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Exploring content-based group recommendation for suggesting restaurants in Havana City

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Abstract: Recommender systems (RSs) are a relevant kind of artificial intelligence-based systems focused on providing users with the information that best fit their preferences and needs in a search space overloaded of possible options. Specifically, group recommender systems (GRSs) are a special type of RS centered on recommending items that are consumed in groups and not individually, being TV program and touristic packages key examples of such items. The current work is focused on proposing a content-based group recommendation approach (CB-GRS) contextualized to the restaurant recommendation domain. In contrast to previous content-based group recommendation models, the proposal incorporates novel stages such as restaurants feature imputation, the generation of a virtual group profile, the use of feature weighting, and the automatic selection of the most appropriate aggregation approach for composing group recommendations. The proposal is evaluated in an original recommendation scenario, related to restaurant from Havana City in Cuba, where several restaurant attributes are identified for applying the proposed CB-GRS approach. The experimental protocol evaluates individually each component of the proposal, evidencing their importance as part of the whole framework. Furthermore, the comparison with previous works has been also developed. The proposed approach can be applied in other recommendation scenarios, and in addition, the developed experimental protocol is generalizable for the evaluation of further content-based individual and group recommendation approaches in the tourism domain.

Keywords: content-based group recommendation, restaurant recommendation, Havana City
Categories: H.3, I.2
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1 Introduction

Recommender systems (RSs) are considered a relevant kind of artificial intelligence-based systems, which main role is to provide online users with the information that best fit their preferences and needs in a search space overloaded of possible options. In this way, the development of internet technologies has exponentially grown the amount of online information available to the users, being difficult the personalized access to the appropriated information items according to each specific user. To solve this issue, RSs have been conceived in several domains such as e-commerce, e-learning, e-services, e-health, and so on [Adomavicius and Tuzhilin 2005, Yera et al. 2022, Yera et al. 2023].

Taking into account their working principle, most of research and development tasks around RSs have been developed under one of the following paradigms: 1) Content-based recommendation, which is based on item and user profiling using all the available information, and where recommendation generation is interpreted as a user-item matching profiles problem; 2) Collaborative filtering recommendation, where it is identified the rating patterns linked to the users that are more similar to the active one, and used such information for the recommendation generation task for the current user; and 3) Hybrid recommendation, which takes the best of the two previous paradigms, combining the item profiling task (content-based), and the rating processing capacity (collaborative filtering).

Based on such approaches, individual RSs have been focused on suggesting the most appropriate items to individual users. However, some specific domains such as e-tourism, have associated items that are consumed in groups and not individually. Movies, TV programs, and touristic packages, are clear examples of such kind of items. For these scenarios, group recommender systems (GRSs) have been developed as a specific kind of recommendation approaches, which are focused on generating items recommendations targeted to a group of users, and that are appropriated to all the users in the group with a larger or lesser extent.

Specifically, while most of GRSs approaches identified by the literature are based on the collaborative filtering paradigm [De Pessemier et al. 2014], recently [Pérez-Almaguer et al. 2021] have discussed the importance of content-based GRS for generating recommendations in scenarios where collaborative filtering does not perform well. A key scenario in this direction is the cold-start context, where it is necessary the recommendation generation with a low number of available preference values. In such cases, it is necessary to support the recommendation generation with the additional information usually linked to the items, which are properly exploited by the content-based recommendation approaches.

Overall, the analysis of the specialized literature identifies too few works centered on the report of new content-based group recommendation approaches (CB-GRSs), as well as its application in specific scenarios. Herein, [Kassak et al. 2016] screen a group recommendation approach that combines individual content-based and collaborative recommendation, aggregating in both cases the generated recommendation lists to compose group recommendation. In other direction, [Nguyen and Ricci 2018] present an interactive system that allows to group of users the subsequent expression of their interests over the items' content, supporting the decision making process, prior to the final recommendation generation. [Pujahari and Sisodia 2020] suggest the incorporation of content-based features to the matrix factorization group recommendation technique, even though do not evaluate the effect of this stage in an individual way. Overall, although most of works exploring content-based group recommendation usually develop and execute the proposed approaches as a component of a larger RS architecture, [Pérez-Almaguer et al. 2021] recently developed an extensive study entirely focused on content-based group recommendation, discussing novel paradigms in this direction, such as 1) the CB-GRS based on recommendation aggregation and individual ranking, 2) the CB-GRS based on recommendation aggregation and user-item matching, and 3) the CB-GRS based on the aggregation of the user profiles. All the proposed methods were evaluated through international datasets for RS and GRS evaluation, such as Movielens and HetRec.

As a natural evolution of the research development around CB-GRS, it is necessary the contextualization of the recently developed CB-GRS to specific GRS scenarios to illustrate their performance. This is the objective of the current work, that introduces the use of a hybrid CB-GRS, to a specific e-tourism context, as a typical GRS scenario.

With this purpose, the current research introduces the use of a hybrid CB-GRS approach over the preferences of TripAdvisor users on restaurants from Havana City. It is relevant that at this moment (February 2023), TripAdvisor has registered 800+ restaurants only from Havana City, being relevant the number of users evaluating such restaurants, and the diversity of attributes values characterizing them, such as type of food, service quality, average price, relative ranking, or number of comments. Such attributes could be relevant for a CB-GRS scenario. Therefore, the contribution of the current research article is three-fold:

- It introduces a novel hybrid content-based group recommendation approach into the context of a restaurant recommendation domain, integrating in this scenario several stages such as the feature values imputation, the use of a weighting scheme, or the automatic aggregation of the recommendations generated for the individual users.
- It evaluates such contextualized approach into a real CB-GRS composed of Havana City restaurant information and user preferences, taken from TripAdvisor. As far as we know, this is one of the first approaches focused on exploring a CB-GRS approach in a real scenario, being an added value the selection of the Havana City context, where it is currently developing an emerging use of ICT tools for supporting society.
- The individual evaluation of the different stages of the proposal. The analysis of these results could provide guidelines for further deployments of this kind of approach in the e-tourism contexts.

The remaining of the paper is structured as follow. Section 2 introduces the research background necessary for the proposal presentation, as well as references to previous related works content-based group recommendation, and restaurant recommendations. Section 3 presents the hybrid content-based group recommendation approach, for the restaurant recommendation domain. Section 4 develops several experiments for evaluating the proposal over a gathered dataset with restaurants from Havana City in Cuba. The analysis of the results includes internal validation and comparison with previous related works. Section 5 concludes the paper, and points out the next future work.

2 Background and related works

This section focuses on providing several fundamental concepts related to content-based recommendation and group recommendation, as well as briefly reviewing works related to content-based group recommendation, and restaurant recommender systems.

2.1 Content-based recommendation

Content-based recommendation approaches [Adomavicius and Tuzhilin 2005] suggest items based on the philosophy of ”Show me more of what I have already liked”. This kind of recommender systems are characterized by a model that describes the items that can be recommended, a way to create a user profile that represents the types of items that the user prefers, and a way to compare each of the items to be recommended with the user's profile to determine which of them will be recommended.

The items to be recommended are usually identified through a set of features or attributes, and the values that each of these attributes can take are known. The preference degree of a user for a subset of items is taken into account and, using learning algorithms, it is possible to construct his or her profile in terms of the same attribute values and therefore, obtain from the remaining items those with the larger utility for the user. Herein, the two most important issues in these systems are the representation of the items and the learning of the user's profile.

According to Adomavicius and Tuzhilin [Adomavicius and Tuzhilin 2005], content-based recommendation is made from:

- User modeling and item modeling, taking into account the TF-IDF (Term Frequency-Inverse Document Frequency) [Adomavicius and Tuzhilin 2005], which is based on the principle that terms with high frequency of occurrence in a document, and with low frequency in the rest of the document set, tend to be more relevant to the document topic.

- Similarity finding between user and item profile. In content-based and collaborative filtering systems, it is necessary to calculate the similarity between users or items. For this purpose, common statistical correlation coefficients are usually used, such as the cosine similarity measure, Pearson's correlation or Jaccard's index, well known in the field of information retrieval [Adomavicius and Tuzhilin 2005].

- Recommendation generation: After calculating the active user's degree of similarity in relation to all possible items to recommend, these items are sorted in a decreasing list according to such degree. Finally, the top N items of this list are returned as recommendations.

While the collaborative filtering approach has been usually identified for its ability of generating appropriate recommendations when a reasonable amount of ratings is available [Adomavicius and Tuzhilin 2005], in those scenarios with an important lack of ratings value it has been necessary the use of content-based recommendations for generating useful recommendations [Kassak et al. 2016]. Usually, this is the case of tourism recommender systems [Nguyen and Ricci 2018], where users tend to provide ratings only about a small set of items, and even in such scenarios is necessary the generation of tailored recommendations. For this reason, the content-based recommendation paradigm will be used in the context of the current research, focused on providing restaurant recommendations in Havana City.

2.2 Recommendation to groups

Traditionally, recommender systems are concerned with recommending items to individual users [Adomavicius and Tuzhilin 2005]. However, in recent years the research community has begun to work over techniques to propose recommendations to groups of users [Castro et al. 2017a].

Most group recommender systems have different information acquisition methods in relation to those applied to individual systems. According to Castro et al [Castro et al.

2017a], group recommendation is currently an increasingly important area of research due to the diversity of scenarios in which it is useful.

The group recommendation problem is usually defined as determining the item (or set of items) that maximizes the prediction value for a group of G_a users.

$$Recommend(I, G_a) = arg_{i_k \in I} max Prediction(i_k, G_a) \quad (1)$$

There are two basic approaches for group recommendation [Castro et al. 2017a]:

- Rating aggregation. Here a pseudo-user is created to contain an aggregation of the preferences of the group members. The recommendation is generated for this pseudo-user as if it were an ordinary user.

  This general approach usually comprises the following stages (Figure 1).

  1. Group members preferences representation.
  2. Pseudo-user creation.
  3. Single-user recommendation generation for the created virtual profile.
  4. Top-n items recommendation delivery for the group.

- Recommendation aggregation. In this case, the recommendations of the group's members are generated by an individual recommendation approach. Afterwards, the group recommendation approach aggregates a single recommendation list for the group, taking as a reference the produced individual recommendations.

  This approach comprises the following stages (Figure 2).

  1. Group members preferences representation.
  2. Single-user recommendation generation for each group member.
  3. Recommendation generation for the group, by aggregating the recommendations tailored to the individual users.
  4. Top-n items recommendation delivery for the group.

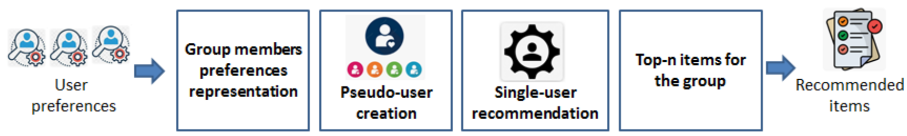


Figure 1: The rating aggregation approach for group recommender systems

In the case of rating aggregation, it is relevant the aggregation approach used for composing the pseudo-user profile that represents the group. Being r_{ui} the preferences associated to the group member u over the item i, the preference r_{Gi} associated to the pseudo-user profile can be calculated, respectively, through the average (Equation 2), minimum (Equation 3), and maximum approaches (Equation 4). Herein, N is the number of members in the group.

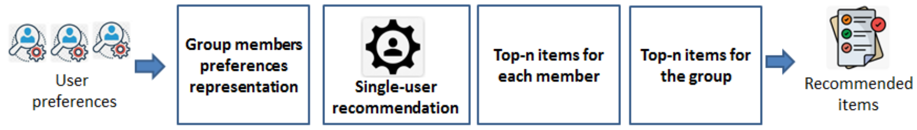


Figure 2: The recommendation aggregation approach for group recommender systems

$$r_{Gi} = \frac{1}{N} \sum_{u \in G} r_{ui} \tag{2}$$

$$r_{Gi} = Min_{u \in G} r_{ui} \tag{3}$$

$$r_{Gi} = Max_{u \in G} r_{ui} \tag{4}$$

In the case of the recommendation aggregation approach, it is relevant the method used for aggregating the predictions p_{ui} generated by the individual recommender system to each group member, into a score p_{Gi} that represents the interest of the group in relation to item i. Equation 5, 6 and 7 respectively illustrate the average, minimum, and maximum-based aggregation approaches for accomplishing this task. Herein, p_{ui} represents the prediction score of the group member u over the item i, and p_{Gi} is the same score, but associated to the group. N is the number of members in the group.

$$p_{Gi} = \frac{1}{N} \sum_{u \in G} p_{ui} \tag{5}$$

$$p_{Gi} = Min_{u \in G} p_{ui} \tag{6}$$

$$p_{Gi} = Max_{u \in G} p_{ui} \tag{7}$$

Overall, the importance of group recommender systems was formally stressed by [Jameson 2004], where the author suggests that systems that recommend items to a group of two or more users, raise a number of challenges that were partially understood and that cannot be covered by individual recommendation.

[Quijano-Sánchez et al. 2013] include an analysis of group personality composition and trust between each group member to improve the accuracy of group recommender systems. In this way, the authors simulate the argumentation process followed by the group, where the members are looking for an agreement, in a more realistic way.

More recently, [De Pessemier et al. 2014] develop an extensive review and evaluation of group recommendation algorithms, studying different data aggregation methods, their influence over group sizes in relation to recommendation accuracy, as well as the results of combining different aggregation schemes. Other criteria such as diversity and serendipity are also explored in this context.

[Castro et al. 2017b] proposed a group recommendation approach based on opinion dynamics that considers the relationship between group's members using a smart weights matrix to drive the recommendation generation process. The authors identify that in some groups the opinions do not agree, hence the weights matrix is modified to reach a consensus value.

More recently, [Felfernig et al. 2018] present a book focused on an easy-to-understand introduction to the field of group recommender systems. Beyond algorithms, the authors deal with aspects such as group recommender user interfaces, evaluation techniques, approaches for handling preferences, as well as different ways to include explanation into group recommender systems.

[Dara et al. 2020] have also presented a recent survey on the state-of-art in group recommender systems taking into account different domains, and analyzing different systems regarding their aggregation schemes and user preference models.

In the last few years, the research community around group recommendation has remained very active. [Yalcin et al. 2021] propose two novel aggregation techniques for hybridizing additive utilitarian and approval voting methods to feature popular items on which group members provided a consensus. [Contreras et al. 2021] have also proposed a collaborative model based on the social interactions that take place in a web-based conversational group recommender system. It allows the group recommender to implicitly infer the different roles within the group, namely, collaborative and leader user. Finally, [Ismailoglu 2022] use the EM algorithm to aggregate the preferences of group members to estimate group ratings and the expertise levels of the group members, in group recommender systems.

However, most of the discussed research works are focused on developing group recommendation models taking as base the collaborative filtering paradigm. In contrast, the current work is focused on proposing a novel content-based group recommendation model, tailored to a specific recommendation domain.

2.3 Previous works in content-based group recommendation

Several authors have been focused in the more recent years, on the development of content-based group recommendation models. In this way, [Pérez-Almaguer et al. 2021] have identified three groups of works based on their characteristics and working approaches: 1) Proposal integrating multiple information sources, 2) Hybrid proposal for the tourism domain, and 3) Proposal integrating content-based and collaborative filtering.

In this sense, the referred analysis identified the development of hybrid group recommender systems that incorporate content-based group recommendation as an additional dimension, in order to improve the overall performance of the system. The works of Pera and Ng [Pera and Ng 2013] and Kassak et al. [Kassak et al. 2016], constitute relevant proposals belonging to this category. However, they do not follow the common content-based recommendation scheme [Adomavicius and Tuzhilin 2005] and their experimentation is limited.

On the other hand, Felfernig et al. [Felfernig et al. 2018] are among the first authors entirely focused on content-based group recommender systems, although in their proposal they only carry out a general modeling of the structure that this type of method would have, without carrying out a deep modeling or experimentation.

Recently, [Pérez-Almaguer et al. 2021] present a taxonomy obtained through a review of the most recent developments in content-based group recommender systems. Based on this taxonomy, three basic content-based group recommender systems (CB-GRS) methods are formalized: 1) CB-GRS based on recommendation aggregation and individual ranking, 2) CB-GRS based on recommendation aggregation and user-item similarity, and 3) CB-GRS based on the aggregation of user profiles. However, these methods are elementary proposals with much potential for improvement.

Beyond these contributions, it is important to highlight that most of the works focused on group recommendation are based on collaborative filtering approaches in which user preferences and similarity calculation play a preponderant role [Adomavicius and Tuzhilin 2005]. This previous analysis highlights the need for the development of the current research, which proposes a new content-based group recommendation system that incorporates advanced features capable of improving the performance of previous proposals, and contextualized to a specific domain such as the restaurant recommendation.

2.4 Previous works in restaurant recommendations

The restaurant recommendation problem has been covered by several authors in recommender systems research.

[Vargas et al. 2011] explore the restaurant recommendation problem, through a feature selection approach for exploring the more relevant contextual attributes. Some of the explored attributes includes service model (latitude, longitude, alcohol, smoking, accessibility, price, etc), user model (marital-status, children, interests, etc), and environmental model (time and weather).

[Noguera et al. 2012] present REJA, a geo-referenced, knowledge-based restaurant recommendation approach, that is supported by the filling of the incomplete preference values provided by the user, being employed this information in the user profiling task.

[Ramirez-Garcia and García-Valdez 2014] presents a restaurant recommendation algorithm based on a contextual post-filtering approach, using the output of a collaborative filtering algorithm as well as contextual information of the user's current situation. The used database was explicitly gathered through questionnaires over 50 users; building a dataset composed of 1422 ratings, 50 users, and 40 restaurants.

[Zhang et al. 2018] also present an innovative personalized restaurant recommendation method that merges group correlations with customer preferences. This approach uses unsupervised methods and a Probabilistic Linguistic Term Set (PLTS) to establish group correlations between customer groups and restaurant groups. The recommendation list is generated by identifying the group that shares the most similarities with the target customer.

More recently, [Gomathi et al. 2019] use natural language processing for gathering positive and negative aspects from TripAdvisor's users opinions in each independent restaurants. The current users are then requested about the preferred features to prioritize in recommendation generation, being suggested as top items those with a higher match between their aspects and such preferred features.

[Fakhri et al. 2019] implements a user-based collaborative filtering approach for restaurant recommendations, and considering two different similarities schemes using a user rating similarity and a user attribute similarity.

In addition, [Zhang et al. 2020] propose a new factorization model that combines multi-view visual information with the implicit feedback data for restaurant prediction and ranking. The visual features (visual information) of images are extracted by using a deep convolution network and are integrated into a collaborative filtering framework.

More recently, [Asani et al. 2021] propose a context-aware recommendation approach that utilizes individuals' comments to extract their food preferences, recommending restaurants that align with those preferences. The system employs a semantic approach to cluster the names of foods mentioned in the comments and analyze the associated sentiments.

[Saelim and Kijsirikul 2022] develop a restaurant recommendation system that utilizes deep neural networks for enabling the learning of latent factors associated with user and item interactions. Additionally, textual information is incorporated through the use of the multi-layer perceptron.

Recently, [Shambour et al. 2023] present a multi-criteria recommendation approach for personalized restaurant recommendations, proposing a hybrid user-item based multi-criteria collaborative filtering method that exploits users' and items' implicit similarities to eliminate the sparseness of rating information.

Overall, the performed analysis reveals a diverse set of works focused on restaurant recommendation. However, several shortcomings can be identified: 1) Several approaches depend of a continuous user interaction that is not always possible [Noguera et al. 2012, Gomathi et al. 2019], 2) They incorporate visual and textual information items that requires additional computational approaches to process them [Zhang et al. 2020, Asani et al. 2021, Saelim and Kijsirikul 2022], 3) They are focused on basic recommendation models and do not incorporate information related to the restaurant recommendation domain [Ramirez-Garcia and García-Valdez 2014, Fakhri et al. 2019], or 4) They are not properly focused on generating top-n restaurant recommendations [Vargas et al. 2011]. In addition, there is a lack of works exploring the group recommendation task in the restaurant domain, considering that even though [Zhang et al. 2018] explores group correlations, the final recommendation is only focused on individual users.

The current contribution is centered a providing a content-based group recommendation approach focused on the restaurants domain. As relevant contribution, the proposal is executed over a gathered dataset of Havana City restaurants in Cuba, through a methodology and feature analysis that is generalizable to other restaurant recommendation scenarios. It is important to remark that while several research works have been focused on exploring the restaurant recommendation domain supported by user reviews [Zuheros et al. 2021], as far as we know our work is pioneer in the restaurant recommendation domain to groups, taking as main source the user preferences and the restaurant feature values.

3 The hybrid content-based group recommendation approach

This section presents the description of the new content-based group recommendation method. Figure 3 shows the general scheme of this new proposal. First, the modeling of the restaurant profiles is performed in a similar way to the traditional content-based recommendation [Adomavicius and Tuzhilin 2005]. At a second stage, it is introduced a feature values imputation step for calculating some missing values, which could lead to a better improvement of the generated recommendations. Once this step is accomplished, the known users' preferences over the corresponding items are used for building the user profiles. Subsequently, the individual profiles of all users in the group are aggregated to obtain the pseudo-user profile representing the group. This pseudo-user profile is added to the set of group members, as a new member for the group. For each group member including the new pseudo-user, a weighted similarity value is computed between their profiles and the profiles of all available items. Once all the user-group-item similarity values are obtained, it is necessary to aggregate the similarity values of all group members for each specific item. This is done to determine the group's preference value for the item. With this objective in mind, an automatic selection of the function is carried out to aggregate these values, depending on the characteristics of the group. After this, the selected aggregation function is used to obtain a score representing the value of each available item, which is used to finally obtain the n first recommendations for the group. The following sections show these steps in detail.

Table 1 introduces the notation used in Figure 3 and in this section, across the proposal presentation.

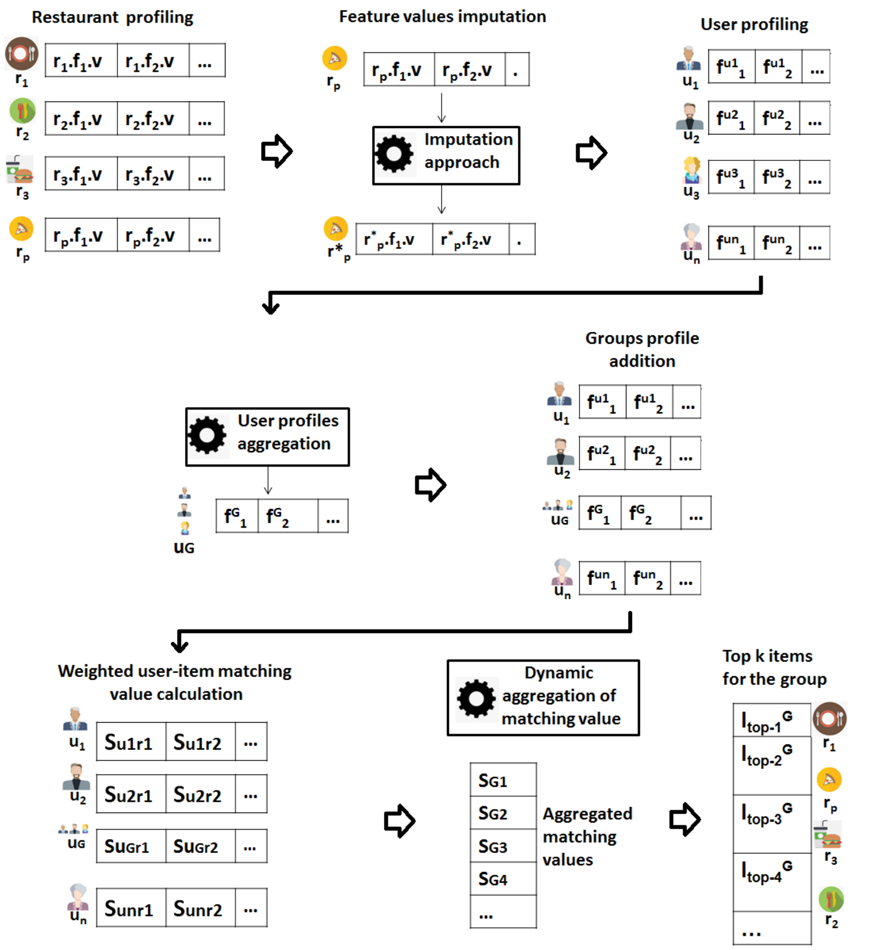


Figure 3: The content-based group recommendation approach for the restaurant domain

3.1 Restaurant profiling

This method will consider an item profile composed of multi-valued features, as could be expected for features that would characterize restaurants.

In this way, here a restaurant will be represented by a vector:

$$r_p = (f_1, f_2, f_3, ..., f_m) \tag{8}$$

where the feature value f_m is associated to nominal or numerical values, in a domain associated to the specific feature m. In several cases, such values would be missing at some specific features.

Term	Meaning
r_p	Restaurant profile.
f_m	Value associated to the feature m.
$r_p.f_k.v$	Value associate to the feature f_k, in the specific restaurant profile. r_p
u	User profile.
f_m^u	Value associated to the feature m, at the user. u
r_{u,r_p}	Rating value associated with the user with the profile u, and the restaurant with the profile r_p.
g	Group profile.
f_m^G	Value associated to the feature m, at the group G.
w_k^u	Weight for the feature k, according to the user u, in the weighting scheme.
S_{ur}^k*	User-restaurant matching value according to the feature k.
S_{ur}	User-restaurant matching value.
S_{Gr}	Score of the restaurant r for the group G.

Table 1: Notation used across the proposal presentation

3.2 Feature values imputation

This procedure considers the imputation of some missing feature values in those cases where a value for a specific unknown feature can be clearly inferred.

$$sim(r_p, r_q) = \frac{|f_k : r_p.f_k = r_q.f_k|}{m} \tag{9}$$

$$r_p.f_k.v = v,\ being\ Fr(v) = max(Fr(r_q.f_k.v)), \forall r_q : sim(r_p, r_q) > \delta \quad (nominal features) \tag{10}$$

$$r_p.f_k.v = avg(r_q.f_k.v), \forall r_q : sim(r_p, r_q) > \delta \quad (numerical features) \tag{11}$$

Equations 9-11 illustrate this imputation procedure, that at first depends on a similarity between restaurants (Equation 9) that is represented by a simple matching between their feature values.

At second, in the case of nominal features (Equation 10), a value $f.k.v$ for an unknown feature at a specific restaurant $r.p$ is calculated as the most frequent value from this attribute in other restaurants similar to the active one. In this case it will be only considered restaurants with a similarity degree over a threshold δ.

For numerical features (Equation 11), the value $f.k.v$ for the unknown feature is calculated as the average of the value of this attribute for other restaurants that are similar to the current one.

3.3 User profiling

Here the multivalued user profiling u_p based on the same feature space of restaurants, is built over the profiles of the restaurants preferred by the current user.

$$u = (f_1^u, f_2^u, f_3^u, ..., f_m^u) \tag{12}$$

In this case the value of f_k^u is calculated in a different way, depending on the nature of the nominal or numerical nature of the attribute.

In the case of a nominal attribute, f_k^u is represented through a set of key-value pairs, representing each possible value of the attribute and its frequency, considering all the preferred items for the current user u (Equation 13).

$$f_k^u = (r_p.f_1.v^u, Fr(r_p.f_1.v^u)), ..., (r_p.f_b.v^u, Fr(r_p.f_b.v^u)), \forall r_{u,r_p} > 3 \quad (13)$$

In the case of the numerical attributes, f_k^u will be calculated as the average of all the f_k values for all the items preferred by the user u (Equation 14).

$$f_k^u = avg(r_p.f_k), \forall r_{u,r_p} > 3 \quad (14)$$

In both cases (Equations 13 and 14), it is considered as preferred restaurants r_p to those with a rating value $r_{u,r_p} > 3$ for a user u.

3.4 Groups' profile addition

Once the user and restaurant profiling are developed, the present proposal aggregates the individual profiles of all users in the group, to create a pseudo-user profile that represents the overall group preferences:

$$g = (f_1^g, f_2^g, f_3^g, ..., f_m^g) \quad (15)$$

This pseudo-user profile is aggregated to the corresponding group, and is treated as a standard group member in the next steps of the recommendation process. The goal of this step is the boosting of the well-defined preferences of the group, attenuating those that are unclear taking into account the nature of the current members.

To build such pseudo-user profile, in the case of the nominal features the value of feature f_k^g is calculated through a set of key-value pairs, in a similar way to individual users, by considering the average of the frequency of each possible feature value, for all the group members (Equation 16).

$$\begin{aligned} f_k^u = (r_p.f_1.v^u, avg(Fr(r_p.f_1.v^u))), ..., (r_p.f_b.v^u, avg(Fr(r_p.f_b.v^u))), \\ u \in G, \forall r_{u,r_p} > 3 \end{aligned} \quad (16)$$

In the case of numerical features, f_k^G is calculated as the average of the f_k^u values (Equation 14) associated to each member of the group (Equation 17).

$$f_k^u = avg(f_k^u), u \in G \quad (17)$$

3.5 Weighted user-item similarity calculation

Considering each user and restaurant profiles, this section performs the calculation of a weighted similarity between them.

Here, the weight value of a feature can be interpreted as the importance of that feature in the recommendation process.

In this research, the weighted scheme proposed by Castro et al., [Castro et al. 2014] will be followed, defining the weight w_k^u for feature k according to user u, as:

$$w_k^u = DC(u, k) \quad (18)$$

Where $DC(u, k)$, is the dependence coefficient between the ratings provided by user u on a set of items and the values of characteristics k for such items. It is formalized as:

$$DC(u,k) = \begin{cases} |PCC_{uk}| \ , \ if\ k\ is\ quantitative \\ VC_{uk} \ , \ if\ k\ is\ qualitative \end{cases} \tag{19}$$

Here, PCC_{uk} is the Pearson correlation coefficient according to the variables R_u and f_{ki} with n_u being the number of ratings considered in this calculation:

$$PCC_{uk} = \frac{\sum_i r_{ui} v^{ki} - \frac{\sum_i r_{ui} \sum_i v^{ki}}{n_u}}{\sqrt{\sum_i (r_{ui}^2) - \frac{(\sum_i r_{ui})^2}{n_u}} \sqrt{\sum_i ((v^{ki})^2) - \frac{(\sum_i v^{ki})^2}{n_u}}} \tag{20}$$

VC_{uk} is the Cramer's V contingency coefficient according to some variables represented by qualitative characteristics:

$$VC_{uk} = \sqrt{\frac{\sum_{k_u} \sum_{k_k \in V^k} \frac{(fr_{k_u,k_k} - \frac{fr_{k_u} fr_{k_k}}{n_u})^2}{\frac{fr_{k_u} fr_{k_k}}{n_u}}}{n_u min(|D_u|, |D_k|)}} \tag{21}$$

In the case of the Cramer's V contingency coefficient, k_u and k_k are respectively the different values in the rating domain r_{ui} and the feature values domain fr_{k_i}, and fr_{k_u} and fr_{k_k} are the respective values of both domains. Furthermore, $frk_u k_k$ is the frequency of the simultaneous co-occurrences of both k_u and k_k. $|Du|$ and $|Dk|$ are the amount of different numbers in the domains of the rating r_u and the feature k.

W_k^u values from Equation 18, are normalized to obtain w_k^u*, which are the weights to be finally used in the user-item matching values calculation.

Here Equation 6 illustrates this approach for performing this task at both the numerical and nominal attributes in a specific feature k. For nominal attributes, it is calculated as the weighted frequency $Fr(F_k.v.u)$ of the associated key $F_k.v_u$ in the user profile u_p, being also $F_k.v_u$ the value associated to the feature k in the restaurant r. On the other hand, for the numerical attributes, it is calculated as the inverse of the distance between the k values f_k and f_k^u in the corresponding user u and restaurant r, multiplied by the calculated weight.

$$S_{ur}^k * = \begin{cases} (w_k^{u*}) * Fr(f_k.v^u) \ , \ for\ k\ nominal\ and\ f_k.v^u\ the\ value\ of\ k \\ \ in\ restaurant\ r \\ (w_k^{u*}) * \frac{1}{|f_k^u - f_k|} \ , \ for\ k\ numerical \end{cases} \tag{22}$$

Finally, the overall user-restaurant matching value is calculated as the average of all the S_{ur}^k* values for each feature k:

$$S_{ur} = \frac{\sum_{k \in K} S_{ur}^k *}{|K|} \tag{23}$$

3.6 Similarity aggregation and final recommendation

Finally, this method requires the definition of an aggregation function to calculate the values of all users in the group in relation to each of the items to be recommended. In this context, the direct use of various aggregation approaches such as average, minimum, or maximum has been previously analyzed. Several authors have suggested that the most appropriate aggregation approach may depend on some group characteristics such as the number of films evaluated, or the compactness of the group [Felfernig et al. 2018]. Based on such evidence, in this step we automatically select the correct aggregation function according to the group characteristics.

$$S_r^G = \begin{cases} \frac{\sum_u S_{ur}}{n} \ , \ if \ \sum_{u \in G} |R_u| < \alpha \\ Max_u S_{ur} \ , \ if \ \sum_{u \in G} |R_u| \geq \alpha \end{cases} \tag{24}$$

Equation 24 formalizes this approach to aggregate the value for all users in the group. With this, the parameter α is defined and its optimal value being obtained experimentally. Here, in the case where the overall amount of ratings predicted by the group is greater than or equal to α, the aggregation approach to use is the Most Pleasure (i.e. maximum). However, if the global amount of rating is below α, then the average aggregation approach is used.

The effect of this automatic selection approaches presented at Equations 24 will be evaluated in the experimental section.

Finally, the aggregated values are sorted in descending order and their associated top k items are retrieved to make the list of recommended items for the group.

4 Experiments over Havana restaurants recommendations to group of users

As it has been referred at the Introduction section, the main goal of this work is the exploration of the performance of a novel CB-GRS approach over a real application domain, which in this case is composed of users linked to Havana City restaurants. Havana is the biggest city in Cuba, with 2.5M of residents and in addition the largest hub of city tourism in Cuba, receiving visitors from the entire world across the entire year.

In this way, from the perspective of e-tourism supported by RSs and personalization tools, the analysis of large scale platform such as TripAdvisor suggests that for this kind of medium-sized cities, while there are some kind of items like hotels with scarce preference values for each user (e.g. each user visits/evaluates only a very few group of hotels in Havana), other items such as restaurants have been more extensively evaluated in such a platform. As results, it can be detected in TripAdvisor users that have evaluated more than a dozen of restaurants in Havana City.

This context becomes Havana restaurants an appropriate scenario for exploring content-based recommendation, regarding that it relies on item features for recommendation generation, which would be guaranteed here taking into account the attributes managed by TripAdvisor for characterizing their attractions. As was previously pointed out, at this moment (February 2023), TripAdvisor has registered 800+ restaurants only from Havana City.

Beyond these data, we think that the most important added value in relation to the use of Havana City as the case study, is related to evidencing that personalization tools and recommender systems are able to be useful and necessary for tourists not only in the largest cities [Nguyen and Ricci 2018], but also in smaller touristic destinations having a less number of touristic attractions.

To explore the performance of the approach presented at Section 3 in this context, this section will detail the approach used for data gathering (Section 4.1), the used experimental protocol (Section 4.2), and the presentation and discussion of the obtained results (Section 4.3).

4.1 Data gathering

The application of the recommendation approach discussed at Section 3 over the Havana restaurants user preferences, requires the data gathering and preparation from the TripAdvisor platform.

We remark that the goal of the current paper is the illustration of a proof-of-concept of this methodology, as well as a screening on the behavior of the discussed CB-GRS with real e-tourism data. In the next future work it will be considered the experimentation with a larger scale dataset.

Specifically, the steps developed for data gathering and preparation:

1. Taking as starting point the most popular and highly valued restaurants in Havana (e.g. Da Alicia, Ricardón, Sensacioones, etc. See tripadvisor.com), it was exhaustively analyzed all the users that have evaluated such kind of restaurants, and have more than five evaluations over other touristic places.

2. For each identified user, it is removed the places that do not belong to the category of restaurants from Havana. In this way, we keep a very small group of evaluation over restaurants from other Cuban cities close to Havana, such as Varadero, Viñales, and Trinidad.

3. Once such procedure is completed, it is obtained a dataset with 40 users and 69 restaurants, that will be used in the referred evaluation. This dataset is currently available on demand.

At last, as a CB-GRS, the item attributes are necessary for evaluating the proposal. Here it will be used additional information available in TripAdvisor about each restaurant, such as type of cuisine, price range, quality/price relationship, quality of service, quality of food, atmosphere, ranking of the restaurant, popularity, etc. This information was analyzed by an expert of the e-tourism and restaurant domain, selecting the following attributes and their corresponding possible values:

1. Prize: cheap, average, expensive.

2. Food and service quality: low, medium, high.

3. Type of cuisine: Cuban, Spanish, Italian Basic, Italian Exclusive, Other.

4. Ranking: Top 20, Top 100, Other.

5. Popularity: High (200+ opinions), Medium (100+ opinions), Low (Other number of opinions).

These five multi-valued attributes will be used for characterizing items in the CB-GRS approach discussed at Section 3.

The next section will present the experimental protocol that will be used for evaluating the discussed recommendation approach.

4.2 Experimental protocol

The proposal evaluation is driven by two metrics usually used for the measurement of effectiveness in group recommendation, which are Precision and NDCG [Gunawardana et al. 2009].

Precision is defined as the proportion of items that were suggested by the recommender system and actually preferred by the user, in relation to the overall number of recommended items (Equation 25) [Gunawardana et al. 2009].

$$Precision = \frac{|recommended\_items \cap preferred\_items|}{|preferred\_items|} \tag{25}$$

The Normalized Discounted Cumulative Gain (NDCG), depends on the Discounted Cumulative Gain (DCG) which is based on the fact that highly relevant items that appear at the end of a search result list should be penalized. DCG, for the user u, is formalized as:

$$DCG_u = \sum_{k=1}^{N} \frac{r_{u,recom_{u,k}}}{log_2(k+1)} \tag{26}$$

where $recom_{u,k} \in I$ is the item recommended to the user u in the position k.

To obtain the $NDCG_u$, this DCG_u value is normalized by dividing it with the best possible DCG value, $DCG_{perfect}$, which is associated to a perfect recommendation list. In such a list, the most preferred items appear first, in relation to those less preferred.

$$NDCG_u = \frac{DCG_u}{DCG_{perfect}} \tag{27}$$

Finally, the $NDCG_u$ for all users u are averaged for reaching the final $NDCG$ value.

Beyond Precision and NDCG, the evaluation with further metrics such as coverage and diversity [Kunaver et al. 2017] are out of the scope of the current work, regarding that the primary goal of the proposed framework is not the reaching of a high coverage or diversity.

Based on Precision and NDCG criteria, the evaluation of the proposed approach is carried out through the following steps [Castro et al. 2017a]:

- Taking as input the user profiles represented by the user's preferred items and the items' characteristics, randomly divides the user's set of ratings into two subsets (training and test), setting 50% of preferences for training and the remaining 50% for test. The global training and test set is made by combining the training and test set of each user.
- Groups of size 3 are constructed, following a training criterion described below.
- For each group, the proposed method is applied on the basis of the training set data, obtaining the first n items recommended for the group.
- The effectiveness of the recommendation is evaluated using the Precision and NDCG metrics for each group. These values are averaged to finally obtain the final value.

In the case of the Precision calculation, it is necessary to consider a preference threshold. Here we consider r>=3, which is a common value for this threshold [Castro et al. 2017a].

In another direction, several methods have been considered by the literature for group composition. These include random formation [De Pessemier et al. 2014], as well as the use of other criteria that guarantee the presence of elements in common among group members [Kassak et al. 2016]. Furthermore, it has been conceived as a valid choice the random group formation, considering that in most group scenarios the members do not necessarily need to be similar or have common features.

For each evaluation scenario, 20 groups of 3 members are formed. For each group, the n best recommendations are generated with n in the ranges [1; 10] with step 1. This protocol is repeated 10 times, the results are averaged, and this result is reported as the final value for the corresponding experimental scenario.

Finally, the current approach will be compared with the most direct antecedent to the current work, also proposed by Pérez-Almaguer et al. [Pérez-Almaguer et al. 2021], and that considers a simple CB-GRS approach considering recommendation aggregation based on user-item matching values, but without any feature weighting, group profile addition, or dynamic selection of the aggregation function. Here it will be evaluated the average and maximum, as static aggregation functions.

4.3 Results

The current section discusses the results associated to the presented experimental protocol. It includes an internal validation and the comparison with previous related works.

4.3.1 Internal validation

Tables 2 and 3 illustrate the performance of the current proposal (GRS), according to the Precision and NDCG metrics. Additionally, the tables present the effect of excluding each one of the independent components, in order to verify their individual effect in the overall framework. Furthermore, Figure 4 presents an screenshot of the presented results, presenting the accuracy results for top 2, top 5, and top 10 recommendations.

Specifically, the following design alternatives are considered.

- **GRS-No Imput:** The proposed framework, excluding the imputation step. The remaining stages of the proposal are carried out, as presented in Section 3.
- **GRS-Only Avg:** The proposed framework, but always using the average aggregation approach for individual members' predictions, instead of the automatic selection of the most appropriate aggregation approach. The remaining stages of the proposal are carried out, as presented in Section 3.
- **GRS-Only Max:** The proposed framework, but always using the Most Pleasure aggregation approach for individual members' predictions, instead of the automatic selection of the most appropriate aggregation approach. The remaining stages of the proposal are carried out, as presented in Section 3.
- **GRS-No Virt:** The proposed framework, but excluding the aggregation of the group's pseudo-user profile as a virtual member of the group. The remaining stages of the proposal are carried out, as presented in Section 3.

– **GRS-No Weights:** The proposed framework, but excluding the use of feature weights in the user-item similarity calculation. The remaining stages of the proposal are carried out, as presented in Section 3.

n	GRS	GRS-No Imput	GRS-Only Avg	GRS-Only Max	GRS-No Virt	GRS-No Weights
1	**0.8266**	0.8116	0.825	0.825	0.8266	0.825
2	**0.8137**	0.8041	0.8112	0.8129	0.8133	0.8116
3	**0.8083**	0.8013	0.8064	0.8077	0.8078	0.8071
4	**0.8054**	0.8	0.8045	0.805	0.8053	0.8048
5	**0.8036**	0.7989	0.8029	0.8032	0.8035	0.8031
6	**0.8022**	0.7984	0.8016	0.8019	0.802	0.8018
7	**0.8011**	0.7978	0.8006	0.8009	0.801	0.8008
8	**0.8003**	0.7974	0.7998	0.8	0.8001	0.8
9	**0.7996**	0.797	0.7992	0.7994	0.7995	0.7993
10	**0.7991**	0.7968	0.7987	0.7989	0.799	0.7988

Table 2: . Evaluation of the different components of the proposal. Precision metric.

n	GRS	GRS-No Imput	GRS-Only Avg	GRS-Only Max	GRS-No Virt	GRS-No Weights
2	0.9828	0.9818	0.9829	0.9826	0.983	**0.9834**
3	0.9798	0.9785	0.9799	0.9796	0.9799	**0.9803**
4	0.9781	0.9768	0.9781	0.9779	0.9781	**0.9785**
5	0.9769	0.9757	0.9768	0.9766	0.977	**0.9773**
6	0.976	0.9747	0.9759	0.9757	0.9761	**0.9765**
7	0.9753	0.974	0.9753	0.975	0.9755	**0.9759**
8	0.9748	0.9734	0.9748	0.9746	0.975	**0.9754**
9	0.9745	0.973	0.9744	0.9742	0.9747	**0.9751**
10	0.9741	0.9726	0.9741	0.9739	0.9744	**0.9748**

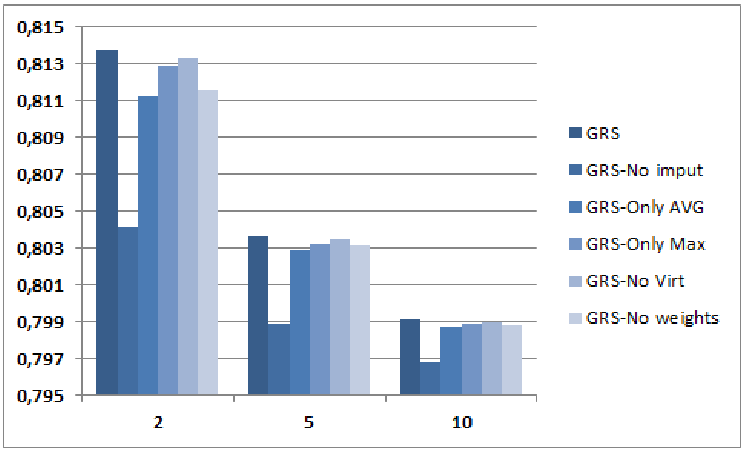
Table 3: Evaluation of the different components of the proposal. NDCG metric.

In the case of Precision (Table 2), it is worthy to mention that for all the top n recommendation lists, the whole framework (GRS) obtains the best performance in relation to the other design alternatives that exclude some of the components of the proposal.

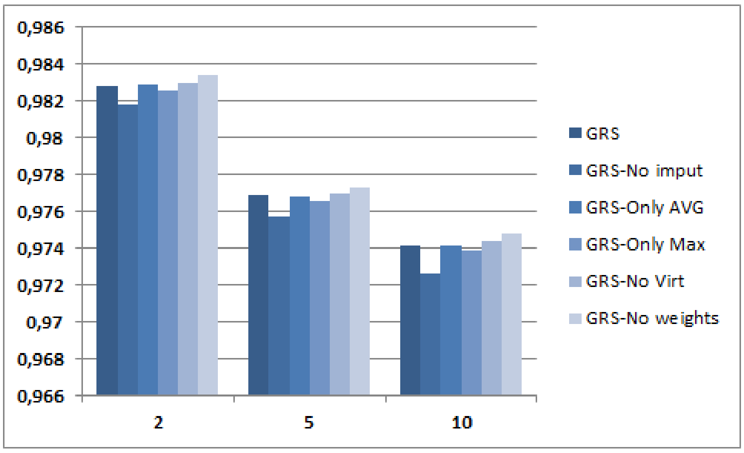
In the case of the *imputation stage*, Table 2 illustrates that its exclusion leads to a relevant decreasing of the Precision, which is remarkable for the small recommendation lists (e.g. for top 1, it decreases from 0.8266 to 0.8116; and for top 2, it decreases from 0.8137 to 0.8041, and so on). Even though for larger recommendation lists the improvement level is lower, it is relevant to mention that this imputation stage is associated to the large Precision improvement of all the stages of the current proposal.

Table 2 also illustrates the Precision results associated to the static application of the average aggregation approach (GRS-Only Avg) and the maximum aggregation approach (GRS-Only Max), without the automatic selection of the aggregation approach (Section 3.6). In this case, it is interesting to point out that both the GRS-Only Avg and the GRS-Only Max approaches, obtain similar results. However, it is relevant that the automatic selection of the most appropriate aggregation approach, that switches between both approaches, outperforms both individual approaches for all scenarios.

Additionally, Table 2 also illustrates the effect of adding the virtual user profile into the group, focused on synthesizing and boosting the overall preference of the current group. In this case, the approach *GRS-No Virt* at Table 2, illustrates the behavior of the current proposal without considering this stage. The table shows that the incorporation



(a) .



(b) .

Figure 4: Evaluation of the different components of the proposal, for top 2, top 5, and top 10 recommendation lists. (a) Precision values. (b) NDCG values.

of this step leads to a moderate but clear improvement in the Precision values, for each sizes of the recommendation list.

Finally, Table 2 presents the approach *GRS-No Weights* as the alternative to the current proposal, that does not consider the use of the weighting scheme presented at Section 3.5. In this case, the comparison with the whole proposal *GRS*, proves that the addition of the weighting scheme, in a similar way to the other analyzed stages, implies an improvement in the Precision values. In this case, the improvement level tends to be more relevant for smaller recommendation lists, specifically for $n \leq 4$. On the other hand, for larger recommendation lists the improvement can be considered as moderate, in a similar way to the GRS-No Virt scenario.

In a different direction, Table 3 presents the results associated to the NDCG metric for the same proposals. Herein, the obtain results are different in relation to the Precision metrics. At first, it is important to note that the performance difference across all the different design alternatives are smaller in relation to the Precision value. However, even in this case, it is important to remark that the whole proposal (GRS) outperforms the approaches that considers the exclusion of the imputation stage (GRS-No imput), and the exclusion of the automatic selection of aggregation function (GRS-Only Avg and GRS-Only Max). It indicates that the addition of these two stages also implies an improvement in the NDCG of the proposal. On the other hand, Table 3 indicates that there are no relevant differences between the whole proposal (GRS), the proposal with the exclusion of the virtual user (GRS-No Virt), and with the exclusion of the weighting scheme (GRS-No Weights). Moreover, in most scenarios the proposal with the exclusion of the weighting scheme, improves the whole proposal for the NDCG approach. Furthermore, it is important to remark that this behavior contrasts with the Precision metric, where the whole proposal reaches the best performance for all the scenarios.

4.3.2 Comparison with previous works

In order to evaluate the current proposal, it is necessary to compare it with the performance of previous proposals in the current scenario of Havana City restaurants.

With this purpose, it is selected a direct antecedent of the current work, which is the basic content-based group recommendation models proposed by [Pérez-Almaguer et al. 2021], supported by the recommendation aggregation paradigm, but without including any of the novel stages introduced by the current paper, such the imputation stage, the virtual user profile aggregation, the automatic selection of the aggregation function, or the use of feature weighting.

Tables 4 and 5 illustrates the results of this comparison according to Precision and NDCG, where *GRS* is the current proposal, *Avg* is the content-based group recommendation approach presented by [Pérez-Almaguer et al. 2021] and using the average aggregation for composing the group recommendations, and *Max* is this same previous approach but using the Most Pleasure (Maximum) aggregation approach for composing the group recommendations. These results are also illustrated in Figure 5, specifically for top 2, top 5, and top 10 recommendations as a screenshot of the whole results.

Top-n	**Current proposal**	**Average**	**Most pleasure**
1	**0.8266**	0.7983	0.8
2	**0.8137**	0.7975	0.7987
3	**0.8083**	0.7973	0.7974
4	**0.8054**	0.7972	0.7971
5	**0.8036**	0.7970	0.7968
6	**0.8022**	0.7967	0.7966
7	**0.8011**	0.7964	0.7963
8	**0.8003**	0.7961	0.7960
9	**0.7996**	0.7959	0.7958
10	**0.7991**	0.7957	0.7957

Table 4: Comparison with previous works. Precision.

As could be expected, Tables 4 and 5 show that for both evaluation metrics, the proposal screened at the current work outperforms both the *Avg* and the *Max* approaches [Pérez-Almaguer et al. 2021] for all the experimental scenarios. The difference becomes more relevant for small recommendation lists, e.g. for top 2 recommendations the current proposal reaches a precision of 0.8137, while the Avg and the Max approaches obtain

Top-n	Current proposal	Average	Most pleasure
2	**0.9828**	0.9814	0.9813
3	**0.9798**	0.9777	0.9775
4	**0.9781**	0.9755	0.9755
5	**0.9769**	0.9741	0.9741
6	**0.9760**	0.9730	0.9730
7	**0.9753**	0.9723	0.9722
8	**0.9748**	0.9717	0.9717
9	**0.9745**	0.9713	0.9712
10	**0.9741**	0.9709	0.9709

Table 5: Comparison with previous works. NDCG.

0.7975 and 0.7987 respectively. For top 10 recommendations, the current approach obtains a precision of 0.7991, while both Avg and Max obtains 0.7957. While this different is less large in relation to the smaller recommendation lists, it is still relevant in the recommendation scenarios [Castro et al. 2017a]. In the case of NDCG it is obtained a similar result, however it is worthy to mention that for larger recommendation lists, the improvement degree of the current proposal becomes larger. As example, for top 10 recommendations the current proposal obtains a NDCG of 0.9741, while both the Avg and the Max approaches obtain 0.9709.

5 Conclusions and Future Work

The current research work has presented a novel content-based group recommendation approach tailored to a restaurant recommendation context. In contrast to previous research focused on individual restaurant recommendation, the current proposal is focused on the group recommendation scenario by proposing a hybrid approach that includes several components such as the feature imputation, the use of a virtual group profile, the use of feature weighting, and the automatic selection of the most appropriate aggregation of the group's members recommendations.

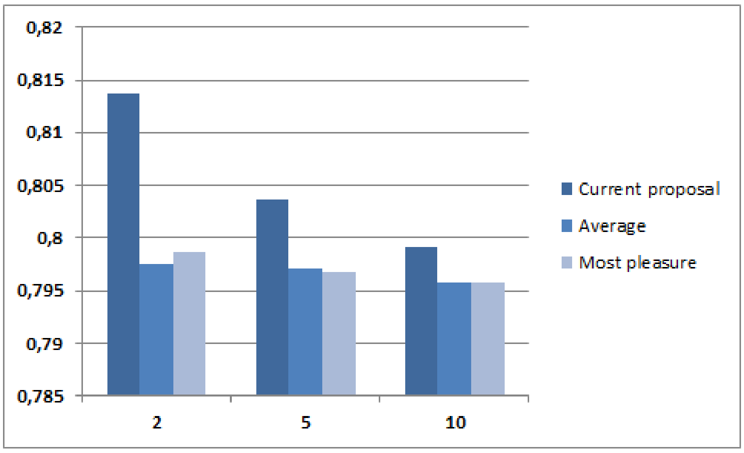
Moreover, as relevant contribution the proposal is executed over a gathered dataset of Havana City restaurants in Cuba, through a methodology and feature analysis that is generalizable to other restaurant recommendation scenarios.

The development of a comprehensive experimentation protocol proved the importance of each individual component as part of the whole recommendation framework. In addition, the experiments showed that the current proposal outperforms other simpler content-based group recommendation approaches.

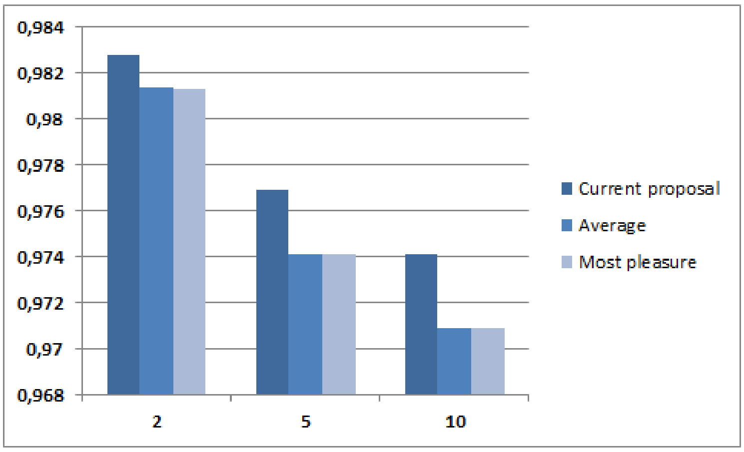
From the viewpoint of the recommender systems community, the results associated to the current paper highlight the value of considering the development of recommendation frameworks for covering specific recommendation environments (in this case restaurant recommendations at a specific city), which are part of a larger domain (tourism).

In relation to the tourism management perspective, taking into account the stakeholders and the decision makers viewpoint, the results associated to the presented framework and the gathered data, suggest that recommender systems and group recommender systems can be also successfully used in other scenarios at a similar product scale, such touristic attractions that are part of a large resort [Carballo-Cruz et al. 2019], or specific facilities inside a hotel [Gonzalez et al. 2022].

Beyond this overall perspective, the next future work will be focused on the exploration of the current approach over other restaurants and related touristic attraction datasets, coming from other locations, in order to evaluate how some characteristics such as the users' preference sparsity level and the amount of missing feature values,



(a) .



(b) .

Figure 5: Comparison against previous approaches, for top 2, top 5, and top 10 recommendation lists. (a) Precision values. (b) NDCG values.

affect the recommendation performance. Furthermore, the fairness dimension of the recommendation generated in this context will be also evaluated [Pitoura et al. 2022].

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