VISUALIZATION OF ATTRIBUTE SPACES INVOLVING PLACES, PEOPLE AND UTTERANCES

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Abstract

Attribute spaces can be thought of as the set of characteristics associated with any class of object, for instance the characteristics of places, people, or representations. In this paper, we report on a study aimed at exploring the interaction of some of these attribute spaces. University students were shown videos of San Diego neighborhoods and asked to report their impressions of the neighborhoods. We also gathered population census attributes to capture an alternative representation of those neighborhoods. These different datasets were then transformed into a series of self-organizing maps (SOMs), with the goal of supporting the generation of insights into places and verbal descriptions of neighborhoods. By visualizing multiple attribute spaces simultaneously, we explore the relationship between different forms of representation and the interaction between attribute spaces. We discuss the major patterns existing in these SOMs, offer insight into the interpretation of such patterns, and conclude by suggesting further areas of research to address issues raised in this study.

1. Introduction

1.1 Attribute Spaces

Places, people, and representations can all be thought of as existing within *attribute spaces* (Skupin, 2007). These attribute spaces are defined by the set of dimensions, or characteristics, that describe given entities. For instance, the attribute space of geographic ***places*** might consider population characteristics, dominant climate and vegetation types, or even the personal impressions that visitors are left with. Meanwhile, the attribute space of ***people*** may entail their personal past, socioeconomic status, religion, and so forth. The experience of place engages these two types of attribute spaces involving people and places. In addition, one encounters the attribute spaces of ***representation***, such as in ***pictorial*** or ***verbal*** form, like when places are described through photographs or oral stories. Adding to this complexity, whoever performs or generates such representations of place will inevitably be influenced by their own personal attributes.

Figure 1 broadly illustrates major relationships among these different types of attribute spaces: an *m*-dimensional person, when presented with a *p*-dimensional representation (e.g., a photograph or video) of an *n*-dimensional geographic space, would describe the *n*-dimensional places within a *v*-dimensional space of verbal utterances. These are the specific relationships explored in this study, guided by the overarching question of whether certain *types of people* make certain *types of statements* about certain *types of places*. This paper reports on some of the results of this study, focusing on how places can be described either via an *n*-dimensional geographic attribute space or a *v*-dimensional verbal utterance space. The *m*-dimensional space of people and the *p*-dimensional space of pictorial representations are beyond the scope of this paper.

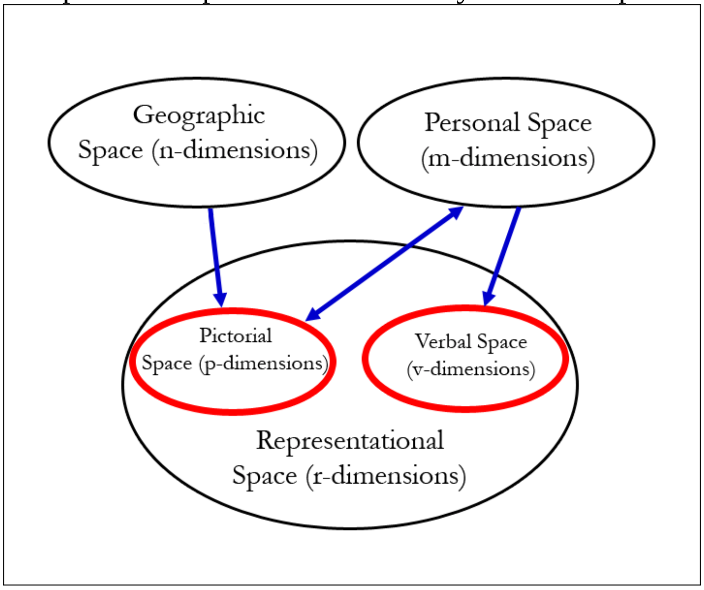

Figure 1. Interactions of m-dimensional people with *r*-dimensional representations of *n*-dimensional geographic space.

1.2 Geovisualization and Self-Organizing Maps

The dominant cartographic paradigm has in recent years broadened to include the use of maps for *exploration* of information, rather than simply for *communication* purposes, as suggested in MacEachren's (1994) 'cartography-cubed' diagram. Geovisualization is the area of cartography that makes visible large amounts of geographic data with the primary goal of exploration and hypothesis building. This process usually occurs in a highly interactive, multifaceted manner (Dykes et al., 2005). The self-organizing map (SOM) is particularly suited to this goal, as it can present high-dimensional attribute spaces in a low-dimensional model, such as a two-dimensional surface, and thereby be used to extract otherwise elusive patterns. The SOM has generated interest in geovisualization for this reason, as well as for its ability to efficiently and effectively handle a large number of high-dimensional objects, its potential implementation of familiar spatial metaphors, and its varied applications (Kohonen, 2001, Skupin, 2002, Watts and Warner, 2009). Furthermore, the SOM can be used to arrange a set of objects on a map based on their similarity to the other objects; in general, the more similar two objects' attributes are, the closer together they would be arranged.

The broader study involved the generation and visual exploration of five different SOMs, based on the following input data sets:

(1) neighborhoods distinguished by population census attributes;
(2) neighborhoods distinguished by the terms uttered by study subjects in response to videos depicting them;
(3) utterances distinguished according to the neighborhoods that they were applied to, based on a transposed form of the second data set (see above);;
(4) study subjects (in our case university students), as described by personal attributes, such as religion, age, and socioeconomic status;
(5) study subjects distinguished by the words they uttered to describe the neighborhoods seen in video depictions.

This paper reports on results involving the first three of these five attribute spaces.

2. Data Gathering and Processing

Three types of data were gathered:

(a) ***population census*** data for all 60 neighborhoods within the city of San Diego,
(b) subjects' ***utterances*** about neighborhoods they watched in the form of videos,
(c) ***personal background*** information provided by subjects who participated in our online survey,

Population census data and subjects' impressions of the neighborhoods were gathered in order to capture two different representations of the *n*-dimensional geographic spaces. This allowed us to compare and contrast two very different conceptualizations of place.

2.1 Utterances about Neighborhoods and Personal Information

We recorded 60 videos, one for each neighborhood. Through various on-campus recruitment strategies, San Diego State University students over the age of 18 were asked to participate in our study. Those who chose to participate then accessed the survey Web site, where they first reported information about their backgrounds and personalities such as their year in school, socioeconomic status, and religion. Each subject then was asked to watch a sequence of twelve one-minute long videos, depicting neighborhoods they picked from a geographic map of San Diego. As each video played, subjects recorded impressions of the neighborhoods in verbal form, either by choosing from a list of 9 pre-defined terms or typing in open responses, or both. The 9 pre-defined terms were “happy”, “sad”, “scary”, “fun”, “wealthy”, “angering”, “lovely”, “dirty”, and “clean”. Only results from those subjects who completed all 12 videos were retained, and the first and last videos for each respondent were discarded (Kirk, 2003). Out of 241 students that participated in the study, 150 students completed it, with results thus being derived from a total of 1,500 videos watched and retained.

All words were reduced to their stems (e.g., “happiness” and “happy” would both be reduced to “happi”) (Porter, 1980). As one would expect, the 9 pre-defined terms were used much more frequently than terms that subjects typed themselves. In order to avoid inadvertent and disproportionate influence of the dimensions presented to the respondents, we normalized the frequencies of each word usage by a couple measures. We first normalized using the TF*IDF formula (Salton and Buckley, 1988), which increases the importance of less-frequently used terms, and then reduced the values to a range of 0 to 1. Students’ personal attributes were first numerically coded and then likewise condensed to a range of 0 to 1.

2.2 Neighborhoods’ Population Census Attributes

In order to capture a comparable representation of places – a different “slice” of reality – we calculated for each neighborhood the approximate population census attributes that one would expect to find within each video’s viewshed. This was accomplished by creating for each attribute a weighted average across all the census blocks in a neighborhood that were within a 100-foot buffer around the path of the video. That resulted in a neighborhood-by-attribute matrix, in which each attribute was finally normalized to a 0-1 range across all neighborhoods.

2.3 Training the Self-Organizing Maps

In addition to the two neighborhood-level data sets discussed above, a third data set was constructed by transposing the utterance data, such that utterances became rows and neighborhoods became columns.

Those three data sets were then used to train three separate SOMs. SOM Analyst, a freely available toolbox for ESRI’s ArcMap (Lacayo and Skupin, 2007; see http://code.google.com/p/somanalyst/), was used for training and post-processing. It was was also employed to overlay input objects onto the trained SOM, such that two-dimensional coordinates could be generated for each object. The original attributes were then joined to the objects to represent the spatial distribution of the attributes across each attribute space. For a more complete description of the principles of SOM training and the specific training algorithm used refer to Kohonen (2001).

3. Visualizations

There are two principal approaches to visualizing *individual* attribute spaces based on the trained SOM (Skupin and Agarwal, 2008), both of which are implemented in this study:

(a) One may visualize the trained model itself, which may range from the display of a particular attribute across all neurons – known as component plane display – to more complex methods, such as derived through computational clustering of neurons.

(b) The trained SOM could be used as type of base map, onto which high-dimensional vectors – of the same dimensionality as the training vectors – can be mapped.

Multiple attribute spaces can be visualized simultaneously, as long as some basis for linking them can be established, typically in the form of object identity. Examples are linked selection of juxtaposed spatializations of two different spaces and the combination of geometry obtained from one attribute space with symbology driven by another. Both are illustrated below.

3.1 Visualizing Individual Attribute Spaces

This section examines three of the SOMs created in this study, with deliberate variation of visualization methods, to illustrate multiple approaches. As noted above, one approach involves looking at the individual dimensions that contributed to the training of the model. The visualization of a single variable in a component plane display is akin to how a single attribute is typically used in choropleth maps. In the latter case, geographic area objects are what attributes are attached to, while in the case of component planes, neurons can be used as area objects with hexagonal or square shape.

Figure 2 illustrates this by juxtaposing a component plane display of the population density attribute with a choropleth map of the same attribute. The SOM has been organized by considering all 136 population census attributes of all neighborhoods, but only one of those dimensions is shown here. In addition to the population density component, neighborhoods are overlaid on the SOM. Note that those two-dimensional locations are computed from *all* 136 attributes. Both visualizations communicate population density distribution, but one shows this distribution across attribute space, while the other shows population density across geographic space. In both displays, lighter colors represent higher values. The most densely populated areas – those areas with the lightest colors – are Golden Hill, City Heights, Normal Heights, and College Area, as evidenced by both maps. Note that the first three of these are neighbors in the SOM, indicating that they are similar with respect to many more attributes, while the College Area is located far away in the SOM, due to marked differences in other attributes, which may include ethnic, age, and other factors.

Turning our attention to the SOM that visualized neighborhoods in terms of how they were described through study subjects' utterances (Figure 3), we observe a different organization of the neighborhoods than in the previous visualization. Remember that this SOM is made up of completely different dimensions, with each term stem (e.g., "intimid", "nature", etc.) driving one dimension. Instead of using component planes and the choropleth method, Figure 3 employs the pie chart method placed at the two-dimensional location assigned to each neighborhood in the SOM. In the geographic map, the neighborhood centroid is used for chart placement. The red and yellow portions indicate the relative number of times that the stems "dirti" and "clean" were uttered for a specific neighborhood.

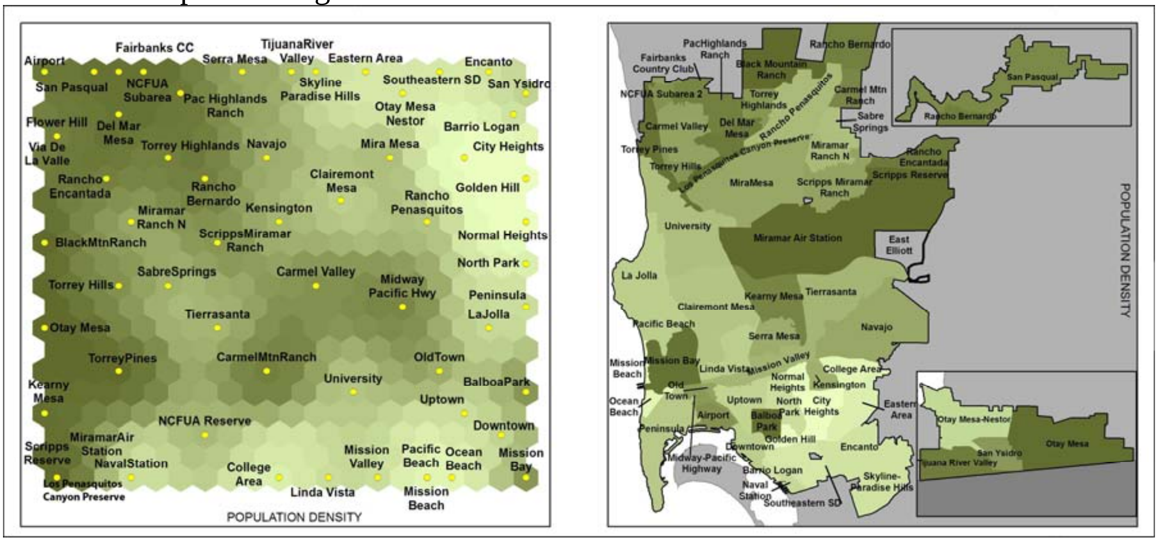

Figure 2. Population density component plane juxtaposed with the choropleth counterpart.

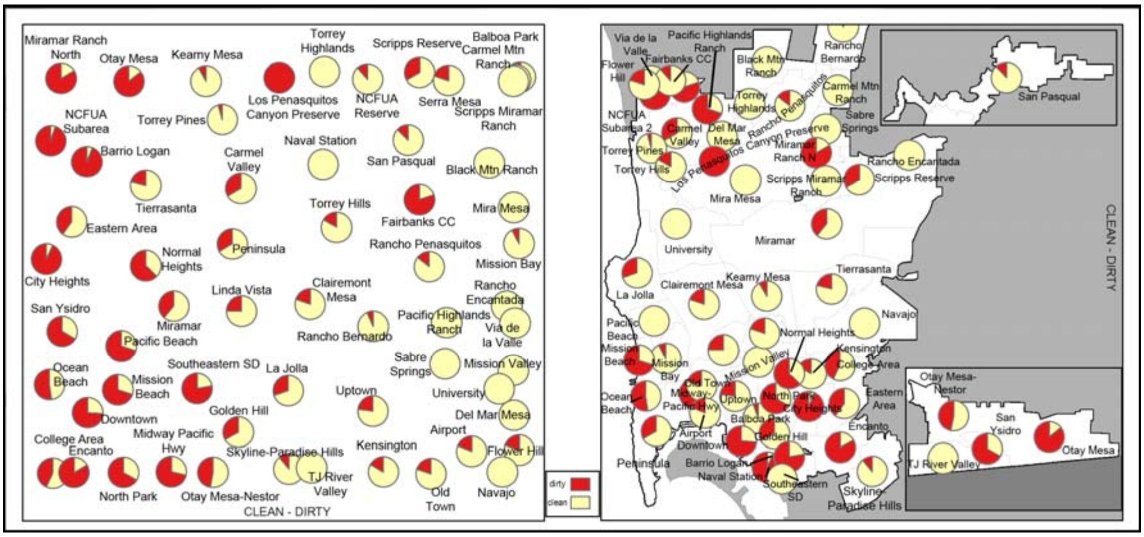

Figure 3. Visualizing neighborhoods organized by their descriptions. Distribution of "dirti" and "clean" across geographic and attribute spaces.

The degree to which these two terms are separated in the SOM indicates that other terms should show strong patterns of co-occurrence. In fact, using bar charts to visualize multiple dimensions simultaneously (Figure 4), strong patterns emerge regarding the arrangement of the neighborhoods in attribute space. Visualizing 6 dimensions with negative connotations (“scari”, “sad”, “ghetto”, “dirti”, “danger”, and “poor”) reveals a strong tendency for neighborhoods viewed negatively to be arranged on the left side of the map. The SOM, without recognizing semantic meanings of terms, organizes this way since people consistently use these negative words to describe neighborhoods on the left, and less to describe the other neighborhoods. In other words, there is general agreement in the negative impressions that subjects had of neighborhoods on the left side of the SOM.

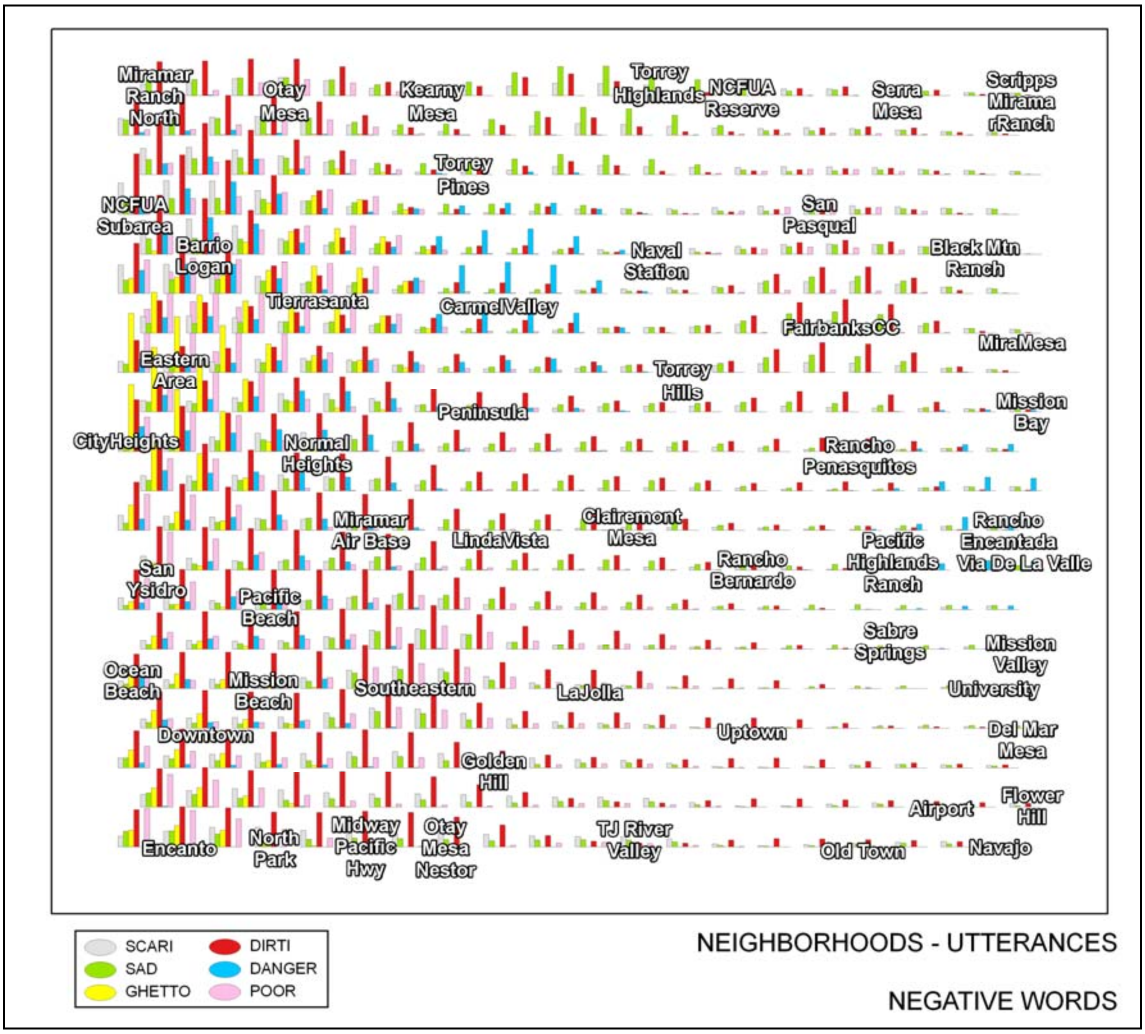

Figure 4. Neighborhoods described negatively tended to orient toward the left side of the map.

Finally, the utterances were arranged according to the neighborhoods that were described with those words. To put it differently, neighborhoods became the words’ attributes (Figure 5). The geometric layout of words is determined by considering which neighborhoods were described with each word; That constitutes a transposing of the previous model. In this component plane display, the proportion with which a neighborhood contributes to each neuron is indicated in pie chart form, with 10 out of 60 neighborhoods included in this display (but all 60 contributed to the training of the SOM as such). Where a neighborhood's color appears, the words in that area were used to describe that neighborhood. For instance, notice that Encanto appears largely negative, in relation to both high- and low-frequency words. In fact, some negative term stems, notably "unkempt" and "powerlin", were used almost exclusively for Encanto. Similar to the geographically adjacent Encanto, other neighborhoods in the southern portion of San Diego tended to be described as "poor", "sad", and "dirti". In contrast, more northern neighborhoods often appear near positive words. For instance, the stems "love", "safe", "wealthi", and "happi" were partly used to describe Serra Mesa (a central neighborhood), but mostly to describe northern neighborhoods. However, anomalies in Figure 8 also stand out: "rundown" was used to describe upscale La Jolla. Scripps Reserve and Los Peñasquitos Canyon Preserve, both natural open areas in northern San Diego, have formed a region closer to positive terms, but have an unexpected presence near negative words. Their rustic, natural appearances in the respective videos may have stimulated different emotional reactions from different respondents. Otherwise, these anomalies may have been ironic responses. As before, semantics of words have influenced the training of this SOM, increasing the likelihood that more similar words would be placed closer together.

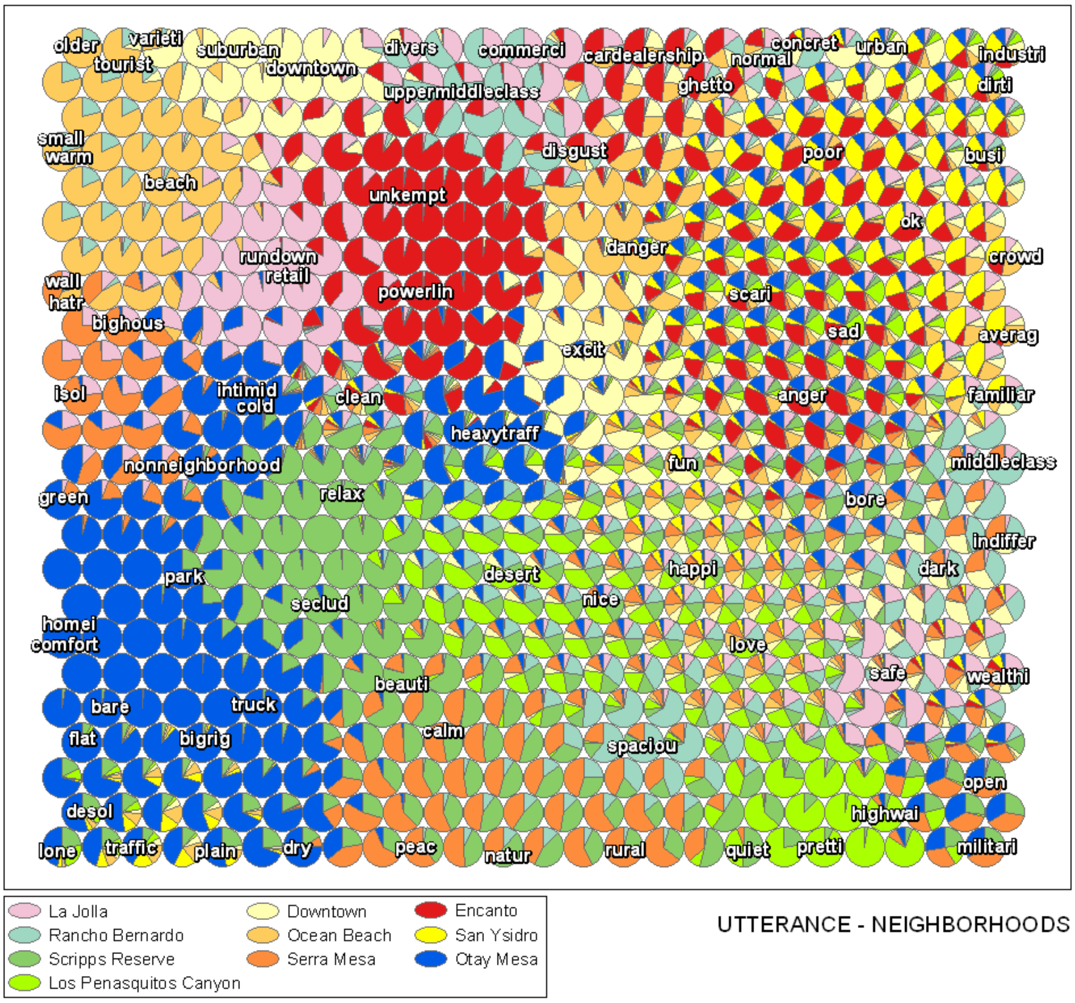

Figure 5. SOM based on utterances, with neighborhoods as attributes.

Note that the respondents themselves were visualized as well, in terms of both their personal attributes and the vocabulary they used while taking the survey. However, as the topic of this paper is the interaction of *n*-dimensional places and *r*-dimensional representations (specifically the *v*-dimensional space of utterances), results from the portion of the project dealing with the analysis of study participants are not discussed here.

3.2 Visualizing Across Attribute Spaces

Visualizing *across* attribute spaces allows us to search for relationships between them and to compare different conceptualizations of place underlying them. In our case, one may ask about differences between places defined in terms of how the population census describes them versus how people describe them.

We can either examine different attribute spaces side-by-side, or derive the geometry from one attribute space and symbolize it with another. Figure 6 illustrates the former. The two attribute spaces of neighborhoods are juxtaposed, to allow visual comparison, linked selection, and other forms of exploration. Clairemont Mesa falls near the center of both SOMs, indicating it might represent the "average" San Diego neighborhood in both Census data and people's impressions of it. Notice how, in the census-based SOM on the left, Via de la Valle is far from Downtown and Mission Valley. In contrast, in the utterance-based SOM, Downtown is far from Via de la Valle and Mission Valley, which are now grouped together on the opposite side of the SOM.

Figure 6. Comparing two attribute spaces side-by-side.

The second method of exploring across attribute spaces involves deriving the geometry from one attribute space and symbolizing from another (Figure 7). The geometric organization of neighborhoods is derived from their population attributes, but symbology is driven by the nine main utterance terms. The dark, saturated colors concentrated in the upper-right corner of the SOM correspond with neighborhoods that had high population density, high minority populations, and high proportion of people who rent their household. These neighborhoods were more consistently described with negative terms, as indicated by the pie chart coloring. Cases where similar pie charts appear far from each other, such as Otay Mesa being separated from those neighborhoods in the upper-right, indicate a more complex relationship between population census attribute space and utterance space.

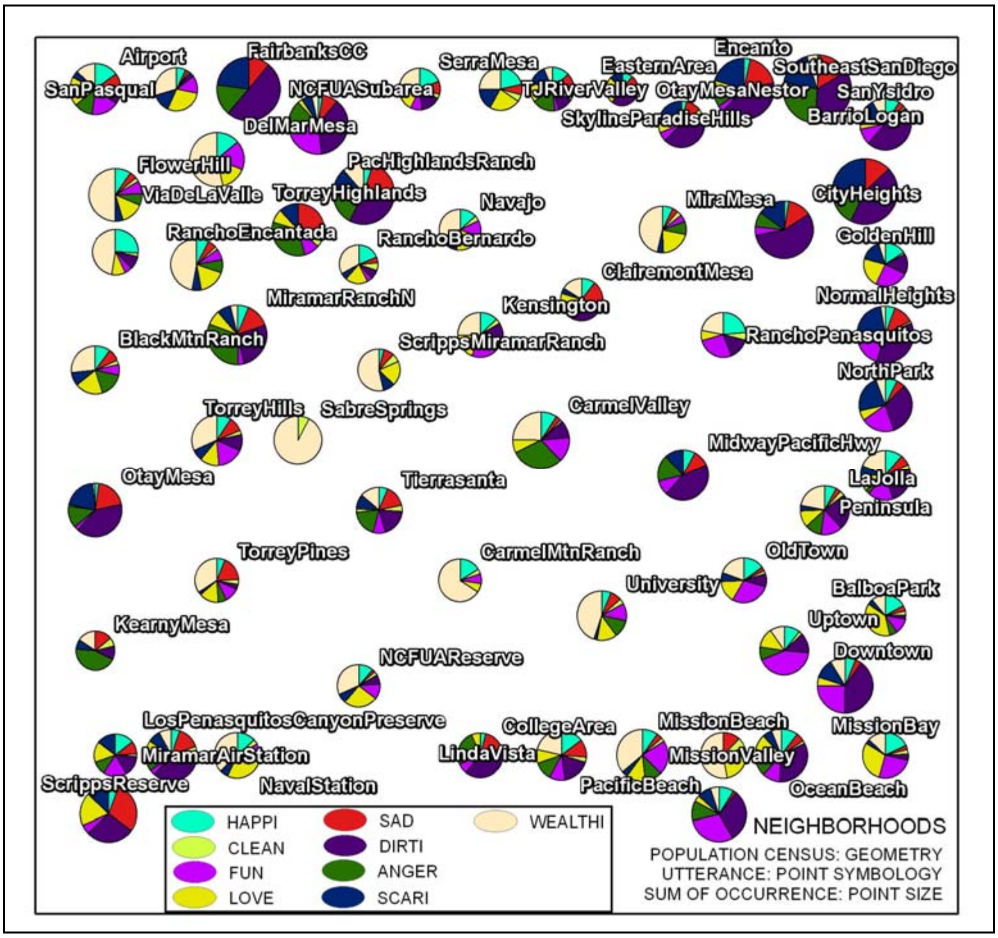

Figure 7. Cross-symbolization of attribute spaces. The geometry was taken from the Census, and symbology from the neighborhoods' descriptions.

4. Discussion

Employing the notion of attribute spaces points towards a novel approach for engaging places, people, and utterances. By utilizing SOMs, we are able to reduce high-dimensional attribute spaces to a low-dimensional display space, facilitating exploration that may lead to knowledge production. In particular, by intersecting attribute spaces, the interaction between these spaces and influences of these spaces on each other both may become more salient.

The examples included in this paper demonstrate that different conceptualizations of places result in varied configurations of places within attribute spaces and ultimately capture different dimensions of geographic "reality." Such differences in organization become prominent when different spatializations are either juxtaposed or when geometry and symbology are fed by different input spaces.

The results presented here hint at possible correlations between the reality of place as expressed by the population census, and reality as expressed through video capture and the induced utterances. Population characteristics captured by a governmental census may indeed *affect* what is visible, by projecting themselves into the visible world captured by video, but the nature of such interaction remains to be ascertained in future studies.

One of the questions arisen in the course of this study is whether researchers' personal attributes affect the place representations they generate. For example, one could alternatively ask residents of neighborhoods to represent their own communities in videos. Our study did not at all address the p-dimensional space of the pictorial content of videos, something that could in the future be addressed through computational analysis of video content. Also, the interaction of subjects' personal attribute spaces on the utterance space was not thoroughly investigated, and might reveal interesting trends. Note also that we only surveyed students, and all of them over the age of 18 and in active enrollment at San Diego State University. Larger demographic diversity among study subjects might well lead to more pronounced differences.

Also, since our stimuli for the study were videos, we may have lost much of the emotional reaction and potential impressions of neighborhoods that one would expect from actually *being in* the neighborhood. Comparative analysis of video and other stimuli, including immersive virtual reality, would be one possible venue. Finally, the extent to which the trained SOMs were visually explored was limited by a lack of available interactive tools. These issues are of course limitations of the current study as much as they are opportunities for future research.

5. References

DYKES, J., MACEACHREN, A. M. & KRAAK, M.-J. (2005) Introduction: Exploring Geovisualization. IN DYKES, J., MACEACHREN, A. M. & KRAAK, M.-J. (Eds.) *Exploring Geovisualization.* Amsterdam, Elsevier.

KIRK, R. E. (2003) Maturation Effect. IN LEWIS-BECK, M. S., BRYMAN, A. & LIAO, T. F. (Eds.) *The Sage Encyclopedia of Social Science Research Methods.* Thousand Oaks, CA, Sage.

KOHONEN, T. (2001) *Self-Organizing Maps,* New York, Springer.

LACAYO, M. & SKUPIN, A. (2007) A GIS-based Visualization Module for Self-Organizing Maps. *Proceedings of 23rd International Cartographic Conference, Moscow, Russia, August 4-10, 2007,* CD-ROM.

MACEACHREN, A. M. (1994) Visualization in Modern Cartography. IN MACEACHREN, A. M. & TAYLOR, D. R. M. (Eds.) *Visualization in Modern Cartography.* New York, Pergamon Press.

PORTER, M. (1980) An Algorithm for Suffix Stripping. *Program,* 14**,** 130-137.

SALTON, G. & BUCKLEY, C. (1988) Term-weighting Approaches in Automatic Text Retrieval. *Information Processing and Management,* 24**,** 513-523.

SKUPIN, A. (2002) A Cartographic Approach to Visualizing Conference Abstracts. *IEEE Computer Graphics and Applications,* 22**,** 50-58.
SKUPIN, A. (2007) Where Do You Want to Go Today [In Attribute Space]? IN MILLER, H. J. (Ed.) *Societies and Cities in the Age of Instant Access.* Springer.
SKUPIN, A. & AGARWAL, P. (2008) Introduction: What Is a Self-organizing Map? IN SKUPIN, A. & AGARWAL, P. (Eds.) *Self-Organising Maps: Applications in Geographic Information Science.* Chichester, England, John Wiley & Sons, Ltd.
WATTS, M. J. & WARNER, S. P. (2009) Estimating the Risk of Insect Species Invasion: Kohonen self-organising Maps Versus K-means Clustering. *Ecological Modelling,* 220**,** 821-829.