neighborhood NH of a data point a_i and a distance function d_S on the statistical attribute S:

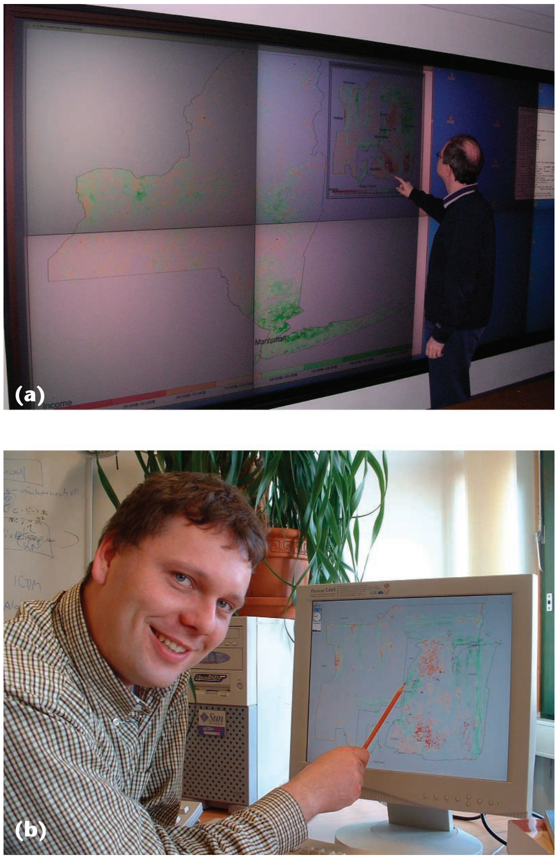
$$\sum_{i=0}^{N-1} \sum_{b_j \in NH(b_i)} d_S(S(b_i), S(b_j)) \to \min$$

This neighborhood function sums up all the differences in S between each point and its neighboring points. We define the function as $NH(b_i) = \{b_j \mid d(b_i, b_j) < \varepsilon\}$.

Because S_i can have a highly nonuniform distribution, applying nonlinear scaling to S before computing distances d_S might also be necessary. In addition, in some situations many similar points might be in some regions of the map, while only a few are in others. In this case, varying ε in the region under consideration might be helpful.



3 **Varying degree of pixel overlap depending on screen resolution. Even with a screen resolution of 1,600 × 1,200, overlap is about 0.3 degrees; 30 percent of our data points (about 12,000 points) from the *US Year 2000 Census Household Income* data set can't be directly placed without overwriting occupied pixels.**



4 **Large displays solve neither the overplotting nor the pixel coherence problems. Only alternative pixel-based visualization techniques can solve these problems. (a) In a conventional map, overplotting obscures data points even on high-resolution displays. (b) In Waldo, we avoid overplotting on a regular LCD-display.**

Related Work

Rather than aggregate data, Gridfit[1] avoids overlap in the 2D display by repositioning pixels locally. In areas with high overlap, however, the repositioning depends on the ordering of the points in the database, which might be arbitrary. Gridfit places the first data item found in the database at its correct position, and moves subsequent overlapping data points to nearby free positions, making their placement quasirandom.

Cartograms are another common technique dealing with advanced map distortion.[2] Cartogram techniques let data analysts trade shape against area and preserve the map's topology to improve map visualization by scaling polygonal elements according to an external parameter. Thus, in cartogram techniques, the rescaling of map regions is independent of a local distribution of the data points. A cartogram-based map distortion provides much better results, but solves neither the overlap nor the pixel coherence problems. Even if the cartogram provides a perfect map distortion (in many cases, achieving a perfect distortion is impossible), many data points might be at the same location, and there might be little pixel coherence. Therefore, cartogram-based distortion is primarily a preprocessing step.

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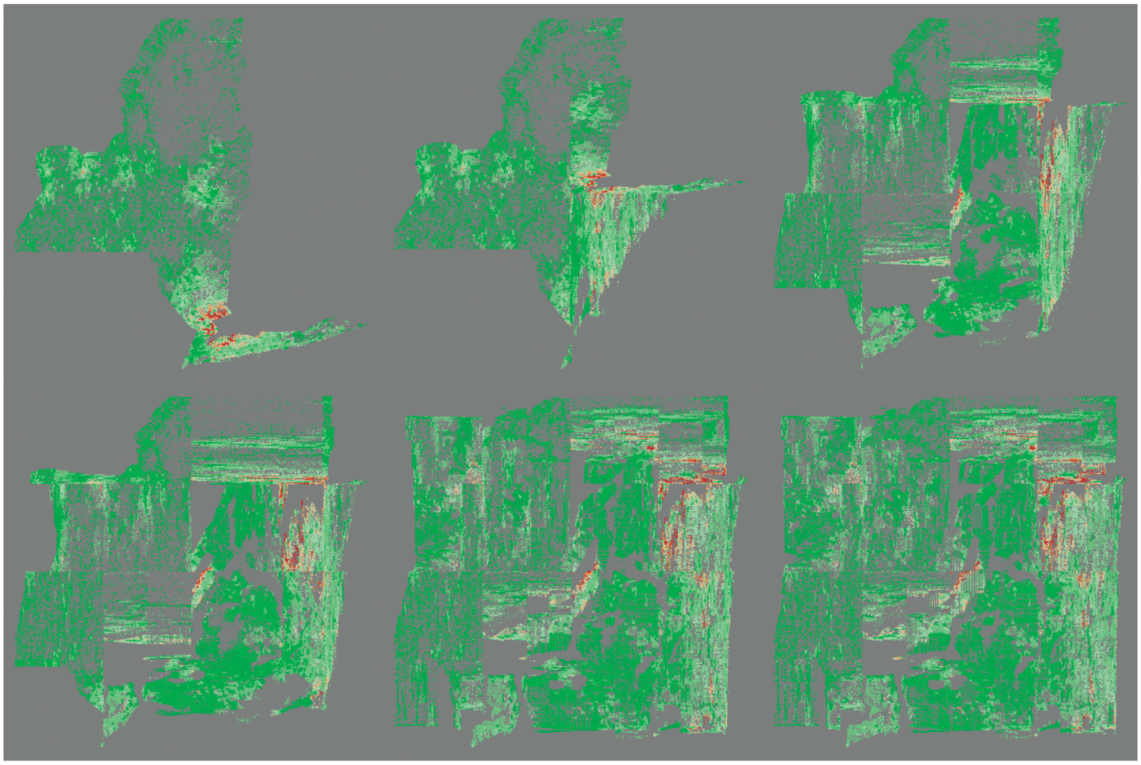
visual representation of data to suit the task at hand. Waldo is a pixel-based visual exploration system combining several relevant interaction techniques. Such techniques let data analysts directly interact with the geospatial data visualizations, dynamically changing them according to the exploration objectives. Waldo also lets analysts relate and combine multiple visualizations.

Waldo is more effective than stand-alone automatic data-mining techniques in that it

- yields results quickly, with a high degree of user satisfaction and confidence in findings;
- lets analysts guide the search and shift or adjust goals on the fly;
- deals with nonhomogeneous and noisy data;
- requires less understanding of complex mathematical or statistical algorithms or parameters; and



5 **Rescaling reduces the size of virtually empty regions, reallocating the unused pixels to dense regions. We created this series by moving Waldo's distortion slider.**

- provides a qualitative overview of data, letting analysts isolate unexpected phenomena for further quantitative analysis.

Basic visualization technique

We use PixelMaps[5] as our basic visualization technique. PixelMaps rescales map subregions to better fit dense, nonuniformly distributed points to unique output positions. The technique is novel in at least two ways:

- It provides meaningful and intuitive graphical representations of large data sets.
- It combines well-founded clustering algorithms with pixel-oriented visualization, thus exploiting a computer's data processing and graphics power and the flexibility, creativity, and domain knowledge of human data analysts.

PixelMaps aims to represent dense areas while preserving some of the key structures of the original geographical space a_i^x, a_i^y, and to allocate all data points to unique display pixels, even in dense regions.

To provide nonoverlap pixel displays, PixelMaps follows a four-step process.

Density-based map distortion. PixelMaps uses recursive partitioning to approximate equal density in the two geographical dimensions a_i^x, a_i^y. Splitting the data set at low-density positions (less than 10 percent of $(l + r)/2$ of the data points) achieves efficient partitioning (gridfile-like operations). Applying every split to two areas with an equal number of points but different input screen space determines the map's distortion. In the first split, for example, PixelMaps considers two areas that each have about 50 percent of the data points but unequal screen space. It then applies distortion to give each half of the data equal area in the output map.

Allocation and scaling. For efficient rescaling, we perform quadtree split operations on the extent of the 2D screen space, causing empty areas to shrink and dense areas to expand.

We propose a new data structure to simultaneously manage allocation and scaling of both data and screen space. It combines gridfiles (to manage input point partitioning) and quadtrees (to manage new screen space positions). The computed rescaling reduces the size of virtually empty regions, reallocating the unused pixels to dense regions. Figure 5 illustrates the rescaling of certain map regions.

Array-based clustering. PixelMaps next computes an array-based clustering of each partition. It divides the third (statistical) dimension into intervals, from minimal to maximal value. The number of intervals depends on the application scenario, and can be user specified. PixelMaps data structure stores each interval's end points in an array. Each interval corresponds to a class (income class, for example) and can be quickly determined for each statistical value using a binary search. PixelMaps then colors pixels according to cluster class indices.

Cluster positioning heuristic. Finally, after rescaling and clustering, PixelMaps assigns data points to pixels, starting with the densest regions and choosing the smallest cluster in each region first. Figure 6 shows our cluster-positioning heuristic. To determine the placement sequence, we sort all final partitions (leaves of the

PixelMaps data structure) by the number of data points contained.

The pixel placement step provides visualizations that trade off position, distance, and cluster preservation.

Exploratory data analysis

Visual data exploration involves three steps in a process so common that researchers have called it the information-seeking mantra[6]:

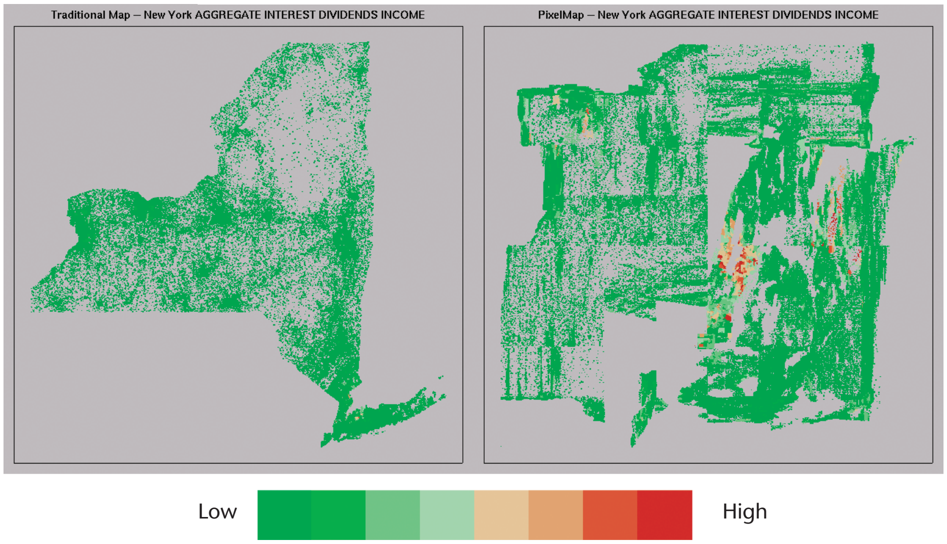
- *Overview*—an analyst examines a summary of the data;
- *Zoom and filter*—the examination might reveal interesting patterns or data subsets meriting further investigation; and
- *Details on demand*—the analyst focuses on the patterns identified in the previous step, inspecting details to form or validate hypotheses.

A PixelMaps overview of geospatial data reveals subsets with interesting structures by allocating larger display areas to dense regions with many potentially interesting subsets and smaller areas to less interesting items. PixelMaps provides the basic visualization technology in Waldo and bridges the gap between the three visual exploration steps.

Visual exploration using Waldo resembles a hypothesis-generation process: PixelMaps lets analysts gain insight into data and thereby develop and confirm new hypotheses. To complement visualization, we can use automatic techniques from statistics, pattern recognition, or machine learning to verify the hypotheses.

```
Data  :  P : data points belonging the same
         partition P;
         $\mathcal{DS}$: Display Space
Result  PixelMap
:
for $P_i \in P$ do
   if $\|P_i\| < min \wedge Var(P_i, Cntrd(P_i)) > \sqrt{\|P_i\|}$
   then
      $C_{Noise} \leftarrow C_{Noise} \cup P_i$;
   else
      $C \leftarrow C \cup P_i$;
   $C \leftarrow$ sort $C$ acc $|P_i|$ with $P_i \in C$;
   for $C_i \in C$ do
      if $|C_i|$ pixels are free around $Cntrd(C_i)$ in $\mathcal{DS}$ then
         $\mathcal{DS} \leftarrow$ SetPixels($C_i$, $Cntrd(C_i)$);
      else
         /* Find Closest Free Pixels */;
         $fp \leftarrow$ FndClsstFrPxls($C_i$, $Cntrd(C_i)$, $\mathcal{DS}$);
         $\mathcal{DS} \leftarrow$ SetPixels($C_i$, $fp$, $\mathcal{DS}$);
   for $C_i \notin C_{Noise}$ do
      if $\mathcal{DS}[pos(p)] == 0$ then
         $\mathcal{DS} \leftarrow$ SetPixel{$p$, $pos(p)$, $\mathcal{DS}$};
      else
         /* Find Closest Free Pixel */;
         $fp \leftarrow$ FndClsstFrPxl($p$, $pos(p)$, $\mathcal{DS}$);
```

6 Cluster-positioning heuristic.


Traditional Map – New York AGGREGATE INTEREST DIVIDENDS INCOME
PixelMap – New York AGGREGATE INTEREST DIVIDENDS INCOME
Low
High

7 Traditional map versus PixelMaps displays using New York state interest and dividend income data for 2000.

Interaction with PixelMaps

Waldo uses several relevant interaction techniques to adjust the visual representation of data to suit the task at hand.

First, *relate and combine* lets analysts display data from several maps in multiple linked views, often with identical coordinate systems. Secondary statistical parameters typically appear on alternative maps, with data points at the same positions but colored by other parameters. This makes it easy to compare parameters and detect local correlations, dependencies, and similar patterns.

Next, *interactive distortion sliders* let analysts adjust the level of detail to change the distortion level. Figure 5 shows the effect of changing spatial distortion.

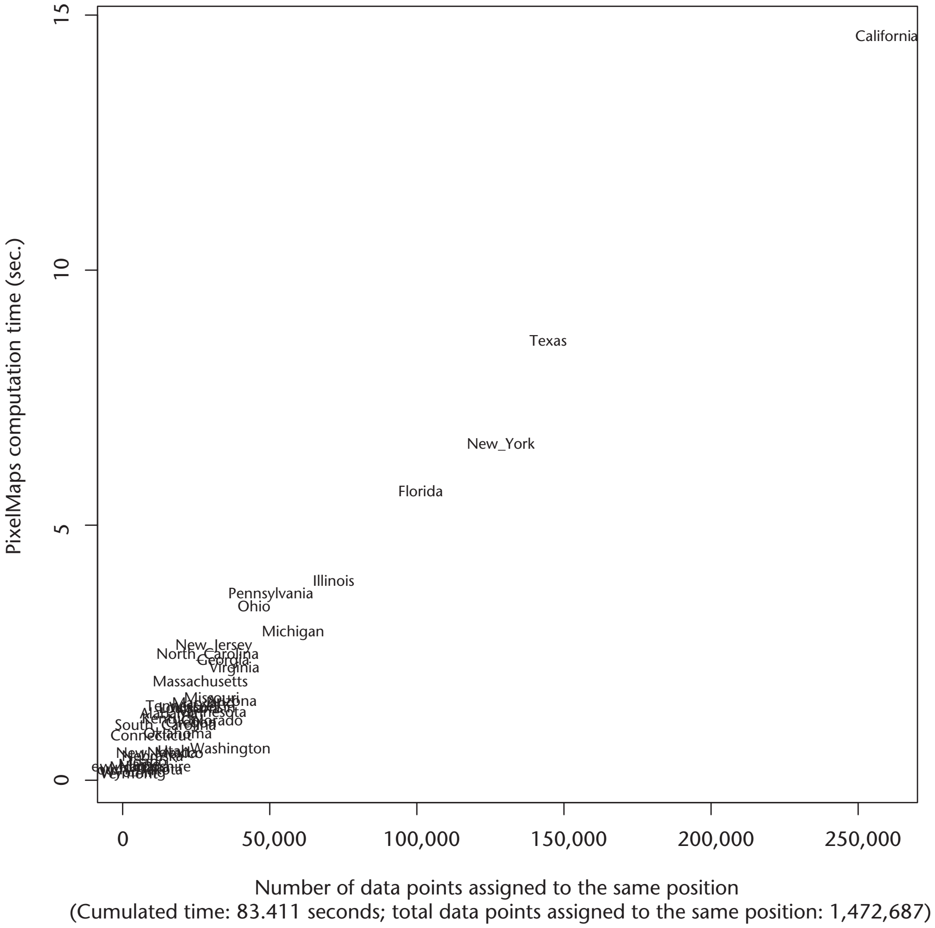
A *selection* mechanism lets analysts isolate a subset of the displayed data for further processing, such as highlighting, filtering, or quantitative analysis. Analysts can select data on the visualization itself (direct manipulation) or through dialog boxes and other queries (indirect manipulation).

Finally, *linking and brushing* lets analysts relate selected items to their representations in other views. For example, an analyst might compare points in PixelMaps to traditional displays such as 2.5D aggregated plots and bar maps.

Application examples

An important issue in visual data mining is determining the effectiveness of the proposed visualizations. Our evaluation compares PixelMaps displays with traditional approaches and provides examples using census records and a telephone call volume data set.

Figure 7 shows a zoomed view of New York using a traditional map and a PixelMap made by Waldo. The degree of overlap for a 1,200 × 1,200 screen resolution



8 **Computation time based on the number of points assigned to the same *xy*-position using a standard screen resolution. Most PixelMaps can be computed in less than 5 seconds. In case of high overplotting, the computation time is suitable for efficient data exploration.**

is 0.82 for the region. We based both visualizations on *US Census Interest and Dividend Household Income* data.

The traditional map provides random results in areas with a high degree of overlap (Manhattan, for example) but leaves sparsely populated areas virtually empty. PixelMaps increases space allotted to the densest regions so all data points can be close together. We ran PixelMaps on the most detailed data we have at the census block level. To demonstrate its scalability, we created individual data points for each household, initially placing them at the block centers. As the figure shows, clusters of households with very high investment income are in Manhattan and Queens, and households with low investment income are in the Bronx and Brooklyn. A salient cluster of wealthy households are on the east side of Central Park.

Census demographic analysis

We performed a census demographics analysis using data sets from the US Census Bureau. For the analysis, we extracted household income, investment income, and the asking price of vacant homes for every state in the US.

The average number of data points assigned to the same position in each state's input data set heavily influences PixelMaps performance, as Figure 8 shows.

California, Texas, New York, and Florida had the most points assigned to the same position and were therefore the most interesting states for PixelMaps. For these four states, we ran PixelMaps in suitable time (less than 20 seconds) for an efficient data exploration; for all other states we ran PixelMaps in real time. We ran the experiments on a 2.4-GHz Intel Xeon computer with a 4-Gbyte main memory.

As Figure 9 shows, household income is strongly correlated to investment income. The figure also shows that California has only a few vacant homes with low or medium asking prices (blue areas indicate nonvacant homes) and that New York has a few vacant homes in less desirable neighborhoods with lower asking prices. Florida has relatively more vacant homes, and the price asked for these houses is strongly correlated with household income in these areas. Although, median household income and investment income are strongly correlated in each state—in particular, wealthy households are noticeable on the east side of Central Park, on Florida's Gold Coast, and on the California coast.

A detailed analysis of PixelMaps efficiency and effectiveness with respect to the defined visual exploration goals is available elsewhere.[5,7]

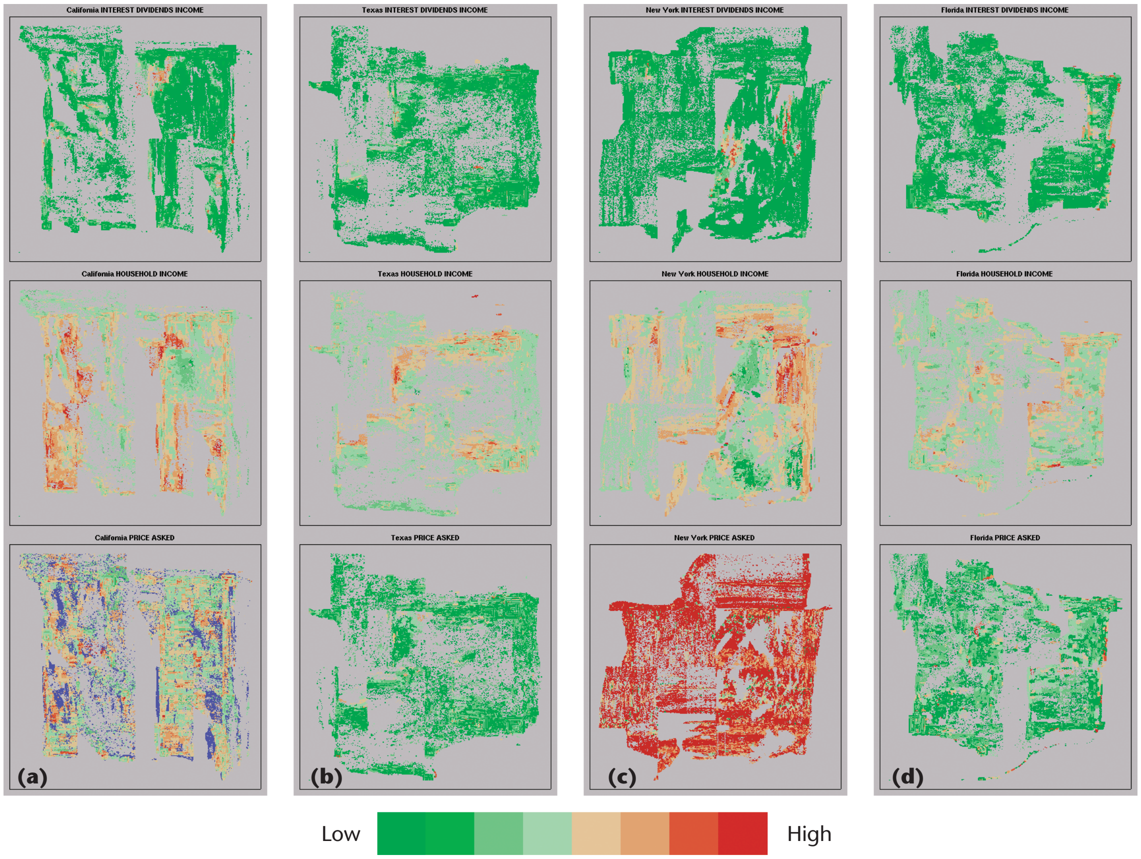
Call volume analysis

Marketing analysts and network engineers look for interesting patterns in network usage data to help them recognize and respond to changing conditions quickly. One of Waldo's key motivations is the need to analyze extremely large customer service data sets. The example visualization in Figure 10 shows the call volume of a telephone service during a 24-hour period.

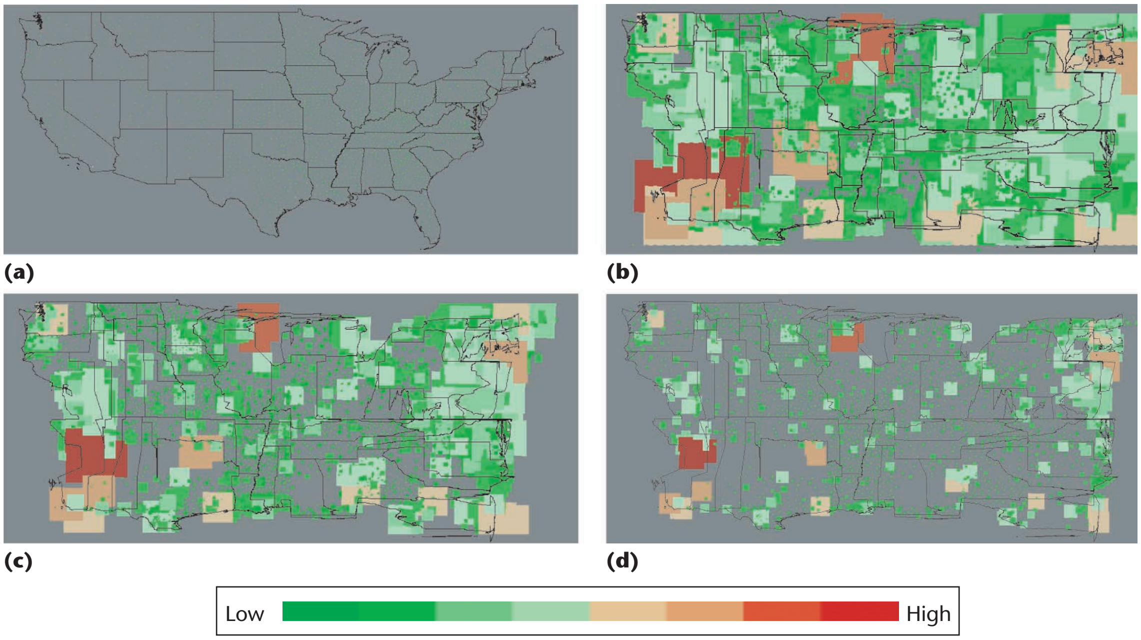
The traditional map (Figure 10a) gives random results in areas with a high degree of overlap while leaving sparsely populated areas virtually empty. The Waldo visualizations (Figures 10b–d) show the advantages of the PixelMaps algorithm. The maps show that New York City and Los Angeles County are the population areas with the highest call volume in the US. The PixelMaps displays can show the local distribution of call volumes in these regions.

Conclusion

Detecting interesting local patterns in large data sets is a key research challenge. Particularly challenging today is finding and deploying efficient and scalable visualization strategies for exploring large geospatial data sets. One way is to share ideas from


California INTEREST DIVIDENDS INCOME
Texas INTEREST DIVIDENDS INCOME
New York INTEREST DIVIDENDS INCOME
Florida INTEREST DIVIDENDS INCOME
California HOUSEHOLD INCOME
Texas HOUSEHOLD INCOME
New York HOUSEHOLD INCOME
Florida HOUSEHOLD INCOME
California PRICE ASKED
Texas PRICE ASKED
New York PRICE ASKED
Florida PRICE ASKED
(a)
(b)
(c)
(d)
Low
High

9 PixelMaps results for US Census demographics analysis showing interest dividends income, median household income, and price asked for (a) California, (b) Texas, (c) New York, and (d) Florida.



10 Call volume analysis using (a) traditional maps and (b–d) PixelMaps with increasing screen resolution: (b) 800 × 347 pixels, (c) 1,024 × 445 pixels, and (d) 1,600 × 695 pixels.

the statistics and machine-learning disciplines with ideas and methods from the information and geovisualization disciplines. PixelMaps in the Waldo system demonstrates how data mining can be successfully integrated with interactive visualization. The increasing scale and complexity of data analysis problems will require tighter integration of interactive geospatial data visualization with statistical data-mining algorithms.

Further information on visual analysis of massive geospatial data sets, as well as an implementation of the PixelMaps algorithm and Waldo, is available at the PixelMaps Project Web site at http://dbvis.inf.uni-konstanz.de/~sips/pixel_based_dm/. ■

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