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Beer Similarity Engine

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Introduction

The beer industry is characterized by an extensive variety of products, each distinguished by unique flavors, ingredients, and brewing techniques. This diversity, while offering consumers a broad spectrum of choices, poses a challenge in identifying beers that align with individual preferences – if a customer wants to try a new beer in a bar, restaurant or even chose one to buy at the supermarket, it could be difficult to choose which beer he or she may like. To mitigate this challenge, our study leverages unsupervised learning and clustering methods to develop a beer similarity engine that identifies beers similar to any given beer in a dataset. The primary objective of this research is to create a system capable of grouping beers based on their intrinsic characteristics and recommending beers within the same group as a specified input beer. By analyzing features such as alcohol percentage, sourness, sweetness, and other flavor and technical attributes, we aim to offer users personalized beer recommendations.

In our study, we employed three clustering methods: Gaussian Mixture Models (GMM), K-Means, and Hierarchical Clustering. To evaluate the effectiveness of these clustering methods, we used two validity indices: the Davies-Bouldin index and the Silhouette score. The results of this study demonstrate that K-Means clustering with 56 clusters offers a robust solution for categorizing beers based on their characteristics, providing users with relatively accurate and meaningful recommendations.

Table of Contents

1. Business Understanding

In modern consumerism, understanding customer preferences is crucial to success. More and more companies realize that the products they sell and the services they provide, should not only meet basic needs but also resonate with the desires and preferences of their target audience. In these times of abundant choices and fierce competition, businesses should go beyond simply offering goods and services, and strive to provide a solution to the customers' needs.

In this matter, the beverage industry is no different than others, and we recommend restaurants and bars invest their resources in products that will benefit the customer experience, which may result in retraining their customers' loyalty, and even attract new ones. Also, by understanding their target audience's preferences, they will be able to use beverages that will be enjoyable to them.

1.1. Project Objectives

The goal of this project is to unravel beer drinkers' product preferences and conceive actionable insights that will assist them in finding new beers they may enjoy. The objectives include:

- Providing a useable tool for restaurants and bars to help identifying beers that may suit their customers' personal taste.
- Finding the underlying key factors behind beer ratings.

These objectives can be measured using the machine learning model's clustering indices. They determine the overall correctness of the chosen clustering.

1.2. Situation Assessment

In this project, we are leveraging a comprehensive dataset comprised of 3,197 records of different types of beer. The dataset contains diverse beer attributes, such as style (lager, ale, wheat, IPA, etc.), alcohol by volume (ABV), international bitterness units (IBU), and corresponding ratings. During the data exploration phase, we noticed that some features are correlated with each other, and that the style field is comprised of 111 distinct values.

In addition, all members of our team are knowledgeable with advanced machine learning models, concepts, and tools, needed to construct a well performing machine learning model and to extract actionable insights.

1.3. Data Mining Goals

Translating the business understanding into a data mining objective: build a robust beer similarity engine that suggests a variety of beers that may suit the user's personal taste.

These objectives are measurable using the machine learnings models' validity indices:

- Silhouette Score – measures how similar each point is to its own cluster compared to other clusters. It provides a score from -1 to 1, where a higher score indicates better-defined clusters. It offers insights into the overall quality and separation of clusters.
- Davis-Bouldin Score – measures the average similarity between each cluster and its most similar cluster. It is based on the ratio of the within-cluster scatter to the between-cluster distance. Lower values indicate better clustering. Provides a measure of cluster quality that balances both compactness and separation.

1.4. Project Plan

- Data understanding – perform exploratory data analysis (EDA) to understand data distributions, statistics, and relationships.
- Cleaning and preprocessing – cleaning the data, address missing values, converting the form of some variables' values (if necessary).
- Modeling– selecting features, constructing various clustering machine learning models, selecting the best model.
- Evaluation – evaluating the models' performance using the measurements specified earlier. testing the engine.
- Conclusion.

2. Data Understanding

The goal behind the creation of this dataset is to create a beer tasting profile based on specific word counts found in reviews, for a classification and similarity systems. The data set consists of both categorial and numerical fields, and contains information regarding important characteristics of the beer, such as percentage of alcohol, IBU and style, and the tasting profiles derived by tasters' reviews (an abstract term that consists of few features, that we will elaborate on in the next section), which are defined by word counts found in up to 25 reviews of each beer. The assumption is that people writing reviews are more than likely describing what they do experience rather than what they do not.

2.1. Data Quality

The dataset is of high quality, with no missing values across any of the variables, ensuring completeness of the data. Additionally, there are no duplicate rows, which confirms the uniqueness of each entry in the dataset.

2.2. Data Description and Exploration

The dataset consists of 25 variables. See appendix A for an example of a sample and a table of basic categorial/numeric statistics, and appendix B for histograms for review data.

<u>Categorical variables</u>

1. **Name:** This variable represents the name of the beer. It is a categorical measure with unique values for each beer.
2. **Style:** This variable indicates the style or type of the beer (e.g., IPA, Stout, Lager). It is a categorical measure with numerous distinct values corresponding to different beer styles. There are 111 unique beer styles, however some are extensions of the main style such as "lager" for example, as described in section 1.2.
3. **Brewery:** This variable represents the name of the brewery that produces the beer. It is a categorical measure with unique values for each brewery. The dataset contains beers manufactured by 934 distinct breweries.
4. **Beer Name (Full):** This variable provides the full name of the beer, which includes the brewery's name and the beer's name. The values of this field are unique, which means that each record show data about a distinct beer with no repetitions.
5. **Description:** This variable contains descriptive text about the beer, including tasting notes and other information. It is a categorical measure with unique text for each beer.

<u>Numeric Variables (continuous)</u>

1. **ABV** (float)**:** This variable represents the alcohol content of the beer, expressed as a percentage of total volume. It ranges from 0% (alcohol-free beers) to around 20%, with most beers falling between 4% and 8%. The distribution is right-skewed, with a few high-ABV beers.
2. **Minimum IBU** (int)**:** This variable indicates the minimum bitterness level of the **style of the beer**, measured in IBU, as the beer's IBU value was not available for each beer. It ranges from 0 to 100, with a distribution that varies widely depending on the beer style.
3. **Maximum IBU** (int)**:** This variable indicates the maximum bitterness level of the **style of the beer**, measured in IBU, as the beer's IBU value was not available for each beer. It also ranges from 0 to 100, with a distribution that varies widely depending on the beer style.

Field 4-15 counts the number of times the field's title had been mentioned in 25 sampled reviews of the current record's beer. See appendix D for examples of words that described each field.

4. **Astringency** (int)**:** astringency means a dry, puckering mouthfeel. Most values clustered around the lower end, indicating that astringency is generally low.
5. **Body** (int)**:** this term means perceived thickness or fullness. Most values clustered around 40 words-count, indicating that the perceived fullness is prominent in this dataset's beers.
6. **Alcohol** (int)**:** This variable measures the alcohol flavor intensity in the beer. Here we witness a right-skewed distribution, and we can see that batches of 25 reviews usually

mention this word 10 times in total, which indicate that most beers do not have a strong taste of alcohol, as expected.

7. **Bitter** (int)**:** this variable indicates the bitterness level perceived in the beer. The distribution is right-skewed, and most values clustered at around 20 words-count, which can indicate that the beers in this dataset usually have moderate degree of bitterness, but some of this have a high degree of bitterness.
8. **Sweet** (int)**:** we can see that generally the beers in this dataset are generally sweet, as most values are clustered at 60 words-count, and that is quite a high count. Some beers were even described with a 150-250 words-count.
9. **Sour** (int)**:** the sourness is generally low or average, as most values are clustered around 10 and 20 words-count. There are several beers that are quite sour as we can see some that range between 100 and 250 words-count.
10. **Salty** (int)**:** almost all beers are not salty as almost all values are at the 0-count bar.
11. **Fruits** (int)**:** this variable indicates the level of fruity flavors perceived in the beer. The distribution varies a lot, though most values are centered at the 0-20 range. However, we can see that there are many beers that are very fruity.
12. **Hoppy** (int)**:** this variable measures the intensity of hop-derived flavors and aromas in the beer (hops are used to balance the sweetness of the malt in beer by adding bitterness), and its distribution is very similar to the one of the fruit variable.
13. **Spices** (int)**:** this variable indicates the level of spice flavors perceived in the beer, and it shows a similar distribution to as the salty feature – meaning almost all beers are not spiced as almost all values are at the 0-count bar.
14. **Malty** (int)**:** this variable measures the intensity of malt-derived flavors in the beer. Its words-count values range widely, which can be expected as this dataset is comprised of many styles of beers, and the malt flavor has a different role and taste in each one.

Fields 15-18 show similar distributions, which most values clustered at around 3.5-4 stars reviews, and a left-skewness that means that some beers scored a very low rating by tasters in terms of each of these domains.

15. **review_aroma** (float)**:** this variable represents the users' rating of the beer's aroma on a scale from 1 to 5.
16. **review_appearance** (float)**:** this variable represents the users' rating of the beer's appearance on a scale from 1 to 5.
17. **review_palate** (float)**:** this variable represents the users' rating of the beer's palate or mouthfeel on a scale from 1 to 5.
18. **review_taste** (float)**:** this variable represents the users' rating of the beer's taste on a scale from 1 to 5.
19. **number_of_reviews** (float)**:** this variable indicates the total number of reviews received for each beer, providing a measure of its popularity. The range is from 1 to several thousand, with a right-skewed distribution, indicating a few beers have received a large number of reviews.
20. **review_overall** (float): this variable signifies the overall rating of the beer as provided by users. This variable is a discrete numeric measure with values ranging from 1 to 5. It encapsulates the general user perception of the beer, independent of the rest of the rating features. This feature's values are unbalanced as most reviews are around 4 stars, and that its distribution appears to approximate a normal distribution with a left skewness, meaning there are not many 1 or 2-star reviews.

Correlations

See appendix C for correlations with review_overall variable. It seems that all the review fields have positive high correlations with the review_overall variable (0.94, 0.92, 0.87, 0.81 correlations respectively). By observing the full correlation matrix which can be found in the script file as a correlation heat map, we can see that the minimum IBU and the maximum IBU fields are positively highly correlated. There is also a strong positive relationship (0.71 correlation) between bitterness and hop flavors, maltiness and body fields (0.75 correlation) and between fruits and sour fields (0.79 correlation).

3. Data Preparation

3.1. Removing correlated columns

In this part, we removed the correlated columns listed above, retaining only one column from each correlated group: Hoppy, Body, Sour, Min IBU, review_taste, review_palate, review_aroma, and review_appearance.

3.2. Removing categories columns

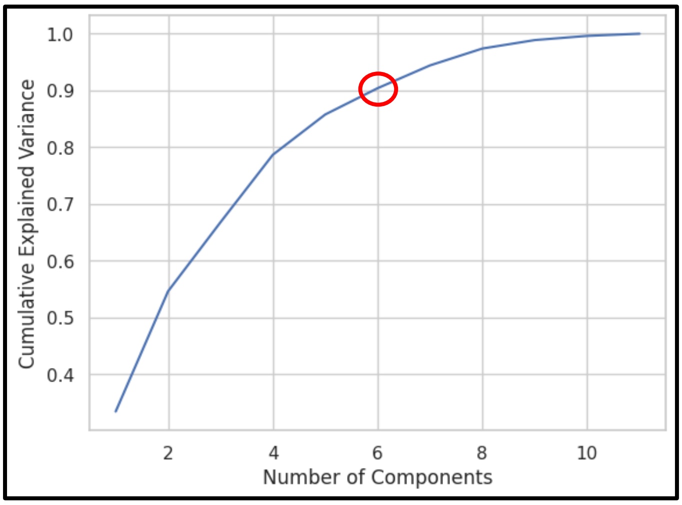
In this part, we removed the categories columns specified above: number_of_reviews, Beer Name (Full), Name, Brewery, Description, Style.

3.3. Scaling

After removing the correlated and categorical columns, we scaled the numeric features using Min Max Scaler. This ensures that all features are on a similar scale, improving the performance of our machine learning models.

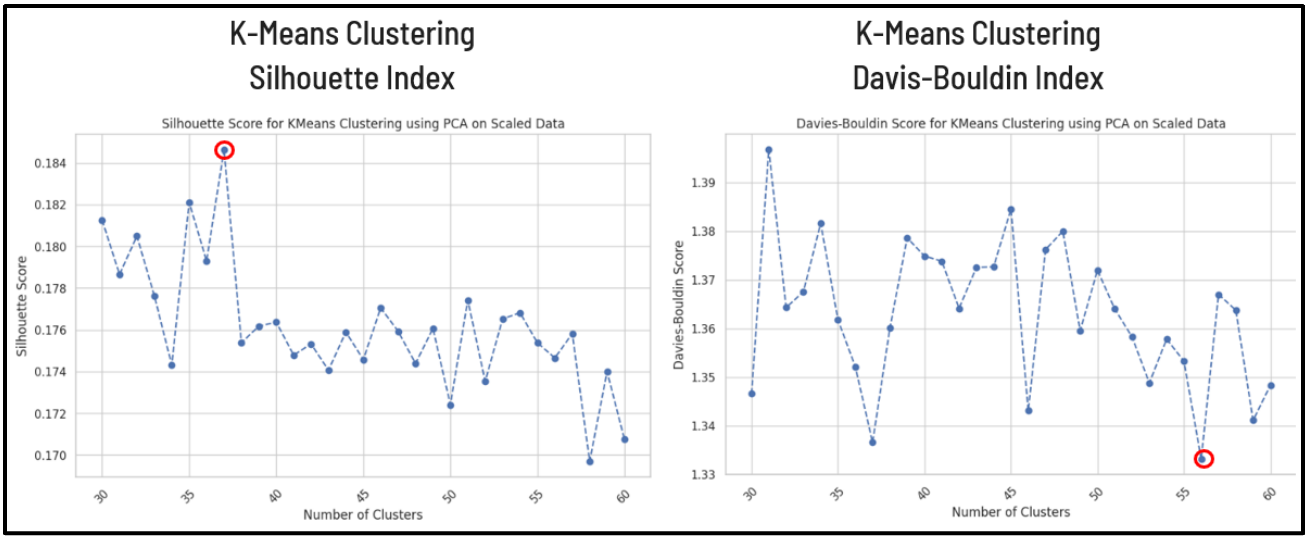
3.4. Dimensions reduction

We used Principal Component Analysis (PCA) on the scaled dataset. We looked for the proper number of components needed to retain at least 90% of explained variance, and we derived that 6 components are needed:



4. Modeling

We used three clustering methods: K-Means, GMM and Hierarchical. In order to validate the clustering, we used two indices: Silhouette and Davis-Bouldin (DB). For each combination of model, dataset and index, we tested the index's score as a function of K (number of clusters). Notably, we focused on determining the optimal K within the range of 30 to 60 clusters. The low number of clusters is problematic in our case, as the dataset is comprised of almost 3,200 distinct beers. Attempting to partition these records into a small number of clusters could lead to each group containing a large number of records. This may not adequately capture the diversity and nuances present in the dataset. Therefore, we examined which clustering algorithm suggests that we use a relatively large number of clusters and yields the best local index score (local maximum for DB index, local minimum for Silhouette index).



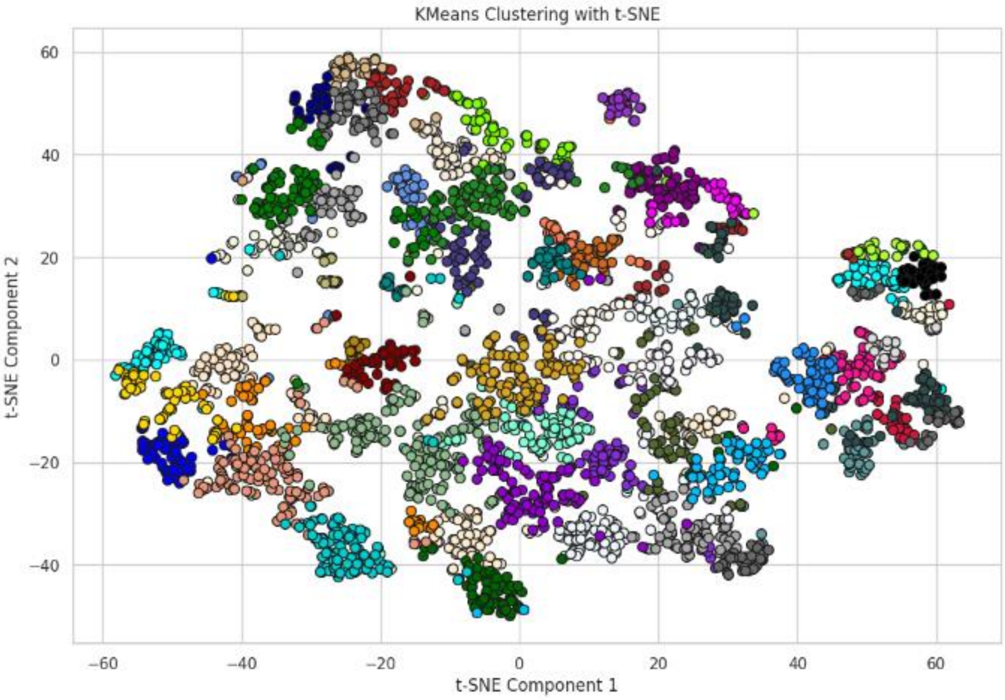
For example, we can see that when using K-Means, the Silhouette score is maximized when K = 37, and the DB score is minimized using 56 clusters. After examining the scores, we constructed a table to compare the results:

		Clustering Model		
		K-Means	**GMM**	**Hierarchical**
Index	**Silhouette** (Maximizing)	0.185 (37)	0.081 (43)	0.142 (31)
	Davies-Bouldin (Minimizing)	1.333 (56)	1.808 (52)	1.47 (39)
	Max Running Time (Seconds)	52	138	20

The running time for each experiment was measured in seconds, and the maximum running time among each algorithm and indexing method was recorded.

The chosen model was K-Means with 56 clusters with a DB score of 1.333.

Using t-SNE, we can visualize the 56 clusters in two dimensions of the chosen model:



5. Evaluation

I this part, we would like to compare model performance against business success criteria, which is mainly to provide a useable tool for restaurants and bars to help identifying beers that may suit their customers' personal taste. In order to examine if our system is indeed informative, we chose a random beer from the dataset (representing a beer that is liked by a bar's customer) and fetched 5 random records, for comparison, from the same cluster of the chosen beer (representing the beers that the system is suggesting the customer):

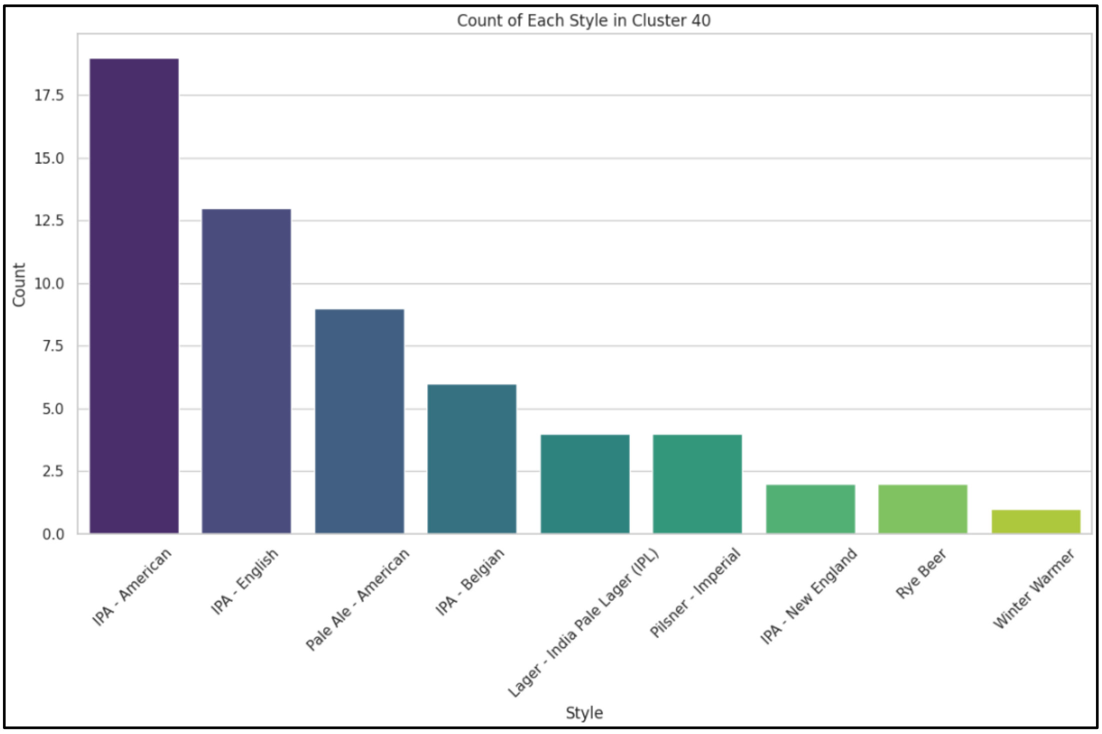
The beer that the customer wanted:

Name	Style	Brewery	Beer Name (Full)	ABV	Min IBU	Max IBU	Astringency	Body	Alcohol	Bitter	Sweet	Sour	Salty	Fruits	Hoppy	Spices	Malty
IPA	IPA - American	SweetWater Brewing Company	SweetWater Brewing Company Sweetwater IPA	6.3	50	70	25	44	13	75	57	58	1	86	103	12	59

The most similar beers to the chosen beer based on its cluster:

Name	Style	Brewery	Beer Name (Full)	ABV	Min IBU	Max IBU	Astringency	Body	Alcohol	Bitter	Sweet	Sour	Salty	Fruits	Hoppy	Spices	Malty
Sculpin	IPA - American	Ballast Point Brewing Company	Ballast Point Brewing Company Ghost Pepper Scu...	7.00	50	70	20	34	12	69	43	53	0	72	92	4	28
A Little Sumpin' Sumpin' Ale	IPA - American	Lagunitas Brewing Company	Lagunitas Brewing Company A Little Sumpin' Sum...	7.50	50	70	15	32	14	58	23	56	1	69	100	2	65
Jai Alai IPA	IPA - American	Cigar City Brewing	Cigar City Brewing Jai Alai IPA	7.50	50	70	21	34	8	44	35	58	0	73	51	10	33
Blind Pig	IPA - American	Russian River Brewing Company	Russian River Brewing Company Blind Pig IPA	6.25	50	70	45	37	7	80	38	69	4	94	140	1	33
Lunch	IPA - American	Maine Beer Company	Maine Beer Company Lunch	7.00	50	70	26	54	15	64	56	79	0	97	102	5	49

We can see that the style of the randomly chosen beers is the same as the chosen beer, their ABV is similar to the ABV value of the chosen beer, the Min IBU – Max IBU range is the same between all 6 beers, and the chosen beers' values of the rest of the numeric features are similar to the chosen beer. By inspecting all records that were assigned to this cluster, we can see that most beers are of style IPA:



Moreover, we wanted to examine the densest cluster. We used Within-Cluster Sum of Squares (WCSS) to measure the total variance within each cluster. WCSS is calculated as the sum of the squared differences between each point and the centroid of its respective cluster. This metric helps in assessing the compactness of the clusters, where a lower WCSS indicates a denser cluster with more similar samples.

The lowest WCSS score is 0.3851. The cluster samples are:

Style	ABV	Min IBU	Max IBU	Astringency	Body	Alcohol	Bitter	Sweet	Sour	Salty	Fruits	Hoppy	Spices	Malty
Lager - European Strong	10.0	15	40	9	36	77	33	59	31	1	36	31	4	32
Lager - European Strong	12.0	15	40	7	21	70	12	33	8	1	11	6	0	27
Lager - European Strong	9.0	15	40	10	27	76	16	53	22	0	10	17	1	49
Lager - European Strong	9.5	15	40	13	37	62	22	83	24	6	30	30	17	52
Lager - European Strong	10.0	15	40	10	9	58	27	44	13	0	15	22	0	39
Lager - European Strong	9.0	15	40	13	17	78	15	37	6	2	11	11	6	39
Lager - European Strong	8.4	15	40	1	19	19	18	63	13	0	15	20	2	30
Lager - Malt Liquor	8.0	10	30	9	19	32	13	40	12	0	10	16	0	43
Lager - Malt Liquor	8.0	10	30	9	39	39	23	44	15	0	14	24	1	43
Lager - Malt Liquor	10.5	10	30	8	21	52	12	50	25	0	33	10	8	31
Lager - Malt Liquor	10.6	10	30	12	19	44	14	32	18	5	14	34	6	62
Lager - Malt Liquor	10.0	10	30	7	25	50	11	82	41	0	49	7	0	47
Lager - Malt Liquor	8.5	10	30	7	29	52	17	31	17	0	13	16	1	38
Lager - Malt Liquor	9.9	10	30	11	60	42	18	60	45	1	51	19	2	58
Lager - Malt Liquor	10.0	10	30	18	40	44	8	57	13	0	20	7	5	57
Lager - Malt Liquor	11.0	10	30	9	33	63	10	79	28	0	36	5	3	51
Lager - Malt Liquor	12.2	10	30	3	15	33	12	48	14	0	27	10	4	30

We can see that the cluster contain 17 samples of "Lager" beer style. The samples show low saltiness scores from the reviews' texts, which is characteristic of Lager beers. The samples have also low spices values, which is consistent with the Lager beer which usually do not contain spices.

At the end of the script, we incorporated a summary cluster statistics table that shows the first and second most common beer styles in each cluster and their proportion relative to the total number of beers in each cluster. The summary cluster statistics table can be found in Appendix E. By observing the proportions of the two most common styles, we can see that many clusters contain a major beer style, indicating that the clustering performance was quite good. Specifically, we can see that cluster #27 is composed entirely of one dominant style: Chile Beer (15 units). Additionally, cluster #31 is made up of 94% Pumpkin Beer and 3% Fruit and Field Beer, both characterized by their fruity taste. Similarly, cluster #54 consists of 31% Wheat Beer - Hefeweizen and 28% Wheat Beer - Witbier. Although many clusters contain a major beer style, some clusters have a lower proportion of these styles. For example, cluster #34 contains 159 units, with the dominant beer style making up 11% and the second most common style 9% (both Lager styles).

6. Future Work –
   The project on the beer similarity engine, which identifies beers similar to any given beer in a dataset, has opened several avenues for future research and development. Some potential areas of future work include:

   - Personalized Recommendation System: Develop a comprehensive recommendation model that focuses on individual preferences rather than just measuring similarities between items. By collecting customer preferences, such as taste, sweetness, bitterness, and alcohol content, the system can recommend beers that best match those characteristics.

   - Real-time Recommendation System: Implement a pilot program in bars to test a real-time recommendation engine that updates suggestions based on user feedback. This system will adapt to evolving preferences and check for strong customer satisfaction. Integration with mobile apps or bar management systems will enhance user interaction and overall experience.

   - Expand the dataset to include a wider variety of beer styles and incorporate negative reviews. This will allow for more comprehensive comparisons between different kinds of beers and improve the accuracy and reliability of the recommendations.

7. Conclusion
   This clustering-based recommendation system generally successfully identifies similar beers, offering users personalized suggestions. The primary objective of creating a system capable of grouping beers based on their intrinsic characteristics and recommending beers within the same group as a specified input beer has been achieved.

   The system is particularly beneficial in scenarios where a customer requests a beer that is not available at the bar. It can identify and recommend alternative beers that the bar does have in stock, closely matching the requested beer's characteristics. This capability enhances customer satisfaction by providing suitable substitutes that align with their preferences.

8. Appendixes

Name	Style	Brewery	Beer Name (Full)	ABV	Min IBU	Max IBU	Astringency	Body	Alcohol	Bitter	Sweet
Amber	Altbier	Alaskan Brewing Co.	Alaskan Brewing Co. Alaskan Amber	5.3	25	50	13	32	9	47	74
Double Bag	Altbier	Long Trail Brewing Co.	Long Trail Brewing Co. Double Bag	7.2	25	50	12	57	18	33	55

Sour	Salty	Fruits	Hoppy	Spices	Malty	review_aroma	review_appearance	review_palate	review_taste	review_overall	number_of_reviews
33	0	33	57	8	111	3.498994	3.636821	3.556338	3.643863	3.847082	497
16	0	24	35	12	84	3.798337	3.846154	3.904366	4.024948	4.034304	481

8.1. Appendix A: statistics tables

Basic statistics table for categorial features

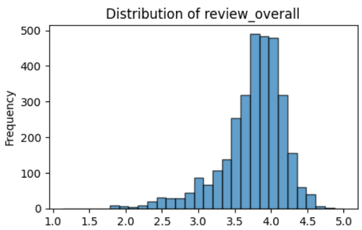
	Name	Style	Brewery	Beer Name (Full)
count	3197	3197	3197	3197
unique	3066	111	934	3197

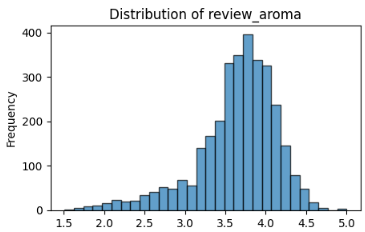
Basic statistics table for numeric features

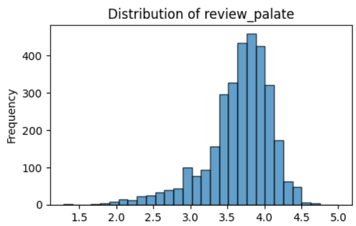
	ABV	Min IBU	Max IBU	Astringency	Body	Alcohol	Bitter	Sweet	Sour	Salty	Fruits	Hoppy
mean	6.53	21.18	38.99	16.52	46.13	17.06	36.36	58.27	33.15	1.02	38.53	40.92
std	2.55	13.24	21.36	10.41	25.95	17.33	25.79	34.28	35.78	2.13	32.3	30.4
min	0	0	0	0	0	0	0	0	0	0	0	0
max	57.5	65	100	81	175	139	150	263	284	48	175	172

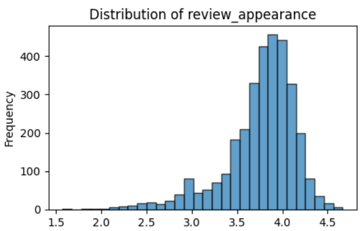
	Spices	Malty	review_ aroma	review_ appearance	review_ palate	review_ taste	review_ overall	number_of_ reviews
mean	18.35	75.33	3.64	3.75	3.66	3.7	3.75	233.28
std	23.76	39.91	0.5	0.4	0.45	0.51	0.44	361.81
min	0	0	1.51	1.57	1.29	1.21	1.14	1
max	184	239	5	4.67	5	5	5	3290

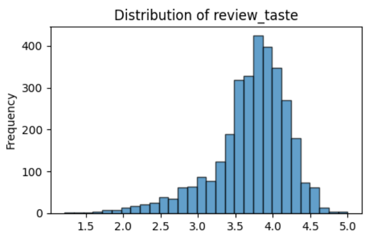
8.2. Appendix B: distributions

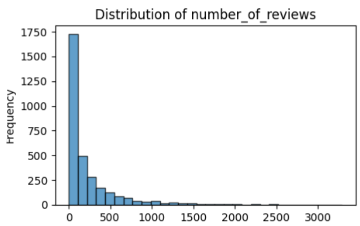












8.3. Appendix C: correlations with review_overall variable

	review_overall		review_overall
review_overall	1	**Malty**	0.21
review_taste	0.94	**Sour**	0.21
review_palate	0.92	**Sweet**	0.21
review_aroma	0.87	**Hoppy**	0.18
review_appearance	0.81	**number_of_reviews**	0.18
Body	0.31	**Astringency**	0.16
Min IBU	0.29	**Spices**	0.14
Max IBU	0.27	**Alcohol**	0.07
Fruits	0.26	**Salty**	-0.01
Bitter	0.26		

8.4. Appendix D: Examples of the words that described each field

Aroma and Flavor		Mouthfeel		Taste	
Spices Words	Fruity Words	Alcoholic Words	Body Words	Bitter Words	Sweet Words
cinnamon	berries	booze	smooth	bitterly	chocolate
ginger	cherry	brandy	creamy	Burned	honey
chile	strawberry	rum	full	coffee	sweetened

8.5. Appendix E: Clusters' statistics

Cluster	Count	Dominant_Style1	Proportion_Style1	Dominant_Style2	Proportion_Style2
0	95	Stout - Irish Dry	0.17	Bitter - English	0.14
1	54	Farmhouse Ale - Saison	0.33	Pale Ale - Belgian	0.19
2	44	Strong Ale - American	0.3	Stout - Russian Imperial	0.25
3	87	Lager - M₪rzen / Oktoberfest	0.17	Lager - Munich Dunkel	0.15
4	53	Winter Warmer	0.26	Strong Ale - English	0.19
5	50	Wheat Beer - Dunkelweizen	0.38	Kvass	0.16
6	89	Mild Ale - English Pale	0.12	Mild Ale - English Dark	0.1
7	35	Barleywine - American	0.66	IPA - Imperial	0.09
8	80	Pale Ale - English	0.19	Pale Ale - American	0.15
9	67	Lager - Light	0.3	Low Alcohol Beer	0.3
10	72	Brown Ale - English	0.22	Porter - English	0.18
11	29	Barleywine - English	0.24	Old Ale	0.21

12	39	Lambic - Fruit	0.31	Lambic - Gueuze	0.18
13	45	Stout - American	0.38	Stout - Foreign / Export	0.31
14	53	Dubbel	0.19	Fruit and Field Beer	0.11
15	42	Porter - Smoked	0.29	Smoked Beer	0.29
16	22	Winter Warmer	0.41	Herb and Spice Beer	0.23
17	44	Fruit and Field Beer	0.39	Wheat Beer - American Pale	0.18
18	36	IPA - Imperial	0.69	IPA - Belgian	0.17
19	25	IPA - Black / Cascadian Dark Ale	0.4	IPA - English	0.16
20	50	Lambic - Traditional	0.32	Happoshu	0.18
21	34	Lambic - Gueuze	0.29	Sour - Berliner Weisse	0.26
22	50	Lager - Rauchbier	0.28	Smoked Beer	0.2
23	17	Lager - Malt Liquor	0.59	Lager - European Strong	0.41
24	52	Wheat Beer - Dunkelweizen	0.23	Wheat Beer - Hefeweizen	0.23
25	73	Pilsner - German	0.33	Pilsner - Bohemian / Czech	0.3
26	74	Porter - Robust	0.14	Stout - Oatmeal	0.12
27	15	Chile Beer	1	Not have	0
28	78	Strong Ale - Belgian Dark	0.4	Quadrupel (Quad)	0.33
29	58	Bock - Maibock	0.17	Bitter - English Extra Special / Strong Bitter (ESB)	0.16
30	66	Lager - Malt Liquor	0.12	Lager - American	0.09
31	32	Pumpkin Beer	0.94	Fruit and Field Beer	0.03
32	50	Lager - European Strong	0.46	Lager - Malt Liquor	0.24
33	120	Lager - European Pale	0.27	Lager - Adjunct	0.18
34	159	Lager - American Amber / Red	0.11	Lager - Vienna	0.09
35	83	Dubbel	0.31	Farmhouse Ale - Bi¨re de Garde	0.17
36	41	Old Ale	0.29	Strong Ale - English	0.24
37	49	Red Ale - Imperial	0.18	Stout - Russian Imperial	0.18
38	96	K¶lsch	0.28	Lager - Helles	0.24
39	94	Stout - Oatmeal	0.12	Porter - American	0.11
40	60	IPA - American	0.32	IPA - English	0.22
41	58	Bitter - English	0.14	Bitter - English Extra Special / Strong Bitter (ESB)	0.1
42	33	Stout - American	0.18	Stout - Oatmeal	0.18
43	31	Stout - American Imperial	0.48	Stout - Russian Imperial	0.35
44	58	IPA - English	0.28	IPA - American	0.24
45	34	Fruit and Field Beer	0.24	Lambic - Fruit	0.18

46	61	Bock - Doppelbock	0.34	Scotch Ale / Wee Heavy	0.28
47	85	Tripel	0.29	Strong Ale - Belgian Pale	0.22
48	27	Quadrupel (Quad)	0.22	Bock - Eisbock	0.19
49	22	IPA - Belgian	0.45	IPA - Imperial	0.23
50	41	Porter - Baltic	0.22	Altbier	0.12
51	59	Happoshu	0.17	Kvass	0.14
52	108	Scottish Ale	0.13	Bock - Traditional	0.11
53	58	Lambic - Fruit	0.36	Sour - Flanders Red Ale	0.17
54	87	Wheat Beer - Hefeweizen	0.31	Wheat Beer - Witbier	0.28
55	23	Strong Ale - American	0.39	Wheat Beer - Wheatwine	0.3