

Human Centered City Planning

1. Introduction

From the daily gadgets to transportation system the world is moving from aiming for mere functionality to seeking to enhance the human experience and city planning is no exemption. Humans have become more aware than ever the impact that their surroundings have on their health and longevity. This study seeks to isolate the aspects of city structure that lend themselves most to human health by exploring and comparing two of the [World's Healthiest Cities](#)

For this study I have picked Vienna and Singapore and will be exploring the structure of the cities to find what these two have in common in spite of their being on different continents with diverse characteristics. Comparing these two cities will show us how what health enhancing qualities exist in both while controlling for the factors that might be due to similarities in climate and cultural practices.

Information gathered from this study will be very useful to city planners and policy makers as we seek to build more of a healthy planet for humans.

2. Data

Our goal is to compare in the structure of both cities so that we can draw conclusions about what characteristics make a city healthy to live in.

To do that we will have to segment the cities into their existing administrative districts and find out what venues are most common in each, clustering them to determine which districts are most similar within each city and then comparing the districts across the two cities.

Vienna is divided into 23 districts, a list of which was scraped from [Austria's Open Data](#) site. This data frame contains the districts of all the cities in Austria but for our study we would only require the part that pertains to Vienna.

Singapore is divided into 55 planning areas as found on [Singapore's Planning Areas Wiki](#). The table contains lots of other information that we will not need for our segmentation.

We will only need the list of districts in each city in order to be able to geocode their coordinates and cluster them based on their most common venues

Foursquare API is used to retrieve the most common venues in each district

3. Methodology

Clustering the cities

Clustering is a form of unsupervised machine learning algorithm used to place observations into groups based on their similarities within the group and their differences from other groups.

Clustering is the perfect machine learning for this exercise as it will allow the classification of similar districts in each country.

In order to do the clustering, we first need data frames for both cities that have the names of their districts and their coordinates

Vienna Location Data frame

The data scraped from the website contained information on all the districts in all of the cities of Austria and not for Vienna.

Out[8]:

	Political District, Key Date 2020	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4
0	Compiled on:	12 November 2020 13:25:43	NaN	NaN	NaN
1	NaN	NaN	NaN	NaN	NaN
2	Fed. Province Identifier	Federal Province	Pol. District Identifier	Political District	Pol. District Code
3	1	Burgenland	101	Eisenstadt(Stadt)	101
4	1	Burgenland	102	Rust(Stadt)	102

Since the only necessary information for the analysis is the district names, the data frame is sliced down to just the columns that contain the city and districts names. The other rows are then conditionally dropped so that only the districts of Vienna remain.

Out[10]:

	Unnamed: 1	Unnamed: 3
0	Vienna	Wien(Stadt)
1	Vienna	Wien 1.,Innere Stadt
2	Vienna	Wien 2.,Leopoldstadt
3	Vienna	Wien 3.,Landstraße
4	Vienna	Wien 4.,Wieden
5	Vienna	Wien 5.,Margareten
6	Vienna	Wien 6.,Mariahilf
7	Vienna	Wien 7.,Neubau
8	Vienna	Wien 8.,Josefstadt
9	Vienna	Wien 9.,Alsergrund
10	Vienna	Wien 10.,Favoriten
11	Vienna	Wien 11.,Simmering
12	Vienna	Wien 12.,Meidling
13	Vienna	Wien 13.,Hietzing

After the rows are dropped, we no longer need the city name to identify the district so the first column is dropped as well. Also the first row in our new data frame does not represent a district but the entire state of Vienna so that is dropped as well to leave a data frame of just the 23 districts of Vienna.

Singapore Data frame

Singapore data that was scrapped is of a different format. All the districts were readily available but there were columns of other information

Out[37]:

	Name (English)	Malay	Chinese	Pinyin	Tamil	Region	Area (km2)	Population[7]	Density (/km2)
0	Ang Mo Kio	NaN	宏茂橋	Hóng mào qiáo	ஆங் மோ கியோ	North-East	13.94	163950	13400
1	Bedok	*	勿洛	Wù luò	பிடோக்	East	21.69	279380	13000
2	Bishan	NaN	碧山	Bì shān	பீஷான்	Central	7.62	88010	12000
3	Boon Lay	NaN	文禮	Wén lǐ	பூன் லே	West	8.23	30	3.6
4	Bukit Batok	*	武吉巴督	Wǔjī bā dū	புக்கிட் பாத்தோக்	West	11.13	153740	14000

After slicing the data frame to just the column that contains the district names, exploratory analysis showed that geocoding would be inaccurate in some cases unless the country was specified since some of district names are not unique to Singapore. The data frame was thus amended to include the country name.

Out[48]:

	Name (English)	Areas
0	Ang Mo Kio	Ang Mo Kio , Singapore
1	Bedok	Bedok , Singapore
2	Bishan	Bishan , Singapore
3	Boon Lay	Boon Lay , Singapore
4	Bukit Batok	Bukit Batok , Singapore
5	Bukit Merah	Bukit Merah , Singapore

Getting the coordinates for both Cities

The next step was getting the latitudes and longitudes for each district. This was easily done with python's Geocoder library and appended to a data frame of districts, latitudes and longitudes.

Out[13]:

	V_Districts	Latitude	Longitude
0	Wien 1.,Innere Stadt	48.209023	16.369851
1	Wien 2.,Leopoldstadt	48.200638	16.426948
2	Wien 3.,Landstraße	48.206791	16.384780
3	Wien 4.,Wieden	48.195803	16.367197
4	Wien 5.,Margareten	48.191727	16.358610
5	Wien 6.,Mariahilf	48.199293	16.352750
6	Wien 7.,Neubau	48.202092	16.349042
7	Wien 8.,Josefstadt	48.210852	16.347360
8	Wien 9.,Alsergrund	48.225073	16.358398
9	Wien 10.,Favoriten	48.174415	16.381225

Out[42]:

	S_Areas	Latitude	Longitude
0	Ang Mo Kio , Singapore	1.370080	103.849523
1	Bedok , Singapore	1.323976	103.930216
2	Bishan , Singapore	1.350986	103.848255
3	Boon Lay , Singapore	1.338550	103.705812
4	Bukit Batok , Singapore	1.349057	103.749591
5	Bukit Merah , Singapore	1.270439	103.828318
6	Bukit Panjang , Singapore	1.379149	103.761413
7	Bukit Timah , Singapore	1.354690	103.776372
8	Central Water Catchment , Singapore	1.375708	103.801743
9	Changi , Singapore	1.351080	103.990064

A map of each of each city with their respective districts superimposed was then created using the python Folium library

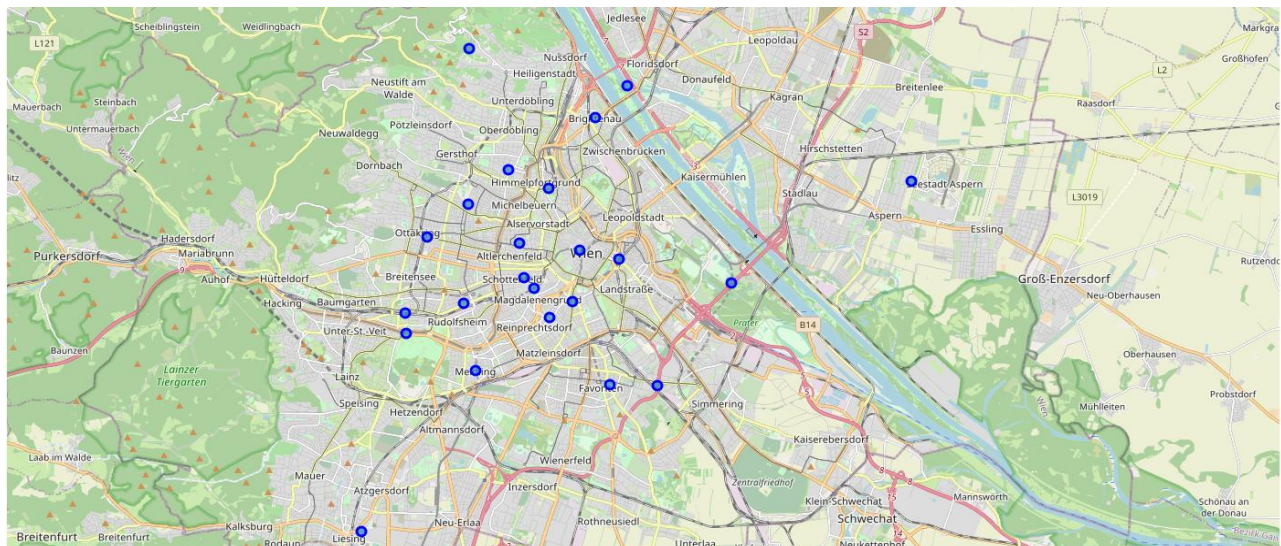


Figure 1Vienna's Districts

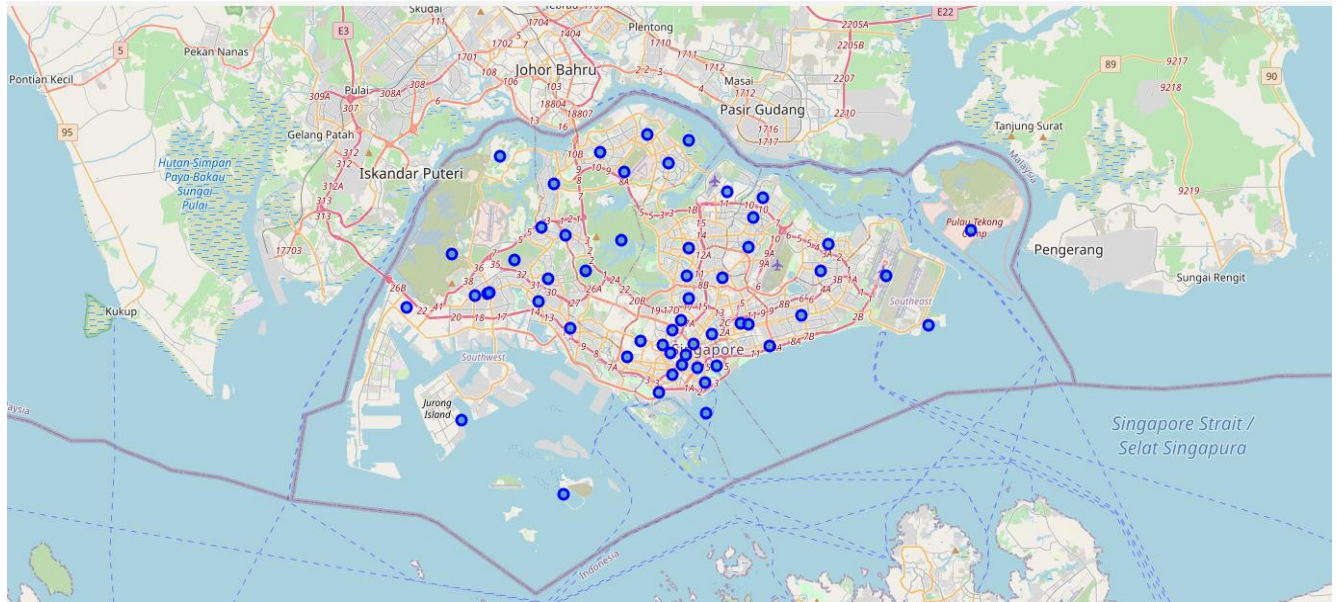


Figure 2 Singapore's Districts

Getting the Venues

So once the coordinates are retrieved then it is time to get the venues in the 500-mile radius and limit it to 100. Foursquare API was used to get the venues in the 500m radius of the identified district.

A function is written to retrieve the venue names and categories for each district in each city and added to new data frames.

Out[21]:

	District	District Latitude	District Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Wien 1.,Innere Stadt	48.209023	16.369851	Stephansplatz	48.208299	16.371880	Plaza
1	Wien 1.,Innere Stadt	48.209023	16.369851	DO & CO Restaurant	48.208240	16.371758	Restaurant
2	Wien 1.,Innere Stadt	48.209023	16.369851	Graben	48.208915	16.369379	Pedestrian Plaza
3	Wien 1.,Innere Stadt	48.209023	16.369851	Stephansdom	48.208626	16.372672	Church
4	Wien 1.,Innere Stadt	48.209023	16.369851	COS	48.209359	16.371591	Clothing Store

Out[46]:

	District	District Latitude	District Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Ang Mo Kio , Singapore	1.37008	103.849523	Old Chang Kee	1.369094	103.848389	Snack Place
1	Ang Mo Kio , Singapore	1.37008	103.849523	FairPrice Xtra	1.369279	103.848886	Supermarket
2	Ang Mo Kio , Singapore	1.37008	103.849523	MOS Burger	1.369170	103.847831	Burger Joint
3	Ang Mo Kio , Singapore	1.37008	103.849523	Face Ban Mian 非板面 (Ang Mo Kio)	1.372031	103.847504	Noodle House
4	Ang Mo Kio , Singapore	1.37008	103.849523	NTUC FairPrice	1.371507	103.847082	Supermarket

181 unique categories were retrieved for Vienna and 227 unique categories for Singapore

Analyzing Each District

To be able to group the districts in each city into clusters based on the similarities of their venues, the most common venue categories in each district are found.

Returning most Common Venues

The venues categories are thus converted into dummy variables so that the districts can grouped the venues that are most common in each.

A function is then written to sort the venue categories into the 10 most common in each district and pass it to new data frame.

Out[28]:

	District	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	Wien 1.,Innere Stadt	Café	Plaza	Hotel	Restaurant	Italian Restaurant	Austrian Restaurant	Cocktail Bar	Bar	Ice Cream Shop	Bakery
1	Wien 2.,Leopoldstadt	Pool	Garden	Disc Golf	Park	Yoga Studio	Dumpling Restaurant	Flea Market	Fast Food Restaurant	Farmers Market	Falafel Restaurant
2	Wien 3.,Landstraße	Austrian Restaurant	Hotel	Gastropub	Ice Cream Shop	Italian Restaurant	Plaza	Café	Noodle House	Comedy Club	Pastry Shop
3	Wien 4.,Wieden	Café	Asian Restaurant	Coffee Shop	Italian Restaurant	Burger Joint	Burrito Place	Restaurant	Sushi Restaurant	Indian Restaurant	Ice Cream Shop
4	Wien 5.,Margareten	Austrian Restaurant	Café	Restaurant	Italian Restaurant	Dessert Shop	Supermarket	Asian Restaurant	Bakery	Coffee Shop	Hotel

Out[52]:

	District	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	Ang Mo Kio , Singapore	Coffee Shop	Dessert Shop	Sandwich Place	Bubble Tea Shop	Food Court	Supermarket	Japanese Restaurant	Fast Food Restaurant	Chinese Restaurant	Ramen Restaurant
1	Bedok , Singapore	Coffee Shop	Japanese Restaurant	Sandwich Place	Chinese Restaurant	Bakery	Food Court	Asian Restaurant	Noodle House	Café	Fast Food Restaurant
2	Bishan , Singapore	Coffee Shop	Food Court	Bubble Tea Shop	Chinese Restaurant	Cosmetics Shop	Supermarket	Asian Restaurant	Ice Cream Shop	Café	Japanese Restaurant
3	Boon Lay , Singapore	Japanese Restaurant	Asian Restaurant	Fast Food Restaurant	Chinese Restaurant	Dessert Shop	Coffee Shop	Park	Indian Restaurant	Gym / Fitness Center	Playground
4	Bukit Batok , Singapore	Coffee Shop	Food Court	Fast Food Restaurant	Chinese Restaurant	Malay Restaurant	Shopping Mall	Grocery Store	Sandwich Place	Frozen Yogurt Shop	Café

Clustering

Now the clustering to put the districts with the most similar characteristics in the same groupings.

K Means clustering is used to group the combinations of the most common venues into 5 distinct clusters

4 districts in Singapore did not have enough venues nearby to be able to fit into any cluster so they were dropped from the data frame.

The clusters in each district falls are shown in different colors below:

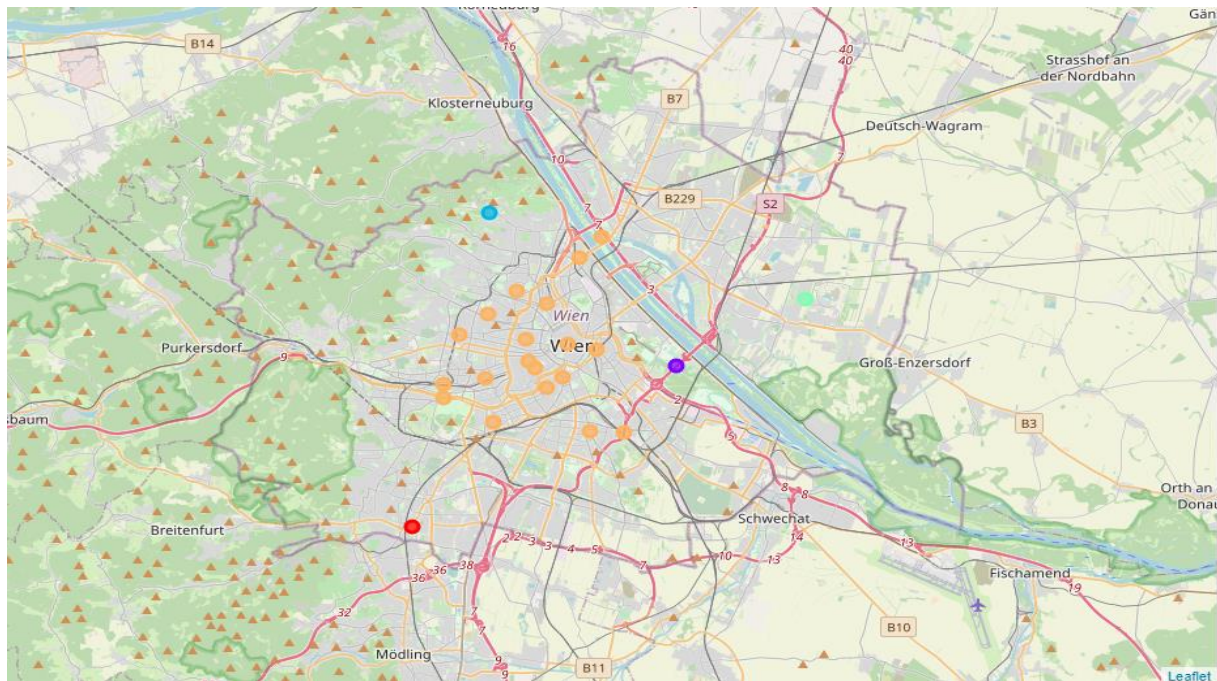


Figure 3 Clusters Of Vienna

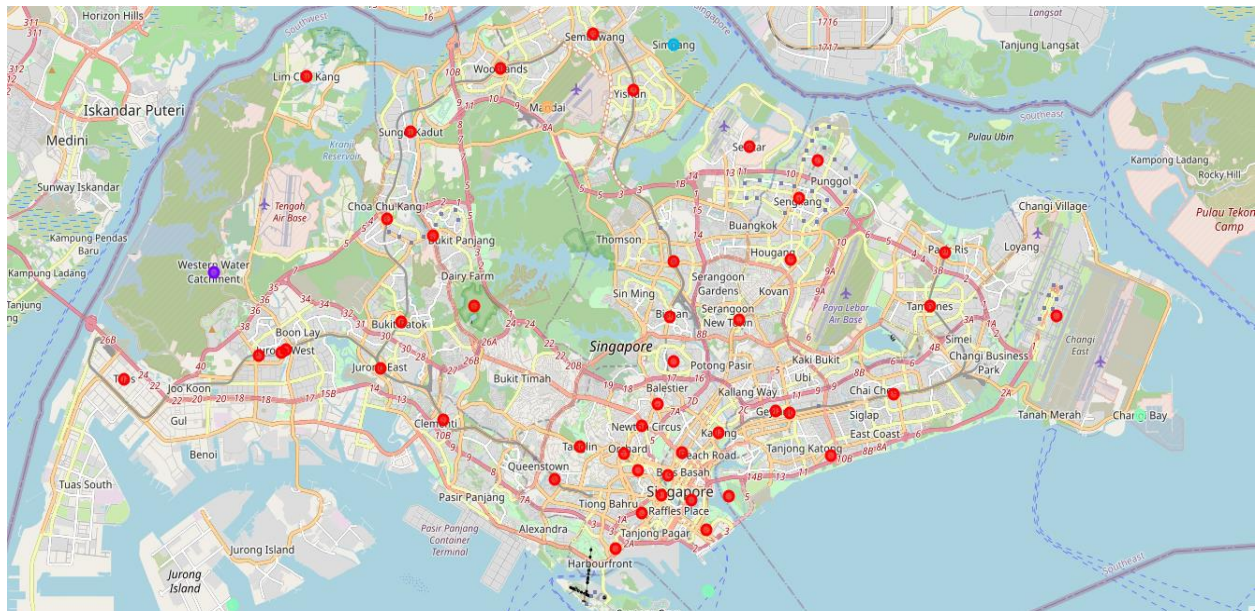


Figure 4 Clusters of Singapore

Greenspace

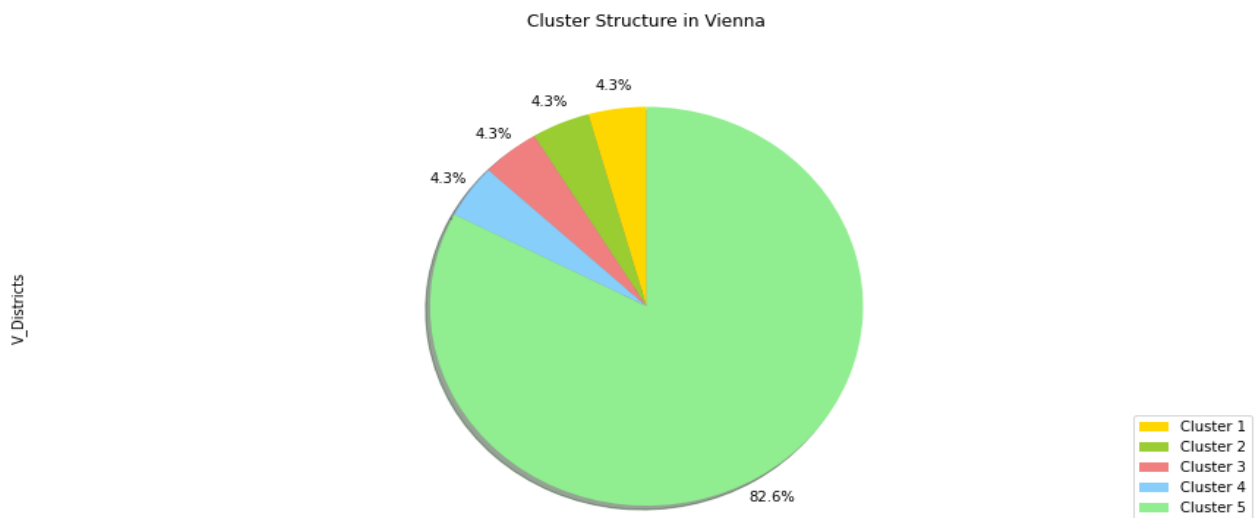
To see the interactions of greenspace we then created a vegetation map and plotted all of the venues on it to see how the cities make use of their greenspace. We use Folium's Stamen Terrain Map to look at the vegetation distribution.

4. Result

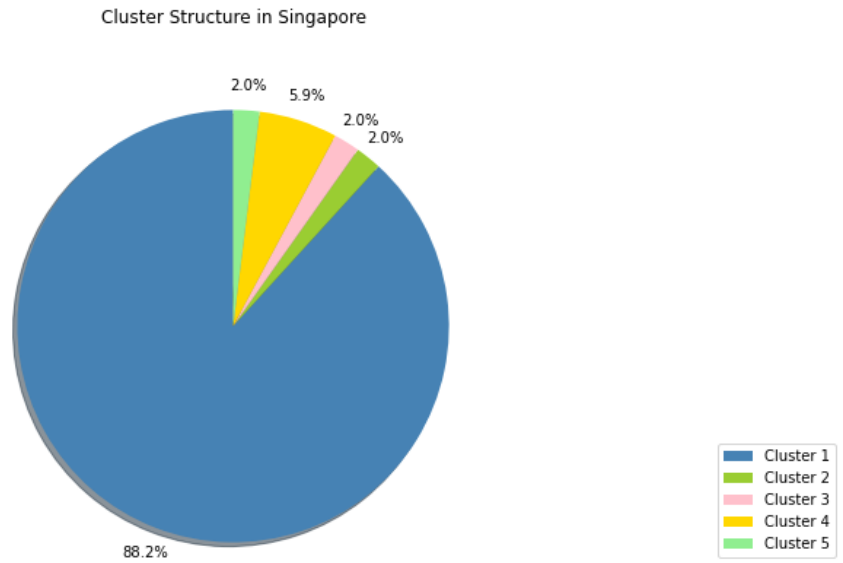
Cluster Comparison

Looking at the clustered maps for both countries, it shows how both have a dominant type of district. It also shows that the other clusters are mostly found on the edges of the city

The cluster structure is as follows:



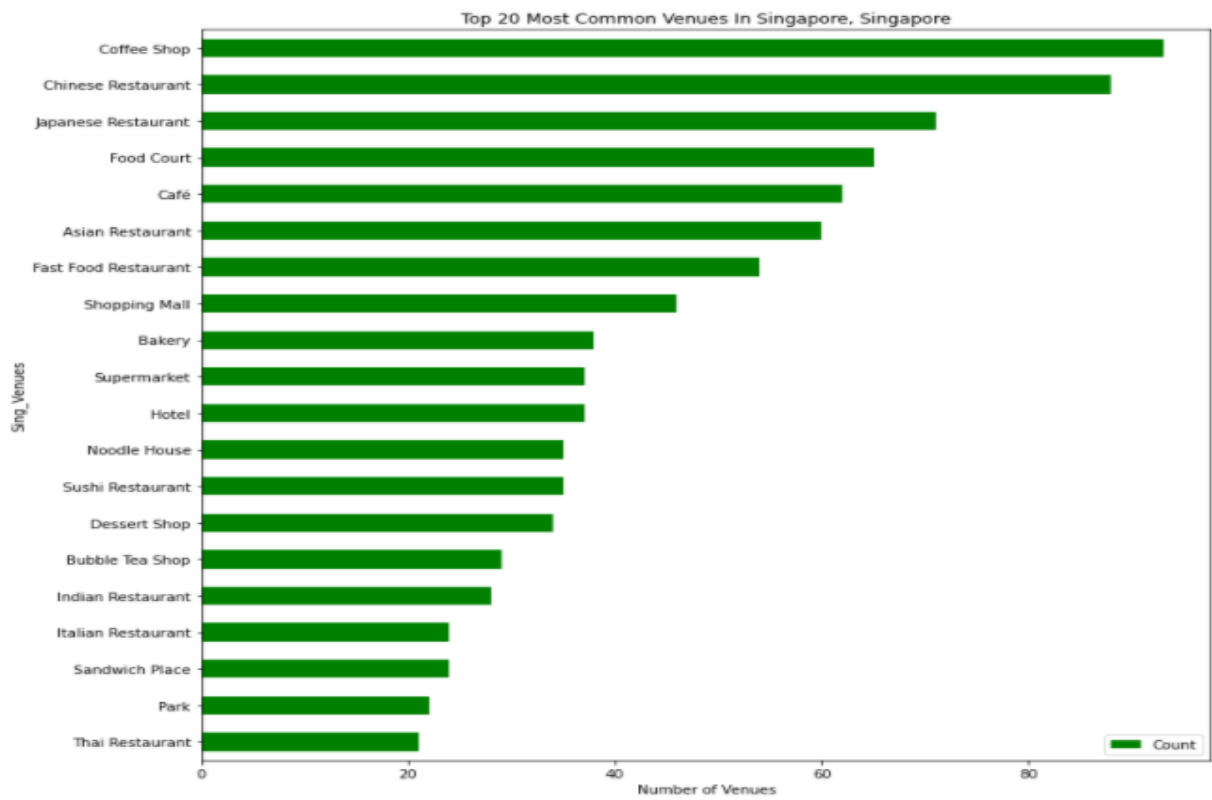
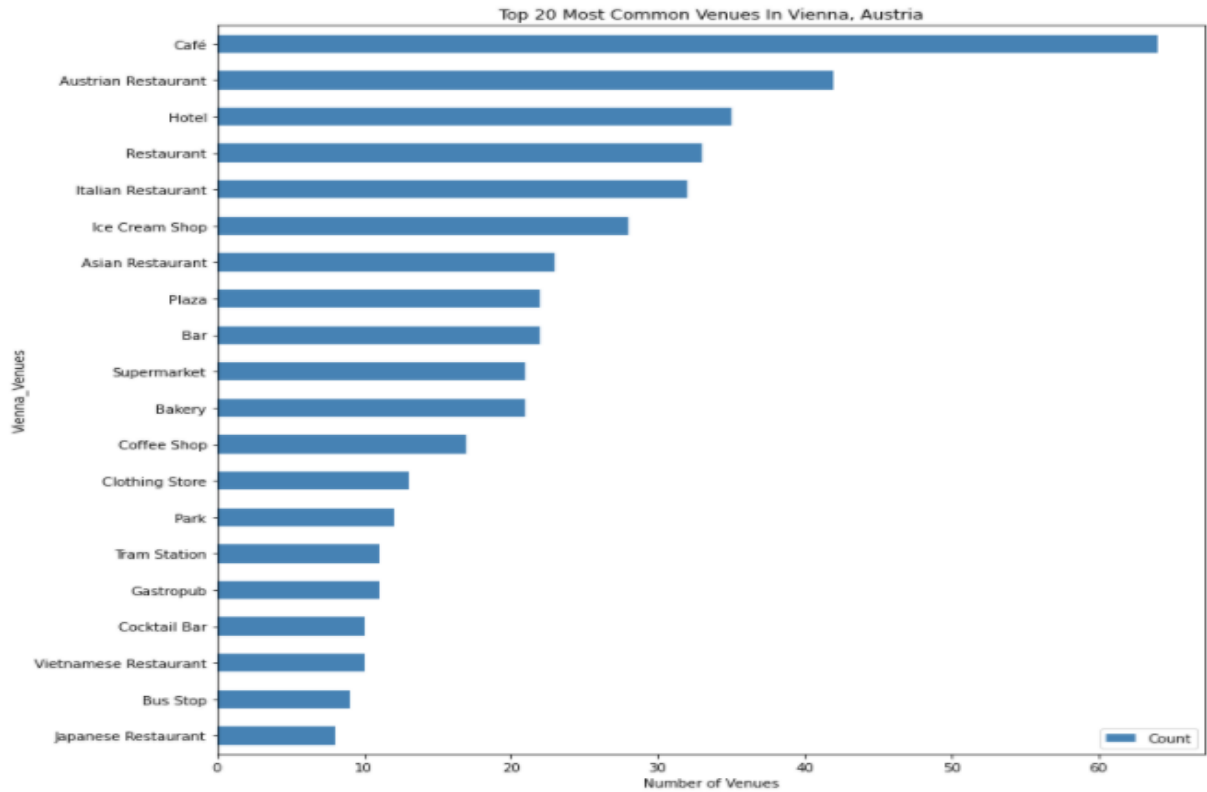
S_Areas



The figures show that in each city, there is one cluster that dominates the structure cluster 5 in Vienna and cluster one in Singapore and that similar percentages (~83% in Vienna and ~88% in Singapore) of the districts are similar enough in to be put in the same cluster.

So the thing that means the clustering of the venues is consistent within the city but now we need to see how similar the venues are across the cities.

Let's now look to see the topmost venues that constitute the majority of both cities and hence the majority clusters



The venue distribution in each city show us the prevalence of places of hospitality (restaurants and hotels) also notice the presence of parks in the most common venues in both cities. Also we see how the restaurants are mostly indigenous to the area.

Greenspace

Greenspace is highly correlated with the health of humans so it is no coincidence that these cities make the list of [Cities with the most Greenspace](https://www.worldatlas.com/articles/cities-with-the-most-greenspace.html). Singapore has 47% and Vienna 45.5% greenspace¹

Looking at the spread of vegetation it shows how some of the returned venues interact with the greenspace in each city

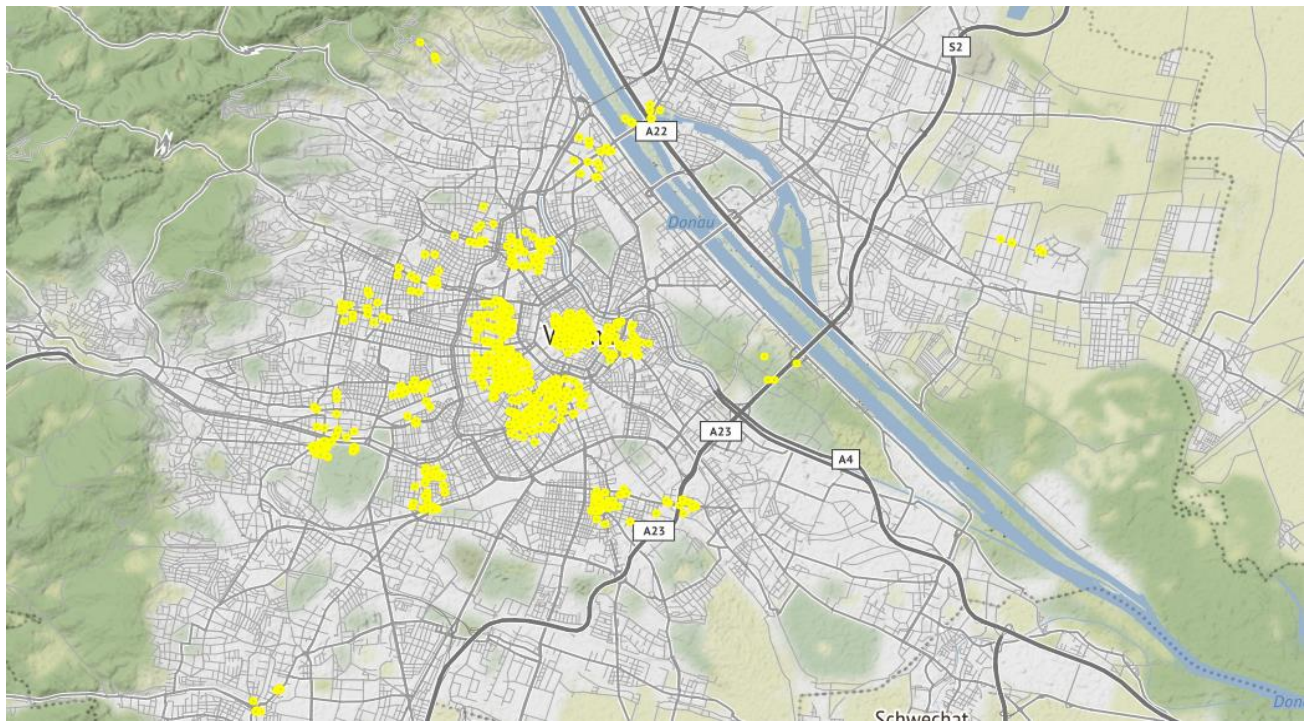


Figure 5 Venues and Greenspace, Vienna

¹ Cities with the Most Greenspace <https://www.worldatlas.com/articles/cities-with-the-most-greenspace.html>

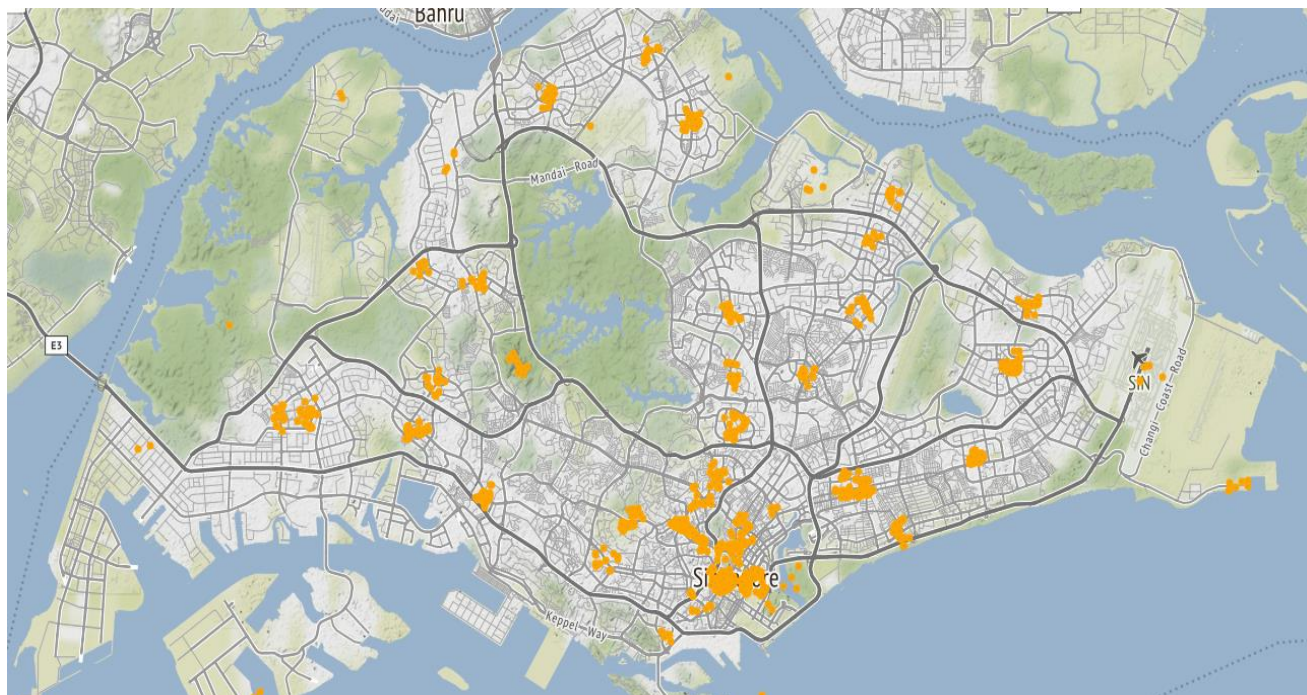


Figure 6 Venues and Greenspace, Singapore

5. Discussion

The health enhancing structure of both cities seems to center more around the leisure and nature component instead of the things that would normally be associated with wellness. For example, there are no gyms or spas in the returned venues but rather a strong presence of local food restaurants, coffee shops and parks.

Based on these results, human centered design seems to be the type of design that allows citizens to naturally have a healthy flow of life. Design that incorporates the natural flow of the environment and makes available more indigenous experiences.

6. Conclusion

In conclusion, healthy cities like Singapore and Vienna provide a worthy blueprint for emulation. Similarities exist between them in spite of their being on different continents that show that structuring a city in a way that it takes advantage of the natural flow and cuisine of the city contributes to human health.