Dublin’s Homeless Road

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1. Introduction

1.1 Background

Homelessness is a major issue in Ireland, being much more acute in Dublin’s area.

There were 10,378 people homeless in the week of April 22nd-28th 2019 across Ireland. This figure includes adults and children. The number of homeless families has increased by 243% since April 2015. More than one in three people in emergency accommodation is a child. However, this number does not include ‘hidden homelessness’ which refers to people who are living in squats or ‘sofa surfing’ with friends. The national figure also does not include people who are sleeping rough.

In the past, most people using emergency accommodation were single adults. But in the last three years, there has been a rapid increase in the number of families becoming homeless, and in April 2019, there were 1,729 families accessing emergency accommodation. This includes 3,794 children.

The causes of homelessness are always complex. Broadly speaking, homelessness can be caused by ‘structural factors’ (like lack of affordable housing, unemployment, poverty, inadequate mental health services, etc) or ‘personal factors’ (like addictions, mental health issues, family breakdown etc). The current rise in family homelessness is driven primarily by structural economic factors.

According to Focus Ireland research and analysis, the overwhelming number of families becoming homeless had their last stable home in the private rented sector, and the crisis in this sector is the immediate cause of their homelessness – landlords selling up or being repossessed, shortage of properties to rent, scarcity of properties accepting rent supplement, and high rents.

Most of the families becoming homeless have never experienced homelessness before and never thought this could happen to them. Thousands more families are struggling on very low incomes or social welfare and many are falling into serious housing difficulties as rents continue to rise.

While the Government has introduced a range of policies to tackle homelessness, the growing number of people becoming homelessness shows they are inadequate. Some of the problems are long running – such as the decision to cut social housing spending by 72% between 2008 and 2012 (€1.38bn to €390m), but short term measures have not been tackled either.

The right to housing is recognized by the United Nations (Article 25 in the Universal Declaration of Human Rights) and the UN has been active in highlighting homelessness as a violation of human rights.

1.2 Problem

Mr. Florin is a homeless person currently located in Dublin city (Mr. Florin is a real homeless person). He has recently noticed an important decrease on the money he is getting when asking for some spare change to people walking by.

Mr. Florin has tried many different things to increase his income without success, like staying in narrow streets so he is noticed, smiling to the people walking by or writing down his situation on board on his side.

This project aims to help Mr. Florin to increase his income, by analyzing which are the places more convenient for him to be and come up with a weekly route that would optimize his income.

1.3 Interest

Having a list of places and a route that would optimize any homeless' person income is very important to make their lives a little bit easier. Apart from that, one of the requirements is that every day the person has to move to a different place, because if the homeless person stays in the same area for many days, different people would start complaining (shop owners, residents, etc..).

2. Data acquisition and cleaning

2.1 Data sources

There is a clear relationship between a location, its venues available around, and the level of alms the population nearby are willing to provide. As an example, people would restrain giving alms near a shopping center, mainly for two reasons, because they usually pay by credit card and the amount of spare change is limited, and because security in those places restrict access to homeless people, even in the surroundings.

Mr. Florin has provided the following list of places that according to his experience, he gets the highest amount of alms (not necessarily in this order):

- Bakery
- Food & Drink Shop
- Pharmacy
- Betting Shop
- Scenic Lookout
- Ice Cream Shop
- Gourmet Shop
- Health Food Store
- Gift Shop
- Bookstore

In order to come up with a route that would optimize income, we would mainly need two types of data. On one hand, locations around Dublin, and on the other hand, all venues available from those locations, so we can gather the locations with the highest amount of venues listed before.

In Ireland counties are subdivided in a unique way, counties into baronies, baronies into parishes, and parishes into townlands. The townland (*baile bó* in Irish) is a unique feature of the Irish landscape and certainly existed long before the parishes and counties. An ancient division dating back to pre-Norman times, it is the common term or English translation for a variety of small local land units that varied in name and meaning throughout the island of Ireland.

For this project, we will get townland information from https://www.townlands.ie where there is a specific dataset here. The main objective is to get the coordinates (latitude and longitude) from each townland in Dublin's area.

We will also use Foursquare API (https://foursquare.com) as data provider for venues around a specific location, this information will be very useful for achieving our objective.

2.2 Data cleaning

The raw data set related to townlands contains 61.076 townlands and 27 parameters for each townland. Most of that data is irrelevant for the purpose of this project. Data cleaning is needed for getting places only from Dublin’s area and the parameters that can provide any meaningful information for the project’s purpose. Once the data is filtered by county Dublin, we check for null values, and there is none.

Regarding the venues dataset from Foursquare, there is no issue, because we can obtain precisely the information we are looking for.

2.3 Feature selection

From the 27 features in the raw dataset, only 5 are necessary for the project’s purpose. Those are:

- Name of the townland (NAME_TAG)
- County name (CO_NAME)
- Civil parish name (CP_NAME)
- Latitude (LATITUDE)
- Longitude (LONGITUDE)

From Foursquare, we will be interested in the following features for each Neighborhood:

- Venue name
- Venue address
- Venue latitude
- Venue longitude
- Venue Category

3. Methodology and exploratory data analysis

3.1 Location data

We explore the amount of townlands in county Dublin, and results are 1052 townlands.

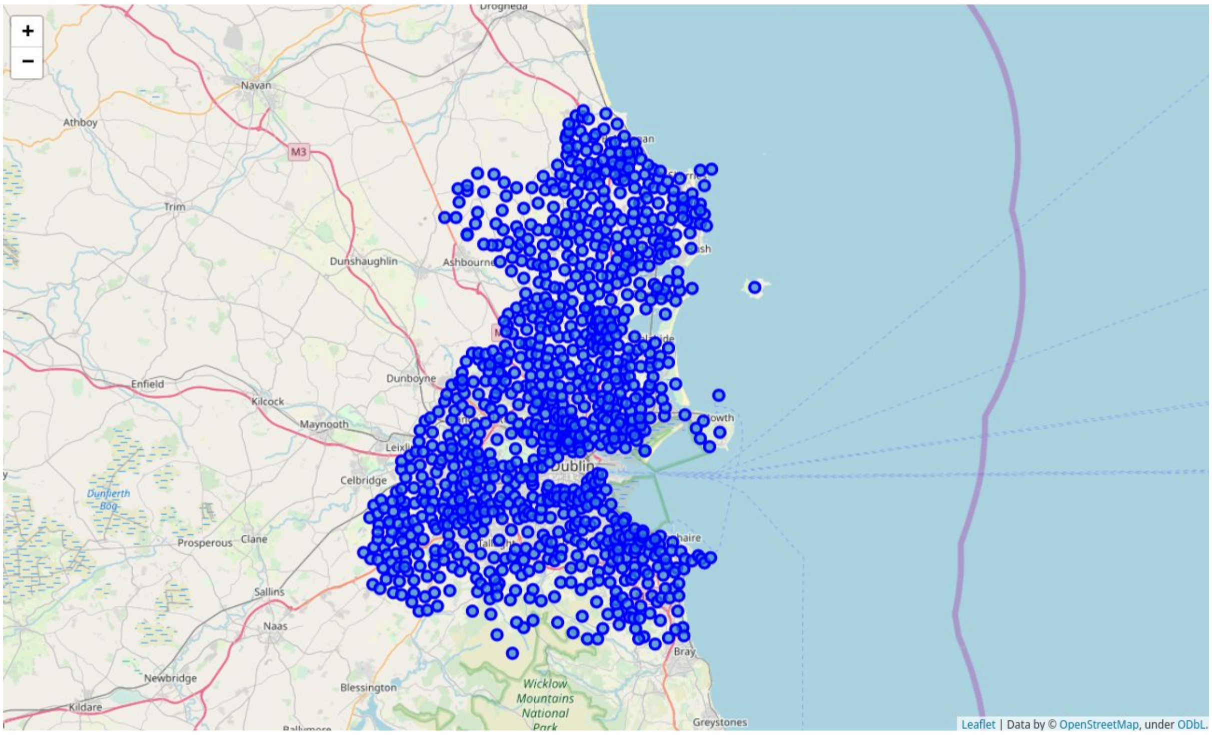

Figure 1. Townlands in county Dublin

We can see in figure 1 that there are too many townlands in county Dublin for our purpose. We need a lower amount of locations for our analysis. For that reason, we explore the amount of Civil Parishes and results are 84.

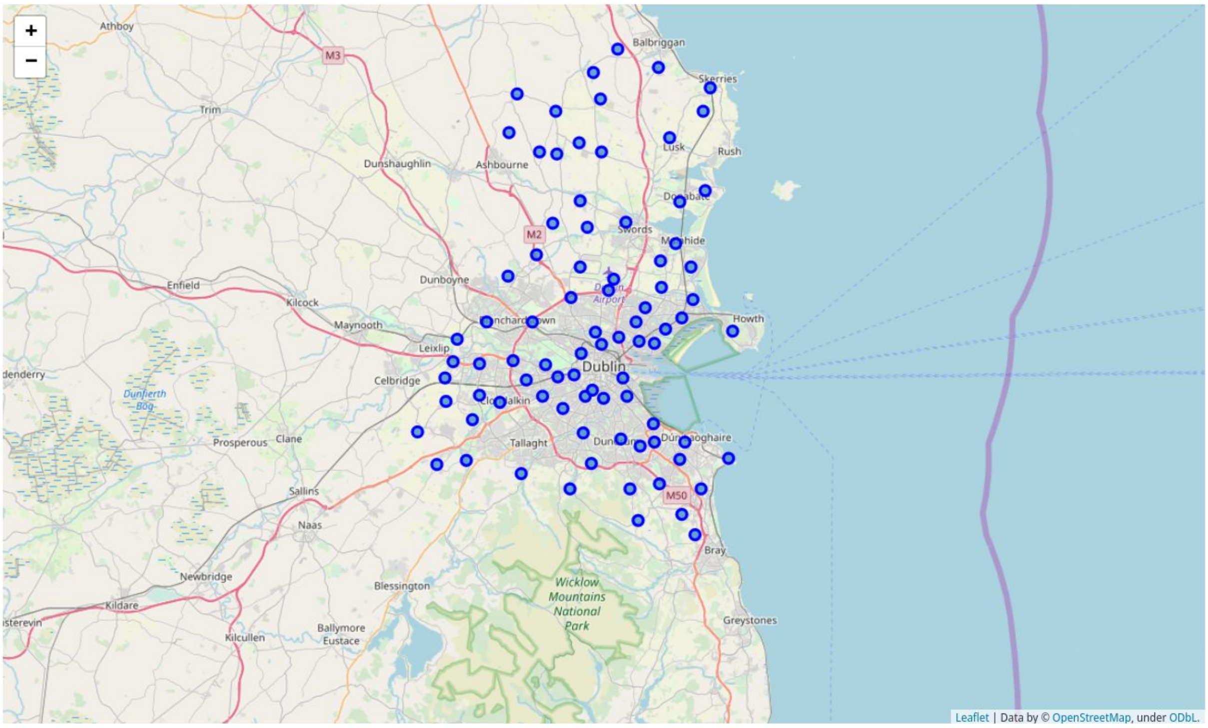

Figure 2. Civil Parishes in county Dublin

This looks much better, we can proceed now to analyse the venues around those locations.

We launch a query to Foursquare API for venues around the locations mentioned before. We establish a radius of 1.500 meters an a limit of 300 venues per location. We get 2.173 venues in total.

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There are  2173 venues in Dublin locations
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	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Address	Venue Latitude	Venue Longitude	Venue Category
0	Aderrig	53.340213	-6.474632	Finnstown Castle Hotel	Newcastle Rd	53.339602	-6.460888	Hotel
1	Aderrig	53.340213	-6.474632	Adamstown Railway Station	Adamstown	53.337099	-6.462584	Train Station
2	Aderrig	53.340213	-6.474632	Peacock Restaurant	Ireland	53.339547	-6.461501	Gastropub
3	Aderrig	53.340213	-6.474632	Londis	Adamstown Ave	53.336752	-6.457966	Convenience Store
4	Aderrig	53.340213	-6.474632	PDM Construction	Airlie Heights	53.350451	-6.469920	Building

Figure 3. Venues from Dublin locations

We analyze the amount of unique categories in the venues, and we can find that there are 217 uniques categories.

We proceed to filter the amount of venues by the list provided by Mr. Florin: Bakery, Food & Drink Shop, Pharmacy, Betting Shop, Scenic Lookout, Ice Cream Shop, Gourmet Shop, Health Food Store, Gift Shop and Bookstore. We get 77 venues from those 10 types around the established locations. We can also see that from the original 84 places analysed, only 37 of them contain at least one of the categories defined previously.

Number of total venues per category

	Neighborhood	Bakery	Betting Shop	Bookstore	Food & Drink Shop	Gift Shop	Gourmet Shop	Health Food Store	Ice Cream Shop	Pharmacy	Scenic Lookout	Count_Venues	Total
37	NaN	15.0	2.0	6.0	15.0	4.0	6.0	4.0	6.0	12.0	7.0	59.0	77.0

Figure 4. Number of venues per category

We analyze the seven locations with the highest number of venues.

	Neighborhood	Bakery	Betting Shop	Bookstore	Food & Drink Shop	Gift Shop	Gourmet Shop	Health Food Store	Ice Cream Shop	Pharmacy	Scenic Lookout	Count_Venues	Total
36	Taney	0	0	2	0	0	0	1	1	2	0	4	6
18	Monkstown	1	0	1	1	0	1	0	1	0	0	5	5
33	St. Peter's	0	0	0	3	0	0	1	1	0	0	3	5
9	Donnybrook	0	0	0	1	0	1	0	1	1	0	4	4
3	Cloghran	0	0	1	1	1	0	0	0	0	1	3	4
26	St Mark's	2	0	0	1	0	1	0	0	0	0	3	4
7	Dalkey	1	0	0	0	0	0	1	0	0	2	2	4

Figure 5. Seven locations with highest number of selected venus

The list above is very useful for our purposes, as it indicates the locations where Mr. Florin can find the highest number of predefined venus and the number of types of venus per location. With this information, we can come up with a weekly route so he could optimise his income.

3.2 Unsupervised machine learning (KMeans)

We may provide further analysis if we are able to group the venues, for that reason, we are going to use an unsupervised machine learning technique called KMeans. It will group venues so we can have a deeper understanding about the locations.

In order to take complexity out of the information to be provided to Mr. Florin, we are going to keep low the number of groups, for that reason we will establish 3 groups (KMeans = 3).

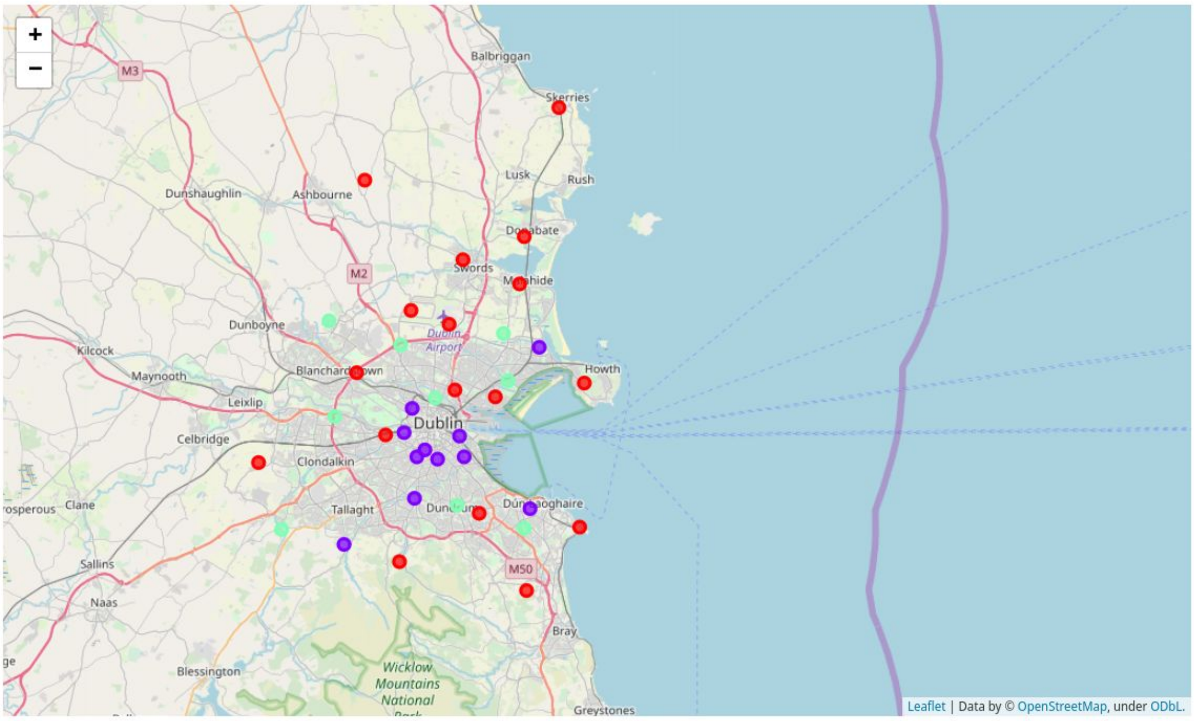

Figure 6. Group locations with predefined venues (3 groups)

4. Results and discussion

In this section we will review the groups obtained and we will come up with a weekly route proposal that would include the locations with the most number of predefined venues.

4.1 Group analysis

From the KMeans algorithm we have obtained 3 groups, as specified. We are going to analyze the results to make sense of how the algorithm has differentiated each group.

<u>Group 1: Locations with low/medium number of venus, mixture types of venues</u>

	Neighborhood	Bakery	Betting Shop	Bookstore	Food & Drink Shop	Gift Shop	Gourmet Shop	Health Food Store	Ice Cream Shop	Pharmacy	Scenic Lookout	Count_Venues	Total
11	Castleknock	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0
13	Cloghran	0.0	0.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	3.0	4.0
17	Clontarf	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0
18	Clonturk	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0
20	Cruagh	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0
22	Dalkey	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	2.0	2.0	4.0
23	Donabate	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	1.0	1.0
33	Holmpatrick	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0
34	Howth	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	1.0	1.0
43	Kilmactalway	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0
44	Kilmacud	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0
52	Malahide	0.0	0.0	0.0	0.0	2.0	2.0	0.0	0.0	0.0	0.0	2.0	4.0
59	Palmerstown	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0
65	Rathmichael	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0
72	St. Jude's	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0
73	St. Margaret's	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0
77	Swords	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0

Figure 7. Group 1 locations

This group of locations shows a mixture of types of venues, and the total amount range from low (1 venue) to medium amount (4 venues). For that reason, we describe this group as “Locations with low/medium number of venus, mixture types of venues”.

<u>Group 2: Locations with medium/high number of venues, Food & Drink oriented</u>

	Neighborhood	Bakery	Betting Shop	Bookstore	Food & Drink Shop	Gift Shop	Gourmet Shop	Health Food Store	Ice Cream Shop	Pharmacy	Scenic Lookout	Count_Venues	Total
3	Baldoyle	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0
24	Donnybrook	0.0	0.0	0.0	1.0	0.0	1.0	0.0	1.0	1.0	0.0	4.0	4.0
31	Grangegorman	1.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	3.0	3.0
53	Monkstown	1.0	0.0	1.0	1.0	0.0	1.0	0.0	1.0	0.0	0.0	5.0	5.0
64	Rathfarnham	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	2.0
68	St Mark's	2.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	3.0	4.0
69	St. Catherine's	0.0	0.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	2.0
71	St. James'	2.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	3.0
74	St. Nicholas Without	1.0	0.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	3.0
75	St. Peter's	0.0	0.0	0.0	3.0	0.0	0.0	1.0	1.0	0.0	0.0	3.0	5.0
78	Tallaght	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0

Figure 8. Group 2 locations

This group of locations shows a clear orientation towards Food & Drink shops, and the total amount range from medium (mostly 3 to 4 venues) to high amount (5 venues). For that reason, we describe this group as “Locations with medium/high number of venus, Food & Drink oriented”.

<u>Group 3: Locations with low/high number of venus, Pharmacy oriented</u>

	Neighborhood	Bakery	Betting Shop	Bookstore	Food & Drink Shop	Gift Shop	Gourmet Shop	Health Food Store	Ice Cream Shop	Pharmacy	Scenic Lookout	Count_Venues	Total
4	Balgriffin	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	2.0	2.0
27	Finglas	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	1.0
38	Kill	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0	1.0	2.0
54	Mulhuddart	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	1.0
58	Palmerston	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	2.0	2.0
62	Raheny	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	1.0
66	Saggart	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	1.0
70	St. George's	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	2.0	3.0
79	Taney	0.0	0.0	2.0	0.0	0.0	0.0	1.0	1.0	2.0	0.0	4.0	6.0

Figure 9. Group 3 locations

This group of locations shows a clear orientation towards Pharmacies, and the total amount range from low (mostly 1 and 2 venues) to high amount (6 venues). For that reason, we describe this group as “Locations with low/high number of venus, Pharmacy oriented”.

4.2 Recommended route

Once we have the predefined venues and found the locations with the highest amount of those venues, we are going to define a recommended route on a daily basis, with useful information for Mr. Florin to increase his income.

Day 1:

```
Day  1
Location:  Taney
Number of venues:  6
Location group:  Low/High number, Pharmacy
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	Venue Category	Venue	Venue Address
72	Bookstore	Eason	Dundrum Town Centre (Level 3 Unit 12-14)
73	Pharmacy	Boots	Dundrum Town Centre (Unit 18 Level 2)
74	Ice Cream Shop	Aussie Ice	Dundrum Town Centre (Level 1 Unit 12a)
75	Health Food Store	The Health Store	Dundrum Town Centre (Level 3 Unit 15a)
76	Pharmacy	McCabes Pharmacy	Dundrum Town Centre (Level 3 Unit 17)
77	Bookstore	Hughes & Hughes Booksellers	Dundrum Town Centre

Figure 10. Day 1 route

Day 2:

```
Day  2
Location:  Monkstown
Number of venues:  5
Location group:  Medium/High number, Food&Drink
```

	Venue Category	Venue	Venue Address
34	Food & Drink Shop	Salt @Avoca	11a Monkstown Crescent
35	Gourmet Shop	Avoca	11a The Crescent
36	Ice Cream Shop	Scrumdiddly's	Kelly's Avenue (Crofton Rd)
37	Bakery	The Natural Bakery	93 George's St Lwr
38	Bookstore	Eason	7 Marine Rd

Figure 11. Day 2 route

Day 3:

```
Day  3
Location:  St. Peter's
Number of venues:  5
Location group:  Medium/High number, Food&Drink
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	Venue Category	Venue	Venue Address
65	Food & Drink Shop	Fallon & Byrne	Dublin
66	Health Food Store	Urban Health	9 Fields Terrace
67	Food & Drink Shop	Best of Italy	Dunville Ave
68	Ice Cream Shop	Scoop	22 Sandford Rd, Ranelagh
69	Food & Drink Shop	Hopsack	Lwr Rathmines Rd

Figure 12. Day 3 route

Day 4:

```
Day  4
Location:  Donnybrook
Number of venues:  4
Location group:  Medium/High number, Food&Drink
```

	Venue Category	Venue	Venue Address
16	Food & Drink Shop	The Good Food Store	Serpentine Ave
17	Ice Cream Shop	Scoop	22 Sandford Rd, Ranelagh
18	Gourmet Shop	Lotts & Co	7 S Lotts Rd
19	Pharmacy	Boots	32 Uppr Baggot St

Figure 13. Day 4 route

Day 5:

```
Day  5
Location:  Cloghran
Number of venues:  4
Location group:  Low/medium number, mixture venues
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	Venue Category	Venue	Venue Address
4	Gift Shop	Irish Memories	Terminal 2 (DUB Airport)
5	Scenic Lookout	Airplane Watching Car Park	Old airport road
6	Food & Drink Shop	Caviar House & Prunier	Terminal 2 (Dublin Airport (DUB))
7	Bookstore	WHSmith	100 Gates, Terminal 1, Dublin Airport (DUB)

Figure 14. Day 5 route

Day 6:

```
Day  6
Location:  St Mark's
Number of venues:  4
Location group:  Medium/High number, Food&Drink
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	Venue Category	Venue	Venue Address
48	Gourmet Shop	Lotts & Co	7 S Lotts Rd
49	Bakery	Il Valentino	5 Gallery Quay, Grand Canal Harbour
50	Food & Drink Shop	The Good Food Store	Serpentine Ave
51	Bakery	Bread 41	Pearse Street

Figure 15. Day 6 route

Day 7:

```
Day  7
Location:  Dalkey
Number of venues:  4
Location group:  Low/medium number, mixture venues
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	Venue Category	Venue	Venue Address
11	Scenic Lookout	Killiney Hill Park	Killiney Hill
12	Scenic Lookout	Dalkey Hill	Torca Rd
13	Bakery	Country Bake	35 Castle St
14	Health Food Store	Select Stores	Tubbermore Rd

Figure 16. Day 7 route

5. Conclusion

Helping any homeless person in any way possible is everybody’s responsibility, even though governments have the highest capacity to tackle the problem, we should not think the homelessness problem will disappear on its own.

Throughout this project, we have shown how data science can help the homeless to increase their income by providing a list of places where they could find the highest amounts of predefined venues, those that provide the highest amount of alms.

We have obtained the data, cleaned it, and got some preliminary insights about the data. We have refined the scope of locations to be analysed and we have obtained some good results.

We have also used an unsupervised machine learning algorithm for grouping the locations in order to facilitate its understanding.

Finally we have obtained three different groups, showing each group different useful information, and we have come up with a daily route plan for Mr. Florin that would help increase his income.

Hopefully, someday machine algorithms will help humans to have a more equal and prosperous society.