Scalable Urban Data Collection From The Web

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Abstract

Easy access to different necessities of daily life makes a city more livable. This has motivated urban planning researchers to quantify urban accessibility from official city data. However, due to the manual nature of data collection, these earlier survey based analyses were limited in scale and scalability, and mostly offered insights on cities of developed countries like the UK and the USA.

Using Google Places data that is crowd-sourced around the world, this paper gathers walkability information for twenty-five cities across five continents. We detail the collection methodology of this unprecedented dataset and show useful applications of this data in urban analysis: e.g., how different areas within a city compare against each other in terms of accessibility and which areas in a city would benefit the most from the least intervention.

Introduction

The growing demand for walkable neighborhoods has made services that calculate walkability (e.g., walkonomics.com, walkscore.com) popular among real estate agents, health-care agencies, and environmentalists. However, these sites needed to process and gather a variety of datasets, which can be financially prohibitive (Quercia et al. 2015). In comparison with these prior works on quantifying accessibility, we propose a scalable method using Google Maps public APIs to crawl web data. This scalable and fine-grained data collection methodology enables us to measure accessibility not only for different areas in a particular city, but for different cities in the world.

Similar to our approach, (Cranshaw et al. 2012) and (Vaca et al. 2015) use web data to identify functional uses in a city. They use data from location based social network Foursquare. However, Foursquare data is sparse for many cities, especially in developing countries. Instead, we leverage the wider coverage of Google Maps data, which is crowd-sourced in almost all cities in the world.

Our data collection methodology based on Google Maps API is detailed in Section . An illustrative analysis using this fine-grained dataset for recommending urban interventions is discussed in Section . Directions of future explorations are outlined in Section and we conclude the paper in Section .

Data collection method: Our data collection method is illustrated in Figure. 1. We divide each city into 200m X 200m square grids, and take the centre of each such square as our centroid or area for analysis. The <lat, lon> coordinates of these centroids or areas are input to the Google Places API. The outputs of the Places API are the details of places in different categories (described later in Table 1), nearby to the area under consideration.

Once a list of places is obtained for each area for the different categories, the nearest place in each category is taken. The <lat, lon> coordinates of the area and the place nearest to that area, are then input to the Google Distance Matrix API. The outputs of the Distance Matrix API are the walking distances and times, to travel from the area to the nearest place. We obtain these values for the nearest place in every category, for each area in the city.

Google does not currently include real time traffic and other such information in its travel time results. Thus the time values are static information, simply based on distances and assuming a typical walking speed. In our subsequent analyses, we therefore mostly use the walking distances and design our metrics and methodologies based on them.

Categories used: The Google Places API offers detailed information in different place categories. The categories used in our analysis are given in Table 1, along with their common purposes in urban lives. To reduce the number of API calls and remain within the API query limits imposed by Google, we combine some very similar categories together using the "|" operator. There are 30 different category blocks, after the "|" based combination. Thus for each centroid or area, there are 30 calls issued to Google Places API, to get the nearby places in those 30 categories.
Cities crawled: We repeat those three steps for as many as 25 cities in both developed and developing countries across the five continents (Table 2). They either belong to the developed or industrialized countries, mostly in Europe, North America and in some countries of East Asia. Or they belong to developing countries in South Asia, Africa or South America.

<table>
<thead>
<tr>
<th>Cities</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barcelona, Berlin, London</td>
<td>Industrialized; Europe.</td>
</tr>
<tr>
<td>Milan, Paris, Rome</td>
<td></td>
</tr>
<tr>
<td>Chicago, New York, San Francisco</td>
<td>Industrialized; North America.</td>
</tr>
<tr>
<td>Seattle, Toronto, Washington</td>
<td></td>
</tr>
<tr>
<td>Beijing, Singapore, Tokyo</td>
<td>Industrialized; Asia.</td>
</tr>
<tr>
<td>Delhi, Jakarta, Kuala Lampur, Mexico, Moscow, Mumbai, Nairobi, Rio</td>
<td>Developing; India, South America, Africa.</td>
</tr>
</tbody>
</table>

Table 2: Cities under study.

We construct one such matrix for each city and all our subsequent analyses will be based on these matrices.

Urban Interventions

Having our data organized as area-by-category distance matrices, we now demonstrate the utility of this fine-grained dataset to analyze urban accessibility and inform simple interventions. To this end, we need to determine which areas are rich (in terms of accessibility) and which are poor.

We cluster the areas in a city that are similar to each other in terms of accessibility diversity. Therefore we cluster the areas based on how diverse are the facilities which are within walking distance of a particular area. We run $K$ means clustering and the resulting clusters for $K = 4$ and $8$ are given in Figure 2 for Barcelona and London. Red denotes lower feature values or less diverse facilities within walking distance, and therefore the corresponding cluster icons denote areas which have poorer accessibilities. Green denotes higher feature values or more diverse facilities within walking distance, and therefore the corresponding cluster icons denote areas which have richer accessibilities. Diversity thus increases gradually from red to green clusters. Following this clustering step, we can take a centroid in a poor cluster, compare its categories with centroids in richer clusters and make recommendations for category addition to improve its diversity.

<table>
<thead>
<tr>
<th>Categories</th>
<th>Purposes</th>
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<tbody>
<tr>
<td>bar—restaurant, bakery, cafe, convenience store—grocery or supermarket</td>
<td>food and daily necessities</td>
</tr>
<tr>
<td>bus station, taxi stand, train station—subway station, bicycle store, parking, gas station</td>
<td>transportation</td>
</tr>
<tr>
<td>shopping mall—department store, clothing store—shoe store—jewelry store</td>
<td>shopping and retail</td>
</tr>
<tr>
<td>doctor—dentist, hospital, beauty salon—hair care—spa—gym</td>
<td>health services</td>
</tr>
<tr>
<td>atm—bank</td>
<td>financial services</td>
</tr>
<tr>
<td>school—university</td>
<td>education</td>
</tr>
<tr>
<td>art gallery—museum, book store, library, movie rental, movie theater, night club</td>
<td>entertainment and tourism</td>
</tr>
<tr>
<td>stadium, amusement park—rv park—campground—zoo—aquarium, park</td>
<td>sports and outdoor activities</td>
</tr>
<tr>
<td>fire station, police</td>
<td>safety</td>
</tr>
<tr>
<td>church—hindu temple—mosque—place of worship—synagogue</td>
<td>religion</td>
</tr>
</tbody>
</table>

Table 1: List of facility categories.
Future Work

As true for any crowd-sourced dataset, we do not expect the Google Maps data to be exhaustive. But given the extensive coverage of Google Maps in terms of cities worldwide, this is an excellent data source for scalable urban analysis. In cities where other data sources are available, like government collected ordnance data or other online map data like Foursquare or OpenStreetMap, these can be used to augment the Google Maps dataset, which we intend to do as part of our future work.

An interesting analysis to be done in future, is informing planning depending on whether a city is mono or poly-centric. (Bawa-Cavia 2011) uses Foursquare checkins to identify highly popular urban areas or urban centers in London, New York and Paris. (Batty 2011) uses the subway ticketing data in London to identify urban mobility hotspots. However, Foursquare data is sparse and subway ticketing data is proprietary and difficult to collect for a large number of cities. Owing to the good coverage of Google Maps, our poly-centricty analysis can therefore compare multiple cities around the world, potentially enhancing the scalability of prior studies on urban centers.

Finally, our extensive dataset can also help us determine how our cities around the world fare against each other in terms of accessibility indeces. We seek to compare walkability between European and American cities, as explored in prior works (Buehler 2014; Litman 2002), and measure indeces in developing countries to quantify accessibility problems. We envision to replicate a wide variety of independently conducted earlier studies and match their results, while providing insights for the many unexplored cities (those in continents such as Asia, Africa and South America), which have received little or no attention before.

Conclusion

Using a scalable methodology, we have gathered web data about urban accessibility and put it to use for answering traditional questions in the urban planning field. We have shown how municipal authorities might profit from crawlable web data to inform evidence-based urban interventions. The private sector might benefit too. For example, since accessibility is associated with quality of city life, websites offering house search (e.g. walkscore.com) might integrate our methodology into their products.

Overall, our proposed methodology for scalable data collection has the potential to study cities around the world, especially those in the developing countries in Asia and Africa, which have been neglected in the literature so far.
References


Buehler, R. 2014. 9 Reasons the U.S. Ended Up So Much More Car-Dependent Than Europe.


