Remapping London Cultural Neighborhoods Through Crowdsourced GPS

INTRODUCTION

Do cultural neighborhood defined by ethnicity overlaps with the natural clustering people created through daily life interactions? The answer to this question underlies constant struggles in urban spaces to redefine geographic neighborhoods based on layers of economic, political, and social interactions beyond a static administrative border. In this research, I would like to propose using crowdsourced GPS tracks from OpenStreetMap dataset to redraw the boundaries of neighborhoods in London based on people-space interactions and compare them against the existing representation of London's cultural districts.

Traditional methods relying on census and demographic data are often slow and insufficient to reflect the dynamic changes of the neighborhood and capture the interactions happened beyond residences. For example, London Chinatown still hosts a large population that is ethnically Chinese today, but the growing trend of gentrification has threatened to appropriate the region as a cultural symbol rather than a living space for the Chinese community [1]. Without an interaction-based representation of the neighborhood, it can be difficult for urban planners and policymakers to locate and quantify changes on the neighborhood level in a holistic manner. GPS tracks can provide a collection of the origin and destination pairs. The volumes of GPS tracks hosted by OpenStreetMap can be forged into a representative people-space or space-space network that mirrors daily interactions to the maximum level.

Despite surging interests in geolocation data in recent years, empirical analyses were rarely done on a neighborhood level. One of the reasons is that constructing a meaningful social network requires big data. The common forms of social flow data, such as transportation records and mobile phone call, can only capture inter-region interactions and often interpreted on a national scale [2]. Other forms of geotagged data, such as social media posts and photo uploads, may tend to capture the younger generation's adventurous experience rather than routines. Therefore, the local interactions within the communities, those that are crucial to cultural activities, are often omitted from these datasets. The other reason is that the methodology to integrate social network with geographic information is still in infancy. Location-based social network (e.g. Tom from Tokyo visited Alice at New York) has only become popular in 2011 [3]. Recently researchers have also just started to explore the impacts built environment could have on social networks [4] and how to integrate social and interpersonal data in GISystem [5]. Therefore, my research to apply GPS tracks to reconstruct cultural neighborhoods can be a valuable attempt to advance the methodology and bridge the gap between Sociology and Geography.

EXPECTATIONS AND HYPOTHESES

If a cultural neighborhood is segregated or self-contained, I will expect it to emerge as an independent cluster during the partitioning of the network because most of the interactions (GPS origins and destinations) should happen within the community. On the opposite, if a cultural neighborhood was turned into a tourist spot, I will expect to see many non-local interactions, manifested by GPS tracks started or ended in a different region. However, it is possible that the GPS generated network will reveal new "cultural neighborhoods" that were never formally defined, or dissolve the myths of the formal ones that only exist in names today.

DATA AND METHODS

The dataset I will use to extract GPS tracks data is the OpenStreetMap (OSM). OpenStreetMap is has been the leading example for Volunteered Geographic Information (VGI) systems on the Internet that is now powering map data on thousands of websites, mobile apps, and hardware devices. Individuals can upload their GPS trajectory, pin down geographic objects such as railways and cafés, and contribute to the correction of geographic information just like editing wikis. Founded in 2004, OSM has attracted 1.7M users by 2014 [6].

London, in particular, is a region well-tagged in OSM dataset. Contrasting OSM and Ordnance Survey dataset — a spatial map dataset created by Great Britain's national mapping agency — has shown considerable overlap between the two, thereby confirming the validity of OSM dataset to represent actual geographic information [6]. Visualization of GPS metadata also indicates London area as one of the regions with the highest coverage.

After extracting the GPS tracks data in London from OSM, I will restructure the data in the form of a location-based social network (LBSN). The origin and destination of the GPS track are the nodes, while the journey between the two points is simplified as a connecting edge. Different from the traditional social network, each of the node also has a geolocation tag attached to it. Then I will apply a partition algorithm [2] to divide the network into non-overlapping clusters that maximize the distinctiveness and minimize the interruption to each node's links. I may need to dig into the community detection literature in social network analysis to find the best approach to such divisions. In the end, I will compare the emerged geolocated network cluster with the actual mapping of current cultural neighborhoods in London and interpret the extent they overlap. Since the focus of this research is on tackling the challenges of transforming GPS tracks into a LBSN and examine the latter with existing cultural neighborhood boundary, I will use current maps of the ethnic neighborhoods in London, an example of which can be found through CityLab [7].

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