

# **Coursera Capstone**

## **IBM Applied Data Science Capstone**

### ***Opening a New Restaurant in Auckland, New Zealand***



By: Hardik Modha  
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## **Introduction**

The population migration, tourism and busy lifestyle in the financial hub of New Zealand i.e. Auckland, leads to surge in food serving business. The restaurants provide ease to singles, working parents, elderly people and tourists who have some inconvenience with cooking. This shows that this food industry is of bright future in terms of monetary return. As a result there are many restaurants in the Auckland suburbs and more will come. The reality is that many such restaurants fail in few years of their business due to poor planning. The prime factor of this failure is the location of the business. As this industry is highly competitive, the serious consideration should be given when deciding the location of business.

## **Problem Statement**

The main objective of this project is to analyze the location of existing restaurants and to select the best location for new restaurant in the Auckland. By using the data science methodology and machine learning techniques, this project aims at providing solution to the following question:

In the Auckland, if an entrepreneur or investor is looking to establish new restaurant, where would you recommend it?

## **Target Audience**

New Zealand is the popular tourist destination in the world whose tourism industry and hospitality sector are one of the major contributors in the GDP. Also, New Zealand is a prominent venue for many international events, and concerts, which are generally held in Auckland. This makes Auckland the first choice for the investor for any business starts up. This project is prepared by particularly targeting to the local entrepreneur who are novice in this industry and also to the financial investors in making investment decision for opening a new restaurant.

## **Data**

To solve this problem the following data will be needed:

- List of suburbs of Auckland, New Zealand. These suburbs are termed as “Neighborhoods” in this project.
- Latitude and Longitude of those neighborhoods. This coordinates will help in plotting the map and getting the venue data.
- Venue data for the restaurants. This data will be used to perform clusters on these neighborhoods.

## Data Collection and Extraction Method

The Wikipedia page ([https://en.wikipedia.org/wiki/Category:Suburbs\\_of\\_Auckland](https://en.wikipedia.org/wiki/Category:Suburbs_of_Auckland)) contains a list of neighborhoods in Auckland. This will be extracted by using the method of web scraping techniques with the help of Python 'Beautifulsoup' packages. After that we will get the geographical coordinates of the neighborhoods using Python 'Geocoder' package which will give us the latitude and longitude of the neighborhoods.

Once the coordinate are collected we will use Foursquare API to get the venue data for those neighborhoods. The reason for using Foursquare API is that, it has one of the largest databases of 105+ million places and is used by over 125,000 developers. Foursquare API will provide many categories of the venue data; we are particularly interested in the restaurant category in order to help us to solve the business problem put forward.

This project will make use of many data science skills, from web scraping (Wikipedia), working with API (Foursquare), data cleaning, data wrangling, to machine learning (K-means clustering) and map visualization (Folium).

In the next section, we will present the Methodology section where we will discuss the steps taken in this project for the data analysis that we did and the machine learning technique that was used.

## **Methodology**

Firstly, we need to get the list of neighborhoods in the city of Auckland from the Wikipedia page ([https://en.wikipedia.org/wiki/Category:Suburbs\\_of\\_Auckland](https://en.wikipedia.org/wiki/Category:Suburbs_of_Auckland)). We will do web scraping by using Python 'requests' and 'beautifulsoup' packages to extract the list of neighborhoods data. However, this is just a list of names. We need to get the geographical coordinates in the form of latitude and longitude in order to be able to use Foursquare API. To do so, we will use the 'Geocoder' package that will allow us to convert address into geographical coordinates in the form of latitude and longitude. After gathering the data, we will populate the data into a pandas Data Frame and then visualize the neighborhoods in a map using 'Folium' package. This allows us to perform a sanity check to make sure that the geographical coordinate's data returned by 'Geocoder' are correctly plotted in the city of Auckland.

Next, we will use Foursquare API to get the top 100 venues that are within a radius of 2000 meters. We need to register a Foursquare Developer Account in order to obtain the Foursquare ID and Foursquare secret key. We then make API calls to Foursquare passing in the geographical coordinates of the neighborhoods in a Python loop. Foursquare will return the venue data in JSON format and we will extract the venue name, venue category, venue latitude and longitude. With the data, we can check how many venues were returned for each neighborhood and examine how many unique categories can be curated from all the returned venues. Then, we will analyze each neighborhood by grouping the rows by neighborhood and taking the mean of the

frequency of occurrence of each venue category. By doing so, we are also preparing the data for use in clustering. Since we are analyzing the “Restaurant” data, we will filter the “Restaurant” as venue category for the neighborhoods.

Lastly, we will perform clustering on the data by using k-means clustering. K-means clustering algorithm identifies k number of centroids, and then allocates every data point to the nearest cluster, while keeping the centroids as small as possible. It is one of the simplest and popular unsupervised machine learning algorithms and is particularly suited to solve the problem for this project. We will cluster the neighborhoods into 3 clusters based on their frequency of occurrence for “Restaurant”. The results will allow us to identify which neighborhoods have higher concentration of restaurants while which neighborhoods have fewer number of restaurants. Based on the occurrence of restaurants in different neighborhoods, it will help us to answer the question as to which neighborhoods are most suitable to open new restaurants.

## Finding

The results from the k-means clustering show that we can categorize the neighborhoods into 3 clusters based on the frequency of occurrence for “Restaurants”:

- Cluster 0: Neighborhoods with Low number of restaurants
- Cluster 1: Neighborhoods with moderate to high number of restaurants
- Cluster 2: Neighborhoods with high concentration of restaurants

The results of the clustering are visualized in the map below with cluster 0 in red colour, cluster 1 in purple colour, and cluster 2 in mint green colour.



## **Discussion**

As observations noted from the map in the finding section, most of the restaurants are concentrated in the central area of Auckland city, with the highest number in cluster 2 and moderate number in cluster 1. On the other hand, cluster 0 has very low number to no restaurants in the neighborhoods. This represents a great opportunity and high potential areas to open new restaurants as there is very little to no competition from existing restaurants. Meanwhile, restaurants in cluster 2 are likely suffering from intense competition due to oversupply and high concentration of restaurants.

From another perspective, the results also show that the oversupply of restaurants mostly happened in the central area of the city, with the suburb area still have very few restaurants. Therefore, this project recommends property developers to capitalize on these findings to open new restaurants in neighborhoods in cluster 0 with little to no competition. Investors with unique selling propositions to stand out from the competition can also open new restaurants in neighborhoods in cluster 1 with moderate to high competition. Lastly, Investors are advised to avoid neighborhoods in cluster 2 which already have high concentration of restaurants and suffering from intense competition.

## **Limitation and Suggestion for Future Researcher**

In this project, we only consider one factor i.e. frequency of occurrence of restaurants, there are other factors such as population and income of residents that could influence the location decision of a new restaurant. However, to the best knowledge of this researcher such data are not available to the neighborhood level required by this project. Future research could devise a methodology to estimate such data to be used in the clustering algorithm to determine the preferred locations to open a new restaurant. In addition, this project made use of the free Sandbox Tier Account of Foursquare API that came with limitations as to the number of API calls and results returned. Future research could make use of paid account to bypass these limitations and obtain more results.

## **Conclusion**

In this project, we have gone through the process of identifying the business problem, specifying the data required, extracting and preparing the data, performing machine learning by clustering the data into 3 clusters based on their similarities, and lastly providing recommendations to the relevant stakeholders i.e. Local entrepreneurs and investors regarding the best locations to open a new restaurant. To answer the business question that was raised in the introduction section, the answer proposed by this project is: The neighborhoods in cluster 0 are the most preferred locations to open a new restaurant. The findings of this project will help the relevant stakeholders to capitalize on the opportunities on high potential locations while avoiding overcrowded areas in their decisions to open a new restaurant.

## Appendix

### Clusters

#### **Neighborhoods in Cluster – 0**

Airport Oaks	Sandringham,	Murrays Bay	Te Atatū South
Ponsonby	Highbrook	Ōtara	Te Papapa
Remuera	Herne Bay	Shelly Park	Birkenhead
Manukau	Henderson North	Hauraki	Birkdale
Mairangi Bay	Orakei	St Johns	Belmont
Lynfield	Manurewa East	Grey Lynn	Beach Haven
Long Bay	Schnapper Rock	Te Atatū	Bayswater
Rosebank, Auckland	Marlborough	Clover Park	Balmoral
Laingholm	Matakatia	Clevedon	Avondale
Konini	Onehunga	Te Atatū Peninsula	Auckland waterfront
Rosehill	One Tree Hill	Cheltenham	Totara Heights
Rothesay Bay	Northcross	Chatswood	Ardmore
Royal Heights	Oratia	Chapel Downs	Totara Vale
Kauri Park	Northcote Central	Castor Bay	Unsworth Heights
Hunua	North Harbour	Campbells Bay	Viaduct Harbour
Howick	Orere Point	Bucklands Beach	Albany
Homai	Oteha	Point Chevalier	McLaren Park

Hobsonville	Owairaka	Pinehill	Mechanics Bay
Hingaia	New Lynn	Parnell	Penrose
Hillsborough, Auckland	Pahurehure	Mission Bay	Parau
Hillpark, Auckland	Māngere East	Papatoetoe	Morningside
Saint Marys Bay	Māngere Bridge	Pakuranga Heights	Mount Eden
Highland Park	Pakuranga	Crown Hill	Dannemora
Conifer Grove	Duders Point	Stanley Bay	Greenlane
Stanmore Bay	Green Bay	Grafton	Sunnyhills
Glenfield	Glenfield North	Glendowie	Sunnynook
Glen Innes	Glen Eden	Sunnyvale	Devonport
Oranga	Ellerslie	East Coast Bays	Flat Bush
Favona	East Tamaki	Takapuna	Tamaki
Fairview Heights	Epsom	Swanson	Eden Valley
Eden Terrace			

### **Neighborhoods in Cluster – 1**

Forrest Hill	Farm Cove	Kelston	Kohimarama
Cockle Bay	Lincoln	Manukau Heights	Manurewa
Bayview	Browns Bay	Newmarket	Māngere
Massey	Ōtāhuhu	Freemans Bay	Henderson

Rānui	Saint Heliers	Point England	Papakura North
Sandspit	Three Kings	Torbay Heights	Titirangi

**Neighborhoods in Cluster – 2**

Blockhouse Bay	Auckland CBD	New Windsor	Eastern Beach
Goodwood Heights	Stillwater	Newton	Greenmount
Glendene, New Zealand	Brookby	Torbay	The Gardens
Ōpaheke	Stonefields	Arch Hill	Army Bay
Wai o Taiki Bay	Vauxhall	Algies Bay	Clendon Park
Takanini	Alfriston	Tamaki City	Narrow Neck
Mount Wellington	Mount Roskill	Mount Albert	Millwater
Paremoremo	Milford	Middlemore	Mellons Bay
Meadowbank	One Tree Hill	Red Beach	Red Hill
Rosedale	Kingsland	Keri Hill	Royal Oak
Huia	Hillcrest	Highbury	Hatfields Beach
Northcote	Southdown	Greenwoods Corner	Greenhithe
Half Moon Bay			