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A Simple Experiment to Guide the Design of a Preference Model

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Abstract. Preferences are part of every day life driving to choice and action. We consider that there is a gap between preferences expressed by people and those we can find in the repositories. In this paper we explore a small set of preferences in the domain of movies, given by humans, in order to understand the expressive possibilities of some languages appearing in the literature: conditional logics and reward logics. After some experiments we contribute with a proposal for reasoning about preferences.

Keywords. Preference Representation, Reasoning with Preferences, Conditional Logics, Reward Logics.

Introduction

Preferences are part of every day life driving to choice and action. According to the Oxford Dictionary of English a preference is *a greater liking for one alternative over another or others*. We humans are constantly expressing complex preferences in natural language, with a great dependence of context and common sense understanding. We decide to study preferences from the AI perspective of deal with preference representation languages adequate to express these complex preferences.

We start guided by the very interesting book of Souhila Kaci, *Working with Preferences: Less Is More* [2]. In the first part of the book she introduces the main preference representation languages using very simple examples to show the representation capacity of each model. Despite the simplicity of the examples it seems clear that no representation language is able to deal with all the usual problems that we can find in practical preference applications: default preferences, lack of context, negative and positive preferences, etc.

From the practical applications point of view it seems to be a lack of practical applications based on preferences. PrefLib[3] is an important library of preference data that contains a lot of datasets but, in our opinion, these datasets are not pure preference problems since they are mainly oriented to voting.

In this paper we describe a simple experiment we performed in order to show how humans express preferences and how these preferences can be expressed using the logi-

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Table 1. Table with the attributes of the movies that has been presented to the participants in the experiment.

#	Actors	Actresses	Directors	Genres
1	Gene Kelly	Leslie Caron	Vincent Minelli	Musical
2	Michael York	Liza Minelli	Bob Fossey	Comedy
3	Frank Sinatra	Debbie Reynolds	Stanley Donen	Adventure
4	Cary Grant	Katharine Hepburn	Gene Kelly	Thriller
5	Humphrey Bogart	Audrey Hepburn	George Sidney	Drama
6	Spencer Tracy	Lauren Bacall	George Cukor	Romance
7	José Ferrer	Ingrid Bergman	John Houston	
8	James Steward	Eva Mary Saint	Stanley Kramer	
9	Woody Allen	Joan Fontaine	Billy Wilder	
10	Martin Landau	Grace Kelly	Alfred Hitchcock	
11	Alan Alda	Scarlett Johansson	Woody Allen	
12	Peter Sellers	Uma Thurman	Blake Edwards	
13	Michael Caine	Mia Farrow		
14	David Niven	Diane Keaton		
15	Sean Connery	Ursula Andrews		

cal languages at hand. This experiment consists on collecting a set of preferences of several volunteers on the domain of movies. In Section 1 the movies domain and the experiment is described. In Section 2 we explain how conditional logics can be applied to represent the preferences of the experiment. Because we detected some problems in using conditional logics, in Section 3 we introduce a new approach based on reward logic, and illustrate it with the set of preferences obtained from the experiment. Section 4 shows the conclusions of our experiment.

1. A simple experiment: movie preferences

The goal of the experiment is to obtain a set of preferences about movies and produce an adequate ordering for them. We presented Table 1 to five volunteers and asked for their preferences using the four attributes shown in the table: actors, actresses, directors and genres. These preferences have to be given in free natural language.

The set of preferences given by the participants range from absolute positive or negative (as *my preferred actress is Audrey Hepburn* or *I do not like musical films*) that can involve some disjunction or conjunction (as in *I prefer a Humphrey Bogart and Lauren Bacall than Katherine Hepburn and Spencer Tracy'*), to rankings (as in *My favorite actor is Michael Caine, then I prefer without any order Cary Grant, Humphrey Bogart, Spencer Tracy, James Steward, Peter Sellers, David Niven and Sean Connery. The remaining ones are the least preferred without order between them*).

When we designed the experiment, we had in mind the list of films show in Table 2. The goal is to give a ranking of these films for each volunteer taking into account the preferences that he has given. The user should agree with that order because it will

Table 2. Movies considered in the experiment. The numbers correspond with the attributes in Table1.

#	Movies	Actors	Actresses	Directors	Genres
ω_1	20,000 Leagues Under the Sea	13	—	—	3,6
ω_2	Alice	—	13	11	2, 6
ω_3	An American in Paris	1	1	1	1,6
ω_4	Anatomy of a Murder	8	—	—	4,5
ω_5	Anchors Aweigh	1,3	—	5	1,2
ω_6	Blue Ice	13	—	—	4
ω_7	Cabaret	2	2	2	1
ω_8	Casablanca	5	7	—	5,6
ω_9	Casino Royale	12, 14	15	—	3,2
ω_{10}	Crimes and Misdemeanors	11,10	—	11	4,5
ω_{11}	Dr. No (James Bond)	15	15	—	3,4
ω_{12}	Guess Who's Coming to Dinner	6	4	8	2,5
ω_{13}	High Society	3	10	—	2,1,6
ω_{14}	Husbands and Wives	9	13	11	2,5,6
ω_{15}	Key Largo	5	6	7	4
ω_{16}	Lovers and Liars	2	—	—	5
ω_{17}	Lucy	—	11	—	4
ω_{18}	Match Point	—	11	11	5,6,4
ω_{19}	North by Northwest	4	8	10	3,4
ω_{20}	Sabrina	5	5	9	2,5,6
ω_{21}	Scoop	—	11	11	2
ω_{22}	Singin' in the Rain	1	—	3,4	2,1,6
ω_{23}	Suspicion	4	—	10	4
ω_{24}	The African Queen	5	4	7	3,6
ω_{25}	The Caine Mutiny	5,7	—	—	5
ω_{26}	The destructors	13	—	—	5
ω_{27}	The Hunt for Red October	15	—	—	3,4
ω_{28}	The Maltese Falcon	5	—	7	5,4
ω_{29}	The Party	12	—	12	2
ω_{20}	The Philadelphia Story	4	4	6	2,6
ω_{31}	The Pink Panther	14,12	—	12	2
ω_{32}	The Rock	15	—	—	3,4
ω_{33}	To Catch a Thief	8	10	10	6,4

respect his preferences[2]. Let us analyze in detail the preferences given by one of the participants, namely $V1$.

1. *I prefer comedy or musical movies than thrillers or adventures.* This is a case of simple interpretation: movies whose genre is comedy or musical are preferred to those of thriller o adventure genre.

$$\{\text{Comedy}, \text{Thriller}\} > \{\text{Adventures}, \text{Musical}\}$$

[2]We use the Internet Movie Database (IMDb) to find the attributes of movies. In particular the genre is subjective, and the user might not agree with. In this case it is possible that the user does not agree with a particular genre classification and then does not agree with the resulting order of preference.

2. *Most of the time Woody Allen is a good director.* The interpretation of this sentence is difficult: he is normally a good director but not always. We can consider a kind of fuzzy preference not considered in the models explained before.

$$\text{WoodyAllen} >_{\text{most of the time}} \{\cdots\}$$

3. *Alfred Hitchcock, John Houston and George Cukor are good directors but when Grace Kelly is the main actress, the quality of the movie is much better.* The difficulty with this sentence is that in fact it contains two statements: the first one states that these directors are good, that is, preferred than other directors, but maybe they are not the best ones;

$$\{\text{AlfredHitchcock}, \text{JohnHouston}, \text{GeorgeCukor}\} >_{\text{good}} \{\cdots\}$$

and the second one states that when Grace Kelly appears in a movie is better. For the context of the sentence it seems that we are talking about movies of the same directors.

$$\{\text{AlfredHitchcock}, \text{JohnHouston}, \text{GeorgeCukor}\} \cap \text{GraceKelly} >_{\text{much better}} \{\text{AlfredHitchcock}, \text{JohnHouston}, \text{GeorgeCukor}\}$$

In both cases the sentences introduce some kind of fuzzy preferences.

4. *A musical movie with Gene Kelly is worse than a thriller with Michael Caine, but better than an adventure movie with Mia Farrow.* This sentence is not ambiguous and easy to interpret.

$$\text{Thriller} \wedge \text{MichaelCaine} > \text{GeneKelly} \wedge \text{Musical} > \text{Adventure} \wedge \text{MiaFarrow}$$

5. *Thrillers are much better when the actors are Gary Grant or Sean Connery.* This is similar to previous sentences.

$$\{\text{Thriller} \wedge \text{GaryGrant}, \text{Thriller} \wedge \text{SeanConnery}\} >_{\text{much better}} \text{Thriller}$$

6. *I prefer any movie with Audrey Hepburn.* It seems that independently of genre, director or other cast he always prefers a movie with Audrey Hepburn.

$$\text{AudreyHepburn} > \{\cdots\}$$

2. Applying Conditional Logics to the Examples

Conditional logic seems to be a natural language to express the preferences given by the volunteers. Conditionals logics are expressed as unweighted comparative preference statements. They can be general preferences like *I prefer comedy to drama* or specific preferences with respect to a context, for instance: *If drama, I prefer Katharine Hepburn to Lauren Bacall*. In general $p > q$ *(prefer p to q)* means that $p \wedge \neg q$ outcomes are preferred to $q \wedge \neg p$ outcomes. We can consider different semantics depending on the different criteria with respect the previous statement.

In *strong* semantics any $p \wedge \neg q$ outcome is preferred to any $q \wedge \neg p$ outcome. In *ceteris paribus* semantics any $p \wedge \neg q$ outcome is preferred to any $q \wedge \neg p$ outcome if the two have the same valuation over variables not appearing in $p \wedge \neg q$ and $q \wedge \neg p$. In both cases and using specificity principles there exist a unique least-specific preorder and a unique

most-specific preorder. The least-specific preorder compute the best outcomes and the most-specific preorder compute the worst.

We will explain how to obtain these preorders for strong semantics based in the notion of not dominated objects using the preferences given by participant $V1$. An outcome is *not dominated* when it is not preferred by any other.

First of all we have to translate the statements given by $V1$ to statements among movies. Thus, the statement of $V1$ saying that he prefers a thriller starred by Michael Caine than a musical starred by Gene Kelly can be translated as $\{\omega_6\} \succ \{\omega_3, \omega_5, \omega_{22}\}$ where $\{\omega_6\}$ ("Blue Ice") is a thriller with Michael Caine and $\{\omega_3, \omega_5, \omega_{22}\}$ are musicals with Gene Kelly. We removed the relations *most of the time* (statement 2) and *good* (statement 3) since both relations do not define clearly the movies involved in the relation. The statements of $V1$ involving movies are the following:

1. $\{\omega_2, \omega_4, \omega_6, \omega_{10}, \omega_{12}, \omega_{14}, \omega_{15}, \omega_{17}, \omega_{18}, \omega_{20}, \omega_{21}, \omega_{23}, \omega_{28}, \omega_{29}, \omega_{30}, \omega_{31}, \omega_{33}\} \succ \{\omega_1, \omega_3, \omega_7, \omega_{24}\}$
3. $\{\omega_{33}\} \succ \{\omega_{15}, \omega_{19}, \omega_{23}, \omega_{24}, \omega_{28}, \omega_{30}\}$
4. $\{\omega_6\} \succ \{\omega_3, \omega_5, \omega_{22}\}$
5. $\{\omega_{11}, \omega_{19}, \omega_{23}, \omega_{27}, \omega_{32}\} \succ \{\omega_4, \omega_6, \omega_{10}, \omega_{15}, \omega_{17}, \omega_{18}, \omega_{28}, \omega_{33}\}$
6. $\{\omega_{20}\} \succ \{\omega_1, \omega_2, \omega_3, \omega_4, \omega_5, \omega_6, \omega_7, \omega_8, \omega_9, \omega_{10}, \omega_{11}, \omega_{12}, \omega_{13}, \omega_{14}, \omega_{15}, \omega_{16}, \omega_{17}, \omega_{18}, \omega_{19}, \omega_{21}, \omega_{22}, \omega_{23}, \omega_{24}, \omega_{25}, \omega_{26}, \omega_{27}, \omega_{28}, \omega_{29}, \omega_{30}, \omega_{31}, \omega_{32}, \omega_{33}\}$

The first not dominated set of movies is: $\{\omega_{20}\}$. Therefore, we leave it from all the statements where it appears:

1 $\{\omega_2, \omega_4, \omega_6, \omega_{10}, \omega_{12}, \omega_{14}, \omega_{15}, \omega_{17}, \omega_{18}, \omega_{21}, \omega_{23}, \omega_{28}, \omega_{29}, \omega_{30}, \omega_{31}, \omega_{33}\} \succ \{\omega_1, \omega_3, \omega_7, \omega_{24}\}$
3 $\{\omega_{33}\} \succ \{\omega_{15}, \omega_{19}, \omega_{23}, \omega_{24}, \omega_{28}, \omega_{30}\}$
4 $\{\omega_6\} \succ \{\omega_3, \omega_5, \omega_{22}\}$
5 $\{\omega_{11}, \omega_{19}, \omega_{23}, \omega_{27}, \omega_{32}\} \succ \{\omega_4, \omega_6, \omega_{10}, \omega_{15}, \omega_{17}, \omega_{18}, \omega_{28}, \omega_{33}\}$

The second not dominated set of movies is: $\{\omega_2, \omega_{11}, \omega_{12}, \omega_{14}, \omega_{21}, \omega_{27}, \omega_{29}, \omega_{31}, \omega_{32}\}$. By leaving them we obtain:

1 $\{\omega_4, \omega_6, \omega_{10}, \omega_{15}, \omega_{17}, \omega_{18}, \omega_{23}, \omega_{28}, \omega_{30}, \omega_{33}\} \succ \{\omega_1, \omega_3, \omega_7, \omega_{24}\}$
3 $\{\omega_{33}\} \succ \{\omega_{15}, \omega_{19}, \omega_{23}, \omega_{24}, \omega_{28}, \omega_{30}\}$
4 $\{\omega_6\} \succ \{\omega_3, \omega_5, \omega_{22}\}$
5 $\{\omega_{19}, \omega_{23}\} \succ \{\omega_4, \omega_6, \omega_{10}, \omega_{15}, \omega_{17}, \omega_{18}, \omega_{28}, \omega_{33}\}$

Here we arrive to a deadlock: it is not possible to find any not dominated movie. In consequence the base contains contradictions: $\omega_{33} \succ \omega_{19} \succ \omega_{33}$ and $\omega_{33} \succ \omega_{23} \succ \omega_{33}$. The movies ω_{19}, ω_{23} and ω_{33} are Hitchcock thrillers. Grace Kelly appears in ω_{33} and Cary Grand in ω_{19} and ω_{23}. It is not possible to deal with both preferences 3 and 5.

We have to remove preference 3 or 5 to avoid the contradiction. In this example we remove preference 3 because contains less relations than 5. Finally, following the same process explained before we can obtain the least-specific preorder:

$\{\omega_{20}\} \succ \{\omega_2, \omega_{11}, \omega_{12}, \omega_{14}, \omega_{19}, \omega_{21}, \omega_{23}, \omega_{27}, \omega_{29}, \omega_{30}, \omega_{31}, \omega_{32}\} \succ \{\omega_4, \omega_6, \omega_{10}, \omega_{15}, \omega_{17}, \omega_{18}, \omega_{28}, \omega_{33}\} \succ \{\omega_1, \omega_3, \omega_5, \omega_7, \omega_{22}, \omega_{24}\}$

This is the result for the simplified set of preferences given by the volunteer. In order to avoid indifferent relations we would need more preferences sentences.

3. A Reward-based Approach

The intuitive idea is the more attributes of an object are involved in positive preferences, the more preferred has to be the object. Thus, for instance, for subject $V1$, a thriller by Hitchcock starred by Grace Kelly and Gary Grant (4 attributes involved in positive preferences) should be preferred to a thriller by Houston starred by James Steward (3 attributes involved). Such idea has some resemblance with penalty/reward logics. In weighted propositional logic the weighted preferences have the form (ϕ_i, a_i) where a_i is the penalty of falsifying the preference formula ϕ_i. The penalty degree of a formula is:

$$p_{(\phi_i,a_i)}(\omega) = \begin{cases} 0 \;\; if \omega \models \phi_i \\ a_i \; otherwise \end{cases}$$

and the global penalty degree is the addition of all the penalties:

$$p(\omega) = \sum \{p_{(\phi_i,a_i)}(\omega) | (\phi_i, a_i) \in \mathcal{N}\}$$

This means that an object is penalized when it does not satisfy a preference. The penalization is higher as much as preferences are not satisfied. For us, the main shortcoming of this logic is that the user has to give a negative assessment for the lack of information. In this sense, the reward logic seems to be more natural since the user has to give a reward for each attribute satisfying a preference. The reward logic is not exactly the reverse of the penalty logic, since the global reward is assessed using the maximum:

$$r(\omega) = \max\{r_{(\phi_i,a_i)}(\omega) | (\phi_i, a_i) \in \mathcal{N}\}$$

Our proposal is close to the reward logic, but in our approach is not necessary to weight the preferences. The idea is to give a weight of 1 to all the statements given as the preferred over other statements. Notice that statements less preferred are handled as the ones that do not appear in any preference. For instance, in statement $\{\text{Comedy}, \text{Thriller}\} > \{\text{Adventures}, \text{Musical}\}$ *comedy* and *thriller* are taken into account with weight 1, whereas *adventures* and *musical* have not weight as, for instance, *drama* that do not appear in any of the statements. This is similar to the specificity principles, in particular, to the least-specific preorder where the best outcomes are computed.

We call *rankings* to relations between three or more items. For instance *A musical movie with Gene Kelly is worse than a thriller with Michael Caine, but better than an adventure movie with Mia Farrow.* is a ranking.

Objects of the universe ω_i are described by attributes, namely $\mathcal{A} = \{A_1 \ldots A_n\}$ that can hold one or more values. In our example, objects of the universe are movies and they are described by 4 attributes: actor, actress, director and genre.

The algorithm we propose is shown in Fig. 1. It begins setting the table cells where the universe objects are described by their attributes to 0. Initially, the algorithm takes into account preferences that are not rankings, i.e., only those preferences involving one or two items are taken into account. The values of the attribute cell in the left part of each one of these preferences (i.e., the one corresponding to the most preferred item) is increased by 1. For each universe object we have the satisfaction degree $\delta(\omega_i)$ with the preferences by adding the values of all their attributes. Then the objects are reorganized

Let $\mathcal{T}_\mathcal{U}$ be the table of universe objects
Set $\mathcal{T}_\mathcal{U}.A_i = 0$, i.e., all the cells of the table are set to 0
Let $\mathcal{P}_> = \{s_i : p_i > q_i\}$ be a set of preferences (excluding rankings)
    for each $s_i \in \mathcal{P}_>$ do $\mathcal{T}_\mathcal{U}.p_i = \mathcal{T}_\mathcal{U}.p_i + 1$ end for
    for each $\omega_i \in \mathcal{T}_\mathcal{U}$ do $\delta(\omega_i) = \sum \omega_i.A_k \; \forall A_k \in \mathcal{A}$ end for
Order the objects of universe in decreasing order according to the values of $\delta(\omega_i)$
Use the rankings (if any) for solving some ties

Figure 1. Reward-like model algorithm.

taking into account such value. Most of time, there are many ties between the assessment of the objects, therefore, the rankings are used to try to avoid some of these ties. Rankings are useful to make more accurate orders of the objects, however we want to remark that: 1) may be the user has not provided any ranking, and 2) the existence of rankings does not guarantees that all (or some) ties could be avoided.

In the next sections we explain the algorithm using the set of preferences given by two of the volunteers, $V1$ and $V2$. The preferences given by these two participants are very different. $V1$ has given only one ranking and the information contained in the preferences is incomplete, this produces many ties that are difficult to avoid. $V2$ has given several rankings which allow to have more information about the preferences of him. This is translated into a more accurate order of the movies.

3.1. Example 1

In this example let us to consider the preferences given by $V1$, already explained in Section 1. The assessment 4 is a ranking, therefore it is not taken into account in the first part of the algorithm. For the remaining assessments, the algorithm begins by filling the Table 3 with 1 in the attributes appearing in the left part of the preferences. In the example, all the movies that are classified as comedies or thrillers have 1 in the attribute corresponding to *genre* because of statement 1; also all the movies by Woody Allen have 1 in the attribute *director* because of statement 2, and so on. Although it is not the case in the movies considered in Table 2, if there was some movie classified as both thriller and comedy, the algorithm will put a 2 in the column *genre*. Let us explain, for instance, the punctuation of 4 for the movie ω_{19} ("North by Northwest"):

- Initially $\omega_{19}.actors = \omega_{19}.actresses = \omega_{19}.directors = \omega_{19}.genres = 0$
- $\omega_{19}.genres = 1$ because of it is a thriller
- $\omega_{19}.directors = 1$ because of it has been directed by Hitchcok
- $\omega_{19}.actors = 1, \omega_{19}.genres = 2$ because it is a thriller starred by Cary Grant

Once all the preferences have been used, the columns of each movie are added (see column labeled *total1*) and the movies reorganized according to the value of that column. Notice that the movies have been grouped in only four groups since $V1$ has not given many information. Notice also that there are a lot of movies that are preferred only because of their genre, but no more information about them is known.

The next step is to use rankings to eliminate ties if possible. In this case, the only ranking is statement 4 that states that thrillers with Michael Caine are preferred to musicals with Gene Kelly. This allows to separate the movie ω_6 ("Blue ice") a thriller starred by Michael Caine from the other films with $total1 = 1$ where, in particular, there is

Table 3. Movies considered in the experiment with their attributes.

#	Movies	Acts	Actes	Dirs	Genres	total1	add	total2
ω_{19}	North by Northwest	1	0	1	2	4		4
ω_{23}	Suspicion	1	0	1	2	4		4
ω_{33}	To Catch a Thief	0	1	2	1	4		4
ω_{11}	Dr. No (James Bond)	1	0	0	2	3		3
ω_{27}	The Hunt for Red October	1	0	0	2	3		3
ω_{32}	The Rock	1	0	0	2	3		3
ω_{2}	Alice	0	0	0	1	2		2
ω_{10}	Crimes and Misdemeanors	0	0	1	1	2		2
ω_{20}	Sabrina	0	1	0	1	2		2
ω_{21}	Scoop	0	0	1	1	2		2
ω_{30}	The Philadelphia Story	0	0	1	1	2		2
ω_{6}	Blue Ice	0	0	0	1	1	0.75	1.75
ω_{4}	Anatomy of a Murder	0	0	0	1	1		1
ω_{5}	Anchors Aweigh	0	0	0	1	1		1
ω_{12}	Guess Who's Coming to Dinner	0	0	0	1	1		1
ω_{13}	High Society	0	0	0	1	1		1
ω_{14}	Husbands and Wives	0	0	0	1	1		1
ω_{15}	Key Largo	0	0	0	1	1		1
ω_{17}	Lucy	0	0	0	1	1		1
ω_{18}	Match Point	0	0	0	1	1		1
ω_{22}	Singin' in the Rain	0	0	0	1	1		1
ω_{28}	The Maltese Falcon	0	0	0	1	1		1
ω_{29}	The Party	0	0	0	1	1		1
ω_{31}	The Pink Panther	0	0	0	1	1		1

the movie ω_3 ("An American in Paris") a musical with Gene Kelly. We added 0.75 in column *add* of ω_6 only for differentiation purposes. The new punctuations are shown in the column labeled as *total2*, where ω_6 has been up in the list. For reasons of space we do not included in the table those movies that do not satisfy any preference (for instance, ω_{25} and ω_{26}). The punctuations are not assessments of how preferred are the films, they only serve to sort the universe objects. Also, the punctuations assessed using the rankings are only to avoid ties and the value we add is not important. The only requirement is to respect the order of preferences. That is to say, let us suppose we have the ranking $p > q > r > s$, a possible assessment should be: 1) to add 0.75 to all the movies satisfying p; 2) to add 0.50 to all the movies satisfying q; and 3) to add 0.25 to all the movies satisfying s. This reorder has to be made taking into account only groups of tied movies. That is to say, we did not added 0.75 to movie ω_6 if it was not tied with movie ω_3.

3.2. Example 2

In order to explain better how rankings can influence the final order of the universe objects, we introduce here the preferences provided by the volunteer $V2$. These preferences are exhaustive in ordering actors and directors, and this produced rankings. Intuitively, $V2$ has given more information about what he prefers, so this should be translated in a order of the movies more accurate than the one obtained by $V1$, where there are many ties. The set of preferences given by $V2$ are the following:

Table 4. Movies considered in the experiment with their attributes.

#	Movies	Acts	Actes	Dirs	Genres	Total1	add	Total2
ω_{30}	The Philadelphia Story	1	2	0	1	4	0.75+0.5	5.25
ω_7	Cabaret	0	1	1	2	4	0.75	4.75
ω_{15}	Key Largo	1	1	0	1	3	0.75+0.50	4.25
ω_8	Casablanca	0	1	0	2	3	0.5	3.5
ω_{19}	North by Northwest	0	0	0	2	2	0.50+0.50	3
ω_{11}	Dr. No (James Bond)	0	0	0	2	2	0.5	2.5
ω_{27}	The Hunt for Red October	0	0	0	2	2	0.5	2.5
ω_{32}	The Rock	0	0	0	2	2	0.5	2.5

1. *My favorite actor is Michael Caine, then I prefer without any order Cary Grant, Humphrey Bogart, Spencer Tracy, James Steward, Peter Sellers, David Niven and Sean Connery. The remaining ones are the least preferred (with no order).*
2. *My favorite directors are Fossey, Cukor, Houston, Wilder and Edwards. Then, I prefer Allen, Minelli, Kramer, Hitchcock and Kelly. The remaining actors are equally preferred.*
3. *I like the couples Bogart and Bacall (10/10) and Grant and K. Hepburn (9/10).*
4. *I like comedies with Woody Allen and Diane Keaton as actors.*
5. *I prefer the musical movies by Fossey*
6. *Relating actresses and genre, I like: K. Hepburn in comedies; L. Minelli in musical; U. Thurman in adventures; and Ingrid Bergman in either romantic or drama.*
7. *I prefer musical, thriller or adventures against the other genres of movies.*

The majority of statements are similar to those of $V1$. Statements 1 and 2 are rankings. In 3, $V2$ has provided a kind of assessment for couples Bogart/Bacall and Grant/Hepburn (10/10 and 9/10 respectively). We do not take into account this assessment and we interpreted that a movie starred by one of these couples is preferred to others. Notice that 4 is not satisfied by any of the movies, this happens because the volunteers are not knowledgeable of the movies we considered and probably they have in mind some other set of movies.

Following the algorithm, the movie's table is filled with items 3, 4, 5, 6 and 7. For space reasons Table 4 only shows the 8 top ranked. Notice that, as can be seen in column *Total1*, these movies are groped in three equally preferred classes. However, when the rankings are taken into account the order of the movies changes. Thus, "The Philadelphia Story" and "Cabaret" are tied as the most preferred ones, but when the rankings are used, "The Philadelphia Story" wins because it has additional points because it is starred by C. Grant (one of his favorite actors behind M. Caine) and it is directed by Cukor, one of his favorite directors, whereas "Cabaret" has extra points only because the director, B. Fossey, is one of the favorites (like Cukor). A similar situation happens with the other ties. "Key Largo" wins "Casablanca" because it is directed by J. Houston and starred by Bogart. The final order of the movies was presented to $V2$ who agrees the top 5 movies. The only difference is that he prefers "Cabaret" to "The Philadelphia Story".

4. Conclusions

After a previous study of the state of the art of preferences, we concluded that there exist a lot of well-known models for preferences but, up to our knowledge, there is a lack of real world bases of complex preferences in different domains. After that we decide to make a simple experiment consisting in obtaining free form set of preferences about movies given by volunteers and to represent them using some of the models we analyzed. In this paper we have studied first the use of conditional logics over those sets of preferences. Despite most of the preferences be close to conditional logics language it is difficult to deal with all the hide meaning contained in the sentences: default preferences depending on context, contradictions because of volunteers did not think in some dependences or priorities among attributes, and so on. For instance, one of the volunteers has ordered exhaustively directors and actors, and this leads to a contradictory ranking of movies. This can be avoiding by extending the language with priorities allowing considering the attributes in a certain order. Thus, for instance, the volunteers could say that the raking of directors is more important than the one of actors.

Secondly, we studied the use of penalty and reward logics. Particularly, we focused on reward logics since it seems natural to put on the top of the ranking those objects having the highest number of preferred attributes. Nevertheless, because the volunteers do not weight their preferences, we proposed a new reward-like model that takes into account each object attribute independently and then adds the assessments. We saw that the rankings of movies resulting from our experiment are close to the order they make of the movies we considered.

In the future we want to extent the development of our model and to explore other existing models: other types of weighted logics for preferences, as guaranteed possibilistic logic and qualitative choice logic; and also other models based on constraints [5], meta-constraints [4], or satisfiability [1].

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