# Collaborative learning of argumentative recommenders

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Recommender systems aim at recommending some item as the most appropriate one for the user. This article introduces a new way of measuring appropriateness for the user: an item is among the most appropriate ones if it is among the preferred items of the user when considering all arguments in favor or against all possible items. We describe precisely this goal and describe what a recommender system aiming for that goal could look like, called an Argumentative Recommender. We also provide a way of testing whether a recommender system has achieved the goal, which can be used to compare such recommender systems, and outline a way of building such a system.

## 1. Introduction

In a situation where a user has to choose an item among a set of possible items, recommender systems aim at recommending some item as most appropriate for the user. In the collaborative learning community, this is usually taken to mean: recommend an item among the most preferred ones for the user. In this article, we want to propose another goal for recommender systems. We keep the global aim of recommending some item as most appropriate for a given user, but propose an original understanding of appropriateness. The goal we propose is to recommend items that are in the Deliberated Preference (DP) of the user, and to defend its claim that the items indeed are in the DP of the user. The DP of the user captures what she prefers when considering all arguments in favor or against all possible items. By contrast, we call "intuitive preference" the notion of preference as usually understood when talking about recommender systems, and which does not consider arguments. Thus, the goal we propose is appropriate when one is interested to help the user form a deliberated judgment about which item is best, rather than identify which item the user intuitively prefers. Because this will be done using systems that argue, we call the kind of system we define here an Argumentative Recommender (AR). Further motivations for this new goal are described in section 2, and it is precisely defined in section 3.

Together with this new goal, it is necessary to propose a corresponding measure of the performance of the recommender system (done in section 4). In the classical approach, measuring the performance of the system amounts to compare its claims (the items it proposes as preferred) to reality (the preference of the user). Because the DP of the user is not directly observable, this direct check of correspondance becomes non applicable. However, as will be shown, the problem of evaluating the quality of an AR can be framed as a prediction problem (although involving different objects), thereby recovering the possibility of empirical validation by confrontation between claims of the system and reality.

Section 5 relates our proposal to the literature. Sections 6 and 7 then sketch one possible way of undertaking this task, applicable in specific context: recommend on the basis of explicit principles coming from decision theory.

This article is an extended version of Cailloux [2018].

## 2. Motivation

This article discusses a notion of preference that possibly changes when confronted to arguments. That is, we assume that the user's knowledge of which item is best for him is not necessarily fixed a priori, and in particular, that the user may change his mind when presented with arguments in favor of, or counter-arguments against, adopting various items.

By contrast, the notion of preference considered by classical recommender systems (usually left implicit) is that the user intuitively knows what he prefers, and that this is the right basis for him to decide. This notion can be related to the conception of preference put forth by von Neumann and Morgenstern [1944, p. 16] in their seminal work (cited by Fishburn [1989]). They write that "It is clear that every measurement – or rather every claim of measurability – must ultimately be based on some immediate sensation (. . . ). In the case of utility the immediate sensation of preference (. . . ) provides this basis." When applied to collaborative filtering, this view suggests that the user does not need help for comparing pairs of item: the job of the system is merely to relieve the user from having to search through the whole set. The user, when presented with a pair of items, knows immediately which one he prefers, possibly after having tried them both. Similarly, when the user has already provided some comparisons of preference, this is the final word about those pairs.

This notion of preference as "intuitive" preference is not always the best basis to ground recommendations. Indeed, the user might be unwilling to judge what is best for her on the sole basis of her unaided intuition. Indeed, there are cases where the user can't easily try out the items. An example is a non repeatable choice, such as choosing a university to study in. More generally, identifying the best choice may require deploying a complex thought process designed to ensure, as much as possible, that all the relevant argument have been taken into account, rather than purely rely on intuition. Consider the decision of which smartphone, or which house, to buy. This particularly applies when a notion of fairness is involved, for example when determining who will receive a prize, or how to distribute revenue in a society, or to which cause I should donate money. Furthermore, the user might appreciate being pointed to some non-salient feature of the items under comparison; for example, a user might feel an intuitive attraction to the plane alternative when chosing a transportation means for holidays, seeing that the flight time is only one hour compared to three hours by train, but change her mind when being reminded that the total travel time should be taken into account. Finally, an argument coming from psychology is that unaided intuition is known to be sensible, in some contexts, to framing effects that would perhaps not be considered relevant (by the user himself) when considering arguments and counter-arguments [Kahneman, 2013]. An example that involves several kinds of the aformentioned concerns is devising a decision procedure to adjudicate credit requests: the decision maker probably wants to include fairness considerations in order to avoid (possibly unconscious) appearance of unjust discriminations. Even if only profit considerations are to bear, the decision maker might want the procedure to go beyond reflecting the bare intuition of an expert.

# 3. Definition of deliberated preference

This section describes the new understanding of preference we propose, called the DP of the user (it is a simplification of the recently proposed concept of deliberated judgment [Cailloux and Meinard, 2018]).

We consider given a set of items $\mathcal{J}$ among which a user $i$ wants to choose. We also consider given a set $S^*$ containing arguments that may possibly help $i$ form a deliberated opinion about which item is best for her. Elements of $S^*$ are not detailed and can be conceived as strings in a natural language. An example of an argument is $s =$ "Item $j$ is better than item $j'$ because $j$ has a good performance on criteria 'price' and 'speed' while item $j'$ has a good performance only on criterion 'aspect', which you do not consider important".

The DP of $i$ is defined as the subset of items that are considered by $i$ as having no item strictly preferred to them, considering all arguments in $S^*$. To define this properly, we assume we can observe the reaction of $i$ to arguments, as follows.

Define $\rhd$ as a binary relation over $\mathcal{J} \times S^*$, representing the results of the following experiments. Present $(j, s)$ and $(j', s')$ to $i$ and let her decide, considering the arguments $s$ and $s'$, which item among $j$ and $j'$ she prefers, if any. Define $(j, s) \rhd (j', s')$ iff $i$ strictly prefers $j$ to $j'$, given $s$ and $s'$. Note that if no strict preference holds, $\rhd$ does not relate these two pairs (thus $(j, s) \not\rhd (j', s')$ and $(j', s') \not\rhd (j, s)$). If the answer of the individual changes when asked several times the same question, we consider that no strict preference holds, as we are interested in the stable part of the individual's preference. The relation $\rhd$ plays here the role of the basic measurement von

Neumann and Morgenstern talk about (see section 2).

The DP $J_i \subseteq \mathcal{J}$ of $i$ in that situation contains an item $j$ iff $\forall (j', s') \in \mathcal{J} \times S^*, \exists s \in S^* \mid (j', s') \not\rhd (j, s)$.

# 4. Prediction of deliberated preference

An AR should be able, given a user, to single out some items as being in his DP, and some items as being not in his DP, and to defend its claims by arguing correspondingly. Formally, an AR $\eta$ has a *scope* $I$, representing a set of users whose DPs it claims to be able to predict. Given a user $i \in I$, $\eta$ returns a tuple $(J_\eta, f_\eta^{\text{def}}, R_\eta, f_\eta^{\text{att}})$ that represents the claims of $\eta$ concerning the user $i$ as well as the necessary means to back up its claims, using functions that we call "attack" and "defense" argumentation strategies, whose roles will appear clearly when validating the claims of $\eta$ as described in the next paragraph. Elements of this tuple depend on $i$, though this is omitted from the notation. In this tuple, $J_\eta \subseteq \mathcal{J}$ is a set of items that $\eta$ claims are among the DP of $i$, $f_\eta^{\text{def}} : J_\eta \times \mathcal{J} \to S^*$ is an argumentation strategy used to defend items in $J_\eta$, $R_\eta \subseteq \mathcal{J} \times \mathcal{J}$ is a binary relation that contains pairs of items $(j, j')$ such that $\eta$ claims that $i$ deliberately prefers $j$ to $j'$, and $f_\eta^{\text{att}} : R_\eta \to S^*$ is an argumentation strategy used to support the claims represented by $R_\eta$.

An AR is correct if, informally, its functions $f_\eta^{\text{def}}$ and $f_\eta^{\text{att}}$ indeed justify its claims. For example, it is required of $f_\eta^{\text{def}}$ that, when given an item $j'$ and given an item $j \in J_\eta$ considered by $\eta$ to be in the DP of $i$, $f_\eta^{\text{def}}$ produces an argument that successfully defends $j$, whatever the argument given in favor of $j'$. More precisely and completely, an AR $\eta$ is said to be *correct* about a user $i$ iff $\forall j \in J_\eta, j' \in \mathcal{J}, s' \in S^* : (j', s') \not\rhd (j, f_\eta^{\text{def}}(j, j'))$ and $\forall (j, j') \in R_\eta, s' \in S^* : (j, f_\eta^{\text{att}}(j, j')) \rhd (j', s')$. An AR is *correct* iff it is correct about all users in its scope.

Importantly, correctness about $i$'s attitude towards arguments implies the validity of the claims concerning the DP of $i$. Formally, an AR is *valid* iff $\forall i \in I : J_\eta \subseteq J_i$ and $R_\eta(\mathcal{J}) \subseteq \mathcal{J} \setminus J_i$, where $R_\eta(\mathcal{J}) = \{j' \in \mathcal{J} \mid (j, j') \in R_\eta \text{ for some } j \in \mathcal{J}\}$ represents the items postulated by $\eta$ as being less good than some other item for $i$. It is an important fact that correctness is sufficient for validity (the proof is omitted).

**Theorem 1** *If an* AR $\eta$ *is correct, then it is valid.* □

This notion of validity cannot be used to definitely prove that a recommender system has correctly captured $i$'s DP. But it can be used to *compare* ARs, by letting them "debate", in the following way. Consider two ARs $\eta$ and $\eta'$ dealing with the same set of items $\mathcal{J}$ and having overlapping scopes (so that the intersection of the users in their scopes is not null). Such ARs could for example have been built by different research teams studing the same recommendation setting. Considering a user $i$ in both their scopes, obtain two tuples, $(J_\eta, f_\eta^{\text{def}}, R_\eta, f_\eta^{\text{att}})$ and $(J_{\eta'}, f_{\eta'}^{\text{def}}, R_{\eta'}, f_{\eta'}^{\text{att}})$. Assume they strongly disagree on the prediction of the DP of $i$, meaning that for some item $j \in \mathcal{J}$, the first system claims that $j$ is in the DP of $i$, thus $j \in J_\eta$, and the second system claims it is not, thus $\exists j' \mid (j', j) \in R_{\eta'}$. Suffices now to let the two systems play against each other and use $i$ as a judge. That is, we obtain an argument from the first system in defense of its claim, $s = f_\eta^{\text{def}}(j, j')$, and an argument from the second system, $s' = f_{\eta'}^{\text{att}}(j', j)$. We present $(j, s)$ and $(j', s')$ to $i$ and accordingly obtain $(j', s') \rhd (j, s)$ or $(j', s') \not\rhd (j, s)$. In the first case, the first system is invalidated, in the second one, the second system is invalidated.

# 5. Relation to existing literature

Approaches exist which propose to estimate a decision-theoretic model that best approximates a user's observed behavior [Greco et al., 2010, Sobrie et al., 2018]. Furthermore, numerous approaches have been proposed for modeling preferences using machine learning methods [Fürnkranz and Hüllermeier, 2010]. Several recent articles in particular use active learning approaches to build a preference model of a user in a recommendation setting [Teso et al., 2016, 2017, Dragone et al., 2018b, Erculiani et al., 2018, Dragone et al., 2018a]. Yet other approaches propose to use argumentation theory [Besnard and Hunter, 2008] to enhance recommender systems [Chesñevar et al., 2009, Rago et al., 2018]. These trends constitute promising areas of investigation for building ARs. Such articles typically are focused on producing concrete recommender systems. By comparison, this article is situated on a more methodological level as it proposes a precise definition of a new goal for recommendation systems, and a way of comparing ARs experimentally when their predictions disagree. Similarly, the very thorough review provided by Nunes and Jannach [2017] exhibit ten articles that generate explanations using collaborative filtering techniques. None of those are interested in a goal similar to ours or use decision-theoretic preference models as explored here (with the interesting exception that Marx et al. [2010] use a model that can be considered as a simplified MAVT model, but this model does not intervene in the collaborative filtering part of their hybrid approach).

The idea of using a human as a judge to compare argumentative systems also appears in the paper of Irving et al. [2018]. There are also articles that are interested in using collaborative filtering on the basis of implicit feedback [Rendle et al., 2009, Hu et al., 2008], an idea somewhat related to ours in the sense that the observed data is not directly the one the model tries to predict. Also somewhat related are articles interested in collecting preference data for improving the learning [Sepliarskaia et al., 2018]. Chen et al. [2018] review techniques that make use of supplementary data in collaborative filtering tasks.

Some works are technically closer to our approach. Johnson [2014] uses logits for matrix factorization for implicit feedback. In that work, the authors model the interaction between a user and an object (0 or 1) as a logit function applied to some latent factors. Their approach cannot be directly applied to model a score. Zhang et al. [2014] use a factorization model which decomposes its latent factors for approximating three matrices (namely the ratings matrix and implicit feedbacks as a user-feature matrix and as an item-feature matrix). The implicit feedback considered in that paper give some information on how relevant a feature is to a user and how relevant it is for an item in a rating. Then, when recommending an object to a user, reconstructing the implicit feedback matrices can be seen as an explanation on this recommendation. Note that it can be seen as an explainable version of [FY: Factorization machine Rendle 2010]

An important literature analyzes necessary and sufficient conditions for the existence of various decision-theoretic models [Krantz et al., 1971, Gonzales, 1996, Bouyssou and Pirlot, 2015], this will be important in conjuction with the approach for building ARs on the basis of such models as exposed in section 6.

Finally, this proposal is strongly related to the field of explainable AI [Zhang and Chen, 2018], although to the best of our knowledge, work therein do not take routes similar to the one proposed here.

# 6. Recommend on the basis of explicit principles

Section 3 described a new kind of recommender system, that consider the recommendation task under a different light, and section 4 described how to evaluate such ARs. But such ARs do not exist yet. One way of building such systems consists in adapting existing works (related references are given in section 5). Another way is to design an AR from the ground up specifically for reaching the goal described here. Although it is not the main point of this conceptual article, roughly sketching a possible way of doing this could help make this proposal more concrete. This section first briefly describes such a possible way in the context of collaborative settings, namely, by using explicit principles, then indicates some conditions on the context that must be fulfilled in order to make the proposed approach applicable. The next section more concretely sketches a way of learning such a model and of studying its performances with numerical experiments.

Consider a collaborative learning setting, where we have collected ratings from users on items, assumed to represent their intuitive rather than deliberated preference. A simple approach to build a proof-of-concept AR in such a context is to represent the DP of $i$ as a weak order $\succeq \subseteq \mathcal{J} \times \mathcal{J}$, and to consider this weak order as representable by a decision theoretic model.

The weak order $\succeq$ corresponds to $R_\eta$ and its maximal elements correspond to $J_\eta$ (though the definition tolerates other possibilities). Decision theory has proposed models to represent preferences of decision makers. Even though decision theory does not explicitly use the concept of deliberated preferences as defined here, because its models are conceived for grounding decisions in sound principles, they might be adequate to model deliberated preferences. The model adopted for this article is Multiple Attribute Value Theory (MAVT) [Keeney and Raiffa, 1993], a set of principles for choice well-known in decision theory.

Existing works [Carenini and Moore, 2006, Labreuche, 2011] describe how to generate arguments in natural language that explain, on the basis of an MAVT model, why an alternative is preferred to another one. This provides a starting point for the step of generating arguments. More generally, by picking functions supported by well-studied decision principles, it is made possible to build arguments on the basis of those same principles, and it might be considered that such arguments will have a fighting chance against counter-arguments.

Finally, assume the intuitive behavior of the user is a noisy version of her DP. (More elaborated developments could incorporate knowledge from experimental psychology about differences between the usual behavior of users and the one dictated by decision-theoretic models [Kahneman, 2013].) Then, our task becomes close to one of classical collaborative learning, as MAVT defines the class of functions among which to select an optimal one during learning. The next section draws on this approach to effectively propose an MAVT-based AR.

The principles on which MAVT rests are applicable in specific contexts: those in which the items (among which the user aims to choose) can be exhaustively described by a set of objective descriptors of the items, known a priori, and which each evaluate the desirability of the items on some aspect. Such aspects are called criteria. Exhaustively described means that the user considers nothing else than the performance of the items on the criteria as relevant for the recommendation. (Although this notion of exhaustivity is of necessity an approximation, there are applications where this approximation will be reasonable.) Thus, consider a set of criteria $\mathcal{C}$ is known, together with corresponding scales $X^c, c \in \mathcal{C}$, and descriptors $b^c : \mathcal{J} \to X^c, c \in \mathcal{C}$, that each describe the items on a specific criterion $c$. Here we use superscripts for criteria indices because we will need subscripts for user indices; these superscripts do not represent exponentiation.

In such a context, an MAVT model representing $\succeq$ is a set of functions $v^c : X^c \to \mathbb{R}$ (one for each criterion) such that $j \succeq j'$ iff $\sum_{c \in C} v^c(b^c(j)) \geq \sum_{c \in C} v^c(b^c(j'))$.

Consider as an example the choice of an apartment to rent for holidays. A reasonable approximation of an exhaustive set of criteria might be: surface of the living room, number of beds, distance to city center, modernity of equipment, presence of a washing machine, price. Other examples where building an AR on the basis of an MAVT model may be appropriate include: buying a smartphone, buying a computer, choosing a flight to reach a given place, choosing who to give a "best student" award among a given classroom, locating a new factory, or choosing a university to study at.

By contrast, a recommendation task is not suitable for the approach proposed in this section if no set of criteria is known that fully describe the desirability of an item. This might be the case if the decision problem incorporates a strong aesthetic dimension, for example, a choice of movie to watch. For such applications, our approach might be applicable to a subset of users, but fail for another set of users who pay attention to dimensions not captured by the criteria, as also observed by Marx et al. [2010].

# 7. Estimating an MAVT model

We are finally left with the concrete task of learning MAVT models that represent the users' DPs in a collaborative learning setting.

Assume we have a set of users $I$ of size $m \in \mathbb{N}$, a set of items $J$ of size $n \in \mathbb{N}$, a set of observed pairs $O \subseteq I \times J$ and a relation $r$ mapping those observed pairs $(i, j) \in O$ to some rating $r_{ij}$, an integer in $[\![1, 5]\!]$ (this notation designates intervals in the integers). We also assume known the set of criteria $\mathcal{C}$ of interest to the user (see section 6). Each criterion $c \in \mathcal{C}$ is associated to a (known) descriptor $b^c : J \to [0, 1]$ which represents the performances of the items on the given criterion. Thus, the scales $X^c$ used for measuring the objective performances of the criteria are here all supposed to be $[0, 1]$, for simplicity.

## 7.1. MAVT with logits

In order to learn an MAVT model per user, we choose here to learn partial value functions that have the same shape for all users, and let the weights of these partial functions vary individually. This assumes that users appreciate trade-offs within a criterion in a similar way, but are differenciated by the importance they give to different criteria. We define, for each user $i$, a weight vector $w_i$ that associates to each criterion $c$ a non negative real number $w_i^c$. The partial value functions are represented by parameterized logit functions, defined as $\sigma(\alpha, \beta, x) = \frac{1}{1+\alpha e^{-\beta x}}$. Thus, the parameters are $\alpha^c, \beta^c$, for each criterion $c$, used for representing the partial value functions shapes; and $w_i^c$, for each criterion $c$ and user $i$.

Let $L$ denote a loss function that compares the ratings $r_{ij}$ to our approximations of the ratings, for $(i,j) \in O$; let $\lambda$ denote a real number used to ponder our two objectives, one aiming for a best fit, another aiming for regularized weights; and let $\|.\|_2^2$ denote the squared L2 norm.

We want to find $\{w_i^c, i \in I, c \in \mathcal{C}\}, \{\alpha^c, c \in \mathcal{C}\}, \{\beta^c, c \in \mathcal{C}\}$ that optimize the following objective:

$$\min_{w,\alpha,\beta} \sum_{(i,j)\in O} L(r_{ij}, \sum_{c\in\mathcal{C}} w_i^c \sigma(\alpha^c, \beta^c, b^c(j))) + \lambda \sum_{i\in I} \|w_i\|_2^2.$$

We force $w_i^c$ and $\alpha^c$ positive to respect the preference direction: we assume the data is encoded so that higher $b^c(j)$ means preferred performance.

Being formulated as an optimization problem, it can be solved using a classical algorithm (like Adam optimizer).

Note that, although using a logit function, our formulation is different from Johnson [2014], as our formulation relies on a MAVT framework and enables us to estimate a score.

We define the partial value functions $v_i^c$ and aggregated value function $v_i$ representing our estimation of the deliberated preferences of user $i$ as $v_i^c(j) = \sigma(\alpha^c, \beta^c, b^c(j))$ and $v_i(j) = \sum_{c\in\mathcal{C}} w_i^c v_i^c(j)$.

## 7.2. Learning an absolutely-scaled version of MAVT

The foregoing approach must be slightly adapted before being usable in the context we postulated. The ratings $r_{ij} \in [\![1, 5]\!]$ that we observe are given on an absolute scale: the lowest point (1) is meaningful, and the unit is fixed. On the contrary, the evaluations given by a classical MAVT model have no zero and no unit: given a value function $v$ representing the user's preferences, the value function $v' = \alpha + \beta v$ represents it equally well, for any constant $\alpha$ and positive constant $\beta$.

To bridge this discrepancy, we add a fictitious criterion $d$ and extend the set of criteria to $D = \mathcal{C} \cup \{d\}$. The learned aggregated value function thus becomes $v_i = \sum_{c\in D} w_i^c v^c$. The partial value function $v^d$ associated to that added criterion is constant, equal to one for its whole domain. The associated weight $w_i^d$, which is learned together with the other parameters, is used to indicate the "bias" of the user $i$. It is interpreted as the value of the "zero" item: if an item has all zero performances, its rating is $w_i^d$. If an item fares better than the zero item, $v_i$ will increase its rating. A consequence of this choice is that the whole range of the scale is not used, which might correspond to the rating behavior of real users. Furthermore, the learned weights are not normalized, and are designed to be interpreted in an absolute sense: $w_i^c$ represents the number of stars added by the corresponding criterion when the item is perfect on that criterion, from the point of view of user $i$.

Our final learning task becomes:

$$\min_{w,\alpha,\beta} \sum_{(i,j)\in O} L(r_{ij}, \sum_{c\in\mathcal{C}} w_i^c \sigma(\alpha^c, \beta^c, b^c(j)) + w_i^d) + \lambda \sum_{i\in I, c\in D} \|w_i^c\|_2^2.$$

## 7.3. Testing with empirical data

The obtained model can be tested in two very different ways. One would involve treating it properly as an AR, and confronting its propositions to the judgments of real users, by comparing its propositions to the ones of another AR in a debate, as indicated in section 4. This is however not yet applicable here, as our model does not produce arguments: we only sketched a first step, aimed at learning MAVT models, which should be included in a strategy similar to the one proposed in section 6 to obtain a full-fledged AR.

Another way to test the obtained model, simpler but less satisfactory, is the more familiar comparison of the predictions of the model to a pre-existing database of (intuitive) preference data. Although the goal of an AR is not to merely predict intuitive preferences (but rather to predict deliberated preferences), it can still be instructive to see how the obtained AR performs with this task. However, because the learning goal we propose is new, it is difficult to find suitable empirical datasets to achieve this comparison. Such dataset should include items that can be objectively described on a set of criteria (such as hotels or smartphones), together with their descriptions, as explained in section 6, and with ratings given by several users, as in a collaborative setting. Such datasets certainly exist within databases of web vendors, or probably could be created by combining several sources of information, but we have not found ready-made publicly available ones. We observe that this is a common problem within recent research involving elaborated preference models, for example, Teso et al. [2016] also use artificial data to test their proposal.

## 7.4. Testing with artificial data

The model can be tested with artificial data, in order to see how robust it is facing perturbations in the data we learn from. This section describes how such data could be generated.

Let us consider that users share a personally-scaled and noisy version of an additive value representation. Let $l(x^1, x^2)$, with $x^1, x^2 \in [0,1], x^1 < x^2$, denote the piecewise linear partial value function $f : [0,1] \to [0,1]$, with discontinuity points at $x^1$ and $x^2$ and $f(0) = 0$, $f(x^1) = 1/3$, $f(x^2) = 2/3$, $f(1) = 1$.

We define partial value functions for each user and criteria so that the average $v^c$ (over all users) is $l(x^{c,1}, x^{c,2})$, with $x^{c,1}$ drawn from a $t(0, 1/2)$ distribution, where $t(a, b)$ denotes the symmetric triangular distribution with extreme points $a$ and $b$, and $x^{c,2}$ drawn from a $t(1/2, 1)$ distribution. For each user $i$ and criterion $c$, we draw the perturbation parameters $\alpha_i^{c,1}$ from $t(-0.5x^{c,1}, 1/2x^{c,1})$ and $\alpha_i^{c,2}$ from $t(-0.5(1-x^{c,2}), 1/2(1-x^{c,2}))$, and define $v_i^c = l(x^{c,1} + \alpha_i^{c,1}, x^{c,2} + \alpha_i^{c,2})$.

We draw the weights of the user $i$ (for each $i$) by drawing $\omega_i^c$, for each criterion, from $tN(1/2, 0.1)$, where $tN$ denotes a normal distribution truncated at zero and one. Then we define $w_i$ as the normalization of $\omega_i$ (so that $\sum_c w_i^c = 1$).

These parameters define together the value functions of each individual: given an item $j$, $v_i(j) = \sum_c w_i^c v_i^c(b_j^c)$. This number is between 0 and 1, with 1 representing an ideal item. Furthermore, for each invocation of $v_i$, we draw an error term $\epsilon$ from $N(0, 0.1)$, representing the noise, where $N$ denotes a normal distribution, and use effectively $v_i' = v_i + \epsilon$.

We draw randomly the performances of a set of items $\mathcal{J}$. For each $j \in \mathcal{J}$ and criterion $c \in \mathcal{C}$, $b_j^c$ is drawn from $tN(0.5, 1)$. Because users tend to not use the full range of the scale offered to them when rating items, we assume a non linear relation from $v_i'$ to the rating. We draw, for each user $i$, a number $z_i$ from a $N(2, 1)$ distribution truncated at zero, scale $v_i$ with $s_i = 5 - z_i$ so that the best item gets five stars, and define $r_{ij} = [s_i v_i'(j) + z_i]$, where the brackets designate the operation of rounding to the closest integer. [YM: et ça donne quoi ?]

# 8. Conclusion

The main goal of this article is to propose a new goal for recommendation systems. Such systems argue for their propositions, and are appropriate when the user does not a priori know which item to choose, not just because of the difficulty of exploring the set of items to choose from, but because of the difficulty of forming a qualified preference. Thus, such systems are appropriate when the user desires some help for choosing by taking all relevant arguments into account, and especially so when the user desires to choose in a systematic, principled way. The article presented the idea generally and abstractly in sections 1 to 5.

A second goal of this article is to sketch a way of building such ARs. To that end, the next two sections became progressively more concrete and less general. Section 6 proposed a way of building an AR by learning models as proposed in decision theory. The intuition is that, first, such models are particularly appropriate to help a user deliberate; second, such models can be learned reasonably easily using techniques known in machine learning; third, such models can "reasonably easily" be used to generate textual arguments understandable by a decision maker thanks to the already existing works in this direction in artificial intelligence and the axiomatic works in decision theory. Section 7 illustrated the second point by describing a way of learning an MAVT model in a collaborative learning setting.

It is important to realize that the general part of this article (sections 2 to 4) is not conceptually dependent on its most concrete parts (sections 6 and 7). ARs could be built on different bases than decision-theoretic models. For example, gathering existing arguments in textual forms on various sources on the web and displaying them as-is to the user, or using natural language processing techniques. Such approaches could overcome an important limitation of the technique described in section 6, as they could be applied even when the exhaustivity of the set of item descriptors is not guaranteed. Similarly, the concept could be applied to settings different than collaborative learning, or using learning techniques different than the one section 7 investigates.

This article has only begun to explore the difficulties that need to be overcome in order to build a complete AR, let alone a working ecosystem of ARs. The concrete approach presented in the later part of this article may be judged naïve, and is incomplete as it does not indicate how to generate arguments from the models learned. Furthermore, methodological issues are to be explored, a work that is also only beginning [Cailloux and Meinard, 2018]. Let us mention two of these methodological issues.

First, although this article contrasts our proposal to a single notion of "intuitive" preference, there are in fact important differences between perspectives taken by various authors in the history of economics about preferences. We can't give here justice to the extensive literature in philosophy and in economics that has discussed this interesting subject [Bruni and Guala, 2001]. This issue is further commented in another article [Meinard and Cailloux, 2018].

Second, it needs to be guaranteed that ARs are not used as propagandist devices to convince users to do what the conceiver of a particular AR desires; on the contrary, a proper debating environment has to be set up (section 4 describes how to let two ARs "debate"), where sufficiently diverse sources of opinions produce ARs, thereby fulfilling the conditions for making reasonably sure that the user's deliberated judgment has been reached. Only in such conditions will this environment be able to help the user legitimately.

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# A. Collaborative filtering with explanations

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