Restaurant Guide App
(Two-Factor Approach)

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I. Introduction: Business Problem

i. Description of the problem:

For this data science problem, we will explore on how a "Restaurant Guide App" improve consumer experience by answering the question; Does the two-factor (Rating and Price) approach sufficient to recommend a venue?

ii. Target audience description:

To help a group of stakeholders further solve the problem, we will address "Cuisine Connoisseurs, Food Enthusiast and Bloggers" who constantly use restaurant guide app for ease of use.

iii. Discussion on why our Target audience care about the problem:

Everything today is accessible by means of smart phones. In the food industry, Cuisine Connoisseurs, Food Enthusiast and Bloggers wants a quick easy way to access venue information. They often want straightforward details without the hassle of too much unnecessary data to influence their decision. Now, how do we improve these experience? Why should they care about the two-factor approach in this data science problem? - The minimalistic comparison data use, which is combining Rating and Price will give our targeted audience better insight in finding great budget-friendly restaurants in downtown areas.

II. Data Section

i. Description of the data:

The data sets generated in this **Data Section** is to provide insights on our proposed problem. We will focus mainly on Downtown Toronto. First, we will get the Latitude and Longitude value of our approximate defined center, which is the downtown area. We then define a query to search within our desired range and limit for restaurant venues using Foursquare API. Respectively, by making calls to the API, we can get the Restaurant Rating and Price. Using Folium plotting library we can visualize our map of the downtown area.

ii. Other datasets in combination with the Foursquare location data:

We will enter coordinates generated from the API for our downtown area to Google Maps. In doing so, we can pinpoint an address for our approximate defined center and further test venue location accuracy and other information. Also, in combination with Foursquare location data, a 'csv file' that depict Rating and Price will be created from the dataset results.

iii. Examples of the data:

- Foursquare Credentials and Version
- The geographical coordinate of Downtown Toronto are 43.6563221, -79.3809161.

- The specific venue category : radius = 500; limit = 10
- JSON file for our dataframe
- Venues_map using folium.Map
- Restaurants IDs using https://api.foursquare.com/v2/venues

iv. Using Data to solve the problem:

With the generated Data, we can make selection of existing restaurant in any category. The map visualization will be use to show the distance of the restaurants within the neighborhood. Part of the JSON file is significant in examining our calls to Foursquare API and to transform our dataframe for analysis. Relatively, making calls to Foursquare location data will get our given values to make our comparison. Eventually, this dataset results will help us solve the question if our two-factor (Rating and Price) approach sufficient to recommend a venue.

v. The Search for a specific venue:

Imagine our targeted audience (Cuisine Connoisseurs, Food Enthusiast and Bloggers) is in a downtown area using the Restaurant Guide App and wanted to find great budget-friendly restaurants. It is a busy town, a quick comparison of several venues in close proximity would be ideal for they're always on the go.

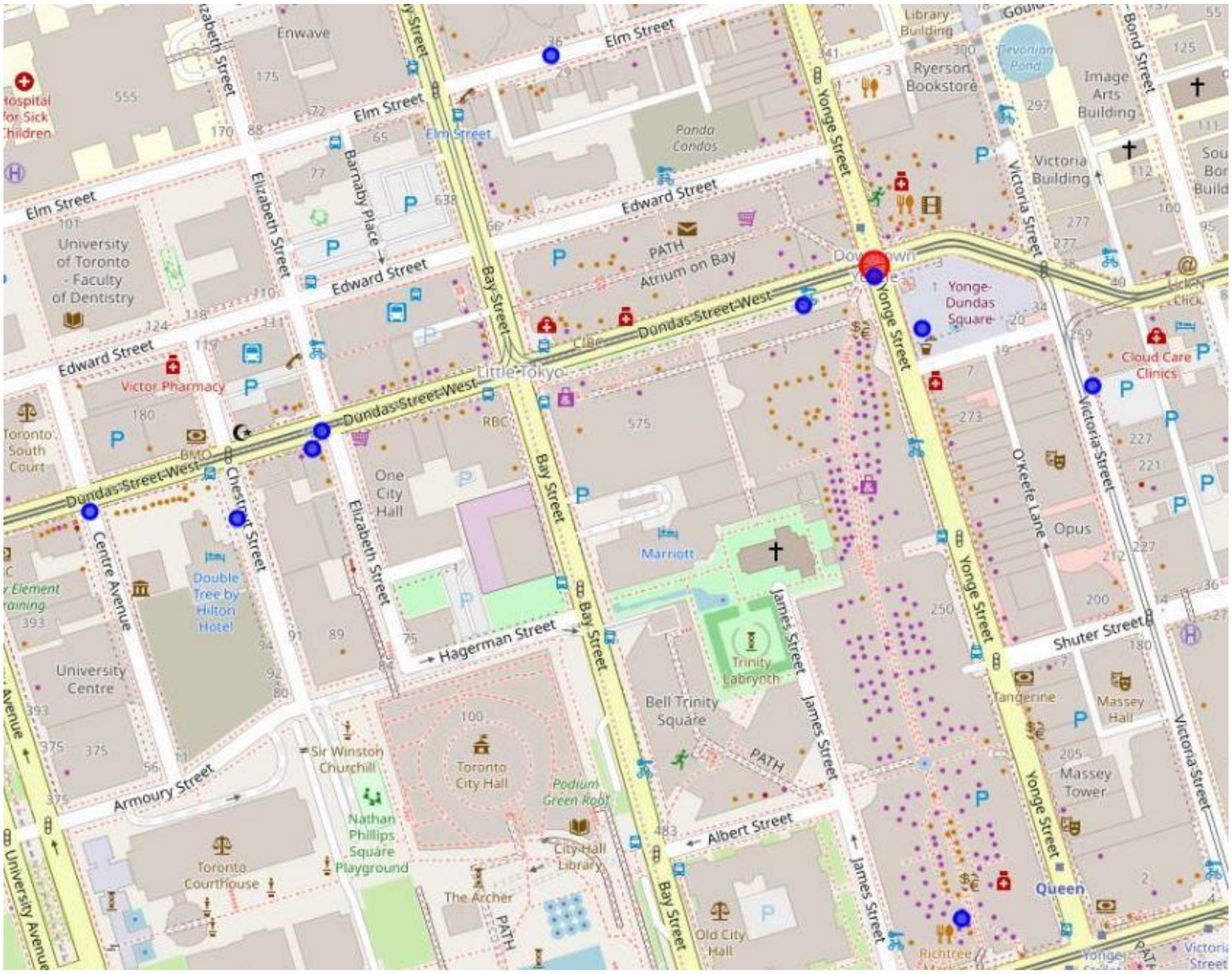
We can accomplish this by doing a query search for our Restaurant within 500 meters from Downtown Toronto and set our limit to 10, through Foursquare API. Now, let us see the filtered result as a table.

Output View

	name	categories	address	lat	lng
0	Hemispheres Restaurant & Bistro	American Restaurant	110 Chestnut Street	43.654884	-79.385931
1	Richtree Natural Market Restaurants	Restaurant	14 Queen St W	43.652614	-79.380231
2	Akashiro Japanese Restaurant & Bar	Sushi Restaurant	220 Yonge St.	43.655965	-79.380541
3	Terrace Restaurant at Elmwood	American Restaurant	NaN	43.656101	-79.381480
4	The Senator Restaurant	Diner	249 Victoria Street	43.655641	-79.379199
5	Subway	Sandwich Place	10 Dundas St. E	43.656260	-79.380920
6	Adega Restaurant	Restaurant	33 Elm St	43.657519	-79.383462
7	Kyoto House Japanese Restaurant	Sushi Restaurant	143 Dundas St. West	43.655381	-79.385270
8	Yueh Tung Chinese Restaurant	Chinese Restaurant	126 Elizabeth St.	43.655281	-79.385337
9	Hong Shing Chinese Restaurant	Chinese Restaurant	195 Dundas St W	43.654925	-79.387089

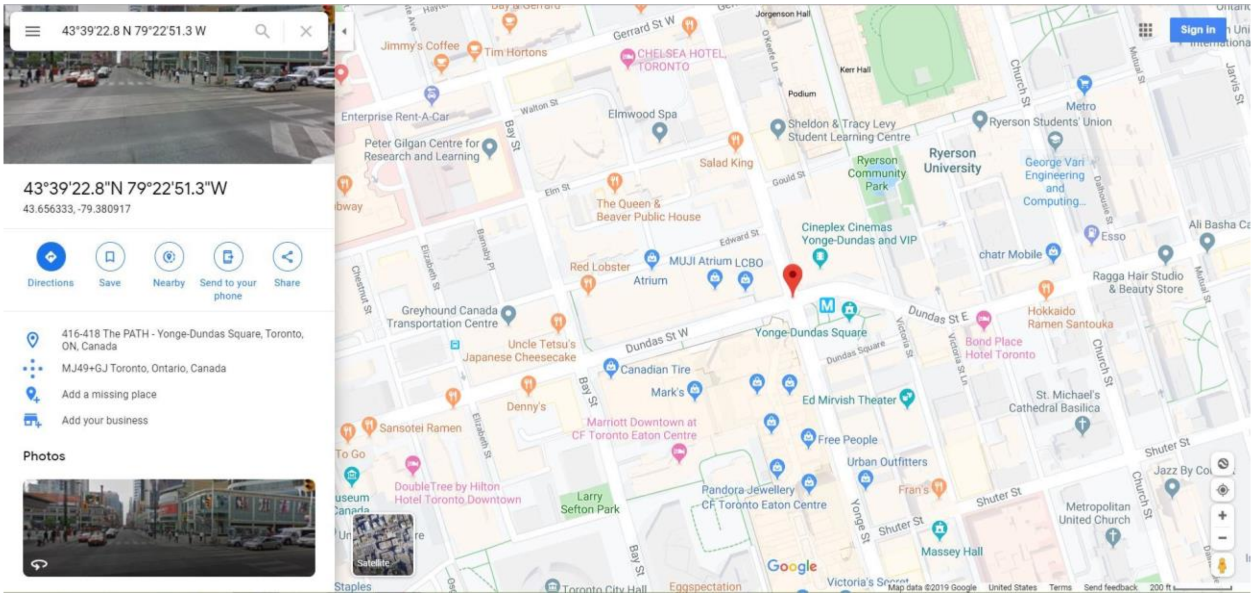
vi. Map of The City's Downtown Area:

Would it be convenient if we could show our targeted audience the map of their search and visualize how far they are from a prospective venue? Let us locate the approximate center and explore neighboring restaurants.



vii. Using Google Maps:

Here, we enter coordinates 43.6563221, -79.3809161 for Downtown Toronto in Google Maps. Result shows; "The PATH - Yonge-Dundas Square, Toronto ON, Canada". This is our approximate defined center and represented by a red circle marker from the generated map above. Using the result, we can test venue location accuracy and other information.



viii. Query Search Results:

Here, we can further explore the restaurants using their ID. Let us examine our filtered table for restaurant within 500 meters with a limit of 10 venues, sorted by distance.

Output View

name	id
Subway	4c6abb8c2c29d13ad2720e41
Akashiro Japanese Restaurant & Bar	4fbbb3ace4b01e39077b4d55
Terrace Restaurant at Elmwood	4edbccaaf9abeea3db5268df
The Senator Restaurant	4ad7929cf964a520500c21e3
Adega Restaurant	4ad4c060f964a52070f720e3
Kyoto House Japanese Restaurant	4ae4b055f964a520229d21e3
Yueh Tung Chinese Restaurant	52a7ae41498eed3af4d0a3fa
Richtree Natural Market Restaurants	4b295e10f964a520ba9d24e3
Hemispheres Restaurant & Bistro	4ad4c05ff964a52048f720e3
Hong Shing Chinese Restaurant	4b2027b5f964a520f82d24e3

ix. Explore Restaurants using their ID

Here, by making calls to Foursquare API we can get the “Given Values”; Rating and Price. We will be using The Senator Restaurant for our pilot call. Then get the Rating and Price for other restaurants using the same process.

Output View

name	id
Subway	4c6abb8c2c29d13ad2720e41
Akashiro Japanese Restaurant & Bar	4fbbb3ace4b01e39077b4d55
Terrace Restaurant at Elmwood	4edbccaaf9abeea3db5268df
The Senator Restaurant	4ad7929cf964a520500c21e3
Adega Restaurant	4ad4c060f964a52070f720e3
Kyoto House Japanese Restaurant	4ae4b055f964a520229d21e3
Yueh Tung Chinese Restaurant	52a7ae41498eed3af4d0a3fa
Richtree Natural Market Restaurants	4b295e10f964a520ba9d24e3
Hemispheres Restaurant & Bistro	4ad4c05ff964a52048f720e3
Hong Shing Chinese Restaurant	4b2027b5f964a520f82d24e3

Here is an example of Foursquare API calls:

```
venue_id = '4ad7929cf964a520500c21e3' # ID of The Senator Restaurant
url = 'https://api.foursquare.com/v2/venues/{}?client_id={}&client_secret
_ID, CLIENT_SECRET, VERSION)
url
```

```
'https://api.foursquare.com/v2/venues/4ad7929cf964a520500c21e3?client_id=
IFZ2RUVKVZ2FPQH&client_secret=FFJNCIUYMDQFICJLZMSZATWNHBBZCTCCZLRLUU1Z3JY
```

```
result = requests.get(url).json()
print(result['response']['venue'].keys())
result['response']['venue']
```

```
dict_keys(['id', 'name', 'contact', 'location', 'canonicalUrl', 'categori
'price', 'likes', 'dislike', 'ok', 'rating', 'ratingColor', 'ratingSignal
e', 'specials', 'photos', 'venuePage', 'reasons', 'description', 'storeId
```

```
try:
    print(result['response']['venue']['rating'])
except:
    print('This venue has not been rated yet.')
```

```
7.9
```

```
try:
    print(result['response']['venue']['price'])
except:
    print('No Details.')
```

```
{'tier': 2, 'message': 'Moderate', 'currency': '$'}
```

x. The New Dataframe: Rating and Price

The API call outputs were extracted to a spreadsheet format to create a new filtered table.

	Restaurant	Rating	Price
0	Subway	5.7	Cheap
1	Akashiro Japanese Restaurant & Bar	5.4	Moderate
2	Terrace Restaurant at Elmwood	NR	Moderate
3	The Senator Restaurant	7.9	Moderate
4	The Elm Tree Restaurant	8.3	ND
5	Hendricks Restaurant & Bar	6.1	Moderate
6	Kyoto House Japanese Restaurant	5.9	Moderate
7	Yueh Tung Chinese Restaurant	7.8	Cheap
8	Richtree Natural Market Restaurants	6.2	Moderate
9	Hemispheres Restaurant & Bistro	NR	ND

We can now sort by category Rating and Price, and “Cheap” as our sub category.

Restaurant	Rating	Price
Subway	5.7	Cheap
Yueh Tung Chinese Restaurant	7.8	Cheap

Table 1

Repeating the same process, we can sort by sub category “Moderate”.

Restaurant	Rating	Price
Akashiro Japanese Restaurant & Bar	5.4	Moderate
Terrace Restaurant at Elmwood	NR	Moderate
The Senator Restaurant	7.9	Moderate
Hendricks Restaurant & Bar	6.1	Moderate
Kyoto House Japanese Restaurant	5.9	Moderate
Richtree Natural Market Restaurants	6.2	Moderate

Table 2

III. Methodology Section

In our Business Problem section, we introduced whether our Restaurant Guide App would be sufficient to recommend a venue focusing only within the Rating and Price. Consequently, from our Data Section, we explained how our datasets were used in solving the business problem. For our **data requirements**, we showed that we need both traditional and non-traditional datasets. Mainly leveraging Foursquare Location Data in conjunction with Google maps and 'csv file' created from the dataset results. Relatively from the **collected data**, we have identified all sources and how they were extracted. Thus, providing us with better **understanding and preparation** on how to execute our data science problem. Using data visualization, we have created our **modeling and evaluation** for the Restaurant Guide App (Two-Factor Approach). We have seen the correlations between cleaning up our unstructured and structured datasets to generate our minimalistic results.

IV. Analysis Section

Stakeholders has to consider the Two-Factor Approach to improve their consumer experience. However, would the gathered datasets enough to deploy this concept? Simple answer is, yes. Let's **analyze** the "Restaurant Guide App" (Two-Factor Approach). Virtually, Table 1 and 2 shows enough data without overwhelming our targeted audience. Cuisine Connoisseurs, Food Enthusiast and Bloggers, who constantly use restaurant guide app for quick venue information, will appreciate this minimalistic comparison. Furthermore, developers can collaborate and utilize the datasets to come up with ways to show the Tables as part of the App. Sometimes, less can influence significant decisions but not to sacrifice functionality. Our tables shows, **"Yueh Tung Chinese Restaurant and The Senator Restaurant"** as our top picks.
Based on the new dataframe, we see categories Rating and Price. Here, we show that the categories influenced our decision to select our preferred restaurants in the downtown area. Without being explicit, we can predict a restaurant with virtually has the most complete values across the board, be our **top picks**. We also have relied on our sub categories Cheap and Moderate, to build our statistical model.

V. Results Section

Utilizing all identified sources for our data, we can make adjustments to our Two-Factor Approach model upon deployment. Moreover, the predictivenes (virtual comparison) of our model can be fine-tuned using the dataset results. Stakeholders can benefit from its simplicity to refine known testing outcome. Most importantly, with an improved consumer experience in place, it will open opportunities for constructive feedback to re-evaluate efficiency of our Restaurant Guide App. As we can virtually see from the tables, we can quickly analyze our top picks. At this point, we had already answered the main question to the data science problem. Our two-factor (Rating and Price) approach is sufficient to recommend a venue.

VI. Discussion Section

Based on the results, we leveraged the power of Foursquare Location Data to the fullest. Additionally, external sources supported our visualization. Using basic Google Map search, we pinpoint our downtown area and approximately test the distance of our neighborhood restaurants. Moreover, the spreadsheet we had created for our new dataframe, simplified the dataset results and became grounds for comparison.
As previously mentioned, "Sometimes, less can influence significant decisions but not to sacrifice functionality". With that in mind, every code and dataset generated, plays a vital part in solving our business problem. Respectively, helped us to create a pattern in improving consumer experience for our targeted audience. The minimalistic functional comparison, assisted our stakeholders to better understand the impact in developing the Restaurant Guide App. As Data Scientist, it is recommended that all datasets, structured or unstructured should be put in consideration.

VII. Conclusion Section

Finally, can we deploy the model into practice? Yes, the proprietary "Restaurant Guide App" (Two-Factor Approach) model is predictive. Therefore, can be revaluated, refine adjustments and apply testing to known outcome. Our model is leverage through the power of Foursquare Location Data and external resources. Hence, we can solve real world issues pertaining to our data science problem. We can now be more competitive in today’s market trend by polishing our dataset to further improve consumer experience.