convert

February 3, 2021

1 The Battle of Neighborhoods

1.1 Section 1 - Introduction/Business Problem

1.1.1 Introduction

Indonesia is a country in Southeast Asia and Oceania, between the Indian and Pacific oceans. It consists of more than seventeen thousand islands, including Sumatra, Java, Sulawesi, and parts of Borneo (Kalimantan) and New Guinea (Papua). Indonesia is the world's largest island country and the 14th-largest country by land area, at 1,904,569 square kilometres (735,358 square miles).

Indonesia is centrally-located along ancient trading routes between the Far East, South Asia and the Middle East, resulting in many cultural practices being strongly influenced by a multitude of religions, including Buddhism, Christianity, Confucianism, Hinduism, and Islam, all strong in the major trading cities. This is why Indonesia is **rich in culture.**

Indonesian cuisine is one of the most diverse, vibrant, and colourful in the world, full of intense flavour. Many regional cuisines exist, often based upon indigenous culture and foreign influences such as Chinese, European, Middle Eastern, and Indian precedents. Rice is the leading staple food and is served with side dishes of meat and vegetables. Spices (notably chilli), coconut milk, fish and chicken are fundamental ingredients. Some popular dishes such as *nasi goreng*, *gado-gado*, *sate*, and *soto* are ubiquitous and considered as national dishes.

1.1.2 Business Idea/Understanding

Indonesian Restaurant that serves all kinds of Indonesian food and beverages. The idea is to introduce Indonesian cultures to the world using Indonesian cuisine as the media. The first step in introducing Indonesian cultures is to gain some exposure from tourist visiting the country. In that case, locate a main tourist destination in Indonesia.

[1]:
```
# Import Libraries
import numpy as np # Library to handle data in a vectorized manner
import pandas as pd # Library for data analysis
import json # Library to handle JSON files
import requests # Library to send HTTP requests using Python


from geopy.geocoders import Nominatim # Convert an address into longitude and␣
 ↪latitude values
```

```
from geopy.extra.rate_limiter import RateLimiter # To perform bulk operations␣
 ↪while gracefully handling error responses and adding delays when needed
from pandas.io.json import json_normalize # Tranform JSON file into a pandas␣
 ↪dataframe

import matplotlib.pyplot as plt # Visualization
import matplotlib.cm as cm
import matplotlib.colors as colors
%matplotlib inline

from sklearn import metrics
from sklearn.cluster import KMeans # Clustering
from sklearn.metrics import silhouette_samples, silhouette_score
from scipy.spatial.distance import cdist

import folium # Map rendering

from bs4 import BeautifulSoup # Library to scrape information from web pages

print('Libraries imported!')
```

```
Libraries imported!
```

Information regarding visitors arrival to Indonesia by port of entry can be found on the internet.

[2]:
```
# Use pandas to scrape table from web page
visit_url = 'https://www.bps.go.id/indicator/16/1017/1/
 ↪jumlah-kedatangan-wisatawan-mancanegara-ke-indonesia-menurut-pintu-masuk.
 ↪html'

request1 = requests.get(visit_url)

visit_url_list = pd.read_html(request1.text)

visit_df = visit_url_list[2]
visit_df = visit_df.droplevel(0, axis=1)
visit_df.head()
```

[2]:

	Bandara	2019	2018	2017
0	Jumlah	16 106 954	15 810 305	14 039 799
1	Bandara Lainnya	5 255 742	4 853 089	3 796 962
2	Batam	1 947 943	1 887 284	1 564 717
3	Kualanamu	244 530	229 586	246 551
4	Ngurah Rai	6 239 543	6 025 760	5 682 248

Since the Dataframe is in Bahasa Indonesia, I am going to translate it to English. The first row of the Dataframe is the **total visitors** that come to Indonesia. Since I need to know the amount of visitors by **each point of entry** and not by total visitors, I have to remove the first row.

[3]:
```
# Remove first row of visit_df dataframe
visit_df = visit_df.drop([0])

# Translate Dataframe
visit_df.columns = ['Airport (Name of Province)', '2019', '2018', '2017']
visit_df.reset_index(inplace=True)
visit_df.drop('index', axis=1, inplace=True)
visit_df['Airport (Name of Province)'] = ['Other Airports', 'Batam (Riau)',␣
↪'Kualanamu (North Sumatra)', 'Ngurah Rai (Bali)', 'Soekarno-Hatta (Jakarta)']
visit_df
```

[3]:

	Airport (Name of Province)	2019	2018	2017
0	Other Airports	5 255 742	4 853 089	3 796 962
1	Batam (Riau)	1 947 943	1 887 284	1 564 717
2	Kualanamu (North Sumatra)	244 530	229 586	246 551
3	Ngurah Rai (Bali)	6 239 543	6 025 760	5 682 248
4	Soekarno-Hatta (Jakarta)	2 419 196	2 814 586	2 749 321

[4]:
```
test = visit_df['2019'].to_list()
print(test)
```

```
['5\u2009255\u2009742', '1\u2009947\u2009943', '244\u2009530',
'6\u2009239\u2009543', '2\u2009419\u2009196']
```

As shown above, column '2019', '2018' and '2017' contain unicode character "u2009" and displayed as "space" character. I need to remove them in order for me to convert the column's datatype to *float*.

[5]:
```
def removeSpace(x):
    if isinstance(x, object):
        return x.replace(u"\u2009", "")
    else:
        return x
```

[6]:
```
visit_df['2019'] = visit_df['2019'].apply(removeSpace)
visit_df['2018'] = visit_df['2018'].apply(removeSpace)
visit_df['2017'] = visit_df['2017'].apply(removeSpace)
visit_df
```

[6]:

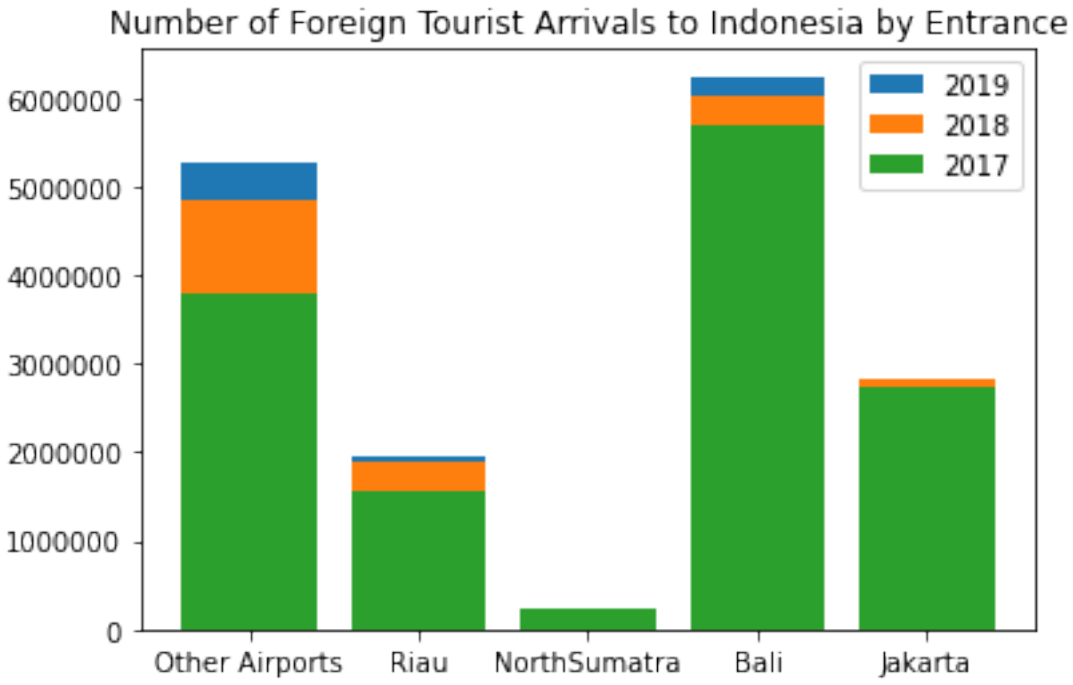
	Airport (Name of Province)	2019	2018	2017
0	Other Airports	5255742	4853089	3796962
1	Batam (Riau)	1947943	1887284	1564717
2	Kualanamu (North Sumatra)	244530	229586	246551
3	Ngurah Rai (Bali)	6239543	6025760	5682248
4	Soekarno-Hatta (Jakarta)	2419196	2814586	2749321

[7]:
```
#Change column datatype from string to float
visit_df['2019'] = visit_df['2019'].astype(float)
```

```
visit_df['2018'] = visit_df['2018'].astype(float)
visit_df['2017'] = visit_df['2017'].astype(float)
```

```
Airport (Name of Province)     object
2019                          float64
2018                          float64
2017                          float64
dtype: object
```

[8]:
```
# Plot the Dataframe
label = ['Other Airports', 'Riau', 'NorthSumatra', 'Bali', 'Jakarta']
fig = plt.figure(figsize=(6, 4))
ax = fig.add_subplot(1, 1, 1)
ax1 = ax.bar(visit_df['Airport (Name of Province)'], visit_df['2019'],␣
 ↪tick_label=label)
ax2 = ax.bar(visit_df['Airport (Name of Province)'], visit_df['2018'],␣
 ↪tick_label=label)
ax3 = ax.bar(visit_df['Airport (Name of Province)'], visit_df['2017'],␣
 ↪tick_label=label)
plt.legend((ax1, ax2, ax3), ('2019', '2018', '2017'))
plt.title('Number of Foreign Tourist Arrivals to Indonesia by Entrance')
plt.gcf().axes[0].yaxis.get_major_formatter().set_scientific(False)
```



Based on the data collected, as of 2019, the main destination for tourist in Indonesia is **Bali**.

Bali is Indonesia's main tourist destination, with a significant rise in tourism since the

1980s. Tourism-related business makes up 80% of its economy.

(https://en.wikipedia.org/wiki/Bali)

That concludes the first section.

1.2 Section 2 - Data Preparation & Foursquare API

1.2.1 Data Preparation

As concluded in section 1, the main destination for tourist in Indonesia is **Bali**. Continuing the discussion from *Business Idea*, in order for the business to thrive, it needs some exposure. The solution to that statement is to find the strategic location to build our restaurant in Bali, where there are alot of venues such as *Hotels*, *Villas*, other *restaurants*, etc..

In this section, my goal is to collect all the information regarding: 1. How many cities are there in Bali province. 2. Each sub-district from every cities. 3. Coordinates (latitude, longitude) from each sub-district. 4. Venues categories in 500m radius from each sub-district coordinates. In order for me to get informaton regarding venues categories, I have to collect it from Foursquare using their API.

This data will have all the information needed that are required for the Explatory Data Analysis and Machine Learning - Clustering model.

1. Collect information regarding cities and regencies in Bali province.

The Bali province is divided into 8 regencies and 1 city. The only city is Denpasar.

[9]:
```
# List of Bali regencies and city
bali_url = 'https://en.wikipedia.org/wiki/Bali'

request2 = requests.get(bali_url)

bali_url_list = pd.read_html(request2.text)

bali_province_df = bali_url_list[2]

bali_province_df = bali_province_df[['Name', 'Capital']]
bali_province_df.drop(9, axis=0)
```

[9]:

	Name	Capital
0	Denpasar City	Denpasar
1	Badung Regency	Mangupura
2	Bangli Regency	Bangli
3	Buleleng Regency	Singaraja
4	Gianyar Regency	Gianyar
5	Jembrana Regency	Negara
6	Karangasem Regency	Amlapura
7	Klungkung Regency	Semarapura
8	Tabanan Regency	Tabanan

2. Collect information regarding sub-districts in Bali province.

Next, I am going to collect sub-district data from each city and regencies.

[10]:
```
# Create function to collect dataframe from webpage
def collectDataframe(url):
    request = requests.get(url)
    url_list = pd.read_html(request.text)
    url_df = url_list[0]
    url_df.drop(url_df.columns[[2, 4]], axis=1, inplace=True)
    return url_df
```

[11]:
```
# Create a list of webpage to collect dataframe
bali_df_list = ['https://kodeposresmi.com/kabupaten-kota/buleleng',
                'https://kodeposresmi.com/kabupaten-kota/buleleng/page/2',
                'https://kodeposresmi.com/kabupaten-kota/buleleng/page/3',
                'https://kodeposresmi.com/kabupaten-kota/buleleng/page/4',
                'https://kodeposresmi.com/kabupaten-kota/buleleng/page/5',
                'https://kodeposresmi.com/kabupaten-kota/buleleng/page/6',
                'https://kodeposresmi.com/kabupaten-kota/buleleng/page/7',
                'https://kodeposresmi.com/kabupaten-kota/buleleng/page/8',
                'https://kodeposresmi.com/kabupaten-kota/buleleng/page/9',
                'https://kodeposresmi.com/kabupaten-kota/buleleng/page/10',
                'https://kodeposresmi.com/kabupaten-kota/buleleng/page/11',
                'https://kodeposresmi.com/kabupaten-kota/buleleng/page/12',
                'https://kodeposresmi.com/kabupaten-kota/buleleng/page/13',
                'https://kodeposresmi.com/kabupaten-kota/buleleng/page/14',
                'https://kodeposresmi.com/kabupaten-kota/buleleng/page/15',
                'https://kodeposresmi.com/kabupaten-kota/denpasar',
                'https://kodeposresmi.com/kabupaten-kota/denpasar/page/2',
                'https://kodeposresmi.com/kabupaten-kota/denpasar/page/3',
                'https://kodeposresmi.com/kabupaten-kota/denpasar/page/4',
                'https://kodeposresmi.com/kabupaten-kota/denpasar/page/5',
                'https://kodeposresmi.com/kabupaten-kota/badung',
                'https://kodeposresmi.com/kabupaten-kota/badung/page/2',
                'https://kodeposresmi.com/kabupaten-kota/badung/page/3',
                'https://kodeposresmi.com/kabupaten-kota/badung/page/4',
                'https://kodeposresmi.com/kabupaten-kota/badung/page/5',
                'https://kodeposresmi.com/kabupaten-kota/badung/page/6',
                'https://kodeposresmi.com/kabupaten-kota/badung/page/7',
                'https://kodeposresmi.com/kabupaten-kota/bangli',
                'https://kodeposresmi.com/kabupaten-kota/bangli/page/2',
                'https://kodeposresmi.com/kabupaten-kota/bangli/page/3',
                'https://kodeposresmi.com/kabupaten-kota/bangli/page/4',
                'https://kodeposresmi.com/kabupaten-kota/bangli/page/5',
                'https://kodeposresmi.com/kabupaten-kota/bangli/page/6',
                'https://kodeposresmi.com/kabupaten-kota/bangli/page/7',
                'https://kodeposresmi.com/kabupaten-kota/bangli/page/8',
                'https://kodeposresmi.com/kabupaten-kota/gianyar',
```

```
                'https://kodeposresmi.com/kabupaten-kota/gianyar/page/2',
                'https://kodeposresmi.com/kabupaten-kota/gianyar/page/3',
                'https://kodeposresmi.com/kabupaten-kota/gianyar/page/4',
                'https://kodeposresmi.com/kabupaten-kota/gianyar/page/5',
                'https://kodeposresmi.com/kabupaten-kota/gianyar/page/6',
                'https://kodeposresmi.com/kabupaten-kota/gianyar/page/7',
                'https://kodeposresmi.com/kabupaten-kota/jembrana',
                'https://kodeposresmi.com/kabupaten-kota/jembrana/page/2',
                'https://kodeposresmi.com/kabupaten-kota/jembrana/page/3',
                'https://kodeposresmi.com/kabupaten-kota/jembrana/page/4',
                'https://kodeposresmi.com/kabupaten-kota/jembrana/page/5',
                'https://kodeposresmi.com/kabupaten-kota/jembrana/page/6',
                'https://kodeposresmi.com/kabupaten-kota/karangasem',
                'https://kodeposresmi.com/kabupaten-kota/karangasem/page/2',
                'https://kodeposresmi.com/kabupaten-kota/karangasem/page/3',
                'https://kodeposresmi.com/kabupaten-kota/karangasem/page/4',
                'https://kodeposresmi.com/kabupaten-kota/karangasem/page/5',
                'https://kodeposresmi.com/kabupaten-kota/karangasem/page/6',
                'https://kodeposresmi.com/kabupaten-kota/karangasem/page/7',
                'https://kodeposresmi.com/kabupaten-kota/karangasem/page/8',
                'https://kodeposresmi.com/kabupaten-kota/klungkung',
                'https://kodeposresmi.com/kabupaten-kota/klungkung/page/2',
                'https://kodeposresmi.com/kabupaten-kota/klungkung/page/3',
                'https://kodeposresmi.com/kabupaten-kota/klungkung/page/4',
                'https://kodeposresmi.com/kabupaten-kota/klungkung/page/5',
                'https://kodeposresmi.com/kabupaten-kota/klungkung/page/6',
                'https://kodeposresmi.com/kabupaten-kota/tabanan',
                'https://kodeposresmi.com/kabupaten-kota/tabanan/page/2',
                'https://kodeposresmi.com/kabupaten-kota/tabanan/page/3',
                'https://kodeposresmi.com/kabupaten-kota/tabanan/page/4',
                'https://kodeposresmi.com/kabupaten-kota/tabanan/page/5',
                'https://kodeposresmi.com/kabupaten-kota/tabanan/page/6',
                'https://kodeposresmi.com/kabupaten-kota/tabanan/page/7',
                'https://kodeposresmi.com/kabupaten-kota/tabanan/page/8',
                'https://kodeposresmi.com/kabupaten-kota/tabanan/page/9',
                'https://kodeposresmi.com/kabupaten-kota/tabanan/page/10',
                'https://kodeposresmi.com/kabupaten-kota/tabanan/page/11',
                'https://kodeposresmi.com/kabupaten-kota/tabanan/page/12',
                'https://kodeposresmi.com/kabupaten-kota/tabanan/page/13',
                'https://kodeposresmi.com/kabupaten-kota/tabanan/page/14'
                ]
```

[12]:
```
# Create an empty Dataframe bali_df and append the iterated bali_df_list object
bali_df = pd.DataFrame()
for i in bali_df_list:
    df_i = collectDataframe(i)
    bali_df = bali_df.append(df_i, ignore_index=True)
```

```
# Filter dataframe to only include word 'Bali' in 'Provinsi' (province) column
bali_df = bali_df[bali_df['Provinsi'].str.contains(r'(?:\s|^)Bali(?:\s|$)')]

# Check dataframe size - The correct size should be 687
print(bali_df.shape)
bali_df.head()
```

```
(717, 3)
```

[12]:

	Provinsi	Kabupaten/Kota	Kelurahan
0	Bali	Kabupaten Buleleng	Banjar
1	Bali	Kabupaten Buleleng	Banjar Tegeha
2	Bali	Kabupaten Buleleng	Banyuatis
3	Bali	Kabupaten Buleleng	Banyusri
4	Bali	Kabupaten Buleleng	Cempaga

[13]:
```
bali_df.drop_duplicates(subset='Kelurahan',keep='first',inplace=True)
print(bali_df.shape)
```

```
(687, 3)
```

Bali province has 687 sub-districts.

3. Collecting coordinates from each sub-district in Bali province.

The next step in this data preparation section is to collect *coordinates* from each sub-district in Bali. These coordinates will be used later in the **Foursquare API** to collect *venue categories*, and those categories will be used to build **Machine Learning - Clustering** model to help us in locating a strategic location to build the restaurant in Bali.

[14]:
```
# Rename column names
bali_df.columns = ['Province', 'Regency/City', 'Sub-District']

# Create new column called 'Geocoder' to improve the accuracy of the geocode
bali_df["Geocoder"] = bali_df["Sub-District"] + ", Bali, Indonesia"
bali_df.head()
```

[14]:

	Province	Regency/City	Sub-District	Geocoder
0	Bali	Kabupaten Buleleng	Banjar	Banjar, Bali, Indonesia
1	Bali	Kabupaten Buleleng	Banjar Tegeha	Banjar Tegeha, Bali, Indonesia
2	Bali	Kabupaten Buleleng	Banyuatis	Banyuatis, Bali, Indonesia
3	Bali	Kabupaten Buleleng	Banyusri	Banyusri, Bali, Indonesia
4	Bali	Kabupaten Buleleng	Cempaga	Cempaga, Bali, Indonesia

[17]:
```
# Using Nominatim geocoder API
geolocator = Nominatim(user_agent='chris_p_bacon_') #crispy bacon! xD
geocode = RateLimiter(geolocator.geocode, min_delay_seconds=1)
bali_df['Location'] = bali_df['Geocoder'].apply(geocode)
```

[18]:
```
# Check 'None' value
bali_df['Location'].isnull().sum()
```

[18]:
```
43
```

There are 43 sub-districts that have 'None' value due to inconsistency in the spelling (e.g., Banyusri spelled as Banyuseri). Since it will take alot of time to replace the value one-by-one, I am going to remove it.

[19]:
```
# Remove 'None' value
bali_df = bali_df.loc[bali_df['Location'].isnull() == False]
bali_df.shape
```

[19]:
```
(644, 5)
```

[20]:
```
# Create 'Latitude' and 'Longitude' columns
bali_df['Latitude'] = bali_df['Location'].apply(lambda loc: loc.latitude)
bali_df['Longitude'] = bali_df['Location'].apply(lambda loc: loc.longitude)
bali_df.head()
```

[20]:

	Province	Regency/City	Sub-District	Geocoder	Location	Latitude	Longitude
0	Bali	Kabupaten Buleleng	Banjar	Banjar, Bali, Indonesia	(Banjar, Bali, Indonesia, (-8.2050113, 114.967…	-8.205011	114.967194
1	Bali	Kabupaten Buleleng	Banjar Tegeha	Banjar Tegeha, Bali, Indonesia	(Banjar Tegeha, Bali, Indonesia, (-8.2042161, …	-8.204216	114.978203
2	Bali	Kabupaten Buleleng	Banyuatis	Banyuatis, Bali, Indonesia	(Banyuatis, Bali, Indonesia, (-8.2629358, 115…	-8.262936	115.031525
4	Bali	Kabupaten Buleleng	Cempaga	Cempaga, Bali, Indonesia	(Cempaga, Bali, 80613, Indonesia, (-8.4430303,…	-8.443030	115.355613
5	Bali	Kabupaten Buleleng	Dencarik	Dencarik, Bali, Indonesia	(Dencarik, Bali, Indonesia, (-8.1857459, 114.9…	-8.185746	114.982595

[21]:
```
# Reset index
bali_df = bali_df.reset_index(drop=True)
```

Since I have collected the coordinates for each sub-district, **'Location'** column is no longer necessary.

[22]:
```
# Drop 'Location' columns
bali_df.drop(columns=['Location'])
bali_df.head()
```

[22]:

	Province	Regency/City	Sub-District	Geocoder
0	Bali	Kabupaten Buleleng	Banjar	Banjar, Bali, Indonesia
1	Bali	Kabupaten Buleleng	Banjar Tegeha	Banjar Tegeha, Bali, Indonesia
2	Bali	Kabupaten Buleleng	Banyuatis	Banyuatis, Bali, Indonesia
3	Bali	Kabupaten Buleleng	Cempaga	Cempaga, Bali, Indonesia

```
4     Bali  Kabupaten Buleleng       Dencarik       Dencarik, Bali, Indonesia

                                                Location  Latitude   Longitude
0  (Banjar, Bali, Indonesia, (-8.2050113, 114.967… -8.205011  114.967194
1  (Banjar Tegeha, Bali, Indonesia, (-8.2042161, … -8.204216  114.978203
2  (Banyuatis, Bali, Indonesia, (-8.2629358, 115… -8.262936  115.031525
3  (Cempaga, Bali, 80613, Indonesia, (-8.4430303,… -8.443030  115.355613
4  (Dencarik, Bali, Indonesia, (-8.1857459, 114.9… -8.185746  114.982595
```

These are the locations of each sub-district as seen on the map.

[24]:
```
# Collect Bali's coordinate
coord_bali = 'Bali, Indonesia'
geolocator_bali = Nominatim(user_agent='chris_p_bacon_xD')
location_bali = geolocator_bali.geocode(coord_bali)
latitude_bali = location_bali.latitude
longitude_bali = location_bali.longitude
print('The geographical coordinate of Bali are {}, {}'.format(latitude_bali,␣
 ↪longitude_bali))

# Create map of Bali
map_bali = folium.Map(location=[latitude_bali, longitude_bali], zoom_start=9.5)

# Add markers to the map
for lat, lng, dist in zip(bali_df['Latitude'], bali_df['Longitude'],␣
 ↪bali_df['Geocoder']):
    label = '{}'.format(dist)
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker([lat, lng],
                        radius=5,
                        popup=label,
                        color='blue',
                        fill=True,
                        fill_color='#FFD700',
                        fill_opacity=0.7,
                        parse_html=False).add_to(map_bali)

map_bali
```

```
The geographical coordinate of Bali are -8.3304977, 115.0906401
```

[24]:
```
<folium.folium.Map at 0xad0f2f5e80>
```

4. Collecting venues location in 500m radius from each sub-district.

In this section, I am going to collect information about venues location from each sub-district. To gain information regarding those venues, I have to use Foursquare API. **Foursquare** lets users search for restaurants, nightlife spots, shops and other places in a location. The app displays personalized recommendations based on factors that include the time of day, a user's check-in

history, their "Tastes" and their venue ratings. I am going to use Foursquare to collect nearby *venues information* from each sub-district's location using its coordinate (**latitude** and **longitude**).

[28]:
```
# Setup Foursquare credentials
CLIENT_ID = '3KHGUYZDYHRJXPMI4WUX5YY2QO021DZUJOGENJUZWAZ2CARH'
CLIENT_SECRET = '3RMCQMDYOM3RB5DDLMC2JCJ2DKW4KIFOZODPTMSMAE2ILOBQ'
VERSION = '20210101' # January 1st, 2021
LIMIT = 100 # default Foursquare API limit value
```

[29]:
```
# Create a function to repeat the process of collecting venues for each␣
↪sub-district
def getNearbyVenues(names, latitudes, longitudes, radius=500): # set radius to␣
↪500 meters

    venues_list = [] #Create an empty list

    for name, lat, lng in zip(names, latitudes, longitudes):
        #Create Foursquare API request URL
        fsq_url = 'https://api.foursquare.com/v2/venues/explore?
↪&client_id={}&client_secret={}&v={}&ll={},{}&radius={}&limit={}'.format(
            CLIENT_ID,
            CLIENT_SECRET,
            VERSION,
            lat,
            lng,
            radius,
            LIMIT)

        # Make the GET request
        results = requests.get(fsq_url).json()["response"]['groups'][0]['items']

        # Collect only relevant information for each nearby venue
        venues_list.append([(
            name,
            lat,
            lng,
            v['venue']['name'],
            v['venue']['location']['lat'],
            v['venue']['location']['lng'],
            v['venue']['categories'][0]['name']) for v in results])

    # Save it into Dataframe
    nearby_venues = pd.DataFrame([item for venue_list in venues_list for item␣
↪in venue_list])
    nearby_venues.columns = ['Sub-District',
                  'Sub-District Latitude',
                  'Sub-District Longitude',
```

```
                  'Venue',
                  'Venue Latitude',
                  'Venue Longitude',
                  'Venue Category']

    return(nearby_venues)
```

Save the newly acquired information about venues in Bali into a new Dataframe.

[30]:
```
bali_venues = getNearbyVenues(names=bali_df['Sub-District'],
                              latitudes=bali_df['Latitude'],
                              longitudes=bali_df['Longitude'])
```

[31]:
```
# Check the shape of new ataframe
print(bali_venues.shape)
bali_venues.head()
```

```
(1612, 7)
```

[31]:

	Sub-District	Sub-District Latitude	Sub-District Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Banjar	-8.205011	114.967194	Hot spring	-8.208671	114.967020	Pool
1	Banyuatis	-8.262936	115.031525	Dapur Hex	-8.264121	115.027539	Salad Place
2	Dencarik	-8.185746	114.982595	Cocoa Grounds	-8.185030	114.980930	Indonesian Restaurant
3	Gesing	-8.278434	115.054750	Banyan Tree	-8.281326	115.056206	Tree
4	Kaliasem	-8.170993	115.024820	villa nyoman	-8.170865	115.024815	Restaurant

[32]:
```
# Save to .csv
bali_venues.to_csv('bali_venues.csv', index=False)
```

Now let's see how many sub-districts that have venues in 500m radius around it.

[42]:
```
venues_bali = bali_venues['Sub-District'].unique()
```

There are 315 sub-districts that have 1 or more venues. Since the goal of this business idea is to find more exposure, that means we have to exclude those sub-districts that have no venues from the 'bali_df' dataframe. The reason behind it is because I will use 'bali_df' dataframe to be merged with cluster labels resulted from machine learning clustering model in the next section (Section 3).

[45]:
```
bali_df = bali_df.loc[bali_df['Sub-District'].isin(venues_bali) == True]
```

[48]:
```
bali_df.shape
```

[48]: (315, 7)

[47]:
```
# Save 'bali_df' to csv
bali_df.to_csv('bali_df.csv', index=False)
```

These are the data that will be used in the Exploratory Data Analysis and to build a Machine Learning - Clustering model to find the location to build the restaurant.

1.3 Section 3 - Exploratory Data Analysis & Clustering Model

In this section, as discussed at the end of section 2, I will explore the dataset and build clustering model based on venues frequencies. The goal of this project is to find the suitable location to build the restaurant. The business idea is to let visitors from other countries to try Indonesian cuisine. To achieve the business idea goal, I need to have more exposure so that people will recognize the restaurant. So that means, I have to find locations where there are alot of venues nearby. So, in short: More Venues = More People = More Exposure **Goal = More Exposure** :D

1.3.1 Exploratory Data Analysis

Let's explore the dataset by looking at how many venue categories are there per sub-district, as well as its unique categories.

To save time from going through Nominatim and Foursquare API, I have saved the dataframe in 'bali_venues' object locally, and I will import that DataFrame to do some exploratory data analysis.

[49]:
```
# Read bali_venues.csv
bali_venue = pd.read_csv('bali_venues.csv')
bali_venue.head()
```

[49]:

	Sub-District	Sub-District Latitude	Sub-District Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Banjar	-8.205011	114.967194	Hot spring	-8.208671	114.967020	Pool
1	Banyuatis	-8.262936	115.031525	Dapur Hex	-8.264121	115.027539	Salad Place
2	Dencarik	-8.185746	114.982595	Cocoa Grounds	-8.185030	114.980930	Indonesian Restaurant
3	Gesing	-8.278434	115.054750	Banyan Tree	-8.281326	115.056206	Tree
4	Kaliasem	-8.170993	115.024820	villa nyoman	-8.170865	115.024815	Restaurant

[50]:
```
# Groupby Sub-District
print(bali_venue.shape)
bali_venue.groupby('Sub-District').count().head()
```

(1612, 7)

[50]:
```
              Sub-District Latitude  Sub-District Longitude  Venue  \
Sub-District
Ababi                             2                       2      2
Abang                             1                       1      1
Abian Tuwung                      1                       1      1
Abianbase                         2                       2      2
Akah                              1                       1      1

              Venue Latitude  Venue Longitude  Venue Category
Sub-District
Ababi                      2                2               2
Abang                      1                1               1
Abian Tuwung               1                1               1
Abianbase                  2                2               2
Akah                       1                1               1
```

[51]:
```
# Unique venue category
print('There are {} unique venue categories.'.format(len(bali_venue['Venue␣
 ↪Category'].unique())))
```

```
There are 231 unique venue categories.
```

Let's do some data exploration. I need to see the **frequency of occurrences** of each venue category. To do that, I have to convert the category datatype from string to boolean (binary) using a method called **One Hot Encoding**. But its not that hot. xD

[52]:
```
# One Hot Encoding
bali_onehot = pd.get_dummies(bali_venue[['Venue Category']], prefix='',␣
 ↪prefix_sep='')

# Add 'Sub-District' column
bali_onehot['Sub-District'] = bali_venue['Sub-District']

# Move 'Sub-District' column to the first column
fixed_columns = [bali_onehot.columns[-1]] + list(bali_onehot.columns[:-1])
bali_onehot = bali_onehot[fixed_columns]

print(bali_onehot.shape)
bali_onehot.head()
```

```
(1612, 232)
```

[52]:

	Sub-District	ATM	Accessories Store	American Restaurant	Antique Shop	\
0	Banjar	0	0	0	0	
1	Banyuatis	0	0	0	0	
2	Dencarik	0	0	0	0	
3	Gesing	0	0	0	0	
4	Kaliasem	0	0	0	0	

```
   Arcade  Arepa Restaurant  Art Gallery  Art Museum  Arts & Crafts Store  \
0       0                 0            0           0                    0
1       0                 0            0           0                    0
2       0                 0            0           0                    0
3       0                 0            0           0                    0
4       0                 0            0           0                    0

   …  Vacation Rental  Vape Store  Vegetarian / Vegan Restaurant  \
0  …                0           0                              0
1  …                0           0                              0
2  …                0           0                              0
3  …                0           0                              0
4  …                0           0                              0

   Video Game Store  Volleyball Court  Water Park  Waterfall  Wine Shop  \
0                 0                 0           0          0          0
1                 0                 0           0          0          0
2                 0                 0           0          0          0
3                 0                 0           0          0          0
4                 0                 0           0          0          0

   Wings Joint  Yoga Studio
0            0            0
1            0            0
2            0            0
3            0            0
4            0            0

[5 rows x 232 columns]
```

Now we can finally get the **frequency of occurences** of each venue category.

[53]:
```
# Groupby 'Sub-District'
bali_grouped = bali_onehot.groupby('Sub-District').mean().reset_index()
bali_grouped.head()
```

[53]:
```
   Sub-District  ATM  Accessories Store  American Restaurant  Antique Shop  \
0         Ababi  0.0                0.0                  0.0           0.0
1         Abang  0.0                0.0                  0.0           0.0
2  Abian Tuwung  0.0                0.0                  0.0           0.0
3     Abianbase  0.0                0.0                  0.5           0.0
4          Akah  0.0                0.0                  1.0           0.0

   Arcade  Arepa Restaurant  Art Gallery  Art Museum  Arts & Crafts Store  \
0     0.0               0.0          0.0         0.0                  0.0
1     0.0               0.0          0.0         0.0                  0.0
2     0.0               0.0          0.0         0.0                  0.0
3     0.0               0.0          0.0         0.0                  0.0
```

```
4     0.0                0.0          0.0         0.0                    0.0

   …  Vacation Rental  Vape Store  Vegetarian / Vegan Restaurant  \
0  …              0.0         0.0                            0.0
1  …              0.0         0.0                            0.0
2  …              0.0         0.0                            0.0
3  …              0.0         0.0                            0.0
4  …              0.0         0.0                            0.0

   Video Game Store  Volleyball Court  Water Park  Waterfall  Wine Shop  \
0               0.0               0.0         0.0        0.0        0.0
1               0.0               1.0         0.0        0.0        0.0
2               0.0               0.0         0.0        0.0        0.0
3               0.0               0.0         0.0        0.0        0.0
4               0.0               0.0         0.0        0.0        0.0

   Wings Joint  Yoga Studio
0          0.0          0.0
1          0.0          0.0
2          0.0          0.0
3          0.0          0.0
4          0.0          0.0

[5 rows x 232 columns]
```

[54]:
```
# Check dataframe size
bali_grouped.shape
```

[54]:
```
(315, 232)
```

I have managed to get the frequency of occurences from each category. Now I can explore which type of venue is **most common in each sub-district.**

[55]:
```
# Create a function to sort the most common venues in descending order
def most_common_venues(row, top_n_venues):
    row_categories = row.iloc[1:]
    row_categories_sorted = row_categories.sort_values(ascending=False)
    return row_categories_sorted.index.values[0:top_n_venues]
```

[56]:
```
top_n_venues = 3
indicators = ['st', 'nd', 'rd']

# Create columns according to number of top venues
columns = ['Sub-District']
for ind in np.arange(top_n_venues):
    columns.append('{}{} Most common venue'.format(ind+1, indicators[ind]))

# Create a new dataframe
```

```
subdist_venues_sorted = pd.DataFrame(columns=columns)
subdist_venues_sorted['Sub-District'] = bali_grouped['Sub-District']

for ind in np.arange(bali_grouped.shape[0]):
    subdist_venues_sorted.iloc[ind, 1:] = most_common_venues(bali_grouped.
 ↪iloc[ind, 1:], top_n_venues)

print(subdist_venues_sorted.shape)
subdist_venues_sorted.head()
```

```
(315, 4)
```

[56]:

	Sub-District	1st Most common venue	2nd Most common venue	3rd Most common venue
0	Ababi	Convenience Store	Coffee Shop	Accessories Store
1	Abang	Volleyball Court	Accessories Store	Outdoors & Recreation
2	Abian Tuwung	Indonesian Restaurant	Accessories Store	Outdoors & Recreation
3	Abianbase	American Restaurant	Hunting Supply	Outdoors & Recreation
4	Akah	American Restaurant	Outdoors & Recreation	Multiplex

Now we are ready to build the **Clustering** model!

1.3.2 Machine Learning - Clustering Model

First things first, let's recall the scatter plot of sub-district from map of Bali.

[57]:
```
# map of Bali
map_bali
```

[57]:
```
<folium.folium.Map at 0xad0f2f5e80>
```

Usually, based on the shape of the scatter plot, we can already tell what is the appropriate value for **k**. (k = number of clusters) But, in this case, I have to find the appropriate value for k. One of the method to do that is by using **Elbow method**. Elbow method is an approach used in determining the number of clusters in the dataset. The method consists of plotting the explained variation as a function of the number of clusters, and picking the elbow of the curve as the number of clusters to use.

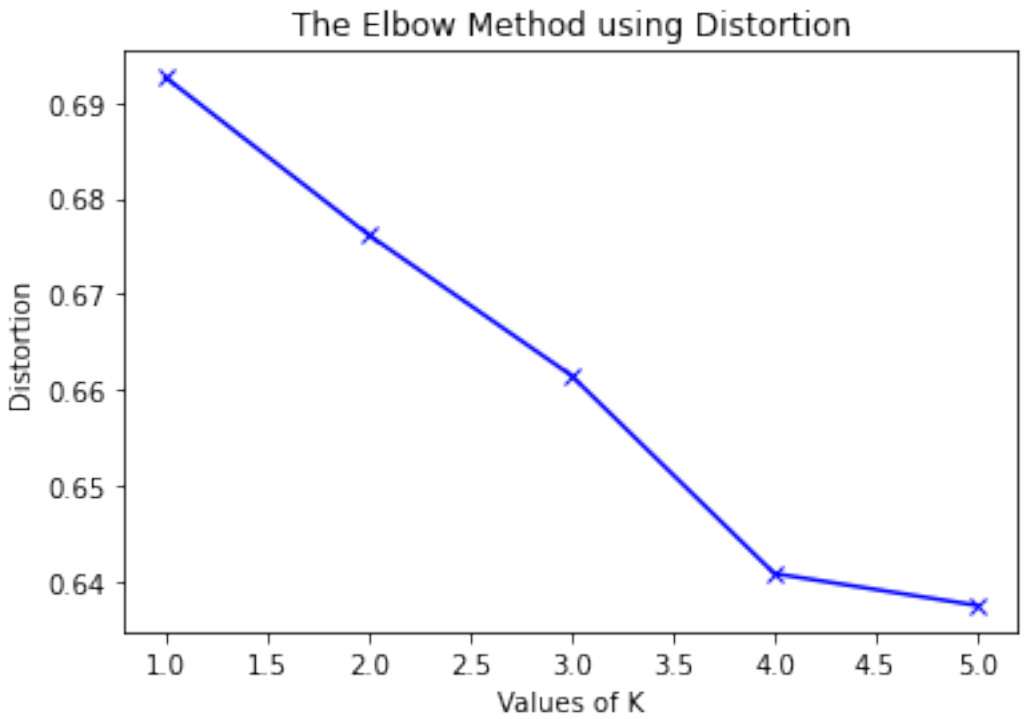
So this is what I am going to do: 1. Repeatedly build a clustering model, using different k value starting from 1 up to 10. 2. Evaluate each model by calculating its Inertia and Distortion. 3. Once I managed to get the right k value, I will build the "appropriate" clustering model.

Step 1 - Clustering model using different k value starting from 1 up to 5

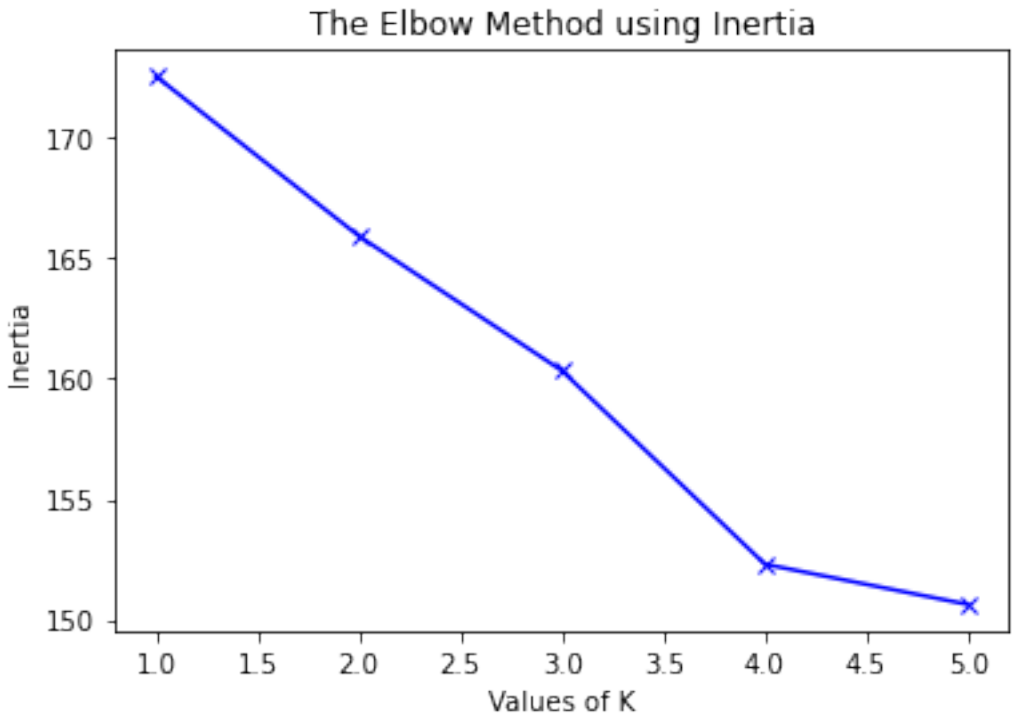
[58]:
```
# Initiate object for clustering dataset
bali_clustering = bali_grouped.drop('Sub-District', 1)

# Build ML clustering model
K = range(1, 6)
distortions = [] # Empty list for distortions
inertias = [] # Empty list for inertia

for k in K:
    # Building and fitting the model
    KMeansModel = KMeans(n_clusters=k, random_state=4)
    KMeansModel.fit(bali_clustering)

    distortions.append(sum(np.min(cdist(bali_clustering, KMeansModel.
 ↪cluster_centers_, 'euclidean'), axis=1)) / bali_clustering.shape[0])
    inertias.append(KMeansModel.inertia_)
```

Step 2 - Evaluate each model's inertia and distortion

[59]:
```
# Visualize the different value of Distortions
plt.plot(K, distortions, 'bx-')
plt.xlabel('Values of K')
plt.ylabel('Distortion')
plt.title('The Elbow Method using Distortion')
plt.show()
```



[60]:
```
# Visualize the different value of Inertia
plt.plot(K, inertias, 'bx-')
plt.xlabel('Values of K')
plt.ylabel('Inertia')
plt.title('The Elbow Method using Inertia')
plt.show()
```



Based on our findings, I think it is safe to choose the value of clusters = 4.

3. Build clustering model

[61]:
```
# Build clustering model
n_clusters = 4 # number of clusters

KMeansModel_bali = KMeans(n_clusters=n_clusters, random_state=4).
 ↪fit(bali_clustering)
KMeansModel_bali.fit(bali_clustering)
cluster_labels = KMeansModel_bali.labels_

print(np.unique(cluster_labels))
```

```
[0 1 2 3]
```

Now let's add the result from the clustering model into the 'bali_clustering' dataframe, and merge

it with 'bali_df' dataframe.

[62]:
```
# Add clustering labels
subdist_venues_sorted.insert(0, 'Cluster Labels', cluster_labels)

# Collect 'bali_df' data and save it to bali_merged object
bali_merged = bali_df

# Merge 'bali_df' with 'subdist_venues_sorted'
bali_merged = bali_merged.join(subdist_venues_sorted.set_index('Sub-District'),␣
↪on='Sub-District')
```

[65]:
```
print(subdist_venues_sorted.shape)
print(bali_merged.shape)
bali_merged.head()
```

```
(315, 5)
(315, 11)
```

[65]:

	Province	Regency/City	Sub-District	Geocoder	Location	Latitude	Longitude	Cluster Labels	1st Most common venue	2nd Most common venue	3rd Most common venue
0	Bali	Kabupaten Buleleng	Banjar	Banjar, Bali, Indonesia	(Banjar, Bali, Indonesia, (-8.2050113, 114.967…	-8.205011	114.967194	1	Pool	Accessories Store	Outdoor Supply Store
2	Bali	Kabupaten Buleleng	Banyuatis	Banyuatis, Bali, Indonesia	(Banyuatis, Bali, Indonesia, (-8.2629358, 115…	-8.262936	115.031525	1	Salad Place	Accessories Store	Outdoors & Recreation
4	Bali	Kabupaten Buleleng	Dencarik	Dencarik, Bali, Indonesia	(Dencarik, Bali, Indonesia, (-8.1857459, 114.9…	-8.185746	114.982595	1	Indonesian Restaurant	Accessories Store	Outdoors & Recreation
5	Bali	Kabupaten Buleleng	Gesing	Gesing, Bali, Indonesia	(Gesing, Bali, 81152 BALI, Indonesia, (-8.2784…	-8.278434	115.054750	1	Tree	Accessories Store	Outdoors & Recreation
7	Bali	Kabupaten Buleleng	Kaliasem	Kaliasem, Bali, Indonesia	(Kaliasem, Bali, 00362, Indonesia, (-8.1709929…	-8.170993	115.024820	1	Seafood Restaurant	Boat or Ferry	Restaurant

Then finally I can visualize the resulting clusters.

1.4 Section 4 - Results & Examination

1.4.1 Results

1. Map of Bali with clusters

I am going to create map of Bali with sub-districts superimposed on top.

[64]:
```
# Create map of bali with sub-district superimposed on top
map_bali_clusters = folium.Map(location=[latitude_bali, longitude_bali],␣
 ↪zoom_start=9.5)

# Set color scheme for the clusters
x = np.arange(n_clusters)
ys = [i + x + (i*x)**2 for i in range(n_clusters)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

# Add markers to the map
for lat, lon, dist, cluster in zip(bali_merged['Latitude'],␣
 ↪bali_merged['Longitude'], bali_merged['Sub-District'], bali_merged['Cluster␣
 ↪Labels']):
    label = folium.Popup(str(dist) + ' Cluster ' + str(cluster),␣
 ↪parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_bali_clusters)

map_bali_clusters
```

[64]:
```
<folium.folium.Map at 0xad111d0c40>
```

The reason why the markers on the map do not resemble shape of clusters is because the clustering model was build based on frequency of occurences from venues of each sub-district, and not from coordinates (latitude, longitude) of each sub-district.

Result 2 - Most common venues of each clusters

Cluster 0

[71]:
```
bali_merged.loc[bali_merged['Cluster Labels'] == 0, bali_merged.columns[[2] +␣
 ↪list(range(8, bali_merged.shape[1]))]].head(10)
```

[71]:

	Sub-District	1st Most common venue	2nd Most common venue	\
60	Musi	Convenience Store	Asian Restaurant	

```
133  Sambirenteng   Balinese Restaurant      Convenience Store
147  Tegal Kertha                Arcade             Food Truck
149     Pedungan     Convenience Store     Chinese Restaurant
177        Tonja     Convenience Store  Indonesian Restaurant
193  Sibang Gede                 River      Accessories Store
208       Dalung     Convenience Store      Accessories Store
211    Tibubeneng     Convenience Store       Asian Restaurant
225       Sading     Convenience Store       Asian Restaurant
264        Catur     Convenience Store      Accessories Store

     3rd Most common venue
60    Outdoor Supply Store
133           Outlet Store
147     Convenience Store
149             BBQ Joint
177        Breakfast Spot
193  Outdoors & Recreation
208           Outlet Store
211            Sports Club
225     Accessories Store
264           Outlet Store
```

Cluster 1

[72]:
```
bali_merged.loc[bali_merged['Cluster Labels'] == 1, bali_merged.columns[[2] +␣
↪list(range(8, bali_merged.shape[1]))]].head(10)
```

[72]:
```
   Sub-District  1st Most common venue  2nd Most common venue  \
0        Banjar                   Pool      Accessories Store
2     Banyuatis            Salad Place      Accessories Store
4      Dencarik  Indonesian Restaurant      Accessories Store
5        Gesing                   Tree      Accessories Store
7      Kaliasem     Seafood Restaurant          Boat or Ferry
13      Temukus     Seafood Restaurant                 Resort
16   Alasangker                   Café      Accessories Store
18       Astina                  Field      Accessories Store
19  Banjar Bali   Fast Food Restaurant  Indonesian Restaurant
20  Banjar Jawa  Indonesian Restaurant     Dim Sum Restaurant

    3rd Most common venue
0    Outdoor Supply Store
2   Outdoors & Recreation
4   Outdoors & Recreation
5   Outdoors & Recreation
7              Restaurant
13   Other Great Outdoors
16  Outdoors & Recreation
18               Mountain
```

```
19     Basketball Stadium
20            Coffee Shop
```

Cluster 2

[73]:
```
bali_merged.loc[bali_merged['Cluster Labels'] == 2, bali_merged.columns[[2] +␣
↪list(range(8, bali_merged.shape[1]))]].head(10)
```

[73]:
```
              Sub-District 1st Most common venue 2nd Most common venue  \
100              Gunungsari              Mountain       Motorcycle Shop
244                Pengotan              Mountain       Motorcycle Shop
250                   Banua              Mountain       Motorcycle Shop
259                 Belanga             BBQ Joint              Mountain
275                 Mengani              Mountain       Motorcycle Shop
278                   Satra              Mountain       Motorcycle Shop
287                Terunyan              Mountain         Shopping Mall
292                 Sulahan              Mountain       Motorcycle Shop
427  Bungaya (Bungaya Kauh)              Mountain       Motorcycle Shop
431                 Sibetan              Mountain       Motorcycle Shop

    3rd Most common venue
100             Multiplex
244             Multiplex
250             Multiplex
259    Accessories Store
275             Multiplex
278             Multiplex
287  Outdoor Supply Store
292             Multiplex
427             Multiplex
431             Multiplex
```

Cluster 3

[70]:
```
bali_merged.loc[bali_merged['Cluster Labels'] == 3, bali_merged.columns[[2] +␣
↪list(range(8, bali_merged.shape[1]))]].head()
```

[70]:
```
    Sub-District 1st Most common venue 2nd Most common venue  \
15     Tirtasari                  Farm     Accessories Store
40   Poh Bergong                  Farm      Asian Restaurant
101      Joanyar                  Farm     Accessories Store
132   Penuktukan                  Farm      Asian Restaurant
239      Bunutin                  Farm     Accessories Store

    3rd Most common venue
15              Mountain
40     Accessories Store
101             Mountain
```

```
132     Accessories Store
239              Mountain
```

Based on the results of each clusters, it appears that each clusters have their own types of venues. **Cluster 0** is the *sub-urb areas* in Bali. **Cluster 1** is mostly the *urban areas* in Bali. (With a view sub-districts as suburb.) **Cluster 2** is the *recreational sites* in Bali. **Cluster 3** is the *rural areas* in Bali.

[81]:
```
# Replacing Cluster Label values & replace index
bali_merged.reset_index(drop=True, inplace=True)
bali_merged['Cluster Labels'] = bali_merged['Cluster Labels'].replace([0, 1, 2,␣
↪3],['Suburb','Urban-Suburb','Recreational Site','Rural'])
```

[82]:
```
# Check the result
bali_merged.head()
```

[82]:

	Province	Regency/City	Sub-District	Geocoder	Location	Latitude	Longitude	Cluster Labels	1st Most common venue	2nd Most common venue	3rd Most common venue
0	Bali	Kabupaten Buleleng	Banjar	Banjar, Bali, Indonesia	(Banjar, Bali, Indonesia, (-8.2050113, 114.967…	-8.205011	114.967194	Urban-Suburb	Pool	Accessories Store	Outdoor Supply Store
1	Bali	Kabupaten Buleleng	Banyuatis	Banyuatis, Bali, Indonesia	(Banyuatis, Bali, Indonesia, (-8.2629358, 115…	-8.262936	115.031525	Urban-Suburb	Salad Place	Accessories Store	Outdoors & Recreation
2	Bali	Kabupaten Buleleng	Dencarik	Dencarik, Bali, Indonesia	(Dencarik, Bali, Indonesia, (-8.1857459, 114.9…	-8.185746	114.982595	Urban-Suburb	Indonesian Restaurant	Accessories Store	Outdoors & Recreation
3	Bali	Kabupaten Buleleng	Gesing	Gesing, Bali, Indonesia	(Gesing, Bali, 81152 BALI, Indonesia, (-8.2784…	-8.278434	115.054750	Urban-Suburb	Tree	Accessories Store	Outdoors & Recreation
4	Bali	Kabupaten Buleleng	Kaliasem	Kaliasem, Bali, Indonesia	(Kaliasem, Bali, 00362, Indonesia, (-8.1709929…	-8.170993	115.024820	Urban-Suburb	Seafood Restaurant	Boat or Ferry	Restaurant

1.5 Section 5 - Discussion

Comments on cluster 0 labeled as 'Suburb'. - Bali is a main tourist destination in Indonesia, it is common to see lots of venues even in *suburb* areas. - Distinguishable by the numbers of

conventional stores that occurred as the most common venue at almost every sub-district, it is also a common thing in *suburb* and *rural* area to have alot of convenience store here in Indonesia, not just in Bali.

Comments on cluster 1 labeled as 'Urban'. - The reason why many sub-districts labeled as *urban* compared to other cluster labels is because the amount of different types of venue categories. - Based on my observation on the 'map_bali_clusters' result, cluster 1 is mostly consist of restaurants and some other types of venue categories. But there are also many *suburb* areas labeled as cluster 1 (e.g. Look at those 5 sub-district near 'Gilimanuk' on the top left of the map.) , that is because restaurants exist even in the *suburb* areas.

Comments on cluster 2 labeled as 'Recreational site'. - Bali is a small island compared to other islands in Indonesia (e.g. Sumatra, Kalimantan, Sulawesi and Java) but it has many mountains perfect for recreational site with mountain views. - "Beaches also can be labeled as recreational site!". True, but mostly, seashore areas in Bali are owned by hotels, villas, and restaurants. That is also the reason why seashores labeled as cluster 1 all over the map.

Comments on cluster 3 labeled as 'Rural'. It can be seen by how many farm categorized as their most common venue by each sub-district in the cluster.

1.6 Section 6 - Conclusion

Based on the results, it is safe to say that I can build a restaurant in **urban areas** in Bali. Bali is a small island and it is a main tourist destination in Indonesia. There are no "uncrowded" areas in Bali, every city/regency is **densely populated**. But let us go back to the *Business Idea* of this project. The goal of this project is to find the most strategic location to build a restaurant, a location where there are alot of activities going on that makes it possible for the restaurant to gain some exposure and recognition. To answer that statement/idea, the best location to build a restaurant is in **Denpasar.**

Denpasar is the only city in Bali, others are regencies. It is obvious/easy to predict or assume that the answer to the Business Idea's question of where is the best location to gain some exposure or recognition would be **Denpasar.** But that is the beauty of Data Science. As Data Scientists, we gain insights from data and make our conclusion based on the result of our analysis, and sometimes, insights from data tell us something new, something different than what we have already known.

That concludes my Capstone Project - The Battle of Neighborhoods. Thank you! :D