Module 12 Project

Individual Project Proposal Draft

Northeastern University, College of Professional Studies

ALY 6080 Integrated Experiential Learning

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Project Title

Optimizing Ad Placements in Los Angeles Using Demographic & Mobility Data

1. Business Problem

In the busy city of Los Angeles, advertisers continuously search for ways to increase the efficiency and effectiveness of physical ad placements. With so much foot traffic and demographic diversity, choosing the best locations for ad campaigns is both important and difficult. This dashboard helps marketing teams, businesses, and local businesses to make data-driven decisions by identifying census block groups (CBGs) that have the most potential for customized advertising.

The goal is to bridge the gap between demographic relevance and real-world mobility behavior, ensuring that ad placements reach the appropriate people in the right places.

2. Data Sources Used

- **SafeGraph Patterns Data**: Provides anonymized mobility information, including visitor counts, dwell time, and home CBGs for places of interest (POIs).
- **U.S. Census Data (via tidycensus)**: Provides demographic data such as median household income, age distribution, and racial composition at the census block group level.

3. Technical Approach

- **Parsing & Cleaning**: Faced difficulty with visitor_home_cbgs column including JSON parsing, null value handling, and flattening nested structures.
- **Merging Datasets**: Combined SafeGraph mobility data with census-based demographic datasets using standardized GEOIDs.
- **Scoring Logic**: We introduced a flexible scoring function:

Score = $(\textbf{Visit Count})^{\beta} \times (\textbf{Dwell Time})^{\gamma}$

Where:

- **Visit Count** represents the number of visits from home CBGs to a given area.
- **Dwell Time** is the median duration visitors spend in that area.
- **β** (beta) and **γ** (gamma) are user-controlled weights that allow advertisers or analysts to emphasize the importance of foot traffic volume vs. visitor engagement.

This dynamic weighting system helps flexible prioritization based on different advertising strategies, for example, giving more importance to prolonged engagement (γ ↑) or maximizing exposure through higher traffic (β ↑).

- **Geospatial Matching**: Integrated POI coordinates to associate CBGs with exact map points for enhanced visualization.
- **Normalization**: Applied min-max scaling for scores to support comparison and ranking.

4. Dashboard Features

- **Interactive Sidebar Filters**:
  - Income quartile (with clear labeling: Low, Lower-middle, Upper-middle, High income)
  - Dominant Age Group
  - Dominant Race Group
  - Adjustable Scoring Weights (β, γ)
  - Top-N CBG selector
- **Map View**:
  - Displays highest-scoring CBGs using Plotly's scatter_mapbox
  - Dynamically updates based on filter selections
- **Summary Table**:
  - Presents key metrics including GEOID, normalized score, visit count, income, and demographic info

5. Key Insights

This dashboard makes it easy for marketing professionals to explore and identify high-traffic zones within Los Angeles that align with specific audience profiles. Whether targeting low-income neighborhoods with strong footfall or high-income zones with prolonged dwell time, advertisers can now fine-tune placement strategies interactively.

6. Conclusion

This concept demonstrates how combining census-based demographic data with real-world foot traffic patterns could result to more intelligent, precise physical ad placement decisions. The dashboard allows for detailed filtering and scoring, as well as spatial intelligence that non-technical stakeholders can understand and act on. With further improvements such as campaign outcome data integration or deeper behavioral classification, this tool can be scaled to support larger urban marketing initiatives.

7. References

1. SafeGraph Inc. (2024). "Places Patterns Dataset." Retrieved from https://www.safegraph.com/
2. U.S. Census Bureau. (2024). "American Community Survey (ACS) 5-Year Data (via tidycensus R package)." Retrieved from https://www.census.gov/
3. Walker, K. (2021). "Analyzing US Census Data with the tidycensus Package." Journal of Open Source Software. https://walker-data.com/tidycensus/