
Peer-graded Assignment

IBM Data Science - Capstone Project

(note that this project has been produced to demonstrate the authors Data Science skill set incorporating Web-Scraping, Foursquare API and Folium Maps)

DECEMBER 28 2019

Introduction

The Objective: Create as you want a problematic idea to solve following the principles used by a data scientist using the principles to leverage relevant Foursquare location data to explore and compare neighbourhoods to solve a problem.

Goals: Investigate and identify a primary location to open a healthy meat-free fast food restaurant using data sources pulled from the web and using methods such as data wrangling, filtering, segmenting, clustering cities suburbs, using visualization tools.

This lab report has sourced information and data, to solve a fictional problem, following the process that a data scientist would usually follow when trying to solve such a problem.

Problem Description

There is a need to find a prime location to open a meat free fast food family, healthy eating takeaway/restaurant in a city within Europe. The chosen city needs to be powered by 100% renewable energy. Before we investigate and identify a primary location to open a healthy family fast food restaurant we will elaborate on the actual problem, the history as to why this problem has come about, and how this project will help contribute to solving the problem.

Background

Over the last 10 years a large family fast food restaurant chain/franchise has recognised a slow decline in its number of customers. Worryingly in the last four years the waning of its customer traffic has increased, it is true that the fast food restaurant category is experiencing a decline in its customer base. But this world-renowned franchise is declining at a faster rate. There are great concerns with in senior management that increased sales on an ever-shrinking customer base and is now on a certain path to brand disaster.

- In 2013 the new CEO at the time was quoted as saying its goal was "To be a modern and progressive burger company."
- An international news agency obtained an internal email in October 2016 which summarized a September meeting with executives and franchisees. It read, "Growing customer counts is our main challenge."

These are two bold statements that did not deliver, as much as the company has focused on:

- Providing great tasting food
- Innovation
- Service Speed
- Focus on franchisee profitable revenue growth
- Building on customer loyalty

The financial health of the franchisee is brand-business imperative and is facing a bleak future.

There is a requirement from senior management to re-engineer the brand or invent a silent sister brand, if it is to have a chance of survival. Without franchisees upholding the brand, shareholders will wind up with nothing to hold.

Description of the problem

It was suggested by the board to outsource this problem to several customer focused trouble-shooters to investigate and propose a solution that will re-engage the brand with its former customer and entice new customers. The feedback from one trouble-shooter has highlighted that the voice of the customer needs to be heard, highlighting extreme changes to former customer's needs, and this is something that the current brand is unable to offer, unless there is radical change. But radical change will deter the current customer base. They suggest creating a new sister brand which focuses on the needs of today's society and concerns.

The customers they are losing tend to be more healthy eating conscious and ultra-concerned by the impact eating meat products has on the climate. Fact 1 in 10 people on the planet are now vegetarian, a statistic that climbing.

The mass production of meat is the single biggest cause of land clearing around the world, if not directly for the animals themselves then indirectly for the monocultures such as corn or soy that feed them.



Environmental degradation also goes together with the global pandemic of chronic diseases including obesity, diabetes, cancer and heart disease.

Having listened to the VOC (voice of the customer) it has become apparent that many of its custom base have aged, and with age comes life experience, education and health concerns. Many now have had family's and will want to pass on everything that they have learned and experienced on to their children. This does not bode well for its future generation customer. The challenge is to create a different opening for those customers that are falling by the wayside.

It has been proposed to consider creating a new brand for a new era, a non-meat family fast food sustainable restaurant brand, with the core ethos on the environment.

What do we mean by sustainable restaurant? using local produce, using reusable packaging, converting waste in to renewable energy, powering the restaurant using renewable energy. This link will help you understand what it means to be a sustainable restaurant: <https://m.theworlds50best.com/sustainable-restaurant-award.html>

They conclude that the current brand has not been progressive enough and that is understandable due to its DNA with its history of meat-based products and are convinced that if this new branded were marketed correctly it will be a huge success. They also highlight how important it is to emphasise and market this brand as environmentally caring and suggest keeping the new brand apart from the old brand as much as possible (from a promoting aspect).

The boards response having reflected on the suggestions by the trouble-shooter have made it very clear that they would like their flagship restaurant to be based in a city sourced by renewable energy, focusing on customers that enjoy fast food but do not eat meat, hence there is the need to identify European countries with a high percentage of vegetarians and vegans. The target audience will be primarily be focused towards families, though also appealing to shoppers, commuters and tourists depending on the choice of city.

Sourced Data

Table 1 - Cities Using Renewable Sources (City-wide electricity Mix)

Cities are increasingly reporting that they are powered by renewable electricity. CDP holds information from over 570 of the world's cities and over 100 cities are now getting at least 70% of their electricity from renewable sources such as hydro, geothermal, solar and wind. This dataset has been compiled of data reported by cities in 2015, 2016 and 2017 in response to our annual questionnaire: <https://data.cdp.net/api/views/ycef-psus/rows.csv?accessType=DOWNLOAD>

Table Preview													View Data	Create Visualization
City ↑	City s...	Coun...	Region	Popu...	Popu...	Access	CDP r...	Biom...	Coal ...	Gas (...)	Geot...	Hyd		
Abasan Al...	Abasan Al...	State of P...	South an...	2015	30,000	Public	2017	5	17	18	0	0		
Abingdon ...	Abingdon	USA	North Am...	2010	55,310	Public	2017	0	36.6	23	0	1		
Addis Ab...	Addis Ab...	Ethiopia	Africa	2008	3,384,569	Public	2017	0	0	0	0	100		
Ajuntame...	Barcelona	Spain	Europe	2015	1,604,555	Public	2017	0	0	8.3	0	5.8		
Alcaldia d...	Alcaldia d...	Venezuela	Latin Am...	2011	35,374	Public	2017	0	0	0	0	100		
Alcaldia d...	Ibaguè	Colombia	Latin Am...	2017	564,077	Public	2017	0	0	0	0	100		
Alcaldia d...	Alcaldia d...	Panama	Latin Am...	2014	1,477,862	Public	2017	0	0	0	0	60		
Alcaldia d...	Riohacha	Colombia	Latin Am...	2017	277,868	Public	2017	0	99.9	0	0	0		
Alcaldia d...	Alcaldia d...	Colombia	Latin Am...	2015	275,207	Public	2017	0	85	15	0	0		
Alcaldia ...	Alcaldia ...	Venezuela	Latin Am...	2015	3,518,590	Public	2017	0	0	0	0	0		
Amiens M...	Amiens M...	France	Europe	2014	175,000	Public	2016	2	0	20	3	5		
Arusha Ci...	Arusha	United Re...	Africa	2012	416,442	Public	2017	0	0	10	0	60		
Auckland ...	Auckland	New Zeal...	South Asi...	2015	1,569,900	Public	2017	1.4	4.3	15.7	16.2	57.1		
Ayuntami...	Chihuahua	Mexico	Latin Am...	2015	841,490	Public	2017	0	0	100	0	0		

We will begin by transforming the data into a panda's data frame, this will allow us to clean and then wrangle and filter the data following the specified criteria highlighted in the recommended requirements. The goal is to create a data frame consisting of seven columns: Continent, Country, City, Population, Renewable Percentage, Longitude, Latitude. We will then filter the data where by the continent is equal to Europe. We will then sort in order Renewable Percentage (high to low), and then by population (high to low). We will then focus on the top five cities with the highest populations and make comparison with the statistics we have on those countries that have the most vegetarians. We will then hope to find at least one country from our statistics in of countries with the most vegetarians in on our list of top five cities/country and then conclude which city to focus our attention on. We will then use visual tools and Foursquare to investigate, analyse, produces results and formulate our final conclusions.

Table 2 - Demographics of Vegetarians and Vegan by Country

All percentages in the following table are raw estimates taken from Wikipedia https://en.wikipedia.org/wiki/Vegetarianism_by_country. The data will be used to help identify which countries have the higher rates of non-meat eaters. This information will be used to help to conclude which city/s we should consider exploring as opportunities to open the new family targeted restaurant.

Table 3 - City Postcodes

In order to use Foursquare, we will need to get the latitude and the longitude coordinates of each suburb of the city as we conclude which are appropriate options to open the first restaurant. Please note that the details of this source will be referenced in section 5.2 of this project, having not yet identified the city we will target to open the new branded restaurant.

Method & Data Analysis: Part 1, Cities Using Renewable Sources

1. Analyze Data to Find European City Suitable to Open Restaurant

1.1. *Download the dataset and transformed into a panda's data frame allowing us to wrangle the data, to conform to the requirements set.*

1.2. Get basic information about your data frame (we can do this by using the info () method)

1.3. Data Wrangling - Evaluating & Clean Data (make some modifications to the original dataset to make it easier to create our future visualizations).

1.3.1. *Count missing values in each column* (find code on [GitHub](#))

1.3.2. *Create Field with Total Percentage Power Created Using Renewable Energies* (find code on [GitHub](#))

1.3.3. *Drop Non-Required Columns* (find code on [GitHub](#))

1.4. Focus on Criteria Request and Filter Out Non-Required Data

1.4.1. *Filter so that only the European cities appear* (find code on [GitHub](#))

1.4.2. *Show only data records where the renewables are greater than or to 75%* (find code on [GitHub](#))

1.4.3. *Rename some of the columns so that they make sense* (find code on [GitHub](#))

1.5. Order Data

1.5.1. *By 'Population' and 'Renewables'*

```
[52]: df_europe_75_Renewables_Population = df_europe_75.sort_values(by=['Renewables', 'Population'], ascending=False)
```

```
[53]: df_europe_75_Renewables_Population
```

```
[53]:
```

	City	Country	Continent	Population	Renewables	Latitude	Longitude
95	Basel	Switzerland	Europe	197005	100.0	47.5619	7.5928
59	Reykjavik	Iceland	Europe	122460	100.0	64.12652	-21.81744
230	Bolzano	Italy	Europe	106397	100.0	46.499681	11.356576
60	Fafe	Portugal	Europe	50845	100.0	41.4508217	-8.1728619
82	Akureyri	Iceland	Europe	18300	100.0	65.688492	-18.126169
308	Aerøskøbing	Denmark	Europe	6200	100.0	54.891456	10.404684
190	Alba-Iulia	Romania	Europe	63536	99.0	46.082337	23.569027
101	Arendal	Norway	Europe	44574	99.0	58.461757	8.77245
216	Oslo	Norway	Europe	658390	98.0	59.9138688	10.7522454
125	Oristano	Italy	Europe	31630	93.0	39.720664	8.898007
223	Lausanne	Switzerland	Europe	140000	90.8	46.5198	6.6335
337	Nyon	Switzerland	Europe	20444	90.8	46.383268	6.234785
249	Bærum Kommune	Norway	Europe	122660	89.0	59.920545	10.593765
297	Braga	Portugal	Europe	182000	79.0	41.533751	-8.438218
219	Porto	Portugal	Europe	238954	75.3	41.1579438	-8.6291053

We now have a data frame consisting of the rows representing cities within Europe that are powered by 75% or more renewable energy and 7 columns headers: City, Country, Continent, Population, Renewables, Latitude and Longitude.

1.6. Cities within Europe that are powered by 75% or more renewable energy (created using Folium)

Fig1.

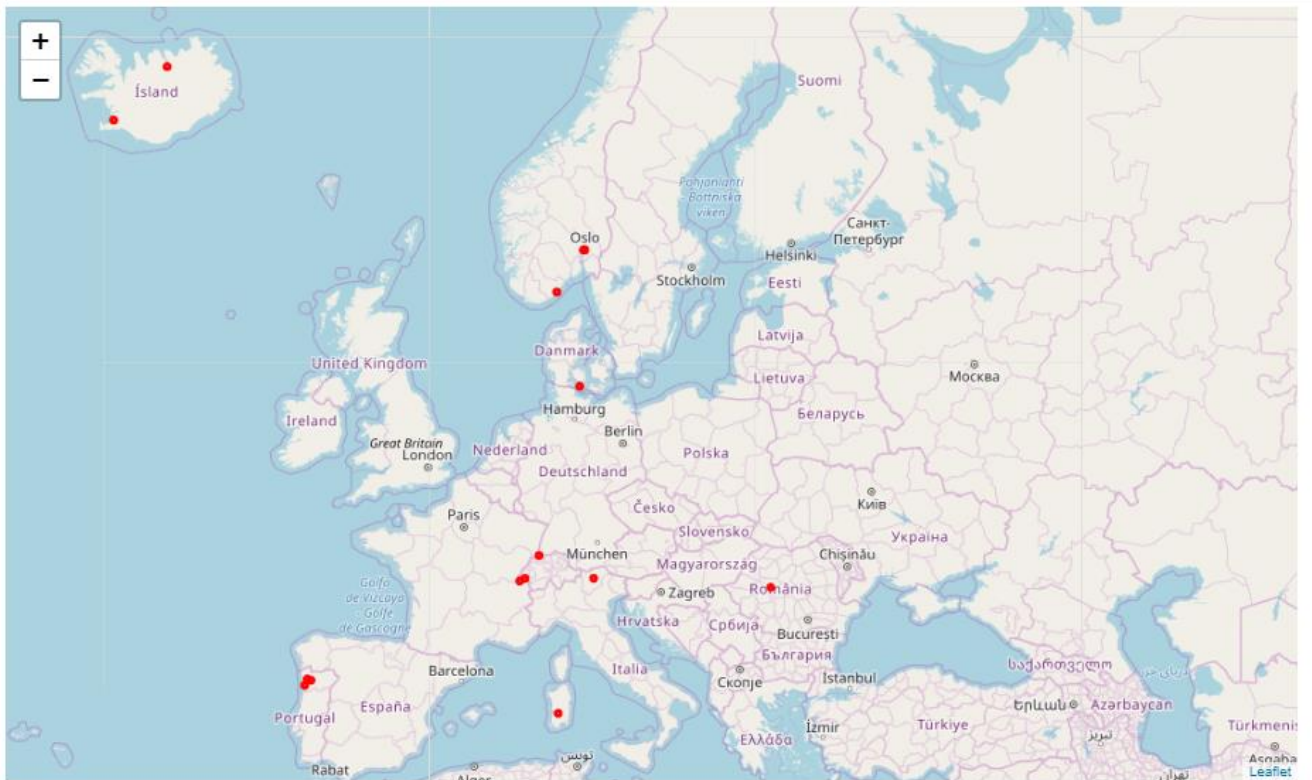


Fig.2

	City	Country	Continent	Population	Renewables (%)	Biomass (%)	Coal (%)	Gas (%)	Geothermal (%)	Hydro (%)	Nuclear (%)	Oil (%)	Solar (%)	Wind (%)	Unknown sources (%)
0	Basel	Switzerland	Europe	197005	100.0	0.8	0.0	0.00	0.0	88.9	0.0	0.00	0.50	9.80	0.0
1	Reykjavik	Iceland	Europe	122460	100.0	0.0	0.0	0.00	30.0	70.0	0.0	0.00	0.00	0.00	0.0
2	Bolzano	Italy	Europe	106397	100.0	0.0	0.0	0.00	0.0	100.0	0.0	0.00	0.00	0.00	0.0
3	Fafe	Portugal	Europe	50845	100.0	0.0	0.0	0.00	0.0	97.0	0.0	0.00	3.00	0.00	0.0
4	Akureyri	Iceland	Europe	18300	100.0	0.0	0.0	0.00	30.0	70.0	0.0	0.00	0.00	0.00	0.0
5	A'ereskøbing	Denmark	Europe	6200	100.0	0.0	0.0	0.00	0.0	0.0	0.0	0.00	10.00	90.00	0.0
6	Alba-Iulia	Romania	Europe	63536	99.0	0.0	0.0	1.00	0.0	96.0	0.0	0.00	2.00	1.00	0.0
7	Arendal	Norway	Europe	44574	99.0	0.0	0.0	0.00	0.0	99.0	0.0	0.00	0.00	0.00	1.0
8	Oslo	Norway	Europe	658390	98.0	0.0	0.0	0.00	0.0	98.0	0.0	0.00	0.00	0.00	2.0
9	Oristano	Italy	Europe	31630	93.0	0.0	0.0	1.00	0.0	90.0	0.0	6.00	3.00	0.00	0.0
10	Lausanne	Switzerland	Europe	140000	90.8	6.3	0.0	0.52	0.0	83.7	7.4	1.28	0.42	0.38	0.0
11	Nyon	Switzerland	Europe	20444	90.8	0.0	0.0	2.50	0.0	86.0	0.0	0.00	4.80	0.00	6.7
12	Bærum Kommune	Norway	Europe	122660	89.0	0.0	0.0	0.00	0.0	89.0	0.0	3.00	0.00	0.00	8.0
13	Braga	Portugal	Europe	182000	79.0	2.0	7.0	1.00	4.0	14.0	2.0	11.00	7.00	52.00	0.0
14	Porto	Portugal	Europe	238954	75.3	11.8	8.2	0.00	0.0	13.9	0.0	0.00	0.00	49.60	16.5

The statistics in fig 2 show:

- six cities in Europe whose energy power sources are 100% sustainable by means of renewable energy
- one city whose population clearly stands from the rest (Oslo, population of 658,390)
- two cities fall into the top three in regards to the highest percentage of renewable energy used to power the city and having one of the larger populations

In **Method & Data Analysis: Part 2** we will investigate which countries in Europe have the highest number of non-meat eaters.

Method & Data Analysis: Part 2, Demographics of Vegetarians and Vegan by Country

2. Analyze Data to Find European City's Where A High Percentage of The Population Are Vegetarians or Vegans
 - 2.1. Download the dataset (*scrape data from Wikipedia*) and transformed into a panda's data frame allowing us to wrangle the data and following the requirements set.
 - 2.2. Get basic information about your data frame (we can do this by using the info () method)
 - 2.3. Data Wrangling - Evaluating & Clean Data (make some modifications to the original dataset to make it easier to create our future visualizations).
 - 2.3.1. Clean Country Data Field, rouge 1st character (find code on GitHub)
 - 2.3.2. Clean Vegetarian Diet Data, rouge characters (find code on GitHub)
 - 2.3.3. Clean Vegan Diet Data, rouge characters (find code on GitHub)
 - 2.3.4. Convert Vegetarian Diet Data to Int, (find code on GitHub)
 - 2.3.5. Convert Vegan Diet Data to Int, (find code on GitHub)
 - 2.3.6. Create Field with Total Percentage of Non-Meat Eaters

```
[127]: df_veg_stats["No Meat Diet"] = df_veg_stats["Vegetarian diet (%)"] + df_veg_stats["Vegan diet (%)"]
```

```
[130]: df_veg_stats.head(10)
```

```
[130]:
```

	Country	Vegetarian diet (%)	Vegan diet (%)	No Meat Diet
0	Argentina	5.0	0.0	5.0
1	Australia	12.0	2.0	14.0
2	Austria	9.0	0.0	9.0
3	Belgium	7.0	0.0	7.0
4	Brazil	14.0	3.0	17.0
5	Canada	9.4	2.3	11.7
6	Chile	6.0	0.0	6.0
7	China	4.0	0.0	4.0
8	Czech Republic	2.0	0.0	2.0
9	Denmark	5.0	0.0	5.0

We now have a clean table of non-meat diet stats by country ready to merge with our table of European cities that use 75% or more renewable energy. In Method & Data Analysis: Part 3 we merge the data tables created in Method & Data Analysis: Part 1 and Part2.

Method & Data Analysis: Part 3, Merge Tables Part 1 & Part 2 By Continent “Europe”

3. Compare European countries with cities powered by renewable energy with the statistics of countries with the higher number of No Meat eaters

3.1. Merge the Tables Created in Part 1 and Part 2 By Country

```
[107]: df_merge_eur = pd.merge(df_europe_75_Renewables_Population, df_veg_stats, on=['Country', 'Country'])
df_merge_eur
```

```
[107]:
```

	City	Country	Continent	Population	Renewables	Latitude	Longitude	Vegetarian diet (%)	Vegan diet (%)	No Meat Diet
0	Basel	Switzerland	Europe	197005	100.0	47.561900	7.592800	14.0	3.0	17.0
1	Lausanne	Switzerland	Europe	140000	90.8	46.519800	6.633500	14.0	3.0	17.0
2	Nyon	Switzerland	Europe	20444	90.8	46.383268	6.234785	14.0	3.0	17.0
3	Bolzano	Italy	Europe	106397	100.0	46.499681	11.356576	7.1	0.6	7.7
4	Oristano	Italy	Europe	31630	93.0	39.720664	8.898007	7.1	0.6	7.7
5	Fafe	Portugal	Europe	50845	100.0	41.450822	-8.172862	1.2	0.6	1.8
6	Braga	Portugal	Europe	182000	79.0	41.533751	-8.438218	1.2	0.6	1.8
7	Porto	Portugal	Europe	238954	75.3	41.157944	-8.629105	1.2	0.6	1.8
8	Ærøskøbing	Denmark	Europe	6200	100.0	54.891456	10.404684	5.0	0.0	5.0
9	Arendal	Norway	Europe	44574	99.0	58.461757	8.772450	2.0	0.2	2.2
10	Oslo	Norway	Europe	658390	98.0	59.913869	10.752245	2.0	0.2	2.2
11	Bærum Kommune	Norway	Europe	122660	89.0	59.920545	10.593765	2.0	0.2	2.2

3.2. Calculate the Estimated Number of Non-Meat Eaters

The calculated estimate number of People in each city that have a meat free diet is derived by using the same percentage of the non-meat eaters in the country the city is located in.

```
[43]: df_merge_eur['No Meat Population'] = (df_merge_eur['Population'] * df_merge_eur['No Meat Diet'])/100
```

```
[44]: df_merge_eur = df_merge_eur.sort_values(by=['No Meat Population', 'Renewables'], ascending=False)
df_merge_eur
```

```
[44]:
```

	City	Country	Continent	Population	Renewables	Latitude	Longitude	Vegetarian diet (%)	Vegan diet (%)	No Meat Diet	No Meat Population
0	Basel	Switzerland	Europe	197005	100.0	47.561900	7.592800	14.0	3.0	17.0	33490.850
1	Lausanne	Switzerland	Europe	140000	90.8	46.519800	6.633500	14.0	3.0	17.0	23800.000
10	Oslo	Norway	Europe	658390	98.0	59.913869	10.752245	2.0	0.2	2.2	14484.580
3	Bolzano	Italy	Europe	106397	100.0	46.499681	11.356576	7.1	0.6	7.7	8192.569
7	Porto	Portugal	Europe	238954	75.3	41.157944	-8.629105	1.2	0.6	1.8	4301.172
2	Nyon	Switzerland	Europe	20444	90.8	46.383268	6.234785	14.0	3.0	17.0	3475.480
6	Braga	Portugal	Europe	182000	79.0	41.533751	-8.438218	1.2	0.6	1.8	3276.000
11	Bærum Kommune	Norway	Europe	122660	89.0	59.920545	10.593765	2.0	0.2	2.2	2698.520
4	Oristano	Italy	Europe	31630	93.0	39.720664	8.898007	7.1	0.6	7.7	2435.510
9	Arendal	Norway	Europe	44574	99.0	58.461757	8.772450	2.0	0.2	2.2	980.628
5	Fafe	Portugal	Europe	50845	100.0	41.450822	-8.172862	1.2	0.6	1.8	915.210
8	Ærøskøbing	Denmark	Europe	6200	100.0	54.891456	10.404684	5.0	0.0	5.0	310.000

3.3. Normalize the Data

By normalizing the data, we can compare statistical values measured on different scales to a notionally common scale.

```
[45]: features_to_normalize = ['No Meat Population', 'Renewables', 'No Meat Diet']  
      # could be ['A', 'B']  
  
df_merge_eur[features_to_normalize] = df_merge_eur[features_to_normalize].apply(lambda x: (x-x.min()) / (x.max()-x.min()))
```

```
[46]: df_merge_eur
```

	City	Country	Continent	Population	Renewables	Latitude	Longitude	Vegetarian diet (%)	Vegan diet (%)	No Meat Diet	No Meat Population
0	Basel	Switzerland	Europe	197005	1.000000	47.561900	7.592800	14.0	3.0	1.000000	1.000000
1	Lausanne	Switzerland	Europe	140000	0.627530	46.519800	6.633500	14.0	3.0	1.000000	0.707938
10	Oslo	Norway	Europe	658390	0.919028	59.913869	10.752245	2.0	0.2	0.026316	0.427192
3	Bolzano	Italy	Europe	106397	1.000000	46.499681	11.356576	7.1	0.6	0.388158	0.237564
7	Porto	Portugal	Europe	238954	0.000000	41.157944	-8.629105	1.2	0.6	0.000000	0.120285
2	Nyon	Switzerland	Europe	20444	0.627530	46.383268	6.234785	14.0	3.0	1.000000	0.095401
6	Braga	Portugal	Europe	182000	0.149798	41.533751	-8.438218	1.2	0.6	0.000000	0.089389
11	Bærum Kommune	Norway	Europe	122660	0.554656	59.920545	10.593765	2.0	0.2	0.026316	0.071985
4	Oristano	Italy	Europe	31630	0.716599	39.720664	8.898007	7.1	0.6	0.388158	0.064058
9	Arendal	Norway	Europe	44574	0.959514	58.461757	8.772450	2.0	0.2	0.026316	0.020211
5	Fafe	Portugal	Europe	50845	1.000000	41.450822	-8.172862	1.2	0.6	0.000000	0.018240
8	Ærøskøbing	Denmark	Europe	6200	1.000000	54.891456	10.404684	5.0	0.0	0.210526	0.000000

In the next part of this report **Method & Data Analysis: Results** we will discuss the results and conclude which city we will choose as to explore using Foursquare, investigating an appropriate location to open the meat free restaurant.

Formulate Results and Conclusions: Part 1 Select City

4. Make observations and discuss results.

Having normalized and merged the data tables we have been able to produce the following graph:

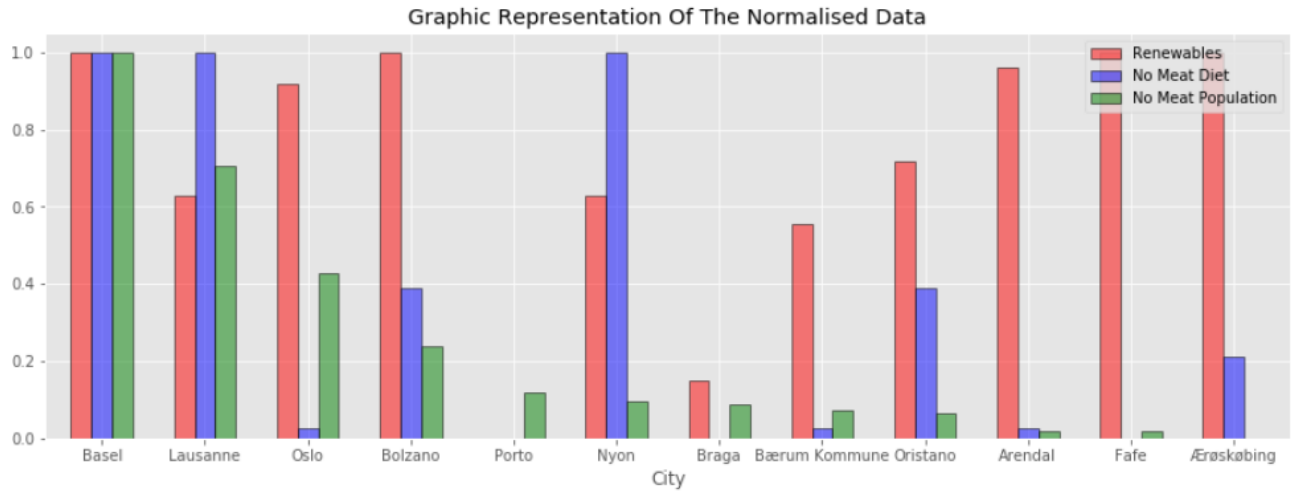
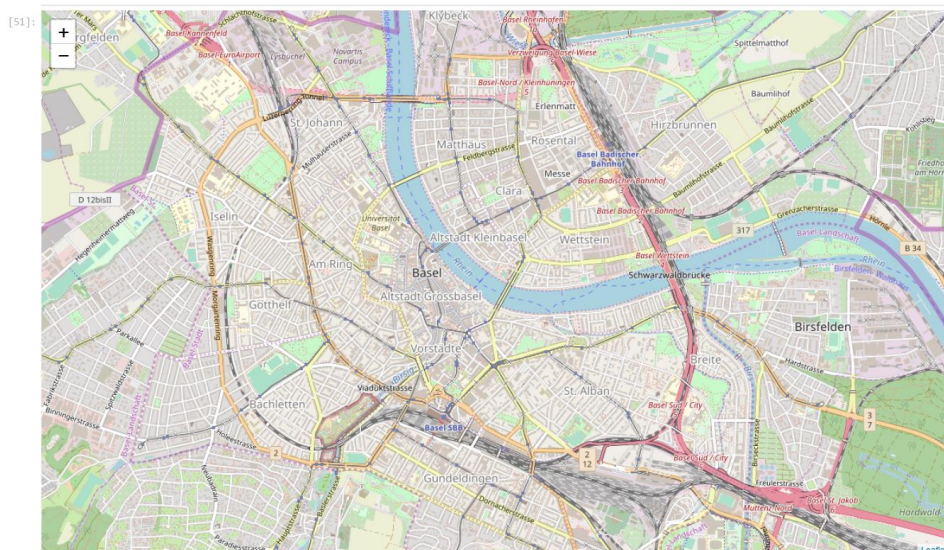


Fig 1. A graphical representation of results based on the specification requirements:

- highest percentage of renewable energy used to power the city of choice (red)
- highest percentage of a countries population that are on a meat free diet (blue)
- highest estimated meat free diet population (green)

Oslo would be an interesting city to track for the future having by far the largest population, knowing that trends across Europe that meat free diets are becoming more popular. The graphical statistics show us that with a very small percentage of the country's population (2.2%) following a non-meat diet, it can challenge for a top three place in our charts. When comparing this to the percentage of Swiss on a meat free diet (17%). Additionally, from a marketing perspective, sourced by 100% renewable energy is more appealing for to the customer.

Basel is the city of choice, it meets the marketing requirements “a city powered 100% by renewable energy”. It is in a country where 17% of the population are on a meat free diet, for which we have estimated (calculated) to have the highest number of non-meat eaters (33490 people). **It has been concluded through this investigation that the most appropriate location to start this new restaurant is in Basel.**



In the next part of this report we will look at exploring the city of Basel, using the Four-Square tools.

Method & Data Analysis: Exploring the Neighborhoods of Basel

5. Explore and cluster the neighborhoods in European City of Choice Where Existing Restaurants Exist (Which neighborhood is suitable for starting a restaurant business?)

To begin the quest to find explore and cluster the neighborhoods in Basel we need to get the coordinates of the postcodes in Basel and the geocodes.

- 5.1. In order to use Four Square, we will need to get the latitude and the longitude coordinates of each neighborhood.
- 5.2. Build a data frame of the postal code for each street along with the suburb name this dataset is about postal codes in Basel.

The data set includes details of all the postcodes in Basel. It includes following fields:

Field	Description
Postcode	A series digits, included in a postal address for the purpose of sorting mail.
Suburb	An administrative subdivision of a major city
Street	A street name within a town or city.
lat	Latitude
lon	Longitude

The Postal data has been scraped from the following site:
<https://addresses.lorenz.lu/oaddach/cityDetail/-1683619>

Sample data:

[59]:	Housenumber	Street	Postcode	City	Suburb	Country	Housename	Place	Hamlet	lat	lon
0	15	Andreasplatz	4001.0	Basel	Altstadt Grossbasel	CH	NaN	NaN	NaN	47.558273	7.586400
1	14	BarfÄsserplatz	4001.0	Basel	Altstadt Grossbasel	CH	NaN	NaN	NaN	47.554394	7.589294
2	24	BarfÄsserplatz	4001.0	Basel	Altstadt Grossbasel	CH	NaN	NaN	NaN	47.554813	7.589135
3	3	FahnengÄsslein	4001.0	Basel	Altstadt Grossbasel	CH	NaN	NaN	NaN	47.556560	7.590167
4	1	Falknerstrasse	4001.0	Basel	Altstadt Grossbasel	CH	NaN	NaN	NaN	47.556656	7.588933
5	11	Falknerstrasse	4001.0	Basel	Altstadt Grossbasel	CH	NaN	NaN	NaN	47.556213	7.589081
6	12	Falknerstrasse	4001.0	Basel	Altstadt Grossbasel	CH	NaN	NaN	NaN	47.556164	7.588882
7	13	Falknerstrasse	4001.0	Basel	Altstadt Grossbasel	CH	NaN	NaN	NaN	47.556076	7.589103
8	16	Falknerstrasse	4001.0	Basel	Altstadt Grossbasel	CH	NaN	NaN	NaN	47.556107	7.588874
9	17	Falknerstrasse	4001.0	Basel	Altstadt Grossbasel	CH	NaN	NaN	NaN	47.555870	7.589167

5.3. Wrangle Data

5.3.1. Drop columns from suburbs (find code on GitHub)

5.3.2. Count Missing Values (see code on GitHub)

5.3.3. Replace Empty Cells With np.nan (see code on GitHub)

5.3.4. Group Data by Suburb (see code on GitHub)

[93]:	PostalCode	Suburb	Street
0	402	St. Alban	Gellertstrasse
1	4001	Altstadt Grossbasel	Andreasplatz.BarfÄsserplatz.FahnengÄsslein.F...
2	4002	Gundeldingen	Gartenstrasse
3	4002	St. Alban	Centralbahnplatz.Centralbahnstrasse.Peter Meri...
4	4003	Am Ring	Missionsstrasse
5	4005	Altstadt Kleinbasel	Greifengasse
6	4012	St. Johann	Wilhelm Klein-Strasse
7	4019	Kleinhüningen	Grenzstrasse
8	4031	Am Ring	Mittlere Strasse
9	4051	Altstadt Grossbasel	Andreasplatz.Augustinergasse.BarfÄssergasse.B...

5.3.5. Merge Post Codes to Formulate Coordinates of Suburbs by Post Code

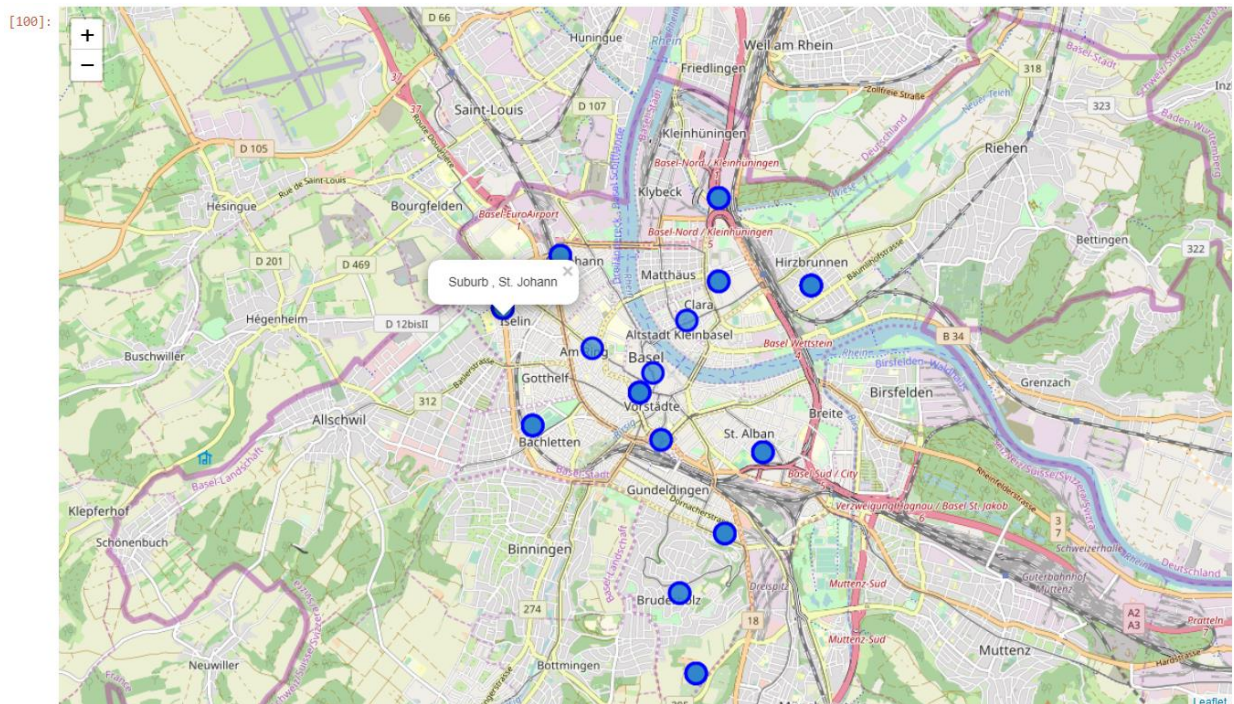
[120]:	PostalCode	Suburb	Street	Latitude	Longitude
0	4001	Altstadt Grossbasel	Andreasplatz,BarfÄ¼sserplatz,FahngÄ¼sslein,F...	47.5564	7.5889
1	4002	Gundeldingen	Gartenstrasse	47.5488	7.5904
2	4002	St. Alban	Centralbahnplatz,Centralbahnstrasse,Peter Meri...	47.5488	7.5904
3	4003	Am Ring	Missionsstrasse	47.5592	7.5788
4	4005	Altstadt Kleinbasel	Greifengasse	47.5623	7.5946
5	4012	St. Johann	Wilhelm Klein-Strasse	47.5667	7.6000
6	4019	Kleinhüningen	Grenzstrasse	47.5667	7.6000
7	4051	Altstadt Grossbasel	Andreasplatz,Augustinergasse,BarfÄ¼ssergasse,B...	47.5542	7.5867
8	4051	Am Ring	Auberg,Austrasse,Binnergerstrasse,Burgunderstr...	47.5542	7.5867
9	4051	Bachletten	Arnold Böcklin-Strasse,Bundesstrasse,Paulusgas...	47.5542	7.5867

5.4. Cluster the neighborhoods in Basel By Suburb - Cluster analysis or clustering is the task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar (in some sense) to each other than to those in other groups (clusters)

```
[100]: # create map of Basel using Latitude and Longitude values
map_base1 = folium.Map(location=[latitude, longitude], zoom_start=12)

# add markers to map
for lat, lng, suburb, street, in zip(basel_post ['Latitude'], basel_post ['Longitude'], basel_post ['Suburb'], basel_post ['Street']):
    label = '{}', {}.format("Suburb ", suburb)
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=10,
        popup=label,
        color='blue',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_base1)

map_base1
```



5.5. Using Foursquare developer Explore surrounding areas of the neighborhoods in Basel

(Foursquare – Used by the world's top companies and more than 150,000 registered developers rely of Foursquare to power geo-tagging, venue search and more in their apps)

5.5.1. In order to use Foursquare, we require login credentials

5.5.2. Using Foursquare we will begin to explore the surrounding areas of Basel

[455]:

	Street	Accessories Store	American Restaurant	Art Museum	Asian Restaurant	Athletics & Sports	Bakery	Bar	Beer Garden	Beer Store	Botanical Garden	Brewery	Bus Station	Bus Stop	Café	Chinese Restaurant	Chocolate Shop	Cocktail Bar	Coffee Shop
0	Achilles Bischoff-Strasse,Arlesheimerstrasse,B...	0.000000	0.000000	0.000000	0.000000	0.000000	0.071429	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.142857	0.000000	0.000000	0.071429	0.000000
1	Aeneas Silvius-Strasse,Airolostrasse,Albert Sc...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	Aeschengraben,Centralbahnplatz,Centralbahnsta...	0.000000	0.000000	0.033333	0.000000	0.000000	0.000000	0.133333	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.033333	0.033333	0.033333
3	Aescherstrasse,Bachlettenstrasse,Bättwilerstra...	0.000000	0.000000	0.000000	0.000000	0.166667	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.166667	0.000000	0.000000	0.000000	0.000000	0.000000
4	Ahornstrasse,Allschwilerplatz,Allschwilerstras...	0.000000	0.000000	0.000000	0.000000	0.000000	0.090909	0.000000	0.000000	0.000000	0.000000	0.000000	0.090909	0.181818	0.000000	0.000000	0.000000	0.000000	0.090909
5	Ahornstrasse,Allschwilerplatz,Allschwilerstras...	0.000000	0.000000	0.000000	0.000000	0.000000	0.090909	0.000000	0.000000	0.000000	0.000000	0.000000	0.090909	0.181818	0.000000	0.000000	0.000000	0.000000	0.090909
6	Akazienweg,Freiburgerstrasse	0.142857	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
7	Alemannengasse,Bannwartweg,Bergallingerstrasse...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
8	Allmendstrasse,Am Bahndamm,An der hohlen Gasse...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
9	Allschwilerstrasse,Altkircherstrasse,Belchenst...	0.000000	0.000000	0.000000	0.000000	0.166667	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.166667	0.000000	0.000000	0.000000	0.000000	0.000000
10	Am Bachgraben,Am Krayenrain,Beckenstrasse,Damm...	0.000000	0.066667	0.000000	0.000000	0.000000	0.066667	0.066667	0.000000	0.000000	0.000000	0.066667	0.000000	0.000000	0.133333	0.000000	0.000000	0.000000	0.000000
11	Am Umschlagbahnhof,Badenstrasse,Bonergasse,Dor...	0.142857	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
12	Amerbachstrasse,Andlaustrasse,Bärenfelsenstr...	0.142857	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
13	Andreasplatz,Augustinerstrasse,BarfÄussergasse,B...	0.000000	0.000000	0.033333	0.000000	0.000000	0.000000	0.133333	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.033333	0.033333	0.033333
14	Andreasplatz,BarfÄusserplatz,FahngängÄtsslein,F...	0.000000	0.000000	0.033333	0.000000	0.000000	0.000000	0.033333	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.100000	0.000000	0.066667	0.000000	0.033333
15	Arnold Böcklin-Strasse,Bundesstrasse,Paulusgas...	0.000000	0.000000	0.033333	0.000000	0.000000	0.000000	0.133333	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.033333	0.033333	0.033333

In the next part of this report we will look at the final conclusions

Formulate Results and Conclusions: Part 3, Cluster Neighborhoods and Conclude

- Run *k* to cluster groups, to start the investigation k=5 cluster groups, we then incremented to eventually k=9 to differentiate further differences between neighborhoods

6.1. Set Number of Cluster

```
[640]: # set number of clusters
kclusters = 9
basel_grouped_clustering = basel_grouped.drop('Street', 1)

# run k-means clustering
kmeans = KMeans(n_clusters=kclusters, random_state=0).fit(basel_grouped_clustering)

# check cluster labels generated for each row in the dataframe
kmeans.labels_[0:10]

[640]: array([2, 8, 6, 3, 7, 7, 1, 4, 4, 3], dtype=int32)

[641]: suburbs_basel = suburbs_basel.rename(columns={'Street':'Street'}, inplace=False)

[642]: # add clustering labels

street_venues_sorted.insert(0, 'Cluster Labels', kmeans.labels_)
basel_merged = basel_post

# merge basel_grouped with basel_data to add latitude/longitude for each neighborhood
basel_merged = basel_merged.join(street_venues_sorted.set_index('Street'), on='Street')

basel_merged.head(20) # check the last columns!
```

[642]:	PostalCode	Suburb	Street	Latitude	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	4001	Altstadt Grossbasel	Andreasplatz,BarfÄusserplatz,FahngengÄrsslein,F...	47.5564	7.5889	6	Swiss Restaurant	Café	Plaza	Hotel	Chocolate Shop	French Restaurant	Fountain	Museum	Pedestrian Plaza	Creperie
1	4002	Gundeldingen	Gartenstrasse	47.5488	7.5904	6	Italian Restaurant	Hotel	Bakery	Bar	Pizza Place	Chocolate Shop	Pub	Café	Gym	Food Court
2	4002	St. Alban	Centralbahnplatz,Centralbahnstrasse,Peter Meri...	47.5488	7.5904	6	Italian Restaurant	Hotel	Bakery	Bar	Pizza Place	Chocolate Shop	Pub	Café	Gym	Food Court
3	4003	Am Ring	Missionsstrasse	47.5592	7.5788	0	Hotel	Middle Eastern Restaurant	Indian Restaurant	Supermarket	Café	Ice Cream Shop	Botanical Garden	Gastropub	Historic Site	Vietnamese Restaurant
4	4005	Altstadt Kleinbasel	Greifengasse	47.5623	7.5946	0	Restaurant	Bar	Bakery	Hotel	Wine Bar	French Restaurant	Performing Arts Venue	Modern European Restaurant	Italian Restaurant	Gourmet Shop
5	4012	St. Johann	Wilhelm Klein-Strasse	47.5667	7.6000	0	Hotel	Thai Restaurant	Supermarket	Steakhouse	Bar	Restaurant	Sandwich Place	Lounge	Plaza	Cocktail Bar

6.2. Using Folium Library, we can create a representation of the clusters (color coded);

```
[643]: # create map
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=13)

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

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in zip(basel_merged['Latitude'], basel_merged['Longitude'], basel_merged['PostalCode'], basel_merged['Cluster Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=20,
        popup=label,
        color=rainbow[cluster-5],
        fill=True,
        fill_color=rainbow[cluster-2],
        fill_opacity=1).add_to(map_clusters)

map_clusters
```


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6.3 Explore Cluster Labels (0-8)

Conclusion

Certain restaurants succeed simply because their locations are so accessible, like restaurants landmarks, the most famous landmarks of Basel are mostly found in cluster 0.

There is plenty of foot traffic in urbanized areas, and restaurants only need to attract customers from the street into their business.

The urbanized areas of Basel have been incorporated in our analysis, clusters 0 to 8 as we move close to the city center the pedestrian areas become denser with foot traffic.

Most successful restaurants—other than the truly elite—are easy to find, and you will find them in city centers or unique locations throughout the world. The city center of Basel can be found situated in clusters labelled 0 and 7.

To conclude I would recommend opening a fast food meat free restaurant in the surroundings of Clusters 0 or 7. The streets that stretch across these clusters are populated with well-established cafes/bars and restaurants, which the city dwellers and workers will be familiar with. The location is a central point of the shops and is equally distance for those living in the surrounding suburbs. I would suggested try and finding a location close to one of Basel's known landmarks to catch the passing tourist trade and near one of the tram stations, this should prove to help guarantee customers and enhance the success of the restaurant.

This report has been written to demonstrate the tools, theories and skills learnt whilst completing modules 1-8 in this IBM Data Science Specialization, helping one to understand the ideas and principles and how apply and analyze more real-life challenges ahead using data-science.