The Brewery Project

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Abstract
The US domestic beer market is undergoing a rapid transition with a significant growth in the craft brewery section. American brewers are experimenting and diversifying brewing styles, and these are being well received by the general public. This project seeks to understand the qualities that distinguish breweries producing some of the best-rated beers. This information can guide the decision making of potential investors looking to expand into the growing beer market.

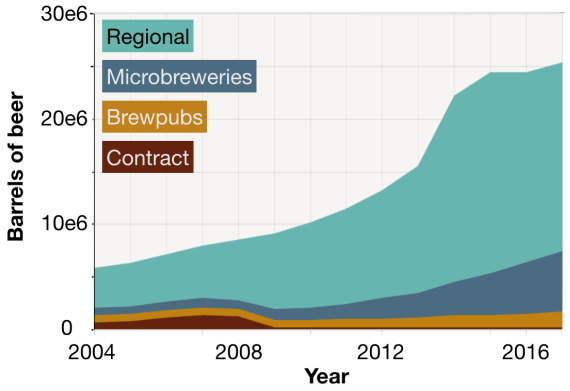
Keywords
Craft beer — Brewery — Machine Learning — FourSquare — BeauifulSoup

Contents

1. Introduction and Background

The American beer landscape is changing. According to the Brewers Assocation[1], craft beers now account for nearly a quarter of the US beer market. Figure 1 shows the growth of *craft breweries* – small and independent brewing companies – since 2007[2].

The increase in the number of craft breweries is marked by a corresponding rise in general interest in craft brews. Figure 2 shows the rise in Google searches for "craft beer" from 2004 to 2018[3]. It would be safe to say that this is the decade of the Craft Beer Revolution.



Source: https://www.brewersassociation.org/statistics/national-beer-sales-production-data/

Figure 1. Growth of craft breweries in the US.

Overall, the beer market in the US shows a decline, as measured by the number of barrels of beer produced annually. Figure 2 shows the taxable production of beer in the US between 2007 and 2017, as reported to the US Treasury Department's Alcohol & Tobacco Tax & Trade Bureau[4]. Nevertheless, craft breweries continue to grow; current figures on Brewers Association indicates a 5% increase in craft beer production, despite an overall -1.2% change in overall beer volume.

Taken together this data suggests that there is a new Craft Beer trend sweeping across the US, and that this is a great time to be brewing craft beer in the country.

2. The Problem

Imagine an investor looking to dive into the craft beer sector and open a new brewery. As with any business endeavor, there are a host of unknowns, including the obtaining of raw material, finding experienced brewers, installation of the industrial

[1] https://www.brewersassociation.org/statistics/national-beer-sales-production-data/

[2] Figure adapted from National beer sales and production data, Brewers Association

[3] Data gathered from Google Trends.

[4] https://www.ttb.gov/beer/beer-stats.shtml

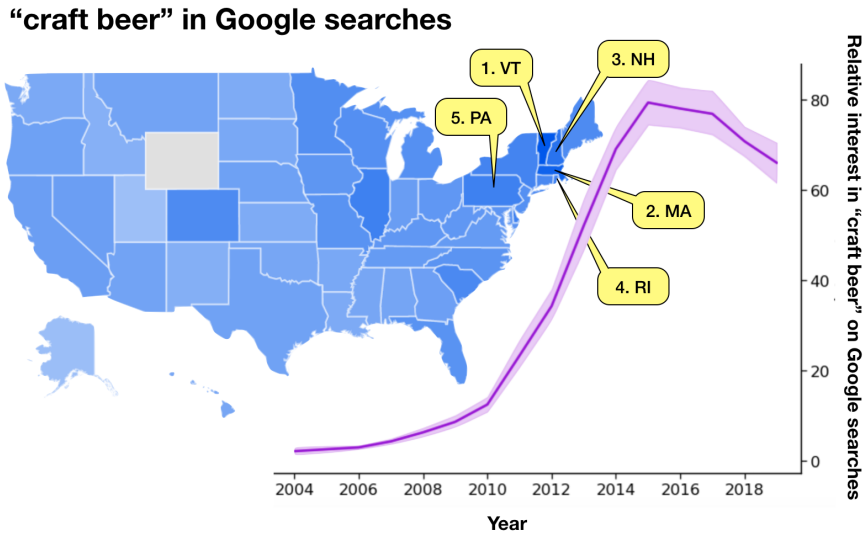


Figure 2. Google searches for “craft beer” between 2004 and 2008. The graph shows the *interest*: number of searches relative to the peak within the period, for each year, aggregated by all months in that year. States are color coded by the relative *interest* in ”craft beer” for this period, with the top 5 states highlighted.

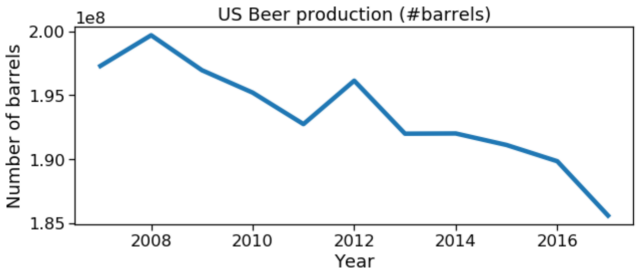


Figure 3. US Beer production (number of taxable barrels) by year. Data gathered from https://www.ttb.gov/beer/beer-stats.shtml

machinery that constitutes a modern brewery, local regulatory constraints, and so forth.

However, above all these issues is the question of the product itself, the brew. Knowing what makes a good brew can be used as a tool to guide the decision for establishing a new brewery – the brewery should share characteristics of other breweries that have been making beer that is consistently appreciated by the drinkers.

What makes a good beer? The very definition of beer and brewing is changing, particularly in the US, where there has not been a long and deep tradition of brewing. For example, the German brewery Weihenstephan, founded in 1040, is nearly a 1000 years old[5], while the first American brewery opened nearly 600 years later[6]. In contrast, American brewers are not saddled with long traditions, and have experimented and expanded the range of beers and beer-making techniques, from the development of American hops like Citra or Centennial or the Randall, designed to infuse beer. In these experimentation and development, can we identify what makes a good brew?

2.1 Towards a solution

In the project, I will use a Data Science approach to answer the question, what makes a high quality beer? I will operationalize the overall quality of a beer as the BeerAdvocate weighted-rank score[7]. As is attributed to the American entrepreneur Seth Godin, “Don’t find customers for your products, find products for your customers.” In this spirit I am looking for those specific products, beers, that are highly valued by the customers.

This allows me to then determine the qualities that define breweries that are brewing these highly rated beers, and use that information to make recommendations to guide the setting up breweries and the brewing of its beers.

3. Data and Approach

The precise goal of this project is to use drinkers’ ratings of individual beers to determine the characteristics of the breweries making these highly-rated beers. These characteristics would then form the basis for recommending the introduction of a new brewery in the market.

Therefore, I will be taking a beer-centric approach. I will first identify the highly-rated beers, and find the various characteristics of these beers including their styles and contents, as well as characteristics of the breweries, operationalized as the neighborhoods and geographical areas where these are located.

[5] https://www.weihenstephaner.de/en/our-brewery/
[6] http://www.beerhistory.com/library/holdings/chronology.shtml
[7] See https://www.beeradvocate.com/community/threads/top-rated-beers-explained.587593/ for a description

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1		ba_rank	beer_name	brewery_nar	style	abv	ba_score	num_ratings	beer_url	brewery_url	style_url	brewery_adc	zips	lat	lng	state
2	0	1	Kentucky Brunc	Toppling Gol	American Im	12	4.84	745	/beer/profile	/beer/profile	/beer/styles/	1600 Prospe	52101	43.34588	-91.77187	IA
3	1	2	Marshmallow H	3 Floyds Brev	Russian Impe	15	4.74	1659	/beer/profile	/beer/profile	/beer/styles/	9750 Indiana	46321	41.55146	-87.50143	IN
4	2	3	Barrel-Aged Abr	Perennial Art	American Im	11	4.74	1492	/beer/profile	/beer/profile	/beer/styles/	8125 Michig	63111	38.5593	-90.25174	MO
5	3	4	Hunahpu's Impe	Cigar City Bre	American Im	11	4.73	1602	/beer/profile	/beer/profile	/beer/styles/	3924 W Spru	33607	27.9638	-82.49537	FL
6	4	5	King Julius	Tree House E	New Englanc	8.3	4.73	934	/beer/profile	/beer/profile	/beer/styles/	129 Sturbrid	1507	42.13514	-71.96961	MA
7	5	6	Heady Topper	The Alchemis	New Englanc	8	4.71	14495	/beer/profile	/beer/profile	/beer/styles/	100 Cottage	5672	44.47539	-72.70225	VT
8	6	7	Very Hazy	Tree House E	New Englanc	8.6	4.72	828	/beer/profile	/beer/profile	/beer/styles/	129 Sturbrid	1507	42.13514	-71.96961	MA
9	7	8	King JJuliusss	Tree House E	New Englanc	8.4	4.73	408	/beer/profile	/beer/profile	/beer/styles/	129 Sturbrid	1507	42.13514	-71.96961	MA
10	8	10	Mornin' Delight	Toppling Gol	American Im	12	4.7	1503	/beer/profile	/beer/profile	/beer/styles/	1600 Prospe	52101	43.34588	-91.77187	IA
11	9	11	SR-71	Toppling Gol	American Im	14	4.71	502	/beer/profile	/beer/profile	/beer/styles/	1600 Prospe	52101	43.34588	-91.77187	IA
12	10	12	Pliny The Young	Russian Rive	American Im	10.3	4.69	3255	/beer/profile	/beer/profile	/beer/styles/	725 4th St, S	95404	38.45761	-122.6932	CA

Figure 4. First 10 rows of the CSV file containing the clean dataframe with beers from the Top 250 list on BeerAdvocate.com

For this project I will use the following primary data sources:

3.0.1 Beer Advocate

I will use BEAUTIFULSOUP to extract the top-rated beers and the BA scores for these beers, along with related information, such as the the ABV (% alcohol), and the brewery. I will then use the name of the brewery to also retrieve the brewery location.

3.0.2 Foursquare Developers

Foursquare is a location technology company that gives access to developers to their location data. Location data includes details of "venues" – businesses, restaurants, parks, etc., in relation to a specified geolocation. I will use this information to build neighborhood profiles of breweries, and use these in predictive models to understand if and how such profiles contribute towards predicting high beer scores.

3.0.3 Brewers Association

Brewers Association compiles a list of over 7,000 US breweries. I will again use BEAUTIFULSOUP to extract the names, addresses, and types of all the US breweries they list. I will use machine learning to derive geographical clusters that would be one of the key characteristics included in models (along with the other variables described above) to predict beer scores.

4. Methodology

As described in the previous section, data will be gathered from multiple sources, collated, and used for analyses. All the scripts and analyses were carried out in JupyterLab notebooks instantiated within an Anaconda environment on a Macbook Pro, using Python 3.

4.1 Retrieving the Raw Data

4.1.1 Beer Advocate

The Beer Advocate website utilizes a Bayesian, weighted-rank score gathered from its users who drink and rate beers across the country. They list their top 250 beers in a single web-page[8]. Using the Python REQUESTS and BEAUTIFULSOUP libraries, I retrieved their top 250 beer list. For each of the beers, I extracted and saved the following:

1. Beer name
2. Beer rank
3. Beer score
4. Beer style
5. Beer ABV[9]
6. Brewery name
7. BeerAdvocate URLs of the beer and brewery

This information was saved to a PANDAS dataframe.

Looping over all the brewery URLs, I captured each brewery page and extracted the address of each brewery. This information was added to the previously saved PANDAS dataframe.

In this process, I found a set of breweries that were outside the US, and I dropped these. A few of the breweries had incorrect or missing zip codes; these were manually entered.

Next, I downloaded a CSV file of US zip codes with their latitude/longitude coordinates from OpenDataSoft[10], and imported this as a PANDAS dataframe. I then cross-referenced each zip code against this database and added latitude, longitude coordinates to each beer in the Beer Advocate dataframe.

After cleaning up missing values, I was left with a dataframe containing 219 beers from the Beer Advocate Top 250 list. This I saved to a CSV and a pickle file. The top 10 rows of the CSV file are shown in Figure 4.

4.1.2 Foursquare data

I used the latitude, longitude coordinates for the breweries to recover characteristics of the neighborhoods where all the breweries are located. For each unique brewery in the Best Beers dataframe, I used the Foursquare API to get all venues in a 10Km radius centered on that brewery's coordinates, retrieving up to a maximum of 100 venues per brewery. The large radius was necessary because the scale of brewery locations is the scale of continental US.

The resulting dataframe from the retrieved Foursquare data is shown in Figure 5.

4.1.3 Brewers Association data

The Brewers Association maintains a fairly exhaustive list of US breweries. I first downloaded the webpage with all US breweries. I then used BEAUTIFULSOUP to extract the

[8] https://www.beeradvocate.com/lists/top/

[9] ABV: Alcohol by Volume, expressed as a %

[10] https://public.opendatasoft.com/explore/dataset/us-zip-code-latitude-and-longitude/export/

```
Done. Recovered a (6190, 5) dataframe.
```

	name	categories	lat	lng	brewery_name
0	Starbucks	Coffee Shop	43.684040	-70.291510	Allagash Brewing Company
1	Tipo	Italian Restaurant	43.677577	-70.281132	Allagash Brewing Company
2	Bruno's	Italian Restaurant	43.689445	-70.293114	Allagash Brewing Company

Figure 5. First 3 rows of the dataframe containing venue data retrieved from Foursquare.

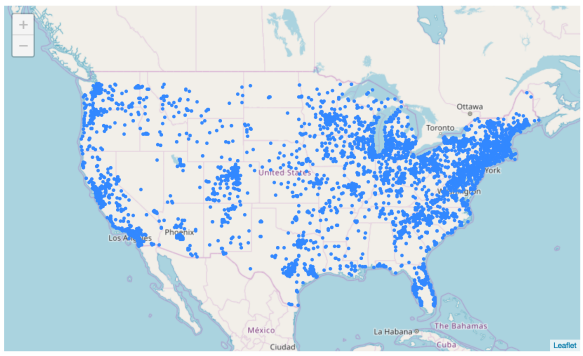


Figure 6. Map showing location of 6,912 breweries in mainland US. Data gathered from https://www.brewersassociation.org/

brewery names, types, and addresses. I then used `REGEX` to search for "CC NNNNN" strings, corresponding to 2-character US state and 5-digit US zip code strings. From these I separated out the state and zip code and saved these as separate variables. I then retrieved all state and zip codes, and the latitude/longitude of each brewery.

For some of the entries, the latitude/longitude information was missing. I manually looked up the two most frequent, and used `GEOPY` to get as many of the rest as I could. The remaining rows with missing latitude/longitude data were dropped. This led to a final sample of 6912 breweries. A `FOLIUM` maps with these breweries marked is shown in Figure 6.

4.2 Machine Learning

In this section I will describe the final form of the data and the machine learning techniques utilized

4.2.1 Geographic clustering of breweries

In this section I will describe the use of a machine learning algorithm to cluster US breweries based on their geographic location.

4.2.2 Segmenting breweries based on neighborhoods

In this section I will describe the use of machine learning algorithms to segment brewery neighborhoods.

4.3 A regression model to predict beer scores

In this section I will describe a regression model to predict beer scores, based on their geographic cluster, their neighborhood, and other properties of the beer such as style and ABV.

5. Results

In this section I will present the observed results.

5.1 Geographic clusters of breweries
5.2 Neighborhood-based segmentation of breweries
5.3 Results of the regression model

6. Discussion

In this section I will include a discussion of the observed results.

7. Conclusions

Finally I will conclude with some recommendations for potential stakeholders interested in entering the growing US beer market.