Identifying Neighborhood Commonality in Two Neighboring Cities Based on Affordability and Trendy Venues

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Introduction:

The analysis discussed in this paper shows how data science techniques can be used to identify and compare affordable, trendy city neighborhoods based on readily available information from sources such as FourSquare and Zillow. This project will analyze and compare the neighborhoods in the two neighboring Ohio cities of Cincinnati and Dayton Ohio. Home value information from Zillow and trendy venue information from FourSquare were combined to enable clusters of similar neighborhoods for quick comparison between the two cities.

The measure this project used for "trendiness" is a count of the nearby breweries and coffee shops. These two venues are useful indicators because they are themselves a current business trend. Also, small scale, craft breweries and craft coffee shops tend to pop up in clusters in up-and-coming trendy neighborhoods where real estate is still affordable but young professionals like to congregate.

Interest in this analysis can apply to multiple parties interested in identifying and comparing different parts of their local or neighboring city. Realtors can better target neighborhoods to specific clients; house hunters can figure out which neighborhoods fit their lifestyles while still being affordable; and investors can identify trendy areas to target or parts of town that are already saturated. Comparing a medium sized city (Dayton), to a larger city (Cincinnati) shows the possibility for compromise between best neighborhood fit, affordability, and commuting time.

Data Acquisition and Cleaning:

The data used in this analysis is all about city neighborhoods and thus it was necessary to collect a variety of pieces of information in order to put the project together. Some of the information was readily available in convenient sources (APIs and web scraping), others required more work to accumulate (manual searches). The collected data includes:

- Name and geographic location (Latitude and Longitude) of each of the neighborhood,
    - https://www.city-data.com/ for city information and lists of neighborhoods,
    - Google Earth (https://earth.google.com/), for neighborhood coordinates,
- Neighborhood home value data,
    - ZILLOW Home Value Index (https://www.zillow.com/home-values/)
- Nearby venue identification based neighborhood coordinates,
    - FourSquare website and API (https://foursquare.com/)

There were two stages of data cleaning for this project, first the neighborhood location and real estate information, and second the FourSquare venue search. The first stage involved scraping the neighborhood names from the City-data website as simple csv data. The neighborhood names made google earth location search quite simple and the exported kml file with coordinates could again be easily parsed out using the python “fastkml” module. Finally, the home value index for each neighborhood was added to this table of general neighborhood information. This series of steps was completed for each of the two cities (Dayton and Cincinnati, Ohio). Afterwards, the saved-off csv file could be read-in by pandas as a dataframe ready for further analysis.

The second step of data acquisition and cleaning involved using the neighborhood coordinates from the first step to query the FourSquare API for the desired venue data. The API returned all of the breweries and coffee shops within the specified radius of each neighborhood. Cleaning of these results was necessary to remove extraneous results (bars and pubs that were not breweries, and cafes that were not coffeeshops). The final results were grouped by neighborhood into simple counts and the resulting tables for both steps of the data acquisition were merged back together and missing data rectified. The last step was to create a “normalized” value column for the home value for easy comparison with the venue count numbers. Table one provides a preview of the data with the first few rows of the dataframe containing the merged data.

Table 1: Sample Data Table After All Acquisition and Cleaning Steps

	Neighborhood	Latitude	Longitude	City	State	County	House Value	Brewery	Coffeeshop	HV_Norm
0	Avondale	39.144963	-84.497811	Cincinnati	OH	Hamilton	81719	0	0	0.81719
1	Bond Hill	39.177785	-84.477659	Cincinnati	OH	Hamilton	111614	0	0	1.11614
2	California	39.065338	-84.419893	Cincinnati	OH	Hamilton	128577	1	0	1.28577
3	Camp Washington	39.137950	-84.537609	Cincinnati	OH	Hamilton	58310	2	2	0.58310
4	Carthage	39.195869	-84.485014	Cincinnati	OH	Hamilton	68406	0	0	0.68406
5	Clifton Heights	39.125934	-84.520908	Cincinnati	OH	Hamilton	298535	8	4	2.98535
6	College Hill	39.198536	-84.548428	Cincinnati	OH	Hamilton	130138	1	0	1.30138
7	Columbia-Tusculum	39.115193	-84.436140	Cincinnati	OH	Hamilton	325009	5	2	3.25009
8	Corryville	39.136807	-84.503866	Cincinnati	OH	Hamilton	158269	1	5	1.58269
9	CUF	39.125115	-84.525842	Cincinnati	OH	Hamilton	161286	8	3	1.61286
10	East End	39.099214	-84.422519	Cincinnati	OH	Hamilton	318827	1	0	3.18827
11	East Price Hill	39.106141	-84.569386	Cincinnati	OH	Hamilton	67706	0	0	0.67706
12	East Walnut HIlls	39.125191	-84.477637	Cincinnati	OH	Hamilton	171615	2	3	1.71615
13	East Westwood	39.150129	-84.566766	Cincinnati	OH	Hamilton	57827	0	0	0.57827
14	English Woods	39.139781	-84.556888	Cincinnati	OH	Hamilton	77999	1	0	0.77999

Handling missing data: there were two cases where missing information needed to be resolved, the first was in finding the home value index information for all of the neighborhoods. Some of the neighborhoods showed no results, so the overall city average was used instead. The second instance was for neighborhoods where no results were found for nearby venues in FourSquare. When recombined with the neighborhood data, those rows resulted in “NAN” values. This was a more straightforward solution; since the error came because no venues met the search criteria, the “NAN” values were replaced with zero.

Methodology:

Exploratory Data Analysis:

The first goal of exploratory data analysis is to understand the data and get a feel for the obvious observable trends. The first two figures plot all of the neighborhood location data as well as the Brewery and Coffeeshop venue location data. The combined set of coordinate data was plotted using the Folium mapping module. Figure 1 displays the Cincinnati data and Figure 2 the Dayton data.

Figure 1: Cincinnati Points of Interest Plotted in Folium.

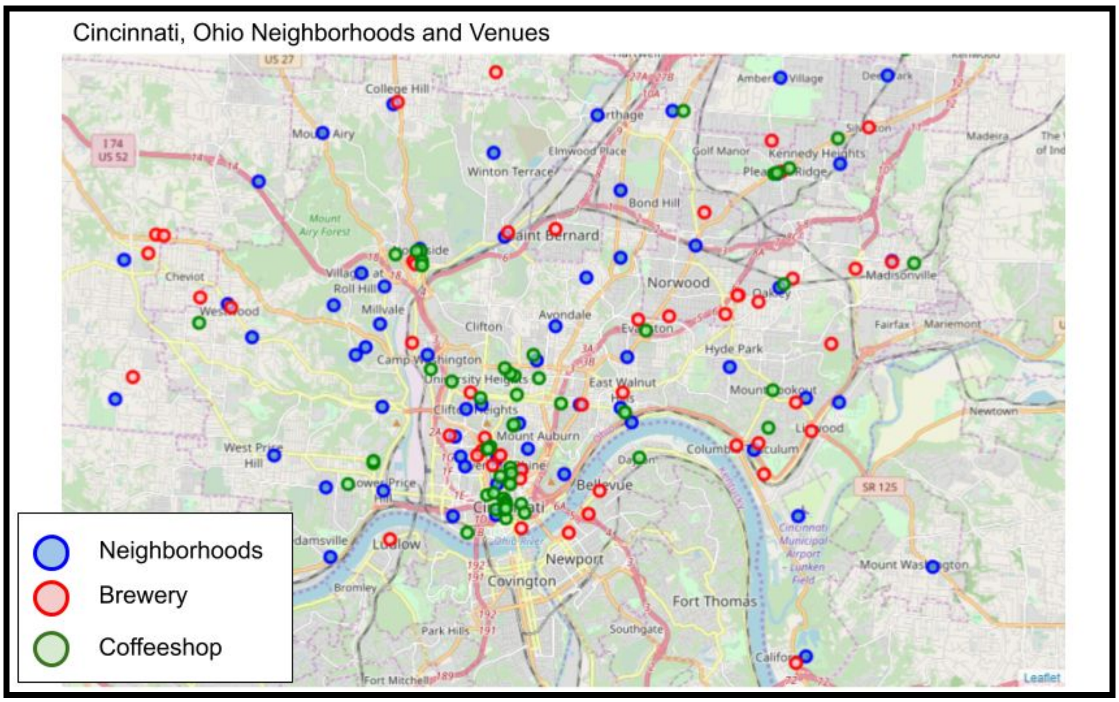
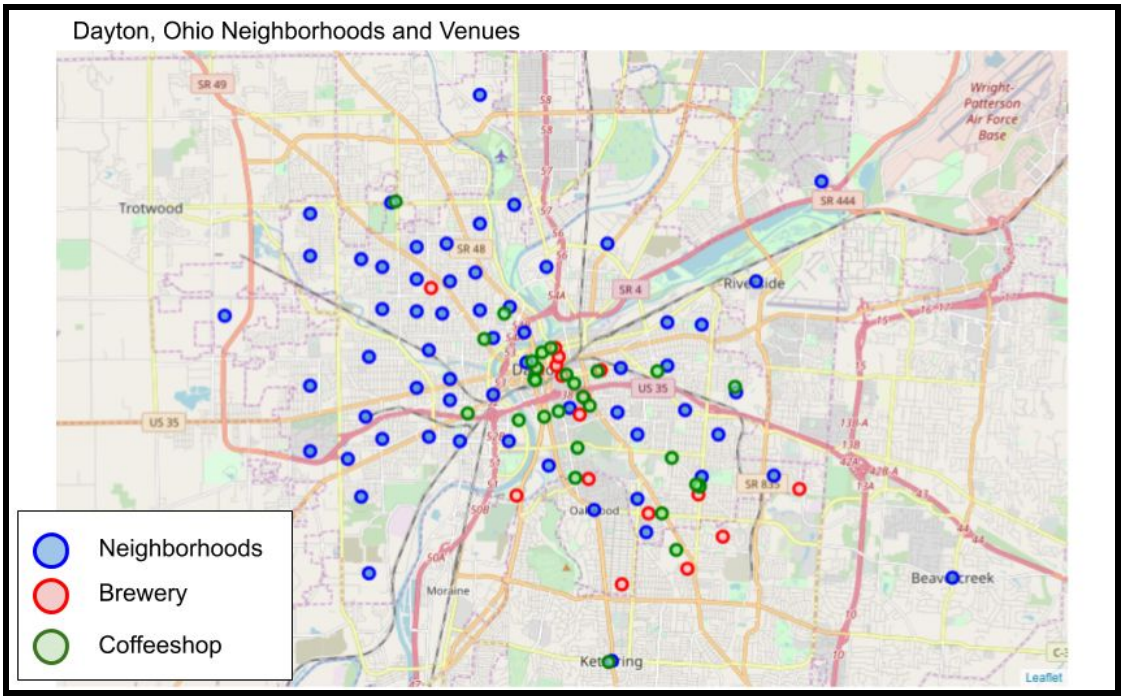


Figure 2: Dayton Points of Interest Plotted in Folium.



It is expected that Cincinnati, as the larger city, would also have a larger total number of both breweries and coffee shops, but the map plots also make it clear that Cincinnati also has a greater spread in its venues. In Cincinnati, nearly every neighborhood appears to have venues nearby; but in Dayton, there are large swaths of neighborhoods without venues.

Figure 3 and Figure 4 show home index value histograms for Cincinnati and Dayton, respectively. Again, cursory analysis of the data shows the clear difference in the average home values of the two cities. The largest bin for Cincinnati home values is the \$128k to \$171k bin whereas the largest bin for Dayton is the \$24k to \$50k bin. Also, the highest price bin for Cincinnati goes up to \$474k but the max Dayton bin is only about half that at \$289k.

Figure 3: Histogram of Home Value Index for Cincinnati Neighborhoods

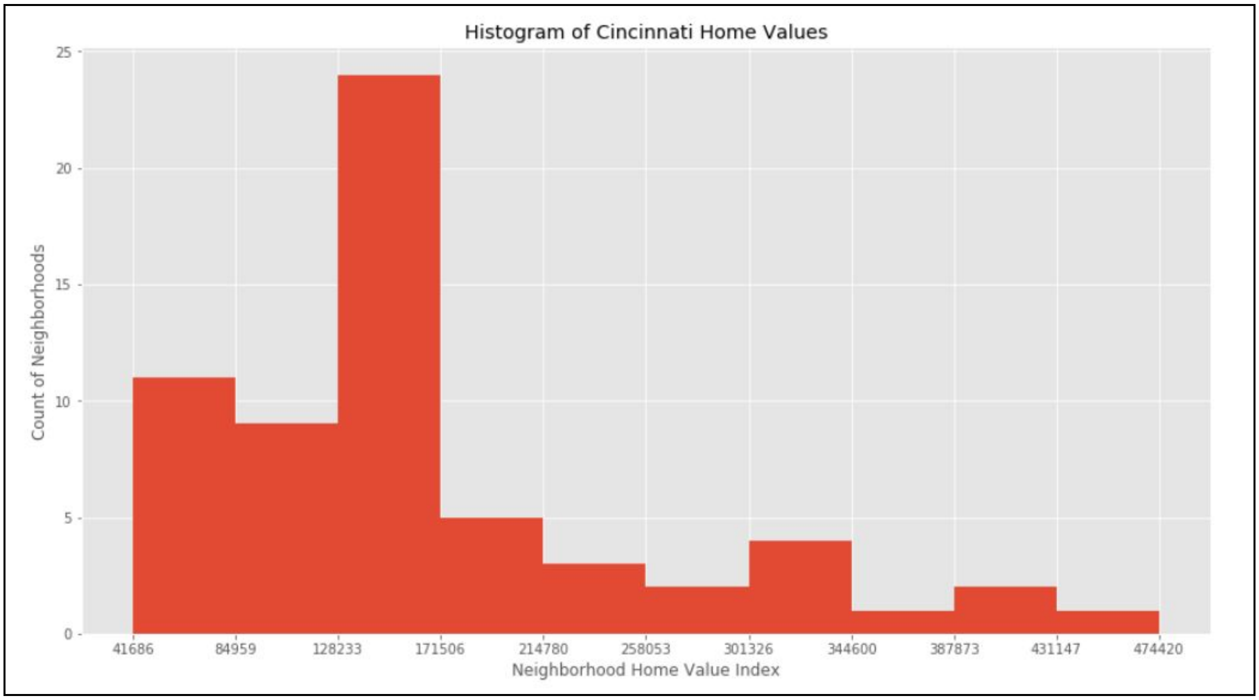
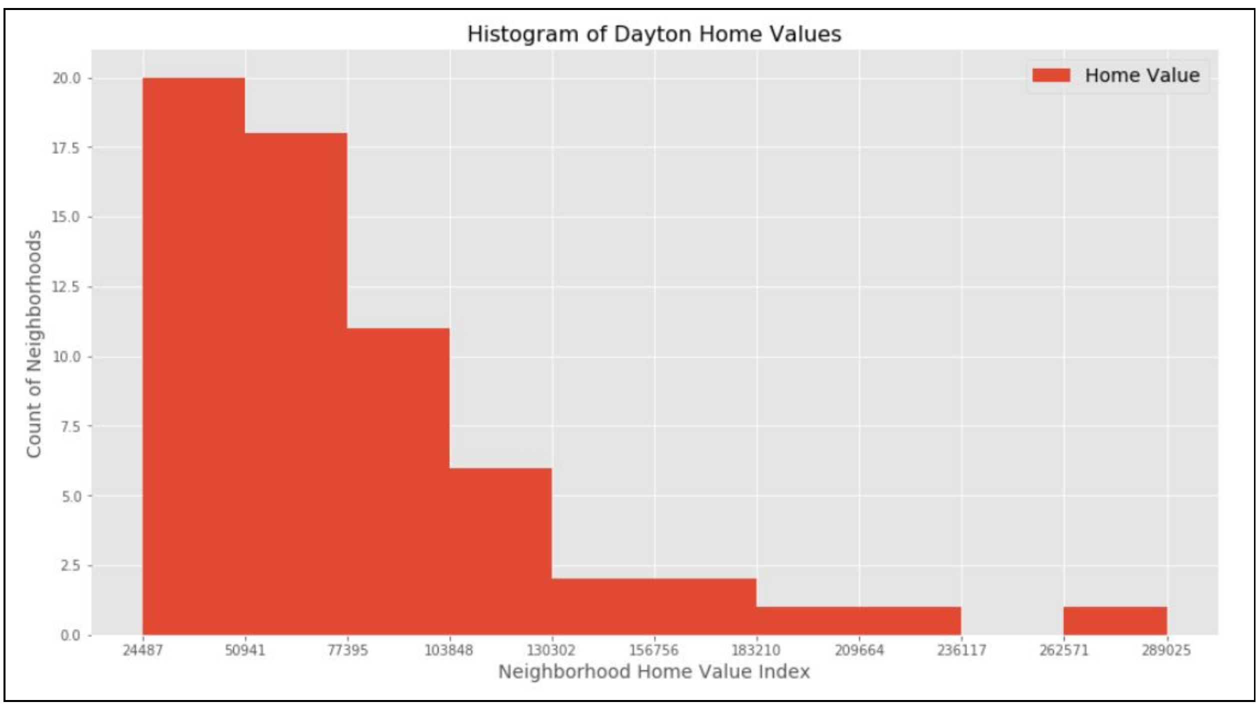


Figure 4: Histogram of Home Value Index for Dayton Neighborhoods



Clustering Analysis:

The preceding exploratory analysis showed the significant differences between the two cities. In order to determine where the commonalities between neighborhoods lie, the scikit learn k-clustering methodology is applied to the data tables to determine the unseen commonalities.

Clustering is a common exploratory data analysis technique to provide intuitive understanding of the structure of data. In essence, it is the task of finding subgroups in the data with similar points in the same cluster while data points in different clusters are very different. The “Kmeans” Algorithm is one of the most common clustering technique. It is an iterative, unsupervised learning method that identifies unique, non-overlapping clusters of data.

For this project, cluster values of 3, 4, and 5 were tested to determine the best outcome. Three was immediately discarded because one glance at the clusters on a folium map provided no real insight into the data. Four clusters was a little better, but still did not provide a good grouping of comparable neighborhoods between the two cities. The results with five clusters looked good and provided useful insights. The results will be presented in the next section.

Results:

The following results show the output and data presentation for the 5 k-cluster analysis of Cincinnati and Dayton neighborhoods. Table 2 shows the output of the df.describe() method for exploring statistical characteristics of each cluster of the data. Cluster 0 was the largest cluster with 72 neighborhoods falling into it and Cluster 1 was the smallest with only 3 neighborhoods (all in Cincinnati,the larger city). The neighborhood counts for clusters 2 ,3, and 4 (29, 7, 13) fall in the middle ground and provide a good set of options for people looking for the characteristics in these clusters.

The mean, min, max, and stdev values for each cluster help to understand where the commonalities lie. Each group appears to have some outliers in Home Value if that category was looked at by itself, but with the k-means clustering, that has to be balanced with the brewery and coffee shop count values.

Figure 5 and Figure 6 plot the feature values for each cluster. In Figure 5,the coffee shop count vs brewery count provides a clean breakdown of neighborhood clusters. Figure 6 appears to be a bit messier with home values more scattered, but upon closer inspection, this also makes sense.

Table 2: Cluster Results for Neighborhood Analysis

Cluster Labels	Measure	Brewery	Coffeeshop	Home Value
Cluster 0	count	72	72	72
	mean	0.36	0.08	$90,864.56
	std	0.48	0.33	$63,613.76
	min	0	0	$24,487.00
	max	1	2	$390,970.00
Cluster Labels	**Measure**	**Brewery**	**Coffeeshop**	**Home Value**
Cluster 1	count	3	3	3
	mean	11.33	14.67	$303,956.67
	std	1.15	2.08	$43,602.83
	min	10	13	$257,691.00
	max	12	17	$344,289.00
Cluster Labels	**Measure**	**Brewery**	**Coffeeshop**	**Home Value**
Cluster 2	count	29	29	29
	mean	2.93	0.97	$161,765.79
	std	1.13	0.73	$101,536.16
	min	2	0	$28,626.00
	max	6	2	$474,420.00
Cluster Labels	**Measure**	**Brewery**	**Coffeeshop**	**Home Value**
Cluster 3	count	7	7	7
	mean	10.14	4	$204,182.00
	std	1.77	1.91	$117,486.74
	min	8	1	$51,128.00
	max	12	7	$415,270.00
Cluster Labels	**Measure**	**Brewery**	**Coffeeshop**	**Home Value**
Cluster 4	count	13	13	13
	mean	2.85	4.38	$143,035.69
	std	1.68	1.50	$62,733.14
	min	1	3	$61,238.00
	max	6	7	$280,686.00

Figure 5: Brewery Count vs Coffee Shop Count, Based on Cluster.

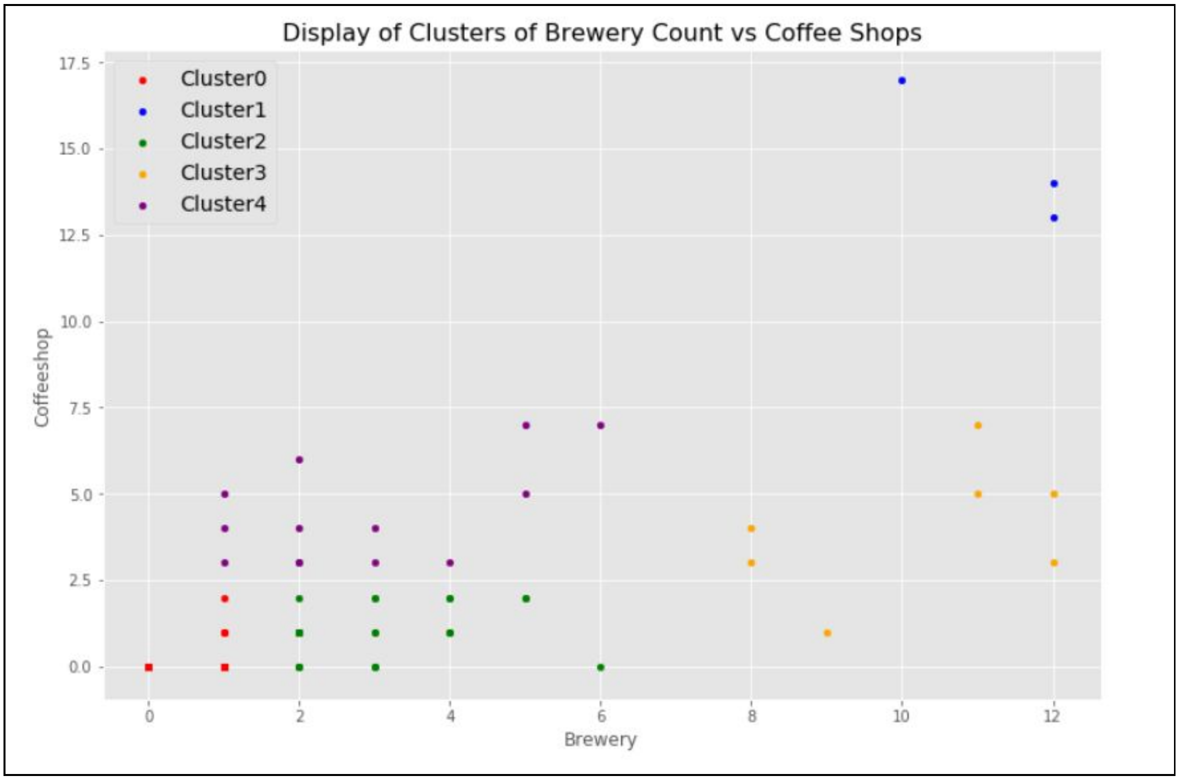
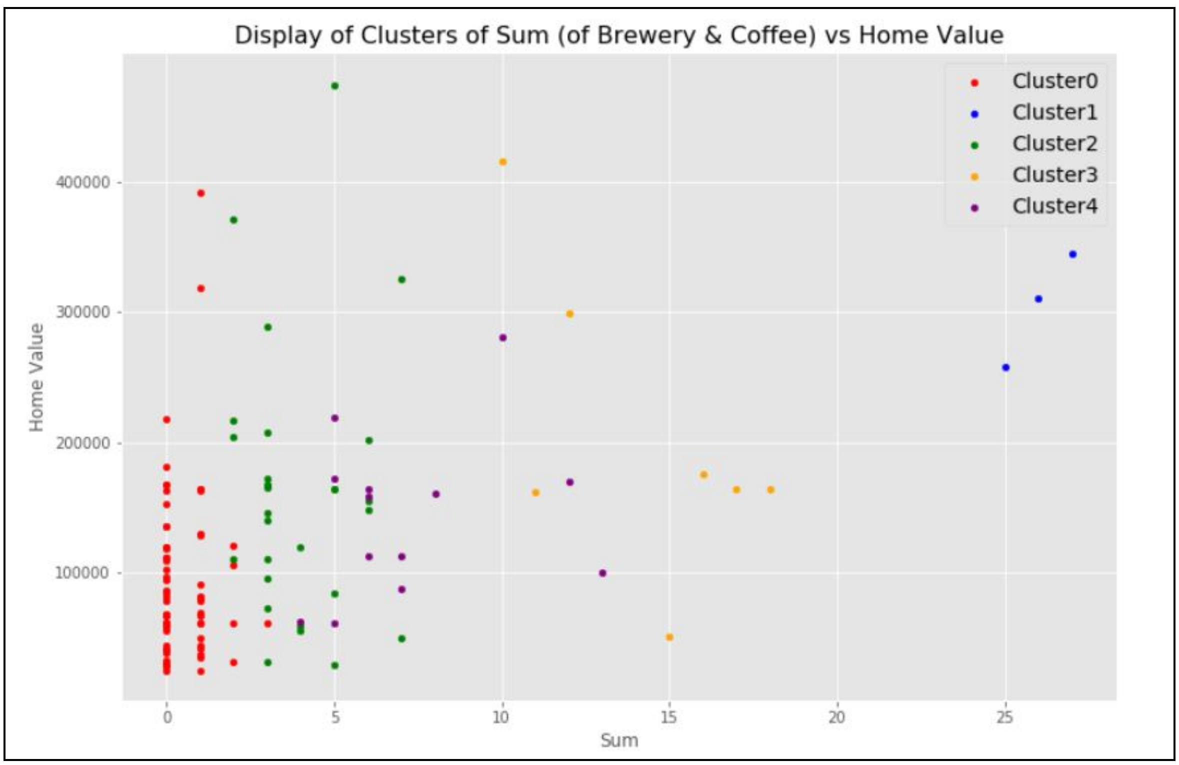


Figure 6: Sum of Brewery & Coffee Shop Counts vs Home Value, Based on Cluster.



Discussion:

The neighborhood discovery, analysis, and clustering project provided interesting and usable results for identifying groups of similar neighborhoods in two different cities. While the exploratory data analysis stage provided some initial ideas of how the two cities compared, and the home value index is a readily understandable measure of the neighborhoods, the clustering analysis provided clear groupings of similar neighborhoods that make the research worthwhile.

The list of clusters breaks down mostly along lines of the number of venues, but with a clear influence on either end by the home value. These cluster break-down observations are:

- **Cluster 0:** This cluster comprises the lower price-range, low-venue count neighborhoods. These are the least desirable neighborhoods in this project.
- **Cluster 1:** This cluster comprises the very high price-range,venue-dense neighborhoods. While these neighborhoods are certainly the top of the market, the housing cost puts them out of most modest budgets and the density of venues suggest there may be little room to expand the market. An additional issue is that this cluster is solely in Cincinnati, which limits its usefulness if you are looking in Dayton.
- **Cluster 2:** This cluster starts to get after the desired results, of affordability and venue density, but is still on the low-end of both, but it does look to overlap a bit with cluster 4.
- **Cluster 3:** This cluster is the opposite of cluster 2, this cluster starts to get on the high-end of affordability and venue count, again with a bit of overlap with cluster 4.
- **Cluster 4:** This cluster is the sweet spot in this analysis. Although a variety of customers might be interested in any of the clusters based on their own circumstances, Cluster 4 provides balanced levels of both affordability and venue density. This cluster also has decent representation in both cities.

Further analysis on this topic could include a variety of other “trendy” venues or incorporating “tips” or other criteria to better distinguish between “chain” venues and the truly “trendy” independent/artisan establishments. Some of the neighborhoods were much larger than others, so it would also be interesting to break the larger neighborhoods into smaller portions. Similar analysis could be conducted for any individual or pair of cities as long as someone was interested in collecting and cleaning the raw data on city neighborhoods.

Conclusion:

Whether you are a real estate customer trying to decide on a new city or new neighborhood, a real estate agent trying to meet customer demands, or an investor looking for a particular market, this neighborhood analysis methodology provides deep and meaningful insights that just cannot be gleaned from simple web searches alone.

At first glance, the medium-sized city of Dayton, Ohio has little in common with its larger neighbor Cincinnati. The average home value in Cincinnati is more than double that of Dayton and the total number of trendy venues (particularly breweries and coffee shops for this project) is also much larger. This cursory investigation at the top level of each city shows its weakness when you start to dive deeper into analyzing individual neighborhoods.

Conducting the data acquisition, exploratory data analysis, and finally the k-means learning algorithm puts all the pieces into place for this deeper understanding of the commonality in neighborhoods between the two cities. The analysis resulted in the identification of 5 clusters of neighborhoods between the two cities. A cluster of generally lower value venue deserts (Cluster 0), the high-rent venue meccas (Cluster 1), and three levels in between. For the particular interest of this project, Cluster 4 was the sweet spot. Cluster 4 included a range of affordable neighborhoods in both cities that had an accessible number of both breweries and coffee shops within walking distance.

Appendix - Full Data Table:

Index	Neighborhood	City	Brewery	Coffeeshop	HV_Norm	Home Value	Latitude	Longitude
0	Arlington Heights	Dayton	0	0	0.30823	30823	39.747656	-84.245002
1	Beavercreek	Dayton	0	0	2.17489	217489	39.709226	-84.063269
2	Belmont	Dayton	3	4	0.87032	87032	39.733461	-84.140875
3	Burkhardt	Dayton	1	1	0.61238	61238	39.759672	-84.151428
4	Carillon	Dayton	1	1	0.31161	31161	39.741796	-84.200474
5	College Hill	Dayton	1	0	0.49168	49168	39.783338	-84.239734
6	Cornell Heights	Dayton	1	0	0.34983	34983	39.77307	-84.239734
7	Dayton View Triangle	Dayton	1	0	0.69062	69062	39.780248	-84.229197
8	DeWeese	Dayton	0	0	0.85244	85244	39.797985	-84.198892
9	Downtown	Dayton	5	7	1.69512	169512	39.760571	-84.194938
10	Eastern Hills	Dayton	0	0	0.66966	66966	39.753472	-84.130321
11	Eastmont	Dayton	1	0	0.91068	91068	39.733611	-84.118445
12	Edgemont	Dayton	0	0	0.61238	61238	39.741735	-84.215658
13	Fairborn	Dayton	1	1	1.2017	120170	39.820892	-84.019379
14	Fairlane	Dayton	0	0	1.02091	102091	39.739513	-84.262119
15	Fairview	Dayton	1	0	0.43714	43714	39.787948	-84.229197
16	Five Oaks	Dayton	1	2	0.61238	61238	39.772847	-84.209435
17	Five Points	Dayton	1	4	0.61238	61238	39.752949	-84.205366
18	Gateway	Dayton	0	0	1.80992	180992	39.803464	-84.103926
19	Grafton Hill	Dayton	3	2	0.83489	83489	39.766232	-84.205481
20	Greenwich Village	Dayton	0	0	0.61238	61238	39.785729	-84.262119
21	Hearthstone	Dayton	1	0	0.81324	81324	39.743467	-84.135598
22	Highview Hills	Dayton	0	0	0.32308	32308	39.728457	-84.246319
23	Hillcrest	Dayton	1	0	0.61238	61238	39.788772	-84.219975
24	Historic Inner East	Dayton	5	2	0.49473	49473	39.759118	-84.165935
25	Kettering	Dayton	0	0	1.53008	153008	39.689504	-84.168827

Index	Neighborhood	City	Brewery	Coffeeshop	HV_Norm	Home Value	Latitude	Longitude
26	Lakeview	Dayton	0	0	0.28596	28596	39.742258	-84.239734
27	Linden Heights	Dayton	0	0	0.78768	78768	39.749135	-84.146152
28	Little Richmond	Dayton	0	0	0.37696	37696	39.771625	-84.288444
29	MacFarlane	Dayton	0	0	0.30235	30235	39.751483	-84.218658
30	McCook Field	Dayton	0	0	0.61238	61238	39.783098	-84.188953
31	McPherson Town Historic District	Dayton	4	3	1.12402	112402	39.767755	-84.195904
32	Miami Chapel	Dayton	0	0	0.61238	61238	39.742823	-84.225245
33	Mount Vernon	Dayton	1	0	0.80498	80498	39.779724	-84.218658
34	North Riverdale	Dayton	0	0	0.40449	40449	39.79338	-84.209435
35	Northern Hills	Dayton	0	0	0.6675	66750	39.795995	-84.262119
36	Northridge Estates	Dayton	0	0	1.19014	119014	39.824165	-84.209435
37	Oakwood	Dayton	2	1	2.89025	289025	39.725337	-84.174106
38	Old North Dayton	Dayton	0	0	0.40527	40527	39.788835	-84.169891
39	Patterson Park	Dayton	4	2	1.47465	147465	39.720196	-84.158023
40	Philadelphia Woods	Dayton	0	0	0.86342	86342	39.798605	-84.2371
41	Pineview	Dayton	0	0	0.40375	40375	39.737643	-84.250269
42	Princeton Heights	Dayton	1	0	0.61393	61393	39.772547	-84.229197
43	Residence Park	Dayton	0	0	0.28228	28228	39.754922	-84.262119
44	Riverdale	Dayton	2	1	0.31871	31871	39.77367	-84.20021
45	Riverside	Dayton	0	0	0.94837	94837	39.779781	-84.124105
46	Roosevelt	Dayton	0	0	0.61238	61238	39.754575	-84.229197
47	Santa Clara	Dayton	1	0	0.36879	36879	39.781897	-84.210752
48	Shroyer Park	Dayton	3	1	1.19828	119828	39.728035	-84.16066
49	South Park	Dayton	6	7	1.00316	100316	39.749641	-84.181757
50	Southern Dayton View	Dayton	1	0	0.24487	24487	39.763366	-84.225245
51	Springfield	Dayton	0	0	0.24525	24525	39.76994	-84.151428
52	Stoney Ridge	Dayton	0	0	1.10993	110993	39.710341	-84.243685

Index	Neighborhood	City	Brewery	Coffeeshop	HV_Norm	Home Value	Latitude	Longitude
53	Twin Towers	Dayton	3	2	0.28626	28626	39.748703	-84.166801
54	University Park	Dayton	3	3	1.12173	112173	39.735846	-84.188348
55	University Row	Dayton	1	0	0.66472	66472	39.772154	-84.221293
56	Walnut Hills	Dayton	3	0	0.72252	72252	39.743446	-84.16066
57	Wesleyan Hill	Dayton	0	0	0.61238	61238	39.784948	-84.246319
58	Westwood	Dayton	0	0	0.61238	61238	39.761713	-84.243685
59	Wolf Creek	Dayton	0	0	0.44064	44064	39.756619	-84.218658
60	Wright View	Dayton	0	0	0.60048	60048	39.769408	-84.140875
61	Oregon	Dayton	6	0	2.0134	201340	39.757308	-84.18249
0	Avondale	Cincinnati	0	0	0.81719	81719	39.144963	-84.497811
1	Bond Hill	Cincinnati	0	0	1.11614	111614	39.177785	-84.477659
2	California	Cincinnati	1	0	1.28577	128577	39.065338	-84.419893
3	Camp Washington	Cincinnati	2	2	0.5831	58310	39.13795	-84.537609
4	Carthage	Cincinnati	0	0	0.68406	68406	39.195869	-84.485014
5	Clifton Heights	Cincinnati	8	4	2.98535	298535	39.125934	-84.520908
6	College Hill	Cincinnati	1	0	1.30138	130138	39.198536	-84.548428
7	Columbia-Tusculum	Cincinnati	5	2	3.25009	325009	39.115193	-84.43614
8	Corryville	Cincinnati	1	5	1.58269	158269	39.136807	-84.503866
9	CUF	Cincinnati	8	3	1.61286	161286	39.125115	-84.525842
10	East End	Cincinnati	1	0	3.18827	318827	39.099214	-84.422519
11	East Price Hill	Cincinnati	0	0	0.67706	67706	39.106141	-84.569386
12	East Walnut HIlls	Cincinnati	2	3	1.71615	171615	39.125191	-84.477637
13	East Westwood	Cincinnati	0	0	0.57827	57827	39.150129	-84.566766
14	English Woods	Cincinnati	1	0	0.77999	77999	39.139781	-84.556888
15	Evanston	Cincinnati	4	1	1.63675	163675	39.13765	-84.475703
16	Hartwell	Cincinnati	0	0	1.08939	108939	39.213392	-84.468554
17	Hyde Park	Cincinnati	1	0	3.9097	390970	39.135248	-84.443733
18	Kennedy Heights	Cincinnati	2	1	1.66743	166743	39.184178	-84.409388
19	Laurel Homes	Cincinnati	12	5	1.63675	163675	39.111171	-84.526054
20	Linwood	Cincinnati	3	0	2.07301	207301	39.126727	-84.409663

Index	Neighborhood	City	Brewery	Coffeeshop	HV_Norm	Home Value	Latitude	Longitude
21	Lower Price Hill	Cincinnati	1	3	0.62791	62791	39.105337	-84.55161
22	Madisonville	Cincinnati	2	1	1.64735	164735	39.160616	-84.393133
23	Millvale	Cincinnati	1	0	1.63675	163675	39.145566	-84.552358
24	Mount Adams	Cincinnati	9	1	4.1527	415270	39.10916	-84.495205
25	Mt Airy	Cincinnati	0	0	1.35905	135905	39.191447	-84.570222
26	Mt Auburn	Cincinnati	11	5	1.75705	175705	39.121487	-84.50911
27	Mt Lookout	Cincinnati	4	1	4.7442	474420	39.127632	-84.419893
28	Mt Washington	Cincinnati	0	0	1.67942	167942	39.086815	-84.380489
29	North Avondale	Cincinnati	2	0	2.04424	204424	39.156814	-84.48813
30	North Fairmount	Cincinnati	1	0	0.41686	41686	39.138151	-84.560218
31	Cumminsville	Cincinnati	2	6	1.60456	160456	39.163687	-84.540185
32	Oakley	Cincinnati	5	5	2.80686	280686	39.154266	-84.428286
33	Over-The-Rhine	Cincinnati	12	13	2.57691	257691	39.112883	-84.515948
34	Paddock Hills	Cincinnati	2	0	2.16981	216981	39.161505	-84.477637
35	Pendleton	Cincinnati	12	14	3.0989	309890	39.110427	-84.508455
36	Pleasant Ridge	Cincinnati	2	3	2.19299	219299	39.181768	-84.428903
37	Prospect Hill	Cincinnati	11	7	1.63675	163675	39.115338	-84.506332
38	Queensgate	Cincinnati	4	1	1.63675	163675	39.099035	-84.529959
39	Downtown Cincinnati	Cincinnati	10	17	3.44289	344289	39.099435	-84.516573
40	Riverside Dr	Cincinnati	2	4	1.63675	163675	39.12191	-84.474283
41	Roselawn	Cincinnati	0	0	1.19458	119458	39.196982	-84.461397
42	Sayler Park	Cincinnati	0	0	1.18802	118802	39.108964	-84.687136
43	Sedamsville	Cincinnati	1	0	1.63675	163675	39.089206	-84.568076
44	South Cumminsville	Cincinnati	3	1	0.55184	55184	39.154583	-84.551048
45	South Fairmount	Cincinnati	0	0	0.55184	55184	39.125615	-84.551888
46	Walnut Hills	Cincinnati	2	1	1.71615	171615	39.125972	-84.490378
47	West End	Cincinnati	12	3	0.51128	51128	39.113605	-84.527496
48	West Price Hill	Cincinnati	0	0	0.96542	96542	39.113725	-84.585477
49	Westwood	Cincinnati	2	0	1.10761	110761	39.142362	-84.592293

Index	Neighborhood	City	Brewery	Coffeeshop	HV_Norm	Home Value	Latitude	Longitude
50	Westwood Historic District	Cincinnati	2	1	1.10761	110761	39.150336	-84.599945
51	Winton Hills	Cincinnati	0	0	1.35169	135169	39.186694	-84.516976
52	Winton Place	Cincinnati	2	1	0.95433	95433	39.166461	-84.513775
53	Delhi	Cincinnati	0	0	1.62711	162711	39.095059	-84.605222
54	Covedale	Cincinnati	1	0	1.62711	162711	39.127335	-84.634832
55	Bridgetown North	Cincinnati	3	0	1.39984	139984	39.16094	-84.632216
56	Monfort Heights	Cincinnati	0	0	1.6719	167190	39.17975	-84.590337
57	North College Hill	Cincinnati	1	1	1.05749	105749	39.218391	-84.550778
58	Finneytown	Cincinnati	2	1	1.45786	145786	39.217793	-84.516976
59	Norwood	Cincinnati	4	2	1.54513	154513	39.16448	-84.45428
60	Amberley	Cincinnati	2	0	3.70642	370642	39.204781	-84.427997
61	Deer Park	Cincinnati	2	1	1.67887	167887	39.205337	-84.394663