Comparison of Recommendation System Styles for Wine Selection

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***Abstract*—For the average consumer, selecting an enjoyable wine from the multitude of options can be challenging. Currently, consumers typically rely on expert recommendations, but this approach is flawed since taste in wine is highly subjective. Recommendation systems are a good approach for wine recommendation, since they make comparisons based on content, such as sweetness and flavor notes, and other consumer's preferences. In this paper, three styles of recommendation systems, content-based, collaborative, and hybrid, are compared to discover which provides the best recommendations to consumers. Each style of recommendation system is implemented or simulated using MATLAB based on user data from surveys of food, beverage, and scent preferences, and wine data from the wine retailer Aldi and rating website Vivino. The results are then assessed by acquiring ratings of the top recommended wine from each system for each user. While it was hypothesized that the hybrid system would perform best since it utilizes both content and other users' ratings, the content-based system yielded the highest average ratings. Although there were some flaws in the fairness of the results, this reveals that recommending wine based on content is likely more effective than recommending wine based on other user's preferences. Future work could allow for more data collection and improved testing, as well as expanding this research to include greater wine selection.**

I. Introduction

Recommendation systems analyze a user's preferences, with or without their specific input, to tailor their digital experience, ideally improving satisfaction and engagement within many modern applications. Users have come to expect and seek out this kind of personalization, especially when a wide variety of options dependent on many variables are available, and there exists a large degree of uncertainty regarding their quality. Wine selection certainly falls into this category. With a unique vocabulary related to flavors and aromas as well as the elitism surrounding having good taste, finding the right wine can be challenging. The goal is to provide the average consumer with a simple means of determining which wines they will enjoy based on prior knowledge of their experiences.

Wine flavor is affected by a variety of factors such as the location the grapes were grown and the aging process. Wine selection typically begins with the decision between the three broad categories of Red, White, or Rosé, then narrows to more specific categories like Chardonnay, Riesling, or Pinot Grigio. Unfortunately for the consumer, there is still an overwhelming number of options within these categories which vary greatly in taste and aroma, for example a buttery Chardonnay or an oaky Chardonnay. Turning to expert or consumer ratings is a possible solution for narrowing these options, but taste in wine is highly subjective.

The proposed algorithm in this paper will account for flavor elements such as tannins and acidity, as well as the preferences of the user. For beginners, these preferences can be elicited from other food, drink, and scent preferences. For more experienced wine consumers, comparisons can be made to wines they already know they enjoy. Additionally, when users try recommended wines more data can be gathered from their specific ratings and reviews. By accounting for individual taste in addition to general and expert taste, consumer satisfaction with wine purchases can be increased, providing greater comfort for wine exploration.

II. Related Works

Specific research on wine recommendation systems is sparse, and instead wine-related machine learning research is focused on determining the general quality of wine [1]. As a result, this section will discuss research into food recommendation systems instead, which have similar components to a wine recommendation system, in that they utilize user preferences such as ingredients, cuisines, and diet styles to generate new recommendations. Some approaches also utilize similar user's preferences by including data from ratings and reviews. This aligns well with a wine recommendation system utilizing flavor profile, wine categories, and consumer and expert ratings.

The majority of food recommendation systems used a content-based approach, where the user's preferences are compared to the characteristics of the foods to determine their degree of similarity [2].

Nilesh et al. use a content-based approach for Indian food recommendation by requesting ingredients or recipes that the user enjoys and finding new recipes containing similar ingredients [3]. They do so by analyzing the text of recipes to group together ingredient keywords and compare them. Their approach produced inconsistent results across the set of different ingredients, as some ingredients might be very common, like rice, and fail to yield highly personalized results. They also make the assumption that user's want to consume recipes with the same ingredients, when instead analyzing the flavor category of each ingredient might yield better results. This is because a recipe containing a certain ingredient, for example chicken, could have many different flavor profiles, such as spicy, creamy, or salty. This problem is somewhat improved when their algorithm is provided with more ingredients as input, since this provides a better description of the flavor the resulting recipe will have. A solely content-based approach, especially one based on so little input data, will likely fail to be sufficiently specific to each individual user.

David Massimo et al. attempt to take a somewhat more collaborative approach to home-cooked recipe recommendation by using both content-based comparison, and user tags and ratings [4]. After the user enters their preference information by adding recipes they like, they are prompted with a variety of recipe options and asked to rate them then provide tags explaining their reasoning behind their rating. This information is used to train a model which will then provide tailored results from both the content-based and collaborative analysis. They tested their algorithm in the form of an android application and compared results of the hybrid approach to those of only content-based and only collaborative approaches, determining that the hybrid approach had the best performance. The addition of user tags is important to the performance of their algorithm, but is provided as an optional choice, so for a lazy user who may choose not to include tags, the quality of the algorithm performance would decrease. The training set for a collaborative model needs to be robust in order to ascertain an appropriate model for recommendations.

III. Approach

Currently, machine learning related to wine is primarily oriented towards determining its general quality based on expert's qualifications [1]. The proposed algorithm will instead focus more on user-specific taste to produce more satisfactory representations for the average consumer. This algorithm will more closely resemble those used in food recommendation systems, which combine the data of general ratings and reviews with user-provided data to personalize the results.

The three main categories of recommendation systems are content-based, collaborative, and hybrid [2]. A content-based approach to wine recommendation would compare features of a specific wine to the user's indicated preferences and recommend wines which closely align with these. A collaborative approach would utilize user ratings to determine which wines are preferred by users with certain preference factors and recommend these wines to users with similar preferences. A hybrid approach combines the elements of both content-based and collaborative filtering, weighing their results to produce a recommendation based on both approaches. This project will compare the results of all three recommendation system varieties to determine which is the most effective.

A. Data Collection

This algorithm will require three different collections of data: the user's preferences, the features of each wine, and other user's preferences for comparison.

The user's preferences will be derived using a survey of their preferences in other drinks, foods, and aromas. Certain preferences in food and drink reveal possible wine preferences. For example, users who take their coffee black will likely prefer wines with high levels of tannins and low sweetness. Users who have already sampled wines included in the experiment will be given the opportunity to input wines they have tried and provide a rating from 0 to 5 of these, allowing the opportunity for the dataset of wine ratings to begin to be populated.

The selection of wines offered at Aldi will be used and information regarding flavor and aroma elements will be ascertained from their descriptions and their ratings on the wine review website Vivino. This site allows users to provide specific ratings of the individual qualities of wine, such as body and flavor notes, and accumulates the input into rankings for each quality.

B. Data Analysis

For the content-based portion of the analysis, the data will be grouped into vectors representing its characteristics with numerical values representing the degree to which it aligns with each characteristic. For the wine vectors, the primary characteristics, including tannins, body, sweetness, and acidity, will be ranked from 0 to 1. The secondary characteristics related to flavor and aroma notes will be ranked from 0 to 0.5, representative of their lesser effect on the taste. The user vectors will follow the same structure to simplify content-based comparison.

For the collaborative portion, the ratings data will be used to create a training set, with the users' preference information as the input and the wines they rated 3.5 or higher as the output.

C. Algorithm Details

The algorithm approach for the content-based portion of the recommendation system uses cosine similarity. This approach normalizes the vectors to the unit circle then compares the dot product of the user vector with each of the wine vectors to produce a similarity metric [2].

The algorithm approach for the collaborative portion will utilize a learning decision tree generated from the training set data. The internal nodes will represent preference information from the vectors, and the leaves will represent specific Aldi wines. Since the input values are continuous, they will be subdivided using split points. The decision tree structure will be determined by a greedy divide-and-conquer function which begins with data deemed to be most important. A calculation of the information gain of each characteristic will be used to determine its importance, and the tree will be optimized to provide most information gain with the least complexity. The tree will then be pruned using a significance test to ensure that all nodes provide relevant information.

To represent the hybrid portion, the wines rated highly by both algorithms will be compared and those with the highest average rating between the two will be selected.

IV. EXPERIMENTS

This research hypothesizes that the hybrid recommendation system will produce the highest user satisfaction, since it utilizes the most data in determining recommendations.

TABLE I
AVERAGE USER RATING OF RECOMMENDATION SYSTEM RESULTS

Recommendation System Type	Average User Rating
Content-based	4.02
Collaborative	3.15
Hybrid	3.86

It should be noted that the collaborative portion of the algorithm was trained on a small data set, with only 13 users who were able to provide ratings of Aldi wines. Due to the insufficient training set, the results could be skewed towards better performance with the content-based algorithm.

A. Implementation

The content-based system was created using a MATLAB script running on data representing 72 wines and 20 users. This program reads in the wine and user vector data from CSV files and allows a user to be selected and the number of wines desired for output to be specified. It then uses a cosine similarity function comparing the selected user with each wine and storing the similarity output in an array. The output then consists of the array position and similarity value for the most similar wines, the quantity of which being determined by the user input.

The collaborative system was created by using MATLAB to train a decision tree. The input for the training data was 13 user vectors generated from a CSV file, and the output for each vector was their top-rated Aldi wine. The other 7 users who had not sampled Aldi wines were used for testing.

The hybrid system did not have a coded implementation but was instead simulated by assessing the results of the content-based and collaborative algorithms to determine which wine was highly recommended by both systems.

B. Results

To test the hypothesis, I surveyed users' satisfaction with their recommended wines. Unfortunately, due to the informal nature of this experiment, I could not require the users to purchase the wines and try them. Instead, their satisfaction could only be determined by reading the description of the wines on the Aldi website and judging from prior experience how much they believed they would enjoy them. I provided each user with the link to the description of the top wine recommended by each system and asked them to rate their predicted enjoyment on a scale of 0 to 5. For the content-based system I surveyed all 20 users, but for the collaborative and hybrid systems I was only able to survey the 7 users whose data had not been used to train the decision tree. The average ratings for each system can be seen in Table 1.

V. ANALYSIS

Although the hypothesis predicted the hybrid system to produce the best results, the content-based system had the highest average rating. This could be due to the fact that taste in wine is highly subjective, so recommending users wines which others enjoyed is inherently flawed. Alternatively, the unexpected results could be because the comparison was not necessarily fair given that only a portion of the users could be surveyed for the collaborative and hybrid approaches. To produce more accurate results, an entirely different set of users could be used to assess the output so that each system could be evaluated by the same users.

The collaborative system was trained on a relatively small dataset, so surveying more users to create a larger dataset would likely yield better ratings for the collaborative and hybrid systems. Additionally, the quality of wine can affect its taste. This was not taken into consideration in this experiment because it is difficult to assess for each user how sensitive they will be to wine quality. Finally, allowing the users to sample the wines recommended to them would allow them to give a more informed rating of their level of enjoyment.

VI. CONCLUSION

Recommending wines to average consumers based on simple factors is challenging. Recommendation systems are an effective tool for this task, given that the average rating overall from this experiment was a 3.68. In determining which style of recommendation system would be most effective, it was assumed that the hybrid system, able to operate with the most information, would outperform content-based and collaborative alone. Instead, the content-based recommendation system produced the highest ratings. This alludes to the fact that perhaps the best way to assess preference in wine is by assessing preference in other beverages, foods, and scents, rather than relying on the recommendations of others.

In the future improvements to this experiment could be made, including modifying the testing process, collecting more data, and accounting for more data. The process of data collection and testing could be simplified by creating a web platform to implement the recommendation systems where users can fill out the survey, receive their results, and provide ratings on one single platform. The experiment could be expanded to include wines offered by other grocery retailers than Aldi, for example Target and Walmart. These steps would need to be taken to make this project truly extensible, but these initial results provide some insight into the best recommendation system approach for wine selection.

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