**Visualization of Individuals' Emotion Changes in Urban Space across Time: A Taxonomy**

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## Abstract

The recent development in location-aware technologies and georeferenced social media provides us massive amount of data regarding individuals' travel and activity participations in urban space across time. This paper develops a framework to systematically visualize the GPS-based activity diaries and associated emotions to better understand emotion changes across time and different activities/travel modes. The three components in the framework are: (1) data representation from Lagrangian or Eulerian perspectives, (2) classes of elementary and synoptic tasks in exploratory analysis of human emotions, and (3) selected visualization methods, with their representation of data and their achievable tasks. The paper presents a taxonomy for data representation and task specification and uses example visualizations to demonstrate how elements in the taxonomy can determine the selection and usage of certain visualization methods. This framework can serve as a reference to systematically select and organize visualizations for a project or identify needs for new methods given the characteristics of new data available in the future.

## 1. Introduction

The recent development in location-aware technologies and georeferenced social media enables us to track individuals' movements and activity participates in urban space across time (Miller and Goodchild 2015, Yang et al. 2017, Yue et al. 2014). Visualizing the spatio-temporal data or the analysis results is a crucial component in geographic data mining and knowledge discovery (Compieta et al. 2007, Miller and Han, 2001, Zheng et al. 2014), and has attracted an increasing amount of attention in recent years across many disciplines (e.g. Andrienko et al. 2007, Demšar et al. 2015, Dodge et al. 2016, Hoeber et al. 2018, Thudt et al. 2016, Zhang et al. 2014).

Despite the volume, variety and velocity of individual's tracking data, these data are "thin" and usually lack of social context (Bollier and Firestone 2010, Hofferth and Moran 2017, Miller and Goodchild 2015). For instance, tracking data collected by Global Positioning System (GPS) and mobile phones are unusually stored as an ordered sequence of geographic coordinates with time stamp. Therefore, additional steps are needed to derive activity locations and durations along the tracking traces, and there is always uncertainty associated with these activity participations (e.g. Zheng et al. 2010, Liao 2007, Xu et al. 2016). Another example is the social media data, which tends to collect certain types of activities and during certain periods of time, and is likely to lack information regarding daily routines such as arriving at the office and shopping at a grocery store (e.g. Jiang et al. 2017, Rashidi et al. 2017, Wu et al. 2014).

GPS-based activity survey is considered as a solution to contextualize the movement trajectories collected by GPS as well as providing both durations and geographic locations of the participated activities (Ding et al. 2017, Stewart et al. 2016, Ta et al. 2016, Xiaoyu et al. 2017). However, the existing studies often focus on deriving individuals' activity space or investigating their physical conditions. Few studies examine individuals' subjective emotions such as happy and stressful.

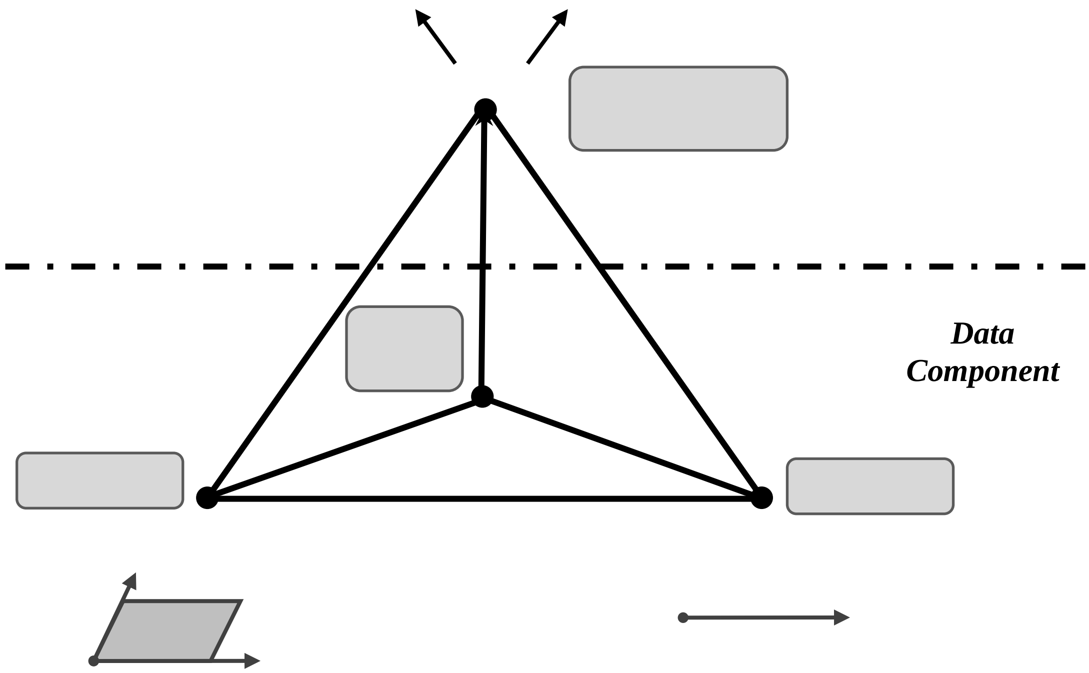
This paper presents a framework to visualize individuals' emotion status attached to their activity and travel. The framework starts with data representation and task specification, continues to the taxonomy description, and finishes with corresponding visualization methods available. The paper uses individuals' emotion status collected along with their daily trips and activity participations as an example to demonstrate this framework and its implementation. The next sections present the methodological framework, example visualization methods, and a conclusion with discussions on future research agenda.

## 2. Methodological Framework

### 2.1 Spatio-temporal Data Representations

Despite the variety in data sources and formats, the data collected for individuals' daily trips and activity participates follows two basic perspectives: Lagrangian and Eulerian. Originally, these are the two basic perspectives to specify the field developed in classical field theory (Batchelor 1973, Landau and Lifshitz 1987). They have been applied widely in animal ecology (e.g. Smouse et al. 2010), and can also be used in studying human mobility behaviors. From *Lagrangian perspective*, the observer follows an individual object as it moves through space and time, and records its spatial locations and timestamps. Vehicle tracking data collected by GPS devices is a typical example of this type. From *Eulerian perspective*, observer stays at specific locations in the space, and records the timestamps when the individual object passes each specific location. Boarding and alighting smart card data is an example of this type.

The data representation and database design, therefore, can be distinguished based on these two perspectives. Figure 1 shows the pyramid framework for object-oriented database design, which include the two major components: data and knowledge (Mennis et al. 2000). In general, the data component refers to the location, time and theme collected and stored in the original source data; the knowledge component refers to the representation of the geographic objects derived from the source data, their characters and behaviors, and the relationship among different objects.




**OBJECT**

**LOCATION**

**TIME**

**THEME**

**x**

**y**

**t**

**$\{a_i\}$**

***Knowledge Component***

**Taxonomy**

**Partonomy**

***What is it?***
***What does it do?***
***Where is it?***
***When is it?***
***What is "in" it?***

Figure 1. Pyramid framework for object-oriented database design (Mennis et al. 2000)

The knowledge that can be discovered from the data is largely determined by the type and format of the source data. Table 1 presents two example data representations: (1) the GPS tracking data corresponding to the Lagrangian type, and (2) the GPS-based activity diaries corresponding to the Eulerian type (,in which the movements between activities may be recorded as tracking data).

Table 1. Data representations from Lagrangian and Eulerian perspectives

| **Data** | **GPS tracking data** | **GPS-based activity diaries** |
|---|---|---|
| Location | a location in geographic space | an activity or trip in state space |
| Time | a point in time (discrete scale) | a period of time (continuous scale) |
| Theme | mobility status (e.g. odometer, speed) | emotion status (e.g. happiness level) |
| **Knowledge** | | |
| Partonomy | sub-trips, dwellings, and stops along an individual's space-time trajectory | activities and possibly their locations, trips with travel modes, and emotions |
| Taxonomy | space-time trajectories, each with an ordered series of tuple (x, y, t, $\{a_i\}$) | individuals, each with an ordered series of tuple (activity, start T, end T, $\{a_i\}$) |

## 2.2 Exploratory Analysis Tasks Specification

Exploratory data analysis was introduced in 1980s as an approach to extract main characteristics of the data before formulating hypotheses, collecting new data, and conducting statistics analysis (Tukey 1977). Visualizing data using various graphical techniques such as box plot, histogram, and scatter plot have been proved to be effective for exploratory data analysis (Tukey 1980). The tasks of exploratory analysis can be categorized into two main types: (1) the *elementary tasks* for exploring *individual* characteristics, and (2) the *synoptic tasks* for exploring *collective* patterns or behaviors (Andrienko and Andrienko 2006). It is essential to include both types since collective behaviors are much more than the simple adding up of individual behaviors (e.g. Liu et al 2009, Lukeman et al, 2010). Table 2 uses GPS-based activity diary and emotion data as an example to describe and compare classes of elementary and synoptic tasks using time interval as reference.

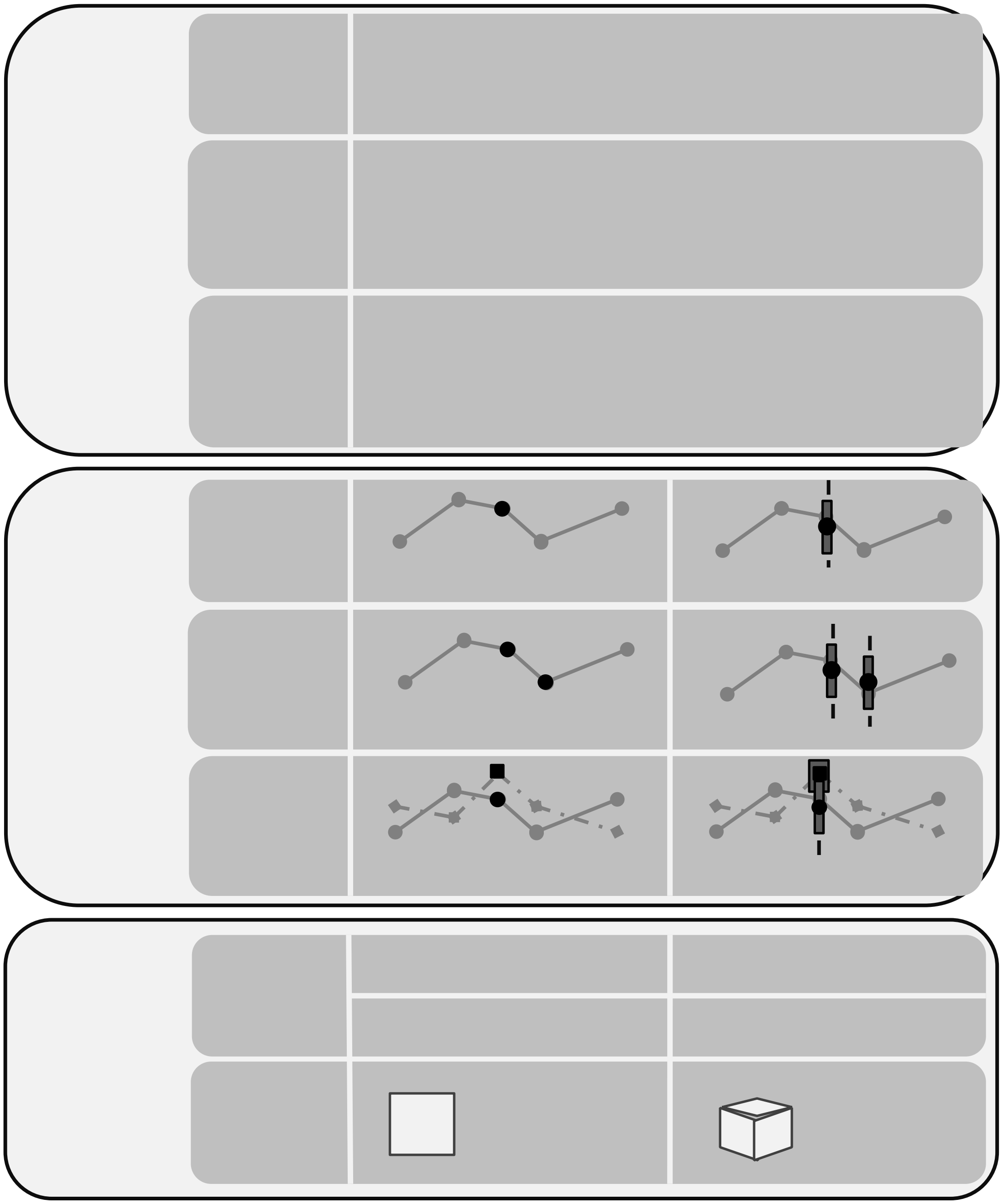
Table 2. Classes of elementary and synoptic tasks in exploratory analysis of human emotions

| **Elementary <individual>** | **Synoptic <collective>** |
|---|---|
| ***Lookup*** | ***Pattern identification*** |
| − *Direct lookup*<br>at is the emotion status of an individual during a specific time point or interval? | − *Behavior characterization*<br>at is the emotions for selected individuals during specific time? |
| − *Inverse lookup*<br>en did an individual feel happy/sad? | − *Inverse lookup*<br>when do individuals usually feel happy/sad? |
| ***Comparison*** | ***Behavior (pattern) identification*** |

| | |
|---|---|
| − *Direct comparison*<br>npare an individual's emotions during different time?<br><br>− *Inverse lookup*<br>compare the time periods when an individual is most/least happy | − *Direct comparison*<br>npare average happiness score between two periods of time<br><br>− *Inverse lookup*<br>what time tends to have the highest or lowest average happiness score |
| **Relation-seeking**<br>− *Between values of attributes*<br>es an individual have similar happy level and meaningful level for daily activities?<br><br>− *Between different reference sets*<br>v does an individual's happy level change throughout the day? | **Relation-seeking**<br>− *Between patterns of attributes*<br>individuals show similar trend for happy level and meaningful level for daily activities?<br><br>− *Between different reference sets*<br>v does the individuals' average happy level change throughout the day? |
| | **Connection-testing**<br>− *Homogeneous behavior*<br>individuals in the same demographic group tend to have similar emotion patterns?<br><br>− *Heterogeneous behavior*<br>individuals' emotion patterns discovered in classes above evolving over time? |

### 2.3 A Visualization Taxonomy

Given the data representation and task specification, a visualization taxonomy can be developed. The taxonomy includes three major components: (1) "*What" to be visualized*, corresponding to the data representation; (2) *"Why" visualize it*, corresponding to the task specification; and (3) "*How" to visualize it*, corresponding to the visualization methods and tools. Figure 2 uses GPS-based activity diaries and emotions as an example to illustrate the taxonomy, which is inherited from the taxonomy developed by Aigner et al. (2011) and modified considering the characters of the source data (Table 1, Table 2) and the emerging web mapping (Haklay et al. 2008)



## WHAT?

### Location

abstract: activity types and travel modes
spatial (opt): GPS locations of an activity or along a trip
granularity: individual, or collective

### Time

scale and scope: continuous, interval-based time

granularity: chronon (smallest unit: second)
arrangement: linear (calendar date) or cyclic (weekday)
primitives: instant, interval or span

**Theme**

data type: event (emotion at the end of a trip or activity)
scale: quantitative, ordinal (e.g. index values from 1 to 7)
variables: multivariate, each emotion has one index value
primitives: instant or interval

**WHY?**

**1st level**

**2nd level**

elementary lookup

**3rd level**

Synoptic lookup
elementary compare
Synoptic comapre
elementary relation seeking
synoptic relation seeking

**HOW?**

**Mapping**

**Dimension**

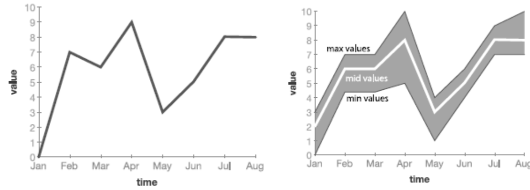
local, static
local, dynamic
online, static
online, dynamic
2D
3D

Figure 2. A Taxonomy of Visual Exploratory Analysis of Spatio-Temporal Data

## 3. Example Visualization Methods

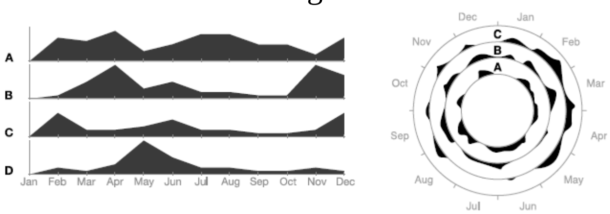
This section presents available example visualization methods that can be used to explore GPS-based activity diaries and emotions data. The main objective is to illustrate how each method is relate to the taxonomy in Figure 2 as well as the data representation and task specification in it. This section focuses on static mapping.

(1) *Line Plot*: elementary and synoptic lookup and compare. Example patterns include: (a) how an individual's happiness level changes over time, and (b) how the minimum, maximum and mean happiness levels for all individuals change over time.



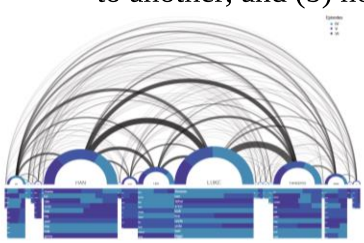
(Aigner et al. 2011)

(2) *Sihouette Graph*: linear or cyclic arrangement; elementary and synoptic compare and relation seeking. Example patterns include: (a) how an individual's emotion index values change over time (e.g. happy, meaningful, stressful, and tired); and (b) how the mean index values for all individuals change across clock time within typical workdays?

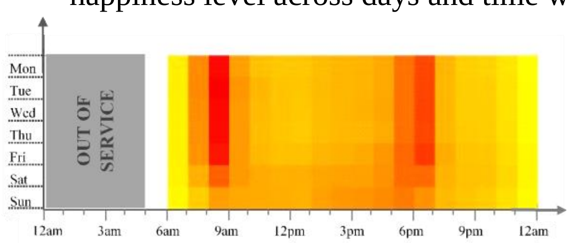


(Harris 1999)

(3) *Arc Diagrams*: state space, synoptic compare and relation seeking. Example patterns include: (a) how individuals' mean happiness level changes as they are moving from one activity/trip to another, and (b) how this pattern varies (or resembles) for different travel modes.

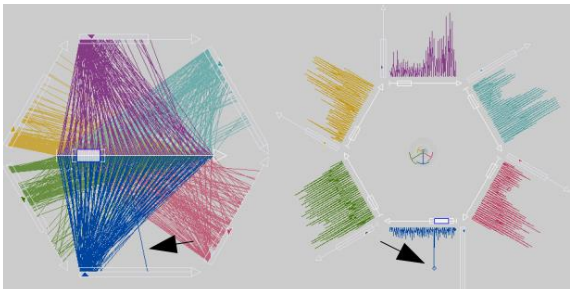

(Gaston S. 2013)

(4) *Tile Maps*: linear and cycle arrangement of time, interval time, synoptic compare and relation seeking. This method is especially useful for multi-dimensional data. It can compare average happiness level across days and time within each day at the same time.

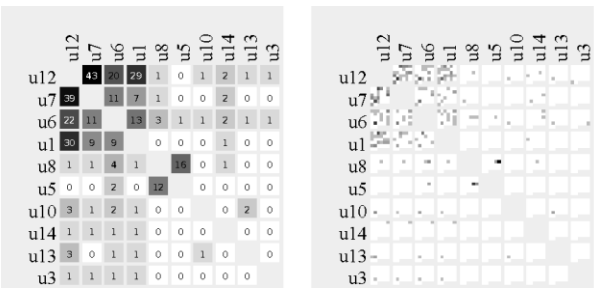


(Song et al. 2017)

(5) *Axes-based with Radial Layout*: synoptic compare and relation seeking, multi-variate. These two methods are useful if we want to examine all emotions at the same time (e.g. 6 emotions including happy, meaningful, tired, stressful, sad, and painful), transitions among them, and patterns across different emotions.

 (Tominski C. et al. 2004)

(6) *Pixel-Oriented Network Visualization*: individual or synoptic relation seeking, multi-variate. These methods can be used to explore transitions among various emotions with more details, such as the probabilities to change from one emotion to another. The method on the right can also show the actual occurrences of transitions throughout the time.



(Stein et al. 2010)

## 4. Conclusion and Discussion

This paper presents a framework to visualize individuals' daily diaries and emotions for using in exploratory analysis of individual and collective behavior patterns. The framework includes three major components: (1) data representation, (2) task specification, and (3) visualization methods. First, the source data is presented from either Lagrangian or Eulerian perspective, which affects the elements in representing space, time, and theme. Second, the visualization tasks can be either elementary tasks for exploring individual behaviors or synoptic tasks for collective behaviors and patterns. Finally, visualization method(s) can be selected or developed based on the previous two components. Projects that needs to visually explore the source data can use this framework as a reference to systematically select and organize visualizations, or identify needs for new methods given the characteristics of new data available in the future.

A direct next step is using diary and emotion data collected in Shenzhen and the programming language Python and R to implement this framework and explore behavior and emotion patterns at both individual and collective levels. Beside static mapping discussed in section 3, interactive and online mapping will also be presented and discusses. The visual exploratory analysis results can advance our understanding on how individuals' emotions are affected by different activities or travel modes as well as how individuals' motions are evolving across time. Another extension to the current research is to include discussion on user evaluation strategies across different user groups with various experiences and background (or even special needs due to disability).

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