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Article

Exploring the Factors that Drive Coffee Ratings

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SUMMARY
Coffee is more than just a morning ritual; it is a cultural staple for many people around the world. One national report showed that 67% of American adults consistently drink coffee daily, a higher percentage than all other common beverages such as tap or bottled water. In this work, we delved into factors influencing coffee quality reviews, such as sweetness, flavor, aftertaste, bean location, and different coffee producers. Using publicly available data from the Coffee Quality Institute (CQI), we analyzed these influencing factors by implementing a regression model via gradient descent with the coffee rating being the attribute of interest to predict (i.e., the target attribute). We hypothesized that both the coffee producer and sweetness are the two most important factors influencing coffee ratings. Our analysis shows that a linear regression model is well suited to analyze this data and as a result, only a few factors contribute significantly to the prediction of coffee ratings. In particular, we find that sweetness is by far the most important factor to predict total cup points, a comprehensive coffee rating based on several sensory and production related attributes, with other sensory related attributes also playing a key role in our analysis. Surprisingly, we see that the coffee producer has very little predictive power in our model. These results give insight into consumer coffee preferences, which is valuable information for manufacturers globally.

INTRODUCTION
Coffee significantly impacts the United States economy, representing around 1.6% of the GDP, highlighting its economic influence and widespread popularity (1). Annually, the average American consumer spends approximately $1,100 on coffee, which is roughly $92 a month (2). Coffee consumption patterns and their influencing factors have been widely studied. For instance, studies have explored various factors influencing consumer decisions in coffee shop settings, including product quality, atmosphere, social factors, promotion, location, and brand (2). Additionally, one study reviewed coffee consumption and purchasing behavior, identifying key insights and gaps for further research. Specifically, their review highlighted that consumer preferences are shaped by health considerations, pleasure, and sustainability. However, the authors identified gaps in the understanding of how individual differences in taste, cultural context, and lifestyle choices affect consumer preferences and purchasing decisions (3). Another study examined consumer preferences for the country of origin of the coffee, i.e., the country the bean was grown in, and quality attributes associated with specialty coffee production, highlighting cross-cultural differences in preferences (4). The study defines culture as shared values, beliefs, and norms that shape consumer preferences, highlighting how these items differ across countries (4). A study on coffee consumption in Poland revealed that Polish coffee consumers tend to prefer conventional brewing methods, indicating a traditionalist approach (5). The research identified three main consumer groups: "Neutral coffee drinkers", individuals who drink coffee mainly out of habit, without a strong preference for type or preparation method, "Ad hoc coffee drinkers", those who consume coffee occasionally and are open to trying different types and preparation methods, and "Non-specific coffee drinkers", consumers who do not have specific preferences and whose choices often vary, to control for consumer consumption patterns (5). The study also found that factors such as quality and flavor (taste and aroma) of the coffee, as well as consumer habits, play a significant role in influencing coffee choice (5). Lastly, another study focused on specialty coffee, where the participants were asked to taste coffee samples and mark the sensory descriptors they recognized from a list (chocolate, caramel, spice, floral notes, etc.). The study found that most participants identified chocolate as the most expected flavor in specialty coffees, followed by caramel, fruit, and nuts. Additionally, flavor was the most frequently cited attribute influencing consumer preference, followed by aroma, and aftertaste (6).

While these studies collectively underscore the versatile nature of preferences in the coffee industry, they also reveal gaps in understanding how specific sensory and non-sensory attributes drive coffee ratings. Addressing these gaps, our research provides a foundation for understanding the complexities of coffee ratings and highlights the need for more in-depth analysis. Our work focuses on attributes surrounding overall product quality in order to understand what drives coffee ratings.

In this work, we have specific expectations about the factors influencing coffee ratings. We hypothesized that sweetness would significantly impact coffee ratings, as sweet drinks are generally popular in western diets. Additionally, we hypothesized that the producer of the coffee, i.e., the company which is responsible for post-harvest processing, would play a crucial role, with producers in regions known for high-quality coffee, such as Colombia and Brazil, having a notable influence on ratings. Moreover, we speculated that coffee producers would influence consumer perceptions of coffee quality and impact ratings. After implementing the

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model, we saw that sweetness is a powerful predictor of total cup points, and more importantly, that a linear regression model produced accurate predictions with respect to the given data. We also note that our findings did not suggest that producers actually played a significant role on ratings. This analysis not only helps us understand consumer preferences, but also provides valuable insights for coffee producers and marketers to improve their products based on data-driven findings.

RESULTS

To better understand consumer coffee preferences, we analyze a dataset provided by the Coffee Quality Institute (CQI). The target attribute of interest was total cup points, a rating in the interval [0,10] given by expert reviewers for a particular coffee sample. The data consists of 997 samples with 24 predictor attributes. The majority of the continuous predictor attributes in the data represent different sensory ratings like flavor and aroma, while most of the discrete attributes give information on the producer and location of the coffee beans.

In order to implement our linear regression model, we first had to verify the basic regression assumptions (i.e., there is no strong multicollinearity among the predictor attributes, the relationship between the predictor attribute and the target attribute are linear in the univariate sense, the residuals are normally distributed, and homoscedasticity of errors). To check the first assumption, we constructed a heat map containing all possible predictor attributes (**Figure 1**). The numerical value inside each box gives the correlation coefficient between the

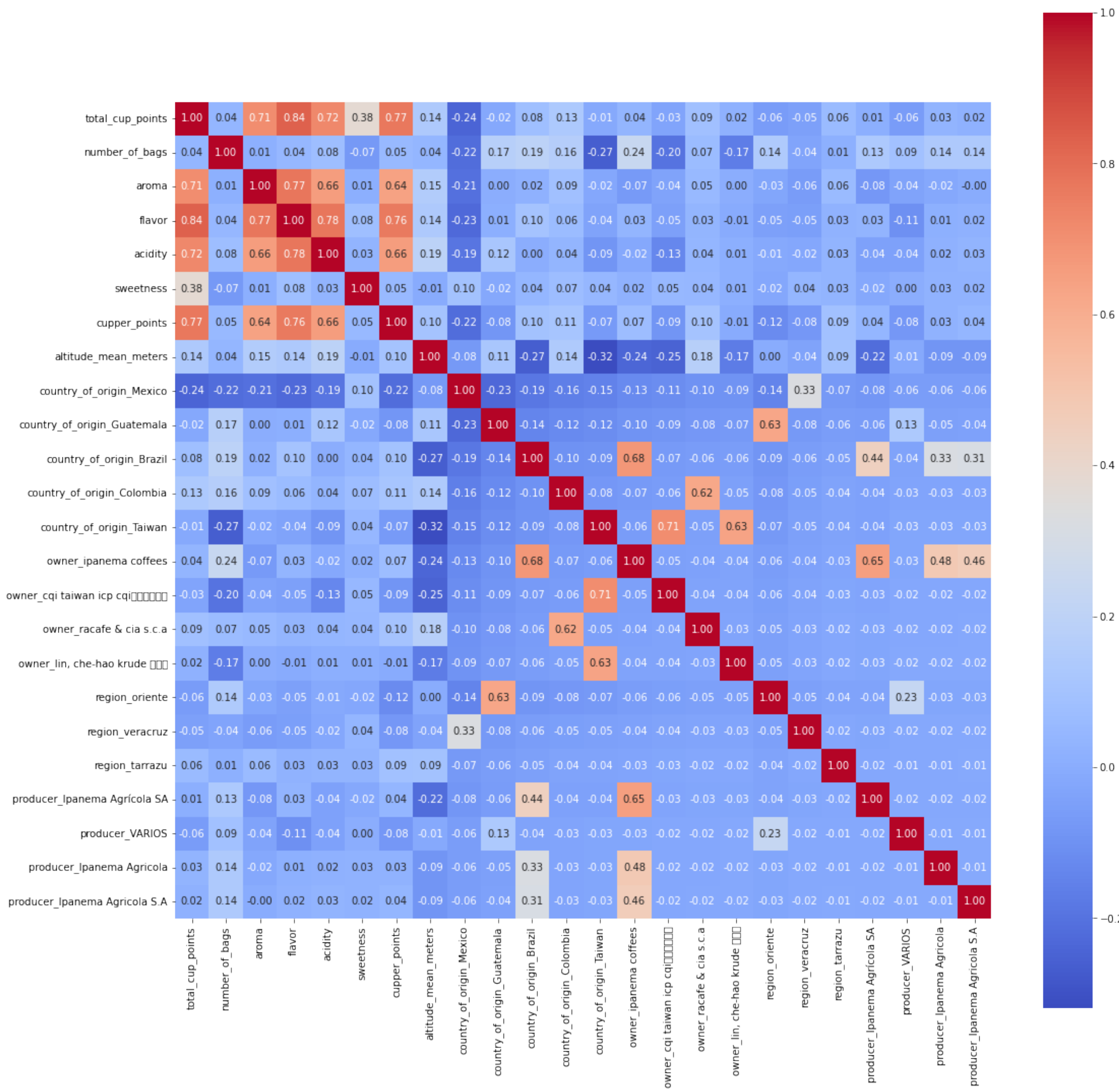

Figure 1: Heat map of all predictor attributes in the data. Each box contains the correlation coefficient between two predictors. The more red the coloring is, the more positively correlated the two predictors are, while the more blue the coloring is, the more negatively correlated the two predictors are. Note the correlation can be between -1 and 1.

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Predictor Variable	Description	Variable Type
acidity	Acidity grade	Continuous
altitude_mean_meters	Mean altitude of the bean's farm	Continuous
aroma	Aroma grade	Continuous
country_of_origin_Mexico	Indicates if bean came from Mexico	Discrete
country_of_origin_Guatemala	Indicates if bean came from Guatemala	Discrete
country_of_origin_Brazil	Indicates if bean came from Brazil	Discrete
country_of_origin_Colombia	Indicates if bean came from Colombia	Discrete
country_of_origin_Taiwan	Indicates if bean came from Taiwan	Discrete
cupper_points	Score based on sensory grades	Continuous
flavor	Flavor grade	Continuous
number_of_bags	Number of bags tested	Continuous
owner_ipanema_coffees	Indicates if the farm owner is Ipanema Coffees	Discrete
owner_cqi_Taiwan_icp	Indicates if the farm owner is CQI Taiwan	Discrete
owner_racafe&cia_sca	Indicates if the farm owner is Racafe & CIA s.c.a.	Discrete
owner_lin_che_hao_krude	Indicates if the farm owner is Lin Che Hao Krude	Discrete
producer_Ipanema_agricola_1	Indicates if the bean producer is Ipanema Agricola 1	Discrete
producer_Ipanema_agricola_2	Indicates if the bean producer is Ipanema Agricola 2	Discrete
producer_Ipanema_agricola_3	Indicates if the bean producer is Ipanema Agricola 3	Discrete
producer_Varios	Indicates if the bean producer is Varios	Discrete
region_Orienta	Indicates if the bean farm region is Orienta	Discrete
region_Veracruz	Indicates if the bean farm region is Veracruz	Discrete
region_Tarrazu	Indicates if the bean farm region is Tarrazu	Discrete
species	Species of coffee bean (arabica or robusta)	Discrete
sweetness	Sweetness grade	Continuous

Table 1: Overview of Predictor Attributes. A description of the different predictor attributes used in our analysis as well as the attribute type, (i.e., continuous or discrete).

two given attributes. We found that there was multicollinearity most prominently present among the altitude predictors and some of the discrete attributes in the data. To account for this, we removed several of these attributes, while the remaining predictors were used to construct the model (**Table 1**).

To gain graphical information about the linear relationship between the continuous predictors and the total cup points score, we fit scatter plots of each predictor against total cup points (**Figure 2**). We saw that aroma, aftertaste, acidity, flavor, and cupper points (an overall sensory score that incorporates aftertaste and flavor) showed a strong linear relationship with total cup points, while the number of bags, sweetness, and altitude predictors showed a weak linear relationship with total cup points.

To satisfy the assumption that the model errors form a normal distribution, we fit a QQ-plot of the residuals (model errors) to test for normality (**Figure 3**). A normal distribution would be indicated by a linear pattern around the red line. Our QQ-plot showed some non-linear pattern around the tails of the data; however, we believed the non-linear pattern at the tails was not strong enough to warrant using a different approach to model the data.

To understand the variance of the residuals, we fit a scatter plot of the residuals against the model predictions (**Figure 4**). A lack of pattern in the scatter plot would mean our model is making consistent predictions across different levels of total cup point scores. Our residual plot showed a lack of pattern, as the data points seem to be randomly dispersed about the red line.

To quantify how well our regression model performed, we computed the R-squared score. The R-squared score measures how much variation in the data is being explained by our model. We calculated the R-squared score to be 0.849. Additionally, the model made an average squared error of 1.093. This shows our model captured nearly 85% of the variation in the data. Moreover, one could expect our model to predict total cup points up to an error of one point on average. The acidity, mean altitude, aroma, country of origin (Mexico), country of origin (Guatemala), country of origin (Brazil), country of origin (Columbia), country of origin (Taiwan), cupper points, flavor, number of bags, producer (Ipanema), region (Orienta), species, and sweetness attributes had the lowest p-values for their respective β coefficients, indicating their significance in modeling total cup points (**Table 2**).

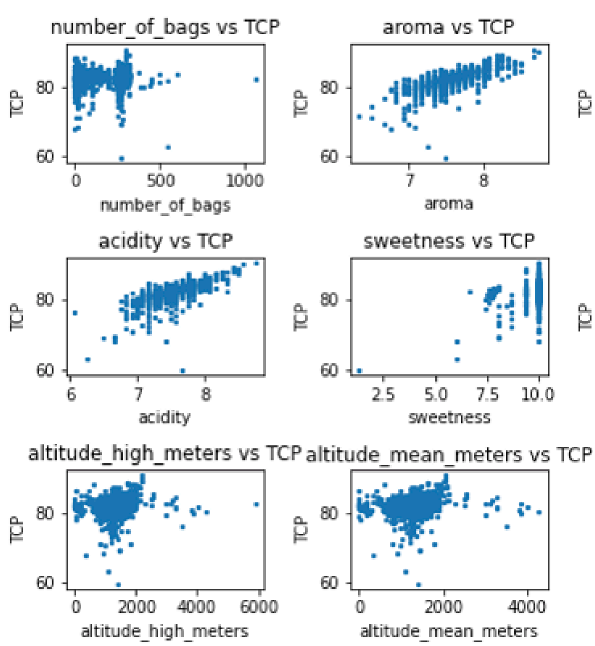

Figure 2: Scatter plots of continuous predictors v.s. the target attribute (total cup points (TCP)). Continuous predictors have been plotted on the x-axis with the total cup points value on the y-axis. These plots highlight whether there is a clear linear relationship between each continuous predictor and the target attribute.

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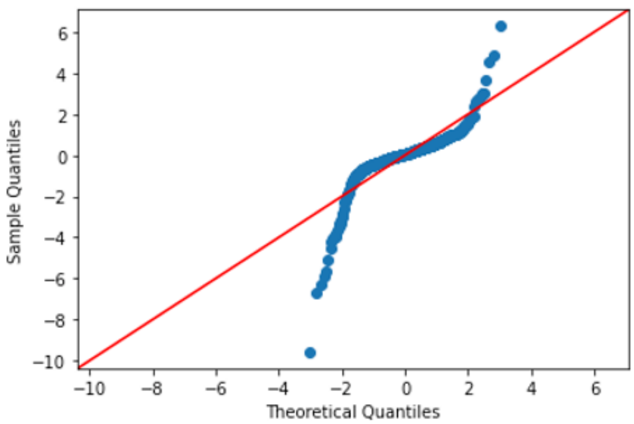

Figure 3: QQ plot of the residuals (model errors). The QQ-plot checks for normality of the residuals by plotting the theoretical quantiles (from a normal distribution (x-axis)) against the residual values (sample quantiles (y-axis)). The red line y=x is also plotted to visualize how the residuals cluster to form a normal distribution.

Furthermore, we see that the sweetness attribute has the largest β coefficient value (**Table 2**). Sweetness has a β coefficient of 26.316; we interpret this result as a one-unit increase of sweetness corresponds to an expected increase of 26.316 total cup points. The other β coefficients can be interpreted in the same fashion.

DISCUSSION

From our experimental results, we found that all of the linear regression assumptions were satisfied. We also found that the linear regression approach was able to model the data consistently. As stated in the results section, our model was able to capture over 84% of the variation in the data. Moreover, the model only makes an average squared error of 1.093 points; thus, businesses of interest could be confident in using our framework to estimate how effective their product could be on the market. Based on our findings, our model agrees with our first hypothesis: that sweetness is an important factor that impacts the total cup points score when modeling the data.

Our model does not support our second hypothesis, i.e., that the producer of the coffee is important towards predicting the total cup points score. We speculated that the producer of the coffee would influence the perception of quality for a given the product, which would in turn help explain the variation in ratings. A possible reason why this hypothesis was not supported is that consumers may prioritize taste and attributes such as sweetness, acidity, and aroma over the specific producer. These findings can aid coffee manufacturing and distributing companies. In particular, we believe coffee shops should focus less on which producer they use, or what region/country the coffee originates and more on optimizing the sensory characteristics of the coffee, such as sweetness, aftertaste, and flavor. Hence, a company can save costs by purchasing less expensive supplies from a different producer and focus on the sensory attributes described above to yield better ratings for their product. To attract new customers, coffee shops can also implement advertisement campaigns revolving around flavor and sweetness to meet customer preferences.

Despite the valuable insights gained from our analysis, some limitations should be addressed. Our study relied on a publicly available dataset that we did not personally collect, which introduces potential underlying biases or issues in the data collection or presentation that we may not have detected. Another potential limitation is our choice of model. While linear regression effectively identified the factors influencing coffee ratings, other techniques like Lasso or Ridge regression could enhance our analysis, as these methods focus on penalizing non-important features during the model learning process (7). This would allow us to refine our process of variable selection to model the total cup points score. Additionally, including other factors that likely influence coffee purchase and enjoyment would provide a more comprehensive analysis. For example, branding and marketing from individual producers might not be as influential when compared to more direct sensory experiences, such as taste and aroma. Consumers may be less aware of the producer when purchasing coffee, especially in settings where coffee is served by larger chains. Similarly, price and convenience were factors that were not included in our model but could potentially affect coffee ratings. Price could play a significant role in consumer perception, as higher-priced coffees might be perceived as higher quality, influencing ratings. Indeed, a previous study reported that price is one of the most significant factors that drive consumer preferences (5). Convenience, such as ease of availability or packaging (e.g., single-serve pods), could also affect consumer satisfaction and ratings, as people often value practicality in their coffee experience. These limitations underscore the need for further research using diverse datasets and models to deepen our understanding of the factors affecting coffee ratings. In our future work, we plan to address some of our limitations by using multiple datasets to provide a more comprehensive analysis. We also intend to find data relating to the attributes not included in our analysis that we discuss above, as we believe they can provide additional information with respect to coffee ratings. Moreover, we plan to explore other methods like Lasso and Ridge regression to enhance our analysis.

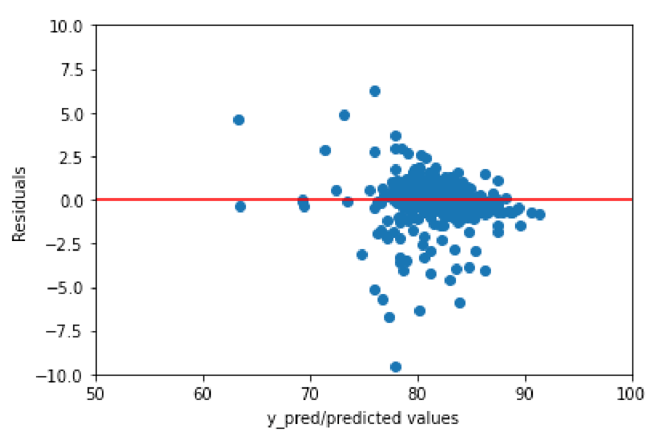

Figure 4: Residual (model error) plot of the linear regression model predictions. Each dot represents the error (y-axis) of a given predicted value (x-axis) using the linear regression model. The red line y = 0 is given to visualize how the residuals cluster about zero error.

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Predictor Variable	β Coefficient	P-Value	Confidence Interval (α = 0.05)
*acidity	4.036	1×10^{-16}	(3.4613, 4.61055)
*altitude_mean_meters	1.054	0.0036	(0.47666, 1.63039)
*aroma	3.753	1×10^{-16}	(3.22977, 4.27584)
*country_of_origin_Mexico	-0.515	1×10^{-16}	(-0.67229, -0.3587)
*country_of_origin_Guatemala	-0.226	0.0161	(-0.41066, -0.04215)
country_of_origin_Brazil	0.076	0.4925	(-0.14111, 0.29293)
*country_of_origin_Colombia	0.256	0.0404	(0.01113, 0.50022)
*country_of_origin_Taiwan	0.464	0.0005	(0.20339, 0.72388)
*cupper_points	9.405	1×10^{-16}	(8.6445, 10.16562)
*flavor	5.564	1×10^{-16}	(5.04662, 6.08319)
*number_of_bags	0.542	0.0481	(0.00462, 1.07934)
owner_ipanema_coffees	-0.085	0.5797	(-0.38805, 0.21723)
owner_cqi_Taiwan_icp	-0.097	0.5640	(-0.42549, 0.23215)
owner_racafe&cia_sca	-0.324	0.0899	(-0.6989, 0.05061)
owner_lin_che_hao_krude	-0.018	0.9270	(-0.41141, 0.3747)
*producer_Ipanema_agricola_1	0.588	0.0105	(-0.44793, 0.76353)
producer_Ipanema_agricola_2	0.158	0.6092	(0.13832, 1.03762)
producer_Ipanema_agricola_3	-0.328	0.3095	(-0.95995, 0.30473)
producer_Varios	-0.264	0.3922	(-0.86992, 0.34154)
*region_Orienta	0.365	0.0076	(0.09745, 0.63257)
region_Veracruz	0.206	0.2886	(-0.17469, 0.58642)
region_Tarrazu	-0.209	0.4080	(-0.70531, 0.28686)
*species	-4.080	1×10^{-16}	(-4.50265, -3.65774)
*sweetness	26.316	1×10^{-16}	(25.2517, 27.38023)

Table 2: β Coefficient Analysis. β coefficients that correspond to the predictor attributes in our model. This table gives information on the p-values (significant attributes) and confidence intervals around the β coefficient values. Predictor attributes with an * have a p-value below 0.05.

Our analysis supports the hypothesis that specific attributes, including the sweetness of the coffee, significantly influences coffee ratings. Our analysis does not however, support our hypothesis that coffee producers significantly influence coffee ratings. We believe this work provides an insight into consumer coffee preferences that suppliers and sellers can use to optimize profits.

MATERIALS AND METHODS

Data Acquisition and Preparation

The dataset we used for this project contains a wide range of attributes that may influence coffee ratings. The data is provided by the *rfordatascience* community (8). Furthermore, the data was collected by the Coffee Quality Institute (CQI), in which 720 trained reviewers provided scores (total cup points) for different types of coffee (9). There are 997 samples in the data, with 24 different predictor attributes, which include detailed information about different coffee beans such as their species and country of origin, as well as sensory ratings like aroma, flavor, sweetness, and aftertaste all measured on a 0-100 scale (**Table 1**).

The main objective of our analysis was to predict a coffee's total cup points score using the given data. The total cup points score is a continuous variable that represents an overall score based on CQI reviews, reflecting the general quality and satisfaction level of the coffee. To make these predictions, we used $p = 24$ predictors to formulate a linear regression model with total cup points as the target attribute (**Table 1**). By incorporating these various predictors into a regression model, we aimed to identify the key factors that most significantly affect coffee ratings.

We provided the attribute descriptions, as well as the attribute type (i.e., discrete or continuous) (**Table 1**). Prior to modeling the data, we converted all discrete variables into dummy variables. For each discrete attribute, not including species, we took the five most common values and created five binary variables that acted as dummy variables. So, if the discrete attribute presented a value that was not one of the top five most common, all of these dummy variables were set to zero. Conversely, if the value of the attribute was one of these five values, one of the dummy variables was set to one, while the other four were set to zero. This allowed us to limit the number of variables substantially. We needed to modify this process, given there were far too many dummy variables with respect to the number of samples we had in the data. We corrected for overabundance of dummy variables with respect to number of samples by defining new categorical variables for the owner, country of origin, region, and producer attributes. We also scaled the continuous predictor attributes to have values between zero and one and created "dummy" variables for the discrete predictor attributes prior to our analysis.

Model Selection and Optimization

As discussed in the results section, we constructed a heat map to check for multi-collinearity between predictors (**Figure 1**). We found that there was multi-collinearity present, and we removed several variables before analysis. Given the total cup points target attribute was continuous and the amount of data we had to model was relatively small and non-complex, we chose to model the data with linear regression. For these type of problems, gradient descent is often employed as the optimization algorithm of choice, as it is a simple and well understood method. Therefore, to predict the total cup points score using the given data, we solved the following linear optimization problem:

$$\min_{\{\beta_0,\beta_1,\dots,\beta_p\}} MSE(X,\beta_0,\beta_1,\dots,\beta_p) := \frac{1}{n}\sum_{i=1}^{n}\left[y^{(i)} - \left(\beta_0 + \beta_1 x_1^{(i)} + \cdots + \beta_p x_p^{(i)}\right)\right]^2, \qquad \text{(Eqn 1)}$$

Where n is the number of samples, $y^{(i)}$ is the ground truth target label for the ith sample in the data, and $\{x1^{(i)}, \dots, xp^{(i)}\}$ are the predictor attributes for the ith sample forming the ithrow of the data matrix

$$X \in \mathbb{R}^{n\times p} \qquad \text{(Eqn 2)}$$

Each β is a learnable weight (regression coefficient) that influences the model's prediction of the target. The Mean-Squared Error (MSE) function is the mean of the sum of the squared differences between the ground truth in the data and the model's prediction (10). In other words, the MSE function calculated the error the model was making, and hence we wanted to find the set of β's which minimizes this function. Since the MSE function is differentiable, we knew the gradient descent algorithm would find an approximate optimal solution. Gradient descent is a first order technique that solves problems of our form using an iterative approach. At each iteration, the algorithm pushed the β's in the direction of the negative gradient, that is, the direction of steepest descent with respect to the MSE function. The update rule for each β at the (k+1)th iteration is given as

$$\beta_j^{(k+1)} = \beta_j^{(k)} - \alpha\frac{\partial MSE}{\partial \beta_j}, \qquad (j = 0,\dots,p) \qquad \text{(Eqn 3)}$$

where $\alpha>0$ is a predetermined small constant that acts as a step size to govern how much we chose to move in the direction of the negative gradient, and the partial derivative of the MSE function with respect to each β is given by

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$$\frac{\partial MSE}{\partial \beta_0} = \frac{-2}{n}\sum_{i=1}^{n}\left(y^{(i)} - \beta_0 + \beta_1 x_1^{(i)} + \cdots + \beta_p x_p^{(i)}\right) \quad \text{(Eqn 4)}$$

if $j = 0$ and

$$\frac{\partial MSE}{\partial \beta_j} = \frac{-2}{n}\sum_{i=1}^{n}\left(y^{(i)} - \beta_0 + \beta_1 x_1^{(i)} + \cdots + \beta_p x_p^{(i)}\right)\cdot x_j^{(i)} \quad \text{(Eqn 5)}$$

for $j > 0$. Let $MSE^{(k)}$ be the error corresponding to the kth iteration of the gradient descent algorithm. We terminated the learning process when $| MSE^{(k)} - MSE^{(k-1)} | < \varepsilon$, where $\varepsilon > 0$ is also a predefined small constant. We denote the resulting β's as β*j ≤ j ≤ p, to represent the optimal coefficients found after the model learning process. Thus, our linear regression model is given by

$$\hat{y} = \beta_0^* + \beta_1^* x_1 + \cdots + \beta_p^* x_p \quad \text{(Eqn 6)}$$

where $\hat{y}$ is used to denote a prediction. After implementing an 80% train and 20% test split of the data, we trained the model with an ε value of 10^{-5} and an α value of 0.2. After training, the resulting model selected sweetness, cupper points, flavor, species, and acidity, as the most important attributes during the learning process.

Materials and Packages Used

We implemented the gradient descent algorithm in Python version 3.8 and used the packages pandas 1.1.5, numpy 1.21.5, matplotlib 3.5.3, scipy 1.7.3, statsmodels 0.13.5, sklearn 1.5.2, and seaborn 0.11.2 in our analysis (our analysis can be found via the following link: https://github.com/ncutrona/HighSchoolCofeeProject/blob/main/Coffee Project.ipynb). The data can be found on GitHub and is publicly available for analysis (12). We did perform preprocessing steps on the data such as removing irrelevant attributes like coffee ID. In addition, missing values of continuous attributes were imputed with the mean value, and missing values of discrete attributes were imputed with the mode value.

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REFERENCES

1. “The Global Coffee Industry.” globalEDGE. https://globaledge.msu.edu/blog/post/55607/the-global-coffee-industry#:~:text=In%20the%20US%20specifically%2C%20economic,the%20country%20with%201%2C695%2C710%20jobs. Accessed 18 May 2024.
2. Bura, Eben C. P., et al. “Analysis of Factors Influencing Consumer Purchase Decisions for Coffee Shops in Tomohon City.” *Asian Journal of Logistics Management*, vol. 2, no. 1, 1 June 2023, https://doi.org/10.14710/ajlm.2023.19046
3. Samoggia, Antonella, and Bettina Riedel. “Coffee Consumption and Purchasing Behavior Review: Insights for Further Research.” *Appetite*, vol. 129, no. 1, Oct. 2018, https://doi.org/10.1016/j.appet.2018.07.002
4. Sepúlveda, Wilmer S., et al. “Consumers’ Preference for the Origin and Quality Attributes Associated with Production of Specialty Coffees: Results from a Cross-Cultural Study.” *Food Research International*, vol. 89, Nov. 2016, https://doi.org/10.1016/j.foodres.2016.03.039
5. Czarniecka-Skubina, Ewa., et al. “Consumer Choices and Habits Related to Coffee Consumption by Poles” *International Journal of Environmental Research and Public Health* 18, no. 8, 2021, https://doi.org/10.3390/ijerph18083948
6. Bressani, Ana P. P., et al. 2021. “Into the Minds of Coffee Consumers: Perception, Preference, and Impact of Information in the Sensory Analysis of Specialty Coffee.” Food Science and Technology, https://doi.org/10.1590/fst.30720
7. Montgomery, Douglas C., et al. “Introduction to Linear Regression Analysis.” 5th ed., John Wiley & Sons, Inc, 2012, pp. 40-42.
8. “Rfordatascience/Tidytuesday.” *GitHub.* https://github.com/rfordatascience/tidytuesday/blob/master/data/2020/2020-07-07/readme.md. Accessed 30 April 2024.
9. “Coffee News.” *Coffee Quality Institute*. https://www.coffeeinstitute.org/. Accessed 20 May 2024.
10. Bretscher, Otto. “Linear Algebra with Applications.” edited by George Lopell, 2nd ed., Prentice Hall, 2001, pp. 9-24.
11. ”Daily coffee consumption at 20-year high, up nearly 40%”. *NCAUSA.* https://www.ncausa.org/Newsroom/Daily-coffee-consumption-at-20-year-high-up-nearly-40#:~:text=NCA%27s%20Spring%202024%20National%20Coffee,since%20the%20Spring%202023%20NCDT. Accessed 21 May 2024.