Which Neighborhood in Atlanta is Best for a Metal Music Venue Business? Considering Transportation, Demographic, and Urban Planning Factors

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CP6542: Transport and GIS Final Report
GitHub: https://github.com/drunken-boat/livehouse-atl

Contents

1 Introduction

Atlanta's city planning vision is committed to fostering an economically viable and community-centric metropolitan area. This vision includes the transformation of Atlanta into a globally recognized destination for entertainment and cultural exchange, welcoming all racial, ethnic, and national groups (Atlanta Department of City Planning, 2021).

The City of Atlanta Department of City Planning (DCP) recognizes the arts as a significant economic catalyst. The DCP intends to invest in vibrant public spaces within neighborhood commercial districts and expand resources to bolster local economies capable of connecting with regional and global networks (DCP, 2021).

Live music venues, vital for the arts and valuable as small businesses, depend on complex systems of cultural and social capital to generate revenue. This revenue can be further capitalized to enhance business growth (Whiting, 2021).

Economic geography theory suggests that the need for access to large and sophisticated markets, with the tendency of music and creative industries to cluster, leads to geographic concentration (Florida et al., 2010).

Metal music, experiencing growth in Atlanta and having regional and even national impact, positions the Southeast as one of the most promising areas in the country for the music business. The "Mass Destruction Music Fest" held in Atlanta in recent years have notably placed the Southeast on the national metal map (Castro, 2017).

Given the growth of metal music and the cultural significance of music venues, the current period presents a favorable opportunity to invest in a metal music venue in Atlanta. However, music venue owners and investors highlight that venues serve as critical sites for negotiating cultural values and market imperatives. Many booking agents and small venue owners often prioritize the cultural space and facilitation to thrive over the pursuit of profit (Carah et al., 2017).

The location for a music venue business is a crucial consideration and an interdisciplinary topic. Therefore, it is essential to integrate transport, geography, urban planning, and sociology to investigate the optimal neighborhood in Atlanta for a metal music venue business.

1.1 Problem Statement

This project aims to identify the best neighborhood in city of Atlanta for a metal music venue business, considering transportation, demographic, and urban planning factors.

1.2 Project Location

The location is the city of Atlanta, which will be referred to as Atlanta for short. It's strategic geographical position and robust transportation system make it a key gateway for the national and international music industry in the southeastern region. According to a 2011 report, the music industry was projected to contribute over 313 million dollars annually to state and local government revenues, with an estimated total employment of 19,955.(Tai, 2014)

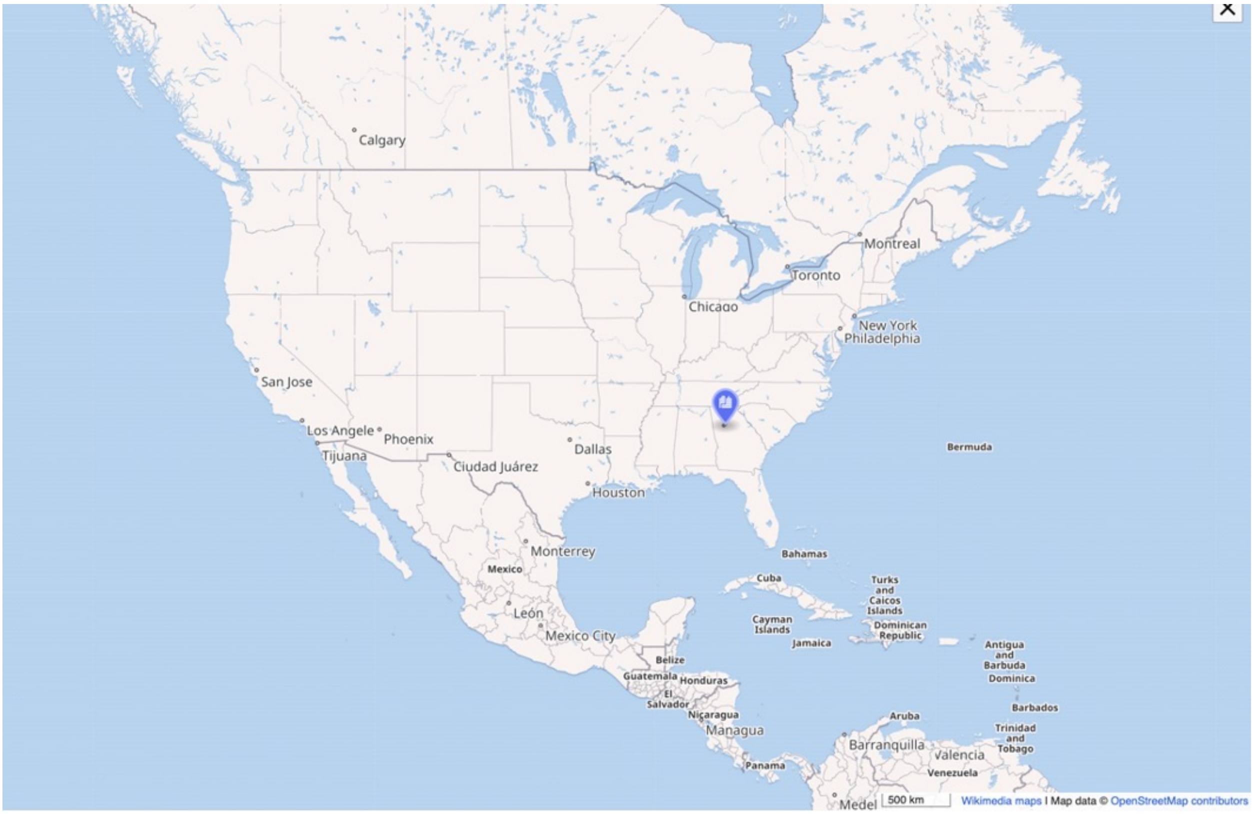


Figure 1: Project Location on Planet Earth

1.3 Terms and Context

Metal Music: A music genre, originated in the UK and US in the late 60s and early 70s. It evolved from blues rock, psychedelic rock, and acid rock, and is known for its powerful sound featuring distorted guitars, long guitar solos, strong beats, and high volume. Metal music lovers are called "metalheads"(Walser, 1993), which is the major consumer of metal music venue business.

Music Venue: A music venue is any location used for a concert or musical performance. Music venues range in size and location, from a small coffeehouse for folk music shows, an outdoor bandstand or a concert hall to an indoor sports stadium. In this project, the music venue is in the same scope yelp's music venue category.

1.4 Conceptual Vision and Model

The conceptual model, which includes spatial and mathematical components, converts transport and demographic factors into measurable metrics. These metrics are represented by scores, and then joined by location, using the area as a weight to aggregate scores for neighborhoods. The neighborhoods with the highest scores are then selected, and restriction layers are applied to determine the most suitable ones. The final step is identifying and conducting a detailed analysis of the neighborhood that is most suitable for a metal music venue business.

1.5 Objectives

The objectives of this project are to:

1. Evaluate the accessibility to current music venues.
2. Identify neighborhoods with high potential for establishing metal music venues, considering transport, demographic, and urban planning factors.
3. Contribute to the promotion of a vibrant music scene in Atlanta.

2 Literature Review

2.1 Music Industry and the Cities

The music industry played a significant role in the economic development of cities, contributing to job creation and economic growth(Florida, 2010) . The importance of live music venues in cities was also highlighted (Whiting, 2021). Carah et al. argued that small live music venues have alternative forms of capital and serve as niche spaces for cultural production (Carah et al., 2021), who explored how owners and managers of original live music venues navigate cultural, commercial, and regulatory forces in hyper-commercialised nightlife precincts.

2.2 Scoiolgy

Tai examined the role of gatekeeping and social capital in live music scenes in the context of Atlanta and Taipei(Tai, 2014). The study provides insights into the dynamics of live music scenes in different cultural contexts. The genre of music also plays a role in the music scene of a city. Walser discussed the powerand preference in heavy metal music(Walser, 1993). Shukla (2022) conducted research on the social psychology and demography of heavy metal.

3 Data Processing and Inclusion

3.1 Data Source

Atlanta Statistical Neighborhood

City of Atlanta Neighborhood Area polygon data were derived from the course materials provided in Lab 2.

Music Venue Point of Interest Points of interest for music venues were obtained through query from the Yelp Business Search API(Yelp, 2023).

Demographic Data: Census Tract The author focused on Atlanta, situated within Fulton and DeKalb counties. The author sourced polygon data from the American Community Survey (ACS) 5-year estimates in 2019 (U.S. Census Bureau, 2019). This data included monthly housing prices, median household income, median age, and racial distribution. The housing prices offered insight into the rental costs for music venues, while the median household income and age highlighted the consumer characteristics of the neighborhood.

Demographic Data: Metalheads' Demography Shukla's 2022 sociology paper provided the age, gender, and racial distribution data of metalheads(Shukla,2022).

Transport Data: Road Network and Parking Lots The author used a Python query with OSMnx (Boeing, 2017) to download the road network polylines and parking lot data(points and polygons) for Atlanta, the retrieving time stamp is November 21st, 2023.

Urban Planning Data: Zoning and Livable Center Initiative Zoning and Livable Center Initiative(LCI) are directly downloaded from fulton county GIS data portal(Fulton County, 2023).

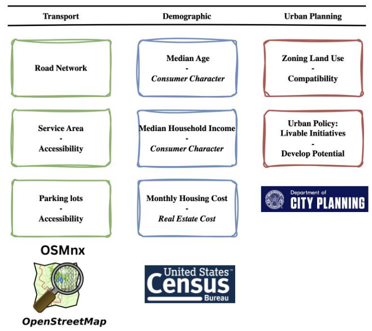


Figure 2: Data source and Usage

3.2 Data Accuracy

This project acknowledges several potential sources of inaccuracies in the data. The OSMnx data, derived from GPS, may exhibit meter-level inaccuracies due to daily variations in accuracy and systematic errors. Additionally, naming inaccuracies may exist (OpenStreetMap Wiki, 2020). The Yelp Business Search API, which returns up to 1000 businesses and excludes businesses without reviews, may not account for some music venues that lack reviews or exceed the limit (Yelp, 2023). Furthermore, the demographic data of metalheads, researched in England, may not fully apply to Atlanta due to differing cultural and historical contexts.

The first two inaccuracies are disregarded as this project operates at the neighborhood level. The potential demographic inaccuracy is mitigated by focusing solely on age distribution, excluding race and gender considerations.

To bolster accuracy, this project utilizes 5-year estimates from the ACS, rather than 1-year estimates. This approach enhances statistical reliability by drawing on a larger data set (U.S. Census Bureau, 2019).

3.3 Data Processing

Before integrating data into the spatial model, two crucial steps are executed. The initial step involves transforming the coordinate reference system to WGS 84 UTM Zone 16. The subsequent step entails conducting a service area analysis in the network. In ArcGIS Pro, music venue points of interest serve as facilities, with time thresholds set at 5, 10, 15, and 20 minutes, and driving designated as the network type (Gutiérrez, 2008).

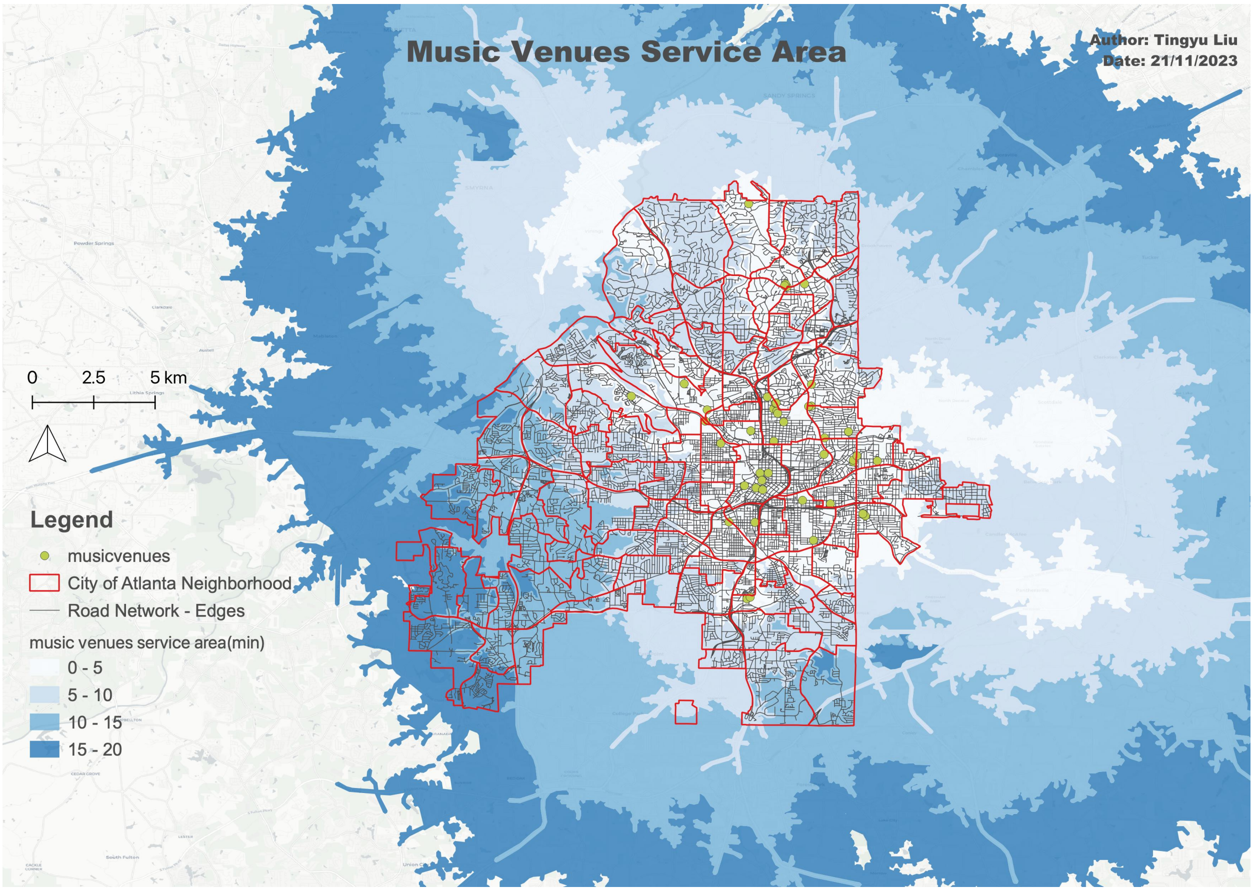


Figure 3: Music Venue Service Area

4 Solution and Methods

4.1 Spatial and Mathematical Model

The spatial and mathematical model involved building a spatial model to convert transport and demographic factors to quantifiable metrics, then ranking neighborhoods based on these metrics to find the top 5 neighborhood candidates. Then, urban planning and transport factors were used as restrictions to select the best suitable one.

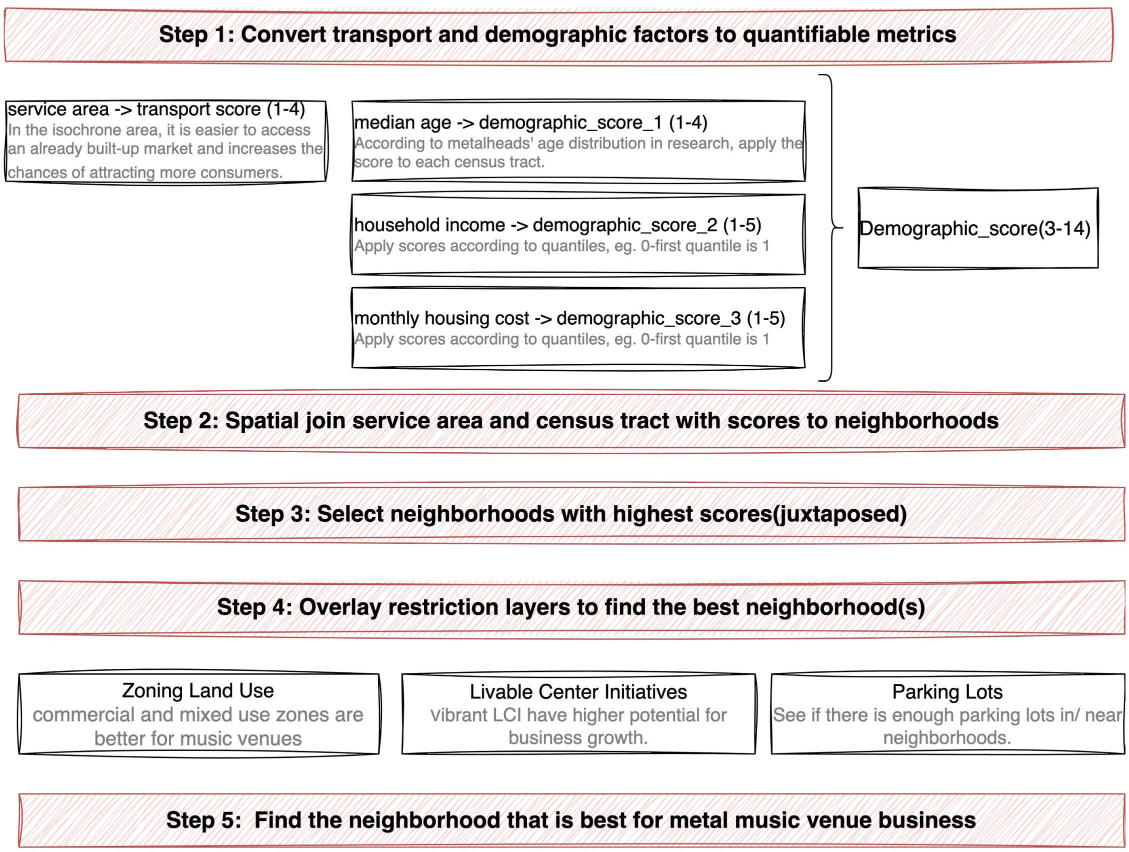


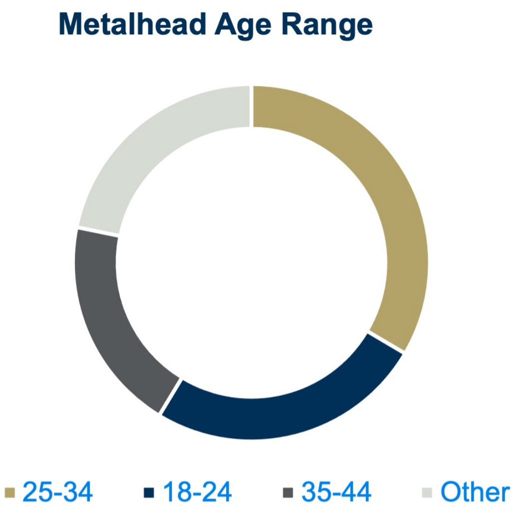
Figure 4: Model Steps

4.2 Model Steps

1. Convert transport and demographic factors to quantifiable metrics.

In the transport factor (network analysis), scores were applied based on accessibility to existing music venues. A higher score indicated shorter driving time to existing music venues. According to economic geography, concentration is beneficial for the music venue business. More accessible places are more familiar to current metalheads, making it easier to build cultural recognition. For instance, a service area within 0-5 minutes driving received a score of 4 out of 4.

In terms of age distribution, the author applied scores to each census tract based on the age distribution of metalheads from the research. A higher score indicated a more similar range to the metalheads' age range. For example, the age range of 25-35 received a score of 4 out of 4.



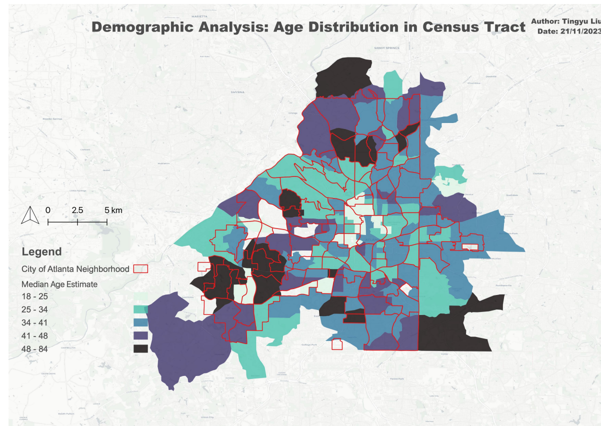
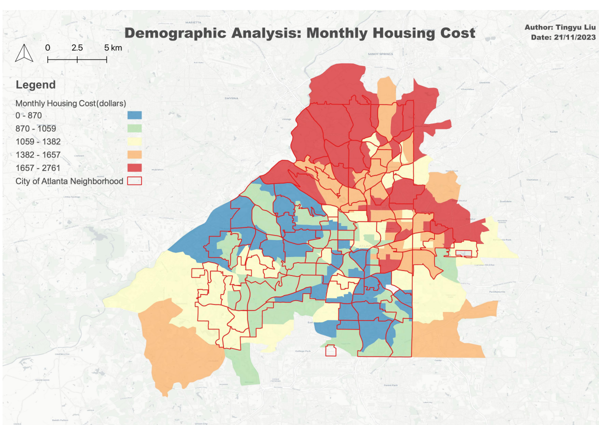


Chart 1: Metalhead's age & Figure 5: Demographic Analysis: Age Spatial Distribution

In the median household income, the author separated income into 5 ranges according to equal quantile and applied scores according to quantiles. A higher score indicated higher consuming capacity. For example, an income range of 102303 - 208750 dollars received a score of 5 out of 5.

In monthly housing cost, the author separated income into 5 ranges according to equal quantile and applied scores according to quantiles. A higher score indicated higher consuming capacity. For example, a monthly housing cost range of 1657 - 2761 dollars received a score of 5 out of 5.



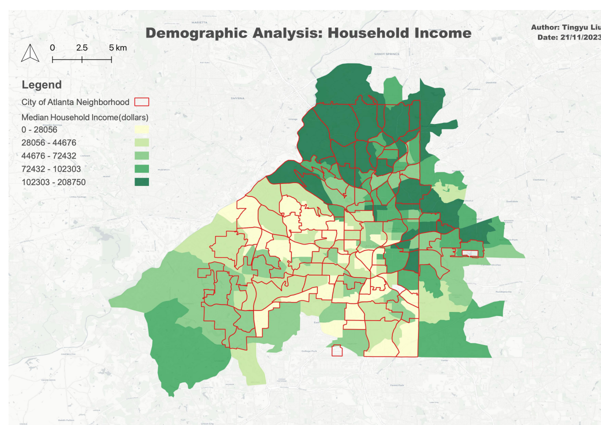


Figure 6: Demographic Analysis: Housing Cost & Figure 7: Demographic Analysis: Household Income

2. Spatial join service area and census tract with scores to neighborhoods

In the first steps, the scores are in the service area polygons or census tract polygon, and considering the objective is to find out the best neighborhood, so the author join score attribute by location, and sum the score in each neighborhoods based on area.

In the initial stages of the process, each service area polygon or census tract polygon is assigned a score, denoted as S_i, where i represents the index of the polygon. The objective is to identify the optimal neighborhood, which necessitates the aggregation of scores by location. This is achieved by associating the score attribute with each neighborhood. The total score, T_j, for a given neighborhood j, is computed by summing the scores of all polygons within the neighborhood, each weighted by their respective area, A_i. Mathematically, this can be represented as:

$$T_j = \sum_{i \in N_j} \frac{A_i}{A_{neighborhood}} \cdot S_i \tag{1}$$

Here, N_j signifies the set of polygons within neighborhood j, and A_{total} is the total area of all polygons. This equation effectively calculates the weighted scores in each neighborhood based on area, aligning with the described procedure.

3. Select neighborhoods with highest scores(juxtaposed)
After summarying up the score to neighborhood, sort final score in descending order, and select the neighborhood that has top score.

4. Overlay restriction layers to find the best neighborhood(s) The author consider two restrictions: urban planning(zoning and LCI) and transport(parking lot).

Land use designated for commercial and mixed-use purposes aligns more effectively with the operational requirements of a music venue business. Furthermore, the LCI(Livable Centers Initiative), which advocates for the creation of vibrant, walkable spaces, provides additional support for these neighborhoods as potential locations for the proposed music venue. The more ratio of commercial and mixed-use area, and the more overlay with LCI, the more suitable for music venue business for a neighborhood.

Metal music events usually occur during the evening hours((Walser, 1993), leading to a majority of the audience opting to drive to the venue. To cater to this demographic, music venues typically undertake one of two strategies. They either allocate substantial financial resources towards the acquisition of a parking lot, or they strategically select a location in close proximity to public parking facilities.

5. Find the neighborhood that is best for metal music venue business

4.3 Integration of Tools and Methods

The author integrated various tools and methods in this study. ArcGIS Pro was used for the Network Analyst (Service Area), and QGIS was used for Layout, Join Attribute by Location, Field Calculator, and Attribute Table. Additionally, Python packages OSMNX, Folium, and Geopandas were used for geo-spatial data collection, processing, and interactive visualization.

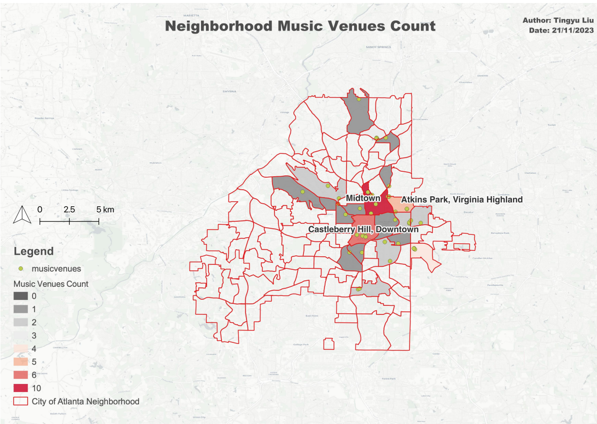
5 Research Results, Discussion, and Conclusion

5.1 Analysis Result

Competitor Analysis

The competitor analysis focuses on the existing music venues in the city of Atlanta, which could potentially pose as business competitors for new metal music venues. This analysis involves examining the spatial distribution of existing music venues, their attributes, and their kernel density.

A significant concentration of music venues is found in mid-eastern Atlanta, demonstrating the economic geography concept of clustering (Florida et al., 2010). Clustering of related businesses can reduce production costs due to competition among suppliers and increased specialization. Interestingly, even same-sector firms can benefit from clustering by attracting more suppliers and customers than they could individually.



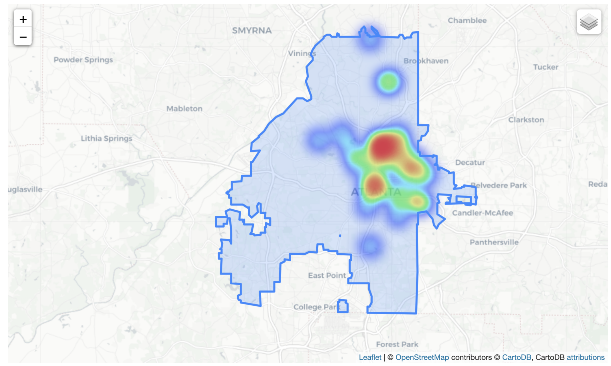


Figure 8: Neighborhood Music Venue Count & Figure 9: Music Venue Kernel Density

Transport Analysis

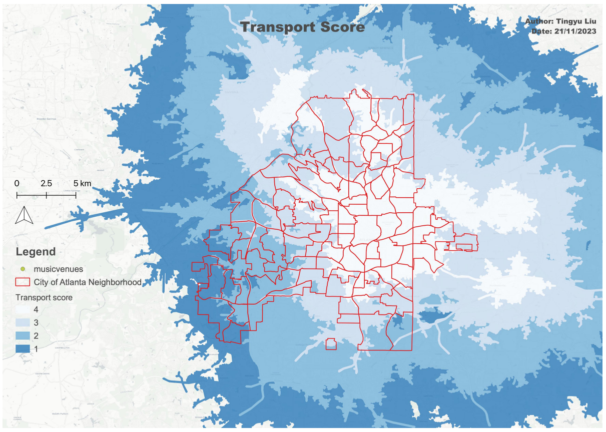
The transport analysis is service area in network analysis, which evaluate the accessibility of existing music venues.

Midtown, distinguished by the highest number of music venues, exhibits a spatial distribution primarily on the eastern side of Atlanta. Neighborhoods with a significant concentration of music venues, such as Midtown, Castleberry Hill, and Akins Park, are centrally located, forming a cluster in the central part of the city.

The areas with the greatest accessibility, defined as those within a 0-5 minute driving time, display a spatial skew when compared to the distribution of music venues. While the music venues are predominantly distributed along an east-west axis, the service area extends more significantly in the north-south direction. This pattern can be largely attributed to the presence of the I-75 and I-85 highways. The influence of transport factors on accessibility and location analysis is evident. Music venues within a shorter driving time achieve higher transport scores, indicating that the proximity to major highways and ease of access are beneficial for the music venue business.

Demographic Analysis

The neighborhoods exhibiting the highest demographic suitability for music venues, in terms of demographic features, are predominantly located on the north and east side of the city of Atlanta. A comparison with the distribution of music venues reveals that the downtown area, despite having a lower demographic score, houses several music venues. This observation underscores the importance of considering transport features, specifically the service area, as it represents existing accessibility. The presence of music venues in areas with lower demographic scores suggests that accessibility may play a significant role in the location of these venues.



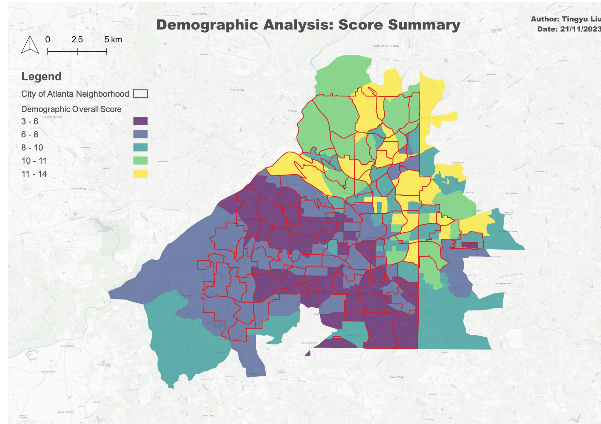
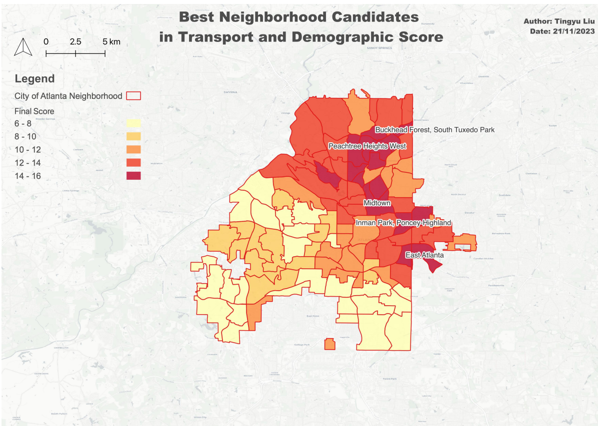


Figure 10: Transport Analysis: Service Area Score & Figure 11: Demographic Analysis: Total Demographic Score

Factor Integration

Upon the integration of transport and demographic scores, the neighborhoods that emerge with the highest scores (16 out of a possible 18) are Midtown, Inman Park, East Atlanta, Peachtree Heights West, and Buckhead Forest. These neighborhoods exhibit advantageous conditions for the establishment of a metal music venue business, as evidenced by their accessibility, demographic composition, and urban planning factors. Through the quantification and amalgamation of these factors, the study identifies these neighborhoods as the most propitious locations for music venue business.



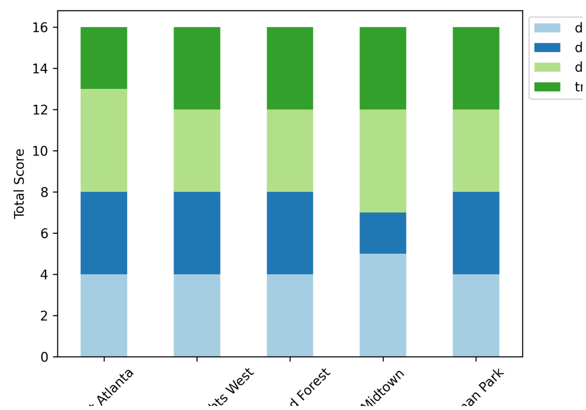


Figure 12: Final Score for Neighborhoods & Chart 2: Total Score Stack Chart

Restriction Analysis

The Midtown, Inman Park, and Buckhead Forest neighborhoods outperform others in terms of zoning and LCI restrictions. This is due to their higher proportion of commercial and mixed-landuse areas, as well as their larger overlay area with LCI. These factors indicate a better business atmosphere, greater popularity walkability, and stronger economic drive.

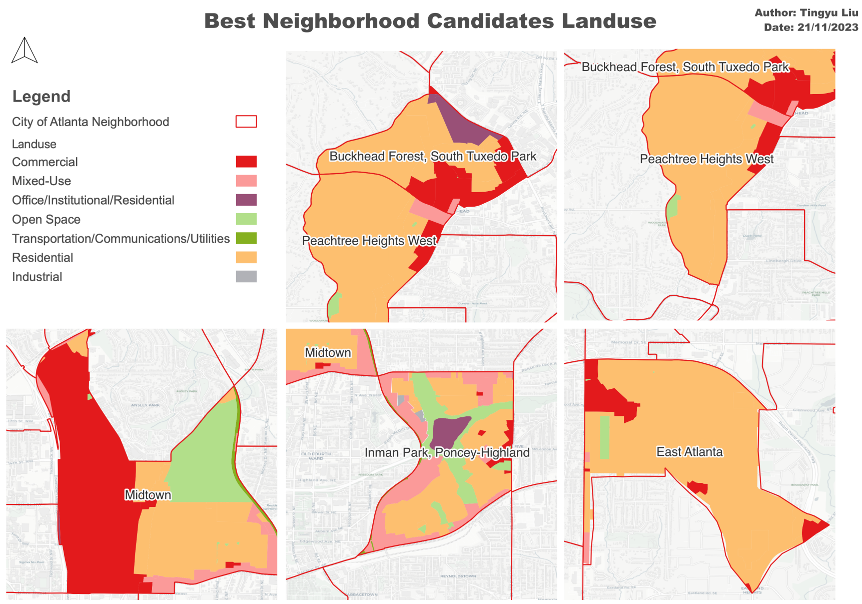


Figure 13: Zoning Restriction Analysis & Figure 14: LCI Restriction Analysis

The figure illustrate the distribution of parking lot amenities within and in the vicinity of each potential neighborhood. Considering the availability of parking lots, Midtown and Inman Park emerge as the most viable options. This conclusion is drawn based on the current distribution and accessibility of parking facilities in these neighborhoods.

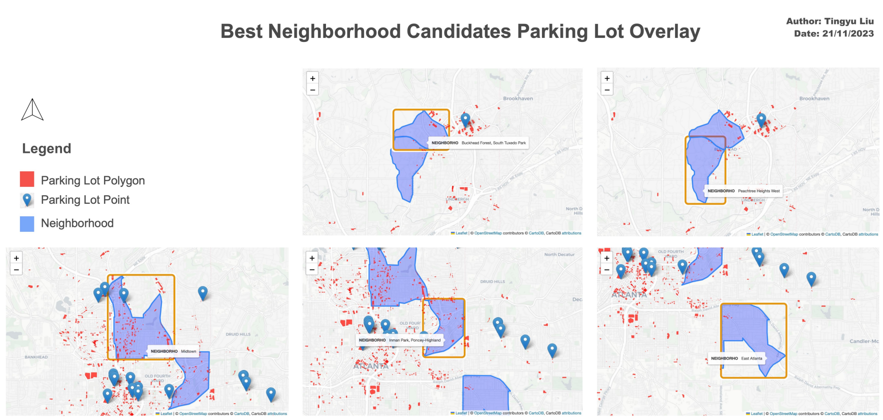


Figure 15: Parking Restriction Analysis

5.2 Conclusion

Upon quantifying both transport and demographic factors, and imposing transport and urban planning factors as constraints, the study concludes that Midtown and Inman Park emerge as the most favorable locations for establishing a metal music venue business.

Midtown, with its well-established music venue business, presents a competitive landscape. It is likely to resonate with the metal music enthusiasts due to its familiarity. However, it is important to consider that the real estate prices in this area are comparatively higher. This venture in Midtown could be characterized as high-risk, high-reward.

On the other hand, Inman Park, with fewer existing music venues, exhibits greater potential for this business, given the suitable conditions it offers. The author proposes Edgewood Avenue, renowned for its restaurant street, as the location for the music venue. However, it's important to note that it's less populated and the household income is lower than Midtown. These factors could influence the success of a music venue in this area.

5.3 Discussion

This study assesses the spatial distribution and service area of existing music venues in Atlanta. It identifies neighborhoods with high potential for establishing metal music venues, considering transportation, demographic, and urban planning factors. The study utilizes two procedures: quantitative matrices ranking and restriction analysis, as spatial and mathematical models.

Merits and Long-term Effects

This study stands out due to its innovative and interdisciplinary approach in transport, GIS, urban planning, and sociology. It integrates concepts from different fields, creating a comprehensive model for location analysis. Furthermore, the research is vertical in nature, delving deep into the subject matter to provide nuanced insights. Also, this study combines city-level location analysis with business-level user profiling. This combination allows for a more holistic understanding of the factors influencing the success of a music venue business.

The long-term effects of this project include promoting a vibrant music scene in Atlanta and providing valuable insights for businesses looking to establish a metal music venue in the city.

Uncertainty and Error

The potential for uncertainty and error in this project primarily stems from the accuracy of the data sources and the assumptions inherent in the spatial and mathematical models.

Data Source Uncertainty and Error

As discussed in the data accuracy section, the data sources, particularly the point of interest data for music venues from Yelp, contain inherent uncertainties and errors. It is worth noting that certain establishments, such as bars and restaurants that host live metal music shows, may not be categorized as music venues and are therefore excluded from this project. For instance, *Boggs Social & Supply*, despite hosting significant metal music events, is categorized as a bar, food truck, or breakfast point of interest, and is not included in the music venue data.

Assumptions in the Spatial and Mathematical Model

While this study integrates various fields and employs a comprehensive model, the complexity of real-life location analysis extends beyond the scope of this research. For example, the process of opening a music venue is influenced by factors such as the investor's social network (Tai, 2014), which are not accounted for in the current model.

Further Work

The integration of machine learning methodologies could potentially enhance the sophistication of the analyses and predictions, thereby revealing patterns and relationships that may not be immediately apparent in the current study. For instance, if data pertaining to metal music venues, transport, and demographics is collected on a national scale and subsequently subjected to rigorous cleaning processes, the application of Principal Component Analysis (PCA) could augment interpretability while simultaneously preserving the maximum amount of information. This could facilitate the identification of features that render a neighborhood suitable for music venues.

Future research could employ Natural Language Processing (NLP) to extract insights from metalheads and venue owners, aiding in identifying locations that optimize social, cultural, and business capital. Additionally, Latent Dirichlet Allocation (LDA) topic modeling in Location-Based Social Networks (LSBN) could reveal meaningful topics and functional regions based on Point of Interest (POI) co-occurrence patterns, enhancing our understanding of metal music enthusiasts' activities and music venue analysis (Gao et al., 2017).

6 Reference

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A Appendix A: Charts

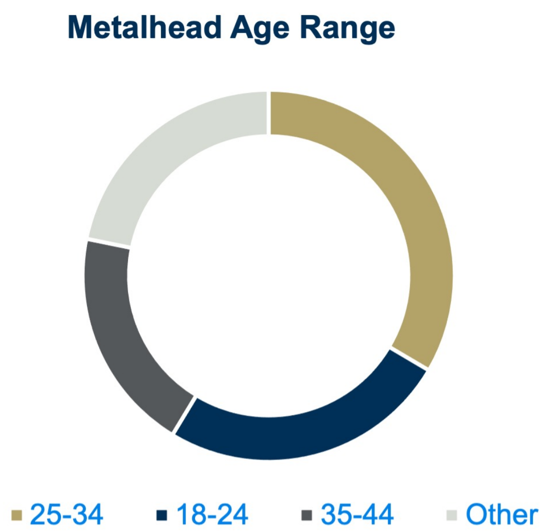


Chart 1: Metalhead's age

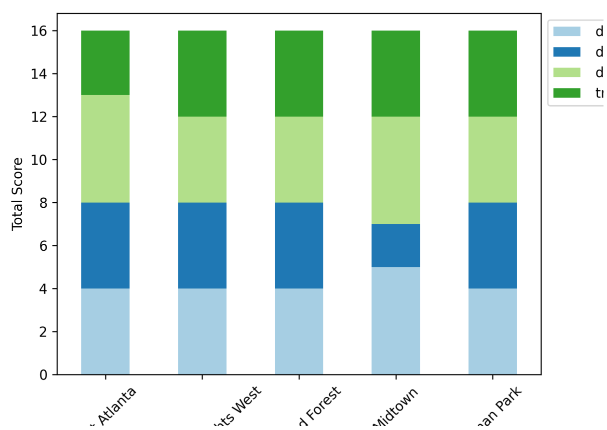


Chart 2: Total Score Stack Chart

B Appendix B: Code for Geo-spatial Data Analysis

1_plot_musicvenues_1124

December 11, 2023

[1]:
```
import geopandas as gpd
import os
import pyarrow.feather
import pandas as pd
import folium
from folium import plugins
from folium.plugins import HeatMap

# set path
current_path = os.getcwd()
root_path = os.path.dirname(current_path)
raw_path = os.path.join(root_path, 'data', 'raw')
process_path = os.path.join(root_path, 'data', 'processed')
# print(raw_path)

input_path = os.path.join(raw_path,  'flat_musicvenues.feather')
output_path = os.path.join(raw_path,'musicvenues','musicvenues.shp')
```

```
/Users/rainylty/opt/anaconda3/envs/city8/lib/python3.10/site-
packages/geopandas/_compat.py:112: UserWarning: The Shapely GEOS version
(3.10.3-CAPI-1.16.1) is incompatible with the GEOS version PyGEOS was compiled
with (3.10.1-CAPI-1.16.0). Conversions between both will be slow.
  warnings.warn(
```

[2]:
```
# read feather data with geopandas and turn it into a geodataframe
df = pd.read_feather(input_path)

# rename geometry column
df = df.rename(columns={'coordinates.latitude': 'lat'})
df = df.rename(columns={'coordinates.longitude': 'lon'})
df = df.rename(columns={'location.display_address': 'address'})

# turn object into string in price column
df['price'] = df['price'].astype(str)
# print(type(df['price'][0]))

gdf = gpd.GeoDataFrame(df, geometry=gpd.points_from_xy(df.lon, df.lat))
gdf.head()
```

[2]:

```
                       id                            alias  \
0  AbAw6Iqjrhts4CFxJD6hDA           bar-margot-atlanta-2
1  ZoFht0viJtWiAt4MeP6zvQ              kats-cafe-atlanta
2  8CV0o1eU0aTD7nDaxPcwzw    domaine-nightclub-atlanta-2
3  fMyqmv7MfjUR4HaA0w_5Ig       dome-in-the-city-atlanta
4  KAMJigcGSquToNvU1hjqZQ  atlanta-symphony-hall-atlanta

                    name                                          image_url  \
0             Bar Margot  https://s3-media2.fl.yelpcdn.com/bphoto/bT1Qdk…
1             Kat's Cafe  https://s3-media3.fl.yelpcdn.com/bphoto/E6KWha…
2      Domaine Nightclub  https://s3-media1.fl.yelpcdn.com/bphoto/ipdvNF…
3       Dome In The City  https://s3-media2.fl.yelpcdn.com/bphoto/Dxt4eu…
4  Atlanta Symphony Hall  https://s3-media3.fl.yelpcdn.com/bphoto/Bh9k4K…

  is_closed                                              url  review_count  \
0     False  https://www.yelp.com/biz/bar-margot-atlanta-2?…           234
1     False  https://www.yelp.com/biz/kats-cafe-atlanta?adj…           273
2     False  https://www.yelp.com/biz/domaine-nightclub-atl…            24
3     False  https://www.yelp.com/biz/dome-in-the-city-atla…             3
4     False  https://www.yelp.com/biz/atlanta-symphony-hall…            13

                                        categories  rating transactions  \
0                           Lounges, Music Venues     4.0     delivery
1                      New American, Music Venues     4.0     delivery
2                                    Music Venues     3.0
3  Venues & Event Spaces, Stadiums & Arenas, Musi…    3.5
4                                    Music Venues     4.0

  …        lon     location.address1 location.address2  \
0 … -84.385511          75 14th St NE
1 … -84.381030       970 Piedmont Ave
2 … -84.384044  1150 Crescent Ave NE              Fl 1
3 … -84.383650  1100 Peachtree St NE              None
4 … -84.384719  1280 Peachtree St NE              None

          location.address3  location.city  location.zip_code  \
0  Four Seasons Hotel Atlanta        Atlanta              30309
1                                    Atlanta              30309
2                                    Atlanta              30309
3                       None         Atlanta              30309
4                       None         Atlanta              30309

 location.country location.state  \
0              US             GA
1              US             GA
2              US             GA
3              US             GA
```

```
4                US             GA

                                                    address  \
0  75 14th St NE, Four Seasons Hotel Atlanta, Atl…
1               970 Piedmont Ave, Atlanta, GA 30309
2      1150 Crescent Ave NE, Fl 1, Atlanta, GA 30309
3            1100 Peachtree St NE, Atlanta, GA 30309
4            1280 Peachtree St NE, Atlanta, GA 30309

                     geometry
0  POINT (-84.38551 33.78688)
1  POINT (-84.38103 33.78112)
2  POINT (-84.38404 33.78592)
3  POINT (-84.38365 33.78488)
4  POINT (-84.38472 33.78935)

[5 rows x 25 columns]
```

[3]:

```
gdf.describe()
gdf.info()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
RangeIndex: 56 entries, 0 to 55
Data columns (total 25 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 56 non-null     object
 1   alias              56 non-null     object
 2   name               56 non-null     object
 3   image_url          56 non-null     object
 4   is_closed          56 non-null     bool
 5   url                56 non-null     object
 6   review_count       56 non-null     int32
 7   categories         56 non-null     object
 8   rating             56 non-null     float64
 9   transactions       56 non-null     object
 10  price              56 non-null     object
 11  phone              56 non-null     object
 12  display_phone      56 non-null     object
 13  distance           56 non-null     float64
 14  lat                56 non-null     float64
 15  lon                56 non-null     float64
 16  location.address1  55 non-null     object
 17  location.address2  43 non-null     object
 18  location.address3  47 non-null     object
 19  location.city      56 non-null     object
 20  location.zip_code  56 non-null     object
 21  location.country   56 non-null     object
```

```
 22  location.state     56 non-null     object
 23  address            56 non-null     object
 24  geometry           56 non-null     geometry
dtypes: bool(1), float64(4), geometry(1), int32(1), object(18)
memory usage: 10.5+ KB
```

[4]:
```
# give gdf a crs, use WGS84 mercator
gdf.crs = {'init': 'epsg:4326'}
```

```
/Users/rainylty/opt/anaconda3/envs/city8/lib/python3.10/site-
packages/pyproj/crs/crs.py:141: FutureWarning: '+init=<authority>:<code>' syntax
is deprecated. '<authority>:<code>' is the preferred initialization method. When
making the change, be mindful of axis order changes:
https://pyproj4.github.io/pyproj/stable/gotchas.html#axis-order-changes-in-
proj-6
  in_crs_string = _prepare_from_proj_string(in_crs_string)
```

[9]:
```
# plot the geodataframe with folium
m = folium.Map(location=[33.7868794367165, -84.3855107579268], zoom_start=11,␣
 ↪tiles='cartodb positron')
# folium.GeoJson(gdf, tooltip=folium.GeoJsonTooltip(fields=['name','price'])).
 ↪add_to(m)
# different colors for different price levels
folium.GeoJson(gdf,
                           tooltip=folium.
 ↪GeoJsonTooltip(fields=['name','price', 'rating',␣
 ↪'review_count','address']),
                           # style_function=lambda x: {'color': 'green' if␣
 ↪x['properties']['price'] == '$' else 'orange' if x['properties']['price'] ==␣
 ↪'$$' else 'red' if x['properties']['price'] == '$$$' else 'black'},
                           # different colors for different rating levels
                           style_function=lambda x: {'color': 'green' if␣
 ↪x['properties']['rating'] >= 4 else 'orange' if x['properties']['rating'] >=␣
 ↪3 else 'red' if x['properties']['rating'] >= 2 else 'black'},
                           ).add_to(m)


m
```

[9]: `<folium.folium.Map at 0x133d930a0>`

[44]:
```
# save geodataframe as shapefile
gdf.to_file(output_path)
```

```
/var/folders/38/ttqg2y215g16g2ng7jd502_c0000gn/T/ipykernel_23326/1322296942.py:2
: UserWarning: Column names longer than 10 characters will be truncated when
saved to ESRI Shapefile.
  gdf.to_file(output_path)
```

[17]:
```python
# draw a heatmap with folium
# make intersection of gdf and polygon
polygon_path = os.path.join(raw_path,␣
  ↪'City_of_Atlanta_Neighborhood_Statistical_Areas/City_of_Atlanta_boundary.
  ↪geojson')
polygon = gpd.read_file(polygon_path)
polygon.crs = {'init': 'epsg:4326'}
# make intersection of gdf and polygon
gdf_intersect = gpd.overlay(gdf, polygon, how='intersection')
# print(gdf_intersect.head())

m_heat = folium.Map(location=[33.7868794367165, -84.3855107579268],␣
  ↪zoom_start=12, tiles='cartodb positron')
m_heat.add_child(HeatMap(data=gdf_intersect[['lat', 'lon']], radius=20))
folium.GeoJson(polygon).add_to(m_heat)
# change the opacity of the heatmap

folium.LayerControl().add_to(m_heat)

m_heat
```

```
/Users/rainylty/opt/anaconda3/envs/city8/lib/python3.10/site-
packages/pyproj/crs/crs.py:141: FutureWarning: '+init=<authority>:<code>' syntax
is deprecated. '<authority>:<code>' is the preferred initialization method. When
making the change, be mindful of axis order changes:
https://pyproj4.github.io/pyproj/stable/gotchas.html#axis-order-changes-in-
proj-6
  in_crs_string = _prepare_from_proj_string(in_crs_string)
```

[17]:
```
<folium.folium.Map at 0x12eaa84c0>
```

[11]:
```python
# add polygon layer
# read polygon data
polygon_path = os.path.join(raw_path,␣
  ↪'City_of_Atlanta_Neighborhood_Statistical_Areas/
  ↪City_of_Atlanta_Neighborhood_Statistical_Areas.shp')
polygon = gpd.read_file(polygon_path)
polygon.head()
# add polygon layer to m
folium.GeoJson(polygon).add_to(m)
m
```

[11]:
```
<folium.folium.Map at 0x133d930a0>
```

[114]:
```python
# count the number of music venues in each neighborhood
# join gdf and polygon
# add a column 'count' to gdf
gdf['count'] = 1
```

```
gdf_polygon = gpd.sjoin(gdf, polygon, how='right', op='within')
gdf_polygon.head()
gdf_polygon.info()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
Int64Index: 130 entries, 0 to 101
Data columns (total 42 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   index_left         49 non-null     float64
 1   id                 49 non-null     object
 2   alias              49 non-null     object
 3   name               49 non-null     object
 4   image_url          49 non-null     object
 5   is_closed          49 non-null     object
 6   url                49 non-null     object
 7   review_count       49 non-null     float64
 8   categories         49 non-null     object
 9   rating             49 non-null     float64
 10  transactions       49 non-null     object
 11  price              49 non-null     object
 12  phone              49 non-null     object
 13  display_phone      49 non-null     object
 14  distance           49 non-null     float64
 15  lat                49 non-null     float64
 16  lon                49 non-null     float64
 17  location.address1  48 non-null     object
 18  location.address2  37 non-null     object
 19  location.address3  40 non-null     object
 20  location.city      49 non-null     object
 21  location.zip_code  49 non-null     object
 22  location.country   49 non-null     object
 23  location.state     49 non-null     object
 24  address            49 non-null     object
 25  count              49 non-null     float64
 26  OBJECTID           130 non-null    int64
 27  NPU                130 non-null    object
 28  STATISTICA         130 non-null    object
 29  POP2010            130 non-null    int64
 30  NEIGHBORHO         130 non-null    object
 31  URL                130 non-null    object
 32  A                  130 non-null    object
 33  pop                130 non-null    int64
 34  white              130 non-null    float64
 35  black              130 non-null    float64
 36  asian              130 non-null    float64
 37  other              130 non-null    float64
```

```
 38   hispanic           130 non-null    float64
 39   GlobalID           130 non-null    object
 40   last_edite         4 non-null      object
 41   geometry           130 non-null    geometry
dtypes: float64(12), geometry(1), int64(3), object(26)
memory usage: 43.7+ KB
```

```
/Users/rainylty/opt/anaconda3/envs/city8/lib/python3.10/site-
packages/IPython/core/interactiveshell.py:3318: FutureWarning: The `op`
parameter is deprecated and will be removed in a future release. Please use the
`predicate` parameter instead.
  if await self.run_code(code, result, async_=asy):
/var/folders/38/ttqg2y215g16g2ng7jd502_c0000gn/T/ipykernel_23326/2126710322.py:6
: UserWarning: CRS mismatch between the CRS of left geometries and the CRS of
right geometries.
Use `to_crs()` to reproject one of the input geometries to match the CRS of the
other.

Left CRS: +init=epsg:4326 +type=crs
Right CRS: EPSG:4326

  gdf_polygon = gpd.sjoin(gdf, polygon, how='right', op='within')
```

[95]:

```python
# convert polygon to geojson
polygon.to_file(os.path.
 ↪join(raw_path,'City_of_Atlanta_Neighborhood_Statistical_Areas','City_of_Atlanta_Neighborhoo
 ↪geojson'), driver='GeoJSON')
```

2_parking_lot

December 11, 2023

[9]:
```python
import osmnx as ox
import geopandas as gpd
from shapely.geometry import MultiPoint, MultiPolygon
import folium
from folium import plugins
import os
```

[10]:
```python
# set path
current_path = os.getcwd()
root_path = os.path.dirname(current_path)
raw_path = os.path.join(root_path, 'data', 'raw')
process_path = os.path.join(root_path, 'data', 'processed')
# print(raw_path)
```

[5]:
```python
# Specify the name of the city and country
place_name = "Atlanta, USA"

# Download the point of interest data
pois = ox.features_from_place(place_name, tags={'amenity':'parking'})

# see how many features were returned
print(len(pois), 'points of interest')
```

```
1365 points of interest
```

[29]:
```python
# plot out the pois
# ax = ox.plot_footprints(pois)

# plot with folium

# plot the geodataframe with folium
m = folium.Map(location=[33.7868794367165, -84.3855107579268], zoom_start=11,␣
 ↪tiles='cartodb positron')
# add poi's 'name' column as pop-up labels for the markers
folium.features.GeoJson(pois,
                                                fill_color="red",␣
 ↪fill_opacity=0.5, stroke=False,
```

```
                                                tooltip=folium.
↪GeoJsonTooltip(fields=['parking','access','fee','capacity']),
                                                ).add_to(m)

polygon_path = os.path.join(raw_path,␣
↪'City_of_Atlanta_Neighborhood_Statistical_Areas/
↪City_of_Atlanta_Neighborhood_Statistical_Areas.shp')
polygon = gpd.read_file(polygon_path)
polygon.head()
# add polygon layer to m
folium.GeoJson(data=polygon, fill=False).add_to(m)

m
```

[29]:
```
<folium.folium.Map at 0x1507299d0>
```

[15]:
```
pois.head(10)
```

[15]:
```
                          amenity                    geometry       name  \
element_type osmid
node         496141022    parking  POINT (-84.39143 33.76207)        NaN
             496141023    parking  POINT (-84.39142 33.76115)        NaN
             497397032    parking  POINT (-84.32157 33.75499)        NaN
             534431138    parking  POINT (-84.38312 33.75679)        NaN
             567065914    parking  POINT (-84.35175 33.79235)        NaN
             600429864    parking  POINT (-84.39090 33.76088)  Interpark
             681262448    parking  POINT (-84.39408 33.75466)        NaN
             795904771    parking  POINT (-84.39821 33.79183)        NaN
             1127136673   parking  POINT (-84.38043 33.75540)        NaN
             1179861872   parking  POINT (-84.38051 33.75715)        NaN

                         old_name operator layer      parking access  fee  \
element_type osmid
node         496141022        NaN      NaN    -1  underground    NaN  NaN
             496141023        NaN      NaN    -1  underground    NaN  NaN
             497397032        NaN      NaN   NaN      surface    yes   no
             534431138        NaN      NaN   NaN          NaN    NaN  NaN
             567065914        NaN      NaN   NaN          NaN    NaN  NaN
             600429864        NaN      NaN   NaN          NaN    NaN  NaN
             681262448        NaN      NaN   NaN      surface    NaN  NaN
             795904771        NaN      NaN   NaN          NaN    NaN  NaN
             1127136673       NaN      NaN   NaN      surface    yes  yes
             1179861872       NaN      NaN   NaN          NaN    NaN  NaN

                         capacity  … phone smoothness access:conditional  \
element_type osmid                 …
node         496141022        NaN  …   NaN        NaN                NaN
```

```
              496141023        NaN  …  NaN        NaN                  NaN
              497397032        NaN  …  NaN        NaN                  NaN
              534431138        100  …  NaN        NaN                  NaN
              567065914        NaN  …  NaN        NaN                  NaN
              600429864        NaN  …  NaN        NaN                  NaN
              681262448        NaN  …  NaN        NaN                  NaN
              795904771        NaN  …  NaN        NaN                  NaN
              1127136673        20  …  NaN        NaN                  NaN
              1179861872        20  …  NaN        NaN                  NaN

                          maxstay:conditional building:part email image ways  \
element_type osmid
node         496141022                    NaN           NaN   NaN   NaN  NaN
             496141023                    NaN           NaN   NaN   NaN  NaN
             497397032                    NaN           NaN   NaN   NaN  NaN
             534431138                    NaN           NaN   NaN   NaN  NaN
             567065914                    NaN           NaN   NaN   NaN  NaN
             600429864                    NaN           NaN   NaN   NaN  NaN
             681262448                    NaN           NaN   NaN   NaN  NaN
             795904771                    NaN           NaN   NaN   NaN  NaN
             1127136673                   NaN           NaN   NaN   NaN  NaN
             1179861872                   NaN           NaN   NaN   NaN  NaN

                          type roof:shape
element_type osmid
node         496141022     NaN        NaN
             496141023     NaN        NaN
             497397032     NaN        NaN
             534431138     NaN        NaN
             567065914     NaN        NaN
             600429864     NaN        NaN
             681262448     NaN        NaN
             795904771     NaN        NaN
             1127136673    NaN        NaN
             1179861872    NaN        NaN

[10 rows x 80 columns]
```

[ ]:

```
# Remove rows with empty geometries
pois = pois[pois.geometry.notnull()]

# Remove rows with invalid geometries
pois = pois[pois.geometry.is_valid]
pois.geometry = pois.geometry.apply(lambda x: x[0] if isinstance(x, MultiPoint)␣
 ↪else x)
# pois.geometry = pois.geometry.apply(lambda x: x[0] if isinstance(x,␣
 ↪MultiPolygon) else x)
```

```
# if the field is a list, drop the list and keep the first element
pois.geometry = pois.geometry.apply(lambda x: x[0] if isinstance(x, list) else␣
↪x)
# save the data as a geojson file
pois.to_file('../data/raw/parking.geojson', driver='GeoJSON')
```

[ ]:
```
# Remove rows with empty geometries
pois = pois[pois.geometry.notnull()]

# Remove rows with invalid geometries
pois = pois[pois.geometry.is_valid]
pois.geometry = pois.geometry.apply(lambda x: x[0] if isinstance(x, MultiPoint)␣
↪else x)
pois.to_file('../data/raw/parking.shp')
# Convert MultiPolygons to Polygons
# pois.geometry = pois.geometry.apply(lambda x: x[0] if isinstance(x,␣
↪MultiPolygon) else x)
```

[38]:
```
# read data in the data/final
gdf_final = gpd.read_file('../data/final/5finalists.geojson')

# add parkingn poi and gdf_final to m_final
m_final = folium.Map(location=[33.7868794367165, -84.3855107579268],␣
↪zoom_start=11, tiles='cartodb positron')
# add gdf_final to m_final
folium.features.GeoJson(gdf_final,
                                                fill_color="blue",␣
↪fill_opacity=0.3, stroke=True,
                                                tooltip=folium.
↪GeoJsonTooltip(fields=['NEIGHBORHO']),
                                                ).add_to(m_final)
# add polygon layer to m
# folium.GeoJson(data=polygon, fill=False).add_to(m_final)
# add poi's 'name' column as pop-up labels for the markers
folium.features.GeoJson(pois,
                                                fill_color="red",␣
↪fill_opacity=0.8, stroke=False,
                                                tooltip=folium.
↪GeoJsonTooltip(fields=['parking','access','fee','capacity']),
                                                ).add_to(m_final)
m_final
```

[38]: <folium.folium.Map at 0x1542ba9d0>

3_score_calculation

December 11, 2023

[5]:
```
import geopandas as gpd
import pandas as pd
```

[ ]:
```
gdf = gpd.read_file('../data/raw/transport_census.geojson')
```

[8]:
```
# Perform the quantile cut on the 'monthly_cost' column
gdf['monthly_housing_costE'] = gdf['monthly_housing_costE'].fillna(0)
gdf['housing_cost_score'] = pd.qcut(gdf['monthly_housing_costE'], 5, labels=[1,␣
↪2, 3, 4, 5]).astype(int)

gdf['hhincomeE'] = gdf['hhincomeE'].fillna(0)
gdf['income_score'] = pd.qcut(gdf['hhincomeE'], 5, labels=[1, 2, 3, 4, 5]).
↪astype(int)
```

[11]:
```
def assign_score(age):
    if 25 <= age < 35:
        return 4
    elif 18 <= age < 25:
        return 3
    elif 35 <= age < 44:
        return 2
    else:
        return 1


gdf['age_score'] = gdf['median_ageE'].apply(assign_score)

# add up the scores to get a final score
gdf['score'] = gdf['age_score'] + gdf['income_score'] +␣
↪gdf['housing_cost_score']
```

[12]:
```
# save back
gdf.to_file("../data/processed/transport_census.geojson", driver='GeoJSON')
```

5_detailed_score

December 11, 2023

[3]:
```
# use pandas and seaborn to plot a stack chart
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt


df = pd.read_csv('../data/final/5finalists_score.csv')
df.head()
```

[3]:
```
                NEIGHBORHO    pop  hhincomeE  owner_occupied_housingE  \
0             East Atlanta   5101     111759                     1467
1  Peachtree Heights West   4874      83243                     1279
2          Buckhead Forest   3372      83243                     1279
3                  Midtown  16218     109426                     1569
4               Inman Park   6196      78182                      412

   renter_occupied_housingE  public_transportE  monthly_housing_costE  \
0                       641                 54                   1589
1                      1792                 63                   1625
2                      1792                 63                   1625
3                      1863                276                   1914
4                       882                117                   1657

   drive_to_workE  demographic  housing cost score  demographic  age score  \
0            2929                                4                        4
1            2786                                4                        4
2            2786                                4                        4
3            2482                                5                        2
4            1237                                4                        4

   demographic income score  demographic total score  \
0                         5                       13
1                         4                       12
2                         4                       12
3                         5                       12
4                         4                       12

   transport score(service area)
```

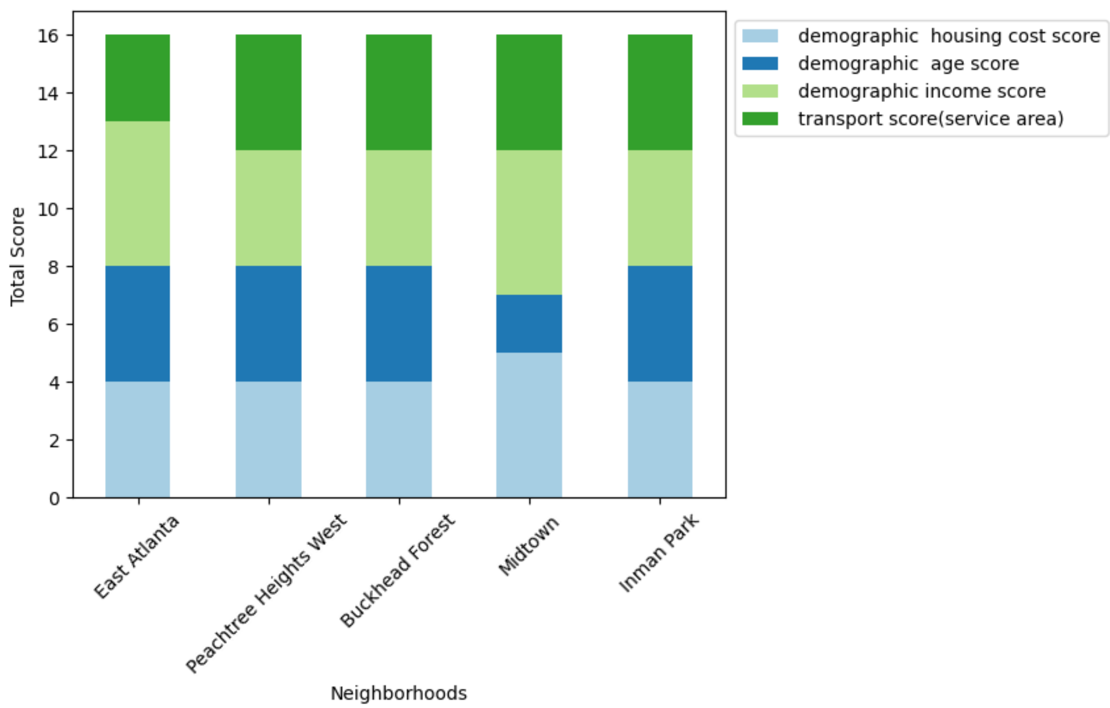
```
0                                    3
1                                    4
2                                    4
3                                    4
4                                    4
```

[ ]:
```python
df = df.drop(df.columns[-2], axis=1)
```

[20]:
```python
df.iloc[:, -4:].plot(kind='bar', stacked=True)
plt.legend(loc='upper left', bbox_to_anchor=(1, 1))

plt.xticks(range(len(df)), df.iloc[:, 0], rotation=45)
plt.xlabel('Neighborhoods')
plt.ylabel('Total Score')
sns.set_palette('Paired')
# plt.show()

plt.savefig('../map/plot/stacked_chart.png', dpi=300)
```



Livehouse Location Optimization in Atlanta

Integrating Transportation and Demographic Factors

Tingyu Liu

Inspired by my old project, Github repo: https://github.com/drunken-boat/livehouse-location-analysis

Background & problem

A **live house** is a Japanese **live music club** – a music venue featuring live music. The term is a Japanese coinage and is mainly used in East Asia.

It most frequently refers to smaller venues, which may double as bars, especially featuring rock, jazz, blues, and folk music.

And this project will emphasize the metal/rock music live house.


Yu Gong Yi Shan → retail store


TANGO → government ideological research center


old MAO → remains

Introduction

- Optimize the allocation of livehouses/music venues in the Atlanta area by integrating transportation and demographic factors.
- Seeks to identify areas with high potential for establishing livehouses.
- Contribute to promotion of a vibrant music scene in Atlanta.

Objectives

1. Identify key factors influencing the location allocation of livehouses/music venues.
2. Analyze the spatial distribution of population and demographic characteristics in the Atlanta area.
3. Evaluate the accessibility to current locations.
4. Develop a methodology for determining optimal livehouse/music venue locations based on the identified factors.

Data

housing price, income – census bearu API

Music venue POI - query from Yelp API

Basemap - OSMX download

Crime data - Atlanta Police Department dataset

Transport (parking lot, road network) - OSMX download

Method - quantitative analysis

data mining

housing price, – census tract

Music venue poi - query from Yelp API

data processing: build location model and prediction model, service area

factors: Accessibility, Competitors, Costs, Parking

data visualization

Python - Geopandas, Folium + JavaScript

Method - qualitative analysis

data collecting

historical, archival, and other documents

in-depth interviews

cognitive maps

data analysis

mapping

tools

[Open Digital Ethnography Archives toolkit]

Estimated outcome

1. Visualization of the spatial distribution of existing livehouses and transportation networks in Atlanta
2. Optimization of livehouse allocation based on transportation accessibility and demographic characteristics
3. A web mapping application in Python that allows users to explore the transportation infrastructure and livehouse locations in Atlanta.
4. Analysis of the impact of transportation accessibility on the success of music venues
5. Identification of potential transportation bottlenecks affecting livehouse accessibility
6. Generation of heat maps of transportation demand and livehouse attendance
7. Calculation of the optimal route for concert-goers to travel between multiple livehouse venues in Atlanta, considering transportation modes and safety.
8. (nice to have)Development of a machine learning model in Python that predicts the success of a livehouse venue based on its proximity to transportation hubs and demographic characteristics in Atlanta…?

Which Neighborhood in Atlanta is Best for a Metal Music Venue Business?

Considering Transportation, Demographic, and Urban Planning Factors

Tingyu Liu

Georgia Tech

Index

Topic and Objectives

1. Evaluate the accessibility to **current** music venues.
2. Identify **neighborhoods** with high **potential** for establishing metal music venues, considering transport, demographic, and urban planning factors.
3. Contribute to promotion of a vibrant music scene in Atlanta.

Transport & GIS:
Network Analysis
Vector Analysis

Business:
Cost Analysis
Competitor analysis
Location analysis

Sociology:
Sub-cultural group(metal music) Analysis

Urban planning:
Zoning
Landuse

Terminal West, a music venue near Georgia Tech


A metal music live

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Method & Tools

Step 1: Convert transport and demographic factors to quantifiable metrics

service area -> transport score (1-4)
In the isochrone area, it is easier to access an already built-up market and increases the chances of attracting more consumers.

median age -> demographic_score_1 (1-4)
According to metalheads' age distribution in research, apply the score to each census tract.

household income -> demographic_score_2 (1-5)
Apply scores according to quantiles, eg. 0-first quantile is 1

monthly housing cost -> demographic_score_3 (1-5)
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Demographic_score(3-14)

Step 2: Spatial join service area and census tract with scores to neighborhoods

Step 3: Select neighborhoods with highest scores(juxtaposed)

Step 4: Overlay restriction layers to find the best neighborhood(s)

Zoning Land Use
commercial and mixed use zones are better for music venues

Livable Center Initiatives
vibrant LCI have higher potential for business growth.

Parking Lots
See if there is enough parking lots in/ near neighborhoods.

Step 5: Find the neighborhood that is best for metal music venue business

Spatial and mathematical model

ArcGIS Pro: Service Area

QGIS: Join attribute by location, Field Calculator, Attribute Table Edit, Layouts

OSMnx

Folium

GeoPandas

Python:

- OSMnx: Network analysis and Data collection
- Folium: Interactive visualization
- Geopandas: Geospatial data processing

Tools used

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Data

Census tract with housing price, household income, age, race – Census Bureau API

Music venue POI - yelp API

Parking lot, Road network - OSMX download

Atlanta Neighborhood Area - Course Material

Transport	Demographic	Urban Planning
Road Network	Median Age - *Consumer Character*	Zoning Land Use - Compatibility
Service Area - Accessibility	Median Household Income - *Consumer Character*	Urban Policy: Livable Initiatives - Develop Potential
Parking lots - Accessibility	Monthly Housing Cost - *Real Estate Cost*	Department of CITY PLANNING
OSMnx OpenStreetMap	United States Census Bureau	

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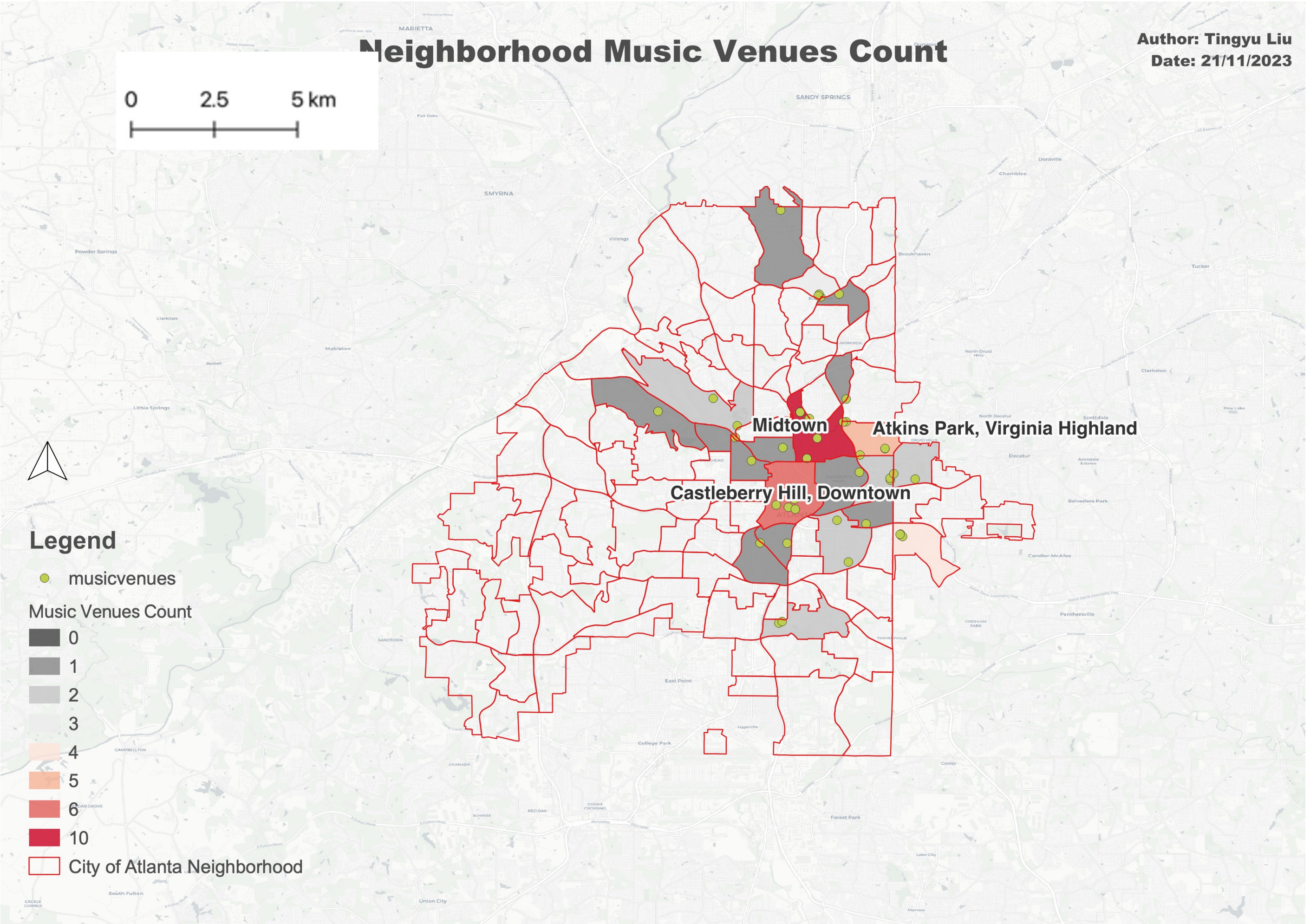
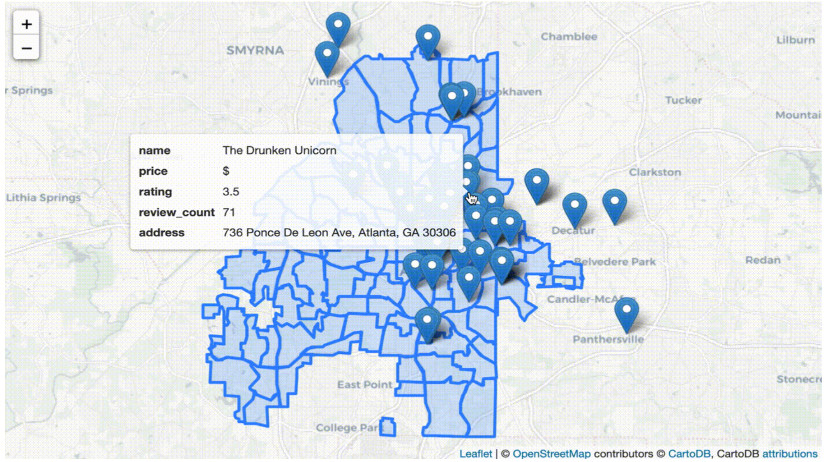
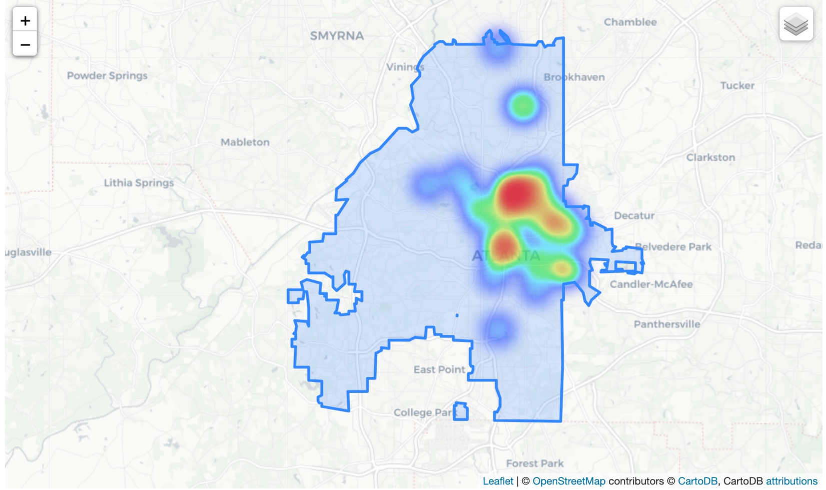
Competitor Analysis: Existing Music Venue



Spatial Distribution of Existing Music Venue



Music Venue Attribute



Music Venue Density

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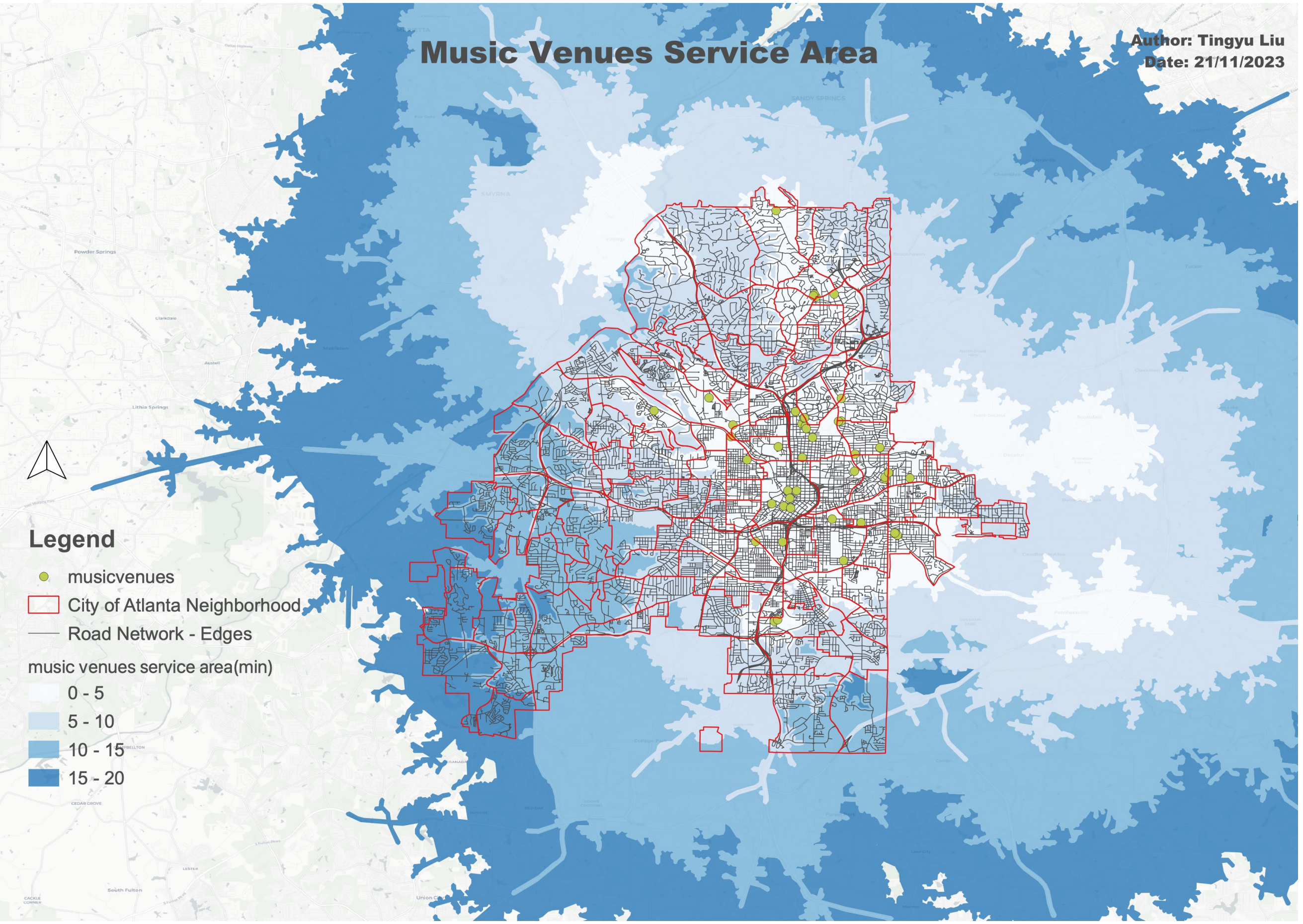
Transport Analysis: Existing Music Venue Service Area



Step 1: Convert transport and demographic factors to quantifiable metrics

Facilities: music venue point of interest

Network: road network

Time threshold: 5, 10,15, 20

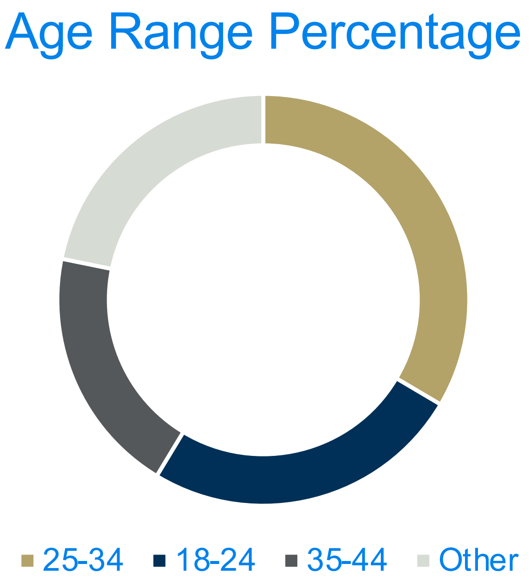
Type: Driving

service area -> transport score (1-4)
In the isochrone area, it is easier to access an already built-up market and increases the chances of attracting more consumers.

Demographic Analysis – Who are metalheads?

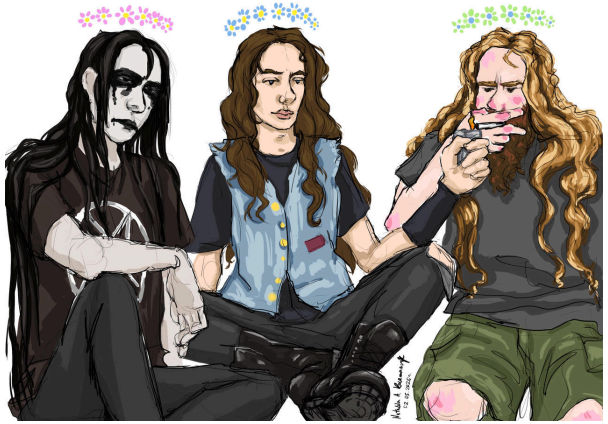
Metalheads are people who enjoy metal music and regularly attend metal music venues = consumers

- Largely white, cis-gendered, and male.
- Age: Majority age range is 18-34
- Most popular in North America and Northern Europe.



Metalheads' age distribution, Shown in research(Shukla,2022)

Typical/ stereotypical metalheads



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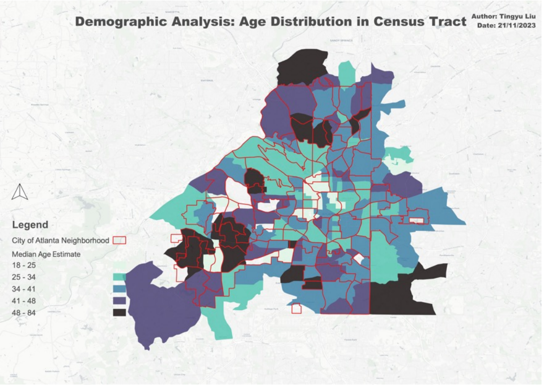
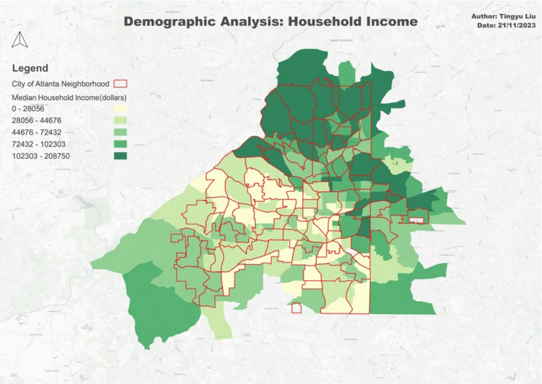
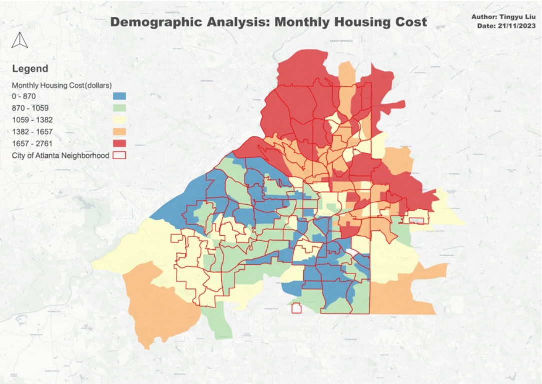
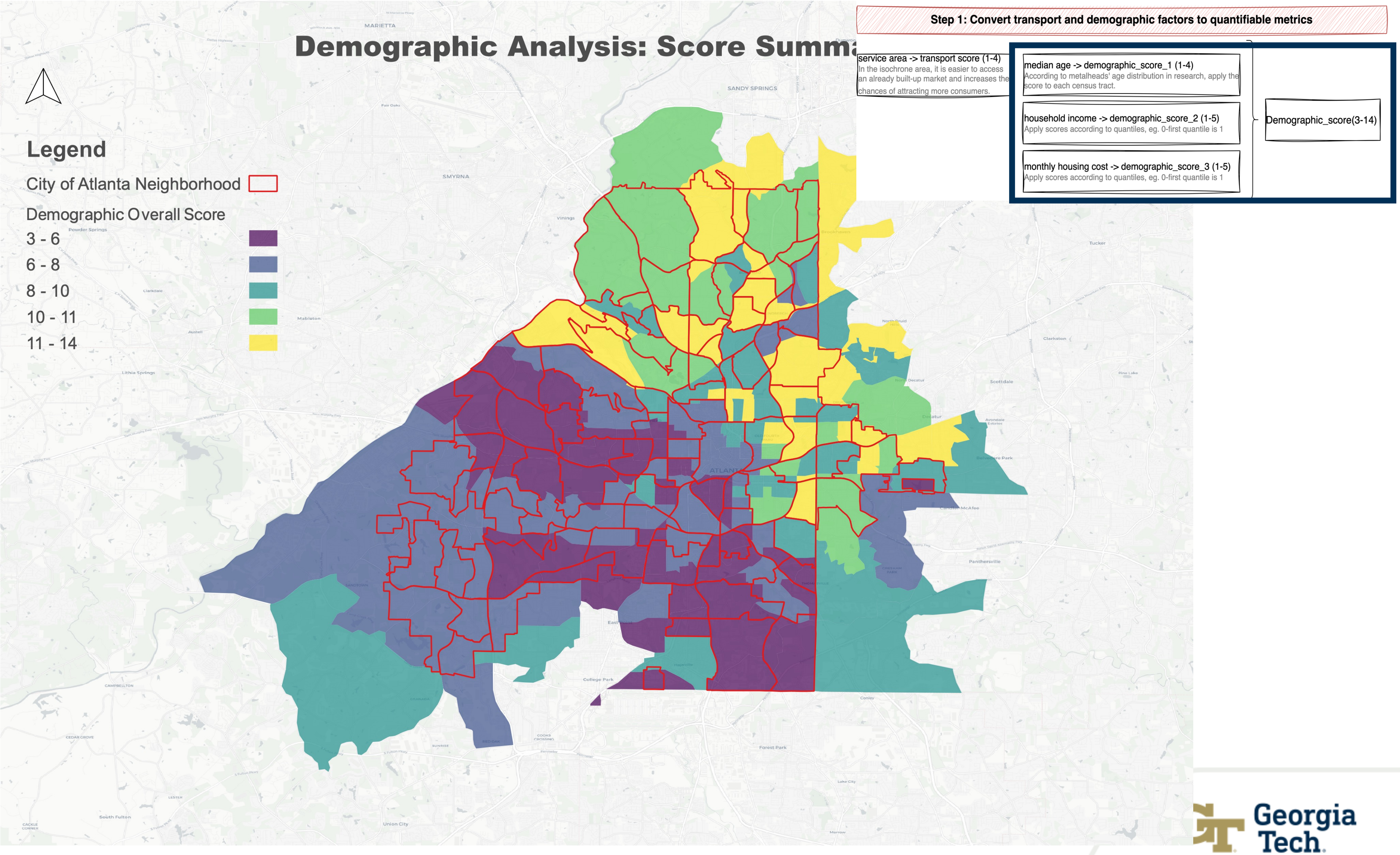
Demographic Analysis – Census Tract









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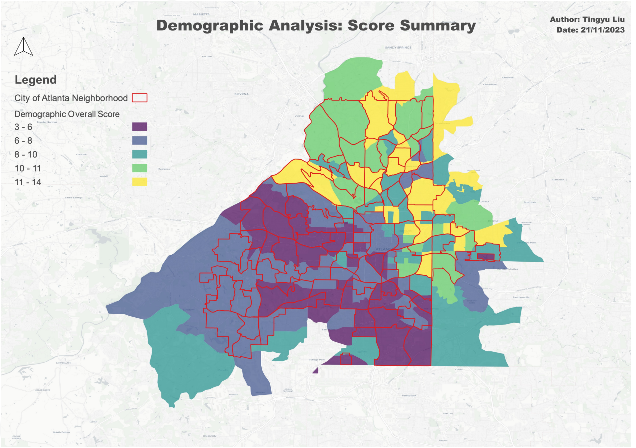
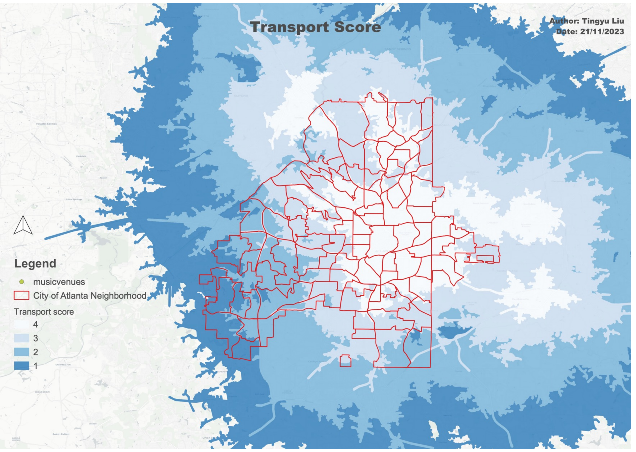
Factor Integration

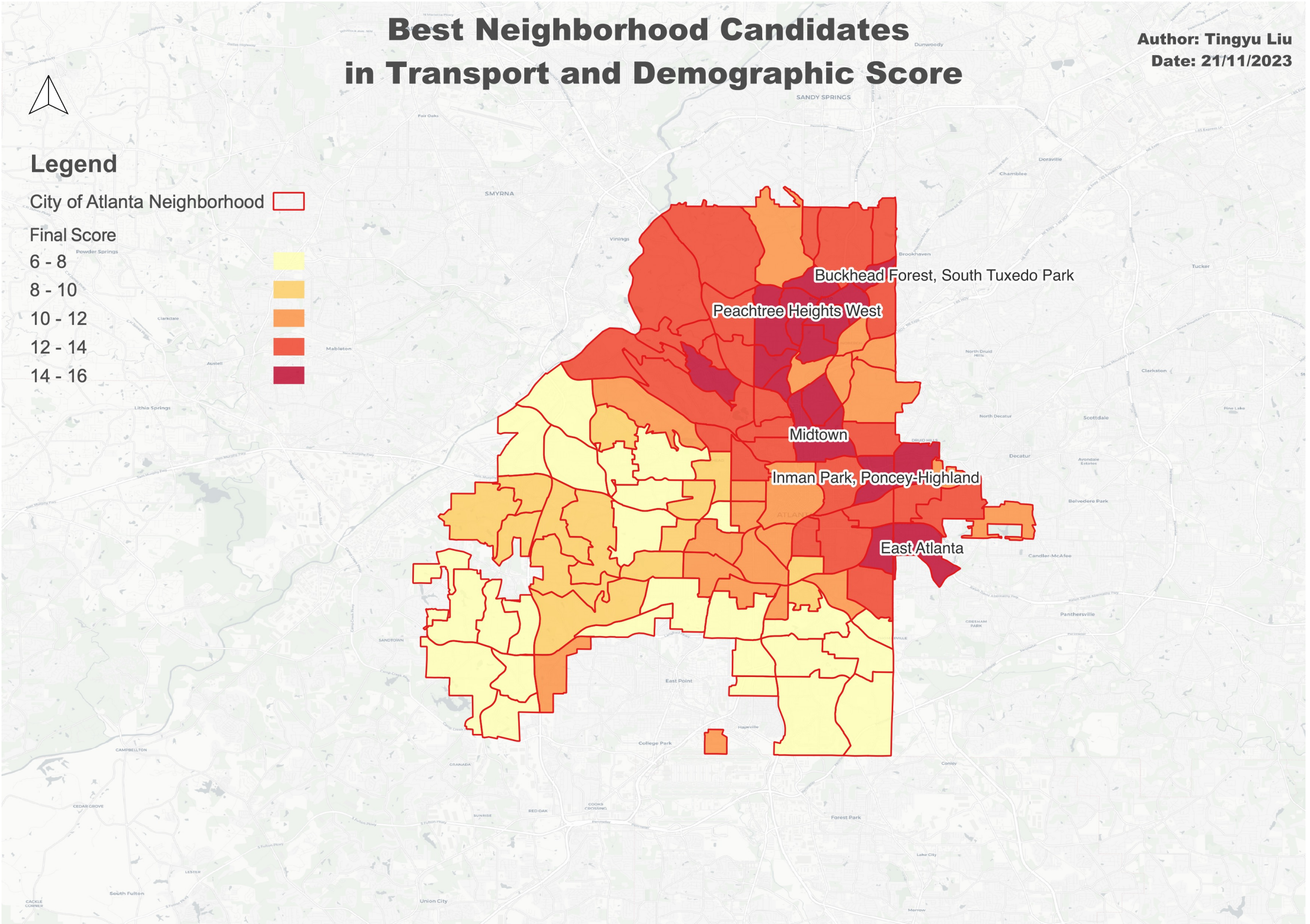
Step 2: Spatial join service area and census tract with scores to neighborhoods



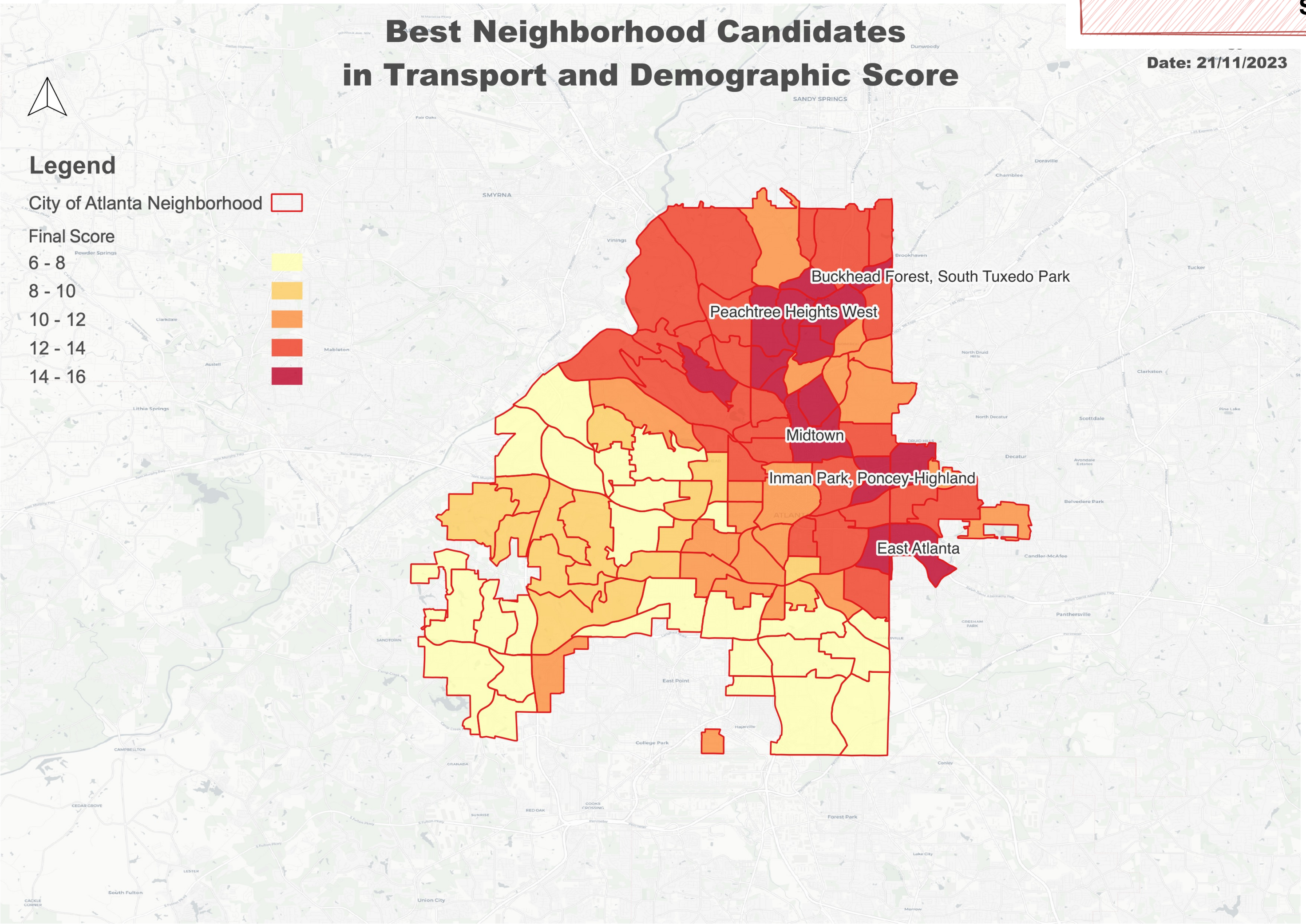


Join attribute(score) by location to each Neighborhoods

Weighted by area



Integrate Transport and Demographic Factors



Step 3: Select neighborhoods with highest scores(juxtaposed)

After adding up the transport and demographic scores, the neighborhoods with the highest score (15/16) are:

Midtown
Inman Park
East Atlanta
Peachtree Heights West
Buckhead Forest

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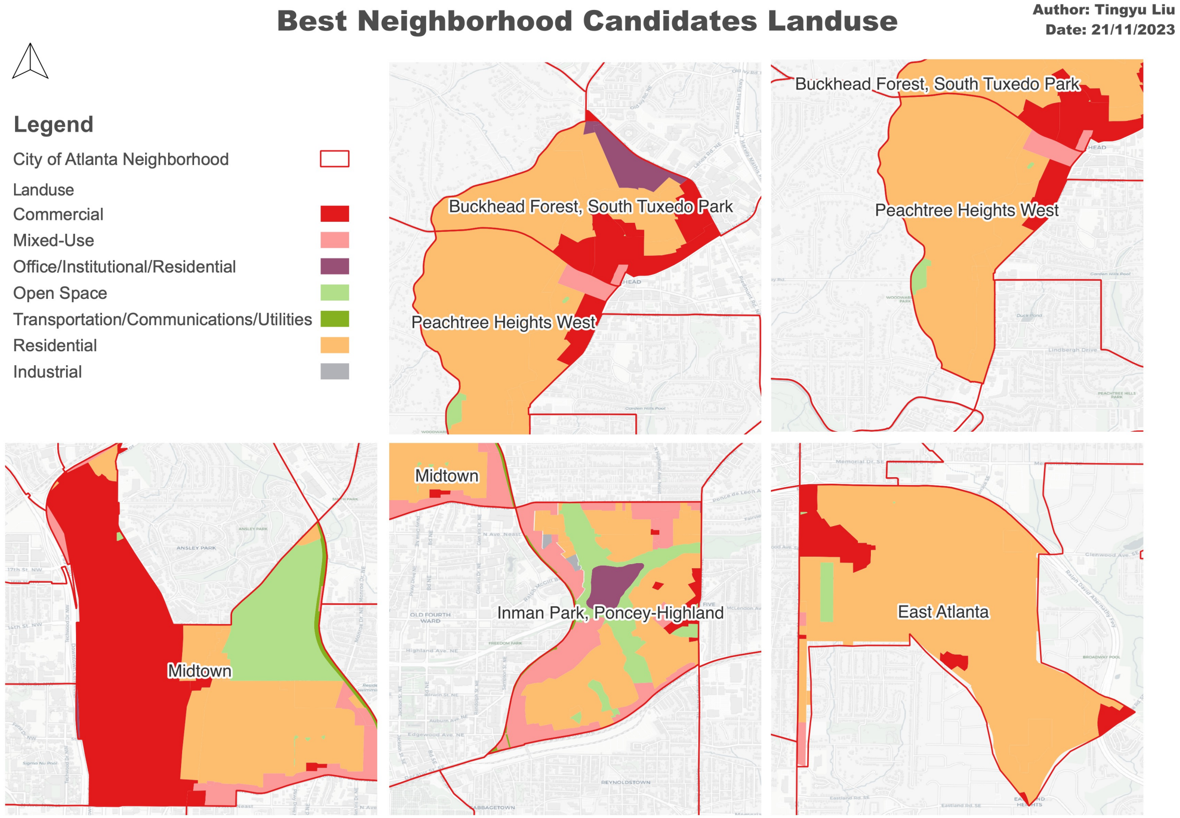
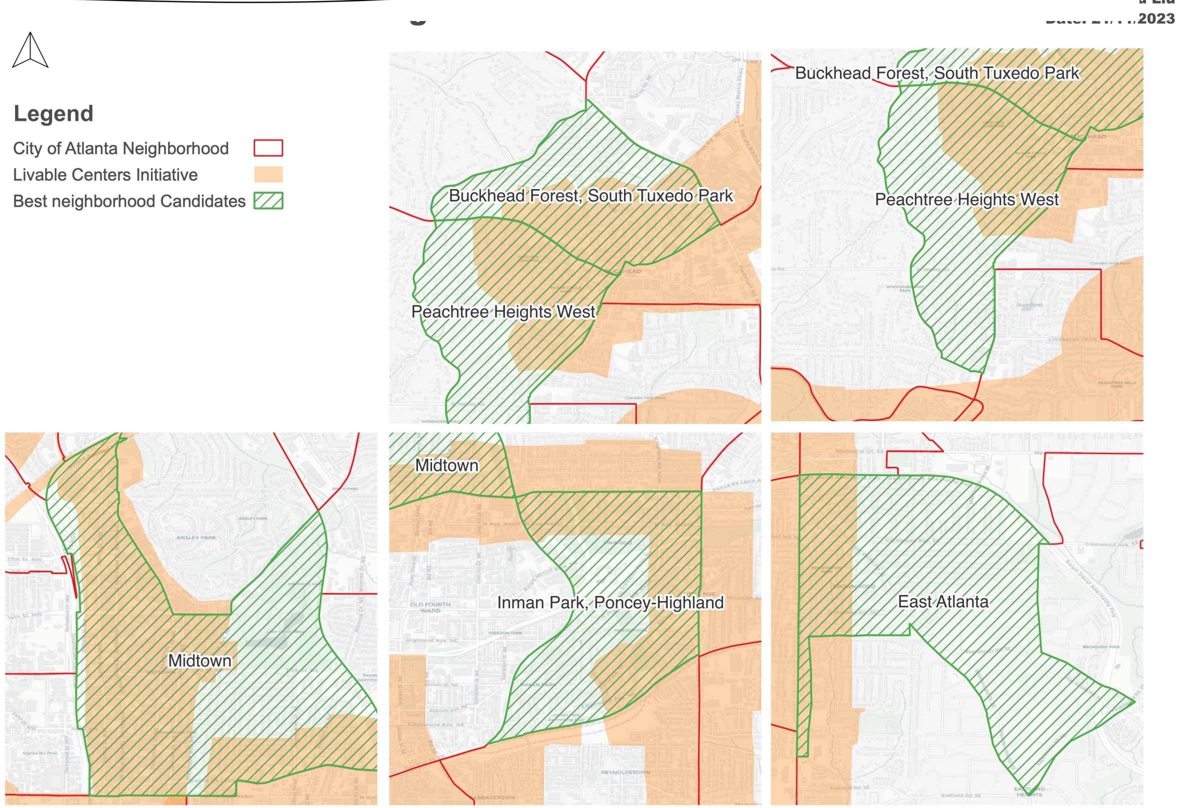
Restrictions: Zoning

Step 4: Overlay restriction layers to find the best neighborhood(s)

Zoning Land Use	Livable Center Initiatives	Parking Lots
commercial and mixed use zones are better for music venues	vibrant LCI have higher potential for business growth.	See if there is enough parking lots in/ near neighborhoods.





The **Midtown, Inman Park, and Buckhead Forest** neighborhoods perform better in terms of zoning restrictions.

Contextual Information: Commercial and mixed-use land use are more suitable for a music venue business. The Livable Centers Initiative encourages vibrant and walkable places.

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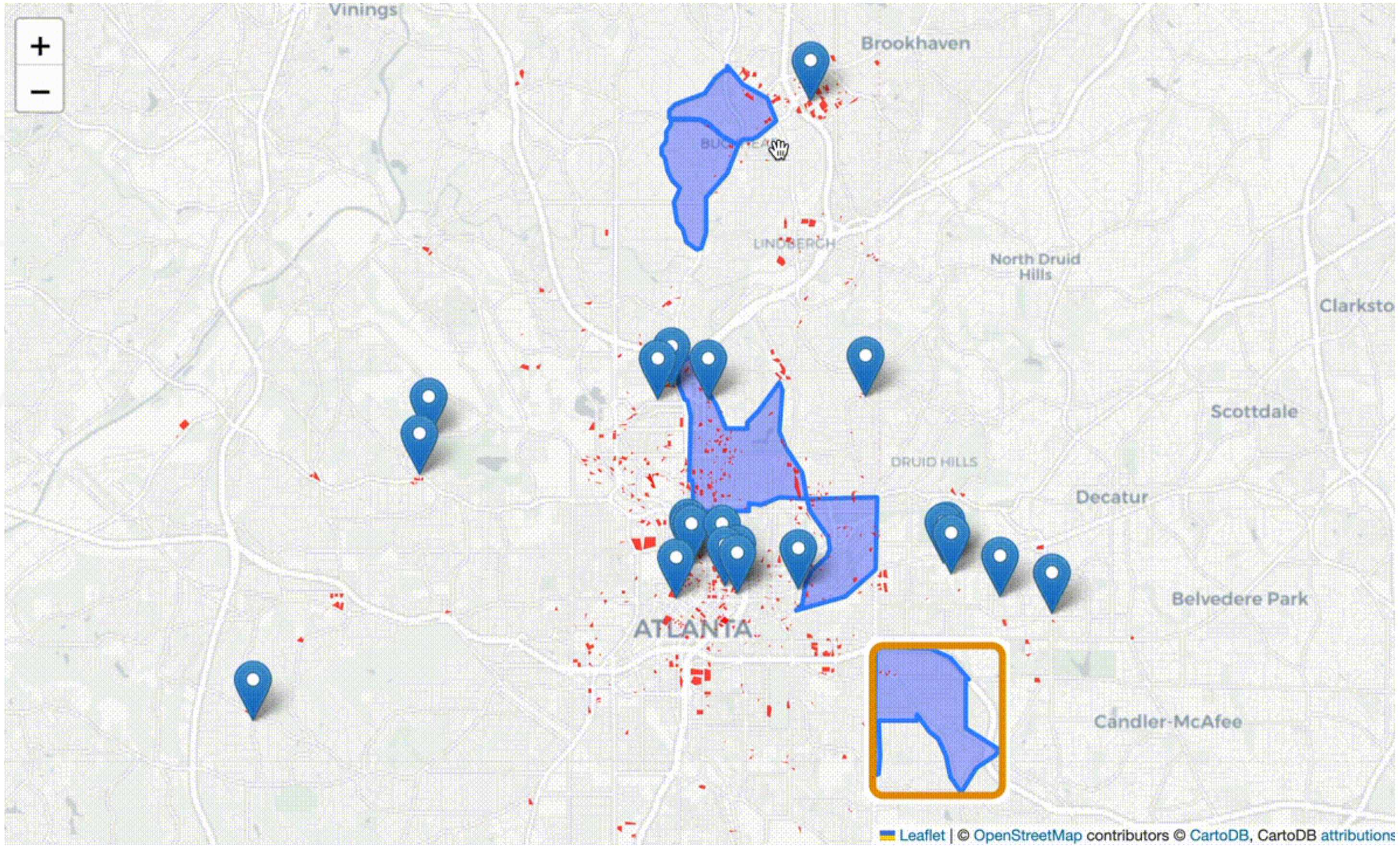

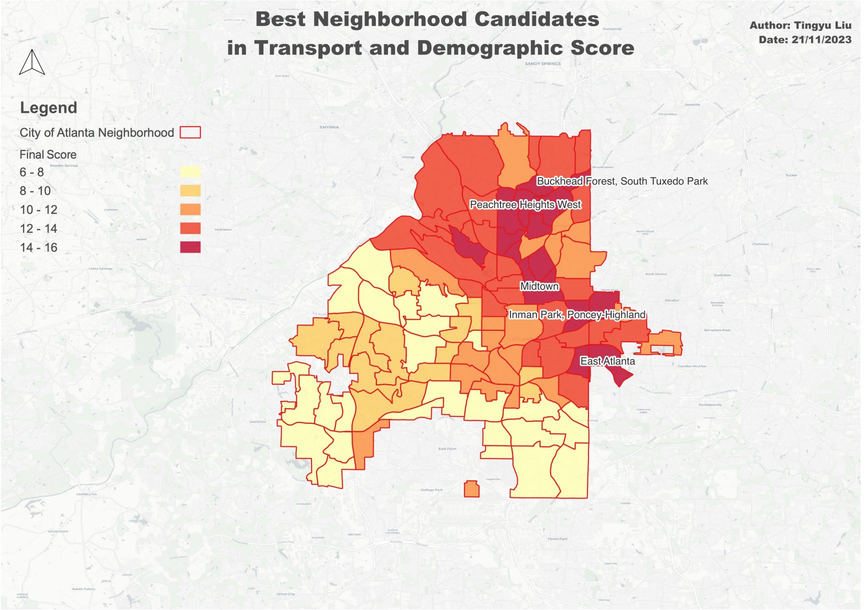

Based on parking lot amenity, **Midtown** and **Inman Park** are the best!

Conclusion and Discussion

After quantifying transport and demographic factors, and using transport and urban planning factors as restrictions, we have determined that **Midtown** and **Inman Park** are the best locations for a metal music venue business.

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In more detail, Midtown has a more established music venue business and is more competitive. It will be more familiar to metalheads, but it is also a high-risk, high-reward type of venture.

Inman Park has higher potential with fewer existing music venues and suitable conditions for this business. Suggested location for music venue will be Edgewood Avenue, which has a restaurant street, however, the real estate price is also higher.

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Reference

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Psyllidis, A., Gao, S., Hu, Y., Kim, E. K., McKenzie, G., Purves, R., Yuan, M., & Andris, C. (2022). Points of Interest (POI): a commentary on the state of the art, challenges, and prospects for the future. Computational Urban Science, 2(20)

Prandi, C., Barricelli, B. R., Mirri, S., & Fogli, D. (2023). Accessible wayfinding and navigation: a systematic mapping study. Universal Access in the Information Society, 22, 185-212

Picture source:

P8: https://www.deviantart.com/nataliaakaczmarczyk/art/Majestatic-Metalheads-893413346

P8-2: https://finance.yahoo.com/news/watch-behaviour-analyst-serve-amusing-103054565.html?guccounter=1&guce_referrer=aHR0cHM6Ly93d3cuZ29vZ2xlLmNvbS8&guce_referrer_sig=AQAAADjXRPMtDjwVAduVO24TNFmF5-Q5qV5R7Q7PLe97yjNCDnfmnQBNLmLcglIAK52qJfKycyFAUQLhgz4LO_vksMEXqBxMnuij0TCzJkWJoUoESeHcfm3cYHgDHy9xuOqGbpBoffQAXnqgf5UuznO-gy58mnE2WS7WPqheNei7BsSl

P14: https://en.wikipedia.org/wiki/Inman_Park#Atlanta's_first_intown_neighborhood_to_gentrify

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Thank you

Open to comments and suggestions!

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