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Final Report: A Recommendation Tool for Real-Estate Neighborhood Search

INTRODUCTION

Background

Accurate information is essential to good decision-making. This is especially true when relocating or investing in real estate. We propose a recommendation tool to aid in selecting a neighborhood. When relocating to a new city, what tools are available to aid in selecting a neighborhood that suits personal preferences? How can one sort through the various attributes that could impact that decision and create a rational analysis in an unfamiliar place? This question and our project could potentially affect anyone involved in searching for a new place to live, investing in real estate, or researching these topics.

From a buyer's standpoint there are several other critical factors that influence a buying choice depending on their own needs. For example, a) a new family would look for the neighborhood demographics, school rating and crime rate b) a fresh college graduate would look for the commute time whereas c) a senior couple might look for a locale close to hospitals and other facilities. For the purposes of this project, our scope is the entire country of the United States of America.

LITERATURE SURVEY

Resident Demographics: Cellmer, Cichulska and Bełej[1] highlight the correlation of different socioeconomic factors based on the mixed geographic regression methods. Reed[2] also confirms that the demographic profile of a household is related to their house prices using principal components analysis and regression analysis models. These two papers highlighted the close relationship between house values, income, and age. In Renwick[3] the representatives from U.S. Census Bureau, Bureau of Labor Statistics, U.S. Department of Health and Human Services et.al. used the American Community Survey to create the housing price index. We likewise reference this data set in our work.
School Ratings: The quality of a public school in Ohio is rated by Haurin and Brasington[4] using specific test scores for a particular age group. As this data is not consistently available across the United States, we follow Hasan and Kumar[5] referencing GreatSchools.org school ratings (GS) to get school ratings based on zip codes for all states. GS computes ratings based on standardized test scores but also considers student progress, college readiness, and equity.
Access to Grocery: Lee and Lim[6] suggest that we consider both proximity and the supply and demand of each geographic region to determine which areas have adequate grocery supply and which are underserved. Widener[7] reminds us that a simple distance metric is not an adequate measure – that true accessibility is determined by both distance and the mode of transportation that one can afford.
Crime: Tita, Petras and Greenbaum[8] indicate that an appropriate crime index must consider the property value and the crime rate – that the crime rate alone will provide disproportionate results relative to property value.
Healthcare: Rivas et al[9] finds a positive and strong correlation between proximity to hospitals and rent costs and housing prices. Van der Zwart, van der Voordt and de Jonge[10] confirm these results in the European market and on private investment in hospitals. Additionally, Boussabaine, Sliteen and Catarina[11] confirmed a positive effect of the usage and availability of healthcare centers on housing and other expenses in a neighborhood.
Diversity*:* Maly[12] defines a racial diversity index, and Farrell and Lee[13] alternatively use an Entropy Index specifically noting the importance of the change and the rate of change in addition to the multi-group makeup at a specific point in time. We use the simpler notion of the diversity index.

Parks and Green Space: De Bruyne and Van Hove[14] references a satisfaction index involving proximity and access to parks and green space and highlights the effect of the travel time to these amenities on housing prices. Williams et al[15] explicitly emphasize the need to distinguish "safe" green spaces with low incidence of crime.

Sustainability: Cloutier, Jambeck and Scott[16] suggest an index to measure a municipality's or community's environmental sustainability by combining various key sustainability efforts. Ultimately we find that this index is impractical to reproduce as it requires multiple disparate data sources that would require significant effort to gather and aggregate.

Summary of Key Attributes: From the work above, we identify data sources for the key attributes that we will use in our solution: demographics (age, population, education, income), racial diversity, crime, grocery access, parks and green space, and school ratings. We select data sources that use U.S. Census tract GEOIDs as the common location identifier.

METHODS

Currently available commercial tools (Zillow, Realtor, Trulia, Apartments.com) focus on available inventory and provide the user with some selection of limited attributes closely related to those properties but fail to consider these other essential decision attributes. Academic studies typically offer a static visualization of a single attribute for a single locale in detail. A single tool that allows these parameters to be dynamically visualized together based on user-selected priorities is not yet available.

Our Innovative Approach

We created a novel tool offering a user three benefits a) it allows a user to select multiple attributes b) prioritize them and c) dynamically visualize their tailored results on a map. We created indices for each of the decision attributes then visualize the resulting weighted index based on the user's preferences.

DATA

With the data sources identified, we downloaded the data using API or scraped the website. The data was cleaned in OpenRefine to resolve issues like missing values and data type conversions. Since the granularity of each dataset was different, PySpark and SQL were used to integrate all the datasets with the common location identifier.

Data Attribute	Data Source	Number of Records (Rows x Columns)		Year
Population	U. S. Census Bureau	242341	12	2020
Sex				
Race				
Home price				
Crime	Federal Bureau of Investigation	3137	24	2021
Grocery	National Neighborhood Data Archive www.openicpsr.org	1036463	31	2017
Parks & Greenspace	U. S. Census Bureau	73058	11	2018
School	U. S. Census Bureau (unified school districts wholly or partially within each county)	16394	4	2020
	Niche www.niche.com (rating for each unified school district)	13822	32	2022

	combined census and niche data (average school district rating for each county)	3067	4	2020 & 2022
GeoID Shape Files	U. S. Census Bureau			2022

Table 1- Dataset sources and record count

Note – All of our data sources were free for public use, so only a few sources are most up to date. For a more commercial project, we could have purchased the latest datasets to run this analysis.

ALGORITHM

Using our pre-processed data containing our feature metrics for each GEOID, we implement our recommendation algorithm.

Feature value calculation and normalization: Individual values are calculated for each feature based on the desired target value. The target value is taken as an input from the user (e.g. median home price of $300k to $500k) or predefined (crime rate should be minimum). The values are normalized to arrive at a scaled index in the range [0,1]:

#	Features	Desired Target	Calculated value (normalized) I_{Attr}
1	Sex Ratio	User selects upper limit and lower limit from the available range shown on a slider	if ($I_{lower\ limit} < I < I_{upper\ limit}$): • then 1 • else 0
2	Median Age		
3	Population		
4	Median Home Prices		
5	Income Per Capita		
6	Racial Diversity	Racial diversity is predefined to be maximum from the available range. It is calculated as an inverse of the standard deviation of the population of four major races.	$I_{diversity} = \frac{1}{\sigma(I_{white}, I_{black}, I_{asian}, I_{hispanic})}$ $Normalized\ value = \frac{I_{diversity}}{(I_{diversity})_{max}}$
7	Grocery availability	Predefined as maximum from the available range	$\frac{I - I_{min}}{I_{max} - I_{min}}$
8	Parks availability		
9	School Rating		
10	Crime Rate	Predefined as minimum from the available range	$1 - \frac{I - I_{min}}{I_{max} - I_{min}}$

User Weights: The user can select a preferred categorical weight of “Low”, “Medium” or “High” for each feature. We define “Low” = 0.0, “Medium” = 0.5, “High” = 1.0

Individual user weight values are normalized so that all weights sum to 1:

$$^{\omega}User\ n\ = \frac{\omega_{User\ selected\ n}}{\sum_{i=1}^{n} \omega_{User\ selected\ n}}$$

User Weighted Average: Our final recommendation index, I_{rec} displayed in the visualization is the weighted average of the individual feature indices,

$$I_{rec} = \omega_{User1} I_{Attr1} + \omega_{User2} I_{Attr2} + \cdots + \omega_{User\,n} I_{Attr\,n},$$

where each $I_{Attr\,n}$ is the unity-based normalized feature index and each $\omega_{User\,n}$ is the user specified weight for that feature (and where $\sum_{i=1}^{n} \omega_{User\,n} = 1$).

USER INTERFACE

We utilize Tableau to implement our user interface and interactive visualization. We plot a choropleth map using the GEOID references to reference the geometric boundaries for the census tract areas and the recommendation index I_{rec} as the resulting value for that area. Ultimately, the index is presented to the user as a five-level categorical variable (a score in the range [1,5]) rather than a continuous color gradient. The tool is hosted on neighborhoodsearch.net to share with potential users and receive their feedback.

EXPERIMENTS / EVALUATION

METRICS

Based on our research we identified two criteria that yield measurable results: *user satisfaction* and *time to reach a decision*. We hope to create a solution that would provide a good user experience and would help make the decision process more efficient. Our efforts to evaluate these criteria are described below.

User satisfaction. We utilize Brooke's standardized usability assessment (SUS)[17] which employs a simple ten question Likert rating to provide an empirical measure of usability.

At scale, we would want to recruit a sufficiently large sample size and utilize multiple evaluations but given the limitations of time and budget we recruited a small sample of family and friends. It is also worth noting that that our respondents are not necessarily target users of our solution since most are not actively in the process of searching for a new neighborhood.

We found that in our sample group, the SUS testing yielded scores (mean SUS = 62.3) that indicate *"marginal" acceptability* based on the adjective ratings summarized by Bangor, Kortum and Miller.[18]

A more thorough approach for evaluation of user satisfaction would split the recruited cohort into control and treatment. Control group would evaluate our comprehensive UX and the treatment would evaluate any combination of individual visualizations they can find on the internet. In this case, it would be important to measure the user satisfaction and time on task simultaneously. Continued efforts on improving user satisfaction would repeat multiple iterations of A/B testing aimed at selecting the various improvements that optimize usability scores.

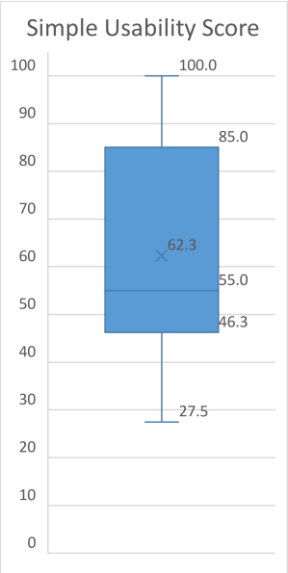

Fig 1. Usability test results

Time to reach a decision. At scale, we wanted to empirically measure "does the solution reduce the time required to make a decision?"

Measuring "time on task" for our project is a complex endeavor. While tasks such as making an airline reservation or picking a movie to watch are relatively short tasks with well-defined completion criteria, exploring neighborhood-level data to identify a preferred place to live does not have such clear boundaries. Because the selection of a neighborhood is related to ultimately selecting a house or

apartment the process is dynamic – constantly changing with market inventory, external constraints (budget, availability), as well as intangible emotional constraints.

With appropriate time and budget, a thorough evaluation would recruit users who are currently searching for a neighborhood and in need of a tool to assist. The "time on task" would then require providing the users with guidelines around how to conduct their search and under what conditions they should consider an initial search "*complete*". With clear and consistent definitions, we could potentially measure the time required to complete the task with and without our solution and determine the statistically significant p-value.

OTHER OBSERVATIONS

In addition to our empirical testing, we note several key observations after using our own solution and watching others use it.

- Base demographic data attributes (Age, Sex) seem to be least interesting to explore. Crime, Grocery Access and Income were of more interest.
- Our initial use of a racial diversity index from Maly[12] proved to be problematic as it was often contradictory. We created a more usable index as defined above.
- In most cases, the recommended neighborhoods are adjacent to each other. It is possible that close neighborhoods have similar demographics due to the physical proximity. In addition, they usually share the same shopping area, parks and greenspace.
- Without context of available housing inventory, the application of our solution is limited. An ideal solution might combine our visualization with one of the commercial solutions (Zillow, Apartments.com, etc.) such that either the available inventory of properties could be viewed as a layer on top of our visualization, or our visualization could be used as an additional filter used to select target properties in the commercial solution.

Some User Experience issues were also noted:

- Initial attribute selection was confusing for some.
- Pan and zoom map navigation was not intuitive for some.
- UX could be improved by being able to view roads, cities and other map features.
- The lack of responsiveness (slow calculations and map redrawing) made some users hesitate as they made filter selections. Viewing an entire state's data decreased responsiveness enough to be disconcerting. Once users filtered to just a few counties, responsiveness was generally acceptable.

Based on these observations, we describe some paths toward improvements below.

CONCLUSIONS / DISCUSSION

CONCLUSIONS

NOTE: All team members have contributed a similar amount of effort.

Our work has resulted in an interesting exploratory tool that has the potential for further refinement especially on the number of dimensions considered. This tool could provide insights to a subset of renters and homebuyers that none of the existing market tools possess. Ultimately, we feel that a more informed decision will produce better results for the user.Our tool provides a unique method for visualizing and understanding data that affects where we live. Mellander, Florida and Stolarick[19] indicate that a more informed choice of location can increase the length of stay.

Additionally, research indicates that there could be potential unintended negative social impact resulting from self-segregating into areas of similar socio-economic status which can serve to worsen disparities that already exist[20]. Those that cannot afford access to the best schools,[21-23] healthy food options[24], parks, and cultural experiences, are more likely to have neighbors, friends, and family with the same disadvantages. Van Ham et al[25] extend this notion to describe and visualize the history of neighborhoods and how disadvantage is propagated over generations.

NEXT STEPS / AREAS FOR IMPROVEMENT

In our observations noted above, we identify several areas for further improvement:

1. **Provide clear user instruction and improve the initial user weight selection.** While our team understood the meaning of the user weights and resulting index – for new users with no background on our project, those aspects of the visualization were not immediately intuitive. Some additional instruction in the form of a help page and some more intuitive UI features would help improve this.
2. **Improve UI responsiveness when zoom level is an entire state or the country.** As the user zooms out to a state, region or the entire country, the UI performance is significantly slower. This could be addressed by referencing aggregated data at higher zoom levels.
3. **Include additional data sources.** Including additional data sources (walkability, access to public transport, entertainment, restaurants, healthcare, and environmental sustainability, air quality) would create a richer and more comprehensive experience.
4. **Improve data granularity.** Two of our data sources (school ratings and crime) were not readily available with the same spatial granularity as the others for the entire country. A more robust product would need to gather the necessary data from multiple available sources and merge the sources for a consistent experience.
5. **Other UX Improvements.** Since our initial user testing, we have implemented some improvements to make the experience more intuitive including repositioning and grouping the selection controls and providing some basic instructions. Some of the limitations experienced by users were inherent limitations of Tableau and a productized version of this project would likely benefit from creating a custom web app or using a dedicated software mapping tool similar to Esri's ArcGIS[26].

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APPENDIX

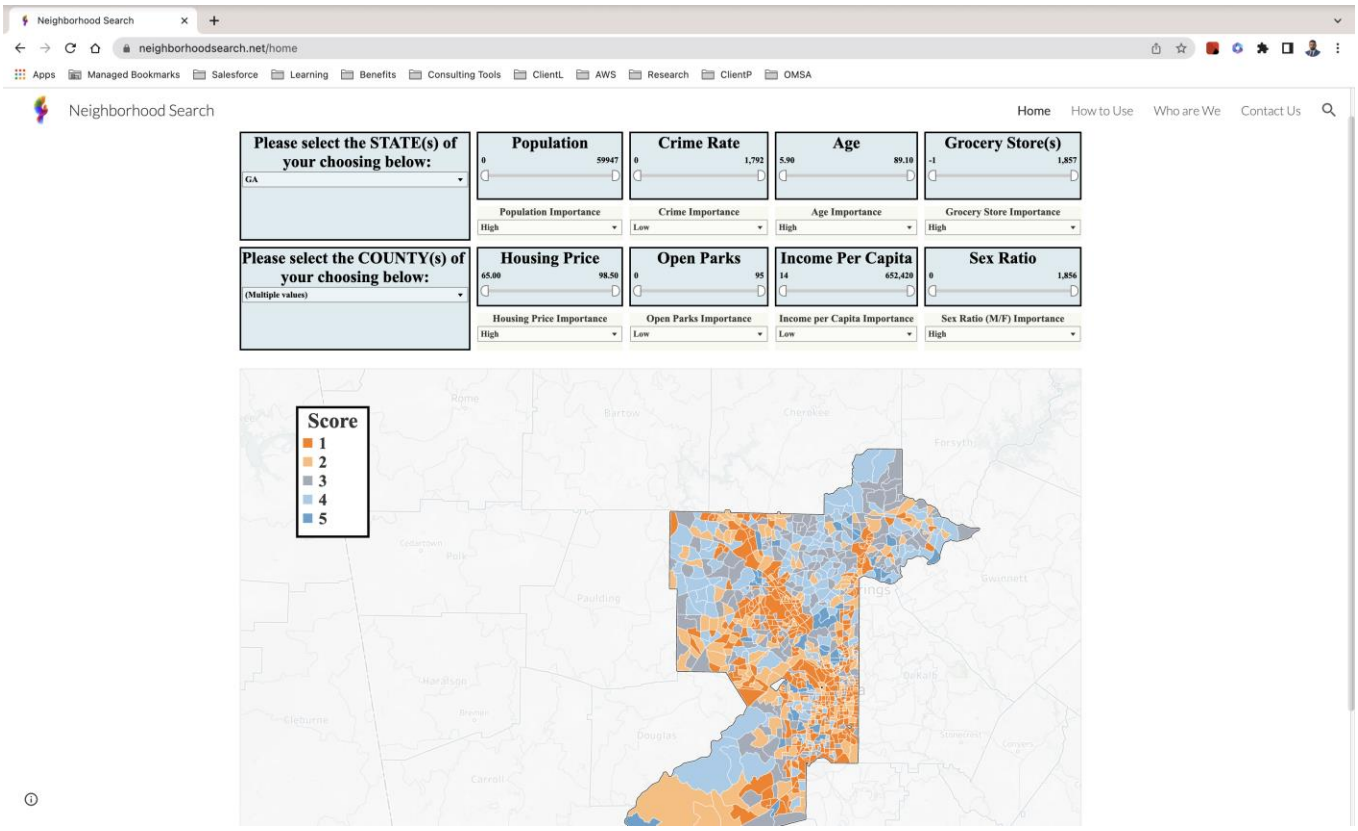

Figure 1. *Screenshot of the User Interface*