

**Developments in Fuzzy Sets,
Intuitionistic Fuzzy Sets,
Generalized Nets and Related Topics.
Volume I: Foundations**

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**Systems Research Institute
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Using bipolar satisfaction degrees in fuzzy querying

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Abstract

As humans often use both independent positive and negative statements when communicating, adequately dealing with heterogeneous bipolarity has become an important topic in recent research on soft computing in information systems. In the context of database systems, bipolarity can be handled as well at the level of database modelling as at the level of database querying. In this paper, the handling of bipolarity in selection conditions of relational database queries is dealt with. More specifically, it is presented how bipolar satisfaction degrees can be used to model query satisfaction in case of heterogeneous bipolar query specifications. Two modelling approaches of heterogeneous bipolar specifications of user preferences in selection conditions are studied and compared with each other. In the first approach, bipolarity is specified inside elementary selection conditions. In the second approach, bipolarity is handled by considering two independent poles of query conditions, hence reflecting bipolarity at the level between elementary selection conditions.

Keywords: Fuzzy database querying, bipolarity, query satisfaction, selection conditions.

1 Introduction

In the context of information handling, the term *bipolarity* usually refers to the fact that information can either be expressed in a positive or in a negative way. Indeed, in human communication some statements express what people consider that is true, positive, preferred, wanted, satisfactory, etc., while other statements express what is false, negative, disliked, unwanted, unsatisfactory, etc. This phenomenon has already been studied in different academic disciplines like psychology, artificial intelligence and information management (cf. [2, 4]).

In these studies, it has been observed that bipolar information in general has *heterogeneous* characteristics [9], which means that positive and negative information do not necessarily have to complement each other. The two major causes of heterogeneity are due to underspecification and over specification of information. With underspecification it is meant that there is a lack of information, which might for example be caused by indifference or by (partial) unavailability of data. Over specification refers to the fact that information can be inconsistent, i.e., it contains data which are contradictory to each other, as human communication in general is not always consistent.

One of the major aims and challenges of modelling and handling information with modern information systems is to adequately deal with and reflect data semantics [11]. This implies that imperfections in the data like imprecision, vagueness, uncertainty, incompleteness or inconsistency, should be modelled and handled as natural as possible without introducing a loss of information. Research on soft computing techniques that are based on fuzzy set theory [14] and its related possibility theory [15, 7] has already resulted in so-called ‘fuzzy’ database techniques which help to solve the problem of imperfect information handling. As well techniques for imperfect data modelling in so-called ‘fuzzy’ databases, as techniques for ‘fuzzy’ querying of both regular and ‘fuzzy’ databases have been developed (see, e.g., [10]). In the remainder of this work, only ‘fuzzy’ querying of regular databases is considered.

‘Fuzzy’ querying techniques support expressing *flexible user preferences* in the query specifications. As such, users can specify what they are searching for using linguistic terms to denote, e.g., search values in elementary conditions, relative importance of elementary conditions, and linguistic quantifiers. In recent years, the issue of handling heterogeneous bipolarity in ‘fuzzy’ query specifications has been studied [8, 5, 3]. Up to now, *query satisfaction* in case of queries with heterogeneous bipolar specifications has mainly been modelled and handled with regular frameworks. As such, a framework of query satisfaction degrees, which take their values in the unit interval $[0, 1]$, is mostly used to support ‘fuzzy’

querying of regular databases. Such an approach implies that during query processing, the heterogeneous bipolarity in the user preferences has to be transformed and reflected into a unipolar satisfaction degree on a single scale, which is no longer heterogeneous.

This loss of heterogeneity in query satisfaction modelling implies that, with respect to a given database record, over and underspecification of a user preference in a query has either to be transformed into a positive or a negative appreciation regarding the fact whether the record belongs to the result set of the query or not. Indifference (or even inconsistency) about the record's membership in the result set could not be reflected. To overcome this kind of information loss, a query satisfaction modelling framework based on *bipolar satisfaction degrees* has recently been presented [12].

In the remainder of this paper, we present how bipolar satisfaction degrees can be used to handle heterogeneous bipolarity in selection conditions of relational database queries. Hereby, we make a distinction between the case where bipolarity is specified inside elementary selection conditions and the case where the bipolarity is handled by considering two independent poles of query conditions, hence reflecting bipolarity at the level between elementary selection conditions. The paper is further structured as follows. In Section 2, we introduce the definition and basic properties of bipolar satisfaction degrees. The techniques for handling heterogeneous bipolarity specified inside and between elementary selection conditions are subsequently described and illustrated in Sections 3 and 4, and compared to each other in Section 5. Finally, some overall conclusions and some specifications of further work in this area are given in Section 6.

2 Bipolar satisfaction degrees

To handle query satisfaction in case of heterogeneous bipolar queries in a semantically richer way, a logical framework based on *bipolar query satisfaction degrees* (BSD's) has been proposed [12].

2.1 Definition and basic characteristics

By definition, a *bipolar satisfaction degree* (BSD) is a pair

$$(s, d), \quad s, d \in [0, 1] \tag{1}$$

that consists of a *satisfaction degree* s and a *dissatisfaction degree* d , which are independent of each other and their values in the unit interval $[0, 1]$. Extreme values for s and d are 0 ('not at all') and 1 ('fully'). As such and as special cases,

the BSD $(1, 0)$ represents ‘fully satisfied, not dissatisfied at all’, whereas $(0, 1)$ represents ‘not satisfied at all, fully dissatisfied’. The set of all BSD’s will be denoted by $\tilde{\mathbb{B}}$, i.e., $\tilde{\mathbb{B}} = \{(s, d) | s, d \in [0, 1]\}$.

The *specification* $\sigma((s, d)) = s + d$ ($\in [0, 2]$) of a BSD (s, d) indicates how the BSD is specified:

- $\sigma((s, d)) < 1$: the BSD is *underspecified*. In the context of query evaluation, this means that there is an amount of indifference (or hesitation), $1 - s - d$, about whether the query is satisfied or not.
- $\sigma((s, d)) = 1$: the BSD is *fully specified*. In fact, in this case it holds that $d = 1 - s$, so this is the case of regular, involutive, query satisfaction modelling.
- $\sigma((s, d)) > 1$: the BSD is *overspecified* and denotes an amount, $s + d - 1$, of conflict regarding the evaluation of the query.

2.2 Basic aggregation of BSD’s

BSD’s can be aggregated in several ways. In this paper, we only describe the standard logical operators for conjunction (\wedge), disjunction (\vee) and negation (\neg). The presented formula’s are all based on the minimum and maximum operators. Alternative aggregation operators, based on other triangular norms and co-norms, can be used if a reinforcement effect is needed or desired.

2.2.1 Conjunction.

The conjunction of two BSD’s $(s_1, d_1), (s_2, d_2) \in \tilde{\mathbb{B}}$ is defined by

$$(s_1, d_1) \wedge (s_2, d_2) = (\min(s_1, s_2), \max(d_1, d_2)). \quad (2)$$

Herewith it is reflected that the conjunction is considered to be satisfactory to the extent that both BSD’s are satisfied and unsatisfactory to the extent that at most one of the BSD’s is unsatisfied.

2.2.2 Disjunction.

The disjunction of two BSD’s $(s_1, d_1), (s_2, d_2) \in \tilde{\mathbb{B}}$ is defined by

$$(s_1, d_1) \vee (s_2, d_2) = (\max(s_1, s_2), \min(d_1, d_2)). \quad (3)$$

2.2.3 Negation.

The negation of a BSD $(s, d) \in \tilde{\mathbb{B}}$ is defined by

$$\neg(s, d) = (d, s). \quad (4)$$

The negation is thus obtained by switching the satisfaction degree and dissatisfaction degree of the BSD.

3 Handling bipolarity inside elementary selection conditions

3.1 Query specification

Heterogeneous bipolar specifications of user preferences inside elementary query selection conditions can formally be modelled with a bipolar extension of fuzzy sets. *Atanassov (intuitionistic) fuzzy sets* (AFS's) [1] are an example of such an extension. An AFS F over a universe U is formally defined by

$$F = \{(x, \mu_F(x), \nu_F(x)) | (x \in U) \wedge (0 \leq \mu_F(x) + \nu_F(x) \leq 1, \forall x \in U)\} \quad (5)$$

where $\mu_F : U \rightarrow [0, 1]$ and $\nu_F : U \rightarrow [0, 1]$ are respectively called the membership and non-membership degree functions and $0 \leq \mu_F(x) + \nu_F(x) \leq 1, \forall x \in U$ reflects the consistency condition, which states that an AFS can not be over specified.

Consider an elementary selection condition c_A on a (relational) database attribute A with domain dom_A which expresses the user's preferences related to the tuple values of A . Then, in its simplest general form c_A can be modelled by an AFS

$$c_A = \{(x, \mu_{c_A}(x), \nu_{c_A}(x)) | (x \in dom_A)\}. \quad (6)$$

The membership function μ_{c_A} defines the positive preferences of the user, i.e., the membership grade $\mu_{c_A}(x)$ associated with a domain value $x \in dom_A$ denotes to what extent x is considered to be satisfactory with respect to attribute A . The non-membership function ν_{c_A} defines the negative preferences of the user, i.e., the non-membership grade $\nu_{c_A}(x)$ associated with a domain value $x \in dom_A$ thus denotes to what extent x is considered to be unsatisfactory. To adequately reflect the real-world cases where user preferences can be over specified the consistency condition for AFSs can even be relaxed, which implies that $\mu_{c_A}(x) + \nu_{c_A}(x) \leq 1, \forall x \in dom_A$ must not necessarily hold.

Table 1: Relation Car

ID	Colour	Fuel consumption	Age
001	Black	5 litres/100km	4 years
002	Red	7 litres/100km	2 years
003	Blue	4 litres/100km	3 years
004	Red	5 litres/100km	7 years

In case the user only has positive preferences, only the membership function μ_{c_A} must be specified and the non-membership function is considered to be the inverse of the membership function, i.e., $\nu_{c_A} = 1 - \mu_{c_A}$. Likewise, if the user only has negative preferences, then only the non-membership function ν_{c_A} must be specified and the membership function is considered to be the inverse of the non-membership function, i.e., $\mu_{c_A} = 1 - \nu_{c_A}$.

3.2 Query evaluation

In general, a query consists of several elementary selection conditions which are interconnected by logical operators.

In the simplest approach, the evaluation $e(c_A)(t)$ of a database tuple t against an elementary selection condition c_A will result in a BSD

$$e(c_A)(t) = (s_{c_A}^t, d_{c_A}^t) = (\mu_{c_A}(t[A]), \nu_{c_A}(t[A])) \quad (7)$$

where $t[A]$ denotes the actual value of attribute A in tuple t . Hence, the satisfaction degree $s_{c_A}^t$ and dissatisfaction degree $d_{c_A}^t$ are respectively obtained from the evaluation of the membership function μ_{c_A} and non-membership function ν_{c_A} .

Composed selection conditions can be evaluated by first evaluating their elementary conditions by applying Eq.7 and then aggregating the resulting elementary BSD's by applying the aggregation operators for conjunction (Eq.2), disjunction (Eq.3) and negation (Eq.4). More advanced aggregation techniques are possible.

3.3 Example

As an example consider that somebody is looking for a second hand car in a simple relational database as represented in Table 1.

Suppose that this person does not want to buy a black car, and prefers a red car which is either younger than 6 years or has an average fuel consumption that is less than 5 litres/100km.

Table 2: Result set of the query

ID	BSD_{Colour}	BSD_{Fuel}	BSD_{Age}	$BSD_{overall}$	Ranking
002	(1, 0)	(0, 1)	(1, 0)	(1, 0)	1
003	(0, 0)	(1, 0)	(1, 0)	(0, 0)	0
004	(1, 0)	(0, 1)	(0, 1)	(0, 1)	-1
001	(0, 1)	(0, 1)	(0.7, 0.3)	(0, 1)	-1

The selection condition for the query that corresponds to these requirements is

$$c_{Colour} \wedge (c_{Fuel} \vee c_{Age})$$

where

- $c_{Colour} = \{(Black, 0, 1), (Red, 1, 0)\}$ (Bipolar preferences.)
The condition is specified by an AFS.
- $c_{Fuel} = \{(1, 1), (2, 1), (3, 1), (4, 1)\}$ (Positive preferences.)
The specification of the membership function is sufficient.
- $c_{Age} = \{(1, 1), (2, 1), (3, 1), (4, 0.7), (5, 0.5), (6, 0.3)\}$ (Positive preferences.) The specification of the membership function is sufficient.

Table 2 represents the car ID’s (*ID*) of the result set of the query, together with their corresponding individual and aggregated BSD’s and ranking value. When assigning equal importance to the satisfaction and dissatisfaction degree of a BSD (s, d), the ranking value is simply computed by taking the difference $s - d$. Only two cars (002 and 003) qualify to satisfy the user’s needs. The blue car (003) is obtained thanks to the modelling of the user’s (implicit) indifference for other colours than black and red, which is represented in the AFS c_{Colour} . With ‘fuzzy’ querying techniques that do not support heterogeneous bipolarity in the query specification cars like 003, although potentially interesting to the user, will not be retrieved.

4 Handling bipolarity between elementary selection conditions

4.1 Query specification

An alternative way to handle heterogeneous bipolar user preferences in selection conditions is to consider the bipolarity at the level of elementary conditions (instead of inside the conditions). This approach is taken in, e.g., [8] where two different poles of conditions are considered: conditions that are really required

and conditions that are preferably satisfied. A tuple then satisfies a query if it at least satisfies the required conditions. Satisfaction of some of the other preferred conditions adds a bonus to the tuple satisfaction.

To illustrate the use of BSD's in such a setting, we study a slightly different, but compatible approach in this section. Hereby, the selection condition of a query is defined by a pair

$$(Q^{pos}, Q^{neg}) \quad (8)$$

of logical expressions Q^{pos} and Q^{neg} , which respectively reflect all the positive and all negative user preferences with respect to the result of the query [6]. Thus, all positive preferences are put together in a composed query condition Q^{pos} and all negative preferences are gathered in the condition Q^{neg} . In this simple approach, the use of the negation operator is not allowed in the specification of Q^{pos} and Q^{neg} (for the sake of clarity). Hence, the composed conditions Q^{pos} and Q^{neg} can respectively be considered as poles of positive and negative conditions.

All elementary conditions in Q^{pos} and Q^{neg} can be specified in a regular ‘fuzzy’ way [13]. This implies that a condition c_A on a (relational) database attribute A with domain dom_A in its simplest form can be modelled by a regular fuzzy set

$$c_A = \{(x, \mu_{c_A}(x)) | (x \in dom_A)\}. \quad (9)$$

If c_A is part of Q^{pos} , then the membership function μ_{c_A} defines the positive preferences of the user regarding the value of A . Thus, the membership grade $\mu_{c_A}(x)$ associated with a domain value $x \in dom_A$ denotes to what extent x is considered to be satisfactory with respect to attribute A . On the other hand, if c_A is part of Q^{neg} , then the membership function μ_{c_A} reflects the user’s negative preferences. Thus, the membership grade $\mu_{c_A}(x)$ then denotes to what extent x is considered to be unsatisfactory with respect to attribute A .

4.2 Query evaluation

Query evaluation is done by separately evaluating Q^{pos} and Q^{neg} . The evaluation of Q^{pos} will result in the satisfaction degree s and the evaluation of Q^{neg} will determine the dissatisfaction degree d of the resulting BSD. During evaluation of both expressions Q^{pos} and Q^{neg} , the elementary conditions are evaluated in a regular way by using the membership function μ_{c_A} . As such, in the simplest approach, the evaluation $e(c_A)[t]$ of a database tuple t against an elementary selection condition c_A will result in a matching degree

$$e(c_A)[t] = \mu_{c_A}(t[A]) \quad (10)$$

where $t[A]$ denotes the actual value of attribute A in tuple t .

The aggregation of the matching degrees is done in accordance with the semantics of the aggregation of BSD's as presented in Section 2. This implies that the following rules are used:

- Aggregation of the positive expression Q^{pos} . Herewith, all matching degrees are interpreted as satisfaction degrees.

- The *conjunction* of two satisfaction degrees $s_1, s_2 \in [0, 1]$ is defined by

$$s_1 \wedge s_2 = \min(s_1, s_2). \quad (11)$$

- The *disjunction* of two satisfaction degrees $s_1, s_2 \in [0, 1]$ is defined by

$$s_1 \vee s_2 = \max(s_1, s_2). \quad (12)$$

- Aggregation of the negative expression Q^{neg} . Herewith, all matching degrees are interpreted as dissatisfaction degrees.

- The *conjunction* of two dissatisfaction degrees $d_1, d_2 \in [0, 1]$ is defined by

$$d_1 \wedge d_2 = \max(d_1, d_2). \quad (13)$$

- The *disjunction* of two dissatisfaction degrees $d_1, d_2 \in [0, 1]$ is defined by

$$d_1 \vee d_2 = \min(d_1, d_2). \quad (14)$$

Besides the minimum and maximum, alternative aggregation operators, based on other triangular norms and co-norms, can be used if a reinforcement effect is needed or desired.

The BSD resulting from the evaluation $e((Q^{pos}, Q^{neg}))(t)$ of a database tuple t against a selection condition (Q^{pos}, Q^{neg}) is then obtained by

$$e((Q^{pos}, Q^{neg}))(t) = (e(Q^{pos})(t), e(Q^{neg})(t)). \quad (15)$$

where $e(Q^{pos})(t)$ and $e(Q^{neg})(t)$ are obtained as described above.

4.3 Example

Reconsider the simple relational database that is represented in Table 1 of Sub-section 3.3 and the same situation where:

The user does not want to buy a black car, and prefers a red car which is either younger than 6 years or has an average fuel consumption that is less than 5 litres/100km.

Table 3: Result set of the query

ID	s_{Colour}	s_{Fuel}	s_{Age}	d_{Colour}	d_{Fuel}	d_{Age}	BSD	Ranking
002	1	0	1	0	1	0	(1, 0)	1
003	0	1	1	0	0	0	(0, 0)	0
004	1	0	0	0	1	1	(0, 1)	-1
001	0	0	0.7	1	1	0	(0, 1)	-1

In this second approach, the selection condition for the query that corresponds to these requirements is

$$(Q^{pos}, Q^{neg})$$

where

- $Q^{pos} = c_{Colour}^{pos} \wedge (c_{Fuel}^{pos} \vee c_{Age}^{pos})$
- $Q^{neg} = c_{Colour}^{neg} \wedge (c_{Fuel}^{neg} \vee c_{Age}^{neg})$

with

- $c_{Colour}^{pos} = \{(Red, 1)\}$
- $c_{Colour}^{neg} = \{(Black, 1)\}$
- $c_{Fuel}^{pos} = \{(1, 1), (2, 1), (3, 1), (4, 1)\}$
- $c_{Fuel}^{neg} = \{(5, 1), (6, 1), (7, 1), (8, 1)\}$
- $c_{Age}^{pos} = \{(1, 1), (2, 1), (3, 1), (4, 0.7), (5, 0.5), (6, 0.3)\}$
- $c_{Age}^{neg} = \{(5, 0.5), (6, 0.7), (7, 1), (8, 1)\}$

Table 3 represents the car ID's (*ID*) of the result set of the query, together with their corresponding individual and aggregated matching degrees, their overall BSD and ranking value, which is again computed by taking the difference $s - d$. According to this method, the same two cars (002 and 003) qualify to satisfy the user's needs. The blue car (003) is again obtained thanks to the modelling of the user's (implicit) indifference for other colours than black and red, which is here reflected by the positive and negative preferences on *Colour*.

5 Comparison

When comparing the two techniques that are described in Sections 3 and 4 it becomes clear that heterogeneous bipolarity in user preferences should *either* be specified inside the elementary query conditions or between. Hence, combining both techniques in a single query formulation does not make sense.

Both examples in Subsections 3.3 and 4.3 reveal that similar query results are obtained on condition that attention is paid to the correct translation of the user preferences. As such, it is important to add the negative or positive counterparts of elementary conditions which are not heterogeneous bipolar.

When modelling the bipolarity inside the elementary query conditions this could be smoothly done as illustrated in Section 3: When using an AFS, the user only has to specify the membership function in case he or she only has positive preferences. The non-membership function is then assumed to be the regular inverse of the membership function. Likewise, in case of only negative preferences the user only has to specify the non-membership function and the membership function is assumed to be the inverse of this non-membership function.

When modelling the bipolarity between the elementary query conditions, the user should take care that for each condition in Q^{neg} , a positive counterpart is present in Q^{pos} and vice versa. In practical cases this could be counter intuitive. Reconsidering the example of Subsection 4.3 it follows that the negative counterparts c_{Fuel}^{neg} and c_{Age}^{neg} , although not explicitly specified in the initial query formulation, can not be safely omitted. Indeed, without these conditions $Q^{neg} = c_{Colour}^{neg}$, such that for the red car 004, Q^{neg} evaluates to 0 and the overall BSD becomes $(0, 0)$ (instead of $(0, 1)$), which would wrongly indicate that the car satisfies the user's preferences.

Hence, from these considerations it clearly follows that AFS's are a natural and ‘intuitive’ means to deal with heterogeneous bipolarity in practical ‘fuzzy’ database querying applications.

6 Conclusions and further work

Techniques to explicitly deal with heterogeneous bipolarity in query specifications give users facilities to express their query preferences in a more natural way. As well positive as negative preferences can be specified in the queries and in those cases where the positive and negative preferences do not complement to each other indifference (or sometimes also inconsistency) is reflected. Explicitly dealing with indifference brings along with it that database tuples which do not satisfy the positive preferences, but do neither satisfy the negative preferences are returned

in the query result. This can provide the user with potentially interesting tuples that otherwise, with regular ‘fuzzy’ querying techniques, would not be retrieved.

From a theoretical point of view, heterogeneous bipolarity in selection conditions can either be specified inside elementary conditions or at the level between elementary conditions. However, from a practical, usability point of view, dealing with bipolarity inside elementary selection conditions best corresponds to the user’s intuition. Atanassov intuitionistic fuzzy sets (AFS’s) offer a convenient and natural means to model the bipolarity in that case.

Bipolar satisfaction degrees (BSD’s) can be used to express query satisfaction in a semantic richer way. They separately and independently indicate to which extent a condition is satisfied and to which extent the condition is not satisfied. In this paper, we presented how BSD’s can be used to deal with heterogeneous bipolar selection conditions. For both kinds of specifications —inside and between elementary conditions— a basic technique for query evaluation has been described and both techniques have been compared to each other.

Further research in this area is welcome. More advanced aggregation techniques for BSD’s are required. There is a need to cope with weights. Another interesting research topic is the more in depth study of the query processing semantics in case of under or over specification of conditions. Furthermore, the use of heterogeneous bipolarity and BSD’s in the other (relational) algebra operators should be studied. In the near future, we plan to continue our research in these directions.

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The papers presented in this Volume 2 constitute a collection of contributions, both of a foundational and applied type, by both well-known experts and young researchers in various fields of broadly perceived intelligent systems.

It may be viewed as a result of fruitful discussions held during the Eighth International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2009) organized in Warsaw on October 16, 2009 by the Systems Research Institute, Polish Academy of Sciences, in Warsaw, Poland, Centre for Biomedical Engineering, Bulgarian Academy of Sciences in Sofia, Bulgaria, and WIT – Warsaw School of Information Technology in Warsaw, Poland, and co-organized by: the Matej Bel University, Banska Bistrica, Slovakia, Universidad Publica de Navarra, Pamplona, Spain, Universidade de Tras-Os-Montes e Alto Douro, Vila Real, Portugal, and the University of Westminster, Harrow, UK:

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The Eighth International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2009) has been meant to commence a new series of scientific events primarily focused on new developments in foundations and applications of intuitionistic fuzzy sets and generalized nets pioneered by Professor Krassimir T. Atanassov. Moreover, other topics related to broadly perceived representation and processing of uncertain and imprecise information and intelligent systems are discussed.

We hope that a collection of main contributions presented at the Workshop, completed with many papers by leading experts who have not been able to participate, will provide a source of much needed information on recent trends in the topics considered.

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