Townsville Suburb Clustering

Introduction

Description and Discussion of Background

Townsville is a major regional centre in Queensland, Australia. It has a population of over 193,000. It is a major government, commercial and defence centre. The Townsville local government area covers 3,736 square kilometres. The area considered in this analysis is about 180 sq kms. Population density in the urban area is just over 1060 persons per sq km. It is generally considered that Townsville is largely the same in its economic and social structure.

This project will seek to cluster the urban suburbs of Townsville to examine this issue. The features used in the cluster analysis can broadly be considered as Lifestyle factors. They are: Socio-Economic Indexes; Access to Public Transport; Animal Complaints; Crime Data; Access to Council Community Facilities; Access to Community Venues.

The variability in a city's population is an important consideration when planning its social and economic development. Town planning may target some programs to certain suburb features, that would not work, or be unnecessary, in other suburbs. For example, the installation of cameras used to monitor for crime. The insights gained from this project would be useful to people moving to or moving within the Townsville District. It can give people an idea of commonalities and differences between suburbs.

Data and Methodology

Data was sourced from several online sites.

Suburb Names

Data Source: https://en.wikipedia.org/wiki/List_of_Townsville_suburbs
Data Preparation: The suburb names were copied from the Wikipedia page into an Excel spreadsheet. This list was then edited to include only the suburbs being considered in this project. Suburbs that were geographically not part of the extended urban area were not included. This data was then read into a pandas dataframe.

```
df.head()
```

	Suburb
0	Townsville City
1	Aitkenvale
2	Annandale
3	Belgian Gardens
4	Castle Hill

Geographic Location Data:

Geographic location data was retrieved using the *geopy* client, with the *Nominatim* geocoder for accessing the OpenStreetMap (OSM) dataset. Location data was added to the pandas dataframe.

```
df.head()
```

	Suburb	latitude	longitude
0	Townsville City	-19.26	146.82
1	Aitkenvale	-19.30	146.77
2	Annandale	-19.31	146.78
3	Belgian Gardens	-19.25	146.79
4	Castle Hill	-19.26	146.80

Socio-Economic Data

Data Source: https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/2033.0.55.0012016?OpenDocument
State Suburb, Indexes, SEIFA 2016

Data Preparation: The data was downloaded as an Excel workbook. The Queensland data (State Suburb Code = 3#####) was copied to a blank spreadsheet. The suburb names from the Townsville Suburbs Excel workbook were copied into the blank spreadsheet. These then became the index keys to extract the four socio-economic indicators from the Queensland data subset lookup table. The formula values were then converted to set values (ie not formula). The table was then read into a pandas dataframe. The suburb name strings were trimmed of trailing and leading spaces.

The 4 Socioeconomic factors included were:

Index of Relative Socio-economic Disadvantage (IRSD)
Index of Relative Socio-economic Advantage and Disadvantage (IRSAD)
Index of Economic Resources (IER)
Index of Education and Occupation (IEO)
A higher number is better.
These indexes loaded into the dataframe as objects, which were converted to numeric values (int64) for processing.

```
se_df.head()
```

	Suburb	rsed	rsead	ier	ieo
0	Townsville City	1055	1059	943	1094
1	Aitkenvale	940	937	915	964
2	Annandale	1077	1068	1069	1051
3	Belgian Gardens	1015	1021	966	1056
4	Castle Hill	1127	1164	1135	1169

This dataframe was then merged with the suburb dataframe (which also contained the geolocation data).

```
df_ec.head()
```

	Suburb	latitude	longitude	rsed	rsead	ier	ieo
0	Townsville City	-19.26	146.82	1055	1059	943	1094
1	Aitkenvale	-19.30	146.77	940	937	915	964
2	Annandale	-19.31	146.78	1077	1068	1069	1051
3	Belgian Gardens	-19.25	146.79	1015	1021	966	1056
4	Castle Hill	-19.26	146.80	1127	1164	1135	1169

Public Transport Availability

Data Source: https://data.gov.au/dataset/ds-dga-7559d6fa-bb12-4407-85d7-4c42718d4ed7/details?q=bus%20shelter
Townsville Bus Stops and Shelters (esri shapefile – zipped)
After downloading and unzipping the Bus_Shelters_Townsville.dbf file was loaded into LibreOffice Calc. The data was then copied into an Excel spreadsheet, where unnecessary features were removed.

stop_id	stop_code	stop_name	stop_lat	stop_long	zone_id	Bus_Shelter
890000	890000	Stockland Elizabeth Street	-19.29803300000	146.76437000000	4	Yes
890001	890001	Anne St at Richard Street	-19.29235100000	146.76662600000	4	Yes
890002	890002	Fulham Rd at Vincent State School	-19.28846900000	146.76421800000	4	Yes
890003	890003	Fulham Rd at Vincent Shopping Centre	-19.28818500000	146.76181100000	4	Yes
890004	890004	Fulham Rd at St James Village	-19.28827400000	146.75970300000	4	Yes

This excel file was loaded into a pandas dataframe. Geolocation data was then used to calculate the number of bus stops within 500m of the geolocation point for each suburb.

```
df_ec.head()
```

	Suburb	latitude	longitude	rsed	rsead	ier	ieo	bus_stop
0	Townsville City	-19.26	146.82	1055	1059	943	1094	13.00
1	Aitkenvale	-19.30	146.77	940	937	915	964	1.00
2	Annandale	-19.31	146.78	1077	1068	1069	1051	7.00
3	Belgian Gardens	-19.25	146.79	1015	1021	966	1056	7.00
4	Castle Hill	-19.26	146.80	1127	1164	1135	1169	0.00

Animal (dog) Complaints made to Council

Data Source: https://data.gov.au/dataset/ds-dga-5a005841-f4f2-4c52-82db-8cce70715d72/details?q=

The downloaded Excel file listed each incident in chronological order;

Animal Type	Complaint Type	Date Received	Suburb	Electoral Division	Year
dog	Attack	July 2020	Alice River	Division 1	2020
dog	Attack	July 2020	Alice River	Division 1	2020
dog	Attack	July 2020	Alice River	Division 1	2020
dog	Enclosure	July 2020	Alice River	Division 1	2020

This raw data was transformed into a pivot table in Excel. The (financial) year 2020 was selected and dogs were selected.

Animal Type	dog						
Year	2020						
Count of Date Received	Column Labels						
Row Labels	Aggressive Animal	Attack	Enclosure	Noise	Private Impound	Wandering	Grand Total
Aitkenvale	13	8	17	31	55	17	141
Alice River	8	9	10	9	3	6	45
Alligator Creek	10	4	2			2	18

This pivot table values were copied to another Excel spreadsheet, which was loaded into a pandas dataframe.

Suburb	Aggressive Animal	Attack	Enclosure	Noise	Private Impound	Wandering	Animal Complaints Grand Total
Aitkenvale	13	8	17	31	55	17	141
Alice River	8	9	10	9	3	6	45
Alligator Creek	10	4	2			2	18
Annandale	9	7	5	8	12	4	45

Dataset is based on the 6 primary complaint categories of

- Aggressive Animal – refers to aggressive dogs
- Attack – refers to dog attacks
- Enclosure – refers to dogs outside their enclosure or with an inadequate enclosure
- Noise – refers to dogs making noise
- Private Impound – refers to dogs that need to be picked up and impounded by Council
- Wandering – refers to wandering dogs

The animal complaints dataframe was merged with the main dataframe.

```
ac_df.head()
```

	Suburb	Aggressive Animal	Attack	Enclosure	Noise	Private Impound	Wandering	Animal Complaints Grand Total
0	Aitkenvale	13.00	8.00	17.00	31.00	55.00	17.00	141
1	Alice River	8.00	9.00	10.00	9.00	3.00	6.00	45
2	Alligator Creek	10.00	4.00	2.00	0.00	0.00	2.00	18
3	Annandale	9.00	7.00	5.00	8.00	12.00	4.00	45
4	Arcadia	0.00	3.00	0.00	0.00	0.00	4.00	7

```
df_ec_ac.head()
```

	Suburb	latitude	longitude	rsed	rsead	ier	ieo	bus_stop	Aggressive Animal	Attack	Enclosure	Noise	Private Impound	Wandering	Animal Complaints Grand Total
0	Townsville City	-19.26	146.82	1055	1059	943	1094	13.00	0.00	2.00	2.00	5.00	4.00	2.00	15
1	Aitkenvale	-19.30	146.77	940	937	915	964	1.00	13.00	8.00	17.00	31.00	55.00	17.00	141
2	Annandale	-19.31	146.78	1077	1068	1069	1051	7.00	9.00	7.00	5.00	8.00	12.00	4.00	45
3	Belgian Gardens	-19.25	146.79	1015	1021	966	1056	7.00	2.00	2.00	4.00	2.00	8.00	2.00	20
4	Castle Hill	-19.26	146.80	1127	1164	1135	1169	0.00	3.00	0.00	0.00	2.00	1.00	1.00	7

Crime Data (July 2019 – June 2020)

Data Source: https://www.data.qld.gov.au/dataset/crime-locations-2000-present/resource/3a1448e0-649b-4b7c-813b-a5a5bb8ea14e
Crime data API was used to access Queensland Crime Database by Suburb. Each API request returned a json file with the requested data.
Typical json file result (first few lines): [{ "Type": "Miscellaneous Offences", "Date": "2019-07-01 00:01:00", "Postcode": "4814", "Area of Interest": "Aitkenvale" }, { "Type": "Other Theft (excl. Unlawful Entry)", "Date": "2019-07-01 15:15:00", "Postcode": "4814", "Area of Interest": "Aitkenvale"

Crime data was extracted from the json file, categorised as a property crime or a person crime, with the respective totals for each added to the suburb record in the main dataframe.

```
df_ec_ac.head()
```

Suburb	latitude	longitude	rsed	rsead	ier	ieo	bus_stop	Aggressive Animal	Attack	Enclosure	Noise	Private Impound	Wandering	Animal Complaints Grand Total	prop_cc	pers_cc
Townsville City	-19.26	146.82	1055	1059	943	1094	13.00	0.00	2.00	2.00	5.00	4.00	2.00	15	476.00	1686.00
Aitkenvale	-19.30	146.77	940	937	915	964	1.00	13.00	8.00	17.00	31.00	55.00	17.00	141	1146.00	589.00
Annandale	-19.31	146.78	1077	1068	1069	1051	7.00	9.00	7.00	5.00	8.00	12.00	4.00	45	230.00	128.00
Belgian Gardens	-19.25	146.79	1015	1021	966	1056	7.00	2.00	2.00	4.00	2.00	8.00	2.00	20	172.00	232.00
Castle Hill	-19.26	146.80	1127	1164	1135	1169	0.00	3.00	0.00	0.00	2.00	1.00	1.00	7	37.00	4.00

Council Community Facilities Were Counted for each Suburb

Data Source: https://data.gov.au/dataset/ds-dga-efa565ea-68cc-4c1d-a298-d5d81afc4343/details?q=
The geojson file was used as it contained geolocation information for each venue.

Typical json file result (first few lines):

{"type":"FeatureCollection","features":[{"type":"Feature","id":"ckan_efa565ea_68cc_4c1d_a298_d5d81afc4343.1","geometry":{"type":"Point","coordinates":[146.81429389,-19.25824839]},"geometry_name":"geom","properties":{"objectid":1,"facility_i":1,"name":"Townsville City Council Customer Service Centre","category":"Administrative","address":"103 Walker Street, Townsville","disability":"Yes","disabili_1":"Ramp, Lift","accessible":"Onsite","accessib_1":"There is one designated accessible parking space which is located in the rear car park. There are accessible parking spaces available in Walker Street and Wills Street","accessib_2":"There is one designated unisex accessible toilet on the ground floor in the forecourt"}},{"type":"Feature","id":"ckan_efa565ea_68cc_4c1d_a298_d5d81afc4343.2","geometry":{"type":"Point","coordinates":[146.81786577,-

The category of facility and the geolocation information for each facility were extracted into a pandas dataframe.

```
cf_df.head()
```

	category	fac_lat	fac_long
0	Administrative	-19.26	146.81
1	Library	-19.26	146.82
2	Theatre	-19.27	146.81
3	Theatre	-19.27	146.81
4	Community Centre	-19.27	146.81

The geolocation information was then used to count the number of Council facilities within 1000m of each Suburb geolocation. This total was added to the main dataframe.

```
df_ec_ac.head()
```

atitude	longitude	rsed	rsead	ier	ieo	bus_stop	Aggressive Animal	Attack	Enclosure	Noise	Private Impound	Wandering	Animal Complaints Grand Total	prop_cc	pers_cc	council_fac
-19.26	146.82	1055	1059	943	1094	13.00	0.00	2.00	2.00	5.00	4.00	2.00	15	476.00	1684.00	4.00
-19.30	146.77	940	937	915	964	1.00	13.00	8.00	17.00	31.00	55.00	17.00	141	1146.00	589.00	1.00
-19.31	146.78	1077	1068	1069	1051	7.00	9.00	7.00	5.00	8.00	12.00	4.00	45	230.00	128.00	0.00
-19.25	146.79	1015	1021	966	1056	7.00	2.00	2.00	4.00	2.00	8.00	2.00	20	172.00	232.00	1.00
-19.26	146.80	1127	1164	1135	1169	0.00	3.00	0.00	0.00	2.00	1.00	1.00	7	37.00	4.00	1.00

Suburb Venue Data

This next section uses Foursquare API to get venue details for each suburb. It counts the number of venues in different categories within 1000m of suburb geolocations.
The defined categories were:
cafe = ['Café', 'Coffee Shop', 'Sandwich Place', 'Pizza Place', 'Juice Bar', 'Ice Cream Shop', 'Fried Chicken Joint', 'Burger Joint']
restaurant = ['Restaurant', 'Steakhouse']
supermarket = ['Supermarket', 'Market', 'Grocery Store']
pub = ['Pub', 'Liquor Store', 'Brewery']
entertainment = ['Theater', 'Multiplex']
recreation = ['Pool', 'Historic Site', 'Football Stadium', 'Bowling Alley', 'Basketball Stadium', 'Art Museum', 'Aquarium', 'Beach']

A json file was returned in response to the API.
Typical json return from FourSquare (first few lines): { "meta": { "code": 200, "requestId": "5f52be68eac69b39120fe129" }, "response": { "headerLocation": "Townsville", "headerFullLocation": "Townsville", "headerLocationGranularity": "city", "totalResults": 25, "suggestedBounds": { "ne": { "lat": -19.292946890999993, "lng": 146.77556542716533 }, "sw": { "lat": -19.31094690900001, "lng": 146.75652897283467 } }, "groups": [{ "type": "Recommended Places", "name": "recommended", "items": [{ "reasons": { "count": 0, "items": [{ "summary": "This spot is popular", "type": "general", "reasonName": "globalInteractionReason" }] }, "venue": { "id": "4d963f3bedc941bd2689925c", "name": "Boost Juice", "location": { "address": "310 Ross River Rd", "lat": -19.299975253741703, "lng": 146.76278951919068, "labeledLatLngs": [{ "label": "display", "lat": -19.299975253741703, "lng": 146.76278951919068 }], "distance": 406, "postalCode": "4814", "cc": "AU", "city": "Aitkenvale", "state": "QLD", "country": "Australia", "formattedAddress": ["310 Ross River Rd", "Aitkenvale QLD 4814", "Australia"] }, "categories": [{ "id": "4bf58dd8d48988d112941735", "name": "Juice Bar", "pluralName": "Juice Bars", "shortName": "Juice Bar", "icon": { "prefix": "https://ss3.4sqi.net/img/categories_v2/food/juicebar_", "suffix": ".png" }, "primary": true }], "photos": { "count": 0, "groups": [] } }, "referralId": "e-0-4d963f3bedc941bd2689925c-0" }, { "reasons": { "count": 0, "items": [{ "summary": "This spot is popular", "type": "general", "reasonName": "globalInteractionReason" }] },

The venue data was extracted from this json file, categorised and counted. The count data was added to the main dataframe.

```
df_ec_ac.head()
```

ive nal	Attack	...	Animal Complaints Grand Total	prop_cc	pers_cc	council_fac	cafe_count	restaurant_count	supermarket_count	pub_count	entertainment_count	recreation_count
.00	2.00	...	15	476.00	1686.00	4.00	12.00	15.00	1.00	4.00	0.00	2.00
.00	8.00	...	141	1146.00	589.00	1.00	5.00	9.00	1.00	1.00	0.00	0.00
.00	7.00	...	45	230.00	128.00	0.00	0.00	2.00	0.00	0.00	0.00	0.00
.00	2.00	...	20	172.00	232.00	1.00	0.00	1.00	0.00	0.00	0.00	1.00
.00	0.00	...	7	37.00	4.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00

This resulted in the final main dataframe with the following features and data types:

```
df_ec_ac.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 45 entries, 0 to 44
Data columns (total 24 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   Suburb                      45 non-null     object
 1   latitude                    45 non-null     float64
 2   longitude                   45 non-null     float64
 3   rsed                        45 non-null     int64
 4   rsead                       45 non-null     int64
 5   ier                         45 non-null     int64
 6   ieo                         45 non-null     int64
 7   bus_stop                    45 non-null     float64
 8   Aggressive Animal           45 non-null     float64
 9   Attack                      45 non-null     float64
 10  Enclosure                   45 non-null     float64
 11  Noise                       45 non-null     float64
 12  Private Impound             45 non-null     float64
 13  Wandering                   45 non-null     float64
 14  Animal Complaints Grand Total  45 non-null  int64
 15  prop_cc                     45 non-null     float64
 16  pers_cc                     45 non-null     float64
 17  council_fac                 45 non-null     float64
 18  cafe_count                  45 non-null     float64
 19  restaurant_count            45 non-null     float64
 20  supermarket_count           45 non-null     float64
 21  pub_count                   45 non-null     float64
 22  entertainment_count         45 non-null     float64
 23  recreation_count            45 non-null     float64
dtypes: float64(18), int64(5), object(1)
```

Suburb	latitude	longitude	rsed	rsead	ier	ieo	bus_stop	Aggressive Animal	Attack	Enclosure	Noise	Private Impound	Wandering	Grand Total	prop_cc	pers_cc	council_fac	cafe_count	restaurant_count	supermarket_count	pub_count	entertainment_count	recreation_count
Townsville City	-19.2622223	146.8158417	1055	1059	943	1094	13	0	2	2	5	4	2	15	476	1677	4	11	14	1	5	0	2
Aitkenvale	-19.3019469	146.7660472	940	937	915	964	1	13	8	17	31	55	17	141	1146	587	1	5	9	1	1	0	0
Annandale	-19.3122951	146.7790291	1077	1068	1069	1051	7	9	7	5	8	12	4	45	230	128	0	0	1	1	0	0	0
Belgian Gardens	-19.2473194	146.7926118	1015	1021	966	1056	7	2	2	4	2	8	2	20	172	232	1	0	1	0	0	0	1
Castle Hill	-19.258033	146.8026248	1127	1164	1135	1169	0	3	0	0	2	1	1	7	37	4	1	0	0	0	1	0	0

Exploratory Data Analysis

There were no missing values (as per .info() result) in the main dataset.

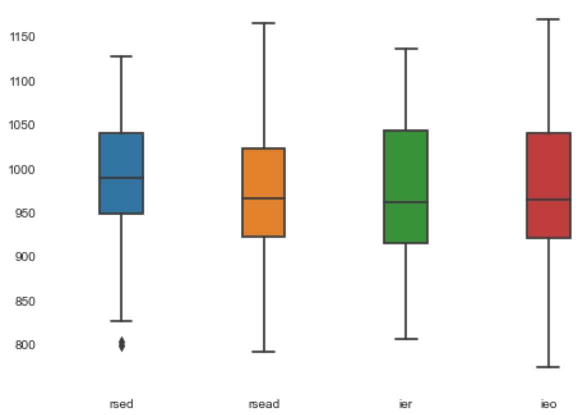
Descriptive Statistics:

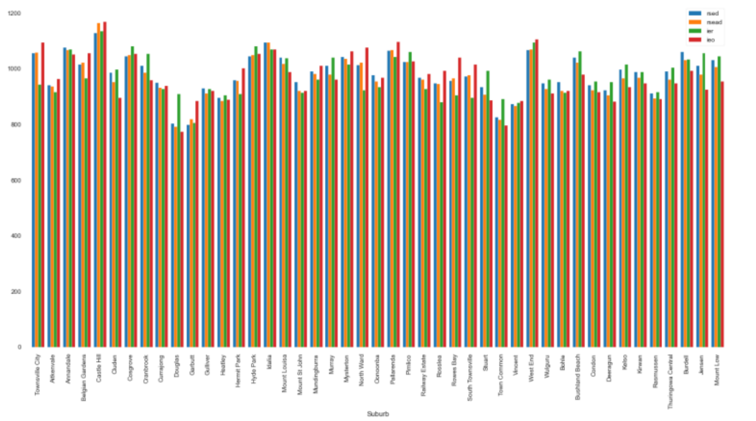
	rsed	rsead	ier	ieo	bus_stop	Aggressive Animal	Attack	Enclosure	Noise	Private Impound	Wandering	Animal Complaints Grand Total
count	45.00	45.00	45.00	45.00	45.00	45.00	45.00	45.00	45.00	45.00	45.00	45.00
mean	981.56	970.69	977.04	972.93	3.76	8.47	5.38	11.40	14.02	15.33	8.82	63.42
std	72.17	75.81	74.09	82.15	3.89	10.16	5.84	12.96	16.23	22.00	8.20	65.55
min	799.00	791.00	805.00	774.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
25%	948.00	922.00	915.00	920.00	0.00	2.00	1.00	2.00	6.00	2.00	3.00	20.00
50%	988.00	966.00	961.00	964.00	3.00	5.00	3.00	6.00	10.00	8.00	6.00	44.00
75%	1040.00	1022.00	1043.00	1039.00	6.00	12.00	8.00	16.00	18.00	17.00	15.00	97.00
max	1127.00	1164.00	1135.00	1169.00	16.00	50.00	26.00	55.00	92.00	96.00	30.00	337.00

	prop_cc	pers_cc	council_fac	cafe_count	restaurant_count	supermarket_count	pub_count	entertainment_count	recreation_count
count	45.00	45.00	45.00	45.00	45.00	45.00	45.00	45.00	45.00
mean	232.96	217.11	0.64	1.47	1.78	0.53	0.29	0.07	0.22
std	276.40	290.71	1.25	2.58	3.19	0.66	0.69	0.25	0.64
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25%	52.00	44.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
50%	172.00	141.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
75%	314.00	267.00	1.00	2.00	3.00	1.00	0.00	0.00	0.00
max	1416.00	1686.00	5.00	14.00	13.00	2.00	4.00	1.00	3.00

Socio-Economic Data

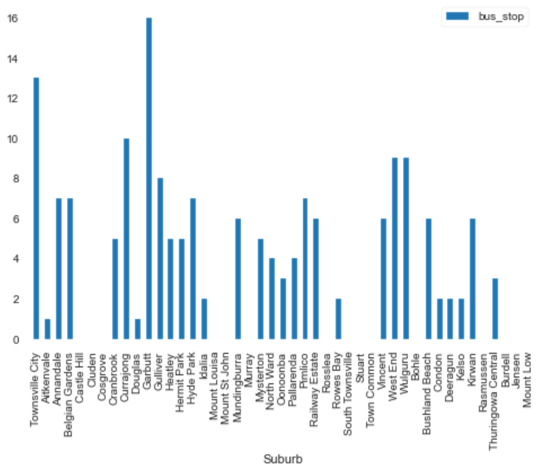
Socio-Economically, Townsville suburbs lie within a relatively narrow band. There does not tend to be any large disparity between suburbs. Only the Index of Relative Socio-economic Disadvantage has a low outlier (worst case), being Garbutt.



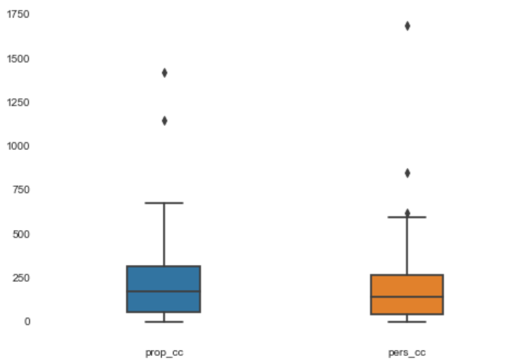


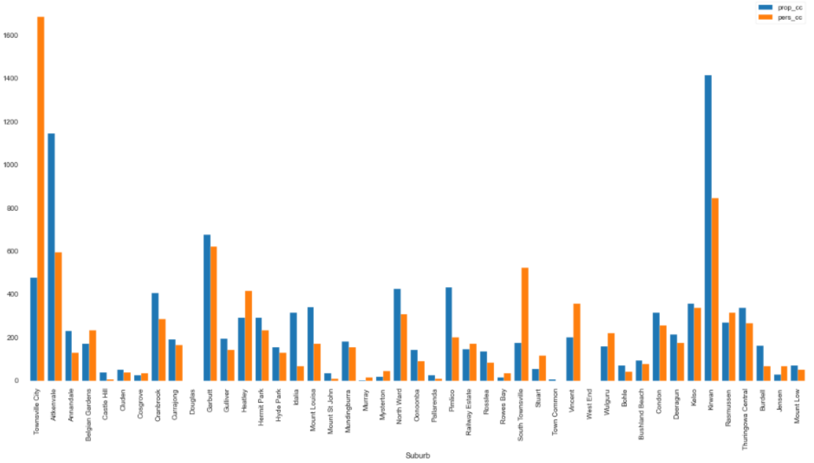
Access to Public Transport

The suburbs with the best access to public transport are Garbutt, Townsville City and Currajong.

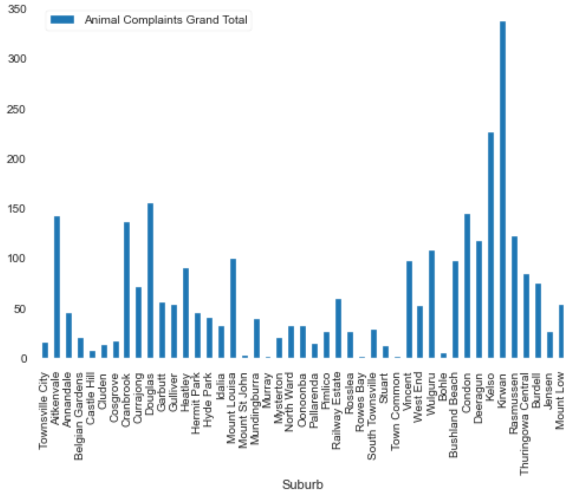


Crime Analysis
As the Boxplots show, both property crime and personal crime are unevenly distributed throughout the suburbs.
Property Crime is worse in Kirwan, Aitkenvale and Garbutt.
Personal Crime is worse in Townsville City, Kirwan and Garbutt.
Property Crime is least in Douglas, West End and Murray.
Personal Crime is least in Douglas, Town Common and West End.
Crime is clearly a problem in Kirwan and Garbutt. Douglas and West End have low crime problems.

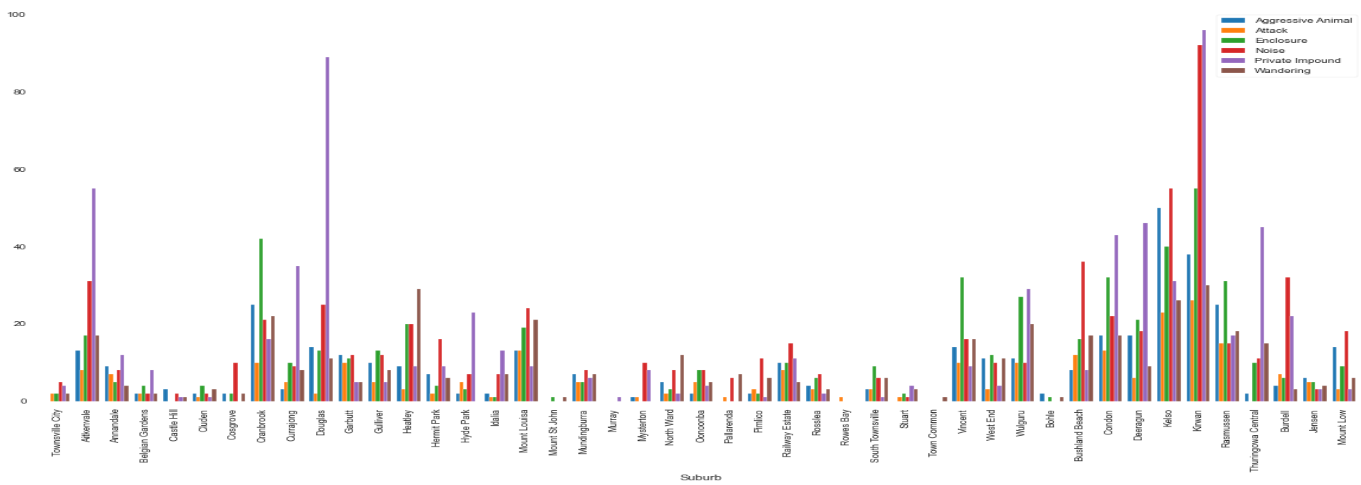




Animal Complaints
In a suburban setting, problems with neighbourhood animals adversely affects the liveability of a suburb.
Total animal complaints were worse in Kirwan, Kelso and Douglas.



Complaints by type:

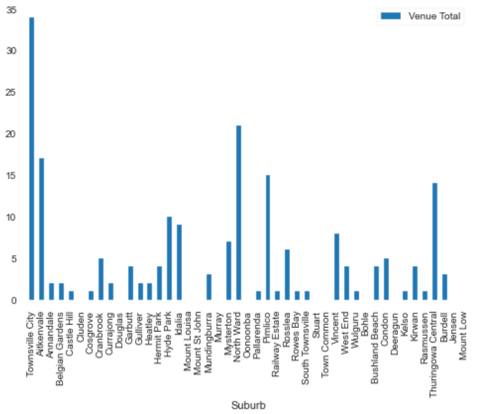


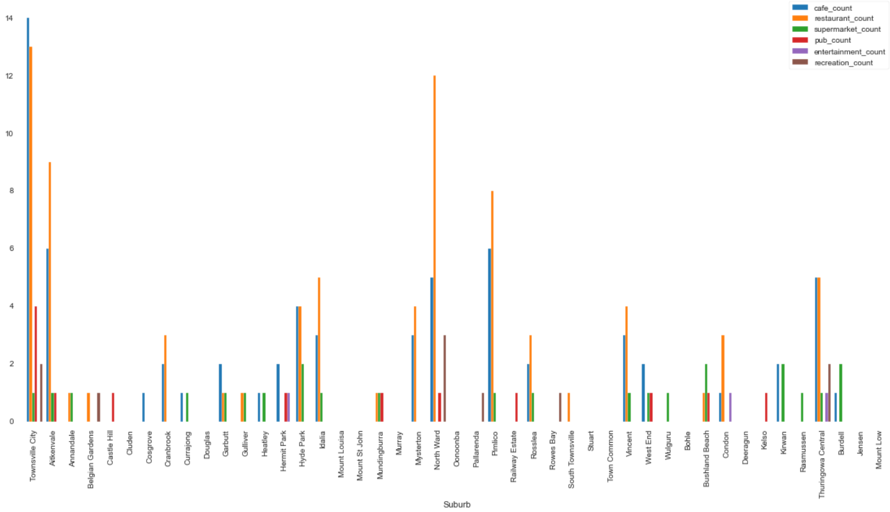
When inspecting the type of complaint Aggressive Animals and Attacks are serious safety risks.
Aggressive Animals are worse in Kelso, Kirwan and Cranbrook.
Attack complaints are worse in Kirwan, Kelso and Rasmussen.
Animal noise complaints are worse in Kirwan, Kelso and Bushland Beach.

Clearly Kirwan and Kelso are problematic regarding animal complaints.
Kirwan, Douglas and Aitkenvale have the highest private impound rates. The Kirwan rate reflects that suburbs animal problem, but the Douglas and Aitkenvale rates may reflect a higher reporting level to council, or they may reflect a higher level of council animal control patrols in these areas.

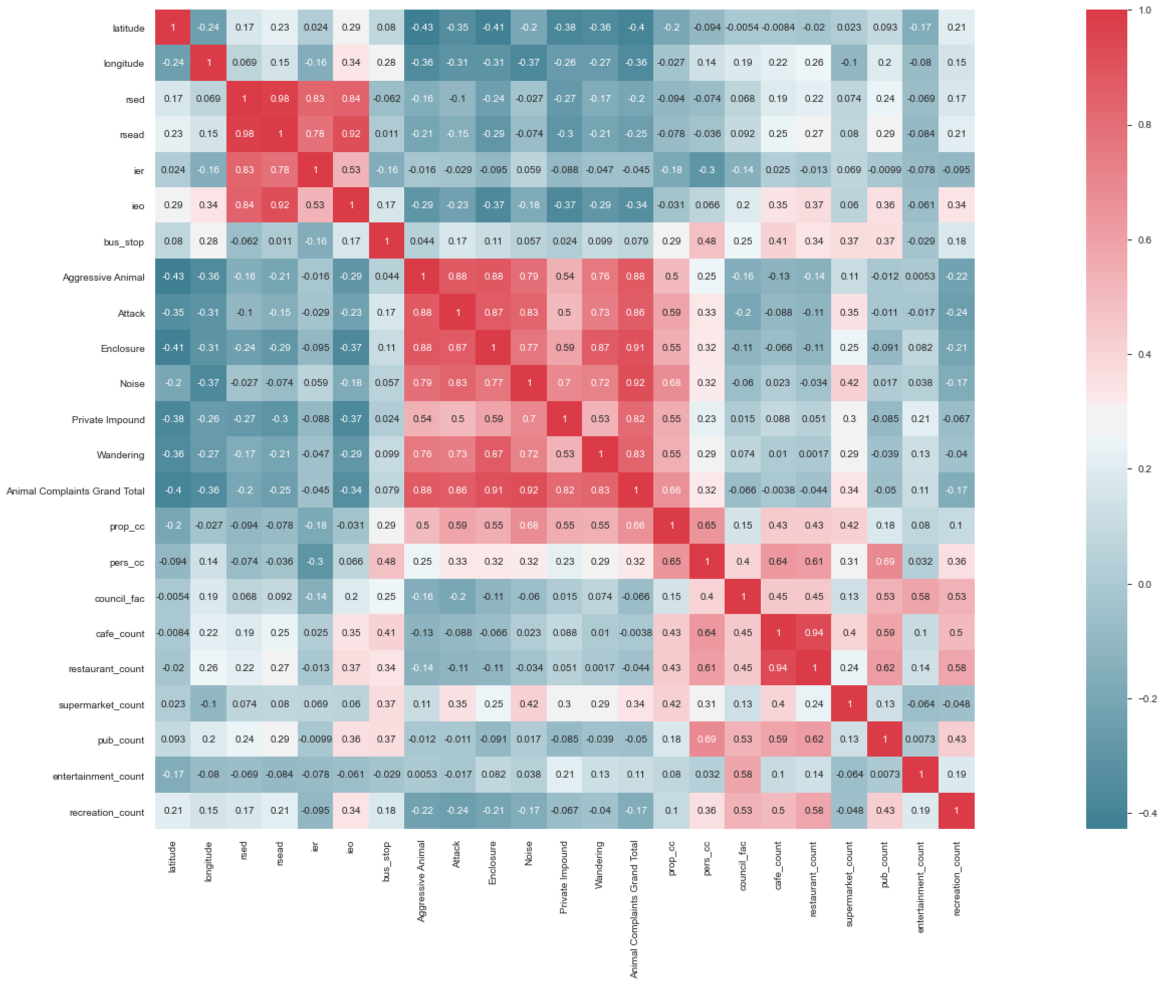
Venues
Venues are clearly unevenly distributed across the suburbs.
As might be expected, the city centres have more venues such as café's and restaurants.
There are more Cafes in Townsville City, Aitkenvale and Pimlico.
There are more restaurants in Townsville City, North Ward and Aitkenvale.
There are more entertainment venues in Hermit Park, Condon and Thuringowa Central.

Venue data must be considered with caution. It is generated from Foursquare data. Data from this source is more complete for large urban centres, such as the State capital and more USA centric.





Correlation *Between Features*



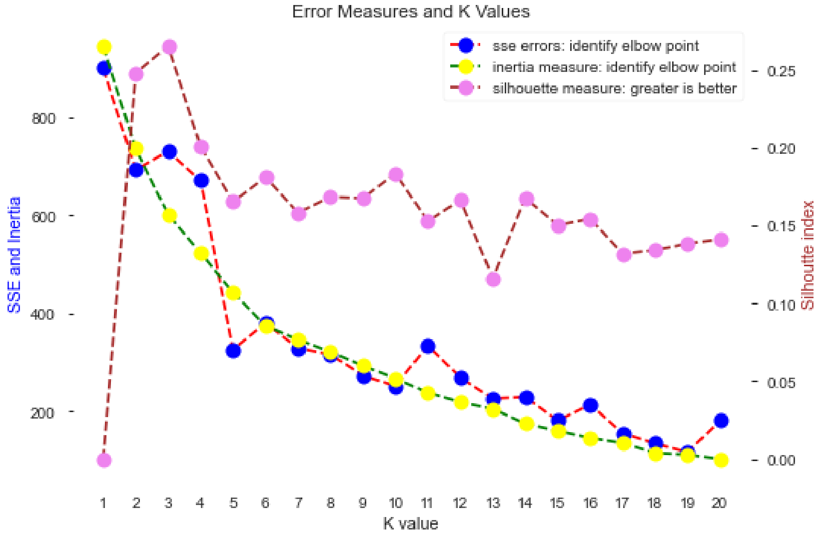
There is a strong correlation between the number of restaurant (type) venues and the number of cafe (type) venues. There is a moderate correlation between the number of Personal Crime incidents and the number of Pub (type) venues. There is a moderate correlation between the number of Property Crimes incidents and the number of Animal Noise Complaints.
There can be a reasonable expectation that there will be a correlation between features that belong to the same domain (ie crime with crime), but it is useful to identify correlations between features of different domains.
There are moderate to strong correlations between the below different domain features:

restaurant count	personal crime counts	0.6110618406595243
café count	personal crime counts	0.6371839687268986
animal complaints grand total	property crime counts	0.6625400410640956
property crime count	animal noise complaints	0.6816049286646086
personal crime counts	pub/bar counts	0.692381988827019

Cluster Analysis

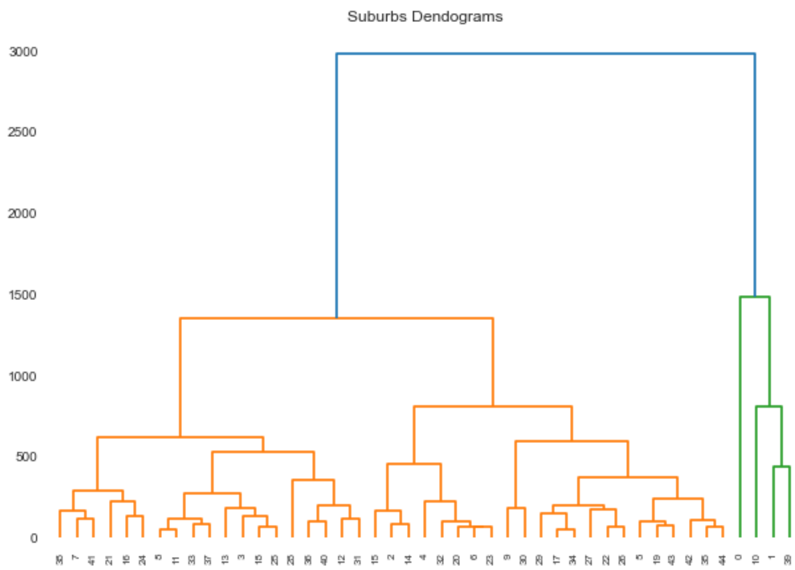
KMeans clustering was used to cluster the suburbs. To identify the best number of clusters to use, KMeans clustering was performed for a range of cluster numbers between 1 and 20. The best number of clusters was identified using the sum of squared errors, the Inertia value and the Silhouette score for each number of clusters. The SSE value and the Inertia plots were looked at to identify an 'elbow point', while the maximum Silhouette score would be for the best number of clusters.

The results for the main dataframe were:

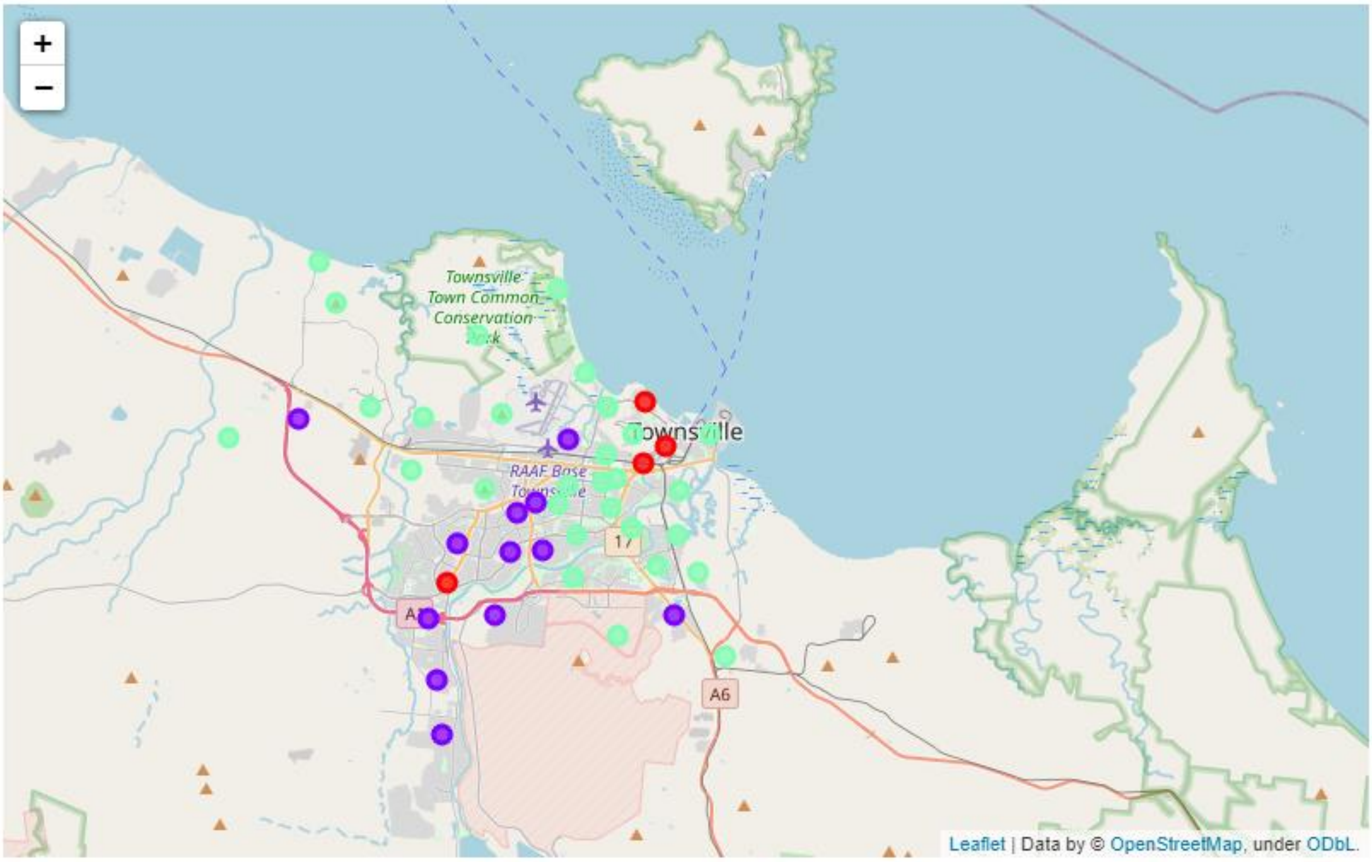


Due to concerns with the fact this is a very small data set (number of cases) compared to the number of features to do a KMeans clustering on, a Principal Components Analysis (PCA) was applied to the main dataframe to reduce the number of features to three. Testing for a range of number of clusters was performed on the PCA dataset, with the following results:

It was considered that Hierarchical clustering modelling may be more suited to the small data set. A dendrogram was produced for the main data set:



Examining the three plots, it was concluded to use three clusters.
After clustering, the cluster labels were assigned to the main dataframe.
A Folium map showed the geographic layout of the suburbs and the cluster they belonged to.



Descriptive Statistics for Clusters

Suburbs in Cluster Zero (label=0) (Red)	Suburbs in Cluster One (label=1) (Purple)	Suburbs in Cluster Two (label=2) (Green)
Townsville City	Aitkenvale	Annandale
Hermit Park	Cranbrook	Belgian Gardens
North Ward	Douglas	Castle Hill
Thuringowa Central	Garbutt	Cluden
	Heatley	Cosgrove
	Vincent	Currajong
	Wulguru	Gulliver
	Condon	Hyde Park
	Deeragun	Idalia
	Kelso	Mount Louisa
	Kirwan	Mount St John
	Rasmussen	Mundingburra
		Murray
		Mysterton
		Oonoonba
		Pallarenda
		Pimlico
		Railway Estate
		Rosslea
		Rowes Bay
		South Townsville
		Stuart
		Town Common
		West End
		Bohle
		Bushland Beach
		Burdell
		Jensen
		Mount Low

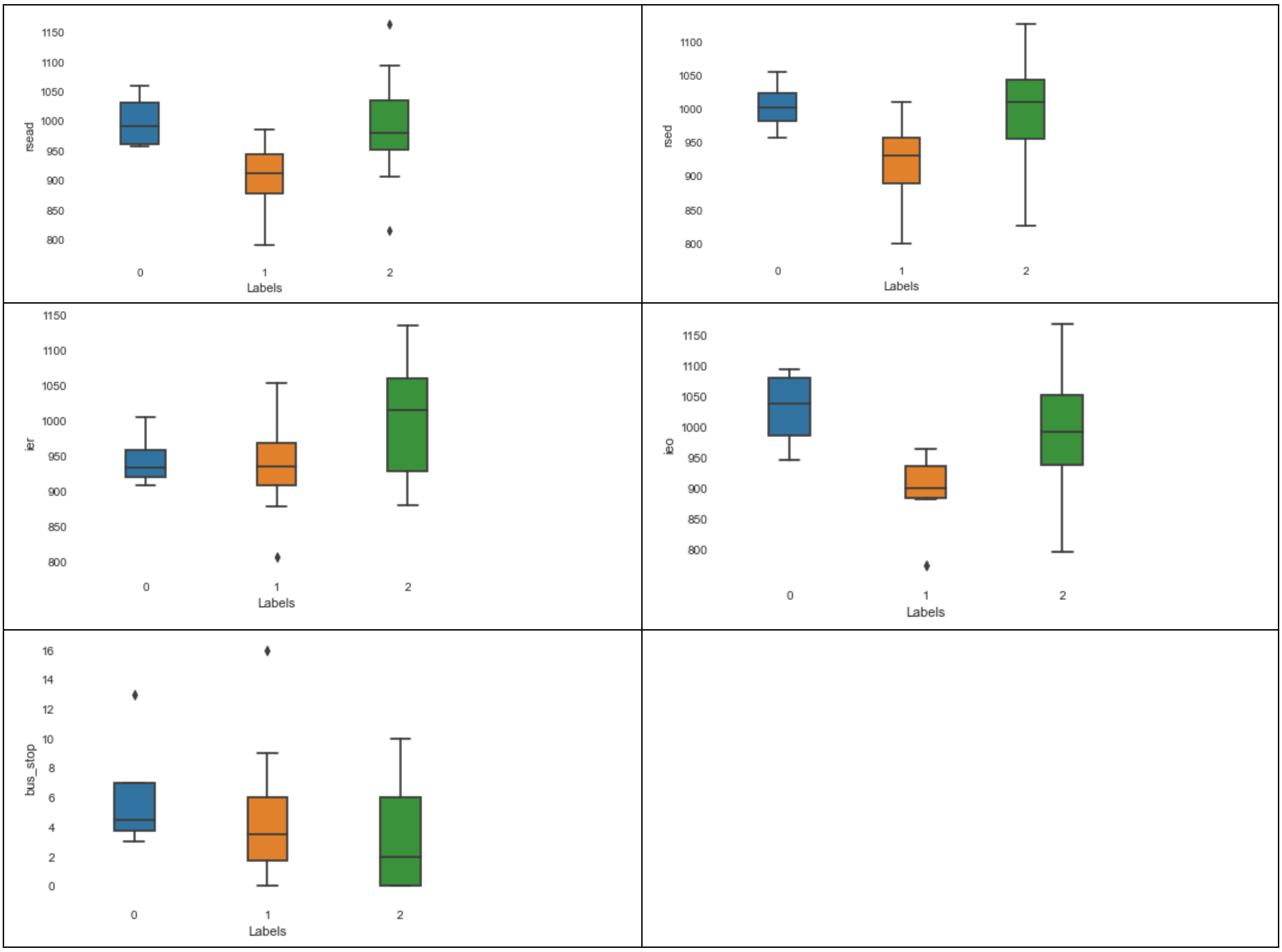
	rsed				rsead				ier				ieo			
	min	max	median	mean	min	max	median	mean	min	max	median	mean	min	max	median	mean
Labels																
0	958	1055	1002	1004.25	957	1059	991.50	999.75	908	1004	932.50	944.25	947	1094	1039.00	1029.75
1	799	1010	931	918.83	791	986	913.00	905.17	805	1053	934.00	937.33	774	964	900.50	902.75
2	826	1127	1011	1004.38	816	1164	981.00	993.79	879	1135	1014.00	998.00	797	1169	993.00	994.14

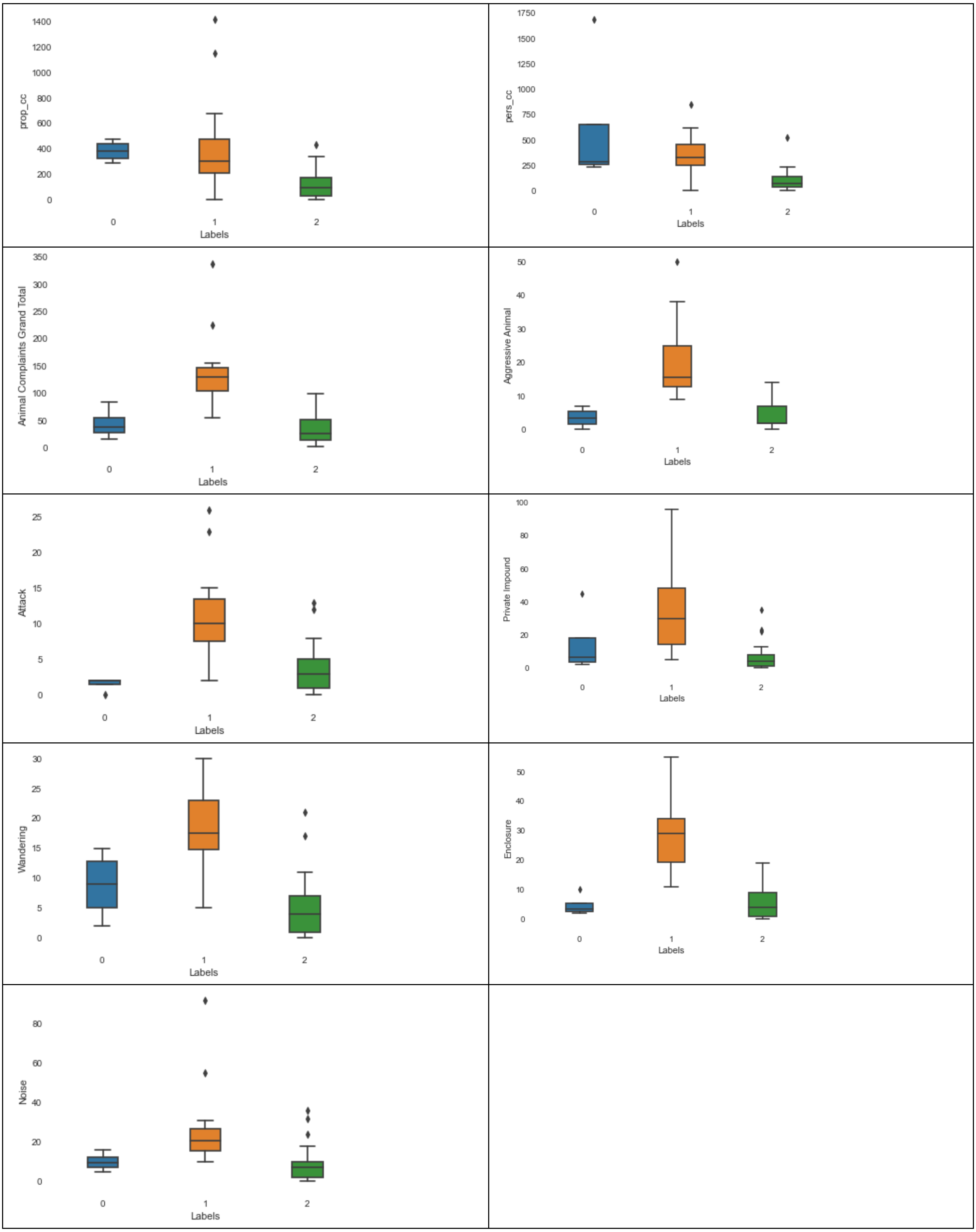
	prop_cc				pers_cc				Animal Complaints Grand Total			
	min	max	median	mean	min	max	median	mean	min	max	median	mean
Labels												
0	293.00	476.00	381.00	382.75	232.00	1686.00	288.00	623.50	15	83	38.00	43.50
1	0.00	1416.00	302.50	453.75	0.00	845.00	325.50	368.08	55	337	128.50	143.67
2	0.00	433.00	94.00	120.93	0.00	524.00	68.00	98.59	1	99	26.00	32.97

	cafe_count				restaurant_count			
	min	max	median	mean	min	max	median	mean
Labels								
0	1.00	11.00	5.00	5.50	2.00	15.00	8.00	8.25
1	0.00	6.00	1.00	1.42	0.00	10.00	0.50	1.75
2	0.00	6.00	0.00	0.90	0.00	8.00	0.00	1.24

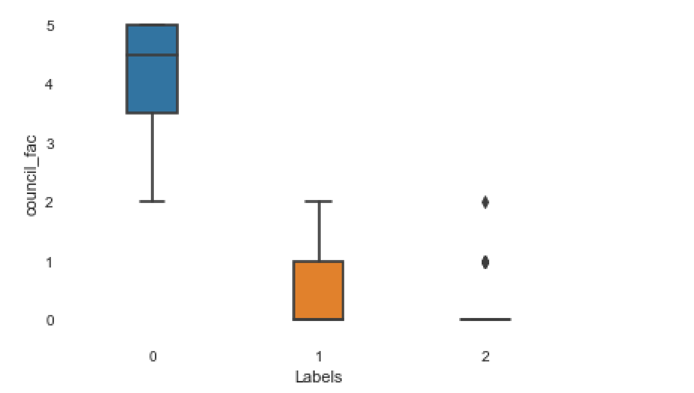
	supermarket_count				pub_count				entertainment_count				recreation_count			
	min	max	median	mean	min	max	median	mean	min	max	median	mean	min	max	median	mean
Labels																
0	0.00	1.00	0.50	0.50	0.00	5.00	1.00	1.75	0.00	1.00	0.50	0.50	0.00	3.00	2.00	1.75
1	0.00	2.00	1.00	0.67	0.00	1.00	0.00	0.17	0.00	1.00	0.00	0.08	0.00	0.00	0.00	0.00
2	0.00	2.00	0.00	0.41	0.00	1.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.10

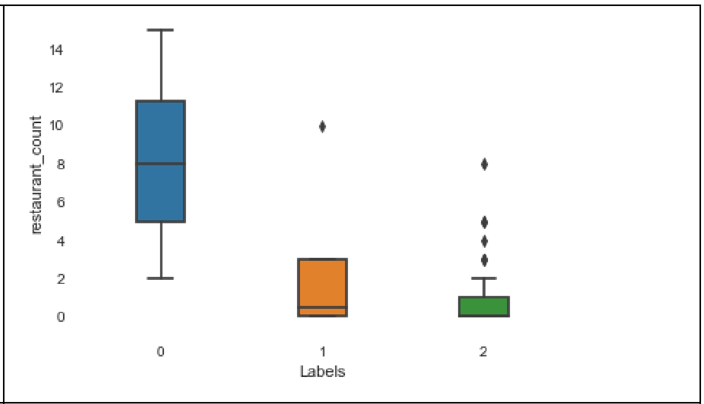
Box Plots for Features by Cluster

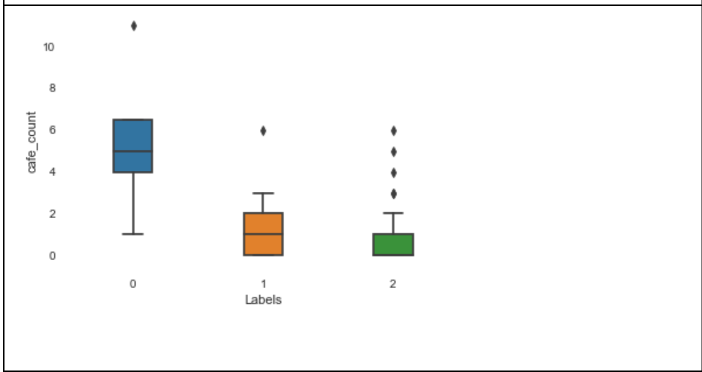


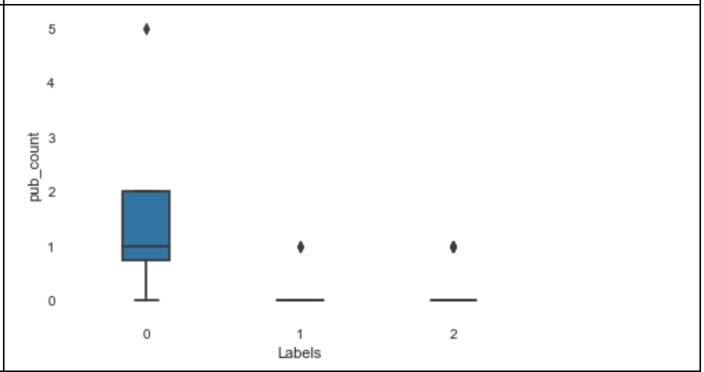


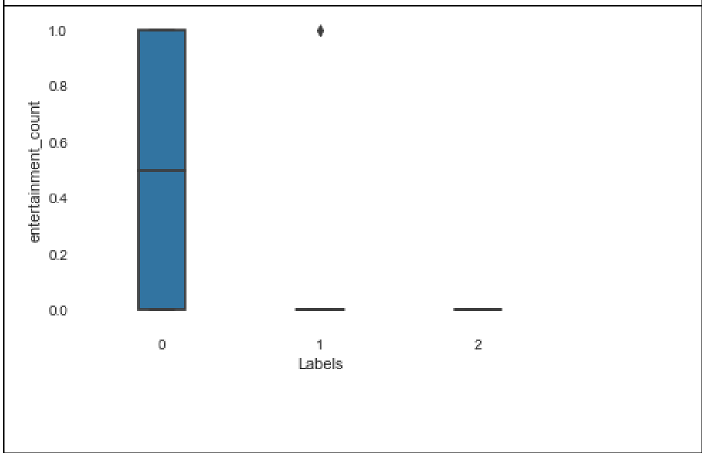
prop_cc
0
200
400
600
800
1000
1200
1400
pers_cc
0
250
500
750
1000
1250
1500
1750
Animal Complaints Grand Total
0
50
100
150
200
250
300
350
Aggressive Animal
0
10
20
30
40
50
Attack
0
5
10
15
20
25
Private Impound
0
20
40
60
80
100
Wandering
0
5
10
15
20
25
30
Enclosure
0
10
20
30
40
50
Noise
0
20
40
60
80
0
1
2
Labels

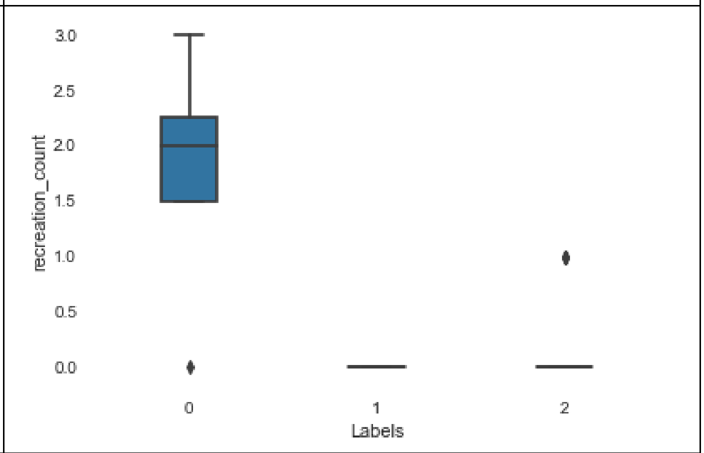

council_fac
5
4
3
2
1
0
0
1
2
Labels

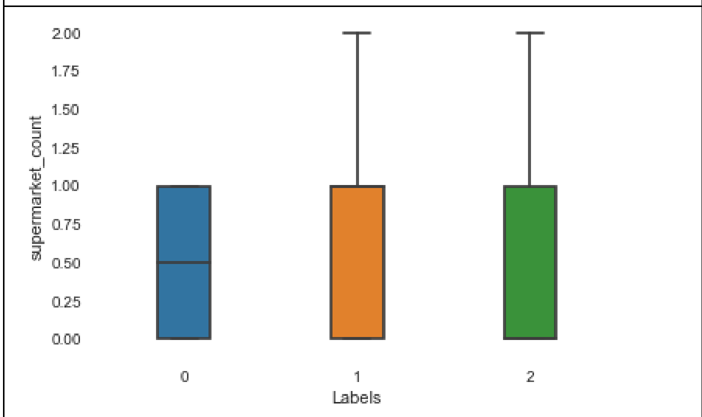

restaurant_count
14
12
10
8
6
4
2
0
0
1
2
Labels


cafe_count
10
8
6
4
2
0
0
1
2
Labels


pub_count
5
4
3
2
1
0
0
1
2
Labels


entertainment_count
1.0
0.8
0.6
0.4
0.2
0.0
0
1
2
Labels


recreation_count
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
1
2
Labels


supermarket_count
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
0
1
2
Labels

Discussion

As noted for the individual suburbs, the suburb clusters are relatively uniform socio-economically. The cluster medians for each index are relatively similar, as is the interquartile range. Cluster 1 is slightly more disadvantaged. Interestingly, cluster 1 is between cluster 0 (high) and cluster 2 (low) for levels of personal and property crime. But cluster 1 does have significant high property crime outliers (Kirwan, Aitkenvale) and a personal crime high outlier. The 'safest' cluster is cluster 2 with the lowest median value, though some of its suburbs do have property crime levels similar to the median levels of cluster 1.

Animal complaints are highest in cluster 1, with some significant high outliers. The most concerning of these would be Attack and Aggressive Animals categories. Targeted animal management campaigns and patrols could improve this situation in these suburbs.

Cluster 0, which consists mainly of highly urban suburbs (ie city area) is where there is the highest concentration of venues, such as cafes and restaurants. This is to be expected in a regional city. More spatially spread out venue centres only start to occur when the population gets well above the Townsville population. Venues such as supermarkets service multiple suburbs but will occur only in the counts for closer suburbs. While public transport is relatively the same between clusters, with some suburbs being notable high outliers, in absolute terms it is low to moderate. This results in personal vehicles being the main mode of transport around the suburbs, which means service venues such as supermarkets do service a wider base than their immediate suburbs.

Conclusion

The clustering of suburbs reveals the liveability of Townsville to be largely uniform. There are no major differences between suburbs across all features. Certainly, in cluster 1 suburbs effort could be directed at animal control policies and actions to address the problems in this area. Cluster 2 suburbs may appeal to families more, higher socio-economic indexes, lower crime counts and lower animal complaints. Cluster 0 may appeal more to singles, or couples without children with high socio-economic indexes (particularly economic opportunity), low animal complaints and high socialising venue counts (cafes, restaurants).

Future Research

Future research could expand on this study by examining several additional suburb features such as: car counts, house prices, housing size and type, public parks, and population densities.