Chatty Maps: A sound map of New York City

GEO 877, Aiello Group

Marco Stutz, Choi Yeung Lo, Mengqi Li, Yilin Wei, Robin Merz

[1]Department of Geography, University of Zurich

Paper to be reviewed: Chatty maps: constructing sound maps of urban areas from social media data

Authors: Luca Maria Aiello, Rossano Schifanella, Daniele Quercia & Francesco Aletta (2016)

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Data path: Aiello's Teams files > Assignment Folder (also on Google Driver)

1. Introduction

Urban sound significantly affects our perception of places. Traditionally, monitoring noise levels involves placing sensors at specific locations to record decibel levels. This method is costly and does not scale effectively across an entire city. Additionally, traditional noise monitoring often focuses on unpleasant sounds, such as traffic and construction noise, while overlooking pleasant sounds like music and natural sounds. To address these limitations, Aiello et al. (2016) introduced a novel approach that uses tagging information from georeferenced social media images to create urban sound maps. They applied this methodology to London and Barcelona, successfully mapping various soundscapes in these cities. Our project aims to replicate their work by generating a sound map for New York City. We will then compare the map with real noise complaint data. In the conclusion of this report, we will provide our perspective on the effectiveness and applicability of this methodology.

2. Data:

(1) Sound Lexicon

Aiello et al. (2016) complied the first urban sound lexicon by extracting 448 sound-related terms from the crowdsourced online repository of sounds, Freesound. The terms were further classified into six categories: Transport, Human, Music, Indoor, Mechanical, and Nature. We downloaded and reviewed the original lexicon. Since the original study areas were London and Barcelona, nearly half of the lexicon is in Spanish, which initially limited the number of images with matching tags. To address this, we used the Freesound API to search for more sound-related terms and extended the lexicon. Additionally, because some tags were not included in the original lexicon, we manually checked the tag list and extracted additional tags to enhance the map's variety. The final sound lexicon list contains 780 terms.

(2) Flickr photos

Georeferenced photos are downloaded from Flickr via API within the bounding box that covers New York City. More than 150K photos with tagging information are obtained from 2014 to 2024.

(3) New York City Noise Complaint Data

We integrated New York City 311 noise complaint data from 2010 to the present, aligning this with the timeframe of the Flickr photo dataset to ensure comparability. To accurately compare these data sources, we randomly sampled the noise complaint records to match the quantity of Flickr photos.

3. Methods

We downloaded the New York City Street centerline (CSCL) from the NYC government's open data source. First, we split the Shapely multilines into individual line segments and created buffers around each segment with a width of 20 meters, resulting in 290,248 buffers on our basemap. After removing duplicate photo IDs, the georeferenced photos were transformed into point class objects.

To manage and analyze these geotagged photos, we developed a spatial indexing algorithm. We began by creating buffers of 20 meters around the street segments and then generated a bounding box that encompassed all these buffer areas. We defined a grid resolution of 2000 meters and calculated the necessary grid cells using Haversine distance. This resulted in a grid overlay within the bounding box, with each cell uniquely identified and its geometric boundaries recorded. We assigned photos to the grid cells by intersecting their coordinates with the cells, ensuring accurate spatial indexing. We verified the distribution of photos within the bounding box, identifying any empty cells (located on the sea). For each street segment buffer, we created a bounding box and checked its intersection with the grid cells to identify relevant cells and photos intersecting each buffer area, ensuring efficient and accurate spatial analysis of urban sounds.

Following the spatial indexing, we focused on the intersection of segment buffers with geotagged photos to analyze relevant tags. We flattened and deduplicated each list of photos associated with the segment buffers. For each segment buffer, we checked if the photo's geographic coordinates fell within the buffer using the 'containsPoint' function. If a photo was within the buffer, we retrieved its tags from the tag dictionary, which included tags relevant to our sound lexicon. We compiled lists of photo IDs, coordinates, and tags inside the buffers and appended these lists to the main data frame. To verify the results, we visualized the data by plotting a segment buffer along with the grid cells it intersected and the photos within those cells, ensuring the accuracy of our intersection process. This detailed analysis allowed us to intersect geotagged photos with segment buffers effectively, providing a basis for generating our urban sound map by analyzing the spatial distribution of sound-related tags within specific urban areas, and to verify this important step.

We further refined our analysis by filtering the segment buffers to include only those that intersected with photos, ensuring only relevant buffers were considered. We categorized the buffers based on their main categories, assigning colors and category names to each buffer for easy identification. This categorization allowed us to visually differentiate between various urban sound categories.

Using the Folium library, we created an interactive map to visualize the segment buffers, the intersecting photos, and their associated tags. The map was centered on our bounding box with a chosen map tile style for clarity. For each buffer, we added polygons representing the buffer areas, colored according to their categories. We also plotted the street segments and colorized them based on their category, providing tooltips and popups for additional context. Furthermore, we added circle markers for each intersecting photo, displaying their tags upon interaction. This interactive map enabled a detailed and intuitive exploration of the urban soundscape, highlighting the spatial distribution of sound-related tags across the city.

To ensure the accuracy of our spatial analysis, we performed a final verification step. We selected a specific segment buffer and retrieved the photos and tags associated with it. By visualizing the buffer and its intersecting photos, we confirmed that the spatial relationships and tag assignments were correctly processed. This step ensured that our urban sound map accurately represented the spatial distribution and categorization of sound-related tags within the city.

4. Result:

(1) Chatty map

The distribution of sound categories in New York City, as represented by photo data from Flickr, provides insights into the city's soundscape. Human and nature sounds dominate, followed by indoor and transport sounds, with music and mechanical sounds being less prevalent. These findings can inform urban planning and environmental strategies to improve the auditory experience in urban settings.

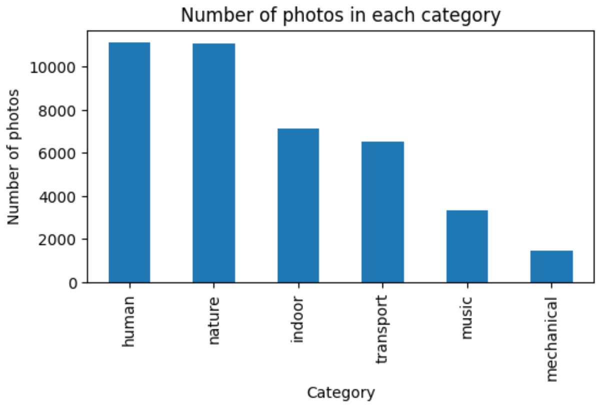

Figure1. The Sound Category Analysis

The Chatty Map results provide a detailed overview of New York City's soundscape. Human sounds, shown in blue, are particularly dominant in Manhattan, reflecting its high density of commercial and residential areas bustling with activity. Nature sounds, in green, are concentrated in parks and green spaces like Central Park, highlighting the city's blend of urban and natural environments.

Indoor sounds, marked in yellow, are dispersed citywide but prominent in dense urban areas, associated with activities in shopping centers, offices, and apartments. Transport sounds, in red, align with major roads, bridges, and transportation hubs, indicating areas with heavy traffic.

Music sounds, represented by purple, are less frequent and localized in cultural hotspots like entertainment districts and concert venues. Mechanical sounds, shown in black, are concentrated in industrial areas such as Queensbridge, reflecting factories, construction sites, and infrastructure noise.

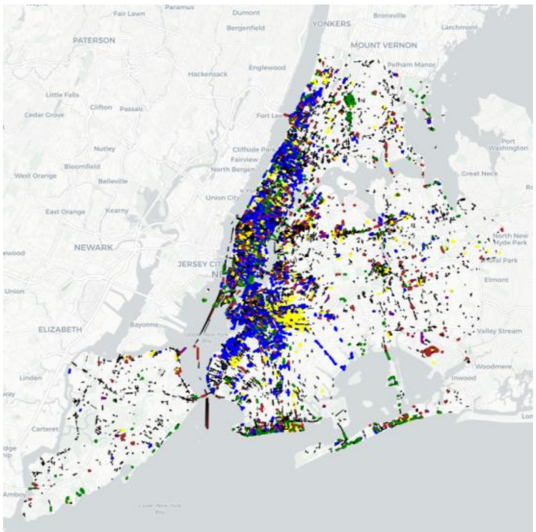

Figure2. The Sound Distribution in New York City

(2) <u>Evaluating the Accuracy of Flickr Photo Tags for Sound Categorization Using NYC 311 Noise Complaint Data</u>

Our study, primarily focused on urban sound mapping, includes a supplementary analysis to evaluate the reliability of social media tags as indicators of urban sounds. We compared these tags with actual noise complaints in New York City.

Our findings indicate significant discrepancies: social and musical events tagged on Flickr are mostly confined to entertainment districts, while noise complaints are more prevalent in residential areas, showing a clear divide between enjoyable and disruptive sounds. Mechanical and transport noises were similarly reported in both datasets, reflecting consistent disturbance. Interestingly, natural sounds—often tagged and viewed positively—had no corresponding noise complaints, revealing a gap in perception. This suggests that social media alone may not provide an accurate picture of urban noise, and a combined approach with traditional complaint data offers a more comprehensive understanding of urban soundscapes.

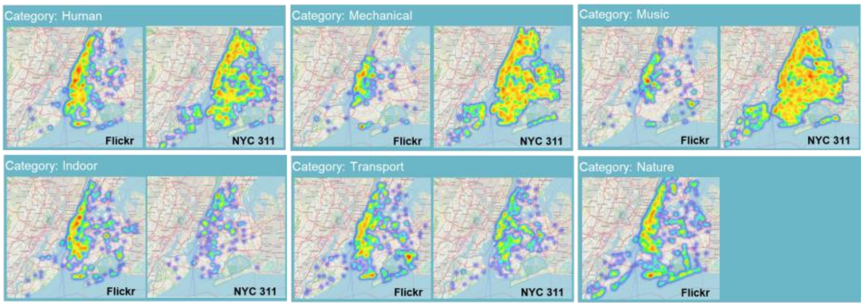

Figure3. The Heat Maps Comparison between Flickr and 311 data

5. Conclusion:

By replicating Aiello et al's (2016) approach, we have generated a soundscape map for New York City by using the georeferenced photo from Flickr with applying spatial algorithms including segment buffering, spatial indexing, and aggregating points in polygon intersection. From the soundscape map, most of the sound activity happened in Manhattan. Human-related sound is the major source of sound in the city, while nature-related sound is more dominant in Central Park, Liberty Island, and Manhattan Beach. By comparing the data of the actual complaint data, there is discrepancy on the noise complaint cases which mainly reported in residential areas in Queens and Brooklyn boroughs.

While the soundscape map generated by tags from social media reflects the urban sound distribution to some extent, we identified several limitations of this study. First, people tend to share more photos when they travel, resulting in a higher concentration of data in Manhattan, a relatively more touristy area. Secondly, we have concerns about the original sound lexicon, which contains around four-hundred words but still generates a large map for London and Barcelona. Our initial result of using the same lexicon did not produce as many segments, as some tags were not necessarily sound-related. Some terms in the lexicon are very vague, for example 'paper' was assigned in indoor categories; and 'metro' is the term of transport category, but it appears in tourist photos with the tag 'metropolis' which might lead to irrelevant data being included.

Nevertheless, our study demonstrates the potential of using georeferenced social media data to create urban sound maps. Future research should focus on refining the lexicon, incorporating more diverse data sources, and exploring methods to balance the distribution of data across different areas. This approach can enhance our understanding of urban soundscapes and contribute to more effective noise management strategies.

6. Reference:

Aiello, Luca & Schifanella, Rossano & Quercia, Daniele & Aletta, Francesco. (2016). Chatty Maps: Constructing sound maps of urban areas from social media data. Royal Society Open Science. 3. 10.1098/rsos.150690.

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