COMP20008 Project Phase 4 Final Report:
Pedestrian-Crash Hotspots in Metropolitan Melbourne (2012-2015)

I. Introduction

Domain: Transport & Health

This report explores one aspect of citizen safety on the roads: pedestrian injuries and fatalities across the Metropolitan Melbourne area.

This report analyzes 31 Local Government Areas (LGAs) within the Metropolitan Melbourne area, across a four-year period (2012-2015). It seeks to answer the following **research questions**:

1. Are there pedestrian crash hotspots in Melbourne Metropolitan? Which LGAs?
2. Where are they geographically?
3. What are potential factors causing these hotspots within an LGA?
4. Are hotspots correlated with density?

II. Data Sources

Primary Datasets: Crash Data

These datasets cover 3 different types of crash outcomes (in blue). URLs can be found in *Appendix 1.1,* more detailed schemas (csv table and xml snippets) can be found in *Appendix 1.2*.

- **Victorian Serious Road Casualties (TAC)** - **xml**
  Dataset contains persons who suffered serious injuries in transport accidents in Victoria. Sustained injuries were all serious enough to be admitted to hospital within 7 days.
  Schema: The file was a 'rowset', contain 'row' elements. Each 'row' contained 'Year', 'Crash_Type', 'Road_User', 'Crash_LGA' and 'Crash_Area_Type', as well as some other tags (see detailed schema).

- **Victoria Road Toll (TAC) - xml**
  Road crash fatalities that occur on Victorian roads and are reported to the Victorian Police. These records are updated daily.
  Schema: The file was a 'ROWSET', contain 'ROW' elements. Each 'ROW' contained 'date_of_accident_tx', 'crash_type_tx', 'road_user_grouping_tx', 'LGA_tx' and 'accident_location_tx', as well as some other tags (see detailed schema).

- **Crashes Last Five Years (VicRoads) - csv**
  This dataset contains information on Victorian road crashes in the last five years. Notably, it includes other injuries (as well as serious injuries and fatalities), as well as crash location coordinates and many other features listed below.
  Schema: Columns include Date_of_Accident, LGA_name, Light_conditions, Pedestrian (as well as others, see *Appendix 1.2*).

Complementary Datasets (added in Phase 3): [1]

- **LGA Boundaries (ABS) – shapefile**
- **Local Government Areas of Victoria (Wikipedia)** *used for LGA land area only* **– html table**
- **Population Estimates 2005-2015 by LGA (ABS) – csv**

[1] Despite the "maximum on 3 datasets", it was impossible to map my data or analyze population density without these datasets. (Population density was suggested by my assessor in my Phase 2 feedback).
As these datasets were complementary, their details & schemas have been included in *Appendix 1.3.*

III. Pre-processing & Integration (1-4pages)

During this phase of the project, I sought to process the open datasets into output csv files that were filtered and integrated, ready to be visualized. There were three csv files (although the third one is a class of csv files) that I needed to create in order to produce visualizations:

1. Crash Counts by LGA
2. Crash Counts divided by Population Density
3. LGA-specific crash records (with features, including co-ordinates and factors)

To minimize redundant code during this phase (in other words to avoid re-writing code for each new file), I decided to learn object-oriented Python to create the following helpful classes:

- **DataSource Object**: initialized for each sourcefile. Contains all methods for cleaning a single dataset.
- **Output Object**: acts like a buffer for a single processed/integrated output file. Stores all the processed rows from each DataSource. Writes to file when all relevant data sources have been processed.

Crash Counts by LGA

I used **ElementTree (xml files)** and **CSV library (csv files)** to delete unnecessary attributes (columns), and eliminate rows/entries from my three primary source files.

I reduced the attributes (12 or so for the xmls, 64 for the csv) into about 5 key attributes: LGA, year, month, day, number of persons injured. In terms of entries, I removed any entries that fell in the following three categories:

- Type of crash or the road user injured was not a pedestrian
- Crashes that occurred in rural Victoria
- Crashes that occurred before 2012 (I was only interested in 2012 – 2015), a four-year window.

When merging the two TAC datasets, I didn't have to worry about duplicate entries as they were published by the same organization and covered two separate types of crashes (serious (hospitalized) injuries and fatalities). This is where I used the VicRoads dataset for "non-serious" injuries. By selecting a different class of crash once again, I eliminated the possibility of duplicates whilst also ensuring I didn't miss out on this class of pedestrian-crash.

During wrangling, I had to ensure there were consistent attributes. For example, date was given in the one xml file as three separate xml elements (day, month, year) while the other xml file contained date as a single string (e.g. "01JAN2015"). The csv file was different yet again with date stored as digits in a string (format "DD/MM/YYYY"). Another discrepancy was that one file referred to LGA Dandenong as 'Greater Dandenong' whilst the other used the single word 'Dandenong'.

Normalizing Crash Counts by Population Density

After desperately digging through open data repositories, I struggled to find a dataset that encompassed population density by LGA for Victoria[2]. At this point, I was forced to add two datasets to calculate population density. LGA population existed as a **csv file**, which I filtered for Year and LGA-name. In contrast, LGA area size was attained by using **BeautifulSoup** to webscrape a **html table** that had quite convoluted tags to work with.[3] To get density, I divided population by area for each Metropolitan LGA.

I then removed the effect of population density on crash counts by normalizing. To do this, I divided the crash count for an LGA by the population density I had calculated. The result was crashes per 'density unit'.

LGA-specific Crash Records

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[2] I did however find information of population density by SLAs and population density for gambling

[3] This was the only source I could find for LGA area size

This was the simplest task. I used the **CSV library** to filter the VicRoads dataset (as it contains coordinates and factors). I removed rows/entries that did not involve pedestrians, did not occur in 2012-2015 or did not occur in the specified LGA. This was output to a separate file for each LGA of interest.

Limitations

There are a few evident limitations with my pre-processing methods. The first relates to the integration for 'Crash Counts by LGA'. I filtered only for 'other injuries' in the VicRoads dataset, however there is a possibility that it contains serious injuries and fatalities that have been missed in the TAC datasets. Although they are both government organizations and these datasets should technically have matching information, this is still possible. Secondly, my method ignores the level of severity of an accident. By simply counting the accident frequency, it ignores the fact that pedestrian fatalities are probably greater contributors to how 'dangerous' an LGA is, when compared with accidents that cause 'non-serious injuries'. I would have liked to examine the effect of weighting severity if I had more time. Finally, my data is also not organized chronologically because it filters an entire dataset at a time and adds it to the buffer. This was fine as it wasn't useful for my hotspots map. However if you wanted to show how the hotspots changed over time, this would definitely be a limiting feature.

IV. Results & Visualizations

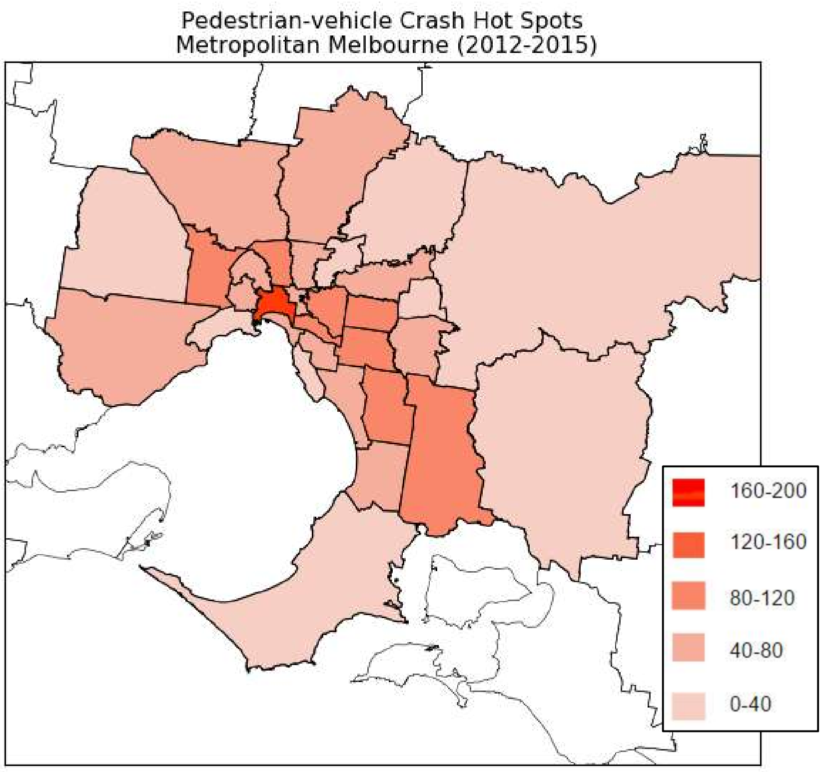
After experimenting with many different visualizations, the following visualizations have been included:

- The most dangerous LGAs (**chloropleth** aka geographical heatmap)
- The most dangerous areas within these LGAs (**dot distribution map**)
- Exploratory analysis into potential factors affecting pedestrian-crashes in selected LGA (**barcharts**)
- Correlation with Density (**scatter plots, boxplots**)

Finding the Most Dangerous Local Government Areas for Pedestrians

This geographical heatmap was created using the processed datasets containing pedestrian crash counts by LGA (*Appendix 2.1*). Preparatory steps in this visualisation included, converting the processed dataset into a dictionary, preparing equidistant buckets using **numpy**, using **BaseMap** to initialize a window to frame the 31 Metro LGAs and render the LGA boundaries from a **shapefile**.

I then searched through all the shapes in the shapefile a second time, looking up the value in the prepared dictionary saving the shape coordinates as a **Polygon** to the correct 'bucket'. I then plotted one 'bucket' at a time (a collection of polygons) with the correct colour.



I faced a lot of difficulties with this visualisation and it was easily the most challenging. I experimented a lot, trying out equal frequency (rather than equal size) buckets, different shapefile-processing libraries (**pyshp**) and rendering normalized data instead of counts.

The results are interesting. Melbourne LGA clearly has the highest collision frequency. From this map it's clear that this is the most dangerous LGA, with other hotspot LGAs being the South-Eastern LGAs and two in the North-West. This map seems to insinuate another pattern however – it seems to perhaps appear to be correlated with density. More on this later.

A Closer Look: Top 5 Most Dangerous LGAs

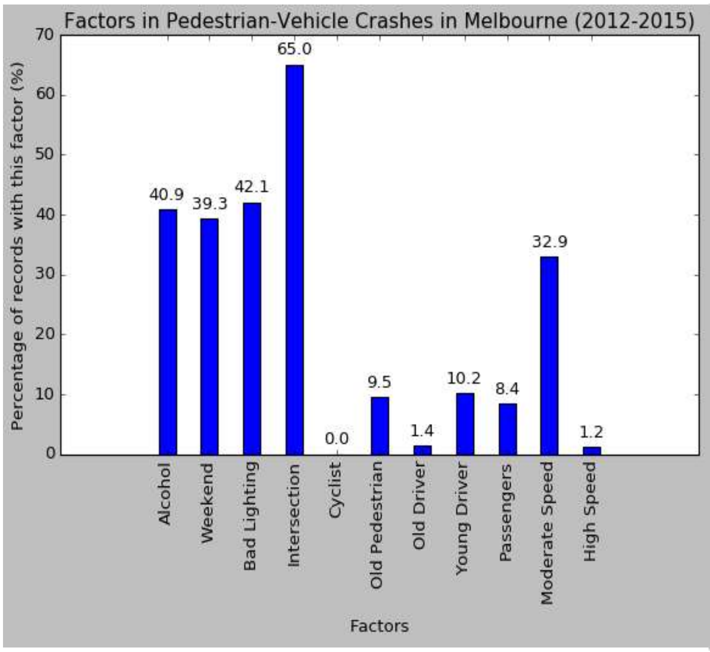
Rank	Local Government Area	Pedestrian Crash Count
1	MELBOURNE	197
2	MORELAND	117
3	GREATER DANDENONG	115
4	MONASH	100
5	BOROONDARA	95

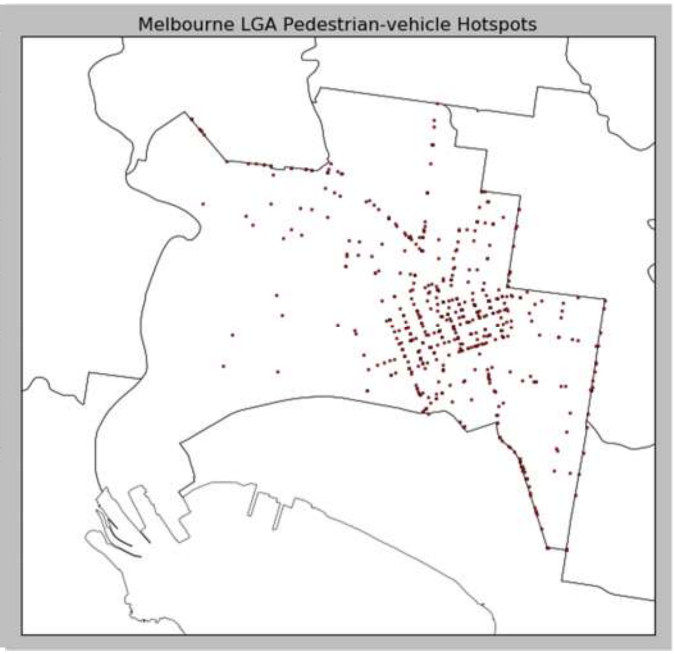
This conveys the top 5 most dangerous LGAs from my analysis. I was actually able to rank the entire Melbourne Metropolitan (*Appendix 2.1*). However, I was interested in taking this knowledge a step further. So, I've sampled the top 3 'most dangerous' LGAs in the following pages, in order to find precise hotspots and analyse the common features and factors of pedestrian crashes in any given LGA.

To map precise hotspots, I created a **dot distribution map** of exact pedestrian-crash locations. I once again used **BaseMap** to map the LGA boundary, then I used filtered LGA-specific data to find the latitude and longitude coordinates of crashes and plotted these using **matplotlib's pyplot**.

In terms of factors, I first narrowed these down to 11 key factors of interest: alcohol, weekend, bad lighting[4], intersection, cyclist, old pedestrian, old driver, young driver, passengers (1 or more), moderate speed (60km/h), high speed (more than 60km/h). Other factors such as type of vehicle, and number of females involved in the crash were excluded as they didn't seem to be very helpful in providing information about factors that could be fixed or improved through education or legislation. In order to clearly visualize the proportion of crashes affected by any one factor, I ended up calculating the <u>percentage</u> of total records for an LGA affected by each factor, and displaying these results in **bar charts (matplotlib)**.

Melbourne





The map shows that hotspots do tend to be concentrated in the Melbourne CBD area, however interestingly, they are quite evenly distributed. The map also shows that the Flemington Rd (North West series of crashes) and the St Kilda Road (Southern border) entries into the CBD seem to be the most

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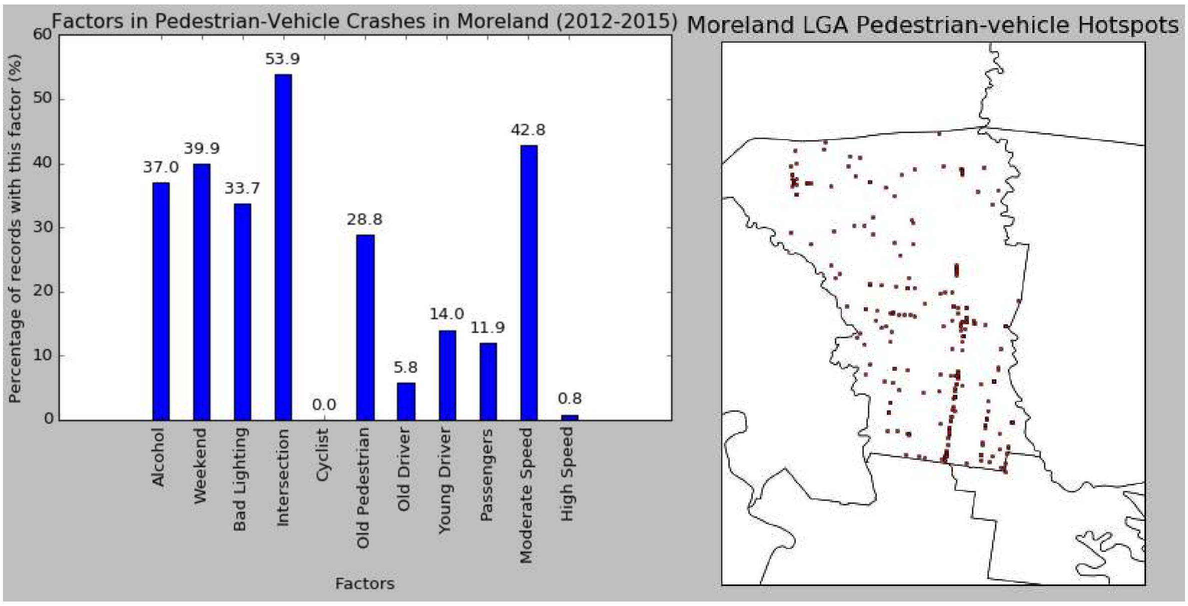
[4] Bad lighting was defined as any lighting that was not daylight (including 'Dusk/dawn' and any lighting conditions that included the terms 'Dark street'.)

dangerous, with denser series of crashes. The South Eastern Barkers Rd and M1 entry points surprisingly have much fewer crashes.

This LGA also has the highest proportion of crashes occurring at intersections (65.0%). Although intersections were found to consistently be the highest contributing factor to crashes (see other LGAs), Melbourne CBD where most of the crashes are occurring, doesn't have terribly complex intersections, unlike some of the 6-point junctions in the other LGAs (Stonnington and Boroondara for example). However, there are a lot more pedestrians. The data also shows almost a third of occurred at a 60km/h (Moderate Speed 32.9%), despite the speed limit in the CBD being 40 km/h. Perhaps more speed cameras to enforce the speed limit as well as stricter law of enforcement the jaywalking ban is required.

Moreland

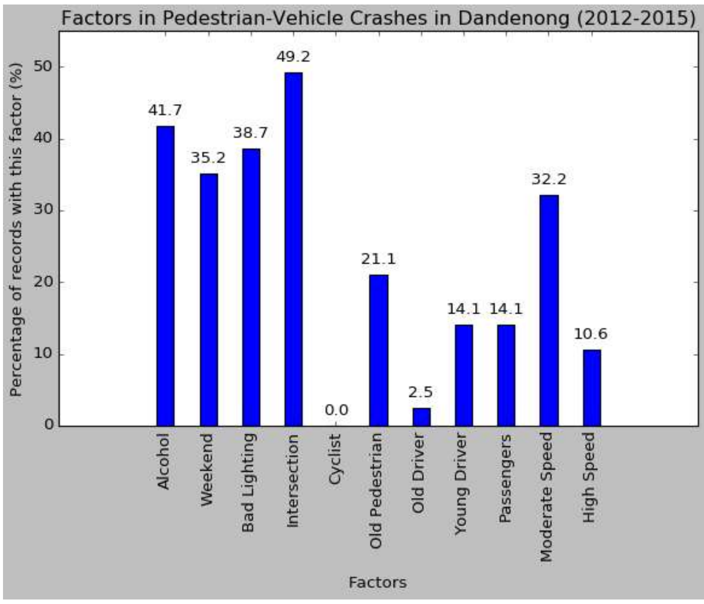


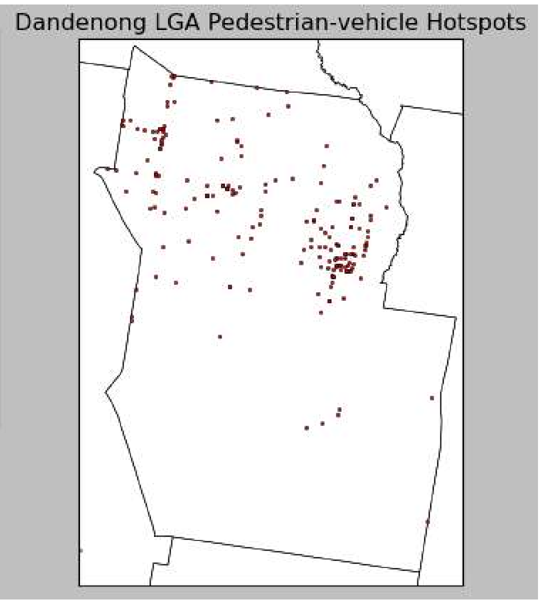
Moreland is an inner North LGA, sitting directly just north of Parkville and Melbourne CBD. The hotspots map shows that Sydney Road from the Brunswick Rd intersection (south), right up until the Bell St intersection is a definite hotspot for vehicle collisions in this LGA. It could be hypothesized that this is because Sydney Rd, which continues from Elizabeth St and Royal parade, is a direct route out of the CBD into the Northern suburbs. However, when you align Sydney Road with Royal Parade (central vertical series of sparse dots in previous *Melbourne LGA* hotspots map), this hypothesis is hard to validate as Royal Parade has very few collisions along this path. Sydney Road is plagued by a single driving lane, cyclists, a tram-line, many shops and bars.[5] The fact that it is quite narrow for such a busy road makes it easy for pedestrians to jaywalk and I tested this myself on a trip to this area.

The barchart reveals that Moreland has the highest proportion of old pedestrian victims and also a relatively high proportion of old drivers[6] (5.8%) and young drivers[7] (14.0%). It would be interesting to see analyse the most common driver demographic in the Sydney Rd area independently of the rest of the LGA. The fact that these proportions currently represent the whole LGA and not Sydney Road alone, is a current limitation of the visualizations in terms of the amount of detail they can provide..

[5] Information gathered by visiting and talking to Brunswick locals for this project.
[6] Closer to Monash and Boroondara percentages than Melbourne or Dandenong (Monash and Boroondara in *Appendix 2.2 & 2.3*)
[7] Like Dandenong, the next LGA examined

Greater Dandenong



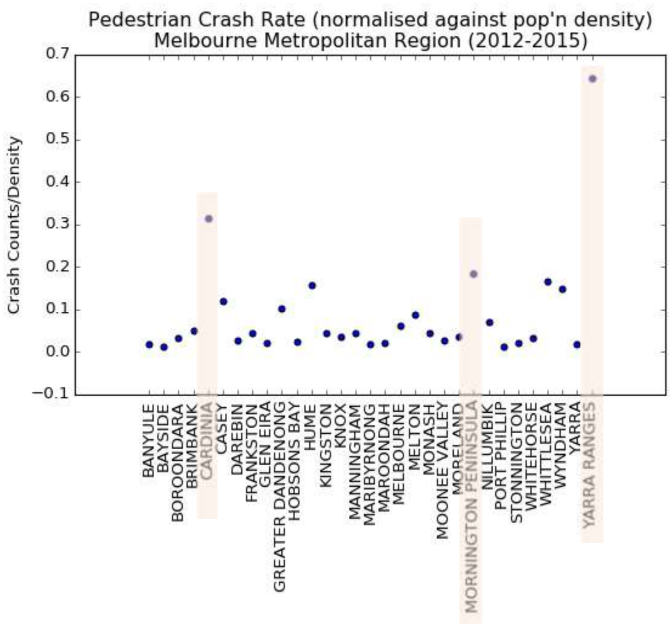


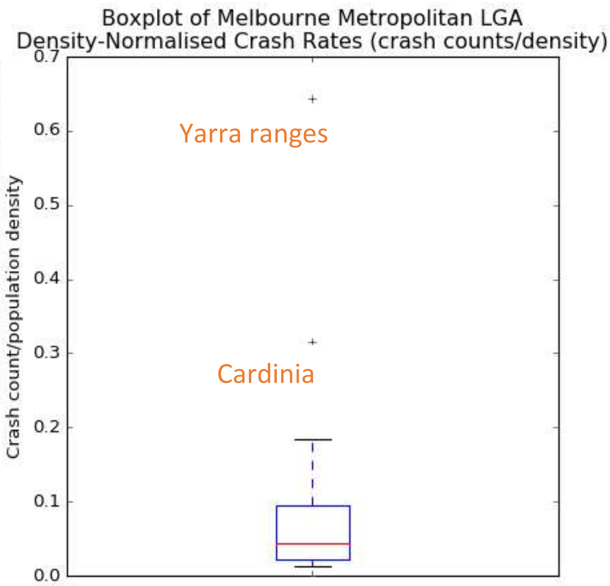
The Dandenong LGA reflects a much higher rate of high-speed related pedestrian-vehicle crashes than most of the other top 5 LGA's, with the only similarity being perhaps Monash. It also interestingly shows the highest proportion of crashes involving alcohol, young drivers and passengers.

This coincides with the hotspots map showing a very dense cluster on the right, which matches a 5-road junction spreading out from the Dandenong Plaza which sits at the heart of the cluster. The Dandenong Plaza is well known as a common social spot and meeting place in this LGA and is popular amongst the youth.[8]

The Effect of Population Density

The chloropleth (geographical heatmap) shared earlier had some interesting results. Melbourne was shown to be the LGA with the highest frequency of pedestrian-crashes. However, we can also hypothesis that this is perhaps due to the fact that it is the most population dense, with the South-Eastern suburbs and Inner North/North-West following in both crash-count frequency and hypothesized population density. To address this, I decided to delve qualitatively into the possible relationship between pedestrian-crashes and population density.

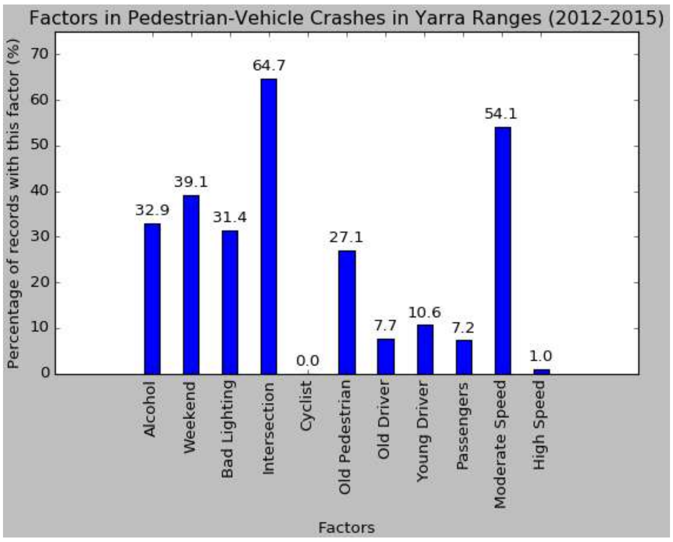


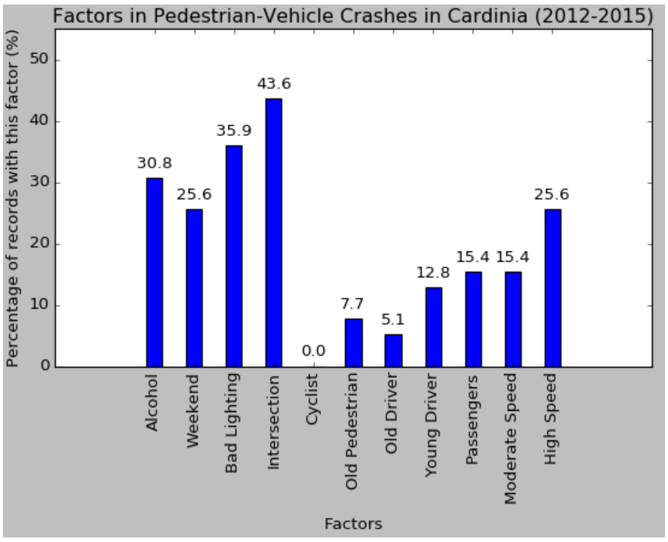


[8] Interviewing young Dandenong residents. As well as some evidence from online articles such as http://blog.gpt.com.au/2015/09/dandenong-plazas-ununiformed-approach-helps-youth/

The first **scatterplot** of the normalized pedestrian-crash frequency measure was created using **matplotlib** and shows that there does seem to be a correlation between crash count and density. This is due to the fact that a large proportion of the normalized values are very small. However, as we can discern, there are quite a few LGAs where the pedestrian crash frequency cannot be accounted for by population density – all of these LGAs (Wyndham, Whittlesea, Yarra Ranges, Kingston, Mornington and Cardinia) sit on the outskirts of Melbourne Metropolitan. The **boxplot** confirms that the distribution is skewed towards lower normalized crash frequencies – however it also reveals two outliers: Yarra Ranges and Cardinia.

Outliers: Yarra Ranges & Cardinia





These two barcharts allow us to see whether Yarra Ranges and Cardinia have similar profiles to account for their unusually high measures of crash frequency when normalized against population density.

Yarra Ranges, displays a very high proportion of crashes involving intersections (64.7%) whilst this only affects 43.6% of crashes in Cardinia. Furthermore 27.1% of crashes in Yarra Ranges involves old pedestrians. Just over half (54.1%) also occur at a moderate speed of 60km/h. Perhaps 40km/h should be introduced for more built-up areas in the Yarra Ranges.

Cardinia on the other hand, has a high proportion of crashes in high-speed zones (over 60km/h). In fact these account for 25.6% of crashes (which is much more significant than the 1.0% in Yarra Ranges). Lighting conditions that are perhaps not ideal is the second biggest most common feature afflicting 35.9% of collisions.

A limitation of this information, is that it is not yet possible to identify precisely why these two LGAs are outliers. Thus far, it seems to be for reasons unique to both LGAs.

Value

The raw data before it was processed and integrated, revealed no information about which LGAs were most significantly affected by high frequencies of pedestrian-vehicle collisions and was spread over all 79 Victorian LGAs, despite the fact 86% of pedestrian-crashes occur in the Metropolitan LGAs.[9] With such limited information, it is difficult for the Victorian Government and local city councils to prioritize and focus efforts on improving pedestrian road safety.

As a result integrating and filtering the thousands of records that were split up across three different datasets, into buckets of 31 Local Government Areas (LGAs) within the Metropolitan Melbourne area and displaying this information visually is much more effective at motivating change. The raw data made it impossible to approach improving pedestrian road safety with direction and purpose.

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[9] 2013 (http://www.tac.vic.gov.au/road-safety/statistics/summaries/pedestrian-statistics)

V. Conclusion

Challenges and Reflections

Overall I found the project an interesting, valuable but challenging experience. My key challenges are:

- **Dealing with questions that deviated from my original research question**

My original intention was to answer the question of *where* pedestrian crash hotspots in Metropolitan Melbourne. However during the course of the projects, my assessors in phase 1 and 2 raised interesting questions. In phase 1, I was asked to consider "the factors impacting the hotspots" and in phase 2 it was mentioned that it was potentially "trivial" if I showed more crashes "in areas that are more dense." I found it quite difficult to approach these points. Despite the fact that they caused a deviation and increased the scope of my project dramatically, I did think integrating these points added depth to my project.

- **Integration of Data: inconsistencies**

It was difficult to uncover all the inconsistencies between the datasets (e.g. it was around Phase 3 that I discovered that 'Dandenong' was referred to as 'Greater Dandenong' in one dataset, resulting in many records missing form my integrated file). To overcome consistencies, I put in place many checkpoints and used an 'Entry' object of my creation to hold variables once I'd hunted, sliced, indexed, swapped case, translated (and so on) to wrangle them into the correct format.

One restriction that limited the granularity of my project to LGA (as opposed to something smaller such as suburb), was the fact that the TAC datasets lacked the detail of the VicRoads dataset.

- **Picking appropriate visualisations**

I found picking the correct visualisation at times to be very challenging. Especially for my additional analysis that included population density and factors involved in pedestrian-crashes.

For density, I tried separate subplots, one subplot with two lines and a scatter with crash counts against population density, before finally realising that a 1D scatter and a boxplot might be the best way to go.

To visualize the factors, I first experimented with heatmaps however quickly found that these lacked clarity when conveying the information. I also tried grouped barcharts to be more space efficient and allow easier comparisons between LGAs however 11 factors was too excessive for this to be effective.

Some of these failed 'dead-ends' have been included in *Appendix 3.1 Failed Experimental Visualisations*

- **Limited datasets for exploring factors**

It would have been nice to incorporate more datasets in the analysis of factors affecting pedestrian-crashes in the area, however the project would not have been feasibly manageable.

- **Mastering new technologies and tools and managing a relatively large amount of code**

Question Resolution

In conclusion, results of this project have aptly answered all of the research questions that were initially set out in the intentions in *Section I*. The results effectively show the location of the most dangerous areas in Metropolitan Melbourne – on an LGA level, as well as more precisely within their LGA. The results also being to highlight some of the common factors affecting pedestrian-crashes, tailored specifically for a single LGA.

Local and State Government would find particular value in the data, as it would allow them to recognise which LGAs do need to improve on pedestrian road safety. It will also give them some starting points on which areas they could try on work on. For example, it might be interesting for Dandenong City Council to see if introducing more speed cameras or police with breathalyzers on weekend evenings near Dandenong Plaza reduces the rate of pedestrian-vehicle collisions in the area. The findings in this report would be even more useful if compounded with information about other forms of collisions in these LGAs.

The citizens of the public will also gain an awareness of which areas within LGAs they should avoid jaywalking at, or should be extra cautious at.

Appendix

Pages 9 -14 consist mostly of the Appendix, which has not been counted in the 8-page limit of the actual report contents. This is all supplementary.

Section 1: Data Sources & Data Sets

1.1 Data Source Links

Primary Data Sources

1. **Victorian Serious Road Casualties (TAC)**
   https://www.data.vic.gov.au/data/dataset/victorian-serious-road-casualties-tac
2. **Crashes Last Five Years (VicRoads)**
   https://www.data.vic.gov.au/data/dataset/crashes-last-five-years
   http://vicroadsopendata.vicroadsmaps.opendata.arcgis.com/datasets/c2a69622ebad42e7baaa8167daa72127_0?uiTab=table
3. **Victoria Road Toll (TAC)**
   https://www.data.vic.gov.au/data/dataset/victorian-road-toll-tac

Complementary Data Sources

4. **LGA Boundaries (ABS)**
   http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/1259.0.30.001July%202011?OpenDocument
5. **Local Government Areas of Victoria (Wikipedia)**
   https://en.wikipedia.org/wiki/Local_government_areas_of_Victoria
6. **Population Estimates 2005-2015 by LGA (ABS)**
   http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3218.02014-15?OpenDocument

1.2 Primary Dataset Schema examples

1. **Crashes Last Five Years (VicRoads)**
   64 total columns/features. This is the schema for the features relevant to my analysis.

Column ID (excel)	Column Index	Feature (Columns)	String Values
A	0	**X**	Signed float coordinate
B	1	**Y**	Signed float coordinate
G	6	**ACCIDENT_DATE**	DD/MM/YYYY e.g. 22/11/2010
I	8	**ALCOHOLTIME**	Yes/No
K	10	**DAY_OF_WEEK**	
N	13	**LIGHT_CONDITIONS**	Day, Dark Street with Lights, Dark Street with unknown lights, Dawn/Dusk
Q	16	**SEVERITY**	
R	17	**SPEED_ZONE**	
X	23	**LGA_NAME**	String name in CAPS (Greater Dandenong is referred to as Dandenong)
AF	31	**OTHERINJURIES**	1 or 0
AJ	35	**BICYCLIST**	Int, 0 or more
AK	36	**PASSENGER** (number of passengers)	Int, 0 or more

AM	38	**PEDESTRIAN**	0 or 1
AS	44	**OLD_PEDESTRIAN**	0 or 1
AT	45	**OLD_DRIVER**	0 or 1
AU	46	**YOUNG_DRIVER**	0 or 1
AV	47	**ALCOHOLTIME**	Yes/No
BM	64	**STAT_DIV_NAME**	Metro/Country

2. **Victorian Serious Road Casualties (TAC)**

```
<ROWSET>
<ROW>
<transaction_num_nb> 90257 </transaction_num_nb>
<Age_Group> 40-59 </Age_Group>
<Year> 2015 </Year>
<Crash_Month> 9 </Crash_Month>
<Crash_Day> 7 </Crash_Day>
<Crash_Time> UNKNOWN </Crash_Time>
<Road_User> PEDESTRIAN </Road_User>
<Gender> MALE </Gender>
<Crash_Type> PEDESTRIAN </Crash_Type>
<Injury_Severity> 1 </Injury_Severity>
<Crash_LGA> BALLARAT </Crash_LGA>
<Crash_Area_Type> RURAL VIC </Crash_Area_Type>
</ROW>
    --- MORE ROWS HERE ----
</ROWSET>
```

3. **Victorian Road Toll (TAC)**

```
<ROWSET>
<ROW>
<transaction_num_nb> 2 </transaction_num_nb>
<accident_location_tx> RURAL VIC </accident_location_tx>
<crash_type_tx> PEDESTRIAN </crash_type_tx>
<LGA_tx> GREATER GEELONG </LGA_tx>
<age_group_tx> 18-20 </age_group_tx>
<road_user_grouping_tx> PEDESTRIAN </road_user_grouping_tx>
<time_of_accident_tx> 00:00 to 01:59 </time_of_accident_tx>
<date_of_accident_tx> 01JAN1987 </date_of_accident_tx>
<gender_tx> MALE </gender_tx>
<accident_day_of_week_tx> THURSDAY </accident_day_of_week_tx>
<level_of_urbanisation_tx> UNKNOWN </level_of_urbanisation_tx>
</ROW>
  --- MORE ROWS HERE ----
</ROWSET>
```

1.3 Complementary Dataset Schemas

4. **LGA Boundaries (ABS) – shapefile**
   Schema: (shapes, records) where shapes are collections of latitude and longitude values and records contain qualitative information about the shape (e.g. LGA name).
5. **Local Government Areas of Victoria (Wikipedia) – html table**
   Contains information about land area size for each LGA. I could not find an alternative data source that contained this information.
6. **Population Estimates 2005-2015 by LGA (ABS) – csv**
   Use: I only used 2012-2015 data for Victoria.
   Schema: The file itself is an excel sheet, containing 5 formatted sheets where the column headers were not in the first row. As a result, I copied the relevant columns into a new file and saved it as a csv so that I could access it like a csv.
   Modified Schema (column headings): LGA, 2012, 2013, 2014, 2015

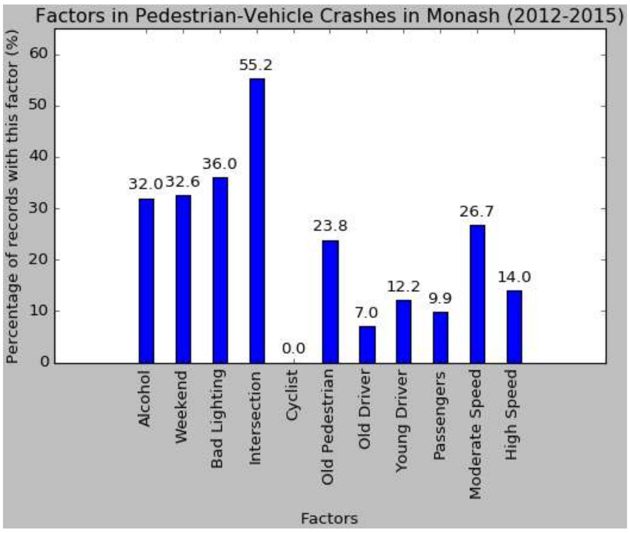
Section 2: Additional Results

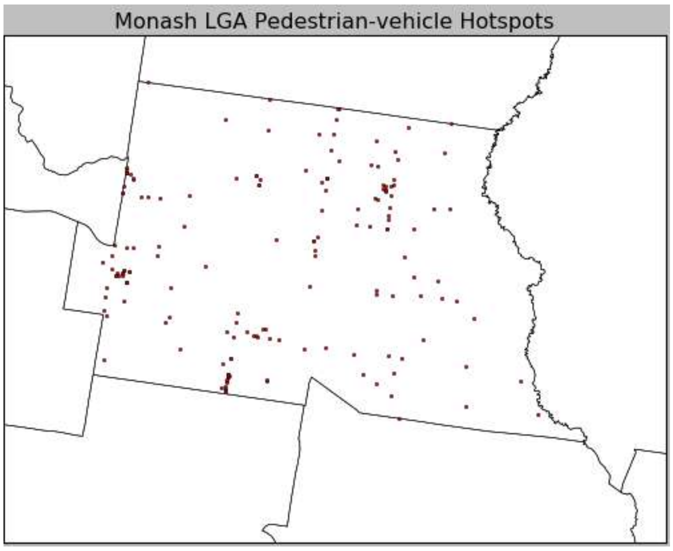
2.1 Ranking of LGA (Highest Pedestrian Crash Counts)

Table created using **pandas library.** It was also output to a csv file.

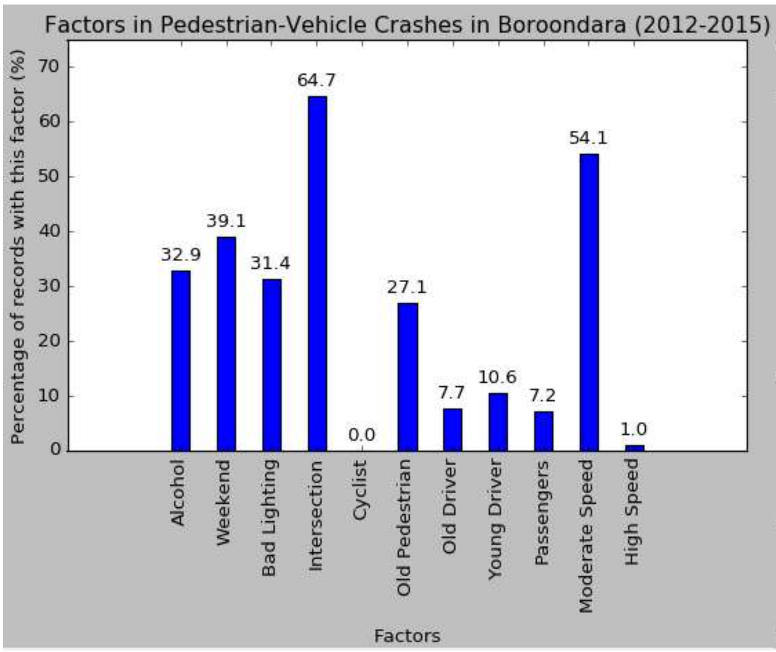
Rank	Local Government Area	Pedestrian Crash Count
1	MELBOURNE	197
2	MORELAND	117
3	GREATER DANDENONG	115
4	MONASH	100
5	BOROONDARA	95
6	STONNINGTON	86
7	WHITEHORSE	85
8	CASEY	82
9	BRIMBANK	81
10	KINGSTON	76
11	MOONEE VALLEY	73
12	GLEN EIRA	73
13	YARRA	73
14	DAREBIN	72
15	PORT PHILLIP	69
16	WHITTLESEA	62
17	HUME	58
18	WYNDHAM	53
19	MARIBYRNONG	49
20	KNOX	48
21	MANNINGHAM	45
22	FRANKSTON	45
23	YARRA RANGES	39
24	MORNINGTON PENINSULA	39
25	BAYSIDE	37
26	MAROONDAH	36
27	BANYULE	36
28	HOBSONS BAY	34
29	MELTON	21
30	CARDINIA	21
31	NILLUMBIK	10

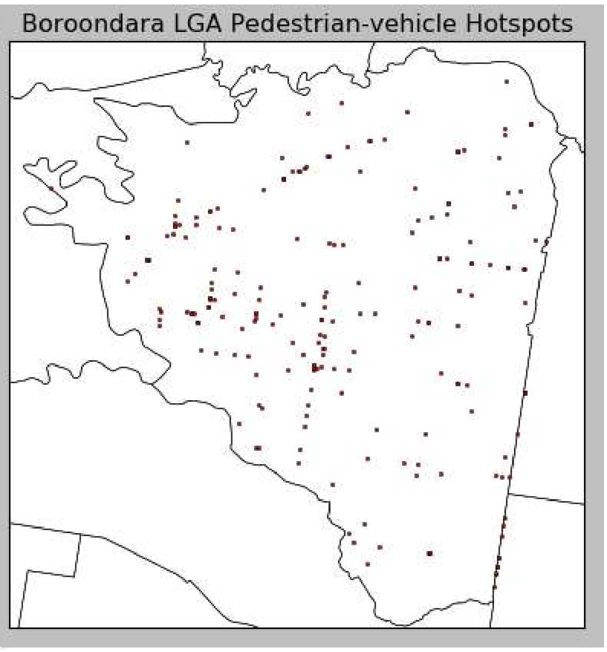
2.2 Monash LGA





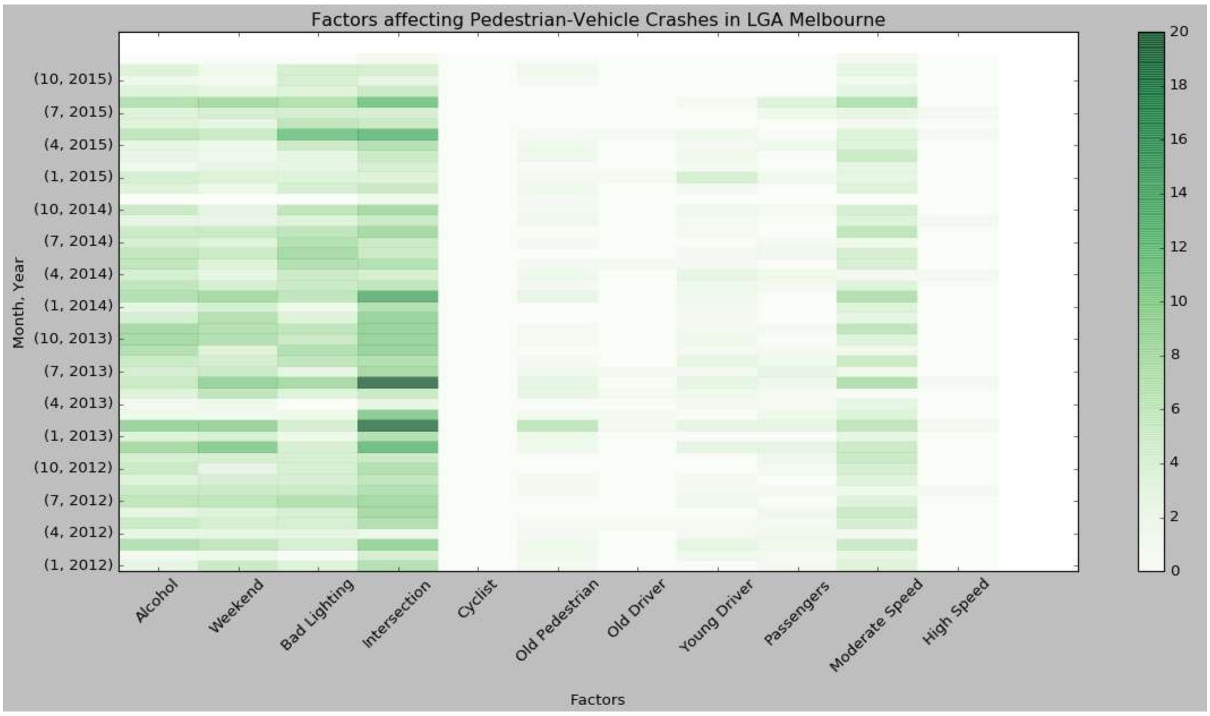
2.3 Boroondara LGA

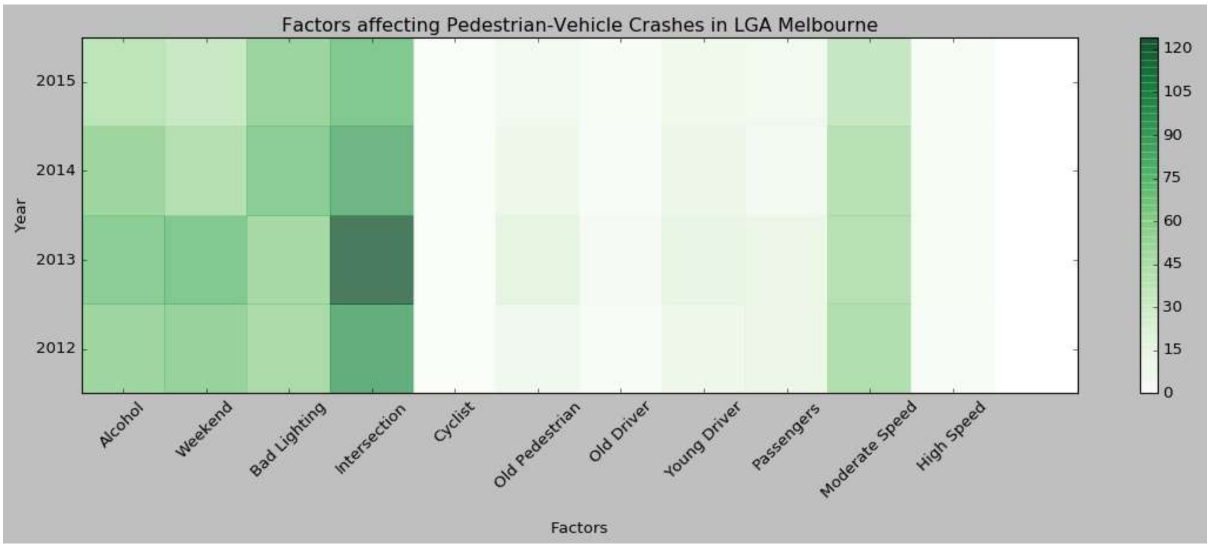


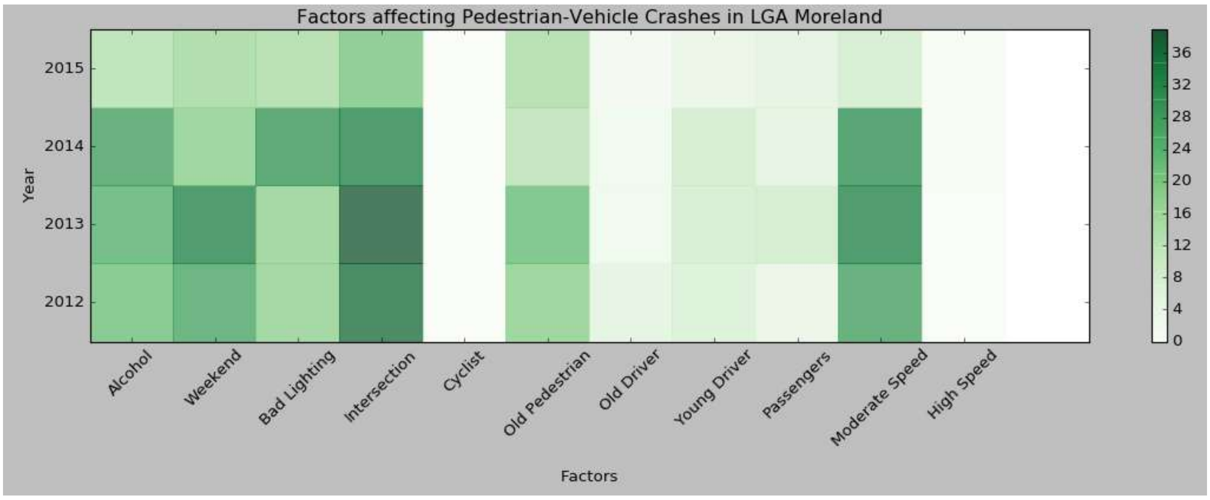


Section 3: Failed Experimental Visualisations

3.1 Heatmaps for Pedestrian-Crash Factors

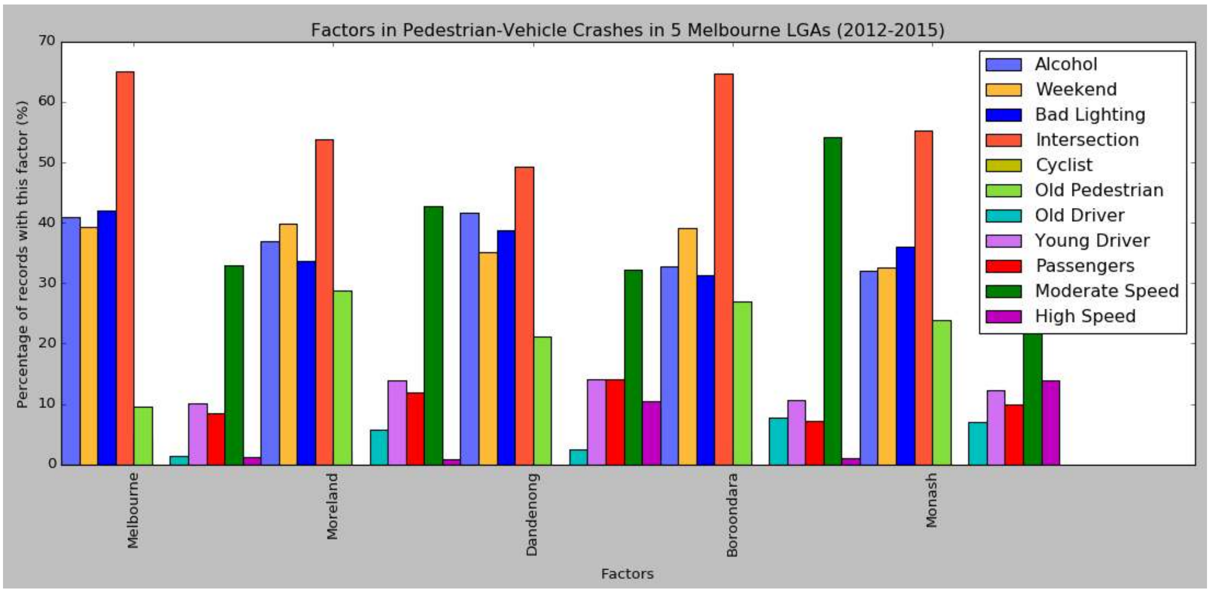






3.2 Grouped Barchart for factors across multiple LGAs

Incomplete and obviously some errors, I just wanted to illustrate that I thought there were too many factors to continue.



3.3 Population Density Visualizations