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Preferences in AI: An overview

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ABSTRACT

This editorial of the special issue "Representing, Processing, and Learning Preferences: Theoretical and Practical Challenges" surveys past and ongoing research on preferences in AI, including references and pointers to the literature. It covers approaches to representation, reasoning and learning of preferences. Methods in AI are contrasted with those in related areas, such as operations research and databases. Finally, we also give a brief introduction to the contents of the special issue.

1. Introduction

Even if the purpose of reasoning is often to support decision making, only since the 1990s has decision theory had much impact on AI, initially in connection with planning under uncertainty (e.g., [1]). The modeling of preferences is a prerequisite for any kind of further decision analysis. It becomes a non-trivial issue as soon as the preferences cannot be expressed in a binary way, distinguishing good alternatives from bad ones, and easily enumerated in terms of an explicit list.

The treatment of human decision problems requires a clear distinction between knowledge (pertaining to the current state of the world) and an agent's preferences among possible states. Mixing binary preferences, easily expressed in logic, with a logical knowledge base leads to 'taking desires for reality'. Knowledge may be pervaded with uncertainty, an issue that has been considered in AI since the emergence of expert systems. In principle, uncertainty may also apply to preferences, but this is less crucial since decision under uncertain preferences is rarely considered. Instead, starting with a set of 'rationality' postulates, the classical framework of Savage's decision theory [2] justifies the probabilistic modeling of the knowledge about the present state of the world, together with a numerical representation of preferences in the form of a value function that precisely assesses the possible results that might be achieved through different actions.

The increasing importance of decision-making to AI has led to a growing focus on the management of preferences [3], especially fostered by the advent of graphical representations [4,5] in the late 1990s, partly inspired by the use of similar representations for knowledge in Bayesian networks. This has let to a series of important workshops [6–11] and to special issues of leading journals [12–14], where other types of representations were discussed as well.

Before presenting the contents of this special issue in Section 5, we start with a brief historical outline in Section 2, where research on preferences in AI is positioned with respect to contributions from operations research (OR) and databases (DB). These fields are especially relevant for AI, although other fields could of course be mentioned, too. In fact, it should be emphasized that preferences is an interdisciplinary topic that can be studied from different perspectives. As an important example, we mention the study of human preferences in psychology, notably in connection with decision making [15,16];

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see [17] for a survey. Such studies may, and to some extent already did, serve as a source of inspiration for AI research and validation of AI models.

The main research topics in AI are then surveyed in more depth in Sections 3 and 4. While the former is focused on representing and reasoning with preferences, the latter is devoted to the learning of preferences.

2. Preferences in AI and related fields

The representation of preferences has been studied in economics, especially in decision theory and in social choice theory, with further developments and applications in OR, long before AI or database researchers became interested in the topic. Here, we briefly outline from what perspectives the modeling of preferences has been studied, and try to highlight the main characteristics of the approaches developed in these fields. We begin our discussion with economics and OR before considering AI and DB contributions.

2.1. Preferences in economics and operations research

Preferences are central not only to individual decision making, but also to collective decision making, known as social choice, and the study of strategic interactions between agents, the topic of game theory. The formal developments of decision theory, social choice and game theory all emerged in economics around the same time (between late 1940s and early 1950s): [18] for decision theory and game theory, [19] for social choice. These areas now play a huge role in AI: decision making under risk and uncertainty in planning (and especially Markov Decision Processes), and social choice and game theory in most formal studies of multi-agent systems (voting, resource allocation, auctions, etc.) [20]. We now briefly outline what economics and OR have provided in terms of preference modeling, which will serve as reference material for the AI research discussed later.

In decision making under uncertainty, a preference relation between acts is built from a probability distribution over the possible pairs of input and output states and from a utility function assessing the value of each result [21]. In Savage's decision theory [2], one act is preferred to another if its expected utility is higher.

Generally speaking, expected utility can be seen as the prototype decision criterion proposed in decision theory. It may be considered as an instance of the relational modeling of preferences viewed as a conjoint measurement problem [22–24], where a binary (preference) relation is defined between objects described by vectors. Each vector encodes an act by the values of its result when performed in different states of the world in the case of decision making under uncertainty, or lists the evaluations of an alternative according to different criteria in case of multiple criteria decision making, or according to different agents in group decision making. Conjoint measurement theory then looks for conditions under which there exists a numerical representation (possibly unique) of the preference relation in the form of a decision criterion. This type of representation requires preferences to be complete and transitive. Intransitive models have been studied as well [25–27].

A decision criterion in decision making under uncertainty aggregates the values of consequences of an act obtained in different states of the world. What is aggregated in multiple criteria decision making, instead, are numerical satisfaction degrees pertaining to the different criteria that are considered. Different types of scales [28,29] can be used for assessing these satisfaction degrees: ordinal scales where only the ordering of the grades is defined, interval scales where numerical grades are defined up to a positive affine transformation, and ratio scales where the grades are defined up to a multiplicative factor. Depending on the type of the scale, different families of aggregation functions may be used (conjunctions, disjunctions, averages, ordered weighted averages (OWAs) [30,31], ordered weighted conjunctions [32], etc.), and many studies have looked for axiomatic characterizations of these families in terms of properties that are easy to interpret in practice [33–38]. However, scoring functions cannot represent all preferences that are strict partial orders [39]. Two important families of aggregation functions have been thoroughly studied in the last three decades [40]: Choquet integrals [41–44,40] on cardinal scales that generalize the weighted average, and Sugeno integrals [45–48,44] on ordinal scales that generalize the median. Being defined for non-additive measures, these two integrals can take into account possible interactions between evaluation criteria (for instance, there is a synergy between two criteria if the sum of their weights is smaller than the weight of their union, in the case of a Choquet integral). Integral-based aggregations have been also extended to bipolar scales [49–52], encompassing models such as cumulative prospect theory [53].

The use of decision criteria, and more generally aggregation functions, reduces the comparison of alternatives to the comparison of single numbers, which naturally leads to maximization or minimization problems. Thus, aggregation functions provide both a global evaluation of alternatives and a basis for rank-ordering them. As it is well known, Pareto ordering is only defined between dominated alternatives. When comparing two vectors, one may only consider the components for which the values are different, and aggregate these discriminating values, giving rise, for instance, to discrimin or discrimax orderings when min or max are used for the aggregation [54,32]. If all the components have equal importance, then the idea of not taking into account identical values in the comparison may be applied to the vectors once their components have been increasingly or decreasingly reordered, giving rise to leximin and leximax complete preorders [55]. Leximin ordering refines the discrimin ordering, which itself refines both the Pareto ordering and the min-based ordering. Beyond Pareto, other orderings are of interest for comparing vectors of numerical values, such as Lorenz dominance (associated with the Pigou–Dalton transfer principle). They were originally introduced in economics for comparing distributions of incomes [56, 55]; see [57,58] for examples of AI applications.

Rather than starting with evaluation vectors, one may take as a departure point a collection of elementary preference relations (each associated with a criterion, or an individual for instance), which reflect different points of view, and study possibilities to aggregate them into a meaningful synthetic relation. When the elementary preference relations are complete preorders (which amounts to starting with ordered lists of alternatives, possibly with ties), Arrow's theorem states the impossibility of obtaining a complete preorder in a non-dictatorial way [19,59]. However, this theorem only holds under an independence assumption stating that the comparison between two candidates only depends on their relative positions in the ordered lists. This condition does not allow for taking the intensity of preferences into account, or to make comparisons with respect to a third alternative. General relational preference structures leave room for incomparability as well as the expression of strict preference and indifference. They have been extended to valued relations for expressing the intensity of preferences [60,61].

2.2. Preferences in AI

In the 1990s, AI researchers started developing qualitative decision frameworks, especially for decision making under uncertainty [62–66]. Some of these frameworks have a Savage-like axiomatic basis, leading to qualitative decision criteria on ordinal scales [67–69], sometimes allowing the uncertainty scale and the preference scale to be not commensurable [70–72]. Qualitative decision making has been more recently extended to bipolar preferences distinguishing between positive and negative features [73,74].

Humans are rarely willing to express their preferences directly in terms of a value function, even if the underlying scale is ordinal. This reluctance is due to the considerable cognitive burden of determining a value function for a large number of alternatives described by multiple attributes. Instead of rating complete alternatives immediately, it is normally much easier and arguably more natural to provide information about preferences in separate pieces, preferably in a qualitative way. For example, binary preference relations [75] are normally easier to specify than value functions, since the qualitative comparison of pairs of alternatives is less difficult than the (quantitative) assessment of single alternatives. However, it is also clear that the specification of complete preference relations would often require too many pairwise comparisons.

A viable alternative, therefore, is to use *preference statements* for describing preferences in a local, contextualized manner. Statements of that kind can be represented with graphical or logical representations. Dealing with alternatives described by multiple features (usually binary ones), the problem is then to compute a partial preorder (leaving room for incomparability), or a complete preorder (which may still have ties) between any pair of alternatives, on the basis of context-dependent preferences expressed between situations partially described by fixing the values of some features. For instance, one may prefer wearing a red shirt to wearing a white one in the context of having a black coat and black pants. This issue has led to a research trend in AI looking for compact representation settings for preferences, which has raised a considerable interest for more than a decade now [5,76,77]. See [78] for an introductory survey mainly oriented towards graphical representations.

We revisit the different types of compact representations and some related issues in the next section. From an AI perspective, the fact that preferences are communicated as a set of pieces of information suggests the same concerns and problems as for knowledge bases, namely reasoning about preferences, revising preferences, and fusing preferences coming from different points of views or different agents. Besides, belief–desire–intention (BDI) agents [79,80] use preference orderings for dealing with goal generation, interactions between desires, obligations and norms and for discussing how an agent may form intentions from beliefs and goals. Thus, various degrees of urgency, utility or preference are associated with individual goals, given certain desires, obligations, norms.[1]

2.3. Preferences in databases

The notion of preferences has also been studied in the database community. Indeed, the use of preferences inside database systems has a number of potential advantages. First, it is desirable to offer more expressive query languages that are able to express a user's requirements in a more faithful way. Second, the use of preferences in queries provides a basis for rank-ordering the retrieved items, which is especially valuable if a query is satisfied by a large set of items. Moreover, a classical query may also have an empty set of answers, while a relaxed (and thus less restrictive) version of the query can still be satisfied by several items in the database, at least to some degree. Thus, it is hardly surprising that preferences have played an important role in database research for more than three decades.

Early proposals distinguish between mandatory conditions and secondary conditions, for example by Lacroix and Lavency [95] who use Boolean expressions for the secondary conditions in order to refine conditions that are higher in the hierarchy of priorities. Flexibility may also be incorporated implicitly in a query by means of similarity relations. For example, Motro

[1] In this survey, we left aside another important use of the idea of preferences in AI which is independent of any decision making concern. Namely, the idea of preferred models of a proposition, expressed by means of a preorder and used for modeling the most normal situations in a given context, plays an important role in many approaches to nonmonotonic reasoning [81–89]. The concern is to determine the most plausible conclusions that can be drawn in an incompletely known situation. In the same spirit, preferences are used in argumentation for modeling the strengths of arguments, where they may be useful for refining the evaluation of arguments, determining the success of attacks between arguments, and repairing the attack relation between arguments [90–94].

[96] extends the usual equality by means of a similarity relation relying on a notion of distance between attribute values of the same domain. Queries are transformed into Boolean conditions using thresholds, and then an ordering process is realized based on the distances.

A preference algebra was proposed by Chomicki [97] for an embedding of preference formulas based on partial order relations into a relational database (and SQL) setting; see also [98–101], and [102] for contextual preferences (essentially equivalent to CP-preferences but developed independently). Attempts at connecting AI and DB research have remained rather limited, with only a few exceptions [103–106].

Fuzzy set-based approaches to data base querying [107–113] and information retrieval [114] use fuzzy set membership functions for describing the preference profiles of the user on each attribute domain involved in the query. This is especially convenient and suitable when dealing with numerical domains, where a continuum of values is to be interfaced for each domain with satisfaction degrees in the unit interval scale. Then, the satisfaction degrees associated with elementary conditions are combined using fuzzy set connectives, which may go beyond conjunctive or disjunctive aggregations. These approaches assume commensurability between the satisfaction degrees pertaining to different attributes occurring in a query; see also [115,116].

More recently, the topic of "skyline computation" has received increasing attention. This line of research started with the pioneering works of Börzsönyi et al. [117] and was continued by other researchers, see e.g., [118–124]. The skyline of a set of items represented as points in a multi-dimensional space (spanned by a set of attributes or *criteria* with totally ordered domains) is simply defined by the subset of items that are non-dominated in a Pareto sense. Clearly, the skyline computation approach does not require any commensurability assumption between satisfaction degrees of criteria. However, since Pareto dominance is a rather weak relation that does not discriminate well between items, the set of skyline points will normally become very large, especially in high dimensions. Different proposals for refining, reducing or ranking the set of skyline points have therefore been made [125–128].

3. Representing preferences and reasoning about preferences

As pointed out in Section 2.2, for going beyond the explicit assessment of each alternative in terms of a degree of satisfaction, or the comparison of each pair of alternatives in a preference relation, compact representation settings are needed. In the following, we recall the main features of the graphical and logical settings that have been developed for that purpose. Besides, we also explore the role of preferences in soft constraint satisfaction and computational social choice.

The AI approach to reasoning about user preferences, like in many other AI problems, has three major components: (i) a mathematical model capturing the cognitive aspects, (ii)'a language for describing models conveniently, and (iii) algorithms for answering queries about these models as efficiently as possible [129].

3.1. Graphical representations

One of the best-known instantiations of the above general scheme is the formalism of *conditional preference networks* (CP-nets) [4,5], along with its various extensions and derivatives [130–136,77]. The language underlying CP-nets corresponds to sets of (conditional) preference statements for values of variables; each statement expressing the user's preference over a single variable. CP-nets adopt the *ceteris paribus* (all else being equal) semantics for statement interpretation. In this conservative semantics, a statement "I prefer $X = x_1$ to $X = x_2$" means that, given any two alternatives that are identical except for the value of X, the user prefers the one assigning x_1 to X to the one assigning x_2. If these two alternatives differ on at least one other attribute as well, then they cannot be compared based on this preference statement alone.

Conditional statements have the same semantics, except that they are restricted to comparisons between elements satisfying the condition. Thus, "I prefer $X = x_1$ to $X = x_2$ given that $Y = y_1$" is interpreted exactly as above, but only for objects that satisfy $Y = y_1$. Thus, CP-nets allow for the expression of preferential independence statements. The model underlying the CP-nets language is the one of strict partial orders. If the user provides consistent information about her preferences, then the binary relation induced by the CP-net is a strict, and usually incomplete, partial order. TCP-nets [132] (for tradeoff-enhanced CP-nets), allows the encoding of conditional relative importance statements between variables.

All algorithms exploit an intermediate graphical representation of preference expressions. The nodes of the graph correspond to the variables and the edges provide information about direct preferential dependencies between them. Each node X in a CP-net is associated with a conditional preference table (CPT) describing the user's preference order for every possible value assignment to the immediate predecessors of X. While not all preference expressions representable as CP-nets are consistent [137], consistency provably holds for acyclic CP-nets [5].

Different types of queries make sense in such a setting: (i) optimization queries that look for a preferentially optimal alternative, (ii) dominance testing queries asking whether a ranking for two alternatives holds in any preference ordering that satisfies the CP-net requirements, and (iii) ordering queries seeking an ordering of a subset of alternatives in a way consistent with the preferences. In preferential reasoning, all three queries are in general NP-hard [138]. Surprisingly, optimization for acyclic CP-nets can be solved in time linear in the number of variables by a simple, top-down traversal of the graph [5]. The situation with dominance testing is not as sharp. While NP-hard in general even for acyclic CP-nets, this query still can be answered efficiently for Boolean attribute variables and certain topologies of the CP-net [5]. The computational complexity of the CP-net approach for dominance queries has motivated the development of tractable approximations [139–141].

CP-nets can also be viewed as strategic games where each player corresponds to a variable, whose domain is the set of actions available to the player, and preferences over a player's actions given the other players' strategies are specified by a conditional preference table [142]; see also [143]. Besides, taking inspiration from CP-nets, conditional importance networks (CI-nets) [144] have recently been introduced for the representation of ordinal preferences over sets of goods, i.e., for handling statements of the form "if I have a set A of goods, and I do not have any of the goods from some other set B, then I prefer the set of goods C over the set of goods D".

CP-nets are primarily oriented towards a qualitative representation of preferences (with the noticeable exception of UCP-nets [131]). A graphical approach for the representation of quantitative preferences is the one based on GAI nets proposed in [145] and further developed in [146–148], which assumes that the set of alternatives is defined as the Cartesian product of finite domains and that an agent's preferences are represented by generalized additive decomposable (GAI) utility functions. Such functions allow an efficient representation of interactions between attributes while preserving some decomposability of the model. See also [149,150] for other types of utility networks.

3.2. Logic-based representations

Propositional logic languages have been considered in AI for the compact encoding of preference relations over a set of alternatives [151]. As stressed in the review article [152], there are two general aspects: the nature of the preorders that can be encoded (e.g., all preorders, all complete preorders) and how succinctly a preference relation can be expressed in those languages.

There is a variety of proposals along this line focusing on ordinal preferences (i.e., representable by a binary relation over the pairs of alternatives). A basic idea is to discriminate between models satisfying a formula expressing a goal and models violating it. This idea can be found in approaches based on weighted propositional formulas [153] such as the ones using penalties and rewards [154,153,155], or in prioritized logics (where the weights have a more qualitative flavor) such as in possibilistic logic [156]. In this latter type of setting, the priority on goals is extended to a preference relation on alternatives, using preference relations initially introduced for default or inconsistency-tolerant reasoning [157]: (i) the best-out ordering, focusing on the most prioritized violated goal, (ii) the leximin ordering which compares the cardinalities of satisfied goals at each level of priority, and (iii) the discrimin ordering [81] which, when comparing two alternatives, does not take into account the goals satisfied by both.

A preference relation based on violated goals only makes a distinction between models satisfying a formula and models violating it. However, if an agent prefers a goal G to be satisfied, we may infer that she also prefers models "close" to this formula to models that are "very different". The Hamming distance is then often used for estimating the closeness between models, thus taking into account the closeness between models in the preference ordering, e.g. [158].

Conditional logics [63,136,77,159] use another kind of setting for expressing that, in a given context, satisfying a formula is preferred to violating it. One then obtains a preference relation based on Z-ranking [160] (introduced for default reasoning). Another form of conditional preferences, in the spirit of CP-nets, are ceteris paribus statements of the general form "all irrelevant things being equal, I prefer $G \wedge \neg G'$ to $\neg G \wedge G'$" for expressing the preferences of G over G' [161,162,62,4]. Indifference statements may be added [163,152]. The preference order is then defined by taking the transitive closure of the union of the dominance relations induced by each conditional preference statement. Such a view of preference between two propositional formulas was first proposed and discussed by philosophers [164–166], and has recently been embedded in a preference logic where preference is a genuine modality [167]; see [168] for a discussion.

Related to prioritized logics is Qualitative Choice Logic [169] that allows for the expression of goals by ordered disjunctions of the form "if possible G, but if G is not possible, then at least G'". QCL formulas can be translated into a stratified knowledge base in possibilistic logic [170], where ordered conjunctions ("at least G, and if possible G'") can be defined as well [171]. Ordered disjunctions have also been introduced in logic programming languages [172–174]. More generally, an important feature of the possibility theory setting is the existence of equivalent representation formats [163] for which there are algorithms for translating one format into another one [175,176]; these are also of interest from a cognitive psychology point of view. These representations include (i) a set of prioritized logical formulas (goals) represented by standard possibilistic formulas, semantically associated with (ii) complete preorders on interpretations (possibility distributions) at the semantical level, (iii) a set of strong possibility formulas [177] describing sets of acceptable interpretations with their level of guaranteed satisfaction, (iv) a set of conditionals (of the form $\Pi(C \wedge G) > \Pi(C \wedge \neg G)$) where Π is a possibility measure, expressing that in context C, having G true is preferred to having it false (other kinds of comparative preferences are studied in [159]), or (v) graphical nets which are the possibilistic counterpart of Bayesian nets [163,178].

CP-nets express only a lower approximation of an agent's preference relation, by allowing her to specify her preference between alternatives differing on a single variable; a complete preorder can generally not be expressed by a CP-net, but only approximated by a CP-net, while any complete preorder can be represented in possibilistic logic. However, a representation using possibilistic logic with symbolic weights (on which some ordering constraints may be known) [179] leaves room for non-comparable alternatives as in CP-nets. Moreover, the use of the ceteris paribus principle always gives priority to the preferences associated to father nodes. Priorities can be freely assigned in a possibilistic logic representation with symbolic weights [179].

Moreover the framework of possibility theory is suitable for bipolar representations that allow for the expression of negative and positive information [180]. Negative preferences reflect what is not (fully) impossible and thus remains potentially possible since it is not rejected. Positive information corresponds to what is actually desirable or satisfactory. The consistency of preferences then requires that the extent to which an interpretation is satisfactory is less or equal to the extent to which it is not rejected [181,182]. Polarities between goals may also be introduced by means of rewards when they are satisfied and by means of constraints inducing costs when they are violated [183]. Another form of two-sided specification is obtained by expressing multiple criteria-based preferences through generic constraints (e.g., induced by the relative importance of criteria) and by means of concrete examples (whose ordering may disagree with generic constraints) [184].

Although reasoning with preferences has mainly focused on dominance and ordering queries, we briefly mention some other aspects here. The logical handling of qualitative decision making problems requires a separate processing of knowledge and preferences (goals) in two separate logic bases [185]. When knowledge is pervaded with qualitative uncertainty (represented in terms of a stratified logic base of formulas with different levels of certainty), and preference is graded (under the form of prioritized goals), which are thus associated, respectively, with a qualitative possibility distribution and an ordinal value function, the optimal decision in terms of qualitative decision criteria can be computed by a logical machinery [186]; see also [187,188] for a logic programming perspective.

There is a research trend in AI concerning information fusion, but very few works focus on preferences fusion. Indeed, many authors seem to implicitly consider that merging pieces of knowledge is the same as fusing preferences (although the former aims at restricting the possible locations of the truth, while the latter is primarily a matter of compromise); see, however [189] for a discussion of the problem in a bipolar setting, and [190] for another view using matroid theory. Similarly, there has been little work on revising preferences, while there exists a huge literature in belief revision. However, [191] discusses how preference change is triggered by belief change, while [192] proposes a dynamic logic of preference upgrade. In a more applied perspective, there is a clear need for refining user preferences in recommender systems on the basis of the users' critiques [193]. Agents may also generate new preferences based on the similarity between new objects and the objects for which preferences are known [194].

3.3. Soft constraints

Knowledge can also be represented and processed in the form of constraints. In practice, however, constraint satisfaction problems are often over-constrained. In order to find a good solution meeting the initial requirements, it is then necessary to relax some constraints in one way or the other. Even if the original problem does have solutions, preferences can be useful in order to distinguish between better or worse ones. For instance, to increase the robustness of solutions, one may want to avoid solutions that satisfy constraints near the boundary of the range of acceptable values.

There are two main ways for softening constraint satisfaction problems. One may either attach a weight to the constraints (where the weight may represent a violation cost, or a level of importance or priority), or assign a degree to each possible tuple in a constraint (e.g., by representing preferences with fuzzy sets of acceptable values). Then, one looks for a solution maximizing the global satisfaction of the constraints, which leads to a constraint optimization problem. Different aggregation attitudes are conceivable: allowing for compromises (with the risk of having some important constraints unsatisfied), or requiring that all the important constraints be satisfied to a high degree (where importance and satisfaction are graded).

A general abstract semi-ring setting that supports different aggregation attitudes and includes the fuzzy set approach [195,196] as a particular case has been proposed in [197]. Moreover, in a mixed CSP, apart from controllable variables whose values may be a matter of preferences and choice, there are uncontrollable variables that create uncertainty, which may be handled in a probabilistic [198–201] or a possibilistic manner [195,202]. The bipolar representation of preferences [203–205] makes a distinction between positive and negative preferences. While soft constraints reflect negative preferences by specifying which solutions are (more or less strongly) rejected, positive preferences point out what would be really satisfactory.[2] Thus, positive preferences are to be understood as criteria for choosing solutions among those satisfying the soft constraints in the best way [208,209].

Algorithmic and complexity issues of soft constraint satisfaction problems have been well-studied [210–215]. Soft constraint satisfaction has been applied to shortest path problems and scheduling [216,202], pattern mining [217] and the negotiation of service level agreement for the management of resources in quality of service [218], among others [219]. Besides, explanations of the proposed solutions may help the user refining her preference and gaining control over the problem solver [220].

Soft constraint optimization finds application in preference-based planning, where user's preferences are expressed by means of soft constraints on a plan to be produced, and may apply to some or all states of a plan. Different preference-based planning languages and automated planning software have been proposed [221–224]. Preference-based web service composition problems offer another application where compact representations are also needed for specifying preferences on service configurations [225–230]. While a significant part of this optimization can be performed offline, some parts may

[2] This distinction is also supported by psychological evidence. Studies in cognitive psychology have shown that positive and negative preferences are indeed felt as different dimensions by humans [206,207].

depend on online information gathering [231]. Goal deliberation for BDI agents may also be viewed as a soft constraint optimization problem where preferences and other utility measures are incorporated [232].

3.4. Computational social choice

In classical social choice theory [233], collective decision making problems are mostly studied from a normative point of view. AI and computer science have raised new concerns, such as algorithmic and complexity issues in the context of voting procedures [234–238], or fair allocation of resources [239], especially when the set of alternatives has a combinatorial structure. Another important issue is how to reason about voting when preferences are incompletely specified or uncertain [240–242].

This has led to the development of a new area, sometimes called computational social choice [243]. Computational social choice, as mentioned above, comprises the computational study of fair allocation mechanisms, which is highly related to combinatorial auctions [244], where the auctioneer offers a set of goods for sale, and bidding languages allow agents to communicate their preferences to the auctioneer; these representations take the form of bids (i.e., combinations of atomic bids that each states the amount the bidder is willing to pay for a subset of goods). For instance, in OR-bidding languages [245–247], the valuation of a bundle of goods is then the maximal value that can be obtained when computing the sum over disjoint bids for subsets of the bundle.

Moreover, results in social welfare theory are not only applicable to human society, but are also of interest in multiple agent systems, e.g., for analyzing the quality of resource allocations. For instance, one may ask for an allocation that maximizes the sum of utilities of the individual agents, or adopting an egalitarian view that maximizes the utility of the poorest agent. If possible, one may also look for an envy-free allocation (no agent would prefer to obtain a bundle that has been allocated to some other agent) [248]. More generally, one may minimize the number of envious agents or the degree of envy of each agent. In cases without a central allocation system, agents negotiate locally by accepting or rejecting deals proposed by some other agents, until a stable situation is reached [249–252].

4. Learning preferences

Apart from modeling languages and representation formalisms, methods for the automatic learning, discovery and adaptation of preferences are essential. Approaches relevant to this area range from preference elicitation where the utility function of a single agent is estimated by asking questions effectively [253–255] to *collaborative filtering* where a customer's preferences are estimated from the preferences of other customers [256,257]. Preference learning can be formalized within various settings, depending, e.g., on the underlying preference model and the type of information provided as an input to the learning system.

As explained above, two main approaches to modeling preferences prevail the literature on choice and decision theory: value functions and preference relations. From a machine learning point of view, these two approaches give rise to two kinds of learning problems: learning value functions and learning (binary) preference relations. The latter deviates more strongly than the former from conventional problems like classification and regression, as it involves the prediction of complex structures, such as rankings or partial order relations, rather than single values. Moreover, training input in preference learning will not, as it is usually the case in supervised learning, be offered in the form of complete examples but may comprise more general types of information, such as relative preferences or different kinds of indirect feedback and implicit preference information [258,259].

In general, a preference learning system is provided with a set of items (e.g., products) for which preferences are known, and the task is to learn a function that predicts preferences for a new set of items (e.g., new products not seen so far), or for the same set of items in a different context (e.g., the same products but for a different user). Frequently, the predicted preference relation is required to form a total order, in which case we also speak of a ranking problem. In fact, among the problems in the realm of preference learning, the task of "learning to rank" has probably received the most attention in the literature so far, and a number of different ranking problems have already been introduced. Based on the type of training data and the required predictions, Fürnkranz and Hüllermeier [260] distinguish between the problems of object ranking [261,262], label ranking [263–266] and instance ranking [267,268].

All of these basic learning tasks can be tackled by similar techniques. As with the distinction between using value functions and binary relations for modeling preferences, two general approaches to preference learning have been proposed in the literature, the first one being based on the idea of learning to evaluate individual alternatives by means of a value function, while the second one seeks to compare (pairs of) competing alternatives, that is, to learn one or more binary preference predicates. Making sufficiently restrictive model assumptions about the structure of a preference relation, one can also try to use the data for identifying this structure. Finally, local estimation techniques à la nearest neighbor can be used, which mostly leads to aggregating preferences in one way or another.

A value function assigns an abstract degree of utility to each alternative under consideration. Depending on the underlying utility scale, which is typically either numerical or ordinal, the problem of learning a (latent) value function from given training data becomes one of regression learning or ordinal classification. Both problems are well-known in machine learning. However, value functions often implicate special requirements and constraints that have to be taken into consideration such as, for example, monotonicity in certain attributes. Besides, as mentioned earlier, training data is not necessarily given in the form of input/output pairs, i.e., alternatives (instances) together with their utility degrees, but may also consist of qualitative feedback in the form of pairwise comparisons, stating that one alternative is preferred to another one and therefore has a higher utility degree. In general, this means that value functions need to be learned from indirect instead of direct training information [258,259].

The learning of binary preference relations that compare alternatives in a pairwise manner is normally simpler, mainly because comparative training information (suggesting that one alternative is better than another one) can be used directly instead of translating it into constraints on a (latent) value function [269,270]. On the other hand, the prediction step may become more difficult, since a binary preference relation learned from data is not necessarily consistent in the sense of being transitive and, therefore, does normally not define a ranking in a unique way. What is needed, therefore, is a ranking procedure than maps a preference relation to a maximally consistent ranking. The difficulty of this problem depends on the concrete consistency criterion used, though many natural objectives (e.g., minimizing the number of object pairs whose ranks are in conflict with their pairwise preference) lead to NP-hard problems [261]. Fortunately, efficient techniques such as simple voting (known as the Borda count procedure in social choice theory) often deliver good approximations, sometimes even with provable guarantees [271,272].

Another approach to learning ranking functions is to proceed from specific model assumptions, that is, assumptions about the structure of the preference relations. This approach is less generic than the previous ones, as it strongly depends on the concrete assumptions made. An example is the assumption that the target ranking of a set of objects described in terms of multiple attributes can be represented as a *lexicographic order* [273–275]. Another example is the assumption that the target ranking can be represented by a CP-net [276]. From a machine learning point of view, assumptions of the above type can be seen as an inductive bias restricting the hypothesis space. Provided the bias is correct, this is clearly an advantage, as it may simplify the learning problem.

Yet another alternative is to resort to the idea of local estimation techniques as prominently represented, for example, by the nearest neighbor estimation principle: Considering the rankings observed in similar situations as representative, a ranking for the current situation is estimated on the basis of these “neighbored” rankings, typically using an averaging-like aggregation operator [263,277]. This approach is in a sense orthogonal to the previous model-based one, as it is very flexible and typically comes with no specific model assumption (except the regularity assumption underlying the nearest neighbor inference principle).

5. Contributions to the special issue

In this section, we give a brief overview of the contributions included in the special issue.

5.1. Representing and reasoning about preferences

Two papers deal with important aspects of conditional preferences. Wilson develops a logic of conditional preferences, comprising a language, a semantics and a proof theory, which can be seen as a generalization of CP-nets and TCP-nets. He presents theoretical and algorithmic tools for checking consistency of preference statements and for deriving a preferential order of outcomes. McGeachie and Doyle propose concrete semantics for conditional multi-attribute ceteris paribus preference comparisons involving quantitative tradeoffs, based on concepts from elementary differential geometry. Interestingly, the semantics proposed by the authors can be seen as an extension of the notion of marginal rate of substitution, which is well known in economics, to the case of multiple continuous or discrete attributes.

Specific formalisms for representing preferences, namely in terms of intervals, and in terms of rules, are proposed respectively by Brafman and by Oztürk, Pirlot and Tsoukias. The latter present a general framework for modeling preferences in terms of interval comparison. Starting from standard (2-point) intervals, they also analyze the more general case of 3-point interval comparison and discuss a further generalization to n-point intervals. Brafman introduces a relational language for the rule-based specification of preferences, which can be used for controlling autonomous systems in a flexible way. This approach is especially useful for the specification of value functions in dynamic environments, in which the description of decision alternatives (in terms of their properties) is not necessarily fixed in advance. Casali, Godo and Sierra introduce a sound and complete logical framework called g-BDI, which supports the modeling of agents in the form of multi-context systems that reason about beliefs, desires and intentions in a graded manner.

Venable, Pini, Rossi and Walsh study the aggregation of the preferences of multiple agents over a set of candidates in the presence of incompleteness and incomparability in their preference orderings. More specifically, they study algorithmic and computational properties of the problem of computing the candidates that are possibly or even necessarily among the maximally preferred ones. Knowledge of these sets of possible and necessary winners is especially interesting in the context of preference elicitation.

5.2. Preference learning

Two contributions are devoted to the learning of preferences and establish a direct connection to the field of machine learning. Yaman, Walsh, Littman and DesJardins present a method for learning preferences from given examples, based on the assumption that the underlying preference relation is a lexicographic order. Instead of finding just a single model consistent with the data, as previous approaches do, they show how to derive predictions from the votes of the collection of all consistent models. WAEGEMAN AND DE BAETS study the ranking representability of a specific type of reciprocal preference relation, namely relations that are naturally produced by methods based on learning by pairwise comparison. More specifically, the authors establish necessary and sufficient conditions under which a set of pairwise bipartite ranking functions can be represented in terms of a single ranking function, in the sense that both representations have the same predictive (ranking) accuracy.

5.3. Decision making

Two papers deal with sequential decision making. KIKUTI, COZMAN AND FILHO study sequential decision making in the case where strategies are not necessarily comparable in terms of expected utility, for example because probability distributions are imprecise. Building on decision tree and influence diagram representations, they investigate different criteria for strategy selection and study computational and algorithmic aspects. JEANTET AND SPANJAARD propose algorithms for optimizing rank dependent utility (RDU) in sequential decision making problems represented with decision trees or influence diagrams.

DUBUS, PERNY AND GONZALES present preference-based search algorithms for multiple criteria and multi-agent decision making, based on the graphical model of generalized additive decomposable (GAI) utility functions. They propose algorithms for multi-objective optimization with various preference models (Pareto and Lorenz dominances, OWA and Tchebycheff).

Finally, LABREUCHE makes an important step toward the automatic "explanation" of a decision prescribed by a multi-attribute decision model. Roughly speaking, focusing on decision models in which each attribute is associated with a weight reflecting its importance, the problem is formalized as finding a subset of maximally important attributes determining the decision.

5.4. Constraint satisfaction and planning

MOFFITT addresses the modeling and optimization of preferences in the context of constraint-based temporal reasoning. The author introduces a constraint system called valued DTP, which is closely related to the disjunctive temporal problems (DTP) with preferences. In order to optimize temporal preferences efficiently, he makes use of search strategies from the decision-based DTP literature. BIENVENU, FRITZ AND MCILRAITH propose a language $\mathcal{LPP}$ based on first-order and linear-temporal logic for expressing rich, temporally-extended user preferences. Notable features of this qualitative language include the ability to specify preferences over evolutions of properties of states as well as over (complex) action occurrences and the possibility for users to indicate the relative strength of their different preferences in order to facilitate aggregation. The language was designed for use in planning, but is also relevant for other dynamical reasoning tasks involving preferences. The authors develop a bounded best-first search planner, called PPLAN, which can be used to generate optimal plans with respect to preferences formulated in their language.

5.5. Applications in economics

Two papers address issues of preference representation in the context of economic applications. CONITZER AND SANDHOLM introduce a bidding language for expressing so-called matching offers over multiple charities for negotiating the donation of money by different parties. They also study the structure and complexity of the corresponding clearing problem, i.e., determining the donation of each bidder and the benefit of each charity, for different types of bids. BELLOSTA, KORNMAN AND VANDERPOOTEN study (electronic) English reverse auctions and, in this context, present a unified framework for modeling multiple attribute preferences that are not necessarily transitive and complete, but only exhibit weaker properties, such as nondominance and fair competition. Moreover, the approach guarantees reasonable properties of the evolution and the outcome of an auction executed by an auction mechanism.

5.6. Databases

The paper by MINDOLIN AND CHOMICKI deals with efficient and compact representations of binary preference relations in a database context. More specifically, they study the idea of "preference contraction", which allows for discarding selected preferences provided that the underlying strict partial order relations are preserved. The authors present algorithms for computing minimal contractions and also study relationships between changes of binary preference relation and belief change in belief revision theory.

6. Concluding remarks

This survey aims at providing a roadmap through a wealth of approaches to preference handling that have been developed by OR, AI, and DB researchers over several decades. It seeks to structure the main ideas, results, and research issues, while indicating references for a deeper study of specific topics. It is also meant as a basis for positioning the contributions in this special issue within the field of preferences in AI.

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