ECAI 2023
K. Gal et al. (Eds.)

doi:10.3233/FAIA230639

Environmentally-Aware Bundle Recommendation Using the Choquet Integral

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Abstract. Nowadays, the environmental footprint of a process has become an important aspect to be considered in each human activity from industrial production to logistics. Despite this increased awareness, environmental friendliness is a quite new aspect in the IT sector and even less considered in the field of recommendation systems. Bundle recommendation aims to generate bundles of associated products that users tend to consume as a whole under certain circumstances, and poses additional challenges in terms of environmental friendliness. Nevertheless, current bundle recommendation systems fail to consider the environmental impact of the product bundle when generating recommendations.

We introduce a new preference-based approach for bundle recommendation exploiting the Choquet integral. This allows us to formalize preferences for coalitions of environmental-related attributes, thus recommending product bundles accounting for synergies among product attributes. An experimental evaluation on a dataset of local food products in Northern Italy shows how the Choquet integral allows to naturally formalize a sensible notion of environmental friendliness, and that standard approaches based on weighted sums of attributes end up recommending bundles with lower environmental friendliness even if weights are explicitly learned to maximize it.

1 Introduction

Human activities are causing irreversible environmental effects, such as climate change and loss of biodiversity [18]. The consumption of products also contributes significantly to individuals' ecological footprint. The production and consumption of more environmentally-friendly products is an essential step towards achieving more sustainable lifestyles. Environmental consciousness involves comprehending the impact of our actions on the environment and committing to behavior changes for safeguarding the planet. Environmental friendliness is intertwined with sustainability which can be defined as "the quality of causing little or no damage to the environment and therefore able to continue for a long time" [8]. Nowadays, the importance of these concepts is being recognized in all areas of human activity, spanning from manufacturing to transportation.

Despite this growing awareness, sustainability remains relatively new in the IT sector and is even less emphasized in the field of recommendation systems. The few works addressing the sustainability of recommendations [16, 17, 23] focus on single-item recommendations.

In this work, we aim to widen the scope of sustainable recommender systems to deal with the environmental friendliness of product bundles rather than single products. Bundling is the act of selling several products or services together, and a bundle recommendation generates bundles of associated products that users tend to consume as a whole under certain circumstances [19]. Researchers have proposed a wide variety of approaches to tackle this task, ranging from constraints-based methods [2, 28, 15, 24, 27] to graph neural networks [7]. None of these approaches however addresses the environmental friendliness of the bundle being recommended.

We start by defining a notion of environmental friendliness based on attributes of the bundle, such as products being located in the same warehouse, or sharing the same conservation method. We then show how this notion can be easily formalized in terms of the Choquet Integral [12], a generalization of the weighted sum that enables the definition of preferences for coalitions of attributes.

The Choquet integral is a non-linear aggregation function that is attractive for preference modeling because it can model different kinds of interactions between criteria, and includes many aggregators as special cases (e.g. linear additive models, min, max and any other order statistics, leximin and leximax, OWA and WOWA). The Choquet integral has received a lot of attention in the last two decades in the field of decision theory [12] and is now widely used in practical decision making. The interest in using Choquet has driven the development of incremental methods for eliciting the parameters of a preference model based on the Choquet integral [3] or machine learning methods for learning these parameters from data [22]. However, to the best of our knowledge, it has never been used to model preferences for bundles of products, nor to model the environmental friendliness of a recommendation.

We leverage the Choquet Integral to develop an environmentally-aware bundle recommendation system for recommending bundles of food products. When used to recommend bundles of local products from Trentino areas in northern Italy, the system consistently recommends bundles with a higher environmental friendliness score than those that could be selected using more traditional weighted sum scores. This is the case even if the weights of the weighted sum are learned so as to maximize the environmental friendliness score on a training set of candidate bundles, confirming the importance of the Choquet Integral in fully capturing the characteristics of the score.

The rest of the work is organized as follows. Section 2 illustrates

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the related work, while Section 3 formalizes the Choquet Integral. Section 4 provides a motivating example to measure the environmental friendliness of a bundle of products. Then, Section 5 describes the problem setting and our approach. This is followed by an experimental evaluation (Section 6) and some concluding remarks (Section 7).

2 Related Work

Bundle recommendation can be defined as the problem of selecting the best group of items from a potentially very large dataset according to some user preferences. This type of recommendation method can involve a series of tasks such as detecting, completing, and ranking bundles as well as generating bundle explanations and bundle auto-naming [21].

Bundle recommendation typically aims to generate bundles of associated products that users tend to consume as a whole under certain circumstances. Association between products are discovered, for instance, by exploiting relations among bundle products as well as between products and users. A recommendation system based on bundles can provide several benefits such as it can help enhance user experience (e.g., complementary items) as well as increase sales revenue for sellers (e.g., cross-selling) [21].

Bundle recommendation systems can exploit different approaches based on [21]:

1. *Constraint-based methods*: Early studies minimize the cost [11] or maximize the expected reward revenue of a bundle in e-commerce [2, 28]. Other methods [15, 24, 27] combine constraints (e.g., price, ratings, user preference) for travel package recommendations.
2. *Data Mining-based methods*. Association rule mining is utilized in [10, 13] for bundle generation and recommendation. In [1], K-means, Apriori algorithm and SVM are adopted to form and recommend bundles.
3. *Preference Elicitation-based methods*. This framework is proposed [9, 25] to learn utility functions for capturing user preference among various features (e.g., cost and quality) over bundles via user feedback.
4. *Factorization-based methods*. Factorization can be used to jointly factorizes user-item, user-bundle interaction matrices and item-item-bundle co-occurrence matrices, to capture user preference over items and bundles [5].
5. *Sequence-based Neural methods*. A work [14] proposed to combine product hierarchy with transaction data or domain knowledge to identify bundle candidates which are then ranked via an LSTM [20] based deep similarity model.
6. *Attention-based methods.* A factorized attention network can be exploited to aggregate items in a bundle to represent the bundle and jointly model user-bundle and user-item interactions [6].
7. *Graph-based Neural methods.* Graph Convolutional Network can be used on the user-item-bundle tripartite graph and perform both item and bundle recommendation tasks for a mutual enhancement [7].

Although our approach could be framed as a constraint-based method; our approach introduces a new variation of the latter by adopting attribute preferences instead of rigid constraints by exploiting the Choquet integral. The latter allows us to assign coalitions of attribute preferences when evaluating product bundle candidates.

Our work aims to introduce a new approach by adopting attribute preferences instead of rigid constraints by exploiting the Choquet integral. The latter allows one to assign attribute preferences when evaluating product bundle candidates.

A recommendation system can be defined as *environmentally aware* when it also considers the environmental footprint of its recommendations individually or as a whole to generate recommendations. Thus, a preference-based approach can be exploited to express and formalize preferences for environmental-related attributes (e.g., product location, and conservation method) and prioritize bundles of products that minimize the environmental footprint.

Although sustainability is a quite new aspect in the IT sector and even less considered in the field of recommender systems, sustainable-aware systems have been proposed. For instance, a multi-stakeholder utility model is proposed for travel itinerary optimization [16] and promoting the production of environmental-friendly products [17]. While [23] proposed a flexible probabilistic framework that uses domain knowledge to identify sustainable products and customers and uses these labels to predict customer purchases.

3 Background

Choquet Integrals are sophisticated rank-dependent aggregators providing a fine control of interactions between any subset of criteria [12]. The Choquet Integral is an aggregation function defined with respect to a capacity (also called fuzzy measure).

Let $\mathcal{X}$ be the set of alternatives (items, products, candidates...) that need to be compared in order to make a decision. Any alternative $x \in \mathcal{X}$ is evaluated with respect to a set of n criteria denoted $N = \{1, \dots, n\}$, and is characterized by a performance vector $(x_1, \dots, x_n)$; for all $i \in N$, $x_i \in [0, 1]$ represents the utility of x with respect to the criterion i. For simplicity, x will indifferently denote the alternative or its performance vector.

For any alternative $x \in \mathcal{X}$, let $(.)$ denote the permutation of $\{1, \cdots, n\}$ which sorts the components of x by increasing order, i.e. $x_{(i)} \leq x_{(i+1)}$ for $i \in [\![1, n-1]\!]$. Let $X_{(i)}$ denote the subset of criteria with respect to which x has an utility greater or equal to $x_{(i)}$, i.e. $X_{(i)} = \{(i), \dots, (n)\}$; note that $X_{(i+1)} \subseteq X_{(i)}$ for all $i \in [\![1, n-1]\!]$ by definition.

In the sequel $X_{(i)}$ will be referred to as the i^{th} *level set* of x and $Y_{(i)}$ will denote the i^{th} *level set* of an alternative $y \in \mathcal{X}$. Let μ be a Choquet capacity, i.e. a set function defined on 2^N where $\mu(A)$ representing the weight attached to coalition A, for any $A \subseteq N$. A capacity must be such that

- $\mu(\emptyset) = 0, \mu(N) = 1$ and
- $\mu(A) \leq \mu(B)$ for all $A \subseteq B \subseteq N$ *(monotonicity)*.

The Choquet integral is defined by:

$$C_\mu(x) = x_{(1)}\mu(X_{(1)}) + \sum_{i=2}^{n} \left[x_{(i)} - x_{(i-1)}\right] \mu(X_{(i)}) \qquad (1)$$

Hence an alternative x is as least as good as y whenever $C_\mu(x) \geq C_\mu(y)$. For example, consider a problem defined on 3 criteria $\{1, 2, 3\}$ and $x = (10, 6, 14)$ and $y = (10, 12, 8)$ two performance vectors. The computation of their Choquet value with the following capacity μ gives:

	$\emptyset$	$\{1\}$	$\{2\}$	$\{3\}$	$\{1,2\}$	$\{1,3\}$	$\{2,3\}$	$\{1,2,3\}$
μ	0	0.1	0.2	0.3	0.5	0.6	0.7	1

$$C_\mu(x) = 6 + (10-6)\mu(\{1,3\}) + (14-10)\mu(\{3\}) = \; 9.6$$
$$C_\mu(y) = 8 + (10-8)\mu(\{1,2\}) + (12-10)\mu(\{2\}) = \; 9.4$$

Hence we have $C_\mu(x) > C_\mu(y)$, meaning that x is strictly preferred to y. In multi-criteria decision making, one needs to ensure that $C_\mu(x) \geq C_\mu(y)$ whenever x weakly Pareto-dominates y (i.e. $x_i \geq y_i$ for all $i \in N$). This property holds due to the monotonicity of v with respect to set inclusion.

An alternative method for computing the Choquet value makes use of Möbius masses. The Möbius masses associated to a capacity μ are such that $\mu(A) = \sum_{B \subseteq A} m(v)$.

$$C(x) = \sum_{\mathcal{V} \subseteq \mathcal{X}} m(\mathcal{V}) \ \min(\{x \mid x \in \mathcal{V}\}) \tag{2}$$

The Choquet integral is quite general as an aggregation method, as it encompasses other aggregators as a special case. In particular, we emphasize two particular cases

- A capacity is *additive* if, for all disjoint $A, B \subseteq N$, we have that $\mu(A \cup B) = \mu(A) + \mu(B)$. If μ is additive, then the Choquet integral reduces to a weighted mean:

$$C_\mu(x) = \sum_{i \in N} \mu(\{i\}) x_i.$$

- A capacity is *symmetric* if, for any subsets A, B, $|A| = |B|$ implies $\mu(A) = \mu(B)$. If μ is symmetric, the Choquet integral reduces to the so-called *Ordered Weighted Average* (OWA) introduced by Yager [26]:

$$C_\mu(x) = \sum_{i \in N} (\mu_{n-i+1} - \mu_{n-i}) f_{\sigma(i)}$$

with $\mu_i = \mu(A)$, such that $|A| = i$, and σ is defined as before.

4 A Motivating Example

Consider the following straightforward example of bundle recommendation in an online marketplace of food products. The platform seeks to promote product bundles that include locally-produced products while minimizing the environmental footprint of the bundle itself. This aims to attract customers who share an interest in environmental responsibility and to raise consciousness regarding a more sustainable method of acquiring products.

In terms of suggesting such products, the following criteria may be defined:

1. **Same warehouse**: This criterion determines whether food items in the bundle are stored in the same warehouse. Intuitively, shipping from a single warehouse minimizes transportation emissions, making the bundle more environmentally friendly.
2. **Low carbon footprint**: This metric allows quantifying the greenhouse gases emitted during the production and refining of the bundle's products. The underlying assumption is that eco-friendly foods have a smaller negative impact on the environment due to their greater sustainability.

Suppose there exist three bundles, b_1, b_2, b_3 with the following scores on the aforementioned criteria: $b_1 = (1, 0)$, $b_2 = (0, 1)$, $b_3 = (0.55, 0.4)$. Here a score of 1 indicates that the respective criterion has been completely satisfied (e.g., all products in the bundle are stored in the same warehouse), while an intermediate score indicates that the criterion is satisfied by only a fraction of the products. By using a simple weighted sum model, it seems appropriate to assign both criteria equal contribution to the aggregated score (e.g., $w_1 = w_2 = 0.5$), this results in the following scores: $\mathrm{WS}(b_1) = \mathrm{WS}(b_2) = 0.5$, $\mathrm{WS}(b_3) = 0.475$. Therefore according to the weighted sum model, b_1 and b_2 should be preferred over b_3.

However, neither b_1 nor b_2 satisfy the requirements that an e-commerce company may have in offering eco-friendly products. The reason for this is that if we supply products from multiple locations (b_2), the bundle's environmental footprint will increase due to the additional transportation required, whereas if we recommend b_1, we would reduce the number of shipments but recommend products that were potentially manufactured in an environmentally harmful manner.

As a consequence, the most sensible recommendation would be b_3, since almost half of the products offered are manufactured in a sustainable manner (which lessens the impact that they have on the environment) and more than half of the products come from the same warehouse (implying that there will be fewer shipments than b_2). By using the weighted sum, however, it is impossible for b_3 to be offered since $\nexists(w_1, w_2)$ such that $\mathrm{WS}(b_3) \geq \mathrm{WS}(b_1), \mathrm{WS}(b_2)$.

Proof Let's assume that there exists $w = (w1, w2)$ that satisfies the following linear system:

$$\begin{cases} 0.55w_1 + 0.4w_2 \geq w_1 \\ 0.55w_1 + 0.4w_2 \geq w_2 \\ w_1 + w_2 = 1 \end{cases}$$

From the third equation of the system[1] we get $w_2 = 1 - w_1$, which replaced in the first two equations gives us:

$$0.55w_1 + 0.4(1 - w_1) \geq w_1$$

$$0.55w_1 + 0.4(1 - w_1) \geq 1 - w_1$$

Solving these inequalities for w_1 yield:

$$w_1 \leq 0.47058$$

$$w_1 \geq 0.5217$$

Thus, in this example, we argue that the weighted sum yields erroneous recommendations. This is due to the fact that when we are maximizing the bundle recommendation using the weighted sum, we implicitly assume independence between criteria, despite the possibility of synergy between them. In fact, in this example, there is a need to model an interaction between the criteria such that their combined effect is greater than the sum of their individual effects.

To adequately represent this synergy in a Choquet Integral setting, the following capacities can be defined:

- $\mu(\{\texttt{sameWarehouse}\}) = 0.1$
- $\mu(\{\texttt{lowCarbonFooprint}\}) = 0.1$
- $\mu(\{\texttt{sameWarehouse}, \texttt{lowCarbonFootprint}\}) = 1$

A Choquet Integral parameterized with these capacities allows the more eco-friendly bundle b_3 to be proposed, as $C(b_3) = 0.415 \geq C(b_1) = C(b_2) = 0.1$.

5 Bundle Recommendation using the Choquet Integral

5.1 Problem Setting

We consider an e-commerce platform from the Trentino area in Northern Italy that recommends local food products. The goal is to

[1] The results trivially generalize to weights $w_1 + w_2 = k$ for any $k > 0$

empower this platform with a bundle recommendation functionality, that proposes a bundle of associated products on each product page.

Given a set of n products $\mathcal{P} = \{p_1, p_2, ..., p_n\}$ and a reference product $p_{ref} \in \mathcal{P}$; the proposed approach aims to suggest a product bundle composed of k products $\mathcal{B} = \{p_1, p_2, ..., p_k \mid p_k \in \mathcal{P}\}$ associated to the reference product p_{ref} (Figure 1).

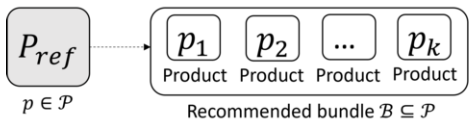

Figure 1. Problem setting

Each product $p_i \in \mathcal{P}$ is characterized by m attributes $\mathcal{Y} = \{y_1, y_2, ..., y_m\}$. In our domain, the relevant attributes for identifying a product and computing the environmental friendliness of a candidate bundle containing it are:

1. Product Name;
2. Production Area;
3. Warehouse Name;
4. Weight;
5. Conservation Method.

For example, the product "Apple Cider Vinegar" is produced in Val di Non, a valley located in Trentino, and it is stored in the warehouse of the city of Trento. It has a weight equal to 700 grams and does not require to be refrigerated.

5.2 *Product-based bundle recommendation*

As already mentioned in Section 2, bundle recommendation can be framed as an optimization problem that aims to select an optimal set of items from a pool of candidates according to a given scoring function for the bundle [19].

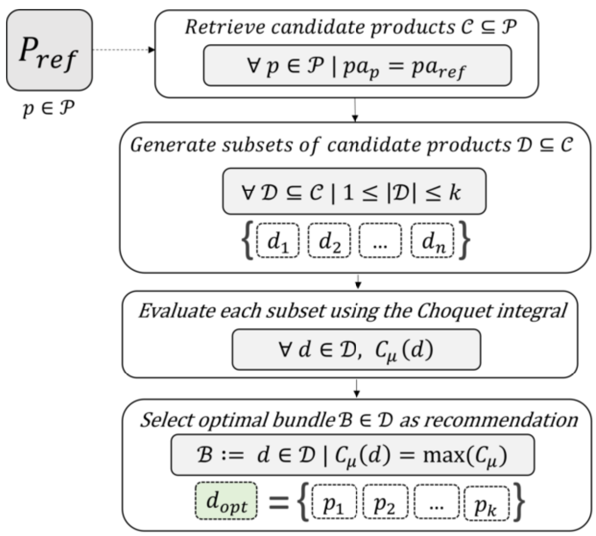

Figure 2. Schema of our approach

The schematic diagram presented in Figure 2 provides a summary of our proposed approach. Firstly, a set of candidate items $\mathcal{C} \subseteq \mathcal{P}$ should be identified by considering a subset of items that can be associated with the reference item $p_{ref} \in \mathcal{P}$. Potential association criteria include shared attributes (e.g., same brand or vendor) or domain-dependent criteria (e.g., market segment or user preferences). In our case, we use the *"Production Area"* (pa) attribute to identify the subset of associated products. Accordingly, the subset of candidate products $\mathcal{C}$ is composed of products having the same production area as the reference product p_{ref}. This product attribute has been chosen to enhance explainability as well as the territoriality of recommendations. The latter is also an important aspect since the considered e-commerce platform aims to promote product territoriality. Product territoriality is used, for instance, to generate territorial product bundles automatically as well as provide users with non-trivial explanations.

Once the set of associated products $\mathcal{C} \subseteq \mathcal{P}$ has been identified as the candidate product set, an optimal subset of products $\mathcal{B} \in \mathcal{C}$ should be selected from them. To achieve this objective, all possible subsets of products with cardinality less than a fixed maximum number k of elements (e.g., $k = 4$) are considered (Equation 3).

$$\forall\, \mathcal{D} \subseteq \mathcal{C} \mid 1 \leq |\mathcal{D}| \leq k. \tag{3}$$

For instance, assuming a user is visualizing the e-commerce page containing the product "Apple Cider Vinegar" (p_{ref}), its production area (pa_{ref} = "Val di Non") is used to retrieve other products produced in the same area (i.e., candidate products $\mathcal{C} \subseteq \mathcal{P}$). Afterwards, all possible subsets of this set of candidate products $\mathcal{D} \subseteq \mathcal{C}$ are generated (Equation 3). All these product subsets are then assessed through some criteria which are evaluated using the Choquet integral as an aggregation function (Section 5.3) which computes a numerical score C_μ for each subset $\mathcal{D} \subseteq \mathcal{C}$. Lastly, the optimal product bundle $\mathcal{B} \in \mathcal{D}$ is selected as a bundle recommendation for $p_{ref} \in \mathcal{P}$ by picking the product subset achieving the highest subset score:

$$\mathcal{B} := d \in \mathcal{D} \mid C_\mu(d) = max(C_\mu)$$

5.3 *Product subsets evaluation*

Each subset of candidate products $\mathcal{D} \subseteq \mathcal{C}$ is characterized by three attributes $\mathcal{X} = \{x_1, x_2, x_3\}$ modelling the properties of the bundle in terms of the relationships between its items. The relevant attributes to characterize the environmental friendliness of a bundle are the following:

1. **Same warehouse** (x_1): the proportion of bundle products that are stored in the same warehouse. This criterion models the preference for product subsets with products from the same physical location, aiming to reduce the environmental footprint of shipping them by *minimizing the number of shipments*;
2. **Same conservation method** (x_2): the fraction of bundle products that have the same method of product conservation. This criterion favors bundles with products requiring the *same type of transport* (e.g., a truck with/without a refrigerated compartment) or the *same parcel type* (e.g., a regular or refrigerated parcel);
3. **Weight similarity** (x_3): a measure of the similarity between the product weights. This is computed as the ratio between the minimum and maximum weight of the products included in the bundle. As bundles having products with similar weights will ideally have a better *packaging*.

The values of these attributes are in the range 0-1 in which 0 represents the least preferred and worst scenario, while a value equal to 1 expresses the preferred and best scenario. The overall preferred case is thus a bundle that contains only products that are located in the same warehouse, have the same conservation method and have identical weight. Nevertheless, these criteria do not have the same importance for maximizing environmental friendliness (Equation 4): being located in the same warehouse (x_1) is more important and preferred in comparison to having the same conservation method (x_2). While bundling products with similar weights (x_3) is the least important criterion among them.

$$x_1 \succ x_2 \succ x_3 \tag{4}$$

The Choquet integral is used to evaluate each candidate bundle $\mathcal{D} \subseteq \mathcal{C}$ according to these criteria. As explained in Section 3, this aggregation function is parameterized by a capacity μ which represents the importance (i.e., weight) of each criterion in the aggregation score. As illustrated in the motivating example, the Choquet integral has the advantage over a standard weighted sum of accounting for the interactions among criteria while keeping, as much as possible, the interpretability of linear models [4]. The capacity values specify preferences for coalitions of attributes, allowing us to evaluate a bundle with respect to their individual attributes and as well with respect to coalitions of attributes.

Note, however, that a precise assessment of the environmental impact of a product bundle would require the capability of tracking all the processes involved (e.g., warehouse management, packing, delivery), needing a large amount of available information would have been needed such as warehouse environmental footprints, vehicle emissions and environmental conditions. In our approach, we make use of the available information to model a score of environmental friendliness to be used as a proxy for the environmental impact.

5.4 *Environmental Friendliness score*

We now show the feasibility of the Choquet Integral in representing a score of environmental friendliness; following the intuition presented in the motivating example (Section 4).

Attributes	Capacity Value
`sameConservationMethod`	0
`similarWeights`	0
`sameWarehouse`	0.25
{sameConservationMethod, similarWeights}	0
{sameWarehouse, similarWeights}	0.5
{sameConservationMethod, sameWarehouse}	0.75
{sameConservationMethod, sameWarehouse, similarWeights}	1

Table 1. Proposed capacity values μ

As shown in Table 1, the capacities for `sameConservation` (x_2) and `similarWeight` (x_3) have been set to zero due to their lack of individual utility in a bundle. Subsequently, considering coalitions of criteria, it is logical to assign distinct significance to the coalition of `sameWarehouse` (x_1) and `similarWeight` (x_3), as well as the combined effect of `sameWarehouse` (x_1) and `sameConservation` (x_2), as both coalitions exhibit a synergistic relationship. However, we believe is not advisable to assign importance to the collection `{sameConservation, similarWeight}`, due to the fact that if there exists a bundle that fulfils this coalition whilst not satisfying `sameWarehouse`, its level of sustainability should remain low.

Furthermore, our approach proposed to adopt the Möbius transform m of the capacity μ (i.e., a different, but equivalent way of writing μ) to enhance the interpretability and explainability of the system. As the Möbius value of an attribute coalition can provide the importance of this coalition "on its own", regardless of the importance of its sub-coalitions [4].

Thus, the product subsets $\mathcal{D} \subseteq \mathcal{C}$ are evaluated, and consequently ranked, through the Choquet integral in its Möbius variant (Equation 2). The latter is used to aggregate all the subset attribute values $\mathcal{X} = \{x_1, x_2, ..., x_i\}$ while jointly considering the capacities of the (coalitions of) attributes (Table 1).

An example of the aggregation scores of the Choquet integral can be seen in Table 2. Lastly, these subsets of candidate products $\mathcal{D} \subseteq \mathcal{C}$ are ordered descendingly and the subset with the highest score computed by the Choquet integral (i.e., C_μ) is picked as recommended bundle $\mathcal{B} \in \mathcal{D}$ for the reference product p_{ref}.

Products	sameC	sameWh	similarW	C_μ
Rondelle melamangio bio Tenero Snack Melamangio	1	0	0.80	0
Confettura di sambuco Succoso mirtillo di bosco	1	0	0.68	0
Confettura di sambuco Sciroppato mirtillo di bosco	1	0	0.85	0
...				
Confettura di mirtillo rosso Mostarda di ribes rosso Mostarda di rosa canina	1	0.42	0.64	0.42
...				
Mostarda di rosa canina Salsa mirtillo rosso	1	1	1	1

Table 2. Output of the aggregation using the Choquet Integral

6 Experiments

Our experimental evaluation aims to study the effectiveness of the Choquet integral in modelling the environmental friendliness of bundles on real data. We thus compare it to an alternative approach that simply models environmental friendliness as a weighted sum of bundle attributes. To make the comparison independent of the choice of the attribute weights, and show that the Choquet integral is *intrinsically* better, we perform a linear regression and learn the weights that maximize the environmental friendliness score of the resulting weighted sum. We perform an analysis to address the following research questions:

1. Does the Choquet integral generate different product bundles in comparison with a weighted sum?
2. Does the Choquet integral generate more environmentally friendly product bundles?
3. Does a recommender system using the Choquet Integral recommend more environmentally friendly product bundles in practice?

6.1 *Bundle comparison*

The first research question was addressed by conducting similarity comparisons between product bundles selected using the weighted sum (baseline) and the Choquet integral (our approach). For each production area, we first randomly discarded a subset of products assuming them to be unavailable and then selected the higher-scoring bundle according to the weighted sum (B_{ws}) and the Choquet integral (B_{chq}). We repeated the procedure 1,000 times and reported average results. We first evaluated the similarity between bundles in terms of products in common, using the Jaccard similarity coefficient:

$$J(B_{ws}, B_{chq}) = \frac{|B_{ws} \cap B_{chq}|}{|B_{ws} \cup B_{chq}|}$$

As can be observed in Figure 3, the Choquet integral selected bundles with different products compared to the weighted sum. Averaging the four production areas considered, the Jaccard similarity is equal to 0.52. This value indicates significant differences between the two approaches, confirming that the Choquet integral generated unique product bundles.

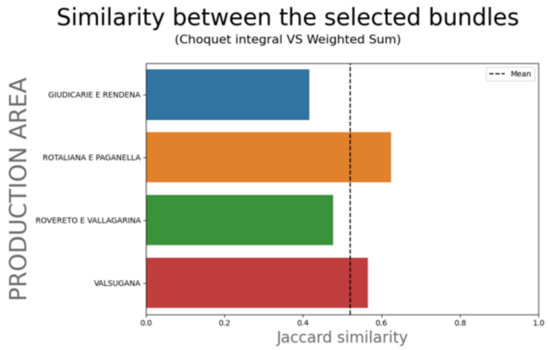

Figure 3. Comparison of the products included in the selected bundles

The second experimental analysis focused on evaluating the impact of the aggregation function on bundle attributes $\mathcal{X}$ and its implications for the environmental friendliness of the bundles.

As outlined in Section 5.3, the ideal scenario for an environmentally-friendly bundle occurs when all products in the bundle are located in the same warehouse ($x_1 = 1$), share the same conservation method ($x_2 = 1$), and have identical weight ($x_3 = 1$). However, these criteria vary in their importance when maximizing the environmental friendliness of a product bundle, as discussed in Section 5.3 and Section 5.4.

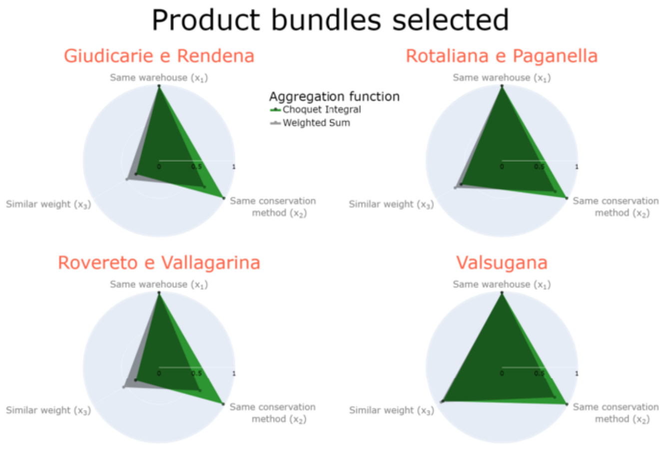

Figure 4. Attributes of the product bundle selected

To compare the effectiveness of the two aggregation functions, radar plots (Figure 4) were used to visually represent the environmental friendliness of the recommended product bundles across different production areas. The findings demonstrated that the use of the Choquet integral resulted in more environmentally friendly product bundles across all production areas. The Choquet integral effectively captured the synergy between x_1 and x_2 while assigning less importance to the criterion x_3. This behaviour was not observed with the weighted sum, as clearly depicted in the two production areas on the left in the radar plots.

Accordingly, it was observed that the utilization of the Choquet integral facilitated the effective modelling of attribute interdependencies. As a result, the preferences expressed in Equation 4 were more comprehensively and accurately satisfied. Consequently, the utilization of the Choquet integral played an important role in maximizing the environmental friendliness of the recommended product bundles.

6.2 *Environmentally friendliness comparison*

The second research question involves assessing the ability of a weighted sum model to approximate the environmental scores. These scores are calculated using a Choquet integral parametrized with the capacities defined in Table 1.

Initially, the Choquet score was computed for each bundle consisting of three items. Afterwards, a linear regression was conducted to determine the weights that produced the most accurate approximation of the Choquet scores. These weights are estimated by solving Equation 5.

$$\begin{aligned} \min_{w_1,w_2,w_3} \; & \sum_{i=1}^{n} (c_i - (w_1 \cdot x_1 + w_2 \cdot x_2 + w_3 \cdot x_3))^2 \\ \text{s.t.} \quad & w_1, w_2, w_3 \geq 0 \\ & \sum_{i=1}^{n} w_i = 1 \\ & \text{solution found: } \hat{w} \approx (0, 0.8684, 0.1315) \end{aligned} \tag{5}$$

Upon parameter estimation, a comparison was made between the Choquet scores of the bundles and their corresponding predicted scores.

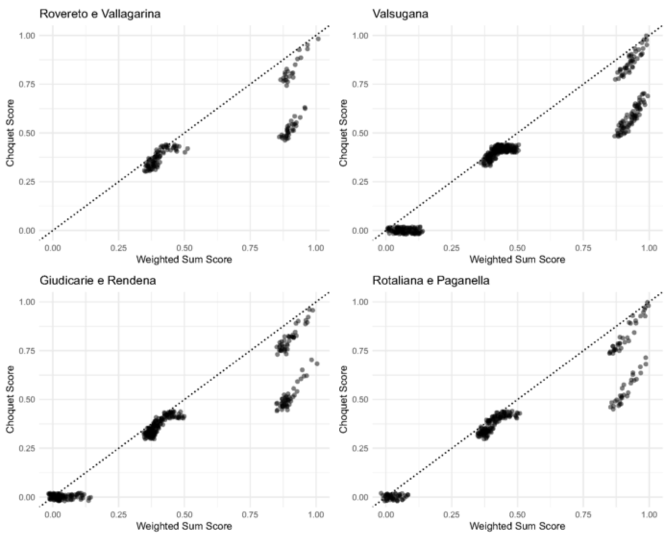

Figure 5. Choquet scores of the bundles and their corresponding predicted scores. To better view the data, jittering was applied.

Figure 5 suggests that there are bundles satisfying extensively all criteria, as shown in the top right corner. Although these observations have highly accurate predictions, there is another cluster of data points with similar weighted-sum scores but a lower Choquet value.

The finding can be explained by the value of the attributes and how the linear model ranks them. Specifically, although `sameWarehouse` and `similarWeight` exhibit a high degree of similarity between the two groups, there exists a disparity in the value of `sameConservation` (1 as opposed to 0.42) linked to the observations. This discrepancy accounts for the difference in the Choquet score. Furthermore, when combined with the fact that the linear model assigns a weight of 0 to `sameConservation` (problem expressed in Equation 5), it can be concluded that the model wrongly treats these two groups of bundles equivalently, thus failing to properly represent the non-linear behavior of the Choquet score. In addition, a residual analysis reveals observable patterns that suggest the insufficient validity of one of the assumptions underlying linear regression. In linear regression, it is expected the residuals follow a random distribution centered around zero, with the absence of any discernible systematic patterns. Nevertheless, this is not the case.

Hence, we claim that the weighted-sum model, despite incorporating optimal parameters, does not exhibit sufficient effectiveness in capturing the synergies among the criteria.

6.3 *Emulating recommendations in real-world settings*

As previously stated, although the linear model exhibits limitations, it may effectively assign appropriate rankings to bundles that demonstrate optimal performance across all three criteria. This phenomenon can be attributed to the exhaustive generation of all possible combinations of products, wherein there exist some combinations that exhibit optimal or near-optimal performance with respect to the given criteria. Consequently, it can be observed that both aggregate functions can potentially indicate the same optimal bundle for all production areas.

Nevertheless, it is a plausible assumption that in actuality, an e-commerce platform may not invariably possess all the products readily available, but rather the opposite. In this case, the absence of a particular product automatically implies the unavailability of all associated bundles.

This rationale led to the formulation of the third research question, and to tackle this problem, we conducted 1,000 simulations where we randomly removed a fraction of items considering them as unavailable. For each simulation and production area, we extracted the bundles having the highest score according to the Choquet integral and the weighted sum respectively. We then computed the regret of the weighted sum recommendation as the difference in environmental friendliness score (which, as shown in Section 5.4, can be formalized as the Choquet integral), between the two bundles.

Following the conclusion of the simulations, an analysis of the collected data was performed. The distribution of regret across the production areas is illustrated in Figure 6. It is evident that the limited availability of certain products has resulted in instances of regret in the recommendations, especially for the Valsugana production area.

Figure 6 also provides a clearer understanding of the frequency by depicting the proportion of recommendations with and without regret. In all production areas, it is noticeable that the weighted-sum model often overlooked the optimal bundle that was available, in favor of a less sustainable alternative. In certain regions, this phenomenon occurs in more than half of all cases.

Thus, with regard to the third research question, it can be stated that a linear model frequently generated inaccurate recommendations, even when applied to a practical situation where certain products are unavailable.

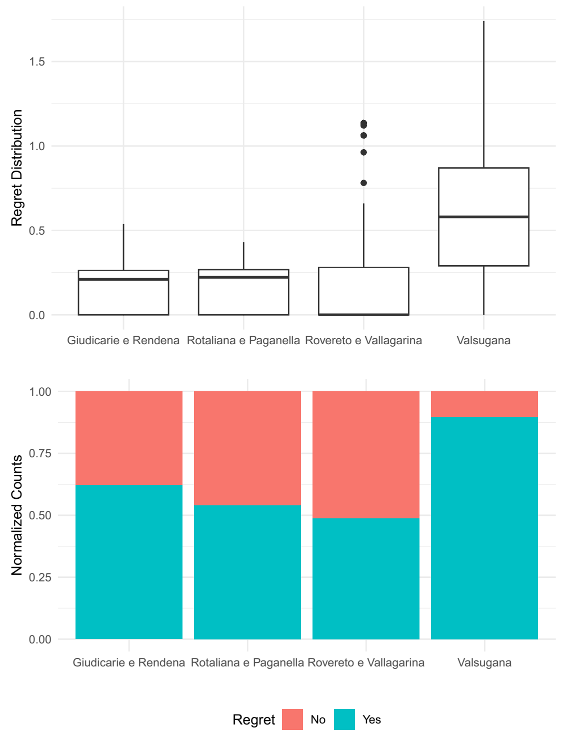

Figure 6. Regret distribution and frequency by production areas

7 Conclusion

In this study, we proposed a novel preference-based approach for bundle recommendation utilizing the Choquet integral, a flexible aggregator commonly used in multi-criteria decision theory. By incorporating the Choquet integral into our framework (Section 5.2), we were able to formalize preferences for coalitions of environmental-related attributes, enabling the recommendation of product bundles that consider synergies among these attributes.

Our experimental evaluation (Section 6) demonstrated that the utilization of the Choquet integral significantly improved the ability of the recommender system to capture a meaningful notion of the environmental friendliness of product bundles. In contrast, conventional approaches based on weighted sums of attributes failed to generate optimal product bundles.

Future research endeavours could focus on further enhancing our preference-based approach for bundle recommendation by incorporating preference elicitation techniques.

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