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Towards a new healthy food decision-making system

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ABSTRACT

Latterly, food recommendation systems have received high attention due to their importance to healthy living. On the recommendation domain, most studies focus on recommendations that suggest healthy products for each user based on their profiles. These types of recommender systems offer additional functionality to persuade users to change their buying behavior profitably. However, these systems must highlight the health preferences of the users and their health problems must be adequately taken into account. In this work, healthy food products recommender systems (RS) are our interest study and more specifically using content-based filtering. We represented this content by the food product composition. Our goal was to provide a healthy recommendation to consumers or citizens around the world, especially at this time when disease abounds. Thus, we developed our new healthy recommendation system (HRS). In this paper, we present a new recommendation process for individuals in the area of healthy eating. Furthermore, we analyze the existing state of the art in recommender system techniques and implement an algorithm that responds to this new process with very satisfactory results from the beginning, to conclude we discuss the research challenges related to the development of this kind of HRS.

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1. INTRODUCTION

recommender systems (RS) can be define as programs that aim to recommend the most appropriate items to specific users by predicting a user's interest in an item while relying on information related to items, users, and interactions between items and users [1], [2]. RS aims to present in front of a user what is supposed to satisfy their needs, preferences, and interests while filtering the information in front of them. This is to facilitate the search task in front of the user and help him save time as well. RS are tools used with the aim of providing appropriate suggestions to users and meeting their needs. Indeed, the suggestions provided are aimed at helping the user to make a decision on which movie to watch, and which product to buy. It is an ingenious way of filtering data to anticipate the user's needs and to reduce the noise induced by the avalanche of information that could eventually cloud his mind. RS has been widely used on the web for commercial and academic purposes [3]. Several examples testify to their success in the commercial domain, which is still booming, such as Amazon and Netflix, they try to offer a two-way profit between the merchant and the user, they offer "tailor-made" suggestions to the users while maximizing the profit of the merchants through an increase in the sales of their products [4]. Tam in his work asserts that recommendation systems are beneficial to boost sales and increasing customer loyalty [5]. They positively contribute to improving their experience and, consequently, to meeting their needs. As a result, recommender systems have been the subject of a large number of academic researchers in various fields and different areas of interest, such as movies, shopping, and others, most of which have been solicited for movies [6].

According to other works, RS are considered a very effective factor in changing the eating behavior of users and facilitating the choice of the healthiest foods. Bad habits, a busy lifestyle, and a lack of willpower, all these reasons lead to neglecting appropriate behaviors even though most people are aware of the importance of healthy eating habits. These issues prevent users from eating healthily [7]. Therefore, diet and nutrition are complex domains that pose many challenges to recommender technologies. Saint recommender systems require the collection of a very large number of food items and their ingredients [8]. In addition, these HRS have the purpose of not only recommending food products based on the user's normal preferences but also recommending healthy food products based on the user's health profile, this will help persuade users to change their eating behavior.

In this paper, we summarize existing research related to recommender system techniques that give recommendations based on consideration of users' preferences as well as their needs. In this context, we propose a new design of a product recommendation system in the healthy food domain. A case study of the implementation of our new healthy recommendation system by applying our algorithm in the healthy food domain. The contributions of this paper are the following: First, we give a brief overview of recommendation approaches. Second, we propose a new process for health decision-making that has an impact on the development of recommendation technologies in the healthy food domain. Third, based on this new process of food recommender systems, we set up an application by highlighting the right answer to the question of to what extent this new process can improve recommender systems to help individuals choose healthy food products that best match their preferences and health status. Finally, we highlight some of the challenges of food recommender systems concerning to user information as a topic for future work.

The remainder of this article is organized as follows. In section 2, we provide an overview of basic recommender techniques. In section 3, we present our novel design of a recommendation system in the health domain. In section 4, we present a case study with the results of the implementation of our proposed solution. In section 5, we summarize.

2. RECOMMENDER SYSTEMS: RECOMMENDATION TECHNIQUES FOR INDIVIDUALS

The history of RS began with Grundy, who took the first primitive step towards automatic RS in libraries [9]. RT are traditionally divided into different categories [10], [11], and are discussed in several works [12]. To develop effective recommender systems, we find various approaches. Typically, we found three categories:

2.1. Content-based approach

Recommendations provided to the user are found based on the similarity between the attributes of the candidate items and the user's profile, which is created based on the attributes of the user's previously preferred items. The content-based technique, also called descriptive profiling, is primarily interested in content, which is in the form of element characteristics. It consists of comparing the list of characteristics of each element, candidate for recommendation, attributes with items previously preferred by a particular user. Similar articles are recommended to users because they liked in the past: similar content. Content-based filtering is based on a basic two-tier function: the first consists of setting up a user profile built using automatic predictions made on the interests of the user, while collecting his opinions *vis-à-vis-vis* the element in question. Note that user profiles are represented in terms of interest lists based on the same attributes of elements. These features are used to assign the similarity of one element to another through the similarity equation. In addition to the user profile, there is also the establishment of an element catalog, also called element profiles or attributes, containing the data (elements) encountered during user navigation. This is an explicit list of attributes for each element encountered. For example, for a book, one might use the genre, author's name, publisher, or other information about the book, and then store these characteristics (eg, in a database). The second step compares the characteristics of each element of the catalog with the profile of the user and retains only the elements which present a high degree of similarity to finally recommend them to the user [13], [14]. The link between an item and a user is made based on the following hypothesis: If the user 'U' likes the items (elements) presenting the characteristics {c1, ...cn}, then we can recommend him items with these same characteristics". Figure 1 illustrates this process.

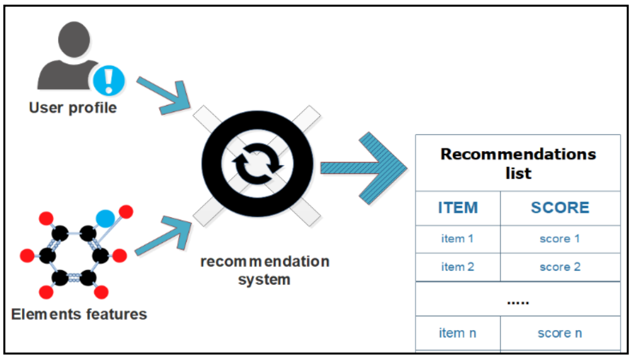

Figure 1. A content-based recommender system

2.2. Collaborative filtering approach

It is based on reviews of users who have had similar preferences in the past. The main concept is that recommendations made by people with similar tastes to the target user are usually relevant. Given the variety of social networks that shape our lives, collaborative filtering (CF) techniques are the most popular and widely used recommendation techniques. In the CF is users with the same interests tend to give the same preference to new and future items. This technique is based on two things. As a priority, criteria are used to select a group of people who have the same preferences and whose choices are collected as a basis for recommendations (nearest neighbors). Second, it also leverages these opinions for larger prior groups with greater influence on recommendations [15]. CF techniques contain very large datasets and are used in various application areas such as finance, healthcare, environmental sensing, and e-commerce. The link between an article and a user is established based on the following assumption: “If users who have liked the same articles as user ‘U’ also like other articles, then these can be recommended to ‘U’”. Figure 2 illustrates this process.

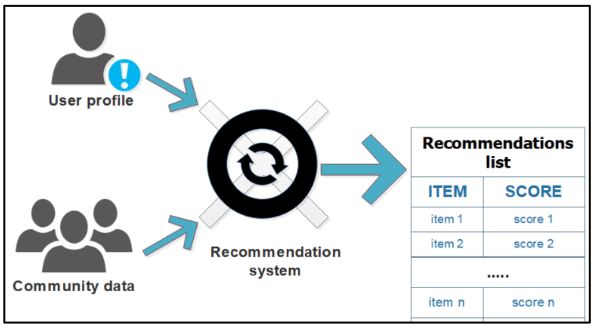

Figure 2. A collaborative recommender system

2.3. Hybrid approach

This approach is based on two or more recommendation techniques. The goal is to increase the accuracy of recommendation systems. However, this approach is based on the combination of the above-mentioned techniques [16], [17]. Hybrid filtration techniques rely on combining the advantages of two or more filtration techniques and overcoming their limitations. These techniques provide more efficient results and improved recommendations [18], [19]. Hybrid technology hybrid filtration schemes can be developed using any of the following strategies: i) Separate recommendations are created using content-based and collaboration-based filters, then a recommendation is established based on a linear combination of the two recommendations [20]. ii) CF and in order to predict recommendations uses content-based features to calculate the similarity between users and find neighbors for [21]. iii) CB techniques can be added to CF capabilities, such as B. CB latent factor models [22]. iv) A traditional probabilistic approach combining collaborative and content-based recommendation prediction techniques [23], [24].

A hybrid recommender system uses components of different types of recommendation approaches or relies on their logic [25]. For example, such a system could use both external knowledge and article attributes, thus combining collaborative and content-based approaches. Figure 3 illustrates this process.

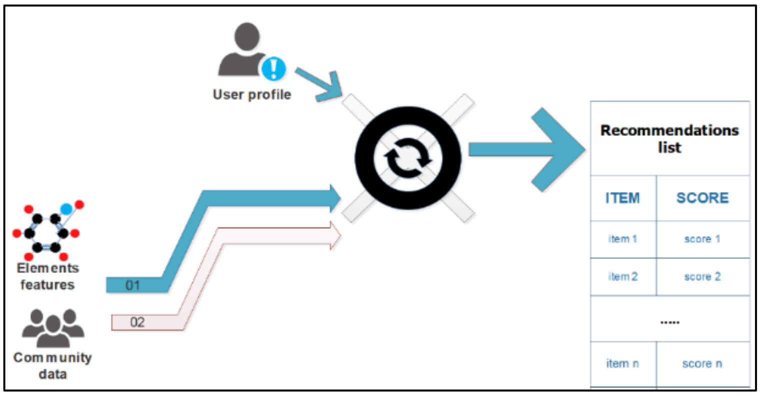

Figure 3. A hybrid recommender system

3. MODELING AND DESIGN OF A NEW HEALTHY FOOD DECISION-MAKING SYSTEM

In this section, we present our contribution which is based on the realization of a healthy recommender system for food products, while using the content-based filtering method. It is a question of recommending similar food products in terms of their food values while considering the profile of the user, to whom we wish to present recommendations, and who will be determined by their health constraint diabetes and high blood sugar level). So that this recommendation is sound. This system is based on two important axes: The first concerns the construction of the grid of product profiles where a profile is defined by the name of the product and its food characteristics with their numerical food values. In our case, we defined the grid beforehand. The second axis concerns the implementation of a recommendation process that we have proposed. This process consists of five stages in the form of layers:

– Input healthy verification layer;
– The quantitative verification layer (quantitive verification layer);
– The healthy verification layer of the output flow (list of products) (output healthy verification layer);
– The qualitative verification layer;
– The layer of the ordering of the list of healthy products recommended (healthy product list recommended layer).

3.1. Our element evaluation grid

In our approach, the construction of our grid is based on food products sold in supermarkets (yogurt, cheese, and compote). It includes a prototype of food products with their profiles. In this section, we present our meta-model of the descriptive profile of a food, and our general view of our elements grid data.

3.1.1. Product profiling

We define the food product profiling (PP) by its name, and its food composition, which we present by the name of each component and its constitutional value in the product. This procedure is based on the descriptive profile of the product on the packaging. We present our meta-model of the descriptive profile of a food product as follows (Figure 4).

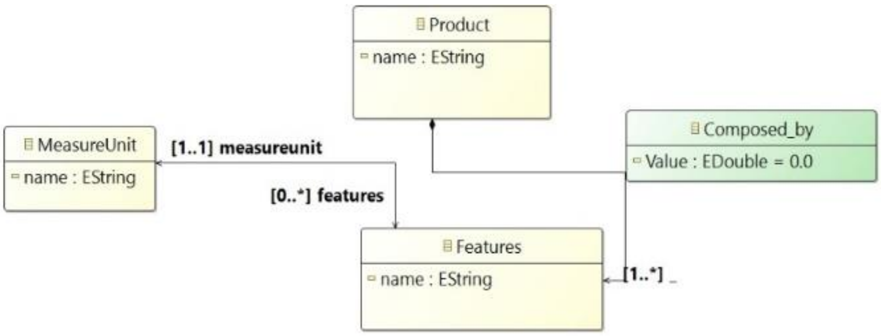

Figure 4. Our meta-model of the descriptive profile of a food product

As an example, we present the profile of the food product “apricot compote” by its name and its food characteristics with their values, for example, “energy (122 Kcal), proteins (0.7 g), lipids (0,2 g), saturated fatty acid (0.1 g). The supply by the PPs of our grid is dynamic and initially, it is based on existing databases.

3.1.2. View of our elements grid

The set of product profiles will form our grid of elements (products). In columns, we put the names of the food characteristics of the products, and in rows, we put the names of the products. See the Table 1. In the Table 2, we present an example of our elements grid. We have a dataset of 40 elements with 32 items (features). See the Table 2.

Table 1. General view of our elements grid data

Features products	F1 (unit of measurement X1)	…	Fn’ (unit of measurement Xn’)
P1	Value of F1 in P1	…	Value of Fn’ in P1
…	…	…	…
Pn	Value of F1 in Pn	…	Value of Fn’ in Pn

Table 2. Overview of an example of our element grid

	Energie (Kcal)(g)	Energie (KJ)	Protéines	Lipides	AC. GRAS Saturés	AC. GRAS MONO-Insaturés	…	SUCRES	AMIDON	…
Chou de Bruxelle, cuit classique	41	173	3	0.3	0.1	0	…	3.1	0.3	…
Chou de Bruxelle, cuit micro-onde	54	226	4.7	0.3	0.1	0	…	4.6	0.3	…
Chou rouge	16	68	0.8	0	0	0	…	1.8	0.2	…
Chou rouge aux pommes en bocal	61	257	1.1	0.1	0.1	0	…	13	0	…
Chou rouge aux pommes, congelé	70	294	1.3	1.6	0.1	0.1	…	11	0.7	…
Chou rouge en bocal	33	137	0.7	0.1	0	0	…	5.4	0	...
Chou rouge, cuit classique	13	52	0.7	0	0	0	...	1.7	0.2	…
Chou rouge, cuit micro-onde	21	88	0.9	0	0	0	…	3.1	0.2	…
Coktail de fruits au sirop en conserve	67	279	0.4	0.1	0	0	…	15.5	0	…
Compote d’abricots	122	512	0.7	0.2	0.1	0	…	28.3	0	…
Compote de cerises	143	599	0.7	0.2	0	0	…	34	0	…
Compote de myrtilles	179	754	0.4	0.5	0.1	0	…	42.8	0	…
Compote de pêches	105	442	0.6	0.4	0.1	0	…	23.3	0.8	...
Compote de pommes	82	339	0.4	0.3	0.1	0	...	18.5	0.5	…
Compote de pommes, sucre réduit	40	168	0.2	0.2	0	0	…	8	0.1	…
Compote de prunes	116	504	0.5	0.4	0.1	0	…	26.3	0.3	…
Lait chocolaté, demi-écrémé	71	297	3.2	1.5	1.1	0.5	…	11.3	0	…
Lait chocolaté, entier	90	380	3.5	2.5	1.1	0.7	…	11.8	1.2	…
Lait chocolaté, maigre	62	258	3.3	0.4	0.3	0.1	…	11	0	…
Lait concentré à l'huile végétal, demi-écrémé	110	460	6.8	4.3	0.5	1.3	…	10.9	0	…
Lait concentré, demi-écrémé	113	472	7.4	4.3	2.9	0.9	…	11.4	0	…
Lait concentré, entier	141	589	7	8	4.9	2.8	…	10.1	0	…
Lait concentré, entier, sucré	288	1209	7	7.5	4.7	3	…	48.3	0	…
Lait concentré, maigre, sucré	269	1123	10	0.2	0.1	0.1	…	56.7	0	…

3.2. Our proposal for the new recommender system process

Processes are very important in order to create visibility and structure. It is essential that they align with a clear mission, vision and strategy. In this section, we propose a new recommendation system based on a new recommendation process. This “healthy recommendation system (HRS)”, we present it in the Figure 5.

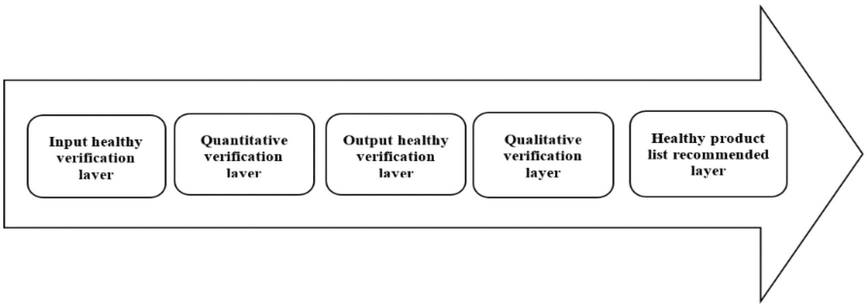

Figure 5. Our new recommender system process

Our system is based on five layers:
- Input healthy verification layer: This layer consists of verifying the health of the input product, on whose content the recommendation will be based. We verify this health by taking into account the health constraints expressed in the user profile defined beforehand and by verifying that the value of each food characteristic of the product in question belongs to the appropriate healthy interval in accordance with the constraints. of the user. The healthy interval is also defined beforehand by medicinal research according to each case. For example, a person with diabetes should not consume products where sugar is present or exceeds a certain threshold. In this case, the appropriate healthy interval for the "sugar" characteristic will be, for example, [0, 0.001] where the limits are expressed in grams. Thus, the membership of the value of the "sugar" characteristic of the input product must be checked in the appropriate healthy interval. If the membership is well verified then the product gets along with the health constraints of the user, we inform him that it is a good choice, and we give the hand to the next step to begin the procedure of recommendation of new healthy products similar to the starter in terms of content (food characteristics). If the membership is not verified, then the product is considered a bad choice for the user and we inform him of this result and we stop our process. We are primarily interested in recommending products from a healthy start in order to arrive at equally healthy recommendations (type of product; bad or good). See Figure 6.
- The quantitative verification layer: this layer consists of searching the product grid for those that have only the same dietary characteristics as the input product. We focus here on the presence of characteristics and not their values.
- The healthy verification layer of the flow (list of products) at output (output healthy verification layer): this consists of verifying the health of the products obtained at the level of the previous layer based on the principle followed in the first layer. We verify that the value of each food characteristic falls within the appropriate healthy range for each product. We only keep the products that respect their belonging to the healthy intervals.
- The qualitative verification layer: In this layer, we measure the similarity between the input product with each product obtained from the previous layer using the euclidean distance. We thus obtain as a result the products with their similarities with the input product.
- The healthy product list recommended layer: here we sort in descending order the result of the previous layer. We thus obtain a list of recommended healthy products ordered with the degrees of similarity next to them showing how similar each product is to the one given as input.

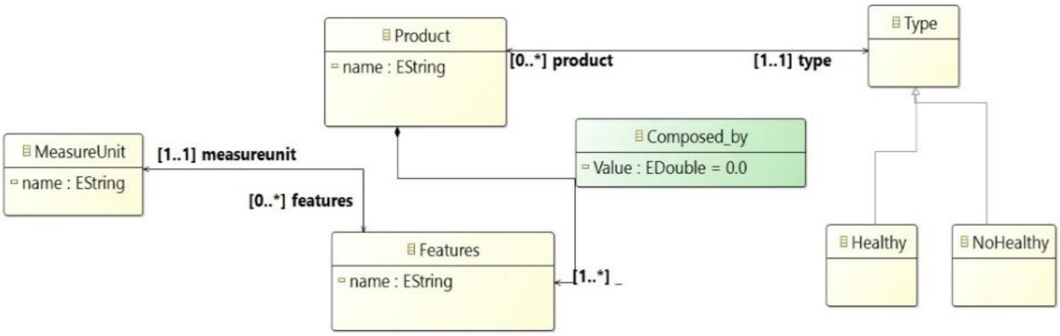

Figure 6. Our meta-model of the type of a food product

This is how we implement our HRS healthy recommendation system, which consists of first checking the healthiness of the input product on which the recommendation will be based and in agreement with the user profile which includes his health constraints. Once the product is healthy, we start the process and make sure to recommend similar healthy products in terms of content. In Figure 7, we present our flowchart summarizing the whole process of our recommendation system.

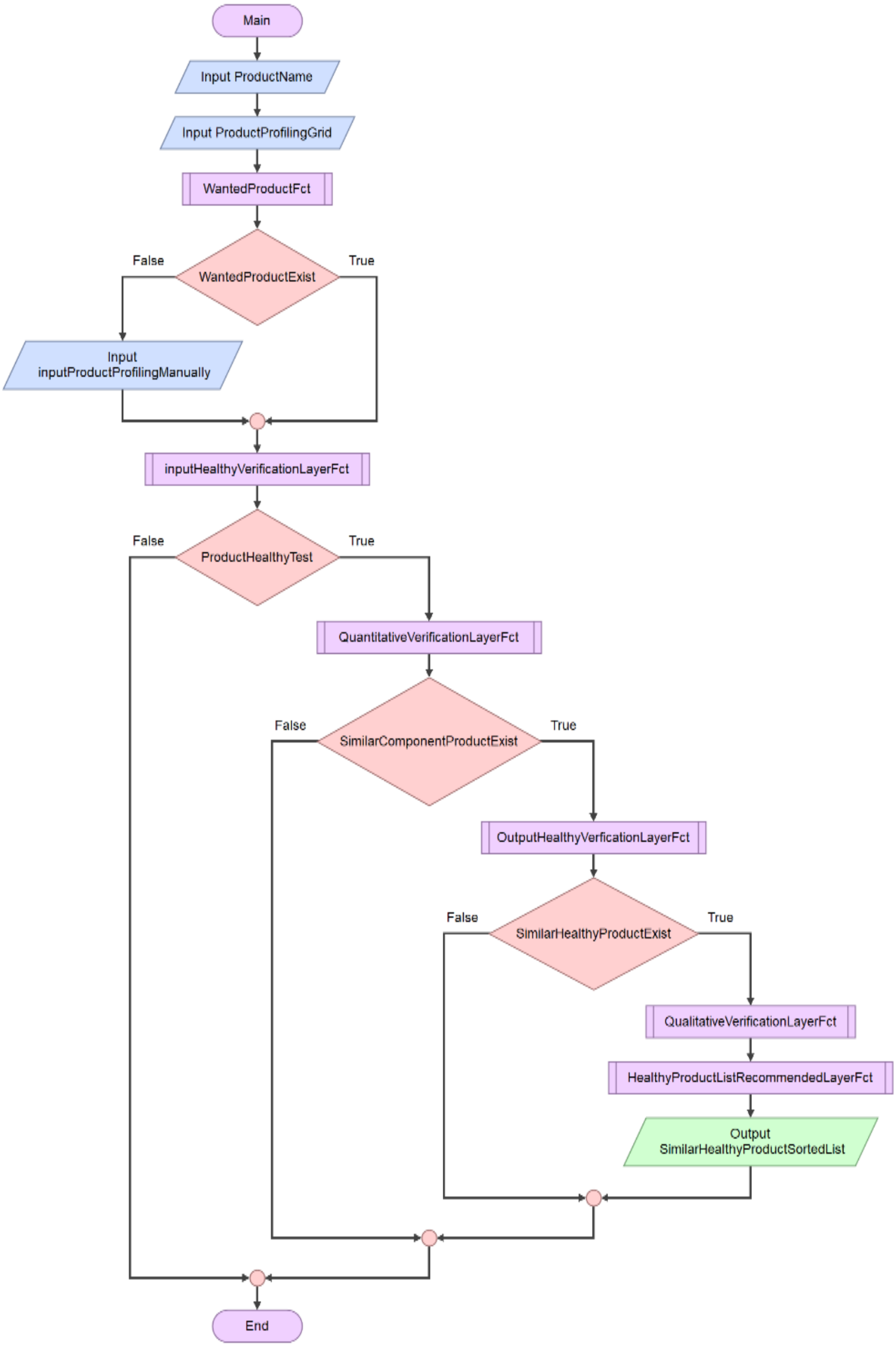

Figure 7. Our flowchart summarizing the entire process of our HRS recommendation system

4. IMPLEMENTATION AND RESULTS

The general objective of the experimental method is to make it possible to establish cause and effect relationships between two parameters. Therefore, the method truly allows us to explain the phenomena studied in terms of a causal relationship. In this section, we describe the implementation details of our recommendation process algorithm realized during this work, starting with the language and libraries used.

4.1. The language and libraries

We implement our algorithm using the programming language python which is an absolute reference language in artificial intelligence: all AI tools are available in python! It is easy to install, uncompiled, fast, and light. The syntaxes developed by python are simple and easy to learn, especially in machine learning, and development times are shorter. We used the panda library, a software library for data manipulation and analysis written for the python programming language. In particular, it provides data structures and operations to manipulate numeric arrays and time series. We also used the Scipy library which is a project to unify and federate a set of python libraries for scientific use. Scipy uses the arrays and matrices of the NumPy module (extensions to the python programming language designed to manipulate matrices or multidimensional arrays and mathematical functions that operate on those arrays).

4.2. Implementation

We load the element (product) evaluation grid containing the profiles of the food products, and we display the header. We load the grid of healthy intervals populated at an excel table. We consider that our input product is "red cabbage". We check its existence in our grid and display its descriptive profile. This product is the one chosen by a user for example. Once he has made this choice (by scanning it for example), we recommend other products similar to it based on its content (food composition).

4.2.1. Layer 1: Input healthy verification layer

The input healthy verification layer, we want to verify the healthiness of the product. If it is healthy, we continue the process otherwise, we stop. We present in the Figure 8 the source code and the output result of this layer. In our case, it is healthy so we can continue the process to the next layer.

Source code:

```
result_input_HVL=input_HVL (wp_index)
if result_input_HVL ==-1:
    print ("Bad product")
else:
    print ("Good product, \n ========== End o
f the Input Healthy verification Layer ======
====")
```

Output:

```
Good product,
 === End of the Input Healthy verif
ication Layer =====
```

Figure 8. The source code and output from input healthy verification layer

4.2.2. Layer 2: Quantitative verification layer

In the quantitative verification layer, we keep the products that have only the same characteristics as the input product. In the Figure 9, we present the result of this layer; there are 6 products that have the same characteristics as the input product (red cabbage).

Output:

```
Number of the products >= same component of the wanted
product=6
====== End of the quantitative verification layer =====
```

Figure 9. The output from quantitative verification layer

4.2.3. Layer 3: Output healthy verification layer

This layer named "Output healthy verification layer" consists of verifying the health of the products obtained at the level of the previous layer based on the principle followed in the first layer. We recall that in this layer, we verify that the value of each food characteristic falls within the appropriate healthy range for each product. We only keep the products that respect their belonging to the healthy intervals. In the Figure 10, we present, in our case the output from output healthy verification layer.

Output:

```
Number of the healthy products >= Same component of the wanted product=3
==== End of the output healthy verification layer ===
```

Figure 10. The output from output healthy verification layer

4.2.4. Layer 4: Qualitative verification layer

In this layer named “Qualitative verification layer”, we measure the similarity between the input products with each product obtained from the previous layer using the Euclidean distance. We thus obtain as a result the products with their similarities with the input product. In the Figure 11, we present the prototype of the function that we have developed.

```
def qualitatiVerification (wp_index):
```

Figure 11. The function prototype of the qualitative verification layer

4.2.5. Layer 5: The healthy product list recommended layer

In the final layer named “healthy product list recommended layer”, we sort in descending order the result of the previous layer. We thus obtain a list of recommended healthy products ordered with the degrees of similarity next to them showing how similar each product is to the one given as input. In Figure 12, we present the source code and output from healthy product list recommended layer. In the result, we have 3 products, which resemble in food value the starting product with a very satisfactory percentage for the first two 100%, and 96.15 and the third with a rate of 0.58%.

Source code:

```
list_healthyProdRecomm = HPLR (wp_
index)
print (“========= Before Sort ====
=====”)
print(list_healthyProdRecomm)
list_healthyProdRecomm.sort(key=la
mbda x: x [1])
print (“========= After Sort =====
====”)
print(list_healthyProdRecomm)
print (“Product recommended:”)
for i in range(len(list_healthyPro
dRecomm)):
    print (“\n “, i+1,” “, product
s [“Product name”] [list_healthyPr
odRecomm[i][0]],” --> “, list_heal
thyProdRecomm[i][1])
```

Output:

```
Product recommended :

 1  Chou rouge en bocal  -->  100.0 % of similarity with the scanned product

 2  Chou rouge aux pommes en bocal  -->  96.15 % of similarity with the scanned product

 3  Chou de Bruxelle, cuit classique  -->  0.58 % of similarity with the scanned product
```

Figure 12. The source code and output from healthy product list recommended layer

5. CONCLUSION

We have developed a healthy recommendation system HRS. First of all, it is a system that uses the content-based filtering method. It allows to recommend products similar to the input product, based on the content. A content concerns the food characteristics with their numerical values. We have seen in the above section that in content-based recommendation systems it is necessary to determine the user profile with the profile of the features by means of some techniques. However, in our case, we are working on product profiles between them and without resorting to profile determination techniques, since we are based on dynamic databases of food products, in which the products are located with their descriptive profiles of the food composition that constitutes them. We talk about the user profile when we thought of being interested in the health of the product, getting along with the profile of the user who has chosen it and from its content we will propose other products. In our case, the input information is not only textual but also numerical expressing how much the food characteristic participates in the constitution of the product in question. The information in our case is structured, we have characteristics with values. We do not have to resort to techniques of construction of product profiles. We build our grid of elements from the descriptive profiles of the products while relying on certain characteristics found in most of the products who's excess or deficiency could form health problems. It is possible to add other characteristics as needed. The healthiness of the product is verified through healthy intervals appropriate to the characteristics in question and in agreement with the user's profile (health constraints). We are currently working with healthy ranges for a given person. Considering the cases of possible constraints requires extensive research in collaboration with scientists and physicians. The work presented in this manuscript suggests many perspectives. We present those which seem to us to be the most important: i) determining the user's profile including his health constraints in an automatic way; ii) to determine automatically the healthy intervals corresponding to each user profile in collaboration with doctors and scientists; and iii) adapt our HRS system to specific diseases (diabetes and blood pressure).

REFERENCES

[1] J. Bobadilla, F. Ortega, A. Hernando, and A. Gutiérrez, "Recommender systems survey," *Knowledge-Based Systems*, vol. 46, pp. 109–132, 2013, doi: 10.1016/j.knosys.2013.03.012.

[2] T. Mahmood and F. Ricci, "Improving recommender systems with adaptive conversational strategies," in *Proceedings of the 20th ACM Conference on Hypertext and Hypermedia, HT'09*, Jun. 2009, pp. 73–82, doi: 10.1145/1557914.1557930.

[3] P. Resnick and H. R. Varian, "Recommender systems," *Communications of the ACM*, vol. 40, no. 3, pp. 56–58, Mar. 1997, doi: 10.1145/245108.245121.

[4] K. N. Rao, "Application domain and functional classification of recommender systems-a survey," *DESIDOC Journal of Library & Information Technology*, vol. 28, no. 3, pp. 17–35, 2008, doi: 10.14429/djlit.28.3.174.

[5] P. Y. Chen, J. Yoon, and S. Y. Wu, "The impact of online recommendations and consumer feedback on sales," in *Proceedings of the International Conference on Information Systems, ICIS 2004*, 2004, pp. 711–724.

[6] K. Y. Tam and S. Y. Ho, "Understanding the impact of Web personalization on user information processing and decision outcomes," *MIS Quarterly: Management Information Systems*, vol. 30, no. 4, pp. 865–890, 2006, doi: 10.2307/25148757.

[7] D. H. Park, H. K. Kim, I. Y. Choi, and J. K. Kim, "A literature review and classification of recommender systems research," *Expert Systems with Applications*, vol. 39, no. 11, pp. 10059–10072, 2012, doi: 10.1016/j.eswa.2012.02.038.

[8] Y. van Pinxteren, G. Geleijnse, and P. Kamsteeg, "Deriving a recipe similarity measure for recommending healthful meals," in *Procedure of the 16th international conference on intelligent user interfaces*, 2011, pp. 105–114, doi: 10.1145/1943403.1943422.

[9] J. Freyne and S. Berkovsky, "Intelligent food planning: Personalized recipe recommendation," in *International Conference on Intelligent User Interfaces, Proceedings IUI*, 2010, pp. 321–324, doi: 10.1145/1719970.1720021.

[10] F. Ricci, L. Rokach, and B. Shapira, *Recommender systems handbook*. USA: Springer US, 2015.

[11] R. Burke, "Hybrid web recommender systems," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 4321 LNCS, B. P, K. A, and N. W, Eds. Berlin: Springer Berlin Heidelberg, 2007, pp. 377–408.

[12] G. Adomavicius and A. Tuzhilin, "Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions," *IEEE Transactions on Knowledge and Data Engineering*, vol. 17, no. 6, pp. 734–749, Jun. 2005, doi: 10.1109/TKDE.2005.99.

[13] P. Anand and R. Nath, "Content-based recommender systems," in *Recommender System with Machine Learning and Artificial Intelligence: Practical Tools and Applications in Medical, Agricultural and Other Industries*, 2020, pp. 165–195.

[14] U. Javed, K. Shaukat, I. A. Hameed, F. Iqbal, T. M. Alam, and S. Luo, "A review of content-based and context-based recommendation systems," *International Journal of Emerging Technologies in Learning*, vol. 16, no. 3, pp. 274–306, 2021, doi: 10.3991/ijet.v16i03.18851.

[15] S. A. Thorat, G. Ashwini, and M. Seema, "Survey on collaborative and content-based recommendation systems," in *International Conference on Smart Systems and Inventive Technology (ICSSIT)*, 2023, pp. 1541–1548, doi: 10.1109/icssit55814.2023.10061072.

[16] Y. Sun, J. Zhou, M. Ji, L. Pei, and Z. Wang, "Development and evaluation of health recommender systems: systematic scoping review and evidence mapping," *Journal of Medical Internet Research*, vol. 25, p. e38184, 2023, doi: 10.2196/38184.

[17] G. Adomavicius and J. Zhang, "Impact of data characteristics on recommender systems performance," *ACM Transactions on Management Information Systems*, vol. 3, no. 1, pp. 1–17, 2010, doi: 10.1145/2151163.2151166.

[18] R. Burke, "Hybrid recommender systems: Survey and experiments," *User Modelling and User-Adapted Interaction*, vol. 12, no. 4, pp. 331–370, 2002, doi: 10.1023/A:1021240730564.

[19] D. Roy and M. Dutta, "A systematic review and research perspective on recommender systems," *Journal of Big Data*, vol. 9, no. 1, pp. 1–36, 2022, doi: 10.1186/s40537-022-00592-5.

[20] F. Ricci, L. Rokach, and B. Shapira, *Recommender systems handbook*, 1st ed. New York: Springer-Verlag New York, 2015, doi: 10.1007/978-1-4899-7637-6_1.

[21] A. B. Barragáns-Martínez, E. Costa-Montenegro, J. C. Burguillo, M. Rey-López, F. A. Mikic-Fonte, and A. Peleteiro, "A hybrid content-based and item-based collaborative filtering approach to recommend TV programs enhanced with singular value decomposition," *Information Sciences*, vol. 180, no. 22, pp. 4290–4311, 2010, doi: 10.1016/j.ins.2010.07.024.

[22] M. Pazzani and D. Billsus, "Content-based recommendation systems," *The adaptive web: methods and strategies of web personalization*, pp. 325–441, 2007.

[23] S. Raghuwanshi and P. Pateriya, "Recommendation systems: techniques, challenges, application, and evaluation," in *Soft Computing for Problem Solving: SocProS 2017*, 2019, pp. 151–164.

[24] D. Elsweiler, H. Hauptmann, and C. Trattner, "Food recommender systems," *Recommender Systems Handbook*, pp. 871–925, 2022.

[25] K. Shah, A. Salunke, S. Dongare, and K. Antala, "Recommender systems: An overview of different approaches to recommendations," in *Proceedings of 2017 International Conference on Innovations in Information, Embedded and Communication Systems, ICIIECS 2017*, 2018, vol. 2018-January, no. 1–4, pp. 1–4, doi: 10.1109/ICIIECS.2017.8276172.

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