Food Recipes Recommender System

BORIS BORISOV, THAO LE, PAVAN AAKASH RANGARAJ, KRISTIAN VAN KUIJK,

Maastricht University, The Netherlands

Eating a variety of food is essential to life. Nowadays, consumers have food restrictions including veganism, vegetarianism, or just following a dietary restriction. Recommender systems are used in our daily life while choosing a restaurant, a coffee place, or in other industries including music and movies. This paper focuses on creating recommendation systems while using different state of the art algorithms. To achieve this, predicting a user's rating of unseen food recipes based on their rating history was implemented. Furthermore, a tag analysis of the given reviews was conducted and an explanation of the recommendation system was implemented. Moreover, a comparison of the performance of the different recommendation algorithms was made. Lastly, we show that for a general use case, our hybrid recommender system performs best. Nevertheless, when it comes to tackling bias, our knowledge-based recommender system should be preferred.

1 INTRODUCTION

Recent research shows that successful food bloggers are getting around 8 million dollars per year [1]. Thus, having access to a recommender system for food blog recipes is highly relevant and useful. One of the main aims of the paper will be to predict users' ratings of unseen food recipes based on their user history. While giving recommendations, we realize that the system sometimes gives non-vegan recipes recommendation to vegan users, hence, we want to tackle that bias in our recommendation algorithms. This paper will implement multiple recommendation algorithms, starting with a content-based approach. Then, collaborative filtering such as the User-User algorithm is introduced. We will also use a knowledge-based recommender system and combine the previous algorithm to build a hybrid recommendation system. Our results will be added to build a group recommendation algorithm using the least misery approach. Furthermore, a tagsplanation of the customer's review is another approach that was introduced in this project.

With that being said, our paper aims to answer the following research questions: "How can we build a good food recommender system for a single user that is based on more than just rating?", "How can we evaluate whether our approaches are suitable for this project?", "How can we tackle vegan bias in the dataset?" and, last but not least, "Why Tagsplanations are useful?". This paper is divided into 5 subsequent sections. Firstly, an overview of related work is presented, followed by an elaboration and justification of our methodology, which includes evaluations and explanations. Then, our results will be presented, followed by a discussion of the results. The last section of the paper includes the conclusion and future research.

2 RELATED WORK

Tagsplanation: There have been several research studies that demonstrate the effectiveness of tagsplanation in explaining recommender systems. A research study by Garima Mishra et al. [7] showed that using social tagging can help optimize research paper recommender systems. Ido Guy et al.[5] went a step further and combined people-based and tags-based algorithms into a hybrid system for social media recommendation and before giving tagsplanation. Jesse Vig et al.[12] built tagsplanation for movies and showed that the overwhelming majority of respondents agreed that tagsplanation helped increase their trust and understanding of the recommender system.

Author's address: Boris Borisov, Thao Le, Pavan Aakash Rangaraj, Kristian Van Kuijk,
Maastricht University, Maastricht, The Netherlands.

Bias: Regarding bias in a recommender system, Himan Abdollahpouri et al. [2] [3] showed how popularity bias has created unfairness in recommender systems and how to intervene it from a user's and an algorithmic perspective. Popularity bias research has been done on niches such as music Òscar Celma et al.[4] and movies recommendations by Yixin Wang et al.[13] . Moreover, a considerable amount of previous work has been done on gender bias in recommender systems by Alessandro B Melchiorre et al.[6] and Dougal Shakespeare et al.[9]. However, recommender systems biases for food recipe has not been explored.

Novelty: In this paper, we offer a novel approach as none of the previous studies about tagsplanation focus on recommending food recipes. We decide to explain our recommendation using the author-generated tags. Moreover, our paper contributes to a gap in research about tackling biases for food recipes recommendations, especially for vegan people.

3 METHODOLOGY

3.1 Dataset

The dataset for this project was obtained from *Food.com*. It was obtained from *Kaggle*. It contains over 160 000 food blog recipes and over 1 000 000 unique reviews from customers over almost 20 years. The dataset was enormously big and we concluded that it will take a lot of computation time and computing power to be processed. We filtered the users with at least 100 ratings and recipes with at least 10 ratings. Moreover, we considered the reviews of the user. Finally, we use two dataframe: user data frame (figure 1) - information about users and their rating and recipe dataframe (figure 2) - information about the recipes. Tagsplanation was investigated, for this, the dataset was left with only the most useful tags. More details of the tagsplanation will follow in section 3.8.

3.2 Feature Engineering and Data Processing

From the dataset, we engineered 6 new boolean features: "dessert", "vegan", "high protein", "low fat", "low sugar", "healthy", and a numerical feature called "difficulty". A "difficulty" score of 1 indicates a hard recipe while 0 is medium, -1 is easy. This feature checks if a recipe has more than 20 steps and more than 13 ingredients then it is a difficult recipe, if it has less than 5 steps and less than 5 ingredients then it is an easy recipe. The thresholds for all 7 new features are determined from histograms of the data distributions. The final dataset with newly engineered features looks like figure 3.

Normalized Rating: For all of our algorithms, we use normalized ratings. Specifically, we subtract each user's ratings by his/her average rating. A negative normalized rating means the user likes the items less than usual, while a positive one indicates the opposite.

3.3 Content-based and Collaborative Filtering Approach

Using the features we engineered, 3 models were built: kNN Regressor, Linear Regressor, and Random Forest Regressor. The regressors will predict which unrated recipes will have higher ratings.

Evaluation: We use *Root Mean Squared Error (RMSE)*, which measures how close our model fits the data. This is used instead of *Mean Square Error* because it is less sensitive to higher error since the values are put in the squared root. Our second approach is based on the assumption that people who liked similar items in the past will like similar items in the future. We use Lenskit's User-User algorithm for this approach.

Evaluation: This system will be combined and evaluated along with content-based in our Hybrid Recommender System.

3.4 Hybrid Recommendation Systems

In order to improve our baseline scores obtained from the Content-based and Collaborative Filtering approach, a Hybrid system that comprises a combination of the 2 baselines approaches was decided to be implemented. This approach implemented in a pipeline manner would fulfil the flaws observed in the 2 baseline approached by capturing *User preference* which was lacking in the *CF approach* and also capturing *User history* which was lacking in the *Content-Based approach*.

Input: The filtered dataset with added features would be provided to the Content-Based algorithm whose output would become the input of the Collaborative Filtering Algorithm.

Evaluation: The Hybrid Recommender System was evaluated on Individual Recommendations, Group Recommendations and Performance with Vegan Bias. The evaluation metric selected was Precision, Recall F1 score. As F1 scores are preferred when comparing models that predict similar items, it is best suited for our Recommender Systems. Precision and Recall are also important metrics when it comes to Recommender Systems thus we use these metrics.

Evaluation Result: The evaluation result for individual recommendations can be found in 4.

3.4.1 Hybrid Based Group Recommendation. Group Recommendations were analysed on how they performed with different Group scenarios (with and without vegan users). This was done to see how the system dealt with vegan bias. We use the least misery strategy to generate recommendations because it is the most suited to recommend food to a group. As it is very common that users refrain from ordering food that is new or is allergic to (ex: Peanuts). Therefore using least misery ensures that the group is not suggested an item that they extremely do not prefer. The results can be seen in 4,5.

3.5 Knowledge-based Approach

In order to better compensate for users with dietary preferences (we will only consider users who follow a vegan diet in our implementation which can be generalized) a knowledge-based RecSys with a Constrained dataset would be a suitable approach.

Constrained dataset: Using the engineered features on our filtered datasets, 10864 vegan recipes were identified. They will now act as the entire dataset for the knowledge-based system thus ensuring the vegan users get better recommendations.

Evaluation: The knowledge-based RecSys was also evaluated on individual recommendation and group recommendation using the F1 score, precision and recall. The results can be seen in 5.

3.5.1 Group Recommendations in Knowledge-based Approach. Group recommendations were obtained again using the least misery strategy on 2 scenarios. *Scenario 1: Users that consists of only Vegan-users* and *Scenario 2: User group consisting of 5 Vegan users and 5 users with no preference.* The results can be found for scenario 1 in 6 and for scenario 2 in 7.

3.6 Tagsplanation

To explain recommendations, we implemented three versions of tagsplanation. All three share the same base implementation: filtering tags and selecting one correlated with high ratings.

Tag Filtering. On one hand, the most frequent tags (which includes some that occur in more than 90% of recipes, figure 6b) do not provide any specific information to the users. The top 3 most frequent tags for instance (*preparation*, *time-to-make* and *course*) could be given to any recipe. This suggests those tags do not make any distinction between recipes, i.e. there is no reason to take them into account to model preferences of users. On the other hand, some of the less recurring tags appear only once or twice, as can be seen in figure 6a. This presents two issues relating to data sparsity. Thereby 15% of the most and 15% of the less frequent tags have been removed (from 560 unique different tags to 393).

Tag Selection. We start by selecting the 10% most used tag on the users' favourites recipes (e.g. rating 4 or 5). Those tags will all have a chance to be selected by our *roulette wheel selection. Roulette wheel selection* is a popular technique in genetic algorithms that guarantees diversity (i.e. each individual or tag, including the *"weakest"*, has a chance of being selected) while having a greater chance of outputting the most popular tag of the user. An example is shown in table 8. The selected tag is then used in the three following methods:

- **Recipe with the same tag** We look for a recipe containing the selected tag. A typical output example: *Because you enjoyed 8 recipes with the tag **salad-dressings**, we believe you will also like **warm bacon dressing for spinach salad** which also has the tag **salad-dressings**.*
- **Recipe with a similar tag** After performing word embedding (we transform our words into vectors. Tags that are often in the same recipes will have similar vectors, hence a greater cosine similarity. An example is shown in table 9), we select one of the 10 most similar tag to our selected tag and search for a recipe containing the similar tag. A typical output example: *Because you enjoyed 10 recipes with the tag **pies-and-tarts**, we believe you will also like **pumpkin caramel cheesecake** which has the similar tag: **cheesecake**.*
- **Recipe with the same tag and a similar tag** Once again, after performing word embedding we select one of the 10 most similar tag to our selected tag and search for a recipe containing the similar tag and the originally selected tag. A typical output example: *Because you enjoyed 9 recipes with the tag **gifts** we believe you will also like **chocolate wows** which has the tag: **gifts** and the similar tag: **drop-cookies**.*

4 EXPERIMENTS AND RESULTS

4.1 Content-based and Collaborative Filtering approach

For this approach, we obtain moderately good models. In particular, our RMSE for each kNN, Linear, and RandomForest Regressors are around 0.888 to 0.978, using normalized ratings. This is not a bad score, however, we can still improve on this using subsequent approaches. Due to the space limit, we will not show the result for Collaborative Filtering, however, the observed metrics for our baseline CF approach can be seen in appendix 1.

4.2 Hybrid recommendations

The evaluation figure of individual recommendations of Hybrid RecSys can be found in 4, the values of the metrics shown in 2. We already notice that we have outperformed our baseline CF-approach.

4.3 Hybrid Group Recommendations

The results of the group recommendations can be found in 4:

The variance between the predicted ratings in *Scenario 1* was found to be **0.02828** which we will be comparing to *Scenario 2*.

The group recommendations for *Scenario 2* can be found in 5.

The variance between the predicted ratings was found to be **0.1631480**, which is nearly 10 times that of *Scenario1*. This shows that the Hybrid Recommender System struggles to capture strict dietary preference of user such as following a vegan diet.

4.4 Knowledge-based recommendation

The result of the individual recommendations can be found in 5, the value of the metric is shown in 3. We once again see a significant improvement compared to the Hybrid RecSys approach.

4.5 Knowledge Based Group Recommendation

The results of the group recommendations for *Scenario 1* can found in 6:

The variance between the predicted ratings in *Scenario1* was found to be **0.00014541172** which is very low. This shows that most of the users in the group strongly agree with the recommendations. We will compare this to *Scenario 2*.

The results of KB group recommendation of *Scenario 2* can be found in 7:

The variance of the ratings was found to be **0.004392597**, although this is much higher than that of *Scenario 1* it is still low compared to **0.1631480** of Hybrid Recommender System in the same situation. This shows that the Knowledge based approach is much better suited to handle diverse user preferences.

4.6 Evaluating Tagsplanation

An online evaluation was conducted. Forty-three participants from the student population of Maastricht University participated voluntarily in a survey. Questions were asked concerning different explanation purposes: *Transparency*, *Trust*, *Effectiveness*, *Persuasiveness* and *Fluency* by Tintarev et al. [8]. Furthermore, Chris van der Lee et al. [11] suggested that those are known to be the most important explanation purposes while others were not relevant to a food recommender system. For instance, *Privacy-Preserving* is less pertinent as knowing which recipes you liked is not privacy concerning issue. The same questions were asked each time for the three different tagsplanation implementation. The results can be found in the appendix.

5 DISCUSSION

5.1 Evaluation

Tagsplanation The two first implementations of tagsplanation have similar results (as shown in the appendix 7). Respondents strongly believe tagsplanation helped in transparency. This is indeed the main goal of tagsplanation as we aim to understand how the system works. Nonetheless, more than one-fourth were neutral whether they thought tagsplanation increases confidence in the system, or whether it helped them make good decisions. Moreover, it is clear results are more mitigated for the third implementation, whether it is about *fluency* or *transparency*. The reason might be the output seems more complicated than it should be, and the recommendations aren't necessarily better than the first two implementations. To conclude about tagsplanation, it is safe to say tagsplanation helps the user explain how the system works. Nonetheless, future improvements can help increase *effectiveness* and *trust* in the system.

Hybrid and Knowledge-based approach The results provided by the Hybrid and Knowledge-based approach are clear and concise. Backed by the predicted ratings from analyzing User preference and User history the results also provide the most accurate among all approaches in general situations as well as diverse situations. Future work can be pursued to increase the *efficiency* and *trust* of the system.

5.2 Vegan bias

Tagsplanation It is clear tagsplanation does not suggest vegan recipes to vegan users. Firstly, by selecting one of the top 10% tags from the user (the tag *vegan* will be in the top 10% tags), there is a high chance we end selecting a tag other than the tag *vegan*, and hence suggesting a non-vegan recipe. Secondly, tags similar to *vegan* are not only present in vegan recipes. For instance, the tags *gifts* or *low-cholesterol* are likely to be related to non-vegan recipes as well. Besides, having a balanced dataset would not solve our issue as tagsplanation would still redirect our users to non-vegan recipes.

Knowledge-based Our knowledge-based model using the least misery approach for group recommendation works very well in tackling vegan bias.

6 CONCLUSION AND FUTURE RESEARCH

In this paper, the implementations of collaborative filtering approach, content-based approach, knowledge-based approach, and hybrid recommendations were evaluated. We claimed to implement and describe every suitable algorithm in the recommender system course. Moreover, Tagsplanation was introduced in the paper and the topic was inspired by the first reading by Tintarev et al. [8]. By analyzing the tags of each review, our group was able to create an evaluation of the recommender system that we introduced in the paper. We conducted an online evaluation with forty-three participants, from which we are satisfied with the results. Coming back to our original research questions, we were able to give recommendations to single user and group recommendations. The vegan bias was tackled in a way that we wanted to suggest only vegan recipes to users that were identified as vegan.

Further research will be to implement health-aware methods. Health problem is a huge topic in recommender systems, this method can be involved by accounting for calorie counts in the recommendation algorithm. Christoph Trattner et al.[10] proposed a calorie-based function that accounts for the differences between the calories the user needs and the calories in a recipe. Of course, there is a trade-off for most users between recommending the user what she wants and what is nutritionally appropriate. This is a trade-off applicable for a large proportion of users and should be optimized.

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7 APPENDICES

A DATASET

	unamed	user	item	date	rating	review
0	4	57222	85009	2011-10-01	5	Made the cheddar bacon topping, adding a sprin...
1	6	124416	120345	2011-08-06	0	Just an observation, so I will not rate. I fo...
2	8	76535	134728	2005-09-02	4	Very good!
3	13	255338	134728	2008-04-11	5	First time using liquid smoke in a recipe. Mad...

Fig. 1. User dataframe.

	name	id	minutes	contributor_id	submitted	tags	nutrition	n_steps	steps	description	ingredients	n_ingredients
0	arriba baked winter squash mexican style	137739	55	47892	2005-09-16	['60-minutes-or-less', 'time-to-make', 'course...	[51.5, 0.0, 13.0, 0.0, 2.0, 0.0, 4.0]	11	['make a choice and proceed with recipe', 'dep...	autumn is my favorite time of year to cook! th...	['winter squash', 'mexican seasoning', 'mixed ...	7
1	a bit different breakfast pizza	31490	30	26278	2002-06-17	['30-minutes-or-less', 'time-to-make', 'course...	[173.4, 18.0, 0.0, 17.0, 22.0, 35.0, 1.0]	9	['preheat oven to 425 degrees f', 'press dough...	this recipe calls for the crust to be prebaked...	['prepared pizza crust', 'sausage patty', 'egg...	6

Fig. 2. Recipe dataframe.

	name	item	minutes	n_steps	steps	description	ingredients	n_ingredients	dessert	vegan	difficulty	high_protein	low_fat	low_sugar	healthy
0	jamba juice at home strawberries wild smoothie	152259	10	4	['pour the apple juice in the blender', 'add t...	from a jamba juice in chicago via the abc7 rec...	['apple juice', 'strawberry', 'banana', 'non-f...	5	False	True	-1	False	True	False	True
1	whatever floats your boat brownies	32204	35	14	['preheat oven to 350f', 'grease an 8 inch squ...	these are absolutely the chewiest, moistest, f...	['butter', 'unsweetened cocoa', 'sugar', 'eggs...	14	True	False	0	False	False	False	False

Fig. 3. Data frame with new features.

A.1 Hybrid recommendations

Metric	Score
Precision	0.7100
Recall	0.75
F1 Score	0.7294

Table 1. CF Evaluation

Metric	Score
Precision	0.8385
Recall	0.7120
F1 Score	0.770

Table 2. Hybrid Recommender Evaluation

Metric	Score
Precision	0.9174
Recall	0.88562
F1 Score	0.90122

Table 3. KB RecSys Evaluation

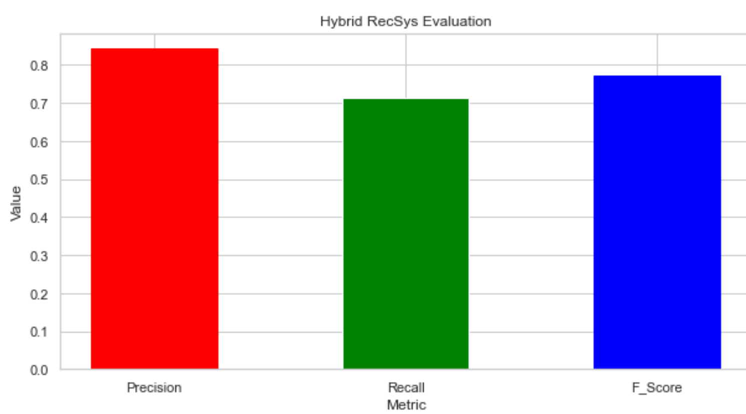


Fig. 4. Hybrid RecSys evaluation

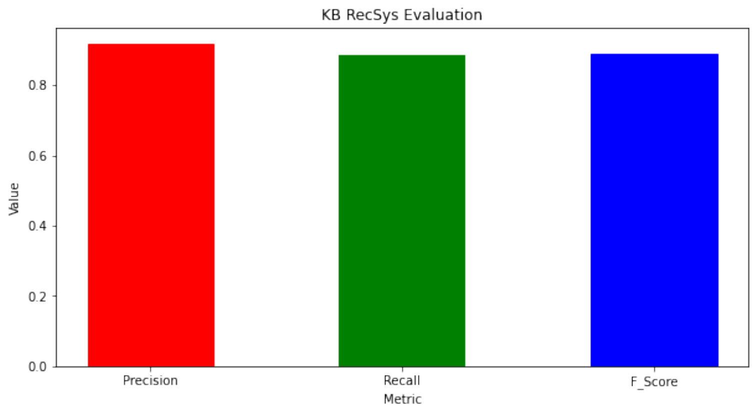


Fig. 5. F1 score of KB RecSys

item	name	least misery rating
11233	avocado milkshake	0.803470
223393	vietnamese beef wraps	0.656
113547	jack daniels chicken	0.654187
70173	deborahs fried spicy cabbage	0.445363
93777	golden carrot cookies	0.394620

Table 4. Scenario 1

item	name	least misery rating
143126	neoclassic chocolate mousse	0.855641
134501	mexican polenta pie	0.158392
169871	artichoke leaves with parmesan	0.02261
167541	buffalo chicken pot pie	0.02261
84098	finnish mushroom salad	0.005478

Table 5. Scenario 2

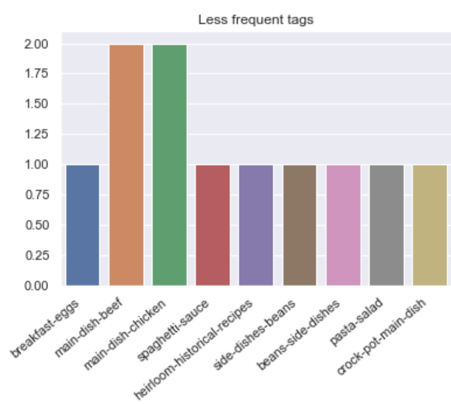
item	name	least misery rating
76381	lima bean spread	0.497301
25560	stuffed cabbage leaf rolls	0.481263
9369	low fat spanish rice	0.481263
28774	ground cilantro coriander chutney	0.470152
156978	hearty spicy tomato vegetable soup	0.461505

Table 6. Scenario:1

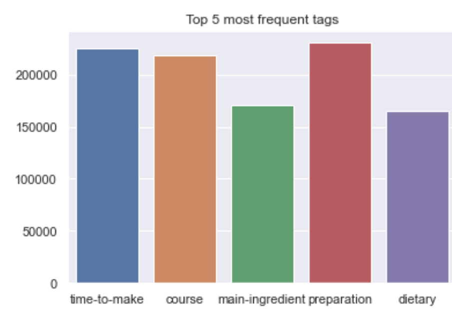
item	name	least misery rating
156978	hearty spicy tomato vegetable soup	0.581505
76381	lima bean spread	0.577301
134105	vegan tapioca almond pudding	0.547368
34602	easy strawberry banana smoothie	0.447382
200148	better than tofu cheescake	0.425324

Table 7. Scenario:1

B TAGS PROCESSING



(a) Less Frequent Tags



(b) Most Frequent Tags

Fig. 6. Tag Frequency Analyses

Table 8. Example of Roulette Wheel Selection with 4 Tags

Tag	Frequency	Probability of being selected
italian	10	$\frac{10}{30} = 0.33$
gluten-free	8	$\frac{8}{30} = 0.27$
spicy	7	$\frac{7}{30} = 0.23$
pies-and-tarts	5	$\frac{10}{30} = 0.17$

Table 9. Most Similar Tags to "Sauces"

Tag	Cosine Similarity
garnishes	0.54
jams-and-preserves	0.43
dips	0.40
marinades-and-rubs	0.39
salad-dressings	0.37

Table 10. Most Similar Tags to "Vegan"

Tag	Cosine Similarity
chick-peas-garbanzos	0.29
gifts	0.27
kosher	0.27
low-cholesterol	0.27
gluten-free	0.25

C ONLINE EVALUATION SURVEY

Fourty-three particicpants from the student population of Maastricht University particicpated voluntarily to a survey. 62.8% of the respondents were students of the University College Maastricht, 20.9% from the Department of Data Science and Knowledge Engineering, 4.7% from the Maastricht Science Program and 11.6% from another Department.

C.1 Answers to tagsplanation implementation 1

The following questions were asked about the Output: *Because you enjoyed 5 recipes with the tag **mexican**, we believe you will also like **campbell's chicken quesadillas fiesta rice** which also has the tag **mexican**.*

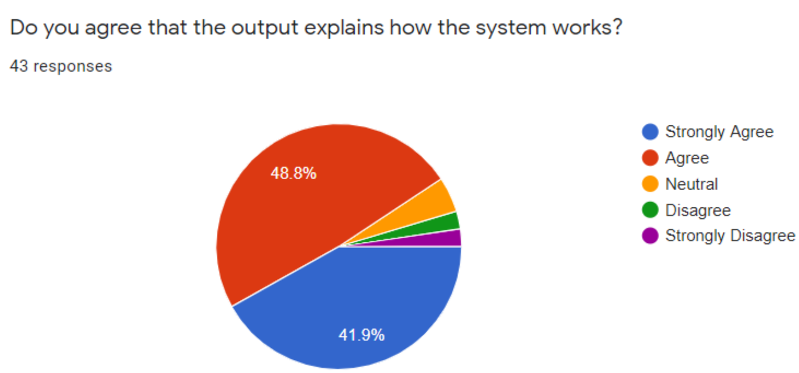
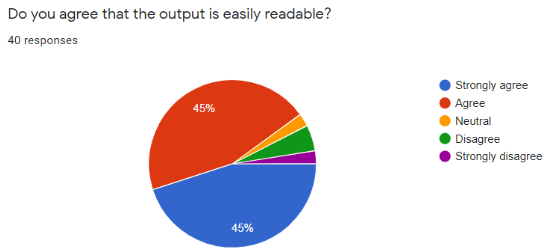
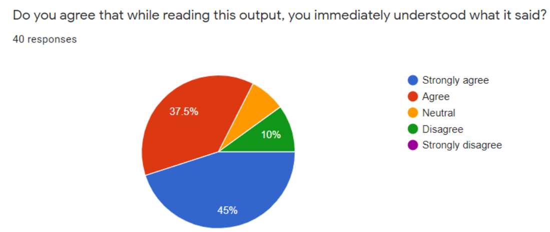


Fig. 7. Answers to the question related to Transparency



(a) Answers to the questions related to readability



(b) Answers to the questions related to understanding

Fig. 10. Answers to the questions related to Fluency

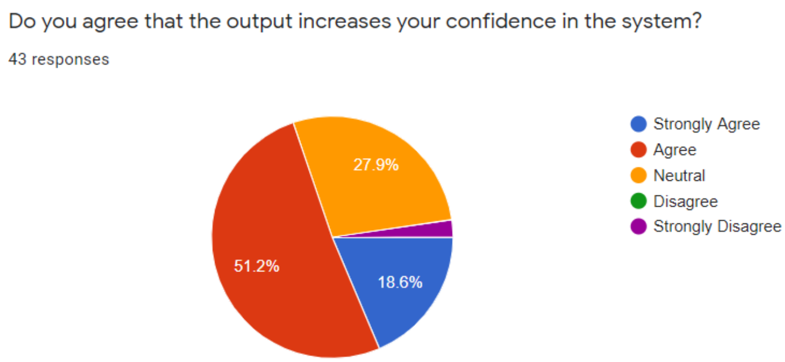


Fig. 8. Answers to the question related to Trust

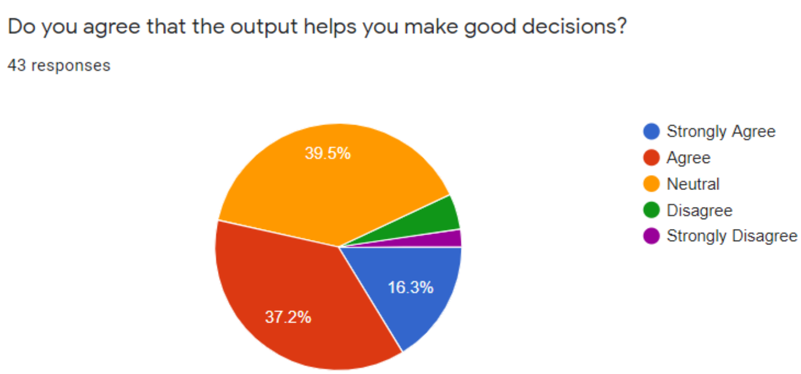


Fig. 9. Answers to the question related to Effectiveness

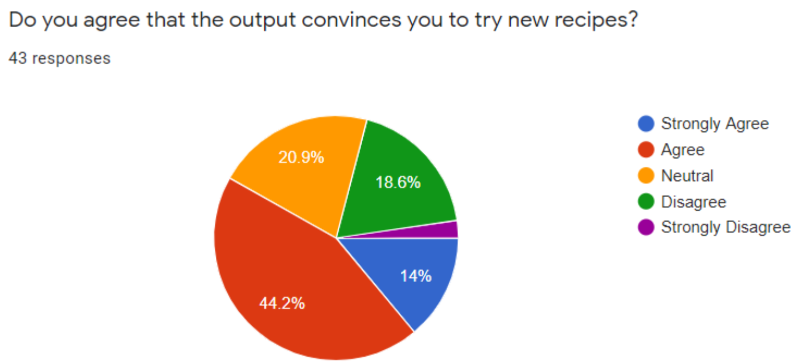


Fig. 11. Answers to the questions relataed to Persuasiveness

C.2 Answers to tagsplanation implementation 2

The Output: *Because you enjoyed 6 recipes with the tag* ***fish****, we believe you will also like* ***thai spicy shrimp salad yaam goong*** *which has the similar tag:* ***shrimp****.*
The responses were identical to implementation 1. To avoid redundancy, we did not add each questions again. Nonetheless, all the answers can be found here.

C.3 Answers to tagsplanation implementation 3

The Output: *Because you enjoyed 5 recipes with the tag* ***ground-beef****, we believe you will also like* ***dudewiches*** *which has the tag:* ***ground-beef*** *and the similar tag:* ***roast-beef****.*

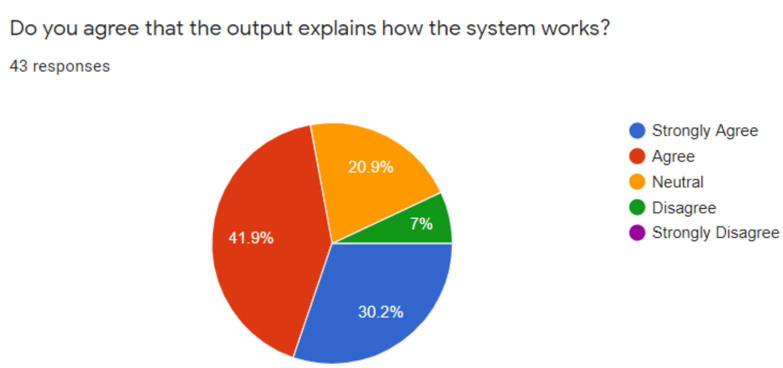


Fig. 12. Answers to the question related to Transparency

(a) Answers to the questions related to readability

(b) Answers to the questions related to understanding

Fig. 15. Answers to the questions related to Fluency

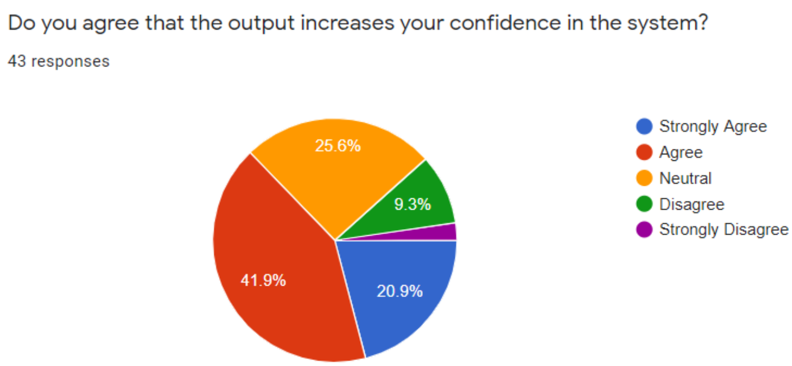


Fig. 13. Answers to the question related to Trust

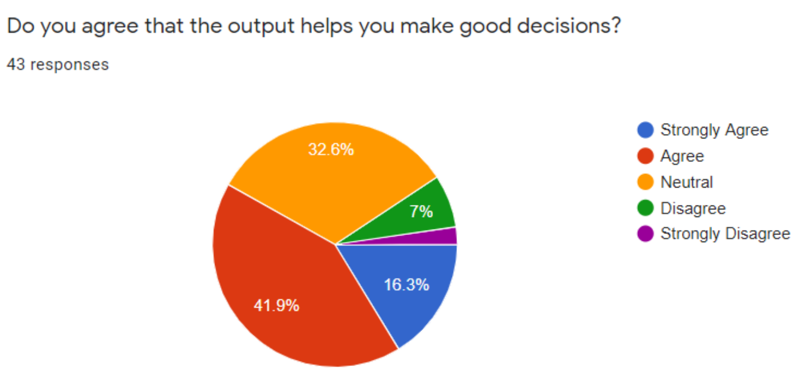


Fig. 14. Answers to the question related to Effectiveness

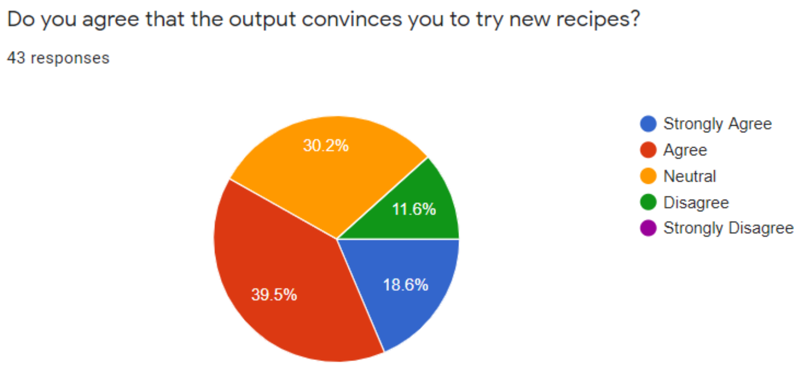


Fig. 16. Answers to the questions relataed to Persuasiveness

C.4 Comments by respondents

Six comments were made by the respondents:

- "I feel bias with the third option because I did not prefer meat on a daily basis."
- "I don't like meat, that is why I feel bias for the 3rd algorithm. However, If I am the user who likes 5 recipes with this tag, it makes sense the algorithm suggests this recipe."
- "I feel bias with the third option because I did not prefer meat on a daily basis."
- "Some of the recipes might 'sound' biasing - for example the first one sounded like an instant dish rather than a recipe"
- "I don't like meat, that is why I feel bias for the 3rd algorithm. However, If I am the user who likes 5 recipes with this tag, it makes sense the algorithm suggests this recipe."
- "I hate algorithms and usually try to deliberately search for something different"

All the detailed answers and comments can be seen here.