Optimizing Taste and Sustainability: Food Recommendations to Reduce Water Footprint

Ofir Ben Moshe Oryan Yehezkel Guy Frankovits

May 11, 2024

Abstract

While most research in food-related studies focuses on retrieving recipes, providing kitchen assistance, or estimating the nutritional and caloric content of meals, there is less emphasis on creating personalized, environmentally conscious food recommendations. This study introduces a novel food recommendation system that incorporates a dynamic weighting of recipes' water footprints (WF) and user preferences. This method allows for the adjustment of importance given to the environmental impact versus personal taste preferences through a grid search optimization. Consequently, our system recommends the top recipes that achieve the highest combined score based on these criteria. By learning from user behavior and encouraging the adoption of more resource-efficient dietary patterns, this approach supports sustainable food consumption. Results from our research show that it is possible to save an average of 50 percent of the amount of water in the user recommendations, while minimally affecting the accuracy of the model.

1 Introduction

Water is an essential element for the survival and well-being of both humans and the planet, serving as a crucial life-sustaining resource. Today, imprudent and excessive water usage has led to various challenges including water scarcity, insufficient drinking water supplies, and pollution. While 70% of the Earth's surface is water-covered, only a limited amount of fresh water is available for essential activities like drinking, washing, and agriculture. Consequently, it is vital to endeavor to minimize water consumption across all sectors, including industrial, food, and domestic uses. To this end, the concept of the water footprint was developed by Arjen Hoekstra. This metric, which represents the total volume of fresh water used to produce the goods and services consumed by an individual or community, aims to enhance global water management strategies. This value can be calculated for specific activities, ranging from the production of crops to the operations of global corporations. The food sector, as highlighted in a recent report by Mekonnen and Gerbens-Leenes, is particularly water-intensive since each food item has its specific water needs. Accordingly, various studies have aimed to define an optimal diet that minimizes water use while promoting health. For instance, Blas et al. found that diets rich in vegetables and legumes and low in red meat not only reduce the water footprint but also improve health outcomes. This aligns with the principles of the Mediterranean diet. However, recent trends indicate a shift towards diets with higher meat and processed food content, similar to the American dietary pattern, which is detrimental to both human health and environmental sustainability.

1.1 Water Footprint

Water scarcity remains a significant global challenge, with water being a fundamental resource for life and ecological balance on Earth. In response, researchers have introduced the "Water Footprint" metric, which measures the impact of human activities on freshwater resources related to the production and disposal of goods and services. This metric complements other environmental impact assessments, such as the ecological footprint, which gauges natural resource consumption, and the carbon footprint, which quantifies greenhouse gas emissions by individuals, businesses, and nations. These indicators are crucial for understanding human impact on the planet, evaluating the environmental consequences of current economic systems, and identifying viable solutions for a sustainable future. The water footprint is versatile; it can be applied to assess water usage by a company, a specific product, or even on a citywide basis. It also calculates water usage for entire nations or globally, encompassing both direct water use, such as drinking and washing, and indirect water use, which includes water consumed in the production of goods and services. This comprehensive approach not only tracks direct and indirect water consumption but also accounts for water pollution from various human activities, offering a broad perspective on the water usage and sustainability of products, corporations, or countries.

1.2 Research Contributions

In this paper, we present a recommendation system that integrates the user's nutritional preferences and accounts for the water footprint of each ingredient. This system makes recommendations for recipes with a low water footprint, ensuring that each suggested dish aligns with the user's dietary needs while promoting reduced water usage in food production.

Our main contribution are:

1. A model that aims to create a balance between the water consumption for the recipe and the user's preferences.

2. A dynamic system that allows each user to decide the degree of importance of water consumption in recipes in relation to their personal preferences.

3. High coverage of recipes compared to the previous article: eliminating the need to predict the user's WF to enable high coverage of recipes, especially for users with a wide range of WF recipes.

The rest of the paper is organized as follows. Section 2 reviews the background. Section 3 describes the methodology in relation to the paper we used. Section 4 presents our experimental results, also in relation to the paper which we based ourselves on. Finally we provide discussion and conclusion in Sections 5 and 6.

2 Background

Nutrition is a fundamental aspect of human well-being and health; however, when food is consumed improperly or in excess, it can lead to various health issues. Therefore, maintaining a balanced and nutritious diet is crucial. Recognizing the importance of nutrition, numerous studies have been conducted to improve consumer health and dietary habits. Trattner and Elsweiler [17] categorized research in food recommendation systems into six classifications: content-based methods, collaborative filtering techniques, hybrid approaches, context-sensitive methods, group-oriented methods, and health-focused methods.

Drawing on prior interactions such as purchases or feedback, a content-based approach recommends components that align closely with a user's demonstrated preferences. This type of recommendation system requires both a detailed product description and a comprehensive user profile to function effectively. Various implementations of this method exist. For instance, Freyne and Berkovsky [9] created personalized recommendations by analyzing a user's specific ingredient preferences; conversely, Harvey and associates [13] accounted for both favored and disliked ingredients. This approach is not limited to textual data; it can be enhanced through visual data since many decisions about food are made visually. Yang and his team [18, 19] discovered that algorithms designed to identify key visual features of food images, such as Convolutional Neural Networks (CNN), can surpass traditional methods.

Collaborative filtering techniques suggest items by evaluating users' preferences, purchases, and activities that are shared among users who appear similar. Freyne and Berkovsky [9] applied Pearson correlation to the ratings matrix to assess the nearest neighbor method. According to Harvey et al.

[[13], SVD surpassed both content and collaborative filtering approaches. Ge, Elahi, and their team [16] developed a matrix factorization strategy for food recommendation systems that integrates user ratings with user-generated tags, achieving significantly better prediction precision than content-based methods and conventional matrix factorization standards.

As noted by Ricci et al. [14], "A hybrid system that merges techniques A and B seeks to leverage the strengths of A to mitigate the shortcomings of B." In the context of food recommendation systems, several studies have demonstrated impressive outcomes: Freyne and Berkovsky [9] employed a hybrid approach that integrated three different recommendation strategies within a single framework, using a switching mechanism aimed at specific user groups. This switching was based on the proportion of items a user had rated relative to the total item pool. Additionally, Harvey and colleagues [13] obtained the most favorable outcomes in their research by combining an SVD method with biases for both users and items.

A recommendation system that incorporates contextual data such as geographical location, social media profiles, device type, and more can be highly effective today. This context is particularly crucial in food recommendation systems; for instance, the method of preparing a meal, its complexity, or the variety of tools needed can enhance the system's efficacy. According to an analysis by Harvey et al. [12], factors such as the clarity of cooking instructions, the nutritional properties of the dish, ingredient availability, and time-specific factors like the day of the week significantly influence users' perceptions of the recommendations.

A group recommender system is designed to collectively suggest items to a group of users by considering their shared preferences. Incorporating the social and behavioral dynamics of group members to craft group-specific recommendations can significantly enhance the relevance of the content provided to different groups. Although this approach could be extremely beneficial for food recommendation tasks, as people often make food decisions not individually but influenced by interactions with friends, family, or colleagues, studies on group-based food recommender systems remain sparse. Berkovsky and Freyne [2] have tested these methods with real users within a household setting. The results demonstrate that such scenarios are effective with family groups; however, it was challenging to generate personalized recommendations for every family member.

The objective of the health-conscious food recommendation system is to assist users in making informed daily dietary choices based on nutritional and health considerations. Consequently, numerous investigations have been pursued in this field. Elsweiler, Hors-Fraile et al. [7]; Elsweiler, Ludwig, Said, Schäfer, and Trattner [8]; Schäfer et al. [15] conducted various research initiatives that integrate nutritional factors into their recommendation algorithms to improve users' health outcomes. Conversely, Ge, Ricci, and Massimo [10] implemented a calorie-tracking approach in their recommendation system. Discussing the balance between offering what users desire versus what is nutritionally prudent, Elsweiler, Harvey, Ludwig, and Said [6] addressed this dilemma for most users. Nutritional and health data for these studies were sourced from the World Health Organization (WHO) (https://www.who.int/, accessed on 22 December 2021) and the United Kingdom Food Standards Agency (FSA) (https://www.food.gov.uk/, accessed on 28 January 2022). Adopting an alternative tactic, Harvey and Elsweiler [[11] created a platform enabling the assembly of daily meal plans that encompass breakfast, lunch, dinner, snacks, and drinks. Ingredient substitution in recipes is yet another method proposed to boost users' health. In their research, Achananuparp and Weber [1] and Teng et al. [16] explored this method to motivate users towards healthier eating habits. However, these interventions still require thorough evaluation within a nutritional framework.

Moreover, water footprint is a critical contemporary issue in sustainability; indeed, a key focus of the United Nations 2030 Agenda (https://sdgs.un.org/2030agenda, accessed on 14 November 2021) is the sustainable management of water resources, aiming to ensure access to clean water and sanitation for all by 2030. To achieve this, it is essential to take measures to reduce the water footprint by promoting environmentally sustainable alternatives in freshwater use by both individuals and corporations. Numerous studies on the subject of water footprint have been authored by Alejandro Blas, Alberto Garrido, and Bárbara Willaarts [5, 3, 4]. These studies extensively explore the effects on water usage, food waste, and household food consumption, initially concentrating on the Spanish region before expanding to European and American contexts. In addition to exploring these factors and consumption patterns, the researchers offer solutions and recommendations based on predictive analyses aimed at reducing overall consumption and, crucially, minimizing water waste.

In their initial study [5], Blas and colleagues explored and contrasted the water footprints of two different diets: the American diet and the Italian diet. The results revealed that the American diet has a 29% higher water footprint than the Mediterranean diet. Considering that the Mediterranean diet consumes less water, the findings suggest it could be beneficial for both health and environmental sustainability. Consequently, it can be inferred that adopting a Mediterranean diet could lead to reduced water footprint usage in both Italy and the United States. Thus, the data supports the theory that diets low in meat are more environmentally sustainable in terms of water preservation, aiding in addressing the health-environment dilemma.

Further investigations by the same team [4] on food consumption and waste in Spanish homes highlighted the critical nature of this issue for long-term environmental sustainability. The study primarily examines the water footprint of Spanish consumers, determining that water usage in Spain amounts to 52.933 hm3, approximately 3302 liters per person per day. Notably, meat, fish, and animal fats (26%), along with dairy products (21%), constitute the bulk of the total water footprint; hence, reducing consumption of these in favor of more fruits, vegetables, and legumes could lead to significant water savings. Moreover, the research looks into how food waste affects the environmental water footprint. In conclusion, the researchers suggest that, from a Spanish perspective, households could achieve more substantial reductions in their food-related water footprint by altering their dietary habits rather than merely reducing food waste.

A recent third study by Blas et al. [3] assesses the Mediterranean diet and compares it to the current dietary trends among Spanish residents. The study indicates that present dietary patterns in Spanish households are shifting towards higher consumption of meat, dairy, and sugary products, and less intake of fruits, vegetables, and grains, diverging from the Mediterranean diet. Consequently, because it is a less water-intensive diet, following a Mediterranean diet would offer health benefits. This view is supported by the finding that adopting a Mediterranean diet in place of current dietary trends in Spain would reduce the water footprint by 753 liters per person per day, given that the highest water-consuming items are of animal origin: meats, animal fats, and dairy products.

2.1 Related work

In our study, we extend the method presented by Gallo et al. in their 2022 work on water footprint-based food recommendation systems, incorporating minor but significant enhancements to refine recipe suggestions further. Gallo and colleagues developed a sophisticated system that intelligently recommends recipes by integrating the water footprint of ingredients, thus aligning with the user's dietary preferences while also promoting sustainable water usage. Their system categorizes recipes and users into different classes based on water usage metrics, allowing for targeted suggestions that gradually steer users towards more sustainable eating habits without compromising dietary preferences.

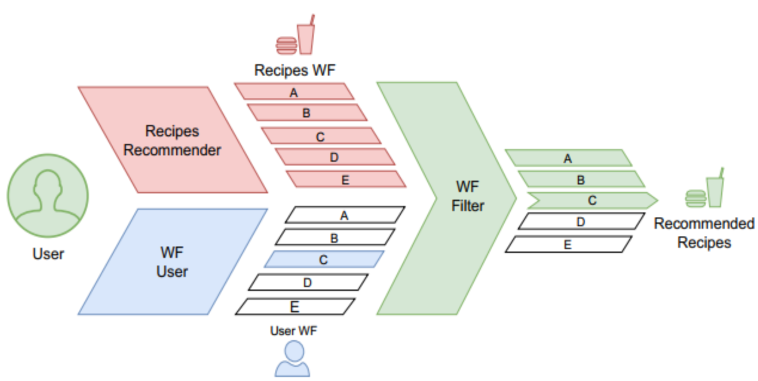

Figure 1: Intuitive diagram explaining the related water footprint-based recipe recommendation system. The system must categorize both recipes and users into five different categories (A, B, C, D, E) before recommending water-saving recipes. In the end, the user will only be offered recipes that have a water quantity used in production lower than or equal to the user's category (in the drawing the user's category is C).

3 Method

Building upon this foundation, our approach introduces adjustments to the algorithm's estimation process. Rather than requiring the user's water footprint rating for filtering recipes initially, we opt to train a model that evaluates the recipe's suitability based on the user's preferences and the recipe's water footprint. This entails penalizing recipes with higher water footprints more than those with lower footprints.

The main goal of this approach is to present a recommendation algorithm that considers both the water footprint and the adaptation of recipes to the user's needs. To achieve this, we rely on knowledge of the user's reviews, order history, and the water footprint associated with the ingredients in each recipe.

3.1 Recipe Water Footprint Weighting

This section delineates the process of assigning weights to all recipes based on their water footprint. To achieve this weighting, it is initially necessary to compute the water footprint (WF_i) for every recipe i in the dataset, as defined by the equation:

$$WFi = \sum_{g=1}^{\infty} wf_g \times qt_g \tag{1}$$

Here, wf_g denotes the water footprint of the g-th ingredient, and qt_g represents the quantity of the g-th ingredient used in recipe i. Utilizing this information facilitates a comparative analysis of the recipes in the dataset in terms of water quantity used in production. Following the calculation, a dataset is compiled containing the recipes and their corresponding water footprints.

To standardize the results within a range of 0 to 1, we experimented with various normalization techniques.

1. **Inverse Normalization** - Method involves dividing each result by the value to ensure that the smallest result corresponds to the highest priority. In this approach, a larger priority value indicates a smaller result. Additionally, we divided the values by 1 to properly order them.

$$\text{recipes\_wf\_norm} = \frac{1}{\text{recipes\_wf}}$$

2. Method employs **minimum-maximum normalization**, which scales the results linearly between 0 and 1 based on the minimum and maximum values in the dataset. Additionally, we subtract the values by 1 to properly order them.

$$\text{recipes\_wf\_norm} = 1 - \left(\frac{\text{recipes\_wf} - \min(\text{recipes\_wf})}{\max(\text{recipes\_wf}) - \min(\text{recipes\_wf})}\right)$$

3. Method utilizes **standard normalization**, wherein the values are adjusted to have a mean of 0 and a standard deviation of 1. Additionally, we multiply the values by -1 to properly order them.

$$\text{recipes\_wf\_norm} = -1 \times \left(\frac{\text{recipes\_wf} - \mu(\text{recipes\_wf})}{\sigma(\text{recipes\_wf})}\right)$$

3.2 Recipe Preference Weighting

We opted to conduct multiple experiments to identify the approach yielding the most favorable outcomes. Each algorithm underwent evaluation and comparison against others using consistent datasets and metrics. To discern the optimal methodology, we conducted experiments on two primary approaches: content-based and collaborative filtering.

3.2.1 Content-Based

The first method we used for creating the recommendation system is called content-based. Instead of comparing users, this approach looks at similarities between recipes. To make good suggestions, we need to study how a user behaves—what they buy and what they like. Then, the system uses this information to find recipes similar to the ones the user prefers and orders often. Similarities between recipes are based on the ingredients they share. But not all ingredients are equally important. Some, like oil or salt, are used in many recipes but don't really show what a user likes. So, we give each ingredient a weight when we compare recipes. To build our system, we used a method called Term Frequency Inverse Document Frequency (TF-IDF) on all the ingredients. This method helps us understand how often ingredients appear in recipes. It gives higher importance to ingredients that are less common. Then, we used something called cosine similarity to see how similar a user's profile is to different recipes. This method looks at all the user's reviews, giving more weight to higher ratings. It finds out which ingredients the user likes the most. Finally, it searches through all the recipes to find the ones with ingredients most similar to the user's preferences. The output is a sorted list of recipes, with the top one being the closest match to what the user likes.

3.2.2 Collaborative Filtering

Another method we explored is called collaborative filtering. We conducted various experiments using different kinds of algorithms to find the best ones. We tried out BaselineOnly, SVD, KNNBasic, KNNBaseline, KNNWithZScore, KNNWithMeans, and CoClustering algorithms. Each of these algorithms works in its own way to predict what users might like. After these experiments, we looked at how well each algorithm predicted user preferences. Basically, these algorithms help us create a list of recipes that match closely with what users like.

The algorithm calculates how likely a user is to rate an item. This is called "rui," where "r" stands for rating, "u" stands for user, and "i" stands for item. The formula for this calculation is given by Equation (2):

$$r_{ui} = b_{ui} + \sum_{j \in N_k^u(i)} \text{sim}(i, j) \cdot (r_{uj} - b_{uj}) \div \sum_{j \in N_k^u(i)} \text{sim}(i, j) \tag{2}$$

Here, b_{ui} is a baseline estimation for an unknown rating r_{ui}, which takes into account the user and item effects as described in Equation (3):

$$b_{ui} = \mu + b_u + b_i \tag{3}$$

In Equation (3), b_u and b_i represent the observed deviations of user u and item i, respectively, from the average. We further adjusted the algorithm using certain parameters. We used a measure called Shrunk Pearson correlation ($\text{sim}(i, j)$) to calculate similarities, computed similarities between recipes instead of users, and set the minimum support number to five. After completing the initial part of the algorithm, we can gather a list of recipes that are likely to be enjoyed most by the user. These recipes are sorted in descending order of preference.

3.3 Recommendation System

In our approach, each rating of a recipe for a user is evaluated based on two factors:

1. $WF_{i,n}$: Represents the total water required for the ingredients used in the recipe i, with normalization method n.

2. $r_{u,i}$: Measures the alignment of the recipe with the user's dietary preferences and tastes with on of the two method, Collaborative Filtering (CF) or Content-Based (CB).

$$Rating_{ui} = \lambda * r_{u,i} + (1 - \lambda) * WF_{i,n} \tag{4}$$

To compute the final score for each recipe, we employ a weighted sum of these two metrics. The weighting parameter, denoted as λ, is used to multiply the WF, while $1 - \lambda$ is used for the cosine similarity score. This approach ensures that the sum of the weights equals one, allowing us to balance the emphasis between environmental impact and user preference seamlessly. By adjusting λ, the system can be tuned to prioritize either sustainability or personal preference to a greater extent, offering flexibility in how recommendations are tailored to individual users or broader dietary guidelines.

4 Evaluation

4.1 Dataset

This study harnessed a comprehensive dataset sourced from PlanEat.eco to underpin its experimental investigations. The dataset, tailored to Italian cuisine enthusiasts, encapsulates an extensive repository of 813 Italian recipes, complemented by user order histories. Notably, each recipe is meticulously cataloged alongside its corresponding user reviews, comprising textual descriptions, timestamps, and ratings ranging from 0 to 5, thereby furnishing rich insights into user preferences and consumption patterns.

The PlanEat dataset affords a granular perspective into Italian culinary traditions, encompassing a diverse array of 524 distinct ingredients meticulously curated to craft authentic recipes. On average, each recipe comprises four ingredients, facilitating nuanced analyses of flavor profiles and ingredient interactions. Additionally, the dataset boasts a robust user engagement history, spanning over a year from March 2020 to July 2021, and encompasses a staggering 81,627 orders emanating from 551 users. Such comprehensive coverage not only ensures the representativeness of the dataset but also furnishes

Number of recipes	813
Number of ingredients	524
Max Number of ingredients in recipe	21
Min Number of ingredients in recipe	1
Avg Number of ingredients in recipe	4
Number of total orders	81627
Number of users	551
Max Number of order for a user	2660
Min Number of order for a user	1
Avg Number of order for a user	148

Table 1: Statistical information about the dataset

a robust foundation for rigorous experimentation and analysis, thereby enriching the scholarly discourse on recommendation system methodologies tailored to culinary domains. For detailed statistical insights and an overview of the dataset's composition, refer to Table 2.

4.2 Experimental Plan

In the evaluation phase of our study, we rigorously scrutinize the performance of two distinct recommendation algorithms: Collaborative Filtering and Content-Based Filtering. Our assessment incorporates a meticulous examination of these algorithms when integrated with various normalization techniques, including Inverse normalization, minimum-maximum normalization, and standard normalization.

4.2.1 Performance Indices

1. **Average Water Footprint (AWF):** The AWF metric plays a pivotal role in our evaluation, representing the average water footprint value derived from the recommendations generated for each user within the dataset. To compute this metric, we execute the recommendation algorithm for each user, aggregating the water footprints of the top 10 suggested recipes per user. The resulting value, termed as average WF in our analysis, signifies the mean of all aggregated water footprint sums across the user cohort.

2. **Hit-Ratio@n (HR@n):** The Hit Ratio metric serves as another cornerstone of our evaluation methodology, quantifying the proportion of users for whom the correct recommendation resides within an N-item suggestion list. Specifically, we adopt the Hit Ratio at N (HR@n) approach, leveraging the Leave-One-Out methodology for robust evaluation. This method involves selecting the most recent user interaction as the test item, while the remaining interactions serve as training data.

4.2.2 Evaluation Procedure

1. **Data Preparation:** Before conducting evaluations, the dataset is preprocessed to ensure its suitability for analysis. This includes handling missing values, encoding categorical variables, and partitioning the data into training and testing sets.

2. **Algorithm Execution:** Each recommendation algorithm, combined with different normalization techniques, is executed on the prepared dataset. For each user, the top 10 recommended recipes are generated based on the algorithm's predictions.

3. **Metric Calculation:** The AWF metric is computed by aggregating the water footprints of the recommended recipes for each user and calculating the average across all users. Conversely, the HR@n metric is determined by iteratively applying the Leave-One-Out methodology to assess the accuracy of the recommendations.

By meticulously following this evaluation methodology, we aim to provide comprehensive insights into the performance characteristics of the recommendation algorithms under consideration, thereby facilitating informed decision-making in real-world applications.

	Their		Ours		Best Params		
Algorithm	Hit Ratio @10	Average WF	Hit Ratio @10	Average WF	Alpha	Beta	Norm
CB	0.15	682.27	**0.16**	**554.03**	1.0	0.8	minmax
BaselineOnly	**0.07**	502.84	0.06	**67.30**	0.2	1	zscore
SVD	**0.14**	501.37	0.13	**76.27**	0.8	0.2	zscore
KNNBasic	**0.11**	497.43	0.07	**100.47**	0.2	0.4	inverse
KNNWithMeans	0.05	501.48	**0.07**	**66.81**	0.4	0.6	inverse
KNNWithZScore	0.03	500.87	**0.10**	**76.48**	1.0	0.8	inverse
KNNBaseline	**0.21**	496.81	0.15	**74.31**	0.6	0.4	minmax
CoClustering	0.06	499.26	**0.15**	**103.49**	0.8	1.0	zscore

Table 2: Comparison of Results between Our Method and Theirs: Our analysis indicates negligible differences in the hit ratio between our method and theirs. However, our approach significantly outperforms theirs in terms of mean water footprint.

5 Results

The primary objective of this experiment was to evaluate the impact of algorithmic adjustments on the outcomes, particularly focusing on the average water consumption recommended per suggestion, and subsequently contrasting these findings with those of the original study. Analyzes primarily centered on hit@10 metrics revealed no statistically significant disparities when compared to the findings of the original article. Notably, out of the ten experimental runs conducted, our method exhibited superior results in five instances, while the remaining five yielded comparable outcomes with no discernible differences.

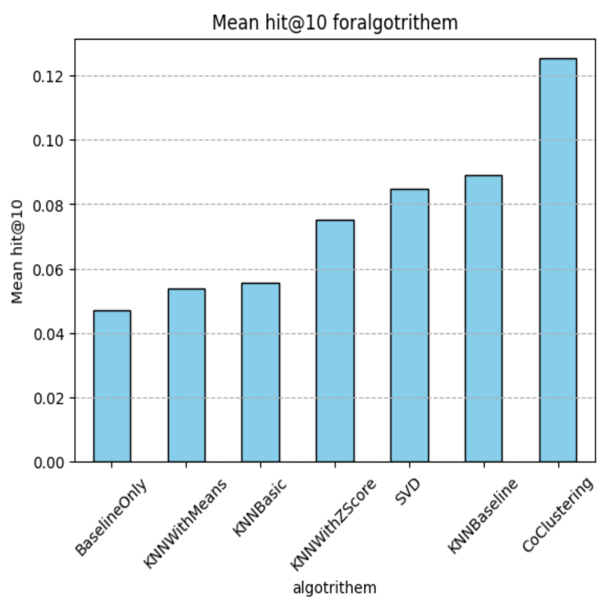

Figure 2: Mean Hit@10 for each algorithm

A pivotal aspect of the investigation revolved around scrutinizing the recommended water savings generated by our algorithm in contrast to those proposed in the original study. The findings revealed a substantial enhancement in this regard, underscoring a noteworthy deviation from the baseline. Notably, while the original methodology advocated an average water consumption of approximately 500 units, our refined approach significantly reduced this figure to an average of around 80 units, translating to an impressive 84 percent reduction in water consumption. Importantly, this remarkable reduction was achieved without any compromise on the quality or efficacy of the recommendations provided.

In summation, this study illuminates the efficacy of algorithmic adjustments in optimizing water consumption recommendations without sacrificing the quality of outcomes. While statistical comparisons reveal no significant disparities in hit@10 metrics, a substantial improvement is discernible in the average water savings recommended by our method when juxtaposed with the original approach.

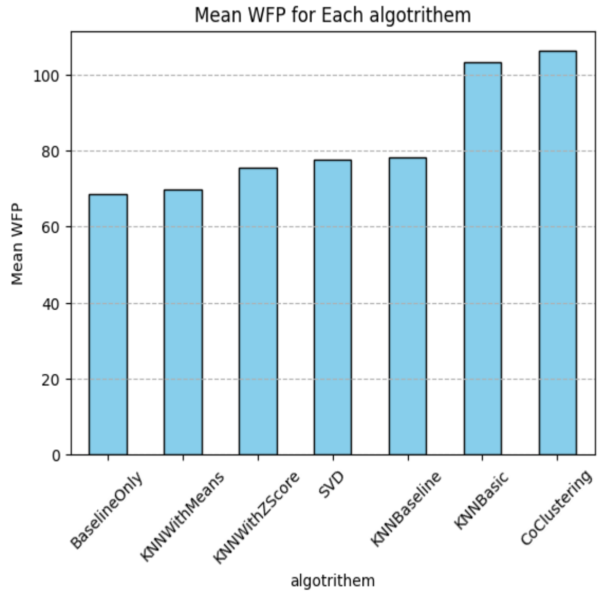

Figure 3: Mean Water Foot Print for each algorithm

6 Discussion

Among the array of algorithms scrutinized, CoClustering emerged as the frontrunner, boasting the highest average hit@10 metric of 0.12. Intriguingly, this algorithm also coincided with the highest recommended water consumption among its counterparts. Conversely, KNNWithMean stood out for its efficacy in minimizing water usage, affirming its superiority in this aspect. This disparity underscores the nuanced trade-offs inherent in algorithm selection, where optimizing one metric may entail compromise in another.

Furthermore, the exploration into the influence of data normalization, alpha, and beta parameters on outcome quality yielded intriguing insights. Contrary to initial expectations, no discernible correlation between these factors and result quality was observed. Rather, it became evident that each algorithm exhibited unique parameter requirements for optimal performance. This highlights the intricate interplay between algorithmic intricacies and parameter selection, negating the notion of a universally optimal parameter set and emphasizing the necessity for tailored parameterization to maximize algorithmic efficacy across diverse scenarios.

7 Conclusion

In conclusion, this article introduced a novel approach to recommendation systems by integrating user preferences with the consideration of water usage in recipe recommendations. Our study has demonstrated a significant advancement over prior methodologies, showcasing the feasibility of preserving recommendation quality while achieving remarkable reductions in water consumption, exceeding 80 percent per recipe. This paradigm shift holds profound implications for environmental sustainability, offering a tangible avenue for mitigating resource strain in culinary practices. Moreover, the findings underscore the viability of our approach for integration into future recipe recommendation systems, paving the way for eco-conscious decision-making without compromising user experience or satisfaction. By amalgamating user preferences with sustainability objectives, our methodology not only enhances the quality of recommendations but also contributes meaningfully to the broader discourse on environmentally conscious computing and its potential applications in diverse domains.

References

[1] Palakorn Achananuparp and Ingmar Weber. Extracting food substitutes from food diary via distributional similarity. *arXiv preprint arXiv:1607.08807*, 2016.

[2] Shlomo Berkovsky and Jill Freyne. Group-based recipe recommendations: analysis of data aggre-

gation strategies. In *Proceedings of the fourth ACM conference on Recommender systems*, pages 111–118, 2010.

[3] Alejandro Blas, Alberto Garrido, Olcay Unver, and Bárbara Willaarts. A comparison of the mediterranean diet and current food consumption patterns in spain from a nutritional and water perspective. *Science of the Total Environment*, 664:1020–1029, 2019.

[4] Alejandro Blas, Alberto Garrido, and Bárbara Willaarts. Food consumption and waste in spanish households: Water implications within and beyond national borders. *Ecological Indicators*, 89:290–300, 2018.

[5] Alejandro Blas, Alberto Garrido, and Bárbara A Willaarts. Evaluating the water footprint of the mediterranean and american diets. *Water*, 8(10):448, 2016.

[6] David Elsweiler, Morgan Harvey, Bernd Ludwig, and Alan Said. Bringing the" healthy" into food recommenders. *Dmrs*, 1533:33–36, 2015.

[7] David Elsweiler, Santiago Hors-Fraile, Bernd Ludwig, Alan Said, Hanna Schäfer, Christoph Trattner, Helma Torkamaan, and André Calero Valdez. Second workshop on health recommender systems: (healthrecsys 2017). In *Proceedings of the Eleventh ACM Conference on Recommender Systems*, pages 374–375, 2017.

[8] David Elsweiler, Bernd Ludwig, Alan Said, Hanna Schaefer, and Christoph Trattner. Engendering health with recommender systems. In *Proceedings of the 10th ACM Conference on Recommender Systems*, pages 409–410, 2016.

[9] Jill Freyne and Shlomo Berkovsky. Intelligent food planning: personalized recipe recommendation. In *Proceedings of the 15th international conference on Intelligent user interfaces*, pages 321–324, 2010.

[10] Mouzhi Ge, Francesco Ricci, and David Massimo. Health-aware food recommender system. In *Proceedings of the 9th ACM Conference on Recommender Systems*, pages 333–334, 2015.

[11] Morgan Harvey and David Elsweiler. Automated recommendation of healthy, personalised meal plans. In *Proceedings of the 9th ACM Conference on Recommender Systems*, pages 327–328, 2015.

[12] Morgan Harvey, Bernd Ludwig, and David Elsweiler. Learning user tastes: a first step to generating healthy meal plans. In *First international workshop on recommendation technologies for lifestyle change (lifestyle 2012)*, volume 18. Citeseer, 2012.

[13] Morgan Harvey, Bernd Ludwig, and David Elsweiler. You are what you eat: Learning user tastes for rating prediction. In *String Processing and Information Retrieval: 20th International Symposium, SPIRE 2013, Jerusalem, Israel, October 7-9, 2013, Proceedings 20*, pages 153–164. Springer, 2013.

[14] Francesco Ricci, Lior Rokach, and Bracha Shapira. Recommender systems: Techniques, applications, and challenges. *Recommender systems handbook*, pages 1–35, 2021.

[15] Hanna Schäfer, Santiago Hors-Fraile, Raghav Pavan Karumur, André Calero Valdez, Alan Said, Helma Torkamaan, Tom Ulmer, and Christoph Trattner. Towards health (aware) recommender systems. In *Proceedings of the 2017 international conference on digital health*, pages 157–161, 2017.

[16] Chun-Yuen Teng, Yu-Ru Lin, and Lada A Adamic. Recipe recommendation using ingredient networks. In *Proceedings of the 4th annual ACM web science conference*, pages 298–307, 2012.

[17] Christoph Trattner and David Elsweiler. Food recommender systems: important contributions, challenges and future research directions. *arXiv preprint arXiv:1711.02760*, 2017.

[18] Longqi Yang, Yin Cui, Fan Zhang, John P Pollak, Serge Belongie, and Deborah Estrin. Plateclick: Bootstrapping food preferences through an adaptive visual interface. In *Proceedings of the 24th acm international on conference on information and knowledge management*, pages 183–192, 2015.

[19] Longqi Yang, Cheng-Kang Hsieh, Hongjian Yang, John P Pollak, Nicola Dell, Serge Belongie, Curtis Cole, and Deborah Estrin. Yum-me: a personalized nutrient-based meal recommender system. *ACM Transactions on Information Systems (TOIS)*, 36(1):1–31, 2017.