Determining the Next Best City to Announce an ICE Ban

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1. Introduction

1.1 Background

With the threat of global warming bearing down on our planet, the pushes over the last decades to reduce humankind's carbon footprint have become shoves to spare the Earth from succumbing to the ravaging forces of climate change. This is a threat unlike many others the human race has ever faced; it does not discriminate on gender, nationality, or income. Temperatures are rising, along with the seas. The polar ice caps are dwindling rapidly, as wildfires rage long beyond what used to be normal fire season in my home state of California. Crops dying beneath sweltering heat as droughts last longer and longer into the fall. The most significant contributor to this threat: carbon dioxide emissions. The United States ranks number two in the world, following China, on CO2 emissions: releasing 5.41 gigatons of it in 2018 (epa.gov). The time to reverse course on the damage done to our planet is past; now all we can hope to do is minimize the damage and hope future generations will have the technology to reverse the irreversible(Rice). With such a substantial number on the table, numerous entities, from cities to companies have declared pledges to become carbon neutral in the coming years. Of this significant number, over a quarter of it is from transportation alone in the United States. This includes air travel, public transportation, and privately owned vehicles. A key element is that last category: 59% of transportation emissions are from light-duty cars. This number is often quoted as the automotive industry begins its pivot toward electric vehicles (EV). Spurred on by the incredible success of Tesla's Model S back in 2012, automakers (after due time) have begun to play catch-up in 2020. They now offer more affordable EVs, to increase the proliferation of these zero-emission vehicles. Some cities and one US state have taken it a step further by declaring complete bans on internal-combustion engined vehicle (ICEV) sales or operations in the coming decade. Los Angeles, Seattle, and New York have announced bans on owning or operating ICE's by 2030 and 2040(New York) (Wikipedia). Not only that, but California has announced a full-scale ban on the sale of non-EV's by 2035.

1.2 Problem

While these bans seem like a step in the right direction, as EVs produce significantly less pollution than their ICE equivalents, there are some questions regarding how this will impact a number of areas relating to the usage of EVs (*Alternative Fuels Data Center: Emissions from Hybrid and Plug-In Electric Vehicles*). Will the grid be able to cope? Will everyone be able to charge their car when they need to? How will cities change as a result of this pivot in transportation? While questions are beyond the scope of this report, what we can determine from the available data is which cities might be best suited for instituting a ban on ICEs, much like the cities mentioned above. If we can accurately predict which cities may be the most likely to be the next to make this decision, we can get a head start on making sure the infrastructure can handle this influx of electric cars. This includes fortifying the grid, installing chargers, and making sure residents of the city are well-informed on the pros of EVs and the nuances of ownership. The main objective of this project is to determine how well-suited a city is to make the switch to EV's. Then I take a closer look at the city to see if any more insights can be determined from the location data provided by Foursquare API.

1.3 Interest

From a business perspective, these cities I rank highly would be ideal opportunities to beat the competition to market by allocating EV inventory there or looking to be the one who is contracted for building out the charging infrastructure. As this technology grows, opportunities grow along with it. Investors looking to hedge their bets on EV-related technology will want to take a closer look at the cities I rank highly here. On the governmental side, this report details the readiness of a city to make the switch to EV only. Depending on an elected official's constituents, a high or low ranking can influence how they vote on issues in Congress, what kind of support they provide local businesses in certain areas, and in what direction they want to take their community. Moreover, corporate social responsibility is a significant factor in attracting better employees, retaining paying customers, and cultivate positive brand recognition (Murphy). Business owners in these locales would do well for themselves and their business to be publicly seen as pushing for a greener city. This report signals a directional change these cities are ready to take, and with it, signals to those looking to get ahead before the announcement of any official plans as these locations are ripe with opportunity. Overall, climate change is no longer a question of ‘if’ or even ‘when’, but ‘how much can we mitigate it?’. With that being said, the data provided here should be a signal to policy makers that their city is able to make the decision to move toward an EV-motivated future sooner than later. Action must be taken, and this report enumerates the states in the best position to do so.

2. Data

2.1 Data Sources

Much of the data I used was readily available from government agencies or Wikipedia. However, some of it had to be manually transcribed as it could not be scraped from the webpage from which it was found, or it was in a format not attainable via my skills in python.

The EV charging station locations were taken from the Alternative Fuels Data Center here.

Determining the most populous city in each state was scraped from Wikipedia here.

Determining the cost of electricity per state was scraped from the state of Nebraska’s website here.

I had to manually create an importable .csv file regarding EV market share per state, year-over-year sales growth, and the percentage of state CO_2 emissions from transportation, but these sources are hyperlinked respectively here and here, as well as cited at the end of this report from EVAdoption.com and the EPA.

The data for state incentives was also unable to be read in via code, but the information is available here from evchargin.enlex.com.

Foursquare API was used to gather common venues in Baltimore, Maryland (spoiler alert)

2.2 Data Cleaning

The data scraped from government websites were full of information. Much too full for my needs in fact. I had to drop tens of thousands of data points on the EV charger location file in order to manage the data effectively. I did this after grouping removing all non-purely-EV chargers and then grouping the chargers by city. As my objective here was to predict the next city to behave similarly to Los Angeles, Seattle, and New York, I determined a common characteristic of those three before moving on. I then scraped data from Wikipedia detailing the population of the largest city in each state. This also required a lot of dropping of columns, as well as US territories that were also included. Thankfully, this was a smaller dataset which made it easier to check for errors. Once again, the columns were renamed before the first significant hurdle of the project: merging the city population data set with the charging location by city data set.

For reasons I still cannot explain, this resulted in the dropping of Hawaii from the merged dataframe. As a result, I had to add Honolulu's information back manually at this stage of the code, confirmed the shape was proper, and then moved on. A second hurdle was that

New York City was not pulled from the initial charger location .csv file properly and only listed one charger rather than the correct number of 343. This also had to be manually input. Thirdly, the datatypes of the new dataframe had to be adjusted to integers so mathematical calculations could be executed on the data. Finally, in order for the chargers per capita information to be visible in the dataframe, I had to format everything out to six decimal places which makes the data less visually appealing. The alternative, however, was to have zero chargers per capita showing for the entire program, then wondering why states scored differently during normalization. I will discuss this more in depth during the methodology section of the report. The price of electricity per state was imported, read and merged on the state with the aforementioned dataframe easily now resulting in a dataframe containing the state, city, chargers per person and cost of electricity. As I mentioned above, I had to manually construct a .csv file with data taken from websites with unique user interfaces that did not play well with scraping or did not allow me to download the data directly. I also manually created a dataframe containing the state-level EV incentives, purely as a demonstration that I had the skills to do so for the sake of displaying competence in the material covered in this course.

Once this was complete, I merged this new dataframe with the previous one to create a master dataframe with the pertinent information I desired.

Moving on to the Foursquare API data, I have to admit I hit a roadblock. There were no useful JSON or .csv files, nor any webpages I could find with Baltimore broken down into neighborhoods or boroughs like New York, for example. My backup plan was to sort the city by zip code, which is roughly the same thing, and provides a similar sense of segmentation. However, the problem herein is that the Foursquare call is from the coordinates at the center of Baltimore, so when I perform the call, all 100 venues, or even up the 300 venues are located in only the three most central zip codes. I had no way around this problem, so the cluster analysis on the zipcodes is rather inconclusive. I will discuss this more in depth in the results section.

3. Feature Selection and Methodology I

3.1 Feature Selection and Rationale

According to MYEV.com and EVAdoption.com, the most important factors when it comes to location friendliness for EVs are charging stations per capita, low electricity rates, and state incentives for purchasing an EV. I decided to include market penetration of EVs as well as year-over-year growth as a signal of trends in the state that would influence how governments and businesses might react. If a state is seeing EV sales double every year, they will be more inclined to consider the feasibility of an ICE ban than a state with negative growth, such as Vermont. Furthermore, this is also useful information to any business owners or entrepreneurs in this space of where to focus their time and energy. Finally, I also included each states' percentage of CO2 emissions that stem directly from transportation. This is because California is ranked among the highest here, with nearly 60% of its emissions from this sector, and not only has its most populous city but also the entire state has decided to ban ICEs. As a result, I believe this statistic plays a significant role in the likelihood a city or state will make the decision to ban ICEs, or at the very least, increase EV incentives.

3.2 Methodology

I broke this project down into two main parts: the first was to determine which state would be the most well-suited to move in a more EV-focused direction and the second to perform more specific location exploration. Part one began with the data cleaning and dataframe creation I mentioned above. Regarding the formatting, once I knew I would be normalizing the data, I wanted to use chargers-per-capita as a metric for rating a city. To have it the other way around (people per chargers) would result in having to take the inverse of the normalization in that column. I decided that it would be more effective to have one line of code doing division here and deal with longer decimals than to have to write ten lines later on cloning, appending and formatting another dataframe with the inverted values.

```
In [1356]: #divide number of chargers by population to get chargers per person
           # yes, this is a small number, but it makes our job normalizing the data
           # easier later on so bear with me
           df6['Chargers per Person'] = df6['Number of Chargers']/df6['Population']
           pd.options.display.float_format = '{:.6f}'.format
           df6.head()
```

Out[1356]:

	State	City	Population	Number of Chargers	Chargers per Person
0	Alabama	Birmingham	209880	23	0.000110
1	Alaska	Anchorage	291538	7	0.000024
2	Arizona	Phoenix	1660272	133	0.000080
3	Arkansas	Little Rock	197881	24	0.000121
4	California	Los Angeles	3994928	768	0.000192

This is the resulting dataset formatted to six decimal places, so the differences in chargers can be seen. The reason for including this feature is fairly self explanatory, but I will offer a short explanation here: this is essentially a metric of how available chargers are for each person. While formatted this way is harder to grasp than people per charger, just know the smaller this number, the more people there are to a charger, and the less likely an individual is to have a charger should they need one. In a sense, it is a measure of convenience. Knowing you can charge when you get to your house is a luxury not everyone has. Public access to chargers for those who live in apartments or park on the street is a significant barrier to EV ownership faced by many.

I also created a dataframe containing how the state voted in the 2020 election, as Democratic states are more likely to favor government action to help the environment (Funk). I included this in the program if you would like to check out the clusters on your own. It also plays well with the normalization, as I turned Democrat into a binary 1 and Republican into 0. This would add to the total score of a state, making it more likely a Democratic state will take the actions discussed here than a Republican-voting state, all else being equal. I left it out simply because I was unsure if the weight of a full point would be too influential once it came to the normalizing stage of the program.

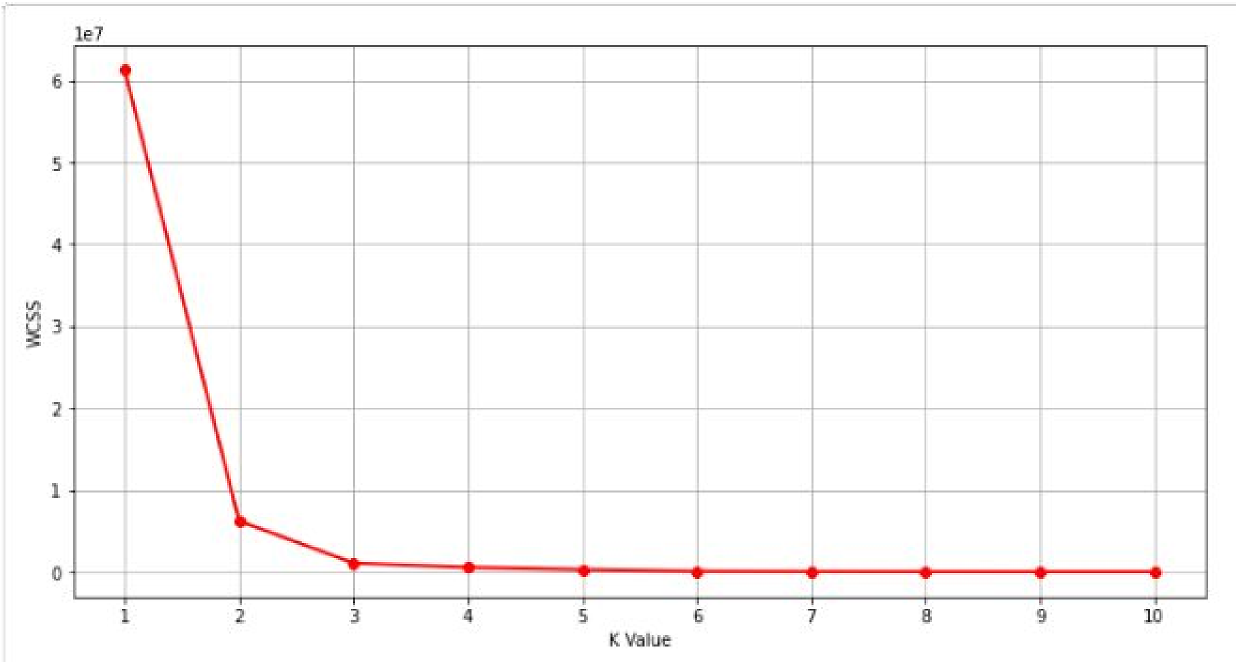
```
In [974]: # create df for how each state voted in the last election
          #using binary operators: Democrat = 1, Republican = 0
          #this is purely for classification purposes
          #Votes = {
              #'State' : ['Alabama', 'Alaska', 'Arizona', 'Arkansas','California', 'Colorado',
                       # 'Connecticut', 'Delaware', 'Florida', 'Georgia', 'Hawaii', 'Idaho', 'Illinois'
                      #  ,'Indiana', 'Iowa', 'Kansas', 'Kentucky', 'Louisiana', 'Maine', 'Maryland',
                      #  'Massachusetts', 'Michigan', 'Minnesota', 'Mississippi', 'Missouri',
                      #  'Montana', 'Nebraska', 'Nevada','New Hampshire', 'New Jersey',
                      #  'New Mexico','New York', 'North Carolina', 'North Dakota', 'Ohio','Oklahoma',
                     #   'Oregon','Pennsylvania','Rhode Island','South Carolina','South Dakota',
                    #    'Tennessee','Texas','Utah','Vermont','Virginia',
                    #    'Washington','West Virginia','Wisconsin','Wyoming'],
             # 'Political Orientation': [0,0,1,0,1,1,1, 1,0,1,0,0,1,0,0,0,0,0,1,1,
                                       #1,1,1,0,0,0,0,1,1,1,1,1,0,0,0,0,1,1,1,0,0,0,0,0,
                                     #  1,1,1,0,1,0]
            #  }
          #df_poli = pd.DataFrame(data=Votes)
          #df_poli.shape
```

Another dataframe I created but left out is one regarding average income per city. Once more, I left it out as I felt income has just as much of an impact on ICE sales as EV sales, and used EVs depreciate quite rapidly, making them a possible investment regardless of income. Once my dataframes had been merged appropriately, the result head looked like this:

This is sorted by Chargers per Person ascending and includes the average cost of electricity, EV market share, sales growth, transportation-specific CO2 emissions as a percentage of total emissions and the state-level EV rebates, ignoring the $7500 one on a federal level. I preserved the positive nature of the CO2 emissions percentages because the higher they are, the more likely it is the state will execute a ban on some level. California ranks number one, with 58% of its CO2 from transportation and Washington

	State	City	Chargers per Person	Average Electricity Ratefor All Sectors(Cents per Kilowatthour)	EV Market Share (2018)	YoY Share % increase (2018/2017)	2018 Co2 Emissions from Transportation	EV Rebate
0	Kansas	Wichita	0.000023	10.720000	0.960000	95.920000	0.304670	0
1	Alaska	Anchorage	0.000024	19.360000	0.590000	59.460000	0.338602	0
2	Montana	Billings	0.000026	8.840000	0.470000	67.860000	0.255259	0
3	South Dakota	Sioux Falls	0.000038	9.970000	0.350000	59.090000	0.427495	0
4	Pennsylvania	Philadelphia	0.000039	10.100000	0.920000	67.270000	0.279246	0

ranks third with 57%. With two out of the top three states announcing bans in their most populous cities, I think this is correlation enough to warrant it as a factor states take into consideration when considering ICE bans. With these key data points, I performed a test to determine how many clusters I should use. The resulting elbow method looked like this:



With this data, I decided on three clusters as two failed to result in much meaningful distinction among states. I ran an unsupervised K-Means algorithm to cluster the states as these tests are a common method of unsupervised machine learning that are quite powerful tools of segmentation. The resulting cluster contained California, New York and Seattle, which I believe to be success on the part of the clustering algorithm, as they contain the cities that have already announced bans on ICEs.

	State	Chargers per Person	Average Electricity Ratefor All Sectors(Cents per Kilowatthour)	EV Market Share (2018)	YoY Share % increase (2018/2017)	2018 Co2 Emissions from Transportation	EV Rebate
4	California	0.000192	16.580000	7.840000	56.180000	0.580572	2500
7	Delaware	0.000467	10.550000	1.270000	47.670000	0.360380	2500
17	Louisiana	0.000045	7.710000	0.280000	86.670000	0.190216	3000
19	Maryland	0.000305	11.570000	1.910000	91.900000	0.472562	3000
31	New York	0.000039	14.830000	1.560000	51.460000	0.440393	2000
36	Oregon	0.000239	8.850000	3.410000	44.490000	0.533036	2500
46	Washington	0.000289	8.000000	4.280000	70.520000	0.575049	2500

A note about formatting is in order: errors abounded when merging on city names, as multiple states had the same city name. To avoid this, I grouped by STATE and this will be shown in the next few screenshots. However, the goal of this project is still to look at the CITY, which we do in Part 2. With a Top 7 (or really Top 4 once you subtract the cities that already have), I began to normalize the data. I imported sklearn preprocessing in order to do so. This made the best value in each column equal to one, then each subsequent value a percentage of that until the least value is zero. However, in order to do this, I had to first invert the Average Cost column by removing it, cloning it to a new dataframe, subtracting one from each value, finding the absolute value of the result, then appending it back to the initial normalized dataframe. I then re-added the state names to the resulting score sheet, as well as a scoring total table. I sorted the values based on the

	State	Chargers Per Person	EV Market Share (2018)	YoY Share % increase (2018/2017)	2018 Co2 Emissions from Transportation	EV Rebate	Average Electricity Ratefor All Sectors(Cents per Kilowatthour)	Row_Total
3	MD	0.621754	0.215608	1.000000	0.723303	1.000000	0.564825	8.250983
6	WA	0.585329	0.529101	0.549040	0.985850	0.500000	0.967306	8.233250
5	OR	0.467461	0.414021	0.000000	0.878224	0.500000	0.871477	6.262367
0	CA	0.358447	1.000000	0.246572	1.000000	0.500000	0.000000	6.210038
2	LA	0.015738	0.000000	0.889686	0.000000	1.000000	1.000000	5.810847
1	DE	1.000000	0.130952	0.067074	0.435920	0.500000	0.679820	5.627533
4	NY	0.000000	0.169312	0.147015	0.640893	0.000000	0.197294	2.309029

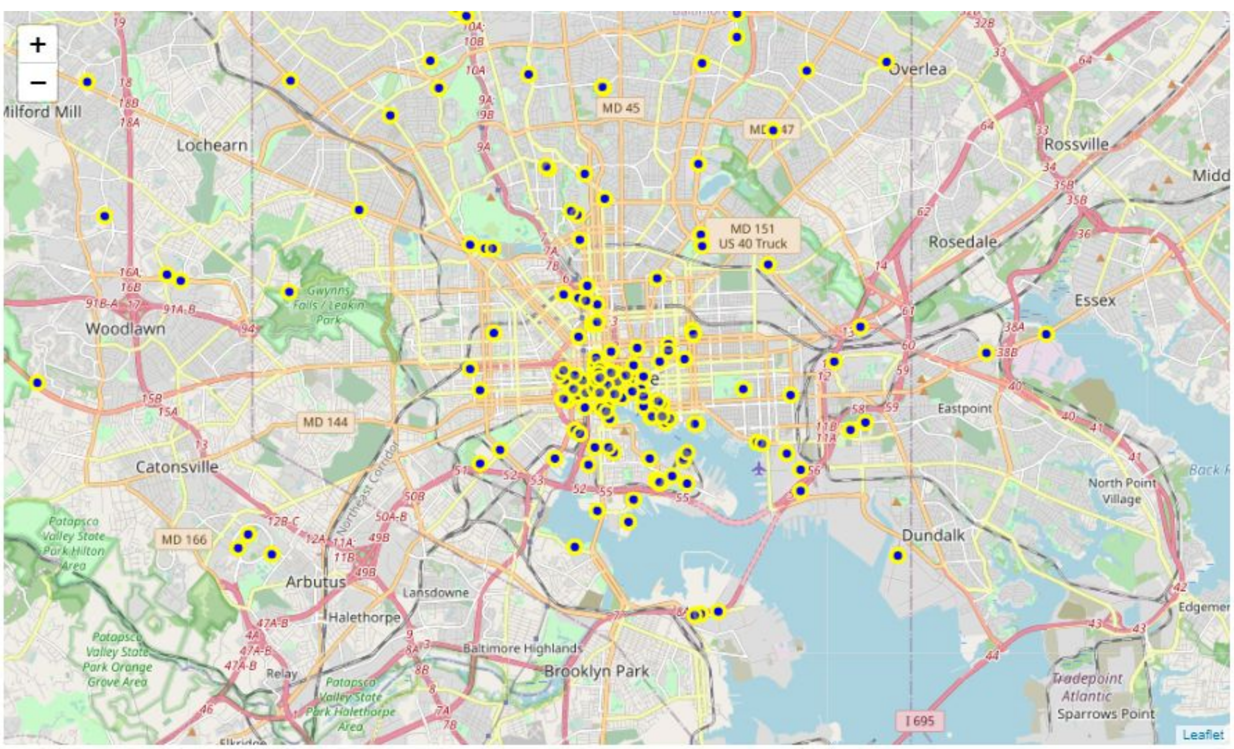
total to find which state scored the highest of the criteria. The result looks like this:

4. Results I

With the scores tabulated, the clustering and normalization reveals that, according to the criteria I deemed important to EV adoption and subsequent governmental actions against ICEs, Baltimore, Maryland is a very good candidate for such action and is worth the attention of politicians in the city, as well as business owners in the EV marketspace in said locale.

5. Feature Selection and Methodology II

With the winning city confirmed, it was time to delve deeper into the location data and find out what kinds of businesses exist in Baltimore and how their charging infrastructure stacks up with potential future demand. With those two questions in mind, I used folium to generate a map, then populated it with the charging stations located in the .csv file from Part 1.



The result is a rather predictable clustering of charging stations in the very center and quickly depleting in quantity as you move from the downtown areas. However, I believe this is a problem in need of rectifying as Baltimore has one of the longest commute times in the country, at 31.5 minutes (Zhang). This means more and more people are coming from further away and may be unable to snag one of concentrated downtown chargers, where they have to vy with other working professionals as well as those who live downtown. Couple this with the fact that 55% of Baltimore residents rent their living space, which in turn decreases the likelihood they have a dedicated place to park and charge a car should they own one, means the downtown charging spots are very competitive (Department of Planning).

As I mentioned above, there are no well-defined resources to segment Baltimore by neighborhood like you can do with the Boroughs of New York. As a result, I was relegated to segmenting by Postal Code. I used Foursquare API to pull nearby venues from Baltimore, then grouped the results by Zip Code. The resulting dataframe head looked like this:

	postalCode	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	21202	39.293297	-76.61049	Baltimore Farmers' Market & Bazaar	39.293297	-76.610490	Farmers Market
1	21202	39.293297	-76.61049	Ida B's Table	39.292654	-76.610420	Southern / Soul Food Restaurant
2	21202	39.293297	-76.61049	Black Sauce @ The Baltimore Farmers' Market	39.293335	-76.610681	Breakfast Spot
3	21202	39.293297	-76.61049	Sotto Sopra	39.294314	-76.615375	Italian Restaurant
4	21202	39.293297	-76.61049	Zeke's Coffee @ Baltimore Farmer's Market	39.293517	-76.609854	Coffee Shop

I then grouped by Zip Code and proceeded to the one-hot encoding in order to determine the frequency of each venue in each Zip Code. The result looked like this:

```
----21201----
           venue  freq
0    Coffee Shop  0.05
1           Café  0.04
2 Sandwich Place  0.04
3    Pizza Place  0.03
4          Hotel  0.03
```

```
----21202----
                venue  freq
0               Hotel  0.05
1 American Restaurant  0.04
2  Italian Restaurant  0.04
3  Seafood Restaurant  0.04
4      Sandwich Place  0.04
```

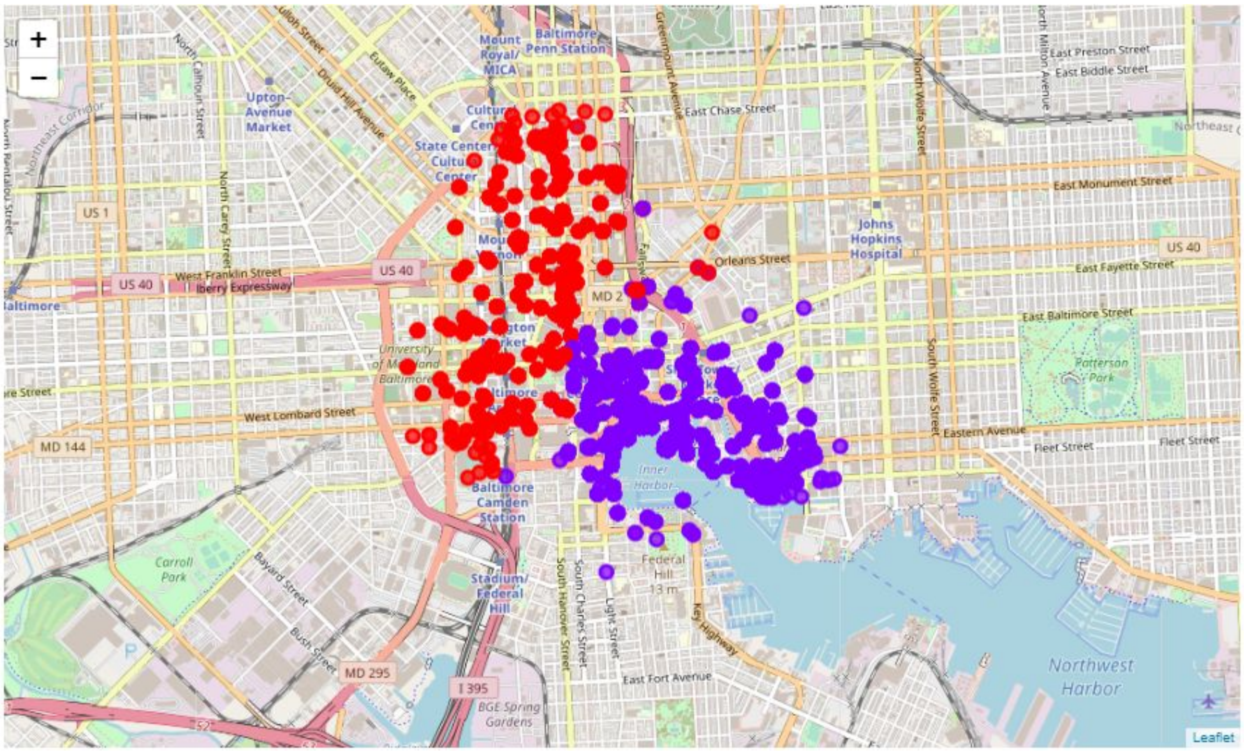
```
----21286----
        venue  freq
0        Café  0.08
1     Theater  0.06
2 Coffee Shop  0.05
3 Pizza Place  0.05
4       Hotel  0.05
```

Unfortunately, there are so many venues in the downtown area, the Foursquare calls within my daily limit only resulted in three Zip codes. As a result, there are only three groups here. With this data, I created a function that returned the most common venues per Zip Code, then appended them to a new dataframe in that order. I performed a second

	postalCode	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6 C
0	21202	39.293297	-76.61049	Baltimore Farmers' Market & Bazaar	39.293297	-76.610490	Farmers Market	1	Hotel	Italian Restaurant	American Restaurant	Seafood Restaurant	Sandwich Place	A
1	21202	39.293297	-76.61049	Ida B's Table	39.292654	-76.610420	Southern / Soul Food Restaurant	1	Hotel	Italian Restaurant	American Restaurant	Seafood Restaurant	Sandwich Place	A
2	21202	39.293297	-76.61049	Black Sauce @ The Baltimore Farmers' Market	39.293335	-76.610681	Breakfast Spot	1	Hotel	Italian Restaurant	American Restaurant	Seafood Restaurant	Sandwich Place	A
3	21202	39.293297	-76.61049	Sotto Sopra	39.294314	-76.615375	Italian Restaurant	1	Hotel	Italian Restaurant	American Restaurant	Seafood Restaurant	Sandwich Place	A

K-means algorithm with three clusters. The resulting dataframe with cluster labels is displayed below:

With these clusters created and labled, I then added them to another folium map.



As you can see, the problem with limited reach of data is present here. The spread does not move very far outside the very center of the downtown area. The red clusters pertain mostly to casual and take-out dining locations such as cafes and coffee shops. The purple locations include more hotels, music venues and travel destinations like aquariums. However, while the foursquare data alone may not offer much insight, when compared with the AFDC data from earlier, we can draw some meaningful conclusions.

6. Discussion and Conclusion

If you juxtapose the charging locations with the clusters in the second map, a disconnect is evident: the greater number of chargers exist in the cluster with places typically associated with shorter stay times. Coffee shops are subject to quick runs on the way to work, sandwich shops and fast food have drive-throughs for meals that you grab and go. On the contrary, hotels, museums, theaters, and sit-down restaurants like in the purple cluster are venues wherein people spend greater periods of time not in their cars. If they are passing through on a work trip, it makes more sense to have chargers at a hotel so someone can charge up their car on a business trip or holiday. Chargers near a sit-down restaurant not only add convenience for those who choose to dine there and can have their car charged while they wait, but also provides a more comfortable place for a traveler to spend their time waiting to charge their EV. Similar arguments can be made for having space to charge your car while spending the day at an aquarium, music festival or theater.

Baltimore ranked mid-pack in the normalization test earlier regarding chargers per capita, and this location analysis goes so far as to show that those chargers are not even in the best possible locations. With that, I recommend the planners in charge of locating EV charging stations take a closer look at the bigger picture location data that may be more beneficial to EV drivers when the time comes to make the switch.

With relatively low electricity costs, great state incentives and steller year-over-year EV sales growth, Baltimore, Maryland could very well be the next big EV sales sector. This transition brings with it a wealth of opportunity; opportunity both for enterprising individuals focused on making a living in the EV marketplace and for politicians trying to push a greener agenda. In conclusion, with some smarter planning, especially with increased production and placement of EV chargers in areas that would benefit commuters and travelers more greatly, Baltimore is lined up to be the next EV hotspot. We are well beyond the point of no return and action to reduce our greenhouse emissions should have been taken yesterday. With the date provided here, I firmly believe Baltimore should make the call and become the fourth US city to ban ICEVs, moving us closer to a better future.

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