Temporal Signatures of Shops' and Restaurants' Opening and Closing Times at Global, Country, and City Scales

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Abstract

Understanding when various facilities (e.g. *Retail Shops* and *Restaurants*) operate across the world and understating if and how this varies across space will lead to deeper insights on urban dynamics and regional cultural variation. In this work, we present the opening and closing times of *Retail Shop* and *Restaurant* Points of Interests (POIs) at a global, country, and city scale. We collected over fourteen million geo-located Facebook POIs with associating metadata on what time these POIs open and close. This data is aggregated at the city, country, and global scales and then visualized as temporal signatures. Results show that facilities' opening and closing times vary across space, suggesting the existence of geographic and cultural influence on facilities' hours of operation.

Keywords: Social Media, Point Of Interest, Temporal Signature, Geosocial.

1. Introduction

Spatiotemporal social media data has been used in GIScience as a tool for estimating population distribution (Steiger, 2015a; Patel, 2016), land use classification (Zhan, 2014; Lansley, 2016), facility popularity (McKenzie, 2015; Stewart, 2015; Sparks, 2016), and more. Yet with these multiple applications the study of this data in GIScience is still relatively underexplored and promising (Steiger, 2015b). A common critique of using social media data in research is that it does not represent the true human population; it only represents the users of that specific social media platform. In this work, instead of using something like a social media check-in service (e.g. Foursquare), we use Facebook Points of Interest (POI) data showing when various facilities open and close throughout the week. While this data does not capture at what time of the day these facilities become popular (as something like check-in data does), this data does remove much of the uncertainty that comes with using social media data as it is reported by an associating POI representative.

McKenzie (2015) uses Foursquare check-in data to look at when various facility types (theme park, football stadium, drug store, etc.) become popular in 3 major cities in the USA and Shanghai, China. McKenzie shows evidence that spatial and cultural effects impact the time when people visit certain types of facilities (i.e. those facilities' temporal signatures), showing that when people go to theme parks and football stadiums in Los Angeles is not necessarily the same time people go to those facilities in New York. Our previous work approaches this facility popularity problem using Twitter data instead of Foursquare, applying standard machine learning and natural language processing methods (Sparks, 2016). We build on that work and McKenzie's (2015) work in this paper by looking at when different facility types open and close in various geographic regions at global, country, and city scales. We analyse *Retail Shop* and *Restaurant* POIs due to their relative abundance in many countries, as well as being facilities that are a good indicator for human activity and mobility. Results suggest that opening and closing times for *Retail Shop* and *Restaurant* POIs are dependent on the geographic region that they are located in.

2. Data

The data used in this work is Facebook POI data. Businesses or various institutions can create a Facebook page for themselves and provide optional metadata. This data provides features like geographic location, a self-classified category description (e.g. *Retail Shop, Restaurant, Museum,* etc.), hours of operation, and more. Using Facebook's Public API and our PlanetSense data collection architecture (Thakur, 2015), we collected over 14 million geo-located POIs distributed across the globe. This data comes from approximately 23,000 cities and 240 countries of independent states and dependent territories. At the country scale, we analysed data from the following five countries: Brazil, Nigeria, Turkey, Iran, and Indonesia (Figure 1). We chose these countries because we wanted some geographic and cultural variation, while also having a range of population in each country. At the city scale, we analysed data from 2 large cities within each country (10 in total). The total number of POIs (which includes *Restaurant*, *Retail*, and many other POI categories), *Restaurant* POIs, and *Retail* POIs for each country can be seen in Table 1.

Figure 1: Map of countries analysed in this paper: (from left to right) Brazil, Nigeria, Turkey, Iran, and Indonesia.

	Restaurant	**Retail**	**Total**
Global	663,296	543,664	14,426,877
Turkey	50,279	30,658	1,080,707
Brazil	33,357	36,561	792,896
Indonesia	8,461	30,628	615,255
Iran	1,595	1,268	26,182
Nigeria	270	867	36,215

Table 1: Number of POIs for each country for Restaurant, Retail and total POIs.

3. Temporal Signatures

In this section, we present temporal signatures of open and close times of *Retail Shops* and *Restaurants* at a global, country, and city scale for selected countries and cities. Temporal signatures, shown below, visualize at what times over a 7-day week *Restaurants* and *Retail Shops* are open and closed, and relatively how many are open at a given time. The x-axis of the temporal signature represents time, and starts on Monday at 12:00 midnight (i.e. the first hour of Monday), and progresses by 15 minute time steps until reaching Sunday at 11:45pm. The y-axis represents how many *Retail Shops* or Res*taurants* are relatively open at that given time. The y-axis is visually normalized so that temporal signatures are more easily comparable when the range of values differs. In order to restrict the length of this paper, in section 3.2 we present only *Retail* temporal signatures at the country level, and in section 3.3 we present only *Restaurant* temporal signatures at the city level.

3.1. Global

Referring to Table 1, approximately 650,000 *Restaurants* and 500,000 *Retail Shops* were used to generate the Global temporal signatures seen in Figure 2. The top temporal signature in Figure 2 shows the open and close times and relative quantity of *Retail Shops* open at a given time. The bottom temporal signature shows the same but for *Restaurants*.

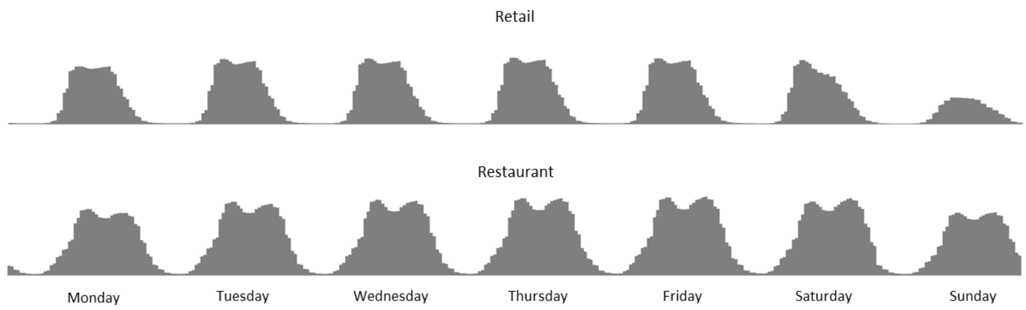

Figure 2: Global temporal signatures for Retail Shops and Restaurants.

In both facility types there is a clear rise and fall indicating day and night cycles. As shown in how long the gap lasts in the signatures during the night-time, *Retail Shops* stay closed for a longer period of time than *Restaurants*. The vast majority of *Restaurants* generally are closed between 3am - 6am (3 hours) whereas the vast majority of *Retail Shops* are closed between 11:00pm – 7:00am (8 hours).

For *Retail Shops*, we see that Monday through Friday is a fairly consistent pattern, while Saturday shows more shops closing earlier in the evening, and Sunday showing a much lower number of shops open throughout the entire day. *Restaurants* show a more consistent pattern across 7 days, with Monday and Sunday showing a slight decrease in the total number of *Restaurants* open. Additionally, we also see a clear division between lunch hours and dinner hours.

3.2. Country

In this section, we only present Iran, Turkey, and Brazil's temporal signatures for *Retail Shops* (Figure 3) because they clearly differ from the Global temporal signature.

In Figure 3 we see that Iran, Turkey, and Brazil's temporal signatures are visually unique from each other and unique from the global average. Iran's temporal signature shows a consistent pattern for every day of the week except Friday. Turkey's temporal signature is unique in that a) while there is a drop in the number of *Retail Shops* open on Sunday, it is not nearly to the extent of Global or Brazil's temporal signatures, b) while other countries' signatures show a drop in shops open in the afternoon, Turkey's signature remains constant during that time, and c) the time between closing and opening the next day is less in Turkey than it is compared to the other temporal signatures, indicating that *Retail Shops* in Turkey stay closed for a shorter period of time. Brazil's temporal signature most resembles the Global temporal signature.

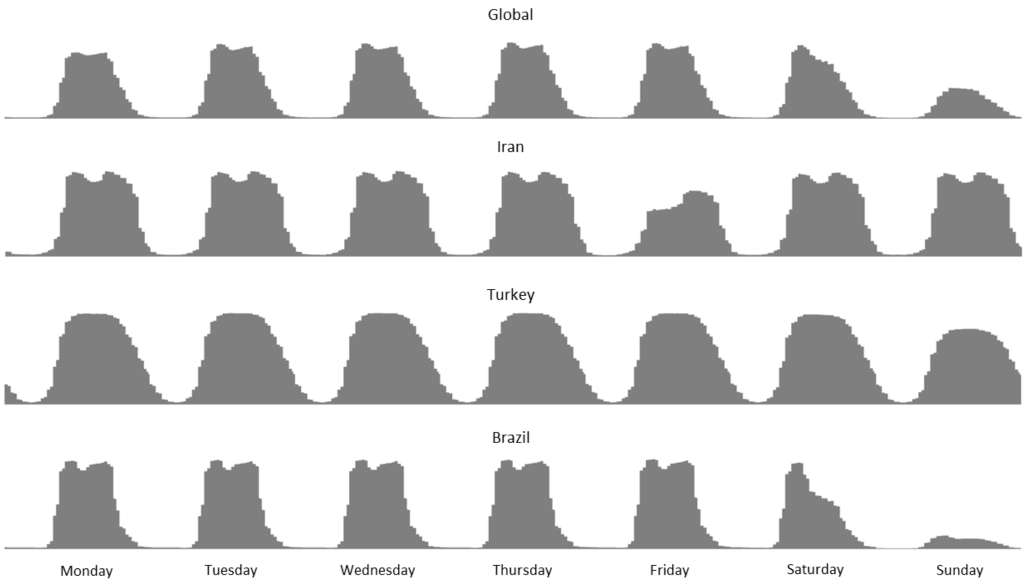

Figure 3: Global vs. Country temporal signatures for Retail Shops.

3.3. City

In this section, we present *Restaurant* temporal signatures for Jakarta (Indonesia), Istanbul (Turkey), and Sao Paulo (Brazil) in Figure 4. We excluded cities from Nigeria and Iran due to paper length restrictions, and also because they were visually similar to their corresponding country signature and the global average.

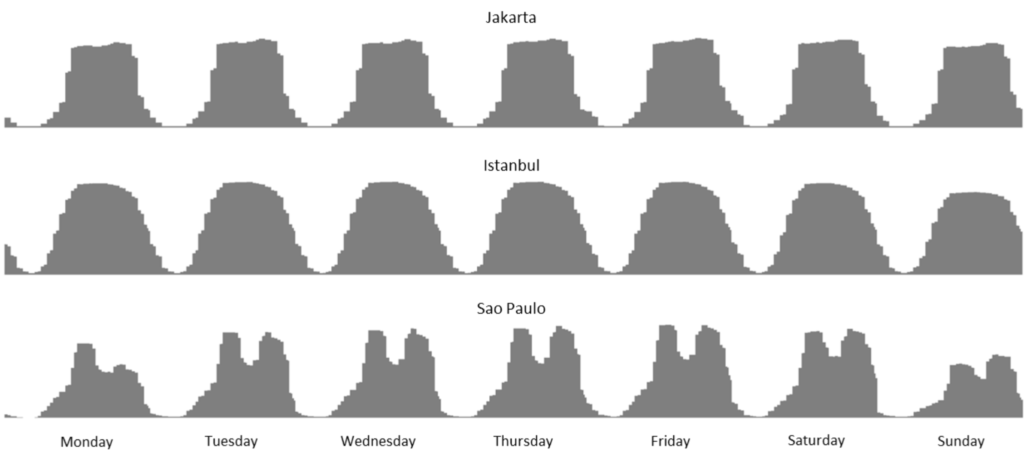

Figure 4: City temporal signatures for Restaurant.

Sao Paulo shows a severe drop between lunch and dinner hours and on Sunday more *Restaurants* are open for dinner than lunch and on Monday more are open for lunch than dinner. In Istanbul, we see no drop between lunch and dinner and almost no drop for Monday or Sunday, which contrasts with Sao Paulo. Similar to Turkey's signature for *Retail Shops*, Istanbul comparatively has *Restaurants* that stay closed for a shorter period of time than Jakarta or Sao Paulo. Jakarta's temporal signature most resembles Istanbul in that there is a relatively consistent pattern Monday through Sunday, with only a slight increase of *Restaurants* open in the evening.

4. Conclusion and Future Work

Results show that when a *Retail Shop* or *Restaurant* opens and closes is generally dependent on geographic location. While both *Retail Shop* and *Restaurant* POIs show variation based on geographic location, *Retail Shops* seems to show more variation than *Restaurants*. *Retail Shops'* temporal signatures in the locations we analysed are expressed 3 ways: the first with Friday being an anomaly (Iran), the second with Sunday and partly Saturday being the anomaly (Global, Brazil), and the third with consistency across each day of the week (Turkey). We expect to continue seeing these differences across facility types, speculating that some facility types might show consistent temporal signatures across geographic locations. In future work, we plan to generate these temporal signatures for every one of the 240 countries and dependent territories in our database and perform some form of cluster analysis or similarity analysis across countries and facility types (expanding the number of facility types we analyse as well). We anticipate that this further investigation can lead to potential cultural and spatial theories and explanations for the shape and variation of the temporal signatures.

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